Classifying Reddit comments that are about physics, chemistry and biology.

- First, we preprocess the corpus using regex and nltk's tokenization and lemmatization
- Then we use word2vec to create a representation for each word
- after that, we cluster the representations in order to find the words that are close together in terms of their meaning
- We then replace all the worlds of each cluster with the representative word of that cluster in the corpus. (this effectively makes sure that all the words in a cluster take the same spot in the bag of words vector.
- Finally, we create a representation for each comment using bag of words and TF-IDF and try to classify the test data set. $\frac{1}{2}$

Contents:

- Pre-processing
- Word2Vec
- Clustering Word2Vec
- · Bag-of-words and TF-IDF
- Bag-of-words and TF-IDF with Word2Vec Topic Modeling

Pre-processing

```
In [2]: import pandas as pd
          import numpy as np
          import nltk
          import string
          import re
          from nltk.tokenize import word tokenize
          from nltk.corpus import stopwords
          from nltk.stem import WordNetLemmatizer
          from nltk.stem.snowball import SnowballStemmer
          from sklearn.preprocessing import LabelEncoder
In [ ]: # nltk.download('stopwords')
          # nltk.download('punkt')
          # nltk.download('wordnet')
          # nltk.download('omw-1.4')
In [2]: raw_train = pd.read_csv("train.csv")
          raw_train.head()
Out[2]:
                                                      Comment
                                                                     Topic
          0 0x840 A few things. You might have negative- frequen...
                                                                    Biology
          1 0xbf0
                          Is it so hard to believe that there exist part...
                                                                   Physics
          2 0x1dfc
                                                  There are bees
                                                                    Biology
                     I'm a medication technician. And that's alot o...
          3 0xc7e
                                                                   Biology
          4 Oxbba
                                     Cesium is such a pretty metal. Chemistry
```

Dataframe Cleanup

```
In [3]: # Convert categorical data to numerical
raw_train['Topic'] = LabelEncoder().fit_transform(raw_train['Topic'])

# Drop the Id column
raw_train = raw_train.drop(columns=["Id"])
raw_train.head()

Out[3]: Comment Topic

0 A few things. You might have negative-frequen... 0

1 Is it so hard to believe that there exist part... 2

2 There are bees 0

3 I'm a medication technician. And that's alot o... 0

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js | Netal. |
```

Text Cleanup

```
In [4]: def text_cleanup_regex(txt: str) -> str:
               # Convert to lower case and remove bounding space
               txt = txt.lower().strip()
               # Remove reddit specific texts
               txt = re.sub("\[removed\]", " ", txt)
txt = re.sub("\[deleted\]", " ", txt)
               # Remove URLs
               txt = re.sub("http\S+", " ", txt)
               txt = re.sub("www\.\S+", " ", txt)
               # Remove everything that is not a letter
               txt = re.sub("[^a-zA-Z]", " ", txt)
               # txt = re.sub('[%s]' % re.escape(string.punctuation), ' ', txt)
               # Remove single and double letter words
               txt = re.sub(r'\b\w{1,2}\b', '', txt)
               return txt
```

```
Cleanup Pipeline
In [5]: english_stopwords = stopwords.words("english")
           lemmatizer = WordNetLemmatizer()
           def text_cleanup_pipeline(txt: str) -> [str]:
               # basic clean up using regex
               txt: str = text_cleanup_regex(txt)
               # tokenize (convert string of words to array of words)
               txt: [str] = word_tokenize(txt)
               # make sure the word is not a stopword
               txt: [str] = [w for w in txt if w not in english_stopwords]
               # take out the root of the word
               txt: [str] = [lemmatizer.lemmatize(w) for w in txt]
               return txt
In [6]: # Clean up comments using text_cleanup_pipeline
           raw_train['Comment'] = raw_train['Comment'].apply(lambda x : text_cleanup_pipeline(x))
           raw_train.head()
Out[6]:
                                               Comment Topic
           0 [thing, might, negative, frequency, dependent,...
               [hard, believe, exist, particular, detect, any...
                                                              2
           2
                                                              Ω
                 [medication, technician, alot, drug, liver, pr...
          3
                                                              0
           4
                                    [cesium, pretty, metal]
                                                              1
In [7]: # Drop rows with empty comment
           size_before_empty_drop = raw_train.shape[0]
           \label{eq:raw_train} \mbox{raw\_train['Comment'].apply(lambda } x \colon \mbox{len}(x) > \emptyset)]
           print("Dropped: {}".format(size_before_empty_drop - raw_train.shape[0]))
           raw_train.head()
          Dropped: 286
Out[7]:
                                               Comment Topic
           0 [thing, might, negative, frequency, dependent,...
                                                              0
                 [hard, believe, exist, particular, detect, any...
          1
                                                              2
           2
                                                              0
           3
                 [medication, technician, alot, drug, liver, pr...
                                                              0
           4
                                    [cesium, pretty, metal]
In [8]: # Convert list of words to string
           \label{local_comment_local_comment_local} $$\operatorname{raw\_train['Comment'].apply(lambda\ x\ :\ "\ ".join(x))}$$
           raw_train.head()
```

```
0 thing might negative frequency dependent selec...
                 hard believe exist particular detect anything ...
           2
                                                               0
                medication technician alot drug liver probably...
           3
                                                               0
           1
                                        cesium pretty metal
                                                               1
In [11]: # Do the same preprocessing for train data
            raw test = pd.read csv("test.csv")
            raw_test['Topic'] = LabelEncoder().fit_transform(raw_test['Topic'])
            raw_test = raw_test.drop(columns=["Id"])
            raw_test['Comment'] = raw_test['Comment'].apply(lambda x : text_cleanup_pipeline(x))
            raw_test = raw_test[raw_test['Comment'].apply(lambda x: len(x) > 0)]
```

To avoid having to preprocess the data again in case something goes wrong, copy the preprocessed data to a new variable.

Comment Topic

raw_test['Comment'] = raw_test['Comment'].apply(lambda x : " ".join(x))

```
In [12]: train_data = raw_train.copy()
train_data.shape

Out[12]: (8409, 2)

In [13]: test_data = raw_test.copy()
test_data.shape

Out[13]: (1586, 2)
```

Word2Vec

Out[8]:

Take out the unique words.

- Get a list o unique words
- Use googles trained W2V to get a vector for each word
- Create a dataframe and combine the words with their vectors
- · Save te data frame to avoid loading the 1.5 Gb model everytime

```
In [38]: from gensim.models import KeyedVectors
           from collections import Counter
In [39]: model = KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin', binary=True)
In [66]: # Select words that have a vector
           unique\_words = np.fromiter((x \ \textbf{for} \ x \ \textbf{in} \ unique\_words \ \textbf{if} \ model.has\_index\_for(x)), \ dtype=unique\_words.dtype)
           print("Size: {}".format(len(unique_words)))
           unique words[10:20]
          Size: 12164
In [67]: # Get the corresponding vector for each word
           unique_words_vectors = np.array(list(map(lambda x: model[x], unique_words)))
          unique_words_vectors.shape
Out[67]: (12164, 300)
In [70]: # Zip words and vectors together
           word_vecs = pd.DataFrame(unique_words_vectors)
           word_vecs.insert(loc=0, column='word', value=unique_words)
           word_vecs.head()
```

```
Out[70]:
                                    word
                                                                                                                                                                                                             8 ...
                                                                                                                                                                                                                                  290
                                                                                                                                                                                                                                                    291
                                                                                                                                                                                                                                                                       292
                     0
                                                                  0.021973 0.041016 0.328125
                                                                                                                                                                             -0.208984
                                                                                                                     -0.113281
                                                                                                                                         -0.337891
                                                                                                                                                            0.082520
                                                                                                                                                                                                 0.410156 ...
                                                                                                                                                                                                                          0.044922
                                                                                                                                                                                                                                            0.449219
                                                                                                                                                                                                                                                              -0.138672
                                                0.163086
                                                                 -0.010132  0.105957  0.229492  -0.070801
                                                                                                                                        -0.458984
                                                                                                                                                            0.206055
                                                                                                                                                                             -0.213867
                                                                                                                                                                                                 0.150391 ...
                                                                                                                                                                                                                        -0.002899
                                                                                                                                                                                                                                            0.392578
                                                                                                                                                                                                                                                              -0.214844
                                       aah
                                               0.064941
                                                                  0.241211
                                                                                  0.054443
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                                                                                                                      -0.075684
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                                                                                                                                                                              -0.163086
                                                                                                                                                                                                -0.243164 ...
                                                                                                                                                                                                                          0.068359
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                                abandon 0.007660
                                                                  0.078613 0.109375 0.339844 -0.208984
                                                                                                                                         0.044678
                                                                                                                                                           -0.036621
                                                                                                                                                                           -0.041992
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                                                                                                                                                                                                                                            0.355469
                                                                                                                                                                                                                                                             -0.205078 0.0
                     3
                     4 abbreviation 0.218750
                                                                -0.209961 0.138672 0.386719 -0.277344 -0.208008
                                                                                                                                                          -0.382812
                                                                                                                                                                            -0.376953
                                                                                                                                                                                                 0.161133 ... -0.020020
                                                                                                                                                                                                                                           -0.084473
                                                                                                                                                                                                                                                              -0.120117 -0.3
                   5 rows × 301 columns
4
                     word_vecs.to_pickle("reddit_w2v.pkl")
                     Load saved vectors
   In [3]: # Load the dataframe from a file
                     output = pd.read_pickle("reddit_w2v.pkl")
                     output.head()
   Out[3]:
                                                            0
                                                                                               2
                                                                                                                                                                                                             8 ...
                                                                                                                                                                                                                                  290
                                                                                                                                                                                                                                                    291
                                                                                                                                                                                                                                                                       292
                                    word
                     0
                                                0.031738
                                                                  0.082520
                                                                                                                                                                             -0.208984
                                                                                                                                                                                                 0.410156 ...
                                                                                                                                                                                                                          0.044922
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                                                                                                                                                                                                                                                             -0.138672
                                                                                                                                                                                                                                                                               -0.2
                                               0.163086 -0.010132 0.105957 0.229492 -0.070801 -0.458984
                                                                                                                                                            0.206055
                                                                                                                                                                             -0.213867
                                                                                                                                                                                                 0.150391 ... -0.002899
                                                                                                                                                                                                                                            0.392578
                                         ab 0.064941
                                                                  0.241211 0.054443 0.191406
                                                                                                                     -0.075684
                                                                                                                                          0.199219
                                                                                                                                                           -0.051514
                                                                                                                                                                              -0.163086
                                                                                                                                                                                                -0.243164 ...
                                                                                                                                                                                                                          0.068359
                                                                                                                                                                                                                                            0.042969
                                                                                                                                                                                                                                                              -0.139648
                                                                                                                                                                                                                                                                               -0.0
                                                                  0.044678 -0.036621 -0.041992
                                abandon 0.007660
                                                                                                                                                                                                 0.192383 ... -0.033203
                                                                                                                                                                                                                                            0.355469
                                                                                                                                                                                                                                                            -0.205078 0.0
                     4 abbreviation 0.218750 -0.209961 0.138672 0.386719 -0.277344 -0.208008
                                                                                                                                                         -0.382812 -0.376953
                                                                                                                                                                                                 0.161133 ... -0.020020
                                                                                                                                                                                                                                          -0.084473
                                                                                                                                                                                                                                                            -0.120117 -0.1
                   5 rows × 301 columns
                     compression_opts = dict(method='zip'
                                                                archive_name='out.csv')
                     output.to_csv("reddit_w2v.zip", index=False, compression=compression_opts)
 In [26]:
                     words = output['word']
                     output: pd.DataFrame = output.iloc[:, 1:301]
                     vectors = output.to_numpy()
                     vectors.shape
                    array([[ 0.03173828, 0.02197266, 0.04101562, ..., 0.01818848,
Out[26]:
                                    -0.37695312, 0.16894531],
                                 [ 0.16308594, -0.01013184, 0.10595703, ..., -0.296875 ,
                                    -0.1171875 , 0.25
                                                                             ],
                                 [ 0.06494141, 0.24121094, 0.05444336, ..., 0.33789062,
                                   -0.05102539, 0.04760742],
                                  [-0.07421875, \ -0.10205078, \ \ 0.20117188, \ \ldots, \ -0.25390625,
                                     0.06054688, -0.21289062],
                                  [ 0.18554688, 0.16894531, 0.00267029, ..., -0.33007812,
                                    0.05004883, -0.21191406],
                                  [-0.08935547, \quad 0.10351562, \quad 0.06787109, \ \dots, \quad 0.0378418 \ , \\
                                     0.05053711, 0.01940918]], dtype=float32)
                     Clustering-Word2Vec
 In [135...
                     from sklearn.cluster import KMeans
                     from sklearn.cluster import MeanShift
                     from sklearn.cluster import DBSCAN
                     \textbf{from} \ \text{sklearn.decomposition} \ \textbf{import} \ \text{PCA}
                     \begin{picture}(100,00) \put(0,0){\line(0,0){100}} \put(0,0){\line(0,0){1
                     from IPython.display import clear_output
                     import time
   In [ ]:
                     pca_vectors = PCA(n_components=2).fit_transform(vectors)
```

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js some of the clustered words

In [145... key_iden = KMeans(n_clusters=10000, random_state=0).fit(pca_vectors)

In [48]: std_vectors = StandardScaler().fit_transform(pca_vectors)

pca_vectors.shape

```
for i in range(key_iden.n_clusters):
                n = words[key_iden.labels_ == i].shape[0]
                if n > 1 and n < 10:
                    print(words[key_iden.labels_ == i].shape)
print(words[key_iden.labels_ == i])
                    time.sleep(1)
                    clear_output(wait=True)
In [184... key_iden.labels_
Out[184]: array([4269, 6165, 546, ..., 3362, 6058, 5095], dtype=int32)
In [151... N_ELEMENTS_UPPER_THRESHOLD = 10
            N_ELEMENTS_LOWER_THRESHOLD = 1
            # Find cluster numbers with proper number of elements
            good_cluster_numbers = []
            for i in range(key_iden.n_clusters):
                n = words[key_iden.labels_ == i].shape[0]
                \label{eq:if_n} \textbf{if} \ n \ > \ N\_ELEMENTS\_LOWER\_THRESHOLD \ \ \\ \textbf{and} \ \ n \ \ < \ N\_ELEMENTS\_UPPER\_THRESHOLD: 
                    good_cluster_numbers.append(i)
            # Find a representation for each cluster (here we take the first word)
            good_cluster_words = []
            for i in good_cluster_numbers:
                good_cluster_words.append(words[key_iden.labels_ == i].iloc[0])
In [172... topic_modeled_train_data = train_data.copy()
            for i, cluster_num in enumerate(good_cluster_numbers):
                for word in words[key_iden.labels_ == cluster_num]:
                    topic_modeled_train_data['Comment'].replace(word, good_cluster_words[i], inplace=True, regex=True)
In [173... | topic_modeled_unique_words: [str] = list(set(" ".join(topic_modeled_train_data['Comment'].str.lower().values.tolist()).split(" ")))
            print("Unique words: {}".format(len(unique_words)))
            print("Topic modeled unique words: {}".format(len(topic_modeled_unique_words)))
            print("Diff: {}".format(len(unique_words) - len(topic_modeled_unique_words)))
            Unique words: 14574
            Topic modeled unique words: 12961
           Diff: 1613
In [200... topic_modeled_test_data = test_data.copy()
            for i. cluster num in enumerate(good cluster numbers):
                for word in words[key_iden.labels_ == cluster_num]:
                    topic_modeled_test_data['Comment'].replace(word, good_cluster_words[i], inplace=True, regex=True)
            Bag-of-words and TF-IDF
```

Bag of Words

```
precision recall f1-score support
                             0.90
                                      0.82
                                                0.86
                             0.79
                                      0.85
                                                0.82
                                                           506
                                               0.85
                            0.84
                                      0.86
                                                           466
                                                0.84
                                                          1586
             macro avg
                             0.84
                                      0.85
                                                0.84
                                                          1586
                            0.85
                                      0.84
                                                0.84
                                                          1586
           weighted avg
           Train Score: 0.8800095136163634
           Test Score: 0.8442622950819673
          TF-IDF
In [109... # TF-IDF
           tfidf_vectorizer = TfidfVectorizer()
           tfidf_train = tfidf_vectorizer.fit_transform(x_train)
           tfidf_test = tfidf_vectorizer.transform(x_test)
In [111... # Classification
           clf = MultinomialNB(alpha=0.1)
           clf.fit(tfidf_train, y_train)
           y_pred = clf.predict(tfidf_test)
           # Classification score
           print(classification_report(y_test, y_pred))
           print("Train Score: {}".format(clf.score(tfidf_train, y_train)))
           print("Test Score: {}".format(clf.score(tfidf_test, y_test)))
                        precision recall f1-score support
```

0.84 0.79 0.85 0.82 506 0.85 0.84 0.85 466 0.84 accuracy 0.84 macro avg 0.84 0.84 weighted avg 0.85 0.84 0.84 1586

Train Score: 0.9086692829111666 Test Score: 0.8430012610340479

Bag-of-words and TF-IDF with Word2Vec Topic Modeling

```
In [201... # Seperate labels
           x_train = topic_modeled_train_data["Comment"]
           y_train = topic_modeled_train_data["Topic"]
           x_test = topic_modeled_test_data["Comment"]
           y_test = topic_modeled_test_data["Topic"]
```

```
Bag of Words
In [202... # BoW
           bow_vectorizer = CountVectorizer()
           bow_train = bow_vectorizer.fit_transform(x_train)
           bow_test = bow_vectorizer.transform(x_test)
In [203... # Classification
           clf = MultinomialNB(alpha=0.1)
           clf.fit(bow_train, y_train)
           y_pred = clf.predict(bow_test)
           # Classification score
           print(classification_report(y_test, y_pred))
           print("Train Score: {}".format(clf.score(bow_train, y_train)))
           print("Test Score: {}".format(clf.score(bow_test, y_test)))
                        precision
                                    recall f1-score support
                     0
                             0.89
                                       0.82
                                                 0.85
                                                            614
                             0.79
                                       0.84
                                                 0.81
                                                            506
                             0.84
                                       0.87
                                                 0.86
               accuracy
                                                 0.84
                                                           1586
```

0.84

0.84

0.84

0.84

0.84

0.84

1586

1586

macro avg weighted avg

TF-IDF

```
In [204... # TF-IDF
                tfidf_vectorizer = TfidfVectorizer()
                tfidf_train = tfidf_vectorizer.fit_transform(x_train)
tfidf_test = tfidf_vectorizer.transform(x_test)
In [205... # Classification
                clf = MultinomialNB(alpha=0.1)
                clf.fit(tfidf_train, y_train)
y_pred = clf.predict(tfidf_test)
                # Classification score
                print(classification_report(y_test, y_pred))
                print("Train Score: {}".format(clf.score(tfidf_train, y_train)))
print("Test Score: {}".format(clf.score(tfidf_test, y_test)))
                                 precision recall f1-score support

    0
    0.88
    0.82
    0.85

    1
    0.79
    0.85
    0.82

    2
    0.85
    0.86
    0.86

                                                                                     614
                                                                                  506
466
               accuracy 0.84 1586
macro avg 0.84 0.84 0.84 1586
weighted avg 0.84 0.84 0.84 1586
                Train Score: 0.904150315138542
                Test Score: 0.8398486759142497
 In [ ]:
```