In [1]:
```
# importing the libraries
from IPython.display import display
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from wordcloud import WordCloud, STOPWORDS
import nltk
from nltk.probability import FreqDist
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from gensim.models import Word2Vec, KeyedVectors
from datasets import load_dataset
import gensim.downloader as api
from sklearn.metrics.pairwise import cosine_similarity
import plotly.express as px
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier, kneighbors_graph
from sklearn.metrics import confusion_matrix, f1_score, accuracy_score
from sklearn.metrics import precision_recall_fscore_support
import warnings
from pandas.core.common import SettingWithCopyWarning
```

In [2]:
```
warnings.simplefilter(action="ignore", category=SettingWithCopyWarning)
```

In [3]:
```
# downloading nltk.punkt
try:
    nltk.data.find('tokenizers/punkt')
except LookupError:
    nltk.download('punkt')
```

Defining relevant functions

In [4]:
```
def word_cloud_plot (data):
    """
    function that creates a word cloud from a specified column of a dataframe
    """
    # create set of stopwords
    stopwords = set(STOPWORDS)

    # Instantiate the word cloud object
    word_cloud = WordCloud(background_color='white',max_words=200,stopwords=stop

    # generate the word cloud
    word_cloud.generate(' '.join(data))

    # To display the word cloud
    plt.figure( figsize=(20,10) )
    plt.imshow(word_cloud, interpolation='bilinear')
    plt.axis('off')
    plt.show()
```

In [5]:
```
def regex_filter(sentence):
    """
    funtion that formats string to remove special characters
    """
```

```
    import re
    return re.sub('[^a-zA-Z]', ' ', sentence)
```

In [6]:
```
def filter_stop_words(token):
    """
    function that removes stopwords from a word-tokenized sentence
    """
    stop_words = set(stopwords.words('english'))
    filtered_token = [word.lower() for word in token if word.lower() not in stop
    return filtered_token
```

In [7]:
```
def stem_words(token):
    """
    function that stems word-tokenized sentences
    """
    ps = PorterStemmer()
    stemmed_token = [ps.stem(word) for word in token]
    return stemmed_token
```

In [8]:
```
def lemmatize_words(token):
    """
    function that lemmatizes word-tokenized sentences
    """
    lem = WordNetLemmatizer()
    lemmatized_token = [lem.lemmatize(word, 'v') for word in token]
    return lemmatized_token
```

In [9]:
```
def join_token(token):
    """
    function that joins word-tokenized sentences back to single string
    """
    return ' '.join(token)
```

In [10]:
```
def get_embeddings(group, model):
    """
    Function for getting embeddings of words from a word2vec model
    """
    group_embedding = []
    group_labels = []

    unique_words = [word for sentence in group for word in sentence]
    unique_words = list(dict.fromkeys(unique_words))

    for word in unique_words:
        if model.wv.__contains__(word):
            group_embedding.append(list(model.wv.__getitem__(word)))
            group_labels.append(word)

    df_embedding = pd.DataFrame(group_embedding)
    df_word = pd.DataFrame(group_labels, columns = ["Word"])
    df = pd.concat([df_word, df_embedding], axis=1)
    return df
```

In [11]:
```
def similarity(words, stem_model=None, lem_model=None, W2V_pretrained=None, GloV
    """
    function that computes similarity between words for up to four models passed
    """
    if stem_model:
```

```
        ps = PorterStemmer()
        stemmed = [ps.stem(word) for word in words]
        try:
            print("Stemmed W2V model similarity between", words[0], "and", words
        except:
            print("Error: Word not in stem model vocabulary")

    if lem_model:
        lem = WordNetLemmatizer()
        lemma = [lem.lemmatize(word, 'v') for word in words]
        try:
            print("Lemmatized W2V model similarity between", words[0], "and", wo
        except:
            print("Error: Word not in lemmatized model vocabulary")

    if W2V_pretrained:
        try:
            print("Word2vec pretrained model similarity between", words[0], "and
        except:
            print("Error: Word not in Word2vec pretrained model vocabulary")

    if GloVe_pretrained:
        try:
            print("GloVe pretrained model similarity between", words[0], "and",
        except:
            print("Error: Word not in GloVe pretrained model vocabulary")
```

In [12]:

```
def tsne_plot(df):
    """
    function that plots annotated scatter plot from a dataframe
    """
    plt.figure(figsize=(18, 18))
    for i in range(len(df)):
        plt.scatter(df.iloc[i,1],df.iloc[i,2])
        plt.annotate(df.iloc[i,0],
                     xy=(df.iloc[i,1], df.iloc[i,2]),
                     xytext=(5, 2),
                     textcoords='offset points',
                     ha='right',
                     va='bottom')
    plt.show()
```

In [13]:

```
def get_sentence_embedding(data, column, train_word_embedding, test_word_embeddi
    """
    function that creates a sentence embedding from the embeddings of the indivi
    sentence_embedding = average of word embeddings for all words in the sentenc
    """
    data.reset_index(inplace=True, drop = True)
    sentence_embeddings = []
    for token in data[column]:
        embeddings = []
        for word in token:
            if word in train_word_embedding.index:
                embeddings.append(train_word_embedding.loc[word])
            else:
                embeddings.append(test_word_embedding.loc[word])

        embedding_array = np.array(embeddings)
        sentence_embedding = np.mean(embedding_array, axis=0)
        sentence_embeddings.append(list(sentence_embedding))
```

```
    features = len(sentence_embeddings[0])
    df = pd.DataFrame(sentence_embeddings, columns = ["feature_"+ str(i+1) for i
    df = pd.concat([data["claim"], df, data["claim_label"]], axis=1)
    return df
```

In [14]:
```
def get_most_similar_words(embedding, n_similar = 1):
    """
    function that returns n_similar most similar words to a particular word in a
    embedding is n x n square matrix of relationship (similarity) between words
    """
    n_similar += 1
    similar = pd.DataFrame(columns = ['most_similar_'+ str(i) for i in range(1,

    embedding_T = embedding.T
    for word in embedding.index:
        most_similar = list(embedding_T.nlargest(n = n_similar, columns = word).
        if word in most_similar:
            most_similar.remove(word)
        else:
            most_similar = most_similar[:-1]

        similar.loc[word] = most_similar

    return similar
```

In [15]:
```
def precision_recall_fscore(y_true, y_pred):
    """
    function that computes the precision, recall and fscore between 2 dataframes
    returns the average precision, recall and fscore across the n_columns
    """
    if len(y_true) != len(y_pred):
        print("Error in dimensions of inputs")
        return

    n_columns = len(y_true)
    metrics = []

    for i in range(n_columns):
        metric = list(precision_recall_fscore_support(y_true.iloc[:,i], y_pred.i
        metrics.append(metric[:-1])

    metrics = np.mean(np.array(metrics), axis=0)

    print("Precision: ", round(metrics[0], 2))
    print("Recall: ", round(metrics[1], 2))
    print("F1_score: ", round(metrics[2], 2))
```

In [16]:
```
def run_knn_opt(X_train, X_val, X_test, y_train, y_val, y_test, k_values):
    """
    function that performs tunning of k_parameter in KNN classifier
    produces confusion matrix, accuracy, fscore and screeplots
    """
    # Developing the Classification Model
    classifier = KNeighborsClassifier()
    classifier.fit(X_train,y_train)

    # Predicting the test set result
    y_pred = classifier.predict(X_test)
```

```
    # Evaluating the Model
    cm = confusion_matrix(y_test,y_pred)

    accuracy_1 = round(100 * accuracy_score(y_test,y_pred), 2)
    f1_score_1 = round(f1_score(y_test, y_pred, average = "weighted"), 2)

    y_pred_train  = classifier.predict(X_train)

    # Making the Confusion Matrix
    cm_train = pd.DataFrame(confusion_matrix(y_train,y_pred_train))
    cm_test = pd.DataFrame(confusion_matrix(y_test,y_pred))

    print("***** Training Set Evaluation *****\n")
    print("confusion Matrix")
    display(cm_train)
    print("Accuracy: ", round(100 * accuracy_score(y_train, y_pred_train), 2))
    print("F1_score: ", round(f1_score(y_train, y_pred_train, average = 'weighte

    print("\n\n***** Test Set Evaluation *****\n")
    print("confusion Matrix")
    display(cm_test)
    print("Accuracy: ", accuracy_1)
    print("F1_score: ", f1_score_1)

    accuracy = {}
    for k in k_values:
        classifier = KNeighborsClassifier(n_neighbors=k)
        classifier.fit(X_train,y_train)

        # Predicting the test set result
        y_pred = classifier.predict(X_val)

        model_accuracy = accuracy_score(y_val, y_pred)

        accuracy[k] = round(model_accuracy * 100, 2)

    # plotting the parameter vs accuracy graph
    sns.lineplot(x = k_values, y = accuracy.values())
```

Downloading the dataset

In [17]:

```
dataset = load_dataset('climate_fever')

df = dataset['test'].to_pandas()
df2 = pd.json_normalize(dataset['test'], 'evidences', ['claim', 'claim_id','clai

data1 = df[['claim', 'claim_label']]
data2 = df2[['evidence','evidence_label']]
```

```
Using custom data configuration default
Reusing dataset climate_fever (C:\Users\jubil\.cache\huggingface\datasets\climat
e_fever\default\1.0.1\3b846b20d7a37bc0019b0f0dcbde5bf2d0f94f6874f7e4c398c579f332
c4262c)
```

Data preparation

Claim Data

In [18]:
```
# filter with regex
data1.loc[:, 'claim_token'] = data1.loc[:, 'claim'].apply(regex_filter)

# Tokenizing the claims
data1.loc[:, 'claim_token'] = data1.loc[:, 'claim_token'].apply(nltk.word_tokeni

# Removing stop words from the claclaim_tokenim tokens
data1.loc[:,'claim_token'] = data1.loc[:,'claim_token'].apply(filter_stop_words)

# Stemming the words
data1.loc[:,'stemmed_words'] = data1.loc[:,'claim_token'].apply(stem_words)

# lemmatizing the words
data1.loc[:,'lemmatized_words'] = data1.loc[:,'claim_token'].apply(lemmatize_wor
```

Evidence Data

In [19]:
```
# Adding the evidences to increase corpus size

# filer with regex
data2.loc[:, ('evidence_token')] = data2.loc[:, ('evidence')].apply(regex_filter

# Tokenizing the claims
data2.loc[:, ('evidence_token')] = data2.loc[:, ('evidence_token')].apply(nltk.w

# Removing stop words from the evidence_token tokens
data2.loc[:,('evidence_token')] = data2.loc[:,('evidence_token')].apply(filter_s

# Stemming the words
data2.loc[:,('stemmed_words')] = data2.loc[:,('evidence_token')].apply(stem_word

# lemmatizing the words
data2.loc[:,('lemmatized_words')] = data2.loc[:,('evidence_token')].apply(lemmat
```

In [20]:
```
from sklearn.model_selection import train_test_split
train_data, test_data = train_test_split(data1[['claim', 'stemmed_words', 'lemma
```

In [21]:
```
# creating the stemmed corpus and lemmatized corpus
corpus_stem = list(data1['stemmed_words']) + list(data2['stemmed_words'])
corpus_lem = list(data1['lemmatized_words']) + list(data2['stemmed_words'])
```

In [22]:
```
# Embeding with Word2Vec
model_stem = Word2Vec(corpus_stem, min_count=1)
model_lem = Word2Vec(corpus_lem, min_count=1)
print(model_stem)
print(model_lem)
```

```
Word2Vec(vocab=7433, size=100, alpha=0.025)
Word2Vec(vocab=8894, size=100, alpha=0.025)
```

In [23]:
```
# Training set embedings [STEMMING]
train_embedding_stem = get_embeddings(list(train_data['stemmed_words']), model_s
train_embedding_stem.set_index("Word", inplace=True)
train_embedding_stem.head()
```

Out[23]:

	0	1	2	3	4	5	6	7
Word								

Word	0	1	2	3	4	5	6	7
pdo	-0.058069	-0.095615	-0.171844	-0.071858	-0.079601	0.101760	-0.038534	0.350794
last	0.129344	-0.026420	-0.247751	0.429562	-0.301935	0.642594	0.259273	1.151914
switch	-0.100526	-0.048171	-0.153815	-0.059770	-0.052847	0.014975	-0.011589	0.203479
cool	-0.206966	-0.331293	-0.674612	0.085045	-0.453418	0.287957	-0.063710	1.229195
phase	-0.247510	-0.192495	-0.483150	-0.181749	-0.240897	0.170438	-0.069693	0.820681

5 rows × 100 columns

In [24]:
```
# Training set embedings [LEMMATIZING]
train_embedding_lem = get_embeddings(list(train_data['lemmatized_words']), model
train_embedding_lem.set_index("Word", inplace=True)
train_embedding_lem.head()
```

Out[24]:

Word	0	1	2	3	4	5	6	7
pdo	-0.082058	-0.002749	-0.149922	0.029300	-0.026633	0.056164	-0.062284	0.238161
last	0.116767	0.150097	-0.338777	0.775092	-0.328577	0.853931	0.234460	1.118828
switch	-0.085543	0.009837	-0.128073	0.015486	-0.014284	-0.020259	-0.020633	0.120251
cool	-0.221649	-0.013471	-0.616471	0.448016	-0.246788	0.268883	-0.056584	0.993765
phase	-0.255514	0.029119	-0.408401	0.088840	-0.098094	0.064607	-0.116262	0.572914

5 rows × 100 columns

Getting the test set embeddings

In [25]:
```
# Test set embedings [STEMMING]
test_embedding_stem = get_embeddings(list(test_data['stemmed_words']), model_ste
test_embedding_stem.set_index("Word", inplace=True)
test_embedding_stem.head()
```

Out[25]:

Word	0	1	2	3	4	5	6	7
trenberth	-0.030867	-0.026301	-0.067528	-0.031943	-0.030662	0.023076	-0.014727	0.125256
view	-0.126726	-0.247313	-0.331300	-0.280714	-0.127458	0.241779	-0.107261	0.71869
clarifi	-0.002986	-0.002799	-0.009108	-0.011050	-0.003012	0.004943	-0.000608	0.022026
paper	-0.130204	-0.279404	-0.403073	-0.511556	-0.056790	0.331567	-0.171662	0.97639
imper	-0.024604	-0.030772	-0.057187	-0.041860	-0.022316	0.034219	-0.019108	0.10885

5 rows × 100 columns

In [26]:
```
# Test set embedings [LEMMATIZING]
```

```
test_embedding_lem = get_embeddings(list(test_data['lemmatized_words']), model_l
test_embedding_lem.set_index("Word", inplace=True)
test_embedding_lem.head()
```

Out[26]:

	0	1	2	3	4	5	6	
Word								
trenberth	-0.056084	0.006425	-0.082589	0.000276	-0.009051	-0.011933	-0.030143	0.0936
view	-0.160306	-0.026396	-0.294816	-0.000945	-0.031492	0.124084	-0.142782	0.481
clarify	-0.008532	-0.002138	-0.009004	0.003041	-0.000329	0.001003	0.001160	0.0151
paper	-0.229856	0.020553	-0.343083	-0.103702	0.030393	0.143458	-0.267128	0.6776
imperative	-0.005703	0.001014	-0.012142	0.003448	-0.001891	-0.005127	-0.003829	0.0156

5 rows × 100 columns

PCA

PCA is used to decompose a multivariate dataset in a set of successive orthogonal components that explain a maximum amount of the variance. In scikit-learn, PCA is implemented as a transformer object that learns components in its fit method, and can be used on new data to project it on these components.

PCA centers but does not scale the input data for each feature before applying the SVD. The optional parameter whiten=True makes it possible to project the data onto the singular space while scaling each component to unit variance. This is often useful if the models down-stream make strong assumptions on the isotropy of the signal: this is for example the case for Support Vector Machines with the RBF kernel and the K-Means clustering algorithm.

Q.1 Using Stemming

In [27]:

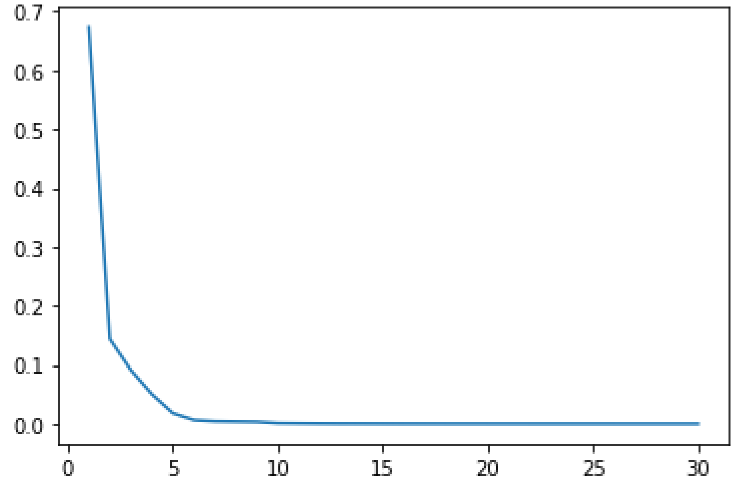
```
from sklearn.decomposition import PCA
n_components = 30
pca = PCA(n_components=n_components)
pca.fit_transform(train_embedding_stem.iloc[:,:].values)
explained_variance = pca.explained_variance_ratio_
```

In [28]:

```
plt.plot(range(1, n_components + 1), explained_variance)
```

Out[28]:

```
[<matplotlib.lines.Line2D at 0x1bbfddf7888>]
```



Notes about Scree Plot

Explained variance tells us how much information can be attributed to each of the principal components. The explained variance reduces as the number of components increases which shows that most of the information is held by the first 5 components. The "elbow" of the graph is where the value of explained variance seems to level off and factors or components to the left of this point should be retained as significant.

Q.2

From the scree plot above, the best dimensionality is 5

In [29]:
```
%%time
# Building optimal PCA model
columns = ['PC_1','PC_2','PC_3','PC_4','PC_5']
pca = PCA(n_components=5)
pca_train = pca.fit_transform(train_embedding_stem.iloc[:,:].values)
pca_train = pd.DataFrame(pca_train, columns = columns)
pca_train.index = train_embedding_stem.index
pca_train.head()
```

Wall time: 33 ms

Out[29]:

	PC_1	PC_2	PC_3	PC_4	PC_5
Word					
pdo	-0.083510	-0.108253	0.050323	-0.157001	-0.040468
last	2.819904	-2.323350	1.826712	-1.381532	0.620075
switch	-0.589701	0.131284	0.000427	0.031251	0.037443
cool	2.864101	-0.508353	1.517785	-0.587547	-0.215213
phase	1.669828	-0.180741	-0.128614	-0.078457	0.035847

In [30]:
```
%%time
pca_test = pca.transform(test_embedding_stem.iloc[:,:].values)
pca_test = pd.DataFrame(pca_test, columns = columns)
pca_test.index = test_embedding_stem.index
pca_test.head()
```

```
Wall time: 2 ms
```

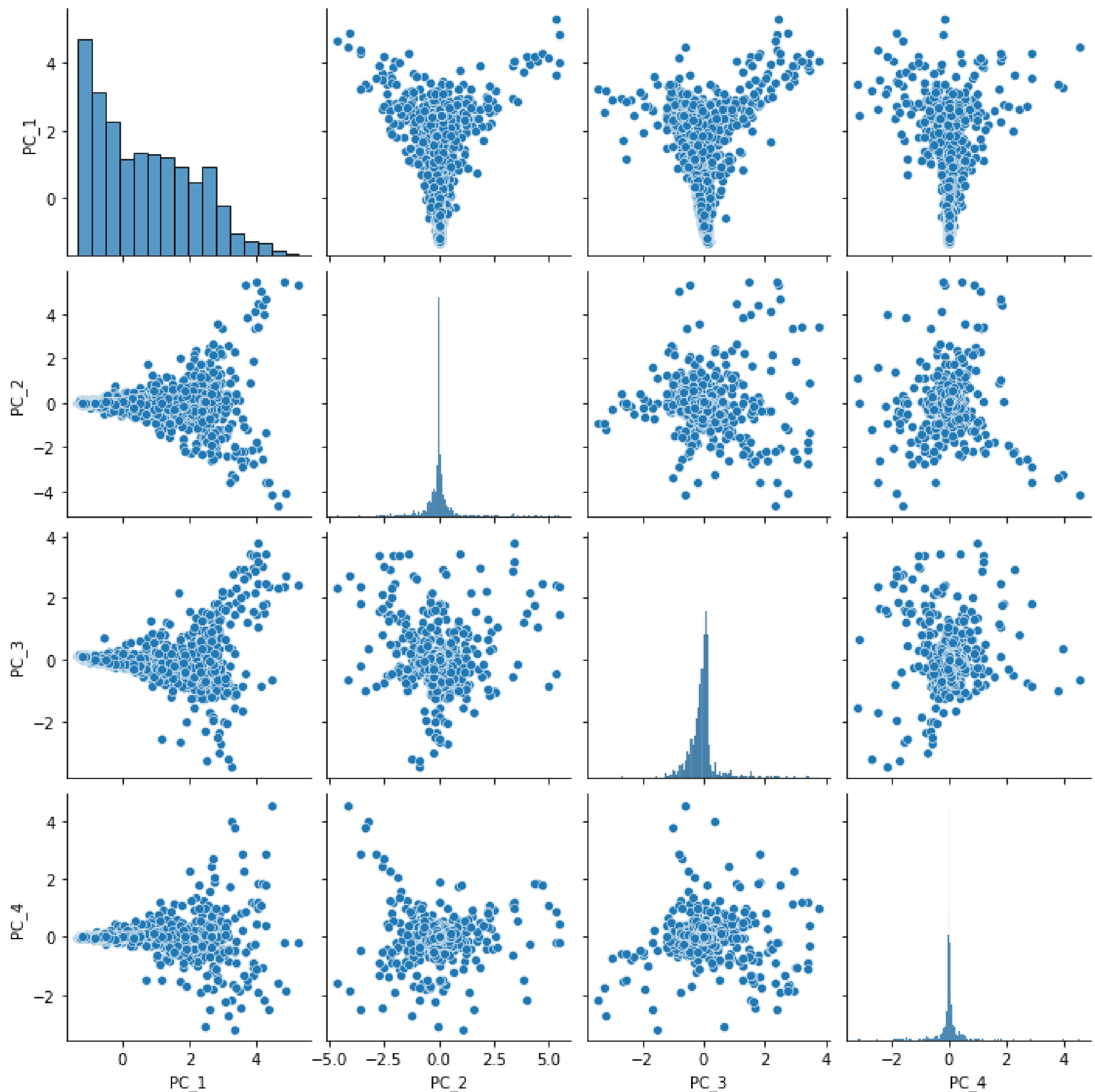
Out[30]:

Word	PC_1	PC_2	PC_3	PC_4	PC_5
trenberth	-0.890984	0.001423	0.063491	-0.036722	-0.004286
view	1.193878	0.053674	-0.462494	-0.346865	-0.138315
clarifi	-1.283384	0.020650	0.113182	-0.028934	-0.025395
paper	2.147941	0.008509	-1.539193	-0.477785	-0.000630
imper	-0.962397	0.007701	0.036301	-0.049047	-0.032961

Q.3

In [31]:
```
sns.pairplot(pca_test.iloc[:,0:4])
```

Out[31]: <seaborn.axisgrid.PairGrid at 0x1bbfd617948>



Discussion on PCA embeddings [STEMMING]

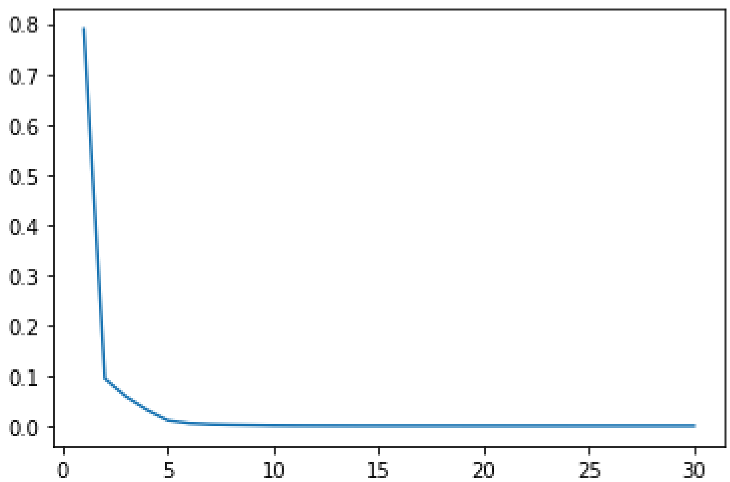
- The first principle component is highly skewed to the left. It has a lot of variance, this is likely because about 70% of the variance in the data comes from this feature
- The variance in the second, third and fourth principal components is quite small
- The first four principal components have little or no correlation with each other.
- The largest range of embeddings in 10.6
- PCA taining speed was 33ms while the transforming of the test set took 2ms.

Using Lemmatization

In [32]:
```
pca = PCA(n_components=30)
pca.fit_transform(train_embedding_lem.iloc[:,:].values)
explained_variance = pca.explained_variance_ratio_
```

In [33]:
```
plt.plot(range(1, n_components + 1), explained_variance)
```

Out[33]: [<matplotlib.lines.Line2D at 0x1bb825ae048>]



Notes about Scree Plot

Explained variance tells us how much information can be attributed to each of the principal components. The explained variance reduces as the number of components increases which shows that most of the information is held by the first 5 components. The "elbow" of the graph is where the value of explained variance seems to level off and factors or components to the left of this point should be retained as significant.

In [34]:
```
%%time
# Building optimal PCA model
pca = PCA(n_components=5)
pca_train_lem = pca.fit_transform(train_embedding_lem.iloc[:,:].values)
pca_train_lem = pd.DataFrame(pca_train_lem, columns = columns)
pca_train_lem.index = train_embedding_lem.index
pca_train_lem.head()
```

Wall time: 34 ms

Out[34]:

	PC_1	PC_2	PC_3	PC_4	PC_5

Word	PC_1	PC_2	PC_3	PC_4	PC_5
Word					
pdo	0.320451	-0.016940	-0.004102	-0.128489	-0.073168
last	3.611756	-2.297777	1.635421	-1.583785	0.539240
switch	-0.229129	0.100527	0.002469	0.024669	0.036328
cool	3.738706	-0.748401	1.201551	-0.541918	-0.291188
phase	2.211786	-0.025988	-0.204429	-0.184994	0.009658

In [35]:

```
%%time
pca_test_lem = pca.transform(test_embedding_lem.iloc[:,:].values)
pca_test_lem = pd.DataFrame(pca_test_lem, columns = columns)
pca_test_lem.index = test_embedding_lem.index
pca_test_lem.head()
```

```
Wall time: 3 ms
```

Out[35]:

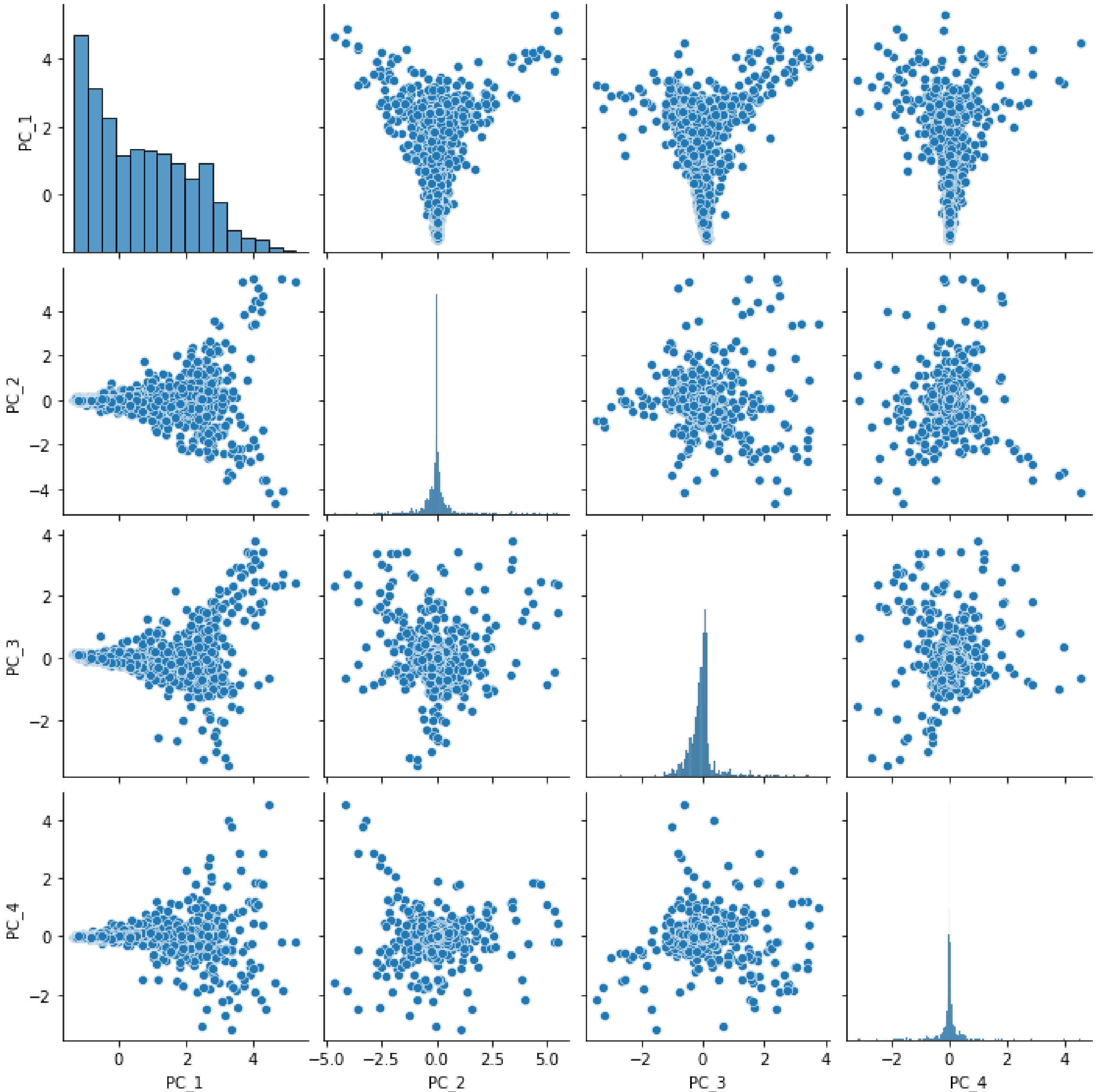
	PC_1	PC_2	PC_3	PC_4	PC_5
Word					
trenberth	-0.384627	0.065187	-0.016495	-0.003597	0.005849
view	1.624084	0.178001	-0.156168	-0.364315	-0.133887
clarify	-0.855369	-0.031719	0.028284	0.001837	-0.006248
paper	2.955323	0.385661	-1.091513	-0.633465	-0.087832
imperative	-0.864130	-0.021895	0.032263	0.002047	-0.009794

In [36]:

```
sns.pairplot(pca_test.iloc[:,0:4])
```

Out[36]:

```
<seaborn.axisgrid.PairGrid at 0x1bb82a68c08>
```



Discussion on PCA embeddings [LEMMATIZING]

- The plots are very similar to the plots from stemming
- The first principle component is highly skewed to the left. It has a lot of variance, this is likely because about 70% of the variance in the data comes from this feature
- The variance in the second, third and fourth principal components is quite small
- The first four principal components have little or no correlation with each other.
- The largest range of embeddings in 10.6
- PCA taining speed was 34ms while the transforming of the test set took 3ms.

Q.4 Cosine Similarity PCA

Getting Cosine Similarity from word2vec Embeddings

Getting Cosine similarity between all words in test set [STEMMING]

In [37]:
```
# set cosine similarity threshold for defining similar words for comparing the d
cos_threshold = 0.99
```

In [38]:
```
cos_sim_w2v = cosine_similarity(test_embedding_stem.iloc[:,:].values, Y=None, de
cos_sim_w2v.shape
```

Out[38]: (1291, 1291)

In [39]:
```
cos_sim_w2v = pd.DataFrame(cos_sim_w2v,
                           columns = list(test_embedding_stem.index),
                           index = list(test_embedding_stem.index)
                          )
cos_sim_w2v.head()
```

Out[39]:

	trenberth	view	clarifi	paper	imper	climat	chang	plan	
trenberth	1.000000	0.986095	0.887195	0.949885	0.988529	0.732192	0.731838	0.981835	0.9
view	0.986095	1.000000	0.911144	0.975003	0.994661	0.820323	0.811189	0.970120	0.9
clarifi	0.887195	0.911144	1.000000	0.899639	0.907879	0.789304	0.779429	0.883671	0.
paper	0.949885	0.975003	0.899639	1.000000	0.974456	0.811218	0.765248	0.942493	0.8
imper	0.988529	0.994661	0.907879	0.974456	1.000000	0.789838	0.782177	0.973528	0.9

5 rows × 1291 columns

In [40]:
```
# create a dataframe of similar words if cosine similarity > cos_threshold
cos_similar_stem = (cos_sim_w2v > cos_threshold).astype(int)
cos_similar_stem.head()
```

Out[40]:

	trenberth	view	clarifi	paper	imper	climat	chang	plan	track	earth	...	troposph
trenberth	1	0	0	0	0	0	0	0	0	0	...	
view	0	1	0	0	1	0	0	0	0	0	...	
clarifi	0	0	1	0	0	0	0	0	0	0	...	
paper	0	0	0	1	0	0	0	0	0	0	...	
imper	0	1	0	0	1	0	0	0	0	0	...	

5 rows × 1291 columns

Getting the most similar word from cosine similarity [STEMMING]

In [41]:
```
cos_most_similar_stem = get_most_similar_words(cos_sim_w2v, n_similar = 5)
cos_most_similar_stem.head()
```

Out[41]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	argu	conspiraci	fact	know	thought
view	said	contradict	un	disput	mani
clarifi	understand	un	group	describ	view
paper	journal	research	articl	scienc	publish

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
imper	said	say	challeng	think	conclus

Getting Cosine similarity between all words in test set [LEMMATIZING]

In [42]:
```
cos_sim_w2v_lem = cosine_similarity(test_embedding_lem.iloc[:,:].values, Y=None,
cos_sim_w2v_lem.shape
```

Out[42]: (1364, 1364)

In [43]:
```
cos_sim_w2v_lem = pd.DataFrame(cos_sim_w2v_lem,
                            columns = list(test_embedding_lem.index),
                            index = list(test_embedding_lem.index)
                           )
cos_sim_w2v_lem.head()
```

Out[43]:

	trenberth	view	clarify	paper	imperative	climate	change	plan
trenberth	1.000000	0.981124	0.936998	0.969893	0.944111	0.979678	0.990865	0.995793
view	0.981124	1.000000	0.933068	0.978201	0.923853	0.980610	0.989329	0.976183
clarify	0.936998	0.933068	1.000000	0.941576	0.887340	0.950119	0.948571	0.928599
paper	0.969893	0.978201	0.941576	1.000000	0.928759	0.993654	0.982433	0.953798
imperative	0.944111	0.923853	0.887340	0.928759	1.000000	0.938000	0.939264	0.931599

5 rows × 1364 columns

In [44]:
```
# create a dataframe of similar words if cosine similarity > cos_threshold
cos_similar_lem = (cos_sim_w2v_lem > cos_threshold).astype(int)
cos_similar_lem.head()
```

Out[44]:

	trenberth	view	clarify	paper	imperative	climate	change	plan	track	earth	...
trenberth	1	0	0	0	0	0	1	1	0	0	...
view	0	1	0	0	0	0	0	0	0	0	...
clarify	0	0	1	0	0	0	0	0	0	0	...
paper	0	0	0	1	0	1	0	0	0	0	...
imperative	0	0	0	0	1	0	0	0	0	0	...

5 rows × 1364 columns

This sparse matrix of word similarity (from cosine similarity) of words from the word2vec embedding will be used as true values (labels) for evaluating the performance of the dimensionality reduction methods.

Getting the most similar word from cosine similarity [LEMMATIZING]

In [45]:
```
cos_most_similar_lem = get_most_similar_words(cos_sim_w2v_lem, n_similar=5)
cos_most_similar_lem.head()
```

Out[45]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	meet	idea	build	renewable	standard
view	certain	agreement	contradict	concept	detail
clarify	harvard	literature	phil	robert	new
paper	research	journal	warn	publish	discuss
imperative	trenberth	electricity	santer	families	represent

Getting Cosine Similarity from PCA Embeddings

Getting Cosine similarity between all words in test set [STEMMING]

In [46]:
```
cos_sim_pca = cosine_similarity(pca_test.iloc[:,:].values, Y=None, dense_output=
cos_sim_pca.shape
```

Out[46]: (1291, 1291)

In [47]:
```
cos_sim_pca = pd.DataFrame(cos_sim_pca,
                           columns = list(pca_test.index),
                           index = list(pca_test.index)
                          )
cos_sim_pca
```

Out[47]:

	trenberth	view	clarifi	paper	imper	climat	chang	p
trenberth	1.000000	-0.904800	0.999470	-0.830558	0.998943	-0.550171	-0.555774	-0.947
view	-0.904800	1.000000	-0.912388	0.960446	-0.888078	0.809737	0.764081	0.890
clarifi	0.999470	-0.912388	1.000000	-0.842599	0.998200	-0.554041	-0.553719	-0.947
paper	-0.830558	0.960446	-0.842599	1.000000	-0.810266	0.738899	0.644748	0.875
imper	0.998943	-0.888078	0.998200	-0.810266	1.000000	-0.518838	-0.526675	-0.941
...	...	...	...	...	...	...	...	
classic	0.998314	-0.894894	0.997071	-0.805667	0.998637	-0.547639	-0.561984	-0.934
feast	0.999128	-0.920122	0.999751	-0.849870	0.997088	-0.572127	-0.570663	-0.949
follow	-0.962687	0.819896	-0.963882	0.754386	-0.966587	0.374792	0.391091	0.854
coupl	-0.719589	0.813939	-0.735436	0.878739	-0.701996	0.488334	0.411012	0.667
recoveri	0.991454	-0.888241	0.990969	-0.791115	0.991972	-0.533228	-0.555604	-0.897

1291 rows × 1291 columns

Getting the most similar word from cosine similarity [STEMMING]

In [48]:
```
cos_most_sim_pca_stem = get_most_similar_words(cos_sim_pca, n_similar=5)
cos_most_sim_pca_stem.head()
```

Out[48]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	exagger	monckton	doom	defici	elderberri

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
view	challeng	expert	mani	think	said
clarifi	ripen	australasian	anyway	computer	gov
paper	publish	research	journal	novemb	sign
imper	denier	anticip	exagger	pollard	notion

In [49]:
```
# create a dataframe of similar words if cosine similarity > cos_threshold
cos_sim_pca_label = (cos_sim_pca > cos_threshold).astype(int)
cos_sim_pca_label.head()
```

Out[49]:

	trenberth	view	clarifi	paper	imper	climat	chang	plan	track	earth	...	troposph
trenberth	1	0	1	0	1	0	0	0	0	0	...	
view	0	1	0	0	0	0	0	0	0	0	...	
clarifi	1	0	1	0	1	0	0	0	0	0	...	
paper	0	0	0	1	0	0	0	0	0	0	...	
imper	1	0	1	0	1	0	0	0	0	0	...	

5 rows × 1291 columns

Comparing the cosine similarity sparse matrix of PCA with word2vec [STEMMING]

In [50]:
```
precision_recall_fscore(cos_similar_stem, cos_sim_pca_label)
```

```
Precision:  0.78
Recall:  0.64
F1_score:  0.57
```

Getting Cosine similarity between all words in test set [LEMMATIZING]

In [51]:
```
cos_sim_pca_lem = cosine_similarity(pca_test_lem.iloc[:,:].values, Y=None, dense
cos_sim_pca_lem.shape
```

Out[51]: (1364, 1364)

In [52]:
```
cos_sim_pca_lem = pd.DataFrame(cos_sim_pca_lem,
                               columns = list(pca_test_lem.index),
                               index = list(pca_test_lem.index))
cos_sim_pca_lem
```

Out[52]:

	trenberth	view	clarify	paper	imperative	climate	change	
trenberth	1.000000	-0.926113	0.975960	-0.863475	0.977849	-0.912885	-0.942733	-0.903
view	-0.926113	1.000000	-0.968612	0.967179	-0.967669	0.974934	0.981706	0.948
clarify	0.975960	-0.968612	1.000000	-0.927385	0.999914	-0.963667	-0.987322	-0.973
paper	-0.863475	0.967179	-0.927385	1.000000	-0.927524	0.992238	0.973719	0.92
imperative	0.977849	-0.967669	0.999914	-0.927524	1.000000	-0.964135	-0.987310	-0.97
...	...	...	...	...	...	...	...	

	trenberth	view	clarify	paper	imperative	climate	change	
feast	0.973497	-0.966052	0.999797	-0.924411	0.999534	-0.961522	-0.986243	-0.976
river	-0.963465	0.959162	-0.991877	0.949300	-0.992673	0.980860	0.992827	0.96
follow	-0.992863	0.919965	-0.977633	0.885112	-0.980084	0.933047	0.955142	0.91
couple	0.974127	-0.969085	0.999950	-0.929691	0.999813	-0.965341	-0.988353	-0.975
recovery	0.978794	-0.966803	0.999713	-0.923357	0.999656	-0.960605	-0.984882	-0.97

1364 rows × 1364 columns

Comparing most similar words in PCA to Word2Vec most similar words [LEMMATIZING]

In [53]:

```
cos_most_sim_pca_lem = get_most_similar_words(cos_sim_pca_lem, n_similar=5)
cos_most_sim_pca_lem.head()
```

Out[53]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	filter	associate	legal	company	drastic
view	certain	agreement	context	fail	note
clarify	gravity	readout	feb	enormous	highly
paper	research	publish	discuss	warn	journal
imperative	draconian	mack	decision	production	stalagmites

In [54]:

```
# create a dataframe of similar words if cosine similarity > cos_threshold
cos_sim_pca_lem_label = (cos_sim_pca_lem > cos_threshold).astype(int)
cos_sim_pca_lem_label.head()
```

Out[54]:

	trenberth	view	clarify	paper	imperative	climate	change	plan	track	earth	...
trenberth	1	0	0	0	0	0	0	0	0	0	...
view	0	1	0	0	0	0	0	0	0	0	...
clarify	0	0	1	0	1	0	0	0	0	0	...
paper	0	0	0	1	0	1	0	0	0	0	...
imperative	0	0	1	0	1	0	0	0	0	0	...

5 rows × 1364 columns

Comparing the cosine similarity sparse matrix of PCA with word2vec [LEMMATIZING]

In [55]:

```
precision_recall_fscore(cos_similar_lem, cos_sim_pca_lem_label)
```

```
Precision:  0.69
Recall:  0.62
F1_score:  0.51
```

Comparing Evaluation Metrics for Cosine Similarity of PCA embeddings

	Precision	Recall	F1 Score
PCA Embeddings of Stemmed Words	0.78	0.64	0.57
PCA Embeddings of Lemmatized Words	0.69	0.62	0.51

Comparing the cosine similarity, Stemming performed better than Lemmatizing

In [56]:
```
words_list = [['man', 'bear'],['heat', 'warm'],['earth', 'global'], ['cold', 'wa
for word in words_list:
    print("The Cos similarity of stemmed PCA embeddings between", word[0], "and"
    print("The Cos similarity of lemmatized PCA embeddings between", word[0], "a
    similarity(words = word,
               stem_model = model_stem,
               lem_model = model_lem
              )
    print("\n")
```

```
The Cos similarity of stemmed PCA embeddings between man and bear is 0.73
The Cos similarity of lemmatized PCA embeddings between man and bear is 0.91
Stemmed W2V model similarity between man and bear = 0.94
Lemmatized W2V model similarity between man and bear = 0.96


The Cos similarity of stemmed PCA embeddings between heat and warm is 0.49
The Cos similarity of lemmatized PCA embeddings between heat and warm is 0.64
Stemmed W2V model similarity between heat and warm = 0.62
Lemmatized W2V model similarity between heat and warm = 0.69


The Cos similarity of stemmed PCA embeddings between earth and global is 0.94
The Cos similarity of lemmatized PCA embeddings between earth and global is 0.95
Stemmed W2V model similarity between earth and global = 0.94
Lemmatized W2V model similarity between earth and global = 0.94


The Cos similarity of stemmed PCA embeddings between cold and warm is 0.48
The Cos similarity of lemmatized PCA embeddings between cold and warm is 0.57
Stemmed W2V model similarity between cold and warm = 0.67
Lemmatized W2V model similarity between cold and warm = 0.67


The Cos similarity of stemmed PCA embeddings between summer and ocean is 0.55
The Cos similarity of lemmatized PCA embeddings between summer and ocean is 0.7
Stemmed W2V model similarity between summer and ocean = 0.71
Lemmatized W2V model similarity between summer and ocean = 0.78


The Cos similarity of stemmed PCA embeddings between summer and winter is 0.99
The Cos similarity of lemmatized PCA embeddings between summer and winter is 0.9
9
Stemmed W2V model similarity between summer and winter = 0.99
Lemmatized W2V model similarity between summer and winter = 0.99
```

Analysis of Cosine similarity

1. **Man and Bear**

These words are not similar, an ideal similarity should be 0.5 or less. The PCA embeddings of stemmed words produced a similarity of 0.73, while the PCA embeddings of lemmatized words produced a similarity of 0.91. This should not be the case considering that these words are not similar. The stemmed Word2Vec model produces a similarity of 0.94 while the lemmatized Word2Vec model produces a similarity of 0.96.

1. **Heat and Warm**

These words are similar, an ideal similarity value should be about 0.7 or 0.8. The PCA embeddings of stemmed words produced a similarity of 0.49, while the PCA embeddings of lemmatized words produced a similarity of 0.64. This is close to our expectation, but not good enough. However, the stemmed Word2Vec model produces a similarity of 0.62 while the lemmatized Word2Vec model produces a similarity of 0.69.

1. **Earth and Global**

These words have a similar context, an ideal similarity value should be about 0.8. The PCA embeddings of stemmed words produced a similarity of 0.94, while the PCA embeddings of lemmatized words produced a similarity of 0.95. However, the stemmed Word2Vec model produces a similarity of 0.94 while the lemmatized Word2Vec model produces a similarity of 0.94. All the similarities here are slightly higher than our expectation.

1. **Cold and Warm**

These words are not similar, an ideal similarity should be 0.5 or less. The PCA embeddings of stemmed words produced a similarity of 0.47, while the PCA embeddings of lemmatized words produced a similarity of 0.59. The PCA model performed well with the relationship. The stemmed Word2Vec model produces a similarity of 0.66 while the lemmatized Word2Vec model produces a similarity of 0.69.

1. **Summer and Ocean**

These words are not similar, an ideal similarity should be 0.6 or less. The PCA embeddings of stemmed words produced a similarity of 0.55, while the PCA embeddings of lemmatized words produced a similarity of 0.7. This should not be the case considering that these words are not similar. The stemmed Word2Vec model produces a similarity of 0.71 while the lemmatized Word2Vec model produces a similarity of 0.78.

1. **Summer and Winter**

These words are opposites, an ideal similarity should be less than 0.5. The PCA embeddings of stemmed words produced a similarity of 0.99, while the PCA embeddings of lemmatized words produced a similarity of 0.99. The stemmed Word2Vec model produces a similarity of 0.99 while the lemmatized Word2Vec model produces a similarity of 0.99. This should not be the case considering that these words are not similar.

Summmary of Analysis

Words	Stemmed PCA	Lemmatized PCA	Stemmed Word2Vec	Lemmatized Word2Vec
Man, Bear	**0.73**	0.91	0.94	0.96

Words	Stemmed PCA	Lemmatized PCA	Stemmed Word2Vec	Lemmatized Word2Vec
Heat, Warm	0.49	0.64	0.62	**0.69**
Earth, Global	0.94	**0.95**	0.94	0.94
Cold, Warm	**0.48**	0.57	0.67	0.67
Summer, Ocean	**0.55**	0.7	0.71	0.78
Summer, Winter	0.99	0.99	0.99	0.99

Best performing model in bold

KNN GRAPH (Word2Vec)

Using KNN on word embedding to get most similar word [STEMMING]

In [57]:
```
knn_similar_stem = kneighbors_graph(test_embedding_stem.iloc[:,:].values, 6, mod
```

In [58]:
```
knn_similar_stem = pd.DataFrame(knn_similar_stem.toarray(),
                                columns = list(test_embedding_stem.index),
                                index = list(test_embedding_stem.index)
                               )
knn_similar_stem.head()
```

Out[58]:

	trenberth	view	clarifi	paper	imper	climat	chang	plan	track	earth	...	troposph
trenberth	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
view	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
clarifi	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
paper	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
imper	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0

5 rows × 1291 columns

In [59]:
```
knn_most_similar_stem = get_most_similar_words(knn_similar_stem, n_similar=5)
knn_most_similar_stem.head()
```

Out[59]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	rooftop	chimney	anyon	seawal	sulphur
view	statist	emerg	question	independ	repres
clarifi	gov	reanalys	ellipt	julia	accret
paper	studi	issu	peer	public	accord
imper	profession	harvard	deconto	hook	watson

Using KNN on word embedding to get most similar word [LEMMATIZING]

In [60]:
```
knn_similar_lem = kneighbors_graph(test_embedding_lem.iloc[:,:].values, 6, mode=
```

In [61]:
```
knn_similar_lem = pd.DataFrame(knn_similar_lem.toarray(),
```

```
                        columns = list(test_embedding_lem.index),
                        index = list(test_embedding_lem.index)
                       )
knn_similar_lem.head()
```

Out[61]:

	trenberth	view	clarify	paper	imperative	climate	change	plan	track	earth	...
trenberth	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
view	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
clarify	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
paper	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
imperative	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...

5 rows × 1364 columns

In [62]:
```
knn_most_similar_lem = get_most_similar_words(knn_similar_lem, n_similar=5)
knn_most_similar_lem.head()
```

Out[62]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	cook	super	aerosols	associate	drastic
view	become	cosmic	likely	question	urban
clarify	statistics	integrity	interactive	feb	mack
paper	number	peer	first	public	accord
imperative	simulations	conducive	feb	citation	steady

The KNN Neighbors of words from the word2vec embedding will be used as true labels for comparing dimensionality reduction methods

KNN GRAPH (PCA)

Using KNN on word embedding to get most similar word [STEMMING]

In [63]:
```
knn_similar_stem_pca = kneighbors_graph(pca_test.iloc[:,:].values, 6, mode='conn
```

In [64]:
```
knn_similar_stem_pca = pd.DataFrame(knn_similar_stem_pca.toarray(),
                        columns = list(pca_test.index),
                        index = list(pca_test.index)
                       )
knn_similar_stem_pca.head()
```

Out[64]:

	trenberth	view	clarifi	paper	imper	climat	chang	plan	track	earth	...	troposph
trenberth	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
view	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
clarifi	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
paper	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0
imper	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0

5 rows × 1291 columns

Comparing most similar words in PCA to Word2Vec most similar words [STEMMING]

In [65]:
```
knn_most_similar_stem_pca = get_most_similar_words(knn_similar_stem_pca, n_simil
knn_most_similar_stem_pca.head()
```

Out[65]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	rooftop	chimney	anyon	seawal	sulphur
view	statist	emerg	question	independ	pari
clarifi	gov	reanalys	ellipt	julia	predetermin
paper	studi	issu	peer	public	accord
imper	profession	harvard	deconto	hook	watson

In [66]:
```
precision_recall_fscore(knn_similar_stem, knn_similar_stem_pca)
```

```
Precision:  0.94
Recall:  0.95
F1_score:  0.94
```

Using KNN on word embedding to get most similar word [LEMMATIZING]

In [67]:
```
knn_similar_lem_pca = kneighbors_graph(pca_test_lem.iloc[:,:].values, 2, mode='c
```

In [68]:
```
knn_similar_lem_pca = pd.DataFrame(knn_similar_lem_pca.toarray(),
                        columns = list(pca_test_lem.index),
                        index = list(pca_test_lem.index)
                       )
knn_similar_lem_pca.head()
```

Out[68]:

	trenberth	view	clarify	paper	imperative	climate	change	plan	track	earth	...
trenberth	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
view	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
clarify	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
paper	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...
imperative	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...

5 rows × 1364 columns

Comparing most similar words in PCA to Word2Vec most similar words [LEMMATIZING]

In [69]:
```
knn_most_similar_lem_pca = get_most_similar_words(knn_similar_lem_pca, n_similar
knn_most_similar_lem_pca.head()
```

Out[69]:

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
trenberth	drastic	view	clarify	paper	imperative

	most_similar_1	most_similar_2	most_similar_3	most_similar_4	most_similar_5
view	likely	trenberth	clarify	paper	imperative
clarify	feb	trenberth	view	paper	imperative
paper	accord	trenberth	view	clarify	imperative
imperative	citation	trenberth	view	clarify	paper

In [70]:
```
precision_recall_fscore(knn_similar_lem, knn_similar_lem_pca)
```

```
Precision:  0.99
Recall:  0.7
F1_score:  0.76
```

Comparing Evaluation Metrics for KNN Graph of PCA embeddings

	Precision	Recall	F1 Score
PCA Embeddings of Stemmed Words	0.94	0.95	0.94
PCA Embeddings of Lemmatized Words	0.99	0.7	0.76

The stemmed PCA model performs better that the lemmatized PCA model.
The lemmatized PCA model has a high precision but a low recall which results to a low fscore.

KNN CLASSIFICATION OF THE CLAIMS USING PCA EMBEDDINGS

Applying KNN on the PCA Sentence Embeddings [STEMMING]

In [90]:
```
# Dropping rows with mislabeled claims
outlier_index = train_data[train_data["claim_label"] == 3].index
train_data.drop(outlier_index, inplace = True)
train_data.reset_index(drop = True, inplace=True)
train_data.shape
```

Out[90]: (1108, 4)

In [91]:
```
outlier_index = test_data[test_data["claim_label"] == 3].index
test_data.drop(outlier_index, inplace = True)
test_data.reset_index(drop = True, inplace=True)
test_data.shape
```

Out[91]: (273, 4)

In [92]:
```
knn_train_stem = train_data[['claim', 'stemmed_words', 'claim_label']]
knn_test_stem = test_data[['claim', 'stemmed_words', 'claim_label']]

# getting the sentence embedding of the training data
knn_train_stem = get_sentence_embedding(knn_train_stem, 'stemmed_words', pca_tra
knn_train_stem.shape
```

Out[92]: (1108, 7)

In [93]:
```
knn_train_stem.head()
```

Out[93]:

	claim	feature_1	feature_2	feature_3	feature_4	feature_5	claim_label
0	When the PDO last switched to a cool phase, gl...	2.304605	-0.967967	1.320831	-0.705482	0.028813	2
1	as time progresses and fossil fuel emissions i...	2.961435	0.381129	0.667582	0.084079	0.196214	2
2	Hurricanes aren't linked to global warming	2.517299	0.087590	1.209453	-0.943510	-0.731021	2
3	Ljungqvist's millennial temperature reconstruc...	0.576780	-0.462915	0.283831	-0.155504	0.014352	2
4	More importantly, the OISM list only contains ...	0.872608	0.297925	-0.755649	-0.485208	-0.282169	2

In [94]:
```
knn_test_stem = get_sentence_embedding(knn_test_stem, 'stemmed_words', pca_train
knn_test_stem.shape
```

Out[94]: (273, 7)

In [95]:
```
knn_test_stem.head()
```

Out[95]:

	claim	feature_1	feature_2	feature_3	feature_4	feature_5	claim_label
0	Trenberth's views are clarified in the paper "...	1.220409	0.508363	-0.070640	-0.563402	-0.386888	0
1	When life is considered, ocean acidification i...	1.739670	0.122007	-0.117421	0.294819	0.021619	1
2	In recent decades this warming has been accomp...	2.374765	-0.501875	0.912189	-0.263308	-0.521272	0
3	while it’s true that studies in some regions s...	1.501689	-0.638804	-0.285267	0.358604	-0.162167	1
4	It is unclear whether global warming is increa...	2.409271	0.320484	1.263103	-0.593837	-0.458476	0

In [96]:
```
X_train = knn_train_stem.iloc[:,1:-1].values
y_train = knn_train_stem.iloc[:,-1].values
X_test = knn_test_stem.iloc[:,1:-1].values
y_test = knn_test_stem.iloc[:,-1].values
```

In [97]:
```
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5, r
```

Getting the optimal value for K

In [98]:
```
run_knn_opt(X_train, X_val, X_test, y_train, y_val, y_test, [1,5,10,15,20,25,30,
```

```
***** Training Set Evaluation *****
```

confusion Matrix

	0	1	2
0	444	25	56
1	118	65	20
2	166	26	188

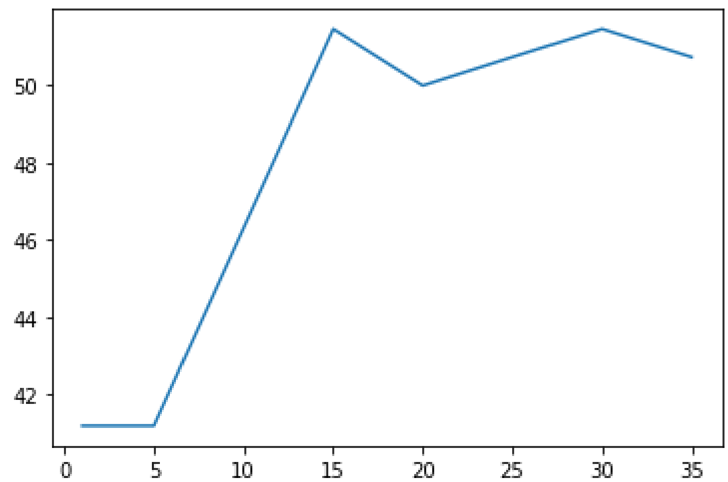
```
Accuracy:  62.91
F1_score:  0.61


***** Test Set Evaluation *****
```

confusion Matrix

	0	1	2
0	55	2	8
1	14	6	4
2	35	3	10

```
Accuracy:  51.82
F1_score:  0.47
```



Building model with the optimal value for K

In [99]:
```
k_opt = 15

classifier = KNeighborsClassifier(n_neighbors = k_opt)
classifier.fit(X_train,y_train)

# Predicting the test set result
y_pred = classifier.predict(X_test)
y_pred_train = classifier.predict(X_train)
y_pred_val = classifier.predict(X_val)


# Evaluating the model
accuracy_test = round(100 * accuracy_score(y_test, y_pred), 2)
cm_test = pd.DataFrame(confusion_matrix(y_test,y_pred))
PRF_test = precision_recall_fscore_support(y_test, y_pred, average='weighted')

accuracy_train = round(100 * accuracy_score(y_train, y_pred_train), 2)
cm_train = pd.DataFrame(confusion_matrix(y_train,y_pred_train))
```

```python
PRF_train = precision_recall_fscore_support(y_train, y_pred_train, average='weig

accuracy_val = round(100 * accuracy_score(y_val, y_pred_val), 2)
cm_val = pd.DataFrame(confusion_matrix(y_val,y_pred_val))
PRF_val = precision_recall_fscore_support(y_val, y_pred_val, average='weighted')

print("***** Test Set Evaluation *****")
print("Confusion Matrix")
display(cm_test)
print("Accuracy: ", accuracy_test)
print("Precision: ", round(PRF_test[0], 2))
print("Recall: ", round(PRF_test[1], 2))
print("F1_score: ", round(PRF_test[2], 2))

print()

print("***** Training Set Evaluation *****")
print("Confusion Matrix")
display(cm_train)
print("Accuracy: ", accuracy_train)
print("Precision: ", round(PRF_train[0], 2))
print("Recall: ", round(PRF_train[1], 2))
print("F1_score: ", round(PRF_train[2], 2))
print()

print("***** Validation Set Evaluation *****")
print("Confusion Matrix")
display(cm_val)
print("Accuracy: ", accuracy_val)
print("Precision: ", round(PRF_val[0], 2))
print("Recall: ", round(PRF_val[1], 2))
print("F1_score: ", round(PRF_val[2], 2))
```

```
***** Test Set Evaluation *****
Confusion Matrix
```

	0	1	2
0	58	1	6
1	19	3	2
2	33	2	13

```
Accuracy:  54.01
Precision:  0.55
Recall:  0.54
F1_score:  0.48

***** Training Set Evaluation *****
Confusion Matrix
```

	0	1	2
0	429	12	84
1	147	21	35
2	242	11	127

```
Accuracy:  52.08
Precision:  0.51
Recall:  0.52
F1_score:  0.47
```

```
***** Validation Set Evaluation *****
Confusion Matrix
```

	0	1	2
0	47	3	14
1	18	2	6
2	25	0	21

```
Accuracy:  51.47
Precision:  0.5
Recall:  0.51
F1_score:  0.48
```

Applying KNN Classification on the PCA Embeddings [LEMMATIZATION]

In [100…

```
knn_train_lem = train_data[['claim', 'lemmatized_words', 'claim_label']]
knn_test_lem = test_data[['claim', 'lemmatized_words', 'claim_label']]
```

In [101…

```
# getting the sentence embedding of the training data
knn_train_lem = get_sentence_embedding(knn_train_lem, 'lemmatized_words', pca_tr
knn_train_lem.shape
```

Out[101… (1108, 7)

In [102…

```
knn_train_lem.head()
```

Out[102…

	claim	feature_1	feature_2	feature_3	feature_4	feature_5	claim_label
0	When the PDO last switched to a cool phase, gl...	2.462266	-0.831696	0.873716	-0.555186	-0.064936	2
1	as time progresses and fossil fuel emissions i...	2.889612	0.471560	0.072281	0.169673	0.172425	2
2	Hurricanes aren't linked to global warming	2.367886	0.102642	1.665804	-0.736424	-0.877432	2
3	Ljungqvist's millennial temperature reconstruc...	0.603359	-0.110147	-0.105968	-0.066657	0.026065	2
4	More importantly, the OISM list only contains ...	1.321917	0.141455	-0.338723	-0.093238	0.029049	2

In [103…

```
knn_test_lem = get_sentence_embedding(knn_test_lem, 'lemmatized_words', pca_trai
knn_test_lem.shape
```

Out[103… (273, 7)

In [104…

```
knn_test_lem.head()
```

Out[104…

	claim	feature_1	feature_2	feature_3	feature_4	feature_5	claim_label
0	Trenberth's views are clarified in the paper "...	2.017787	0.171955	0.138198	-0.326197	-0.156192	0

	claim	feature_1	feature_2	feature_3	feature_4	feature_5	claim_label
1	When life is considered, ocean acidification i...	1.997855	0.176684	-0.033770	0.177260	0.013192	1
2	In recent decades this warming has been accomp...	2.120780	-0.475521	0.590851	0.185268	-0.335002	0
3	while it's true that studies in some regions s...	1.603195	-0.479668	-0.350677	0.253162	-0.012201	1
4	It is unclear whether global warming is increa...	1.836290	0.089946	0.716937	-0.274150	-0.345470	0

In [105…

```
X_train = knn_train_lem.iloc[:,1:-1].values
y_train = knn_train_lem.iloc[:,-1].values
X_test = knn_test_lem.iloc[:,1:-1].values
y_test = knn_test_lem.iloc[:,-1].values
```

In [106…

```
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5, r
```

Getting the optimal value for K

In [107…

```
run_knn_opt(X_train, X_val, X_test, y_train, y_val, y_test, [1,5,10,15,20,25,30,
```

```
***** Training Set Evaluation *****

confusion Matrix
```

	0	1	2
0	437	23	65
1	114	61	28
2	198	19	163

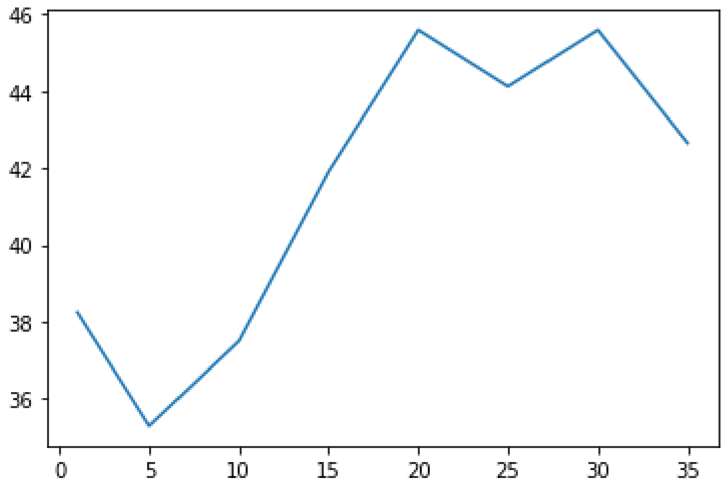
```
Accuracy:  59.66
F1_score:  0.57


***** Test Set Evaluation *****

confusion Matrix
```

	0	1	2
0	48	7	10
1	11	7	6
2	30	3	15

```
Accuracy:  51.09
F1_score:  0.49
```



Building model with the optimal value for K

In [111…
```
k_opt = 30

classifier = KNeighborsClassifier(n_neighbors = k_opt)
classifier.fit(X_train,y_train)

# Predicting the test set result
y_pred = classifier.predict(X_test)
y_pred_train = classifier.predict(X_train)
y_pred_val = classifier.predict(X_val)


# Evaluating the model
accuracy_test = round(100 * accuracy_score(y_test, y_pred), 2)
cm_test = pd.DataFrame(confusion_matrix(y_test,y_pred))
PRF_test = precision_recall_fscore_support(y_test, y_pred, average='weighted')

accuracy_train = round(100 * accuracy_score(y_train, y_pred_train), 2)
cm_train = pd.DataFrame(confusion_matrix(y_train,y_pred_train))
PRF_train = precision_recall_fscore_support(y_train, y_pred_train, average='weig

accuracy_val = round(100 * accuracy_score(y_val, y_pred_val), 2)
cm_val = pd.DataFrame(confusion_matrix(y_val,y_pred_val))
PRF_val = precision_recall_fscore_support(y_val, y_pred_val, average='weighted')

print("***** Test Set Evaluation *****")
print("Confusion Matrix")
display(cm_test)
print("Accuracy: ", accuracy_test)
print("Precision: ", round(PRF_test[0], 2))
print("Recall: ", round(PRF_test[1], 2))
print("F1_score: ", round(PRF_test[2], 2))

print()

print("***** Training Set Evaluation *****")
print("Confusion Matrix")
display(cm_train)
print("Accuracy: ", accuracy_train)
print("Precision: ", round(PRF_train[0], 2))
print("Recall: ", round(PRF_train[1], 2))
print("F1_score: ", round(PRF_train[2], 2))
print()
```

```
print("***** Validation Set Evaluation *****")
print("Confusion Matrix")
display(cm_val)
print("Accuracy: ", accuracy_val)
print("Precision: ", round(PRF_val[0], 2))
print("Recall: ", round(PRF_val[1], 2))
print("F1_score: ", round(PRF_val[2], 2))
```

```
***** Test Set Evaluation *****
Confusion Matrix
```

	0	1	2
0	53	1	11
1	18	0	6
2	38	0	10

```
Accuracy:  45.99
Precision:  0.36
Recall:  0.46
F1_score:  0.38

***** Training Set Evaluation *****
Confusion Matrix
```

	0	1	2
0	445	3	77
1	150	8	45
2	261	1	118

```
Accuracy:  51.53
Precision:  0.54
Recall:  0.52
F1_score:  0.45

***** Validation Set Evaluation *****
Confusion Matrix
```

	0	1	2
0	51	1	12
1	17	2	7
2	37	0	9

```
Accuracy:  45.59
Precision:  0.46
Recall:  0.46
F1_score:  0.39
```

KNN Classification for PCA

- The optimal value of K in KNN classification for the stemmed PCA model was 15 and for the lemmatized PCA model, optimal k was 30.

PCA KNN Model Evaluation

- Stemmed Corpus | | Accuracy | Precision | Recall | F1 Score | | --- | --- | --- |--- |-- | | Training Set | 52.08 | 0.51 | 0.52 | 0.47| | Validation| 51.47 | 0.5 | 0.51 | 0.48| | Test Set | 54.01 | 0.55 | 0.54 | 0.48|
- Lemmatized Corpus | | Accuracy | Precision | Recall | F1 Score | | --- | --- | --- |--- |-- | | Training Set | 51.53 | 0.54 | 0.52 | 0.45| | Validation| 45.59 | 0.46 | 0.46 | 0.39| | Test Set | 45.99 | 0.36 | 0.46 | 0.38|

Word2Vec KNN Model Evaluation (From CM1)

- Stemmed Corpus | | Accuracy | Precision | Recall | F1 Score | | --- | --- | --- |--- |-- | | Training Set | 50.81 | 0.52 | 0.51 | 0.45| | Validation| 52.21 | 0.6 | 0.52 | 0.47| | Test Set | 51.82 | 0.46 | 0.52 | 0.44|
- Lemmatized Corpus | | Accuracy | Precision | Recall | F1 Score | | --- | --- | --- |--- |-- | | Training Set | 51.9 | 0.55 | 0.52 | 0.45| | Validation| 46.32 | 0.45 | 0.46 | 0.4| | Test Set | 43.8 | 0.33 | 0.44 | 0.36|

Comparing the PCA KNN Model to the Word2Vec KNN Model

- The PCA model had a better performance on the test set and also a higher training set performance but performed slightly worse on the validation set for the stemmed corpus.
- The PCA model also had a higher test set performance. It also performed better on the validation set but performed slightly less on the training set compared to the Word2Vec KNN model for the lemmatized corpus.

```
In [ ]:
```