In [1]:

```
# import libraries
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt
%matplotlib inline

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

Amazon Employee Access Challenge

Overview

When an employee at any company starts work, they first need to obtain the computer access necessary to fulfill their role. This access may allow an employee to read/manipulate resources through various applications or web portals. It is assumed that employees fulfilling the functions of a given role will access the same or similar resources. It is often the case that employees figure out the access they need as they encounter roadblocks during their daily work (e.g. not able to log into a reporting portal). A knowledgeable supervisor then takes time to manually grant the needed access in order to overcome access obstacles. As employees move throughout a company, this access discovery/recovery cycle wastes a nontrivial amount of time and money.

There is a considerable amount of data regarding an employee's role within an organization and the resources to which they have access. Given the data related to current employees and their provisioned access, models can be built that automatically determine access privileges as employees enter and leave roles within a company. These auto-access models seek to minimize the human involvement required to grant or revoke employee access.

Objective

The objective of this competition is to build a model, learned using historical data, that will determine an employee's access needs, such that manual access transactions (grants and revokes) are minimized as the employee's attributes change over time. The model will take an employee's role information and a resource code and will return whether or not access should be granted.

ML Problem

So our aim is to develop a Machine Learning model that takes an employee’s access request as input which contains details about the employee’s attributes like role, department etc.. and the model has to decide whether to provide access or not. Here the dataset provided by Amazon contains real historic data collected from 2010 and 2011.The Performance metric used in this case study is AUC score.

Data Information

https://www.kaggle.com/c/amazon-employee-access-challenge/data

Data Description

The data consists of real historical data collected from 2010 & 2011. Employees are manually allowed or denied access to resources over time. You must create an algorithm capable of learning from this historical data to predict approval/denial for an unseen set of employees.

File Descriptions

train.csv - The training set. Each row has the ACTION (ground truth), RESOURCE, and information about the employee's role at the time of approval test.csv - The test set for which predictions should be made. Each row asks whether an employee having the listed characteristics should have access to the listed resource.

Column Descriptions

Column Name	Description
ACTION	ACTION is 1 if the resource was approved, 0 if the resource was not
RESOURCE	An ID for each resource
MGR_ID	The EMPLOYEE ID of the manager of the current EMPLOYEE ID record; an employee may have only one manager at a time
ROLE_ROLLUP_1	Company role grouping category id 1 (e.g. US Engineering)
ROLE_ROLLUP_2	Company role grouping category id 2 (e.g. US Retail)
ROLE_DEPTNAME	Company role department description (e.g. Retail)
ROLE_TITLE	Company role business title description (e.g. Senior Engineering Retail Manager)
ROLE_FAMILY_DESC	Company role family extended description (e.g. Retail Manager, Software Engineering)
ROLE_FAMILY	Company role family description (e.g. Retail Manager)
ROLE_CODE	Company role code; this code is unique to each role (e.g. Manager)

Data Analysis

In [2]:
```
train = pd.read_csv('data/train.csv')
test = pd.read_csv('data/test.csv')
```

In [3]:
```
train.shape
```

Out[3]:
```
(32769, 10)
```

In [4]:
```
test.shape
```

Out[4]: (58921, 10)

Train Data Analysis

In [5]:
```
train.columns
```

Out[5]:
```
Index(['ACTION', 'RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_
2',
       'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMIL
Y',
       'ROLE_CODE'],
      dtype='object')
```

In [6]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32769 entries, 0 to 32768
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   ACTION            32769 non-null  int64
 1   RESOURCE          32769 non-null  int64
 2   MGR_ID            32769 non-null  int64
 3   ROLE_ROLLUP_1     32769 non-null  int64
 4   ROLE_ROLLUP_2     32769 non-null  int64
 5   ROLE_DEPTNAME     32769 non-null  int64
 6   ROLE_TITLE        32769 non-null  int64
 7   ROLE_FAMILY_DESC  32769 non-null  int64
 8   ROLE_FAMILY       32769 non-null  int64
 9   ROLE_CODE         32769 non-null  int64
dtypes: int64(10)
memory usage: 2.5 MB
```

In [7]:
```
train.head()
```

Out[7]:

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME	ROLE_

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME	ROLE_
0	1	39353	85475	117961	118300	123472	
1	1	17183	1540	117961	118343	123125	
2	1	36724	14457	118219	118220	117884	
3	1	36135	5396	117961	118343	119993	
4	1	42680	5905	117929	117930	119569	

In [8]:
```
train.describe()
```

Out[8]:

	ACTION	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_D
count	32769.000000	32769.000000	32769.000000	32769.000000	32769.000000	327
mean	0.942110	42923.916171	25988.957979	116952.627788	118301.823156	1189
std	0.233539	34173.892702	35928.031650	10875.563591	4551.588572	189
min	0.000000	0.000000	25.000000	4292.000000	23779.000000	46
25%	1.000000	20299.000000	4566.000000	117961.000000	118102.000000	1183
50%	1.000000	35376.000000	13545.000000	117961.000000	118300.000000	1189
75%	1.000000	74189.000000	42034.000000	117961.000000	118386.000000	1205
max	1.000000	312153.000000	311696.000000	311178.000000	286791.000000	2867

In [9]:
```
# unique values
for i in train:
    print(i, len(train[i].unique()))
```

```
ACTION 2
RESOURCE 7518
MGR_ID 4243
ROLE_ROLLUP_1 128
ROLE_ROLLUP_2 177
ROLE_DEPTNAME 449
```

```
ROLE_TITLE 343
ROLE_FAMILY_DESC 2358
ROLE_FAMILY 67
ROLE_CODE 343
```

ROLE_TITLE and ROLE_CODE columns has same no. of entries, In other words we can say both columns are same. ACTION is our class label.

In [10]:
```
train.isna().sum()
```

Out[10]:
```
ACTION              0
RESOURCE            0
MGR_ID              0
ROLE_ROLLUP_1       0
ROLE_ROLLUP_2       0
ROLE_DEPTNAME       0
ROLE_TITLE          0
ROLE_FAMILY_DESC    0
ROLE_FAMILY         0
ROLE_CODE           0
dtype: int64
```

In [11]:
```
train.duplicated().sum()
```

Out[11]:
```
0
```

There is no duplicated and missing values in the train dataset

Test Data Analysis

In [12]:
```
test.columns
```

Out[12]:
```
Index(['id', 'RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_2',
       'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMIL
Y',
```

```
       'ROLE_CODE'],
      dtype='object')
```

In [13]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58921 entries, 0 to 58920
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   id                58921 non-null  int64
 1   RESOURCE          58921 non-null  int64
 2   MGR_ID            58921 non-null  int64
 3   ROLE_ROLLUP_1     58921 non-null  int64
 4   ROLE_ROLLUP_2     58921 non-null  int64
 5   ROLE_DEPTNAME     58921 non-null  int64
 6   ROLE_TITLE        58921 non-null  int64
 7   ROLE_FAMILY_DESC  58921 non-null  int64
 8   ROLE_FAMILY       58921 non-null  int64
 9   ROLE_CODE         58921 non-null  int64
dtypes: int64(10)
memory usage: 4.5 MB
```

In [14]:
```
test.head()
```

Out[14]:

	id	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_DEPTNAME	ROLE_TITLE
0	1	78766	72734	118079	118080	117878	11787[illegible]
1	2	40644	4378	117961	118327	118507	11886[illegible]
2	3	75443	2395	117961	118300	119488	11817[illegible]
3	4	43219	19986	117961	118225	118403	12077[illegible]
4	5	42093	50015	117961	118343	119598	11842[illegible]

In [15]:
```
test.describe()
```

Out[15]:

	id	RESOURCE	MGR_ID	ROLE_ROLLUP_1	ROLE_ROLLUP_2	ROLE_D
count	58921.000000	58921.000000	58921.000000	58921.000000	58921.000000	589
mean	29461.000000	39383.739482	26691.645050	117028.638041	118316.334091	1188
std	17009.171942	33717.397122	35110.244281	10805.446548	4284.678750	179
min	1.000000	0.000000	25.000000	4292.000000	23779.000000	46
25%	14731.000000	18418.000000	4663.000000	117961.000000	118096.000000	1183
50%	29461.000000	33248.000000	14789.000000	117961.000000	118300.000000	1189
75%	44191.000000	45481.000000	46512.000000	117961.000000	118386.000000	1204
max	58921.000000	312136.000000	311779.000000	311178.000000	194897.000000	2776

In [16]:

```
# unique value
for i in test:
    print(i, len(test[i].unique()))
```

```
id 58921
RESOURCE 4971
MGR_ID 4689
ROLE_ROLLUP_1 126
ROLE_ROLLUP_2 177
ROLE_DEPTNAME 466
ROLE_TITLE 351
ROLE_FAMILY_DESC 2749
ROLE_FAMILY 68
ROLE_CODE 351
```

In [17]:

```
test.isna().sum()
```

Out[17]:

```
id                  0
RESOURCE            0
MGR_ID              0
ROLE_ROLLUP_1       0
ROLE_ROLLUP_2       0
ROLE_DEPTNAME       0
```

```
ROLE_TITLE          0
ROLE_FAMILY_DESC    0
ROLE_FAMILY         0
ROLE_CODE           0
dtype: int64
```

In [18]:
```
test.duplicated().sum()
```

Out[18]:
```
0
```

There is no duplicated and missing values in the test dataset

Analysing Individual Columns

ACTION

In [19]:
```
train['ACTION'].value_counts()
```

Out[19]:
```
1    30872
0     1897
Name: ACTION, dtype: int64
```

In [20]:
```
approved_actions = train[train.ACTION==1]
```

In [21]:
```
rejected_actions = train[train.ACTION==0]
```

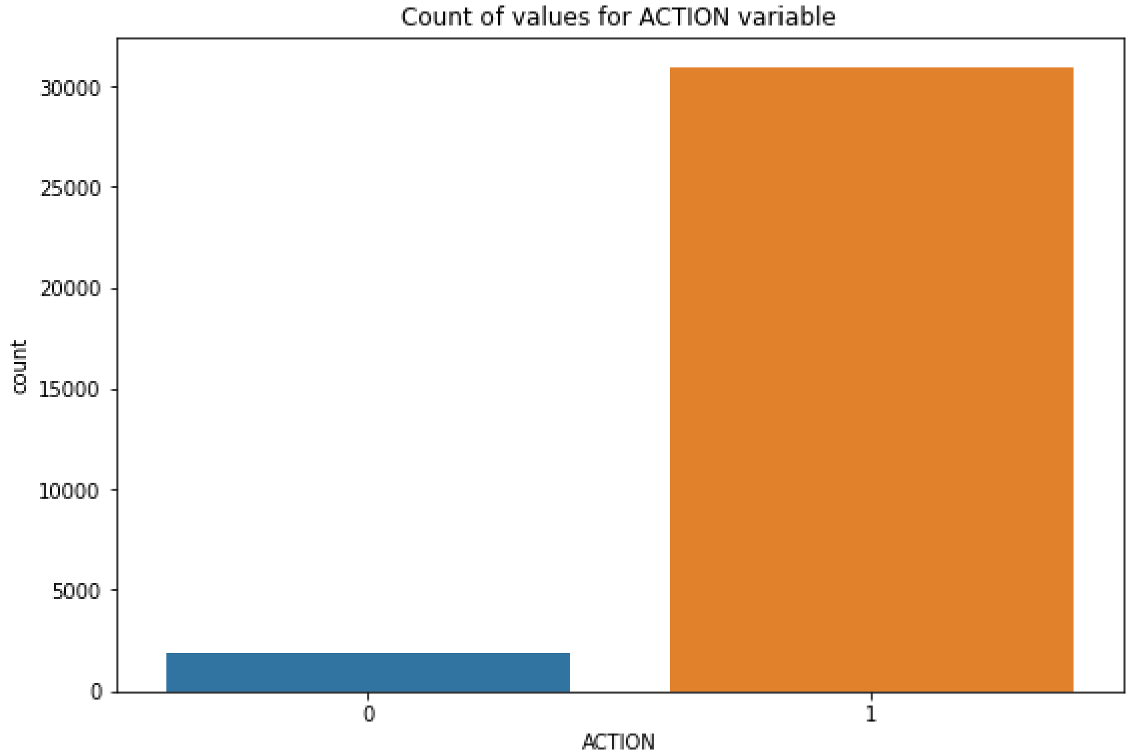
In [22]:
```
approved_actions.shape
```

Out[22]:
```
(30872, 10)
```

In [23]:
```
rejected_actions.shape
```

Out[23]:
```
(1897, 10)
```

In [24]:
```
plt.figure(figsize=(9,6));
sb.countplot(x='ACTION',data=train);
plt.title('Count of values for ACTION variable');
```

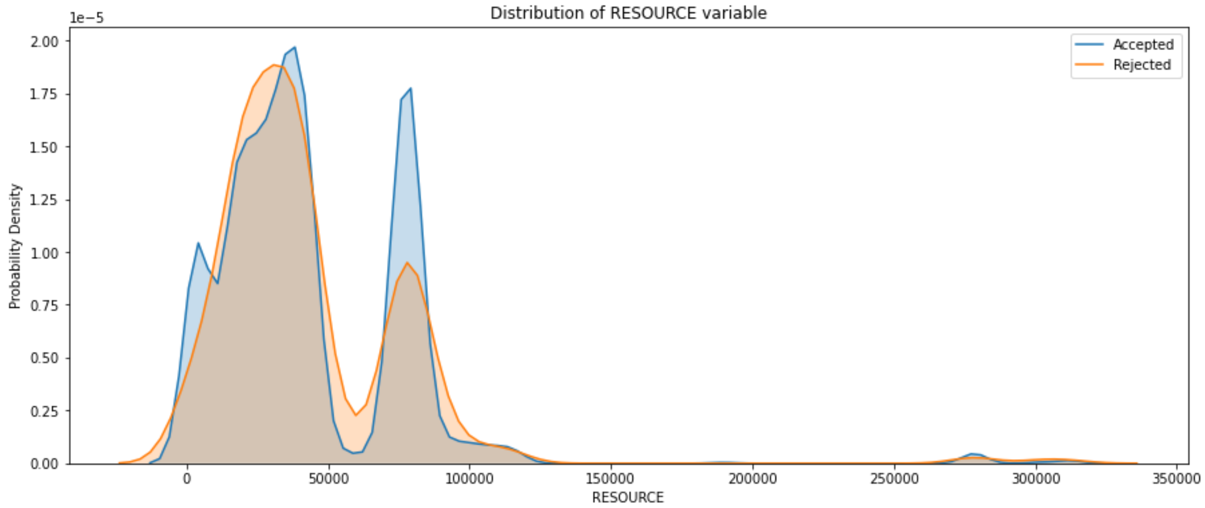


As per the graph we have imbalanced data set, frequency of approved requests are much greater than rejected one. So we have to find out some ways to make this dataset balance.

RESOURCE

In [25]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['RESOURCE'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['RESOURCE'],label='Rejected',shade=True);
plt.title('Distribution of RESOURCE variable');
```

```
plt.xlabel('RESOURCE');
plt.ylabel('Probability Density');
```



In [26]:
```
# Top five approved requests
approved_actions['RESOURCE'].value_counts()[:5]
```

Out[26]:
```
4675     836
79092    468
75078    405
3853     398
25993    390
Name: RESOURCE, dtype: int64
```

In [27]:
```
# Another Top five approved requests
approved_actions['RESOURCE'].value_counts()[5:10]
```

Out[27]:
```
75834    294
6977     283
32270    279
42085    237
17308    236
Name: RESOURCE, dtype: int64
```

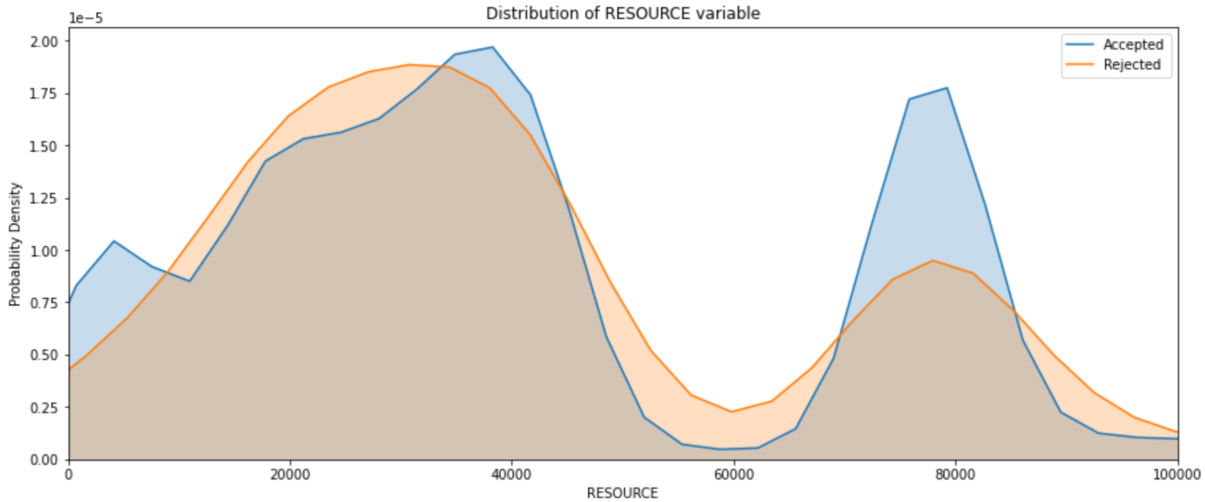
In [28]:
```
# Top five rejected requests
rejected_actions['RESOURCE'].value_counts()[:5]
```

Out[28]:
```
20897    42
18072    29
13878    22
25993    19
27416    19
Name: RESOURCE, dtype: int64
```

In [29]:
```
# Another Top five rejected requests
rejected_actions['RESOURCE'].value_counts()[5:10]
```

Out[29]:
```
7543     17
79092    16
32270    16
6977     16
32642    13
Name: RESOURCE, dtype: int64
```

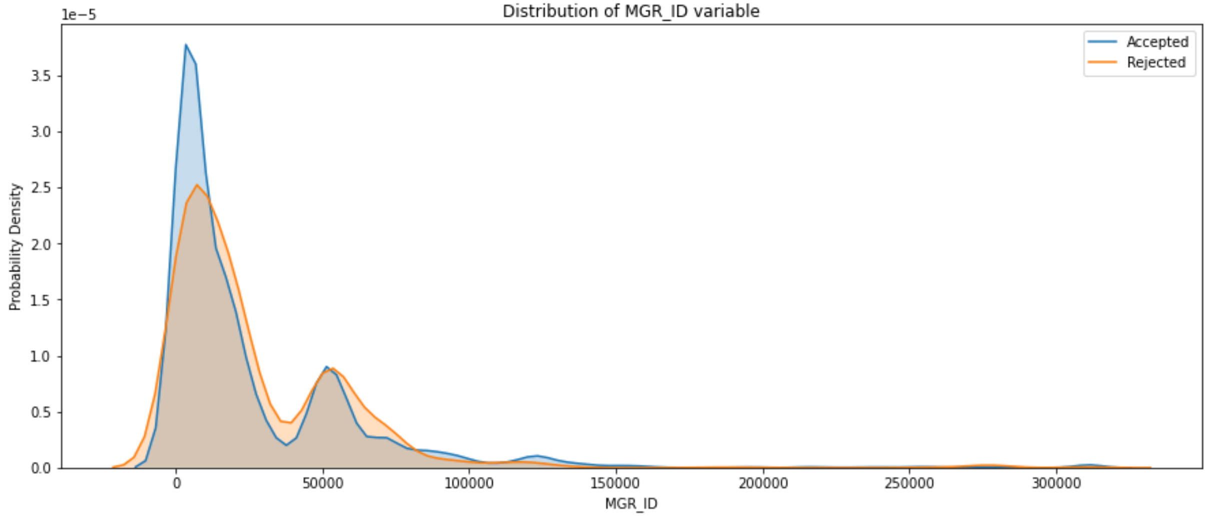
In [30]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['RESOURCE'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['RESOURCE'],label='Rejected',shade=True);
plt.title('Distribution of RESOURCE variable');
plt.xlim(0,100000)
plt.xlabel('RESOURCE');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 70K-90K Approved requests are higher than the rejected ones

MGR_ID

In [31]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['MGR_ID'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['MGR_ID'],label='Rejected',shade=True);
plt.title('Distribution of MGR_ID variable');
plt.xlabel('MGR_ID');
plt.ylabel('Probability Density');
```



In [32]:
```
# Top 5 Approved Actions for attribute MGR_ID
approved_actions['MGR_ID'].value_counts()[:5]
```

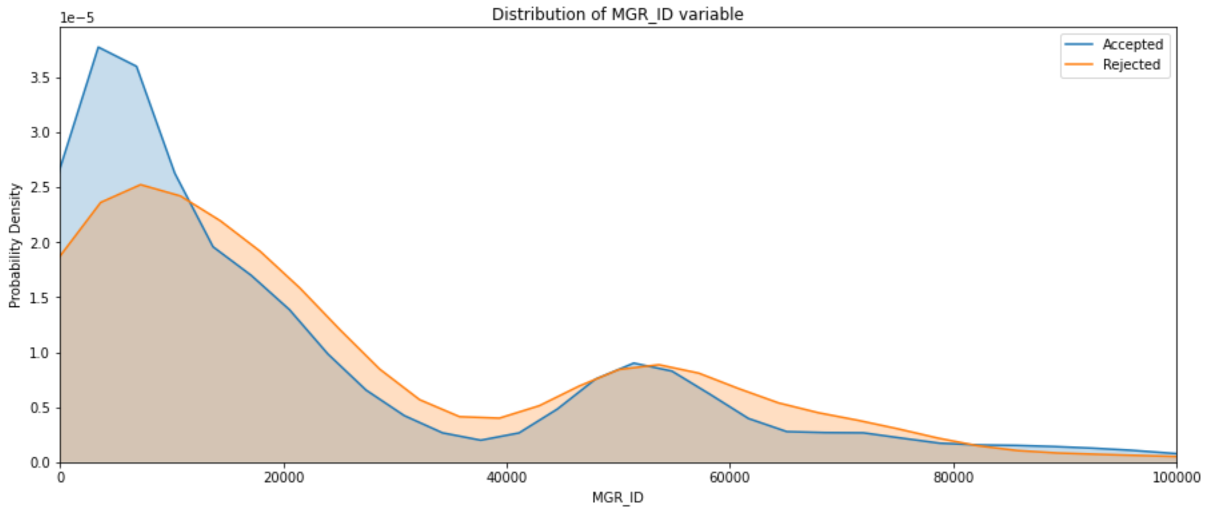
Out[32]:
```
770     147
2270     96
2594     71
2014     67
1350     67
Name: MGR_ID, dtype: int64
```

In [33]:
```
# Top 5 Rejected Actions for attribute MGR_ID
rejected_actions['MGR_ID'].value_counts()[:5]
```

Out[33]:
```
54618    30
4084     17
46526    16
70062    16
4743     14
Name: MGR_ID, dtype: int64
```

In [34]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['MGR_ID'],label='Accepted',shade=True);
```

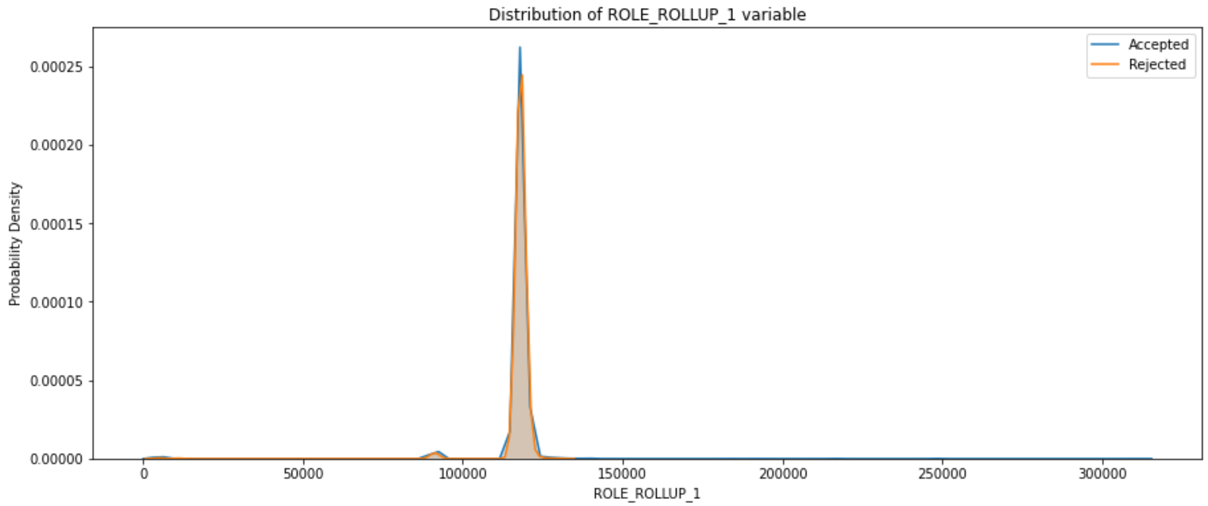
```
sb.kdeplot(rejected_actions['MGR_ID'],label='Rejected',shade=True);
plt.title('Distribution of MGR_ID variable');
plt.xlim(0,100000)
plt.xlabel('MGR_ID');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 0-20K Approved requests are higher than the rejected ones

ROLE_ROLLUP_1

In [35]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_ROLLUP_1'],label='Accepted',shade=Tru
e);
sb.kdeplot(rejected_actions['ROLE_ROLLUP_1'],label='Rejected',shade=Tru
e);
plt.title('Distribution of ROLE_ROLLUP_1 variable');
plt.xlabel('ROLE_ROLLUP_1');
plt.ylabel('Probability Density');
```



In [36]:

```
# Top 5 Approved Actions for attribute ROLE_ROLLUP_1
approved_actions['ROLE_ROLLUP_1'].value_counts()[:5]
```

Out[36]:

```
117961    20320
117902      714
91261       695
118315      474
118212      385
Name: ROLE_ROLLUP_1, dtype: int64
```

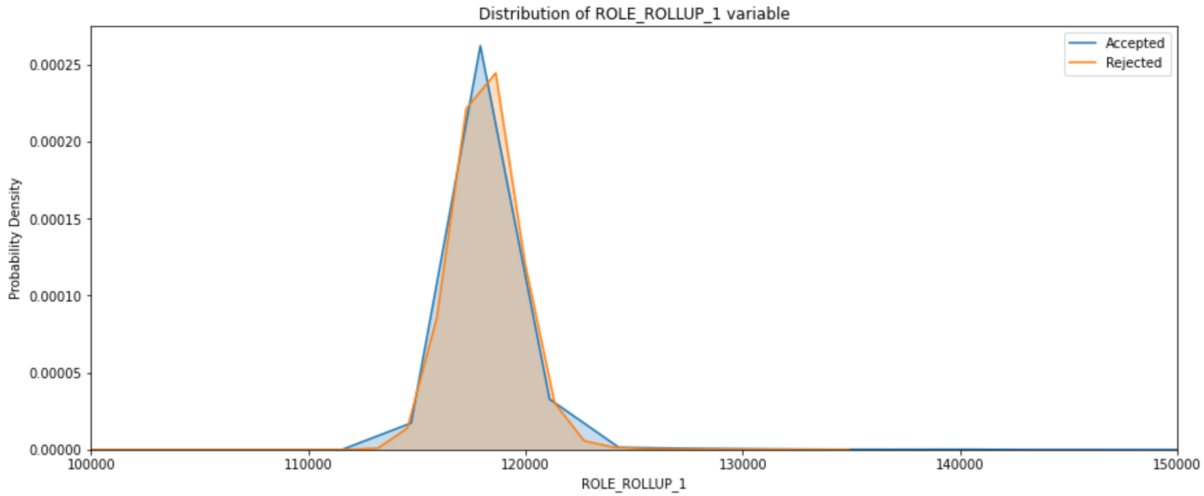
In [37]:

```
# Top 5 Rejected Actions for attribute ROLE_ROLLUP_1
rejected_actions['ROLE_ROLLUP_1'].value_counts()[:5]
```

Out[37]:

```
117961    1087
118256      73
119062      50
118290      44
118079      42
Name: ROLE_ROLLUP_1, dtype: int64
```

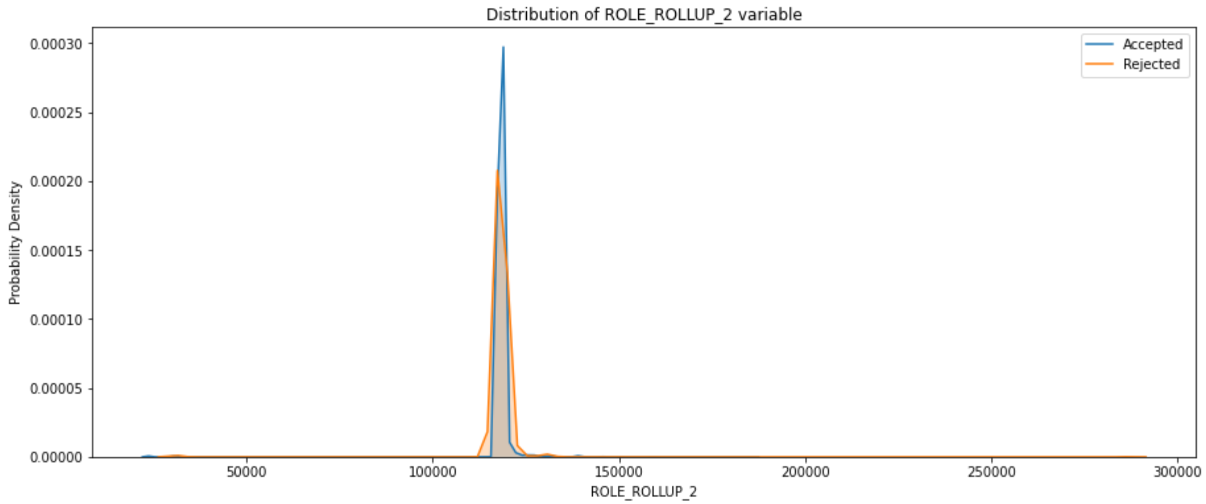
In [38]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_ROLLUP_1'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_ROLLUP_1'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_ROLLUP_1 variable');
plt.xlim(100000,150000)
plt.xlabel('ROLE_ROLLUP_1');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that trends are almost similar

ROLE_ROLLUP_2

In [39]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_ROLLUP_2'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_ROLLUP_2'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_ROLLUP_2 variable');
plt.xlabel('ROLE_ROLLUP_2');
plt.ylabel('Probability Density');
```



In [40]:
```
# Top 5 Approved Actions for attribute ROLE_ROLLUP_2
approved_actions['ROLE_ROLLUP_2'].value_counts()[:5]
```

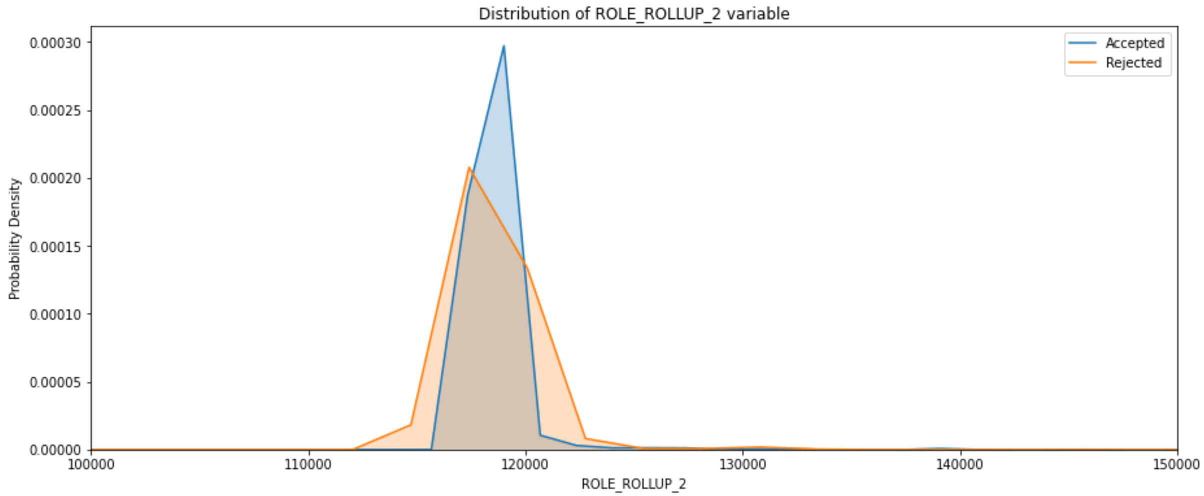
Out[40]:
```
118300    4230
118343    3823
118327    2521
118225    2438
118386    1639
Name: ROLE_ROLLUP_2, dtype: int64
```

In [41]:
```
# Top 5 Rejected Actions for attribute ROLE_ROLLUP_2
rejected_actions['ROLE_ROLLUP_2'].value_counts()[:5]
```

Out[41]:
```
118300    194
118052    185
118386    157
118343    122
118327    120
Name: ROLE_ROLLUP_2, dtype: int64
```

In [42]:
```
plt.figure(figsize=(15,6));
```

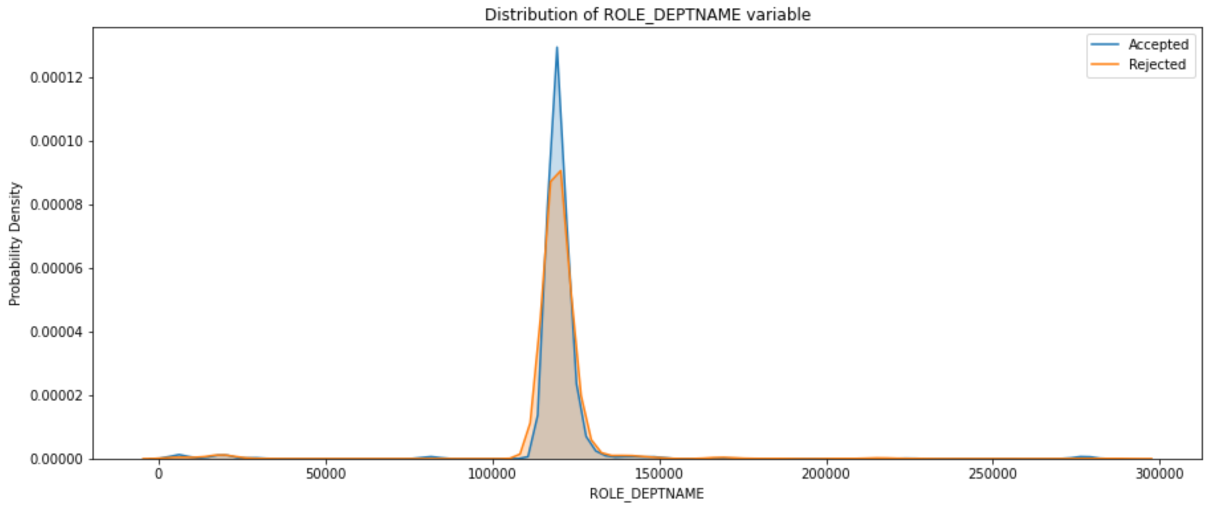
```
sb.kdeplot(approved_actions['ROLE_ROLLUP_2'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_ROLLUP_2'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_ROLLUP_2 variable');
plt.xlim(100000, 150000)
plt.xlabel('ROLE_ROLLUP_2');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 110K-120K Approved requests are higher than the rejected ones

ROLE_DEPTNAME

In [43]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_DEPTNAME'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_DEPTNAME'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_DEPTNAME variable');
plt.xlabel('ROLE_DEPTNAME');
plt.ylabel('Probability Density');
```



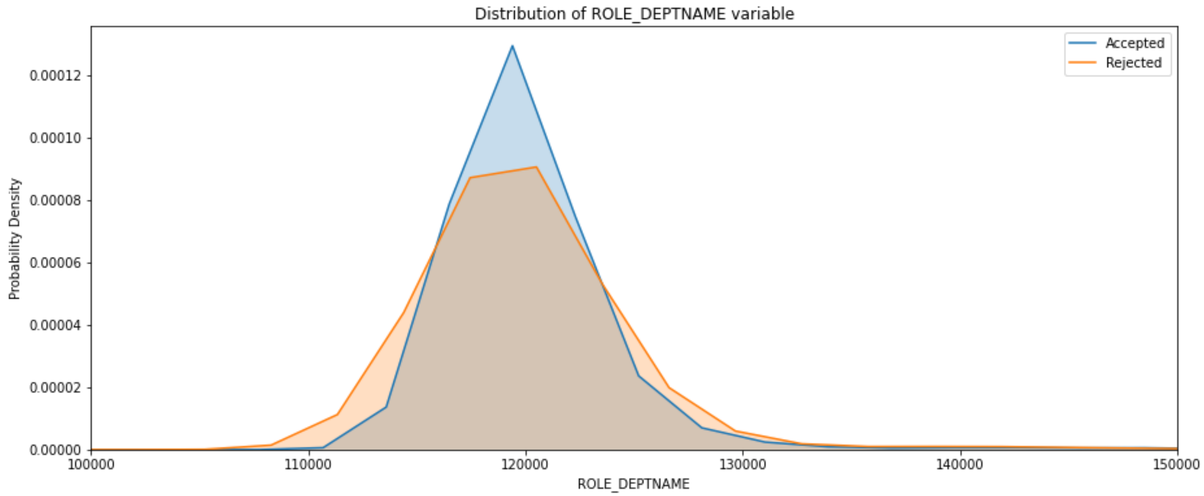
In [44]:
```
# Top 5 Approved Actions for attribute ROLE_DEPTNAME
approved_actions['ROLE_DEPTNAME'].value_counts()[:5]
```

Out[44]:
```
117878    1064
117941     700
118514     589
117945     570
117920     541
Name: ROLE_DEPTNAME, dtype: int64
```

In [45]:
```
# Top 5 Rejected Actions for attribute ROLE_DEPTNAME
rejected_actions['ROLE_DEPTNAME'].value_counts()[:5]
```

Out[45]:
```
117945    89
118992    77
117878    71
117941    63
117920    56
Name: ROLE_DEPTNAME, dtype: int64
```

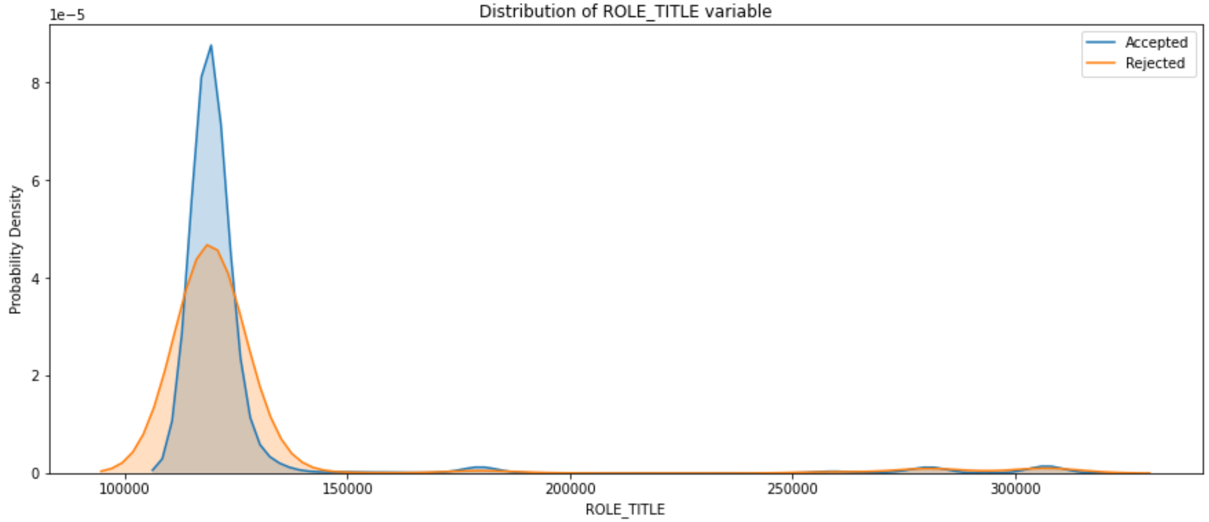
In [46]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_DEPTNAME'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_DEPTNAME'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_DEPTNAME variable');
plt.xlim(100000, 150000)
plt.xlabel('ROLE_DEPTNAME');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 110K-130K Approved requests are higher than the rejected ones

ROLE_TITLE

In [47]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_TITLE'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_TITLE'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_TITLE variable');
plt.xlabel('ROLE_TITLE');
plt.ylabel('Probability Density');
```



In [48]:
```
# Top 5 Approved Actions for attribute ROLE_TITLE
approved_actions['ROLE_TITLE'].value_counts()[:5]
```

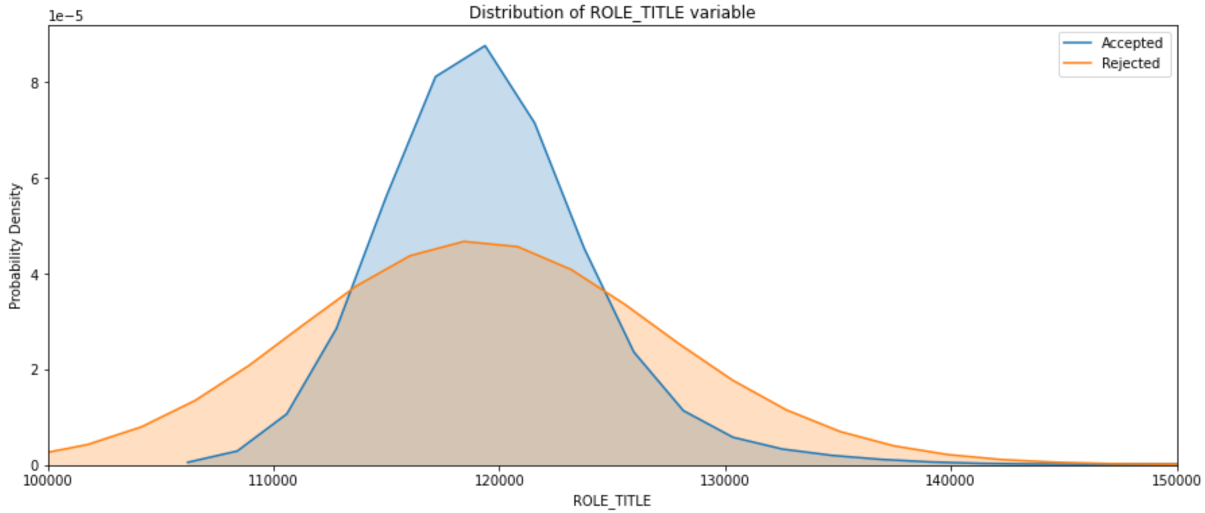
Out[48]:
```
118321    4279
117905    3467
118784    1647
117879    1117
118568     965
Name: ROLE_TITLE, dtype: int64
```

In [49]:
```
# Top 5 Rejected Actions for attribute ROLE_TITLE
rejected_actions['ROLE_TITLE'].value_counts()[:5]
```

Out[49]:
```
118321    370
117879    139
118784    125
117905    116
118568     78
Name: ROLE_TITLE, dtype: int64
```

In [50]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_TITLE'],label='Accepted',shade=True);
```

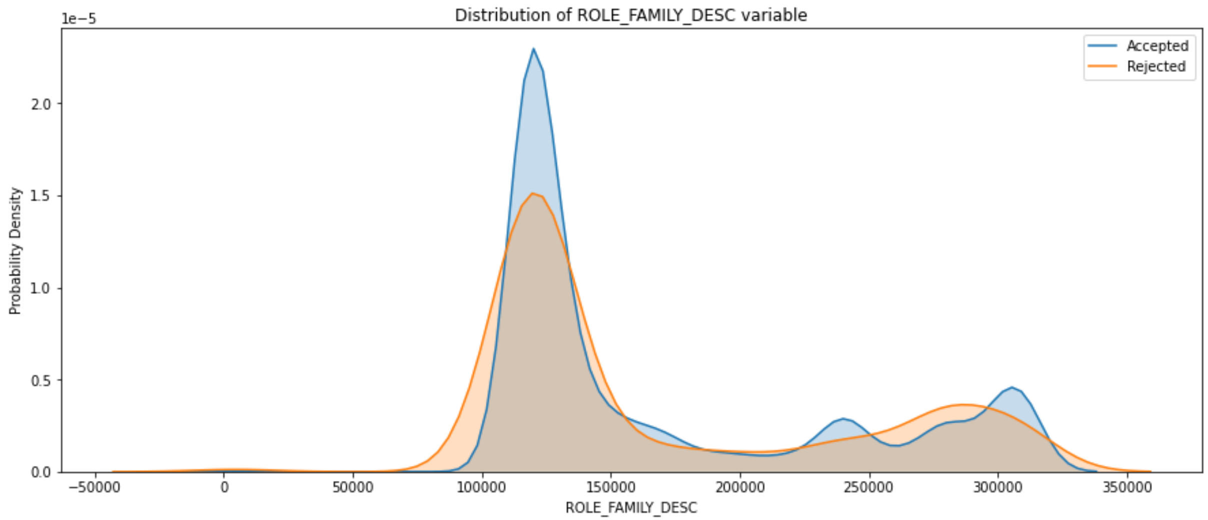
```
sb.kdeplot(rejected_actions['ROLE_TITLE'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_TITLE variable');
plt.xlim(100000, 150000)
plt.xlabel('ROLE_TITLE');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 110K-130K Approved requests are higher than the rejected ones

ROLE_FAMILY_DESC

In [51]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_FAMILY_DESC'],label='Accepted',shade=
True);
sb.kdeplot(rejected_actions['ROLE_FAMILY_DESC'],label='Rejected',shade=
True);
plt.title('Distribution of ROLE_FAMILY_DESC variable');
plt.xlabel('ROLE_FAMILY_DESC');
plt.ylabel('Probability Density');
```



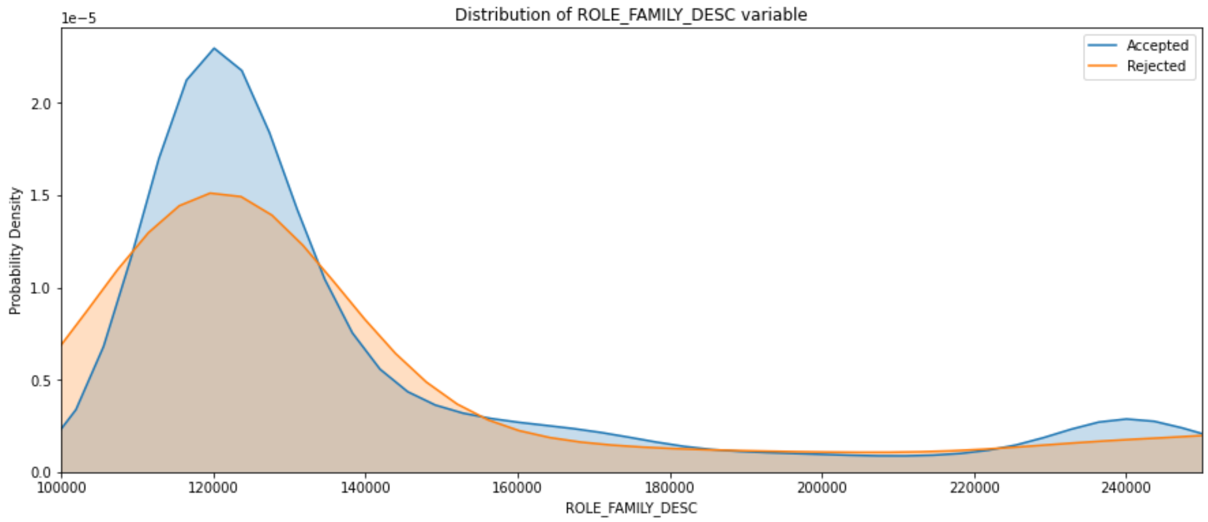
In [52]:
```
# Top 5 Approved Actions for attribute ROLE_FAMILY_DESC
approved_actions['ROLE_FAMILY_DESC'].value_counts()[:5]
```

Out[52]:
```
117906    6437
240983    1189
117913     649
279443     615
117886     478
Name: ROLE_FAMILY_DESC, dtype: int64
```

In [53]:
```
# Top 5 Rejected Actions for attribute ROLE_FAMILY_DESC
rejected_actions['ROLE_FAMILY_DESC'].value_counts()[:5]
```

Out[53]:
```
117906    459
240983     55
117886     52
279443     50
117897     39
Name: ROLE_FAMILY_DESC, dtype: int64
```

In [54]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_FAMILY_DESC'],label='Accepted',shade=
True);
sb.kdeplot(rejected_actions['ROLE_FAMILY_DESC'],label='Rejected',shade=
True);
plt.title('Distribution of ROLE_FAMILY_DESC variable');
plt.xlim(100000, 250000)
plt.xlabel('ROLE_FAMILY_DESC');
plt.ylabel('Probability Density');
```

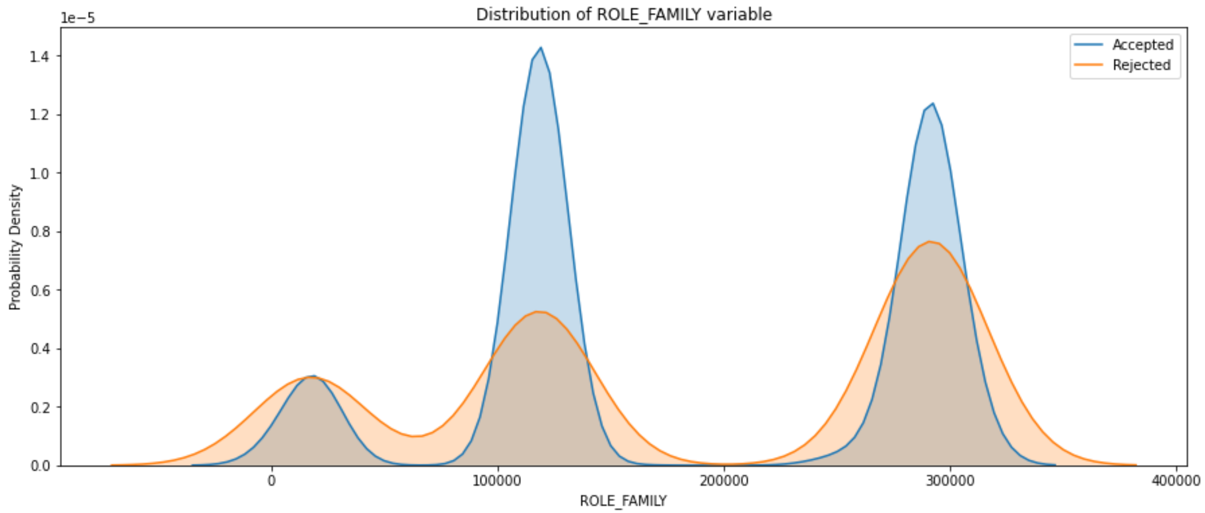


Looking at above KDE plot we can say that b/w 100K-140K Approved requests are higher than the rejected ones

ROLE_FAMILY

In [55]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_FAMILY'],label='Accepted',shade=True
);
sb.kdeplot(rejected_actions['ROLE_FAMILY'],label='Rejected',shade=True
);
plt.title('Distribution of ROLE_FAMILY variable');
```

```
plt.xlabel('ROLE_FAMILY');
plt.ylabel('Probability Density');
```



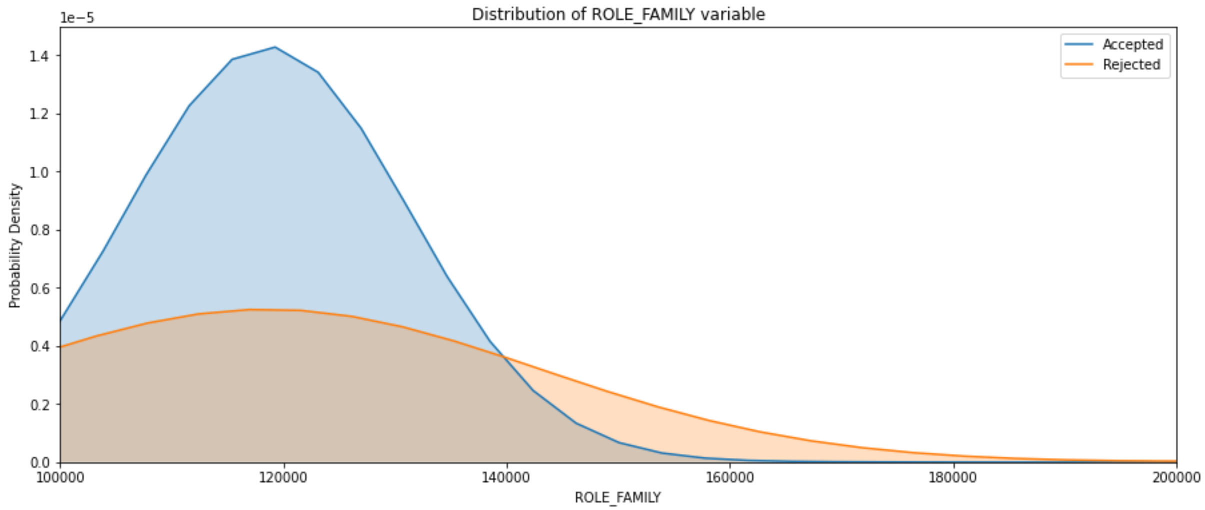
In [56]:
```
# Top 5 Approved Actions for attribute ROLE_FAMILY
approved_actions['ROLE_FAMILY'].value_counts()[:5]
```

Out[56]:
```
290919    10347
118424     2616
19721      2393
117887     2302
118398     1232
Name: ROLE_FAMILY, dtype: int64
```

In [57]:
```
# Top 5 Rejected Actions for attribute ROLE_FAMILY
rejected_actions['ROLE_FAMILY'].value_counts()[:5]
```

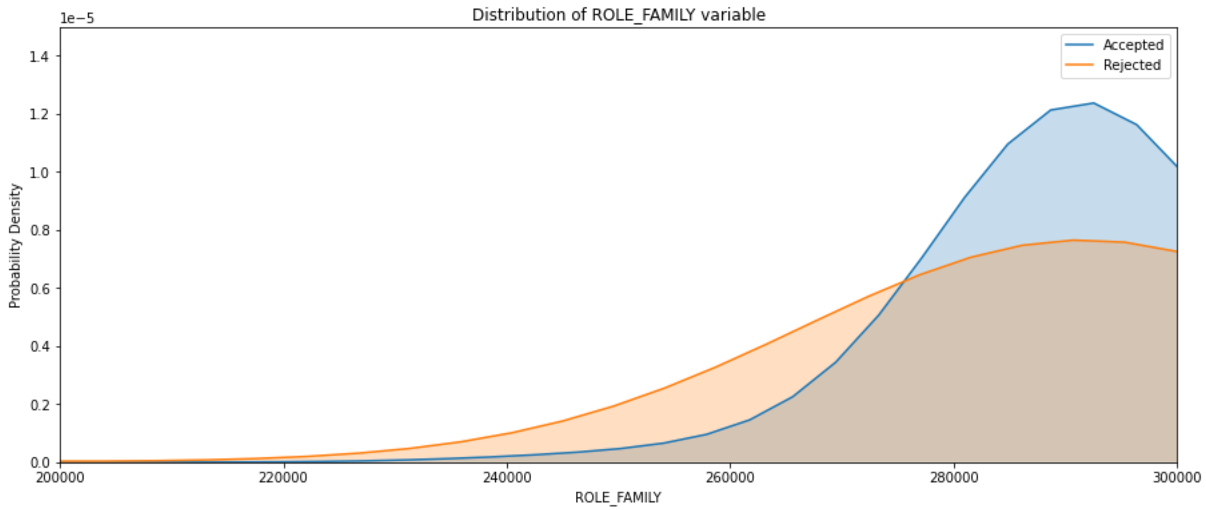
Out[57]:
```
290919    633
19721     243
292795    181
117887     98
118424     74
Name: ROLE_FAMILY, dtype: int64
```

In [58]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_FAMILY'],label='Accepted',shade=True
);
sb.kdeplot(rejected_actions['ROLE_FAMILY'],label='Rejected',shade=True
);
plt.title('Distribution of ROLE_FAMILY variable');
plt.xlim(100000, 200000)
plt.xlabel('ROLE_FAMILY');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 100K-140K Approved requests are higher than the rejected ones

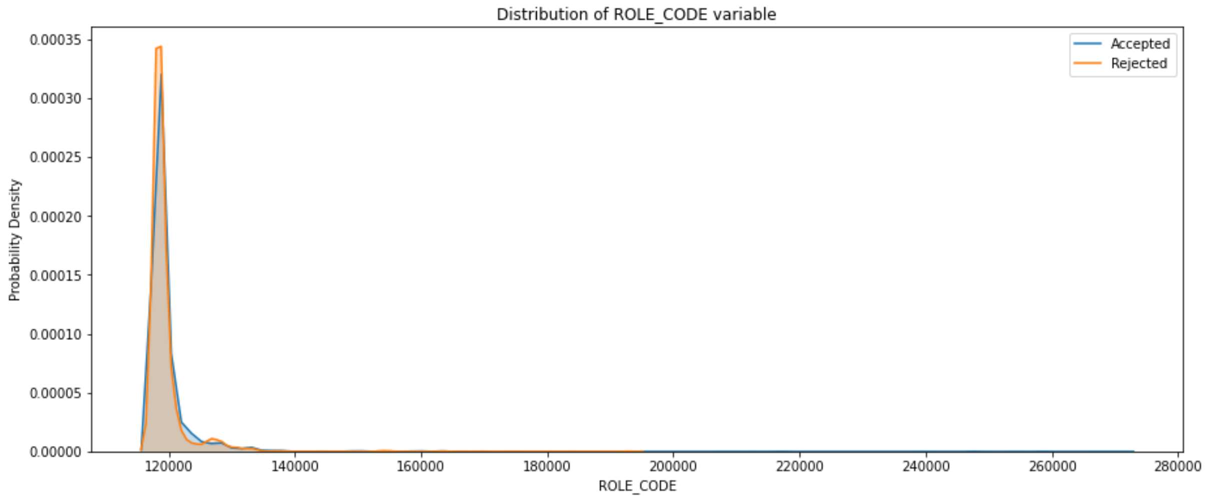
In [59]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_FAMILY'],label='Accepted',shade=True
);
sb.kdeplot(rejected_actions['ROLE_FAMILY'],label='Rejected',shade=True
);
plt.title('Distribution of ROLE_FAMILY variable');
plt.xlim(200000, 300000)
plt.xlabel('ROLE_FAMILY');
plt.ylabel('Probability Density');
```



Looking at above KDE plot we can say that b/w 260K-300K Approved requests are higher than the rejected ones

ROLE_CODE

In [60]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_CODE'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_CODE'],label='Rejected',shade=True);
plt.title('Distribution of ROLE_CODE variable');
plt.xlabel('ROLE_CODE');
plt.ylabel('Probability Density');
```



In [61]:
```
# Top 5 Approved Actions for attribute ROLE_CODE
approved_actions['ROLE_CODE'].value_counts()[:5]
```

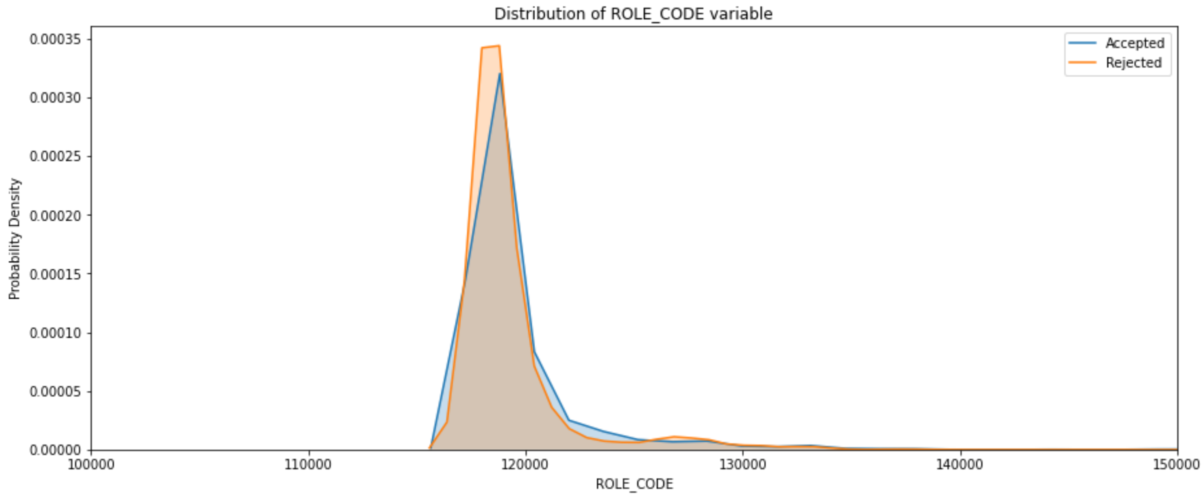
Out[61]:
```
118322    4279
117908    3467
118786    1647
117880    1117
118570     965
Name: ROLE_CODE, dtype: int64
```

In [62]:
```
# Top 5 Rejected Actions for attribute ROLE_CODE
rejected_actions['ROLE_CODE'].value_counts()[:5]
```

Out[62]:
```
118322    370
117880    139
118786    125
117908    116
118570     78
Name: ROLE_CODE, dtype: int64
```

In [63]:
```
plt.figure(figsize=(15,6));
sb.kdeplot(approved_actions['ROLE_CODE'],label='Accepted',shade=True);
sb.kdeplot(rejected_actions['ROLE_CODE'],label='Rejected',shade=True);
```

```
plt.title('Distribution of ROLE_CODE variable');
plt.xlim(100000, 150000)
plt.xlabel('ROLE_CODE');
plt.ylabel('Probability Density');
```

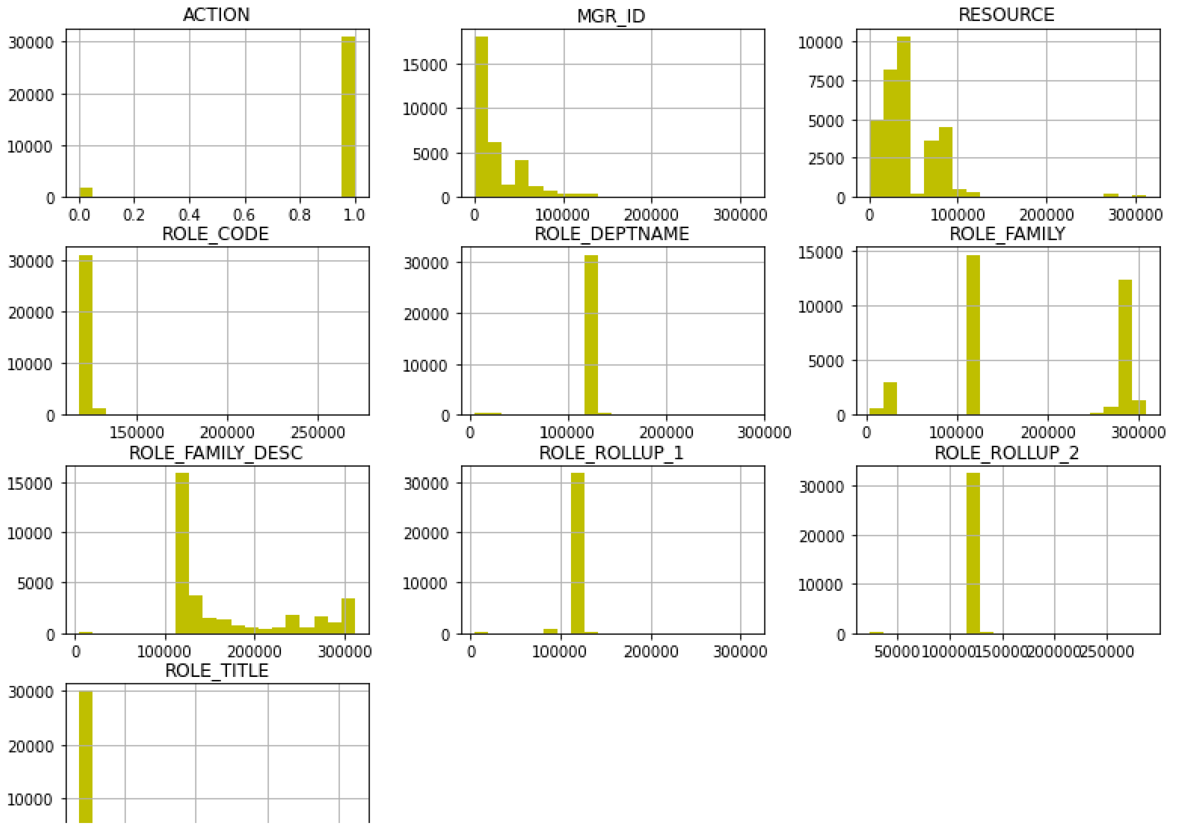


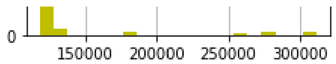
Looking at above KDE plot we can say that b/w trends are almost similar for both classes

In [64]:
```
train[['ACTION', 'RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'ROLE_ROLLUP_2'
,
       'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMILY'
,
       'ROLE_CODE']].hist(figsize=(13,10),bins=20,color='Y')
```

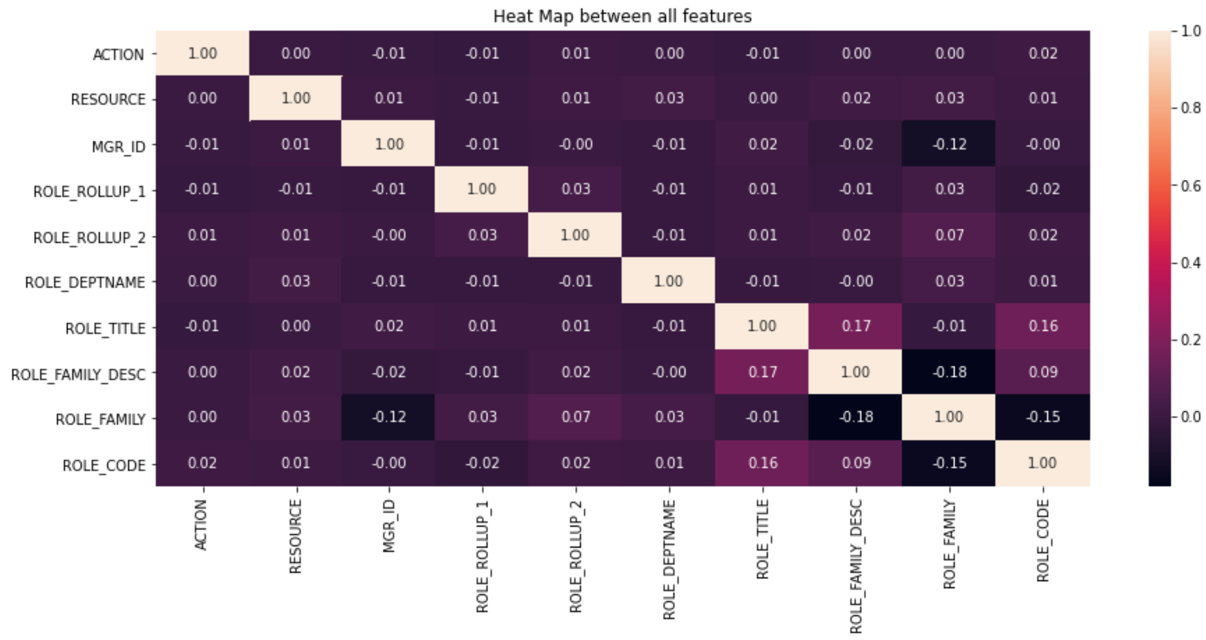
Out[64]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f3215f11d
30>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3216020a
90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3216021c
50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f3215fdb6
d8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f321a68d7
f0>,
```

```
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f32181216
a0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f32160ad1
d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3215ef21
98>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3215ef25
50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f3215ed21
d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3215e769
e8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f3215df3b
e0>]],
      dtype=object)
```





In [65]:
```
plt.figure(figsize=(15,6));
sb.heatmap(train.corr(), annot=True, fmt='.2f');
plt.title('Heat Map between all features');
```



Observation

1. Almost all values are 0 expect corelation b/w (ROLE_FAMILY_DESC, ROLE_TITLE) and (ROLE_CODE, ROLE_TITLE)
2. Corelation b/w ROLE_FAMILY_DESC and ROLE_TITLE is 0.17
3. Corelation b/w ROLE_CODE and ROLE_TITLE is 0.16

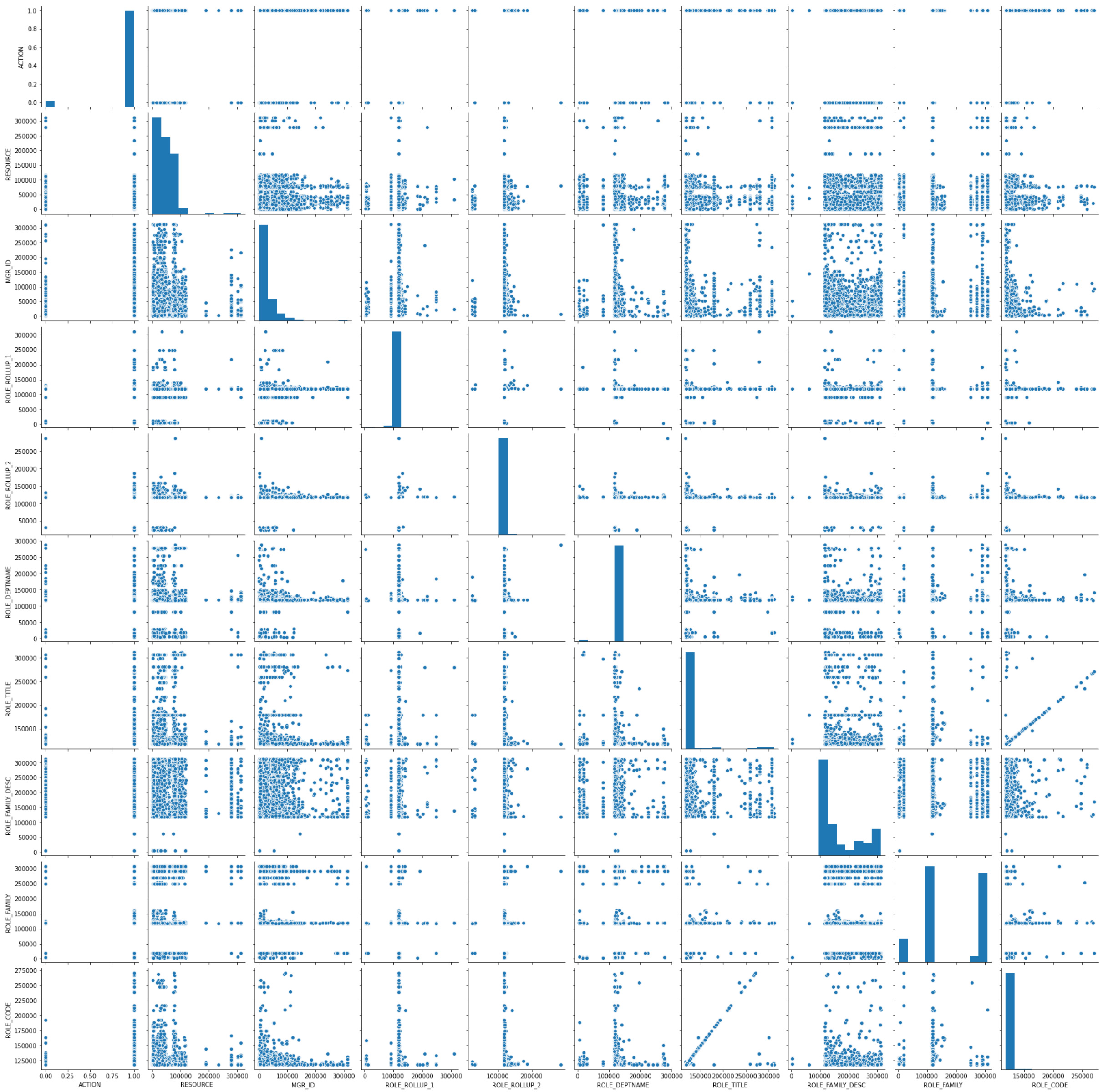
In [67]:
```
plt.figure(figsize=(15,6))
```

```
sb.pairplot(train[['ACTION', 'RESOURCE', 'MGR_ID', 'ROLE_ROLLUP_1', 'RO
LE_ROLLUP_2',
       'ROLE_DEPTNAME', 'ROLE_TITLE', 'ROLE_FAMILY_DESC', 'ROLE_FAMILY'
,
       'ROLE_CODE']])
```

Out[67]:

```
<seaborn.axisgrid.PairGrid at 0x7f320fd371d0>
```

```
<Figure size 1080x432 with 0 Axes>
```


ACTION
RESOURCE
MGR_ID
ROLE_ROLLUP_1
ROLE_ROLLUP_2
ROLE_DEPTNAME
ROLE_TITLE
ROLE_FAMILY_DESC
ROLE_FAMILY
ROLE_CODE

Observation:

There is only relationship b/w ROLE_CODE and ROLE_TITLE

```
In [ ]:
```