Master Degree in Computer Science

Natural Language Processing

Introduction to language models

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sed noli modo

A language model in essentially a **probability distribution** over a **sequence of words**

$$p(w_1, w_2, \ldots, w_n)$$

which can be used for a surprisingly high number of tasks, including *document search*, *document classification*, *text summarization*, *text generation*, *machine translation*, and many others

Note: Instead of estimating the probability distribution of words, we can work at a finer granularity on the distribution of substrings of fixed length in words (e.g., characters, 2-chars blocks)

Example 1
A LM may be used to guess the next word in a sequence

$p(w_n \mid w_1, w_2, \ldots, w_{n-1})$

Yesterday → you → studied, → what → are → you → doing → ... ?
→ today

Example 2
Or to guess the author (or any other categorical attribute) of as text

$p(author \mid w_1, w_2, \ldots, w_{n-1})$

"Twenty years from now you will be more disappointed
by the things that you didn't do than by the ones you did do"
→ Mark Twain

Example 3
Or to select the correct translation for a sentence

$p(e_1, e_2, \ldots, e_n \mid w_1, w_2, \ldots, w_n)$

"ci sono molti esempi"
→ "there are many examples"
~~→ "are there many examples"~~

1. **Statistical Language Models**: Estimate the probability distribution of words by enforcing statistical techniques such as n-grams *maximum likelihood estimation (MLE)* or *Hidden Markov Models (HMM)*

2. **Neural Language Models**: Popularized by Bengio et al. 2003, each word is associated with an embedding vector of fixed size and a Neural Network is used to estimate the next word given a sequence of k preceding words

Bengio, Y., Ducharme, R., Vincent, P., & Jauvin, C. (2003). *A neural probabilistic language model*. Journal of machine learning research, 3(Feb), 1137-1155

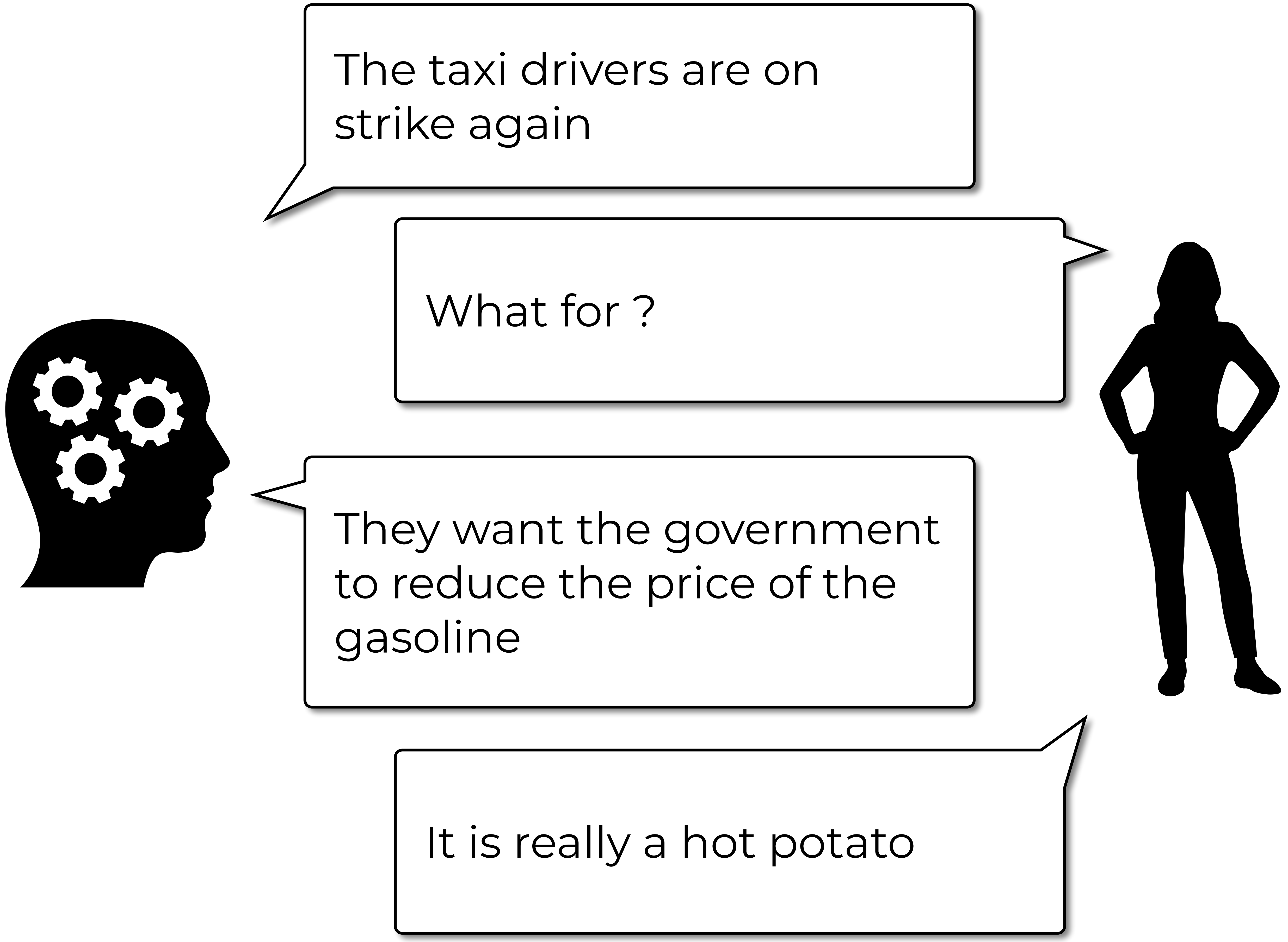
Natural language is often ambiguous and hard to understand

- It’s like throwing the baby out with the bathwater

- Really, Sherlock? No! You are clever

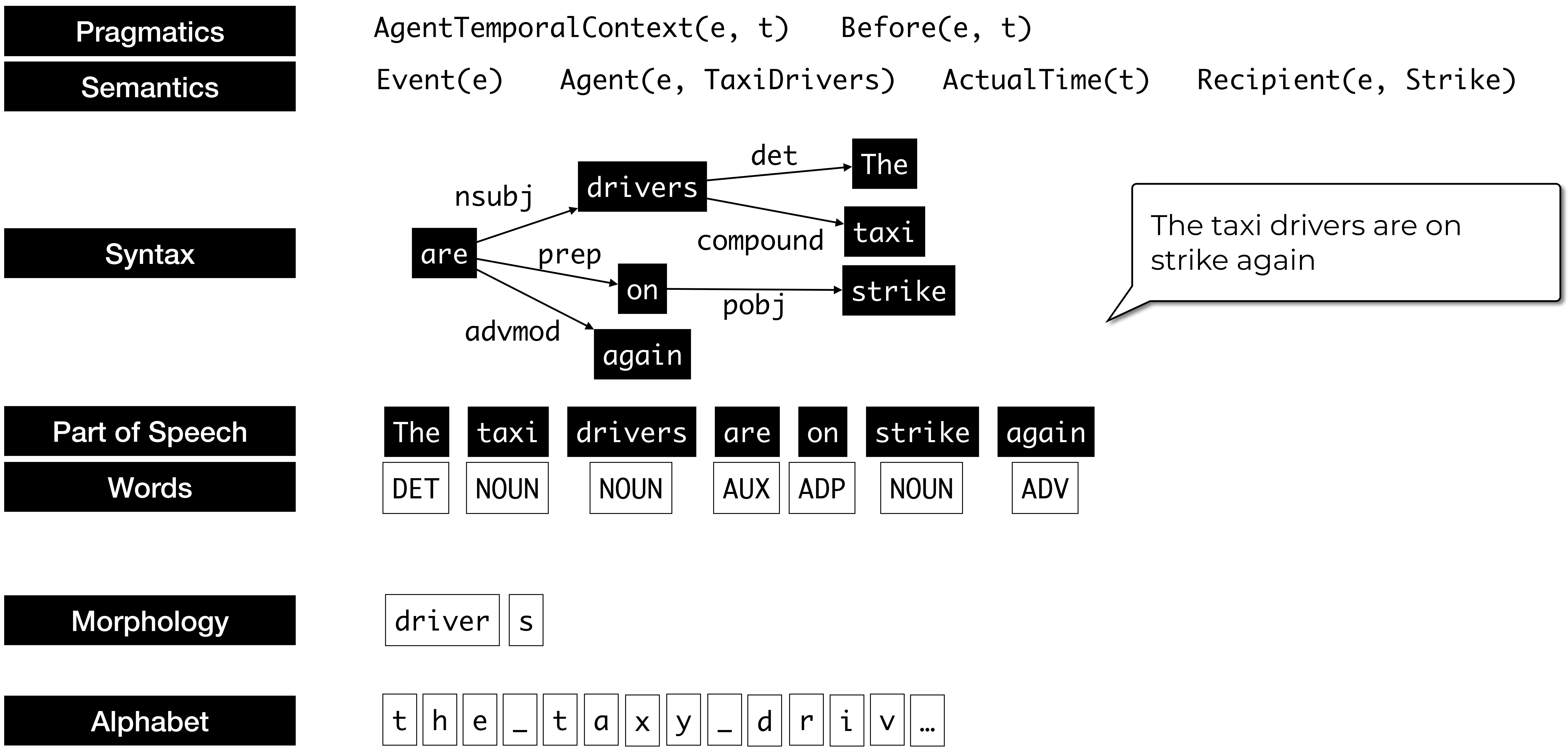
- Leonard: "Hey, Penny. How's work?"
  Penny: "Great! I hope I'm a waitress at the Cheesecake Factory for my whole life!"
  Sheldon: "Was that sarcasm?"
  Penny: "No."
  Sheldon: "Was that sarcasm?"
  Penny: “Yes."

- Finding a good man is like finding a needle in a haystack



Li, Y., Su, H., Shen, X., Li, W., Cao, Z., & Niu, S. (2017). Dailydialog: A manually labelled multi-turn dialogue dataset. *arXiv preprint arXiv:1710.03957.*

Language has many possible levels of interpretation

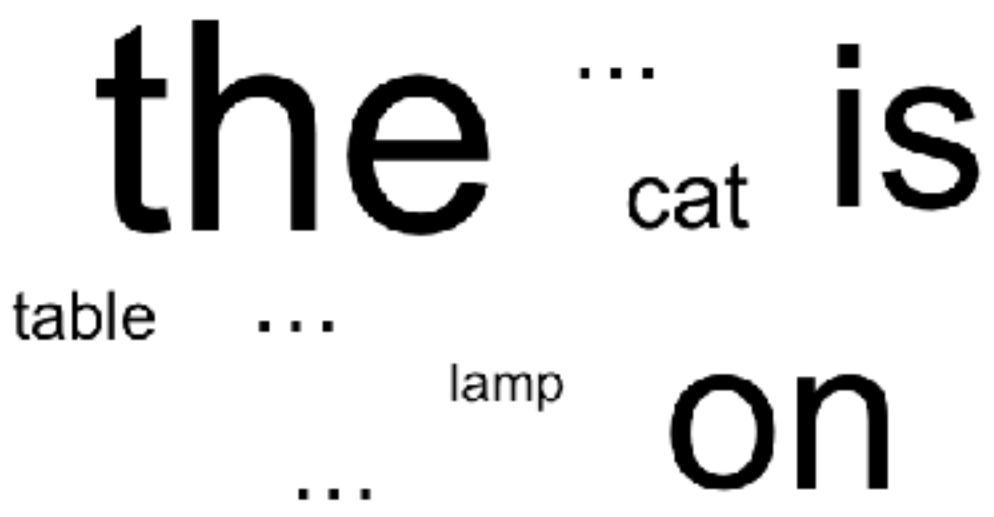


Paradigm shift: human language as a prediction problem

Instead of thinking the language as a set of predefined expressions, we can think it as a generative game

Ingredient 1: **Vocabulary**

- It's a collection of words we can use
- The biggest they are the most frequently they are used in language



Tech

We can associate each word *w* with a probability in the dictionary, based on their frequency in a corpus of texts, by dividing the frequency of w by the sum of the frequencies of all the words in the corpus

Formally

$$P(w) = \frac{count(w)}{\sum_{i=0}^{n} count(w_i)}$$

Paradigm shift: human language as a prediction problem

Instead of thinking the language as a set of predefined expressions, we can think it as a generative game

Ingredient 2: **Pick-up procedure**

- We select a word in the vocabulary according to their distribution of probability
- In other terms, we pick up more frequently the most probable words and less frequently the less probable ones
- This can be done one step at a time, thus generating a text word-by-word

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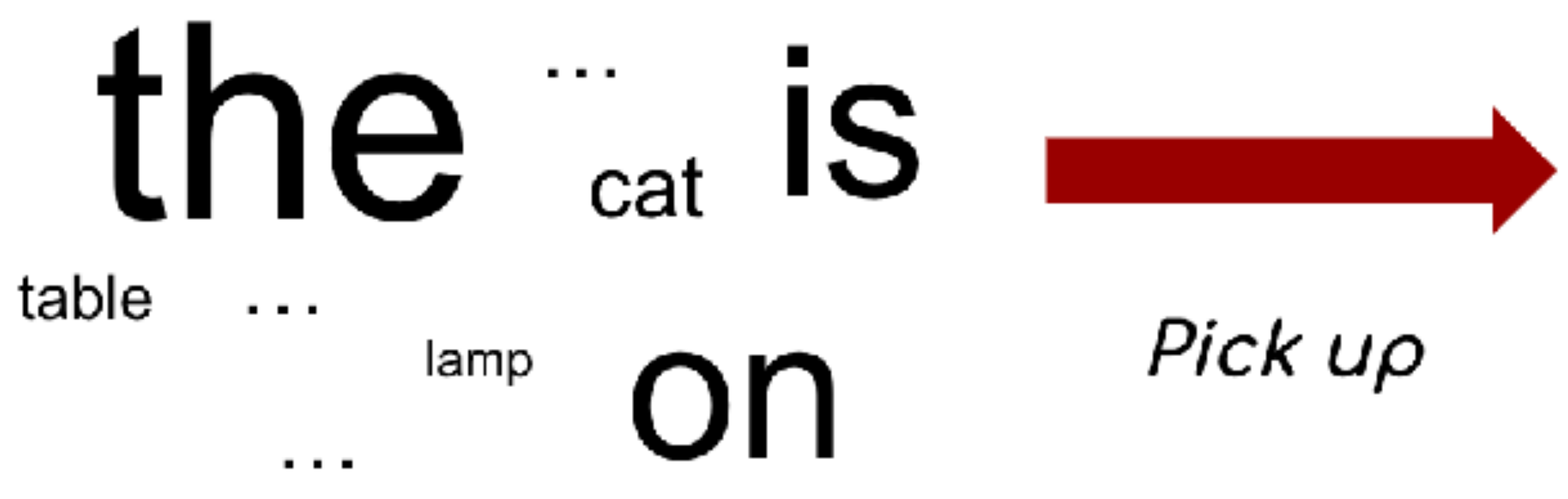
Since words are chosen independently from the others, the joint probability P("the is the table … on") is just the product of the probabilities we used to select the single words



Step 1 the

Step 2 is

Step 3 the

Step 4 table

… …

Step n on

Formally

$$P(w_1, w_2, \ldots, w_n) = P(w_1)P(w_2)\ldots P(w_n)$$

Paradigm shift: human language as a prediction problem

Now, the text "the is the table … on" is not a good emulation of a human real sentence

One of the reasons is that **humans do not choose words to use in a sentence independently from the words they are chosen previously in the same sentence**

Ingredient 3: **Conditional probability**

- During the generation game, the probability of the words in the vocabulary changes at each step depending on the words that have been chosen previously

Tech

We can still use a corpus this way: the probability of a word w to be the next word after a sequence w1 .. wn is given by the number of times we observe w after w1 .. wn divided by the number of times we observe any word after w1 .. wn

Intuition

Make a bet on the next word I'm going to say if I start my sentence by saying:

The President is called Barack [..?..]

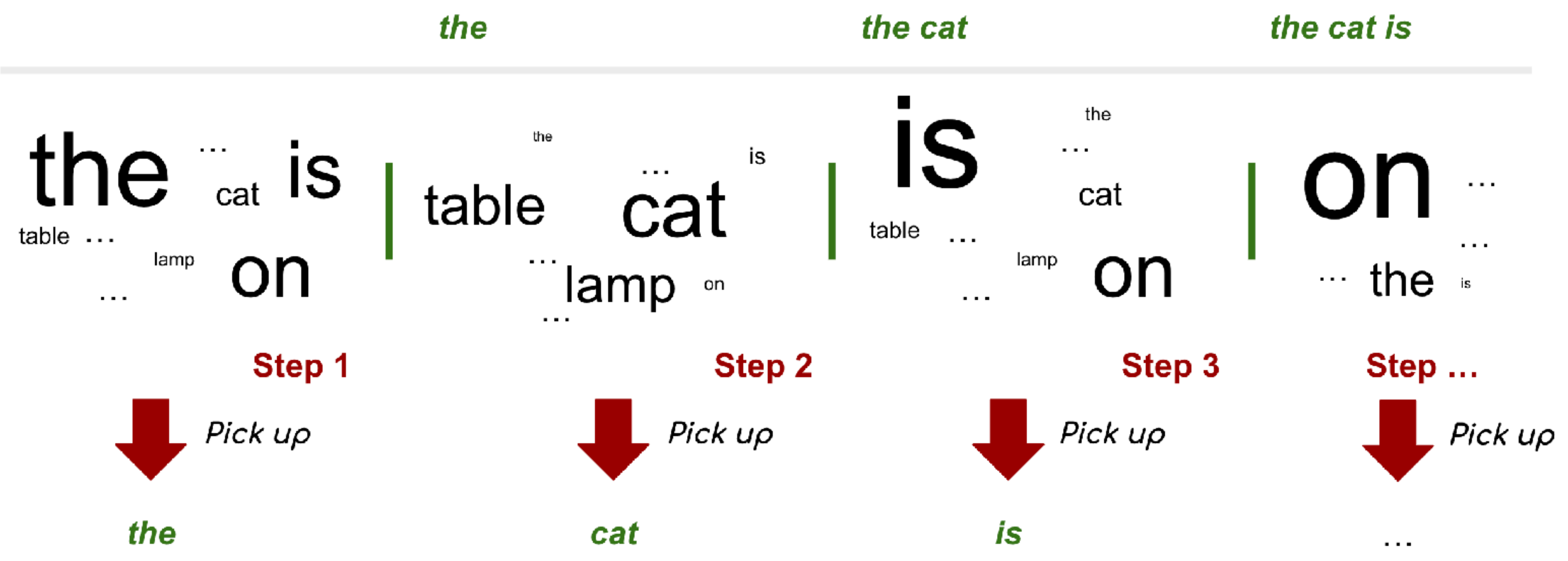
Make a bet of which of the two is my next word when I say:

Good [the] vs **Good [morning]**

How can we use this behaviour?

$$P(w \mid w_1 \dots w_n) = \frac{count(w, w_1, \dots, w_n)}{count(w_1, \dots, w_n)}$$

Paradigm shift: human language as a prediction problem



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The joint probability of the whole sentence now can be split in a chain of conditional probabilities, which is the probability of words at a given step depending on the results of the previous steps:

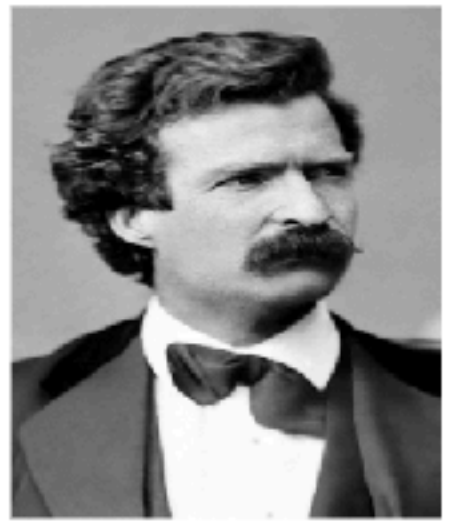
$$P(w_1, \ldots, w_n) = P(w_1)P(w_2 \mid w_1), \ldots, P(w_n \mid w_1, \ldots, w_{n-1})$$

Language models

These types of machines that are able to estimate the probability of the next word in a sequence are called **language models**

Interesting properties:

- They are **generative models**, that is we can use them to generate a new text
- All the **probabilities are estimated starting from a corpus of texts**, meaning that we can build different models from different corpora (e.g., we can emulate different languages, different authors, different text styles, and so on)
- We can also use them to compute the **probability of a text given a model**, which means that, if we have different models from different corpora, we can estimate the probability of a text to be in a given language, written by a given author, be compliant with a given style, and so on)



Mark Twain corpus

Mark Twain LM
MLM

James Joyce corpus

James Joyce LM
JML

T = *"It is better to keep your mouth closed and let people think you are a fool than to open it and remove all doubt"*

MLM(T) > JML(T)

The quote is from Mark Twain

Markov assumption

The idea of language models is pretty good, but there is a **big issue**:

- Everything is based on the idea that at **step n** we need to estimate the probability distribution of words based on the **previous sequence w 1, w 2, ..., w n-1**
- To do so, we need to count how many times in a corpus we observe **w 1, w 2, ..., w n-1** and **w 1, w 2, ..., w n**

It is better to keep your mouth closed and let people think you are a fool than to open it and remove all | doubt

There are two issues:

- Keep track of all the sequences and sub sequences in large corpora is unfeasible
- Even in very large corpora, observing a long sequence like "It is better to keep your mouth closed and let people think you are a fool than to open it and remove all" a sufficient number of times to have a reliable estimation is almost impossible

Markov assumption

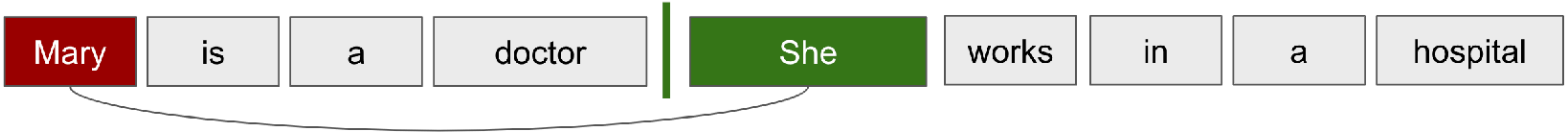
A possible workaround, is to assume that language generation can be modeled as a **Markov process**, where the probability of a word does not depend on the whole previous sequence but only on a (small) previous subsequence

P(the cat is on the table) = P(the) x P(cat | the) x P(is | the, cat) x **P(on | cat, is)** x **P(the | is, on)** x **P(table | on, the)**

here the model *forgets* what was before in the sentence and only relies on the **last two words**

This assumption is effective in many cases ...

... but not when we deal with **long term dependencies**



Chain rule and Markov chain models

$$P(w_1 w_2 w_3 \ldots w_m) = \prod_i^m P(w_i \mid w_1, w_2, \ldots, w_{i-1})$$

$$P(\textbf{the taxi drivers are}\ldots) = P(\textbf{the}) \times P(\textbf{taxi} \mid \textbf{the}) \times P(\textbf{drivers} \mid \textbf{the}, \textbf{taxi}) \times P(\textbf{are} \mid \textbf{the}, \textbf{taxi}, \textbf{drivers}) \times \ldots$$

Markov process: words are generated one at a time until the end of the sentence is generated

$$P(w_1 w_2 w_3 \ldots w_m) = \prod_i^m P(w_i \mid w_{i-n}, \ldots, w_{i-2}, w_{i-1})$$

N-order Markov assumption: we assume that a word depends only on the previous *n* words

$$\textit{with } n = 2 : P(w_1 w_2 w_3 \ldots w_m) = \prod_i^m P(w_i \mid w_{i-2}, w_{i-1})$$

$$P(\textbf{the taxi drivers are}\ldots) = P(\textbf{the}) \times P(\textbf{taxi} \mid \textbf{the}) \times P(\textbf{drivers} \mid \textbf{taxi}) \times P(\textbf{are} \mid \textbf{drivers}) \times \ldots$$

Intuitively, we want to measure how **surprised** the model is to observe an event, given its probability. The surprise is inverse to the probability of the event.

$$S(x) = \log\left(\frac{1}{p(x)}\right) = -\log(p(x))$$

Surprise is a measure of how unlikely a single outcome of a possible event is. **Entropy** generalizes surprise as the expected value of the surprise across every possible outcome, that is the sum of the surprise of every outcome multiplied by the probability it happens

$$H(e) = -\sum_i p(e)_i \log(p(e)_i)$$

The **perplexity** is then defined as the exponential of the entropy

$$PP(e) = 2^{H(e)}$$

We can use this idea for evaluating a test set and comparing the words there with the probabilities estimated by the model, to see how much *surprised* (how much perplexity) the model gets observing unseen data

Perplexity

Perplexity is a form of intrinsic evaluation for a model. In particular, we aim at evaluating the model performance independent of the specific tasks its executing.
Perplexity measures how uncertain a model is about the predictions it makes. Low perplexity means only that a model is **confident**, **not accurate**.

Text as a sequence

Textual data may be modeled as a sequence in many ways

Sequence of characters P → e → r → s → o → n

Sequence of words a → person → in → a → blue → shirt

Sequence of syntax tags DT → NN → IN → DT → JJ → NN

Sequences in text are informative

Sequential information is not informative. The events that compose the sequence are independent one from the other.

a → person → in → a → blue → shirt

Sequential information is informative. The order of words depends on the previous words.

Sequences in text are informative

Learning a sequence means that we can predict the next element of the sequence exploiting the sequence order assuming to keep a memory of the sequence elements

	g	g a	g a m
r	0.28	0.07	0
o	0.20	0	0
e	0.17	0	0.75
a	0.10	0	0
l	0.10	0.19	0
m	0	0.15	0
#END	0	0	0.25

#START →

a	0.59
two	0.11
the	0.04
an	0.03
three	0.03
people	0.02

#START a person in →

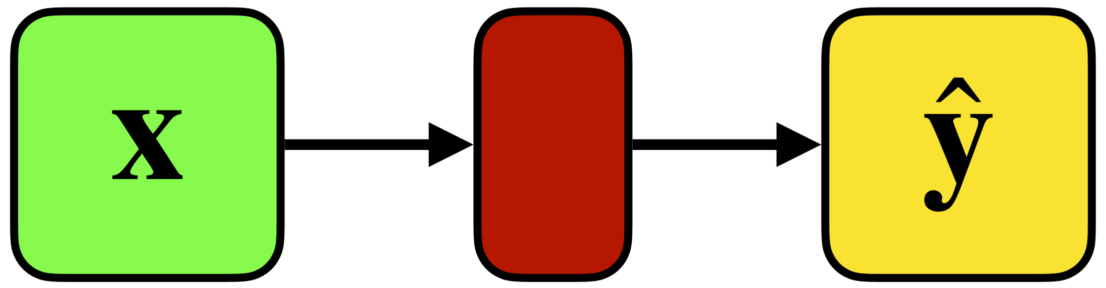
a	0.70
blue	0.03
black	0.03
an	0.03
red	0.02
the	0.02

#START a person in a blue →

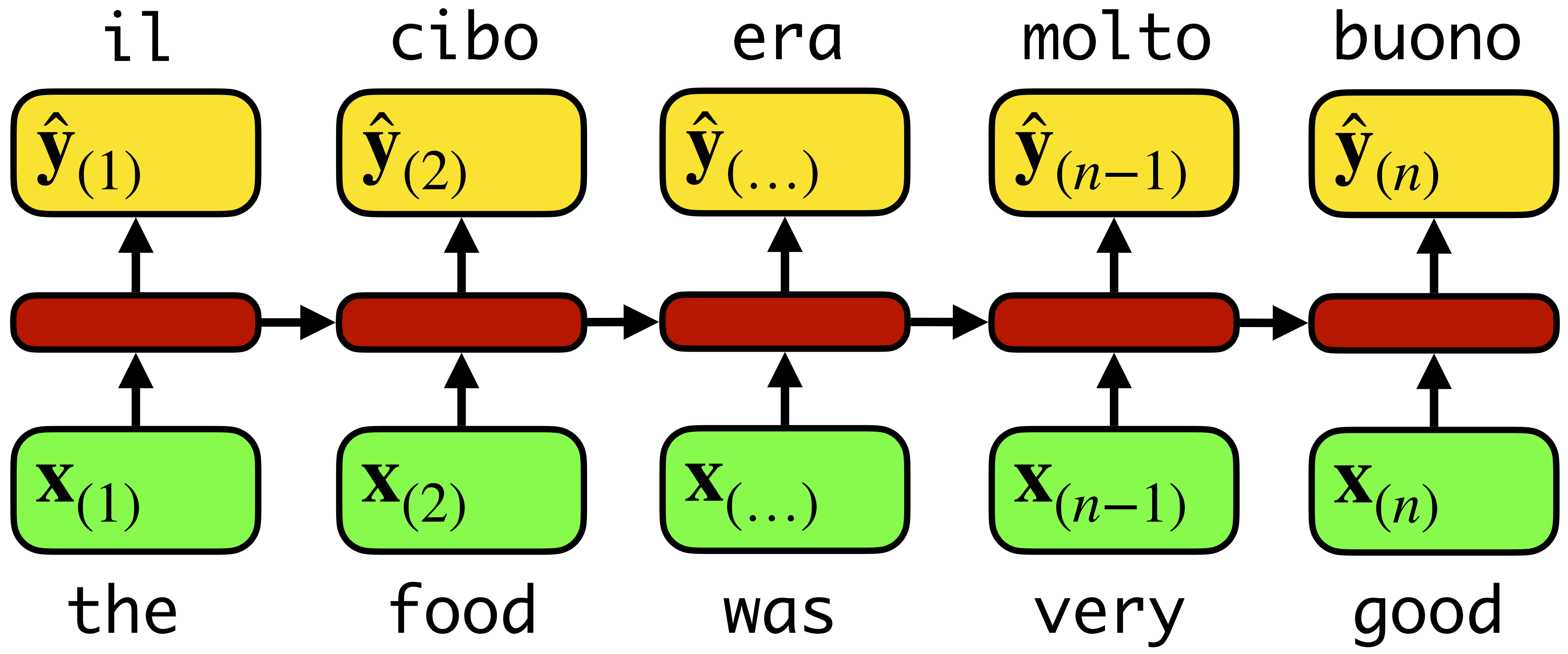
shirt	0.37
jacket	0.20
suit	0.08
hat	0.07
kayak	0.03
outfit	0.03

Applications of sequence learning

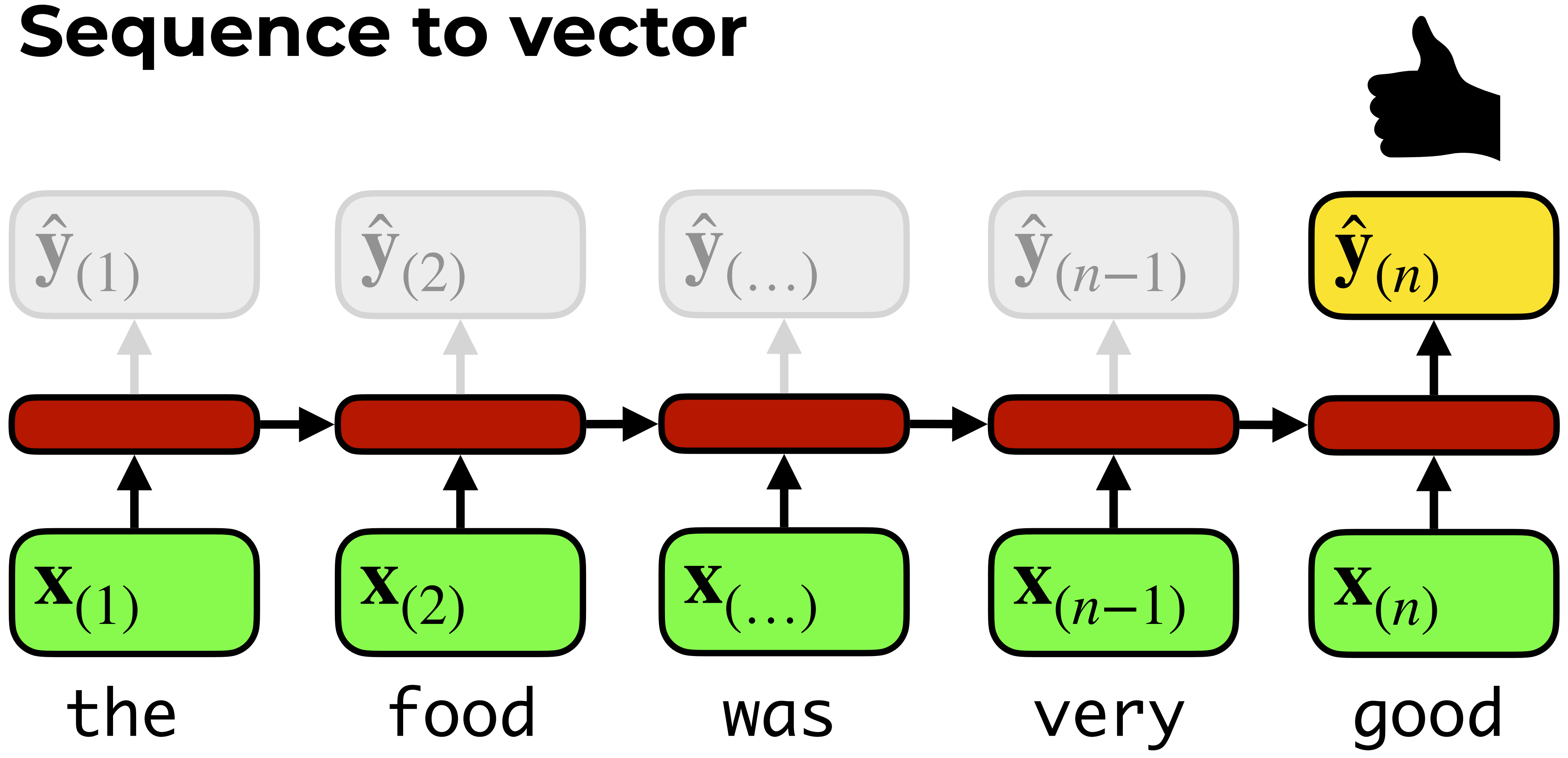
Using the notion of linear transformation as a building block, we can use sequence learning for several different tasks



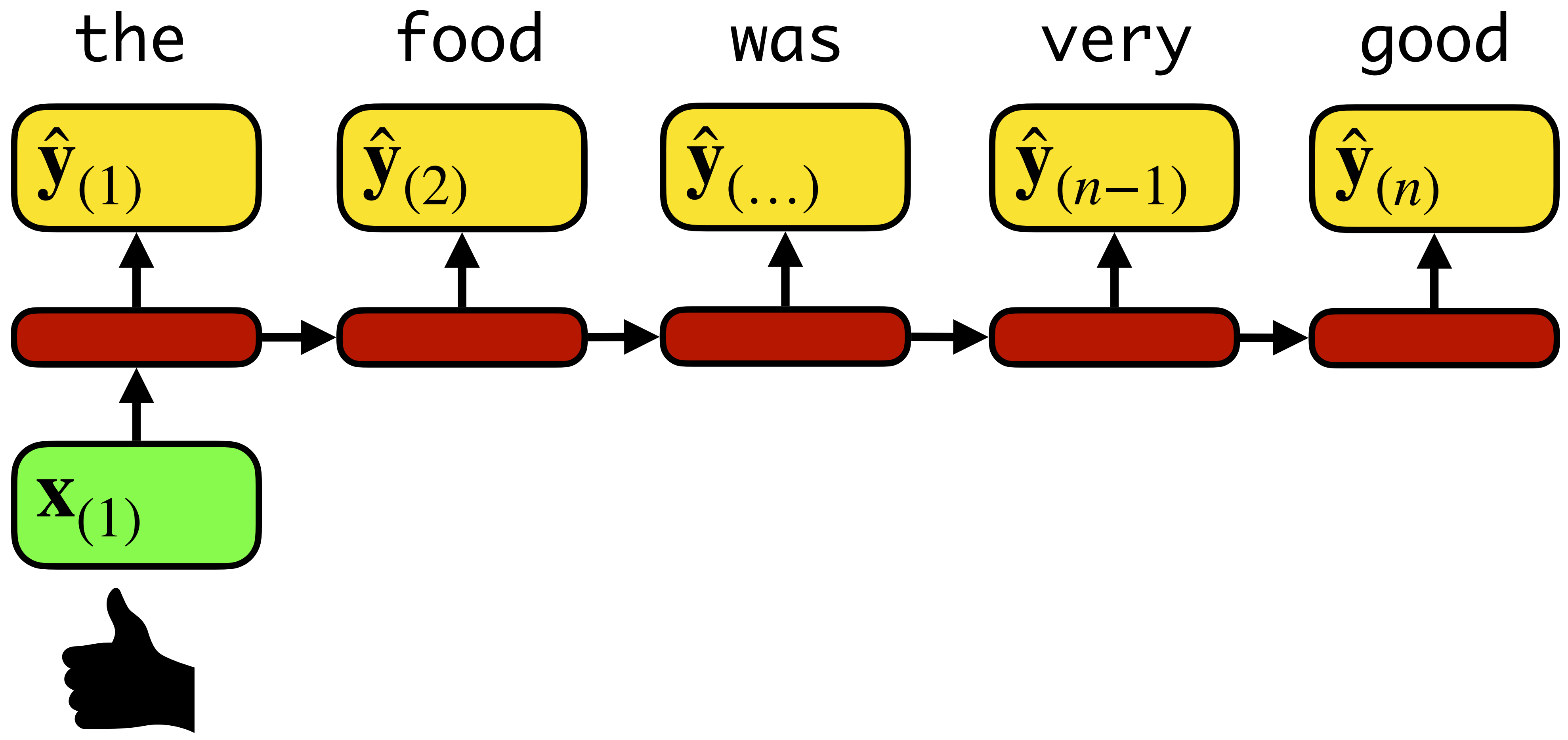
Sequence to sequence



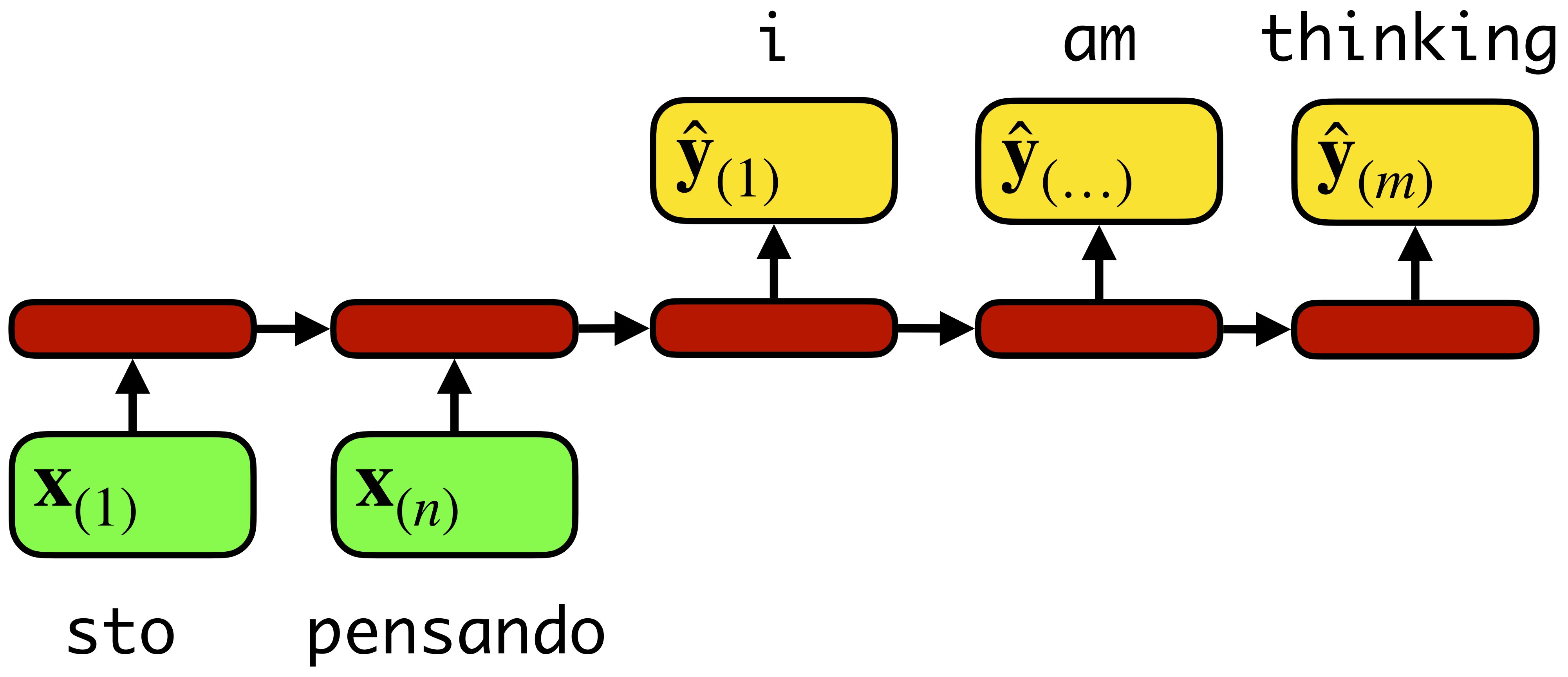
Sequence to vector



Vector to sequence



Encoder-decoder



To deal with text sequences we need to change the learning model

Bag of words learning **is not** sequence learning

```
The food was good,
the service was bad
```

Encoding

In the BOW encoding step, we lose the information provided by the word order in the text

```
The food was bad,
the service was good
```