In [390]: df = pd.read\_csv("datasets\_1291\_2355\_Automobile\_data.csv") ##importing dataset

In [391]: df.head()

### Out[391]:

symboling	normalized- losses	make	fuel- type	aspiration	num- of- doors	body- style	drive- wheels	engine- location	wheel- base	•
3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6	
3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6	
1	?	alfa- romero	gas	std	two	hatchback	rwd	front	94.5	
2	164	audi	gas	std	four	sedan	fwd	front	99.8	
2	164	audi	gas	std	four	sedan	4wd	front	99.4	
	3 3 1 2	3 ? 3 ? 1 ? 2 164	3 ? alfa-romero 3 ? alfa-romero 1 ? alfa-romero 2 164 audi	3 ? alfaromero gas 3 ? alfaromero gas 1 ? alfaromero gas 1 ? alfaromero gas 2 164 audi gas	3 ? alfa-romero gas std 3 ? alfa-romero gas std 1 ? alfa-romero gas std 2 164 audi gas std	symboling normalized-losses make type aspiration of-doors  3	symboling normalized-losses make type aspiration of-doors style  3 ? alfa-romero gas std two convertible  3 ? alfa-romero gas std two convertible  1 ? alfa-romero gas std two hatchback  2 164 audi gas std four sedan	symboling normalized-losses make type aspiration of-doors body-style wheels  3 ? alfa-romero gas std two convertible rwd  3 ? alfa-romero gas std two convertible rwd  1 ? alfa-romero gas std two hatchback rwd  2 164 audi gas std four sedan fwd	symboling normalized-losses make type aspiration of-doors body-style wheels location  3 ? alfa-romero gas std two convertible rwd front  3 ? alfa-romero gas std two convertible rwd front  1 ? alfa-romero gas std two hatchback rwd front  2 164 audi gas std four sedan fwd front	symboling hormalized-losses make type aspiration of-doors style wheels location wheel-base  3 ? alfa-romero gas std two convertible rwd front 88.6  3 ? alfa-romero gas std two hatchback rwd front 94.5  2 164 audi gas std four sedan fwd front 99.8

5 rows × 26 columns

### In [463]: df.info() # dataset info

<class 'pandas.core.frame.DataFrame'> Int64Index: 193 entries, 0 to 204 Data columns (total 26 columns):

Ducu	COTAMINIS (COCAT 20 )	•	
#	Column	Non-Null Count	Dtype
0	symboling	193 non-null	int64
1	normalized-losses	193 non-null	object
2	make	193 non-null	object
3	fuel-type	193 non-null	object
4	aspiration	193 non-null	object
5	num-of-doors	193 non-null	object
6	body-style	193 non-null	object
7	drive-wheels	193 non-null	object
8	engine-location	193 non-null	object
9	wheel-base	193 non-null	float64
10	length	193 non-null	float64
11	width	193 non-null	float64
12	height	193 non-null	float64
13	curb-weight	193 non-null	int64
14	engine-type	193 non-null	object
15	num-of-cylinders	193 non-null	object
16	engine-size	193 non-null	int64
17	fuel-system	193 non-null	object
18	bore	193 non-null	object
19	stroke	193 non-null	object
20	compression-ratio	193 non-null	float64
21	horsepower	193 non-null	object
22	peak-rpm	193 non-null	object
23	city-mpg	193 non-null	int64
24	highway-mpg	193 non-null	int64
25	price	193 non-null	object
dtype	es: float64(5), into	54(5), object(16)	)

memory usage: 40.7+ KB

# In [393]: df.describe() # dataset stats

# Out[393]:

	symboling	wheel- base	length	width	height	curb-weight	engine- size	comp
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	20
mean	0.834146	98.756585	174.049268	65.907805	53.724878	2555.565854	126.907317	11
std	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	
min	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	
25%	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	i
50%	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	!
75%	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	!
max	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	2
4								

```
In [394]: ## EDA
In [464]: df.isnull().sum() # checking for missing values
Out[464]: symboling
                                  0
           normalized-losses
                                  0
           make
                                  0
           fuel-type
                                  0
           aspiration
                                  0
           num-of-doors
                                  0
           body-style
                                  0
           drive-wheels
                                  0
           engine-location
                                  0
           wheel-base
                                  0
           length
                                  0
           width
                                  0
           height
                                  0
           curb-weight
                                  0
           engine-type
                                  0
           num-of-cylinders
                                  0
           engine-size
                                  0
           fuel-system
                                  0
                                  0
           bore
           stroke
                                  0
           compression-ratio
                                  0
           horsepower
                                  0
                                  0
           peak-rpm
                                  0
           city-mpg
           highway-mpg
                                  0
                                  0
           price
           dtype: int64
In [396]: # so no missing values
In [397]: df.shape
Out[397]: (205, 26)
In [398]: df.columns
Out[398]: Index(['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
                   'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
                   'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
                   'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke', 'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
                   'highway-mpg', 'price'],
                  dtype='object')
In [465]: df['symboling'].nunique() ## checking for our target class
Out[465]: 6
```

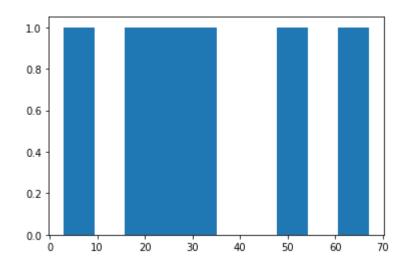
```
In [400]: df['symboling'].value_counts()
```

Out[400]: 0 67 1 54 2 32 3 27

-1 22 -2 3

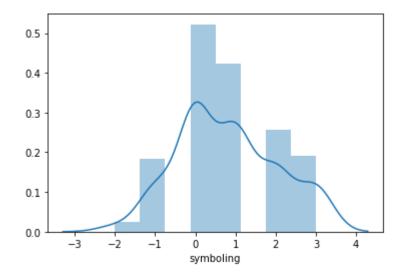
Name: symboling, dtype: int64

```
In [401]: plt.hist(df['symboling'].value_counts())
```



In [466]: sns.distplot(df['symboling']) # visualizing distribution of targert columns

Out[466]: <matplotlib.axes.\_subplots.AxesSubplot at 0x19b55d6a460>



In [403]: df.head()

Out[403]:

	symboling	normalized- losses	make	fuel- type	aspiration	num- of- doors	body- style	drive- wheels	engine- location	wheel- base	
(	3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6	
•	3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6	
2	2 1	?	alfa- romero	gas	std	two	hatchback	rwd	front	94.5	
3	3 2	164	audi	gas	std	four	sedan	fwd	front	99.8	
4	. 2	164	audi	gas	std	four	sedan	4wd	front	99.4	

5 rows × 26 columns

In [404]: df

Out[404]:

	symboling	normalized- losses	make	fuel- type	aspiration	num- of- doors	body- style	drive- wheels	engine- location	wheel base
0	3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6
1	3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6
2	1	?	alfa- romero	gas	std	two	hatchback	rwd	front	94.
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.

