COMP 494 Final Project

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Bank Marketing

The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be (or not) subscribed.

The dataset is ordered by date (from May 2008 to November 2010).

Table of Contents:

Data Importing and Pre-processing

In [139…

```
# import libraries needed
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn import tree
```

In [75]:

```
# read in file
df = pd.read_csv('bank_marketing.csv', sep=";")
```

In [76]:

```
df.default.value_counts()
```

Out[76]:

```
no     43113
yes      792
Name: default, dtype: int64
```

In [77]:
```
#check number of rows and columns
df.shape #45,211 rows and 17 columns
```

Out[77]:
```
(45211, 17)
```

In [78]:
```
#count the number of categorical variables
cat_count = 0
for dtype in df.dtypes:
    if dtype == 'object':
        cat_count = cat_count + 1
```

In [79]:
```
print('# of categorical variables:',cat_count)
print('# of continuous variables:',df.shape[1] - cat_count)
```

```
# of categorical variables: 10
# of continuous variables: 7
```

In [80]:
```
#check the column names
df.columns
```

Out[80]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'deposit'],
      dtype='object')
```

In [83]:
```
# checking data types of each columns
column_data_types = df.dtypes
print(column_data_types)
```

```
age          float64
job           object
marital       object
education     object
default       object
balance        int64
housing       object
loan          object
contact       object
day            int64
month         object
duration       int64
campaign       int64
pdays          int64
previous       int64
poutcome      object
deposit       object
dtype: object
```

Handling missing data

In [81]:
```
#missing data (as percentages)
cleaned_df = df
total = df.isnull().sum().sort_values(ascending=False)
percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
```

Out[81]:

	Total	Percent
contact	1383	0.030590
age	1339	0.029617
default	1306	0.028887
marital	0	0.000000
education	0	0.000000
balance	0	0.000000
housing	0	0.000000
loan	0	0.000000
job	0	0.000000
day	0	0.000000
month	0	0.000000
duration	0	0.000000
campaign	0	0.000000
pdays	0	0.000000
previous	0	0.000000
poutcome	0	0.000000
deposit	0	0.000000

In [82]:
```
# Find the number of nulls for each column
null_counts = df.isnull().sum()
print(null_counts)
```

```
age          1339
job             0
marital         0
education       0
default      1306
balance         0
housing         0
loan            0
contact      1383
day             0
month           0
duration        0
campaign        0
pdays           0
previous        0
poutcome        0
deposit         0
dtype: int64
```

In [84]:
```
# inserting the average age of column into the null values of age
average_age =df['age'].mean()
cleaned_df['age'].fillna(average_age, inplace=True)
```

In [85]:
```
# assigning "unknown" to all contact that have null values
cleaned_df['contact'].fillna("unknown", inplace=True)
```

In [86]:
```
# assigning "no" to all values in default column that are NaN
cleaned_df['default'].fillna("no", inplace=True)
```

In [87]:
```
null_counts = cleaned_df.isnull().sum()
print(null_counts)
```

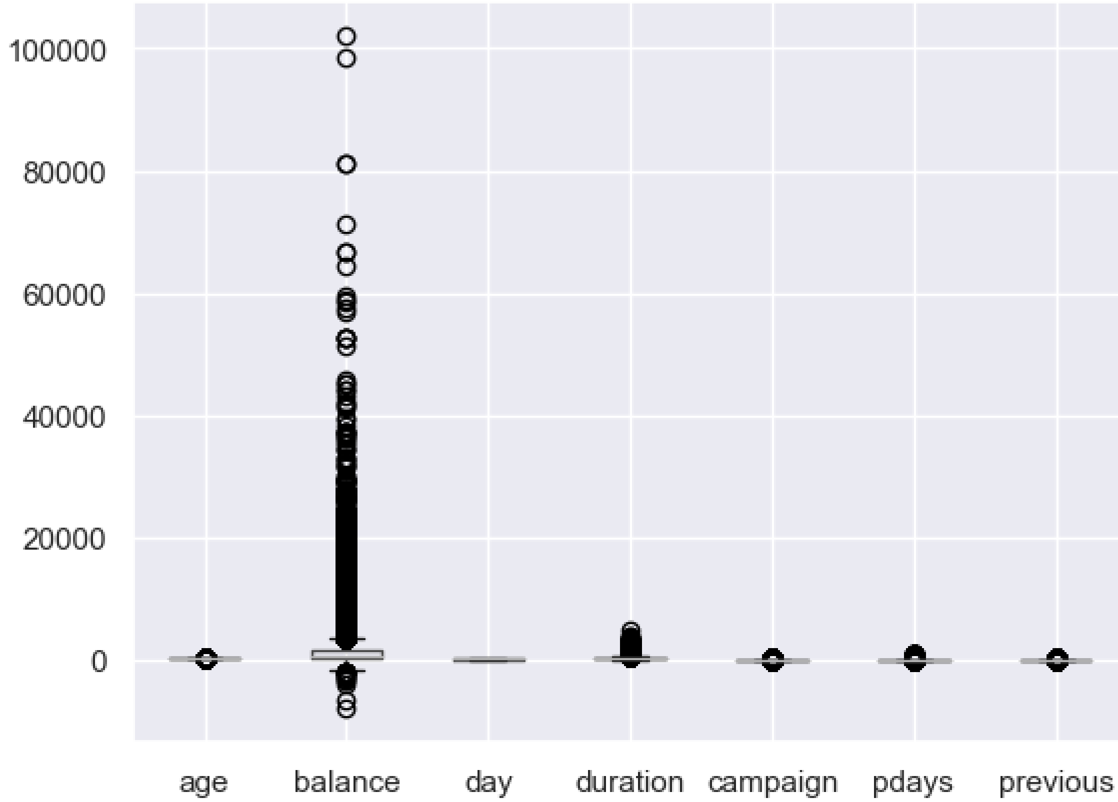
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
deposit      0
dtype: int64
```

