Gridsearching a Decision Tree & Random Forest, to find best hyperparameter values

Import dependencies, load data

In [1]:

```
from preprocessor import data_cleaner, data_sampler
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score,GridSearchCV

from sklearn.metrics import plot_roc_curve, plot_confusion_matrix, roc_cu

from sklearn.ensemble import BaggingClassifier, RandomForestClassifier

import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

```

In [2]:

```
X_train, y_train = data_cleaner("../data/train.csv.zip")
X_test, y_test = data_cleaner("../data/test.csv.zip")
X_train, y_train = data_sampler(X_train,y_train)
```

Decision Tree

In [3]:

```
from sklearn.tree import DecisionTreeClassifier, plot_tree
```

First gridsearch

My best guess at a range of values to test

In [4]:

```
dtc_grid = DecisionTreeClassifier()

# define parameter grid to search
grid = [
    {'criterion': ['gini', 'entropy', 'log_loss'],
    'splitter': ['best','random'],
    'max_depth': [2,5,10],
    'min_samples_split':[2,5,10],
    'min_samples_leaf':[1,5,10],
    'max_features':[None,'auto'],
    'max_leaf_nodes':[10,50,100]}
]

gridsearch = GridSearchCV(estimator=dtc_grid,param_grid=grid,scoring='f1
gridsearch.fit(X_train,y_train)

grid_pred = gridsearch.predict(X_test)
grid_report = classification_report(y_test,grid_pred,output_dict=True)
grid_report = pd.DataFrame(grid_report).iloc[:,0:3]
grid_report
```

Out[4]:

	0	1	accuracy
precision	0.989611	0.693619	0.914075
recall	0.904094	0.958116	0.914075
f1-score	0.944922	0.804690	0.914075
support	21177.000000	4799.000000	0.914075

In [5]:

```
gridsearch.best_params_
```

Out[5]:

```
{'criterion': 'entropy',
 'max_depth': 10,
 'max_features': None,
 'max_leaf_nodes': 100,
 'min_samples_leaf': 10,
 'min_samples_split': 2,
 'splitter': 'best'}
```

second gridsearch

The values with the greatest magnitude were chosen for Max_depth, max_features,max_leaf_nodes,min_samples_leaf. So the next gridsearch will include these chosen values as the low end of the range that is being searched.

In [6]:

```
grid_two = [
    {'criterion': ['gini'],
    'max_depth': [10,25,50],
    'max_features': ['log2',10,20],
    'max_leaf_nodes': [100,150,200],
    'min_samples_leaf': [10,25,50],
    'min_samples_split': [2],
    'splitter': ['best']}
]

gridsearch_two = GridSearchCV(estimator=dtc_grid,param_grid=grid_two,sco
gridsearch_two.fit(X_train,y_train)

```

Out[6]:

```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=3,
             param_grid=[{'criterion': ['gini'], 'max_depth': [10, 25, 50],
                          'max_features': ['log2', 10, 20],
                          'max_leaf_nodes': [100, 150, 200],
                          'min_samples_leaf': [10, 25, 50],
                          'min_samples_split': [2], 'splitter': ['best']}],
             scoring='f1')
```

In [7]:

```

grid_two_pred = gridsearch_two.predict(X_test)
grid_two_report = classification_report(y_test,grid_two_pred,output_dict
grid_two_report = pd.DataFrame(grid_two_report).iloc[:,0:3]
grid_two_report
```

Out[7]:

	0	1	accuracy
precision	0.989449	0.744284	0.931244
recall	0.925532	0.956449	0.931244
f1-score	0.956424	0.837133	0.931244
support	21177.000000	4799.000000	0.931244

In [8]:

```
gridsearch_two.best_params_
```

Out[8]:

```
{'criterion': 'gini',
 'max_depth': 25,
 'max_features': 20,
 'max_leaf_nodes': 200,
 'min_samples_leaf': 10,
 'min_samples_split': 2,
 'splitter': 'best'}
```

third gridsearch

Max_depth, max_leaf_nodes, continue selecting the greatest value. Max_features is still unclear.

In [9]:

```
grid_three = [
    {'criterion': ['gini'],
    'max_depth': [50,100,200],
    'max_features': [15,20,23],
    'max_leaf_nodes': [200,300,500],
    'min_samples_leaf': [10],
    'min_samples_split': [2],
    'splitter': ['best']}
    ]

gridsearch_three = GridSearchCV(estimator=dtc_grid,param_grid=grid_three,
gridsearch_three.fit(X_train,y_train)

grid_three_pred = gridsearch_three.predict(X_test)
grid_three_report = classification_report(y_test,grid_three_pred,output_
grid_three_report = pd.DataFrame(grid_three_report).iloc[:,0:3]
grid_three_report
```

Out[9]:

	0	1	accuracy
precision	0.989899	0.769115	0.939098
recall	0.934835	0.957908	0.939098
f1-score	0.961580	0.853192	0.939098
support	21177.000000	4799.000000	0.939098

In [10]:

```
gridsearch_three.best_params_
```

Out[10]:

```
{'criterion': 'gini',
 'max_depth': 50,
 'max_features': 20,
 'max_leaf_nodes': 500,
 'min_samples_leaf': 10,
 'min_samples_split': 2,
 'splitter': 'best'}
```

fourth gridsearch

Everything seems to be getting zeroed in on except for max_leaf_nodes.

In [11]:

```
grid_four = [
    {'criterion': ['gini'],
    'max_depth': [75,100,125],
    'max_features': [18,19,20],
    'max_leaf_nodes': [500,750,1000],
    'min_samples_leaf': [5,10,15],
    'min_samples_split': [2],
    'splitter': ['best']}
    ]

gridesearch_four = GridSearchCV(estimator=dtc_grid,param_grid=grid_four,s
gridesearch_four.fit(X_train,y_train)

grid_four_pred = gridesearch_four.predict(X_test)
grid_four_report = classification_report(y_test,grid_four_pred,output_di
grid_four_report = pd.DataFrame(grid_four_report).iloc[:,0:3]
grid_four_report
```

Out[11]:

	0	1	accuracy
precision	0.990585	0.781224	0.943024
recall	0.939038	0.960617	0.943024
f1-score	0.964123	0.861682	0.943024
support	21177.000000	4799.000000	0.943024

In [12]:

```
gridesearch_four.best_params_
```

Out[12]:

```
{'criterion': 'gini',
 'max_depth': 100,
 'max_features': 18,
 'max_leaf_nodes': 750,
 'min_samples_leaf': 5,
 'min_samples_split': 2,
 'splitter': 'best'}
```

fifth gridsearch

In [13]:

```
grid_five = [
    {'criterion': ['gini'],
    'max_depth': [115,125,150,175],
    'max_features': [19],
    'max_leaf_nodes': [600,750,900],
    'min_samples_leaf': [5],
    'min_samples_split': [2],
    'splitter': ['best']}
    ]

gridsearch_five = GridSearchCV(estimator=dtc_grid,param_grid=grid_five,s
gridsearch_five.fit(X_train,y_train)

grid_five_pred = gridsearch_five.predict(X_test)
grid_five_report = classification_report(y_test,grid_five_pred,output_di
grid_five_report = pd.DataFrame(grid_five_report).iloc[:,0:3]
grid_five_report
```

Out[13]:

	0	1	accuracy
precision	0.991308	0.807088	0.950685
recall	0.947821	0.963326	0.950685
f1-score	0.969077	0.878313	0.950685
support	21177.000000	4799.000000	0.950685

In [14]:

```
gridsearch_five.best_params_
```

Out[14]:

```
{'criterion': 'gini',
 'max_depth': 115,
 'max_features': 19,
 'max_leaf_nodes': 750,
 'min_samples_leaf': 5,
 'min_samples_split': 2,
 'splitter': 'best'}
```

sixth gridsearch

In [15]:

```
grid_six = [
    {'criterion': ['gini'],
    'max_depth': [125,135,150],
    'max_features': [19],
    'max_leaf_nodes': [550,600,650],
    'min_samples_leaf': [5],
    'min_samples_split': [2],
    'splitter': ['best']}
    ]

gridsearch_six = GridSearchCV(estimator=dtc_grid,param_grid=grid_six,scor
gridsearch_six.fit(X_train,y_train)

grid_six_pred = gridsearch_six.predict(X_test)
grid_six_report = classification_report(y_test,grid_six_pred,output_dict
grid_six_report = pd.DataFrame(grid_six_report).iloc[:,0:3]
grid_six_report
```

Out[15]:

	0	1	accuracy
precision	0.990839	0.783531	0.943833
recall	0.939793	0.961659	0.943833
f1-score	0.964641	0.863505	0.943833
support	21177.000000	4799.000000	0.943833

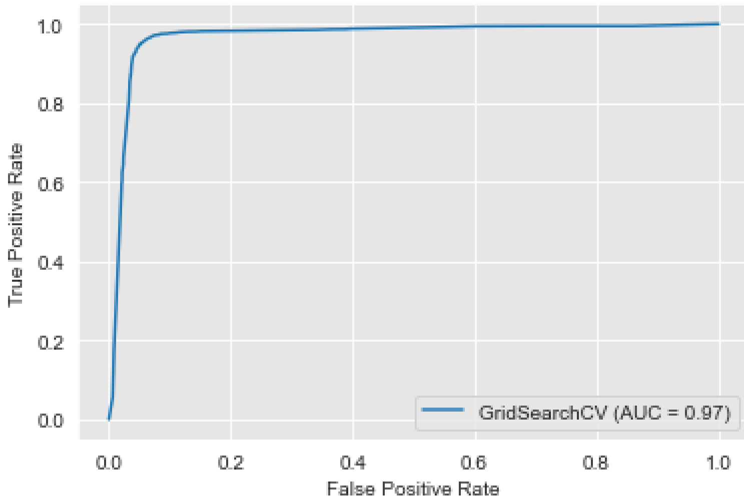
Observations:

F1, precision, and recall performance continue to decrease after the fourth gridsearch. So, the the best_params_ of gridsearch_four will be used as a start point to gridsearch a random forest and bagging tree.

Gridsearch_four.best_params_ returns the following dict:
{'criterion': 'gini',
'max_depth': 125,
'max_features': 19,
'max_leaf_nodes': 750,
'min_samples_leaf': 5,
'min_samples_split': 2,
'splitter': 'best'}

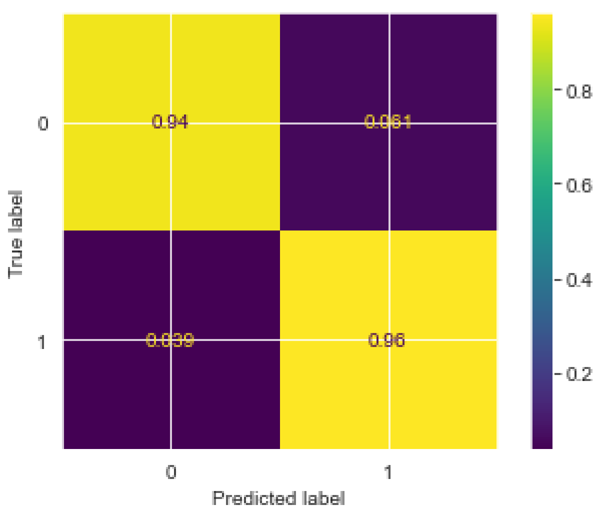
In [16]:

```
plot_roc_curve(gridesearch_four,X_test,y_test)
plt.show()
```



In [17]:

```
plot_confusion_matrix(gridesearch_four,X_test,y_test,normalize='true')
plt.show()
```



BaggingClassifier

baseline model (default bagging parameters)

In [18]:

```
bagging_tree = DecisionTreeClassifier(criterion='gini',
                                      max_depth=125,
                                      max_features=19,
                                      max_leaf_nodes=750,
                                      min_samples_leaf=5,
                                      min_samples_split=2,
                                      splitter='best')

tree_bagger = BaggingClassifier(base_estimator=bagging_tree)
tree_bagger.fit(X_train,y_train)
tree_bagger_pred = tree_bagger.predict(X_test)
tree_bagger_report = classification_report(y_test,tree_bagger_pred,outpu
tree_bagger_report = pd.DataFrame(tree_bagger_report).iloc[:,0:3]
tree_bagger_report

```

Out[18]:

	0	1	accuracy
precision	0.992680	0.789277	0.946528
recall	0.941351	0.969369	0.946528
f1-score	0.966335	0.870102	0.946528
support	21177.000000	4799.000000	0.946528

Gridsearch bagging classifier

First gridsearch

In [19]:

```
from sklearn.ensemble import BaggingClassifier

bagging_tree = DecisionTreeClassifier(criterion='gini',
                                      max_depth=125,
                                      max_features=19,
                                      max_leaf_nodes=750,
                                      min_samples_leaf=5,
                                      min_samples_split=2,
                                      splitter='best')

tree_bagger = BaggingClassifier()

bag_grid = [{
    'base_estimator':[bagging_tree],
    'n_estimators':[5,10,15,20],
    'max_samples':[1.0,3.0,5.0],
    'max_features':[1.0,5.0,10.0],
    'bootstrap':[True,False],
    'bootstrap_features':[True,False],
    'n_jobs':[3]
}]

bagged_grid = GridSearchCV(estimator=tree_bagger,param_grid=bag_grid,scor
bagged_grid.fit(X_train,y_train)
bagged_grid_pred = bagged_grid.predict(X_test)
bagged_grid_report = classification_report(y_test,bagged_grid_pred,outpu
bagged_grid_report = pd.DataFrame(bagged_grid_report).iloc[:,0:3]
bagged_grid_report

```

Out[19]:

	0	1	accuracy
precision	0.994590	0.804598	0.951956
recall	0.946215	0.977287	0.951956
f1-score	0.969800	0.882574	0.951956
support	21177.000000	4799.000000	0.951956

In [20]:

```
bagged_grid_report
```

Out[20]:

	0	1	accuracy
precision	0.994590	0.804598	0.951956
recall	0.946215	0.977287	0.951956
f1-score	0.969800	0.882574	0.951956
support	21177.000000	4799.000000	0.951956

In [21]:
```
bagged_grid.best_params_
```

Out[21]:
```
{'base_estimator': DecisionTreeClassifier(max_depth=125, max_features=19, m
ax_leaf_nodes=750,
                        min_samples_leaf=5),
 'bootstrap': False,
 'bootstrap_features': True,
 'max_features': 1.0,
 'max_samples': 1.0,
 'n_estimators': 20,
 'n_jobs': 3}
```

Second gridsearch

-searching only n_estimators

In [22]:
```
second_bag_grid = [{
    'base_estimator':[bagging_tree],
    'n_estimators':[20,23,25,30],
    'max_samples':[1.0],
    'max_features':[1.0],
    'bootstrap':[False],
    'bootstrap_features':[True],
    'n_jobs':[3]
}]

second_bagged_grid = GridSearchCV(estimator=tree_bagger,param_grid=secon
second_bagged_grid.fit(X_train,y_train)
second_bagged_grid_pred = second_bagged_grid.predict(X_test)
second_bagged_grid_report = classification_report(y_test,second_bagged_g
second_bagged_grid_report = pd.DataFrame(second_bagged_grid_report).iloc
second_bagged_grid_report
```

Out[22]:

	0	1	accuracy
precision	0.994573	0.796130	0.949569
recall	0.943288	0.977287	0.949569
f1-score	0.968252	0.877456	0.949569
support	21177.000000	4799.000000	0.949569

In [23]:
```
second_bagged_grid.best_params_
```

Out[23]:
```
{'base_estimator': DecisionTreeClassifier(max_depth=125, max_features=19, m
ax_leaf_nodes=750,
                        min_samples_leaf=5),
 'bootstrap': False,
 'bootstrap_features': True,
 'max_features': 1.0,
 'max_samples': 1.0,
 'n_estimators': 23,
 'n_jobs': 3}
```

finding best n_estimators

Here I re-run the same cell(s) adjusting only n_estimators to find the value that improves F1 the most.

In [24]:
```
n_trees_bagger = BaggingClassifier(base_estimator=bagging_tree,
                                   bootstrap=False,
                                   bootstrap_features=True,
                                   n_estimators=31,
                                   n_jobs=3)

n_trees_bagger.fit(X_train,y_train)

n_trees_pred = n_trees_bagger.predict(X_test)
n_trees_report = classification_report(y_test,n_trees_pred,output_dict=T
n_trees_report = pd.DataFrame(n_trees_report).iloc[:,0:3]
n_trees_report
```

Out[24]:

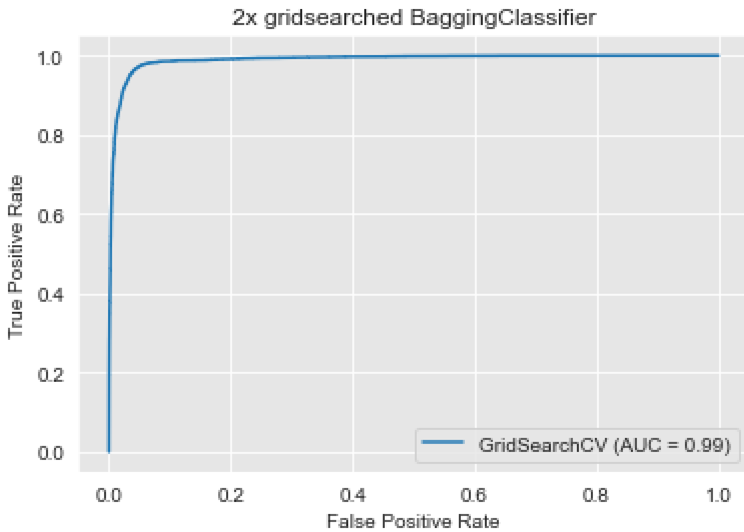
	0	1	accuracy
precision	0.994274	0.794841	0.94903
recall	0.942910	0.976037	0.94903
f1-score	0.967911	0.876169	0.94903
support	21177.000000	4799.000000	0.94903

Observations:

The best performing Bagging classifier is the second grid searches best parameters

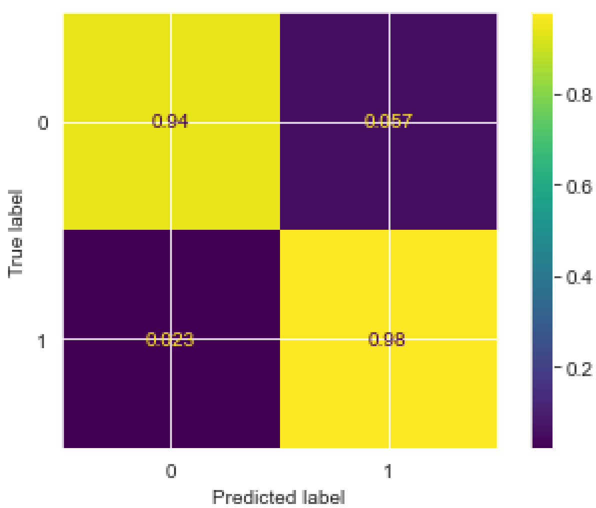
In [25]:

```
plot_roc_curve(second_bagged_grid,X_test,y_test)
plt.title('2x gridsearched BaggingClassifier')
plt.show()
```



In [26]:

```
plot_confusion_matrix(second_bagged_grid,X_test,y_test,normalize='true')
plt.show()
```



Random Forest

Baseline RF

In [27]:

```
RFC = RandomForestClassifier(n_jobs=3)
RFC.fit(X_train,y_train)

rfc_pred = RFC.predict(X_test)
rfc_report = classification_report(y_test,rfc_pred,output_dict='true')
rfc_report = pd.DataFrame(rfc_report).iloc[:,0:3]
rfc_report
```

Out[27]:

	0	1	accuracy
precision	0.994494	0.831618	0.959155
recall	0.955187	0.976662	0.959155
f1-score	0.974444	0.898323	0.959155
support	21177.000000	4799.000000	0.959155

Tuning RF hyperparameters

using the best_params_ from the decision tree model gridsearch_four

In [28]:

```
RFC_tuned = RandomForestClassifier(criterion='entropy',
                                    max_depth=125,
                                    max_features=20,
                                    max_leaf_nodes=750,
                                    min_samples_leaf=5,
                                    min_samples_split=2)
RFC_tuned.fit(X_train,y_train)

rfc_tuned_pred = RFC_tuned.predict(X_test)

rfc_tuned_report = classification_report(y_test,rfc_tuned_pred,output_di
rfc_tuned_report = pd.DataFrame(rfc_tuned_report).iloc[:,0:3]
rfc_tuned_report
```

Out[28]:

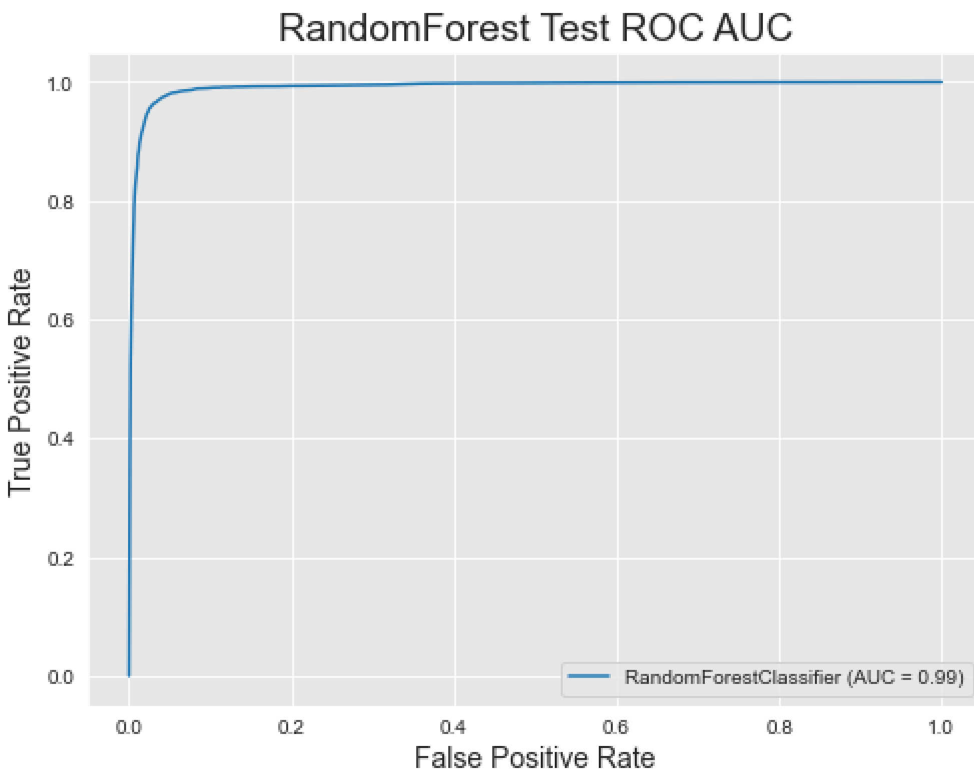
	0	1	accuracy
precision	0.993930	0.795679	0.949068
recall	0.943288	0.974578	0.949068
f1-score	0.967947	0.876089	0.949068
support	21177.000000	4799.000000	0.949068

Observations:

Random forest default settings consistently outperforms parameters used from best decision tree. Computational demands are too great to perform a gridsearch

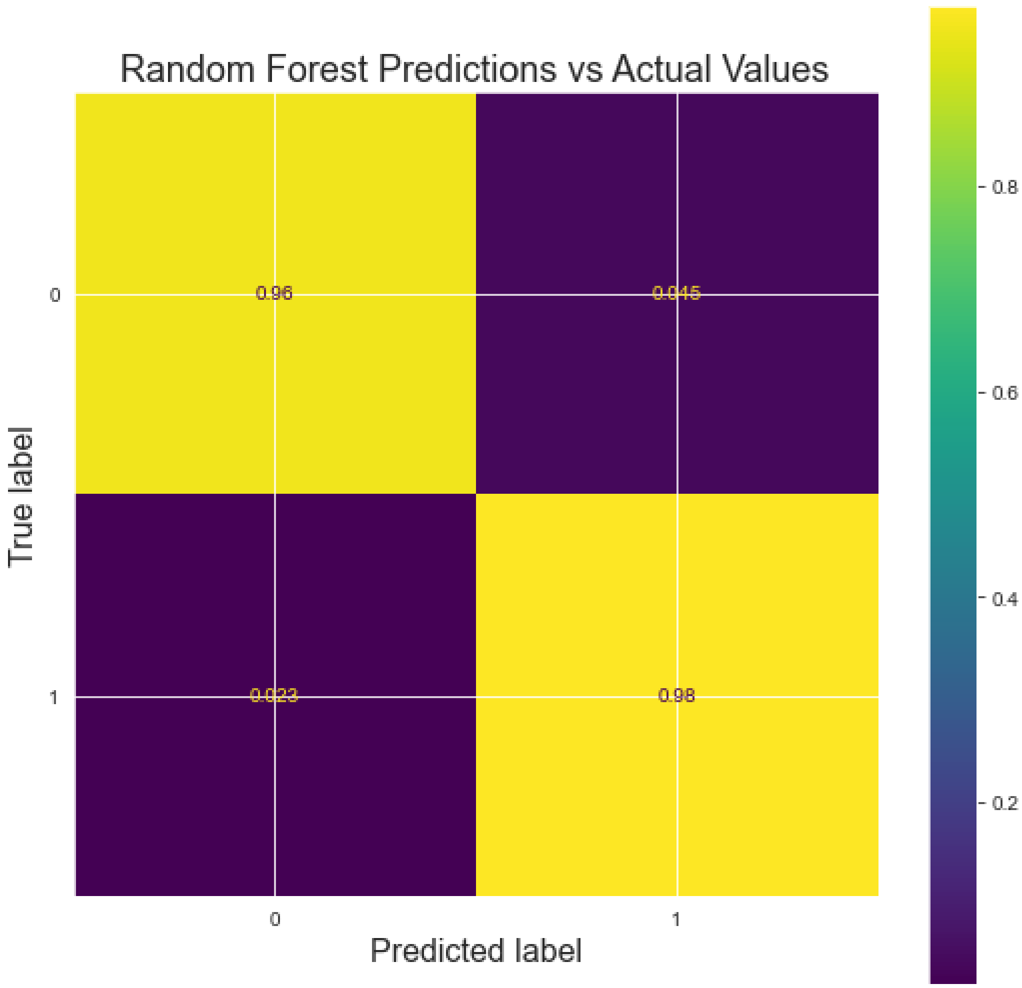
In [29]:

```
# baseline Random Forest ROC AUC
fig, ax = plt.subplots(figsize=(8, 6))
plot_roc_curve(RFC,X_test,y_test,ax=ax)
ax.set_title("RandomForest Test ROC AUC",fontsize=19)
ax.set_ylabel('True Positive Rate',fontsize=14)
ax.set_xlabel('False Positive Rate',fontsize=14)
plt.show()
```



In [30]:

```
# baseline Random Forest confusion matrix
fig, ax = plt.subplots(figsize=(9, 9))
plot_confusion_matrix(RFC,X_test,y_test,normalize='true',ax=ax)
ax.set_title("Random Forest Predictions vs Actual Values",fontsize=18)
ax.set_ylabel('True label',fontsize=16)
ax.set_xlabel('Predicted label',fontsize=16)
plt.show()
```

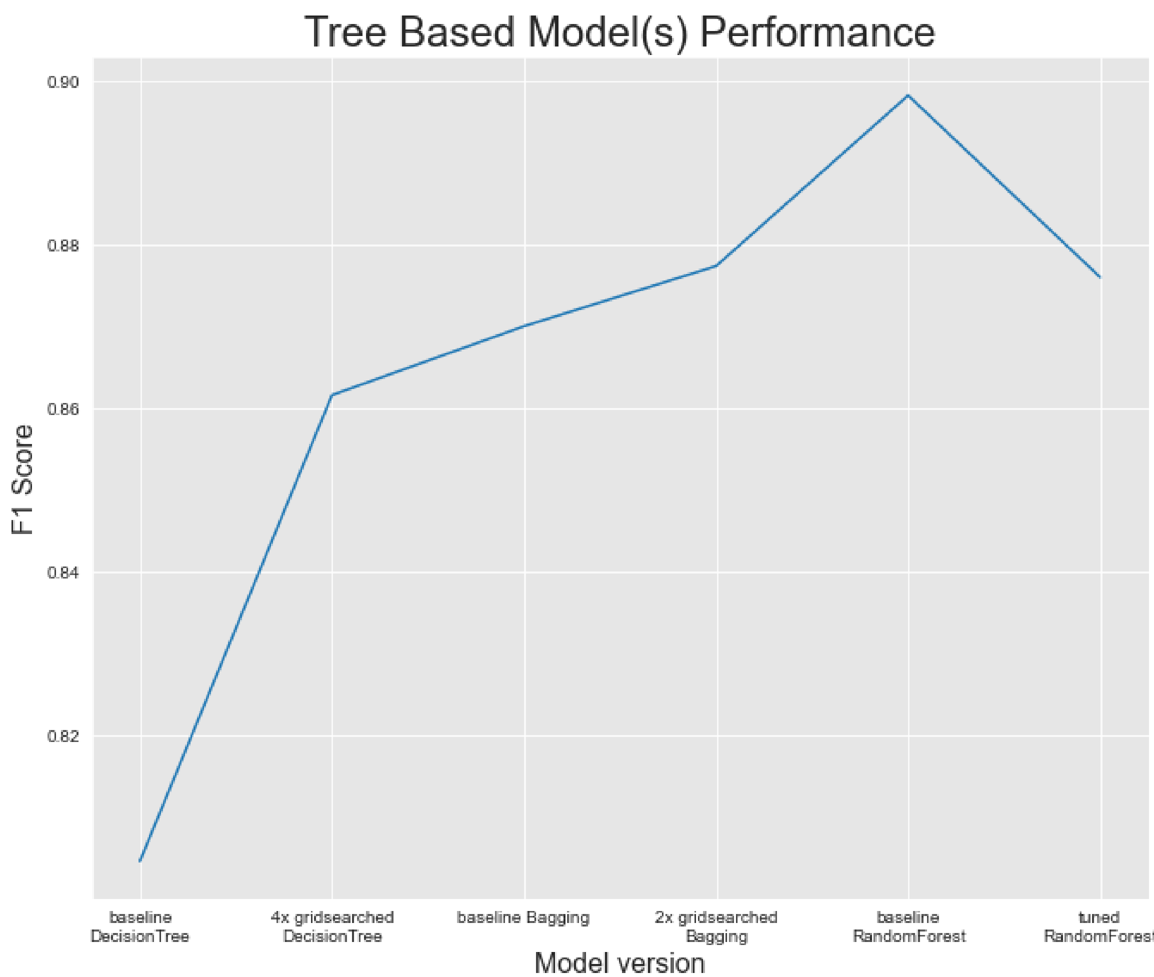


Iterative Performance Visualization

F1 Score

In [31]:

```
f1_scores = [
        grid_report['1'][2],
        grid_four_report['1'][2],
        tree_bagger_report['1'][2],
        second_bagged_grid_report['1'][2],
        rfc_report['1'][2],
        rfc_tuned_report['1'][2]
        ]

plt.figure(figsize=(11,9))
x = ['baseline\nDecisionTree',
        '4x gridsearched\nDecisionTree',
        'baseline Bagging',
        '2x gridsearched\nBagging',
        'baseline\nRandomForest',
        'tuned\nRandomForest']
y = f1_scores
plt.plot(x,y)

plt.title('Tree Based Model(s) Performance',fontsize=24)
plt.ylabel('F1 Score',fontsize=16)
plt.xlabel('Model version',fontsize=16)
plt.show()
```



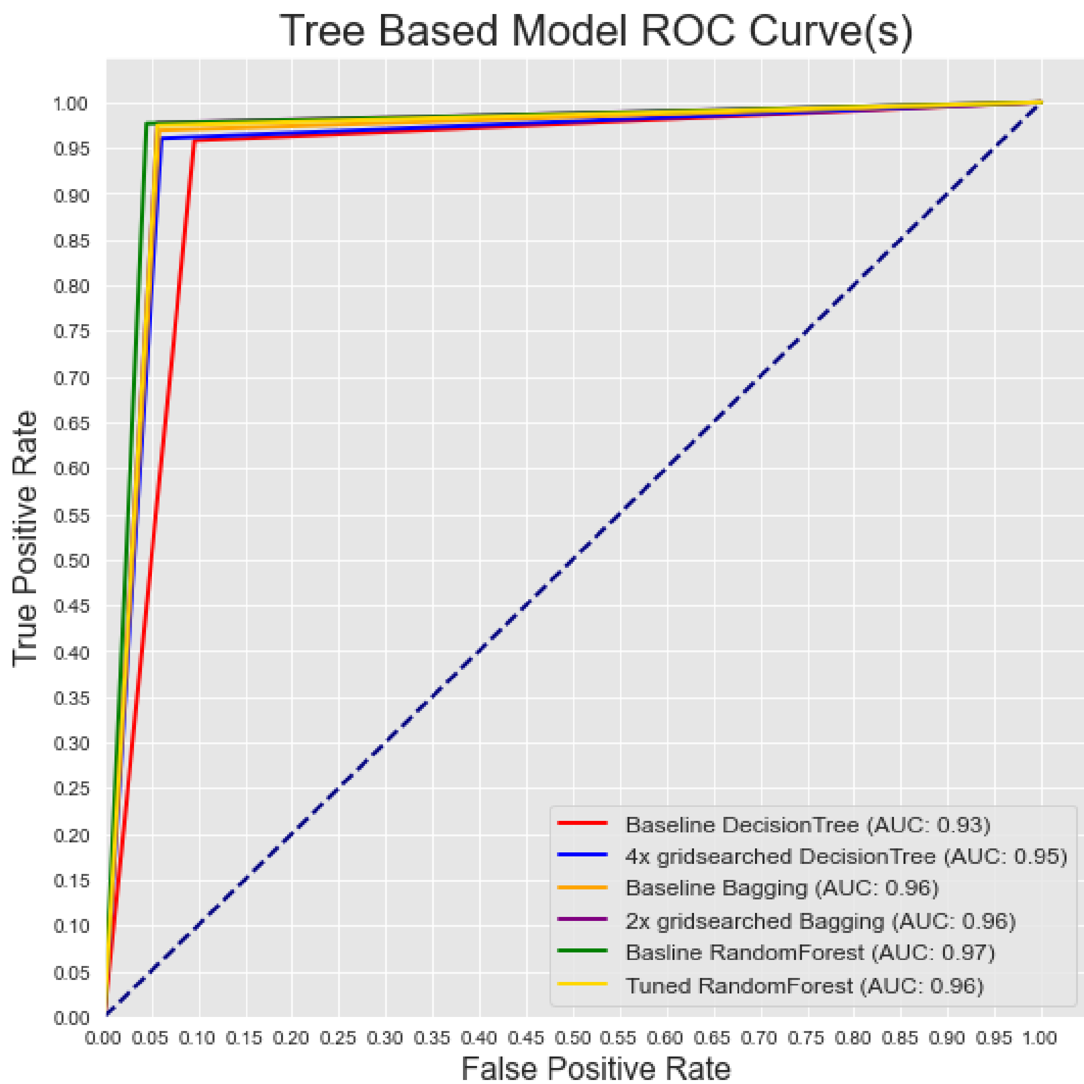
ROC AUC Curve

In [32]:

```
# calculate auc's
# first decision tree gridsearch
base_gridsearch_fpr , base_gridsearch_tpr, base_gridsearch_thresholds = r
base_gridsearch_auc = auc(base_gridsearch_fpr, base_gridsearch_tpr)

# best (fourth) decision tree gridsearch
gridsearch_four_fpr , gridsearch_four_tpr, gridsearch_four_thresholds = r
gridsearch_four_auc = auc(gridsearch_four_fpr, gridsearch_four_tpr)

# baseline bagging
base_bagging_fpr , base_bagging_tpr, base_bagging_thresholds = roc_curve
base_bagging_auc = auc(base_bagging_fpr, base_bagging_tpr)

# second gridsearched bagging
second_grid_bagging_fpr , second_grid_bagging_tpr, second_grid_bagging_tl
second_grid_bagging_auc = auc(second_grid_bagging_fpr, second_grid_baggi

# baseline random forest
base_rfc_fpr , base_rfc_tpr, base_rfc_thresholds = roc_curve(y_test, rfc_
base_rfc_auc = auc(base_rfc_fpr, base_rfc_tpr)

# tuned random forest
tuned_rfc_fpr , tuned_rfc_tpr, tuned_rfc_thresholds = roc_curve(y_test, r
tuned_rfc_auc = auc(tuned_rfc_fpr, tuned_rfc_tpr)

auc_list = [base_gridsearch_auc,gridsearch_four_auc,base_bagging_auc,sec
```

In [33]:

```
plt.figure(figsize=(9,9))
lw = 2

plt.plot(base_gridsearch_fpr, base_gridsearch_tpr, color='red',
         lw=lw, label=f'Baseline DecisionTree (AUC: {round(base_gridsear
plt.plot(gridsearch_four_fpr, gridsearch_four_tpr, color='blue',
         lw=lw, label=f'4x gridsearched DecisionTree (AUC: {round(gridse
plt.plot(base_bagging_fpr,base_bagging_tpr, color='orange',
         lw=lw, label=f'Baseline Bagging (AUC: {round(base_bagging_auc,2
plt.plot(second_grid_bagging_fpr,second_grid_bagging_tpr, color='purple'
         lw=lw, label=f'2x gridsearched Bagging (AUC: {round(second_grid_
plt.plot(base_rfc_fpr,base_rfc_tpr, color='green',
         lw=lw, label=f'Basline RandomForest (AUC: {round(base_rfc_auc,2
plt.plot(tuned_rfc_fpr,tuned_rfc_tpr, color='gold',
         lw=lw, label=f'Tuned RandomForest (AUC: {round(tuned_rfc_auc,2)

# Formatting
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.05])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate',fontsize=16)
plt.ylabel('True Positive Rate',fontsize=16)
plt.title('Tree Based Model ROC Curve(s)',fontsize=22)
plt.legend(loc="lower right",prop={'size':12})

plt.show()
```



True Positive rate

In [34]:

```
prediction_labels = ['Baseline\nDecisionTree',
                     '4x Gridsearched\nDecisionTree',
                     'Baseline Bagging',
                     '2x Gridsearched\nBagging',
                     'Baseline\nRandomForest',
                     'Tuned\nRandomForest']
predictions = [grid_pred,grid_four_pred,tree_bagger_pred,second_bagged_gr

tprs = []
fprs = []

tnrs = []
fnrs = []

for pred in predictions:
    matrix = confusion_matrix(y_test,pred,normalize='true')
    tprs.append(matrix[1][1])
    fprs.append(matrix[0][1])
    tnrs.append(matrix[0][0])
    fnrs.append(matrix[1][0])

```

In [35]:

```
fig,(ax1,ax2) = plt.subplots(nrows=2,sharex=True)
ax1.set_title("Tree Based Model(s) Predictive Performance",fontsize=24)
ax1.plot(range(0,6),tprs,color='green',label='True Positive Rate')
ax1.plot(range(0,6),tnrs,color='lightgreen',label='True Negative Rate')

ax1.set_ylabel("Positive classification rate",fontsize=16)

ax2.plot(range(0,6),fprs,color='red',label='False Positive Rate')
ax2.plot(prediction_labels,fnrs,color='pink',label='False Negative Rate'

ax2.set_ylabel("False classification rate",fontsize=16)
ax2.set_xlabel("Model version",fontsize=16)

ax2.set_xticklabels(prediction_labels,fontsize=12)

fig.set_size_inches(9, 9)
fig.tight_layout()
fig.legend(loc='center right',prop={'size':15})
plt.show()
```

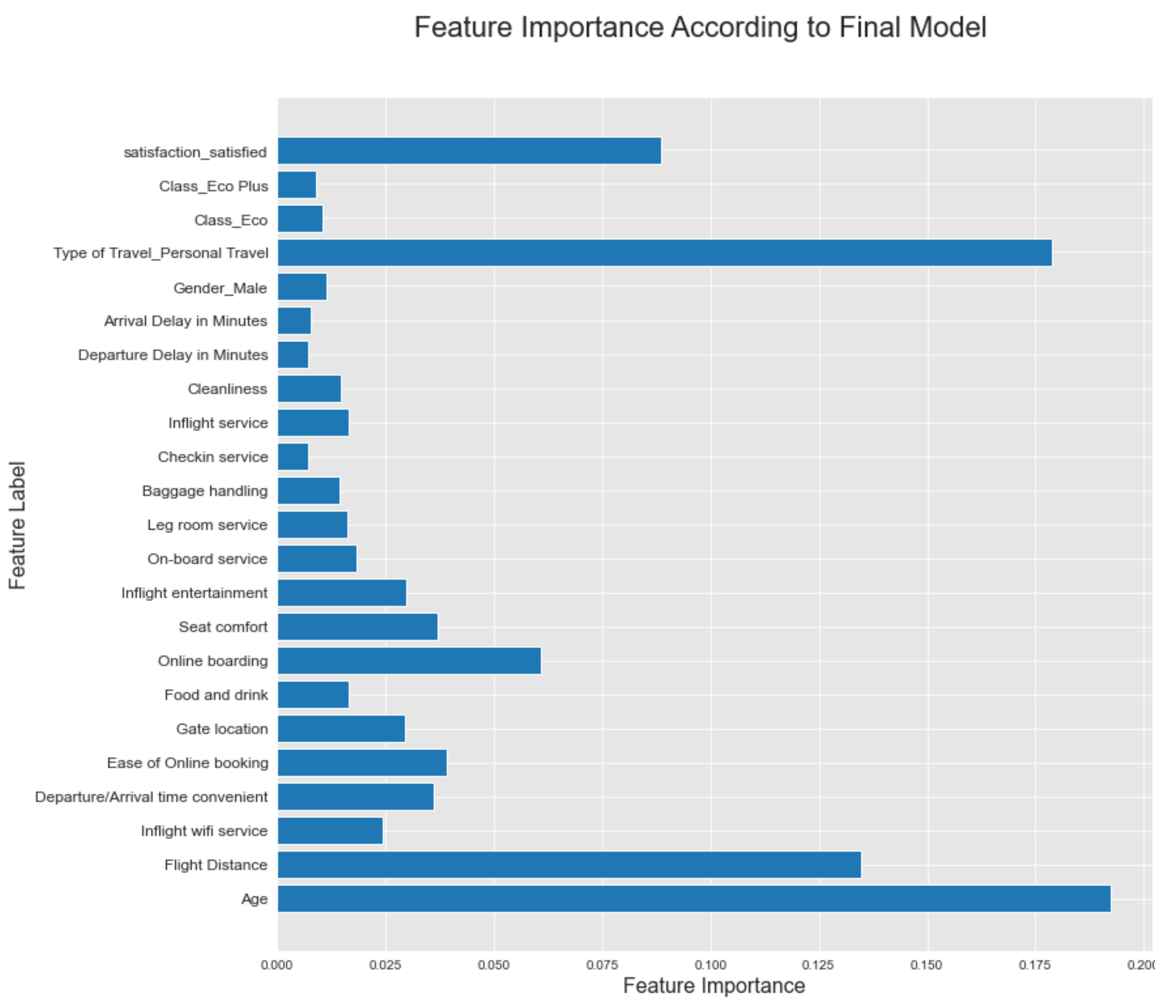
```
<ipython-input-35-343fadc337f4>:14: UserWarning: FixedFormatter should only
be used together with FixedLocator
  ax2.set_xticklabels(prediction_labels,fontsize=12)
```

Final Model Interpretation and Evaluation

Plot Random Forest Feature Importance

In [439]:

```
def plot_feature_importances(model):
    n_features = X_train.shape[1]
    plt.figure(figsize=(12,12))
    plt.barh(range(n_features), model.feature_importances_, align='cente
    plt.yticks(np.arange(n_features), X_train.columns.values,fontsize=12
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(RFC)
plt.suptitle("\nFeature Importance According to Final Model",fontsize=22
plt.xlabel('Feature Importance',fontsize=16)
plt.ylabel('Feature Label',fontsize=16)
plt.show()
```



Concatenate Train and Test Samples for Analysis

In [44]:

```
# concat X and y, train and test samples into a single df for descriptive
X_evaluate = pd.concat([X_train,X_test])
y_evaluate = pd.concat([y_train,y_test])
eval_df = pd.concat([y_evaluate,X_evaluate],axis=1)
eval_df.head()
```

Out[44]:

	disloyal Customer	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	c
0	0	13	460	3	4	3	1	5	3	
1	0	61	214	3	3	3	3	4	5	
2	0	47	1276	2	4	2	3	2	2	
3	0	52	2035	4	3	4	4	5	5	
4	0	12	308	2	4	2	2	1	2	

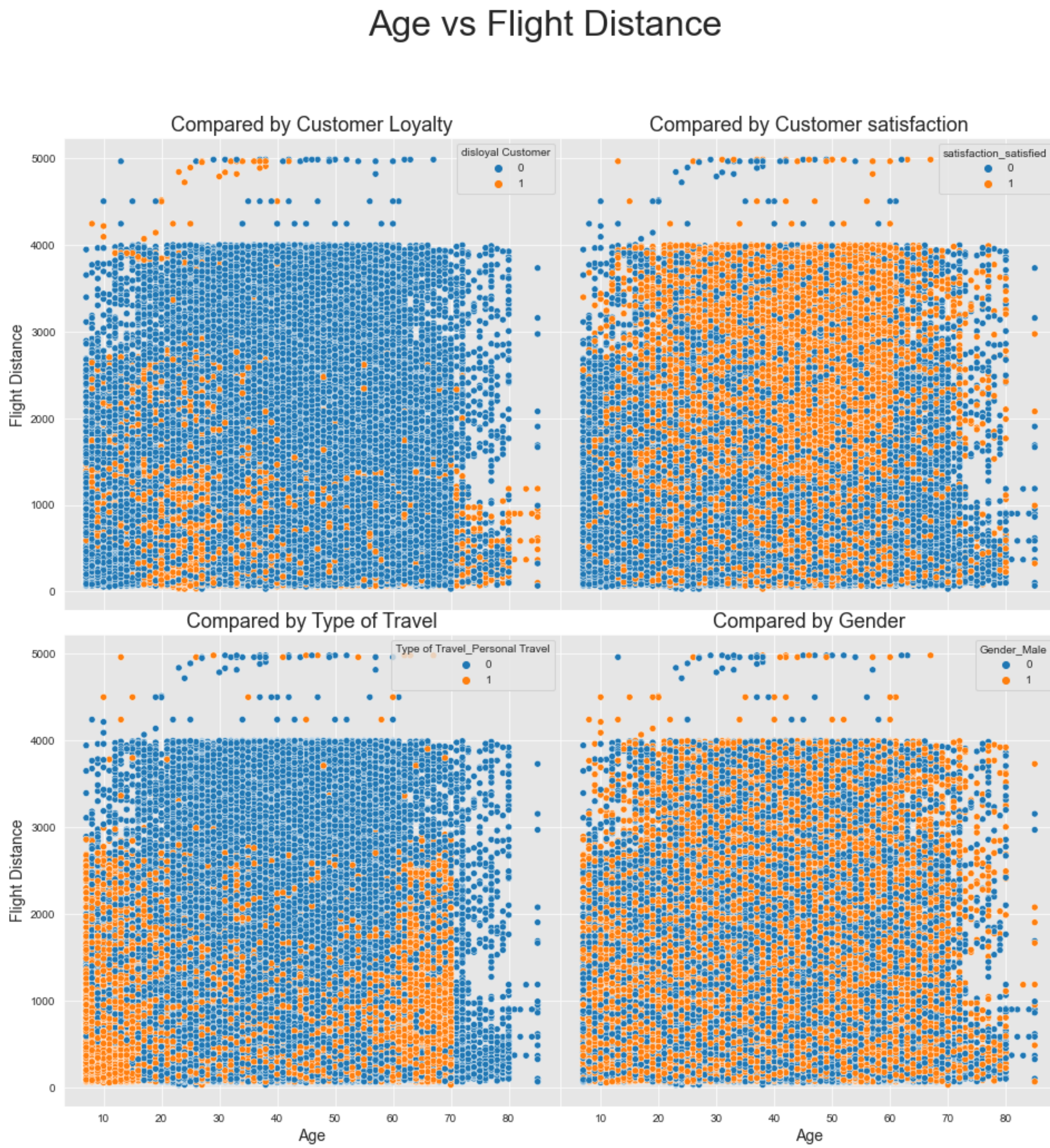
5 rows × 24 columns

Age vs. Flight Distance by Customer Loyalty

In [728]:

```
fig,axs = plt.subplots(2,2,figsize=(16,16),sharex=True,sharey=True)

loy = sns.scatterplot(x=eval_df.Age,y=eval_df['Flight Distance'],hue=eval
axs[0,0].set_title('Compared by Customer Loyalty',fontsize=18)
axs[0,0].set_ylabel('Flight Distance',fontsize=14)
axs[0,0].set_xlabel('Age',fontsize=14)

sat = sns.scatterplot(x=eval_df.Age,y=eval_df['Flight Distance'],hue=eval
axs[0,1].set_title('Compared by Customer satisfaction',fontsize=18)
axs[0,1].set_ylabel('Flight Distance',fontsize=14)
axs[0,1].set_xlabel('Age',fontsize=14)

bix = sns.scatterplot(x=eval_df.Age,y=eval_df['Flight Distance'],hue=eval
axs[1,0].set_title('Compared by Type of Travel',fontsize=18)
axs[1,0].set_ylabel('Flight Distance',fontsize=14)
axs[1,0].set_xlabel('Age',fontsize=14)

gen = sns.scatterplot(x=eval_df.Age,y=eval_df['Flight Distance'],hue=eval
axs[1,1].set_title('Compared by Gender',fontsize=18)
axs[1,1].set_ylabel('Flight Distance',fontsize=14)
axs[1,1].set_xlabel('Age',fontsize=14)


fig.suptitle('Age vs Flight Distance',fontsize=32)
plt.subplots_adjust(wspace=.001,hspace=.05)
plt.show()
```

```
c:\Users\zethu\anaconda3\envs\learn-env\lib\site-packages\IPython\core\pyla
btools.py:132: UserWarning: Creating legend with loc="best" can be slow wit
h large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



The above plot isn't incredibly telling in and of itself, however there are some noteable clusters. Its obvious that loyal customers tend to be more satisfied, but the focus of this analysis is to discover what is stopping disloyal customer from becoming loyal. With that in mind, there is a cluster of 16-39 year old, flying less than 300 miles, that are mostly disloyal but relatively even between satisfied and disatisfeid. It also appears that 70+ year olds are more likely to be satisfied if they fly more than 1500 miles, while most of the disloyal customers in this age group fly less than 1500 miles. It also appears that business travel accoutns for a significant portion of the aformentioned age groups.

Survey Responses Based on Age, Flight Distance, Purpose for Travel

In [281]:

```
# inspect disloyal customers between 15 and 40, for flights less than 30
disloyal_youth_df = eval_df.loc[(eval_df['Age']<40)&(eval_df['Age']>15)&

disloyal_youth_survey_dict ={}
for col in disloyal_youth_df.iloc[:,3:17].columns:
    disloyal_youth_survey_dict[col]=disloyal_youth_df[col].sum()

youth_colors = []
for val in disloyal_youth_survey_dict.values():
    if val <195000:
        youth_colors.append('orangered')
    elif val > 210000:
        youth_colors.append('mediumseagreen')
    else:
        youth_colors.append('gold')
```

In [278]:

```
# Inspect Disloyal Senior (70+) Customers, for flights less than 1500 mi
disloyal_seniors_df = eval_df.loc[(eval_df['Age']>70)&(eval_df['disloyal

disloyal_seniors_survey_dict ={}
for col in disloyal_seniors_df.iloc[:,3:17].columns:
    disloyal_seniors_survey_dict[col]=disloyal_seniors_df[col].sum()

seniors_colors = []
for val in disloyal_seniors_survey_dict.values():
    if val <840:
        seniors_colors.append('orangered')
    elif val > 930:
        seniors_colors.append('mediumseagreen')
    else:
        seniors_colors.append('gold')
```

In [348]:

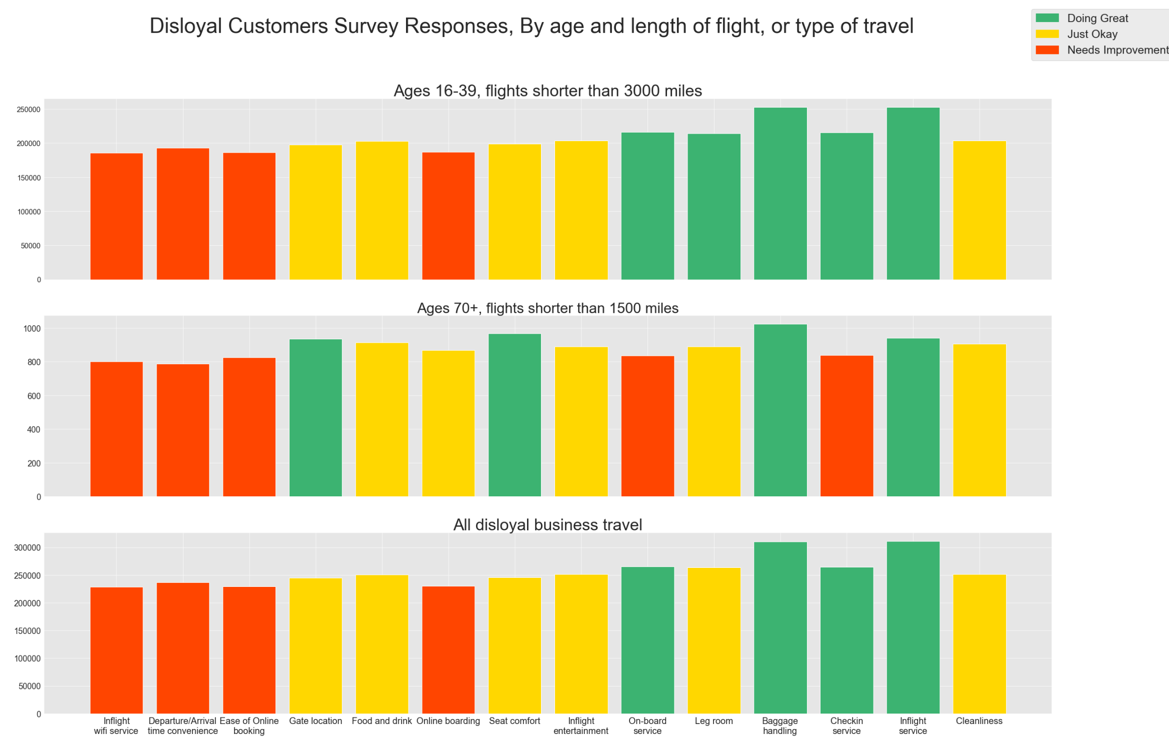
```
# Inspect Disloyal business travel, all distances
disloyal_business_df = eval_df.loc[(eval_df['Type of Travel_Personal Tra

disloyal_business_survey_dict = {}
for col in disloyal_business_df.iloc[:,3:17].columns:
    disloyal_business_survey_dict[col] = disloyal_business_df[col].sum()

disloyal_business_colors = []
for val in disloyal_business_survey_dict.values():
    if val <239000:
        disloyal_business_colors.append('orangered')
    elif val > 264000:
        disloyal_business_colors.append('mediumseagreen')
    else:
        disloyal_business_colors.append('gold')
```

In [700]:

```
import matplotlib.patches as mpatches
from matplotlib.lines import Line2D

red_patch = mpatches.Patch(color='orangered', label='Needs Improvement')
yellow_patch = mpatches.Patch(color='gold', label='Just Okay')
green_patch = mpatches.Patch(color='mediumseagreen',label='Doing Great')

x_labels = ['Inflight\nwifi service',
'Departure/Arrival\ntime convenience',
'Ease of Online\nbooking',
'Gate location',
'Food and drink',
'Online boarding',
'Seat comfort',
'Inflight\nentertainment',
'On-board\nservice',
'Leg room',
'Baggage\nhandling',
'Checkin\nservice',
'Inflight\nservice',
'Cleanliness']

fig,axs = plt.subplots(3,1,figsize=(40,25),sharex=True)

axs[0].bar(x=list(disloyal_youth_survey_dict.keys()),height=list(disloya
axs[0].set_yticklabels([0,50000,100000,150000,200000,250000],fontsize=16
axs[0].set_title('Ages 16-39, flights shorter than 3000 miles',fontsize=


axs[1].bar(x=list(disloyal_seniors_survey_dict.keys()),height=list(disloy
axs[1].set_yticklabels([0,200,400,600,800,1000],fontsize=18)
axs[1].set_xticklabels(x_labels,fontsize=20)
axs[1].set_title("Ages 70+, flights shorter than 1500 miles",fontsize=32

axs[2].bar(x=list(disloyal_business_survey_dict.keys()),height=list(disl
axs[2].set_yticklabels([0,50000,100000,150000,200000,250000,300000],font
axs[2].set_xticklabels(x_labels,fontsize=20)
axs[2].set_title("All disloyal business travel",fontsize=36)


fig.legend(handles=[green_patch,yellow_patch,red_patch],prop={'size':25}
fig.suptitle("Disloyal Customers Survey Responses, By age and length of
plt.show()
```

```
<ipython-input-700-573ec48e6e41>:26: UserWarning: FixedFormatter should
only be used together with FixedLocator
  axs[0].set_yticklabels([0,50000,100000,150000,200000,250000],fontsize
=16)
<ipython-input-700-573ec48e6e41>:31: UserWarning: FixedFormatter should
only be used together with FixedLocator
  axs[1].set_yticklabels([0,200,400,600,800,1000],fontsize=18)
<ipython-input-700-573ec48e6e41>:32: UserWarning: FixedFormatter should
only be used together with FixedLocator
  axs[1].set_xticklabels(x_labels,fontsize=20)
```

```
<ipython-input-700-573ec48e6e41>:36: UserWarning: FixedFormatter should only be used together with FixedLocator
  axs[2].set_yticklabels([0,50000,100000,150000,200000,250000,300000],fontsize=18)
<ipython-input-700-573ec48e6e41>:37: UserWarning: FixedFormatter should only be used together with FixedLocator
  axs[2].set_xticklabels(x_labels,fontsize=20)
```



Across both age groups as well as for all business travel, Inflight wifi, departure/arrival time convenience and ease of online booking all scored in the bottom quartile of overall customer satisfaction. Food and drink, and cleanliness are just average for accross the board. Baggage hadnlign and Inflight wifi score in the fourth quartile accross the board.

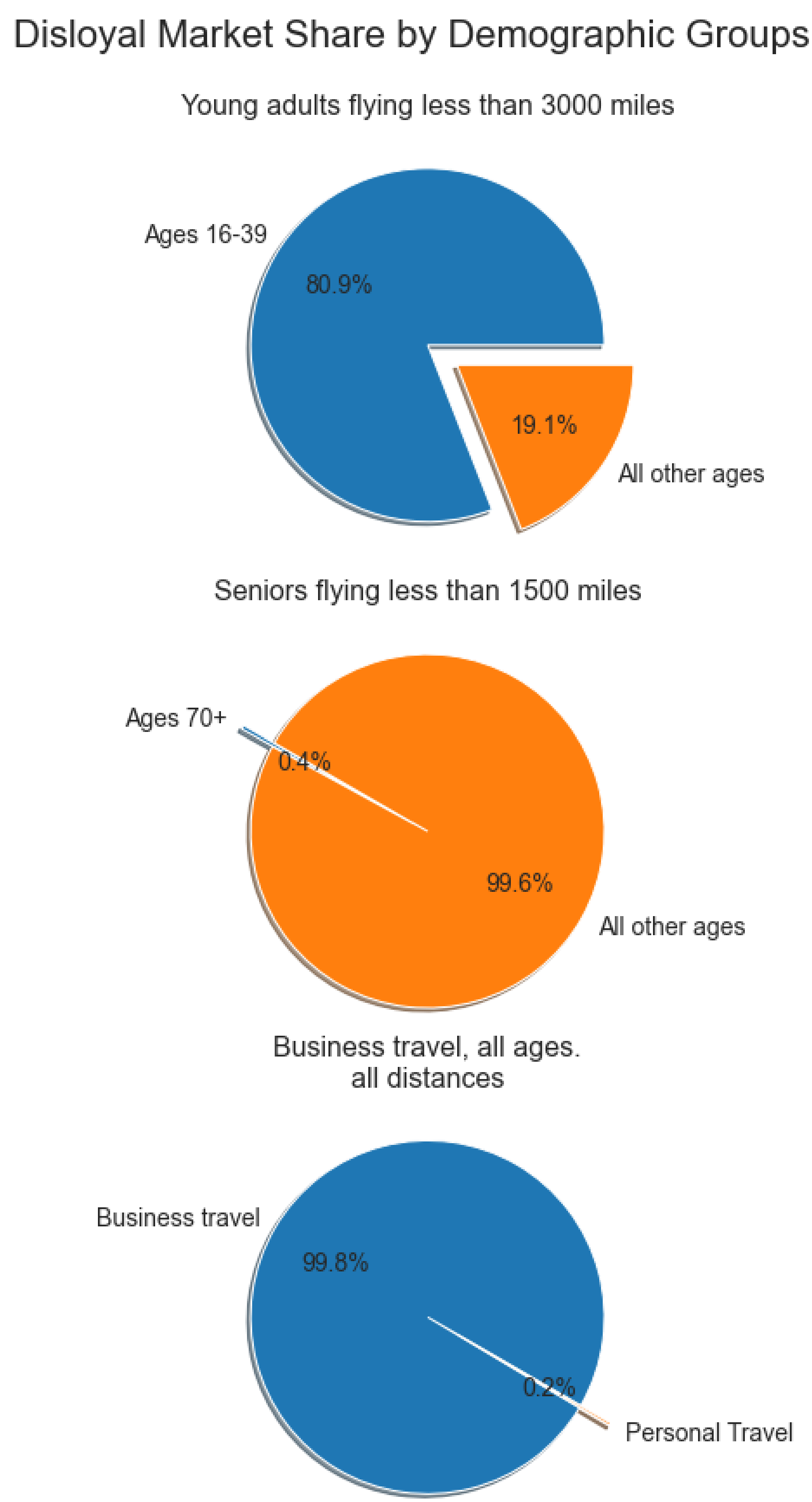
Online boarding, one of the top 5 most important features to the model, is in the bottom quartile for young adults as well as businss travel, and only about average for seniors. Businss travel and young adults are well pleased with the check-in service but it is highly disliked by seniors. Gate Location is just okay for businss travelers and young adults, but seniors are highly satisfied here.

Based on this graph I would recommend focusing on improving the online experience (boarding and booking) for young adults and businss travelers, and improve inflight wifi, food and drink, seat comfort, and overall cleanliness. Departure/Arrival times and gate locations would probably have significant impact if improved but it is likely impossible to improve these things strictly internally.

Market Share by Age and Purpose for Travel

In [429]:

```
fig,axs = plt.subplots(3,1,figsize=(10,15))
axs[0].pie([len(disloyal_youth_df),(len(eval_df.loc[eval_df['disloyal Cu
        labels=['Ages 16-39','All other ages'],
        startangle=0,
        shadow=True,
        explode=[0,0.2],
        autopct='%1.1f%%',
        textprops={'fontsize':14})
axs[0].set_title("Young adults flying less than 3000 miles",fontsize=16)


axs[1].pie([len(disloyal_seniors_df),(len(eval_df.loc[eval_df['disloyal (
        labels=['Ages 70+','All other ages'],
        startangle=150,
        shadow=True,
        explode=[.2,0],
        autopct='%1.1f%%',
        textprops={'fontsize':14})
axs[1].set_title("Seniors flying less than 1500 miles",fontsize=16)

axs[2].pie([len(disloyal_business_df),(len(eval_df.loc[eval_df['disloyal
        labels=['Business travel','Personal Travel'],
        startangle=-30,
        shadow=True,
        explode=[0,0.2],
        autopct='%1.1f%%',
        textprops={'fontsize':14})
axs[2].set_title("Business travel, all ages.\nall distances",fontsize=16

fig.suptitle("\n\nDisloyal Market Share by Demographic Groups",fontsize=
plt.subplots_adjust(hspace=0.1)
plt.show()
```



Examination of the market share of each of group shows that improving satisfaction for senior customers would probably have a significant impact on overall business performance. Based on the above figure it is clearly best to focus on improving the customer experience for business traveler's and young adults, obviously there is likely much overlap between these two groups.

Survey Responses by Customer Loyalty and Satisfaction

In [524]:

```
# sum of survey responses for disloyal satisfied customers
disloyal_survey_satisfied = {}
for col in eval_df.iloc[:,3:17].columns:
    disloyal_survey_satisfied[col] = eval_df.loc[(eval_df['disloyal Custo

disloyal_satisfied_colors = []
for val in disloyal_survey_satisfied.values():
    if val < np.quantile(list(disloyal_survey_satisfied.values()),0.25):
        disloyal_satisfied_colors.append('orangered')
    elif val > np.quantile(list(disloyal_survey_satisfied.values()),0.75
        disloyal_satisfied_colors.append('mediumseagreen')
    else:
        disloyal_satisfied_colors.append('gold')

# sum of survey responses for disloyal disatisfied customers
disloyal_survey_disatisfied = {}
for col in eval_df.iloc[:,3:17].columns:
    disloyal_survey_disatisfied[col] = eval_df.loc[(eval_df['disloyal Cu

disloyal_disatisfied_colors = []
for val in disloyal_survey_satisfied.values():
    if val < np.quantile(list(disloyal_survey_disatisfied.values()),0.25
        disloyal_disatisfied_colors.append('orangered')
    elif val > np.quantile(list(disloyal_survey_disatisfied.values()),0.
        disloyal_disatisfied_colors.append('mediumseagreen')
    else:
        disloyal_disatisfied_colors.append('gold')

#########################################################

# sum of survey responses for loyal satisfied customers
loyal_survey_satisfied = {}
for col in eval_df.iloc[:,3:17].columns:
    loyal_survey_satisfied[col] = eval_df.loc[(eval_df['disloyal Custome

loyal_satisfied_colors = []
for val in loyal_survey_satisfied.values():
    if val < np.quantile(list(loyal_survey_satisfied.values()),0.25):
        loyal_satisfied_colors.append('orangered')
    elif val > np.quantile(list(loyal_survey_satisfied.values()),0.75):
        loyal_satisfied_colors.append('mediumseagreen')
    else:
        loyal_satisfied_colors.append('gold')

# sum of survey responses for loyal disatisfied customers
loyal_survey_disatisfied = {}
for col in eval_df.iloc[:,3:17].columns:
    loyal_survey_disatisfied[col] = eval_df.loc[(eval_df['disloyal Custo

loyal_disatisfied_colors = []
for val in loyal_survey_disatisfied.values():
    if val < np.quantile(list(loyal_survey_disatisfied.values()),0.25):
        loyal_disatisfied_colors.append('orangered')
    elif val > np.quantile(list(loyal_survey_disatisfied.values()),0.75)
        loyal_disatisfied_colors.append('mediumseagreen')
    else:
```

```
        loyal_disatisfied_colors.append('gold')
```

In [ ]:

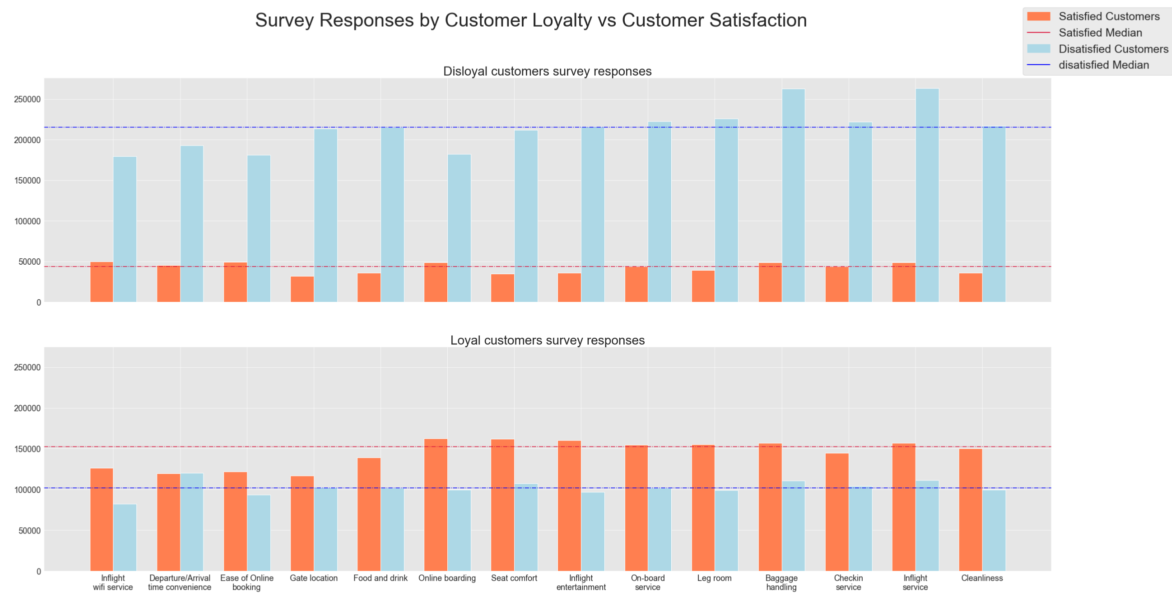
```
Line2D([0],[0],color='coral',lw=2,label='')
```

In [735]:

```
satisfied_patch = mpatches.Patch(color='coral', label='Satisfied Custome
disatisfied_patch = mpatches.Patch(color='lightblue', label='Disatisfied
satisfied_median = Line2D([0],[0],color='crimson',lw=2,label='Satisfied M
disatisfied_median = Line2D([0],[0],color='blue',lw=2,label='disatisfied

width = .35

x_labels = ['Inflight\nwifi service',
'Departure/Arrival\ntime convenience',
'Ease of Online\nbooking',
'Gate location',
'Food and drink',
'Online boarding',
'Seat comfort',
'Inflight\nentertainment',
'On-board\nservice',
'Leg room',
'Baggage\nhandling',
'Checkin\nservice',
'Inflight\nservice',
'Cleanliness']

x = np.arange(len(x_labels))

fig,axs = plt.subplots(2,1,figsize=(40,20),sharex=True)

axs[0].bar(x= x + width/2,height=list(disloyal_survey_disatisfied.values
axs[0].axhline(np.quantile(list(disloyal_survey_disatisfied.values()),0.

axs[0].bar(x= x - width/2,height=list(disloyal_survey_satisfied.values()
axs[0].axhline(np.quantile(list(disloyal_survey_satisfied.values()),0.5)

axs[0].set_title('Disloyal customers survey responses',fontsize=28)
axs[0].set_yticklabels([0,50000,100000,150000,200000,250000],fontsize=18



axs[1].bar(x= x - width/2,height=list(loyal_survey_satisfied.values()),w
axs[1].axhline(np.quantile(list(loyal_survey_satisfied.values()),0.5),co

axs[1].bar(x= x + width/2,height=list(loyal_survey_disatisfied.values())
axs[1].axhline(np.quantile(list(loyal_survey_disatisfied.values()),0.5),

axs[1].set_title('Loyal customers survey responses',fontsize=28)
axs[1].set_ylim(0,275000)
plt.xticks(x,x_labels,fontsize=18)
plt.yticks(fontsize=18)


fig.legend(handles=[satisfied_patch,satisfied_median,disatisfied_patch,d
fig.suptitle("Survey Responses by Customer Loyalty vs Customer Satisfact
plt.show()
```

```
<ipython-input-735-8d324d897e82>:34: UserWarning: FixedFormatter should
```

```
only be used together with FixedLocator
  axs[0].set_yticklabels([0,50000,100000,150000,200000,250000],fontsize
=18)
```



As one would expect disloyal customers tend to be more disatisfied. Unlike they're loyal counter parts, disloyal customers are displeased the most with checkin service and inflight service. They are also more displeased than usual with on-board service, leg room, check-in service, and cleanliness.

Based on this figure with consideration to feature importance of the predictive model, I recommend focusing on improving services involved with the check-in and boarding process as well as the in-flight experience; esepcially in-flight entertainment, online boarding, and seat comfort.

Age and Flight Distance by Customer Loyalty and Satisfaction

In [623]:

```
# bar heights for loyal satisfied customers
loyal_satisfied_flight_distance = eval_df['Flight Distance'].loc[(eval_d
loyal_satisfied_flight_ranges = pd.cut(loyal_satisfied_flight_distance,b

loyal_satisfied_flight_heights = []
for interval in loyal_satisfied_flight_ranges:
    chunk = sum((loyal_satisfied_flight_distance>interval.left)&(loyal_sa
    loyal_satisfied_flight_heights.append(chunk)

# bar heights for loyal but disatisfied customers
loyal_disatisfied_flight_distance = eval_df['Flight Distance'].loc[(eval_
loyal_disatisfied_flight_ranges = pd.cut(loyal_disatisfied_flight_distan

loyal_disatisfied_flight_heights = []
for interval in loyal_disatisfied_flight_ranges:
    chunk = sum((loyal_disatisfied_flight_distance>interval.left)&(loyal_
    loyal_disatisfied_flight_heights.append(chunk)

# bar heights for disloyal but satisfied customers
disloyal_satisfied_flight_distance = eval_df['Flight Distance'].loc[(eva
disloyal_satisfied_flight_ranges = pd.cut(disloyal_satisfied_flight_dista

disloyal_satisfied_flight_heights = []
for interval in disloyal_satisfied_flight_ranges:
    chunk = sum((disloyal_satisfied_flight_distance>interval.left)&(dislo
    disloyal_satisfied_flight_heights.append(chunk)
disloyal_satisfied_flight_heights = [-x for x in disloyal_satisfied_fligh

# bar heights for disloyal and disatisfied customers
disloyal_disatisfied_flight_distance = eval_df['Flight Distance'].loc[(ev
disloyal_disatisfied_flight_ranges = pd.cut(disloyal_disatisfied_flight_

disloyal_disatisfied_flight_heights = []
for interval in disloyal_disatisfied_flight_ranges:
    chunk = sum((disloyal_disatisfied_flight_distance>interval.left)&(dis
    disloyal_disatisfied_flight_heights.append(chunk)
disloyal_disatisfied_flight_heights = [-x for x in disloyal_disatisfied_
```

In [665]:

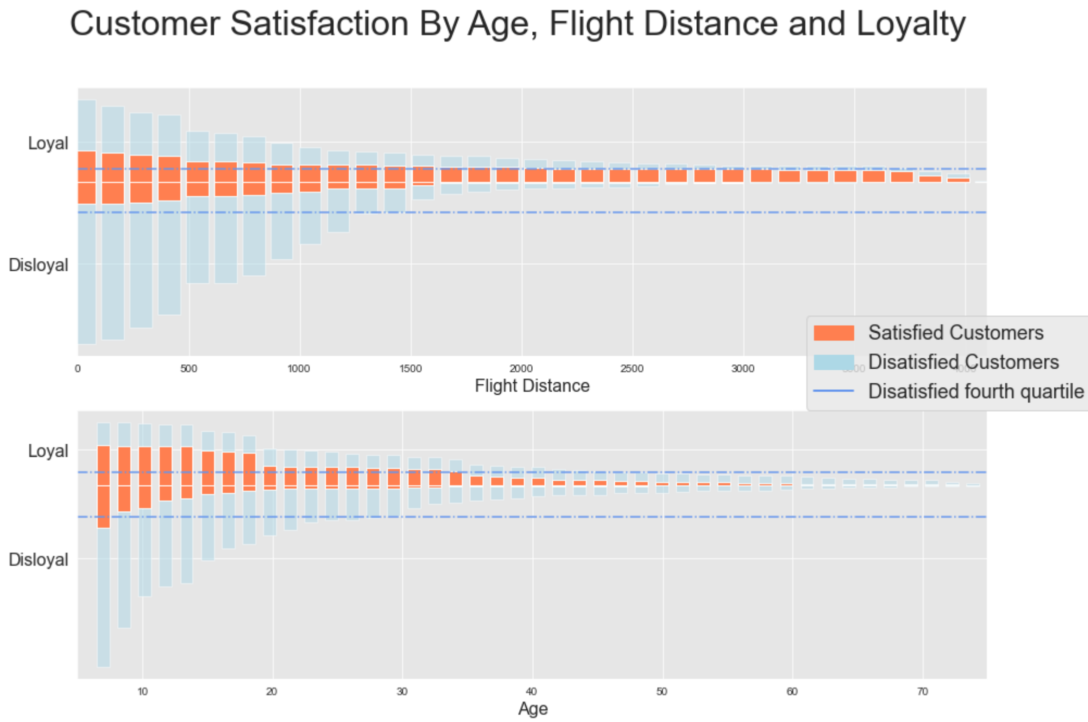
```
# bar heights for loyal satisfied customers
loyal_satisfied_age = eval_df['Age'].loc[(eval_df['satisfaction_satisfie
loyal_satisfied_age_ranges = pd.cut(loyal_satisfied_age,bins=50).value_c

loyal_satisfied_age_heights = []
for interval in loyal_satisfied_age_ranges:
    chunk = sum((loyal_satisfied_age>interval.left)&(loyal_satisfied_age
    loyal_satisfied_age_heights.append(chunk)

# bar heights for loyal but disatisfied customers
loyal_disatisfied_age = eval_df['Age'].loc[(eval_df['satisfaction_satisf
loyal_disatisfied_age_ranges = pd.cut(loyal_disatisfied_age,bins=50).val

loyal_disatisfied_age_heights = []
for interval in loyal_disatisfied_age_ranges:
    chunk = sum((loyal_disatisfied_age>interval.left)&(loyal_disatisfied_
    loyal_disatisfied_age_heights.append(chunk)

# bar heights for disloyal but satisfied customers
disloyal_satisfied_age = eval_df['Age'].loc[(eval_df['satisfaction_satis
disloyal_satisfied_age_ranges = pd.cut(disloyal_satisfied_age,bins=50).v

disloyal_satisfied_age_heights = []
for interval in disloyal_satisfied_age_ranges:
    chunk = sum((disloyal_satisfied_age>interval.left)&(disloyal_satisfi
    disloyal_satisfied_age_heights.append(chunk)
disloyal_satisfied_age_heights = [-x for x in disloyal_satisfied_age_hei

# bar heights for disloyal and disatisfied customers
disloyal_disatisfied_age = eval_df['Age'].loc[(eval_df['satisfaction_sat
disloyal_disatisfied_age_ranges = pd.cut(disloyal_disatisfied_age,bins=5

disloyal_disatisfied_age_heights = []
for interval in disloyal_disatisfied_age_ranges:
    chunk = sum((disloyal_disatisfied_age>interval.left)&(disloyal_disat
    disloyal_disatisfied_age_heights.append(chunk)
disloyal_disatisfied_age_heights = [-x for x in disloyal_disatisfied_age_
```

In [653]:

```
flight_x_ticks = np.linspace(min(eval_df['Flight Distance']),max(eval_df
age_x_ticks = np.linspace(min(eval_df['Age']),max(eval_df['Age']),num=50
```

In [713]:

```
satisfied_patch = mpatches.Patch(color='coral', label='Satisfied Custome
disatisfied_patch = mpatches.Patch(color='lightblue', label='Disatisfied
satisfied_quartile = Line2D([0],[0],color='cornflowerblue',lw=2,label='D

fig,axs = plt.subplots(2,1,figsize=(15,10))

axs[0].bar(x=flight_x_ticks,height=loyal_satisfied_flight_heights,color=
axs[0].bar(x=flight_x_ticks,height=loyal_disatisfied_flight_heights,bott
            color='lightblue',width=100,alpha=0.5)
axs[0].axhline(np.quantile(loyal_disatisfied_flight_heights,0.75),color=

axs[0].bar(x=flight_x_ticks,height=disloyal_satisfied_flight_heights,col
axs[0].bar(x=flight_x_ticks,height=disloyal_disatisfied_flight_heights,b
            color='lightblue',width=100,alpha=0.5)
axs[0].axhline(np.quantile(disloyal_disatisfied_flight_heights,0.25),col
axs[0].set_xlim(0,4100)
axs[0].set_yticks(ticks=[3000,-6000])
axs[0].set_yticklabels(['Loyal','Disloyal'],fontsize=16)
axs[0].set_xlabel("Flight Distance",fontsize=16)



axs[1].bar(x=age_x_ticks,height=loyal_satisfied_age_heights,color='coral
axs[1].bar(x=age_x_ticks,height=loyal_disatisfied_age_heights,bottom=loy
            color='lightblue',width=1,alpha=0.5)
axs[1].axhline(np.quantile(loyal_disatisfied_age_heights,0.75),color='co

axs[1].bar(x=age_x_ticks,height=disloyal_satisfied_age_heights,color='co
axs[1].bar(x=age_x_ticks,height=disloyal_disatisfied_age_heights,bottom=
            color='lightblue',width=1,alpha=0.5)
axs[1].axhline(np.quantile(disloyal_disatisfied_age_heights,0.25),color=
axs[1].set_xlim(5,75)
axs[1].set_yticks(ticks=[2500,-5000])
axs[1].set_yticklabels(['Loyal','Disloyal'],fontsize=16)
axs[1].set_xlabel("Age",fontsize=16)

fig.legend(handles=[satisfied_patch,disatisfied_patch,satisfied_quartile
fig.suptitle("Customer Satisfaction By Age, Flight Distance and Loyalty"
plt.show()
```



Based on the figure above, the most disatisfaction to address is for flights shorter than 1500 miles, and customers under the age of 40. Its also interesting to not that there is just not much data on disloyal customers traveling farther than 2500 miles.

Based on this figure I recommend focusing on improve checkin-in, boarding, and in-flight services for flights under 2000 miles and customers under age 40

Conclussion

The data used in this analysis does not contain any information on the revenue or profits made from each ticket represented; there is some details on the flight itself and most of the data represents the subject satisfaction report of the customer represented. So it is impossible to make any recomendations at this point about how to drive profits, but it is posible to make recomendations on how to increase customer satisfaction and which populations within the market are the most disatisfied.

The Random Forest feature importance showed that the age of the customer, wether the travel is for business or personal, the distance of the flight,and wether or not the customer was satisfeid were the most important features (in terms of the model making predictions) by a significant margin, so my broad strategy was to analyze the survey responses for based on various subsets of those features.

The broad patterns I see are that disloyal customers are the most displeased with the process of actually getting on the plane, and some in-flight services need improvement. The most important groups to focus on improving services for is young adults (16-39) and business travel (all ages) based on rate of disatisfaction and market share.

Specific pain points to investigate for improvement is the UX for online booking as well as online boarding. Customers are also very displeased with internet related services in-flight, specifically wifi and entertainment. Improving customer wifi service should improve satisfaction with entertainment as well. Customer accross the board are apathetic about cleanliness as well as food and drink. Seat comfort, of course, could use some improvement. Customer's are extremely disatisfied with departure/arival times, and gate locations, but I don't think there is much that can be done about these issues without serious cooperation and concession with other airlines. I believe more impactful change could be made quicker and more economically with the aformentioned pain points.

Type *Markdown* and LaTeX: α^2