lab10b

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0.1 Classification with word2vec

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We will be tackling a classification problem by first creating word embeddings, and comparing this to alternative approaches.

During this tutorial, you will need some of the following libraries, let's install them first if you don't have them:

```
In [0]: !pip install bs4
        !pip install sklearn
        !pip install nltk
        !pip install gensim
        !pip install lxml
```

```
Requirement already satisfied: bs4 in /usr/local/lib/python3.6/dist-packages (0.0.1)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.6/dist-packages (from b
Requirement already satisfied: sklearn in /usr/local/lib/python3.6/dist-packages (0.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from skl
Requirement already satisfied: scipy>=0.17.0 in /usr/local/lib/python3.6/dist-packages (from sc
Requirement already satisfied: numpy>=1.11.0 in /usr/local/lib/python3.6/dist-packages (from sc
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from sci
Requirement already satisfied: nltk in /usr/local/lib/python3.6/dist-packages (3.2.5)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from nltk) (1.12
Requirement already satisfied: gensim in /usr/local/lib/python3.6/dist-packages (3.6.0)
Requirement already satisfied: scipy>=0.18.1 in /usr/local/lib/python3.6/dist-packages (from ge
Requirement already satisfied: six>=1.5.0 in /usr/local/lib/python3.6/dist-packages (from gensi
Requirement already satisfied: smart-open>=1.2.1 in /usr/local/lib/python3.6/dist-packages (fro
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from ge
Requirement already satisfied: boto>=2.32 in /usr/local/lib/python3.6/dist-packages (from smart
Requirement already satisfied: boto3 in /usr/local/lib/python3.6/dist-packages (from smart-open
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from smart-o
Requirement already satisfied: s3transfer<0.3.0,>=0.2.0 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: botocore<1.14.0,>=1.13.2 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packages (from r
```

```
Requirement already satisfied: docutils<0.16,>=0.10 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: python-dateutil<3.0.0,>=2.1; python_version >= "2.7" in /usr/lo
Requirement already satisfied: lxml in /usr/local/lib/python3.6/dist-packages (4.2.6)
```

Now we can import some libraries that we will use:

```
In [0]: import logging
        import pandas as pd
        import numpy as np
        from numpy import random
        import gensim
        import nltk
        import lxml
        from sklearn.model_selection import train_test_split
        from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
        from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
        import matplotlib.pyplot as plt

        %matplotlib inline
```

0.2 TFIDF with logistic regression

0.2.1 Preparing the dataset

The classification problem at hand is to predict the tag that belongs to a stack overflow post. The data from Google BigQuery is publicly available at this Cloud Storage URL:
https://storage.googleapis.com/tensorflow-workshop-examples/stack-overflow-data.csv.
We can read it directly into a pandas dataframe.

```
In [0]: url = "https://storage.googleapis.com/tensorflow-workshop-examples/stack-overflow-data

        df = pd.read_csv(url, encoding = 'latin-1')
```

Let's start by having a look at our data:

```
In [0]: # only keep data that has a tag (is labeled):
        df = df[pd.notnull(df['tags'])]

        # display first ten rows:
        df.head(10)
```

```
Out[0]:                                                 post           tags
        0  what is causing this behavior  in our c# datet...             c#
        1  have dynamic html load as if it was in an ifra...       asp.net
        2  how to convert a float value in to min:sec  i ...   objective-c
        3  .net framework 4 redistributable  just wonderi...           .net
        4  trying to calculate and print the mean and its...        python
        5  how to give alias name for my website  i have ...       asp.net
```

```
6  window.open() returns null in angularjs  it wo...      angularjs
7  identifying server timeout quickly in iphone  ...         iphone
8  unknown method key  error in rails 2.3.8 unit ...  ruby-on-rails
9  from the include  how to show and hide the con...      angularjs
```

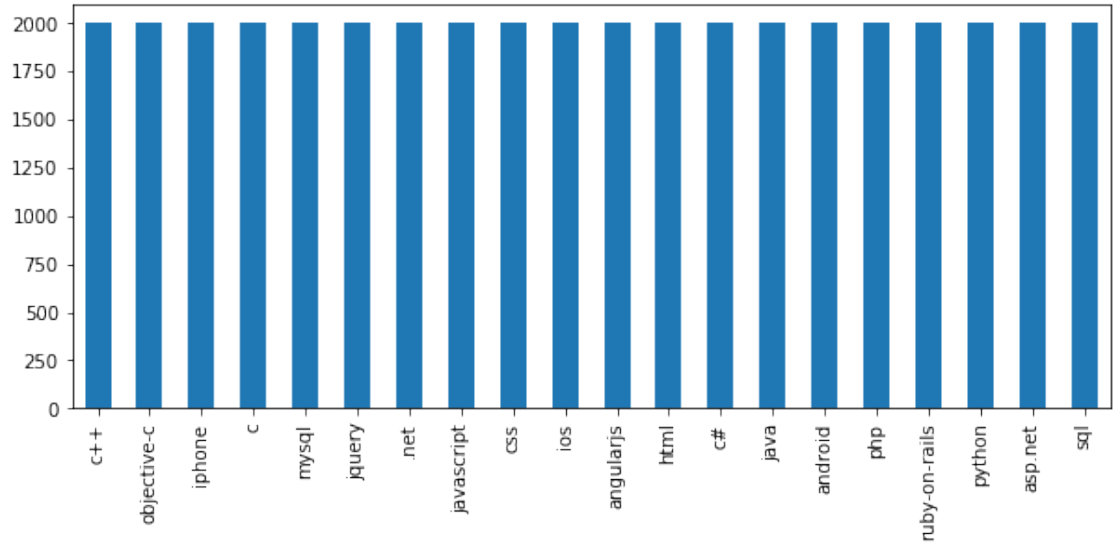
The size of our model will depend on how many unqiue words are in the dataset (meaning in the article text or posts):

```
In [0]: # Count the number of words:
        df['post'].apply(lambda x: len(x.split(' '))).sum()

Out[0]: 10286120
```

We have over 10 million words in the data. That's a lot!
Let's visualise our dataset:

```
In [0]: # visualising dataset
        plt.figure(figsize=(10,4))
        df.tags.value_counts().plot(kind='bar');
```



As you can see, the classes are very well balanced.
Now let's have a look at the data of the posts ('post' columns) in more detail:

```
In [0]: print(df['post'].values[10])
```

```
when we need interface c# <blockquote>    <strong>possible duplicate:</strong><br>    <a href= h
```

As you can see, the text needs to be cleaned up a bit. Below we use the nltk toolkit to remove spaces, html tags, stopwords, symbols etc. Below we define a function to remove stop words, replace / and other symbols with spaces, ...

```
In [0]: # note: slower students may wish to skip this step to finish the lab in class
        from nltk.corpus import stopwords
        import re
        from bs4 import BeautifulSoup

        # load a list of stop words
        nltk.download('stopwords')


        REPLACE_BY_SPACE_RE = re.compile('[/(){}\[\]\|@,;]')
        BAD_SYMBOLS_RE = re.compile('[^0-9a-z #+_]')
        STOPWORDS = set(stopwords.words('english'))

        def clean_text(text):
            """
                text: a string
                return: modified initial string
            """
            text = BeautifulSoup(text, 'html.parser').text # HTML decoding
            text = text.lower() # lowercase text
            text = REPLACE_BY_SPACE_RE.sub(' ', text) # replace REPLACE_BY_SPACE_RE symbols by
            text = BAD_SYMBOLS_RE.sub('', text) # delete symbols which are in BAD_SYMBOLS_RE f
            text = ' '.join(word for word in text.split() if word not in STOPWORDS) # delete s
            return text
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Now we can apply the newly defined function on the column of df 'post'.

```
In [0]: df['post'] = df['post'].apply(clean_text)
```

Let's check the results:

```
In [0]: print(df['post'].values[10])
```

```
need interface c# possible duplicate would want use interfaces need interface want know use exa
```

This looks a lot better!

Now how many unique words do we have in this cleaned up dataset?

