Predicting success for a bank telemarketing call

Siddarth Reddy Karuka

Final Project – Python for Data Science

Abstract

Telemarketing calls require a lot of resources, has very little success ratio, and can be annoying. Banks often make such telemarketing calls to advertise and to get customers to subscribe for their products. This project aims to predict the success of these telemarketing calls using the data available from UCI Machine Learning Repository. The project uses four different classification models, compares their outcomes and provides suggestion on model to be used. It is found that either Logistic Regression or k-neighbors classifier can be used depending on the business needs.

Motivation

- Telemarketers make an average of 300-500 calls in an eight-hour day
- Banking institutions are no exception
- Telemarketing calls are annoying when we receive too many of them

What if we can predict the success of a call?

- We can reduce the number of calls by calling only the ones that are likely to subscribe
- This means less calls for the telemarketer, and less annoying calls for the people who might not be interested – a win win situation that saves money and time for everyone involved

Dataset

- This project uses “Bank Marketing Data Set” from the UCI Machine Learning Repository.

Dataset information:

> *“ 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 ('yes') or not ('no') subscribed. ”*

- This dataset contains 41188 data points, with 20 input variables, and one output variable

Variables involved

Input variables:

- Bank client data:

  1 - age (numeric)
  2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')
  3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
  4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')
  5 - default: has credit in default? (categorical: 'no','yes','unknown')
  6 - housing: has housing loan? (categorical: 'no','yes','unknown')
  7 - loan: has personal loan? (categorical: 'no','yes','unknown')

- Related with the last contact of the current campaign:

  8 - contact: contact communication type (categorical: 'cellular','telephone')
  9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
  10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
  11 - duration: last contact duration, in seconds (numeric)

- 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: 'failure','nonexistent','success')

- Social and economic context attributes

  16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)
  17 - cons.price.idx: consumer price index - monthly indicator (numeric)
  18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)
  19 - euribor3m: euribor 3 month rate - daily indicator (numeric)
  20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):

21 - y - has the client subscribed a term deposit? (binary: 'yes','no')

Data preparation and exploration

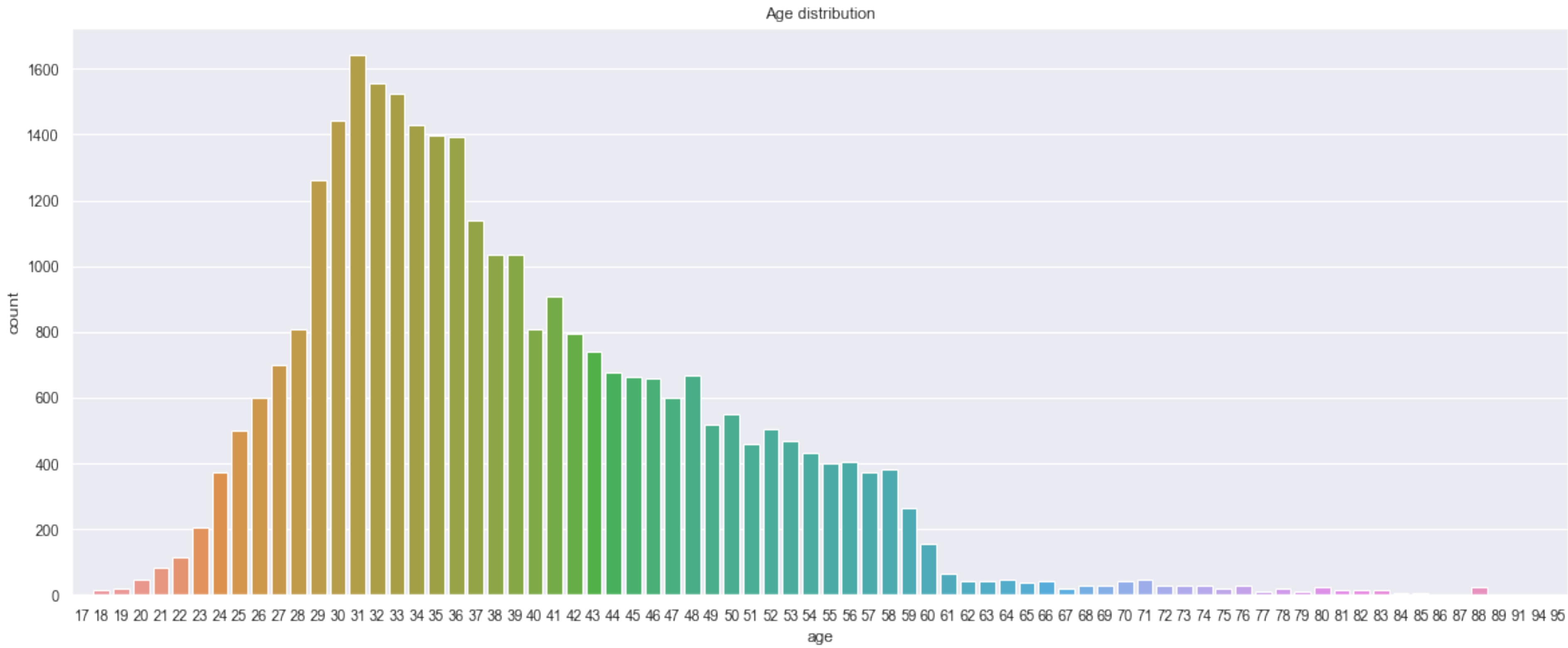
- Doesn't contain any empty fields, but has several "unknown" values in various fields
  - Deleted 10700 out of 41188 rows that contain "unknown" values

- Check for types of variables
  - Contains object, int64 and float64

- Look at the distribution of various parameters (graphs in the next few slides)
  - Age, Job, Marital status, Education
  - Check to see how much of our data has credit in default, has housing or personal loan
  - Duration of the telemarketing call

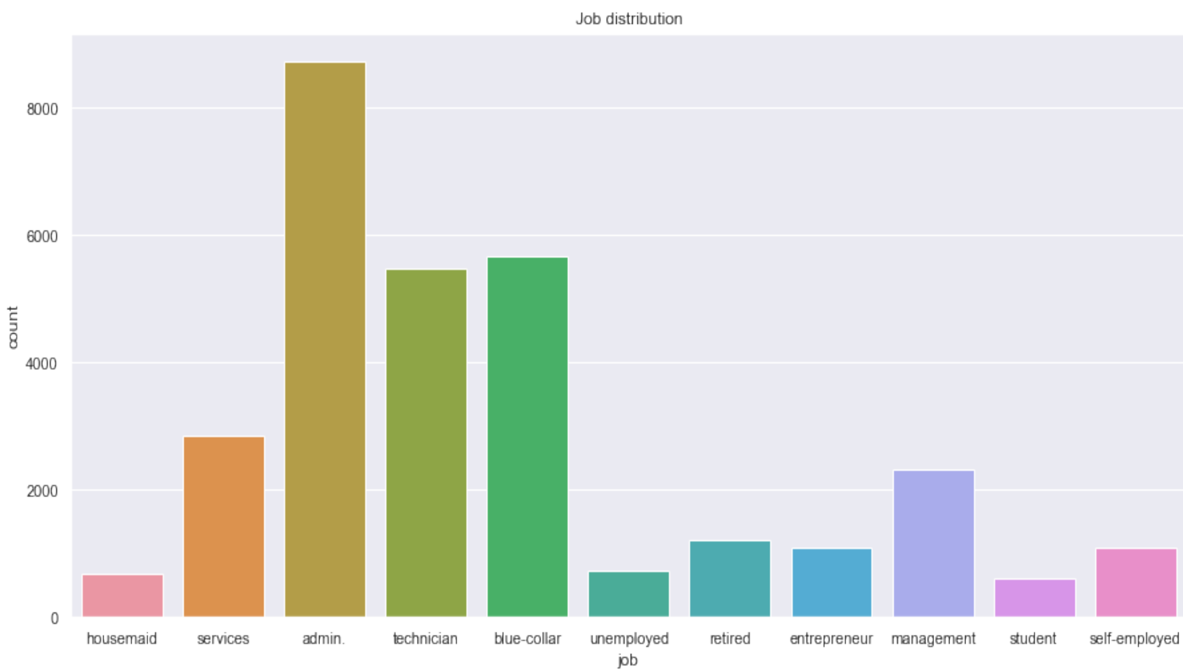
  (This basic exploration helped identify minor issues like having calls with zero seconds duration, which doesn't make sense when telemarketing)

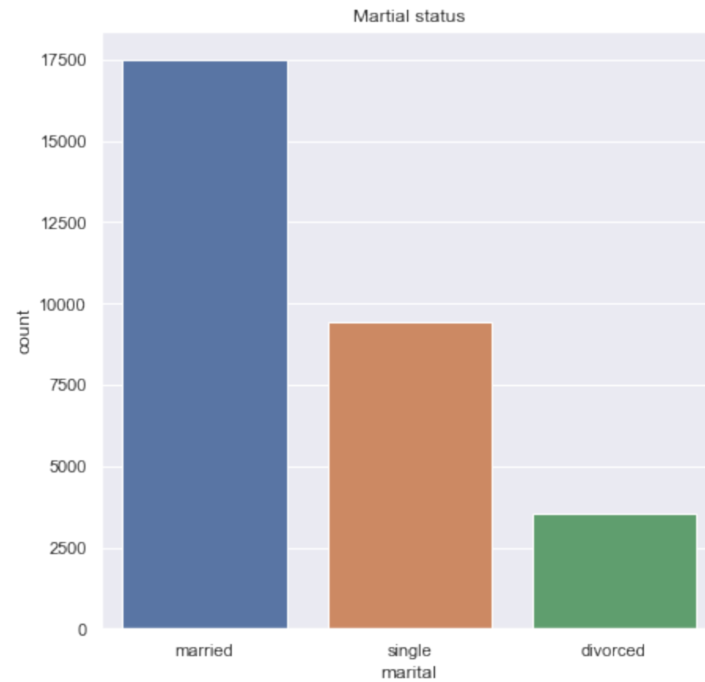
Exploratory figures



Age distributions shows that there's very few people above age 60 (probably the bank did not contact many people who retired), and none below age 18 (may be age restriction for opening an account). It looks like the bank targeted mid-career people

Exploratory figures

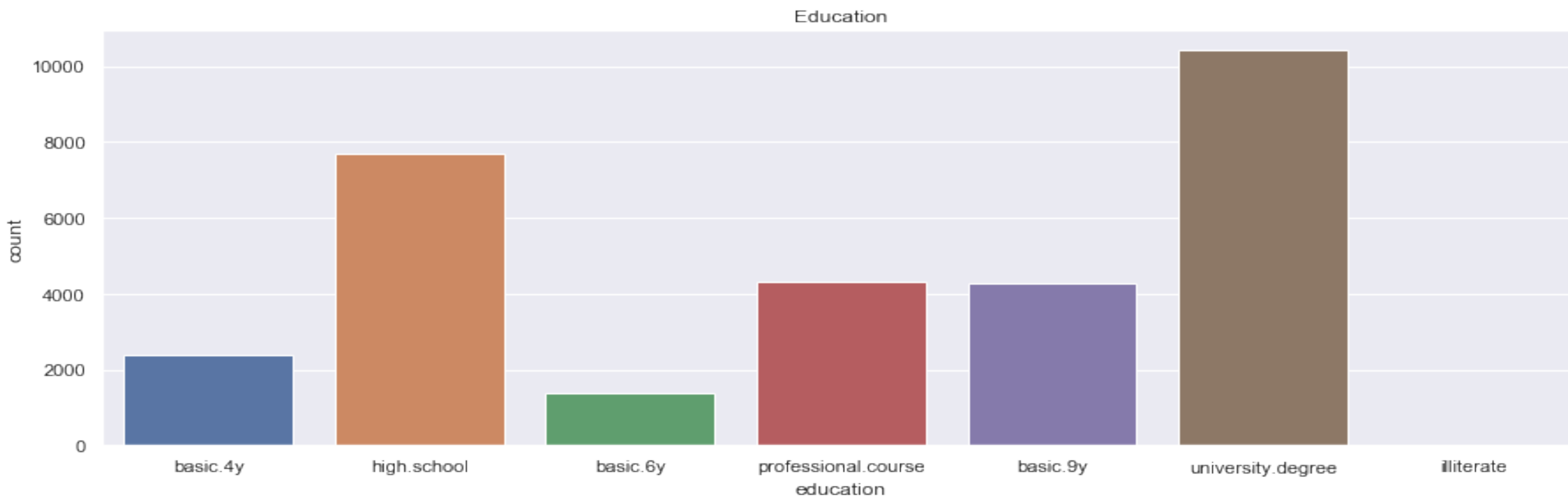




Most people who were contacted have administrative jobs, where as people who were unemployed or students or housemaids were on the lower end of the spectrum

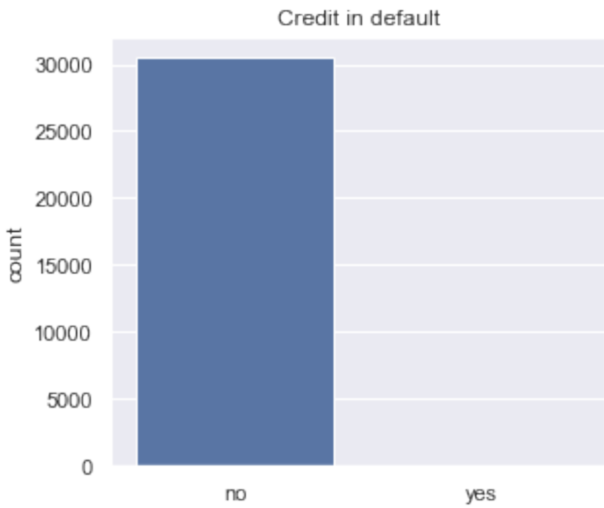
There are more married people in the database than singles and divorced combined.

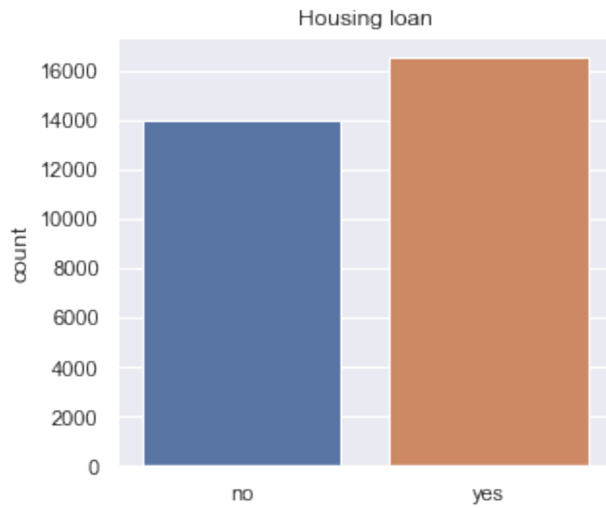
Exploratory figures

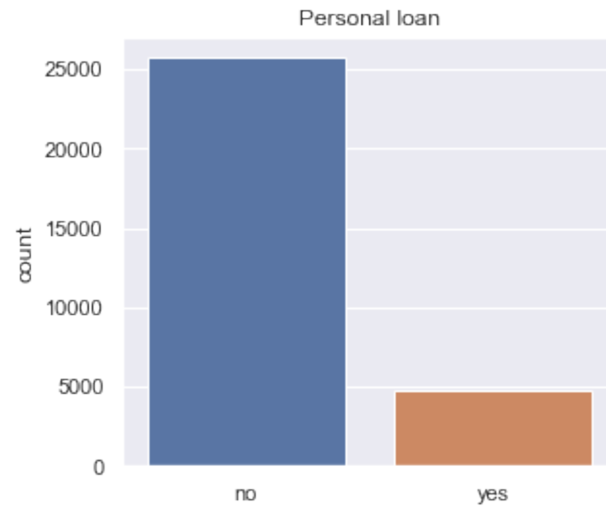


More than 10000 people had a university degree, where as only 11 people were illiterate

Exploratory figures

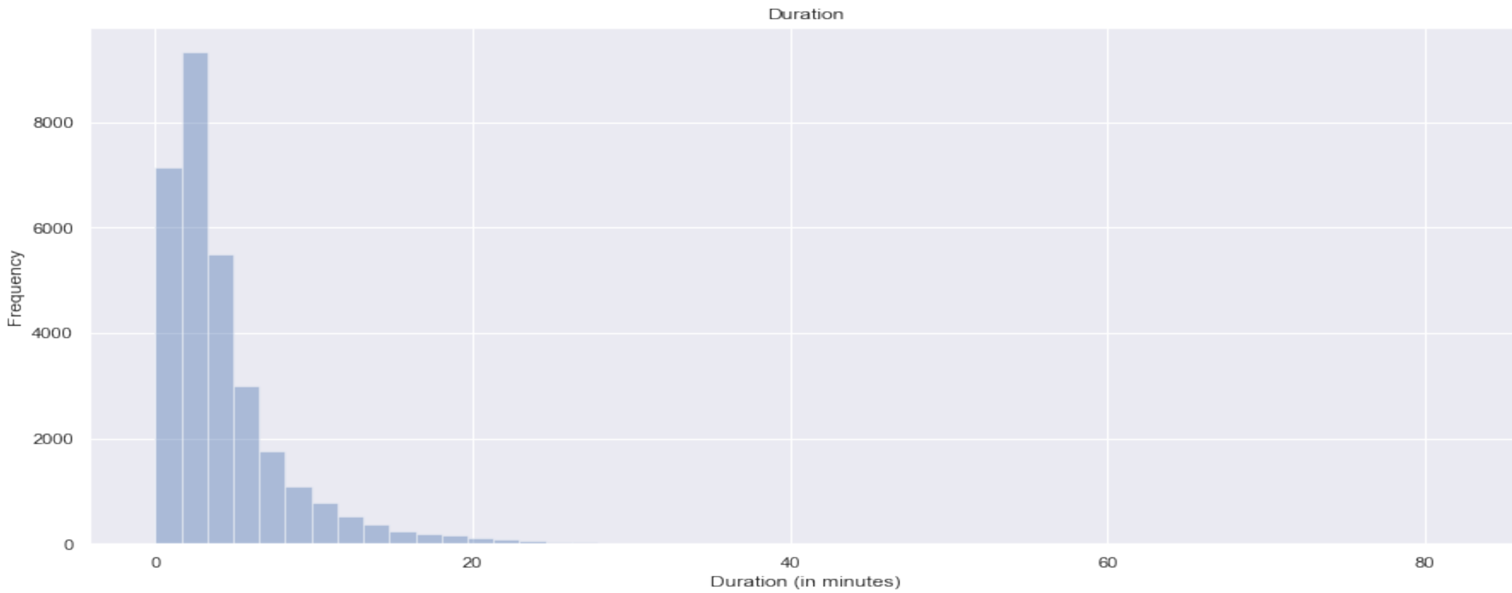






- Only 3 out of 30488 people had their credit in default
- More than half of the people had housing loan
- Very few people have a personal loan

Exploratory figures



The average call duration for these telemarketing calls is 4.32 minutes. The longest one was around 82 minutes, and the shortest reported ones are 0 seconds (4 entries with 0 seconds, not exactly sure how this can be classified as a telemarketing call – these four records are dropped)

Call duration isn't really a predictive variable as we won't know the value of this variable until the call is made, and we will know the output (success or failure) after the call. The "duration" variable is thus dropped out of the dataset

Research Questions

- Can we predict the success of a telemarketing call with the given parameters?
- If so, what model can we use and how much better would it be than the current scenario?

Methods - details

- Predicting success is a binary classification problem.

- Four classification models are employed and the outcomes are discussed
  1. Logistic Regression classifier
  2. k-neighbors classifier
  3. Random Forest classifier
  4. Decision Tree classifier

- Categorical variables were converted to numerical variables (using get_dummies) as most machine learning models can only deal with numerical values.

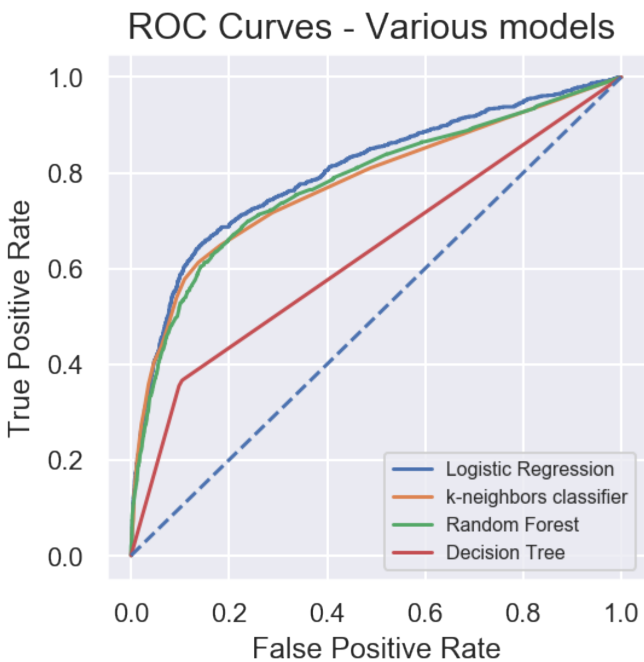
- The dataset is divided into training (75%) and testing (25%) sets, and the classification models are built upon the training set and used on the testing set to check for their performance.

