IEMS 5780 / IERG 4080
Building and Deploying Scalable Machine Learning Services

Lecture 4 - Text Classification (2)

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Advanced Topics in Document Representation

Limitations

- Bag-of-word (BoW) and vector space models is very commonly used in text classification
- However, they has certain limitations:
  1. Ignoring the **order** of the words
     - Consider `a tea bag` vs. `a bag of tea`
  2. Ignoring the **context** of the words
     - "... take the earliest **train** tomorrow morning ..."
     - "... will **train** a new model tomorrow morning ..."
  3. Ignoring **compound nouns**
     - `dress shirt` vs. `dress`
  4. Do not handle words with **similar** meanings
     - `cellphones` vs. `smartphones`
  5. Cannot handle **new words**

Advanced Topics

- To address these problems, we will consider:
  - Consider **n-grams**
  - Consider **character n-grams**
  - Use **dimensionality reduction** techniques
  - **Word embeddings**

N-grams

N-grams

- In our previous examples, we break a document into tokens, which are **individual words**
- We call these tokens of individual words **unigrams**

```
sentence = "London is the capital and most populous city of England and the United Kingdom"
sentence.lower().split(" ")
# [
#    'london', 'is', 'the', 'capital', 'and',
#    'most', 'populous', 'city', 'of', 'England',
#    'and', 'the', 'united', 'kingdom'
# ]
```

- In this example, it would be desirable to capture the existence of the phrase `United Kingdom` (both `united` and `kingdom` can appear separately and have different meanings)
- Such kind of features may be **useful** when performing text classification

N-grams

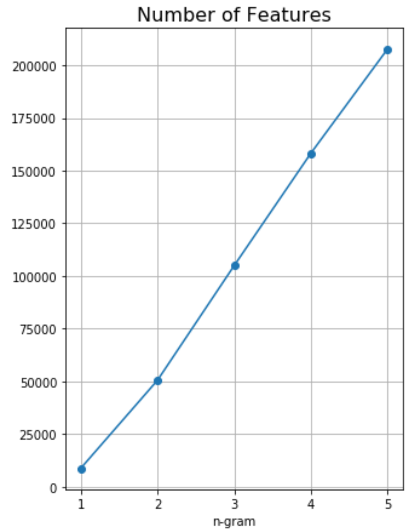
- Instead of treating every single token as a feature, we can also treat **every two consecutive pair of tokens** as a feature (i.e. **bi-grams**)

```
sentence = "London is the capital and most populous city of England and the United Kingdom"
tokens = sentnce.lower().split(" ")
bigrams = []
for i in range(len(tokens)-1):
    bigrams.append("{} {}".format(tokens[i], tokens[i+1]))
# bigrams = [
#     'london is',
#     'is the',
#     ...
#     'the united',
#     'united kingdom.'
# ]
```

N-grams: Number of Features

- Somtimes, we may also consider **tri-grams** or more
- But be **cautious** when adding n-gram features
- Using n-grams **significantly increase** the number of features
  - **More parameters** to learn in your model
  - May not give significant improvement but requires longer time to train

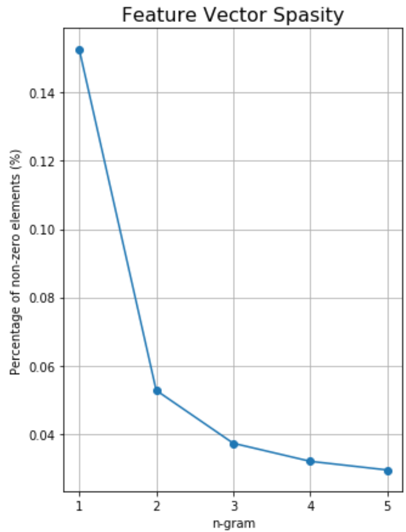
- (Right: number of features agains n-grams used for the SMS Spam dataset)



N-gram: Feature Sparsity

- Another potential problem of using large n-grams is **data sparsity**
- Each **n-gram** (other than unigrams) may only be found in very few documents
- You are more likely to have **unseen n-grams** in the test data
- You also will use up a lot of **memory** and **storage**

- (Right: Number of non-zero elements in all feature vectors for the SMS Spam dataset)



N-gram

- Given the advantages and disadvantages of n-gram features, **when** shall we use them?
- Answering this usually requires **doing experiments**, and depends on the problem(s) at hand
- Something to consider:
    - Do we see any **significant** or **desirable** increase in classification performance?
    - How much more **computing resources** are required (e.g. RAM)
    - **Time** required to train the model
    - Is the amount of data **large enough** to make the n-gram features meaningful?

Using N-gram in Scikit-learn

- You can easily enable n-gram features when using the **`CountVectorizer`** or the **`TfidfVectorizer`**
- Set the **`ngram_range`** parameter using a tuple (e.g. **`(1, 3)`** means that we want to use unigrams, bi-grams and tri-grams as features)

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
clf = Pipeline([
    ('vec', CountVectorizer(ngram_range=(1, 3))),
    ('nb', MultinomialNB())
])
clf.fit(X_train, y_train)
```

Character N-grams

- In addition to n-grams of words, we sometimes may even consider **character n-grams**
- Using character n-grams allow us to capture **sub-words** information
- E.g. `compu` inside `computation` and `computer` may indicate that the input is about the same topic to a certain extent
- A more general approach compared to **stemming**

```
# some character n-grams
# for "an apple"
{
    'an',
    'an ',
    'ap',
    'app',
    ...
    'ppl',
    'pple'
}
```

Character N-grams in Scikit-learn

- You can also easily generate **character-level n-grams** in scikit-learn by setting the `analyzer` parameter
- There are two different modes: `char` and `char_wb`
  - `char` treats the whole document as a string
  - `char_wb` generates n-grams that does NOT cross word boundaries

```
docs = [
    "an apple"
]
vectorizer = CountVectorizer(analyzer='char_wb', ngram_range=(2, 4))
vectorizer.fit(docs)
vectorizer.vocabulary_
# {' a': 0, ' an': 1, ' an ': 2, ' ap': 3, ' app': 4, ... }
# Note that n-grams on the edges of the words are padded with spaces
```

class: center, middle

Dimensionality of Feature Vectors

- **Feature vectors** in text classification are usually very long (**high dimensional**)
  - Commonly used words in the order of thousands
  - New words, names and abbreviations
  - Will be longer if we use **n-grams**
- **Problems** of high dimensionality
  - Model is very complex
  - Models with many features require **a lot of data** to train
  - Require more **memory** during training/prediction
  - Require more **storage space** to persist the model
- Hence, it is desirable if we can **represent the data with fewer dimensions**

Problems with Bag-of-Words Model

- In additional to the problem of high dimensionality, the bag-of-words model also suffers from other problems
- **Synonyms**:
  - Words with same or similar meanings occupy different dimensions
  - They are totally **orthogonal** in the vector space
- Consider:

$$
\begin{aligned}
car &= (0, 0, 0, 0, 0, 0, 1, 0, 0) \\
vehicle &= (0, 1, 0, 0, 0, 0, 0, 0, 0)
\end{aligned}
$$

- Image two documents, one with the word `car`, another with the word `vehicle`, we can never tell that they are somehow related with the above representation.

Dimensionality Reduction

- There are two major ways of finding dense vectors with fewer dimensions to represent words or documents
- **Method 1: Co-occurrence**
  - Words that appears together tend to be similar
  - Converting a one-hot vector into a dense vector by finding **common topics** among words
  - Example: Latent Semantic Analysis
- **Method 2: Context**
  - Words that have similar contexts are similar
  - Converting a one-hot vector into a dense vector by optimizing values in vector based on **similar contexts**
  - Example: Word embeddings

Distributional Representation

- Counting **co-occurrence** between words allow us to understand how similar they are
- Example:
  - "networking" usually appears with **protocols**
  - "football" usually appears with **goals**
- Words having the same **probability distributions** are similar
- We can then represent words and documents in terms of **topics** instead of high dimensional vectors

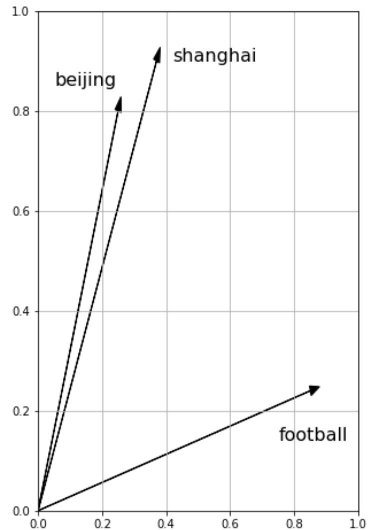
networking = 0.62 x computer + 0.13 x social

(0, 0, 1, 0, …, 0, 0, 0) ⟶ (0.62, 0.13, 0.00, 0.00, 0.00)

N-grams | Topics

Distributed Representation

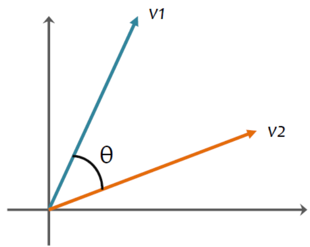
- Words having **similar context** are considered similar
- Context refers to the words that **appear before and after** the target word
- Example:
  - **"deep learning using GPU"**: "deep", "learning", "using" forms the context of "GPU"
  - **"Beijing is a city in China"** vs. **"Shanghai is a city in China"**: "Beijing" and "Shanghai" have similar contexts
- We can optimize vectors of words such that words that have similar contexts have vectors **close** to each other



Cosine Similarity

- We can calculate **similarity** between two vectors using **cosine similarity**
- It measures how **close** the two vectors' **directions** are

$$sim(v_1, v_2) = \cos(\theta) = \frac{v_1 \cdot v_2}{||v_1|| \times ||v_2||}$$



Cosine Similarity in Python

- Example: computing similarity between documents

```
from numpy import array, dot
from numpy.linalg import norm

words = ["chinese", "medicine", "doctor", "food", "restaurants"]
d1 = array([0.8, 0.9, 0.0, 0.1, 0.0])  # about chinese medicine
d2 = array([0.0, 1.2, 1.5, 0.2, 0.0])  # about doctor & medicine
d3 = array([1.3, 0.1, 0.0, 2.0, 1.5])  # about chinese food

dot(d1, d2) / (norm(d1) * norm(d2))  # 0.47136989433874532
dot(d1, d3) / (norm(d1) * norm(d3))  # 0.39038367556371473
dot(d2, d3) / (norm(d2) * norm(d3))  # 0.09549164248532343
```

Latent Semantic Analysis (LSA)

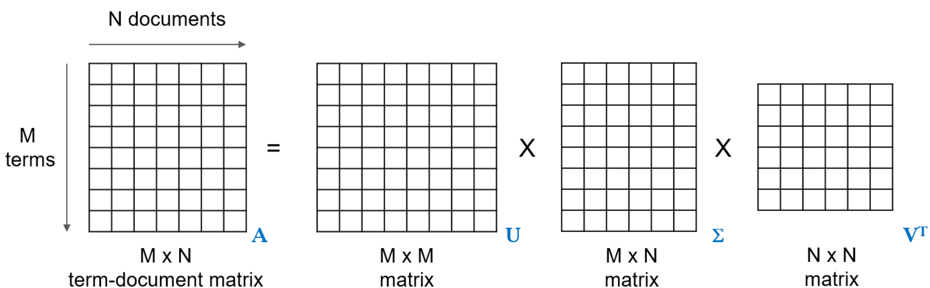
Latent Semantic Analysis

- One way to obtain a dense vector representation of words and documents is **latent semantic analysis**
- Assume that we have a set of training data, in which we have **5 documents**, and our **vocabulary size is 10**
- Using the bag-of-word model, we can represent this training data set as a **term-document matrix**

	d_0	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9
w_0	**0**	**1**	**0**	**0**	**2**	**0**	**0**	**3**	**2**	**0**
w_1	0	0	1	0	0	0	1	0	0	2
w_2	0	1	2	0	0	1	0	0	0	1
w_3	2	0	0	1	1	0	0	1	0	0
w_4	1	1	0	0	0	1	1	0	1	0

Latent Semantic Analysis

- LSA uses a mathematical tool called **singular value decomposition** to factorize the term-document matrix into **three** matrices
- In Σ, the values on the diagonal are called *singular values**, which indicates how important the topics are in the data



Latent Semantic Analysis

- LSI tries to group **documents with similar words**, as well as **words that usually appear together**
- Check the animation on https://en.wikipedia.org/wiki/Latent_semantic_analysis
- These groups can be considered as some **topics** in the data
- Intuitively, the number of **topics** should be fewer than the number of **words**
- We can then use **topics** to represent words and documents

Latent Semantic Analysis

- After the decomposition, the size of Σ actually represents **the number of topics** that can be found in the data (it is always smaller or equal to the number of words)
- However, some topics may only be noise (words that appear less frequently and are not able to be grouped)
- To reduce the dimension of the data, we can choose only to keep the **top** k singular values, and to represent words and documents using the k **dimensions**

$$\text{Document in reduced dimension} = U_k \Sigma_k V_k^T$$

Example

- Let's consider running LSA on a simple data set

```
# We have four documents as below
docs = [
    "chinese medicine doctor",        # about chinese medicie
    "chinese companies stock price",  # about stock price of chinese companies
    "medicine doctor hospital",       # about medicine
    "stock market option price"       # about stock market
]
```

Performing SVD in Python

- Singular value decomposition can be done using the function **`scipy.linalg.svd`** in the SciPy package ([documentation]())
- It returns the matrices U and V, as well as the singular values

```
from sklearn.feature_extraction.text import CounterVectorizer
from scipy.linalg import svd

vectorizer = CountVectorizer()
A = vectorizer.fit_transform(docs)
A.vocabulary_
# {'chinese': 0, 'companies': 1, 'doctor': 2, 'hospital': 3, 'market': 4,
#  'medicine': 5, 'option': 6, 'price': 7, 'stock': 8}

U, ss, V = svd(A.todense().transpose(), full_matrices=True)
```

Performing SVD in Python

```
U = array([[-0.41,  0.21, -0.54, -0.41,  0.35, -0.21,  0.35,  0.16,  0.16],
           [-0.27, -0.08, -0.43,  0.39,  0.05,  0.17,  0.05, -0.52, -0.52],
           [-0.22,  0.58,  0.15, -0.09, -0.32, -0.55, -0.32, -0.2 , -0.2 ],
           [-0.08,  0.3 ,  0.26,  0.71,  0.35, -0.21,  0.35,  0.16,  0.16],
           [-0.24, -0.17,  0.45, -0.24,  0.7 , -0.02, -0.3 , -0.18, -0.18],
           [-0.22,  0.58,  0.15, -0.09, -0.03,  0.76, -0.03,  0.04,  0.04],
           [-0.24, -0.17,  0.45, -0.24, -0.3 , -0.02,  0.7 , -0.18, -0.18],
           [-0.52, -0.25,  0.03,  0.15, -0.2 ,  0.02, -0.2 ,  0.68, -0.32],
           [-0.52, -0.25,  0.03,  0.15, -0.2 ,  0.02, -0.2 , -0.32,  0.68]])

ss = array([2.5 , 2.21, 1.46, 0.86])

V = array([[-0.34, -0.69, -0.21, -0.61],
           [ 0.62, -0.17,  0.66, -0.38],
           [-0.17, -0.62,  0.38,  0.66],
           [-0.69,  0.34,  0.61, -0.21]])
```

Latent Semantic Analysis

- You can also perform latent semantic analysis easily using the **`TruncatedSVD`** class in scikit-learn

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import TruncatedSVD

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(docs)    # X is a term-document matrix (transposed)

svd = TruncatedSVD(n_components=2)    # Apply SVD on the matrix, keep 2 dimensions
svd.fit(X)
```

Latent Semantic Analysis

- Now the **svd** model can be used to transform the documents

```
for doc, (i, j) in enumerate(svd.transform(X)):
    print("Doc {}: ({:7.3f}, {:7.3f})".format(doc+1, i, j))

# Prints the following:
# Doc 1: (  0.846,   1.370)
# Doc 2: (  1.720,  -0.368)
# Doc 3: (  0.519,   1.465)
# Doc 4: (  1.522,  -0.845)

# The documents for reference
# docs = [
#    "chinese medicine doctor",        # about chinese medicie
#    "chinese companies stock price",  # about stock price of chinese companies
#    "medicine doctor hospital",       # about medicine
#    "stock market option price"       # about stock market
# ]
```

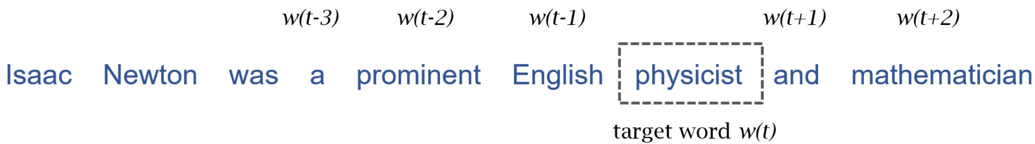
Word Embeddings

Word Embeddings

- Word vectors or embeddings are **dense vector** representation of words
- A type of **distributed representation** of words
- Word embeddings can be obtained by trainnig a neural network on a large corpus of text data
- Training samples are genrated from the corpus usually using a **sliding window** to define contexts
- Commonly used algorithms:
    - Word2Vec https://code.google.com/archive/p/word2vec/
    - GloVe https://nlp.stanford.edu/projects/glove/
    - fastText https://fasttext.cc/

Introduction to Word2Vec

- **Basic idea**: A word's meaning is given by the words that frequently appear around it
- For a word w in a document, its context is the set of words that appear near it
- **"Near"** can be defined by a **sliding window of certain size**
- Word2vec (Mikolov et al. 2013) is an algorithm for learning word vectors



Word2Vec

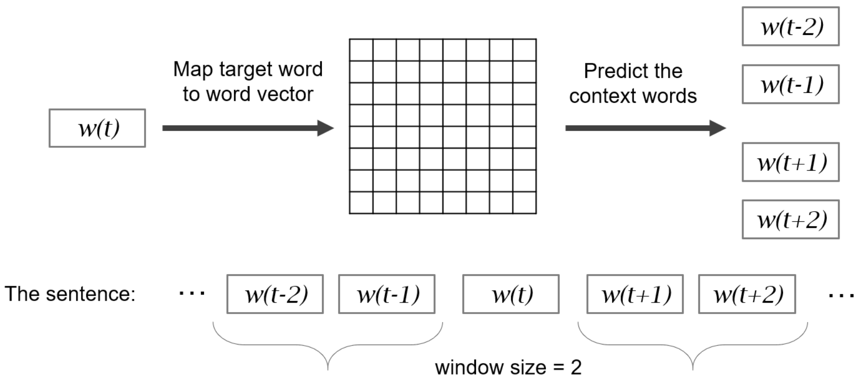
- Word2vec obtains word embeddings by creating a new way of **supervised training** out of **unlabelled** data
- **Basic concept**:
  - Assume that we have a vocabulary of size N
  - For each word in this vocabulary, we initialize a random vector of dimension D (Usually D is about 100 to 300)
  - For each context window, we compute the **probability** of **each context word** given the **target word** using the **similarity** between their vectors
  - We keep adjusting the values of the vectors to maximize these probabilities

Word2Vec

- It turns out that **training** word vectors can be done using a neural network
- To train a neural network in a supervised way, we need to have some labelled data
- There are two ways to train a word vectors:
  1. **Skip-gram (SG)**
     - For each context window, the **target word** (or **center word**) is the **input**
     - The **context words** on the left and right are the **output**
  2. **Continuous Bag of Words (CBoW)**
     - For each context window, the **context words** are the **input**
     - The **target word** is the **output**

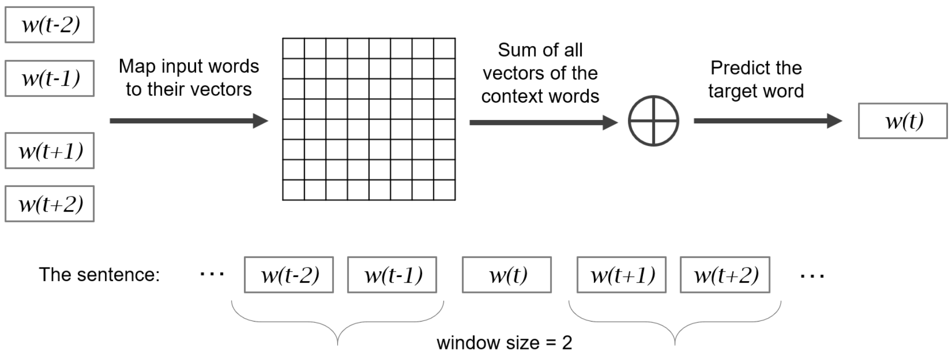
Skip-gram Mode

- In the Skip-gram mode, the neural network is trained by using the **target word as input**, and the **context words as output**
- Task: train the model to output most likely context words given a target word



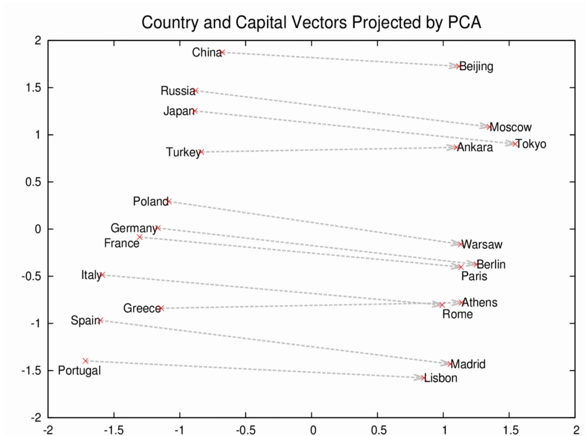
Continuous Bag-of-Words Mode

- In the CBoW mode, the neural network is trained by using the **context words as input**, and the **target word as output**
- Task: using the context words to **predict** which would be the missing target word



Word Embeddings

- The trained word vectors show some interesting characteristics



Ref: [Distributed Representations of Words and Phrases and their Compositionality] (Mikolov et. al 2013)

Word2Vec in Python

- You can play with word vectors using the `gensim` Python package
- Obtain **pre-trained word vectors** from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit?usp=sharing (Note: the file is 1.5GB compressed)

```
from gensim.models.KeyedVectors import load_word2vec_format

model = load_word2vec_format('GoogleNews-vectors-negative300.bin', binary=True)

# Get vector similarity
model.similarity("big", "huge")

# Get the vector of the word "great" (a 300-d vector)
model["great"]

# Find another word that is most similar to the given words
model.most_similar(["apple", "orange"])
```

fastText

fastText

- fastText is a library for **text classification** and **representation learning**
- An efficient implementation of a shallow neural network for text classification using word embeddings
- Comes with command line programs for training, testing and generating predictions
- **Python API** available
- Functions
    - Supervised learning: support **multi-class** classification
    - Unsupervised learning: learning **word embeddings** from input texts

fastText

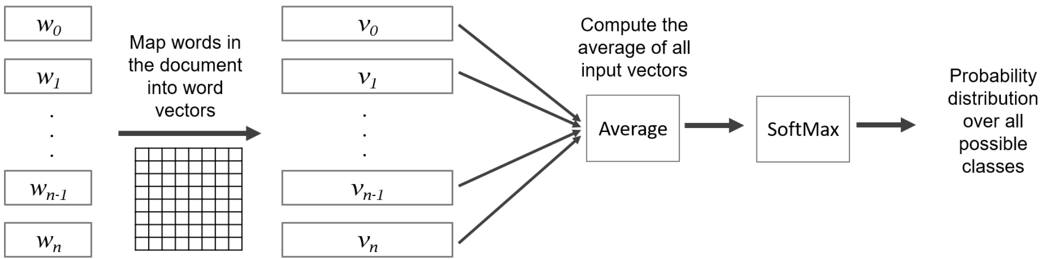
- **Supervised learning**: fastText can be used to train a text classification model for **binary** or **multi-class** classification
- The model is a shallow **neural network**, which first converts n-grams into **word embeddings**, takes the **average** of the vectors, and passes that to a **softmax** function to generate predictions
- Ref: Bag of Tricks for Efficient Text Classification

- *"We can train fastText on more than one billion words in less than ten minutes using a standard multicore-CPU, and classify half a million sentences among 312K classes in less than a minute."*

fastText

- The **softmax function** is a generalized **logistic function**, it converts a vector of real values into another vector whose entries have values ranges from **0 to 1**, and all the entries **sum to 1**

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum e^{z_i}}$$



fastText

- The **word embedding** layer can be **trained** using the training data, or can be initialized with **pre-trained word vectors**
- Example of pre-trained vectors: https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md

```
香港 0.45552 -0.15176 -0.1004 0.24804 -0.27378 -0.11551 -0.020922 ...
英國 0.46771 0.047616 -0.28287 0.52437 0.34216 -0.1907 0.28798 ...
足球隊 -0.15141 -0.26691 -0.22635 0.19575 0.32993 -0.45426 -0.24766 ...
足球 -0.37035 -0.27073 -0.033765 0.4996 0.62468 -0.35905 -0.087886 ...
```

```
soccer -0.27709 -0.42679 0.070863 0.64454 0.17607 -0.27767 0.031067 ...
football -0.52819 -0.39955 -0.014546 0.22658 0.13472 -0.48197 0.17063 ...
country -0.025361 -0.26752 0.35494 0.081725 -0.022434 -0.030652 -0.15959 ...
bicycle 0.063549 0.032542 -0.019717 0.1974 -0.11146 -0.3778 0.059583 ...
```

fastText

- To try a text classifier using fastText, you need to preprocess your data into a specific format:
  - Each line contains a single document
  - The label (class) of the document should have the prefix **`__label__`**
- Note that all symbols and punctuations will be preserved (texts are tokenized using spaces or tabs)
- For example:

```
__label__sports top 100 nba players for 2018-19
__label__finance stock market update: over 150 stocks hit 52-week lows on NSE
__label__travel gap year holidays: 11 reasons to take a year off to travel in your 30s
...
```

fastText in Python

- Assuming that your training data is stored in a file named **`train.txt`**

```
from fastText import train_supervised    # import the supervised training function

model = train_supervised(
        input="train.txt",   # training data file
        epoch=25,            # epoch: number of times going through the data
        lr=1.0,              # learning rate
        wordNgrams=2,        # n-gram features
        verbose=2,           # whether to print out more messages
        minCount=1           # minimum number of times a token should appear
)
model.save_model("model.bin")  # save model to a file named "model.bin"
```

- Refer to the [full documentaton] for the list of parameters

fastText in Python

- Predicting using fastText

```
from fastText import load_model

# load a trained model named "model.bin"
model = load_model("model.bin")

# text data
text = "Manchester United revenues hit record of £590m"

# Ask for the top 2 predicted classes
labels, scores = model.predict(text, k=2)

# labels is a tuple of labels e.g. (('__label__sports', '__label__finance'))
# scores is an array of scores e.g. array([0.9997472, 0.0000234])
```

Assignment 1

Assignment 1

- Text classification + Telegram Bot
- Deadline: 19th October, 2018 (Friday)
- Two tasks:
  1. Train a **text classifier** for movie review classification
  2. Deploy the text classifier as a **Telegram Bot**

Assignment 1

- **Task 1**
  - Train classifier using 1) **naive Bayes**, 2) **logistic regression**, 3) **fastText**
  - Submit a **Jupyter notebook** with all the steps and results
- **Task 2**
  - Make your model available to other people via **Telegram**
  - Write a script that keeps receiving message from users, and use the model to generate predictions

References

- Application of text classification:

  Globally Scalable Web Document Classification Using Word2Vec

  (From SmartNews)

End of Lecture 4