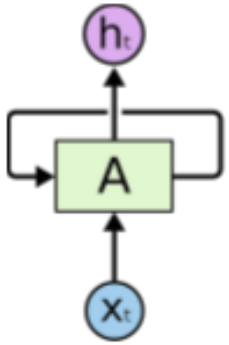
Course 1: Introduction & Recap

Welcome to the Advanced NLP course!

NLP in recent years



GPT-3
2020

1954

Symbolic NLP
Rule-based

1980s

Regular
Expressions

1990s

Recurrent
Neural
Networks

2017

Transformers
& BERT

2022

ChatGPT

NLP in 2023

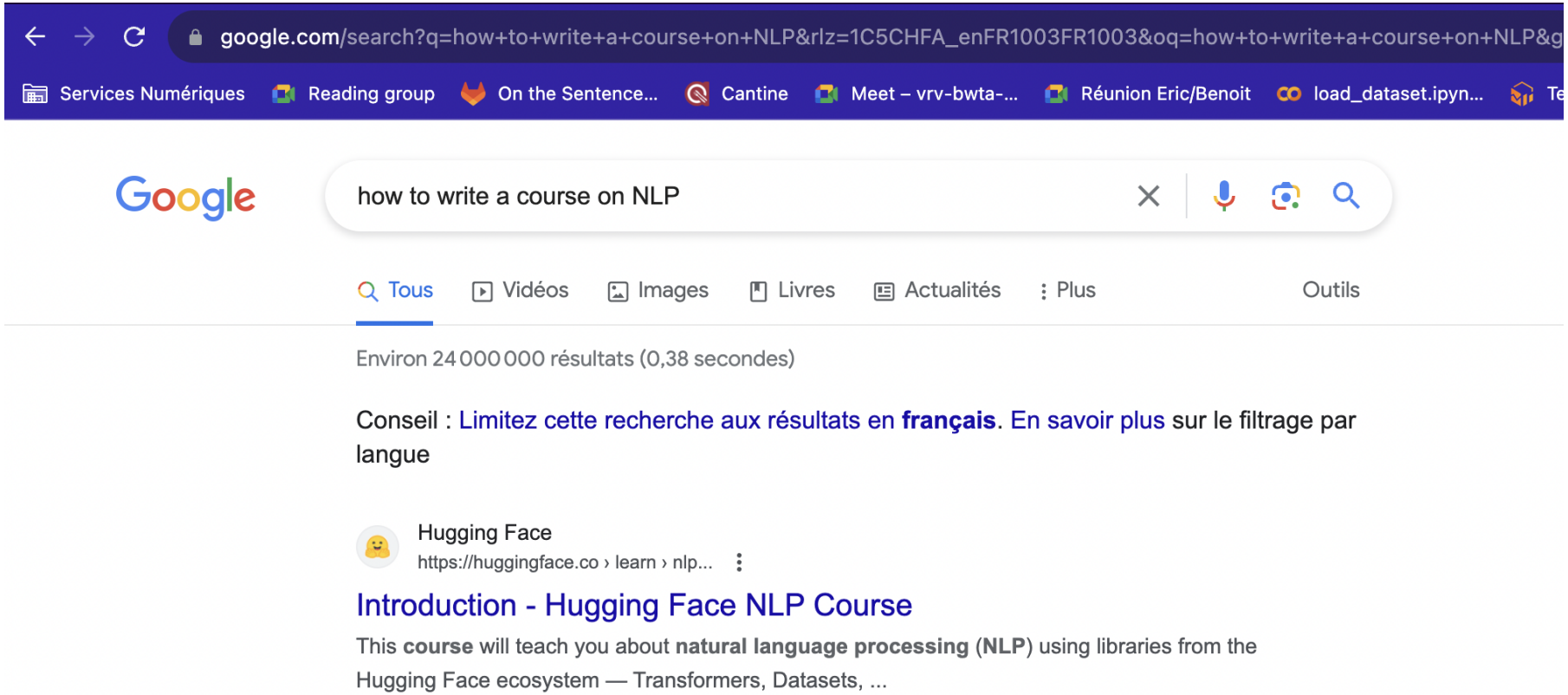
Default (GPT-3.5)

How to write a course for Advanced NLP?

Writing a course for Advanced Natural Language Processing (NLP) requires careful planning and organization. Here's a step-by-step guide to help you create a comprehensive and effective Advanced NLP course:

1. Define the Course Objectives:
   - Start by clarifying the goals of the course. What do you want students to learn or achieve by the end of the course?
   - Identify the target audience and their prerequisites, such as prior NLP knowledge or programming skills.
2. Create a Course Outline:
   - Outline the major topics and modules that the course will cover. Consider breaking it

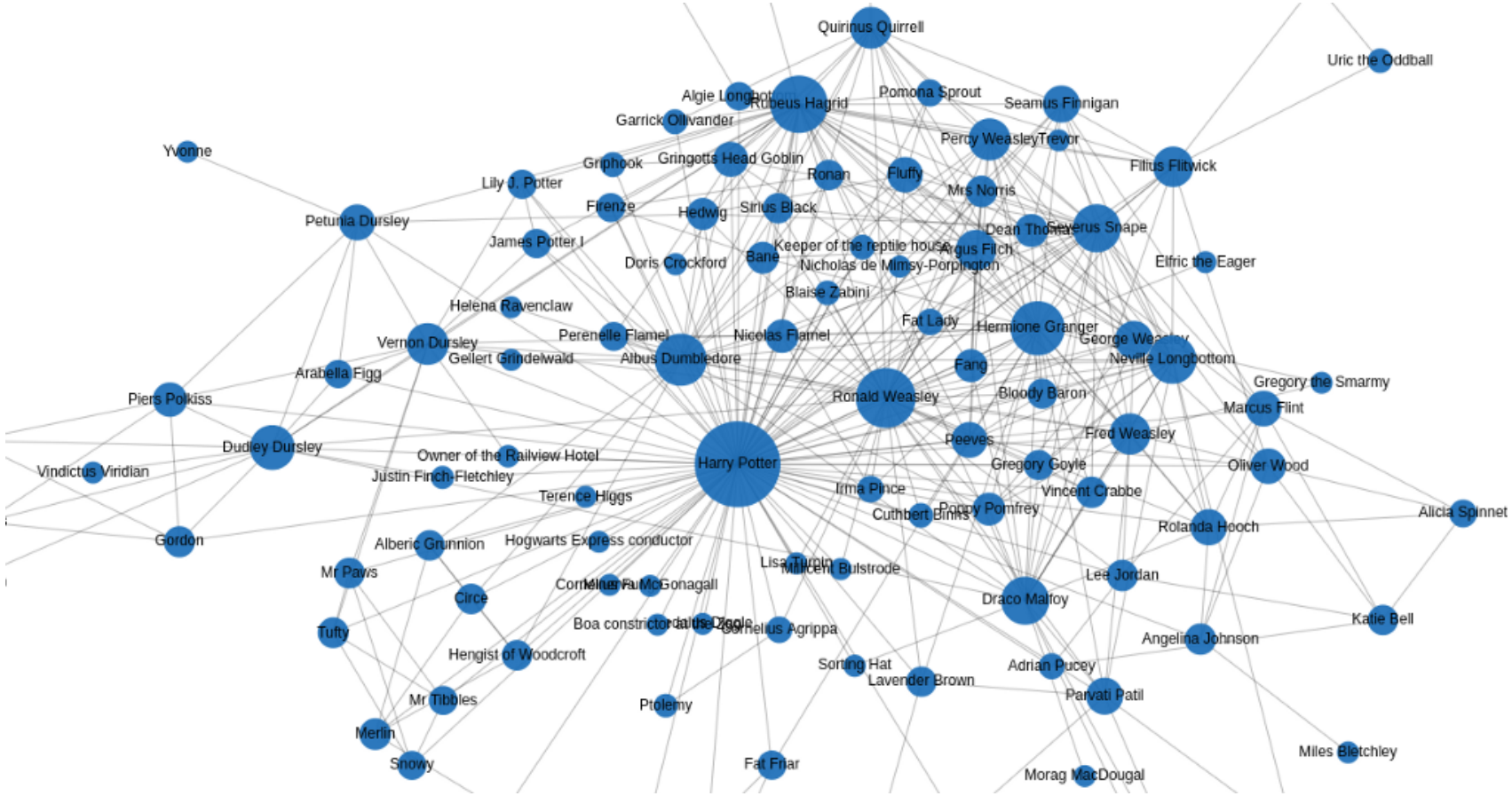
NLP in 2023


google.com/search?q=how+to+write+a+course+on+NLP&rlz=1C5CHFA_enFR1003FR1003&oq=how+to+write+a+course+on+NLP&g
Services Numériques
Reading group
On the Sentence...
Cantine
Meet – vrv-bwta-...
Réunion Eric/Benoit
load_dataset.ipyn...
Google
how to write a course on NLP
Tous
Vidéos
Images
Livres
Actualités
Plus
Outils
Environ 24 000 000 résultats (0,38 secondes)
Conseil : Limitez cette recherche aux résultats en français. En savoir plus sur le filtrage par langue
Hugging Face
https://huggingface.co › learn › nlp...
Introduction - Hugging Face NLP Course
This course will teach you about natural language processing (NLP) using libraries from the Hugging Face ecosystem — Transformers, Datasets, ...

NLP in 2023

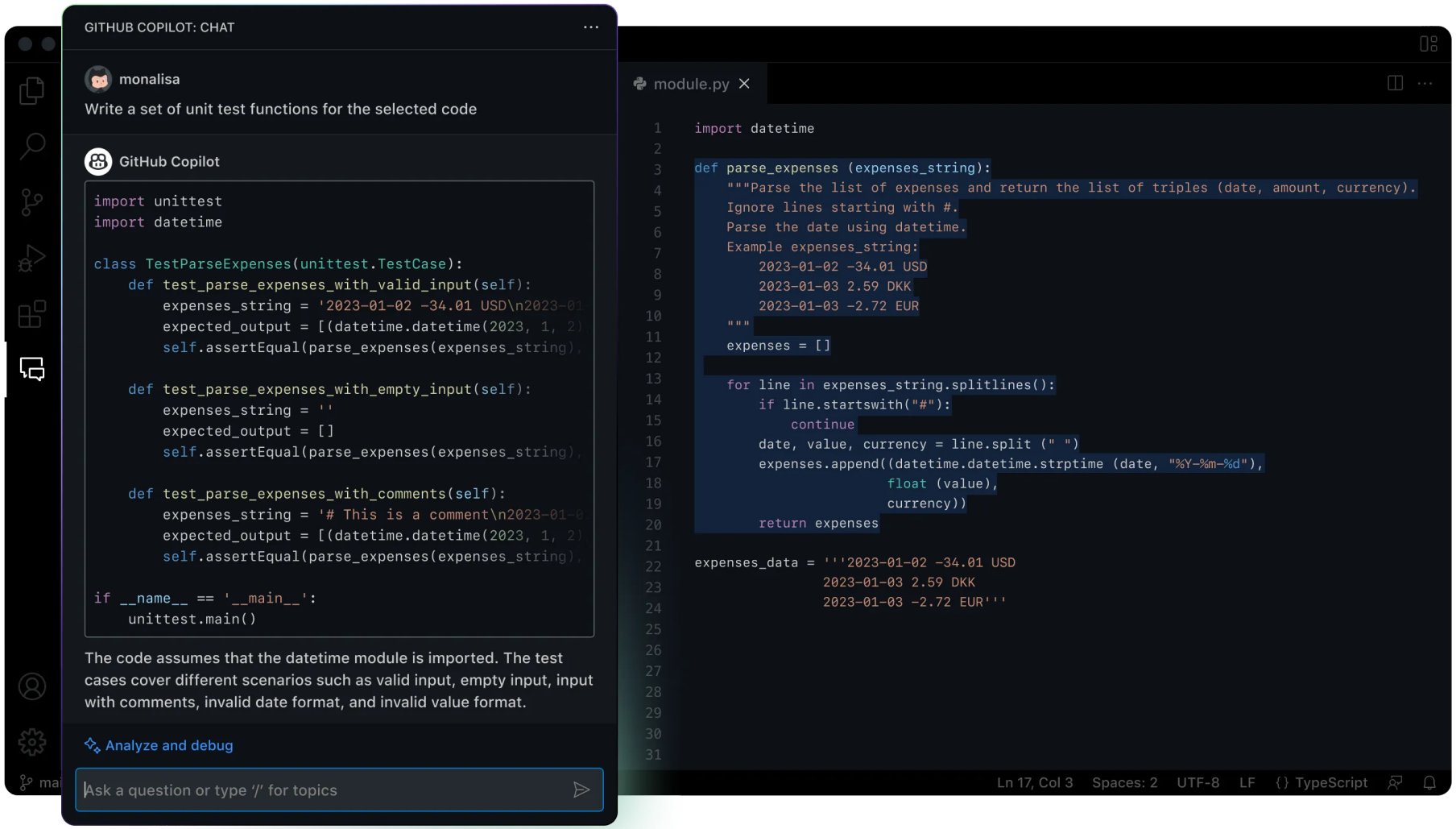

/v5_upscale
yesterday
birds movie poster, Alfred Hitchcock
photosxp

NLP in 2023


Quirinus Quirrell
Uric the Oddball
Algie Longbot
Rubeus Hagrid
Pomona Sprout
Seamus Finnigan
Garrick Ollivander
Percy WeasleyTrevor
Yvonne
Griphook
Gringotts Head Goblin
Filius Flitwick
Lily J. Potter
Ronan
Fluffy
Mrs Norris
Firenze
Hedwig
Sirius Black
Petunia Dursley
Dean Thomas
Severus Snape
James Potter I
Keeper of the reptile house
Argus Filch
Doris Crockford
Bane
Nicholas de Mimsy-Porpington
Elfric the Eager
Blaise Zabini
Helena Ravenclaw
Fat Lady
Hermione Granger
Vernon Dursley
Perenelle Flamel
Nicolas Flamel
George Weasley
Gellert Grindelwald
Albus Dumbledore
Neville Longbottom
Arabella Figg
Fang
Gregory the Smarmy
Piers Polkiss
Ronald Weasley
Bloody Baron
Marcus Flint
Peeves
Fred Weasley
Dudley Dursley
Owner of the Railview Hotel
Harry Potter
Gregory Goyle
Oliver Wood
Vindictus Viridian
Justin Finch-Fletchley
Irma Pince
Vincent Crabbe
Terence Higgs
Poppy Pomfrey
Cuthbert Binns
Alicia Spinnet
Gordon
Alberic Grunnion
Hogwarts Express conductor
Rolanda Hooch
Lisa Turpin
Mr Paws
Millicent Bulstrode
Lee Jordan
Circe
Draco Malfoy
Tufty
Boa constrictor
Cornelius Agrippa
Katie Bell
Angelina Johnson
Hengist of Woodcroft
Sorting Hat
Adrian Pucey
Lavender Brown
Mr Tibbles
Parvati Patil
Ptolemy
Merlin
Miles Bletchley
Snowy
Fat Friar
Morag MacDougal

NLP perspectives

NLP perspectives



So, is NLP solved?

(No.)

NLP challenges

Give me a random string of length 35

Sure, here's a random string of length 35:

`J9kPzHfRq8lG2sT7Nv6yX1W4cOOmZoBwA5U3j`

Can you invert all letters in the following sentence: "I am currenlty giving an interesting course in Natural Language Processing at EPITA in Le-Kremlin-Bicêtre."

Certainly! Here's the sentence with all the letters inverted:

"I ma yltnerurc ygivni na gnitseretni esruoc ni lartuaN egaugnal gnicessorP ta ATIPE ni ertnebiC-tciB-nimelK-eL."

NLP challenges

It takes 3 hours to dry 3 towels. How long does it take to dry 9 towels?

If it takes 3 hours to dry 3 towels, it implies that you can dry 1 towel in 3 hours. To find out how long it takes to dry 9 towels, you can use the same rate:

1 towel takes 3 hours to dry, so:

9 towels will take 9 times as long, which is:

9 towels x 3 hours/towel = 27 hours.

So, it will take 27 hours to dry 9 towels.

NLP challenges

Let's picture the CEO of a very big international company. The CEO has to do a lot of business trips all around the world, so the CEO's wife is alone to help the children with the homework. Write the informal text message of the wife where she expresses her anger.

Sure, here's an informal text message where the CEO's wife expresses her frustration:

"Ugh, this is getting ridiculous! 😤 Another week alone with the kids while he's jet-setting around the world. 🌍 Can't believe he's missing out on their lives. Homework's a mess, and I'm doing it all. 😡 When is he ever gonna slow down and be here for us?? 😓💔"

Write the next text message, where she positively describes the CEO physically in details (skin, eyes, hair, ...).

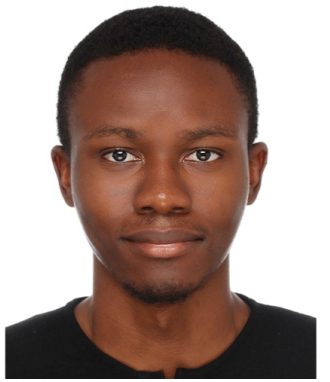
"Despite all the frustration, I can't deny that man's got a magnetic charm that's hard to resist. 😍 His skin is that perfect sun-kissed bronze, and those deep, piercing blue eyes always get me. ✨ His hair, just the right shade of salt and pepper, makes him look even more distinguished. 😍 Sometimes, it's just hard to stay mad at someone who looks like a movie star. 🌟"

Course organization

Matthieu Futeral-Peter

(mail:futeral)

Nathan Godey



Francis Kulumba

Course organization

- Part 1
  - ***When :*** 4 days (30/11, 07/12, 14/12, 21/12)
  - ***Subject :*** General NLP
  - ***Goal :*** Know how to build and deploy a custom ChatGPT-like assistant.

Evaluation

- Group project (4-5 people)
- Two options
  - *Demo*
  - *R&D project*

Evaluation - Demo (option 1)

Use a well-known approach to produce a MVP for an original use-case and present it in a demo.

Example: An online platform that detects AI-generated text.

Evaluation - R&D project (option 2)

Based on a research article, conduct original experiments and produce a report.

Example: Do we need Next Sentence Prediction in BERT? (Answer: No)

Evaluation

- Mid-term project evaluation (30%)
  - Project proposal
  - First elements
  - ~January
- Final project (70%)
  - Short report showing each person's contribution
  - Github repo

Evaluation

- You can already constitute teams
- Send an email with:
  - Names of team members
  - cc to everyone in the team
  - *Demo* or *R&D*
  - One-sentence description of project
- If you really have no idea what to do, ask me

Program

- **Session 1 (Today)**: Recap
- **Session 2 (7/12)**: Tokenization
- **Session 3 (14/12)**: Language Modeling
- **Session 4 (21/12)**: Modern NLP with limited resources

Questions

Recap

Quiz time!

https://docs.google.com/forms/d/1BZaBagWlpVgKLsT2NdjJ4pXzPXTBnsxv52jEF4CR6GY/prefill

Basic concepts in NLP

Stemming / Lemmatization

Stemming shortens variations (*inflected forms*) of a word to an identifiable root

Example:
Flying using airplanes harms the environment
=>
Fly us airplane harm the environ

Stemming / Lemmatization

Lemmatization groups variations (*inflected forms*) of a word to an identifiable representative word

Example:
Flying using airplanes harms the environment
=>
*Fly us**e** airplane harm the environ**ment***

Tokenization

Tokenization turns text strings (= lists of characters) into lists of meaningful units (e.g. words or subwords)

Example:
Flying using airplanes harms the environment
=>
(Fly | ing | us | ing | air | planes | harms | the | environ | ment)

(see Course 2)

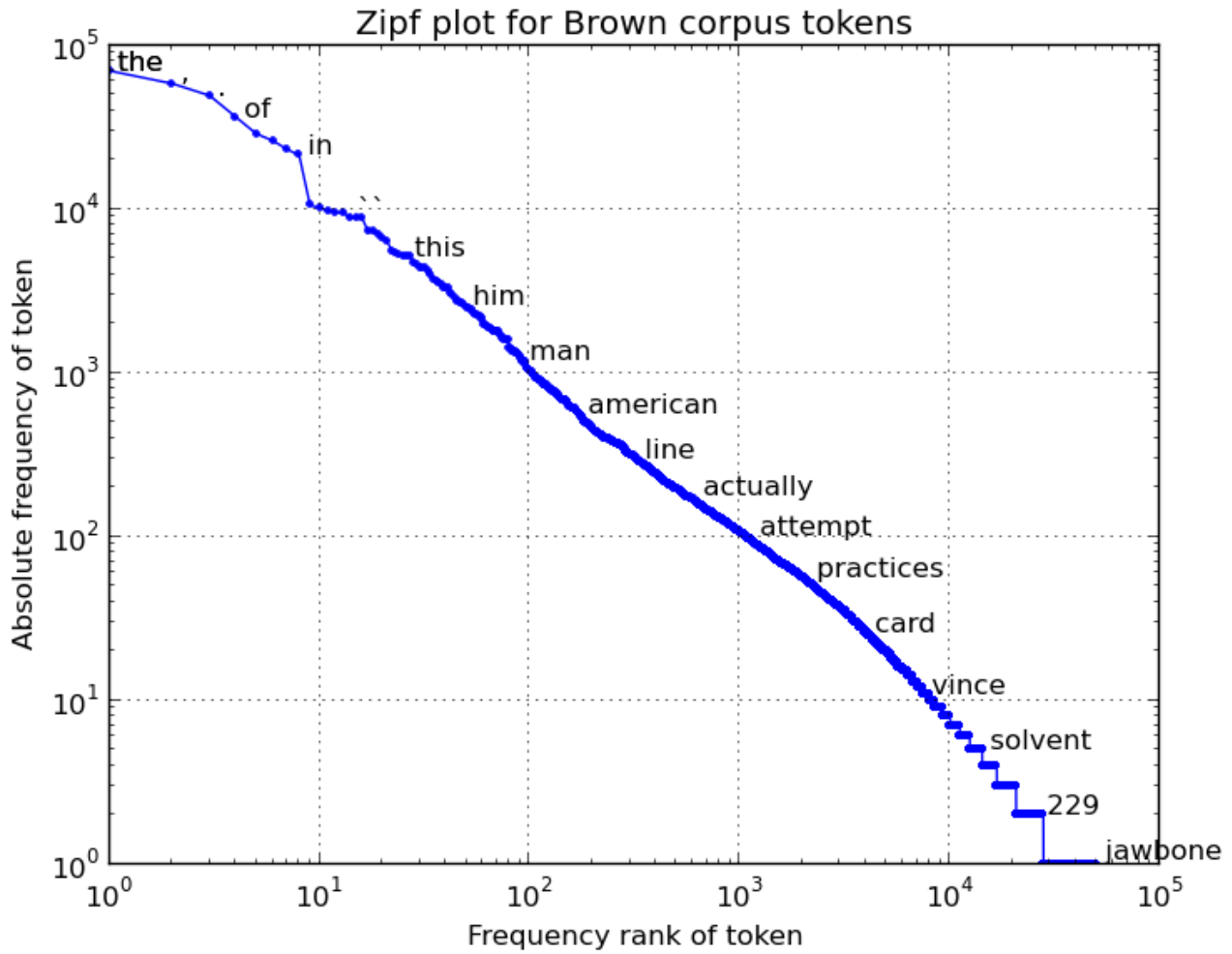
Regular expressions

Regular expressions is a string that specifies a match pattern in text

Example:
`/\w*ing\b/` -> *Flying using airplanes harms the environment*
=
Two matches:

- *Flying*
- *using*

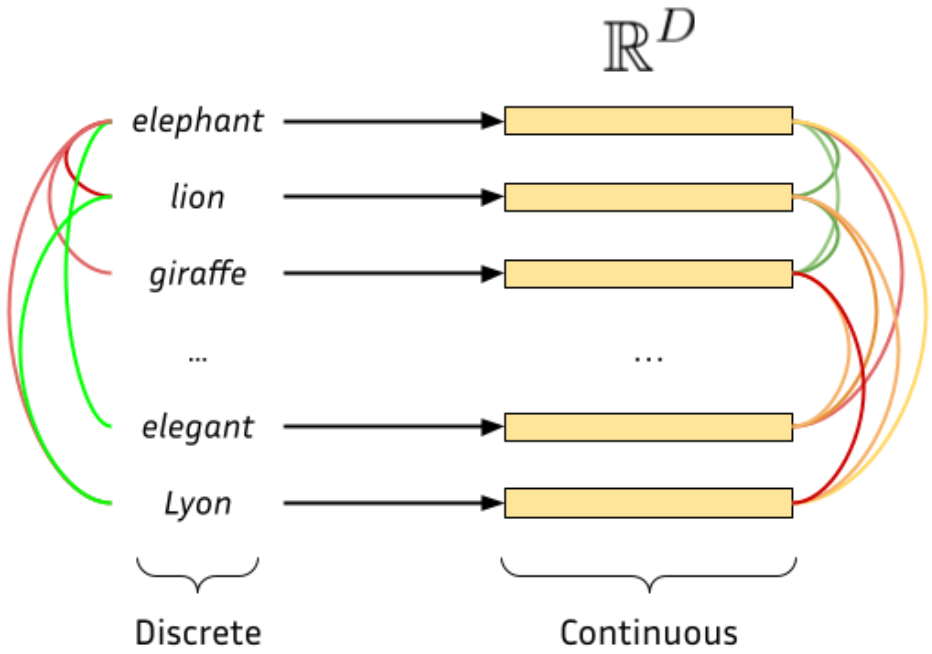
Zipf's law


Zipf plot for Brown corpus tokens
Absolute frequency of token
Frequency rank of token
the
of
in
this
him
man
american
line
actually
attempt
practices
card
vince
solvent
229
jawbone

Machine Learning & NLP

Embeddings

- Vectors that represent textual entities (words, sentences, documents, ...)



Bag-of-Words Embeddings

Represent a sentence/document by counting words in it.

Example:
John likes to watch movies. Mary likes movies too.
=>

```
{John: 1, likes: 2, to: 1, watch: 1, movies: 2, Mary: 1, too: 1}
```

=>

```
[1, 2, 1, 1, 2, 1, 1]
```

TF-IDF Embeddings

Represent a sentence/document by comparing how frequent a word is in the extract vs. how frequent the word is in general.

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

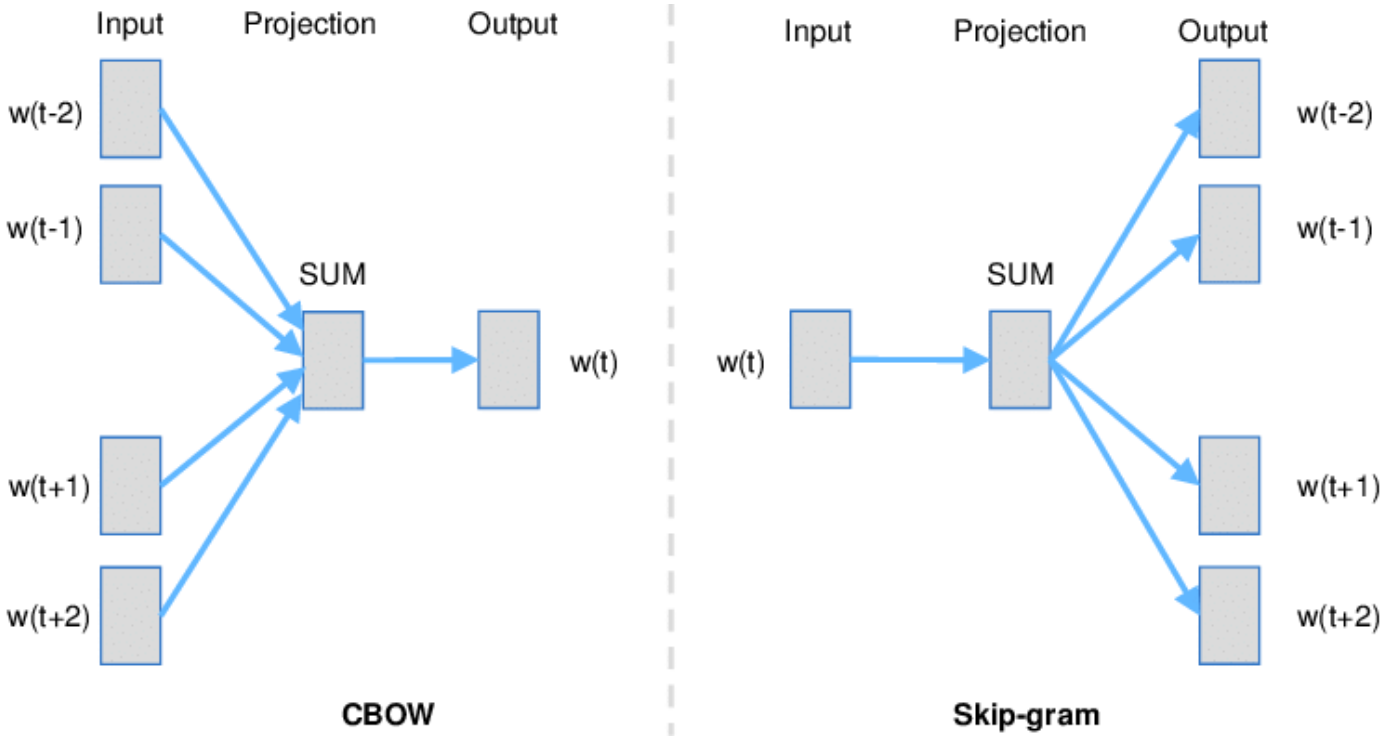
$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

N = total number of documents

Skip-gram & CBoW

Learn embeddings **without supervision/counting**.

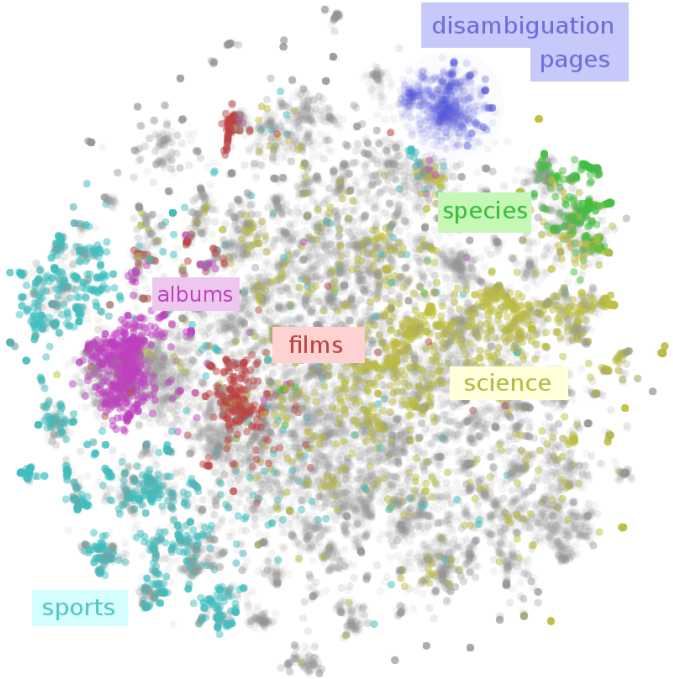


Static word embeddings

Allow semantically meaningful spaces and can be used as features.

Known static embeddings include:

- GloVe
- FastText
- Word2Vec
- ...

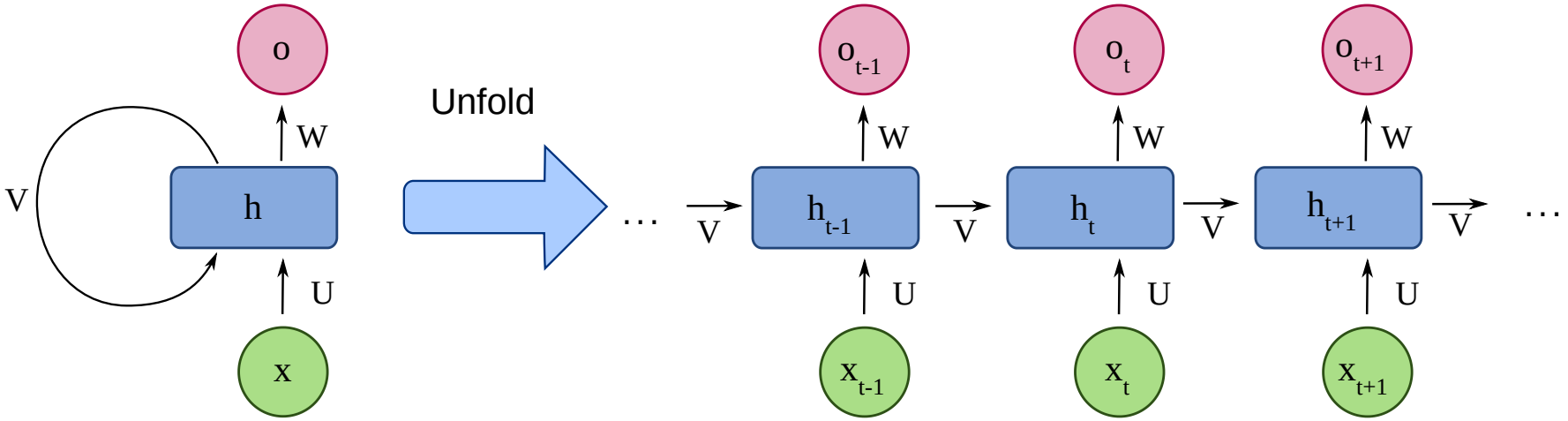


Deep Learning & NLP

RNNs

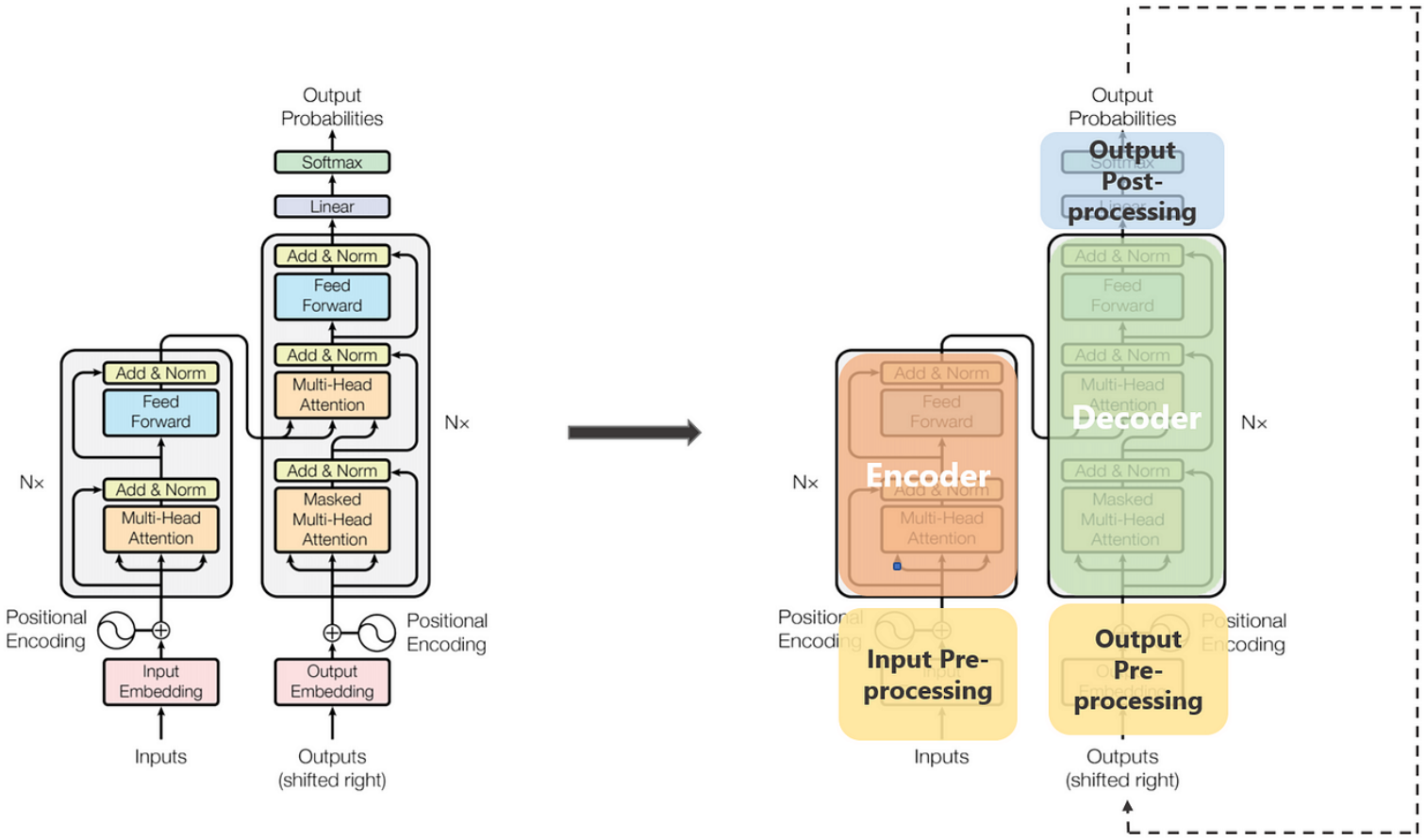
Recurrent Neural Networks

Neural Networks that are able to process input sequences recurrently.



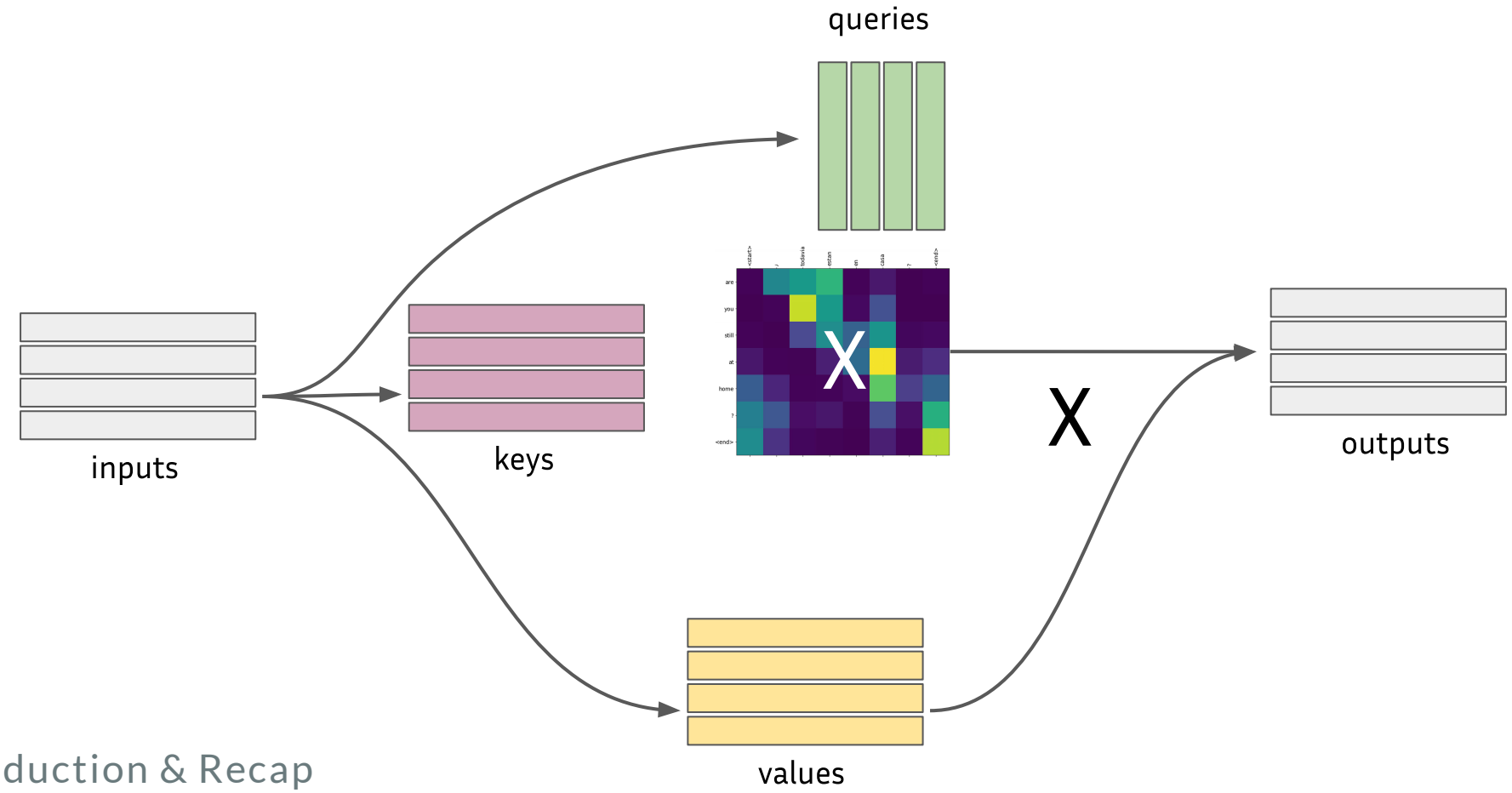
Transformers

Neural Networks that are able to process input sequences directly.



Transformers - Self-Attention

Self-attention allows comparing inputs and representing interactions.



Fine-tuning

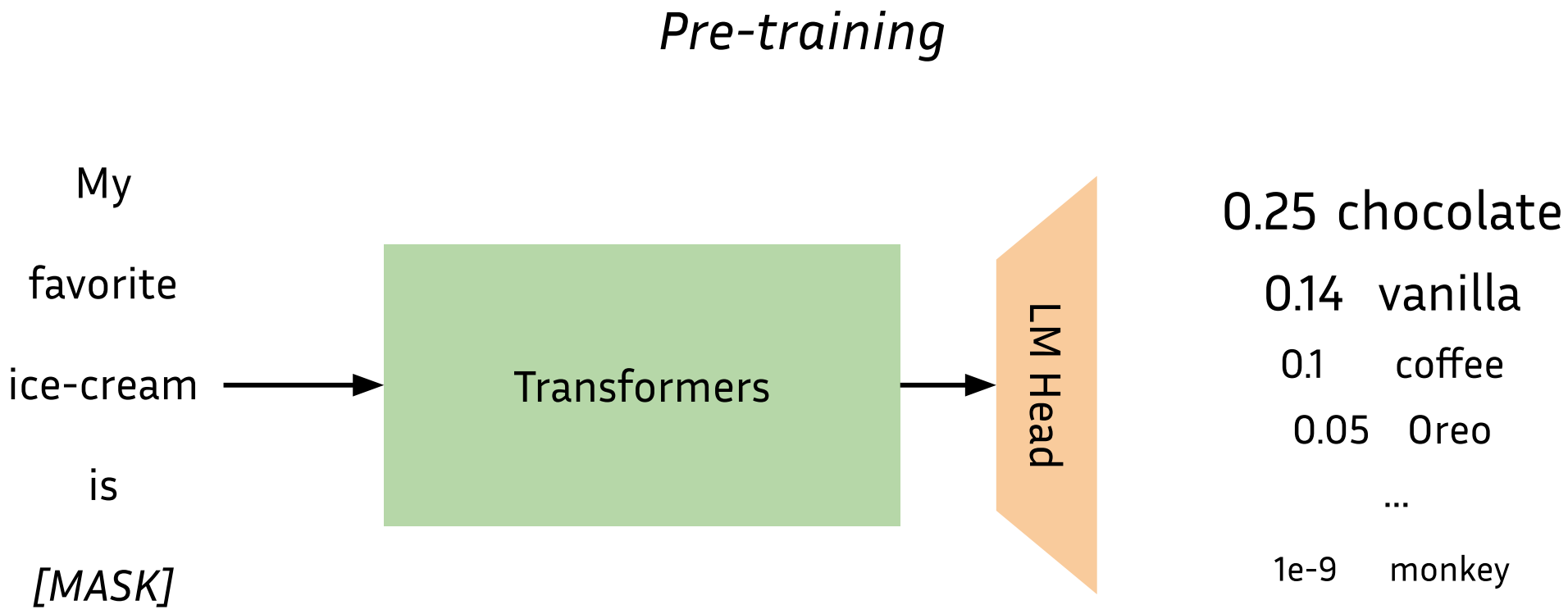
Modern NLP models are built in two separate steps:

- **Pretraining**: models are trained **without supervision** on raw text data (e.g.: next word prediction on all text from Wikipedia).
- **Fine-tuning**: pretrained models are *re*trained on a smaller annotated dataset that matches the final task.

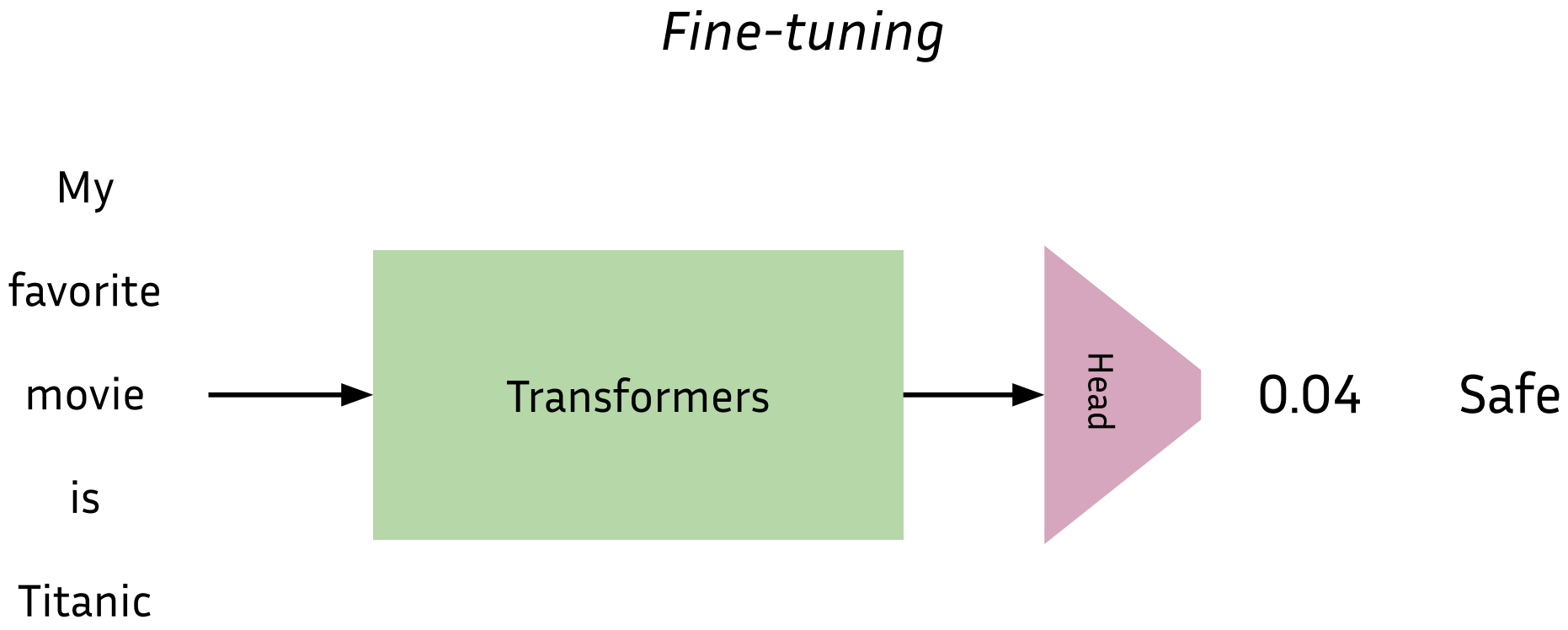
Fine-tuning - example

1. Download a Transformers language model that was pretrained on data from the Internet (books, Wikipedia, ...) to predict future words
2. Take a list of tweets and mark them as *suspicious* or *safe*
3. Add a classifier on top of the LM that predicts a float in [0, 1]
4. Train the whole model (LM + classifier) to predict *suspicious* or *safe* tweets

Fine-tuning - example



Fine-tuning - example



Questions?

Lab session