Introduction to Natural Language Processing

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Language Processing: goals

Interdisciplinary field, whose goal is to get computers to perform useful tasks [..] like enabling human-machine communication, improving human-human communication, or simply doing useful processing of text or speech.

Speech and Language Processing (Jurafsky & Manning) (Chapter I)

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Applications ?

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$\rightarrow$ Conversational agent - what does HAL imply ?

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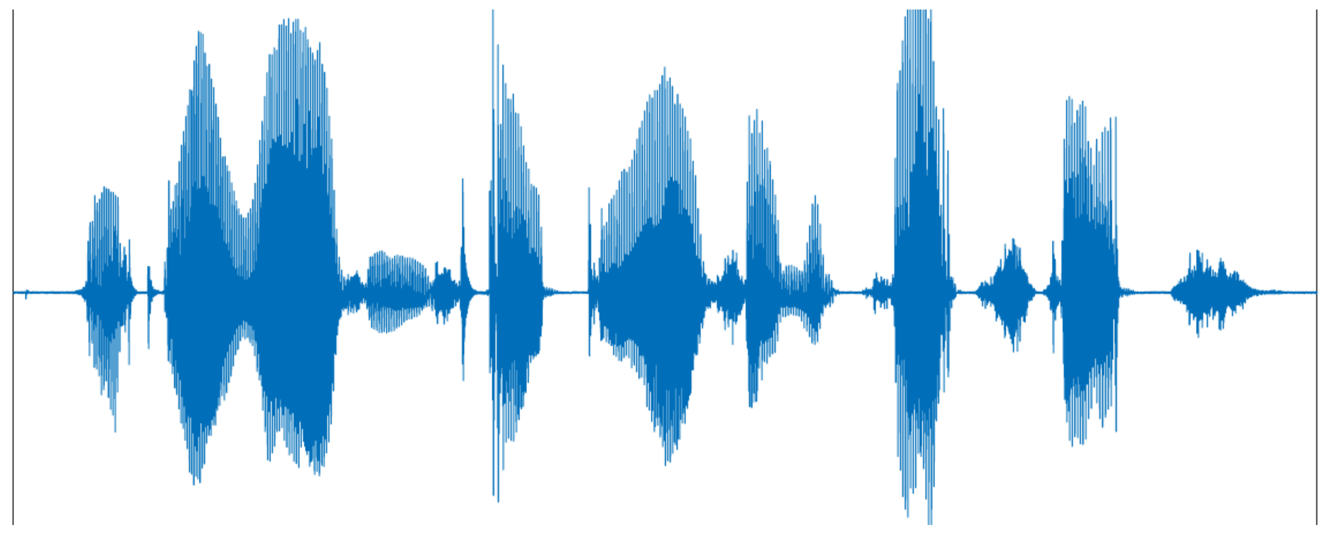
- Language input: *speech recognition*, *language understanding*
- Language output: *dialogue planning*, *speech synthesis*
- Information *retrieval*, *extraction*, and doing *inference* from it

Analyzing language: tasks involved



Signal

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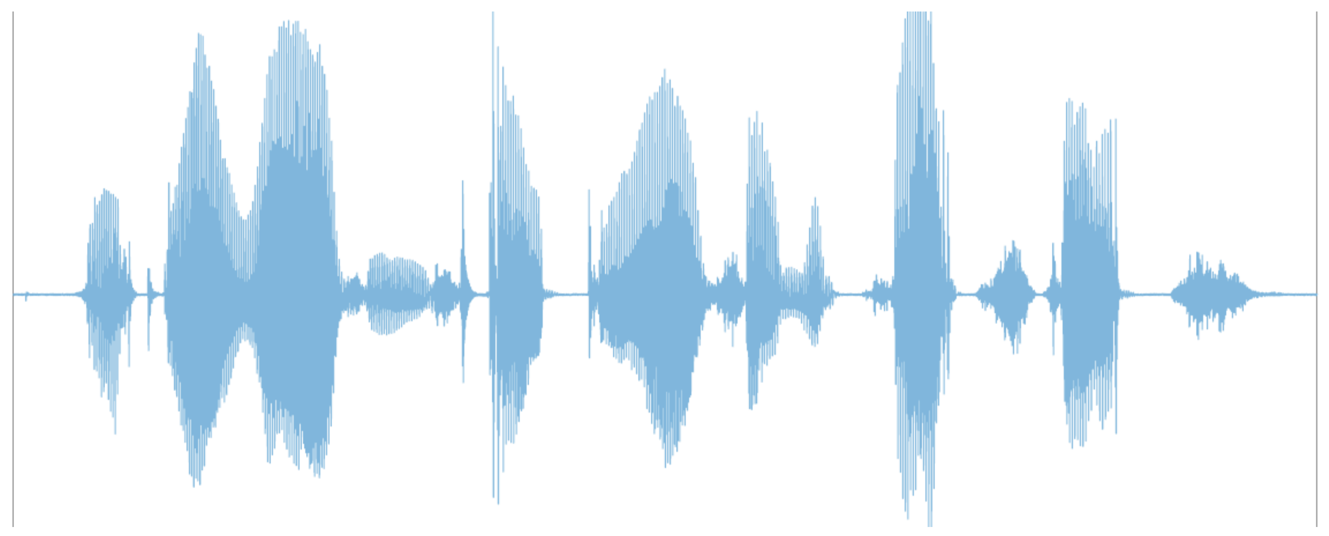

$$\begin{tikzcd}\text{Signal} \arrow[d] \\ \text{Phonemes}\end{tikzcd}$$

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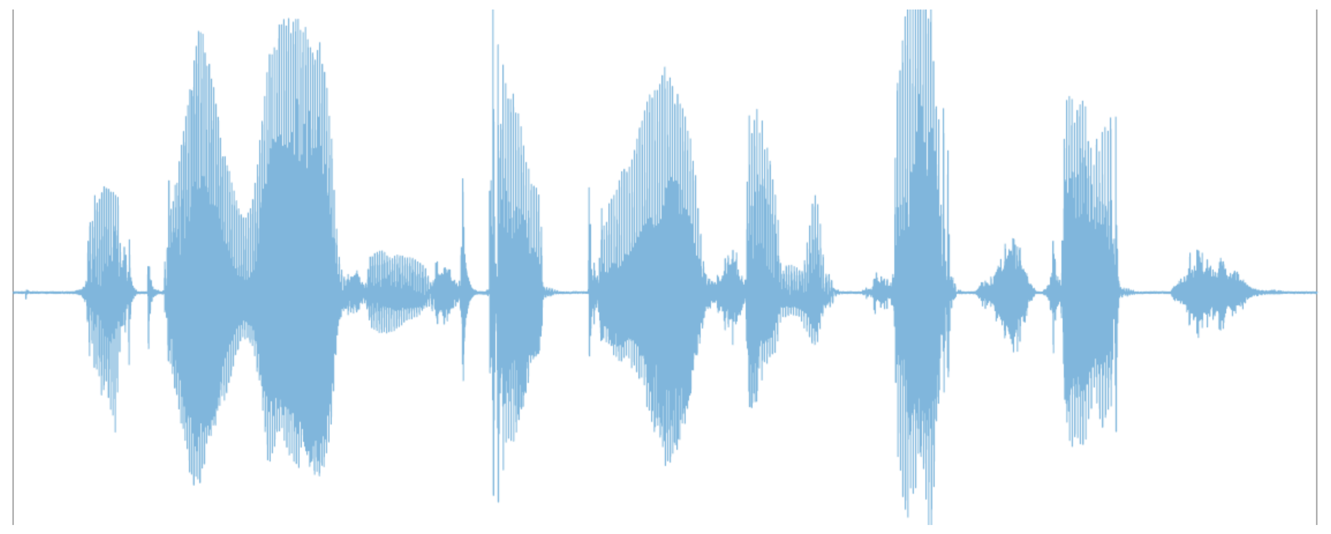

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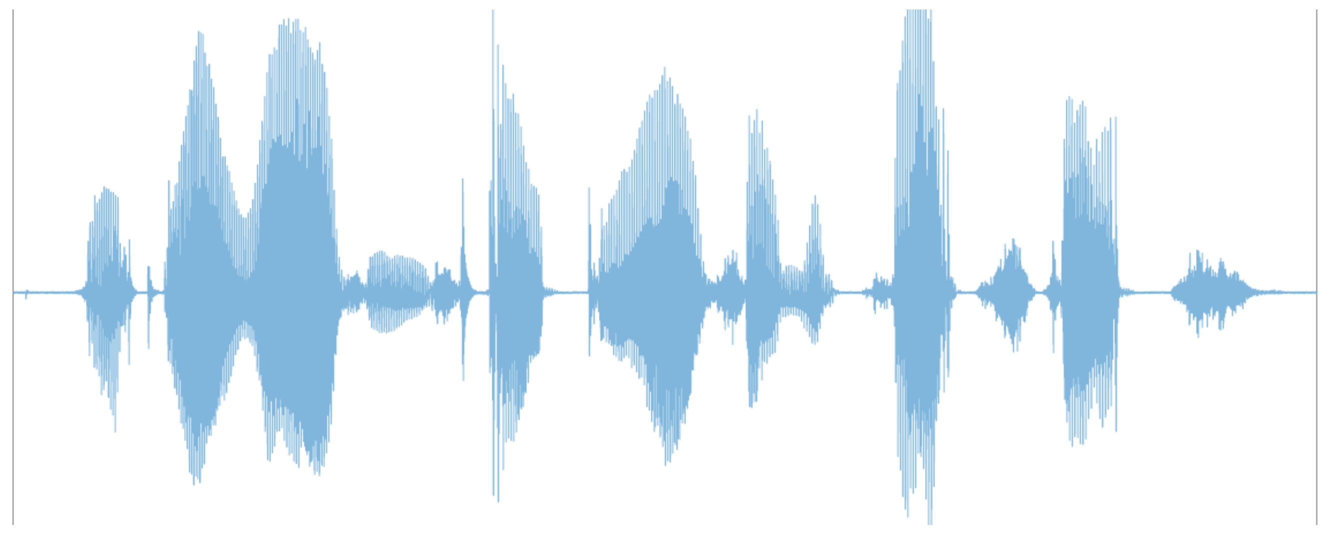

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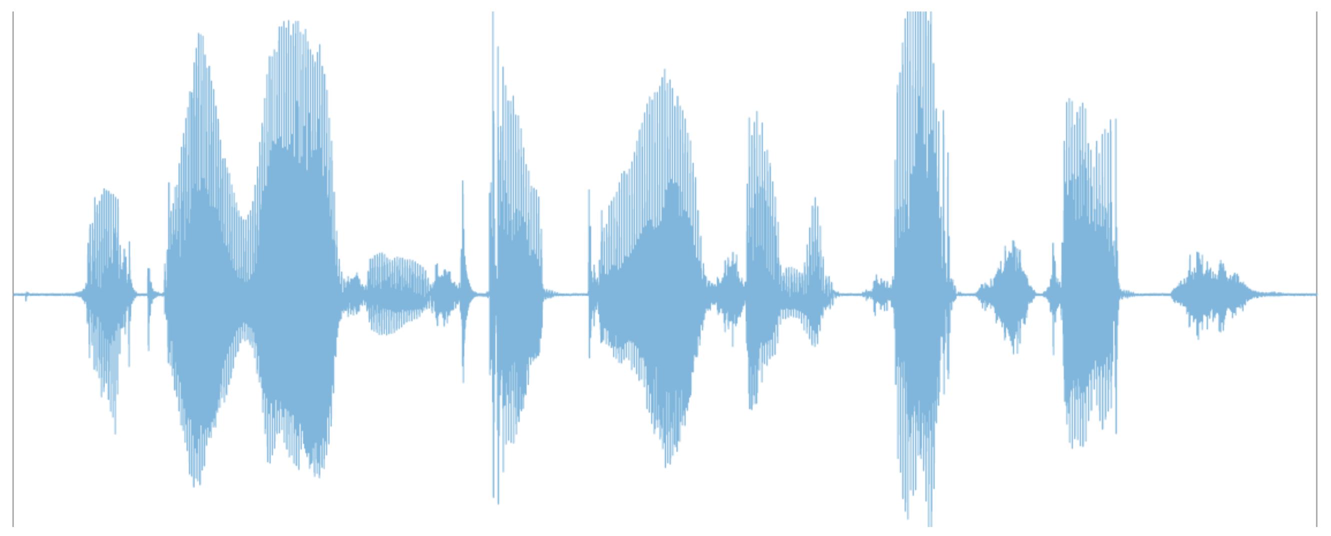

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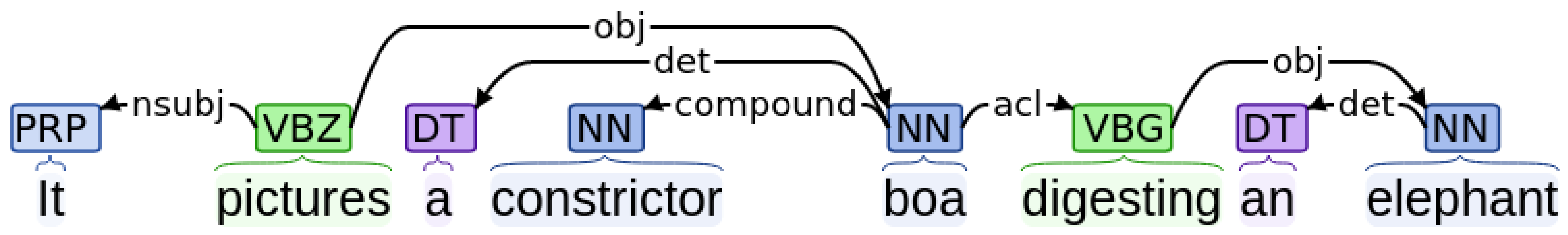

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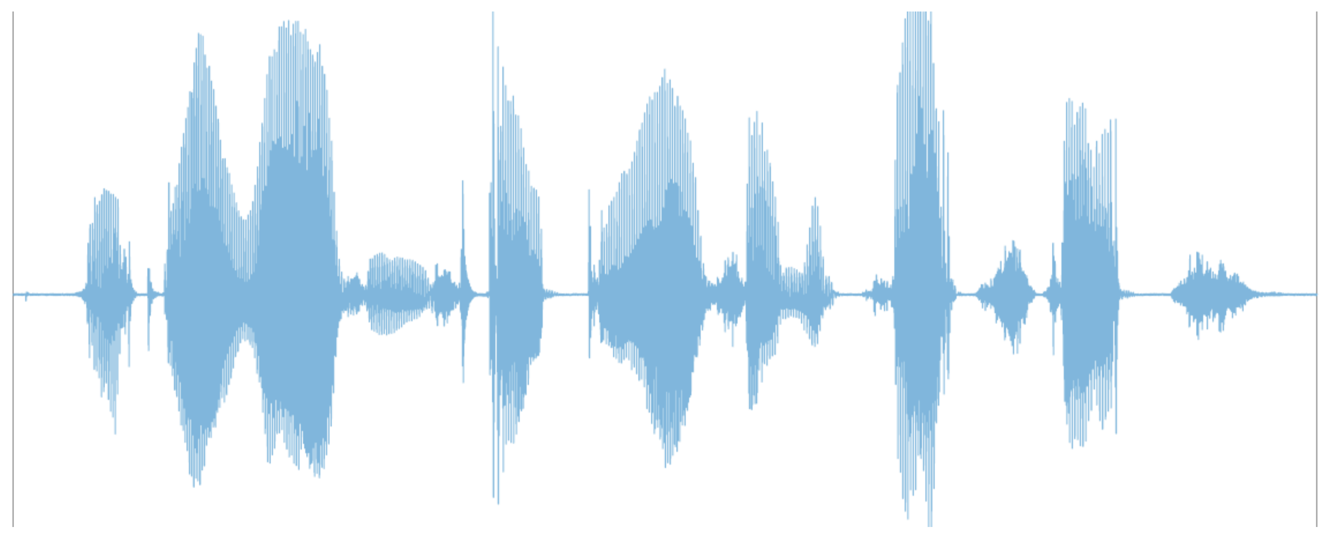

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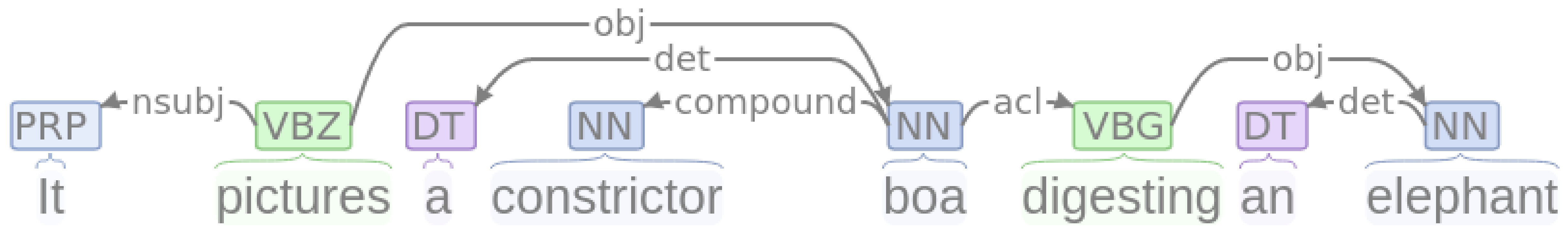

```
(p / picture-01
   :ARG0 (i / it)
   :ARG1 (b2 / boa
            :mod (c / constrictor)
            :ARG0-of (d / digest-01
                         :ARG1 (e / elephant))))
```

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\text{Abstract Meaning Representation}
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Different kinds of linguistic knowledge

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Segmentation

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- Not trivial: many possible uses for any punctuation symbol
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$\rightarrow$ This is usually called **tokenization**

- Pieces are called *tokens*: not necessarily words anymore
- More on that later !

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Lexical treatment

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  - *Derivational* morphology
    (*happy* $\rightarrow$ *happiness*, *teach* $\rightarrow$ *teacher*)
    Formation: changes meaning, grammatical category

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Structural knowledge to assemble words: Syntax

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Structural knowledge to assemble words: Syntax

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  $\rightarrow$ Validity in *position* and *agreement*
- Can be encoded in various ways (*constituency trees, dependency trees*) with their own pros and cons

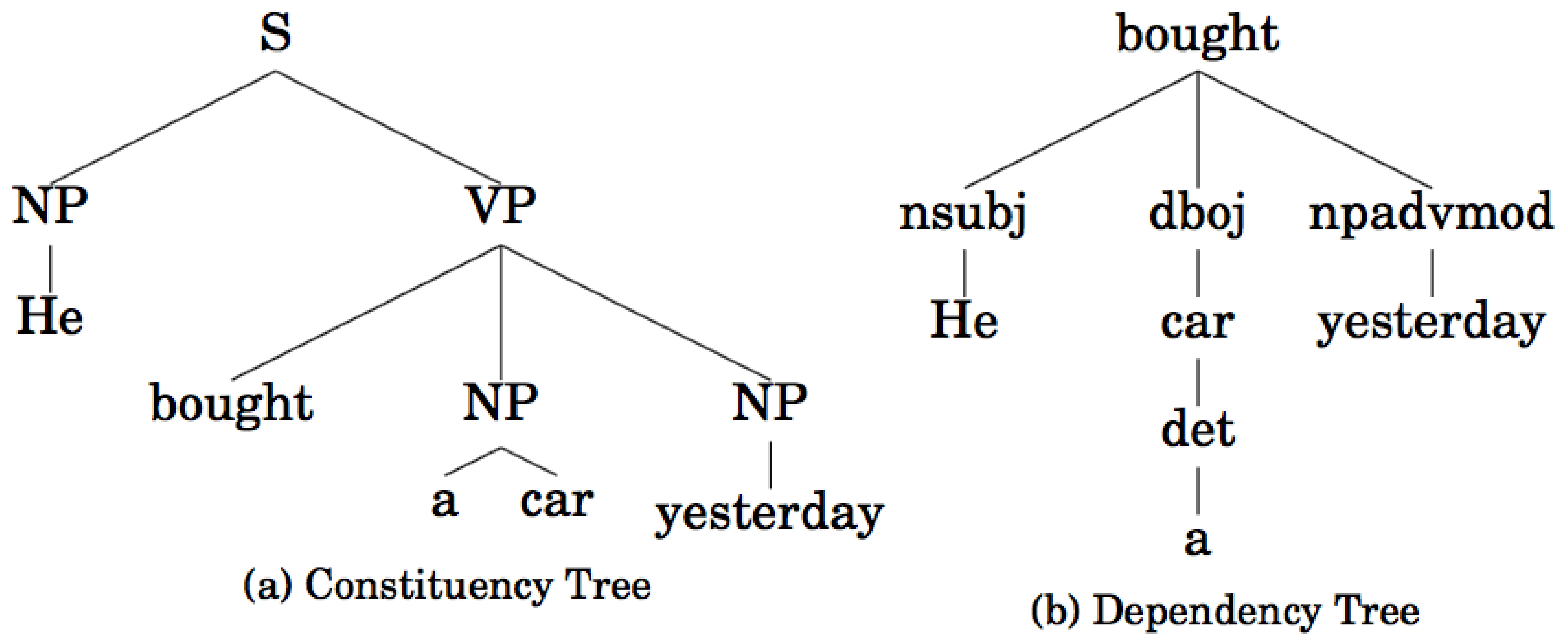

Fig. 3: Examples of the results of constituency and dependency parsing.

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Pragmatics

- How context influences meaning
- Meaning depends on speaker intent, situation, and shared knowledge (implicit, social context)
  Can you close the window ? / It's cold in here... / Oh, great, air conditionning in winter !

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Plus, *implicit* knowledge:

- Background, **commonsense knowledge**
- Contextual knowledge

makes things difficult...

Winograd Schema Challenge

A *Winograd Schema* is a **small reading comprehension test** involving a single binary question

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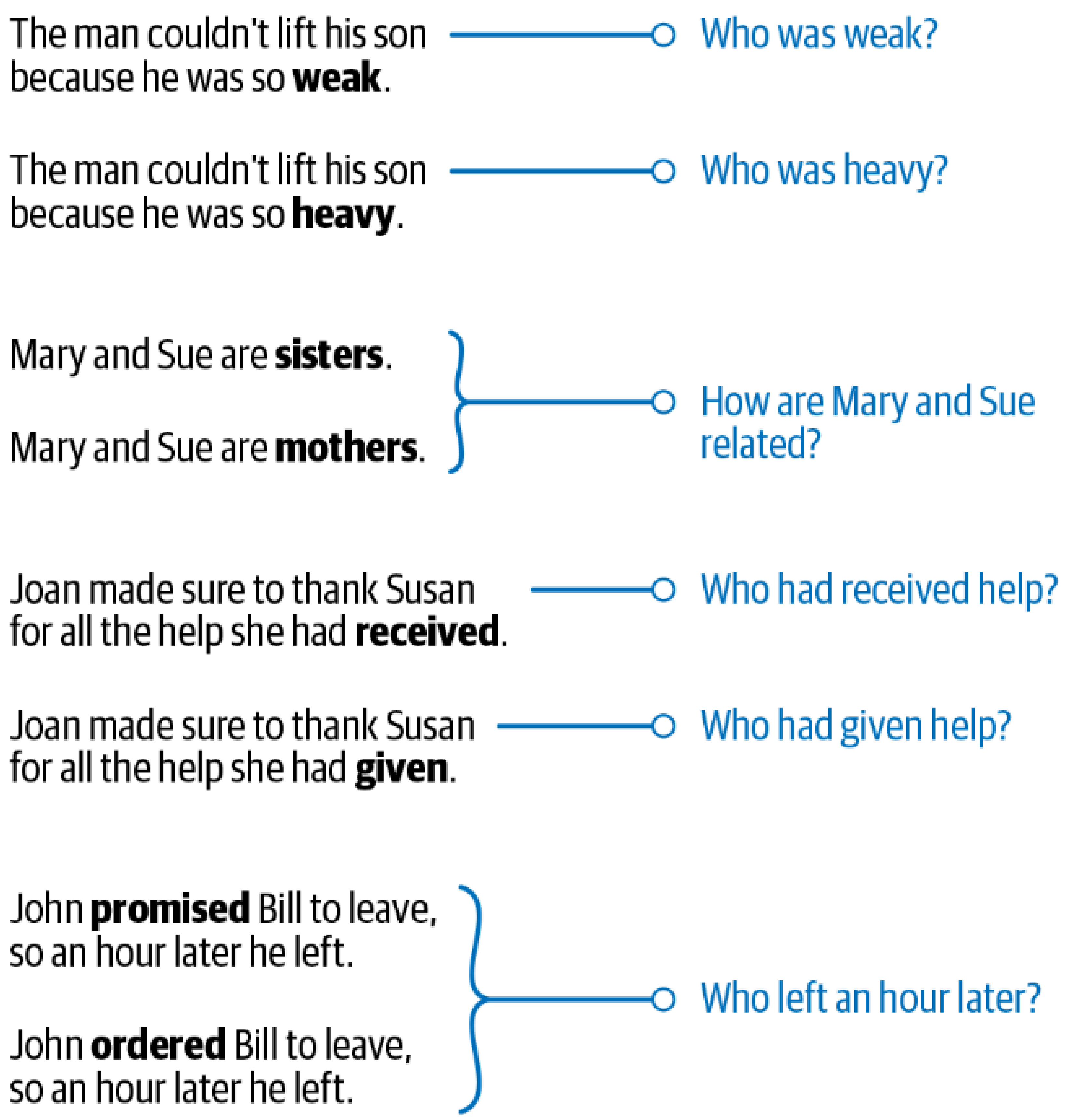

The man couldn't lift his son because he was so **weak**.
Who was weak?
The man couldn't lift his son because he was so **heavy**.
Who was heavy?
Mary and Sue are **sisters**.
Mary and Sue are **mothers**.
How are Mary and Sue related?
Joan made sure to thank Susan for all the help she had **received**.
Who had received help?
Joan made sure to thank Susan for all the help she had **given**.
Who had given help?
John **promised** Bill to leave, so an hour later he left.
John **ordered** Bill to leave, so an hour later he left.
Who left an hour later?

Examples of ambiguity in language from the Winograd Schema Challenge

From "Practical Language Processing, Figure 1-7, Chapter 1"

Statistical NLP

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  - A large amount of material and resources (+computational)
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    - Community effort: shared tasks, evaluation campaigns
- .. and now soon represented the state-of-the-art for almost any task; now, **deep learning**

Schedule and instructions

- 12/09 - Introduction to **Text Processing and Symbolic Text Representations**
  - 19/09 - Text pre-processing, representations and visualization
- 26/09 - Introduction to **Language Modeling and Text Generation**
  - 03/10 - Introduction to language modeling
- 10/10 - **Word Embeddings**, Algorithms and Applications
  - 17/10 - Topic modeling and classification (Graded)
- 24/10 - **Sequence models**, Encoders and Decoders, Contextual Representations and Transfer Learning for NLP Tasks
  - 07/11 - Machine Translation (Graded, Mini project)
- 14/11 - **Structured Prediction** in NLP
  - 21/11 - Structured prediction

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- 28/11 - **Large Language Models** and **Societal Impact**
- 05/12 - **Sentiment Analysis**: Towards Transparent Models
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Evaluation:

- **Labs 3** (*10%*) and **4** (*20%*) will be graded
- **Exam** (*70%*, with limited personal notes)
  - Questions focused on the course: *general knowledge, methodology, good practices*
  - Small exercises *based on the labs*

Basic text processing

What is the bare minimum to process text ?

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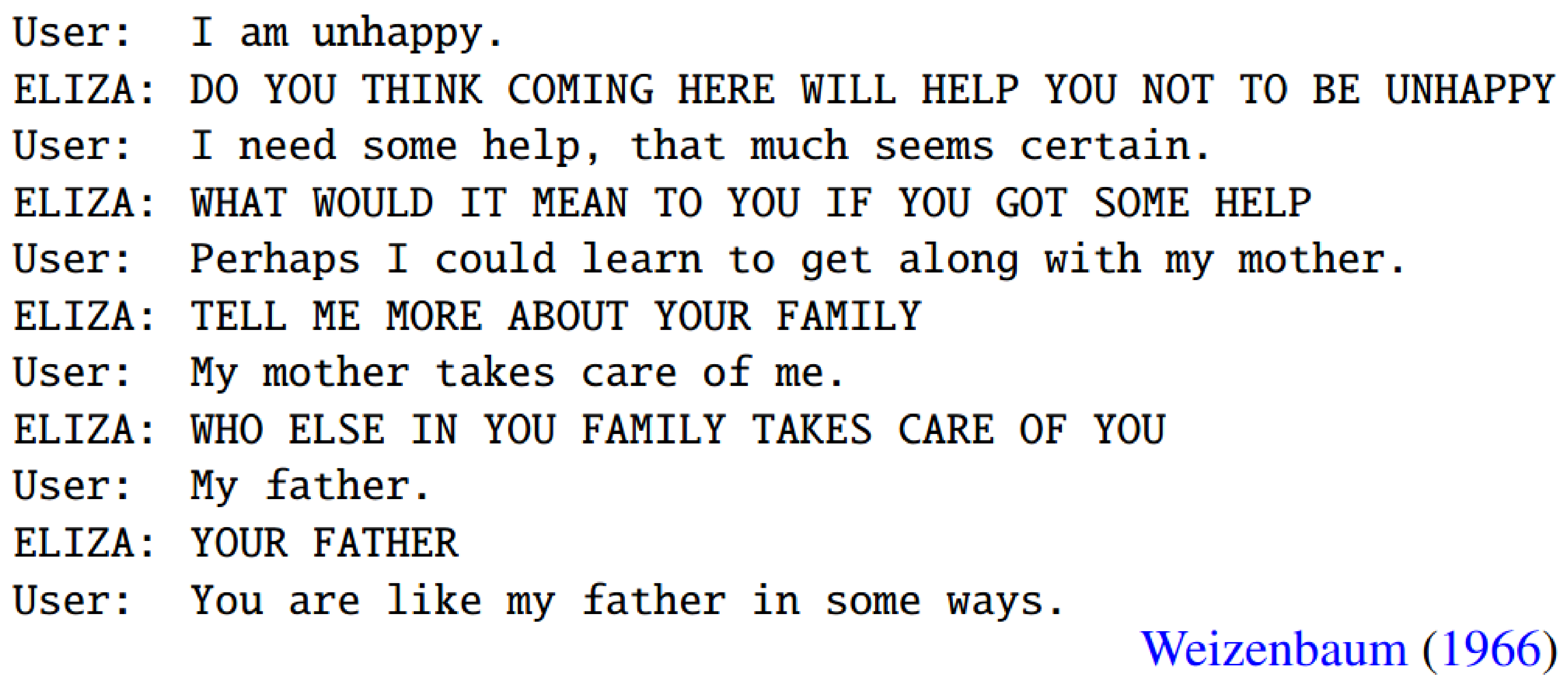

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User:   I need some help, that much seems certain.
ELIZA:  WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP
User:   Perhaps I could learn to get along with my mother.
ELIZA:  TELL ME MORE ABOUT YOUR FAMILY
User:   My mother takes care of me.
ELIZA:  WHO ELSE IN YOU FAMILY TAKES CARE OF YOU
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User:   You are like my father in some ways.
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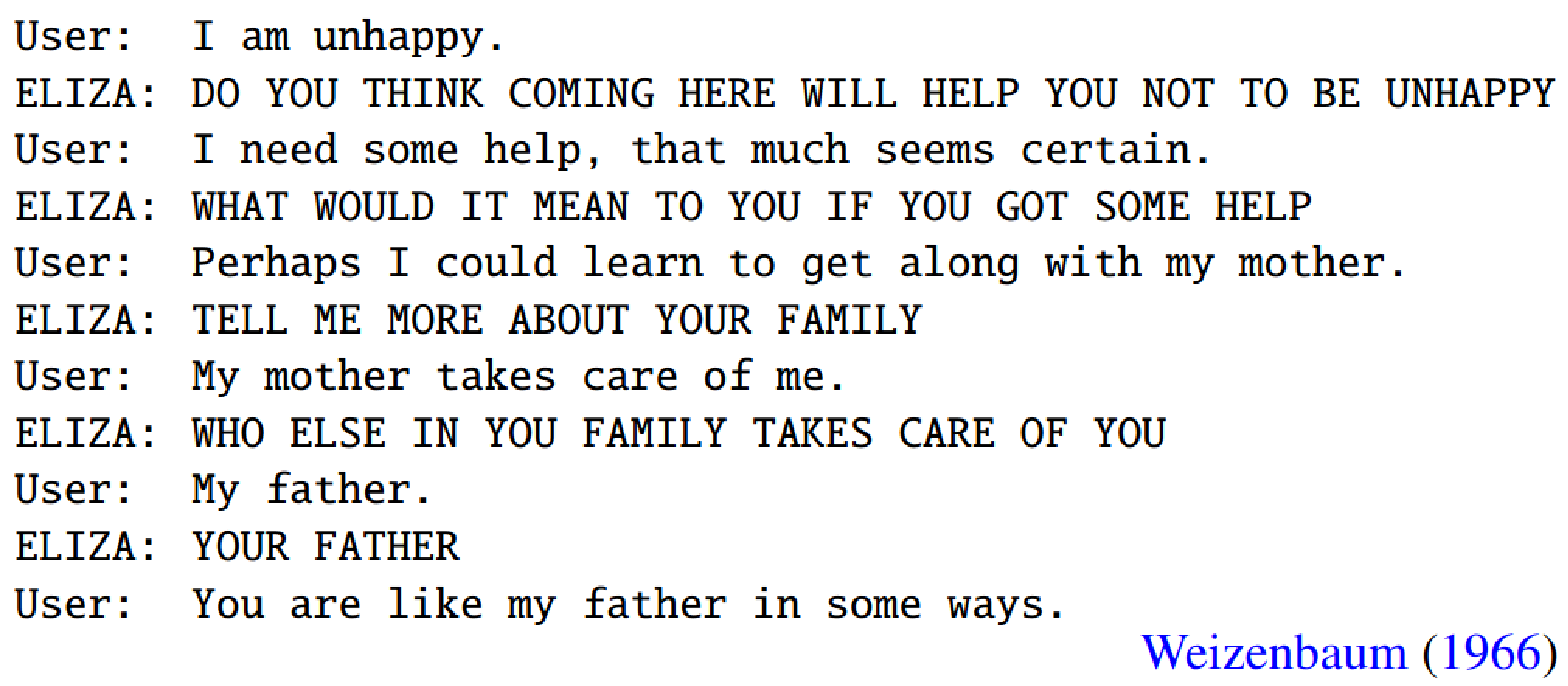

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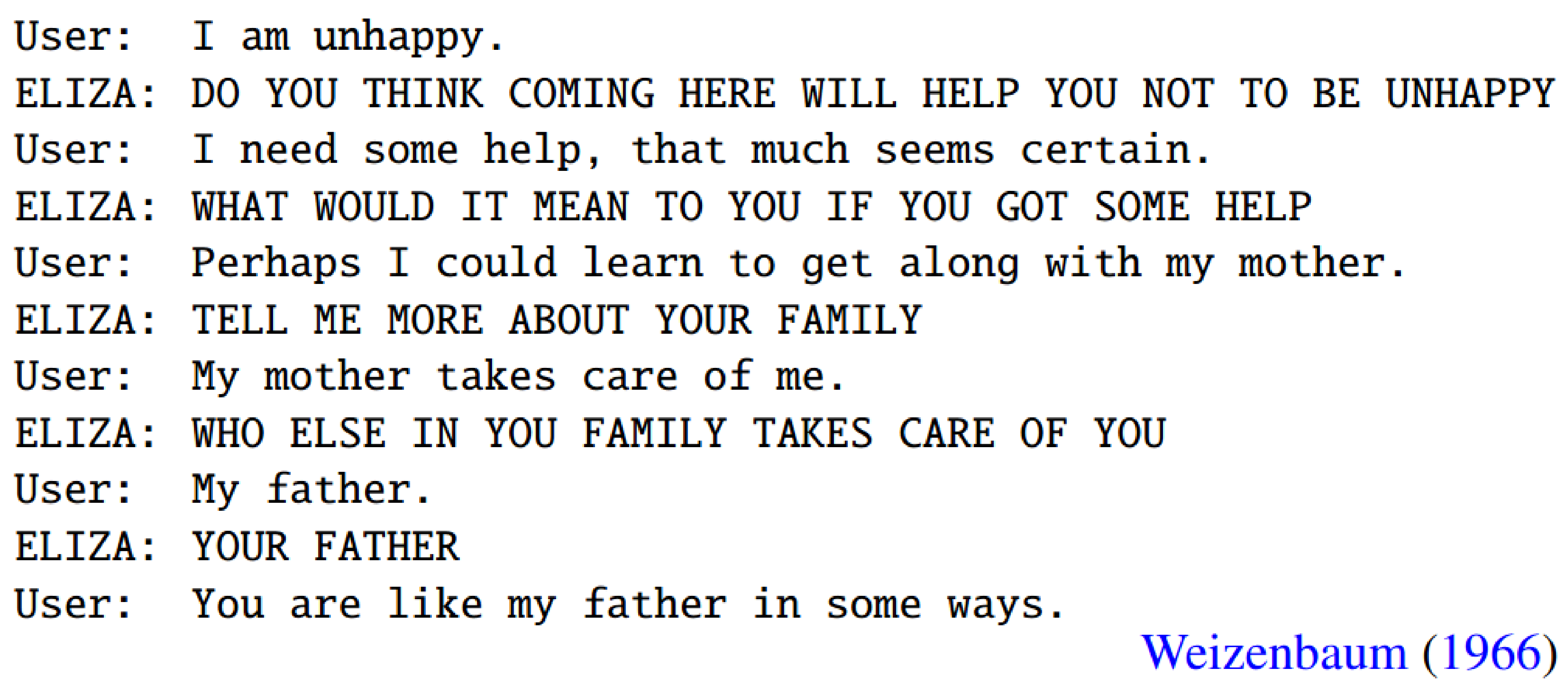

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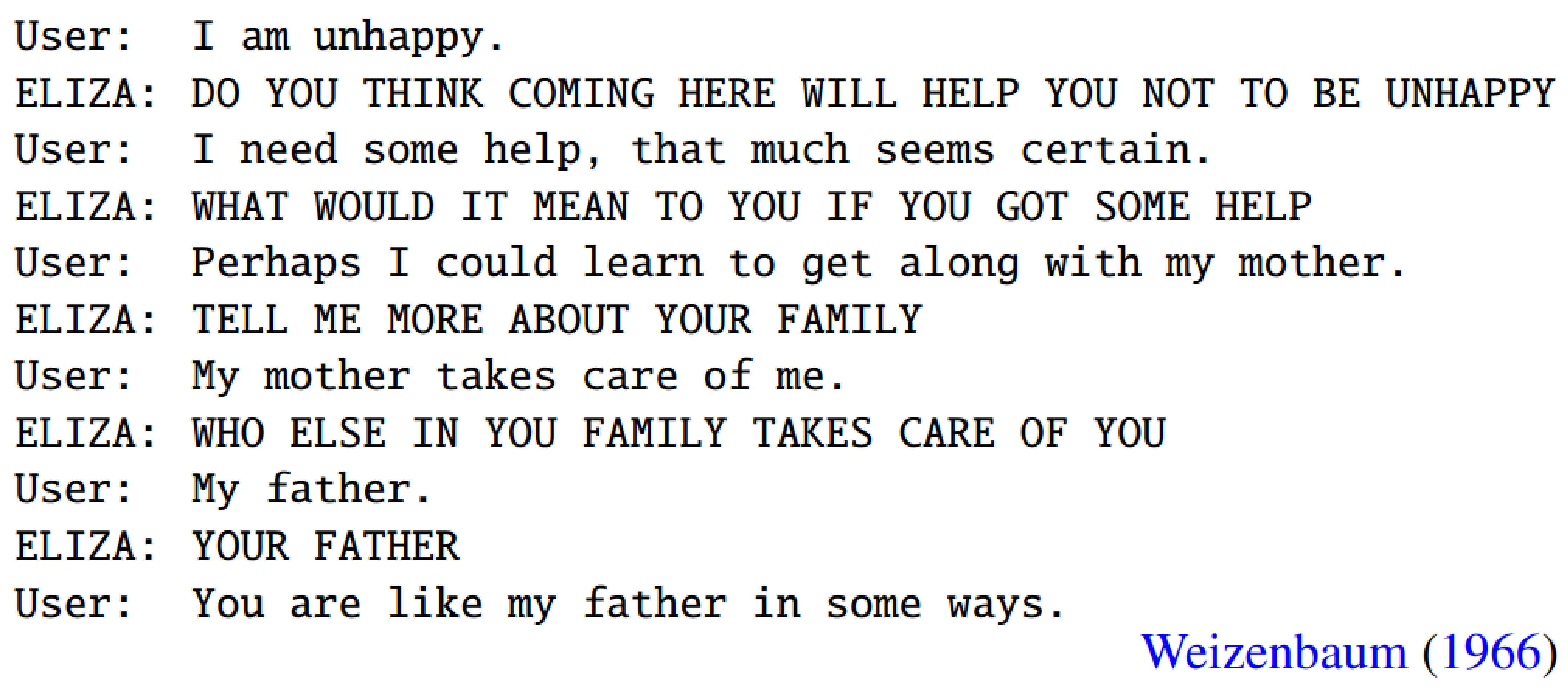

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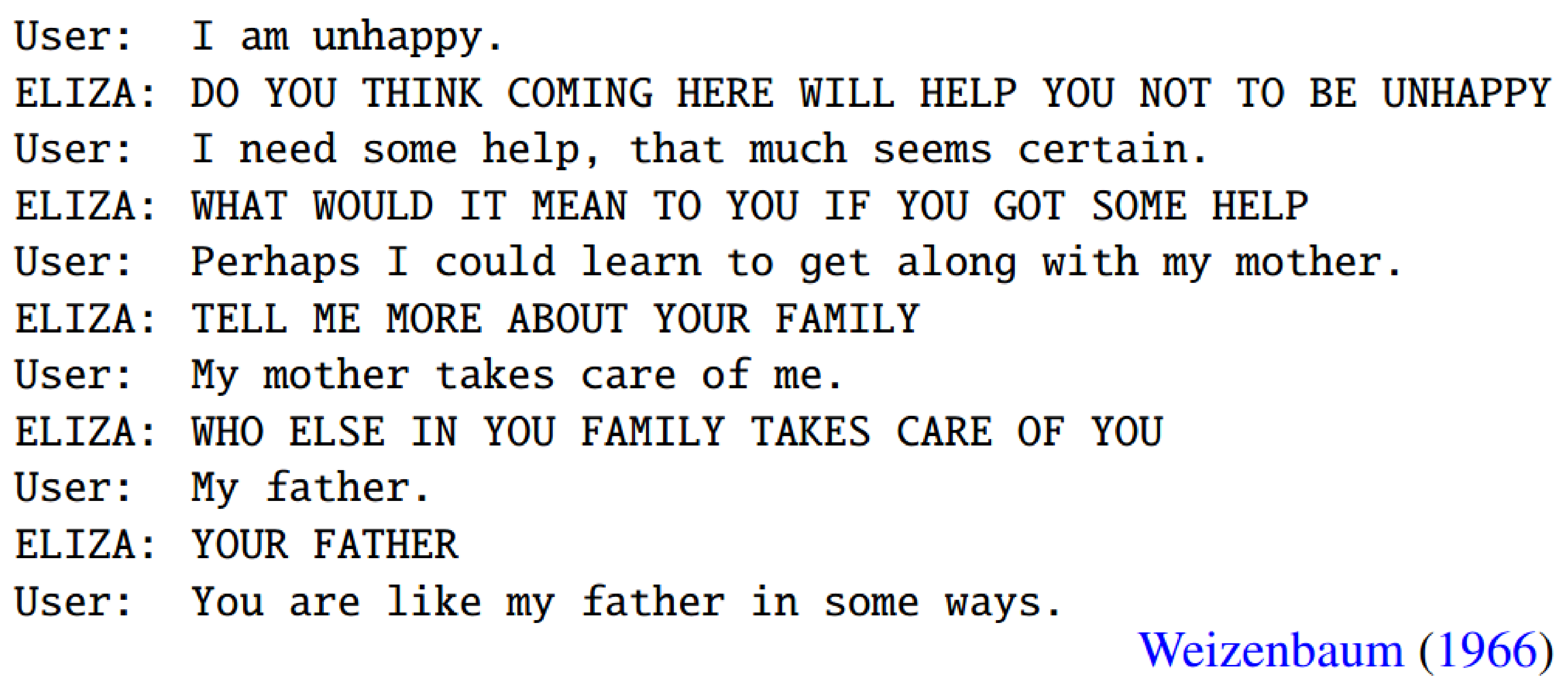

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→ For pattern matching: **regular expressions !**

→ Used then for **text normalization** and **tokenization**

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An algebraic notation for characterizing a set of string - used practically everywhere !

$\rightarrow$ Can be used to find desired occurrences of words in a large text !

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```
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- Replacing '*the*' with '*The*' `s/the/The`
- Capturing any string ending with '*er*': `/(.*)er/`
- Getting a superlative: `s/the (.*)er/the (\1)est/`

Regular expressions and ELIZA

Regular expressions also allows for more complex fonctionalities.. but especially, allows for **ELIZA**:

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$\rightarrow$ Has a series or cascade of regular expression substitutions, matching and changing some part of the input lines:

- Input lines are uppercased
- Change all instances of MY to YOUR, I'M to YOU ARE, etc...
- Then, other patterns are replaced:

Regular expressions and ELIZA

Regular expressions also allows for more complex fonctionalities.. but especially, allows for **ELIZA**:

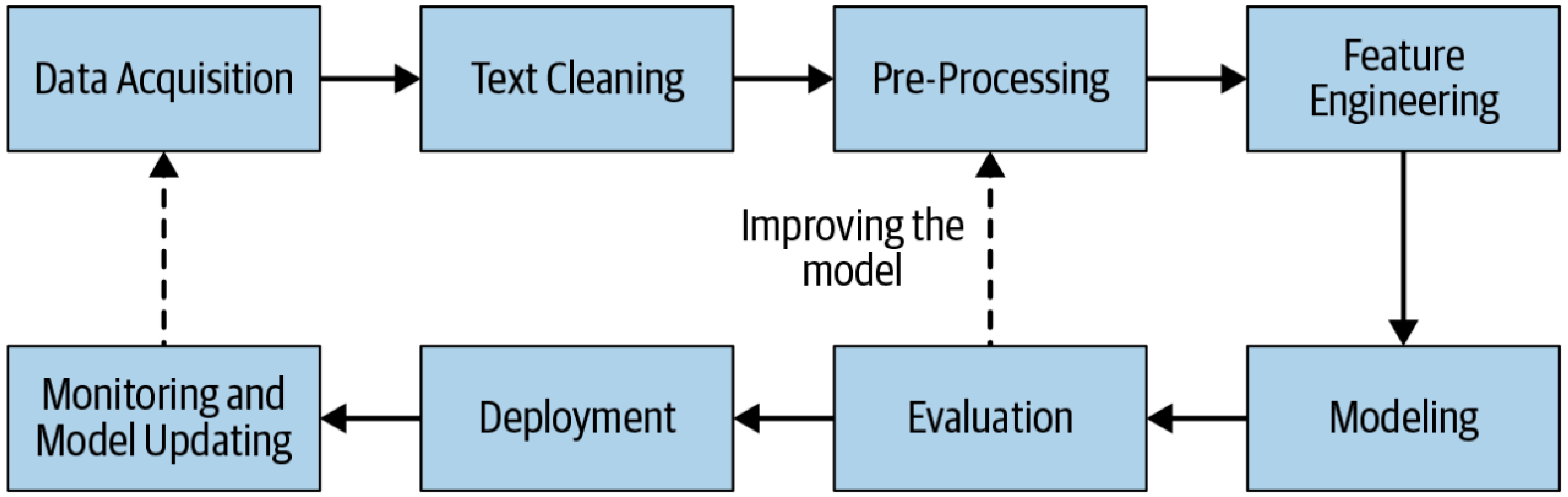
$\rightarrow$ Early NLP system that imitated a *Rogerian psychotherapist*, by Joseph Weizenbaum (1966)

$\rightarrow$ Has a series or cascade of regular expression substitutions, matching and changing some part of the input lines:

- Input lines are uppercased
- Change all instances of MY to YOUR, I'M to YOU ARE, etc...
- Then, other patterns are replaced:

```
s/.* I’M (depressed|sad) .*/I AM SORRY TO HEAR YOU ARE \1/
s/.* I AM (depressed|sad) .*/WHY DO YOU THINK YOU ARE \1/
s/.* all .*/IN WHAT WAY/
s/.* always .*/CAN YOU THINK OF A SPECIFIC EXAMPLE/
```

How to build an NLP application ?



General NLP Pipeline. *From "Practical Language Processing, Figure 2-1, Chapter 2"*

Crucial steps:

- **Acquiring data** - even for rule-based system, if only for *evaluation*
- **Pre-processing**
- Feature Engineering $\rightarrow$ classical approaches *vs* modern **Text representation** through deep learning
- **Evaluation** - *intrinsic* and *extrinsic*

A few definitions

What are the *objects* we will work on ?

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$\rightarrow$ Example:

"*I showed my masterpiece to the grown−ups, and asked them whether the drawing frightened them.*"

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- Genre (news, scientific, fiction..), specific domain (medical, law...)

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Data Statements for Natural Language Processing: Toward Mitigating System Bias and Enabling Better Science (Bender & Friedman, 2018)

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Resources are unevenly distributed along languages ! Still, they are very diverse. For example:

- Lexical Databases like **WordNet** (but also for other languages)
- Labeled data for many tasks - will allow supervised learning
- Careful: *annotation* is a difficult and subjective process

Pre-processing: Tokenization

The first step to any task: pre-process the text, which begins by segmenting it into words. This is **tokenization !**

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$\rightarrow$ After **tokenization,** the set of tokens are listed in a vocabulary $\mathcal{V}$ (*word types*)

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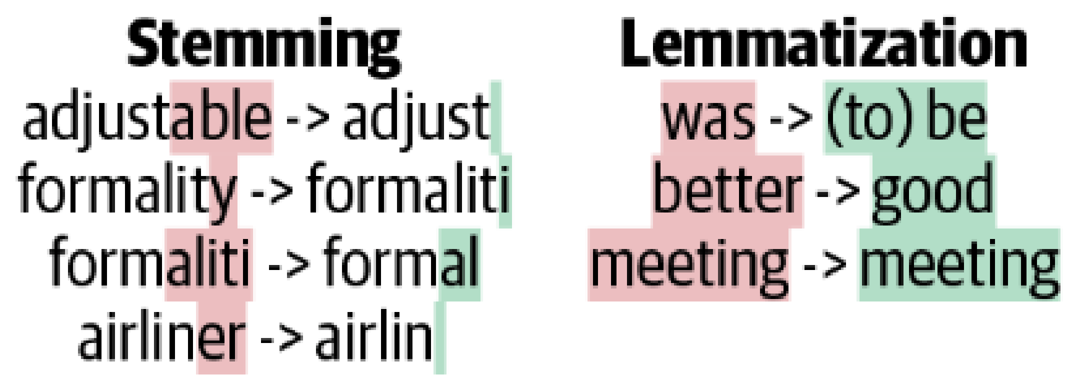

Stemming	Lemmatization
adjustable -> adjust	was -> (to) be
formality -> formaliti	better -> good
formaliti -> formal	meeting -> meeting
airliner -> airlin	

From "Practical Language Processing, Figure 2-7, Chapter 2"

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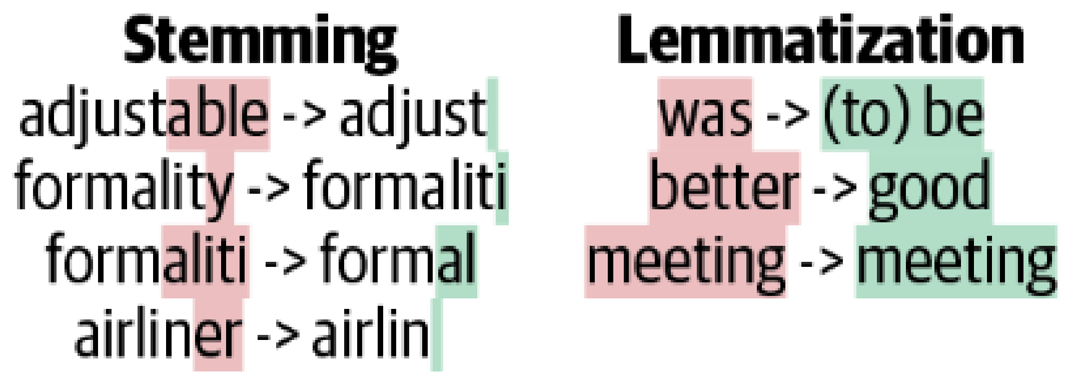

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$\rightarrow$ Let's think ahead: what would be the advantages of the various strategies for text normalization ?

Issues with Tokenization

- **Word-level tokenization:**
  - Treats different forms of the same root as separate (e.g., “low”, “lowest”, “lowered”, etc)
  - This implies separate parameters !
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- A middle ground ?
  - **Byte Pair Encoding (1994)** used for **Subword Tokenization**

    Neural machine translation of rare words with subword units (Sennrich et al, 2016)
  - Now the norm for modern models

Byte Pair Encoding: Algorithm

We usually begin from *pre-tokenized* word-level tokens:

- $\mathcal{V} \leftarrow$ All characters in the training data, including an *end of word character*
- While $|\mathcal{V}| < K$:
    - Tokenize the data with the current $\mathcal{V}$
        - Taking the *longest possible prefix* each time
    - Count the frequency of adjacent token pairs in the data
    - Choose the pair $\{l, r\}$ that occurs most frequently
    - Add the pair to the vocabulary as a new token: $\mathcal{V} \leftarrow \mathcal{V} \cup \{lr\}$

The algorithm saves the **merges, in order**, and applies them in order when splitting new words

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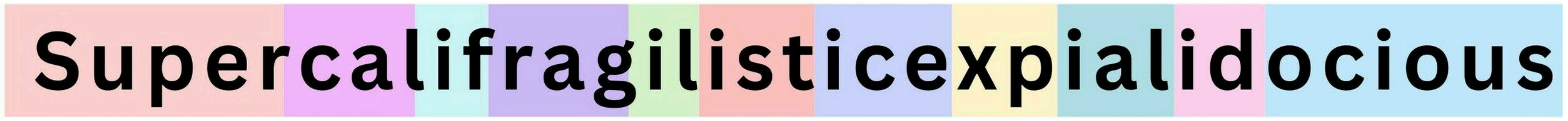
Example:

```
l o w _ : 5
l o w e r _ : 2
n e w e s t _ : 6
w i d e s t _ : 3
```

Properties and variants

- Usually include frequent words and frequent subwords
  - Often, **morphemes** (*the smallest meaning-bearing unit of a language*)



- **WordPiece** *(Schuster et al., 2012)*:
  - Used by Google for their models
  - Merge is different (maximizes *likelihood*, not frequency)
  - Merge order is not saved: tokenization uses *the longest subword* first
- **SentencePiece** *(Kudo et al., 2018)*: applied to any algorithm
  - Replaces *whitespaces* by a special token and does not apply pre-tokenization
  - Very useful for languages without segmentation between words
- Many other variants (using *bytes, soft tokenization...*)

Sentence tokenization

What is a sentence ?

The format will heavily depend on the target task

- For many classification tasks, labels are at a higher level
  - **Labeled document**: possibly many sentences
- For core NLP tasks, it’s more complicated

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    - Ideally, it:
        - has a **complete syntactic structure**
        - is **semantically related to other sentences**
    - In practice, it is *typograhically marked*, but:
        - The full stop may be ambiguous, the uppercase too
        - Difficulty with embedded sentences (e.g, with quotes)
        - No clear markers in some languages

Tokens versus type

Type: an element of the vocabulary
Token: an instance of that type in running text

Relationship ?

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- **Heaps Law = Herdan's Law:**
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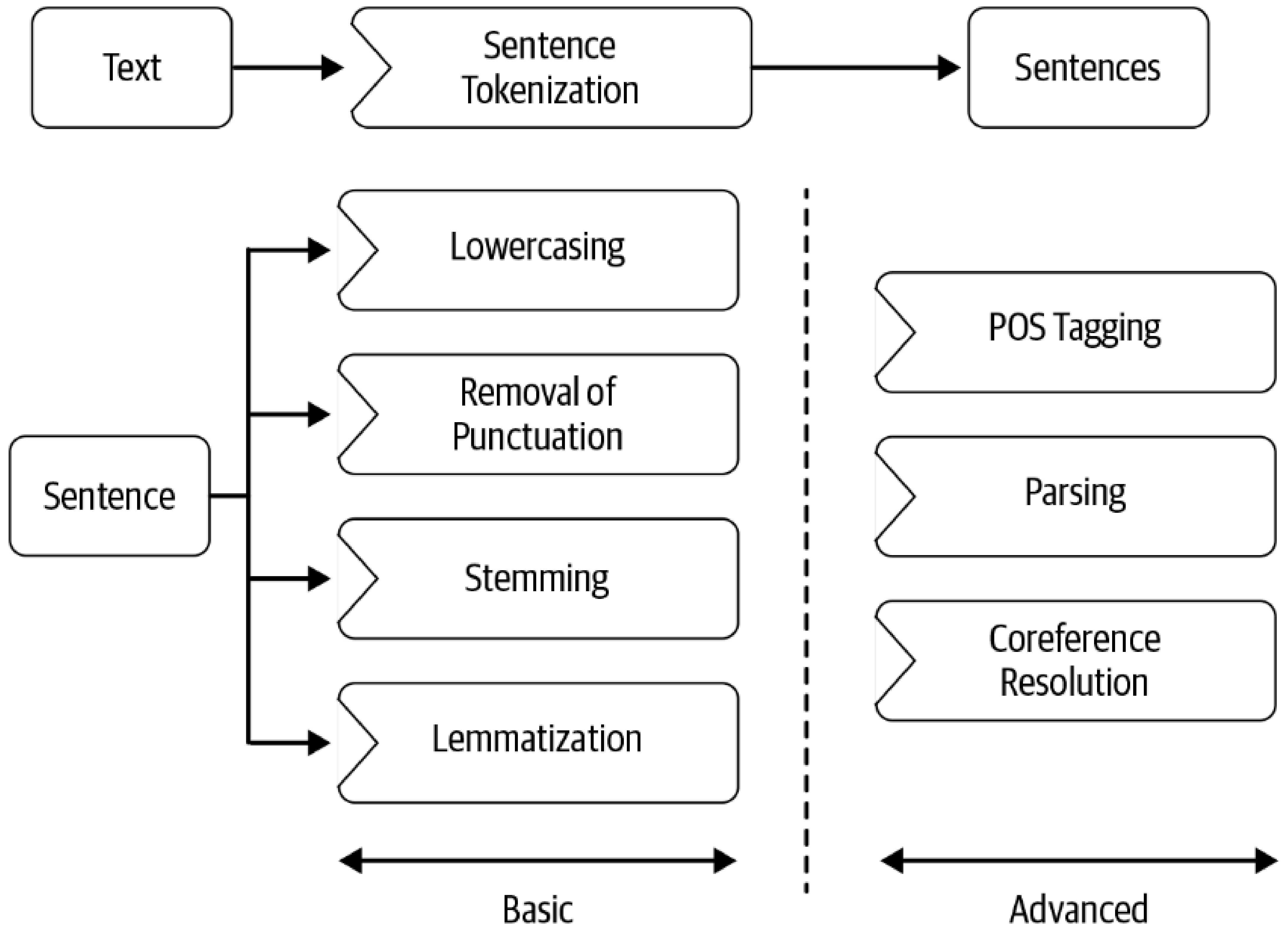
  where k and β are determined empirically
- For English text corpora, $10 < k < 100$ and $0.4 < \beta < 0.6$

	N	$\lvert\mathcal{V}\rvert$
Switchboard	2.4 million	20 thousand
Shakespeare	884 thousand	31 thousand
Google N-gram	1 trillion	13 million

Pre-processing: summary



Summary of pre-processing steps. *From "Practical Language Processing, Figure 2-11, Chapter 2"*

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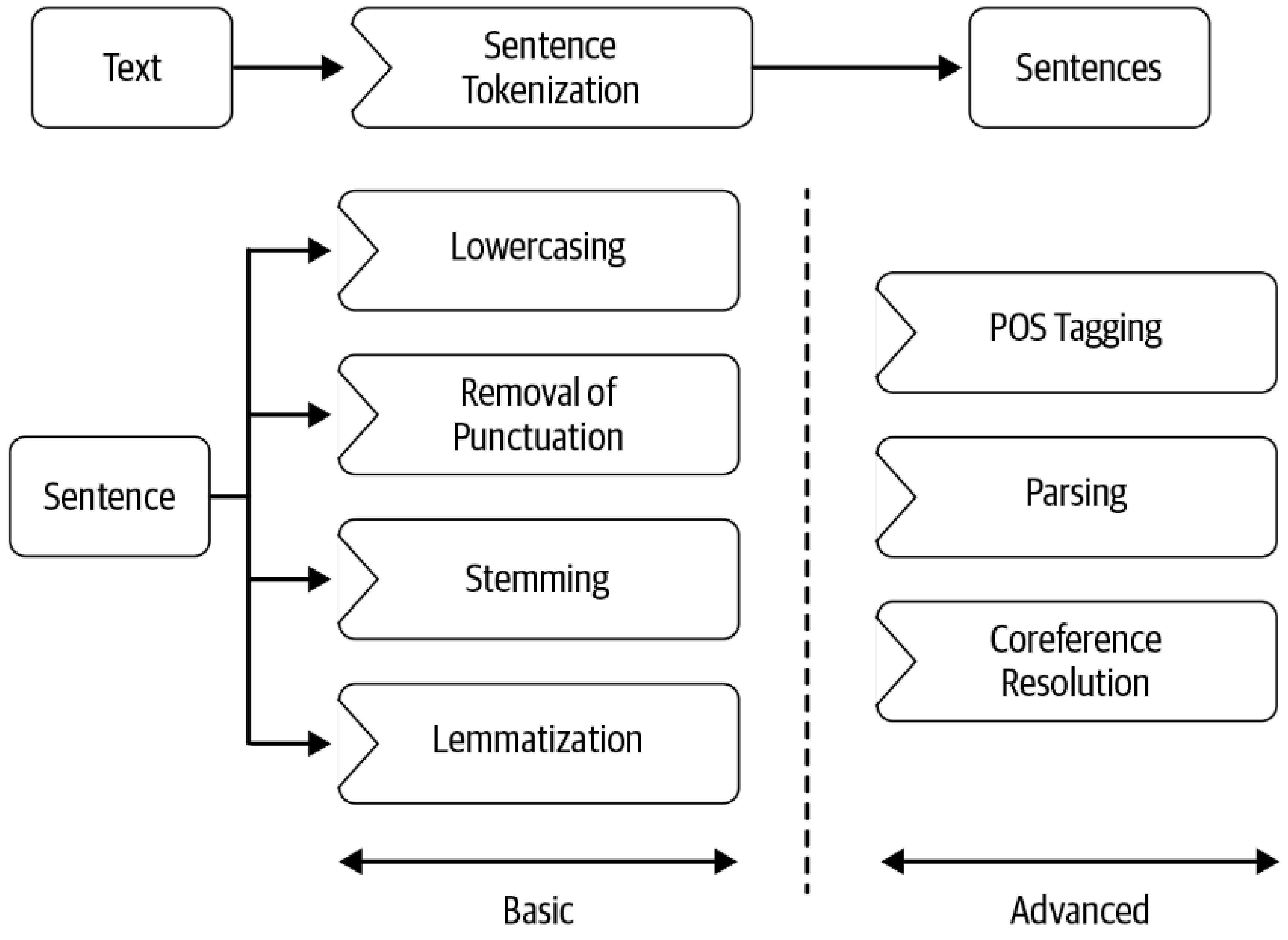

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$\rightarrow$ Possible advanced steps depending on the target task !

A case study: classic methods for document representation and classification

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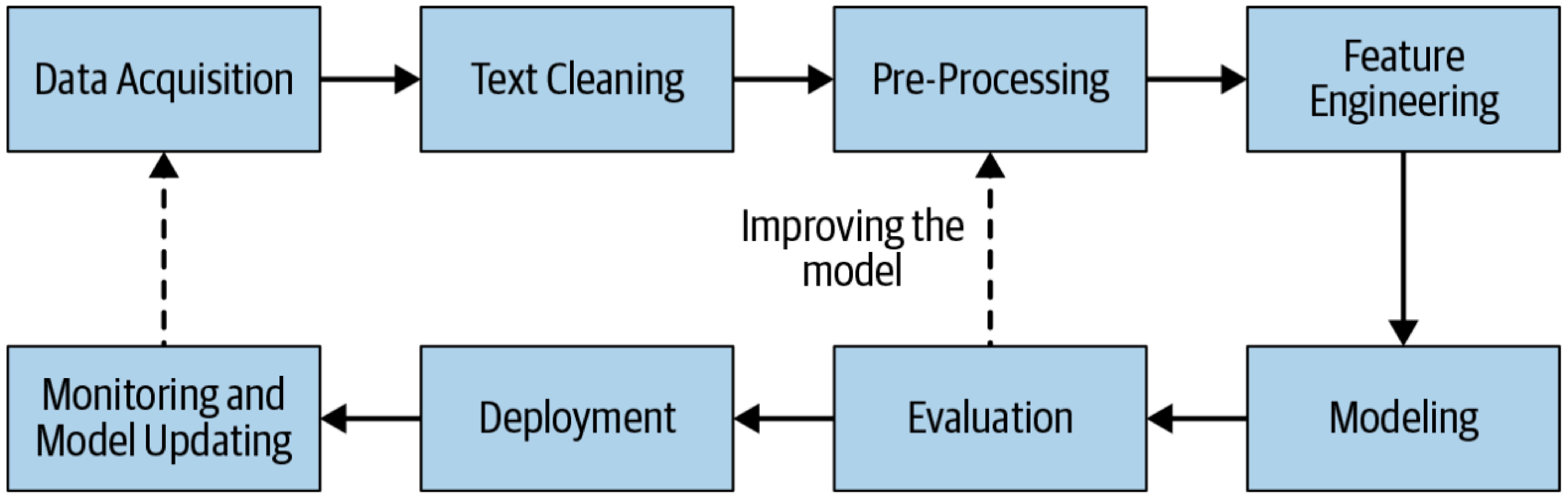

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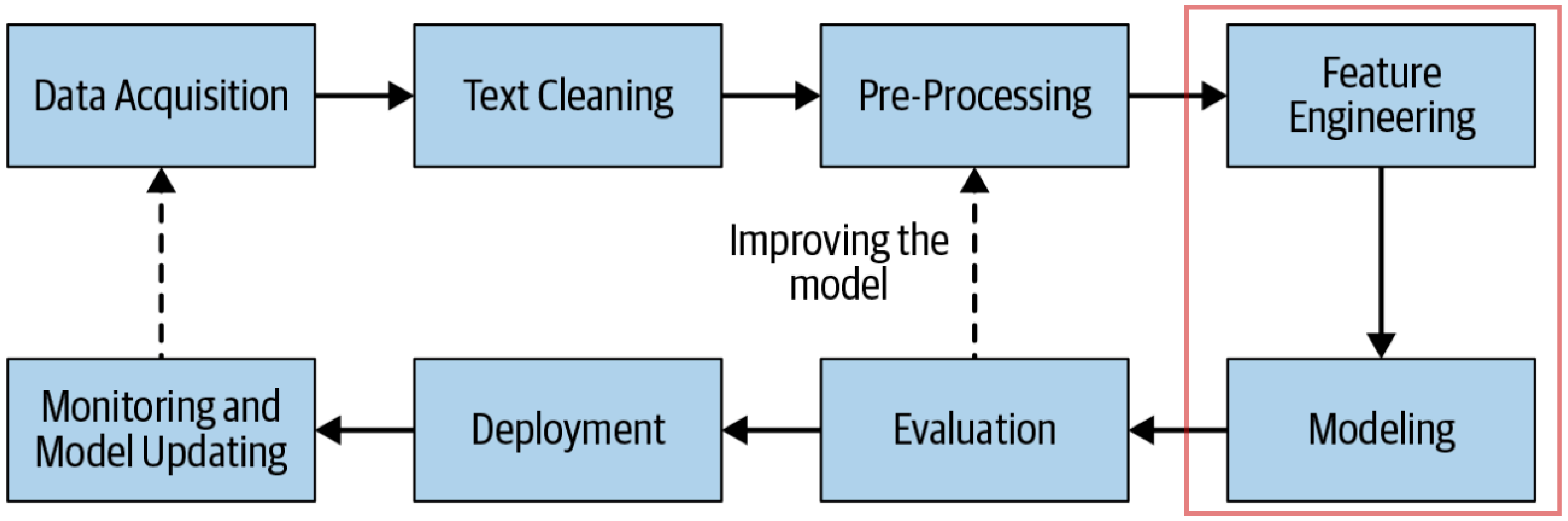

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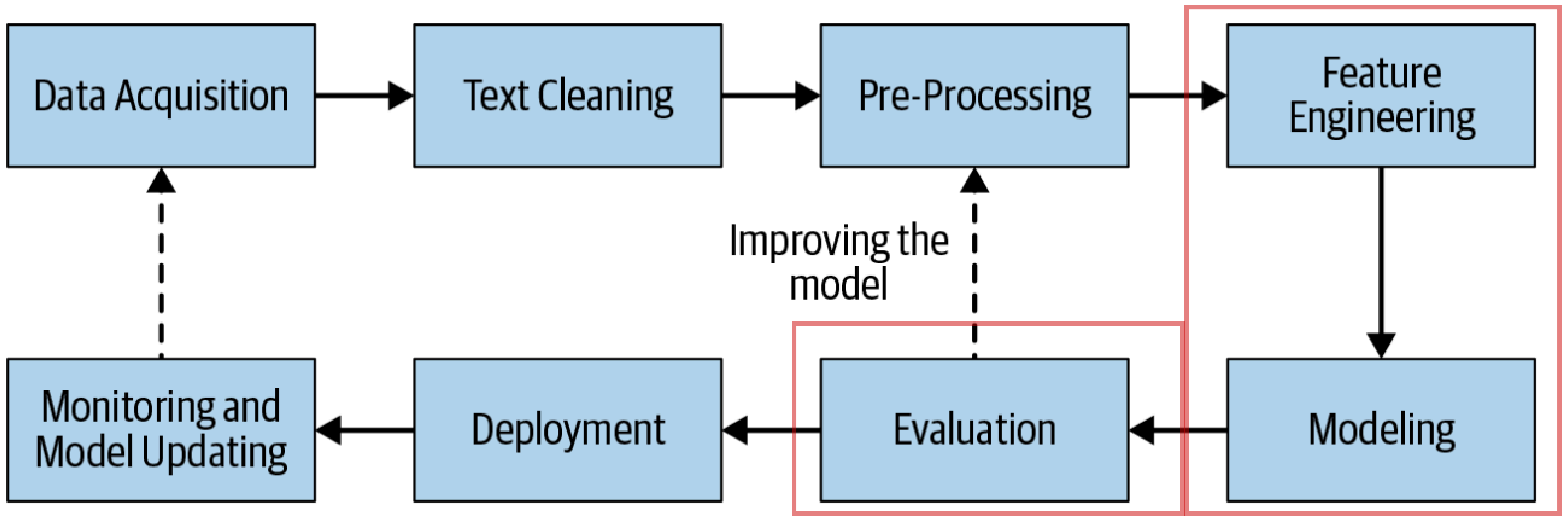

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- Well-defined and understood metrics, making evaluation straightforward

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$\rightarrow \mathbf{T} =$

(Term-document matrix)

	I	the	down	walked	street	avenue	walk	ran	city
Doc_1	1	1	1	1	1	0	0	0	0
Doc_2	1	1	1	1	0	1	0	0	0
Doc_3	1	1	1	0	1	0	0	1	0
Doc_4	1	1	1	0	0	0	1	0	1
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  - ...or learn a classifier model that will use *word frequencies* as features $\rightarrow$ *Naïve Bayes* is the simplest, assuming independance between words
- Also useful for document clustering, information retrieval.... why ?

Model: Naïve Bayes

Multinomial naive Bayes classifier: a *generative* (why ?) linear classifier that naïvely assumes that features are independant

- Goal: for a document d return the class $\hat{c}$ with maximum a posteriori probability among classes: $\hat{c} = \mathrm{argmax}_{c \in \mathcal{C}} P(c|d)$

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- Idea: we compute $\mathbb{P}(w|c)$ as the frequency of w among all documents $d \in \mathcal{D}$ of class c:

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  - This is Maximum Likelihood Estimation (MLE): D*emonstration* ?

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- It is legitimate (and practical !) to represent a document d with its bag-of-word representation $\mathbf{d}$!
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- **Training Algorithm**: Given data $\mathcal{D}$ and classes $\mathcal{C}$
    - Create the vocabulary $\mathcal{V}$ from documents $d \in \mathcal{D}$
    - From $\mathcal{D}$: For each class $c \in \mathcal{C}$: compute the log-prior $\log \mathbb{P}(c)$
        - For each word $w \in \mathcal{V}$ compute the log-likelihood $\log \mathbb{P}(w|c)$

Classification with Naïve Bayes

- It is legitimate (and practical !) to represent a document d with its bag-of-word representation $\mathbf{d}$!
    - Practical points: use log-probabilities (why ?), use *smoothing*

- **Training Algorithm**: Given data $\mathcal{D}$ and classes $\mathcal{C}$
    - Create the vocabulary $\mathcal{V}$ from documents $d \in \mathcal{D}$
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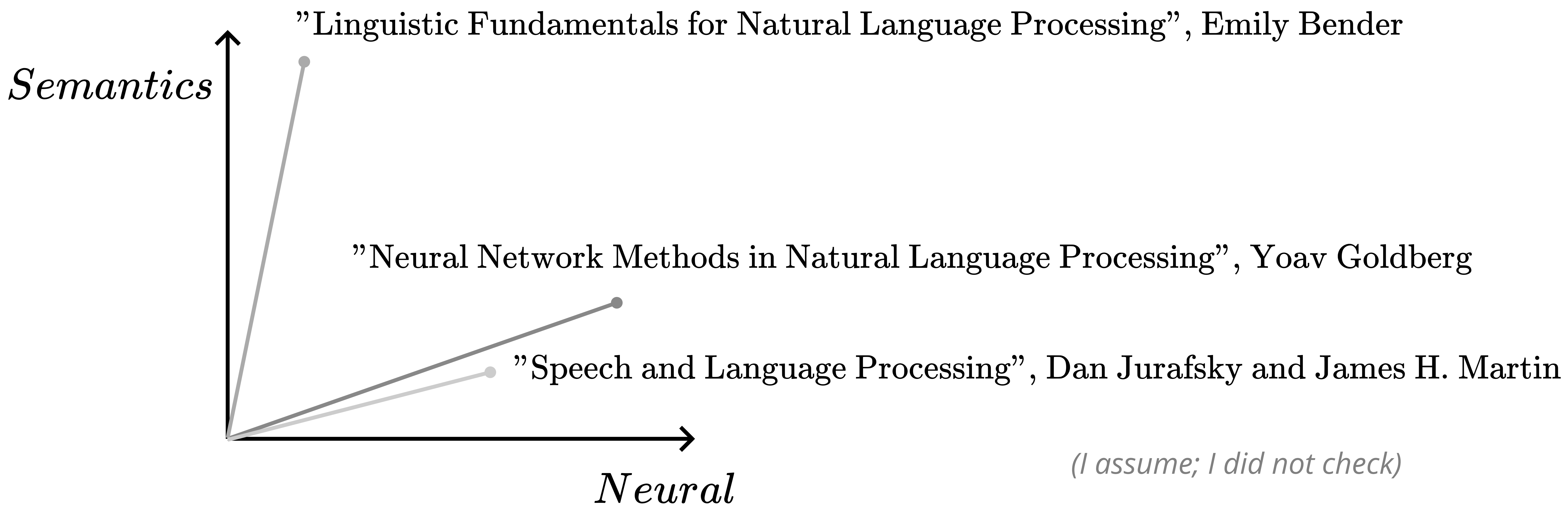
- **Inference Algorithm**: Given document d to classify:
    - For each class $c \in \mathcal{C}$:$S(c) = \log \mathbb{P}(c)$
        - For each position $i \in d$:
            - If $w_i \in \mathcal{V}$: $S(c) = S(c) + \log \mathbb{P}(w_i|c)$
    - Return $\text{argmax}_{c \in \mathcal{C}} S(c)$

Document as Vectors


"Linguistic Fundamentals for Natural Language Processing", Emily Bender
Semantics
"Neural Network Methods in Natural Language Processing", Yoav Goldberg
"Speech and Language Processing", Dan Jurafsky and James H. Martin
Neural
(I assume; I did not check)

- Words are **dimension** of *documents vectors*
- You can vizualize vectors in a particular set of dimensions of your choosing
- Vectors should be *similar* for documents that are related

But what does "similar" mean here ?

Similarity between documents: cosine

The **cosine** of the angle between the document vectors is the most common similarity metric in NLP

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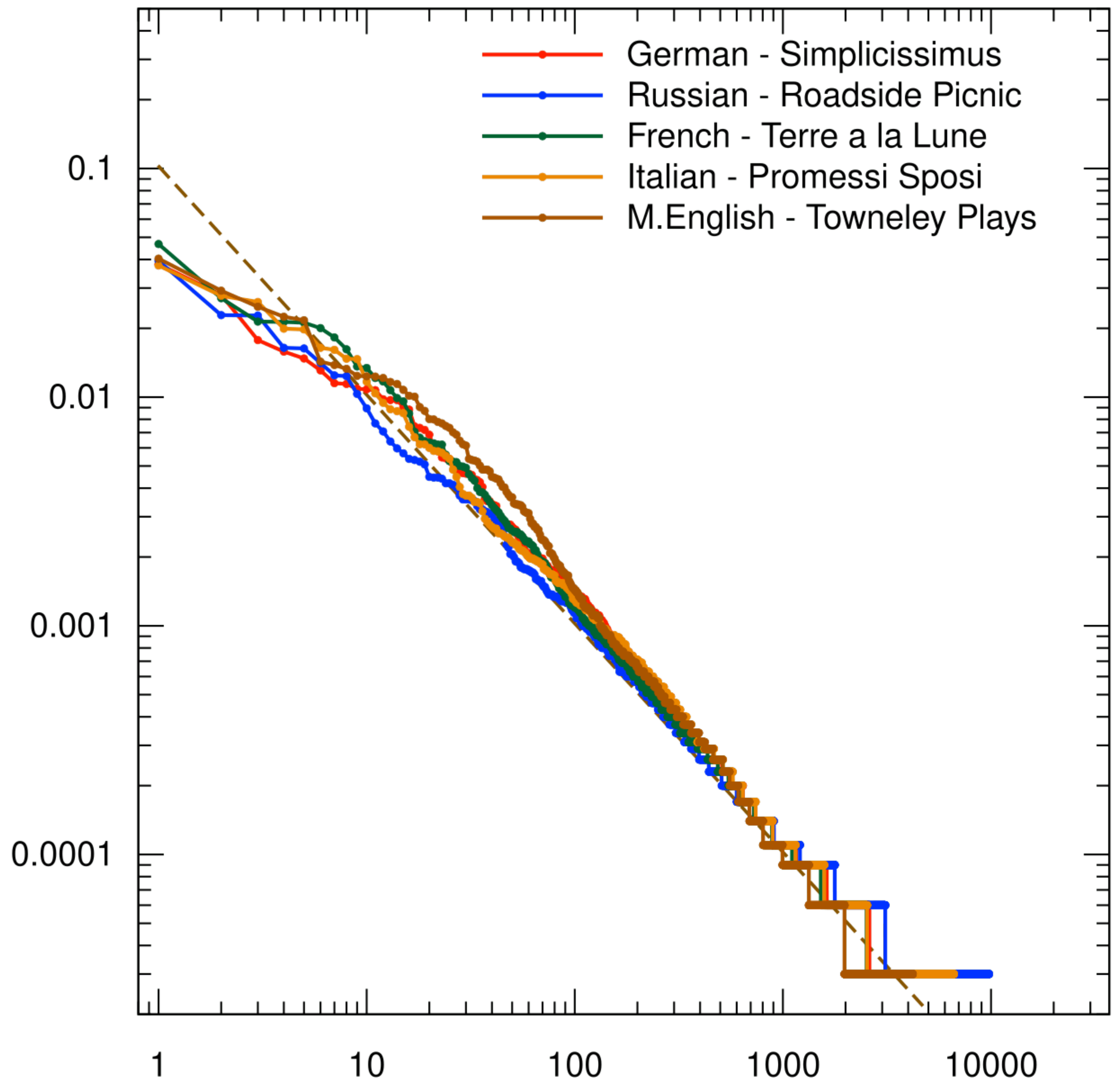
Still, frequency is not the best measure of association between words:

- It is **skewed** $\rightarrow$ *Zipf*'s law
- Very frequent words are rarely the most useful for classification

Difficulty 1: Zipf's law

Sparsity: tied to **Zipf's Law**: $frequency \propto 1/rank$



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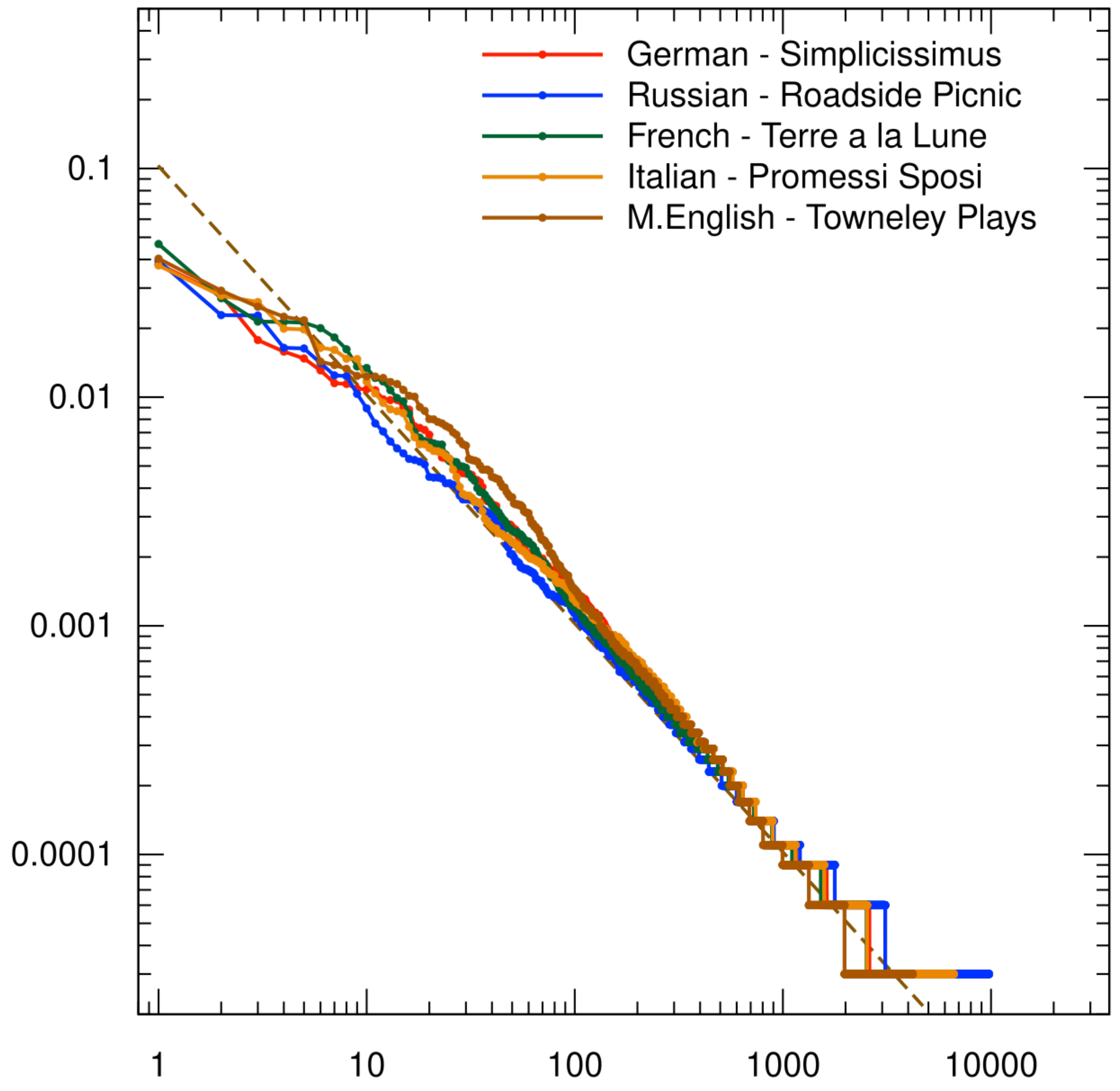

- Zipf's law seems to hold for most natural languages and many language-related phenomena
  - Examples: *meaning-frequency law, law of abbreviation*

Features: TF-IDF Representations

What would be a better way than directly removing frequent-but-not-significant words (called *stopwords*) ?

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The weight given to word w in document d is $\mathrm{TF}(w,d) \times \mathrm{IDF}(w)$:

- What happens if a word is present in every document ?

Model: Logistic regression

A *discriminative* linear classifier: learns directly $\mathbb{P}(c|d)$ through computing a **linear score** and applying a **logistic function**.

- Binary case: for a set of documents $d \in \mathcal{D}$ represented by vectors $\mathbf{d}$ learn a vector $\mathbf{w}$ and a bias b maximizing the likelihood of making a good classification into $c = 1$ or $c = 0$.

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- Here, the training is made through **gradient descent**: we minimize that loss function by finding iteratively the direction in which the loss decreases the most and updating the weights accordingly

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The model is easily extended to a multinomial case through using a matrix $\mathbf{W}$, a vector $\mathbf{b}$ and the *softmax* function (more on that later)

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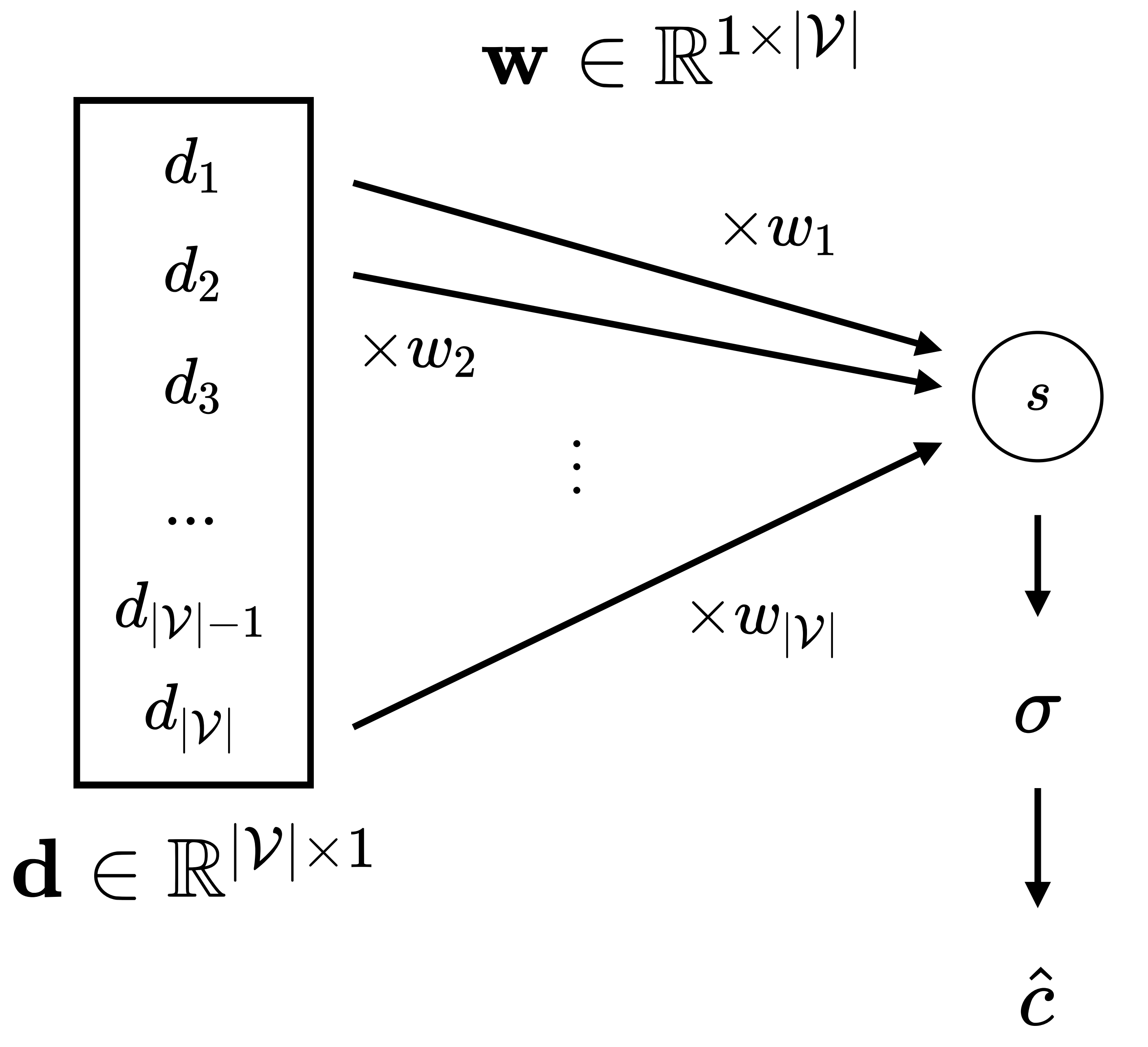

$\mathbf{w} \in \mathbb{R}^{1\times|\mathcal{V}|}$
d_1
d_2
d_3
$\dots$
$d_{|\mathcal{V}|-1}$
$d_{|\mathcal{V}|}$
$\times w_1$
$\times w_2$
$\times w_{|\mathcal{V}|}$
s
σ
$\hat{c}$
$\mathbf{d} \in \mathbb{R}^{|\mathcal{V}|\times 1}$

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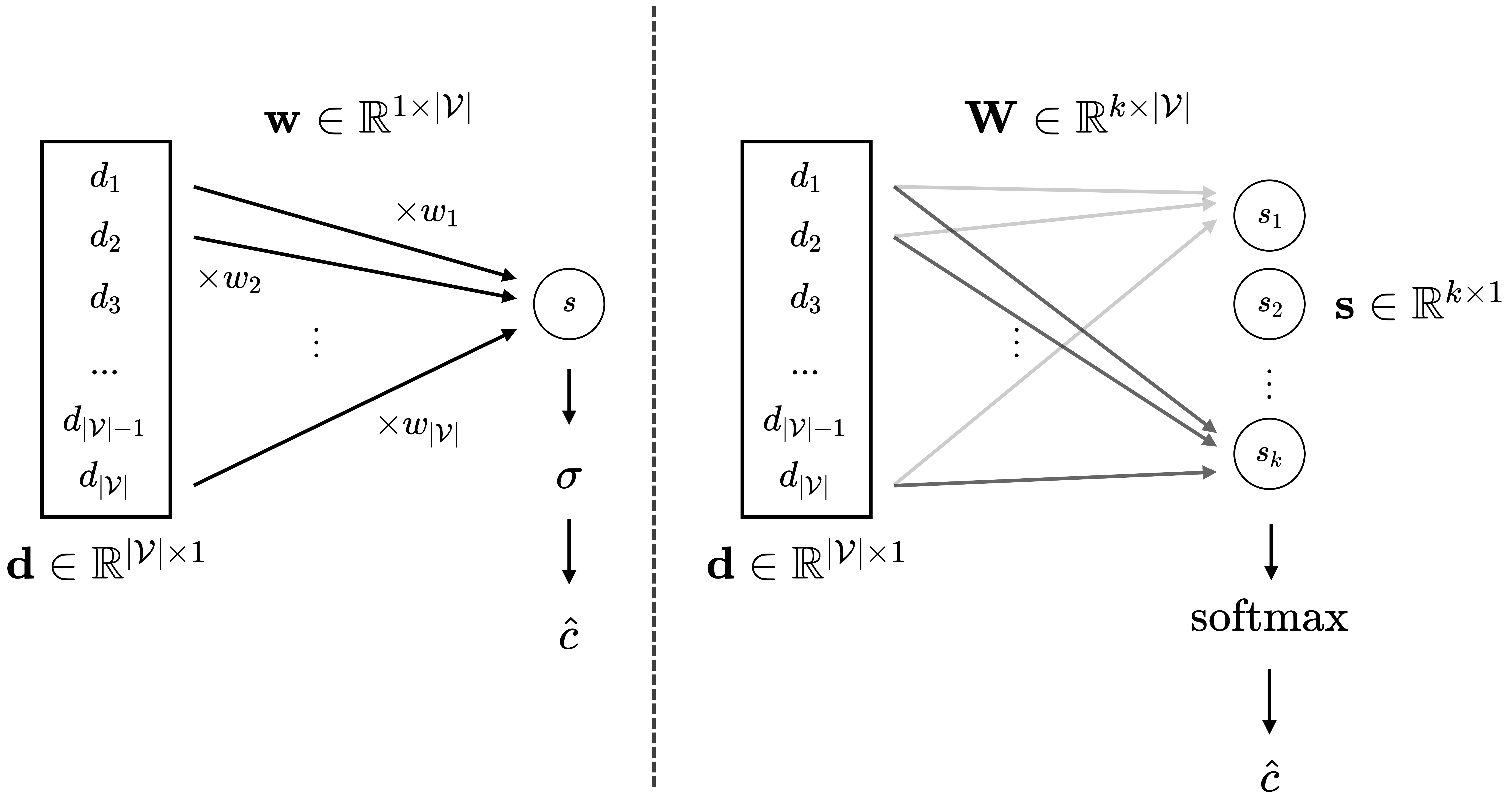


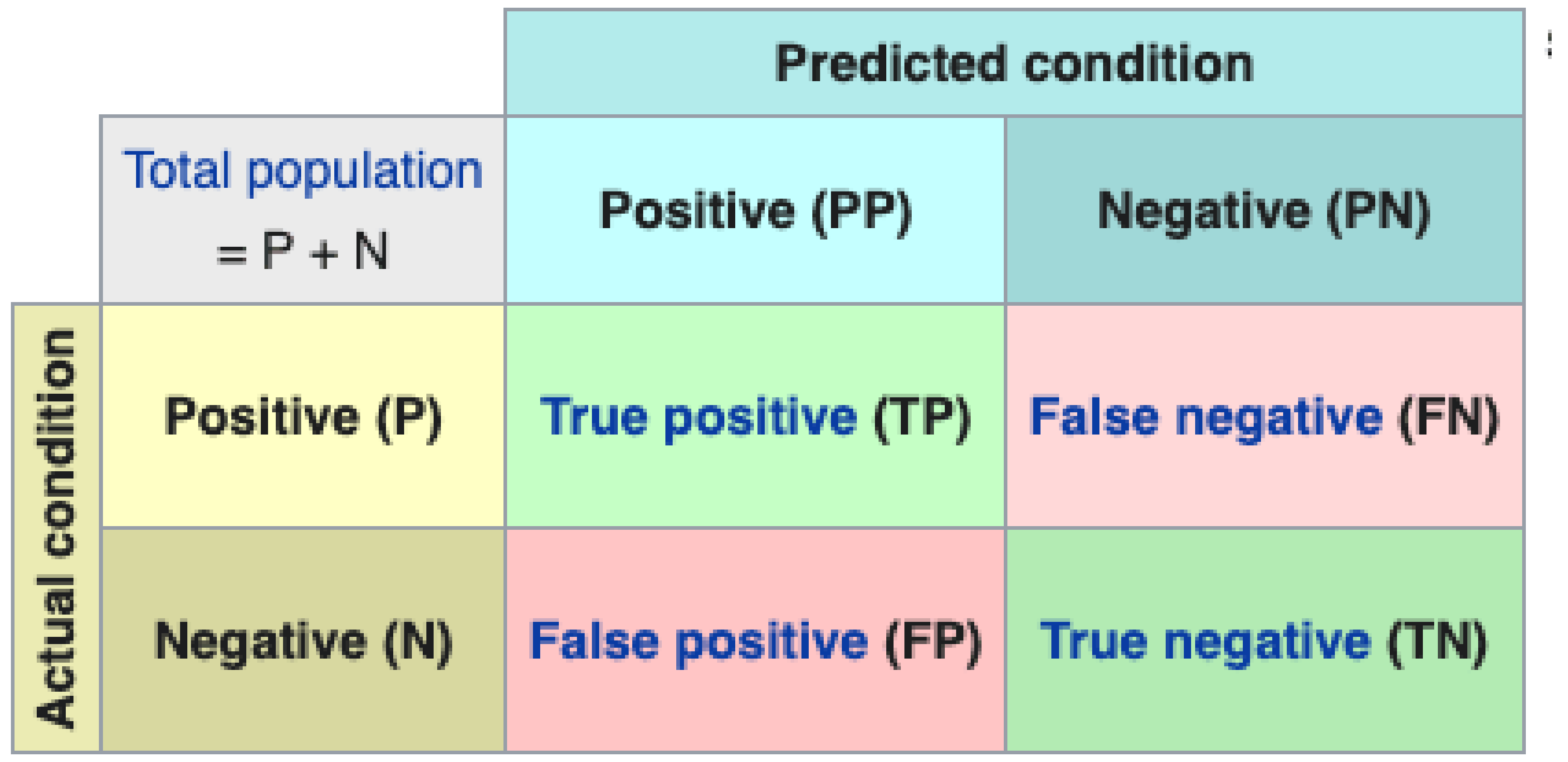
$\mathbf{w} \in \mathbb{R}^{1\times|\mathcal{V}|}$
d_1
d_2
d_3
...
$d_{|\mathcal{V}|-1}$
$d_{|\mathcal{V}|}$
$\times w_1$
$\times w_2$
$\times w_{|\mathcal{V}|}$
s
σ
$\hat{c}$
$\mathbf{d} \in \mathbb{R}^{|\mathcal{V}|\times 1}$
$\mathbf{W} \in \mathbb{R}^{k\times|\mathcal{V}|}$
d_1
d_2
d_3
...
$d_{|\mathcal{V}|-1}$
$d_{|\mathcal{V}|}$
s_1
s_2
s_k
$\mathbf{s} \in \mathbb{R}^{k\times 1}$
softmax
$\hat{c}$
$\mathbf{d} \in \mathbb{R}^{|\mathcal{V}|\times 1}$

Evaluation: Accuracy

- As usual: reserve held-out validation set for *hyperparameters tuning* and test set for evaluation
- Simplest measure: **Accuracy**

$$acc(\hat{\mathbf{y}},\mathbf{y}) = \frac{1}{|\mathcal{D}|}\sum_{d\in\mathcal{D}|}\delta(\hat{y}^d = y^d)$$

- For each label $c \in \mathcal{C}$, look at the *type* of
  - Errors: False positive (**FP**) and False negative (**FN**)
  - Correct predictions: True positive (**TP**) and True negative (**TN**)



		Predicted condition	
	Total population = P + N	Positive (PP)	Negative (PN)
Actual condition	Positive (P)	True positive (TP)	False negative (FN)
	Negative (N)	False positive (FP)	True negative (TN)

Better metrics: F-measures and Macro

- Compute **recall** and **precision**:

$$Recall(\hat{\mathbf{y}}, \mathbf{y}, c) = \frac{TP}{TP + FN} \qquad Precision(\hat{\mathbf{y}}, \mathbf{y}, c) = \frac{TP}{TP + FP}$$

- F-measure: combines recall (r) and precision (p) using the *harmonic mean*

$$\text{F-measure}(\hat{\mathbf{y}}, \mathbf{y}, c) = \frac{2rp}{r + p}$$

- Evaluating **multi-class classification**:
  - Balance across instances: Add up **TP**, **FP**, **TN**, **FN** over classes and compute the **Micro** F-measure
  - When classes are **imbalanced**, average over classes: **Macro** F-measure:

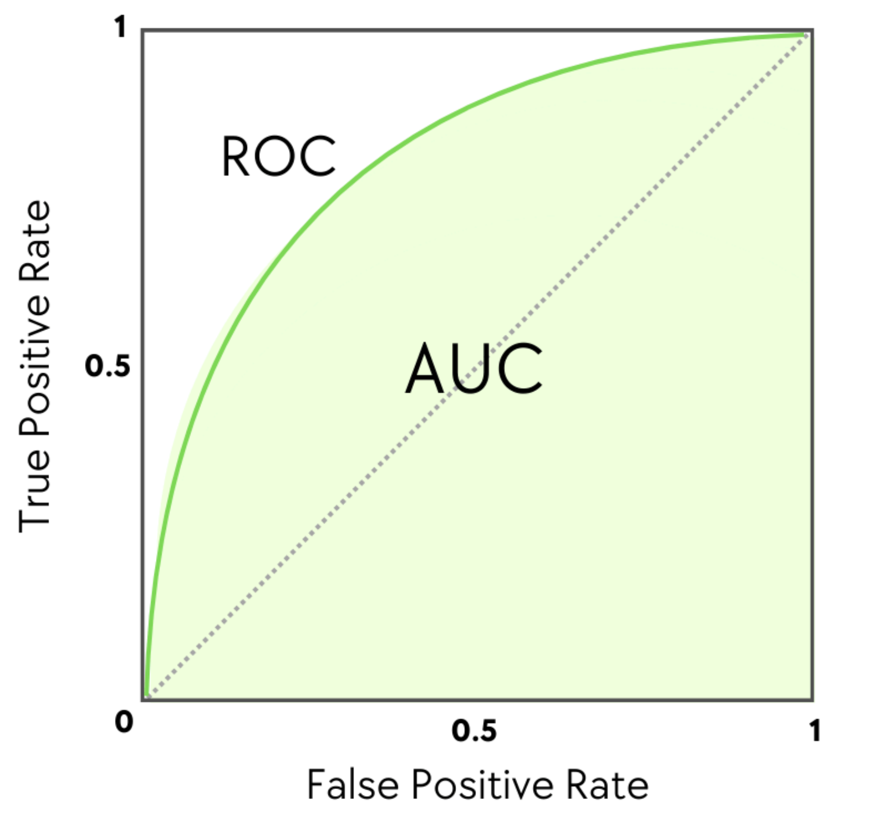
$$\text{Macro-F}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} \text{F-measure}(\hat{\mathbf{y}}, \mathbf{y}, c)$$

AUC: Area Under the Curve

- Area Under the **ROC** (*Receiver Operating Characteristic*) Curve
  - **ROC**: $\mathrm{TPR}_s = f(\mathrm{FPR}_s)$ for different classification threshold s
    - TPR: *True Positive Ratio* $= Recall$
    - FPR: *False Positive Ratio*

$$\mathrm{FPR} = \frac{FP}{FP + TN}$$

- A metric for measuring the quality of a model **independently from the classification threshold** s
  - Usually, $s = \frac{1}{2}$
  - Can be adapted to unbalanced tasks $\rightarrow$ Anomaly detection
- The higher the AUC, the better



Back to difficulty 2: Ambiguity

To go further, NLP systems usually need to *uncover the* ***structure*** of text, which is made difficult by:

- **Lexical ambiguity**: *homography*, *polysemy*
- **Syntactic ambiguity**
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    - Task: Part-of-speech tagging, Word sense disambiguation
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    - Task: Dependency parsing
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  - Task: Semantic parsing

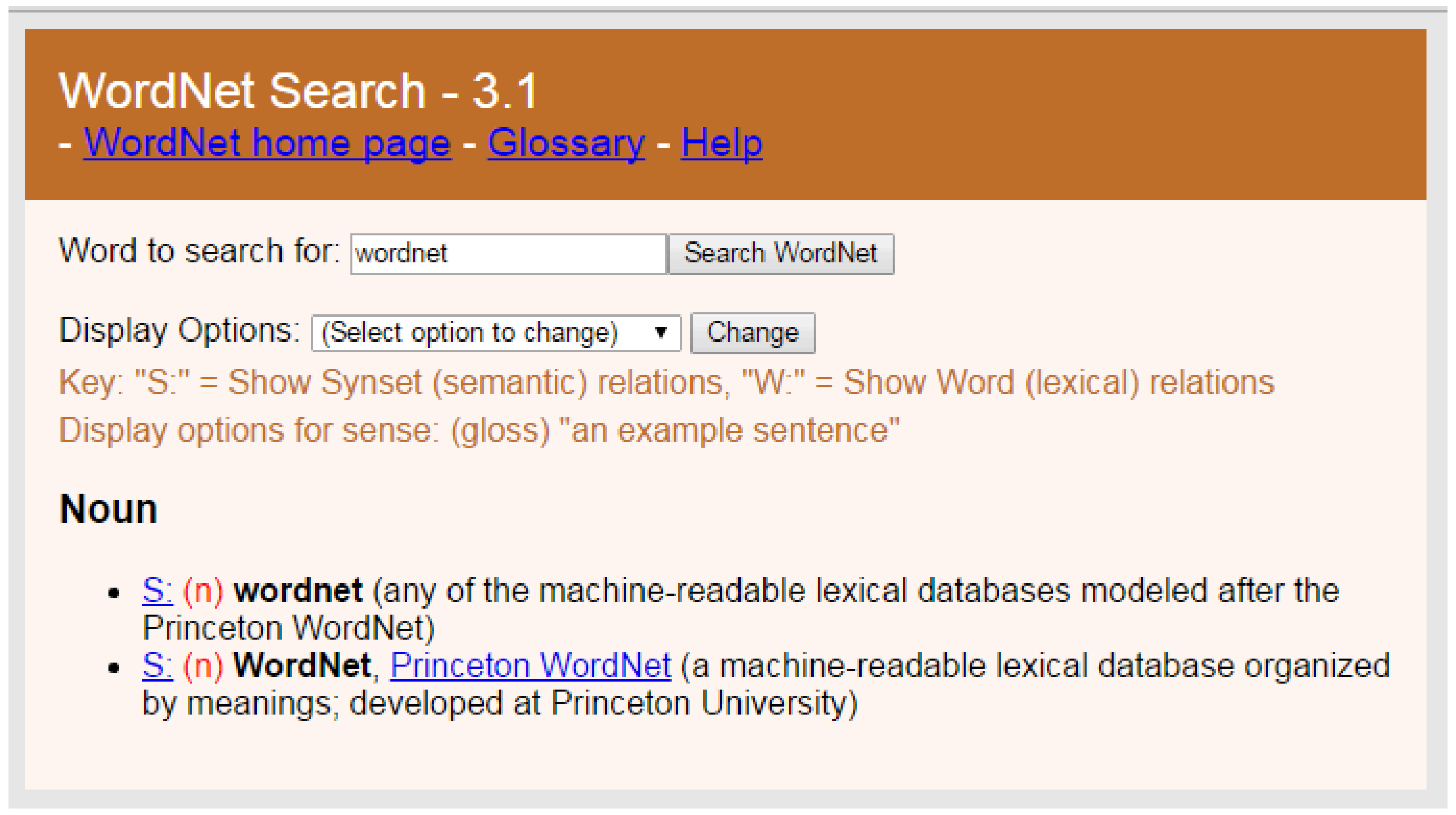
Again, things are complicated by lacking *implicit knowledge*:

- Background, commonsense knowledge
- Contextual knowledge

Features: *Implicit* representations

Beyond being counted, words can be represented by **explicit** features:

- List of **attributes** describing the object
- Natural language definition (*dictionnary*)
- Other lexical resources, including senses and associated properties, morphological features: *WordNet*



WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: wordnet Search WordNet

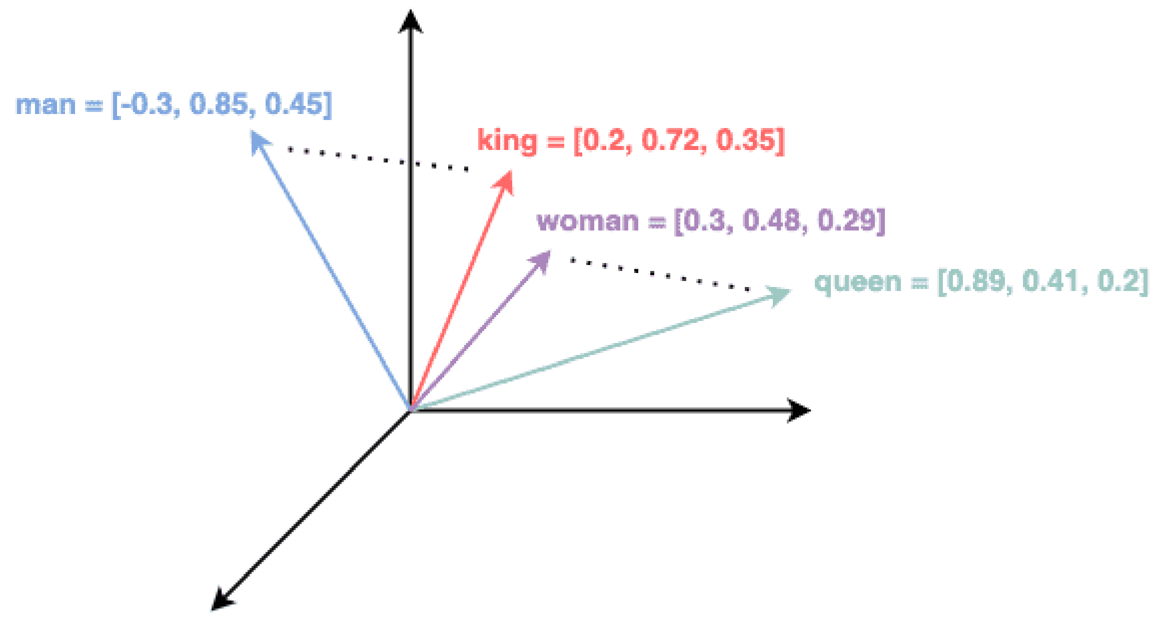
Display Options: (Select option to change) Change
Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations
Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **wordnet** (any of the machine-readable lexical databases modeled after the Princeton WordNet)
- S: (n) **WordNet**, Princeton WordNet (a machine-readable lexical database organized by meanings; developed at Princeton University)

$\rightarrow$ Move to *implicit* features: with **distributed representations**

- **Vector spaces** for words: encode **contextual** information
  - *Distributional hypothesis*: two words are similar if they have similar contexts
  - Create sparse then dense representations $\rightarrow$ Embeddings



Model: using context

Work on modelisation of the **context** - which is, most of the time, the *surrounding sequence*:

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- Generative modeling:
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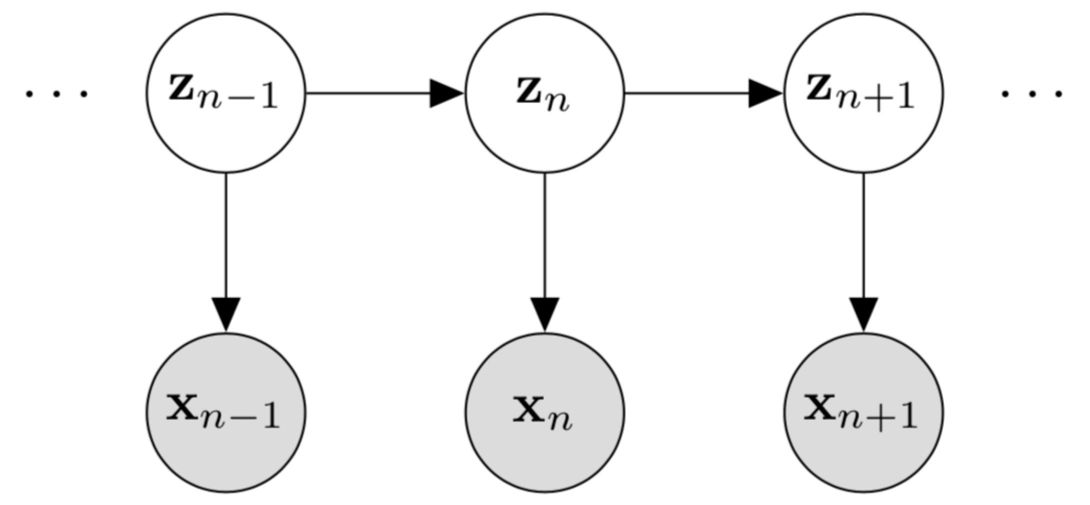

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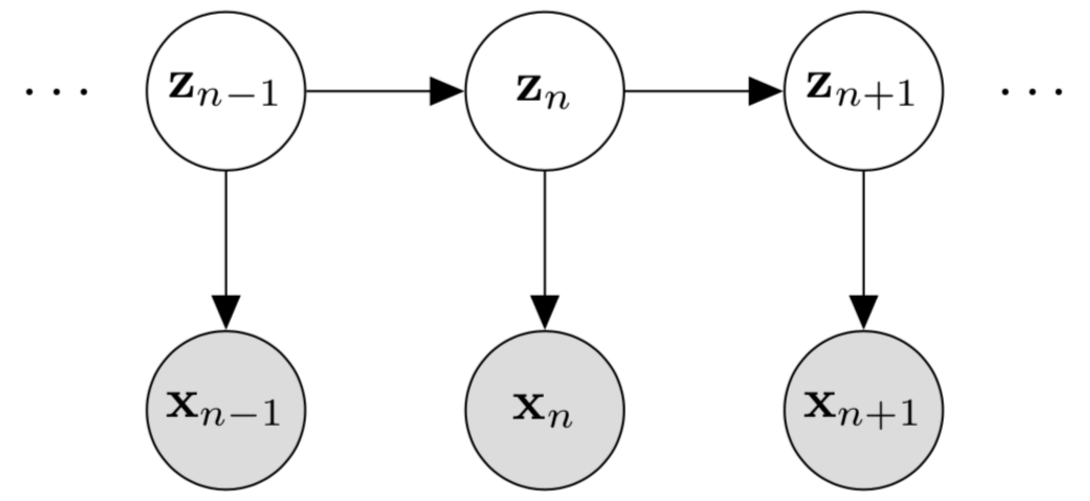

- In this class: *Deep learning sequential models*
  - Architectures and objectives designed to take advantage of **large-scale unlabelled datasets**
  - Interaction with **traditional tasks**, **structures** ?
  - Integration of **exterior knowledge** ?