Final Project - Travel Insurance Predictions Team 7

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ADS-505 Final Project - Travel Insurance Predictions

Team: #7

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Date: 10/12/2021

Programmin Language: Python Code

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1 Problem statement

About the Client

The client in this data mining project is a tour & travels company that is offering travel insurance package to their customers. This new insurance package also includes COVID-19 coverage for their flights. However, the client wants to know which customers based on their data base history are potential purchasers who may be interested in buying this new insurance package. Previously, the insurance package was offered to some of the customers in 2019 and data was collected from the performance and sales of the package during that period. The sample data given has close to 2000 customers from that period. The client is requesting information on which customer are most likely going to buy the travel insurance given their information such as employment type, income level, etc.

Business Problem

The client may use the solutions presented to them for customer-targeted advertising of the new travel insurance package. Also, data visualizations provided will help derive interesting insights about their potential buyers in order to optimize marketing strategies.

Data Mining Problem

- A supervised classification task, where the outcome variable of interest is *TravelInsurance* that indicates whether the customer will buy the travel insurance. Performance metrics should take in consideration the positive class of buyers/purchasers.
- Find out interesting patterns and trends for better customer segmentations through data exploration and visualizations.
- An unsupervised task, where the goal is to cluster customers.

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2 Packages

Python code:

[1]:
```
%%javascript
IPython.OutputArea.prototype._should_scroll = function(lines) {
    return false;
}
```

```
<IPython.core.display.Javascript object>
```

[2]:
```
from pathlib import Path
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression, LogisticRegression,␣
↪LogisticRegressionCV
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
import scikitplot as skplt
from mord import LogisticIT
from sklearn import preprocessing
import random
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import cross_val_score, GridSearchCV
from dmba import regressionSummary, stepwise_selection, plotDecisionTree
from dmba import regressionSummary, stepwise_selection
from dmba import forward_selection, backward_elimination, exhaustive_search
from dmba import classificationSummary, gainsChart, liftChart
from dmba.metric import AIC_score
from tabulate import tabulate
import matplotlib.patches as mpatches
from sklearn import *
import sklearn as skl
import warnings; warnings.filterwarnings("ignore")
from IPython.display import display_html; from itertools import chain,cycle

pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 1000)
```

```
pd.set_option('display.colheader_justify', 'center')
pd.set_option('display.precision', 3)
pd.options.display.float_format = '{:.3f}'.format

sns.set_theme(style="whitegrid")
plt.rcParams['figure.figsize'] = [13,9]
```

---

3 Data Set

Data Dictionary

1. **Age** - Age Of The Customer
2. **Employment Type** - The Sector In Which Customer Is Employed
3. **GraduateOrNot** - Whether The Customer Is College Graduate Or Not
4. **AnnualIncome** - The Yearly Income Of The Customer In Indian Rupees[Rounded To Nearest 50 Thousand Rupees]
5. **FamilyMembers** - Number Of Members In Customer's Family
6. **ChronicDisease** - Whether The Customer Suffers From Any Major Disease Or Conditions Like Diabetes/High BP or Asthama,etc.
7. **FrequentFlyer** - Derived Data Based On Customer's History Of Booking Air Tickets On Atleast 4 Different Instances In The Last 2 Years[2017-2019].
8. **EverTravelledAbroad** - Has The Customer Ever Travelled To A Foreign Country[Not Necessarily Using The Company's Services]
9. **TravelInsurance** - Did The Customer Buy Travel Insurance Package During Introductory Offering Held In The Year 2019.

Python code:

[3]:
```
# Load data set
df = pd.read_csv("../../Data/TravelInsurancePrediction.csv")

# First few rows of data set
df.head(3)
```

[3]:
```
   Age        Employment Type        GraduateOrNot  AnnualIncome  FamilyMembers
ChronicDiseases FrequentFlyer EverTravelledAbroad  TravelInsurance
0  31          Government Sector        Yes          400000          6
1              No                No                  0
1  31   Private Sector/Self Employed       Yes         1250000          7
0              No                No                  0
2  34   Private Sector/Self Employed       Yes          500000          4
1              No                No                  1
```

---

4 Exploratory Data Analysis (EDA)

- Graphical and non-graphical representations of relationships between the response variable and predictor variables

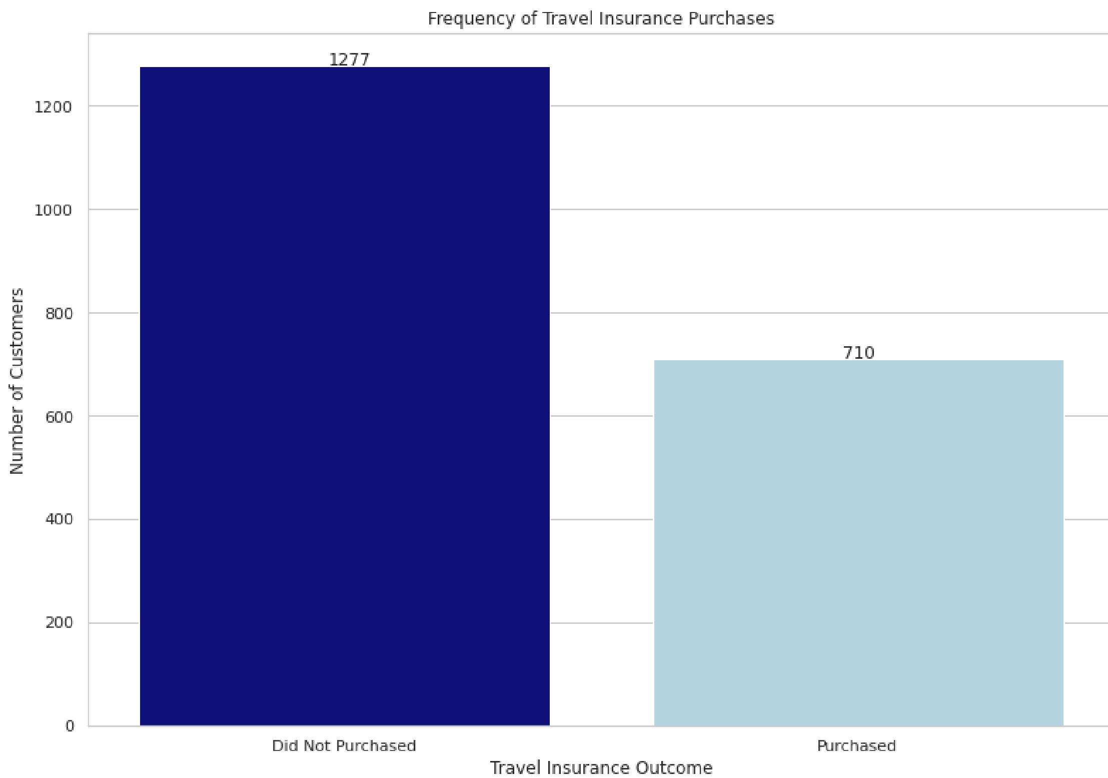
---

4.1 Exploring Response Variable - TravelInsurance

- Examine the frequency of travel insurance purchases
- 0 = No
- 1 = Yes

Python code:

[4]:
```
# Graph count plot of Non-Purchases vs. Purchases
ax = sns.countplot(data=df, x="TravelInsurance", palette = ["darkblue",␣
↪"lightblue"])

# Add count labels
for p, label in zip(ax.patches, df['TravelInsurance'].value_counts()):
    ax.annotate(label, (p.get_x()+0.37, p.get_height()+0.15))

# Graph Properties
plt.title("Frequency of Travel Insurance Purchases")
plt.xticks([0, 1], ["Did Not Purchased", "Purchased"])
plt.xlabel("Travel Insurance Outcome")
plt.ylabel('Number of Customers')
plt.show()
```



Summary

- There is a higher number of customers who flew without buying travel insurance in this sample data set.

4.2 Examing customers' Age

- Age distributions
- Age with Target Variable Overlaid
- Normalized Histogram with Target Overlaid on Age
- Age Group Comparisons (20s vs. 30s)
- Percentage of Purchases between Age groups (20s vs. 30s)

4.2.1 Age Distribution

Python code:

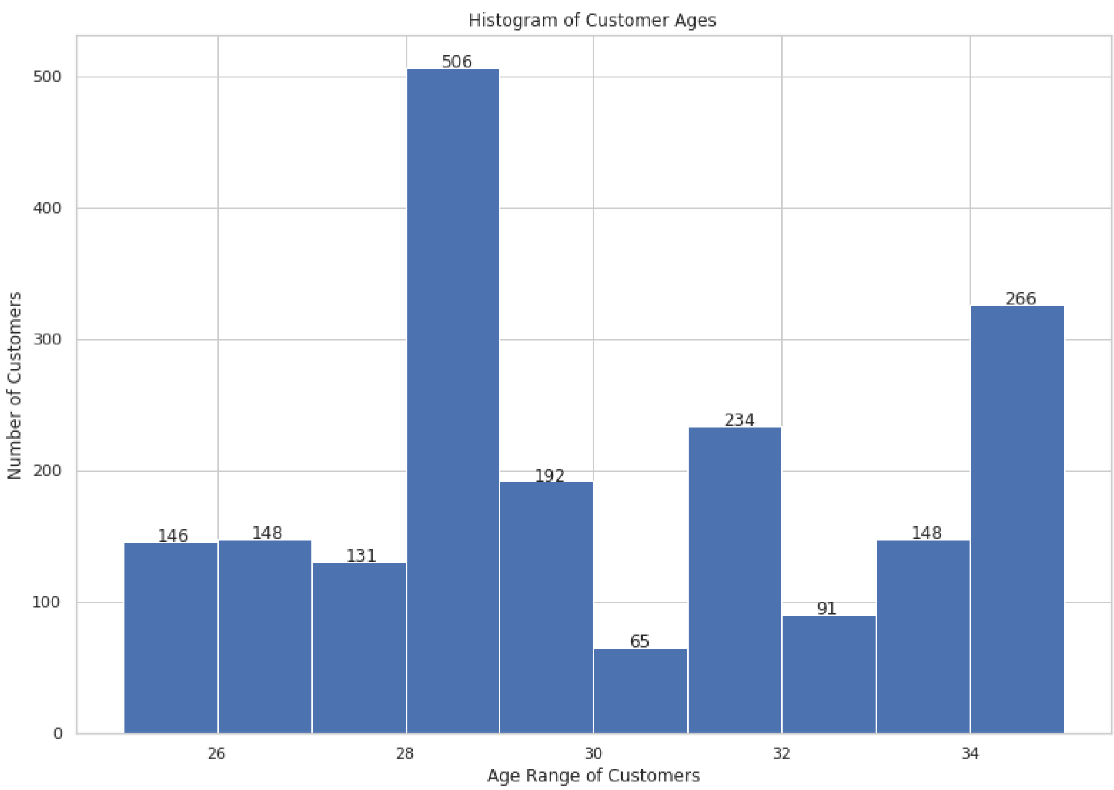
[5]:
```
# Get a range of customer ages
age = pd.DataFrame({'Age': df['Age'].value_counts().sort_index()})
age
```

[5]:

	Age
25	146
26	148

```
27   131
28   506
29   192
30    65
31   234
32    91
33   148
34   266
35    60
```

[6]:
```python
# Histogram of Age and set the range of bins from 25-35
bins = np.arange(25, 36)
ax = df['Age'].plot.hist(bins=bins)

# add labels
for p, label in zip(ax.patches, df['Age'].value_counts().sort_index()):
    ax.annotate(label, (p.get_x() + 0.37, p.get_height() + 0.15))

# title and axis
plt.title("Histogram of Customer Ages")
plt.xlabel("Age Range of Customers")
plt.ylabel("Number of Customers")
plt.show()
```



