

BERT & ELMO

Tinkoff.ru

Как использовать LM в прикладных NLP задачах



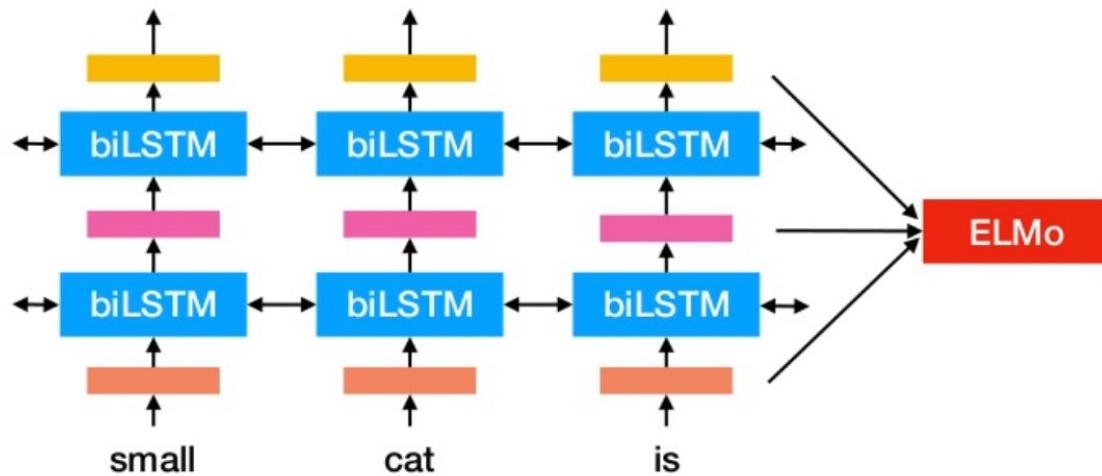


NLP задачи, с которыми приходится сталкиваться

- Классификация текстов
- Кластеризация текстов
- Генерация текстов
- Распознавание именованных сущностей (NER)
- Тегирование текстов
- Ранжирование текстов
- Рекомендательные системы

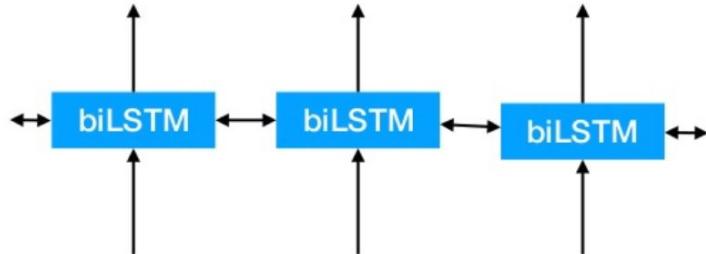


ELMO





ELMO = bi-LM



Forward LM

$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^N p(t_k | t_1, t_2, \dots, t_{k-1})$$

Backward LM

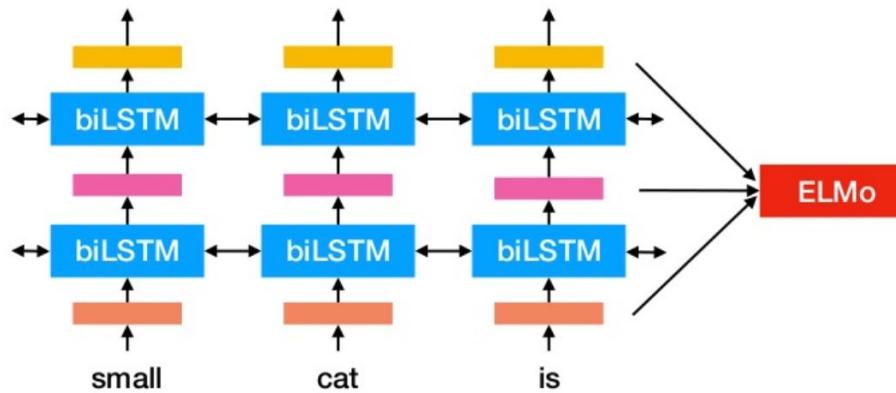
$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^N p(t_k | t_{k+1}, t_{k+2}, \dots, t_N)$$

Bi-LM

$$\begin{aligned} \sum_{k=1}^N (& \log p(t_k | t_1, \dots, t_{k-1}; \Theta_x, \vec{\Theta}_{LSTM}, \Theta_s) \\ & + \log p(t_k | t_{k+1}, \dots, t_N; \Theta_x, \vec{\Theta}_{LSTM}, \Theta_s)) \end{aligned}$$



ELMO



$$\begin{aligned} R_k &= \{\mathbf{x}_k^{LM}, \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} \mid j = 1, \dots, L\} \\ &= \{\mathbf{h}_{k,j}^{LM} \mid j = 0, \dots, L\}, \end{aligned}$$

$$\text{ELMo}_k^{task} = E(R_k; \Theta^{task}) = \gamma^{task} \sum_{j=0}^L s_j^{task} \mathbf{h}_{k,j}^{LM}.$$

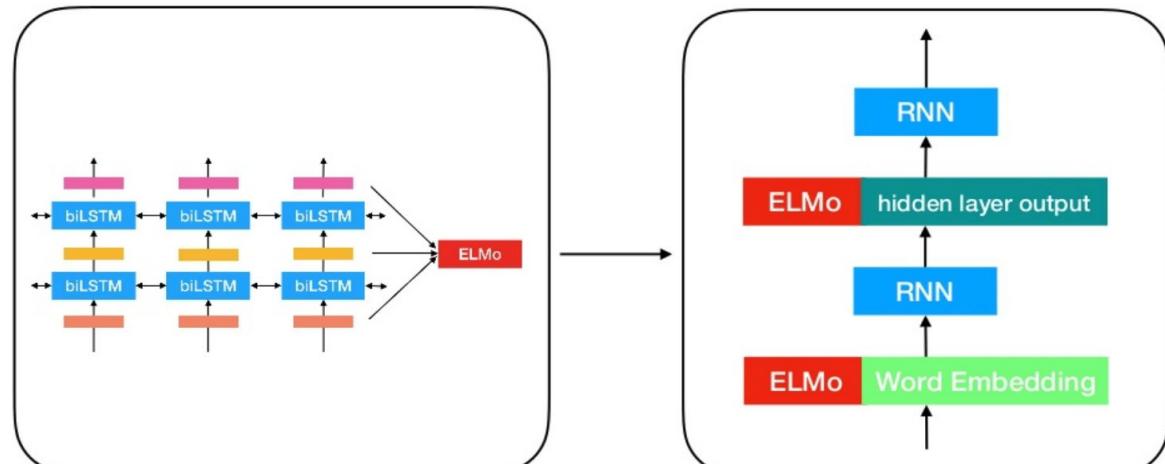


ELMo в прикладных задачах

Добавляем контекстные представления на каждом (или не на каждом) слое архитектуры

| Task | Input Only | Input & Output | Output Only |
|-------|-------------|----------------|-------------|
| SQuAD | 85.1 | 85.6 | 84.8 |
| SNLI | 88.9 | 89.5 | 88.7 |
| SRL | 84.7 | 84.3 | 80.9 |

Table 3: Development set performance for SQuAD, SNLI and SRL when including ELMo at different locations in the supervised model.





ELMO до и после

| TASK | PREVIOUS SOTA | | OUR BASELINE | ELMo + BASELINE | INCREASE (ABSOLUTE/ RELATIVE) |
|-------|----------------------|------------------|-----------------|--------------------|-------------------------------------|
| SQuAD | SAN | 84.4 | 81.1 | 85.8 | 4.7 / 24.9% |
| SNLI | Chen et al. (2017) | 88.6 | 88.0 | 88.7 ± 0.17 | 0.7 / 5.8% |
| SRL | He et al. (2017) | 81.7 | 81.4 | 84.6 | 3.2 / 17.2% |
| Coref | Lee et al. (2017) | 67.2 | 67.2 | 70.4 | 3.2 / 9.8% |
| NER | Peters et al. (2017) | 91.93 ± 0.19 | 90.15 | 92.22 ± 0.10 | 2.06 / 21% |
| SST-5 | McCann et al. (2017) | 53.7 | 51.4 | 54.7 ± 0.5 | 3.3 / 6.8% |



Разные слои сохраняют разную информацию

| Task | Baseline | Last Only | All layers | |
|-------|----------|-----------|-------------|-----------------|
| | | | $\lambda=1$ | $\lambda=0.001$ |
| SQuAD | 80.8 | 83.1 | 84.4 | 85.3 |
| SNLI | 88.1 | 89.1 | 89.3 | 89.5 |
| SRL | 81.6 | 84.1 | 84.6 | 84.8 |

Table 2: Development set performance for SQuAD, SNLI and SRL comparing using all layers of the biLM (with different choices of regularization strength λ) to just the top layer.

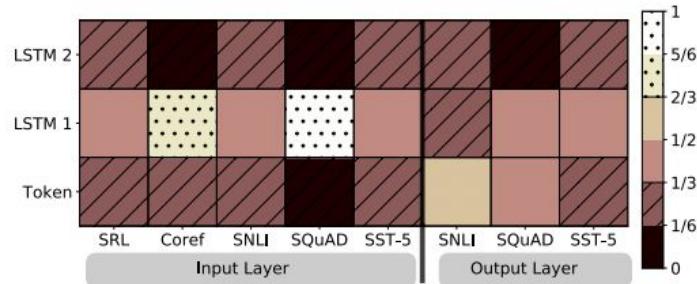


Figure 2: Visualization of softmax normalized biLM layer weights across tasks and ELMo locations. Normalized weights less than 1/3 are hatched with horizontal lines and those greater than 2/3 are speckled.



LM when low on DATA

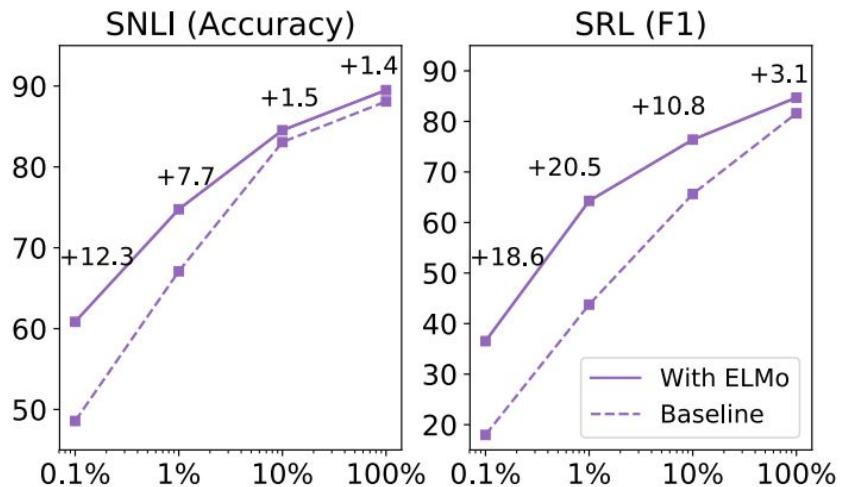
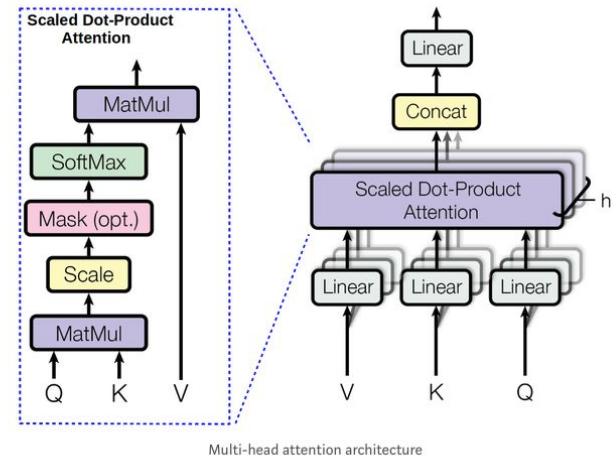
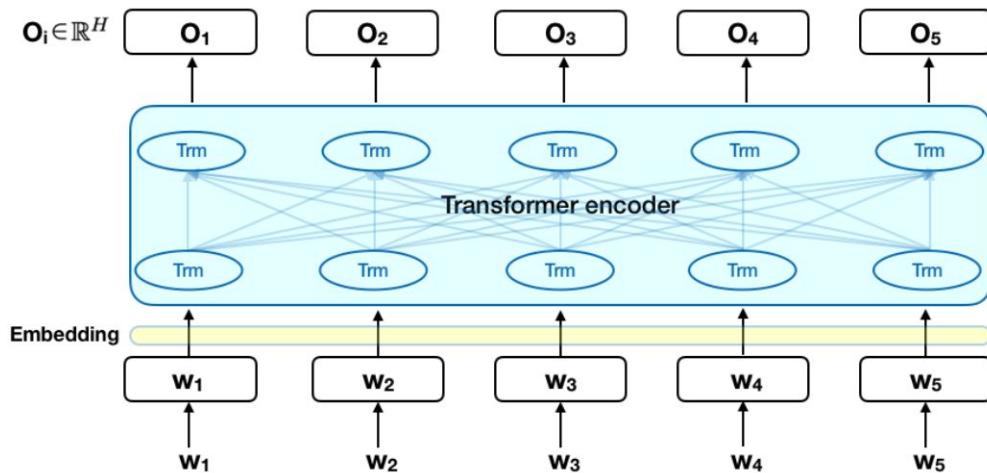


Figure 1: Comparison of baseline vs. ELMo performance for SNLI and SRL as the training set size is varied from 0.1% to 100%.

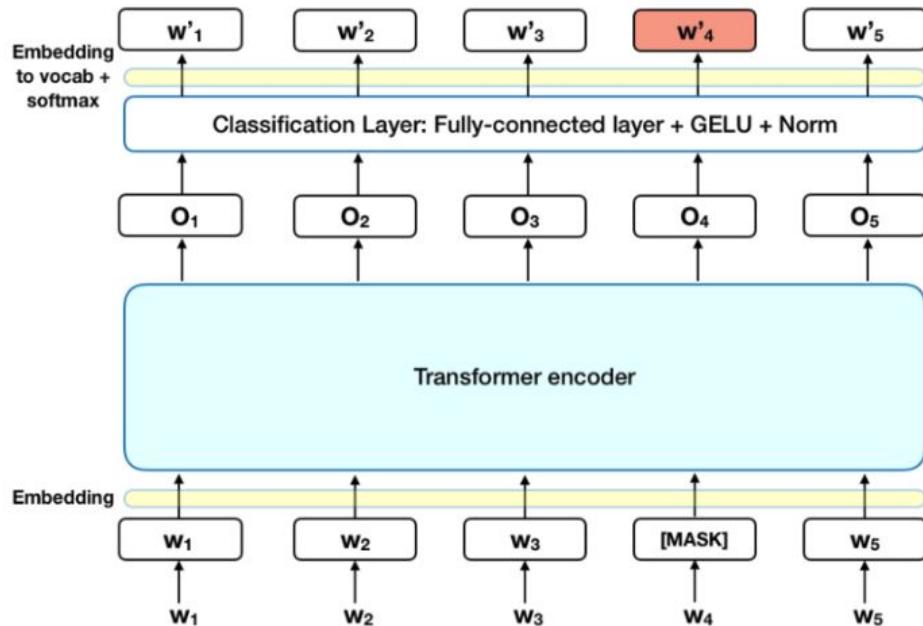


BERT



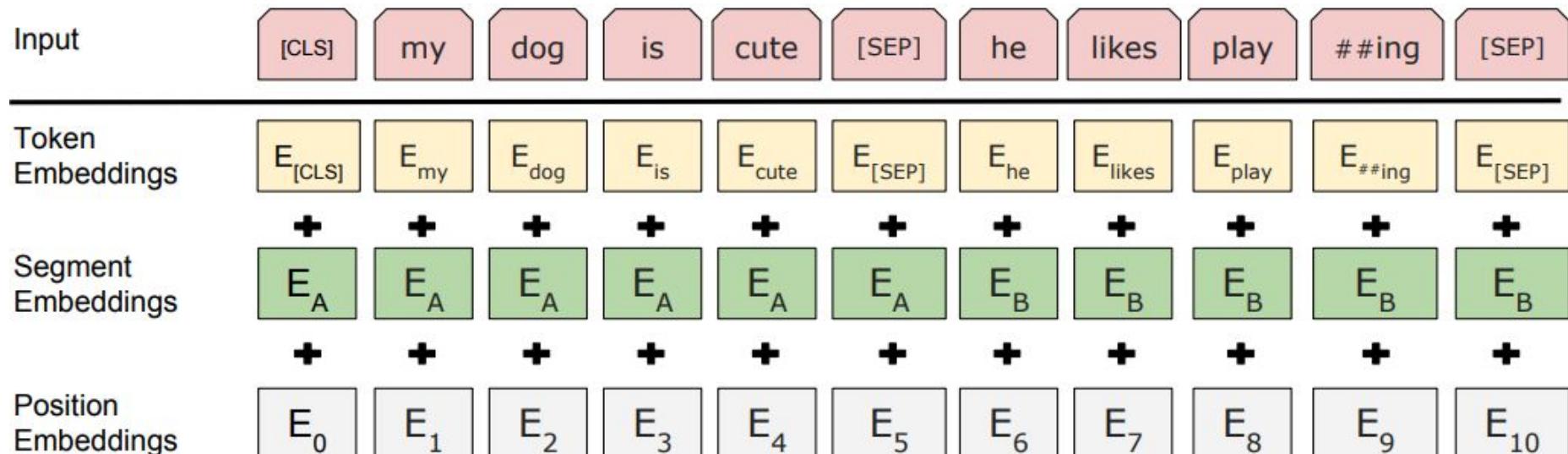


Как обучается BERT



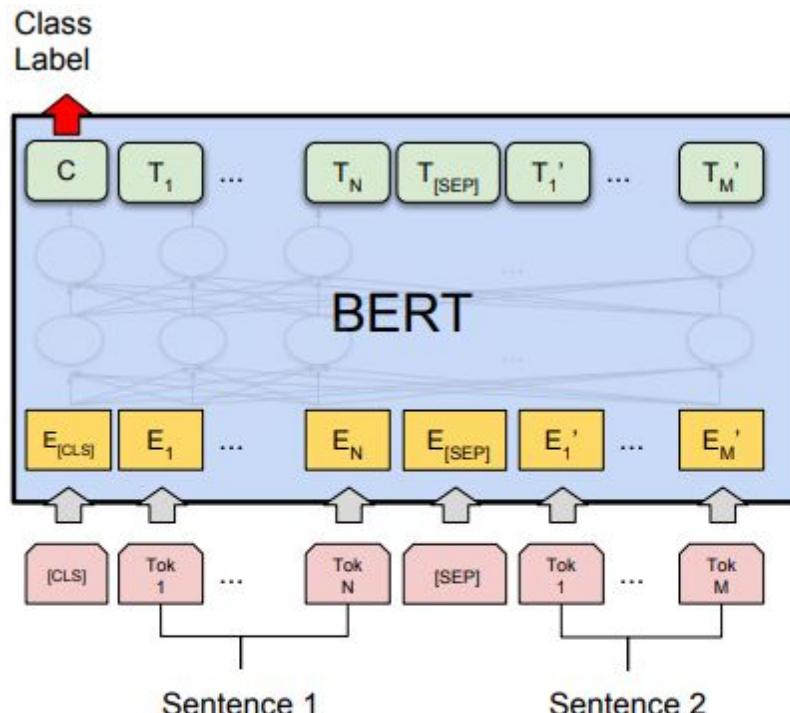


BERT input representation

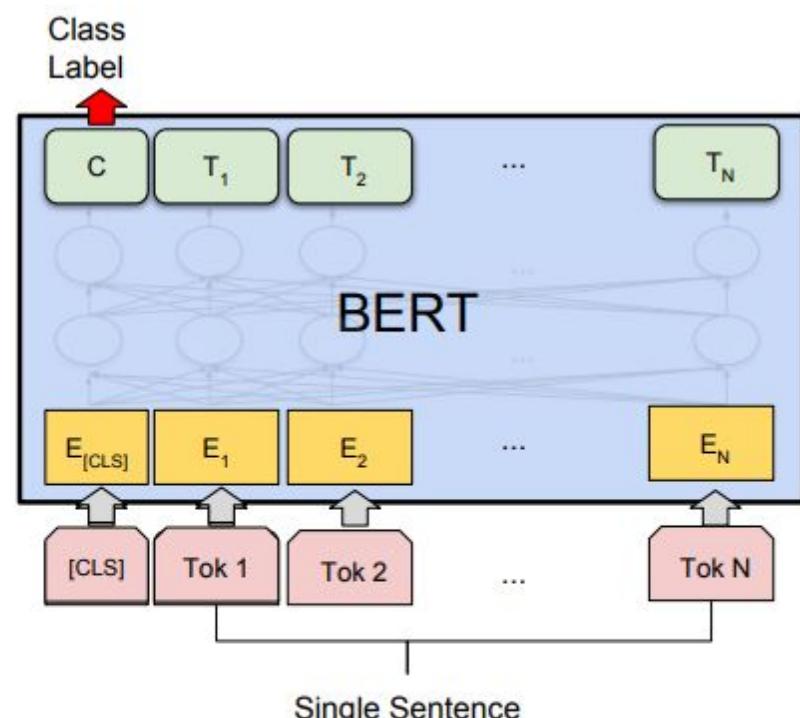




Применение для различных задач (1)



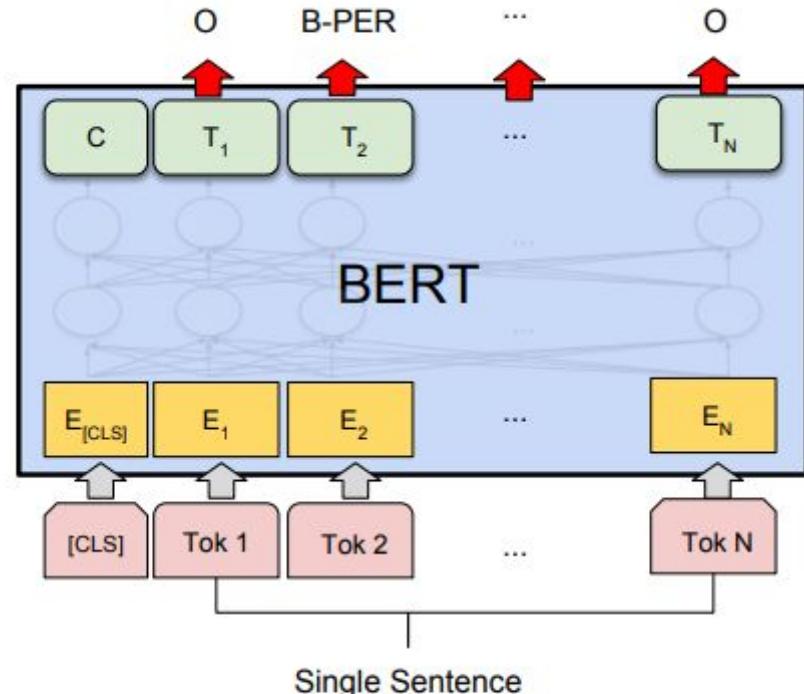
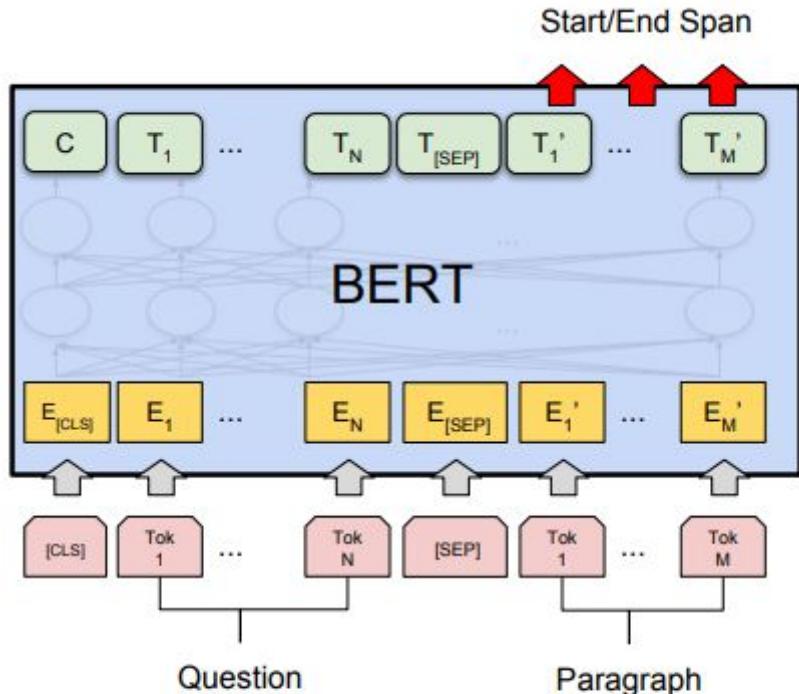
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



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



Применение для различных задач (2)

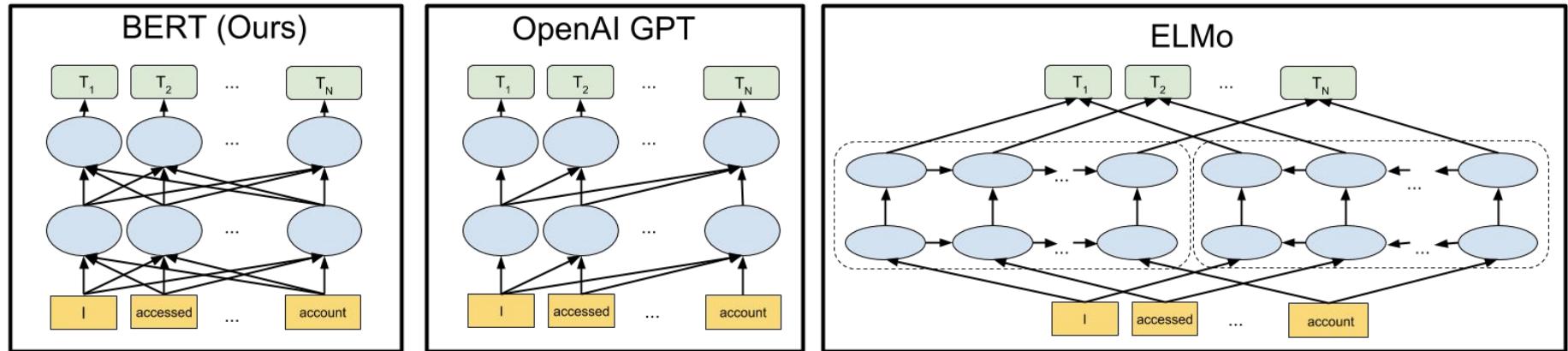


(c) Question Answering Tasks:
SQuAD v1.1

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



Сравнение архитектур ELMO, BERT и GPT





BERT vs ELMO

| System | MNLI-(m/mm) | QQP | QNLI | SST-2 | CoLA | STS-B | MRPC | RTE | Average |
|-----------------------|------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| | 392k | 363k | 108k | 67k | 8.5k | 5.7k | 3.5k | 2.5k | - |
| Pre-OpenAI SOTA | 80.6/80.1 | 66.1 | 82.3 | 93.2 | 35.0 | 81.0 | 86.0 | 61.7 | 74.0 |
| BiLSTM+ELMo+Attn | 76.4/76.1 | 64.8 | 79.9 | 90.4 | 36.0 | 73.3 | 84.9 | 56.8 | 71.0 |
| OpenAI GPT | 82.1/81.4 | 70.3 | 88.1 | 91.3 | 45.4 | 80.0 | 82.3 | 56.0 | 75.2 |
| BERT _{BASE} | 84.6/83.4 | 71.2 | 90.1 | 93.5 | 52.1 | 85.8 | 88.9 | 66.4 | 79.6 |
| BERT _{LARGE} | 86.7/85.9 | 72.1 | 91.1 | 94.9 | 60.5 | 86.5 | 89.3 | 70.1 | 81.9 |

Table 1: GLUE Test results, scored by the GLUE evaluation server. The number below each task denotes the number of training examples. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set. OpenAI GPT = (L=12, H=768, A=12); BERT_{BASE} = (L=12, H=768, A=12); BERT_{LARGE} = (L=24, H=1024, A=16). BERT and OpenAI GPT are single-model, single task. All results obtained from <https://gluebenchmark.com/leaderboard> and <https://blog.openai.com/language-unsupervised/>.



Спасибо за внимание!
Вопросы?