Our goal is to build a model that predicts if the client will subscribe a term deposit.

Step 1: Load the dataset

In [11]:
```
import pandas as pd
df = pd.read_csv('bank.csv')
df = df.dropna()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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: 6.9+ MB
```

Here we can see that a lot of columns are shown as object data type, which means categorical. Some categorical columns need to be dropped and some categorical columns can be convert to boolean type.

Step 2: Data cleaning.

We need to replace categorical columns with boolean or numerical values in order to use them in building the model.

In [12]:
```
#Drop categorical variables
df = df.drop(['job', 'marital', 'education'], axis=1)
#Replace categorical columns with boolean or numerical values
df = df.replace({'default': {'yes': 1, 'no': 0, 'unknown': 2}})
df = df.replace({'housing': {'yes': 1, 'no': 0, 'unknown': 2}})
df = df.replace({'loan': {'yes': 1, 'no': 0, 'unknown': 2}})
df = df.replace({'contact': {'cellular': 1, 'telephone': 0}})
df = df.replace({'month': {'jan':1, 'feb':2, 'mar':3, 'apr':4, 'may':5,
'jun':6, 'jul':7, 'aug':8, 'sep':9, 'oct':10, 'nov':11, 'dec':12}})
df = df.replace({'day_of_week': {'mon':1, 'tue':2, 'wed':3, 'thu':4, 'fr
i':5, 'sat':6, 'sun':7}})
df = df.replace({'poutcome': {'success': 1, 'failure': 0, 'nonexistent':
2}})
df = df.replace({'y': {'yes': 1, 'no': 0}})
df.head()
```

Out[12]:

	age	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previc
0	56	0	0	0	0	5	1	261	1	999	
1	57	2	0	0	0	5	1	149	1	999	
2	37	0	1	0	0	5	1	226	1	999	
3	40	0	0	0	0	5	1	151	1	999	
4	56	0	0	1	0	5	1	307	1	999	

Now we have all columns with numerical values and ready to create the model.

Step 3: Split the dataset into 2 parts, 60% training data, 40% validation data.

In [13]:
```
len(df)
```

Out[13]: 41188

Right now, the whole dataset contains 41188 observations. We can put 24712 observations into training data, and 16476 observations into validation data.

In [14]:
```
import numpy as np
rows_for_training = np.random.choice( df.index, 24712, False )
training = df.index.isin(rows_for_training)
df_training = df[training]
df_validation = df[~training]
len(df_training), len(df_validation)
```

Out[14]:
```
(24712, 16476)
```

This code is being created by first generating 24712 random rows to df_training dataframe. And the rest will be put into df_validation dataframe. This gives us about 60% training set and 40% validation set.

Step 4: Create a model using the training dataset using the scikit-learn's logistic regression tool. And test the model using the validation dataset.

In [39]:
```
from sklearn.linear_model import LogisticRegression
def fit_model_to (training):
    predictors = training.iloc[:,:-1]
    response = training.iloc[:,-1]
    model = LogisticRegression(max_iter=10000)
    model.fit(predictors, response)
    return model

def score_model (M, validation):
    predictions = M.predict(validation.iloc[:,:-1] )
    TP = (validation['y'] & predictions).sum()
    FP = (~validation['y'] & predictions).sum()
    FN = (validation['y'] & ~predictions).sum()
    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    return 2 * precision * recall / (precision + recall)

model = fit_model_to(df_training)
score_model(model, df_training), score_model(model, df_validation)
```

Out[39]:
```
(0.5036674816625917, 0.5111864406779661)
```

The values retured are the F1 score from training dataset and validation dataset. F1 score represents how good our model is by using the precision and recall values. We can see that both F1 score for training and validation datasets are relatively low. Possible reason is that we have high number of predictor variables. It's likely that some of predictors do not predict our response variable well.

Step 5: Create a better model to predict the response variable.

In [37]:
```
def fit_model_to (training):
    # fit the model the same way as step 4
    predictors = training.iloc[:,:-1]
    response = training.iloc[:,-1]
    model = LogisticRegression(max_iter=10000)
    model.fit(predictors, response)
    # fit another model to standardized predictors in order to compare t
he coefficients with the same scale
    standardized = (predictors - predictors.mean()) / predictors.std()
    standard_model = LogisticRegression(max_iter=10000)
    standard_model.fit(standardized, response)
    # get that model's coefficients and display them
    coeffs = pd.Series(standard_model.coef_[0], index=predictors.columns
)
    sorted = np.abs(coeffs).sort_values( ascending=False )  # sort the c
oefficients from the most important to the least
    coeffs = coeffs.loc[sorted.index]
    print(coeffs)
    # return the model fit to the actual predictors
    return model


model = fit_model_to(df_training)
print(score_model(model, df_training), score_model(model, df_validation
))
```

```
emp.var.rate     -1.624788
duration          1.187808
cons.price.idx    0.720433
euribor3m         0.573574
contact           0.482546
nr.employed      -0.352327
pdays            -0.309206
cons.conf.idx     0.244659
default          -0.210787
campaign         -0.152812
poutcome          0.130479
month            -0.096149
loan             -0.057195
previous         -0.044306
age               0.034874
day_of_week       0.022312
housing           0.004019
dtype: float64
0.5036674816625917 0.5111864406779661
```

Here the coefficients are sorted in order of their importance to predict the model. We can perform a series of trial and error to see which columns to keep in the modeling in order to perform a higher F1 score.

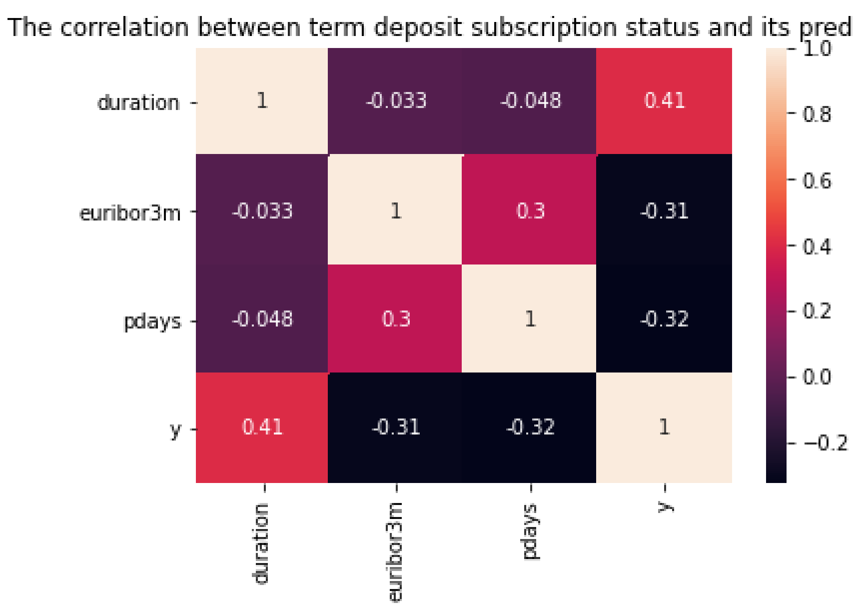
In [222]:
```
columns = ['duration','euribor3m','pdays','y']
model = fit_model_to( df_training.loc[:,columns] )
score_model( model, df_training.loc[:,columns] ), score_model( model, df
_validation.loc[:,columns] )
```

Out[222]:
```
(0.47861323728050426, 0.4836376162590424)
```

Here are the final predictors that we decided to keep after experimenting various combinations. As you may notice, the F1 score is lower than the F1 score using all predictors. We decided to only keep these 3 variables to minimize correlation between predictors while maintaining relatively good F1 score. By reducing 17 variables to 3, this will significantly reduce the resources needed to gather the data.

Step 6: Create a visualization between the predictors and repsonse variable

In [223]:
```
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
df_final = df.loc[:, columns]
correlation_coefficients = np.corrcoef(df_final, rowvar=False )
sns.heatmap( correlation_coefficients, annot=True )
plt.yticks( np.arange(4)+0.5, df_final.columns, rotation=0 )
plt.xticks( np.arange(4)+0.5, df_final.columns, rotation=90 )
plt.title('The correlation between term deposit subscription status and
 its predictors')
plt.show()
```



Here is the heatmap showing the correlation between the final predictors that we chose and the term deposit subscription status. As we can see that there is no strong correlation between each predictors. And there are slightly moderate correlation between the subscription status and 3 predictors. This may explain the relatively low F1 score that we got from modeling.