

LECTURE 5: NATURAL LANGUAGE PROCESSING APPLICATIONS OF LLMS

Creating Business Value with Generative AI
Fall 2025



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

01. October 2025

Magnus Bender
Assistant Professor



WHY THIS LECTURE?



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

01. October 2025

Magnus Bender
Assistant Professor

2



WHY THIS LECTURE?

- This lecture focuses on practical applications of classification, a core task in Natural Language Processing (NLP).

WHY THIS LECTURE?

- This lecture focuses on practical applications of classification, a core task in Natural Language Processing (NLP).
- Almost anything you do with an LLM uses – to some extent – classification.
 - Asking an LLM to evaluate whether something is a good idea; quality of idea is a „class“
 - Asking an LLM to generate text in a particular style; style is a "class"

WHY THIS LECTURE?

- This lecture focuses on practical applications of classification, a core task in Natural Language Processing (NLP).
- Almost anything you do with an LLM uses – to some extent – classification.
 - Asking an LLM to evaluate whether something is a good idea; quality of idea is a „class“
 - Asking an LLM to generate text in a particular style; style is a "class"
- Today's class will introduce some core concepts of classification, and we'll take a deeper dive into the specifics of how the two empirical papers do classification.

THIS LECTURE RELATIVE TO YOUR PROJECT

This lecture is intended to give you:

THIS LECTURE RELATIVE TO YOUR PROJECT

This lecture is intended to give you:

1. A better understanding of breaking down a process from the technical, NLP oriented, side

THIS LECTURE RELATIVE TO YOUR PROJECT

This lecture is intended to give you:

1. A better understanding of breaking down a process from the technical, NLP oriented, side
2. A better sense of how you can classify (or more general: analyze) things:
 - customer emails,
 - product reviews,
 - ...

THIS LECTURE RELATIVE TO YOUR PROJECT

This lecture is intended to give you:

1. A better understanding of breaking down a process from the technical, NLP oriented, side
2. A better sense of how you can classify (or more general: analyze) things:
 - customer emails,
 - product reviews,
 - ...
3. An overview of NLP tasks across disciplines that you can try to match to your use-case.

AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks

AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks
 - What do we often want to do with large collections of documents?

AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks
 - What do we often want to do with large collections of documents?
 - What are the different kinds of tasks?
 - How do they work?

AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks
 - What do we often want to do with large collections of documents?
 - What are the different kinds of tasks?
 - How do they work?
 - Which kind of task requires which type of model and/ or available data
 - Which kind of task may not be suitable for an LLM

AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks
 - What do we often want to do with large collections of documents?
 - What are the different kinds of tasks?
 - How do they work?
 - Which kind of task requires which type of model and/ or available data
 - Which kind of task may not be suitable for an LLM
- NLP tasks with LLMs (readings)

AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks
 - What do we often want to do with large collections of documents?
 - What are the different kinds of tasks?
 - How do they work?
 - Which kind of task requires which type of model and/ or available data
 - Which kind of task may not be suitable for an LLM
- NLP tasks with LLMs (readings)
 - How well do they perform – at least according to the readings
 - How do we know, and what can we do with

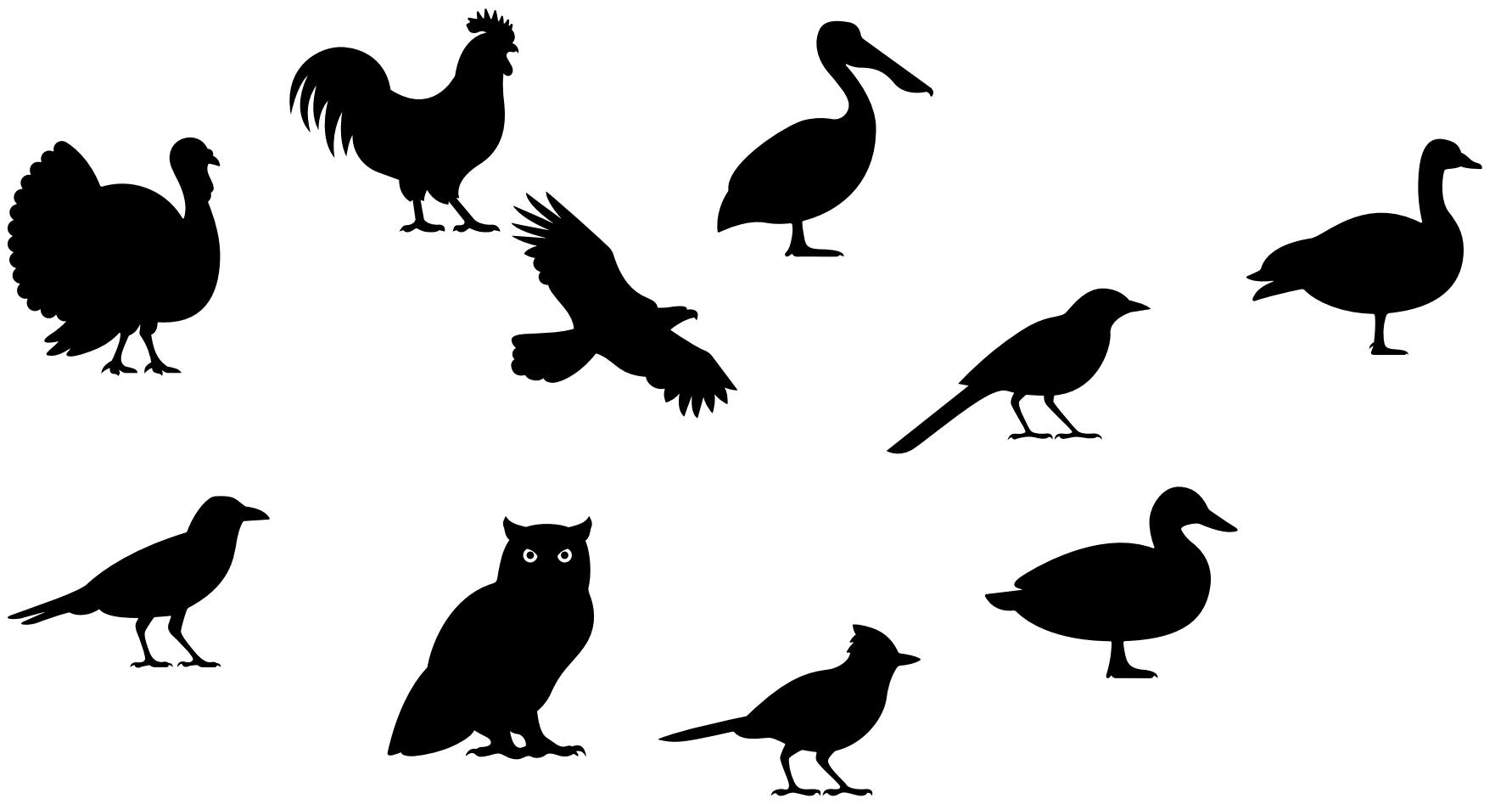
AGENDA FOR TODAY

- Natural Language Processing (NLP) tasks
 - What do we often want to do with large collections of documents?
 - What are the different kinds of tasks?
 - How do they work?
 - Which kind of task requires which type of model and/ or available data
 - Which kind of task may not be suitable for an LLM
- NLP tasks with LLMs (readings)
 - How well do they perform – at least according to the readings
 - How do we know, and what can we do with
- A very brief overview of NLP tasks across different disciplines, for your inspiration

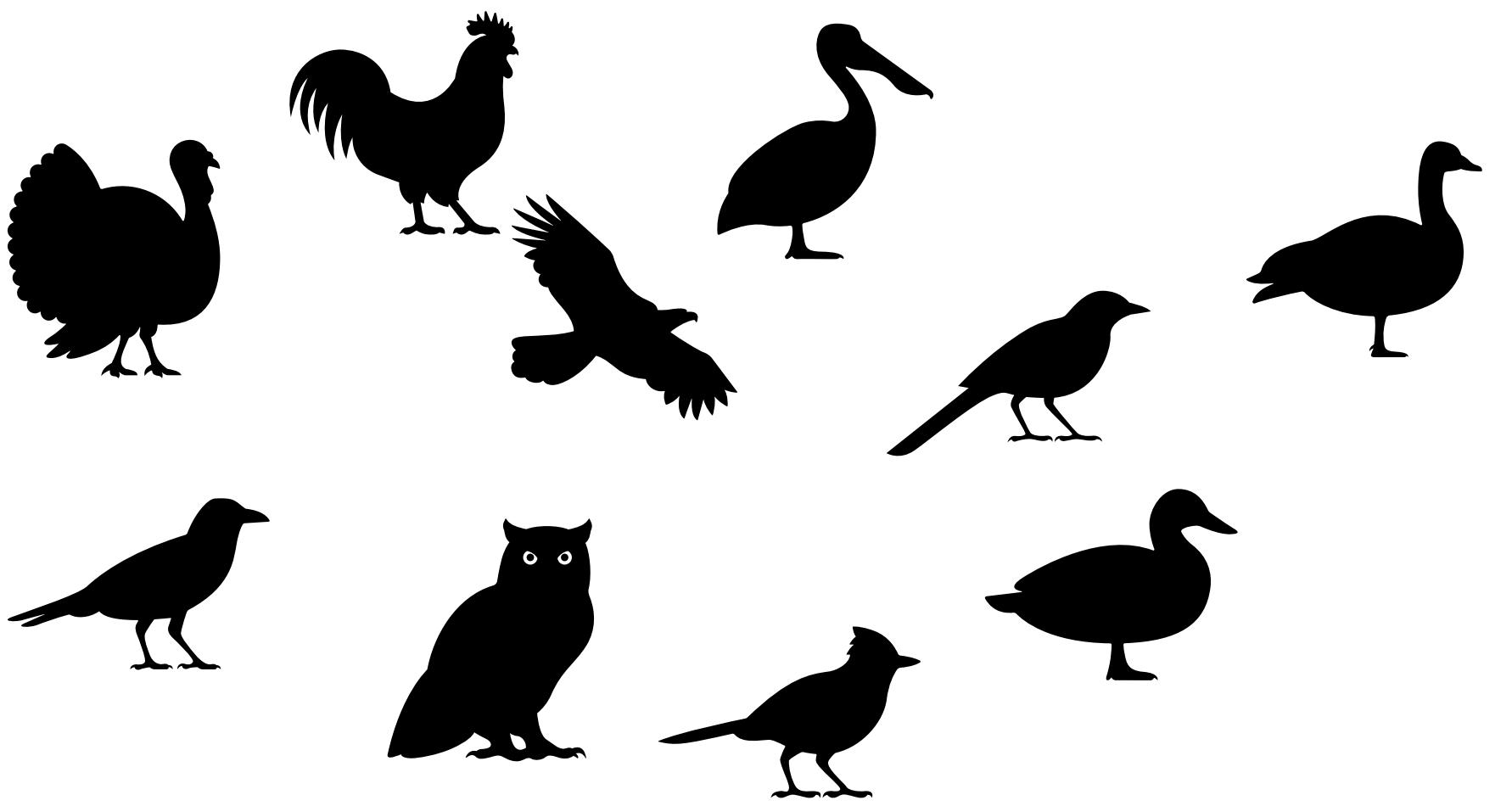
CLASSIFICATION

... in a machine learning context

What are these things?!?



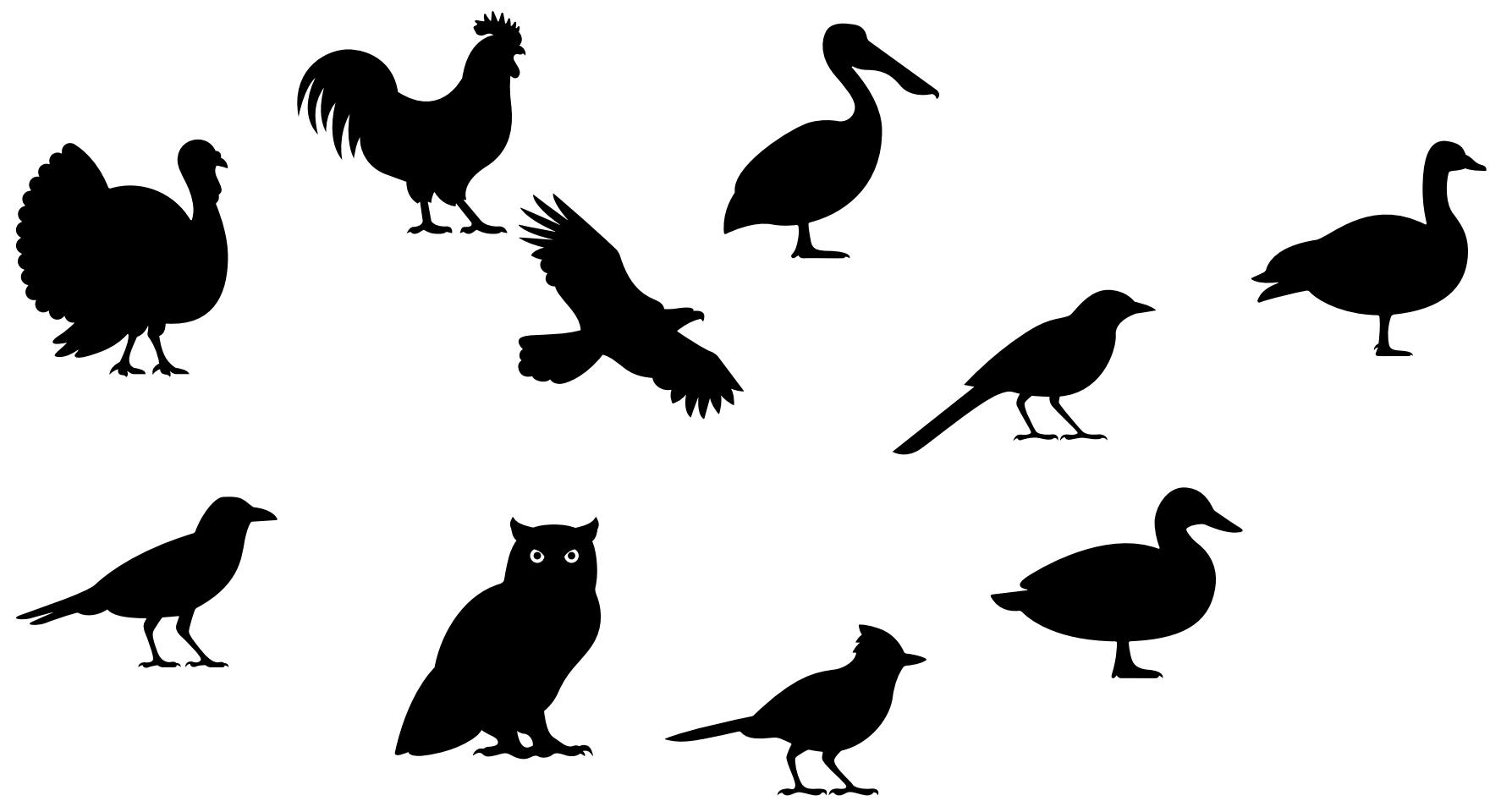
What are these things?!?



Bird **classes**:

- Hen
- Duck
- Goose
- ...

What are these things?!?



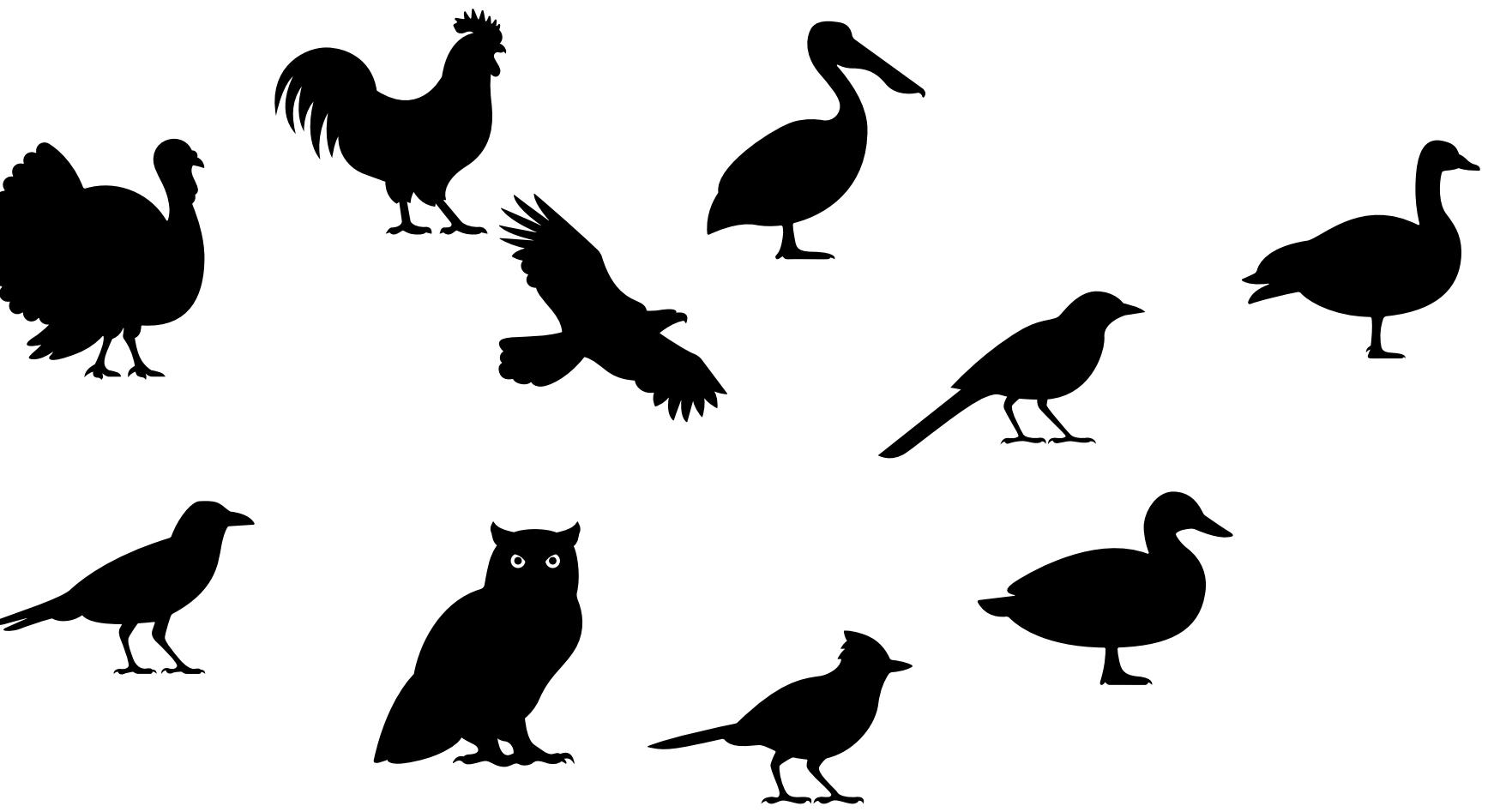
Bird **features**:

- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

- Hen
- Duck
- Goose
- ...

CORE CONCEPTS: FEATURES AND CLASSES



Bird **features**:

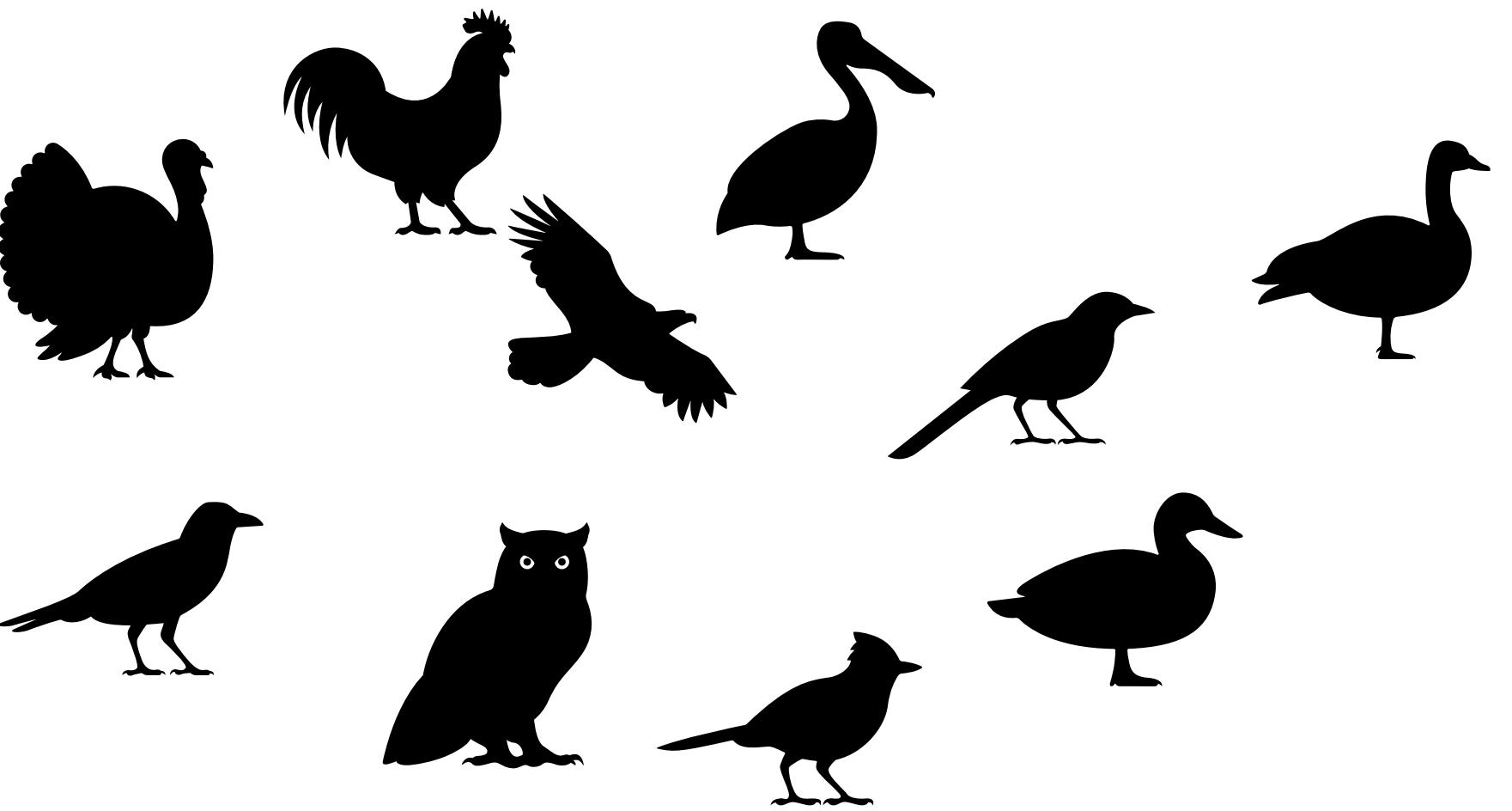
- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

- Hen
- Duck
- Goose
- ...

CORE CONCEPTS: FEATURES AND CLASSES

- **Features:** Specific (processed data) that defines a thing both in its own right, and in contrast to other things



Bird **features**:

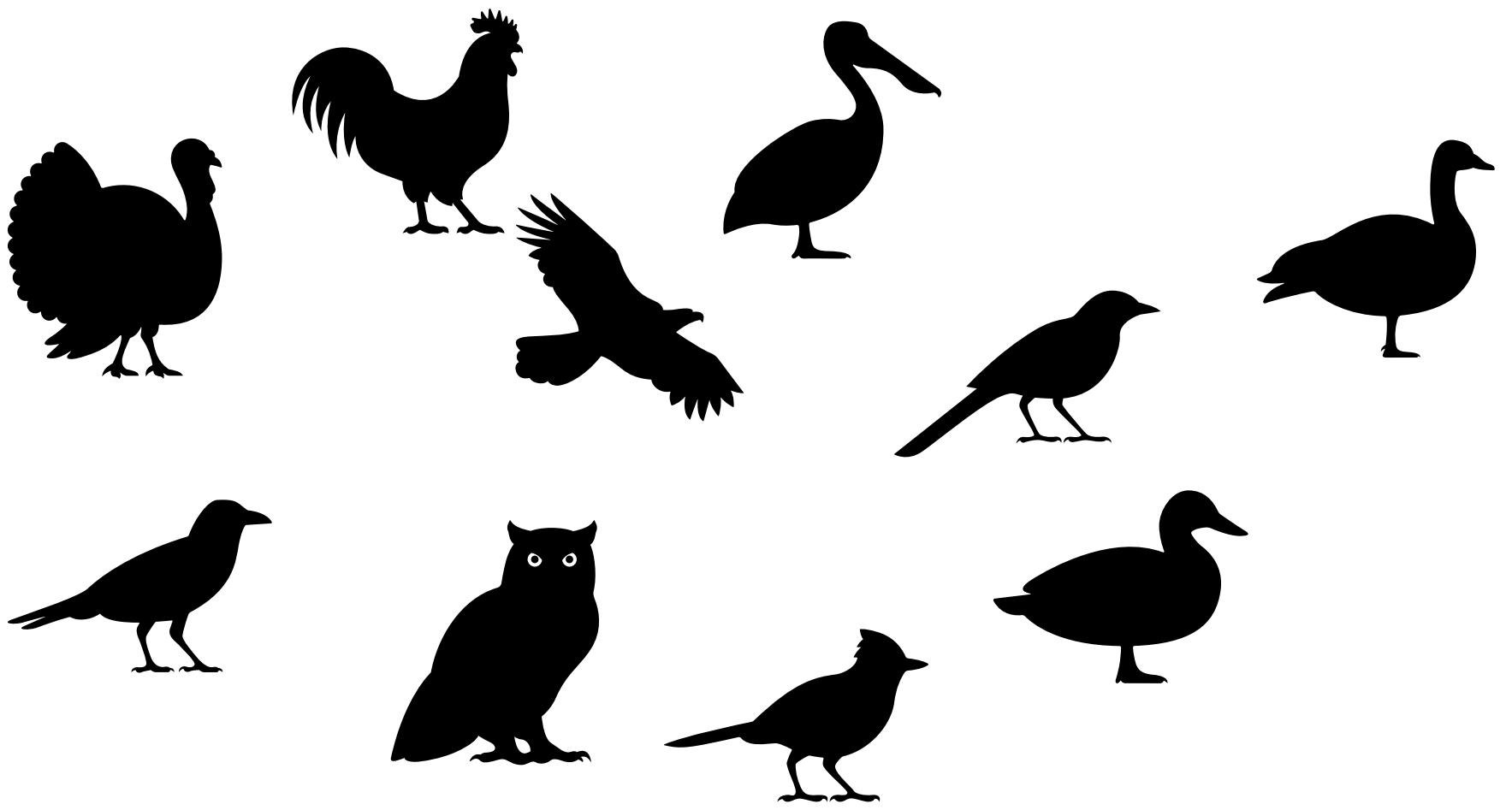
- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

- Hen
- Duck
- Goose
- ...

CORE CONCEPTS: FEATURES AND CLASSES

- **Features:** Specific (processed data) that defines a thing both in its own right, and in contrast to other things
- **Classes:** Collections of things with shared features that we want to think of as a “something”



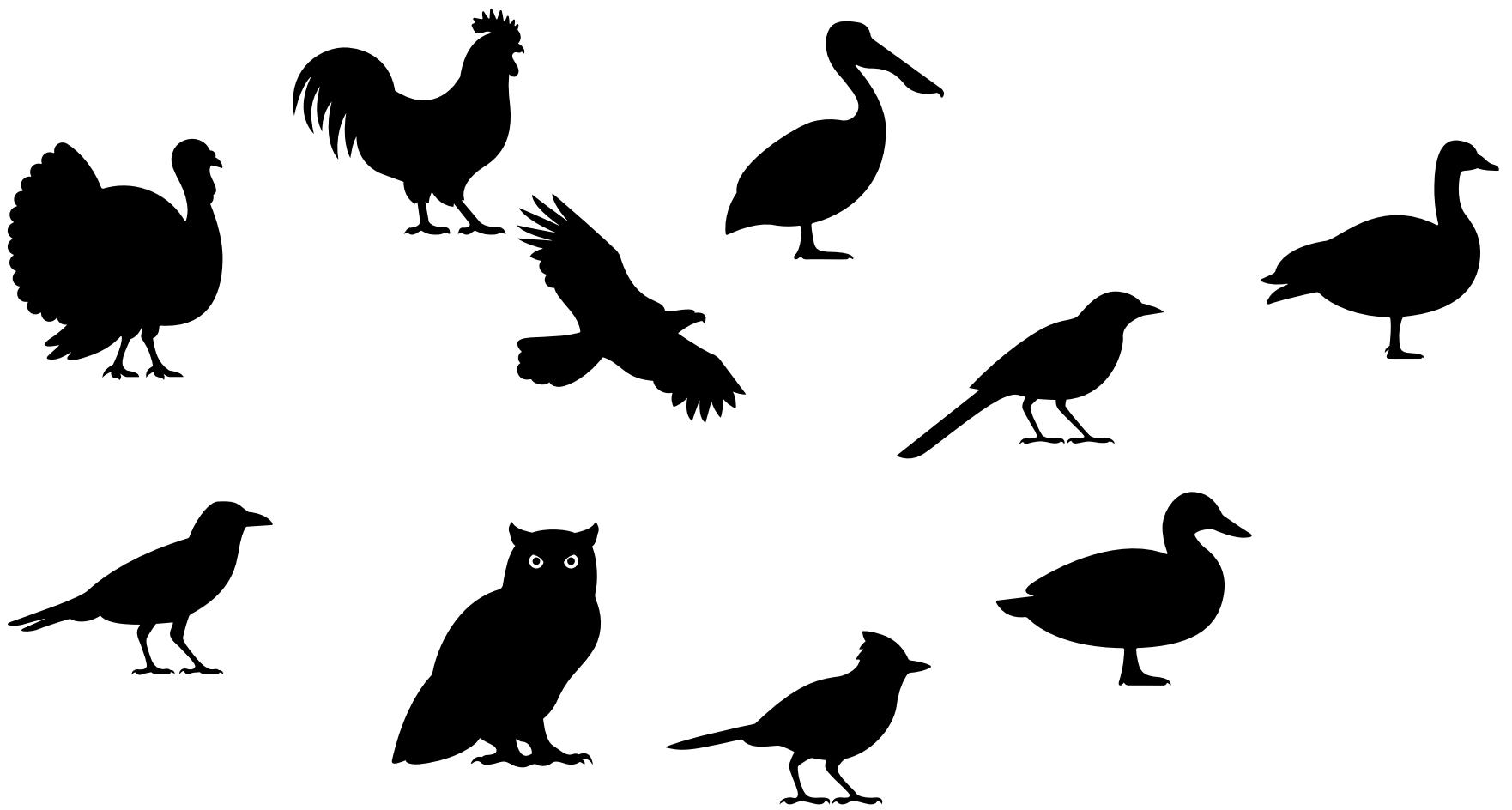
Bird features:

- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird classes:

- Hen
- Duck
- Goose
- ...

WHAT'S HARD ABOUT THAT?



Bird **features**:

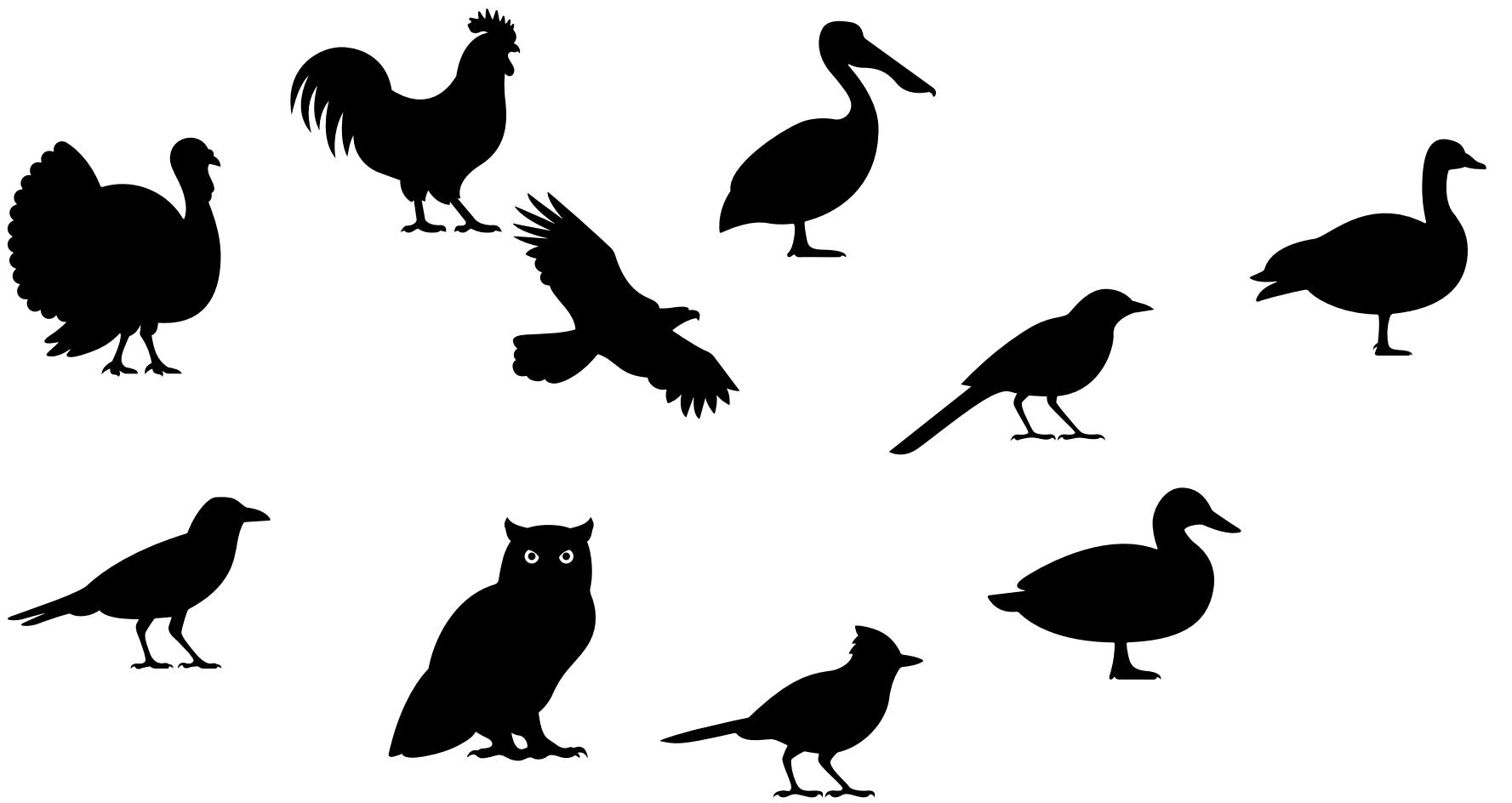
- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

- Hen
- Duck
- Goose
- ...

WHAT'S HARD ABOUT THAT?

Features and classes seem easy enough, right?



Bird **features**:

- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

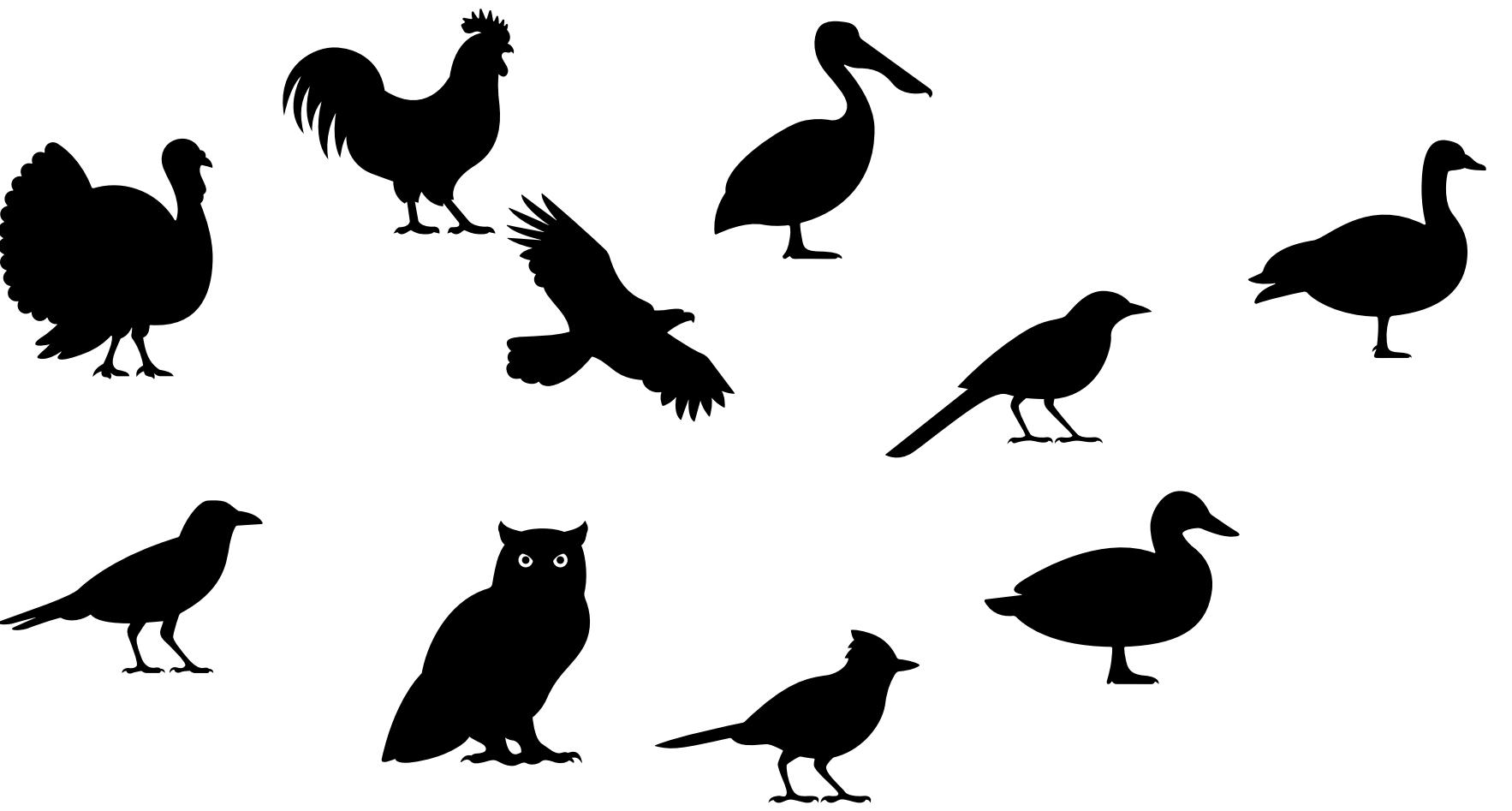
Bird **classes**:

- Hen
- Duck
- Goose
- ...

WHAT'S HARD ABOUT THAT?

Features and classes seem easy enough, right?

For birds, biologists have already done most of the work for us and defined features, like birds. They have structured the data for us.



Bird **features**:

- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

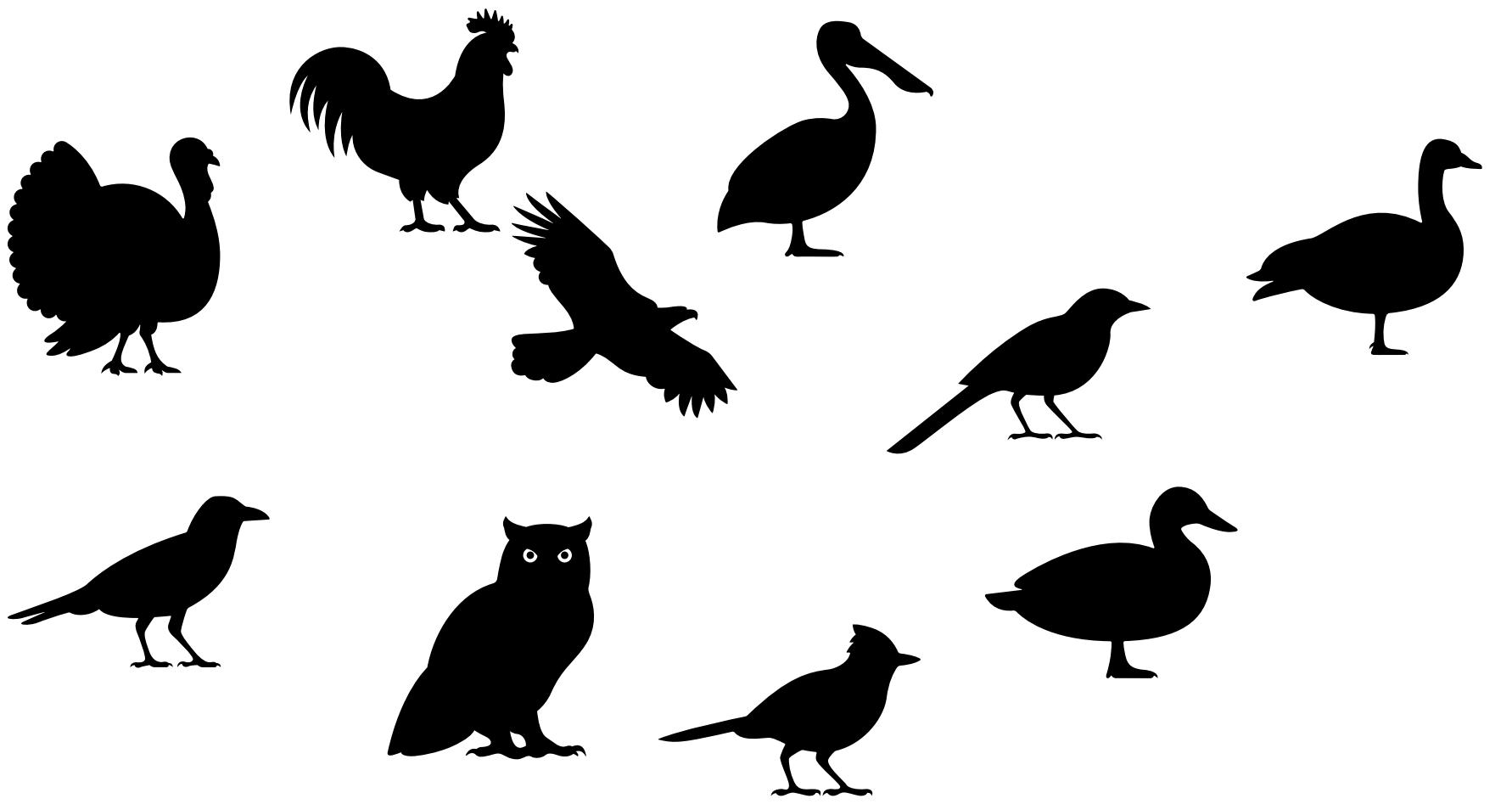
- Hen
- Duck
- Goose
- ...

WHAT'S HARD ABOUT THAT?

Features and classes seem easy enough, right?

For birds, biologists have already done most of the work for us and defined features, like birds. They have structured the data for us.

When we work with unstructured text data, we often need to identify and define these ourselves.



Bird **features**:

- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

- Hen
- Duck
- Goose
- ...

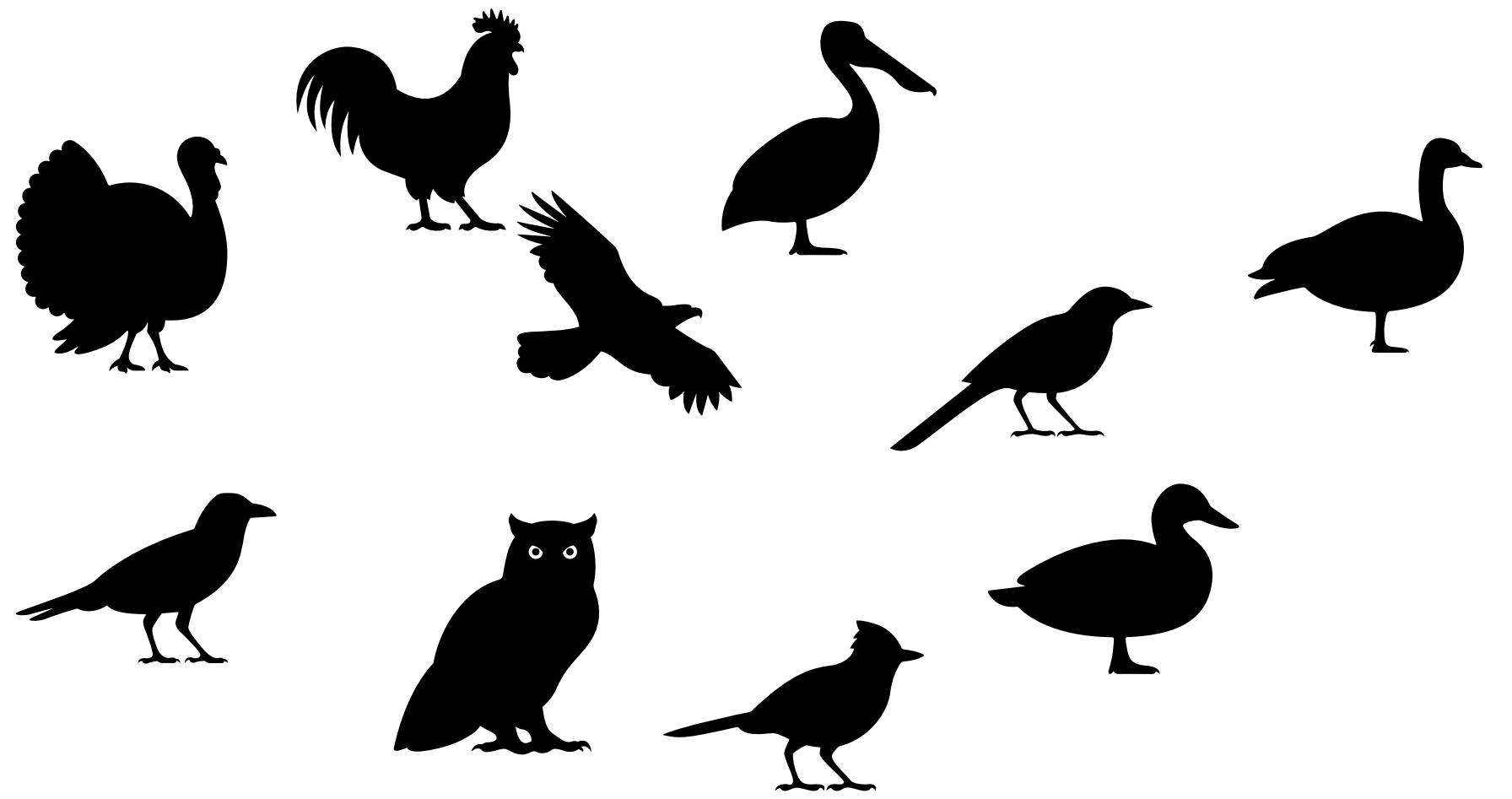
WHAT'S HARD ABOUT THAT?

Features and classes seem easy enough, right?

For birds, biologists have already done most of the work for us and defined features, like birds. They have structured the data for us.

When we work with unstructured text data, we often need to identify and define these ourselves.

And tell, e.g., ChatGPT about them!



Bird **features**:

- Length of beak
- Shape of beak
- Color of beak
- Body posture
- Color of feathers
- Size
- ...

Bird **classes**:

- Hen
- Duck
- Goose
- ...

HOW?



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

01. October 2025

Magnus Bender
Assistant Professor

8



HOW?

- The process of
 - i. Defining
 - ii. Identifying, and
 - iii. Extracting

features and classes, and articulating them in ways that an LLM will understand, relative to your data.

HOW?

- The process of
 - i. Defining
 - ii. Identifying, and
 - iii. Extractingfeatures and classes, and articulating them in ways that an LLM will understand, relative to your data.
- In today's readings, these were all "pre-defined". But you might let your classes and features emerge from your data, rather than pre-defining them.

HOW?

- The process of
 - i. Defining
 - ii. Identifying, and
 - iii. Extractingfeatures and classes, and articulating them in ways that an LLM will understand, relative to your data.
- In today's readings, these were all "pre-defined". But you might let your classes and features emerge from your data, rather than pre-defining them.
- Keep in mind:
Classification features should not just define a class in its own right. They should define what makes the class different from other classes.

NLP TASK: SENTIMENT ANALYSIS



WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- **Customer Feedback Analysis:** Automatically process and categorize large volumes of customer reviews, surveys, and support tickets to uncover trends, sentiments, and key concerns.

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- **Customer Feedback Analysis:** Automatically process and categorize large volumes of customer reviews, surveys, and support tickets to uncover trends, sentiments, and key concerns.
- **Market and Competitive Intelligence:** Analyze vast amounts of news articles, social media posts, and industry reports to identify emerging market trends, competitor strategies, and shifts in consumer preferences.

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- **Customer Feedback Analysis:** Automatically process and categorize large volumes of customer reviews, surveys, and support tickets to uncover trends, sentiments, and key concerns.
- **Market and Competitive Intelligence:** Analyze vast amounts of news articles, social media posts, and industry reports to identify emerging market trends, competitor strategies, and shifts in consumer preferences.
- **Content Classification and Organization:** Efficiently classify, tag, and organize large collections of business documents, emails, or contracts for easier retrieval and compliance.

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- **Customer Feedback Analysis:** Automatically process and categorize large volumes of customer reviews, surveys, and support tickets to uncover trends, sentiments, and key concerns.
- **Market and Competitive Intelligence:** Analyze vast amounts of news articles, social media posts, and industry reports to identify emerging market trends, competitor strategies, and shifts in consumer preferences.
- **Content Classification and Organization:** Efficiently classify, tag, and organize large collections of business documents, emails, or contracts for easier retrieval and compliance.
- **Sentiment and Opinion Mining:** Detect customer sentiment and opinions across social media, forums, and online platforms to inform product development, marketing strategies, and brand reputation management.

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- **Customer Feedback Analysis:** Automatically process and categorize large volumes of customer reviews, surveys, and support tickets to uncover trends, sentiments, and key concerns.
- **Market and Competitive Intelligence:** Analyze vast amounts of news articles, social media posts, and industry reports to identify emerging market trends, competitor strategies, and shifts in consumer preferences.
- **Content Classification and Organization:** Efficiently classify, tag, and organize large collections of business documents, emails, or contracts for easier retrieval and compliance.
- **Sentiment and Opinion Mining:** Detect customer sentiment and opinions across social media, forums, and online platforms to inform product development, marketing strategies, and brand reputation management.
- **Risk and Compliance Monitoring:** Leverage NLP to scan and analyze regulatory documents, legal contracts, and financial reports to ensure compliance and identify potential risks or breaches.

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- Natural Language Processing has been around for a long time (since 1950s)

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- Natural Language Processing has been around for a long time (since 1950s)
 - Automatic translation
 - **Sentiment analysis**
 - Text generation
 - Text classification

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- Natural Language Processing has been around for a long time (since 1950s)
 - Automatic translation
 - **Sentiment analysis**
 - Text generation
 - Text classification
- The techniques used for these varied, but are all, by now, completely outdated

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- Natural Language Processing has been around for a long time (since 1950s)
 - Automatic translation
 - **Sentiment analysis**
 - Text generation
 - Text classification
- The techniques used for these varied, but are all, by now, completely outdated
- However: **Outdated does not imply useless!**

WHAT CAN WE DO WITH LLMS THAT ARE NOT JUST CHATBOTS?

- Natural Language Processing has been around for a long time (since 1950s)
 - Automatic translation
 - **Sentiment analysis**
 - Text generation
 - Text classification
- The techniques used for these varied, but are all, by now, completely outdated
- However: **Outdated does not imply useless!**
 - *We still have horses after we invented cars or trains after we invented planes.*

SENTIMENT ANALYSIS, PRE-2017

SENTIMENT ANALYSIS, PRE-2017

To measure the sentiment of a text, we used to:

SENTIMENT ANALYSIS, PRE-2017

To measure the sentiment of a text, we used to:

1. Load a dictionary of words:

Sentiment Analysis Word Lists Dataset
Words that Define Emotions: A Sentiment Lexicon

Data Card Code (1) Discussion (0) Suggestions (0)

About Dataset

Dataset Description:
This dataset comprises two text files, one containing a list of positive words and the other a list of negative words. These files are intended to serve as essential resources for sentiment analysis and natural language processing tasks.

- Positive Words File: This file contains a collection of words and terms that typically convey positive sentiment or emotions. These words are often associated with happiness, satisfaction, approval, or positive experiences.
- Negative Words File: The second file includes a compilation of words and phrases that commonly express negative sentiments or emotions. These words are often related to displeasure, disappointment, criticism, or negative experiences.

Use Cases:
The dataset can be used in various applications and research areas, including:

1. **Sentiment Analysis:** Researchers and developers can employ these word lists to help assess the sentiment of text data and categorize it as positive, negative, or neutral.
2. **Text Classification:** These datasets can be utilized in text classification tasks, such as determining the sentiment of product reviews, social media posts, or customer feedback.
3. **Emotion Detection:** The words in these lists can aid in emotion detection and understanding the emotional tone of text.

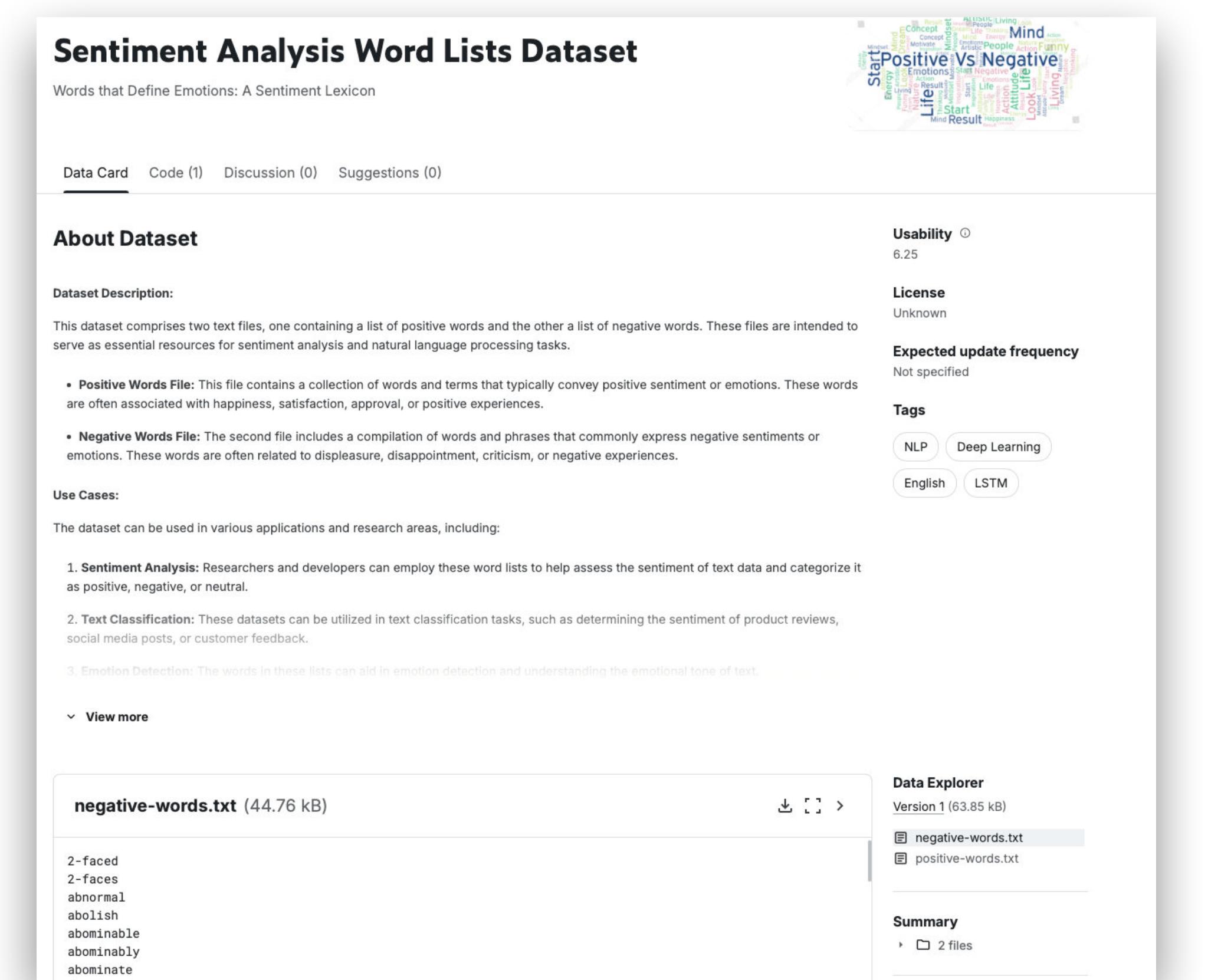
View more

negative-words.txt (44.76 kB)

2-faced
2-faces
abnormal
abolish
abominable
abominably
abominate

Data Explorer
Version 1 (63.85 kB)
negative-words.txt
positive-words.txt

Summary
2 files



SENTIMENT ANALYSIS, PRE-2017

To measure the sentiment of a text, we used to:

1. Load a dictionary of words:

- *positive*
- *negative*

Sentiment Analysis Word Lists Dataset

Words that Define Emotions: A Sentiment Lexicon

Data Card Code (1) Discussion (0) Suggestions (0)

About Dataset

Dataset Description:

This dataset comprises two text files, one containing a list of positive words and the other a list of negative words. These files are intended to serve as essential resources for sentiment analysis and natural language processing tasks.

• **Positive Words File:** This file contains a collection of words and terms that typically convey positive sentiment or emotions. These words are often associated with happiness, satisfaction, approval, or positive experiences.

• **Negative Words File:** This file contains a collection of words and terms that typically convey negative sentiment or emotions. These words are often associated with sadness, dissatisfaction, disapproval, or negative experiences.

Use Cases:

The data can be used for:

1. Sentiment analysis as positive words

2. Text classification for social media monitoring

3. Emotion detection

4. View sentiment analysis

positive-words.txt (19.09 kB)

affirmative

affluence

affluent

afford

affordable

affordably

affordable

agile

agilely

agility

agreeable

agreeableness

agreeably

all-around



Usability 6.25

License Unknown

Expected update frequency Not specified

Tags

negative-words.txt (44.76 kB)

adulteration

adulterier

adversarial

adversary

adverse

adversity

afflict

affliction

afflictive

affront

afraid

aggravate

aggravating

aggravation

aggression

aggressive

aggressiveness

SENTIMENT ANALYSIS, PRE-2017

To measure the sentiment of a text, we used to:

1. Load a dictionary of words:
 - *positive*
 - *negative*
2. Computationally read through a document

Sentiment Analysis Word Lists Dataset

Words that Define Emotions: A Sentiment Lexicon

Data Card Code (1) Discussion (0) Suggestions (0)

About Dataset

Dataset Description:

This dataset comprises two text files, one containing a list of positive words and the other a list of negative words. These files are intended to serve as essential resources for sentiment analysis and natural language processing tasks.

- Positive Words File: This file contains a collection of words and terms that typically convey positive sentiment or emotions. These words are often associated with happiness, satisfaction, approval, or positive experiences.
- Negative Words File: This file contains a collection of words and terms that typically convey negative sentiment or emotions. These words are often associated with sadness, dissatisfaction, disapproval, or negative experiences.

Use Cases:

The data can be used for various NLP applications, such as sentiment analysis, opinion mining, and text classification. It can also be used for generating positive and negative reviews, or for improving the performance of machine learning models that deal with情感 analysis.

1. Sentiment Analysis: The dataset can be used to train machine learning models for sentiment analysis, which involves determining the sentiment (positive or negative) of a piece of text. This can be applied to various domains, such as social media monitoring, customer feedback analysis, and product reviews.

2. Text Generation: The dataset can be used to generate positive or negative text samples. For example, it can be used to generate positive reviews for a product or negative reviews for a competitor's product. This can be useful for testing NLP models or for generating training data for machine learning models.

3. Emotion Recognition: The dataset can be used to train machine learning models for emotion recognition, which involves identifying the emotions expressed in a piece of text. This can be applied to various domains, such as customer service, mental health, and social media monitoring.

View Data

positive-words.txt (19.09 kB)

affirmative
affluence
affluent
afford
affordable
affordably
afordable
agile
agilely
agility
agreeable
agreeableness
agreeably
all-around

negative-words.txt (44.76 kB)

adulteration
adulterier
adversarial
adversary
adverse
adversity
afflict
affliction
afflictive
affront
afraid
aggravate
aggravating
aggravation
aggression
aggressive
aggressiveness



SENTIMENT ANALYSIS, PRE-2017

To measure the sentiment of a text, we used to:

1. Load a dictionary of words:
 - *positive*
 - *negative*
2. Computationally read through a document
3. Count the number of positive and negative words:
 - Add them all up (+1 for positive words, -1 for negative words)

Sentiment Analysis Word Lists Dataset
Words that Define Emotions: A Sentiment Lexicon

Data Card Code (1) Discussion (0) Suggestions (0)

About Dataset

Dataset Description:
This dataset comprises two text files, one containing a list of positive words and the other a list of negative words. These files are intended to serve as essential resources for sentiment analysis and natural language processing tasks.

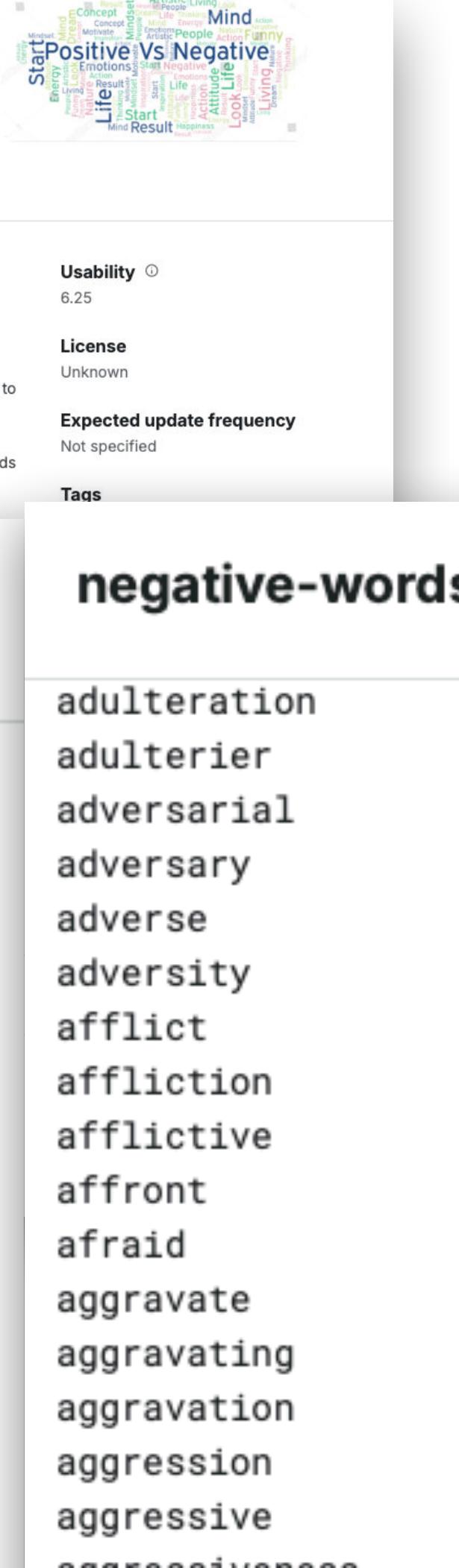
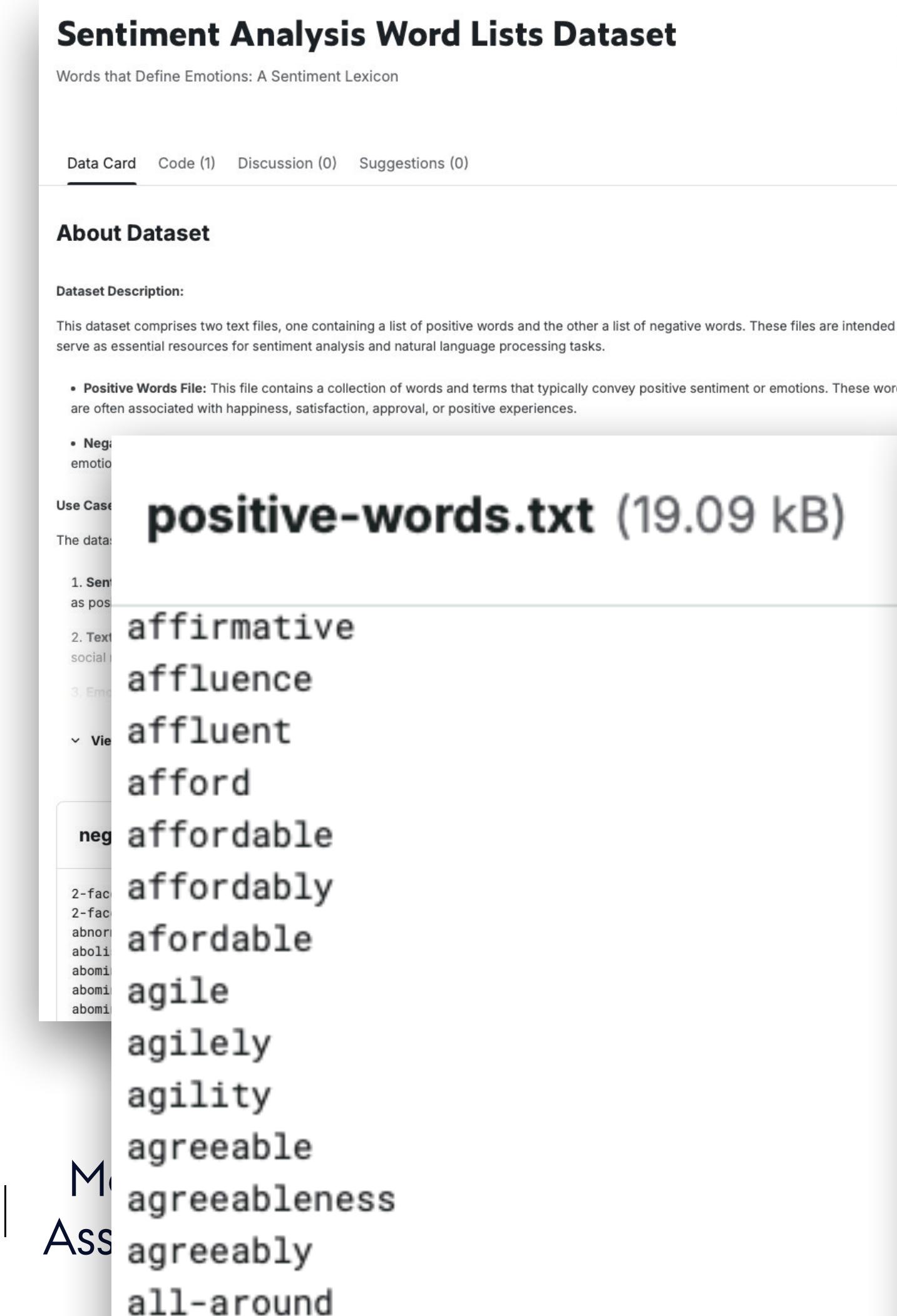
- Positive Words File: This file contains a collection of words and terms that typically convey positive sentiment or emotions. These words are often associated with happiness, satisfaction, approval, or positive experiences.
- Negative Words File: This file contains a collection of words and terms that typically convey negative sentiment or emotions. These words are often associated with sadness, dissatisfaction, disapproval, or negative experiences.

positive-words.txt (19.09 kB)

affirmative
affluence
affluent
afford
affordable
affordably
affordable
agile
agilely
agility
agreeable
agreeableness
agreeably
all-around

negative-words.txt (44.76 kB)

adulteration
adulterier
adversarial
adversary
adverse
adversity
afflict
affliction
afflictive
affront
afraid
aggravate
aggravating
aggravation
aggression
aggressive
aggressiveness



SENTIMENT ANALYSIS, PRE-2017

To measure the sentiment of a text, we used to:

1. Load a dictionary of words:
 - *positive*
 - *negative*
2. Computationally read through a document
3. Count the number of positive and negative words:
 - Add them all up (+1 for positive words, -1 for negative words)
4. Obtain a result:
 - if the sum is $> 0 \rightarrow$ positive sentiment
 - if the sum is $< 0 \rightarrow$ negative sentiment

Sentiment Analysis Word Lists Dataset
Words that Define Emotions: A Sentiment Lexicon

Data Card Code (1) Discussion (0) Suggestions (0)

About Dataset

Dataset Description:
This dataset comprises two text files, one containing a list of positive words and the other a list of negative words. These files are intended to serve as essential resources for sentiment analysis and natural language processing tasks.

• **Positive Words File:** This file contains a collection of words and terms that typically convey positive sentiment or emotions. These words are often associated with happiness, satisfaction, approval, or positive experiences.

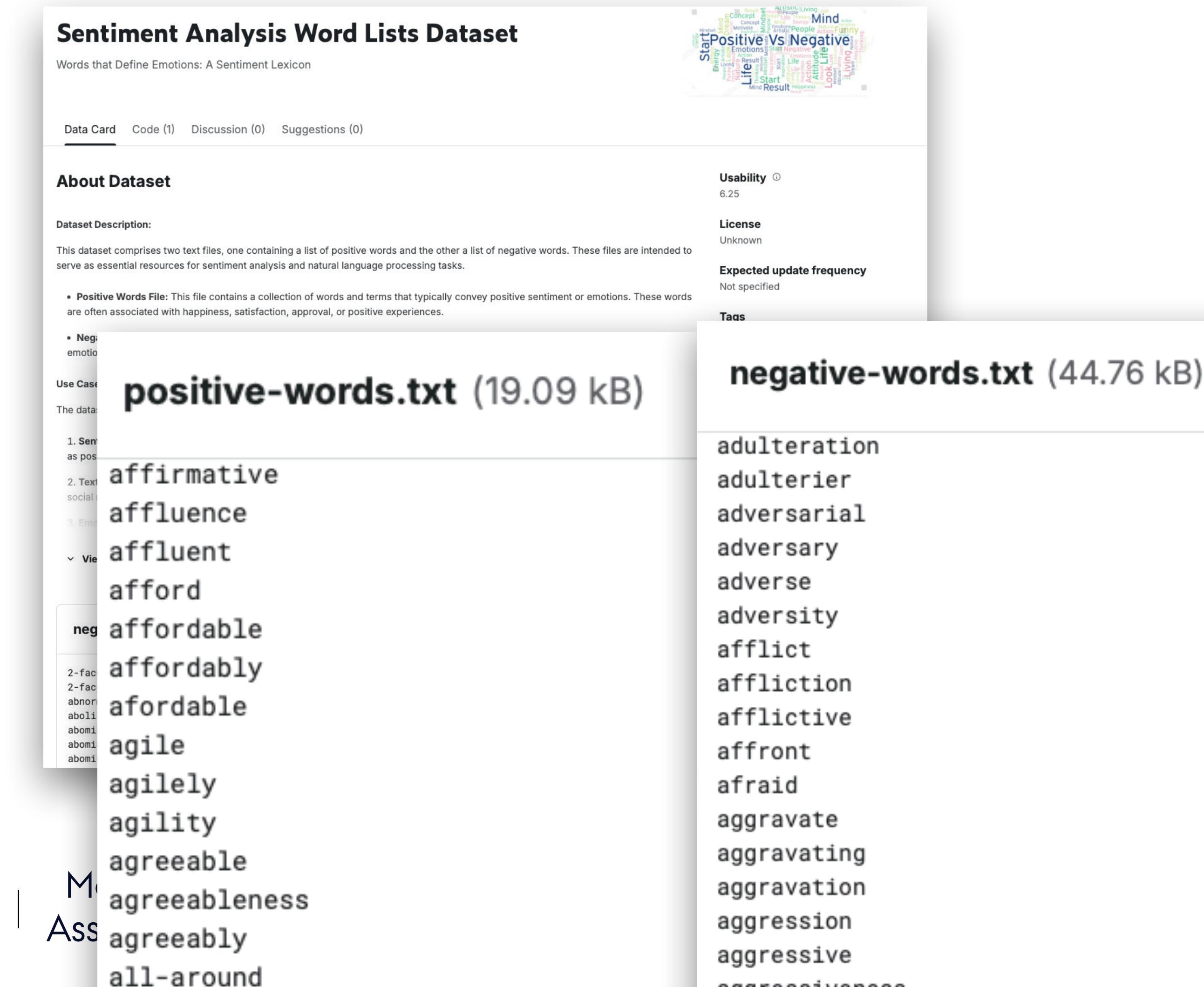
• **Negative Words File:** This file contains a collection of words and terms that typically convey negative sentiment or emotions. These words are often associated with sadness, dissatisfaction, disapproval, or negative experiences.

positive-words.txt (19.09 kB)

affirmative
affluence
affluent
afford
affordable
affordably
affordable
affordably
afordable
agile
agilely
agility
agreeable
agreeableness
Agreeable
Agreeableness
agreeably
all-around

negative-words.txt (44.76 kB)

adulteration
adulterier
adversarial
adversary
adverse
adversity
afflict
affliction
afflictive
affront
afraid
aggravate
aggravating
aggravation
aggression
aggressive
aggressiveness



PROBLEMS WITH THIS OLD-SCHOOL METHOD

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative
- Synonym phrases don't count:

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative
- Synonym phrases don't count:
 - „He **cheated** the system“ → negative

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative
- Synonym phrases don't count:
 - „He **cheated** the system“ → negative
 - „He dodged the rules“ → neutral

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative
- Synonym phrases don't count:
 - „He **cheated** the system“ → negative
 - „He dodged the rules“ → neutral
- Large Language Models can avoid many of the traps that these older *dictionary-approaches* fell in.

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative
- Synonym phrases don't count:
 - „He **cheated** the system“ → negative
 - „He dodged the rules“ → neutral
- Large Language Models can avoid many of the traps that these older *dictionary-approaches* fell in.
 - No dependency on language and use-case specific list

PROBLEMS WITH THIS OLD-SCHOOL METHOD

- Context matters, word count does not:
 - „In **spite** the **horrifyingly bad** weather, things worked out **well**.“ → negative
- Synonym phrases don't count:
 - „He **cheated** the system“ → negative
 - „He dodged the rules“ → neutral
- Large Language Models can avoid many of the traps that these older *dictionary-approaches* fell in.
 - No dependency on language and use-case specific list
 - ...

LLMS TO ASSIST WITH PROBLEMS & PROCESSES

- Today, focus on the *technical* site
- Or: „What NLP tasks do LLMs offer and how can I use them to solve my problem?“

EXAMPLES FROM LECTURE 2



EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items
2. Automatic forwarding of customer's e-mails to correct department

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items
2. Automatic forwarding of customer's e-mails to correct department → The best matching department to handle the case

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items
2. Automatic forwarding of customer's e-mails to correct department → The best matching department to handle the case
3. Inspection of CVs of applicants for a position

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items
2. Automatic forwarding of customer's e-mails to correct department → The best matching department to handle the case
3. Inspection of CVs of applicants for a position → „Complete“ or „Incomplete“ for each CV

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items
2. Automatic forwarding of customer's e-mails to correct department → The best matching department to handle the case
3. Inspection of CVs of applicants for a position → „Complete“ or „Incomplete“ for each CV
4. Selection of the applicant to hire for a position

EXAMPLES FROM LECTURE 2

1. Personalized recommendations of items in an online shop → Some relevant item out of all available items
2. Automatic forwarding of customer's e-mails to correct department → The best matching department to handle the case
3. Inspection of CVs of applicants for a position → „Complete“ or „Incomplete“ for each CV
4. Selection of the applicant to hire for a position → The best applicant out of all applicants

1. RECOMMENDATIONS



- What are good recommendations?
 - Increased customer satisfaction
 - Increased sales for the provider



1. RECOMMENDATIONS



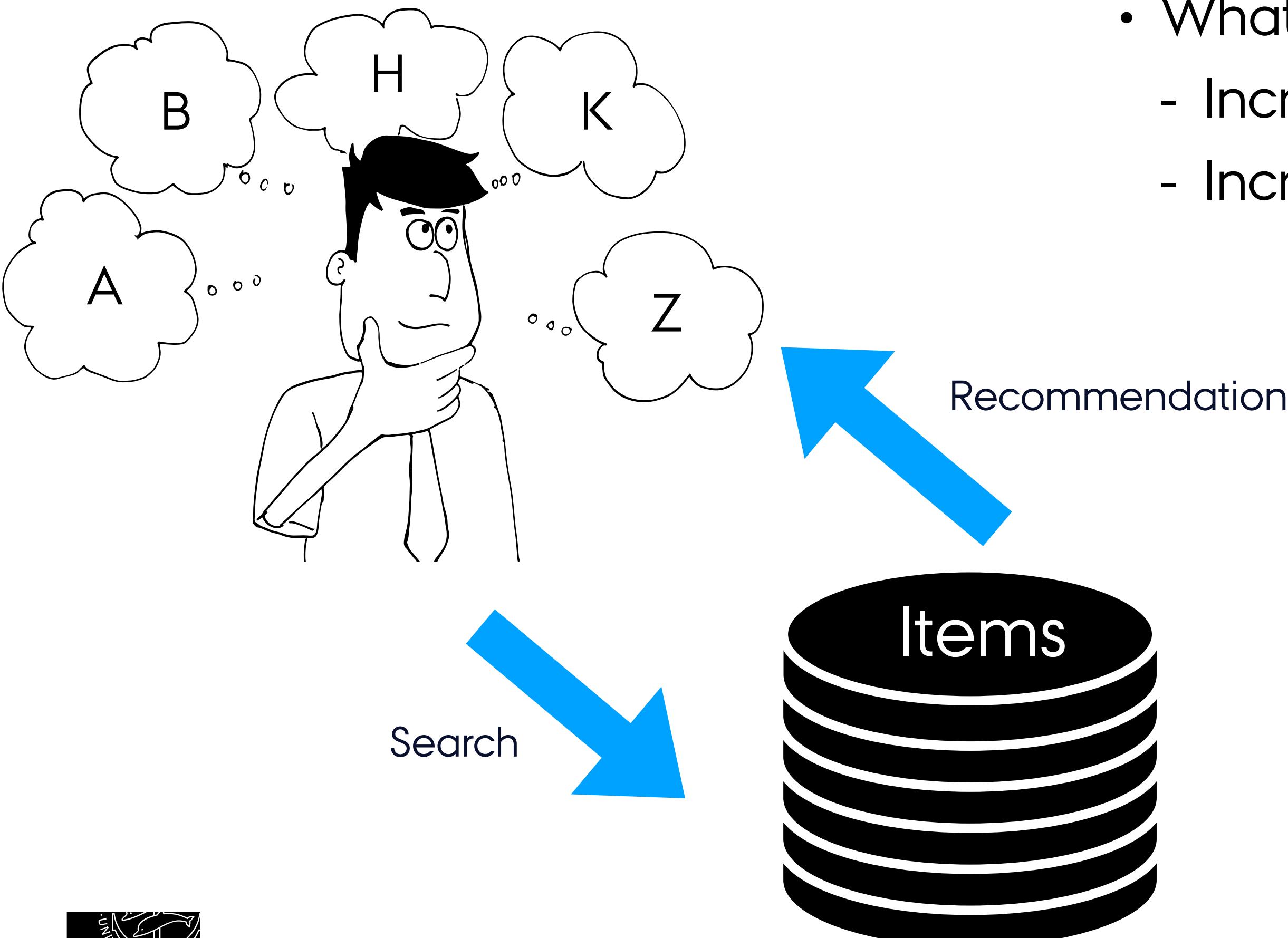
Search



01. October 2025

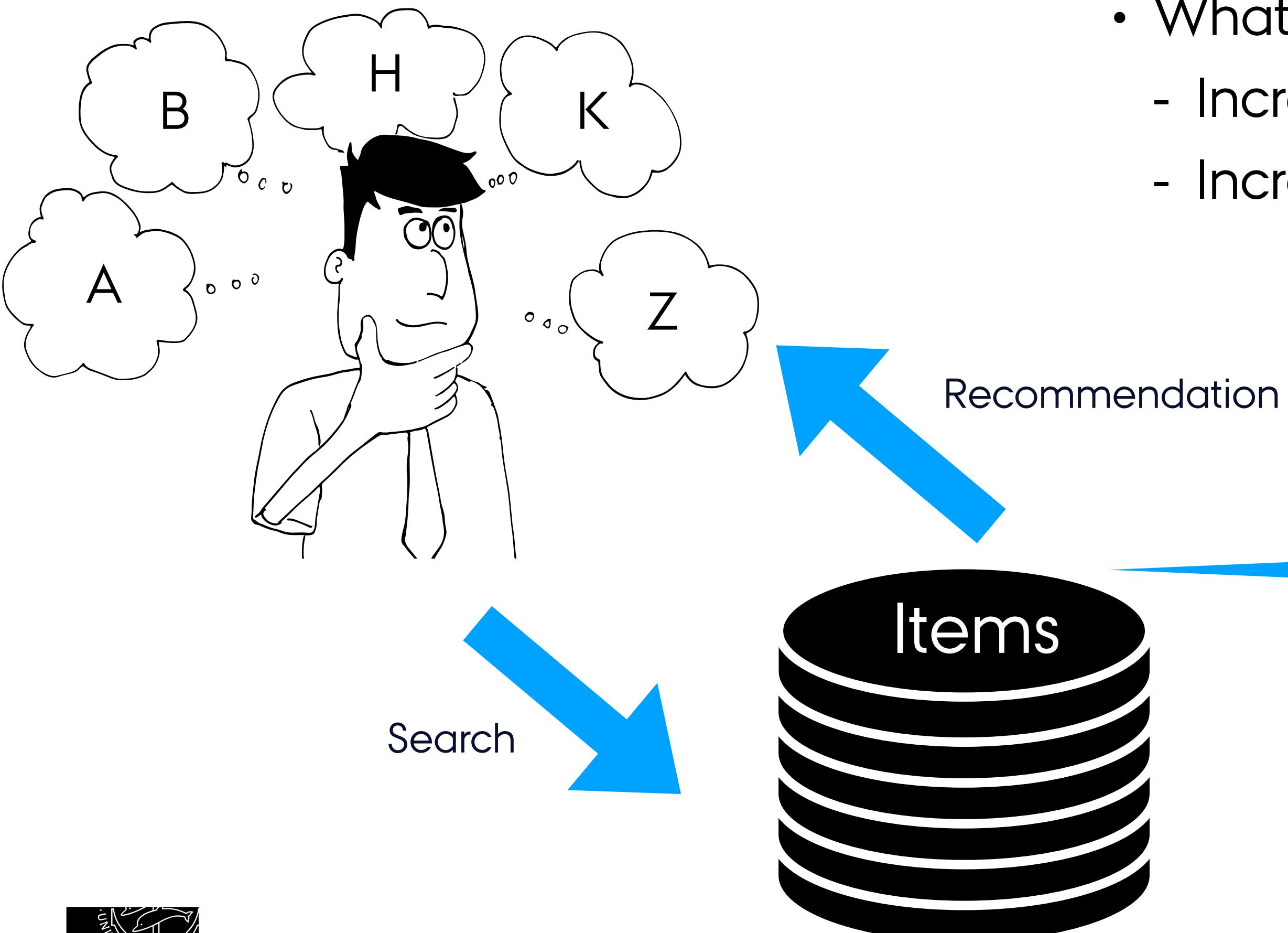
Magnus Bender
Assistant Professor

1. RECOMMENDATIONS



- What are good recommendations?
 - Increased customer satisfaction
 - Increased sales for the provider

1. RECOMMENDATIONS



- What are good recommendations?
 - Increased customer satisfaction
 - Increased sales for the provider

- Predict how strong a “customer's” interest in an object is
- Recommend to “customers” precisely those objects from the set of all existing objects that are of most interest.

amazon.com

amazon

Deliver to Denmark

All artificial intelligence a modern approach

EN Hello, sign in Account & Lists Returns & Orders Cart

All Today's Deals Prime Video Registry Gift Cards Customer Service Sell

books Categories New & Trending Deals & Rewards Best Sellers & More Memberships More Your Books

AI Agents in Action

Shop Manning Publications

Sponsored

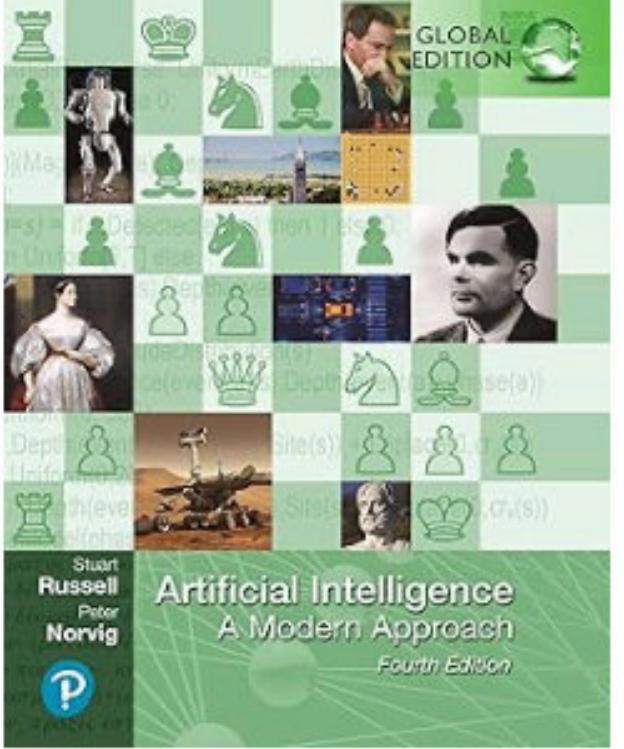
Books > Computers & Technology > Computer Science > AI & Machine Learning > Intelligence & Semantics

Artificial Intelligence: A Modern Approach, Global Edition 4th Edition

by Peter Norvig (Author), Stuart Russell (Author)

4.7  516 ratings

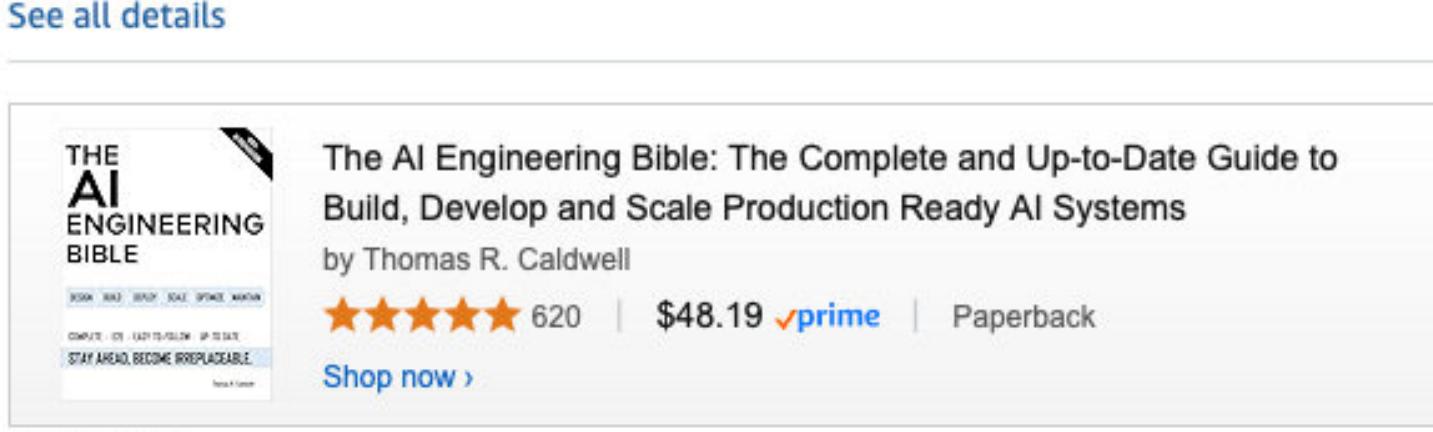
The long-anticipated revision of *Artificial Intelligence: A Modern Approach* explores the full breadth and depth of the field of artificial intelligence (AI). The 4th Edition brings readers up to date on the latest technologies, presents concepts in a more unified manner, and offers new or expanded coverage of machine learning, deep learning, transfer learning, multi agent systems, robotics, natural language processing, causality, probabilistic programming, privacy, fairness, and safe AI.





Follow the author

Peter Norvig 





Frequently bought together





Paperback \$60.00

Other Used and New from \$51.00

-33% \$60.00

List Price: \$89.73

No Import Fees Deposit & \$21.56 Shipping to Denmark [Details](#)

Delivery Friday, October 10

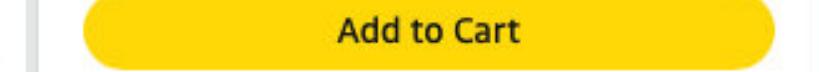
Or fastest delivery Thursday, October 2.

Order within 4 hrs 26 mins



In Stock

Quantity: 1





Ships from Amazon

Sold by Rbowbooks

Returns 30-day refund / replacement

Payment Secure transaction

Add a gift receipt for easy returns



amazon.com

amazon

Deliver to Denmark

All artificial intelligence a modern approach

EN Hello, sign in Account & Lists Returns & Orders Cart

All Today's Deals Prime Video Registry Gift Cards Customer Service Sell

books Categories New & Trending Deals & Rewards Best Sellers & More Memberships More Your Books

AI Agents in Action

Shop Manning Publications

Sponsored

Books > Computers & Technology > Computer Science > AI & Machine Learning > Intelligence & Semantics

Artificial Intelligence: A Modern Approach, Global Edition 4th Edition

by Peter Norvig (Author), Stuart Russell (Author)

4.7 516 ratings

The long-anticipated revision of *Artificial Intelligence: A Modern Approach* explores the full breadth and depth of the field of artificial intelligence (AI). The 4th Edition brings readers up to date on the latest technologies, presents concepts in a more unified manner, and offers new or expanded coverage of machine learning, deep learning, transfer learning, multi agent systems, robotics, natural language processing, causality, probabilistic programming, privacy, fairness, and safe AI.

[Report an issue with this product or seller](#)

ISBN-10: 1292401133 ISBN-13: 978-1292401133 Edition: 4th Publisher: Pearson

Read sample

Follow the author

Peter Norvig [Follow](#)

See all details

The AI Engineering Bible: The Complete and Up-to-Date Guide to Build, Develop and Scale Production Ready AI Systems by Thomas R. Caldwell

4.5 620 | \$48.19 Paperback [Shop now](#)

Frequently bought together

[View all 3 items](#)

Paperback \$60.00

Other Used and New from \$51.00

-33% \$60.00

List Price: \$89.73

No Import Fees Deposit & \$21.56 Shipping to Denmark [Details](#)

Delivery **Friday, October 10**

Or fastest delivery **Thursday, October 2**. Order within **4 hrs 26 mins**

[Deliver to Denmark](#)

In Stock

Quantity: 1

Add to Cart

Buy Now

Ships from Amazon

Sold by Rbowbooks

Returns 30-day refund / replacement

Payment Secure transaction

Add a gift receipt for easy returns

Add to List

Sponsored

amazon Deliver to Denmark All artificial intelligence a modern approach

All Today's Deals Prime Video Registry Gift Cards Customer Service Sell

books Categories New & Trending Deals & Rewards Best Sellers & More

AI Agents in Action

Books > Computers & Technology > Computer Science > AI & Machine Learning > Intelligence & Semantics

Artificial Intelligence: A Modern Approach Global Edition 4th Edition

by Peter Norvig (Author), Stuart Russell (Author)

4.7 ★★★★★ 516 ratings

The long-anticipated revision of *Artificial Intelligence: A Modern Approach*, Global Edition, presents a new or expanded coverage of machine learning, systems, robotics, natural language processing, fairness, and safe AI.

Report an issue with this product or seller

ISBN-10: 1292401133 ISBN-13: 978-1292401133

Read sample

Follow the author

Peter Norvig Follow

The AI Engineering Bible: The Complete and Up-to-Date Guide to Build, Develop and Scale Production Ready AI Systems

by Thomas R. Caldwell

★★★★★ 620 | \$48.19 prime Paperback

Shop now

Frequently bought together

Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow: Concepts, Tools, and Techniques for Machine Learning Systems

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter

The Elements of Statistical Learning: Data Mining, Inference, and Prediction

An Introduction to Statistical Learning: with Applications in Python

Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python

amazon.com Hello, sign in Account & Lists

All artificial intelligence a modern approach

The AI Engineering Bible: The Complete and Up-to-Date Guide to Build, Develop and Scale Production Ready AI Systems

by Thomas R. Caldwell

★★★★★ 620 | \$48.19 prime Paperback

Shop now

Frequently bought together

This item: Artificial Intelligence: A Modern Approach, Global Edition

Deep Learning (Adaptive Computation and Machine Learning series)

Build a Large Language Model (From Scratch)

Total price: \$173.27

Add all 3 to Cart

These items are shipped from and sold by different sellers. Show details

More items to explore

Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow: Concepts, Tools, and Techniques for Machine Learning Systems

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter

The Elements of Statistical Learning: Data Mining, Inference, and Prediction

An Introduction to Statistical Learning: with Applications in Python

Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python

Designing Data Intensive Systems: Principles and Tools for Scalability, Fault Tolerance, and Performance

amazon Deliver to Denmark All artificial intelligence a modern approach

All Today's Deals Prime Video Registry Gift Cards Customer Service Sell books Categories New & Trending Deals & Rewards Best Sellers & More AI Agents in Action

Books > Computers & Technology > Computer Science > AI & Machine Learning > Intelligence & Semantics

Artificial Intelligence: A Modern Approach Global Edition 4th Edition by Peter Norvig (Author), Stuart Russell (Author) 4.7 ★★★★★ 516 ratings

The long-anticipated revision of *Artificial Intelligence: A Modern Approach*, Global Edition, presents comprehensive coverage of machine learning, systems, robotics, natural language processing, fairness, and safe AI.

Report an issue with this product or seller

ISBN-10: 1292401133 ISBN-13: 978-1292401133

Read sample

Follow the author: Peter Norvig Follow

Frequently bought together

More items to explore

The AI Engineering Bible: The Complete and Up-to-Date Guide to Build, Develop and Scale Production Ready AI Systems by Thomas R. Caldwell 4.5 ★★★★★ 620 \$48.19 prime Paperback Shop now

Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow: Concepts, Tools, and Techniques for Machine Learning Systems by Aurélien Géron 4.5 ★★★★★ 748 \$48.25 \$19.65 shipping

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter by Wes McKinney 4.5 ★★★★★ 444 \$43.99 \$17.86 shipping

The Elements of Statistical Learning: Data Mining, Inference, and Prediction by Trevor Hastie, Robert Tibshirani, Jerome Friedman 4.5 ★★★★★ 1,321 Hardcover \$58.75 Get it as soon as Monday, Oct 13 \$18.86 shipping

An Introduction to Statistical Learning: with Applications in Python by Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani 4.5 ★★★★★ 98 Hardcover #1 Best Seller \$70.25 Get it as soon as Thursday, Oct 16 \$18.98 shipping

Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python by Peter Bruce, Andrew Bruce, Peter Gedeck 4.5 ★★★★★ 925 Paperback \$45.25 \$17.07 shipping

Designing Data Intensive Applications: The Big Data Scalability Solution by Chip Huyen 4.5 ★★★★★ 1,000 Paperback #1 Best Seller \$40.00 \$17.01 shipping

amazon.com Hello, sign in Account & Lists

Deliver to Denmark All artificial intelligence a modern approach

The AI Engineering Bible: The Complete and Up-to-Date Guide to Build, Develop and Scale Production Ready AI Systems by Thomas R. Caldwell 4.5 ★★★★★ 620 \$48.19 prime Paperback Shop now

Frequently bought together

More items to explore

Sponsored

Shop now

Ships from Ama **Sold by** RBO **Returns** 30-c **Payment** Secu

Add a gift receipt

Add to List

Other sellers on

New & Used (19) fr

Total price: \$173.27

Add all 3 to Cart

i These items are shipped from and sold by different sellers. Show details

01. October 2025 | MAGNUS BENDER Assistant Professor

17

AARHUS BSS DEPARTMENT OF MANAGEMENT AARHUS UNIVERSITY

ASSOCIATION AACSB ACCREDITED

AMBA ACCREDITED

EFMD EQUIS ACCREDITED

<https://www.amazon.com/Artificial-Intelligence-Modern-Approach-Global/dp/1292401133/>

amazon Deliver to Denmark All artificial intelligence a modern approach

All Today's Deals Prime Video Registry Gift Cards Customer Service Sell

books Categories New & Trending Deals & Rewards Best Sellers & More

AI Agents in Action

Books > Computers & Technology > Computer Science > AI & Machine Learning > Intelligence & Semantics

Artificial Intelligence: A Modern Approach 4th Edition

by Peter Norvig (Author), Stuart Russell (Author)

4.7 ★★★★★ 516 ratings

The long-anticipated revision of *Artificial Intelligence: A Modern Approach*, Global Edition, presents a breadth and depth of the field of artificial intelligence to date on the latest technologies, presents new or expanded coverage of machine learning, systems, robotics, natural language processing, fairness, and safe AI.

Report an issue with this product or seller

ISBN-10: 1292401133 ISBN-13: 978-1292401133

Read sample

Follow the author

Peter Norvig Follow

The AI Engineering Bible: Build, Develop and Scale Pr

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques for Building Intelligent Systems

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter

The AI Job Shift: How to Transition Into AI-Supported Careers

San Francisco: The AI Capital of the World

AI Agents Millionaire: [3 in 1] 1000+ Automation Secrets to Skyrocket Profits, Rein...

Co-Intelligence: Living and Working with AI

Customer Success In The World Of Artificial Intelligence

Frequently bought together

DEPARTMENT OF MANAGEMENT AARHUS UNIVERSITY

amazon Deliver to Denmark All artificial intelligence a modern approach

THE AI ENGINEERING BIBLE

Sponsored

Frequently bought together

This item: Artificial Intelligence: A Modern Approach, Global Edition

Deep Learning (Adaptive Computation and Machine Learning series)

\$60.00 \$61.60

More items to explore

Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow: Concepts, Tools, and Techniques for Building Intelligent Systems

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter

The AI Job Shift: How to Transition Into AI-Supported Careers

San Francisco: The AI Capital of the World

AI Agents Millionaire: [3 in 1] 1000+ Automation Secrets to Skyrocket Profits, Rein...

Co-Intelligence: Living and Working with AI

Customer Success In The World Of Artificial Intelligence

Frequently bought together

DEPARTMENT OF MANAGEMENT AARHUS UNIVERSITY

amazon.com

Videos

Help others learn more about this product by uploading a video!

Upload your video

About the author

Follow authors to get new release updates, plus improved recommendations.

Peter Norvig

I live in Palo Alto, CA with my wife and two children. I am currently the Director of Research for Google, and I am teaching an Introduction to AI class at Stanford University. You can buy some of my books here at Amazon.

Follow

Related products with free delivery on eligible orders

Sponsored | Try Prime for unlimited fast, free shipping

The AI Job Shift: How to Transition Into AI-Supported Careers

San Francisco: The AI Capital of the World

AI Agents Millionaire: [3 in 1] 1000+ Automation Secrets to Skyrocket Profits, Rein...

Co-Intelligence: Living and Working with AI

Customer Success In The World Of Artificial Intelligence

01. October 2025 | Assistant Professor

17

EQUIS ACCREDITED

AMBA ACCREDITED

https://www.amazon.com/Artificial-Intelligence-Modern-Approach-Global/dp/1292401133/

amazon Deliver to Denmark All artificial intelligence a modern approach

All Today's Deals Prime Video Registry Gift Cards Customer Service Sell

books Categories New & Trending Deals & Rewards Best Sellers & More

AI Agents in Action

Books > Computers & Technology > Computer Science > AI & Machine Learning > Intelligence & Semantics

Artificial Intelligence: A Modern Approach 4th Edition

by Peter Norvig (Author), Stuart Russell (Author)

4.7 ★★★★★ 516 ratings

The long-anticipated revision of *Artificial Intelligence: A Modern Approach*, Global Edition, presents a breadth and depth of the field of artificial intelligence to date on the latest technologies, presents new or expanded coverage of machine learning, systems, robotics, natural language processing, fairness, and safe AI.

Report an issue with this product or seller

ISBN-10: 1292401133 ISBN-13: 978-1292401133

Read sample

Follow the author

Peter Norvig Follow

The AI Engineering Bible: Build, Develop and Scale Pr

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques for Building Intelligent Systems

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter

The AI Job Shift: How to Transition Into AI-Supported Careers

San Francisco: The AI Capital of the World

AI Agents Millionaire: [3 in 1] 1000+ Automation Secrets to Skyrocket Profits, Rein...

Co-Intelligence: Living and Working with AI

CUSTOMER SUCCESS In The World Of Artificial Intelligence

Frequently bought together

DEPARTMENT OF MANAGEMENT AARHUS UNIVERSITY

amazon Deliver to Denmark All artificial intelligence a modern approach

THE AI ENGINEERING BIBLE

Sponsored

Frequently bought together

This item: Artificial Intelligence: A Modern Approach, Global Edition

Deep Learning (Adaptive Computation and Machine Learning series)

\$60.00 \$61.60

More items to explore

Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow: Concepts, Tools, and Techniques for Building Intelligent Systems

Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter

The AI Job Shift: How to Transition Into AI-Supported Careers

San Francisco: The AI Capital of the World

AI Agents Millionaire: [3 in 1] 1000+ Automation Secrets to Skyrocket Profits, Rein...

Co-Intelligence: Living and Working with AI

CUSTOMER SUCCESS In The World Of Artificial Intelligence

Frequently bought together

DEPARTMENT OF MANAGEMENT AARHUS UNIVERSITY

amazon.com

Videos

Help others learn more about this product by uploading a video!

Upload your video

About the author

Follow authors to get new release updates, plus improved recommendations.

Peter Norvig

I live in Palo Alto, CA with my wife and two children. I am currently the Director of Research for Google, and I am teaching an Introduction to AI class at Stanford University. I have written several books on AI, including "Artificial Intelligence: A Modern Approach" and "The Big Picture".

Follow

Related products with free delivery on eligible orders

Sponsored

The AI Job Shift: How to Transition Into AI-Supported Careers

San Francisco: The AI Capital of the World

AI Agents Millionaire: [3 in 1] 1000+ Automation Secrets to Skyrocket Profits, Rein...

Co-Intelligence: Living and Working with AI

CUSTOMER SUCCESS In The World Of Artificial Intelligence

01. October 2025 | Assistant Professor

17 EQUIS ACCREDITED AMBA ACCREDITED

SHOPPING CART TRANSACTIONS

- Given transactions in the form of shopping carts of different people
- Looking for recommendations of additional items for each person or shopping cart

Transaction ID	Person ID	Items
1	1	Bread, Oatmeal, Potatoes
2	2	Apples, Bread, Sugar
3	3	Apples, Bread, Potatoes, Sugar
4	2	Bread, Potatoes, Sugar
5	4	Bread, Oatmeal, Potatoes, Sugar

RECOMMENDATION GENERATION

RECOMMENDATION GENERATION

- Content-based

RECOMMENDATION GENERATION

- Content-based
 - Requires knowledge about the items themselves
 - Requires no knowledge about previous orders

RECOMMENDATION GENERATION

- Content-based
 - Requires knowledge about the items themselves
 - Requires no knowledge about previous orders

→ Provides recommendations of content-wise similar items

RECOMMENDATION GENERATION

- Content-based
 - Requires knowledge about the items themselves
 - Requires no knowledge about previous orders
- Provides recommendations of content-wise similar items
- Collaborative

RECOMMENDATION GENERATION

- Content-based
 - Requires knowledge about the items themselves
 - Requires no knowledge about previous orders
- Provides recommendations of content-wise similar items
- Collaborative
 - Requires knowledge previous orders and transactions
 - Requires **no knowledge about the items** themselves

RECOMMENDATION GENERATION

- Content-based
 - Requires knowledge about the items themselves
 - Requires no knowledge about previous orders

→ Provides recommendations of content-wise similar items
- Collaborative
 - Requires knowledge previous orders and transactions
 - Requires **no knowledge about the items** themselves

→ Provides recommendations of items other persons chose in this situation

Person ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, 2x Bread, 2x Sugar, Potatoes
3	Apples, Bread, Potatoes, Sugar
4	Bread, Oatmeal, Potatoes, Sugar

RECOMMENDATION GENERATION

- Content-based
 - Requires knowledge about the items themselves
 - Requires no knowledge about previous orders

→ Provides recommendations of content-wise similar items
- Collaborative
 - Requires knowledge previous orders and transactions
 - Requires **no knowledge about the items** themselves

→ Provides recommendations of items other persons chose in this situation

 - i. Identify similar persons
 - ii. Identify similar transactions, i.e., item combination in shopping cart

Person ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, 2x Bread, 2x Sugar, Potatoes
3	Apples, Bread, Potatoes, Sugar
4	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$
 - Correct in all transactions containing { Apples }

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$
 - Correct in all transactions containing $\{ \text{Apples} \}$
 - $\{ \text{Bread} \} \rightarrow \{ \text{Apples} \}$

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$
 - Correct in all transactions containing $\{ \text{Apples} \}$
 - $\{ \text{Bread} \} \rightarrow \{ \text{Apples} \}$
 - Correct only in 2 out of 5 transactions containing $\{ \text{Bread} \}$

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$
 - Correct in all transactions containing $\{ \text{Apples} \}$
 - $\{ \text{Bread} \} \rightarrow \{ \text{Apples} \}$
 - Correct only in 2 out of 5 transactions containing $\{ \text{Bread} \}$
- Recommendation generation:

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$
 - Correct in all transactions containing $\{ \text{Apples} \}$
 - $\{ \text{Bread} \} \rightarrow \{ \text{Apples} \}$
 - Correct only in 2 out of 5 transactions containing $\{ \text{Bread} \}$
- Recommendation generation:
 - Create those rules, only keep the ones sufficiently often correct

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

ASSOCIATION RULE LEARNING

- Collaborative approach
- Algorithmic approach to mine association rules
 - $\{ \text{Item in cart} \} \rightarrow \{ \text{Implies further items} \}$
- Applied to our example transactions:
 - $\{ \text{Apples} \} \rightarrow \{ \text{Bread, Sugar} \}$
 - Correct in all transactions containing $\{ \text{Apples} \}$
 - $\{ \text{Bread} \} \rightarrow \{ \text{Apples} \}$
 - Correct only in 2 out of 5 transactions containing $\{ \text{Bread} \}$
- Recommendation generation:
 - Create those rules, only keep the ones sufficiently often correct
 - Use rules to suggest new items to customers

Transaction ID	Items
1	Bread, Oatmeal, Potatoes
2	Apples, Bread, Sugar
3	Apples, Bread, Potatoes, Sugar
4	Bread, Potatoes, Sugar
5	Bread, Oatmeal, Potatoes, Sugar

2. FORWARD E-MAILS

- More technical rewrite of problem:

2. FORWARD E-MAILS

- More technical rewrite of problem:
 - Problem:
Classification of e-mails to a department for handling based on content

2. FORWARD E-MAILS

- More technical rewrite of problem:
 - Problem:
Classification of e-mails to a department for handling based on content
 - Class information:
Name and description of each available department

2. FORWARD E-MAILS

- More technical rewrite of problem:
 - Problem:
Classification of e-mails to a department for handling based on content
 - Class information:
Name and description of each available department
 - Training data:
Large amount of previously received e-mails labeled with responsible department

2. FORWARD E-MAILS

- More technical rewrite of problem:
 - Problem:
Classification of e-mails to a department for handling based on content
 - Class information:
Name and description of each available department
 - Training data:
Large amount of previously received e-mails labeled with responsible department
 - Input:
A newly received e-mail

2. FORWARD E-MAILS

- More technical rewrite of problem:
 - Problem:
Classification of e-mails to a department for handling based on content
 - Class information:
Name and description of each available department
 - Training data:
Large amount of previously received e-mails labeled with responsible department
 - Input:
A newly received e-mail
 - Output:
The most suitable department for handling

2. FORWARD E-MAILS

- More technical rewrite of problem:
 - Problem:
Classification of e-mails to a department for handling based on content
 - Class information:
Name and description of each available department
 - Training data:
Large amount of previously received e-mails labeled with responsible department
 - Input:
A newly received e-mail
 - Output:
The most suitable department for handling
 - Risk:
Low (e-mail forwarded to wrong department, just manually forward to correct)

EXAMPLE: WORDS IN E-MAILS

Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,

I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]

Subject: Request for a Service-Contract Offer

Dear Support,

I am interested in obtaining a service contract for our current it equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]

EXAMPLE: WORDS IN E-MAILS

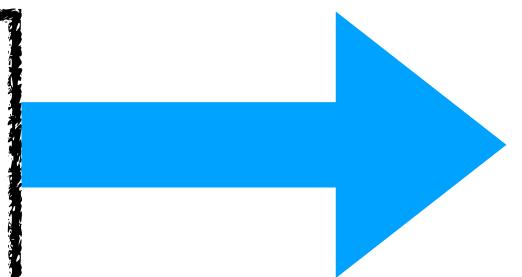
Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,

I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]



Legal Department

Subject: Request for a Service-Contract Offer

Dear Support,

I am interested in obtaining a service contract for our current it equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]

EXAMPLE: WORDS IN E-MAILS

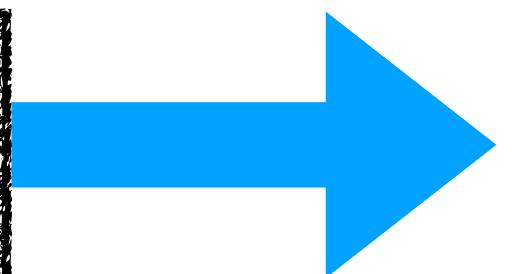
Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,

I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]



Legal Department

Subject: Request for a Service-Contract Offer

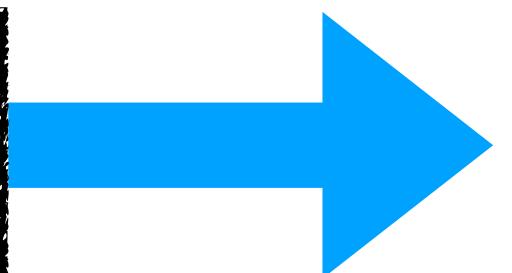
Dear Support,

I am interested in obtaining a service contract for our current it equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]



Sales Department

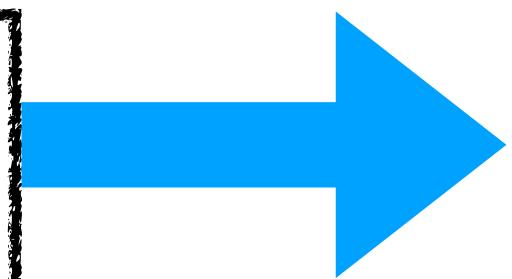
EXAMPLE: WORDS IN E-MAILS

Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,
I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]



Legal Department

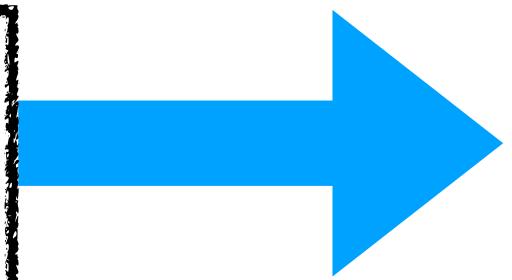
Subject: Request for a Service-Contract Offer

Dear Support,
I am interested in obtaining a service contract for our current IT equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]



Sales Department

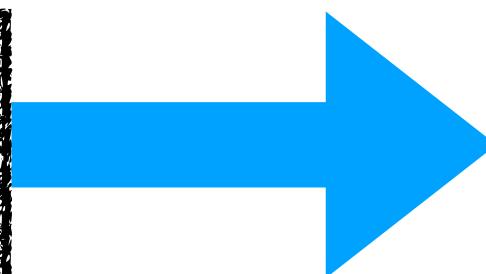
EXAMPLE: WORDS IN E-MAILS

Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,
I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]



Legal Department

- „GDPR“
- „contract“
- „personal“, „data“
- „personal data“

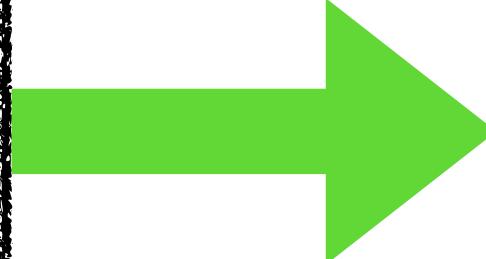
Subject: Request for a Service-Contract Offer

Dear Support,
I am interested in obtaining a service contract for our current it equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]



Sales Department

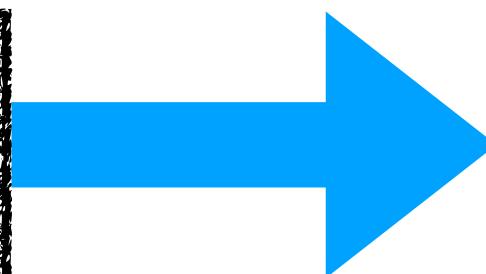
EXAMPLE: WORDS IN E-MAILS

Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,
I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]



Legal Department

- „GDPR“
- „contract“
- „personal“, „data“
- „personal data“

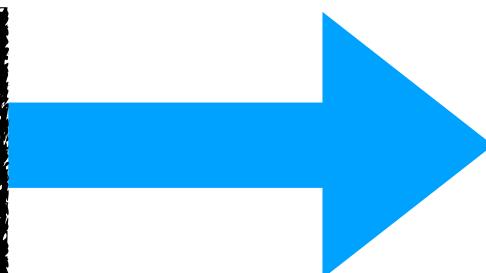
Subject: Request for a Service-Contract Offer

Dear Support,
I am interested in obtaining a service contract for our current it equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]



Sales Department

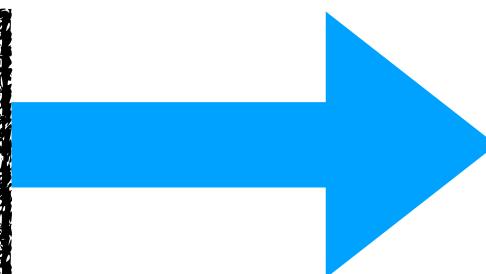
EXAMPLE: WORDS IN E-MAILS

Subject: Request for Access to Personal Data - Art. 15 GDPR

Dear Support,
I am writing to exercise my right of access under Article 15 of the EU General Data Protection Regulation (GDPR). Please provide me with a complete copy of all personal data you hold about me, including but not limited to:

- Account information and usage logs
- Correspondence and communications
- Contract informations
- Any third-party data sources you have combined with my data

[...]



Legal Department

- „GDPR“
- „contract“
- „personal“, „data“
- „personal data“

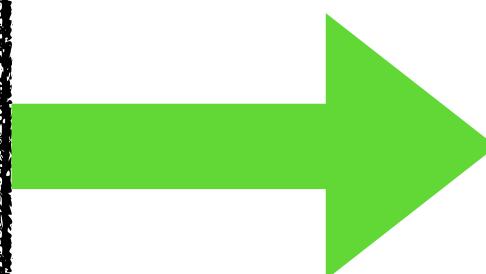
Subject: Request for a Service-Contract Offer

Dear Support,
I am interested in obtaining a service contract for our current it equipment, mostly the 25 office computers. Please send me a formal offer.

Could you please provide me with:

- The available contract lengths (12 months, 24 months, etc.)

[...]



Sales Department

- „offer“
- „contract“
- „service“, „contract“
- „service contract“

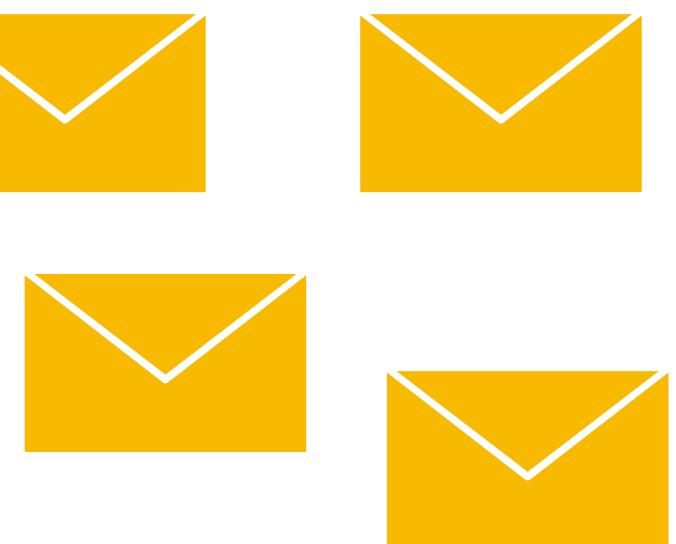
LOOKING AT THE WORDS

- How to identify relevant words? (automatically)



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

LOOKING AT THE WORDS

- How to identify relevant words? (automatically)
 - Sets of e-mails, one per department for handling



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

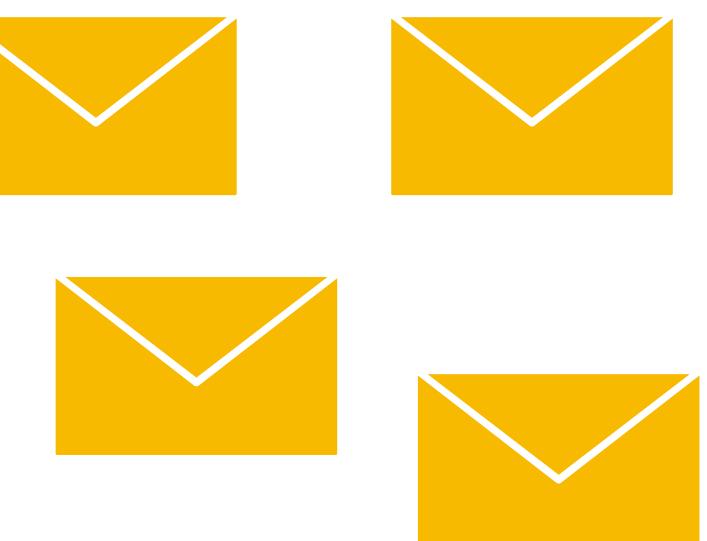
LOOKING AT THE WORDS

- How to identify relevant words? (automatically)
 - Sets of e-mails, one per department for handling
- Identify pivotal words for assigning to each department



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

LOOKING AT THE WORDS

- How to identify relevant words? (automatically)
 - Sets of e-mails, one per department for handling
- Identify pivotal words for assigning to each department
 - Generally less relevant words:
 - ▶ „a“, „the“, „is“, „and“ → so-called *stopwords*



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

LOOKING AT THE WORDS

- How to identify relevant words? (automatically)
 - Sets of e-mails, one per department for handling
- Identify pivotal words for assigning to each department
 - Generally less relevant words:
 - ▶ „a“, „the“, „is“, „and“ → so-called *stopwords*
 - Topic specific words
 - ▶ „contract“, „customer“, „support“



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

LOOKING AT THE WORDS

- How to identify relevant words? (automatically)
 - Sets of e-mails, one per department for handling
- Identify pivotal words for assigning to each department
 - Generally less relevant words:
 - ▶ „a“, „the“, „is“, „and“ → so-called *stopwords*
 - Topic specific words
 - ▶ „contract“, „customer“, „support“
 - Department specific words
 - ▶ „GDPR“, „offer“



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

LOOKING AT THE WORDS

- How to identify relevant words? (automatically)
 - Sets of e-mails, one per department for handling
- Identify pivotal words for assigning to each department
 - Generally less relevant words:
 - ▶ „a“, „the“, „is“, „and“ → so-called *stopwords*
 - Topic specific words
 - ▶ „contract“, „customer“, „support“
 - Department specific words
 - ▶ „GDPR“, „offer“
- Word combinations
 - Use bi-grams or tri-grams, i.e., „service contract“, „personal data“



Legal Department:

- „GDPR“
- „contract“
- „personal“, „data“
 - „personal data“



Sales Department:

- „offer“
- „contract“
- „service“, „contract“
 - „service contract“

TEXT CLASSIFICATION USING TF-IDF

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)
 - Count the occurrence of each word per e-mail

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)
 - Count the occurrence of each word per e-mail
 - Divide by number of words in e-mail to take length of e-mail into account

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)
 - Count the occurrence of each word per e-mail
 - Divide by number of words in e-mail to take length of e-mail into account
- Inverse-Document-Frequency (IDF)

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)
 - Count the occurrence of each word per e-mail
 - Divide by number of words in e-mail to take length of e-mail into account
- Inverse-Document-Frequency (IDF)
 - Identify *rare*, thus *pivotal* words:
 - Word present in all sets for all departments *not specific*
 - Word often present in one set for one department *very specific*

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)
 - Count the occurrence of each word per e-mail
 - Divide by number of words in e-mail to take length of e-mail into account
- Inverse-Document-Frequency (IDF)
 - Identify *rare*, thus *pivotal* words:
 - Word present in all sets for all departments *not specific*
 - Word often present in one set for one department *very specific*
- Combine together:

Term-Frequency & Inverse-Document-Frequency → TF-IDF

TEXT CLASSIFICATION USING TF-IDF

- Term-Frequency (TF)
 - Count the occurrence of each word per e-mail
 - Divide by number of words in e-mail to take length of e-mail into account
- Inverse-Document-Frequency (IDF)
 - Identify *rare*, thus *pivotal* words:
 - Word present in all sets for all departments *not specific*
 - Word often present in one set for one department *very specific*
- Combine together:
Term-Frequency & Inverse-Document-Frequency → TF-IDF

→ Relevance value for each word

Compare relevant words extracted from a new mail to the relevant words per department → Assign mail to this department

SIDE NOTE: TF-IDF FORMAL

$$tf \cdot idf_{t,d} = tf_{t,d} \cdot idf_t = \frac{t_d}{|d|} \cdot \log \left(\frac{N}{df_t} \right)$$

using

t = Word

d = E-Mail

$|d|$ = Number of words in e-mail d

N = Number of overall e-mails

df_t = Number of documents containing word t

SIDE NOTE: TF-IDF FORMAL

- Defined for each word (term) and each e-mail (document)

$$tf.\ idf_{t,d} = tf_{t,d} \cdot idf_t = \frac{t_d}{|d|} \cdot \log \left(\frac{N}{df_t} \right)$$

using

t = Word

d = E-Mail

$|d|$ = Number of words in e-mail d

N = Number of overall e-mails

df_t = Number of documents containing word t

SIDE NOTE: TF-IDF FORMAL

- Defined for each word (term) and each e-mail (document)
- Produces a per-word score representing the relevance of each word present in any of the e-mails (corpus)

$$tf\cdot idf_{t,d} = tf_{t,d} \cdot idf_t = \frac{t_d}{|d|} \cdot \log\left(\frac{N}{df_t}\right)$$

using

t = Word

d = E-Mail

$|d|$ = Number of words in e-mail d

N = Number of overall e-mails

df_t = Number of documents containing word t

SIDE NOTE: TF-IDF FORMAL

- Defined for each word (term) and each e-mail (document)
- Produces a per-word score representing the relevance of each word present in any of the e-mails (corpus)
- Get the pivotal words in e-mail for assigning to departments

$$tf.\ idf_{t,d} = tf_{t,d} \cdot idf_t = \frac{t_d}{|d|} \cdot \log \left(\frac{N}{df_t} \right)$$

using

t = Word

d = E-Mail

$|d|$ = Number of words in e-mail d

N = Number of overall e-mails

df_t = Number of documents containing word t

SIDE NOTE: TF-IDF FORMAL

- Defined for each word (term) and each e-mail (document)
- Produces a per-word score representing the relevance of each word present in any of the e-mails (corpus)
- Get the pivotal words in e-mail for assigning to departments
- Use these words

$$tf.\ idf_{t,d} = tf_{t,d} \cdot idf_t = \frac{t_d}{|d|} \cdot \log \left(\frac{N}{df_t} \right)$$

using

t = Word

d = E-Mail

$|d|$ = Number of words in e-mail d

N = Number of overall e-mails

df_t = Number of documents containing word t

TECHNICAL PROCESS

TECHNICAL PROCESS

Legal Department



Sales Department



Training Data

(Sets of e-mails per department)



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

01. October 2025

Magnus Bender
Assistant Professor

26



TECHNICAL PROCESS

Legal Department



Sales Department



Training Data
(Sets of e-mails per department)

Pivotal Words
(Specific words per department)

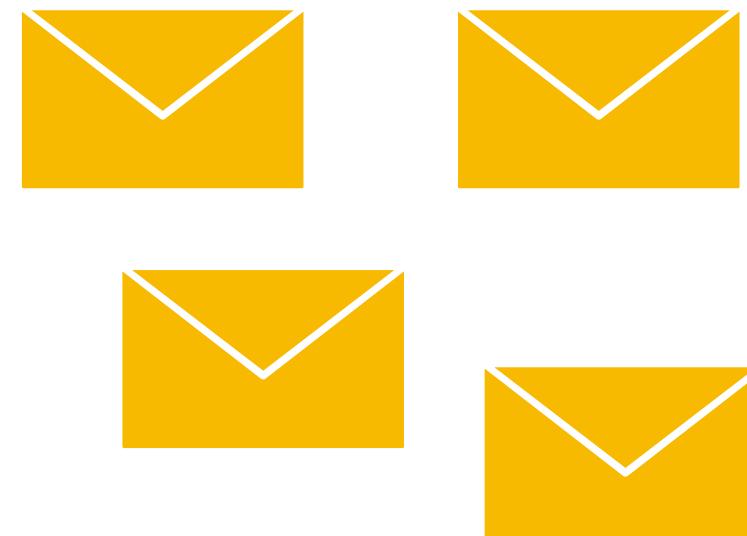


TECHNICAL PROCESS

Legal Department



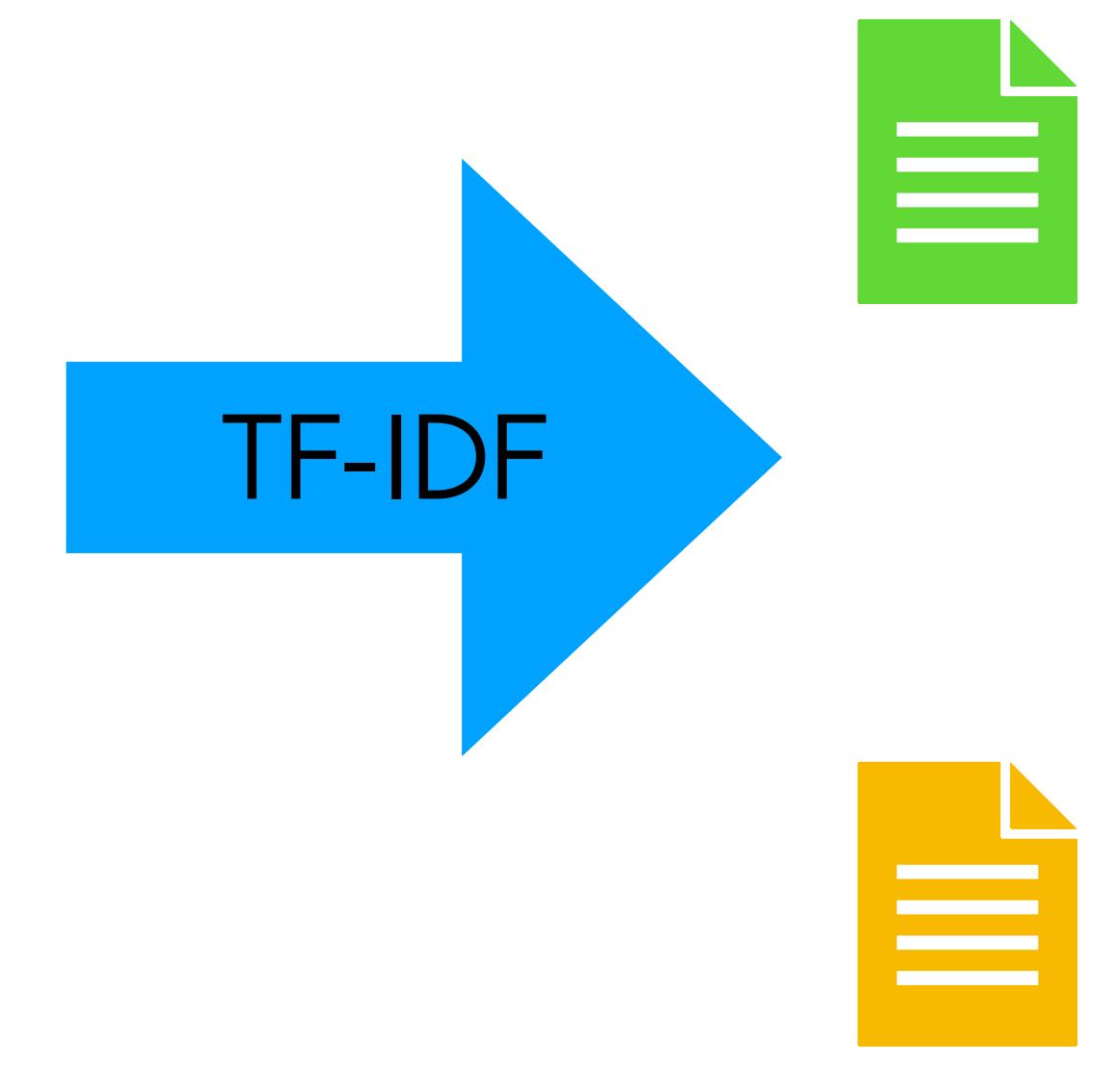
Sales Department



Training Data
(Sets of e-mails per department)



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY



Pivotal Words
(Specific words per department)

01. October 2025

Magnus Bender
Assistant Professor

26

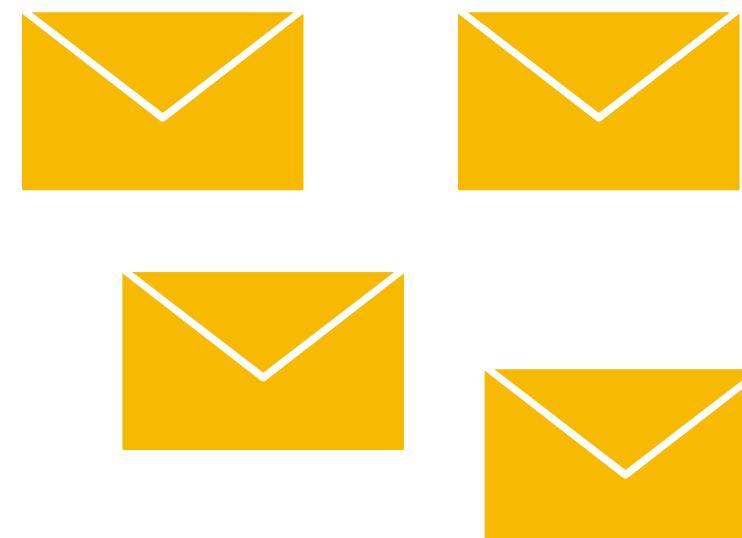


TECHNICAL PROCESS

Legal Department



Sales Department

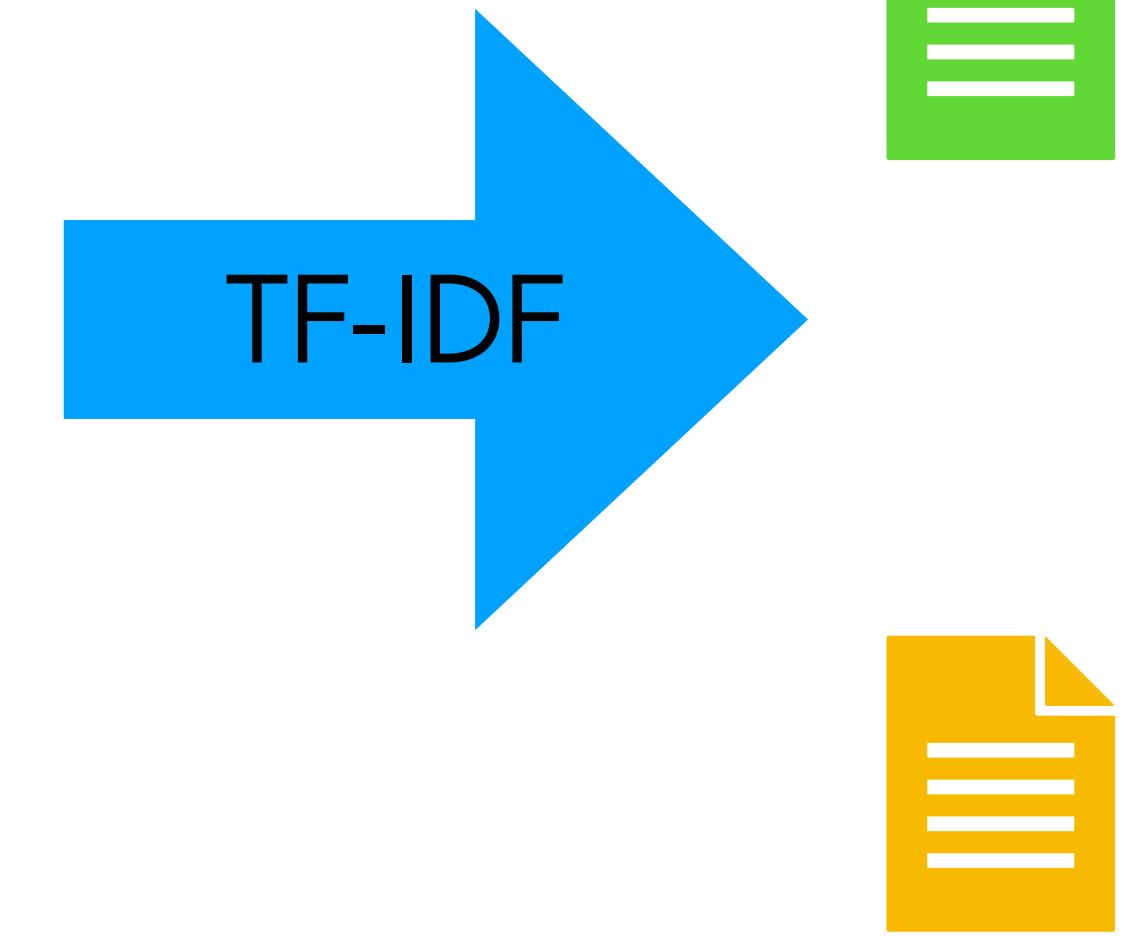


Training Data
(Sets of e-mails per department)



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

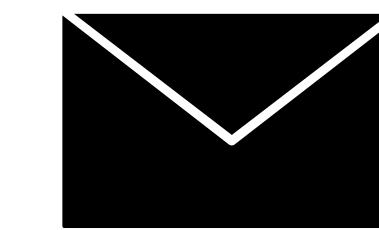
TF-IDF



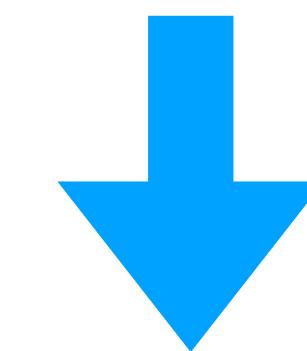
Pivotal Words
(Specific words per department)

01. October 2025

Magnus Bender
Assistant Professor



New e-mail



26

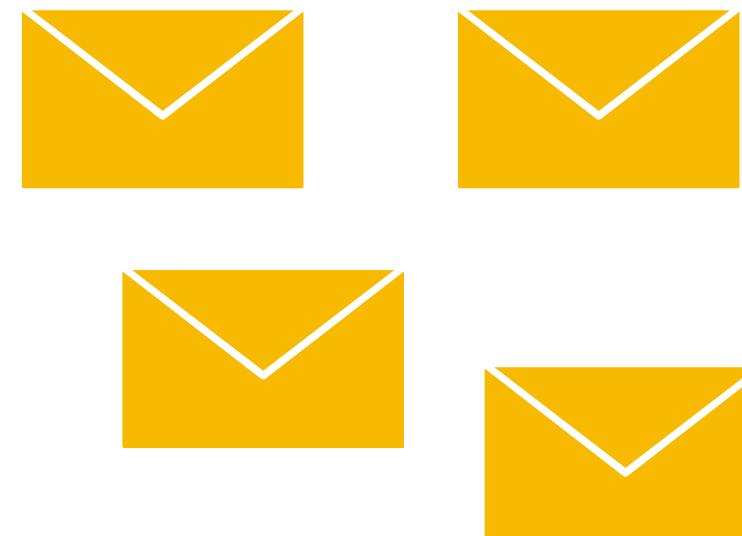


TECHNICAL PROCESS

Legal Department



Sales Department



Training Data
(Sets of e-mails per department)



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

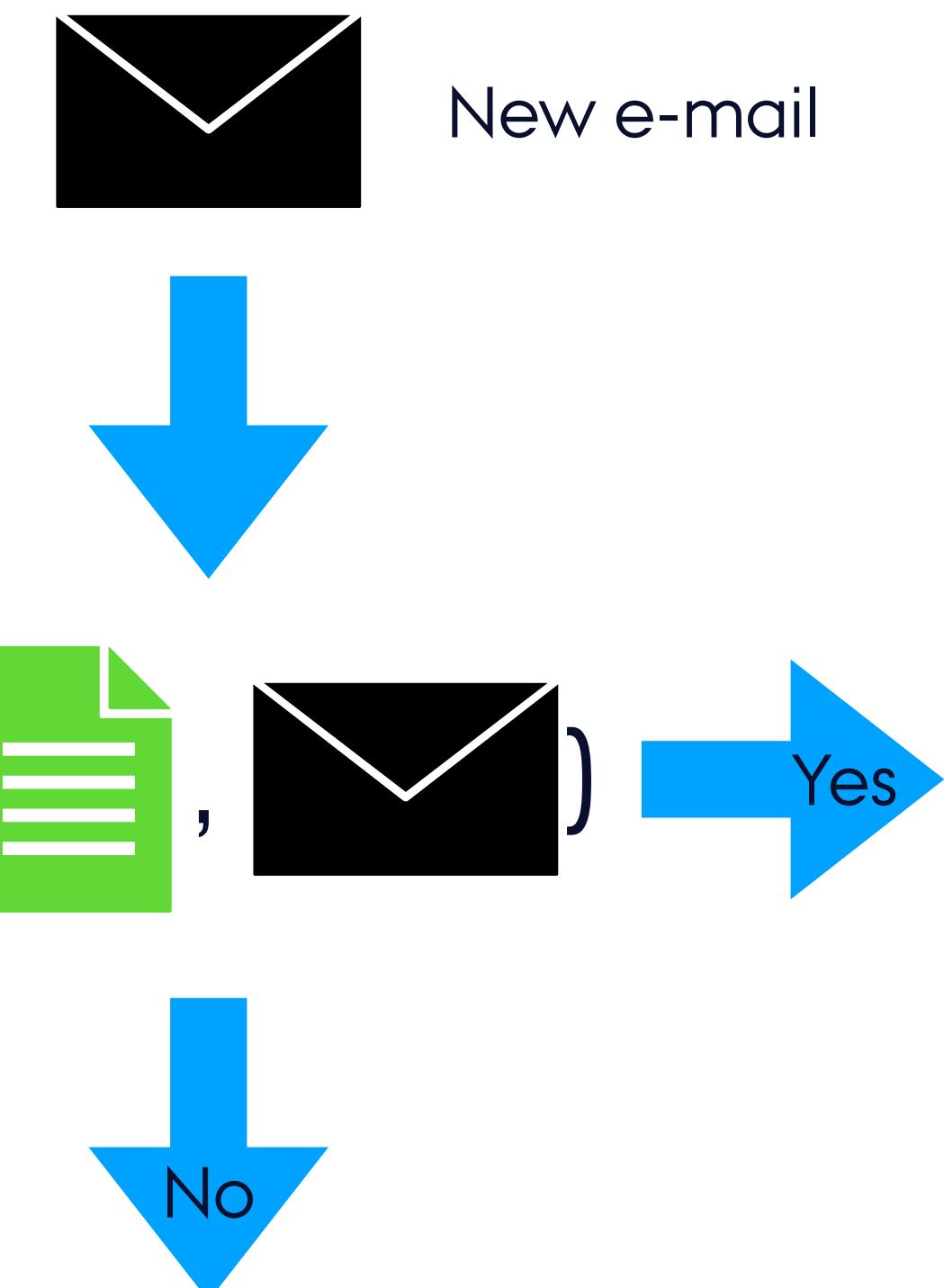
TF-IDF



Pivotal Words
(Specific words per department)

01. October 2025

Magnus Bender
Assistant Professor

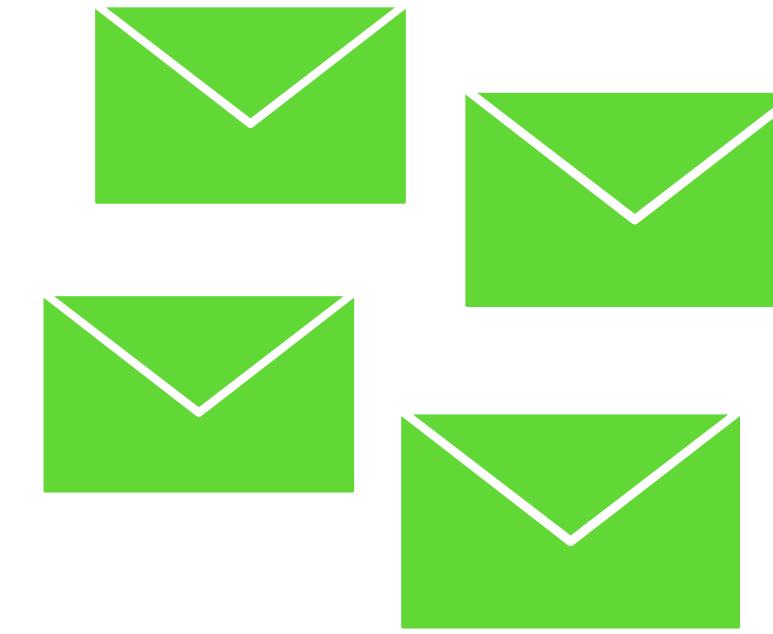


26

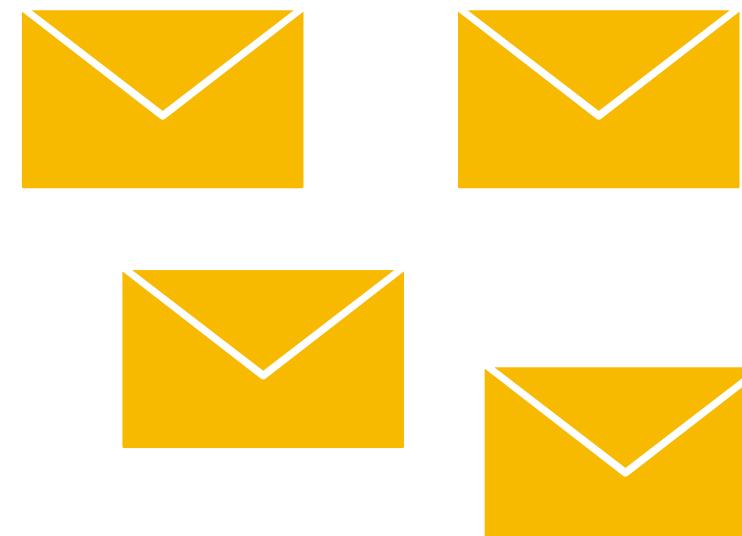


TECHNICAL PROCESS

Legal Department



Sales Department



Training Data
(Sets of e-mails per department)



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

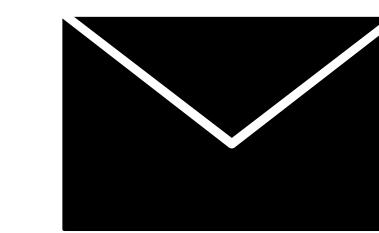
TF-IDF



Pivotal Words
(Specific words per department)

01. October 2025

Magnus Bender
Assistant Professor



New e-mail



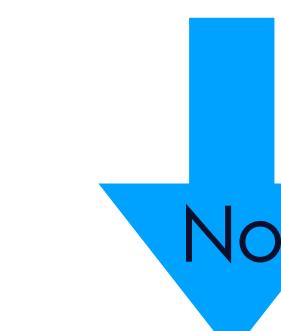
Similar(



)

Yes

Forward to legal
department



No

26



TECHNICAL PROCESS

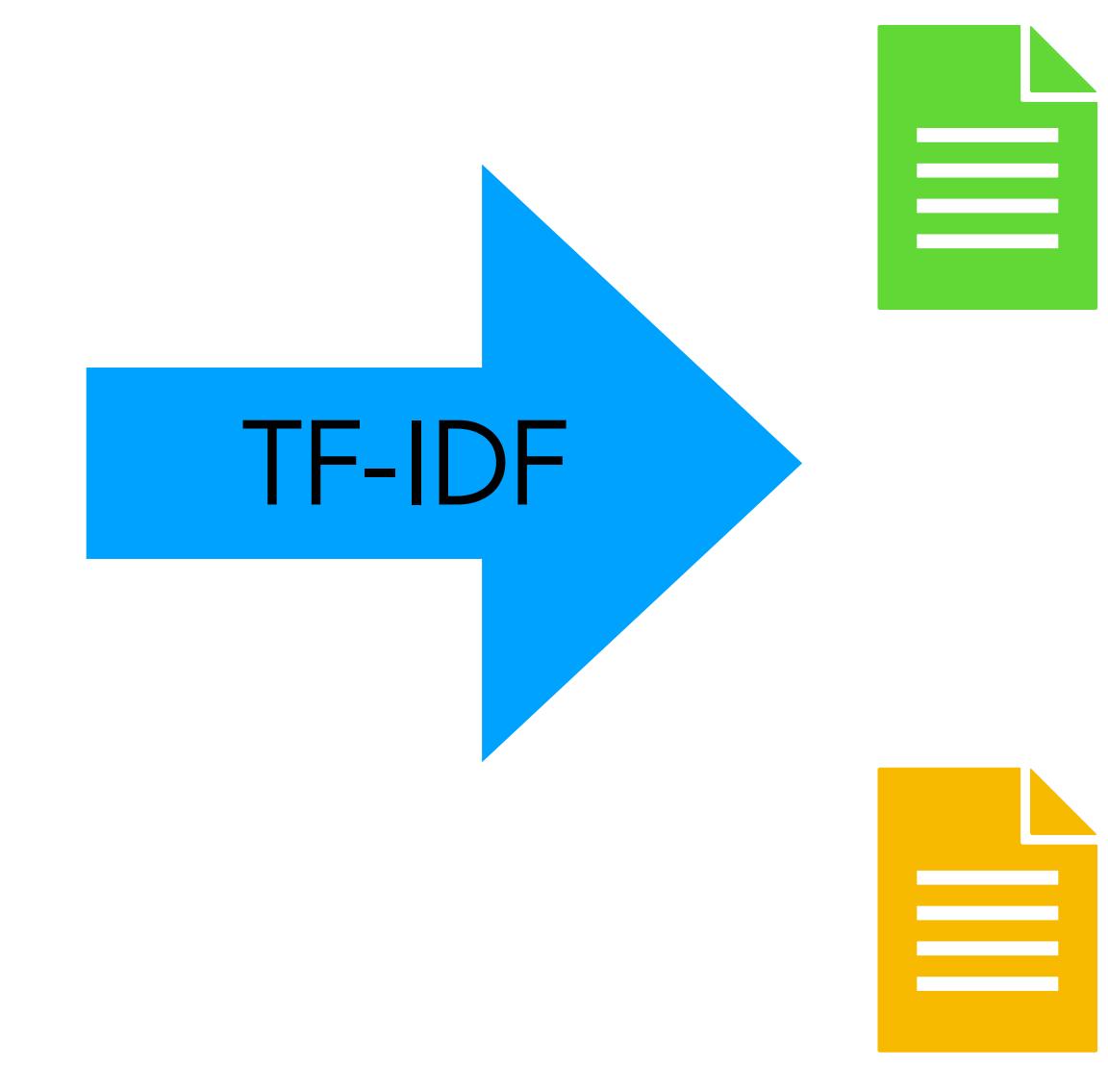
Legal Department



Training Data
(Sets of e-mails per department)



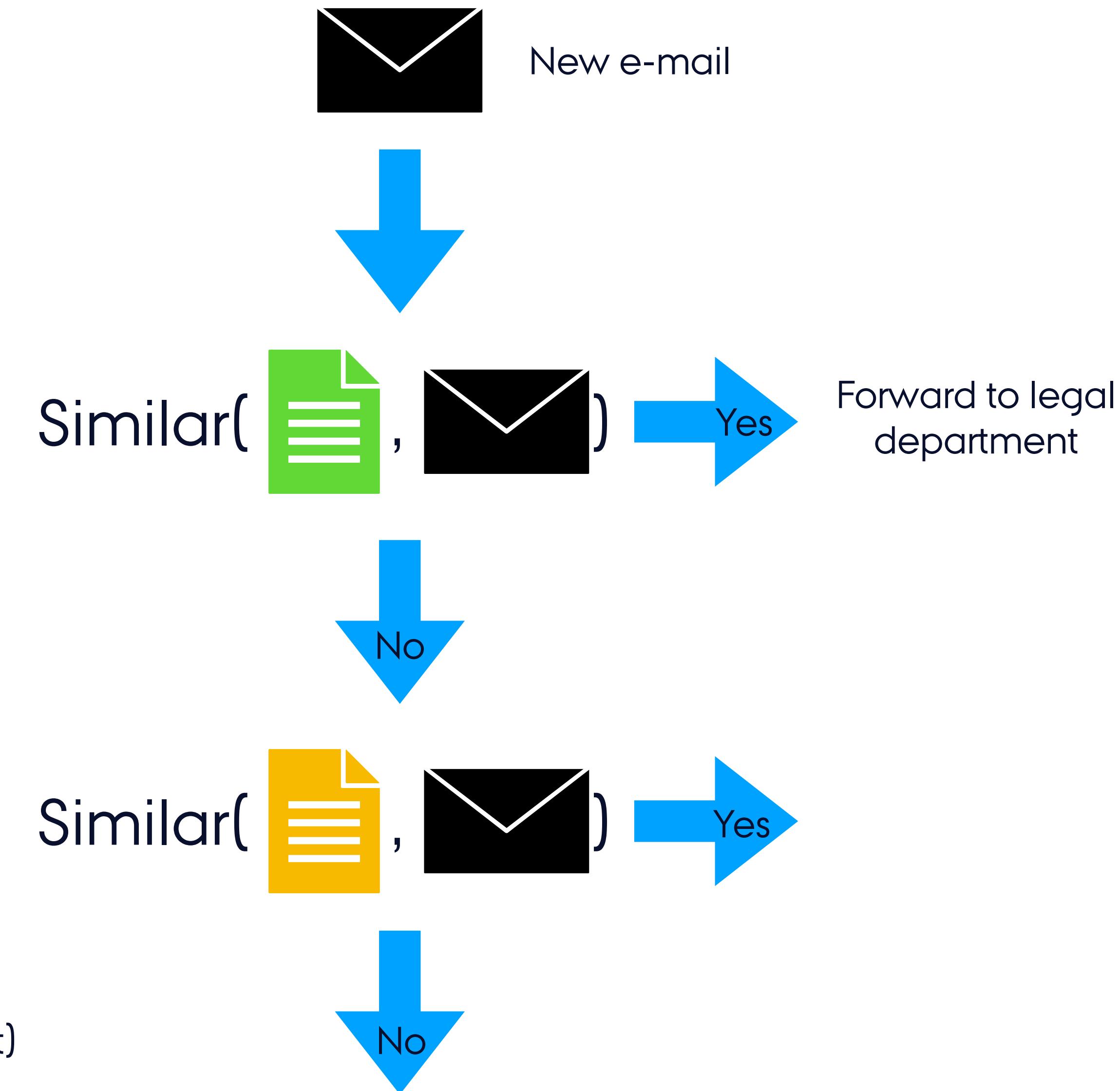
DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY



Pivotal Words
(Specific words per department)

01. October 2025

Magnus Bender
Assistant Professor



26



TECHNICAL PROCESS

Legal Department



Sales Department



Training Data
(Sets of e-mails per department)



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

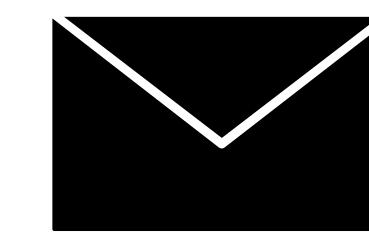
TF-IDF



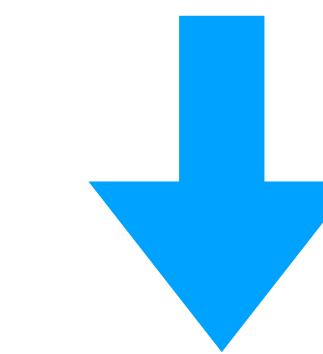
Pivotal Words
(Specific words per department)

01. October 2025

Magnus Bender
Assistant Professor



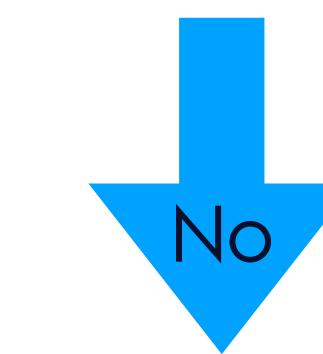
New e-mail



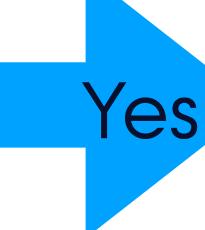
Similar(



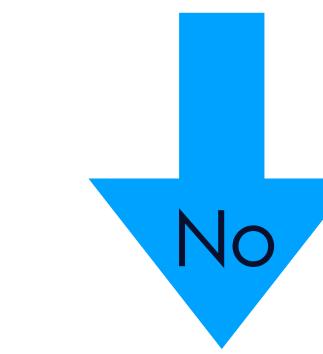
Forward to legal
department



Similar(



Forward to sales
department



...

26



TEXT CLASSIFICATION USING LLMS

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training
 - Trained model is fixed to the departments available in training data

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training
 - Trained model is fixed to the departments available in training data
- b) List and describe the available departments as part of the prompt and ask LLM to select the most appropriate

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training
 - Trained model is fixed to the departments available in training data
- b) List and describe the available departments as part of the prompt and ask LLM to select the most appropriate
 - No training or training data required, less programming

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training
 - Trained model is fixed to the departments available in training data
- b) List and describe the available departments as part of the prompt and ask LLM to select the most appropriate
 - No training or training data required, less programming
 - Changes in departments can be easily implemented by updating prompts

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training
 - Trained model is fixed to the departments available in training data
- b) List and describe the available departments as part of the prompt and ask LLM to select the most appropriate
 - No training or training data required, less programming
 - Changes in departments can be easily implemented by updating prompts
 - Constant cost and resource requirements

TEXT CLASSIFICATION USING LLMS

- a) Train an LLM on the previously received e-mails and labels
 - Requires huge amount of data, training hardware, programming skills
 - May require less hardware, resources after training
 - Trained model is fixed to the departments available in training data
- b) List and describe the available departments as part of the prompt and ask LLM to select the most appropriate
 - No training or training data required, less programming
 - Changes in departments can be easily implemented by updating prompts
 - Constant cost and resource requirements
 - Providers like OpenAI may update their models → may require changing prompt

3. INSPECTION OF CVS

- More technical rewrite of problem:

3. INSPECTION OF CVS

- More technical rewrite of problem:
 - Problem:
Classification of CVs as „complete“ or „incomplete“ based on content

3. INSPECTION OF CVS

- More technical rewrite of problem:
 - Problem:
Classification of CVs as „complete“ or „incomplete“ based on content
 - Class information:
Name and description of „complete“ or „incomplete“, i.e., rules for required information in CV

3. INSPECTION OF CVS

- More technical rewrite of problem:
 - Problem:
Classification of CVs as „complete“ or „incomplete“ based on content
 - Class information:
Name and description of „complete“ or „incomplete“, i.e., rules for required information in CV
 - Training data:
Not necessarily available, as required information in CVs changes from case to case

3. INSPECTION OF CVS

- More technical rewrite of problem:
 - Problem:
Classification of CVs as „complete“ or „incomplete“ based on content
 - Class information:
Name and description of „complete“ or „incomplete“, i.e., rules for required information in CV
 - Training data:
Not necessarily available, as required information in CVs changes from case to case
 - Input:
A PDF file of an CV

3. INSPECTION OF CVS

- More technical rewrite of problem:
 - Problem:
Classification of CVs as „complete“ or „incomplete“ based on content
 - Class information:
Name and description of „complete“ or „incomplete“, i.e., rules for required information in CV
 - Training data:
Not necessarily available, as required information in CVs changes from case to case
 - Input:
A PDF file of an CV
 - Output:
„complete“ or „incomplete“

3. INSPECTION OF CVS

- More technical rewrite of problem:
 - Problem:
Classification of CVs as „complete“ or „incomplete“ based on content
 - Class information:
Name and description of „complete“ or „incomplete“, i.e., rules for required information in CV
 - Training data:
Not necessarily available, as required information in CVs changes from case to case
 - Input:
A PDF file of an CV
 - Output:
„complete“ or „incomplete“
 - Risk:
Medium to high (rejection of applicant, even though CV is complete; unable to observe *error*)

TEXT CLASSIFICATION USING LLM OR PYTHON

TEXT CLASSIFICATION USING LLM OR PYTHON

a) Implement a rule-based classifier in Python

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing
 - No errors if all rules are correctly and fully implemented, but difficult to archive

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing
 - No errors if all rules are correctly and fully implemented, but difficult to archive
- b) List and describe the required information in a CV as part of the prompt and ask LLM to check if everything is included

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing
 - No errors if all rules are correctly and fully implemented, but difficult to archive
- b) List and describe the required information in a CV as part of the prompt and ask LLM to check if everything is included
 - No training or training data required, less programming

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing
 - No errors if all rules are correctly and fully implemented, but difficult to archive
- b) List and describe the required information in a CV as part of the prompt and ask LLM to check if everything is included
 - No training or training data required, less programming
 - Changes in required information can be easily implemented by updating prompt

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing
 - No errors if all rules are correctly and fully implemented, but difficult to archive
- b) List and describe the required information in a CV as part of the prompt and ask LLM to check if everything is included
 - No training or training data required, less programming
 - Changes in required information can be easily implemented by updating prompt
 - Constant cost and resources requirements

TEXT CLASSIFICATION USING LLM OR PYTHON

- a) Implement a rule-based classifier in Python
 - Requires programming skills, time for implementation
 - Requires less hardware and resources after implementing
 - No errors if all rules are correctly and fully implemented, but difficult to archive
- b) List and describe the required information in a CV as part of the prompt and ask LLM to check if everything is included
 - No training or training data required, less programming
 - Changes in required information can be easily implemented by updating prompt
 - Constant cost and resources requirements
 - Providers like OpenAI may update their models → may require changing prompt

4. SELECTION OF APPLICANT

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:
 - Problem:
Selection of the best fitting applicant based on CVs of all applicants

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:
 - Problem:
Selection of the best fitting applicant based on CVs of all applicants
 - Available Information:
Requirement for the position based on job offer

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:
 - Problem:
Selection of the best fitting applicant based on CVs of all applicants
 - Available Information:
Requirement for the position based on job offer
 - Input:
The PDF files of the CVs of all applicants

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:
 - Problem:
Selection of the best fitting applicant based on CVs of all applicants
 - Available Information:
Requirement for the position based on job offer
 - Input:
The PDF files of the CVs of all applicants
 - Output:
The best fitting applicant

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:
 - Problem:
Selection of the best fitting applicant based on CVs of all applicants
 - Available Information:
Requirement for the position based on job offer
 - Input:
The PDF files of the CVs of all applicants
 - Output:
The best fitting applicant
 - Risk:
High to unacceptable (rejection because of system's misunderstanding, ...; unable to observe *error*)

Not compatible
with AI-Act!

4. SELECTION OF APPLICANT

- More technical rewrite of problem:
 - Problem:
Selection of the best fitting applicant based on CVs of all applicants
 - Available Information:
Requirement for the position based on job offer
 - Input:
The PDF files of the CVs of all applicants
 - Output:
The best fitting applicant
 - Risk:
High to unacceptable (rejection because of system's misunderstanding, ...; unable to observe *error*)

Very vague rules (from job offer) used
for a very explicit decision (hire).
Thereby, hardly any supervision or
transparency.

BACK TO THE EXAMPLES

BACK TO THE EXAMPLES

Task Description

Personalized

1 recommendations of items
in an online shop

2 Automatic forwarding of
customer's e-mails to
correct department

3 Inspection of CVs of
applicants for a position

4 Selection of the applicant to
hire for a position

BACK TO THE EXAMPLES

	Task Description	Input	Output
1	Personalized recommendations of items in an online shop	User-selected item	Relevant items
2	Automatic forwarding of customer's e-mails to correct department	E-mail text	Suitable department
3	Inspection of CVs of applicants for a position	PDF file of CV	„Complete“ or „Incomplete“
4	Selection of the applicant to hire for a position	PDF files of CVs	Best applicant

BACK TO THE EXAMPLES

	Task Description	Input	Output	Formalized Problem
1	Personalized recommendations of items in an online shop	User-selected item	Relevant items	Top- k choice
2	Automatic forwarding of customer's e-mails to correct department	E-mail text	Suitable department	Classification
3	Inspection of CVs of applicants for a position	PDF file of CV	„Complete“ or „Incomplete“	Classification
4	Selection of the applicant to hire for a position	PDF files of CVs	Best applicant	Top-1 choice

BACK TO THE EXAMPLES

	Task Description	Input	Output	Formalized Problem	(Training) Data
1	Personalized recommendations of items in an online shop	User-selected item	Relevant items	Top- k choice	Previous transactions
2	Automatic forwarding of customer's e-mails to correct department	E-mail text	Suitable department	Classification	Previous e-mails assigned to departments (or rules for LLM)
3	Inspection of CVs of applicants for a position	PDF file of CV	„Complete“ or „Incomplete“	Classification	Rules about necessary information, examples
4	Selection of the applicant to hire for a position	PDF files of CVs	Best applicant	Top-1 choice	Requirements of position, (prob. examples)

BACK TO THE EXAMPLES

	Task Description	Input	Output	Formalized Problem	(Training) Data	LLM
1	Personalized recommendations of items in an online shop	User-selected item	Relevant items	Top- k choice	Previous transactions	not suitable
2	Automatic forwarding of customer's e-mails to correct department	E-mail text	Suitable department	Classification	Previous e-mails assigned to departments (or rules for LLM)	suitable, but not required
3	Inspection of CVs of applicants for a position	PDF file of CV	„Complete“ or „Incomplete“	Classification	Rules about necessary information, examples	suitable and helpful
4	Selection of the applicant to hire for a position	PDF files of CVs	Best applicant	Top-1 choice	Requirements of position, (prob. examples)	required*

INTERIM SUMMARY



INTERIM SUMMARY

- The use-case heavily influences the tools to use

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - ▶ From the outer workflow site: The problem located in its overall (business) process/environment
 - ▶ From the inner technical site:

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - ▶ From the outer workflow site: The problem located in its overall (business) process/environment
 - ▶ From the inner technical site:
 - The inputs and expected outputs of the system and model

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

INTERIM SUMMARY

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - ▶ From the outer workflow site: The problem located in its overall (business) process/environment
 - ▶ From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs
- There are old-school and new (LLM-based) NLP techniques
 - Old-school techniques require specific data formats or do lossy pre-processing

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs
- There are old-school and new (LLM-based) NLP techniques
 - Old-school techniques require specific data formats or do lossy pre-processing
 - LLMs are de-facto the only solution to process text of unknown structure

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs
- There are old-school and new (LLM-based) NLP techniques
 - Old-school techniques require specific data formats or do lossy pre-processing
 - LLMs are de-facto the only solution to process text of unknown structure
- LLMs are quite easy to get started with
 - The task description is given in natural language, the output is natural language again

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs
- There are old-school and new (LLM-based) NLP techniques
 - Old-school techniques require specific data formats or do lossy pre-processing
 - LLMs are de-facto the only solution to process text of unknown structure
- LLMs are quite easy to get started with
 - The task description is given in natural language, the output is natural language again
 - But it may be difficult to get reliable and steady results

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs
- There are old-school and new (LLM-based) NLP techniques
 - Old-school techniques require specific data formats or do lossy pre-processing
 - LLMs are de-facto the only solution to process text of unknown structure
- LLMs are quite easy to get started with
 - The task description is given in natural language, the output is natural language again
 - But it may be difficult to get reliable and steady results
 - It may become expensive

INTERIM SUMMARY

- The use-case heavily influences the tools to use
 - You need to understand your problem from both sides:
 - From the outer workflow site: The problem located in its overall (business) process/environment
 - From the inner technical site:
 - The inputs and expected outputs of the system and model
 - The information the model uses for making decisions, i.e., data available for training or the rules to provide

- There are typical NLP task and more Data Science (none text-focused) task
 - The latter may be solved without any NLP techniques or LLMs
- There are old-school and new (LLM-based) NLP techniques
 - Old-school techniques require specific data formats or do lossy pre-processing
 - LLMs are de-facto the only solution to process text of unknown structure
- LLMs are quite easy to get started with
 - The task description is given in natural language, the output is natural language again
 - But it may be difficult to get reliable and steady results
 - It may become expensive
 - There might be less computational intensive alternatives

READINGS



AARHUS
BSS
DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

01. October 2025

Magnus Bender
Assistant Professor



READINGS TODAY

- Show LLMs being used to solve many of these older tasks, focusing on *classification*.

READINGS TODAY

- Show LLMs being used to solve many of these older tasks, focusing on *classification*.
 - Sentiment analysis
 - ▶ Is the text fundamentally positive or negative?

READINGS TODAY

- Show LLMs being used to solve many of these older tasks, focusing on *classification*.
 - Sentiment analysis
 - ▶ Is the text fundamentally positive or negative?
 - Emotion analysis
 - ▶ Which emotions are present in the text?

READINGS TODAY

- Show LLMs being used to solve many of these older tasks, focusing on *classification*.
 - Sentiment analysis
 - ▶ Is the text fundamentally positive or negative?
 - Emotion analysis
 - ▶ Which emotions are present in the text?
 - Offensiveness
 - ▶ Is this text intended to offend someone?

READINGS TODAY

- Show LLMs being used to solve many of these older tasks, focusing on *classification*.
 - Sentiment analysis
 - ▶ Is the text fundamentally positive or negative?
 - Emotion analysis
 - ▶ Which emotions are present in the text?
 - Offensiveness
 - ▶ Is this text intended to offend someone?
 - Stance detection
 - ▶ Given an issue, does the text agree with or disagree with this issue?

READINGS TODAY

- Show LLMs being used to solve many of these older tasks, focusing on *classification*.
 - Sentiment analysis
 - ▶ Is the text fundamentally positive or negative?
 - Emotion analysis
 - ▶ Which emotions are present in the text?
 - Offensiveness
 - ▶ Is this text intended to offend someone?
 - Stance detection
 - ▶ Given an issue, does the text agree with or disagree with this issue?
 - Frame detection
 - ▶ What is the framing of a particular news story

GILARDI ET AL.

- The study uses GPT to "annotate" data.
- Text-annotation is the catch-all term for adding analytical indicators to data.
- Their data consist of four different datasets, comprising a total of 6183 documents, distributed across tweets and newspaper articles.
- Specifically, their study compares GPT with
 - human non-expert annotators, and
 - trained human annotators (e.g. expert coders)

ChatGPT outperforms crowd workers for text-a

Fabrizio Gilardi^{a,1} , Maysam Alizadeh^a , and Maël Kubli^a 

Edited by Mary Waters, Harvard University, Cambridge, MA; received March 27, 2023; accepted June 2, 2023

Many NLP applications require manual text annotations for a variety of tasks, notably to train classifiers or evaluate the performance of unsupervised models. Depending on the size and degree of complexity, the tasks may be conducted by crowd workers on platforms such as MTurk as well as trained annotators, such as research assistants. Using four samples of tweets and news articles ($n = 6,183$), we show that ChatGPT outperforms crowd workers for several annotation tasks, including relevance, stance, topics, and frame detection. Across the four datasets, the zero-shot accuracy of ChatGPT exceeds that of crowd workers by about 25 percentage points on average, while ChatGPT's intercoder agreement exceeds that of both crowd workers and trained annotators for all tasks. Moreover, the per-annotation cost of ChatGPT is less than \$0.003—about thirty times cheaper than MTurk. These results demonstrate the potential of large language models to drastically increase the efficiency of text classification.

GILARDI ET AL.

- Five different classification tasks:
 - relevance (does this relate to politics, or to content moderation?),
 - stance (is this in favor of, against, or neutral to a specific piece of legislation?)
 - topics (six different classes),
 - and two kinds of frame detection (16 different classes).
- They use the same codebook (i.e. instructions) as they gave to their trained annotators as prompt to GPT and to the MTurk annotators.
- Finally, they compare how well GPT performs.

THEIR APPROACH IN DETAILS

- So, they have some text in a big list that they iterate over
- Write an instruction that outlines the task, provides a definition of all the possible classes, and instruct the LLM to only respond with the name of the relevant class.
- Sends the instruction as system instructions + "here's the tweet I picked, please label it as 'Relevant' or 'Irrelevant':"+ text "
- Have the LLM respond with "Relevant" or "Irrelevant"
- Add the response to a list, and finally compare with "human coders" later.

SUPPLEMENTARY MATERIAL

277 **S1. Annotation Codebooks**

278 Not all of the annotations described in these codebooks were
279 conducted for every dataset in our study. First, the manual annotations
280 we use as a benchmark were performed in a previous study, except
281 for the new 2023 sample, which was specifically annotated for this
282 current study. Second, certain annotation tasks are not applicable
283 to all datasets. For instance, stance analysis, problem/solution,
284 and topic modeling were not suitable for analyzing tweets from US
285 Congress members. This is because these tweets cover a wide range
286 of issues and topics, unlike content moderation topics, which are
287 more focused. For news articles, our attempts at human annotation
288 for stance, topic, and policy frames were not successful. This was
289 because the articles primarily revolved around platform policies,
290 actions, and criticisms thereof.

291 **A. Background on content moderation (to be used for all tasks except
292 the tweets from US Congressmembers).** For this task, you will be
293 asked to annotate a sample of tweets about content moderation.
294 Before describing the task, we explain what we mean by “content
295 moderation”.

296 “Content moderation” refers to the practice of screening and
297 monitoring content posted by users on social media sites to determine
298 if the content should be published or not, based on specific
299 rules and guidelines. Every time someone posts something on a platform
300 like Facebook or Twitter, that piece of content goes through
301 a review process (“content moderation”) to ensure that it is not
302 illegal, hateful or inappropriate and that it complies with the rules
303 of the site. When that is not the case, that piece of content can be
304 removed, flagged, labeled as or ‘disputed’.

305 Deciding what should be allowed on social media is not always
306 easy. For example, many sites ban child pornography and terrorist
307 content as it is illegal. However, things are less clear when it comes
308 to content about the safety of vaccines or politics, for example.
309 Even when people agree that some content should be blocked, they
310 do not always agree about the best way to do so, how effective it is,
311 and who should do it (the government or private companies, human
312 moderators, or artificial intelligence).

313 **B. Background on political tweets (to be used for tweets by the US
314 Congress members).** For this task, you will be asked to annotate
315 a sample of tweets to determine if they include political content
316 or not. For the purposes of this task, tweets are “relevant” if they
317 include political content, and “irrelevant” if they do not. Before
318 describing the task, we explain what we mean by “political content”.

319 “Political content” refers to any tweets that pertain to politics
320 or government policies at the local, national, or international level.
321 This can include tweets that discuss political figures, events, or
322 issues, as well as tweets that use political language or hashtags.
323 To determine if tweets include political content or not, consider
324 several factors, such as the use of political keywords or hashtags,
325 the mention of political figures or events, the inclusion of links to
326 news articles or other political sources, and the overall tone and
327 sentiment of the tweet, which may indicate whether it is conveying
328 a political message or viewpoint.

329 **C. Task 1: Relevance (Content Moderation).** For each tweet in the
330 sample, follow these instructions:

- 331 1. Carefully read the text of the tweet, paying close attention to
332 details.
- 333 2. Classify the tweet as either relevant (1) or irrelevant (0).

347 **D. Task 2: Relevance (Political Content).** For each tweet in the sample,
348 follow these instructions:

- 349 1. Carefully read the text of the tweet, paying close attention to
350 details.
- 351 2. Classify the tweet as either relevant (1) or irrelevant (0).

352 Tweets should be coded as RELEVANT if they include POLITICAL
353 CONTENT, as defined above. Tweets should be coded as
354 IRRELEVANT if they do NOT include POLITICAL CONTENT,
355 as defined above.

356 **E. Task 3: Problem/Solution Frames.** Content moderation can be
357 seen from two different perspectives:

- 358 Content moderation can be seen as a PROBLEM; for example,
359 as a restriction of free speech
- 360 Content moderation can be seen as a SOLUTION; for example,
361 as a protection from harmful speech

362 For each tweet in the sample, follow these instructions:

- 363 1. Carefully read the text of the tweet, paying close attention to
364 details.
- 365 2. Classify the tweet as describing content moderation as a prob-
366 lem, as a solution, or neither.

367 Tweets should be classified as describing content moderation as a
368 PROBLEM if they emphasize negative effects of content moderation,
369 such as restrictions to free speech, or the biases that can emerge
370 from decisions regarding what users are allowed to post.

371 Tweets should be classified as describing content moderation as a
372 SOLUTION if they emphasize positive effects of content moderation,
373 such as protecting users from various kinds of harmful content,
374 including hate speech, misinformation, illegal adult content, or
375 spam.

376 Tweets should be classified as describing content moderation as
377 NEUTRAL if they do not emphasize possible negative or positive
378 effects of content moderation, for example if they simply report on
379 the content moderation activity of social media platforms without
380 linking them to potential advantages or disadvantages for users or
381 stakeholders.

382 **F. Task 4: Policy Frames (Content Moderation).** Content moderation,
383 as described above, can be linked to various other topics, such as
384 health, crime, or equality.

385 For each tweet in the sample, follow these instructions:

- 386 1. Carefully read the text of the tweet, paying close attention to
387 details.
- 388 2. Classify the tweet into one of the topics defined below.

389 The topics are defined as follows:

- 390 • ECONOMY: The costs, benefits, or monetary/financial impli-
391 cations of the issue (to an individual, family, community, or to
392 the economy as a whole).
- 393 • Capacity and resources: The lack of or availability of physical,
394 geographical, spatial, human, and financial resources, or the
395 capacity of existing systems and resources to implement or
396 carry out policy goals.
- 397 • MORALITY: Any perspective—or policy objective or action
398 (including proposed action) that is compelled by religious doc-
399 trine or interpretation, duty, honor, righteousness or any other

- 413 • POLICY PRESCRIPTION AND EVALUATION: Particular
414 policies proposed for addressing an identified problem, and
415 figuring out if certain policies will work, or if existing policies
416 are effective.

- 417 • LAW AND ORDER, CRIME AND JUSTICE: Specific policies
418 in practice and their enforcement, incentives, and implications.
419 Includes stories about enforcement and interpretation of laws
420 by individuals and law enforcement, breaking laws, loopholes,
421 fines, sentencing and punishment. Increases or reductions in
422 crime.

- 423 • SECURITY AND DEFENSE: Security, threats to security,
424 and protection of one’s person, family, in-group, nation, etc.
425 Generally an action or a call to action that can be taken to
426 protect the welfare of a person, group, nation sometimes from
427 a not yet manifested threat.

- 428 • HEALTH AND SAFETY: Health care access and effectiveness,
429 illness, disease, sanitation, obesity, mental health effects, pre-
430 vention of or perpetuation of gun violence, infrastructure and
431 building safety.

- 432 • QUALITY OF LIFE: The effects of a policy on individuals’
433 wealth, mobility, access to resources, happiness, social struc-
434 tures, ease of day-to-day routines, quality of community life,
435 etc.

- 436 • CULTURAL IDENTITY: The social norms, trends, values
437 and customs constituting culture(s), as they relate to a specific
438 policy issue.

- 439 • PUBLIC OPINION: References to general social attitudes,
440 polling and demographic information, as well as implied or
441 actual consequences of diverging from or “getting ahead of”
442 public opinion or polls.

- 443 • POLITICAL: Any political considerations surrounding an is-
444 sue. Issue actions or efforts or stances that are political, such
445 as partisan filibusters, lobbyist involvement, bipartisan efforts,
446 deal-making and vote trading, appealing to one’s base, men-
447 tions of political maneuvering. Explicit statements that a
448 policy issue is good or bad for a particular political party.

- 449 • EXTERNAL REGULATION AND REPUTATION: The
450 United States’ external relations with another nation; the
451 external relations of one state with another; or relations be-
452 tween groups. This includes trade agreements and outcomes,
453 comparisons of policy outcomes or desired policy outcomes.

- 454 • OTHER: Any topic that does not fit into the above categories.

- 455 • G. Task 5: Policy Frames (Political Content). Political content, as
456 described above, can be linked to various other topics, such as
457 health, crime, or equality.

458 For each tweet in the sample, follow these instructions:

- 459 1. Carefully read the text of the tweet, paying close attention to
460 details.
- 461 2. Classify the tweet into one of the topics defined below.

462 The topics are defined as follows:

- 463 • ECONOMY: The costs, benefits, or monetary/financial impli-
464 cations of the issue (to an individual, family, community, or to
465 the economy as a whole).
- 466 • Capacity and resources: The lack of or availability of physical,
467 geographical, spatial, human, and financial resources, or the
468 capacity of existing systems and resources to implement or
469 carry out policy goals.

- 470 • CONSTITUTIONALITY AND JURISPRUDENCE: The con-
471 straints imposed on or freedoms granted to individuals, gov-
472 ernment, and corporations via the Constitution, Bill of Rights
473 and other amendments, or judicial interpretation. This deals
474 specifically with the authority of government to regulate, and
475 the authority of individuals/corporations to act independently
476 of government.

- 477 • POLICY PRESCRIPTION AND EVALUATION: Particular
478 policies proposed for addressing an identified problem, and
479 figuring out if certain policies will work, or if existing policies
480 are effective.

- 481 • LAW AND ORDER, CRIME AND JUSTICE: Specific policies
482 in practice and their enforcement, incentives, and implications.
483 Includes stories about enforcement and interpretation of laws
484 by individuals and law enforcement, breaking laws, loopholes,
485 fines, sentencing and punishment. Increases or reductions in
486 crime.

- 487 • SECURITY AND DEFENSE: Security, threats to security,
488 and protection of one’s person, family, in-group, nation, etc.
489 Generally an action or a call to action that can be taken to
490 protect the welfare of a person, group, nation sometimes from
491 a not yet manifested threat.

- 492 • HEALTH AND SAFETY: Health care access and effectiveness,
493 illness, disease, sanitation, obesity, mental health effects, pre-
494 vention of or perpetuation of gun violence, infrastructure and
495 building safety.

- 496 • QUALITY OF LIFE: The effects of a policy on individuals’
497 wealth, mobility, access to resources, happiness, social struc-
498 tures, ease of day-to-day routines, quality of community life,
499 etc.

- 500 • CULTURAL IDENTITY: The social norms, trends, values
501 and customs constituting culture(s), as they relate to a specific
502 policy issue.

- 503 • PUBLIC OPINION: References to general social attitudes,
504 polling and demographic information, as well as implied or
505 actual consequences of diverging from or “getting ahead of”
506 public opinion or polls.

- 507 • POLITICAL: Any political considerations surrounding an is-
508 sue. Issue actions or efforts or stances that are political, such
509 as partisan filibusters, lobbyist involvement, bipartisan efforts,
510 deal-making and vote trading, appealing to one’s base, men-
511 tions of political maneuvering. Explicit statements that a
512 policy issue is good or bad for a particular political party.

- 513 • EXTERNAL REGULATION AND REPUTATION: The
514 United States’ external relations with another nation; the
515 external relations of one state with another; or relations be-
516 tween groups. This includes trade agreements and outcomes,
517 comparisons of policy outcomes or desired policy outcomes.

- 518 • OTHER: Any topic that does not fit into the above categories.

- 519 • H. Task 6: Stance Detection. In the context of content moderation,
520 Section 230 is a law in the United States that protects websites and
521 other online platforms from being held legally responsible for the
522 content posted by their users. This means that if someone posts
523 something illegal or harmful on a website, the website itself cannot
524 be sued for allowing it to be posted. However, websites can still
525 choose to moderate content and remove anything that violates their
526 own policies.

527 For each tweet in the sample, follow these instructions:

GILARDI ET AL.

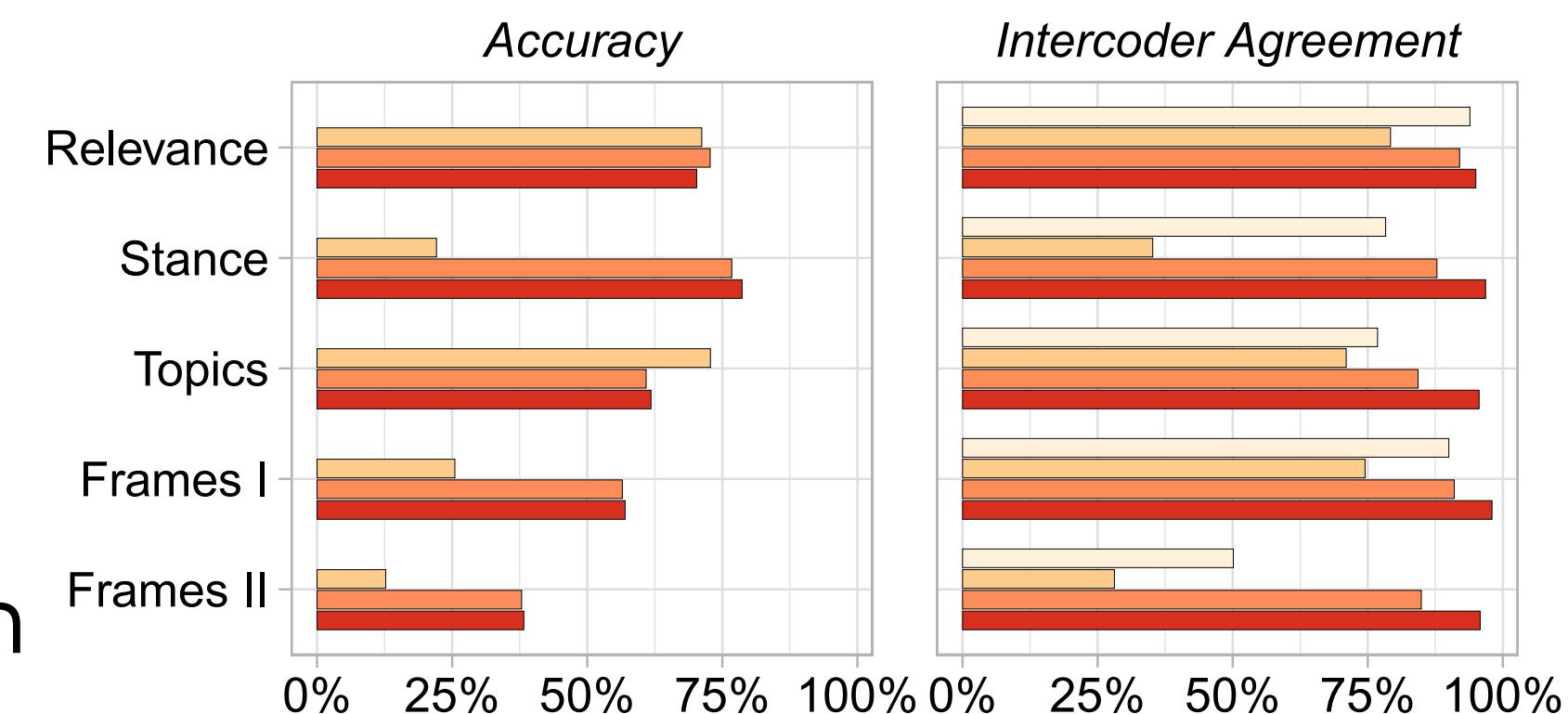
So what are we looking at? Let's take some time.

Differences in accuracy between the classification tasks, both for tweets and news articles

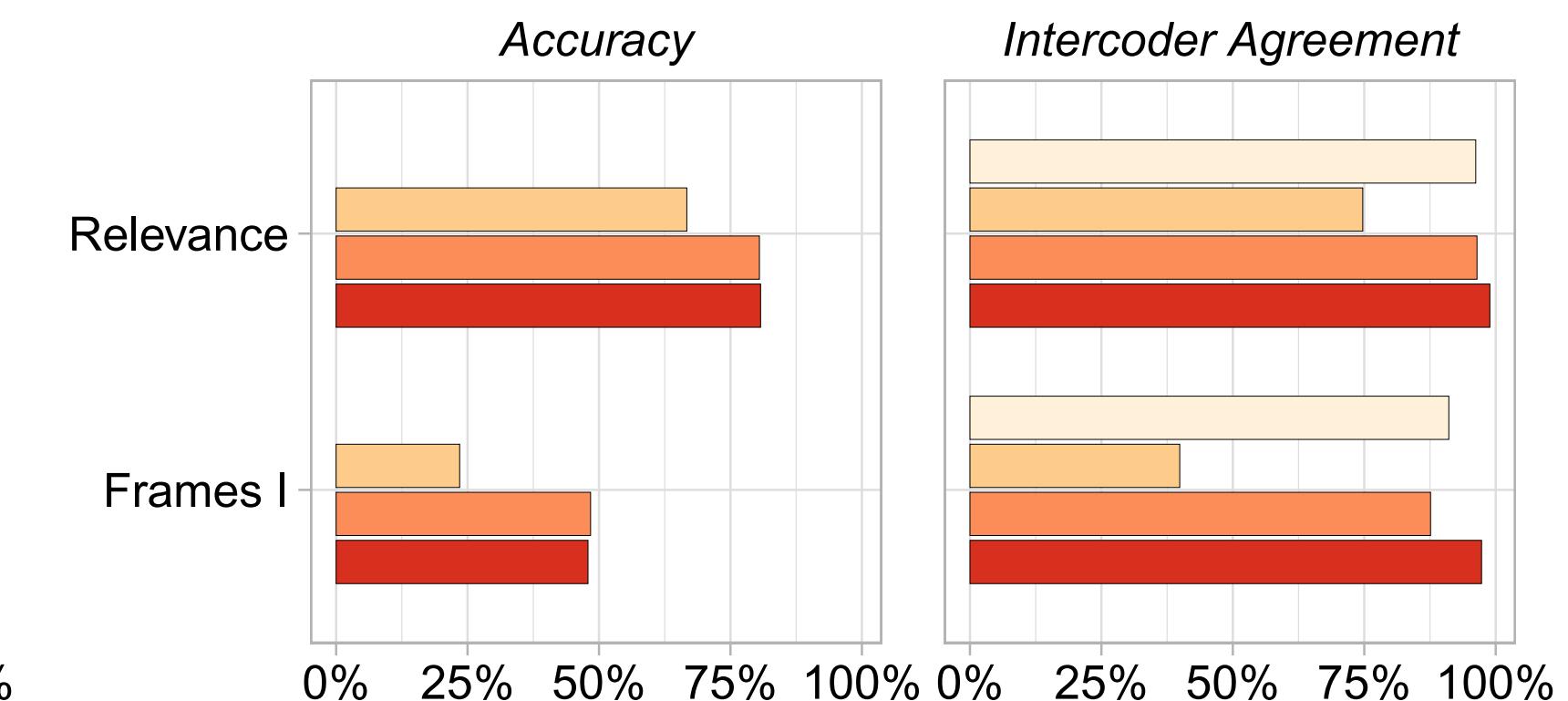
High intercoder reliability between trained annotators and GPT.

What does all this tell us?

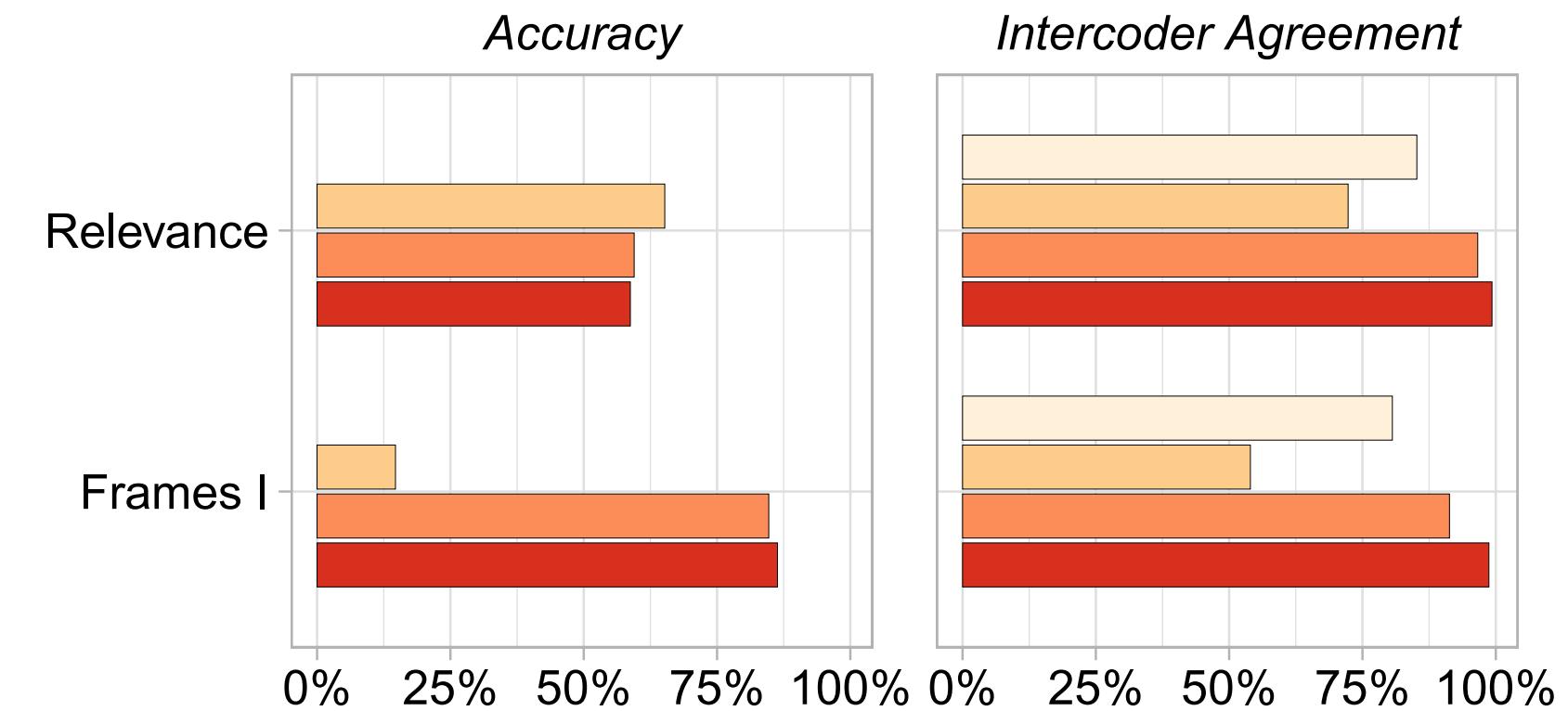
A Tweets (2020–2021)



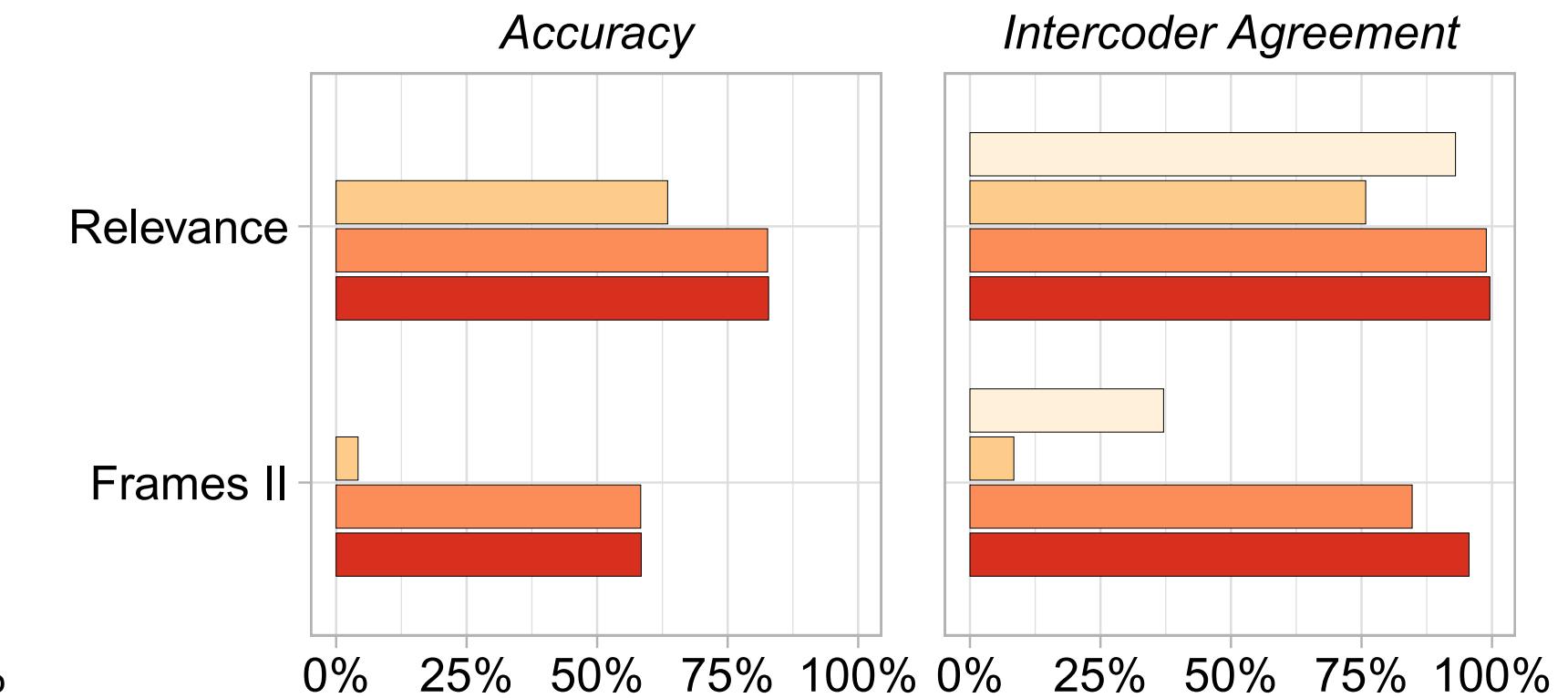
B News Articles (2020–2021)



C Tweets (2023)



D Tweets (2017–2022)



Trained annotators MTurk ChatGPT (temp 1) ChatGPT (temp 0.2)

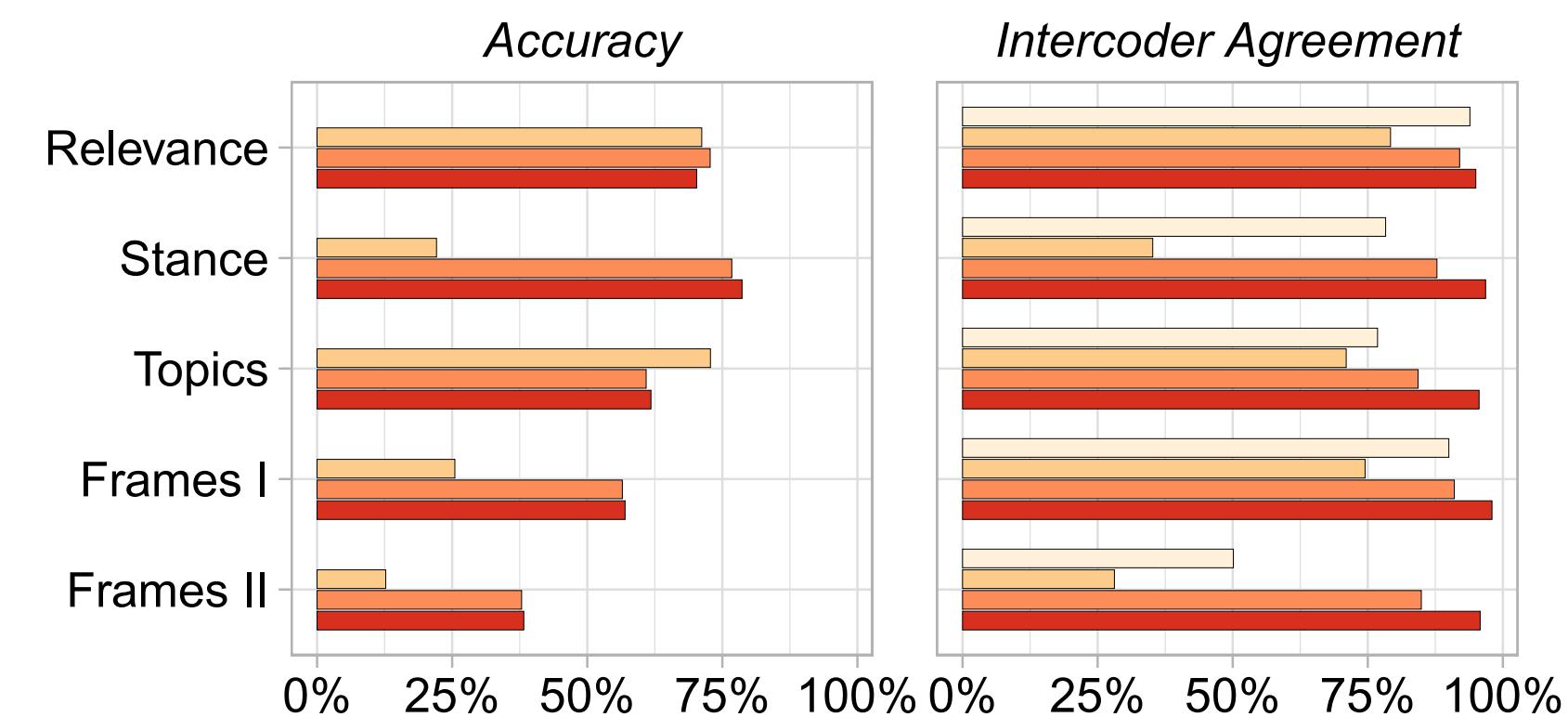
GILARDI ET AL.

