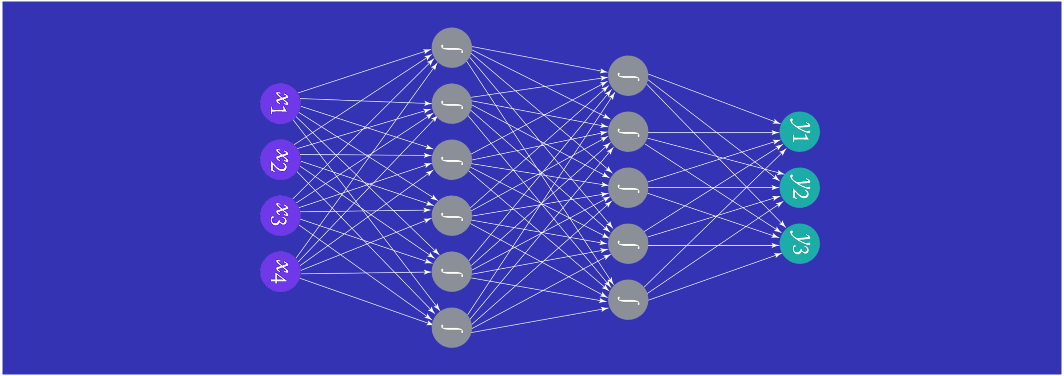
Neural networks in NLP: hype or more?

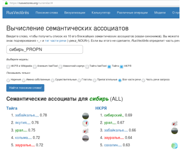


Andrey Kutuzov
University of Oslo, Language Technology Group
4-th Kolmogorov seminar in computational linguistics, Moscow, 25 April 2019

Who's here?

- I am Andrey Kutuzov.
- Master degree in computational linguistics from NRU HSE.
- Industrial past: *Lionbridge*, *Mail.ru Search*.
- Now doing my PhD and teaching at the University of Oslo.
  - Deep learning, computational linguistics...
- One of the maintainers of the *RusVectōrēs* project (word embeddings for Russian) [Kutuzov and Kuzmenko, 2017].
- Contributing to the *Gensim* library [Řehůřek and Sojka, 2010].

https://www.mn.uio.no/ifi/english/



https://rusvectores.org

https://github.com/RaRe-Technologies/gensim

What I will talk about?

- There are 4 take-home messages in the talk.
- Look for slides with large friendly red letters:

Take-home message

Like this one

About NLP

Linguistics

About NLP

Linguistics

Statistics

About NLP

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Statistics

Deep learning

About NLP

- Computational Linguistics (CL);

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- More or less the same field:
  1. academic studying of language from computational point of view;
  2. solving practical language tasks:
     - analysis (natural language understanding)
     - synthesis (‘natural’ language generation)

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  - chat bots
  - summarization
  - virtual personal assistants (*Алиса*, *Siri*, *Alexa*, *Cortana*)...

Surprise: language is not simple

Yoav Goldberg Follow

Senior Lecturer at Bar Ilan University. Working on NLP. Recently with Neural Nets. Published a book about it. http://www.cs.biu.ac.il/~yogo/

Jun 9, 2017 · 14 min read

An Adversarial Review of "Adversarial Generation of Natural Language"

Or, for fucks sake, DL people, leave language alone and stop saying you solve it.

https://medium.com/@yoav.goldberg/an-adversarial-review-of-adversarial-generation-of-natural-language-409ac3378bd7

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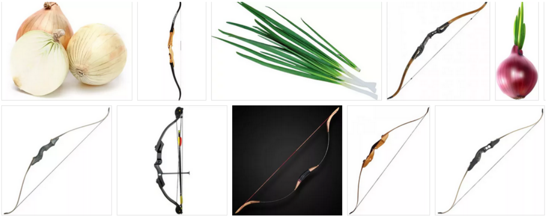
  - disambiguation:
    - «*Лук* (???) был просто *огонь* (???)»
  - ...and of course, many, many more.
  - Linguistic knowledge provides scaffolding for machine learning systems.



Take-home message #1

Language data is complex and specific

NLP needs linguistics

Deep Learning comes as no surprise in the history of NLP

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  - machine translation boom in the 1950s.

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'Kolmogorov complexity' — the length of minimal computer program reproducing an object (model size)

- Computational power of the humanity is growing...
- ...but it doesn't help rule-based methods: they don't scale well.
- Rule-based description of an object of a given complexity does not speed up.

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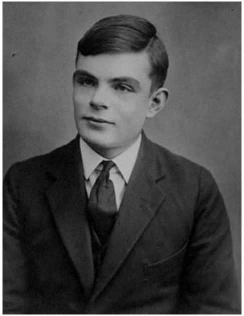
- ...since it is almost entirely built around machine learning.
- We train our systems on large corpora.
- Neural networks: a type of ML algorithms.

Artificial neural networks have been around for a long time

'Machines of this character can behave in a very complicated manner when the number of units is large.'

Alan Turing, 'Intelligent Machinery'

[Turing, 1948]



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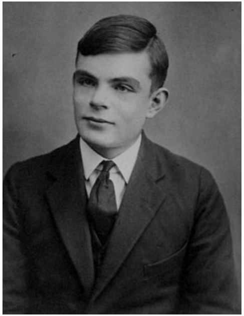

...but the 60s, 70s and 80s were 'AI winter'. A handful of rebels continued to ~~resist the Empire~~ play with training neural networks...

27.03.2019: Deep Learning founding fathers received 'computer science Nobel prize': ACM Turing Award

'...for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing... in computer vision, speech recognition, natural language processing, and robotics'

Neural networks revival

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- In nearly any complex NLP task, neural systems are better than 'classic' linear models.
- '*Do we even need anything else?*'
  - Not a spoiler any more: yes, we also need linguistics.
  - Often, we also need huge amounts of training data.

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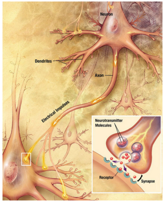

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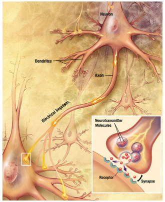

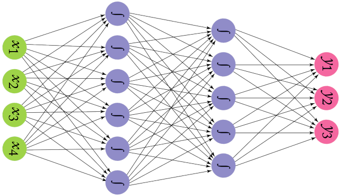

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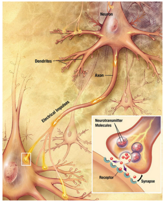

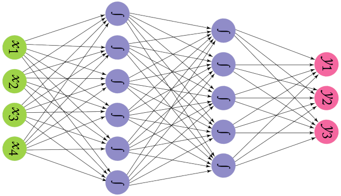

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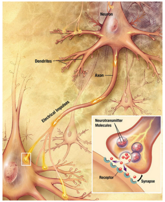

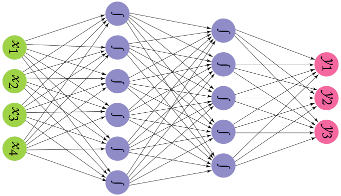

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- Hence, neural networks are vectors, weights arrays and differentiation. Not so sexy, but true.

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- They were shown to be able to approximate any function.
  - ...given enough layers and neurons (computational units) in these layers.
- Non-linear transformations between layers make it possible to process data which is not linearly separable.
- This is the reason ANNs work better.

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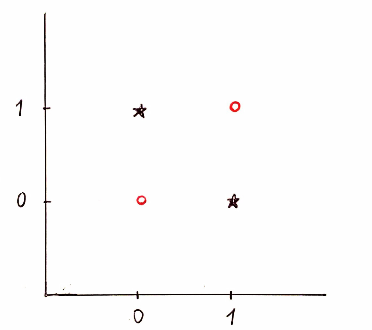

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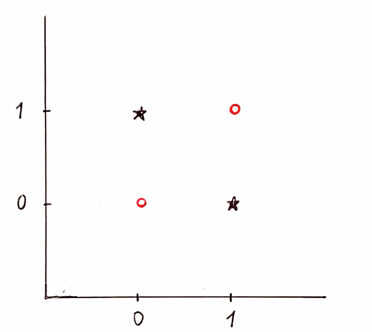

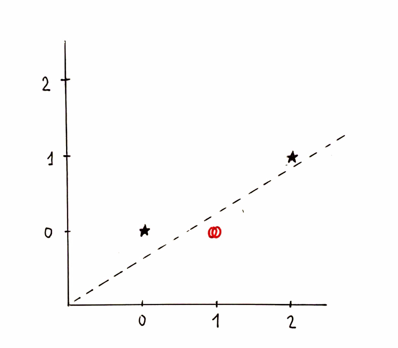

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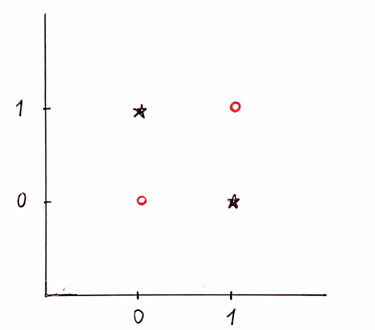

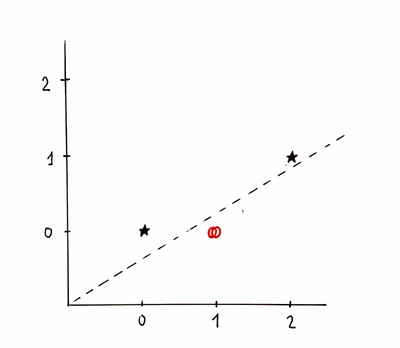

ANNs learn such transformations.

Take-home message #2

Deep Learning is a logical development of NLP

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- Such representations are called embeddings (e.g., word embeddings).

word2vec: representing words with vectors is commonplace now

(Dmitry Malkov)

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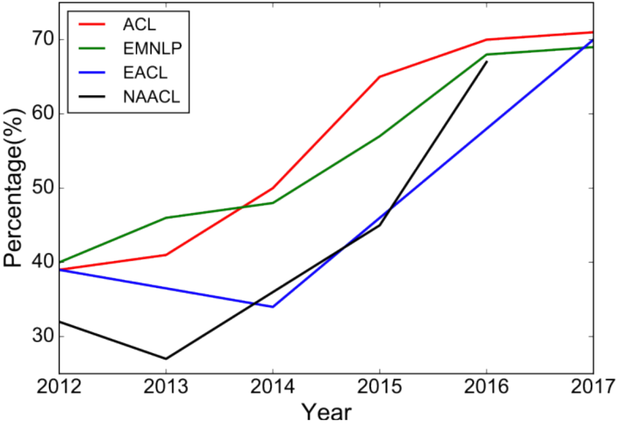
- Pre-trained models: easily fine-tuned for your tasks.
- Elementary 'bricks' are combined into different complex architectures.
- Hardware today is comparatively cheap and powerful (GPUs, TPUs).

Steamroller, or DL at the NLP conferences



[Young et al., 2018]

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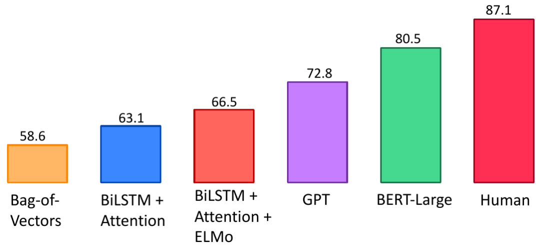

`https://gluebenchmark.com/`, [Wang et al., 2018]

Funny things happen sometimes

OpenAI trained a language model but didn't publish it (for fear of malicious usage):

VIEW CODE READ PAPER

Our model, called GPT-2 (a successor to GPT), was trained simply to predict the next word in 40GB of Internet text. Due to our concerns about malicious applications of the technology, we are not releasing the trained model. As an experiment in responsible disclosure, we are instead releasing a much smaller model for researchers to experiment with, as well as a technical paper.

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NLP folks are not much grateful for that:

(((J()(J() 'yoav))))
@yoavgo
Читать

В ответ @aCraigPfeifer

we can generate all the stories on the @OpenAI blog post on a single CPU core, after training on just a handful of blogposts for several minutes.

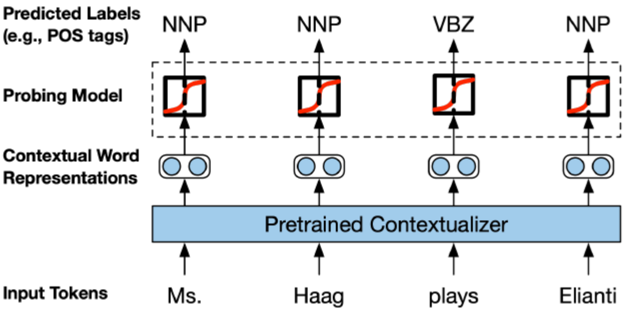
10:21 - 15 февр. 2019 г.

Problem: interpretability of predictions made by a cascade of representations

XKCD

Probing tasks

We need linguistics to diagnose: to find out what exactly our models learn:



[Liu et al., 2019], [Belinkov and Glass, 2019]

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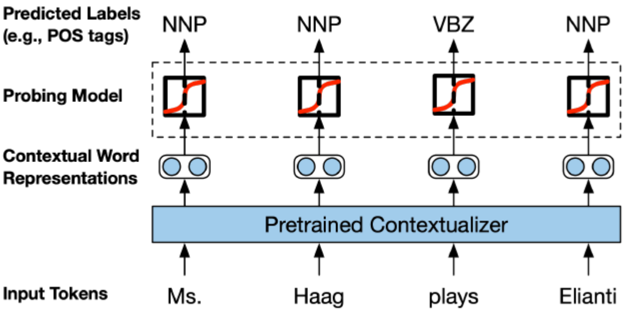

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NB: correlation does not imply causation!

Do deep networks help to enrich our linguistic knowledge?

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Latent syntax trees learned by a network:

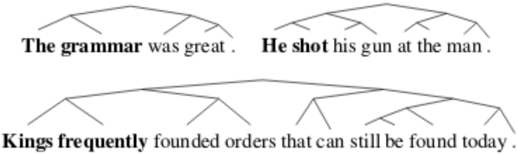

Figure 4: The ST-Gumbel models often form constituents from the first two words of sentences.

[Williams et al., 2018]

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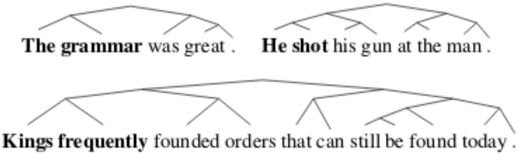

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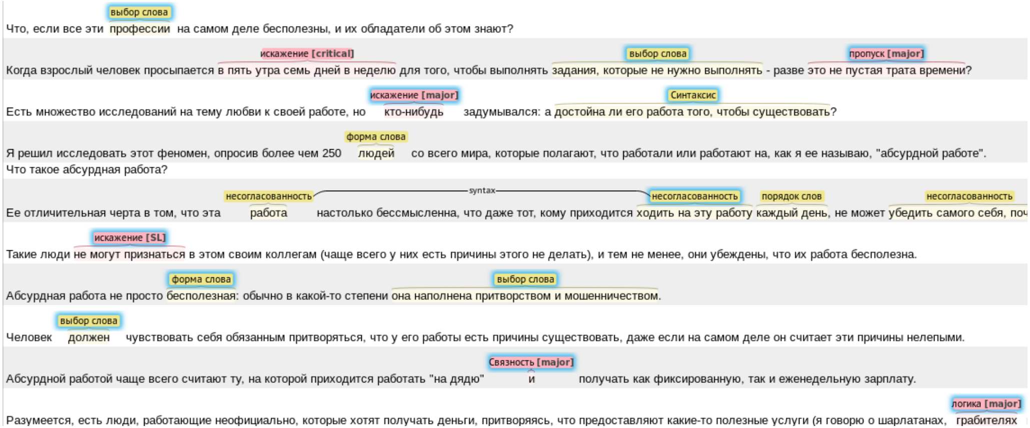
Problem: lack of annotated data



annotation of translators' mistakes (`https://rus-ltc.org`)

Take-home message #3

Deep learning in NLP is not over-hyped. Do it now!

- *But the 'classic' ML 20 years ago was not over-hyped either.*
- *Thus, DL is not some final solution to automatic language analysis and synthesis.*
- *Something different will come in the future, solving DL problems.*

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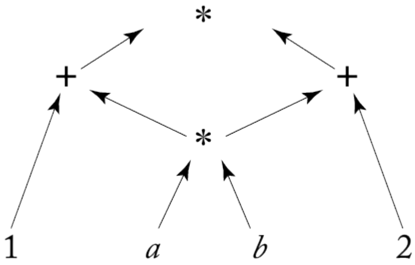
- TensorFlow by *Google* [Abadi et al., 2015] `https://tensorflow.org/`
- PyTorch by *Facebook* [Paszke et al., 2017] `https://pytorch.org/`

Under the hood of frameworks: computation graph



directed acyclic graph (DAG)

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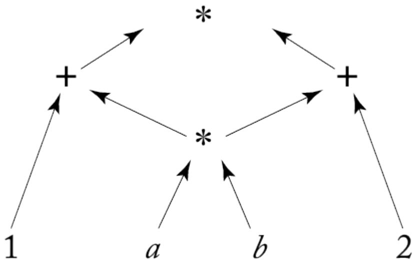

directed acyclic graph (DAG)

- Representation of a mathematical expression calculation;

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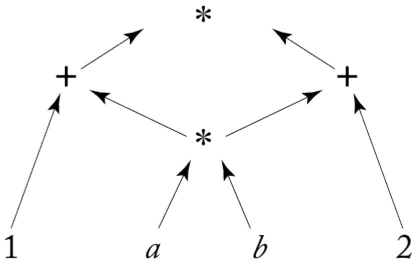

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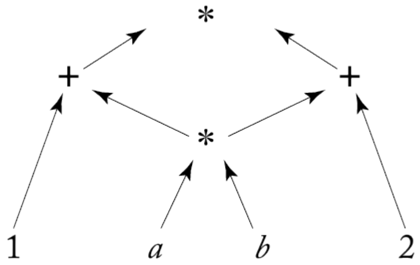

directed acyclic graph (DAG)

- Representation of a mathematical expression calculation;
- all operations and variables are nodes in the graph;
- allows to easily design arbitrarily complex and deep architectures (must be differentiable).

TensorFlow or PyTorch? What's the difference?

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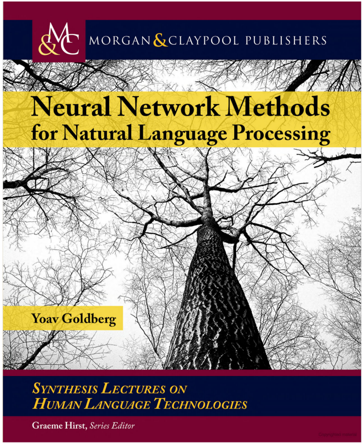
Both frameworks are research and production ready. Just use the one you know better.

Take-home message #4

NLP+DL frameworks: choice between *PyTorch* and *TensorFlow*.
Both are good.

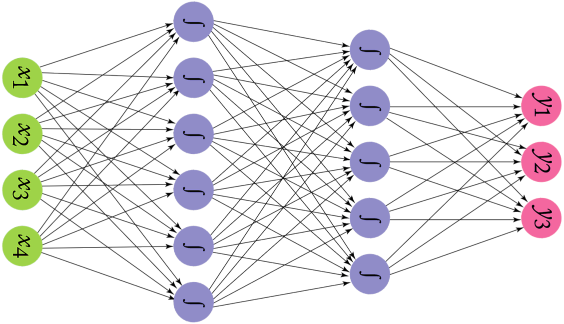
Further reading



- Yoav Goldberg: *Neural Network Methods for Natural Language Processing* [Goldberg, 2017].
- Sebastian Ruder blog (`http://ruder.io/`)

Questions?

Neural networks in NLP:
hype or more?



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