

Lecture

Knowledge-based Systems

Part 4 – Pre-trained Language Models

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Exam

- In total 21 students have participated in the survey.
- The exam date is **01.08.2022 16:00 -18:00.**
- Die globale **Anmeldephase** läuft vom **02.05.2022** bis **13.05.2022**
- **Where?** I'll update you

Pooling exam date

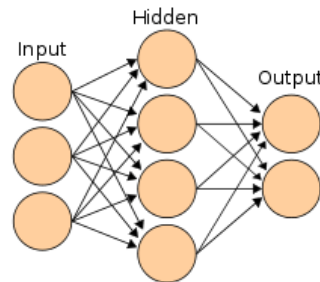
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Check all dates in which you can take the exam. The exam is schriftlich and takes 2 hours.

Response	Average	Total
01.08.2022 16:00-18:00	<div><div></div></div> 62%	13
02.08.2022 16:00-18:00	<div><div></div></div> 57%	12
03.08.2022 10:00-12:00	<div><div></div></div> 48%	10
Total responses to question	<div><div></div></div> 100%	21/21

Recall ...

- **What is (artificial) intelligence?** The ability to acquire and apply knowledge and skills to achieve complex goals.
- **Symbolic:** Knowledge is encoded by symbols that refer to the knowledge.
- **connectionist:** Knowledge is **embedded** in parameters of a model.



Any other open questions?



In this lecture, you learn about ...

- **Pretrained language models (LMs)**
 - Unidirectional
 - Bidirectional
- **LMs as knowledge base**
 - LMs and factual knowledge
 - LMs and linguistic knowledge
 - LMs and word sense knowledge

Unidirectional Language Models

- Given an input sequence of tokens $\mathbf{w} = [w_1, w_2, \dots, w_N]$, unidirectional language models assign a probability $p(\mathbf{w})$ to the sequence.
- This probability is calculated as follows

$$p(\mathbf{w}) = \prod_t p(w_t | w_{t-1}, \dots, w_1).$$

Example

$$\begin{aligned} P_{(w_1, w_2, \dots, w_n)} &= p(w_1)p(w_2|w_1)p(w_3|w_1, w_2)\dots p(w_n|w_1, w_2, \dots, w_{n-1}) \\ &= \prod_{i=1}^n p(w_i|w_1, \dots, w_{i-1}) \end{aligned}$$

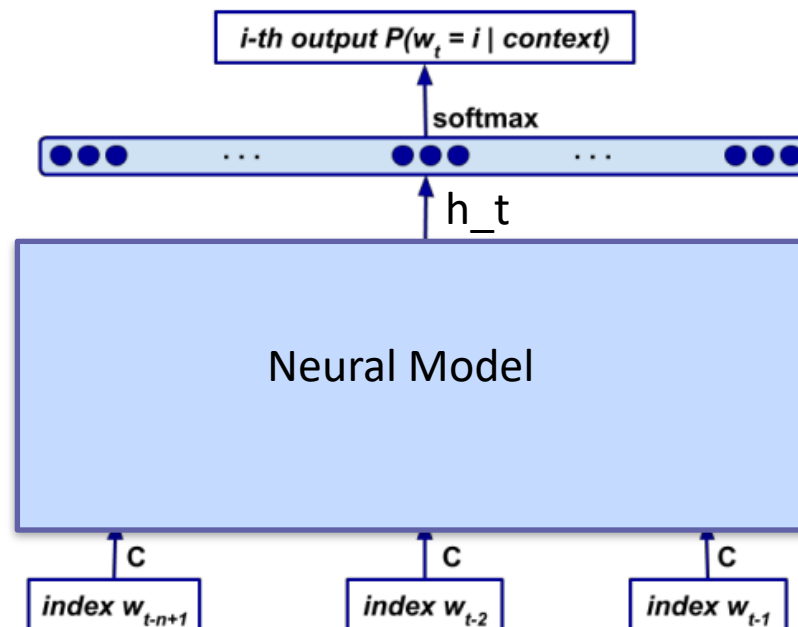
S = Where are we going

The diagram illustrates the context and the word being predicted. A bracket under the words 'Where are we' is labeled 'Previous words (Context)'. An arrow points from this bracket to the word 'going', which is labeled 'Word being predicted'.

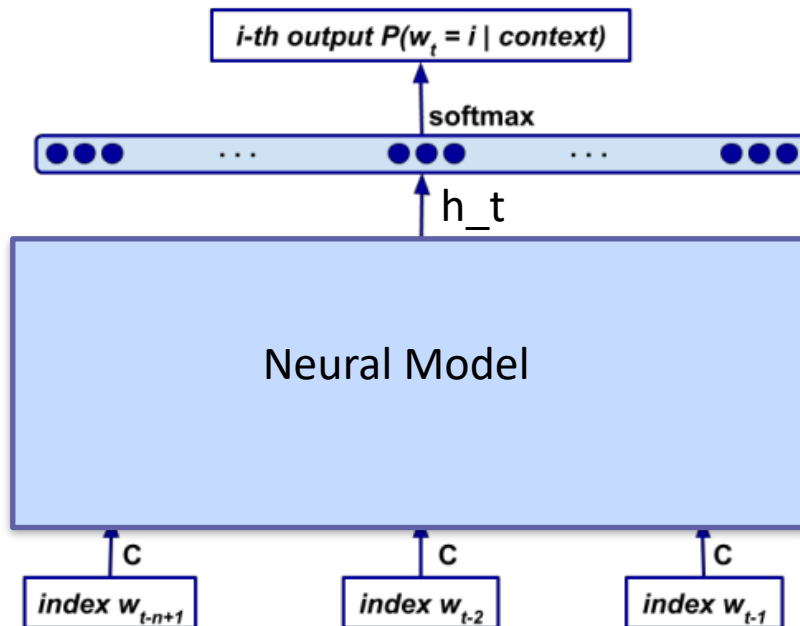
$$P(S) = P(\text{Where}) \times P(\text{are} \mid \text{Where}) \times P(\text{we} \mid \text{Where are}) \times P(\text{going} \mid \text{Where are we})$$

How to get the probability?

- There are different ways to define the probability function
 - $p(w_t | w_{(t-1)}, \dots, w_1)$
- State-of-the-art LMs use deep neural models and softmax to estimate the probability



More formally

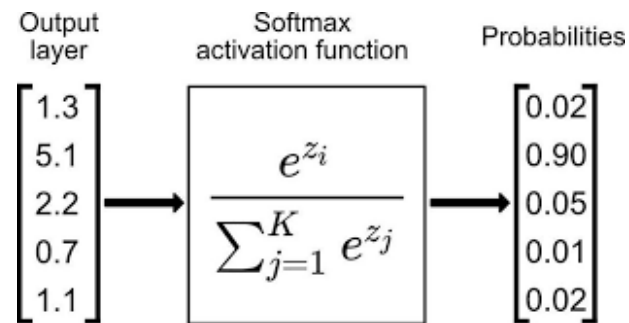


$$p(w_t \mid w_{t-1}, \dots, w_1) = \text{softmax}(\mathbf{W}\mathbf{h}_t + \mathbf{b})$$

parameter of the output layer

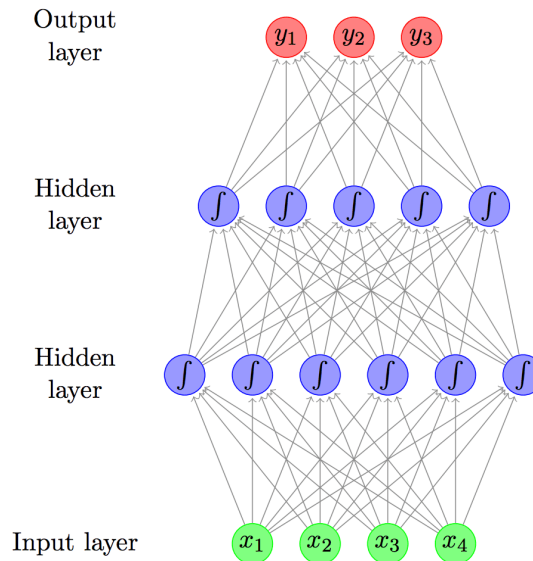
output vector of a neural network at position t

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$



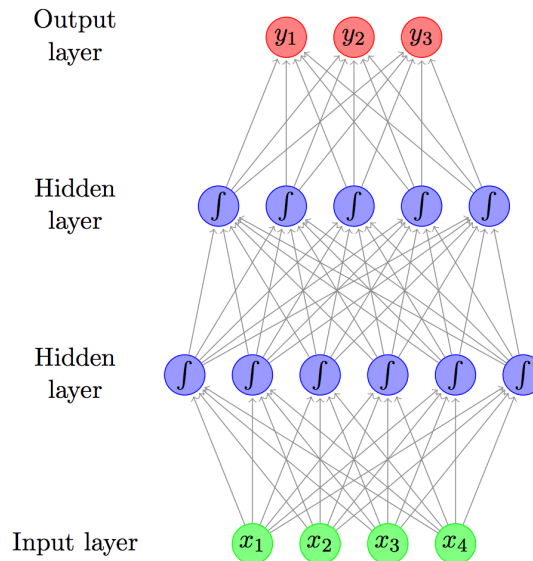
Knowledge is embedded

- The knowledge about words and their relations in a language is encoded in the parameters (connections) of the neural language model



Knowledge is embedded

- The knowledge about words and their relations in a language is encoded in the parameters (connections) of the neural language model



Today, we assume that the model already knows the knowledge. The model is **pretrained**.
“How to train LMs” is what we discuss in next lectures.

Architecture of Neural Language Models

- The difference in the neural language models is in how they compute h_t
- Different architectures have been explored
 - Multi-layer-perceptron
 - Convolutional layers
 - Recurrent neural networks
 - Transformers (self-attention mechanism)

Examples of unidirectional LM

- **Fairseq-fconv** (<http://proceedings.mlr.press/v70/dauphin17a.html>)
 - Convolutional neural model
- **Transformer-XL** (<https://arxiv.org/abs/1901.02860>)
 - Transformer-based model

Bidirectional Language Models

- In many downstream applications we mostly care about having access to contextual representations of words,
- word representations are a function of the **entire context** of a unit of text such as a sentence or paragraph, and not only conditioned on previous words.

$$p(w_i) = p(w_i | w_1, \dots, w_{i-1}, w_{i+1}, \dots, w_N)$$

Examples of Bidirectional LM

- **ELMo** (<https://allenai.org/allennlp/software/elmo>)
 - Deep RNN-based LM
 - At each layer, one LSTM processes words from left to right, the other processes words from right to left)
- **BERT**
 - Transformer-based LM
 - Uses self-attention mechanism to condition representations of a word on its left and right context
- **BART**
 - Transformer-based LM
- **RoBERTa**
 - Transformer-based LM
- **GPT**
 - Transformer-based LM



Practice I

- Use google Colab (<https://colab.research.google.com>)
 - More information (<https://huggingface.co/course/chapter0/1>)
- Try out 20 different contexts to see what words BERT suggests for the next word
 - <https://rb.gy/3k5bsc>

- We observed that symbolic KB can give us factual knowledge about world
- **Google RE:** place_of_death, date_of_birth, education_degree, place_of_birth (<https://code.google.com/archive/p/relation-extraction-corpus/>)



LM and factual knowledge

- Define a template to query LMs
 - place_of_death → [S] died in [O]

```
▶ result = unmasker(" Diego de Arroyo died in [MASK].")  
print([r["token_str"] for r in result])
```

```
↳ ['madrid', 'manila', 'lima', 'seville', 'barcelona']
```