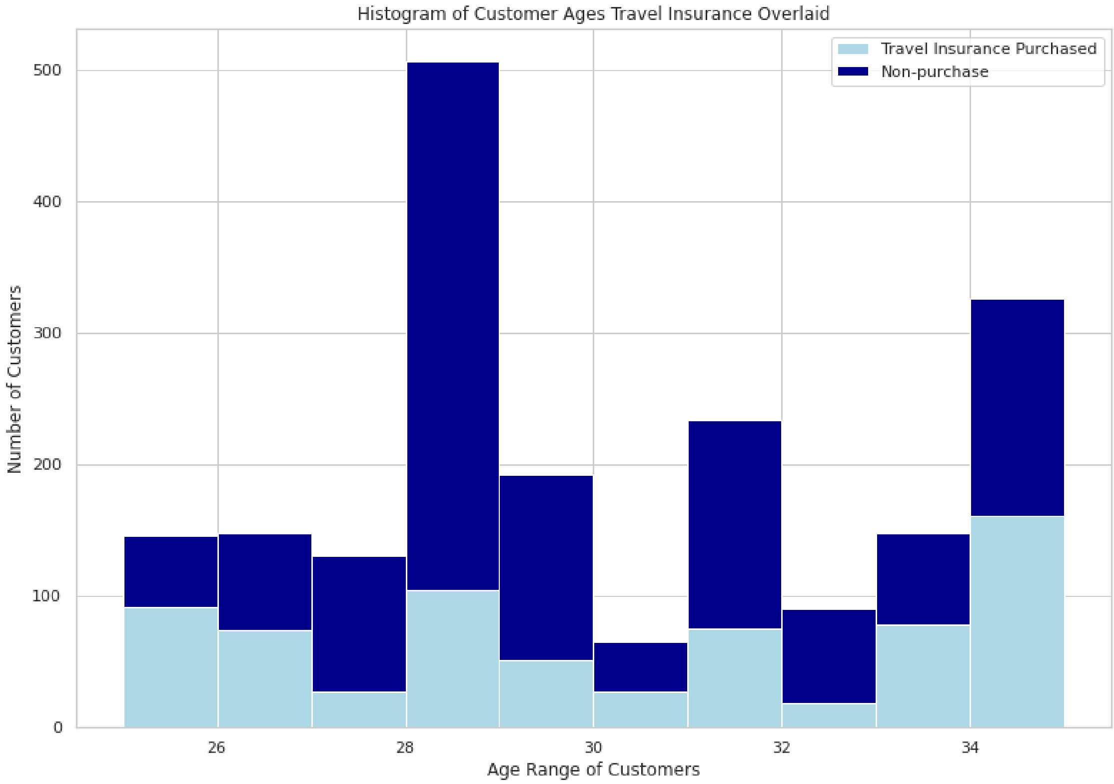
Summary

- There are 506 customers who are 28 years-old which is visualized as the most in this data set
- While customers who are 30 years-old are the least in this data set.

4.2.2 Age with Target Variable Overlaid

Python code:

[7]:
```
# Set up plot with response overlaid
n, bins, patches = plt.hist(
    [
        df[df['TravelInsurance'] == 1]['Age'],
        df[df['TravelInsurance'] == 0]['Age']
    ],
    bins=10,
    stacked=True,
    color=["lightblue", "darkblue"],
)

# title and axis
labels = ["Travel Insurance Purchased", "Non-purchase"]
plt.legend(labels)
plt.title("Histogram of Customer Ages Travel Insurance Overlaid")
plt.xlabel("Age Range of Customers")
plt.ylabel('Number of Customers')
plt.show()
```



Summary

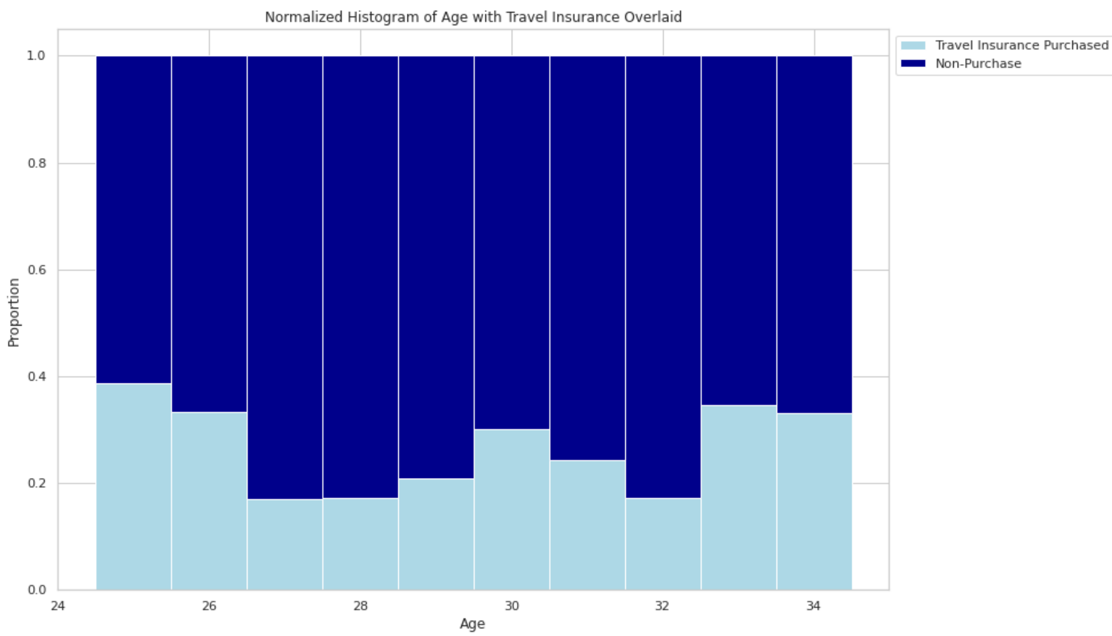
- It is difficult to compare between age groups with target variable overlaid
- Therefore, it is better to focus on one class from the target variable and analyze age in a normalized histogram.
- The following is visualized below.

4.2.3 Normalized Histogram with Target Variable Overlaid on Age

Python code:

[8]:
```
# Create normalized histogram for age groups by target overlay
n_table = np.column_stack((n[0], n[1]))  # stack the tables
n_norm = n_table / n_table.sum(axis=1)[:,
                                        None]  # create normalized tables by sum
ourbins = np.column_stack((bins[0:10], bins[1:11]))  # create table bins

p1 = plt.bar(x=ourbins[:, 0],
             height=n_norm[:, 0],
             width=ourbins[:, 1] - ourbins[:, 0],color = "lightblue")  # first␣
↪bar chart
p2 = plt.bar(
    x=ourbins[:, 0],
```

```
    height=n_norm[:, 1],
    width=ourbins[:, 1] - ourbins[:, 0],  # second bar chart
    bottom=n_norm[:, 0], color = "darkblue")
# Annotate legend, title with x and y labels
plt.legend(['Travel Insurance Purchased', 'Non-Purchase'],
           bbox_to_anchor=(1, 1))
plt.title('Normalized Histogram of Age with Travel Insurance Overlaid')
plt.xlabel('Age')
plt.ylabel('Proportion')
plt.show()
```



Summary

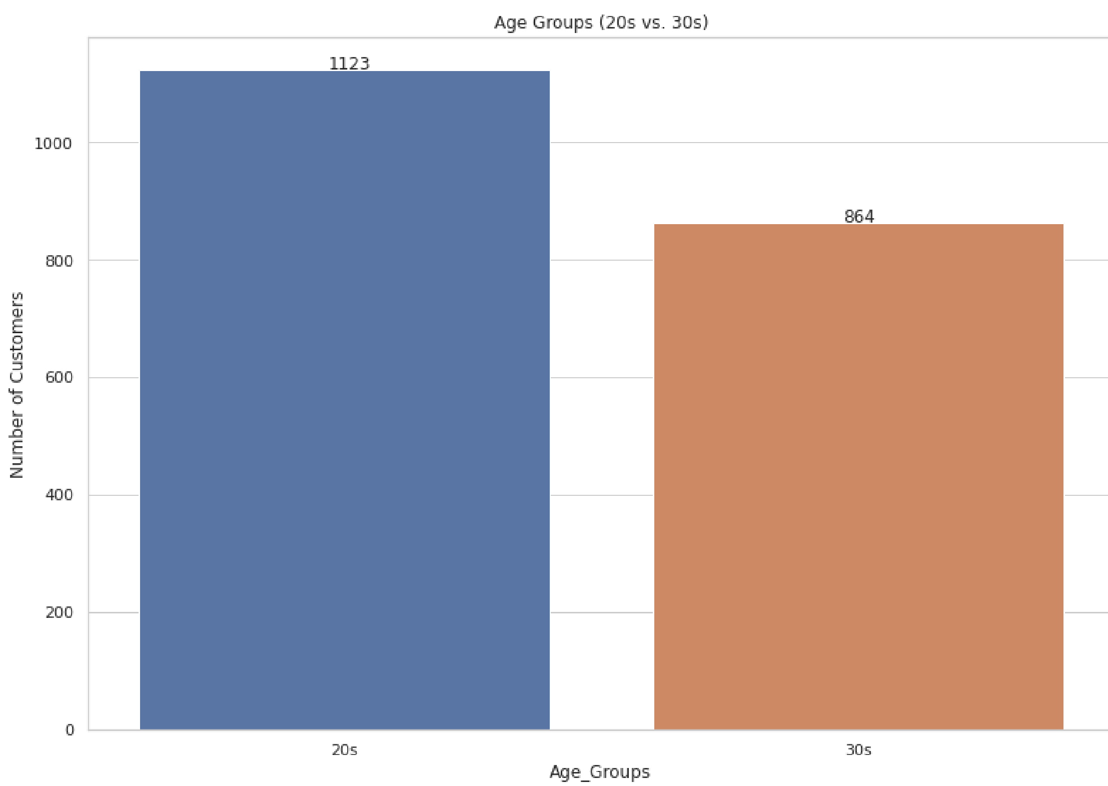
- Insights for this graph show that it may be better to compare age classified into 2 groups instead such as customers who are in their twenties (20s) vs customers in their thirties (30s).

4.2.4 Age Groups Comparison (20s vs. 30s)

Python code:

[9]:
```
# Create function to categorize age groups
def age_groups(x):
    '''
    x: This is a value from df['Age']
    returns each as a new categorical value of 20s or 30s
    '''
    if x < 30:
```

```
        return '20s'
    else:
        return '30s'


# Apply age_groups function on each value
age_groups = pd.DataFrame(
    {'Age_Groups': df['Age'].apply(lambda x: age_groups(x)),
     'AnnualIncome':df['AnnualIncome'],
    'TravelInsurance':df['TravelInsurance']})

# Graph count plot of age groups (20s vs. 30s)
ax = sns.countplot(data=age_groups, x="Age_Groups", order=['20s', '30s'])

# add labels
for p, label in zip(ax.patches, age_groups['Age_Groups'].value_counts()):
    ax.annotate(label, (p.get_x()+0.37, p.get_height()+0.15))
plt.title("Age Groups (20s vs. 30s)")
plt.ylabel('Number of Customers')
plt.show()
```



Summary

- Before visualizing the target variable overlaid, we can see here that after binning age into two groups, there are more customers who are in their 20s than customers in their 30s in this data set.

