DistilBERT,
a distilled version of BERT: smaller, faster, cheaper and lighter

- 저자:
  - Victor SANH, Lysandre DEBUT, Julien CHAUMOND, Thomas WOLF
    (**Hugging Face**)
- 발표:
  - Presenter: 윤주성
  - Date: 191204

Who is an Author?

- AAAI를 들고 있는 NLP 하던 분인 듯
- Thomas Wolf(huggingface)와 주로 작업하는 듯함

Victor Sanh

FOLLOW

Hugging Face
Verified email at huggingface.co

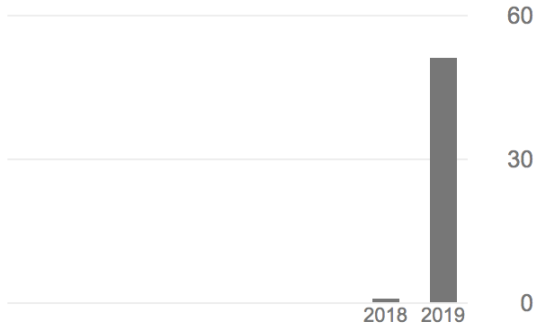
Natural Language Processing Machine Learning Computer Vision Deep Learning

GET MY OWN PROFILE

TITLE	CITED BY	YEAR
A hierarchical multi-task approach for learning embeddings from semantic tasks V Sanh, T Wolf, S Ruder Proceedings of the AAAI Conference on Artificial Intelligence 33, 6949-6956	26	2019
TransferTransfo: A Transfer Learning Approach for Neural Network Based Conversational Agents T Wolf, V Sanh, J Chaumond, C Delangue arXiv preprint arXiv:1901.08149	18	2019
DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter V Sanh, L Debut, J Chaumond, T Wolf arXiv preprint arXiv:1910.01108	9 *	2019
HuggingFace's Transformers: State-of-the-art Natural Language Processing T Wolf, L Debut, V Sanh, J Chaumond, C Delangue, A Moi, P Cistac, ... arXiv preprint arXiv:1910.03771		2019

Cited by

	All	Since 2014
Citations	53	53
h-index	3	3
i10-index	2	2



느낀점

- 일단 논문이 짧다. 좋아.
- soft target probability로 CE한거랑, MLM, Cosine Embedding Loss만으로 좋은 성적을 얻음 (cosine embedding을 사용한건 기여할 만함)
- 최근 나왔던 MobileBERT처럼 Attention에 자체에 대해서 distillation하지 않아도 나쁘지 않은 결과가 나오는구나 싶긴함 물론 MobileBERT가 더 최신이니 Attention 자체에 대해서도 적용하면 좋겠지만.. 이건 BERT끼리만 가능한 approach니..
- weight initialization을 teacher network 에서 가져오는것도 나쁘진 않았음(layer 차이가 나서 좀 다르긴하지만)
- pre-train도 distillation 쓰고, fine-tune도 distillation 쓰면 잘되는건 알겠음.. 괜찮은 방법이긴한데 여러케이스가 존재할 수 있을것 같아 좀 더 비교가 필요해보임

Abstract

- NLP에서 large-scale pre-trained models에서 Transfer Learning하는게 매우 보편화됨
- 그에 따라 computational training or inference가 제한되는 환경(one-the-edge)에서 이런 모델을 돌리는게 challenge가 됨
- 본 논문에서는 DistilBERT라는 좀 더 작은 general purpose language representation model을 pre-train 하는 방법을 제안하고자 함
- 대부분의 이전 연구들은 task-specific models을 만드는데 집중되어있었지만, 저자는 pre-training phase때 knowledge distillation하는데 집중함
- 모델 크기는은 버트대비 40%감소했고 언어 이해 능력은 97%로 유지했고 속도도 60% 더 빠름
- pre-training할 때, inductive biases를 larger model로부터 학습하기 위해 3가지를 조합한 loss를 제안함(`language modeling, distillation and cosine-distance losses`)
- 제안하는 더 작고, 빠르고, 가벼운(smaller, faster and lighter (~~smaller와 lighter 차이가 뭐야..~~)) 모델은 더 적은 비용으로 pre-train도 할 수 있음
- capabilities for on-device computation에 대해 proof-of-concetp experiment와 비교할만한 on-device 연구들을 통해 설명할 것임

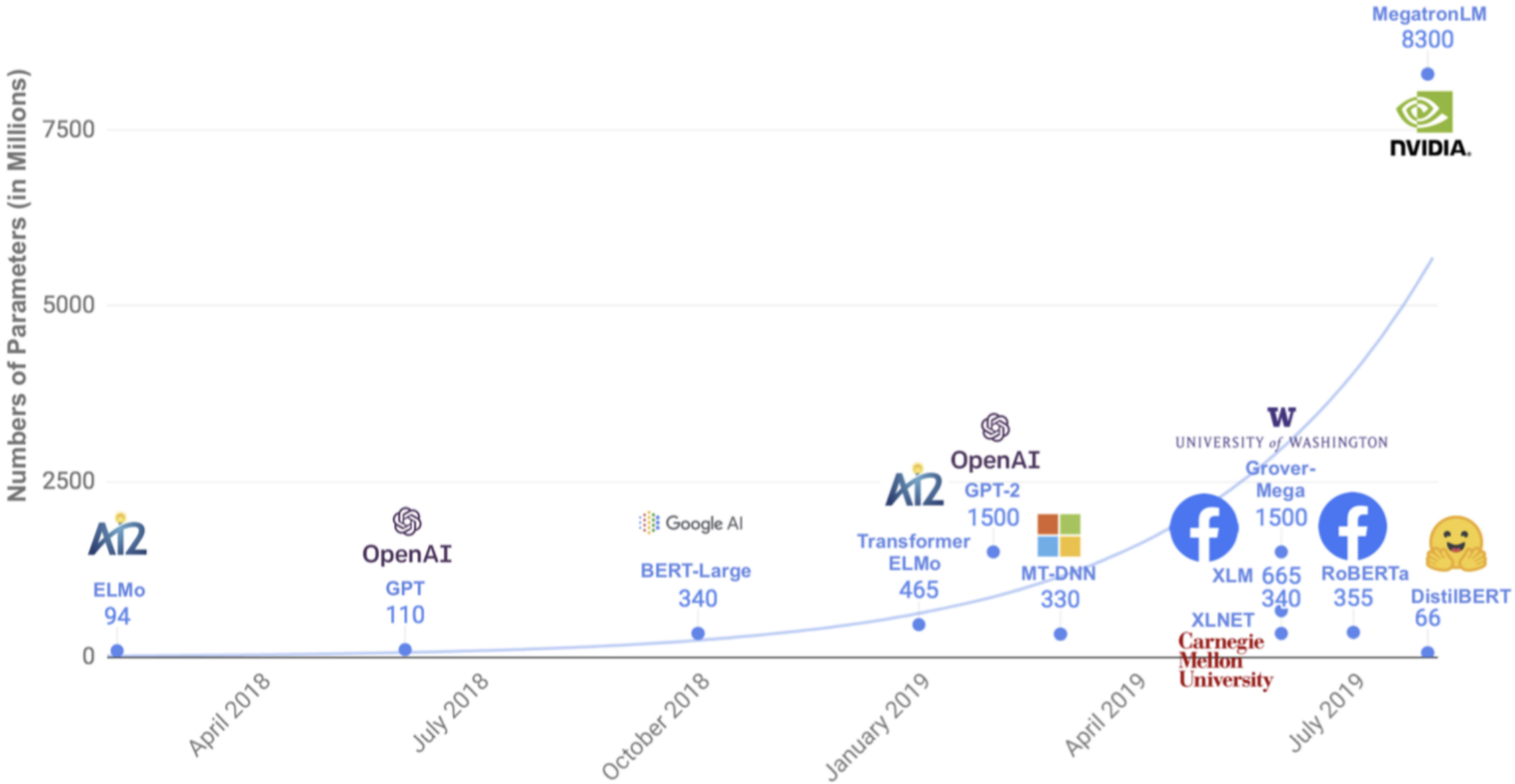


Figure 1: **Parameter counts of several recently released pretrained language models.**

1. Introduction

- 모델 성능은 좋아졌지만 빈번하게 수백만의 파라미터를 갖게되었고 현재까지의 연구로는 더 모델크기를 키우면 downstream task에서 더 높은 성능이 나오고 있음
- 모델이 커지는건 몇가지 우려를 낳고 있음
  - 첫째는, 환경적 비용이 문제가됨 (`First is the environmental cost of exponentially scaling these models' computational requirements as mentioned in Schwartz et al. [2019], Strubell et al. [2019]`)
  - 둘째는, on-device에서 real-time으로 실행하면 새로운 application들을 가능케해줄수있을지라도, 계산비용이 증가하고 필요한 메모리가 커져서 다양한 곳에 적용하기엔 어렵게 만듬(`Second, while operating these models on-device in real-time has the potential to enable novel and interesting language processing applications, the growing computational and memory requirements of these models may hamper wide adoption`)
- 본 논문에서는 knoledge distillation으로 경량화한 LM 모델도 비슷한 성능을 낼수 있는걸 보임. 경량화했으니 학습 비용도 적음
- 3가지의 loss를 써서, bigger Trasnformer LM로 supervision해서 distillation한 결과 40% smaller Transformer를 만듬 (60% 더 빠른 inference time 갖게됨)

2. Knowledge distillation

- **Knowledge distillation** (Bucila et al., 2006, Hinton et al., 2015)은 모델을 압축하는 기술임
  - the student model(compact model)은 the teacher model(larger model or ensemble of models)을 재생산하기 위해 학습됨
  - 지도학습에서 분류모델은 instance class를 예측하기위해 학습되는데, gold label의 estimated probability를 최대로하게 끔 학슴함
  - 보통의 training objective는 모델이 예측한 확률 분포와 one-hot empirical distribution of training labels의 cross-entropy를 최소화하게끔 함
  - 학습셋에서 잘 동작하는 모델은 correct class에 대해서 output distribution을 높은값을 갖는 확률로 예측하고 나머지는 거의 0에 가까운 확률로 예측하게됨
  - 하지만 이러한 "0"("near-zero")에 가까운 확률들중 일부는 다른것보다 더 큰데, model의 generalization capbilities를 반영하고 test set에서 얼마나 잘 동작할지를 보여줌

2. Knowledge distillation

- **Training loss**
  - the student는 soft target probabilities of the teacher에 대한 distillation loss로 학습함
  - t_i는 teacher고 s_i는 student라 할때 Loss는 다음과 같음

$$L_{ce} = \sum_i t_i * \log\left(s_i\right) \text{ where } t_i \text{ (resp. } s_i\text{)}$$

  - 이러한 목적함수는 the full teacher distribution을 활용할 수 있어서 충분한 training signal이 됨
  - Hinton을 따라, *softmax-temperature*를 사용했음

$$p_i = \frac{\exp\left(z_i / T\right)}{\sum_j \exp\left(z_j / T\right)}$$

  - T는 output distribution의 soomthness를 조절하는 텀이고, z_i는 class i에 대한 model score를 의미함
  - 학습시에는 same temperature T를 student & teacher에게 적용하고 inference할때는 T 값을 1로 셋팅해서 standard *softmax*를 사용함
  - the final training objective는 distillation loss L_{ce}를 the supervised training loss와 linear combination한 것임
    - maksed language modeling loss L_{mlm} (~~BERT니까..~~)
    - cosine embedding loss L_{cos} (하다보니 발견하게 되었다고 함, student model과 teacher model의 hidden states vectors의 방향을 align 해줌! (~~오...!~~))

Loss 관련 코드

```
s_logits, s_hidden_states = self.student(input_ids=input_ids, attention_mask=attention_mask)     # (bs, seq_length, voc_size)
with torch.no_grad():
        t_logits, t_hidden_states = self.teacher(input_ids=input_ids, attention_mask=attention_mask) # (bs, seq_length, voc_size)

loss_ce = self.ce_loss_fct(F.log_softmax(s_logits_slct/self.temperature, dim=-1),
                           F.softmax(t_logits_slct/self.temperature, dim=-1)) * (self.temperature)**2

loss = self.alpha_ce*loss_ce
loss_mlm = self.lm_loss_fct(s_logits.view(-1, s_logits.size(-1)), lm_labels.view(-1))
loss += self.alpha_mlm * loss_mlm

loss_mse = self.mse_loss_fct(s_logits_slct, t_logits_slct)/s_logits_slct.size(0) # Reproducing batchmean reduction
loss += self.alpha_mse * loss_mse

s_hidden_states = s_hidden_states[-1]                               # (bs, seq_length, dim)
t_hidden_states = t_hidden_states[-1]                               # (bs, seq_length, dim)
mask = attention_mask.unsqueeze(-1).expand_as(s_hidden_states)      # (bs, seq_length, dim)
assert s_hidden_states.size() == t_hidden_states.size()
dim = s_hidden_states.size(-1)

s_hidden_states_slct = torch.masked_select(s_hidden_states, mask)        # (bs * seq_length * dim)
s_hidden_states_slct = s_hidden_states_slct.view(-1, dim)                # (bs * seq_length, dim)
t_hidden_states_slct = torch.masked_select(t_hidden_states, mask)        # (bs * seq_length * dim)
t_hidden_states_slct = t_hidden_states_slct.view(-1, dim)                # (bs * seq_length, dim)

target = s_hidden_states_slct.new(s_hidden_states_slct.size(0)).fill_(1) # (bs * seq_length,)
loss_cos = self.cosine_loss_fct(s_hidden_states_slct, t_hidden_states_slct, target)
loss += self.alpha_cos * loss_cos
```

Code Reference: https://github.com/huggingface/transformers/blob/7edb51f3a516ca533797fb2bb2f2b7ce86e0df70/examples/distillation/distiller.py#L366

3. DistilBERT: a distilled version of BERT

Student architecture

- the student - DistilBERT는 BERT의 general architecture과 같음
- The token-type embeddings and the pooler are removed while the number of layers is reduced by a factor of 2 (레이어수는 2배 감소)
- Transformer architecture에서 쓰이는 대부분의 Ops인 linear layer나 layer normalisation은 modern linear algebra frameworks로 highy optimized됨
- 조사결과, last dimension (hidden size dimension)에 대한 변형은 layer 개수 변경에 비하면 computation efficiency에서 큰 임팩트가 없음을 알게됨
- 그렇기 때문에 레이어를 줄이는 것에 포커스를 맞춤

Student Initialization

- 최적화와 모델 구조 선택뿐만 아니라, 올바른 initialization 방법을 찾는게 중요함
- teacher model과 student model의 dim이 같으니, teacher model에서 빼오자 (`Taking advantage of the common dimensionality between teacher and student networks, we initialize the student from the teacher by taking one layer out of two`)

3. DistilBERT: a distilled version of BERT

Distillation

- RoBERTa(Roberta: A robustly optimized bert pretraining approach) 논문에서 나온 버트를 학습시키기 위한 best practices를 적용함
  - gradient accumulation (up to 4K examples per batch)
  - dynamic masking
  - without NSP objective

Data and compute power

- DistilBERT는 original BERT와 같은 학습 corpus(English Wikipedia and Toronto Book Corpus)를 사용함
- 8개의 16GB V100 GPU로 90시간 정도 학습함 (RoBERTa의 경우 1024개의 32GB V100으로 하루 학습)

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	77.6	48.9	84.3	88.6	89.3	89.5	71.3	91.7	91.2	43.7
DistilBERT	76.8	49.1	81.8	90.2	90.2	89.2	62.9	92.7	90.7	44.4

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

General Language Understanding

- DistilBERT의 language understanding과 generalization capabilities 를 확인하기 위해 General Language Understanding

4. Experiments

4.1 Downstream task benchmark

Downstream tasks

- As shown in Table 2, DistilBERT is only 0.6% point behind BERT in test accuracy on the IMDb benchmark while being 40% smaller. On SQuAD, DistilBERT is within 3.5 points of the full BERT
- we could add another step of distillation during the adaptation phase by fine-tuning DistilBERT on SQuAD using a BERT model previously fine-tuned on SQuAD as a teacher for an additional term in the loss (knowledge distillation)
- two successive steps of distillation, one during the pre-training phase and one during the adaptation phase.
    - 한마디로하면, fine-tuning도 fine-tune 된 teacher을 이용해서 하겠다는 것임
    - 결과는 매우 잘됨.. Table 2에서 DistilBERT (D)가 이것임

4. Experiments

4.1 Downstream task benchmark

Size and inference speed

- 속도에 대한건 Table 3에 정리함
- the inference time needed to do a full pass on the STS- B development set on CPU (Intel Xeon E5-2690 v3 Haswell @2.9GHz) using a batch size of 1
- DistilBERT has 40% fewer parameters than BERT and is 60% faster than BERT

On device computation

- on-the-edge applications에서 DistilBERT가 쓸만한지 테스트해보기 위해 QA 모바일앱을 만듬
- 총 용량을 207 MB까지 낮췄음(quantization 이용하면 더 줄일 수 있음)
- We compare the average inference time on a recent smartphone (iPhone 7 Plus) against our previously trained question answering model based on BERT-base. Excluding the tokenization step, DistilBERT is 71% faster than BERT, and the whole model weighs 207 MB (which could be further reduced with quantization)

4. Experiments

4.2 Ablation study

- Table 4 presents the deltas with the full triple loss: removing the Masked Language Modeling loss has little impact while the two distillation losses account for a large portion of the performance.

Table 4: **Ablation study.** Variations are relative to the model trained with triple loss and teacher weights initialization.

Ablation	**Variation on GLUE macro-score**
$\emptyset$ - L_{cos} - L_{mlm}	-5.06
L_{ce} - $\emptyset$ - L_{mlm}	-4.07
L_{ce} - L_{cos} - $\emptyset$	-1.90
Triple loss + random weights initialization	-4.83

5. Related work

- Task-specific distillation
  - Tang et al. [2019] transfer fine-tune classification model BERT to an LSTM-based classifier
  - Chatterjee [2019] distill BERT model fine-tuned on SQuAD in a smaller Transformer model previ- ously initialized from BERT
  - Turc et al. [2019] use the original pretraining objective to train smaller student, then fine-tuned via distillation.
  - 저자는 general-purpose pre-training distillation이 task-specific distillation보다 좋다고 주장(`it beneficial to use a general-purpose pre-training distillation rather than a task-specific distillation.`)
- Multi-distillation
  - Yang et al. [2019] combine the knowledge of an ensemble of teachers using multi-task learning to regularize the distillation.
  - However, as shown in the ablation study, leveraging the teacher's knowledge with initialization and additional losses leads to substantial gains.
- Other compression techniques
  - Pruning:
    - Recent developments in weights pruning reveal that it is possible to remove some heads in the self-attention at test time without significantly degrading the performance Michel et al. [2019].
  - Quantization:
    - Some layers can be reduced to one head. A separate line of study leverages quantization to derive smaller models (Gupta et al. [2015])

6. Conclusion and future work

- DistilBERT를 소개함
- BERT의 genenral-purpose pre-trained version이며 40% 더 작고, 60% 더 빠르면서, 97%의 the language understanding capabilities를 유지함
- general-purpose language model이 distillation을 통해서도 성공적으로 학습이 됨을 밝히면서 각 components를 ablation study로 분석함
- edge applications에서도 설득력있는 옵션이라는걸 입증함 (~~약간 더 개선이 필요해보이는데..~~)