CREDIT CARD LEAD PREDICTION

Happy Customer Bank is a mid-sized private bank that deals in all kinds of banking products, like Savings accounts, Current accounts, investment products, credit products, among other offerings. The bank also cross-sells products to its existing customers and to do so they use different kinds of communication like tele-calling, e-mails, recommendations on net banking, mobile banking, etc. In this case, the Happy Customer Bank wants to cross sell its credit cards to its existing customers. The bank has identified a set of customers that are eligible for taking these credit cards. Now, the bank is looking for your help in identifying customers that could show higher intent towards a recommended credit card, given:

Customer details (gender, age, region etc.)

Details of his/her relationship with the bank (Channel_Code,Vintage, 'Avg_Asset_Value etc.)

GETTING LIBRARIES

In [2]:

```
# Import Libraries
import warnings
warnings.filterwarnings('ignore')
import time
import numpy as np
import pandas as pd
pd.options.display.float_format = '{:.2f}'.format
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
# Print versions of libraries
print(f"Numpy version : Numpy {np.__version__}")
print(f"Pandas version : Pandas {pd.__version__}")
print(f"Seaborn version : Seaborn {sns.__version__}")
print(f"SkLearn version : SkLearn {sklearn.__version__}")
# Magic Functions for In-Notebook Display
%matplotlib inline
# Setting seabon style
sns.set(style='darkgrid', palette='colorblind')
```

```
Numpy version : Numpy 1.19.5
Pandas version : Pandas 1.1.5
Seaborn version : Seaborn 0.11.1
SkLearn version : SkLearn 0.22.2.post1
```

Load Data

In [3]:

```
train = pd.read_csv('train.csv', encoding='latin_1')
# Converting all column names to lower case
train.columns = train.columns.str.lower()
train
```

Out[3]:

	id	gender	age	region_code	occupation	channel_code	vintage	credit_produ
0	NNVBBKZB	Female	73	RG268	Other	X3	43	N
1	IDD62UNG	Female	30	RG277	Salaried	X1	32	N
2	HD3DSEMC	Female	56	RG268	Self_Employed	X3	26	N
3	BF3NC7KV	Male	34	RG270	Salaried	X1	19	N

	id	gender	age	region_code	occupation	channel_code	vintage	credit_produ
4	TEASRWXV	Female	30	RG282	Salaried	X1	33	N
...	...	...	...	...	...	...	...	
245720	BPAWWXZN	Male	51	RG284	Self_Employed	X3	109	Na
245721	HFNB7JY8	Male	27	RG268	Salaried	X1	15	N
245722	GEHAUCWT	Female	26	RG281	Salaried	X1	13	N
245723	GE7V8SAH	Female	28	RG273	Salaried	X1	31	N
245724	BOCZSWLJ	Male	29	RG269	Salaried	X1	21	N

245725 rows × 11 columns

LETS CHECK FOR DUPLICATES

In [4]:
```
train['id'].nunique() #SINCE THERE ARE 245725 ROWS WE ARE SAFE FROM DUPLICATES!
```

Out[4]: 245725

In [5]:
```
test = pd.read_csv('test.csv', encoding='latin_1')
# Converting all column names to lower case
test.columns = test.columns.str.lower()
test.head()
```

Out[5]:

	id	gender	age	region_code	occupation	channel_code	vintage	credit_product	avg_a
0	VBENBARO	Male	29	RG254	Other	X1	25	Yes	
1	CCMEWNKY	Male	43	RG268	Other	X2	49	NaN	
2	VK3KGA9M	Male	31	RG270	Salaried	X1	14	No	
3	TT8RPZVC	Male	29	RG272	Other	X1	33	No	
4	SHQZEYTZ	Female	29	RG270	Other	X1	19	No	

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

Out[6]:

	age	vintage	avg_account_balance	is_lead
count	245725.00	245725.00	245725.00	245725.00
mean	43.86	46.96	1128403.10	0.24
std	14.83	32.35	852936.36	0.43
min	23.00	7.00	20790.00	0.00
25%	30.00	20.00	604310.00	0.00
50%	43.00	32.00	894601.00	0.00
75%	54.00	73.00	1366666.00	0.00
max	85.00	135.00	10352009.00	1.00

In [7]:
```
test.describe()
```

Out[7]:

	age	vintage	avg_account_balance
count	105312.00	105312.00	105312.00
mean	43.87	46.84	1134194.63
std	14.87	32.27	866242.99
min	24.00	7.00	22597.00
25%	30.00	20.00	603982.25
50%	43.00	32.00	896634.50
75%	54.00	73.00	1371598.25
max	85.00	135.00	9908858.00

If you notice, age and vintage have quite common stats in both train and test data.

Exploratory Data Analysis

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 245725 entries, 0 to 245724
Data columns (total 11 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   245725 non-null  object
 1   gender               245725 non-null  object
 2   age                  245725 non-null  int64
 3   region_code          245725 non-null  object
 4   occupation           245725 non-null  object
 5   channel_code         245725 non-null  object
 6   vintage              245725 non-null  int64
 7   credit_product       216400 non-null  object
 8   avg_account_balance  245725 non-null  int64
 9   is_active            245725 non-null  object
 10  is_lead              245725 non-null  int64
dtypes: int64(4), object(7)
memory usage: 20.6+ MB
```

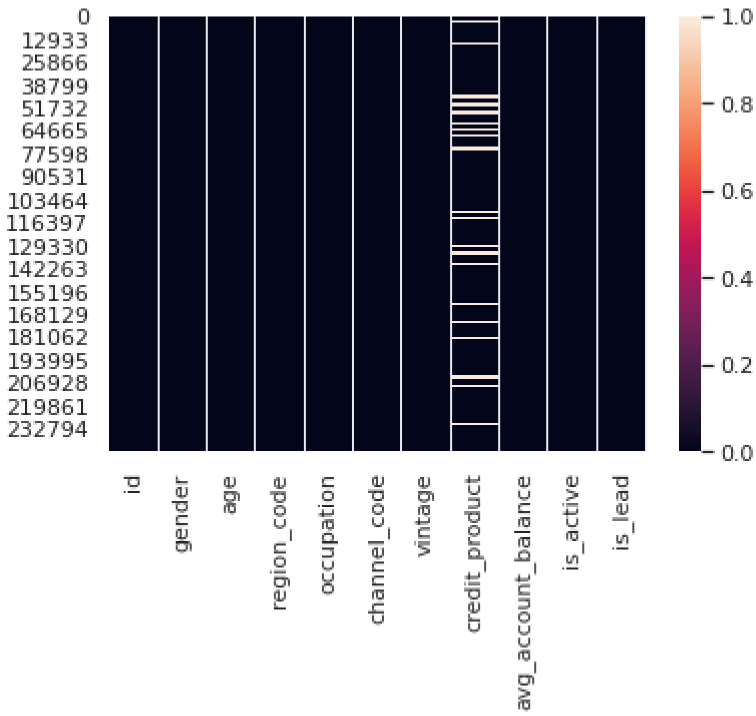
In [9]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 105312 entries, 0 to 105311
Data columns (total 10 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   105312 non-null  object
 1   gender               105312 non-null  object
 2   age                  105312 non-null  int64
 3   region_code          105312 non-null  object
 4   occupation           105312 non-null  object
 5   channel_code         105312 non-null  object
 6   vintage              105312 non-null  int64
 7   credit_product       92790 non-null   object
 8   avg_account_balance  105312 non-null  int64
 9   is_active            105312 non-null  object
dtypes: int64(3), object(7)
memory usage: 8.0+ MB
```

Lets check for Null Values in both train and test

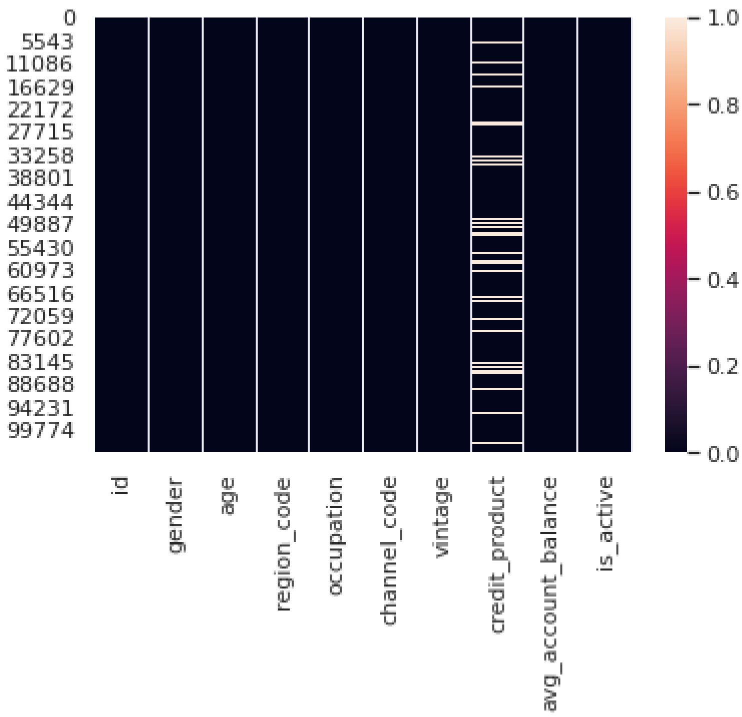
In [10]:
```
sns.heatmap(train.isnull())
# Seems like Credit_Product has some!
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1b31d88210>



In [11]:
```
sns.heatmap(test.isnull())
# Seems like Credit_Product has some!
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1b2957c990>



Highlights

- Dataset contains details of 245725 transactions with 31 features.
- Except for credit_product which contains 216400 rows, there is no missing data in our dataset, every column contain exactly 245725 rows
- Except for id which is nothing but like a primary, rest all features can be analysed!
- Similarly except for number of rows everything is quite similar in test data

- Instead of imputuing, droping the NaN values in credit_product, lets just assign a third category to them in both train and test data, which is notassigned

In [12]:
```
train['credit_product'].fillna('notassigned', inplace=True)
test['credit_product'].fillna('notassigned', inplace=True)
```

Now, Count unique values of label

In [13]:
```
print(train['is_lead'].value_counts())
print('\n')
print(train['is_lead'].value_counts(normalize=True))
```

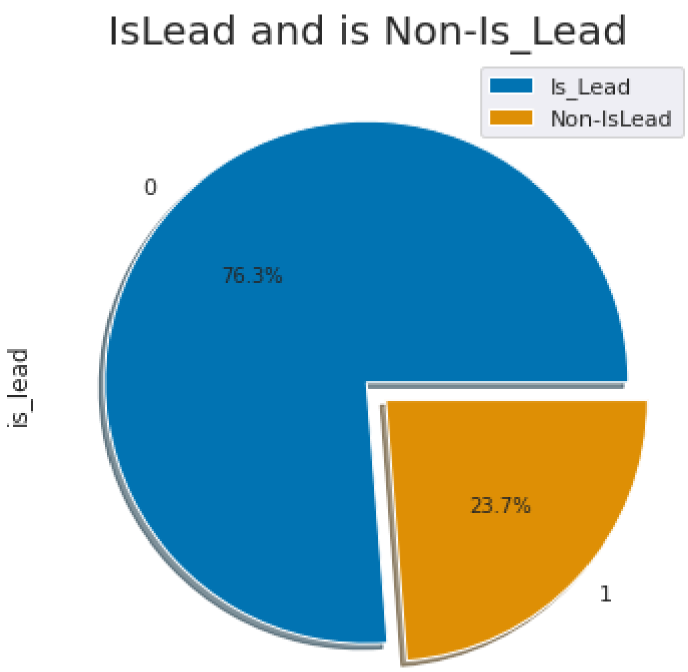
```
0    187437
1     58288
Name: is_lead, dtype: int64


0   0.76
1   0.24
Name: is_lead, dtype: float64
```

Highlights

This dataset has 58288 Non-Is_Lead and 187437 Is_Lead. The dataset is unbalanced, the positive class (Is_Lead) account for 23.7% of all data. Most of the data are Is_Lead. If we use this dataframe as the base for our predictive models and analysis, our algorithms will probably overfit since it will "assume" that most data are Is_Lead. But we don't want our model to assume, we want our model to detect patterns that predicts whether the person will be the lead or not based on the given details of the person.

In [14]:
```
# train['credit_product'].fillna('NotMentioned', inplace=True)
train["is_lead"].value_counts().plot(kind = 'pie',explode=[0, 0.1],figsize=(6, 6),au
plt.title("IsLead and is Non-Is_Lead",fontsize=20)
plt.legend(["Is_Lead", "Non-IsLead"])
plt.show()
```



Getting all the numeric terms:

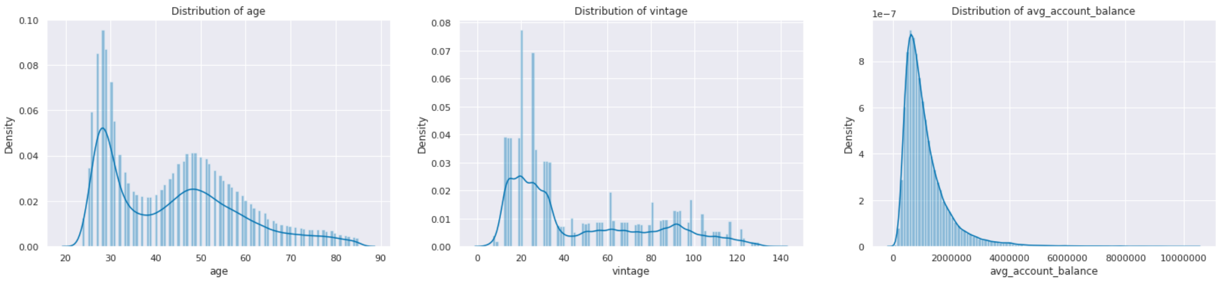
In [15]:
```
col = list(train.columns)
```

```python
text = ('id', 'channel_code', 'is_active','gender', 'region_code', 'occupation', 'cr
for i in text:
  col.remove(i)
col
```

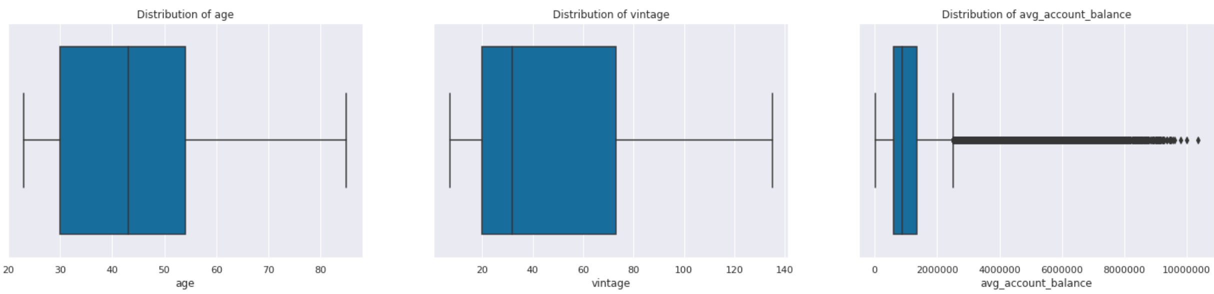
Out[15]: ['age', 'vintage', 'avg_account_balance']

Plotting the distribution of all numeric columns

In [16]:
```python
fig, axs = plt.subplots(ncols=3,figsize=(25,5))
j = 0
for i in col:
  axs[j].set_title("Distribution of {c}".format(c=i))
  sns.distplot(train[i], bins=100, ax=axs[j])
  j=j+1
  plt.ticklabel_format(style='plain', axis='x')
plt.show()
```

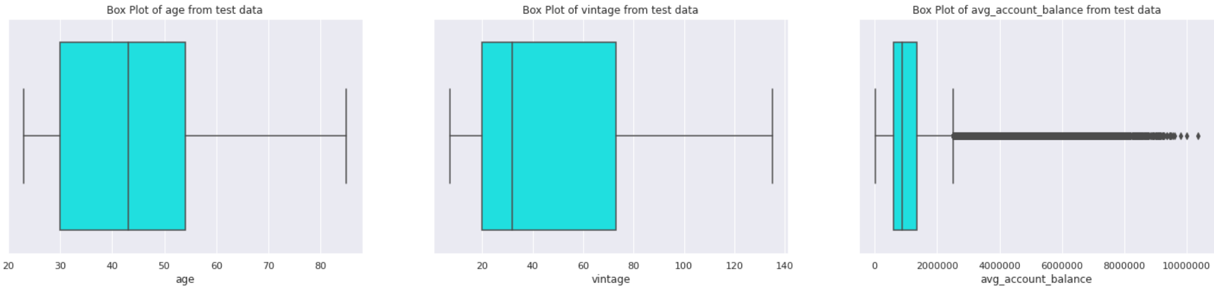


In [17]:
```python
fig, axs = plt.subplots(ncols=3,figsize=(25,5))
j = 0
for i in col:
  axs[j].set_title("Distribution of {c}".format(c=i))
  sns.boxplot(train[i], ax=axs[j])
  j=j+1
  plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



Looks like we have some outliers in avg_account_balance. Lets see at the boxplots of all the features with respect to class.

In [18]:
```python
fig, axs = plt.subplots(ncols=3,figsize=(25,5))
j = 0
for i in col:
  axs[j].set_title("Box Plot of {c} from test data".format(c=i))
  sns.boxplot(train[i], ax=axs[j], color='cyan')
  j=j+1
  plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



Now, since we dont want these outliers to affect models performance, lets get rid of them.

In [19]:
```
train.describe()
```

Out[19]:

	age	vintage	avg_account_balance	is_lead
count	245725.00	245725.00	245725.00	245725.00
mean	43.86	46.96	1128403.10	0.24
std	14.83	32.35	852936.36	0.43
min	23.00	7.00	20790.00	0.00
25%	30.00	20.00	604310.00	0.00
50%	43.00	32.00	894601.00	0.00
75%	54.00	73.00	1366666.00	0.00
max	85.00	135.00	10352009.00	1.00

SINCE SIMILAR PATTERN OF OUTLIERS ARE NOTICED IN BOTH TRAINING AND TESTING DATA, SO LETS JUST CONVERT THE CONTINUOUS FEATURES IN A PARTICULAR RANGE RATHER THEN DROPPING OUTLIERS.

In [20]:
```
age = test['age'].values
nage = []
vintage = test['vintage'].values
nvintage = []
avg_account_balance = test['avg_account_balance'].values
navg_account_balance = []
for i in age:
  i = int(i)
  if i>=23 and i<=30:
    nage.append('agerange1')
  if i>30 and i<=43:
    nage.append('agerange2')
  if i>43 and i<=54:
    nage.append('agerange3')
  if i>54 and i<=85:
    nage.append('agerange4')
  if i>85:
    nage.append('agerange5')
for j in vintage:
  j = int(j)
  if j>=7 and j<=20:
    nvintage.append('vintageagerange1')
  if j>20 and j<=32:
    nvintage.append('vintageagerange2')
  if j>32 and j<=73:
    nvintage.append('vintageagerange3')
  if j>73 and j<=135:
    nvintage.append('vintageagerange4')
  if j>135:
```

```
    nvintage.append('vintageagerange5')
for k in avg_account_balance:
  k = int(k)
  if k>=20790 and k<=604310:
    v = 'balancerange1'
    navg_account_balance.append(v)
  if k>604310 and k<=894601:
    v = 'balancerange2'
    navg_account_balance.append(v)
  if k>894601 and k<=1366666:
    v = 'balancerange3'
    navg_account_balance.append(v)
  if k>1366666 and k<=10352009:
    v = 'balancerange4'
    navg_account_balance.append(v)
  if k>10352009:
    v = 'balancerange5'
    navg_account_balance.append(v)
```

In [21]:

```
test['age']=nage
test['vintage']=nvintage
test['avg_account_balance']=navg_account_balance
test
```

Out[21]:

	id	gender	age	region_code	occupation	channel_code	vintage
0	VBENBARO	Male	agerange1	RG254	Other	X1	vintageagerange2
1	CCMEWNKY	Male	agerange2	RG268	Other	X2	vintageagerange3
2	VK3KGA9M	Male	agerange2	RG270	Salaried	X1	vintageagerange1
3	TT8RPZVC	Male	agerange1	RG272	Other	X1	vintageagerange3
4	SHQZEYTZ	Female	agerange1	RG270	Other	X1	vintageagerange1
...	...	...	...	...	...	...	...
105307	DBENJOYI	Male	agerange3	RG268	Salaried	X2	vintageagerange4
105308	CWQ72DWS	Male	agerange4	RG277	Other	X2	vintageagerange4
105309	HDESC8GU	Male	agerange2	RG254	Salaried	X4	vintageagerange1
105310	2PW4SFCA	Male	agerange3	RG254	Other	X3	vintageagerange4
105311	F2NOYPPZ	Male	agerange1	RG256	Salaried	X1	vintageagerange2

105312 rows × 10 columns

In [22]:

```
age = train['age'].values
nage = []
vintage = train['vintage'].values
nvintage = []
avg_account_balance = train['avg_account_balance'].values
navg_account_balance = []
for i in age:
  if i>=23 and i<=30:
    nage.append('agerange1')
  if i>30 and i<=43:
    nage.append('agerange2')
  if i>43 and i<=54:
    nage.append('agerange3')
  if i>54 and i<=85:
```

```
        nage.append('agerange4')
      if i>85:
        nage.append('agerange5')
    for j in vintage:
      if j>=7 and j<=20:
        nvintage.append('vintageagerange1')
      if j>20 and j<=32:
        nvintage.append('vintageagerange2')
      if j>32 and j<=73:
        nvintage.append('vintageagerange3')
      if j>73 and j<=135:
        nvintage.append('vintageagerange4')
      if j>135:
        nvintage.append('vintageagerange5')
    for k in avg_account_balance:
      if k>=20790 and k<=604310:
        v = 'balancerange1'
        navg_account_balance.append(v)
      if k>604310 and k<=894601:
        v = 'balancerange2'
        navg_account_balance.append(v)
      if k>894601 and k<=1366666:
        v = 'balancerange3'
        navg_account_balance.append(v)
      if k>1366666 and k<=10352009:
        v = 'balancerange4'
        navg_account_balance.append(v)
      if k>10352009:
        v = 'balancerange5'
        navg_account_balance.append(v)
```

In [23]:

```
train['age']=nage
train['vintage']=nvintage
train['avg_account_balance']=navg_account_balance
train
```

Out[23]:

	id	gender	age	region_code	occupation	channel_code	vintage
0	NNVBBKZB	Female	agerange4	RG268	Other	X3	vintageagerange3
1	IDD62UNG	Female	agerange1	RG277	Salaried	X1	vintageagerange2
2	HD3DSEMC	Female	agerange4	RG268	Self_Employed	X3	vintageagerange2
3	BF3NC7KV	Male	agerange2	RG270	Salaried	X1	vintageagerange1
4	TEASRWXV	Female	agerange1	RG282	Salaried	X1	vintageagerange3
...	...	...	...	...	...	...	..
245720	BPAWWXZN	Male	agerange3	RG284	Self_Employed	X3	vintageagerange4
245721	HFNB7JY8	Male	agerange1	RG268	Salaried	X1	vintageagerange1
245722	GEHAUCWT	Female	agerange1	RG281	Salaried	X1	vintageagerange1
245723	GE7V8SAH	Female	agerange1	RG273	Salaried	X1	vintageagerange2
245724	BOCZSWLJ	Male	agerange1	RG269	Salaried	X1	vintageagerange2

245725 rows × 11 columns

ENCODING THE DATA

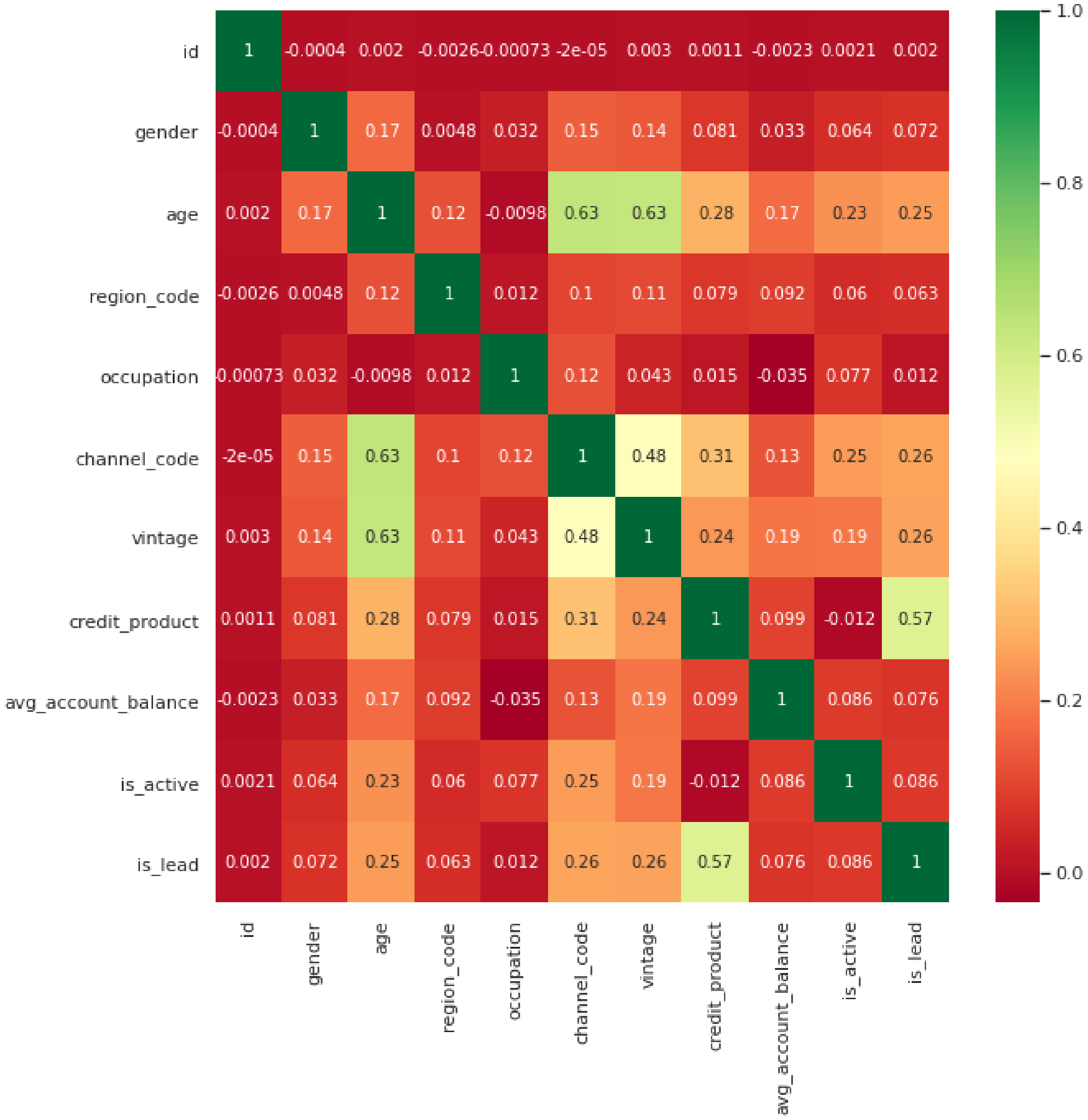
In [24]:

```
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
for x in train:
    if train[x].dtypes=='object':
        train[x] = le.fit_transform(train[x].astype(str))
```

GETTING CORRELATION BETWEEN ALL THE VARIABLES

In [25]:
```
X = train.iloc[:,0:8]  #independent columns
y = train.iloc[:,-1]    #target column i.e Is_Active
#get correlations of each features in dataset
corrmat = train.corr(method='pearson')
top_corr_features = corrmat.index
plt.figure(figsize=(10,10))
#plot heat map
g=sns.heatmap(train[top_corr_features].corr(method='pearson'),annot=True,cmap="RdYlG
```



Dropping some features with low correlation

In [26]:
```
train.drop('id', axis = 1, inplace=True)
train.drop('region_code', axis = 1, inplace=True)
```

In [27]:
```
train
```

Out[27]:

	gender	age	occupation	channel_code	vintage	credit_product	avg_account_balance	is_ac

	gender	age	occupation	channel_code	vintage	credit_product	avg_account_balance	is_ac
0	0	3	1	2	2	0	2	
1	0	0	2	0	1	0	0	
2	0	3	3	2	1	0	3	
3	1	1	2	0	0	0	0	
4	0	0	2	0	2	0	1	
...	...	...	...	...	...	...	...	
245720	1	2	3	2	3	2	3	
245721	1	0	2	0	0	0	1	
245722	0	0	2	0	0	0	1	
245723	0	0	2	0	1	0	0	
245724	1	0	2	0	1	0	2	

245725 rows × 9 columns

Now lets start building our model.

In [28]:
```
X = train.iloc[:,:-1] # X value contains all the variables except labels
y = train.iloc[:,-1] # these are the labels
```

We create the test train split first

In [29]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3)
```

We have now fit and transform the data into a scaler for accurate reading and results.

In [30]:
```
from sklearn.preprocessing import MinMaxScaler
mms = MinMaxScaler()
X_scaled = pd.DataFrame(mms.fit_transform(X_train), columns=X_train.columns)
X_test_scaled = pd.DataFrame(mms.transform(X_test), columns=X_test.columns)
```

We have addressed the issue of oversampling here.

In [31]:
```
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
X_balanced, y_balanced = oversample.fit_resample(X_scaled, y_train)
X_test_balanced, y_test_balanced = oversample.fit_resample(X_test_scaled, y_test)
```

In [32]:
```
y_train.value_counts()
```

Out[32]:
```
0    131178
1     40829
Name: is_lead, dtype: int64
```

In [33]:
```
pd.core.series.Series(y_balanced).value_counts()
```

Out[33]:
```
1    131178
0    131178
dtype: int64
```

In [34]:
```
y_test.value_counts()
```

Out[34]:
```
0    56259
1    17459
Name: is_lead, dtype: int64
```

In [35]:
```
pd.core.series.Series(y_test_balanced).value_counts()
```

Out[35]:
```
1    56259
0    56259
dtype: int64
```

We notice in the value counts above that label types are now balanced, that is the problem of oversampling is solved now. We will now implement decision tree algorithm

First we will do grid search to get the best parameters

In [36]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
params = {'max_depth':list(range(0,30)),
          'criterion' : ["gini", "entropy"],
          'max_features' : ["int","float","None", "auto", "sqrt", "log2"]
         }
grid_search_cv = GridSearchCV(DecisionTreeClassifier(), params, verbose=1, cv=3)
grid_search_cv.fit(X_balanced, y_balanced)
model = grid_search_cv.best_estimator_
```

```
Fitting 3 folds for each of 360 candidates, totalling 1080 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 1080 out of 1080 | elapsed:  1.3min finished
```

Training the model based on above parameters

In [37]:
```
model = grid_search_cv.best_estimator_
print(model)
```

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=24, max_features='log2', 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, presort='deprecated',
                       random_state=None, splitter='best')
```

In [38]:
```
train_scores = []
test_scores = []

tic = time.perf_counter()
model.fit(X_balanced, y_balanced)
train_score = model.score(X_balanced, y_balanced)
train_scores.append(train_score)
test_score = model.score(X_test_balanced, y_test_balanced)
test_scores.append(test_score)
toc = time.perf_counter()
print(toc-tic)

#Train Accuracy
from sklearn.metrics import roc_auc_score
print("TRAINING ACCURACY: ", roc_auc_score(y_balanced, model.predict_proba(X_balance

#Test Accuracy
from sklearn.metrics import roc_auc_score
print("TESTING ACCURACY: ", roc_auc_score(y_test_balanced, model.predict_proba(X_tes

# Save the model as a pickle in a file
import joblib
joblib.dump(model, 'CCLD.pkl')
```

```
0.324994189999984
```

```
TRAINING ACCURACY:  0.8990487278752355
TESTING ACCURACY:  0.8743874431647329
```

Out[38]:

```
['CCLD.pkl']
```

In [39]:

```python
# MAKING A FUNCTION FOR PREDICTION
def prediction(test): #enter the file as a data frame
    IDlite = np.array(test['id'])
    le = LabelEncoder()
    test.drop('region_code', axis = 1, inplace=True)
    for x in test:
        if test[x].dtypes=='object':
            test[x] = le.fit_transform(test[x].astype(str))
    test = test.iloc[:,1:] # X value contains all the variables except ID
    mms = MinMaxScaler()
    test = pd.DataFrame(mms.fit_transform(test), columns=test.columns)
    test = np.array(test)
    # Load the model from the file
    model = joblib.load('CCLD.pkl')
    # Use the loaded model to make predictions
    a = model.predict(test)
    return IDlite, a
```

In [40]:

```python
test
```

Out[40]:

	id	gender	age	region_code	occupation	channel_code	vintage
0	VBENBARO	Male	agerange1	RG254	Other	X1	vintageagerange2
1	CCMEWNKY	Male	agerange2	RG268	Other	X2	vintageagerange3
2	VK3KGA9M	Male	agerange2	RG270	Salaried	X1	vintageagerange1
3	TT8RPZVC	Male	agerange1	RG272	Other	X1	vintageagerange3
4	SHQZEYTZ	Female	agerange1	RG270	Other	X1	vintageagerange1
...	...	...	...	...	...	...	...
105307	DBENJOYI	Male	agerange3	RG268	Salaried	X2	vintageagerange4
105308	CWQ72DWS	Male	agerange4	RG277	Other	X2	vintageagerange4
105309	HDESC8GU	Male	agerange2	RG254	Salaried	X4	vintageagerange1
105310	2PW4SFCA	Male	agerange3	RG254	Other	X3	vintageagerange4
105311	F2NOYPPZ	Male	agerange1	RG256	Salaried	X1	vintageagerange2

105312 rows × 10 columns

MAKING PREDICTION AND SAVING INTO Solution.csv

In [41]:

```python
ID, Is_Lead = prediction(test) #getting ID and Is_Lead

#making a data frame
import pandas as pd
import numpy as np
dataset = pd.DataFrame({'ID': ID, 'Is_Lead': list(Is_Lead)}, columns=['ID', 'Is_Lead

#saving the data frame as csv
dataset.to_csv(path_or_buf='Solution.csv', sep=',', index=None)
```

Entire code:

In [42]:

```python
#IMPORTING LIBRARIES
import numpy as np
import pandas as pd
pd.options.display.float_format = '{:.2f}'.format
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
from xgboost import XGBClassifier
import joblib
# Print versions of libraries
print(f"Numpy version : Numpy {np.__version__}")
print(f"Pandas version : Pandas {pd.__version__}")
print(f"Seaborn version : Seaborn {sns.__version__}")
print(f"SkLearn version : SkLearn {sklearn.__version__}")
# Magic Functions for In-Notebook Display
%matplotlib inline
# Setting seabon style
sns.set(style='darkgrid', palette='colorblind')

#GETTING THE DATA
train = pd.read_csv('train.csv', encoding='latin_1')
# Converting all column names to lower case
train.columns = train.columns.str.lower()

test = pd.read_csv('test.csv', encoding='latin_1')
# Converting all column names to lower case
test.columns = test.columns.str.lower()
test.head()
print("")
print("SOME INSIGHTS ON WHAT KIND OF DATA ARE WE WORKING ON")
print("")
print("Information about the training data")
print("")
print(train.info())
print("")
print("Decription of the continuous features of training data")
print("")
print(train.describe())
print("")
print("")
print("")
print("Information about the testing data")
print("")
print(test.info())
print("")
print("Decription of the continuous features of testing data")
print("")
print(test.describe())
print("")
def training(train, test):
    #assign a third category to the missing data
    train['credit_product'].fillna('notassigned', inplace=True)
    test['credit_product'].fillna('notassigned', inplace=True)
    #Assigning range to the continuous data in both training and testing
    age = test['age'].values
    nage = []
    vintage = test['vintage'].values
    nvintage = []
    avg_account_balance = test['avg_account_balance'].values
    navg_account_balance = []
```

```
for i in age:
  i = int(i)
  if i>=23 and i<=30:
    nage.append('agerange1')
  if i>30 and i<=43:
    nage.append('agerange2')
  if i>43 and i<=54:
    nage.append('agerange3')
  if i>54 and i<=85:
    nage.append('agerange4')
  if i>85:
    nage.append('agerange5')
for j in vintage:
  j = int(j)
  if j>=7 and j<=20:
    nvintage.append('vintageagerange1')
  if j>20 and j<=32:
    nvintage.append('vintageagerange2')
  if j>32 and j<=73:
    nvintage.append('vintageagerange3')
  if j>73 and j<=135:
    nvintage.append('vintageagerange4')
  if j>135:
    nvintage.append('vintageagerange5')
for k in avg_account_balance:
  k = int(k)
  if k>=20790 and k<=604310:
    v = 'balancerange1'
    navg_account_balance.append(v)
  if k>604310 and k<=894601:
    v = 'balancerange2'
    navg_account_balance.append(v)
  if k>894601 and k<=1366666:
    v = 'balancerange3'
    navg_account_balance.append(v)
  if k>1366666 and k<=10352009:
    v = 'balancerange4'
    navg_account_balance.append(v)
  if k>10352009:
    v = 'balancerange5'
    navg_account_balance.append(v)
test['age']=nage
test['vintage']=nvintage
test['avg_account_balance']=navg_account_balance
age = train['age'].values
nage = []
vintage = train['vintage'].values
nvintage = []
avg_account_balance = train['avg_account_balance'].values
navg_account_balance = []
for i in age:
  i = int(i)
  if i>=23 and i<=30:
    nage.append('agerange1')
  if i>30 and i<=43:
    nage.append('agerange2')
  if i>43 and i<=54:
    nage.append('agerange3')
  if i>54 and i<=85:
    nage.append('agerange4')
  if i>85:
    nage.append('agerange5')
for j in vintage:
  j = int(j)
  if j>=7 and j<=20:
```

```
      nvintage.append('vintageagerange1')
    if j>20 and j<=32:
      nvintage.append('vintageagerange2')
    if j>32 and j<=73:
      nvintage.append('vintageagerange3')
    if j>73 and j<=135:
      nvintage.append('vintageagerange4')
    if j>135:
      nvintage.append('vintageagerange5')
  for k in avg_account_balance:
    k = int(k)
    if k>=20790 and k<=604310:
      v = 'balancerange1'
      navg_account_balance.append(v)
    if k>604310 and k<=894601:
      v = 'balancerange2'
      navg_account_balance.append(v)
    if k>894601 and k<=1366666:
      v = 'balancerange3'
      navg_account_balance.append(v)
    if k>1366666 and k<=10352009:
      v = 'balancerange4'
      navg_account_balance.append(v)
    if k>10352009:
      v = 'balancerange5'
      navg_account_balance.append(v)
  train['age']=nage
  train['vintage']=nvintage
  train['avg_account_balance']=navg_account_balance
  #Label Encoding our data.
  le = LabelEncoder()
  for x in train:
      if train[x].dtypes=='object':
          train[x] = le.fit_transform(train[x].astype(str))
  #Dropping some columns with low accuracy
  train.drop('id', axis = 1, inplace=True)
  train.drop('region_code', axis = 1, inplace=True)
  #Now lets start building our model.
  X = train.iloc[:,:-1] # X value contains all the variables except labels and ID
  y = train.iloc[:,-1] # these are the labels

  # We create the test train split first
  X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3)

  #We have now fit and transform the data into a scaler for accurate reading and r
  mms = MinMaxScaler()
  X_scaled = pd.DataFrame(mms.fit_transform(X_train), columns=X_train.columns)
  X_test_scaled = pd.DataFrame(mms.transform(X_test), columns=X_test.columns)

  #Now we carryout oversampling to adjust the class distribution of a data set
  oversample = SMOTE()
  X_balanced, y_balanced = oversample.fit_resample(X_scaled, y_train)
  X_test_balanced, y_test_balanced = oversample.fit_resample(X_test_scaled, y_test
  '''
  To get the best hyper-parameters for our model we are going to use GridSearchCV.
  # from sklearn.tree import DecisionTreeClassifier
  # from sklearn.model_selection import GridSearchCV
  # params = {'max_depth':list(range(0,30)),
  #           'criterion' : ["gini", "entropy"],
  #           'max_features' : ["int","float","None", "auto", "sqrt", "log2"]
  #          }
  # grid_search_cv = GridSearchCV(DecisionTreeClassifier(), params, verbose=1, cv=
  # grid_search_cv.fit(X_balanced, y_balanced)
  # model = grid_search_cv.best_estimator_
  # We will now train Decision tree model on the data.
```

```
    '''
    print("")
    print("Training Model")
    print("")
    import time #just to check how much time it takes to train
    train_scores = []
    test_scores = []
    tic = time.perf_counter()
    model = DecisionTreeClassifier(criterion='entropy', max_depth=27, max_features='
    model.fit(X_balanced, y_balanced)
    toc = time.perf_counter() #time ends here
    print("it took {tt} seconds".format(tt=tic-toc))
    model.fit(X_balanced, y_balanced)
    toc = time.perf_counter() #time ends here
    print("it took {tt} seconds".format(tt=tic-toc))

    #Train Accuracy
    from sklearn.metrics import roc_auc_score
    print("TRAINING ACCURACY: ", roc_auc_score(y_balanced, model.predict_proba(X_bal

    #Test Accuracy
    from sklearn.metrics import roc_auc_score
    print("TESTING ACCURACY: ", roc_auc_score(y_test_balanced, model.predict_proba(X

    # Save the model as a pickle in a file
    return model

# MAKING A FUNCTION FOR PREDICTION
def prediction(test, model): #enter the file as a data frame'
    print("")
    print("PROCESSING THE DATA TO BE PREDICTED")
    IDlite = np.array(test['id'])
    le = LabelEncoder()
    test.drop('region_code', axis = 1, inplace=True)
    for x in test:
        if test[x].dtypes=='object':
            test[x] = le.fit_transform(test[x].astype(str))
    test = test.iloc[:,1:] # X value contains all the variables except ID
    mms = MinMaxScaler()
    test = pd.DataFrame(mms.fit_transform(test), columns=test.columns)
    test = np.array(test)
    # Use the loaded model to make predictions
    a = model.predict(test)
    print("Completed.")
    return IDlite, a

#training the model and getting the predictions
model = training(train, test)
ID, Is_Lead = prediction(test, model) #getting ID and Is_Lead

#making a data frame
import pandas as pd
import numpy as np
dataset = pd.DataFrame({'ID': ID, 'Is_Lead': list(Is_Lead)}, columns=['ID', 'Is_Lead

#saving the data frame as csv
dataset.to_csv(path_or_buf='Solution.csv', sep=',', index=None)
```

```
Numpy version : Numpy 1.19.5
Pandas version : Pandas 1.1.5
Seaborn version : Seaborn 0.11.1
SkLearn version : SkLearn 0.22.2.post1

SOME INSIGHTS ON WHAT KIND OF DATA ARE WE WORKING ON

Information about the training data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 245725 entries, 0 to 245724
Data columns (total 11 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   245725 non-null  object
 1   gender               245725 non-null  object
 2   age                  245725 non-null  int64
 3   region_code          245725 non-null  object
 4   occupation           245725 non-null  object
 5   channel_code         245725 non-null  object
 6   vintage              245725 non-null  int64
 7   credit_product       216400 non-null  object
 8   avg_account_balance  245725 non-null  int64
 9   is_active            245725 non-null  object
 10  is_lead              245725 non-null  int64
dtypes: int64(4), object(7)
memory usage: 20.6+ MB
None

Decription of the continuous features of training data

            age   vintage  avg_account_balance   is_lead
count 245725.00 245725.00            245725.00 245725.00
mean      43.86     46.96           1128403.10      0.24
std       14.83     32.35            852936.36      0.43
min       23.00      7.00             20790.00      0.00
25%       30.00     20.00            604310.00      0.00
50%       43.00     32.00            894601.00      0.00
75%       54.00     73.00           1366666.00      0.00
max       85.00    135.00          10352009.00      1.00
```

```
Information about the testing data

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 105312 entries, 0 to 105311
Data columns (total 10 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   105312 non-null  object
 1   gender               105312 non-null  object
 2   age                  105312 non-null  int64
 3   region_code          105312 non-null  object
 4   occupation           105312 non-null  object
 5   channel_code         105312 non-null  object
 6   vintage              105312 non-null  int64
 7   credit_product       92790 non-null   object
 8   avg_account_balance  105312 non-null  int64
 9   is_active            105312 non-null  object
dtypes: int64(3), object(7)
memory usage: 8.0+ MB
None

Decription of the continuous features of testing data

            age   vintage  avg_account_balance
count 105312.00 105312.00            105312.00
mean      43.87     46.84           1134194.63
std       14.87     32.27            866242.99
min       24.00      7.00             22597.00
25%       30.00     20.00            603982.25
50%       43.00     32.00            896634.50
75%       54.00     73.00           1371598.25
max       85.00    135.00           9908858.00
```

```
Training Model

it took -0.24278326299997843 seconds
it took -0.4796951390000004 seconds
TRAINING ACCURACY:  0.897331178506964
TESTING ACCURACY:  0.8773589101008836

PROCESSING THE DATA TO BE PREDICTED
Completed.
```

In [42]: