Exploratory Data Analysis of the H1B data set --- (2011 to 2016)

https://www.kaggle.com/nsharan/h-1b-visa ***Source of data***

Context :

H-1B visas are a category of employment-based, non-immigrant visas for temporary foreign workers in the United States. For a foreign national to apply for H1-B visa, a US employer must offer them a job and submit a petition for a H-1B visa to the US immigration department. This is also the most common visa status applied for and held by international students once they complete college or higher education and begin working in a full-time position.

The following articles contain more information about the H-1B visa process:

Overview of Data

This dataset contains five year's worth of H-1B petition data, with approximately 3 million records overall. The columns in the dataset include case status, employer name, worksite coordinates, job title, prevailing wage, occupation code, and year filed.

In [259…

```
import numpy as np
import matplotlib
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('seaborn')
```

Reading and cleaning the Data

First let us begin with reading and cleaning the data.
The column unnamed 0 is removed.

1. Drop the rows having na values and remove high value outliers
2. We would analyse the data as 2 sets Certified cases and denied cases
3. Observing the head and the info of the data Frame we see that data has 2877765 rows and is summarised as below

   Data columns (total 10 columns): **Column Non-Null Count Dtype**

   - CASE_STATUS 2877765 non-null object

- EMPLOYER_NAME 2877765 non-null object
- SOC_NAME 2877765 non-null object
- JOB_TITLE 2877765 non-null object
- FULL_TIME_POSITION 2877765 non-null object
- PREVAILING_WAGE 2877765 non-null float64
- YEAR 2877765 non-null float64
- WORKSITE 2877765 non-null object
- lon 2877765 non-null float64
- lat 2877765 non-null float64 dtypes: float64(4), object(6) memory usage: 241.5+ MB

In [260…

```
df = pd.read_csv('h1b_kaggle.csv')
df = df.dropna(axis=0)
df.drop('Unnamed: 0',inplace=True ,axis=1)
# Do Some cleaning to remove duplicates with different cases
df['EMPLOYER_NAME'] = df['EMPLOYER_NAME'].apply(lambda x : x.upper())
df['SOC_NAME']= df['SOC_NAME'].apply(lambda x : x.title())
df['JOB_TITLE']= df['JOB_TITLE'].apply(lambda x : x.title())
df['FULL_TIME_POSITION'] = df['FULL_TIME_POSITION'].apply(lambda x : x.upper())
df['WORKSITE'] = df['WORKSITE'].apply(lambda x : x.title())
```

In [261…

```
df.head(5)
```

Out[261…

	CASE_STATUS	EMPLOYER_NAME	SOC_NAME	JOB_TITLE	FULL_TIME_POSITION	PREVAILING_WAGE	YEAR	WORKSITE	l
0	CERTIFIED-WITHDRAWN	UNIVERSITY OF MICHIGAN	Biochemists And Biophysicists	Postdoctoral Research Fellow	N	36067.0	2016.0	Ann Arbor, Michigan	-83.7430
1	CERTIFIED-WITHDRAWN	GOODMAN NETWORKS, INC.	Chief Executives	Chief Operating Officer	Y	242674.0	2016.0	Plano, Texas	-96.6988
2	CERTIFIED-WITHDRAWN	PORTS AMERICA GROUP, INC.	Chief Executives	Chief Process Officer	Y	193066.0	2016.0	Jersey City, New Jersey	-74.0776
3	CERTIFIED-WITHDRAWN	GATES CORPORATION, A WHOLLY-OWNED SUBSIDIARY O...	Chief Executives	Regional Presiden, Americas	Y	220314.0	2016.0	Denver, Colorado	-104.9902
4	WITHDRAWN	PEABODY INVESTMENTS CORP.	Chief Executives	President Mongolia And India	Y	157518.4	2016.0	St. Louis, Missouri	-90.1994

In [262…

```
df.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2877765 entries, 0 to 3002444
Data columns (total 10 columns):
 #   Column              Non-Null Count    Dtype  
---  ------              --------------    -----  
 0   CASE_STATUS         2877765 non-null  object 
 1   EMPLOYER_NAME       2877765 non-null  object 
 2   SOC_NAME            2877765 non-null  object 
 3   JOB_TITLE           2877765 non-null  object 
 4   FULL_TIME_POSITION  2877765 non-null  object 
 5   PREVAILING_WAGE     2877765 non-null  float64
 6   YEAR                2877765 non-null  float64
 7   WORKSITE            2877765 non-null  object 
 8   lon                 2877765 non-null  float64
 9   lat                 2877765 non-null  float64
dtypes: float64(4), object(6)
memory usage: 241.5+ MB
```

In [263…

```
total_certified_cases = df[df['CASE_STATUS']=='CERTIFIED']
certified_cases = total_certified_cases[total_certified_cases['PREVAILING_WAGE']<150000]
```

In [264…

```
certified_cases.head(3)
```

Out[264…

	CASE_STATUS	EMPLOYER_NAME	SOC_NAME	JOB_TITLE	FULL_TIME_POSITION	PREVAILING_WAGE	YEAR	WORKSITE	lor
22	CERTIFIED	LOMICS, LLC	Chief Executives	Ceo	Y	99986.00	2016.0	San Diego, California	-117.16108
23	CERTIFIED	UC UNIVERSITY HIGH SCHOOL EDUCATION INC.	Chief Executives	Chief Financial Officer	Y	99986.00	2016.0	Chula Vista, California	-117.08419
29	CERTIFIED	PERSPECTIVES OF FREEDOM FOUNDATION, INC	Chief Executives	Executive Director	Y	95295.98	2016.0	Weston, Florida	-80.39977

Exploring Wage Distribution for Certified Cases

We get the certified cases and remove very high and very low outliers . Plot the count of certfied cases against the wages we conclude the below

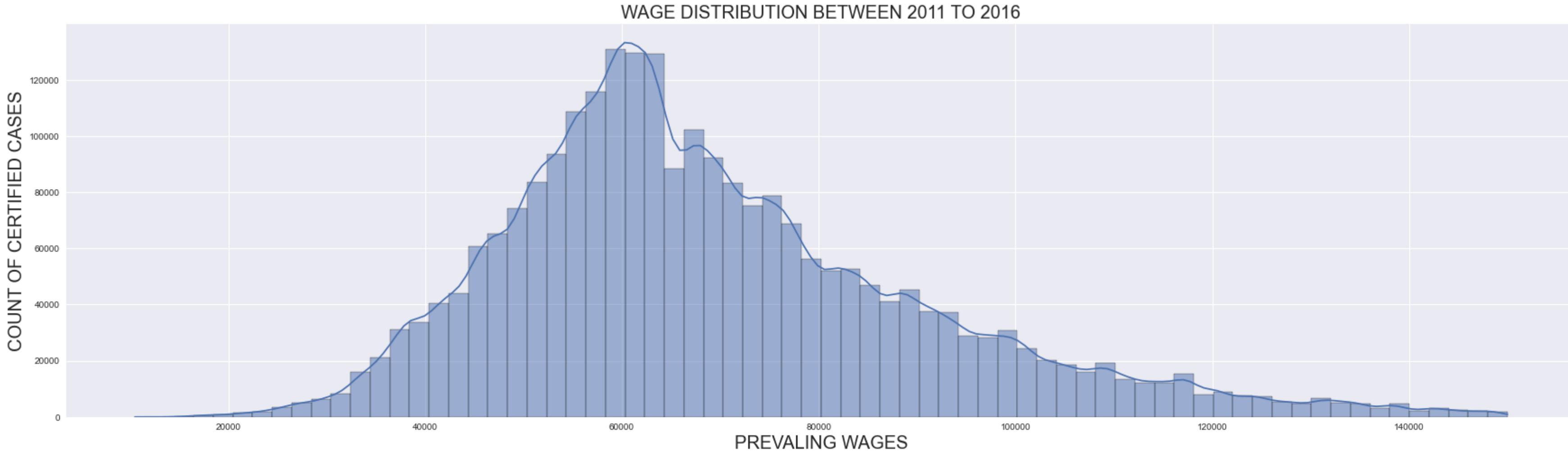
- There are wages varying between 20K per annum to 150K per annum
- Most of them get in the salary bracket of 55k to 70K
- The data is not normally distributed about the peak ,but a little more towards higher end

In [265…

```
plt.figure(figsize=(30,8))
sns.histplot(certified_cases['PREVAILING_WAGE'],edgecolor='black',bins=70,kde=True)
plt.xlabel('PREVALING WAGES',size=20)
plt.ylabel('COUNT OF CERTIFIED CASES', size=20)
plt.title('WAGE DISTRIBUTION BETWEEN 2011 TO 2016',size=20)
```

Out[265…

```
Text(0.5, 1.0, 'WAGE DISTRIBUTION BETWEEN 2011 TO 2016')
```



H1B Count Over Years

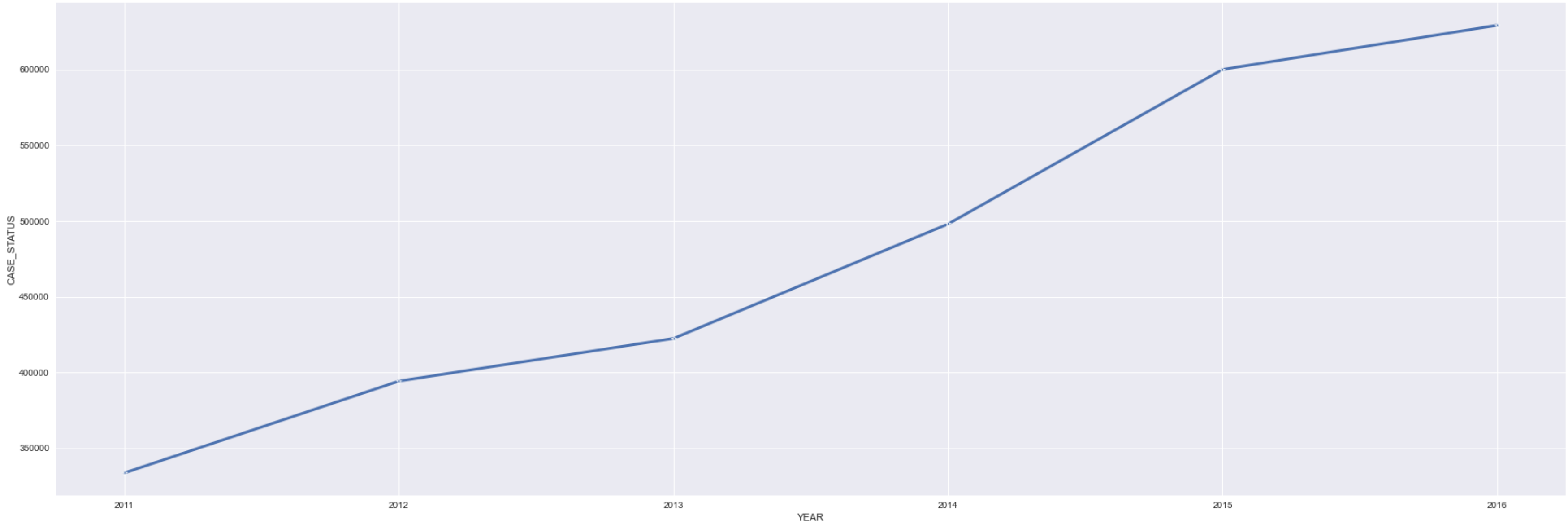
We Observe a gradual increase in the count of certified H1b applications from the period of 2011 to 2016 . This indicates that demand of specialized skills was on the rise in the US. It would be interesting to see if we have data beyond 2016 and see if Trump policies has caused any decline in this

In [266…

```
yearwise = df.groupby('YEAR').count()
plt.figure(figsize=(30,10))
sns.lineplot(data=yearwise['CASE_STATUS'],linewidth=3, marker='*')
```

Out[266…

```
<AxesSubplot:xlabel='YEAR', ylabel='CASE_STATUS'>
```



Who are the main benificiaries of H1B

Below represents as to who are the main benificaries of H1B. It is predominately dominated by Indian IT companies.

- The below table represents the count and a graphical representation of the same

In [267…

```
top_twenty=certified_cases['EMPLOYER_NAME'].value_counts()[:20]
top_twenty.to_frame()
```

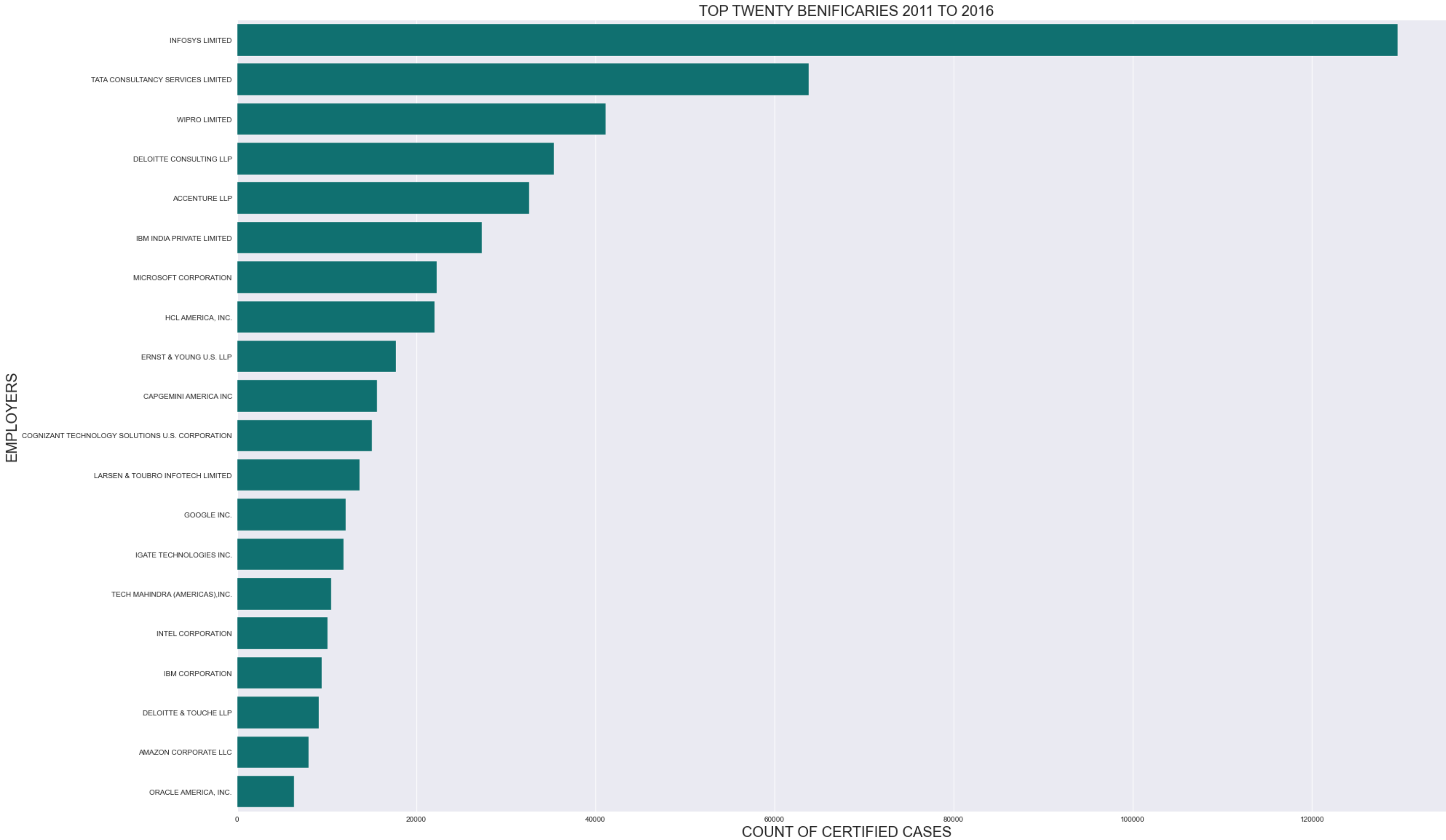
Out[267…

	EMPLOYER_NAME
INFOSYS LIMITED	129572
TATA CONSULTANCY SERVICES LIMITED	63801
WIPRO LIMITED	41170
DELOITTE CONSULTING LLP	35350
ACCENTURE LLP	32598
IBM INDIA PRIVATE LIMITED	27290
MICROSOFT CORPORATION	22267
HCL AMERICA, INC.	22024
ERNST & YOUNG U.S. LLP	17724

	EMPLOYER_NAME
CAPGEMINI AMERICA INC	15603
COGNIZANT TECHNOLOGY SOLUTIONS U.S. CORPORATION	15058
LARSEN & TOUBRO INFOTECH LIMITED	13657
GOOGLE INC.	12110
IGATE TECHNOLOGIES INC.	11850
TECH MAHINDRA (AMERICAS),INC.	10517
INTEL CORPORATION	10082
IBM CORPORATION	9437
DELOITTE & TOUCHE LLP	9082
AMAZON CORPORATE LLC	8002
ORACLE AMERICA, INC.	6336

In [268…

```
plt.figure(figsize=(30,20))
sns.barplot(x=top_twenty.values,y=top_twenty.index,color='teal')
plt.xlabel('COUNT OF CERTIFIED CASES',size=20)
plt.ylabel('EMPLOYERS', size=20)
plt.title('TOP TWENTY BENIFICARIES 2011 TO 2016',size=20)
plt.show()
```

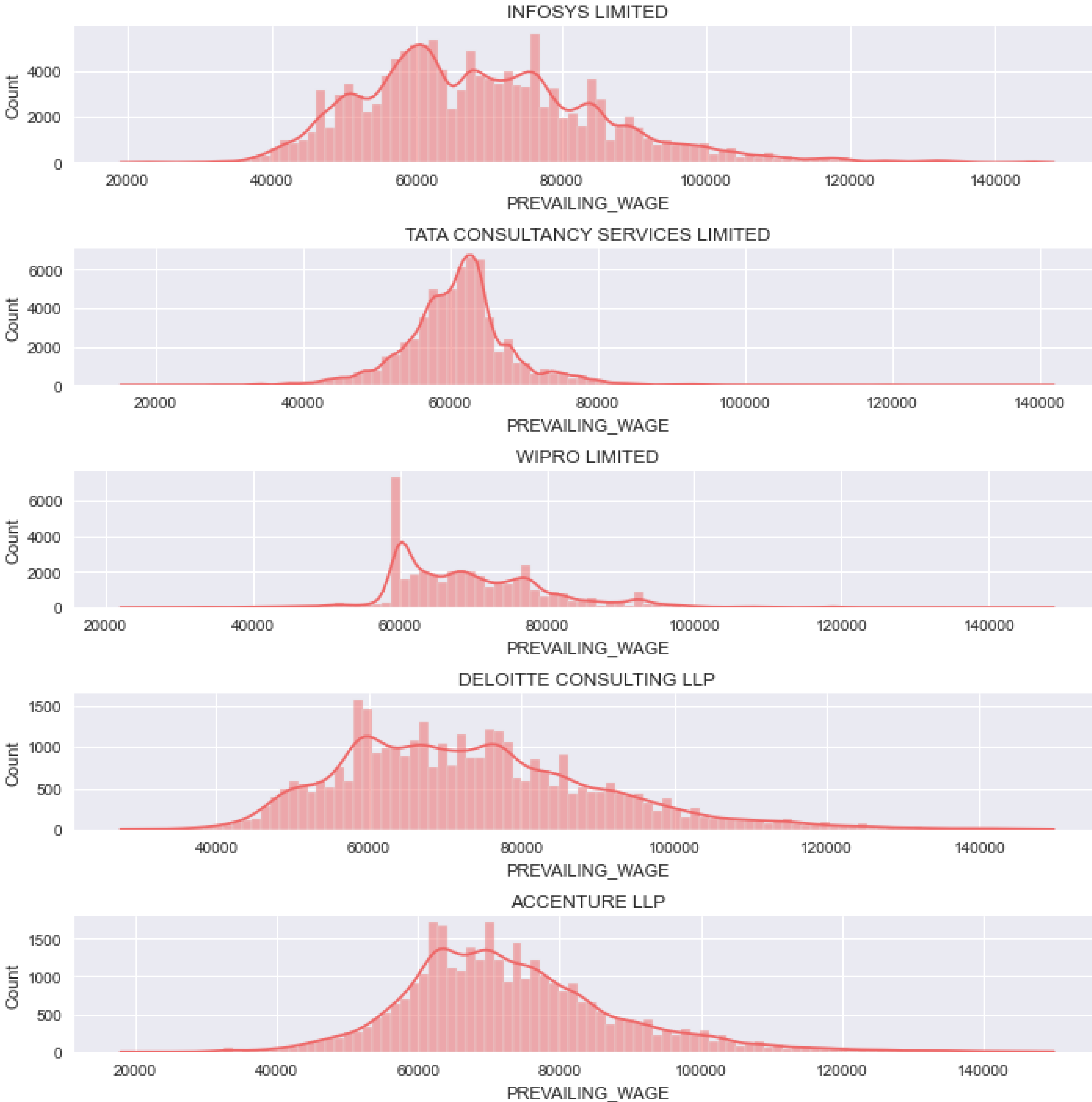


- We also take the top 5 benificaries of H1B and see how their salary is distributed

In [269…

```
f,axes = plt.subplots(nrows=5,ncols=1, figsize=(10,10),sharey=False)
rowcount=0
companies = top_twenty.index[:5]
for company in companies:
    axes[rowcount].set_title(company)
    wage = certified_cases[certified_cases['EMPLOYER_NAME']==company]['PREVAILING_WAGE']
    sns.histplot(data=wage ,ax=axes[rowcount],bins=100,edgecolor='#E6E6E6', color='#EE6666', kde=True)
    rowcount+=1

plt.tight_layout()
```


INFOSYS LIMITED
Count
0
2000
4000
20000
40000
60000
80000
100000
120000
140000
PREVAILING_WAGE
TATA CONSULTANCY SERVICES LIMITED
Count
0
2000
4000
6000
20000
40000
60000
80000
100000
120000
140000
PREVAILING_WAGE
WIPRO LIMITED
Count
0
2000
4000
6000
20000
40000
60000
80000
100000
120000
140000
PREVAILING_WAGE
DELOITTE CONSULTING LLP
Count
0
500
1000
1500
40000
60000
80000
100000
120000
140000
PREVAILING_WAGE
ACCENTURE LLP
Count
0
500
1000
1500
20000
40000
60000
80000
100000
120000
140000
PREVAILING_WAGE

What are the top roles and What roles get highest pay

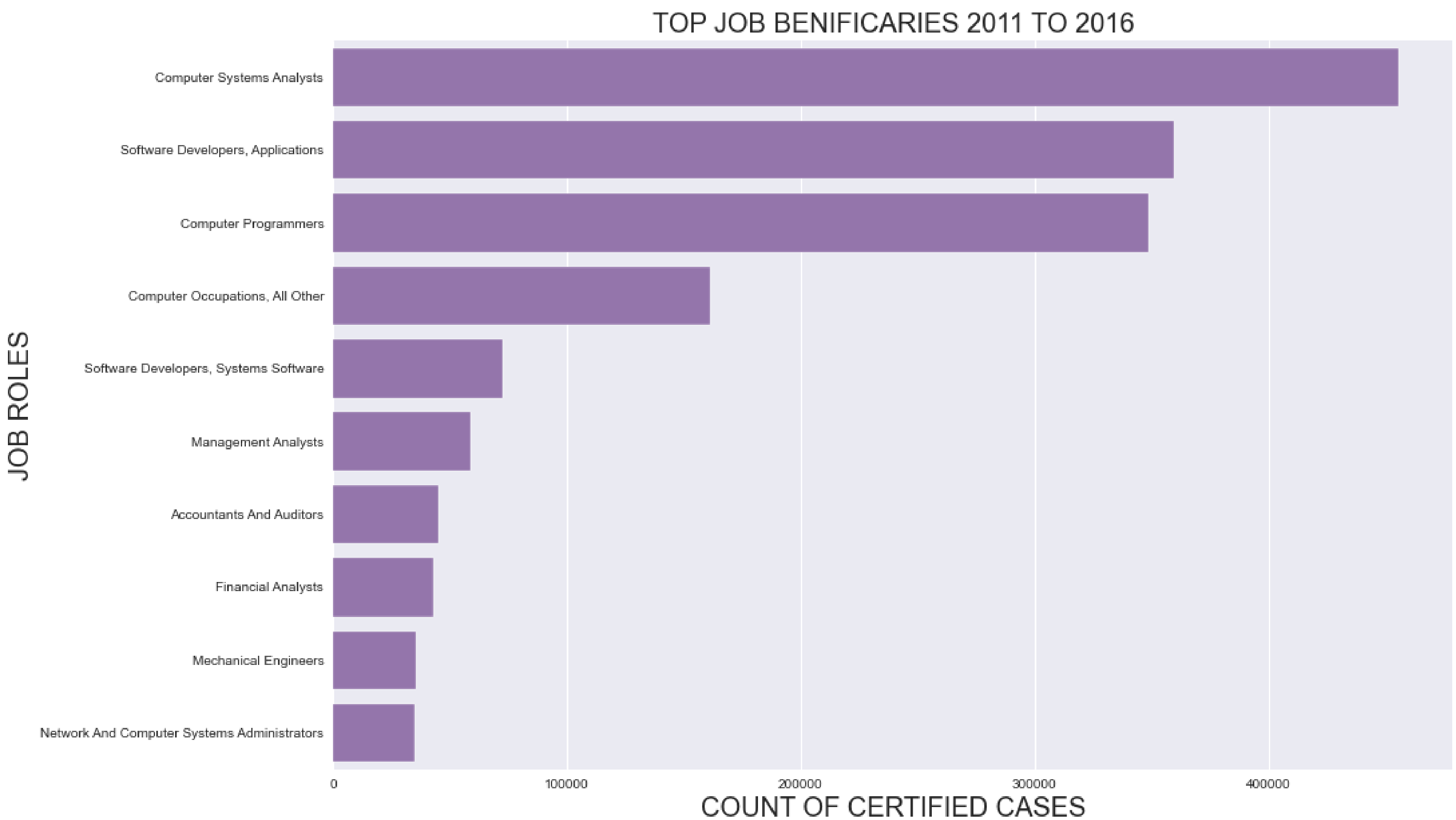
Below 2 graphs demoonstrates which are the top job benificaries and high paying jobs from 2011 to 2016

In [270…

```
top_roles = certified_cases['SOC_NAME'].value_counts().head(10)
plt.figure(figsize=(15,10))
sns.barplot(y = top_roles.index ,x = top_roles.values ,color='m')
plt.xlabel('COUNT OF CERTIFIED CASES',size=20)
plt.ylabel('JOB ROLES', size=20)
plt.title('TOP JOB BENIFICARIES 2011 TO 2016',size=20)
```

Out[270…

```
Text(0.5, 1.0, 'TOP JOB BENIFICARIES 2011 TO 2016')
```



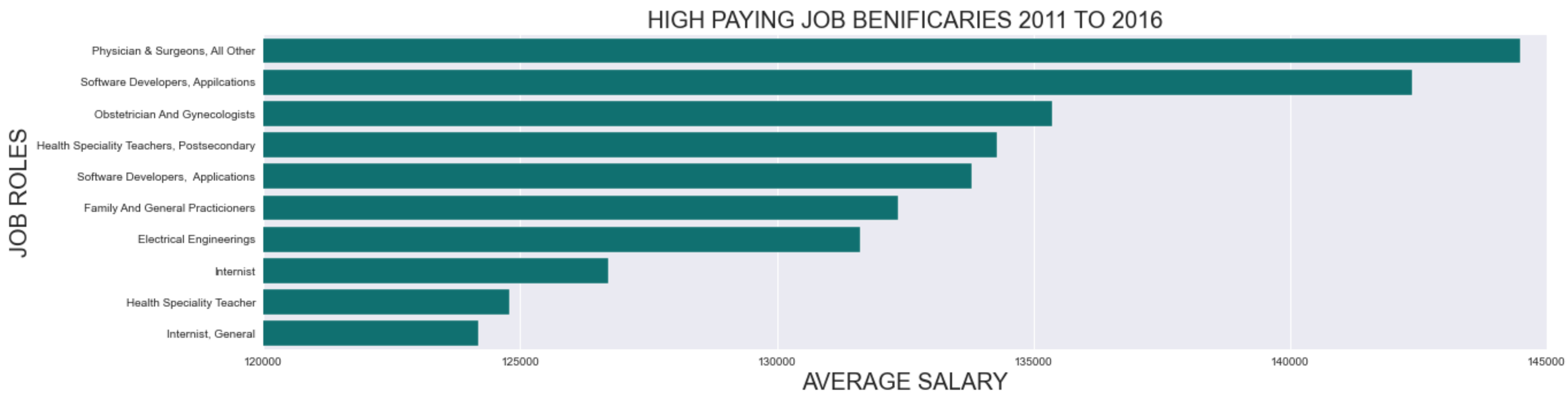
In [271…

```
top_payers = certified_cases.groupby(by=['SOC_NAME'])['PREVAILING_WAGE'].mean()
```

```
top_payers = top_payers.sort_values(ascending=False)[:10]
plt.figure(figsize=(20,5))
sns.barplot(y = top_payers.index ,x = top_payers.values ,color='teal')
plt.xlabel('AVERAGE SALARY',size=20)
plt.ylabel('JOB ROLES', size=20)
plt.title('HIGH PAYING JOB BENIFICARIES 2011 TO 2016',size=20)
plt.xlim((120000,145000))
```

Out[271…

```
(120000.0, 145000.0)
```

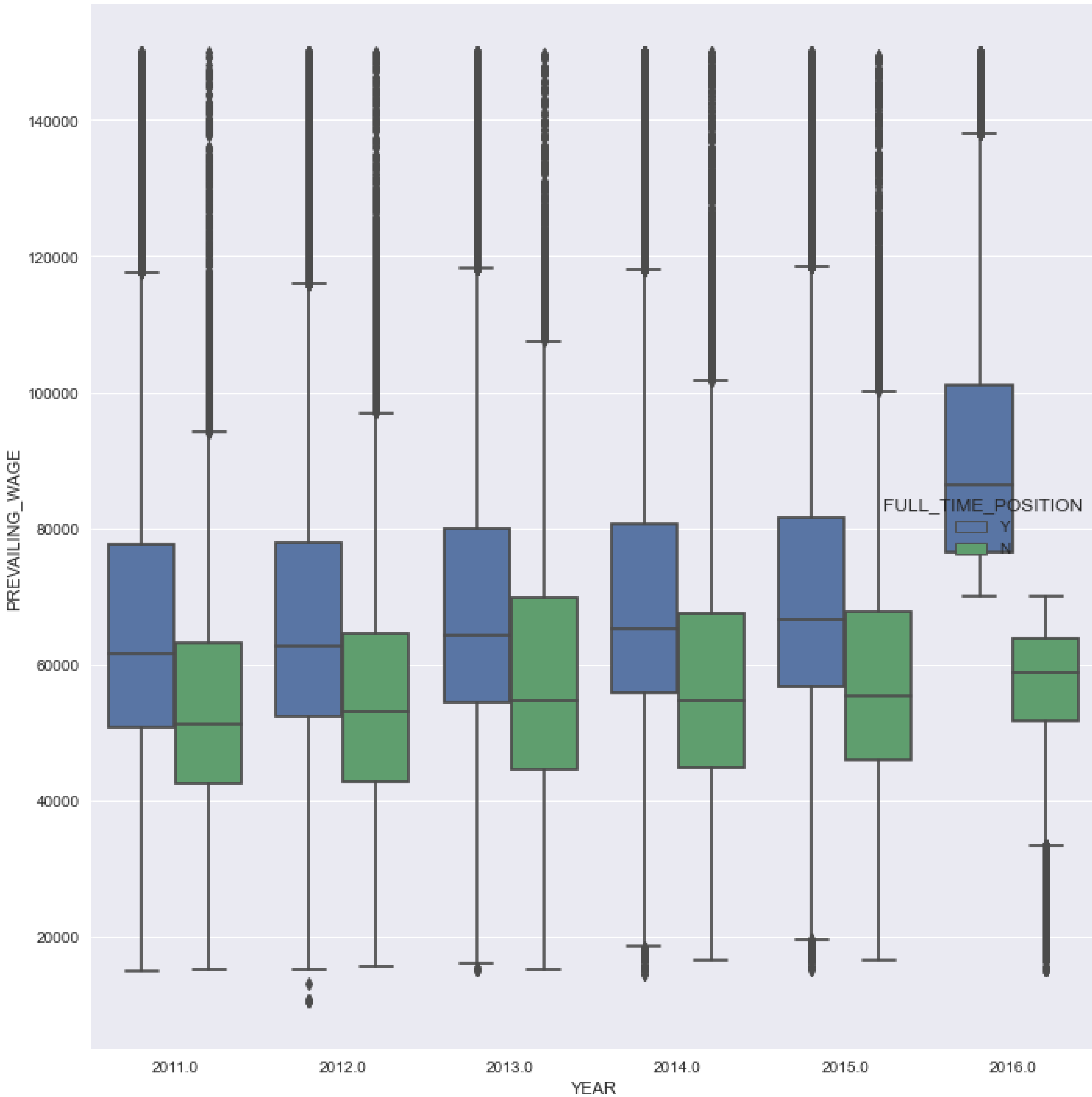


How does Full time Employee fare against Part timers over the Years ?

IN 2016 partime employees earned significantly lower

In [272…

```
plt.figure(figsize=(10,10))
sns.boxplot(data=certified_cases, x='YEAR', y='PREVAILING_WAGE',hue='FULL_TIME_POSITION')
plt.tight_layout()
```


140000
120000
100000
80000
60000
40000
20000
PREVAILING_WAGE
FULL_TIME_POSITION
Y
N
2011.0
2012.0
2013.0
2014.0
2015.0
2016.0
YEAR

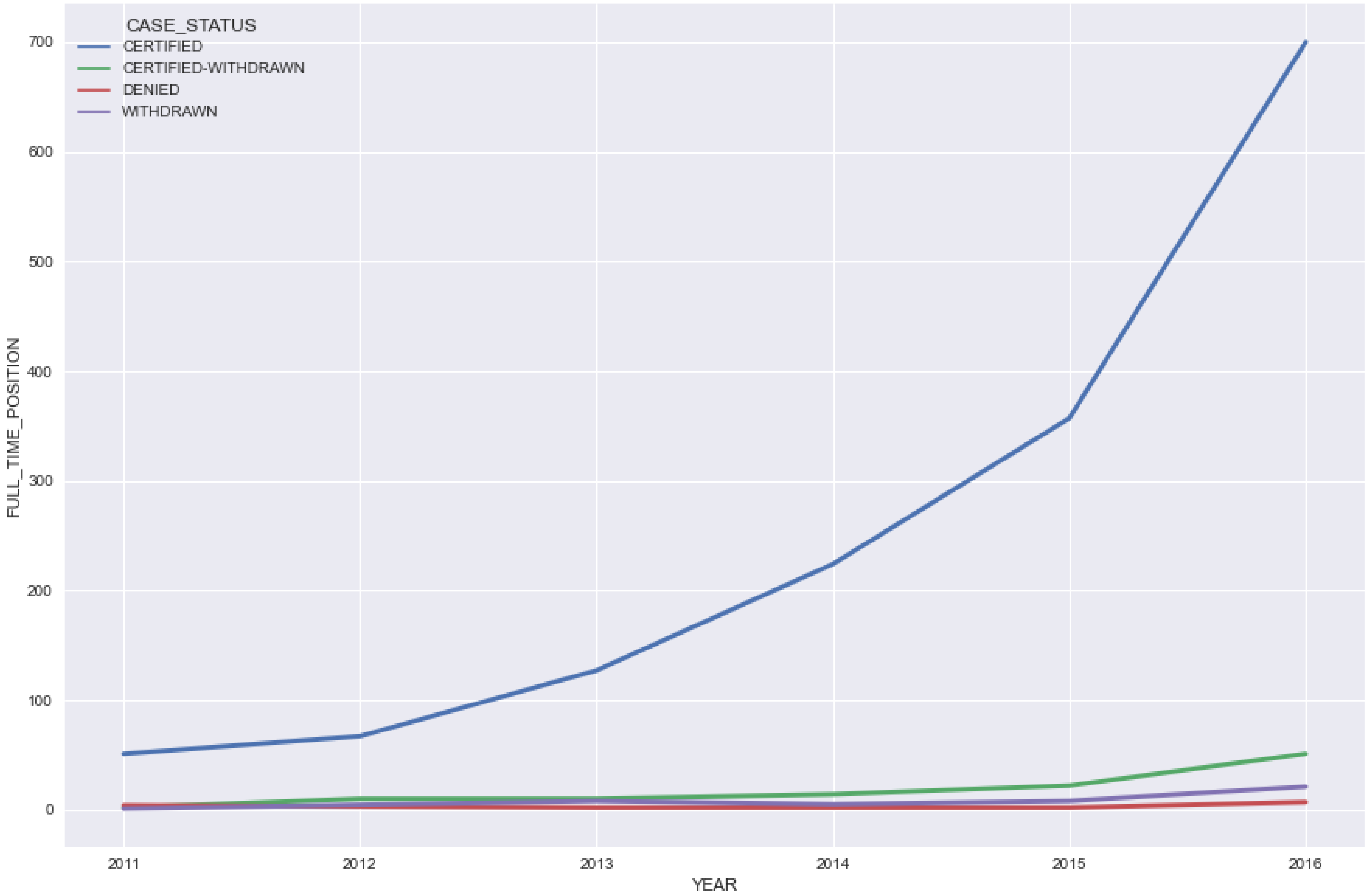
How are Data Engineers doing ?

There is a very good spike in the number of Certified cases for a data Engineer .. Looks like a Promising career

In [273…
```
data_eng =df[df['JOB_TITLE'].str.contains('Data Engineer')].groupby(['YEAR','CASE_STATUS']).count()
data_eng = data_eng.reset_index(level= 'CASE_STATUS')
```

In [274…
```
plt.figure(figsize=(15,10))
sns.lineplot(data=data_eng, x= data_eng.index ,y= 'FULL_TIME_POSITION', hue = 'CASE_STATUS', linewidth=3)
```

Out[274…
```
<AxesSubplot:xlabel='YEAR', ylabel='FULL_TIME_POSITION'>
```



Conclusion

These are some of the basic analysis of H1B applications . H1B has always generated good political opinions, data suggests inspite of these there are constant demand and growth Of course we did not have data to analyse the 'Trump effect' !

```
In [ ]:
```