In [41]:

```python
#Importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#Reading the historical_data
df=pd.read_csv("Historical_data.csv")
#Reading the processed historical_data
data=pd.read_csv("Historical_data 01.csv")
#Reading the new_customer_data
new_data=pd.read_csv("new_customer_wow.csv")
#Getting dummy values for columns with categorical data for historical_data
data=pd.get_dummies(data,columns=['job_type','marital','education','communication_type',
                                  'month','prev_campaign_outcome'])
#Getting dummy values for columns with categorical data for new_customer_data
new_data=pd.get_dummies(new_data,columns=['job_type','marital','education','communication_type',
                                          'month','prev_campaign_outcome'])
#Dropping the unnessecary columns from historical_data
data = data.drop(['month_dec','prev_campaign_outcome_unknown','communication_type_unknown',
                  'marital_divorced','job_type_unknown','education_unknown'],axis='columns')
#Dropping the unnessecary columns from new_customer_data
new_data = new_data.drop(['month_dec','prev_campaign_outcome_unknown','communication_type_unknown',
                          'marital_divorced','job_type_unknown','education_unknown'],axis='columns')
```

In [42]:

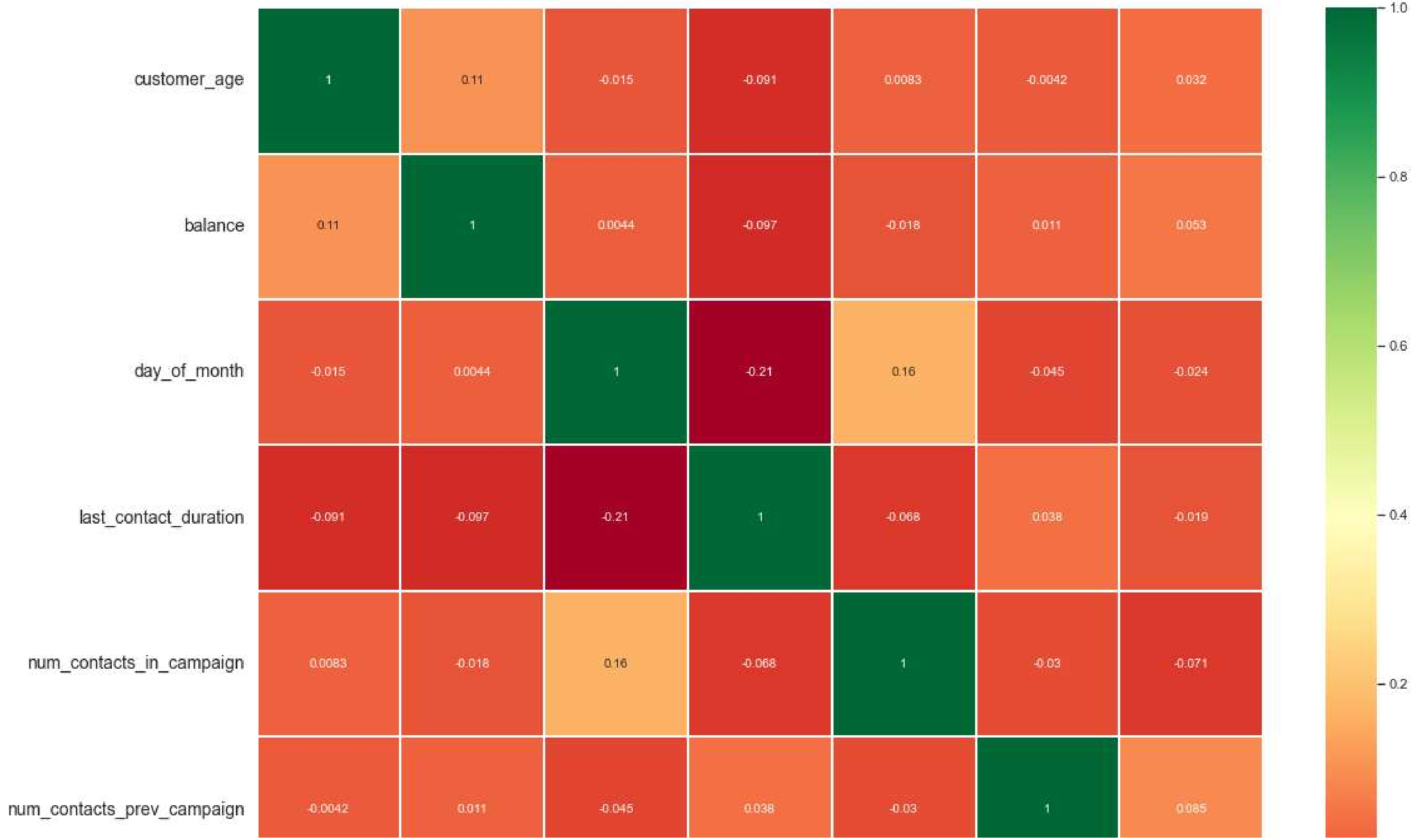
```python
#Basic description of historical_data
df.describe()
```

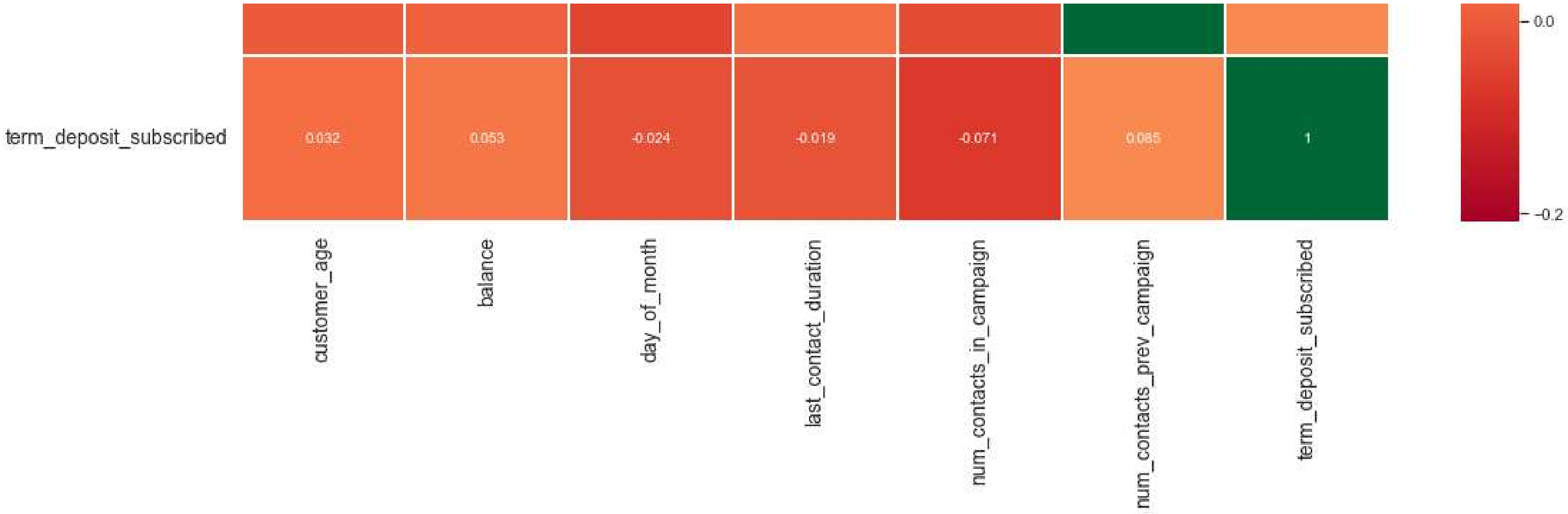
Out[42]:

	customer_age	balance	day_of_month	last_contact_duration	num_contacts_in_campaign	num_contacts_prev_campaign	term_deposit_subscribed
count	23403.000000	23603.000000	23880.000000	23880.000000	23784.000000	23880.000000	23880.000000
mean	40.394821	1363.966106	15.796315	854.879648	2.775353	0.583836	0.106198
std	10.753045	3019.583085	8.321136	74.537616	3.148117	2.624465	0.308097
min	18.000000	-8020.000000	1.000000	661.000000	1.000000	0.000000	0.000000
25%	32.000000	71.000000	8.000000	809.000000	1.000000	0.000000	0.000000
50%	38.000000	443.000000	16.000000	871.000000	2.000000	0.000000	0.000000
75%	48.000000	1410.500000	21.000000	897.000000	3.000000	0.000000	0.000000
max	93.000000	98419.000000	31.000000	1019.000000	63.000000	275.000000	1.000000

In [43]:

```
#correlation matrix of numeric variables
from sklearn.preprocessing import StandardScaler
import seaborn as sns
corr = df.corr()

sns.heatmap(corr,annot=True,cmap='RdYlGn',linewidths=0.2,annot_kws={'size':10})
fig=plt.gcf()
fig.set_size_inches(18,15)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.show()
```





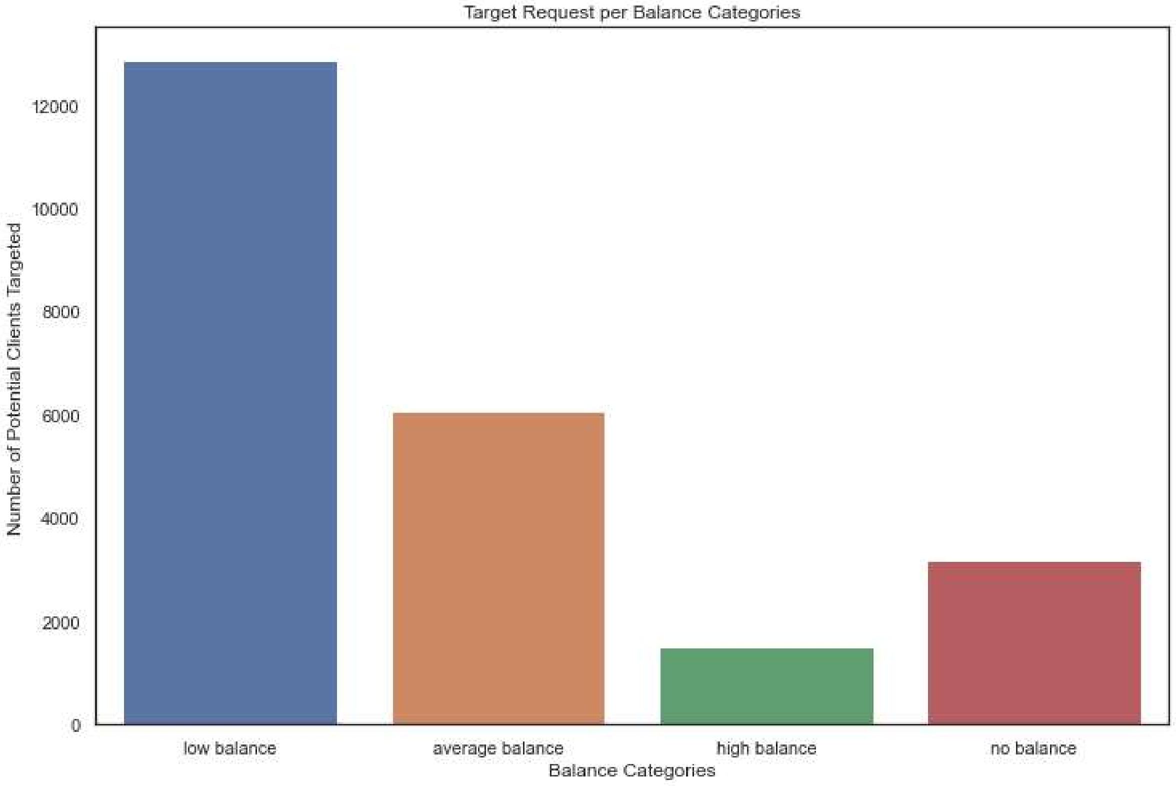
In [44]:

```
#Grouping balance in categories
df['balance_categories'] = np.nan

lst = [df]

for column in lst:
    column.loc[column['balance'] <= 0, 'balance_categories'] = 'no balance'
    column.loc[(column['balance'] > 0) & (column['balance'] <= 1000), 'balance_categories'] = 'low balance'
    column.loc[(column['balance'] > 1000) & (column['balance'] <= 5000), 'balance_categories'] = 'average balance'
    column.loc[column['balance'] > 5000, 'balance_categories'] = 'high balance'

df.head()
df['balance_categories'].value_counts()
#We find most of the customers belong in low balance category
```

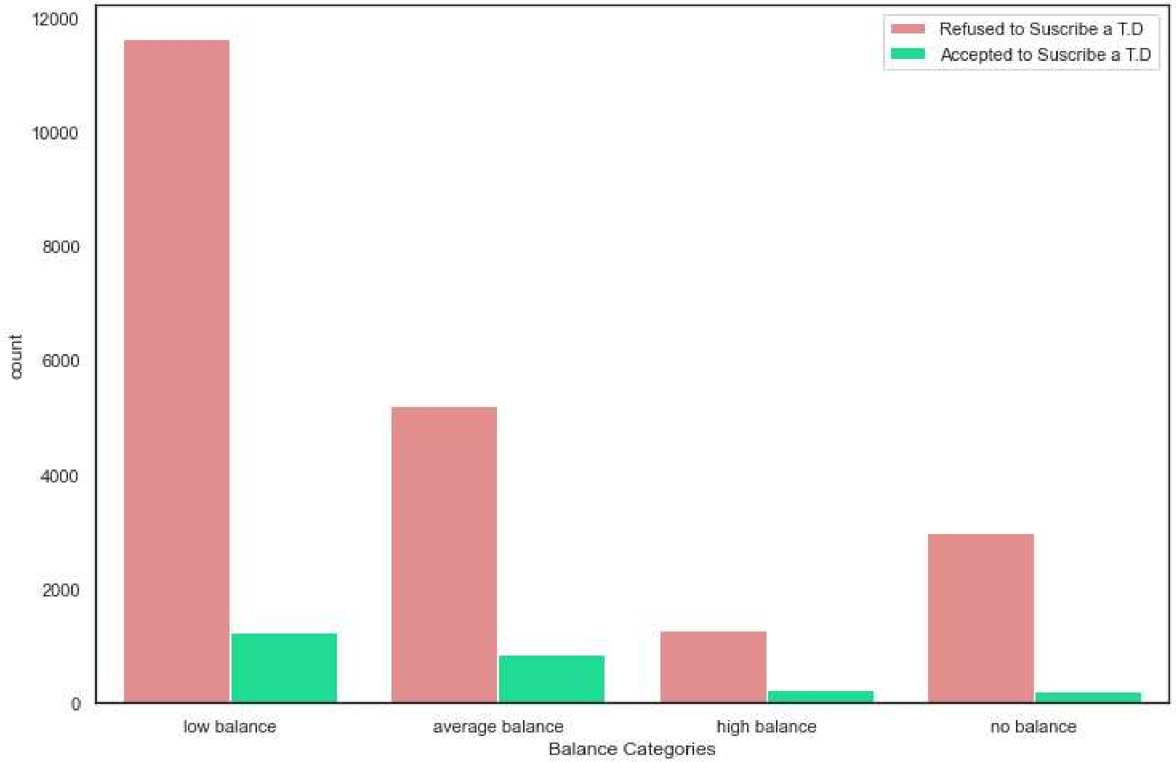
Out[44]:

```
low balance        12861
average balance     6066
no balance          3172
high balance        1504
Name: balance_categories, dtype: int64
```

In [45]:
```
#Plotting the balance categories along number of customers in each category
fig, ax = plt.subplots(figsize=(12,8))
g = sns.countplot(x="balance_categories", data=df)

plt.title("Target Request per Balance Categories")
plt.xlabel('Balance Categories')
plt.ylabel("Number of Potential Clients Targeted")

plt.show()
```

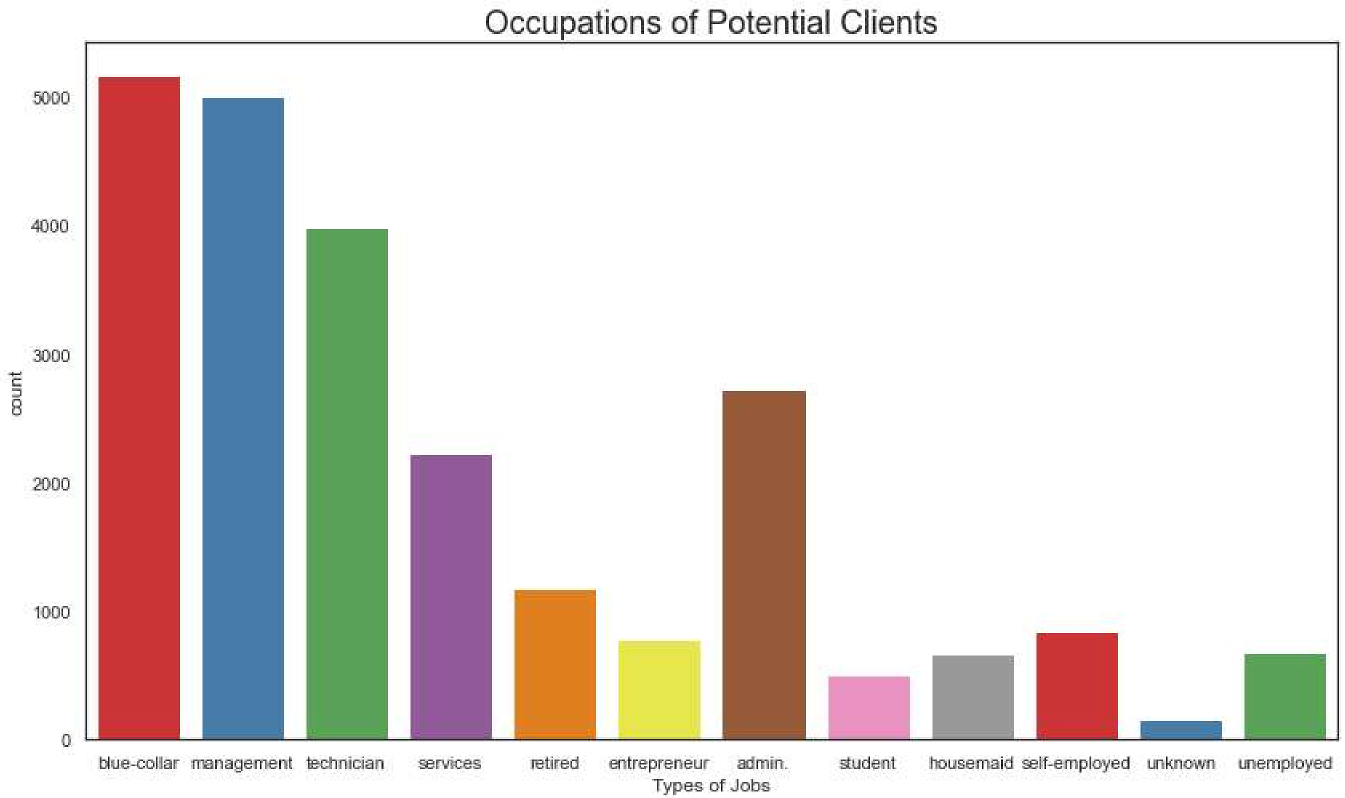


In [46]:
```
#plotting balance categories to see difference realtion between people subscribing and people not subscribing
fig, ax = plt.subplots(figsize=(12,8))
g = sns.countplot(x="balance_categories", data=df, hue='term_deposit_subscribed', palette={0:'#F08080', 1:'#00FA9A'})

legend_name = plt.legend()
legend_name.get_texts()[0].set_text('Refused to Suscribe a T.D')
legend_name.get_texts()[1].set_text('Accepted to Suscribe a T.D')
plt.xlabel('Balance Categories')


plt.show()
#The graph shows that average and high balance category are more likely to open a term deposit account
```



In [47]:

```
#plotting different job types in historical_data
sns.set(style="white")
fig, ax = plt.subplots(figsize=(14,8))
sns.countplot(x="job_type", data=df, palette="Set1")
ax.set_title("Occupations of Potential Clients", fontsize=20)
ax.set_xlabel("Types of Jobs")
plt.show()
```



In [48]:
```
#Setting the value for X and Y to train the model
x=data[['customer_age', 'default', 'balance', 'housing_loan',
       'personal_loan', 'last_contact_duration', 'day_of_month',
       'num_contacts_in_campaign', 'num_contacts_prev_campaign',
       'job_type_admin.', 'job_type_blue-collar', 'job_type_entrepreneur',
       'job_type_housemaid', 'job_type_management', 'job_type_retired',
       'job_type_self-employed', 'job_type_services', 'job_type_student',
       'job_type_technician', 'job_type_unemployed', 'marital_married',
       'marital_single', 'education_primary', 'education_secondary',
       'education_tertiary', 'communication_type_cellular',
       'communication_type_telephone', 'month_apr', 'month_aug', 'month_feb',
       'month_jan', 'month_jul', 'month_jun', 'month_mar', 'month_may',
       'month_nov', 'month_oct', 'month_sep', 'prev_campaign_outcome_failure',
       'prev_campaign_outcome_other', 'prev_campaign_outcome_success']]
y=data['term_deposit_subscribed']
```

In [49]:
```
#Fitting the Random Forest Regression model with help of historical_data
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators = 100,random_state = 0)
regressor.fit(x,y)
y_pred= regressor.predict(x)
#Finding R2 Score of the regression model
R2_score=regressor.score(x,y)
print('R2 Score:', R2_score)
```

```
R2 Score: 0.8844552588169639
```

In [50]:
```
#calculating error values in prediction model
from sklearn.metrics import accuracy_score
from sklearn import metrics
meanAbErr = metrics.mean_absolute_error(y, y_pred)
meanSqErr = metrics.mean_squared_error(y, y_pred)
rootMeanSqErr = np.sqrt(metrics.mean_squared_error(y, y_pred))

print('Mean Absolute Error:', meanAbErr)
print('Mean Square Error:', meanSqErr)
print('Root Mean Square Error:', rootMeanSqErr)
```

```
Mean Absolute Error: 0.05724302620456467
Mean Square Error: 0.010972717666948437
Root Mean Square Error: 0.10475074065107338
```

In [51]:
```python
#Finding importance of each data type using Gini importance
importances = regressor.feature_importances_

print("Feature ranking:")

for f in range(x.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))
```

```
Feature ranking:
1. feature 30 (0.000589)
2. feature 35 (0.002478)
3. feature 1 (0.003041)
4. feature 26 (0.003360)
5. feature 12 (0.003635)
6. feature 29 (0.003837)
7. feature 28 (0.004503)
8. feature 14 (0.004709)
9. feature 31 (0.004859)
10. feature 39 (0.005033)
11. feature 17 (0.005526)
12. feature 34 (0.005564)
13. feature 19 (0.005675)
14. feature 11 (0.005814)
15. feature 38 (0.006585)
16. feature 15 (0.007198)
17. feature 27 (0.008130)
18. feature 25 (0.009469)
19. feature 37 (0.009679)
20. feature 22 (0.009884)
21. feature 16 (0.009938)
22. feature 36 (0.010270)
23. feature 4 (0.010670)
24. feature 21 (0.011446)
25. feature 10 (0.011548)
26. feature 9 (0.012107)
27. feature 32 (0.012423)
28. feature 24 (0.012662)
29. feature 13 (0.012892)
30. feature 23 (0.013773)
31. feature 20 (0.013775)
32. feature 18 (0.013964)
33. feature 33 (0.014855)
34. feature 3 (0.018763)
35. feature 8 (0.030454)
36. feature 7 (0.053076)
37. feature 6 (0.079099)
38. feature 5 (0.101328)
39. feature 40 (0.117083)
40. feature 0 (0.129882)
41. feature 2 (0.200426)
```

In [52]:

```
#Extracting customer_id from new_customer_data
customer_id=new_data['customer_id']
#Setting dataset for prediction from new_customer_data
x_new=new_data[['customer_age', 'default', 'balance', 'housing_loan',
       'personal_loan', 'last_contact_duration', 'day_of_month',
       'num_contacts_in_campaign', 'num_contacts_prev_campaign',
       'job_type_admin.', 'job_type_blue-collar', 'job_type_entrepreneur',
       'job_type_housemaid', 'job_type_management', 'job_type_retired',
       'job_type_self-employed', 'job_type_services', 'job_type_student',
       'job_type_technician', 'job_type_unemployed', 'marital_married',
       'marital_single', 'education_primary', 'education_secondary',
       'education_tertiary', 'communication_type_cellular',
       'communication_type_telephone', 'month_apr', 'month_aug', 'month_feb',
       'month_jan', 'month_jul', 'month_jun', 'month_mar', 'month_may',
       'month_nov', 'month_oct', 'month_sep', 'prev_campaign_outcome_failure',
       'prev_campaign_outcome_other', 'prev_campaign_outcome_success']]
```

In [53]:

```
#predicting regression values
prediction=regressor.predict(x_new)
#Concatenating customer_id and prediction value
out=pd.DataFrame({'customer_id':customer_id,'forest value':prediction})
#Exporting data to xlsx file
out.to_excel('Prediction.xlsx')
```