Problem Statement: Campaign for selling personal loans

This case is about a bank (Thera Bank) which has a growing customer base. Majority of these customers are liability customers (depositors) with varying size of deposits. The number of customers who are also borrowers (asset customers) is quite small, and the bank is interested in expanding this base rapidly to bring in more loan business and in the process, earn more through the interest on loans. In particular, the management wants to explore ways of converting its liability customers to personal loan customers (while retaining them as depositors). A campaign that the bank ran last year for liability customers showed a healthy conversion rate of over 9% success. This has encouraged the retail marketing department to devise campaigns with better target marketing to increase the success ratio with minimal budget.

The department wants to build a model that will help them identify the potential customers who have higher probability of purchasing the loan. This will increase the success ratio while at the same time reduce the cost of the campaign. The file Bank.xls contains data on 5000 customers. The data include customer demographic information (age, income, etc.), the customer's relationship with the bank (mortgage, securities account, etc.), and the customer response to the last personal loan campaign (Personal Loan). Among these 5000 customers, only 480 (= 9.6%) accepted the personal loan that was offered to them in the earlier campaign.

Column descriptions

ID - Customer ID, Age- Customer's age in completed years, Experience - #years of professional experience, Income - Annual income of the customer, ZIPCode - Home Address ZIP code, Family - Family size of the customer, CCAvg - Avg. spending on credit cards per month, Education - Education Level. 1: Undergrad; 2: Graduate; 3: Advanced/Professional, Mortgage - Value of house mortgage if any, Personal Loan - Did this customer accept the personal loan offered in the last campaign?, Securities - Account Does the customer have a securities account with the bank?, CD Account - Does the customer have a certificate of deposit (CD) account with the bank?, Online - Does the customer use internet banking facilities?, CreditCard - Does the customer uses a credit card

In [545]:

```
#importing the needed packages
import numpy as np
import pandas as pd
import seaborn as sns; sns.set(style="ticks", color_codes=True)
import warnings; warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
import time
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn import svm


#Setting style for seaborn charts
sns.set_context("talk", font_scale=0.75, rc={"lines.linewidth": 2.5})
```

In [546]:

```
# Reading the training data set to study the features

train_df = pd.read_csv("Bank_Personal_Loan_Modelling.csv")
train_df.head(10)
```

Out[546]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account	CD Account	Online	CreditCa
0	1	25	1	49	91107	4	1.6	1	0	0	1	0	0	
1	2	45	19	34	90089	3	1.5	1	0	0	1	0	0	
2	3	39	15	11	94720	1	1.0	1	0	0	0	0	0	
3	4	35	9	100	94112	1	2.7	2	0	0	0	0	0	
4	5	35	8	45	91330	4	1.0	2	0	0	0	0	0	
5	6	37	13	29	92121	4	0.4	2	155	0	0	0	1	
6	7	53	27	72	91711	2	1.5	2	0	0	0	0	1	
7	8	50	24	22	93943	1	0.3	3	0	0	0	0	0	
8	9	35	10	81	90089	3	0.6	2	104	0	0	0	1	
9	10	34	9	180	93023	1	8.9	3	0	1	0	0	0	

In [547]:

```
# Let us inspect the attribute information

train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
ID                    5000 non-null int64
Age                   5000 non-null int64
Experience            5000 non-null int64
Income                5000 non-null int64
ZIP Code              5000 non-null int64
Family                5000 non-null int64
CCAvg                 5000 non-null float64
Education             5000 non-null int64
Mortgage              5000 non-null int64
Personal Loan         5000 non-null int64
Securities Account    5000 non-null int64
CD Account            5000 non-null int64
Online                5000 non-null int64
CreditCard            5000 non-null int64
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

intermediate observation :

Interesting finding from above is, there seems to be several categorical features like account types (CD account, credit card account, Securities account, online account etc.) from the data displayed above, we need to find out whether these are really the integer types or need to be changed as categorical types with 0 & 1 being the only possible values. Default pandas read csv has marked these attributes as integer(int64) type.

In [548]:
```
#inspecting the max, min, median, mean, count to study the data further

train_df.describe().T
```

Out[548]:

	count	mean	std	min	25%	50%	75%	max
ID	5000.0	2500.500000	1443.520003	1.0	1250.75	2500.5	3750.25	5000.0
Age	5000.0	45.338400	11.463166	23.0	35.00	45.0	55.00	67.0
Experience	5000.0	20.104600	11.467954	-3.0	10.00	20.0	30.00	43.0
Income	5000.0	73.774200	46.033729	8.0	39.00	64.0	98.00	224.0
ZIP Code	5000.0	93152.503000	2121.852197	9307.0	91911.00	93437.0	94608.00	96651.0
Family	5000.0	2.396400	1.147663	1.0	1.00	2.0	3.00	4.0
CCAvg	5000.0	1.937938	1.747659	0.0	0.70	1.5	2.50	10.0
Education	5000.0	1.881000	0.839869	1.0	1.00	2.0	3.00	3.0
Mortgage	5000.0	56.498800	101.713802	0.0	0.00	0.0	101.00	635.0
Personal Loan	5000.0	0.096000	0.294621	0.0	0.00	0.0	0.00	1.0
Securities Account	5000.0	0.104400	0.305809	0.0	0.00	0.0	0.00	1.0
CD Account	5000.0	0.060400	0.238250	0.0	0.00	0.0	0.00	1.0
Online	5000.0	0.596800	0.490589	0.0	0.00	1.0	1.00	1.0
CreditCard	5000.0	0.294000	0.455637	0.0	0.00	0.0	1.00	1.0

Understanding from above :

1. ID seems to be irrelevant
2. Age seems to be ranging between 23 and 67 with median/mean ~ 45. At first glance, this data looks okay without outliers
3. Experience - seem to have outlier with NEGATIVE value in the data Need to investigate this further
4. Income - Not much evidence from min and max observations
5. Zip code - We will study this data more, as we might get geographical significance for people who might have bought the loan
6. Family - Looks okay with values of family size ranging from 1 to 4. Looks okay without outliers
7. CCAvg - Not much information given on this field, need to study the distribution
8. Education - Same as above, need to study the distribution. Not much evident information has been disclosed
9. Personal Loan - This would be the target to predict, we will assess whether given data in problem statement is right i.e. only 480 people purchased personal loan with 9.6% from overall population of training set
10. Mortgage account alone looks like stand out from other account? minimum is zero and max is 635, median and mean looks weird
11. Security Account till Credit card account - seems to be categorical features

Need to inspect further to study further from distribution :

Income, Zip code, CCAvg, Education, Mortgage

Very evident outlier :

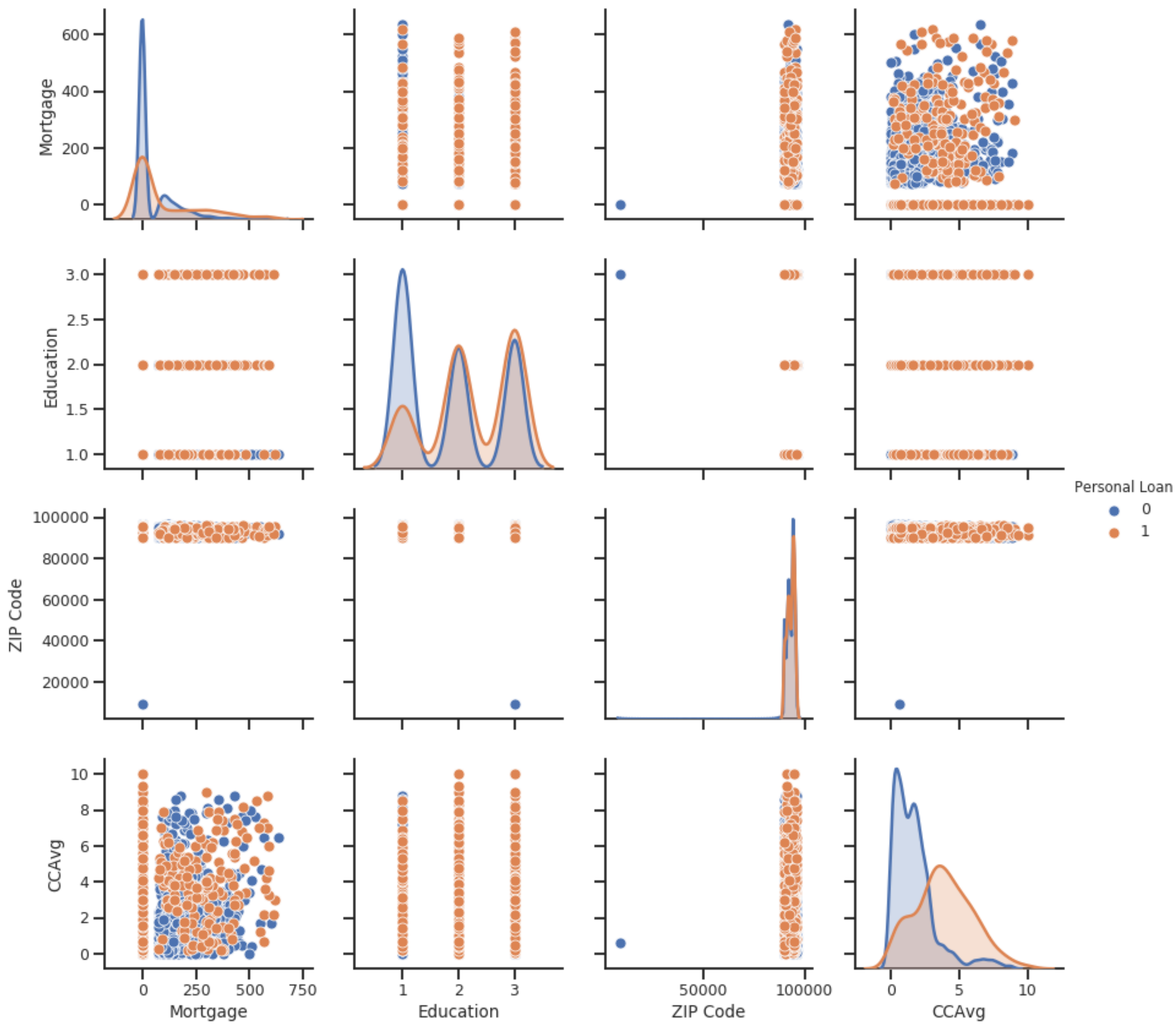
Experience as it has negative values

Features seeming okay at first glance

Age, Categorical features from security account till credit card account

In [549]:
```python
#straight away plotting the pair plot for the features wanting to study further
sns.pairplot(train_df,
             vars=["Mortgage", "Education", "ZIP Code", "CCAvg"],
             height = 3,
             diag_kind="kde", hue="Personal Loan")
```

Out[549]: <seaborn.axisgrid.PairGrid at 0x7f0424795160>



Analysis of Mortgage :

1) Mortgage vs CC Avg - seems to be linearly separable when placed in higher order feature space 2) Mortgage vs Zip code - Seems to have outlier, need to inspect Zip code separately 3) Mortgage vs Education - seems to be linearly separable when placed in higher order feature space 4) Distribution of Mortgage - There are multimodal peaks for both classes 0 & 1 of personal loan. Need to investigate further

Analysis of Education

Clearly there are 3 classes of education - It can be split into 3 distinct categorical features to study further

Analysis of Zip Code

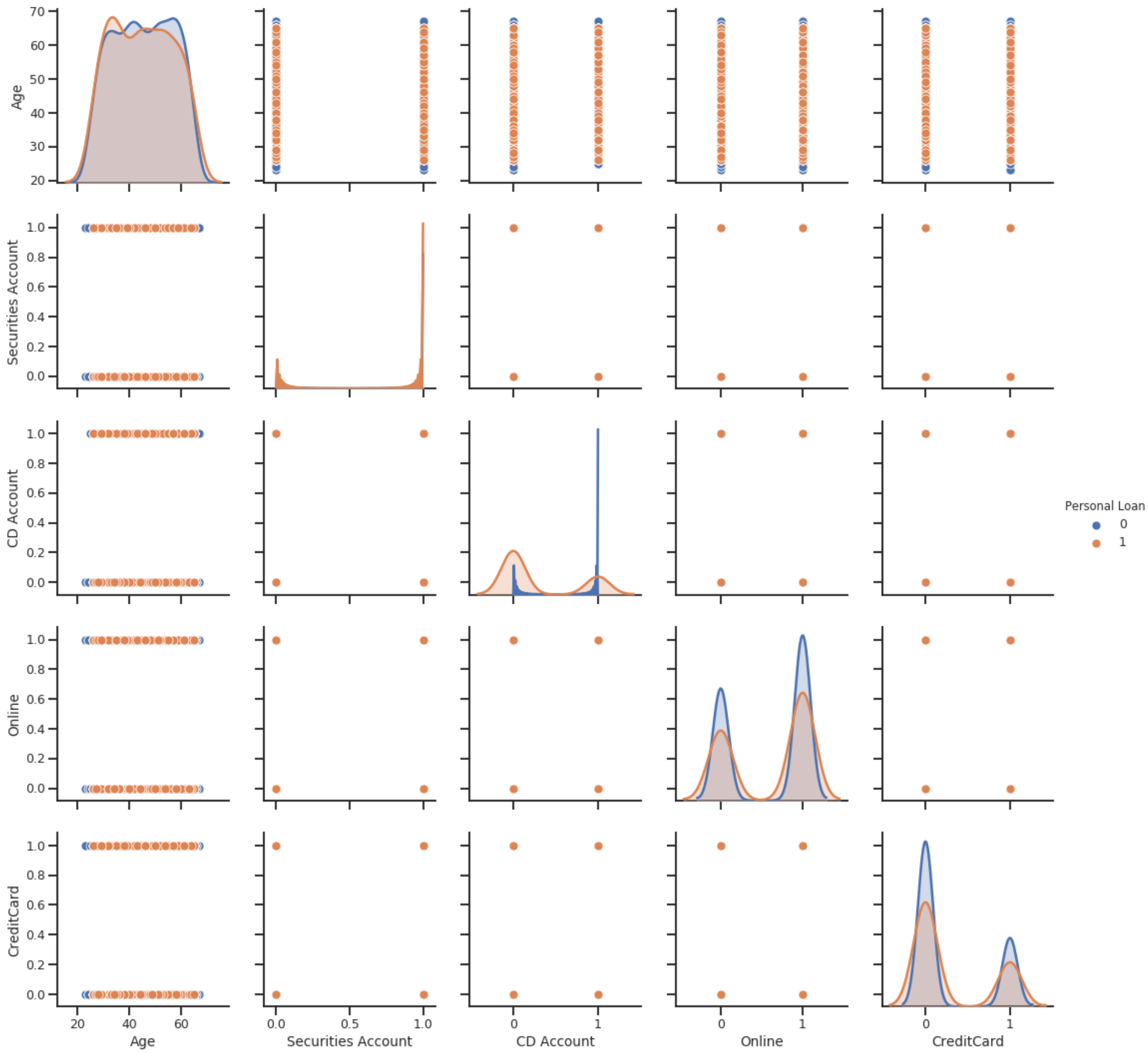
There is ONE outlier while studying interaction of zip code with every other feature varibale, need to inspect this outlier

Analysis of CC Avg

There are multimodal peaks for class zero and almost close to symmetrical for class one except for semi second peak in distribution

In [550]:
```
#straight away plotting the pair plot for the features that seemed okay from dataset
sns.pairplot(train_df,
             vars=["Age", "Securities Account", "CD Account", "Online", "CreditCard"],
             height = 3,
             diag_kind="kde", hue = "Personal Loan")
```

Out[550]: <seaborn.axisgrid.PairGrid at 0x7f04247d66a0>

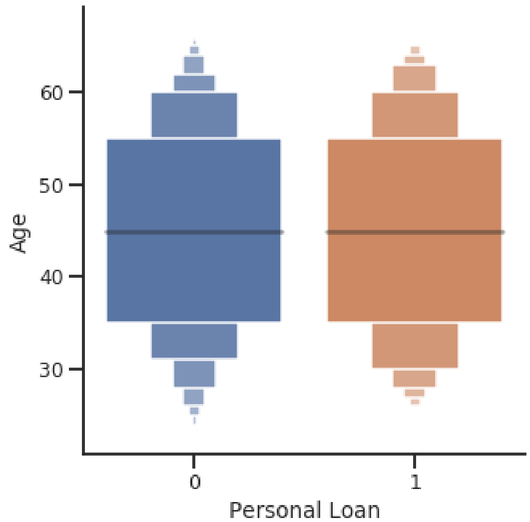


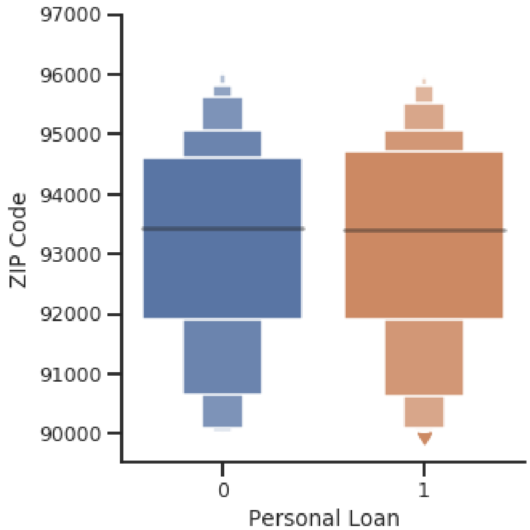
Analysis of Age, Securities Account, CD Account, Online, CreditCard

1) Nothing abnormal observed, there are signficant overalp in clases but may be separable in higher dimensions. Will investigate further on securities, CD and Online

In [551]:

```
#Plotting the age & Zip code Vs Personal Loan - Box Plot

sns.catplot(x="Personal Loan", y="Age", kind="boxen", data=train_df);
sns.catplot(x="Personal Loan", y="ZIP Code", kind="boxen", data=train_df[train_df['ZIP Code'
```





Observation

Clearly, Zip Code < 20000 is outlier. Taking the outlier out of equation, both Age and Zip code have significant overlap in classes and it seem separable if put in higher dimensional order in feature space

In [552]:
```python
#studing similar plot for other accounts - Online Account
sns.catplot(x="Online", y="Age", row="Personal Loan",
                kind="box", height=3, aspect=4,
                data=train_df)
```

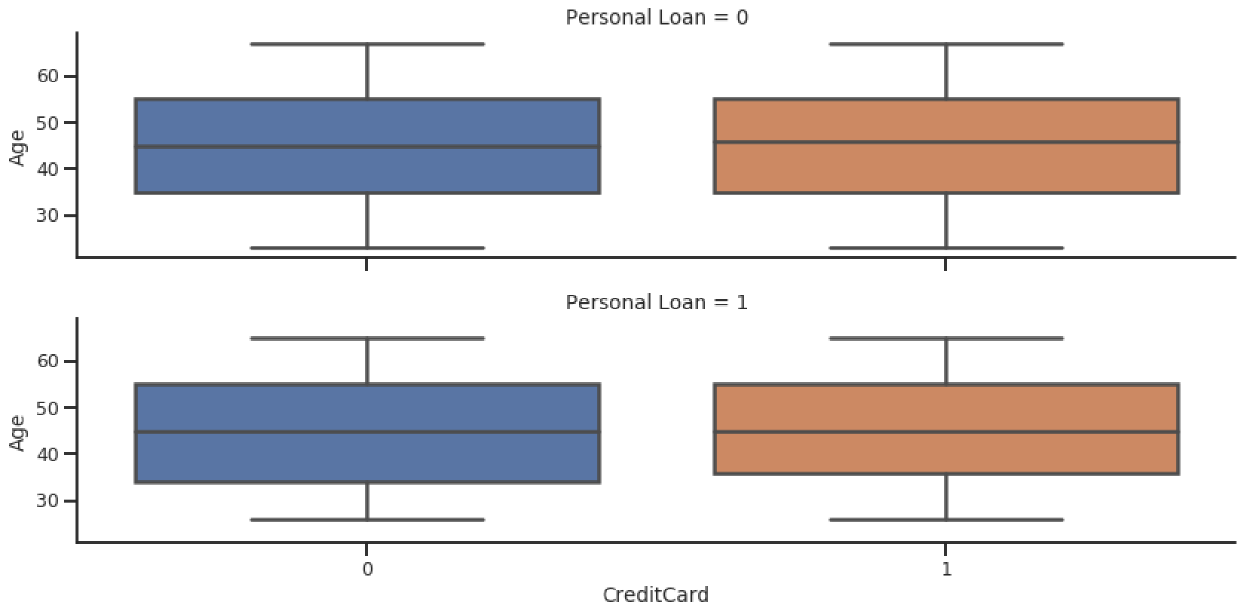
Out[552]: <seaborn.axisgrid.FacetGrid at 0x7f04268d6358>

In [553]:
```python
#studing similar plot for other accounts - Security Accounts
sns.catplot(x="Securities Account", y="Age", row="Personal Loan",
                kind="box", height=3, aspect=4,
                data=train_df)
```

Out[553]: <seaborn.axisgrid.FacetGrid at 0x7f0424cf04a8>

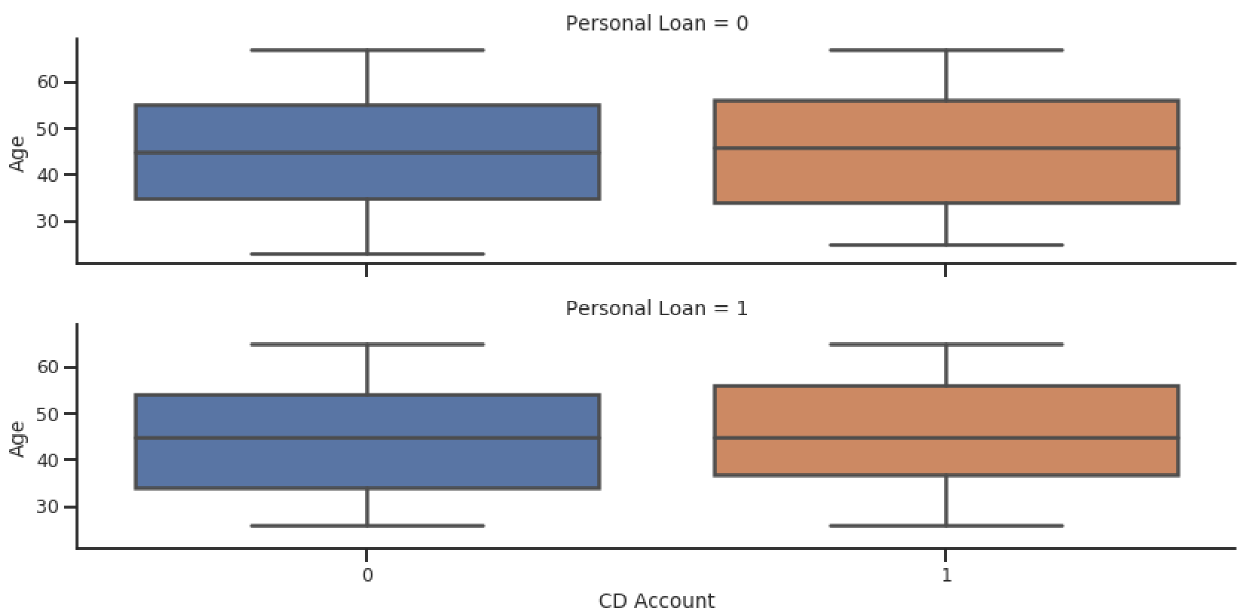
In [554]:
```
#studing similar plot for other accounts - Credit Card
sns.catplot(x="CreditCard", y="Age", row="Personal Loan",
                kind="box", height=3, aspect=4,
                data=train_df)
```

Out[554]: <seaborn.axisgrid.FacetGrid at 0x7f04251e7438>



In [555]:
```
#studing similar plot for other accounts - CD Account
sns.catplot(x="CD Account", y="Age", row="Personal Loan",
                kind="box", height=3, aspect=4,
                data=train_df)
```

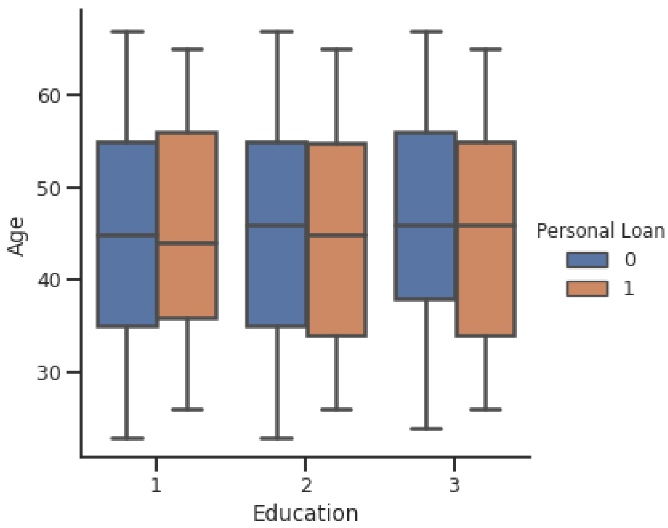
Out[555]: <seaborn.axisgrid.FacetGrid at 0x7f0445c15400>



Observation from Last Above FOUR BOX Plots

By studying the box plots of CD Account, Online Account, Securities Account & Credit Card Account --> It is very evident that there is significant overlap in classes. Proceeding further!

In [556]:
```
# Studing Education - Box Plot to look for personal loan class Vs Education
sns.catplot(x="Education", y="Age", hue="Personal Loan", kind="box", data=train_df);
```

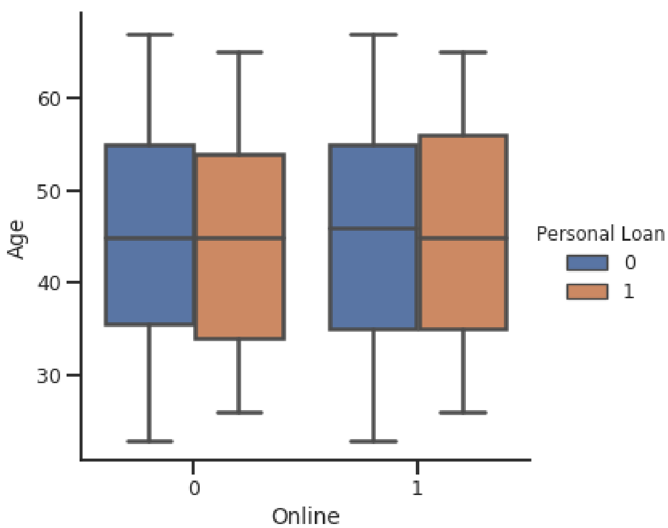


Observation for Education

1) This can be converted as categorical variables for 1, 2 and 3 --> Very evident for overlap in classes like other features

small signs of customers with higher education & young age has better chance of purchasing loan + customer with lower education & Old age has better chance of purchasing loan based on above box plot - VERY SMALL INDICATIONS THOUGH, NOT MUCH SIGNIFICANT

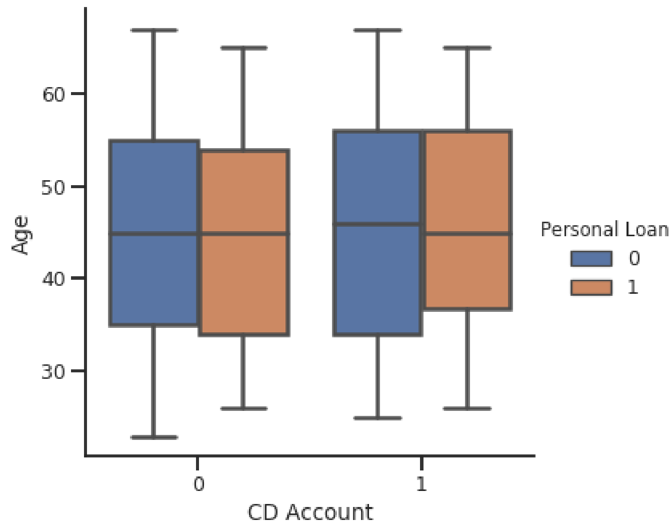
In [557]:
```
sns.catplot(x="Online", y="Age", hue="Personal Loan", kind="box", data=train_df);
```

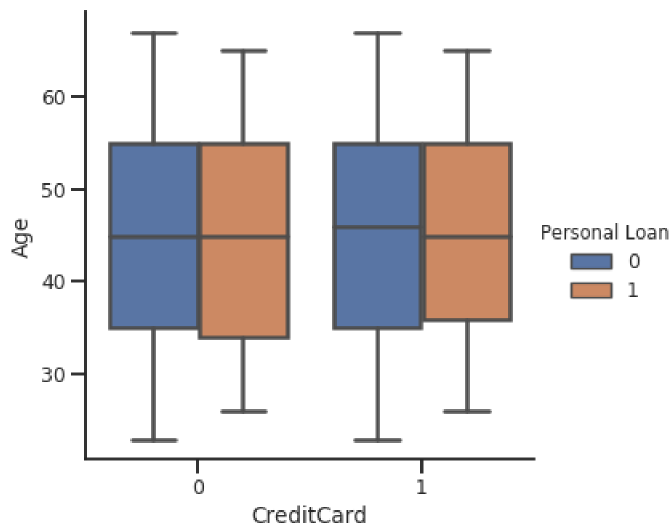


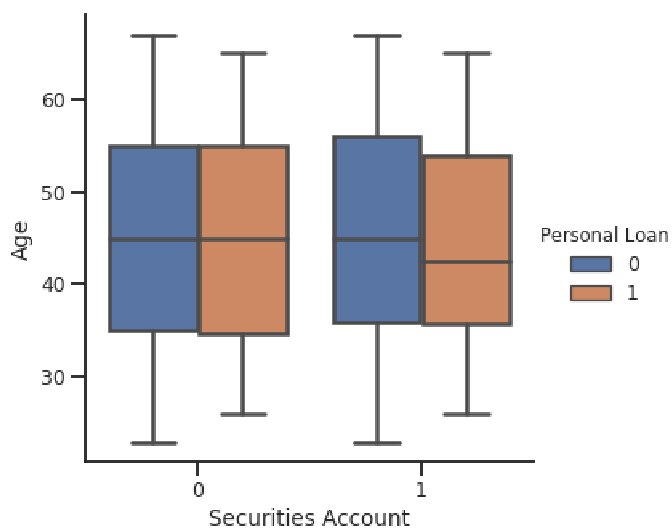
small signs of customers having online account & older age has better chance of purchasing loan + customer with NO Online account & younger age has better chance of purchasing loan based on above box plot - VERY SMALL INDICATIONS THOUGH, NOT MUCH SIGNIFICANT

In [558]:

```
sns.catplot(x="CD Account", y="Age", hue="Personal Loan", kind="box", data=train_df);
sns.catplot(x="CreditCard", y="Age", hue="Personal Loan", kind="box", data=train_df);
sns.catplot(x="Securities Account", y="Age", hue="Personal Loan", kind="box", data=train_df)
```





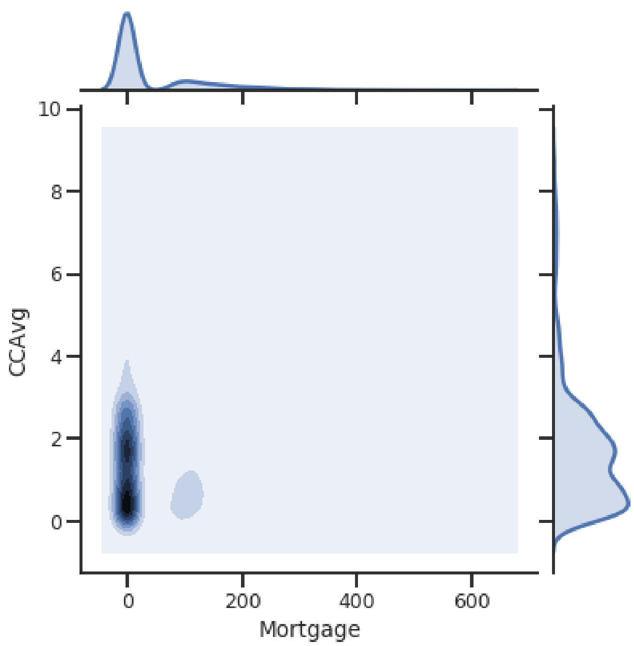


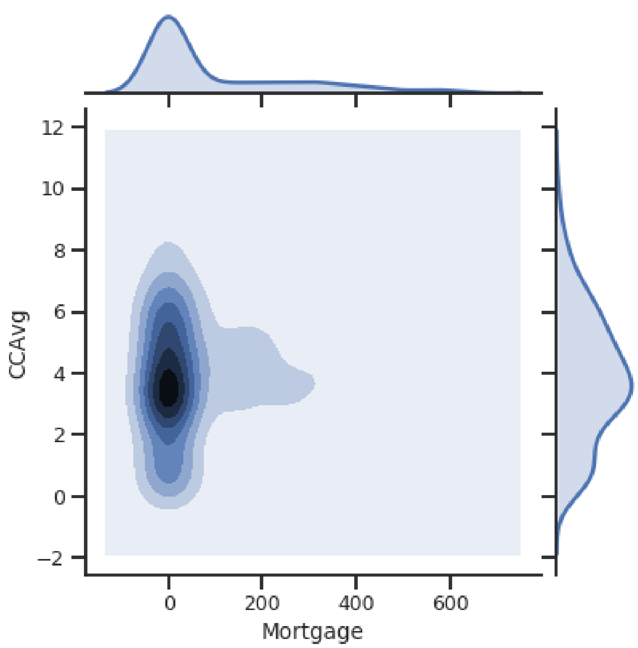
VERY SMALL SIGNS observed with younger age customers with NO Securities or CD or Credit card account has

better chance of purchasing loan as well. VERY SMALL INDICATIONS though, NOT a significant indicator

In [559]:
```
sns.jointplot(x="Mortgage", y="CCAvg", kind='kde', data=train_df[train_df['Personal Loan'] =
sns.jointplot(x="Mortgage", y="CCAvg", kind='kde', data=train_df[train_df['Personal Loan'] =
```

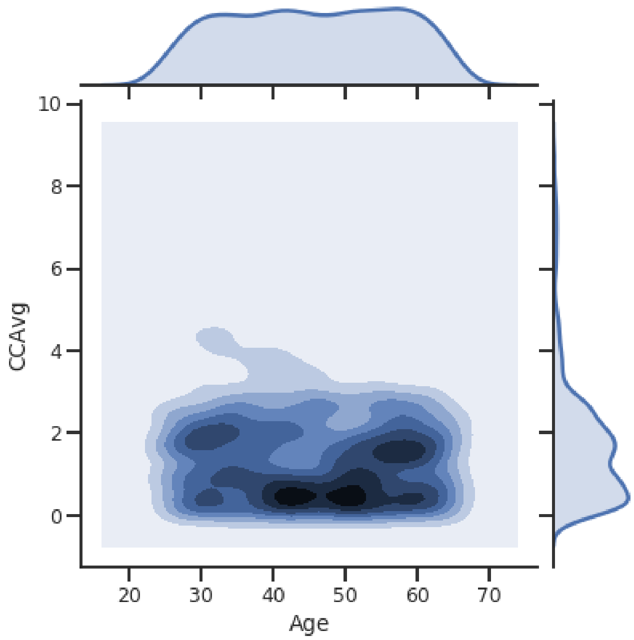
Out[559]:
```
<seaborn.axisgrid.JointGrid at 0x7f0424d3ab38>
```

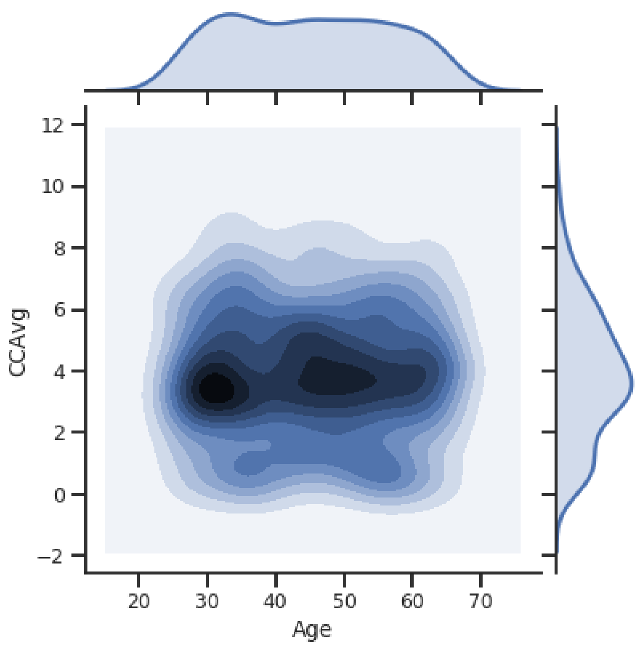




In [560]:
```
sns.jointplot(x="Age", y="CCAvg", kind='kde', data=train_df[train_df['Personal Loan'] == 0])
sns.jointplot(x="Age", y="CCAvg", kind='kde', data=train_df[train_df['Personal Loan'] == 1])
```

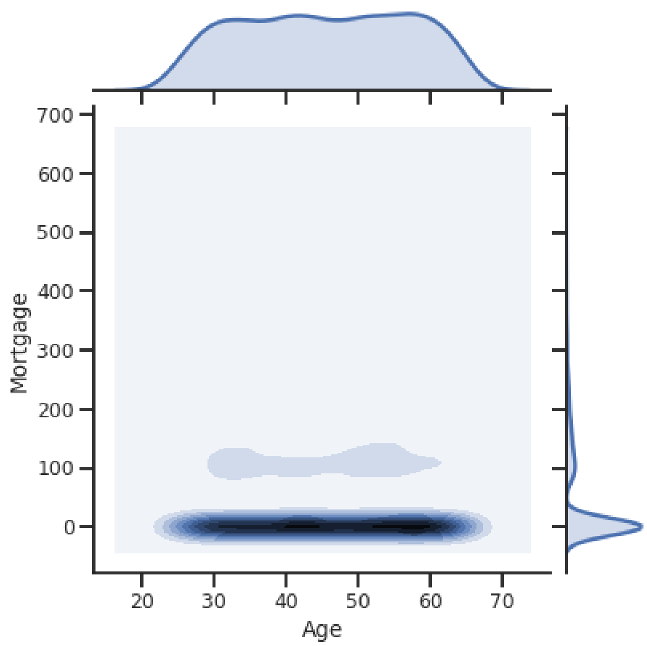
Out[560]: <seaborn.axisgrid.JointGrid at 0x7f0446053518>

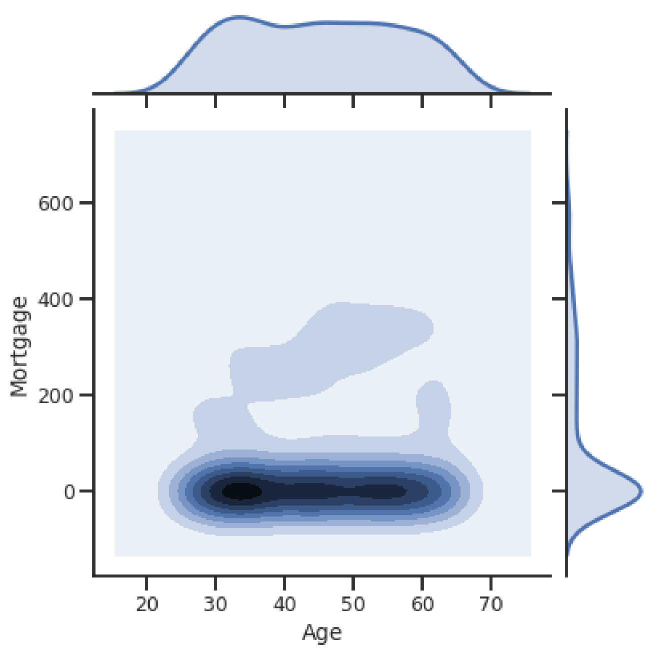




In [561]:
```
sns.jointplot(x="Age", y="Mortgage", kind='kde', data=train_df[train_df['Personal Loan'] ==
sns.jointplot(x="Age", y="Mortgage", kind='kde', data=train_df[train_df['Personal Loan'] ==
```

Out[561]: <seaborn.axisgrid.JointGrid at 0x7f041fa25be0>





INTERESTING Observations from above distribution joint plots with respect to Target Variable

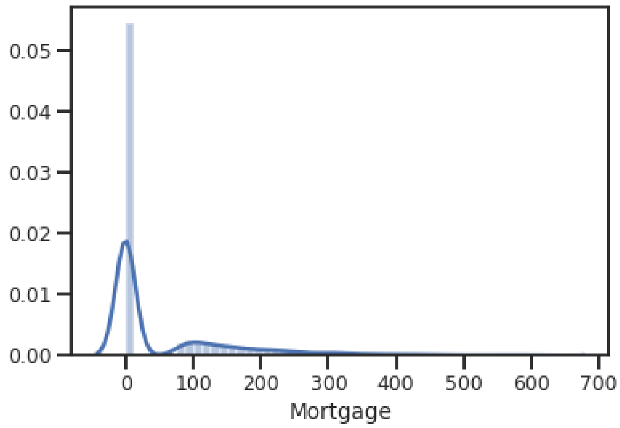
observation 1

Customers who DID NOT purchase personal loan --> They had very LOW CCAvg, LOW Mortgage between 30-60 Age groups

observation 2

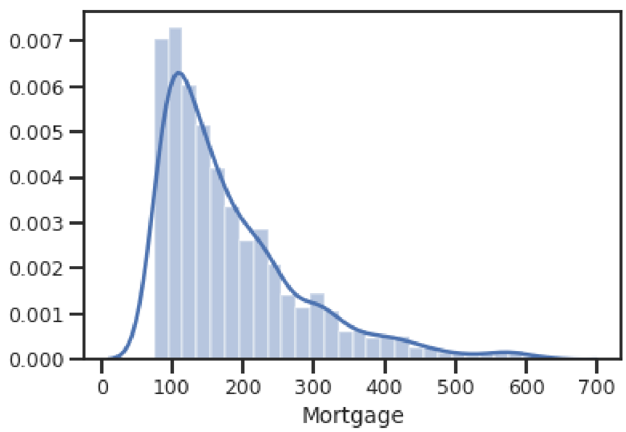
Customers who DID purchase personal loan --> They had CCAvg ranging between 0 and 8, with most frequent customers between around 4-7 (which is SIGNIFICANTLY higher than observation 1) & VARYING MORTGAGE between 30-60 Age groups

In [562]:
```
#It is also evident only few customers have postive mortgage values
sns.distplot(train_df["Mortgage"]);
```



In [563]:
```
sns.distplot(train_df[train_df.Mortgage > 0].Mortgage)
```

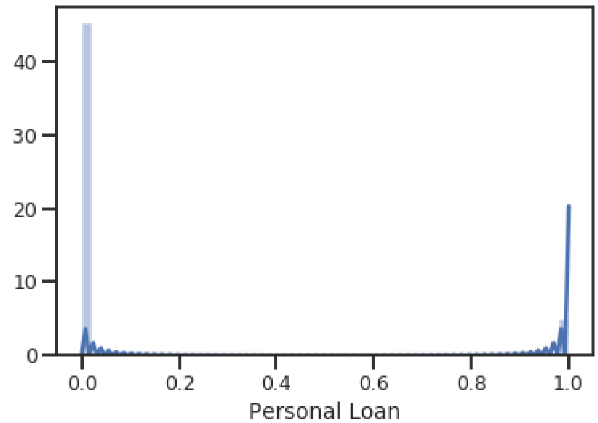
Out[563]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0445feee80>



Observation on Mortgage

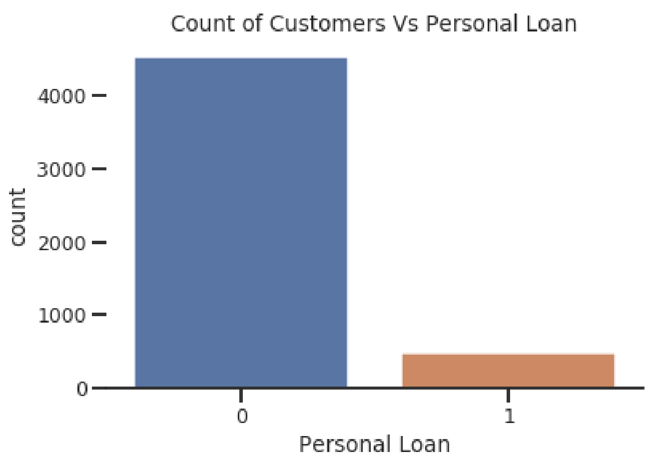
More common Mortgage values with customers who have mortgage is around 100-300 approximately

In [564]:
```python
sns.distplot(train_df["Personal Loan"]);
```



In [565]:
```python
sns_plot = sns.countplot(x="Personal Loan", data=train_df)
sns.despine(left=True)
plt.title("Count of Customers Vs Personal Loan")
```

Out[565]:
```
Text(0.5, 1.0, 'Count of Customers Vs Personal Loan')
```



In [566]:
```python
train_df.groupby(by="Personal Loan", sort=True).count()
```

Out[566]:

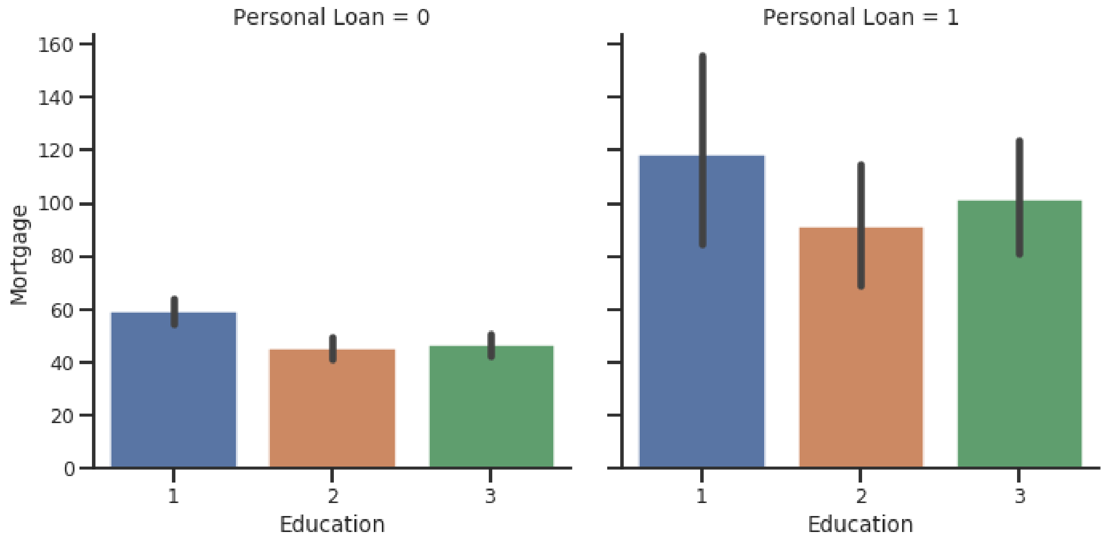
Personal Loan	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Securities Account	CD Account	Online	CreditCa
0	4520	4520	4520	4520	4520	4520	4520	4520	4520	4520	4520	4520	45
1	480	480	480	480	480	480	480	480	480	480	480	480	48

Observation on Target Variable - Personal Loan

Like given in problem description, customers who accepted the personal loan offered is only 480, out of entire 5000 population in training set

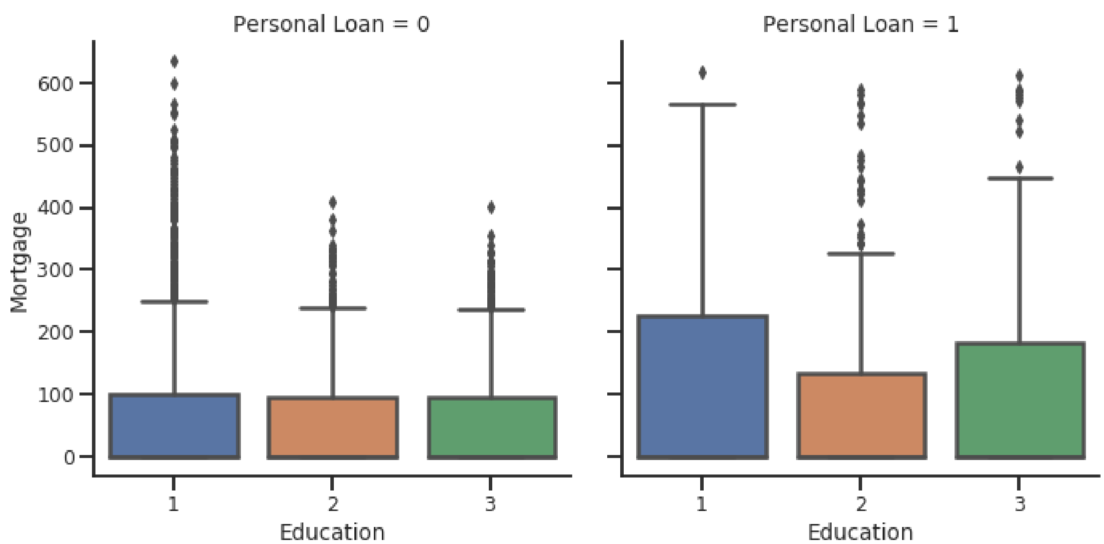
In [567]:
```
sns.catplot(x="Education", y="Mortgage", col="Personal Loan", kind='bar', data=train_df, leg
```

Out[567]: <seaborn.axisgrid.FacetGrid at 0x7f0445d95e10>



In [568]:
```
sns.catplot(x="Education", y="Mortgage", col="Personal Loan", kind='box', data=train_df, leg
```

Out[568]: <seaborn.axisgrid.FacetGrid at 0x7f041f48ff60>

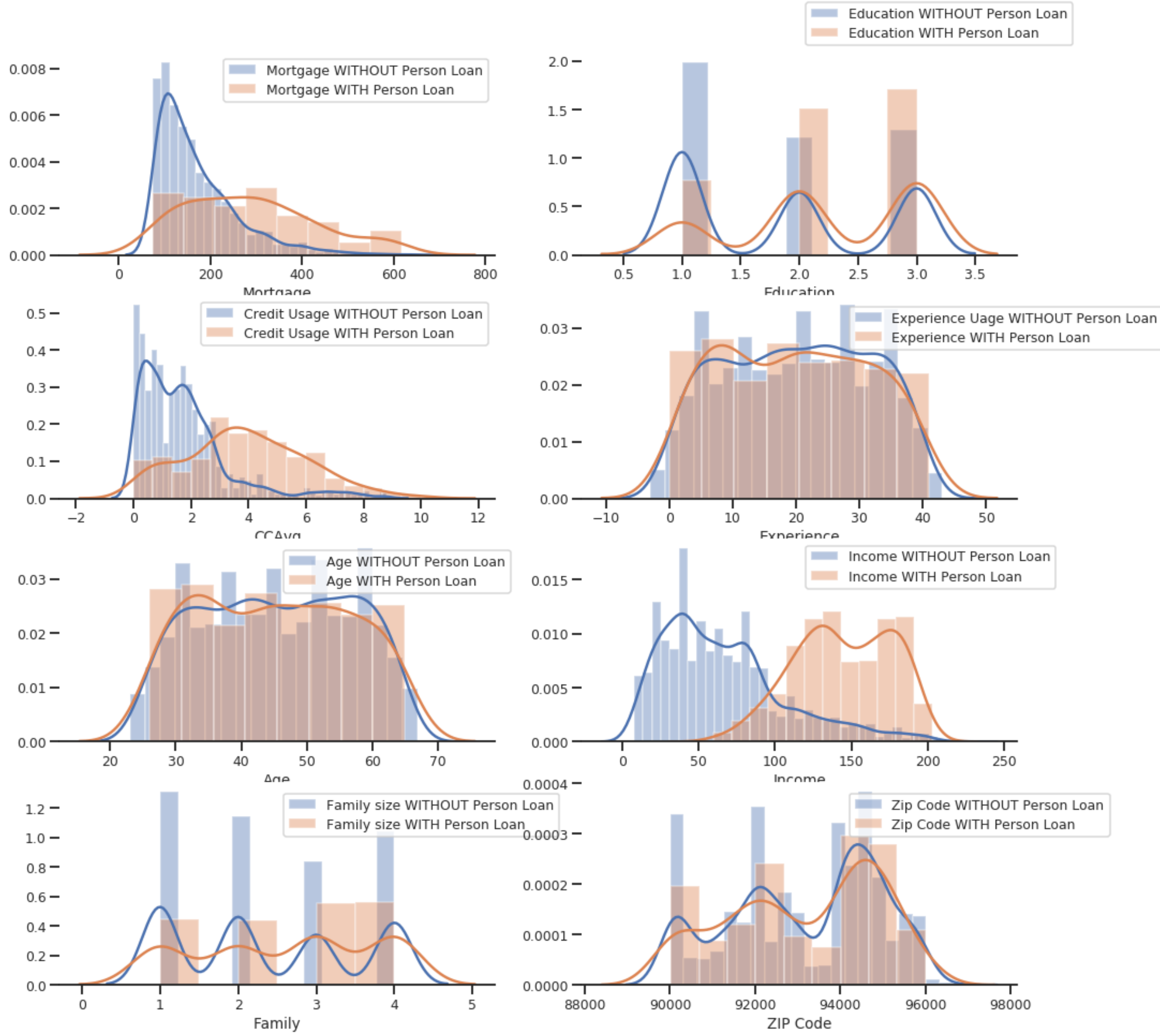


Another interesting Observation on target variable with respect to Education & Mortgage Vs Target

There are lot of customers who has higher mortgage values between 100 and 300 --> they seem to have purchased personal loan, in particular, this pattern seems to be common with education level 1 and 3 to be specifci

In [569]:

```
########## Studying the target variable distribution with respect to other input feature var

f, axes = plt.subplots(4,2, figsize=(16, 16), sharex=False)

sns.distplot(train_df[(train_df.Mortgage > 0) &
          (train_df['Personal Loan'] == 0)].Mortgage, label="Mortgage WITHOUT Person Loan",
sns.distplot(train_df[(train_df.Mortgage > 0) &
          (train_df['Personal Loan'] == 1)].Mortgage, label="Mortgage WITH Person Loan", ax=

sns.distplot(train_df[train_df['Personal Loan'] == 0].Education, label="Education WITHOUT Pe
sns.distplot(train_df[train_df['Personal Loan'] == 1].Education, label="Education WITH Perso

sns.distplot(train_df[train_df['Personal Loan'] == 0]['CCAvg'], label="Credit Usage WITHOUT
sns.distplot(train_df[train_df['Personal Loan'] == 1]['CCAvg'], label="Credit Usage WITH Per

sns.distplot(train_df[train_df['Personal Loan'] == 0]['Experience'], label="Experience Uage
sns.distplot(train_df[train_df['Personal Loan'] == 1]['Experience'], label="Experience WITH

sns.distplot(train_df[train_df['Personal Loan'] == 0]['Age'], label="Age WITHOUT Person Loan
sns.distplot(train_df[train_df['Personal Loan'] == 1]['Age'], label="Age WITH Person Loan",

sns.distplot(train_df[train_df['Personal Loan'] == 0]['Income'], label="Income WITHOUT Perso
sns.distplot(train_df[train_df['Personal Loan'] == 1]['Income'], label="Income WITH Person L

sns.distplot(train_df[train_df['Personal Loan'] == 0]['Family'], label="Family size WITHOUT
sns.distplot(train_df[train_df['Personal Loan'] == 1]['Family'], label="Family size WITH Per

sns.distplot(train_df[(train_df['ZIP Code'] > 20000) &
          (train_df['Personal Loan'] == 0)]['ZIP Code'], label="Zip Code WITHOUT Person Loan
sns.distplot(train_df[(train_df['ZIP Code'] > 20000) &
          (train_df['Personal Loan'] == 1)]['ZIP Code'], label="Zip Code WITH Person Loan",


axes[0,0].legend(bbox_to_anchor=(1, 1), loc='best')
axes[0,1].legend(bbox_to_anchor=(0.5, 1), loc='best')
axes[1,0].legend(bbox_to_anchor=(1, 1), loc='best')
axes[1,1].legend(bbox_to_anchor=(0.6, 0.7), loc='best')
axes[2,0].legend(bbox_to_anchor=(0.5, 0.7), loc='best')
axes[2,1].legend(bbox_to_anchor=(0.5, 1), loc='best')
axes[3,0].legend(bbox_to_anchor=(0.5, 0.7), loc='best')
axes[3,1].legend(bbox_to_anchor=(0.6, 0.7), loc='best')


sns.despine(left=True)
#f.legend()
```



Summary of above Target Variable Distribution :-

1) Mortgage, CCAvg and Income features are continuous and have very visible influence on customers purchasing personal loan. i.e., a) relatively higher income customers have better probability of purchasing personal loan b) People who have higher mortgage have better probability of purchasing personal loan c) relatively higher credit usage has higher probability of purchasing personal loan

Family size also seem to play a small role, higher family size customers seem to have higher chances of purchasing personal loan from the bank (on a relative scale compared to smaller family size).

but can there be multi collinearity between Credit usage, income and mortgage? i.e. People with higher income will obviously tend to have higher credit usage, mortgage & have chances of buying personal loan? We will find it out by deriving correlation between input attributes & if these 3 interactions have higher dependency/correlation - they have to be dropped except for one feature as it will not add any value to classifciation problem

Other inferences 1 :-

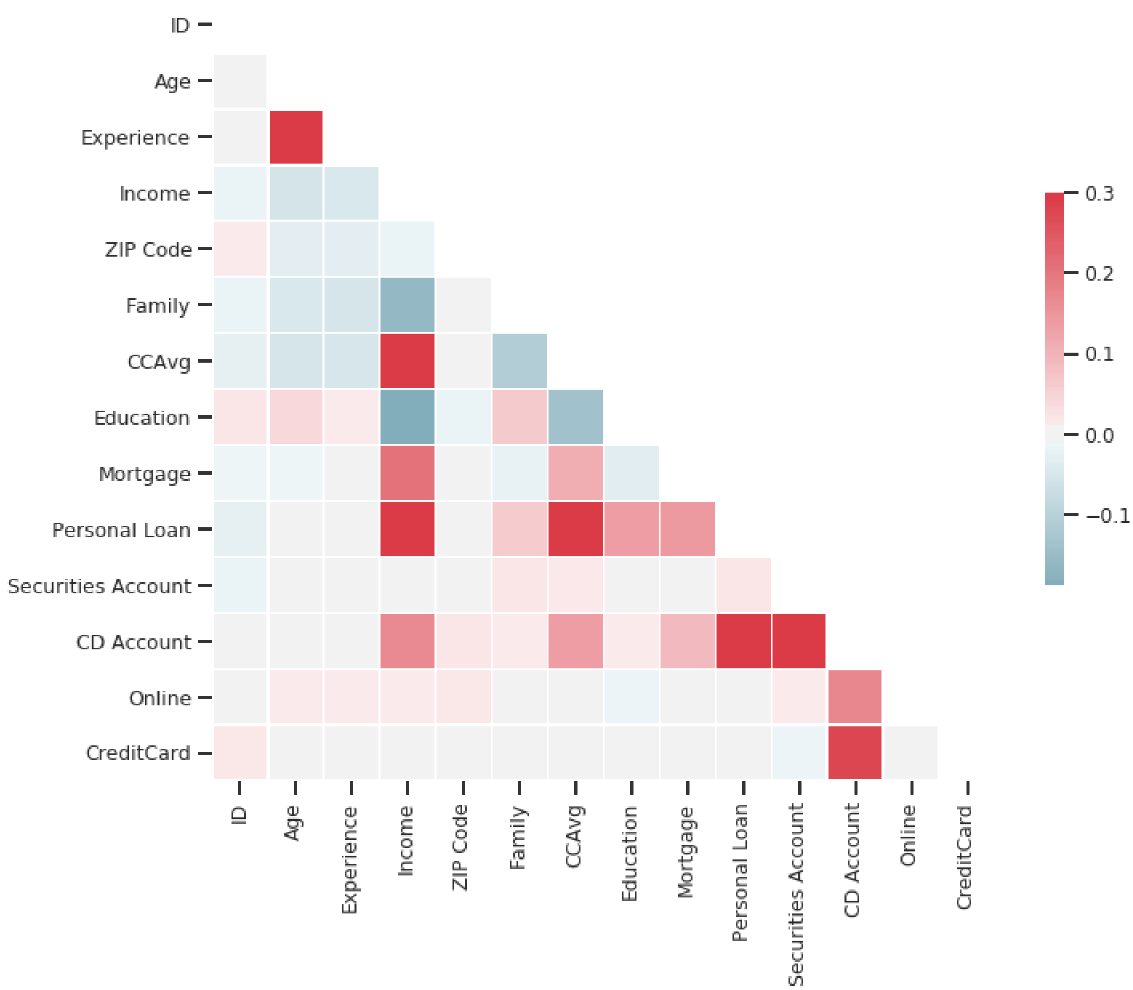
1) Age, Zip code and Experience doesn't convey any evident classification distribution individually.

Other inferences 2 :-

2) Education and Family seem to have some influence in classification of people purchasing personal loan. Can these play a role of being a key feature along with age or experience? May be, may be not! Need to find out during modeling only

In [570]:
```
# Compute the correlation matrix
corr = train_df.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[570]: <matplotlib.axes._subplots.AxesSubplot at 0x7f041ee877b8>



Conclusion from Correlation Matrix :

1:- We can infer that, CC Avg, Mortgage and Income seem to have some kind of correlation between them. With the value being around 0.3, it might be smaller value still, but these are the strongest correlation among all features between them on relative scale

2:- Age & Experience seem to have strongest correlation between them

KEY CONCLUSION:- One of (income, CC Avg, Mortgage) or all 3 + one of (Age, Experience) + Family size + Zip(if any location can be extracted from zip, it would be great categorical candidate) + Other categorical feature are essential

candidates to start on base model

Feature Types : Categorical

Family, Education, Securities, CD Account, Online, Credit Card

Feature Types : Continuous

Age, Experience, Income, Zip Code, CC Avg, Mortgage

Feature Types : Target to classify

Personal Loan

Features to IGNORE

ID

In [571]:
```
##############################################################################################
#### THERE ARE 312 customers, i.e. majority of minority class of having to purchase personal
######################## i.e. we cannot drop this feature, it has to be used in combination
##############################################################################################

train_df[(train_df.Mortgage == 0) &
          (train_df['Personal Loan'] == 1)].count()
```

Out[571]:
```
ID                     312
Age                    312
Experience             312
Income                 312
ZIP Code               312
Family                 312
CCAvg                  312
Education              312
Mortgage               312
Personal Loan          312
Securities Account     312
CD Account             312
Online                 312
CreditCard             312
dtype: int64
```

In [572]:
```
##############################################################################################
#### Wish Zip code carries some location information, but below random inspection SHOWS OTHE
##################################################### So this CAN BE dropped ##################
##############################################################################################

train_df['ZIP Code'].unique()[:50]
```

Out[572]:
```
array([91107, 90089, 94720, 94112, 91330, 92121, 91711, 93943, 93023,
       94710, 90277, 93106, 94920, 91741, 95054, 95010, 94305, 91604,
       94015, 90095, 91320, 95521, 95064, 90064, 94539, 94104, 94117,
       94801, 94035, 92647, 95814, 94114, 94115, 92672, 94122, 90019,
       95616, 94065, 95014, 91380, 95747, 92373, 92093, 94005, 90245,
       95819, 94022, 90404, 93407, 94523])
```

UPDATING FINALIZED FEATURES (after our above last 2 analysis):-

income, CC Avg, Mortgage + one of (Age, Experience) + Family size + Zip(if any location can be extracted from zip, it would be great categorical candidate) + Other categorical feature are essential candidates to start on base model

Feature Types : Categorical

Family, Education, Securities, CD Account, Online, Credit Card

Feature Types : Continuous

Age, Experience, Income, CC Avg, Mortgage

Feature Types : Target to classify

Personal Loan

Features to IGNORE

ID, Zip Code

In [573]:
```
#### let us get rid of space between feature names for easy usage in feature engineering ###
train_df.columns = [c.replace(' ', '_') for c in train_df.columns]
train_df.columns
```

Out[573]:
```
Index(['ID', 'Age', 'Experience', 'Income', 'ZIP_Code', 'Family', 'CCAvg',
       'Education', 'Mortgage', 'Personal_Loan', 'Securities_Account',
       'CD_Account', 'Online', 'CreditCard'],
      dtype='object')
```

In [574]:
```
####### Converting to categorical data type as they are created as type int but they are tru

categorical_features = ['Family', 'Education', 'Securities_Account', 'CD_Account', 'Online',

for feature in categorical_features:
    train_df[feature] = train_df[feature].astype('category')

train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
ID                    5000 non-null int64
Age                   5000 non-null int64
Experience            5000 non-null int64
Income                5000 non-null int64
ZIP_Code              5000 non-null int64
Family                5000 non-null category
CCAvg                 5000 non-null float64
Education             5000 non-null category
Mortgage              5000 non-null int64
Personal_Loan         5000 non-null int64
Securities_Account    5000 non-null category
CD_Account            5000 non-null category
Online                5000 non-null category
CreditCard            5000 non-null category
dtypes: category(6), float64(1), int64(7)
memory usage: 342.5 KB
```

In [575]:
```
####### Inspecting the size of total columns #######
train_df.columns.size
```

Out[575]: 14

In [576]:
```
####### Doing Pandas get dummies to transform the categorical variables #######

to_transform_categories = ['Family', 'Education'] ## Remaining categorical features are alre
temp_df = pd.get_dummies(train_df[to_transform_categories], prefix=to_transform_categories)
temp_df.head()
```

Out[576]:

	Family_1	Family_2	Family_3	Family_4	Education_1	Education_2	Education_3
0	0	0	0	1	1	0	0
1	0	0	1	0	1	0	0
2	1	0	0	0	1	0	0
3	1	0	0	0	0	1	0
4	0	0	0	1	0	1	0

In [577]:
```
####### dropping the irrelavnt original features and concatenating the actual categoricals #
train_df.drop(to_transform_categories, axis=1, inplace=True)
train_df = pd.concat([train_df, temp_df], axis=1)
train_df.head()
```

Out[577]:

	ID	Age	Experience	Income	ZIP_Code	CCAvg	Mortgage	Personal_Loan	Securities_Account	CD_Account	Online	Credi
0	1	25	1	49	91107	1.6	0	0	1	0	0	
1	2	45	19	34	90089	1.5	0	0	1	0	0	
2	3	39	15	11	94720	1.0	0	0	0	0	0	
3	4	35	9	100	94112	2.7	0	0	0	0	0	
4	5	35	8	45	91330	1.0	0	0	0	0	0	

In [578]:
```
####### Dropping irrelant ID and Zip Code as concluded in above analysis #######

drop_columns = ['ID', 'ZIP_Code']
train_df.drop(drop_columns, axis=1, inplace=True)
train_df.head()
```

Out[578]:

	Age	Experience	Income	CCAvg	Mortgage	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	Family_1
0	25	1	49	1.6	0	0	1	0	0	0	(
1	45	19	34	1.5	0	0	1	0	0	0	(
2	39	15	11	1.0	0	0	0	0	0	0	1
3	35	9	100	2.7	0	0	0	0	0	0	1
4	35	8	45	1.0	0	0	0	0	0	1	(

In [579]:
```
#### LAST FEW STEPs refined our feature set to 17 trainable features for base model, ALL SET

train_df.columns.size
```

Out[579]: 17

In [580]:
```
#### Split the training data set into X & Y ####
X = train_df.drop('Personal_Loan', axis=1)
y = train_df['Personal_Loan']
```

In [581]:
```
### 16 input features in total ###
X.shape
```

Out[581]:
```
(5000, 16)
```

In [582]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
```

In [583]:
```
### CONFIGURING THE MODELS TO TRAIN ###

dict_classifiers = {
    "Logistic Regression": LogisticRegression(),
    "Nearest Neighbors": KNeighborsClassifier(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(max_depth=8,n_estimators=1000),
    "Naive Bayes": GaussianNB(),
    "Support Vector": svm.SVC()
    }
```

In [584]:

```python
###### ACTUAL MODEL TRAINING LOGIC ########

def bulk_train(X_train, Y_train, X_test, Y_test, no_classifiers = 5, verbose = True):
    model_list_pickle = {}

    for classifier_name, classifier in list(dict_classifiers.items())[:no_classifiers]:
        start_time = time.clock()
        if verbose:
            print("Training {c} - Start ".format(c=classifier_name))
        classifier.fit(X_train, np.ravel(Y_train,order='C'))
        end_time = time.clock()
        total_time_to_train = end_time - start_time
        train_score = classifier.score(X_train, Y_train)
        test_score = classifier.score(X_test, Y_test)
        if verbose:
            print(train_score, test_score)

        ############# Also GOING TO CROSS VALIDATE ##############
        from sklearn.model_selection import cross_val_score
        accuracies_cv= cross_val_score(estimator = classifier, X = X_train, y = y_train, cv
        accuracies_cv_mean=accuracies_cv.mean()*100
        print("%s : Mean Accuracy from CV is %s %%"%(classifier_name,accuracies_cv_mean))
        accuracies_cv_std=accuracies_cv.std()*100
        print("%s : Standard Deviation from CV %s %%"%(classifier_name,accuracies_cv_std))
        ################# END OF CROSS VALIDATE #################

        model_list_pickle[classifier_name] = {'model': classifier,
                                              'train_score': train_score,
                                              'test_score': test_score,
                                              'train_time': total_time_to_train,
                                              'crossval_avg_accuracy': accuracies_cv_mean,
                                              'crossval_std': accuracies_cv_std
                                             }

        if verbose:
            print("trained {c} in {f:.2f} s".format(c=classifier_name, f=total_time_to_train

    return model_list_pickle
```

In [585]:
```
#### FUNCTION TO RECORD MODEL METRICS AS DATAFRAME ###

def print_confusion_matrix(model_list, X_test):
    cls_key = [key for key in model_list.keys()]
    cm_df_values = [[]]
    cm_df_cols = ['classifer', 'True_Positive', 'True_Negative', 'False_Postive', 'False_Neg
                  'Train_AccuracyScore','Test_AccuracyScore', 'CrossVal_Accuracy%', 'CrossVa
    for i in range(0, len(cls_key)):
        predictions = model_list[cls_key[i]]['model'].predict(X_test)
        cm = confusion_matrix(y_test, predictions)
        cr = classification_report(y_test, predictions)
        print("\n###### Confusion Matrix Summary for [%s] ######\n"%(cls_key[i]))
        print(cm)
        print("\n###### Classification Report for [%s] ######\n"%(cls_key[i]))
        print(cr)
        if (i == 0) :
            cm_df_values = [[cls_key[i], cm[1,1], cm[0,0], cm[0,1], cm[1,0],
                            model_list[cls_key[i]]['train_score'], model_list[cls_key[i]]['t
                            model_list[cls_key[i]]['crossval_avg_accuracy'], model_list[cls_
        else :
            cm_df_values = cm_df_values + [[cls_key[i], cm[1,1], cm[0,0], cm[0,1], cm[1,0],
                                           model_list[cls_key[i]]['train_score'], model_list
                                           model_list[cls_key[i]]['crossval_avg_accuracy'],

    cm_df = pd.DataFrame(data=cm_df_values, columns=cm_df_cols)
    print("\n###### Exiting Confusion Matrix Summary ######\n")
    return cm_df

#TN (0,0), FP (0,1), FN (1,0), TP (1,1)
```

In [586]:
```
### METHOD TO SUMMARIZE THE MODEL TRAINING i.e. just to PRINT THE OUTCOME ###

def log_train_summary(model_list, sort_by='test_score'):
    cls_key = [key for key in model_list.keys()]
    test_local = [model_list[key]['test_score'] for key in cls_key]
    training_local = [model_list[key]['train_score'] for key in cls_key]
    training_time_local = [model_list[key]['train_time'] for key in cls_key]

    df_ = pd.DataFrame(data=np.zeros(shape=(len(cls_key),4)), columns = ['classifier', 'trai
    for i in range(0,len(cls_key)):
        df_.loc[i, 'classifier'] = cls_key[i]
        df_.loc[i, 'train_score'] = training_local[i]
        df_.loc[i, 'test_score'] = test_local[i]
        df_.loc[i, 'train_time'] = training_time_local[i]

    #overriding the sort clause passed in function to get list of sort criteria for now
    print(df_.sort_values(by=['test_score','train_score'], ascending=False))
```

In [587]:
```
from sklearn.metrics import f1_score, roc_auc_score, roc_curve
def generate_auc_roc_curve(clf, X_test):
    y_pred_proba = clf.predict_proba(X_test)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_test,  y_pred_proba)
    auc = roc_auc_score(y_test, y_pred_proba)
    plt.plot(fpr,tpr,label="AUC ROC Curve with Area Under the curve ="+str(auc))
    plt.legend(loc=4)
    plt.show()
    pass
```

In [588]:

```python
### Training with Different Models - Logistics Regression, KNN, NB, SVM, Random Forest and D

models_list = bulk_train(X_train, y_train, X_test, y_test, no_classifiers = 6, verbose=False
print("\n")
print("############ CONSOLIDATED MODEL TRAINING SUMMARY ############")
print("############### ######################## ###################")
log_train_summary(models_list)
print("############### ######################## ###################")
```

```
Logistic Regression : Mean Accuracy from CV is 95.80112420742792 %
Logistic Regression : Standard Deviation from CV 0.9348877725124194 %
Nearest Neighbors : Mean Accuracy from CV is 90.42983184702382 %
Nearest Neighbors : Standard Deviation from CV 1.2377041386791727 %
Decision Tree : Mean Accuracy from CV is 98.1425212800571 %
Decision Tree : Standard Deviation from CV 0.32107241316387186 %
Random Forest : Mean Accuracy from CV is 98.34284874628715 %
Random Forest : Standard Deviation from CV 0.3997878953647907 %
Naive Bayes : Mean Accuracy from CV is 89.5148902673258 %
Naive Bayes : Standard Deviation from CV 1.2797690536684705 %
Support Vector : Mean Accuracy from CV is 90.74289282827964 %
Support Vector : Standard Deviation from CV 0.445094057786574 %


############ CONSOLIDATED MODEL TRAINING SUMMARY ############
############### ######################## ###################
            classifier  train_score  test_score  train_time
3        Random Forest     0.992286    0.988667    1.208397
2        Decision Tree     1.000000    0.984000    0.005467
0  Logistic Regression     0.960000    0.964000    0.020560
5       Support Vector     0.975429    0.900667    0.426401
4          Naive Bayes     0.896286    0.900667    0.003780
1    Nearest Neighbors     0.940286    0.898000    0.008591
############### ######################## ###################
```

In [589]:
```
#### Printing Confusion Matrix #####
confusion_matrix_df = print_confusion_matrix(models_list, X_test)
```

```
###### Confusion Matrix Summary for [Logistic Regression] ######

[[1333   10]
 [  44  113]]

###### Classification Report for [Logistic Regression] ######

              precision    recall  f1-score   support

           0       0.97      0.99      0.98      1343
           1       0.92      0.72      0.81       157

   micro avg       0.96      0.96      0.96      1500
   macro avg       0.94      0.86      0.89      1500
weighted avg       0.96      0.96      0.96      1500


###### Confusion Matrix Summary for [Nearest Neighbors] ######

[[1297   46]
 [ 107   50]]

###### Classification Report for [Nearest Neighbors] ######

              precision    recall  f1-score   support

           0       0.92      0.97      0.94      1343
           1       0.52      0.32      0.40       157

   micro avg       0.90      0.90      0.90      1500
   macro avg       0.72      0.64      0.67      1500
weighted avg       0.88      0.90      0.89      1500


###### Confusion Matrix Summary for [Decision Tree] ######

[[1333   10]
 [  14  143]]

###### Classification Report for [Decision Tree] ######

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1343
           1       0.93      0.91      0.92       157

   micro avg       0.98      0.98      0.98      1500
   macro avg       0.96      0.95      0.96      1500
weighted avg       0.98      0.98      0.98      1500


###### Confusion Matrix Summary for [Random Forest] ######

[[1342    1]
 [  16  141]]

###### Classification Report for [Random Forest] ######

              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1343
           1       0.99      0.90      0.94       157

   micro avg       0.99      0.99      0.99      1500
```

```
   macro avg       0.99      0.95      0.97      1500
weighted avg       0.99      0.99      0.99      1500


###### Confusion Matrix Summary for [Naive Bayes] ######

[[1255   88]
 [  61   96]]

###### Classification Report for [Naive Bayes] ######

              precision    recall  f1-score   support

           0       0.95      0.93      0.94      1343
           1       0.52      0.61      0.56       157

   micro avg       0.90      0.90      0.90      1500
   macro avg       0.74      0.77      0.75      1500
weighted avg       0.91      0.90      0.90      1500


###### Confusion Matrix Summary for [Support Vector] ######

[[1338    5]
 [ 144   13]]

###### Classification Report for [Support Vector] ######

              precision    recall  f1-score   support

           0       0.90      1.00      0.95      1343
           1       0.72      0.08      0.15       157

   micro avg       0.90      0.90      0.90      1500
   macro avg       0.81      0.54      0.55      1500
weighted avg       0.88      0.90      0.86      1500


###### Exiting Confusion Matrix Summary ######
```

In [590]:

```
confusion_matrix_df
```

Out[590]:

	classifer	True_Positive	True_Negative	False_Postive	False_Negative	Train_AccuracyScore	Test_AccuracyScore	CrossVal
0	Logistic Regression	113	1333	10	44	0.960000	0.964000	
1	Nearest Neighbors	50	1297	46	107	0.940286	0.898000	
2	Decision Tree	143	1333	10	14	1.000000	0.984000	
3	Random Forest	141	1342	1	16	0.992286	0.988667	
4	Naive Bayes	96	1255	88	61	0.896286	0.900667	
5	Support Vector	13	1338	5	144	0.975429	0.900667	

Observation from ML modelling & Classification Metrics of Confusion Matrix/Classification Reports :

ATTEMPT 1

Feature Types : Categorical

Family, Education, Securities, CD Account, Online, Credit Card

Feature Types : Continuous

Age, Experience, Income, CC Avg, Mortgage

Feature Types : Target to classify

Personal Loan

Features to IGNORED

ID, Zip Code

Model Evaluation - KNN vs Naive Bayes Vs Logistics Regression :

a) With intention of model being able to find customers who has better chances of purchasing the loan from the bank, False Negative would be one of the key metrics while classifying the customer. i.e., if customer has intentions to get loan but due to model prediction of "Not a right candidate" for loan purchase (false negative) --> bank might not approach this customer and thereby has chance of loosing one potential candidate from taking loan from the bank.

b) Along with above, we would also be evaluating model with BETTER CHANCE OF PREDICTING CLASS 1 i.e., model that can identify well the customers who can purchase the loan. F1 score for class 1 would also be a key metric.

b) KNN algorithm is having training accuracy score of 94%, test accuracy score of 89.8%, average cross validated accuracy of 90.4% with standard deviation of 1.23. F1 score for class 1 is 0.40, which is very less as it struggles to identify the customers who can purchase the loan.

STD average score in cross validation is 1.23% which is a very good sign of model performing consistent without larger deviations (less than 5%)

c) Naive Bayes is having training accuracy score of 89.6%, test accuracy score of 90%, average cross validated accuracy of 89.5% with standard deviation of 1.27. F1 score for class 1 is 0.56, which is still less(even though it is better than KNN) as it struggles to identify the customers who can purchase the loan. Also to be noted, this model is having higher chances of underfitting due to test score being higher than training score

STD average score in cross validation is 1.27% which is a very good sign of model performing consistent without larger deviations (less than 5%)

d) Logistics Regression is having training accuracy score of 96%, test accuracy score of 96.4%, average cross validated accuracy of 95.8% with standard deviation of 0.93. F1 score for class 1 is 0.81, which is a good sign as this model has higher chances of identifying the potential customers who can purchase the loan.

STD average score in cross validation is 0.93% which is a very good sign of model performing consistent without larger deviations (less than 5%)

e) On evaluating the models for MISCLASSIFICATION ERRORS - FALSE NEGATIVE & FALSE POSITIVE, KNN and Naive Bayes are both performing poor. Logistics Regression is clearly performing better over KNN & NB. However, for further exploration - I went ahead and tried tree based algorithms which cleary edge even Logistics Regression. However evaluating/fine tuning tree based algorithms is not in scope of this project assignment and hence parking it aside.

e) Since we noticed couple of models facing underfitting scenario - Logistics Regression and Naive Bayes, let us explore the room for opportunities in feature engineering and see whether we can fine tune this further before making final conclusion.

Conclusion of Attempt 1 (which model did better?)

conclusion 1:

Out of Logistics Regression, KNN and Naive Bayes - Based on above detailed assessment with combination of trianing score, cross validated test score, Standard Deviation, Mis-classification errors(i.e. less number of False Negatives and False Positives), i) Logistiscs Regression - better than KNN and NB ii) KNN - better than NB iii) NB - in the last

conclusion 2:

Outside above 3 algorithms, Support Vector and Random Forest performed way better than Logistics Regression.

conclusion 3:

Standard deviation of all the models are less than 5%

conclusion 4:

I would be happy to apply all 3 Logistics Regression, Support Vector and Random Forest & do hyper parameter tuning to see if we can chose best of these 3 better algorithms for this use case

ONE OPPORTUNITY WHICH WE HAVE IS --> We have kept the continuous features as continuous values i.e. we did not scale them yet. This can add a big difference while training as model can treat higher numbers in continuous feature set with higher importance & let us find it out whether it would make any difference if we scale them out!!

In [591]:

```
train_df.head()
#### Age, Experience, Income, CCAvg, Mortgage has to be scaled/normalized - they are continu
```

Out[591]:

	Age	Experience	Income	CCAvg	Mortgage	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	Family_1
0	25	1	49	1.6	0	0	1	0	0	0	(
1	45	19	34	1.5	0	0	1	0	0	0	(
2	39	15	11	1.0	0	0	0	0	0	0	1
3	35	9	100	2.7	0	0	0	0	0	0	1
4	35	8	45	1.0	0	0	0	0	0	1	(

In [592]:

```
#### Scaling the features using Robust Scaler as it provides better handling against outlier
from sklearn.preprocessing import RobustScaler
continous_features = ['Age','Experience', 'Income', 'CCAvg', 'Mortgage']
norm_df = train_df[continous_features].copy()

f_scale = RobustScaler().fit(norm_df[continous_features].values)
norm_df[continous_features] = f_scale.transform(norm_df[continous_features].values)
```

In [593]:

```
norm_df[continous_features].head()
```

Out[593]:

	Age	Experience	Income	CCAvg	Mortgage
0	-1.0	-0.95	-0.254237	0.055556	0.0
1	0.0	-0.05	-0.508475	0.000000	0.0
2	-0.3	-0.25	-0.898305	-0.277778	0.0
3	-0.5	-0.55	0.610169	0.666667	0.0
4	-0.5	-0.60	-0.322034	-0.277778	0.0

In [594]:
```
scaled_df = train_df.copy()
scaled_df.drop(continous_features, axis=1, inplace=True)
scaled_df = pd.concat([scaled_df, norm_df], axis=1)
scaled_df.head()
```

Out[594]:

	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	Family_1	Family_2	Family_3	Family_4	Education_1
0	0	1	0	0	0	0	0	0	1	1
1	0	1	0	0	0	0	0	1	0	1
2	0	0	0	0	0	1	0	0	0	1
3	0	0	0	0	0	1	0	0	0	0
4	0	0	0	0	1	0	0	0	1	0

In [595]:
```
scaled_df.shape
```

Out[595]: (5000, 17)

In [596]:
```
###########################################################
## MODEL ATTEMPT 2 AFTER SCALING CONTINOUS FEATURES ####
###########################################################

X_scaled = scaled_df.drop('Personal_Loan', axis=1)
y_scaled = scaled_df['Personal_Loan']
X_train_scaled, X_test_scaled, y_train_scaled, y_test_scaled = train_test_split(X_scaled, y_
models_list = bulk_train(X_train_scaled, y_train_scaled, X_test_scaled, y_test_scaled, no_cl
print("\n")
print("############ POST FEATURE SCALING:- CONSOLIDATED MODEL TRAINING SUMMARY ############"
print("############### ######################## ##############################\n")
log_train_summary(models_list)
```

```
Logistic Regression : Mean Accuracy from CV is 95.77206297893979 %
Logistic Regression : Standard Deviation from CV 0.7824822622882883 %
Nearest Neighbors : Mean Accuracy from CV is 95.91345025557061 %
Nearest Neighbors : Standard Deviation from CV 0.7711430481191502 %
Decision Tree : Mean Accuracy from CV is 98.08570495619206 %
Decision Tree : Standard Deviation from CV 0.461709842432316 %
Random Forest : Mean Accuracy from CV is 98.31427731771572 %
Random Forest : Standard Deviation from CV 0.3928121536458724 %
Naive Bayes : Mean Accuracy from CV is 89.48623697219686 %
Naive Bayes : Standard Deviation from CV 1.2463382626103319 %
Support Vector : Mean Accuracy from CV is 97.31468058631381 %
Support Vector : Standard Deviation from CV 0.7113240974331877 %


############ POST FEATURE SCALING:- CONSOLIDATED MODEL TRAINING SUMMARY ############
############### ######################## ##############################

            classifier  train_score  test_score  train_time
3        Random Forest     0.992571    0.988667    1.194176
2        Decision Tree     1.000000    0.982000    0.005208
5       Support Vector     0.977143    0.978000    0.054499
0  Logistic Regression     0.958286    0.963333    0.015556
1    Nearest Neighbors     0.967714    0.957333    0.070720
4          Naive Bayes     0.896000    0.900667    0.003822
```

In [597]:
```
print("############### ######################## ###################")
#### Printing Confusion Matrix #####
confusion_matrix_df = print_confusion_matrix(models_list, X_test_scaled)
```

```
############### ######################## ###################

###### Confusion Matrix Summary for [Logistic Regression] ######

[[1332   11]
 [  44  113]]

###### Classification Report for [Logistic Regression] ######

              precision    recall  f1-score   support

           0       0.97      0.99      0.98      1343
           1       0.91      0.72      0.80       157

   micro avg       0.96      0.96      0.96      1500
   macro avg       0.94      0.86      0.89      1500
weighted avg       0.96      0.96      0.96      1500


###### Confusion Matrix Summary for [Nearest Neighbors] ######

[[1343    0]
 [  64   93]]

###### Classification Report for [Nearest Neighbors] ######

              precision    recall  f1-score   support

           0       0.95      1.00      0.98      1343
           1       1.00      0.59      0.74       157

   micro avg       0.96      0.96      0.96      1500
   macro avg       0.98      0.80      0.86      1500
weighted avg       0.96      0.96      0.95      1500


###### Confusion Matrix Summary for [Decision Tree] ######

[[1330   13]
 [  14  143]]

###### Classification Report for [Decision Tree] ######

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1343
           1       0.92      0.91      0.91       157

   micro avg       0.98      0.98      0.98      1500
   macro avg       0.95      0.95      0.95      1500
weighted avg       0.98      0.98      0.98      1500


###### Confusion Matrix Summary for [Random Forest] ######

[[1342    1]
 [  16  141]]

###### Classification Report for [Random Forest] ######

              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1343
           1       0.99      0.90      0.94       157
```

```
   micro avg       0.99      0.99      0.99      1500
   macro avg       0.99      0.95      0.97      1500
weighted avg       0.99      0.99      0.99      1500


###### Confusion Matrix Summary for [Naive Bayes] ######

[[1255   88]
 [  61   96]]

###### Classification Report for [Naive Bayes] ######

              precision    recall  f1-score   support

           0       0.95      0.93      0.94      1343
           1       0.52      0.61      0.56       157

   micro avg       0.90      0.90      0.90      1500
   macro avg       0.74      0.77      0.75      1500
weighted avg       0.91      0.90      0.90      1500


###### Confusion Matrix Summary for [Support Vector] ######

[[1342    1]
 [  32  125]]

###### Classification Report for [Support Vector] ######

              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1343
           1       0.99      0.80      0.88       157

   micro avg       0.98      0.98      0.98      1500
   macro avg       0.98      0.90      0.94      1500
weighted avg       0.98      0.98      0.98      1500


###### Exiting Confusion Matrix Summary ######
```

In [598]:

```
confusion_matrix_df
```

Out[598]:

	classifer	True_Positive	True_Negative	False_Postive	False_Negative	Train_AccuracyScore	Test_AccuracyScore	CrossVal
0	Logistic Regression	113	1332	11	44	0.958286	0.963333	
1	Nearest Neighbors	93	1343	0	64	0.967714	0.957333	
2	Decision Tree	143	1330	13	14	1.000000	0.982000	
3	Random Forest	141	1342	1	16	0.992571	0.988667	
4	Naive Bayes	96	1255	88	61	0.896000	0.900667	
5	Support Vector	125	1342	1	32	0.977143	0.978000	

In [599]:
```python
train_df.head()
```

Out[599]:

	Age	Experience	Income	CCAvg	Mortgage	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	Family_1
0	25	1	49	1.6	0	0	1	0	0	0	0
1	45	19	34	1.5	0	0	1	0	0	0	0
2	39	15	11	1.0	0	0	0	0	0	0	1
3	35	9	100	2.7	0	0	0	0	0	0	1
4	35	8	45	1.0	0	0	0	0	0	1	0

In [600]:
```python
scaled_df.head()
```

Out[600]:

	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	Family_1	Family_2	Family_3	Family_4	Education_1
0	0	1	0	0	0	0	0	0	1	1
1	0	1	0	0	0	0	0	1	0	1
2	0	0	0	0	0	1	0	0	0	1
3	0	0	0	0	0	1	0	0	0	0
4	0	0	0	0	1	0	0	0	1	0

In [601]:
```python
### We do have experience data being negative for the training set, however NONE of them con
### I don't think we should worry about this

train_df[train_df['Experience'] < 0].groupby(by='Personal_Loan').count()
```

Out[601]:

Personal_Loan	Age	Experience	Income	CCAvg	Mortgage	Securities_Account	CD_Account	Online	CreditCard	Family_1
0	52	52	52	52	52	52	52	52	52	52

In [602]:
```python
## This may be interestesing data to look at - With NO experience, there are customers who b
train_df[train_df['Experience'] == 0].groupby(by='Personal_Loan').count()
```

Out[602]:

Personal_Loan	Age	Experience	Income	CCAvg	Mortgage	Securities_Account	CD_Account	Online	CreditCard	Family_1
0	59	59	59	59	59	59	59	59	59	59
1	7	7	7	7	7	7	7	7	7	7

In [603]:

```python
##########################################################################################
### In my opinion, Experience of ZERO with higher income seem to be OUTLIER & NEGATIVE EXPER
##########################################################################################
train_df[(train_df['Experience'] == 0) & (train_df['Personal_Loan'] == 1)]
```

Out[603]:

	Age	Experience	Income	CCAvg	Mortgage	Personal_Loan	Securities_Account	CD_Account	Online	CreditCard	Fami
151	26	0	132	6.50	0	1	0	0	0	1	
160	29	0	134	6.50	0	1	0	0	0	0	
1337	26	0	179	2.10	0	1	0	0	0	0	
3084	26	0	129	0.70	0	1	0	0	0	0	
3747	26	0	83	3.90	0	1	0	0	1	0	
4282	26	0	195	6.33	0	1	1	1	1	0	
4425	26	0	164	4.00	301	1	0	0	1	0	

In [604]:

```python
from sklearn.feature_selection import SelectFromModel
from sklearn.svm import LinearSVC
feature_select = SelectFromModel(LinearSVC(penalty="l1", dual=False, tol=1e-3))
```

In [605]:

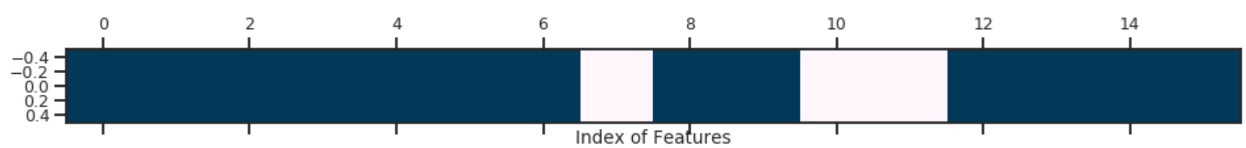
```python
feature_select.fit(X_train_scaled, y_train_scaled)
X_train_fs1 = feature_select.transform(X_train_scaled)
print("Original Training set shape: ", X_train_scaled.shape)
print("After feature selection, Training set shape: ", X_train_fs1.shape)
```

```
Original Training set shape:  (3500, 16)
After feature selection, Training set shape:  (3500, 13)
```

In [606]:

```python
mask = feature_select.get_support()
plt.matshow(mask.reshape(1,-1), cmap='PuBu')
plt.xlabel('Index of Features')
```

Out[606]: Text(0.5, 0, 'Index of Features')



In [607]:

```python
print("Feature omitted by automatic feature selection thru LinearSVC : %s"%(X_train_scaled.c
X_test_fs1 = feature_select.transform(X_test_scaled)
```

```
Feature omitted by automatic feature selection thru LinearSVC : Index(['Family_4', 'Education
_3', 'Age'], dtype='object')
```

In [608]:
```
models_list = bulk_train(X_train_fs1, y_train_scaled, X_test_fs1, y_test_scaled, no_classifi
```

```
Logistic Regression : Mean Accuracy from CV is 95.7148382552394 %
Logistic Regression : Standard Deviation from CV 0.7637664074777079 %
Nearest Neighbors : Mean Accuracy from CV is 95.88528722683452 %
Nearest Neighbors : Standard Deviation from CV 0.6559682495904073 %
Decision Tree : Mean Accuracy from CV is 97.91378565189454 %
Decision Tree : Standard Deviation from CV 0.48063379629827263 %
Random Forest : Mean Accuracy from CV is 97.91443918492628 %
Random Forest : Standard Deviation from CV 0.46103028168107696 %
Naive Bayes : Mean Accuracy from CV is 89.08631650637382 %
Naive Bayes : Standard Deviation from CV 1.225426156032006 %
Support Vector : Mean Accuracy from CV is 97.28619149077602 %
Support Vector : Standard Deviation from CV 0.6393603328047534 %
```

In [609]:
```
print("\n")
print("##### AFTER AUTOMATED FEATURE SELECTION: CONSOLIDATED MODEL TRAINING SUMMARY #####")
print("############### ######################## ###################")
log_train_summary(models_list)
```

```


##### AFTER AUTOMATED FEATURE SELECTION: CONSOLIDATED MODEL TRAINING SUMMARY #####
############### ######################## ###################
            classifier  train_score  test_score  train_time
3        Random Forest     0.988571    0.985333    1.095189
5       Support Vector     0.977143    0.978000    0.052489
2        Decision Tree     1.000000    0.975333    0.003071
0  Logistic Regression     0.957714    0.962667    0.021708
1    Nearest Neighbors     0.969143    0.960000    0.026148
4          Naive Bayes     0.892286    0.897333    0.002045
```

In [610]:
```python
print("############### ######################## ###################")
#### Printing Confusion Matrix #####
confusion_matrix_df = print_confusion_matrix(models_list, X_test_fs1)
```

```
############### ######################## ###################

###### Confusion Matrix Summary for [Logistic Regression] ######

[[1332   11]
 [  45  112]]

###### Classification Report for [Logistic Regression] ######

              precision    recall  f1-score   support

           0       0.97      0.99      0.98      1343
           1       0.91      0.71      0.80       157

   micro avg       0.96      0.96      0.96      1500
   macro avg       0.94      0.85      0.89      1500
weighted avg       0.96      0.96      0.96      1500


###### Confusion Matrix Summary for [Nearest Neighbors] ######

[[1343    0]
 [  60   97]]

###### Classification Report for [Nearest Neighbors] ######

              precision    recall  f1-score   support

           0       0.96      1.00      0.98      1343
           1       1.00      0.62      0.76       157

   micro avg       0.96      0.96      0.96      1500
   macro avg       0.98      0.81      0.87      1500
weighted avg       0.96      0.96      0.96      1500


###### Confusion Matrix Summary for [Decision Tree] ######

[[1325   18]
 [  19  138]]

###### Classification Report for [Decision Tree] ######

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1343
           1       0.88      0.88      0.88       157

   micro avg       0.98      0.98      0.98      1500
   macro avg       0.94      0.93      0.93      1500
weighted avg       0.98      0.98      0.98      1500


###### Confusion Matrix Summary for [Random Forest] ######

[[1342    1]
 [  21  136]]

###### Classification Report for [Random Forest] ######

              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1343
           1       0.99      0.87      0.93       157
```

```
   micro avg       0.99      0.99      0.99      1500
   macro avg       0.99      0.93      0.96      1500
weighted avg       0.99      0.99      0.98      1500


###### Confusion Matrix Summary for [Naive Bayes] ######

[[1251   92]
 [  62   95]]

###### Classification Report for [Naive Bayes] ######

              precision    recall  f1-score   support

           0       0.95      0.93      0.94      1343
           1       0.51      0.61      0.55       157

   micro avg       0.90      0.90      0.90      1500
   macro avg       0.73      0.77      0.75      1500
weighted avg       0.91      0.90      0.90      1500


###### Confusion Matrix Summary for [Support Vector] ######

[[1342    1]
 [  32  125]]

###### Classification Report for [Support Vector] ######

              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1343
           1       0.99      0.80      0.88       157

   micro avg       0.98      0.98      0.98      1500
   macro avg       0.98      0.90      0.94      1500
weighted avg       0.98      0.98      0.98      1500


###### Exiting Confusion Matrix Summary ######
```

In [611]:

```
confusion_matrix_df
```

Out[611]:

	classifer	True_Positive	True_Negative	False_Postive	False_Negative	Train_AccuracyScore	Test_AccuracyScore	CrossVal
0	Logistic Regression	112	1332	11	45	0.957714	0.962667	
1	Nearest Neighbors	97	1343	0	60	0.969143	0.960000	
2	Decision Tree	138	1325	18	19	1.000000	0.975333	
3	Random Forest	136	1342	1	21	0.988571	0.985333	
4	Naive Bayes	95	1251	92	62	0.892286	0.897333	
5	Support Vector	125	1342	1	32	0.977143	0.978000	

Observation/Conclusion after Auto Feature Selection technique using LinearSVC with L1 Regularization :

Attempt 3

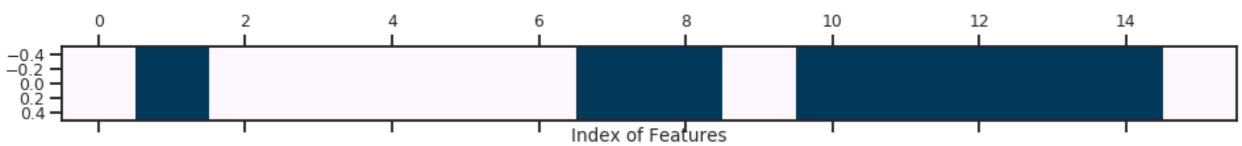
When "LinearSVC" model was used to select the relevant features using SelectFromModel API, 'Family_4', 'Education_2', 'Age' were ignored before the model training. After filtering the omitted features, retraining DID NOT provide any betterment from previous model evaluations except for Support Vector Classification algorithm. i.e. Logistics Regressin, KNN and Naive Bayes did not have much improvement in F1 score(for class 1), Train/Test scores and Standard deviations. However Support Vector Classification had significant reduction in Mis-Classifictaion errors(i.e. reduction of false negatives) + F1 score for class 1 improved to 0.90 from 0.88 (Model improved 2% more to identify the customers purchasing the loan).

Conclusion Based on this feature selection technique using LinearSVC - Support Vector Classification did better. No change in Logistics regression, KNN and Naive Bayes compared to Attempt 1 & Attempt 2

In [612]:
```
feature_select = SelectFromModel(RandomForestClassifier(n_estimators=100, random_state=42),
feature_select.fit(X_train_scaled, y_train_scaled)
X_train_fs2 = feature_select.transform(X_train_scaled)
print("Original Training set shape: ", X_train_scaled.shape)
print("After feature selection, Training set shape: ", X_train_fs2.shape)
mask = feature_select.get_support()
plt.matshow(mask.reshape(1,-1), cmap='PuBu')
plt.xlabel('Index of Features')
```

```
Original Training set shape:  (3500, 16)
After feature selection, Training set shape:  (3500, 8)
```

Out[612]:
```
Text(0.5, 0, 'Index of Features')
```



In [613]:
```
print("Feature OMITTED by automatic feature selection thru Random Forest : %s"%(X_train_scal
print("##############################################################################")
print("Feature CONSIDERED by automatic feature selection thru Random Forest : %s"%(X_train_s
X_test_fs2 = feature_select.transform(X_test_scaled)
```

```
Feature OMITTED by automatic feature selection thru Random Forest : Index(['Securities_Accoun
t', 'Online', 'CreditCard', 'Family_1', 'Family_2',
       'Family_3', 'Education_2', 'Mortgage'],
      dtype='object')
##############################################################################
Feature CONSIDERED by automatic feature selection thru Random Forest : Index(['CD_Account',
'Family_4', 'Education_1', 'Education_3', 'Age',
       'Experience', 'Income', 'CCAvg'],
      dtype='object')
```

In [614]:
```
models_list = bulk_train(X_train_fs2, y_train_scaled, X_test_fs2, y_test_scaled, no_classifi
```

```
Logistic Regression : Mean Accuracy from CV is 95.40063254160674 %
Logistic Regression : Standard Deviation from CV 0.8393231229236656 %
Nearest Neighbors : Mean Accuracy from CV is 96.82847510125447 %
Nearest Neighbors : Standard Deviation from CV 0.6052191315198083 %
Decision Tree : Mean Accuracy from CV is 96.74292268275074 %
Decision Tree : Standard Deviation from CV 0.8952014505396986 %
Random Forest : Mean Accuracy from CV is 97.62864163322617 %
Random Forest : Standard Deviation from CV 0.4240783990256459 %
Naive Bayes : Mean Accuracy from CV is 89.54378869565114 %
Naive Bayes : Standard Deviation from CV 1.3462707702089525 %
Support Vector : Mean Accuracy from CV is 97.05729166302233 %
Support Vector : Standard Deviation from CV 0.6751275974374114 %
```

In [615]:
```
print("\n")
print("##### AFTER AUTOMATED FEATURE SELECTION: CONSOLIDATED MODEL TRAINING SUMMARY #####")
print("############### ######################## ###################")
log_train_summary(models_list)
```

```
##### AFTER AUTOMATED FEATURE SELECTION: CONSOLIDATED MODEL TRAINING SUMMARY #####
############### ######################## ###################
            classifier  train_score  test_score  train_time
3        Random Forest     0.989143    0.979333    1.053869
5       Support Vector     0.973429    0.972667    0.039925
1    Nearest Neighbors     0.979143    0.971333    0.022661
2        Decision Tree     1.000000    0.970667    0.003309
0  Logistic Regression     0.954286    0.956667    0.012392
4          Naive Bayes     0.896286    0.906667    0.001453
```

In [616]:
```python
print("############### ######################## ###################")
#### Printing Confusion Matrix #####
confusion_matrix_df = print_confusion_matrix(models_list, X_test_fs2)
```

```
############### ######################## ###################

###### Confusion Matrix Summary for [Logistic Regression] ######

[[1332   11]
 [  54  103]]

###### Classification Report for [Logistic Regression] ######

              precision    recall  f1-score   support

           0       0.96      0.99      0.98      1343
           1       0.90      0.66      0.76       157

   micro avg       0.96      0.96      0.96      1500
   macro avg       0.93      0.82      0.87      1500
weighted avg       0.96      0.96      0.95      1500


###### Confusion Matrix Summary for [Nearest Neighbors] ######

[[1340    3]
 [  40  117]]

###### Classification Report for [Nearest Neighbors] ######

              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1343
           1       0.97      0.75      0.84       157

   micro avg       0.97      0.97      0.97      1500
   macro avg       0.97      0.87      0.91      1500
weighted avg       0.97      0.97      0.97      1500


###### Confusion Matrix Summary for [Decision Tree] ######

[[1333   10]
 [  34  123]]

###### Classification Report for [Decision Tree] ######

              precision    recall  f1-score   support

           0       0.98      0.99      0.98      1343
           1       0.92      0.78      0.85       157

   micro avg       0.97      0.97      0.97      1500
   macro avg       0.95      0.89      0.92      1500
weighted avg       0.97      0.97      0.97      1500


###### Confusion Matrix Summary for [Random Forest] ######

[[1342    1]
 [  30  127]]

###### Classification Report for [Random Forest] ######

              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1343
           1       0.99      0.81      0.89       157
```

```
   micro avg       0.98      0.98      0.98      1500
   macro avg       0.99      0.90      0.94      1500
weighted avg       0.98      0.98      0.98      1500


###### Confusion Matrix Summary for [Naive Bayes] ######

[[1260   83]
 [  57  100]]

###### Classification Report for [Naive Bayes] ######

              precision    recall  f1-score   support

           0       0.96      0.94      0.95      1343
           1       0.55      0.64      0.59       157

   micro avg       0.91      0.91      0.91      1500
   macro avg       0.75      0.79      0.77      1500
weighted avg       0.91      0.91      0.91      1500


###### Confusion Matrix Summary for [Support Vector] ######

[[1340    3]
 [  38  119]]

###### Classification Report for [Support Vector] ######

              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1343
           1       0.98      0.76      0.85       157

   micro avg       0.97      0.97      0.97      1500
   macro avg       0.97      0.88      0.92      1500
weighted avg       0.97      0.97      0.97      1500


###### Exiting Confusion Matrix Summary ######
```

In [617]:
```
confusion_matrix_df
```

Out[617]:

	classifer	True_Positive	True_Negative	False_Postive	False_Negative	Train_AccuracyScore	Test_AccuracyScore	CrossVal
0	Logistic Regression	103	1332	11	54	0.954286	0.956667	
1	Nearest Neighbors	117	1340	3	40	0.979143	0.971333	
2	Decision Tree	123	1333	10	34	1.000000	0.970667	
3	Random Forest	127	1342	1	30	0.989143	0.979333	
4	Naive Bayes	100	1260	83	57	0.896286	0.906667	
5	Support Vector	119	1340	3	38	0.973429	0.972667	

Observation/Conclusion after Auto Feature Selection technique thru Random Forest:

Attempt 4

When "RandomForestClassifier" model was used to select the relevant features from select from model API, half of the features were ignored as irrelevant based on feature importance.

Features marked as NOT Important

'Securities_Account', 'Online', 'CreditCard', 'Family_1', 'Family_2','Family_3', 'Education_2', 'Mortgage'

Features marked as Important

'CD_Account', 'Family_4', 'Education_1', 'Education_3', 'Age','Experience', 'Income', 'CCAvg'

Remarks on above feature selection technique :

It kind of makes sense as it seem like, features that were having relatively stronger correlation within themselves were marked as not important.

Conclusion 1:

After filtering the omitted features, KNN's true positives improved + F1 score for class 1 improved + Standard deviation decreased + train/test score increased + Mis-Classification errors reduced

Conclusion 2:

Logistics Regression & Naive Bayes have small decrease in perforamce for F1 score, standard deviation, train/test score parameters.

Conclusion 3:

Hence, would rank KNN as first, Logistics regression as second & Naive Bayes as Third. Random Forest and Support Vector did better in Attempt 3 compared to Attempt 4, though both these still perform better than KNN and logistics regression

Final Conclusion

Overall we did EDA of features/target, attempt ML model with FOUR different feature engineering strategies - 1) AS IS taking all the features 2) Scaling the continuous features 3) Automated feature selection using LinearSVC 4) Automated Feature selection using Random Forest Classifier. Below would be the consolidated summary.

NOTE : LR represents Logistics Regression, KNN represents Nearest Neighbors, NB represents Naive Bayes in below summary

AS IS,Taking all the features

1. **F1 score(for class 1 i.e. customers to purchase loan):** LR 0.81, KNN 0.40 NB 0.56
2. **Train/cross validated TestScore:** LR 0.96, KNN 0.94, NB 0.89
3. **Standard deviation observed:** LR 0.93%, KNN 1.23%, NB 1.27%
4. **Number of Mis-classifications:** LR 54, KNN 153, NB 149

Scaling of Continuous Features

1. **F1 score(for class 1 i.e. customers to purchase loan):** LR 0.80, KNN 0.74 NB 0.56
2. **Train/cross validated TestScore:** LR 0.96, KNN 0.97, NB 0.89
3. **Standard deviation observed:** LR 0.78%, KNN 0.77%, NB 1.24%
4. **Number of Mis-classifications:** LR 55, KNN 64, NB 149

Automated feature selection using linear SVC

1. **F1 score(for class 1 i.e. customers to purchase loan):** LR 0.80, KNN 0.78 NB 0.55
2. **Train/cross validated TestScore:** LR 0.96, KNN 0.97, NB 0.89
3. **Standard deviation observed:** LR 0.78%, KNN 0.72%, NB 1.2%
4. **Number of Mis-classifications:** LR 55, KNN 58, NB 154

Automated feature selection using Random Forest Classifier

1. **F1 score(for class 1 i.e. customers to purchase loan):** LR 0.76, KNN 0.84 NB 0.59
2. **Train/cross validated TestScore:** LR 0.95, KNN 0.97, NB 0.89
3. **Standard deviation observed:** LR 0.83%, KNN 0.6%, NB 1.3%
4. **Number of Mis-classifications:** LR 65, KNN 43, NB 140

From observations around all the different approaches, Logistics Regression has consistently performed with higher training/test score and higher F1 score for class 1 that can identify the customers who can purchase loan and lower standard deviations(less than 5%) and very low miss classifications of false negatives and false positives. Hence I would prefer Logistics Regression as best model among the three i.e. between Logistics Regression, KNN and Naive Bayes.

If hyper parameter tuning using grid search & resampling of minority class can be done on Logistics Regression along with weight calculation of different class labels, model has potential to become more stable to predict with 98% of accuracy all the time for identification of customers to purchase loan.

Note : I kept Support Vector machine, Decision Tree and Random Forest in equation during training phase in all different approaches, and it is very evident that Logistics Regression, Support Vector Machine and Random Forest consistently performed better while evaulating the model using above evaluation criteria.

In [618]:

```
##############################################################################################
################# Beyond Conclusion - Model Optimization #####################################
##############################################################################################

### So far, we have X_train - Original Feature set ####################
### X_train_scaled - Feature set with normalized continuous features ###
### X_train_fs1 - Array of features selected by SVC ####################
### X_train_fs2 - Array of features selected by RandomForestClassifer ##
#########################################################################
```

In [619]:

```
##############################################################################################
##### Experiment to use logistics Regression model fine tuning by calculating class weight f
############# majority and minority class and evaluate on test data ########################
##############################################################################################
from sklearn.utils import class_weight

class_weight.compute_class_weight('balanced', np.unique(y_train_scaled), y_train_scaled)
clf_weighted = LogisticRegression(random_state=0,class_weight='balanced').fit(X_train_scaled
y_pred = clf_weighted.predict(X_test_scaled)
```

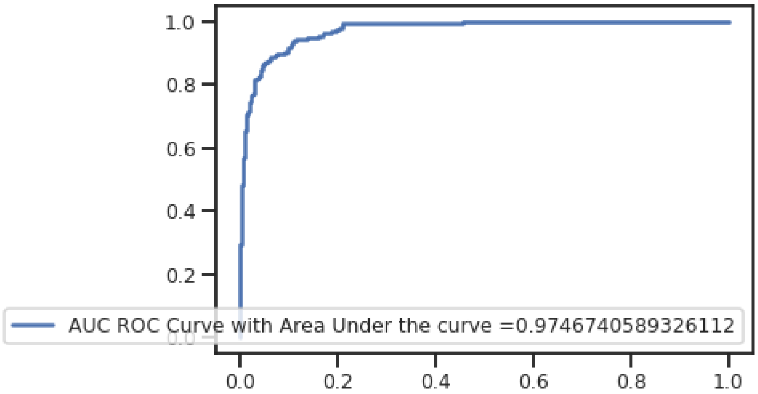
In [620]:

```
#############################################################################
#### How class weights have been calculated #################################
##### Class 0 has been majority population and has been penalized rightly###
##### Class 1 has been minority population and has been rewarded rightly ###
#############################################################################
class_weight.compute_class_weight('balanced', np.unique(y_train_scaled), y_train_scaled)
```

Out[620]:

```
array([0.55083412, 5.41795666])
```

In [621]:
```
#AUC curve of Logistics Regression post class weight calcuation for majority and minority cl
generate_auc_roc_curve(clf_weighted, X_test_scaled)
```



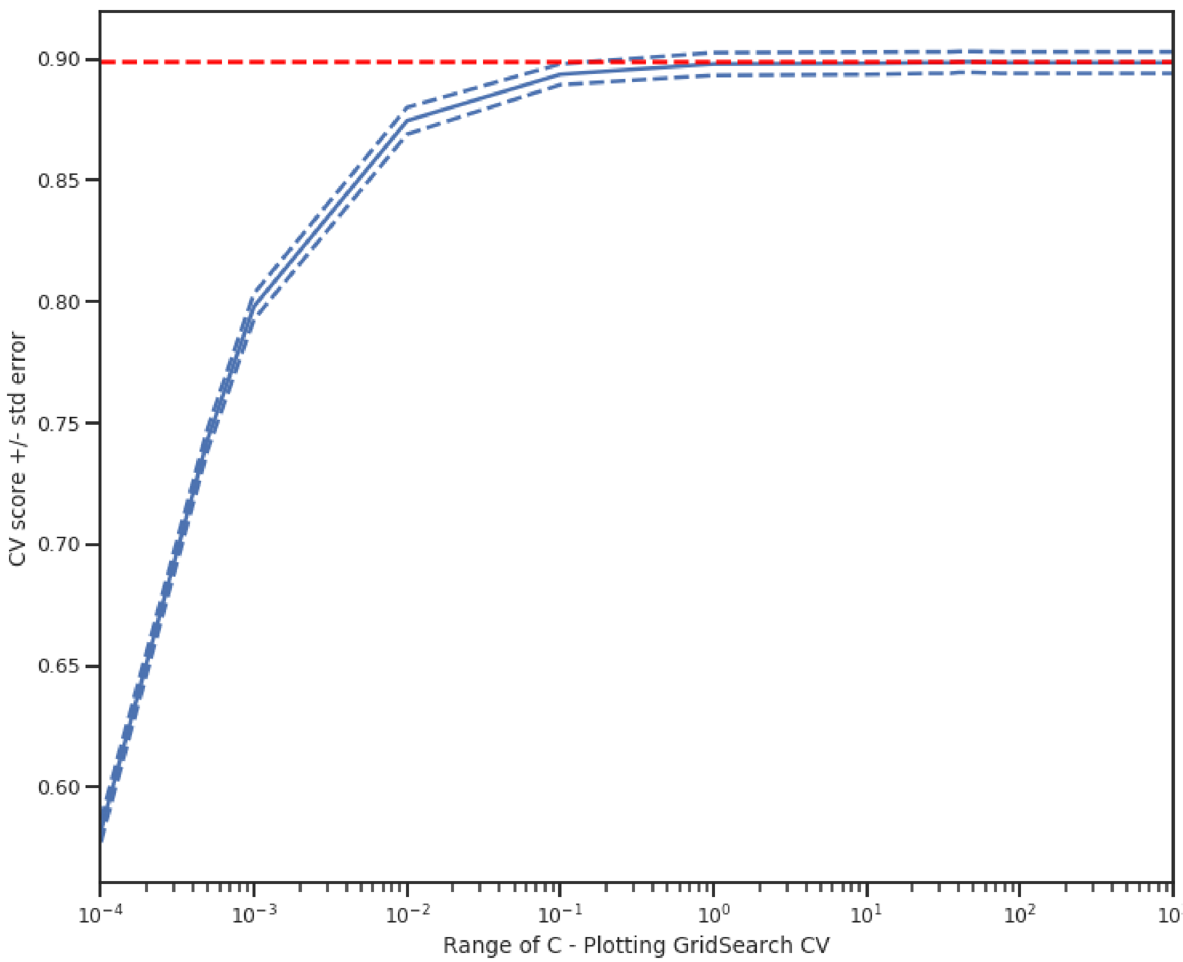
In [666]:
```
###############################################################
#Hyper parameter tuning between 2 classification models #######
### choosing Logistics Regression & Random Forest because #####
######### these 2 models have consistently did better #########
############ based on above evaluation summary ################
###############################################################

from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
n_folds = 5
pipe = Pipeline([('model_gs' , LogisticRegression())])

param_grid_logisticsRegression = [
    {'model_gs' : [LogisticRegression(class_weight='balanced')],
     'model_gs__penalty' : ['l2'],
     'model_gs__C' : [0.0001, 0.0005, 0.001, 0.01, 0.1,
                      1, 10, 25, 35, 40,
                      50, 75, 90, 100,120, 150, 250, 500,1000],
    'model_gs__solver' : ['liblinear']}
]


#choosing njobs as -1 to have parallel processing
grid = GridSearchCV(pipe, param_grid = param_grid_logisticsRegression,cv = n_folds, verbose=
```

In [623]:

```
def plot_crossval_grap(best_grid_search_model, x_range) :
    ### Extract mean score, standard deviation from the best fit model ###
    scores_avg = np.array(best_grid_search_model.cv_results_['mean_test_score'])
    scores_std = best_grid_search_model.cv_results_['std_test_score']
    ### This is masked array, hence we need to use filled to convert this to normal array
    x_crange = best_grid_search_model.cv_results_[x_range].filled()
    std_error = scores_std / np.sqrt(n_folds)

    scores_avg = np.array(best_grid_search_model.cv_results_['mean_test_score'])
    #print(scores_avg.shape)
    scores_std = best_grid_search_model.cv_results_['std_test_score']
    ### This is masked array, hence we need to use filled to convert this to normal array
    x_crange = best_grid_search_model.cv_results_[x_range].filled()
    #print(x_crange.shape)
    std_error = scores_std / np.sqrt(n_folds)
    plt.figure().set_size_inches(12, 10)
    plt.semilogx(x_crange, scores_avg)
    plt.semilogx(x_crange, scores_avg + std_error, 'b--')
    plt.semilogx(x_crange, scores_avg - std_error, 'b--')
    plt.ylabel('CV score +/- std error')
    plt.xlabel('Range of C - Plotting GridSearch CV')
    plt.axhline(np.max(scores_avg), linestyle='--', color='red')
    plt.xlim([x_crange[0], x_crange[-1]])
```

In [667]:
```
best_clf_1 = grid.fit(X_train_scaled, y_train_scaled)
plot_crossval_grap(best_clf_1,'param_model_gs__C')
best_clf.best_estimator_
print("Best Estimator : ", best_clf_1.best_estimator_)
print("Training Score : %.4f"%(best_clf_1.score(X_train_scaled, y_train_scaled)))
print("Testing Score : %.4f"%(best_clf_1.score(X_test_scaled, y_test_scaled)))
```

```
Fitting 5 folds for each of 19 candidates, totalling 95 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  95 out of  95 | elapsed:    0.5s finished

Best Estimator :  Pipeline(memory=None,
     steps=[('model_gs', LogisticRegression(C=40, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False))])
Training Score : 0.8997
Testing Score : 0.8987
```

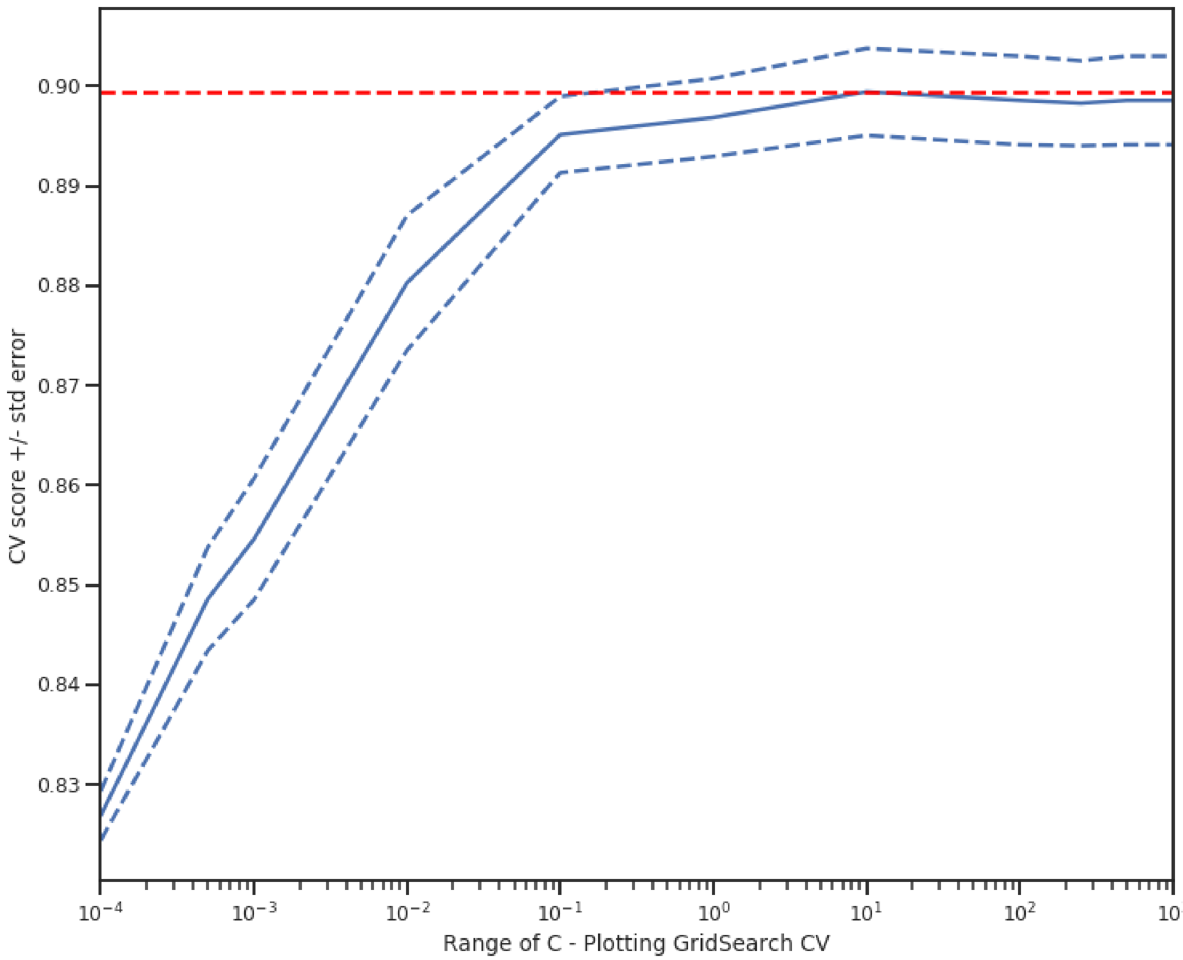


In [625]:
```
#### Avaiable paramters to Tune ####
best_clf_2.estimator.get_params().keys()
```

Out[625]:
```
dict_keys(['memory', 'steps', 'model_gs', 'model_gs__C', 'model_gs__class_weight', 'model_gs_
_dual', 'model_gs__fit_intercept', 'model_gs__intercept_scaling', 'model_gs__max_iter', 'mode
l_gs__multi_class', 'model_gs__n_jobs', 'model_gs__penalty', 'model_gs__random_state', 'model
_gs__solver', 'model_gs__tol', 'model_gs__verbose', 'model_gs__warm_start'])
```

In [656]:
```
best_clf_2 = grid.fit(X_train, y_train)
plot_crossval_grap(best_clf_2,'param_model_gs__C')
print("Best Estimator : ", best_clf_2.best_estimator_)
print("Training Score : %.4f"%(best_clf_2.score(X_train, y_train)))
print("Testing Score : %.4f"%(best_clf_2.score(X_test, y_test)))
```

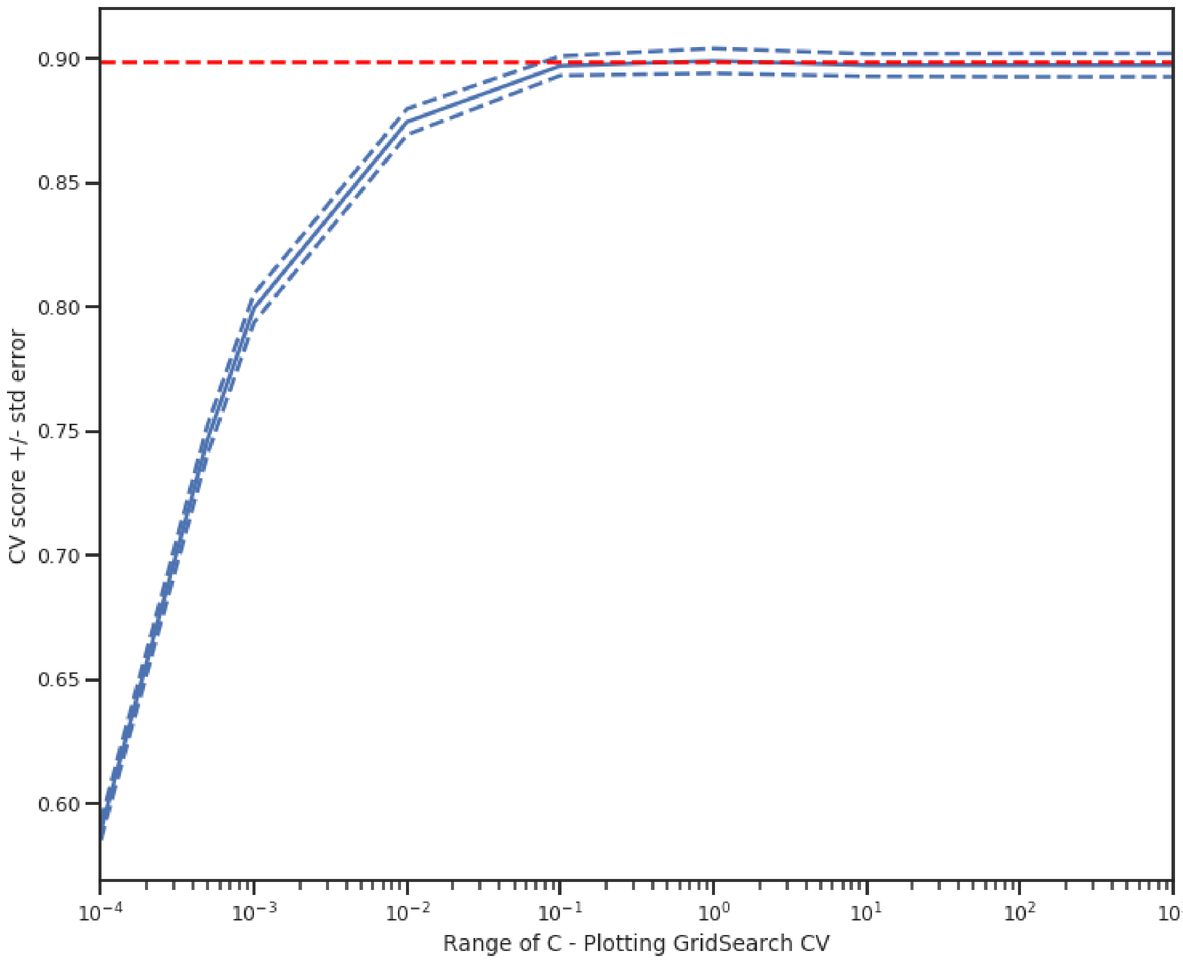
```
Fitting 5 folds for each of 11 candidates, totalling 55 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  55 out of  55 | elapsed:    0.5s finished

Best Estimator :  Pipeline(memory=None,
     steps=[('model_gs', LogisticRegression(C=10, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False))])
Training Score : 0.8997
Testing Score : 0.8980
```



In [657]:

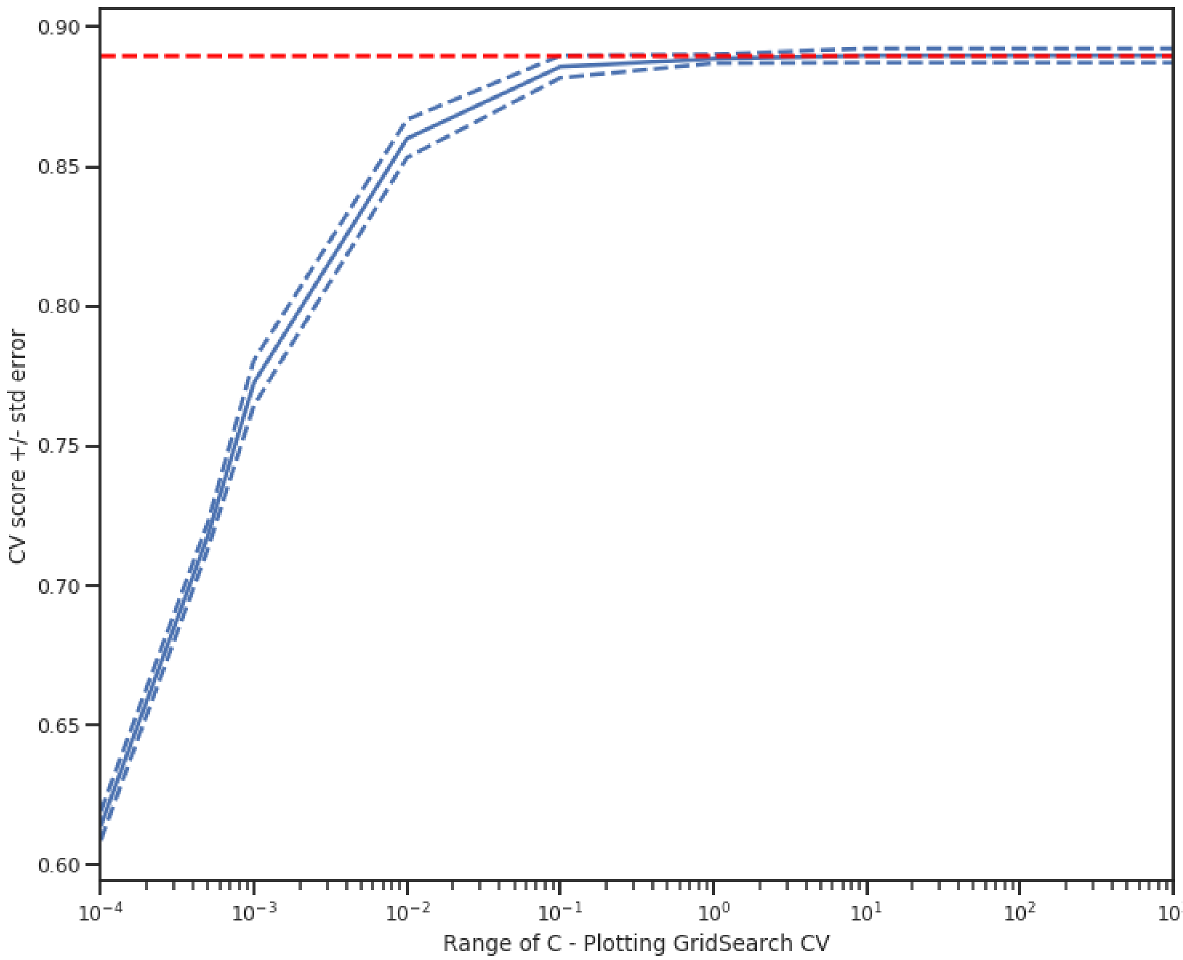
```
best_clf_3 = grid.fit(X_train_fs1, y_train_scaled)
plot_crossval_grap(best_clf_3, 'param_model_gs__C')
print("Best Estimator : ", best_clf_3.best_estimator_)
print("Training Score : %.4f"%(best_clf_3.score(X_train_fs1, y_train_scaled)))
print("Testing Score : %.4f"%(best_clf_3.score(X_test_fs1, y_test_scaled)))
```

```
Fitting 5 folds for each of 11 candidates, totalling 55 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  55 out of  55 | elapsed:    0.3s finished

Best Estimator :  Pipeline(memory=None,
     steps=[('model_gs', LogisticRegression(C=1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False))])
Training Score : 0.9000
Testing Score : 0.9007
```



In [658]:
```
best_clf_4 = grid.fit(X_train_fs2, y_train_scaled)
plot_crossval_grap(best_clf_4, 'param_model_gs__C')
print("Best Estimator : ", best_clf_4.best_estimator_)
print("Training Score : %.4f"%(best_clf_4.score(X_train_fs2, y_train_scaled)))
print("Testing Score : %.4f"%(best_clf_4.score(X_test_fs2, y_test_scaled)))
```

```
Fitting 5 folds for each of 11 candidates, totalling 55 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  55 out of  55 | elapsed:    0.2s finished

Best Estimator :  Pipeline(memory=None,
     steps=[('model_gs', LogisticRegression(C=10, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False))])
Training Score : 0.8943
Testing Score : 0.8947
```



In [629]:
```
#### NOTE : Test Score, after above optimization has gone lesser than Train score ######
################ Applied L1 penalty, C = 0.0001 after grid search #####################
################# Model is no longer overfitting #######################################
########################################################################################
```

In [630]:
```
param_grid_trees = [
    {'model_gs' : [RandomForestClassifier(class_weight='balanced')],
     'model_gs__max_depth': [24, 32, 40],
     'model_gs__min_samples_leaf': [1, 2],
     'model_gs__n_estimators': [250,300, 350]}
]
param_grid_trees
```

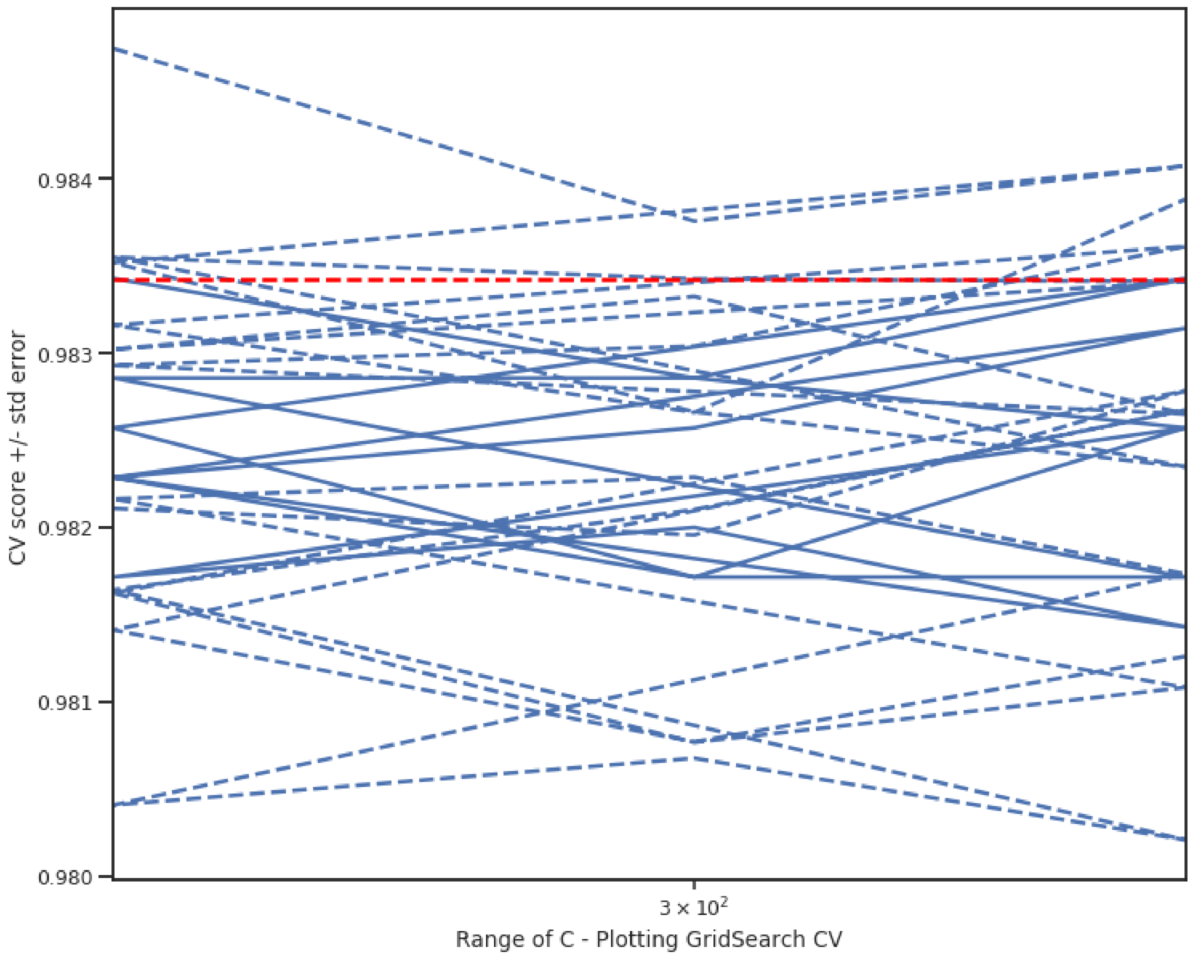
Out[630]:
```
[{'model_gs': [RandomForestClassifier(bootstrap=True, class_weight='balanced',
               criterion='gini', max_depth=None, max_features='auto',
               max_leaf_nodes=None, min_impurity_decrease=0.0,
               min_impurity_split=None, min_samples_leaf=1,
               min_samples_split=2, min_weight_fraction_leaf=0.0,
               n_estimators='warn', n_jobs=None, oob_score=False,
               random_state=None, verbose=0, warm_start=False)],
  'model_gs__max_depth': [24, 32, 40],
  'model_gs__min_samples_leaf': [1, 2],
  'model_gs__n_estimators': [250, 300, 350]}]
```

In [631]:
```
grid_rf = GridSearchCV(pipe, param_grid = param_grid_trees,cv = n_folds, verbose=True, n_job
best_clf_rf = grid_rf.fit(X_train_scaled, y_train_scaled)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    2.5s
[Parallel(n_jobs=-1)]: Done  90 out of  90 | elapsed:    7.2s finished
```

In [670]:
```
from sklearn.metrics import roc_auc_score
plot_crossval_grap(best_clf_rf, 'param_model_gs__n_estimators')
print("Best Estimator : ", best_clf_rf.best_estimator_)
print("Training Score : %.4f"%(best_clf_rf.score(X_train_scaled, y_train_scaled)))
print("Testing Score : %.4f"%(best_clf_rf.score(X_test_scaled, y_test_scaled)))
```

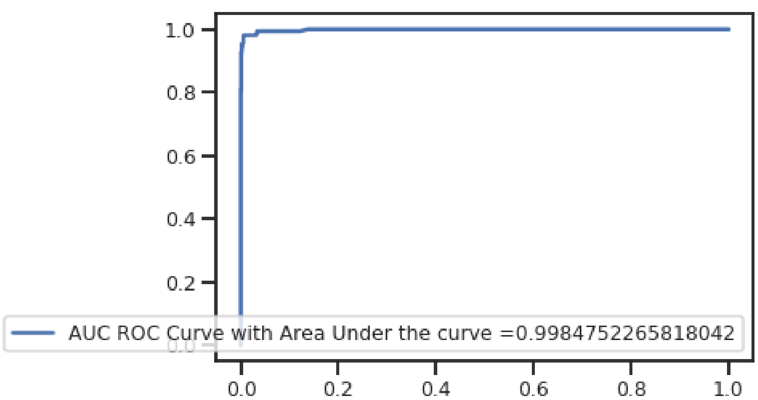
```
Best Estimator :  Pipeline(memory=None,
     steps=[('model_gs', RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=24, max_features='auto',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=250, n_jobs=None, oob_score=False,
            random_state=None, verbose=0, warm_start=False))])
Training Score : 1.0000
Testing Score : 0.9907
```



In [671]:

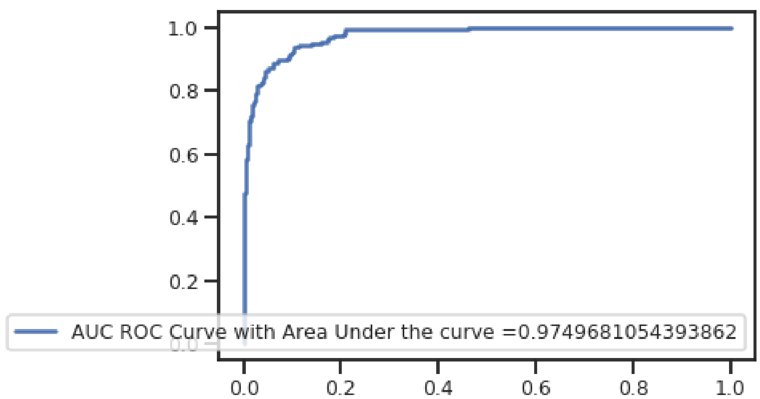
```
########## True, Negatives, False Positives, True Positives, False Negatives of Random Fores
######################## Post Grid Search Optimizations ########################################
grid_rf_pred = best_clf_rf.predict(X_test_scaled)
print(confusion_matrix(y_test_scaled, grid_rf_pred))
print(classification_report(y_test_scaled, grid_rf_pred))

y_pred_proba = best_clf_rf.predict_proba(X_test_scaled)
print("ROC AUC Score: ", roc_auc_score(y_test_scaled, y_pred_proba[:,1]))
#AUC curve of Logistics Regression post class weight calcuation for majority and minority cl
generate_auc_roc_curve(best_clf_rf, X_test_scaled)

######### Class 1 prediction accuracy(F1) is 95% which is very good, as class 1 belonged to 
############# ONLY ONE FALSE POSITIVE and 13 FALSE NEGATIVE, LOWEST AMONG ALL THE MODELs ABO
###################### This Score is on Test set, i.e. Unseen data ###########################
############## This model has better chance of identifying the customer to purchase loan ###
###############################################################################################
```

```
[[1342    1]
 [  13  144]]
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1343
           1       0.99      0.92      0.95       157

   micro avg       0.99      0.99      0.99      1500
   macro avg       0.99      0.96      0.97      1500
weighted avg       0.99      0.99      0.99      1500

ROC AUC Score:  0.9984752265818042
```



In [672]:
```
########## True, Negatives, False Positives, True Positives, False Negatives of Random Fores
####################### Post Grid Search Optimizations ######################################
grid_logisticsreg_pred = best_clf_1.predict(X_test_scaled)
confusion_matrix(y_test_scaled, grid_logisticsreg_pred)

print(confusion_matrix(y_test_scaled, grid_logisticsreg_pred))
print(classification_report(y_test_scaled, grid_logisticsreg_pred))

y_pred_proba_lg = best_clf_1.predict_proba(X_test_scaled)
print("ROC AUC Score: ", roc_auc_score(y_test_scaled, y_pred_proba_lg[:,1]))
#AUC curve of Logistics Regression post class weight calcuation for majority and minority cl
generate_auc_roc_curve(best_clf_1, X_test_scaled)


######### Class 1 prediction accuracy(F1) is 66% which is average, as class 1 belonged to MI
############## This model has 66% chance of identifying the customer to purchase loan ######
############################################################################################
```

```
[[1201  142]
 [  10  147]]
              precision    recall  f1-score   support

           0       0.99      0.89      0.94      1343
           1       0.51      0.94      0.66       157

   micro avg       0.90      0.90      0.90      1500
   macro avg       0.75      0.92      0.80      1500
weighted avg       0.94      0.90      0.91      1500

ROC AUC Score:  0.9749681054393862
```



Additional Conclusion - After hyper parameter tuning/model optimization techniques applied on logistics regression & Random Forest, lowest mis-classification rate (False Negatives & False Positives) on test set and Highest Accuracy on training set was observed to be from Random Forest model.

Fine tuned model has 95% chance of identifying customers who can purchase the loan from bank

In [ ]: