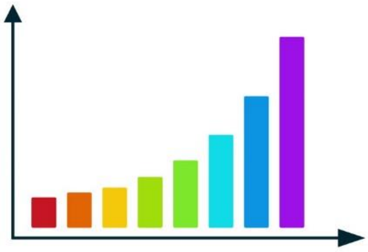

DMPA Project

Analyzing Bank Marketing Dataset for effectiveness of campaign

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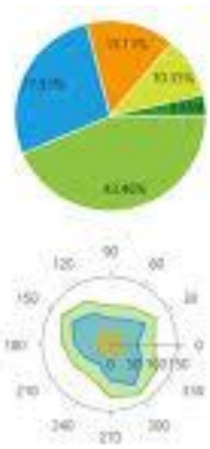


Information about predictors in our dataset: -

```
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

<u>Client data: -</u>

In [5]:
```
bank_client = bank.iloc[: , 0:7]
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: -

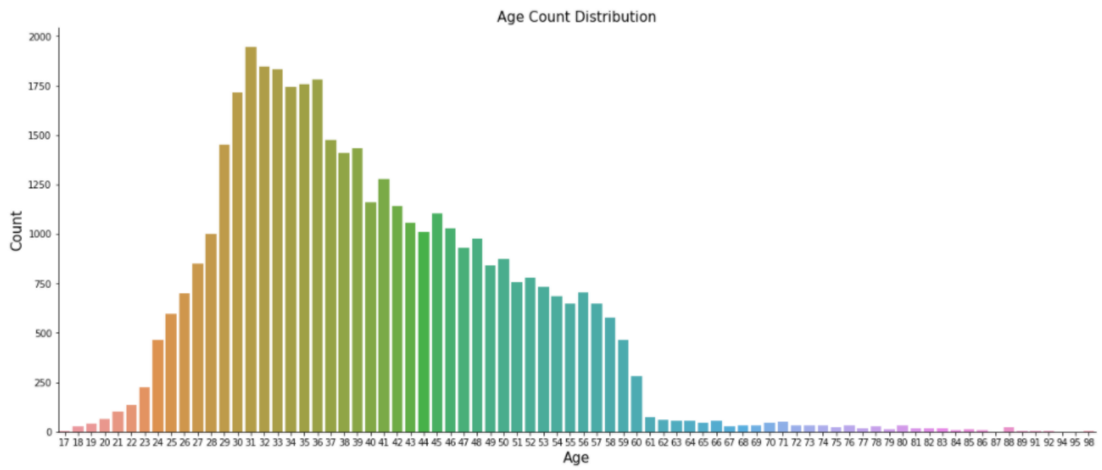
- Firstly, we find the max, minimum and null values

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

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

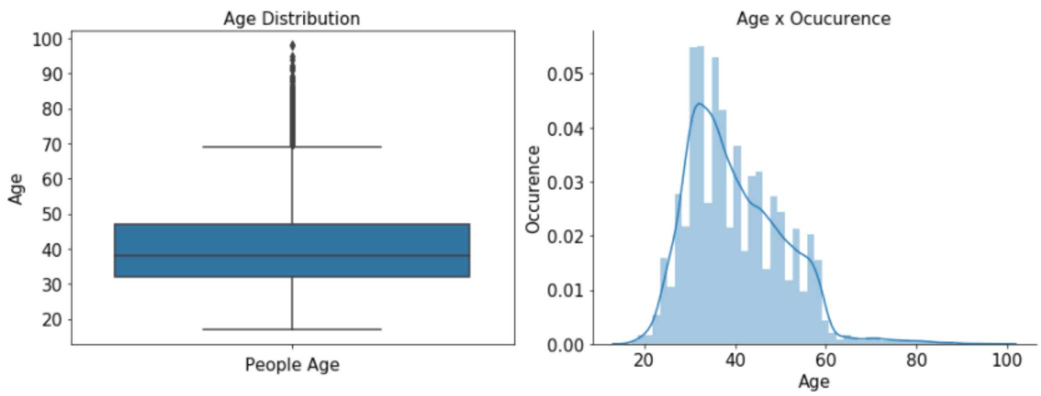
- Secondly, we tried to find importance of AGE by plotting the graphs

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



In [8]:

```python
fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
sns.boxplot(x = 'age', data = bank_client, orient = 'v', ax = ax1)
ax1.set_xlabel('People Age', fontsize=15)
ax1.set_ylabel('Age', fontsize=15)
ax1.set_title('Age Distribution', fontsize=15)
ax1.tick_params(labelsize=15)

sns.distplot(bank_client['age'], ax = ax2)
sns.despine(ax = ax2)
ax2.set_xlabel('Age', fontsize=15)
ax2.set_ylabel('Occurence', fontsize=15)
ax2.set_title('Age x Ocucurence', fontsize=15)
ax2.tick_params(labelsize=15)

plt.subplots_adjust(wspace=0.5)
plt.tight_layout()
```



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

In [9]:

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

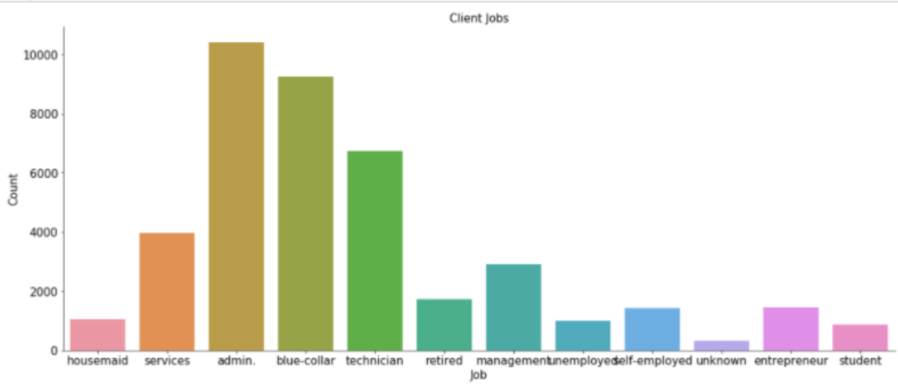
```
MEAN: 40.0
STD : 10.4
```

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

2- Jobs: -

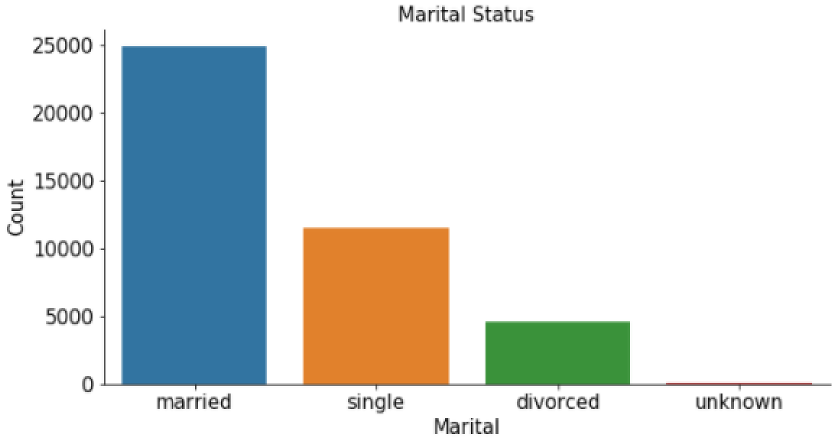
In [10]:

```python
# What kind of jobs clients this bank have?
fig, ax = plt.subplots()
fig.set_size_inches(20, 8)
sns.countplot(x = 'job', data = bank_client)
ax.set_xlabel('Job', fontsize=15)
ax.set_ylabel('Count', fontsize=15)
ax.set_title('Client Jobs', fontsize=15)
ax.tick_params(labelsize=15)
sns.despine()
```



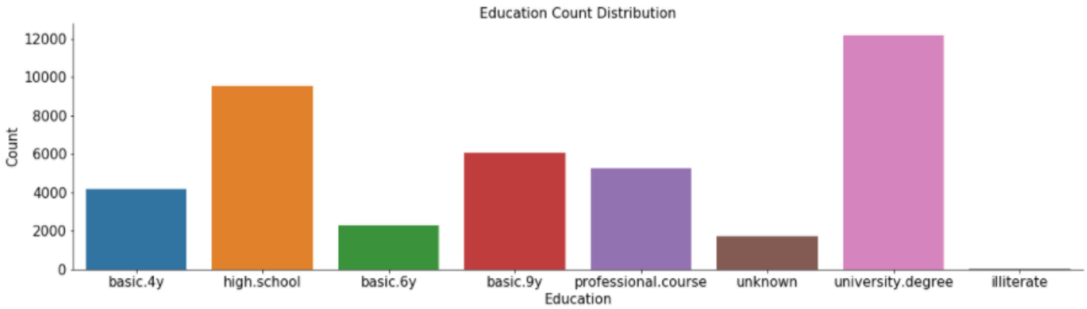
3- Marital: -

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



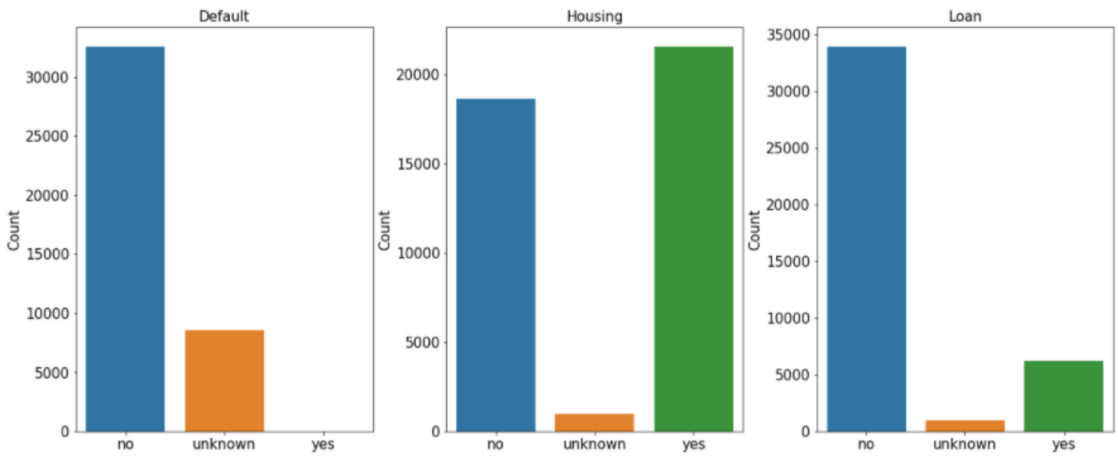
4- Education: -

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



5- Default, Housing, Loan: -

In [13]:
```python
# Default, has credit in default ?
fig, (ax1, ax2, ax3) = plt.subplots(nrows = 1, ncols = 3, figsize = (20,8))
sns.countplot(x = 'default', data = bank_client, ax = ax1, order = ['no', 'unknown', 'yes'])
ax1.set_title('Default', fontsize=15)
ax1.set_xlabel('')
ax1.set_ylabel('Count', fontsize=15)
ax1.tick_params(labelsize=15)

# Housing, has housing loan ?
sns.countplot(x = 'housing', data = bank_client, ax = ax2, order = ['no', 'unknown', 'yes'])
ax2.set_title('Housing', fontsize=15)
ax2.set_xlabel('')
ax2.set_ylabel('Count', fontsize=15)
ax2.tick_params(labelsize=15)

# Loan, has personal loan ?
sns.countplot(x = 'loan', data = bank_client, ax = ax3, order = ['no', 'unknown', 'yes'])
ax3.set_title('Loan', fontsize=15)
ax3.set_xlabel('')
ax3.set_ylabel('Count', fontsize=15)
ax3.tick_params(labelsize=15)

plt.subplots_adjust(wspace=0.25)
```



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

In [14]:
```python
print('Default:\n No credit in default:'      , bank_client[bank_client['default'] == 'no']     ['age'].count(),
              '\n Unknown credit in default:', bank_client[bank_client['default'] == 'unknown']['age'].count(),
              '\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]:
```python
print('Housing:\n No housing in loan:'      , bank_client[bank_client['housing'] == 'no']     ['age'].count(),
              '\n Unknown housing in loan:', bank_client[bank_client['housing'] == 'unknown']['age'].count(),
              '\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]:
```python
print('Housing:\n No to personal loan:'      , bank_client[bank_client['loan'] == 'no']     ['age'].count(),
              '\n Unknown to personal loan:', bank_client[bank_client['loan'] == 'unknown']['age'].count(),
              '\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]:
```
# Label encoder order is alphabetical
from sklearn.preprocessing import LabelEncoder
labelencoder_X = LabelEncoder()
bank_client['job']       = labelencoder_X.fit_transform(bank_client['job'])
bank_client['marital']   = labelencoder_X.fit_transform(bank_client['marital'])
bank_client['education']= labelencoder_X.fit_transform(bank_client['education'])
bank_client['default']   = labelencoder_X.fit_transform(bank_client['default'])
bank_client['housing']   = labelencoder_X.fit_transform(bank_client['housing'])
bank_client['loan']      = labelencoder_X.fit_transform(bank_client['loan'])
```

In [18]:
```
#binning age and then label encoding the attribute
def age(dataframe):
    dataframe.loc[dataframe['age'] <= 32, 'age'] = 1
    dataframe.loc[(dataframe['age'] > 32) & (dataframe['age'] <= 47), 'age'] = 2
    dataframe.loc[(dataframe['age'] > 47) & (dataframe['age'] <= 70), 'age'] = 3
    dataframe.loc[(dataframe['age'] > 70) & (dataframe['age'] <= 98), 'age'] = 4

    return dataframe

age(bank_client);
```

Final client data: -

In [19]:
```
print(bank_client.shape)
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]:
```
# Slicing DataFrame to treat separately, make things more easy
bank_related = bank.iloc[: , 7:11]
bank_related.head()
```

Out[20]:

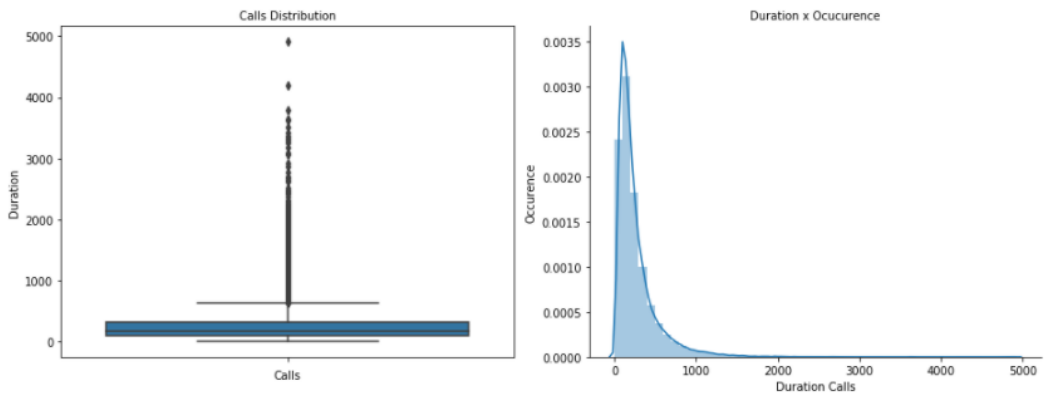
	contact	month	day_of_week	duration
0	telephone	may	mon	261
1	telephone	may	mon	149
2	telephone	may	mon	226
3	telephone	may	mon	151
4	telephone	may	mon	307

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

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

1- Duration

In [22]:
```python
fig, (ax1, ax2) = plt.subplots(nrows = 1, ncols = 2, figsize = (13, 5))
sns.boxplot(x = 'duration', data = bank_related, orient = 'v', ax = ax1)
ax1.set_xlabel('Calls', fontsize=10)
ax1.set_ylabel('Duration', fontsize=10)
ax1.set_title('Calls Distribution', fontsize=10)
ax1.tick_params(labelsize=10)

sns.distplot(bank_related['duration'], ax = ax2)
sns.despine(ax = ax2)
ax2.set_xlabel('Duration Calls', fontsize=10)
ax2.set_ylabel('Occurence', fontsize=10)
ax2.set_title('Duration x Ocucurence', fontsize=10)
ax2.tick_params(labelsize=10)

plt.subplots_adjust(wspace=0.5)
plt.tight_layout()
```



Analysis on duration of contact with customer: -

In [23]:
```python
print("Max duration  call in minutes:  ", round((bank_related['duration'].max()/60),1))
print("Min duration  call in minutes:   ", round((bank_related['duration'].min()/60),1))
print("Mean duration call in minutes:   ", round((bank_related['duration'].mean()/60),1))
print("STD duration  call in minutes:   ", round((bank_related['duration'].std()/60),1))
# 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]:
```python
# Quartiles
print('1º Quartile: ', bank_related['duration'].quantile(q = 0.25))
print('2º Quartile: ', bank_related['duration'].quantile(q = 0.50))
print('3º Quartile: ', bank_related['duration'].quantile(q = 0.75))
print('4º Quartile: ', bank_related['duration'].quantile(q = 1.00))

print('Duration calls above: ', bank_related['duration'].quantile(q = 0.75) +
                      1.5*(bank_related['duration'].quantile(q = 0.75) - bank_related['duration'].quantile(q = 0.25)), 'are
```

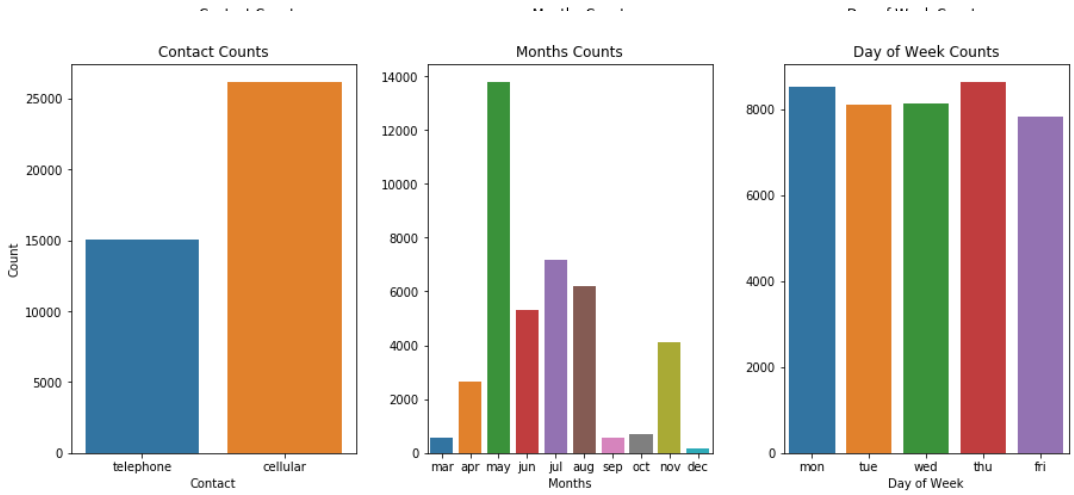
```
1º Quartile:  102.0
2º Quartile:  180.0
3º Quartile:  319.0
4º Quartile:  4918.0
Duration calls above:  644.5 are outliers
```

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

```
Numerber of outliers:  2963
Number of clients:  41188
Outliers are: 7.19 %
```

2- Contact, Month, Day of Week

In [27]:
```python
fig, (ax1, ax2, ax3) = plt.subplots(nrows = 1, ncols = 3, figsize = (15,6))
sns.countplot(bank_related['contact'], ax = ax1)
ax1.set_xlabel('Contact', fontsize = 10)
ax1.set_ylabel('Count', fontsize = 10)
ax1.set_title('Contact Counts')
ax1.tick_params(labelsize=10)

sns.countplot(bank_related['month'], ax = ax2, order = ['mar', 'apr', 'may', 'jun', 'jul', 'aug', 'sep', 'oct', 'nov', 'dec'
ax2.set_xlabel('Months', fontsize = 10)
ax2.set_ylabel('')
ax2.set_title('Months Counts')
ax2.tick_params(labelsize=10)

sns.countplot(bank_related['day_of_week'], ax = ax3)
ax3.set_xlabel('Day of Week', fontsize = 10)
ax3.set_ylabel('')
ax3.set_title('Day of Week Counts')
ax3.tick_params(labelsize=10)

plt.subplots_adjust(wspace=0.25)
```



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

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

In [30]:
```python
def duration(data):

    data.loc[data['duration'] <= 102, 'duration'] = 1
    data.loc[(data['duration'] > 102) & (data['duration'] <= 180)  , 'duration']    = 2
    data.loc[(data['duration'] > 180) & (data['duration'] <= 319)  , 'duration']   = 3
    data.loc[(data['duration'] > 319) & (data['duration'] <= 644.5), 'duration'] = 4
    data.loc[data['duration']  > 644.5, 'duration'] = 5

    return data
duration(bank_related);
```

Last Campaign data is: -

In [31]:
```
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]:
```
bank_se = bank.loc[: , ['emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed']]
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]:
```
bank_o = bank.loc[: , ['campaign', 'pdays','previous', 'poutcome']]
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]:
```
bank_o['poutcome'].unique()
```

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

In [35]:
```
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]:
bank_final= pd.concat([bank_client, bank_related, bank_se, bank_o], axis = 1)
bank_final = bank_final[['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
                     'contact', 'month', 'day_of_week', 'duration', 'emp.var.rate', 'cons.price.idx',
                     'cons.conf.idx', 'euribor3m', 'nr.employed', 'campaign', 'pdays', 'previous', 'poutcome']]
bank_final.shape

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

Splitting data into training and testing

```
In [37]:
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(bank_final, y, test_size = 0.2, random_state = 101) #check test_size

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
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]:
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
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]:
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
logpred = logmodel.predict(X_test)


print(confusion_matrix(y_test, logpred))
print(round(accuracy_score(y_test, logpred),2)*100)
LOGCV = (cross_val_score(logmodel, X_train, y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy').mean())

[[7106  173]
 [ 618  341]]
90.0
```

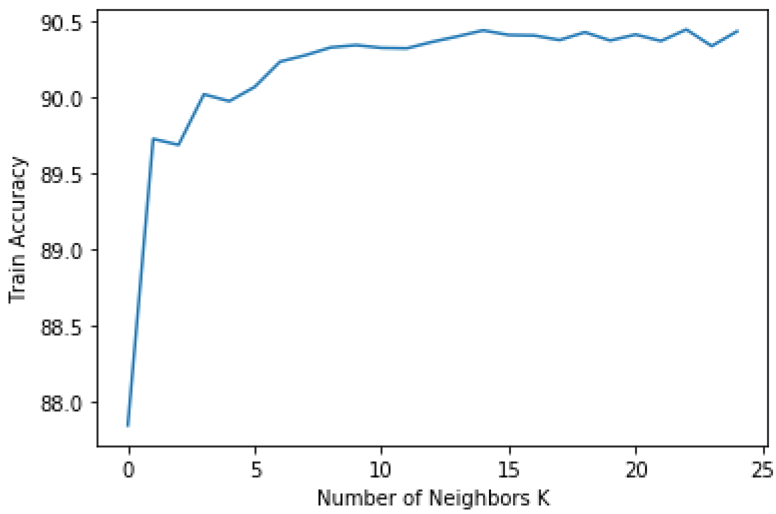
2- KNN-

In [41]:
```python
from sklearn import model_selection
from sklearn.neighbors import KNeighborsClassifier

X_trainK, X_testK, y_trainK, y_testK = train_test_split(bank_final, y, test_size = 0.2, random_state = 101)

#Neighbors
neighbors = np.arange(0,25)

#Create empty list that will hold cv scores
cv_scores = []

#Perform 10-fold cross validation on training set for odd values of k:
for k in neighbors:
    k_value = k+1
    knn = KNeighborsClassifier(n_neighbors = k_value, weights='uniform', p=2, metric='euclidean')
    kfold = model_selection.KFold(n_splits=10, random_state=123)
    scores = model_selection.cross_val_score(knn, X_trainK, y_trainK, cv=kfold, scoring='accuracy')
    cv_scores.append(scores.mean()*100)
    print("k=%d %0.2f (+/- %0.2f)" % (k_value, scores.mean()*100, scores.std()*100))

optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print ("The optimal number of neighbors is %d with %0.1f%%" % (optimal_k, cv_scores[optimal_k]))

plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Train Accuracy')
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]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=22)
knn.fit(X_train, y_train)
knnpred = knn.predict(X_test)

print(confusion_matrix(y_test, knnpred))
print(round(accuracy_score(y_test, knnpred),2)*100)
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]:
```
from sklearn.svm import SVC
svc= SVC(kernel = 'sigmoid')
svc.fit(X_train, y_train)
svcpred = svc.predict(X_test)
print(confusion_matrix(y_test, svcpred))
print(round(accuracy_score(y_test, svcpred),2)*100)
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]:
```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(criterion='gini') #criterion = entopy, gini
dtree.fit(X_train, y_train)
dtreepred = dtree.predict(X_test)

print(confusion_matrix(y_test, dtreepred))
print(round(accuracy_score(y_test, dtreepred),2)*100)
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]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators = 200)#criterion = entopy,gini
rfc.fit(X_train, y_train)
rfcpred = rfc.predict(X_test)

print(confusion_matrix(y_test, rfcpred ))
print(round(accuracy_score(y_test, rfcpred),2)*100)
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]:
```
from sklearn.naive_bayes import GaussianNB
gaussiannb= GaussianNB()
gaussiannb.fit(X_train, y_train)
gaussiannbpred = gaussiannb.predict(X_test)
probs = gaussiannb.predict(X_test)

print(confusion_matrix(y_test, gaussiannbpred ))
print(round(accuracy_score(y_test, gaussiannbpred),2)*100)
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]:
```
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
xgbprd = xgb.predict(X_test)

print(confusion_matrix(y_test, xgbprd ))
print(round(accuracy_score(y_test, xgbprd),2)*100)
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]:
```
from sklearn.ensemble import GradientBoostingClassifier
gbk = GradientBoostingClassifier()
gbk.fit(X_train, y_train)
gbkpred = gbk.predict(X_test)
print(confusion_matrix(y_test, gbkpred ))
print(round(accuracy_score(y_test, gbkpred),2)*100)
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]:
```
models = pd.DataFrame({
                  'Models': ['Random Forest Classifier', 'Decision Tree Classifier', 'Support Vector Machine',
                              'K-Near Neighbors', 'Logistic Model', 'Gausian NB', 'XGBoost', 'Gradient Boosting'],
                  'Score':  [RFCCV, DTREECV, SVCCV, KNNCV, LOGCV, GAUSIAN, XGB, GBKCV]})

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	Gausian NB	0.845038