Master Degree in Computer Science

Information Retrieval

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

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

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

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

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

"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

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

"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

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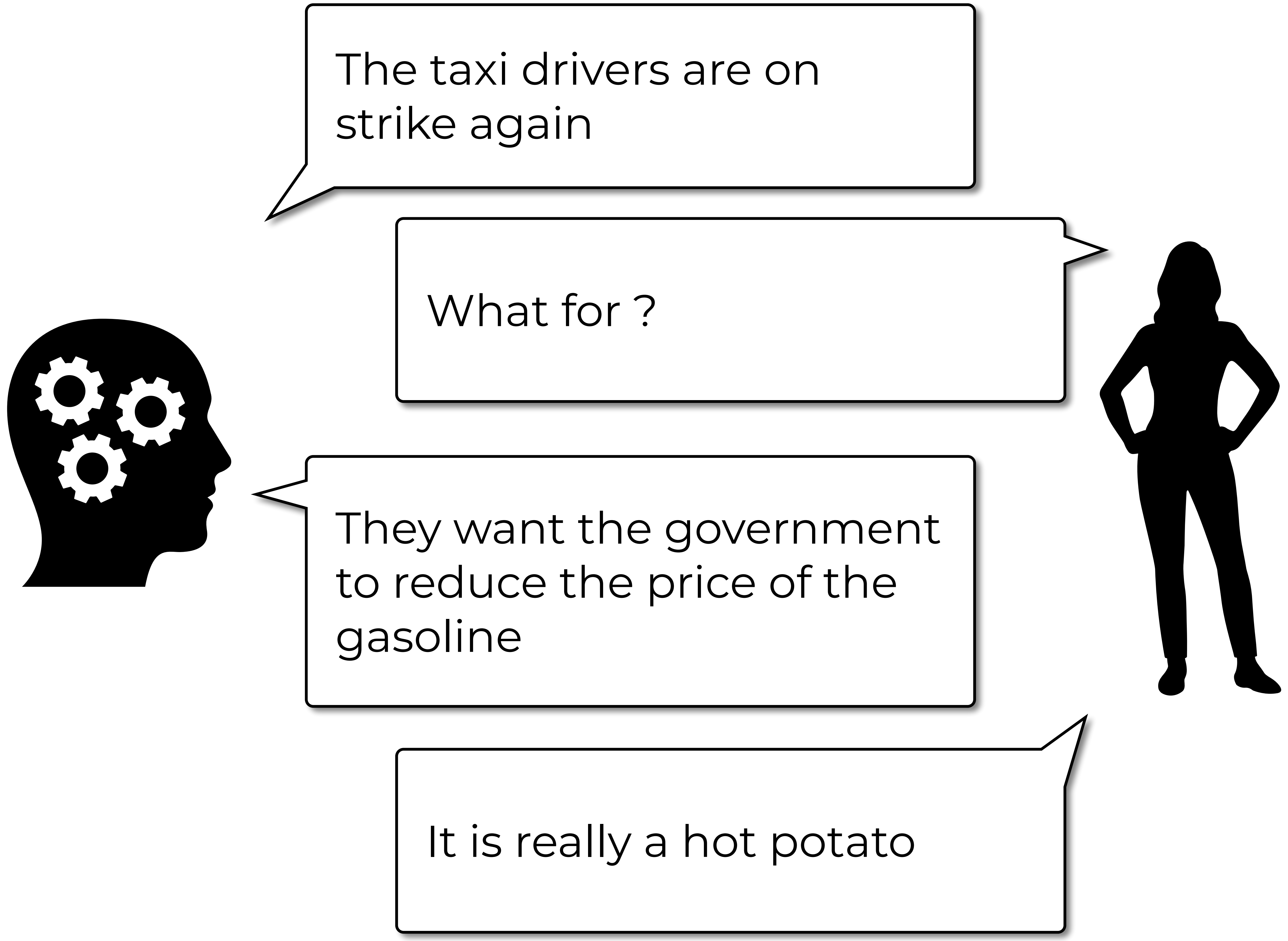
LA STATALE