```
In [0]: df['post'].apply(lambda x: len(x.split(' '))).sum()
```

```
Out[0]: 3424194
```

Now we have over 3 million words to work with.

Before we start creating some classifiers, let's split our dataset in a test set (for evaluation) and training set:

```
In [0]: X = df.post
        y = df.tags
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state =
```

0.2.2 Logistic regression

Now that we have our features, we can train a classifier to try to predict the tag of a post. We will start with logistic regression and TFIDF representation which provides a nice baseline for this task.

To make the vectorizer => transformer => classifier easier to work with, we will use Pipeline class in Scikit-Learn that behaves like a compound classifier.

```
In [0]: from sklearn.linear_model import LogisticRegression
        from sklearn.pipeline import Pipeline
        from sklearn.feature_extraction.text import TfidfTransformer

        # we define a Pipeline, which first represents our features as TFID
        # Then performs logistic regression
        logreg = Pipeline([('vect', CountVectorizer()),
                           ('tfidf', TfidfTransformer()),
                           ('clf', LogisticRegression(n_jobs=1, C=1e5)),
                          ])
        logreg.fit(X_train, y_train)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarning: De
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:469: FutureWarning: De
  "this warning.", FutureWarning)
```

```
Out[0]: Pipeline(memory=None,
                 steps=[('vect',
                         CountVectorizer(analyzer='word', binary=False,
                                         decode_error='strict',
                                         dtype=<class 'numpy.int64'>, encoding='utf-8',
                                         input='content', lowercase=True, max_df=1.0,
                                         max_features=None, min_df=1,
                                         ngram_range=(1, 1), preprocessor=None,
                                         stop_words=None, strip_accents=None,
                                         token_pattern='(?u)\\b\\w\\w+\\b',
                                         tokenizer=None, vocabulary=None)),
                        ('tfidf',
                         TfidfTransformer(norm='l2', smooth_idf=True,
                                          sublinear_tf=False, use_idf=True)),
                        ('clf',
                         LogisticRegression(C=100000.0, class_weight=None, dual=False,
                                            fit_intercept=True, intercept_scaling=1,
                                            l1_ratio=None, max_iter=100,
                                            multi_class='warn', n_jobs=1, penalty='l2',
                                            random_state=None, solver='warn',
                                            tol=0.0001, verbose=0, warm_start=False))],
                 verbose=False)
```

How well does it work?

```
In [0]: # to show the computation time:
        %%time

        y_pred = logreg.predict(X_test)

        print('accuracy %s' % accuracy_score(y_pred, y_test))
        print(classification_report(y_test, y_pred))
```

```
accuracy 0.7826666666666666
              precision    recall  f1-score   support

        .net       0.70      0.62      0.66       613
     android       0.91      0.90      0.91       620
   angularjs       0.97      0.94      0.95       587
     asp.net       0.78      0.77      0.78       586
           c       0.77      0.81      0.79       599
          c#       0.60      0.58      0.59       589
         c++       0.77      0.76      0.76       594
         css       0.81      0.86      0.84       610
        html       0.69      0.71      0.70       617
         ios       0.61      0.59      0.60       587
      iphone       0.64      0.64      0.64       611
        java       0.83      0.83      0.83       594
  javascript       0.78      0.78      0.78       619
      jquery       0.84      0.85      0.84       574
       mysql       0.80      0.83      0.82       584
 objective-c       0.65      0.64      0.65       578
         php       0.82      0.84      0.83       591
      python       0.91      0.91      0.91       608
ruby-on-rails       0.96      0.94      0.95       638
         sql       0.78      0.83      0.80       601

    accuracy                           0.78     12000
   macro avg       0.78      0.78      0.78     12000
weighted avg       0.78      0.78      0.78     12000

CPU times: user 1.13 s, sys: 1.35 ms, total: 1.14 s
Wall time: 1.15 s
```

That's quite a good accuracy. Now let's see if we can combine word2vec with logistic regression by feeding the new embedded representation to our logistic regression instead of the bag of words.

0.3 Word2vec embedding and Logistic Regression

Let's load a pretrained word2vec model, and use the embedding representation as input to a simple classifier (i.e. logistic regression).

You can use the word2vec model you trained in lab 10a, or load this (quite big, 1.5GB) pre-trained word2vec model: https://s3.amazonaws.com/dl4j-distribution/GoogleNews-vectors-negative300.bin.gz

Note: it can take a while to load. (takes 2min for me)

```
In [0]: !wget "https://s3.amazonaws.com/dl4j-distribution/GoogleNews-vectors-negative300.bin.gz
```

```
--2019-10-31 03:30:16--  https://s3.amazonaws.com/dl4j-distribution/GoogleNews-vectors-negative
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.216.177.197
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.216.177.197|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1647046227 (1.5G) [application/x-gzip]
Saving to: GoogleNews-vectors-negative300.bin.gz

GoogleNews-vectors- 100%[===================>]   1.53G  56.3MB/s    in 23s

2019-10-31 03:30:40 (67.3 MB/s) - GoogleNews-vectors-negative300.bin.gz saved [1647046227/1647
```

Once the file is on your system:

```
In [0]: %%time
        from gensim.models import Word2Vec

        wv = gensim.models.KeyedVectors.load_word2vec_format("GoogleNews-vectors-negative300.bi
        wv.init_sims(replace=True)
        print('Model loaded')
```

```
/usr/local/lib/python3.6/dist-packages/smart_open/smart_open_lib.py:398: UserWarning: This func
  'See the migration notes for details: %s' % _MIGRATION_NOTES_URL


Model loaded
CPU times: user 2min 3s, sys: 4.3 s, total: 2min 7s
Wall time: 2min 7s
```

If you are interested how good these pretrained embeddings are, you could try some of the similarity tests we did in Lab 10a.

As we have multiple words for each post, we will need to somehow combine them. A common way to achieve this is by averaging the word vectors per document. It could also be summation or weighted addition. The function below takes as input a list of words and the w2v model wv. Then it retrieves the vector embeddings for each of the words and averages them.

```
In [0]: def word_averaging(wv, words):
            # averages a set of words 'words' given their wordvectors 'wv'

            all_words, mean = set(), []
```

```
            # for each word in the list of words
            for word in words:
                # if the words are alread vectors, then just append them
                if isinstance(word, np.ndarray):
                    mean.append(word)
                # if not: first get the vector embedding for the words
                elif word in wv.vocab:
                    mean.append(wv.syn0norm[wv.vocab[word].index])
                    all_words.add(wv.vocab[word].index)


            if not mean:
                # error handling in case mean cannot be calculated
                logging.warning("cannot compute similarity with no input %s", words)
                return np.zeros(wv.vector_size,)

            # use gensim's method to calculate the mean of all the words appended to mean list
            mean = gensim.matutils.unitvec(np.array(mean).mean(axis=0)).astype(np.float32)
            return mean

        def  word_averaging_list(wv, text_list):
            return np.vstack([word_averaging(wv, post) for post in text_list ])
```

Below, we explore a different way to create tokens out of sentences, by using the nltk toolkit.

```
In [0]: import nltk.data
        nltk.download('punkt')

        def w2v_tokenize_text(text):
            # create tokens, a list of words, for each post. This function will do some cleani
            tokens = []
            for sent in nltk.sent_tokenize(text, language='english'):
                for word in nltk.word_tokenize(sent, language='english'):
                    if len(word) < 2:
                        continue
                    tokens.append(word)
            return tokens
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Let's split the dataset in training and test set like before, and tokenize each of the datasets

```
In [0]: train, test = train_test_split(df, test_size=0.3, random_state = 42)

        test_tokenized = test.apply(lambda r: w2v_tokenize_text(r['post']), axis=1).values
        train_tokenized = train.apply(lambda r: w2v_tokenize_text(r['post']), axis=1).values
```