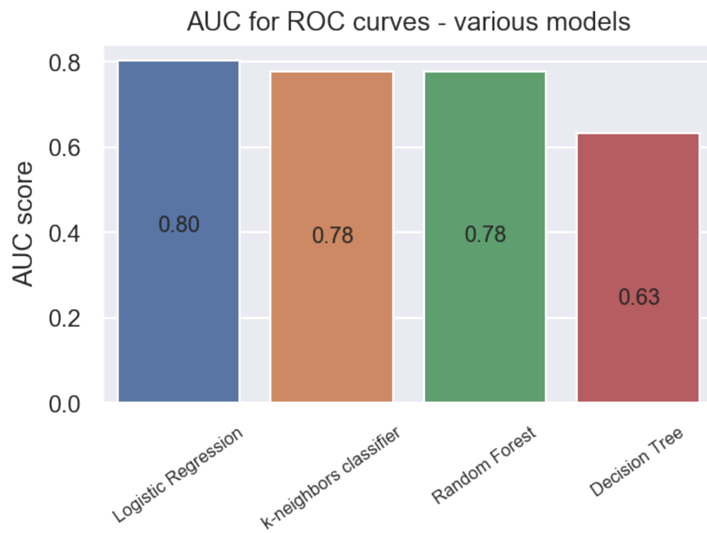
- Metrics like AUC-ROC score, accuracy_score, and confusion matrix are used to decide among the models

Methods - appropriateness

- Although there are several more classification models, only a few basic ones are used in this project.
- Machine learning models, such as the ones used here, have optimum performance when the dataset is a balanced one. However, the dataset we have here is imbalanced. (Only 12.6 % success)
- An appropriate fix to this problem would be to collect more data. But that's not a possibility for this project.
- An alternative would be to under-sample or over-sample the training data set. Under-sampling causes loss of information, so over-sampling is used here (Refer to SMOTE for more details)
- Converting categorical variables to numerical can be done in various ways (LabelEncoder or OneHotEncoder or get_dummies). This project uses get_dummies. Further discussion on appropriateness of this can be found in the documented ipython notebook
- Given variables were not on the same scale, so they were scaled using RobustScaler so that the predictive model can attribute equal weights to every variable.

Findings



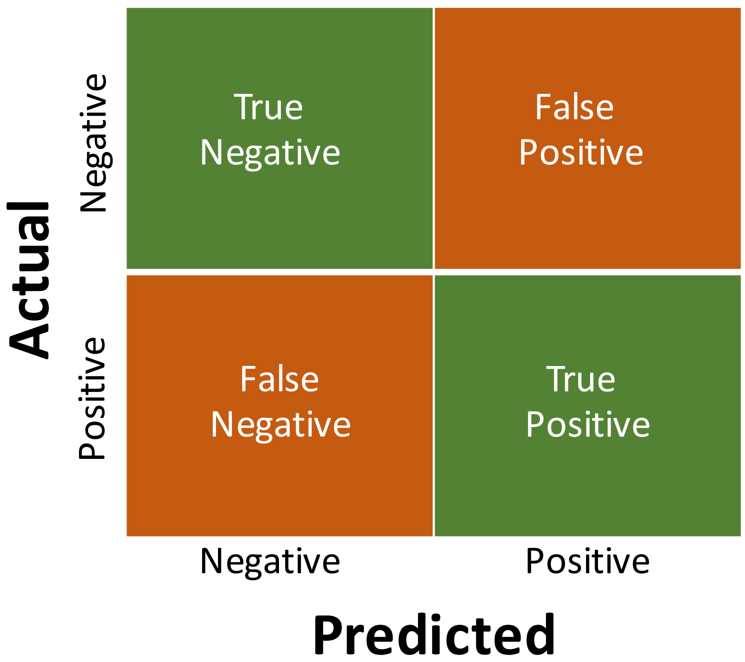


AUC score	Grade
0.90 – 1.00	Excellent
0.80 – 0.89	Good
0.70 – 0.79	Fair
0.50 – 0.69	Poor
0.00 – 0.49	Fail

An ROC (Receiver Operating Characteristic) curve tells us the ability of a model to distinguish true positives from false positives. More specifically, we can look at AUC (Area Under Curve) for this ROC and decide how good the model is. A 100% inaccurate model would have an AUC score of 0, a 100% accurate model would have an AUC score of 1, and a random distribution by chance would yield an AUC score of 0.5

In the above models, Logistic Regression has the best AUC score, but very close to k-neighbors classifier and Random Forest. The AUC score of Decision Tree classifier tells us that it isn't a good model for our project.

Confusion matrix



$$Accuracy = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

A confusion matrix is another metric that's regularly used for judging the performance of a model. The above figure indicates that k-neighbors classifier is the most accurate among the four models we have.

Further thoughts on model selection

Selecting a model just based on accuracy can cause harm in certain situations. In this particular situation, where a bank tries telemarketing to get a customer to subscribe for fixed term deposit, it is important to not lose customers.

In the previous slide, it was shown that the k-neighbors classifier is the most accurate among all the models. But if one chooses to go with the predictions of this model, the model would falsely predict the 724 customers (circled above) as people who wouldn't subscribe to the bank product, where as they were actually going to subscribe. So it is also important to take these losses into account when choosing a model

Comparing statistics

	Actual (test dataset)	Logistic Regression	K-neighbors classifier
Total calls made	7622	1801	416
Success %	13.1 %	37.3 % (~3 fold increase)	66.1 % (~5 fold increase)
Total duration of all calls	549 hours	130 hours (76% reduction)	30 hours (94% reduction)
# of customers / accounts gained	999	672 (32% loss)	275 (72% loss)

Limitations

- As shown in the previous slides, there's a trade off between accuracy and loss in customers
- A more sophisticated model (such as Neural Network) could probably perform better, so that's something that can be done as an extension to this project in the future
- These models were built upon an imbalanced dataset, so the appropriateness of these models can be questioned, but can be addressed as more data is collected.
- Various metrics are available for comparing models, so there might be more suitable metrics than the ones chosen here

Conclusions

So what model to use?

- The answer depends on various other factors. Further information is required to make this decision.
  - Is the business trying to expand?
  - What's the long term benefit from gaining a customer?
  - Is it trying to save money?
  - Does it cost more in telemarketing for 100 hours than it costs more in gaining 397 customers?
  - Would the business be more interested in not making unwanted telemarketing calls to save it's image?

- An appropriate response for the first two questions might require a Logistic Regression model, where as a focus on saving money/time/image based on the answers to the last three questions would require a k-neighbors classifier model

References

1. https://www.quora.com/How-many-calls-do-telemarketers-make-in-a-day
2. https://archive.ics.uci.edu/ml/datasets/Bank+Marketing?package=regsel&version=0.2
3. https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
4. https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html
5. https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
6. https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html
7. https://scikit-learn.org/stable/modules/generated/sklearn.metrics.auc.html
8. https://scikit-learn.org/stable/modules/generated/sklearn.metrics.accuracy_score.html
9. https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html
10. https://en.wikipedia.org/wiki/Confusion_matrix
11. https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.SMOTE.html
12. https://seaborn.pydata.org/
13. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html
14. http://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.get_dummies.html
15. https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html
16. https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.LabelEncoder.html
17. https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.RobustScaler.html
18. https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html

Predicting if a Customer Subscribes for Fixed Term Deposit - Bank Telemarketing

Project by Siddarth Karuka

Data Source: https://archive.ics.uci.edu/ml/datasets/Bank+Marketing#
(https://archive.ics.uci.edu/ml/datasets/Bank+Marketing#)

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
import seaborn as sns
from matplotlib.pyplot import figure
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score,
precision_recall_curve, average_precision_score
sns.set()
```

In [2]:
```
data = pd.read_csv('./bank-additional/bank-additional-full.csv',delimite
r=';')
```

Input variables:

Bank client data:

1 - age (numeric)

2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')

3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)

4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

5 - default: has credit in default? (categorical: 'no','yes','unknown')

6 - housing: has housing loan? (categorical: 'no','yes','unknown')

7 - loan: has personal loan? (categorical: 'no','yes','unknown')

Related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: 'cellular','telephone')

9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')

10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

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: 'failure','nonexistent','success')

Social and economic context attributes:

16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)

17 - cons.price.idx: consumer price index - monthly indicator (numeric)

18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)

19 - euribor3m: euribor 3 month rate - daily indicator (numeric) [More info here (https://www.euribor-rates.eu/)](https://www.euribor-rates.eu/)

20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):

21 - y - has the client subscribed a term deposit? (binary: 'yes','no')

In [3]:
```
data.head()
```

Out[3]:

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

5 rows × 21 columns

In [4]:
```
data.shape
```

Out[4]:
```
(41188, 21)
```

```
In [5]: data.isna().any()
```

```
Out[5]: age               False
        job               False
        marital           False
        education         False
        default           False
        housing           False
        loan              False
        contact           False
        month             False
        day_of_week       False
        duration          False
        campaign          False
        pdays             False
        previous          False
        poutcome          False
        emp.var.rate      False
        cons.price.idx    False
        cons.conf.idx     False
        euribor3m         False
        nr.employed       False
        y                 False
        dtype: bool
```

No NANs or empty fields

But we can see fields with "unknown" values, which I would like to remove from my data

---

In [6]:
```
data.dtypes
```

Out[6]:
```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
dtype: object
```

In [7]:
```
objects_list = ['job','marital','education','default','housing','loan',
'contact','month','day_of_week',
               'poutcome','y']
```

In [8]:
```
mask = np.column_stack([data[col].str.contains(r"unknown", na=False) for
col in objects_list])
unknown_data=data.loc[mask.any(axis=1)]
unknown_data.shape
```

Out[8]:
```
(10700, 21)
```

It looks like 10700 out of 41188 rows have some column with an unknown value.

It's better to remove all those rows as to not affect my data analysis

---

In [9]:
```
clean_data = data
clean_data=clean_data.drop(unknown_data.index)
clean_data.shape
```

Out[9]:
```
(30488, 21)
```

check that clean_data no longer has any rows with "unknown" values:

In [10]:
```
new_mask = np.column_stack([clean_data[col].str.contains(r"unknown", na=
False) for col in objects_list])
clean_data.loc[new_mask.any(axis=1)]
```

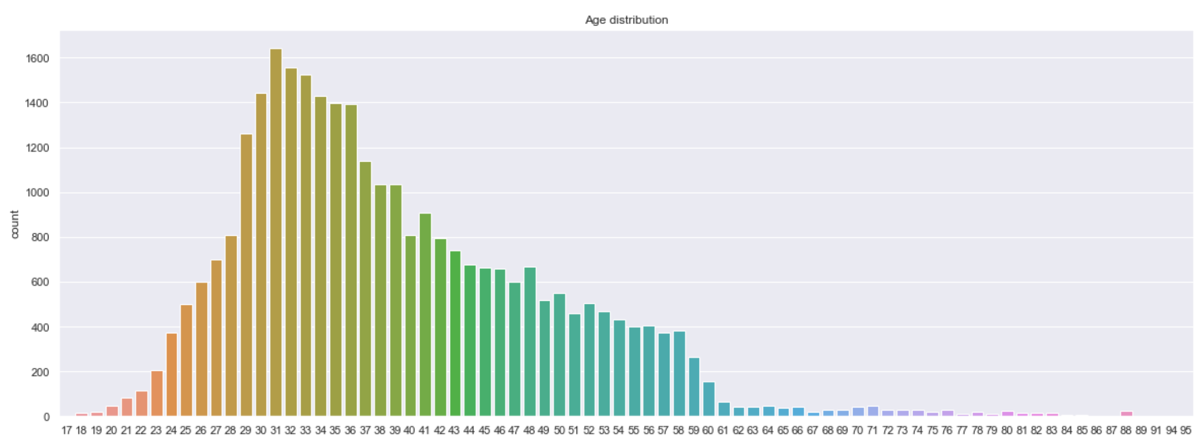
Out[10]:

age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campai

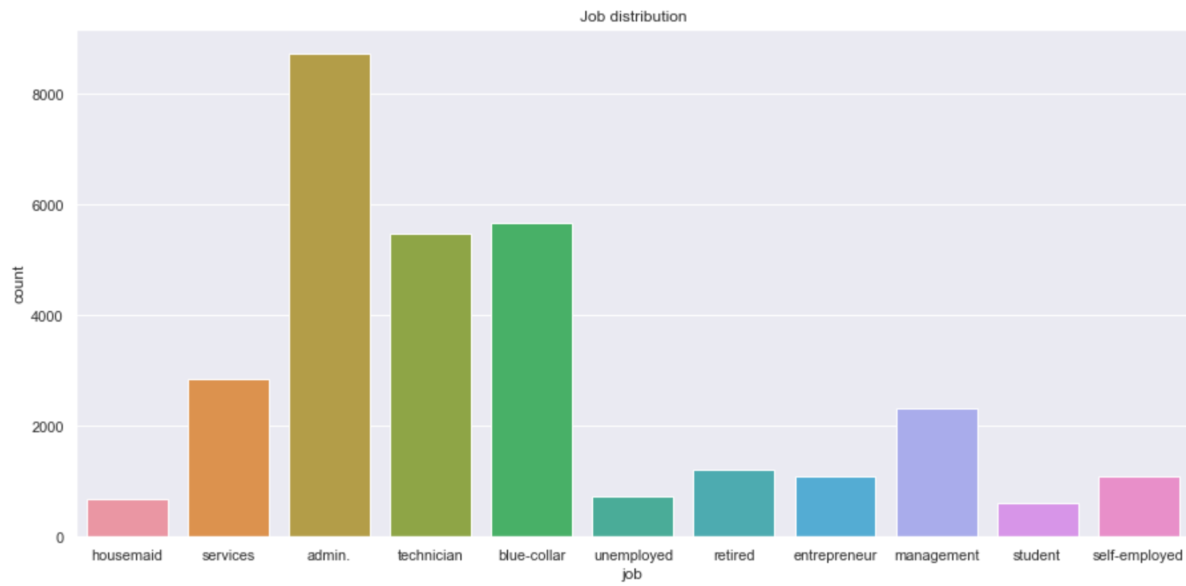
0 rows × 21 columns

Explore bank client data

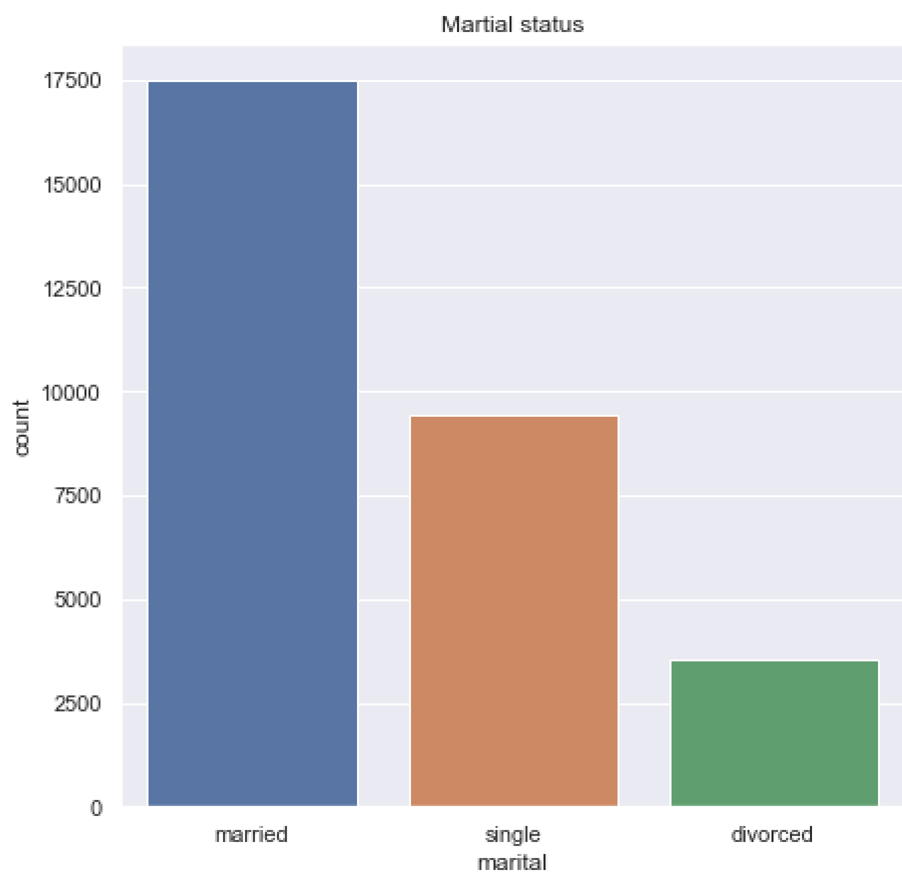
In [11]:
```
plt.figure(figsize=(20,7))
sns.countplot(clean_data.age)
plt.title('Age distribution');
```



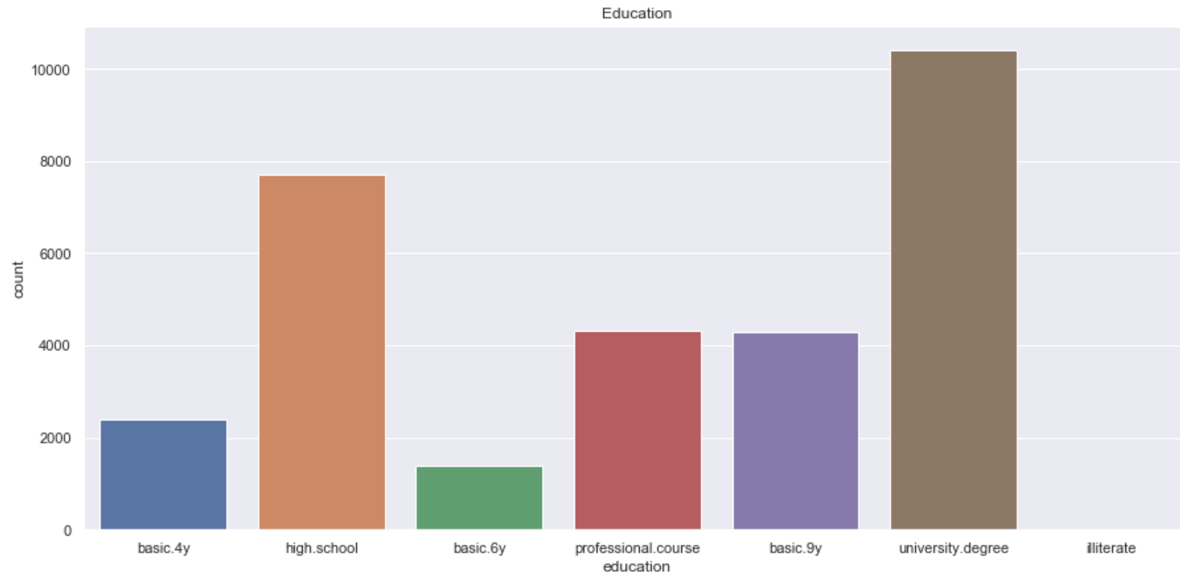
In [12]:
```
plt.figure(figsize=(15,7))
sns.countplot(clean_data.job)
plt.title('Job distribution');
```



In [13]:
```
plt.figure(figsize=(7,7))
sns.countplot(clean_data.marital)
plt.title('Martial status');
```



In [14]:
```
plt.figure(figsize=(15,7))
sns.countplot(clean_data.education)
plt.title('Education');
```



In [15]:
```
# check to see if there's a non-zero number in illiterate column as the
 bar isn't visually identifiable
clean_data.education.value_counts()
```

Out[15]:
```
university.degree      10412
high.school             7699
professional.course     4321
basic.9y                4276
basic.4y                2380
basic.6y                1389
illiterate                11
Name: education, dtype: int64
```

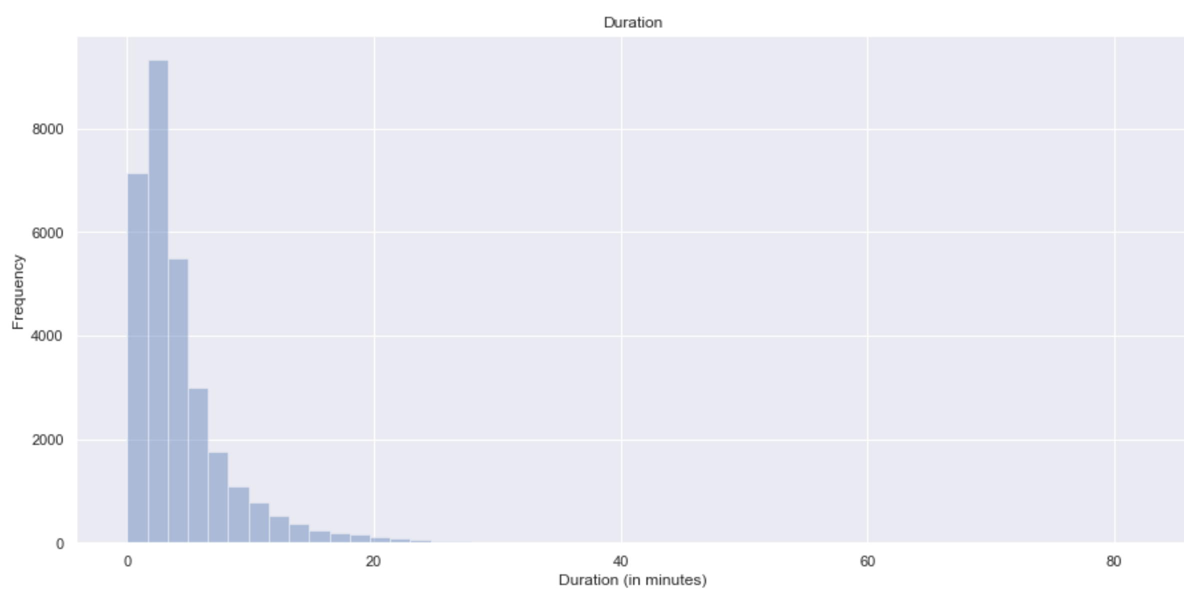
In [16]:
```
fig,ax = plt.subplots(1,3,figsize=(16, 5))
sns.countplot(clean_data.default,ax=ax[0])
sns.countplot(clean_data.housing,ax=ax[1])
sns.countplot(clean_data.loan,ax=ax[2])
ax[0].set(title='Credit in default',xlabel='')
ax[1].set(title='Housing loan',xlabel='')
ax[2].set(title='Personal loan',xlabel='')
plt.subplots_adjust(wspace=0.25);
```

Non-predictive variable

Call duration isn't really a predictive variable as one wouldn't know the value of this variable before making a telemarketing call, and one would the result after making the call. So we need to drop this from our list of variables that we use to build a predictive model. But first let's take a look at the distribution

In [17]:
```
plt.figure(figsize=(15,7))
ax=sns.distplot(clean_data['duration']/60, kde=False)
plt.title('Duration')
ax.set(ylabel='Frequency',xlabel='Duration (in minutes)');
```

```
/Users/Siddarth/anaconda3/lib/python3.7/site-packages/scipy/stats/stat
s.py:1713: FutureWarning: Using a non-tuple sequence for multidimension
al indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`.
In the future this will be interpreted as an array index, `arr[np.array
(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [18]:
```
clean_data.duration.describe()
```

Out[18]:
```
count    30488.000000
mean       259.484092
std        261.714262
min          0.000000
25%        103.000000
50%        181.000000
75%        321.000000
max       4918.000000
Name: duration, dtype: float64
```

In [19]:
```
print((clean_data.duration == 0).value_counts())
clean_data[clean_data.duration == 0]
```

```
False    30484
True         4
Name: duration, dtype: int64
```

Out[19]:

	age	job	marital	education	default	housing	loan	contact	month	da
6251	39	admin.	married	high.school	no	yes	no	telephone	may	
23031	59	management	married	university.degree	no	yes	no	cellular	aug	
28063	53	blue-collar	divorced	high.school	no	yes	no	cellular	apr	
33015	31	blue-collar	married	basic.9y	no	no	no	cellular	may	

4 rows × 21 columns

Maximum call duration is 81.96 minutes, with the average being 4.32 minutes.

Also, it appears that there are 4 calls with 0 seconds duration. Not sure how this can be taken into account. Let's drop these rows, and the duration column entirely

In [20]:
```
clean_data=clean_data.drop(columns=['duration'])
```

Convert categorical to numerical

In the next step I would like to convert all categorical values to numerical values. There are a few ways to do this that I know of:

- LabelEncoder from sklearn
- OneHotEncoder from sklearn
- get_dummies from pandas

Using LabelEncoder can introduce unwanted patterns for machine learning purposes. OneHotEncoder and get_dummies are similar from my understanding, but the difference would be in what they convert. OneHotEncoder can't process strings, so one has to go through both LabelEncoder followed by OneHotEncoder.

I'll use get_dummies

In [21]:
```
clean_data.head()
```

Out[21]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	
2	37	services	married	high.school	no	yes	no	telephone	may	
3	40	admin.	married	basic.6y	no	no	no	telephone	may	
4	56	services	married	high.school	no	no	yes	telephone	may	
6	59	admin.	married	professional.course	no	no	no	telephone	may	

In [22]:
```
# Exclude target variable
numerical_clean_data = pd.get_dummies(clean_data.loc[:,clean_data.column
s!='y'])
```

In [23]:
```
# join target variable
numerical_clean_data['y']=clean_data.loc[:,'y']
```

I'll use LabelEncoder to the target variable (Yes = 1, No = 0), as using get_dummies creates two columns with redundant information (basically the two columns will complement each other), and we can use either of these to predict the sucess of a telemarketing call

---

In [24]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
numerical_clean_data['y'] = le.fit_transform(numerical_clean_data['y'])
```

In [25]:
```
numerical_clean_data.head()
```

Out[25]:

	age	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.em
0	56	1	999	0	1.1	93.994	-36.4	4.857	
2	37	1	999	0	1.1	93.994	-36.4	4.857	
3	40	1	999	0	1.1	93.994	-36.4	4.857	
4	56	1	999	0	1.1	93.994	-36.4	4.857	
6	59	1	999	0	1.1	93.994	-36.4	4.857	

5 rows × 57 columns

In [26]:
```
numerical_clean_data.pdays.value_counts()
```

Out[26]:
```
999    29178
3        381
6        363
4        102
2         53
9         53
12        50
7         50
5         43
10        40
13        33
11        25
15        22
1         21
14        17
0         14
8         13
16         8
17         6
18         5
19         3
22         3
21         2
25         1
26         1
27         1
Name: pdays, dtype: int64
```

Scaling of factors

The factors that we use for predicting the outcome have different ranges of possible values. It would be better if we scale them so that one particular varibale doesn't dominate due to the range of numerical values it has.

There are two types of scalers available in sklearn

- StandardScaler
- RobustScaler

StandardScaler used the mean and standard deviation, where as RobustScaler uses Median and Quartiles. RobustScaler can deal with outliers more effectively than the StandardScaler

---

Scaling should be performed after splitting the data into train and test sets, as test set would include data that the model shouldn't have seen before (and including this in scaling would affect the scaling criteria)

In [27]:
```python
X = numerical_clean_data.loc[:,numerical_clean_data.columns!='y']
y = numerical_clean_data.loc[:,'y']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25
, random_state = 7);
```

In [28]:
```python
from sklearn.preprocessing import StandardScaler,RobustScaler
rb_sc = RobustScaler()
st_sc = StandardScaler()
X_train  = rb_sc.fit_transform(X_train[X_train.columns])
X_test = rb_sc.transform(X_test[X_test.columns]);
# Notice the use of same scaling for test data set (using transform inst
ead of fit_transform)
```

In [29]:
```python
X_train
```

Out[29]:
```
array([[-1.42857143e-01, -5.00000000e-01,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-1.42857143e-01,  0.00000000e+00,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-7.14285714e-02,  5.00000000e-01,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       ...,
       [ 0.00000000e+00, -5.00000000e-01,  0.00000000e+00, ...,
         1.00000000e+00, -1.00000000e+00,  0.00000000e+00],
       [ 1.28571429e+00, -5.00000000e-01,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [ 1.35714286e+00,  0.00000000e+00, -9.90000000e+02, ...,
         1.00000000e+00, -1.00000000e+00,  0.00000000e+00]])
```

Before we train a model, let us check how the target variable is distributed. More specifically, we want to see if the data set is a balanaced one, i.e., if the success and failure occur at approximately the same scale.

In [30]:
```python
numerical_clean_data['y'].value_counts()
```

Out[30]:
```
0    26629
1     3859
Name: y, dtype: int64
```

It appears that the data is imbalanced, having only a few successful telemarketing calls compared to the failures. We will need to balance the training set so that the model doesn't get skewed. (Note: We only balance the training set, as balancing the entire dataset doesn't represent the real data set, and our model would perform poorly upon testing)

In [31]:
```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=12, ratio = 1.0)
X_train_sm, y_train_sm = sm.fit_sample(X_train, y_train)
```

In [32]:
```
print('Training data before Over Sampling: \n',y_train.value_counts())
```

```
Training data before Over Sampling:
 0    20006
1     2860
Name: y, dtype: int64
```

In [33]:
```
unique, counts = np.unique(y_train_sm, return_counts=True)
print('Training data after Over Sampling: \n',unique, counts)
```

```
Training data after Over Sampling:
 [0 1] [20006 20006]
```

In [34]:
```
y_test.value_counts()
```

Out[34]:
```
0    6623
1     999
Name: y, dtype: int64
```

Logistic Regression

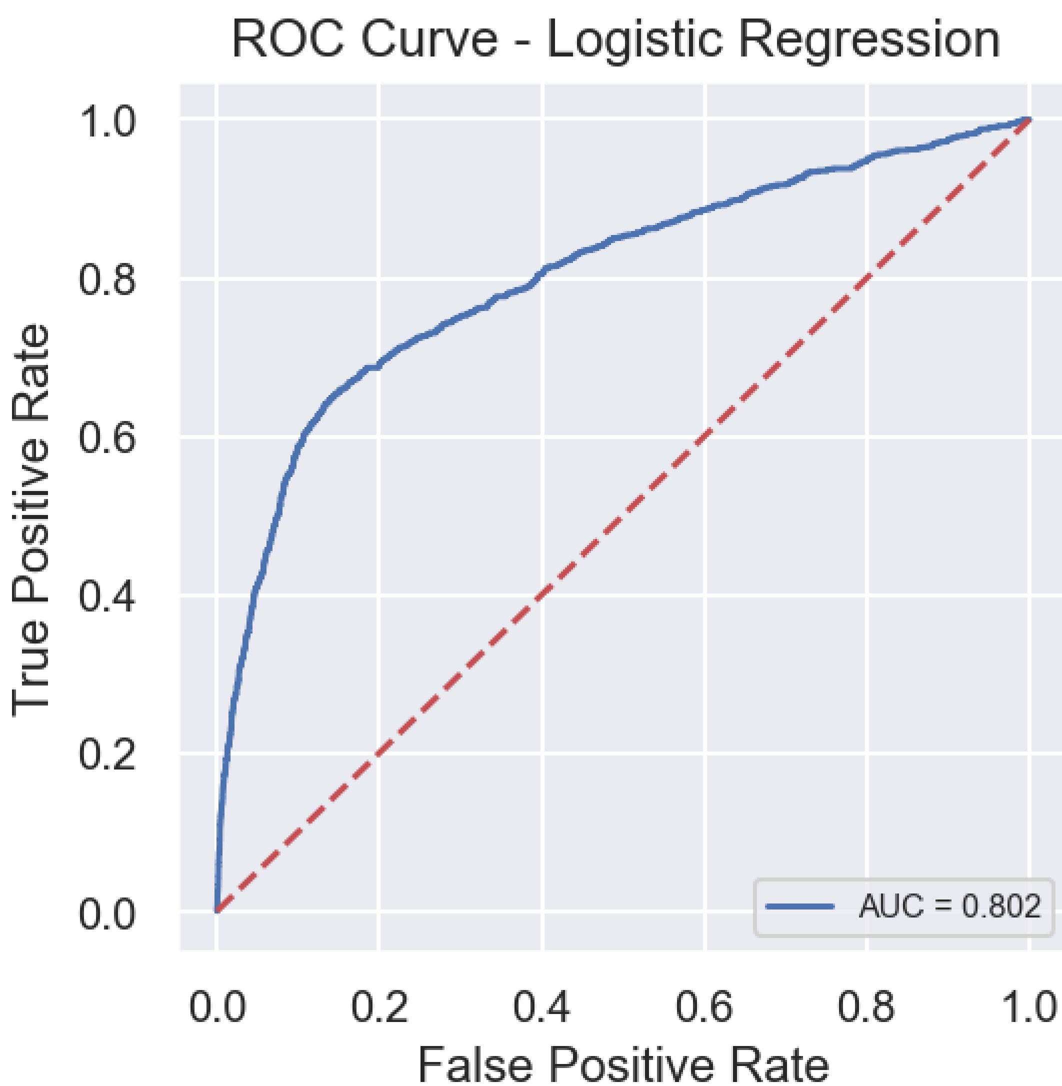
[Logistic Regression (aka logit, MaxEnt) classifier (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html).

In [35]:
```
from sklearn.linear_model import LogisticRegression
model_log = LogisticRegression(fit_intercept=False,solver='liblinear')
model_log.fit(X_train_sm,y_train_sm)
model_log_pred = model_log.predict(X_test)
```

In [36]:
```
print('accuracy score: ',accuracy_score(y_true = y_test, y_pred = model_
log_pred))
print('precision score: ',precision_score(y_true = y_test, y_pred = mode
l_log_pred))
conf_m_log = confusion_matrix(y_test,model_log_pred)
print('confusion matrix: \n',conf_m_log)
```

```
accuracy score:  0.8089740225662556
precision score:  0.3731260410882843
confusion matrix:
 [[5494 1129]
 [ 327  672]]
```

In [37]:
```
figure(figsize=(4, 4),dpi=144)
from sklearn import metrics
prob_log = model_log.predict_proba(X_test)
pred_log = prob_log[:,1]
fpr_log, tpr_log, threshold_log = roc_curve(y_test, pred_log)
roc_auc_log = metrics.auc(fpr_log, tpr_log)
plt.plot(fpr_log, tpr_log, 'b', label = 'AUC = %0.3f' % roc_auc_log)
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC Curve - Logistic Regression ',fontsize=13)
plt.ylabel('True Positive Rate',fontsize=12)
plt.xlabel('False Positive Rate',fontsize=12)
plt.legend(loc = 'lower right', prop={'size': 8});
```



k-neighbors classifier

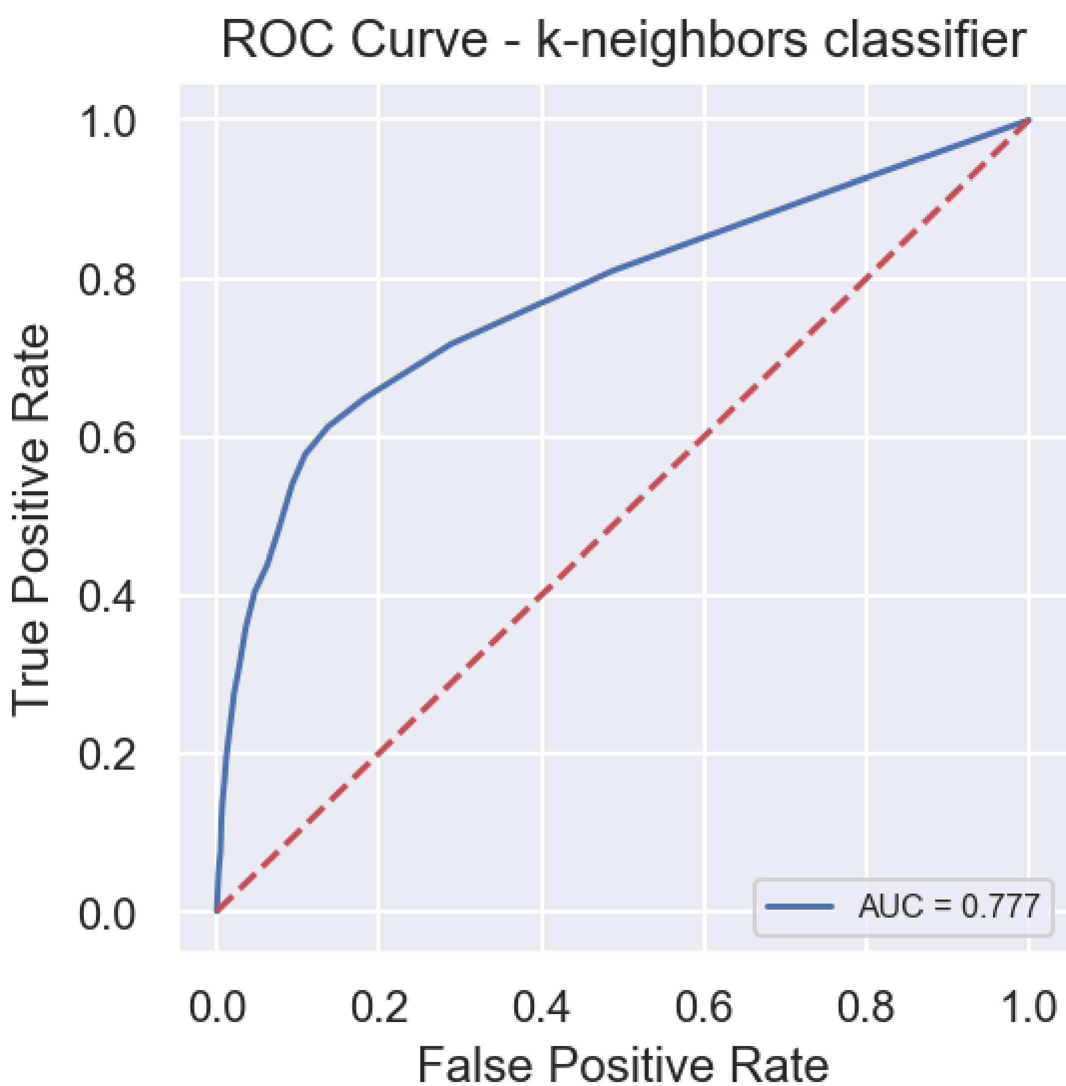
[Classifier implementing the k-nearest neighbors vote (https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html)](https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html).

In [38]:
```
from sklearn.neighbors import KNeighborsClassifier
model_knn = KNeighborsClassifier(n_neighbors=25)
model_knn.fit(X_train, y_train)
model_knn_pred = model_knn.predict(X_test)
```

In [39]:
```
print('accuracy score: ',accuracy_score(y_true = y_test, y_pred = model_
knn_pred))
print('precision score: ',precision_score(y_true = y_test, y_pred = mode
l_knn_pred))
conf_m_knn = confusion_matrix(y_test,model_knn_pred)
print('confusion matrix: \n',conf_m_knn)
```

```
accuracy score:  0.8865127263185516
precision score:  0.6610576923076923
confusion matrix: 
 [[6482  141]
 [ 724  275]]
```

In [40]:
```
figure(figsize=(4, 4),dpi=144)
prob_knn = model_knn.predict_proba(X_test)
pred_knn = prob_knn[:,1]
fpr_knn, tpr_knn, threshold_knn = roc_curve(y_test, pred_knn)
roc_auc_knn = metrics.auc(fpr_knn, tpr_knn)
plt.plot(fpr_knn, tpr_knn, 'b', label = 'AUC = %0.3f' % roc_auc_knn)
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC Curve - k-neighbors classifier',fontsize=13)
plt.ylabel('True Positive Rate',fontsize=12)
plt.xlabel('False Positive Rate',fontsize=12)
plt.legend(loc = 'lower right', prop={'size': 8});
```



Random Forest

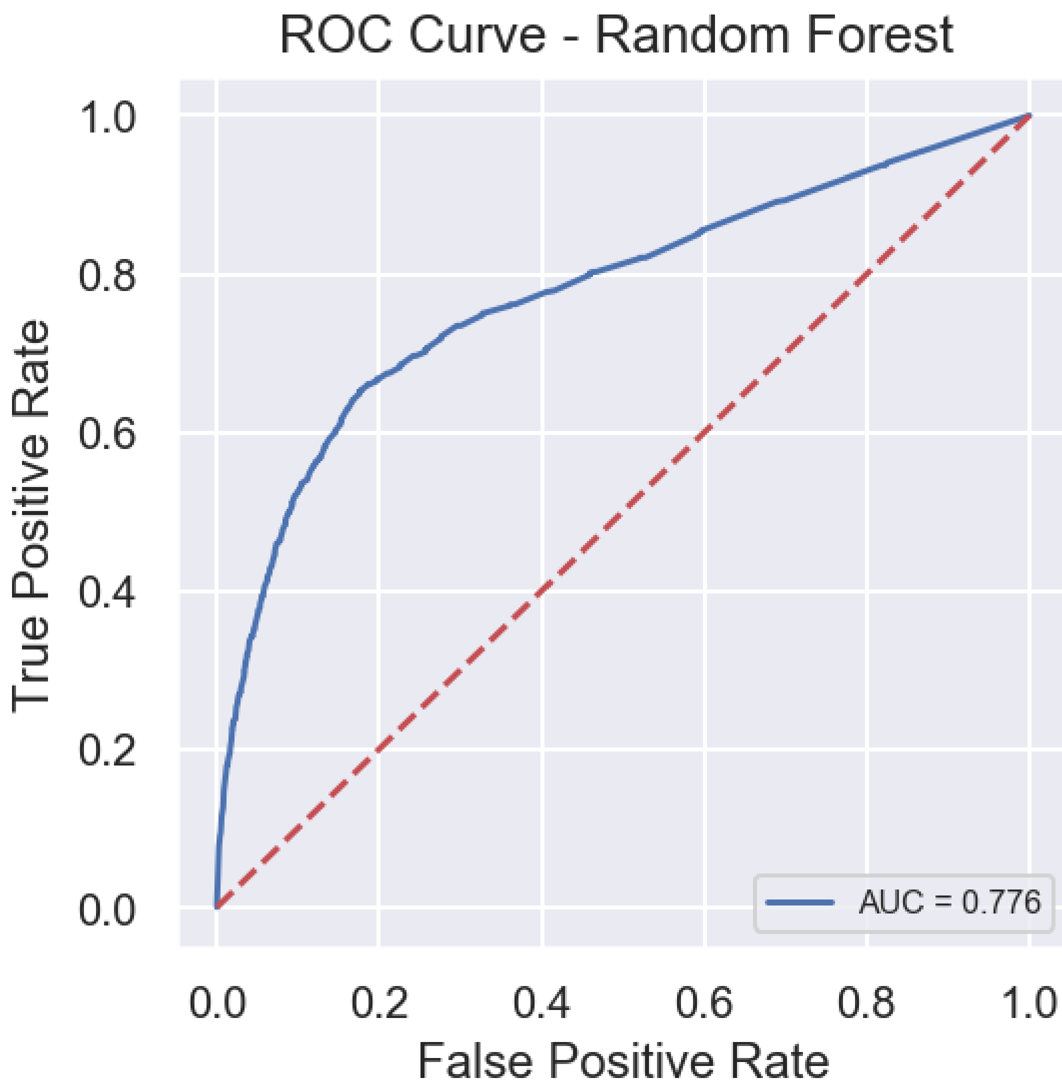
[A random forest classifier (https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html)](https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html).

In [41]:
```
from sklearn.ensemble import RandomForestClassifier
model_rfc = RandomForestClassifier(n_estimators = 100)
model_rfc.fit(X_train, y_train)
model_rfc_pred = model_rfc.predict(X_test)
```

In [42]:
```
print('accuracy score: ',accuracy_score(y_true = y_test, y_pred = model_
rfc_pred))
print('precision score: ',precision_score(y_true = y_test, y_pred = mode
l_rfc_pred))
conf_m_rfc = confusion_matrix(y_test,model_rfc_pred)
print('confusion matrix: \n',conf_m_rfc)
```

```
accuracy score:  0.8785095775387037
precision score:  0.564373897707231
confusion matrix:
 [[6376  247]
 [ 679  320]]
```

```
In [43]: figure(figsize=(4, 4),dpi=144)
prob_rfc = model_rfc.predict_proba(X_test)
pred_rfc = prob_rfc[:,1]
fpr_rfc, tpr_rfc, threshold_rfc = roc_curve(y_test, pred_rfc)
roc_auc_rfc = metrics.auc(fpr_rfc, tpr_rfc)
plt.plot(fpr_rfc, tpr_rfc, 'b', label = 'AUC = %0.3f' % roc_auc_rfc)
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC Curve - Random Forest ',fontsize=13)
plt.ylabel('True Positive Rate',fontsize=12)
plt.xlabel('False Positive Rate',fontsize=12)
plt.legend(loc = 'lower right', prop={'size': 8});
```



Decision Tree

[A decision tree classifier (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html)](https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html).

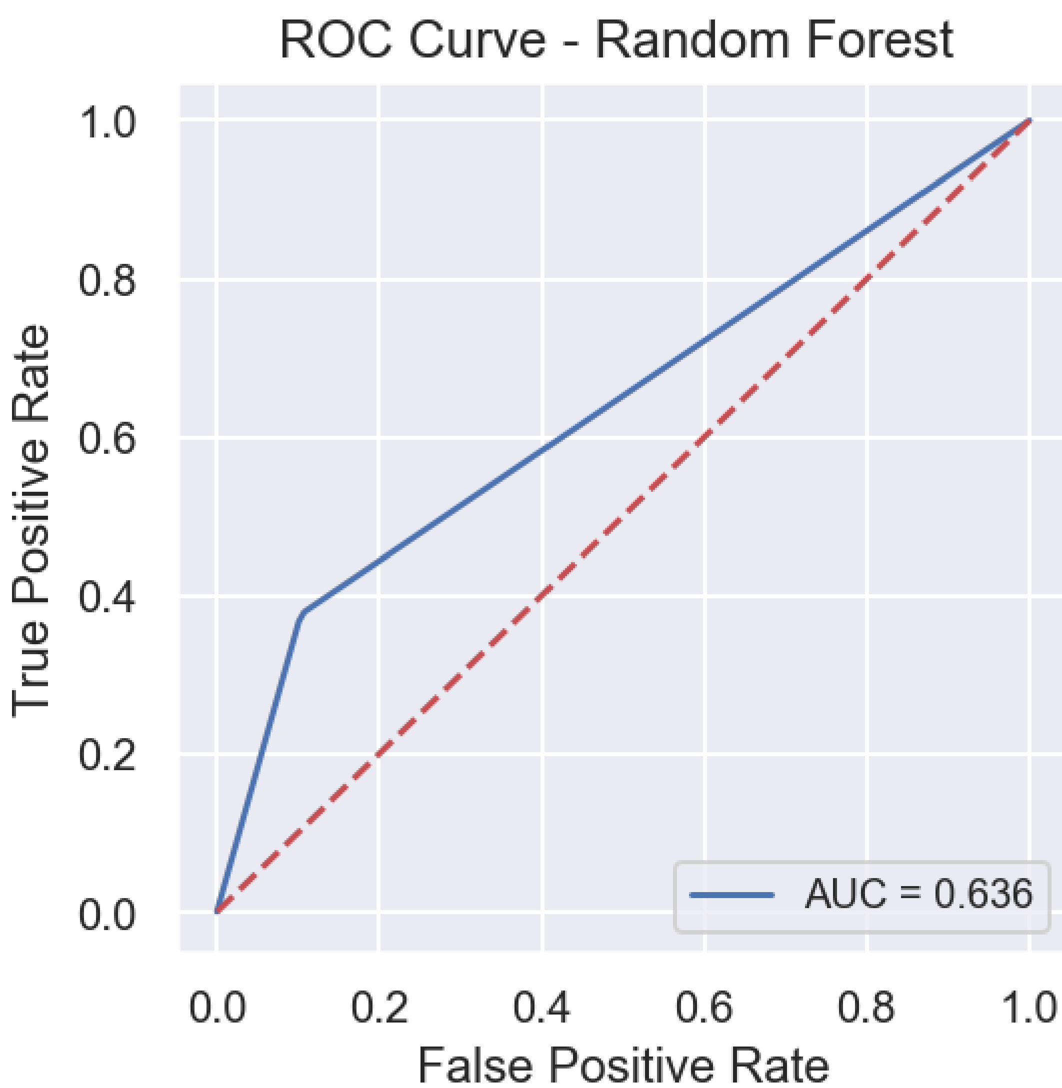
In [44]:
```
from sklearn.tree import DecisionTreeClassifier
model_dtree = DecisionTreeClassifier(criterion='gini')
model_dtree.fit(X_train, y_train)
model_dtree_pred = model_dtree.predict(X_test)
```

In [45]:
```
print('accuracy score: ',accuracy_score(y_true = y_test, y_pred = model_
dtree_pred))
print('precision score: ',precision_score(y_true = y_test, y_pred = mode
l_dtree_pred))
conf_m_dtree = confusion_matrix(y_test,model_dtree_pred)
print('confusion matrix: \n',conf_m_dtree)
```

```
accuracy score:  0.8293098924166885
precision score:  0.35424710424710426
confusion matrix: 
 [[5954  669]
 [ 632  367]]
```

In [46]:

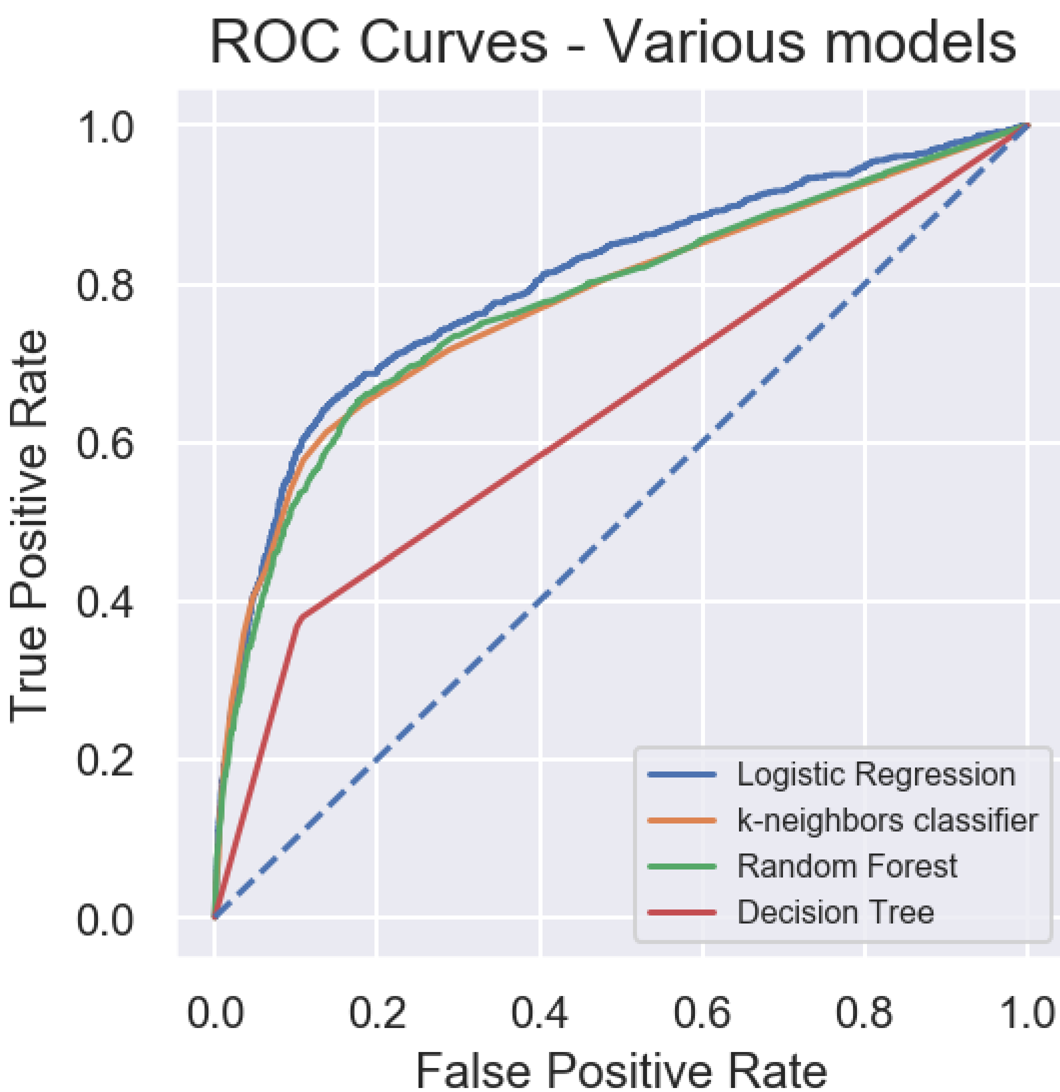
```
figure(figsize=(4, 4),dpi=144)
prob_dtree = model_dtree.predict_proba(X_test)
pred_dtree = prob_dtree[:,1]
fpr_dtree, tpr_dtree, threshold_dtree = roc_curve(y_test, pred_dtree)
roc_auc_dtree = metrics.auc(fpr_dtree, tpr_dtree)
plt.plot(fpr_dtree, tpr_dtree, 'b', label = 'AUC = %0.3f' % roc_auc_dtre
e)
plt.plot([0, 1], [0, 1],'r--')
plt.title('ROC Curve - Random Forest ',fontsize=13)
plt.ylabel('True Positive Rate',fontsize=12)
plt.xlabel('False Positive Rate',fontsize=12)
plt.legend(loc = 'lower right', prop={'size': 10});
```



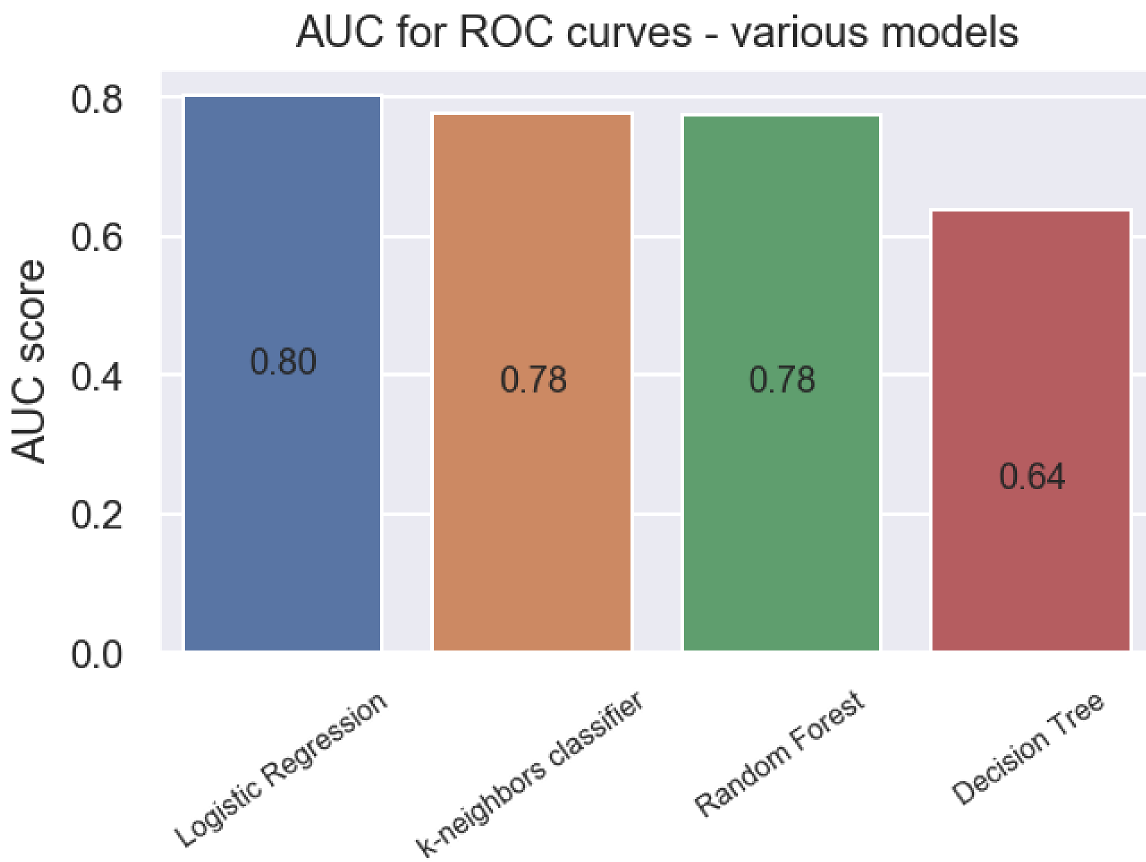
So what model to use?

Let's see how they compare in terms of ROC and AUC-ROC score

In [47]:
```
figure(figsize=(4, 4),dpi=144)
plt.plot(fpr_log, tpr_log, label = 'Logistic Regression')
plt.plot(fpr_knn, tpr_knn, label = 'k-neighbors classifier')
plt.plot(fpr_rfc, tpr_rfc, label = 'Random Forest')
plt.plot(fpr_dtree, tpr_dtree, label = 'Decision Tree')
plt.plot([0, 1], [0, 1],'b--')
plt.title('ROC Curves - Various models ',fontsize=15)
plt.ylabel('True Positive Rate',fontsize=12)
plt.xlabel('False Positive Rate',fontsize=12)
plt.legend(loc = 'lower right', prop={'size': 8});
```



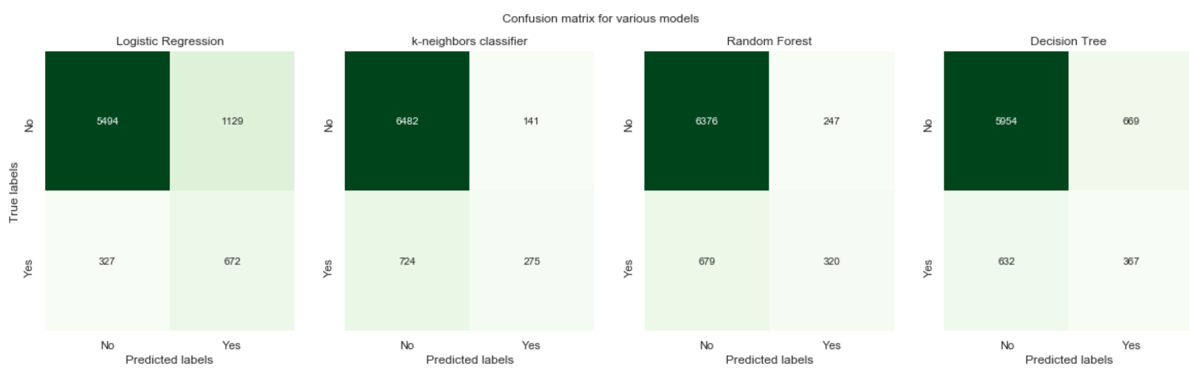
In [48]:
```
figure(figsize=(5, 3),dpi=144)
x=['Logistic Regression','k-neighbors classifier','Random Forest','Decis
ion Tree']
y=[roc_auc_log,roc_auc_knn,roc_auc_rfc,roc_auc_dtree]
g=sns.barplot(x,y)
g.set_xticklabels(g.get_xticklabels(), rotation=35,fontsize=8)
g.set_ylabel('AUC score')
g.set_title('AUC for ROC curves - various models')
for p in g.patches:
    height = p.get_height()
    plt.text(p.get_x()+p.get_width()/2.,
            height-0.4,
            '{:1.2f}'.format(height),
            ha="center")
```



In [49]:

```
figure(figsize=(5, 3),dpi=144)
x=['Logistic Regression','k-neighbors classifier','Random Forest','Decis
ion Tree']
y=[precision_score(y_true = y_test, y_pred = model_log_pred),\
  precision_score(y_true = y_test, y_pred = model_knn_pred),\
  precision_score(y_true = y_test, y_pred = model_rfc_pred),\
  precision_score(y_true = y_test, y_pred = model_dtree_pred)]
g=sns.barplot(x,y)
g.set_xticklabels(g.get_xticklabels(), rotation=35,fontsize=8)
g.set_ylabel('Accuracy')
g.set_title('Accuracy - various models')
for p in g.patches:
    height = p.get_height()
    plt.text(p.get_x()+p.get_width()/2.,
            height-0.23,
            '{:1.2f}'.format(height),
            ha="center")
```

In [50]:
```
fig,ax = plt.subplots(1,4,figsize=(20, 5))
sns.heatmap(conf_m_log, annot=True,cmap='Greens',fmt='g',ax=ax[0],cbar=False); #annot=True to annotate cells
ax[0].set_xlabel('Predicted labels');ax[0].set_ylabel('True labels');
ax[0].set_title('Logistic Regression');
ax[0].xaxis.set_ticklabels(['No', 'Yes']); ax[0].yaxis.set_ticklabels(['No', 'Yes'])
sns.heatmap(conf_m_knn, annot=True,cmap='Greens',fmt='g',ax=ax[1],cbar=False);
ax[1].set_xlabel('Predicted labels')
ax[1].set_title('k-neighbors classifier');
ax[1].xaxis.set_ticklabels(['No', 'Yes']); ax[1].yaxis.set_ticklabels(['No', 'Yes'])
sns.heatmap(conf_m_rfc, annot=True,cmap='Greens',fmt='g',ax=ax[2],cbar=False);
ax[2].set_xlabel('Predicted labels')
ax[2].set_title('Random Forest');
ax[2].xaxis.set_ticklabels(['No', 'Yes']); ax[2].yaxis.set_ticklabels(['No', 'Yes'])
sns.heatmap(conf_m_dtree, annot=True,cmap='Greens',fmt='g',ax=ax[3],cbar=False);
ax[3].set_xlabel('Predicted labels')
ax[3].set_title('Decision Tree');
ax[3].xaxis.set_ticklabels(['No', 'Yes']); ax[3].yaxis.set_ticklabels(['No', 'Yes'])
fig.suptitle('Confusion matrix for various models');
```



Taking a closer look at the outcomes of various models

The AUC-ROC scores are very close for Logistic Regression, k-nearest classifier and Random Forest. Decision Tree model doesn't stand in the same class as other models.

However, if we look at the accuracy scores, k-neighbours classifier has the highest accuracy, which means that if we make calls based on this model's prediction, most of those calls would be a success (compared to other models).

But, if we look at the confusion matrix, there's a difference in how these models make mistakes. k-neighbours classifier has most accuracy, but only captured 275 out of 999 successful customers. Logistic Regression on the other hand captured 672 out of 999 successful customers, but at the expense of making more calls.

Let me explain what's going on:

A model can predict "No" when the true label is actually "Yes", known as "False Negatives". That means the model predicted that the customer wouldn't subscribe, but based on the data, the customer actually did subscribe. So if we used this model prediction outcome, we wouldn't make a call and thus would lose a potential customer.

Based on the four prediction models that we used, we have two possible options.

- Use k-neighbours classification, make fewer calls but with greater accuracy
- Use Logistic Regression, gain more customers but with less accuracy than k-neighbours classification (still greater than not using a model)

Let's compare numbers

Let's consider our test scenario to see how much it actually helps to implement this prediction model.

In our test scenario, there are 7622 calls made to potential customers. After making these calls by spending 549 hours (taking an average of 4.32 minutes per call), 999 of them subscribed to the term deposit (13.1% success).

If we use our Logistic Regression model, we would make 1801 calls, out of which 672 would be a success (37.3% success). This would be approximately a three fold increase in success, while losing 327 customers (32% loss in customers) and saving 419 hours of time (76% reduction in time spent calling)

If we use the k-neighbours classifier model, we would make 416 calls, out of which 275 would be a success (66.1% success). This would be approximately a five fold increase in success, while losing 724 customers (72% loss in customers) and saving 518 hours of time (94% reduction in time spent calling)

Conclusion

So what model to use?

Well, that depends on various other factors. We need a lot more information to make this decision.

- Is the business trying to expand?
- What's the long term benefit from gaining a customer?
- Is it trying to save money?
- Does it cost more in telemarketing for 100 hours than it costs more in gaining 397 customers?
- Would the business be more interested in not making unwanted telemarketing calls to save it's image?

An appropriate response for the first two questions might require a Logistic Regression model, where as a focus on saving money/time/image based on the answers to the last three questions would require a k-neighbours classifier model

In [ ]:
```

```