워드 임베딩과 문서 표현

- 워드 임베딩이란?
- 워드 임베딩 방법론: word2vec, fastText, GloVe
- 문서표현 방법: ELMo, BERT

문서 분류와 문서 클러스터링 문제

- 머신러닝 방법론
  - 문서 분류: kNN, NB, SVM, random forest 등
  - 문서 클러스터링: K-Means, DBSCAN
- 주요 이슈
  - 문서 벡터를 어떻게 구성할 것인가?
  - 유사도 계산 기법은?

문서 벡터의 구성

- 문서의 특징을 가장 잘 표현하는 feature vector
- Keyword 추출 및 키워드 가중치 계산: TF-IDF

- 예) SVM 학습데이터: example1.tar.gz -- 로이터 뉴스기사
    - train.dat(2천개), test.dat(600개)
    - words: 9,947 terms are extracted

  https://download.joachims.org/svm_light/examples/example1.tar.gz

SVM example1: train.dat, test.dat, words

train.dat | test.dat | words

```
977 1 6:0.0394818835476958 11:0.010436379800545 15:0.00795697050873869 26:0.0301567899808728 27:0.0135249148075739 29:0.0674778841926948 31:0.0177039764265539 3
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980 1 15:0.188437715840106 28:0.203076572401634 158:0.197385390277138 176:0.142546636568 204:0.165090087892139 2216:0.37464991325394 7038:0.570477684779504 8747
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982 1 6:0.0120259484621456 27:0.0233444518081582 28:0.0296018517433357 29:0.0291172658749587 31:0.0305576508527073 42:0.0239832788068884 80:0.0261007140363266 88:
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```

train.dat | test.dat | words

```
1 v
2 ct
3 shr
4 net
5 qtr
6 said
7 rev
8 wheat
9 tonn
10 agricultur
11 bank
12 oil
13 export
14 grain
15 inc
16 corn
17 trade
18 rate
19 soybean
20 loss
21 olon
22 usda
23 th
24 div
25 dollar
26 share
27 pct
28 acquir
29 company
30 profit
31 corp
32 dividend
33 issu
34 import
35 crop
36 bond
37 market
38 money
39 barrel
40 debt
41 price
42 product
43 coupon
44 avg
45 qtly
46 curenc
47 note
48 record
49 underwrit
50 deficit
```

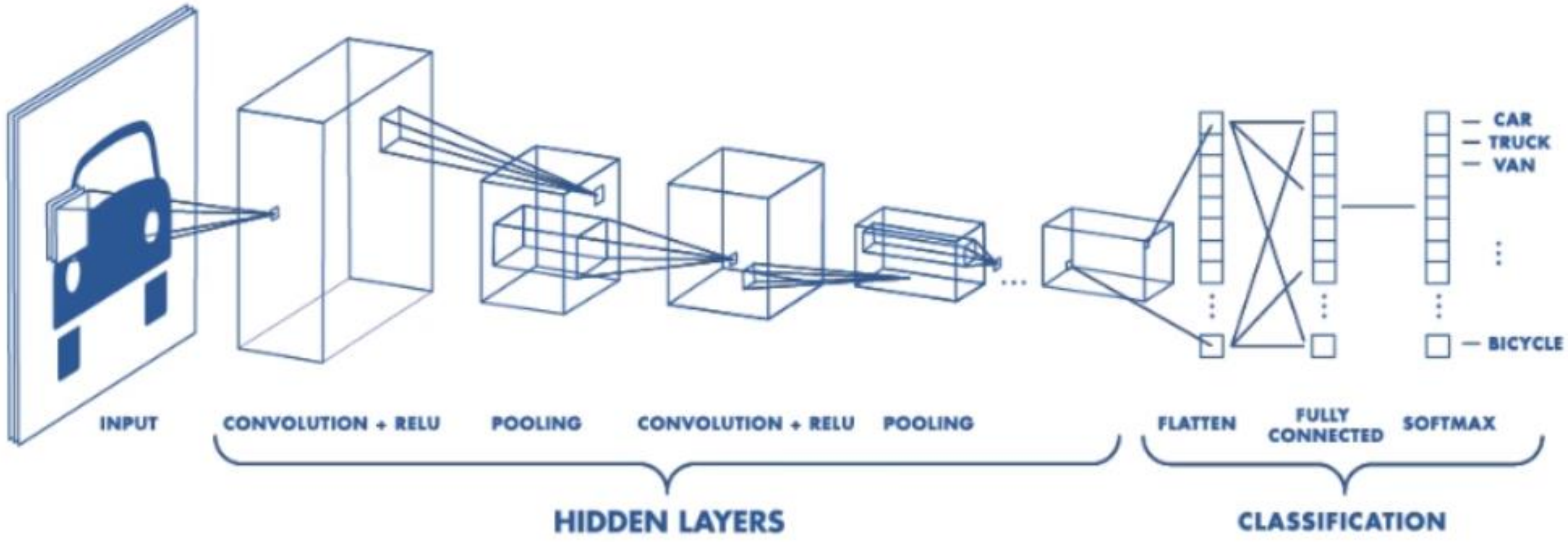
문서 벡터 구성의 문제점

- 문서 벡터의 차원수 문제
  - Feature(키워드) 개수: 수십만~수백만개
  - 저장 공간의 문제

- 차원 축소(dimensionality reduction)
  - Feature selection
  - 고차원 데이터를 저차원 공간으로 투영
    - PCA, LDA, LSA 등

심층 뉴럴네트워크를 이용한 차원 축소

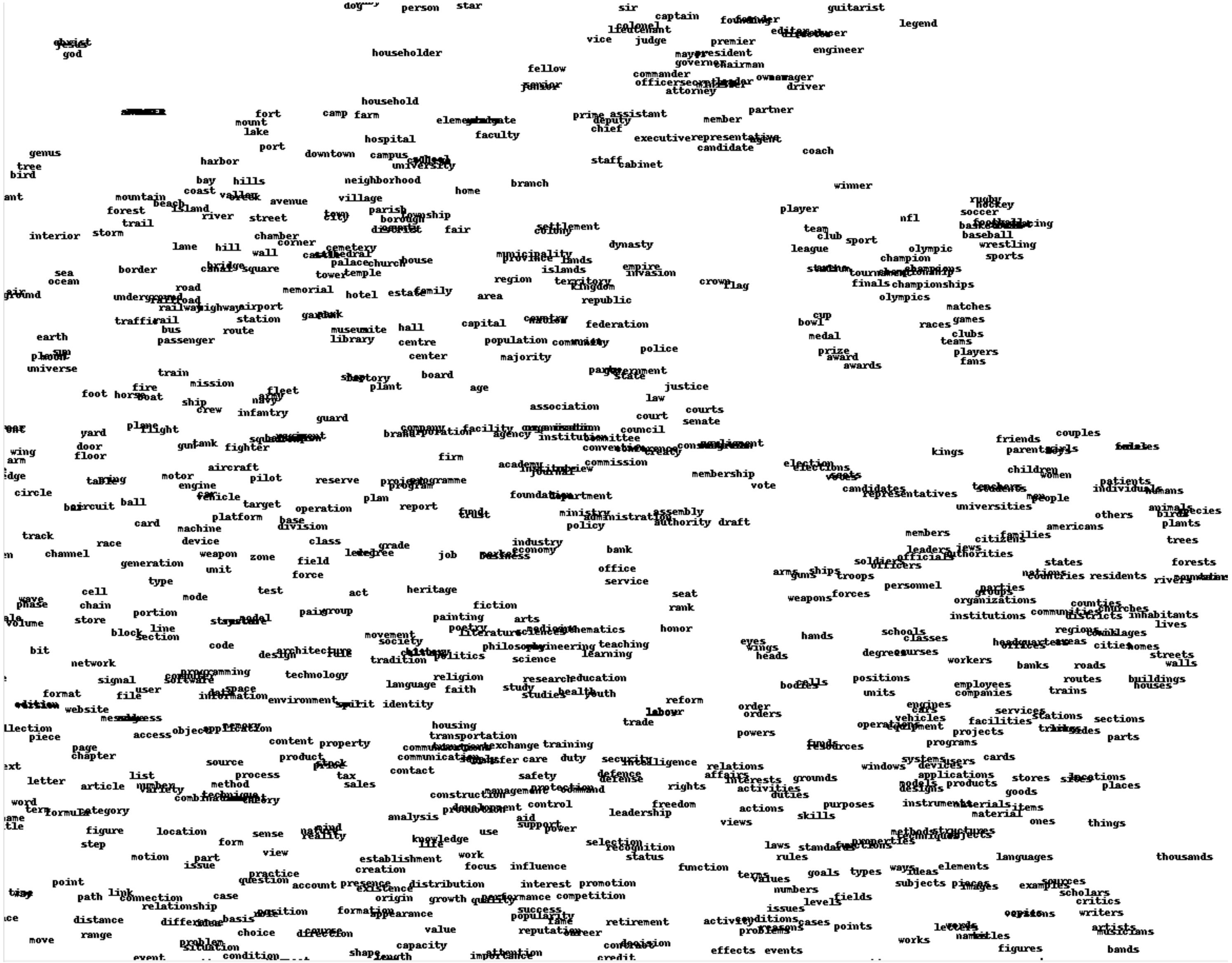
- 입력 벡터 → 은닉층 → 출력 벡터
- CNN(Convolutional Neural Network)

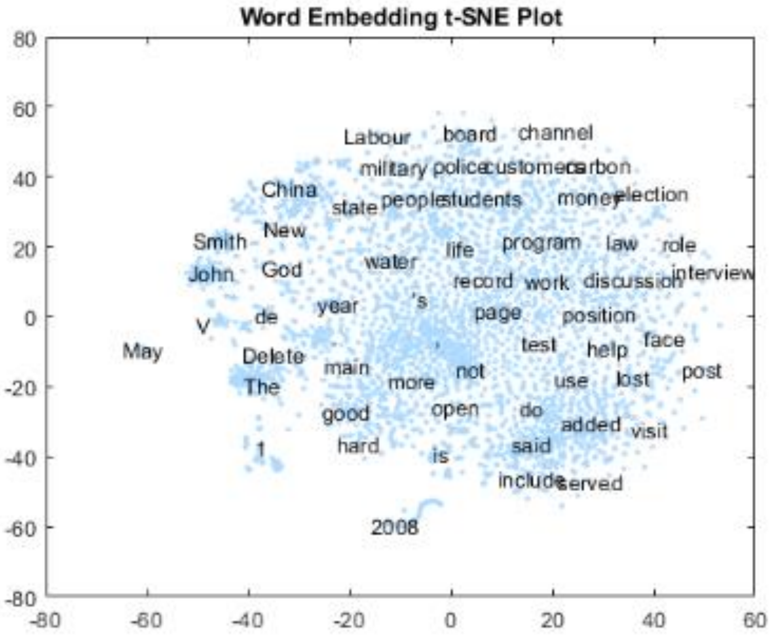


워드 임베딩: 단어 벡터(word vector) 구성

- 단어의 특징을 가장 잘 표현하는 벡터
  - “You shall know a word by the company it keeps”, J. R. Firth (1957)
  - “Efficient Estimation of Word Representations in Vector Space”
- 대규모 텍스트 말뭉치로부터 단어 벡터 학습
- DNN(Deep Neural Network)으로 구현

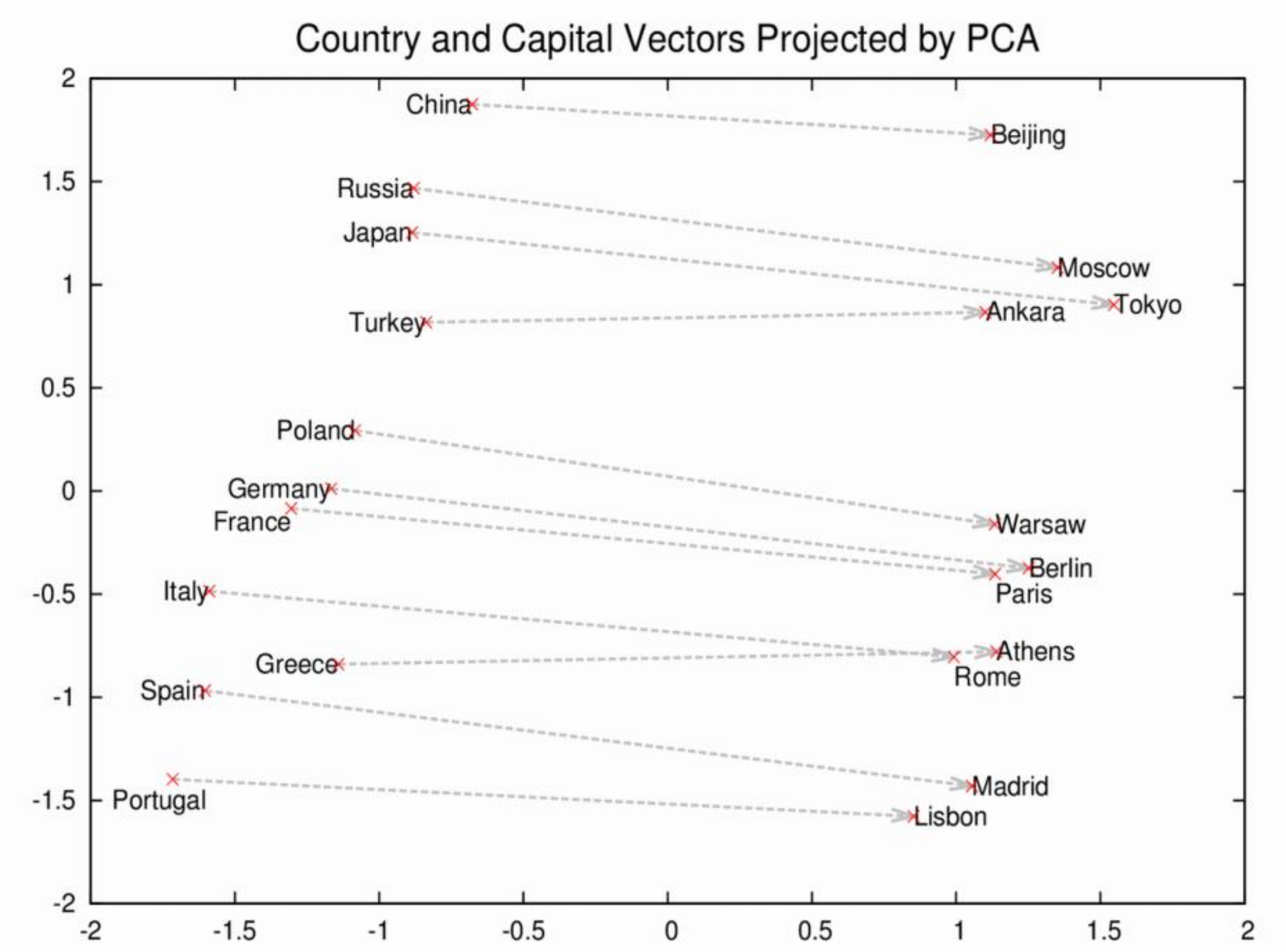
Joseph Turian's map of 2500 English words
produced by using t-SNE on the word feature vectors learned by Collobert & Weston, ICML 2008





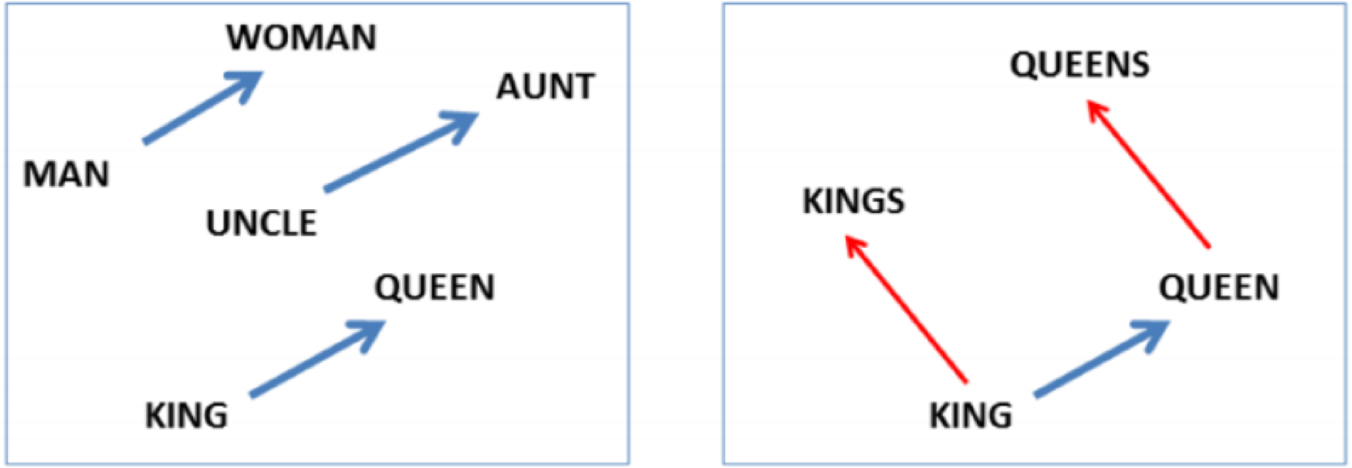
http://www.cs.toronto.edu/~hinton/turian.png

단어 벡터의 방향성



Country and Capital Vectors Projected by PCA
China
Beijing
Russia
Japan
Moscow
Tokyo
Turkey
Ankara
Poland
Germany
France
Warsaw
Berlin
Paris
Italy
Greece
Athens
Rome
Spain
Madrid
Portugal
Lisbon
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2

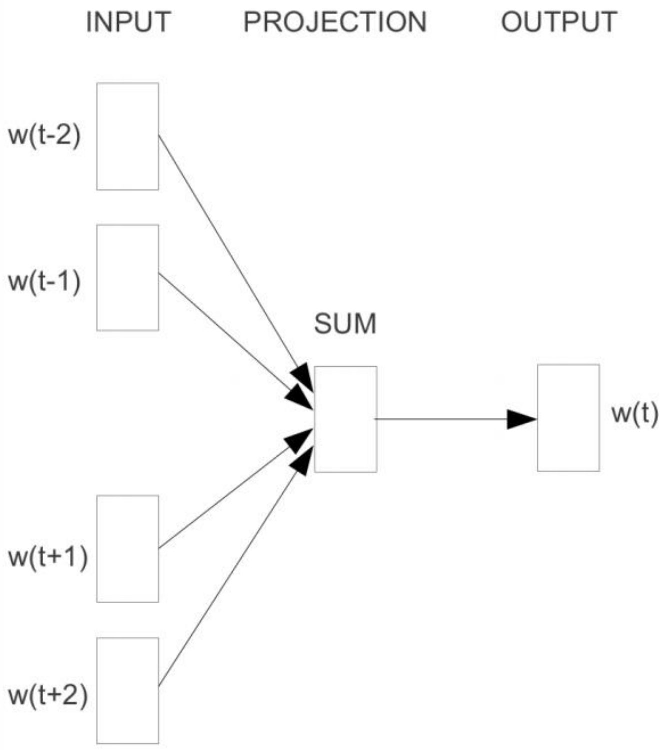
man is to woman as king is to ?



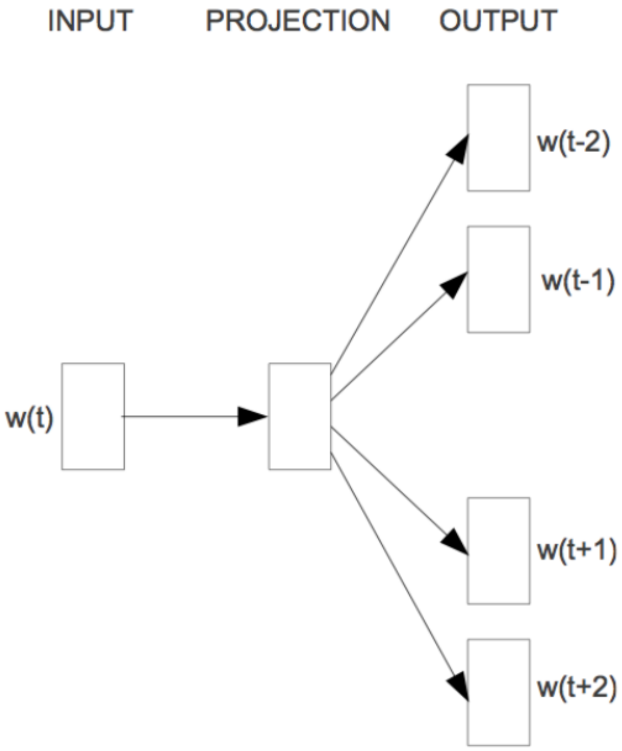
(Mikolov et al., NAACL HLT, 2013)

Word2vec: CBOW, skip-gram

- PageRank 알고리즘



CBOW



Skip-gram

- CBOW(Continuous Bag-Of-Words)
  - 좌우 문맥으로부터 현재 단어 예측
  - 학습속도 빠름, 대규모 학습말뭉치에 적합

- Continuous skip-gram
  - Skip-gram: n-gram with a gap(현재 단어)
  - 빈도가 높은 단어 벡터를 잘 표현함
  - 학습 속도 느림

Using word2vec

- Original: http://word2vec.googlecode.com/svn/trunk/
  - https://code.google.com/p/word2vec/
- C++11 version: https://github.com/jdeng/word2vec
- Python: http://radimrehurek.com/gensim/models/word2vec.html
- Java: https://github.com/ansjsun/word2vec_java
  - http://deeplearning4j.org/word2vec
- Parallel java: https://github.com/siegfang/word2vec
- CUDAversion: https://github.com/whatupbiatch/cuda-word2vec

https://code.google.com/archive/p/word2vec/

- word2vec - Revision 42: /trunk
  - LICENSE
  - README.txt
  - compute-accuracy.c
  - demo-analogy.sh
  - demo-classes.sh
  - demo-phrase-accuracy.sh
  - demo-phrases.sh
  - demo-train-big-model-v1.sh
  - demo-word-accuracy.sh
  - demo-word.sh
  - distance.c
  - makefile
  - questions-phrases.txt
  - questions-words.txt
  - word-analogy.c
  - word2phrase.c
  - word2vec.c

- Run 'make' to compile word2vec tool
- Run the demo scripts:
  - ./demo-word.sh
  - ./demo-analogy.sh
  - ./demo-phrases.sh

Ex) Word similarities in word2vec

Sweden
Similar words

Word	Cosine distance
norway	0.760124
denmark	0.715460
finland	0.620022
switzerland	0.588132
belgium	0.585835
netherlands	0.574631
iceland	0.562368
estonia	0.547621
slovenia	0.531408
floorball_federation	0.529570
luxembourg	0.529477
czech_republic	0.528778
slovakia	0.526340
romania	0.524281
kista	0.522488
helsinki_vantaa	0.519936
swedish	0.519901
balrog_ik	0.514556
portugal	0.502495
russia	0.500196
slovakia_slovenia	0.496051
ukraine	0.495712
chur	0.484225
thailand_togo	0.479172
crimea_ukraine	0.478596

Harvard
Similar words

Word	Cosine distance
yale	0.638970
cambridge	0.612665
university	0.597709
faculty	0.588422
harvey_mudd	0.578338
johns_hopkins	0.575645
graduate	0.570294
undergraduate	0.565881
professor	0.563657
mcgill	0.562168
ph_d	0.558665
california_berkeley	0.555539
yale_university	0.550480
harvard_crimson	0.549848
princeton	0.544070
college	0.542838
oxford	0.531948
barnard_college	0.530800
professors	0.529959
princeton_university	0.529763
ucl	0.527395
doctorates	0.526292
doctoral	0.523317
cambridge_massachusetts	0.519657
juris_doctor	0.518845
graduate_student	0.518815
postgraduate	0.515757

Interesting properties of word2vec

- vector('Paris') - vector('France') + vector('Italy’)
  is very close to vector('Rome')
- vector('king') - vector('man') + vector('woman’)
  is close to vector('queen')

- Simple demo by running demo-analogy.sh

How to measure

- Quality of the word vectors
  ./demo-word-accuracy.sh -- word relation test set
  ./demo-phrase-accuracy.sh -- phrase relation test set
- Word clustering
  ./demo-classes.sh

Where to obtain the training data

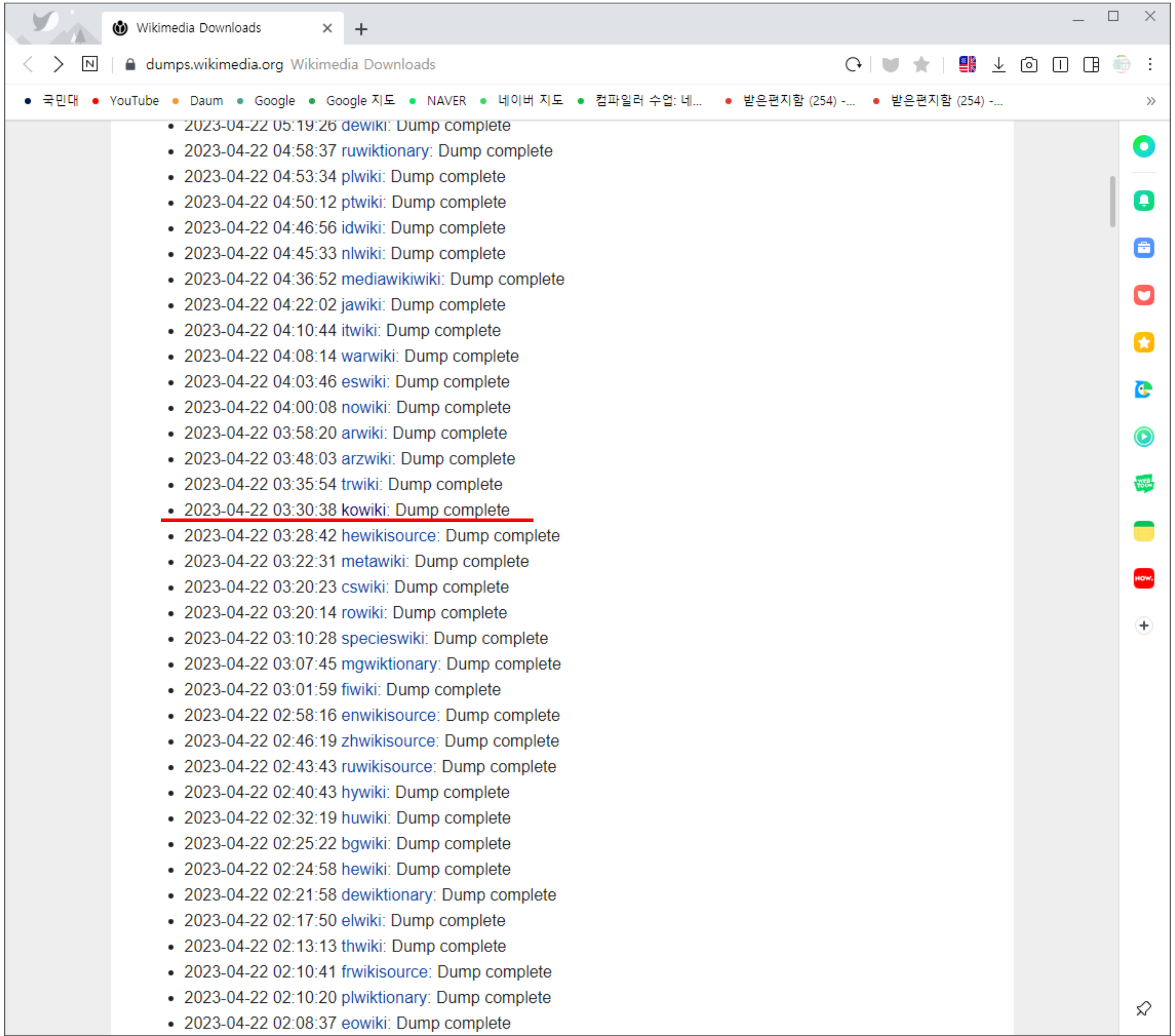
- Latest Wikipedia dump
  - https://dumps.wikimedia.org/backup-index.html

- WMT11 site: text data for several languages
  - http://www.statmt.org/wmt11/translation-task.html#download
  - Statistical M.T. -- http://statmt.org/

- UMBC webbase corpus around 3 billion words

- Polyglot
  - https://sites.google.com/site/rmyeid/projects/polyglot

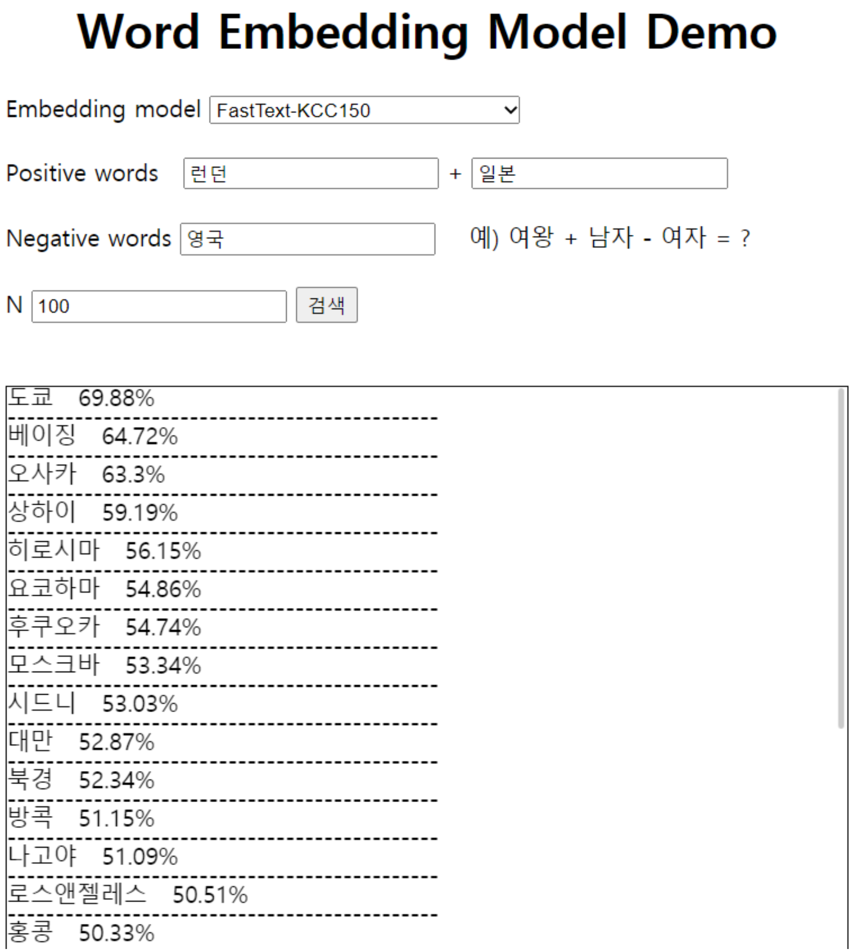
https://dumps.wikimedia.org/backup-index.html



Word Embedding 데모, 실습

- http://nlp.kookmin.ac.kr/kcc/word2vec/
- http://nlp.kookmin.ac.kr/kcc/word2vec/demo

- https://bitbucket.org/aboSamoor/word2embeddings
- https://sites.google.com/site/rmyeid/projects/polyglot
- https://remykarem.github.io/word2vec-demo/
- http://nbviewer.jupyter.org/gist/aboSamoor/6046170



Demo: similar words

https://sites.google.com/site/rmyeid/projects/polyglot

Online Demo

The demo shows words proximity in the embedding space. Given a word we calculate its neighbours in the space according to the Euclidean distance. In case, you are using the latest version of Firefox 23.0+, this demo will be blocked by default. Here are instructions on how to disable protection and enable the demo. Otherwise, you can have direct access to the demo at <wordrepresentation.appspot.com>.

Obama | English | Search

Examples:

- English
  - Bush vs bush
  - Apple vs apple
  - Mumbai vs Bombay
  - Apple vs Google
  - accelerating
- Russian
  - Москва (Moscow)
  - водка (Vodka)
  - Путин (Putin)
  - Пушкин (Pushkin)
  - USA

Rank	Word	L2 Distance
0	Apple	0.0
1	Dell	3.21376
2	Paramount	3.73771
3	Mac	3.75451
4	Flex	3.95375
5	Link	3.97127
6	Fox	4.12825
7	HP	4.13556
8	Oracle	4.24255
9	Cream	4.26531
10	Shell	4.29036
11	Dot	4.32141
12	AOL	4.3369
13	Safari	4.46203
14	Flash	4.55888
15	Bell	4.60953
16	Diamond	4.61724
17	Mercury	4.66379
18	AMC	4.686
19	Dial	4.78557
20	Rhino	4.79876

Rank	Word	L2 Distance
0	apple	0.0
1	tomato	2.1517
2	bean	2.28461
3	onion	2.32823
4	potato	2.33879
5	chicken	2.6566
6	chocolate	2.68221
7	lemon	2.70843
8	almond	2.73388
9	berry	2.77824
10	pepper	2.80792
11	strawberry	2.85157
12	chili	2.86959
13	sausage	2.88144
14	egg	2.90296
15	dessert	2.91029
16	peach	2.91455
17	mango	2.94624
18	turkey	3.00063
19	coconut	3.04677
20	pea	3.08457

Using it in Python

- Gensim Python Library
  https://radimrehurek.com/gensim/index.html

- Gensim Tutorials
  https://radimrehurek.com/gensim/tutorial.html

- Visualization -- Scikit-Learn t-SNE
  http://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html

Word Embedding Methods

- Word2vec
- GloVe
- FastText
- ELMo
- BERT: ALBERT, RoBERTa
- XLNet
- ELECTRA
- GPT-2

- Evaluation(MRC): SQuAD, RACE, GLUE, etc

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

https://www.aclweb.org/anthology/N19-1423.pdf (NAACL'2019)

Code and pre-trained models: https://github.com/google-research/bert

Pre-trained Language Representations

- *Feature-based* approach : ELMo (Peters et al., 2018a)
    - pre-trained representations as additional features

- *Fine-tuning* approach : OpenAI GPT (Radford et al., 2018)
    - introduces minimal task-specific parameters
    - simply fine-tuning all pretrained parameters

- Two approaches use *unidirectional language models* to learn general language representations

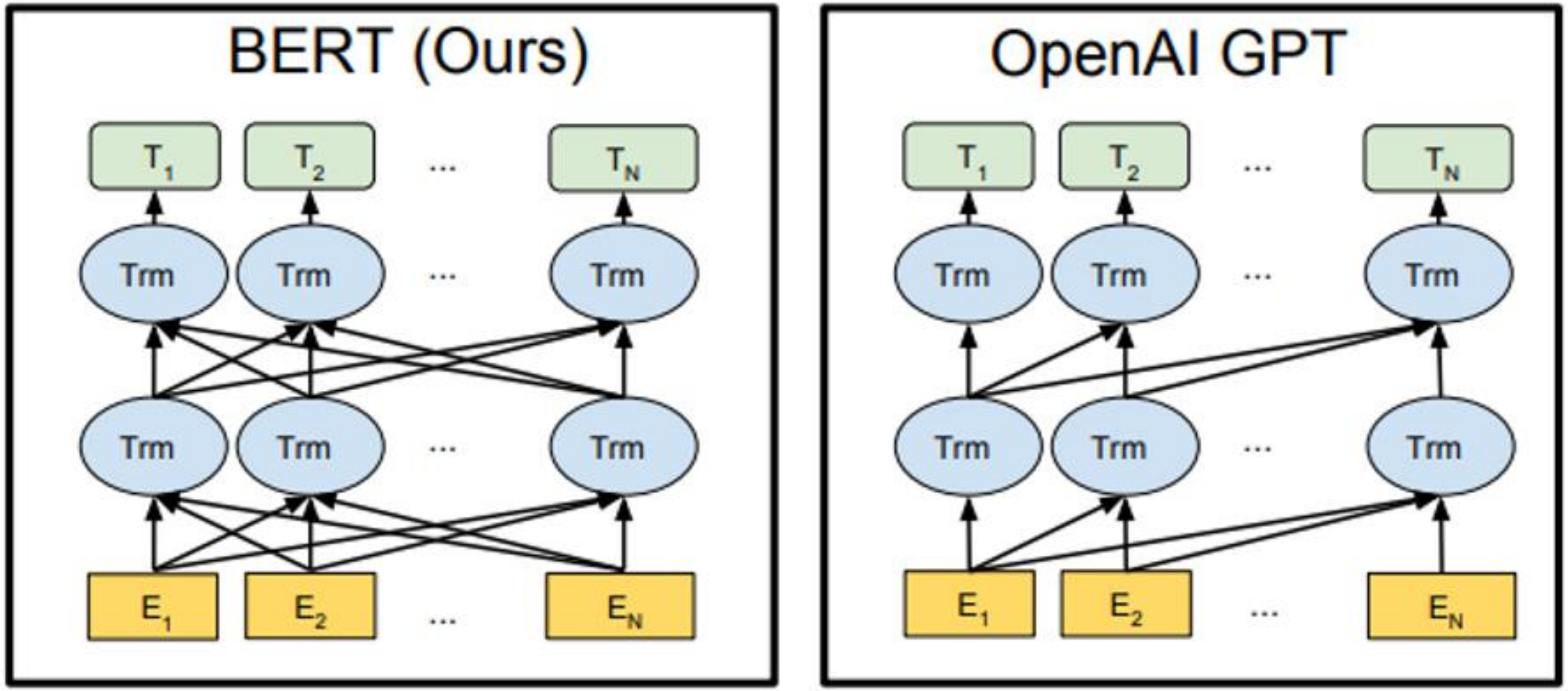
BERT: focused on *bidirectional pre-training*

- Improve the fine-tuning based approach by using

- "masked language model" (MLM)
  - randomly masks some of the tokens from the input,
  - and predicts the original vocabulary

- "next sentence prediction"
  - jointly pretrains text-pair representations.

BERT vs. GPT


BERT (Ours)
T1 T2 ... TN
Trm Trm ... Trm
Trm Trm ... Trm
E1 E2 ... EN
OpenAI GPT
T1 T2 ... TN
Trm Trm ... Trm
Trm Trm ... Trm
E1 E2 ... EN

State-of-the-art results on SQuAD and RACE

Models	SQuAD1.1 dev	SQuAD2.0 dev	SQuAD2.0 test	RACE test (Middle/High)
Single model (from leaderboard as of Sept. 23, 2019)				
BERT-large	90.9/84.1	81.8/79.0	89.1/86.3	72.0 (76.6/70.1)
XLNet	94.5/89.0	88.8/86.1	89.1/86.3	81.8 (85.5/80.2)
RoBERTa	94.6/88.9	89.4/86.5	89.8/86.8	83.2 (86.5/81.3)
UPM	-	-	89.9/87.2	-
XLNet + SG-Net Verifier++	-	-	90.1/87.2	-
ALBERT (1M)	94.8/89.2	89.9/87.2	-	86.0 (88.2/85.1)
ALBERT (1.5M)	**94.8/89.3**	**90.2/87.4**	**90.9/88.1**	**86.5 (89.0/85.5)**
Ensembles (from leaderboard as of Sept. 23, 2019)				
BERT-large	92.2/86.2	-	-	-
XLNet + SG-Net Verifier	-	-	90.7/88.2	-
UPM	-	-	90.7/88.2	
XLNet + DAAF + Verifier	-	-	90.9/88.6	-
DCMN+	-	-	-	84.1 (88.5/82.3)
ALBERT	**95.5/90.1**	**91.4/88.9**	**92.2/89.7**	**89.4 (91.2/88.6)**

Table 10: State-of-the-art results on the SQuAD and RACE benchmarks.

SQuAD   Home   Explore 2.0   Explore 1.1

SQuAD2.0

The Stanford Question Answering Dataset

What is SQuAD?

Stanford **Qu**estion **A**nswering **D**ataset (SQuAD) is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or *span*, from the corresponding reading passage, or the question might be unanswerable.

SQuAD2.0 combines the 100,000 questions in SQuAD1.1 with over 50,000 unanswerable questions written adversarially by crowdworkers to look similar to answerable ones. To do well on SQuAD2.0, systems must not only answer questions when possible, but also determine when no answer is supported by the paragraph and abstain from answering.

Explore SQuAD2.0 and model predictions

SQuAD2.0 paper (Rajpurkar & Jia et al. '18)

SQuAD 1.1, the previous version of the SQuAD dataset, contains 100,000+ question-answer pairs on 500+ articles.

Explore SQuAD1.1 and model predictions

SQuAD1.0 paper (Rajpurkar et al. '16)

Getting Started

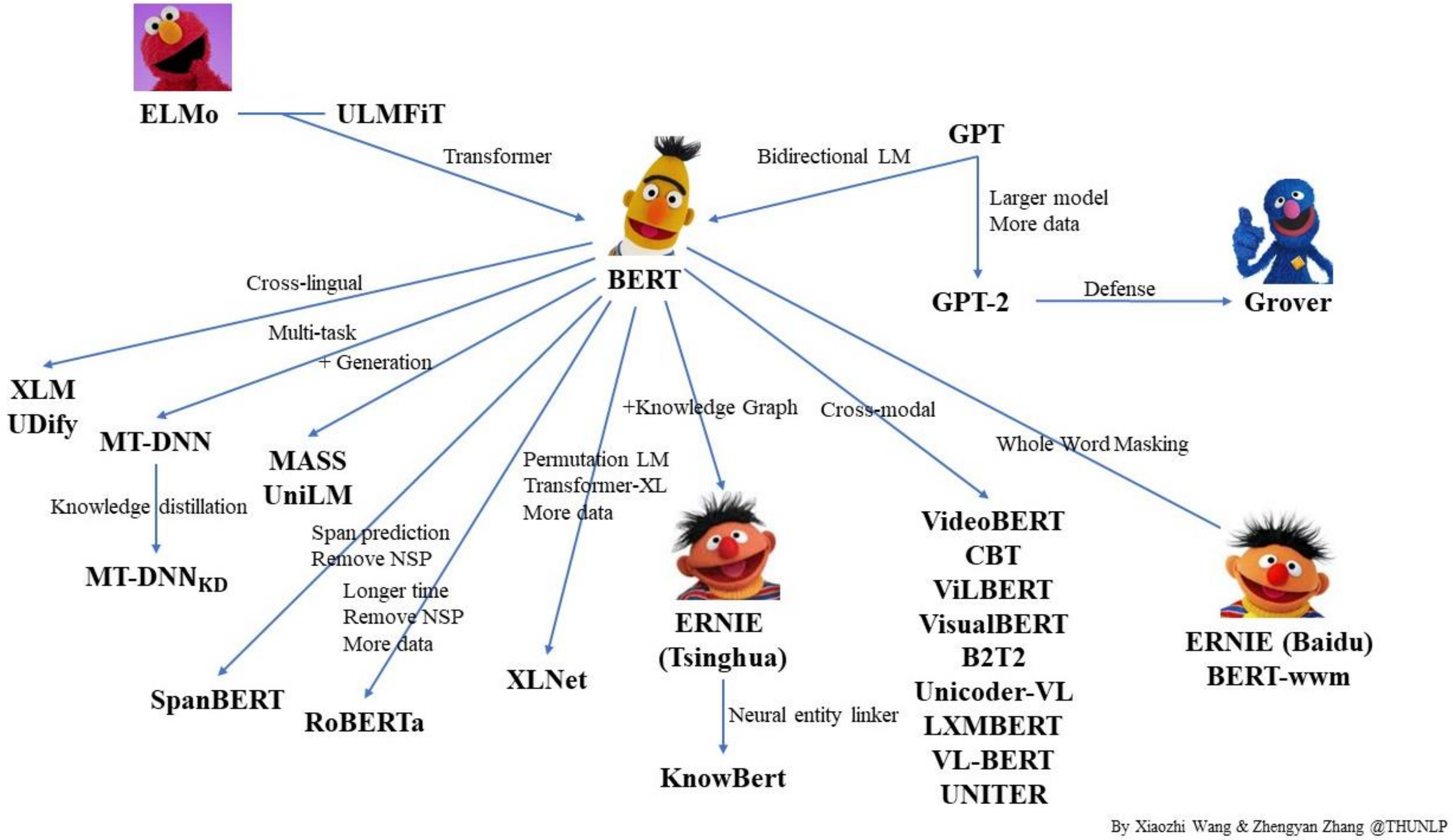
We've built a few resources to help you get started with the dataset.
Download a copy of the dataset (distributed under the CC BY-SA 4.0 license):

Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph.

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Jun 04, 2021	IE-Net (ensemble) *RICOH_SRCB_DML*	**90.939**	**93.214**
2 Feb 21, 2021	FPNet (ensemble) *Ant Service Intelligence Team*	90.871	93.183
3 May 16, 2021	IE-NetV2 (ensemble) *RICOH_SRCB_DML*	90.860	93.100
4 Apr 06, 2020	SA-Net on Albert (ensemble) *QIANXIN*	90.724	93.011
5 May 05, 2020	SA-Net-V2 (ensemble) *QIANXIN*	90.679	92.948
5 Apr 05, 2020	Retro-Reader (ensemble) *Shanghai Jiao Tong University* http://arxiv.org/abs/2001.09694	90.578	92.978
5 Feb 05, 2021	FPNet (ensemble) *YuYang*	90.600	92.899
6 Apr 18, 2021	TransNets + SFVerifier + SFEnsembler (ensemble) *Senseforth AI Research* https://www.senseforth.ai/	90.487	92.894
6 Dec 01, 2020	EntitySpanFocusV2 (ensemble) *RICOH_SRCB_DML*	90.521	92.824

ELMo, BERT, GPT



BERT의 성능 비교

	BERT	RoBERT	DistilBERT	XLNet
Size (millions)	**Base**: 110 **Large**: 340	**Base**: 110 **Large**: 340	**Base**: 66	**Base**: ~110 **Large**: ~340
Training Time	**Base**: 8 x V100 x 12 days* **Large**: 64 TPU Chips x 4 days (or 280 x V100 x 1 days*)	**Large**: 1024 x V100 x 1 day; 4-5 times more than BERT.	**Base**: 8 x V100 x 3.5 days; 4 times less than BERT.	**Large**: 512 TPU Chips x 2.5 days; 5 times more than BERT.
Performance	Outperforms state-of-the-art in Oct 2018	2-20% improvement over BERT	5% degradation from BERT	2-15% improvement over BERT
Data	16 GB BERT data (Books Corpus + Wikipedia). 3.3 Billion words.	160 GB (16 GB BERT data + 144 GB additional)	16 GB BERT data. 3.3 Billion words.	**Base**: 16 GB BERT data **Large**: 113 GB (16 GB BERT data + 97 GB additional). 33 Billion words.
Method	BERT (Bidirectional Transformer with MLM and NSP)	BERT without NSP**	BERT Distillation	Bidirectional Transformer with Permutation based modeling

Comparison of BERT and recent improvements over it

BERT vs XLNet

Model	MNLI	QNLI	QQP	RTE	SST-2	MRPC	CoLA	STS-B	WNLI
Single-task single models on dev									
BERT [2]	86.6/-	92.3	91.3	70.4	93.2	88.0	60.6	90.0	-
XLNet	**89.8/-**	**93.9**	**91.8**	**83.8**	**95.6**	**89.2**	**63.6**	**91.8**	-
Single-task single models on test									
BERT [10]	86.7/85.9	91.1	89.3	70.1	94.9	89.3	60.5	87.6	65.1
Multi-task ensembles on test (from leaderboard as of June 19, 2019)									
Snorkel* [29]	87.6/87.2	93.9	89.9	80.9	96.2	91.5	63.8	90.1	65.1
ALICE*	88.2/87.9	95.7	**90.7**	83.5	95.2	92.6	**68.6**	91.1	80.8
MT-DNN* [18]	87.9/87.4	96.0	89.9	**86.3**	96.5	92.7	68.4	91.1	89.0
XLNet*	**90.2/89.7**†	**98.6**†	90.3†	**86.3**	**96.8**†	**93.0**	67.8	**91.6**	**90.4**

Source: https://arxiv.org/abs/1906.08237

References

- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient Estimation of Word Representations in Vector Space. In Proceedings of Workshop at ICLR, 2013.
- Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. Distributed Representations of Words and Phrases and their Compositionality. In Proceedings of NIPS, 2013.
- Tomas Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic Regularities in Continuous Space Word Representations. In Proceedings of NAACL HLT, 2013.
- GloVe: Global Vectors for Word Representation
- XLNet: Generalized Autoregressive Pretraining for Language Understanding
- SQuAD -- https://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture10-QA.pdf
- GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding

정리

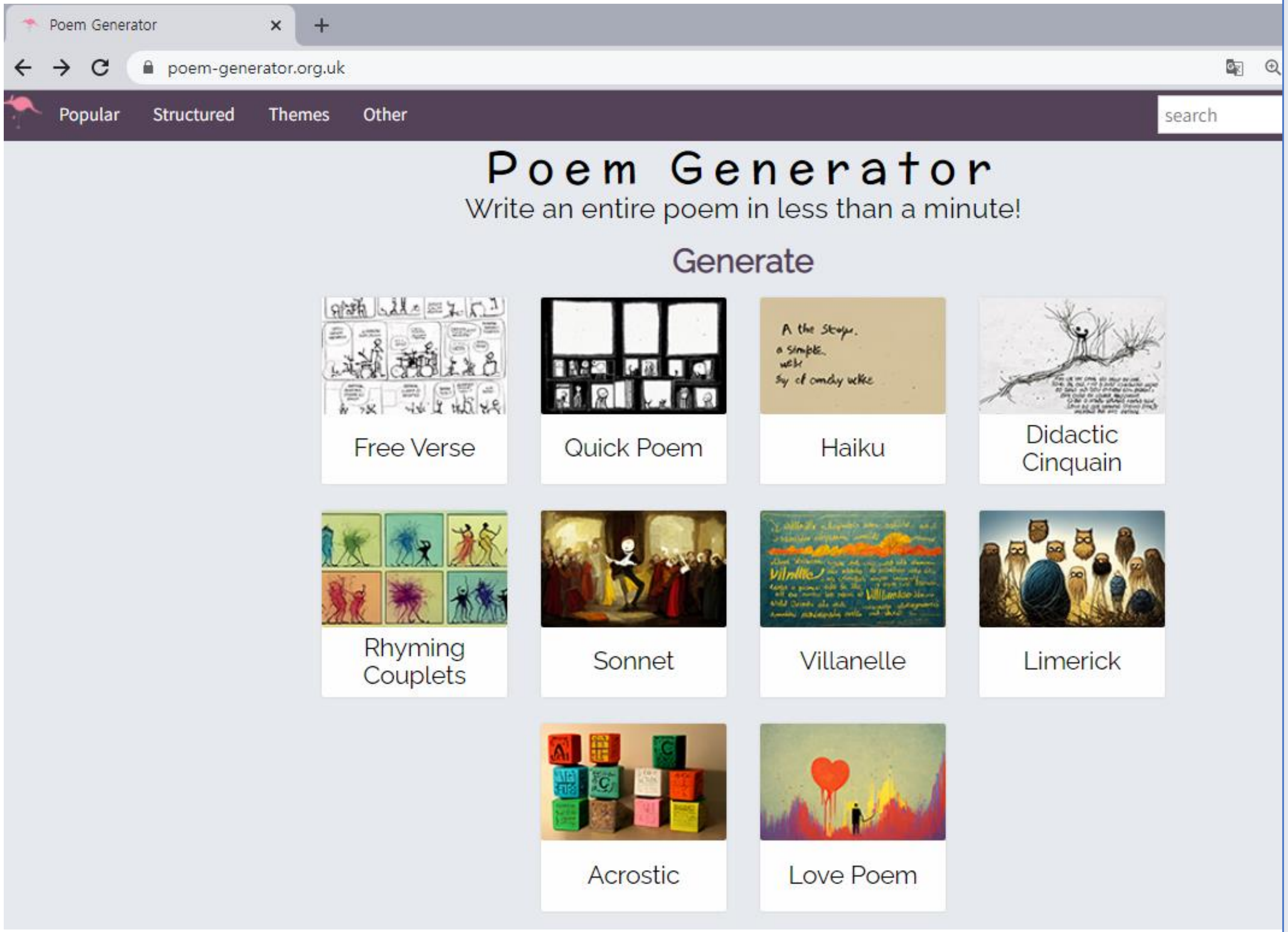
1. 워드 임베딩은 어떻게 활용되는가?

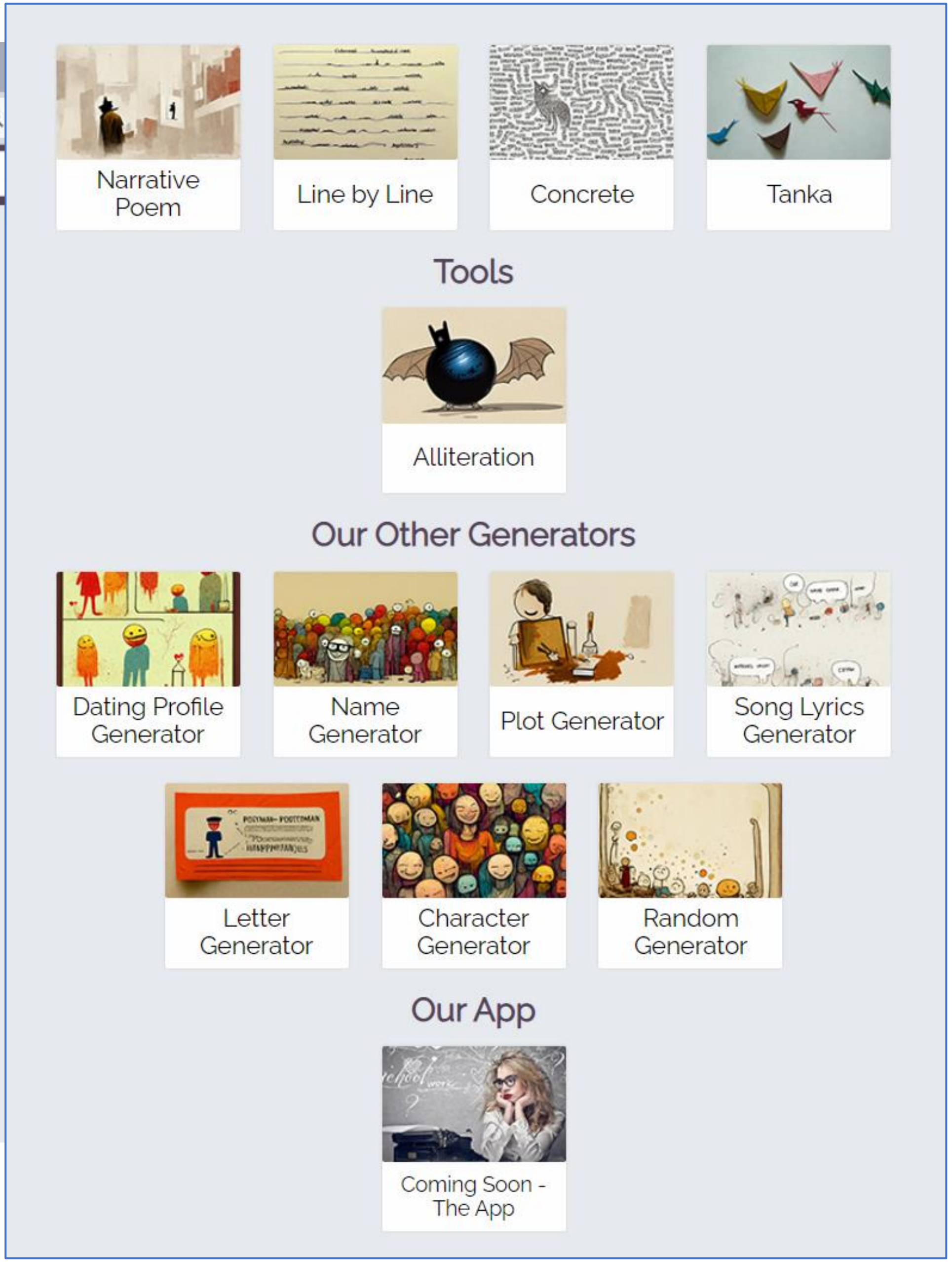
2. 형태소 분석(또는 품사 태깅)의 필요성은 무엇인가?

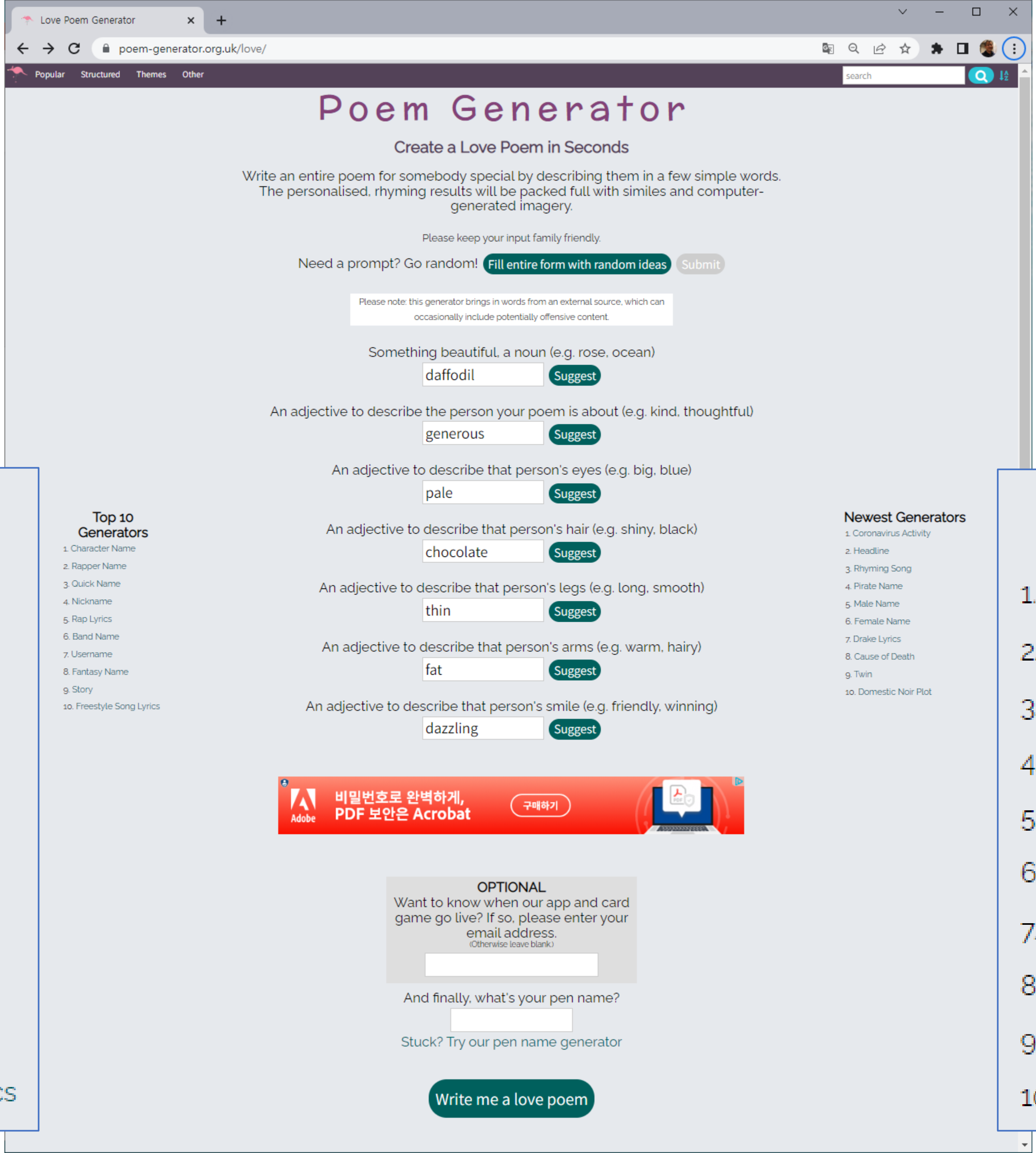
3. Subword 토크나이저의 필요성은 무엇인가?

4. BERT 모델의 특징 및 활용 분야는 무엇인가?

https://www.poem-generator.org.uk/







Top 10 Generators

1. Character Name
2. Rapper Name
3. Quick Name
4. Nickname
5. Rap Lyrics
6. Band Name
7. Username
8. Fantasy Name
9. Story
10. Freestyle Song Lyrics

Newest Generators

1. Coronavirus Activity
2. Headline
3. Rhyming Song
4. Pirate Name
5. Male Name
6. Female Name
7. Drake Lyrics
8. Cause of Death
9. Twin
10. Domestic Noir Plot