I wonder why the accuracy for MTurk is so low on stance, and frames

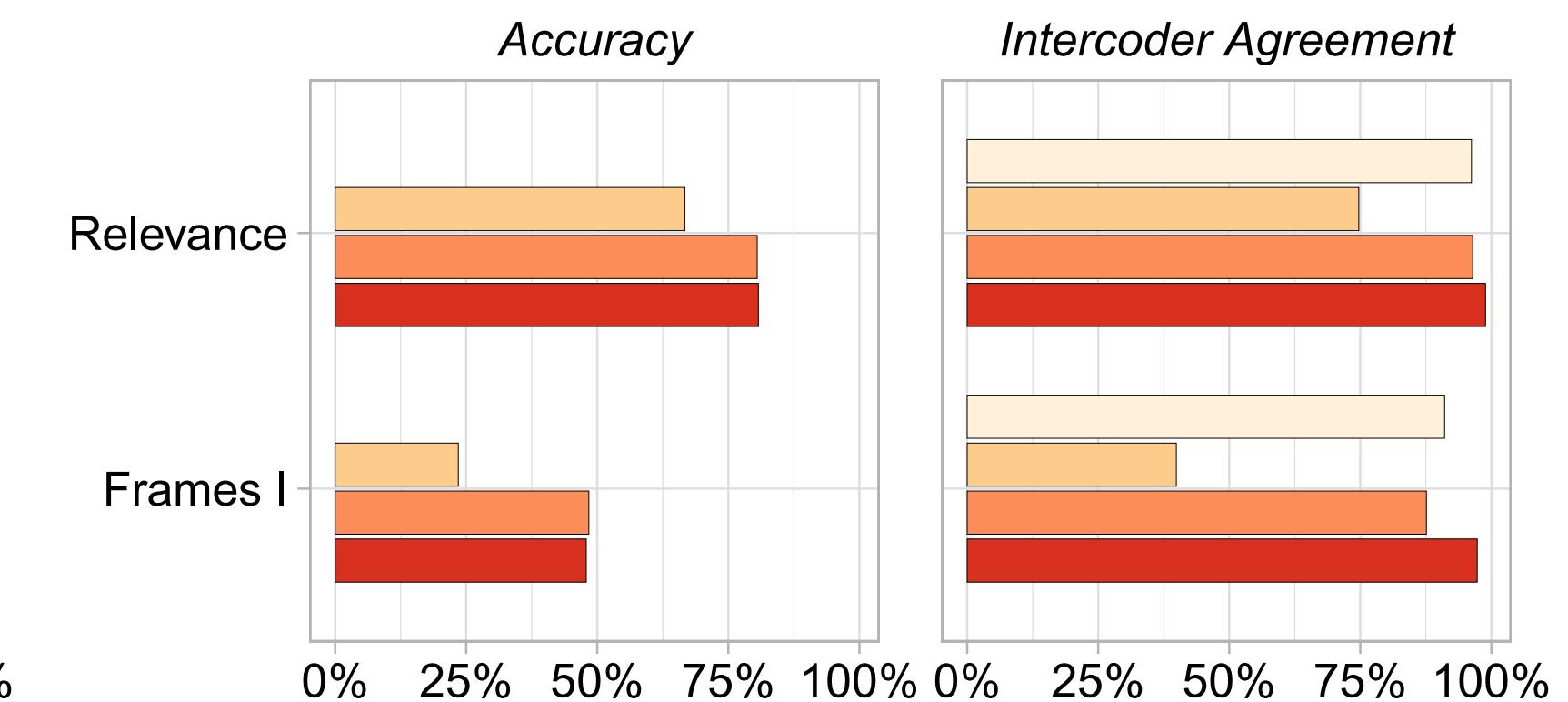
I wonder why intercoder agreement is important for GPT, especially at low temperatures

I wonder how many tweets or news articles fell into each category within their datasets.

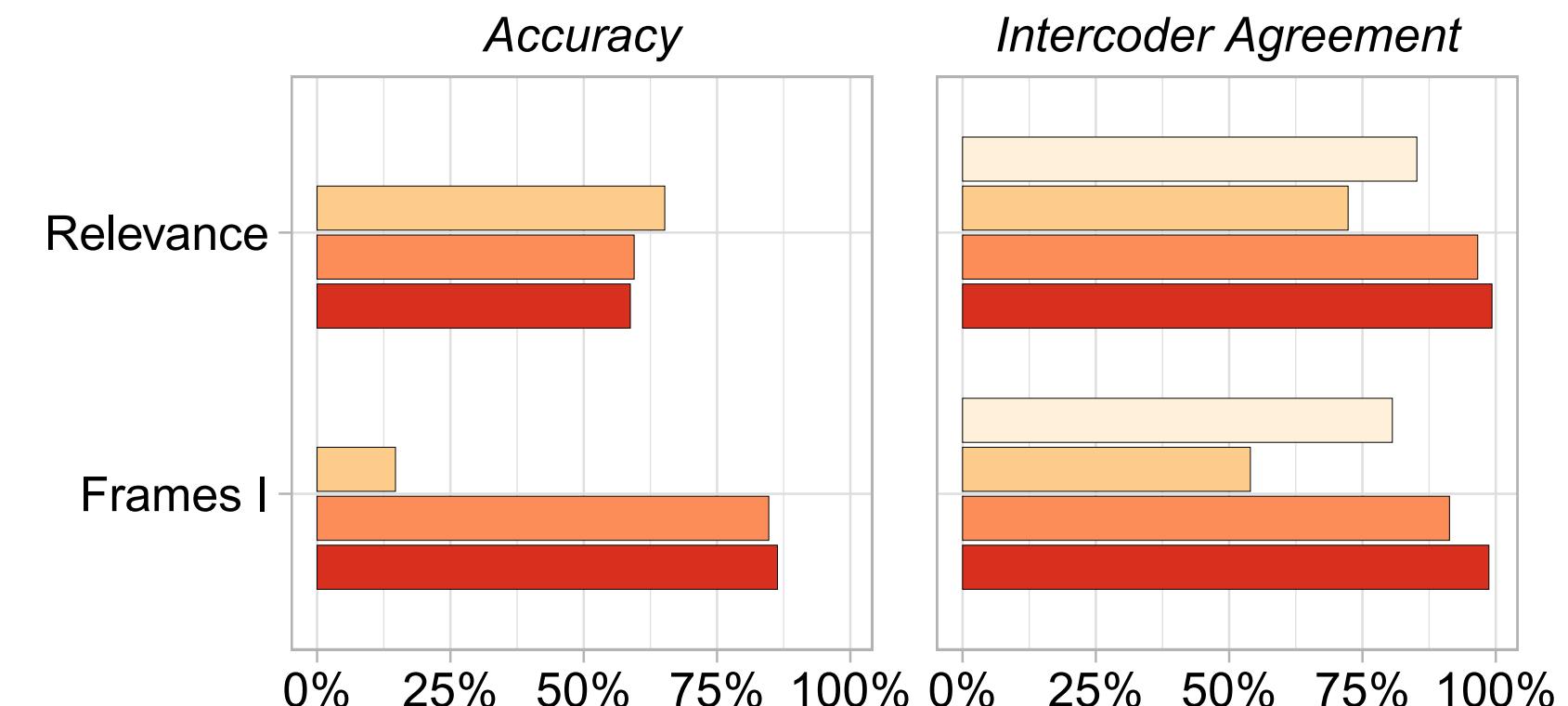
A Tweets (2020–2021)



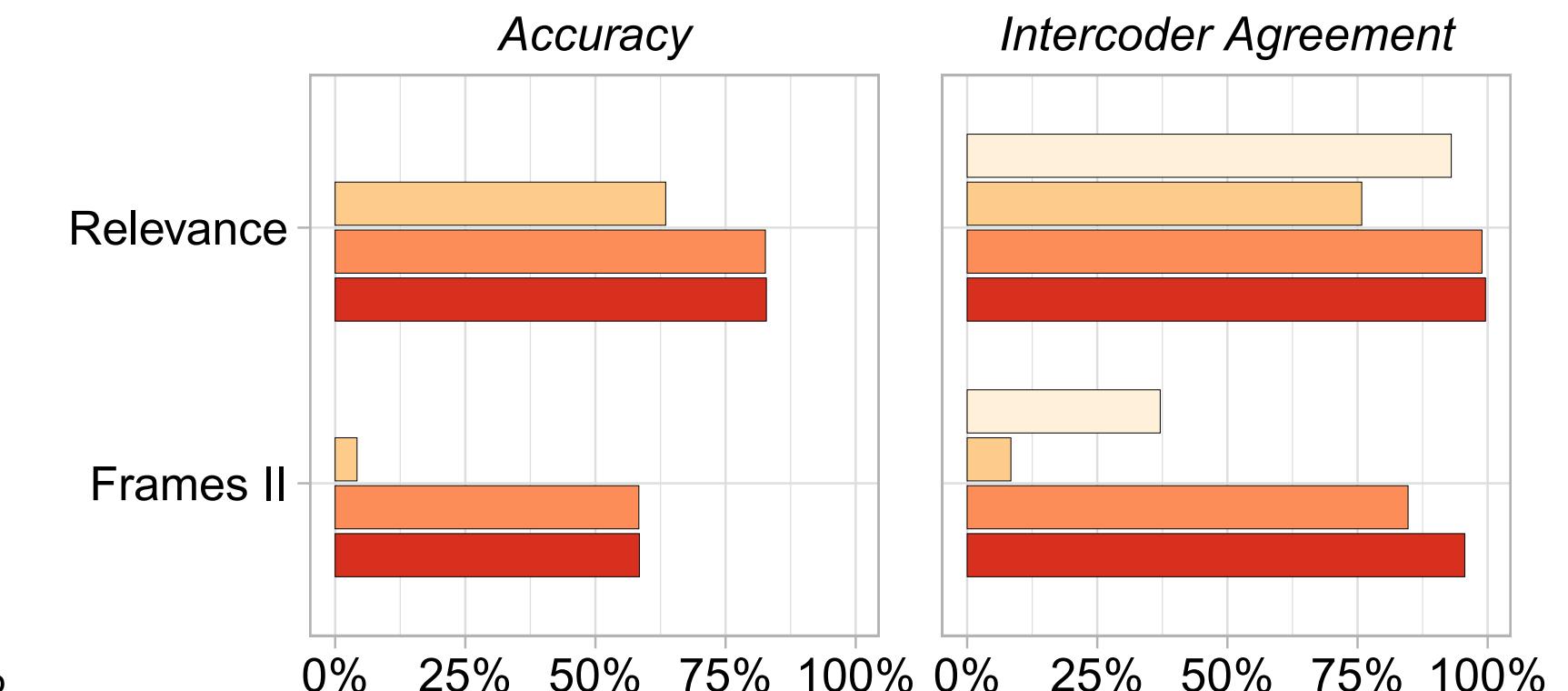
B News Articles (2020–2021)



C Tweets (2023)



D Tweets (2017–2022)



Trained annotators MTurk ChatGPT (temp 1) ChatGPT (temp 0.2)

RATHJE ET AL.

- Rathje et al. do a similar study but focusing on detecting/ classifying psychological constructs
 - Sentiment: positive/negative
 - Emotions: Anger/joy/Sadness/Optimism
 - Offensiveness: yes/no
 - Discrete sentiment: 1 (very negative) – 7 (very positive)
 - Moral foundations



The image shows a research article from the Proceedings of the National Academy of Sciences (PNAS). The title of the article is "GPT is an effective tool for multilingual psychological text analysis". The article is a RESEARCH ARTICLE in the field of PSYCHOLOGICAL AND COGNITIVE SCIENCES. It is marked as OPEN ACCESS. The authors listed are Steve Rathje, Dan-Mircea Mirea, Ilia Sucholutsky, Raja Marjeh, Claire E. Robertson, and Jay J. Van Bavel. The article was edited by Terrence Sejnowski and received May 30, 2023, and accepted June 18, 2024. The text analysis is described as being effective for multilingual psychological text analysis. The article is associated with the Salk Institute for Biological Studies in La Jolla, CA.

RATHJE ET AL. DATA

Rely entirely on existing datasets

→ This is a good thing – something you should consider too!

SemEval 2017 dataset:

<https://huggingface.co/datasets/midas/semeval2017>

Table 1. Description of datasets used

Dataset	Construct	Text type	Size of dataset	Labels	Language	Number of Speakers (millions)
Sentiment of English tweets (2017)	Sentiment	Tweets	12,283	Positive, Negative, Neutral	English	1,450
Sentiment of Arabic tweets (2017)	Sentiment	Tweets	6,100	Positive, Negative, Neutral	Arabic	630
Discrete emotions in English tweets (2020)	Discrete Emotions	Tweets	1,421	Anger, Joy, Sadness, Optimism	English	1,450
Discrete emotions in Indonesian tweets (2020)	Discrete Emotions	Tweets	440	Anger, Fear, Sadness, Love, Joy	Indonesian	300
Offensiveness in English tweets (2019)	Offensiveness	Tweets	860	Offensive, Not Offensive	English	1,450
Offensiveness in Turkish tweets (2020)	Offensiveness	Tweets	3,528	Offensive, Not Offensive	Turkish	88
Sentiment & discrete emotions in news headlines (2023)	Sentiment, Discrete emotions	News headlines	213	1 = very negative; 7 = very positive	English	1,450
Sentiment of African tweets (2023)	Sentiment	Tweets	748	Positive, Negative, Neutral	Swahili	220
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Hausa	72
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Amharic	57.5
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Yoruba	55
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Igbo	42
	Sentiment	Tweets	949	Positive, Negative, Neutral	Twi	17.5
	Sentiment	Tweets	1,026	Positive, Negative, Neutral	Kinyarwanda	15
	Sentiment	Tweets	234	Positive, Negative, Neutral	Tsonga	7
Moral Foundations in Reddit Comments (2022)	Moral Foundations	Reddit Comments	16,123	Care, Proportionality, Equality, Loyalty, Authority, Purity, Moral Sentiment	English	1,450

We used 15 different datasets which contained 47,925 manually annotated tweets and news headlines in 12 languages from various language families, annotated for four different psychological constructs (sentiment, discrete emotions, offensiveness, and moral foundations). Datasets 7 to 16 were not publicly available on the internet at the time GPT was trained in 2021, and thus could not have influenced the training dataset.

RATHJE ET AL. DATA

Rely entirely on existing datasets

→ This is a good thing – something you should consider too!

SemEval 2017 dataset:

<https://huggingface.co/datasets/midas/semeval2017>

Table 1. Description of datasets used

Dataset	Construct	Text type	Size of dataset	Labels	Language	Number of Speakers (millions)
Sentiment of English tweets (2017)	Sentiment	Tweets	12,283	Positive, Negative, Neutral	English	1,450
Sentiment of Arabic tweets (2017)	Sentiment	Tweets	6,100	Positive, Negative, Neutral	Arabic	630
Discrete emotions in English tweets (2020)	Discrete Emotions	Tweets	1,421	Anger, Joy, Sadness, Optimism	English	1,450
Discrete emotions in Indonesian tweets (2020)	Discrete Emotions	Tweets	440	Anger, Fear, Sadness, Love, Joy	Indonesian	300
Offensiveness in English tweets (2019)	Offensiveness	Tweets	860	Offensive, Not Offensive	English	1,450
Offensiveness in Turkish tweets (2020)	Offensiveness	Tweets	3,528	Offensive, Not Offensive	Turkish	88
Sentiment & discrete emotions in news headlines (2023)	Sentiment, Discrete emotions	News headlines	213	1 = very negative; 7 = very positive	English	1,450
Sentiment of African tweets (2023)	Sentiment	Tweets	748	Positive, Negative, Neutral	Swahili	220
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Hausa	72
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Amharic	57.5
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Yoruba	55
	Sentiment	Tweets	1,000	Positive, Negative, Neutral	Igbo	42
	Sentiment	Tweets	949	Positive, Negative, Neutral	Twi	17.5
	Sentiment	Tweets	1,026	Positive, Negative, Neutral	Kinyarwanda	15
	Sentiment	Tweets	234	Positive, Negative, Neutral	Tsonga	7
Moral Foundations in Reddit Comments (2022)	Moral Foundations	Reddit Comments	16,123	Care, Proportionality, Equality, Loyalty, Authority, Purity, Moral Sentiment	English	1,450

We used 15 different datasets which contained 47,925 manually annotated tweets and news headlines in 12 languages from various language families, annotated for four different psychological constructs (sentiment, discrete emotions, offensiveness, and moral foundations). Datasets 7 to 16 were not publicly available on the internet at the time GPT was trained in 2021, and thus could not have influenced the training dataset.

THEIR PROMPTS

Table 2. Prompt table

Sentiment analysis (categorical)	Emotion detection (categorical)	Offensiveness	Sentiment analysis (Likert)	Emotion detection (Likert)	Moral foundations
<p>Is the sentiment of this (Arabic/ Swahili/...) text positive, neutral, or negative?</p> <p>Answer only with a number: 1 if positive, 2 if neutral, and 3 if negative.</p> <p>Here is the text: <i>[Tweet text]</i></p>	<p>Which of these [number of] emotions-[list of emotions]-best represents the mental state of the person writing the following (Indonesian) text?</p> <p>Answer only with a number: 1 if [emotion1], 2 if [emotion2], [...].</p> <p>Here is the text: <i>[Tweet text]</i></p>	<p>Is the following (Turkish) post offensive?</p> <p>Answer only with a number: 1 if offensive, and 0 if not offensive. Here is the post: <i>[Tweet text]</i></p>	<p>How negative or positive is this headline on a 1 to 7 scale?</p> <p>Answer only with a number, with 1 being “very negative” and 7 being “very positive.” Here is the headline: <i>[Headline text]</i></p>	<p>How much [emotion] is present in this headline on a 1 to 7 scale? Answer only with a number, with 1 being “no [emotion]” and 7 being “a great deal of [emotion].”</p> <p>Here is the headline: <i>[Headline text]</i></p>	<p>Does the following Reddit comment express the moral foundation of [moral foundation] (i.e., [definition of moral foundation])?</p> <p>Please answer only with a number: 1 if yes and 0 if no.</p> <p>Here is the Reddit comment: <i>[Reddit comment text]</i></p>

Shown are all the prompts used for each construct. Non-English prompts were derived from the English prompts by specifying the language the text was written in. Prompts in combination with the tweet or headline text were run for each text entry in the dataset using the GPT API.

Note

As reported in the paper, they do not use the system instructions at all. They send this as a "user" message. They inject which language the text is in. They ask GPT to respond in numbers.

OVERALL RESULTS

- What do we notice here?
- **Note:** We will cover F1 score in the lecture on validating LLMs. But for now, briefly, it is a way to report performance that takes into account the frequencies of codes.
- Smaller languages generally perform worse than English
- **But overall, GPT performs pretty okay**

Table 3. GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo Results

Language	Construct	GPT-3.5 Turbo (April 2023)		GPT-4 (April 2023)		GPT-4 Turbo (February 2024)	
		Accuracy	F1	Accuracy	F1	Accuracy	F1
English	Sentiment	0.673	0.685	0.566	0.633	0.638	0.640
Arabic	Sentiment	0.700	0.720	0.655	0.707	0.702	0.746
English	Discrete emotions	0.738	0.714	0.816	0.779	0.810	0.782
Indonesian	Discrete emotions	0.686	0.686	0.741	0.740	0.786	0.787
English	Offensiveness	0.769	0.721	0.801	0.746	0.782	0.725
Turkish	Offensiveness	0.836	0.752	0.857	0.709	0.877	0.762
Swahili	Sentiment	0.596	0.560	0.492	0.488	0.507	0.507
Hausa	Sentiment	0.591	0.590	0.448	0.399	0.688	0.682
Amharic	Sentiment	0.206	0.226	0.737	0.609	0.779	0.646
Yoruba	Sentiment	0.542	0.506	0.607	0.579	0.689	0.681
Igbo	Sentiment	0.624	0.597	0.643	0.622	0.593	0.590
Twi	Sentiment	0.406	0.408	0.538	0.505	0.582	0.491
Kinyarwanda	Sentiment	0.574	0.574	0.622	0.624	0.670	0.661
Tsonga	Sentiment	0.291	0.281	0.311	0.302	0.449	0.448
Average	-	0.588	0.571	0.631	0.603	0.682	0.653

OVERALL RESULTS

- Things that I wonder about:
 1. Accuracy for sentiment isn't great.
 2. It's higher for Arabic than English which is surprising.
 3. We don't know the distributions of the scores, so it's hard to tell if the model just predicts the same thing over and over

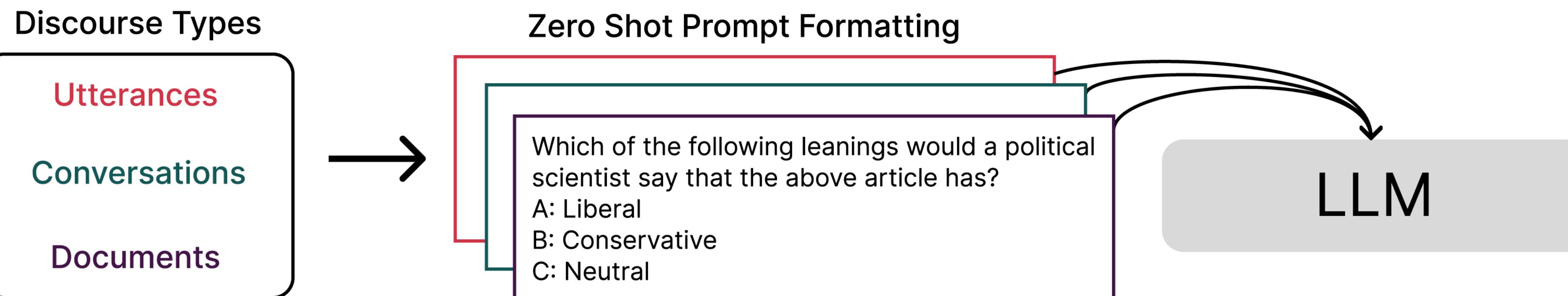
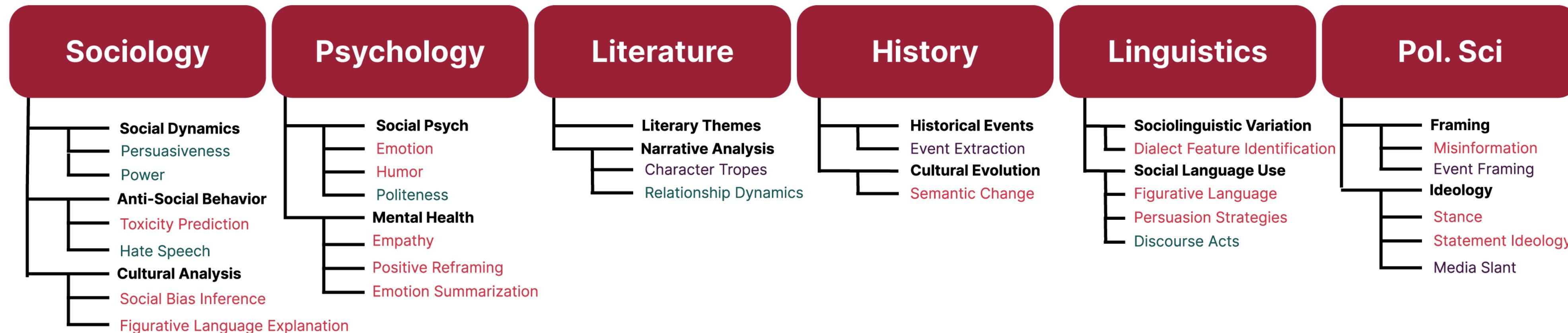
Table 3. GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo Results

Language	Construct	GPT-3.5 Turbo (April 2023)		GPT-4 (April 2023)		GPT-4 Turbo (February 2024)	
		Accuracy	F1	Accuracy	F1	Accuracy	F1
English	Sentiment	0.673	0.685	0.566	0.633	0.638	0.640
Arabic	Sentiment	0.700	0.720	0.655	0.707	0.702	0.746
English	Discrete emotions	0.738	0.714	0.816	0.779	0.810	0.782
Indonesian	Discrete emotions	0.686	0.686	0.741	0.740	0.786	0.787
English	Offensiveness	0.769	0.721	0.801	0.746	0.782	0.725
Turkish	Offensiveness	0.836	0.752	0.857	0.709	0.877	0.762
Swahili	Sentiment	0.596	0.560	0.492	0.488	0.507	0.507
Hausa	Sentiment	0.591	0.590	0.448	0.399	0.688	0.682
Amharic	Sentiment	0.206	0.226	0.737	0.609	0.779	0.646
Yoruba	Sentiment	0.542	0.506	0.607	0.579	0.689	0.681
Igbo	Sentiment	0.624	0.597	0.643	0.622	0.593	0.590
Twi	Sentiment	0.406	0.408	0.538	0.505	0.582	0.491
Kinyarwanda	Sentiment	0.574	0.574	0.622	0.624	0.670	0.661
Tsonga	Sentiment	0.291	0.281	0.311	0.302	0.449	0.448
Average	-	0.588	0.571	0.631	0.603	0.682	0.653

red = worse than previous version

green = better than previous version

FOR INSPIRATION: WHAT KINDS OF QUESTIONS CAN YOU ANSWER WITH NLP-TASKS



WHEN READING PAPERS ON LLMS, IF YOU WANT TO ACTUALLY KNOW WHAT THEY DID

Read the supplementary materials (appendix in pdf, source code repositories on GitHub) and look at:

- What do their data look like?
- What did their code look like? Do I understand how it works?
- Which figures and tables didn't make it into the paper, and what do they add to the story?
- How did they prompt?
- And how did they instruct the model to respond?

PRACTICAL TIPS FOR YOUR PROJECT WORK

- The articles from today give you
 - Specific things that you can do with LLMs, and for each of those a source of data and a source of code + inspiration
 - At least a dozen available datasets that you could build on, e.g.,
 - semeval = pre-labelled sentiment evaluations
 - CovidET = pre-labelled emotions in reddit posts about COVID
 - Misinfo Reaction Frames = pre-labelled 'intention' dataset
- Think about how you can use either of them or search for further datasets.

SUMMARIZE TODAY

- Take home messages.

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks
- For each problem to solve using LLMs, take a look at both sides
 - The outside (use-case) and the inside (technical)

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks
- For each problem to solve using LLMs, take a look at both sides
 - The outside (use-case) and the inside (technical)
- LLMs are not suitable for every problem, but for many
 - LLMs are good in processing unstructured (textual) content

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks
- For each problem to solve using LLMs, take a look at both sides
 - The outside (use-case) and the inside (technical)
- LLMs are not suitable for every problem, but for many
 - LLMs are good in processing unstructured (textual) content
 - ▶ If you do not need to look at content, LLMs will not help

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks
- For each problem to solve using LLMs, take a look at both sides
 - The outside (use-case) and the inside (technical)
- LLMs are not suitable for every problem, but for many
 - LLMs are good in processing unstructured (textual) content
 - ▶ If you do not need to look at content, LLMs will not help
 - ▶ If you have quite strict rules, it may be more reliable to implement those rules in code

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks
- For each problem to solve using LLMs, take a look at both sides
 - The outside (use-case) and the inside (technical)
- LLMs are not suitable for every problem, but for many
 - LLMs are good in processing unstructured (textual) content
 - If you do not need to look at content, LLMs will not help
 - If you have quite strict rules, it may be more reliable to implement those rules in code
 - There are old-school NLP tasks, which can be carried out in a fast and convenient way without LLMs

WHY SO MANY NON-LLM EXAMPLES

- You need to get a feeling about different NLP tasks
- For each problem to solve using LLMs, take a look at both sides
 - The outside (use-case) and the inside (technical)
- LLMs are not suitable for every problem, but for many
 - LLMs are good in processing unstructured (textual) content
 - If you do not need to look at content, LLMs will not help
 - If you have quite strict rules, it may be more reliable to implement those rules in code
 - There are old-school NLP tasks, which can be carried out in a fast and convenient way without LLMs
 - LLMs are still a super to get startet, but at some point a different implementation may be much more efficient

TUTORIAL ON FRIDAY

- Outlook this week

TUTORIAL ON FRIDAY

- Outlook this week
 - Data type annotations in Python and custom data types using pydantic

TUTORIAL ON FRIDAY

- Outlook this week
 - Data type annotations in Python and custom data types using pydantic
 - Use the OpenAI API for analyzing and retrieving structured data

TUTORIAL ON FRIDAY

- Outlook this week
 - Data type annotations in Python and custom data types using pydantic
 - Use the OpenAI API for analyzing and retrieving structured data
- Preparation (or do it on Friday)
 - Think about a (small) use-case where LLMs can help to extract structured data from (unstructured) text.

TUTORIAL ON FRIDAY

- Outlook this week
 - Data type annotations in Python and custom data types using pydantic
 - Use the OpenAI API for analyzing and retrieving structured data
- Preparation (or do it on Friday)
 - Think about a (small) use-case where LLMs can help to extract structured data from (unstructured) text.
 - Have one or two short example input texts ready (may use ChatGPT to create them!)

TUTORIAL ON FRIDAY

- Outlook this week
 - Data type annotations in Python and custom data types using pydantic
 - Use the OpenAI API for analyzing and retrieving structured data
- Preparation (or do it on Friday)
 - Think about a (small) use-case where LLMs can help to extract structured data from (unstructured) text.
 - Have one or two short example input texts ready (may use ChatGPT to create them!)
 - Example
 - Each employee reports their daily time recordings and time spent per project via e-mail
 - Transfer all the information from the e-mails to a structured Excel sheet

EXAMPLE: TIME TRACKING VIA E-MAILS

Subject: Time Tracking Report - Monday, 2 September 2025

Dear Alex,

I began my workday at eight fifteen in the morning and wrapped up at five twenty-five in the afternoon. During that time I dedicated three hours and ten minutes to the Customer Portal redesign, starting at eight thirty and concluding at eleven forty. After a short break I shifted focus to the API integration for the new payment gateway, working from twelve fifteen until two twenty-five, which amounts to two hours and ten minutes. The remainder of the afternoon, from two thirty until five twenty-five, was spent on the quarterly performance analytics dashboard, where I logged exactly two hours and fifty minutes of development and testing.

Please let me know if you need any further details or clarification on any of the tasks.

Best regards,
Jordan



QUESTIONS & FEEDBACK: LECTURE(S) & TUTORIAL(S)

Menti Q&A



DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY