3	name year selling_price km_driven fuel seller_type transmission owner mileage engine max_power torque seats 0 Maruti Swift Dzire VDI 2014 450000 145500 Diesel Individual Manual First Owner 23.4 kmpl 1248 CC 74 bhp 190Nm@ 2000rpm 5.0 1 Skoda Rapid 1.5 TDI Ambition 2014 370000 120000 Diesel Individual Manual Second Owner 21.14 kmpl 1498 CC 103.52 bhp 250Nm@ 1500-2500rpm 5.0 2 Honda City 2017-2020 EXi 2006 158000 140000 Petrol Individual Manual Third Owner 17.7 kmpl 1497 CC 78 bhp 12.7@ 2,700(kgm@ rpm) 5.0 3 Hyundai i20 Sportz Diesel 2010 225000 127000 Diesel Individual Manual First Owner 23.0 kmpl 1396 CC 90 bhp 22.4 kgm at 1750-2750rpm 5.0 4 Maruti Swift VXI BSIII 2007 130000 120
< F	data.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 8128 entries, 0 to 8127 Data columns (total 13 columns): # Column Non-Null Count Dtype 0 name 8128 non-null object</class>
	year 8128 non-null int64 2 selling_price 8128 non-null int64 3 km_driven 8128 non-null int64 4 fuel 8128 non-null object 5 seller_type 8128 non-null object 6 transmission 8128 non-null object 7 owner 8128 non-null object 8 mileage 7907 non-null object 9 engine 7907 non-null object
n	10 max_power 7913 non-null object 11 torque 7906 non-null object 12 seats 7907 non-null float64 dtypes: float64(1), int64(3), object(9) memory usage: 825.6+ KB data.shape
	(8128, 13) data.describe() year selling_price km_driven seats count 8128.000000 8.128000e+03 8.128000e+03 7907.000000 mean 2013.804011 6.382718e+05 6.981951e+04 5.416719
	mean 2013.804011 6.382718e+05 6.981951e+04 5.416719 std 4.044249 8.062534e+05 5.655055e+04 0.959588 min 1983.000000 2.999900e+04 1.000000e+00 2.000000 25% 2011.000000 2.549990e+05 3.500000e+04 5.000000 50% 2015.000000 4.500000e+05 6.000000e+04 5.000000 75% 2017.000000 6.750000e+05 9.800000e+04 5.000000
	<pre>max 2020.000000 1.000000e+07 2.360457e+06 14.000000 # remove kmpl from mileage and convert it into float type from object type data['mileage'] = data['mileage'].apply(lambda x: float(x.split()[0]) if type(x)==str else np.nan) data['mileage'] = data['mileage'].astype("float") # remove CC from engine variable</pre>
	<pre>data['engine'] = data['engine'].apply(lambda x: x.replace("CC","") if type(x)==str else np.nan) # remove bhp from max_power and convert it into float type from object type data['max_power'] = data['max_power'].apply(lambda x : x.split()[0] if type(x)==str else np.nan) data.isnull().sum()</pre>
	name 0 year 0 year 0 selling_price 0 km_driven 0 fuel 0 seller_type 0 transmission 0 owner 0 mileage 221 engine 221 max_power 215 torque 222
S	seats 221 dtype: int64 data.drop(['torque'],inplace=True,axis=1) data.dropna(inplace=True)
(data.shape (7907, 12) data.info()
]	<pre><class 'pandas.core.frame.dataframe'=""> Int64Index: 7907 entries, 0 to 8127 Data columns (total 12 columns): # Column Non-Null Count Dtype</class></pre>
	5 seller_type 7907 non-null object 6 transmission 7907 non-null object 7 owner 7907 non-null object 8 mileage 7907 non-null float64 9 engine 7907 non-null object 10 max_power 7907 non-null object 11 seats 7907 non-null float64 dtypes: float64(2), int64(3), object(7) memory usage: 803.1+ KB
	data[data['max_power'].str.contains('bhp')] name year selling_price km_driven fuel seller_type transmission owner mileage engine max_power seats 4933 Maruti Omni CNG 2000 80000 100000 CNG Individual Manual Second Owner 10.9 796 bhp 8.0
(<pre># we have one row containing only bhp with no value in it, lets drop it data = data[data['max_power'].str.contains('bhp') == False] data.shape (7906, 12)</pre>
	<pre>sns.boxplot(x=data['mileage']) </pre> <pre><axessubplot:xlabel='mileage'></axessubplot:xlabel='mileage'></pre>
