TRANSFORMERS & THEIR OFFSPRINGS

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AI Run

attention is...

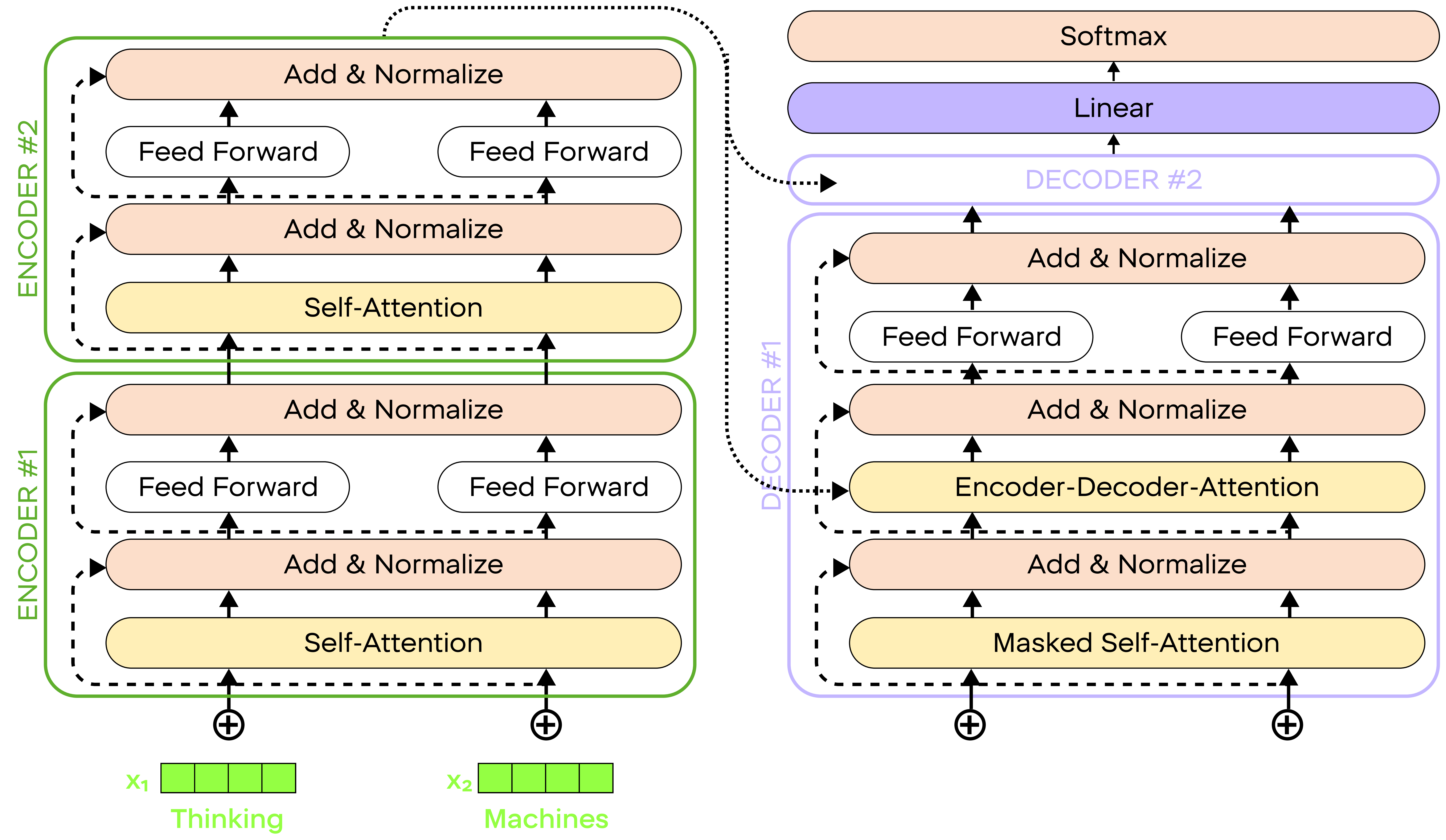
$$Attention(Q, V, K) = Softmax(\frac{QK^T}{\sqrt{d}})V$$

возможность отловить более сложные зависимости и концепции

позиционные эмбеддинги

чуть удобнее параллелить вычисления

attention is...



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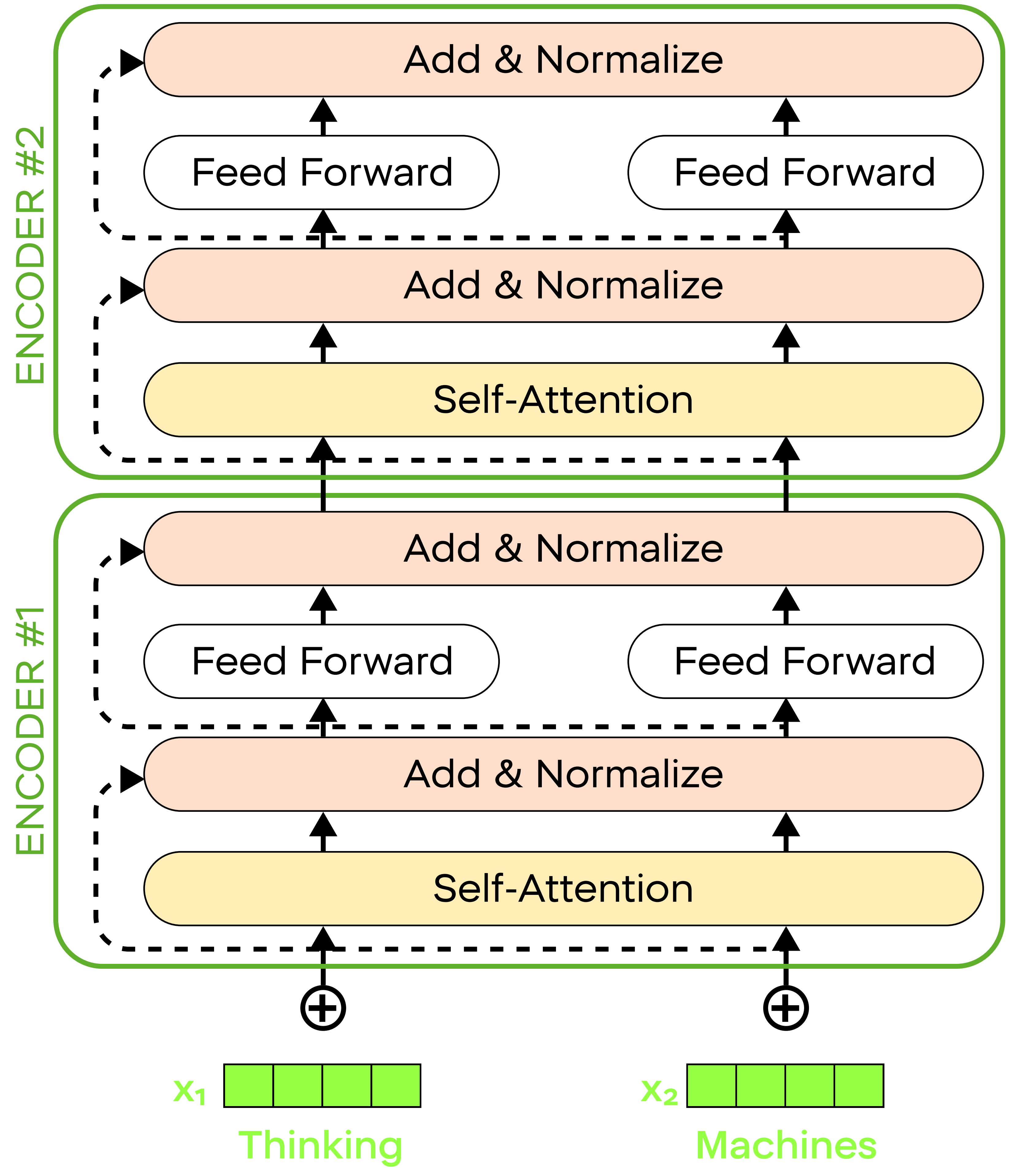
BERT

BIDIRECTIONAL
ENCODER
REPRESENTATIONS
FROM
TRANSFORMERS

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding: https://arxiv.org/abs/1810.04805

bert



Ключевые отличия:

- Два направления (использует контекст и справа, и слева)
- Состоит только из энкодеров

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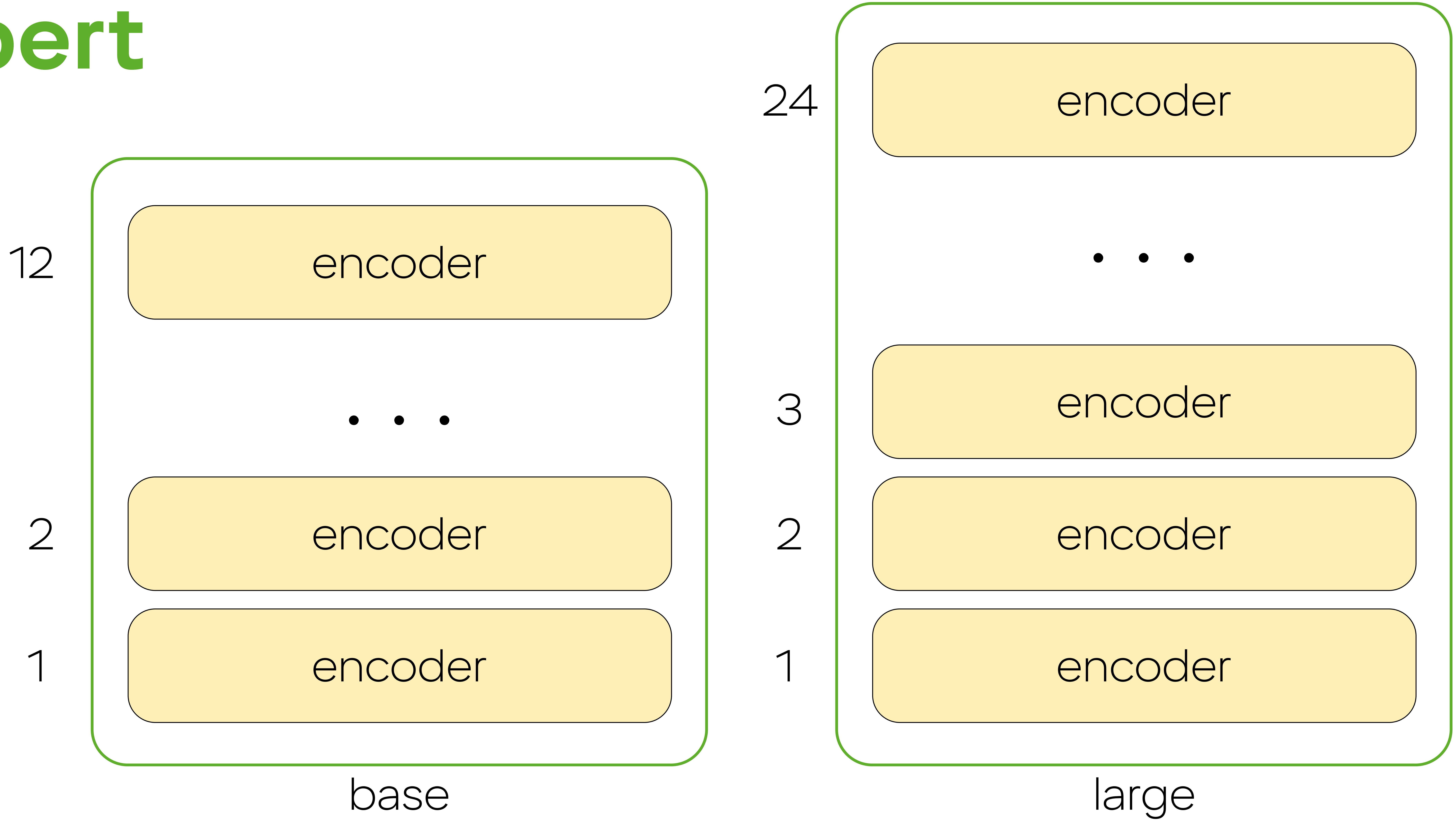
bert


12
encoder
2
encoder
1
encoder
base
24
encoder
3
encoder
2
encoder
1
encoder
large

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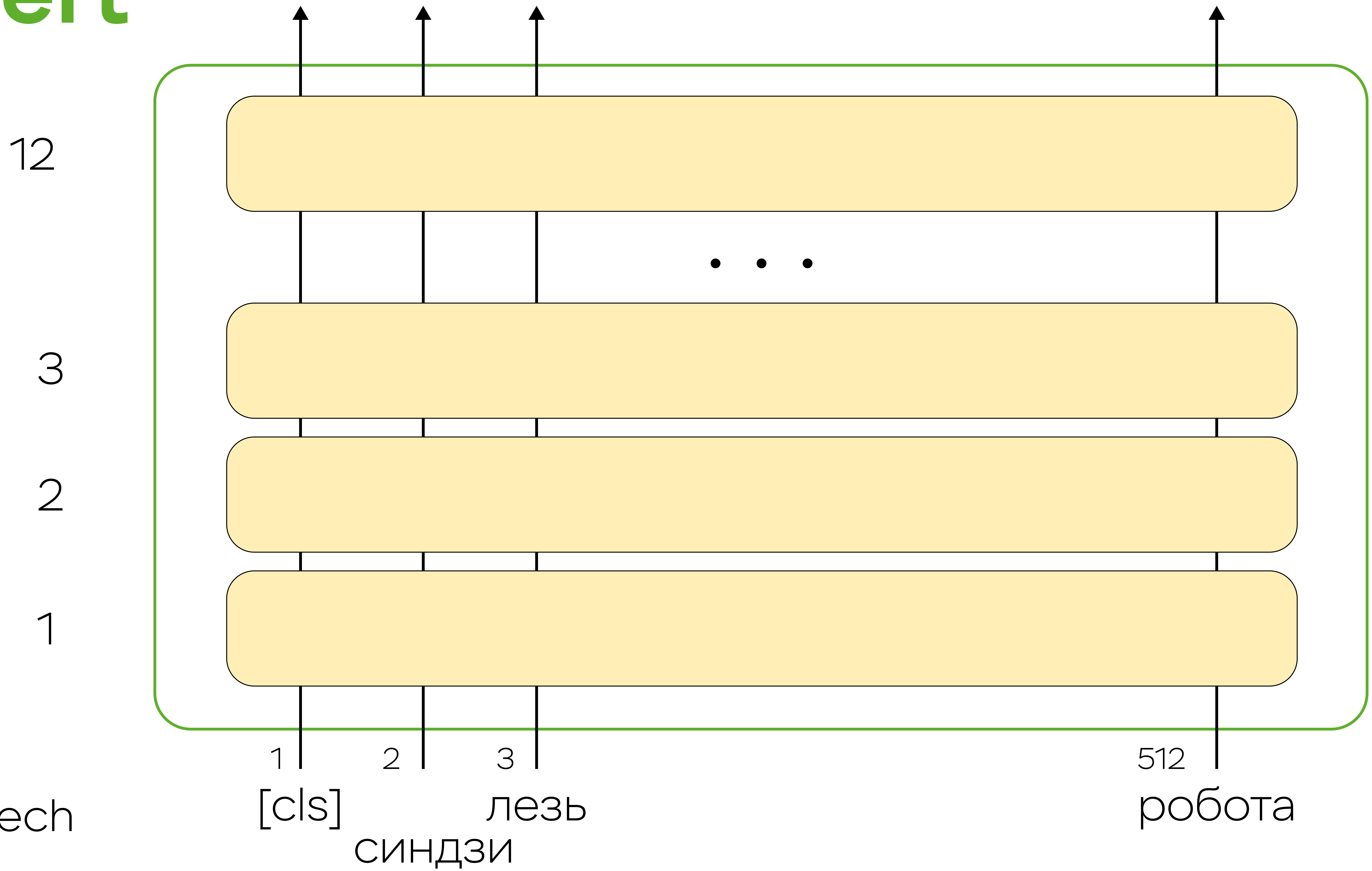
bert



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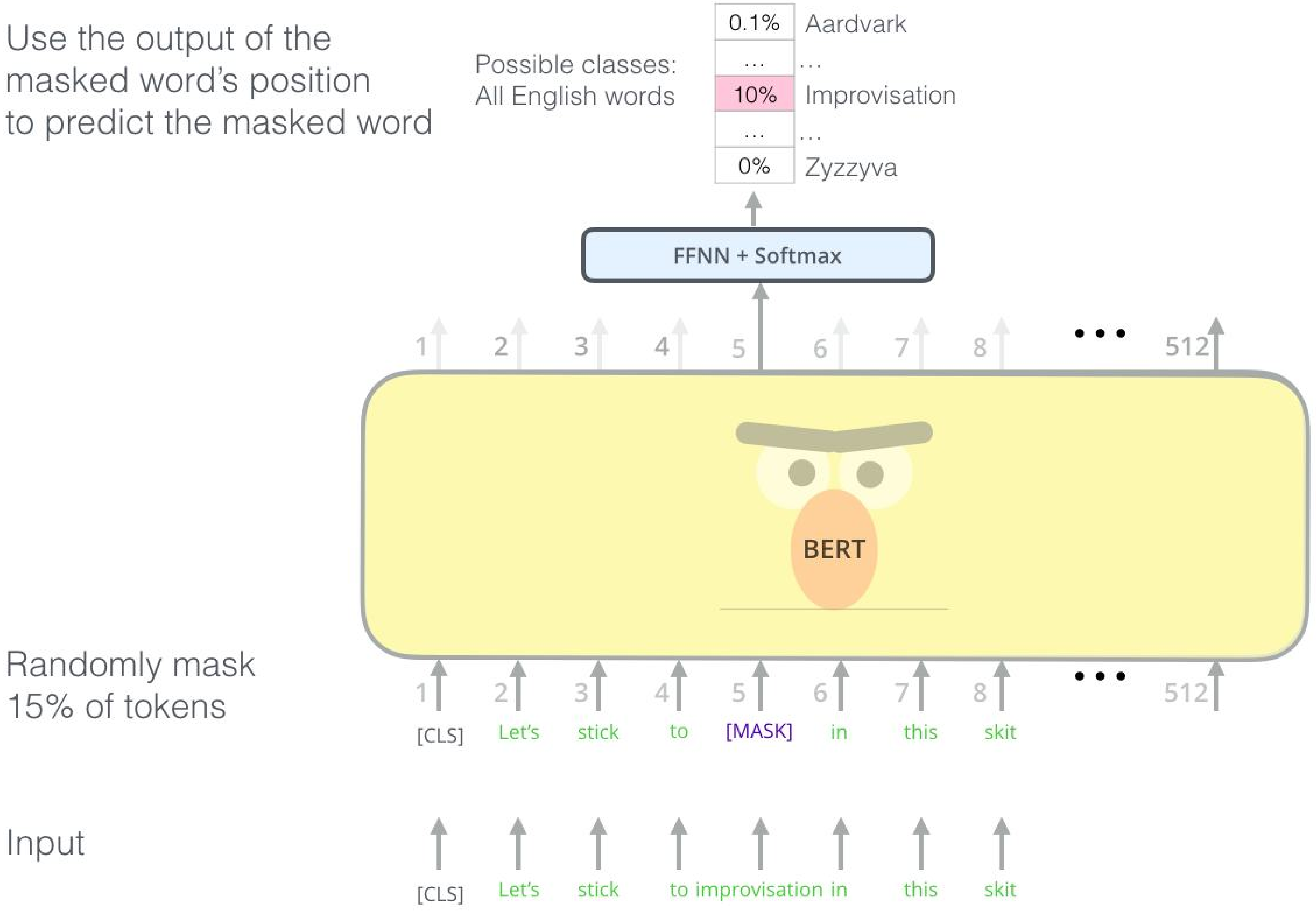
bert

два подхода к обучению:

1. mlm: masked language model



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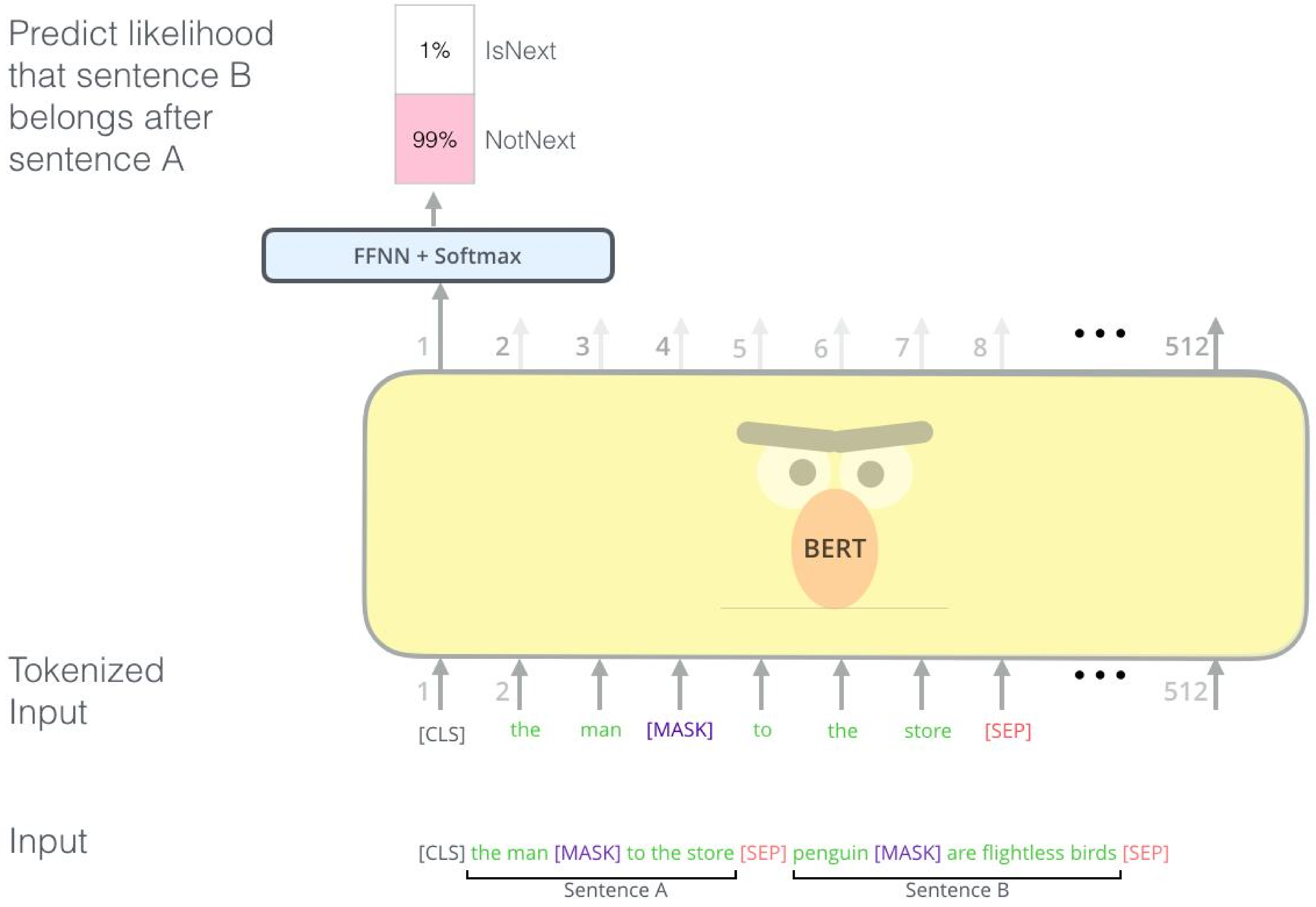
bert: train

два подхода к обучению:

2. two-sentence task



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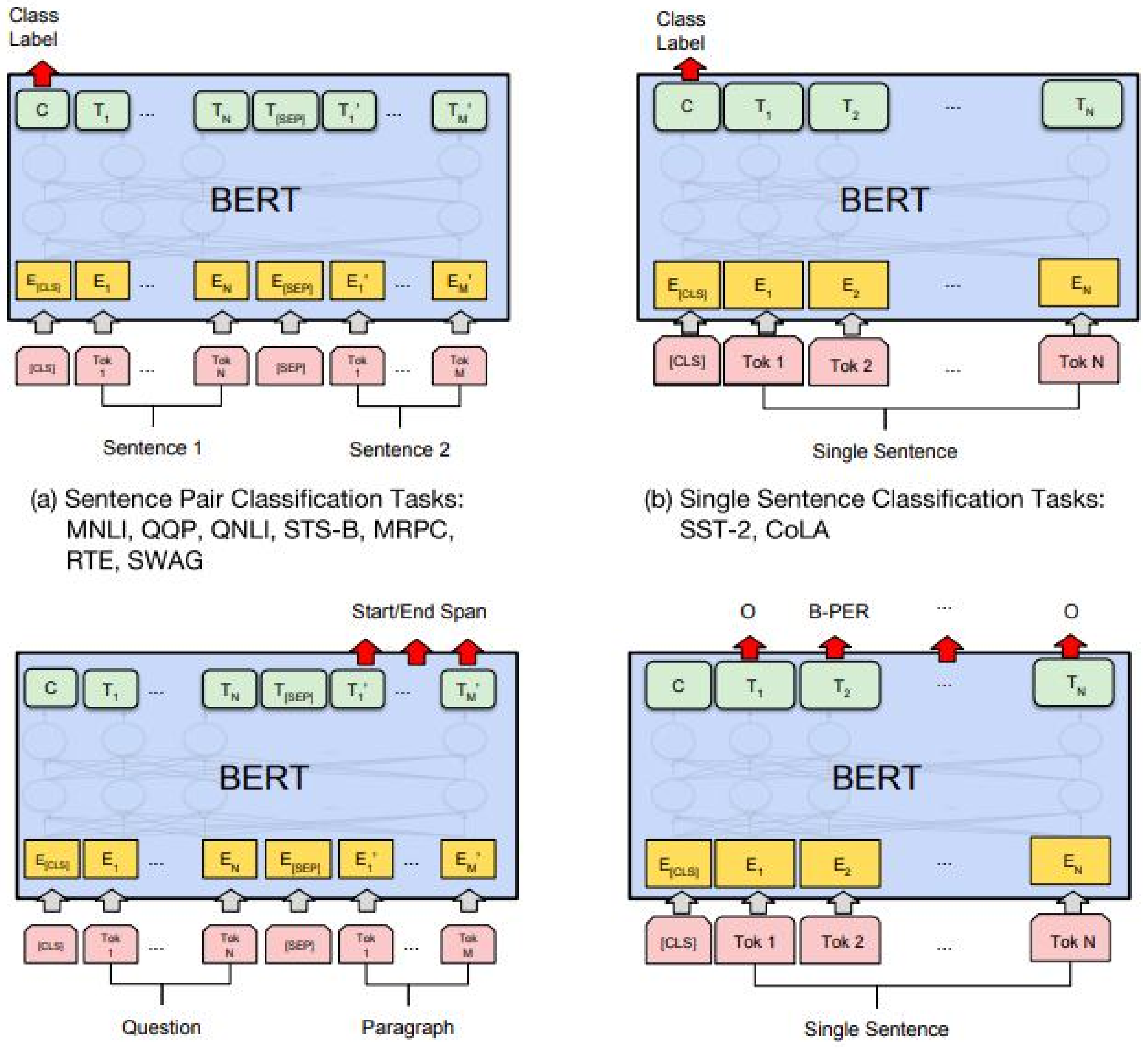
bert: различные задачи



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

WORD PIECE —

$$score = \frac{freq\_of\_pair[w_1, w_2]}{freq[w_1] * freq[w_2]}$$

“мама мыла раму, маму мыла рама”

1. vocab = [“м”, “а”, “р”, “у”...]
2. vocab += [“ма”, “му”, ...] пары с наивысшим скором
3. vocab.size == n: stop

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BERT:
THE OFFSPRINGS

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DISTILBERT

$$L(X,W) = \alpha \cdot H(y, \sigma(z_s, T=1)) + \beta \cdot H(\sigma(z_t, T=\tau), \sigma(z_s, T=\tau))$$

1. Запустим две модели: исходную и меньшую
2. При обучении меньшей будем использовать выходы большей модели и учить меньшую их повторить

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DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter: https://arxiv.org/abs/1910.01108

distilbert

Table 1: **DistilBERT retains 97% of BERT performance.** Comparison on the dev sets of the GLUE benchmark. ELMo results as reported by the authors. BERT and DistilBERT results are the medians of 5 runs with different seeds.

Model	**Score**	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B	WNLI
ELMo	68.7	44.1	68.6	76.6	71.1	86.2	53.4	91.5	70.4	56.3
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89.0	53.5
DistilBERT	77.0	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

Table 2: **DistilBERT yields to comparable performance on downstream tasks.** Comparison on downstream tasks: IMDb (test accuracy) and SQuAD 1.1 (EM/F1 on dev set). D: with a second step of distillation during fine-tuning.

Model	IMDb (acc.)	SQuAD (EM/F1)
BERT-base	93.46	81.2/88.5
DistilBERT	92.82	77.7/85.8
DistilBERT (D)	-	79.1/86.9

Table 3: **DistilBERT is significantly smaller while being constantly faster.** Inference time of a full pass of GLUE task STS-B (sentiment analysis) on CPU with a batch size of 1.

Model	# param. (Millions)	Inf. time (seconds)
ELMo	180	895
BERT-base	110	668
DistilBERT	66	410

ROBERTA

1. Теперь маскируем текст не на этапе препроцессинга, а прямо при обучении
2. Не обучаемся на предсказании следующего предложения

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RoBERTa: A Robustly Optimized BERT Pretraining Approach: https://arxiv.org/abs/1907.11692

roberta

Model	SQuAD 1.1/2.0	MNLI-m	SST-2	RACE
Our reimplementation (with NSP loss):				
SEGMENT-PAIR	90.4/78.7	84.0	92.9	64.2
SENTENCE-PAIR	88.7/76.2	82.9	92.1	63.0
Our reimplementation (without NSP loss):				
FULL-SENTENCES	90.4/79.1	84.7	92.5	64.8
DOC-SENTENCES	90.6/79.7	84.7	92.7	65.6
$\text{BERT}_{\text{BASE}}$	88.5/76.3	84.3	92.8	64.3
$\text{XLNet}_{\text{BASE}}$ (K = 7)	–/81.3	85.8	92.7	66.1
$\text{XLNet}_{\text{BASE}}$ (K = 6)	–/81.0	85.6	93.4	66.7

Table 2: Development set results for base models pretrained over BOOKCORPUS and WIKIPEDIA. All models are trained for 1M steps with a batch size of 256 sequences. We report F1 for SQuAD and accuracy for MNLI-m, SST-2 and RACE. Reported results are medians over five random initializations (seeds). Results for $\text{BERT}_{\text{BASE}}$ and $\text{XLNet}_{\text{BASE}}$ are from Yang et al. (2019).

roberta

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7
$\text{XLNet}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	94.0/87.8	88.4	94.4
+ additional data	126GB	2K	500K	94.5/88.8	89.8	95.6

Table 4: Development set results for RoBERTa as we pretrain over more data (16GB → 160GB of text) and pretrain for longer (100K → 300K → 500K steps). Each row accumulates improvements from the rows above. RoBERTa matches the architecture and training objective of $\text{BERT}_{\text{LARGE}}$. Results for $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ are from Devlin et al. (2019) and Yang et al. (2019), respectively. Complete results on all GLUE tasks can be found in the Appendix.

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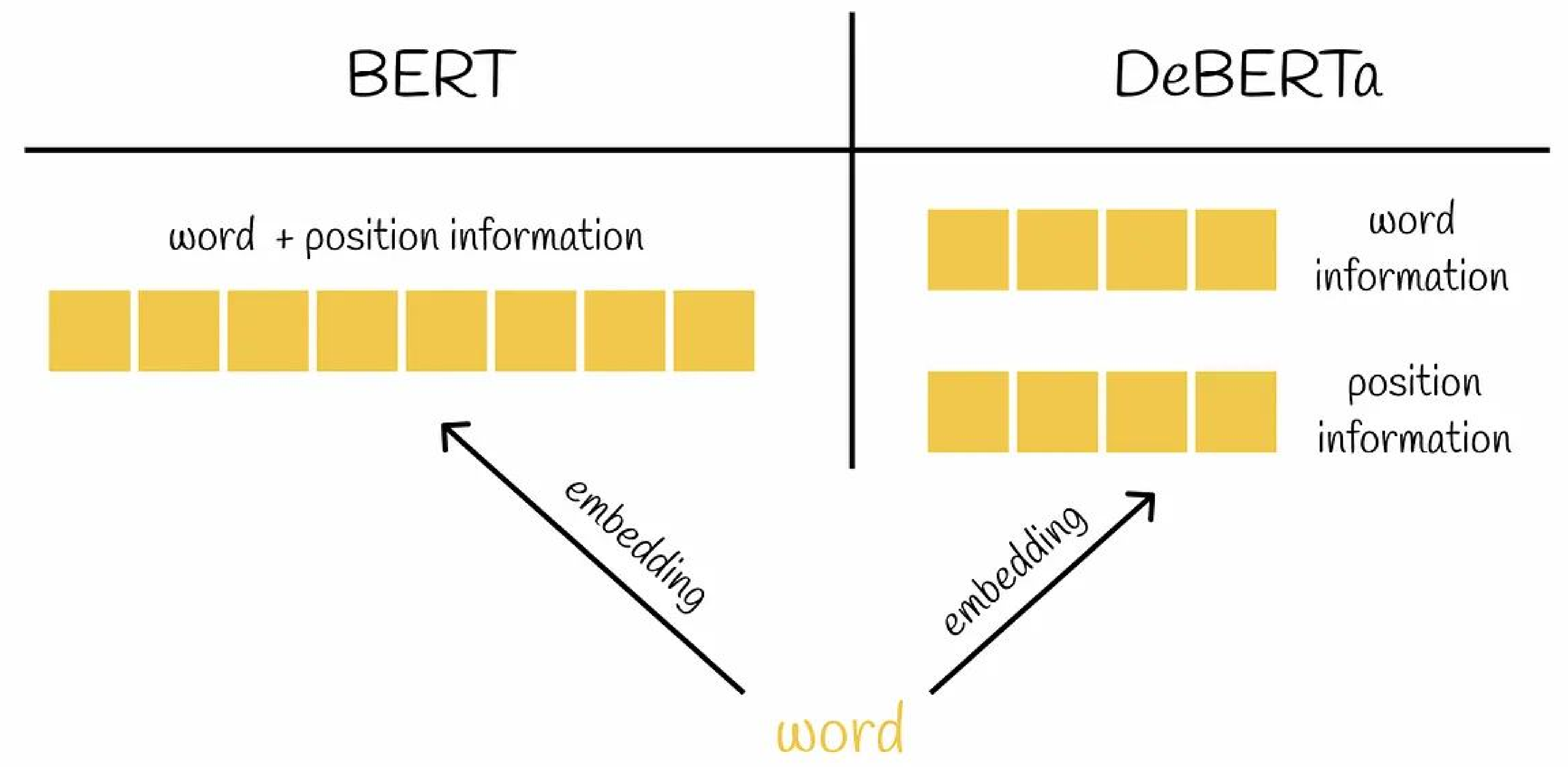
DEBERTA



1. Вместо одного эмбеддинга для слова теперь два: отдельно позиционный, отдельно слово
2. Немного изменена архитектура
3. Считывает относительную позицию, а не абсолютную

deberta

Model	MNLI-m/mm Acc	SQuAD v1.1 F1/EM	SQuAD v2.0 F1/EM	RACE Acc	ReCoRD F1/EM	SWAG Acc	NER F1
BERT_{large}	86.6/-	90.9/84.1	81.8/79.0	72.0	-	86.6	92.8
ALBERT_{large}	86.5/-	91.8/85.2	84.9/81.8	75.2	-	-	-
RoBERTa_{large}	90.2/90.2	94.6/88.9	89.4/86.5	83.2	90.6/90.0	89.9	93.4
XLNet_{large}	90.8/90.8	95.1/89.7	90.6/87.9	85.4	-	-	-
Megatron_{336M}	89.7/90.0	94.2/88.0	88.1/84.8	83.0	-	-	-
DeBERTa_{large}	**91.1/91.1**	**95.5/90.1**	**90.7/88.0**	**86.8**	**91.4/91.0**	**90.8**	**93.8**
$\text{ALBERT}_{xxlarge}$	90.8/-	94.8/89.3	90.2/87.4	86.5	-	-	-
$\text{Megatron}_{1.3B}$	90.9/91.0	94.9/89.1	90.2/87.1	87.3	-	-	-
$\text{Megatron}_{3.9B}$	91.4/91.4	95.5/90.0	91.2/88.5	89.5	-	-	-

Table 2: Results on MNLI in/out-domain, SQuAD v1.1, SQuAD v2.0, RACE, ReCoRD, SWAG, CoNLL 2003 NER development set. Note that missing results in literature are signified by "-".