In [76]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.ticker as tcr
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import validation_curve
```

In [77]:

```
data = pd.read_csv('/home/amybirdee/hobby_projects/propensity_to_buy/Propensity_data.cs
v', delimiter = ',', \
                       low_memory = False)
```

Preliminary data checks

In [78]:

```
#the data consist of a user id and 0s and 1s to show whether they clicked on various it
ems on the page and ultimately
#whether or not they placed an order
data.head()
```

Out[78]:

	UserID	basket_icon_click	basket_add_list	basket_add_detail	sort_by	image_picker	a
0	a720-6b732349-a720-4862-bd21-644732	0	0	0	0	0	
1	b74a-6b737717-b74a-45c3-8c6a-421140	0	1	0	1	0	
2	7775-6b73b976-7775-4324-b1d9-622031	0	0	0	0	0	
3	4b8a-6b74bd36-4b8a-4d10-a008-67143	0	0	0	0	0	
4	7009-6b768104-7009-4526-9da6-129024	0	0	0	0	0	

5 rows × 21 columns

In [79]:

```
#232,000 rows of data
data.shape
```

Out[79]:

```
(232239, 21)
```

In [80]:

```
#don't need the id column so dropping this
data = data.drop('UserID', axis = 1)
data.head()
```

Out[80]:

	basket_icon_click	basket_add_list	basket_add_detail	sort_by	image_picker	account_pag
0	0	0	0	0	0	
1	0	1	0	1	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

In [81]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 232239 entries, 0 to 232238
Data columns (total 20 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   basket_icon_click        232239 non-null  int64
 1   basket_add_list          232239 non-null  int64
 2   basket_add_detail        232239 non-null  int64
 3   sort_by                  232239 non-null  int64
 4   image_picker             232239 non-null  int64
 5   account_page_click       232239 non-null  int64
 6   promo_banner_click       232239 non-null  int64
 7   detail_wishlist_add      232239 non-null  int64
 8   list_size_dropdown       232239 non-null  int64
 9   closed_minibasket_click  232239 non-null  int64
 10  checked_delivery_detail  232239 non-null  int64
 11  checked_returns_detail   232239 non-null  int64
 12  sign_in                  232239 non-null  int64
 13  saw_checkout             232239 non-null  int64
 14  saw_sizecharts           232239 non-null  int64
 15  saw_delivery             232239 non-null  int64
 16  saw_account_upgrade      232239 non-null  int64
 17  saw_homepage             232239 non-null  int64
 18  returning_user           232239 non-null  int64
 19  ordered                  232239 non-null  int64
dtypes: int64(20)
memory usage: 35.4 MB
```

Exploratory data analysis

In [82]:

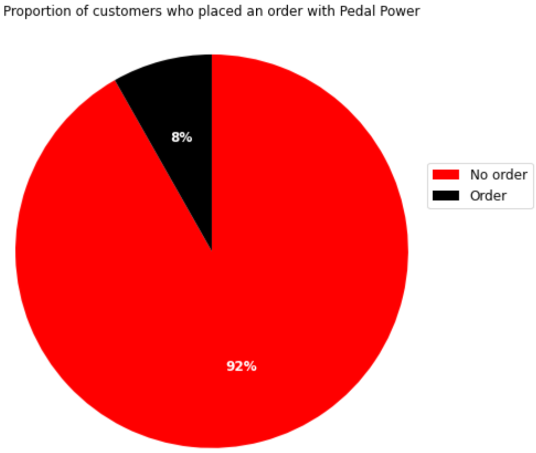
```
#checking the proportion of customers who place an order - only 8% place an order so th
is must be a high ticket item. Will
#assume this is an interactive exercise bike for the rest of the analysis
order = data.groupby('ordered').size().to_frame().reset_index().rename(columns = {0: 'c
ount'})
order
```

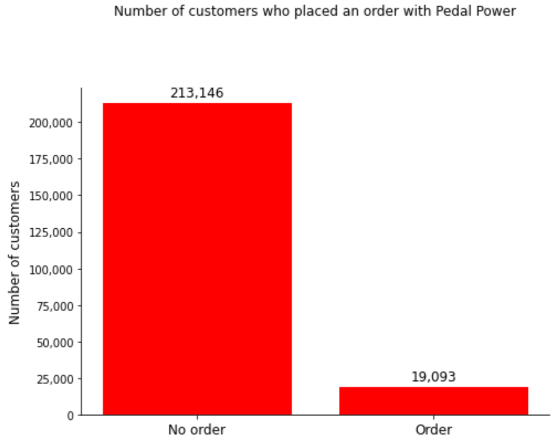
Out[82]:

	ordered	count
0	0	213146
1	1	19093

In [149]:

```
#creating chart
fig = plt.figure(figsize = (15, 6))
ax = plt.subplot(1, 2, 1)

_, _, autotexts = plt.pie(order['count'], colors = ['red', 'black'], radius = 1.5, auto
pct = ('%.0f%%'), \
                          counterclock = False, startangle = -270)

plt.legend(labels = ['No order', 'Order'], loc = 'right', bbox_to_anchor = (1.5, 0.7),
fontsize = 12)

#setting the colour of percentage labels to white
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_weight('bold')
    autotext.set_fontsize(12)

plt.title('Proportion of customers who placed an order with Pedal Power', y = 1.2, font
size = 12)

#second chart
ax = plt.subplot(1, 2, 2)

plt.bar(order['ordered'], order['count'], color = 'red')

#removing chart borders
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

#adding data labels for bars
bars = plt.bar(order['ordered'], order['count'], color = 'red')

for bar in bars:
    yval = bar.get_height()
    #the '{:,}' command adds a thousand separator to the labels
    ax.annotate('{:,}'.format(yval),
    xy = (bar.get_x() + bar.get_width() / 2, yval),
    #shows label position on x and y axis
    xytext = (0, 3),
    textcoords = 'offset points', ha = 'center', va = 'bottom', fontsize = 12)

#function to add comma separator to labels
def comma(x, pos):
    return format(x, "6,.0f")

#this code adds a comma separater to the y tick marks
ax.yaxis.set_major_formatter(tcr.FuncFormatter(comma))

plt.xticks(order['ordered'], labels = ['No order', 'Order'], fontsize = 12)
plt.ylabel('Number of customers', fontsize = 12)
plt.title('Number of customers who placed an order with Pedal Power', y = 1.2, fontsize
= 12)
plt.tight_layout()

plt.savefig('order_proportion_and_volumes')
```





In [84]:

```
#grouping by customers who added the bike to their wishlist and/or placed an order
wishlist = data.groupby(['detail_wishlist_add', 'ordered']).size().to_frame().reset_ind
ex().\
rename(columns = {0: 'count'})
wishlist
```

Out[84]:

	detail_wishlist_add	ordered	count
0	0	0	211508
1	0	1	18899
2	1	0	1638
3	1	1	194

In [85]:

