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Evaluation on Sentence Embeddings by Semantic Similarity

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Word Embedding vs Sentence Embedding

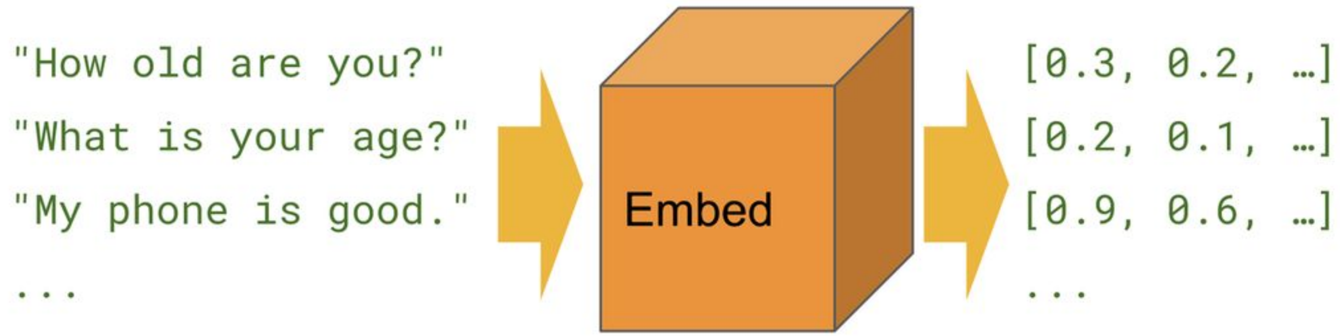
What is Word Embedding?

- Built vector representation to identify the semantic and syntaxes of the word, why?
- Calculate the distance to figure out if two data points are similar to each other or not
- Popular techniques are Word2Vec, GloVe, and etc.

Sentence Embedding

- Extension of Word Embedding
- Represents the entire sentences semantic information as vectors
- Allows the machine to understand the context, intension, and other nuances from the sentence

Sentence Embedding

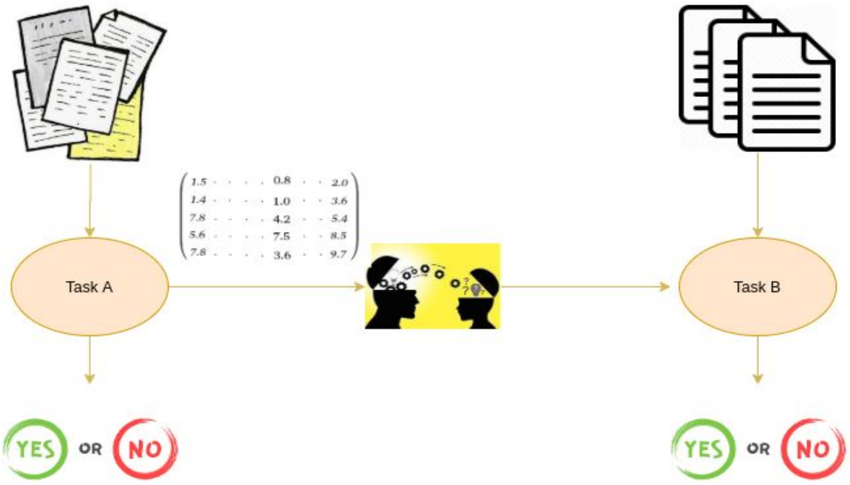


Objective

To compare the performance of different pre-trained models on calculating the semantic similarity score with the same input sentences

Transfer Learning and Pre-Trained Word Embeddings

- Pre-trained embedding is a form of transfer learning.
- It captures both the semantic and syntactic meaning when it is trained on large datasets.
- Time saving and accessible



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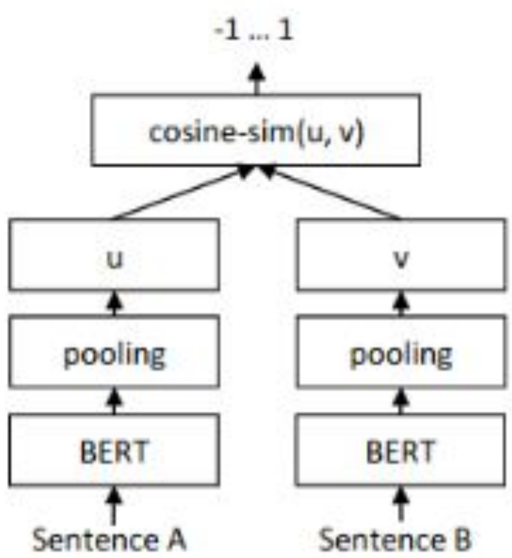
Pre-Trained Models

1. Sentence-BERT
2. Doc2Vec
3. Universal Sentence Encoder
    a. Transformer
    b. Deep Averaging Network (DAN)

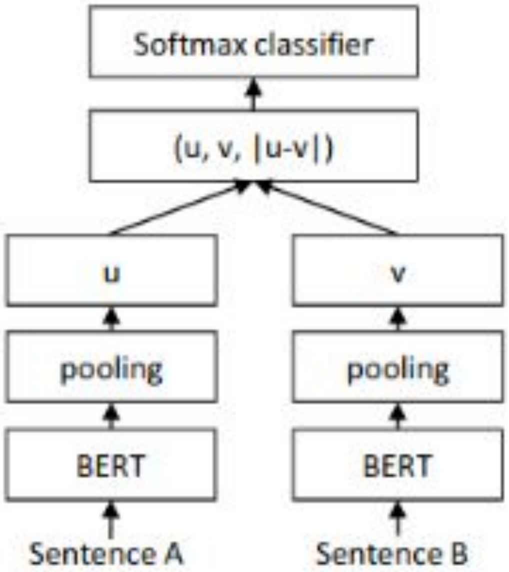
Sentence BERT

SentenceBERT

- Siamese network like architecture(build on minimal training data) with 2 sentence as an input
- regression or classification models



Sentence-BERT for sentence similarity(Regression Task)

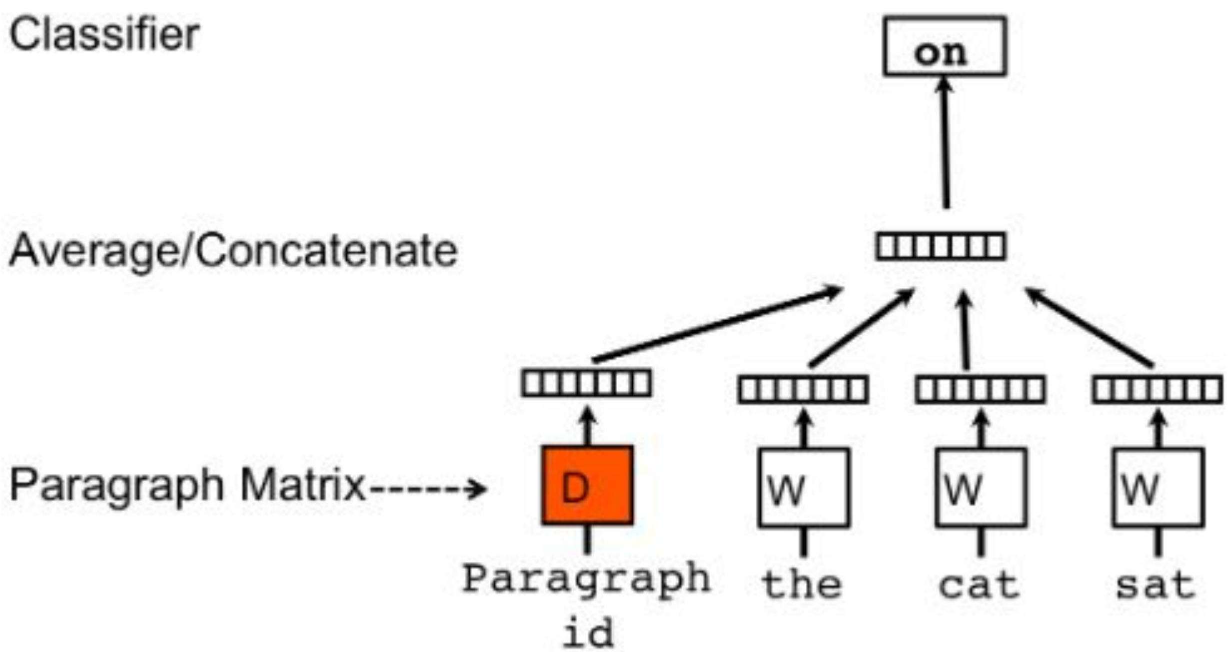


Sentence-BERT for Classification task

Doc2Vec

- Unsupervised learning approach to represent paragraph or sentence in vectors based off Word2Doc

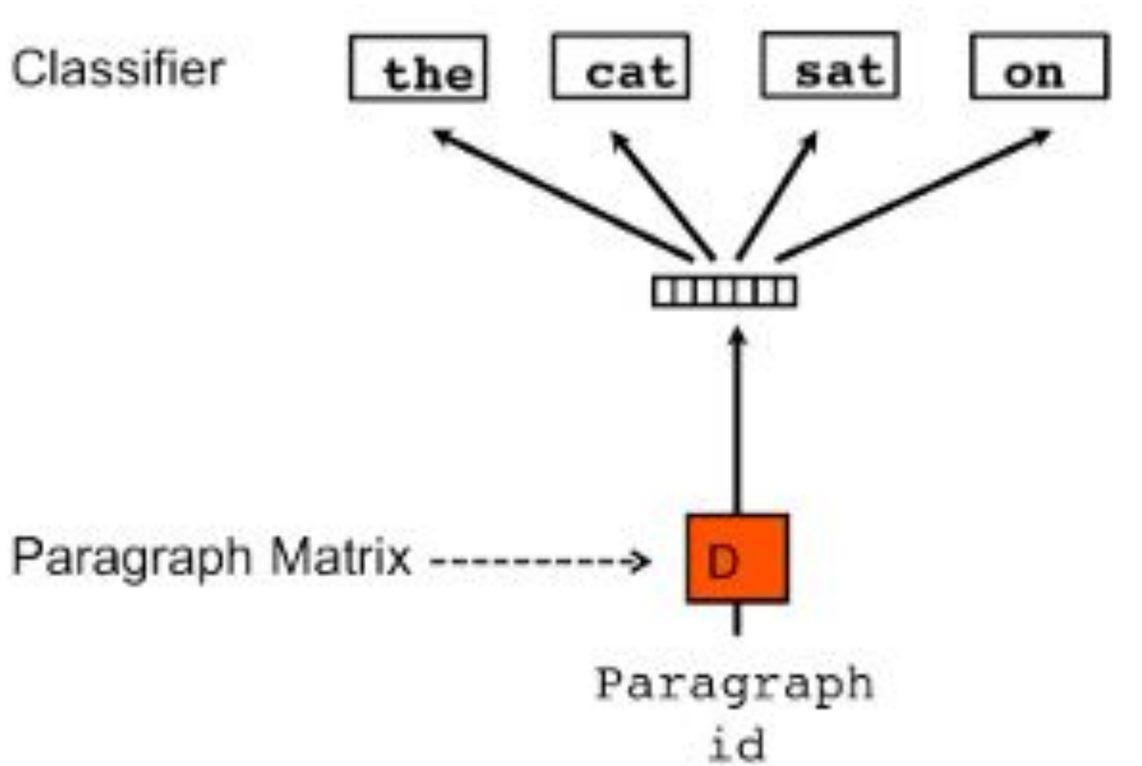
Distributed memory model(PVDM)



Doc2Vec

Distributed Bag of Words

- **extract features of a paragraph through optimization with sampled words**



Universal Sentence Encoder

- One of the most well-performing sentence embedding techniques
- Sentence gets converted to a 512-dimensional vector
- Feasible for multi-tasking
- Two types of model:
  - Transformer
  - Deep Averaging Network (DAN)

	Transformer model	Deep Averaging Network (DAN) model
Vector Length	512	512
Encoding time with sentence length	Non-Linear	Linear
Memory usage	High	Medium
Accuracy	Very High	High

Implementation Doc2Vec

```
# Install TF-Hub&libraries
!pip3 install --upgrade tensorflow-gpu
!pip3 install tensorflow-hub

import nltk
nltk.download('punkt')
from nltk.tokenize import word_tokenize
import numpy as np

#input
sentences = ["Did you watch the movie Glass?",
             "Be careful, I just broke a glass cup",
             "This window is made of glass.",
             "He doesn't usually wear glasses."]
```

```
from gensim.models.doc2vec import Doc2Vec, TaggedDocument
tagged_data = [TaggedDocument(d, [i]) for i, d in enumerate(tokenized_sent)]
tagged_data
```

```
[TaggedDocument(words=['did', 'you', 'watch', 'the', 'movie', 'glass', '?'], tags=[0]),
 TaggedDocument(words=['be', 'careful', ',', 'i', 'just', 'broke', 'a', 'glass', 'cup'], tags=[1]),
 TaggedDocument(words=['this', 'window', 'is', 'made', 'of', 'glass', '.'], tags=[2]),
 TaggedDocument(words=['he', 'does', "n't", 'usually', 'wear', 'glasses', '.'], tags=[3])]
```

```
test_doc = word_tokenize("This glass cup is fragile".lower())
test_doc_vector = model.infer_vector(test_doc)
model.docvecs.most_similar(positive = [test_doc_vector])
```

```
[(0, -0.05732543021440506),
 (2, -0.07792545855045319),
 (1, -0.10838853567838669),
 (3, -0.13605502247810364)]
```

Implementation Sentence-BERT

```
#load model
from sentence_transformers import SentenceTransformer
sbert_model = SentenceTransformer('bert-base-nli-mean-tokens')
```

```
#function that returns cosine similarity between the two vectors
def cosine(u, v):
    return np.dot(u, v) / (np.linalg.norm(u) * np.linalg.norm(v))
```

```
query = "This glass cup is fragile"
query_vec = sbert_model.encode([query])[0]
```

```
for sent in sentences:
  sim = cosine(query_vec, sbert_model.encode([sent])[0])
  print("Sentence = ", sent, "; similarity = ", sim)
```

```
Sentence =  Did you watch the movie Glass? ; similarity =  0.2366257
Sentence =  Be careful, I just broke a glass cup ; similarity =  0.46764034
Sentence =  This window is made of glass. ; similarity =  0.6351793
Sentence =  He doesn't usually wear glasses. ; similarity =  0.6418279
```

Implementation USE

```
module_url = "https://tfhub.dev/google/universal-sentence-encoder/4"
model = hub.load(module_url)

# For the first message
sentence_embeddings = model(messages)
query = "The bright spot in the sky at night is a star"
query_vec = model([query])[0]

random.seed(10)
for sent in messages:
  sim = cosine(query_vec, model([sent])[0])
  print("Sentence = ", sent, "; similarity = ", sim)
```

```
Sentence =  That person is a real rock star ; similarity =  0.18940803
Sentence =  I did not know the sun was a star ; similarity =  0.5535026
Sentence =  twinkle twinkle little star ; similarity =  0.4428834
Sentence =  please have this star shaped cake ; similarity =  0.2860058
```

```
# For the Second message
sentence_embeddings = model(messages1)
query = "This glass cup is fragile"
query_vec = model([query])[0]

random.seed(10)
for sent in messages1:
  sim = cosine(query_vec, model([sent])[0])
  print("Sentence = ", sent, "; similarity = ", sim)
```

```
Sentence =  Did you watch the movie Glass ; similarity =  0.3120871
Sentence =  Be careful, I just broke a glass cup ; similarity =  0.6632582
Sentence =  This window is made of glass ; similarity =  0.6765582
Sentence =  He does not usually wear glasses ; similarity =  0.1990158
```

```
USE_large = hub.load("https://tfhub.dev/google/universal-sentence-encoder-large/5")

# For the first message
random.seed(10)
query = "The bright spot in the sky at night is a star"
query_vec = USE_large([query])[0]

for sent in messages:
  sim = cosine(query_vec, USE_large([sent])[0])
  print("Sentence = ", sent, "; similarity = ", sim)
```

```
Sentence =  That person is a real rock star ; similarity =  0.2584718
Sentence =  I did not know the sun was a star ; similarity =  0.57124144
Sentence =  twinkle twinkle little star ; similarity =  0.37080938
Sentence =  please have this star shaped cake ; similarity =  0.22781506
```

```
# For the second message
random.seed(10)
query = "This glass cup is fragile"
query_vec = USE_large([query])[0]

for sent in messages1:
  sim = cosine(query_vec, USE_large([sent])[0])
  print("Sentence = ", sent, "; similarity = ", sim)
```

```
Sentence =  Did you watch the movie Glass ; similarity =  0.29692373
Sentence =  Be careful, I just broke a glass cup ; similarity =  0.5774079
Sentence =  This window is made of glass ; similarity =  0.6119121
Sentence =  He does not usually wear glasses ; similarity =  0.17812516
```

Results

"The bright spot in the sky at night is a star"

```
messages = [
    "That person is a real rock star",
    "I did not know the sun was a star",
    "twinkle twinkle little star",
    "please have this star shaped cake"
]
```

	Sentence 1	Sentence 2	Sentence 3	Sentence 4
Sentence-BERT	0.442	0.587	0.568	0.455
Doc2Vec	0.289	0.249	0.505	0.125
USE Transformer	0.189	0.554	0.443	0.286
USE DAN	0.258	0.571	0.371	0.228

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Results

"This glass cup is fragile"

```
messages1 = [
    "Did you watch the movie Glass",
    "Be careful, I just broke a glass cup",
    "This window is made of glass",
    "He does not usually wear glasses"
]
```

	Sentence 1	Sentence 2	Sentence 3	Sentence 4
Sentence-BERT	0.251	0.468	0.617	0.645
Doc2Vec	0.282	0.112	0.218	0.162
USE Transformer	0.312	0.663	0.677	0.199
USE DAN	0.297	0.577	0.612	0.178

Conclusion & Future Work

- Each model has its best performing text tasks, so better to choose model based on the task(e.g. semantic relatedness or sentiment analysis)
- There is a consensus between the two sub-models understand USE
- Doc2Vec model seems to have a different similarity scores comparing to other models
- USE seems to be most reliable models (among the three models) in presenting semantic similarity scores
- Discover more pre-trained models, like stsb-mpnet-base-v2 and stsb-roberta-base-v2 to compare the results

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