Practice II

- Use your notebook in Google Colab (<https://colab.research.google.com>)
- Download the **Google RE dataset** (<https://code.google.com/archive/p/relation-extraction-corpus/>)
 - Focus on “**place of birth**”, “**date of birth**” and “**place of death**” relations
 - **How many facts do exist for each relation?**
- Define **a template for each relation** to query a LM
- Select a LM, e.g. BERT, RoBERTA, ELMo, ...
- **For how many facts does the selected LM return the correct value?**
 - **compute P@1**
 - P@k: Is the correct value among the k top outputs that the LM returns?
- Write a report in overleaf **without screen shots**

- **ConceptNet**
 - a multi-lingual knowledge base,
 - built on top of Open Mind Common Sense (OMCS) sentences
 - OMCS represents commonsense relationships between words and/or phrases
 - English part of ConceptNet has single-token objects covering 16 relations
 - For this knowledge source there is no explicit alignment of facts to Wikipedia sentences.

LMs and commonsense relationships between words

- ConceptNet

-

ConceptNet	AtLocation	You are likely to find a overflow in a ____.	drain	sewer [-3.1], canal [-3.2], toilet [-3.3], stream [-3.6], drain [-3.6]
	CapableOf	Ravens can ____.	fly	fly [-1.5], fight [-1.8], kill [-2.2], die [-3.2], hunt [-3.4]
	CausesDesire	Joke would make you want to ____.	laugh	cry [-1.7], die [-1.7], laugh [-2.0], vomit [-2.6], scream [-2.6]
	Causes	Sometimes virus causes ____.	infection	disease [-1.2], cancer [-2.0], infection [-2.6], plague [-3.3], fever [-3.4]
	HasA	Birds have ____.	feathers	wings [-1.8], nests [-3.1], feathers [-3.2], died [-3.7], eggs [-3.9]
	HasPrerequisite	Typing requires ____.	speed	patience [-3.5], precision [-3.6], registration [-3.8], accuracy [-4.0], speed [-4.1]
	HasProperty	Time is ____.	finite	short [-1.7], passing [-1.8], precious [-2.9], irrelevant [-3.2], gone [-4.0]
	MotivatedByGoal	You would celebrate because you are ____.	alive	happy [-2.4], human [-3.3], alive [-3.3], young [-3.6], free [-3.9]
	ReceivesAction	Skills can be ____.	taught	acquired [-2.5], useful [-2.5], learned [-2.8], combined [-3.9], varied [-3.9]
	UsedFor	A pond is for ____.	fish	swimming [-1.3], fishing [-1.4], bathing [-2.0], fish [-2.8], recreation [-3.1]

Practice III

Add text cell

```
result = unmasker("Birds have [MASK].")  
print([r["token_str"] for r in result])
```

```
['wings', 'eyes', 'feathers', 'nectar', 'nests']
```

Linguistics knowledge

- subject-verb agreement in English

```
▶ result = unmasker("the game that the guard hates [MASK] bad .")  
print([r["token_str"] for r in result])
```

```
['is', 'was', 'the', 'goes', 'sounds']
```


Practice IV

- How to get dataset for subject-verb agreement?
 - Go to wikipedia or any other textual corpus in NLTK
 - Extract 1000 sentences
 - Mask all verbs
 - How to automatically find which word is a verb? Use NLTK or SpaCy
- https://github.com/BeckyMarvin/LM_syneval
- For how many sentences your LM returns a verb that is in agreement with its subject? Report P@1
- Write a paragraph about this experiment in overleaf.

Linguistics knowledge

- **Anaphora**
 - “**Tina** went to bed as soon as **she** reached home”,
 - both Tina and she refer to the same person.
 - Tina is called an “**antecedent**” and she an “**anaphor**”.

Linguistics knowledge

- **Reflexive anaphora**

- are those that use reflexive pronouns, i.e., pronouns that end in –self or –selves.
- When a sentence's subject and object refers to the same individual, we use reflexive anaphora
 - "*Peter shot **himself** in the foot.*"
 - "*Peter bounced the ball to **himself**."*
 - "*Amy and Lizzie cried **themselves** to sleep.*"

- Reflexive Anaphora

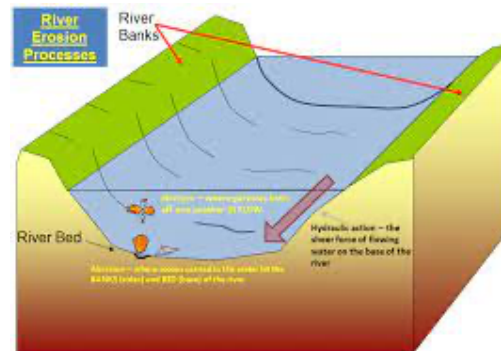
```
▶ result = unmasker("Amy and Lizzie cried [MASK] to sleep.")  
print([r["token_str"] for r in result])
```

```
↳ ['themselves', 'herself', 'me', 'them', 'him']
```

LMs and word sense knowledge

- The word sense disambiguation (WSD) task is typically formulated as labeling words in context with their senses as defined by a dictionary or other lexical resource.

“The **bank** will not be accepting cash on Saturdays.”



LMs and word sense knowledge

- Many resources exist to support work on word senses.
- **WordNet**
 - Provides a fine-grained and comprehensive inventory of words and their senses for English.
- Several large annotated corpora have been constructed using WordNet senses,
 - SemCor
 - OntoNotes: has sense annotations for nouns and verbs,
 - Pattern Dictionary of English Prepositions (PDEP) corpus

LMs and word sense knowledge

```
[58] result = unmasker("The bank will not be accepting cash on Saturdays. bank is a [MASK].")  
      print([r["token_str"] for r in result])
```

```
['bank', 'failure', 'banks', 'mistake', 'business']
```

```
▶ result = unmasker("The river overflowed the bank. bank is a [MASK].")  
  print([r["token_str"] for r in result])
```

```
↳ ['river', 'bank', 'lake', 'pond', 'wall']
```

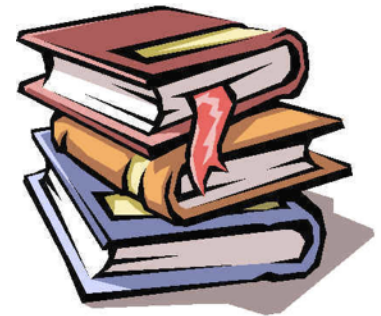
Summary

- **Pretrained language models (LMs)**
 - Unidirectional
 - Bidirectional
- **LMs as knowledge base**
 - LMs and factual knowledge
 - LMs and linguistic knowledge
 - LMs and word sense knowledge

Readings

Mandatory

- <https://aclanthology.org/D19-1250.pdf>
- <https://arxiv.org/pdf/1901.05287.pdf>
- <https://aclanthology.org/2021.blackboxnlp-1.43.pdf>



Practice V

- Use your notebook in Google Colab (<https://colab.research.google.com>)
- Play with embeddings of some words
- <https://www.shanelynn.ie/word-embeddings-in-python-with-spacy-and-gensim/>
- **Check the relation between countries and cities**
- **The word representation of which word is the nearest to the output vector of $v(\text{king}) - v(\text{man}) + v(\text{woman})$?**
- Relations between words in a language can be mapped to mathematical relations between their embeddings in an embedding space

Practice VI

- Open GPT-3 playground: <https://beta.openai.com/playground>
- Give it some hints (a.k.a prompts) and let it complete the rest of the text?
“This is a text about knowledge base systems. We aim at “
- Does it look knowledgeable?
- Test it for various properties of knowledge bases
 - *“Tail is part of a cat. Is this claim valid?”*
 - *“Birds can fly. is it correct?” Vs “Birds cannot fly. is it correct?”*
 - *“Musician is part of orchestra. Arm is par of a musician. Can we claim that arm is part of orchestra?”*
- **Find an example that GPT-3 does not have any knowledge about?**