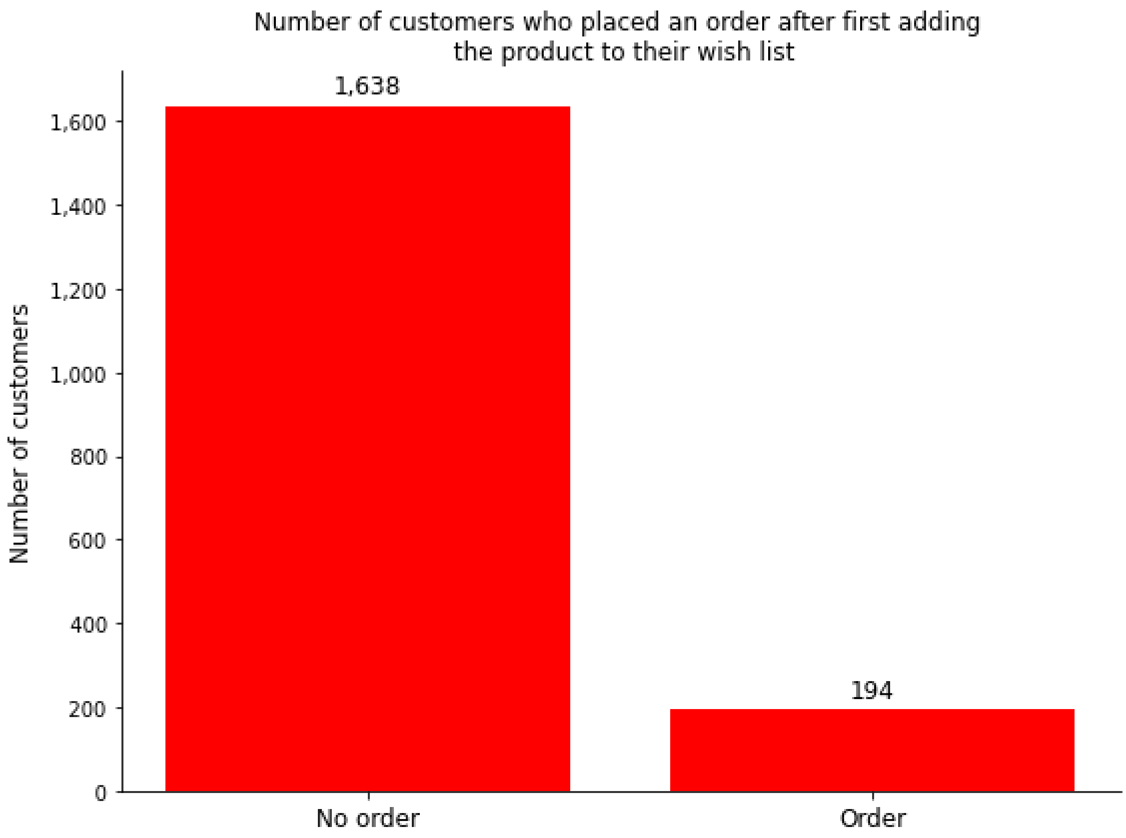
```
#filtering for users who added to wishlist only
wishlist = wishlist[wishlist['detail_wishlist_add'] == 1].reset_index(drop = True)
wishlist
```

Out[85]:

	detail_wishlist_add	ordered	count
0	1	0	1638
1	1	1	194

In [153]:

```
#creating chart
fig = plt.figure(figsize = (8, 6))
ax = plt.subplot(1, 1, 1)

plt.bar(wishlist['ordered'], wishlist['count'], color = 'red')

#removing chart borders
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

#adding data labels for bars
bars = plt.bar(wishlist['ordered'], wishlist['count'], color = 'red')

for bar in bars:
    yval = bar.get_height()
    #the '{:,}' command adds a thousand separator to the labels
    ax.annotate('{:,}'.format(yval),
    xy = (bar.get_x() + bar.get_width() / 2, yval),
    #shows label position on x and y axis
    xytext = (0, 3),
    textcoords = 'offset points', ha = 'center', va = 'bottom', fontsize = 12)

#function to add comma separator to labels
def comma(x, pos):
    return format(x, "6,.0f")

#this code adds a comma separater to the y tick marks
ax.yaxis.set_major_formatter(tcr.FuncFormatter(comma))

plt.xticks(wishlist['ordered'], labels = ['No order', 'Order'], fontsize = 12)
plt.ylabel('Number of customers', fontsize = 12)
plt.title('Number of customers who placed an order after first adding \n the product to
their wish list', y = 1.0, fontsize = 12)
plt.tight_layout()

plt.savefig('wishlist_volumes')
```



In [87]:

```
#grouping by customers who are returning customers
returning = data.groupby('returning_user').size().sort_values(ascending = False).to_fra
me().reset_index().\
rename(columns = {0: 'count'})
returning
```

Out[87]:

	returning_user	count
0	1	155441
1	0	76798

In [88]:

```
#grouping by customers who are returning customers and placed an order
returning_ordered = data.groupby(['returning_user', 'ordered']).size().to_frame().reset
_index().\
rename(columns = {0: 'count'})
returning_ordered
```

Out[88]:

	returning_user	ordered	count
0	0	0	70663
1	0	1	6135
2	1	0	142483
3	1	1	12958

In [89]:

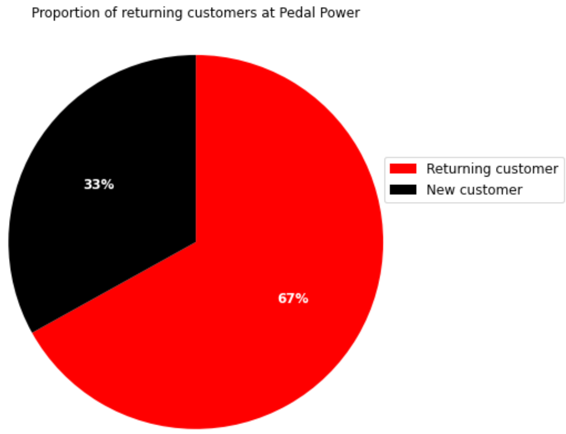
```
#filtering for returning users
returning_ordered = returning_ordered[returning_ordered['returning_user'] == 1].reset_i
ndex(drop = True)
returning_ordered
```

Out[89]:

	returning_user	ordered	count
0	1	0	142483
1	1	1	12958

In [150]:

```
#creating chart
fig = plt.figure(figsize = (15, 6))
ax = plt.subplot(1, 2, 1)

_, _, autotexts = plt.pie(returning['count'], colors = ['red', 'black'], radius = 1.5, 
autopct = ('%.0f%%'), \
                          counterclock = False, startangle = -270)

plt.legend(labels = ['Returning customer', 'New customer'], loc = 'right', bbox_to_anch
or = (1.7, 0.7), fontsize = 12)

#setting the colour of percentage labels to white
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_weight('bold')
    autotext.set_fontsize(12)

plt.title('Proportion of returning customers at Pedal Power', y = 1.2, fontsize = 12)

#second chart
ax = plt.subplot(1, 2, 2)

plt.bar(returning_ordered['ordered'], returning_ordered['count'], color = 'red')

#removing chart borders
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

#adding data labels for bars
bars = plt.bar(returning_ordered['ordered'], returning_ordered['count'], color = 'red')

for bar in bars:
    yval = bar.get_height()
    #the '{:,}' command adds a thousand separator to the labels
    ax.annotate('{:,}'.format(yval),
    xy = (bar.get_x() + bar.get_width() / 2, yval),
    #shows label position on x and y axis
    xytext = (0, 3),
    textcoords = 'offset points', ha = 'center', va = 'bottom', fontsize = 12)

#function to add comma separator to labels
def comma(x, pos):
    return format(x, "6,.0f")

#this code adds a comma separater to the y tick marks
ax.yaxis.set_major_formatter(tcr.FuncFormatter(comma))

plt.xticks(returning_ordered['ordered'], labels = ['No order', 'Order'], fontsize = 12)
plt.ylabel('Number of customers', fontsize = 12)
plt.title('Number of returning customers who placed an order with \n Pedal Power', y = 
1.2, fontsize = 12)
plt.tight_layout()

plt.savefig('returning_proportion_and_volumes')
```



In [91]:

```
#grouping by customers who went to the checkout page
checkout = data.groupby('saw_checkout').size().sort_values(ascending = False).to_frame
().reset_index().\
rename(columns = {0: 'count'})
checkout
```

Out[91]:

	saw_checkout	count
0	0	191159
1	1	41080

In [92]:

```
#grouping by customers who saw the checkout page and placed an order
checkout_ordered = data.groupby(['saw_checkout', 'ordered']).size().to_frame().reset_in
dex().\
rename(columns = {0: 'count'})
checkout_ordered
```

