

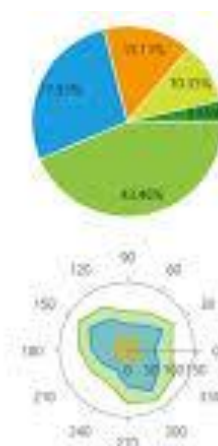
DMPA Project

Analyzing Bank Marketing Dataset for effectiveness of campaign

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Information about predictors in our dataset: -

```
In [3]: 1 #attribute information
        2 bank.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
#   Column                Non-Null Count  Dtype
---  -
0   age                   41188 non-null  int64
1   job                   41188 non-null  object
2   marital               41188 non-null  object
3   education             41188 non-null  object
4   default               41188 non-null  object
5   housing               41188 non-null  object
6   loan                  41188 non-null  object
7   contact               41188 non-null  object
8   month                 41188 non-null  object
9   day_of_week           41188 non-null  object
10  duration              41188 non-null  int64
11  campaign              41188 non-null  int64
12  pdays                41188 non-null  int64
13  previous              41188 non-null  int64
14  poutcome              41188 non-null  object
15  emp.var.rate          41188 non-null  float64
16  cons.price.idx        41188 non-null  float64
17  cons.conf.idx         41188 non-null  float64
18  euribor3m             41188 non-null  float64
19  nr.employed           41188 non-null  float64
20  y                     41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

We divided our data(predictors) in 4 parts

- Client related data
- Bank related data
- Social and economic related data
- Other factors that can be related

We have done exploratory data analysis, Pre-processing for each of the divided part individually

Client data: -

```
In [5]: 1 bank_client = bank.iloc[:, 0:7]
        2 bank_client.head()
```

Out[5]:

	age	job	marital	education	default	housing	loan
0	56	housemaid	married	basic.4y	no	no	no
1	57	services	married	high.school	unknown	no	no
2	37	services	married	high.school	no	yes	no
3	40	admin.	married	basic.6y	no	no	no
4	56	services	married	high.school	no	no	yes

Now we will do exploratory data analysis for each of the predictor individually

1- Age: -

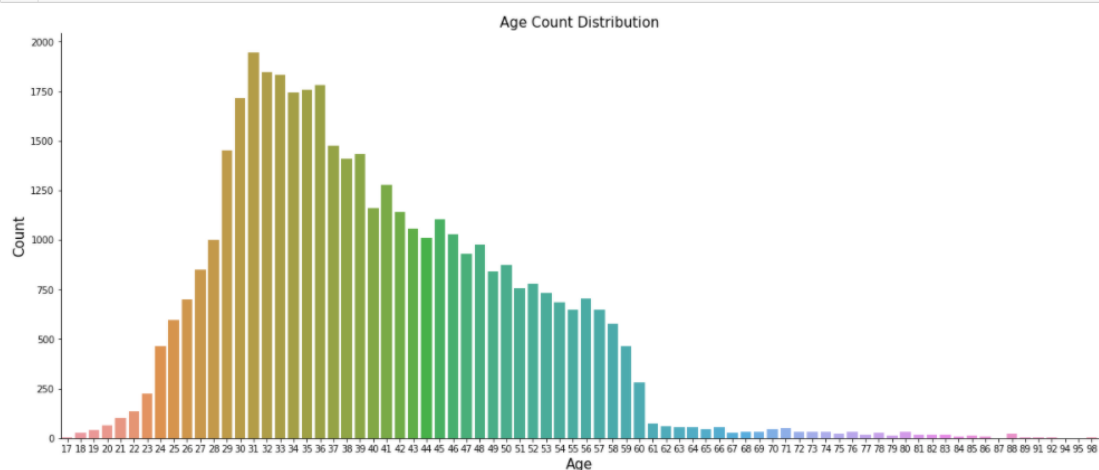
- Firstly, we find the max, minimum and null values

```
In [6]: 1 #Trying to find some strange values or null values
        2 print('Min age: ', bank_client['age'].max())
        3 print('Max age: ', bank_client['age'].min())
        4 print('Null Values: ', bank_client['age'].isnull().any())
```

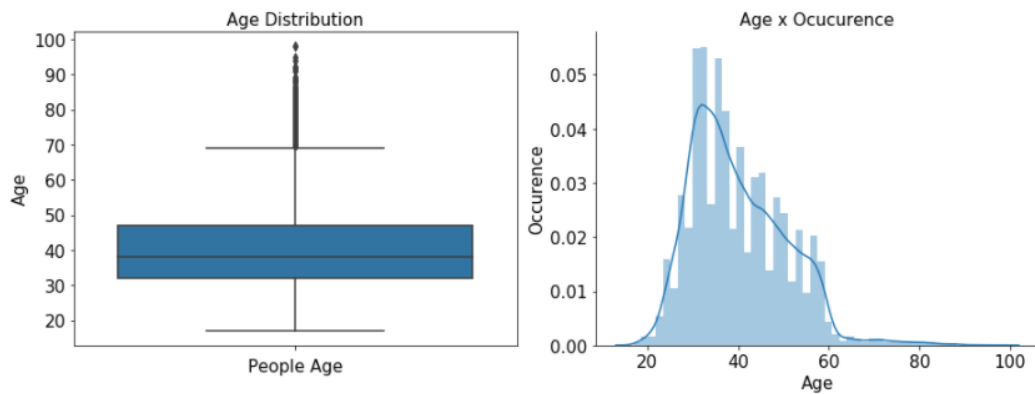
Min age: 98
Max age: 17
Null Values: False

- Secondly, we tried to find importance of AGE by plotting the graphs

```
In [7]: 1 fig, ax = plt.subplots()
        2 fig.set_size_inches(20, 8)
        3 sns.countplot(x = 'age', data = bank_client)
        4 ax.set_xlabel('Age', fontsize=15)
        5 ax.set_ylabel('Count', fontsize=15)
        6 ax.set_title('Age Count Distribution', fontsize=15)
        7 sns.despine()
```



```
In [8]: 1 fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
2 sns.boxplot(x = 'age', data = bank_client, orient = 'v', ax = ax1)
3 ax1.set_xlabel('People Age', fontsize=15)
4 ax1.set_ylabel('Age', fontsize=15)
5 ax1.set_title('Age Distribution', fontsize=15)
6 ax1.tick_params(labelsize=15)
7
8 sns.distplot(bank_client['age'], ax = ax2)
9 sns.despine(ax = ax2)
10 ax2.set_xlabel('Age', fontsize=15)
11 ax2.set_ylabel('Occurrence', fontsize=15)
12 ax2.set_title('Age x Occurrence', fontsize=15)
13 ax2.tick_params(labelsize=15)
14
15 plt.subplots_adjust(wspace=0.5)
16 plt.tight_layout()
```



- Also, we find Mean and Standard Deviation as this will give us the spread of our data

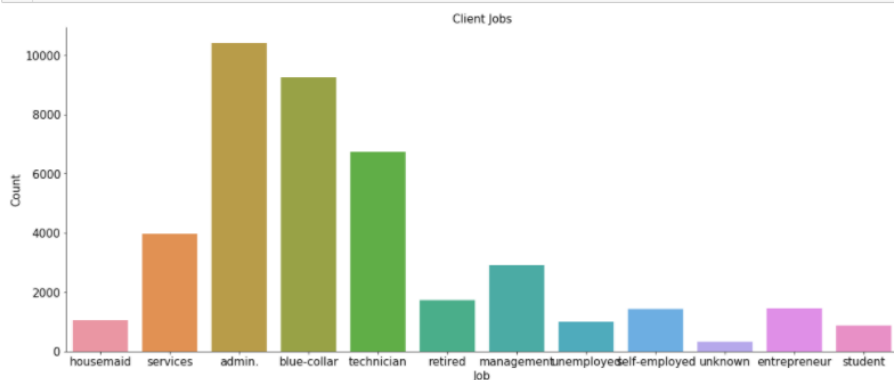
```
In [9]: 1 # Calculating some values to evaluate this independent variable
2 print('MEAN:', round(bank_client['age'].mean(), 1))
3 # A low standard deviation indicates that the data points tend to be close to the mean or expected value
4 # A high standard deviation indicates that the data points are scattered
5 print('STD :', round(bank_client['age'].std(), 1))
```

MEAN: 40.0
STD : 10.4

Conclusion about 'AGE' variable: according to the graph we find that age can be related to the output variable 'y'.

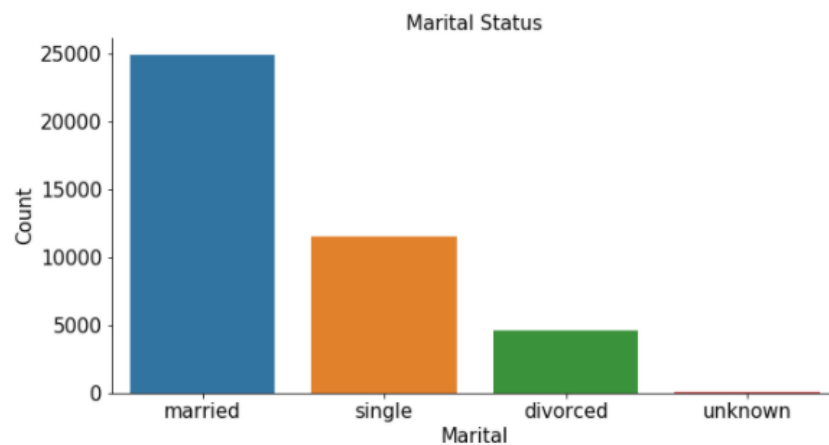
2- Jobs: -

```
In [10]: 1 # What kind of jobs clients this bank have?
2 fig, ax = plt.subplots()
3 fig.set_size_inches(20, 8)
4 sns.countplot(x = 'job', data = bank_client)
5 ax.set_xlabel('Job', fontsize=15)
6 ax.set_ylabel('Count', fontsize=15)
7 ax.set_title('Client Jobs', fontsize=15)
8 ax.tick_params(labelsize=15)
9 sns.despine()
```



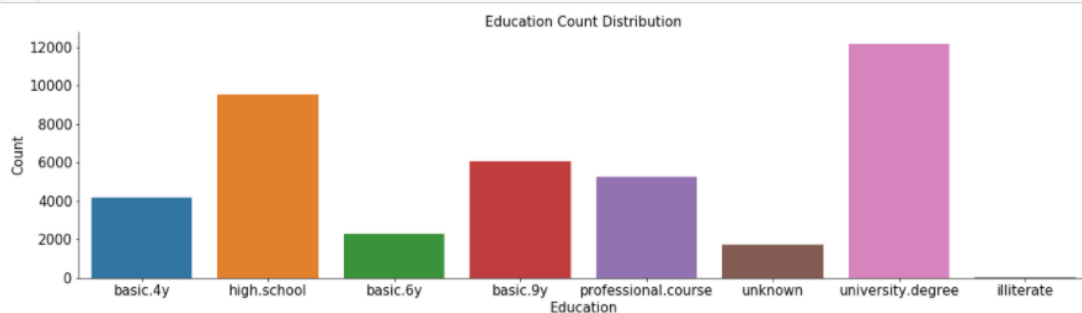
3- Marital: -

```
In [11]: 1 #Marital Status of clients
2 fig, ax = plt.subplots()
3 fig.set_size_inches(10, 5)
4 sns.countplot(x = 'marital', data = bank_client)
5 ax.set_xlabel('Marital', fontsize=15)
6 ax.set_ylabel('Count', fontsize=15)
7 ax.set_title('Marital Status', fontsize=15)
8 ax.tick_params(labelsize=15)
9 sns.despine()
```



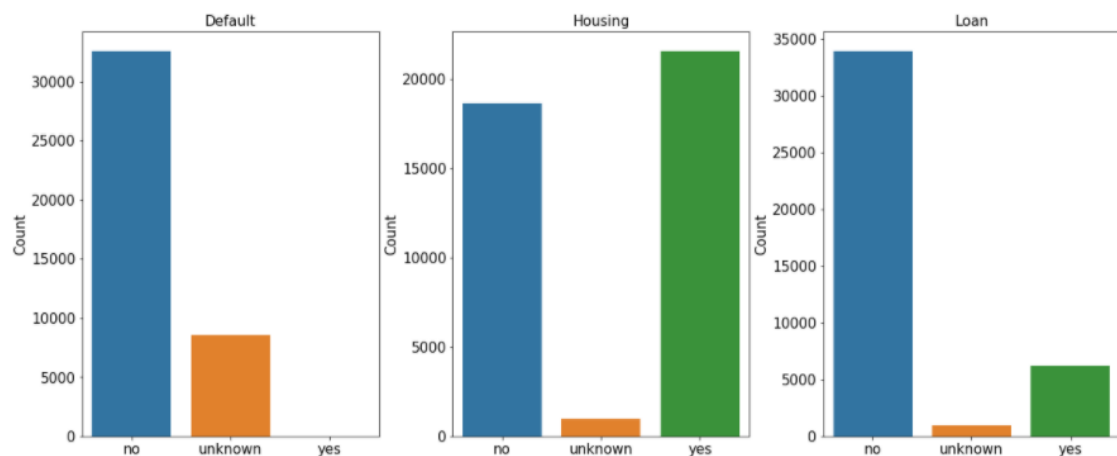
4- Education: -

```
In [12]: 1 # Educational status of the clients
2 fig, ax = plt.subplots()
3 fig.set_size_inches(20, 5)
4 sns.countplot(x = 'education', data = bank_client)
5 ax.set_xlabel('Education', fontsize=15)
6 ax.set_ylabel('Count', fontsize=15)
7 ax.set_title('Education Count Distribution', fontsize=15)
8 ax.tick_params(labelsize=15)
9 sns.despine()
```



5- Default, Housing, Loan: -

```
In [13]: 1 # Default, has credit in default ?
2 fig, (ax1, ax2, ax3) = plt.subplots(nrows = 1, ncols = 3, figsize = (20,8))
3 sns.countplot(x = 'default', data = bank_client, ax = ax1, order = ['no', 'unknown', 'yes'])
4 ax1.set_title('Default', fontsize=15)
5 ax1.set_xlabel('')
6 ax1.set_ylabel('Count', fontsize=15)
7 ax1.tick_params(labelsize=15)
8
9 # Housing, has housing loan ?
10 sns.countplot(x = 'housing', data = bank_client, ax = ax2, order = ['no', 'unknown', 'yes'])
11 ax2.set_title('Housing', fontsize=15)
12 ax2.set_xlabel('')
13 ax2.set_ylabel('Count', fontsize=15)
14 ax2.tick_params(labelsize=15)
15
16 # Loan, has personal loan ?
17 sns.countplot(x = 'loan', data = bank_client, ax = ax3, order = ['no', 'unknown', 'yes'])
18 ax3.set_title('Loan', fontsize=15)
19 ax3.set_xlabel('')
20 ax3.set_ylabel('Count', fontsize=15)
21 ax3.tick_params(labelsize=15)
22
23 plt.subplots_adjust(wspace=0.25)
```



Since the graph does not provide exact numbers, we try to find the exact numbers.

```
In [14]: 1 print('Default:\n No credit in default:', bank_client[bank_client['default'] == 'no'] ['age'].count(),
2          '\n Unknown credit in default:', bank_client[bank_client['default'] == 'unknown'] ['age'].count(),
3          '\n Yes to credit in default:', bank_client[bank_client['default'] == 'yes'] ['age'].count())
```

```
Default:
No credit in default: 32588
Unknown credit in default: 8597
Yes to credit in default: 3
```

```
In [15]: 1 print('Housing:\n No housing in loan:', bank_client[bank_client['housing'] == 'no'] ['age'].count(),
2          '\n Unknown housing in loan:', bank_client[bank_client['housing'] == 'unknown'] ['age'].count(),
3          '\n Yes to housing in loan:', bank_client[bank_client['housing'] == 'yes'] ['age'].count())
```

```
Housing:
No housing in loan: 18622
Unknown housing in loan: 990
Yes to housing in loan: 21576
```

```
In [16]: 1 print('Housing:\n No to personal loan:', bank_client[bank_client['loan'] == 'no'] ['age'].count(),
2          '\n Unknown to personal loan:', bank_client[bank_client['loan'] == 'unknown'] ['age'].count(),
3          '\n Yes to personal loan:', bank_client[bank_client['loan'] == 'yes'] ['age'].count())
```

```
Housing:
No to personal loan: 33950
Unknown to personal loan: 990
Yes to personal loan: 6248
```

Now, we pre-process the categorical data: -

```
In [17]: 1 # Label encoder order is alphabetical
2 from sklearn.preprocessing import LabelEncoder
3 labelencoder_X = LabelEncoder()
4 bank_client['job'] = labelencoder_X.fit_transform(bank_client['job'])
5 bank_client['marital'] = labelencoder_X.fit_transform(bank_client['marital'])
6 bank_client['education'] = labelencoder_X.fit_transform(bank_client['education'])
7 bank_client['default'] = labelencoder_X.fit_transform(bank_client['default'])
8 bank_client['housing'] = labelencoder_X.fit_transform(bank_client['housing'])
9 bank_client['loan'] = labelencoder_X.fit_transform(bank_client['loan'])

In [18]: 1 #binning age and then Label encoding the attribute
2 def age(dataframe):
3     dataframe.loc[dataframe['age'] <= 32, 'age'] = 1
4     dataframe.loc[(dataframe['age'] > 32) & (dataframe['age'] <= 47), 'age'] = 2
5     dataframe.loc[(dataframe['age'] > 47) & (dataframe['age'] <= 70), 'age'] = 3
6     dataframe.loc[(dataframe['age'] > 70) & (dataframe['age'] <= 98), 'age'] = 4
7
8     return dataframe
9
10 age(bank_client);
```

Final client data: -

```
In [19]: 1 print(bank_client.shape)
2 bank_client.head()
```

(41188, 7)

```
Out[19]:
```

	age	job	marital	education	default	housing	loan
0	3	3	1	0	0	0	0
1	3	7	1	3	1	0	0
2	2	7	1	3	0	2	0
3	2	0	1	1	0	0	0
4	3	7	1	3	0	0	2

Bank Campaign related data: -

```
In [20]: 1 # Slicing DataFrame to treat separately, make things more easy
2 bank_related = bank.iloc[:, 7:11]
3 bank_related.head()
```

```
Out[20]:
```

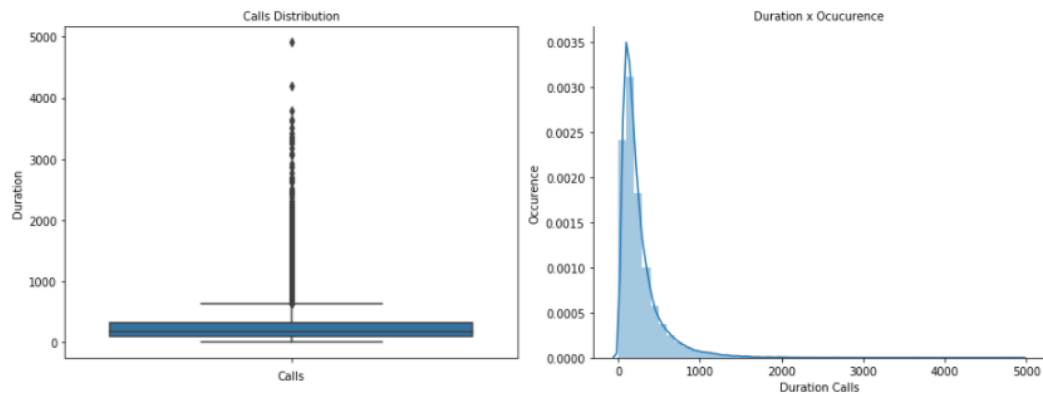
	contact	month	day_of_week	duration
0	telephone	may	mon	261
1	telephone	may	mon	149
2	telephone	may	mon	226
3	telephone	may	mon	151
4	telephone	may	mon	307

```
In [21]: 1 bank_related.isnull().any()
```

```
Out[21]: contact      False
month        False
day_of_week  False
duration     False
dtype: bool
```

1- Duration

```
In [22]: 1 fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
2         sns.boxplot(x = 'duration', data = bank_related, orient = 'v', ax = ax1)
3         ax1.set_xlabel('Calls', fontsize=10)
4         ax1.set_ylabel('Duration', fontsize=10)
5         ax1.set_title('Calls Distribution', fontsize=10)
6         ax1.tick_params(labelsize=10)
7
8         sns.distplot(bank_related['duration'], ax = ax2)
9         sns.despine(ax = ax2)
10        ax2.set_xlabel('Duration Calls', fontsize=10)
11        ax2.set_ylabel('Occurence', fontsize=10)
12        ax2.set_title('Duration x Ocurence', fontsize=10)
13        ax2.tick_params(labelsize=10)
14
15        plt.subplots_adjust(wspace=0.5)
16        plt.tight_layout()
```



Analysis on duration of contact with customer: -

```
In [23]: 1 print("Max duration call in minutes: ", round((bank_related['duration'].max()/60),1))
2         print("Min duration call in minutes: ", round((bank_related['duration'].min()/60),1))
3         print("Mean duration call in minutes: ", round((bank_related['duration'].mean()/60),1))
4         print("STD duration call in minutes: ", round((bank_related['duration'].std()/60),1))
5         # Std close to the mean means that the data values are close to the mean

Max duration call in minutes: 82.0
Min duration call in minutes: 0.0
Mean duration call in minutes: 4.3
STD duration call in minutes: 4.3
```

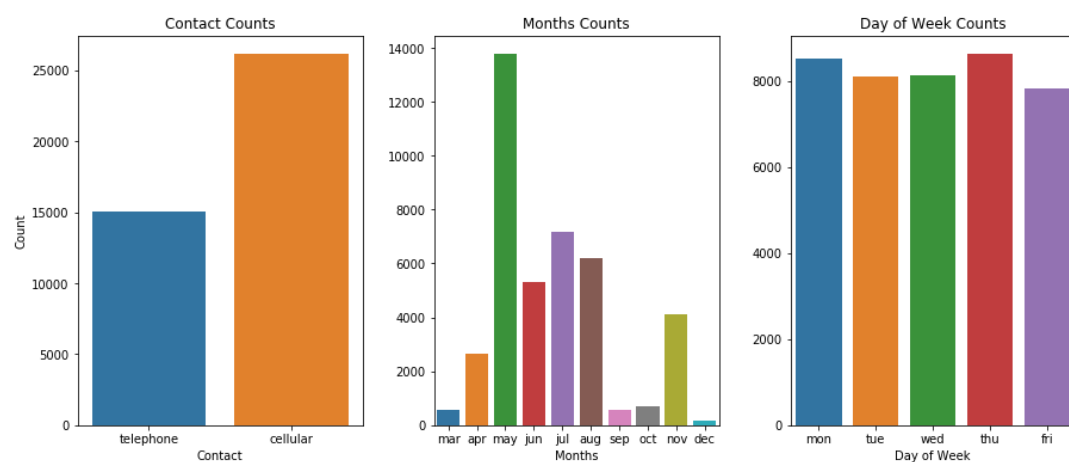
```
In [24]: 1 # Quartiles
2         print('1ª Quartile: ', bank_related['duration'].quantile(q = 0.25))
3         print('2ª Quartile: ', bank_related['duration'].quantile(q = 0.50))
4         print('3ª Quartile: ', bank_related['duration'].quantile(q = 0.75))
5         print('4ª Quartile: ', bank_related['duration'].quantile(q = 1.00))
6
7         print('Duration calls above: ', bank_related['duration'].quantile(q = 0.75) +
8               1.5*(bank_related['duration'].quantile(q = 0.75) - bank_related['duration'].quantile(q = 0.25)), 'are
9
1        1ª Quartile: 102.0
10       2ª Quartile: 180.0
11       3ª Quartile: 319.0
12       4ª Quartile: 4918.0
13       Duration calls above: 644.5 are outliers
```

```
In [25]: 1 print('Number of outliers: ', bank_related[bank_related['duration'] > 644.5]['duration'].count())
2         print('Number of clients: ', len(bank_related))
3         #Outliers in %
4         print('Outliers are:', round(bank_related[bank_related['duration'] > 644.5]['duration'].count()*100/len(bank_related),2), '%
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```


2- Contact, Month, Day of Week

```
In [27]: 1 fig, (ax1, ax2, ax3) = plt.subplots(nrows = 1, ncols = 3, figsize = (15,6))
2 sns.countplot(bank_related['contact'], ax = ax1)
3 ax1.set_xlabel('Contact', fontsize = 10)
4 ax1.set_ylabel('Count', fontsize = 10)
5 ax1.set_title('Contact Counts')
6 ax1.tick_params(labelsize=10)
7
8 sns.countplot(bank_related['month'], ax = ax2, order = ['mar', 'apr', 'may', 'jun', 'jul', 'aug', 'sep', 'oct', 'nov', 'dec'])
9 ax2.set_xlabel('Months', fontsize = 10)
10 ax2.set_ylabel('')
11 ax2.set_title('Months Counts')
12 ax2.tick_params(labelsize=10)
13
14 sns.countplot(bank_related['day_of_week'], ax = ax3)
15 ax3.set_xlabel('Day of Week', fontsize = 10)
16 ax3.set_ylabel('')
17 ax3.set_title('Day of Week Counts')
18 ax3.tick_params(labelsize=10)
19
20 plt.subplots_adjust(wspace=0.25)
```



Now we pre-process the data as these are categorical in nature

```
In [28]: 1 # Label encoder order is alphabetical
2 from sklearn.preprocessing import LabelEncoder
3 labelencoder_X = LabelEncoder()
4 bank_related['contact'] = labelencoder_X.fit_transform(bank_related['contact'])
5 bank_related['month'] = labelencoder_X.fit_transform(bank_related['month'])
6 bank_related['day_of_week'] = labelencoder_X.fit_transform(bank_related['day_of_week'])
```

```
In [30]: 1 def duration(data):
2
3     data.loc[data['duration'] <= 102, 'duration'] = 1
4     data.loc[(data['duration'] > 102) & (data['duration'] <= 180), 'duration'] = 2
5     data.loc[(data['duration'] > 180) & (data['duration'] <= 319), 'duration'] = 3
6     data.loc[(data['duration'] > 319) & (data['duration'] <= 644.5), 'duration'] = 4
7     data.loc[data['duration'] > 644.5, 'duration'] = 5
8
9     return data
10 duration(bank_related);
```

Last Campaign data is: -

```
In [31]: 1 bank_related.head()
```

```
Out[31]:
```

	contact	month	day_of_week	duration
0	1	6	1	3
1	1	6	1	2
2	1	6	1	3
3	1	6	1	2
4	1	6	1	3

Social and economic related Data: -

```
In [32]: 1 bank_se = bank.loc[:, ['emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed']]
2 bank_se.head()
```

```
Out[32]:
```

	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
0	1.1	93.994	-36.4	4.857	5191.0
1	1.1	93.994	-36.4	4.857	5191.0
2	1.1	93.994	-36.4	4.857	5191.0
3	1.1	93.994	-36.4	4.857	5191.0
4	1.1	93.994	-36.4	4.857	5191.0

Other attributes: -

```
In [33]: 1 bank_o = bank.loc[:, ['campaign', 'pdays', 'previous', 'poutcome']]
2 bank_o.head()
```

```
Out[33]:
```

	campaign	pdays	previous	poutcome
0	1	999	0	nonexistent
1	1	999	0	nonexistent
2	1	999	0	nonexistent
3	1	999	0	nonexistent
4	1	999	0	nonexistent

Since data is categorical, we must do some pre-processing: -

```
In [34]: 1 bank_o['poutcome'].unique()
```

```
Out[34]: array(['nonexistent', 'failure', 'success'], dtype=object)
```

```
In [35]: 1 bank_o['poutcome'].replace(['nonexistent', 'failure', 'success'], [1,2,3], inplace = True)
```

We have now completed the pre-processing and visualization. Now, we have to combine all the divided data in one and then split it into training and testing data.

```
In [36]: 1 bank_final= pd.concat([bank_client, bank_related, bank_se, bank_o], axis = 1)
2 bank_final = bank_final[['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
3 'contact', 'month', 'day_of_week', 'duration', 'emp.var.rate', 'cons.price.idx',
4 'cons.conf.idx', 'euribor3m', 'nr.employed', 'campaign', 'pdays', 'previous', 'poutcome']]
5 bank_final.shape

Out[36]: (41188, 20)
```

Splitting data into training and testing

```
In [37]: 1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(bank_final, y, test_size = 0.2, random_state = 101) #check test_size
3
4 from sklearn.model_selection import KFold
5 from sklearn.model_selection import cross_val_score
6 from sklearn.metrics import confusion_matrix, accuracy_score
7 k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

Since there is high difference in values, we must do standardise these values:-

```
In [39]: 1 from sklearn.preprocessing import StandardScaler
2 sc_X = StandardScaler()
3 X_train = sc_X.fit_transform(X_train)
4 X_test = sc_X.transform(X_test)
```

Here our pre-processing task is completed, now data is ready for modelling.

Model Creation and Testing Accuracy

1- Logistic Regression: -

```
In [40]: 1 from sklearn.linear_model import LogisticRegression
2 logmodel = LogisticRegression()
3 logmodel.fit(X_train,y_train)
4 logpred = logmodel.predict(X_test)
5
6
7 print(confusion_matrix(y_test, logpred))
8 print(round(accuracy_score(y_test, logpred),2)*100)
9 LOGCV = (cross_val_score(logmodel, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

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```

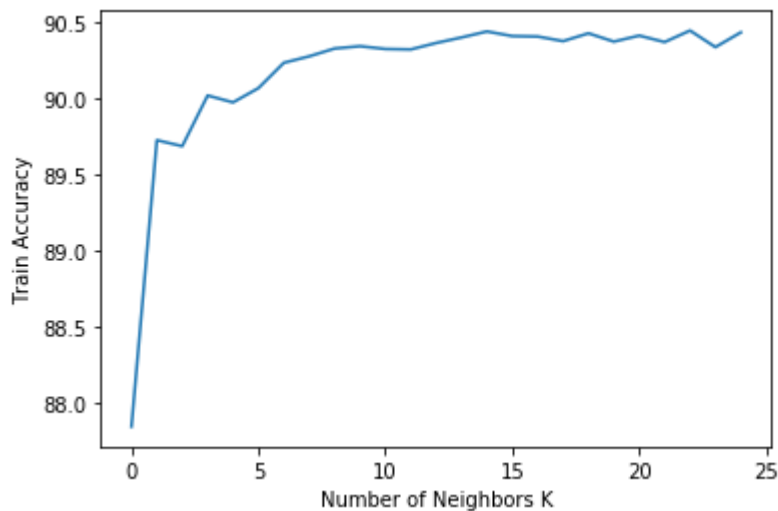
2- KNN-

```
In [41]: 1 from sklearn import model_selection
2 from sklearn.neighbors import KNeighborsClassifier
3
4 X_trainK, X_testK, y_trainK, y_testK = train_test_split(bank_final, y, test_size = 0.2, random_state = 101)
5
6 #Neighbors
7 neighbors = np.arange(0,25)
8
9 #Create empty list that will hold cv scores
10 cv_scores = []
11
12 #Perform 10-fold cross validation on training set for odd values of k:
13 for k in neighbors:
14     k_value = k+1
15     knn = KNeighborsClassifier(n_neighbors = k_value, weights='uniform', p=2, metric='euclidean')
16     kfold = model_selection.KFold(n_splits=10, random_state=123)
17     scores = model_selection.cross_val_score(knn, X_trainK, y_trainK, cv=kfold, scoring='accuracy')
18     cv_scores.append(scores.mean()*100)
19     print("k=%d %0.2f (+/- %0.2f)" % (k_value, scores.mean()*100, scores.std()*100))
20
21 optimal_k = neighbors[cv_scores.index(max(cv_scores))]
22 print ("The optimal number of neighbors is %d with %0.1f%%" % (optimal_k, cv_scores[optimal_k]))
23
24 plt.plot(neighbors, cv_scores)
25 plt.xlabel('Number of Neighbors K')
26 plt.ylabel('Train Accuracy')
27 plt.show()
```

Here we try to find optimal k values by checking all values between 1 to 25.

Result: -

```
k=1 87.84 (+/- 0.59)
k=2 89.73 (+/- 0.50)
k=3 89.69 (+/- 0.49)
k=4 90.02 (+/- 0.51)
k=5 89.98 (+/- 0.41)
k=6 90.07 (+/- 0.47)
k=7 90.24 (+/- 0.41)
k=8 90.28 (+/- 0.48)
k=9 90.33 (+/- 0.46)
k=10 90.35 (+/- 0.49)
k=11 90.33 (+/- 0.51)
k=12 90.32 (+/- 0.59)
k=13 90.37 (+/- 0.51)
k=14 90.40 (+/- 0.48)
k=15 90.44 (+/- 0.47)
k=16 90.41 (+/- 0.50)
k=17 90.41 (+/- 0.50)
k=18 90.38 (+/- 0.52)
k=19 90.43 (+/- 0.45)
k=20 90.38 (+/- 0.48)
k=21 90.42 (+/- 0.46)
k=22 90.37 (+/- 0.48)
k=23 90.45 (+/- 0.44)
k=24 90.34 (+/- 0.49)
k=25 90.44 (+/- 0.47)
The optimal number of neighbors is 22 with 90.4%
```



Here we found best accuracy at k=22

Selecting k=22

```
In [42]: 1 from sklearn.neighbors import KNeighborsClassifier
2 knn = KNeighborsClassifier(n_neighbors=22)
3 knn.fit(X_train, y_train)
4 knnpred = knn.predict(X_test)
5
6 print(confusion_matrix(y_test, knnpred))
7 print(round(accuracy_score(y_test, knnpred),2)*100)
8 KNNCV = (cross_val_score(knn, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[7163  116]
 [ 706  253]]
90.0
```

3- Support Vector Classifier

```
In [43]: 1 from sklearn.svm import SVC
2 svc = SVC(kernel = 'sigmoid')
3 svc.fit(X_train, y_train)
4 svcpred = svc.predict(X_test)
5 print(confusion_matrix(y_test, svcpred))
6 print(round(accuracy_score(y_test, svcpred),2)*100)
7 SVCCV = (cross_val_score(svc, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[6719  560]
 [ 605  354]]
86.0
```

4- Decision Tree

```
In [44]: 1 from sklearn.tree import DecisionTreeClassifier
2 dtree = DecisionTreeClassifier(criterion='gini') #criterion = entropy, gini
3 dtree.fit(X_train, y_train)
4 dtreepred = dtree.predict(X_test)
5
6 print(confusion_matrix(y_test, dtreepred))
7 print(round(accuracy_score(y_test, dtreepred),2)*100)
8 DTREECV = (cross_val_score(dtree, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[6811  468]
 [ 491  468]]
88.0
```

5- Random Forest

```
In [45]: 1 from sklearn.ensemble import RandomForestClassifier
2 rfc = RandomForestClassifier(n_estimators = 200)#criterion = entropy,gini
3 rfc.fit(X_train, y_train)
4 rfcpred = rfc.predict(X_test)
5
6 print(confusion_matrix(y_test, rfcpred ))
7 print(round(accuracy_score(y_test, rfcpred),2)*100)
8 RFCCV = (cross_val_score(rfc, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[6987  292]
 [ 515  444]]
90.0
```

6- Gaussian Naive Bayes

```
In [46]: 1 from sklearn.naive_bayes import GaussianNB
2 gaussiannb= GaussianNB()
3 gaussiannb.fit(X_train, y_train)
4 gaussiannbpred = gaussiannb.predict(X_test)
5 probs = gaussiannb.predict(X_test)
6
7 print(confusion_matrix(y_test, gaussiannbpred ))
8 print(round(accuracy_score(y_test, gaussiannbpred),2)*100)
9 GAUSIAN = (cross_val_score(gaussiannb, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[6451  828]
 [ 433  526]]
85.0
```

7- XGBoost

```
In [47]: 1 from xgboost import XGBClassifier
2 xgb = XGBClassifier()
3 xgb.fit(X_train, y_train)
4 xgbprd = xgb.predict(X_test)
5
6 print(confusion_matrix(y_test, xgbprd ))
7 print(round(accuracy_score(y_test, xgbprd),2)*100)
8 XGB = (cross_val_score(estimator = xgb, X = X_train, y = y_train, cv = 10).mean())

[[6999  280]
 [ 482  477]]
91.0
```

8- Gradient Boosting

```
In [48]: 1 from sklearn.ensemble import GradientBoostingClassifier
2 gbk = GradientBoostingClassifier()
3 gbk.fit(X_train, y_train)
4 gbkpred = gbk.predict(X_test)
5 print(confusion_matrix(y_test, gbkpred ))
6 print(round(accuracy_score(y_test, gbkpred),2)*100)
7 GBKCV = (cross_val_score(gbk, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[7023  256]
 [ 487  472]]
91.0
```

Conclusion: - As shown below, Gradient Boosting and XGBoost had the highest score. However, by research, it shows that XGBoost has a lower training time hence that is most favourable model.

```
In [49]: 1 models = pd.DataFrame({
2         |     'Models': ['Random Forest Classifier', 'Decision Tree Classifier', 'Support Vector Machine',
3         |             'K-Near Neighbors', 'Logistic Model', 'Gaussian NB', 'XGBoost', 'Gradient Boosting'],
4         |     'Score': [RFCCV, DTRECV, SVCCV, KNNCV, LOGCV, GAUSIAN, XGB, GBKCV]})
5
6 models.sort_values(by='Score', ascending=False)
```

```
Out[49]:
```

	Models	Score
7	Gradient Boosting	0.914203
6	XGBoost	0.912200
0	Random Forest Classifier	0.910046
4	Logistic Model	0.909772
3	K-Near Neighbors	0.904613
1	Decision Tree Classifier	0.884401
2	Support Vector Machine	0.856055
5	Gaussian NB	0.845038