205 rows × 26 columns

```
In [405]: df['normalized-losses'].value_counts()
Out[405]: ?
                   41
           161
                   11
           91
                    8
                    7
           150
           134
                     6
           104
                     6
           128
                     6
           102
                     5
                     5
           103
                     5
           168
                     5
           95
                     5
           65
           94
                     5
                     5
           85
                     5
           74
                     4
           93
                     4
           122
           106
                     4
           118
                     4
           148
                     4
           154
                     3
                     3
           101
                     3
           125
           83
                     3
           137
                     3
                     3
           115
                     2
           119
                     2
           194
                     2
           192
                     2
           145
                     2
           108
                     2
           87
                     2
           129
                     2
           110
           158
                     2
                     2
           81
                     2
           164
                     2
           89
                     2
           188
                     2
           153
           197
                     2
           113
                     2
           90
                     1
           186
                     1
           142
                     1
           256
                     1
           98
                     1
           121
                     1
           231
                     1
           107
                     1
                     1
           78
            77
           Name: normalized-losses, dtype: int64
```

```
In [406]: ## now we have to remove all the ? values with mean
In [407]: df['normalized-losses'].replace('?',np.NaN,inplace=True) # handling '?'
In [408]: from sklearn.impute import SimpleImputer
In [467]: imp = SimpleImputer(missing_values=np.nan,strategy='mean') # imputing columns word
In [410]: df.replace('?',np.NaN,inplace=True)
In [411]: # imp.fit_transform(df['normalized-losses'])
```

```
In [412]: df['normalized-losses'].value_counts()
Out[412]: 161
                   11
           91
                    8
           150
                     7
           134
                     6
           104
                     6
           128
                     6
           65
                     5
                     5
           94
                     5
           103
                     5
           168
                     5
           95
                     5
           102
           85
                     5
                     5
           74
           122
                     4
                     4
           93
                     4
           118
           148
                     4
           106
                     4
                     3
           125
           101
                     3
                     3
           154
                     3
           83
           137
                     3
           115
                     3
                     2
           87
                     2
           145
                     2
           192
                     2
           108
                     2
           119
                     2
           129
                     2
           194
                     2
           110
           197
                     2
           113
                     2
                     2
           81
                     2
           164
                     2
           188
                     2
           89
                     2
           153
           158
                     2
                     1
           186
           142
                     1
           98
                     1
           90
                     1
           256
                     1
           231
                     1
           77
                     1
           107
                     1
           78
                     1
           121
           Name: normalized-losses, dtype: int64
```

```
In [413]: num count =0 # getting the mean of the df column
          summ=0
          for i in df['normalized-losses']:
               if i is np.NaN:
                   continue
               else:
                   summ+=int(i)
                   num count+=1
          mean= summ/num count
          print(mean)
          122.0
In [414]: | df['normalized-losses'].replace(np.NaN,122,inplace=True)
In [415]: | df['fuel-system'].value_counts()
Out[415]: mpfi
                   94
          2bbl
                   66
          idi
                   20
          1bbl
                   11
          spdi
                    9
                    3
          4bbl
          spfi
                    1
          mfi
                    1
          Name: fuel-system, dtype: int64
In [416]: col_list =df.columns.tolist()
In [417]: categorical_cols = [i for i in df.columns if df[i].dtype=='object' and df[i].nuni
In [418]: categorical cols
                              ## getting all categorical columns
Out[418]: ['make',
            'fuel-type',
            'aspiration',
            'num-of-doors',
            'body-style',
            'drive-wheels',
            'engine-location',
            'engine-type',
            'num-of-cylinders',
            'fuel-system']
```

```
In [419]: |df[categorical_cols].nunique()
Out[419]: make
                               22
          fuel-type
                                2
          aspiration
                                2
                                2
          num-of-doors
                                5
          body-style
          drive-wheels
                                3
                                2
          engine-location
          engine-type
                                7
                                7
          num-of-cylinders
                                8
          fuel-system
          dtype: int64
```

In [420]: df

Out[420]:

	symboling	normalized- losses	make	fuel- type	aspiration	num- of- doors	body- style	drive- wheels	engine- location	wheel base
0	3	122	alfa- romero	gas	std	two	convertible	rwd	front	88.6
1	3	122	alfa- romero	gas	std	two	convertible	rwd	front	88.6
2	1	122	alfa- romero	gas	std	two	hatchback	rwd	front	94.
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4
200	-1	95	volvo	gas	std	four	sedan	rwd	front	109.
201	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.
202	-1	95	volvo	gas	std	four	sedan	rwd	front	109.
203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.
204	-1	95	volvo	gas	turbo	four	sedan	rwd	front	109.

205 rows × 26 columns

```
In [421]: #from sklearn.preprocessing import LabelEncoder,LabelBinarizer
```

```
In [422]: df['price'].isna().sum()
```

Out[422]: 4

```
In [423]: df.dropna(inplace=True)
```

```
In [424]: df.isna().sum()
Out[424]: symboling
                                0
          normalized-losses
                                0
          make
                                0
          fuel-type
                                0
                                0
           aspiration
           num-of-doors
                                0
                                0
          body-style
          drive-wheels
                                0
                                0
           engine-location
          wheel-base
                                0
           length
                                0
          width
                                0
                                0
          height
          curb-weight
                                0
                                0
          engine-type
          num-of-cylinders
           engine-size
                                0
           fuel-system
                                0
          bore
                                0
          stroke
                                0
           compression-ratio
                                0
                                0
          horsepower
                                0
           peak-rpm
                                0
           city-mpg
          highway-mpg
                                0
          price
                                0
          dtype: int64
In [425]: df_numeric = pd.get_dummies(df,columns=categorical_cols) # one hot encoding date
```

In [426]: df\_numeric

#### Out[426]:

	symboling	normalized- losses	wheel- base	length	width	height	curb- weight	engine- size	bore	stroke	 cyli
0	3	122	88.6	168.8	64.1	48.8	2548	130	3.47	2.68	
1	3	122	88.6	168.8	64.1	48.8	2548	130	3.47	2.68	
2	1	122	94.5	171.2	65.5	52.4	2823	152	2.68	3.47	
3	2	164	99.8	176.6	66.2	54.3	2337	109	3.19	3.4	
4	2	164	99.4	176.6	66.4	54.3	2824	136	3.19	3.4	
		•••									
200	-1	95	109.1	188.8	68.9	55.5	2952	141	3.78	3.15	
201	-1	95	109.1	188.8	68.8	55.5	3049	141	3.78	3.15	
202	-1	95	109.1	188.8	68.9	55.5	3012	173	3.58	2.87	
203	-1	95	109.1	188.8	68.9	55.5	3217	145	3.01	3.4	
204	-1	95	109.1	188.8	68.9	55.5	3062	141	3.78	3.15	

193 rows × 71 columns

```
In [427]: df_numeric.astype('float64').dtypes ## typecasting all numeric columns to float6
```

#### Out[427]: symboling

```
normalized-losses
                     float64
                     float64
wheel-base
length
                     float64
width
                     float64
fuel-system_idi
                     float64
fuel-system_mfi
                     float64
fuel-system mpfi
                     float64
fuel-system_spdi
                     float64
fuel-system_spfi
                     float64
Length: 71, dtype: object
```

```
In [428]: ## splitting dataset into feature and target columns
```

float64

```
In [429]: y = df_numeric['symboling'] # target columns
```

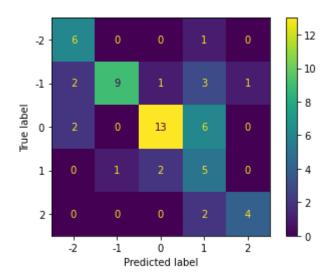
```
In [430]: y
Out[430]:
                     3
                     3
                     1
            2
            3
                     2
            4
                     2
            200
                    -1
            201
                    -1
            202
                    -1
            203
                    -1
            204
                    -1
            Name: symboling, Length: 193, dtype: int64
In [431]:
           df_numeric.drop(['symboling'],axis=1,inplace=True)
           X = df_numeric # feature columns
In [433]: X
Out[433]:
                   normalized-
                               wheel-
                                                               curb-
                                                                     engine-
                                                                                            compression-
                                       length
                                              width
                                                     height
                                                                              bore
                                                                                    stroke
                       losses
                                 base
                                                             weight
                                                                        size
                                                                                                    ratio
               0
                          122
                                 88.6
                                        168.8
                                                64.1
                                                        48.8
                                                               2548
                                                                         130
                                                                              3.47
                                                                                      2.68
                                                                                                      9.0
                1
                          122
                                 88.6
                                        168.8
                                                64.1
                                                        48.8
                                                               2548
                                                                         130
                                                                              3.47
                                                                                      2.68
                                                                                                      9.0
               2
                          122
                                 94.5
                                        171.2
                                                65.5
                                                        52.4
                                                               2823
                                                                         152
                                                                              2.68
                                                                                                      9.0
                                                                                      3.47
                3
                          164
                                 99.8
                                        176.6
                                                66.2
                                                        54.3
                                                               2337
                                                                         109
                                                                              3.19
                                                                                       3.4
                                                                                                     10.0
                          164
                                 99.4
                                        176.6
                                                        54.3
                                                                         136
                4
                                                66.4
                                                               2824
                                                                              3.19
                                                                                       3.4
                                                                                                      8.0
                            ...
                                           ...
                                                                          ...
               ...
              200
                           95
                                 109.1
                                        188.8
                                                68.9
                                                        55.5
                                                               2952
                                                                         141
                                                                              3.78
                                                                                      3.15
                                                                                                      9.5
              201
                           95
                                 109.1
                                        188.8
                                                68.8
                                                        55.5
                                                               3049
                                                                         141
                                                                              3.78
                                                                                                      8.7
                                                                                      3.15
              202
                           95
                                 109.1
                                        188.8
                                                68.9
                                                        55.5
                                                               3012
                                                                         173
                                                                              3.58
                                                                                      2.87
                                                                                                      8.8
              203
                           95
                                 109.1
                                        188.8
                                                68.9
                                                        55.5
                                                                              3.01
                                                                                                     23.0
                                                               3217
                                                                         145
                                                                                       3.4
             204
                           95
                                 109.1
                                        188.8
                                                68.9
                                                        55.5
                                                               3062
                                                                         141
                                                                              3.78
                                                                                                      9.5
                                                                                      3.15
            193 rows × 70 columns
  In [ ]:
In [434]: X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state =
In [435]: X_train.shape,X_test.shape,y_train.shape,y_test.shape
Out[435]: ((135, 70), (58, 70), (135,), (58,))
```

In [436]: ## buidling model

```
In [437]: df['normalized-losses'].value_counts()
Out[437]: 122
                   34
           161
                   11
           91
                    8
           104
                    6
           134
                     6
           128
                     6
           85
                     5
                     5
           94
                     5
           103
                     5
           102
                     5
           168
           95
                     5
           74
                     5
                     5
           65
                     4
           93
                     4
            118
                     4
           122
           106
                     4
           148
                     3
                     3
           150
                     3
           101
                     3
           154
                     3
           83
           137
                     3
           115
                     3
                     3
           125
                     2
           192
                     2
           197
                     2
           108
           194
                     2
                     2
           87
                     2
           119
                     2
           129
                     2
           188
           158
                     2
                     2
           113
                     2
           81
                     2
           89
                     2
           153
                     2
           164
           145
                     2
           110
                     2
           231
                     1
           256
                     1
           142
                     1
           121
                     1
           77
                     1
           107
                     1
           78
                     1
           98
                     1
                     1
           186
           90
           Name: normalized-losses, dtype: int64
```

```
In [438]: | gnb = GaussianNB() # initialize model
In [439]: gnb.fit(X train,y train) ## fit model on train data
Out[439]: GaussianNB()
In [440]: y pred = gnb.predict(X test) # get y pred
In [441]: |print(accuracy_score(y_test,y_pred)) # accuracy score
          0.6379310344827587
In [445]: |print(confusion_matrix(y_test,y_pred)) ## our multiclass confusion metrics
          [[6 0
                  0 1
                        0]
           [29131]
           [ 2 0 13 6 0]
           [ 0
               1
                  2
                    5
                       0]
                  0
                    2 4]]
           [ 0 0
In [449]: y_pred ## y_pred
Out[449]: array([ 1,
                     3, -1,
                             2, 0,
                                    1, 0, -1, -1, -1, -1,
                                                           2,
                                                               2,
                                                                   0,
                                                                              2,
                                    0, 1, 1,
                                                0, 2, 0, 1, 3,
                                                                   0, -1,
                                                                           1,
                     1, 1, 0, 2,
                    2, -1, 2, 1, 2, 2, -1,
                                                1, -1, 2,
                                                           3, 2,
                                                                  2,
                                    2,
                                        2], dtype=int64)
                                1,
In [451]: |print(recall_score(y_test,y_pred,average=None)) # recall score
          [0.85714286 0.5625
                                0.61904762 0.625
                                                     0.66666667]
In [453]: print(precision_score(y_test,y_pred,average=None)) # precision score
          [0.6
                     0.9
                                0.8125
                                          0.29411765 0.8
                                                              1
In [456]: |print(f1_score(y_test,y_pred,average=None)) # f1_score
          [0.70588235 0.69230769 0.7027027 0.4
                                                     0.72727273]
In [459]: from sklearn.metrics import plot confusion matrix
```

In [460]: plot\_confusion\_matrix(gnb,X\_test,y\_test)



In [461]: | ## thus we successfully build GaussianNB model on Automobile dataset