- 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

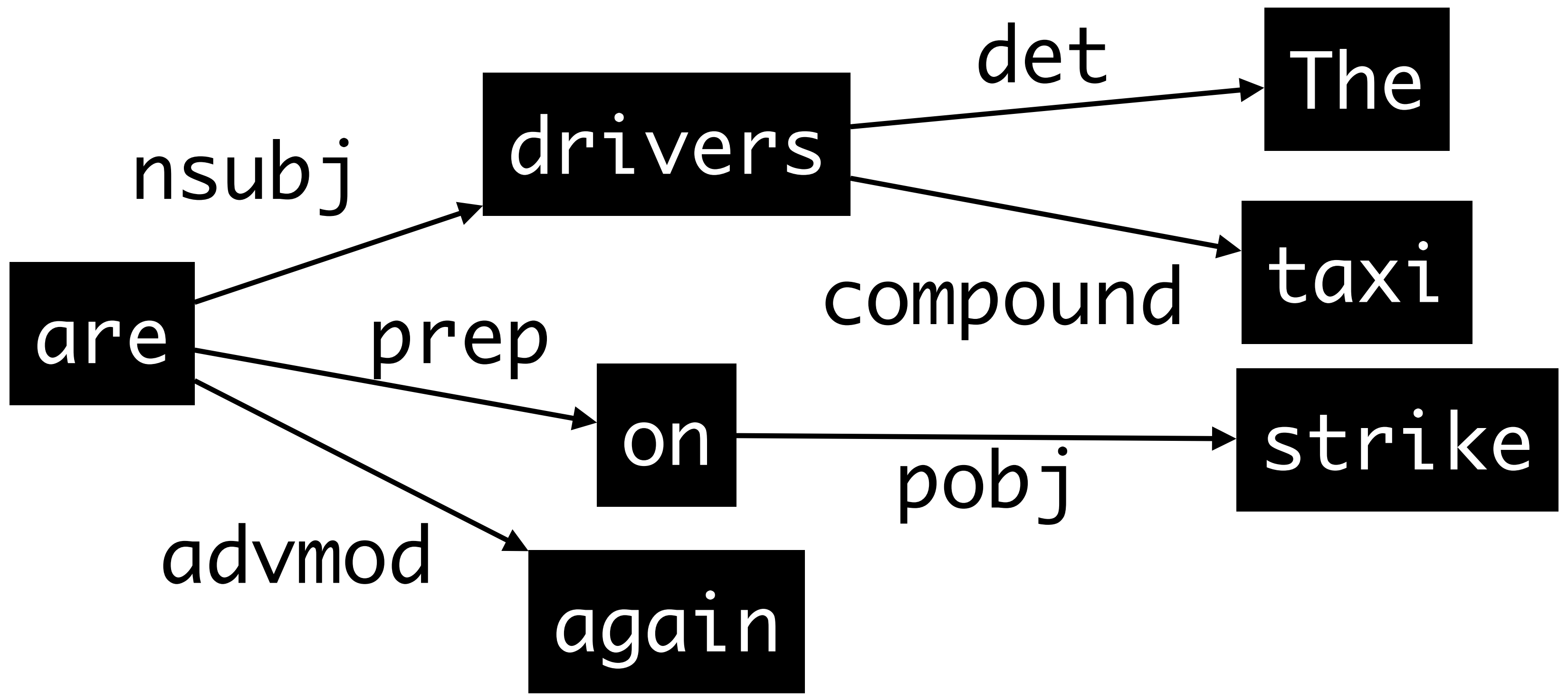
Pragmatics

`AgentTemporalContext(e, t)` `Before(e, t)`

Semantics

`Event(e)` `Agent(e, TaxiDrivers)` `ActualTime(t)` `Recipient(e, Strike)`

Syntax



The taxi drivers are on strike again

Part of Speech

Words

The	taxi	drivers	are	on	strike	again
DET	NOUN	NOUN	AUX	ADP	NOUN	ADV

Morphology

driver | s

Alphabet

t | h | e | _ | t | a | x | y | _ | d | r | i | v | …

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 →

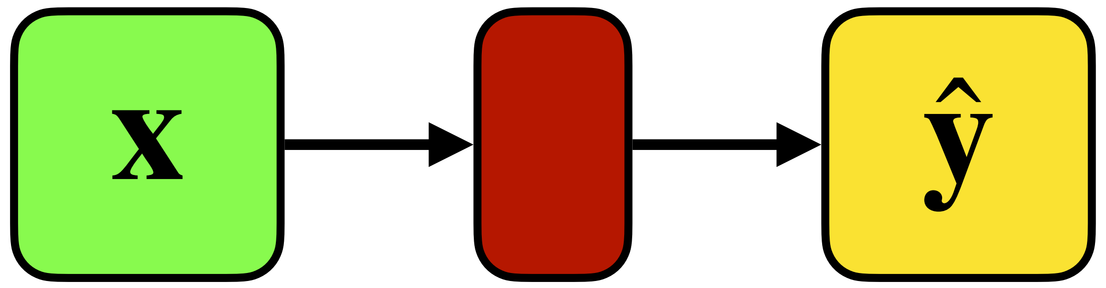
a	0.70
blue	0.03
black	0.03
an	0.03
red	0.02
the	0.02

#START a person in a blue →

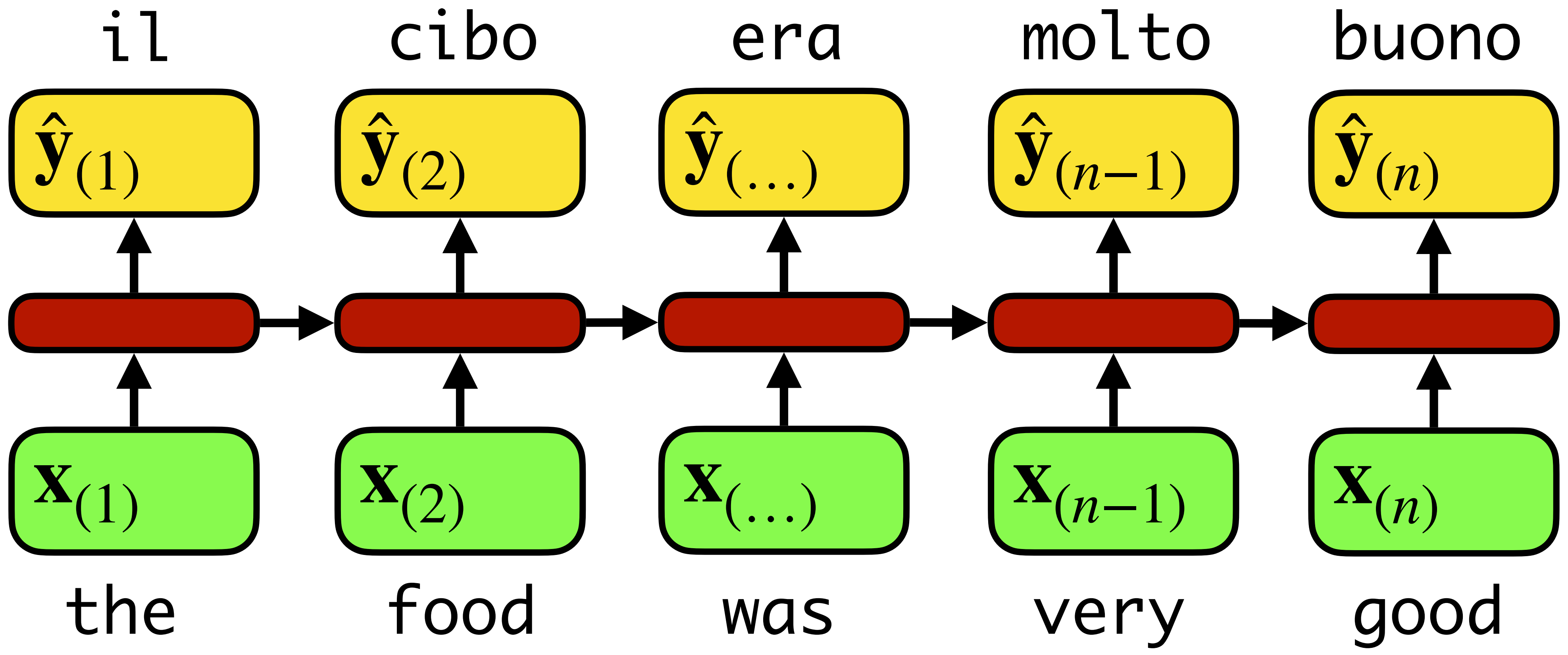
shirt	0.37
jacket	0.20
suit	0.08
hat	0.07
kayak	0.03
outfit	0.03