	#from above boxplot we see some cars having 0 mileage, it does not makesense, need to drop them data[data["mileage"]==0] name year selling_price km_driven fuel seller_type transmission owner mileage engine max_power seats fall Tata Indica Vista Aura Safire Anniversary Edition 2009 135000 28900 Petrol Individual Manual Second Owner 0.0 1172 65 5.0 Hyundai Santro Xing GL 2009 120000 90000 Petrol Individual Manual Second Owner 0.0 1086 62 5.0
1 2 2 2 2 2	1649 Hyundai Santro Xing GL 2008 105000 128000 Petrol Individual Manual First Owner 0.0 1086 62 5.0 1676 Mercedes-Benz M-Class ML 350 4Matic 2011 1700000 110000 Diesel Individual Automatic Third Owner 0.0 2987 165 5.0 2137 Land Rover Freelander 2 TD4 HSE 2013 1650000 64788 Diesel Dealer Automatic First Owner 0.0 2179 115 5.0 2366 Hyundai Santro Xing (Non-AC) 2010 110000 80000 Petrol Individual Manual Second Owner 0.0 1086 62.1 5.0 2725 Hyundai Santro Xing (Non-AC) 2013 184000 15000 Petrol Individual Manual First Owner 0.0 1086 62.1 5.0
	4527 Mercedes-Benz M-Class ML 350 4Matic 2011 1700000 110000 Diesel Individual Automatic Third Owner 0.0 2987 165 5.0 5276 Hyundai Santro Xing GL 2008 175000 40000 Petrol Individual Manual First Owner 0.0 1086 62 5.0 5843 Volkswagen Polo GT TSI BSIV 2014 574000 28080 Petrol Dealer Automatic First Owner 0.0 1197 103.25 5.0 5846 Volkswagen Polo GT TSI BSIV 2014 575000 28100 Petrol Dealer Automatic First Owner 0.0 1197 103.25 5.0 5900 Mahindra Bolero Pik-Up FB 1.7T 2020 679000 5000 Diesel Individual Manual First Owner 0.0 1086 62 5.0 6534 Hyundai Santro Xing GL 2010 150000 110000 Petrol Individual Manual First Owner 0.0 1086 62
7	6629 Mahindra Bolero Pik-Up CBC 1.7T 2019 722000 80000 Diesel Individual Manual First Owner 0.0 2523 70 2.0 6824 Hyundai Santro Xing GL 2011 150000 40000 Petrol Individual Manual Fourth & Above Owner 0.0 1086 62 5.0 7002 Hyundai Santro Xing (Non-AC) 2010 110000 80000 Petrol Individual Manual Second Owner 0.0 1086 62.1 5.0 7337 Mercedes-Benz GLC 220d 4MATIC 2017 3300000 60000 Diesel Dealer Automatic First Owner 0.0 1950 194 5.0 # drop ows having 0 mileage data = data[data["mileage"]!=0]
	<pre>data = data[data[mileagew]!=0] data['engine']=data['engine'].astype(int) sns.boxplot(x=data['engine']) <axessubplot:xlabel='engine'></axessubplot:xlabel='engine'></pre>
!	500 1000 1500 2000 2500 3000 3500
<]	data.info() <class 'pandas.core.frame.dataframe'=""> Int64Index: 7889 entries, 0 to 8127 Data columns (total 12 columns): # Column Non-Null Count Dtype</class>
n	0 name 7889 non-null object 1 year 7889 non-null int64 2 selling_price 7889 non-null int64 3 km_driven 7889 non-null object 4 fuel 7889 non-null object 5 seller_type 7889 non-null object 6 transmission 7889 non-null object 7 owner 7889 non-null object 8 mileage 7889 non-null float64 9 engine 7889 non-null int32 10 max_power 7889 non-null object 11 seats 7889 non-null float64 dtypes: float64(2), int32(1), int64(3), object(6) memory usage: 770.4+ KB
	291 Hyundai Grand i10 Sportz 2017 450000 50000 Petrol Individual Manual First Owner 18.90 1197 85.8 5.0 370 Jaguar XE 2016-2019 2.0L Diesel Prestige 2017 2625000 9000 Dealer Dealer Automatic First Owner 13.60 1999 177 5.0 371 Lexus ES 300h 2019 5150000 20000 Petrol Dealer Automatic First Owner 22.37 2487 214.56 5.0
	372 Jaguar XF 2.0 Diesel Portfolio 2017 3200000 45000 Diesel Dealer Automatic First Owner 19.33 1999 177 5.0
1:	### Tata Indigo CR4 2013 290000 25000 Diesel Individual Manual First Owner 23.57 1396 70 5.0 ### 187 rows × 12 columns data=data.drop_duplicates() data.shape
((6702, 12) # let's extact how many years old the car is from year column and drop year column data["old"] = 2022-data["year"] data.drop(["year"], axis=1, inplace=True)
3	data.info() <class 'pandas.core.frame.dataframe'=""> Int64Index: 6702 entries, 0 to 8125 Data columns (total 12 columns): # Column Non-Null Count Dtype</class>
	Selling_price
C	11 old 6702 non-null int64 dtypes: float64(2), int32(1), int64(3), object(6) memory usage: 654.5+ KB data.drop('name',inplace=True,axis=1) from sklearn.preprocessing import LabelEncoder
	<pre>le=LabelEncoder() data['fuel']=le.fit_transform(data['fuel']) data['seller_type']=le.fit_transform(data['seller_type']) data['transmission']=le.fit_transform(data['transmission']) data['owner']=le.fit_transform(data['owner'])</pre> data.head(20)
	selling_price km_driven fuel seller_type transmission owner mileage max_power seats old 0 450000 145500 1 1 1 0 23.40 1248 74 5.0 8 1 370000 120000 1 1 1 2 21.14 1498 103.52 5.0 8 2 158000 140000 3 1 1 4 17.70 1497 78 5.0 16 3 225000 127000 1 1 1 0 23.00 1396 90 5.0 12 4 130000 120000 3 1 1 0 16.10 1298 88.2 5.0 15
	5 440000 45000 3 1 1 0 20.14 1197 81.86 5.0 5 6 96000 175000 2 1 1 0 17.30 1061 57.5 5.0 15 7 45000 5000 3 1 1 2 16.10 796 37 4.0 21 8 350000 90000 1 1 1 0 23.59 1364 67.1 5.0 11 9 200000 169000 1 1 1 0 20.00 1399 68.1 5.0 9 10 500000 68000 1 1 1 2 19.01 1461 108.45 5.0 8
11 11 11 11 11 11 11 11 11 11 11 11 11	11 92000 100000 3 1 1 2 17.30 993 60 5.0 17 12 280000 140000 1 1 1 2 19.30 1248 73.9 5.0 13 14 180000 90000 3 1 1 2 18.90 1061 67 5.0 13 15 400000 40000 3 1 1 0 18.15 1198 82 5.0 6 16 778000 70000 1 1 1 2 24.52 1248 88.5 7.0 6 17 500000 53000 1 1 1 2 23.00 1396 90 5.0 10
1 2	18
	<pre>r=data.drop(['selling_price'], axis=1) from sklearn.preprocessing import LabelEncoder le=LabelEncoder() fitted=le.fit_transform(X_train['fuel']) from sklearn.model_selection import train_test_split</pre>
	<pre>x_train, x_test, y_train, y_test=train_test_split(x, y, test_size=0.30, random_state=1) from sklearn.linear_model import LinearRegression line_reg=LinearRegression() line_reg.fit(x_train, y_train) #Now predicting on the test data</pre>
	<pre>#Now predicting on the test data y_pred=line_reg.predict(x_test) print(y_pred) [320678.29636595 436426.74020904 441899.14118783 491766.58907966 333322.05451381 602850.07792214] # compare the actual output values for X_test with the predicted values</pre>
	<pre># compare the actual output values for X_test with the predicted values df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred}) df.reset_index(inplace=True, drop=True)</pre>
	df
	Actual Predicted 0 48000 320678.296366 1 43000 436426.740209 2 40000 441899.141188 3 35000 452265.922270 4 28000 356332.079158 2006 34500 33000 591235.334784 2007 491766.589080
	Actual Predicted 0 480000 320678.296366 1 430000 436426.740209 2 400000 41899.141188 3 350000 452265.922270 4 280000 356332.079158 2006 345000 334345.154750 2007 33000 591235.334784 2008 550000 491766.589080 2009 199000 333322.054514 2010 650000 602850.077922 2011 rows × 2 columns #Showing the difference between the actual and predicted value
	Actual Predicted 0 48000 320678.296366 1 430000 48646.740209 2 400000 441889.141188 3 350000 452265.922270 4 280000 365332.079158 2006 345000 334345.154750 2007 330000 591235.334784 2008 550000 491766.589080 2009 199000 333322.054514 2010 650000 602850.077922 0011 rows × 2 columns #Showing the difference between the actual and predicted value df1 = df.head(25) df1.plot(kind='bar', figsize=(16,10)) plt.show()
	Actual Predicted 0 480000 320678.296366 1 430000 484899.141188 3 350000 452265.922270 4 280000 356332.079158 2000 34500 334345.154750 2007 330000 591225.334784 2008 550000 491766.589080 2009 199000 333322.054514 2010 650000 602850.077922 0011 rows × 2 columns #Showing the difference between the actual and predicted value df1 = df.head(25) df1.plot(kind='bar', figsize=(16,10)) plt.show()