4.2.5 Percentage of Travel Insurance Purchases on Various Features

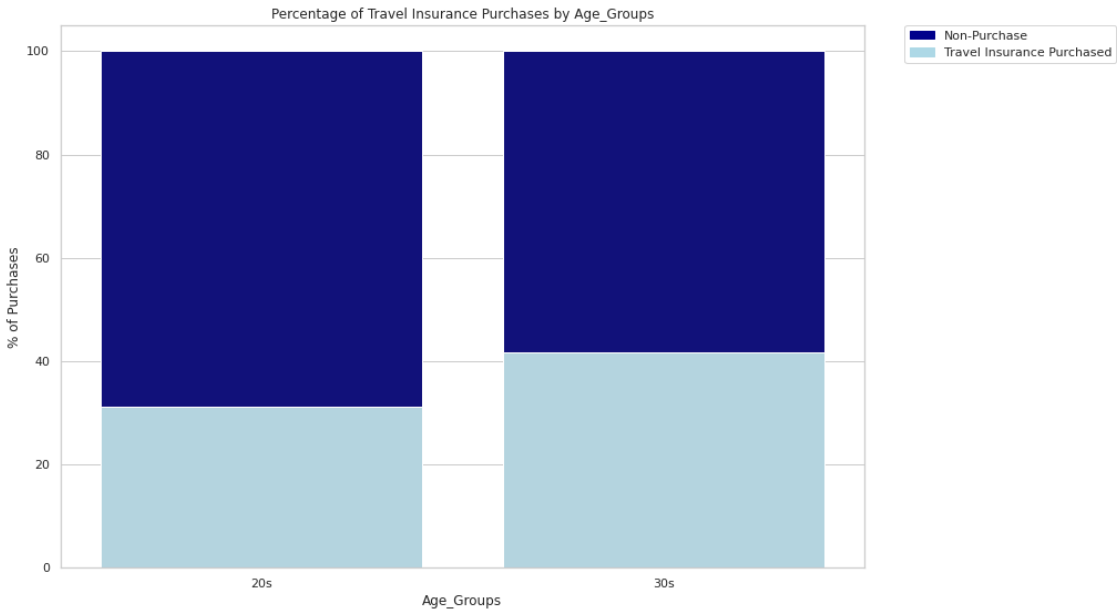
Python code:

[10]:
```
def make_stacked_barcharts(df, x):
    '''
    Takes in a data frame 'df' and a column 'x'
    and returns a stacked bar chart of the column
    with the percentage of purchases overlaid

    '''

    # Calculate total counts from both groups
    total = df.groupby(x)['TravelInsurance'].count().reset_index()

    # Calculate total counts from only purchases
    purchase = df[df.TravelInsurance == 1].groupby(
        x)['TravelInsurance'].count().reset_index()

    # get percentages for purchases
    purchase['TravelInsurance'] = [
        i / j * 100
        for i, j in zip(purchase['TravelInsurance'], total['TravelInsurance'])
    ]

    # get percentages
    total['TravelInsurance'] = [
        i / j * 100
        for i, j in zip(total['TravelInsurance'], total['TravelInsurance'])
    ]

    # bar chart 1 -> top bars (group of 'TravelInsurance=0')
    bar1 = sns.barplot(x, y="TravelInsurance", data=total, color='darkblue')

    # bar chart 2 -> bottom bars (group of 'TravelInsurance=1')
    bar2 = sns.barplot(x,
                       y="TravelInsurance",
                       data=purchase,
                       color='lightblue')

    # add legend
    top_bar = mpatches.Patch(color='darkblue', label='Non-Purchase')
    bottom_bar = mpatches.Patch(color='lightblue',
                                label='Travel Insurance Purchased')
```

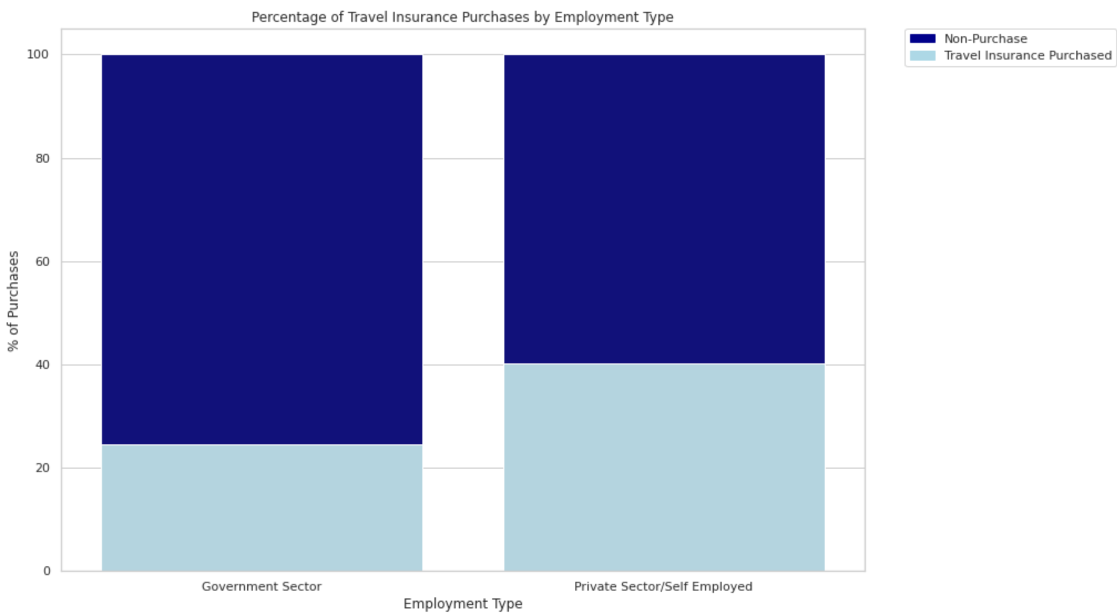
```python
    plt.legend(handles=[top_bar, bottom_bar],
               bbox_to_anchor=(1.05, 1),
               loc=2,
               borderaxespad=0.)
    # Aesthetics
    plt.title("Percentage of Travel Insurance Purchases by " + x)
    plt.xlabel(x)
    plt.ylabel("% of Purchases")

    # Change ticks on x-axis for ChronicDiseases column
    if x == "ChronicDiseases":
        chronicdiease = [0, 1]
        labels = ['No', 'Yes']
        plt.xticks(chronicdiease, labels)

    # show the graph
    plt.show()
```

[11]:

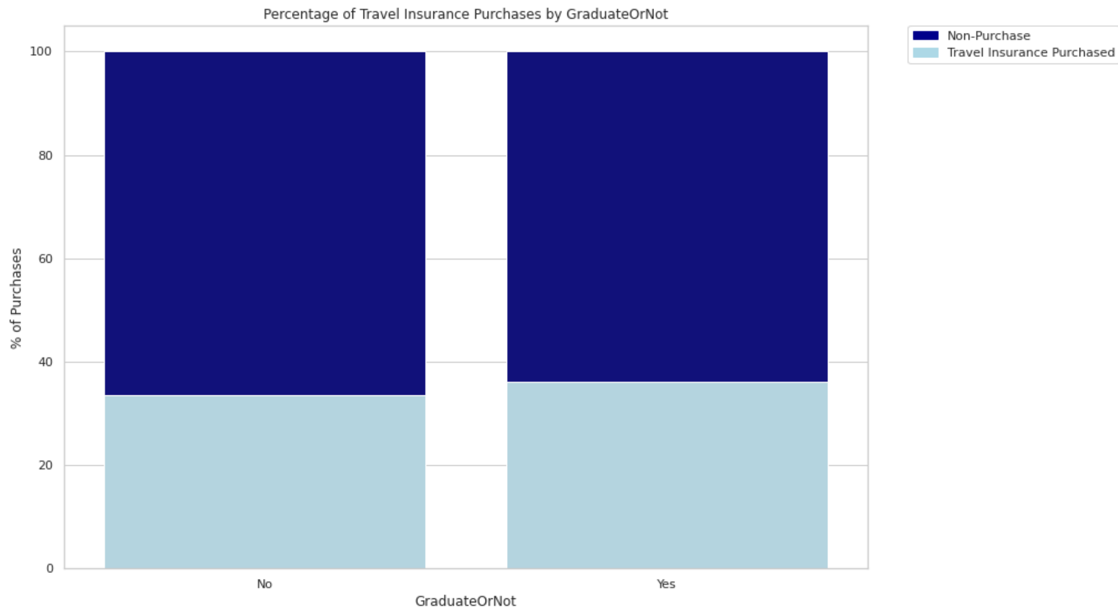
```python
# Call stacked bar chart function
make_stacked_barcharts(age_groups, 'Age_Groups')

# Make stacked bar charts on various columns
plot_columns = [
    'Employment Type', 'GraduateOrNot', 'ChronicDiseases', 'FrequentFlyer',
    'EverTravelledAbroad'
]

# Plot each column
for i in plot_columns:
    make_stacked_barcharts(df, i)
```

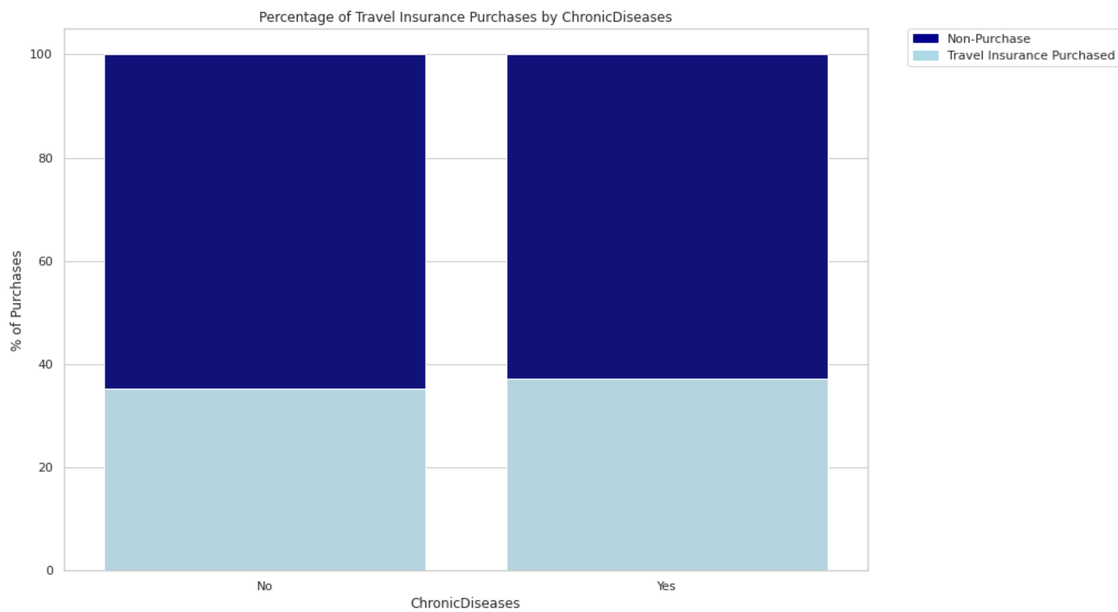


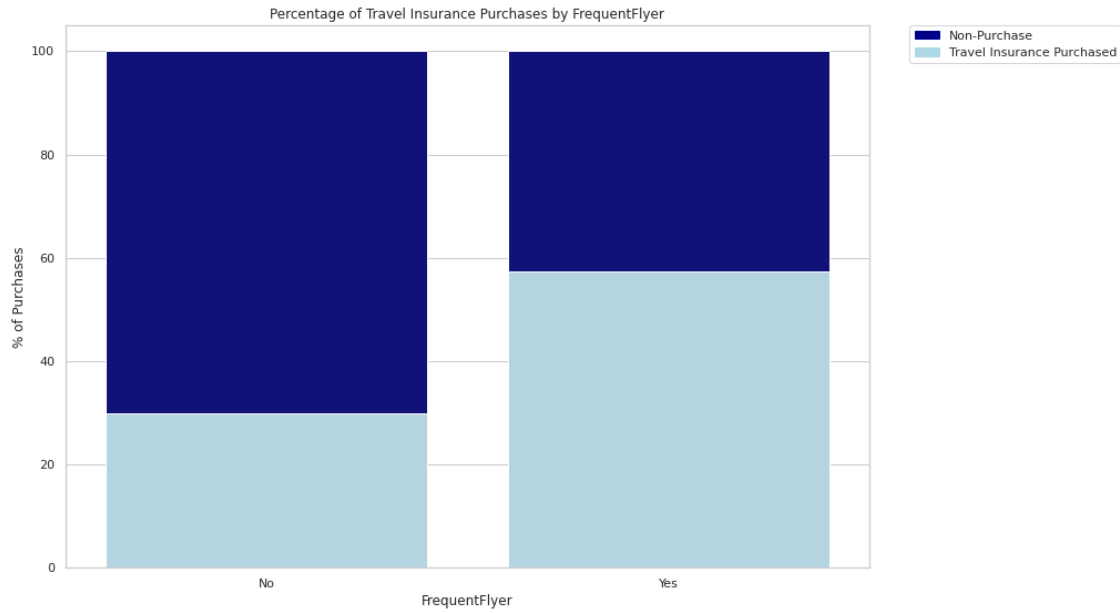
Percentage of Travel Insurance Purchases by Age_Groups
Non-Purchase
Travel Insurance Purchased
% of Purchases
0
20
40
60
80
100
20s
30s
Age_Groups

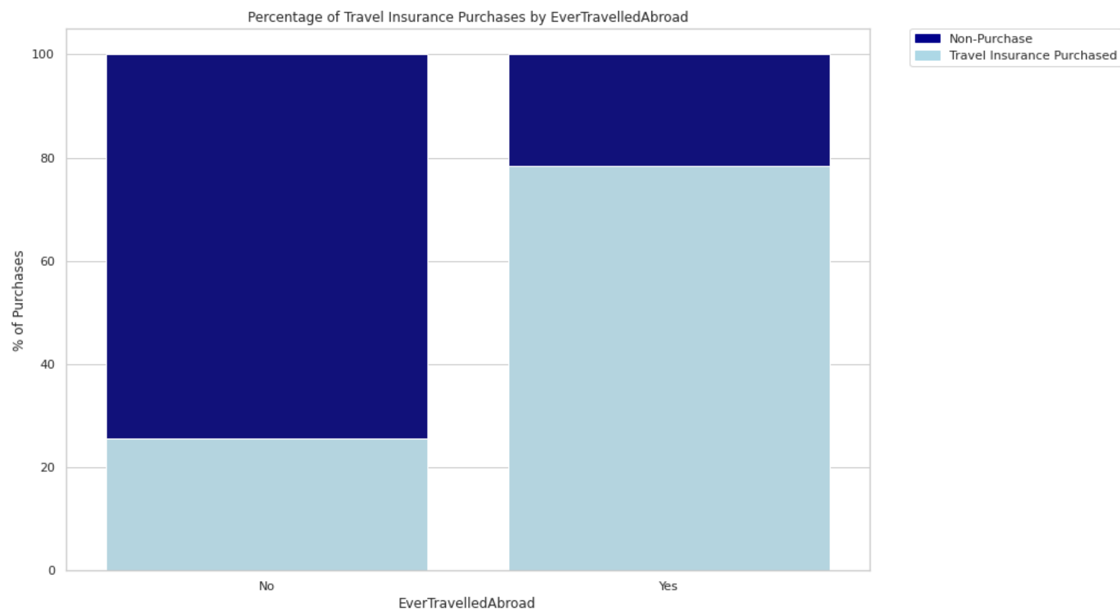


Percentage of Travel Insurance Purchases by Employment Type
Non-Purchase
Travel Insurance Purchased
% of Purchases
0
20
40
60
80
100
Government Sector
Private Sector/Self Employed
Employment Type


Percentage of Travel Insurance Purchases by GraduateOrNot
Non-Purchase
Travel Insurance Purchased
% of Purchases
0
20
40
60
80
100
No
Yes
GraduateOrNot


Percentage of Travel Insurance Purchases by ChronicDiseases
Non-Purchase
Travel Insurance Purchased
% of Purchases
0
20
40
60
80
100
No
Yes
ChronicDiseases





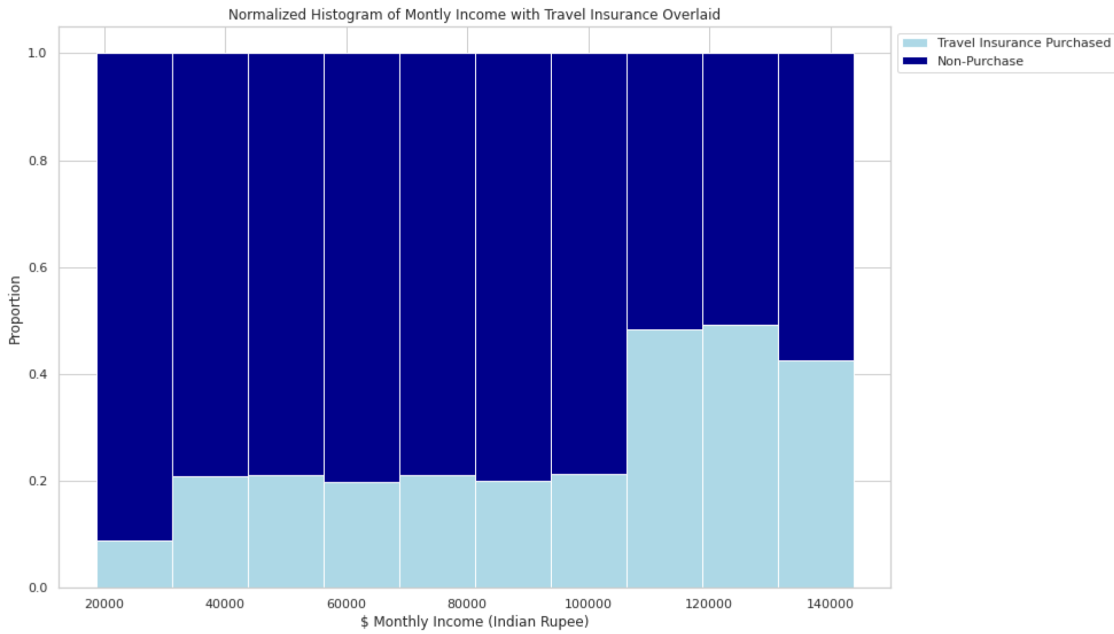
Summary

- There is a higher proportion of customers in their 30s that purchased travel insurance.
- There is a higher proportion of customers who works in a private sector or is self-employed that purchased travel insurance.
- There is no significant difference in proportion between customers who are a college graduate or not that purchased travel insurance.

- This also applies to customers with or without chronic diseases that purchased travel insurance.
- However, there is a higher proportion of customers who are frequent flyers and/or have traveled abroad that purchased travel insurance.

4.3 Monthly Income (Indian Rupee) Range

[12]:
```
# Counts by Monthly Rupee
n = np.array([[20.,  63.,  60.,  67.,  41.,  67.,  74., 191.,  84.,  43.],
        [208., 239., 223., 273., 153., 268., 274., 204.,  87.,  58.]])

# Bins for Montly Rupee
bins= np.array([ 25000.,  37500.,  50000.,  62500.,  75000.,  87500., 100000.,
        112500., 125000., 137500., 150000.])

               # Create normalized histogram for groups by target overlay
n_table = np.column_stack((n[0], n[1]))  # stack the tables
n_norm = n_table / n_table.sum(
        axis=1)[:, None]  # create normalized tables by sum
ourbins = np.column_stack((bins[0:10], bins[1:11]))  # create table bins

p1 = plt.bar(x=ourbins[:, 0],
                 height=n_norm[:, 0],
                 width=ourbins[:, 1] - ourbins[:, 0],
                 color="lightblue")  # first bar chart
p2 = plt.bar(
        x=ourbins[:, 0],
        height=n_norm[:, 1],
        width=ourbins[:, 1] - ourbins[:, 0],  # second bar chart
        bottom=n_norm[:, 0],
        color="darkblue")
    # Annotate legend, title with x and y labels
plt.legend(['Travel Insurance Purchased', 'Non-Purchase'],
               bbox_to_anchor=(1, 1))
plt.title('Normalized Histogram of Montly Income with Travel Insurance␣
 ↪Overlaid')
plt.xlabel('$ Monthly Income (Indian Rupee)')
plt.ylabel('Proportion of Flyers')
plt.show()
```



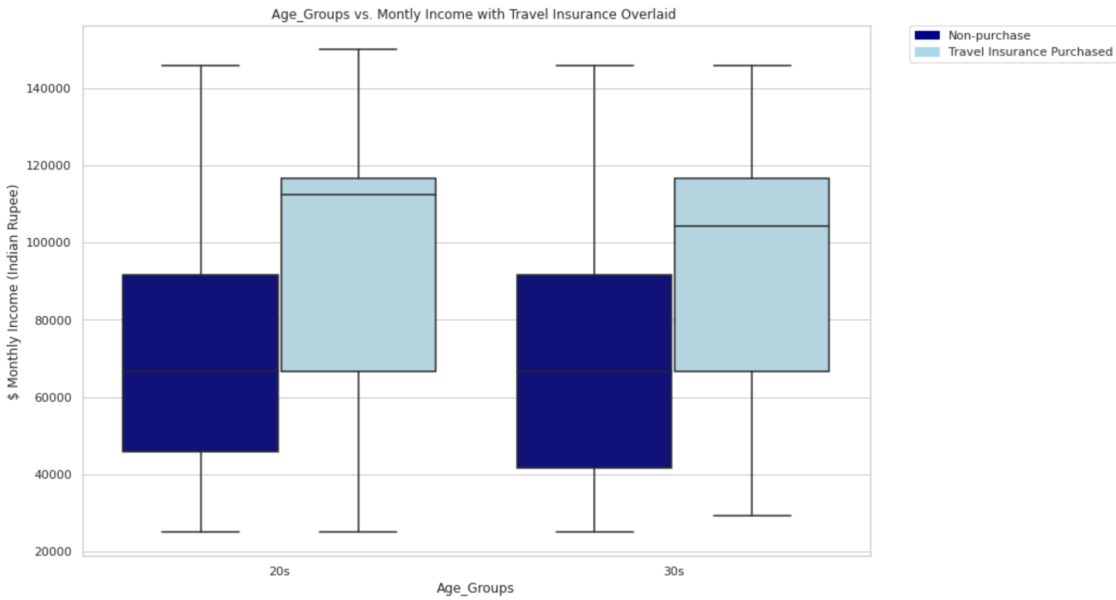
4.4 Side-by-side Box-plots between Annual Income and Different Attributes

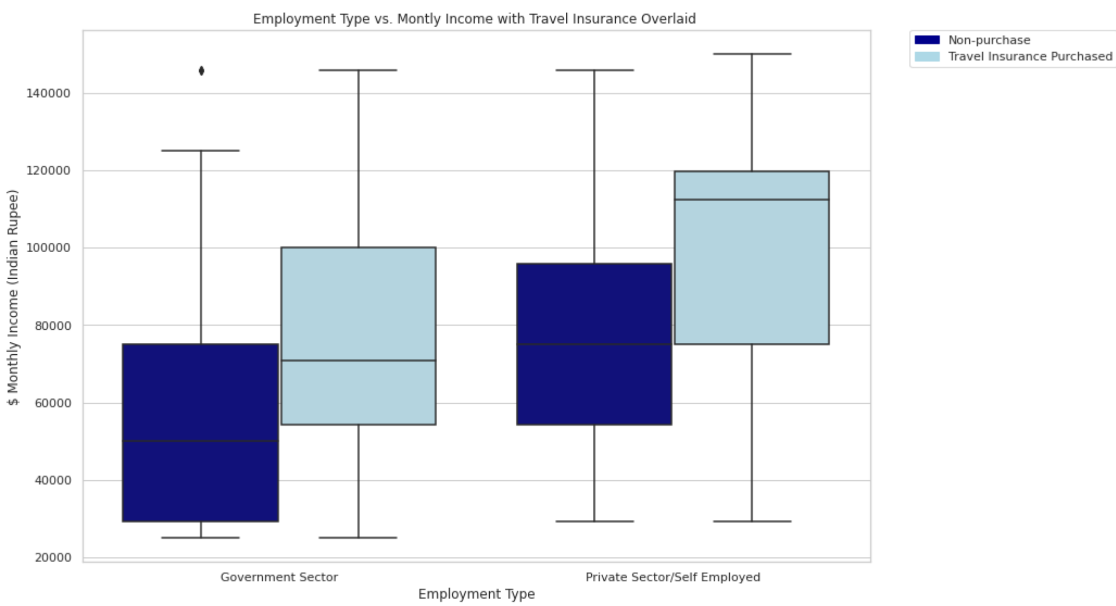
Python code:

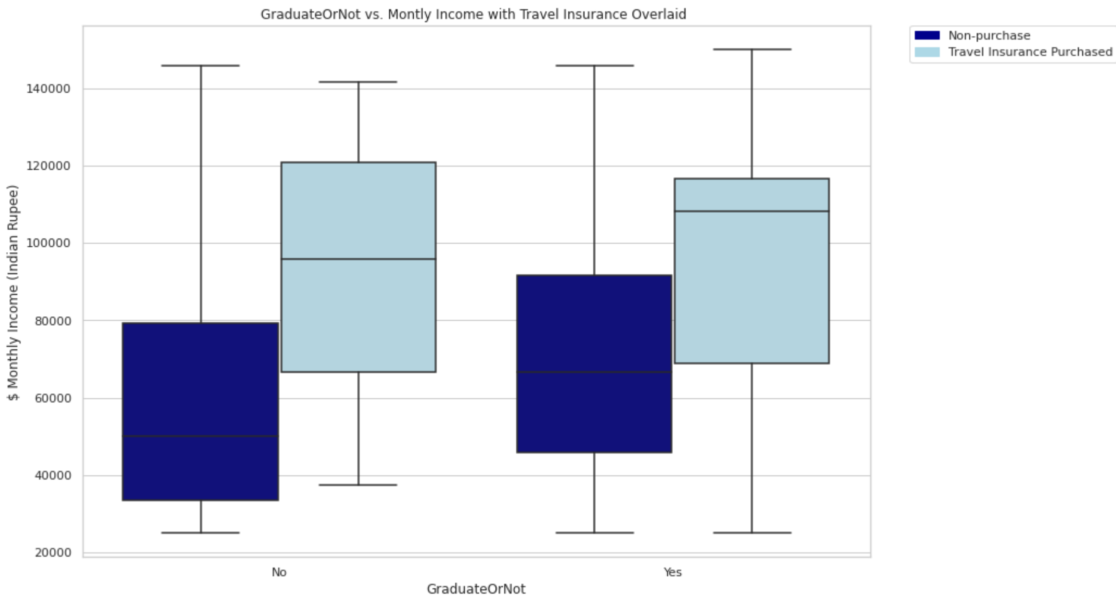
[13]:
```
def make_boxplots(df, x):
    '''
    Takes in 'x' as a column from data frame 'df'
    and returns a side by side box-plot of
    x on the x-axis and AnnualIncome on the y-axis
    seperated by different colors noted by TravelInsurance

    '''

    # Palatte to color the target variable
    palatte = {0: "darkblue", 1: "lightblue"}

    # Change x-axis labels if age_groups or GraduatedOrNot
    order = None
    if x == "Age_Groups":
        order = ["20s", "30s"]
    if x == "GraduateOrNot":
        order = ["No", "Yes"]

    #Convert AnnualIncome to Monthly
    df['Monthly_Income'] = round(df['AnnualIncome']/12,2)
```

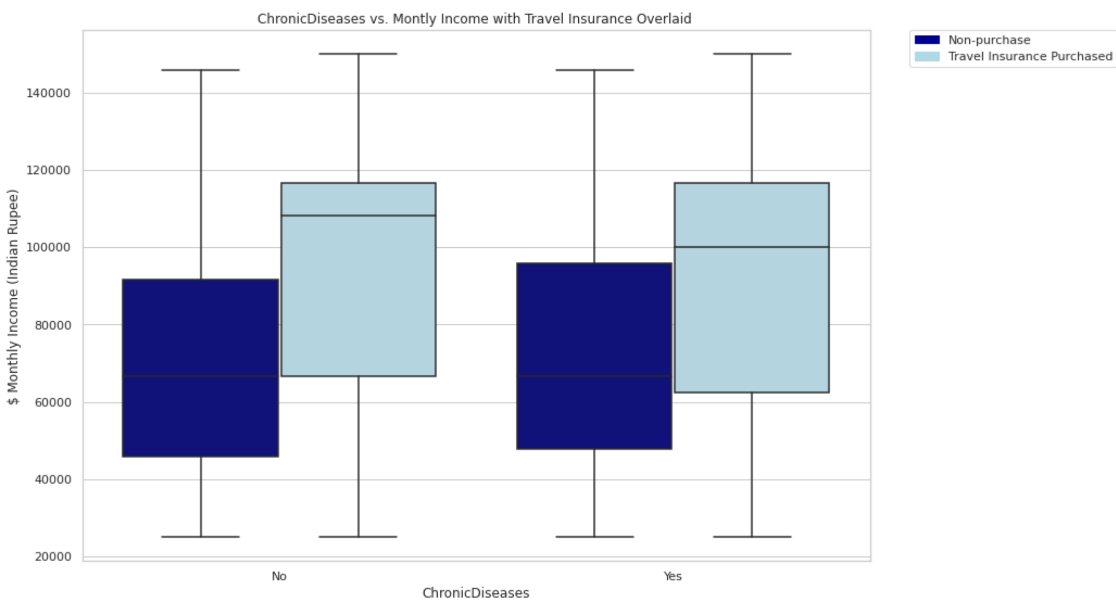
```python
    # Boxplot
    sns.boxplot(x=x,
                y="Monthly_Income",
                hue="TravelInsurance",
                data=df,
                order=order,
                palette=palatte)

    # Legend properties
    top_bar = mpatches.Patch(color='darkblue', label='Non-purchase')
    bottom_bar = mpatches.Patch(color='lightblue',
                                label='Travel Insurance Purchased')
    plt.legend(handles=[top_bar, bottom_bar],
               bbox_to_anchor=(1.05, 1),
               loc=2,
               borderaxespad=0.)

    # Graph Properties
    plt.title(x + " vs. Montly Income with Travel Insurance Overlaid ")
    plt.xlabel(x)
    plt.ylabel("$ Monthly Income (Indian Rupee)")

    # Change ticks on x-axis for ChronicDiseases column
    if x == "ChronicDiseases":
        chronicdiease = [0, 1]
        labels = ['No', 'Yes']
        plt.xticks(chronicdiease, labels)

    # show the graph
    plt.show()
```

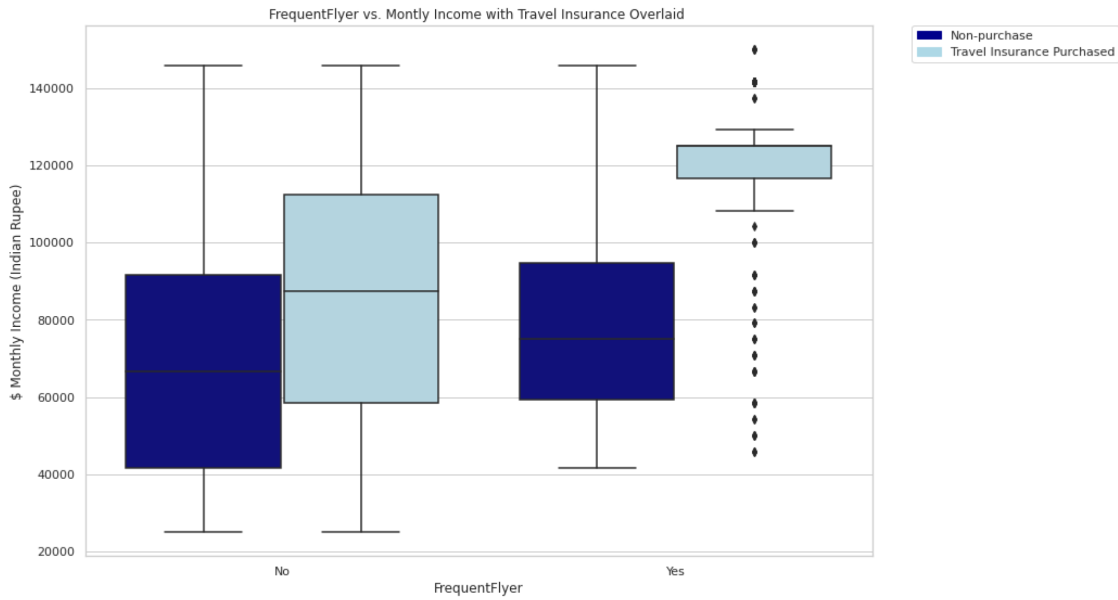
[14]:
```python
# call stacked bar chart function
make_boxplots(age_groups, 'Age_Groups')

# call boxplot function on various columns
plot_columns = ['Employment Type', 'GraduateOrNot','ChronicDiseases',␣
 ↪'FrequentFlyer',
       'EverTravelledAbroad']

# plot each column
for i in plot_columns:
    # boxplot function
    make_boxplots(df, i)
```

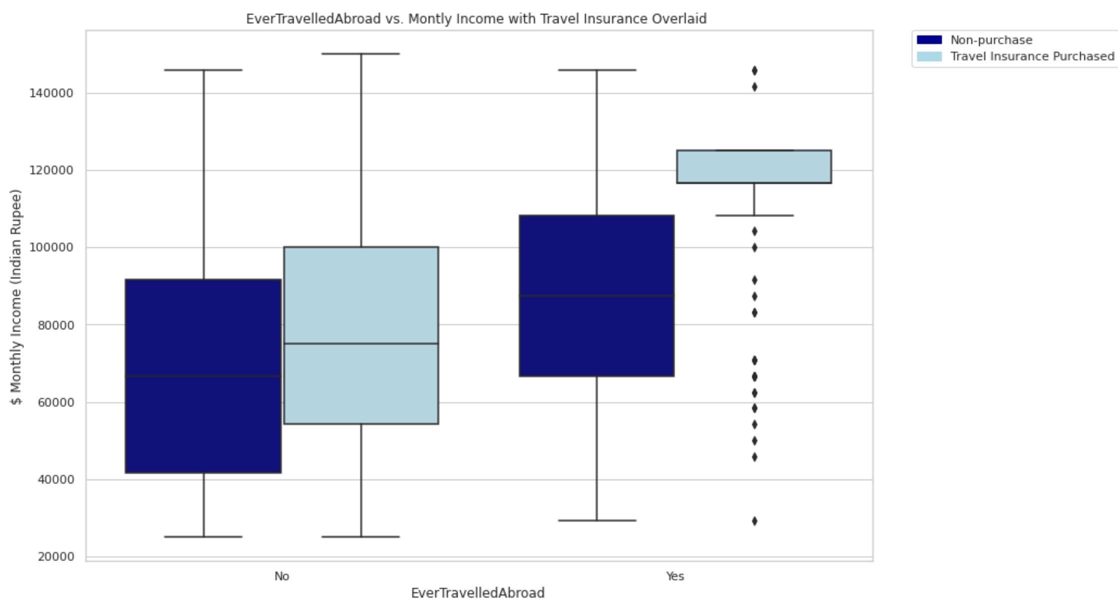

Age_Groups vs. Montly Income with Travel Insurance Overlaid
Non-purchase
Travel Insurance Purchased
$ Monthly Income (Indian Rupee)
140000
120000
100000
80000
60000
40000
20000
20s
30s
Age_Groups


Employment Type vs. Montly Income with Travel Insurance Overlaid
Non-purchase
Travel Insurance Purchased
$ Monthly Income (Indian Rupee)
140000
120000
100000
80000
60000
40000
20000
Government Sector
Private Sector/Self Employed
Employment Type


GraduateOrNot vs. Montly Income with Travel Insurance Overlaid
Non-purchase
Travel Insurance Purchased
$ Monthly Income (Indian Rupee)
140000
120000
100000
80000
60000
40000
20000
No
Yes
GraduateOrNot


ChronicDiseases vs. Montly Income with Travel Insurance Overlaid
Non-purchase
Travel Insurance Purchased
$ Monthly Income (Indian Rupee)
140000
120000
100000
80000
60000
40000
20000
No
Yes
ChronicDiseases





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5 Feature Engineering and Pre-Processing

- Invent new columns
- Handle missing values, outliers, correlated features, etc.

Python code:

- Bin age into age groups

[15]:
```python
# Create function to categorize age groups
def age_groups(x):
    '''
    x: This is a value from df['Age']
    returns each as a new categorical value of 20s or 30s
    '''
    if x < 30:
        return '20s'
    else:
        return '30s'

# group age into 20s and 30s
df['Age'] = df['Age'].apply(lambda x: age_groups(x))
df = df.rename(columns = {'Age':'Age_Groups'})
df.head()
```

[15]:
```
  Age_Groups        Employment Type        GraduateOrNot  AnnualIncome
FamilyMembers  ChronicDiseases FrequentFlyer EverTravelledAbroad
TravelInsurance  Monthly_Income
0      30s                Government Sector        Yes          400000          6
1              No              No             0          33333.330
1      30s     Private Sector/Self Employed        Yes         1250000          7
0              No              No             0         104166.670
2      30s     Private Sector/Self Employed        Yes          500000          4
1              No              No             1          41666.670
3      20s     Private Sector/Self Employed        Yes          700000          3
1              No              No             0          58333.330
4      20s     Private Sector/Self Employed        Yes          700000          8
1             Yes              No             0          58333.330
```

- Create poor- lower - middle - high income classes

[16]:
```python
# Create function to categorize wealth groups
def wealth_groups(x):
    '''
    x: This is a value from df['Monthly_Income']
    returns each as a new categorical value of 20s or 30s

    The range for categorizing income class

    - Poor Class:  2500- 6500 per month

    - Lower Class:  6500- 15000 per month

    - Middle Class:  15000- 100000 per month

```

```
    - Upper Class:  100000- 350000 per month

    '''

    if x <= 6500:
        return 'poor'
    elif x <= 15000:
        return 'lower'
    elif x <= 100000:
        return 'middle'
    else:
        return 'upper'

# group Monthly Income into wealth groups
df['AnnualIncome'] = df['Monthly_Income'].apply(lambda x: wealth_groups(x))
df = df.drop('Monthly_Income', axis = 1)
df = df.rename(columns = {'AnnualIncome':'Income_Class'})
df.head()
```

[16]:

```
  Age_Groups        Employment Type        GraduateOrNot Income_Class
FamilyMembers  ChronicDiseases FrequentFlyer EverTravelledAbroad
TravelInsurance
0      30s              Government Sector       Yes        middle            6
1              No               No            0
1      30s     Private Sector/Self Employed       Yes         upper            7
0              No               No            0
2      30s     Private Sector/Self Employed       Yes        middle            4
1              No               No            1
3      20s     Private Sector/Self Employed       Yes        middle            3
1              No               No            0
4      20s     Private Sector/Self Employed       Yes        middle            8
1             Yes               No            0
```

- Convert Family Members to household size categories

[17]:

```
# Create function to categorize age groups
def household_groups(x):
    '''
    x: This is a value from df['FamilyMembers']
    returns each as a new categorical value of 20s or 30s

    The range for categorizing income class

    - 1 = single

    - 2-4 = small
```

```
    - 5-10 = medium

    - >10 = large

    '''

    if x == 1:
        return 'single'
    elif x <= 4:
        return 'small'
    elif x <= 10:
        return 'medium'
    else:
        return 'large'


# group Family Members into household groups
df['FamilyMembers'] = df['FamilyMembers'].apply(lambda x: household_groups(x))
df = df.rename(columns = {'FamilyMembers':'Household_Size'})
df.head()
```

[17]:

```
  Age_Groups        Employment Type        GraduateOrNot Income_Class
Household_Size  ChronicDiseases FrequentFlyer EverTravelledAbroad
TravelInsurance
0     30s                Government Sector        Yes        middle         medium
1               No               No                0
1     30s     Private Sector/Self Employed        Yes         upper         medium
0               No               No                0
2     30s     Private Sector/Self Employed        Yes        middle          small
1               No               No                1
3     20s     Private Sector/Self Employed        Yes        middle          small
1               No               No                0
4     20s     Private Sector/Self Employed        Yes        middle         medium
1              Yes               No                0
```

- Convert Binary Categorical Variable values to 0/1

[18]:

```
# Convert Frequent Flyer to 0/1 binary values
df['FrequentFlyer'] = np.where((df['FrequentFlyer'] == 'No'), 0, 1)

# Convert Ever Traveled Abroad to 0/1 binary values
df['EverTravelledAbroad'] = np.where((df['EverTravelledAbroad'] == 'No'), 0, 1)
```

```
# Convert GraduateOrNot to 0/1 binary values
df['GraduateOrNot'] = np.where((df['GraduateOrNot'] == 'No'),0,1)

# first few rows
df.head()
```

[18]:

```
  Age_Groups        Employment Type         GraduateOrNot Income_Class
Household_Size  ChronicDiseases  FrequentFlyer  EverTravelledAbroad
TravelInsurance
0      30s                Government Sector         1          middle
medium              1               0                0                  0
1      30s     Private Sector/Self Employed         1           upper
medium              0               0                0                  0
2      30s     Private Sector/Self Employed         1          middle
small              1               0                0                  1
3      20s     Private Sector/Self Employed         1          middle
small              1               0                0                  0
4      20s     Private Sector/Self Employed         1          middle
medium              1               1                0                  0
```

- One hot encode categorical variables to dummy variables

[19]:

```
# one-hot encoding the categorical variables
df = pd.get_dummies(df)
df.head()
```

[19]:

```
   GraduateOrNot  ChronicDiseases  FrequentFlyer  EverTravelledAbroad
TravelInsurance  Age_Groups_20s  Age_Groups_30s  Employment Type_Government
Sector  Employment Type_Private Sector/Self Employed  Income_Class_middle
Income_Class_upper  Household_Size_medium  Household_Size_small
0         1               1               0                0                  0
0              1                         1
0                               1                    0                    1
0
1         1               0               0                0                  0
0              1                         0
1                               0                    1                    1
0
2         1               1               0                0                  1
0              1                         0
1                               1                    0                    0
1
3         1               1               0                0                  0
1              0                         0
1                               1                    0                    0
1
4         1               1               1                0                  0
```

1 0 0
1 1 0 1
0

---

6 Data splitting

- Training, validation, and test sets
- Since there does not exist a class imbalance problem, we split the data set into 75% training and 25% validation.

Python code:

[20]:
```
# Response Variable
outcome = 'TravelInsurance'
y = df[outcome]

# features - Do not use Target_B or Target_D
predictors = [
    'GraduateOrNot', 'ChronicDiseases', 'FrequentFlyer', 'EverTravelledAbroad',
    'Age_Groups_20s', 'Age_Groups_30s', 'Employment Type_Government Sector',
    'Employment Type_Private Sector/Self Employed', 'Income_Class_middle',
    'Income_Class_upper', 'Household_Size_medium', 'Household_Size_small'
]
X = df[predictors]

# Set seed to 1 and split on 30% validation
train_X, valid_X, train_y, valid_y = train_test_split(X,
                                                      y,
                                                      test_size=0.25,
                                                      random_state=1)

# Check dimensions
train_X.shape, valid_X.shape
```

[20]: ((1490, 12), (497, 12))

---

7 Model building strategies

- Describing main research questions and appropriate analytics methods

Python code:

[ ]:
```

```

---

8 Model performance and hyper-parameter tuning

- Model tuning, comparison, and evaluations

8.1 Decision Tree

Python code:

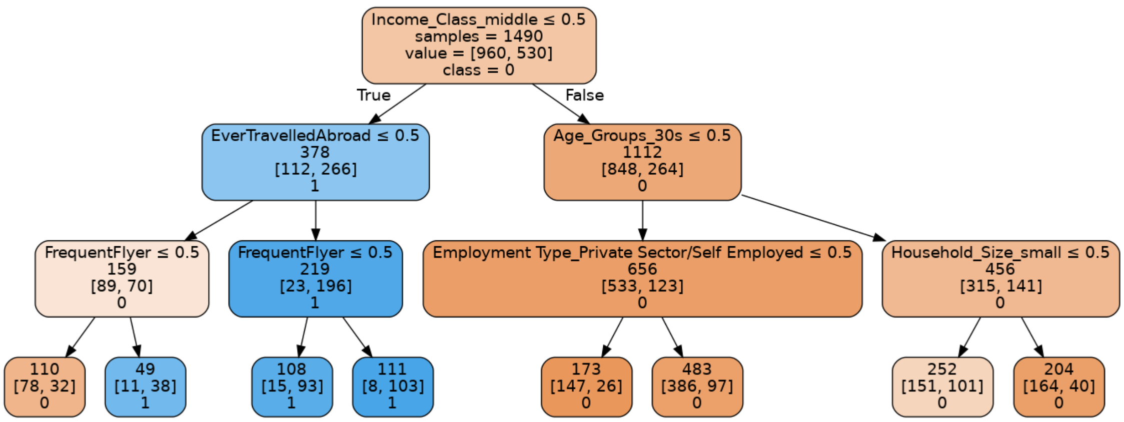
[21]:
```
# user grid search to find optimized tree
param_grid = {
    'max_depth': [5, 10, 15, 20, 25],
    'min_impurity_decrease': [0, 0.001, 0.005, 0.01],
    'min_samples_split': [10, 20, 30, 40, 50],
}

# Run Exhaustive Search
gridSearch = GridSearchCV(DecisionTreeClassifier(random_state=1), param_grid,␣
 ↪cv=5, n_jobs=-1)
gridSearch.fit(X=train_X, y=train_y)

# Initial Parameters
print('Initial Score: ', gridSearch.best_score_)
print('Initial parameters: ', gridSearch.best_params_)


# Improving the parameters
param_grid = {
    'max_depth': [3, 4, 5, 6, 7, 8],
    'min_impurity_decrease': [0, 0.001, 0.002, 0.003, 0.005, 0.006, 0.007, 0.
 ↪008],
    'min_samples_split': [6,7,8,9,10,11,12]
}

# Run Exhaustive Search with fine-tuned parameters
gridSearch = GridSearchCV(DecisionTreeClassifier(random_state=1), param_grid,␣
 ↪cv=5, n_jobs=-1)
gridSearch.fit(train_X, train_y)

# Final parameters
print('Improved Score: ', gridSearch.best_score_)
print('Improved parameters: ', gridSearch.best_params_)

# Final Decision Tree
tree_model = gridSearch.best_estimator_

# Fit to Training Data
tree_model.fit(train_X, train_y)
```

```
Initial Score:  0.7785234899328859
Initial parameters:  {'max_depth': 5, 'min_impurity_decrease': 0.005,
'min_samples_split': 10}
Improved Score:  0.7785234899328859
Improved parameters:  {'max_depth': 3, 'min_impurity_decrease': 0,
'min_samples_split': 6}
```

[21]:
```
DecisionTreeClassifier(max_depth=3, min_impurity_decrease=0,
                       min_samples_split=6, random_state=1)
```

[22]:
```
# Plot Decision tree
plotDecisionTree(tree_model,
                 feature_names=train_X.columns,
                 class_names=tree_model.classes_)
```

[22]:



8.2 Adaboost Decision Tree Classifier

Python code:

[23]:
```
# ADA Boost Model using the previous decision tree
adaboost_model = AdaBoostClassifier(n_estimators=100, base_estimator=tree_model)

# fit to training data
adaboost_model.fit(train_X, train_y)
```

[23]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=3,
min_impurity_decrease=0,
                                                         min_samples_split=6,
                                                         random_state=1),
                   n_estimators=100)
```

8.3 Random Forest Classifier

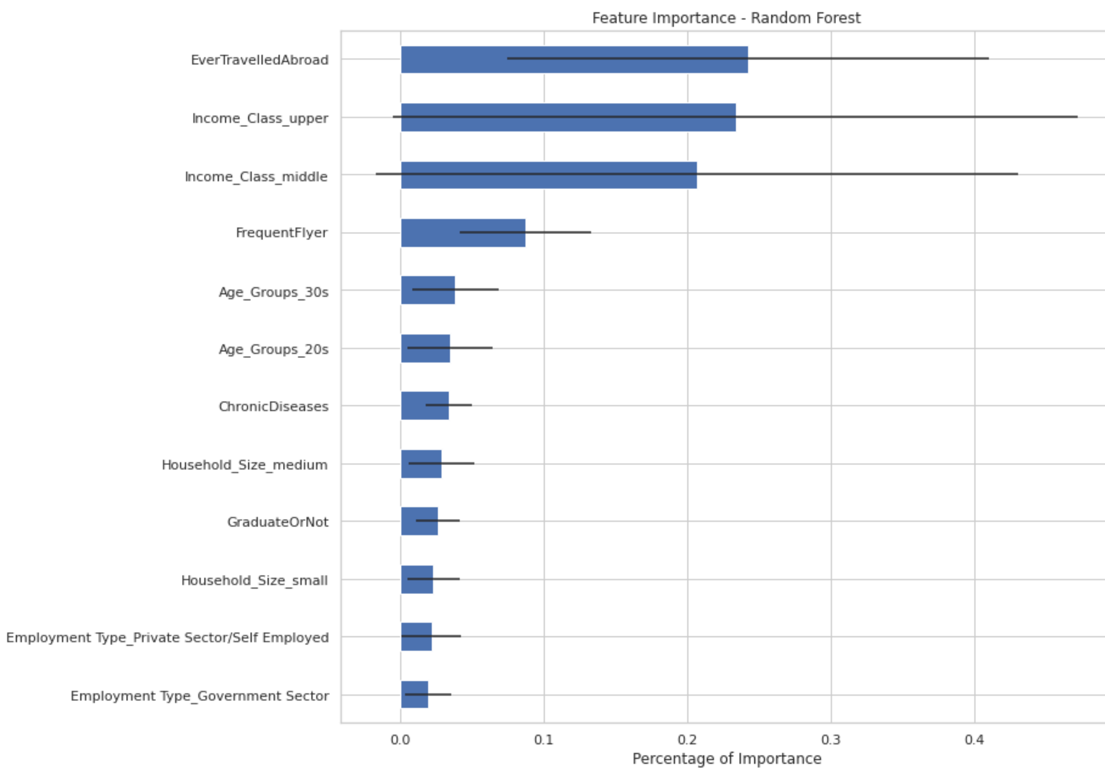
Python code:

[24]:
```
# Create the parameter grid based on the results of random search

param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100],
    'max_features': [2, 3],
    'min_samples_leaf': [3,4, 5],
    'min_samples_split': [8, 9, 10],
    'n_estimators': [100, 200, 300]
}

# Create a based model with class weights
rf = RandomForestClassifier()

# Instantiate the grid search model
grid_search = GridSearchCV(estimator=rf,
                           param_grid=param_grid,
                           cv=3,
                           n_jobs=-1)

# fit to training data to get the best parameters
grid_search.fit(train_X, train_y)

# best parameters - final random forest model
rf_model = RandomForestClassifier(**grid_search.best_params_)

# Fit final model to training set
rf_model.fit(train_X, train_y)
```

[24]:
```
RandomForestClassifier(max_depth=90, max_features=3, min_samples_leaf=5,
                       min_samples_split=10)
```

[25]:
```
# Features Importance
importances = rf_model.feature_importances_
std = np.std([tree.feature_importances_ for tree in rf_model.estimators_],
             axis=0)

# Turn features importance into data frame
rf_df = pd.DataFrame({
    'feature': train_X.columns,
    'importance': importances,
    'std': std
})
```

```
# Sort importance by highest to lowest
rf_df = rf_df.sort_values('importance')

# Plot error bar plot on feature importance
ax = rf_df.plot(kind='barh', xerr='std', x='feature', legend=False)
plt.title("Feature Importance - Random Forest")
plt.xlabel("Percentage of Importance")
plt.ylabel("")
plt.tight_layout()
plt.show()
```



8.4 Logistic Regression

[26]:
```
param_grid = {
    'penalty': ['l1', 'l2'],
    'C': np.logspace(-4, 4, 20),
    'solver': ['liblinear', 'saga']
}

# Create grid search object
gridSearch = GridSearchCV(LogisticRegression(random_state=1, max_iter=5000),
                          param_grid=param_grid,
```

```
                          cv=5,
                          n_jobs=-1)

# Fit to training data
gridSearch.fit(train_X, train_y)

# Final parameters
print('Final Score: ', gridSearch.best_score_)
print('Final parameters: ', gridSearch.best_params_)

# Final logistic regression model
logit_model = gridSearch.best_estimator_
```

```
Final Score:  0.7657718120805369
Final parameters:  {'C': 0.004832930238571752, 'penalty': 'l2', 'solver':
'liblinear'}
```

[27]:

```
# Train logistic regression model to find the best predictors
def train_model(variables):
    if len(variables) == 0:
        return None
    model = LogisticRegressionCV(penalty="l2",
                                 solver='liblinear',
                                 cv=5,
                                 random_state=1,
                                 max_iter=5000)
    return model.fit(train_X[variables], train_y)


# Return the accuracy score in the validation set over each predictor
def score_model(model, variables):
    if len(variables) == 0:
        return 0
    logit_reg_valid = model.predict(valid_X[variables])
    return -accuracy_score(valid_y,
                           [1 if p > 0.5 else 0 for p in logit_reg_valid])


# Use step-wise regression to select the best subset of features
logit_model, best_variables = stepwise_selection(predictors,
                                                 train_model,
                                                 score_model,
                                                 direction='forward',
                                                 verbose=True)
print("\n\t Best Variables Selected: ", best_variables)

# Use the previous columns
```

```
columns = best_variables

# Fit to Training Data with previous columns
logit_model.fit(train_X[columns], train_y)
```

```
Variables: GraduateOrNot, ChronicDiseases, FrequentFlyer, EverTravelledAbroad,
Age_Groups_20s, Age_Groups_30s, Employment Type_Government Sector, Employment
Type_Private Sector/Self Employed, Income_Class_middle, Income_Class_upper,
Household_Size_medium, Household_Size_small
Start: score=0.00, constant
Step: score=-0.77, add EverTravelledAbroad
Step: score=-0.79, add Income_Class_middle
Step: score=-0.80, add FrequentFlyer
Step: score=-0.80, unchanged None

         Best Variables Selected:  ['EverTravelledAbroad',
'Income_Class_middle', 'FrequentFlyer']
```

[27]:
```
LogisticRegressionCV(cv=5, max_iter=5000, random_state=1, solver='liblinear')
```

8.5 Multi-Layered Neural Network

[28]:
```
# user grid search to find optimized hidden layers
param_grid = {
    'hidden_layer_sizes': [(1), (2), (3), (4), (5)],
}

# Run Exhaustive search for neural networks hyper-parameters
gridSearch = GridSearchCV(MLPClassifier(activation='logistic',
                                        solver='lbfgs',
                                        random_state=1,
                                        max_iter=5000),
                          param_grid,
                          cv=5,
                          n_jobs=-1,
                          return_train_score=True)
# Fit to training set
gridSearch.fit(train_X, train_y)

# Initial Scores and hyper-parameters
print('Initial score: ', gridSearch.best_score_)
print('Initial parameters: ', gridSearch.best_params_)

# Look at Initial Scores with averages
display = ['param_hidden_layer_sizes', 'mean_test_score', 'std_test_score']
pd.DataFrame(gridSearch.cv_results_)[display]
```

```
Initial score:  0.7718120805369127
Initial parameters:  {'hidden_layer_sizes': 1}
```

[28]:

	param_hidden_layer_sizes	mean_test_score	std_test_score
0	1	0.772	0.018
1	2	0.772	0.009
2	3	0.772	0.020
3	4	0.756	0.020
4	5	0.766	0.020

[29]:

```
# user grid search to fine-tune hyper-parameters
param_grid = {
    'hidden_layer_sizes': [(1, 2), (1, 3), (1, 4), (1, 5), (1, 6)],
}

# Run Exhaustive search for fine-tuning the hyper-parameters
gridSearch = GridSearchCV(MLPClassifier(activation='logistic',
                                        solver='lbfgs',
                                        random_state=1,
                                        max_iter=5000),
                          param_grid,
                          cv=5,
                          n_jobs=-1,
                          return_train_score=True)
# Fit to training set
gridSearch.fit(train_X, train_y)

# Improved Scores and hyper-parameters
print('Improved score: ', gridSearch.best_score_)
print('Final parameters: ', gridSearch.best_params_)

# Look at fine-tuned hyper-parameters with averages
display = ['param_hidden_layer_sizes', 'mean_test_score', 'std_test_score']

# Final Network
network_model = gridSearch.best_estimator_

# Fit to training data
network_model.fit(train_X, train_y)

# Results
pd.DataFrame(gridSearch.cv_results_)[display]
```

```
Improved score:  0.7751677852348993
Final parameters:  {'hidden_layer_sizes': (1, 3)}
```

[29]:

	param_hidden_layer_sizes	mean_test_score	std_test_score
0	(1, 2)	0.768	0.017
1	(1, 3)	0.775	0.012
2	(1, 4)	0.768	0.018
3	(1, 5)	0.770	0.012
4	(1, 6)	0.771	0.013

8.6 K-Nearest Neighbors

Python code:

[30]:
```
# Store all accuracies by K
accuracy_by_K = []

# Fit models of different K values and predict the validation set
for K in range(1, 12):
    # Fit each K model
    knn = KNeighborsClassifier(n_neighbors=K)

    # Fit to training data
    knn.fit(train_X, train_y)

    # Add each result to dictionary
    accuracy_by_K.append({
        'K':
        K,
        'Training Accuracy':
        accuracy_score(train_y, knn.predict(train_X)),
        'Validation Accuracy':
        accuracy_score(valid_y, knn.predict(valid_X))
    })

# Turn list of K values and accuracies into data frame
knn_accuracy = pd.DataFrame(accuracy_by_K)
knn_accuracy.index = knn_accuracy['K']
knn_accuracy.drop(['K'], axis=1)
```

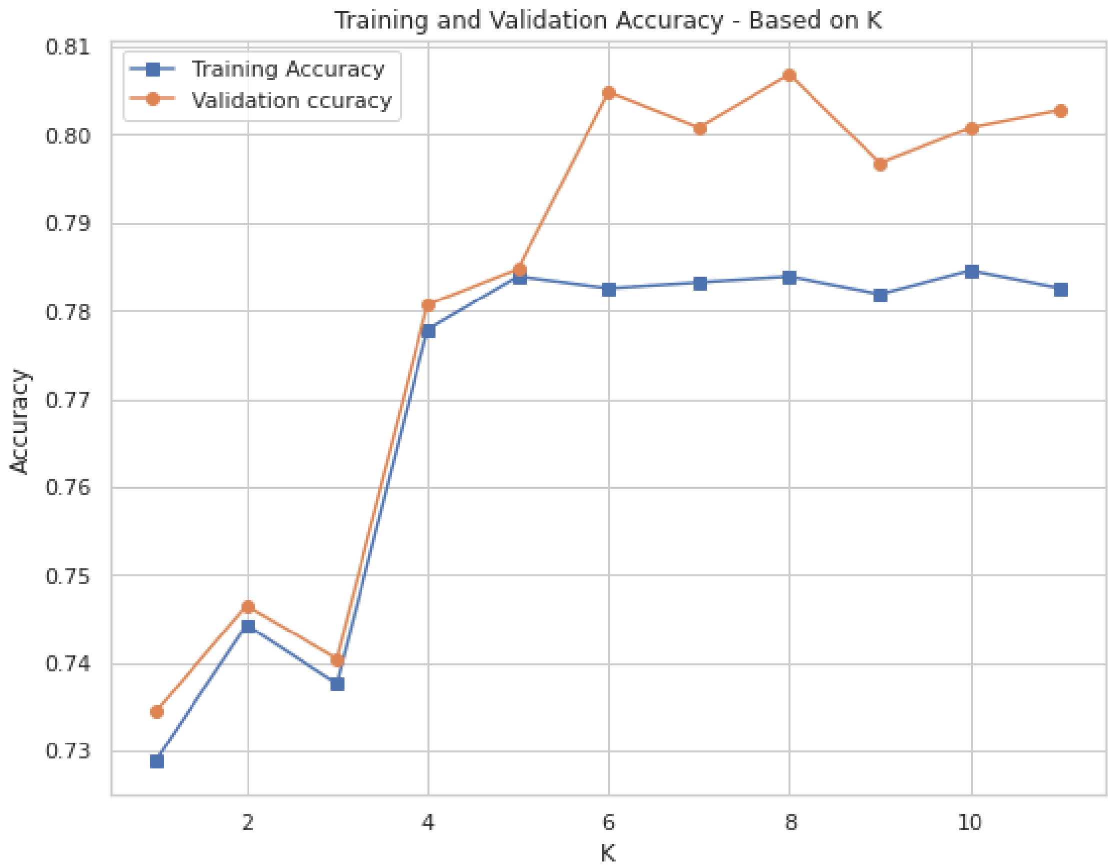
[30]:

K	Training Accuracy	Validation Accuracy
1	0.729	0.734
2	0.744	0.746
3	0.738	0.740
4	0.778	0.781
5	0.784	0.785
6	0.783	0.805
7	0.783	0.801
8	0.784	0.807

```
9         0.782                 0.797
10        0.785                 0.801
11        0.783                 0.803
```

[31]:

```
# Plot K-values by different accuracies
fig, ax = plt.subplots(figsize=(9, 7))

# Training Accuracy
ax.plot(knn_accuracy.K,
        knn_accuracy['Training Accuracy'],
        label='Training Accuracy',
        marker='s')

# Validation Set
ax.plot(knn_accuracy.K,
        knn_accuracy['Validation Accuracy'],
        label='Validation ccuracy',
        marker='o')

ax.set_title("Training and Validation Accuracy - Based on K")
ax.set_xlabel('K')
ax.set_ylabel('Accuracy')
ax.legend()
plt.show()
```



[32]:
```
# Final Model where k = 8
knn_model = KNeighborsClassifier(n_neighbors=8)

# Fit to training data
knn_model.fit(train_X, train_y)
```

[32]:
```
KNeighborsClassifier(n_neighbors=8)
```

8.7 Multinomial Naive Bayes

[33]:
```
# Multinomial naive bayes model
mnb_model = MultinomialNB(alpha=0.01)

# fit to training data
mnb_model.fit(train_X, train_y)
```

[33]:
```
MultinomialNB(alpha=0.01)
```

8.8 Linear Discrimant Analysis

[34]:
```
# Linear Discriminant Analysis
lda_model = LinearDiscriminantAnalysis()

# fit to training data
lda_model.fit(train_X, train_y)
```

[34]:
```
LinearDiscriminantAnalysis()
```

---

9 Results and final model selection

- Performance measures on test Set

9.0.1 All Model's Confusion Matrices

Python code:

[35]:
```
def DisplayMultiply(*args, titles=cycle(['']), html_str=''):
    '''
    This function modifies how each confusion matrix is displayed
    '''

    for df, title in zip(args, chain(titles, cycle(['</br>']))):
        html_str += '<th style="text-align:center"><td style="vertical-align:
↪top">'
        html_str += f"<h6 style='text-align:center'>{title}</h5>"
        html_str += df.to_html().replace('table',
                                         'table style="display:inline"')

    display_html(html_str, raw=True)


Bold = ['\033[1m', '\033[0m']


class ConstructedModel:
    def __init__(self, title, algorithm):
        '''
        This function initializes variables passed into this class
        from the input and uses it compute performance metric
        scores or print the confusion matrix
        '''

        # Title
        self.title = title
```

```
        # Columns used by logistic regression
        self.columns = columns

        # Fit to training data and predict test if this is a logistic model
        if self.title == 'Logistic Regression':
            # fit to training with selected columns
            self.algorithm = algorithm.fit(train_X[columns], train_y)

            # make predictions on test set with selected columns
            self.y_pred = self.algorithm.predict(valid_X[columns])

        # Else = all other models that are not logistic regression
        else:
            self.algorithm = algorithm.fit(train_X, train_y)
            self.y_pred = self.algorithm.predict(valid_X)

        # confusion matrix
        cmtx_alg = skl.metrics.confusion_matrix

        # F1 Measure
        f1measure = metrics.f1_score

        # Convert confusion matrix to data frame
        self.cmtx = pd.DataFrame(
            cmtx_alg(valid_y, self.y_pred, labels=[0, 1]),
            index=['Actual: {:}'.format(x) for x in [0, 1]],
            columns=['Predicted: {:}'.format(x) for x in [0, 1]])

        # Accuracy
        self.Accuracy = metrics.accuracy_score(valid_y, self.y_pred)

        # Precision
        self.Precision = metrics.precision_score(valid_y,
                                                 self.y_pred,
                                                 average='binary')
        # Recall
        self.Recall = metrics.recall_score(valid_y,
                                           self.y_pred,
                                           labels=[1, 2],
                                           average='micro')
        # F1 Measure
        self.F1Measure = f1measure(valid_y, self.y_pred, average='binary')

    def print_confusion_matrix(self):
        '''
        This function prints out the confusion matrix of each model
```

```
        using the validation set
        '''

        # Print line to seperate each confusion matrix
        print(f'_______________________________________________________')
        print(f'\n{Bold[0]} {self.title} - Confusion Matrix {Bold[1]}')
        DisplayMultiply(self.cmtx)
```

[36]:

```
# Create a dictionary of model names and the actual models
Models_parameters = {
    'dtree': ['Decision tree', tree_model],
    'ada': ['AdaBoost Decision Tree', adaboost_model],
    'rf': ['Random Forest', rf_model],
    'logit': ['Logistic Regression', logit_model],
    'nnet': ['Neural Network', network_model],
    'knn': ['K-Nearest Neighbors', knn_model],
    'mnb': ['Multinomial Naive Bayes', mnb_model],
    'lda': ['Linear Discriminant Analysis', lda_model]
}

# Collect information about models into a dictonary
Models = {}

# For each model, pass it to the ConstructedModel class to print confusion␣
 ↪matrix
for short_name, [title, method] in Models_parameters.items():

    # Pass model to class
    Models[short_name] = ConstructedModel(title, method)

    # Print out confusion matrix
    Models[short_name].print_confusion_matrix()
```

```
_______________________________________________________

 Decision tree - Confusion Matrix
_______________________________________________________

 AdaBoost Decision Tree - Confusion Matrix
_______________________________________________________

 Random Forest - Confusion Matrix
_______________________________________________________

 Logistic Regression - Confusion Matrix
```

Neural Network - Confusion Matrix

K-Nearest Neighbors - Confusion Matrix

Multinomial Naive Bayes - Confusion Matrix

Linear Discriminant Analysis - Confusion Matrix

9.0.2 All Models' Performance Metrics

[37]:

```
# Evaluate performance
EvalTable = pd.DataFrame()

for short_name, model in Models.items():
    # Accuracy
    EvalTable.loc[model.title, 'Accuracy'] = model.Accuracy

    # Precision
    EvalTable.loc[model.title, 'Precision'] = model.Precision

    # Recall
    EvalTable.loc[model.title, 'Recall'] = model.Recall

    # F1-Measure
    EvalTable.loc[model.title, 'F1Measure'] = model.F1Measure

EvalTable
```

[37]:

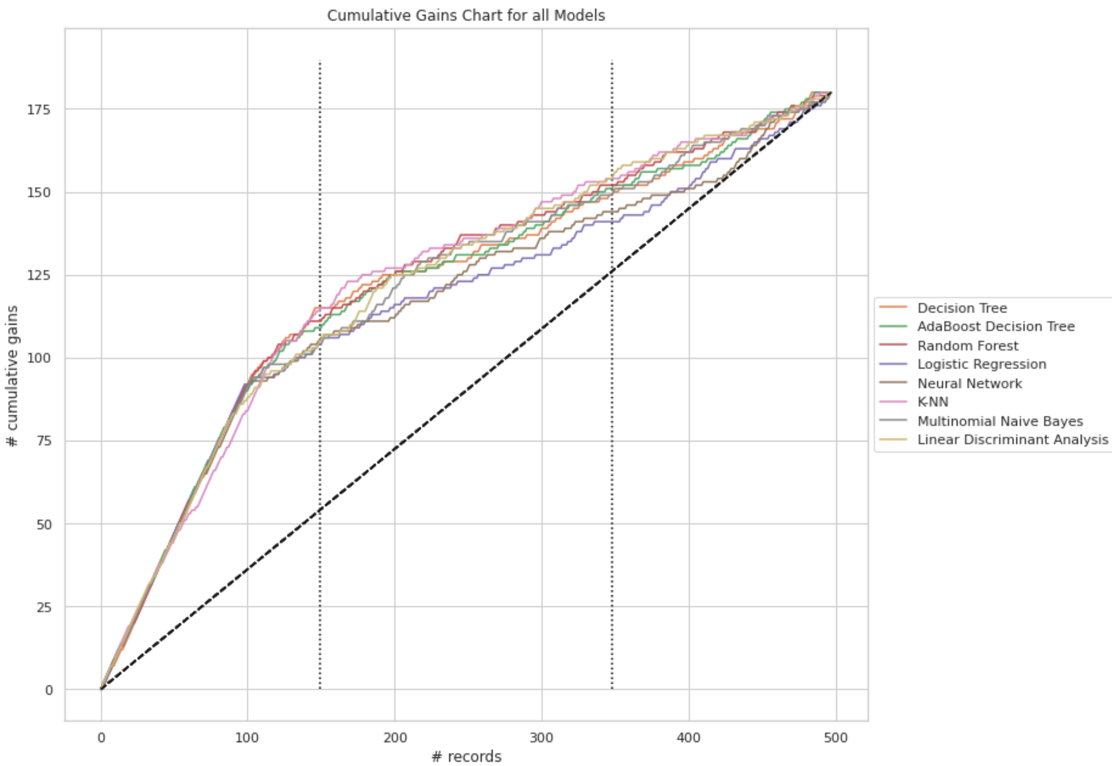
	Accuracy	Precision	Recall	F1Measure
Decision tree	0.809	0.929	0.511	0.659
AdaBoost Decision Tree	0.801	0.879	0.522	0.655
Random Forest	0.811	0.906	0.533	0.671
Logistic Regression	0.805	0.911	0.511	0.655
Neural Network	0.807	0.920	0.511	0.657
K-Nearest Neighbors	0.807	0.856	0.561	0.678
Multinomial Naive Bayes	0.767	0.732	0.561	0.635
Linear Discriminant Analysis	0.775	0.762	0.550	0.639

9.0.3 All Models' Gains Chart

[38]:
```
def cum_gains(model):
    '''
    This function returns a data frame
    with the actual value from a training/validation set
    the model's predicted probabilities of the positive class
    and the predicted class label

    '''
    # Logistic Regression uses feature selections
    if model == logit_model:
        model_result = pd.DataFrame({
            'actual':
            valid_y,
            'p(1)':
            model.predict_proba(valid_X[columns])[:, 1]
        })
        model_result = model_result.sort_values(by=['p(1)'], ascending=False)
        return model_result.actual

    # Other models did not
    else:
        # Results - grab positive predictions
        model_result = pd.DataFrame({
            'actual': valid_y,
            'p(1)': model.predict_proba(valid_X)[:, 1]
        })

        # Sort values by positive class probabiities
        model_result = model_result.sort_values(by=['p(1)'], ascending=False)

        # return results as gains chart
        return model_result.actual
```

[39]:
```
# Decision Tree
ax = gainsChart(cum_gains(tree_model), label='Decision Tree', color='C1')

# ADA Boost
gainsChart(cum_gains(adaboost_model),
           label='AdaBoost Decision Tree',
           color='C2',
           ax=ax)

# Random Forest
gainsChart(cum_gains(rf_model), label='Random Forest', color='C3', ax=ax)
```

```python
# Logistic Regression
gainsChart(cum_gains(logit_model),
           label='Logistic Regression',
           color='C4',
           ax=ax)

# Neural Network
gainsChart(cum_gains(network_model), label='Neural Network', color='C5', ax=ax)

# K-NN
gainsChart(cum_gains(knn_model), label='K-NN', color='C6', ax=ax)

# Multinomial Naive Bayes
gainsChart(cum_gains(mnb_model),
           label='Multinomial Naive Bayes',
           color='C7',
           ax=ax)

# Linear Discriminant Analysis
gainsChart(cum_gains(lda_model),
           label='Linear Discriminant Analysis',
           color='C8',
           ax=ax)

# Graph properties
ax.vlines(x=[len(valid_y) * 0.3, len(valid_y) * 0.7],
          ymin=0,
          ymax=190,
          linestyles='dotted',
          color='black')

plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.title("Cumulative Gains Chart for all Models")
plt.tight_layout()
plt.show()
```



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10 Discussion and conclusion

- Address the problem statement and suggestions that could go beyond the scope of the course

[ ]: