Intro

Natural Language Processing
(Machine translation)

Stage 1. Rules described by humans

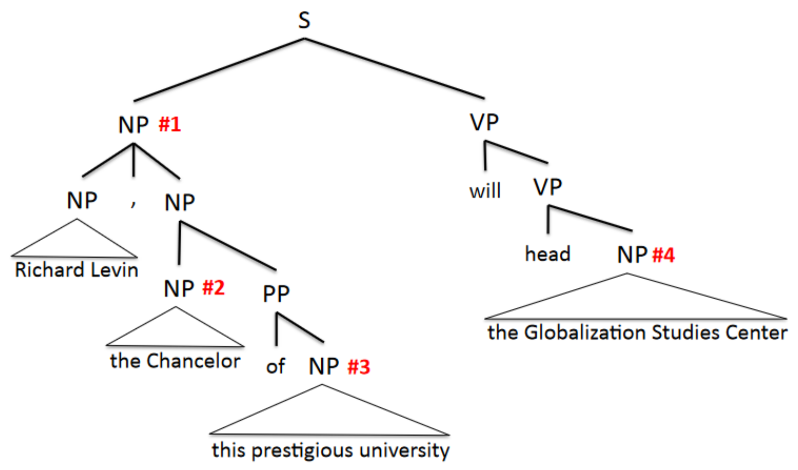


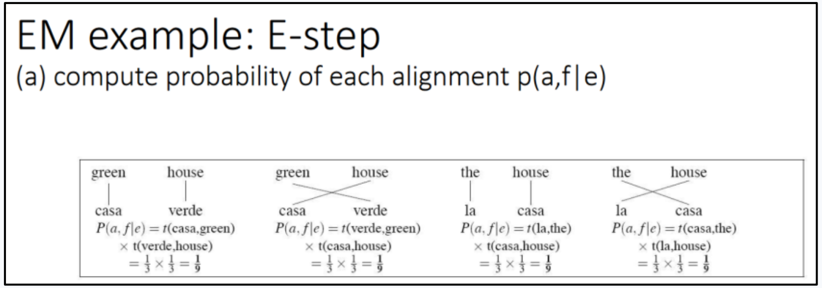
Figure 1: Example of left-to-right breadth-first tree traversal. The numbers indicate the order in which the NPs are visited.

https://nlp.stanford.edu/pubs/coreference-emnlp10.pdf

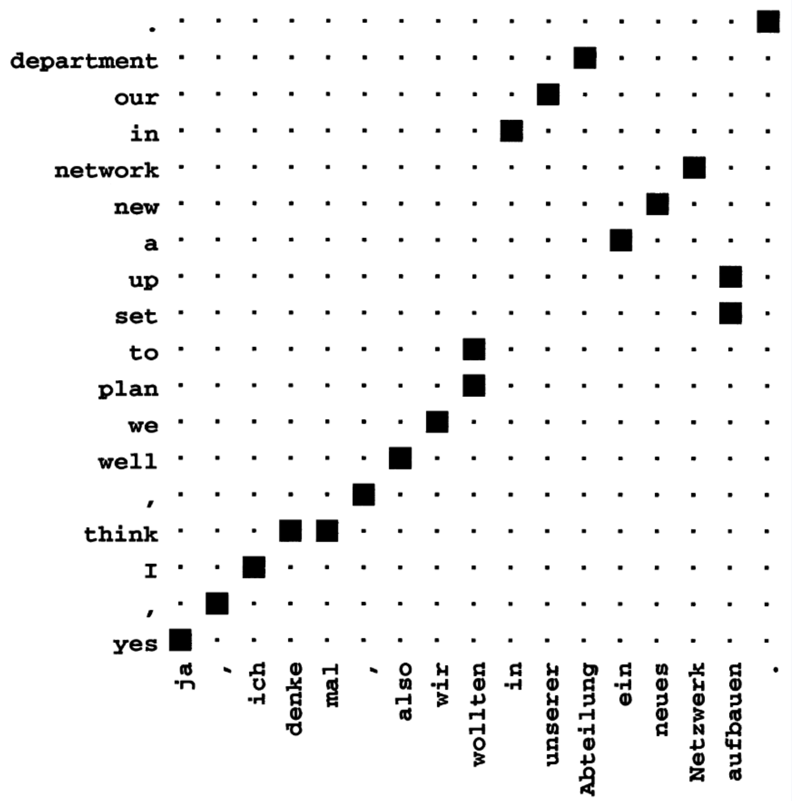
Natural Language Processing (Machine translation)

Stage 1. Rules described by humans

Stage 2. Statistical rules: computer learns from data



https://www.cs.umd.edu/class/fall2017/cmsc723/slides/slides_18.pdf



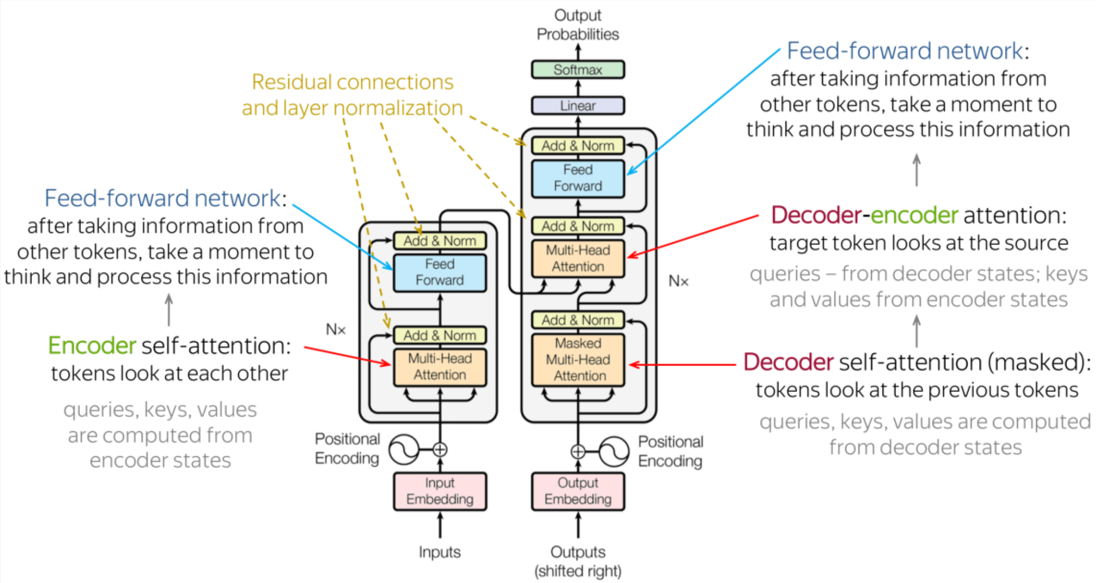
https://aclanthology.org/J04-4002.pdf

Natural Language Processing (Machine translation)

Stage 1. Rules described by humans

Stage 2. Statistical rules: computer learns from data

Stage 3. Transformers make a breakthrough

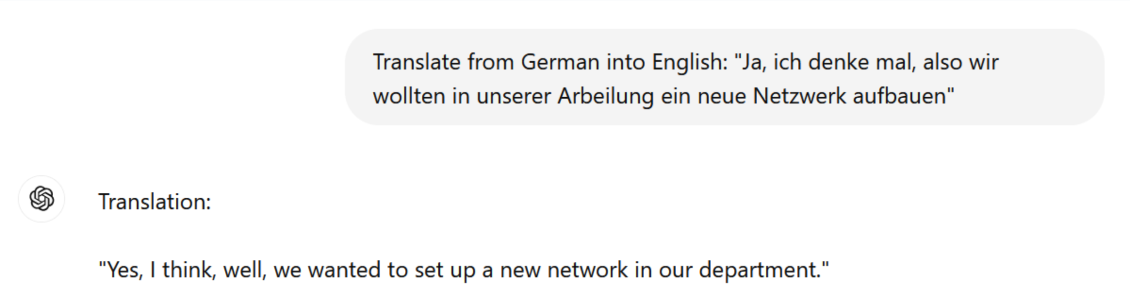


https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Natural Language Processing (Machine translation)

Stage 1. Rules described by humans

Stage 2. Statistical rules: computer learns from data



Stage 3. Transformers make a breakthrough

Stage 4. Just ask ChatGPT nicely

https://chatgpt.com/

Natural Language Processing
(Machine translation)

Stage 1. Rules described by humans

Stage 2. Statistical rules: computer learns from data

Stage 3. Transformers make a breakthrough

Stage 4. Just ask ChatGPT nicely

Summarization

Stage 1. Nope

Stage 2. Nope

Stage 3. Extractive

Stage 4. Generative

Natural Language Processing (Machine translation)

```
  Welcome to
                  EEEEEE  LL      IIII   ZZZZZZ   AAAAA
                  EE      LL       II       ZZ   AA   AA
                  EEEEE   LL       II     ZZZ    AAAAAAA
                  EE      LL       II    ZZ      AA   AA
                  EEEEEE  LLLLLL  IIII ZZZZZZ    AA   AA

  Eliza is a mock Rogerian psychotherapist.
  The original program was described by Joseph Weizenbaum in 1966.
  This implementation by Norbert Landsteiner 2005.


ELIZA: Is something troubling you ?
YOU:   Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU:   They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU:   Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU:   He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU:   It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:
```

Stage 4. Just ask ChatGPT nicely

Dialog systems

Stage 1. ELIZA

Stage 2. ?

Stage 3. Retrieval-based

Stage 4. Generative

Natural Language Processing
(Machine translation)

Stage 1. Rules described by humans

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Stage 4. Just ask ChatGPT nicely

Dialog systems

Stage 1. ELIZA

Stage 2. ?

Stage 3. Retrieval-based

Stage 4. Generative

About this course

- Intro to ML as it seems in 2024

- Coding rather than math

- Looking much deeper than just the ChatGPT interface

Course plan

1. Exploring existing models
2. How to evaluate models

3+4. How models are trained

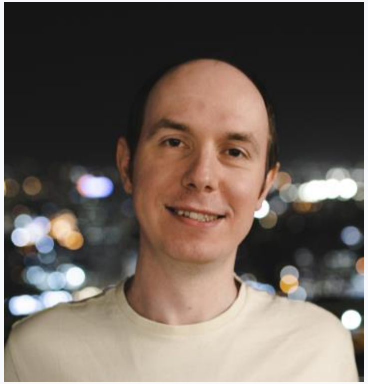
5. How to help ML with retrieval

6-7. Neural networks & fine tuning

8-9. ML for sequences

10-12. LLM internals

Course team



Stanislav Fedotov

AI Content Lead at
Nebius Academy

Will tell about:
LLM applications
Core ML

Tatiana Gaintseva

PhD Student at Queen
Mary University of London

Will tell about:
Neural networks

Karina Zainullina

Research Engineer
(LLMs) at Nebius

Will tell about:
LLM internals

Intro to LLMs

Large Language Models (LLMs)

Language models: They create completions for texts

> In the wastelands of mine echoes of forgotten tales whisper through the barren soil.

Large: They are large indeed and very capable

OpenAI GPT

Anthropic Claude

Google Gemini

LLaMA by Meta

Qwen

MISTRAL AI_

Intro to LLMs
(coding time)

What is Machine Learning

Not ML vs ML: machine translation

Not ML: using expert knowledge or rule-based systems

"The cat is sleeping on the windowsill. It looks very peaceful in the sunlight."

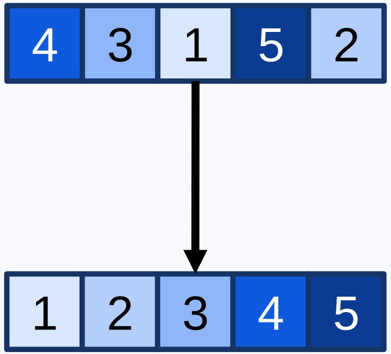
El gato está durmiendo en el alféizar de la ventana. Se ve muy tranquilo bajo la luz del sol.

Not ML vs ML: array sorting

Not ML: using a textbook algorithm

python

```python
def quick_sort(arr):
    if len(arr) <= 1:
        return arr
    else:
        pivot = arr[len(arr) // 2]
        left = [x for x in arr if x < pivot]
        middle = [x for x in arr if x == pivot]
        right = [x for x in arr if x > pivot]
        return quick_sort(left) + middle + quick_sort(right)
```



Not ML vs ML: machine translation

Training data

English: **Object**
The rain started suddenly, soaking everything in minutes.
Spanish: **Target**
La lluvia comenzó de repente, empapando todo en minutos.

English:
She smiled as she watched the children playing in the garden.
Spanish:
Sonrió mientras miraba a los niños jugando en el jardín.

Training algorithm

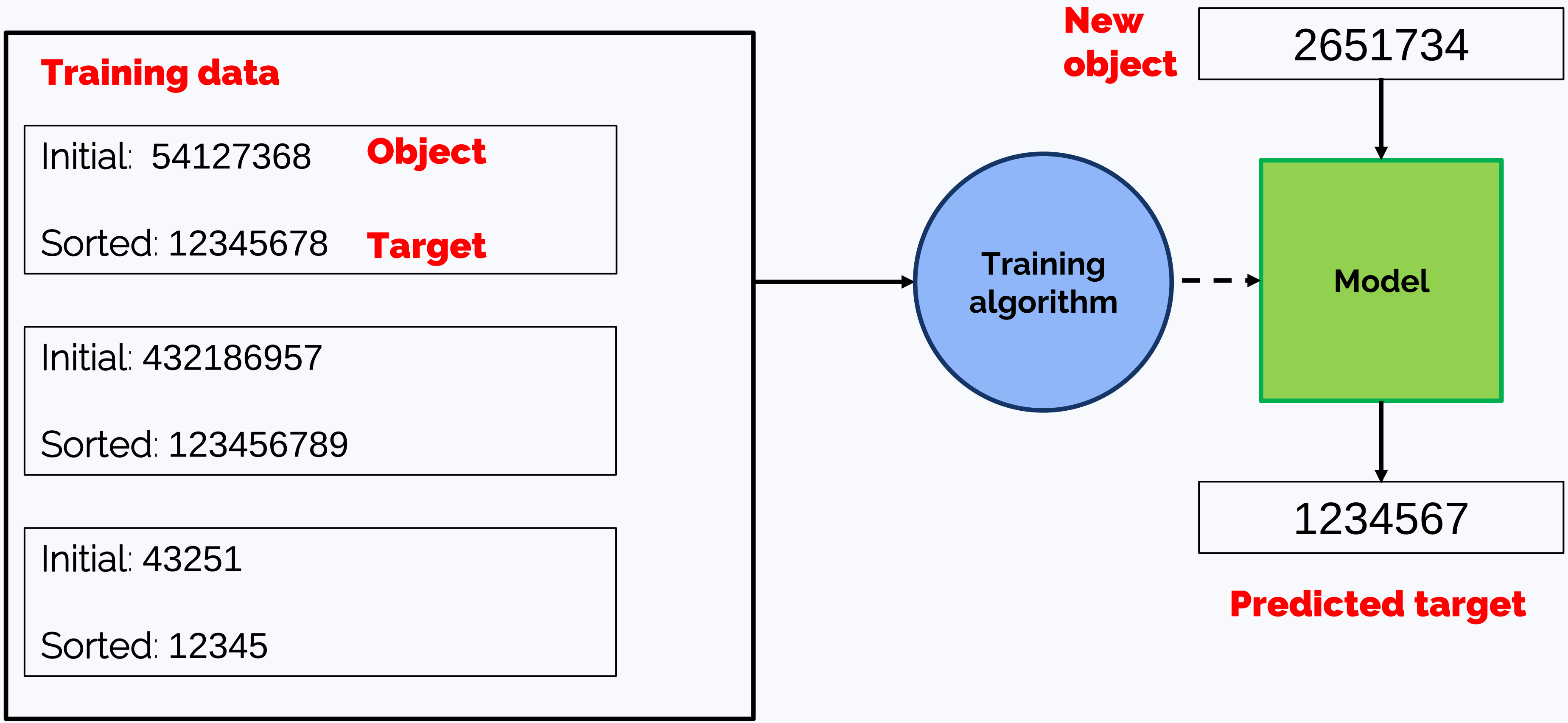
Model

New object

After a long day at work, he finally sat down with a warm cup of tea, enjoying the quiet evening.

Después de un largo día de trabajo, finalmente se sentó con una taza de té caliente, disfrutando de la tranquila noche. **Predicted target**

Not ML vs ML: array sorting

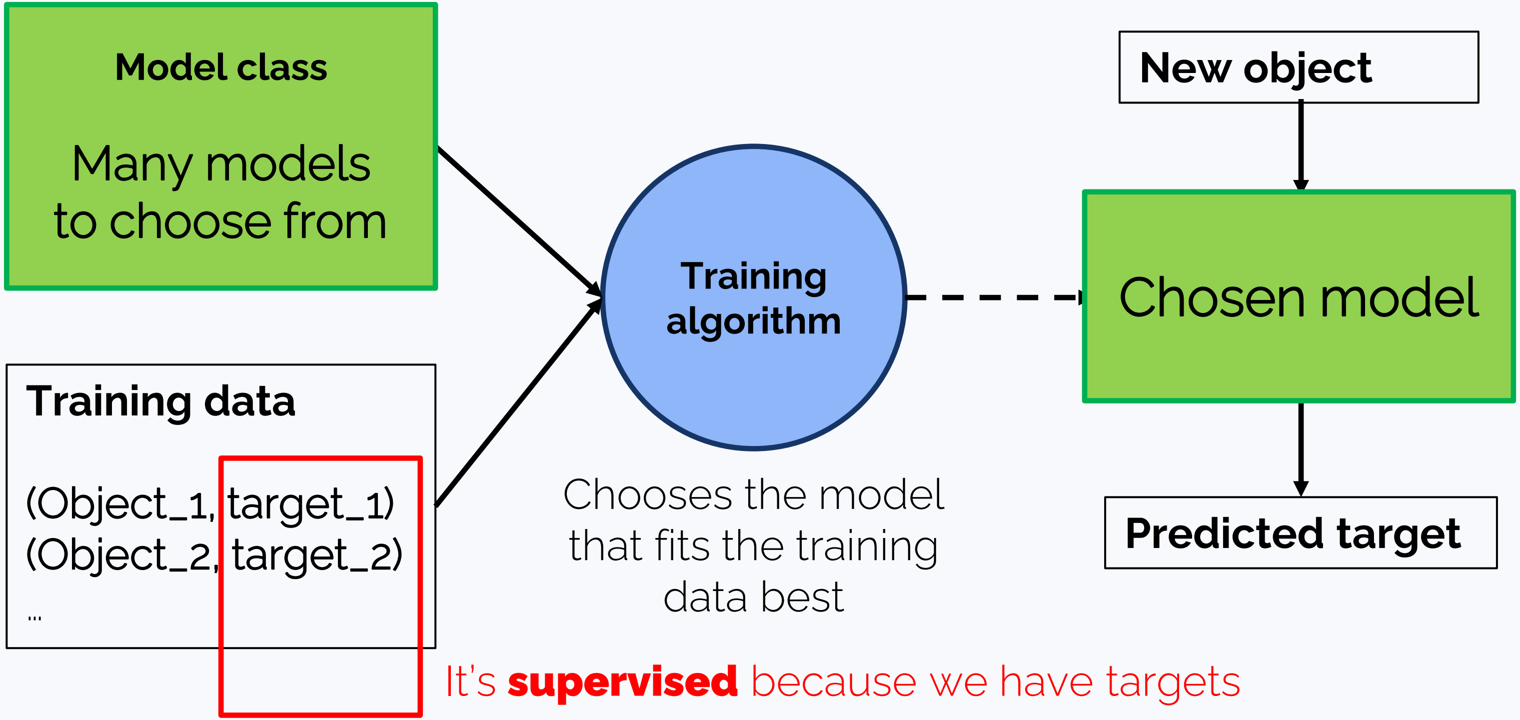


Not ML vs ML: correctness vs accuracy

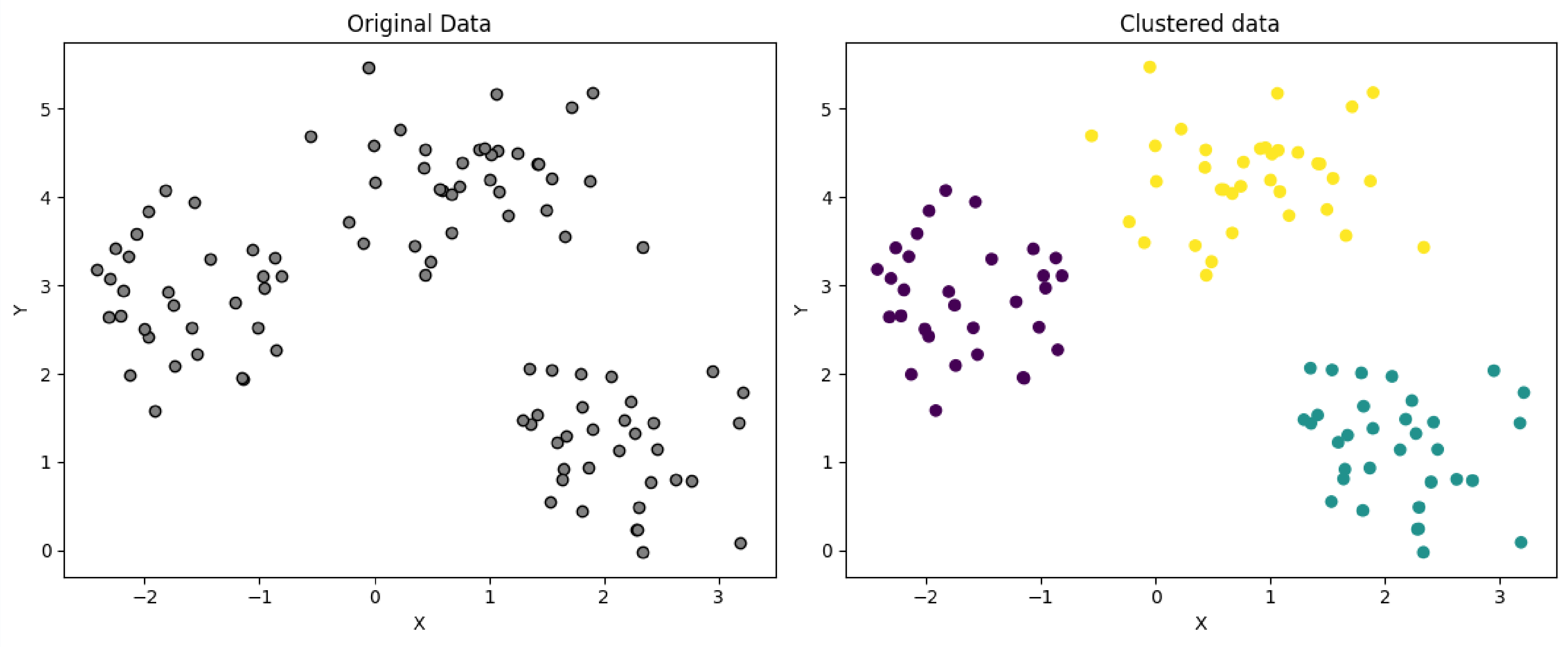
Textbook algorithm is either correct or not correct. Its correctness can be assessed.

ML model is usually obscure and not interpretable ($\Rightarrow$ not verifiable). It does a right thing with a certain accuracy.

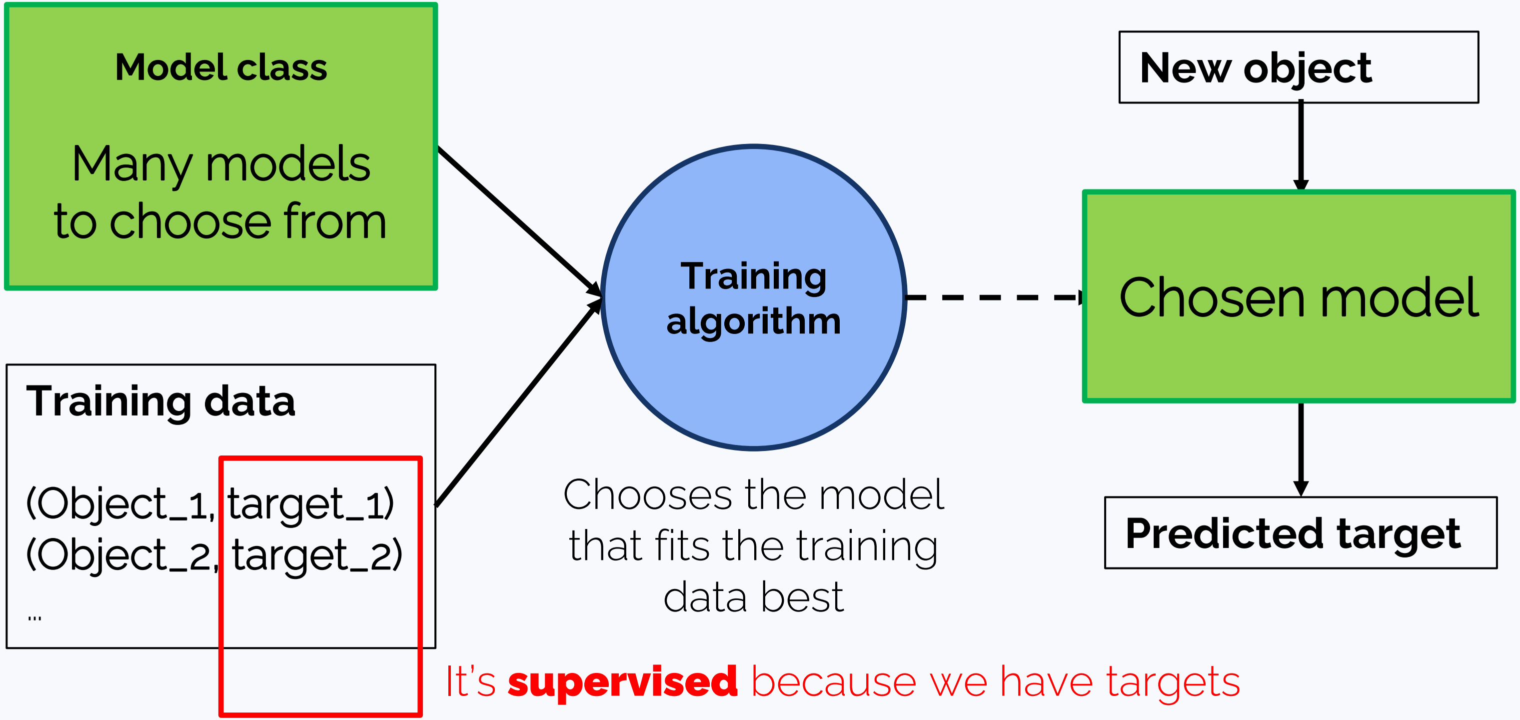
Supervised learning



An example of unsupervised learning: Clustering



Supervised learning



What is a model?

Spam classification

Model class

Many models to choose from

Greetings to all participants of the chat! There is an option to earn money in a remote format!
Suitable for everyone 18+
There is free training.Income from $700 per week
If you are interested, write + in hp.

Verified!

Reliable people are required for a job! You only need a mobile device and 2-3 hours every day.
If you're new to the business, I'll teach you everything. My interest is a % of your earnings.

Spam!

Hi folks! I'm doing my Master's now, but I have 2-3 hours a day that I could use for a pet project. Can you recommend me something?

Not spam!

Training algorithm

Chosen model

Spam!

Mimicking an expert with a linear rule

+0	+1.5	+0	-2	+5
A	job	for	everyone	18+!

+0	-1	+0	+0	+4	+0	+0	+3
My	interest	is	a	%	of	your	earnings.

Total:

+10.5

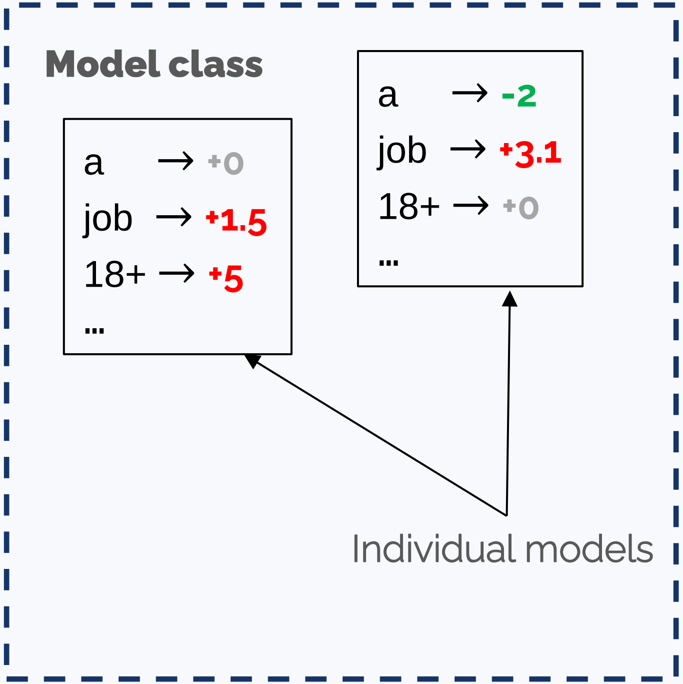
Spam!

Mimicking → **Modeling**

Our model is:

Linear classification + Bag of Words

1. Each word has a weight
2. Sum all word weights in a text
3. If the sum is positive, it's spam; otherwise, it's not spam



+0	+1.5	+0	-2	+5
A	job	for	everyone	18+!

Total:

+4.5

Spam!

Our model is:

Linear classification + Bag of Words

1. Each word has a weight
2. Sum all word weights in a text
3. If the sum is positive, it's spam; otherwise, it's not spam

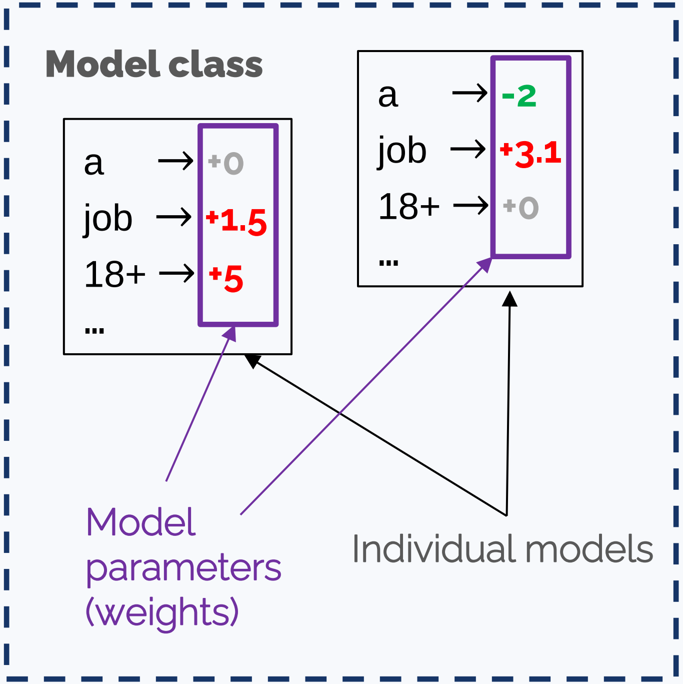
+0 +1.5 +0 -2 +5

A job for everyone 18+!

Total:

+4.5

Spam!



Our model is:

Linear classification + Bag of Bigrams

1. Each bigram (two consecutive words) has a weight
2. Sum all bigram weights in a text
3. If the sum is positive, it's spam; otherwise, it's not spam

+0 -2

A job for everyone 18+!

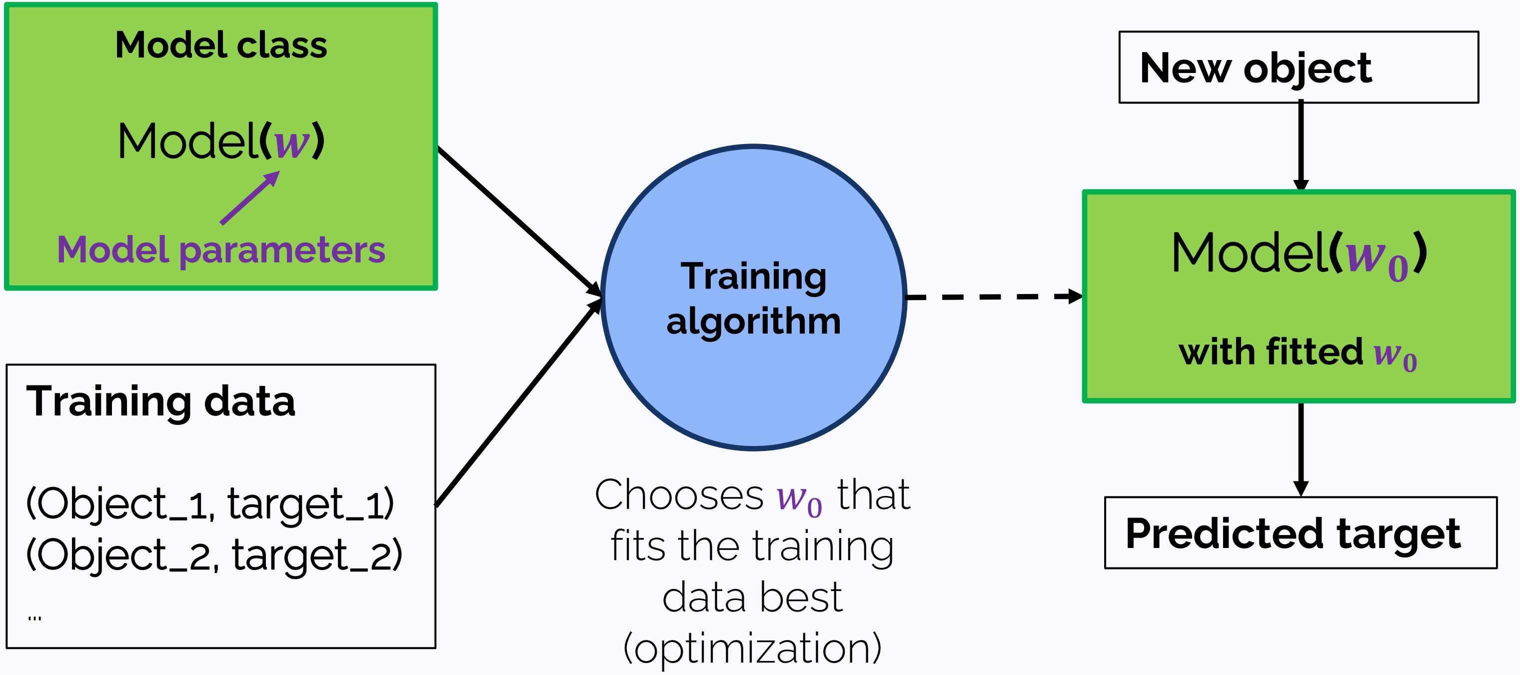
+1.5 +5

Total:

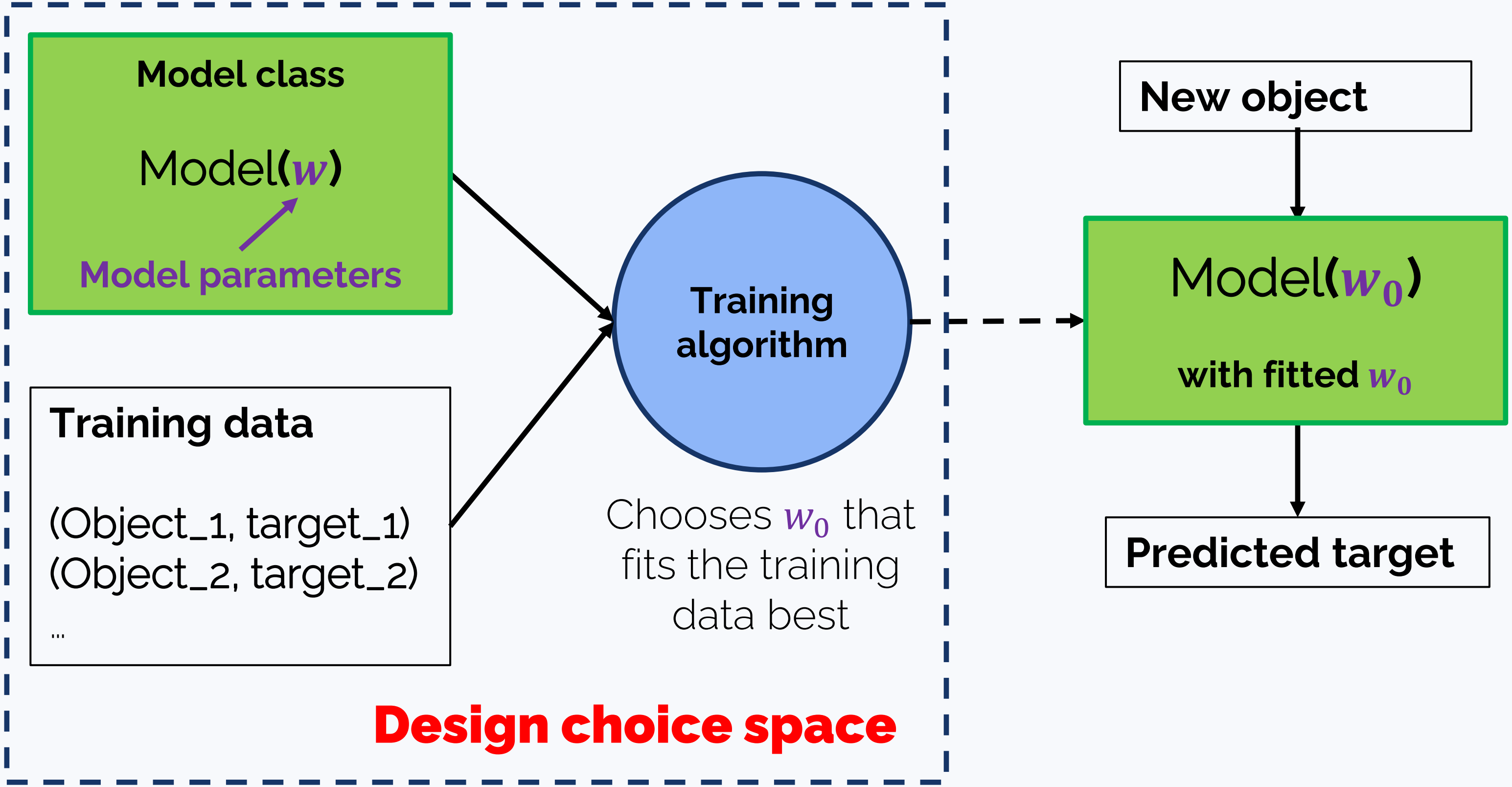
+4.5

Spam!

Supervised learning



Supervised learning



A more exciting task

Yet another task: next word prediction

In the wastelands of mine -> echoes

In a quaint village where the sun painted the rooftops golden each morning -> a

ChatGPT struggles with generating -> responses

Yet another task: next word prediction

In the wastelands of mine, echoes of forgotten tales whisper through the barren soil.

In a quaint village where the sun painted the rooftops golden each morning, a curious cat named Whiskers embarked on daily adventures that were the talk of the townsfolk

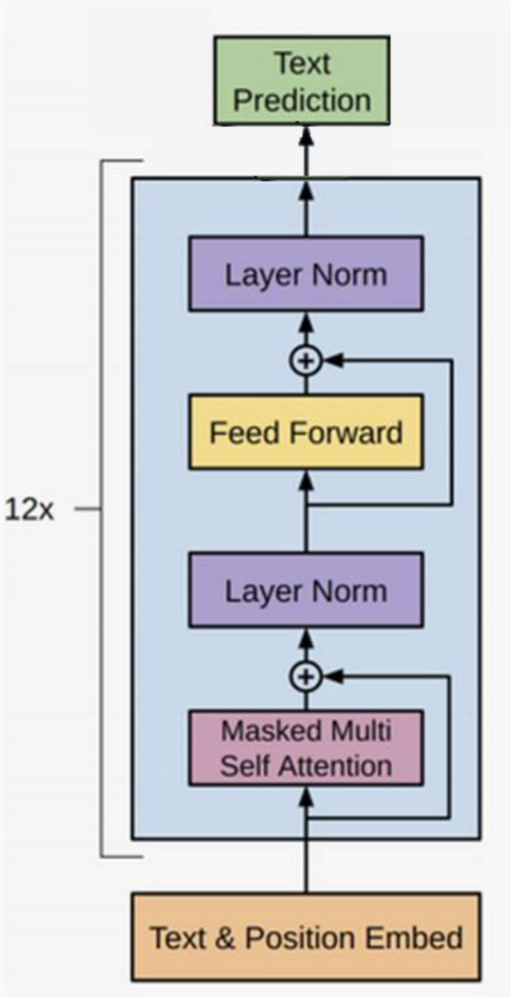
ChatGPT struggles with generating responses that require access to real-time information or events that occurred after its last training data update.

Yes, it's about LLMs ;)

An LLM predicts the next ~~word~~ token

A typical Large Language Model (LLM) consists of blocks with **trainable parameters** inside.

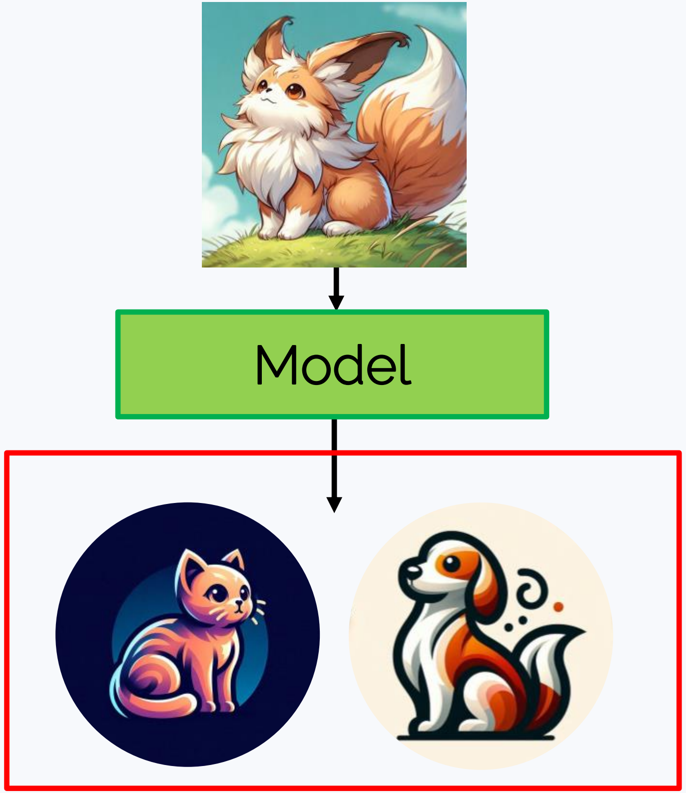
Design choice:
- Architecture
- Training dataset
- Optimization details
- and more

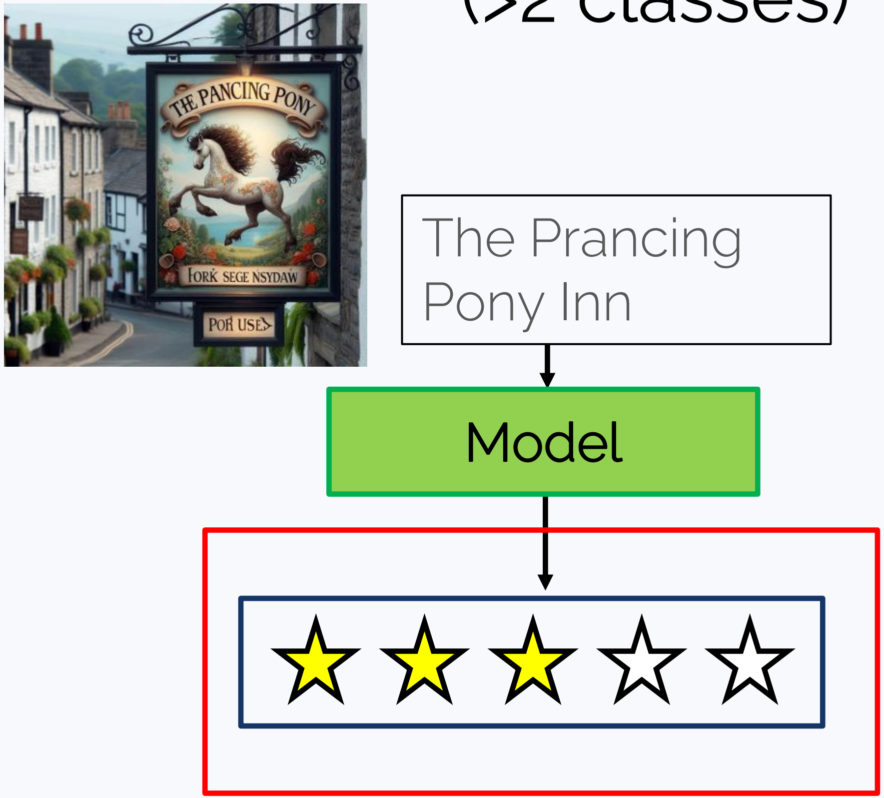


ML tasks taxonomy (based on output types)

Binary classification
(2 classes)

Multiclass classification
(>2 classes)





Regression:
predicting a real number

Address: 11 Cavendish Square...
Month: December
...

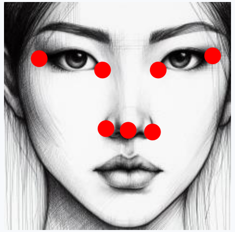
Model

Your estimated electricity bill
for December is:

423.13 GBP

Multiple regression:
predicting several real numbers

Model



(x_1, y_1)
(x_2, y_2)
...

Text

Model

The image shows a man, likely a teacher, sitting at a desk in front of a blackboard. He has a serious....

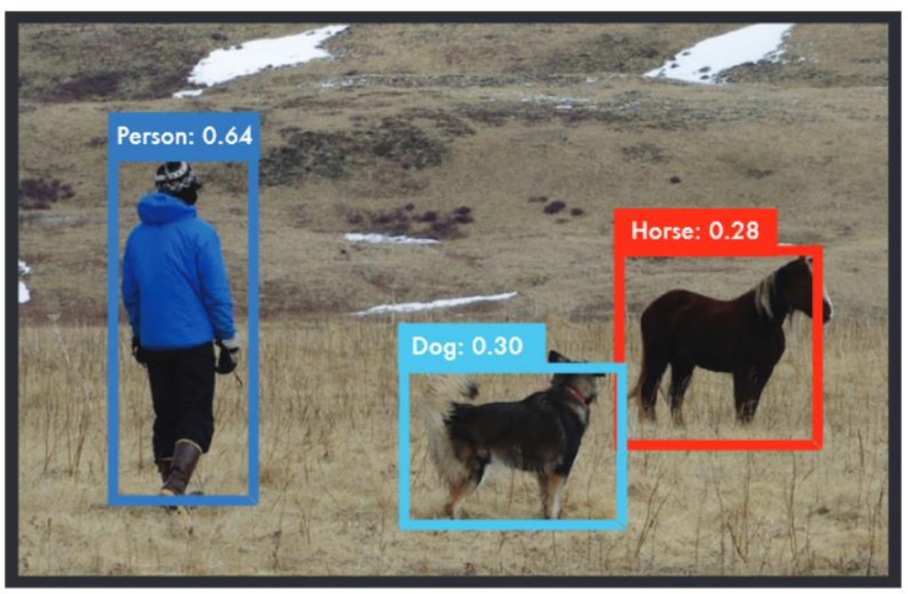
Image

Change background to: London

Model

More examples of complex ML problems

- **Object detection**
- Video object tracking
- Protein structure prediction



YOLO, https://arxiv.org/pdf/1506.02640

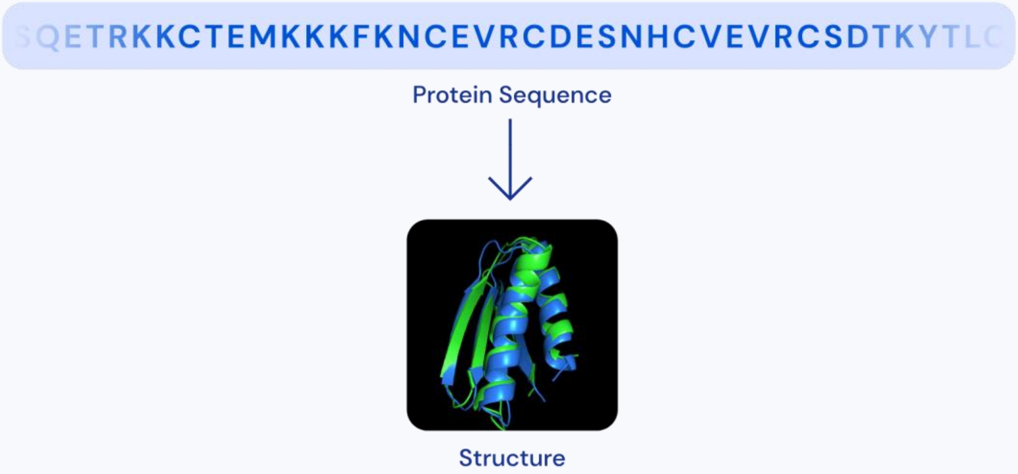
More examples of complex ML problems

- Object detection
- **Video object tracking**
- Protein structure prediction

https://github.com/gaomingqi/Track-Anything

More examples of complex ML problems

- Object detection
- Video object tracking
- **Protein structure prediction**



AlphaFold https://www.nature.com/articles/s41586-021-03819-2

Are LLMs just classifiers?!

Vocabulary
of tokens:

In the wastelands of mine

/**
and
Vader
dreams
echoes
123
…

Discriminative models

VS

generative models

How many apples are there in the picture?

Model

There are two apples

Discriminative models

VS

generative models

What is depicted in the picture?

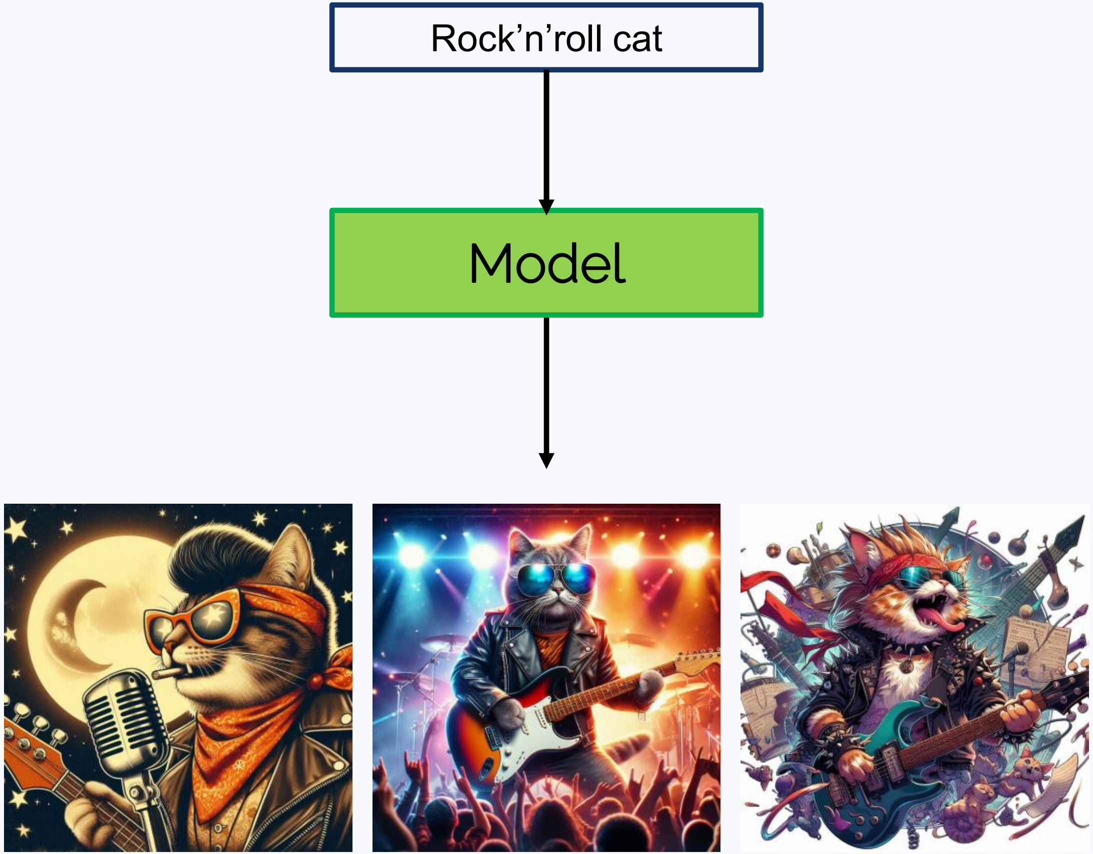
Model

- A man with apples
- A depressed man
- A classroom scene

Discriminative models

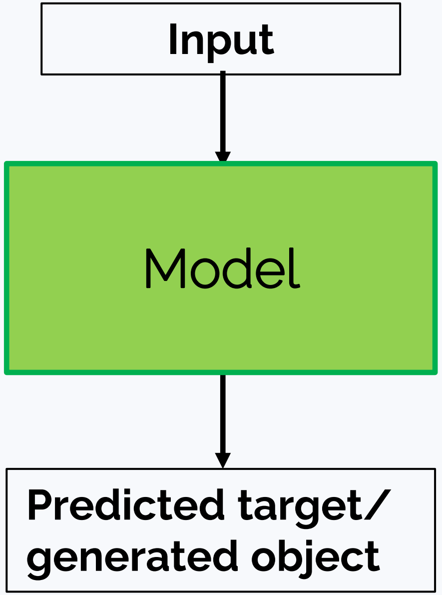
VS

generative models



Discriminative models vs generative models

Classification
Regression
Detection
...
Prediction of a target



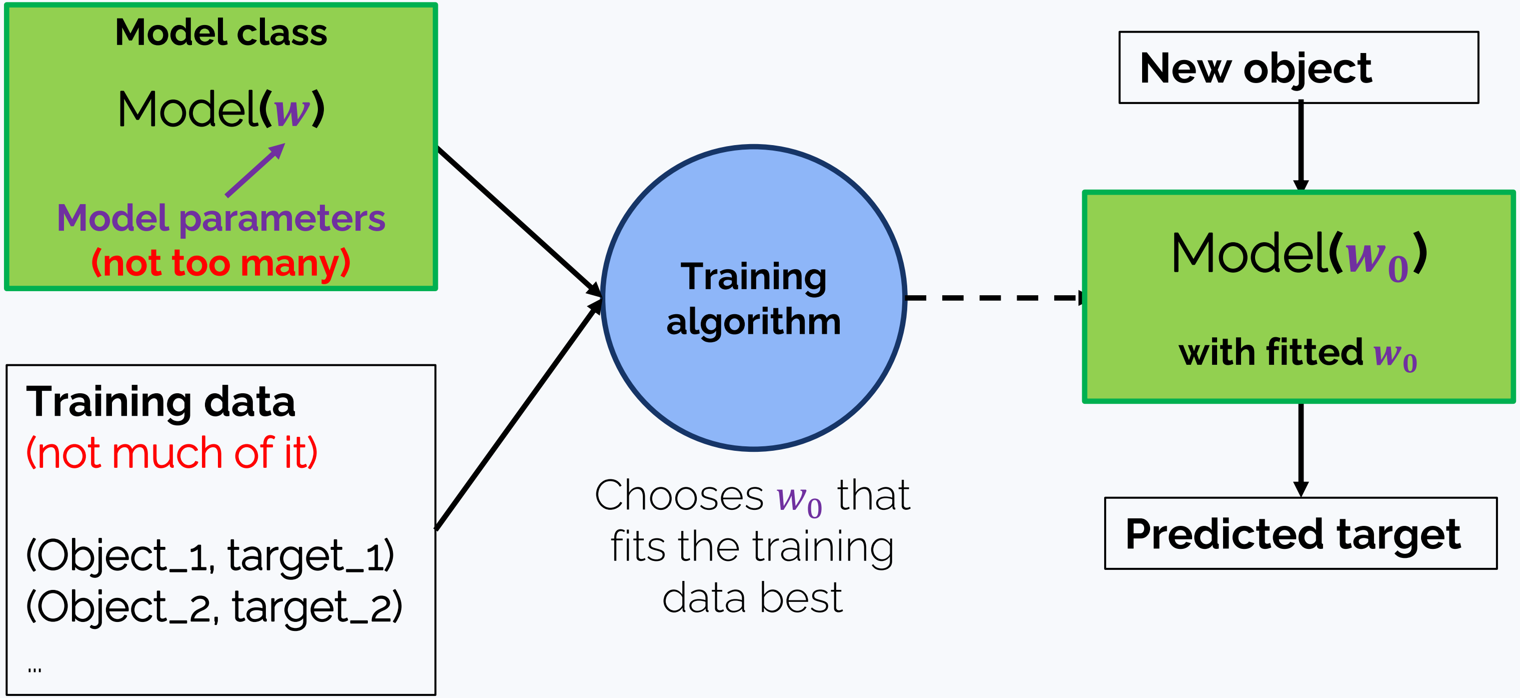
Conditional generation:
Generation of new objects, conditioned on some input objects

For every object, there is a correct target

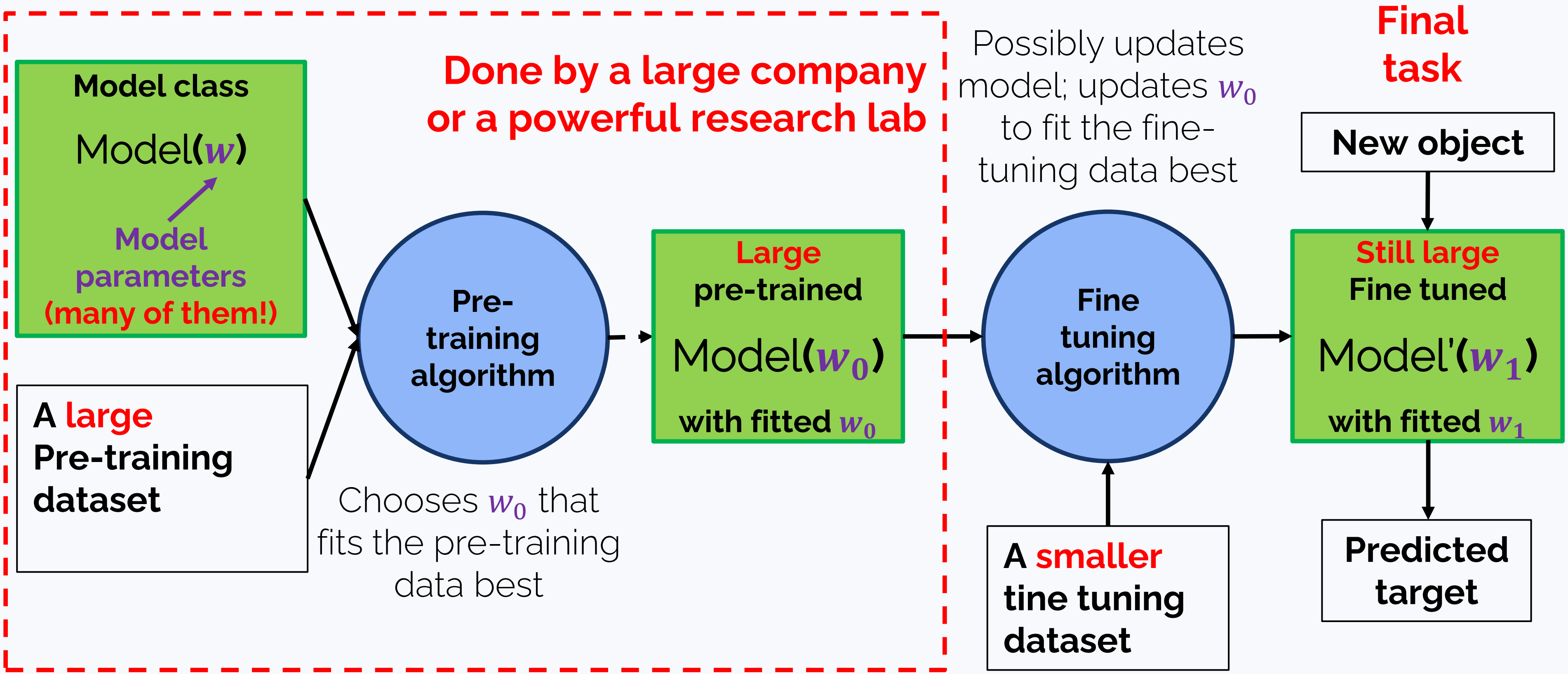
For every object, there are many acceptable targets

A glimpse at the evolution of Machine Learning

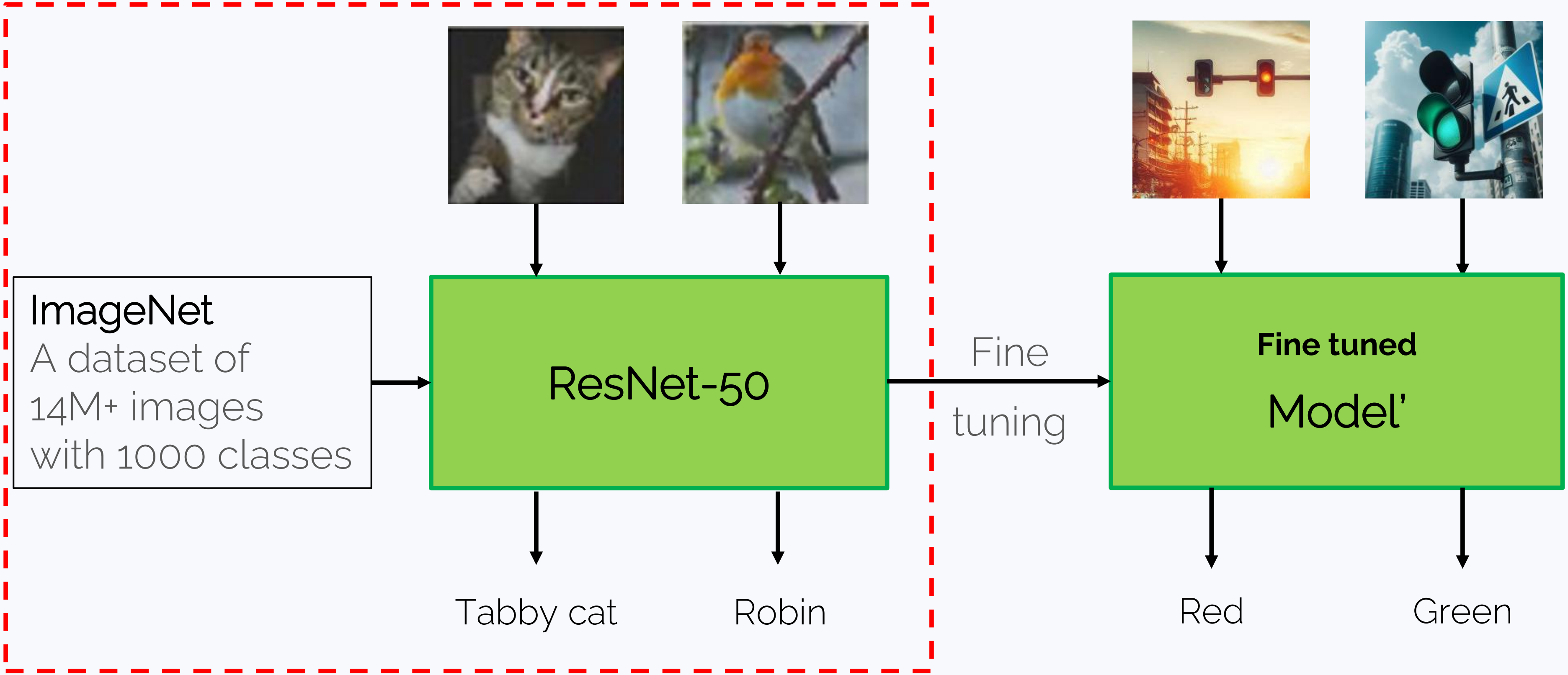
Pre-mid-2010s:
train your own model from scratch



Mid-2010s-2022: the era of large pre-trained models



Mid-2010s-2022: the era of large pre-trained models



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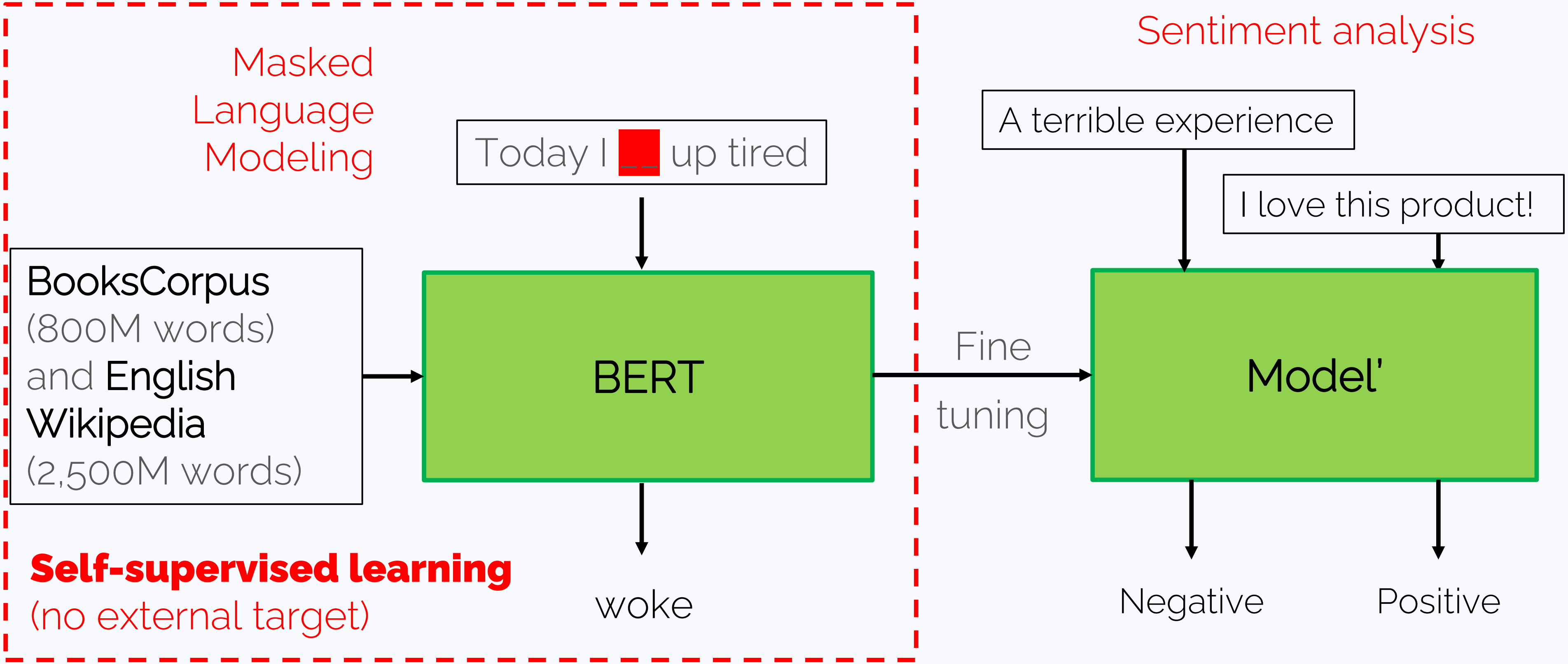

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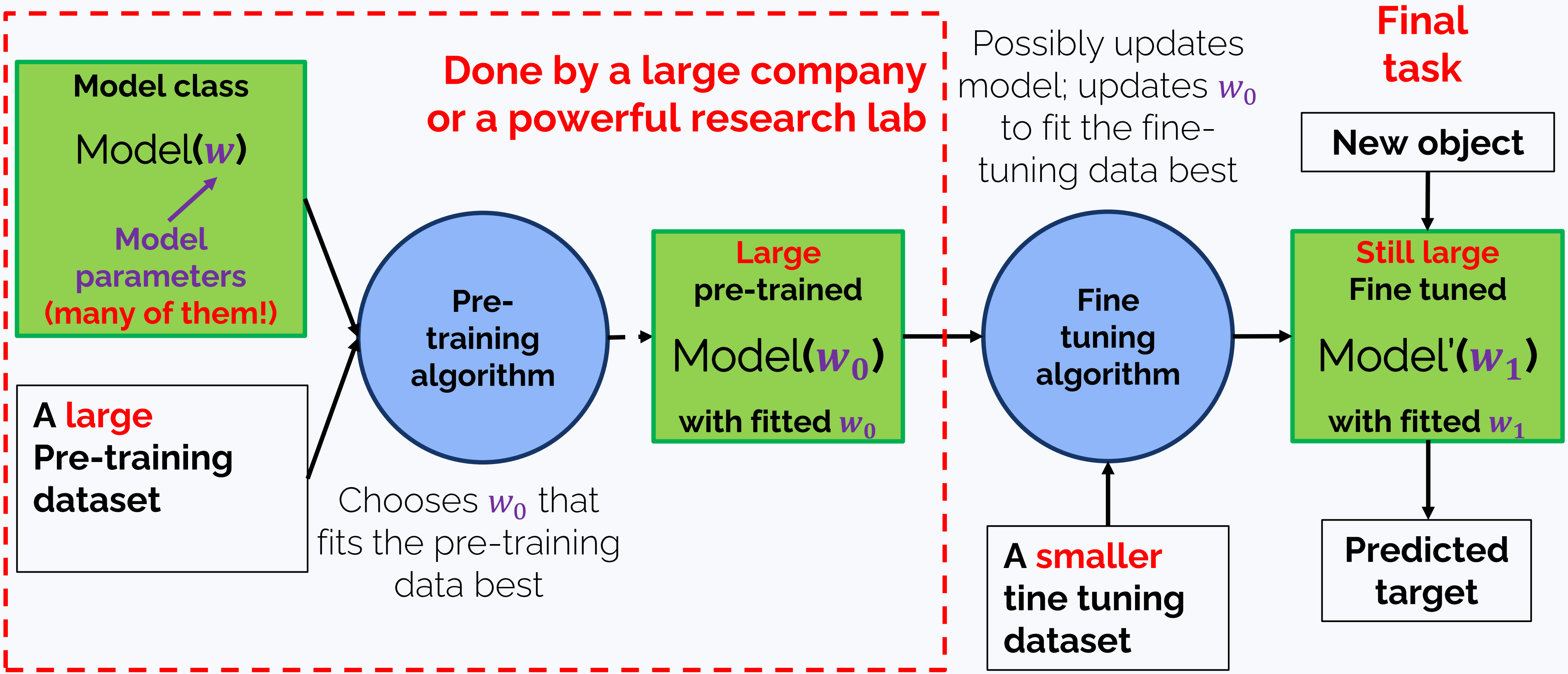

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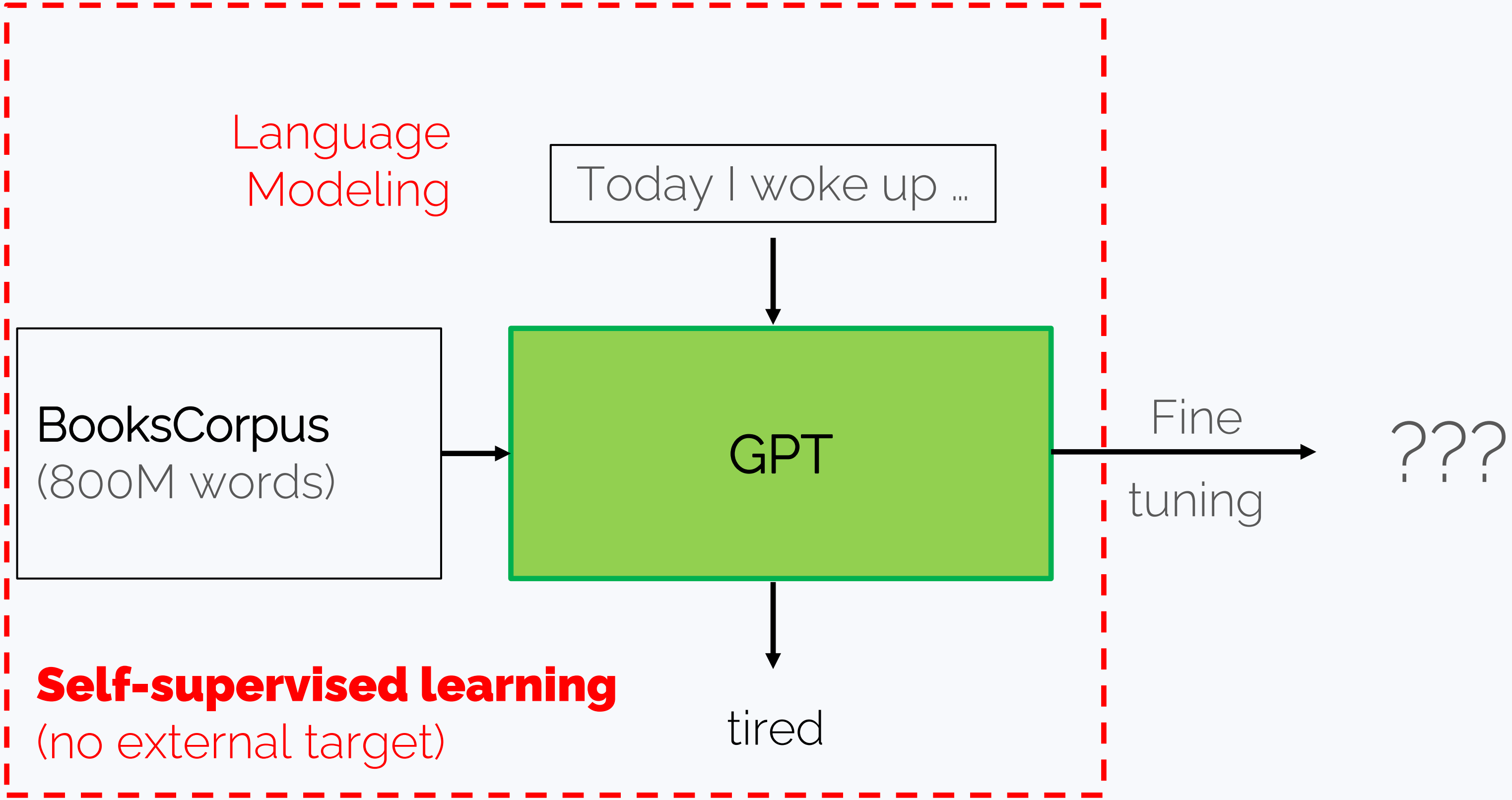
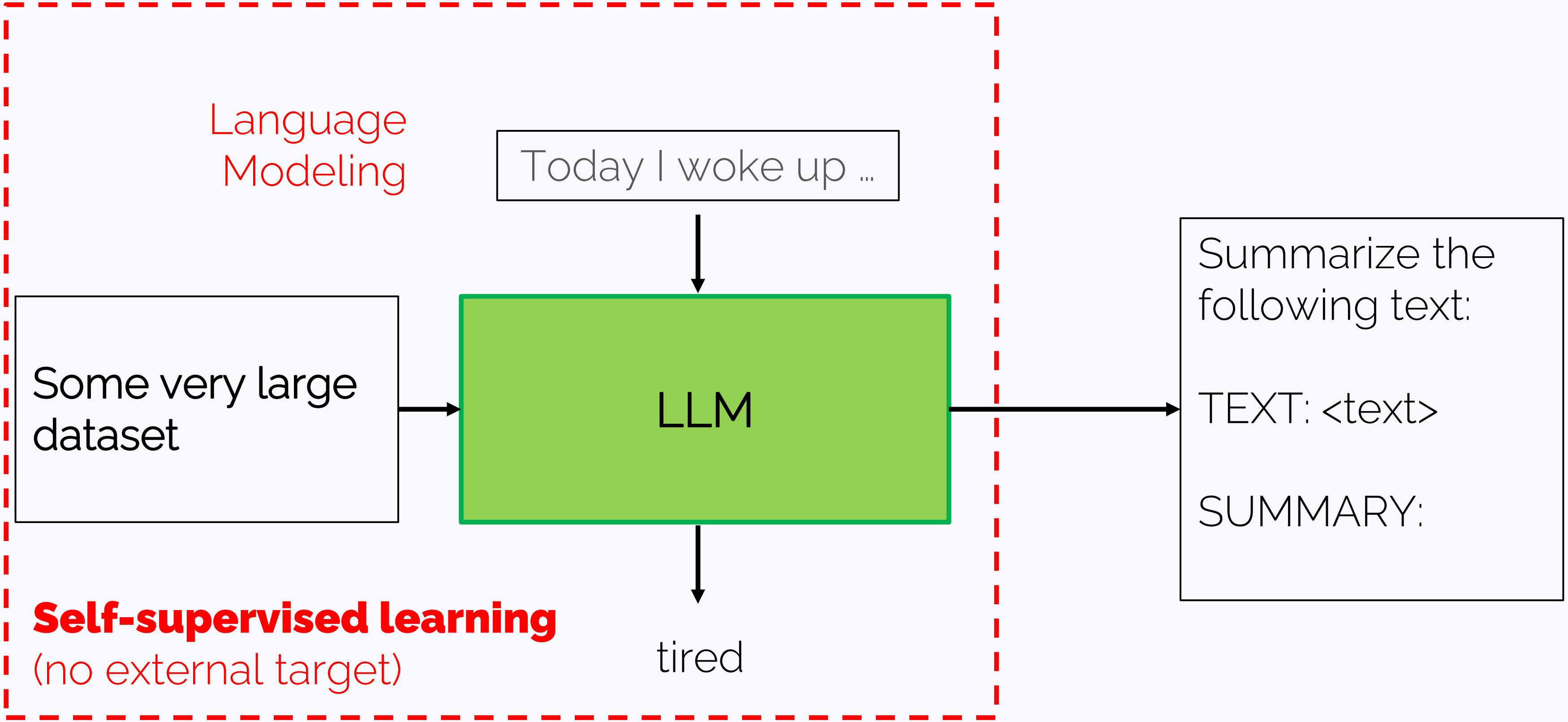
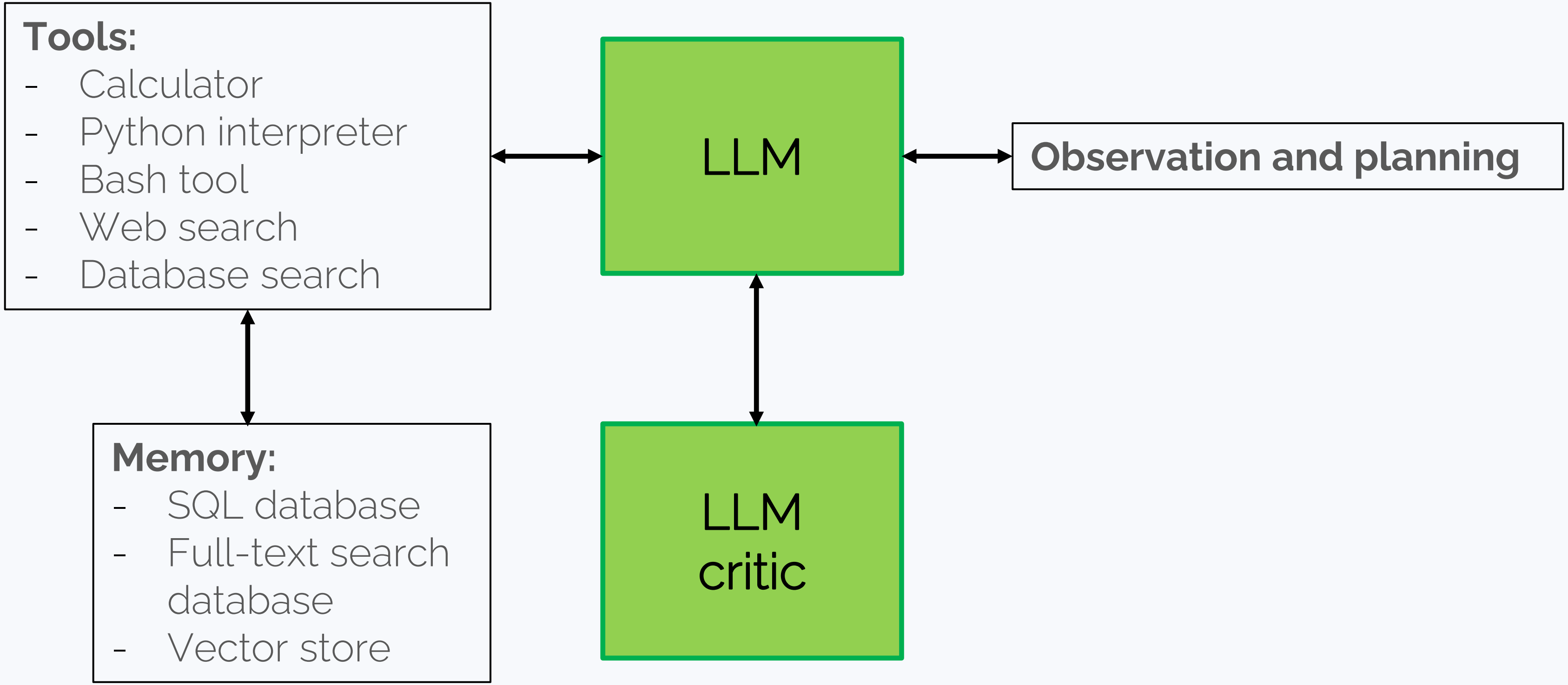


2022-onward: GenAI comes



2023-onward: LLM agents



What you should be aware of while working with LLMs

Format

Sometimes, it's hard to make an LLM give you a simple yes/no answer. You'll see that in the homework!

If you can do something with BERT, do it with BERT, not LLMs.

Hallucinations

Extrinsic. Factuality failures, like:

- Wrongly mentioning real-world facts.
- Inventing things that never existed,

Not to be confused with **knowledge cut-off**.

In-context. Getting confused about whatever was in the prompt.
The longer the prompt, the more likely hallucinations are.

If you can do something with BERT, do it with BERT, not LLMs.

What we have learnt today

- How to use LLM APIs and what features can save your money or speed up generation.
- What is Supervised Learning
- What is Self-Supervised Learning and how large pre-trained models contribute to today's ML
- What is the difference between generative and discriminative models
- What to keep in mind when working with LLMs

What we have learnt today

- How to use LLM APIs
- What is Supervised Learning
- What is Self-Supervised Learning
- How large pre-trained models changed ML
- What is the difference between generative and discriminative models
- What LLMs are capable of and what to keep in mind while working with them

Next time

- How to evaluate ML models: from precision and recall to LLM-as-a-Judge

- How to navigate the LLM zoo

- How few-shot examples, reasoning, critique, and chaining help LLMs with their jobs

- How to create an LLM agent that will delete all the files from your computer