Out[92]:

	saw_checkout	ordered	count
0	0	0	191159
1	1	0	21987
2	1	1	19093

In [93]:

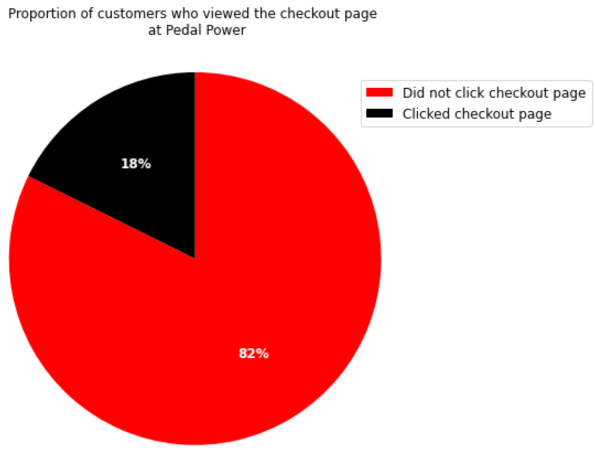
```
#filtering for users who saw the checkout page
checkout_ordered = checkout_ordered[checkout_ordered['saw_checkout'] == 1].reset_index(
drop = True)
checkout_ordered
```

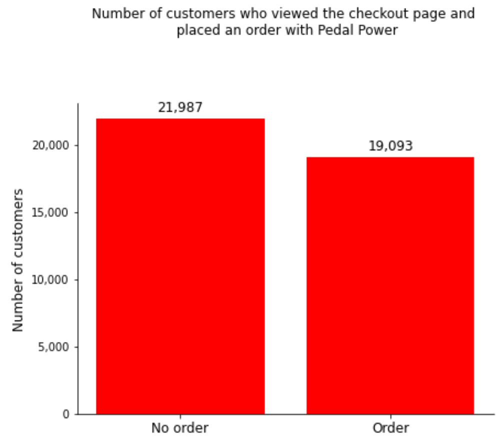
Out[93]:

	saw_checkout	ordered	count
0	1	0	21987
1	1	1	19093

In [151]:

```
#creating chart
fig = plt.figure(figsize = (15, 6))
ax = plt.subplot(1, 2, 1)

_, _, autotexts = plt.pie(checkout['count'], colors = ['red', 'black'], radius = 1.5, a
utopct = ('%.0f%%'), \
                          counterclock = False, startangle = -270)

plt.legend(labels = ['Did not click checkout page', 'Clicked checkout page'], loc = 'ri
ght', bbox_to_anchor = (1.8, 1.0), \
           fontsize = 12)

#setting the colour of percentage labels to white
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_weight('bold')
    autotext.set_fontsize(12)

plt.title('Proportion of customers who viewed the checkout page \n at Pedal Power', y =
1.2, fontsize = 12)

#second chart
ax = plt.subplot(1, 2, 2)

plt.bar(checkout_ordered['ordered'], checkout_ordered['count'], color = 'red')

#removing chart borders
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

#adding data labels for bars
bars = plt.bar(checkout_ordered['ordered'], checkout_ordered['count'], color = 'red')

for bar in bars:
    yval = bar.get_height()
    #the '{:,}' command adds a thousand separator to the labels
    ax.annotate('{:,}'.format(yval),
    xy = (bar.get_x() + bar.get_width() / 2, yval),
    #shows label position on x and y axis
    xytext = (0, 3),
    textcoords = 'offset points', ha = 'center', va = 'bottom', fontsize = 12)

#function to add comma separator to labels
def comma(x, pos):
    return format(x, "6,.0f")

#this code adds a comma separater to the y tick marks
ax.yaxis.set_major_formatter(tcr.FuncFormatter(comma))

plt.xticks(checkout_ordered['ordered'], labels = ['No order', 'Order'], fontsize = 12)
plt.ylabel('Number of customers', fontsize = 12)
plt.title('Number of customers who viewed the checkout page and \n placed an order with
Pedal Power',\
            y = 1.2, fontsize = 12)
plt.tight_layout()

plt.savefig('saw_checkout_proportion_and_volumes')
```

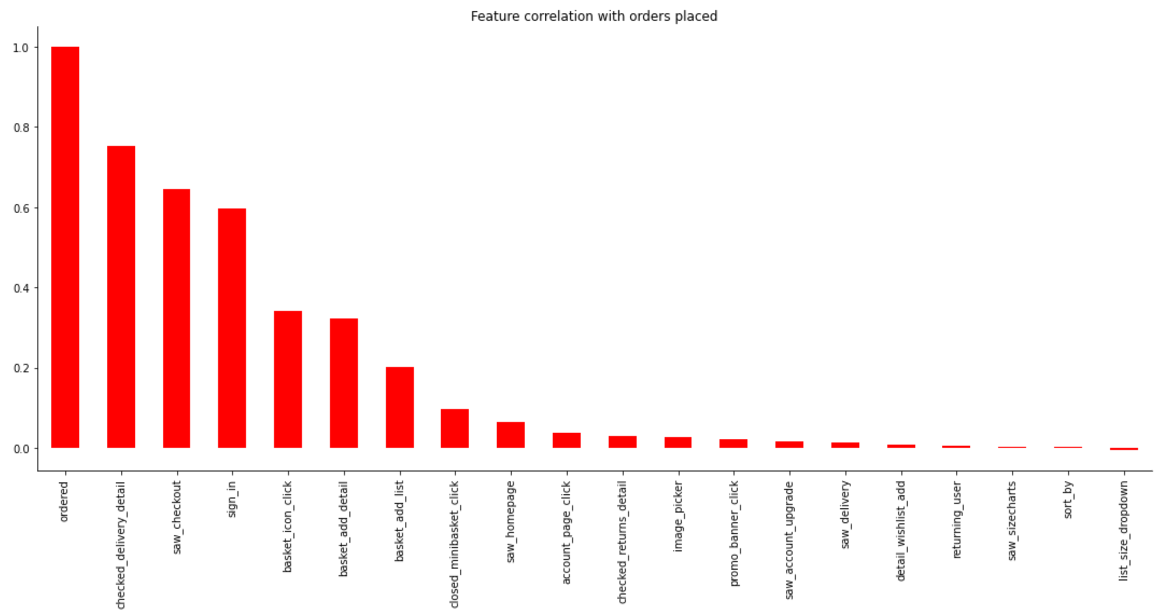




Correlation analysis

In [95]:

```
#plot correlations between target feature (orderded) and all other features - checking
 delivery and viewing the checkout\
#page is most positively correlated with orders and list dropdown is most negatively co
rrelated
fig = plt.figure(figsize = (15, 8))
ax = plt.subplot()
data.corr()['ordered'].sort_values(ascending = False).plot(kind = 'bar', color = 'red')
plt.title('Feature correlation with orders placed', fontsize = 12)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10)
plt.tight_layout()
plt.savefig('correlation')
```



In [96]:

```
#splting data into dependent and independent variables
y = data.ordered.values

X = data.drop('ordered', axis = 1)

#saving the X value columns to a separate list for reassigning after scaling the data
data_columns = X.columns
```

In [97]:

```
#splitting data into training and testing datasets - we are dealing with only 0/1 numbe
rs so no need to scale
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
= 42)
```

In [98]:

```
#checking shape of training and testing sets - all records are there
print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)
print('y_train shape:', y_train.shape)
print('y_test shape:', y_test.shape)
```

```
X_train shape: (185791, 19)
X_test shape: (46448, 19)
y_train shape: (185791,)
y_test shape: (46448,)
```

