Tamkang University
淡江大學

文字探勘
(Text Mining)

文本表達特徵工程
(Feature Engineering for Text Representation)

1082TM05
MBA, BDABI, TKU (E3611) (8480) (Spring 2020)
Mon, 7, 8, 9 (14:10-17:00) (B206)

Chichang Jou
周清江
Associate Professor
副教授
cjou@mail.tku.edu.tw

Min-Yuh Day
戴敏育
Associate Professor
副教授
myday@mail.tku.edu.tw

Dept. of Information Management, Tamkang University
淡江大學 資訊管理學系

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2020/03/02	文字探勘課程介紹 (Course Orientation on Text Mining)
2	2020/03/09	文字探勘基礎：自然語言處理 (Foundations of Text Mining: Natural Language Processing; NLP)
3	2020/03/16	Python自然語言處理 (Python for Natural Language Processing)
4	2020/03/23	處理和理解文本 (Processing and Understanding Text)
5	2020/03/30	文本表達特徵工程 (Feature Engineering for Text Representation)
6	2020/04/06	人工智慧文本分析個案研究 I (Case Study on Artificial Intelligence for Text Analytics I)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
7	2020/04/13	文本分類 (Text Classification)
8	2020/04/20	文本摘要和主題模型 (Text Summarization and Topic Models)
9	2020/04/27	期中報告 (Midterm Project Report)
10	2020/05/04	文本相似度和分群 (Text Similarity and Clustering)
11	2020/05/11	語意分析和命名實體識別 (Semantic Analysis and Named Entity Recognition; NER)
12	2020/05/18	情感分析 (Sentiment Analysis)

課程大綱 (Syllabus)

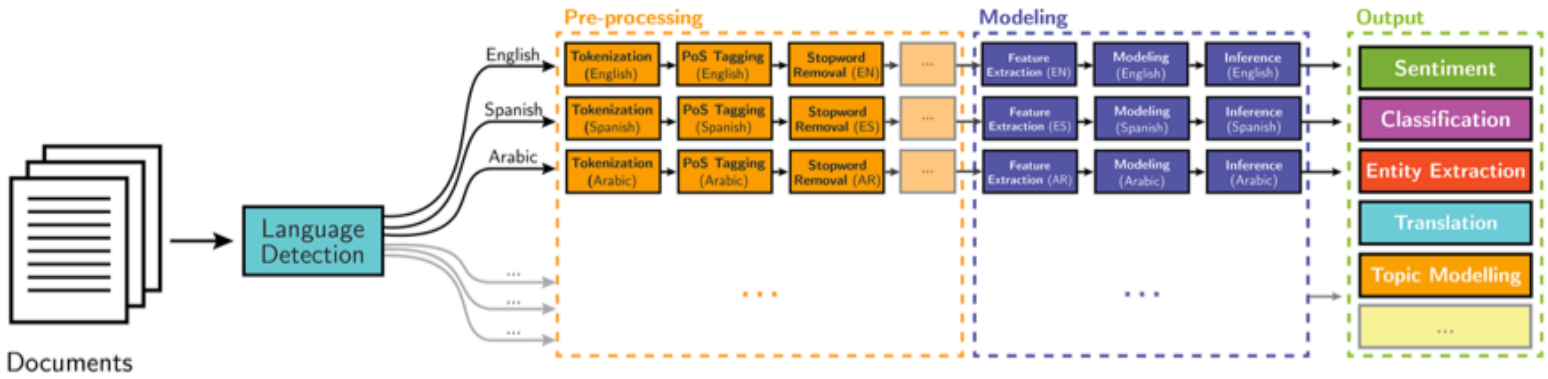
週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2020/05/25	人工智慧文本分析個案研究 II (Case Study on Artificial Intelligence for Text Analytics II)
14	2020/06/01	深度學習和通用句子嵌入模型 (Deep Learning and Universal Sentence-Embedding Models)
15	2020/06/08	問答系統與對話系統 (Question Answering and Dialogue Systems)
16	2020/06/15	期末報告 I (Final Project Presentation I)
17	2020/06/22	期末報告 II (Final Project Presentation II)
18	2020/06/29	教師彈性補充教學

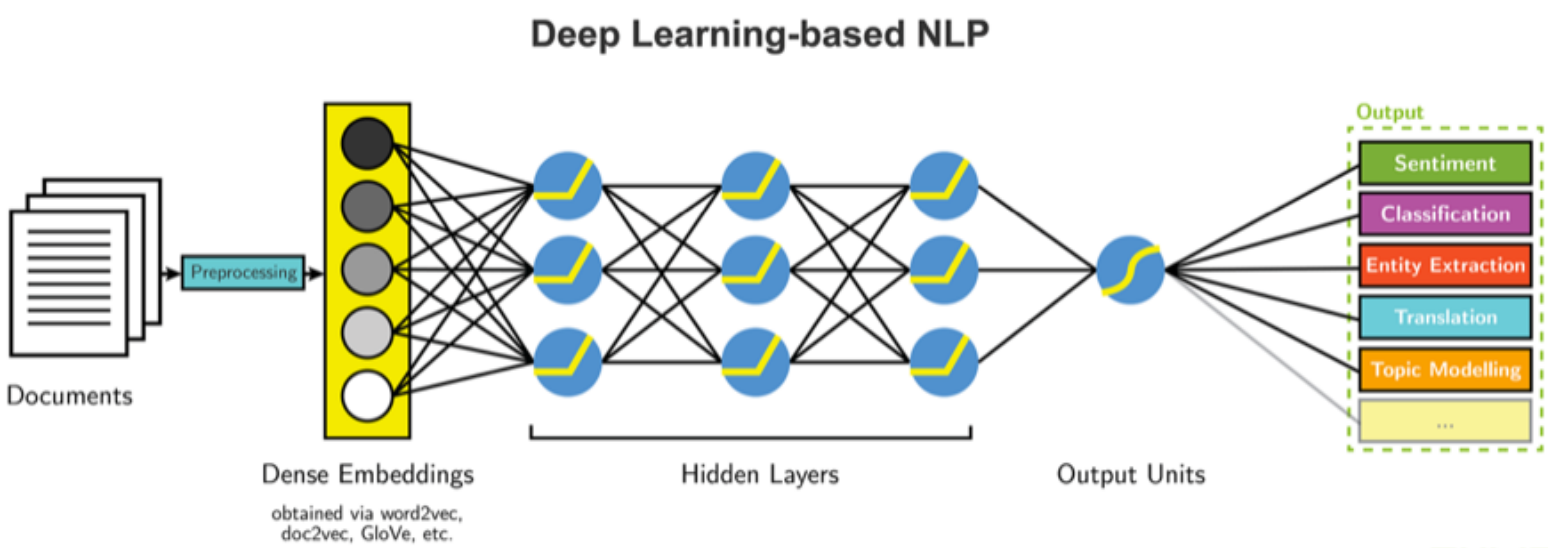
Outline

- Traditional Feature Engineering for Text Data
  - Bag of Words Model
  - Bag of N-Grams Model
  - TF-IDF Model
- Advanced Word Embeddings with Deep Learning
  - Word2Vec Model
  - Robust Word2Vec Models with Gensim
  - GloVe Model
  - FastText Model

Feature Engineering for Text Representation

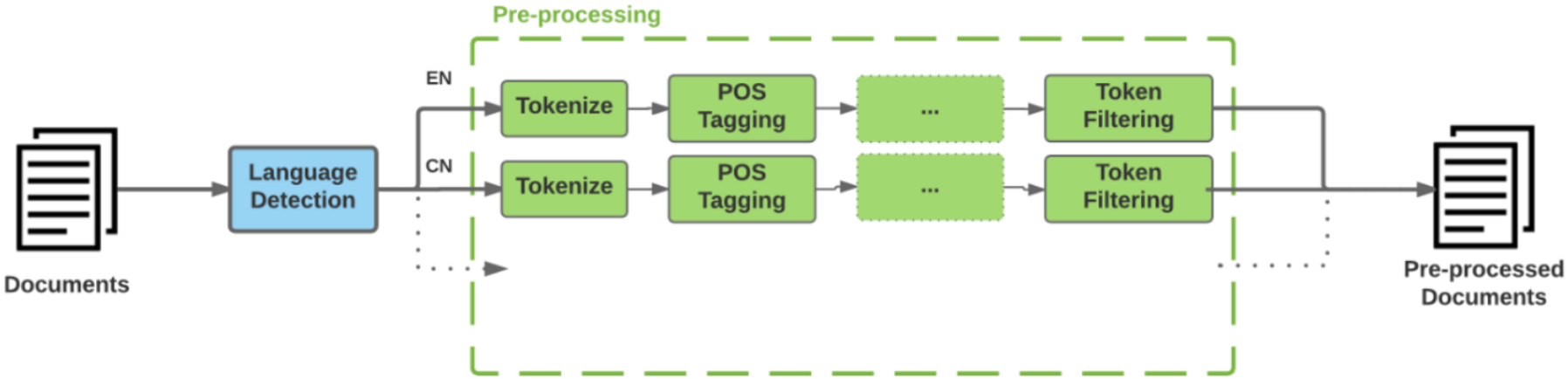
NLP

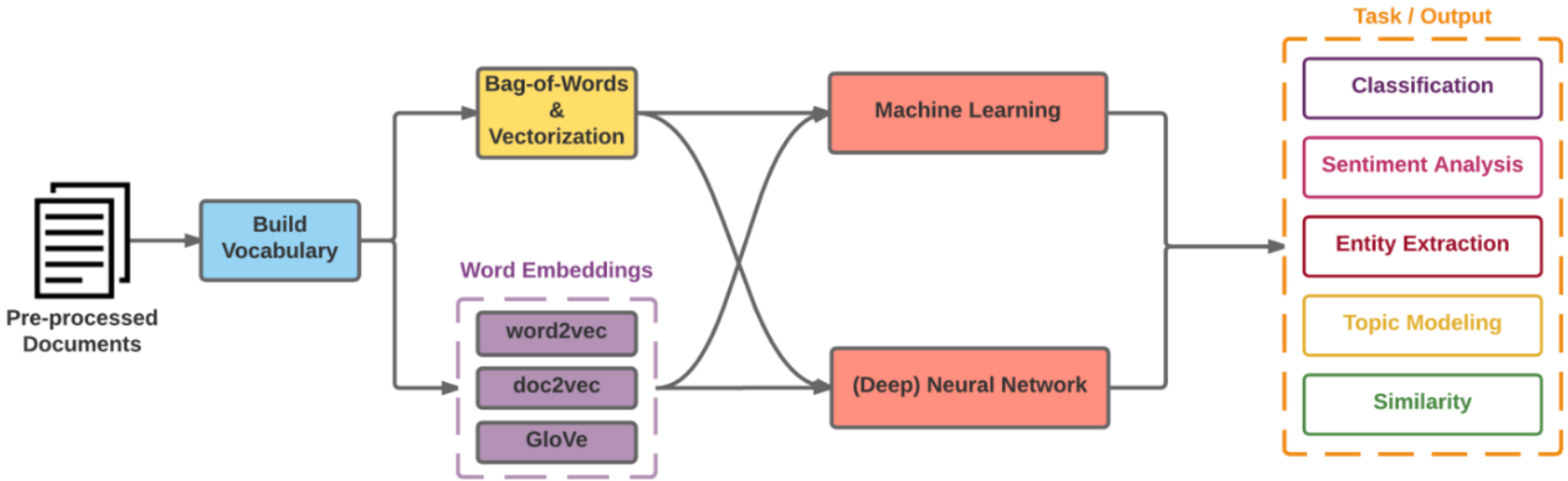




Source: http://blog.aylien.com/leveraging-deep-learning-for-multilingual/

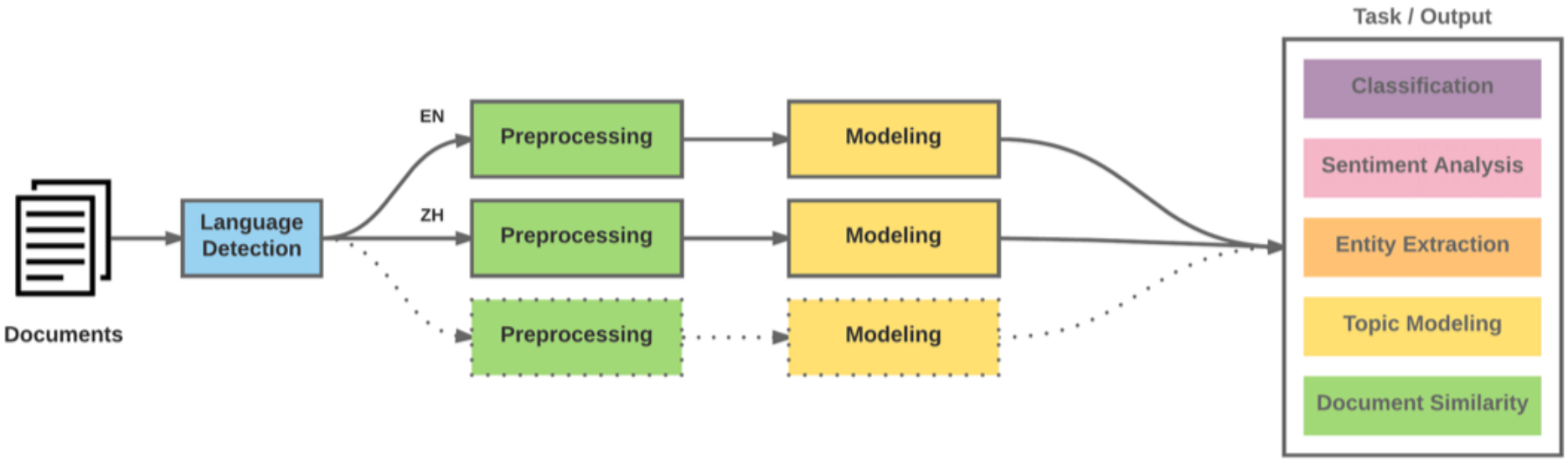
Modern NLP Pipeline





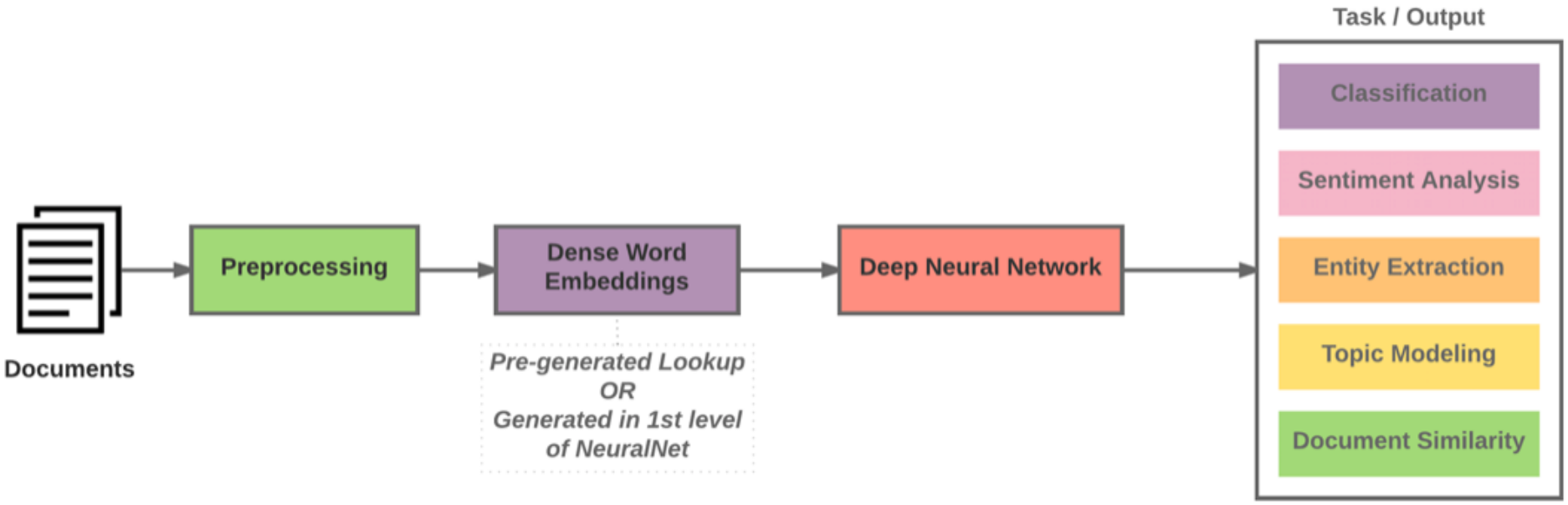
Source: https://github.com/fortiema/talks/blob/master/opendata2016sh/pragmatic-nlp-opendata2016sh.pdf

Modern NLP Pipeline



Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

Deep Learning NLP



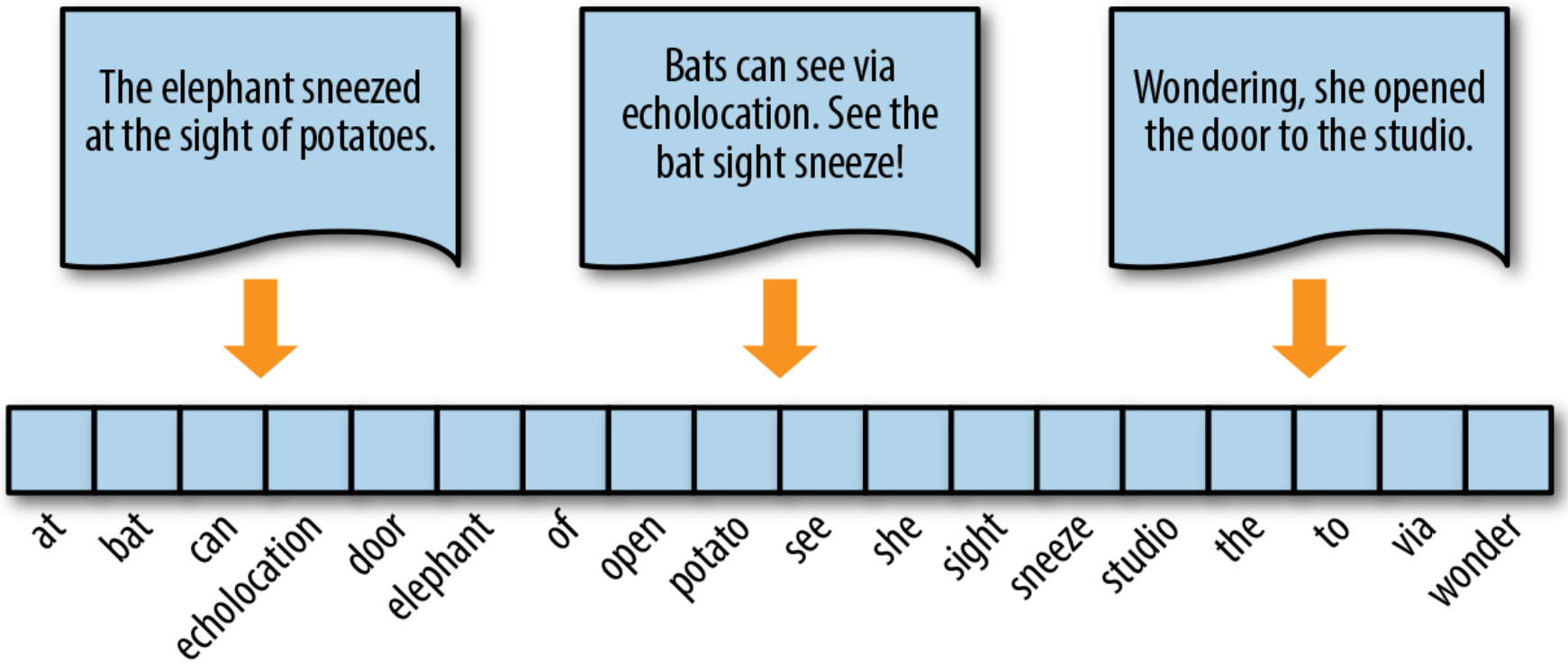
Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

Overview of Text Vectorization Methods

Vectorization Method	Function	Good For	Considerations
Frequency	Counts term frequencies	Bayesian models	Most frequent words not always most informative
One-Hot Encoding	Binarizes term occurrence (0, 1)	Neural networks	All words equidistant, so normalization extra important
TF–IDF	Normalizes term frequencies across documents	General purpose	Moderately frequent terms may not be representative of document topics
Distributed Representations	Context-based, continuous term similarity encoding	Modeling more complex relationships	Performance intensive; difficult to scale without additional tools (e.g., Tensorflow)

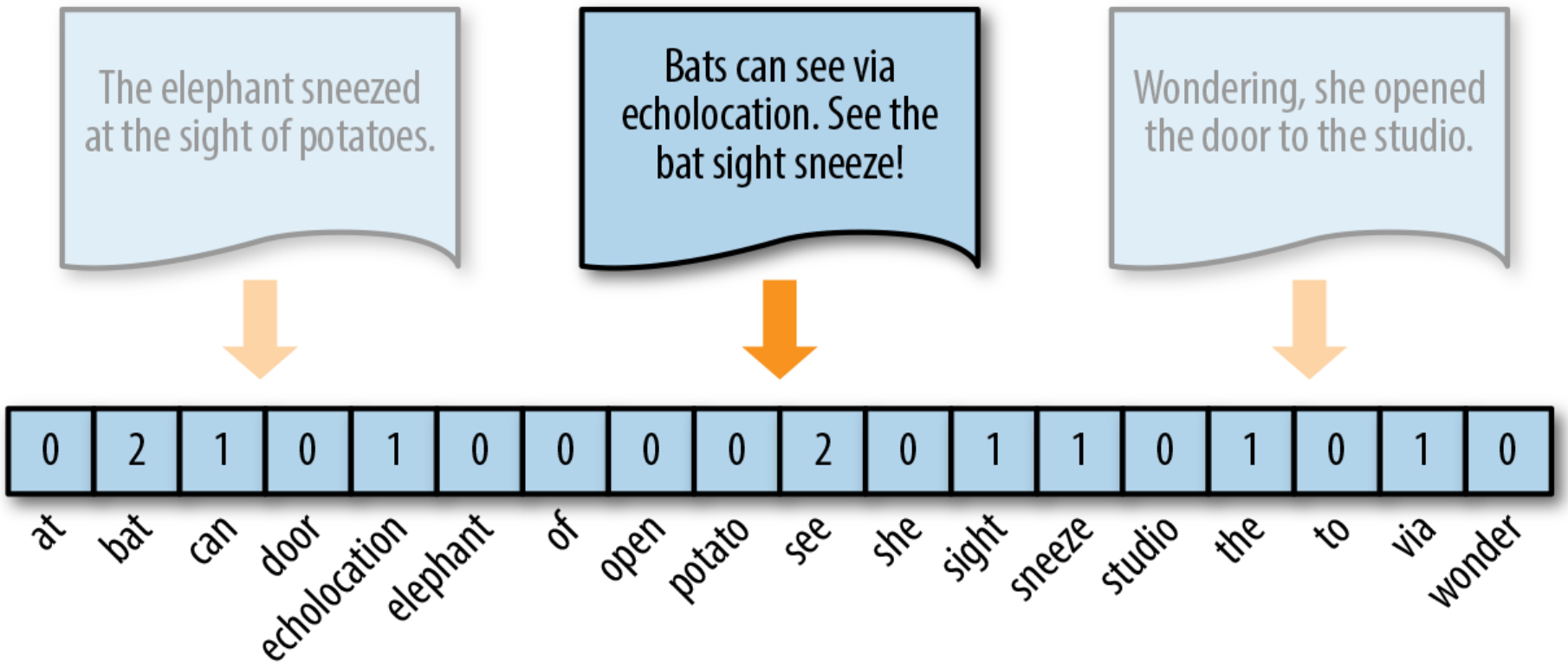
Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

Encoding Documents as Vectors

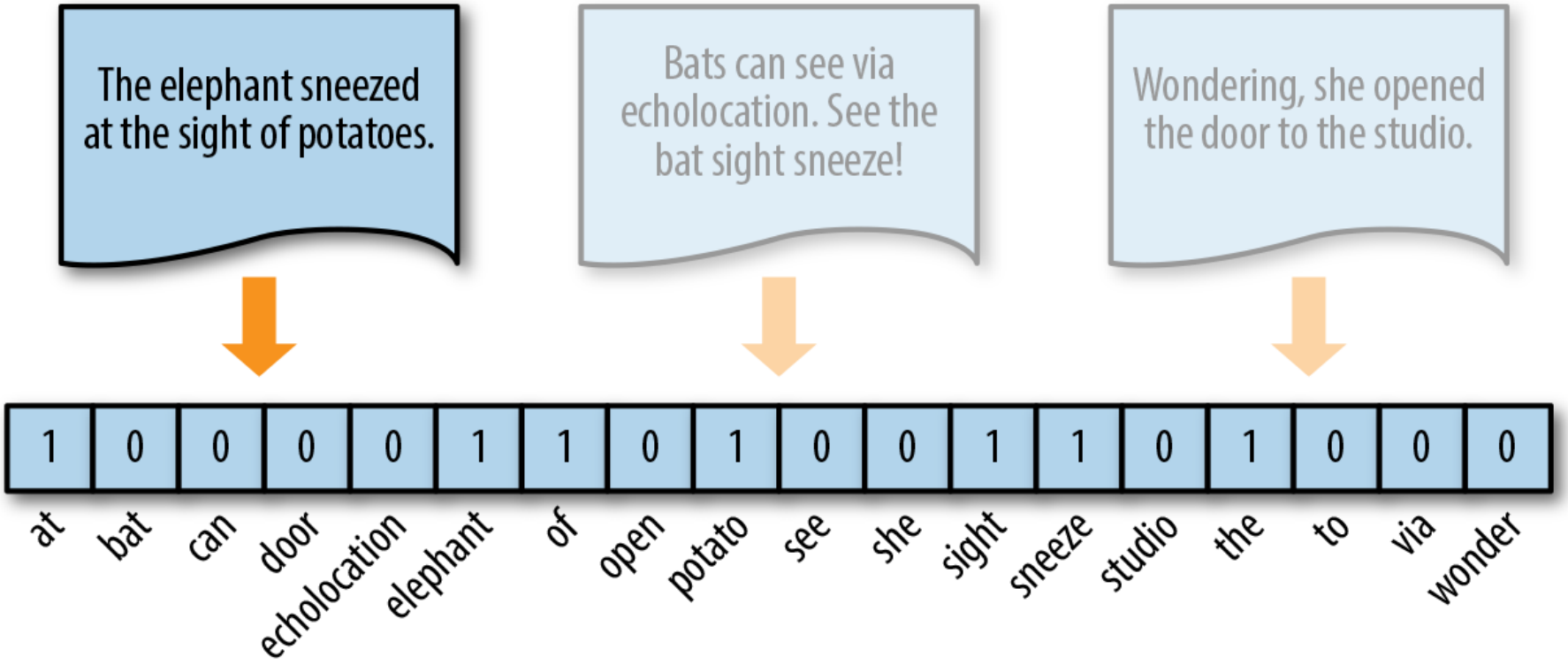


Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

Token Frequency as Vector Encoding

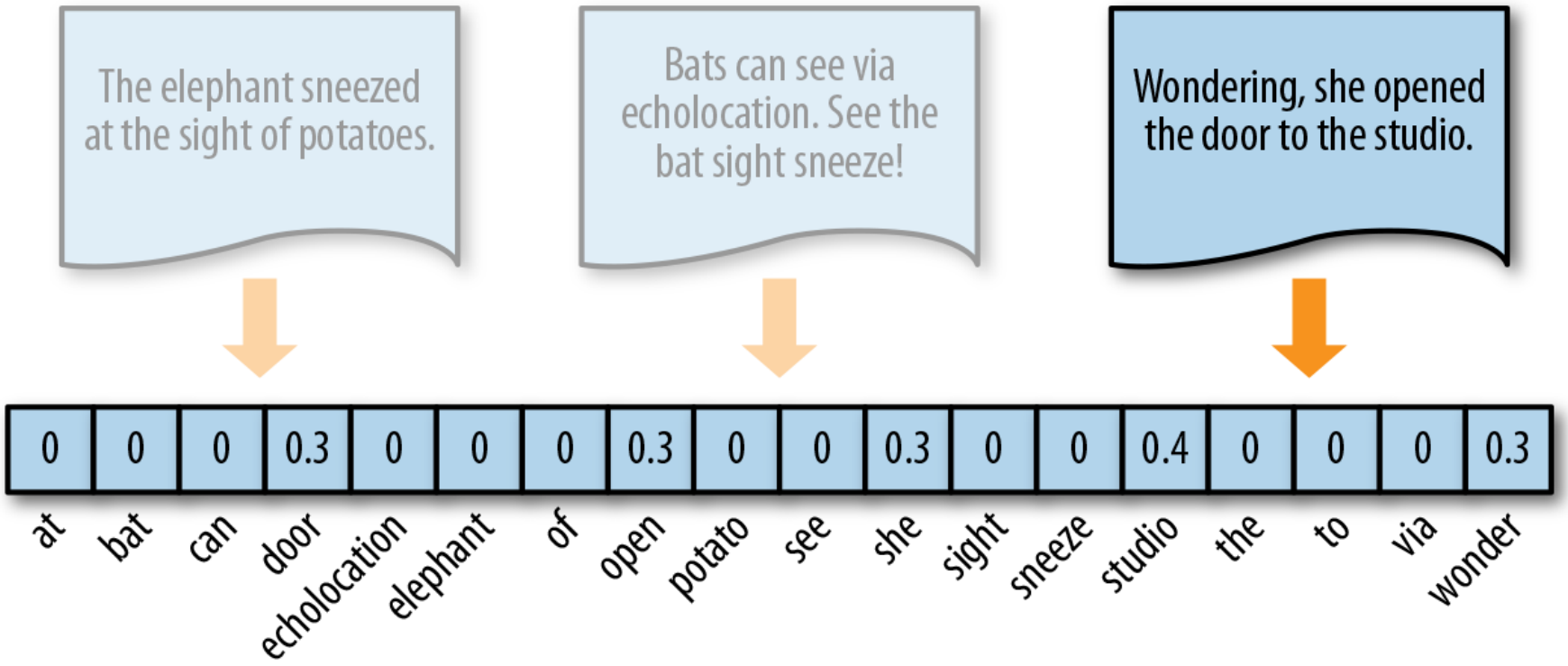


One-hot Encoding



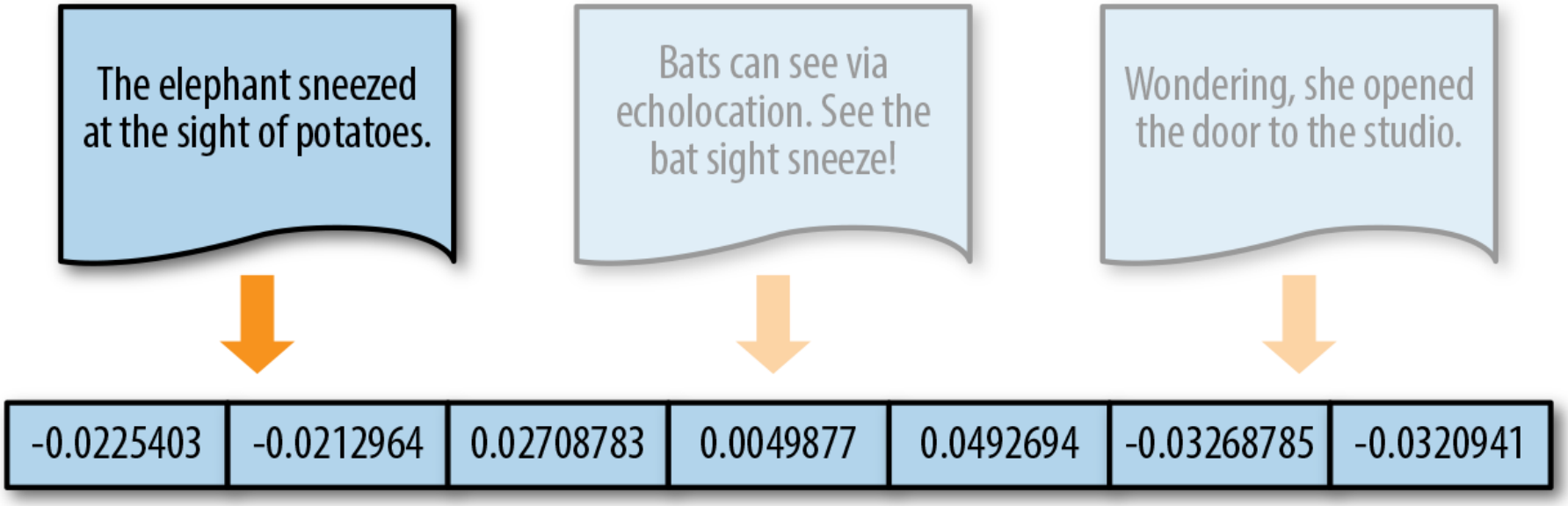
Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

TF-IDF Encoding



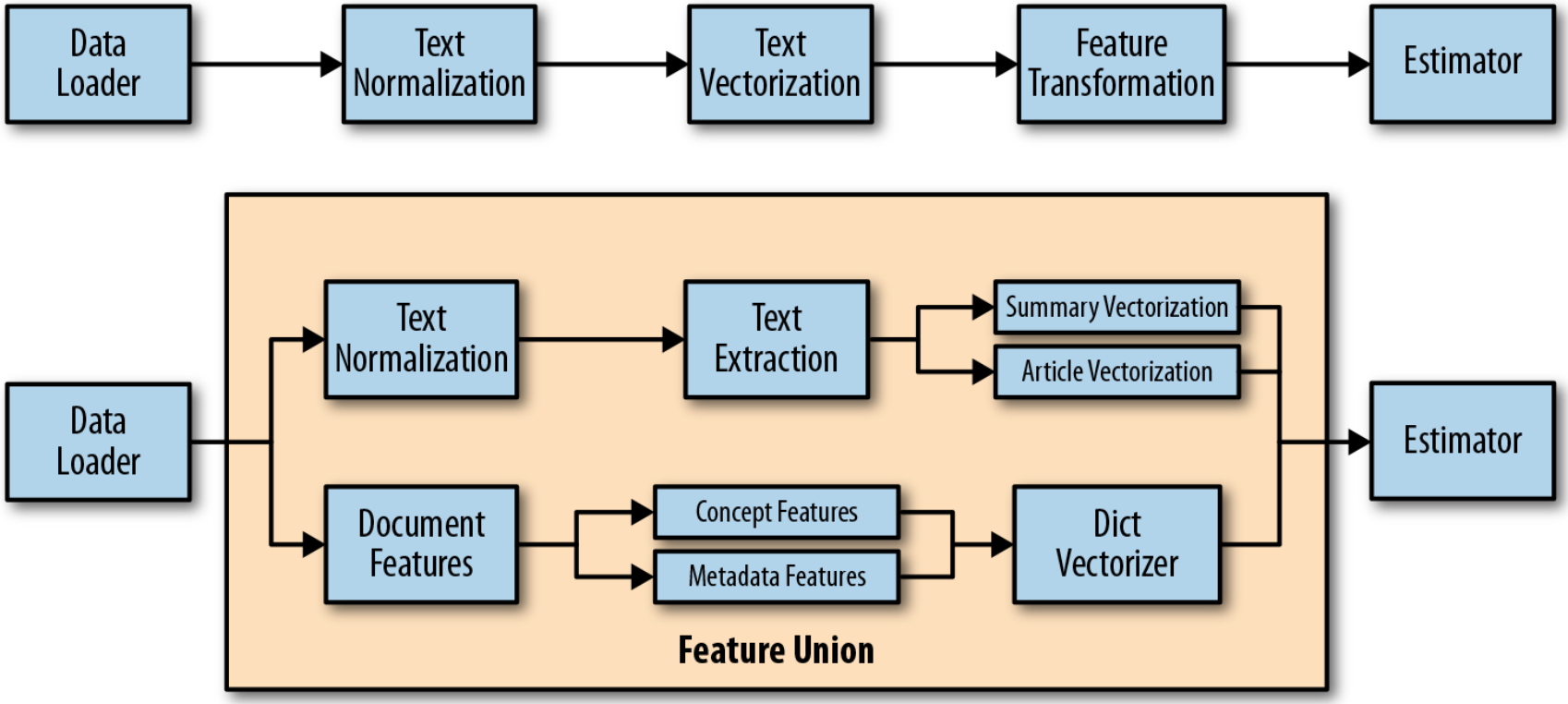
Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

Distributed Representation



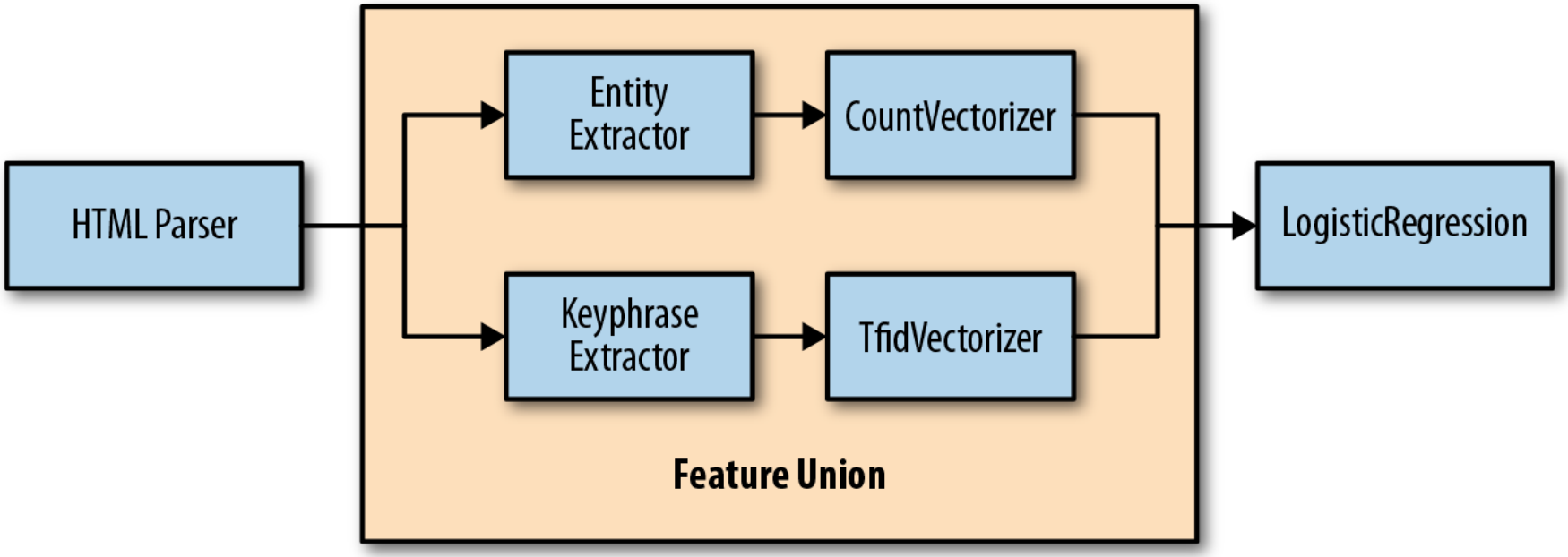
Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

Pipelines for Text Vectorization and Feature Extraction



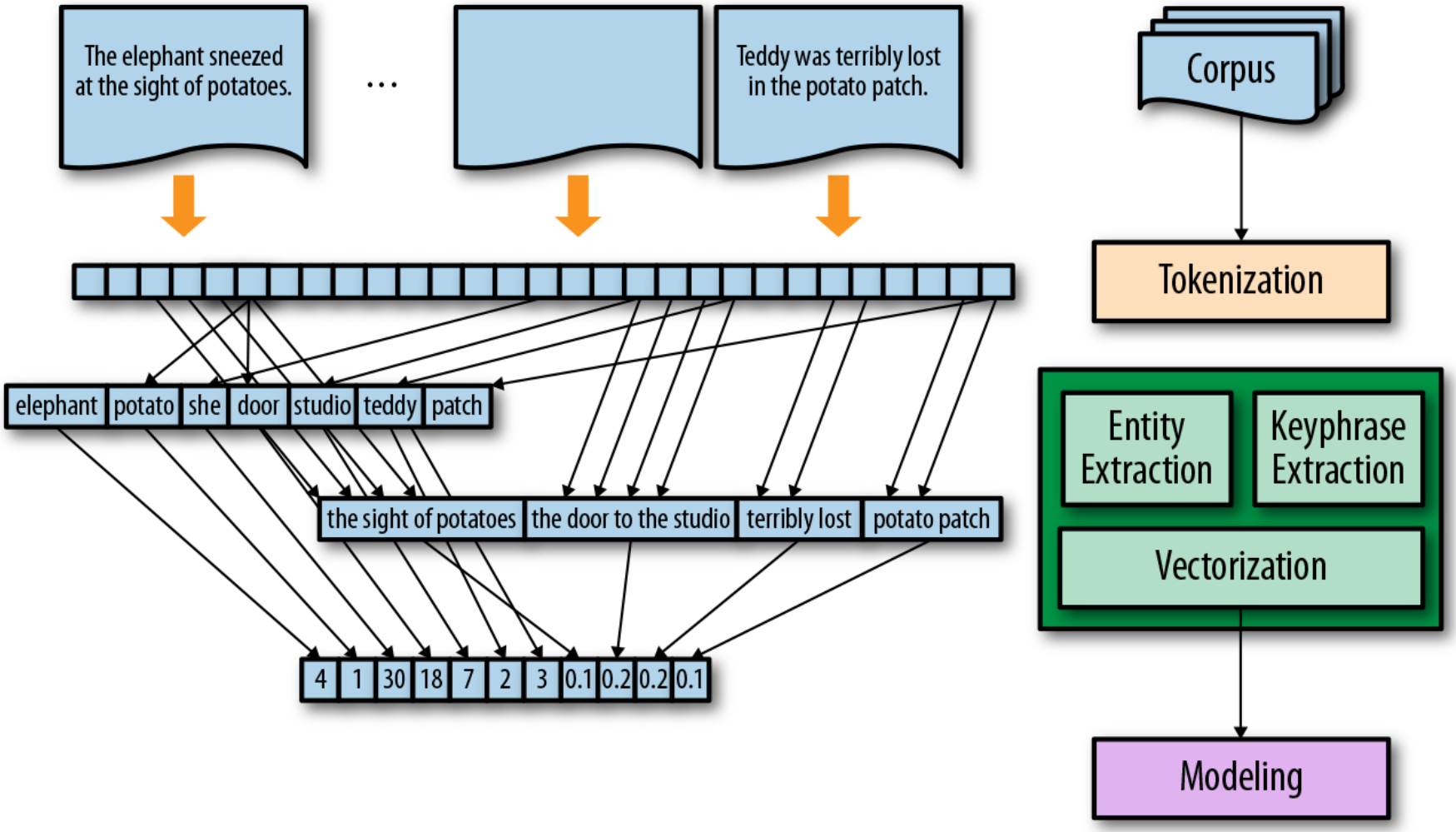
Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

Feature Unions for Branching Vectorization



Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

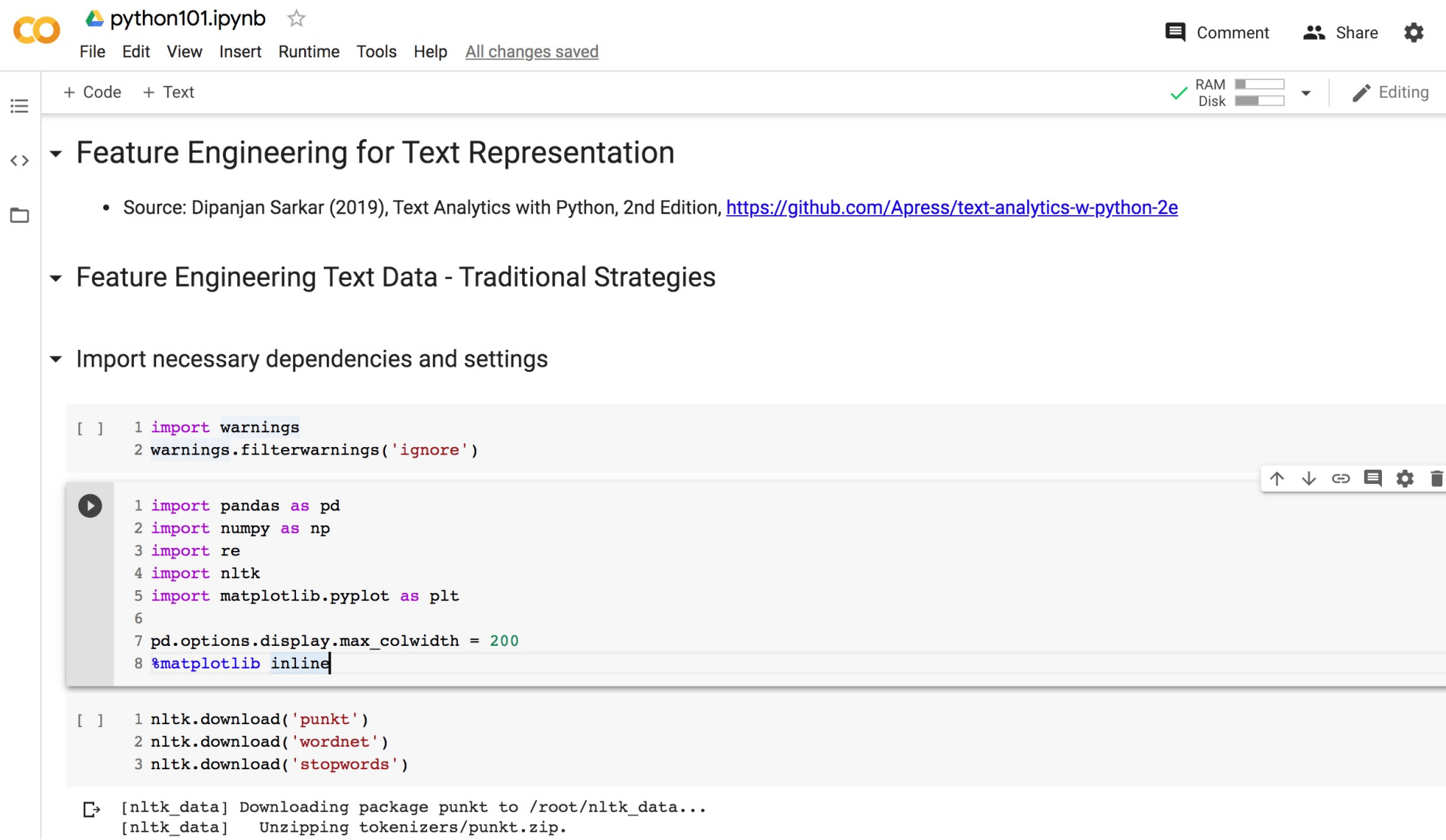
Feature Extraction and Union



Source: Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media.

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/imtkupython101

```
corpus = ['The sky is blue and beautiful.',
'Love this blue and beautiful sky!',
'The quick brown fox jumps over the lazy dog.',
"A king's breakfast has sausages, ham, bacon, eggs, toast and
beans",
'I love green eggs, ham, sausages and bacon!',
'The brown fox is quick and the blue dog is lazy!',
'The sky is very blue and the sky is very beautiful today',
'The dog is lazy but the brown fox is quick!'
]
labels = ['weather', 'weather', 'animals', 'food', 'food',
'animals', 'weather', 'animals']

corpus = np.array(corpus)
corpus_df = pd.DataFrame({'Document': corpus,
'Category': labels})
corpus_df = corpus_df[['Document', 'Category']]
corpus_df
```

https://tinyurl.com/imtkupython101

```
corpus = np.array(corpus)
corpus_df = pd.DataFrame({'Document': corpus,
'Category': labels})
corpus_df = corpus_df[['Document', 'Category']]
corpus_df
```

	Document	Category
0	The sky is blue and beautiful.	weather
1	Love this blue and beautiful sky!	weather
2	The quick brown fox jumps over the lazy dog.	animals
3	A king's breakfast has sausages, ham, bacon, eggs, toast and beans	food
4	I love green eggs, ham, sausages and bacon!	food
5	The brown fox is quick and the blue dog is lazy!	animals
6	The sky is very blue and the sky is very beautiful today	weather
7	The dog is lazy but the brown fox is quick!	animals

https://tinyurl.com/imtkupython101

```
wpt = nltk.WordPunctTokenizer()
stop_words = nltk.corpus.stopwords.words('english')

def normalize_document(doc):
# lower case and remove special characters\whitespaces
doc = re.sub(r'[^a-zA-Z\s]', '', doc, re.I|re.A)
doc = doc.lower()
doc = doc.strip()
# tokenize document
tokens = wpt.tokenize(doc)
# filter stopwords out of document
filtered_tokens = [token for token in tokens if token not in
stop_words]
# re-create document from filtered tokens
doc = ' '.join(filtered_tokens)
return doc

normalize_corpus = np.vectorize(normalize_document)
norm_corpus = normalize_corpus(corpus)
norm_corpus
```

https://tinyurl.com/imtkupython101

```
from sklearn.feature_extraction.text import CountVectorizer
# get bag of words features in sparse format
cv = CountVectorizer(min_df=0., max_df=1.)
cv_matrix = cv.fit_transform(norm_corpus)
cv_matrix
```

```
# view non-zero feature positions in the sparse matrix
print(cv_matrix)
```

```
# view dense representation
# warning might give a memory error if data is too big
cv_matrix = cv_matrix.toarray()
cv_matrix
```

```
array([
[0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0],
[0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0],
[0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0],
[1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0],
[1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0],
[0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0],
[0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 1],
[0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0]])
```

https://tinyurl.com/imtkupython101

```
# get all unique words in the corpus
vocab = cv.get_feature_names()
# show document feature vectors
pd.DataFrame(cv_matrix, columns=vocab)
```

```
1 # get all unique words in the corpus
2 vocab = cv.get_feature_names()
3 # show document feature vectors
4 pd.DataFrame(cv_matrix, columns=vocab)
```

	bacon	beans	beautiful	blue	breakfast	brown	dog	eggs	fox	green	ham	jumps	kings	lazy	love	quick	sausages	sky	toast	today
0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0
2	0	0	0	0	0	1	1	0	1	0	0	1	0	1	0	1	0	0	0	0
3	1	1	0	0	1	0	0	1	0	0	1	0	1	0	0	0	1	0	1	0
4	1	0	0	0	0	0	0	1	0	1	1	0	0	0	1	0	1	0	0	0
5	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0	1	0	0	0	0
6	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1
7	0	0	0	0	0	1	1	0	1	0	0	0	0	1	0	1	0	0	0	0

https://tinyurl.com/imtkupython101

```
# you can set the n-gram range to 1,2 to get unigrams as well as bigrams
bv = CountVectorizer(ngram_range=(2,2))
bv_matrix = bv.fit_transform(norm_corpus)

bv_matrix = bv_matrix.toarray()
vocab = bv.get_feature_names()
pd.DataFrame(bv_matrix, columns=vocab)
```

	bacon eggs	beautiful sky	beautiful today	blue beautiful	blue dog	blue sky	breakfast sausages	brown fox	dog lazy	eggs ham	eggs toast	fox jumps	fox quick	green eggs	ham bacon	ham sausages	jumps lazy	kings breakfast
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0
3	1	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	1
4	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0
5	0	0	0	0	1	0	0	1	1	0	0	0	1	0	0	0	0	0
6	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0

https://tinyurl.com/imtkupython101

```
from sklearn.feature_extraction.text import TfidfTransformer

tt = TfidfTransformer(norm='l2', use_idf=True, smooth_idf=True)
tt_matrix = tt.fit_transform(cv_matrix)

tt_matrix = tt_matrix.toarray()
vocab = cv.get_feature_names()
pd.DataFrame(np.round(tt_matrix, 2), columns=vocab)
```

	bacon	beans	beautiful	blue	breakfast	brown	dog	eggs	fox	green	ham	jumps	kings	lazy	love	quick	sausages	sky	toast	today
0	0.00	0.00	0.60	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.0
1	0.00	0.00	0.49	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.49	0.00	0.0
2	0.00	0.00	0.00	0.00	0.00	0.38	0.38	0.00	0.38	0.00	0.00	0.53	0.00	0.38	0.00	0.38	0.00	0.00	0.00	0.0
3	0.32	0.38	0.00	0.00	0.38	0.00	0.00	0.32	0.00	0.00	0.32	0.00	0.38	0.00	0.00	0.00	0.32	0.00	0.38	0.0
4	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.39	0.00	0.47	0.39	0.00	0.00	0.00	0.39	0.00	0.39	0.00	0.00	0.0
5	0.00	0.00	0.00	0.37	0.00	0.42	0.42	0.00	0.42	0.00	0.00	0.00	0.00	0.42	0.00	0.42	0.00	0.00	0.00	0.0
6	0.00	0.00	0.36	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.72	0.00	0.5
7	0.00	0.00	0.00	0.00	0.00	0.45	0.45	0.00	0.45	0.00	0.00	0.00	0.00	0.45	0.00	0.45	0.00	0.00	0.00	0.0

https://tinyurl.com/imtkupython101

```
from sklearn.feature_extraction.text import TfidfVectorizer

tv = TfidfVectorizer(min_df=0., max_df=1., norm='l2',
                     use_idf=True, smooth_idf=True)
tv_matrix = tv.fit_transform(norm_corpus)
tv_matrix = tv_matrix.toarray()

vocab = tv.get_feature_names()
pd.DataFrame(np.round(tv_matrix, 2), columns=vocab)
```

	bacon	beans	beautiful	blue	breakfast	brown	dog	eggs	fox	green	ham	jumps	kings	lazy	love	quick	sausages	sky	toast	today
0	0.00	0.00	0.60	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.0
1	0.00	0.00	0.49	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.49	0.00	0.0
2	0.00	0.00	0.00	0.00	0.00	0.38	0.38	0.00	0.38	0.00	0.00	0.53	0.00	0.38	0.00	0.38	0.00	0.00	0.00	0.0
3	0.32	0.38	0.00	0.00	0.38	0.00	0.00	0.32	0.00	0.00	0.32	0.00	0.38	0.00	0.00	0.00	0.32	0.00	0.38	0.0
4	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.39	0.00	0.47	0.39	0.00	0.00	0.00	0.39	0.00	0.39	0.00	0.00	0.0
5	0.00	0.00	0.00	0.37	0.00	0.42	0.42	0.00	0.42	0.00	0.00	0.00	0.00	0.42	0.00	0.42	0.00	0.00	0.00	0.0
6	0.00	0.00	0.36	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.72	0.00	0.5
7	0.00	0.00	0.00	0.00	0.00	0.45	0.45	0.00	0.45	0.00	0.00	0.00	0.00	0.45	0.00	0.45	0.00	0.00	0.00	0.0

https://tinyurl.com/imtkupython101

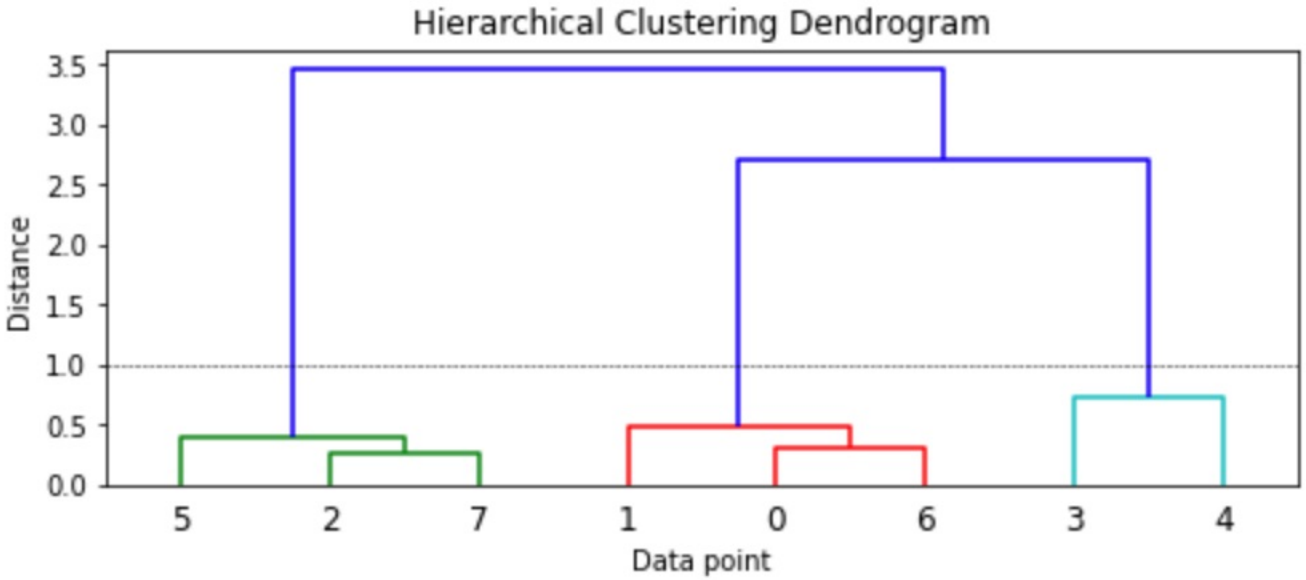
```
1 from scipy.cluster.hierarchy import dendrogram, linkage
2
3 Z = linkage(similarity_matrix, 'ward')
4 pd.DataFrame(Z, columns=['Document Cluster 1', 'Document Cluster 2',
5                          'Distance', 'Cluster Size'], dtype='object')
```

	Document Cluster 1	Document Cluster 2	Distance	Cluster Size
0	2	7	0.253098	2
1	0	6	0.308539	2
2	5	8	0.386952	3
3	1	9	0.489845	3
4	3	4	0.732945	2
5	11	12	2.69565	5
6	10	13	3.45108	8

https://tinyurl.com/imtkupython101

```
1 plt.figure(figsize=(8, 3))
2 plt.title('Hierarchical Clustering Dendrogram')
3 plt.xlabel('Data point')
4 plt.ylabel('Distance')
5 dendrogram(Z)
6 plt.axhline(y=1.0, c='k', ls='--', lw=0.5)
```

```
<matplotlib.lines.Line2D at 0x7ff7b5d793c8>
```



https://tinyurl.com/imtkupython101

```
1 from scipy.cluster.hierarchy import fcluster
2 max_dist = 1.0
3
4 cluster_labels = fcluster(Z, max_dist, criterion='distance')
5 cluster_labels = pd.DataFrame(cluster_labels, columns=['ClusterLabel'])
6 pd.concat([corpus_df, cluster_labels], axis=1)
```

	Document	Category	ClusterLabel
0	The sky is blue and beautiful.	weather	2
1	Love this blue and beautiful sky!	weather	2
2	The quick brown fox jumps over the lazy dog.	animals	1
3	A king's breakfast has sausages, ham, bacon, eggs, toast and beans	food	3
4	I love green eggs, ham, sausages and bacon!	food	3
5	The brown fox is quick and the blue dog is lazy!	animals	1
6	The sky is very blue and the sky is very beautiful today	weather	2
7	The dog is lazy but the brown fox is quick!	animals	1

https://tinyurl.com/imtkupython101

```
from sklearn.decomposition import LatentDirichletAllocation
lda = LatentDirichletAllocation(n_components=3, max_iter=10000, random_state=0)
#lda = LatentDirichletAllocation(n_topics=3, max_iter=10000, random_state=0)
dt_matrix = lda.fit_transform(cv_matrix)
features = pd.DataFrame(dt_matrix, columns=['T1', 'T2', 'T3'])
features
```

	T1	T2	T3
0	0.832191	0.083480	0.084329
1	0.863554	0.069100	0.067346
2	0.047794	0.047776	0.904430
3	0.037243	0.925559	0.037198
4	0.049121	0.903076	0.047802
5	0.054902	0.047778	0.897321
6	0.888287	0.055697	0.056016
7	0.055704	0.055689	0.888607

https://tinyurl.com/imtkupython101

```
1 tt_matrix = lda.components_
2 for topic_weights in tt_matrix:
3     topic = [(token, weight) for token, weight in zip(vocab, topic_weights)]
4     topic = sorted(topic, key=lambda x: -x[1])
5     topic = [item for item in topic if item[1] > 0.6]
6     print(topic)
7     print()
```

```
[('sky', 4.332439442470133), ('blue', 3.373774254787669), ('beautiful', 3.3323650509884386), ('today', 1.3325579855138987), ('love

[('bacon', 2.33269586574902), ('eggs', 2.33269586574902), ('ham', 2.33269586574902), ('sausages', 2.33269586574902), ('love', 1.33

[('brown', 3.3323473548404405), ('dog', 3.3323473548404405), ('fox', 3.3323473548404405), ('lazy', 3.3323473548404405), ('quick',
```

https://tinyurl.com/imtkupython101

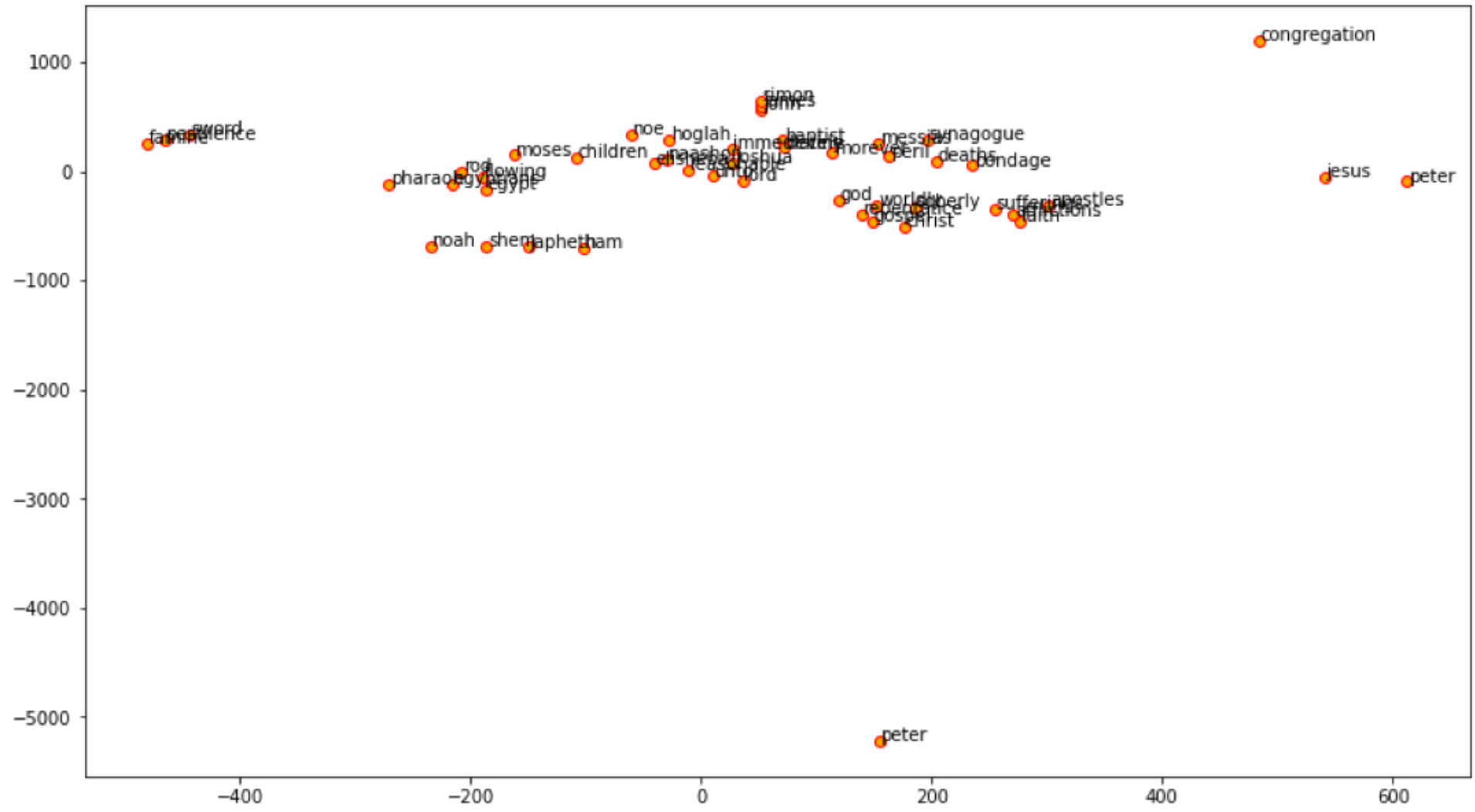
```
from sklearn.cluster import KMeans

km = KMeans(n_clusters=3, random_state=0)
km.fit_transform(features)
cluster_labels = km.labels_
cluster_labels = pd.DataFrame(cluster_labels, columns=['ClusterLabel'])
pd.concat([corpus_df, cluster_labels], axis=1)
```

	Document	Category	ClusterLabel
0	The sky is blue and beautiful.	weather	1
1	Love this blue and beautiful sky!	weather	1
2	The quick brown fox jumps over the lazy dog.	animals	2
3	A king's breakfast has sausages, ham, bacon, eggs, toast and beans	food	0
4	I love green eggs, ham, sausages and bacon!	food	0
5	The brown fox is quick and the blue dog is lazy!	animals	2
6	The sky is very blue and the sky is very beautiful today	weather	1
7	The dog is lazy but the brown fox is quick!	animals	2

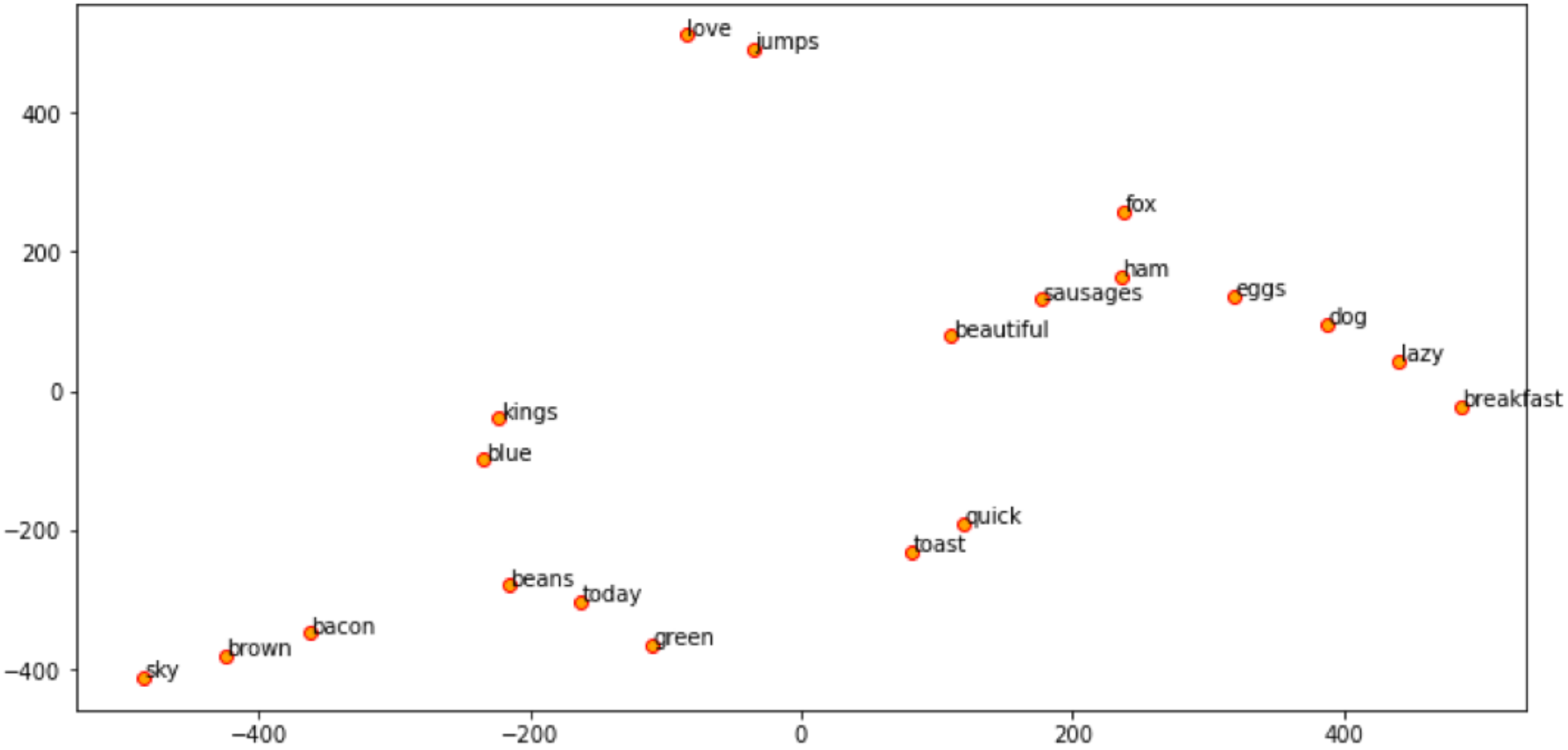
https://tinyurl.com/imtkupython101

```
from gensim.models import word2vec

# tokenize sentences in corpus
wpt = nltk.WordPunctTokenizer()
tokenized_corpus = [wpt.tokenize(document) for document in norm_bible]

# Set values for various parameters
feature_size = 100 # Word vector dimensionality
window_context = 30 # Context window size
min_word_count = 1 # Minimum word count
sample = 1e-3 # Downsample setting for frequent words

w2v_model = word2vec.Word2Vec(tokenized_corpus, size=feature_size,
window=window_context, min_count=min_word_count,
sample=sample, iter=50)

# view similar words based on gensim's model
similar_words = {search_term: [item[0] for item in
w2v_model.wv.most_similar([search_term], topn=5)]
for search_term in ['god', 'jesus', 'noah', 'egypt', 'john', 'gospel',
'moses','famine']}
similar_words
```

https://tinyurl.com/imtkupython101



https://tinyurl.com/imtkupython101



https://tinyurl.com/imtkupython101

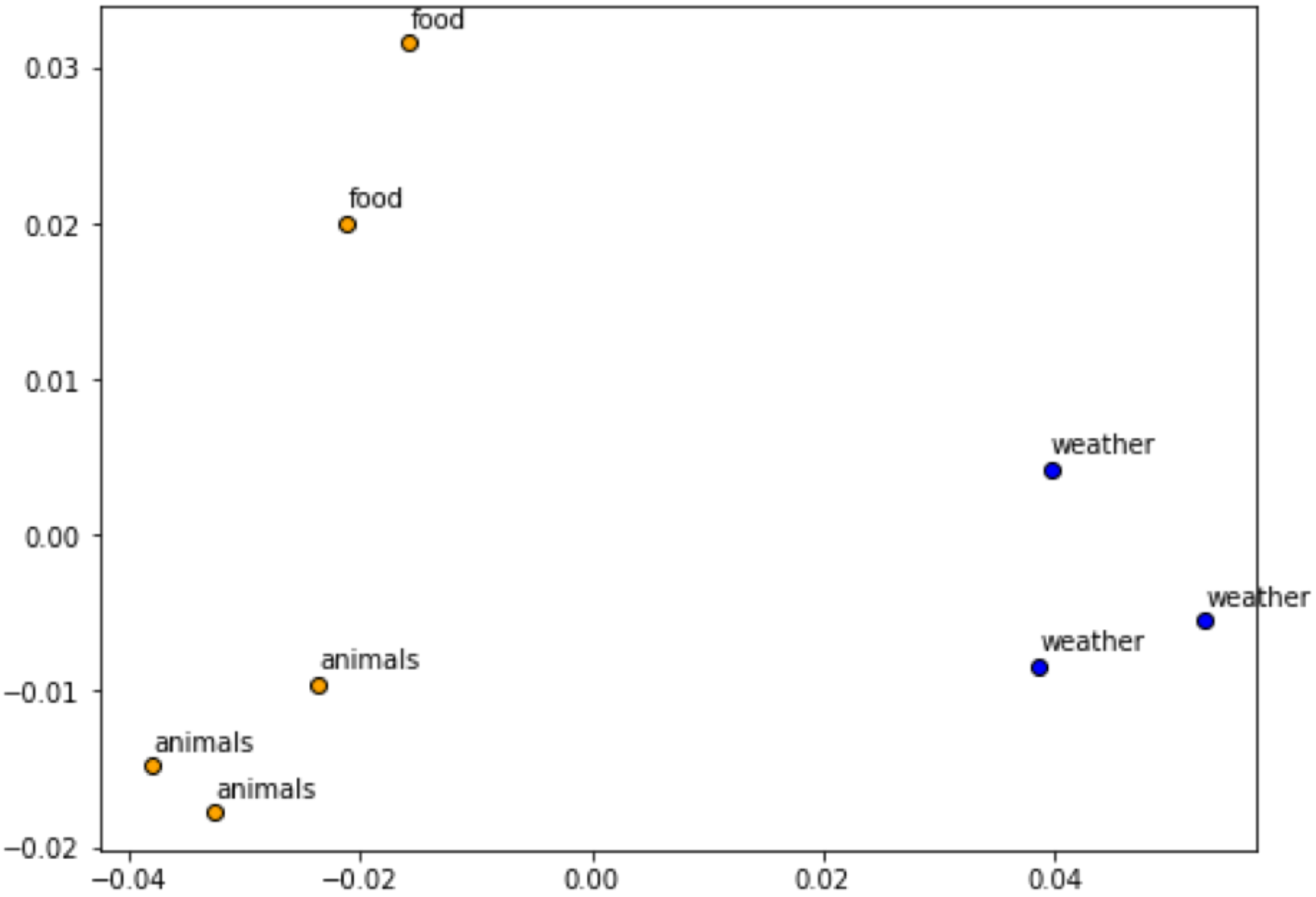
```
w2v_model.wv.most_similar([search_term], topn=5)]
```

```
{'egypt': ['egyptians', 'pharaoh', 'bondage', 'flowing',
'rod'], 'famine': ['pestilence', 'peril', 'deaths',
'morever', 'sword'], 'god': ['lord', 'worldly', 'soberly',
'reasonable', 'unto'], 'gospel': ['christ', 'faith',
'repentance', 'sufferings', 'afflictions'], 'jesus':
['peter', 'messias', 'immediately', 'apostles',
'synagogue'], 'john': ['james', 'baptist', 'devine',
'peter', 'simon'], 'moses': ['congregation', 'elisheba',
'naashon', 'joshua', 'children'], 'noah': ['shem',
'japheth', 'ham', 'noe', 'hoglah']}
```

https://tinyurl.com/imtkupython101

```
from sklearn.decomposition import PCA

pca = PCA(n_components=2, random_state=0)
pcs = pca.fit_transform(w2v_feature_array)
labels = ap.labels_
categories = list(corpus_df['Category'])
plt.figure(figsize=(8, 6))

for i in range(len(labels)):
label = labels[i]
color = 'orange' if label == 0 else 'blue' if label == 1
else 'green'
annotation_label = categories[i]
x, y = pcs[i]
plt.scatter(x, y, c=color, edgecolors='k')
plt.annotate(annotation_label, xy=(x+1e-4, y+1e-3),
xytext=(0, 0), textcoords='offset points')
```

https://tinyurl.com/imtkupython101



https://tinyurl.com/imtkupython101

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

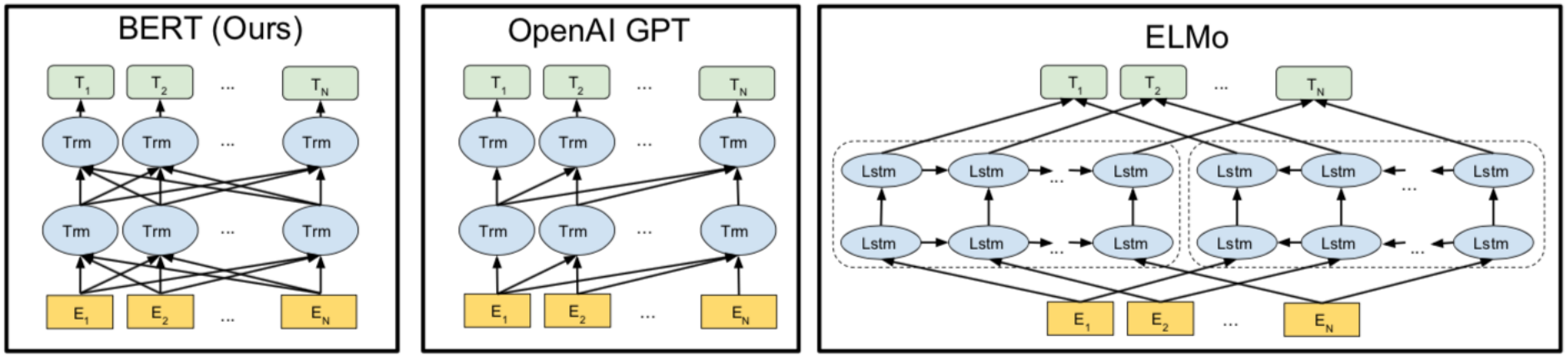
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT

Bidirectional Encoder Representations from Transformers

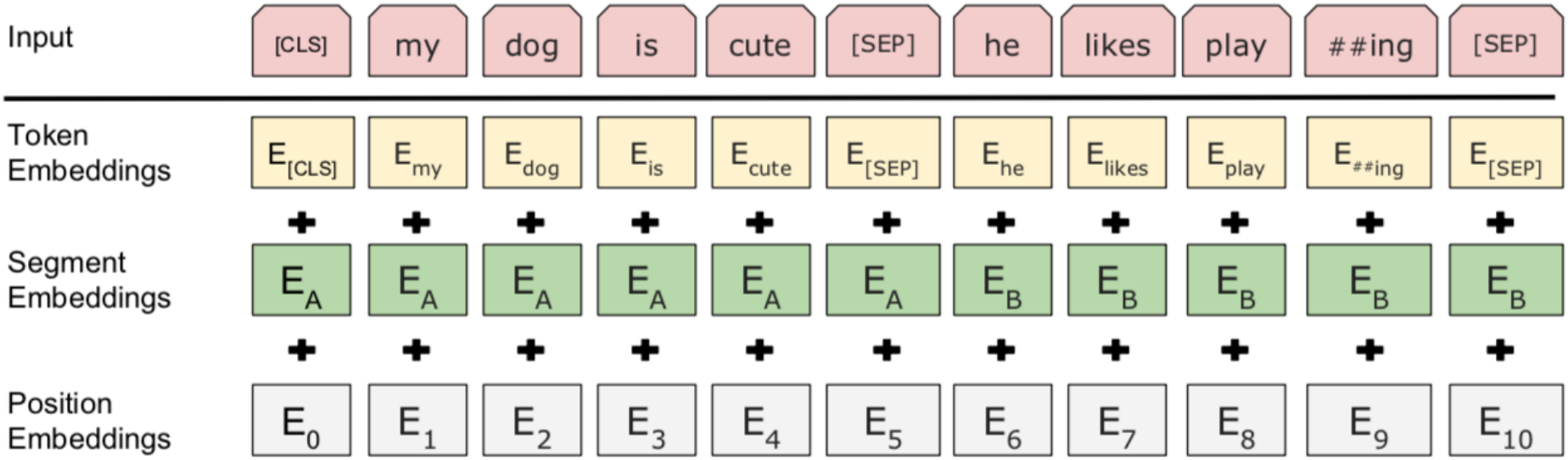


Pre-training model architectures

BERT uses a bidirectional Transformer.
OpenAI GPT uses a left-to-right Transformer.
ELMo uses the concatenation of independently trained left-to-right and right- to-left LSTM to generate features for downstream tasks.
Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

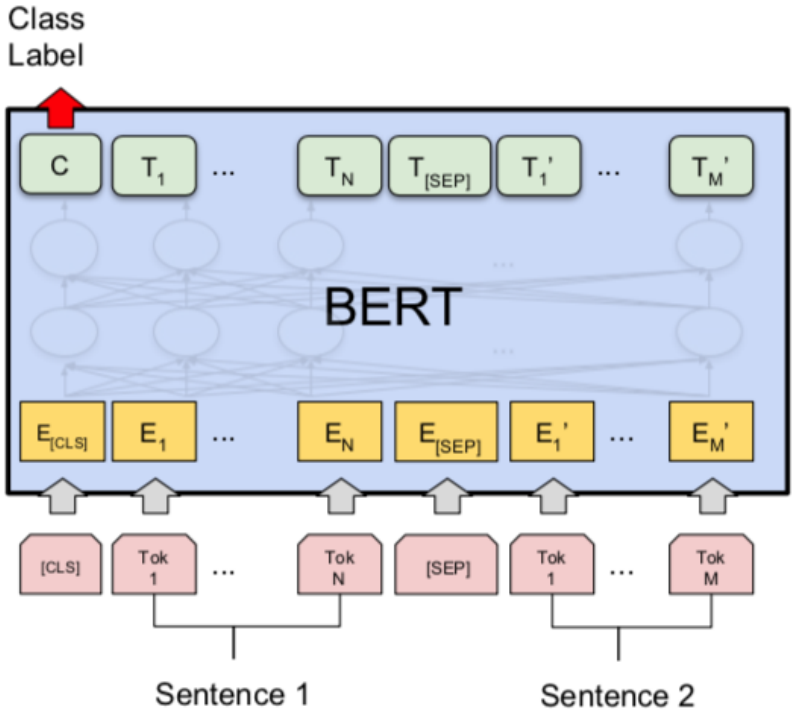
BERT input representation



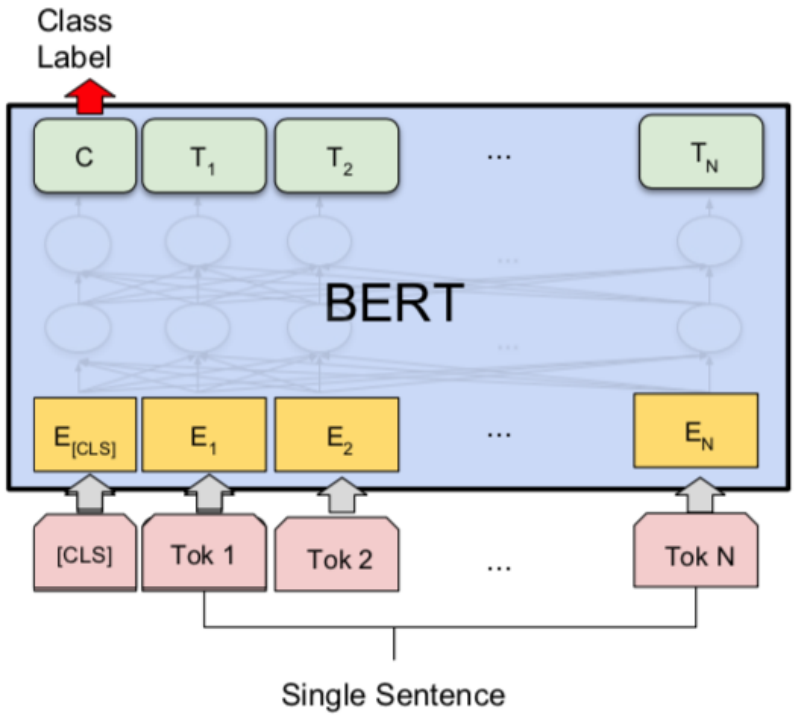
The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT Sequence-level tasks



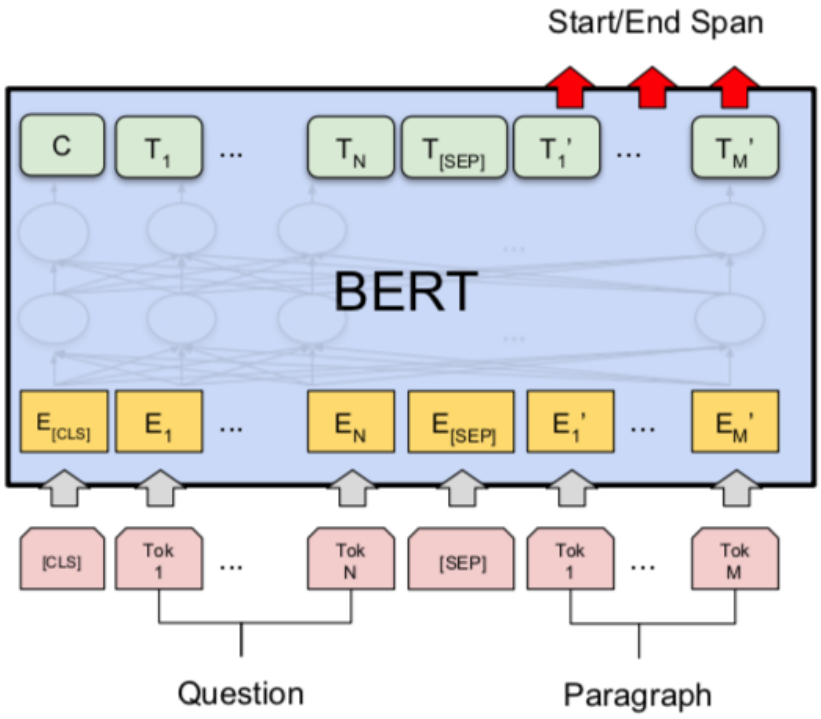
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



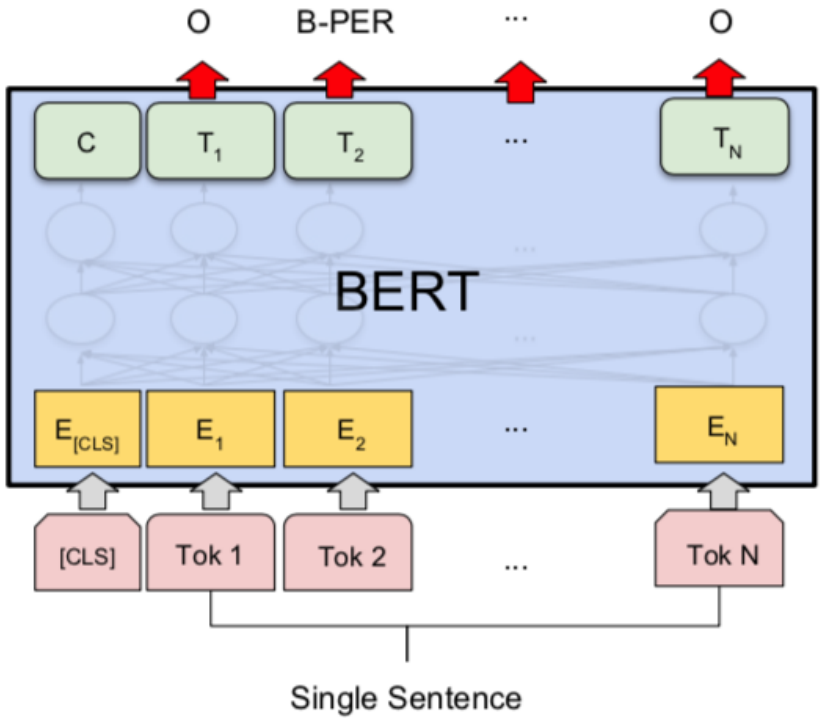
(b) Single Sentence Classification Tasks: SST-2, CoLA

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT Token-level tasks



(c) Question Answering Tasks: SQuAD v1.1



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

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

General Language Understanding Evaluation (GLUE) benchmark

GLUE Test results

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
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
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

MNLI: Multi-Genre Natural Language Inference
QQP: Quora Question Pairs
QNLI: Question Natural Language Inference
SST-2: The Stanford Sentiment Treebank
CoLA: The Corpus of Linguistic Acceptability
STS-B:The Semantic Textual Similarity Benchmark
MRPC: Microsoft Research Paraphrase Corpus
RTE: Recognizing Textual Entailment

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

Facebook Research FastText

Pre-trained word vectors
Word2Vec
wiki.zh.vec (861MB)
332647 word
300 vec

Pre-trained word vectors for 90 languages, trained on Wikipedia using fastText.

These vectors in dimension 300 were obtained using the skip-gram model with default parameters.

https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md

Source: Bojanowski, Piotr, Edouard Grave, Armand Joulin, and Tomas Mikolov. "Enriching word vectors with subword information." *arXiv preprint arXiv:1607.04606* (2016).

Facebook Research FastText Word2Vec: wiki.zh.vec

(861MB) (332647 word 300 vec)

wiki.zh.vec

```
31845 yg -0.3978 0.49084 -0.54621 0.078991 0.8584 -0.26163 -0.45787 0.060828 0.36513 -0.03771 0.80791 0.16613 1.4828 -0.89862 0.085965
31846 迴圈 -0.034834 0.71651 -0.4377 0.48344 0.31117 -0.51783 -0.40156 -0.057097 0.31535 -0.088301 0.23436 0.30884 1.2932 -0.6704 0.21
31847 ぶっ -0.23267 0.39349 -0.90806 -0.53805 0.59308 -0.31819 -0.64229 0.16871 0.10086 0.09342 1.0914 -0.16019 1.6954 -0.70604 -0.218
31848 三公 0.54129 0.55641 -0.4348 0.25094 0.1631 -0.10326 -0.54099 0.064742 0.13175 0.10217 0.84938 -0.10287 1.312 -0.74969 0.24025 -
31849 水貨 -0.14451 0.80455 -0.6145 0.55905 0.58307 -0.02559 -0.41088 -0.19056 -0.09178 0.33935 1.1927
31850 刚才 0.19347 0.553 -0.64736 0.26358 0.83816 -0.24098 -0.83997 -0.16232 -0.024786 -0.2483 0.69732
31851 無知 -0.0089777 0.90866 -0.25306 0.72983 0.67791 -0.3285 -0.63835 0.075295 0.4774 -0.04134 0.721
31852 好轉 -0.026068 0.92676 -0.47469 0.50129 0.67343 -0.32509 -0.32917 0.066499 0.3875 0.0011722 0.66
31853 紀事 0.40541 0.67654 -0.5351 0.30329 0.43042 -0.24675 -0.19287 0.34207 0.35516 -0.076331 0.85916
31854 變回 -0.089933 0.88136 -0.43524 0.59963 0.6403 -0.70981 -0.56788 -0.074018 0.16905 -0.086594 0.6
31855 牟尼 -0.26578 0.6434 0.028982 -0.044001 0.88297 -0.17646 -0.64672 0.040483 0.43653 0.084908 0.74
31856 埋藏 -0.0985 0.85082 -0.33363 0.24784 0.71518 -0.59054 -0.73731 0.050949 0.36726 -0.076886 0.817
31857 正大 0.21069 0.27605 -0.83862 -0.099698 0.47894 -0.32196 -0.38288 -0.01892 0.40548 -0.029619 0.7
31858 kis -0.30595 0.18482 -0.71287 -0.314 0.44776 -0.44245 -0.36447 -0.23723 0.00098801 -0.2528 0.608
31859 合奏 0.1841 0.60874 -0.51376 -0.48002 0.21506 -0.55515 -0.71746 0.030735 0.39508 -0.40856 0.6226
31860 精兵 0.25619 0.77186 -0.48847 0.23118 0.27254 0.21305 -0.3517 0.47305 0.24882 -0.34756 1.025 0.18
31861 疲勞 -0.072521 1.0381 -0.51933 0.19421 0.67573 -0.45204 -0.20126 0.22704 0.44196 0.018401 0.3473
31862 襯 -0.11771 1.4272 -1.0849 0.77532 0.87026 -0.6892 -0.3521 0.036517 0.42727 -0.1871 0.82789 -0.0
31863 小貓 -0.21554 0.73988 -0.39628 0.044656 1.0602 -0.67047 -0.54102 0.11888 0.1693 0.19343 1.0841 0.
31864 lai -0.25451 0.31596 -0.29228 -0.19144 0.99059 -0.24459 -0.66342 0.063093 -0.061142 -0.22749 0.6
31865 偏東 -0.50835 1.0943 0.043918 0.29173 1.0161 -0.32493 -0.27305 0.026946 0.46811 -0.3874 1.4049 0.
31866 大约是 -0.35726 -0.03476 -0.28672 0.075447 0.18175 -0.39421 -0.32088 0.025225 0.34808 0.074744 0.
31867 franch -0.6046 -0.3235 0.024041 -0.2756 0.74761 -0.14654 0.0082566 -0.10071 0.53593 -0.17374 0.2
31868 brazilian -0.54029 -0.63905 -0.094006 -0.68768 0.33263 -0.1583 -0.060424 0.20644 0.46234 -0.0764
31869 夾竹桃 -0.4361 0.011429 -0.078896 -0.078186 0.37747 -0.052101 -0.096683 0.10769 0.62661 -0.37252
31870 continent -0.37761 -0.72151 -0.42248 -0.81768 0.5016 -0.48569 0.13464 0.12644 0.32292 0.18099 0.
31871 我还是 0.097443 0.28929 -0.14202 0.034027 0.50621 -0.1647 -0.45849 -0.16198 0.13965 -0.33451 0.61
31872 vienna -0.25827 -0.050966 0.050502 -0.63466 0.4949 -0.17448 -0.59978 0.20269 0.37532 0.059419 0.
31873 固态 -0.12678 0.4556 -0.27108 0.12506 0.52106 -0.058477 -0.69296 0.12162 0.26508 -0.089028 0.752
31874 吉普 -0.33693 0.48335 -0.58455 0.13722 0.74856 -0.24529 -0.41125 -0.13832 0.33871 -0.12051 0.864
31875 實物 0.030096 0.65756 -0.67982 0.2203 0.38492 -0.19001 -0.53136 -0.10322 0.24523 0.15287 0.92591
31876 教职 0.11559 0.67087 -0.5111 0.14955 0.61417 -0.51571 -0.47901 0.29445 0.37629 -0.24232 0.4608 -
31877 惕 0.50469 1.5357 -0.64393 0.48668 0.69479 -0.23443 -0.47863 0.16288 0.3347 -0.51673 0.86777 0.0
31878 岸上 0.088323 0.85815 -0.485 0.30383 0.75965 -0.25031 -0.76678 0.12805 0.37641 -0.088752 0.65012
31879 议和 0.26835 0.94854 -0.27972 0.097623 0.43305 -0.031361 -0.57406 0.21608 0.3324 -0.36823 0.6987
31880 aka -0.21332 0.11216 -0.48872 -0.18531 0.79093 -0.34221 -0.51122 0.10067 0.29963 -0.075253 0.642
31881 滑鐵盧 -0.28726 0.88014 -0.39751 -0.056992 0.37408 -0.16967 -0.20673 -0.048533 -0.1978 -0.13107 0
```

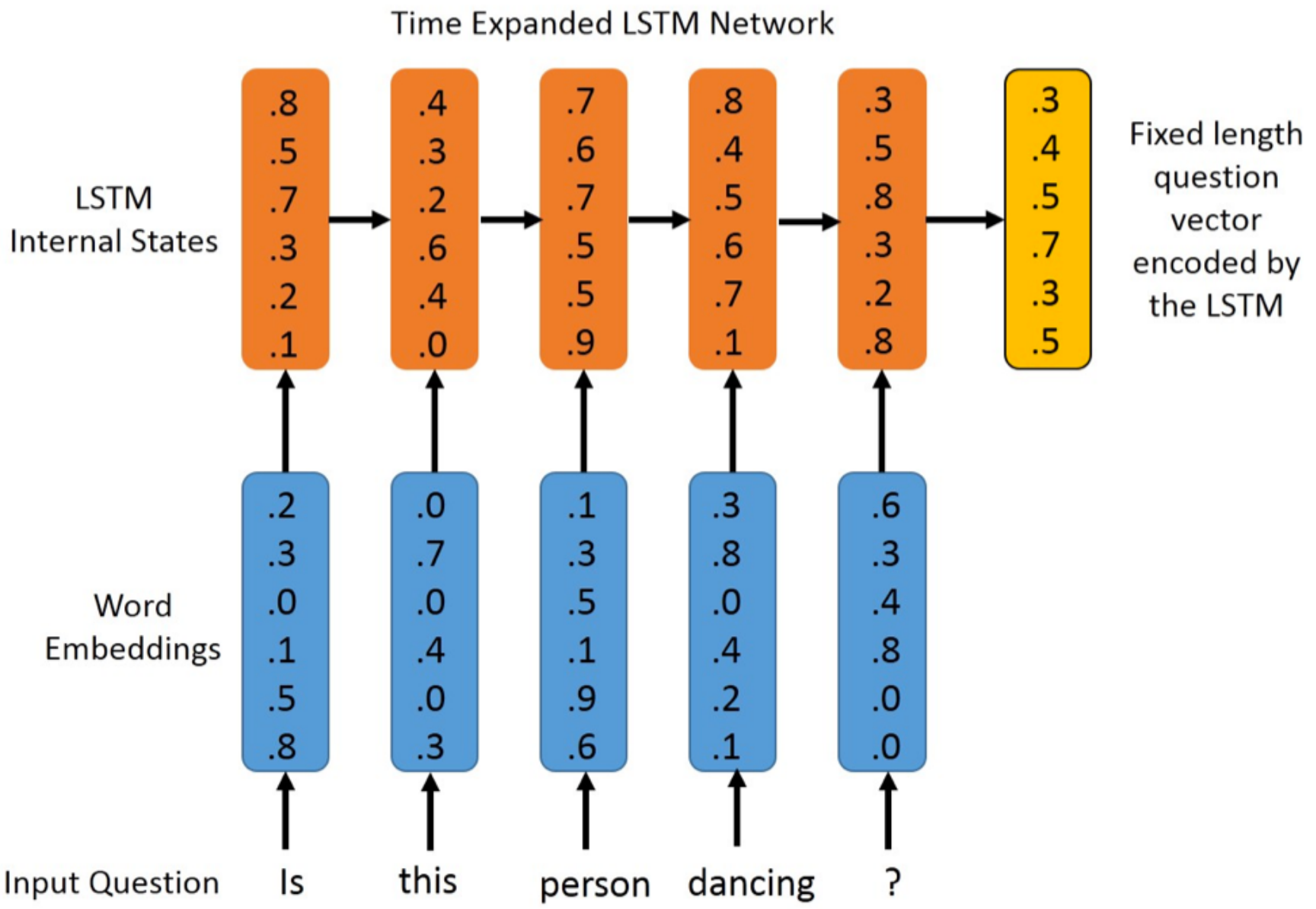
Models

The models can be downloaded from:

- Afrikaans: *bin+text*, *text*
- Albanian: *bin+text*, *text*
- Arabic: *bin+text*, *text*
- Armenian: *bin+text*, *text*
- Asturian: *bin+text*, *text*
- Azerbaijani: *bin+text*, *text*
- Bashkir: *bin+text*, *text*
- Basque: *bin+text*, *text*
- Belarusian: *bin+text*, *text*
- Bengali: *bin+text*, *text*
- Bosnian: *bin+text*, *text*
- Breton: *bin+text*, *text*
- Bulgarian: *bin+text*, *text*
- Burmese: *bin+text*, *text*
- Catalan: *bin+text*, *text*
- Cebuano: *bin+text*, *text*
- Chechen: *bin+text*, *text*
- Chinese: *bin+text*, *text*
- Chuvash: *bin+text*, *text*
- Croatian: *bin+text*, *text*
- Czech: *bin+text*, *text*

https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md

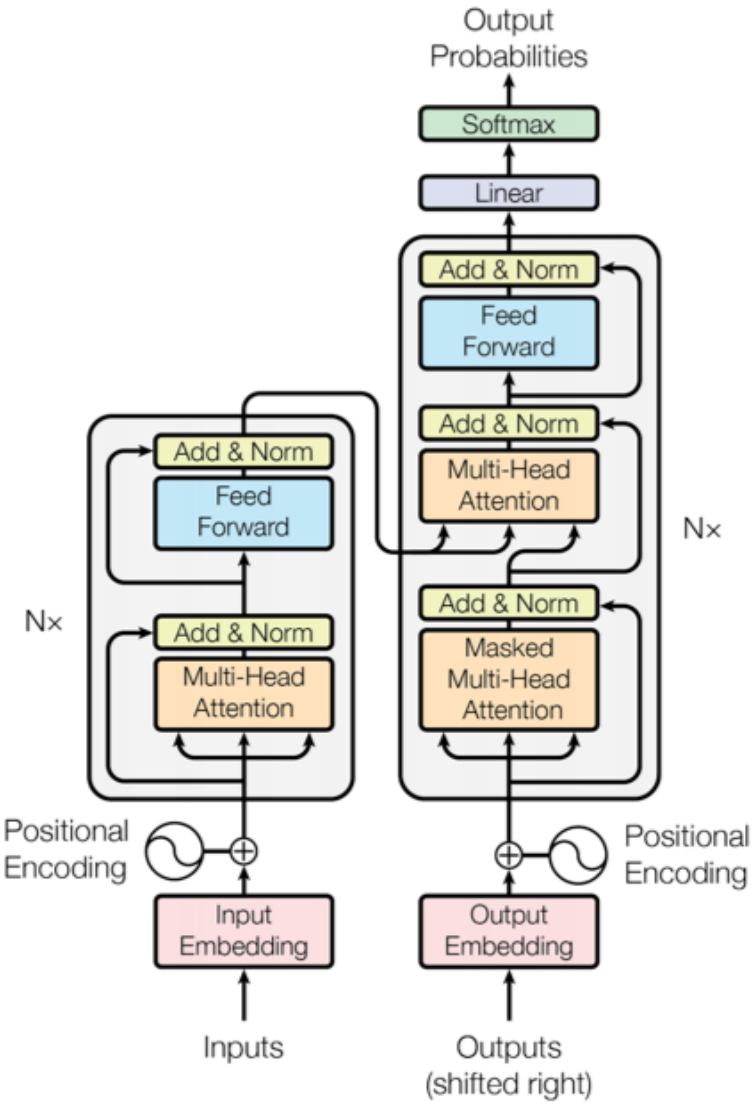
Word Embeddings in LSTM RNN



Source: https://avisingh599.github.io/deeplearning/visual-qa/

Transformer (Attention is All You Need)

(Vaswani et al., 2017)

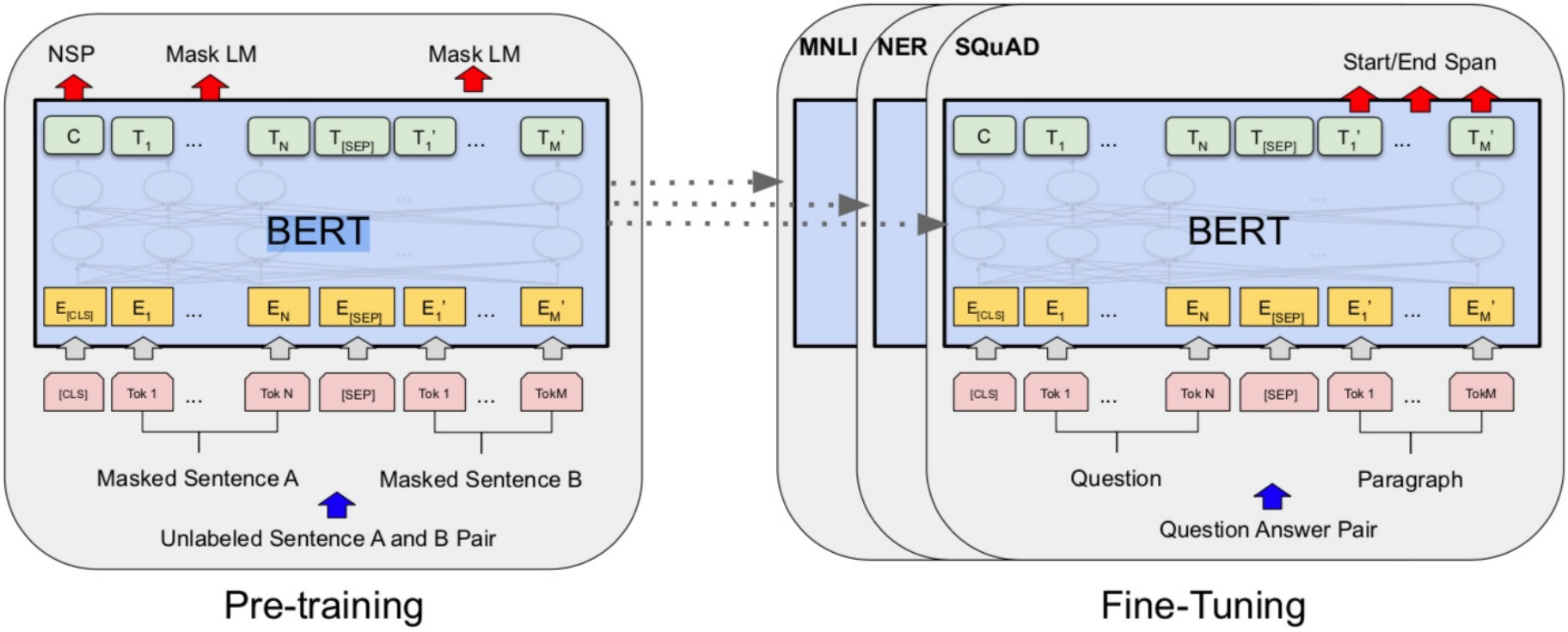


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

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

BERT (Bidirectional Encoder Representations from Transformers)

Overall pre-training and fine-tuning procedures for BERT

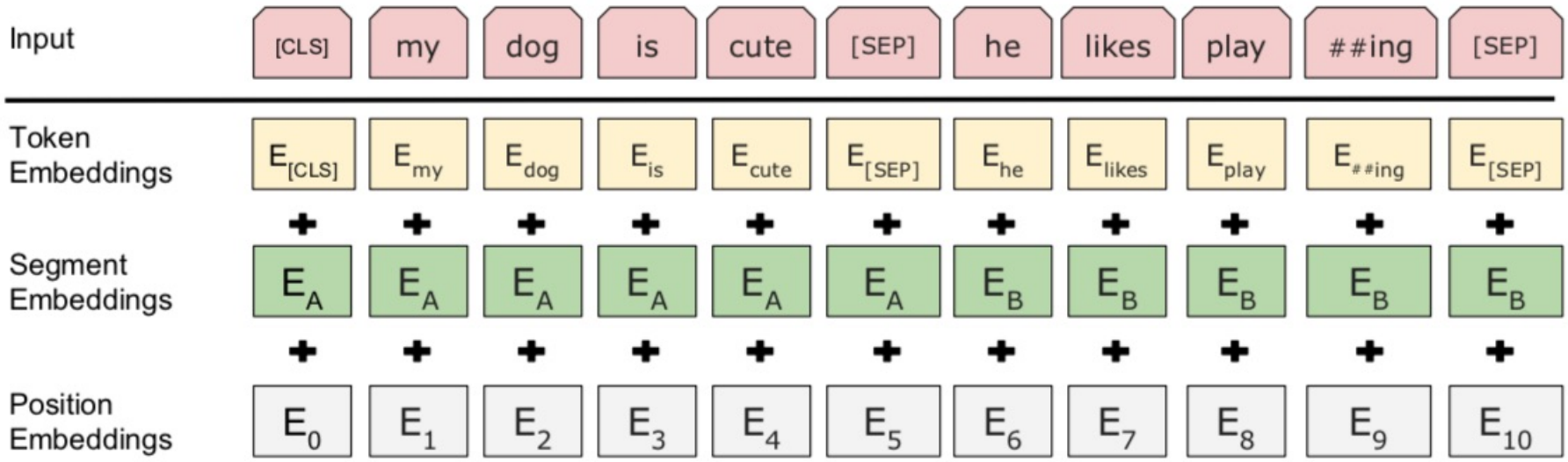


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

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

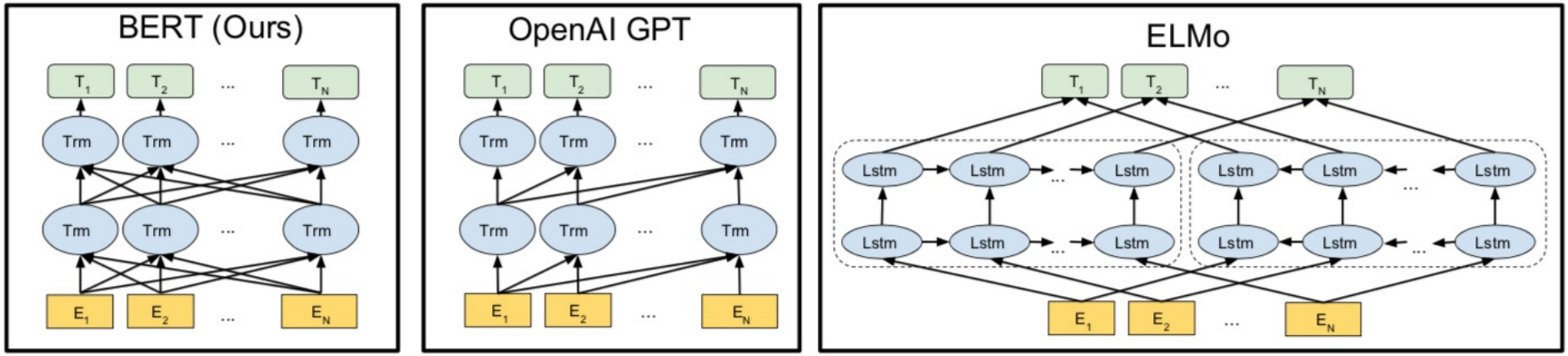
BERT (Bidirectional Encoder Representations from Transformers)

BERT input representation



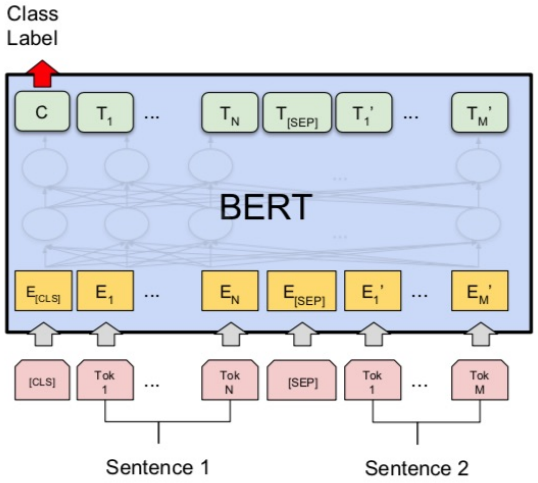
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT, OpenAI GPT, ELMo

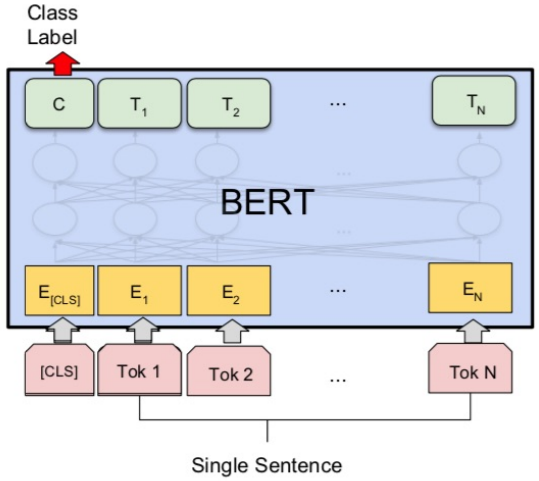


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

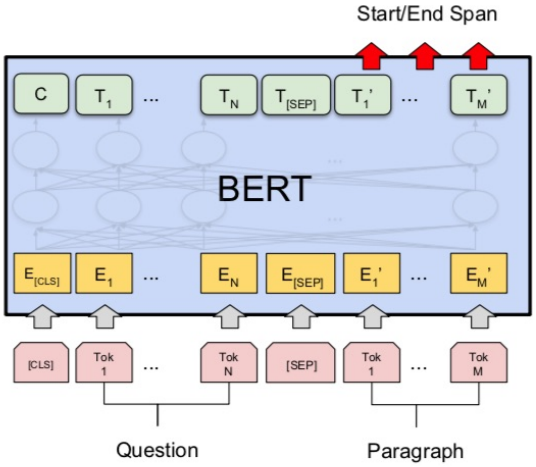
Fine-tuning BERT on Different Tasks



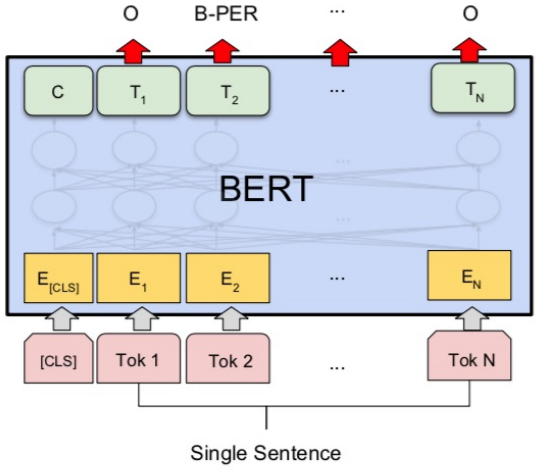
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



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



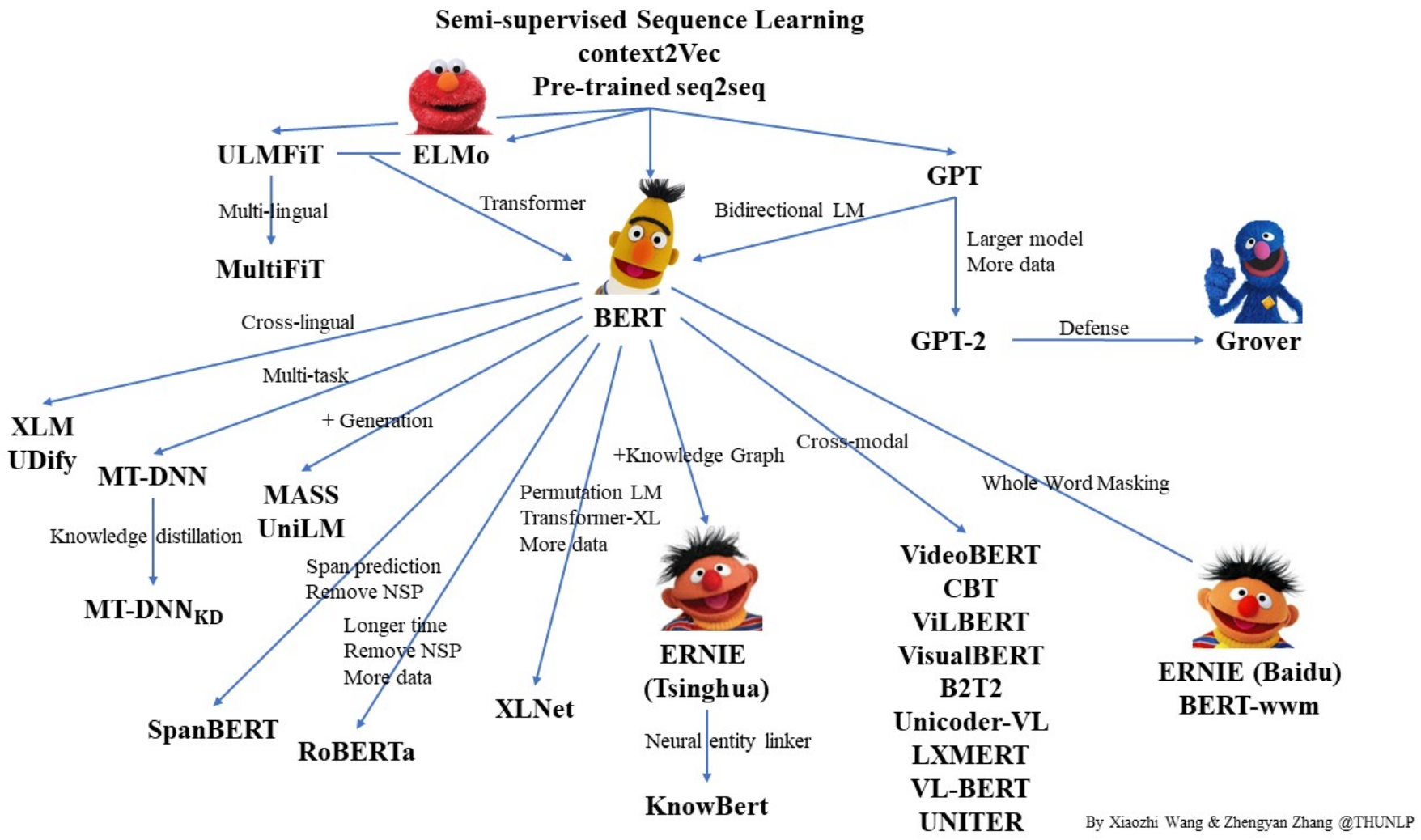
(c) Question Answering Tasks: SQuAD v1.1



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

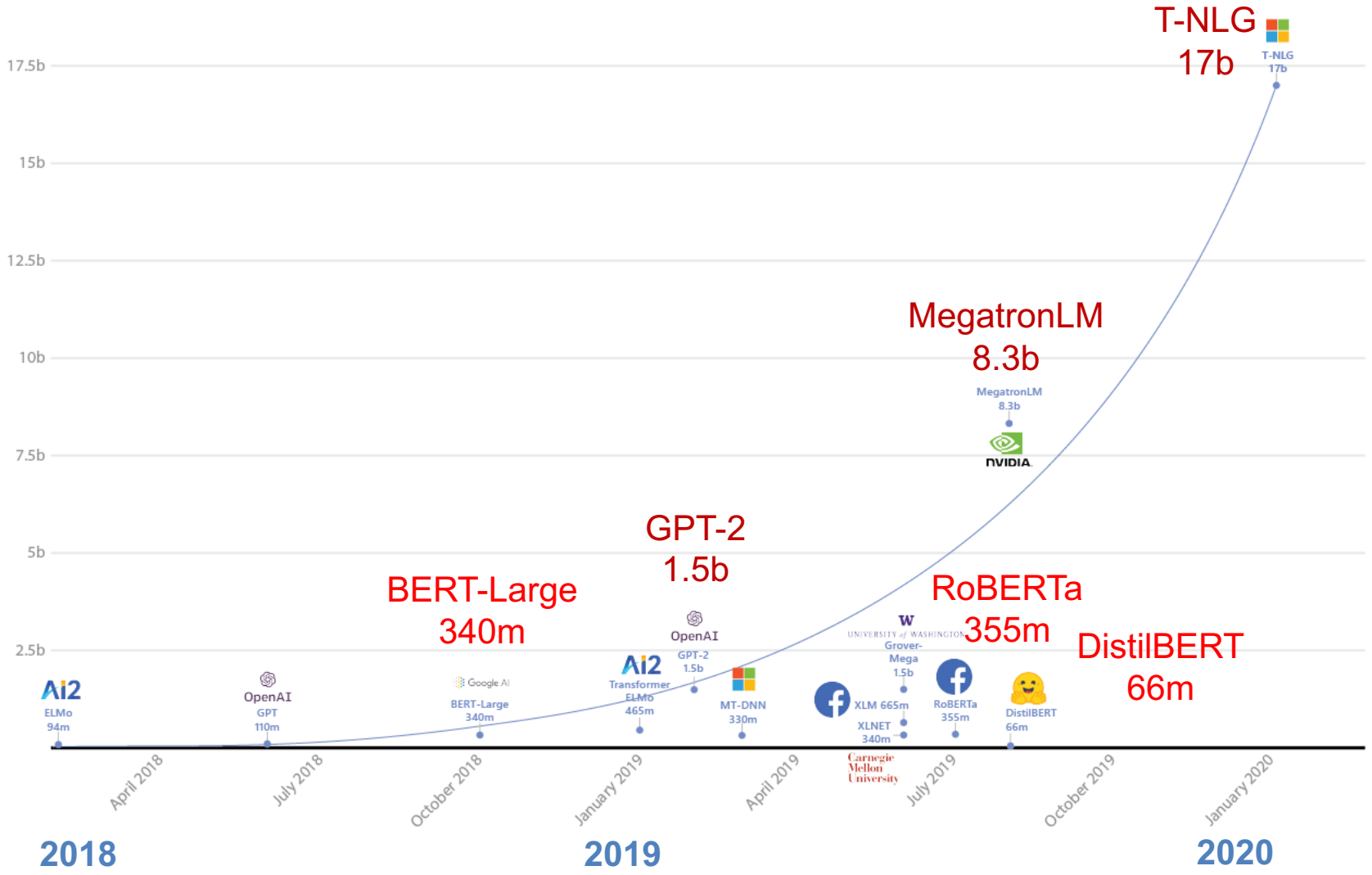
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Pre-trained Language Model (PLM)



Source: https://github.com/thunlp/PLMpapers

Turing Natural Language Generation (T-NLG)



Source: https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/

Transformers

State-of-the-art Natural Language Processing for TensorFlow 2.0 and PyTorch

- Transformers
  - pytorch-transformers
  - pytorch-pretrained-bert
- provides state-of-the-art general-purpose architectures
  - (BERT, GPT-2, RoBERTa, XLM, DistilBert, XLNet, CTRL...)
  - for Natural Language Understanding (NLU) and Natural Language Generation (NLG) with over 32+ pretrained models in 100+ languages and deep interoperability between TensorFlow 2.0 and PyTorch.

Source: https://github.com/huggingface/transformers

Transfer Learning in Natural Language Processing

Source: Sebastian Ruder, Matthew E. Peters, Swabha Swayamdipta, and Thomas Wolf (2019), "Transfer learning in natural language processing." In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Tutorials, pp. 15-18.

NLP Benchmark Datasets

Task	Dataset	Link
Machine Translation	WMT 2014 EN-DE WMT 2014 EN-FR	http://www-lium.univ-lemans.fr/~schwenk/cslm_joint_paper/
Text Summarization	CNN/DM Newsroom DUC Gigaword	https://cs.nyu.edu/~kcho/DMQA/ https://summari.es/ https://www-nlpir.nist.gov/projects/duc/data.html https://catalog.ldc.upenn.edu/LDC2012T21
Reading Comprehension Question Answering Question Generation	ARC CliCR CNN/DM NewsQA RACE SQuAD Story Cloze Test NarativeQA Quasar SearchQA	http://data.allenai.org/arc/ http://aclweb.org/anthology/N18-1140 https://cs.nyu.edu/~kcho/DMQA/ https://datasets.maluuba.com/NewsQA http://www.qizhexie.com/data/RACE_leaderboard https://rajpurkar.github.io/SQuAD-explorer/ http://aclweb.org/anthology/W17-0906.pdf https://github.com/deepmind/narrativeqa https://github.com/bdhingra/quasar https://github.com/nyu-dl/SearchQA
Semantic Parsing	AMR parsing ATIS (SQL Parsing) WikiSQL (SQL Parsing)	https://amr.isi.edu/index.html https://github.com/jkkummerfeld/text2sql-data/tree/master/data https://github.com/salesforce/WikiSQL
Sentiment Analysis	IMDB Reviews SST Yelp Reviews Subjectivity Dataset	http://ai.stanford.edu/~amaas/data/sentiment/ https://nlp.stanford.edu/sentiment/index.html https://www.yelp.com/dataset/challenge http://www.cs.cornell.edu/people/pabo/movie-review-data/
Text Classification	AG News DBpedia TREC 20 NewsGroup	http://www.di.unipi.it/~gulli/AG_corpus_of_news_articles.html https://wiki.dbpedia.org/Datasets https://trec.nist.gov/data.html http://qwone.com/~jason/20Newsgroups/
Natural Language Inference	SNLI Corpus MultiNLI SciTail	https://nlp.stanford.edu/projects/snli/ https://www.nyu.edu/projects/bowman/multinli/ http://data.allenai.org/scitail/
Semantic Role Labeling	Proposition Bank OneNotes	http://propbank.github.io/ https://catalog.ldc.upenn.edu/LDC2013T19

Source: Amirsina Torfi, Rouzbeh A. Shirvani, Yaser Keneshloo, Nader Tavvaf, and Edward A. Fox (2020). "Natural Language Processing Advancements By Deep Learning: A Survey." arXiv preprint arXiv:2003.01200.

Summary

- Traditional Feature Engineering for Text Data
  - Bag of Words Model
  - Bag of N-Grams Model
  - TF-IDF Model
- Advanced Word Embeddings with Deep Learning
  - Word2Vec Model
  - Robust Word2Vec Models with Gensim
  - GloVe Model
  - FastText Model

References

- Dipanjan Sarkar (2019),
  Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress.
  https://github.com/Apress/text-analytics-w-python-2e
- Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python,
  O'Reilly Media.
  https://www.oreilly.com/library/view/applied-text-analysis/9781491963036/