In [88]:
```
cleaned_df.shape
```

Out[88]:
```
(45211, 17)
```

Handling Outliers

In [91]:
```
# create boxplot showing all the outliers
cleaned_df.boxplot()
plt.show()
cleaned_df.describe()
```



Out[91]:

	age	balance	day	duration	campaign	pdays
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.924781	1362.272058	15.806419	258.163080	2.763841	40.197828
std	10.452521	3044.765829	8.322476	257.527812	3.098021	100.128746
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000

In [92]:
```
# do not remove outliers
cleaned_without_outliers_df = cleaned_df.copy()
```

In [94]:
```
summary_stats = df.describe()

print(summary_stats)
```

```
                age        balance           day      duration      campaign  \
count  45211.000000   45211.000000  45211.000000  45211.000000  45211.000000
mean      40.924781    1362.272058     15.806419    258.163080      2.763841
std       10.452521    3044.765829      8.322476    257.527812      3.098021
min       18.000000   -8019.000000      1.000000      0.000000      1.000000
25%       33.000000      72.000000      8.000000    103.000000      1.000000
50%       39.000000     448.000000     16.000000    180.000000      2.000000
75%       48.000000    1428.000000     21.000000    319.000000      3.000000
max       95.000000  102127.000000     31.000000   4918.000000     63.000000

              pdays      previous
count  45211.000000  45211.000000
mean      40.197828      0.580323
std      100.128746      2.303441
min       -1.000000      0.000000
25%       -1.000000      0.000000
50%       -1.000000      0.000000
75%       -1.000000      0.000000
max      871.000000    275.000000
```

Making necessary columns to be binary values

In [95]:
```
# changing deposit to binary variable (no==0, yes==1)
cleaned_without_outliers_df['deposit'] = cleaned_df['deposit'].map({'no': 0, 'y
```

In [96]:
```
# chaning other categorical variables to be binary (no==0, yes==1)
cleaned_without_outliers_df['default'] = cleaned_df['default'].map({'no': 0, 'y
cleaned_without_outliers_df['housing'] = cleaned_df['housing'].map({'no': 0, 'y
cleaned_without_outliers_df['loan'] = cleaned_df['loan'].map({'no': 0, 'yes': 1
```

In [97]:
```
cleaned_without_outliers_df['housing'].head(5)
```

Out[97]:
```
0    1
1    1
2    1
3    1
4    0
Name: housing, dtype: int64
```

Finished data cleaning of the Bank_Marketing.csv file - moving onto analysis now

Data Analysis and Visualization

In [100…
```
# installing necessary libraries/modules
```

In [101…
```
!pip3 install xgboost
```

```
Requirement already satisfied: xgboost in /Users/hiromigonzalez/opt/anaconda3/
lib/python3.9/site-packages (1.7.5)
Requirement already satisfied: numpy in /Users/hiromigonzalez/opt/anaconda3/li
b/python3.9/site-packages (from xgboost) (1.21.5)
Requirement already satisfied: scipy in /Users/hiromigonzalez/opt/anaconda3/li
b/python3.9/site-packages (from xgboost) (1.9.1)
```

In [24]:
```
cleaned_without_outliers_df.head()
```

Out[24]:

	age	job	marital	education	default	balance	housing	loan	contact	day	montl
0	58.0	management	married	tertiary	0	2143	1	0	unknown	5	may
1	44.0	technician	single	secondary	0	29	1	0	unknown	5	may
2	33.0	entrepreneur	married	secondary	0	2	1	1	unknown	5	may
3	47.0	blue-collar	married	unknown	0	1506	1	0	unknown	5	may
4	33.0	unknown	single	unknown	0	1	0	0	unknown	5	may

Encoding

In [109…

```
# label encoding
cleaned_without_outliers_df.job.value_counts()
```

Out[109]:

```
blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```

In [110…

```
# one hot encoding
cleaned_without_outliers_df.marital.value_counts()
```

Out[110]:

```
married     27214
single      12790
divorced     5207
Name: marital, dtype: int64
```

In [111…

```
# one hot encode
cleaned_without_outliers_df.education.value_counts()
```

Out[111]:

```
secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education, dtype: int64
```

In [112…

```
# one hot encode
cleaned_without_outliers_df.contact.value_counts()
```

Out[112]:

```
cellular     28410
unknown      13992
telephone     2809
Name: contact, dtype: int64
```

In [113…

```
# manually label them and sure labels are in the proper order
cleaned_without_outliers_df.month.value_counts()
```

Out[113]:
```
may     13766
jul      6895
aug      6247
jun      5341
nov      3970
apr      2932
feb      2649
jan      1403
oct       738
sep       579
mar       477
dec       214
Name: month, dtype: int64
```

In [114…
```
# one hot encode
cleaned_without_outliers_df.poutcome.value_counts()
```

Out[114]:
```
unknown     36959
failure      4901
other        1840
success      1511
Name: poutcome, dtype: int64
```

In [115…
```
# try to predict depost column
# based on the info we have we are trying to predict if they will make a deposi
```

In [116…
```
new_df = cleaned_without_outliers_df.copy()
```

In [117…
```
# look up Classifier rather then regression, the different
new_df.head()
```

Out[117]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mont
0	58.0	management	married	tertiary	0	2143	1	0	unknown	5	ma
1	44.0	technician	single	secondary	0	29	1	0	unknown	5	ma
2	33.0	entrepreneur	married	secondary	0	2	1	1	unknown	5	ma
3	47.0	blue-collar	married	unknown	0	1506	1	0	unknown	5	ma
4	33.0	unknown	single	unknown	0	1	0	0	unknown	5	ma

In [118…
```
month_labels = {
    'jan': 1,
    'feb': 2,
    'mar': 3,
    'apr': 4,
    'may': 5,
    'jun': 6,
    'jul': 7,
    'aug': 8,
    'sep': 9,
    'oct': 10,
    'nov': 11,
    'dec': 12
}

new_df['month'] = new_df['month'].map(month_labels)
```

In [119…
```
new_df.head()
```

Out[119]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mont
0	58.0	management	married	tertiary	0	2143	1	0	unknown	5	
1	44.0	technician	single	secondary	0	29	1	0	unknown	5	
2	33.0	entrepreneur	married	secondary	0	2	1	1	unknown	5	
3	47.0	blue-collar	married	unknown	0	1506	1	0	unknown	5	
4	33.0	unknown	single	unknown	0	1	0	0	unknown	5	

In [120…
```
encoder = LabelEncoder()
new_df['job'] = encoder.fit_transform(new_df['job'])
```

In [121…
```
new_df.head()
```

Out[121]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	durat
0	58.0	4	married	tertiary	0	2143	1	0	unknown	5	5	
1	44.0	9	single	secondary	0	29	1	0	unknown	5	5	
2	33.0	2	married	secondary	0	2	1	1	unknown	5	5	
3	47.0	1	married	unknown	0	1506	1	0	unknown	5	5	
4	33.0	11	single	unknown	0	1	0	0	unknown	5	5	

In [122…
```
new_df = pd.get_dummies(new_df, columns=['marital', 'education', 'contact','pou
```

In [123…
```
new_df.head()
```

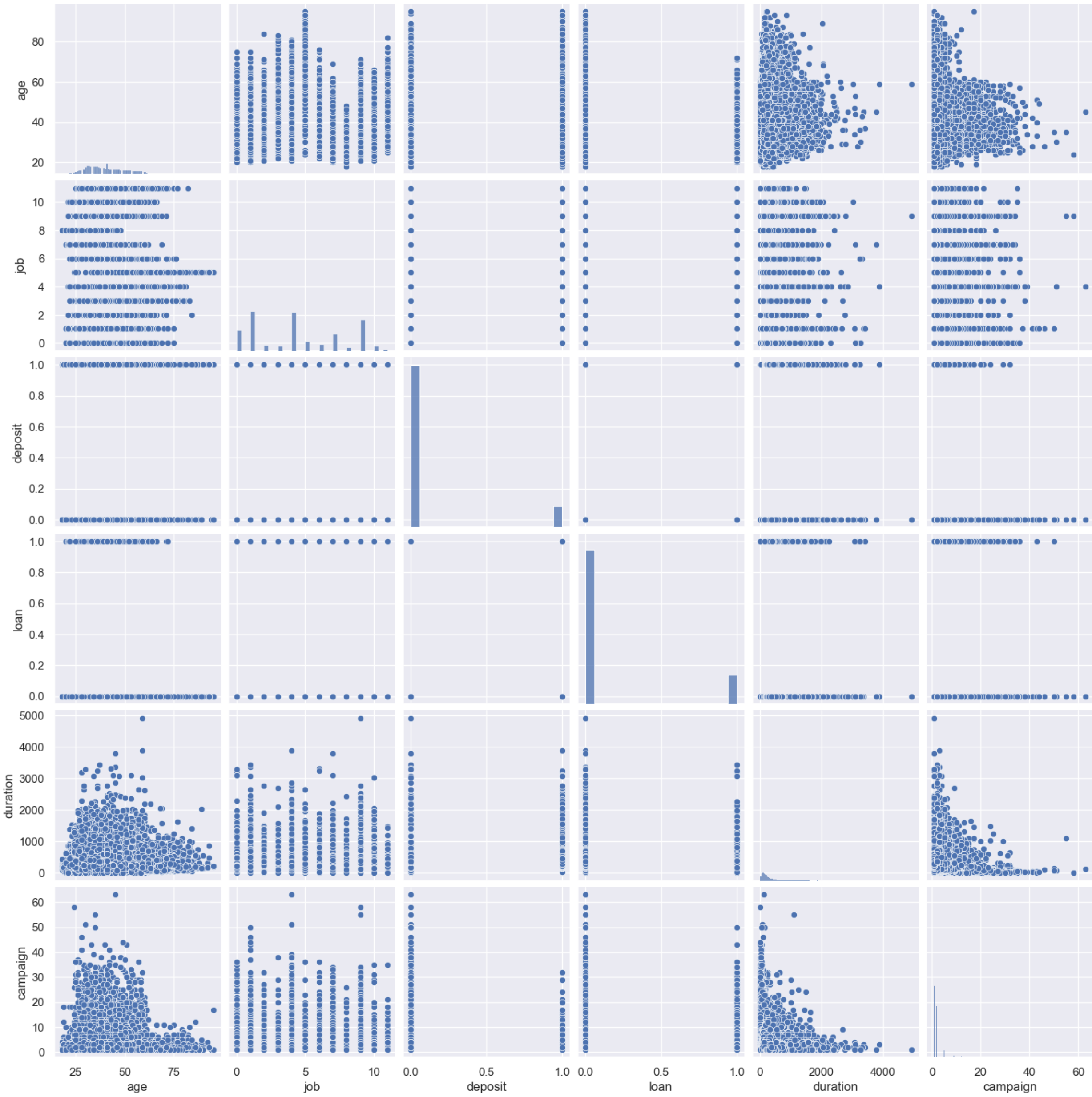
Out[123]:

	age	job	default	balance	housing	loan	day	month	duration	campaign	...	education_
0	58.0	4	0	2143	1	0	5	5	261	1	...	
1	44.0	9	0	29	1	0	5	5	151	1	...	
2	33.0	2	0	2	1	1	5	5	76	1	...	
3	47.0	1	0	1506	1	0	5	5	92	1	...	
4	33.0	11	0	1	0	0	5	5	198	1	...	

5 rows × 27 columns

Target Variable Scatterplots

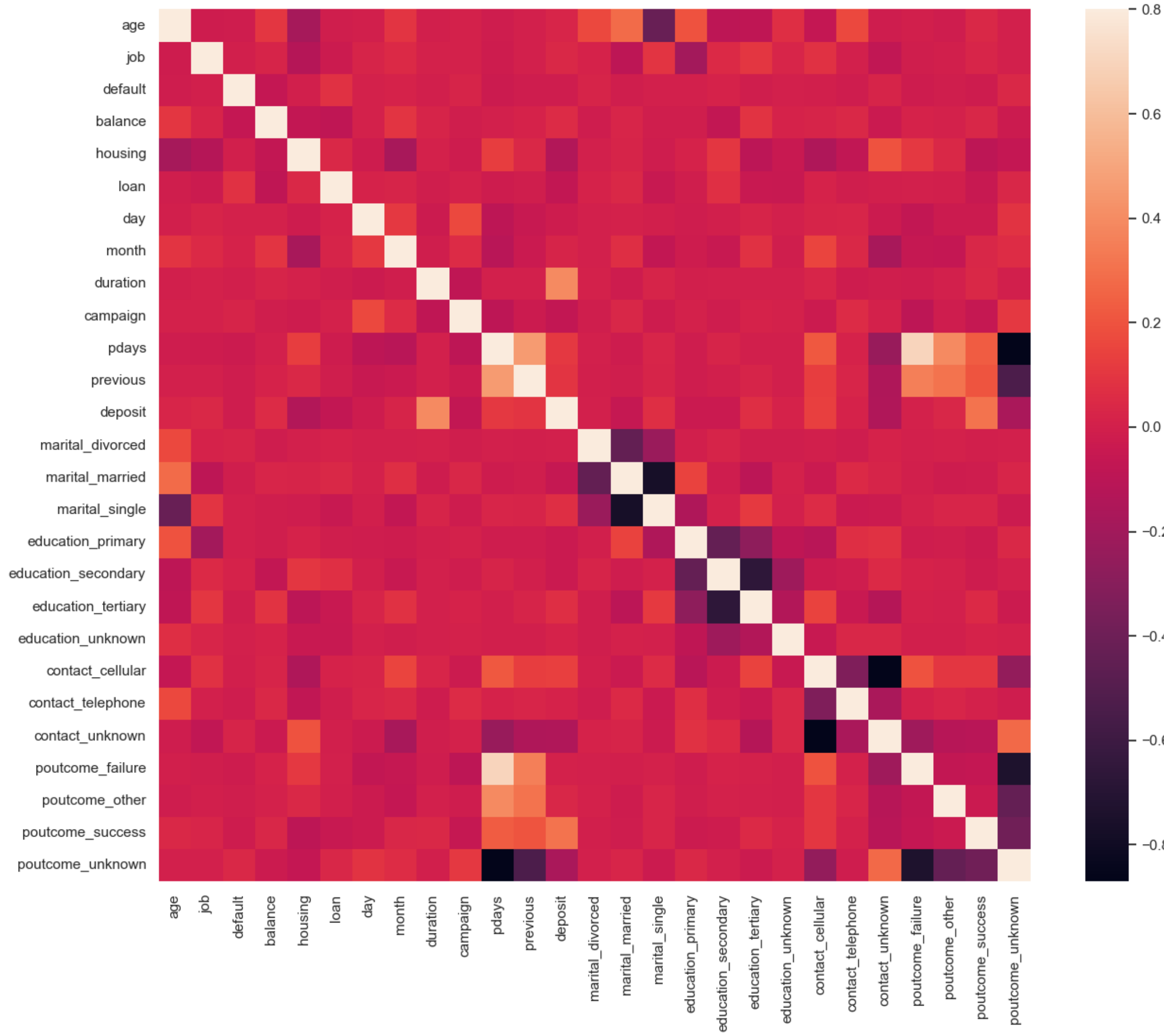
In [124…
```
sns.set()
cols = ['age', 'job','default','housing','loan','day','month','duration','campa
        'education_tertiary', 'education_unknown', 'contact_cellular', 'contact_
        'poutcome_failure', 'poutcome_other', 'poutcome_success', 'poutcome_unkn
sns.pairplot(new_df[['age', 'job', 'deposit', 'loan', 'duration', 'campaign']],
plt.show()
# the more people that were ina. campaign were more likely to open a deposit
```



Correlation Matrix

In [126…

```
#Correlation map to see how features are correlated deposite
corrmat = new_df.corr()
f, ax = plt.subplots(figsize=(15, 12))
sns.heatmap(corrmat, vmax=.8, square=True)
plt.show()
```



Logistic Regression

In [133…
```
# Split the data into features (X) and the target variable (y)
X = new_df[['age', 'job','default','housing','loan','duration','campaign','educ
        'education_tertiary', 'education_unknown', 'contact_cellular', 'contact_
        'poutcome_failure', 'poutcome_other', 'poutcome_success', 'poutcome_unkn
y = new_df[['deposit']]
```

In [134…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random
```

In [135…
```
model = LogisticRegression()
```

In [136…
```
model.fit(X_train, y_train)
```

```
/Users/hiromigonzalez/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/
validation.py:993: DataConversionWarning: A column-vector y was passed when a
1d array was expected. Please change the shape of y to (n_samples, ), for exam
ple using ravel().
  y = column_or_1d(y, warn=True)
/Users/hiromigonzalez/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear
_model/_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (status=
1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regress
ion
  n_iter_i = _check_optimize_result(
```

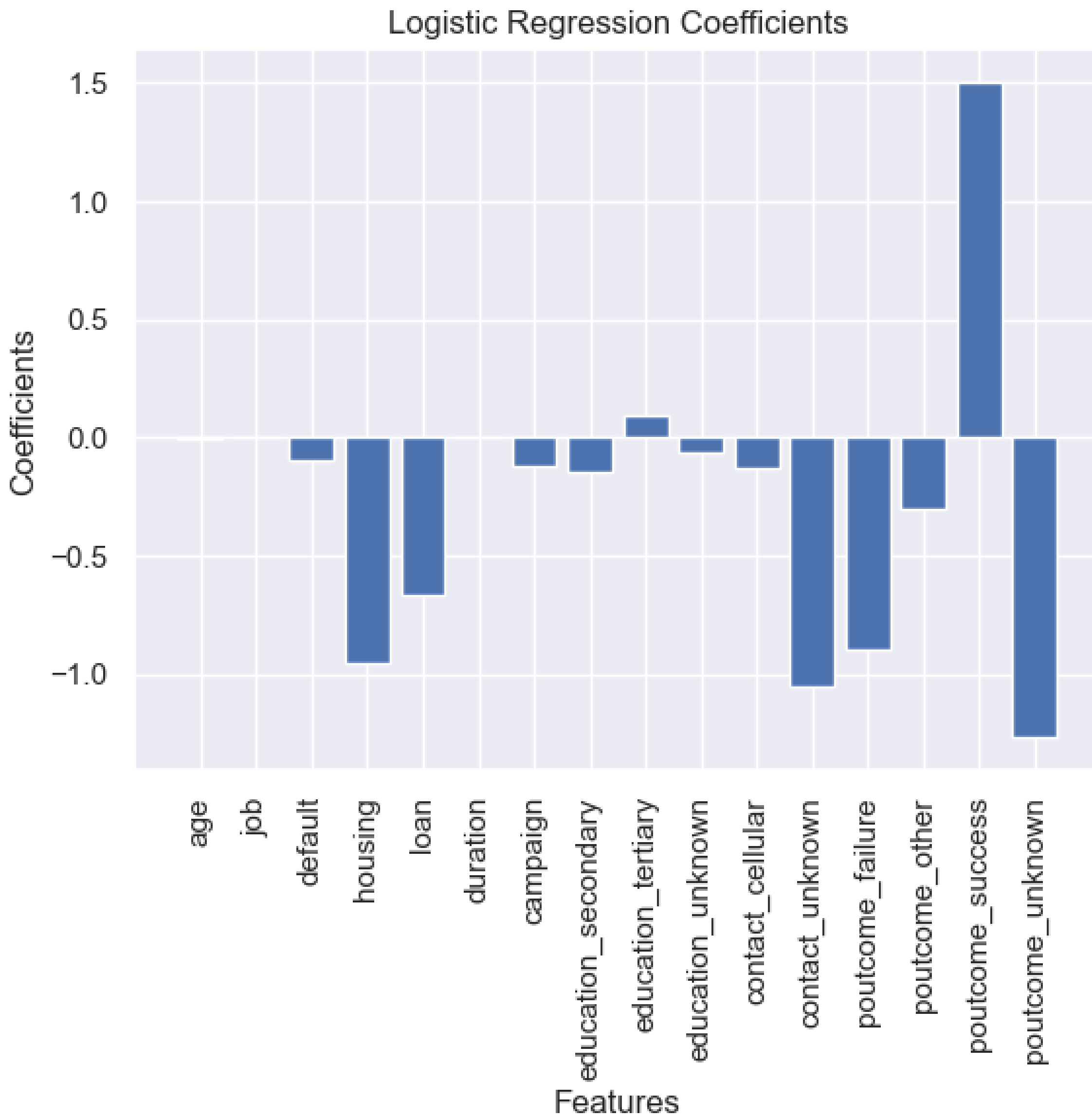
Out[136]:
```
LogisticRegression()
```

In [140…
```
# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[7758  194]
 [ 747  344]]
              precision    recall  f1-score   support

           0       0.91      0.98      0.94      7952
           1       0.64      0.32      0.42      1091

    accuracy                           0.90      9043
   macro avg       0.78      0.65      0.68      9043
weighted avg       0.88      0.90      0.88      9043
```

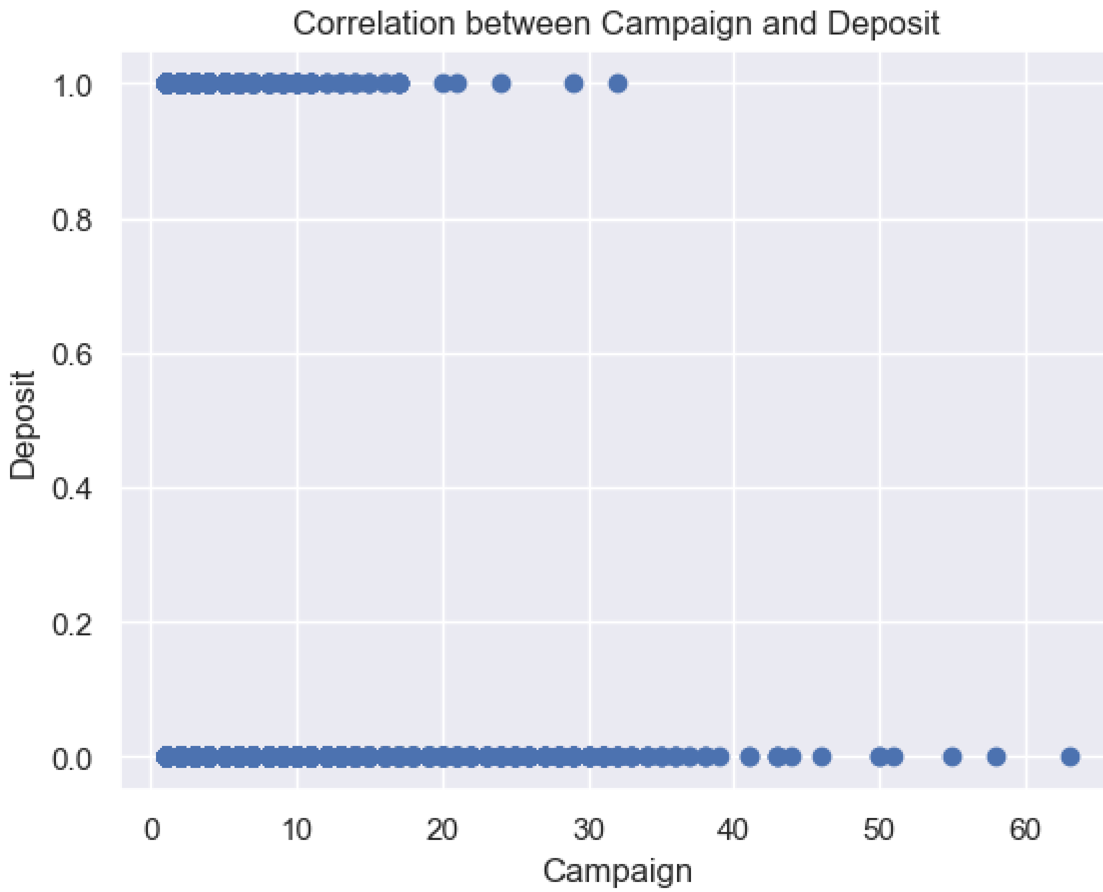
These metrics indicate that the model performs better for predicting when there won't be a deposit (0), as it has higher precision, recall, and F1-score compared to predicting when there will be a deposit (1).

In [148…
```
# Get the coefficients and their corresponding feature names
coefficients = model.coef_[0]
feature_names = X.columns

# Create a bar plot
plt.bar(feature_names, coefficients)
plt.xlabel('Features')
plt.ylabel('Coefficients')
plt.title('Logistic Regression Coefficients')
plt.xticks(rotation=90)  # Rotate x-axis labels if needed for better readabilit
plt.show()
```



In [46]:

```
deposit = new_df['deposit']
campaign = new_df['campaign']
plt.scatter(campaign, deposit)
plt.xlabel('Campaign')
plt.ylabel('Deposit')
plt.title('Correlation between Campaign and Deposit')
plt.show()
```



Data Analytics

In [149…

```
from sklearn.linear_model import Lasso, LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold, cross_val_score
from sklearn.metrics import mean_squared_error
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb
from sklearn.metrics import accuracy_score
```

import xgboost as xgb from sklearn.metrics import accuracy_score

Init classifier

xgb_cl = xgb.XGBClassifier()

Fit

xgb_cl.fit(X_train, y_train)

Predict

preds = xgb_cl.predict(X_test)

In [150…

```
X = new_df[['age', 'job','default','housing','loan','duration','campaign','educ
        'education_tertiary', 'education_unknown', 'contact_cellular', 'contact_
        'poutcome_failure', 'poutcome_other', 'poutcome_success', 'poutcome_unkn
```

```
y = new_df[['deposit']]

# create classification model and fit the data
xgb_cl = xgb.XGBClassifier()
```

In [151…

```
xgb_cl.fit(X,y)
```

Out[151]:

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [152…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, ranc
```

In [153…

```
model = xgb.XGBClassifier()
```

In [154…

```
model.fit(X_train, y_train)
```

Out[154]:

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [155…

```
# make the prediction on test
y_test_prediction = model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_test_prediction))
print(f"RMSE: {rmse}")
```

```
RMSE: 0.3248014219932712
```

In [156…

```
# now fine the RMSE of the train set
y_train_predict = model.predict(X_train)

# calculate the RMSE on the train set now
rmse_train = np.sqrt(mean_squared_error(y_train, y_train_predict))
print(f"RMSE train: {rmse_train}")
```

```
RMSE train: 0.26505749273045415
```

-from sklearn.model_selection import KFold, cross_val_score

-from sklearn.tree import DecisionTreeClassifier

-from sklearn.neighbors import KNeighborsClassifier

In [157…

```
clf = RandomForestClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy_random_forest_classifier = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy_random_forest_classifier}")
```

```
/var/folders/54/937x7kcn6m79plvcfs7pl6zw0000gn/T/ipykernel_36408/4237262992.p
y:2: DataConversionWarning: A column-vector y was passed when a 1d array was e
xpected. Please change the shape of y to (n_samples,), for example using ravel
().
  clf.fit(X_train, y_train)
Accuracy: 0.8904124737365918
```

In [158…

```
# now we will run a decision tree classifier test
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy_decision_tree_classifier = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy_decision_tree_classifier}")
```

```
Accuracy: 0.8500497622470419
```

In [159…

```
clf = KNeighborsClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy_Kneightbors_classifier = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy_Kneightbors_classifier}")
```

```
/Users/hiromigonzalez/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighb
ors/_classification.py:198: DataConversionWarning: A column-vector y was passe
d when a 1d array was expected. Please change the shape of y to (n_samples,),
for example using ravel().
  return self._fit(X, y)
/Users/hiromigonzalez/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighb
ors/_classification.py:228: FutureWarning: Unlike other reduction functions
(e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves
the axis it acts along. In SciPy 1.11.0, this behavior will change: the defaul
t value of `keepdims` will become False, the `axis` over which the statistic i
s taken will be eliminated, and the value None will no longer be accepted. Set
`keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
Accuracy: 0.8752626340816101
```

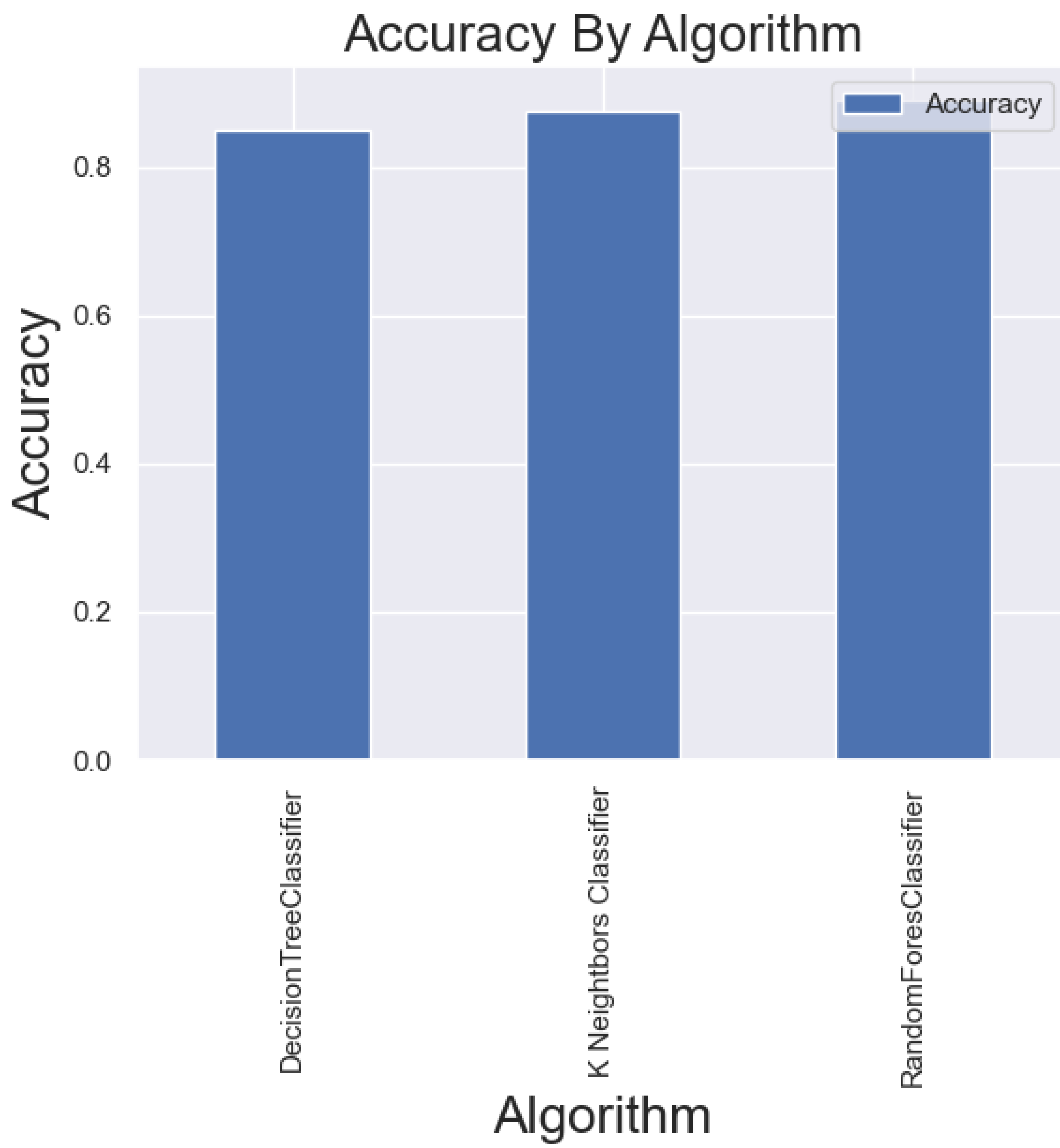
In [160…

```
# plot accuracy for each algorithm
data = {'RandomForesClassifier':[accuracy_random_forest_classifier], 'DecisionT
        'K Neightbors Classifier': [accuracy_Kneightbors_classifier]}
data_df = pd.DataFrame(data=data).T.reset_index().sort_values(by = [0],ascendin
data_df.columns = ['Algorithm', 'Accuracy']
data_df.head()
```

Out[160]:

	Algorithm	Accuracy
1	DecisionTreeClassifier	0.850050
2	K Neightbors Classifier	0.875263
0	RandomForesClassifier	0.890412

In [161…
```
data_df.plot(kind='bar',x = 'Algorithm', y = 'Accuracy')
plt.xlabel("Algorithm",fontsize=20)
plt.ylabel("Accuracy",fontsize=20)
plt.title("Accuracy By Algorithm",fontsize=20)
plt.show()
```



Variable Importance Plot

In [162…
```
clf = RandomForestClassifier()
clf.fit(X_train, y_train)
importances = clf.feature_importances_
# Create a DataFrame with feature names and importances
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance': importa
# Sort the DataFrame by importance values in descending order
importance_df = importance_df.sort_values(by='Importance', ascending=False)
# Plot the variable importance
plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'], importance_df['Importance'])
plt.xlabel('Importance')
```

```
plt.ylabel('Feature')
plt.title('Variable Importance')
plt.show()
```

```
/var/folders/54/937x7kcn6m79plvcfs7pl6zw0000gn/T/ipykernel_36408/1652506768.p
y:2: DataConversionWarning: A column-vector y was passed when a 1d array was e
xpected. Please change the shape of y to (n_samples,), for example using ravel
().
  clf.fit(X_train, y_train)
```