Logistic regression

In [99]:

```
#fitting the model - using a sag solver as this is faster for large datasets which we h
ave
logistic_model = LogisticRegression(solver = 'sag', random_state = 42)
logistic_model.fit(X_train, y_train)
```

Out[99]:

```
LogisticRegression(random_state=42, solver='sag')
```

In [100]:

```
#predicting the purchase values for X_train and X_test
y_pred_train = logistic_model.predict(X_train)
y_pred_test = logistic_model.predict(X_test)
```

In [101]:

```
#evaluating the model - finding the residual differences between train data and predict
ed train data
residuals = np.abs(y_train - y_pred_train)

#print value counts of predicted values
print(pd.Series(residuals).value_counts())

print('')

#print normalised value counts for predicted values - 98% of order predictions were cor
rect on the train data set
print(pd.Series(residuals).value_counts(normalize = True))
```

```
0    182591
1      3200
dtype: int64

0    0.982776
1    0.017224
dtype: float64
```

In [102]:

```
#evaluating the model for the test data - finding the residual differences between test
data and predicted test data
residuals_test = np.abs(y_test - y_pred_test)

#print value counts of predicted values
print(pd.Series(residuals_test).value_counts())

print('')

#print normalised value counts for predicted values - 98% of order predictions were cor
rect on the test data set
print(pd.Series(residuals_test).value_counts(normalize = True))
```

```
0    45705
1      743
dtype: int64

0    0.984004
1    0.015996
dtype: float64
```

In [103]:

```
#definitions
#precision - how precise the predictions are or TP / (TP + FP). (Out of the times the m
odel said the customer would order,
#how many times did they actually order)

#recall - what percentage of the class we're interested in were captured by the model o
r TP / (TP + FN). (Out of all the
#customers that ordered, what percentage did the model predict as 'going to order')

#accuracy - measures what percentage of predictions the model got right or (TP + TN) /
 (TP + FP + TN + FN).

#F1 score - harmonic mean of precision and recall - can't have a high F1 score without
 a strong model underneath.
#F1 = 2(precision * recall) / (precision + recall)
#F1 score penalises model heavily if it's skewed towards precison or recall
```

In [104]:

```
#printing the confusion matrix - we are trying to limit false positives (i.e. when we p
redict a customer will place an order
#but they don't). When trying to limit false positives we want to optimise on precision
rather than recall

#41957 = true negative, 3748 = true positive, 56 = false negative, 687 = false positive
matrix = confusion_matrix(y_test, y_pred_test)
print('Confusion matrix \n', matrix)
```

```
Confusion matrix
 [[41957   687]
 [   56  3748]]
```

In [105]:

```
#visualising the confusion matrix with labels
y_test_df = pd.Series(y_test)
y_pred_test_df = pd.Series(y_pred_test)

pd.crosstab(y_test_df, y_pred_test_df, rownames = ['True'], colnames = ['Predicted'], m
argins = True).reset_index()
```

Out[105]:

Predicted	True	0	1	All
0	0	41957	687	42644
1	1	56	3748	3804
2	All	42013	4435	46448

In [106]:

```
#concatenating the series into a dataframe and adding a new row to describe what the re
sult is in each. The function uses
#if statements to define the result

results = pd.concat([y_test_df, y_pred_test_df], axis = 1).rename(columns = {0: 'actua
l', 1: 'prediction'})

def regression_results(row):
    if row['actual'] == 1 and row['prediction'] == 1:
        return 'actual = ordered and prediction = ordered - True positive'
    if row['actual'] == 0 and row['prediction'] == 0:
        return 'actual = did not order and prediction =  did not order - True negative'
    if row['actual'] == 0 and row['prediction'] == 1:
        return 'actual = did not order but prediction = ordered - False positive'
    if row['actual'] == 1 and row['prediction'] == 0:
        return 'actual = ordered but prediction = did not order - False negative'

#applying the above function to a new row
results['result'] = results.apply(lambda row: regression_results(row), axis = 1)
print(results.head())
```

```
   actual  prediction                                             result
0       0           0  actual = did not order and prediction =  did n...
1       0           0  actual = did not order and prediction =  did n...
2       0           0  actual = did not order and prediction =  did n...
3       0           0  actual = did not order and prediction =  did n...
4       0           0  actual = did not order and prediction =  did n...
```

In [107]:

```
#grouping the results to compare with the confustion matrix
results_grouped = results.groupby('result').size()
results_grouped
```

Out[107]:

```
result
actual = did not order and prediction =  did not order - True negative
41957
actual = did not order but prediction = ordered - False positive
687
actual = ordered and prediction = ordered - True positive
3748
actual = ordered but prediction = did not order - False negative
56
dtype: int64
```

In [108]:

```
#printing out the scores for precision, recall, accuracy and F1 for y_test and y_pred_t
est
print(metrics.classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     42644
           1       0.85      0.99      0.91      3804

    accuracy                           0.98     46448
   macro avg       0.92      0.98      0.95     46448
weighted avg       0.99      0.98      0.98     46448
```

In [109]:

```
#another way to print the scores, pos_label tells sklearn what class you want to print
 - we want 1 as that's the 'will
#order' class

precision_train = precision_score(y_train, y_pred_train, pos_label = 1)
precision_test = precision_score(y_test, y_pred_test, pos_label = 1)

recall_train = recall_score(y_train, y_pred_train, pos_label = 1)
recall_test = recall_score(y_test, y_pred_test, pos_label = 1)

accuracy_train = accuracy_score(y_train, y_pred_train)
accuracy_test = accuracy_score(y_test, y_pred_test)

f1_train = f1_score(y_train, y_pred_train, pos_label = 1)
f1_test = f1_score(y_test, y_pred_test, pos_label = 1)

print('Precision train: ', round(precision_train, 2))
print('Precision test: ', round(precision_test, 2))
print('')
print('Recall train: ', round(recall_train, 2))
print('Recall test: ', round(recall_test, 2))
print('')
print('Accuracy train: ', round(accuracy_train, 2))
print('Accuracy test: ', round(accuracy_test, 2))
print('')
print('F1 train: ', round(f1_train, 2))
print('F1 test: ', round(f1_test, 2))
print('')
```

```
Precision train:  0.84
Precision test:  0.85

Recall train:  0.98
Recall test:  0.99

Accuracy train:  0.98
Accuracy test:  0.98

F1 train:  0.9
F1 test:  0.91
```

In [110]:

```
#calculating probabilities scores for test and train sets
prob_train = logistic_model.predict_proba(X_train)
prob_test = logistic_model.predict_proba(X_test)

#keeping probabilities for positive outcome only (the threshold is 0.5 which means, if
 the predicted probability of the
#class for an instance is less than 0.5, that instance is predicted to be in class 0 (t
he negative class). If the
#probability of the class for an instance is equal or greater than 0.5, the instance is
classified as class 1.)
prob_train_order = prob_train[:, 1]
prob_test_order = prob_test[:, 1]

#calculate false positive rate (fpr), true positive rate (tpr) and thresholds for train
set
train_fpr, train_tpr, train_thresholds = roc_curve(y_train, prob_train_order)

#calculate false positive rate (fpr), true positive rate (tpr) and thresholds for test
 set
test_fpr, test_tpr, test_thresholds = roc_curve(y_test, prob_test_order)
```

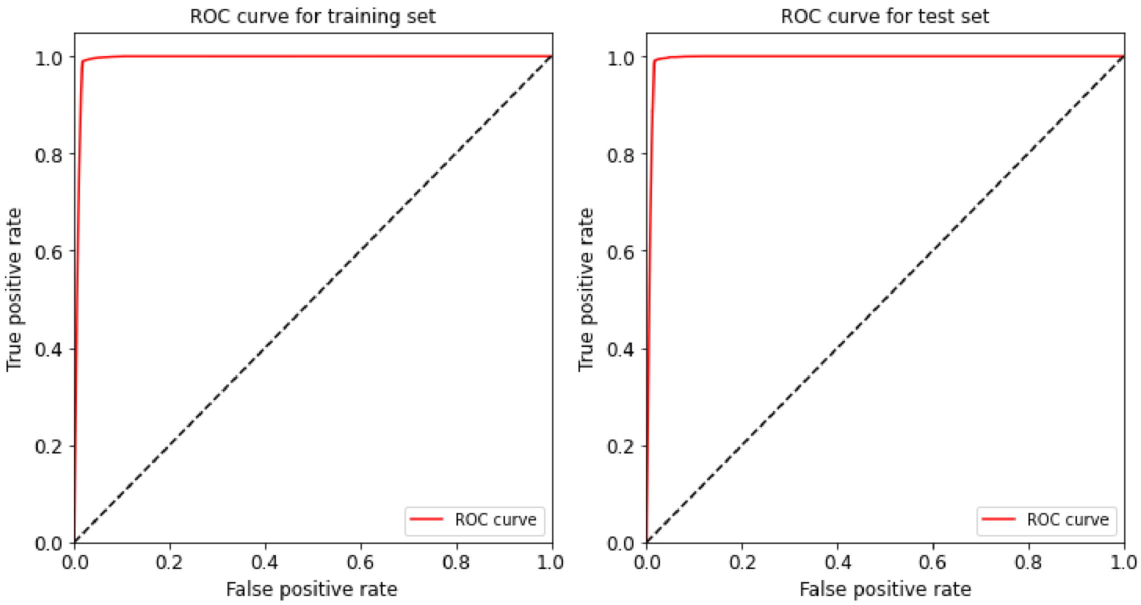
In [111]:

```
#calculating AUC (Area Under Curve) - this gives a single numeric metric to evaluate th
e model. An AUC value of 1 would
#represent a perfect classifier. If AUC = 0.5 the classifier only has 50% preision. AUC
scores above 0.99 so pretty good.

auc_train = auc(train_fpr, train_tpr)
auc_test = auc(test_fpr, test_tpr)
print('Training AUC: ', round(auc_train, 5))
print('Testing AUC: ', round(auc_test, 5))
```

```
Training AUC:  0.99289
Testing AUC:  0.99328
```

In [112]:

```
#plotting an ROC (Receiver Operator Characteristic) curve to evaluate the model perform
ance visually. It illustrates the
#true positive rate against the false positive rate of our classifier. Best performing
 models will have an ROC curve that
#hugs the upper left corner of the graph. This would represent that we correctly classi
fy the positives much more often
#than we incorrectly classify them.

fig = plt.figure(figsize = (12, 6))
ax = plt.subplot(1, 2, 1)
plt.plot(train_fpr, train_tpr, label = 'ROC curve', color = 'red')

#plotting diagonal line from zero which represents a model that guesses incorrectly for
every correct guess
plt.plot([0, 1], [0, 1], color = 'black', linestyle = 'dashed')
plt.xlim([0, 1])
plt.ylim([0, 1.05])

plt.legend()
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel('False positive rate', fontsize = 12)
plt.ylabel('True positive rate', fontsize = 12)
plt.title('ROC curve for training set', fontsize = 12)

ax = plt.subplot(1, 2, 2)
plt.plot(test_fpr, test_tpr, label = 'ROC curve', color = 'red')

#plotting diagonal line from zero which represents a model that guesses incorrectly for
every correct guess
plt.plot([0, 1], [0, 1], color = 'black', linestyle = 'dashed')
plt.xlim([0, 1])
plt.ylim([0, 1.05])

plt.legend()
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel('False positive rate', fontsize = 12)
plt.ylabel('True positive rate', fontsize = 12)
plt.title('ROC curve for test set', fontsize = 12)
plt.savefig('ROC_curves')
```



In [113]:

```
#the ROC curve shows a near perfect classifier. Looking at the data to double check thi
s is correct - it is - these figures
#match the confusion matrix
print('counts for test set:')
print(pd.Series(y_test).value_counts())
print('')
print('counts for predictions on test set:')
print(pd.Series(y_pred_test).value_counts())
```

```
counts for test set:
0    42644
1     3804
dtype: int64

counts for predictions on test set:
0    42013
1     4435
dtype: int64
```

Random Forest

In [114]:

```
#first runningthe data through a random forest model with default hyperparameters
default_forest = RandomForestClassifier(random_state = 42)
default_model = default_forest.fit(X_train, y_train)
default_y_pred = default_model.predict(X_test)
```

In [115]:

```
#printing the confusion matrix - 669 false postives versus 687 with the logistic regres
sion so random forest performed
#better in reducing false positives

#41975 = true negative, 3703 = true positive, 101 = false negative, 669 = false positiv
e
matrix = confusion_matrix(y_test, default_y_pred)
print('Confusion matrix \n', matrix)
```

```
Confusion matrix
 [[41975   669]
 [  101  3703]]
```

In [116]:

```
#printing out the scores for precision, recall, accuracy and F1 for y_test and default_
y_pred - accuracy and precision
#are same as logistic regression
print(metrics.classification_report(y_test, default_y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     42644
           1       0.85      0.97      0.91      3804

    accuracy                           0.98     46448
   macro avg       0.92      0.98      0.95     46448
weighted avg       0.99      0.98      0.98     46448
```

In [117]:

```
#will tune some of the hyperparameters of the random forest model to see if scores can
 be improved. will tune number of
#estimators, max depth, min sample split and min sample leaf. Starting with n_estimator
s - this shows the number of trees in
#the forest. Default value is 10

num_est = [50, 100, 250, 500, 750]

#preparing to create a validation curve - this is a tool that shows how accuracy change
s with changes in the model
#parameters.
#cv = cross validation - it's used to test the effectiveness of machine learning models
and is a resampling procedure
train_score_num_est, test_score_num_est = validation_curve(
                                            RandomForestClassifier(),
                                            X = X_train, y = y_train,
                                            param_name = 'n_estimators',
                                            param_range = num_est,
                                            cv = 5,
                                            scoring = 'accuracy')
```

In [118]:

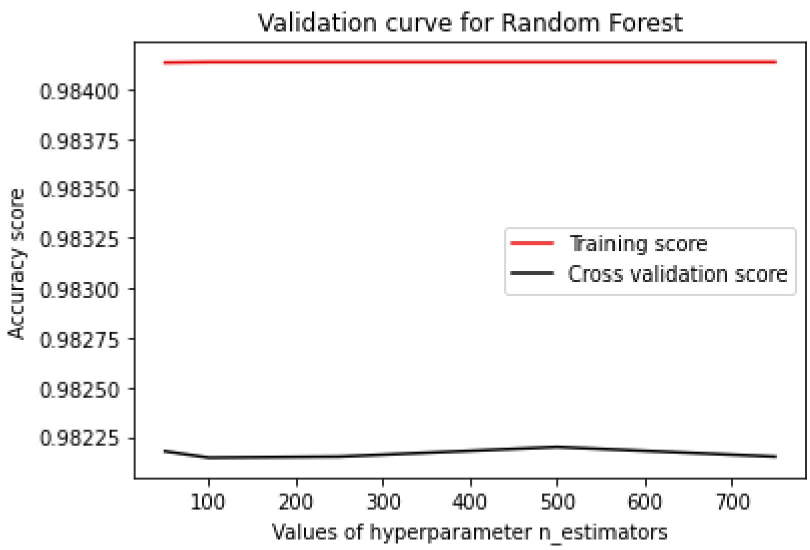
```
#to plot the validation curve, we need the mean of the 5 cross validation scores - calc
ulating mean and standard deviation
#for train and test sets

mean_train_score_num_est = np.mean(train_score_num_est, axis = 1)
std_train_score_num_est = np.std(train_score_num_est, axis = 1)

mean_test_score_num_est = np.mean(test_score_num_est, axis = 1)
std_test_score_num_est = np.std(test_score_num_est, axis = 1)
```

In [119]:

```
#plotting the validation curve - large difference between training scores and cross val
idation scores but the training set
#still had an average accuracy of 98% for each of the three cross validations. The two
 lines are ever so slightly closer
#at 50 estimaters so will use this in tuned model

plt.plot(num_est, mean_train_score_num_est, label = 'Training score', color = 'red')
plt.plot(num_est, mean_test_score_num_est, label = 'Cross validation score', color = 'b
lack')

plt.title('Validation curve for Random Forest')
plt.xlabel('Values of hyperparameter n_estimators')
plt.ylabel('Accuracy score')
plt.legend(loc = 'best')
```

Out[119]:

```
<matplotlib.legend.Legend at 0x7fa1eaa3c358>
```



In [120]:

```
#tuning max_depth which specifies the maximum depth of each tree. The default is none w
hich means that each tree will
#expand until each leaf is pure, i.e. where all the data on the leaf comes from the sam
e class

depth = [1, 5, 10, 20, 30]

#preparing to create the cross validation curve

train_score_depth, test_score_depth = validation_curve(
                                            RandomForestClassifier(),
                                            X = X_train, y = y_train,
                                            param_name = 'max_depth',
                                            param_range = depth,
                                            cv = 5,
                                            scoring = 'accuracy')
```

In [121]:

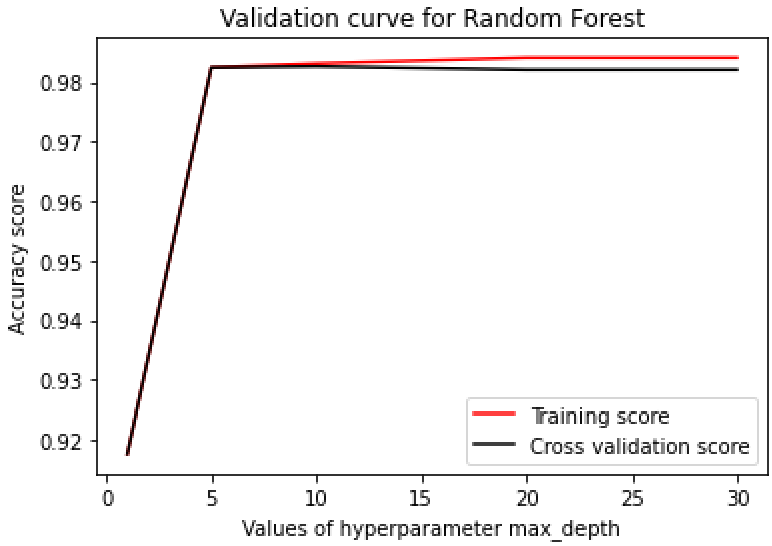
```
#calculating mean and standard deviation for train and test sets

mean_train_score_depth = np.mean(train_score_depth, axis = 1)
std_train_score_depth = np.std(train_score_depth, axis = 1)

mean_test_score_depth = np.mean(test_score_depth, axis = 1)
std_test_score_depth = np.std(test_score_depth, axis = 1)
```

In [122]:

```
#both the training and cross validations scores are highst at a tree depth of 5 so this
will be used in the final model

plt.plot(depth, mean_train_score_depth, label = 'Training score', color = 'red')
plt.plot(depth, mean_test_score_depth, label = 'Cross validation score', color = 'blac
k')

plt.title('Validation curve for Random Forest')
plt.xlabel('Values of hyperparameter max_depth')
plt.ylabel('Accuracy score')
plt.legend(loc = 'best')
```

Out[122]:

```
<matplotlib.legend.Legend at 0x7fa1eb56b7b8>
```



In [123]:

```
#tuning min_samples_split which is the minimum number of samples reqired to split an in
ternal leaf node.
#The default value is 2 which means that each internal leaf node must have at least two
sampls before it can split into a
#more specific classification

sample_split = [5, 10, 15, 20, 25]

#preparing to create the cross validation curve

train_score_split, test_score_split = validation_curve(
                                            RandomForestClassifier(),
                                            X = X_train, y = y_train,
                                            param_name = 'min_samples_split',
                                            param_range = sample_split,
                                            cv = 5,
                                            scoring = 'accuracy')
```

In [124]:

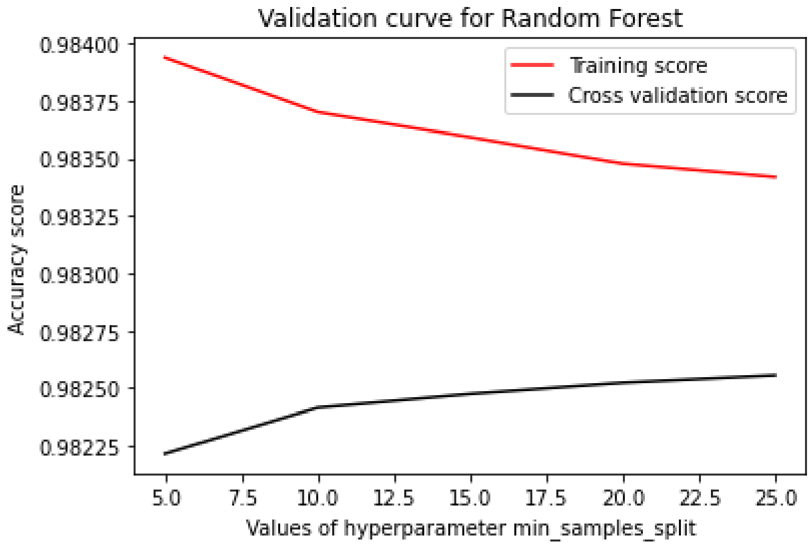
```
#calculating mean and standard deviation for train and test sets

mean_train_score_split = np.mean(train_score_split, axis = 1)
std_train_score_split = np.std(train_score_split, axis = 1)

mean_test_score_split = np.mean(test_score_split, axis = 1)
std_test_score_split = np.std(test_score_split, axis = 1)
```

In [125]:

```
#cross validation score is highest at 10 samples and then starts to flatten out. At thi
s point accuracy is falling but it's
#still high at 98.3%. Will therefore go with 10 samples before a leaf node can split -
 this should be ok given that we
#have over 100,000 samples in the training set

plt.plot(sample_split, mean_train_score_split, label = 'Training score', color = 'red')
plt.plot(sample_split, mean_test_score_split, label = 'Cross validation score', color =
'black')

plt.title('Validation curve for Random Forest')
plt.xlabel('Values of hyperparameter min_samples_split')
plt.ylabel('Accuracy score')
plt.legend(loc = 'best')
```

Out[125]:

```
<matplotlib.legend.Legend at 0x7fa1eaecd668>
```



In [126]:

```
#tuning min_samples_leaf which is the minimum number of samples required to be a leaf n
ode. The default is 1 which means
#that every leaf must have at least one sample that it classifies

sample_leaf = [2, 4, 6, 8, 10]

#preparing to create the cross validation curve

train_score_leaf, test_score_leaf = validation_curve(
                                            RandomForestClassifier(),
                                            X = X_train, y = y_train,
                                            param_name = 'min_samples_leaf',
                                            param_range = sample_leaf,
                                            cv = 5,
                                            scoring = 'accuracy')
```

In [127]:

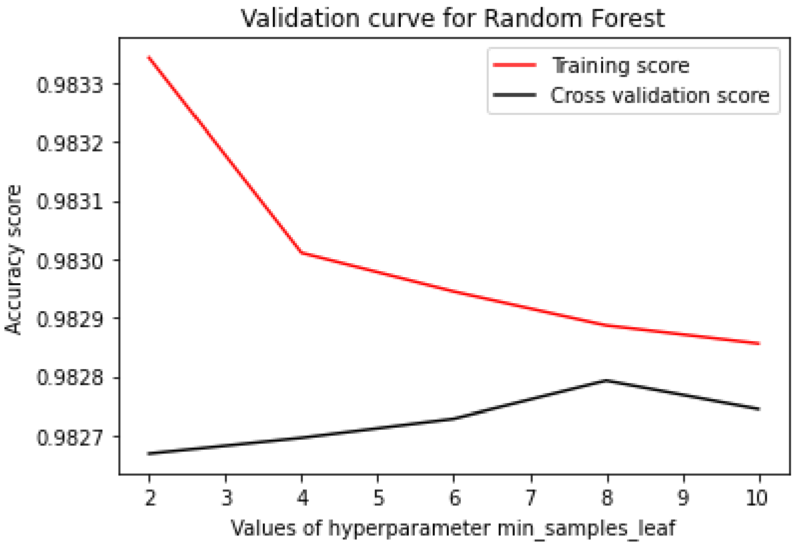
```
#calculating mean and standard deviation for train and test sets

mean_train_score_leaf = np.mean(train_score_leaf, axis = 1)
std_train_score_leaf = np.std(train_score_leaf, axis = 1)

mean_test_score_leaf = np.mean(test_score_leaf, axis = 1)
std_test_score_leaf = np.std(test_score_leaf, axis = 1)
```

In [128]:

```
#cross validation score is highest at 6 samples. At this point accuracy is falling but
 it's still high at 98.3%. Will
#therefore go with 8 samples as the minumum for each leaf node to classify

plt.plot(sample_leaf, mean_train_score_leaf, label = 'Training score', color = 'red')
plt.plot(sample_leaf, mean_test_score_leaf, label = 'Cross validation score', color =
'black')

plt.title('Validation curve for Random Forest')
plt.xlabel('Values of hyperparameter min_samples_leaf')
plt.ylabel('Accuracy score')
plt.legend(loc = 'best')
```

Out[128]:

```
<matplotlib.legend.Legend at 0x7fa1eaa4de10>
```



In [139]:

```
#now putting our new hyperparameters into the final model

tuned_forest = RandomForestClassifier(n_estimators = 50, max_depth = 5, min_samples_spl
it = 10, min_samples_leaf = 8,
                                       random_state = 42)

tuned_model = tuned_forest.fit(X_train, y_train)

tuned_y_pred = tuned_model.predict(X_test)
```

In [140]:

```
#printing the confusion matrix - 711 false positives versus 669 in default forest

#41933 = true negative, 3752 = true positive, 52 = false negative, 711 = false positive
matrix = confusion_matrix(y_test, tuned_y_pred)
print('Confusion matrix \n', matrix)
```

```
Confusion matrix
 [[41933   711]
 [   52  3752]]
```

In [141]:

```
#printing out the scores for precision, recall, accuracy and F1 for y_test and default_
y_pred - accuracy and precision
#are same as logistic regression and default random forest when printed to 2 dp
print(metrics.classification_report(y_test, tuned_y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     42644
           1       0.84      0.99      0.91      3804

    accuracy                           0.98     46448
   macro avg       0.92      0.98      0.95     46448
weighted avg       0.99      0.98      0.98     46448
```

In [142]:

```
#printing all scores for all models for class 1 on the test sets. Default model has a h
igher precision score than the tuned
#model and logistic regression model also had a higher precision score then tuned mode
l. Logistic regression model also has
#a higher accuracy and F1 score than both random forest models although differences are
small

#precision
log_reg_precision = precision_score(y_test, y_pred_test, pos_label = 1)
default_forest_precision = precision_score(y_test, default_y_pred, pos_label = 1)
tuned_forest_precision = precision_score(y_test, tuned_y_pred, pos_label = 1)

#recall
log_reg_recall = recall_score(y_test, y_pred_test, pos_label = 1)
default_forest_recall = recall_score(y_test, default_y_pred, pos_label = 1)
tuned_forest_recall = recall_score(y_test, tuned_y_pred, pos_label = 1)

#accuracy
log_reg_accuracy = accuracy_score(y_test, y_pred_test)
default_forest_accuracy = accuracy_score(y_test, default_y_pred)
tuned_forest_accuracy = accuracy_score(y_test, tuned_y_pred)

#f1 score
log_reg_f1 = f1_score(y_test, y_pred_test, pos_label = 1)
default_forest_f1 = f1_score(y_test, default_y_pred, pos_label = 1)
tuned_forest_f1 = f1_score(y_test, tuned_y_pred, pos_label = 1)

print('Logistic regression precision: ', round(log_reg_precision, 5))
print('Default Random Forest precision: ', round(default_forest_precision, 5))
print('Tuned Random Forest precision: ', round(tuned_forest_precision, 5))
print('')
print('Logistic regression recall: ', round(log_reg_recall, 5))
print('Default Random Forest recall: ', round(default_forest_recall, 5))
print('Tuned Random Forest recall: ', round(tuned_forest_recall, 5))
print('')
print('Logistic regression accuracy: ', round(log_reg_accuracy, 5))
print('Default Random Forest accuracy: ', round(default_forest_accuracy, 5))
print('Tuned Random Forest accuracy: ', round(tuned_forest_accuracy, 5))
print('')
print('Logistic regression F1: ', round(log_reg_f1, 5))
print('Default Random Forest F1: ', round(default_forest_f1, 5))
print('Tuned Random Forest F1: ', round(tuned_forest_f1, 5))
```

```
Logistic regression precision:  0.8451
Default Random Forest precision:  0.84698
Tuned Random Forest precision:  0.84069

Logistic regression recall:  0.98528
Default Random Forest recall:  0.97345
Tuned Random Forest recall:  0.98633

Logistic regression accuracy:  0.984
Default Random Forest accuracy:  0.98342
Tuned Random Forest accuracy:  0.98357

Logistic regression F1:  0.90982
Default Random Forest F1:  0.90582
Tuned Random Forest F1:  0.90771
```

In [143]:

```
#calculating probabilities scores for test sets
default_prob = default_model.predict_proba(X_test)
tuned_prob = tuned_model.predict_proba(X_test)

#keeping probabilities for positive outcome only (the threshold is 0.5 which means, if
 the predicted probability of the
#class for an instance is less than 0.5, that instance is predicted to be in class 0 (t
he negative class). If the
#probability of the class for an instance is equal or greater than 0.5, the instance is
classified as class 1.)
default_prob_order = default_prob[:, 1]
tuned_prob_order = tuned_prob[:, 1]

#calculate false positive rate (fpr), true positive rate (tpr) and thresholds for test
 set
test_fpr_d, test_tpr_d, test_thresholds_d = roc_curve(y_test, default_prob_order)
test_fpr_t, test_tpr_t, test_thresholds_t = roc_curve(y_test, tuned_prob_order)
```

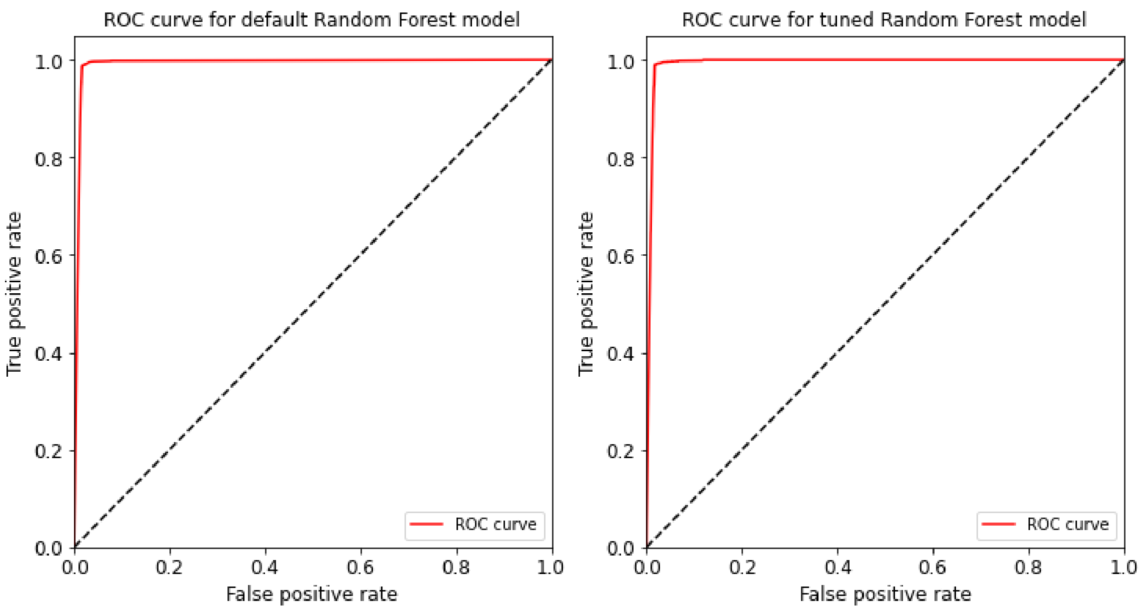
In [144]:

```
#calculating AUC (Area Under Curve) - AUC is higher for the tuned model. But logistic r
egression model is still higher than
#both (0.99328)

default_auc = auc(test_fpr_d, test_tpr_d)
tuned_auc = auc(test_fpr_t, test_tpr_t)
print('Default AUC: ', round(default_auc, 5))
print('Tuned_AUC: ', round(tuned_auc, 5))
```

```
Default AUC:  0.99187
Tuned_AUC:  0.9926
```

In [145]:

```
#plotting an ROC curves for random forest models - again they show a very good model, s
imilar to the logistic regression

fig = plt.figure(figsize = (12, 6))
ax = plt.subplot(1, 2, 1)
plt.plot(test_fpr_d, test_tpr_d, label = 'ROC curve', color = 'red')

#plotting diagonal line from zero which represents a model that guesses incorrectly for
every correct guess
plt.plot([0, 1], [0, 1], color = 'black', linestyle = 'dashed')
plt.xlim([0, 1])
plt.ylim([0, 1.05])

plt.legend()
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel('False positive rate', fontsize = 12)
plt.ylabel('True positive rate', fontsize = 12)
plt.title('ROC curve for default Random Forest model', fontsize = 12)

ax = plt.subplot(1, 2, 2)
plt.plot(test_fpr_t, test_tpr_t, label = 'ROC curve', color = 'red')

#plotting diagonal line from zero which represents a model that guesses incorrectly for
every correct guess
plt.plot([0, 1], [0, 1], color = 'black', linestyle = 'dashed')
plt.xlim([0, 1])
plt.ylim([0, 1.05])

plt.legend()
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel('False positive rate', fontsize = 12)
plt.ylabel('True positive rate', fontsize = 12)
plt.title('ROC curve for tuned Random Forest model', fontsize = 12)
plt.savefig('RF_ROC_curves')
```



In [146]:

```
#checking feature importance in default model
feature_importance = pd.Series(default_model.feature_importances_, index = X.columns)
feature_importance.sort_values(ascending = False, inplace = True)
print(feature_importance)
```

```
checked_delivery_detail    0.486037
saw_checkout               0.218194
sign_in                    0.152668
basket_add_detail          0.044707
basket_icon_click          0.042424
basket_add_list            0.012417
saw_delivery               0.007964
saw_homepage               0.006766
list_size_dropdown         0.005295
checked_returns_detail     0.005062
returning_user             0.004297
closed_minibasket_click    0.003183
image_picker               0.002450
promo_banner_click         0.002180
sort_by                    0.002065
detail_wishlist_add        0.001568
account_page_click         0.001540
saw_account_upgrade        0.000899
saw_sizecharts             0.000284
dtype: float64
```

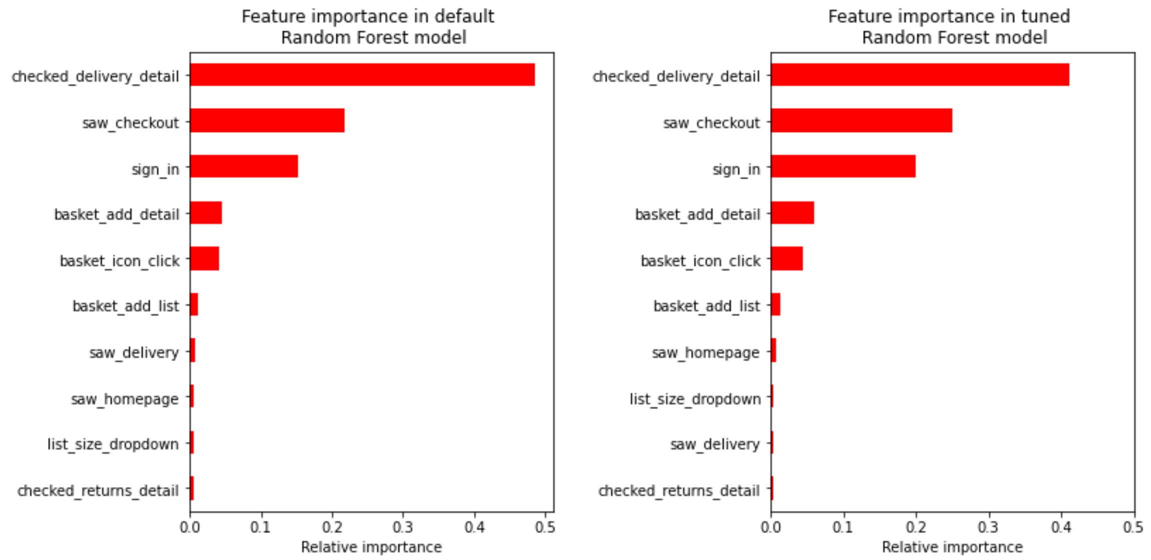
In [147]:

```
#checking feature importance in tuned model
feature_importance_t = pd.Series(tuned_model.feature_importances_, index = X.columns)
feature_importance_t.sort_values(ascending = False, inplace = True)
print(feature_importance_t)
```

```
checked_delivery_detail    0.410433
saw_checkout               0.250969
sign_in                    0.200023
basket_add_detail          0.059542
basket_icon_click          0.044216
basket_add_list            0.013162
saw_homepage               0.006571
list_size_dropdown         0.004283
saw_delivery               0.003197
checked_returns_detail     0.002900
returning_user             0.001676
image_picker               0.001168
closed_minibasket_click    0.000848
detail_wishlist_add        0.000462
account_page_click         0.000291
sort_by                    0.000162
promo_banner_click         0.000044
saw_account_upgrade        0.000037
saw_sizecharts             0.000016
dtype: float64
```

In [148]:

```
#plotting feature importance for default model
plt.figure(figsize = (12,6))
ax = plt.subplot(1, 2, 1)

feature_importance.nlargest(10).plot(kind = 'barh', color = 'red').invert_yaxis()
plt.xlabel('Relative importance')
plt.title('Feature importance in default \n Random Forest model', fontsize = 12)

ax = plt.subplot(1, 2, 2)

feature_importance_t.nlargest(10).plot(kind = 'barh', color = 'red').invert_yaxis()
plt.xlabel('Relative importance')
ax.set_xlim(0.0, 0.5)
plt.title('Feature importance in tuned \n Random Forest model', fontsize = 12)

plt.subplots_adjust(wspace = 0.6)
plt.savefig('feature_importance')
plt.show()
```



In [ ]:

In [ ]: