02 – Language modelling

IA161 Natural Language Processing in Practice

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1. Introduction to Language Modelling

2. N-grams

3. Evaluation of Language Models

4. Neural Networks and Language Modelling

5. Practical part: generating random texts

Language models—what are they good for?

- assigning scores to sequencies of words
- predicting words
- generating text

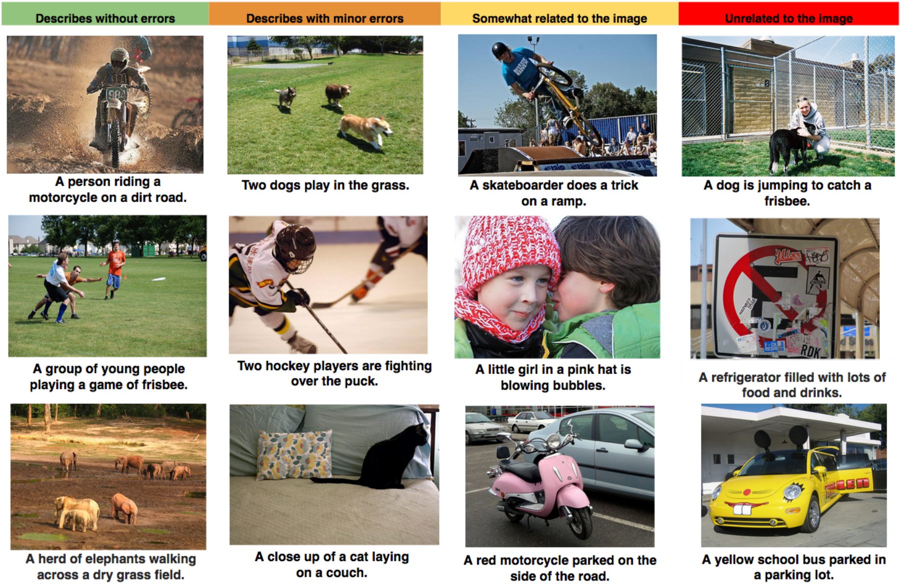
⇒

- statistical machine translation
- automatic speech recognition
- optical character recognition

Predicting words

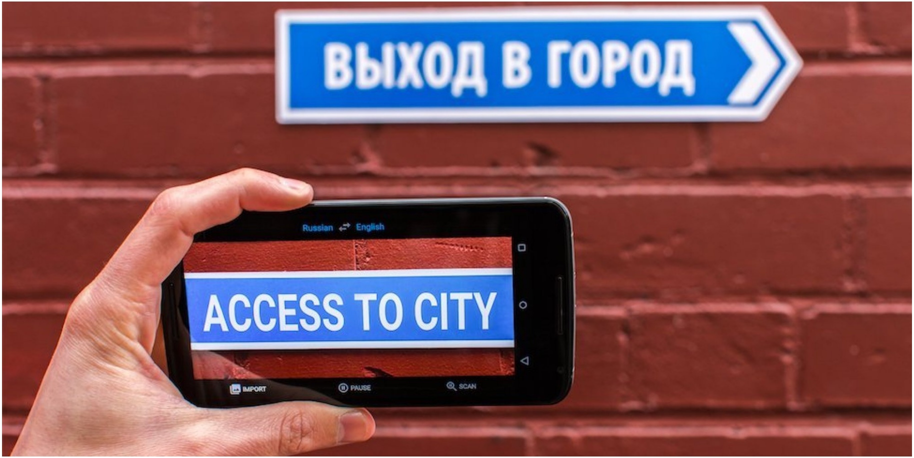
Do you speak ...
Would you be so ...
Statistical machine ...
Faculty of Informatics, Masaryk ...
WWII has ended in ...
In the town where I was ...
Lord of the ...

Generating text

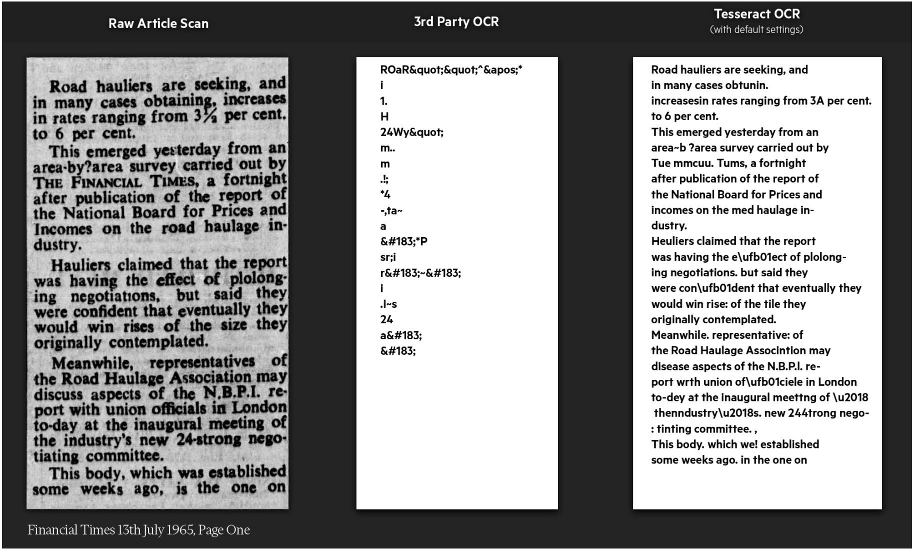


Describes without errors	Describes with minor errors	Somewhat related to the image	Unrelated to the image
A person riding a motorcycle on a dirt road.	Two dogs play in the grass.	A skateboarder does a trick on a ramp.	A dog is jumping to catch a frisbee.
A group of young people playing a game of frisbee.	Two hockey players are fighting over the puck.	A little girl in a pink hat is blowing bubbles.	A refrigerator filled with lots of food and drinks.
A herd of elephants walking across a dry grass field.	A close up of a cat laying on a couch.	A red motorcycle parked on the side of the road.	A yellow school bus parked in a parking lot.

MT + OCR


ВЫХОД В ГОРОД
Russian ⇄ English
ACCESS TO CITY
IMPORT
PAUSE
SCAN

OCR



Raw Article Scan

Road hauliers are seeking, and in many cases obtaining, increases in rates ranging from 3½ per cent. to 6 per cent.

This emerged yesterday from an area-by?area survey carried out by THE FINANCIAL TIMES, a fortnight after publication of the report of the National Board for Prices and Incomes on the road haulage industry.

Hauliers claimed that the report was having the effect of plolonging negotiations, but said they were confident that eventually they would win rises of the size they originally contemplated.

Meanwhile, representatives of the Road Haulage Association may discuss aspects of the N.B.P.I. report with union officials in London to-day at the inaugural meeting of the industry's new 24-strong negotiating committee.

This body, which was established some weeks ago, is the one on

Financial Times 13th July 1965, Page One

3rd Party OCR

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Language models – probability of a sentence

- LM is a probability distribution over all possible word sequences.
- What is the probability of utterance of s?

Probability of sentence

p_{LM}(Catalonia President urges protests)
p_{LM}(President Catalonia urges protests)
p_{LM}(urges Catalonia protests President)
...

Ideally, the probability should strongly correlate with fluency and intelligibility of a word sequence.

N-gram models

- an approximation of long sequencies using short n-grams
- a straightforward implementation
- an intuitive approach
- good local fluency

Randomly generated text

“Jsi nebylo vidět vteřin přestal po schodech se dal do deníku a položili se táhl ji viděl na konci místnosti 101,” řekl důstojník.

Hungarian

A társaság kötelezettségeiért kapta a középkori temploma az volt, hogy a felhasználók az adottságai, a felhasználó azonosítása az egyesület alapszabályát.

N-gram models, naïve approach

$$W = w_1, w_2, \cdots, w_n$$

$$p(W) = \prod_i p(w_i | w_1 \cdots w_{i-1})$$

Markov's assumption

$$p(W) = \prod_i p(w_i | w_{i-2}, w_{i-1})$$

$$p(\textit{this is a sentence}) = p(\textit{this}) \times p(\textit{is}|\textit{this}) \times p(a|\textit{this}, \textit{is}) \times p(\textit{sentence}|\textit{is}, a)$$

$$p(a|\textit{this}, \textit{is}) = \frac{|\textit{this is a}|}{|\textit{this is}|}$$

Sparse data problem.

Computing, LM probabilities estimation

Trigram model uses 2 preceding words for probability learning. Using **maximum-likelihood estimation**:

$$p(w_3|w_1, w_2) = \frac{count(w_1, w_2, w_3)}{\sum_w count(w_1, w_2, w)}$$

quadrigram: *(lord, of, the, ?)* ()

w	**count**	$p(w)$
rings	30,156	0.425
flies	2,977	0.042
well	1,536	0.021
manor	907	0.012
dance	767	0.010
...		

Large LM – n-gram counts

How many unique n-grams in a corpus?

order	unique	singletons
unigram	86,700	33,447 (38.6%)
bigram	1,948,935	1,132,844 (58.1%)
trigram	8,092,798	6,022,286 (74.4%)
4-gram	15,303,847	13,081,621 (85.5%)
5-gram	19,882,175	18,324,577 (92.2%)

Corpus: Europarl, 30 M tokens.

Language models smoothing

The problem: an n-gram is missing in the data but is in a *sentence* $\rightarrow$ $p(\mathit{sentence}) = 0$.

We need to assign non-zero p for *unseen data*. This must hold:

$$\forall w. p(w) > 0$$

The issue is more pronounced for higher-order models.

Smoothing: an attempt to amend real counts of n-grams to expected counts in any (unseen) data.

Add-one, Add-α, Good–Turing smoothing

Deleted estimation

We can find unseen n-grams in another corpus. N-grams contained in one of them and not in the other help us to estimate general amount of unseen n-grams.

E.g. bigrams not occurring in a training corpus but present in the other corpus million times (given the amount of all possible bigrams equals 7.5 billions) will occur approx.

$$\frac{10^6}{7.5 \times 10^9} = 0.00013\times$$

Interpolation and back-off

Previous methods treated all unseen n-grams the same. Consider trigrams

beautiful young girl
beautiful young granny

Despite we don't have any of these in our training data, the former trigram should be more probable.

We will use probability of lower order models, for which we have necessary data:

young girl
young granny
beautiful young

Interpolation

$$p_I(w_3|w_1w_2) = \lambda_1 p(w_3) \times \lambda_2 p(w_3|w_2) \times \lambda_3 p(w_3|w_1w_2)$$

If we have enough data we can trust higher order models more and assign a higher significance to corresponding n-grams.

p_I is probability distribution, thus this must hold:

$$\forall \lambda_n : 0 \leq \lambda_n \leq 1$$
$$\sum_n \lambda_n = 1$$

Quality and comparison of LMs

We need to compare quality of various LM (various orders, various data, smoothing techniques etc.)

1. extrinsic (WER, MT, ASR, OCR)
2. intrinsic (perplexity) evaluation

A good LM should assign a higher probability to a good (looking) text than to an incorrect text. For a fixed test text we can compare various LMs.

Cross-entropy

$$\begin{aligned} H(p_{LM}) &= -\frac{1}{n}\log p_{LM}(w_1, w_2, \ldots w_n) \\ &= -\frac{1}{n}\sum_{i=1}^{n}\log p_{LM}(w_i | w_1, \ldots w_{i-1}) \end{aligned}$$

Cross-entropy is average value of negative logarithms of words probabilities in testing text. It corresponds to a measure of uncertainty of a probability distribution. **The lower the better**.

A good LM should reach entropy close to real entropy of language. That can't be measured directly but quite reliable estimates exist, e.g. Shannon's game. For English, entropy is estimated to approx. 1.3 bit per letter.

Perplexity

$$PP = 2^{H(p_{LM})}$$

Perplexity is a simple transformation of cross-entropy.

A good LM should not waste p for improbable phenomena.

The lower entropy, the better → the lower perplexity, the better.

Comparing smoothing methods (Europarl)

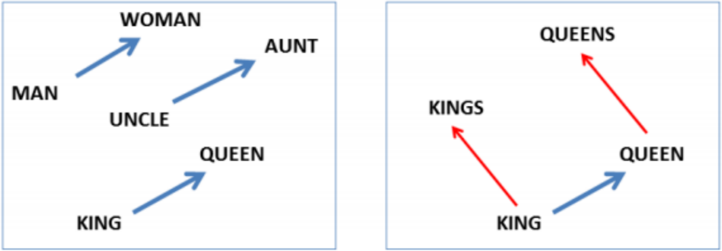
method	**perplexity**
add-one	382.2
add-α	113.2
deleted est.	113.4
Good–Turing	112.9

Neural Networks

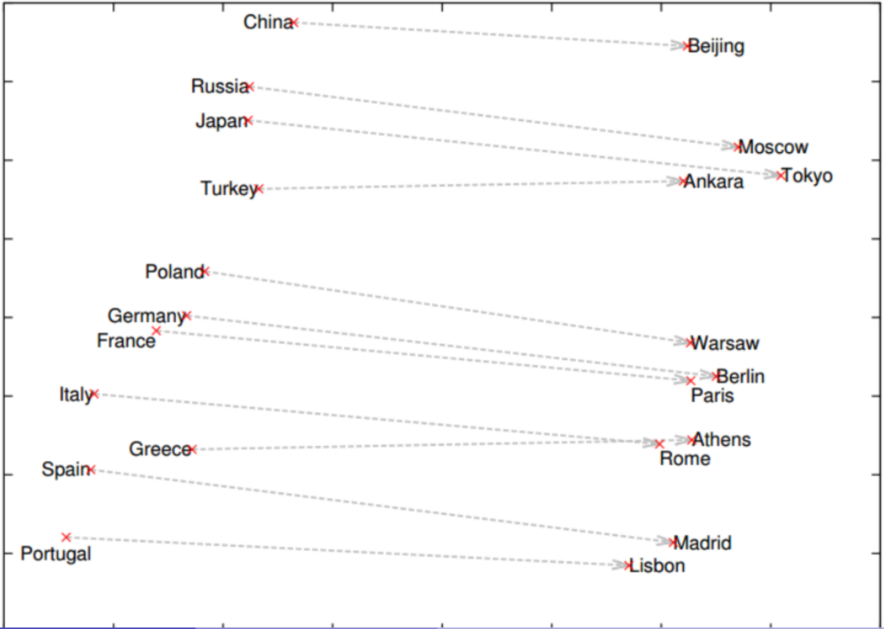
- no probabilities, only scores
- One-hot representation of words: `[ 0 0 0 0 0 0 1 0 0 0 0 ]`
- adapting a model means changes in the whole network

Distributional Representation of Words

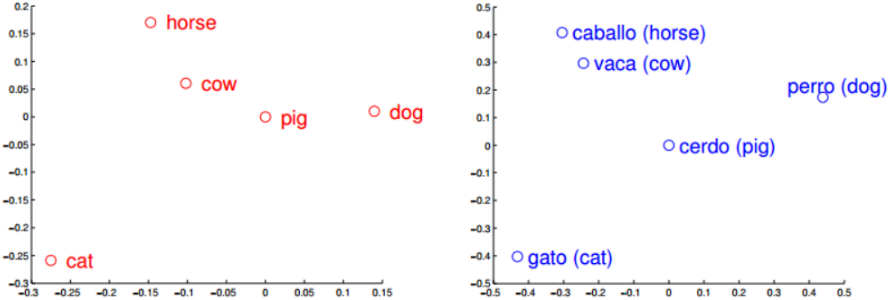
- goal: more compact representation of vectors
- limited dimensionality (500–1000)
- [Mikolov et al., 2013]
- word vectors capture many linguistic properties (gender, tense, plurality, even semantic concepts like “capital city of”)



Features: vector arithmetics I



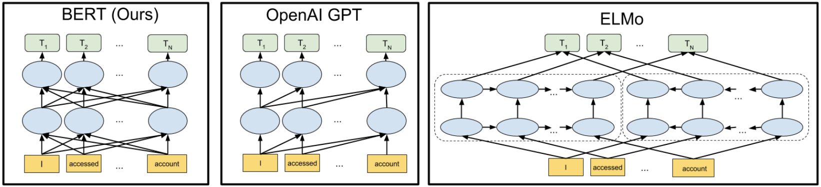
Features: vector arithmetics II



State-of-the-art neural models

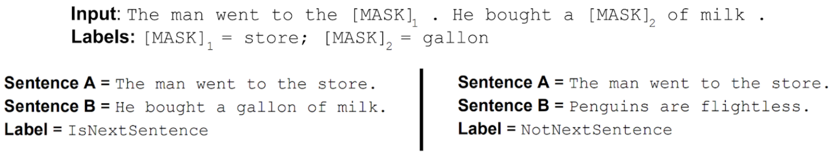
Using context to compute token/sentence/document embedding via transformes.[Vaswani et al., 2017]

- BERT = Bidirectional Encoder Representations from Transformers [Devlin et al., 2018]
- GPT = Generative Pre-trained Transformer [Brown et al., 2020]
- many varians: tokenization, attention, encoder/decoder connections



BERT

- Google
- encoder only
- pre-training on raw text
- masking tokens, is-next-sentence
- big pre-trained models available
- domain (task) adaptation



Input: The man went to the [MASK]$_1$. He bought a [MASK]$_2$ of milk .
Labels: [MASK]$_1$ = store; [MASK]$_2$ = gallon

Sentence A = The man went to the store.
Sentence B = He bought a gallon of milk.
Label = IsNextSentence

Sentence A = The man went to the store.
Sentence B = Penguins are flightless.
Label = NotNextSentence

GPT

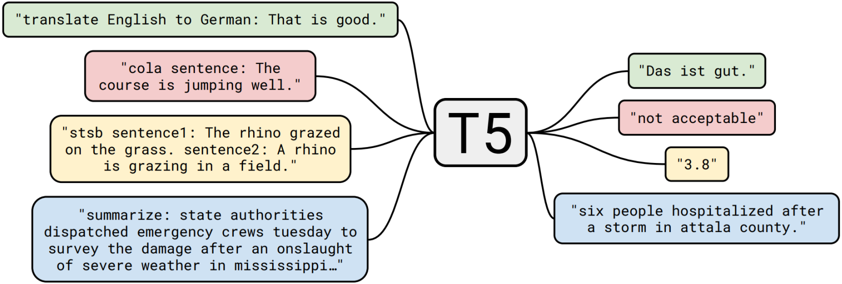
- Open AI
- decoder only
- GPT-2: 1.5 billion parameters
- GPT-3: 175 billion parameters
- very good text generation
  → potentially harmful applications
- Misuse of Language Models
- bias – generate stereotyped or prejudiced content: gender, race, religion
- Sep 2020: Microsoft have "exclusive" use of GPT-3

GPT vs n-grams

- training GPT
- multiple (1–n) training examples in one step
- predicting all tokens in one step

T5: Text-To-Text Transfer Transformer

- Google AI
- transfer learning
- C4: Colossal Clean Crawled Corpus


"translate English to German: That is good."

"cola sentence: The course is jumping well."

"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."

"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"

"Das ist gut."

"not acceptable"

"3.8"

"six people hospitalized after a storm in attala county."

Evaluation of language models

- standard multi-task benchmarks
- GLUE (`https://gluebenchmark.com`)
- SuperGLUE (`https://super.gluebenchmark.com`)
- XTREME Cross-Lingual Transfer Evaluation of Multilingual Encoders (`https://sites.research.google/xtreme`)
- perplexity is not used anymore

Libraries and Frameworks

- Dive into Deep Learning: online book
  `https://d2l.ai`
- Hugging Face Transformers: many ready to use models
  `https://huggingface.co/transformers`
- GluonNLP: reproduction of latest research results
  `https://nlp.gluon.ai`
- low level libraries: NumPy, PyTorch, TensorFlow, MXNet

References I

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Devlin, J., Chang, M., Lee, K., and Toutanova, K. (2018).
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CoRR, abs/1810.04805.

Mikolov, T., Yih, W.-t., and Zweig, G. (2013).
Linguistic regularities in continuous space word representations.
In *HLT-NAACL*, pages 746–751.

References II

- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017).
  Attention is all you need.
  CoRR, abs/1706.03762.

- Vinyals, O., Toshev, A., Bengio, S., and Erhan, D. (2014).
  Show and Tell: A Neural Image Caption Generator.
  ArXiv e-prints.

GPT language models

The goal of the task is:

- create a simple GPT language models from own data
- generate random text using models
- compare quality of generated text

GPT language models

Start with the colab notebook: `https://colab.research.google.com/drive/1GSS_KlTVkrNNqGBi6MmZ6AMgHcIQDczq?usp=sharing`

- R.U.R. by Josef Capek (155kB)
  `https://gutenberg.org/files/59112/59112-0.txt`
- 1984 book
  `https://gutenberg.net.au/ebooks01/0100021.txt`
- Shakespeare plays (1.1 MB)
  `https://raw.githubusercontent.com/karpathy/char-rnn/master/data/tinyshakespeare/input.txt`
- Any other data, any language (even programming languages)

GPT language models

Tasks:

- Generate text using character-level neural LM.
  Describe the quality of generated text with regard to selected parameters.
- Implement BPE subword tokenization into GPT model.
  Compare to the character-level model.