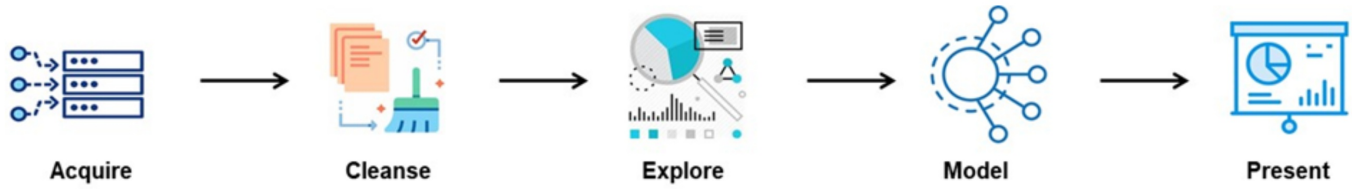
How strong is a freelancer profile?

Background

- **Scalifier** - Help scale/level-up- businesses
- **Goal:** Use Data Science and Analytics to help boost freelancer profiles
  - Optimize the search rank of profiles
  - Come up with a metric to evaluate a profile
  - Find the most important features that influence search rank
  - Predict search rank for new profile
- Search Engine Optimization
- **Tools:** Python, Scikit-learn, AWS, ELK

Project Workflow



Problem Statement

We have data showing user profiles on the Upwork website. This data is labeled for the searchRank for every user based on their skill (querySkill). We want to use this data to predict what the searchRank would be for an out-of-sample user once we have the data listed on their Upwork profile.

Library Imports

In [167]:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.impute import SimpleImputer

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier


import warnings
warnings.filterwarnings('ignore')
```

In [168]:

```
plt.rcParams['figure.figsize'] = (12, 5)
```

In [169]:

```
df = pd.read_json('/content/drive/MyDrive/Scrapper/allProfilesUpdated.json')
```

In [170]:

```
df.head()
```

Out[170]:

	recno	ciphertext	shortName	title	description	portrait
0	13422873	~01525501ed621c1619	Balbinder S.	Full Stack Developer	Hi, I am Balbinder,\nI have been doing app dev...	https://www.upwork.com/profile-portraits/c1GnS...
1	27520224	~0194a7954c0c0b0b93	Kishori L.	Web developer : ASP.NET	Have 5+ years of web development using NET Fra...	https://www.upwork.com/profile-portraits/c1imZ...
2	10621482	~01706ebd6c67d45486	Vladislav G.	Ecommerce Development / iOS / Cross-platform d...	Over the recent 5 years I've developed native ...	https://www.upwork.com/profile-portraits/c1NX3...
3	20961751	~01f462eda81681ab22	Matthew H.	SEO Web Content Specialist	The big push in SEO best practices is to estab...	https://www.upwork.com/profile-portraits/c1yip...
4	31620881	~01658c07fb14af66fc	Hussain M.	.NET,VBA,Python,Azure/AWS, SQL, Typescript, An...	Hello My name is Hussain Murtaza, I am a Senio...	https://www.upwork.com/profile-portraits/c1LXU...

5 rows × 46 columns

Data Cleaning

In [171]:

```
df['combinedTotalEarnings']
```

Out[171]:

```
0          275612.50
1        56062604.80
2        27630978.69
3            7308.17
4            9541.00
            ...
4775         2948.83
4776        17652.84
4777           50.00
4778        15965.02
4779        70324.69
Name: combinedTotalEarnings, Length: 4780, dtype: float64
```

In [172]:

```
len(df)
```

Out[172]:

```
4780
```

In [173]:

In [173]:

```
## Check for missing data
df.isnull().sum()
```

Out[173]:

```
recno                              0
ciphertext                         0
shortName                          0
title                              0
description                        0
portrait                           2
location                           0
hourlyRate                         0
lastActivity                       0
totalHoursBilled                   0
totalPortfolioItems                0
totalPassedTests                   0
skills                             0
groups                          4582
agencies                        2606
nss100                             0
highlighting                       0
rankInfo                           0
topRatedStatus                     0
certificates                    4780
portfolioItems                  4780
extendedAgencies                3413
combinedTotalRevenue             298
totalHourlyJobs                    0
totalFpJobs                        0
hideEarnings                       0
hideJss                            0
combinedTotalEarnings            298
bestMatchOccupationUid          4780
occupationProfiles              4780
personUid                          0
topTalentGroup                    13
isServiceProfile                   0
descriptionSanitized               0
shortNameSanitized                 0
titleSanitized                     0
url                                0
topRatedStatusEx                4780
uid                                0
searchRank                         0
querySkill                         0
querySkillUid                      0
date_scrapped                      0
totalRevenue                    4780
combinedRecentEarnings          4780
combinedAverageRecentEarnings   4780
dtype: int64
```

There seems to be quite a few columns with missing values. After manually looking at these columns, we can choose to drop them as they do not provide any information that can help us model the rank.

In [174]:

```
df.shape
```

Out[174]:

```
(4780, 46)
```

In [175]:

```
df.drop(['groups', 'agencies', 'certificates', 'portfolioItems', 'extendedAgencies', 'bes
tMatchOccupationUid', 'occupationProfiles', 'topRatedStatusEx', 'totalRevenue', 'combined
RecentEarnings', 'combinedAverageRecentEarnings'], axis=1, inplace=True)
```

In [176]:

```
df.shape
```

Out[176]:

```
(4780, 35)
```

In [177]:

```
columns = df.columns.to_list()
print(columns)
```

```
['recno', 'ciphertext', 'shortName', 'title', 'description', 'portrait', 'location', 'hou
rlyRate', 'lastActivity', 'totalHoursBilled', 'totalPortfolioItems', 'totalPassedTests',
'skills', 'nss100', 'highlighting', 'rankInfo', 'topRatedStatus', 'combinedTotalRevenue',
'totalHourlyJobs', 'totalFpJobs', 'hideEarnings', 'hideJss', 'combinedTotalEarnings', 'pe
rsonUid', 'topTalentGroup', 'isServiceProfile', 'descriptionSanitized', 'shortNameSanitiz
ed', 'titleSanitized', 'url', 'uid', 'searchRank', 'querySkill', 'querySkillUid', 'date_s
crapped']
```

Having removed the columns with missing values, we find that there are still some attributes that do not contribute to the rank and hence we can drop them:

ciphertext (Encrypted) Highlighting rankInfo (Encrypted) hideJss (all 0) isServiceProfile (all FALSE) totalPassedTests (all 0) We can go ahead and drop these variables.

In [178]:

```
df.drop(['ciphertext', 'highlighting', 'rankInfo', 'hideJss', 'isServiceProfile', 'total
PassedTests'], axis=1, inplace=True)
```

In [179]:

```
df.shape
```

Out[179]:

```
(4780, 29)
```

There is still some cleaning to do before we have our final dataset that we can use to start modeling. The columns description, shortName and title have a sanitzed version. Comparing these columns manually, we find that the content of the two columns are more or less the same and hence it would not make much sense to have both of them in our dataset. Let us go ahead and drop the unsanitized versions of these columns.

In [180]:

```
df.drop(['title', 'description', 'shortName'], axis=1, inplace=True)
```

In [181]:

```
df.shape
```

Out[181]:

```
(4780, 26)
```

In [182]:

```
df.columns
```

Out[182]:

```
Index(['recno', 'portrait', 'location', 'hourlyRate', 'lastActivity',
       'totalHoursBilled', 'totalPortfolioItems', 'skills', 'nss100',
       'topRatedStatus', 'combinedTotalRevenue', 'totalHourlyJobs',
       'totalFpJobs', 'hideEarnings', 'combinedTotalEarnings', 'personUid',
       'topTalentGroup', 'descriptionSanitized', 'shortNameSanitized',
       'titleSanitized', 'url', 'uid', 'searchRank', 'querySkill',
       'querySkillUid', 'date_scrapped'],
      dtype='object')
```

Now we can go over individual columns that require cleaning.

hourlyRate

The hourlyRate column contains values in a dictionary where the first key is the currencyCode and the second key is the respective amount. Let us check the unique currencies accepted.

In [183]:

```
currency_codes = [item.get('currencyCode') for item in df['hourlyRate']]
unique_currency_codes = list(set(currency_codes))
print(unique_currency_codes)
```

```
['USD']
```

We notice that all the amounts listed in the hourlyRate column are in USD. Therefore, we can extract the amount from the dictionaries listed in this column and hence make it completely quantitative.

In [184]:

```
hourly_rates = [item.get('amount') for item in df['hourlyRate']]
df['hourlyRate'] = hourly_rates
```

Skills

In [185]:

```
df['skills'][0]
```

Out[185]:

```
[{'skill': {'name': 'php', 'prettyName': 'PHP'},
  'skillUrl': '/search/profiles/?q=skills%3Aphp',
  'uid': '996364628025274385'},
 {'skill': {'name': 'api-development', 'prettyName': 'API Development'},
  'skillUrl': '/search/profiles/?q=skills%3Aapi-development',
  'uid': '1031626714051493888'},
 {'skill': {'name': 'laravel-framework', 'prettyName': 'Laravel'},
  'skillUrl': '/search/profiles/?q=skills%3Alaravel-framework',
  'uid': '1031626753368899584'},
 {'skill': {'name': 'ajax', 'prettyName': 'AJAX'},
  'skillUrl': '/search/profiles/?q=skills%3Aajax',
  'uid': '1031626711270670336'},
 {'skill': {'name': 'jquery', 'prettyName': 'jQuery'},
  'skillUrl': '/search/profiles/?q=skills%3Ajquery',
  'uid': '1031626751737315328'},
 {'skill': {'name': 'magento-2', 'prettyName': 'Magento 2'},
  'skillUrl': '/search/profiles/?q=skills%3Amagento-2',
  'uid': '1031626755600269312'},
 {'skill': {'name': 'ionic-framework', 'prettyName': 'Ionic Framework'},
  'skillUrl': '/search/profiles/?q=skills%3Aionic-framework',
  'uid': '1031626749644357632'},
 {'skill': {'name': 'django-framework', 'prettyName': 'Django'},
  'skillUrl': '/search/profiles/?q=skills%3Adjango-framework',
  'uid': '1031626732309299200'},
 {'skill': {'name': 'ios-development', 'prettyName': 'iOS Development'},
  'skillUrl': '/search/profiles/?q=skills%3Aios-development',
  'uid': '1031626749656940544'},
 {'skill': {'name': 'android-app-development',
    'prettyName': 'Android App Development'},
  'skillUrl': '/search/profiles/?q=skills%3Aandroid-app-development',
  'uid': '1031626712726093824'},
 {'skill': {'name': 'website-security', 'prettyName': 'Website Security'},
  'skillUrl': '/search/profiles/?q=skills%3Awebsite-security',
  'uid': '1110580738796277760'},
 {'skill': {'name': 'soap', 'prettyName': 'SOAP'},
```

```
  'skillUrl': '/search/profiles/?q=skills%3Asoap',
  'uid': '1031626780984197120'}]
```

What we need is a list of all the prettyNames of skills within each entry. Let us try and extract that.

In [186]:

```
main_skill_list = []
for item in df['skills']:
  skill_list = []
  for i in range(len(item)):
    skill_list.append(item[i]['skill']['prettyName'])
  main_skill_list.append(skill_list)
```

In [187]:

```
df['skills'] = main_skill_list
```

personUid and uid

The personUid and uid columns seem to be identical. Let us check this.

In [188]:

```
df['personUid'].equals(df['uid'])
```

Out[188]:

```
True
```

In [189]:

```
df.drop(['personUid'], axis=1, inplace=True)
```

In [190]:

```
df.head()
```

Out[190]:

	recno	portrait	location	hourlyRate	lastActivity	totalHoursBilled	totalPortfolioItems	
0	13422873	https://www.upwork.com/profile-portraits/c1GnS...	{'country': 'United States', 'city': 'Palm Coa...	110.0	2021-06-13T00:00:00.000Z	9495.500000	35	D A
1	27520224	https://www.upwork.com/profile-portraits/c1imZ...	{'country': 'India', 'city': 'Mohali', 'state'...	14.0	2020-09-10T00:00:00.000Z	1396.166667	5	j
2	10621482	https://www.upwork.com/profile-portraits/c1NX3...	{'country': 'Ukraine', 'city': 'Kharkiv', 'sta...	39.0	2020-02-06T00:00:00.000Z	1200.761034	2	D A
3	20961751	https://www.upwork.com/profile-portraits/c1yip...	{'country': 'United States', 'city': 'Joplin',...	40.0	2021-06-14T00:00:00.000Z	35.333333	3	I
4	31620881	https://www.upwork.com/profile-portraits/c1LXU...	{'country': 'Pakistan', 'city': 'Multan', 'sta...	20.0	2021-06-14T00:00:00.000Z	118.500000	7	

5 rows × 25 columns

In [191]:

```
## QuerySkill

df['querySkill'].value_counts()
```

Out[191]:

```
API Development                500
OOPS                           500
Real Time Stream Processing    500
AngularJS                      500
iOS Development                500
HTML5                          500
Mobile UI Design               500
Symfony                        500
Android App Development        500
Test Automation                170
Git                            100
Mobile Programming              10
Name: querySkill, dtype: int64
```

We see that the following skills have very few records to work with - Test Automation, Git, Mobile Programming. Let's remove these records so we have enough data for each skill.

In [192]:

```
index_names = df[ (df['querySkill'] == 'Test Automation') | (df['querySkill'] == 'Git')
| (df['querySkill'] == 'Mobile Programming')].index
```

In [193]:

```
df.drop(index_names, inplace=True)
```

In [194]:

```
## Converting rank into bins

df['searchRank'].describe()
```

Out[194]:

```
count    4500.000000
mean      250.500000
std       144.353319
min         1.000000
25%       125.750000
50%       250.500000
75%       375.250000
max       500.000000
Name: searchRank, dtype: float64
```

In [195]:

```
bins = [0,100,200,300,400, np.inf]
names = ['0-100', '101-200', '201-300', '301-400', '401-500']

df['searchRankRange'] = pd.cut(df['searchRank'], bins, labels=names)
```

In [196]:

```
df['searchRankRange']
```

Out[196]:

```
0       401-500
1       101-200
2       401-500
```

```
3       301-400
4         0-100
         ...
4775    401-500
4776    201-300
4777      0-100
4778    101-200
4779    101-200
Name: searchRankRange, Length: 4500, dtype: category
Categories (5, object): ['0-100' < '101-200' < '201-300' < '301-400' < '401-500']
```

Now that we have a cleaned dataset, we can start framing our problem statement. Our goal is to model the rank and we have data for each search query. With the following assumptions, we can formulate the problem statement:

- **The querySkill attribute is the is the skill that is entered in the search bar to fetch the results that we have obtained. This attribute is agnostic to the number of queries as we will have an aribitrary number of search queries in the future.**
- **We do not know what the nss100 and totalFpJobs mean currently, and hence we will omit them for the time being while modeling the rank.**
- **The rankInfo attribute is encrypted by Upwork and hence we cannot use it as a target variable. The encryption is beyond the scope of our task at hand.**

Exploratory Data Analysis

Before we start engineering features, we need to complete a few steps :

- **Identifying numerical and categorical data**
- **Quantifying missing data**
- **Determining cardinality of categorical variables**
- **Pinpointing rare categories in categorical variables**
- **Identifying a linear relationship**
- **Identifying a normal distribution**
- **Distinguishing variable distribution**
- **Highlighting outliers**

Identifying numerical and categorical data

In [197]:

```
len(df)
```

Out[197]:

```
4500
```

In [198]:

```
cols = df.columns
numeric_cols = df._get_numeric_data().columns
numeric_cols
```

Out[198]:

```
Index(['recno', 'hourlyRate', 'totalHoursBilled', 'totalPortfolioItems',
       'nss100', 'combinedTotalRevenue', 'totalHourlyJobs', 'totalFpJobs',
       'hideEarnings', 'combinedTotalEarnings', 'uid', 'searchRank',
       'querySkillUid'],
      dtype='object')
```

Quantifying missing data

In [199]:

```
len(df)
```

Out[199]:

```
4500
```

In [200]:

```
df.isnull().sum()
```

Out[200]:

```
recno                     0
portrait                  2
location                  0
hourlyRate                0
lastActivity              0
totalHoursBilled          0
totalPortfolioItems       0
skills                    0
nss100                    0
topRatedStatus            0
combinedTotalRevenue    286
totalHourlyJobs           0
totalFpJobs               0
hideEarnings              0
combinedTotalEarnings   286
topTalentGroup           13
descriptionSanitized      0
shortNameSanitized        0
titleSanitized            0
url                       0
uid                       0
searchRank                0
querySkill                0
querySkillUid             0
date_scrapped             0
searchRankRange           0
dtype: int64
```

In [201]:

```
## Percentage of missing values

df.isnull().mean()
```

Out[201]:

```
recno                   0.000000
portrait                0.000444
location                0.000000
hourlyRate              0.000000
lastActivity            0.000000
totalHoursBilled        0.000000
totalPortfolioItems     0.000000
skills                  0.000000
nss100                  0.000000
topRatedStatus          0.000000
combinedTotalRevenue    0.063556
totalHourlyJobs         0.000000
totalFpJobs             0.000000
hideEarnings            0.000000
combinedTotalEarnings   0.063556
topTalentGroup          0.002889
descriptionSanitized    0.000000
shortNameSanitized      0.000000
titleSanitized          0.000000
url                     0.000000
uid                     0.000000
searchRank              0.000000
querySkill              0.000000
```

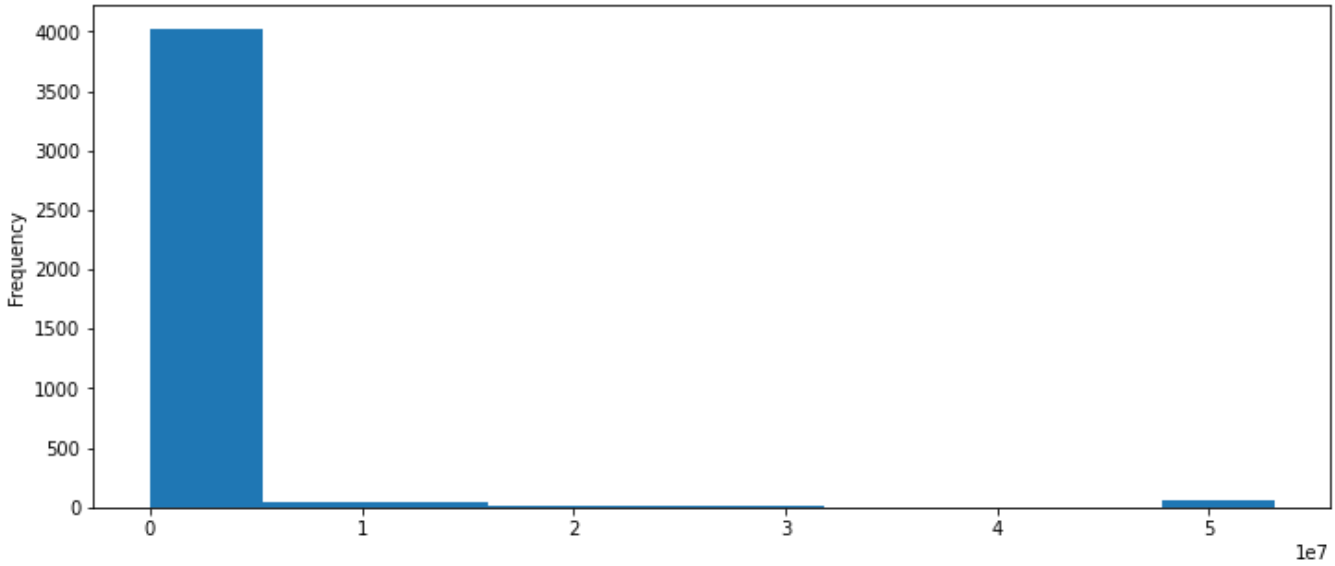
```
querySkillUid            0.000000
date_scrapped            0.000000
searchRankRange          0.000000
dtype: float64
```

In [202]:

```
## Imputing missing values (numeric)

df['combinedTotalRevenue'].plot(kind='hist')
```

Out[202]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf8611090>
```

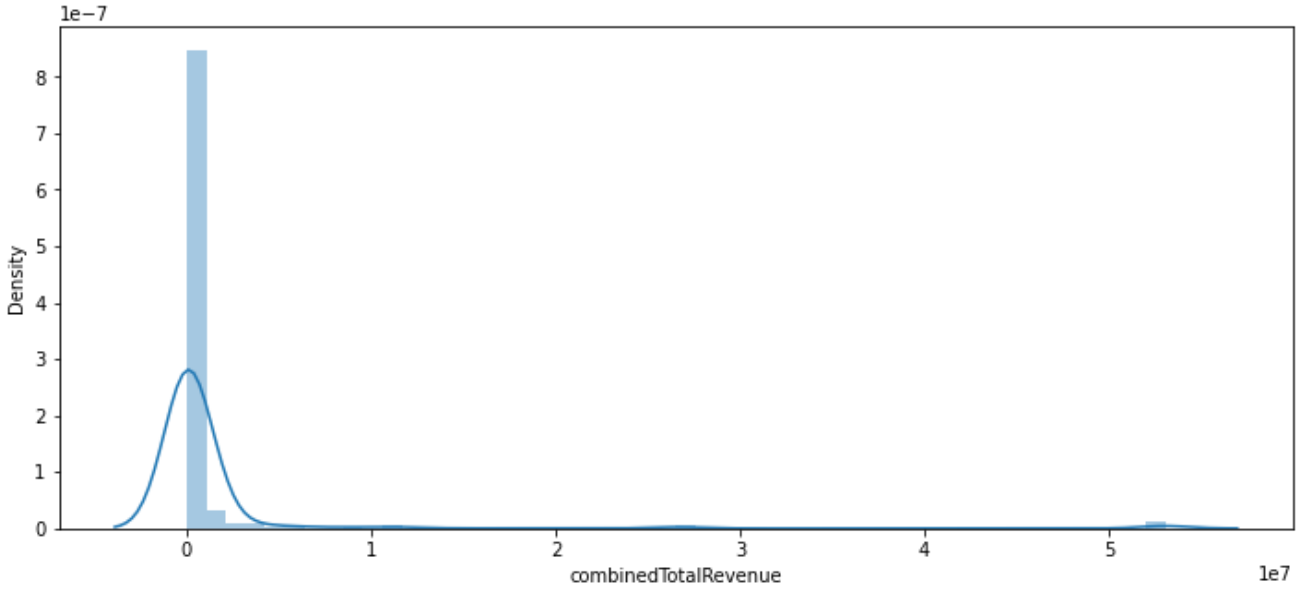


In [203]:

```
sns.distplot(df['combinedTotalRevenue'])
```

Out[203]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf70a3910>
```

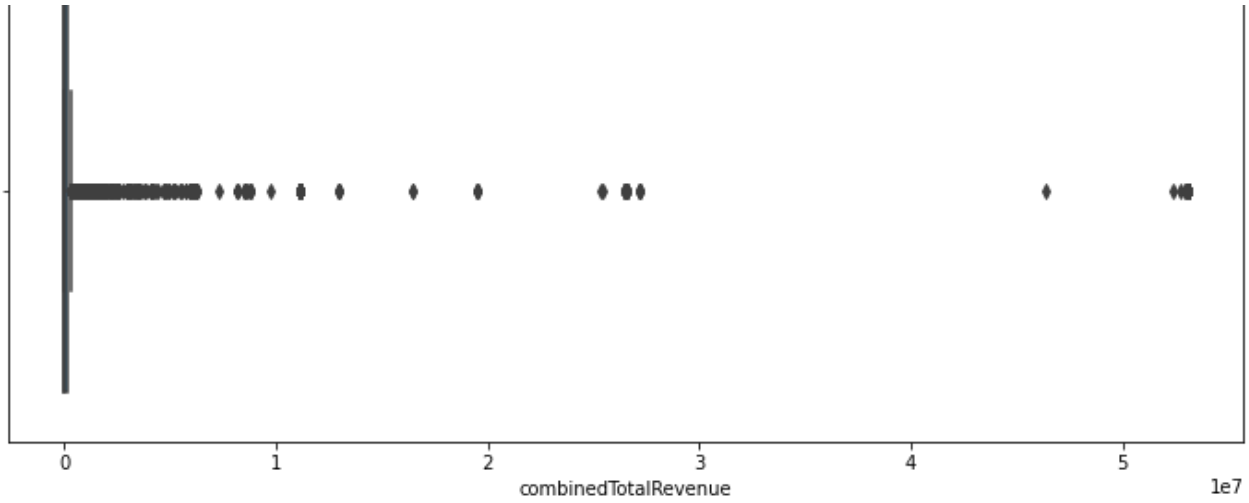


In [204]:

```
sns.boxplot(df['combinedTotalRevenue'])
```

Out[204]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf5cb2750>
```



In [205]:

```
Q1_rev = df['combinedTotalRevenue'].quantile(0.25)
Q3_rev = df['combinedTotalRevenue'].quantile(0.75)
IQR_rev = Q3_rev - Q1_rev
```

In [206]:

```
((df['combinedTotalRevenue'] < (Q1_rev - 1.5*IQR_rev)) | (df['combinedTotalRevenue'] > (
Q3_rev + 1.5*IQR_rev))).sum()
```

Out[206]:

662

Since the combinedTotalRevenue column contains a significant number of outliers, we would want to impute using the median and not the mean.

In [207]:

```
imputer = SimpleImputer(missing_values = np.nan, strategy='median')
```

In [208]:

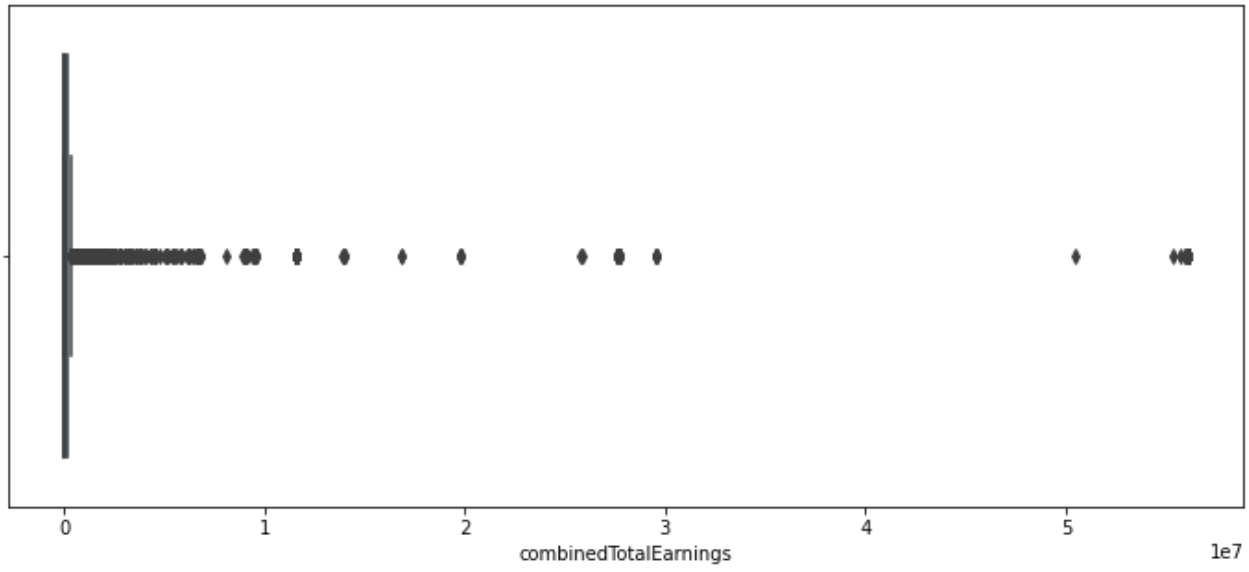
```
df[['combinedTotalRevenue']] = imputer.fit_transform(df[['combinedTotalRevenue']])
```

In [209]:

```
## combinedTotalEarnings
sns.boxplot(df['combinedTotalEarnings'])
```

Out[209]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf575ad10>



In [210]:

```
Q1_ear = df['combinedTotalEarnings'].quantile(0.25)
Q3_ear = df['combinedTotalEarnings'].quantile(0.75)
IQR_ear = Q3_ear - Q1_ear
```

In [211]:

```
((df['combinedTotalEarnings'] < (Q1_ear - 1.5*IQR_ear)) | (df['combinedTotalEarnings'] >
(Q3_ear + 1.5*IQR_ear))).sum()
```

Out[211]:

```
661
```

We find the same case for combinedTotalEarnings, and so we will impute by median.

In [212]:

```
df[['combinedTotalEarnings']] = imputer.fit_transform(df[['combinedTotalEarnings']])
```

In [213]:

```
df.isnull().sum()
```

Out[213]:

```
recno                     0
portrait                  2
location                  0
hourlyRate                0
lastActivity              0
totalHoursBilled          0
totalPortfolioItems       0
skills                    0
nss100                    0
topRatedStatus            0
combinedTotalRevenue      0
totalHourlyJobs           0
totalFpJobs               0
hideEarnings              0
combinedTotalEarnings     0
topTalentGroup           13
descriptionSanitized      0
shortNameSanitized        0
titleSanitized            0
url                       0
uid                       0
searchRank                0
querySkill                0
querySkillUid             0
date_scrapped             0
searchRankRange           0
dtype: int64
```

In [214]:

```
## Imputing categorical data

from sklearn_pandas import CategoricalImputer

c_imputer = CategoricalImputer()
df['topTalentGroup'] = c_imputer.fit_transform(df['topTalentGroup'])
```

In [215]:

```
df.isnull().sum()
```

Out[215]:

```
recno                     0
```

```
portrait                  2
location                  0
hourlyRate                0
lastActivity              0
totalHoursBilled          0
totalPortfolioItems       0
skills                    0
nss100                    0
topRatedStatus            0
combinedTotalRevenue      0
totalHourlyJobs           0
totalFpJobs               0
hideEarnings              0
combinedTotalEarnings     0
topTalentGroup            0
descriptionSanitized      0
shortNameSanitized        0
titleSanitized            0
url                       0
uid                       0
searchRank                0
querySkill                0
querySkillUid             0
date_scrapped             0
searchRankRange           0
dtype: int64
```

Cardinality of categorical variables

In [216]:

```
## topRatedStatus
```

In [217]:

```
df['topRatedStatus'].value_counts()
```

Out[217]:

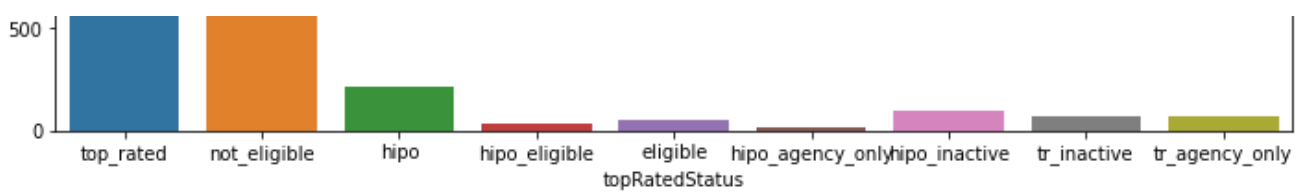
```
top_rated           2334
not_eligible        1610
hipo                 218
hipo_inactive        100
tr_inactive           68
tr_agency_only        68
eligible              56
hipo_eligible         31
hipo_agency_only      15
Name: topRatedStatus, dtype: int64
```

In [218]:

```
sns.countplot(df['topRatedStatus'])
```

Out[218]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf48cd410>
```



In [219]:

```
## topTalentGroup

df['topTalentGroup'].value_counts()
```

Out[219]:

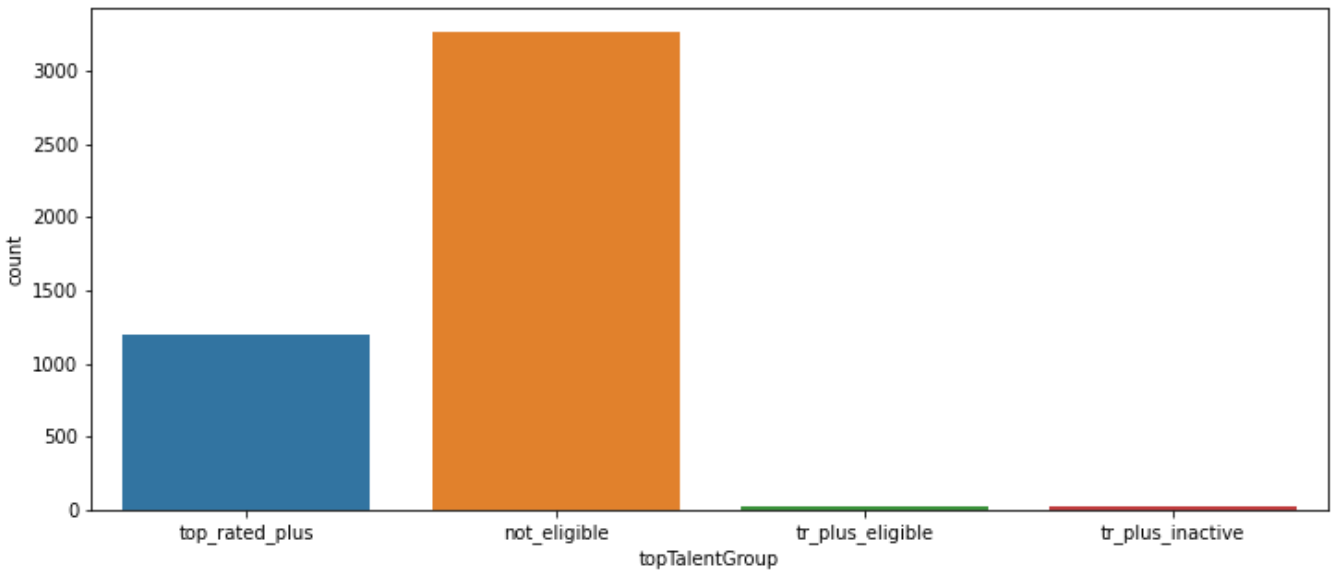
```
not_eligible         3262
top_rated_plus       1197
tr_plus_eligible       23
tr_plus_inactive       18
Name: topTalentGroup, dtype: int64
```

In [220]:

```
sns.countplot(df['topTalentGroup'])
```

Out[220]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf3b97990>
```



In [221]:

```
df['querySkill'].value_counts()
```

Out[221]:

```
API Development                500
OOPS                           500
Real Time Stream Processing    500
AngularJS                      500
iOS Development                500
HTML5                          500
Mobile UI Design               500
Symfony                        500
Android App Development        500
Name: querySkill, dtype: int64
```

In [222]:

```
df['querySkill'].value_counts()
```

Out[222]:

```
API Development                500
OOPS                           500
```

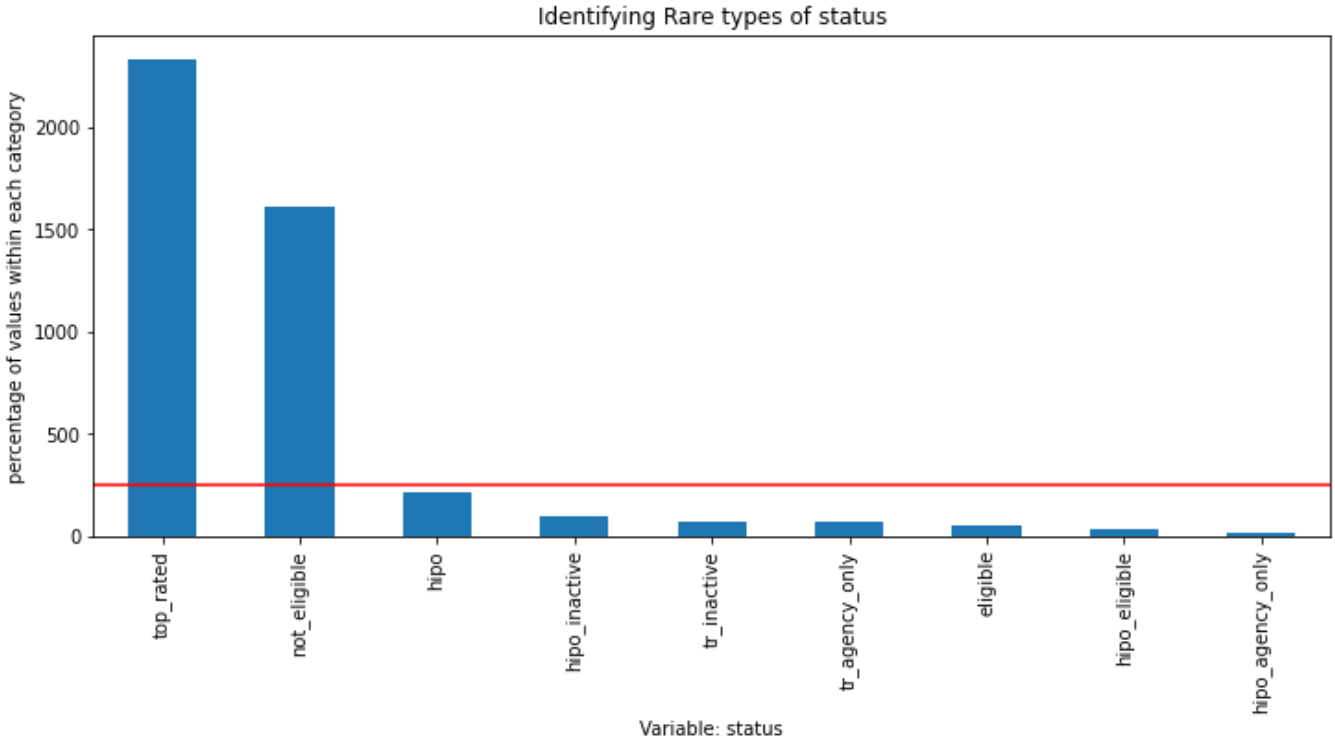
```
Real Time Stream Processing    500
AngularJS                      500
iOS Development                500
HTML5                          500
Mobile UI Design               500
Symfony                        500
Android App Development        500
Name: querySkill, dtype: int64
```

In [223]:

```
## Reducing cardinality
```

In [224]:

```
fig = df['topRatedStatus'].value_counts().sort_values(ascending=False).plot.bar()
fig.axhline(y=250, color='red')
fig.set_ylabel('percentage of values within each category')
fig.set_xlabel('Variable: status')
fig.set_title('Identifying Rare types of status')
plt.show()
```



We see that most values within the top_rated status are either top_rated or not_eligible. We can map all the other categories into one category called "Other".

In [225]:

```
df['topRatedStatus'].value_counts()
```

Out[225]:

```
top_rated           2334
not_eligible        1610
hipo                 218
hipo_inactive        100
tr_inactive           68
tr_agency_only        68
eligible              56
hipo_eligible         31
hipo_agency_only      15
Name: topRatedStatus, dtype: int64
```

In [226]:

```
label_map = {'top_rated': 'top_rated', 'not_eligible': 'not_eligible', 'hipo': 'Other',
```

```
'hipo_inactive': 'Other', 'tr_inactive': 'Other', 'tr_agency_only': 'Other', 'eligible':
'Other', 'hipo_eligible': 'Other', 'hipo_agency_only': 'Other'}

df['topRatedStatus'] = df['topRatedStatus'].apply(lambda x: label_map[x])
```

In [227]:

```
df['topRatedStatus'].value_counts()
```

Out[227]:

```
top_rated       2334
not_eligible    1610
Other            556
Name: topRatedStatus, dtype: int64
```

Similarly for the talent groups:

In [228]:

```
df['topTalentGroup'].value_counts()
```

Out[228]:

```
not_eligible         3262
top_rated_plus       1197
tr_plus_eligible       23
tr_plus_inactive       18
Name: topTalentGroup, dtype: int64
```

In [229]:

```
talent_label_map = {'not_eligible': 'not_eligible', 'top_rated_plus': 'top_rated_plus',
'tr_plus_eligible': 'Other', 'tr_plus_inactive': 'Other'}
df['topTalentGroup'] = df['topTalentGroup'].apply(lambda x: talent_label_map[x])
```

In [230]:

```
df['topTalentGroup'].value_counts()
```

Out[230]:

```
not_eligible      3262
top_rated_plus    1197
Other               41
Name: topTalentGroup, dtype: int64
```

In [231]:

```
X = df[['hourlyRate', 'totalHoursBilled', 'totalPortfolioItems', 'skills', 'topRatedStat
us', 'combinedTotalRevenue', 'totalHourlyJobs', 'totalFpJobs', 'hideEarnings', 'combinedT
otalEarnings', 'topTalentGroup', 'descriptionSanitized', 'titleSanitized', 'querySkill',
'searchRankRange' ]]
```

Feature Engineering

With the features we currently have, we can either create new features or modify the existing features to create new attributes that might have an influence on the ranking. Let explore some of them :

- **skillPresent = check if querySkill is present in set of skills of the freelancer**
- **HoursPerJob = totalHoursBilled/totalHourlyJobs**

In [232]:

```
X['skillPresent'] = X.apply(lambda x: x.querySkill in x.skills, axis=1)
X['skillPresent'] = X['skillPresent'].astype(int)
X.head()
```

Out[232]:

	hourlyRate	totalHoursBilled	totalPortfolioItems	skills	topRatedStatus	combinedTotalRevenue	totalHourlyJobs	tot
0	110.0	9495.500000	35	[PHP, API Development, Laravel, AJAX, jQuery, ...	top_rated	254100.57	70	
1	14.0	1396.166667	5	[ASP.NET MVC, Angular, jQuery, AJAX, ASP.NET, ...	top_rated	53061481.28	7	
2	39.0	1200.761034	2	[iOS Development, Objective-C, Apple Xcode, SQ...	top_rated	26506670.76	6	
3	40.0	35.333333	3	[SEO Writing, Blog Writing, Article Writing, C...	top_rated	6224.34	3	
4	20.0	118.500000	7	[API, Database Architecture, Website Developme...	top_rated	7995.80	8	

In [233]:

```
## Hours per job

X['hoursPerJob'] = X['totalHoursBilled']/X['totalHourlyJobs']
```

In [234]:

```
X.head()
```

Out[234]:

	hourlyRate	totalHoursBilled	totalPortfolioItems	skills	topRatedStatus	combinedTotalRevenue	totalHourlyJobs	tot
0	110.0	9495.500000	35	[PHP, API Development, Laravel, AJAX, jQuery, ...	top_rated	254100.57	70	
1	14.0	1396.166667	5	[ASP.NET MVC, Angular, jQuery, AJAX, ASP.NET, ...	top_rated	53061481.28	7	
2	39.0	1200.761034	2	[iOS Development, Objective-C, Apple Xcode, SQ...	top_rated	26506670.76	6	
3	40.0	35.333333	3	[SEO Writing, Blog Writing, Article Writing, C...	top_rated	6224.34	3	
4	20.0	118.500000	7	[API, Database Architecture, Website Developme...	top_rated	7995.80	8	

Identifying linear relationships

In [235]:

```
print(df.columns)
```

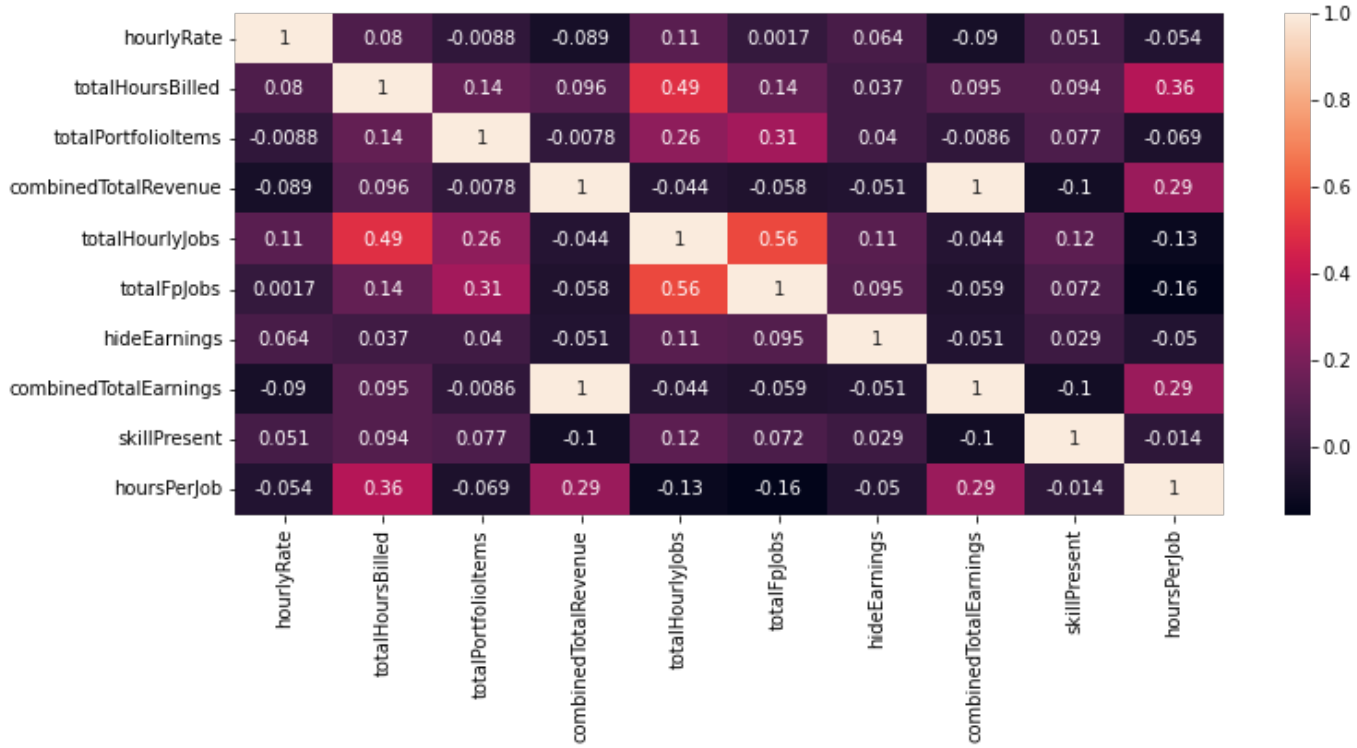
```
Index(['recno', 'portrait', 'location', 'hourlyRate', 'lastActivity',
       'totalHoursBilled', 'totalPortfolioItems', 'skills', 'nss100',
       'topRatedStatus', 'combinedTotalRevenue', 'totalHourlyJobs',
       'totalFpJobs', 'hideEarnings', 'combinedTotalEarnings',
       'topTalentGroup', 'descriptionSanitized', 'shortNameSanitized',
       'titleSanitized', 'url', 'uid', 'searchRank', 'querySkill',
       'querySkillUid', 'date_scrapped', 'searchRankRange'],
      dtype='object')
```

In [236]:

```
sns.heatmap(X.corr(), annot=True)
```

Out[236]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6bf373f790>
```



There are several interesting insights from this:

- **There is significant correlation between totalHourlyJobs and totalHoursBilled - which makes sense because the more jobs you do, the more hours you put in. (0.49)**
- **There is also a significant correlation between totalFpJobs and totalHourlyJobs. (0.56)**
- **Finally, there is a huge correlation between combinedTotalRevenue and combinedTotalEarnings. The reason for this is simply because combinedTotalEarnings = combinedTotalRevenue + incentives**

Based on the above insigths, we can drop a few correlated features that would hinder the precision of the estimated coefficients.

In [237]:

```
X.drop(columns=['totalHourlyJobs', 'totalFpJobs', 'combinedTotalRevenue'], inplace=True)
```

In [238]:

```
X.head()
```

Out[238]:

	hourlyRate	totalHoursBilled	totalPortfolioItems	skills	topRatedStatus	hideEarnings	combinedTotalEarnings	topT
0	110.0	9495.500000	35	[PHP, API Development, Laravel, AJAX, jQuery, ...	top_rated	0	275612.50	top_
1	14.0	1396.166667	5	[ASP.NET MVC, Angular, jQuery, AJAX, ASP.NET, ...	top_rated	0	56062604.80	top_
2	39.0	1200.761034	2	[iOS Development, Objective-C, Apple Xcode, SQ...	top_rated	0	27630978.69	top_
3	40.0	35.333333	3	[SEO Writing, Blog Writing, Article Writing, C...	top_rated	0	7308.17	r
4	20.0	118.500000	7	[API, Database Architecture, Website Developme...	top_rated	0	9541.00	r

Encoding categorical variables

In [239]:

```
encoded_X = pd.get_dummies(X[['topRatedStatus', 'topTalentGroup', 'hideEarnings']])
```

In [240]:

```
X = pd.concat([X, encoded_X], axis=1)
X.head()
```

Out[240]:

	hourlyRate	totalHoursBilled	totalPortfolioItems	skills	topRatedStatus	hideEarnings	combinedTotalEarnings	topT
0	110.0	9495.500000	35	[PHP, API Development, Laravel, AJAX, jQuery, ...	top_rated	0	275612.50	top_
1	14.0	1396.166667	5	[ASP.NET MVC, Angular, jQuery, AJAX, ASP.NET, ...	top_rated	0	56062604.80	top_
2	39.0	1200.761034	2	[iOS Development, Objective-C, Apple Xcode, SQ...	top_rated	0	27630978.69	top_
3	40.0	35.333333	3	[SEO Writing, Blog Writing, Article Writing, C...	top_rated	0	7308.17	r
4	20.0	118.500000	7	[API, Database Architecture,	top_rated	0	9541.00	r

	hourlyRate	totalHoursBilled	totalPortfolioItems	Website skills Developme...	topRatedStatus	hideEarnings	combinedTotalEarnings	topT

5 rows × 21 columns

In [241]:

```
X.drop(['topRatedStatus', 'hideEarnings', 'topTalentGroup'], axis=1, inplace=True)
```

In [242]:

```
X.drop(['titleSanitized', 'descriptionSanitized', 'skills'], axis=1, inplace=True)
```

In [243]:

```
X.head()
```

Out[243]:

	hourlyRate	totalHoursBilled	totalPortfolioItems	combinedTotalEarnings	querySkill	searchRankRange	skillPresent	hour
0	110.0	9495.500000	35	275612.50	API Development	401-500	1	13
1	14.0	1396.166667	5	56062604.80	OOPS	101-200	0	19
2	39.0	1200.761034	2	27630978.69	API Development	401-500	0	20
3	40.0	35.333333	3	7308.17	Real Time Stream Processing	301-400	0	1
4	20.0	118.500000	7	9541.00	API Development	0-100	1	1

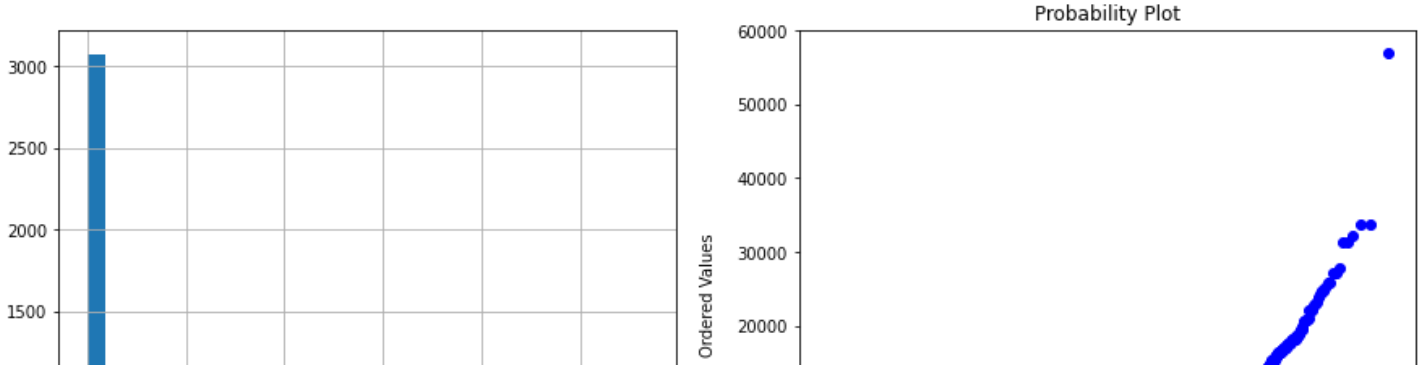
- **Transfroming variables with the logarithm : The logarithm function is commonly used to transform variables. It has a strong effect on the shape of the variable distribution and can be applied to positive variables.**
- **To evaluate the effect of the transformation on the variable distribution, we will create a funciton that takes a dataframe and a variable name and plots a histogram next to a QQ plot.**

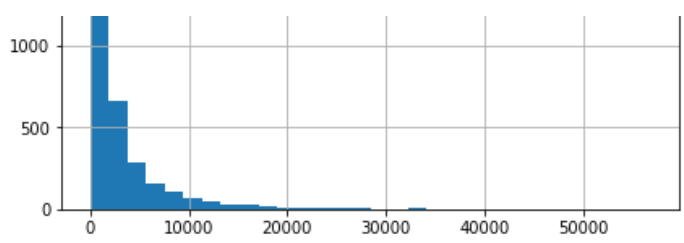
In [244]:

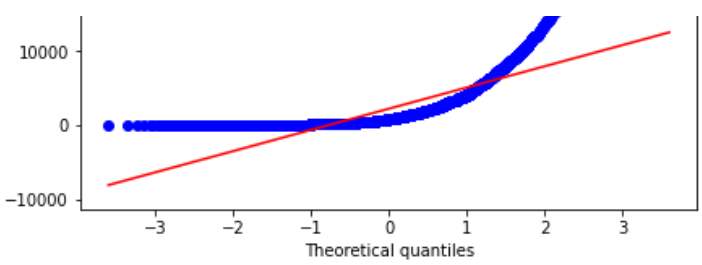
```
import scipy.stats as stats

def diagnostic_plots(df, variable):
  plt.figure(figsize=(15,6))
  plt.subplot(1,2,1)
  df[variable].hist(bins=30)
  plt.subplot(1,2,2)
  stats.probplot(df[variable], dist='norm', plot=plt)
  plt.show()
```

In [245]:

```
diagnostic_plots(X, 'totalHoursBilled')
```



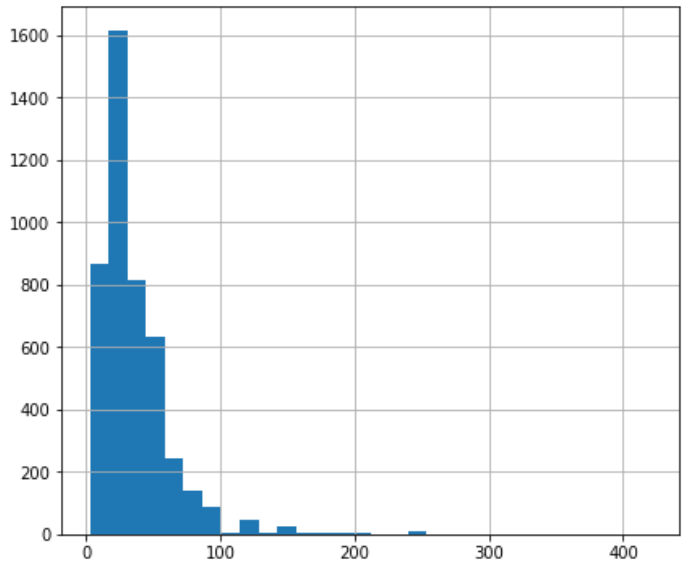


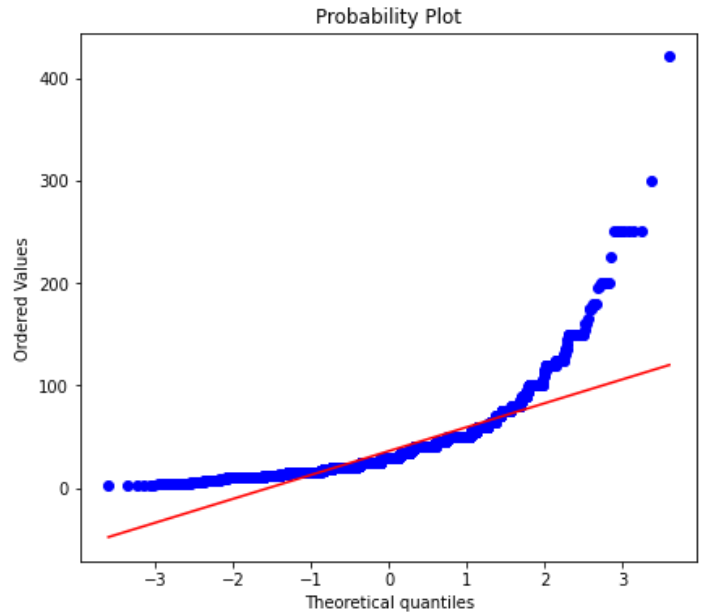


As we can see, the distribution in the data is clearly skewed and doesn not seem to follow a normal distribution. Let us check if we can transform the data to make it more normal. Before that, let us look at some more examples before the transformation.

In [246]:

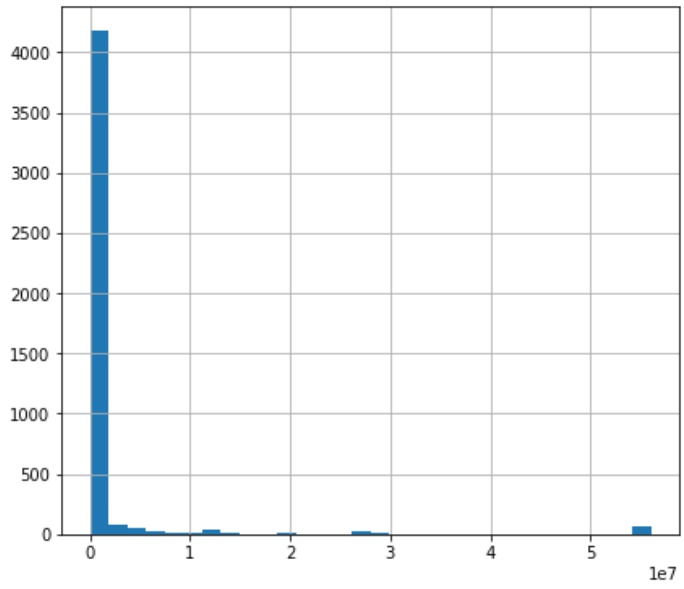
```
diagnostic_plots(X, 'hourlyRate')
```

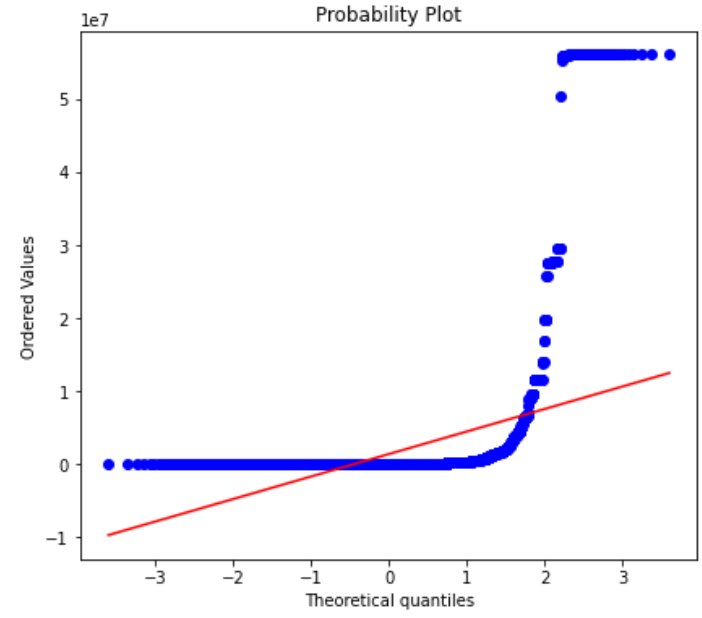




In [247]:

```
diagnostic_plots(X, 'combinedTotalEarnings')
```





In [248]:

```
to_log = ['hourlyRate', 'totalHoursBilled','combinedTotalEarnings' ]
X_log = X[to_log].applymap(lambda x: np.log(x+1))
X_log.columns = 'log_'+ X_log.columns
X_log.head()
```

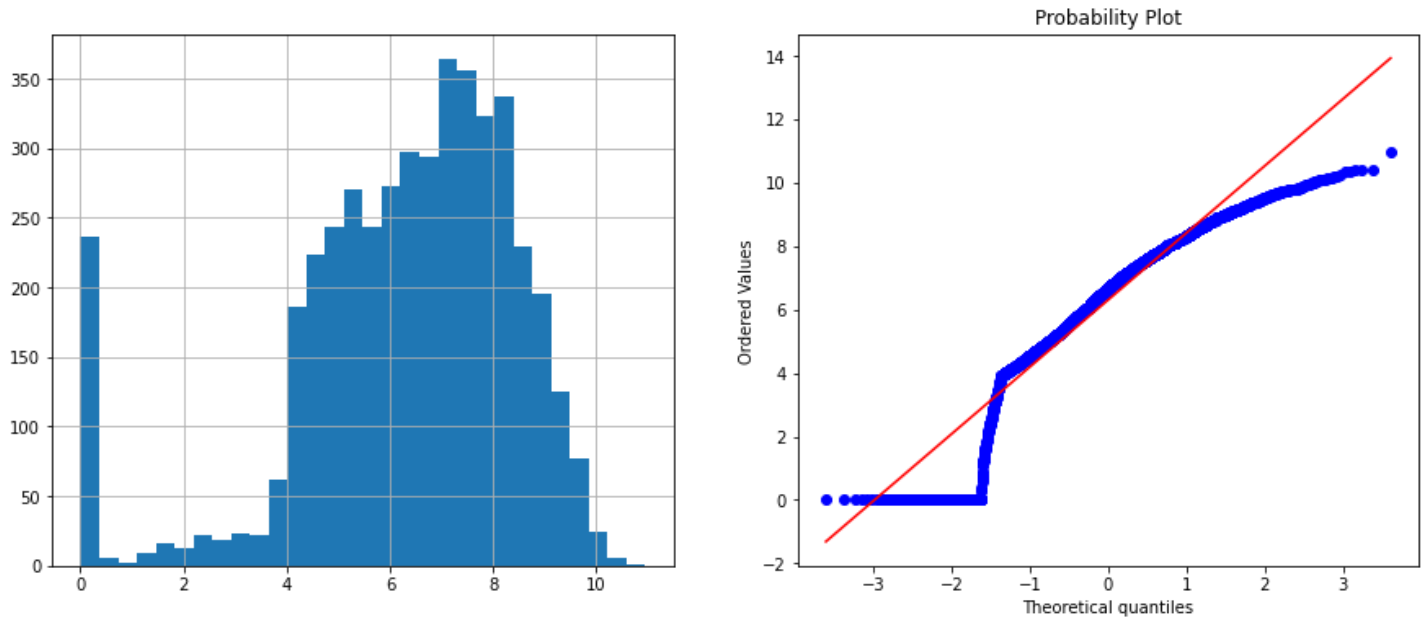
Out[248]:

Out[248]:

	log_hourlyRate	log_totalHoursBilled	log_combinedTotalEarnings
0	4.709530	9.158679	12.526755
1	2.708050	7.242202	17.841980
2	3.688879	7.091543	17.134448
3	3.713572	3.592736	8.896885
4	3.044522	4.783316	9.163458

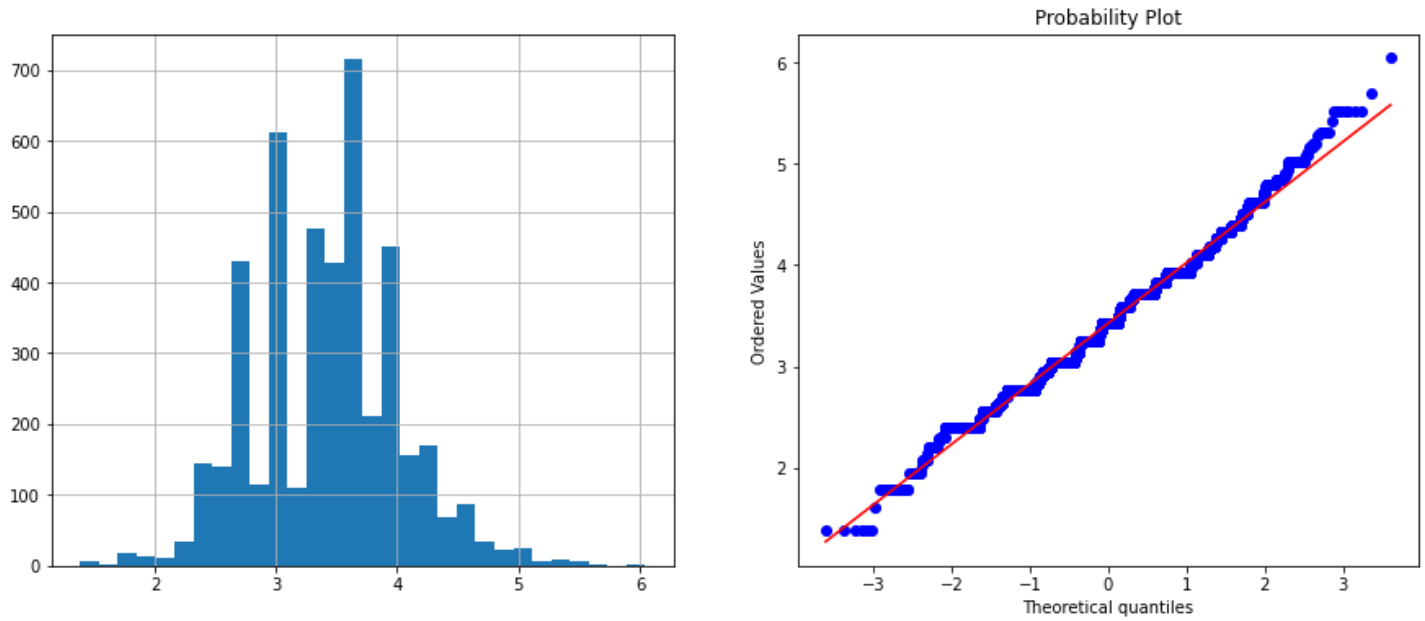
In [249]:

```
diagnostic_plots(X_log, 'log_totalHoursBilled')
```



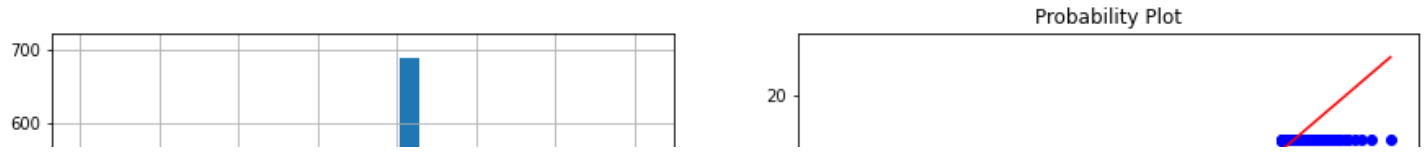
In [250]:

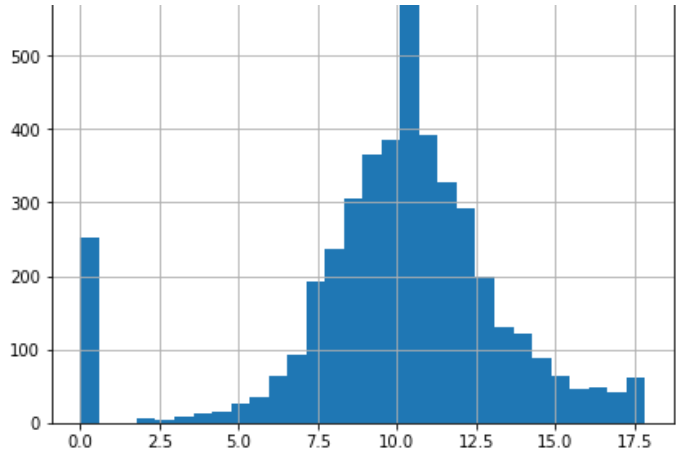
```
diagnostic_plots(X_log, 'log_hourlyRate')
```

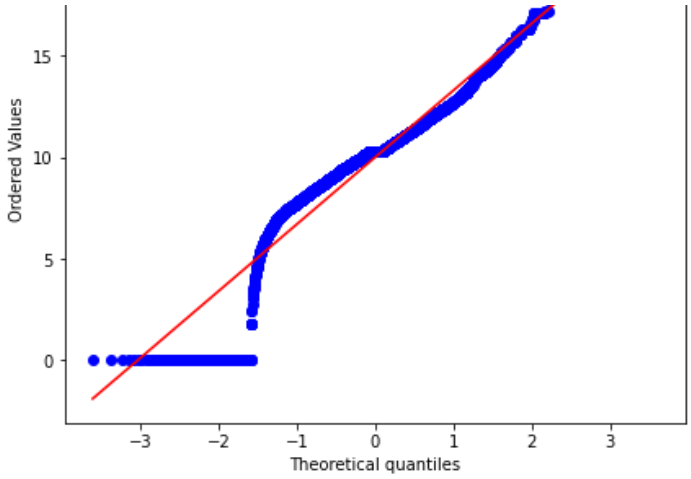


In [251]:

```
diagnostic_plots(X_log, 'log_combinedTotalEarnings')
```







In [252]:

```
X = pd.concat([X, X_log], axis=1)
```

In [253]:

```
X[['hoursPerJob']] = imputer.fit_transform(X[['hoursPerJob']])
```

In [254]:

```
X.head()
```

Out[254]:

	hourlyRate	totalHoursBilled	totalPortfolioItems	combinedTotalEarnings	querySkill	searchRankRange	skillPresent	hou
0	110.0	9495.500000	35	275612.50	API Development	401-500	1	13
1	14.0	1396.166667	5	56062604.80	OOPS	101-200	0	19
2	39.0	1200.761034	2	27630978.69	API Development	401-500	0	20
3	40.0	35.333333	3	7308.17	Real Time Stream Processing	301-400	0	1
4	20.0	118.500000	7	9541.00	API Development	0-100	1	1

In [255]:

```
X.drop(['hourlyRate', 'totalHoursBilled', 'combinedTotalEarnings'], axis=1, inplace=True
)
```

In [256]:

```
X.head()
```

Out[256]:

	totalPortfolioItems	querySkill	searchRankRange	skillPresent	hoursPerJob	topRatedStatus_Other	topRatedStatus_not_e
0	35	API Development	401-500	1	135.650000	0	
1	5	OOPS	101-200	0	199.452381	0	
2	2	API Development	401-500	0	200.126839	0	
3	3	Real Time Stream Processing	301-400	0	11.777778	0	
4	7	API	0-100	1	14.810500	0	

	totalPortfolioItems	querySkill	searchRankRange	skillPresent	hoursPerJob	topRatedStatus_Other	topRatedStatus_not_e
4	7	Development	0-100	1	14.812500	0	

Modeling

In [257]:

```
X[['searchRankRange']].values
```

Out[257]:

```
array([['401-500'],
       ['101-200'],
       ['401-500'],
       ...,
       ['0-100'],
       ['101-200'],
       ['101-200']], dtype=object)
```

In [258]:

```
X_groups = X.groupby('querySkill')
X_groups_list = [X_groups.get_group(x) for x in X_groups.groups]
```

In [259]:

```
X.head()
```

Out[259]:

	totalPortfolioItems	querySkill	searchRankRange	skillPresent	hoursPerJob	topRatedStatus_Other	topRatedStatus_not_e
0	35	API Development	401-500	1	135.650000	0	
1	5	OOPS	101-200	0	199.452381	0	
2	2	API Development	401-500	0	200.126839	0	
3	3	Real Time Stream Processing	301-400	0	11.777778	0	
4	7	API Development	0-100	1	14.812500	0	

In [260]:

```
def logistic_regression_model(data):
  X = data[['totalPortfolioItems', 'skillPresent', 'hoursPerJob', 'topRatedStatus_Other'
, 'topRatedStatus_not_eligible', 'topRatedStatus_top_rated', 'topTalentGroup_Other', 'top
TalentGroup_not_eligible', 'topTalentGroup_top_rated_plus', 'log_hourlyRate', 'log_totalH
oursBilled', 'log_combinedTotalEarnings']]
  y = data[['searchRankRange']].values
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
  lr = LogisticRegression()
  lr.fit(X_train, y_train)
  return lr.score(X_test, y_test)
```

In [261]:

```
def group_predictions_lr(data):
  return data.groupby('querySkill').apply(logistic_regression_model)
```

In [262]:

```
print(group_predictions_lr(X))
```

```
querySkill
```

```
API Development                 0.15
Android App Development         0.21
AngularJS                       0.28
HTML5                           0.35
Mobile UI Design                0.24
OOPS                            0.40
Real Time Stream Processing     0.20
Symfony                         0.18
iOS Development                 0.20
dtype: float64
```

In [263]:

```
def knn_model(data):
  X = data[['totalPortfolioItems', 'skillPresent', 'hoursPerJob', 'topRatedStatus_Other'
, 'topRatedStatus_not_eligible', 'topRatedStatus_top_rated', 'topTalentGroup_Other', 'top
TalentGroup_not_eligible', 'topTalentGroup_top_rated_plus', 'log_hourlyRate', 'log_totalH
oursBilled', 'log_combinedTotalEarnings']]
  y = data[['searchRankRange']].values
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
  knn = KNeighborsClassifier()
  knn.fit(X_train, y_train)
  return knn.score(X_test, y_test)
```

In [264]:

```
def group_predictions_knn(data):
  return data.groupby('querySkill').apply(knn_model)
```

In [265]:

```
print(group_predictions_knn(X))
```

```
querySkill
API Development                 0.22
Android App Development         0.22
AngularJS                       0.27
HTML5                           0.25
Mobile UI Design                0.35
OOPS                            0.38
Real Time Stream Processing     0.20
Symfony                         0.13
iOS Development                 0.26
dtype: float64
```

In [266]:

```
def dt_model(data):
  X = data[['totalPortfolioItems', 'skillPresent', 'hoursPerJob', 'topRatedStatus_Other'
, 'topRatedStatus_not_eligible', 'topRatedStatus_top_rated', 'topTalentGroup_Other', 'top
TalentGroup_not_eligible', 'topTalentGroup_top_rated_plus', 'log_hourlyRate', 'log_totalH
oursBilled', 'log_combinedTotalEarnings']]
  y = data[['searchRankRange']].values
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
  dt = DecisionTreeClassifier(random_state=0)
  dt.fit(X_train, y_train)
  return dt.score(X_test, y_test)
```

In [267]:

```
def group_predictions_dt(data):
  return data.groupby('querySkill').apply(dt_model)
```

In [268]:

```
print(group_predictions_dt(X))
```

```
querySkill
API Development                 0.23
Android App Development         0.33
AngularJS                       0.26
HTML5                           0.27
```

```
HTML5                          0.37
Mobile UI Design               0.40
OOPS                           0.44
Real Time Stream Processing    0.42
Symfony                        0.28
iOS Development                0.41
dtype: float64
```

In [308]:

```
def rf_model(data):
  X = data[['totalPortfolioItems', 'skillPresent', 'hoursPerJob', 'topRatedStatus_Other'
, 'topRatedStatus_not_eligible', 'topRatedStatus_top_rated', 'topTalentGroup_Other', 'top
TalentGroup_not_eligible', 'topTalentGroup_top_rated_plus', 'log_hourlyRate', 'log_totalH
oursBilled', 'log_combinedTotalEarnings']]
  y = data[['searchRankRange']].values
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
  rf = RandomForestClassifier()
  rf.fit(X_train, y_train)
  return rf.score(X_test, y_test)
```

In [309]:

```
def group_predictions_rf(data):
  return data.groupby('querySkill').apply(rf_model)
```

In [310]:

```
print(group_predictions_rf(X))
```

```
querySkill
API Development                0.32
Android App Development        0.30
AngularJS                      0.26
HTML5                          0.41
Mobile UI Design               0.38
OOPS                           0.61
Real Time Stream Processing    0.35
Symfony                        0.44
iOS Development                0.41
dtype: float64
```

In [271]:

```

```