

Text generation with transformers

Outline

- Language models
- GPT and related transformer decoders
- Text generation methods
- Controllable text generation
- ChatGPT & InstructGPT: Reinforcement Learning from Human Feedback (RLHF)

Language models

Language modeling

- Modeling something means to **predicting probability** of some action in a **given context**.
- Language Models (LMs) estimate the probability of different linguistic units: symbols, tokens, token sequences.

Web search engine / ...

I saw a cat|

I saw a cat on the chair

I saw a cat running after a dog

I saw a cat in my dream

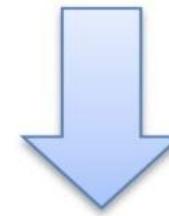
I saw a cat book

We deal with LMs every day!

- We can choose one option between the same sounding (similar) phrases:

Я хочу назвать моего кота Наполеон.

Я хочу назвать моего кота на поле он.



Я хочу назвать моего кота Наполеон.

- For automatic models, the probability of the sentence will help in the solution.

Probability of sentence: Intuition

- "Probability of a sentence" = as much as possible in natural language.
- Only a specific language is considered:

$P(\text{Кот лежит на диване}) > P(\text{На диване кот лежит})$

$P(\text{Красивая девочка играла в мяч}) > P(\text{В мяч играла девочка красивая})$

LMs in NLP

- It is very difficult to know the real probability of a sequence of tokens.
- But we can use a language model to approximate this probability.
- Like all models, language models “behave well” in some cases and “badly” in others.



Proper language modelling

The goal of language modelling: **assign a probability to any text (aka sequence of words/tokens)**

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What for?

- “More probable” sometimes means “better”
 - Can be used for spelling correction, translation, speech recognition etc.
- By sampling from this distribution, one can generate texts

Proper language modelling

The goal of language modelling: **assign a probability to any text**

How?

Solution: chain rule

$$\begin{aligned} P(\text{Я хочу назвать кота Наполеон}) &= \\ &= P(\text{Наполеон}|\text{Я хочу назвать кота}) \times P(\text{Я хочу назвать кота}) = \\ &= P(\text{Наполеон}|\text{Я хочу назвать кота}) \times P(\text{кота}|\text{Я хочу назвать}) \times \\ &\quad P(\text{назвать}|\text{Я хочу}) \times P(\text{хочу}|\text{я}) \times P(\text{я}) \end{aligned}$$

LMs in NLP

- Language models can be divided into two types:
 - **Count-based Models** (Statistical) - statistical language models.
 - **Neural Language Models** - language models based on neural networks.

n-gram language models

$$P(\text{text}) = P(w_0 w_1 \dots w_m) = \prod_{i=0}^m P(w_i | w_0 \dots w_{i-1})$$

n-gram language models

$$P(\text{text}) = P(w_0 w_1 \dots w_m) = \prod_{i=0}^m P(w_i | w_0 \dots w_{i-1})$$

Markov assumption: we can predict the probability of some future unit without looking too far into the past (on a current step distant words do not matter much)

$$P(w_i | w_0 \dots w_{i-1}) \approx P(w_i | w_{\textcolor{red}{i-n}} \dots w_{i-1})$$

n-gram language models

$$P(\text{text}) = P(w_0 w_1 \dots w_m) = \prod_{i=0}^m P(w_i | w_0 \dots w_{i-1})$$

- Simplifying assumption: distant words do not matter much

$$P(w_i | w_0 \dots w_{i-1}) \approx P(w_i | w_{i-n} \dots w_{i-1})$$

How to estimate P :

- $P = C(n\text{-gram}) / \sum C(n\text{-gram})$

< s > I am Sam < /s >
< s > Sam I am < /s >
< s > I do not like green eggs and ham < /s >

$$\begin{aligned} P(I|< s >) &= \frac{2}{3} = .67 & P(Sam|< s >) &= \frac{1}{3} = .33 & P(am|I) &= \frac{2}{3} = .67 \\ P(< /s >|Sam) &= \frac{1}{2} = 0.5 & P(Sam|am) &= \frac{1}{2} = .5 & P(do|I) &= \frac{1}{3} = .33 \end{aligned}$$

n-gram language models

Before

$$P(I \text{ saw a cat on a mat}) =$$

- $P(I)$
- $P(saw | I)$
- $P(a | I \text{ saw})$
- $P(cat | I \text{ saw a})$
- $P(on | I \text{ saw a cat})$
- $P(a | I \text{ saw a cat on})$
- $P(mat | I \text{ saw a cat on a})$

After (3-gram)

$$P(I \text{ saw a cat on a mat}) =$$

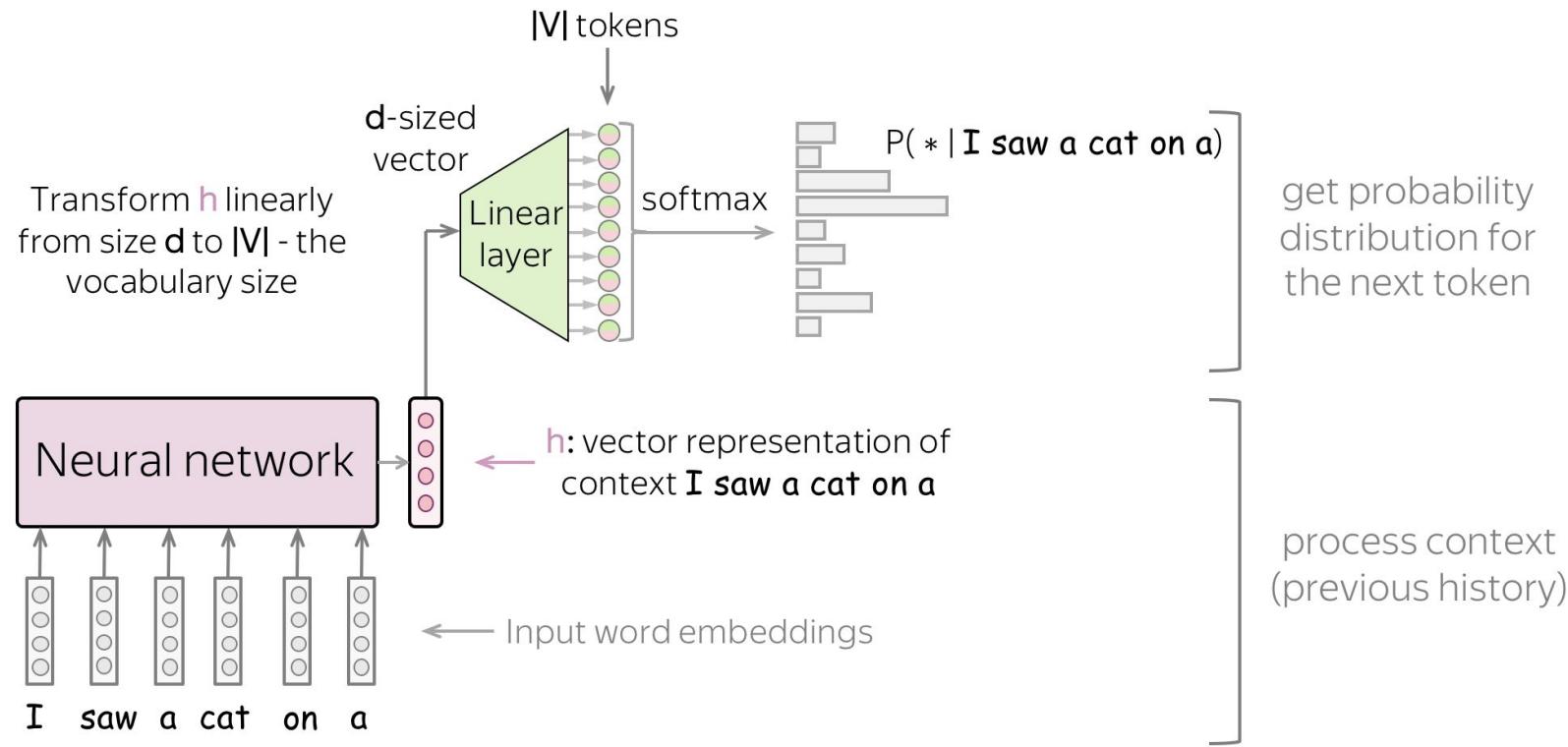


ignore use

- $P(I) \longrightarrow P(I)$
- $P(saw | I) \longrightarrow P(saw | I)$
- $P(a | I \text{ saw}) \longrightarrow P(a | I \text{ saw})$
- $P(cat | I \text{ saw a}) \longrightarrow P(cat | saw a)$
- $P(on | I \text{ saw a cat}) \longrightarrow P(on | a cat)$
- $P(a | I \text{ saw a cat on}) \longrightarrow P(a | cat on)$
- $P(mat | I \text{ saw a cat on a}) \longrightarrow P(mat | on a)$

Neural language models

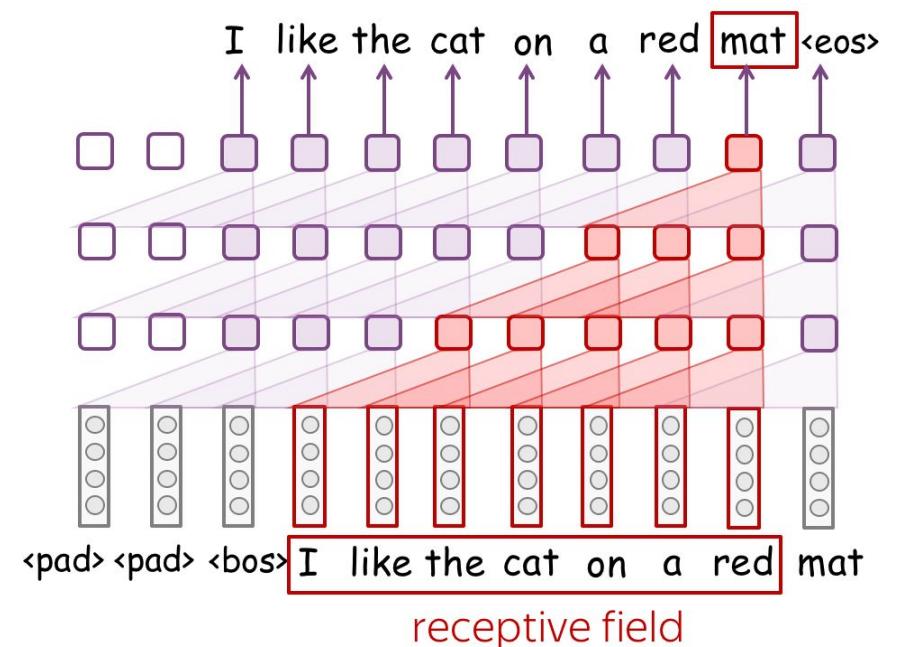
Neural LMs encode *the context* into a vector representation and then predict probability distribution of the *next token*.



CNN language models (Fixed Window Neural Language Models)

- What are the **improvements** in comparison with N-gram LM:
 - No sparsity problem

CNN: a strictly limited receptive field;
training is very fast because it can run in parallel on all time steps

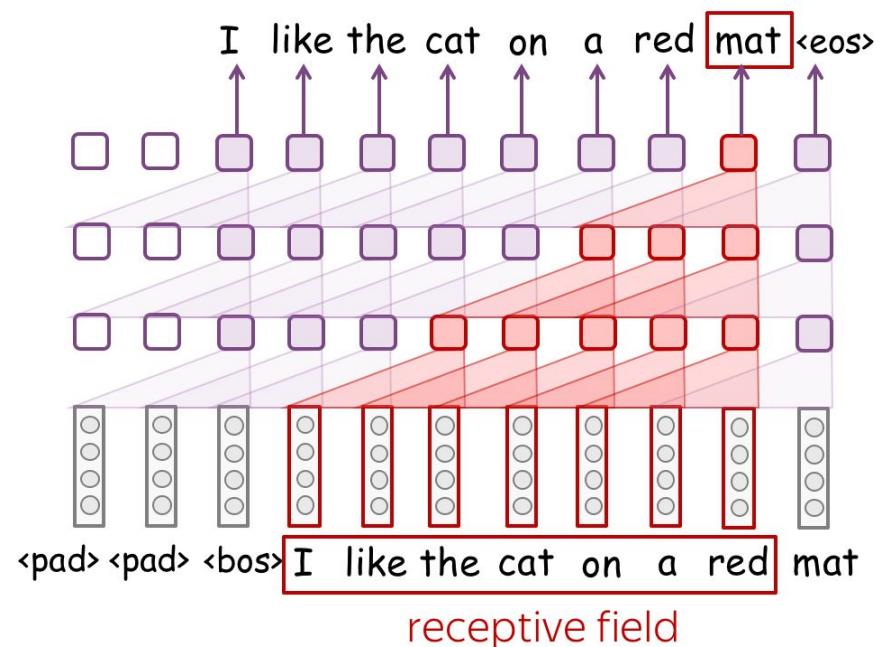


*In practice, when training RNNs, gradient flows only for n time steps backward, so the models do not learn to account for very distant context

CNN language models (Fixed Window Neural Language Models)

- What are the **improvements** in comparison with N-gram LM:
 - No sparsity problem
- What **problems** remained:
 - Fixed size windows - very small, cannot be changed
 - Fixed word order
 - Weights can only be used inside the window

CNN: a strictly limited receptive field; training is very fast because it can run in parallel on all time steps



RNN language models

- Final distribution:

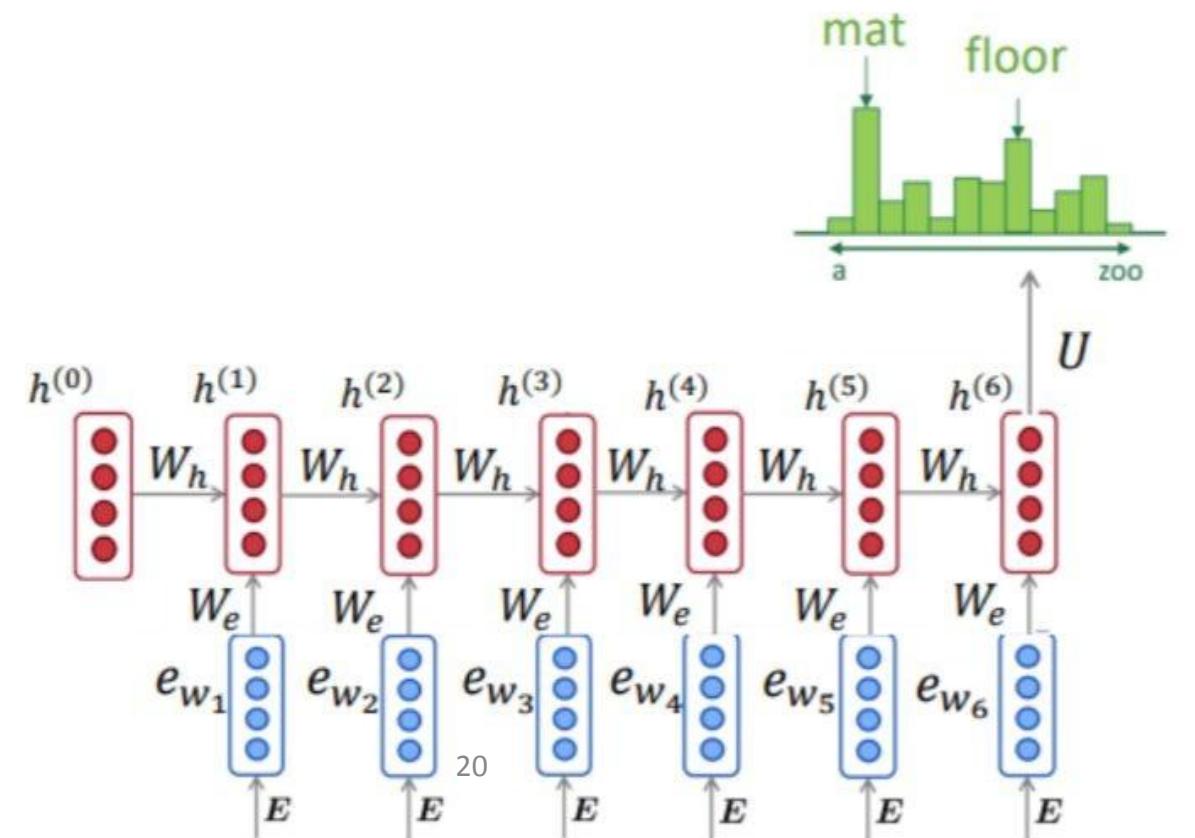
$$\hat{y} = \text{softmax}(Uh + b_2) \in R^{|V|}$$

- Hidden states

$$h^{(t)} = \sigma(W_h h^{(t-1)} + W_x e^{(t-1)} + b_1)$$

- Word embeddings

- Words

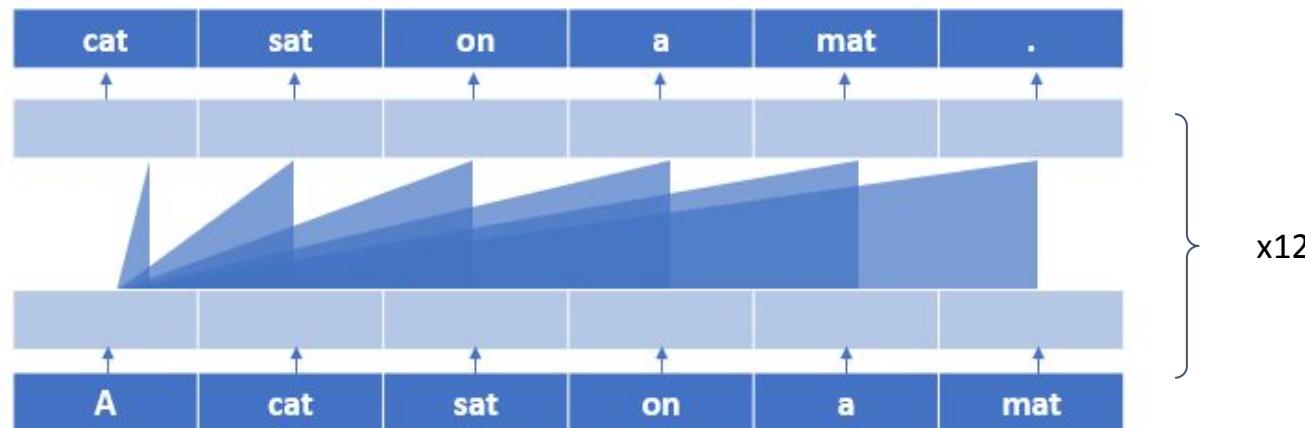


<bos> Котик очень тихо спал на
 $x^{(i-6)} \quad x^{(i-5)} x^{(i-4)} \quad x^{(i-3)} \quad x^{(i-2)} \quad x^{(i-1)}$

*In practice, when training RNNs, gradient flows only for n time steps backward, so the models do not learn to account for very distant context

Transformer language models

- **Attention** => they have direct access to previous tokens
- Support longer contexts than CNNs
- Train faster than RNNs, because do not require recurrence



Perplexity and likelihood

How good a language model is?

Perplexity and likelihood

How good a language model is?

When we train a LM, we (*equivalently*)

- *maximize log-likelihood:* $LL = \log p(\text{text}) = \sum_{i=1}^n \log p(y_i | y_{<i})$
- *minimize cross-entropy:* $CE = -\frac{1}{n} \sum_{i=1}^n \log p(y_i | y_{<i}) = -\frac{LL}{n}$
- *minimize perplexity:* $ppl = \frac{1}{p(\text{text})} = e^{CE} = e^{-\frac{LL}{n}} = e^{-\frac{1}{n} \sum_{i=1}^n \log p(y_i | y_{<i})}$

Perplexity and likelihood

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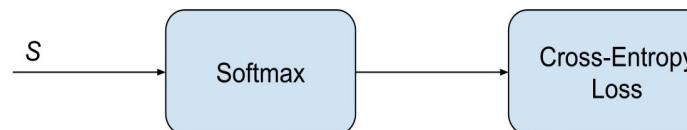
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To evaluate a model, we *calculate the same scores on test texts*

Categorical Cross-Entropy loss (Softmax loss)

In its output, autoregressive language models predict probability distribution over all tokens in a given vocabulary. It is a Categorical problem:

- We need Softmax to normalize probability



$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \quad CE = -\sum_i^C t_i \log(f(s)_i)$$

- Cross Entropy over softmax now looks like

$$CE = -\log \left(\frac{e^{s_p}}{\sum_j^C e^{s_j}} \right)$$

Pytorch: [CrossEntropyLoss](#).

TensorFlow: [softmax_cross_entropy](#).

Language modeling as a pretraining objective

- It is **difficult** (even for humans)
 - *Autoregressive modeling is more difficult than masked language modeling*
*The autoregressive model is a feed-forward model, that predicts the future word from a set of words in a given context.
- It forces the model to **learn lots of aspects of the language and the world**
- It requires **no inputs except the texts**
- **No such problems** with hyperparameters as in MLM

Everything as language modelling

Most NLP problems can be formulated as text continuation problems

Few Shot Prompt and Predicted Answer

The following are multiple choice questions about high school mathematics.

How many numbers are in the list 25, 26, ..., 100?
(A) 75 (B) 76 (C) 22 (D) 23
Answer: B

Compute $i + i^2 + i^3 + \dots + i^{258} + i^{259}$.

(A) -1 (B) 1 (C) i (D) $-i$

Answer: A

If 4 daps = 7 yaps, and 5 yaps = 3 baps, how many daps equal 42 baps?

(A) 28 (B) 21 (C) 40 (D) 30

Answer: C

Translate each sentence into a string of emojis.

English: That cat ate the fish.

Emojis: 🐱cá吃过魚

English: What is this, a house for ants?

Emojis: 🏠🐜❓

English: The quick brown fox jumps over the lazy dog.

Emojis: 🐺🦊🦊🦊

English: One small step for man, one giant leap for mankind.

Emojis: 🚀🌕🌐🚀

Everything as language modelling

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A single good LM can learn to solve them all!

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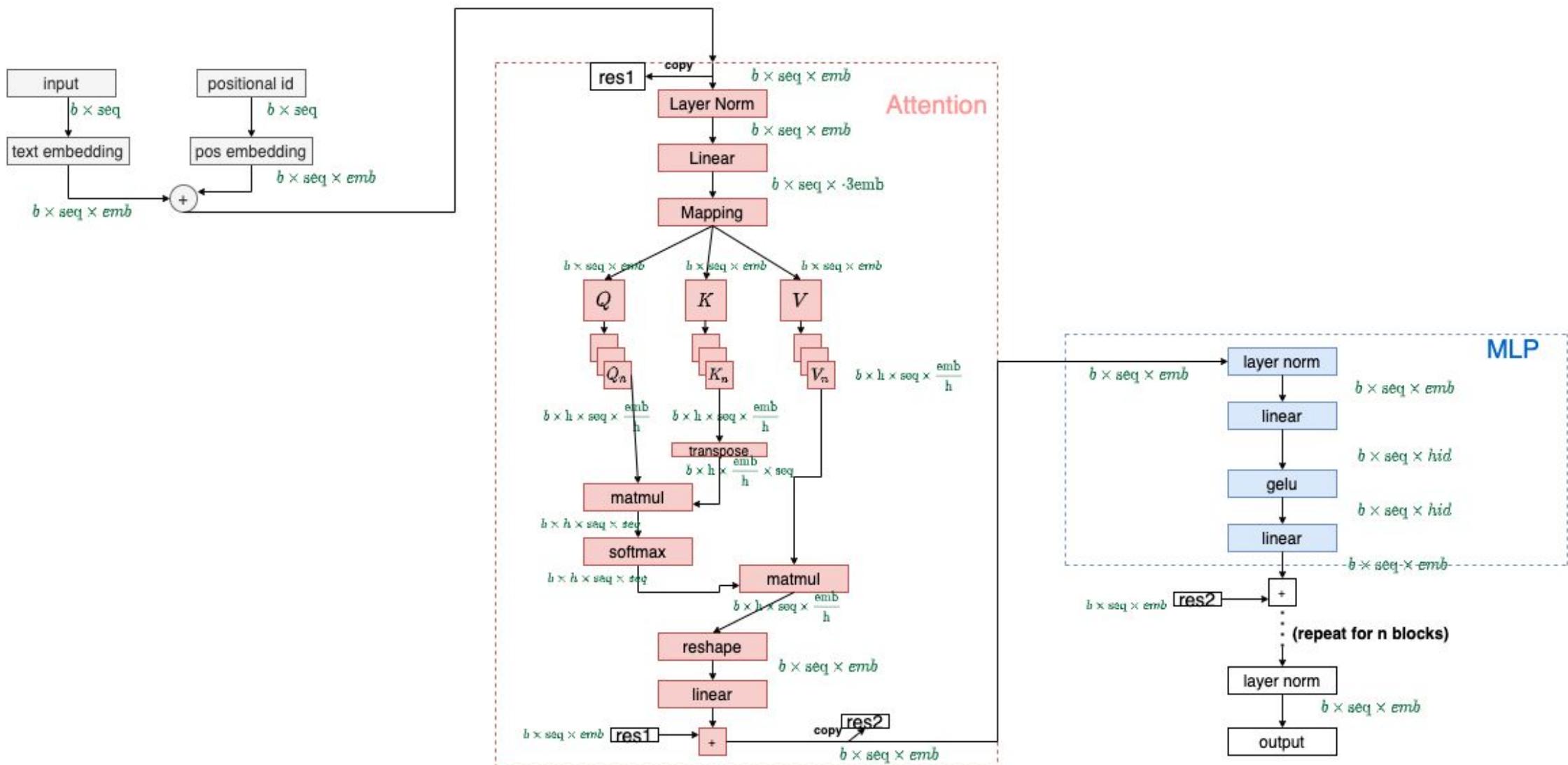
The GPT family

Generative Pretrained Transformers

The **main idea**:

- *Pretrain a large transformer* decoder on the language modelling task
- Formulate another NLP task as *text continuation*
- Use the LM to solve this task with little or no fine-tuning

GPT architecture

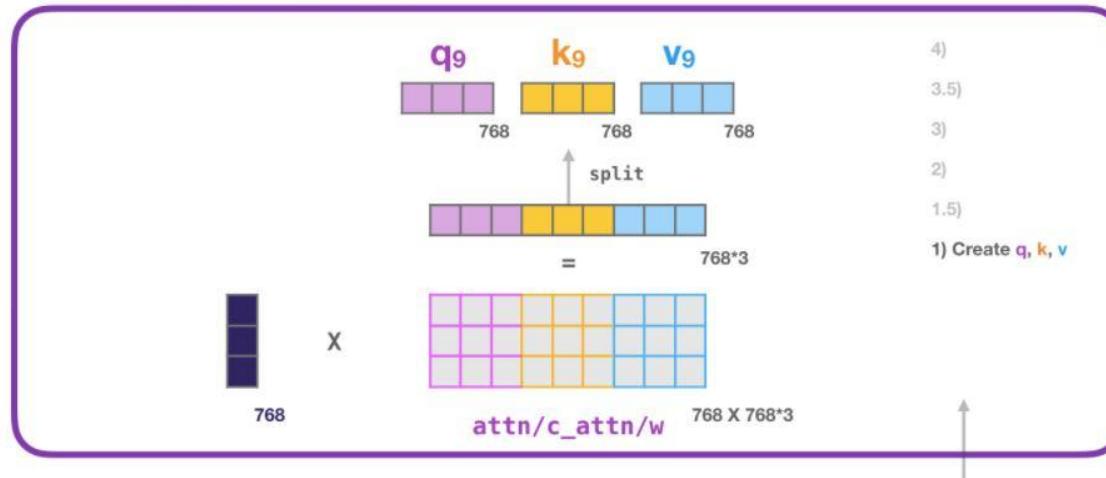


How GPT looks in the real world?

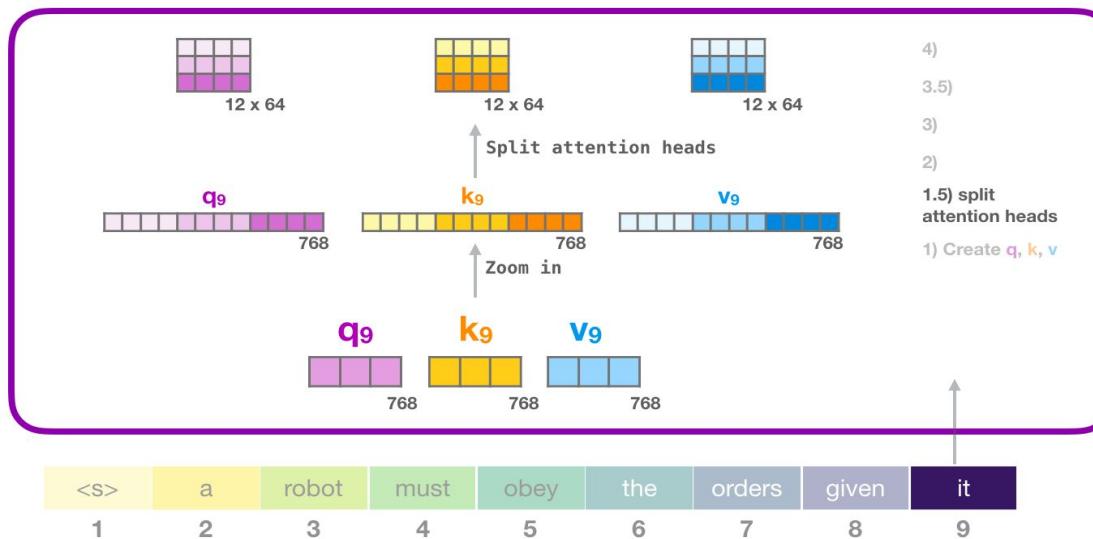
```
gpt2.transformer.h[1]
```

```
GPT2Block(  
    (ln_1): LayerNorm((768,), eps=1e-05, elementwise_affine=True)  
    (attn): GPT2Attention(  
        (c_attn): Conv1D() [768, 2304]  
        (c_proj): Conv1D() [768, 768]  
        (attn_dropout): Dropout(p=0.1, inplace=False)  
        (resid_dropout): Dropout(p=0.1, inplace=False)  
    )  
    (ln_2): LayerNorm((768,), eps=1e-05, elementwise_affine=True)  
    (mlp): GPT2MLP(  
        (c_fc): Conv1D() [768, 3072]  
        (c_proj): Conv1D() [3072, 768]  
        (act): NewGELUActivation()  
        (dropout): Dropout(p=0.1, inplace=False)  
    )  
)
```

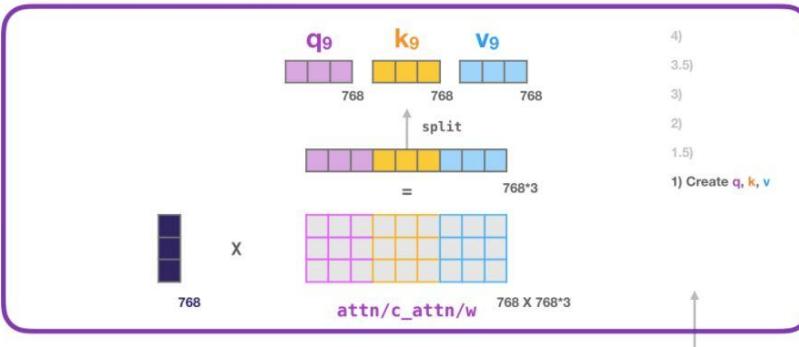
GPT2 Self-Attention



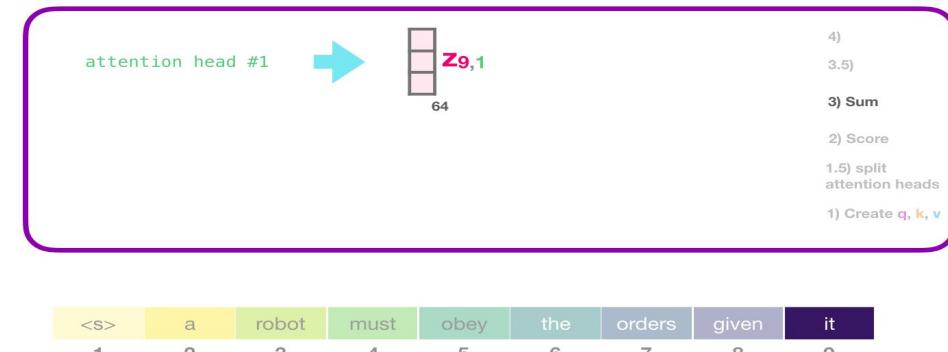
GPT2 Self-Attention



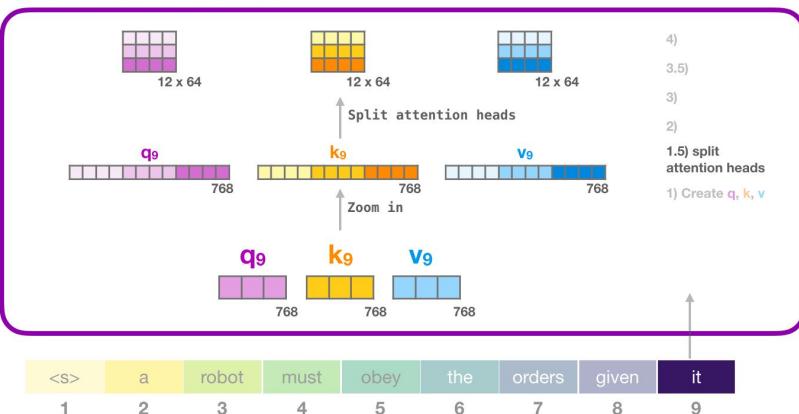
GPT2 Self-Attention



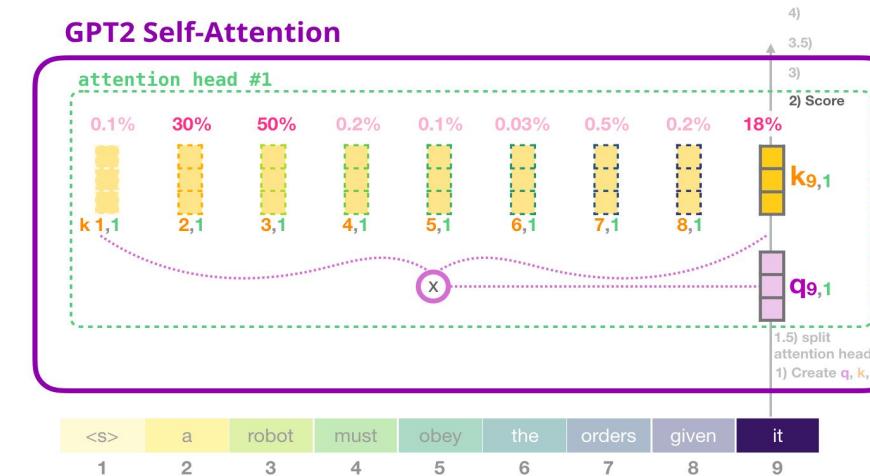
GPT2 Self-Attention



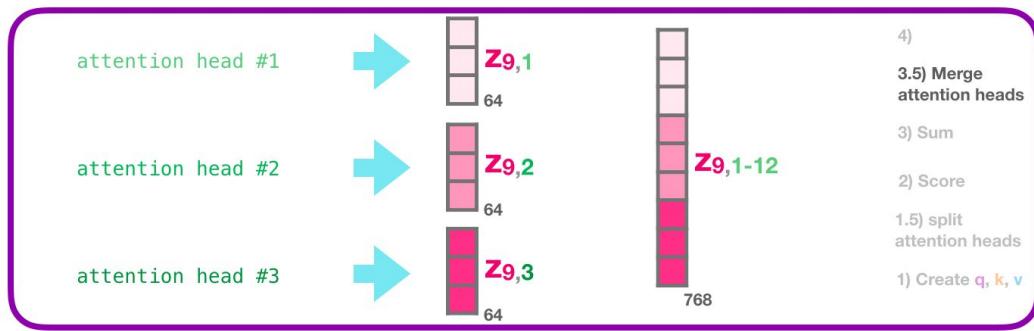
GPT2 Self-Attention



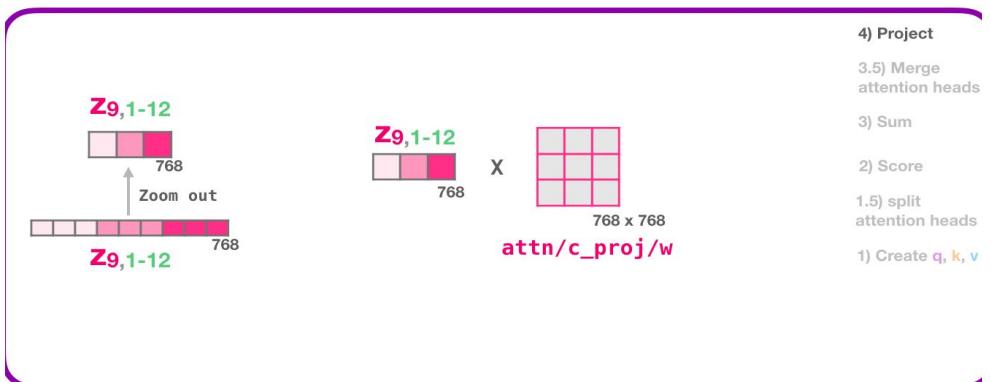
GPT2 Self-Attention



GPT2 Self-Attention

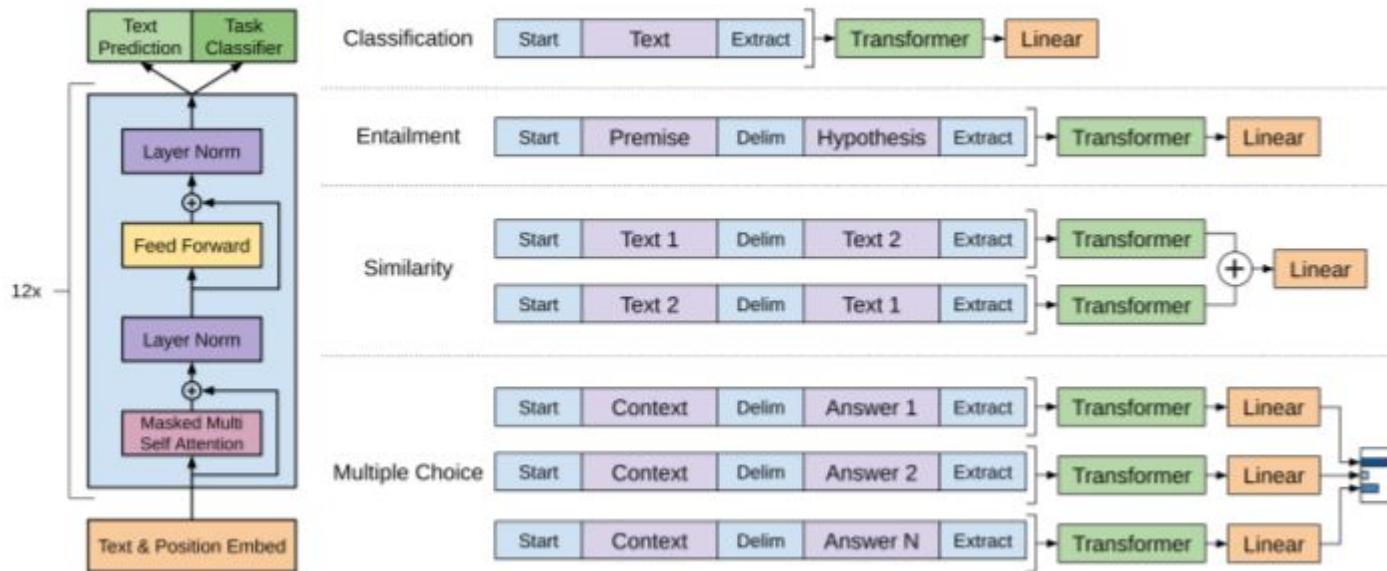


GPT2 SELF-ATTENTION



GPT-1

- *Improving Language Understanding by Generative Pre-Training, Radford et al, 2018*
 - The paper was published several months before BERT
- Idea: pre-train a transformer decoder on the LM problem, then fine-tune on NLU tasks
 - GPT-1 is trained on BookCorpus dataset bases on 7000 unpublished books
 - GPT-1 is fine-tuned on classification, semantic proximity detection, natural language generation, and question-answer tasks
 - GPT-1 is evaluated on 12 tasks and be SOTA for 8 of them.



GPT-2

- *Language Models are Unsupervised Multitask Learners, Radford et al, 2019*
- **Idea:** if we increase a model size, we increase performance!
- Scale GPT up:
 - Train on **40GB** of WebText, up to **1.5B** params (vs 117M in GPT-1)
 - Perplexity on multiple test LM datasets improves with model size and does not saturate
- The models show good zero-shot performance on reading comprehension, question answering, even fr-en translation
- The largest model generates fluent and well-structured texts

GPT-3

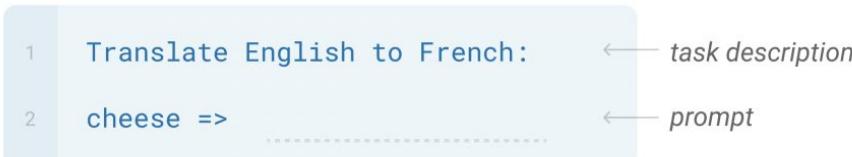
- *Language Models are Few-Shot Learners, Brown et al, 2020*
- Scale GPT-2 further: **570GB training data, up to 175B parameters**

GPT-3

- *Language Models are Few-Shot Learners, Brown et al, 2020*
- Scale GPT-2 further: **570GB training data**, up to **175B parameters**
- **Few-shot approach**
 - apply to NLP tasks without fine-tuning: the only “learning” takes place with few training examples being part of a prompt

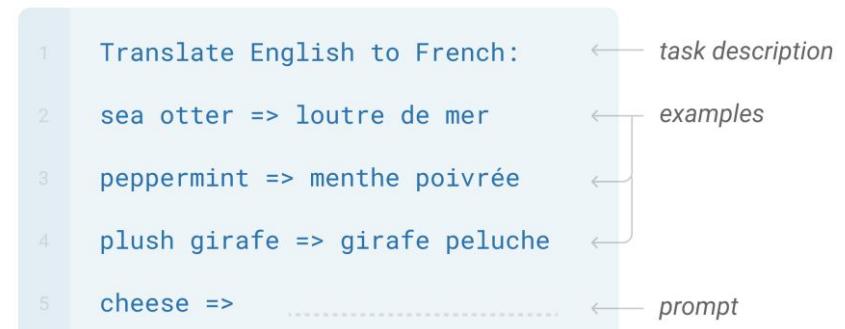
Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.



Few-shot

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



GPT-3 application examples: NLU

Prompt

The following is a list of companies and the categories they fall into:

Apple, Facebook, Fedex

Apple
Category:

Sample response

Technology

Facebook

Category: Social Media

Fedex

Category: Delivery

A simple prompt for extracting airport codes from text.

Prompt

Extract the airport codes from this text:

Text: "I want to fly from Los Angeles to Miami."

Airport codes: LAX, MIA

Text: "I want to fly from Orlando to Boston"

Airport codes:

Sample response

MCO, BOS

GPT-3 application examples: NLG

Explain a piece of Python code in human understandable language.

Prompt

```
# Python 3
def remove_common_prefix(x, prefix, ws_prefix):
    x["completion"] = x["completion"].str[len(prefix) :]
    if ws_prefix:
        # keep the single whitespace as prefix
        x["completion"] = " " + x["completion"]
    return x
```

Explanation of what the code does

#

Sample response

The code above is a function that takes a dataframe and a prefix as input and returns a dataframe with the prefix removed from the completion column.

Turn a product description into ad copy.

Prompt

Write a creative ad for the following product to run on Facebook aimed at parents:

Product: Learning Room is a virtual environment to help students from kindergarten to high school excel in school.

Sample response

Are you looking for a way to help your child excel in school? Look no further than Learning Room! Our virtual environment is designed to help students from kindergarten to high school learn and grow. With our help, your child will be able to get ahead in school and achieve their academic goals.

GPT-3 application examples: code generation

Translate text into programmatic commands.

Prompt

Convert this text to a programmatic command:

Example: Ask Constance if we need some bread

Output: send-msg `find constance` Do we need some bread?

Contact the ski store and figure out if I can get my skis fixed before I leave on Thursday

Sample response

send-msg `find ski-store` Can I get my skis fixed before I leave on Thursday?

Translate natural language to SQL queries.

Prompt

```
### Postgres SQL tables, with their properties:  
#  
# Employee(id, name, department_id)  
# Department(id, name, address)  
# Salary_Payments(id, employee_id, amount, date)  
#  
### A query to list the names of the departments which employed  
more than 10 employees in the last 3 months  
SELECT
```

Sample response

```
DISTINCT department.name  
FROM department  
JOIN employee ON department.id = employee.department_id  
JOIN salary_payments ON employee.id =  
salary_payments.employee_id  
WHERE salary_payments.date > (CURRENT_DATE - INTERVAL '3  
months')  
GROUP BY department.name  
HAVING COUNT(employee.id) > 10;
```

Details of GPT implementation

- All GPTs are almost vanilla transformer decoders
 - GPT-3 also uses sparse attention alongside classical one
 - details are unknown
- Byte-level BPE vocabulary, ~50K tokens
- Context window of 2048 tokens in GPT-3

| Model Name | n_{params} | n_{layers} | d_{model} | n_{heads} | d_{head} | Batch Size | Learning Rate |
|-----------------------|---------------------|---------------------|--------------------|--------------------|-------------------|------------|----------------------|
| GPT-3 Small | 125M | 12 | 768 | 12 | 64 | 0.5M | 6.0×10^{-4} |
| GPT-3 Medium | 350M | 24 | 1024 | 16 | 64 | 0.5M | 3.0×10^{-4} |
| GPT-3 Large | 760M | 24 | 1536 | 16 | 96 | 0.5M | 2.5×10^{-4} |
| GPT-3 XL | 1.3B | 24 | 2048 | 24 | 128 | 1M | 2.0×10^{-4} |
| GPT-3 2.7B | 2.7B | 32 | 2560 | 32 | 80 | 1M | 1.6×10^{-4} |
| GPT-3 6.7B | 6.7B | 32 | 4096 | 32 | 128 | 2M | 1.2×10^{-4} |
| GPT-3 13B | 13.0B | 40 | 5140 | 40 | 128 | 2M | 1.0×10^{-4} |
| GPT-3 175B or "GPT-3" | 175.0B | 96 | 12288 | 96 | 128 | 3.2M | 0.6×10^{-4} |

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.

GPT-4

- *Based on GPT*
- Accepts image and text inputs, emitting text outputs
- Model context 8,192 tokens
- There is a version with 32,768 tokens (50 text pages)
- **NO PAPER**
- **NO INFORMATION about its architecture**

Архитектура:

Любопытно, что GPT-4 закрыла собой долгие споры о том, куда все-таки нужно ставить LayerNorm в Трансформере!

GPT-like models

- GPT-Neo by EleutherAI (English, public reproduction of GPT-3)
- LaMDA by Google (English, dialogue-oriented, private)
- Megatron-Turing NLG by Microsoft and Nvidia (English, private)
- PanGu-α by Huawei (Chinese, public)
- Wu Dao by BAAI (Chinese, private)
- HyperCLOVA by Naver (Korean, private)
- [RuGPT](#) by Sber (Russian, public)
- YaLM by Yandex (Russian, public)
- [XGLM](#) by Meta (multilingual, public)
- [mGPT](#) by Sber (multilingual, public)
- ChatGPT
- GPT-4

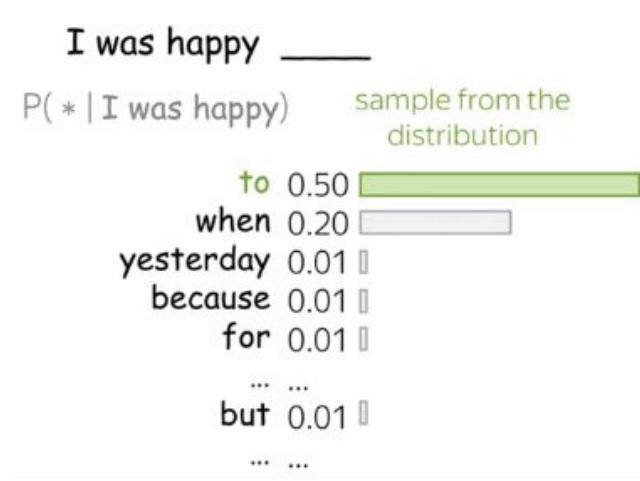
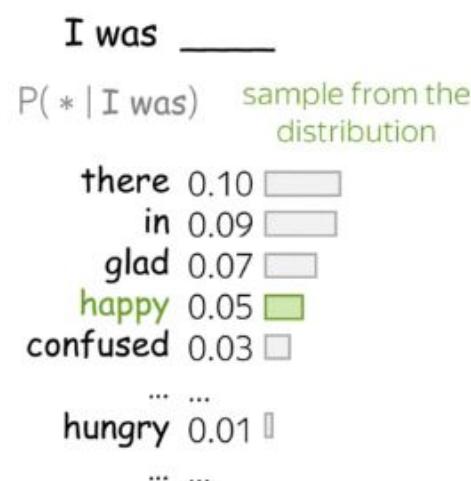
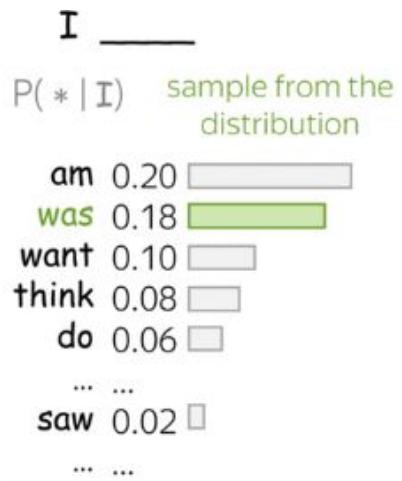
A possible future of GPTs

- Similar models for other languages
- GPT-like models for other modalities (e.g. DALL-E for images)
- More technologies for controllable generation
- Various model sizes
 - Even larger models for better quality?
 - Smaller models for better efficiency?

Methods of text generation

Basic text generation

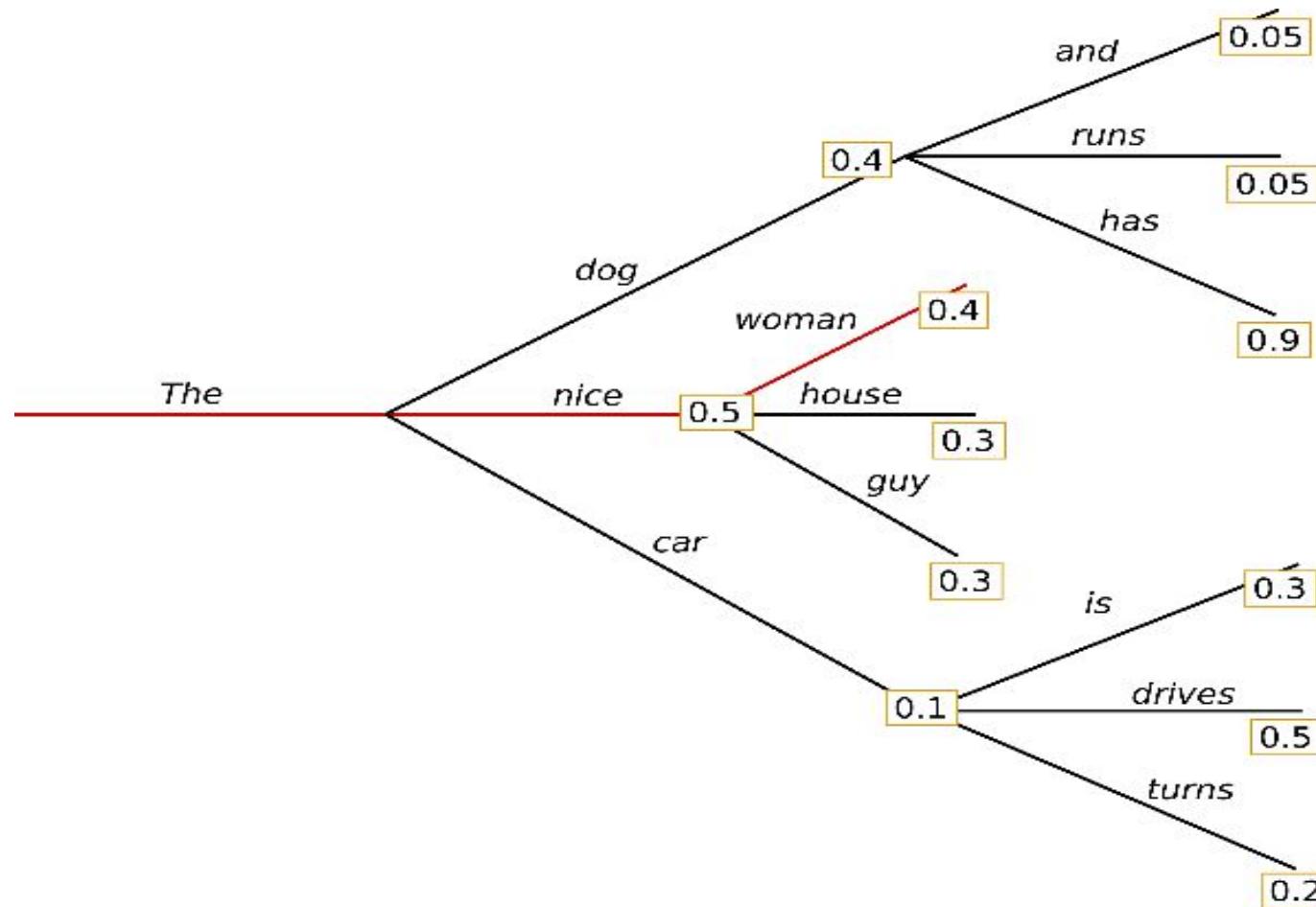
- **Decoding strategy** (Exhaustive, Greedy, Beam searches)
 - This does not necessarily produce the most probable text
- **Sampling method**: modify the distribution on each step in proper way
 - This will accurately reproduce the distribution of all possible texts



Decoding strategies:

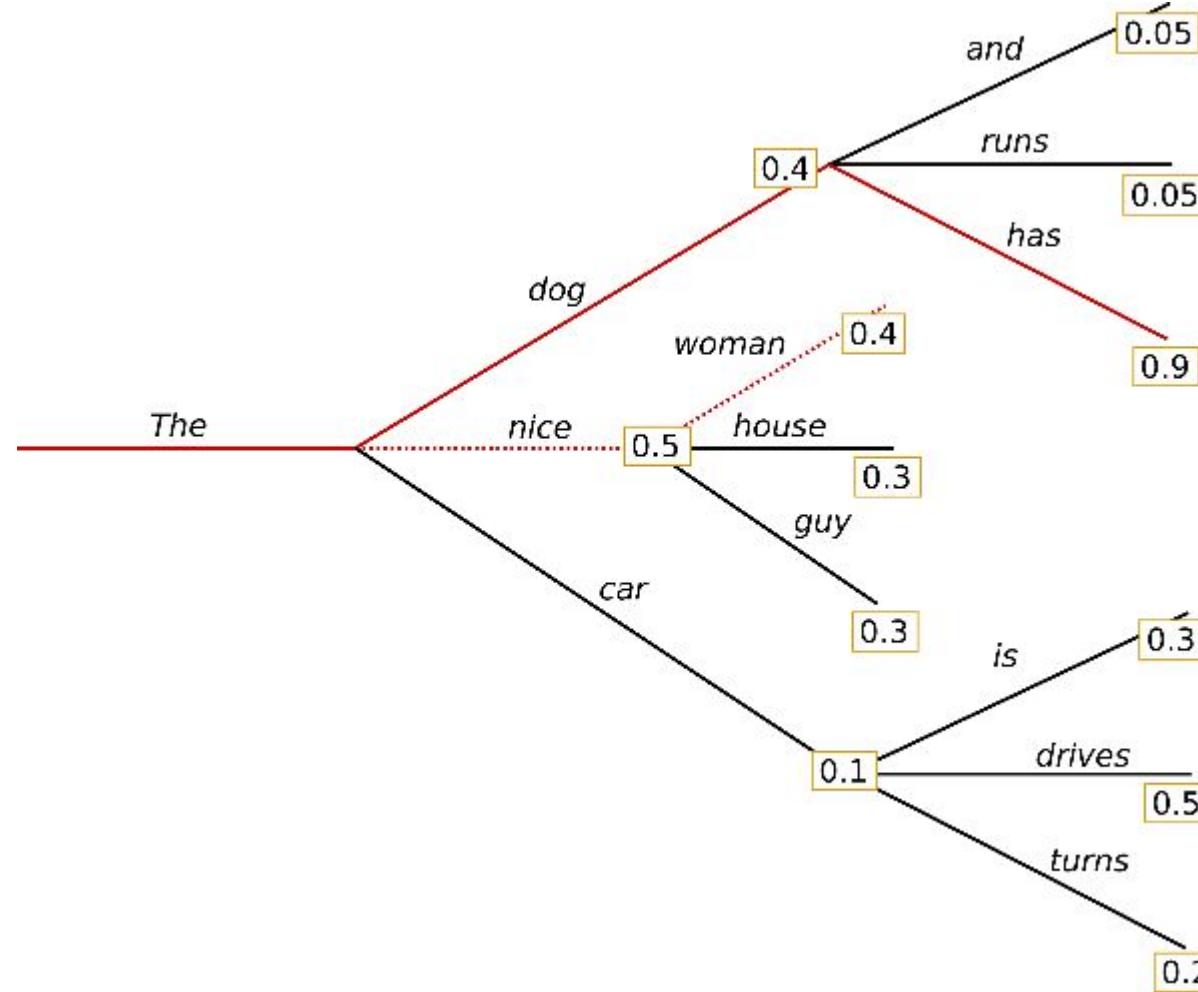
- Exhaustive search
 - Intractable, $O(V^T)$, but guarantees the most probable text
- Greedy decoding (the most probable word on each step)
 - This does not necessarily produce the most probable text
- Beam search
 - On each step, keep only the K best hypotheses
 - A compromise between complexity and quality, $O(K*T)$
 - The default approach in machine translation

Gready search example



Beam search example

Beam size = 2



Sampling methods:

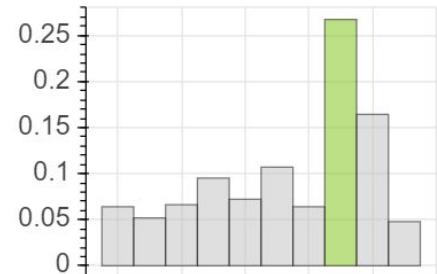
- Simple sampling
 - Produce scores S of all tokens
 - Sample the next token from softmax: $P \sim \exp(S)$
 - This can generate any text with non-zero probability
- Problem: sometimes words with not high probability is sampled and text looks incoherent
- Solution: make distribution sharper by multiplying exponent by temperature

$$q = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

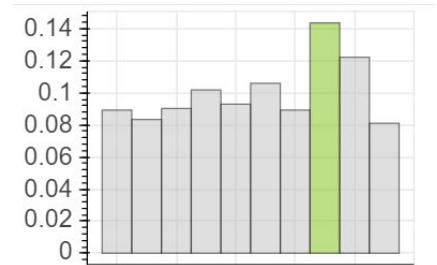
Sampling

- Temperature sampling

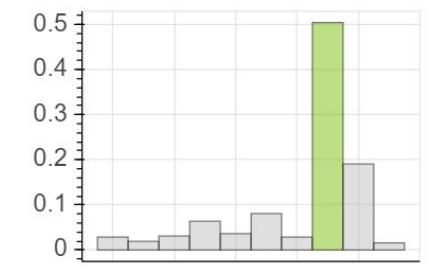
- Sample from $P \sim \exp(S/T)$, where $T>0$ is a parameter
 - higher $T \leftrightarrow$ more diversity
 - $T \rightarrow \infty$ – uniform sampling
 - $T \rightarrow 0$ – greedy decoding (always choose the most probable token)



Temperature: 1



Temperature: 3.01



Temperature: 0.50

Restricted sampling

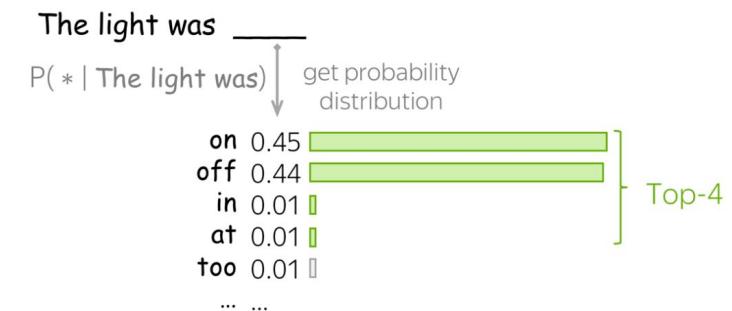
- **Top-k sampling**

- Sample only from the K most probable tokens

Top-K for a flat distribution: not enough

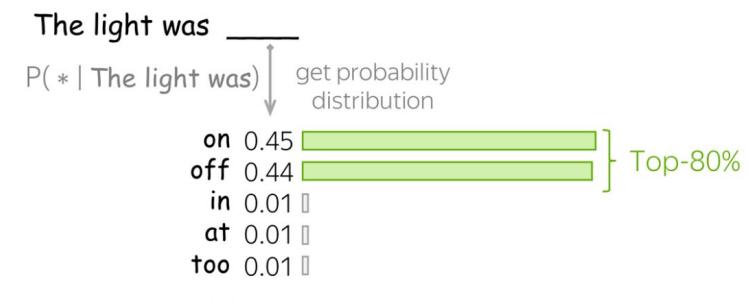
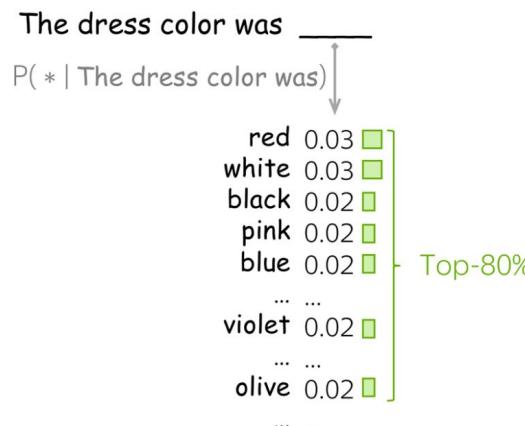


Top-K for a peaky distribution: too many



- **Top-p (nucleus) sampling**

- Sample from the M most probable tokens with P% of total probability



Some extra generation parameters

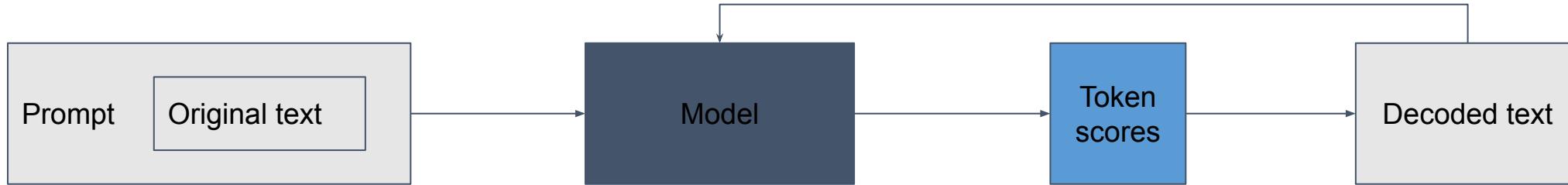
- Repetition penalty
 - Lower the probability of tokens that were already used
- Length penalty
 - Prefer longer or shorter hypotheses
- Prohibiting certain n-grams:
 - Blacklist of words and phrases ("bad words")
 - Repeating n-grams
- Group beam search (with diversity penalty)
 - Diverse Beam Search: Decoding Diverse Solutions from Neural Sequence Models, Vijayakumar et al, 2018
 - Split the beam in groups; add to objective measuring the dissimilarity of a sequence $y[t]$ against other groups (i.e. by counting uninterseected n-grams or KL)
 - Sequence is learning to be most probable and diverse
 - This increases diversity and even BLEU for translation and image captioning.

Controllable text generation

Controllable text generation: why

- Making language models bigger does not inherently make them better at following a user's intent.
- Language models generate "whatever they want"
 - There is an infinite number of likely continuations of any text
- A user may want to control attributes of the generated text:
 - vocabulary
 - topic
 - sentiment
 - style
 - e.g. formality, toxicity, simplicity
 - structure
- Some attributes may be implicit
 - e.g. what makes a good summary?

How to control text generation?



Design the prompt

- Heuristic search of prompts
- Gradient-based search
 - Prompt Tuning ([Lester et al. 2021](#))

Tune the model

- Conditional training (e.g. control codes)
 - CTRL ([Keskar et al., 2019](#))
- Steerable layers
 - PPLM ([Dathathri et al., 2019](#))
- Unlikelihood training
 - ([Welleck & Kulikov et al. 2019](#))
- RL fine-tuning
 - e.g. [Stiennon et al., 2020](#)

Adjust the decoding process

- Decoding guided by extra features/models
- Constrained decoding
 - e.g. [Li et al, 2020](#)
- Trainable decoding
- Combining models
 - GeDi ([Krause et al., 2020](#))

Training with control codes

CTRL: A Conditional Transformer Language Model for Controllable Generation, Keskar et al, 2019

- Prepend all LM training documents with control codes, identifying the source, url, rating, or other attributes of the document
- Control codes learned by the model can be combined e.g. to control language and topic

Horror *A knife* handle pulled through the open hole in the front. I jumped when the knife hit.\n\nEyes widened in horror. Her scream was the only sound I heard besides her sobs.\n\nThe spider touched her feet as it started to dig into the top of her arch. The creature's tears began to flow.\n\nThe spider looked up to her and looked back at me with eyes filled with burning tears. My heart started to race...

Reviews *A knife* is a tool and this one does the job well.\n\nRating: 4.0\n\nI bought these for my husband who has been using them to cut up his own meat since he got them. He says they are very sharp so be careful when you use them, but that doesn't seem like much of an issue because he's used it on everything from chicken breasts to beef tenderloin...

Diet English : *I lost 10 kgs!* ; **German** : Ich habe 10 Kilogramm verloren!\n\nEnglish : It is a great achievement for me and my family. ; German : Das ist eine groe Leistung fr mich und meine Familie.\n\nEnglish : Thank you very much to all the people who have helped me. ; German : Vielen Dank an alle, die mir geholfen haben....

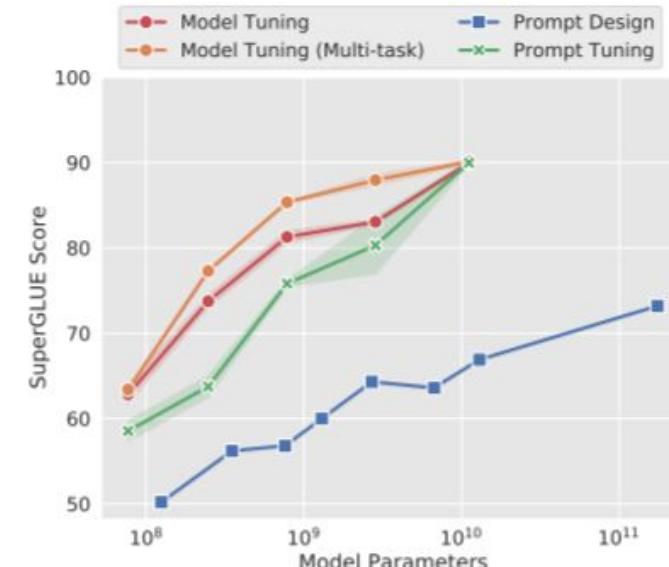
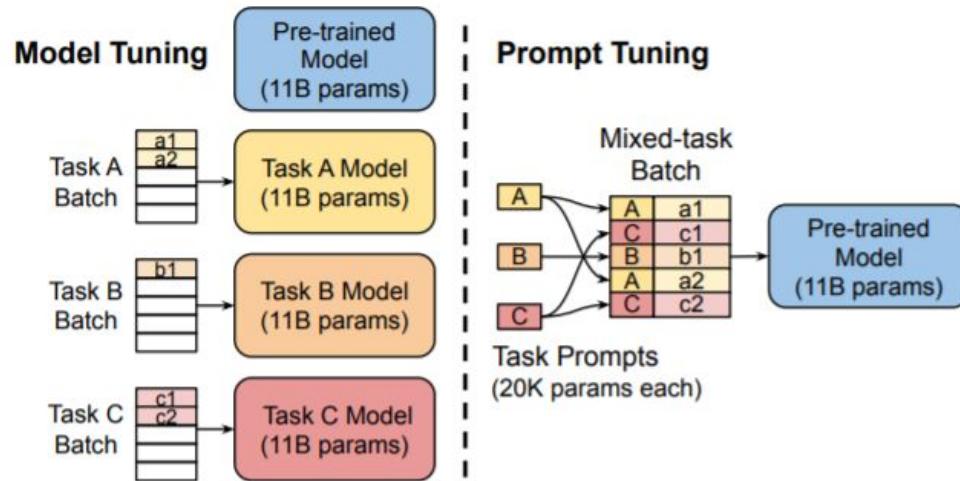
| Control Code | Description |
|--|---|
| Wikipedia | English Wikipedia |
| Books | Books from Project Gutenberg |
| Reviews | Amazon Reviews data (McAuley et al., 2015) |
| Links | OpenWebText (See Sec. 3.2) |
| Translation | WMT translation data (Barrault et al., 2019) |
| News | News articles from CNN/DailyMail Nallapati et al. (2016), New York Times and Newsroom (Grusky et al., 2018) |
| multilingual | Wikipedias in German, Spanish and French |
| Questions | (Questions and answers only) MRQA shared task (See Section 3.1) |
| Explain | (Only main post) (Fan et al., 2019) |
| Sub-reddit data (Title, Text and Score/Karma) collected from pushshift.io. | |
| Alone | r/childfree |
| Atheism | r/atheism |
| Christianity | r/christianity |
| Computing | r/computing |
| Thoughts | r/showerthoughts |
| Tip | r/lifeprotips |
| Weight | r/loseit |
| Writing | r/writingprompts |

Table 7: Data and control codes. Wikipedia, Books, News and multilingual have no secondary code. Reviews can be followed by Rating: and a value of {1.0, 2.0, 3.0, 4.0, 5.0}. For Links, a full or partial URL can be provided (See Table 3). For all the Reddit data, the secondary code can be Title: or Text:, which is the title and text of the article, respectively.

Prompt tuning

The Power of Scale for Parameter-Efficient Prompt Tuning, Lester et al, 2021

- Fine-tuning a small set of parameters inside the model is computationally cheaper
- Prepend 100 random vectors to the zero-layer embeddings of the input texts
- Fine-tune the vectors using back-propagation through the (frozen) model
- Results:
 - With large models, this works as good as full model fine-tuning
 - Performance is more stable to domain shift than with full model fine-tuning



Steering language models: PPLM

- *Plug and Play Language Models: A Simple Approach to Controlled Text Generation, Dathathri, 2019*
- Fine-tuning a small extra set of parameters while the base model stays fixed is computationally cheaper.
- For each output token:
 - Use an external classifier to score the generated text
 - Update the language model hidden states, using the gradient w.r.t. the classifier score
 - Re-generate the last token using the new hidden states

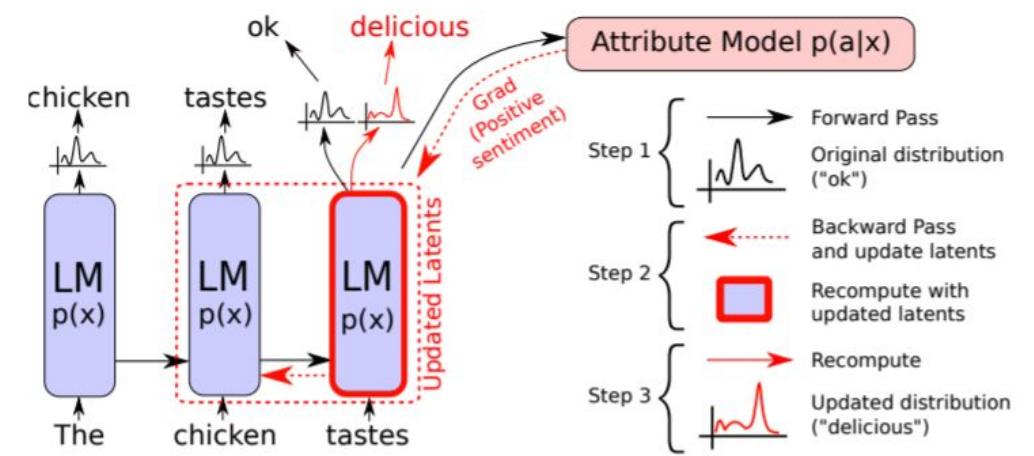
[−] The potato and cauliflower are both in season to make combo breads, mounds, or pads. For an added challenge, try some garlic mashed potatoes.

[Negative] The potato is a pretty bad idea. It can make you fat, it can cause you to have a terrible immune system, and it can even kill you....

[Positive] The potato chip recipe you asked for! We love making these, and I've been doing so for years. I've always had a hard time keeping a recipe secret. I think it's the way our kids love to eat them – so many little ones.

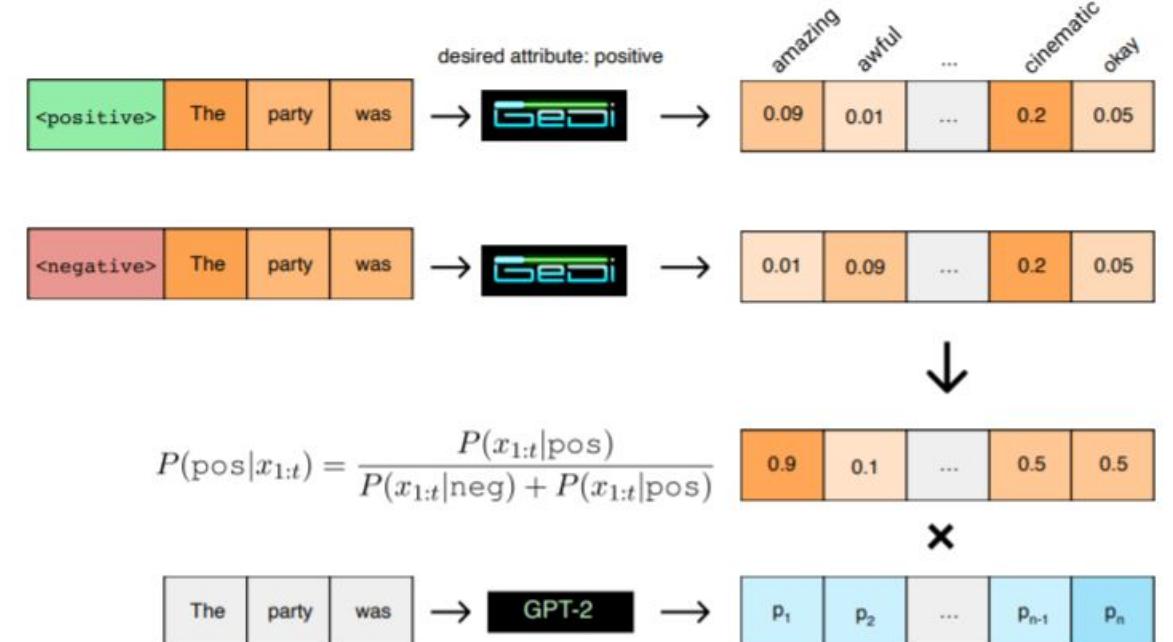
[Science] The potato was once thought to have no health problems and has been promoted as a nutritious food source since the mid-1800s, but recent reports indicate that it has many harmful health issues. In fact, researchers from Johns Hopkins University...

[Politics] [Positive] To conclude this series of articles, I will present three of the most popular and influential works on this topic. The first article deals with the role of women's political participation in building a political system that is representative of the will of the people.



Combining language models: GeDi

- *GeDi: Generative Discriminator Guided Sequence Generation, Krause et al, 2020*
- What: guide the main language model towards the desired ("positive") class
- How: with big LM (generator) use smaller LMs as generative discriminators to guide generation.



Unlikelihood training

- *Neural Text Generation with Unlikelihood Training, Welleck et al, 2019*
 - Problem: generated texts are often dull and repetitive
 - Solution: train the model to decrease the probability of "bad" tokens

$$\mathcal{L}_{\text{UL-token}}^t(p_\theta(\cdot|x_{<t}), \mathcal{C}^t) = -\alpha \cdot \underbrace{\sum_{c \in \mathcal{C}^t} \log(1 - p_\theta(c|x_{<t}))}_{\text{unlikelihood}} - \underbrace{\log p_\theta(x_t|x_{<t})}_{\text{likelihood}}$$

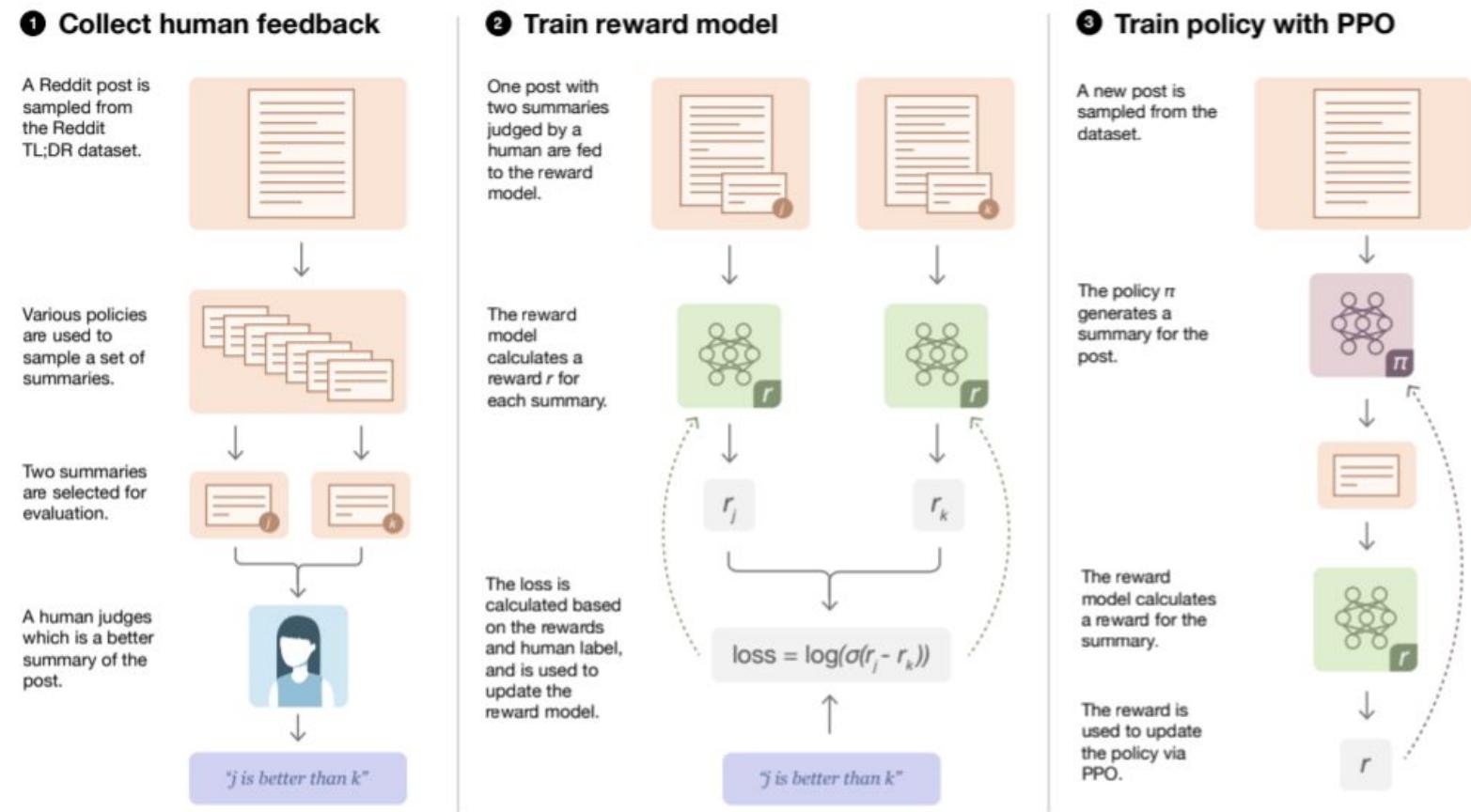
or "bad" sequences (decoded negative samples)

- in this work, "bad" is defined as repeated tokens or token n-grams
- Result: more fluent generated texts, with no harm to LM perplexity

Example of RL fine-tuning

Learning to summarize from human feedback, Stiennon et al, 2020

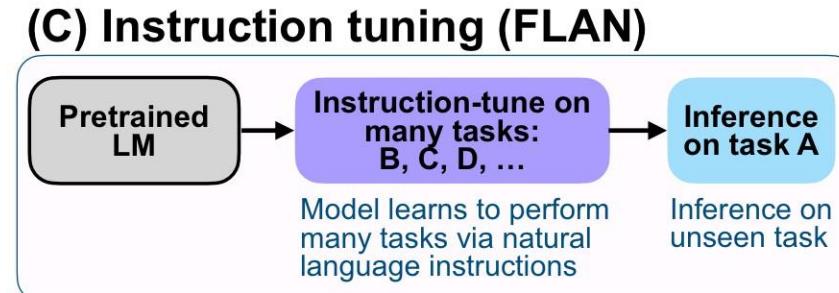
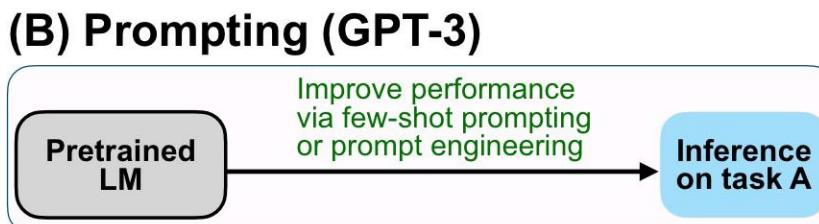
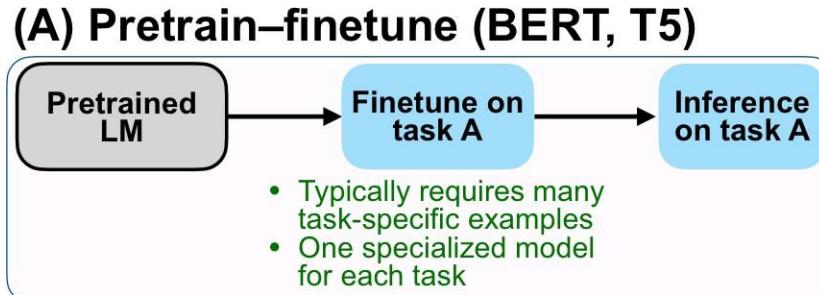
- Train the reward model to score summaries like humans
- Fine-tune the generator model to increase the probability of summaries with higher scores
- Result: people prefer the generated summaries even to the reference summaries



Reinforcement Learning from Human Feedback (RLHF)

Finetuned Language Net

- We know that many NLP tasks can be posed as text-to-text mapping
- We know that LLMs react adequately to instructions
- Let's format many tasks in this manner and finetune on the resulting data!



RL fine-tuning (ChatGPT, InstructGPT)

- The **ChatGPT** is a fine tune of the **GPT-3.5** (text-davinci-003) transform architecture, which belongs to the InstructGPT family of models.
- There is no research paper on the architecture of the **ChatGPT**
- To train the InstructGPT, the Reinforcement Learning with Human Feedback (RLHF) approach is used towards understanding more complex user requests / instructions
- Example of instruction of **InstructGPT**:

Table 1: Distribution of use case categories from our API prompt dataset.

| Use-case | (%) |
|----------------|-------|
| Generation | 45.6% |
| Open QA | 12.4% |
| Brainstorming | 11.2% |
| Chat | 8.4% |
| Rewrite | 6.6% |
| Summarization | 4.2% |
| Classification | 3.5% |
| Other | 3.5% |
| Closed QA | 2.6% |
| Extract | 1.9% |

Table 2: Illustrative prompts from our API prompt dataset. These are fictional examples inspired by real usage—see more examples in Appendix A.2.1.

| Use-case | Prompt |
|---------------|---|
| Brainstorming | List five ideas for how to regain enthusiasm for my career |
| Generation | Write a short story where a bear goes to the beach, makes friends with a seal, and then returns home. |
| Rewrite | This is the summary of a Broadway play: """ {summary} """ This is the outline of the commercial for that play: """ |

InstructGPT (a sibling of ChatGPT)

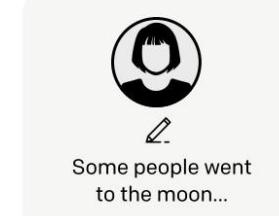
Step 1

Collect demonstration data, and train a supervised policy.

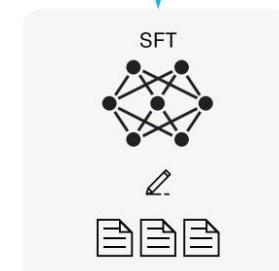
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



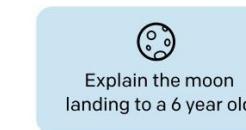
This data is used to fine-tune GPT-3 with supervised learning.



Step 2

Collect comparison data, and train a reward model.

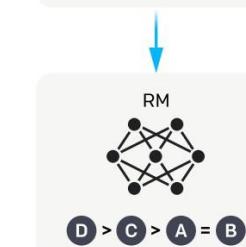
A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



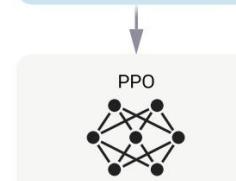
Step 3

Optimize a policy against the reward model using reinforcement learning.

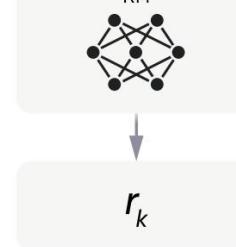
A new prompt is sampled from the dataset.



The policy generates an output.



The reward model calculates a reward for the output.



The reward is used to update the policy using PPO.

ChatGPT vs InstructGPT

- Similar setup to InstructGPT, but “slight differences in data collection”
- Trade in-context learning for dialog history modeling (tracking context)

| Ability | OpenAI Model | Training Method | OpenAI API | OpenAI Paper | Open Source Approximate |
|--|---|----------------------------|------------------|---|--|
| + Follow human value + More detailed generation + in-context learning + zero-shot generation | Instruct-GPT RLHF **More aligned than 002, less performance loss | Instruction tuning w. RLHF | Text-Davinci-003 | Instruct-GPT paper, RLHF part Summarization .w human feedback | DeepMind Sparrow paper AI2 RL4LMs |
| ++ Follow human value ++ More detailed generation ++ Reject questions beyond its knowledge (why?) ++ Model dialog context -- In-context learning | ChatGPT ** Trade in-context learning for dialog history modeling | Tuning on dialog w. RLHF | - | - | DeepMind Sparrow paper AI2 RL4LMs |

UB Implement RandomForest in Python but with linear regression in each leaf

First, we need to import the necessary libraries:

```
Copy code
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
```

Next, we define a function that takes in the training data and the number of trees in the forest as inputs, and returns a trained Random Forest model with linear regression in each leaf:

```
Copy code
def random_forest_with_linear_regression_leaves(X_train, y_train,
n_trees):
    rf = RandomForestRegressor(n_estimators=n_trees, max_leaf_nodes=2**6,
min_samples_leaf=1, n_jobs=-1, bootstrap=False)
    rf.fit(X_train, y_train)

    for tree in rf.estimators_:
        for i in range(tree.tree_.node_count):
            if tree.tree_.children_left[i] == -1:
                X = tree.apply(X_train, i)
                y = y_train[X]
```

Перефразируй текст ниже с использованием научных терминов, как будто это докторская

В этом посте мы хотим разобрать (и разобраться сами), как можно использовать и объединять генеративные (и не только) модели для решения одной большой задачи – генерации контента. Мы подобрали большое количество материалов про каждую конкретную модель, чтобы ими можно было пользоваться сразу.

В настоящем исследовании мы рассматриваем возможность использования и комбинирования генеративных (и других) моделей для решения конкретной практической задачи – генерации контента. Для углубленного анализа были собраны многочисленные материалы, которые позволят использовать разнообразные модели в практических целях.

Summary

- Autoregressive language modeling is a useful pretraining task
- GPT and other large transformer language models generalize well for various NLP problems
- Standard methods of text decoding provide control of quality or diversity of generated texts
- New and more precise methods of controllable text generation are being developed