IS883: Synthesizing Digital Efforts

Mohannad Elhamod

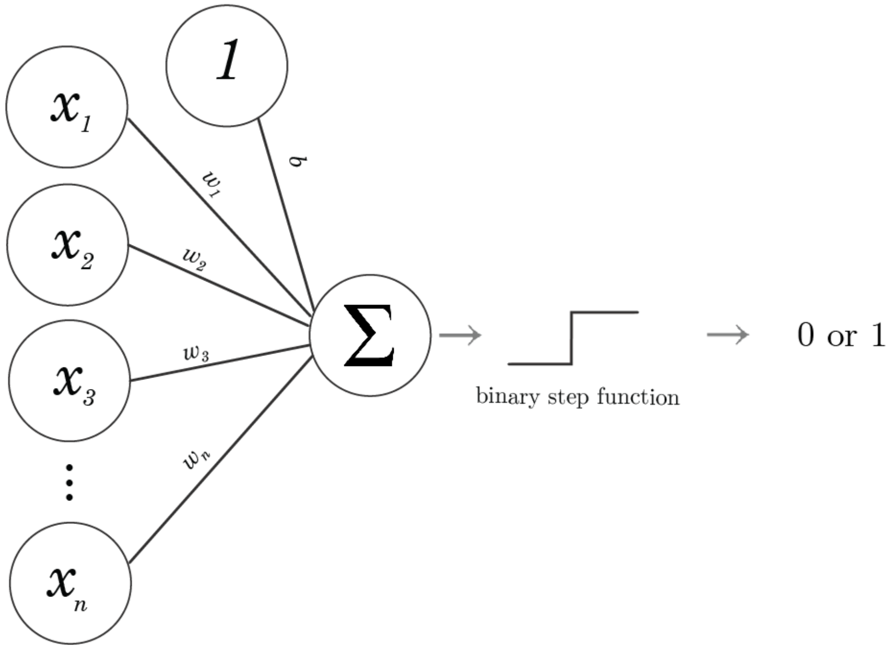
Neural Networks

Boston University Questrom School of Business

The building block: The Perceptron

- Demo

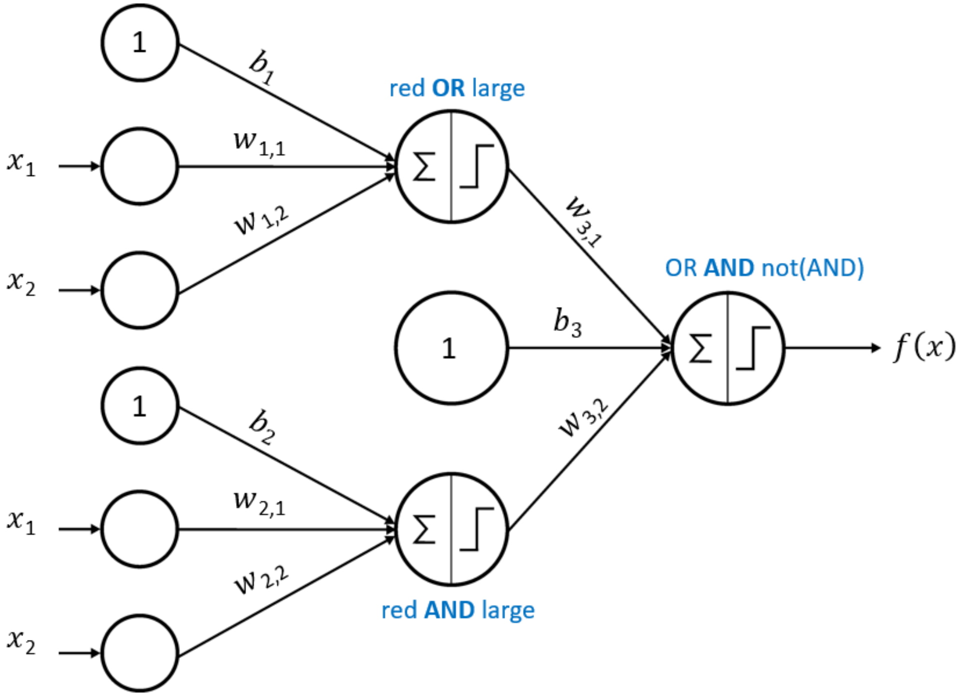
- Can we work around the “linear separability” issue”?



Adam Dhala

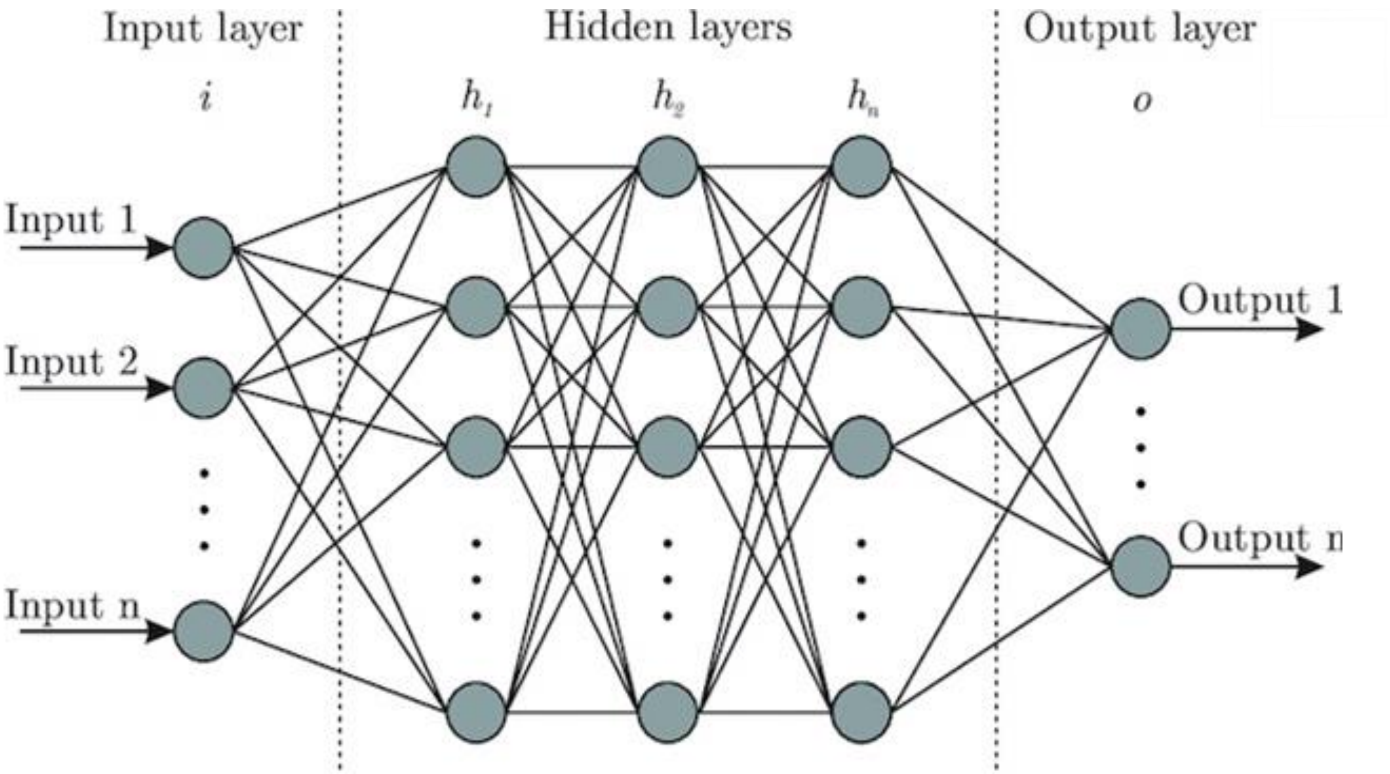
Power in Numbers: Multiple Perceptrons

- Demo



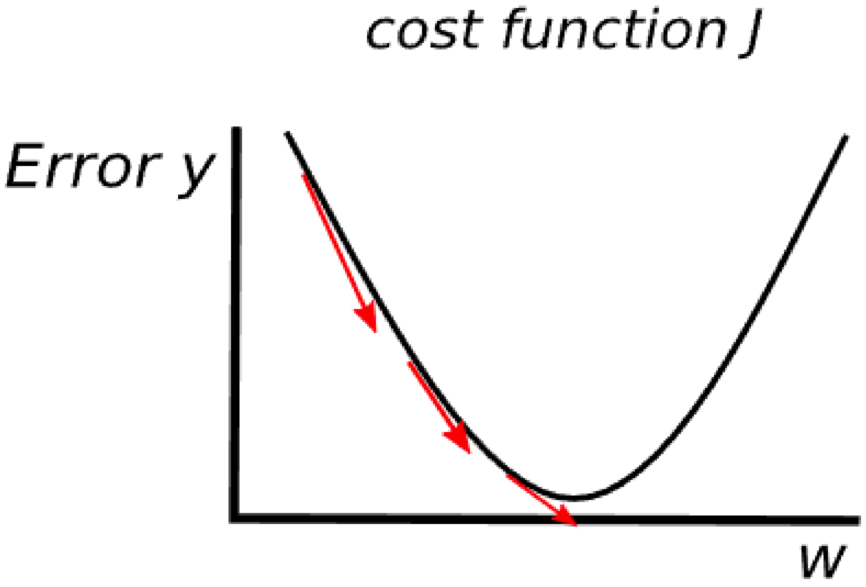
western-neuralnets.ca

Neural Newtorks



Optimization

- A neural network has “weights” (or “parameters”).
- We want to assign these weights the values that lead to the lowest error.
    - Error ≡ loss ≡ cost function
    - Generally using gradient descent with backpropagation.



Elvira Siegel

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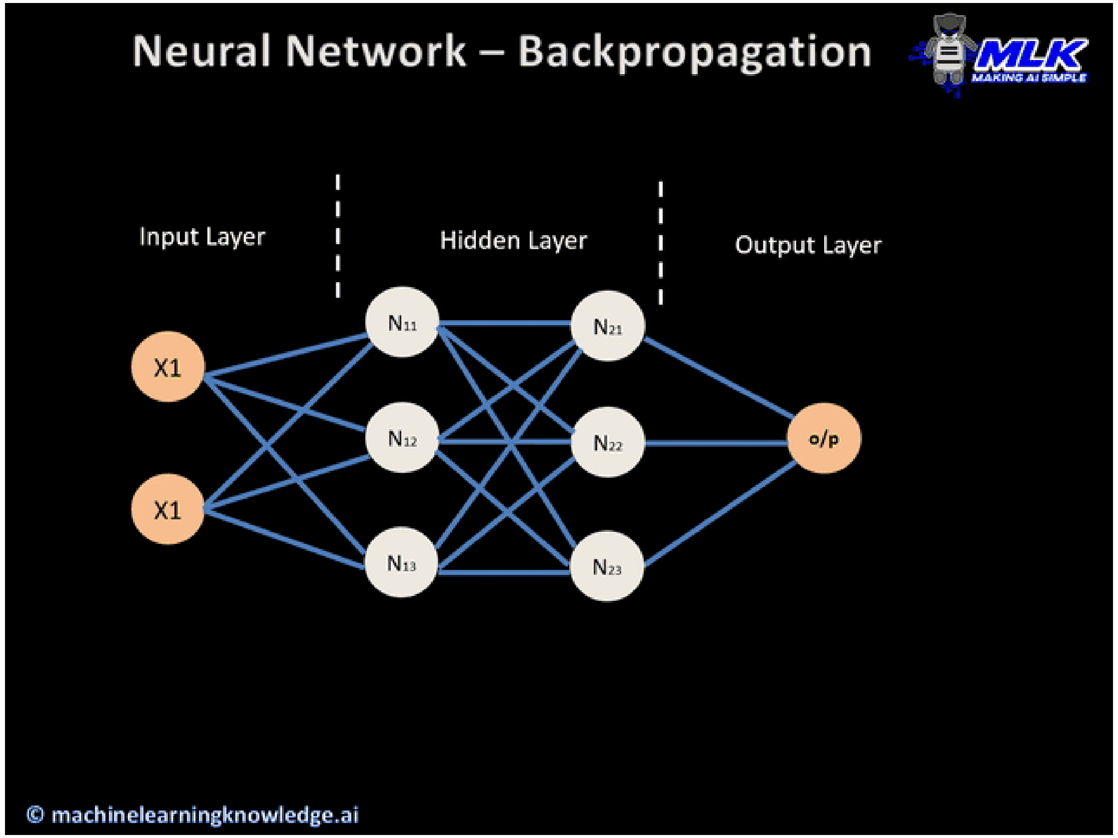
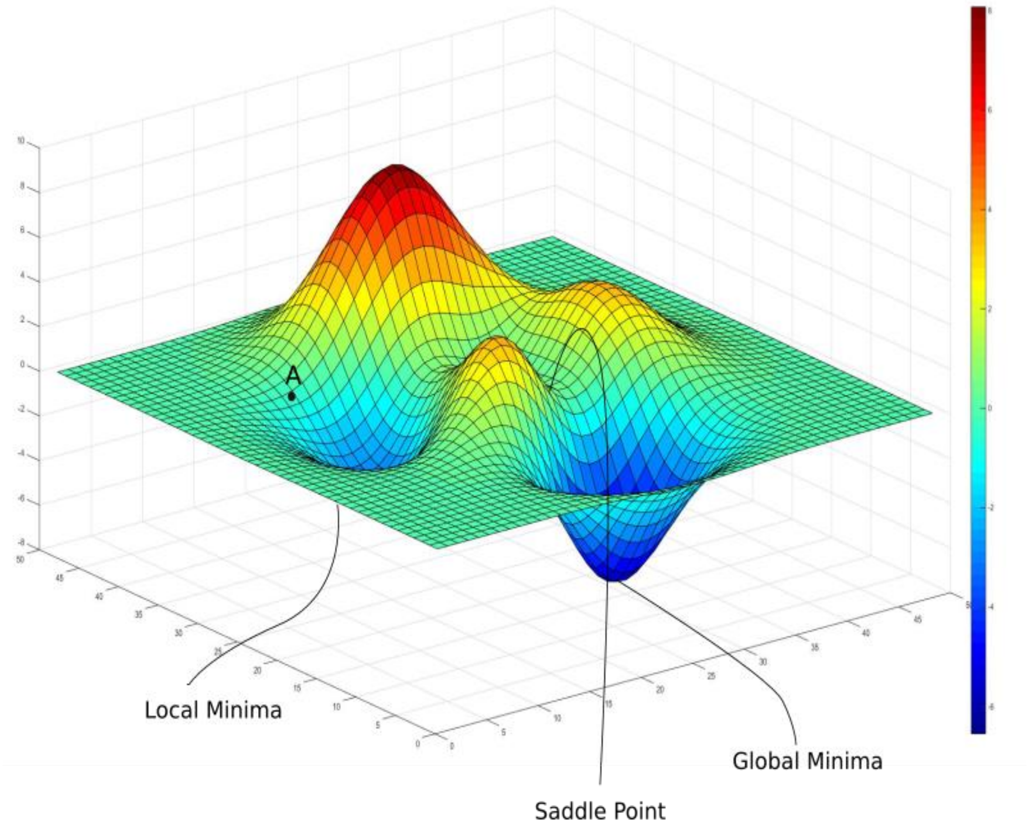


Optimization

- Can we always achieve lowest error?
- Demo



TechTalks

Are the results bad?

- Check against a benchmark!
  - paperswithcode.com
  - kaggle.com
  - **huggingface.com

How do I improve my results?

- Best way: Get more GOOD data
  - If not, clean-up existing data.
- Are you overfitting or underfitting?
  - Overfitting: get more data or use a less complex model.
  - Underfitting: get a more complex model.
- Keep it simple!
  - Start with a simple model, simple data, simple code.
  - Test by component
  - Test by example

Language Modeling

What is a model?

Britannica

Search Britannica...

scientific modeling

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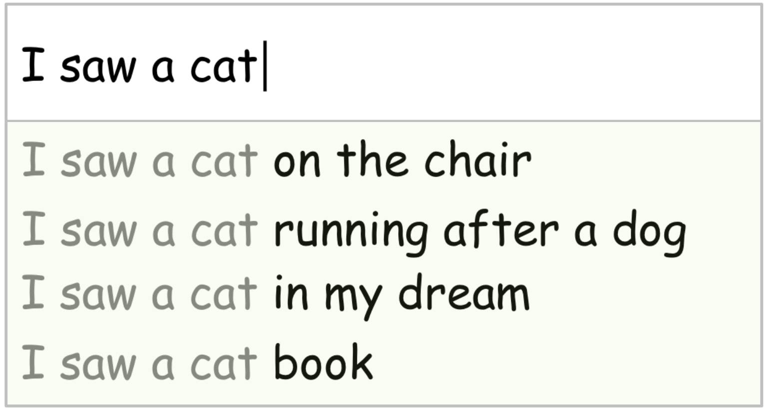
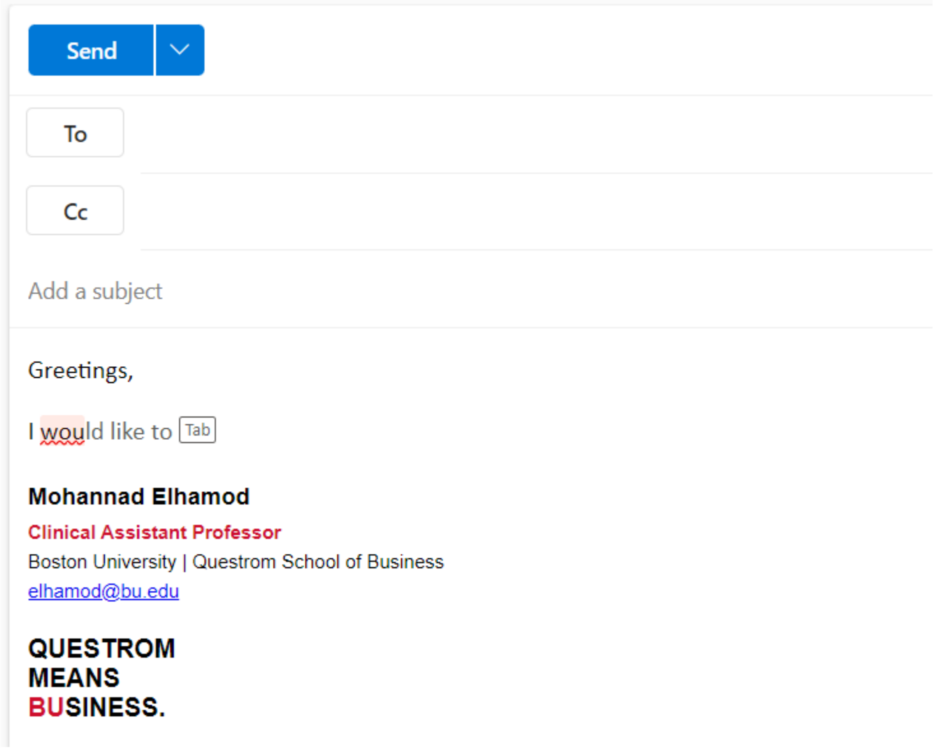
scientific modeling, the generation of a physical, conceptual, or mathematical representation of a real phenomenon that is difficult to observe directly. Scientific models are used to explain and predict the behaviour of real objects or systems and are used in a variety of scientific disciplines, ranging from physics and chemistry to ecology and the Earth sciences. Although modeling is a central component of modern science, scientific models at best are approximations of the objects and systems that they represent—they are not exact replicas. Thus, scientists constantly are working to improve and refine models.

What is language modeling?...

Web search engine / ...



Lena-voita



What is language modeling?...

I grabbed the branch and broke it.

I went to the branch and deposited some money.

Context matters!

What is language modeling?...

- I went to ____.
- I woke up at 7 am and went to ___.
- I woke up at 7 am, packed my book and notebook, and went to ____.

The more context, the more certain

What is language modeling?...

I went to the branch and deposited some money.

I went to the bank and deposited some money.

I went to the ATM and deposited some money.

> Words which frequently appear in **similar contexts** have **similar meaning**.

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Natural Language Processing (NLP)

Includes text generation:

- Text completion.
- Text summarization.
- Question answering.

But there are also many other tasks such as Text classification: (e.g., Sentiment analysis, Reviews, Fake news) or word classification.

Formalizing our thoughts

- It seems we process language sequentially**.
- So, language modeling is the chaining of word probabilities.

$$P(\text{I saw a cat on } \dots) = \underbrace{P(\text{I}) \cdot P(\text{saw}|\text{I}) \cdot P(\text{a}|\text{I saw}) \cdot P(\text{cat}|\text{I saw a}) \cdot P(\text{on}|\text{I saw a cat})}_{\text{Probability of I saw a cat on}} \cdot \underbrace{\dots}$$

Lena-voita

- How do we calculate these probabilities?

counting…

$$P(\text{cat}) = \frac{N(\text{"cat" in corpus})}{N(\text{all words in corpus})}$$

$$P(\text{cat} \mid \text{my}) = \frac{N(\text{"my cat" in corpus})}{N(\text{"my" in corpus})}$$

Can you foresee any problem with this calculation?...

N-grams

Instead, let's just use a context of ***fixed-length.***

P(I saw a cat on a mat) =

P(I)
· P(saw | I)
· P(a | I saw)
· P(cat | I saw a)
· P(on | I saw a cat)
· P(a | I saw a cat on)
· P(mat | I saw a cat on a)

- n=3 (trigram model): $P(y_t|y_1, \ldots, y_{t-1}) = P(y_t|y_{t-2}, y_{t-1})$,
- n=2 (bigram model): $P(y_t|y_1, \ldots, y_{t-1}) = P(y_t|y_{t-1})$,
- n=1 (unigram model): $P(y_t|y_1, \ldots, y_{t-1}) = P(y_t)$.

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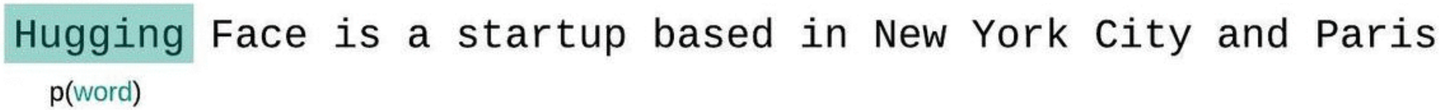
N-grams

Context is like a sliding window into the past.



[Huggingface]

Context size

- I went to the beach…
- My wife sat next to me. She was replying to some emails, and…
- the bird stole our sandwich. Then…
- it started raining suddenly and ___.

- Longer context: predictable outcome.
- Shorter context: Too unpredictable.

In-Class Work

Neural Nets in Language Modeling

Continued…

Fast Forward…

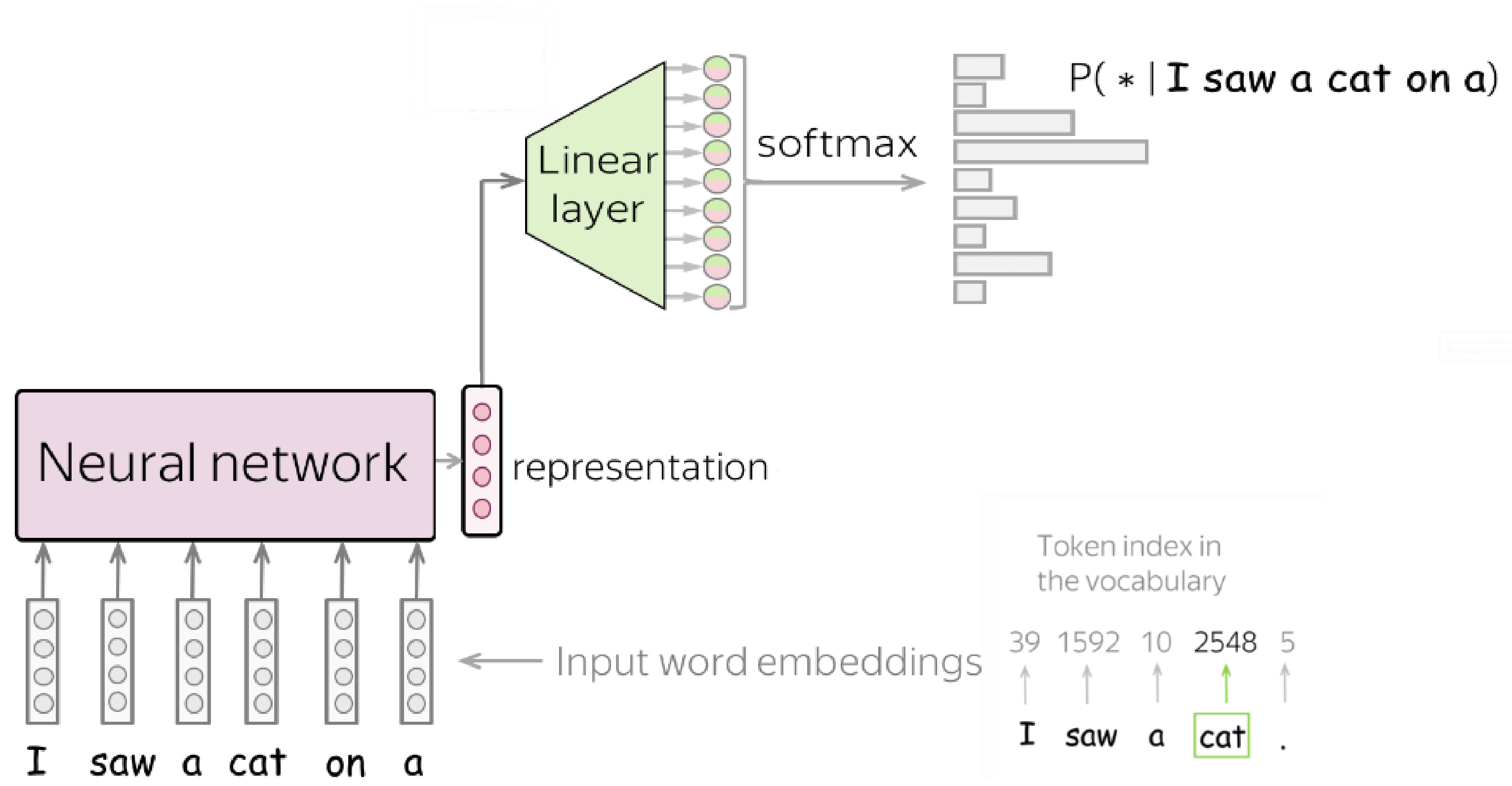
As neural networks arrived at the scene, they were utilized for language modeling.

- N-grams look for exact prefixes, which is limiting…
- However, neural networks can learn more interesting relationships between the words.

Example: All humans are mortal. Socrates is a human. Therefore,

Socrates is mortal.

General Model Architecture



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Can you see any issue with inputting words in an NN?

What is an embedding?

- It is the numeric representation of data.
- Example for images.

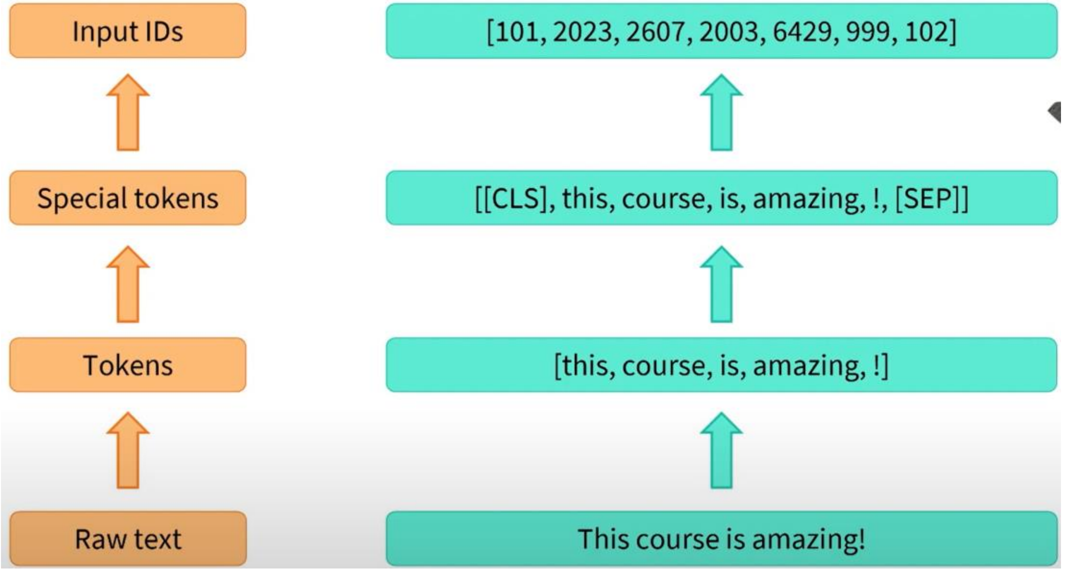
Word Embeddings

- We ideally want related words (i.e., *similar* meanings) to have smaller distances.
- Demo
- Examples:
  1. Word2Vec (Google)
  2. GloVe (Stanford)
  3. Train your own!

Tokenization

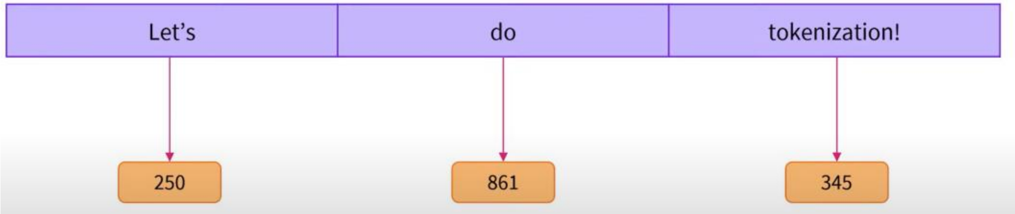
- Inputs can only be numbers.
- We need to convert the text into tokens (e.g., words).
- Each token can then be represented as a number.

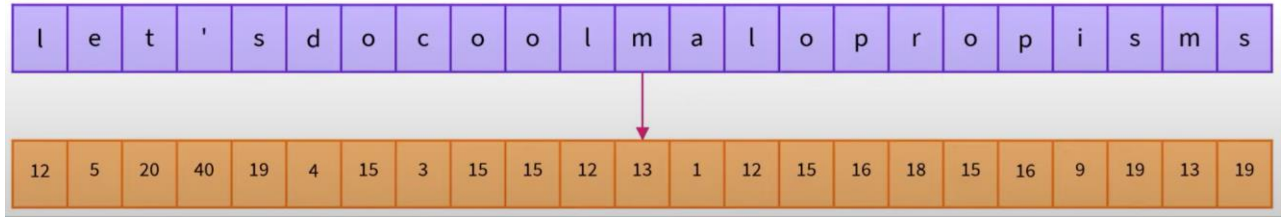
Huggingface



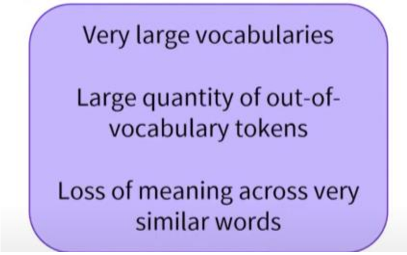
What Level of Tokenization to Use?

Huggingface

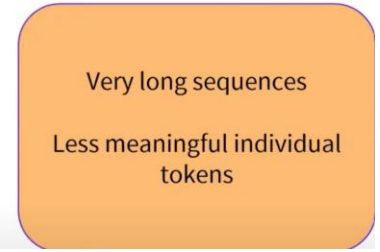




Issues?

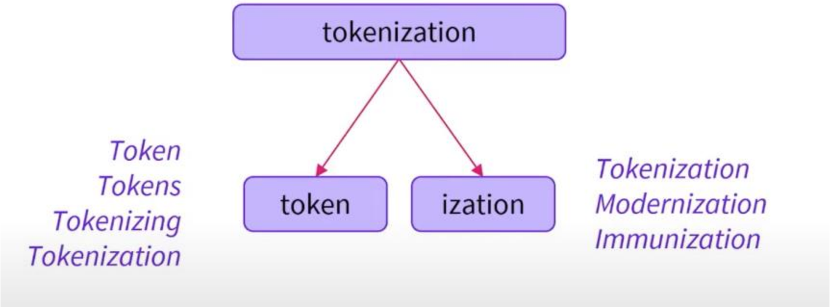


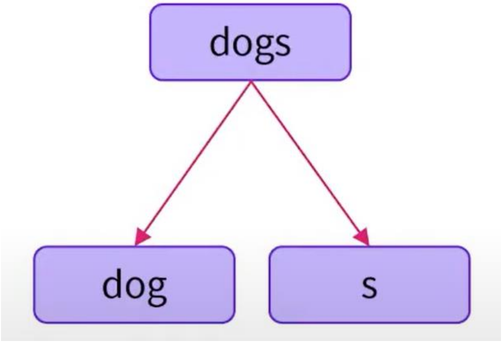
Issues?



What Level of Tokenization to Use?

How about sub-words?

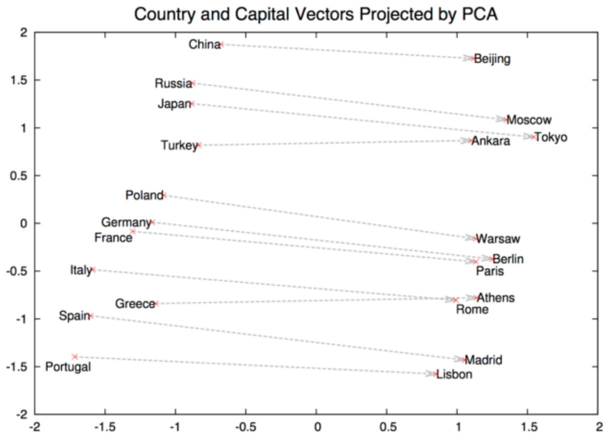




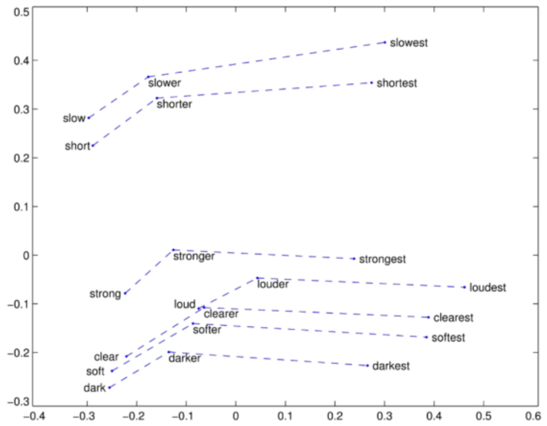
Word Embeddings

Since word embeddings carry *meaning*, certain directions in their space carry certain significance:

- Demo (dimensionality)



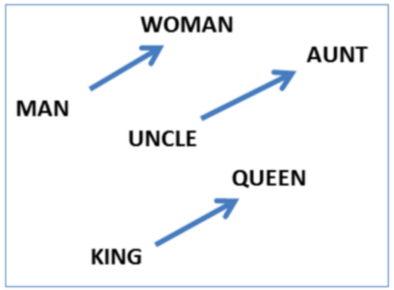
Word2Vec

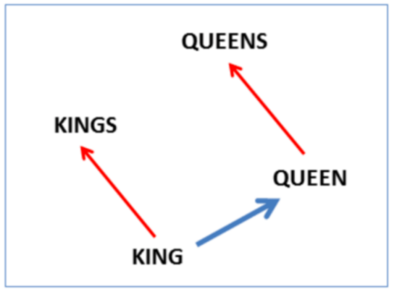


GloVe

semantic: v(king) – v(man) + v(woman) ≈ v(queen)

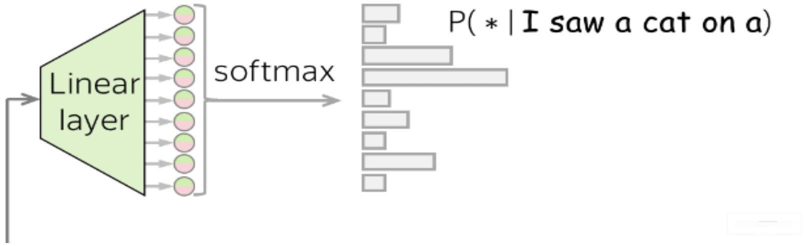
syntactic: v(kings) – v(king) + v(queen) ≈ v(queens)

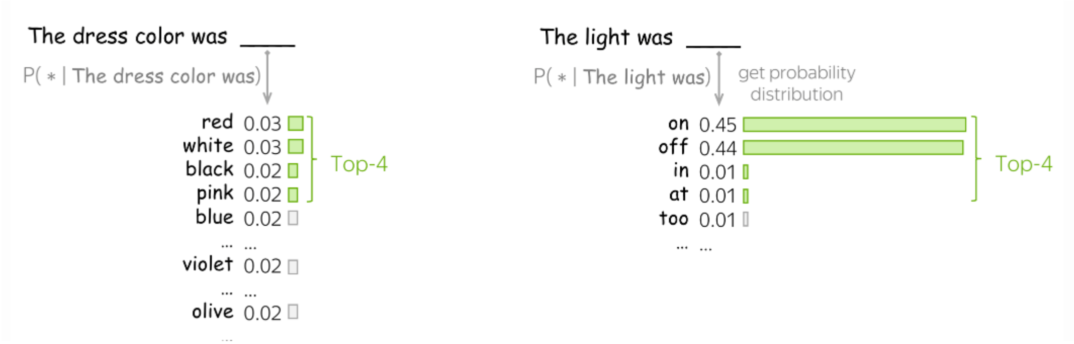


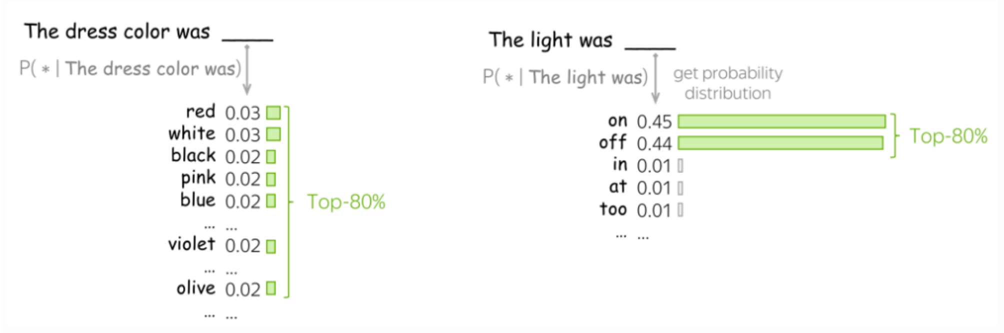


Sampling The Distribution

- Always take top probability?
  - That makes the model deterministic (no creativity).
- Alternative?
  - Top-k or top-p.







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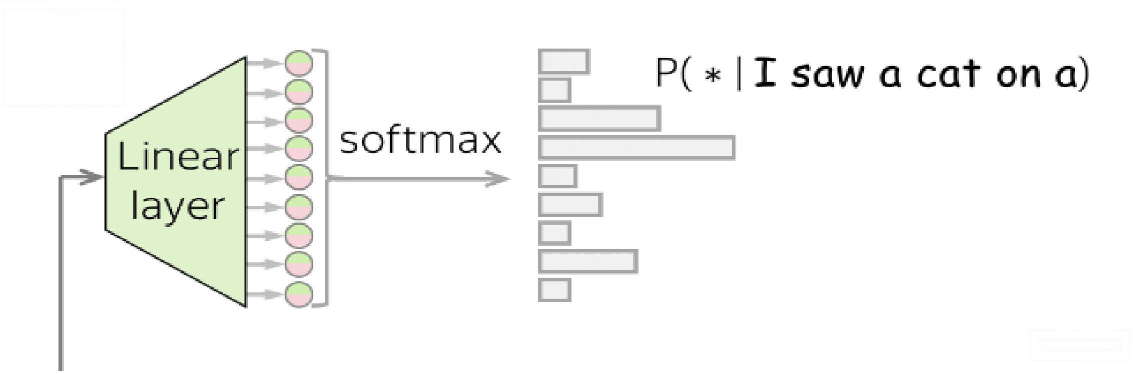
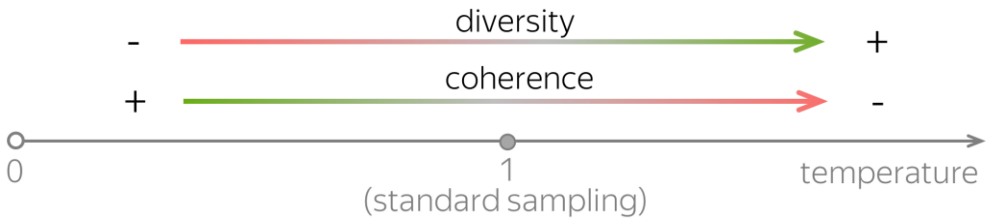
Sampling The Distribution

- Some words have way higher probability than others.
- This can be manually tuned through temperature.
- [Demo]





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Measuring The Metric

- What are we looking for?
  - A model that is not surprised by the text it is seeing.
- We use *perplexity*.
  - Takes values between 1 and the number of possible tokens.
  - Smaller is better.
  - Demo

Fast Forward…

- There exists many types of Neural Nets for language modeling:
  - CNNs
  - RNNs (Demo)
  - LSTMs…

- Generally, Neural Nets learn an *embedding* that represents the *entire prefix* to predict the next word.

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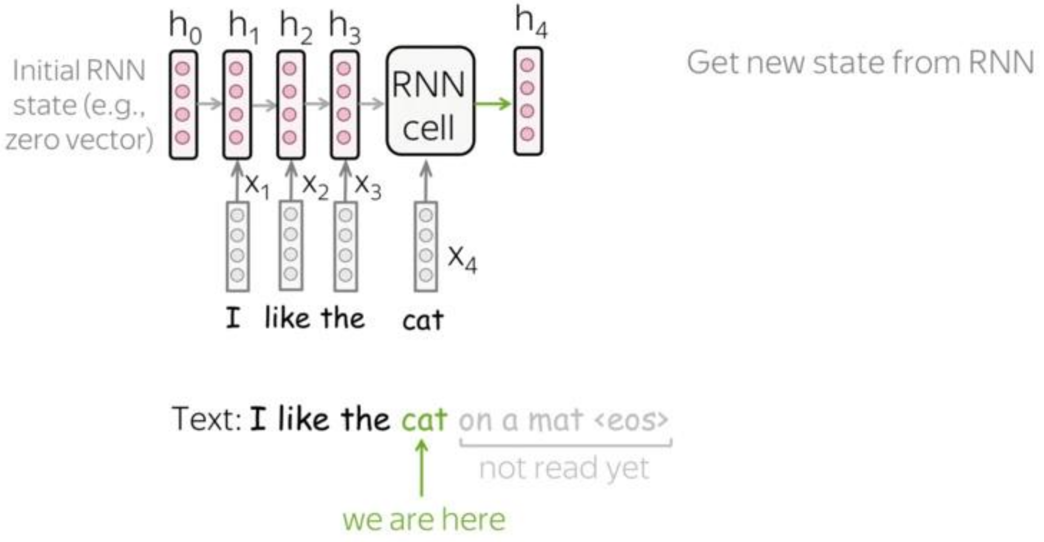
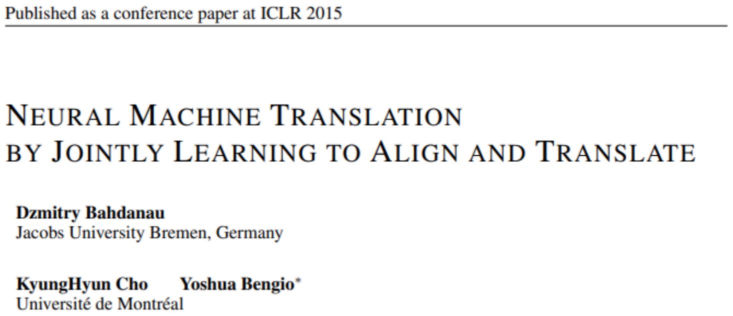


Attention!

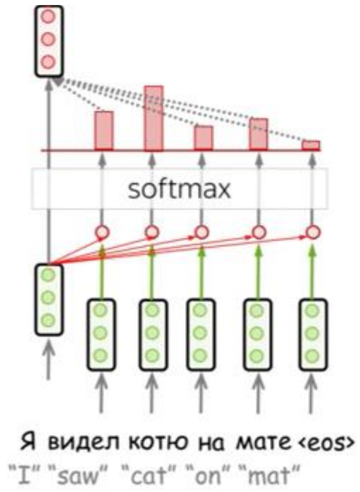
- These types of Neural Nets, however, suffered from various issues:
  - E.g., *catastrophic forgetting*, where earlier context in longer sentences tends to be forgotten.
- In 2015, *attention* in Neural Nets was invented:
  - It allowed models to attend to different parts of the sentence (instead of a single representation).


Published as a conference paper at ICLR 2015

NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

KyungHyun Cho **Yoshua Bengio***
Université de Montréal



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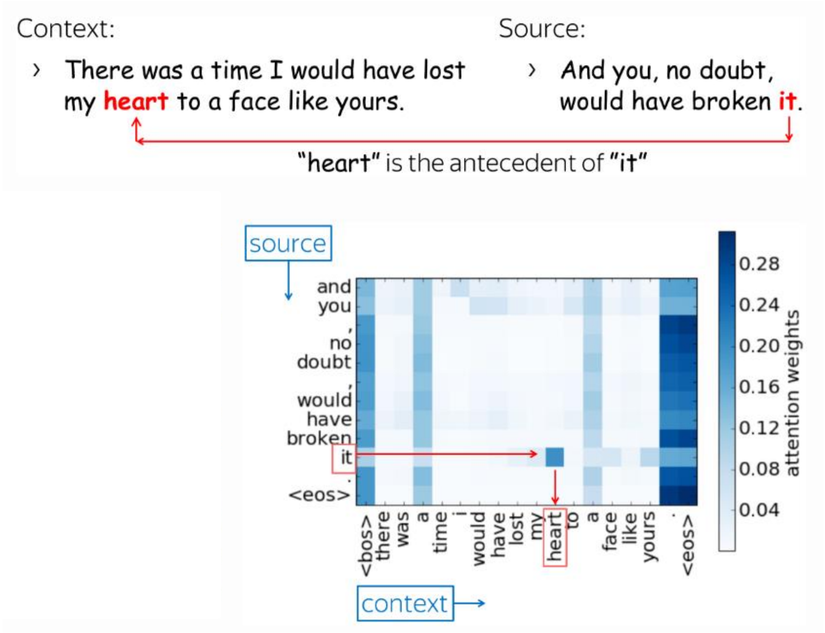
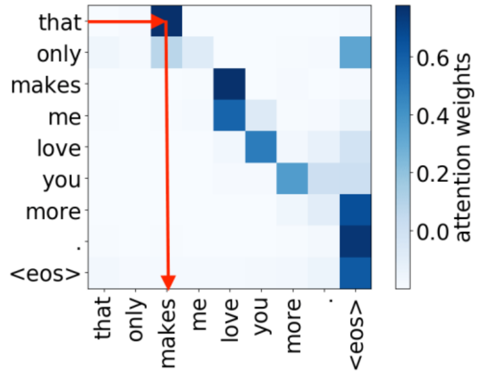
Attention!

- Once each part has its own embedding, different types of *relationships* can be learned!

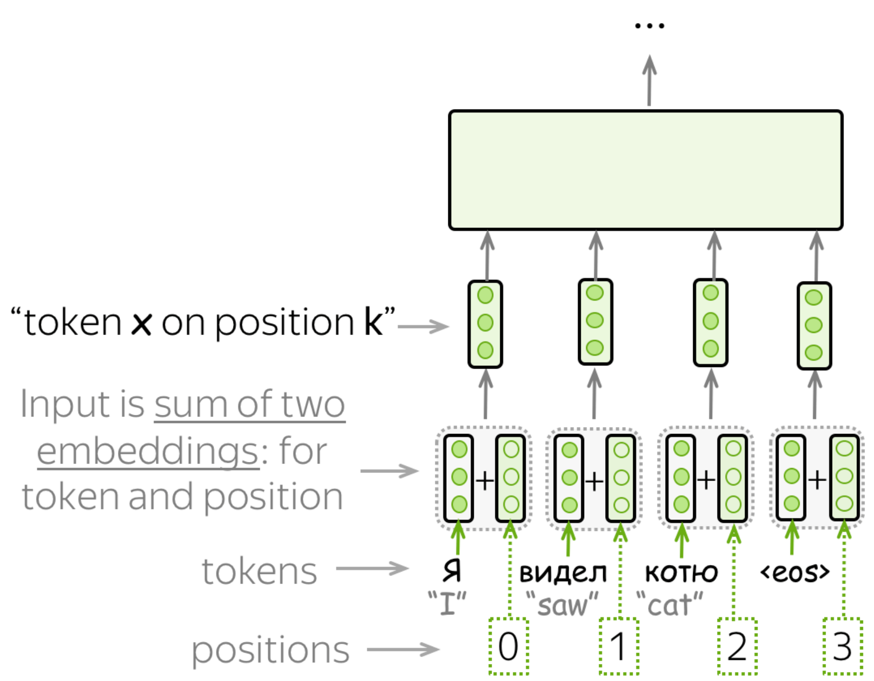




Subject -> verb

Order Matters: Positional Encoding!

- Since token embeddings do not contain information about the location of the word, they should be combined with a *positional encoding.*



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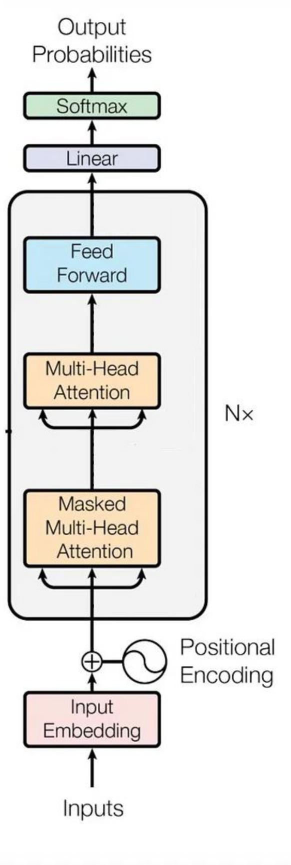
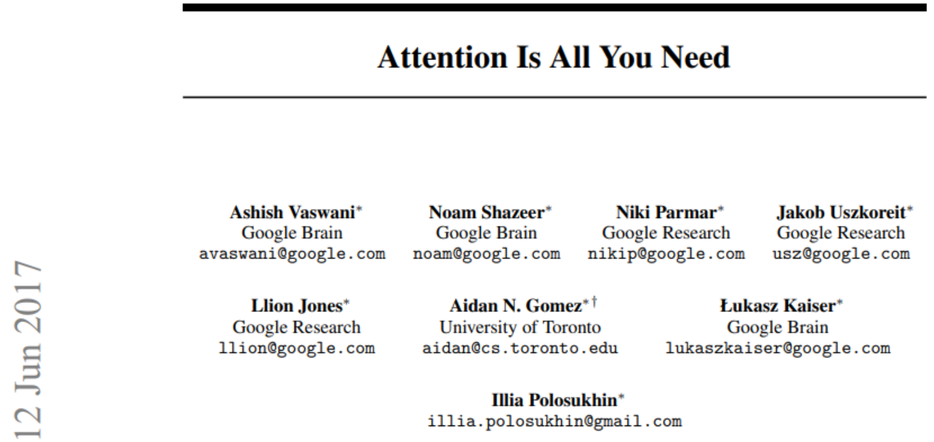
The Transformer is born!



Javinkarla



12 Jun 2017

Attention Is All You Need

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