Language Technology and Artificial Intelligence

Trends and perspectives

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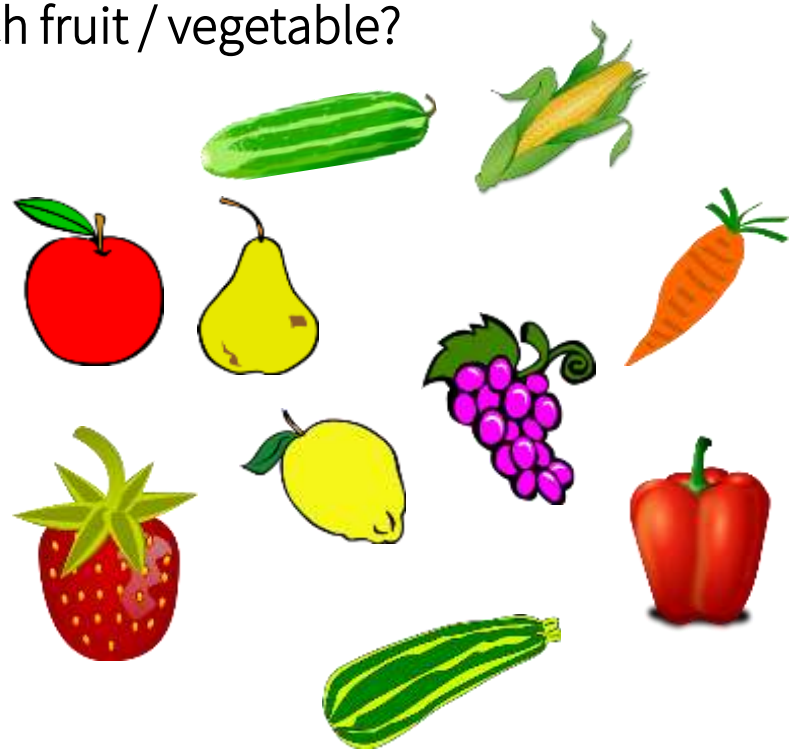
Neural networks
& Pre-trained language models

Classical Machine Learning: Predict Output Classes from Input Features

Camera

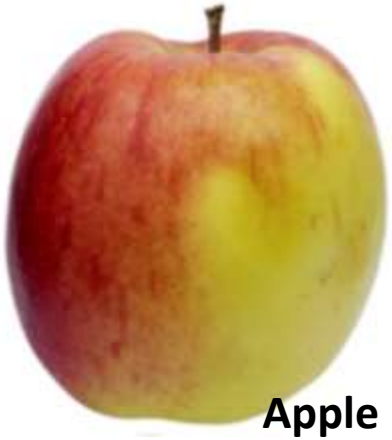
Which fruit / vegetable?



what are good features?

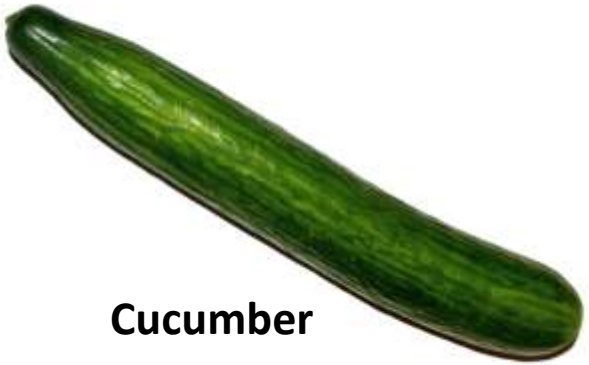
Predict Output Classes from Input Features

Output classes:



Apple

Tomato



Cucumber

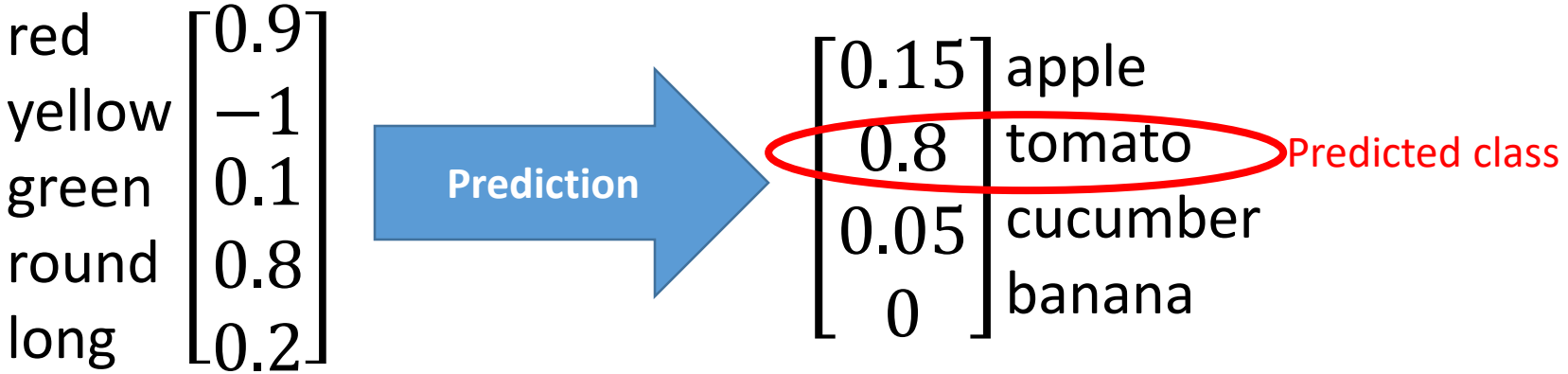
Banana

Features:

- **red**
- **yellow**
- **green**
- **round**
- **long**

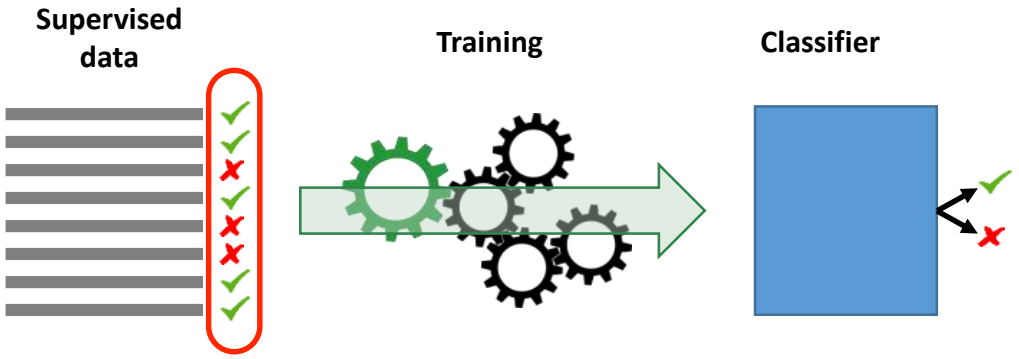
Predict Output Classes from Input Features

- We can represent inputs and outputs as vectors
  - **Input:** values of input features (``redness'', roundness, …)
  - **Output:** probability of every output class



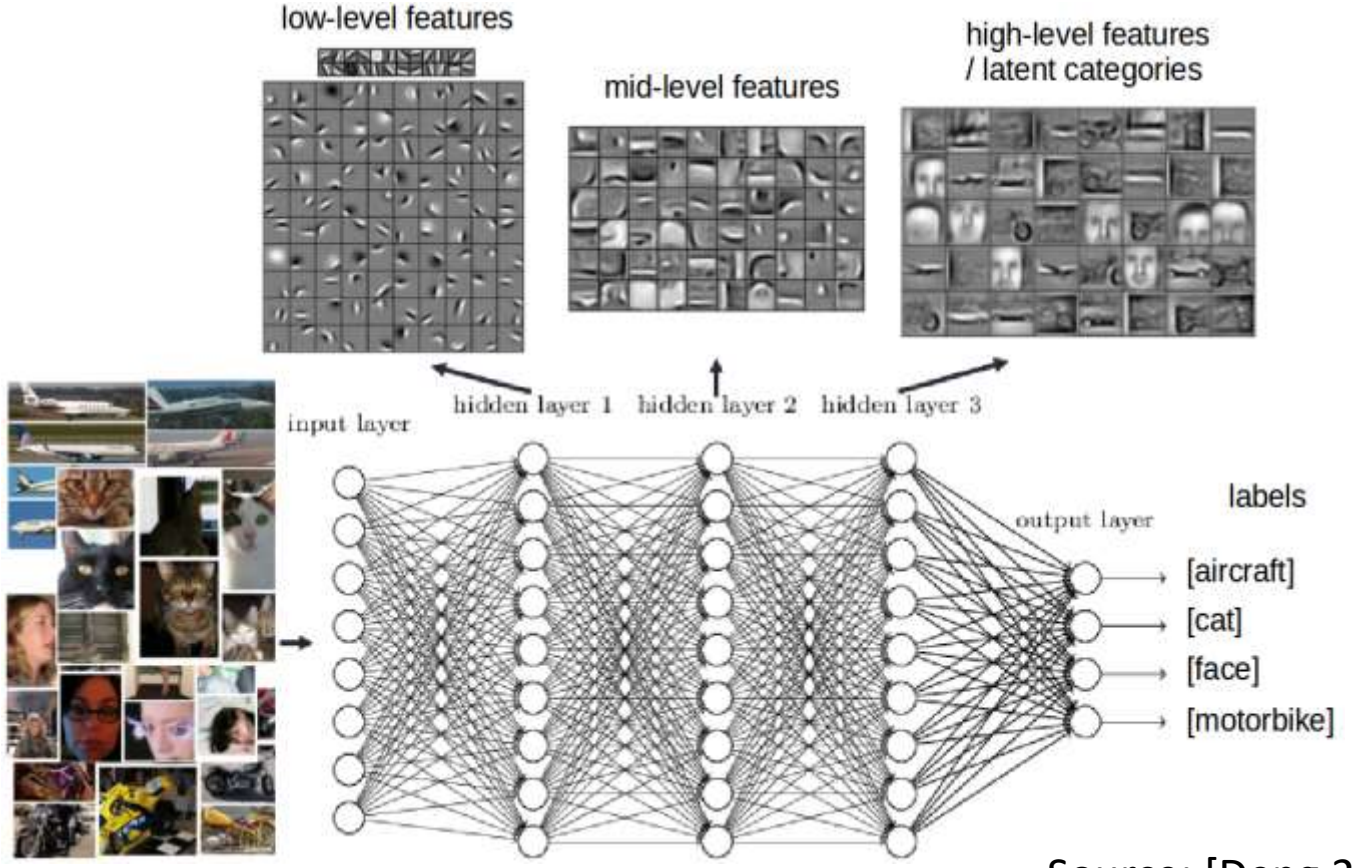
Training & Evaluation

- The training algorithm needs
  - **examples** to learn from
  - a way to **measure** whether it makes progress
- Annotation/labels:
  - Experts look at inputs, and **annotate** the correct output **labels**
  - Sometimes labels can be obtained as a side-product of some activity (Users move emails in SPAM folder)



Representation learning
= deep learning = neural networks

- **Raw input** instead of defined feature representation:
  - Images: Pixels
  - Text: Sequence of words or characters
- **Learn higher-level abstractions**

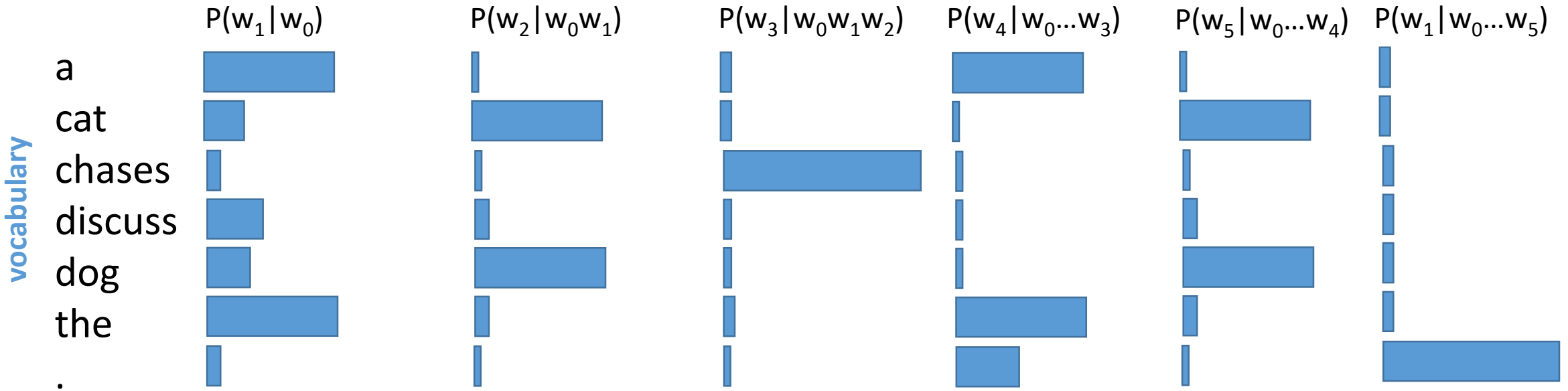


Source: [Deng 2009; Lee 2009]

What is a (statistical) language model? (LM)

- Statistical model that **predicts text** that fits well for a given **context** (typically also text)
  - Predict one **word** that is highly likely given a **prompt** (previous words)
  - For predicting an entire text, repeat the process (i.e., extend the prompt with previously predicted words)
  - To predict a text from scratch, use an extra symbol <START> as the initial prompt

Language model (toy example)



<START>	the	dog	chases	a	cat	.
w_0	w_1	w_2	w_3	w_4	w_5	w_6

Demo: GPT-3

- Popular language models:
  - BERT, trained on 3300M words (Wikipedia+BooksCorpus)
  - GPT-3, trained on 500000M words (CommonCrawl+Webtext2+Books+Wikipedia)
- GPT-3 [Brown 2020], https://openai.com/api/
- GPT-J, https://huggingface.co/EleutherAI/gpt-j-6B

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My name is Benjamin Roth, I am a researcher at the University of Vienna, specializing in Machine Learning and Digital Philology. Today I will talk about trends and perspectives of language technology and artificial intelligence.

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My name is Benjamin Roth, I am a researcher at the University of Vienna, specializing in Machine Learning and Digital Philology. Today I will talk about trends and perspectives of language technology and artificial intelligence.

First I will make a brief survey of trends in the development of language technology. I will look at the development of algorithms for language generation, language translation, parsing and language understanding. I will then say a few words about the future of artificial intelligence.

Language technology can be seen as the field of applications of artificial intelligence to language. It is not surprising that the development of language technology is driven by progress in artificial intelligence. The number of applications of language technology has increased dramatically in the last few years. The application areas cover important aspects of our society like education, commerce, business, government and entertainment.

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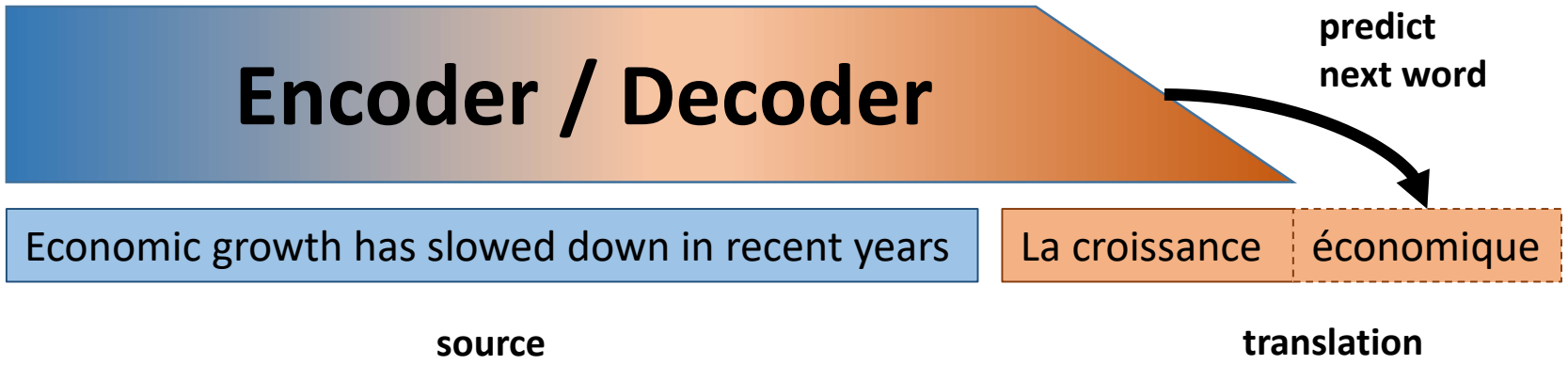
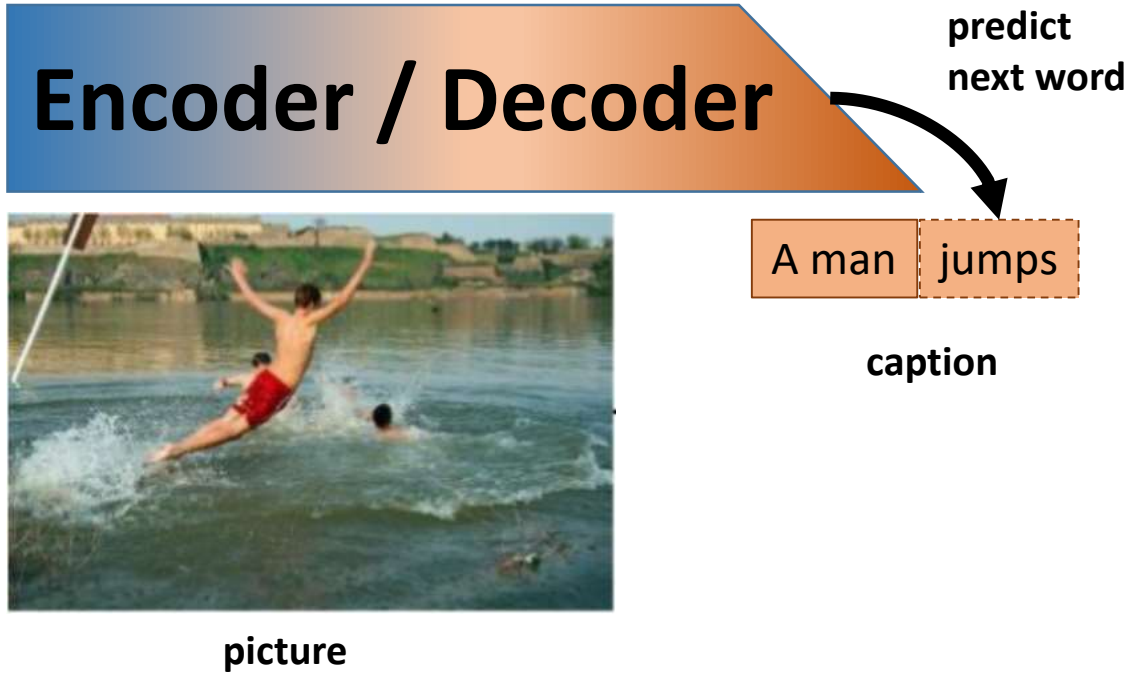
Neural Machine Translation



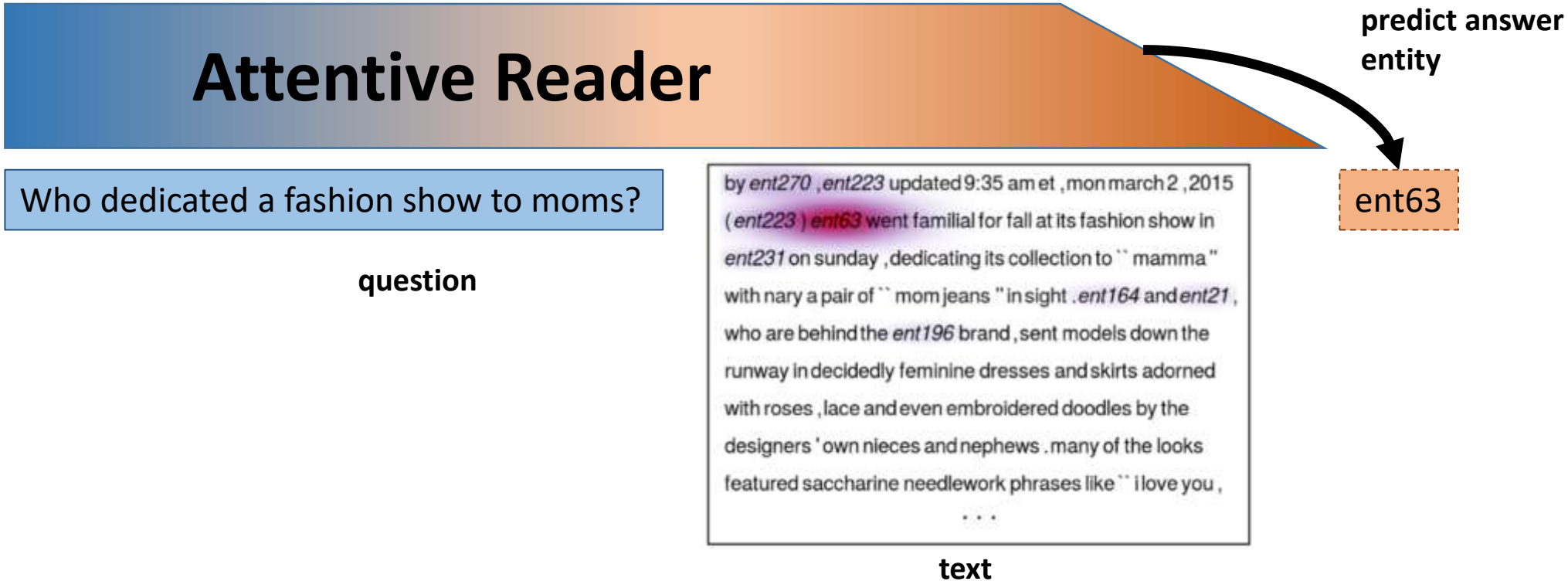
[Sutskever 2014; Bahdanau 2015; Vaswani 2017 …]

Image captioning



[Kiros 2014; Mao 2014; Xu 2015;…]

Question Answering



[Hermann 2015, Seo 2017, …]

Deep learning limitations (and how to overcome them)

- Lack of training data
  - → domain adaptation, transfer learning [Howard & Ruder 2018]
  - → unsupervised pre-training [Devlin 2018, Brown 2020]
- Difficulty to leverage human expertise
  - → combine with rule-based systems, weak supervision [Ratner 2017, Sedova 2021]
- Lack of insight
  - → Automated explanations [Poerner 2018, Sydorova 2019]

Perspectives & open problems

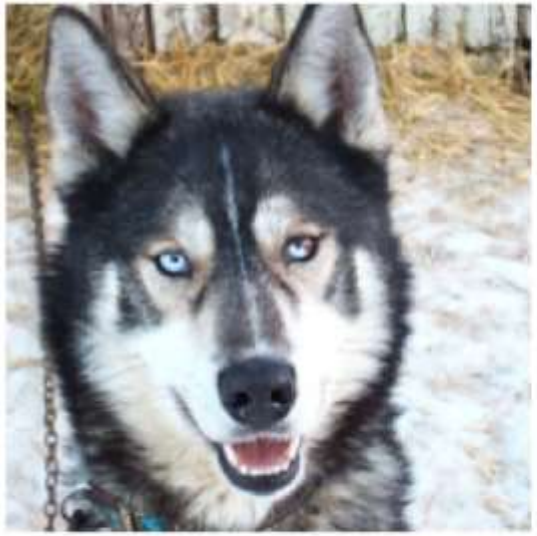
Statistical models = intelligence?

- **No.** ([Bender & Koller, 2020], tradition of [Searle, 1980])
  - Just repetition of already observed superficial patterns.
  - You wouldn't rely on a language model (or a parrot) on advice for fighting a bear.
  - **But:** The models **do** generalize to some degree.
- **Why not?**
  (e.g. Glue Benchmark [Wang 2019], tradition of [Turing, 1950])
  - Ultimately we need to rely on observed behaviour.
  - Define a task, and measure success rate on examples not seen in training.
  - Intelligence is task-specific, not a global property.

Transparent and explainable predictions

- Why is a husky classified as a wolf? (LIME [Ribeiro 2016])
- Why is a social media post classified as hate speech? (Hatecheck [Röttger 2021])
- Why is a loan approved or rejected?

→ Which explanations methods are reliable? [Poerner 2018, Sydorova 2019]



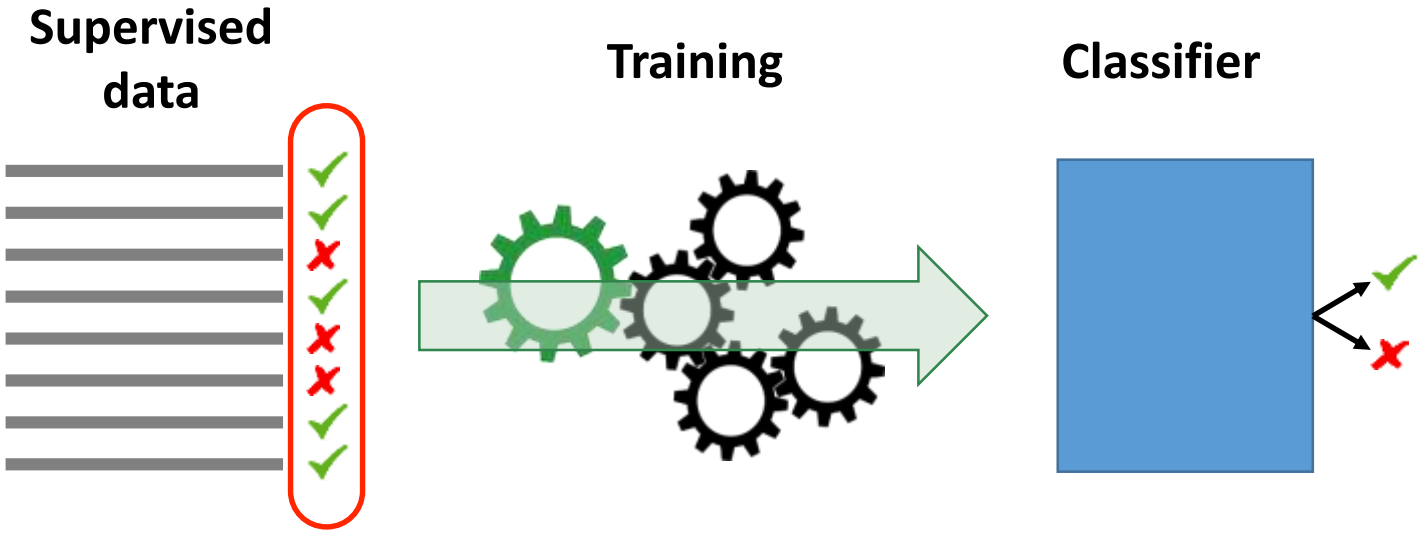
(a) Husky classified as wolf

(b) Explanation

- **Right to explanation** (EU GDPR Recital 71):
  - ``[safeguards include …] the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision.''

Expert knowledge or annotated data?

- Supervised training: learn a function that maps an input to an output based on labeled examples



But what if labels are not available?

→ Combine machine learning with expert knowledge encoded in Rules! [Sedova 2021]

knodle

Outlook

- Modern neural language models
  - leverage enormous amounts of data
  - on some tasks achieve performance not thought possible before
- These are exciting times!
- Now, we need to think more about
  - transparency, accountability and fairness
  - what we understand by *intelligence*
  - how to flexibly approach problems without training data

Thank you!
Questions?

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