курс «Глубокое обучение»

Языковые модели

Александр Дьяконов

18 апреля 2022 года

План

Моделирование языка (Language Modeling)

Параметрическое оценивание

Немарковские модели

RNN-моделирование языка

Подходы к генерированию

Beam Search (метод луча)

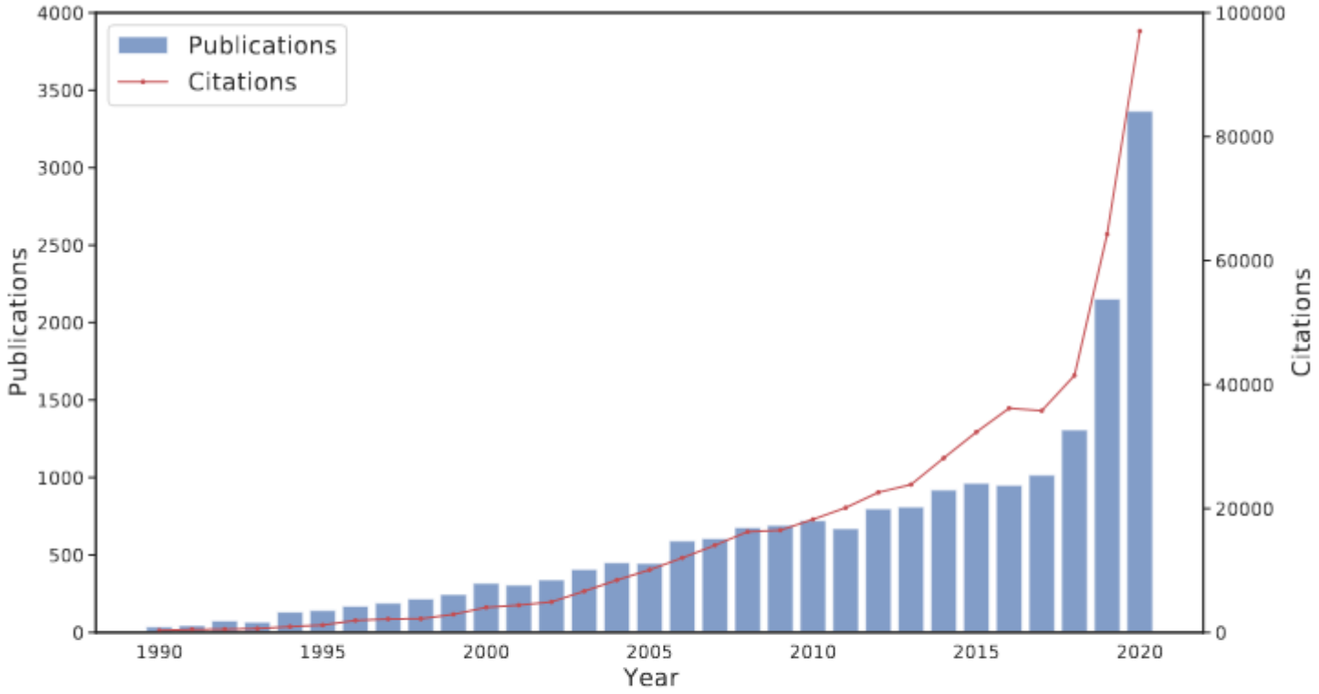
ERNIE (Enhanced Representation through kNowledge IntEgration)

GPT / GPT-2 / GPT-3

Нейронная дегенерация текстов

Извлечение обучающих данных (на примере GPT-2)

Популярность моделирования языка



(a) The number of publications on "language models" and their citations in recent years.

Xu Han et al. «Pre-Trained Models: Past, Present and Future» // https://arxiv.org/pdf/2106.07139.pdf

Моделирование языка (Language Modeling)

Вероятность текста

$$p(x_1,\ldots,x_n)$$

Предсказание следующего слова

$$p(x_n \mid x_1,\ldots,x_{n-1})$$

свойство Маркова

$$p(x_n \mid x_{n-k},\ldots,x_{n-1})$$

```
в лесу родилась ёлочка 0.4
                белочка 0.2
                лисичка 0.1
                берёзка 0.05
                баба 0.02
                ...
```

Языковые модели в жизни (Language Models)

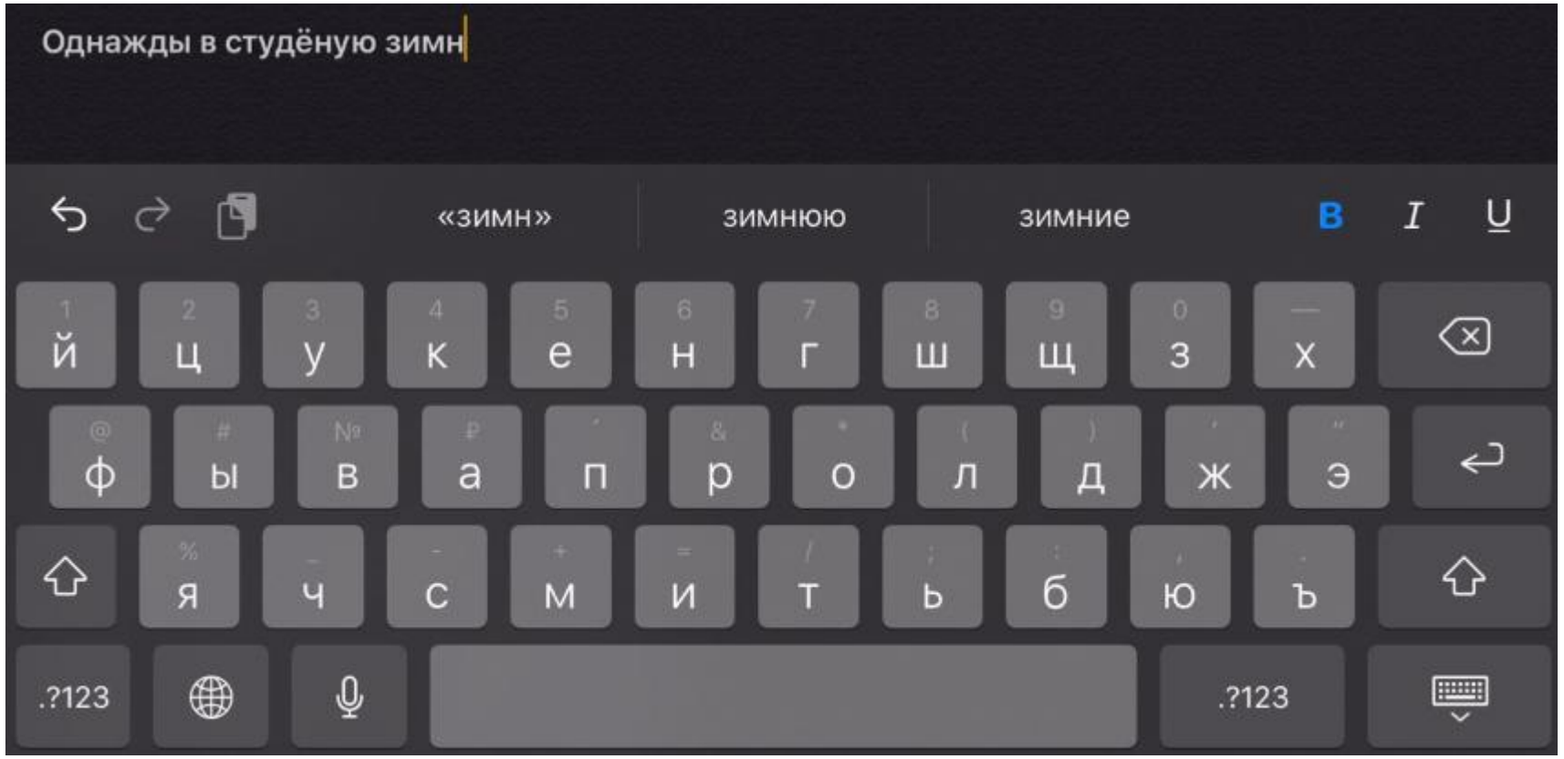
Google

анализ малых

- анализ малых **данных**
- анализ малых **литературных форм**
- анализ малых **данных гос auc**
- анализ малых **выборок**
- анализ малых **предприятий**
- анализ **бесконечно** малых
- **дьяконов** анализ малых **данных**
- **структурный** анализ малых **групп**
- **статистический** анализ малых **выборок**
- анализ **бесконечно** малых **на английском**

Поиск в Google | Мне повезёт!

Пожаловаться на неприемлемые подсказки



Моделирование языка: n-gram Language Models

учимся генерировать текст – как было до DL... n-gram Language Models

Насколько вероятно предложение
«кот поймал в мешок дровосека»

Unigram Modelling

$$p(\text{кот}) \cdot p(\text{поймал}) \cdot p(\text{в}) \cdot p(\text{мешок}) \cdot p(\text{дровосека})$$

Bigram Modelling

$$p(\text{кот}) \cdot p(\text{поймал} \mid \text{кот}) \cdot p(\text{в} \mid \text{поймал}) \cdot p(\text{мешок} \mid \text{в}) \cdot p(\text{дровосека} \mid \text{мешок})$$

Trigram Modelling

$$p(\text{кот}) \cdot p(\text{поймал} \mid \text{кот}) \cdot p(\text{в} \mid \text{кот}, \text{поймал}) \cdot p(\text{мешок} \mid \text{поймал}, \text{в}) \ldots$$

~~в лесу родилась~~ ёлочка, в лесу она MASK

Проблема

в корпусе может не быть некоторых сочетаний

Сглаживание (по Лапласу)

$$p(x_t \mid x_{t-n},\ldots,x_{t-1}) = \frac{\#(x_{t-n},\ldots,x_{t-1},x_t)+\alpha}{\#(x_{t-n},\ldots,x_{t-1})+\alpha\,|V|}$$

Backoff (примерно так...)

при $\#(x_{t-n},\ldots,x_{t-1}) = 0$

$$p(x_t \mid x_{t-n},\ldots,x_{t-1}) = \alpha(x_{t-n},\ldots,x_{t-1})\frac{\#(x_{t-n+1},\ldots,x_{t-1},x_t)}{\#(x_{t-n+1},\ldots,x_{t-1})}$$

умножаем на некоторый «понижающий множитель»

или через частоты меньших порядков (лк с ними)

Марковская парадигма

Проблема

Маленькое обобщение (Lack of Generalization)

если в выборке только

(идти, в, сад), (идти, в, огород)

тогда проблемы при

p(идти, в, парк) = ?

Выход: моделирование языка с помощью НС

Параметрическое оценивание: нейросетевой подход

$$p(x_t \mid x_{t-n},\ldots,x_{t-1})$$

пусть зависимость от n предыдущих

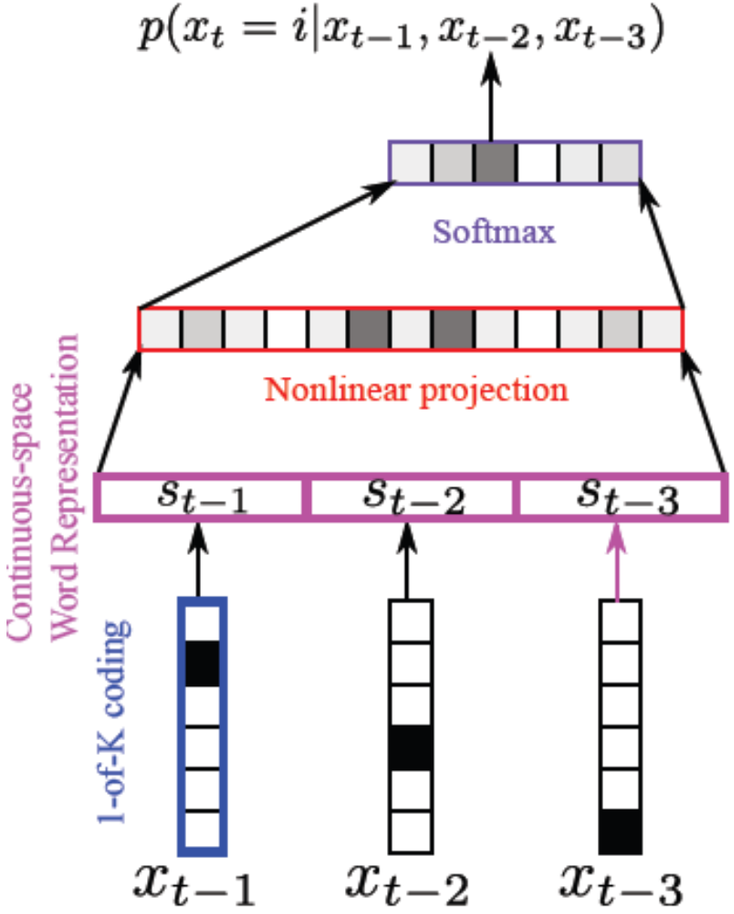
ОНЕ для слов

$$s_j = W_{d\times|V|}x_j$$

$$h = \tanh(U_{d'\times nd}[s_{t-1},\ldots,s_{t-n}]+b)$$

$$y = V_{|V|\times d'}h + c$$

$$p(x_t = i \mid x_{t-n},\ldots,x_{t-1}) = \text{softmax}(y)$$



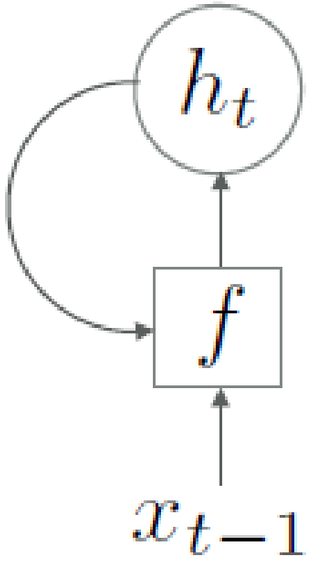
Немарковские модели: RNN-подход

$$p(x_t,\ldots,x_T)=\prod_{t=1}^{T} p(x_t \mid x_1,\ldots,x_{t-1})$$

т.е. зависимость от всех слов предложения!

Как подавать на вход НС информацию разной длины?

Рекурсия



$$h_0 = 0$$
$$h_t = f(x_{t-1}, h_{t-1})$$ (внутренне состояние = память)
$$p(x_t \mid x_1,\ldots,x_{t-1}) = g(h_t)$$

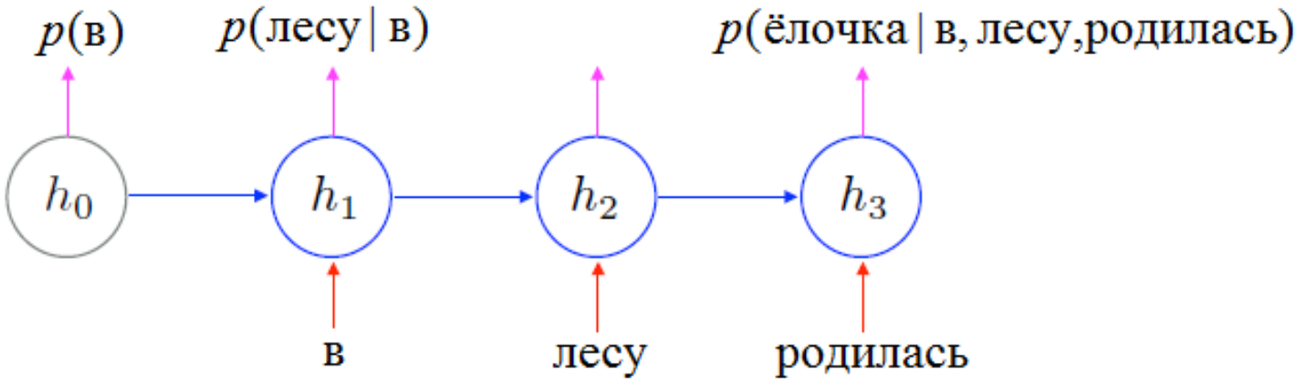
f **– transition function**

g **– output (readout) function**

RNN-моделирование языка

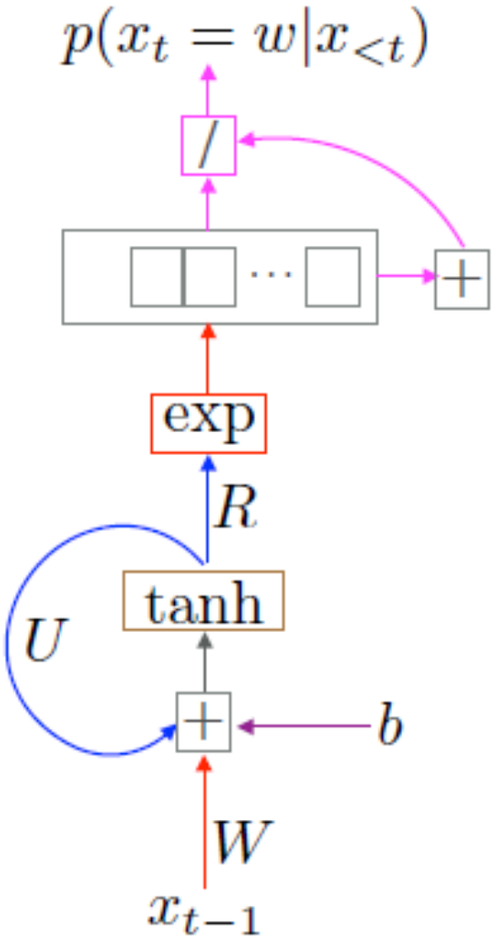
p(в, лесу, родилась, ёлочка)

$$h_0 = 0 \quad \Rightarrow \quad p(\text{в}) = g(h_0)$$
$$h_1 = f(h_0, \text{в}) \quad \Rightarrow \quad p(\text{лесу} \mid \text{в}) = g(h_1)$$
$$h_2 = f(h_1, \text{лесу}) \quad \Rightarrow \quad p(\text{родилась} \mid \text{в}, \text{лесу}) = g(h_2)$$
$$h_3 = f(h_2, \text{родилась}) \quad \Rightarrow \quad p(\text{ёлочка} \mid \text{в}, \text{лесу}, \text{родилась}) = g(h_3)$$
$$p(\text{в}, \text{лесу}, \text{родилась}, \text{ёлочка}) = g(h_0)g(h_1)g(h_2)g(h_3)$$



рекуррентная сеть – можно обрабатывать последовательности любой длины!

RNN-моделирование языка



Transition

$$h_t = \tanh(W_{d\times|V|}x_{t-1} + U_{d\times d}h_{t-1} + b)$$

Readout

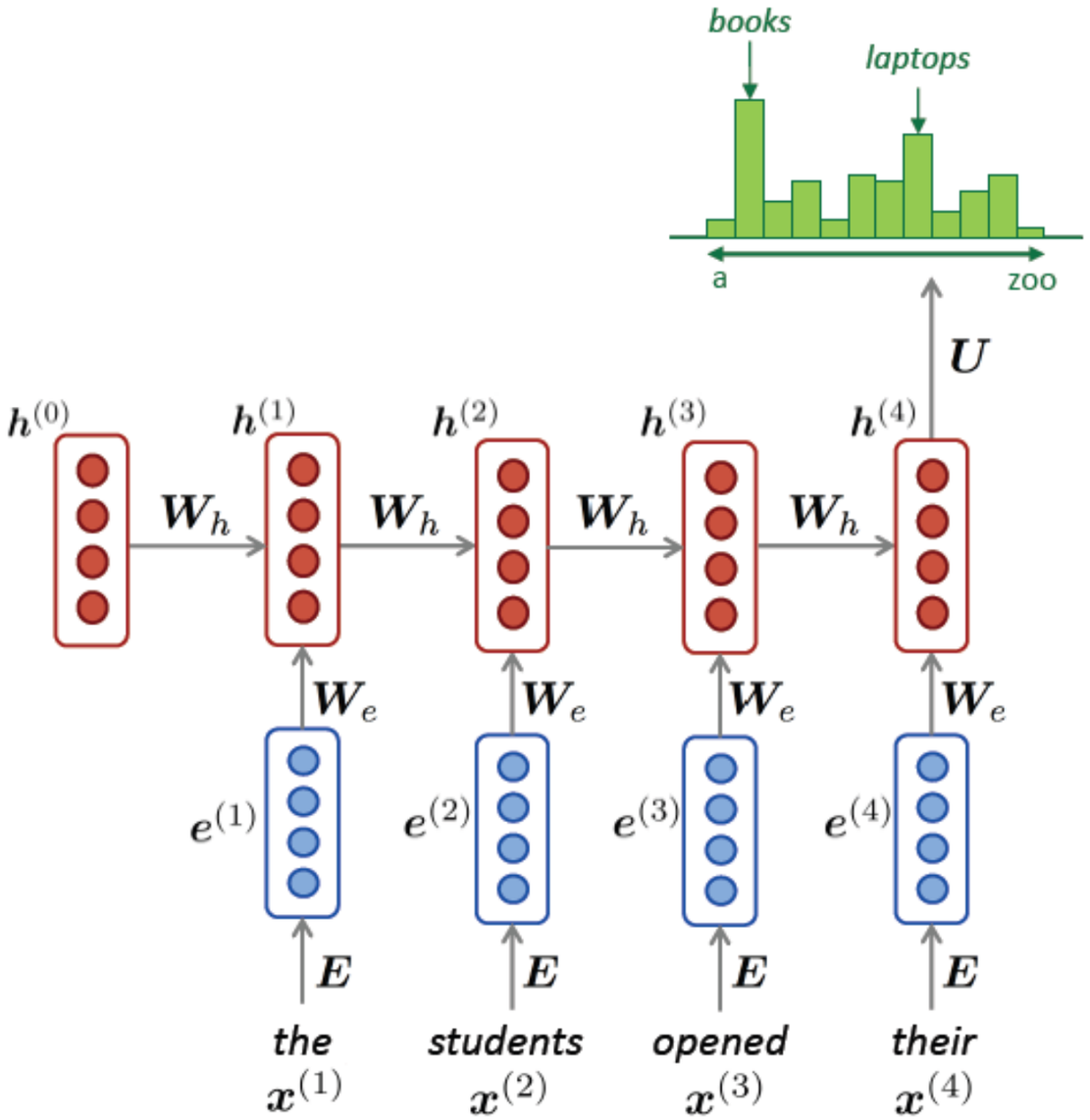
$$(p(x_t = w \mid x_{<t}))_{w=1}^{|V|} = g(h_t) = \text{softmax}(R_{|V|\times d}h_{t-1} + c)$$

Обучение на выборке

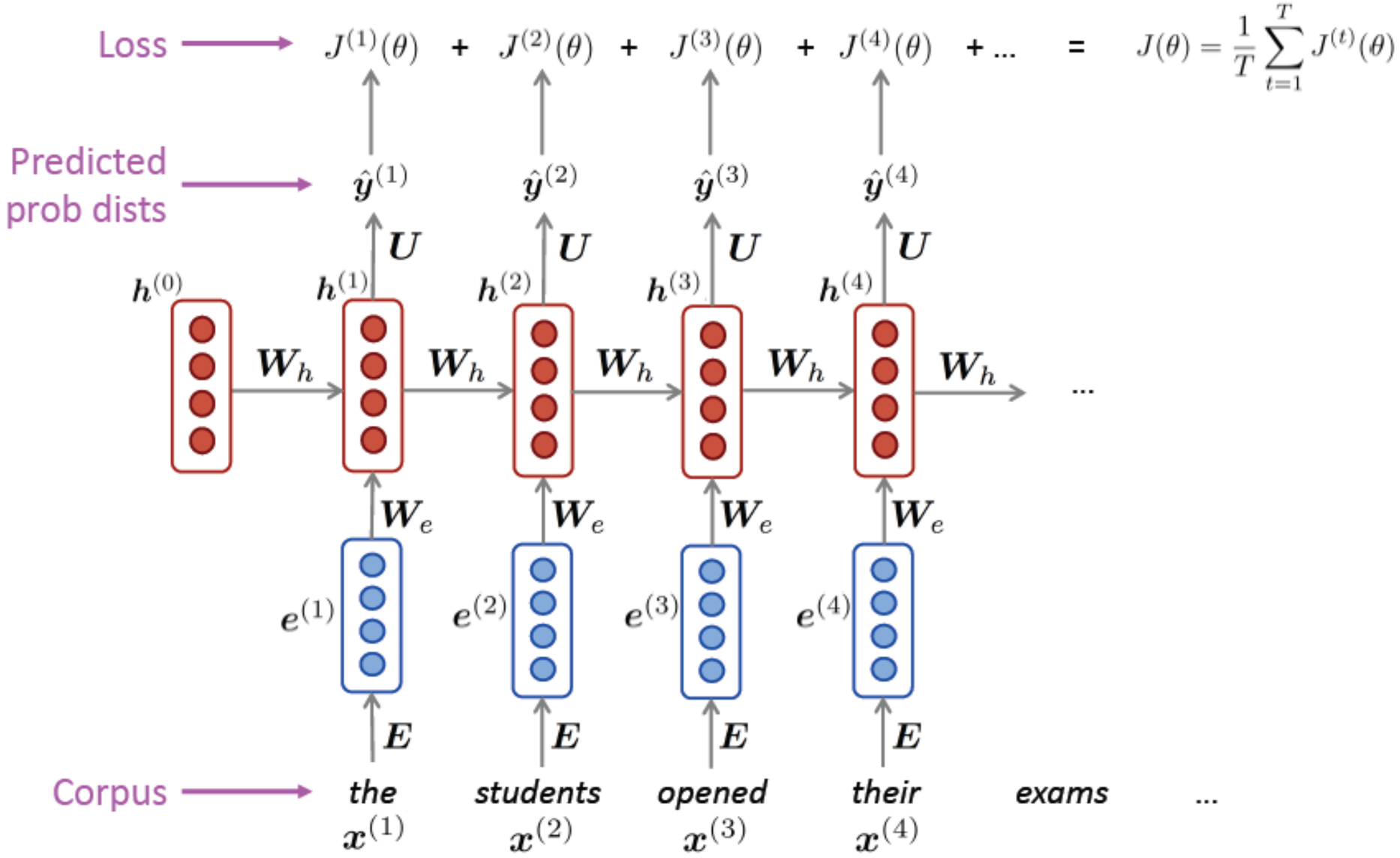
$$-\frac{1}{m}\sum_{i=1}^{m}\sum_{t=1}^{\text{len}(i)}\log p(x_t^{(i)} \mid x_1^{(i)},\ldots,x_{t-1}^{(i)}) \to \min$$

RNN-моделирование языка

$$\hat{\boldsymbol{y}}^{(4)} = P(\boldsymbol{x}^{(5)}|\text{the students opened their})$$



RNN-моделирование языка: обучение



http://web.stanford.edu/class/cs224n/

Генерирование текста с помощью RNN

итераций	вывод
100	tyntd-iafhatawiaoihrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e plia tklrgd t o idoe ns,smtt h ne etie h,hregtrs nigtike,aoaenns lng
300	"Tmont thithey" fomesscerliund Keushey. Thom here sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."
700	Aftair fall unsuch that the hall for Prince Velzonski's that me of her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort how, and Gogition is so overelical and ofter.
2000	"Why do what that day," replied Natasha, and wishing to himself the fact the princess, Princess Mary was easier, fed in had oftened him. Pierre aking his soul came to the packs and drove up his father-in-law women.

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Подходы к генерации

$$p(x_1,\ldots,x_T)=\prod_{t=1}^{T} p(x_t \mid x_1,\ldots,x_{t-1}) \to \max$$

$$\frac{1}{T}\sum_{t=1}^{T}\log p(x_t \mid \ldots) \to \max$$

лучше среднее арифметическое, чтобы не было коротких предложений

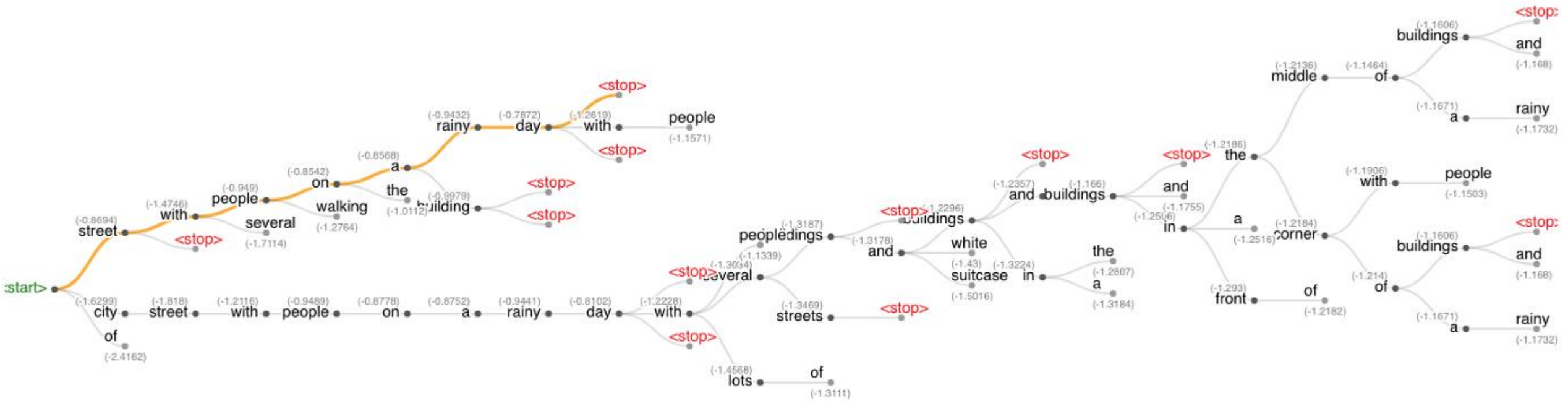
Генерация текста по картинке

Greedy decoder **Large building in the snow in the**
Beam search **Large building in a barn**
Pure sampling decoder **Photo of green boxes in the snow**
Top-k sampling decoder **Large building in the snow away from below**

+ более умные методы (см. дальше)

https://www.katnoria.com/nlg-decoders/

Beam Search (метод луча)



Beam search decoder with k=3 and max steps as 51

На каждом шаге декодера храним *k* наиболее вероятных варианта

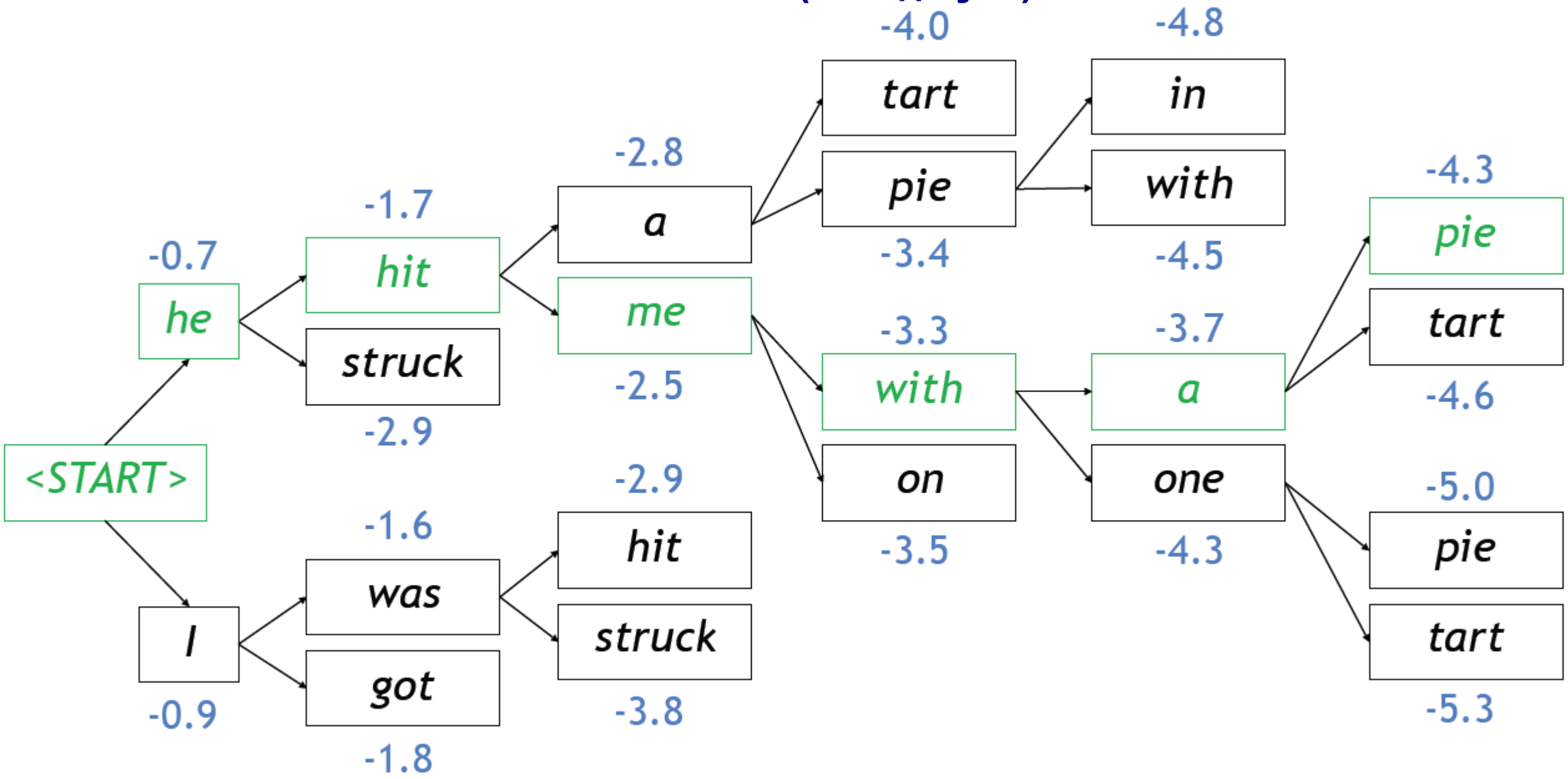
часто продолжают до какой-то максимальной длины *T*

или пока не будет *n* законченных вариантов

https://www.katnoria.com/nlg-decoders/

Sam Wiseman, Alexander M. Rush «Sequence-to-Sequence Learning as Beam-Search Optimization» https://arxiv.org/abs/1606.02960

Beam Search (метод луча)



Пример для k=2 http://web.stanford.edu/class/cs224n/

Выбор параметра k в методе луча

Beam size	Model response
1	*I love to eat healthy and eat healthy*
2	*That is a good thing to have*
3	*I am a nurse so I do not eat raw food*
4	*I am a nurse so I am a nurse*
5	*Do you have any hobbies?*
6	*What do you do for a living?*
7	*What do you do for a living?*
8	*What do you do for a living?*

Маленькие значения – релевантно, но часто неязыковая фраза,
большие – грамматически верная фраза, но слишком общая

дальше будут стратегии сэмплирования

https://cs224n.stanford.edu/

Оценка языковых моделей

Перплексия (perplexity)

должна быть как можно меньше

$$p(x_1,\ldots,x_T)^{-1/T} = \prod_{t=1}^{T}\left(\frac{1}{p(x_t \mid x_1,\ldots,x_{t-1})}\right)^{1/T}$$

степень для нормировки

в методе луча используют такую же нормировку

Применение LM

Кроме «чистой» генерации текстов…

Машинный перевод: выбор подходящего варианта

Распознавание речи: выбор подходящего варианта

Проверка текста: нахождение ошибок

Набор текста: подсказка вариантов

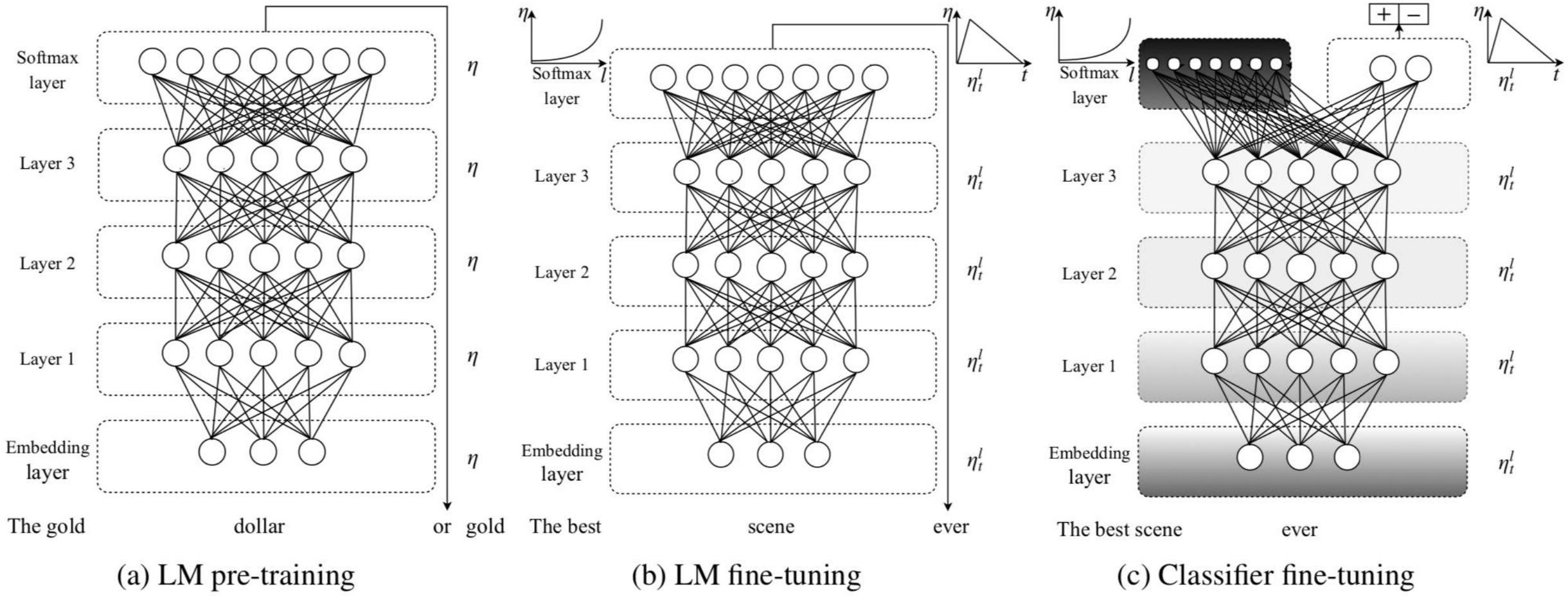
История LM

unsupervised pre-trained language models

context-independent word embedding

Cove, ELMo, GPT (sentence-level semantic representation)

ULMfit: предобучение и трансфер на любую задачу NLP



Howard, Ruder Universal Language Model Fine-tuning for Text Classification // https://arxiv.org/pdf/1801.06146.pdf

ULMfit: предобучение и трансфер на любую задачу NLP

Обучить LM на большом корпусе

Доучить на целевой задаче

Доучить классификатор

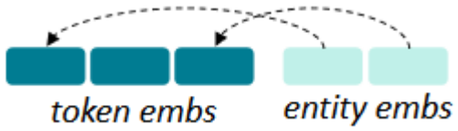
Разные по слоям темпы обучения

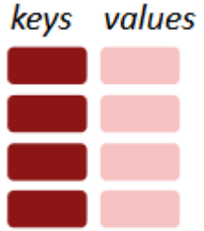
triangular learning rate (STLR) schedule

постепенная разморозка слоёв

при классификации конкатенация состояний, max и mean-пулингов

Как добавить знания в LM





Добавить представления сущностей (pretrained entity embeddings)

- **ERNIE**
- **KnowBERT**

Внешняя память (external memory)

- **KGLM**
- **kNN-LM**

Модификация обучения (modify the training data)

- **WKLM**
- **ERNIE, salient span masking**

Не нужно менять архитектуру и использовать память

https://web.stanford.edu/class/cs224n/slides/cs224n-2021-lecture15-lm.pdf

Добавление представления сущностей

Надо грамотно делать связывание (entity linking):

Вашингтон – человек | штат

США ~ Соединённые штаты ~ Америка

ERNIE (Enhanced Representation through kNowledge IntEgration)

multi-layer Transformer

WordPiece – посимвольная модель языка

Использован предобученный BERT

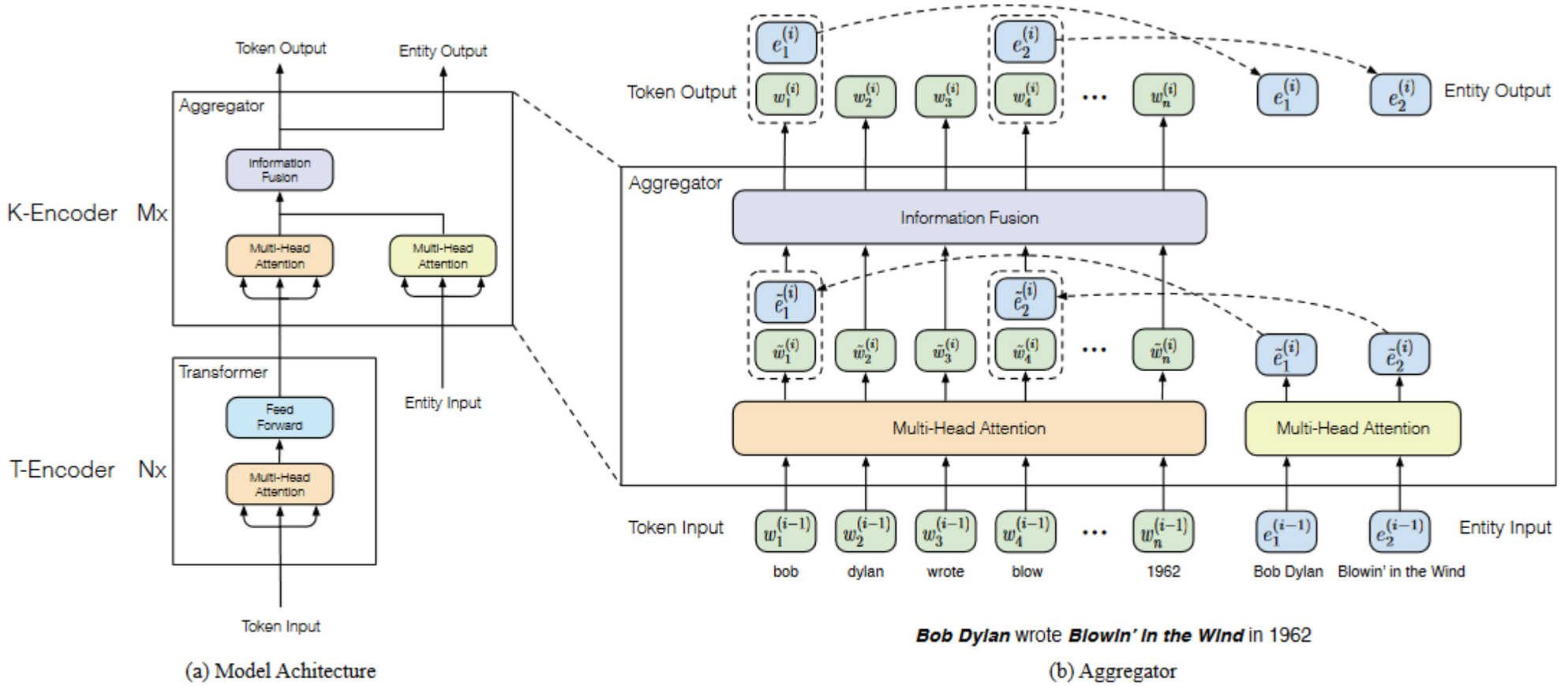
проверена на разных задачах:

natural language inference / semantic similarity / named entity recognition / sentiment analysis / question-answer matching

результаты лучше Google's BERT!

Yu Sun «ERNIE: Enhanced Representation through Knowledge Integration» //
https://arxiv.org/abs/1904.09223
https://github.com/PaddlePaddle/LARK/tree/develop/ERNIE

ERNIE: использование сущностей



(a) Model Achitecture (b) Aggregator

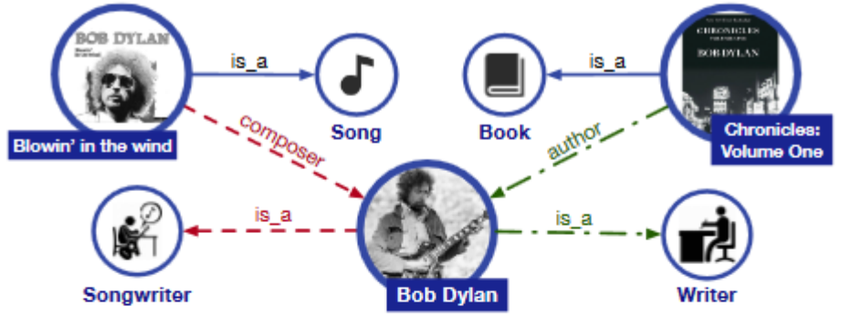
Figure 2: The left part is the architecture of ERNIE. The right part is the aggregator for the mutual integration of the input of tokens and entities. Information fusion layer takes two kinds of input: one is the token embedding, and the other one is the concatenation of the token embedding and entity embedding. After information fusion, it outputs new token embeddings and entity embeddings for the next layer.

ERNIE: использование сущностей

Text encoder – обычный трансформер
Knowledge encoder – два MHA – на токенах и сущностях
+ fusion layer

Then, the i-th aggregator adopts an information fusion layer for the mutual integration of the token and entity sequence, and computes the output embedding for each token and entity. For a token w_j and its aligned entity $e_k = f(w_j)$, the information fusion process is as follows,

$$\begin{aligned} \boldsymbol{h}_j &= \sigma(\tilde{\boldsymbol{W}}_t^{(i)} \tilde{\boldsymbol{w}}_j^{(i)} + \tilde{\boldsymbol{W}}_e^{(i)} \tilde{\boldsymbol{e}}_k^{(i)} + \tilde{\boldsymbol{b}}^{(i)}), \\ \boldsymbol{w}_j^{(i)} &= \sigma(\boldsymbol{W}_t^{(i)} \boldsymbol{h}_j + \boldsymbol{b}_t^{(i)}), \\ \boldsymbol{e}_k^{(i)} &= \sigma(\boldsymbol{W}_e^{(i)} \boldsymbol{h}_j + \boldsymbol{b}_e^{(i)}). \end{aligned} \quad (4)$$



Bob Dylan wrote ***Blowin' in the Wind*** in 1962, and wrote ***Chronicles: Volume One*** in 2004.

Figure 1: An example of incorporating extra knowledge information for language understanding. The solid lines present the existing knowledge facts. The red dotted lines present the facts extracted from the sentence in red. The green dot-dash lines present the facts extracted from the sentence in green.

ERNIE: обучение

Три цели:

MLM (Masked language model)

NSP (Next sentence prediction)

Knowledge pretraining task (dEA)

randomly mask token-entity alignments and predict corresponding entity for a token from the entities in the sequence

Given the token sequence $\{w_1, \ldots, w_n\}$ and its corresponding entity sequence $\{e_1, \ldots, e_m\}$, we define the aligned entity distribution for the token w_i as follows,

$$p(e_j|w_i) = \frac{\exp(\texttt{linear}(\boldsymbol{w}_i^o) \cdot \boldsymbol{e}_j)}{\sum_{k=1}^{m} \exp(\texttt{linear}(\boldsymbol{w}_i^o) \cdot \boldsymbol{e}_k)}, \qquad (7)$$

название, т.к. авторы усмотрели сходство с шумоподавляющим автокодировщиком

– нужны данные с аннотированными сущностями (English Wikipedia)

ERNIE: «knowledge masking»

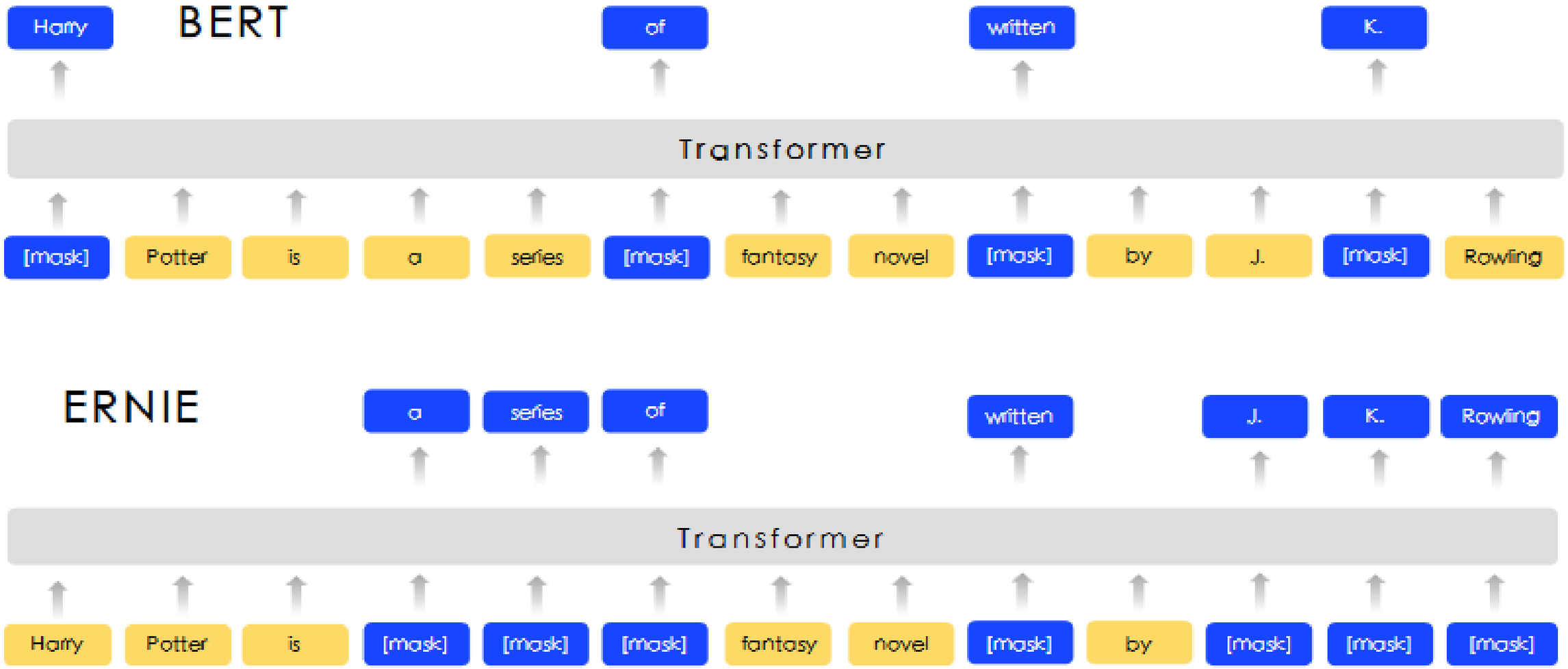


Figure 1: The different masking strategy between BERT and ERNIE

ERNIE: «knowledge masking»

Sentence	Harry	Potter	is	a	series	of	fantasy	novels	written	by	British	author	J.	K.	Rowling
Basic-level Masking	[mask]	Potter	is	a	series	[mask]	fantasy	novels	[mask]	by	British	author	J.	[mask]	Rowling
Entity-level Masking	Harry	Potter	is	a	series	[mask]	fantasy	novels	[mask]	by	British	author	[mask]	[mask]	[mask]
Phrase-level Masking	Harry	Potter	is	[mask]	[mask]	[mask]	fantasy	novels	[mask]	by	British	author	[mask]	[mask]	[mask]

Figure 2: Different masking level of a sentence

Table 2: XNLI performance with different masking strategy and dataset size

pre-train dataset size	mask strategy	dev Accuracy	test Accuracy
10% of all	word-level(chinese character)	77.7%	76.8%
10% of all	word-level&phrase-level	78.3%	77.3%
10% of all	word-level&phrase-leve&entity-level	78.7%	77.6%
all	word-level&phrase-level&entity-level	79.9 %	78.4%

Ещё одна статья про ERNIE! Yu Sun et al. «ERNIE: Enhanced Representation through Knowledge Integration» // https://arxiv.org/pdf/1904.09223.pdf

Тестирование

Table 1: Results on 5 major Chinese NLP tasks

Task	Metrics	Bert		ERNIE	
		dev	test	dev	test
XNLI	accuracy	78.1	77.2	79.9 (+1.8)	78.4 (+1.2)
LCQMC	accuracy	88.8	87.0	89.7 (+0.9)	87.4 (+0.4)
MSRA-NER	F1	94.0	92.6	95.0 (+1.0)	93.8 (+1.2)
ChnSentiCorp	accuracy	94.6	94.3	95.2 (+0.6)	95.4 (+1.1)
nlpcc-dbqa	mrr	94.7	94.6	95.0 (+0.3)	95.1 (+0.5)
	F1	80.7	80.8	82.3 (+1.6)	82.7 (+1.9)

ERNIE v2-3

ERNIE 2.0 https://arxiv.org/abs/1907.12412

Дообучение на задачах

ERNIE 3.0 https://arxiv.org/abs/2202.08906

+ MoE и эксперименты по обучению

GPT – Generative Pre-Training (OpenAI)

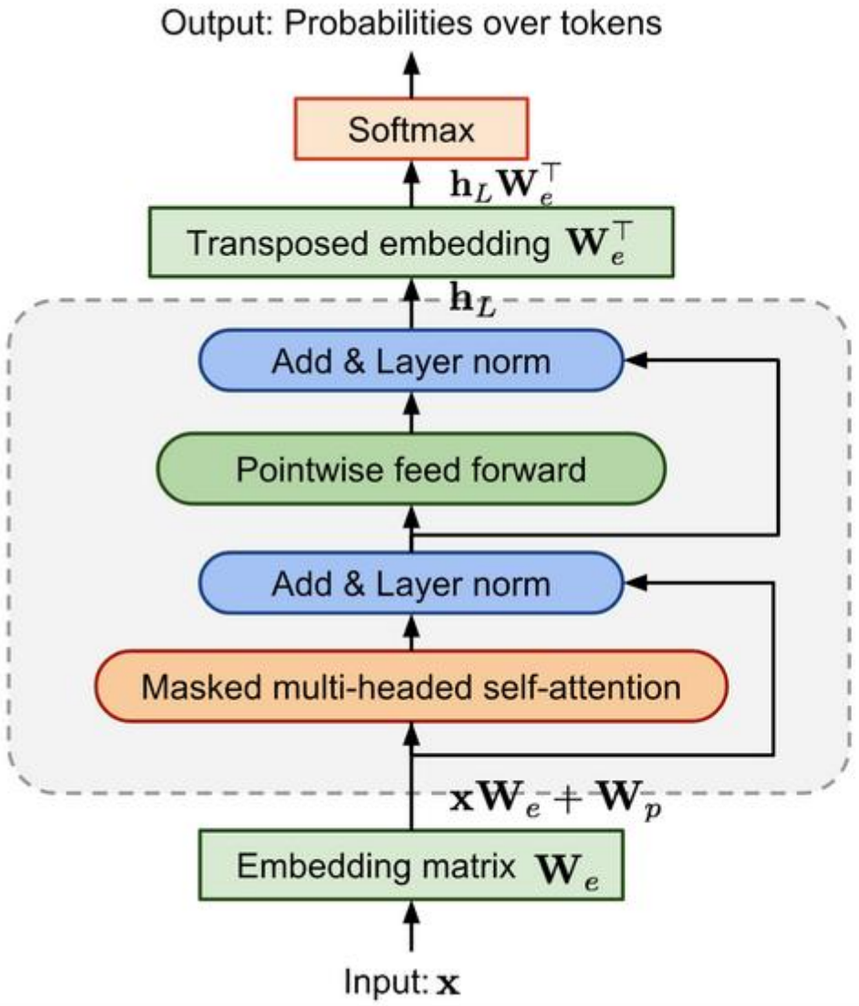
- Декодировщик (Transformer-Decoder), 12 слоёв, 12 головок
- Однонаправленная (Unidirectional), masked self-attention
- Предсказываем следующее слово
- BPE-кодировка (40 000 слияний)
- d=768 для кодирования токенов
- GELU
- 100 эпох, 64 в батче, 512 токенов
- Supervised fine-tuning – 3 эпохи (чаще)

Идея из ELMo + трансформер, у ELMo поднастройка на каждую задачу с помощью коэф. из разных слоёв, у GPT – такого нет

Обучение на BooksCorpus (7000 unpublished books)

Alec Radford Improving Language Understanding by Generative Pre-Training https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/language-unsupervised/language_understanding_paper.pdf

GPT (OpenAI) – архитектура



Transformer Block
Repeat x L=12

$$\mathbf{h}_\ell = \text{transformer\_block}(\mathbf{h}_{\ell-1})$$
$$\ell = 1, \ldots, L$$

https://lilianweng.github.io/lil-log/2019/01/31/generalized-language-models.html

GPT (OpenAI) – архитектура

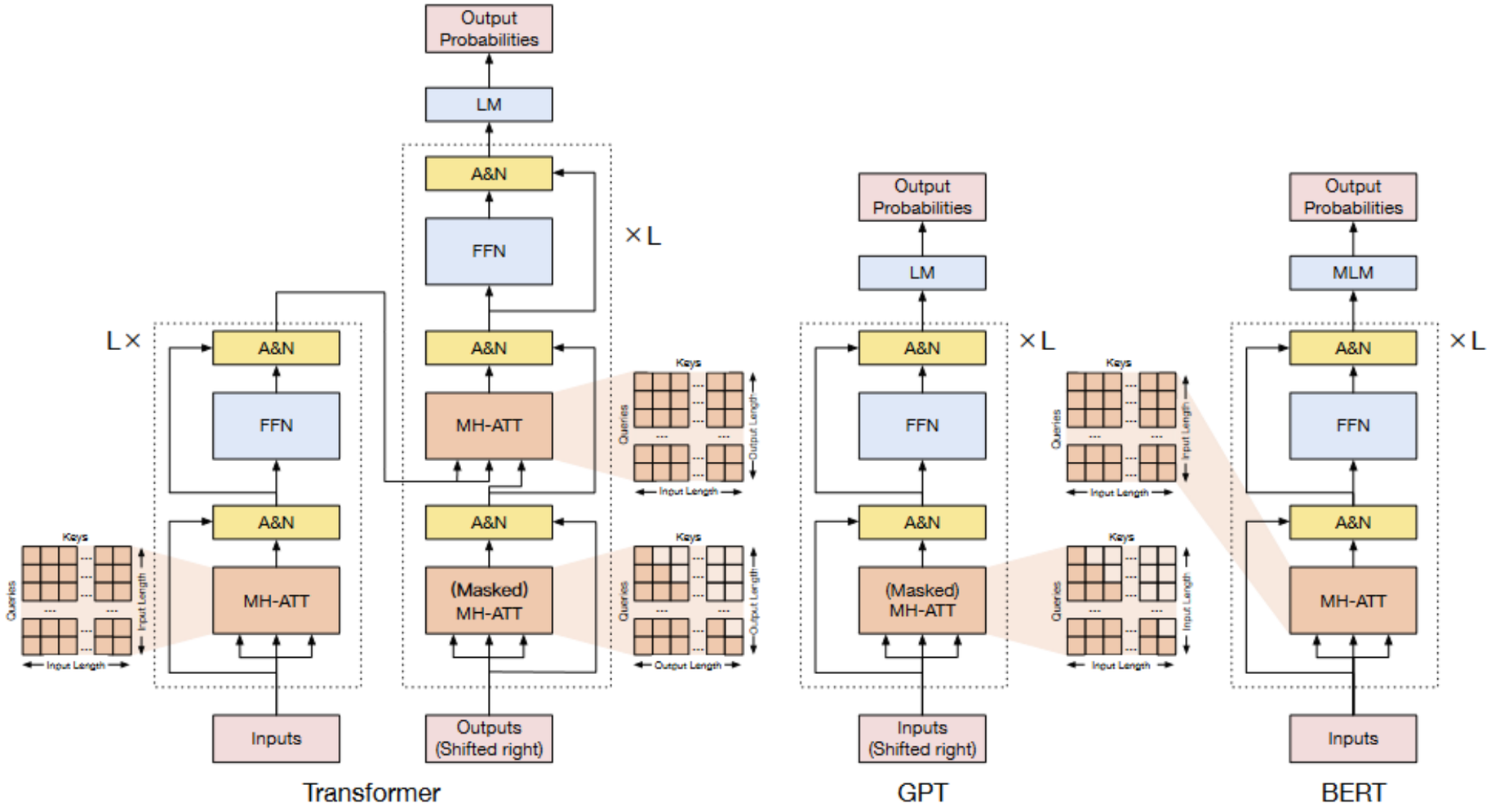


Figure 5: The architecture of Transformer, GPT, and BERT.

https://arxiv.org/pdf/2106.07139.pdf

GPT (OpenAI) – моделирование языка

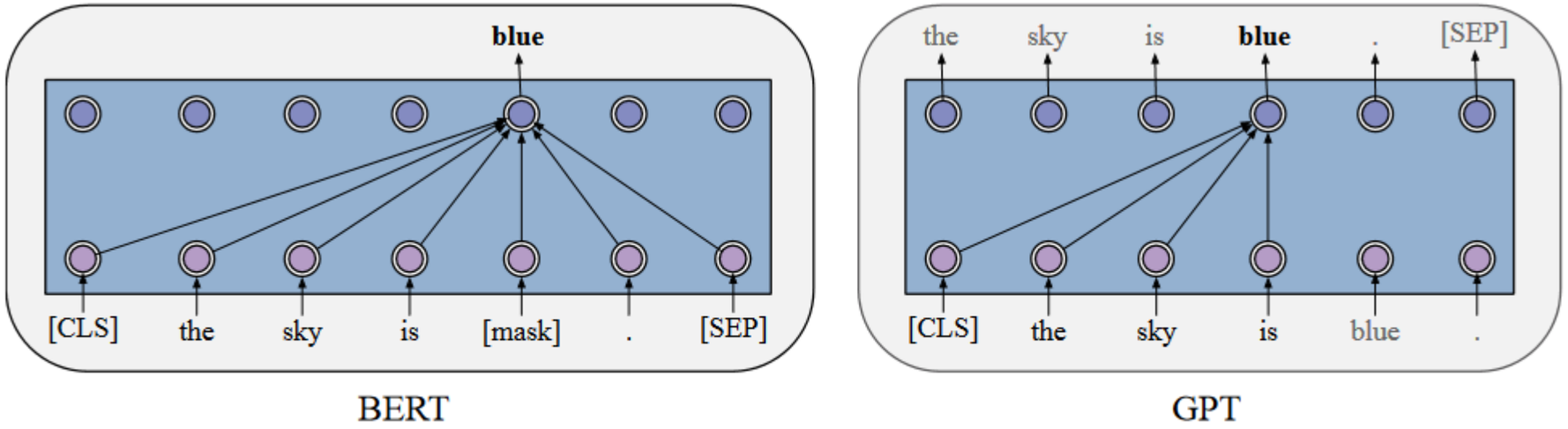


Figure 7: The difference between GPT and BERT in their self-attention mechanisms and pre-training objectives.

$$\mathcal{L}(\mathcal{X}) = \sum_{i=1}^{n+1} \log P(x_i | x_{i-k}, ..., x_{i-1}; \Theta)$$

GPT (OpenAI) – настройка на конкретную задачу

Пример – классификация

Пропускаем через трансформер (декодировщик)
используем скрытое состояние только последнего токена

$$P(y \mid x_1, \ldots, x_n) = \text{softmax}(\mathbf{h}_L^{(n)} \mathbf{W}_y)$$

ошибка = сумма ошибки LM и классификации:

$$\mathcal{L}_{\text{cls}} = \sum_{(\mathbf{x},y)\in\mathcal{D}} \log P(y \mid x_1, \ldots, x_n) = \sum_{(\mathbf{x},y)\in\mathcal{D}} \log \text{softmax}(\mathbf{h}_L^{(n)}(\mathbf{x}) \mathbf{W}_y)$$

$$\mathcal{L}_{\text{LM}} = -\sum_i \log p(x_i \mid x_{i-k}, \ldots, x_{i-1})$$

$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \lambda \mathcal{L}_{\text{LM}}$$

GPT (OpenAI) – любая задача не требует изменения архитектуры

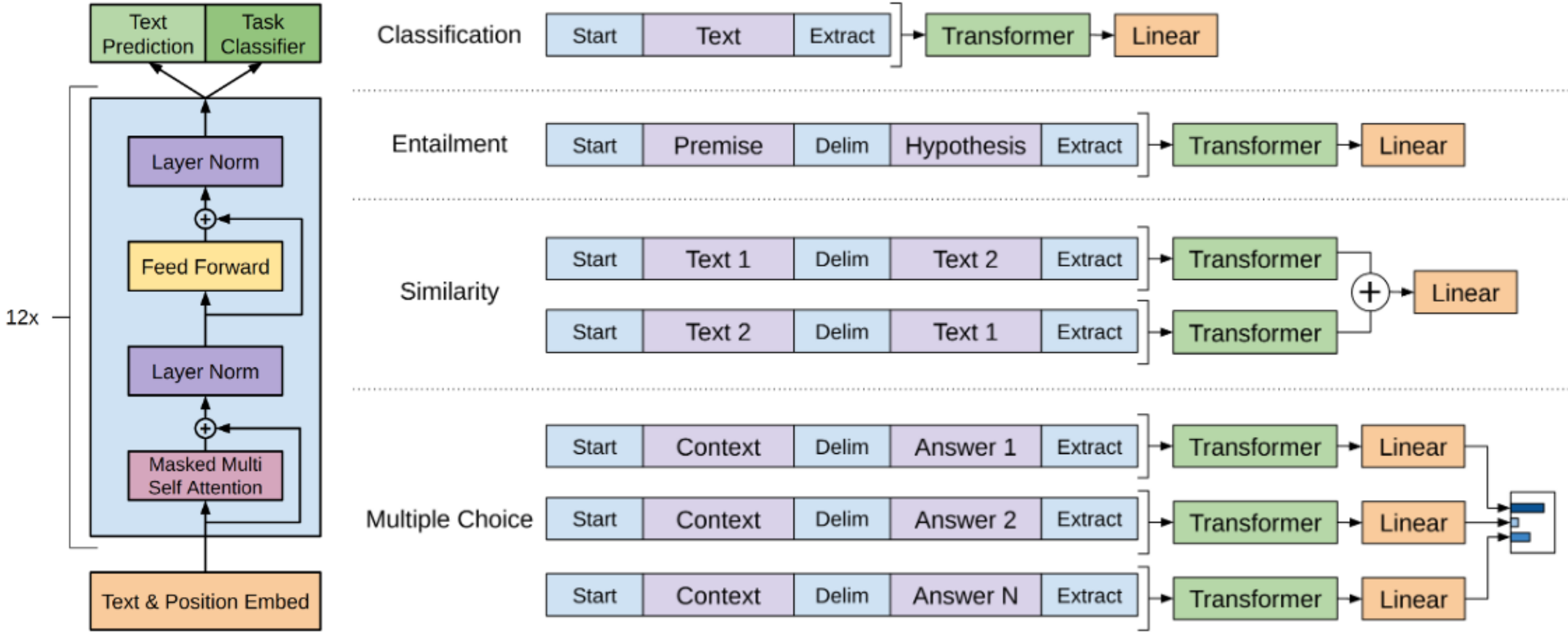
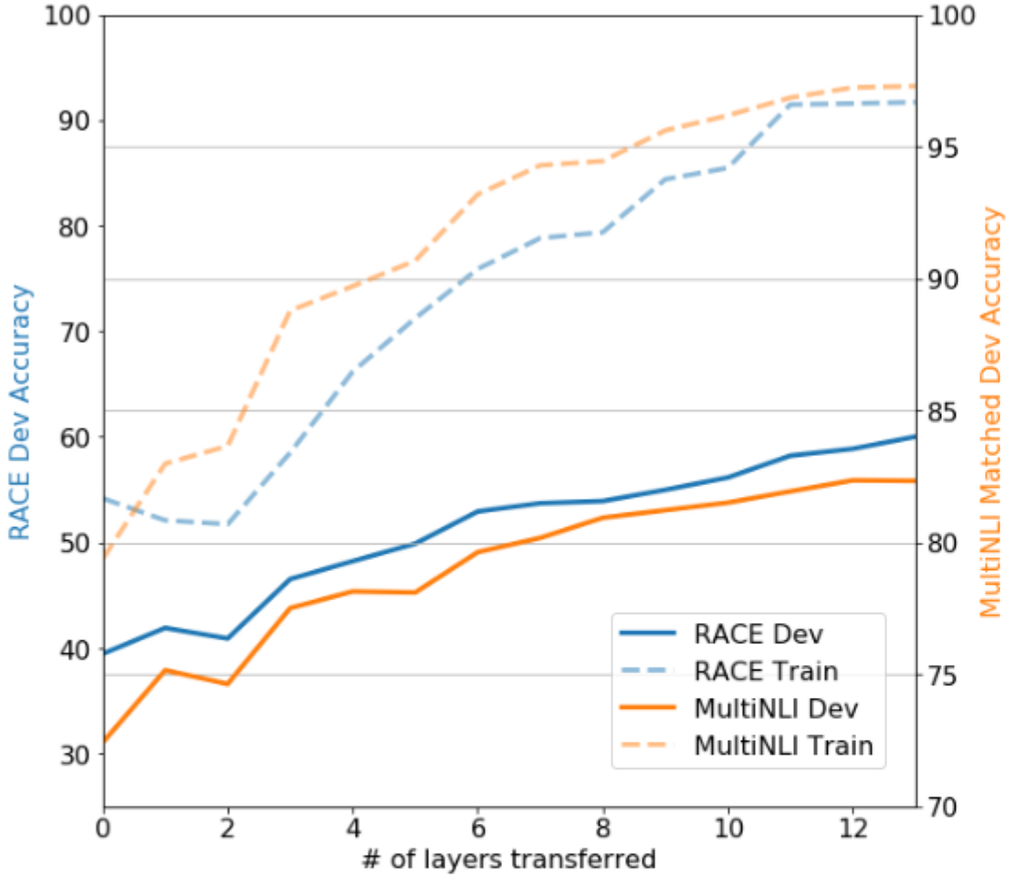


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

если в задаче несколько входных предложений – они разделяются спецтокеном

GPT (OpenAI)



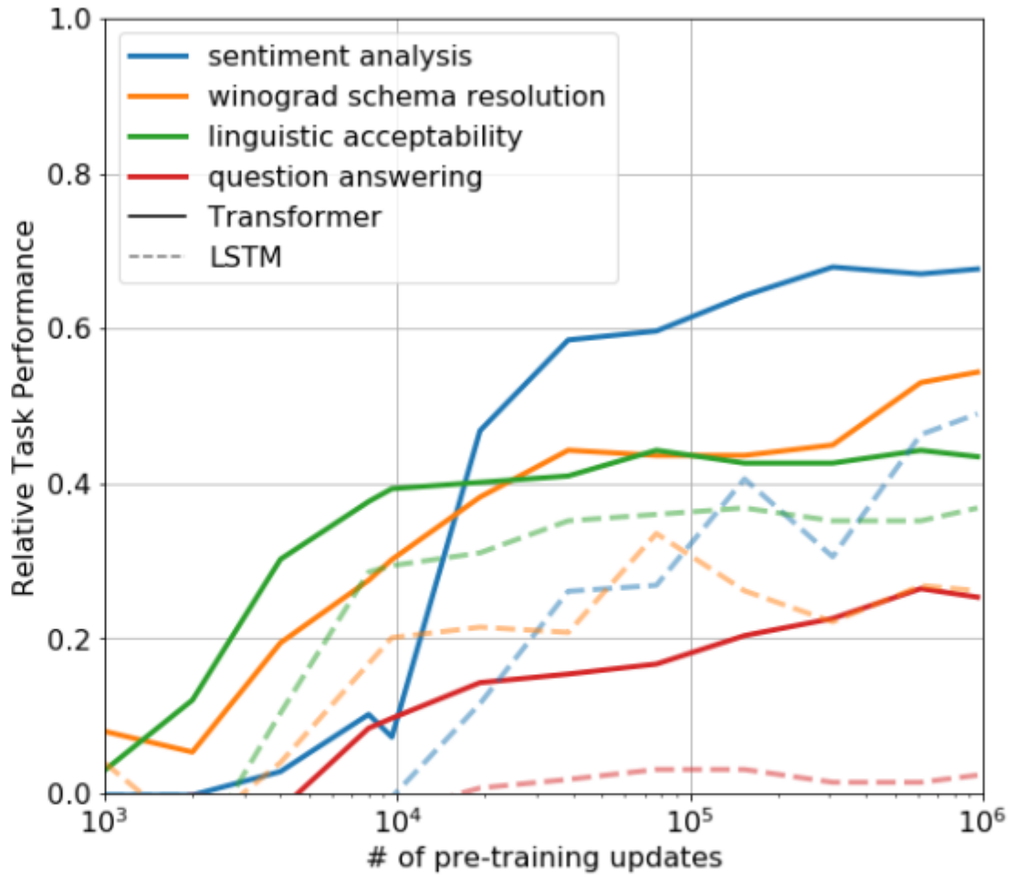


Figure 2: (**left**) Effect of transferring increasing number of layers from the pre-trained language model on RACE and MultiNLI. (**right**) Plot showing the evolution of zero-shot performance on different tasks as a function of LM pre-training updates. Performance per task is normalized between a random guess baseline and the current state-of-the-art with a single model.

GPT2 (2019, OpenAI)

1.5 млрд параметров (10×GPT)

обучение – новый датасет «WebText»

BPE (было)

MQAN

(new←GPT-1) Layer normalization → вход каждого под-блока / после self-attention-блока

(new←GPT-1) другая инициализация

vocabulary = 50 257 (стал больше)

context size = 1024 (больше)

batchsize = 512 (больше)

при инициализации меньше вес Residual layers

SOTA 7 из 8 задач (zero-shot setting – без подстраивания под задачи)

https://blog.openai.com/better-language-models/

https://d4mucfpksywv.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

GPT2 – размеры

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

Table 2. Architecture hyperparameters for the 4 model sizes.

d – размерность пространства представления токенов

48, а не 12 слоёв

GPT2 – датасет «WebText»

~ 1 млн web-страниц / 45 млн ссылок / 8 млн. документов 40Гб

ссылки с Reddit ≥3 кармы (т.е. отбором человека)

удалили Wiki ! (чтобы тестировать на других датасетах)

экстракторы текстов:

Dragnet (Peters & Lecocq, 2013) and Newspaper (https://github.com/codelucas/newspaper)

Есть гипотеза, что Wiki плоха для обучения…

GPT2 – Предобработка

lower-casing

tokenization

out-of-vocabulary tokens

Unicode → UTF-8

BPE (Byte Pair Encoding)

потом кодируем частые слова и буквы (из которых состоят редкие слова)

GPT2 – задачи

- question answering
- machine translation
- reading comprehension
- summarization

Решение всех задач на основе – Language modeling

$$p(x) = \prod_{i=1}^{n} p(s_n | s_1, \ldots, s_{n-1})$$

p(output |input, task) – с помощью трансформера

предсказывает следующее слово в предложении
тут нет маскирования как в BERT

GPT2 – фишки

специальная архитектура (encoders/decoders Kaiser et al., 2017)

специальные алгоритмы (inner/outer loop optimization framework of MAML Finn et al., 2017)

с помощью языка MQAN (Multitask Learning as Question Answering) – McCann et al. (2018):

«переведи …»

«ответь на вопрос …»

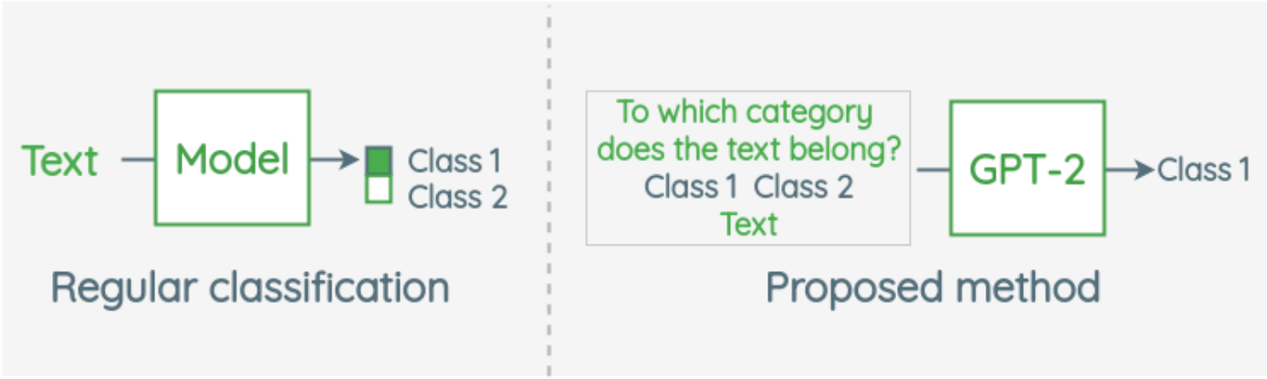
«TL;DR:»

– надо задавать правильные вопросы;)

без дообучения с учителем на специализированных данных!

zero-shot task transfer – особая концепция в NLP

GPT2 – MQAN



Question	Text	Answer
To which category does the text belong?:" Positive Sentiment ", " Negative Sentiment "	the film is one of the year's best	Positive Sentiment

GPT2 – MQAN

Facts	Q: What is human life expectancy in the United States? A: Human life expectancy in the United States is 78 years. Q: Which is heavier, a mouse or an elephant? A: An elephant is heavier than a mouse. Q: Who was president of the United States in 1801? A: Thomas Jefferson was president of the United States in 1801. Q: Who was president of the United States in 1600? A: Queen Elizabeth I was president of the United States in 1600.
Common Sense	Q: What is your favorite animal? A: My favorite animal is a dog.
Logic	Q: When counting, what number comes before 100? A: Ninety-nine comes before 100. Q: Reverse the following array: [1, 3, 5, 6, 10, 4, 2, 77] A: [10, 6, 4, 2, 77, 3, 5, 1]

https://lacker.io/ai/2020/07/06/giving-gpt-3-a-turing-test.html

Результат 2019 – GPT2

Language Models are Unsupervised Multitask Learners

	LAMBADA (PPL)	LAMBADA (ACC)	CBT-CN (ACC)	CBT-NE (ACC)	WikiText2 (PPL)	PTB (PPL)	enwik8 (BPB)	text8 (BPC)	WikiText103 (PPL)	1BW (PPL)
SOTA	99.8	59.23	85.7	82.3	39.14	46.54	0.99	1.08	18.3	**21.8**
117M	**35.13**	45.99	**87.65**	**83.4**	**29.41**	65.85	1.16	1.17	37.50	75.20
345M	**15.60**	55.48	**92.35**	**87.1**	**22.76**	47.33	1.01	**1.06**	26.37	55.72
762M	**10.87**	**60.12**	**93.45**	**88.0**	**19.93**	**40.31**	**0.97**	**1.02**	22.05	44.575
1542M	**8.63**	**63.24**	**93.30**	**89.05**	**18.34**	**35.76**	**0.93**	**0.98**	**17.48**	42.16

Table 3. Zero-shot results on many datasets. No training or fine-tuning was performed for any of these results. PTB and WikiText-2 results are from (Gong et al., 2018). CBT results are from (Bajgar et al., 2016). LAMBADA accuracy result is from (Hoang et al., 2018) and LAMBADA perplexity result is from (Grave et al., 2016). Other results are from (Dai et al., 2019).

Alec Radford et. al. «Language Models are Unsupervised Multitask Learners»
https://www.ceid.upatras.gr/webpages/faculty/zaro/teaching/alg-ds/PRESENTATIONS/PAPERS/2019-Radford-et-al_Language-Models-Are-Unsupervised-Multitask-%20Learners.pdf

Question	Generated Answer	Correct	Probability
Who wrote the book the origin of species?	Charles Darwin	✓	83.4%
Who is the founder of the ubuntu project?	Mark Shuttleworth	✓	82.0%
Who is the quarterback for the green bay packers?	Aaron Rodgers	✓	81.1%
Panda is a national animal of which country?	China	✓	76.8%
Who came up with the theory of relativity?	Albert Einstein	✓	76.4%
When was the first star wars film released?	1977	✓	71.4%
What is the most common blood type in sweden?	A	✗	70.6%
Who is regarded as the founder of psychoanalysis?	Sigmund Freud	✓	69.3%
Who took the first steps on the moon in 1969?	Neil Armstrong	✓	66.8%
Who is the largest supermarket chain in the uk?	Tesco	✓	65.3%
What is the meaning of shalom in english?	peace	✓	64.0%
Who was the author of the art of war?	Sun Tzu	✓	59.6%
Largest state in the us by land mass?	California	✗	59.2%
Green algae is an example of which type of reproduction?	parthenogenesis	✗	56.5%
Vikram samvat calender is official in which country?	India	✓	55.6%
Who is mostly responsible for writing the declaration of independence?	Thomas Jefferson	✓	53.3%
What us state forms the western boundary of montana?	Montana	✗	52.3%
Who plays ser davos in game of thrones?	Peter Dinklage	✗	52.1%
Who appoints the chair of the federal reserve system?	Janet Yellen	✗	51.5%
State the process that divides one nucleus into two genetically identical nuclei?	mitosis	✓	50.7%
Who won the most mvp awards in the nba?	Michael Jordan	✗	50.2%
What river is associated with the city of rome?	the Tiber	✓	48.6%
Who is the first president to be impeached?	Andrew Johnson	✓	48.3%
Who is the head of the department of homeland security 2017?	John Kelly	✓	47.0%
What is the name given to the common currency to the european union?	Euro	✓	46.8%
What was the emperor name in star wars?	Palpatine	✓	46.5%
Do you have to have a gun permit to shoot at a range?	No	✓	46.4%
Who proposed evolution in 1859 as the basis of biological development?	Charles Darwin	✓	45.7%
Nuclear power plant that blew up in russia?	Chernobyl	✓	45.7%
Who played john connor in the original terminator?	Arnold Schwarzenegger	✗	45.2%

Table 5. The 30 most confident answers generated by GPT-2 on the development set of Natural Questions sorted by their probability according to GPT-2. None of these questions appear in WebText according to the procedure described in Section 4.

GPT3 (2020, OpenAI)

Архитектура как в GPT2, но 96 слоёв, 96 головок

dim(word embeddings) = 12 888 (вместо 1600)

окно контекста = 2048 (вместо 1024)

175 млрд параметров (100×GPT2, 10×Turing NLG)

«alternating dense and locally banded sparse attention patterns»

как в Sparse-трансформере

Обучающий датасет – больше данных

Тестирование в режиме few-shot без fine-tuning

Не файнтьюнили GPT-3 под задачу!

Генерация совсем правдоподобных историй

on-the-fly tasks – на которых не обучалась (сложить два числа, запрос SQL и т.п.)

https://arxiv.org/abs/2005.14165

GPT3 – Обучающий датасет

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

Table 2.2: Datasets used to train GPT-3. "Weight in training mix" refers to the fraction of examples during training that are drawn from a given dataset, which we intentionally do not make proportional to the size of the dataset. As a result, when we train for 300 billion tokens, some datasets are seen up to 3.4 times during training while other datasets are seen less than once.

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.

GPT3 – zero/one/few-shot learning

The three settings we explore for in-context learning

Zero-shot

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

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

One-shot

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

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

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

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

Traditional fine-tuning (not used for GPT-3)

Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.

```
sea otter => loutre de mer             ← example #1
        ↓
   gradient update
        ↓
peppermint => menthe poivrée           ← example #2
        ↓
   gradient update
        ↓
        ...
        ↓
plush giraffe => girafe peluche        ← example #N
        ↓
   gradient update
        ↓
cheese =>                              ← prompt
```

Figure 2.1: Zero-shot, one-shot and few-shot, contrasted with traditional fine-tuning. The panels above show four methods for performing a task with a language model – fine-tuning is the traditional method, whereas zero-, one-, and few-shot, which we study in this work, require the model to perform the task with only forward passes at test time. We typically present the model with a few dozen examples in the few shot setting. Exact phrasings for all task descriptions, examples and prompts can be found in Appendix G.

GPT3 (2020, OpenAI)

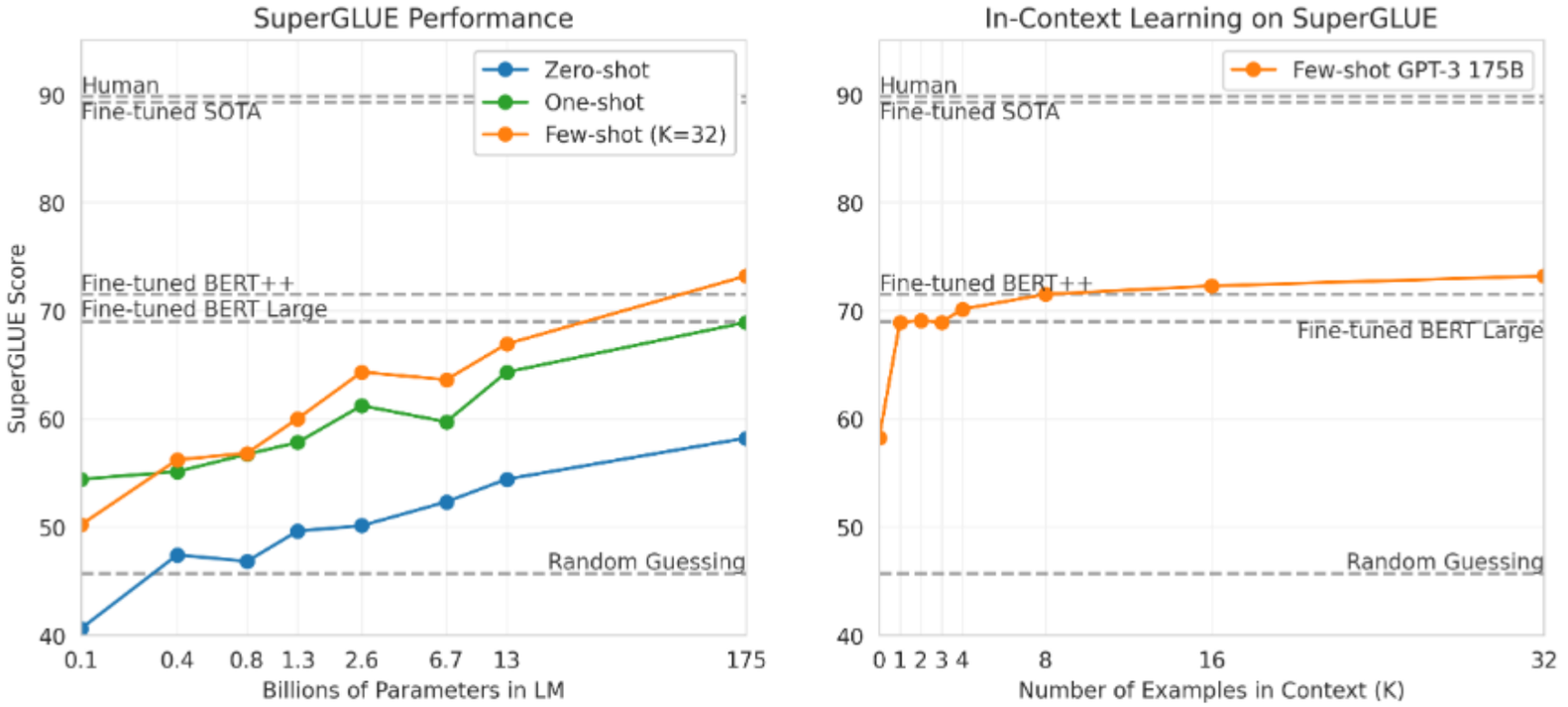


Figure 3.8: Performance on SuperGLUE increases with model size and number of examples in context. A value of $K = 32$ means that our model was shown 32 examples per task, for 256 examples total divided across the 8 tasks in SuperGLUE. We report GPT-3 values on the dev set, so our numbers are not directly comparable to the dotted reference lines (our test set results are in Table 3.8). The BERT-Large reference model was fine-tuned on the SuperGLUE training set (125K examples), whereas BERT++ was first fine-tuned on MultiNLI (392K examples) and SWAG (113K examples) before further fine-tuning on the SuperGLUE training set (for a total of 630K fine-tuning examples). We find the difference in performance between the BERT-Large and BERT++ to be roughly equivalent to the difference between GPT-3 with one example per context versus eight examples per context.

но SuperGLUE не самое хорошее задание для GPT-3

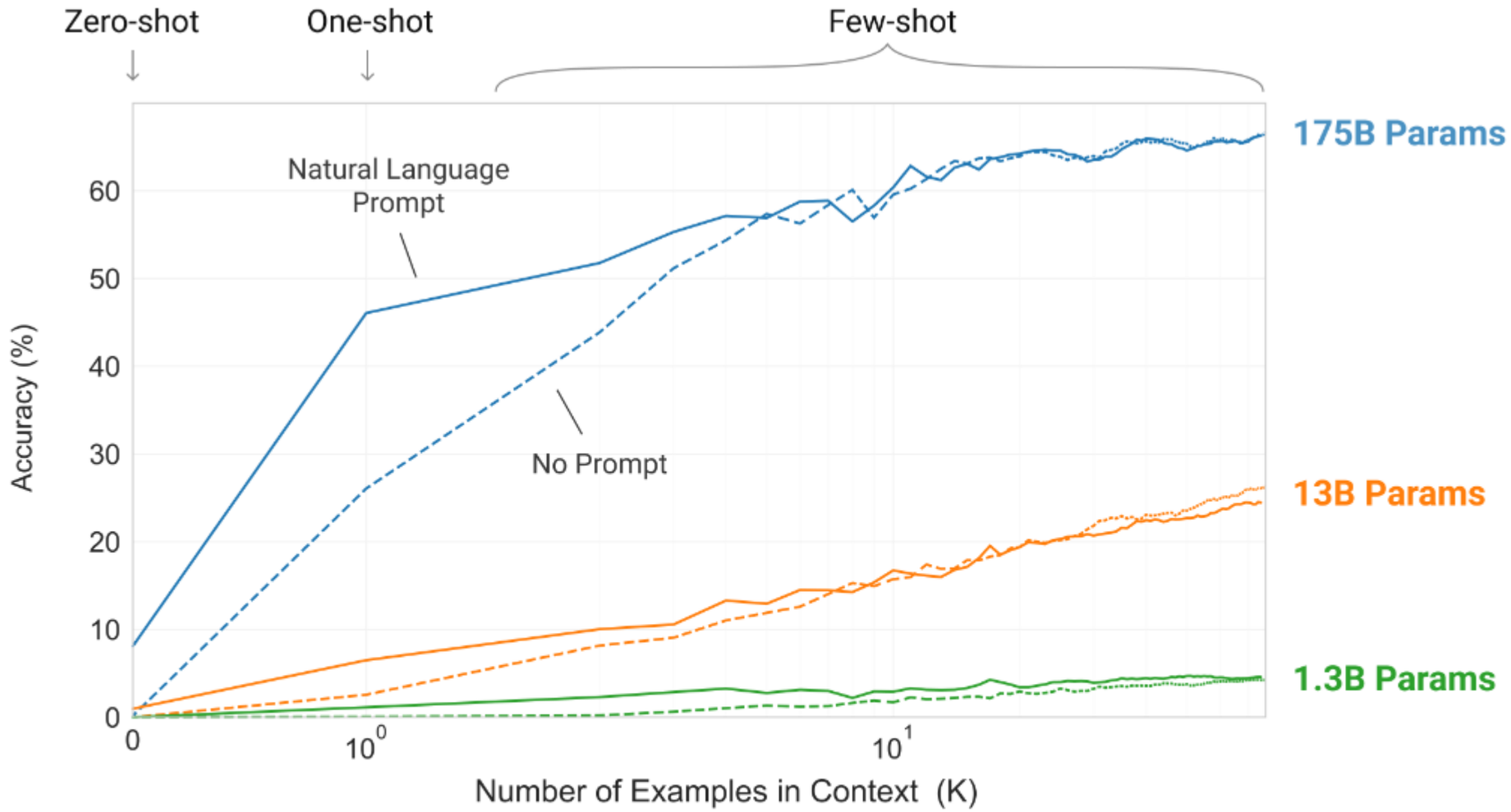


Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning curves" for large models demonstrate improved ability to learn a task from contextual information. We see qualitatively similar behavior across a wide range of tasks.

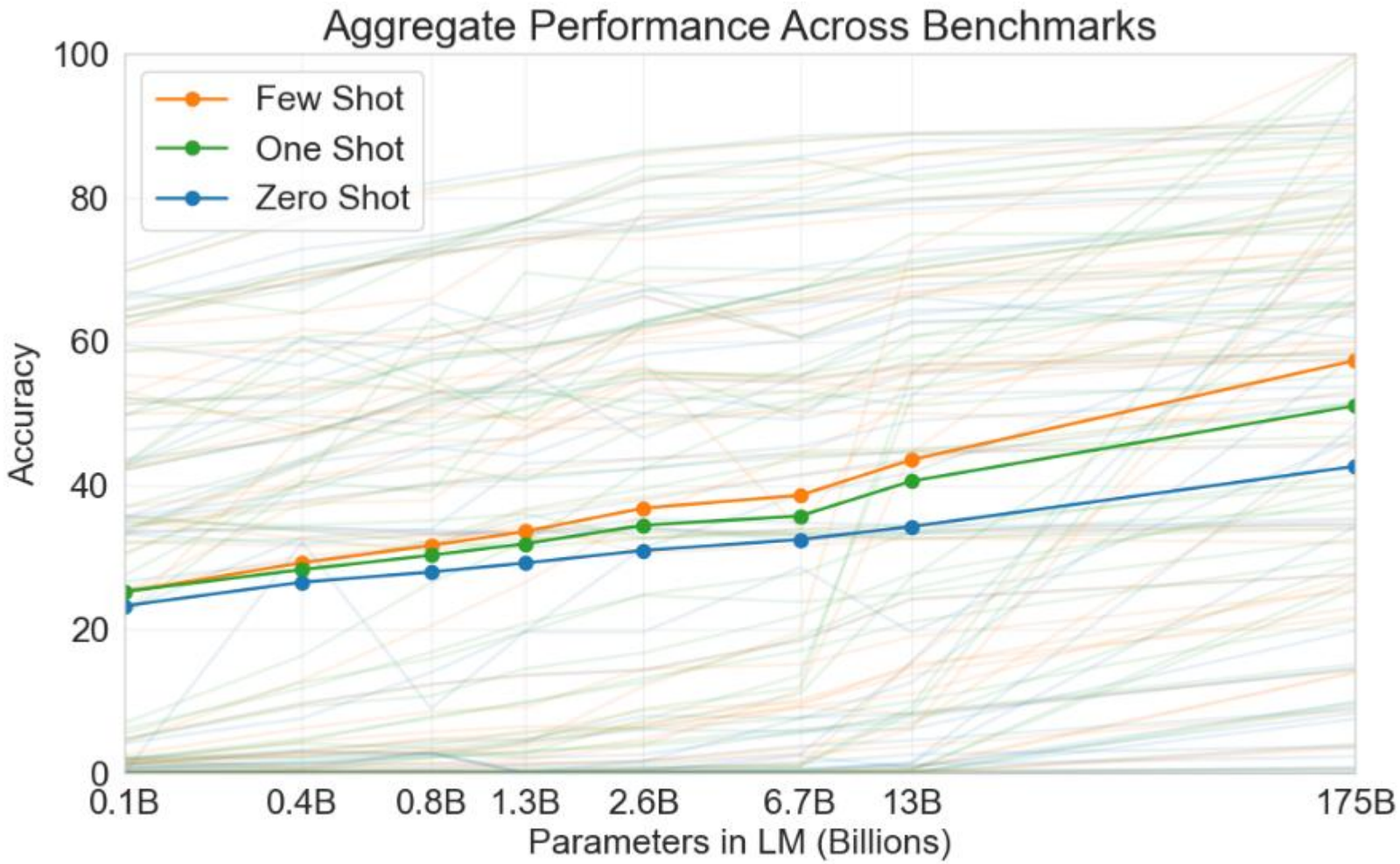
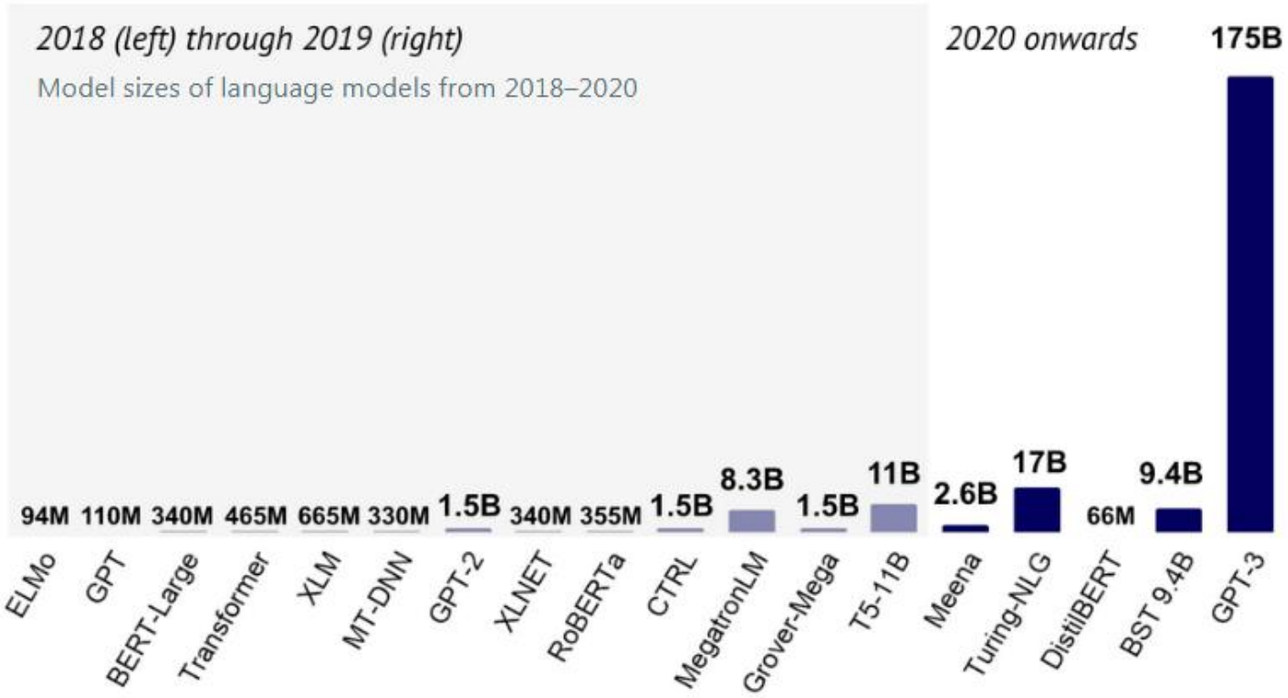
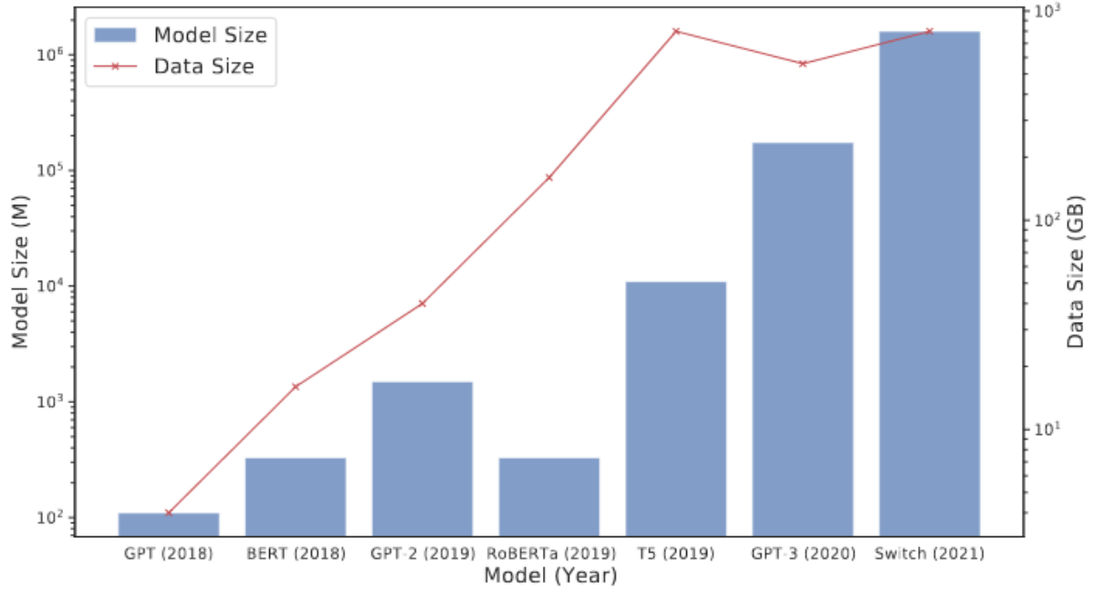


Figure 1.3: Aggregate performance for all 42 accuracy-denominated benchmarks While zero-shot performance improves steadily with model size, few-shot performance increases more rapidly, demonstrating that larger models are more proficient at in-context learning. See Figure 3.8 for a more detailed analysis on SuperGLUE, a standard NLP benchmark suite.

GPT3 – размер модели





(b) The model size and data size applied by recent NLP PTMs. A base-10 log scale is used for the figure.

https://www.stateof.ai/

https://arxiv.org/pdf/2106.07139.pdf

Нейронная дегенерация текста

Огромные проблемы генерации текстов, обзор на основе работ

Ari Holtzman, Jan Buys, Maxwell Forbes, Yejin Choi «The Curious Case of Neural Text Degeneration» // https://arxiv.org/abs/1904.09751

Sean Welleck, et. al. «Neural Text Generation with Unlikelihood Training» // https://arxiv.org/pdf/1908.04319.pdf

Open-ended Generation

есть «контекст» $x_1,\ldots,x_m, m < T$

$$p(x_t,\ldots,x_T) = \prod_{t=1}^{T} p(x_t \mid x_1,\ldots,x_{t-1})$$

open – т.к. не ответ на вопрос, не суммаризация и т.п.

Проблемы «дегенерации текстов»

- **Огромная статистическая разница (distributional differences) между человеческим и машинным текстом [1]**
  Человеческий язык очень специфичен!

- **Декодирование (decoding strategies) сильно влияет на качество [1]**
  выход: Nucleus Sampling

- **Использование правдоподобия и стандартное декодирование приводит к повторам в тексте и неестественности [2]**
  высокочастотные токены – слишком часто
  низкочастотные – слишком редко

- **Архитектура трансформера приводит к повторениям**
  следующее слово встречается среди 128 предыдущих в 63% случаях, в обычной речи – 49% (+ дальше)

- **Обучение на стандартных корпусах никак не учитывает специфику решаемой задачи**

Проблемы GPT-2

Context:

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Continuation (BeamSearch, b=10):

"The unicorns were able to communicate with each other, they said unicorns. a statement that the unicorns. Professor of the Department of Los Angeles, the most important place the world to be recognition of the world to be a of the world to be a of the world to be a of the world to be a of the world to be a of the world to be a of the world to be a of the world to be a of the world to be a of the world to be a of the...

Figure 1: Beam search leads to degenerate text, even when generated from GPT-2-117M, in stark contrast with the admirable quality of the text decoded using *top-k* sampling (Radford et al., 2019). The *continuation* is machine generated, conditioned on the *context* provided by a human. Blue text highlights decoded words that have occurred previously in the text.

Стратегии декодирования, которые максимизировали вероятность текста провалились

$$\prod_{t=m+1}^{T} p(x_t \mid x_1, \dots x_m, \dots, x_{t-1}) \to \max$$

жадная (Greedy decoding)

beam search (успешен в non-open-ended generation tasks: machine translation, data-to-text generation, summarization)

Проблемы GPT-2

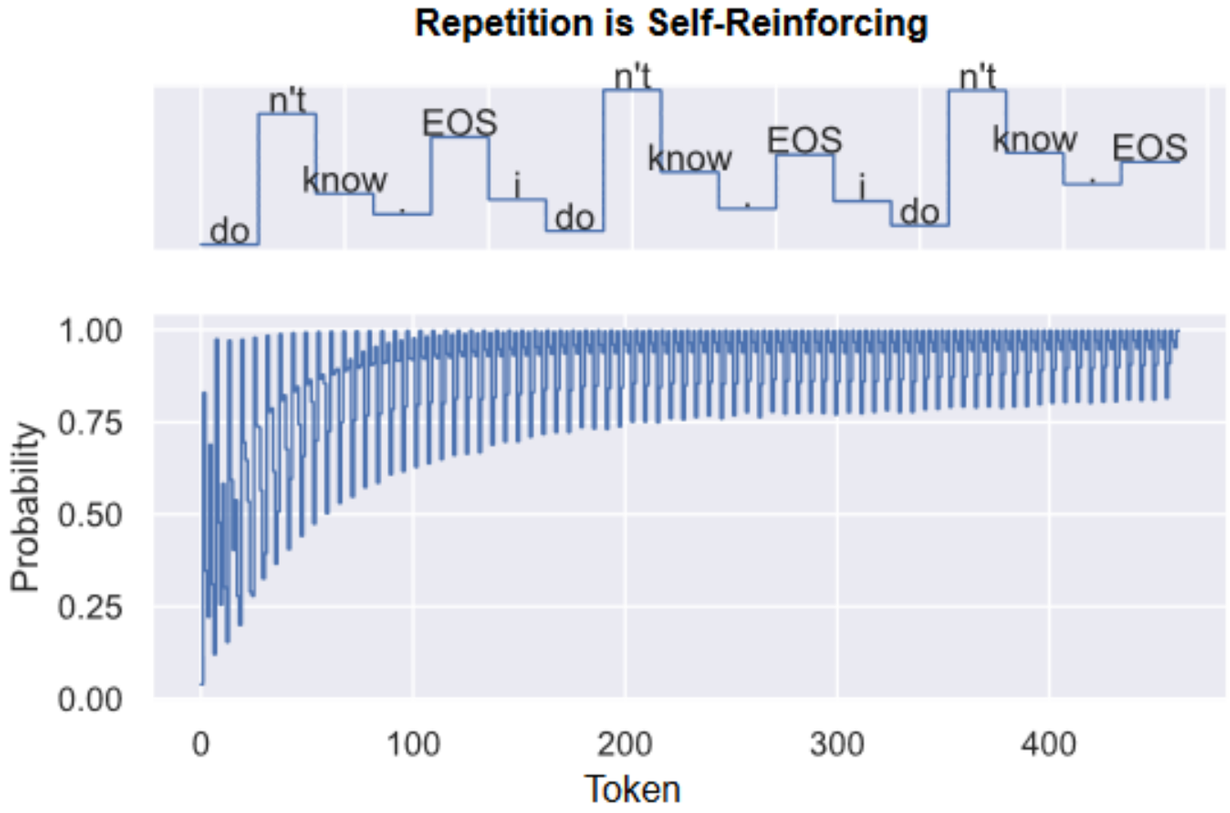


Figure 3: The probability of repetition increases with each instance of repetition, creating a positive-feedback loop.

Генерация превращается в повтор «I don't know»

Это связывают с архитектурой трансформера

Проблемы GPT-2

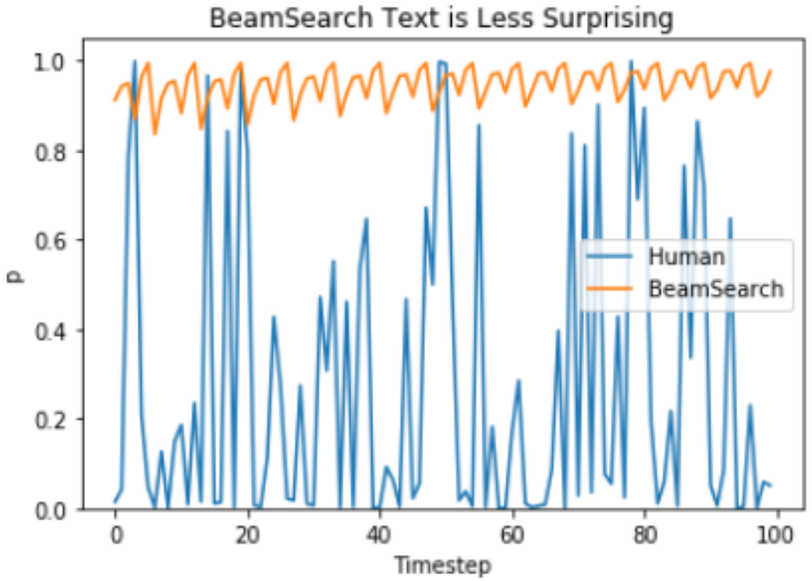


Figure 2: The probability assigned to tokens generated by humans and beam search using GPT-2-117M. Note the increased variance that characterizes the richness of human text.

Human	BeamSearch
…get your hopes up. I saw him once and I have no intention of being near him anytime soon. He sat on the edge, the wind tossing around his hair. It was going to be seriously wind-blown later. I sat down next to him and I was trying to forget the dwarfs mangled body. I shook and hugged myself. Are you cold? He asked, his voice full of concern. I just shrugged and squeezed my eyes shut. I saw Kojas glowing eyes and sword, the…	…looked at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds. He looks at the clouds…

Человеческий текст более непредсказуем!

В сгенерированных текстах на 40% меньше уникальных токенов

Это не лечится увеличением обучения (Radford et al., 2019)

Prefix	*Lyrically the song has excerpts of different languages including French , Spanish ,*
GPT2-greedy	German , Italian , Portuguese , Spanish , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , ...
GPT2-top3	German , Italian , Portuguese , Spanish , Portuguese , Portuguese, Italian and Spanish. It is also available in English, French and Spanish. In addition to its lyrics, the album features a number of original songs, ...
GPT2-nucleus-0.3	German , Italian , Portuguese , Spanish , Portuguese , Italian , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , ...
Prefix	*The first pair of pereiopods is armed with a large , asymm*
GPT2-greedy	etrical, and long-range laser cannon. The second pair is armed with a large , asymmetrical, and long-range laser cannon. The third pair is armed with a large , asymmetrical, and long-range laser cannon. The fourth pair is armed with a large ...
GPT2-top3	etrical, and highly mobile head, and the second pair has a small , asymmetrical, and highly mobile head. The second pair has a large and highly mobile head, and the third pair is armed with a large and highly mobile head. The first pair ...
GPT2-nucleus-0.3	etrical head and a large body. The first pair of pereiopods is armed with a large , asymmetrical head and a large body. The first pair of pereiopods is armed with a large , asymmetrical head and a large body. The first pair of pereiopods is armed ...

Table 1: Top: Degenerate repetition in completions from a state-of-the-art large-scale language model (Radford et al., 2019). The examples contain single-word repetitions, phrase-level repetitions, and structural repetitions where some tokens within a repeating phrase vary. Recently proposed stochastic samplers (top-k, nucleus) exhibit degeneration based on hyper-parameter settings.

Проблемы GPT-2

генерация наиболее вероятных текстов приводит к повторениям в сгенерированных текстах и их неестественности

Широкое и узкое распределения

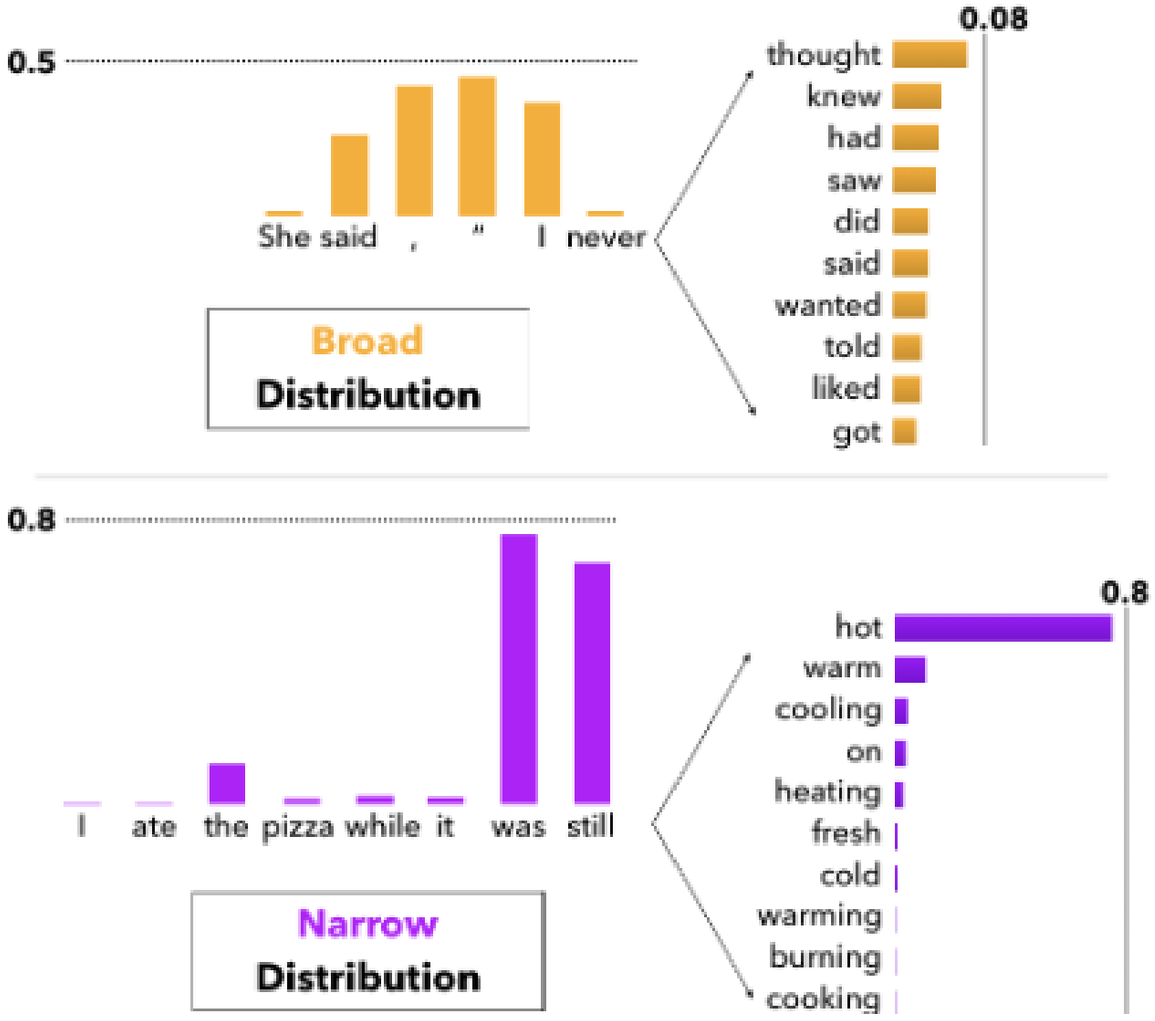


Figure 5: Examples of the probability mass assigned two partial human sentences by GPT, and the resulting **broad** and **narrow** distributions. Broad distributions lead to a large number of tokens with moderate shares of probability mass. In contrast, narrow confidence distributions (less common in open-ended generation) concentrate the overwhelming majority of probability mass into just a few tokens.

Стратегии сэмплирования – для борьбы с дегенерацией
Stochastic Decoding

1. Сэмплирование с температурой

$$p(x_t = x \mid x_1,\ldots,x_{t-1}) = \text{softmax}(u_1 / \tau,\ldots,u_l / \tau)$$

2. Топ-k (Top-k Sampling)

$$p'(x_t = x \mid x_1,\ldots,x_{t-1}) = \begin{cases} p(x_t = x \mid x_1,\ldots,x_{t-1}) / p', & x \in \text{top}(k), \\ 0, & \text{иначе.} \end{cases}$$

3. Nucleus (Top-p) Sampling

вместо используем $\text{top}(k)$

$$\sum_{x \in \text{sort}} p(x_t = x \mid x_1,\ldots,x_{t-1}) \geq p$$

но есть мнение [2], что сами вероятности неадекватны

Стратегии сэмплирования

4. Penalized sampling

$$p(x_t = x \mid x_1, \ldots, x_{t-1}) = \text{softmax}(u_1 / (\tau\theta_1), \ldots, u_l / (\tau\theta_l))$$

штраф за вхождение в контекст:

$$\theta_i = \begin{cases} 1, & i \notin g, \\ \theta, & i \in g, \end{cases}$$

Так боремся с повторами

Nitish Shirish Keskar, et al. «CTRL: A Conditional Transformer Language Model for Controllable Generation» // https://arxiv.org/abs/1909.05858

В идеале детерминистические и стохастические – в зависимости от задачи

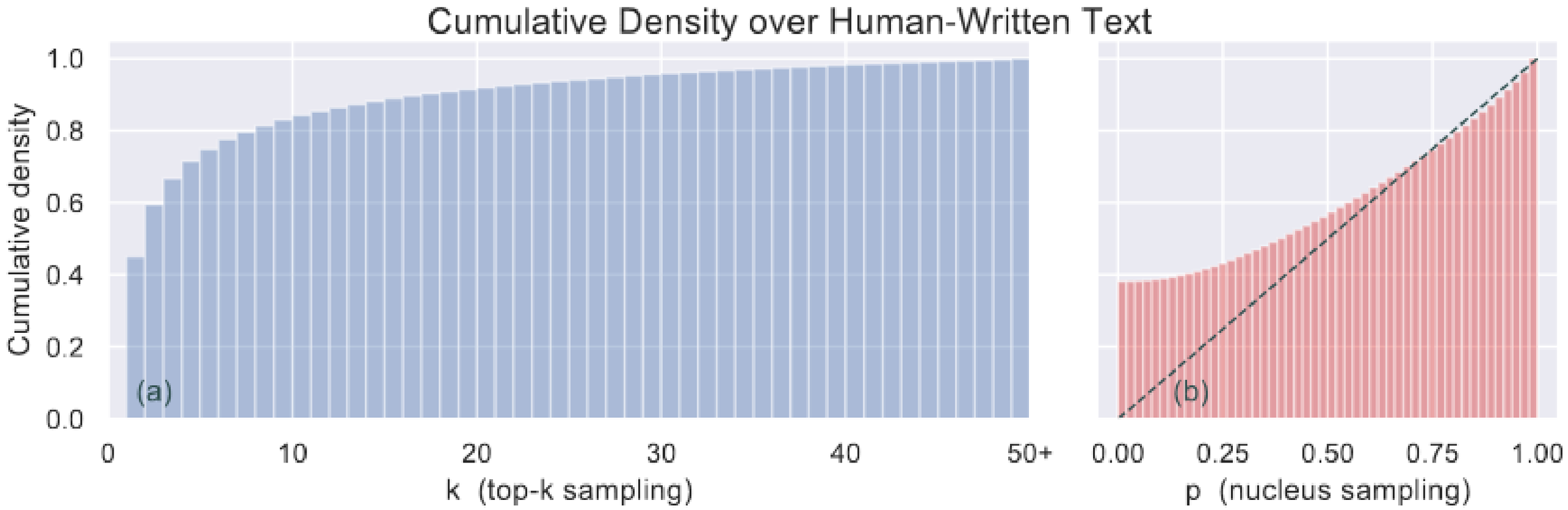


Figure 7: The left-hand side graph illustrates the diminishing returns received as the k increases in top-k, which contrasts with the increasing returns of Nucleus Sampling (right) that allows values of p close to 1 to act very similarly to pure sampling without risk of sampling from the low-confidence tail. The height of a bar encodes the cumulative density of the minimum value of k (for top-k sampling) or p (for Nucleus sampling) required to assign a non-zero probability to the *gold* next word prediction over a corpus of human-written text.

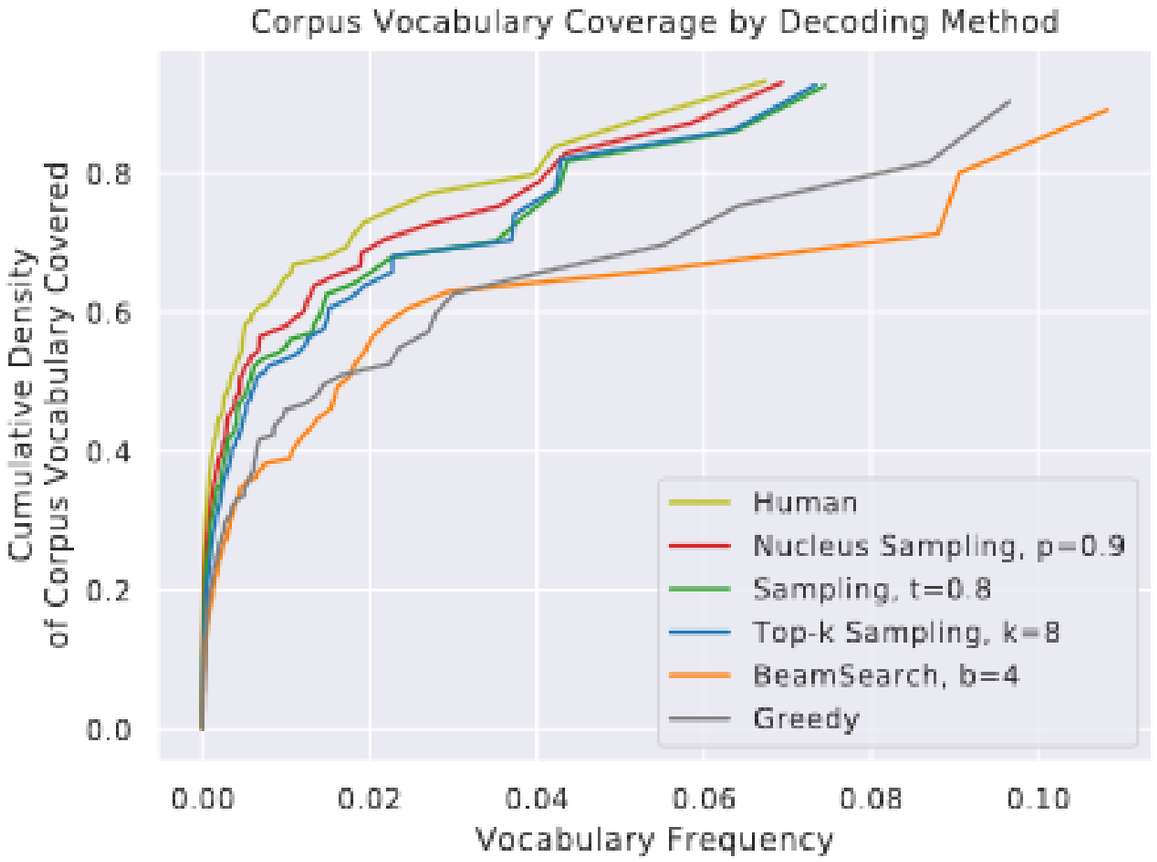


Figure 8: A chart describing the distributional differences between n-gram frequencies of human and machine text. The complete separation of likelihood maximization and stochastic methods, stochastic clearly closer to human, indicates an inherent issue with a likelihood maximization as a decoding objective.

🗣 **Context**: On days when he woke early, the president liked to have coffee in the oval office. There was something about watching the sky grow lighter and lighter as you sat your pajama'd behind in the most powerful chair in the free world, sipping marine strength coffee, that you just couldn't achieve anywhere else.

💰 **Greedy**: He'd been in the oval office for over a year now, and he'd never been so happy to be there. He'd been in the oval office for almost a year, and he'd never been so happy to be there.

🚦 **BeamSearch** (k=4): The President was a man of his word. He was a man of his word. He was a man of his word. He was a man of his word. He was a man of his word. He was a man of his word.

🥄 **Sampling** (t=1.0): You couldn't be sure if that's what you were really doing, and If you decided to take the day off. The president wanted you to take the day off, but he wanted to maintain a curfew and use his influence wisely.

🇰 **Top-k Sampling** (k=8): "I'm sorry, sir." "No, it's okay, son," the president said. "I understand." "You're going to have to make a special trip down there to get that kid. He has no idea where he's going."

⚛ **Nucleus Sampling** (p=0.9): But that wasn't what drew the president's attention. He'd been seated for maybe a minute when he noticed the other man. What was the guy doing here?

🗣 **Gold**: He was therefore disagreeably surprised to find a man in an understated grey suit sitting in that selfsame chair sipping tea. The president turned around and went looking for his chief of staff.

Unlikelihood training [2]

Ориентация на оптимизацию правдоподобия – ошибка!

из-за неё повторы и неестественность

и глобально, не умеем максимизировать правдоподобие всей последовательности

Unlikelihood loss [2]

Идея: определяем «запрещённое множество» – штрафуем слова оттуда

The key idea behind the unlikelihood loss is decreasing the model's probability of certain tokens, called *negative candidates*. Given a sequence $(x_1, \ldots, x_T)$ and a set of negative candidate tokens $\mathcal{C}^t = \{c_1, \ldots, c_m\}$, where each $c_j \in \mathcal{V}$, we define the unlikelihood loss for step t as:

$$\mathcal{L}_{\text{UL}}^t(p_\theta(\cdot|x_{<t}), \mathcal{C}^t) = -\sum_{c \in \mathcal{C}^t} \log(1 - p_\theta(c|x_{<t})). \tag{4}$$

The loss decreases as $p_\theta(c|x_{<t})$ decreases.

Token level objective

Реализация идеи:

Given a sequence $(x_1, \ldots, x_T)$, the token-level objective applies the unlikelihood loss to a set of negative candidates at each time-step of maximum likelihood training:

$$\mathcal{L}^t_{\text{UL-token}}(p_\theta(\cdot|x_{<t}), \mathcal{C}^t) = -\alpha \cdot \underbrace{\sum_{c \in \mathcal{C}^t} \log(1 - p_\theta(c|x_{<t}))}_{\text{unlikelihood}} - \underbrace{\log p_\theta(x_t|x_{<t})}_{\text{likelihood}}. \quad (5)$$

We propose a candidate set which uses the previous context tokens:

$$\mathcal{C}^t_{\text{prev-context}} = \{x_1, \ldots, x_{t-1}\} \setminus \{x_t\}. \quad (6)$$

Intuitively, the unlikelihood loss with this candidate set makes (i) incorrect repeating tokens less likely, as the previous context contains potential repeats, and (ii) frequent tokens less likely, as these tokens appear often in the previous context. This candidate set is also efficient to compute and requires no additional supervision.

Sequence level objective

Штраф за повторы последовательностей

Intuitively, the negative candidates can identify problematic tokens for the loss to penalize. We choose to penalize repeating n-grams in the continuation:

$$\mathcal{C}^t_{\text{repeat-n}} = \{x_t\} \text{ if } (x_{t-i}, \dots, x_t, \dots, x_{t+j}) \in x_{<t-i} \text{ for any } (j-i) = n, i \le n \le j, \qquad (10)$$

which says that the token x_t is the (single) negative candidate for step t if it is part of a repeating n-gram.

Evaluation metrics

Repetition As a token-level metric for repetition, we use the fraction of next-token (top-1) predictions that occur in the previous ℓ tokens (**rep/ℓ**). That is, given a validation set $\mathcal{D}$ of length-T sequences,

$$\frac{1}{|\mathcal{D}|T}\sum_{\mathbf{x}\in\mathcal{D}}\sum_{t=1}^{T}\mathbb{I}\left[\arg\max p_\theta(x|\mathbf{x}_{<t}) \in \mathbf{x}_{t-\ell-1:t-1}\right]. \tag{11}$$

We use the portion of duplicate n-grams (**seq-rep-n**) in a generated sequence to measure sequence-level repetition. That is, for a continuation $\mathbf{x}_{k+1:k+N}$ we compute,

$$1.0 - \frac{|\text{unique n-grams}(\mathbf{x}_{k+1:k+N})|}{|\text{n-grams}|}, \tag{12}$$

and average over continuations. **seq-rep-n** is zero when the continuation has no repeating n-grams, and increases towards 1.0 as the model repeats. We compute **seq-rep-n** on the continuation rather than the full completion since we are interested in measuring degenerate repeats in the continuation.

Evaluation metrics

Token Distribution We quantify a model's predicted token distribution using the number of unique tokens. As a token-level metric (**uniq**), we use the number of unique next-token predictions on the validation set, i.e. $|\{\arg\max p(x_t|x_{<t}) \mid x_{<t} \in \mathcal{D}_{\text{valid}}\}|$. As a sequence-level metric (**uniq-seq**) we use the number of unique tokens in continuations of prefixes from the validation set (subsection 6.1).

Language Modeling Quality To quantify a model's language modeling quality we use the standard perplexity metric (**ppl**), and next-token greedy prediction accuracy (**acc**).

Experiments

		seq-rep-4
Prefix	*... Lyrically the song has excerpts of different languages including French , Spanish*	
$\mathcal{L}_{\text{MLE}}$	, Italian , Spanish , Italian , Spanish , Italian , Spanish , Spanish , Portuguese	0.744
$\mathcal{L}_{\text{UL-token+seq}}$	, and German . In the first verse , the protagonist sings about being a " girl who 's been in love with someone else " , while the second verse describes the relationship between the protagonist and her lover . In the third verse , the protagonist sings about	0.063
Prefix	*... with timely advice from General Lee , adopted a strong defensive position that was virtually*	
$\mathcal{L}_{\text{MLE}}$	impregnable . Lee 's forces were well prepared for the night , and the battle was a disaster . Lee 's forces were well prepared for the night , and the battle was a disaster . Lee 's forces were well prepared for the night , and the battle was	0.617
$\mathcal{L}_{\text{UL-token+seq}}$	impregnable . The Americans were also able to use the boats to bombard the fort from the rear , and the guns fired at the British ships in the harbor . The British bombardment began at 9 : 30 am , when the first shots were fired on the	0.000

Experiments

Prefix	*... starboard engines and was going to crash . " We 're going in ,"*	
$\mathcal{L}_{\text{MLE}}$	he said . " We 're going to crash . We 're going to crash . We 're going to crash . We 're going to crash . We 're going to crash . We 're going to crash . We 're going to crash . We 're going to	0.787
$\mathcal{L}_{\text{UL-token+seq}}$	Hood said . " I 'm going to make sure we 're going to get back to the water . " The order to abandon ship was given by Admiral Beatty , who ordered the remaining two battlecruisers to turn away . At 18 : 25 , Hood turned his	0.000
Prefix	*... career - high 27 points on 8 - for - 11 shooting with three rebounds*	
$\mathcal{L}_{\text{MLE}}$	and two assists . On January 3 , 2012 , he was named to the 2012 13 All - Atlantic 10 first team . On February 3 , 2012 , he was named to the Atlantic 10 first team . On February 5 , 2012 , he was named	0.277
$\mathcal{L}_{\text{UL-token+seq}}$	and a career - high 7 assists against the Minnesota Timberwolves . On February 3 , 2012 , he was named to the 2012 All - NBA First Team . On March 7 , 2012 , he was named one of five finalists for the Naismith Award , which is	0.064

Table 2: Example greedy completions, showing the last 15 tokens of a 50 token prefix, and 50-token continuations. The completions show representative examples of the MLE model's degenerate single token repetition (top), phrase-level repetition (middle two), and 'structural' repetition (bottom), as well as the proposed method's ability to fix these degenerate behaviors.

Model	search	seq-rep-4	uniq-seq	ppl	acc	rep	wrep	uniq
$\mathcal{L}_{\text{MLE}}$	greedy	.442	10.2k	**24.52**	**.401**	.619	.345	11.5k
	beam	.507	9.2k					
$\mathcal{L}_{\text{UL-token}}$	greedy	**.267**	**12.0k**	25.68	.397	**.568**	**.304**	**12.3k**
	beam	**.330**	**11.0k**					
$\mathcal{L}_{\text{UL-seq}}$	greedy	.134	11.7k	**23.95**	**.408**	.606	.331	12.4k
	beam	.015	16.1k					
$\mathcal{L}_{\text{UL-token+seq}}$	greedy	**.051**	**14.6k**	25.37	.401	**.553**	**.288**	**13.3k**
	beam	**.012**	**16.9k**					
Human	-	.005	18.9k	-	-	.479	-	18.9k

Table 3: Results for token-level objectives (upper) and sequence-level fine-tuning (lower) according to sequence-level (left) and token-level (right) metrics using the **validation subset of wikitext-103**. The best metrics achieved by both token-level and sequence-level models using both greedy and beam search are shown in bold. rep and wrep use $\ell = 128$; relative rankings hold for other ℓ.

UL-token – было

UL-seq – (10)

UL-token+seq – их комбинация

Model	search	seq-rep-4	uniq-seq	ppl	acc	rep	wrep	uniq
$\mathcal{L}_{\text{MLE}}$	greedy	.453	10.4k	**25.701**	**.394**	.629	.355	11.7k
	beam	.528	9.4k					
$\mathcal{L}_{\text{UL-token}}$	greedy	**.276**	**12.5k**	27.020	.390	**.575**	**.309**	**12.6k**
	beam	**.336**	**11.6k**					
$\mathcal{L}_{\text{UL-seq}}$	greedy	.144	12.1k	**25.112**	**.401**	.613	.338	12.7k
	beam	.014	17.5k					
$\mathcal{L}_{\text{UL-token+seq}}$	greedy	**.059**	**15.2k**	26.839	.394	**.559**	**.293**	**13.6k**
	beam	**.012**	**18.1k**					

Table 4: Results for token-level objectives (upper) and sequence-level fine-tuning (lower) according to sequence-level (left) and token-level (right) metrics using the **test subset of Wikitext-103**.

Instructions: You will be shown an excerpt from a Wikipedia article, with two possible continuations. **DO NOT** try to find the original article on Wikipedia.

Please read the excerpt and the continuations, and select which continuation is **more natural**. Focus on the **quality of the writing**, and try to **disregard factual errors**.

Excerpt:
...(who left in early 1980). The organization flew" the first international relief airlift to Cambodia since 1975" , delivering medicine to Phnom - Penh. Operation California had airlifted more than $ 3 million worth of aid by October 1979. Since then,...

... Operation USA has become a highly acclaimed aid organization that is involved in helping people in different ways around the world. In 1982, Operation California sent" the first private airlift from the U.S. to Poland" , delivering 200, 000 of medical supplies and medicine ; that year Operation California also airlifted medical supplies to Lebanon. In 1983, Operation California delivered aid to the children of Vietnam and Cambodia. Operation California provided aid to the earthquake victims in Mexico City in 1985, as well as working in cooperation with the

...the UN has provided humanitarian assistance to the country. The UN also provides humanitarian assistance to the country.

Humanitarian aid

The UN also provides humanitarian assistance to the country. The UN also provides humanitarian assistance to the country.

Humanitarian aid

The UN also provides humanitarian assistance to the country.

Humanitarian aid

The UN also provides humanitarian assistance to the country.

Which of these two continuations is **more natural**?

○ Continuation A is **more natural**.

○ Continuation B is **more natural**.

Please enter a very brief reason (a few words or a sentence) explaining your choice:

(If you do not give a reason, your hit may be rejected)

You must ACCEPT the HIT before you can submit the results.

Model 1		Model 2	Win rate
$\mathcal{L}_{\text{MLE}}$ baseline		$\mathcal{L}_{\text{UL-token}}$	62%
$\mathcal{L}_{\text{MLE}}$ baseline		$\mathcal{L}_{\text{UL-seq}}$	*70%
$\mathcal{L}_{\text{MLE}}$ baseline	*beaten by*	$\mathcal{L}_{\text{UL-token+seq}}$	*84%
$\mathcal{L}_{\text{UL-token}}$		$\mathcal{L}_{\text{UL-token+seq}}$	*72%
$\mathcal{L}_{\text{UL-seq}}$		$\mathcal{L}_{\text{UL-token+seq}}$	58%
$\mathcal{L}_{\text{MLE}}$ baseline		Reference	*74%
$\mathcal{L}_{\text{UL-token}}$	*beaten by*	Reference	*68%
$\mathcal{L}_{\text{UL-seq}}$		Reference	56%
$\mathcal{L}_{\text{UL-token+seq}}$		Reference	52%

Table 5: **Human evaluation results**. Human evaluators preferred generations from our models over the baseline model, and $\mathcal{L}_{\text{UL-token+seq}}$ outperformed our other variants. The sequence-tuned models approach human-level performance. Comparisons marked with * are statistically significant (one-sided binomial test, $p < .05$).

WritingPrompts dataset of (Fan et al., 2018).

Each example consists of a contextof 5 sentences with a maximum of 200 tokens;the task is to continue the text by generating the200 next tokens (the continuation).

Извлечение обучающих данных (на примере GPT-2)

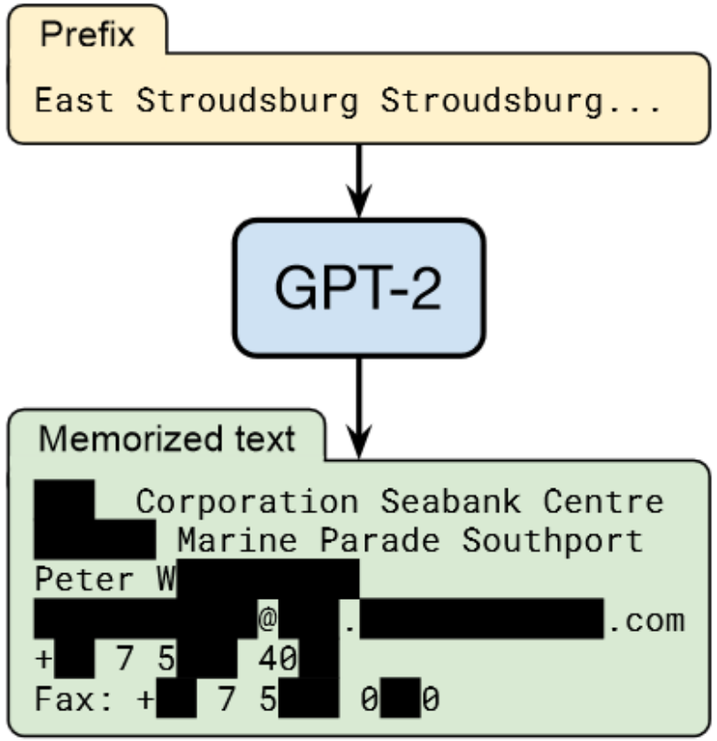


Figure 1: **Our extraction attack.** Given query access to a neural network language model, we extract an individual person's name, email address, phone number, fax number, and physical address. The example in this figure shows information that is all accurate so we redact it to protect privacy.

Nicholas Carlini et al. «Extracting Training Data from Large Language Models» // https://arxiv.org/pdf/2012.07805.pdf

«Атаки на сеть» – по извлечению персональной информации

Сети обучают на больших корпусах, в которых есть и персональные данные:
names, phone numbers, and email addresses
Например, GMail's auto-complete model – обучалось на частной переписке!

Можно ли их выудить из обученной модели?

Ошибочно считалость, что SOTA-модели не переобучены $\Rightarrow$ нет опасности
у GPT-2 ошибка на обучении на 10% меньше, чем ошибка на тесте

«membership inference attack» – есть ли такой пример в обучении [Reza Shokri, 2017]
«model inversion attacks» – извлечение конкретных примеров

«differentially-private training» – хороший способ защиты, но сейчас не о нём…

«Атаки на сеть» – по извлечению персональной информации

Definition 1 (Model Knowledge Extraction) *A string s is* extractable[4] *from an LM f_θ if there exists a prefix c such that:*

$$s \leftarrow \underset{s' :\, |s'|=N}{\arg\max}\, f_\theta(s' \mid c)$$

Definition 2 (k-Eidetic Memorization) *A string s is k-eidetic memorized (for $k \geq 1$) by an LM f_θ if s is extractable from f_θ and s appears in at most k examples in the training data X: $|\{x \in X : s \subseteq x\}| \leq k$.*

«Атаки на сеть» – по извлечению персональной информации

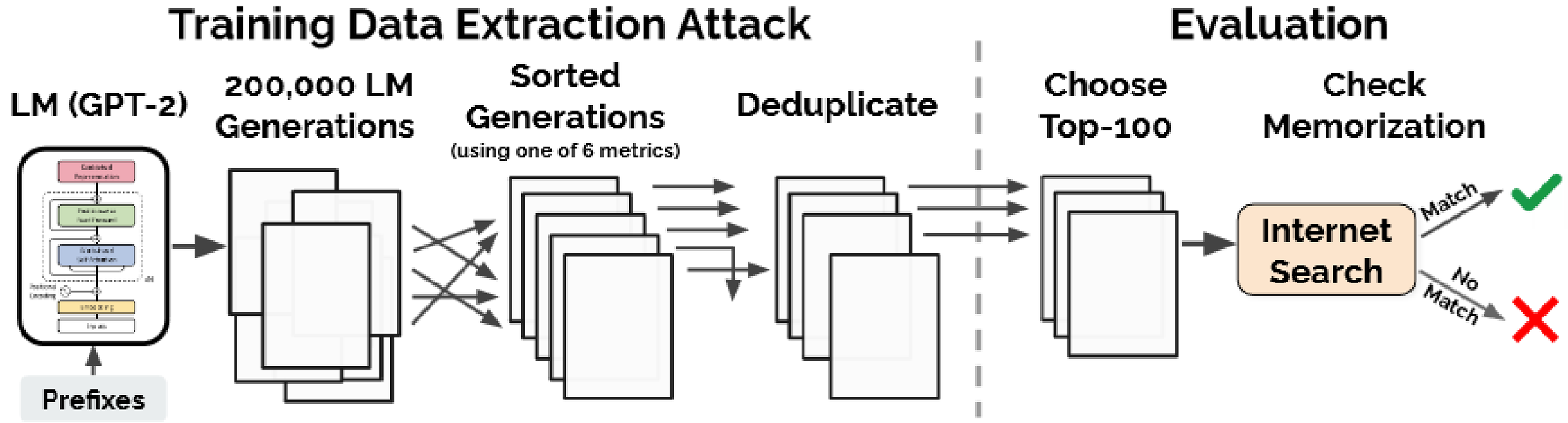


Figure 2: **Workflow of our extraction attack and evaluation. Attack.** We begin by generating many samples from GPT-2 when the model is conditioned on (potentially empty) prefixes. We then sort each generation according to one of six metrics and remove the duplicates. This gives us a set of potentially memorized training examples. **Evaluation.** We manually inspect 100 of the top-1000 generations for each metric. We mark each generation as either memorized or not-memorized by manually searching online, and we confirm these findings by working with OpenAI to query the original training data.

«Атаки на сеть» – по извлечению персональной информации

подаём префикс (генерируем 256 токенов)

модель генерирует 200 000 примеров

используем разные стратегии сэмплирования

1) top-n (изначальная)

2) Decaying Temperature – температура уменьшается при генерации

$$\mathrm{softmax}(z/t)$$

3) Conditioning on Internet Text (+ top-n) – начать с естественного контекста (Common Crawl)

предсказываем, где могло быть запоминание

1) смотрим на перплексию

2-3) смотрим на перплексию GPT-2 small / GPT-2 medium

(если у более примитивной модели перплексия меньше, то у нас запоминание)

4) как сильно сжимает текст zlib (+ тут отлавливание повторений)

5) Comparing to Lowercased Text (сравнение с перплексией этого же текста в нижнем регистре)

6) Perplexity on a Sliding Window (50 токенов)

«Атаки на сеть» – по извлечению персональной информации

число конфигураций эксперимента

3 (способов сэмплирования) × 6 (оценок дословности)

выбираем по 100 примеров из 1000

всего 1800 примеров

из них нашли 604 запоминания

параллельно устраняем fuzzy-дубликаты

интернет поиск + ассесоры для нахождения, есть где-то такая фраза дословно

ищем дословные повторы в обучении

(сравнение по 3-граммам)

Category	Count
US and international news	109
Log files and error reports	79
License, terms of use, copyright notices	54
Lists of named items (games, countries, etc.)	54
Forum or Wiki entry	53
Valid URLs	50
Named individuals (non-news samples only)	46
Promotional content (products, subscriptions, etc.)	45
High entropy (UUIDs, base64 data)	35
Contact info (address, email, phone, twitter, etc.)	32
Code	31
Configuration files	30
Religious texts	25
Pseudonyms	15
Donald Trump tweets and quotes	12
Web forms (menu items, instructions, etc.)	11
Tech news	11
Lists of numbers (dates, sequences, etc.)	10

Table 1: Manual categorization of the 604 memorized training examples that we extract from GPT-2, along with a description of each category. Some samples correspond to multiple categories (e.g., a URL may contain base-64 data). Categories in **bold** correspond to personally identifiable information.

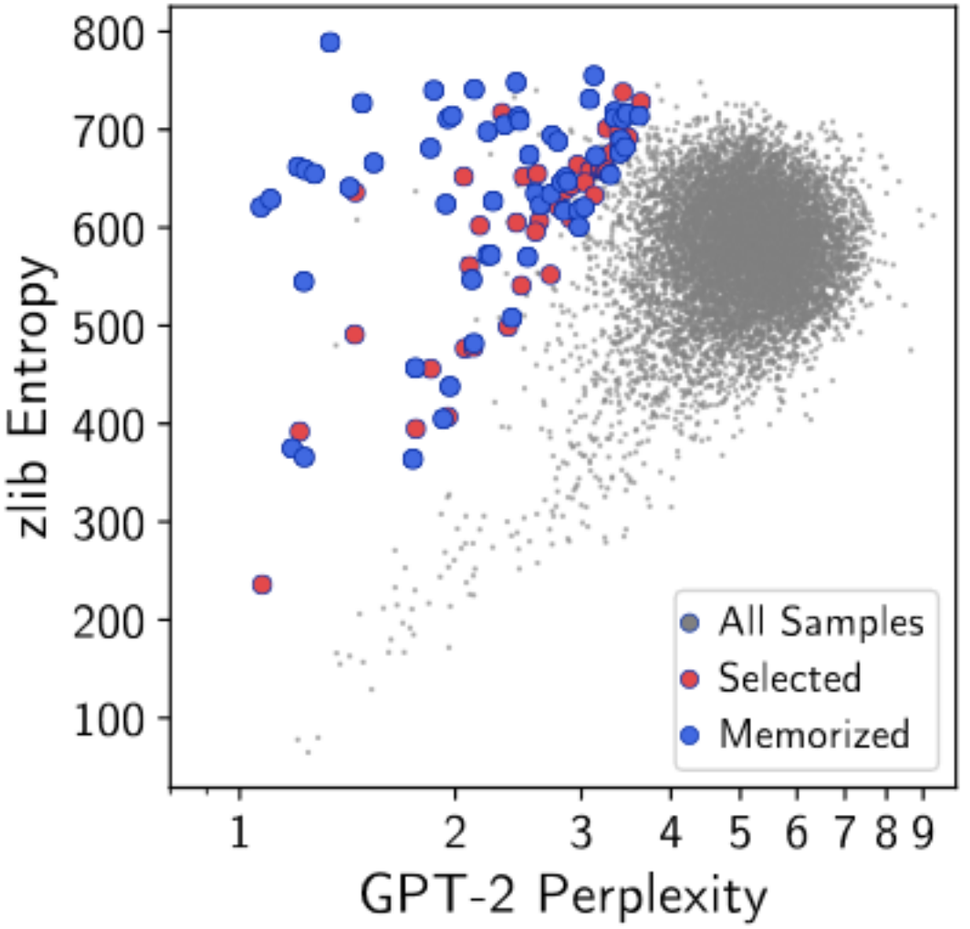


Figure 3: The zlib entropy and the perplexity of GPT-2 XL for 200,000 samples generated with top-n sampling. In red, we show the 100 samples that were selected for manual inspection. In blue, we show the 59 samples that were confirmed as memorized text. Additional plots for other text generation and detection strategies are in Figure 4.

Inference Strategy	Text Generation Strategy		
	Top-n	Temperature	Internet
Perplexity	9	3	39
Small	41	42	58
Medium	38	33	45
zlib	59	46	67
Window	33	28	58
Lowercase	53	22	60
Total Unique	191	140	273

Table 2: The number of memorized examples (out of 100 candidates) that we identify using each of the three text generation strategies and six membership inference techniques. Some samples are found by multiple strategies; we identify 604 unique memorized examples in total.

Memorized String	Sequence Length	Occurrences in Data	
		Docs	Total
`Y2...`[redacted]`...y5`	87	1	10
`7C...`[redacted]`...18`	40	1	22
`XM...`[redacted]`...WA`	54	1	36
`ab...`[redacted]`...2c`	64	1	49
`ff...`[redacted]`...af`	32	1	64
`C7...`[redacted]`...ow`	43	1	83
`0x...`[redacted]`...C0`	10	1	96
`76...`[redacted]`...84`	17	1	122
`a7...`[redacted]`...4b`	40	1	311

Table 3: **Examples of $k = 1$ eidetic memorized, high-entropy content that we extract** from the training data. Each is contained in *just one* document. In the best case, we extract a 87-characters-long sequence that is contained in the training dataset just 10 times in total, all in the same document.

total – длина последовательности, в которой он нашёлся

UUID: 1e4bd2a8-e8c8-4a62-adcd-40a936480059

Google search – 3 documents containing this UUID

GPT-2 training – 1 document

Некорректные запоминания

Пример, когда два разных запоминания склеиваются:

**GPT-2 generates a news article about the (real) murder of a woman in 2013,
but then attributes the murder to one of the victims of a nightclub shooting in Orlando in 2016.**

Instagram biography of a pornography producer + describe an American fashion model as a pornography actress

Есть примеры данных, которые уже удалили из Интернета

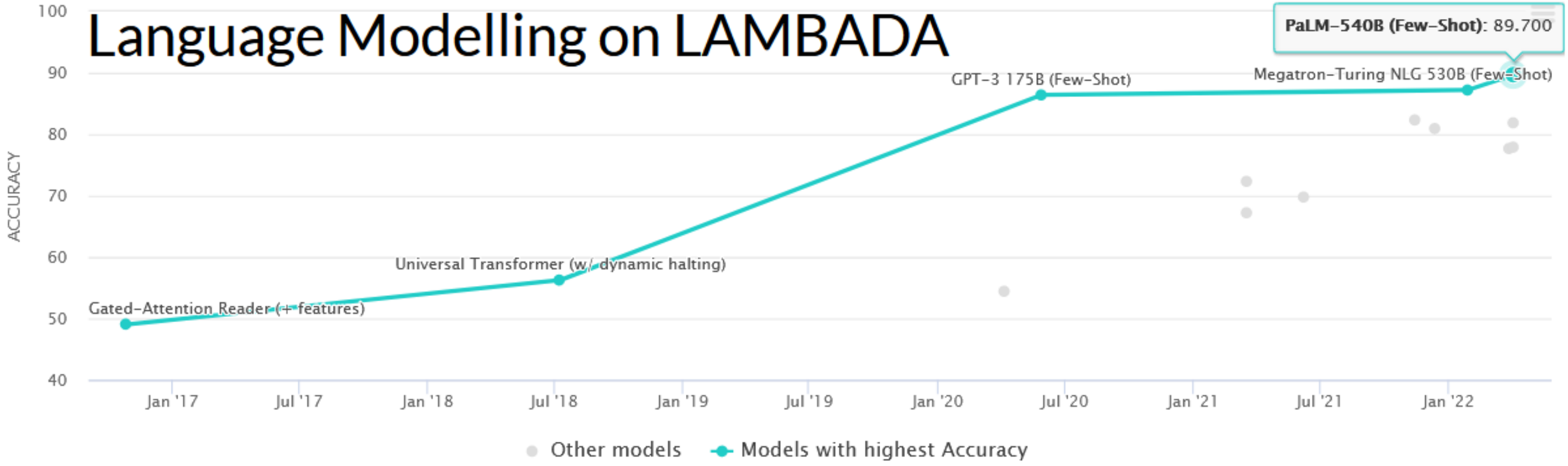
**Большие последовательности: 1450 строк кода,
the entirety of the MIT, Creative Commons, and Project Gutenberg licenses**

Число π

GPT-2 will complete the prompt «3.14159» with the first 25 digits
beam-search – 500 digits
«pi is 3.14159» – 799 digits
«pi begins 3.14159» – 824 digits

контекст важен!
(а это не учитывалось в эксперименте)

SotA


Language Modelling on LAMBADA
PaLM-540B (Few-Shot): 89.700
Megatron-Turing NLG 530B (Few-Shot)
GPT-3 175B (Few-Shot)
Universal Transformer (w/ dynamic halting)
Gated-Attention Reader (+ features)
ACCURACY
100
90
80
70
60
50
40
Jan '17
Jul '17
Jan '18
Jul '18
Jan '19
Jul '19
Jan '20
Jul '20
Jan '21
Jul '21
Jan '22
Other models
Models with highest Accuracy

Итог

ULMfit	01.2018	fast.ai	1 GPU-дней
GPT	06.2018	OpenAI	240 GPU-дней
BERT	10.2018	Google AI	265 TPU-дней
GPT-2	02.2019	OpenAI	>2048 TPU-дней

Языковые модели – предсказывают следующее слово

есть простые n-граммные, если рекуррентные / трансформерные – позволяют учесть весь контекст

Ссылки

хороший курс «Natural Language Processing with Deep Learning»

http://web.stanford.edu/class/cs224n/

Обзор стратегий декодирования

https://lilianweng.github.io/lil-log/2021/01/02/controllable-neural-text-generation.html