```
In [3]: import pandas as pd
        import re
        import string
        from wordcloud import WordCloud
        import matplotlib.pyplot as plt
        from nltk.tokenize import word_tokenize
        from nltk.stem import WordNetLemmatizer
        import numpy as np
In [4]: data= pd.read_csv('/Users/spring/Desktop/BA Data/BA_data.csv')
In [3]: data.columns
Out[3]: Index(['Unnamed: 0', 'Job Title', 'Salary Estimate', 'Job Descript
        ion',
                'Rating', 'Company Name', 'Location', 'Headquarters', 'Size
        ', 'Founded',
                'Type of ownership', 'Industry', 'Sector', 'Revenue', 'Comp
        etitors',
                'Easy Apply', 'job_description_cleaned', 'job_description_f
        ormatted',
               'index'],
              dtype='object')
In [4]: data.shape
Out[4]: (6162, 19)
In [5]: | df=data.copy()
In [6]: | df.drop(columns = 'Unnamed: 0', inplace= True)
        df.drop(columns = 'job_description_cleaned' , inplace= True)
        df.drop(columns = 'job_description_formatted' , inplace= True)
In [7]: df.shape
Out[7]: (6162, 16)
In [ ]:
In [ ]: |# Assign Column 'Industry' to its occupation code (2022 NAICS)
```

```
In [9]: |df.Industry.unique()
                 rindheide fransaction riocessing ,
                'Beauty & Personal Accessories Stores',
                'Automotive Parts & Accessories Stores', 'Chemical Manufact
        uring',
                'Department, Clothing, & Shoe Stores', 'K-12 Education',
                'Transportation Management', 'Miscellaneous Manufacturing',
                'Logistics & Supply Chain', 'Catering & Food Service Contra
        ctors',
                'Health Care Products Manufacturing', 'Drug & Health Stores
                'Wholesale', 'Membership Organizations', 'Oil & Gas Service
        s',
                'Sporting Goods Stores', 'Gas Stations', 'Truck Rental & Le
        asing',
                'Express Delivery Services',
                'Cable, Internet & Telephone Providers', 'Metals Brokers',
                'Grocery Stores & Supermarkets', 'Pet & Pet Supplies Stores
                'Education Training Services', 'Financial Analytics & Resea
        rch',
                               ITaananastatian Fanisamant Mannfaatnaisal
In [6]: # According to 2022 NAICS (North American Industry Classification S
        df['Industry']=[x.lower() for x in data['Industry']]
        # 62-- Health care and Social assistance
        df.loc[df['Industry'].str.contains("health care"), 'Industry'] = '6
        df.loc[df['Industry'].str.contains("social assistance"), 'Industry'
        df.loc[df['Industry'].str.contains("preschool & child care"), 'Indu
        # 51-- Information: Web search portal and Internet publishing
        df.loc[df['Industry'].str.contains("internet"), 'Industry'] = '51'
        df.loc[df['Industry'].str.contains("it services"), 'Industry'] = '5
        df.loc[df['Industry'].str.contains("motion picture production & dis
        df.loc[df['Industry'].str.contains("tv broadcast & cable networks")
        df.loc[df['Industry'].str.contains("biotech & pharmaceuticals"), 'I
        df.loc[df['Industry'].str.contains("publish"), 'Industry'] = '51'
        df.loc[df['Industry'].str.contains("telecommunications services"),
        df.loc[df['Industry'].str.contains("news outlet"), 'Industry'] = '5
        # 61—— Educational Services: Sports and Recreation
        df.loc[df['Industry'].str.contains("sports & recreation"), 'Industr
        df.loc[df['Industry'].str.contains("colleges"), 'Industry'] = '61'
        df.loc[df['Industry'].str.contains("universities"), 'Industry'] = '
        df.loc[df['Industry'].str.contains("education training services"),
        df.loc[df['Industry'].str.contains("k-12 education"), 'Industry'] =
        # 52-- Finance and Insurance: Banking
        df.loc[df['Industry'].str.contains("insurance"), 'Industry'] = '52'
        df.loc[df['Industry'].str.contains("bank"), 'Industry'] = '52'
        df.loc[df['Industry'].str.contains("venture capital"), 'Industry']
        df.loc[df['Industry'].str.contains("brokerage"), 'Industry'] = '52'
df.loc[df['Industry'].str.contains("lond"), 'Industry'] = '52'
```

```
unitoclari Thanstry Jesti Contaths/ tena /, Thanstry J - 32
df.loc[df['Industry'].str.contains("financial transaction processin")
df.loc[df['Industry'].str.contains("stock exchanges"), 'Industry']
# 54-- Professional, Scientific, and Technical Services
df.loc[df['Industry'].str.contains("research"), 'Industry'] = '54'
df.loc[df['Industry'].str.contains("advertising"), 'Industry'] = '5
df.loc[df['Industry'].str.contains("marketing"), 'Industry'] = '54'
df.loc[df['Industry'].str.contains("consult"), 'Industry'] = '54'
df.loc[df['Industry'].str.contains("engineering"), 'Industry'] = '5
df.loc[df['Industry'].str.contains("architectural"), 'Industry'] =
df.loc[df['Industry'].str.contains("enterprise software"), 'Industr
df.loc[df['Industry'].str.contains("accounting"), 'Industry'] = '54
df.loc[df['Industry'].str.contains("video games"), 'Industry'] = '5
df.loc[df['Industry'].str.contains("logistics & supply chain"), 'In
# 23--Construction
df.loc[df['Industry'].str.contains("building"), 'Industry'] = '23'
df.loc[df['Industry'].str.contains("construction"), 'Industry'] = '
# 72-- Accommodation and Food Services
df.loc[df['Industry'].str.contains("restaurant"), 'Industry'] = '72
df.loc[df['Industry'].str.contains("food"), 'Industry'] = '72'
df.loc[df['Industry'].str.contains("hotels, motels, & resorts"), 'I
# 42-- Wholesale Trade: Computer and Computer Peripheral Equipment
df.loc[df['Industry'].str.contains("computer hardware & software"),
df.loc[df['Industry'].str.contains("wholesale"), 'Industry'] = '42'
df.loc[df['Industry'].str.contains("metals brokers"), 'Industry'] =
# 56-- Administrative and Support and Waste Management and Remediat
df.loc[df['Industry'].str.contains("staffing"), 'Industry'] = '56'
df.loc[df['Industry'].str.contains("outsourcing"), 'Industry'] = '5
df.loc[df['Industry'].str.contains("security services"), 'Industry'
df.loc[df['Industry'].str.contains("travel agencies"), 'Industry']
# 53- Real Estate and Rental and Leasing
df.loc[df['Industry'].str.contains("real estate"), 'Industry'] = '5
df.loc[df['Industry'].str.contains("truck rental & leasing"), 'Indu
df.loc[df['Industry'].str.contains("rental"), 'Industry'] = '53'
df.loc[df['Industry'].str.contains("consumer electronics & applianc
df.loc[df['Industry'].str.contains("self-storage services"), 'Indus
# 92-- Public Administration: Regulation and Administration of Comm
df.loc[df['Industry'].str.contains("federal agencies"), 'Industry']
df.loc[df['Industry'].str.contains("utilities"), 'Industry'] = '92'
# 71-- Arts, Entertainment, and Recreation
```

```
df.loc[df['Industry'].str.contains("gambling"), 'Industry'] = '71'
df.loc[df['Industry'].str.contains("recreation"), 'Industry'] = '71
df.loc[df['Industry'].str.contains("museums, zoos & amusement parks
# 81-- Other Services (except Public Administration)
df.loc[df['Industry'].str.contains("repair & maintenance"), 'Indust
df.loc[df['Industry'].str.contains("health, beauty, & fitness"), 'I
df.loc[df['Industry'].str.contains("health fundraising organization
df.loc[df['Industry'].str.contains("grantmaking foundations"), 'Ind
df.loc[df['Industry'].str.contains("membership organizations"), 'In
df.loc[df['Industry'].str.contains("religious organizations"), 'Ind
# 44-- car dealer and Cosmetics, Beauty Supplies, cloth store, phar
df.loc[df['Industry'].str.contains("vehicle dealers"), 'Industry']
df.loc[df['Industry'].str.contains("beauty & personal accessories s
df.loc[df['Industry'].str.contains("automotive parts & accessories
df.loc[df['Industry'].str.contains("department, clothing, & shoe st
df.loc[df['Industry'].str.contains("gas stations"), 'Industry'] = '
df.loc[df['Industry'].str.contains("drug & health stores"), 'Indust
df.loc[df['Industry'].str.contains("grocery stores"), 'Industry'] =
df.loc[df['Industry'].str.contains("supermarkets"), 'Industry'] = '
df.loc[df['Industry'].str.contains("convenience stores & truck stop
df.loc[df['Industry'].str.contains("home furniture & housewares sto
df.loc[df['Industry'].str.contains("home centers & hardware stores"
# 45-- Retail trade: sport goods stores and pet
df.loc[df['Industry'].str.contains("retail stores"), 'Industry'] =
df.loc[df['Industry'].str.contains("sporting goods stores"), 'Indus
df.loc[df['Industry'].str.contains("pet & pet supplies stores"), 'I
df.loc[df['Industry'].str.contains("general merchandise & superstor
# 33--manufacturing
df.loc[df['Industry'].str.contains("manufacturing"), 'Industry'] =
df.loc[df['Industry'].str.contains("aerospace & defense"), 'Industr
df.loc[df['Industry'].str.contains("audiovisual"), 'Industry'] = '3
df.loc[df['Industry'].str.contains("radio"), 'Industry'] = '33'
# 92-- Federal, State, and Local Government,
df.loc[df['Industry'].str.contains("government"), 'Industry'] = '92
df.loc[df['Industry'].str.contains("regional agencies"), 'Industry'
# 21-- Mining, Quarrying, and Oil and Gas Extraction
df.loc[df['Industry'].str.contains("oil & gas services"), 'Industry
df.loc[df['Industry'].str.contains("oil & gas exploration & product
# 48-- Transportation
df.loc[df['Industry'].str.contains("transportation management"), 'I
```

```
df.loc[df['Industry'].str.contains("express detivery services'), 'I
df.loc[df['Industry'].str.contains("shipping"), 'Industry'] = '48'
df.loc[df['Industry'].str.contains("cruise ships"), 'Industry'] = '
df.loc[df['Industry'].str.contains("trucking"), 'Industry'] = '48'

# 11--Agriculture, Forestry, Fishing and Hunting
df.loc[df['Industry'].str.contains("farm support services"), 'Indus

# industry-- energy and legal not have efficient info and is meanig
# so this industry is not considered and assign it as -1.

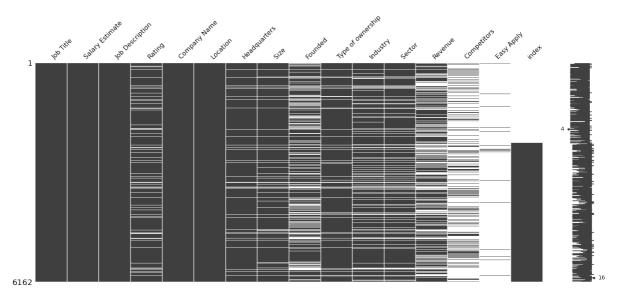
df['Industry'].replace(to_replace="energy", value='-1', inplace=True
df['Industry'].replace(to_replace="legal", value='-1', inplace=True
```

```
In [11]: df.Industry.unique()
```

In [7]: # -1 is replaced by nan value
df.replace([-1, '-1', 'Unknown', 'Unknown / Non-Applicable'], np.na

In [13]: # check missing value distribution
import missingno as msno
msno.matrix(df)

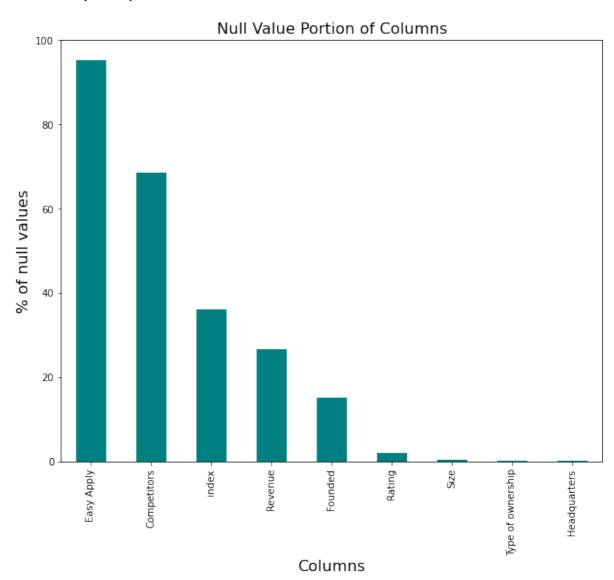
#### Out[13]: <AxesSubplot:>



```
In [ ]: '''
         Data is (MCAR) Missing completely at Random.
         Missing value exist in these columns:
         -- Rating, Headquarters, size, founded, type of ownership, industry,
         Among them, only industry is considered.
         1.1.1
In [14]: |msno.matrix(df.sort_values('Industry'))
Out[14]: <AxesSubplot:>
 In [ ]:
         This implies MCAR. Deleting instances is likely a good idea.
         111
In [15]: # only not null value in column Industry are kept.
         df = df[df['Industry'].notna()]
In [16]: df.shape
Out[16]: (5234, 16)
```

```
In [17]: # calculate % of null value in each column and sort them in descend
    null_portion = df.isnull().sum().sort_values(ascending=False)/len(d
    # make a plot
    null_portion[ null_portion>0.1].plot(kind='bar', figsize=(10,8), co
    plt.xlabel("Columns", fontsize=16)
    plt.ylabel("% of null values", fontsize=16);
    plt.title("Null Value Portion of Columns", fontsize=16)
```

Out[17]: Text(0.5, 1.0, 'Null Value Portion of Columns')



```
In [40]: # calculate % of null value in each row and sort them in descending
         row_null_portion = df.isnull().sum(axis=1).sort_values(ascending=Fa
         row_null_portion
Out[40]: 893
                 0.133741
                 0.133741
         391
         402
                 0.133741
         4192
                 0.114635
         4006
                 0.114635
         3337
                 0.000000
         5146
                 0.000000
         5419
                 0.000000
         2454
                 0.000000
         3133
                 0.000000
         Length: 5234, dtype: float64
 In [ ]:
         each row is kept due to their low row_null portion.
In [18]: # Check the frequency counts of the values of output feature (Indus
         df.Industry.value_counts()
Out[18]: 51
               1522
                943
         54
         56
                643
         52
                580
         62
                409
         42
                394
         61
                158
         33
                152
         92
                123
         44
                 72
         81
                 55
         72
                 42
         53
                 35
         45
                 30
         23
                 28
         21
                 24
         48
                  18
         71
                  6
         Name: Industry, dtype: int64
 In [8]: df.rename(columns= {df.columns[10]: 'Industry_code'}, inplace = Tru
 In [9]: # change column name from job title to position
         df.rename(columns={ df.columns[0]: 'position'}, inplace = True)
```

	In [1	10]:	df.	head(2)								
	Out[1	10]:		position	Salary Estimate	Job Description	Rating	Company Name	Location	Headquarters		
			0	Data Analyst, Center on Immigration and Justic	37 <i>K</i> – 66K (Glassdoor est.)	Are you eager to roll up your sleeves and harn	3.2	Vera Institute of Justice\n3.2	New York, NY	New York, NY		
			1	Quality Data Analyst	37 <i>K</i> – 66K (Glassdoor est.)	Overview\n\nProvides analytical and technical	3.8	Visiting Nurse Service of New York\n3.8	New York, NY	New York, NY		
	In [2	22]:	df	['positio	n']							
	Out[2	[22]:	<pre>Data Analyst, Center on Immigration and Justic Quality Data Analyst</pre>									
			2 3 4	Sen	ior Data	Analyst, Insigh	its & A	Analytics	Team Analyst			
			615 615 616	58 59	Data Analyst â Junior Security Analytics Data Engineer							

Patient Safety Physician or Safety Scientist -...

Name: position, Length: 5234, dtype: object

6161

```
In [11]: # Assign relevant job positions to certain broad job title
                   # using keywords to assign detailed job titles to certain broad job
                    df['position']=[x.upper() for x in df['position']]
                    df['description']=[x.upper() for x in df['Job Description']]
                   df.loc[df['position'].str.contains("SCIENTIST"), 'position'] = 'Dat
                    df.loc[df['position'].str.contains('ENGINEER'), 'position']='Machine
                    df.loc[df['position'].str.contains('PRINCIPAL STATISTICAL PROGRAMME
                    df.loc[df['position'].str.contains('PROGRAMMER'), 'position']='Machi
                    df.loc[df['position'].str.contains('MODELER'), 'position']='Machine
                    df.loc[df['position'].str.contains('MACHINE LEARNING'), 'position']=
                    df.loc[df['position'].str.contains('ANALYST'), 'position'] = 'Data
                    df.loc[df['position'].str.contains('STATISTICIAN'), 'position'] = '
                    df.loc[df['position'].str.contains('COMPUTATIONAL BIOLOGIST'), 'pos
                    df.loc[df['position'].str.contains('MANAGER'), 'position']='Data Sci
                   df.loc[df['position'].str.contains('CONSULTANT'), 'position']='Data
                    df.loc[df['position'].str.contains('DATA SCIENCE'), 'position']='Dat
                    df.loc[df['position'].str.contains('DIRECTOR'), 'position']='Data Sc
                   df.loc[df['position'].str.contains('MANAGEMENT'), 'position']='Data
                    df.loc[df['position'].str.contains('CONSULTING'), 'position']='Data
                   df.loc[df['position'].str.contains('ARCHITECT'), 'position']='Data a
                    df.loc[df['position'].str.contains('RESEARCH'), 'position']='Reseach
In [12]: | df.position=df[(df.position == 'Data Scientist') | (df.position == 'Data Scientist') |
                   df.position=['Others' if x is np.nan else x for x in df.position]
In [25]: | df.position.value_counts()
Out[25]: Data Analyst
                                                                                  2536
                    Data Scientist
                                                                                   1556
                    Machine Learning Engineer
                                                                                     842
                    Data Science Manager
                                                                                     230
                    Reseacher
                                                                                       34
                    Data architect
                                                                                      20
                    Others
                                                                                       16
                    Name: position, dtype: int64
```

```
In [26]: # Amount of vacany position for each job position
    position=df.groupby(['position'])['Industry_code'].count()
    position=position.reset_index(name='Industry_code')
    position=position.sort_values(['Industry_code'],ascending=False)

    print('Amount of new created roles :', '\n\n', position)
```

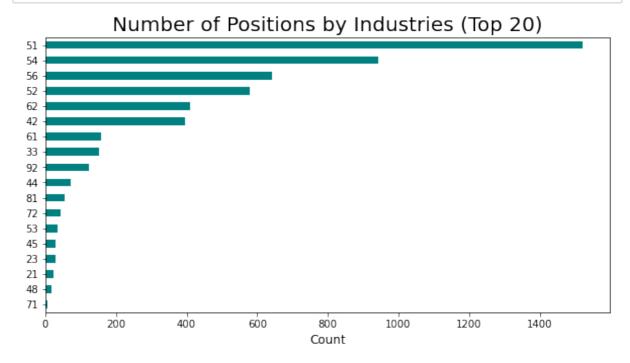
Amount of new created roles:

	position	<pre>Industry_code</pre>
0	Data Analyst	2536
2	Data Scientist	1556
4	Machine Learning Engineer	842
1	Data Science Manager	230
6	Reseacher	34
3	Data architect	20
5	Others	16

# **5.1.1 Vacant Positions by Industry**

```
In [27]: # Amount of vacancy Positions by industry

Industry = df.groupby(['Industry_code']).count().sort_values('posit Industry['position'].plot(kind='barh',figsize = (10,5),color='teal' plt.xlabel('Count', size = 12) plt.ylabel('') plt.yticks(size = 10) plt.yticks(size = 10) plt.xticks(size = 10) plt.title('Number of Positions by Industries (Top 20)', size = 20) plt.show()
```



```
In []:
```

```
In [24]: | df_model= df_clean.copy()
In [26]: | df_model.description_clean = df_model.description_clean.astype(str)
In [27]: # Focus on classifiying job description to right job position:
         # explore the difference of asymmetry information between job descr
         from nltk.stem import PorterStemmer
         from sklearn.feature_extraction.text import TfidfVectorizer
         from sklearn.preprocessing import LabelEncoder
         from sklearn.model_selection import train_test_split
         X= df_model.description_clean
         Y= df_model.position
         X=[re.sub(r''[^a-zA-Z0-9]+'', '', k) for k in X]
         X=[re.sub("[0-9]+",' ',k) for k in X]
         #applying stemmer
         ps = PorterStemmer()
         X = [ps.stem(k) for k in X]
         #Note: I have not removed stop words because there are important ke
         tfidf=TfidfVectorizer()
         # one-hot encoding
         label_enc= LabelEncoder()
         X= tfidf.fit_transform(X)
         Y= label_enc.fit_transform(Y)
         x_train,x_test,y_train,y_test= train_test_split(X,Y,stratify=Y,test
         # divide train dataset into train and validation subsets.
         x_train_1,x_val_1,y_train_1,y_val_1= train_test_split(x_train, y_tr
 In [ ]: |x_test,y_test
         x_train_1, y_train_1
         x_val_1,, y_val_1
```

# 4.1.1 Support Vector Machine (SVM) with RBF Kernels

```
In [139]:
          from sklearn.svm import SVC
          from sklearn.metrics import accuracy_score,confusion_matrix,classif
          from sklearn.linear_model import SGDClassifier
          from sklearn.ensemble import GradientBoostingClassifier
          from sklearn.naive_bayes import MultinomialNB
          from sklearn.model_selection import cross_validate
          # first algorithm SVM: SVM classification
          svm= SVC(kernel='rbf')
          svm.fit(x_train,y_train)
          svm_y=svm.predict(x_test)
          print('Accuracy of SVM :', accuracy_score(y_test,svm_y))
          print ('Confusion Matrix of SVM : ', '\n\n', confusion_matrix(y_tes
          print(1(y_test,svm_y))
          Accuracy of SVM : 0.8690932311621967
          Confusion Matrix of SVM:
           [[735
                   1 13
                           0
                               12
                                    0]
           [ 26
                    25
                               0
                                   01
                18
                          0
           [ 37
                               8
                  0 422
                          0
                                   01
                              3
           [ 2
                  0
                     0
                          1
                                   01
           [ 43
                     30
                          0 180
                                   01
                  0
           [ 4
                  0
                      1
                          0
                                   511
                               0
                        precision
                                      recall f1-score
                                                         support
                     0
                              0.87
                                        0.97
                                                  0.91
                                                             761
                     1
                              0.95
                                        0.26
                                                  0.41
```

```
In []:
        not all recall score is high, which means a part of job description
        The reason could be high similarity of two job description or the a
        1.1.1
```

0.90

0.17

0.71

0.50

0.58

0.87

0.88

0.29

0.79

0.67

0.87

0.66

0.86

2

3

4

5

accuracy

macro avg

weighted avg

0.86

1.00

0.89

1.00

0.93

0.87

69

6

467

253

1566

1566

1566

10

```
In [135]: #crossfold Validation of 7 folds for SVM
          cross val SVM= cross validate(svm, x train, y=y train,cv=7, return
```

# 4.1.3 Multinomial Naive Bayes (MNB)

# In [244]: # Naive Bayes classification NB= MultinomialNB() NB.fit(x\_train,y\_train) NB\_y= NB.predict(x\_test) print('Accuracy of Naive Bayes :', accuracy\_score(y\_test,NB\_y)) print ('Confusion Matrix of Naive Bayes : ', '\n\n', confusion\_matr print(classification\_report(y\_test,NB\_y))

Accuracy of Naive Bayes: 0.5830140485312899 Confusion Matrix of Naive Bayes:

[[755	0	) (	5 0	0	0]			
[ 68	0	1	0	0	0]			
[312	0	155	0	0	0]			
[ 6	0	0	0	0	0]			
[243	0	7	0	3	0]			
[ 10	0	0	0	0	0]]			
			preci	ision		recall	f1–score	support
		0		0.54		0.99	0.70	761
		1		0.00		0.00	0.00	69
		2		0.92		0.33	0.49	467
		3		0.00		0.00	0.00	6
		4		1.00		0.01	0.02	253
		5		0.00		0.00	0.00	10
accu	ıra	су					0.58	1566
macro	) a	ıvg		0.41		0.22	0.20	1566
weighted	l a	ıvg		0.70		0.58	0.49	1566

/Users/spring/opt/anaconda3/lib/python3.8/site-packages/sklearn/me trics/\_classification.py:1318: UndefinedMetricWarning: Precision a nd F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this b ehavior.

\_warn\_prf(average, modifier, msg\_start, len(result))
/Users/spring/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/\_classification.py:1318: UndefinedMetricWarning: Precision a
nd F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero\_division` parameter to control this b
ehavior.

\_warn\_prf(average, modifier, msg\_start, len(result))
/Users/spring/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/\_classification.py:1318: UndefinedMetricWarning: Precision a
nd F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero\_division` parameter to control this b
ehavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

```
In [142]: #crossfold Validation of 7 folds for NB
          cross_val_NB=sklearn.model_selection.cross_validate(NB, x_train, y=
          print ('NB Train fit score is : ', '\n\n', cross_val_NB ['train_sco
          print ('NB TEST score is : ', '\n\n', cross_val_NB ['test_score'])
          NB Train fit score is:
           [0.59456869 0.60543131 0.59808307 0.5942492 0.5971246 0.5988502
          1
           0.59565634]
          NB TEST score is:
           [0.59003831 0.56704981 0.58045977 0.55555556 0.56704981 0.5604606
          5
           0.585412671
```

## 4.1.2 SGD Classifier

```
In [148]: # 3rd Classifier SGDC
          # SGD classification
          from sklearn.linear_model import SGDClassifier
          sqd= SGDClassifier()
          sgd.fit(x_train,y_train)
          sgd_y=sgd.predict(x_test)
          print('Accuracy of SGD :', accuracy_score(y_test,sgd_y))
          print ('Confusion Matrix of SGD : ', '\n\n', confusion_matrix(y_tes
          print(classification_report(y_test,sgd_y))
```

Accuracy of SGD: 0.8920817369093231 Confusion Matrix of SGD:

[ 1 (	3 18 9 22 1 431 0 0 2 22 0 1	3 0 14 0 0 0 10 2 3 0 204 0 0	0] 0] 0] 0] 0] 5]]		
		precision	recall	f1–score	support
	0 1 2 3 4 5	0.91 0.83 0.87 1.00 0.88 1.00	0.95 0.42 0.92 0.33 0.81 0.50	0.93 0.56 0.90 0.50 0.84 0.67	761 69 467 6 253 10
accu macro weighted	avg	0.92 0.89	0.66 0.89	0.89 0.73 0.89	1566 1566 1566

```
In [150]: sorted(cross_val_SGD.keys())
Out[150]: ['fit_time', 'score_time', 'test_score']
In [151]: #crossfold Validation of 7 folds for SGD
          cross_val_SGD=sklearn.model_selection.cross_validate(sgd, x_train,
          print ('SGD Train fit score is : ', '\n\n', cross_val_SGD ['train_s
          print ('SGD TEST score is : ', '\n\n', cross_val_SGD ['test_score']
          SGD Train fit score is:
           [0.9942492 0.99361022 0.99392971 0.99520767 0.99520767 0.9942510
          4
           0.99329288]
          SGD TEST score is:
           [0.91954023 0.88122605 0.90613027 0.89463602 0.89463602 0.8982725
          5
           0.857965451
In [153]: #Classifier: XGBOOST classification
          from sklearn.ensemble import GradientBoostingClassifier
          xqboost= GradientBoostingClassifier(n estimators=90)
          xgboost.fit(x_train,y_train)
          xgboost_y=xgboost.predict(x_test)
          print('Accuracy of XGB00ST :', accuracy_score(y_test,xgboost_y))
          print ('Confusion Matrix of XGBOOST : ', '\n\n', confusion_matrix(y)
          print(classification_report(y_test,xgboost_y))
          Accuracy of XGB00ST : 0.8729246487867177
          Confusion Matrix of XGB00ST:
                         1 15
                                   1]
           [[728
                   4 12
           [ 23
                 23 22
                              1
                                  01
                          0
           [ 33
                 3 413
                          1
                             16
                                  11
                                  01
           1
                  0
                     1
                          1
                              3
           [ 37
                  3
                     14
                          0 197
                                  21
                                  511
           Γ
             4
                  0
                      1
                          0
                              0
                        precision
                                      recall f1-score
                                                         support
                     0
                             0.88
                                        0.96
                                                  0.92
                                                             761
                                                  0.45
                     1
                             0.70
                                        0.33
                                                              69
                     2
                             0.89
                                        0.88
                                                  0.89
                                                             467
                     3
                             0.33
                                        0.17
                                                  0.22
                                                               6
                     4
                             0.85
                                        0.78
                                                  0.81
                                                             253
                     5
                             0.56
                                                  0.53
                                        0.50
                                                              10
                                                  0.87
                                                            1566
              accuracy
                             0.70
                                                  0.64
             macro avg
                                        0.60
                                                            1566
          weighted avg
                             0.87
                                        0.87
                                                  0.87
                                                            1566
```

# 4.1.4 Gradient Boosting Classifier (GB) and AdaBoost Classifier (AB)

```
In [29]: # model
         # 1.
               Adaptive Boosting classifier (AdaBoostClassifier from sklearn
         from sklearn.ensemble import AdaBoostClassifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.model selection import GridSearchCV
         param_grid = {"base_estimator__criterion" : ["gini", "entropy"],
                       "base_estimator__splitter" : ["best", "random"],
                       "n_estimators": [1, 10, 20],
                       'learning_rate': [1.0, 2.0, 3.0],
         tree = DecisionTreeClassifier(random_state = 42, class_weight = "ba
         ada = AdaBoostClassifier(base_estimator =tree)
         grid_search_Ada = GridSearchCV(ada, param_grid=param_grid)
         grid_search_Ada.fit(x_train,y_train)
         print('{}, {}'.format(grid_search_Ada.best_params_,grid_search_Ada.
         {'base_estimator__criterion': 'gini', 'base_estimator__splitter':
         'random', 'learning_rate': 2.0, 'n_estimators': 20}, 0.86355589768
         52227
In [30]: from sklearn.metrics import precision_score, recall_score
In [32]: # average= average
         # and find their average weighted by support (the number of true in
         # This alters 'macro' to account for label imbalance;
         # it can result in an F-score that is not between precision and rec
         adaBoost_pred= grid_search_Ada.predict(x_test)
         results = {}
         results['ada boost:'] = 'Acc: {:.2f}, Prec: {:.2f}, Recall: {:.2f}'
         print(results)
         {'ada boost:': 'Acc: 0.89, Prec: 0.86, Recall: 0.65'}
 In [ ]: |x_test,y_test
         x_train_1, y_train_1
         x_val_1, y_val_1
```

## 4.4. Deep NN

```
In [34]: x_train_1.shape
```

Out[34]: (3011, 37002)

#### In [42]:

# could compare resuts that Relu function could be set as prelu and
# PReLU is similar to Relu

model = Sequential([
 Dense(5, input\_shape = [37002], activation="PReLU"),
 Dense(11, activation="relu"),
 Dense(18, activation="softmax") #using softmax for last layer b
])

#### In [44]: model.summary()

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 5)	185020
dense_4 (Dense)	(None, 11)	66
dense_5 (Dense)	(None, 18)	216

Total params: 185,302 Trainable params: 185,302 Non-trainable params: 0

```
In [45]: #compile model
        model.compile(loss="sparse_categorical_crossentropy",
                  optimizer="sgd" , #stochastic gradient descent
                  metrics=["sparse_categorical_accuracy"])
In [46]: |x_train,x_test,y_train,y_test
Out[46]: (<4302x37002 sparse matrix of type '<class 'numpy.float64'>'
              with 1042966 stored elements in Compressed Sparse Row form
        at>,
        <1844x37002 sparse matrix of type '<class 'numpy.float64'>'
               with 441635 stored elements in Compressed Sparse Row forma
        t>,
        array([2, 2, 2, ..., 4, 4, 4]),
        array([1, 0, 0, ..., 0, 2, 4]))
In [47]: | x_train_1.sort_indices()
        x_val_1.sort_indices()
        x test.sort indices()
In [48]: #fit model
        history = model.fit(x_train_1, y_train_1, validation_data= (x_val_1
        01 - sparse categorical accuracy: 0.9754 - val loss: 0.4755 - val
        sparse categorical accuracy: 0.8730
        Epoch 296/400
        61/61 [============== ] - 1s 8ms/step - loss: 0.129
        4 - sparse_categorical_accuracy: 0.9774 - val_loss: 0.4760 - val_s
        parse_categorical_accuracy: 0.8737
        Epoch 297/400
        84 - sparse_categorical_accuracy: 0.9777 - val_loss: 0.4859 - val_
        sparse categorical accuracy: 0.8699
        Epoch 298/400
        61/61 [============== ] - 0s 6ms/step - loss: 0.128
        1 - sparse_categorical_accuracy: 0.9771 - val_loss: 0.4765 - val_s
        parse_categorical_accuracy: 0.8737
        Epoch 299/400
        4 - sparse categorical accuracy: 0.9777 - val loss: 0.4814 - val s
        parse_categorical_accuracy: 0.8706
        Epoch 300/400
In [ ]: x_test,y_test
```

```
In [49]: #-- make predictions: use sum function for mutiple output lables.

test_predict = model.predict(x_test).sum(axis=1)

from sklearn.metrics import mean_absolute_error

mae_1 = mean_absolute_error(y_test, test_predict)

print('Test Error: {}'.format(mae_1))
```

58/58 [============= ] - 0s 4ms/step Test Error: 1.3101952341981151

```
In [50]: # Complete the code and plot your model
    import matplotlib.pyplot as plt

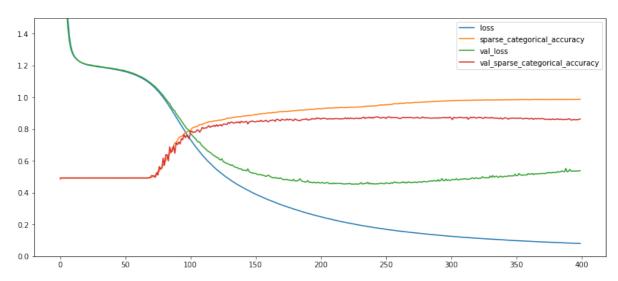
pd.DataFrame(history.history).plot(figsize=(14, 6))

plt.gca().set_ylim(0, 1.5)

# is your model overfitting or underfitting?
# A model is overfitting when: loss on train set decreasing; loss o

# if there is a overfitting/underfitting problem, you might need to
```

#### Out[50]: (0.0, 1.5)



# 4. Simple RNN

```
In []: # Simple RNN
In []: x_nn_train, y_nn_train
    x_nn_valid, y_nn_valid
```

```
In [919]: # Detect hardware, return appropriate distribution strategy
          try:
              # TPU detection. No parameters necessary if TPU NAME environmen
              # set: this is always the case on Kaggle.
              tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
              print('Running on TPU ', tpu.master())
          except ValueError:
              tpu = None
          if tpu:
              tf.config.experimental_connect_to_cluster(tpu)
              tf.tpu.experimental.initialize_tpu_system(tpu)
              strategy = tf.distribute.experimental.TPUStrategy(tpu)
          else:
              # Default distribution strategy in Tensorflow. Works on CPU and
              strategy = tf.distribute.get_strategy()
          print("REPLICAS: ", strategy.num_replicas_in_sync)
          REPLICAS:
                     1
In [985]: from keras.preprocessing import sequence, text
          from keras.layers import GlobalMaxPooling1D, Conv1D, MaxPooling1D,
          from keras.layers.embeddings import Embedding
          from keras.layers.recurrent import LSTM, GRU,SimpleRNN
          X_NN = df_model.description_clean
          Y_NN = df_model.position
          x_nn_train, x_nn_valid, y_nn_train, y_nn_valid = train_test_split(X)
                                                             stratify=Y_NN,
                                                             random_state=42,
                                                             test_size=0.2, sh
In [986]: # using keras tokenizer here
          token = text.Tokenizer(num words=None)
          max_len = 1500
          token.fit_on_texts(list(x_nn_train) + list(x_nn_valid))
          x_nn_train_seq = token.texts_to_sequences(x_nn_train)
          x_nn_valid_seq = token.texts_to_sequences(x_nn_valid)
          #zero pad the sequences
          x_nn_train_pad = sequence.pad_sequences(x_nn_train_seq, maxlen=max_
          x_nn_valid_pad = sequence.pad_sequences(x_nn_valid_seq, maxlen=max_
          word_index = token.word_index
In [988]: # change datatype from pandas series to numpy adarray
          y_nn_train= y_nn_train.to_numpy()
          y nn valid= y nn valid.to numpy()
```

```
In [989]: #Initialzie an OneHotEncoder object
          ohe = OneHotEncoder(handle_unknown='value')
          # nominal feature (position) is encoded using one-hot encoding
          # apply the encoding on training and validation set
          y_nn_train_ohe = ohe.fit_transform(y_nn_train)
          y_nn_valid_ohe = ohe.fit_transform(y_nn_valid)
 In [ ]:
In [990]: %time
          with strategy.scope():
          # A simpleRNN without any pretrained embeddings and one dense layer
            # loss: categorical_crossentropy - categorical;
              # loss: sparse_categorical_crossentropy loss- int encoder is re
              # thus use categorical_crossentropy because y_nn_train_ohe data
              model nn = Sequential()
              model nn.add(Embedding(len(word index) + 1,
                                300,
                                input_length=max_len))
              model_nn.add(SimpleRNN(100))
              model_nn.add(Dense(6, activation='softmax'))
              model_nn.compile(loss='categorical_crossentropy', optimizer='ad
          model nn.summary()
          Model: "sequential 146"
                                        Output Shape
           Layer (type)
                                                                   Param #
           embedding 10 (Embedding)
                                        (None, 1500, 300)
                                                                   10184700
           simple_rnn_8 (SimpleRNN)
                                        (None, 100)
                                                                   40100
           dense 214 (Dense)
                                        (None, 6)
                                                                   606
          Total params: 10,225,406
          Trainable params: 10,225,406
          Non-trainable params: 0
          CPU times: user 326 ms, sys: 135 ms, total: 461 ms
          Wall time: 461 ms
  In [ ]:
In [991]: |type(x_nn_train_pad)
Out[991]: numpy.ndarray
In [992]: |type(y_nn_train_ohe)
```

Out[992]: pandas.core.frame.DataFrame

```
In [993]: |y_nn_train
Out[993]: array(['Machine Learning Engineer', 'Data Scientist', 'Data Analys
         t', ...,
                'Data Analyst', 'Machine Learning Engineer',
                'Machine Learning Engineer'], dtype=object)
In [970]: model_nn.fit(x_nn_train_pad, y_nn_train_ohe, epochs=5, batch_size=6
         # Multiplying by Strategy to run on TPU's
         Epoch 1/5
         66/66 [============= ] - 114s 2s/step - loss: 1.19
         07 - accuracy: 0.5163
         Epoch 2/5
         66/66 [============ ] - 119s 2s/step - loss: 0.77
         95 - accuracy: 0.7245
         Epoch 3/5
         66/66 [============== ] - 139s 2s/step - loss: 0.63
         68 - accuracy: 0.7856
         Epoch 4/5
         66/66 [============= ] - 110s 2s/step - loss: 0.38
         39 - accuracy: 0.8757
         Epoch 5/5
         66/66 [============= ] - 92s 1s/step - loss: 0.294
         5 - accuracy: 0.9001
Out[970]: <keras.callbacks.History at 0x7fb285855a00>
 In [ ]:
 In [ ]: # RNN: LSTM
         x_train,x_test,y_train,y_test
 In [ ]:
 In [ ]:
```

```
In [ ]:
  In [ ]:
In [732]: |pip install imageai --upgrade
          WARNING: Ignoring invalid distribution -cipy (/Users/spring/opt/an
          aconda3/lib/python3.8/site-packages)
          WARNING: Ignoring invalid distribution -cipy (/Users/spring/opt/an
          aconda3/lib/python3.8/site-packages)
          Collecting imageai
            Downloading imageai-2.1.6-py3-none-any.whl (160 kB)
                                          | 160 kB 930 kB/s eta 0:00:0
          1
          Collecting opency-python
            Downloading opencv_python-4.6.0.66-cp36-abi3-macosx_10_15_x86_64
          .whl (46.4 MB)
                                                 || 46.4 MB 12.0 MB/s eta 0:00
          :01
                                                  | 4.1 MB 4.9 MB/s eta 0:00:
          09
          Collecting keras==2.4.3
            Downloading Keras-2.4.3-py2.py3-none-any.whl (36 kB)
          Collecting pillow==7.0.0
            Downloading Pillow-7.0.0-cp38-cp38-macosx_10_9_x86_64.whl (2.1 M
          B)
```

```
In [733]: # adjust model complexity
         # Self-normalizing neural model could replace Batch normalization
          import matplotlib.pyplot as plt
          import tensorflow as tf
          from tensorflow import keras
          from tensorflow.keras.layers import BatchNormalization
         model2 = keras.models.Sequential([
             BatchNormalization( input_shape = [34125]), # all layers in Ke
             keras.layers.Dense(10, activation="elu", kernel_initializer=kera
             BatchNormalization(),
             keras.layers.Dense(8, activation="elu",kernel_initializer=keras
             BatchNormalization(),
             keras.layers.Dense(6, activation="elu", kernel initializer=keras
             BatchNormalization(),
             keras.layers.Dense(18, activation="softmax")
         ])
In [734]:
         model2.compile(loss="sparse_categorical_crossentropy",
                       optimizer="sqd",
                       metrics=["sparse_categorical_accuracy"])
         history_2 = model2.fit(x_train, y_train, epochs=400,
                             validation_data=(x_test, y_test), verbose = 0, b
          pd.DataFrame(history 2.history).plot(figsize=(8, 5))
          plt.grid(True)
          plt.gca().set_ylim(0, 2)
                                                  Traceback (most recent c
          TypeError
          all last)
          Input In [734], in <cell line: 5>()
               1 model2.compile(loss="sparse_categorical_crossentropy",
                               optimizer="sgd",
                               metrics=["sparse_categorical_accuracy"])
          validation_data=(x_test, y_test), verbo
          se = 0, batch\_size = 50)
```

```
File ~/opt/anaconda3/lib/python3.8/site-packages/tensorflow/python
/framework/func_graph.py:1147, in func_graph_from_py_func.<locals>
.autograph handler(*args, **kwargs)
   1145 except Exception as e: # pylint:disable=broad-except
          if hasattr(e, "ag_error_metadata"):
   1146
            raise e.ag error metadata.to exception(e)
-> 1147
   1148
          else:
            raise
   1149
TypeError: in user code:
    File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/
keras/engine/training.py", line 1021, in train_function *
        return step_function(self, iterator)
    File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/
keras/engine/training.py", line 1010, in step_function **
    File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/
keras/engine/training.py", line 1000, in run_step **
    File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/
keras/engine/training.py", line 859, in train_step
    File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/
keras/utils/traceback_utils.py", line 67, in error_handler
    TypeError: Exception encountered when calling layer "batch_nor
malization_4" (type BatchNormalization).
    Failed to convert elements of SparseTensor(indices=Tensor("Des
erializeSparse:0", shape=(None, 2), dtype=int64), values=Tensor("D
eserializeSparse:1", shape=(None,), dtype=float32), dense_shape=Te
nsor("stack:0", shape=(2,), dtype=int64)) to Tensor. Consider cast
ing elements to a supported type. See <a href="https://www.tensorflow.org/a">https://www.tensorflow.org/a</a>
pi docs/python/tf/dtypes
(https://www.tensorflow.org/api docs/python/tf/dtypes) for support
ed TF dtypes.
    Call arguments received:
      • inputs=<tensorflow.python.framework.sparse_tensor.SparseTe
nsor object at 0x7fb261732e20>
      • training=True
plt.show()
```

```
In []: # save_fig("keras_learning_curves_graph")
    plt.show()
    model2.evaluate(x_test, y_test)
In []:
In []:
```

```
In [ ]:
  In [ ]:
  In [ ]: x_train,y_train,x_test, y_test
  In [ ]:
  In [ ]:
  In [ ]: # Expand input data:
          \# x-- job position and job description
          # y-- industry_code
In [236]: df_model.columns
Out[236]: Index(['position', 'Rating', 'Headquarters', 'Size', 'Founded',
                  'Type of ownership', 'Industry_code', 'Sector', 'Revenue',
                  'Competitors', 'Job_state', 'description_clean', 'skill_set
                  'min_salary_$K', 'max_salary_$K', 'avg_salary_$K',
                  'Headquarters_State'],
                dtype='object')
  In [ ]:
          X= df_model[['description_clean', 'position']]
          Y= df_model.Industry_code
          X=[re.sub(r''[^a-zA-Z0-9]+'', '', k) for k in X]
          X=[re.sub("[0-9]+",' ',k) for k in X]
          #applying stemmer
          ps = PorterStemmer()
          X = [ps.stem(k) for k in X]
          #Note: I have not removed stop words because there are important ke
          tfidf=TfidfVectorizer()
          label enc=LabelEncoder()
          X= tfidf.fit transform(X)
          Y= label_enc.fit_transform(Y)
          x_train,x_test,y_train,y_test=train_test_split(X,Y,stratify=Y,test_
  In [ ]:
  In [ ]: # NER with regexptagger
```

```
In [173]: # Named Entity Recognition (two most likely trees could belong to o
          # and they're considered as continuous and put into chunk)
          # tag consecutive NNPs as one NE
          from nltk import ne_chunk, pos_tag, word_tokenize
          from nltk.tree import Tree
          def get_continuous_chunks(text):
              chunked = ne_chunk(pos_tag(word_tokenize(text)))
              prev = None
              continuous chunk = []
              current chunk = []
              for i in chunked:
                  if type(i) == Tree:
                      current_chunk.append(" ".join([token for token, pos in
                  elif current chunk:
                      named_entity = " ".join(current_chunk)
                      if named_entity not in continuous_chunk:
                          continuous_chunk.append(named_entity)
                          current_chunk = []
                  else:
                      continue
              if current_chunk:
                  named_entity = " ".join(current_chunk)
                  if named_entity not in continuous_chunk:
                      continuous_chunk.append(named_entity)
                      current chunk = []
              return continuous_chunk
  In [ ]:
In [243]: # Apply get_continuous_chunks and add as one new column
          df_model['NER_set'] = df['Job Description'].apply(get_continuous_ch
  In []: # use this new column as input to classify
In [246]: df_model['NER_set']
Out[246]: 0
                  [Data Analyst, Veras Center, Justice, CIJ, Ver...
          1
                  [Overview, Quality Management, Quality, HEDIS,...
                  [Senior Data, Insights, Analytics, Customer Op...
          2
          3
                  [Agile, Digital Strategy, Technology, Creative...
          4
                  [ABOUT FANDUEL, FanDuel Group, FanDuel, FanDue...
          6157
                  [Us Tachyon, Digital, Tachyon Technologies, Ro...
                  [Job, Interpret, Develop, Acquire, Identify, F...
          6158
                  [Job DescriptionThe, Python, Splunk, ELK, Elas...
          6159
                  [Security Analytics Data Engineer, MSSQL, SSRS...
          6160
                  [UCB, Europe, US, UCB At UCB, Patient Safety, ...
          6161
          Name: NER_set, Length: 5218, dtype: object
 In [ ]:
```

```
In [186]: import nltk
          nltk.download('maxent_ne_chunker')
          nltk.download('words')
           [nltk_data] Downloading package maxent_ne_chunker to
           [nltk_data]
                           /Users/spring/nltk_data...
           [nltk data]
                         Package maxent ne chunker is already up-to-date!
           [nltk data] Downloading package words to /Users/spring/nltk data..
           [nltk_data]
                        Unzipping corpora/words.zip.
Out[186]: True
In [232]: txt_3= df['Job Description']
          type(txt_3)
Out[232]: pandas.core.series.Series
In [234]: # change format from series to string
          txt_3= txt_3.to_string()
          type(txt 3)
Out[234]: str
In [235]: # all chunks put together
          get_continuous_chunks(txt_3)
Out[235]: ['Job',
            'Data Analyst',
           'Veras Center',
           'Justice',
           'CIJ',
            'Vera Institute',
            'Veras Center Justice',
           'CIJ CIJ',
           'Data Analyst Centers',
           'CIJ AWS',
            'Caspio',
            'SQL',
           'R',
            'Python',
            'Data Analyst Justice',
            'CIJ Unaccompanied Childrens Program',
            'UCP',
            'Legal Orientation Program',
            'Custodians',
In [248]: # Apply as new column
          df model['NER_set'] = df_clean_2['description_clean'].apply(get_con
  In [ ]:
```

```
In [ ]: |# new function that nned to explore
          def conditions(tree node):
               return tree node.height() == 2
              def coninuous_entities(self, input_text, file_handle):
                 from nltk import ne_chunk, pos_tag, word_tokenize
                 from nltk.tree import Tree
                 # Note: Currently, the chunker categorizes only 2 'NNP' toget
                 docs = input text.split('\n')
                 for input_text in docs:
                     chunked_data = ne_chunk(pos_tag(word_tokenize(input_text)
                     child_data = [subtree for subtree in chunked_data.subtree
                     named entities = []
                     for child in child data:
                         if type(child) == Tree:
                             named_entities.append(" ".join([token for token,
                     # Dump all entities to file for now, we will see how to g
                     if file handle is not None:
                         file handle.write('\n'.join(named entities) + '\n')
                 return named entities
In [310]: |df_clean['description_clean']
Out[310]: 0
                   are, you, eager, to, roll, up, your, sleeve, and, harne...
          1
                   overview, provides, analytical, and, technical, sup...
          2
                   were, looking, for, a, senior, data, analyst, who, ha, ...
          3
                   requisition, remoteyes, we, collaborate, we, create...
          4
                   about, fanduel, group, fanduel, group, is, a, worldcl...
                   about, u, tachyon, technology, is, a, digital, transf...
          6157
                   job,description,interpret,data,analyze,result,...
          6158
                   job, description the, security, analytics, data, eng...
          6159
          6160
                   the, security, analytics, data, engineer, will, inte...
                   help,u,transform,patient,life,at,ucb,we,put,ou...
          6161
          Name: description_clean, Length: 5218, dtype: object
In [313]: |df['Job Description']
Out[313]: 0
                   Are you eager to roll up your sleeves and harn...
          1
                   Overview\n\nProvides analytical and technical ...
          2
                   We're looking for a Senior Data Analyst who ha...
                   Requisition NumberRR-0001939\nRemote:Yes\nWe c...
          3
          4
                   ABOUT FANDUEL GROUP\n\nFanDuel Group is a worl...
          6157
                   About Us\n\nTachyon Technologies is a Digital ...
          6158
                   Job description\nInterpret data, analyze resul...
          6159
                   Job DescriptionThe Security Analytics Data Eng...
                   The Security Analytics Data Engineer will inte...
          6160
                   Help us transform patients' lives.\nAt UCB, we...
          6161
          Name: Job Description, Length: 5234, dtype: object
```

In []: # use Spacy to find top 100 entity and relative skills

```
In [314]: | import en_core_web_sm
          import spacy
          nlp = en_core_web_sm.load()
          # list to store extracted skill keywords
          skill_list = []
          # feed the entire corpus into batches of 100 samples at a time
          for i in range(0,len(df), 100):
              # for the last batch
              if i+np.mod(2253,100)==len(df):
                  # combine job descriptions of 100 samples into a single str
                  text = " ".join(des for des in df['Job Description'][i:len(
              else:
                  text = " ".join(des for des in df['Job Description'][i:i+10
              # process raw text with the nlp object that holds all informati
              #features and relationships
              doc = nlp(text)
              # loop over the named entities
              for entity in set(doc.ents):
                  # select entities with label 'ORG'
                  if entity.label_ == 'ORG':
                      # add to the list
                      skill list.append(entity.text)
```

```
In [340]: from collections import Counter
          # count how many times each entity appears in the list
          word count = Counter(skill list)
          # print the top 100 named entities
          word count.most common(100)
Out[340]: [('SQL', 2930),
           ('SAS', 797),
('AI', 555),
           ('Hadoop', 553),
           ('Data Analyst', 541),
           ('IBM', 515),
           ('Bachelor', 453),
           ('BI', 431),
           ('ML', 411),
('TX', 403),
           ('Data Science', 394),
           ('Big Data', 364),
           ('ETL', 299),
           ('NLP', 261),
           ('Data Scientist', 255),
           ('PowerPoint', 247),
           ('Computer Science', 242),
           ('GSK', 238),
           ('SQL Server', 230),
  In [ ]: # based on (Spacy Skill extraction) skill_set, extract skill as new
  In [ ]:
In [354]:
          skill label = ['ORG']
          # make a list of actual skills extracted from the corpus (100)
          'BI', 'Business Intelligence',
                       'Big Data', 'ETL', 'NLP', 'PowerPoint',
                        'Microsoft Office', 'Microsoft', 'Microsoft Excel',
                       'ML', 'Machine Learning', 'SVM',
                       'SPSS', 'Oracle', 'Power BI', 'TensorFlow', 'JavaScript' 'Matlab', 'MATLAB',
                       'UAT', 'IoT', 'MIS'
          def extract skills(text):
              doc = nlp(text)
              results = [(ent.text) for ent in doc.ents if ent.label_ in skil
              return results
          df_clean_2['spacy_skill_set'] = df['Job Description'].apply(extract)
```

```
In [355]: df_clean_2['spacy_skill_set']
Out[355]: 0
                                                                    [SQL]
                                                 [SQL, SAS, PowerPoint]
           1
           2
                                                          [BI, SQL, SQL]
           3
                                                                    [SQL]
           4
                                                              [SQL, SQL]
           6157
                                     [SQL, JavaScript, ETL, SPSS, SAS]
           6158
           6159
                    [Big Data, Oracle, Big Data, Oracle, SQL, SSRS...
                    [Big Data, Oracle, Big Data, Oracle, SQL, SSRS...
           6160
           6161
           Name: spacy_skill_set, Length: 5218, dtype: object
  In [ ]:
  In [ ]: # add match skills to new column
In [346]: df_clean_2['skill_set'] = df_clean['skill_set']
  In [ ]:
          spac= df_clean_2['spacy_skill_set'].copy()
In [370]:
           spac.astype(str)
Out [370]:
           0
                                                                  ['SQL']
                                           ['SQL', 'SAS', 'PowerPoint']
           1
           2
                                                    ['BI', 'SQL', 'SQL']
                                                                  ['S0L']
           3
           4
                                                          ['SQL', 'SQL']
           6157
                    ['SQL', 'JavaScript', 'ETL', 'SPSS', 'SAS']
['Big Data', 'Oracle', 'Big Data', 'Oracle', '...
           6158
           6159
                    ['Big Data', 'Oracle', 'Big Data', 'Oracle',
           6160
           6161
           Name: spacy skill set, Length: 5218, dtype: object
In [348]: # change column name: skill_set to regex_skill_set
           df_clean_2.rename(columns={'skill_set': 'regex_skill_set'}, inplace
```

```
df_clean_2.head(5)
Out[374]:
                                            description_clean
                                                                           regex_skill_set spacy_skill_set
                                                                              Python, SQL
               0
                   are, you, eager, to, roll, up, your, sleeve, and, harne...
                                                                                                    [SQL]
                                                                                               [SQL, SAS,
                   overview, provides, analytical, and, technical, sup...
                                                                                     SQL
               1
                                                                                               PowerPoint]
               2
                   were,looking,for,a,senior,data,analyst,who,ha,...
                                                                 SQL, Tableau, Visualization
                                                                                            [BI, SQL, SQL]
                                                                 SQL, Tableau, Agile, Power
                  requisition,remoteyes,we,collaborate,we,create...
                                                                                                    [SQL]
                                                                           Bl. Visualization
                  about,fanduel,group,fanduel,group,is,a,worldcl...
                                                                  Python, SQL, Visualization
                                                                                               [SQL, SQL]
In [383]:
                  skill_set using regex
              df_clean.head(2)
Out [383]:
                                                                             Type of
                  position Rating Headquarters
                                                                                     Industry code Sector
                                                        Size Founded
                                                                          ownership
                     Data
                                                   201 to 500
                                                                           Nonprofit
                                                                                                       Non-
               0
                                                                                                 62
                               3.2
                                    New York, NY
                                                                1961.0
                                                   employees
                                                                        Organization
                                                                                                      Profit
                   Analyst
                                                     10000 +
                                                                           Nonprofit
                                                                                                     Health
                      Data
                               3.8
                                    New York, NY
                                                                1893.0
                                                                                                 62
                   Analyst
                                                   employees
                                                                        Organization
                                                                                                       Care
In [384]:
              df_clean_2['position'] = df_clean['position']
              df clean 2['Industry code']=df clean['Industry code']
In [385]:
             df_clean_2.head(3)
Out [385]:
                                            description_clean
                                                              regex_skill_set spacy_skill_set position Ind
                                                                                                  Data
               0
                                                                 Python, SQL
                                                                                        [SQL]
                   are, you, eager, to, roll, up, your, sleeve, and, harne...
                                                                                                Analyst
                                                                                  [SQL, SAS,
                                                                                                  Data
                  overview, provides, analytical, and, technical, sup...
                                                                        SQL
                                                                                  PowerPoint]
                                                                                                Analyst
                                                                SQL, Tableau,
                                                                                                  Data
                  were,looking,for,a,senior,data,analyst,who,ha,...
                                                                                [BI, SQL, SQL]
                                                                  Visualization
                                                                                                Analyst
In [421]:
              X_2 = df_clean_2[['description_clean', 'regex_skill_set','position'
In [522]: Y_2 = df_clean_2 [['Industry_code']]
In [595]: x_train_2_ohe .shape
Out [595]: (3652, 258)
```

In [374]: # skill\_set using SpaCy

```
In [525]:
          Y_2.shape
Out [525]: (5218, 1)
In [563]: import warnings
          warnings.filterwarnings("ignore")
In [682]: # Input: description_clean, regex_skill_set, position (next time wi
          # Output: Industry_code
          X_2 = df_clean_2[['description_clean', 'regex_skill_set','position'
          Y_2 = df_clean_2 [['Industry_code']]
          # divide input as train and test dataset
          x_train_2,x_test_2,y_train_2,y_test_2= train_test_split(X_2,Y_2, st
In [684]: x_train_2.shape
Out[684]: (3652, 3)
In [685]: y_train_2.shape
Out[685]: (3652, 1)
In [686]: # divide train dataset into train and validatio subsets.
          x_train_3,x_val_2,y_train_3,y_val_2= train_test_split(x_train_2, y_
In [687]: x_{train_3.shape}
Out [687]: (2556, 3)
  In []: # train, validation and test datasets name
          x_train_3,x_val_2, x_test_2
          y_train_3,y_val_2, y_test_2
In [688]: # deal with categorical data 'regex_skill_set' and 'position'(exclu
          from category_encoders.one_hot import OneHotEncoder
          #Initialzie an OneHotEncoder object
          ohe = OneHotEncoder(handle_unknown='value')
          #Learn and apply the encoding on training set
          x_train_3_ohe = ohe.fit_transform(x_train_3[['regex_skill_set','pos
```

```
In [689]: |x_train_3_ohe.head(3)
Out [689]:
                regex_skill_set_1 regex_skill_set_2 regex_skill_set_3 regex_skill_set_4 regex_skill_set_4
           3391
                            1
                                         0
           1520
                                         0
                                                       0
                                                                     0
                            1
            961
                                                                     0
                            1
          3 rows × 216 columns
In [700]: #Apply the encoding on train and testing set
          x_test_2_ohe = ohe.transform(x_test_2[['regex_skill_set','position'
           x_val_2_ohe = ohe.transform(x_val_2[['regex_skill_set','position']]
  In [ ]: x_test_2_ohe
          y_test_2_enc
In [699]: # integer encodeuse: label encoder to encode industry_code
           label_encoder = LabelEncoder()
          y_train_3_enc = label_encoder.fit_transform(y_train_3)
           y_val_2_enc= label_encoder.fit_transform(y_val_2)
           y_test_2_enc= label_encoder.fit_transform(y_test_2)
  In [ ]:
In [692]: y_train_2_enc
Out[692]: array([13, 11, 11, ..., 11, 10, 11])
  In [ ]: # train, validation and test datasets name
          x_train_3_ohe,x_val_2_ohe, x_test_2
          y_train_3_enc,y_val_2_enc, y_test_2_enc
  In [ ]:
          !!!!!! How to connect ohe—hot encoded two columns with job descript
```

```
In [570]: whether or not do smote !!!!!
          y_train_2.value_counts()
Out[570]: Industry_code
          51
                            1062
          54
                             659
          56
                             448
          52
                             404
          62
                             286
          42
                             276
          61
                             110
          33
                             105
          92
                              86
          44
                              50
          81
                              38
          72
                              29
          53
                              24
          45
                              21
          23
                              20
                              17
          21
          48
                              13
          71
                               4
          dtype: int64
In [849]:
          from keras.models import Sequential
          from keras.layers import Dense
          from keras.layers import Dropout
          from keras.layers import AlphaDropout
          from keras.utils.vis_utils import plot_model
          #this code is to randomness fix the randomness in the process
          #so we can get reproducible results (not 100%, but to reduce the va
          #but it is totally up to whether to set this up
          from numpy.random import seed
          np.random.seed(1)
          from tensorflow import random
          random.set_seed(2)
          import random as rn
          rn.seed(1234)
  In []: # train, validation and test datasets name
          x_train_3_ohe,x_val_2, x_test_2
          y_train_3_enc,y_val_2, y_test_2_enc
In [694]: |x_train_3_ohe.shape
Out [694]: (2556, 216)
```

```
In [856]: initializer = tf.keras.initializers.HeNormal()

model_2 = Sequential([
    Dropout(.2, input_shape = [216]), # dropout 后面一定要跟 input_s
    Dense(20, activation="relu"),
    Dense(21, activation="relu"),
    Dense(3, kernel_initializer=initializer),
    AlphaDropout(.3),
    Dense(18, activation="softmax") #using softmax for last layer b
])
```

### In [857]: model\_2.summary()

Model: "sequential\_127"

Layer (type)	Output Shape	Param #
dropout_10 (Dropout)	(None, 216)	0
dense_196 (Dense)	(None, 20)	4340
dense_197 (Dense)	(None, 21)	441
dense_198 (Dense)	(None, 3)	66
<pre>alpha_dropout_8 (AlphaDropo ut)</pre>	(None, 3)	0
dense_199 (Dense)	(None, 18)	72

\_\_\_\_\_\_

Total params: 4,919 Trainable params: 4,919 Non-trainable params: 0

```
In [870]: x_train_3_ohe.info()
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2556 entries, 3391 to 312

Columns: 216 entries, regex\_skill\_set\_1 to position\_6

dtypes: int64(216) memory usage: 4.2 MB

```
In [873]: # change datatype to float
         x_train_3_ohe = x_train_3_ohe.astype(float)
 In [ ]:
In [876]: #fit model
         history = model_2.fit(x_train_3_ohe, y_train_3_enc, validation_data
         Epoch 1/400
         52/52 [============== ] - 1s 8ms/step - loss: 2.917
         8 - sparse_categorical_accuracy: 0.0485 - val_loss: 2.8245 - val_s
         parse_categorical_accuracy: 0.2719
         Epoch 2/400
         52/52 [============== ] - 0s 4ms/step - loss: 2.855
         4 - sparse_categorical_accuracy: 0.0646 - val_loss: 2.7641 - val_s
         parse_categorical_accuracy: 0.2911
         Epoch 3/400
         52/52 [============= ] - 0s 3ms/step - loss: 2.788
         9 - sparse_categorical_accuracy: 0.0782 - val_loss: 2.7069 - val_s
         parse_categorical_accuracy: 0.2911
         Epoch 4/400
         52/52 [============= ] - 0s 3ms/step - loss: 2.744
         3 - sparse_categorical_accuracy: 0.1827 - val_loss: 2.6512 - val_s
         parse_categorical_accuracy: 0.2911
         Epoch 5/400
         52/52 [=============== ] - 0s 3ms/step - loss: 2.686
         7 - sparse_categorical_accuracy: 0.2829 - val_loss: 2.5980 - val_s
In [878]: #-- make predictions: use sum function for mutiple output lables.
         test_predict_2 = model_2.predict(x_val_2_ohe).sum(axis=1)
In [879]: from sklearn.metrics import mean_absolute_error
         mae = mean_absolute_error(y_val_2_enc, test_predict_2)
         print('Test Error: {}'.format(mae))
```

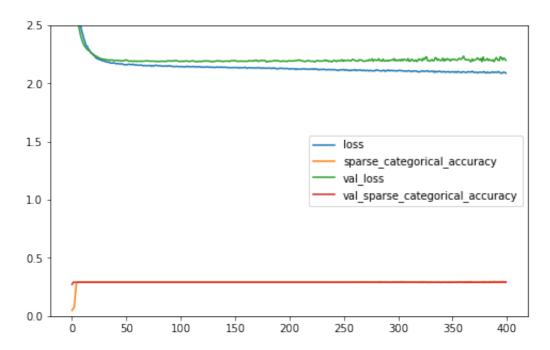
Test Error: 7.614963513275567

```
In [880]: #Complete the code and plot your model
import matplotlib.pyplot as plt
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.gca().set_ylim(0, 2.5)

#is your model overfitting or underfitting?
#A model is overfitting when:
#loss on train set decreasing
#loss on valid set stable/increasing

# if there is a overfitting/underfitting problem, you might need to
```

#### Out[880]: (0.0, 2.5)



```
In []:
```

In [ ]: x\_train\_3\_ohe, y\_train\_3\_enc
x\_val\_2\_ohe, y\_val\_2\_enc

In [881]: x\_train\_3\_ohe.shape

Out[881]: (2556, 216)

```
In [ ]:
 In [ ]:
 In [ ]:
 In [ ]:
In [281]: | regex_map
'(?i)\\WHadoop\\W?': 'Hadoop',
           '(?i)SQL\\w*': 'SQL',
           '(?i)\\WTableau\\W?': 'Tableau',
           '(?i)\\WTensorFlow\\W?': 'TensorFlow',
           '(?i)\\WAgile\\W?': 'Agile',
           '(?i)\\WPower\\s?BI\\W?': 'Power BI',
           '(?i)\\WSSAS\\W?': 'SSaS',
           '(?i)\\WAlgorithms?\\W?': 'Algorithm',
           '(?i)Java\\w*': 'Java',
           '(?i)\\WVisualization\\W?': 'Visualization'}
 In [ ]:
          df_regex = pd.DataFrame({'skills': ['R', 'Python', 'Hadoop', 'SQL', 'Ta
                       'Regex': ['\WR\W+\s*','(?i)\WPython\W','(?i)\WHadoop\W
                       "(?i)\WTensorFlow\W?","(?i)\WAgile\W?","(?i)\WPower\s
                       "(?i)\WSSAS\W?","(?i)\WAlgorithms?\W?",'(?i)Java\w*','
          df_clean_2 = pd.DataFrame(df_clean['description_clean'])
          regex map = dict(zip(df regex.Regex, df regex.skills))
          def skill_collection(row):
              matches = []
              for reg in regex_map:
                  if re.search(reg, row):
                      matches.append(regex map[reg])
              return ', '.join(matches)
          df_clean_2['skill_set'] = df_clean_2['description_clean'].apply(ski
 In [ ]:
 In []: #
 In [ ]: use feature importance to filter columns
 In [ ]: |df_model
  In [ ]:
```

```
In [ ]:
  In [ ]:
In [337]: # data set used is df_clean
            y= df_clean.Industry
            X = df_clean.drop(columns = 'Industry')
In [340]: y .shape
Out [340]:
            (10020,)
  In [ ]:
  In [ ]:
  In [ ]:
  In [ ]:
  In [ ]:
In [319]:
           df_model= df_clean.copy()
In [327]: | df_model['position'] = pd.DataFrame(df_model['position'])
           pd.Series(df_model['position']).to_frame()
In [335]:
Out [335]:
                                 position
                              Data Analyst
                0
                1
                              Data Analyst
                2
                              Data Analyst
                3
                              Data Analyst
                4
                              Data Analyst
             10015 Machine Learning Engineer
             10016 Machine Learning Engineer
             10017 Machine Learning Engineer
             10018 Machine Learning Engineer
             10019
                             Data Scientist
            10020 rows × 1 columns
```

```
In [ ]: # 1. column 'position' is nominal, so use one-hot encoding
  In [ ]: | from category_encoders.one_hot import OneHotEncoder
          #Initialzie an OneHotEncoder object
          ohe = OneHotEncoder(handle_unknown='value')
          #Learn and apply the encoding on training set
          d = ohe.fit transform(df model['position'])
 In [ ]:
  In [ ]:
In [315]: # data set used is df_clean
          y= df_clean.Industry
          X = df_clean.drop(columns = 'Industry')
  In [ ]:
  In [ ]:
In [190]: X= df[['Job Description', 'position']]
In [317]: # Split data into train and test sets as well as for validation and
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size
  In [ ]:
```

```
In [318]: # Setup the Bagging classifier (BaggingClassifier from sklearn)
          from sklearn.ensemble import BaggingClassifier
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.tree import DecisionTreeClassifier
          #Set Bagging parameters
          baggging_params = {
              'base_estimator': DecisionTreeClassifier(max_depth = 10),
              'n_estimators': 100,
              'max_samples': 1.0,
              'max_features': 1.0,
              'bootstrap': True,
              'bootstrap_features': False,
              'n jobs': -1,
              'random state' : 42
          }
          #Initiate a BaggingClassifier object using the parameters set above
          bagging = BaggingClassifier(**baggging_params)
          #Fit the BaggingClassifier object on the resampled training data
          bagging.fit(X train, y train)
          _RemoteTraceback
                                                     Traceback (most recent c
          all last)
           RemoteTraceback:
          Traceback (most recent call last):
            File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/jo
          blib/externals/loky/process_executor.py", line 436, in _process_wo
          rker
              r = call_item()
            File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/jo
          blib/externals/loky/process_executor.py", line 288, in __call__
              return self.fn(*self.args, **self.kwargs)
            File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/jo
          blib/_parallel_backends.py", line 595, in __call__
              return self.func(*args, **kwargs)
            File "/Users/spring/opt/anaconda3/lib/python3.8/site-packages/jo
          blib/parallel.py", line 262, in __call__
 In [ ]:
 In [ ]:
 In [ ]:
  In [ ]:
  In [ ]:
```

In [ ]:	
In [ ]:	
In [ ]:	
In [ ]:	