Car Type Classification

Description

Train a ML model to predict the cost of insurance

Importing Libraries

Here we will import some useful Libraries such as `pandas`, `numpy`, `matplotlib` and `sklearn`

In [1]:
```
import pandas as pd;
import numpy as np;
import matplotlib.pyplot as plt;
import seaborn as sns;
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import f1_score, accuracy_score, classification_report
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from joblib import dump, load
```

Loading Data

Load data into dataframe so that it can be easily processed and analysed.

In [2]:
```
df = pd.read_csv('./data/insurance_sample.csv');
df_copy = pd.read_csv('./data/insurance_sample.csv');
df.head()
```

Out[2]:

	id	_user_id	gender	driver_age	state	zip_code	vehicle_make	vehicle_cost_new	vehicle_year	vehicle_ownership	...	prov2name	prov3high	prov3low
0	1	322256	MALE	43	TX	78701	Chevrolet	25000	2010	Impala	...	Safeco	115	101
1	2	316440	MALE	43	KS	67005	Chevrolet	25000	2016	Impala	...	Safeco	130	114
2	3	316549	MALE	43	KS	67846	Chevrolet	25000	2016	Impala	...	Safeco	139	122
3	4	321183	MALE	43	MO	64506	Chevrolet	25000	2016	Impala	...	Safeco	138	122
4	5	321188	MALE	43	IA	51534	Chevrolet	25000	2016	Impala	...	Safeco	141	124

5 rows × 39 columns

Exploratory Data Analysis

Now we will do an EDA on the dataset to find out anamoly, null values and other discrepancies among the data.

In [3]:
```
df.shape
```

Out[3]: (14139, 39)

In [4]:
```
predictor = ['id', '_user_id', 'gender', 'driver_age', 'state', 'zip_code',
       'vehicle_make', 'vehicle_cost_new', 'vehicle_year', 'vehicle_ownership',
       'home_ownership', 'prior_carrier', 'prior_liability_limit',
       'first_name', 'marital_status', 'vehicle_model',
       'years_with_prior_carrier', 'years_licensed', 'driver_count',
       'vehicle_count', 'version', 'high', 'low']
target_variable = ['prov1high', 'prov1low',
        'prov2high', 'prov2low', 'prov3high',
       'prov3low',  'prov4high', 'prov4low',
       'prov5high', 'prov5low']
```

In [5]:
```
df.describe()
```

Out[5]:

	id	_user_id	driver_age	zip_code	vehicle_cost_new	vehicle_year	years_with_prior_carrier	years_licensed	driver_count	vehicle_
count	14139.000000	14139.000000	14139.0	14139.000000	14139.0	14139.000000	14139.0	14139.0	14139.0	14
mean	7070.000000	316680.468279	43.0	56455.630030	25000.0	2013.000000	10.0	20.0	1.0	
std	4081.722063	4164.631912	0.0	26212.474584	0.0	2.449576	0.0	0.0	0.0	
min	1.000000	309529.000000	43.0	7002.000000	25000.0	2010.000000	10.0	20.0	1.0	
25%	3535.500000	313085.500000	43.0	33157.000000	25000.0	2010.000000	10.0	20.0	1.0	
50%	7070.000000	316633.000000	43.0	53901.000000	25000.0	2013.000000	10.0	20.0	1.0	
75%	10604.500000	320171.500000	43.0	79065.000000	25000.0	2016.000000	10.0	20.0	1.0	
max	14139.000000	323966.000000	43.0	99403.000000	25000.0	2016.000000	10.0	20.0	1.0	

8 rows × 23 columns

We looked at some statistical information about the dataset. Now we will look at each and every column to analyse how it impacts the output variable and which one of them are not important to us.

In [6]:
```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

Out[6]:
```
id                          0
_user_id                    0
gender                      0
driver_age                  0
state                       0
zip_code                    0
vehicle_make                0
vehicle_cost_new            0
vehicle_year                0
vehicle_ownership           0
home_ownership              0
prior_carrier               0
prior_liability_limit       0
first_name                  0
last_name                   0
marital_status              0
vehicle_model               0
years_with_prior_carrier    0
years_licensed              0
driver_count                0
vehicle_count               0
version                     0
high                        0
low                         0
prov1high                   0
prov1low                    0
prov1name                   0
prov2high                   0
prov2low                    0
prov2name                   0
prov3high                   0
prov3low                    0
prov3name                   0
prov4high                   0
prov4low                    0
prov4name                   0
prov5high                   0
prov5low                    0
prov5name                   0
dtype: int64
```

There are no null values present in the dataset but there are a bunch of columns which might not be useful for our model. Some of them have only single value in the column and one particular column has an outlier.

Graphical Univariate Analysis

In this section we will look into the graphical representation of the data to collect some more information to support our goal.

We will also remove those columns which have only one unique value throughout a column.

In [7]:
```
colums_to_remove = []
for col in df.columns:
    if((len(df[col].unique()) == 1)):
        colums_to_remove.append(col)
```

Relationship between `vehicle_model` and `vehicle_ownership` is quite strange. Now we will look into if these columns are identical.

In [8]:
```
df[['vehicle_model','vehicle_ownership']]
```

Out[8]:

	vehicle_model	vehicle_ownership
0	Impala	Impala
1	Impala	Impala
2	Impala	Impala
3	Impala	Impala
4	Impala	Impala
...	...	...
14134	Impala	Impala
14135	Impala	Impala
14136	Impala	Impala
14137	Impala	Impala
14138	Focus	Focus

14139 rows × 2 columns

In [9]:
```
sum(df['vehicle_model'] == df['vehicle_ownership'])
```

Out[9]: 14139

We will also remove the columns which have no significance to our classification model, which are `version`, `vehicle_model`, `id`, `_user_id`.

In [10]:
```
colums_to_remove.append('version'); #Because version is different at only one row and all other rows have same value
s
colums_to_remove.append('vehicle_model'); #Because vehicle model and vehicle ownership capture same information for
 all the records, so we will be keeping only one.
# ID columns have unique value for every row so they won't be  useful to us.
colums_to_remove.append('id');
colums_to_remove.append('_user_id');
colums_to_remove.append('high');
colums_to_remove.append('low');
```

Below is a full list of columns we are gonna be removing and columns that we will use for our classification model.

In [11]:
```
colums_to_remove
```

Out[11]:
```
['gender',
 'driver_age',
 'vehicle_cost_new',
 'home_ownership',
 'prior_carrier',
 'prior_liability_limit',
 'first_name',
 'marital_status',
 'years_with_prior_carrier',
 'years_licensed',
 'driver_count',
 'vehicle_count',
 'prov1name',
 'prov2name',
 'prov3name',
 'prov4name',
 'prov5name',
 'version',
 'vehicle_model',
 'id',
 '_user_id',
 'high',
 'low']
```

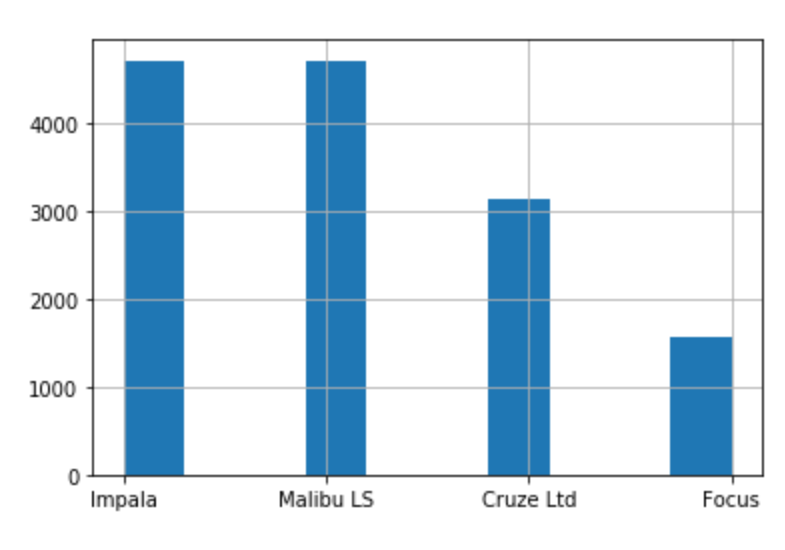
In [12]:
```
predictor = [x for x in predictor if x not in colums_to_remove]
predictor
```

Out[12]: ['state', 'zip_code', 'vehicle_make', 'vehicle_year', 'vehicle_ownership']

Now we will look into few histograms to study the pattern of some properties.

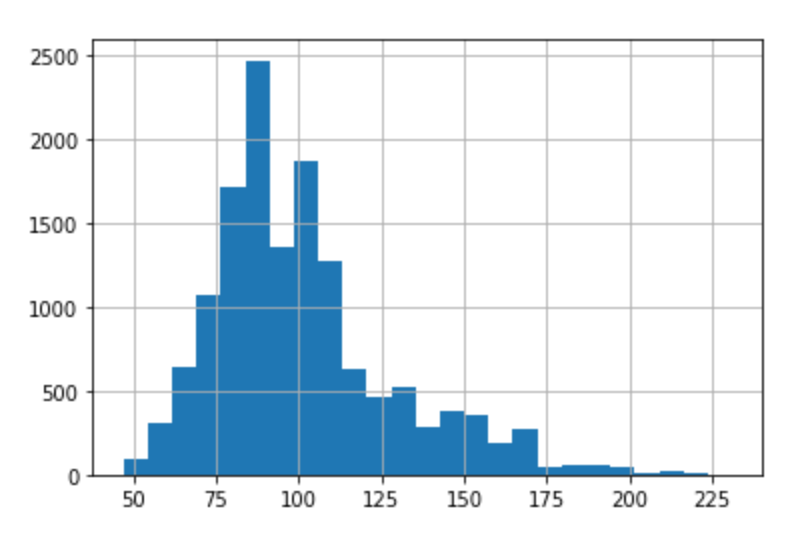
In [13]:
```
df['vehicle_model'].hist()
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x12b10b48>



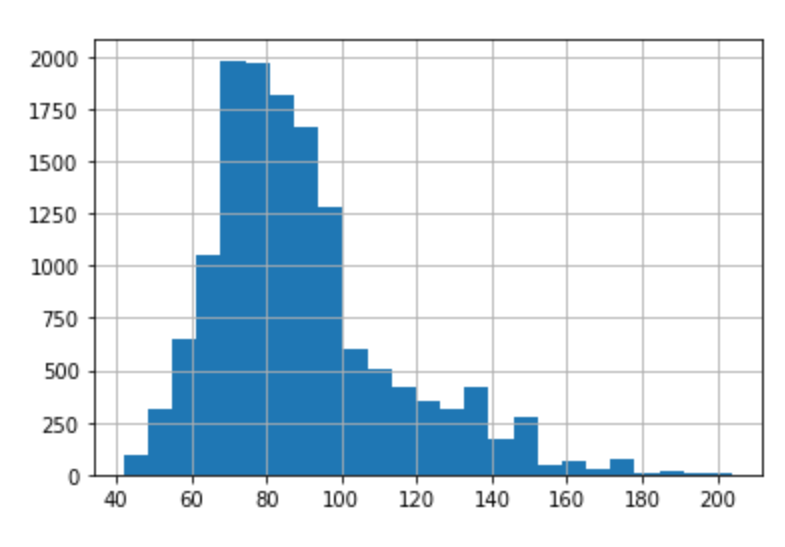
In [14]:
```
df['prov1high'].hist(bins=25)
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x12251848>



In [15]:
```
df['prov1low'].hist(bins=25)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x127ebb48>



Data Preprocessing

In this part we will be preparing our data for the model training.

First of all we need to convert categorical properties to numerical ones so that these can be used within our model. We are gonna create dummy properties to capture all the information represented by the categorical variables.

In [16]:
```
categorical_variables = ['state', 'zip_code', 'vehicle_make', 'vehicle_year', 'vehicle_ownership']
```

In [17]:
```
df = df[predictor + target_variable].copy()
```

In [18]:
```
df
```

Out[18]:

	state	zip_code	vehicle_make	vehicle_year	vehicle_ownership	prov1high	prov1low	prov2high	prov2low	prov3high	prov3low	prov4high	prov4low
0	TX	78701	Chevrolet	2010	Impala	84	74	88	80	115	101	143	127
1	KS	67005	Chevrolet	2016	Impala	103	91	103	92	130	114	107	95
2	KS	67846	Chevrolet	2016	Impala	114	101	106	95	139	122	114	101
3	MO	64506	Chevrolet	2016	Impala	97	86	95	86	138	122	91	81
4	IA	51534	Chevrolet	2016	Impala	66	59	90	81	141	124	75	67
...	...	...	...	...	...	...	...	...	...	...	...	...	...
14134	NE	68310	Chevrolet	2013	Impala	93	82	97	87	127	111	153	135
14135	NE	68818	Chevrolet	2013	Impala	93	82	97	87	127	111	153	135
14136	NE	68787	Chevrolet	2013	Impala	93	82	97	87	127	111	153	135
14137	NE	68601	Chevrolet	2013	Impala	93	82	97	87	127	111	153	135
14138	CO	80831	Ford	2010	Focus	91	81	71	64	119	104	80	71

14139 rows × 15 columns

In [19]:
```
dum_df = pd.get_dummies(df, columns=categorical_variables)
dum_df.head()
```

Out[19]:

	prov1high	prov1low	prov2high	prov2low	prov3high	prov3low	prov4high	prov4low	prov5high	prov5low	...	zip_code_99403	vehicle_make_Chevrolet
0	84	74	88	80	115	101	143	127	111	98	...	0	1
1	103	91	103	92	130	114	107	95	138	121	...	0	1
2	114	101	106	95	139	122	114	101	141	123	...	0	1
3	97	86	95	86	138	122	91	81	135	119	...	0	1
4	66	59	90	81	141	124	75	67	106	93	...	0	1

5 rows × 1381 columns

Now we will extract the features or descriptors which are being used to train the model

In [20]:
```
dum_df_predictor = dum_df.drop(target_variable, axis=1)
```

In [21]:
```
dum_df_predictor
```

Out[21]:

	state_AL	state_AR	state_AZ	state_CA	state_CO	state_DC	state_FL	state_GA	state_IA	state_ID	...	zip_code_99403	vehicle_make_Chevrolet
0	0	0	0	0	0	0	0	0	0	0	...	0	1
1	0	0	0	0	0	0	0	0	0	0	...	0	1
2	0	0	0	0	0	0	0	0	0	0	...	0	1
3	0	0	0	0	0	0	0	0	0	0	...	0	1
4	0	0	0	0	0	0	0	0	1	0	...	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
14134	0	0	0	0	0	0	0	0	0	0	...	0	1
14135	0	0	0	0	0	0	0	0	0	0	...	0	1
14136	0	0	0	0	0	0	0	0	0	0	...	0	1
14137	0	0	0	0	0	0	0	0	0	0	...	0	1
14138	0	0	0	0	1	0	0	0	0	0	...	0	0

14139 rows × 1371 columns

We will use a label encoder from sklearn llibrary to create those dummy variables.

In [22]:
```
dum_df_target = dum_df[target_variable]
```

In [23]:
```
dum_df_target
```

Out[23]:

	prov1high	prov1low	prov2high	prov2low	prov3high	prov3low	prov4high	prov4low	prov5high	prov5low
0	84	74	88	80	115	101	143	127	111	98
1	103	91	103	92	130	114	107	95	138	121
2	114	101	106	95	139	122	114	101	141	123
3	97	86	95	86	138	122	91	81	135	119
4	66	59	90	81	141	124	75	67	106	93
...	...	...	...	...	...	...	...	...	...	...
14134	93	82	97	87	127	111	153	135	129	113
14135	93	82	97	87	127	111	153	135	129	113
14136	93	82	97	87	127	111	153	135	129	113
14137	93	82	97	87	127	111	153	135	129	113
14138	91	81	71	64	119	104	80	71	108	95

14139 rows × 10 columns

Model Training

We will be dividing the dataset into two sets Training and Test dataset with the ratio of 70:30. As we have to predict the continuous variable insurance, so a linear regression model was trained on the extracted descriptors to predict the cost of insurance

Splitting the data into training and test dataset.

In [24]:
```
data, X_test, target, y_test = train_test_split(dum_df_predictor,dum_df_target, shuffle=True, test_size=0.3, random_
state=15)
```

Training the Linear regression model from sklearn

In [25]:
```
# importing the model
from sklearn.linear_model import LinearRegression
model = LinearRegression()
# Fit linear model by passing training dataset
model.fit(data,target)
```

Out[25]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

Getting the predictions from the model on the unseen dataset

In [26]:
```
# Predicting the target variable for test datset
predictions = model.predict(X_test)
```

In [34]:
```
X_test
```

Out[34]:

	state_AL	state_AR	state_AZ	state_CA	state_CO	state_DC	state_FL	state_GA	state_IA	state_ID	...	zip_code_99403	vehicle_make_Chevrolet
1652	0	0	0	0	0	0	0	1	0	0	...	0	1
2297	0	0	0	0	0	0	0	0	0	0	...	0	1
3291	0	0	0	0	0	0	0	0	0	0	...	0	1
8784	0	0	0	0	0	0	0	0	0	0	...	0	0
8399	0	0	0	0	0	0	0	0	0	0	...	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2111	0	0	0	0	0	0	0	0	0	0	...	0	1
11687	0	0	0	0	0	0	1	0	0	0	...	0	1
4439	0	0	0	0	0	0	0	0	0	0	...	0	1
2152	0	0	0	0	0	0	0	0	0	0	...	0	1
10551	0	0	0	0	0	0	0	0	0	0	...	0	1

4242 rows × 1371 columns

In [ ]:
```
Comparing the predictions by the model with the actual values
```

In [39]:
```
predictions[:,0]
```

Out[39]:
```
array([113.375  , 190.625  ,  67.15625, ...,  99.96875,  85.375  ,
        93.65625])
```

In [41]:
```
y_test['prov1high']
```

Out[41]:
```
1652     114
2297     194
3291      68
8784     188
8399      88
        ...
2111      88
11687    121
4439     101
2152      85
10551     93
Name: prov1high, Length: 4242, dtype: int64
```

In [42]:
```
predictions[:,1]
```

Out[42]:
```
array([100.125  , 168.8125 ,  59.6875 , ...,  89.09375,  75.78125,
        82.78125])
```

In [43]:
```
y_test['prov1low']
```

Out[43]:
```
1652     101
2297     172
3291      60
8784     167
8399      78
        ...
2111      78
11687    107
4439      90
2152      76
10551     82
Name: prov1low, Length: 4242, dtype: int64
```

Saving the predictions in the csv format

In [37]:
```
from numpy import asarray
from numpy import savetxt
savetxt('predictions.csv', predictions, delimiter=',')
```

In [29]:
```
y_test.head()
```

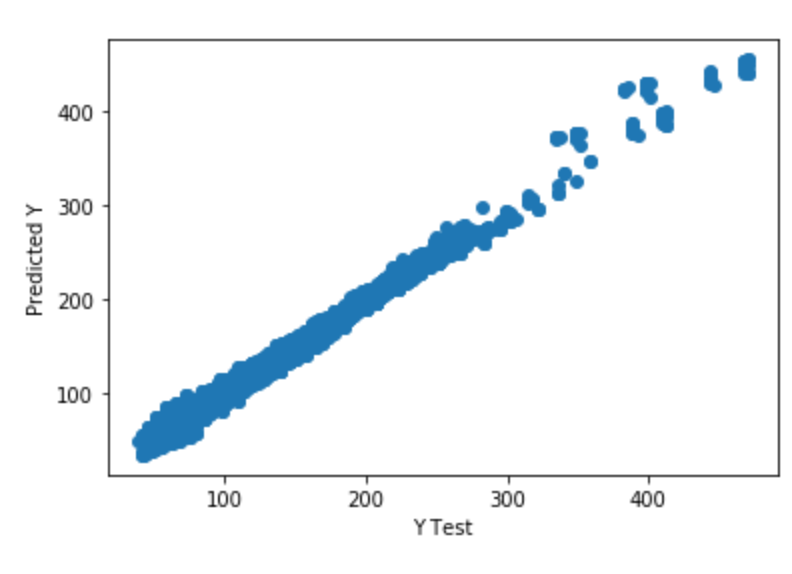
Out[29]:

	prov1high	prov1low	prov2high	prov2low	prov3high	prov3low	prov4high	prov4low	prov5high	prov5low
1652	114	101	126	113	164	144	135	119	169	148
2297	194	172	141	127	154	135	155	138	219	192
3291	68	60	65	59	122	108	67	59	80	70
8784	188	167	142	127	136	119	221	196	191	168
8399	88	78	81	73	109	96	101	90	113	99

To compare the predictions with the actual values, a scatter plot has been plotted to get the overall idea how well the model is performing on the unseen dataset.

In [279]:
```
import matplotlib.pyplot as plt
plt.scatter(y_test,predictions)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

Out[279]: Text(0, 0.5, 'Predicted Y')



After running the model on the unseen dataset to get predictions, it is concluded from the above plot that the model predicitons of cost of insurance are quite close in comparison to original values. There is a great scope to tune this model with more data to get more accuracte predictions.

In [ ]:
```
Since we have concluded our study, we should save this model for the future use.
```

In [44]:
```
dump(model, 'Carinsuranceprediction.joblib')
```

Out[44]: ['Carinsuranceprediction.joblib']

In [ ]: