In [1]: import pandas as pd import numpy as np import matplotlib.pyplot as plt import nltk import warnings warnings.filterwarnings('ignore') In [2]: | title = pd.read\_csv('title.csv') print(title.shape) title.head() (10000, 3)Out[2]: original\_grade emp\_title default 0 C global config engineer 1 C warehouse office clerk D assembly 3 Α 0 customer service security supervisor In [3]: title.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 10000 entries, 0 to 9999 Data columns (total 3 columns): # Column Non-Null Count Dtype -----O original grade 10000 non-null object emp title 9167 non-null object 10000 non-null int64 default dtypes: int64(1), object(2) memory usage: 234.5+ KB In [4]: title.rename(columns= {'original\_grade':'grade'}, inplace=True) In [5]: round(100 \* title.emp\_title.value\_counts(normalize= True, dropna= False),2).head() Out[5]: NaN 8.33 manager 2.18 2.04 owner teacher 2.01 1.23 driver Name: emp\_title, dtype: float64 In [6]: | title.dropna(inplace= True) round(100 \* title.emp\_title.value\_counts(normalize= True, dropna= False),2).head() Out[6]: manager 2.38 owner 2.23 teacher 2.19 driver 1.34 1.06 Name: emp\_title, dtype: float64 In [7]: title.emp\_title.nunique() Out[7]: 4741 Removing accented characters to make sure that the characters are converted and standardized into ASCII characters. In [8]: import unicodedata def remove\_accented\_chars(text): text = unicodedata.normalize('NFKD', text).encode('ascii', 'ignore').decode('utf-8', 'ignore') return text In [9]: title['emp\_title'] = title['emp\_title'].apply(lambda x: str(x)) In [10]: title.emp\_title = title.emp\_title.apply(lambda x: remove\_accented\_chars(x)) In [11]: title.emp title.shape Out[11]: (9167,) In [12]: | title.emp\_title.nunique() Out[12]: 4741 **Removing Special Characters** In [13]: import re def remove\_special\_characters(text, remove\_digits=False): pattern =  $r'[^a-zA-z0-9\s]'$  if not remove\_digits else  $r'[^a-zA-z\s]'$ text = re.sub(pattern, '', text) return text In [14]: title.emp\_title = title.emp\_title.apply(lambda x: remove\_special\_characters(x, remove\_digits= True)) In [15]: title.emp\_title.shape Out[15]: (9167,) In [16]: | title.emp\_title.nunique() Out[16]: 4723 Remove stopwords In [17]: from nltk.corpus import stopwords stop\_words = stopwords.words('english') In [18]: type(stop\_words) Out[18]: list In [19]: from nltk.tokenize import word\_tokenize def remove\_stopwords(text, is\_lower\_case=False): tokens = word tokenize(text) #tokens = [token.strip() for token in tokens] if is lower case: filtered\_tokens = [token for token in tokens if token not in stop\_words] filtered\_tokens = [token for token in tokens if token.lower() not in stop\_words] filtered text = ' '.join(filtered\_tokens) return filtered text In [20]: title.emp\_title = title.emp\_title.apply(lambda x: remove\_stopwords(x)) In [21]: title.emp title.shape Out[21]: (9167,) title.emp\_title.nunique() In [22]: Out[22]: 4322 spacy-Noun Chunks In [23]: import spacy nlp = spacy.load("en core web sm") title['doc'] = title.emp\_title.apply(lambda x: nlp(x)) In [24]: title.head() Out[24]: grade emp\_title default doc 0 С global config engineer (global, config, engineer) 1 warehouse office clerk (warehouse, office, clerk) D 2 assembly 0 (assembly) customer service Α (customer, service) С security supervisor (security, supervisor) In [25]: type(title.doc[0]) Out[25]: spacy.tokens.doc.Doc In [26]: def get noun root(doc): root\_lst=[] try: for chunk in doc.noun\_chunks: root lst.append(chunk.root.text) except: pass return root\_lst In [27]: title['noun\_root'] = title.doc.apply(lambda x: get\_noun\_root(x)) In [28]: title.head() Out[28]: grade emp\_title default doc noun\_root 0 global config engineer (global, config, engineer) [engineer] 1 warehouse office clerk (warehouse, office, clerk) [clerk] assembly (assembly) [assembly] 3 Α 0 customer service (customer, service) [service] С security supervisor (security, supervisor) [supervisor] In [29]: title.emp\_title.nunique() Out[29]: 4322 number of noun root for each emp\_title In [30]: title['num\_roots']= [len(root) for root in title['noun\_root']] In [31]: title.head() Out[31]: emp\_title default grade doc noun\_root num\_roots 1 0 global config engineer (global, config, engineer) [engineer] 1 warehouse office clerk (warehouse, office, clerk) 1 [clerk] 2 D assembly (assembly) [assembly] 3 Α 0 customer service [service] 1 (customer, service) С security supervisor 0 (security, supervisor) [supervisor] In [32]: title.num\_roots.value\_counts() Out[32]: 1 8546 581 2 40 Name: num\_roots, dtype: int64 In [33]: title = title[title.num\_roots != 0] In [34]: len(title) Out[34]: 8586 In [35]: title[title.num\_roots == 2].head() Out[35]: emp\_title default doc grade noun\_root num\_roots Ε hes advisor (he, s, advisor) 2 [he, advisor] 760 (case, managet, loan) 2 В case managet loan 0 [case, loan] 837 В sales chat banker (sales, chat, banker) [sales, banker] 2 923 С right way agent 0 2 (right, way, agent) [way, agent] teaching assistant iii (teaching, assistant, iii) 2 1115 [assistant, iii] title[title.num\_roots == 2]['noun\_root'].apply(pd.Series) In [36]: Out[36]: 1 0 50 he advisor 760 case loan 837 sales banker 923 agent way 1115 iii assistant 1144 analyst iii 1280 underwriters assistant 1458 specialist 1577 manager server 1585 writer 1611 ii programs 1766 manager assistant 2140 president affairs 2168 officer iii 2507 technician veterans 2768 aide technician 2814 d 2965 planning analysis 3380 iii provider 3502 3644 iii counselo director 3714 4007 officer eeo 4209 executive counsel 4496 driver dc 5123 head teacher 5763 team production 5935 representative 7017 manager nicu 7153 paraeducator iii 7296 director educators assistant 7512 teachers 7626 sorter part 7781 administrator iii 7970 analyst iii 8050 servicesales associate 8150 analyst iii 8290 president founder 8540 vice development 9765 analyst In [37]: root = round(100 \* title.loc[title.num\_roots == 1, 'noun\_root'].value\_counts(normalize= True, dropna= F **alse**),2).head(11) Out[37]: [manager] 14.84 [driver] 3.41 3.02 [engineer] 2.93 [teacher] 2.88 [owner] 2.81 [supervisor] 2.66 [specialist] 2.38 [technician] [analyst] 2.33 [director] 2.22 2.22 [officer] Name: noun root, dtype: float64 split into train and test In [38]: df = pd.concat([title.noun root.apply(pd.Series)[0] , title['grade']], axis= 1) df.columns = ['noun root', 'grade'] df.head() Out[38]: noun\_root grade 0 engineer С 1 clerk С assembly D service 3 Α С supervisor In [39]: y = df['grade'].replace({'A':0, 'B': 1, 'C':2, 'D': 3, 'E':4, 'F':5, 'G':6}) print(y.shape) y.head() (8586,)Out[39]: 0 2 3 3 0 2 Name: grade, dtype: int64 In [40]: | X = df['noun\_root'] print(X.shape) X.head() (8586,)Out[40]: 0 engineer clerk assembly 3 service supervisor Name: noun\_root, dtype: object In [41]: from sklearn.model selection import train test split X\_Train, X\_Test, y\_Train, y\_Test = train\_test\_split(X, y, test\_size=0.30, random\_state= 42) In [42]: | y\_Train.value\_counts() Out[42]: 1 1827 2 1583 0 1506 852 3 192 4 42 8 Name: grade, dtype: int64 In [43]: | y\_Test.value\_counts() Out[43]: 1 783 2 682 0 644 3 361 94 10 5 2 Name: grade, dtype: int64 In [44]: X\_Train.shape, y\_Train.shape Out[44]: ((6010,), (6010,)) TFIDF, bag-of-words In [45]: from sklearn.feature\_extraction.text import TfidfVectorizer tfidf = TfidfVectorizer(use\_idf=**True**) #tfidf = TfidfVectorizer() tfidf.fit(X\_Train) X\_Train\_tfidf = tfidf.transform(X\_Train) X\_Test\_tfidf = tfidf.transform(X\_Test) tfidf.get\_feature\_names() In [46]: df\_idf = pd.DataFrame(tfidf.idf\_, index= tfidf.get\_feature\_names(), columns=["idf\_weights"]) # sort ascending df idf.sort\_values(by=['idf\_weights']) Out[46]: idf\_weights manager 2.928266 driver 4.408042 4.470238 teacher supervisor 4.519563 engineer 4.565548 9.008199 hygienst 9.008199 icare information 9.008199 9.008199 ownergroomer youthdevelopment 9.008199 777 rows × 1 columns The lower the IDF value of a word, the less unique. **Model Evaluation** In [58]: **from sklearn.metrics import** confusion matrix def conf mat(y true, y pred, set name): print('Confusion Matrix on ', set\_name) cnf\_table = pd.DataFrame(confusion\_matrix(y\_true, y\_pred), index = ['A','B', 'C','D','E','F','G'], columns=['predicted\_A', 'predicted\_B', 'predicted\_C', 'predicted\_D', 'predicted\_E', 'pre dicted F'\ ,'predicted\_G']) return cnf table **MultinomialNB** In [61]: from sklearn.model\_selection import train\_test\_split from sklearn.feature extraction.text import CountVectorizer from sklearn.feature\_extraction.text import TfidfTransformer from sklearn.naive\_bayes import MultinomialNB from imblearn.over sampling import SMOTE from imblearn.pipeline import Pipeline X\_Train, X\_Test, y\_Train, y\_Test = train\_test\_split(X, y, test\_size=0.30, random\_state= 42) title\_clf = Pipeline([('vect', CountVectorizer()), ('tfidf', TfidfTransformer()), ('smote', SMOTE(random\_state= 42)), ('clf', MultinomialNB())]) In [70]: title\_clf.fit(X\_Train, y\_Train) y\_pred\_test = title\_clf.predict(X\_Test) y\_pred\_train = title\_clf.predict(X\_Train) from sklearn.metrics import accuracy\_score print('Accuracy on train set: ', round(100 \* accuracy\_score(y\_Train, y\_pred\_train),2)) conf\_mat(y\_Train, y\_pred\_train, 'Train') Accuracy on train set: 26.59 Confusion Matrix on Train Out[71]: predicted\_A predicted\_B predicted\_C predicted\_D predicted\_E predicted\_F predicted\_G Α 445 95 151 132 360 171 152 В 212 399 154 181 500 224 157 С 195 105 396 138 394 209 146 D 106 212 68 70 222 105 69 Ε 14 13 115 24 16 F 7 0 2 23 4 1 5 0 0 8 In [72]: print('Accuracy on test set: ', round(100 \* accuracy\_score(y\_Test, y\_pred\_test),2)) conf\_mat(y\_Test, y\_pred\_test, 'Test') Accuracy on test set: 14.48 Confusion Matrix on Test Out[72]: predicted\_A predicted\_B predicted\_C predicted\_D predicted\_E predicted\_F predicted\_G 144 58 77 60 166 76 63 В 173 102 73 96 84 192 63 С 140 71 90 60 188 73 60 D 74 33 34 42 94 50 34 Ε 19 11 13 12 24 10 5 F 3 3 0 1 1 1 1 G **SVC** In [75]: from sklearn.feature\_extraction.text import CountVectorizer count vect = CountVectorizer() # this steps generates word counts for the words in your docs X\_train\_counts = count\_vect.fit\_transform(X\_Train) X\_test\_counts = count\_vect.transform(X\_Test) from sklearn.feature extraction.text import TfidfTransformer tf\_transformer = TfidfTransformer(use\_idf=False).fit(X\_train\_counts) X\_Train\_tf = tf\_transformer.transform(X\_train\_counts) X\_Test\_tf = tf\_transformer.transform(X\_test\_counts) from imblearn.over\_sampling import SMOTE smote = SMOTE(random state= 42) X\_Train\_tf\_smote , y\_Train\_smote = smote.fit\_resample(X\_Train\_tf, y\_Train) In [76]: from sklearn.svm import SVC from skopt import BayesSearchCV from sklearn.model\_selection import RepeatedStratifiedKFold from sklearn.model\_selection import RandomizedSearchCV params = dict() params['C'] = (1e-6, 100.0, 'log-uniform') params['gamma'] = (1e-6, 100.0, 'log-uniform') params['degree'] = (1,5)params['kernel'] = ['linear', 'poly', 'rbf', 'sigmoid'] cv = RepeatedStratifiedKFold(n splits=10, n repeats=3, random state=1) search = RandomizedSearchCV(SVC(), params, n jobs=-1, cv=cv) search.fit(X\_Train\_tf\_smote, y\_Train\_smote) Out[76]: RandomizedSearchCV(cv=RepeatedStratifiedKFold(n repeats=3, n splits=10, random state=1), estimator=SVC(), n jobs=-1, param distributions={'C': (1e-06, 100.0, 'log-uniform'), 'degree': (1, 5), 'gamma': (1e-06, 100.0, 'log-uniform'), 'kernel': ['linear', 'poly', 'rbf', 'sigmoid']}) In [77]: search.best params Out[77]: {'kernel': 'rbf', 'gamma': 100.0, 'degree': 5, 'C': 100.0} In [84]: y pred train = search.predict(X Train tf smote) y pred test = search.predict(X Test tf) print('Accuracy on train set: ', round(100 \* accuracy\_score(y\_Train\_smote, y\_pred\_train),2)) cm = conf mat(y Train smote, y pred train, 'train set')  $\mathsf{cm}$ Accuracy on train set: 57.57 Confusion Matrix on train set Out[84]: predicted\_A predicted\_B predicted\_C predicted\_D predicted\_E predicted\_F predicted\_G 2 Α 810 246 136 468 143 В 384 609 525 192 18 95 4 С 420 275 436 491 190 13 2 7 D 1042 5 314 186 106 167 Ε 110 83 45 372 1204 13 0 F 29 57 3 168 125 1445 0 G 0 1816 print('Accuracy on test set: ', round(100 \* accuracy\_score(y\_Test, y\_pred\_test),2)) cm = conf\_mat(y\_Test, y\_pred\_test, 'test set') Accuracy on test set: 22.48 Confusion Matrix on test set Out[83]: predicted\_A predicted\_B predicted\_C predicted\_D predicted\_E predicted\_F predicted\_G Α 183 154 56 186 58 3 В 5 196 199 74 243 65 1 С 172 166 72 197 68 6 1 D 29 5 2 80 91 123 31 Ε 18 31 11 32 2 0 0 F 2 2 0 1 4 1 0 G 0