data_jobs

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1 Data Jobs

TABLE OF CONTENTS: 0. Introduction 1. Data Input 2. Data Processing/Cleaning 3. Data Visualization/EDA * 3.1. Most Frequent Tools Per Job
* 3.2. Most Frequent Skills Per Job
* 3.3. Job Postings by Company 4. Data Predicting/Forecasting * 4.1. Logistic Regression (One vs. All) w/ TFIDF * 4.2. Logistic Regression (Multinomial) w/ TFIDF * 4.3. Decision Tree w/ TFIDF * 4.4. K-Nearest Neighbors w/ TFIDF * 4.5. Naive Bayes w/ TFIDF * 4.6. Choose Best Model and Optimize Hyperparameters 5. Conclusion

1.1 0. Introduction:

The purpose of this project is to examine the skills and tools desired by employers for data related jobs (i.e. *Data Analyst*, *Data Scientist*, *Data Engineer*). The motivation for the project is two-fold. First, I am personally interested in data-related careers, and the skills and tools in demand from employers. Second, while job boards are helpful in searching for jobs, there is a lack of consistency in displaying which skills/tools are desired. In other words, job boards such as Indeed and Linkedin do not have any filtering functions or ways to aggregate by skills/tools mentioned in the job advertisement. There is usually filtering functions for location, seniority, industry, etc but the filtering does not go down to the necessary level of detail for skills/tools. Furthermore, job announcements are inconsistent on where they place the text for required skills/tools. Sometimes, it is under 'Qualifications', 'Requirements', 'Skills', 'Responsibilities', or other sections. Thus, it is necessary to do some level of web scraping and text preprocessing prior to analysis.

This project will try to answer these questions: - What tools/skills are most in demand for a Data Analyst? - What tools/skills are most in demand for a Data Engineer? - What tools/skills are most in demand for a Data Scientist? - Which companies post the most data-related job openings? - Can a classifier be built which predicts job role/title (Data Analyst, Data Engineer or Data Scientist) based on job description?

1.2 1. Data Input:

Data was collected from Linkedin and Indeed job sites via a custom, seperate web scraping script.

[70]:
```
# load required libraries
import os
import re
import glob
import string
```

```python
import inspect
import time
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from geopy.geocoders import Nominatim
from geopy.exc import GeocoderTimedOut
from collections import Counter

# NLP libraries
import nltk
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import regexp_tokenize, TweetTokenizer, sent_tokenize,␣
↪word_tokenize
from nltk.tokenize.treebank import TreebankWordDetokenizer
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
from nltk.util import bigrams, trigrams, ngrams
from gensim.parsing.preprocessing import preprocess_documents, preprocess_string
#nltk.download('wordnet')

# sklearn libraries
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
↪f1_score, classification_report, plot_confusion_matrix,␣
↪precision_recall_curve, auc, average_precision_score,␣
↪plot_precision_recall_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.decomposition import PCA
```

[71]:
```python
def get_jobs_data(filename):

    # get current parent directory and data folder path
    par_directory = os.path.dirname(os.getcwd())
    data_directory = os.path.join(par_directory, 'data/raw')

    # retrieve job files
    files = glob.glob(os.path.join(data_directory, filename))
```

```python
    # create empty dataframe, loop over files and concatenate data to dataframe
    df_jobs = pd.DataFrame()
    for f in files:
        data = pd.read_csv(f)
        df_jobs = pd.concat([df_jobs, data], axis=0, sort='False')

    # reset index
    df_jobs = df_jobs.reset_index(drop=True)

    return df_jobs

df_jobs = get_jobs_data('*DATA*jobs_*.csv')

# print data and length
df_jobs.head()
```

[71]:

```
                        applicants                         company  \
0  Be among the first 25 applicants                           Microf
1  Be among the first 25 applicants                              NaN
2  Be among the first 25 applicants                            Adobe
3                   114 applicants       Prescryptive Health, Inc.
4                    30 applicants  Source One Technical Solutions

  company_rating date   date_posted         date_scraped employment_type  \
0            NaN  NaN   7 hours ago  2021-03-18 08:10:59       Full-time
1            NaN  NaN  10 hours ago  2021-03-18 08:10:59      Internship
2            NaN  NaN   2 hours ago  2021-03-18 08:10:59       Full-time
3            NaN  NaN  14 hours ago  2021-03-18 08:10:59       Full-time
4            NaN  NaN  12 hours ago  2021-03-18 08:10:59        Contract

                             industries            job_function  \
0             Marketing and Advertising  Information Technology
1                                   NaN  Information Technology
2             Marketing and Advertising  Information Technology
3  Information Technology and Services  Information Technology
4  Information Technology and Services  Information Technology

                                            job_text  \
0  ['', 'Eligible for participation in the Compan…
1  ['', 'Qualifications', "Understand the day-to-…
2  ['', 'Define, measure and track key metrics to…
3  ['', '\tPrescryptive Health is putting an end …
4  ['', 'Qualifications', '• Analytical and data …

                  job_title                        location  \
0              Data Analyst                     Roswell, GA
```

```
1                Data Analyst  New York City Metropolitan Area
2  2021 Intern - Data Analyst        California, United States
3                Data Analyst                      Redmond, WA
4                Data Analyst                     Richboro, PA

    seniority_level
0  Mid-Senior level
1       Entry level
2        Internship
3  Mid-Senior level
4         Associate
```

1.3 2. Data Processing/Cleaning:

[72]:

```
# view descriptive info on dataframe
df_jobs.info()
df_jobs.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148882 entries, 0 to 148881
Data columns (total 13 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   applicants       66417 non-null   object
 1   company          148341 non-null  object
 2   company_rating   51562 non-null   object
 3   date             80727 non-null   object
 4   date_posted      65432 non-null   object
 5   date_scraped     68155 non-null   object
 6   employment_type  68155 non-null   object
 7   industries       67733 non-null   object
 8   job_function     68034 non-null   object
 9   job_text         148882 non-null  object
 10  job_title        142640 non-null  object
 11  location         132605 non-null  object
 12  seniority_level  68155 non-null   object
dtypes: object(13)
memory usage: 14.8+ MB
```

[72]:

```
                              applicants   company company_rating  \
count                              66417    148341          51562
unique                               178     19535           5481
top     Be among the first 25 applicants  Facebook   3.9 out of 5
freq                               50729      2130           3330

                         date  date_posted         date_scraped employment_type  \
count                   80727        65432                68155           68155
```

```
unique                   5316          103                  114             7
top     2020-07-27 12:04:05  5 hours ago  2020-09-03 10:26:32       Full-time
freq                       19         3575                 1000         61401

                                 industries job_function job_text  \
count                                 67733        68034   148882
unique                                  137           84    79058
top     Information Technology and Services  Engineering       []
freq                                  22862        25019     5245

             job_title      location   seniority_level
count           142640        132605             68155
unique           29997          5951                 7
top     Data Scientist  New York, NY  Mid-Senior level
freq             14214          6165             20342
```

[73]:

```
# clean jobs description data
def clean_jobs(df):

    # clean job text data with empty list, reg expressions, and appending to␣
↪list
    clean_text = []

    for x in df['job_text']:

        x = re.sub(r'(?<=[.,])(?=[^\s])', r' ', x)
        x = re.sub(r'<[A-Za-z/]*\>+', '', x)
        x = re.sub(r'\\xa0', '', x)
        x = re.sub(r'\\n', '', x)
        x = re.sub(r'Data Analyst', '', x)
        x = re.sub(r'Data Engineer', '', x)
        x = re.sub(r'Data Scientist', '', x)

        clean_text.append(x)

    df['clean_text'] = clean_text

    # clean date columns by filling in missing values, converting to pd␣
↪datetime format
    df['date'].update(df.pop('date_scraped'))
    df['date'] = pd.to_datetime(df['date'])

    # clean rating columns by extracting rating string
    df['company_rating'] = [x.split('out')[0] if type(x) != float else x for x␣
↪in df['company_rating']]

    # drop NA, duplicates, and uncessary columns
```

```python
    df = df.drop_duplicates(subset=['clean_text', 'job_title'])
    df = df.dropna(subset=['clean_text', 'job_title'])
    df = df[df['clean_text'] != '[]']
    df = df.drop(columns=['date_posted', 'seniority_level', 'applicants',␣
 ↪'job_function', 'employment_type'])

    # filter for jobs with description length greater than 10 words
    df['job_text_length'] = df['clean_text'].apply(lambda x: len(x))
    df = df[df['job_text_length'] >= 10]

    # reset dataframe index
    df.reset_index(drop=True, inplace=True)

    return df

df_jobs = clean_jobs(df_jobs)

# print number of jobs and data sample
print('Number of Jobs: {}'.format(len(df_jobs)))
df_jobs.head()
```

```
Number of Jobs: 77694
```

[73]:

```
                       company company_rating                 date  \
0                        Microf            NaN  2021-03-18 08:10:59
1                           NaN            NaN  2021-03-18 08:10:59
2                         Adobe            NaN  2021-03-18 08:10:59
3      Prescryptive Health, Inc.            NaN  2021-03-18 08:10:59
4  Source One Technical Solutions            NaN  2021-03-18 08:10:59

                           industries  \
0            Marketing and Advertising
1                                  NaN
2            Marketing and Advertising
3  Information Technology and Services
4  Information Technology and Services

                                            job_text  \
0  ['', 'Eligible for participation in the Compan…
1  ['', 'Qualifications', "Understand the day-to-…
2  ['', 'Define, measure and track key metrics to…
3  ['', '\tPrescryptive Health is putting an end …
4  ['', 'Qualifications', '• Analytical and data …

                job_title                          location  \
0            Data Analyst                       Roswell, GA
1            Data Analyst  New York City Metropolitan Area
```

```
2  2021 Intern - Data Analyst        California, United States
3                Data Analyst                   Redmond, WA
4                Data Analyst                  Richboro, PA

                                          clean_text  job_text_length
0  ['', 'Eligible for participation in the Compan…             6529
1  ['', 'Qualifications', "Understand the day-to-…             1169
2  ['', 'Define, measure and track key metrics to…             1940
3  ['', '\tPrescryptive Health is putting an end …             3053
4  ['', 'Qualifications', '• Analytical and data …             1100
```

[74]:

```
# function used to geocode locations and override timeout error
#def geocode_location(location):
#    time.sleep(1)
#    geopy = Nominatim(user_agent="my_project")
#    try:
#        return geopy.geocode(location,exactly_one=True, country_codes='us')
#    except GeocoderTimedOut:
#        return do_geocode(location)

#df_jobs['geocoded_location']=df_jobs['location'].apply(lambda x:␣
↪geocode_location(x) if x != None else None)

# create latitude and longitude column from geocoded location
#df_jobs['latitude'] = df_jobs['geocoded_location'].apply(lambda x: x[1][0] if␣
↪x != None else None)
#df_jobs['longitude'] = df_jobs['geocoded_location'].apply(lambda x: x[1][1] if␣
↪x != None else None)
#print(df_jobs.head())
```

[75]:

```
# filter for job titles with Data Scientist, Data Engineer, or Data Analyst
def filter_jobs(df):

    # filter for data scientist, data engineer, or data analyst
    df_jobs = df[(df['job_title'].str.contains('Data Scientist', case=False)) |␣
↪(df['job_title'].str.contains('Data Engineer', case=False)) |␣
↪(df['job_title'].str.contains('Data Analyst', case=False))].copy()

    # add identifying column for data scientist (#0) and data engineer (#1), or␣
↪data analyst (#2)
    df_jobs['label'] = df_jobs['job_title'].apply(lambda x: 0 if 'Scientist' in␣
↪x or 'scientist' in x or 'SCIENTIST' in x else 1 if 'Engineer' in x or␣
↪'engineer' in x or 'ENGINEER' in x else 2 if 'Analyst' in x or 'analyst' in␣
↪x or 'ANALYST' in x else '')
    df_jobs = df_jobs.dropna(subset=['label'])
    df_jobs.reset_index(inplace=True, drop=True)
```

```
    # print number of jobs and counts of each job title
    print('\nCounts of Job Titles (0=Data Scientist, 1=Data Engineer, 2=Data␣
↪Analyst): \n\n{}'.format(df_jobs['label'].value_counts()))

    return df_jobs

df_jobs = filter_jobs(df_jobs)
```

```
Counts of Job Titles (0=Data Scientist, 1=Data Engineer, 2=Data Analyst):

1    15206
0    14692
2     7364
Name: label, dtype: int64
```

1.4 3. Data Visualization/EDA

1.4.1 3.1 Most Frequent Tools per Job

[76]:
```
# visualize job skills/tools per job title
def data_tools(df, title):

    # filter jobs for job title & count
    #df_jobs = df[df['label'] == label]
    df_jobs = df[(df['job_title'].str.contains(title, case=False))]
    num_jobs = len(df_jobs)

    # Tokenize the article: tokens
    tokens = [word_tokenize(x) for x in df_jobs['job_text']]
    tokens = [item for sublist in tokens for item in sublist]

    # Convert the tokens into lowercase: lower_tokens
    lower_tokens = [t.lower() for t in tokens]

    # # Retain alphabetic words: alpha_only
    alpha_only = [t for t in lower_tokens if t.isalpha()]

    # set stop words
    stop_words = set(stopwords.words('english'))

    # # Remove all stop words: no_stops
    no_stops = [t for t in alpha_only if t not in stop_words]

    # # Instantiate the WordNetLemmatizer
    wordnet_lemmatizer = WordNetLemmatizer()
```

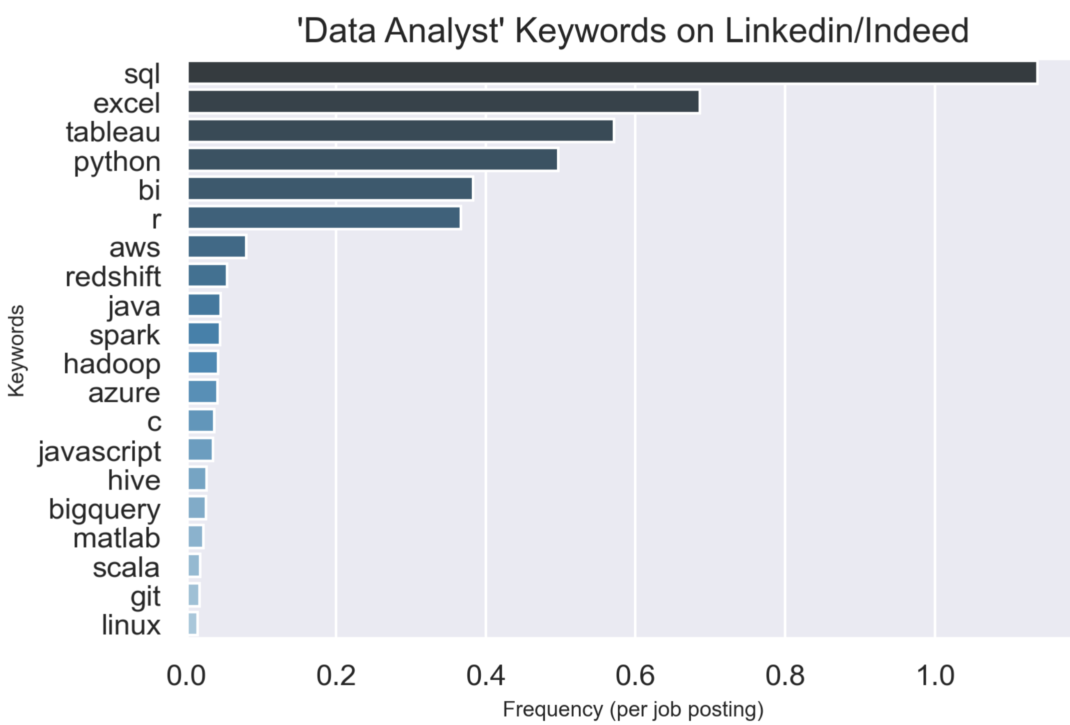
```
    # # Lemmatize all tokens into a new list: lemmatized
    lemmatized = [wordnet_lemmatizer.lemmatize(t) for t in no_stops]
    print(type(lemmatized))

    # # Create the bag-of-words: bow
    bow = Counter(lemmatized)

    # create dataframe from dictionary
    df_count = pd.DataFrame.from_dict(bow, orient='index').reset_index()
    df_count.columns = ['keywords', 'counts']
    df_count = df_count.sort_values(by ='counts' , ascending=False,␣
↪ignore_index=True)
    df_count['avg_frequency_per_job'] = df_count['counts'] / num_jobs

    # create list of data tools
    data_tools = ['airflow', 'azure', 'aws', 'bi', 'bigquery', 'c', 'c++',␣
↪'d3', 'docker', 'ec2', 'excel', 'git', 'hadoop', 'hive',
                  'java','javascript', 'jenkins','jupyter', 'kafka', 'keras',␣
↪'kuberenetes', 'linux', 'luigi', 'matlab', 'mongodb',
                  'pearl', 'python', 'pytorch', 'r', 'react', 'redshift',␣
↪'ruby', 'sas', 'scala', 'scikit-learn', 'sql', 'spark', 'tableau',␣
↪'tensorflow']

    # filter keyword counts for data tools
    df_count = df_count[df_count['keywords'].isin(data_tools)]
    df_count.reset_index(drop=True, inplace=True)

    # Print the 20 most common tools
    print('\n' + title + ' Top Keywords:\n\n', df_count.iloc[:20])

    # plot the 20 most common tools
    sns.set()
    fig, ax = plt.subplots(dpi=300) #, figsize = (3, 5), )
    sns.barplot(x="avg_frequency_per_job", y="keywords", data=df_count.iloc[:
↪20], palette="Blues_d")
    plt.title(label = "'" + title + "'"  + ' Keywords on Linkedin/Indeed',␣
↪fontsize=13)
    plt.xlabel('Frequency (per job posting)', fontsize=8)
    plt.ylabel('Keywords', fontsize=8)

    # ax.set(title = "'" + title + "'"  + ' Keywords on Linkedin/Indeed')
    plt.show()
```

[77]:
```
data_tools(df_jobs, 'Data Analyst')
```

```
<class 'list'>
```

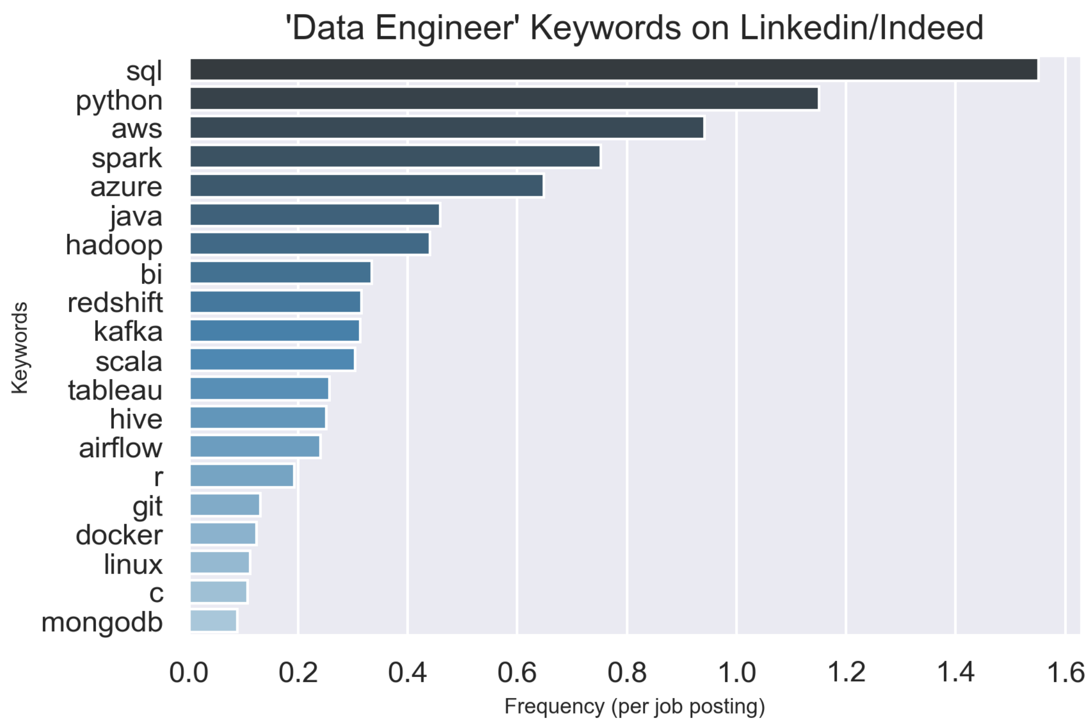
Data Analyst Top Keywords:

	keywords	counts	avg_frequency_per_job
0	sql	8649	1.137428
1	excel	5215	0.685823
2	tableau	4343	0.571147
3	python	3779	0.496975
4	bi	2915	0.383351
5	r	2787	0.366518
6	aws	608	0.079958
7	redshift	416	0.054708
8	java	346	0.045502
9	spark	343	0.045108
10	hadoop	322	0.042346
11	azure	313	0.041163
12	c	286	0.037612
13	javascript	272	0.035771
14	hive	203	0.026696
15	bigquery	198	0.026039
16	matlab	174	0.022883
17	scala	138	0.018148
18	git	136	0.017885
19	linux	111	0.014598



[78]:
```
data_tools(df_jobs, 'Data Engineer')
```

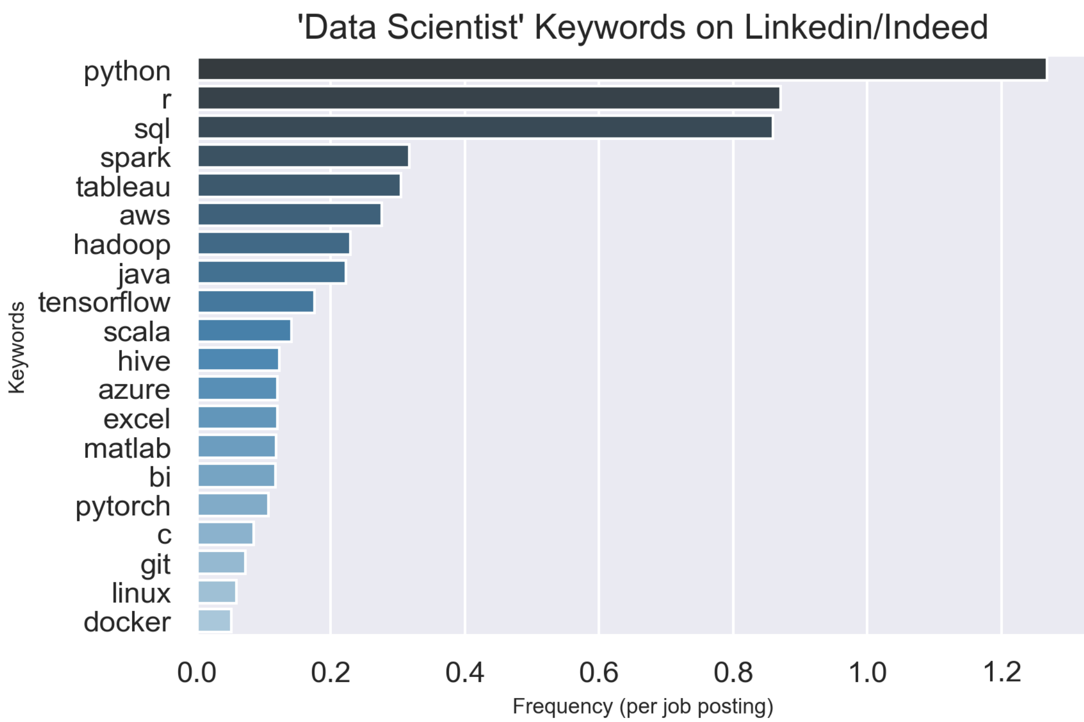
```
<class 'list'>

Data Engineer Top Keywords:

     keywords  counts  avg_frequency_per_job
0         sql   23581               1.551586
1      python   17491               1.150875
2         aws   14321               0.942295
3       spark   11438               0.752599
4       azure    9853               0.648309
5        java    6980               0.459271
6      hadoop    6704               0.441111
7          bi    5089               0.334847
8    redshift    4803               0.316028
9       kafka    4765               0.313528
10      scala    4614               0.303593
11    tableau    3911               0.257336
12       hive    3823               0.251546
13    airflow    3656               0.240558
14          r    2932               0.192920
15        git    1999               0.131530
16     docker    1886               0.124095
17      linux    1712               0.112646
18          c    1645               0.108238
19    mongodb    1357               0.089288
```



[79]:
```
data_tools(df_jobs, 'Data Scientist')
```

```
<class 'list'>

Data Scientist Top Keywords:

      keywords  counts  avg_frequency_per_job
0       python   18520               1.268146
1            r   12715               0.870652
2          sql   12551               0.859422
3        spark    4626               0.316763
4      tableau    4452               0.304848
5          aws    4036               0.276363
6       hadoop    3356               0.229800
7         java    3255               0.222884
8   tensorflow    2566               0.175705
9        scala    2060               0.141057
10        hive    1804               0.123528
11       azure    1763               0.120720
12       excel    1761               0.120583
13      matlab    1735               0.118803
14          bi    1720               0.117776
15     pytorch    1569               0.107436
16           c    1245               0.085251
```

```
17        git   1059              0.072514
18      linux    865              0.059230
19     docker    760              0.052041
```



1.4.2 3.2 Most Frequent Skills per Job

[80]:
```python
# preprocess job description string
def preprocess_text(df):

    df = df.copy()

    processed_text = []

    for x in df['clean_text']:

        # # Convert the tokens into lowercase: lower_tokens
        lower_tokens = [x.lower()]

        # # Convert tokens
        tokenize = [word_tokenize(x) for x in lower_tokens]

        # # # Retain alphabetic words: alpha_only
        alpha_only = [i for item in tokenize for i in item if i.isalpha()]
```

```
        # set stop words
        stop_words = set(stopwords.words('english'))

        # # Remove all stop words: no_stops
        no_stops = [i for i in alpha_only if i not in stop_words]

        # # Instantiate the WordNetLemmatizer
        wordnet_lemmatizer = WordNetLemmatizer()

        # # Lemmatize all tokens into a new list: lemmatized
        lemmatized = [wordnet_lemmatizer.lemmatize(i) for i in no_stops]

        processed_text.append(lemmatized)

    df['processed_text'] = processed_text

    return df

df_jobs = preprocess_text(df_jobs)

df_jobs.head()
```

[80]:

```
                          company company_rating                date  \
0                           Microf            NaN 2021-03-18 08:10:59
1                              NaN            NaN 2021-03-18 08:10:59
2                            Adobe            NaN 2021-03-18 08:10:59
3        Prescryptive Health, Inc.            NaN 2021-03-18 08:10:59
4  Source One Technical Solutions            NaN 2021-03-18 08:10:59

                           industries  \
0          Marketing and Advertising
1                                NaN
2          Marketing and Advertising
3  Information Technology and Services
4  Information Technology and Services

                                            job_text  \
0  ['', 'Eligible for participation in the Compan…
1  ['', 'Qualifications', "Understand the day-to-…
2  ['', 'Define, measure and track key metrics to…
3  ['', '\tPrescryptive Health is putting an end …
4  ['', 'Qualifications', '• Analytical and data …

                job_title                          location  \
0            Data Analyst                       Roswell, GA
1            Data Analyst  New York City Metropolitan Area
```

```
2  2021 Intern - Data Analyst        California, United States
3                Data Analyst                     Redmond, WA
4                Data Analyst                    Richboro, PA

                                          clean_text  job_text_length  label  \
0  ['', 'Eligible for participation in the Compan…             6529      2
1  ['', 'Qualifications', "Understand the day-to-…             1169      2
2  ['', 'Define, measure and track key metrics to…             1940      2
3  ['', '\tPrescryptive Health is putting an end …             3053      2
4  ['', 'Qualifications', '• Analytical and data …             1100      2

                                      processed_text
0  [participation, company, group, medical, plan,…
1  [understand, issue, business, face, better, un…
2  [measure, track, key, metric, guide, execution…
3  [health, putting, end, nation, prescription, d…
4  [analytical, data, visualization, skill, requi…
```

[81]:

```python
def ngram_generator(df, n, title):

    # filter for job title
    df_jobs = df[(df['job_title'].str.contains(title, case=False))]

    # create empty list
    ngram_list = []

    # loop over every row in df_jobs['clean_text']
    for x in df_jobs['processed_text']:

        # join each list of strings into sentence
        joined = [' '.join(x)]

        # create list of trigrams within each row
        ngram = [list(ngrams(item.split(), n)) for item in joined]

        # append list of trigrams to empty list
        ngram_list.append(ngram)

    # extract item within each sublist
    ngram_list = [item for sublist in ngram_list for item in sublist]

    # extract each item within sublist again for Counter (list is unhashable)
    ngram_list = [item for sublist in ngram_list for item in sublist]

    # print the 20 most common grams via Counter function

    return list(Counter(ngram_list).most_common(20))
```

1.4.3 Data Analyst

[82]:
```python
ngram_generator(df_jobs, 2, 'Data Analyst')
```

[82]:
```
[(('indeed', 'center'), 4958),
 (('data', 'analysis'), 4766),
 (('year', 'experience'), 4627),
 (('job', 'review'), 3781),
 (('review', 'salary'), 3781),
 (('communication', 'skill'), 3470),
 (('data', 'set'), 2654),
 (('data', 'visualization'), 2597),
 (('personal', 'information'), 2520),
 (('computer', 'science'), 2503),
 (('job', 'company'), 2481),
 (('company', 'certification'), 2480),
 (('salary', 'resume'), 2479),
 (('lab', 'advice'), 2479),
 (('advice', 'job'), 2479),
 (('certification', 'event'), 2479),
 (('event', 'indeed'), 2479),
 (('center', 'indeed'), 2479),
 (('indeed', 'sell'), 2479),
 (('sell', 'personal'), 2479)]
```

1.4.4 Data Engineer

[83]:
```python
ngram_generator(df_jobs, 2, 'Data Engineer')
```

[83]:
```
[(('year', 'experience'), 17273),
 (('data', 'pipeline'), 13777),
 (('big', 'data'), 10145),
 (('computer', 'science'), 9833),
 (('data', 'warehouse'), 8137),
 (('experience', 'working'), 6087),
 (('data', 'engineering'), 5705),
 (('best', 'practice'), 5316),
 (('indeed', 'center'), 5290),
 (('machine', 'learning'), 5190),
 (('data', 'modeling'), 5123),
 (('data', 'quality'), 5099),
 (('data', 'set'), 5083),
 (('degree', 'computer'), 5077),
 (('experience', 'data'), 4989),
 (('data', 'source'), 4939),
 (('communication', 'skill'), 4908),
 (('data', 'science'), 4892),
```

```
 (('data', 'model'), 4689),
 (('job', 'review'), 4160)]
```

1.4.5 Data Scientist

```
[84]: ngram_generator(df_jobs, 2, 'Data Scientist')
```

```
[84]: [(('machine', 'learning'), 23459),
 (('data', 'science'), 20154),
 (('year', 'experience'), 11336),
 (('computer', 'science'), 10376),
 (('data', 'analysis'), 6340),
 (('data', 'set'), 5859),
 (('communication', 'skill'), 5749),
 (('indeed', 'center'), 5020),
 (('data', 'visualization'), 4594),
 (('experience', 'data'), 4501),
 (('job', 'review'), 4374),
 (('review', 'salary'), 4374),
 (('related', 'field'), 4358),
 (('big', 'data'), 4308),
 (('python', 'r'), 4240),
 (('deep', 'learning'), 4175),
 (('r', 'python'), 3815),
 (('data', 'mining'), 3754),
 (('data', 'source'), 3749),
 (('programming', 'language'), 3533)]
```

1.4.6 3.3 Most Frequent Companies Posting Jobs

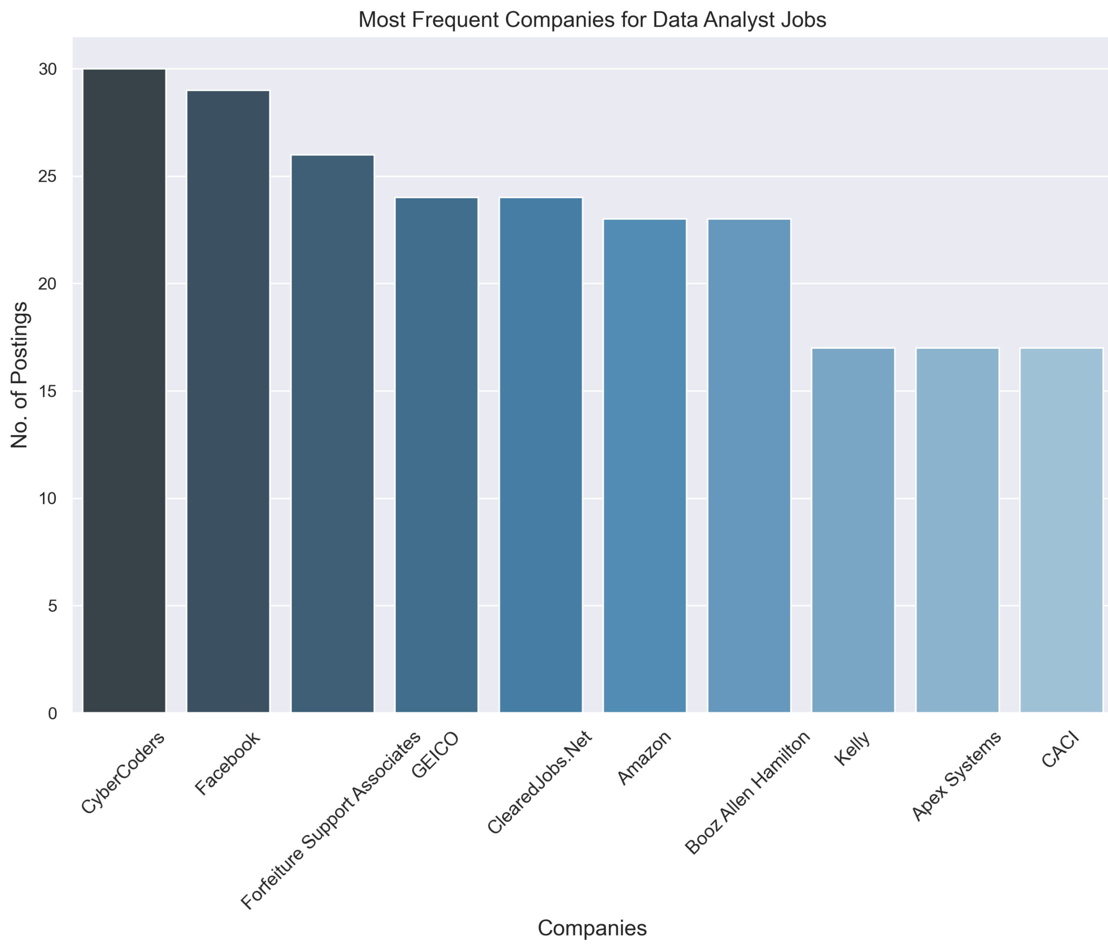
```
[85]: def job_companies(df, title):

    # replace various Amazon company names with Amazon
    df['company'] = df['company'].replace(to_replace = 'Amazon Web Services␣
↪(AWS)', value = 'Amazon')
    df['company'] = df['company'].replace(to_replace = 'Amazon.com Services␣
↪LLC', value = 'Amazon')
    df['company'] = df['company'].replace(to_replace = 'Amazon Web Services,␣
↪Inc.', value = 'Amazon')

    # print value counts for companies to determine top 20 companies for each␣
↪type of job posting
    title_companies = df[(df['job_title'].str.contains(title,␣
↪case=False))]['company'].value_counts().iloc[:20]
    print('\nMost Frequent Companies for {} Job Postings: \n\n{}'.format(title,␣
↪title_companies))
```

```
    # plot most frequent companies
    sns.set()
    fig, ax = plt.subplots(figsize = (12,8), dpi=250)
    sns.barplot(x = title_companies.iloc[:10].index, y= title_companies.iloc[:
↪10].values, palette="Blues_d")
    plt.title(label = "Most Frequent Companies for " + title + " Jobs",␣
↪fontsize=14)
    plt.xlabel('Companies', fontsize=14)
    plt.ylabel('No. of Postings', fontsize=14)
    plt.xticks(rotation=45, fontsize=12)
    plt.show()
```

1.4.7 Data Analyst

[86]:
```
job_companies(df_jobs, 'Data Analyst')
```

```
Most Frequent Companies for Data Analyst Job Postings:

CyberCoders                   30
Facebook                      29
Forfeiture Support Associates 26
GEICO                         24
ClearedJobs.Net               24
Amazon                        23
Booz Allen Hamilton           23
Kelly                         17
Apex Systems                  17
CACI                          17
Intuit                        17
Insight Global                16
Tesla                         15
Robert Half                   14
Kforce Inc                    14
Piper Companies               14
Guidehouse                    13
UnitedHealth Group            13
Vanguard                      13
Microsoft                     13
Name: company, dtype: int64
```

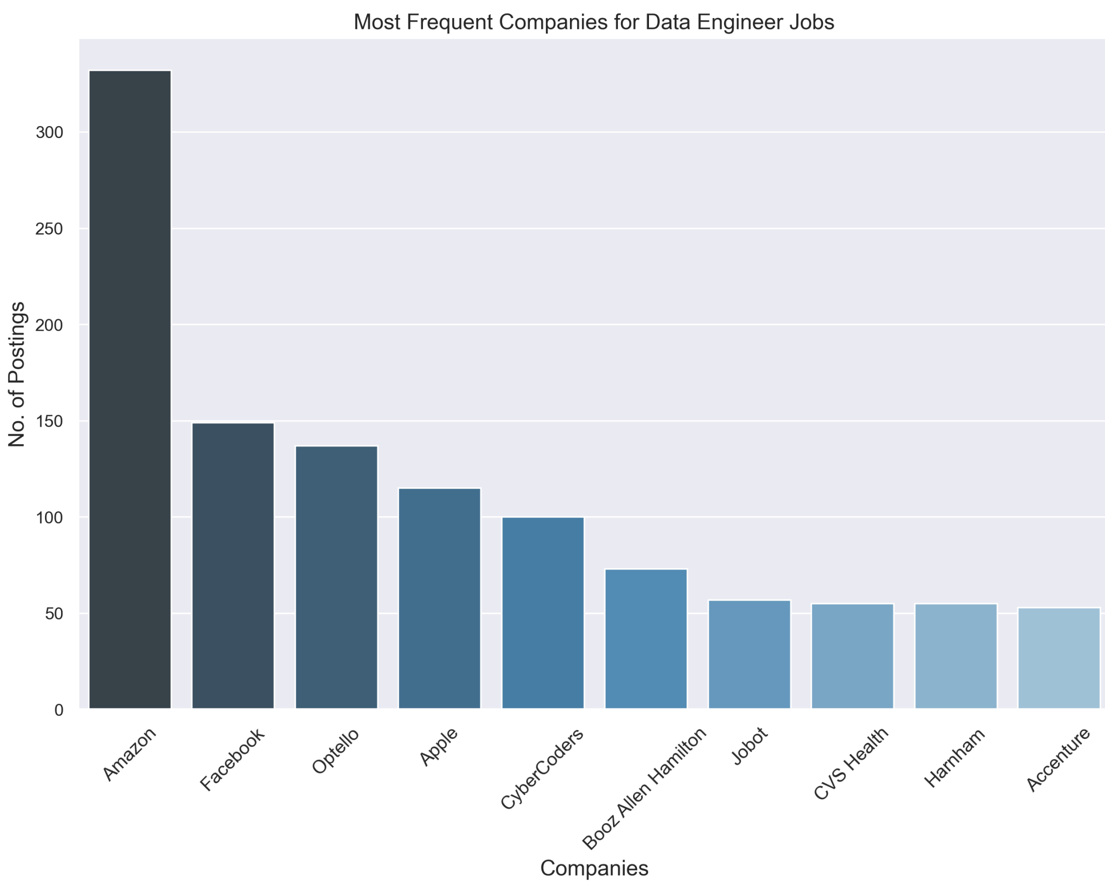


1.4.8 Data Engineer

[87]:
```python
job_companies(df_jobs, 'Data Engineer')
```

```
Most Frequent Companies for Data Engineer Job Postings:

Amazon                  332
Facebook                149
Optello                 137
Apple                   115
CyberCoders             100
Booz Allen Hamilton      73
Jobot                    57
CVS Health               55
Harnham                  55
Accenture                53
Cognizant                51
```

```
Deloitte                 47
USAA                     47
Quantitative Systems     46
Tesla                    45
UnitedHealth Group       45
Apex Systems             44
Idexcel                  44
Brooksource              39
Capgemini                38
Name: company, dtype: int64
```

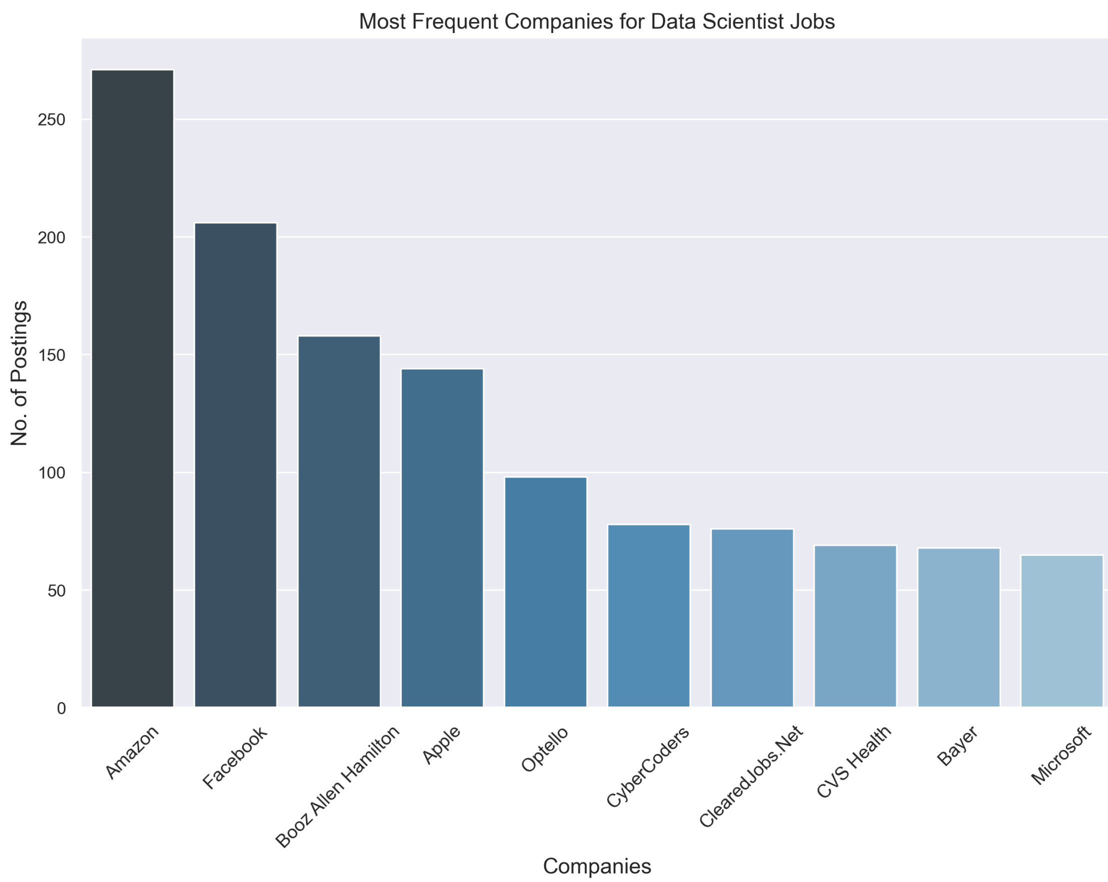


1.4.9 Data Scientist

[88]:
```
job_companies(df_jobs, 'Data Scientist')
```

```
Most Frequent Companies for Data Scientist Job Postings:

Amazon                        271
Facebook                      206
```

```
Booz Allen Hamilton          158
Apple                        144
Optello                       98
CyberCoders                   78
ClearedJobs.Net               76
CVS Health                    69
Bayer                         68
Microsoft                     65
IBM                           65
Leidos                        60
Deloitte                      57
JPMorgan Chase Bank, N.A.     53
Harnham                       53
Guidehouse                    52
Walmart                       51
Spotify                       50
Mitre Corporation             49
PayPal                        48
Name: company, dtype: int64
```



1.5 4. Data Prediction

[89]:
```
# # make series of job text for just Data Engineer and Data Scientist roles
def remove_obvious_words(df):

    updated_words = []

    for x in df['processed_text']:

        x = str(x)
        x = x.replace('scientist', '')
        x = x.replace('engineer', '')
        x = x.replace('analyst', '')

        # append updated strings to list
        updated_words.append(x)

    df['processed_text'] = updated_words

    return df

df_jobs = remove_obvious_words(df_jobs)
df_jobs.head()
```

[89]:
```
                         company company_rating                 date  \
0                          Microf            NaN 2021-03-18 08:10:59
1                             NaN            NaN 2021-03-18 08:10:59
2                           Adobe            NaN 2021-03-18 08:10:59
3        Prescryptive Health, Inc.            NaN 2021-03-18 08:10:59
4   Source One Technical Solutions            NaN 2021-03-18 08:10:59

                             industries  \
0            Marketing and Advertising
1                                   NaN
2            Marketing and Advertising
3  Information Technology and Services
4  Information Technology and Services

                                              job_text  \
0  ['', 'Eligible for participation in the Compan…
1  ['', 'Qualifications', "Understand the day-to-…
2  ['', 'Define, measure and track key metrics to…
3  ['', '\tPrescryptive Health is putting an end …
4  ['', 'Qualifications', '• Analytical and data …

                  job_title                        location  \
0              Data Analyst                     Roswell, GA
```

```
1                 Data Analyst  New York City Metropolitan Area
2  2021 Intern - Data Analyst        California, United States
3                 Data Analyst                     Redmond, WA
4                 Data Analyst                    Richboro, PA

                                        clean_text  job_text_length  label  \
0  ['', 'Eligible for participation in the Compan…             6529      2
1  ['', 'Qualifications', "Understand the day-to-…             1169      2
2  ['', 'Define, measure and track key metrics to…             1940      2
3  ['', '\tPrescryptive Health is putting an end …             3053      2
4  ['', 'Qualifications', '• Analytical and data …             1100      2

                                    processed_text
0  ['participation', 'company', 'group', 'medical…
1  ['understand', 'issue', 'business', 'face', 'b…
2  ['measure', 'track', 'key', 'metric', 'guide',…
3  ['health', 'putting', 'end', 'nation', 'prescr…
4  ['analytical', 'data', 'visualization', 'skill…
```

[90]:
```python
# create feature and target series from dataframe
df_feature = df_jobs[(df_jobs['label'] == 0) | (df_jobs['label'] == 1) |␣
↪(df_jobs['label'] == 2)].loc[:, 'processed_text']
df_target = df_jobs[(df_jobs['label'] == 0) | (df_jobs['label'] == 1) |␣
↪(df_jobs['label'] == 2)].loc[:, 'label']
```

[91]:
```python
# apply TF-IDF based feature representation
tfidf_vectorizer = TfidfVectorizer()
df_feature_TFIDF = tfidf_vectorizer.fit_transform(df_feature)

# split train/test data 80/20
X_train, X_test, y_train, y_test = train_test_split(df_feature_TFIDF,
                                                    df_target,
                                                    train_size=0.8,
                                                    random_state=20)
```

[92]:
```python
# create empty dataframe to store model results and scores
model_results = pd.DataFrame(columns=['model', 'accuracy', 'precision',␣
↪'recall', 'f1'])
model_results
```

[92]:
```
Empty DataFrame
Columns: [model, accuracy, precision, recall, f1]
Index: []
```

1.5.1 4.1 Logistic Regression (One vs. All) w/ TFIDF (Model 1)

[93]:
```
# define logistic regression, fit to model
logreg_OVR_TFIDF = LogisticRegression(multi_class = 'ovr')
#log_reg_CV = LogisticRegression(solver='liblinear', penalty='l1')
logreg_OVR_TFIDF.fit(X_train, y_train)
```

[93]:
```
LogisticRegression(multi_class='ovr')
```

[94]:
```
# compute y-prediction and accuracy, recall, precision, and f1 scores
y_pred = logreg_OVR_TFIDF.predict(X_test)
mod1_acc = accuracy_score(y_test, y_pred)
mod1_recall = recall_score(y_test, y_pred, average='macro')
mod1_precision = precision_score(y_test, y_pred, average='macro')
mod1_f1 = f1_score(y_test, y_pred, average='macro')

# print accuracy, recall, precision, f1 score, detailed report
print('----------------------------------------')
print('Model 1 accuracy: ', round(mod1_acc,3))
print('Model 1 recall: ', round(mod1_recall,3))
print('Model 1 precision: ', round(mod1_precision,3))
print('Model 1 f1 : ', round(mod1_f1,3))
print('Model 1 classification report: \n',classification_report(y_test, y_pred))
```

```
----------------------------------------
Model 1 accuracy:  0.872
Model 1 recall:  0.853
Model 1 precision:  0.863
Model 1 f1 :  0.857
Model 1 classification report:
               precision    recall  f1-score   support

           0       0.87      0.89      0.88      2900
           1       0.90      0.91      0.90      3025
           2       0.82      0.76      0.79      1528

    accuracy                           0.87      7453
   macro avg       0.86      0.85      0.86      7453
weighted avg       0.87      0.87      0.87      7453
```

[95]:
```
# append model results to dataframe
    # append to dataframe
model_results = model_results.append({'model': 'LogReg_OVR_TFIDF',
                      'accuracy':round(mod1_acc,3),
                      'recall': round(mod1_recall,3),
                      'precision': round(mod1_precision,3),
```

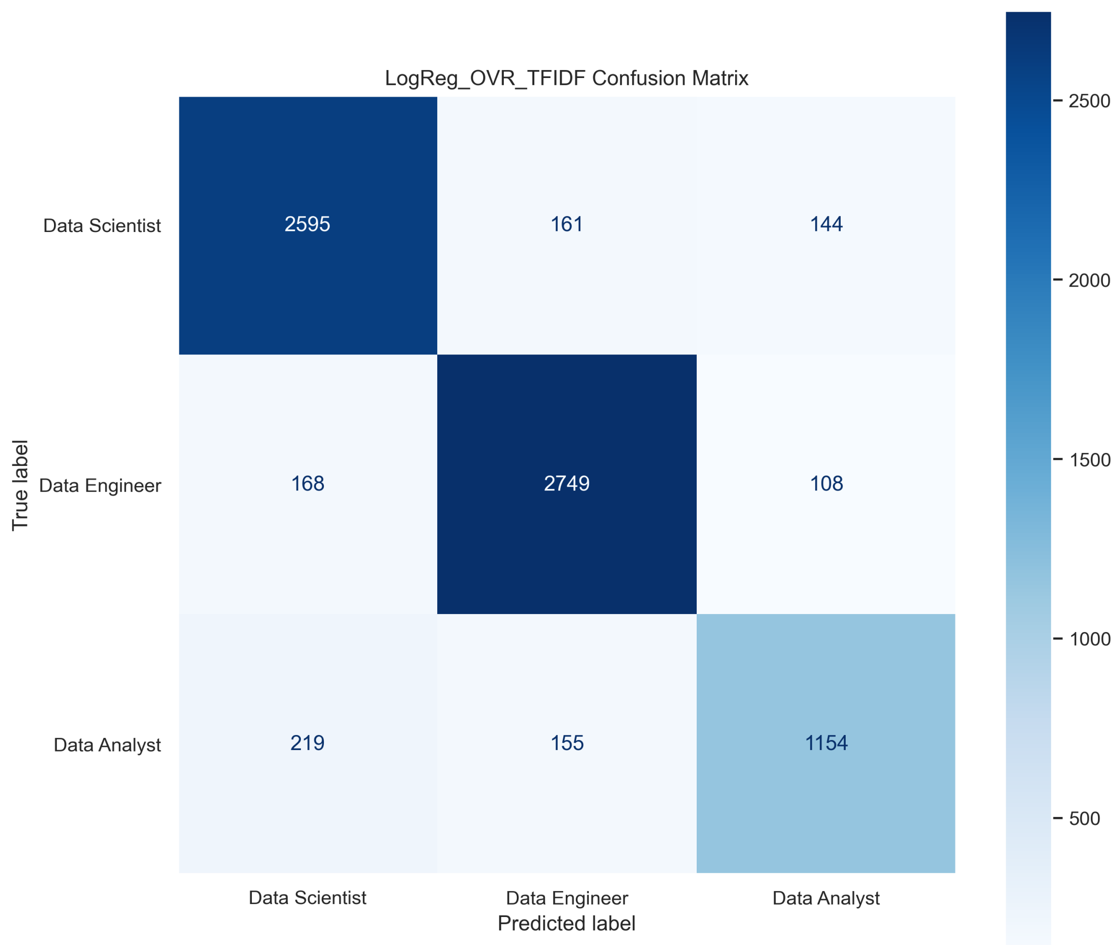
```
                                'f1': round(mod1_f1,3)}, ignore_index=True)

model_results
```

[95]:

	model	accuracy	precision	recall	f1
0	LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857

[96]:

```
fig, ax = plt.subplots(figsize=(10, 10), dpi=300)

plot_confusion_matrix(logreg_OVR_TFIDF, X_test, y_test,
                             display_labels=['Data Scientist', 'Data Engineer',␣
 ↪'Data Analyst'],
                             cmap=plt.cm.Blues, ax=ax)
ax.set_title('LogReg_OVR_TFIDF Confusion Matrix')

plt.grid(None)
plt.show()
```



1.5.2 4.2 Logistic Regression (Multinomial) w/ TF-IDF (Model 2)

[97]:
```
# define logistic regression, fit to model
↪
logreg_multi_TFIDF = LogisticRegression(multi_class = 'multinomial')
logreg_multi_TFIDF.fit(X_train, y_train)
```

```
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[97]:
```
LogisticRegression(multi_class='multinomial')
```

[98]:
```
# compute y-prediction and accuracy, recall, precision, and f1 scores
y_pred = logreg_multi_TFIDF.predict(X_test)
mod2_acc = accuracy_score(y_test, y_pred)
mod2_recall = recall_score(y_test, y_pred, average = 'macro')
mod2_precision = precision_score(y_test, y_pred, average = 'macro')
mod2_f1 = f1_score(y_test, y_pred, average = 'macro')

# print accuracy, recall, precision, f1 score, detailed report
print('---------------------------------------')
print('Model 2 accuracy: ', round(mod2_acc,3))
print('Model 2 recall: ', round(mod2_recall,3))
print('Model 2 precision: ', round(mod2_precision,3))
print('Model 2 f1 : ', round(mod2_f1,3))
print('Model 2 classification report: \n',classification_report(y_test, y_pred))
```

```
---------------------------------------
Model 2 accuracy:  0.88
Model 2 recall:  0.865
Model 2 precision:  0.87
Model 2 f1 :  0.867
Model 2 classification report:
               precision    recall  f1-score   support

           0       0.88      0.90      0.89      2900
           1       0.91      0.91      0.91      3025
           2       0.82      0.78      0.80      1528
```

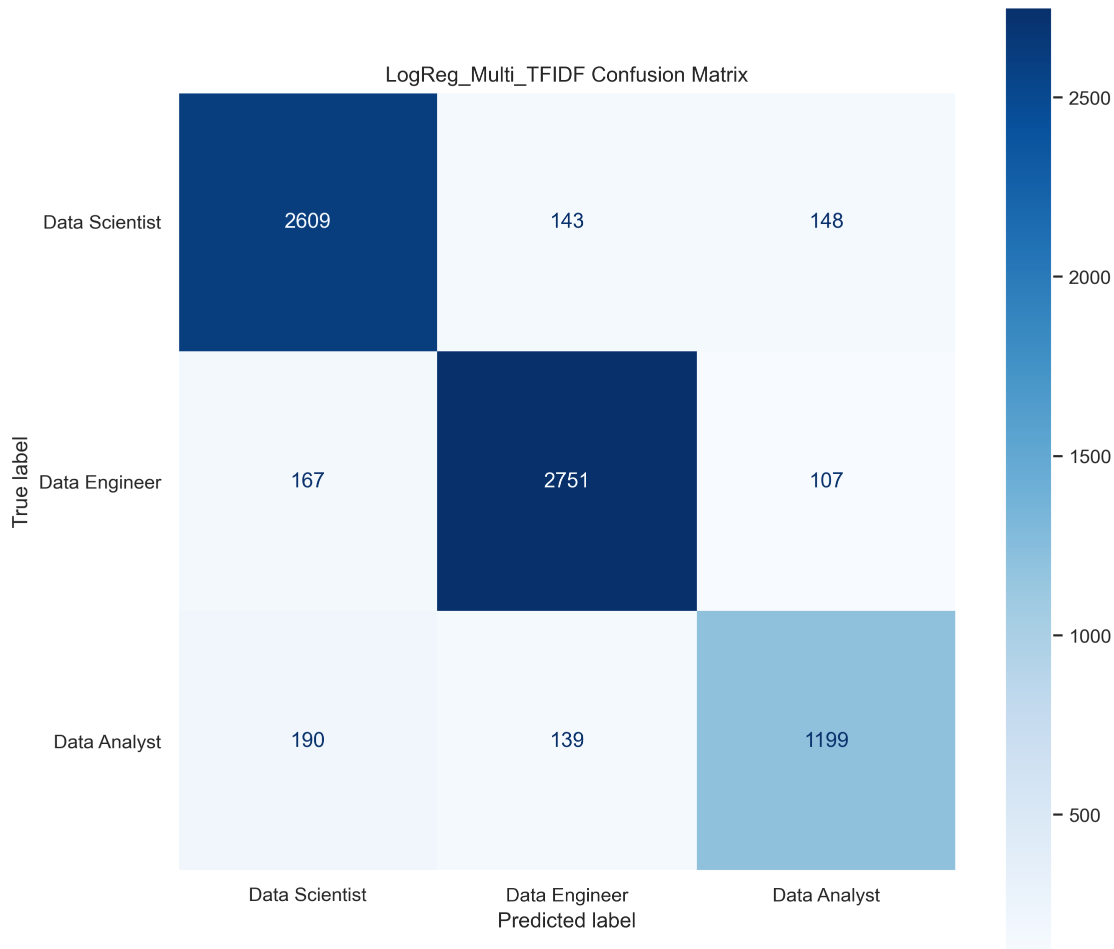
```
    accuracy                           0.88      7453
   macro avg       0.87      0.86      0.87      7453
weighted avg       0.88      0.88      0.88      7453
```

[99]:
```
# append model results to dataframe
model_results = model_results.append({'model': 'LogReg_Multi_TFIDF',
                      'accuracy':round(mod2_acc,3),
                      'recall': round(mod2_recall,3),
                      'precision': round(mod2_precision,3),
                      'f1': round(mod2_f1,3)}, ignore_index=True)

model_results
```

[99]:

	model	accuracy	precision	recall	f1
0	LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857
1	LogReg_Multi_TFIDF	0.880	0.870	0.865	0.867

[100]:
```
fig, ax = plt.subplots(figsize=(10, 10), dpi=300)

plot_confusion_matrix(logreg_multi_TFIDF, X_test, y_test,
                             display_labels=['Data Scientist', 'Data Engineer',␣
 ↪'Data Analyst'],
                             cmap=plt.cm.Blues, ax=ax)
ax.set_title('LogReg_Multi_TFIDF Confusion Matrix')

plt.grid(None)
plt.show()
```



[101]:
```
# get importance
importance = logreg_multi_TFIDF.coef_[0]

# create empty dataframe
feature_list = []

# summarize feature importance
for i,v in enumerate(importance):
    if v > 0.5:
        feature_list.append(dict({'number': i, 'feature': tfidf_vectorizer.
 ↪get_feature_names()[i], 'weight': v}))

    if v < -0.5:
        feature_list.append(dict({'number': i, 'feature': tfidf_vectorizer.
 ↪get_feature_names()[i], 'weight': v}))
```

```python
df_important_features = pd.DataFrame(feature_list, columns=['number',␣
 ↪'feature', 'weight'])
print('Top Words (Features) for Predicting Data Scientist job: \n\n',␣
 ↪df_important_features.sort_values(by='weight', ascending=False).iloc[:10])
print('\nTop Words (Features) for Predicting Data Engineering job: \n\n',␣
 ↪df_important_features.sort_values(by='weight', ascending=True).iloc[:10])
```

```
Top Words (Features) for Predicting Data Scientist job:

      number      feature    weight
907    48453      science  7.777486
584    29640     learning  4.649844
656    33423        model  4.069614
979    52744    statistic  3.172504
741    39188          phd  3.087836
384    19632   experiment  3.069617
816    43674       python  3.014489
603    30837      machine  2.977213
34      1472    algorithm  2.881187
980    52747  statistical  2.796520

Top Words (Features) for Predicting Data Engineering job:

      number   feature    weight
364    18681       etl -3.263001
251    12488      data -2.651070
199    10283  computer -2.625002
748    39382  pipeline -2.580755
375    18938     excel -2.412889
972    52048       sql -2.392477
845    45100  redshift -2.355992
862    45795    report -2.233023
89      5039  bachelor -1.817858
463    22865    google -1.766926
```

1.5.3 4.3 Decision Tree w/ TF-IDF (Model 3)

[102]:
```python
# train a Decision Tree Classifier
dtree_TFIDF = DecisionTreeClassifier(max_depth = 3)
dtree_TFIDF.fit(X_train, y_train)
y_pred = dtree_TFIDF.predict(X_test)
```

[103]:
```python
# compute y-prediction and accuracy, recall, precision, and f1 scores
y_pred = dtree_TFIDF.predict(X_test)
mod3_acc = accuracy_score(y_test, y_pred)
mod3_recall = recall_score(y_test, y_pred, average = 'macro')
mod3_precision = precision_score(y_test, y_pred, average = 'macro')
```

```
mod3_f1 = f1_score(y_test, y_pred, average = 'macro')

# print accuracy, recall, precision, f1 score, detailed report
print('---------------------------------------')
print('Model 3 accuracy: ', round(mod3_acc,3))
print('Model 3 recall: ', round(mod3_recall,3))
print('Model 3 precision: ', round(mod3_precision,3))
print('Model 3 f1 : ', round(mod3_f1,3))
print('Model 3 classification report: \n',classification_report(y_test, y_pred))
```

```
---------------------------------------
Model 3 accuracy:  0.648
Model 3 recall:  0.599
Model 3 precision:  0.697
Model 3 f1 :  0.611
Model 3 classification report:
               precision    recall  f1-score   support

           0       0.79      0.58      0.67      2900
           1       0.57      0.86      0.69      3025
           2       0.74      0.36      0.48      1528

    accuracy                           0.65      7453
   macro avg       0.70      0.60      0.61      7453
weighted avg       0.69      0.65      0.64      7453
```

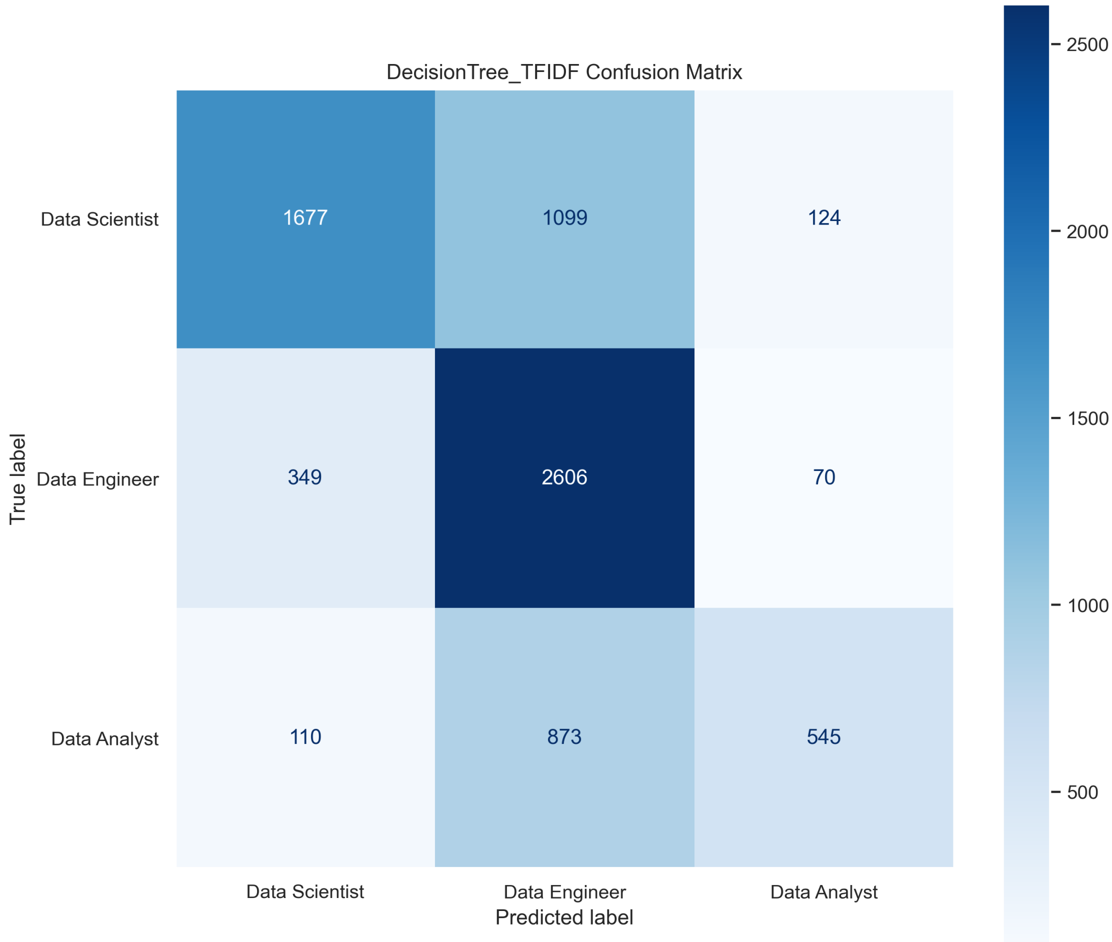
[104]:
```
# append model results to dataframe
model_results = model_results.append({'model': 'DecisionTree_TFIDF',
                      'accuracy':round(mod3_acc,3),
                      'recall': round(mod3_recall,3),
                      'precision': round(mod3_precision,3),
                      'f1': round(mod3_f1,3)}, ignore_index=True)

model_results
```

[104]:

	model	accuracy	precision	recall	f1
0	LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857
1	LogReg_Multi_TFIDF	0.880	0.870	0.865	0.867
2	DecisionTree_TFIDF	0.648	0.697	0.599	0.611

[105]:
```
fig, ax = plt.subplots(figsize=(10, 10), dpi=300)

plot_confusion_matrix(dtree_TFIDF, X_test, y_test,
                             display_labels=['Data Scientist', 'Data Engineer',␣
 ↪'Data Analyst'],
                             cmap=plt.cm.Blues, ax=ax)
```

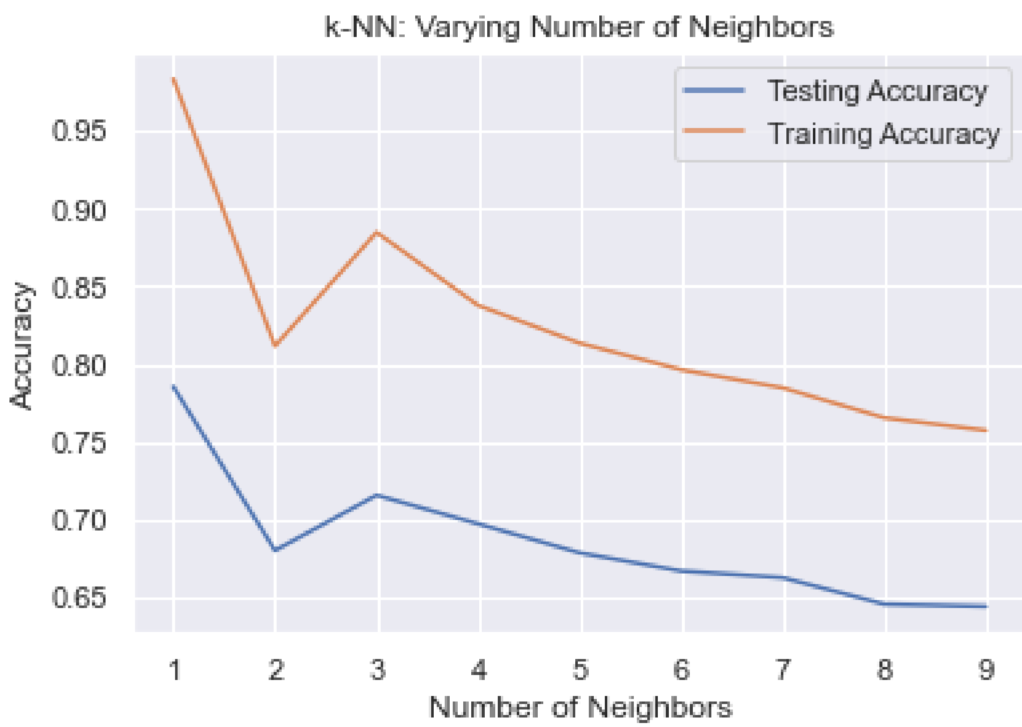
```
ax.set_title('DecisionTree_TFIDF Confusion Matrix')

plt.grid(None)
plt.show()
```



1.5.4 4.4 K-Nearest Neighbors w/ TF-IDF (Model 4)

[106]:
```
# setup plot to determine optimal number of neighbors
neighbors = np.arange(1, 10)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

# Loop over different values of k
for i, k in enumerate(neighbors):
    # Setup a k-NN Classifier with k neighbors: knn
    knn = KNeighborsClassifier(n_neighbors= k)
```

```
    # Fit the classifier to the training data
    knn.fit(X_train, y_train)

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the testing set
    test_accuracy[i] = knn.score(X_test, y_test)

# Generate plot
plt.title('k-NN: Varying Number of Neighbors')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```



[107]:
```
# train an KNN Classifier
KNN_TFIDF = KNeighborsClassifier(n_neighbors = 3)
KNN_TFIDF.fit(X_train, y_train)
```

[107]: KNeighborsClassifier(n_neighbors=3)

[108]:

```
# compute y-prediction and accuracy, recall, precision, and f1 scores
y_pred = KNN_TFIDF.predict(X_test)
mod4_acc = accuracy_score(y_test, y_pred)
mod4_recall = recall_score(y_test, y_pred, average = 'macro')
mod4_precision = precision_score(y_test, y_pred, average = 'macro')
mod4_f1 = f1_score(y_test, y_pred, average = 'macro')

# print accuracy, recall, precision, f1 score, detailed report
print('---------------------------------------')
print('Model 4 accuracy: ', round(mod4_acc,3))
print('Model 4 recall: ', round(mod4_recall,3))
print('Model 4 precision: ', round(mod4_precision,3))
print('Model 4 f1 : ', round(mod4_f1,3))
print('Model 4 classification report: \n',classification_report(y_test, y_pred))
```

```
---------------------------------------
Model 4 accuracy:  0.716
Model 4 recall:  0.68
Model 4 precision:  0.802
Model 4 f1 :  0.697
Model 4 classification report:
               precision    recall  f1-score   support

           0       0.60      0.95      0.74      2900
           1       0.91      0.61      0.73      3025
           2       0.90      0.48      0.63      1528

    accuracy                           0.72      7453
   macro avg       0.80      0.68      0.70      7453
weighted avg       0.79      0.72      0.71      7453
```

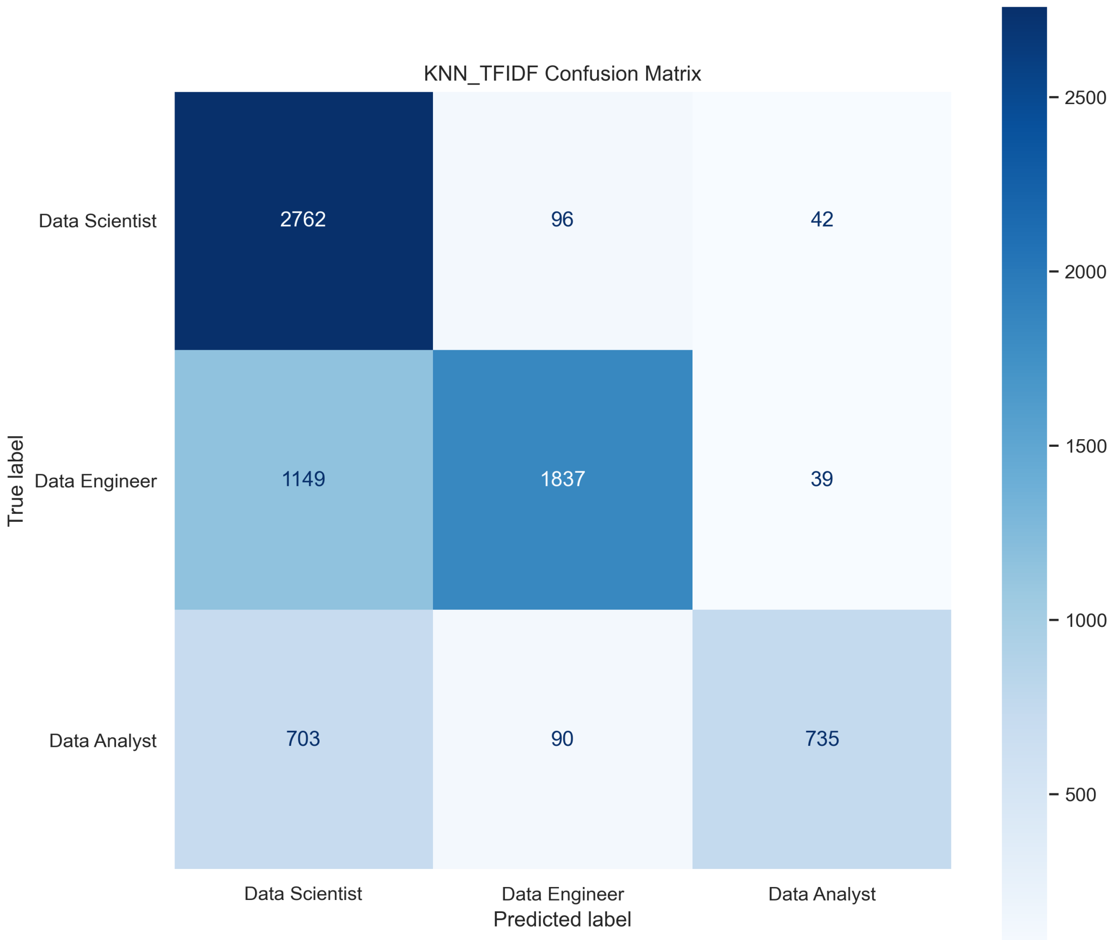
[109]:

```
# append model results to dataframe
model_results = model_results.append({'model': 'KNN_TFIDF',
                      'accuracy':round(mod4_acc,3),
                      'recall': round(mod4_recall,3),
                      'precision': round(mod4_precision,3),
                      'f1': round(mod4_f1,3)}, ignore_index=True)

model_results
```

[109]:

	model	accuracy	precision	recall	f1
0	LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857
1	LogReg_Multi_TFIDF	0.880	0.870	0.865	0.867
2	DecisionTree_TFIDF	0.648	0.697	0.599	0.611
3	KNN_TFIDF	0.716	0.802	0.680	0.697

```
[110]: fig, ax = plt.subplots(figsize=(10, 10), dpi=300)

plot_confusion_matrix(KNN_TFIDF, X_test, y_test,
                             display_labels=['Data Scientist', 'Data Engineer',␣
 ↪'Data Analyst'],
                             cmap=plt.cm.Blues, ax=ax)
ax.set_title('KNN_TFIDF Confusion Matrix')

plt.grid(None)
plt.show()
```



1.5.5 4.5 Naive Bayes w/ TF-IDF (Model 5)

```
[111]: # convert to non-sparse matrix for GaussianNB
X_train = X_train.todense()
X_test = X_test.todense()
```

```
# train a GaussianNB Classifier
GaussianNB_TFIDF = GaussianNB()
GaussianNB_TFIDF.fit(X_train, y_train)
```

[111]: GaussianNB()

[112]:
```
# compute y-prediction and accuracy, recall, precision, and f1 scores
y_pred = GaussianNB_TFIDF.predict(X_test)
mod5_acc = accuracy_score(y_test, y_pred)
mod5_recall = recall_score(y_test, y_pred, average = 'macro')
mod5_precision = precision_score(y_test, y_pred, average = 'macro')
mod5_f1 = f1_score(y_test, y_pred, average = 'macro')

# print accuracy, recall, precision, f1 score, detailed report
print('---------------------------------------')
print('Model 5 accuracy: ', round(mod5_acc,3))
print('Model 5 recall: ', round(mod5_recall,3))
print('Model 5 precision: ', round(mod5_precision,3))
print('Model 5 f1 : ', round(mod5_f1,3))
print('Model 5 classification report: \n',classification_report(y_test, y_pred))
```

```
---------------------------------------
Model 5 accuracy:  0.613
Model 5 recall:  0.643
Model 5 precision:  0.66
Model 5 f1 :  0.611
Model 5 classification report:
               precision    recall  f1-score   support

           0       0.75      0.59      0.66      2900
           1       0.86      0.54      0.66      3025
           2       0.37      0.79      0.51      1528

    accuracy                           0.61      7453
   macro avg       0.66      0.64      0.61      7453
weighted avg       0.72      0.61      0.63      7453
```

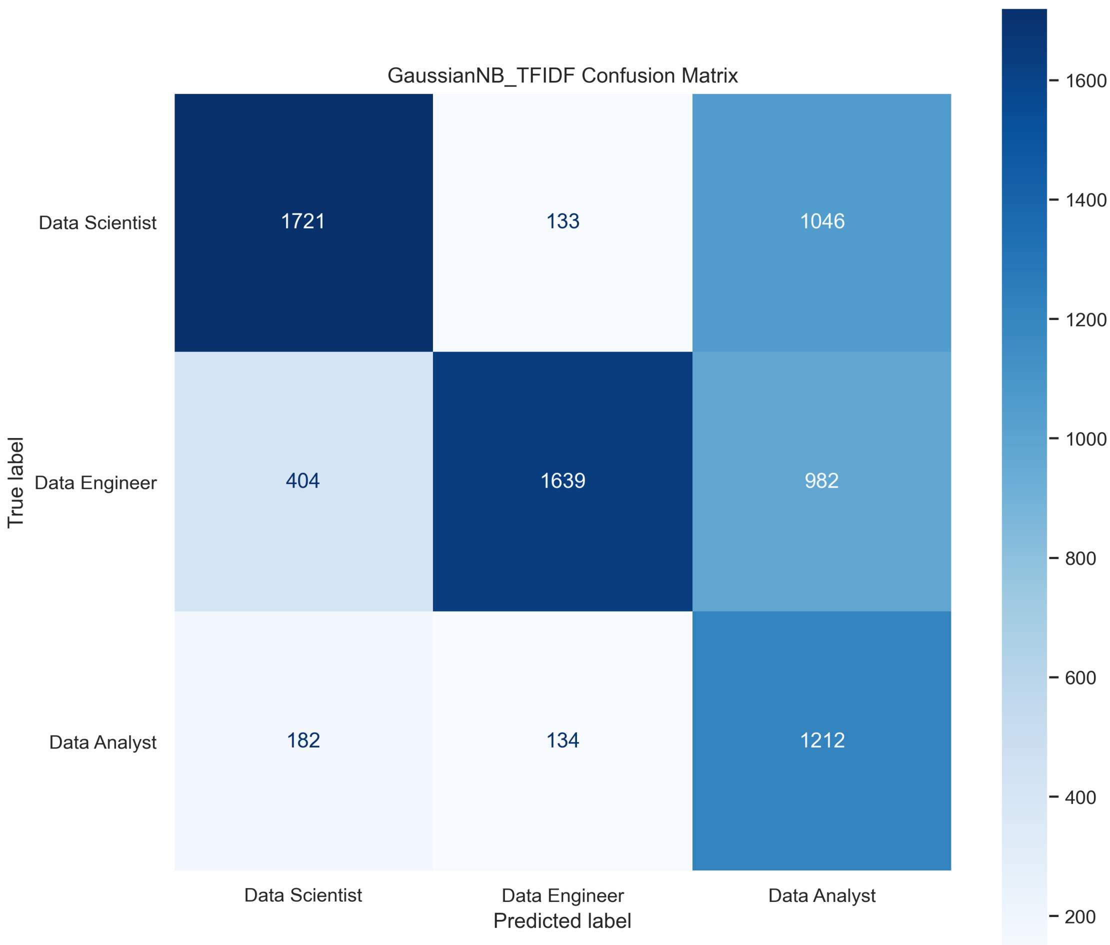
[113]:
```
# append model results to dataframe
model_results = model_results.append({'model': 'GaussianNB_TFIDF',
                      'accuracy':round(mod5_acc,3),
                      'recall': round(mod5_recall,3),
                      'precision': round(mod5_precision,3),
                      'f1': round(mod5_f1,3)}, ignore_index=True)


model_results
```

[113]:

	model	accuracy	precision	recall	f1
0	LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857
1	LogReg_Multi_TFIDF	0.880	0.870	0.865	0.867
2	DecisionTree_TFIDF	0.648	0.697	0.599	0.611
3	KNN_TFIDF	0.716	0.802	0.680	0.697
4	GaussianNB_TFIDF	0.613	0.660	0.643	0.611

[114]:

```
fig, ax = plt.subplots(figsize=(10, 10), dpi=300)

plot_confusion_matrix(GaussianNB_TFIDF, X_test, y_test,
                             display_labels=['Data Scientist', 'Data Engineer',␣
 ↪'Data Analyst'],
                             cmap=plt.cm.Blues, ax=ax)
ax.set_title('GaussianNB_TFIDF Confusion Matrix')

plt.grid(None)
plt.show()
```



1.5.6 4.6 Choose Best Model and Optimize Hyperparameters

[115]:
```
# split train/test data 80/20
X_train, X_test, y_train, y_test = train_test_split(df_feature_TFIDF,
                                                    df_target,
                                                    train_size=0.8,
                                                    random_state=20)


# scale data
sc = StandardScaler(with_mean=False)
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

[116]:
```
# choose parameters
tuned_parameters = [{'estimator__C': [100, 10, 1, 0.1, 0.01]}]

# find optimal C by grid search and fit
logreg_OVR = OneVsRestClassifier(LogisticRegression(max_iter=1000))
grid = GridSearchCV(logreg_OVR, tuned_parameters, scoring = 'f1_weighted',␣
 ↪verbose=2, cv=3)
grid.fit(X_train, y_train)

# print best score/parameter
print(grid.best_score_)
print(grid.best_params_)

# compute y-prediction
y_pred = grid.predict(X_test)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
[CV] estimator__C=100 …
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   47.4s remaining:    0.0s

[CV] … estimator__C=100, total=  47.4s
[CV] estimator__C=100 …

/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[CV] … estimator__C=100, total=  49.1s
[CV] estimator__C=100 …
```

```
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[CV] … estimator__C=100, total=  47.0s
[CV] estimator__C=10 …
```

```
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
```

```
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[CV] … estimator__C=10, total=  46.9s
[CV] estimator__C=10 …
```

```
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
```

```
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[CV] … estimator__C=10, total=  47.3s
[CV] estimator__C=10 …
```

```
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[CV] … estimator__C=10, total=  47.5s
[CV] estimator__C=1 …
[CV] … estimator__C=1, total=  38.8s
[CV] estimator__C=1 …
[CV] … estimator__C=1, total=  38.1s
[CV] estimator__C=1 …
[CV] … estimator__C=1, total=  33.7s
[CV] estimator__C=0.1 …
[CV] … estimator__C=0.1, total=  15.8s
[CV] estimator__C=0.1 …
[CV] … estimator__C=0.1, total=  14.1s
[CV] estimator__C=0.1 …
[CV] … estimator__C=0.1, total=  13.6s
[CV] estimator__C=0.01 …
[CV] … estimator__C=0.01, total=   7.4s
[CV] estimator__C=0.01 …
[CV] … estimator__C=0.01, total=   7.2s
[CV] estimator__C=0.01 …
[CV] … estimator__C=0.01, total=   7.5s
```

```
[Parallel(n_jobs=1)]: Done  15 out of  15 | elapsed:  7.7min finished
```

```
0.8764449715162215
{'estimator__C': 0.01}
```

[117]:

```
mod6_acc = accuracy_score(y_test, y_pred)
mod6_recall = recall_score(y_test, y_pred, average = 'macro')
mod6_precision = precision_score(y_test, y_pred, average = 'macro')
mod6_f1 = f1_score(y_test, y_pred, average = 'macro')

# print accuracy, recall, precision, f1 score, detailed report
print('---------------------------------------')
print('Model 6 accuracy: ', round(mod6_acc,3))
print('Model 6 recall: ', round(mod6_recall,3))
print('Model 6 precision: ', round(mod6_precision,3))
print('Model 6 f1 : ', round(mod6_f1,3))
print('Model 6 classification report: \n',classification_report(y_test, y_pred))
```

```
---------------------------------------
Model 6 accuracy:  0.891
Model 6 recall:  0.873
```

```
Model 6 precision:  0.882
Model 6 f1 :  0.877
Model 6 classification report:
               precision    recall  f1-score   support

           0       0.89      0.91      0.90      2900
           1       0.91      0.93      0.92      3025
           2       0.84      0.78      0.81      1528

    accuracy                           0.89      7453
   macro avg       0.88      0.87      0.88      7453
weighted avg       0.89      0.89      0.89      7453
```

[118]:

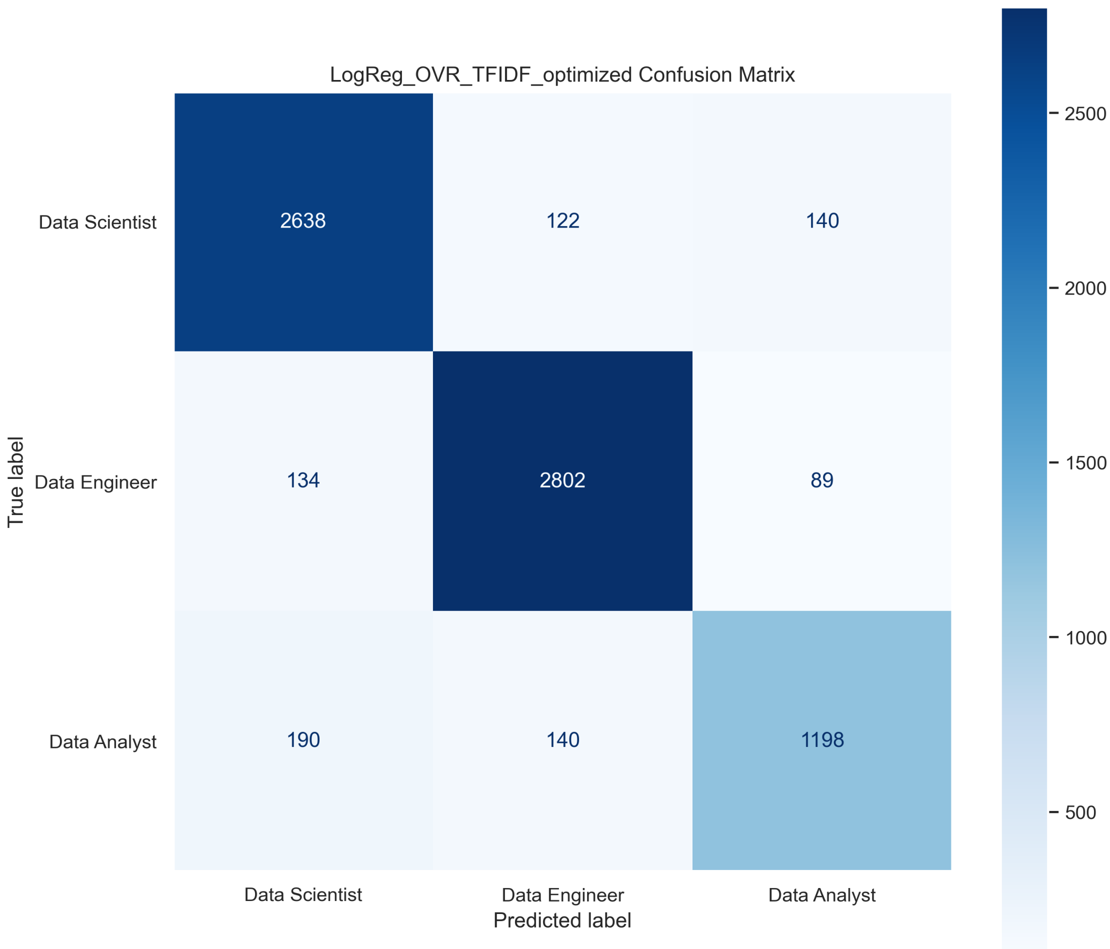
```
# append model results to dataframe
model_results = model_results.append({'model': 'LogReg_OVR_TFIDF_optimized',
                      'accuracy':round(mod6_acc,3),
                      'recall': round(mod6_recall,3),
                      'precision': round(mod6_precision,3),
                      'f1': round(mod6_f1,3)}, ignore_index=True)

model_results = model_results.sort_values(by='accuracy')
model_results
```

[118]:

	model	accuracy	precision	recall	f1
4	GaussianNB_TFIDF	0.613	0.660	0.643	0.611
2	DecisionTree_TFIDF	0.648	0.697	0.599	0.611
3	KNN_TFIDF	0.716	0.802	0.680	0.697
0	LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857
1	LogReg_Multi_TFIDF	0.880	0.870	0.865	0.867
5	LogReg_OVR_TFIDF_optimized	0.891	0.882	0.873	0.877

[120]:

```
fig, ax = plt.subplots(figsize=(10, 10), dpi=300)

plot_confusion_matrix(grid, X_test, y_test,
                            display_labels=['Data Scientist', 'Data Engineer',␣
 ↪'Data Analyst'],
                            cmap=plt.cm.Blues, ax=ax)
ax.set_title('LogReg_OVR_TFIDF_optimized Confusion Matrix')

plt.grid(None)
plt.show()
```



1.6 5. Conclusion

This project reviewed data-related job postings and tried to answer the following questions. The answers and results are shown below:

1.6.1 What tools/skills are most in demand for a *Data Analyst?*

For a Data Analyst, the top desired tools are: *sql, excel, tableau, python, and r.* The top desired skills (after parsing through some useless bigrams) are: *data analysis, communication skill, and data visualization.* See section 3.1 for the full list and plot of tools/skills frequency.

1.6.2 What tools/skills are most in demand for a *Data Engineer?*

For a Data Engineer, the top desired tools are: *sql, python, aws, spark, and azure.* The top desired skills (after parsing through some useless bigrams) are: *data pipeline, big data, and data warehouse.* See section 3.1 for the full list and plot of tools/skills frequency.

1.6.3 What tools/skills are most in demand for a *Data Scientist?*

For a Data Scientist, the top desired tools are: *python, r, sql, spark, and tableau.* The top desired skills (after parsing through some useless bigrams) are: *machine learning, data analysis, and communication skill.* See section 3.1 for the full list and plot of tools/skills frequency.

1.6.4 Which companies post the mose job openings?

For Data Analyst postings, the top companies are: *ClearedJobs.Net, GEICO, CyberCoders, Booz Allen Hamilton, and Apex Systems.* See section 3.3 for the full list and plot of job company frequency.

For Data Engineer postings, the top companies are: *Amazon, Optello, Facebook, Apple, and CyberCoders.* See section 3.3 for the full list and plot of job company frequency.

For Data Scientist postings, the top companies are: *Amazon, Facebook, Booz Allen Hamilton, Apple, and Optello.* See section 3.3 for the full list and plot of job company frequency.

1.6.5 Can a classifier be built which predicts job role/title (Data Analyst, Data Scientist, or Data Engineer) based on job description?

Five different initial models were chosen for the multi-class (three class) classification problem. These models included the following: Logisitic Regression (One vs. All), Logistic Regression (Multinomial), K-Nearest Neighbor, Decision Tree, and Naive Bayes. Based on an initial fitting of the model types to the classification problem and collecting model metrics, the Logistic Regression model performed the best. This model type was then further optimized via a hyperpareter grid search. The resulting best model, LogReg_OVR_TFIDF_optimized, is shown below with model performace metrics

Model	Accuracy	Precision	Recall	f1
GaussianNB_TFIDF	0.613	0.660	0.643	0.611
DecisionTree_TFIDF	0.648	0.697	0.599	0.611
KNN_TFIDF	0.716	0.802	0.680	0.697
LogReg_OVR_TFIDF	0.872	0.863	0.853	0.857
LogReg_Multi_TFIDF	0.880	0.870	0.865	0.867
LogReg_OVR_TFIDF_optimized	0.891	0.882	0.873	0.877

Next steps for improving model performance include trying additional model types, additional hyperparameter tuning (e.g. more solvers, more C estimators, more penalty terms, etc), review imbalanced classes and upsample/downsample appropriately, and try different NLP cleaning approaches (e.g. add more stopwords).