Advanced NLP Tasks

Contents

- 1. Named Entity Recognition (NER)
 - a. Part-of-Speech Tagging (POS)
 - b. Conditional Random Field (CRF)
- 2. Sentiment Analysis
- 3. QuestionAnswering (QA)
- 4. Natural Language Inference (NLI)
 - a. Going further: LM as knowledge graphs
- 5. Exploit LLMs capacities: Chain-of-thoughts & In context learning

Named Entity Recognition (NER)

NER

Named entity recognition (NER), aims at identifying real-world entity mentions from texts, and classifying them into predefined types.

Gold Dataset

Suxamethonium infusion rate and observed fasciculations.

Suxamethonium chloride (Sch) was administred i.v.

NER

We wish to predict an output vector $\mathbf{y}=(y_1,y_1,\ldots,y_L)$, of random variables, given an observed characteristic vector

$$\mathbf{x} = (x_1, x_2, \ldots, x_L)$$

y takes it value from a list of N possible values.

Part-of-Speech Tagging (POS)

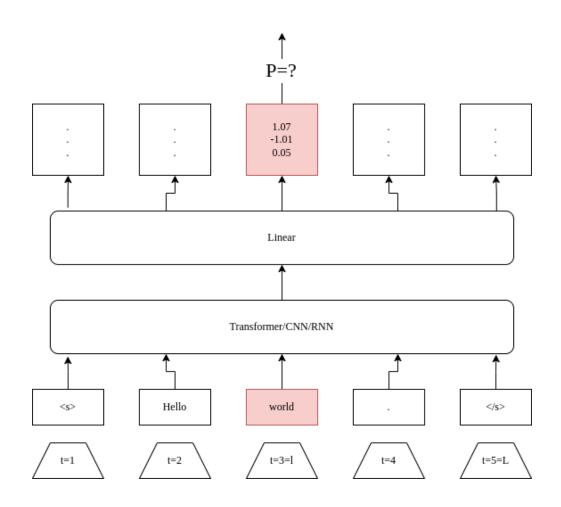
POS is the process of mapping words in a text with a label corresponding to their grammatical class.

```
("He", "likes", "to", "drink", "tea"), \rightarrow ("PERSONAL PRONOUN", "VERB", "TO", "VERB", "NOUN").
```

Part-of-Speech Tagging (POS)

There several levels of granularity.: using the tag set for english

("He", "likes", "to", "drink", "tea"), \rightarrow ("PRP", "VBP", "TO", "VB", "NN").



For each token in a sentence at position l we want to compute a probability p to belong to a class n.

$$p: f(\mathbf{x}, \theta)_l \mapsto ?$$

with $p \in [0,1]$

Using the softmax function?

$$p:f(\mathbf{x}, heta)_l^{\mapsto}rac{e^{f(\mathbf{x}, heta)_l^{(n)}}}{\sum_{n'=1}^N e^{f(\mathbf{x}, heta)_l^{(n')}}}$$

The probability given by the softmax function will not encode non-local dependencies!

We need to take sequential decisions: what if we add transition scores into our softmax?

$$p: f(\mathbf{x}, heta)_l \mapsto rac{e^{f(\mathbf{x}, heta)_l^{(n)} + t(y_l^{(n)}, y_{l-1})}}{\sum_{n'=1}^N e^{f(\mathbf{x}, heta)_l^{(n')} + t(y_l^{(n')}, y_{l-1})}}$$

But this is the probability for one token to belong to a class, we want to compute the probability of a whole sequence of label at once...

$$P(\mathbf{y}|\mathbf{x}) = \prod_{l=2}^{L} p(\mathbf{y}|f(\mathbf{x}, heta)_l)$$

$$=\prod_{l=2}^{L}rac{e^{f(\mathbf{x}, heta)_{l}^{(n)}+t(y_{l}^{(n)},y_{l-1})}}{\sum_{n'=1}^{N}e^{f(\mathbf{x}, heta)_{l}^{(n')}+t(y_{l}^{(n')},y_{l-1})}}$$

$$P(\mathbf{y}|\mathbf{x}) = rac{exp[\sum_{l=2}^{L} \left(f(\mathbf{x}, heta)_{l}^{(n)} + t(y_{l}^{(n)}, y_{l-1})
ight)]}{\sum_{n'=1}^{N} exp[\sum_{l=2}^{L} \left(f(\mathbf{x}, heta)_{l}^{(n')} + t(y_{l}^{(n')}, y_{l-1})
ight)]}$$

$$=rac{exp[\sum_{l=2}^{L}\left(U(\mathbf{x},y_{l}^{(n)})+T(y_{l}^{(n)},y_{l-1})
ight)]}{\sum_{n'=1}^{N}exp[\sum_{l=2}^{L}\left(U(\mathbf{x},y_{l}^{(n')})+T(y_{l}^{(n')},y_{l-1})
ight)]}$$

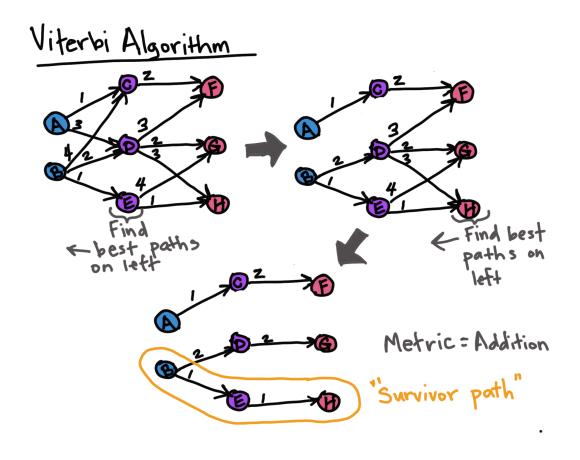
$$=rac{exp[\sum_{l=2}^L \left(U(\mathbf{x},y_l^{(n)})+T(y_l^{(n)},y_{l-1})
ight)]}{Z(\mathbf{x})}$$

 $Z(\mathbf{x})$ is commonly referred as the partition function. However, its not trivial to compute: we'll end up with a complexity of $\mathcal{O}(N^L)$.

Where N is the number of possible labels and L the sequence length.

How do we proceed?

14



NER Transition Matrix

B

C(B=3) C(B=1) C(B=20)

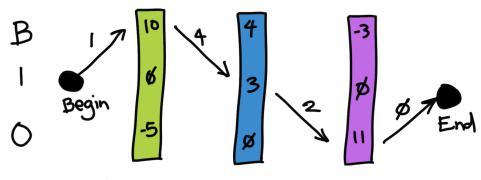
C(1=20) C(1=20)

C(0=20)

C= cost function

$$\infty$$
 = wouldn't happen

Linear-Chain CRF Decoded



Python comments help

Best path: B > 1 > 0 Best score: 1+10+4+3+2+11+10=31

Negative log-likelihood:

$$egin{aligned} \mathcal{L} &= -log(P(\mathbf{y}|\mathbf{x})) \ &= -log(rac{exp[\sum_{l=2}^{L} \left(U(\mathbf{x}, y_l^{(n)}) + T(y_l^{(n)}, y_{l-1})
ight)]}{Z(\mathbf{x})}) \ &= -[log(exp[\sum_{l=2}^{L} \left(U(\mathbf{x}, y_l^{(n)}) + T(y_l^{(n)}, y_{l-1})
ight)]) - log(Z(\mathbf{x}))] \ &= log(Z(\mathbf{x})) - \sum_{l=2}^{L} \left(U(\mathbf{x}, y_l^{(n)}) + T(y_l^{(n)}, y_{l-1})
ight)) \end{aligned}$$

There is an effective way to compute $log(Z(\mathbf{x}))$ with a complexity of $\mathcal{O}(L)$ using the Log-Sum-Exp trick.

$$egin{aligned} log(Z(\mathbf{x})) &= log(\sum_{n'=1}^{N} exp[\sum_{l=2}^{L} \left(U(\mathbf{x}, y_{l}^{(n')}) + T(y_{l}^{(n')}, y_{l-1})
ight)]) \ &= c + log(\sum_{n'=1}^{N} exp[\sum_{l=2}^{L} \left(U(\mathbf{x}, y_{l}^{(n')}) + T(y_{l}^{(n')}, y_{l-1})
ight) - c]) \end{aligned}$$

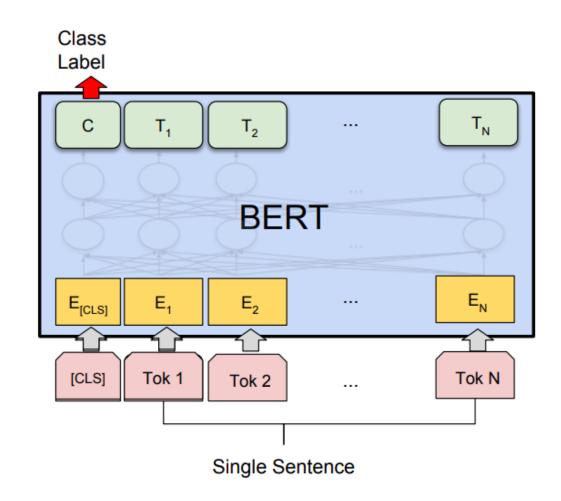
19

If we fix

$$c=max\{U(\mathbf{x},y_l^{(1)})+T(y_l^{(1)},y_{l-1}),\ldots,U(\mathbf{x},y_l^{(N)})+T(y_l^{(N)},y_{l-1})\}$$
 we ensure that the largest positive exponentiated term is $exp(0)=1$.

Sentiment analysis is a sentence classification task aiming at **automatically mapping data to their sentiment**.

It can be **binary** classification (e.g., positive or negative) or **multiclass** (e.g., enthusiasm, anger, etc)



The loss can be the likes of cross-entropy (CE), binary cross-entropy (BCE) or KL-Divergence (KL).

$$\mathcal{L}_{CE} = -rac{1}{N}\sum_{n'=1}^{N}y^{(n)}.\,log(f(\mathbf{x}, heta)^{(n)})$$

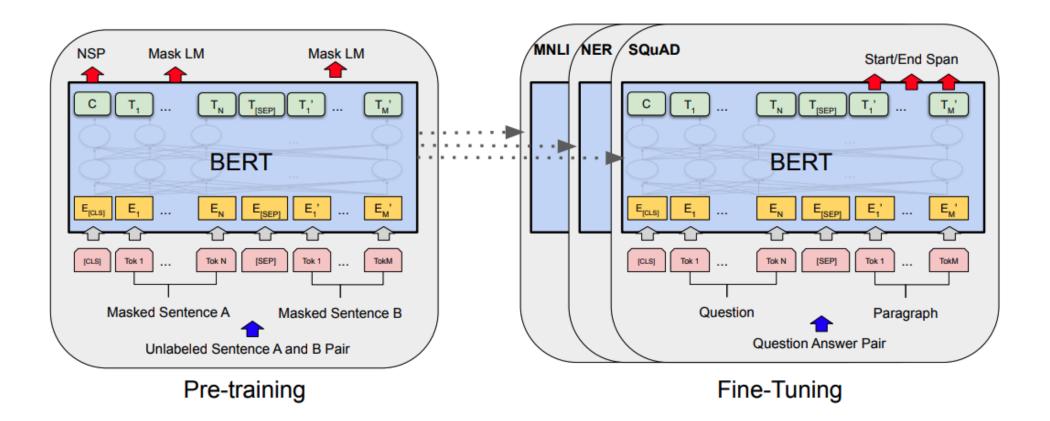
$$\mathcal{L}_{BCE} = -y^{(n)}.\,log(f(\mathbf{x}, heta)^{(n)}) + (1-y^{(n)}).\,(1-f(\mathbf{x}, heta)^{(n)})$$

$$\mathcal{L}_{KL} = -rac{1}{N} \sum_{n'=1}^{N} y^{(n)}.log(rac{y^{(n)}}{f(\mathbf{x}, heta)^{(n)}})$$

24

QA is the task of **retrieving a span of text from a context** that is best suited to answer a question.

This task is extractive -> information retrieval





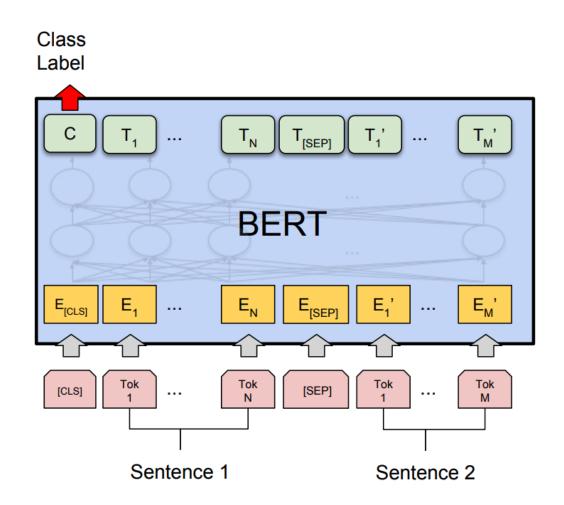
The loss is the cross entropy over the output of the starting token and the ending one:

$$\mathcal{L}_{CE_{QA}} = \mathcal{L}_{CE_{start}} + \mathcal{L}_{CE_{end}}$$

NLI is the task of **determining whether a "hypothesis" is true** (entailment), false (contradiction), or undetermined (neutral) given a "premise". [1]

Premise	Label	Hypothesis
A man inspects the uniform of a figure in some East Asian country.	contradiction	The man is sleeping.
An older and younger man smiling.	neutral	Two men are smiling and laughing at the cats playing on the floor.
A soccer game with multiple males playing.	entailment	Some men are playing a sport.

32



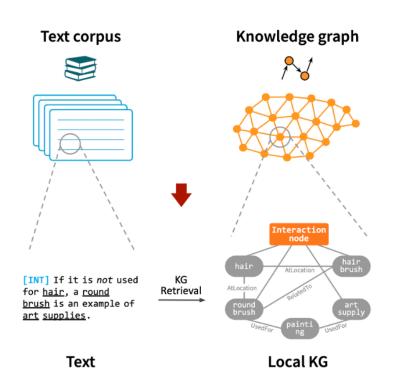
The loss is simply the cross entropy or the divergence over the output of the CLS token and the true label.

$$\mathcal{L}_{NLI} = \mathcal{L}_{CE_{CLS}}$$

We are trying to compress the information about both sentence in one CLS token via attention and decide about their relationship.

Is it possible to help the model infering more information with les text data?

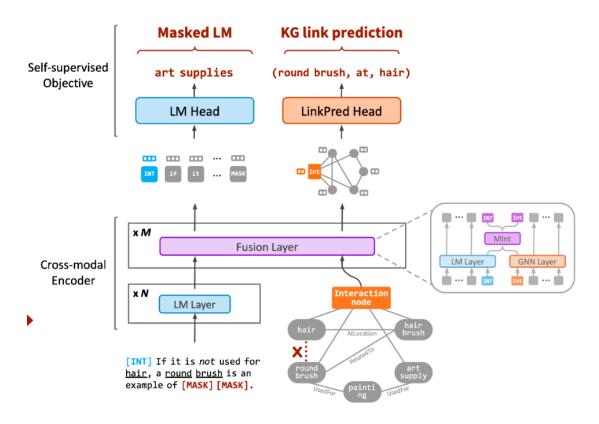
Yasunaga, M., Bosselut, A., Ren, H., Zhang, X., Manning, C. D., Liang, P. S., & Leskovec, J. (2022). <u>Deep bidirectional language-knowledge</u> graph pretraining. Advances in Neural Information Processing Systems, 35, 37309-37323.



Raw data

Course 6: Advanced NLP Tasks

36



Pretrain

This architecture *involves a KG ready to use beforeheaad and pre-training from scratch*. How can we better **perform NLP task without having to retrain or fine-tune** a model?

Exploit LLMs capacities: Chain-of-thoughts & In context Learning

ICL enables LLMs to learn new tasks using natural language prompts without explicit retraining or fine-tuning.

The efficacy of ICL is closely tied to the model's scale, training data quality, and domain specificity.

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French: 

sea otter => loutre de mer 

peppermint => menthe poivrée

plush girafe => girafe peluche

cheese => 

prompt
```

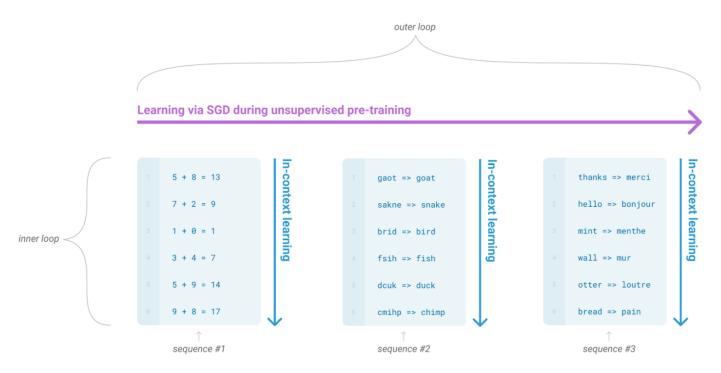


Figure 1.1: Language model meta-learning. During unsupervised pre-training, a language model develops a broad set of skills and pattern recognition abilities. It then uses these abilities at inference time to rapidly adapt to or recognize the desired task. We use the term "in-context learning" to describe the inner loop of this process, which occurs within the forward-pass upon each sequence. The sequences in this diagram are not intended to be representative of the data a model would see during pre-training, but are intended to show that there are sometimes repeated sub-tasks embedded within a single sequence.

$$p(\mathsf{output}|\mathsf{prompt}) = \int_{\mathsf{concept}} p(\mathsf{output}|\mathsf{concept},\mathsf{prompt}) p(\mathsf{concept}|\mathsf{prompt}) d(\mathsf{concept}). \tag{1}$$

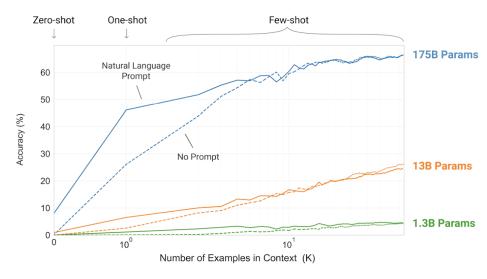


Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning curves" for large models demonstrate improved ability to learn a task from contextual information. We see qualitatively similar behavior across a wide range of tasks.

(a) Few-shot

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A:

(Output) The answer is 8. X

(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: The answer (arabic numerals) is

(Output) 8 X

(b) Few-shot-CoT

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A

(Output) The juggler can juggle 16 balls. Half of the balls are golf balls. So there are 16 / 2 = 8 golf balls. Half of the golf balls are blue. So there are 8 / 2 = 4 blue golf balls. The answer is 4. ✓

(d) Zero-shot-CoT (Ours)

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: Let's think step by step.

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.

Questions?

References

[1] https://paperswithcode.com/task/natural-language-inference