Applications of sequence learning

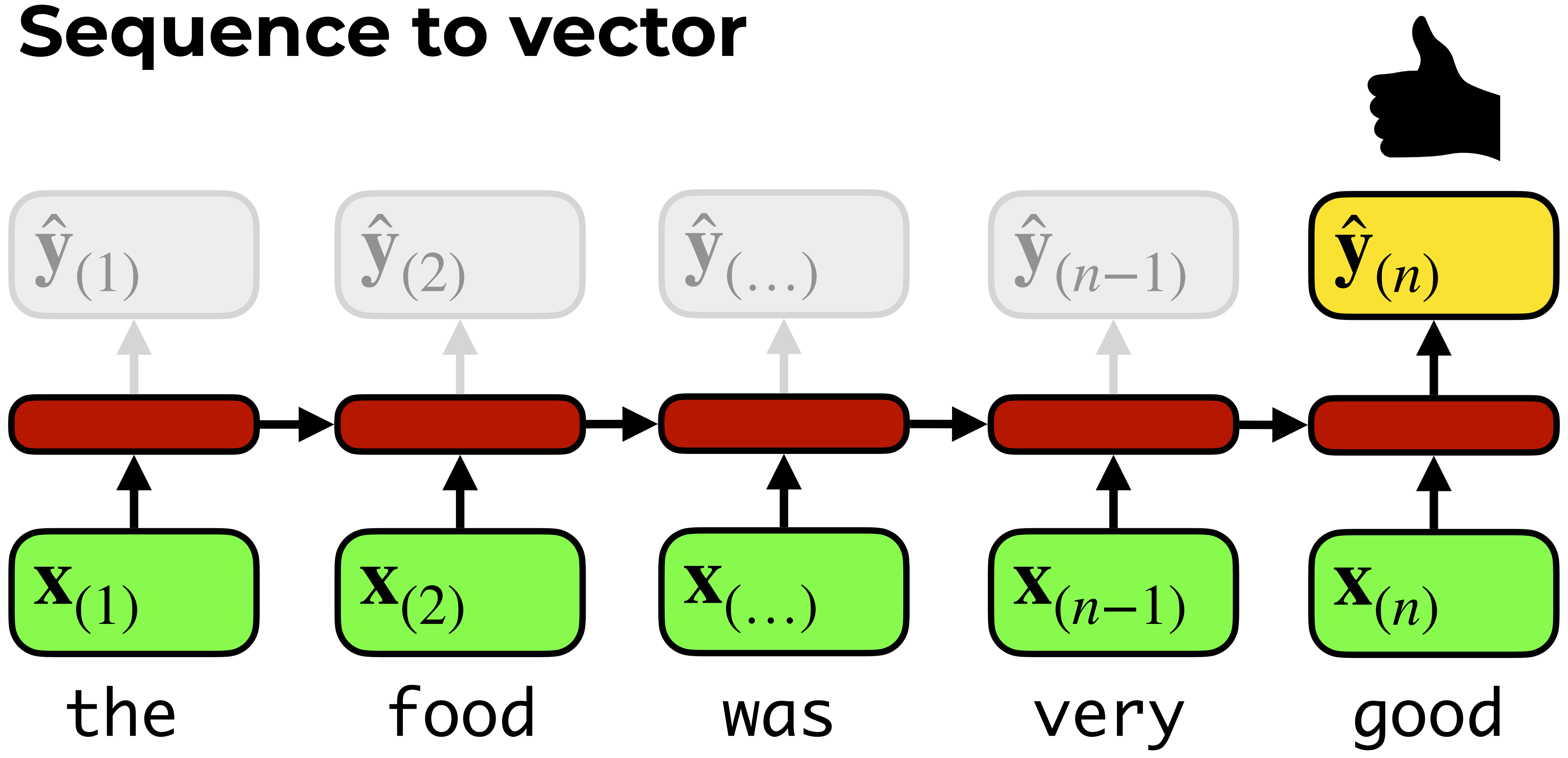
Using the notion of linear transformation as a building block, we can use sequence learning for several different tasks



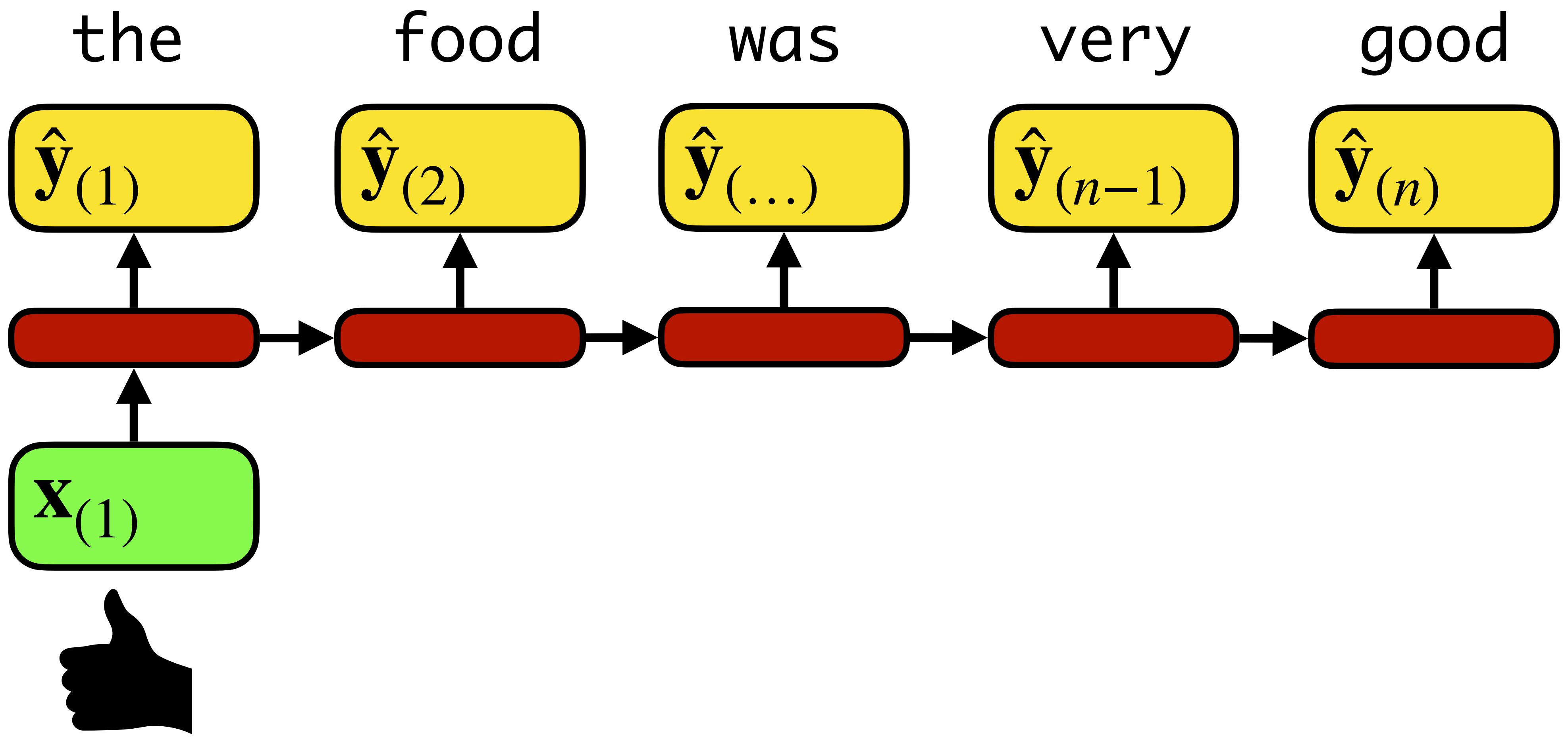
Sequence to sequence



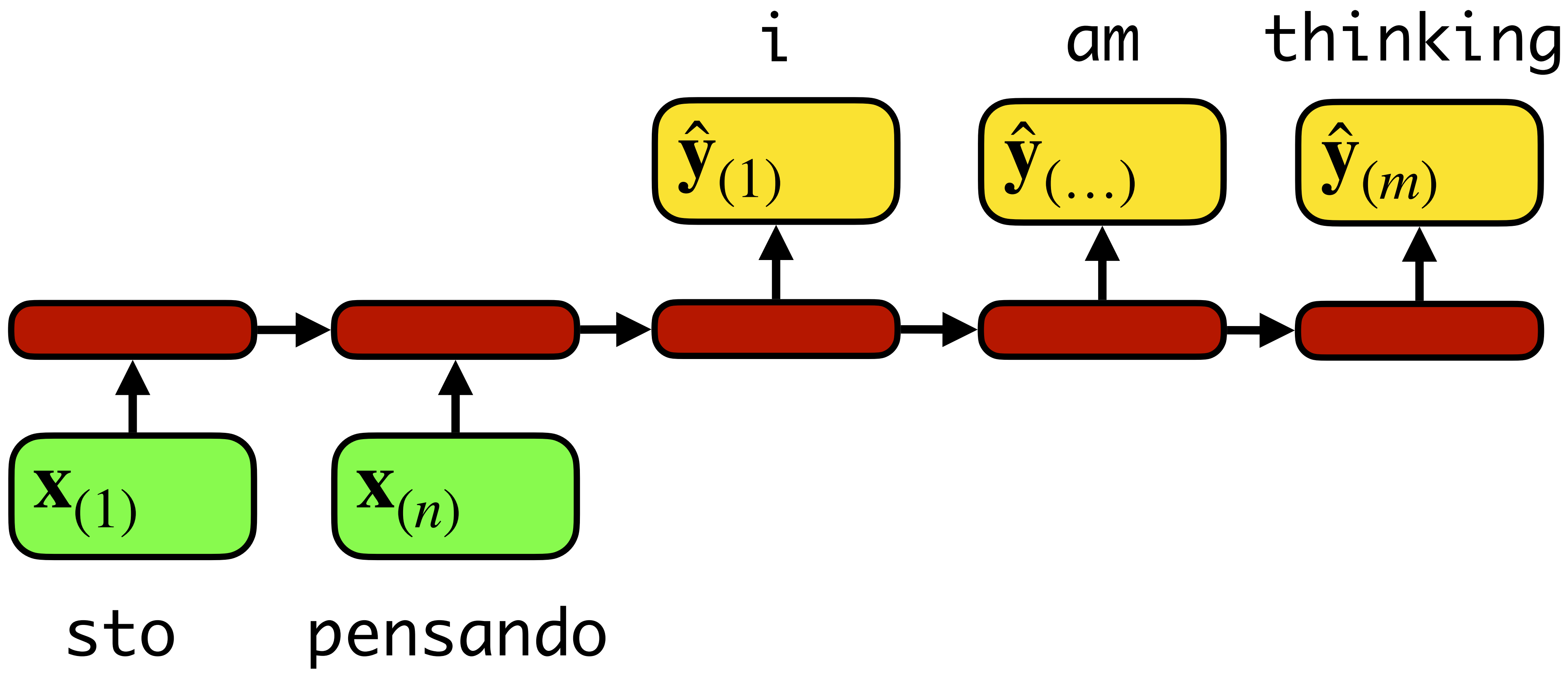
Sequence to vector



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
```