SkillFactory

Language modelling
Sequence to Sequence task

Sidorov Nikita

MLE (NLP) Sber

What we will learn today

- Task of modelling text;
- LM as a formula;
- examples of application language modelling (LM);
- classical approach for LM;
- how to measure quality of language model;
- Neural LM;
- loss for neural LM;
- generation techniques;
- sequence to sequence tasks.

Modelling language

What we want from language model?

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We want to somehow forecast future words by some previous context.

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What we want from language model?

We want to somehow forecast future words by some previous context.

It means -> **Language Models (LM) estimate probability of token or several tokens in a row.**

LM in formula

We can say that our model needs to compute probability of a sentence

$$P_{(w_1, w_2, \ldots, w_n)} = p(w_1)p(w_2|w_1)p(w_3|w_1, w_2) \ldots p(w_n|w_1, w_2, .., w_{n-1})$$
$$= \prod_{i=1}^{n} p(w_i|w_1, \ldots, w_{i-1})$$

LM in formula

Related task: compute probability of upcoming word.

$$p(w_n | w_1, w_2, .., w_{n-1})$$

LM in formula

Model that compute

either this ->

$$p(w_n | w_1, w_2, .., w_{n-1})$$

or this ->

$$P_{(w_1, w_2, \ldots, w_n)} = \prod_{i=1}^{n} p(w_i | w_1, \ldots, w_{i-1})$$

is called Language Model.

LM in formula

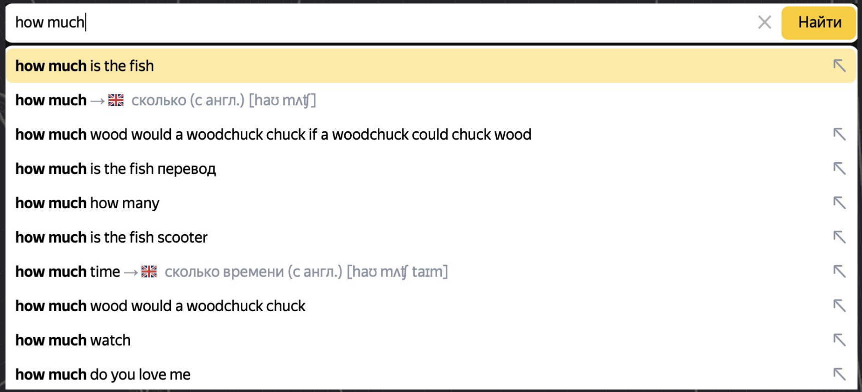
$$S = \underbrace{\text{Where are we}}_{\text{Previous words (Context)}}\ \text{going}$$

Word being predicted

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

Applications of LM

- machine translation
- spelling correction
- web search engine
- keyboard advices
- authors identification
- etc



LM formula calculation

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$$P(\text{going} \mid \text{Where are we}) = \frac{\mathit{Count}(\text{Where are we going})}{\mathit{Count}(\text{Where are we})}$$

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What`s the problem to compute it?

1. **It is too many possible sentences!**
2. **We`ll never see enough data for estimating this.**

Markov assumption

Simplifying assumption:

P(going | Where are we) ≈ P(going| we)

OR

P(going | Where are we) ≈ P(going| are we)

Markov assumption

More formally: $P(y_t \mid y_1, y_2, \dots, y_{t-1}) = P(y_t \mid y_{t-n+1}, \dots, y_{t-1})$

The probability of word depends only on **fixed** number of previous words.

N-gram LM

How to build it?

1. Make a simplification assumption x^{t+1} depends only on preceding *n-1* words.

$$P(\boldsymbol{x}^{(t+1)}|\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(1)}) = P(\boldsymbol{x}^{(t+1)}|\overbrace{\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)}}^{n\text{-1 words}})$$

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2. Move from probabilities to counts of corresponding n-grams.

N-gram LM example

Assume we have 4-gram language model.

when the lector come into the class, the students opened their ______

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Tip:
In practice usually use 5-gram model

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For example, in our corpus we have:

- “students opened their” occurred 1000 times
- “students opened their books” occurred 400 times -> P(books| context) = 0.4
- “students opened their notebooks” occurred 200 times -> P(notebooks| context) = 0.2

Problems with N-gram LM

- can not memorize long context
- can be 0 occurrence of specific n-gram
- can be 0 occurrence of specific n-1 gram
- storing problem (long n-grams significantly increase size of LM)

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Evaluation metric tells us how well our model does on test dataset.

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First approach

1. Evaluate each of your LM on your task (MT system, spelling correction)

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This approach named **extrinsic evaluation**.
Sometimes evaluation can take days or even weeks.

How to evaluate quality of LM

Second approach

It is cold **intrinsic**. We will explore metrics called **perplexity**.

Idea: better model assigns higher probability to the word that actually occurs.

Perplexity

Intuition: When reading a new text, how much is model “surprised”?

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Perplexity is the probability of the test set normalized by the number of words.

$$\text{perplexity} = \prod_{t=1}^{T} \left(\frac{1}{P_{\text{LM}}(\boldsymbol{x}^{(t+1)} \mid \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})} \right)^{1/T}$$

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Minimizing perplexity is the same as maximizing the probability.

Perplexity intuition

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Let`s suppose a sentence consisting of random digits. For example length of sentence is 5.

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P(W) = P($w_1 w_2 w_3 w_4 w_5$) = $P(w) = \left(\left(\frac{1}{10}\right)^5\right)^{-1/5}$ = 10

Perplexity intuition

Best perplexity score is 1. If the model is perfect and assigns probability 1 to correct tokens.

The worst perplexity is |V|. If the model knows nothing about the data, it assigns probability 1/|V| to all tokens, regardless of context.

Recap: what we need form LM

$$P(y_1, y_2, \dots, y_n) = P(y_1) \cdot P(y_2|y_1) \cdot P(y_3|y_1, y_2) \cdot \dots \cdot P(y_n|y_1, \dots, y_{n-1}) = \prod_{t=1}^{n} P(y_t|y_{<t})$$

<u>We need to</u>: define how to compute the conditional probabilities $P(y_n|y_1 \dots y_{n-1})$

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We need to: define how to compute the conditional probabilities $P(y_n|y_1 \dots y_{n-1})$

In neural networks, we do as usually:

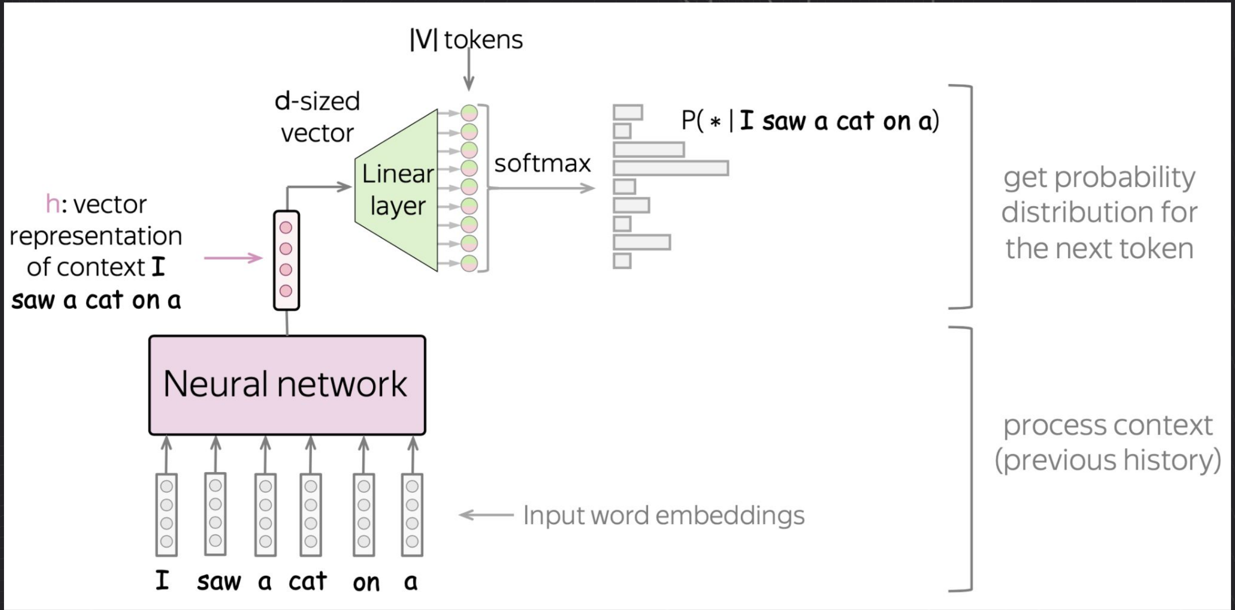
Train a NN to predict them.

Neural LM

General view:

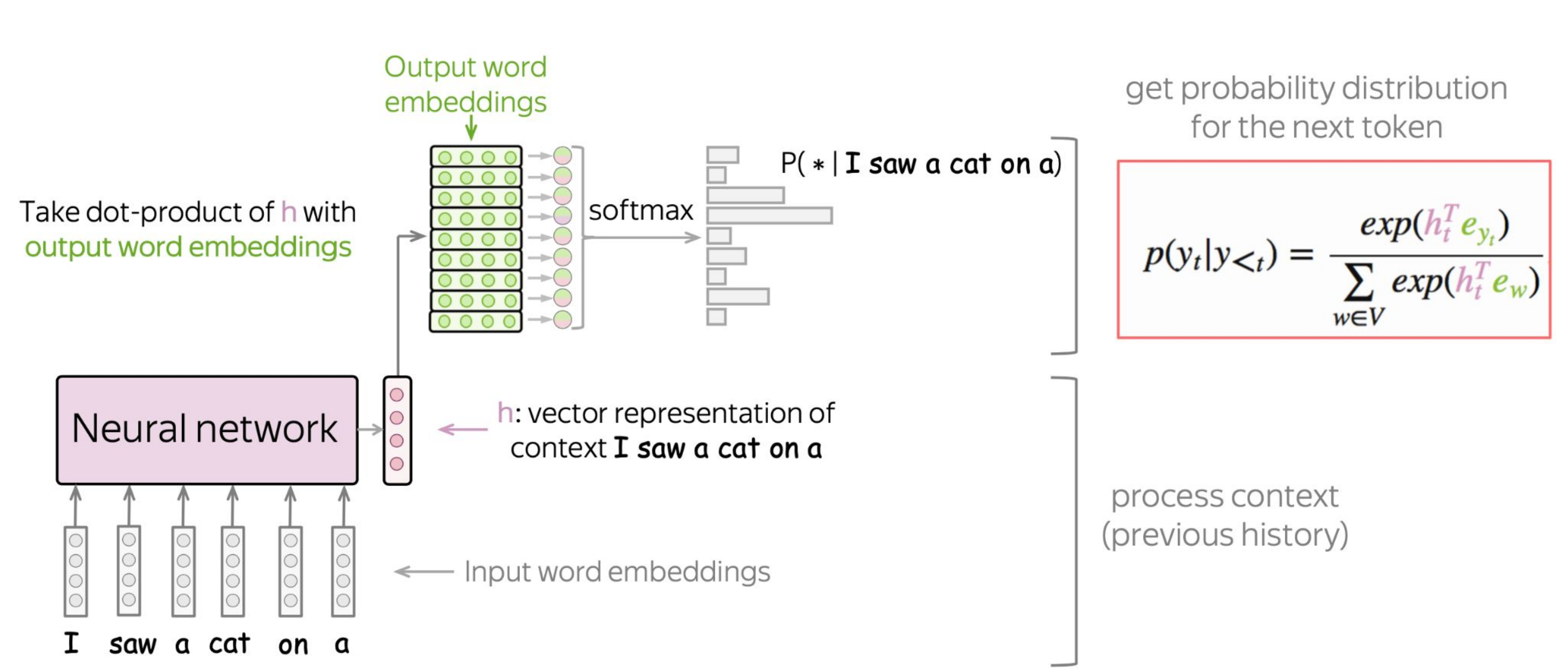
- process context (get vector representation of the previous context)
- evaluate probabilities (predict probability distribution for next token)

Neural LM



example from [Lena Voita NLP course]()

Neural LM



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Training neural LM

What kind of task we are solving in terms of Machine Learning?

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Multiclass classification!

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What kind of task we are solving in terms of Machine Learning?

Multiclass classification!

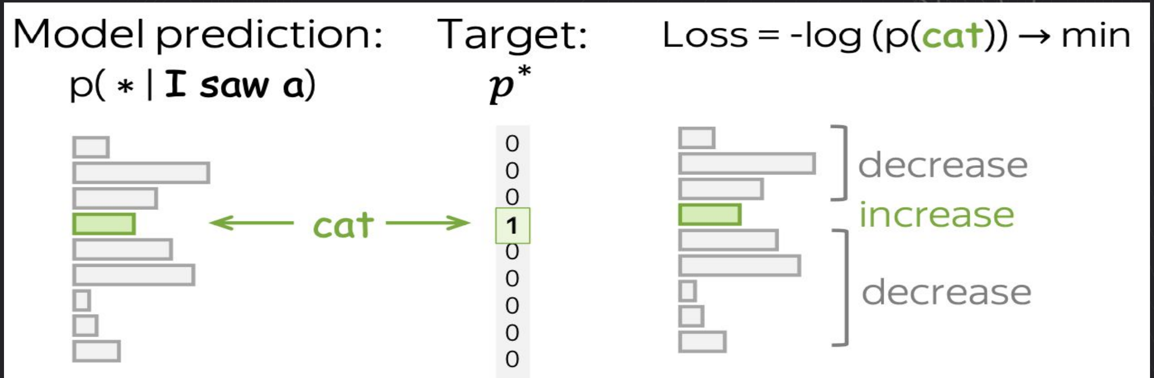
That's why we need cross-entropy loss function.

$$CCE(p, t) = -\sum_{c=1}^{C} t_{o,c} \log\left(p_{o,c}\right)$$

Training neural LM

Target word

Training example: I saw a cat on a mat <EOS>



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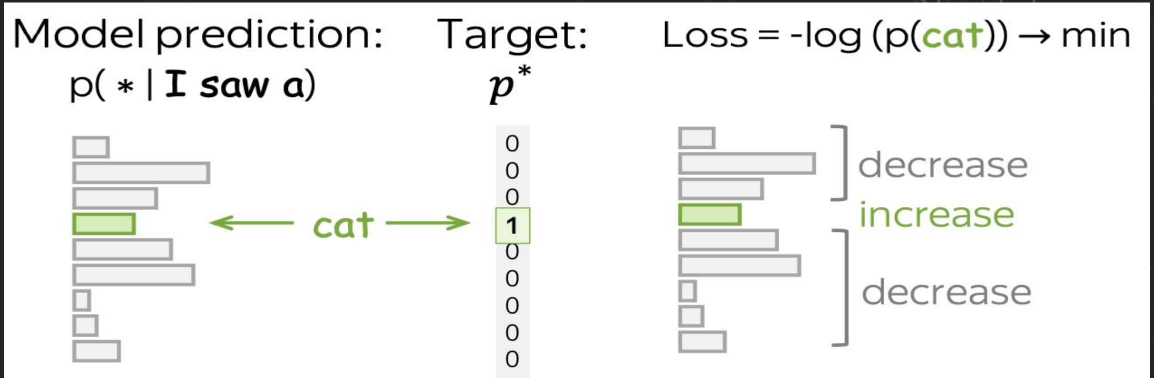

Cross-entropy loss:

$$-\sum_{i=1}^{|V|} p_i^* \cdot \log P(y_t = i|x) \rightarrow min \; (p_k^* = 1, p_i^* = 0, i \neq k)$$

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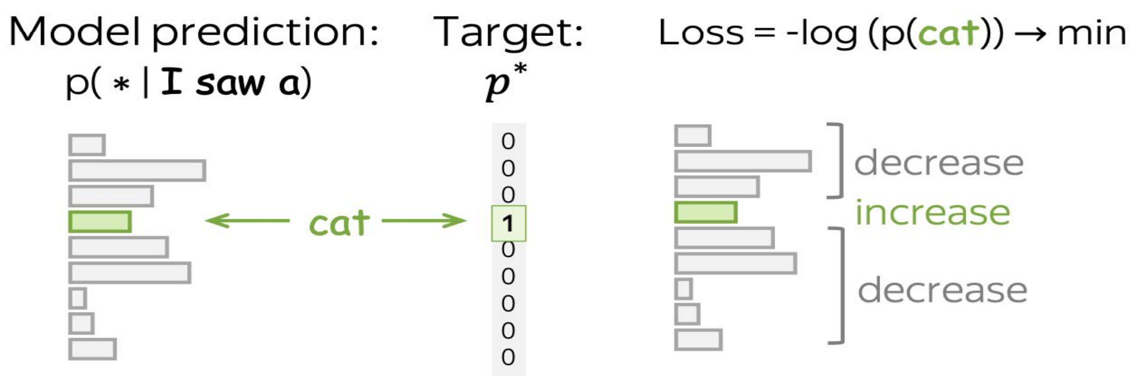

Cross-entropy loss:

$$-\sum_{i=1}^{|V|} p_i^* \cdot \log P(y_t = i|x) \rightarrow min \ (p_k^* = 1, p_i^* = 0, i \neq k\ )$$

For OHE targets,
this is equivalent to

$$-\log P(y_t = cat|x) \rightarrow min$$

example from Lena Voita NLP course

Again to perplexity

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$$= \prod_{t=1}^{T} \left(\frac{1}{\hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}}} \right)^{1/T} = \exp\left(\frac{1}{T} \sum_{t=1}^{T} -\log \hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}} \right) = \exp(J(\theta))$$

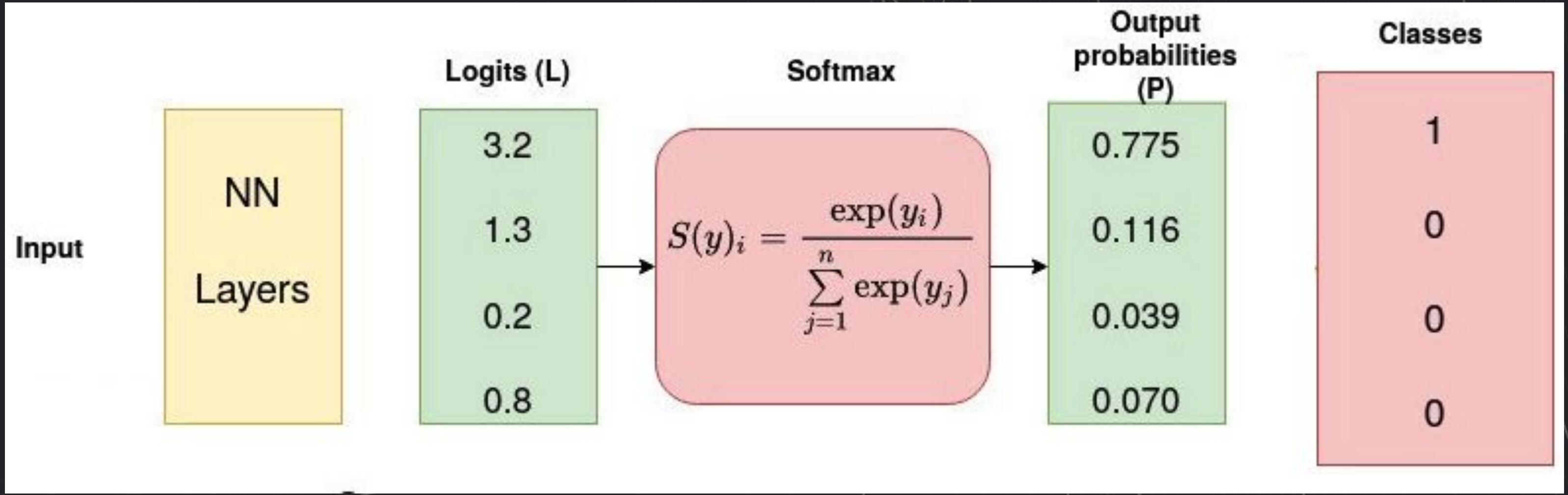
Text generation strategies

We want our generated texts to be:

- texts has to make sense (coherence)
- their must differ from each other (diversity)

Text generation strategies

Before that for determinism we used Softmax.



Text generation strategies

Now we will use special for of softmax - softmax with temperature.

$$\frac{\exp(h^T w)}{\sum_{w_i \in V} \exp(h^T w_i)} \rightarrow \frac{\exp\left(\frac{h^T w}{\tau}\right)}{\sum_{w_i \in V} \exp\left(\frac{h^T w_i}{\tau}\right)}$$

τ - softmax temperature

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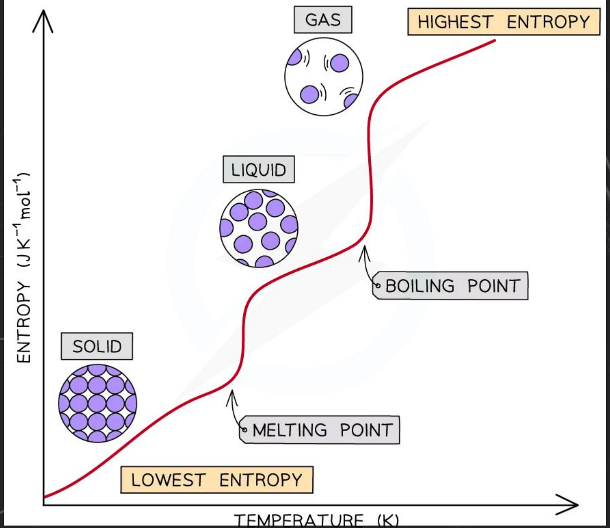
τ - softmax temperature

Intuition: divide by some temperature to change total entropy of system



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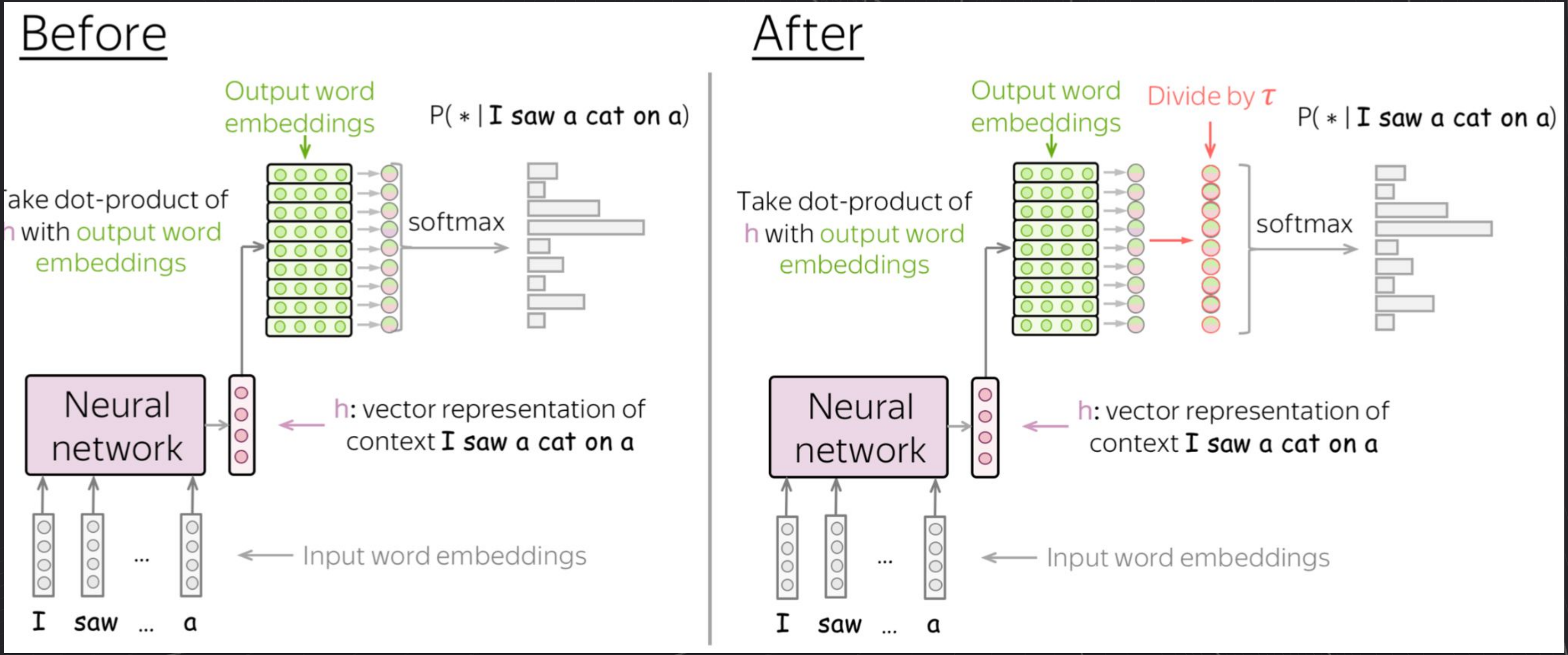
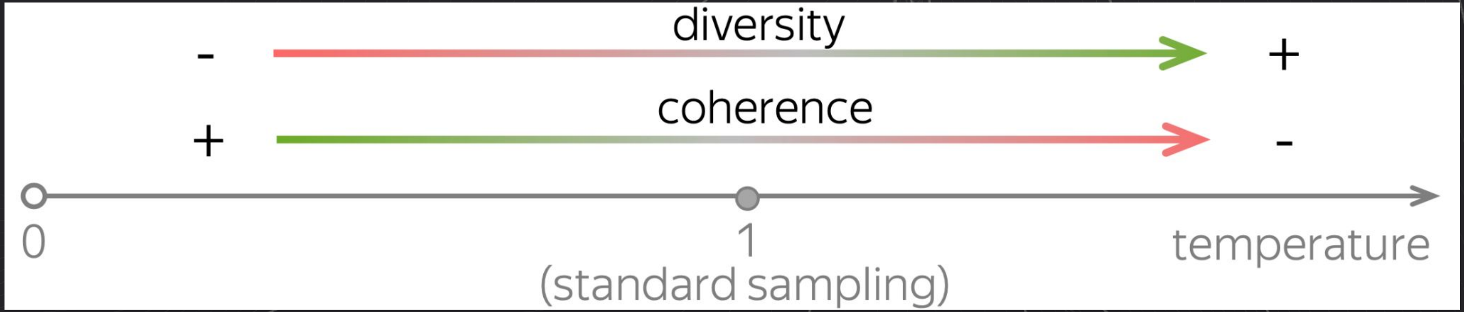


Text generation strategies

Both increasing and decreasing improve one of coherence and diversity, but hurt other

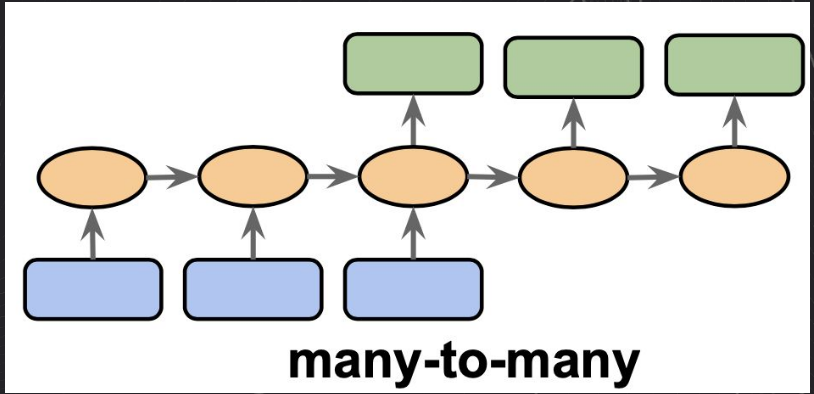


Other types of sampling

- Top-k sampling
- Top-p (Nucleus) sampling

Sequence to Sequence task

Traditionally seq2seq task is associated with translation from one language to another. It doesn't have to be human languages



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Statistical machine translation

We want to find best English sentence *y,* for given Russian sentence *x.*

$$\mathrm{argmax}_y\ P(y|x)$$

It's all like human deal with this task.

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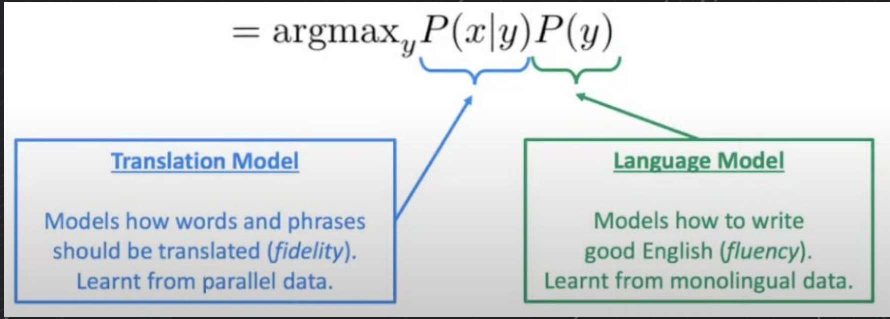
If apply Bayes Rule we will break this down into two components:



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Problems of Statistical MT

- systems had many separately-designed components
- lots of feature engineering
- need to design features to capture particular language phenomena
- lots of human effort to maintain
- reported effort for every language pair

Comparison of different MT approaches

Human deal with this task like this

$\text{argmax}_y\ P(y|x)$

Computer deal with this task like this

$\text{argmax}_y\ P(y|x, \theta)$

where p - some neural model,

and θ - parameters of model

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Neural approach for MT

Computer deal with this task like this

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Questions we need to ask?

modeling
How does the model for $p(y|\, x, \theta)$ look like?

learning
How to find best θ?

search
How to find the argmax?

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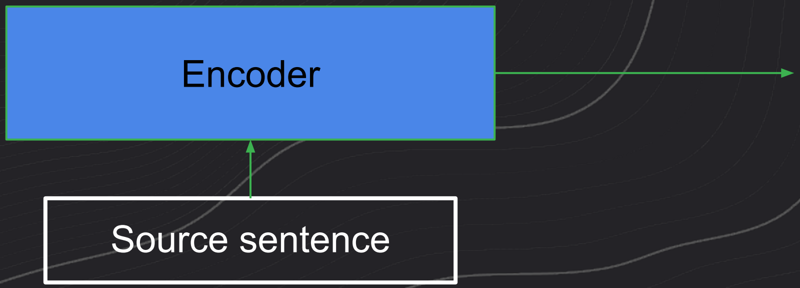
Encoder-Decoder Framework

The standard modeling paradigm:

- Encoder - reads the source sentence and builds its representation



Encoder-Decoder Framework

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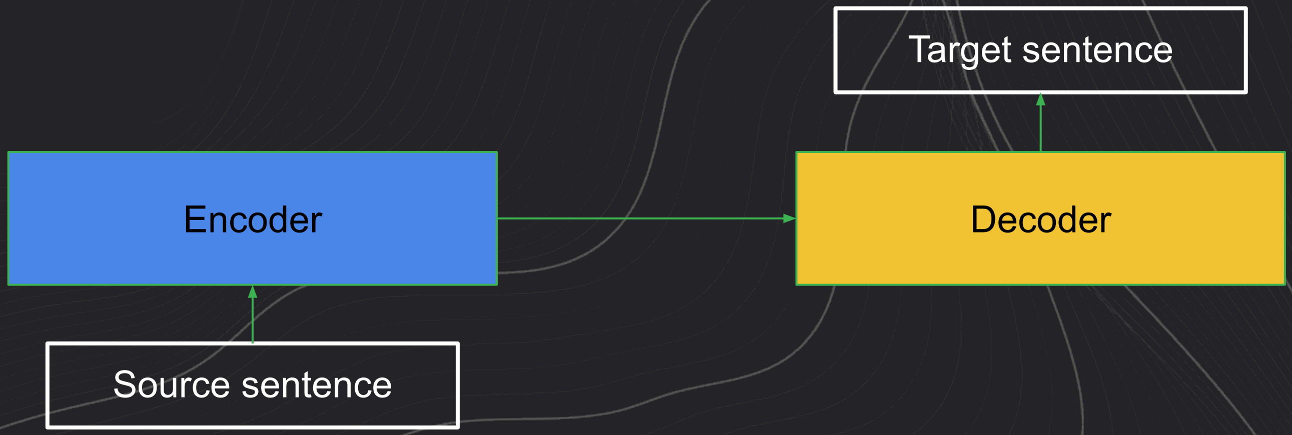
- Encoder - reads the source sentence and builds its representation
- Decoder - uses source representation from the encoder to generate the target sequence



Conditional Language Modeling

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Conditional Language Modeling

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$$P(y_1, y_2, \dots, y_n) = \prod_{t=1}^{n} p(y_t | y_{<t})$$

Conditional

Language models:

$$P(y_1, y_2, \dots, y_n, | x) = \prod_{t=1}^{n} p(y_t | y_{<t}, x)$$

condition on source x

Terminology

- Language model
- conditional probability
- Markov assumption
- n-gram
- extrinsic/intrinsic metric
- perplexity
- cross-entropy
- softmax
- temperature softmax
- top-k/top-p sampling
- seq2seq
- encoder
- decoder
- conditional modeling