UCI Bank Marketing

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Introduction

The goal of this project was to use classification model to predict if a client subscribe to the bank term deposit or not. The data is related with direct marketing campaigns of a banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

Feature Description & Exploratory Data Analysis

Data

The dataset contains 45211 examples with 17 features for each, 10 of which are categorical and 7 numeric.

1. Age (numeric)
2. job: type of job (categorical)
3. marital: marital status (categorical)
4. education (categorical)
5. default: has credit in default? (categorical)
6. housing: has housing loan? (categorical)
7. loan: has personal loan? (categorical)

Data

Related with the last contact of the current campaign :

8. contact: contact communication type (categorical)

9. month: last contact month of year (categorical)

10. day_of_week: last contact day of the week (categorical)

11. duration: last contact duration, in seconds (numeric).

Data

Other attributes

12. campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)

13. pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

14. previous: number of contacts performed before this campaign and for this client (numeric)

15. poutcome: outcome of the previous marketing campaign (categorical)

16. Social and economic context attributes

17. y - has the client subscribed a term deposit? (Binary: 'yes','no’)

Data cleaning

Present Data Information :

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
None
```

Rename target column :

```
# rename target column
df.rename(columns ={'y':'deposit'} , inplace = True)
```

```
df.head()
```

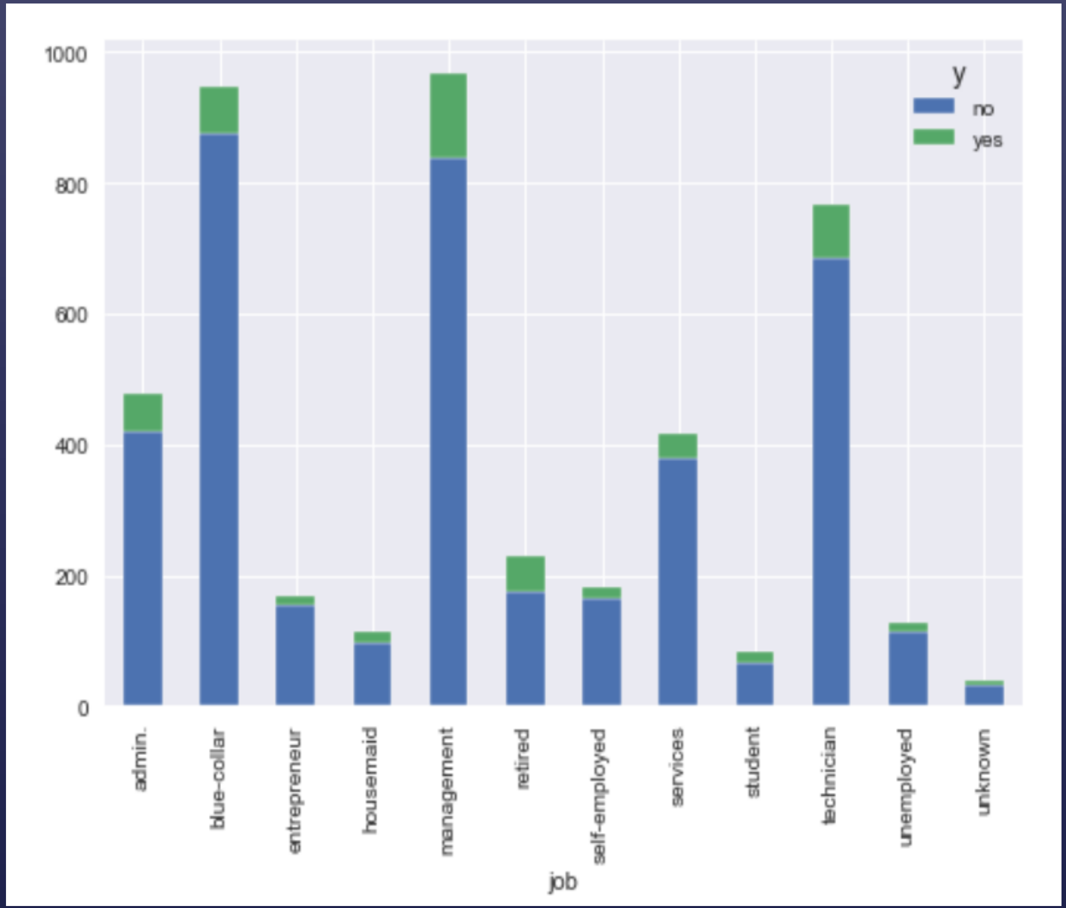
	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

```
df.describe()
```

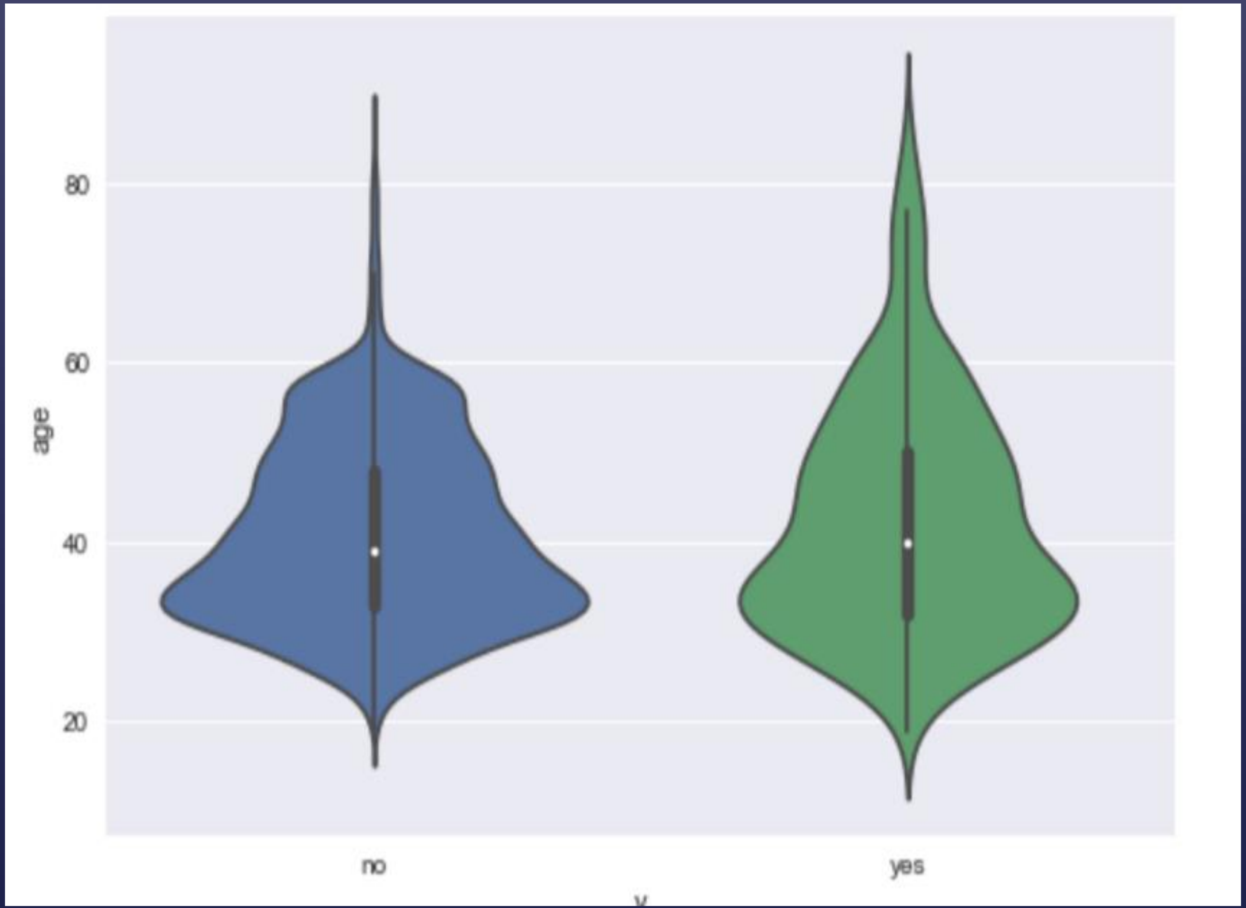
	age	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

Job , Age

Job of Client

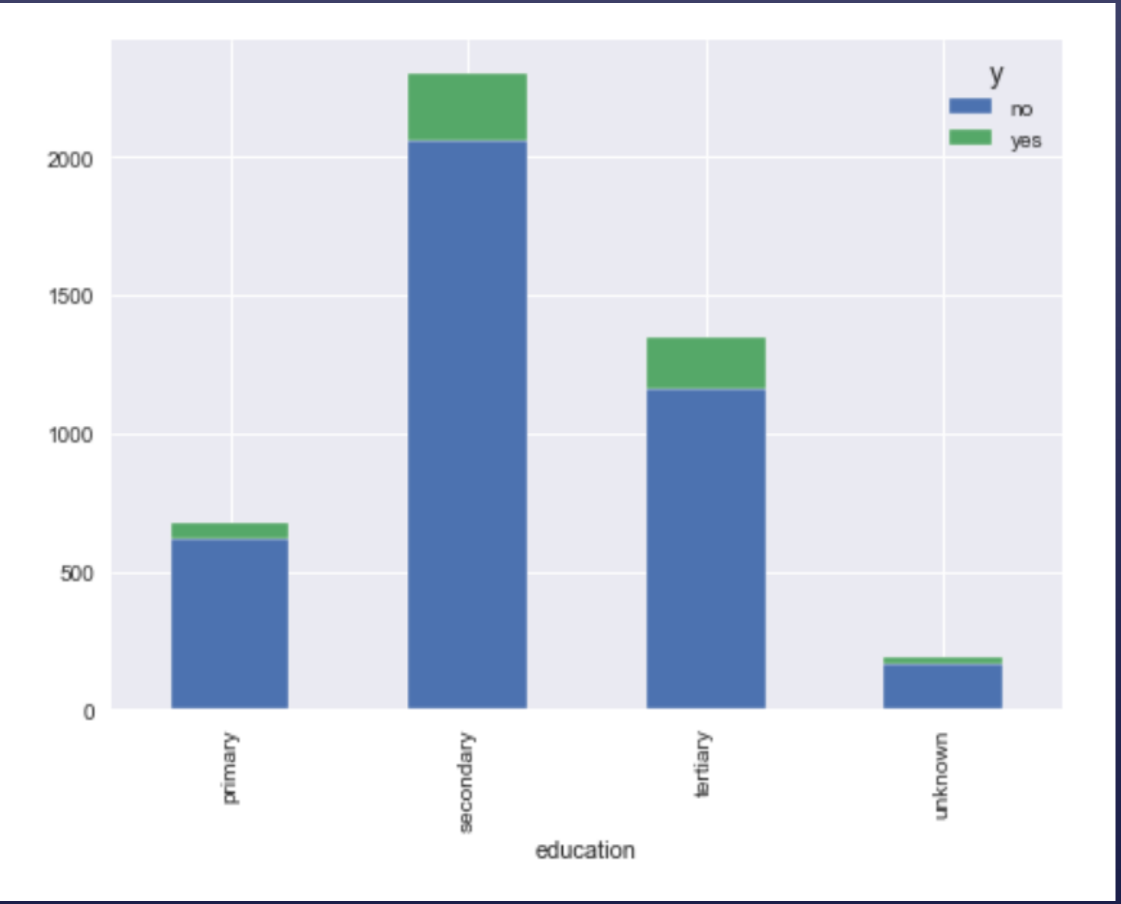


Age of Client

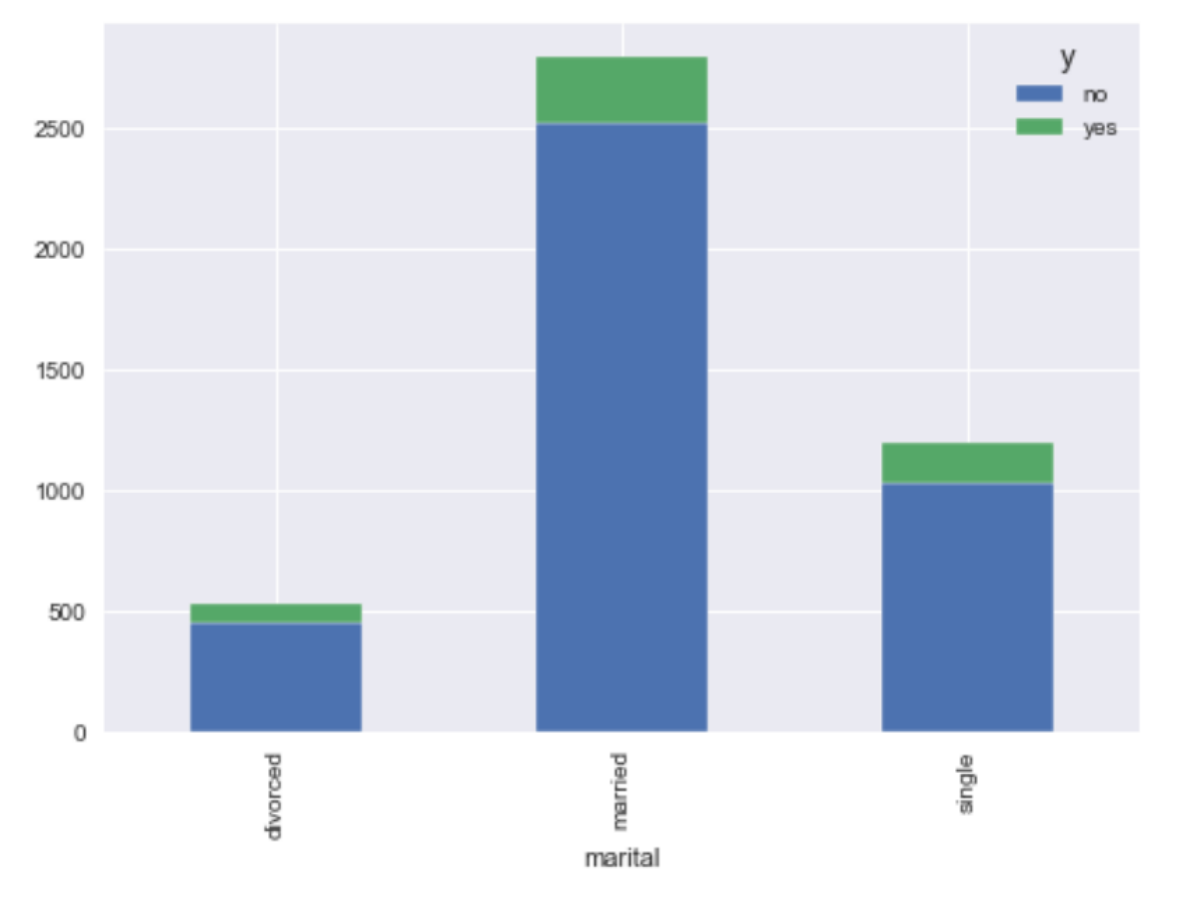


Marital , Education

Marital status of Client

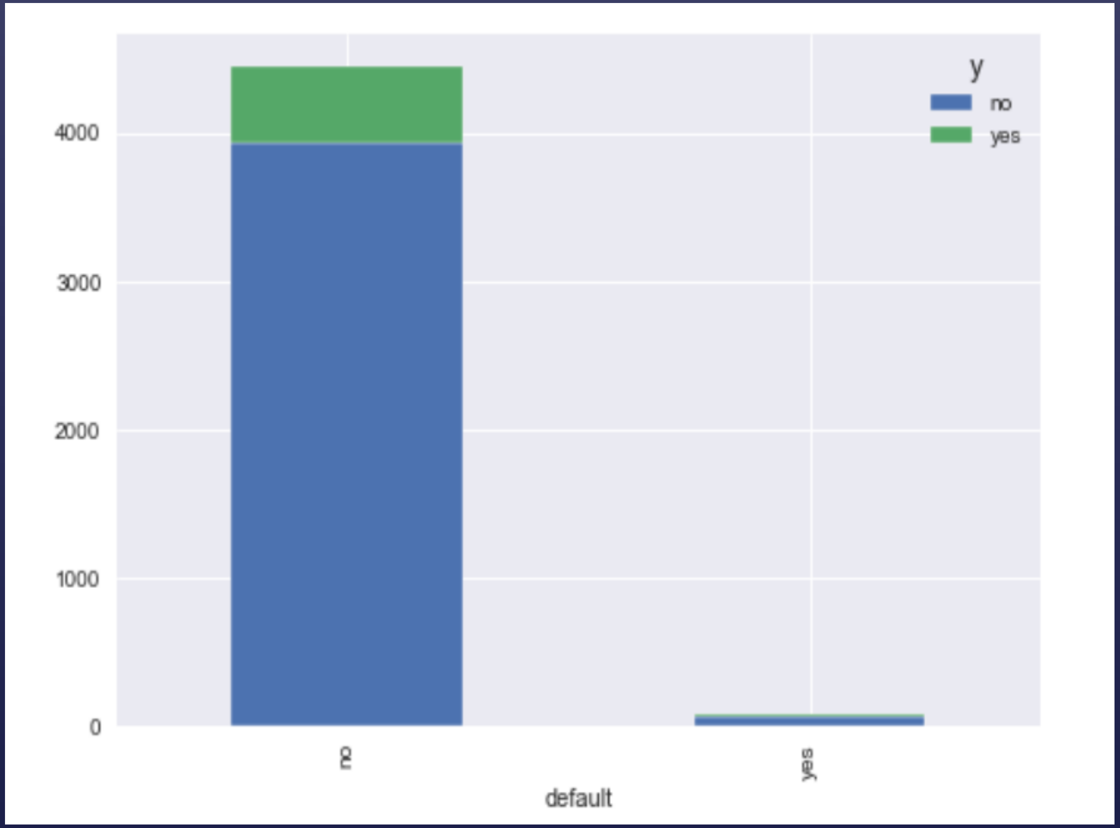


Education Type of Client

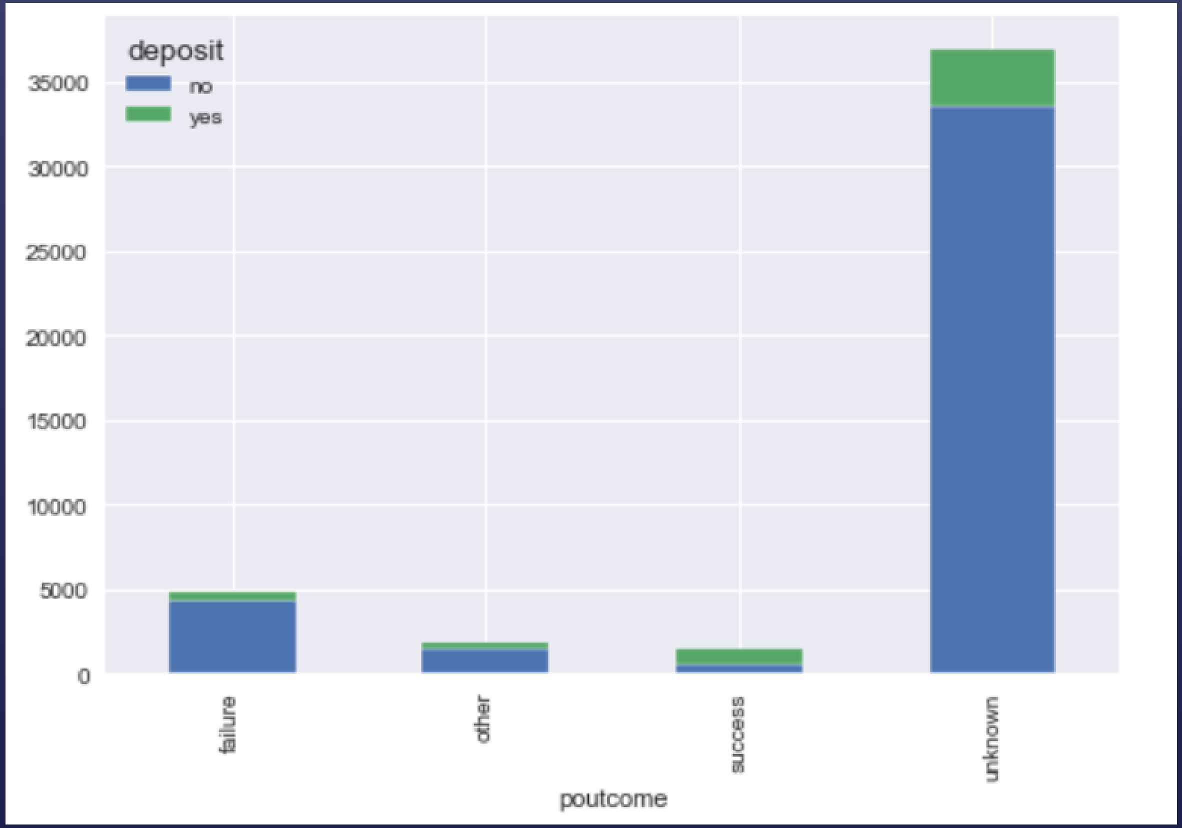


Default ,poutcome

Default - it tells whether the client has credit in bank or not?

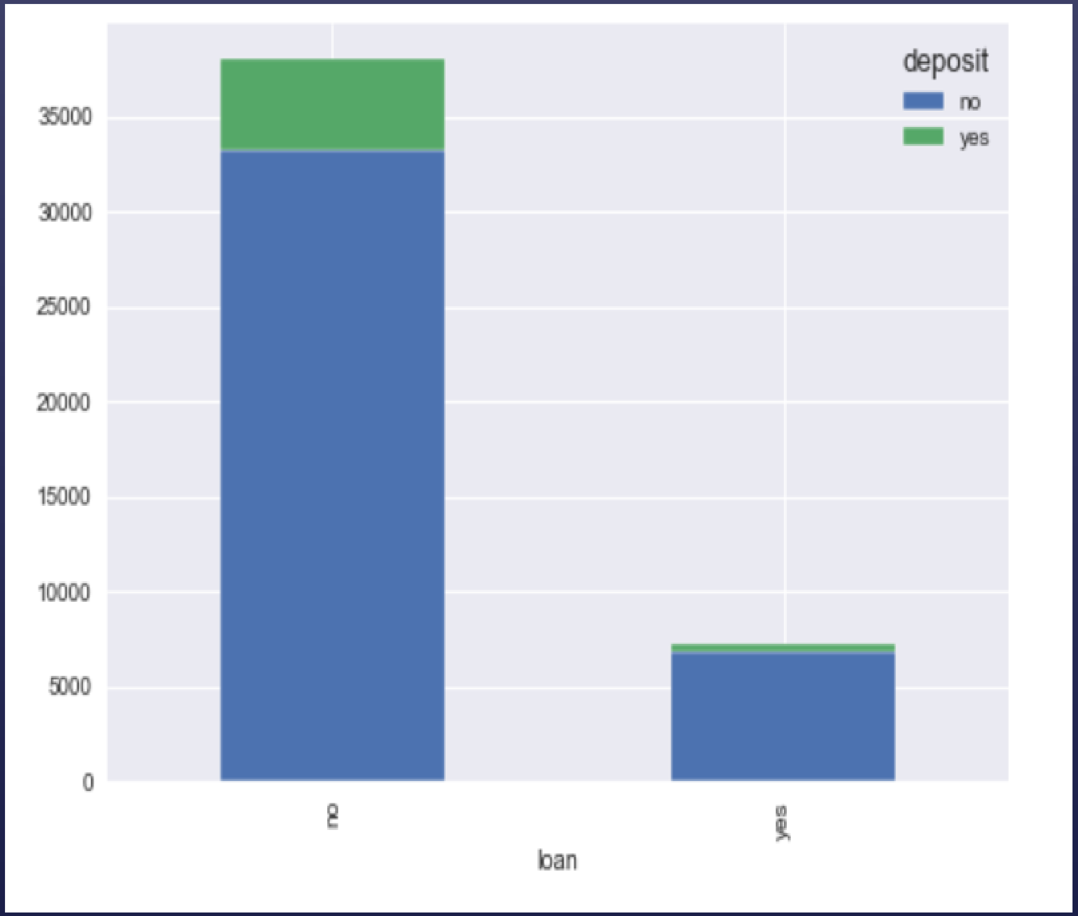


Poutcome – The outcome of previous marketing campaign

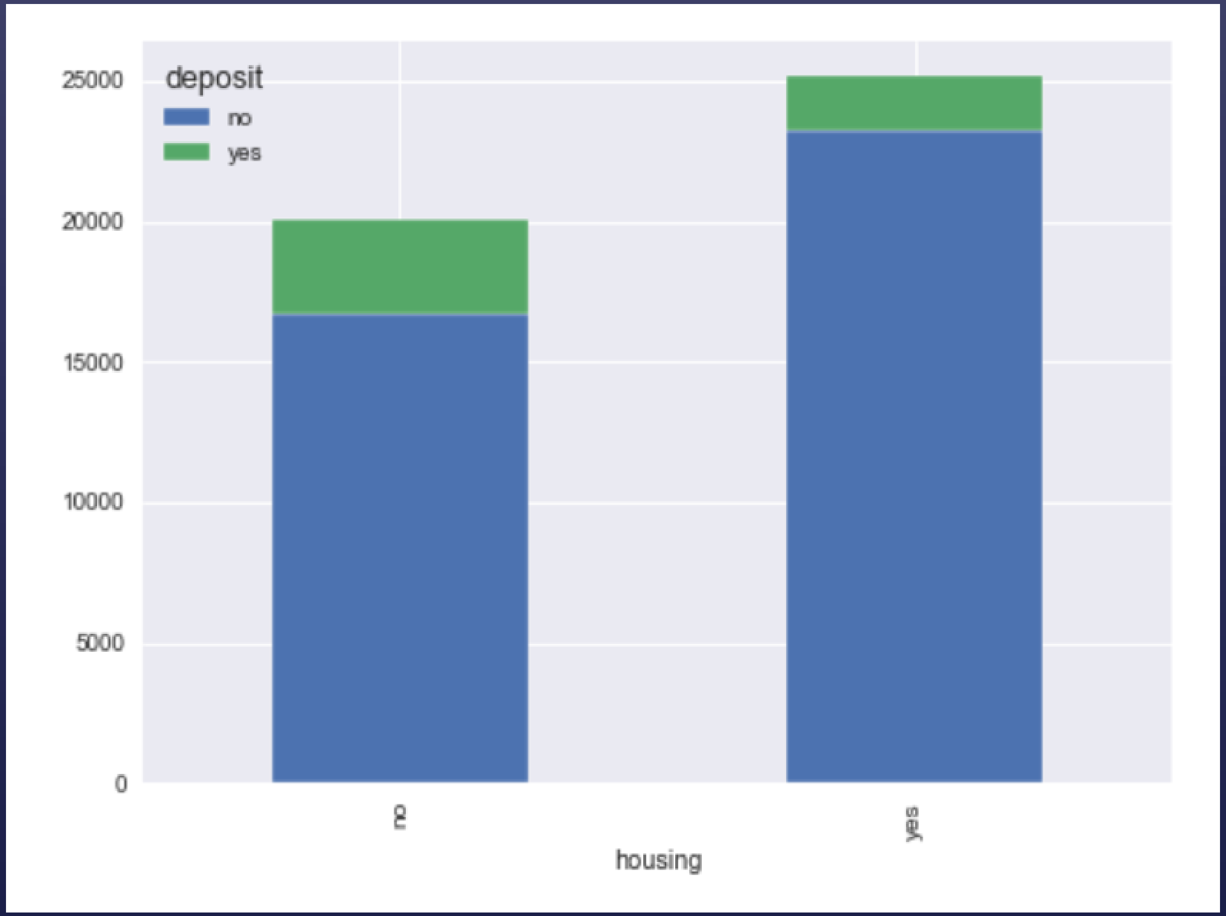


Housing, Loan

Loan - Whether the client has got any personal loan from bank ?

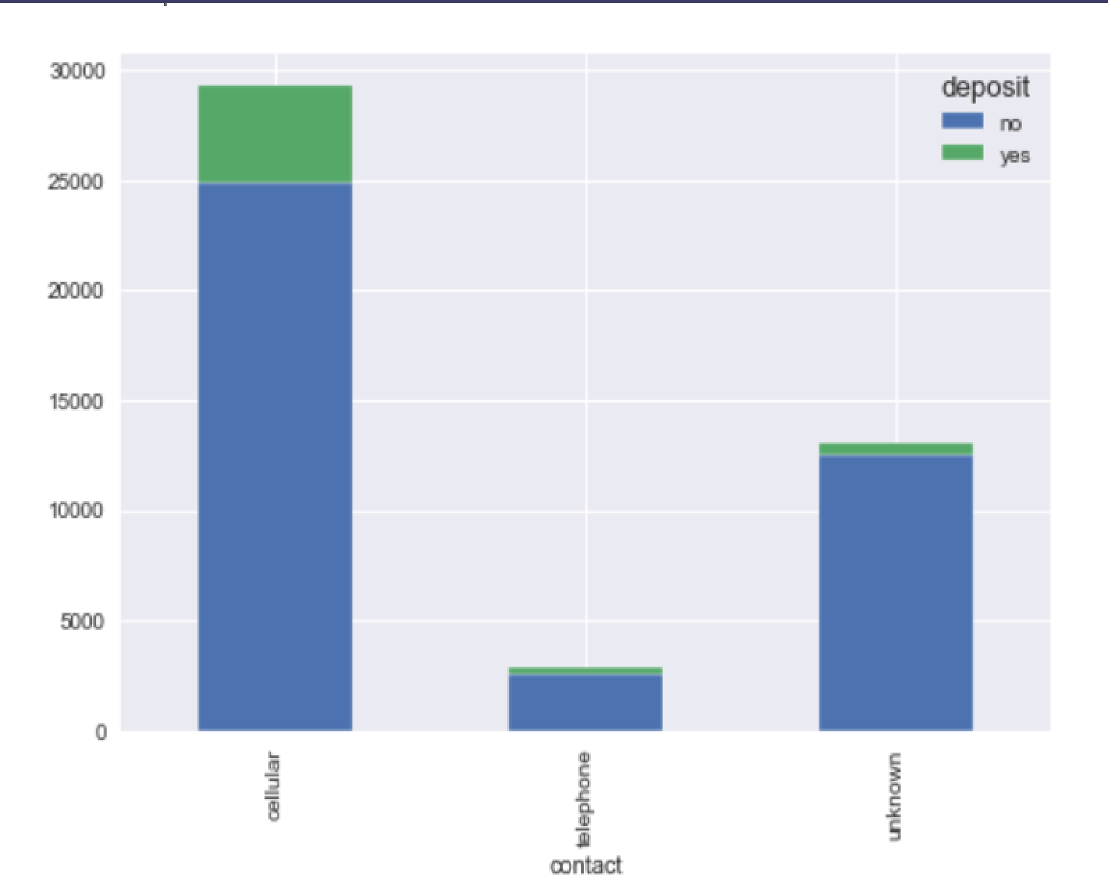


Housing – Whether the client has got any housing loan from bank ?

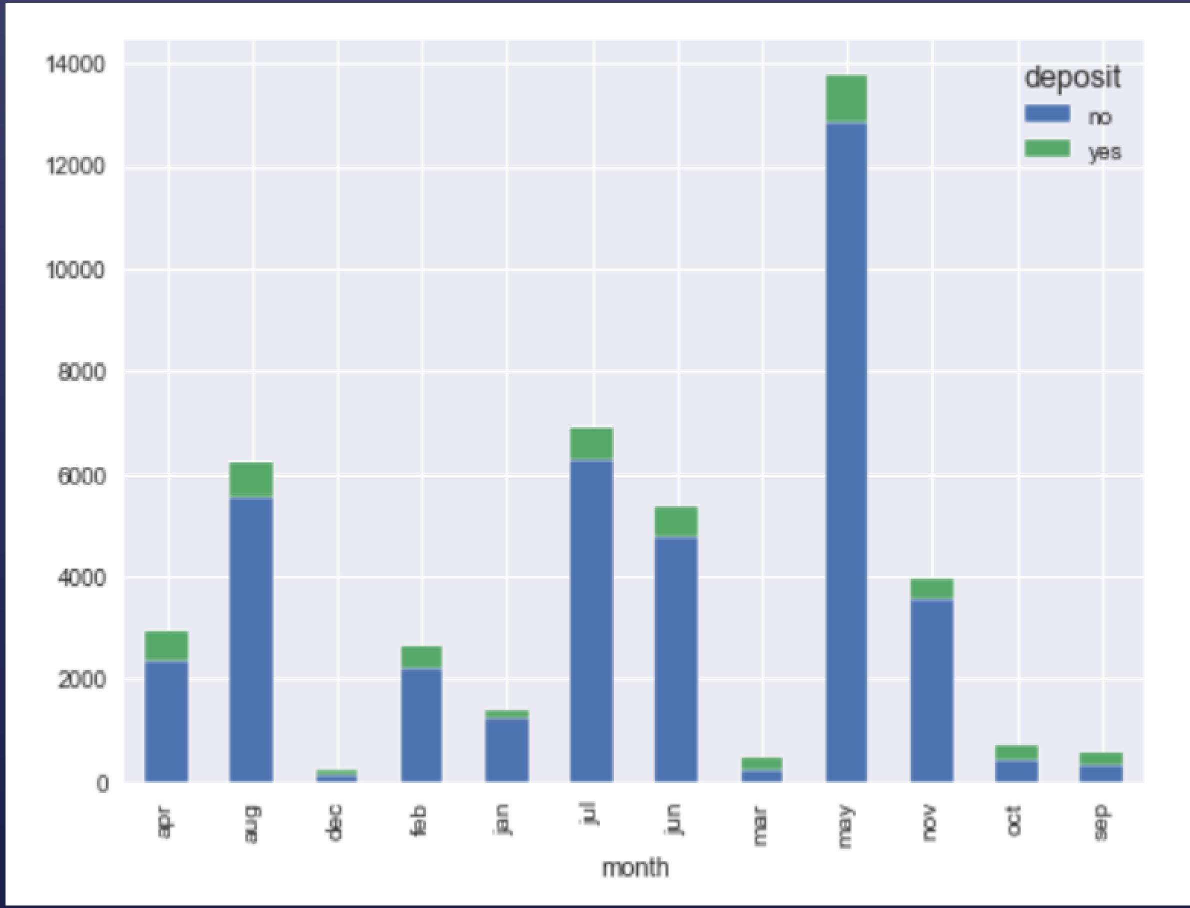


Contact, Month

Contact – way of communication

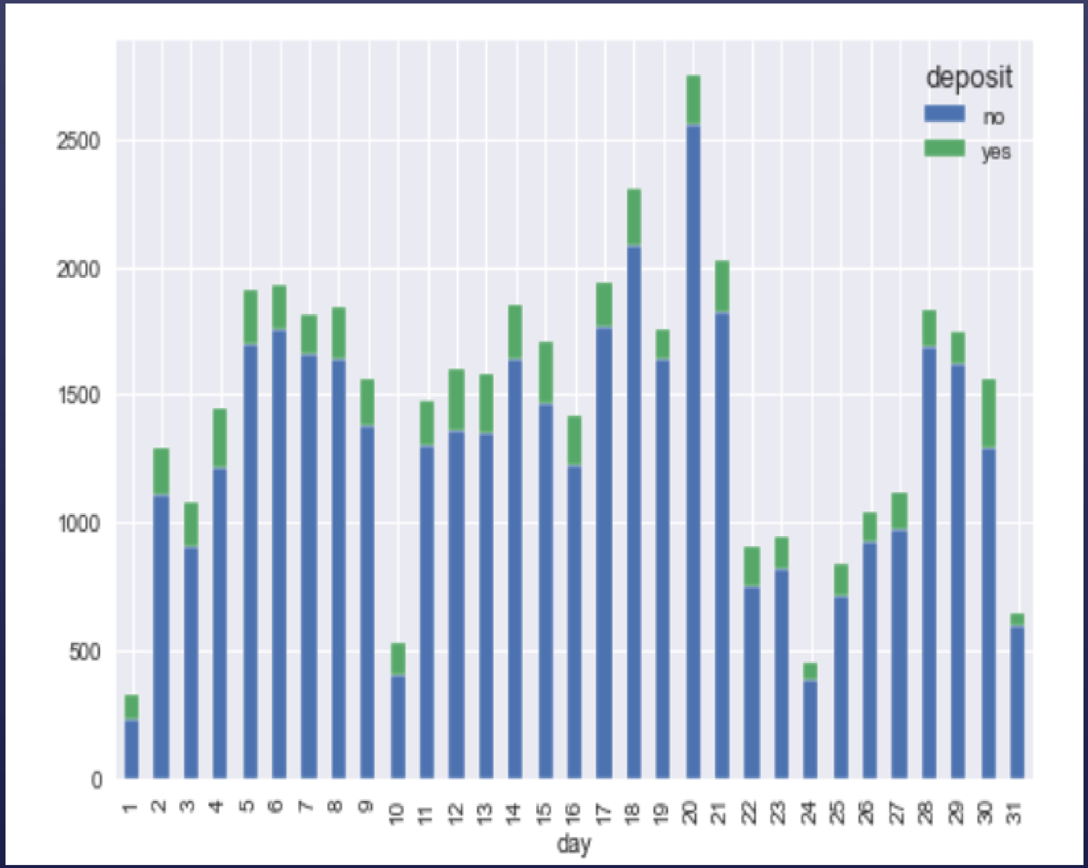


Month – Month of communication

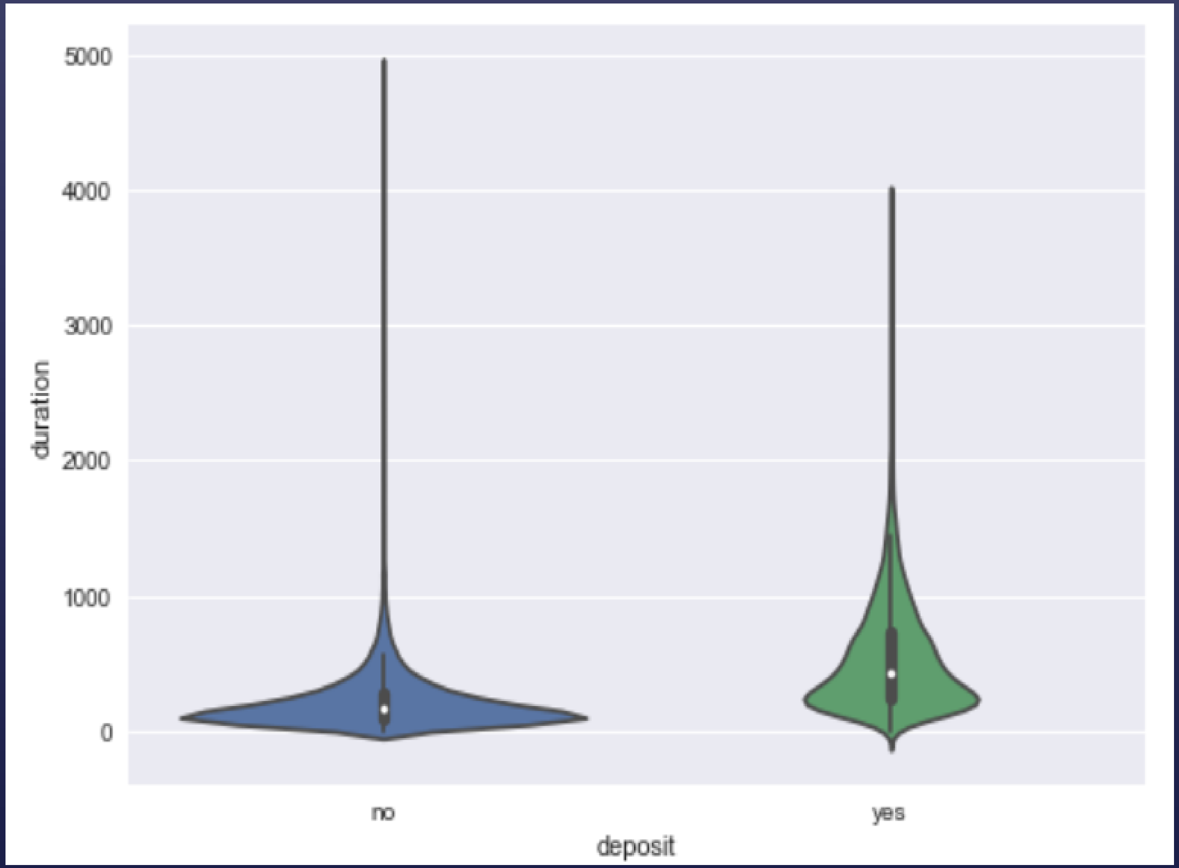


Day, Duration

Day – day of the month for contact

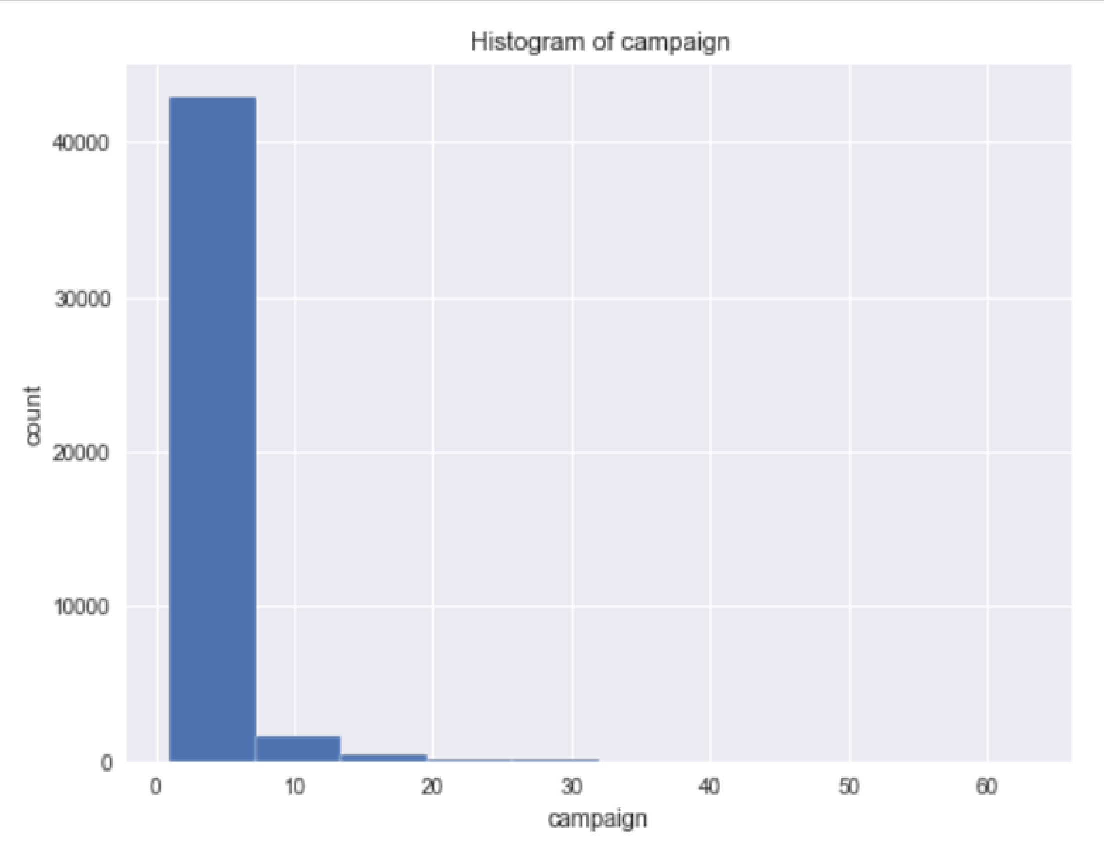


Duration – duration of last call

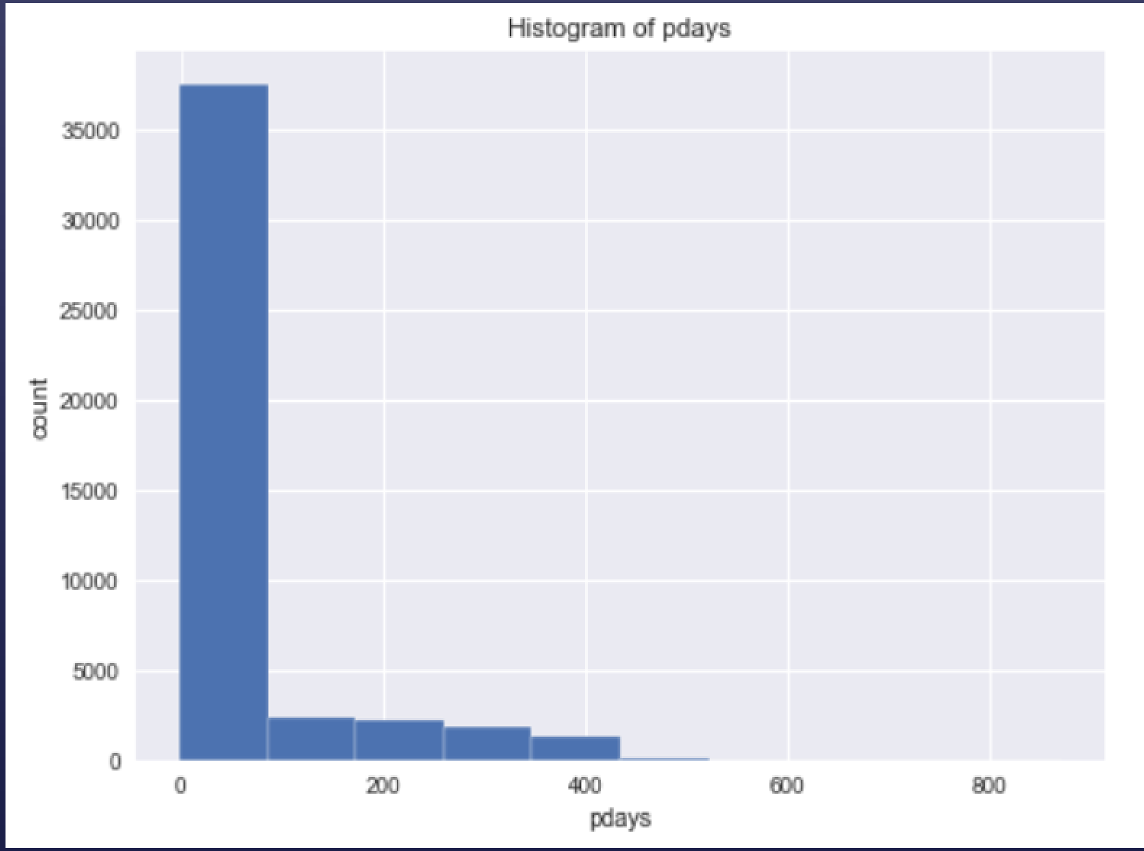


Campaign, pdays

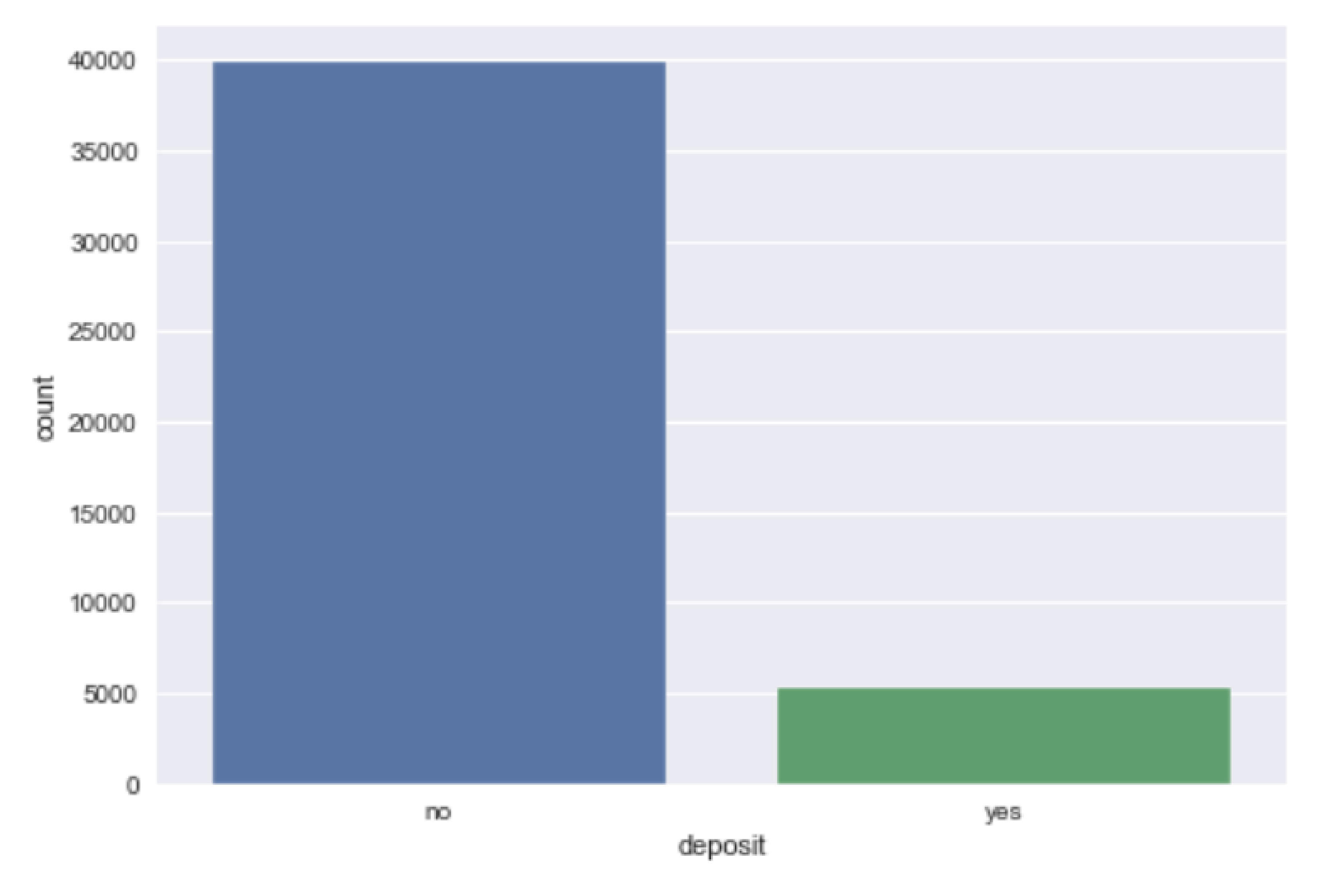
Campaign – Number of times this client was contacted during this campaign



Pdays – number of days that passed after the client was last contacted in previous campaign



Deposit (Target Variable)



Preprocessing

Converting categorical features to binary variables

Replacing yes and no from deposit column by 1 and 0 to convert categorical feature to numerical feature for :

- Deposit
- Loan
- Default
- Housing

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
0	58	management	married	tertiary	1	2143	0	1	unknown	5	may	261	1	-1	0	unknown	0
1	44	technician	single	secondary	1	29	0	1	unknown	5	may	151	1	-1	0	unknown	0
2	33	entrepreneur	married	secondary	1	2	0	0	unknown	5	may	76	1	-1	0	unknown	0
3	47	blue-collar	married	unknown	1	1506	0	1	unknown	5	may	92	1	-1	0	unknown	0
4	33	unknown	single	unknown	1	1	1	1	unknown	5	may	198	1	-1	0	unknown	0

Category encoder (one-hot).

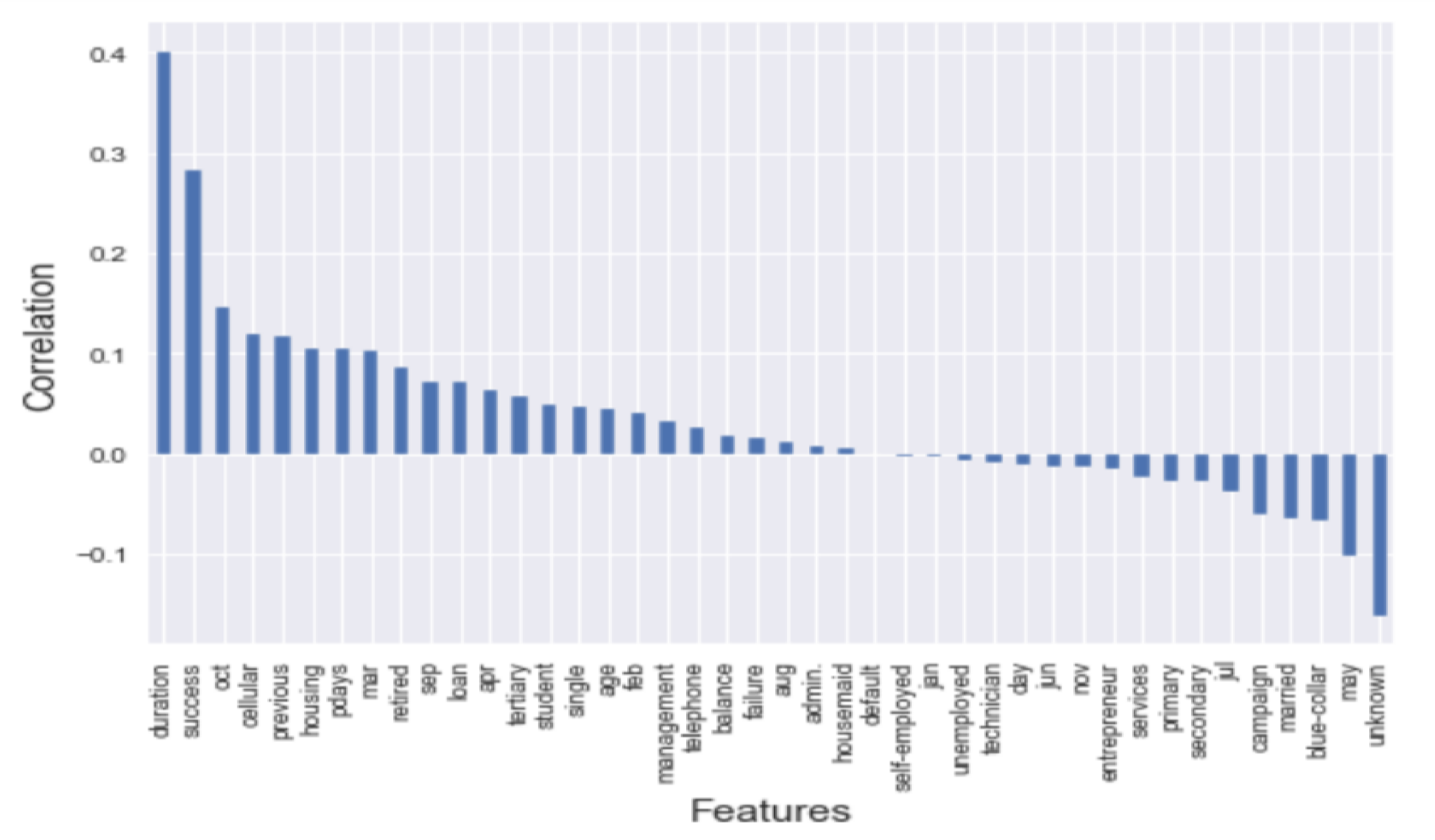
One hot encoding for marital feature to convert categorical feature to numerical feature so we Dropped the original column and Dropped one of the resultant columns for :

- Marital
- Education
- Job
- Contact
- Month
- Poutcome

	age	default	balance	housing	loan	day	duration	campaign	pdays	previous	...	jul	jun	mar	may	nov	oct	sep	failure	success	unknown
0	58	1	2143	0	1	5	261	1	-1	0	...	0	0	0	1	0	0	0	0	0	1
1	44	1	29	0	1	5	151	1	-1	0	...	0	0	0	1	0	0	0	0	0	1
2	33	1	2	0	0	5	76	1	-1	0	...	0	0	0	1	0	0	0	0	0	1
3	47	1	1506	0	1	5	92	1	-1	0	...	0	0	0	1	0	0	0	0	0	1
4	33	1	1	1	1	5	198	1	-1	0	...	0	0	0	1	0	0	0	0	0	1

All Features are converted to numerical

Correlation with Class variable ‘Deposit'



Split Dataset for Training and Testing

```
# Select Features
feature = bank.drop('deposit', axis=1)

# Select Target
target = bank['deposit']

# Set Training and Testing Data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(feature,target,test_size=0.2,random_state=1)

# Show the Training and Testing Data
print('Shape of training feature:', X_train.shape)
print('Shape of testing feature:', X_test.shape)
print('Shape of training label:', y_train.shape)
print('Shape of training label:', y_test.shape)
```

```
Shape of training feature: (36168, 42)
Shape of testing feature: (9043, 42)
Shape of training label: (36168,)
Shape of training label: (9043,)
```

Numerical transformations (scaling) after splitting

```
###we tried to scale before splitting by applying this code :

#from sklearn.preprocessing import StandardScaler
#scaler = StandardScaler()
#num_cols = ['age', 'balance', 'day', 'campaign', 'pdays', 'previous']
#bank[num_cols] = scaler.fit_transform(bank[num_cols])
#bank.head()


#### and the result is haigh accuarcy in all the algorithms,cuz the data leakage So we decide to split then scale

#scaling
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
X_train =scaler.fit_transform(X_train)
X_test =scaler.transform(X_test)
```

Handling The Class Imbalance : SMOTE

As we can see our class distribution is more or less similar, SO our data is imbalance because it is %88 no and %12 yes SO we need to deal with imbalance by apply SMOTE

```
df["deposit"].value_counts()
```

```
no     39922
yes     5289
Name: deposit, dtype: int64
```

Class Distribution

```
# smote
import imblearn.over_sampling
n_pos = np.sum(y_train == 1)
n_neg = np.sum(y_train == 0)
ratio = {1 : n_pos * 4, 0 : n_neg}

smote = imblearn.over_sampling.SMOTE(sampling_strategy=ratio, random_state = 42)

X_train, y_train = smote.fit_resample(X_train, y_train)
```

Build the Data Model

```
def evaluate_model(model, x_test, y_test):
    from sklearn import metrics

    # Predict Test Data
    y_pred = model.predict(x_test)

    # Calculate accuracy, precision, recall, f1-score, and kappa score
    acc = metrics.accuracy_score(y_test, y_pred)
    prec = metrics.precision_score(y_test, y_pred)
    rec = metrics.recall_score(y_test, y_pred)
    f1 = metrics.f1_score(y_test, y_pred)

    # Calculate area under curve (AUC)
    y_pred_proba = model.predict_proba(x_test)[::,1]
    fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba)
    auc = metrics.roc_auc_score(y_test, y_pred_proba)

    # Display confussion matrix
    cm = metrics.confusion_matrix(y_test, y_pred)

    return {'acc': acc, 'prec': prec, 'rec': rec, 'f1': f1,'fpr': fpr, 'tpr': tpr, 'auc': auc, 'cm': cm}
```

Models :

- Decision Tree
- Random Forest
- Naive Bayes
- K-Nearest Neighbours

Decision Tree

```
from sklearn import tree

# Building Decision Tree model
dtc = tree.DecisionTreeClassifier(criterion = 'entropy',random_state=0)
dtc.fit(X_train, y_train)
# Evaluate Model
dtc_eval = evaluate_model(dtc, X_test, y_test)

# Print result
print('Accuracy:', dtc_eval['acc'])
print('Precision:', dtc_eval['prec'])
print('Recall:', dtc_eval['rec'])
print('F1 Score:', dtc_eval['f1'])
print('Area Under Curve:', dtc_eval['auc'])
print('Confusion Matrix:\n', dtc_eval['cm'])
```

```
Accuracy: 0.8659736813004534
Precision: 0.4363207547169811
Recall: 0.5285714285714286
F1 Score: 0.47803617571059437
Area Under Curve: 0.7194339690085968
Confusion Matrix:
 [[7276  717]
 [ 495  555]]
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier

# Building Random Forest model
rf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy',random_state=0)
rf.fit(X_train, y_train)
# Evaluate Model
rf_eval = evaluate_model(rf, X_test, y_test)

# Print result
print('Accuracy:', rf_eval['acc'])
print('Precision:', rf_eval['prec'])
print('Recall:', rf_eval['rec'])
print('F1 Score:', rf_eval['f1'])
print('Area Under Curve:', rf_eval['auc'])
print('Confusion Matrix:\n', rf_eval['cm'])
```

```
Accuracy: 0.8981532677208891
Precision: 0.5776173285198556
Recall: 0.45714285714285713
F1 Score: 0.5103668261562999
Area Under Curve: 0.9037471478019459
Confusion Matrix:
 [[7642  351]
 [ 570  480]]
```

Naive Bayes

```
from sklearn.naive_bayes import GaussianNB

# Building Naive Bayes model
nb = GaussianNB()
nb.fit(X_train, y_train)
# Evaluate Model
nb_eval = evaluate_model(nb, X_test, y_test)

# Print result
print('Accuracy:', nb_eval['acc'])
print('Precision:', nb_eval['prec'])
print('Recall:', nb_eval['rec'])
print('F1 Score:', nb_eval['f1'])
print('Area Under Curve:', nb_eval['auc'])
print('Confusion Matrix:\n', nb_eval['cm'])
```

```
Accuracy: 0.84739577573814
Precision: 0.3894101876675603
Recall: 0.5533333333333333
F1 Score: 0.45712037765538943
Area Under Curve: 0.8066458150882023
Confusion Matrix:
 [[7082  911]
 [ 469  581]]
```

K-Nearest Neighbors

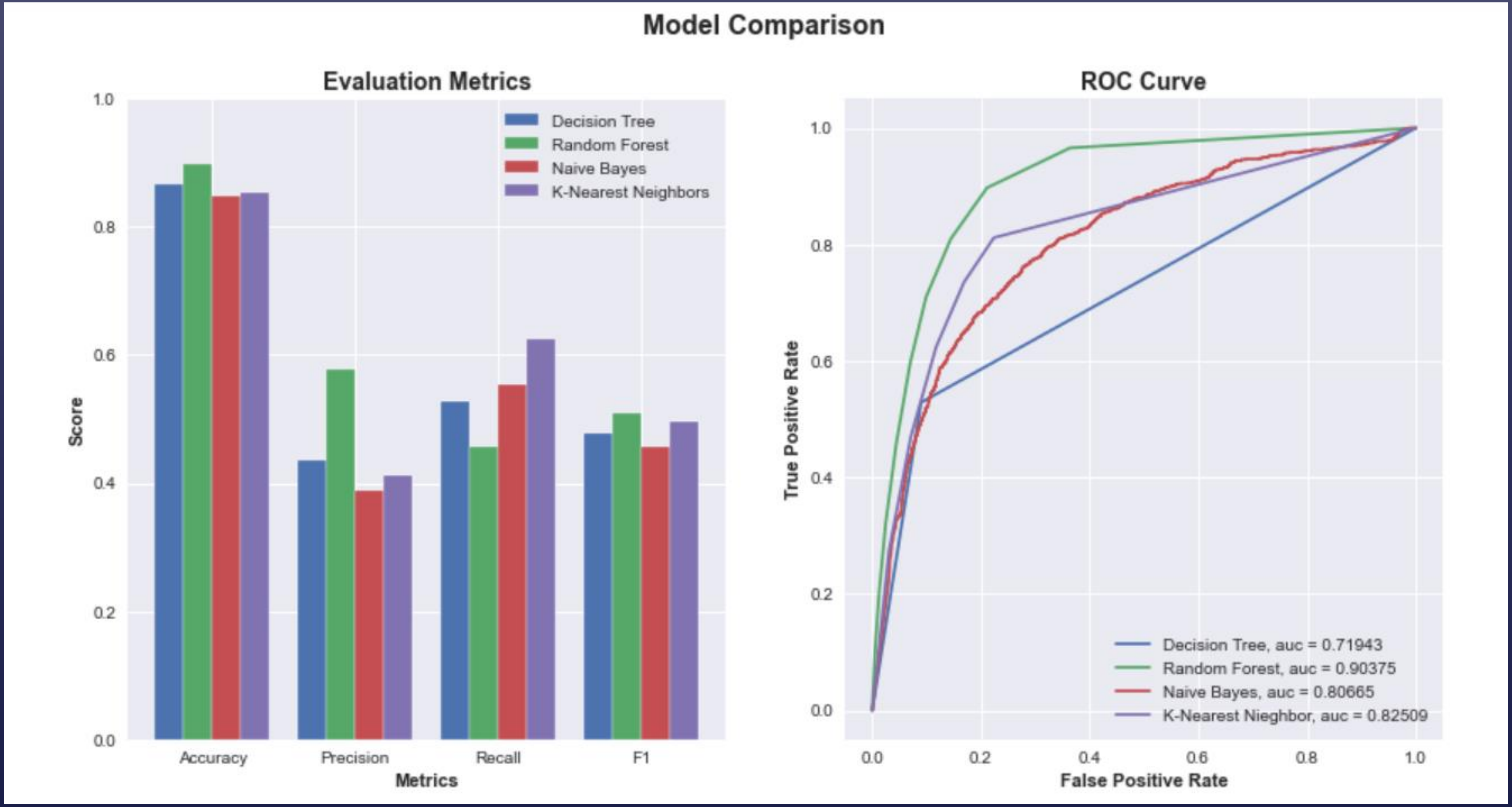
```
from sklearn.neighbors import KNeighborsClassifier

# Building KNN model
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
# Evaluate Model
knn_eval = evaluate_model(knn, X_test, y_test)

# Print result
print('Accuracy:', knn_eval['acc'])
print('Precision:', knn_eval['prec'])
print('Recall:', knn_eval['rec'])
print('F1 Score:', knn_eval['f1'])
print('Area Under Curve:', knn_eval['auc'])
print('Confusion Matrix:\n', knn_eval['cm'])
```

```
Accuracy: 0.8525931659847396
Precision: 0.41117388575015695
Recall: 0.6238095238095238
F1 Score: 0.4956488838441165
Area Under Curve: 0.8250911809738283
Confusion Matrix:
 [[7055  938]
 [ 395  655]]
```

Model Comparison



Model Evaluation and Selection

Classifier	Accuracy	Precision	recall	F1	ROC
Decision Tree	0.86	0.43	0.53	0.48	0.72
Random Forest	0.90	0.58	0.46	0.51	0.90
Naive Bayes	0.85	0.39	0.55	0.46	0.80
K-Nearest Neighbours	0.85	0.41	0.62	0.50	0.82

We select Random forest because it has the highest ROC, accuracy , Precision and F1

conclusion

For a simple model we can see that our model did decently on classifying the data. But there are still some weakness on our model, like recall metric where we only get about 62%. This means that our model are only able to detect 62% of potential customer and miss the other 38% in KNN. The best AUC score of 0.90 comes from Random Forest . The results of Decision Tree is less.

In these times of crisis preserving the relationship with best customers is more crucial than ever. Using these results bank can specifically target clients and gain higher success in their endeavours. Saving a lot of time by not focusing on clients with less probability is yet another advantages of this project.

References

Scikit-learn Documentation

The 5 Classification Evaluation metrics every Data Scientist must know

The Python Graph Gallery - Grouped Bar Plot

Bank Marketing Dataset | Kaggle

UCI Machine Learning Repository: Bank Marketing Data Set

Thank You