We can then average the position per post in this new dataset using the functions we defined above and based on our word2vec model wv.

```
In [0]: X_train_word_average = word_averaging_list(wv,train_tokenized)
        X_test_word_average = word_averaging_list(wv,test_tokenized)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:13: DeprecationWarning: Call to de
  del sys.path[0]
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):
WARNING:root:cannot compute similarity with no input []
WARNING:root:cannot compute similarity with no input ['ngrepeat']
```

Now we can feed this new representation into the logistic regression:

```
In [0]: from sklearn.linear_model import LogisticRegression
        logreg = LogisticRegression(n_jobs=1, C=1e5)
        logreg = logreg.fit(X_train_word_average, train['tags'])
        y_pred = logreg.predict(X_test_word_average)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarning: Def
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:469: FutureWarning: Def
  "this warning.", FutureWarning)
```

How accurate is this averaged word2vec model with logistic regression?

```
In [0]: print('accuracy %s' % accuracy_score(y_pred, test.tags))
        print(classification_report(test.tags, y_pred))
```

```
accuracy 0.6375
              precision    recall  f1-score   support

         .net       0.62      0.59      0.61       613
     android        0.74      0.76      0.75       620
    angularjs       0.65      0.67      0.66       587
      asp.net       0.53      0.52      0.52       586
            c       0.70      0.77      0.73       599
           c#       0.44      0.39      0.41       589
          c++       0.65      0.60      0.63       594
          css       0.73      0.80      0.76       610
         html       0.60      0.61      0.60       617
          ios       0.56      0.52      0.54       587
       iphone       0.55      0.50      0.52       611
         java       0.61      0.61      0.61       594
   javascript       0.65      0.65      0.65       619
       jquery       0.61      0.57      0.59       574
```

```
              precision    recall  f1-score   support

       mysql       0.70      0.71      0.71       584
  objective-c       0.42      0.43      0.43       578
         php       0.68      0.70      0.69       591
      python       0.76      0.78      0.77       608
ruby-on-rails       0.82      0.83      0.82       638
         sql       0.65      0.71      0.68       601

    accuracy                           0.64     12000
   macro avg       0.63      0.64      0.63     12000
weighted avg       0.63      0.64      0.64     12000
```

Now you can see that the accuracy went down! Oh no! Why is that? Because we used a very naive approach, to average our vectors. The way around it would be doc2vec, which learns relationships between documents (posts in this case), instead of words. The accuracy could also improve by using a different classifier instead of logistic regression, or by changing the aggregation strategy.

0.4 Doc2vec and Logistic Regression (advanced)

The idea of word2vec can be extended to documents whereby instead of learning feature representations for words, we learn it for sentences or documents. To get a general idea of a word2vec, think of it as a mathematical average of the word vector representations of all the words in the document. Doc2Vec extends the idea of word2vec, however words can only capture so much, there are times when we need relationships between documents and not just words.

The way to train doc2vec model for our Stack Overflow questions and tags data is very similar with when we trained multi-class text classification with word2vec and logistic regression above.

First, we label the sentences. Gensim's Doc2Vec implementation requires each document/paragraph to have a label associated with it that indicates if it's part of the test or training set. We do this by using the TaggedDocument method. The format will be "TRAIN_i" or "TEST_i" where "i" is a dummy index of the post.

First let's import the necessary libraries.

```
In [0]: from tqdm import tqdm
        from gensim.models import doc2vec
        from sklearn import utils
        import gensim
        from gensim.models.doc2vec import TaggedDocument
        import re
```

Let's start by defining a function that labels our documents in the corpus. We just give them dummy labels TRAIN_i or TEST_i for post i. Given a corpus and labels, we return a variable that includes a label indicating if it's test or training data.

```
In [0]: def label_sentences(corpus, label_type):
            """
            Gensim's Doc2Vec implementation requires each document/paragraph to have a label a
            We do this by using the TaggedDocument method. The format will be "TRAIN_i" or "TE
```

```
        a dummy index of the post.
        """
        labeled = []
        for i, v in enumerate(corpus):
            label = label_type + '_' + str(i)
            labeled.append(doc2vec.TaggedDocument(v.split(), [label]))
        return labeled
```

Just like above we split our dataset up in test and training data.

```
In [0]: X_train, X_test, y_train, y_test = train_test_split(df.post, df.tags, random_state=0, t
        X_train = label_sentences(X_train, 'Train')
        X_test = label_sentences(X_test, 'Test')
        all_data = X_train + X_test
```

Let's have a look how our data looks at this moment:

```
In [0]: all_data[:10]
```

```
Out[0]: [TaggedDocument(words=['fulltext', 'search', 'php', 'pdo', 'returning', 'result', 'sear
         TaggedDocument(words=['select', 'everything', '1', 'table', 'x', 'rows', 'another', 'i
         TaggedDocument(words=['r', 'cannot', 'resolved', 'variable', 'importing', 'project',
         TaggedDocument(words=['efficient', 'way', 'get', 'values', 'object', 'based', 'id', 'l
         TaggedDocument(words=['aspnet', 'limit', 'parameter', 'length', 'querystring', 'proble
         TaggedDocument(words=['ruby', 'rails', 'fetch', 'display', 'descendent', 'records', 'p
         TaggedDocument(words=['canceling', 'fade', 'effect', 'tooltip', 'hover', 'need', 'tool
         TaggedDocument(words=['ajax', 'calender', 'working', 'ie', 'using', 'ajax', 'calender
         TaggedDocument(words=['c++', 'random', 'number', 'generator', 'hung', 'whenever', 'att
         TaggedDocument(words=['bit', 'vector', 'looked', 'online', 'good', 'seem', 'find', 'go
```

Gensim allows us to build a model very easily. We can vary the parameters to fit your data:

- dm=0 , distributed bag of words (DBOW) is used.
- vector_size=300 , 300 vector dimensional feature vectors.
- negative=5 , specifies how many "noise words" should be drawn.
- min_count=1, ignores all words with total frequency lower than this.
- alpha=0.065 , the initial learning rate.

We initialize the model and train for 30 epochs. (slower computers may want to train for less epochs). Be sure to set your runtime to TPU/GPU hardware acceleration! Maybe test with a lower amount of epochs first to see how high you can go during class time!

```
In [0]: model_dbow = Doc2Vec(dm=0, vector_size=300, negative=5, min_count=1, alpha=0.065, min_a
        model_dbow.build_vocab([x for x in tqdm(all_data)])
```

```
100%|| 40000/40000 [00:00<00:00, 1619281.72it/s]
```

```
In [0]: for epoch in range(30):
            model_dbow.train(utils.shuffle([x for x in tqdm(all_data)]), total_examples=len(all
            model_dbow.alpha -= 0.002
            model_dbow.min_alpha = model_dbow.alpha
```

```
100%|| 40000/40000 [00:00<00:00, 1742363.28it/s]
100%|| 40000/40000 [00:00<00:00, 2388283.79it/s]
100%|| 40000/40000 [00:00<00:00, 2230775.45it/s]
100%|| 40000/40000 [00:00<00:00, 2113079.34it/s]
100%|| 40000/40000 [00:00<00:00, 2212710.82it/s]
100%|| 40000/40000 [00:00<00:00, 2216657.55it/s]
100%|| 40000/40000 [00:00<00:00, 2333279.93it/s]
100%|| 40000/40000 [00:00<00:00, 3057295.72it/s]
100%|| 40000/40000 [00:00<00:00, 2741688.76it/s]
100%|| 40000/40000 [00:00<00:00, 3026903.13it/s]
100%|| 40000/40000 [00:00<00:00, 2683882.20it/s]
100%|| 40000/40000 [00:00<00:00, 2664657.41it/s]
100%|| 40000/40000 [00:00<00:00, 2356847.09it/s]
100%|| 40000/40000 [00:00<00:00, 2838640.34it/s]
100%|| 40000/40000 [00:00<00:00, 2127765.22it/s]
100%|| 40000/40000 [00:00<00:00, 2252701.00it/s]
100%|| 40000/40000 [00:00<00:00, 2347185.99it/s]
100%|| 40000/40000 [00:00<00:00, 2467709.42it/s]
100%|| 40000/40000 [00:00<00:00, 2876998.37it/s]
100%|| 40000/40000 [00:00<00:00, 2293253.87it/s]
100%|| 40000/40000 [00:00<00:00, 2717838.33it/s]
100%|| 40000/40000 [00:00<00:00, 2094481.54it/s]
100%|| 40000/40000 [00:00<00:00, 3184680.62it/s]
100%|| 40000/40000 [00:00<00:00, 2300549.32it/s]
100%|| 40000/40000 [00:00<00:00, 2630936.03it/s]
100%|| 40000/40000 [00:00<00:00, 2480809.13it/s]
100%|| 40000/40000 [00:00<00:00, 2181182.04it/s]
100%|| 40000/40000 [00:00<00:00, 2462963.68it/s]
100%|| 40000/40000 [00:00<00:00, 2129736.98it/s]
100%|| 40000/40000 [00:00<00:00, 2881247.49it/s]
```

Now let's define a function to the vectors out of this trained model, so that we can feed them into the logistic regression:

```
In [0]: def get_vectors(model, corpus_size, vectors_size, vectors_type):
            """
            Get vectors from trained doc2vec model
            :param doc2vec_model: Trained Doc2Vec model
            :param corpus_size: Size of the data
            :param vectors_size: Size of the embedding vectors
            :param vectors_type: Training or Testing vectors
            :return: list of vectors
            """
            vectors = np.zeros((corpus_size, vectors_size))
            for i in range(0, corpus_size):
                prefix = vectors_type + '_' + str(i)
                vectors[i] = model.docvecs[prefix]
            return vectors
```

We can use this function to create a vectorised training and test set with 1 entry per document for the input in classification models such as logistic regression.

```
In [0]: train_vectors_dbow = get_vectors(model_dbow, len(X_train), 300, 'Train')
        test_vectors_dbow = get_vectors(model_dbow, len(X_test), 300, 'Test')
```

We can now feed these vectors to the classifier again:

```
In [0]: logreg = LogisticRegression(n_jobs=1, C=1e5)
        logreg.fit(train_vectors_dbow, y_train)

        logreg = logreg.fit(train_vectors_dbow, y_train)
        y_pred = logreg.predict(test_vectors_dbow)

        print('accuracy %s' % accuracy_score(y_pred, y_test))
        print(classification_report(y_test, y_pred))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarning: De
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:469: FutureWarning: De
  "this warning.", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarning: De
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:469: FutureWarning: De
  "this warning.", FutureWarning)


accuracy 0.8081666666666667
               precision    recall  f1-score   support

         .net       0.72      0.69      0.70       589
      android       0.89      0.91      0.90       661
    angularjs       0.95      0.95      0.95       606
      asp.net       0.79      0.78      0.79       613
            c       0.82      0.89      0.85       601
           c#       0.73      0.72      0.72       585
          c++       0.85      0.79      0.82       621
          css       0.83      0.86      0.84       587
         html       0.70      0.67      0.69       560
          ios       0.68      0.65      0.66       611
       iphone       0.67      0.68      0.68       593
         java       0.81      0.84      0.83       581
   javascript       0.80      0.79      0.79       608
       jquery       0.86      0.85      0.85       593
        mysql       0.83      0.83      0.83       592
  objective-c       0.71      0.65      0.68       597
          php       0.83      0.85      0.84       604
       python       0.89      0.93      0.91       610
ruby-on-rails       0.94      0.95      0.94       595
```

```
          sql       0.81      0.84      0.82       593

     accuracy                           0.81     12000
    macro avg       0.81      0.81      0.81     12000
 weighted avg       0.81      0.81      0.81     12000
```

80%, that is the best result so far! Remember, we can actually use any classifier with this method! So up to you to make your project as efficient as possible :)

Try using a different classifiers, e.g. Decision tree or SVM. Does that influence the results?

New methods are coming out every day in the field of data science. Just at the end of August 2019, the first implementation of BERT for document classfication was published: DocBERT: https://arxiv.org/abs/1904.08398

0.5 References

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