DATA PREDICTION MODEL

(BASED ON DATA SCIENCE)

MINOR PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degree

Of

BACHELOR OF TECHNOLOGY

In

MECHANICAL AND AUTOMATION ENGINEERING

By

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ABSTRACT

Predictive analytics is a term mainly used in statistical and analytics techniques. This term is drawn from statistics, machine learning, database techniques and optimization techniques. It predicts the future by analyzing current and historical data. The future events and behaviour of variables can be predicted using the models of predictive analytics.

Nowadays MNCs and Big Marts keep the track of their sales data of each and every individual item for predicting future demand of the customer and update the inventory management as well. These data stores basically contain a large number of customer data and individual item attributes in a data warehouse. Further, anomalies and frequent patterns are detected by mining the data store from the data warehouse. The resultant data can be used for predicting future sales volume with the help of different machine learning techniques for the MNCs. In this paper, we propose a predictive model using Multi-Linear Regression technique for predicting the sales of automobile company and forecast the estimated value of their respective models w.r.t year.

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Certificate

It is certified that the work contained in this report titled *“**DATA PREDICTION MODEL** “*is the original work done by Mohd. Faizan *(00696203617)*, Gaurav *(41196203617)*, Akshit Gupta *(41296203617)* Dhruv Parasher *(41596203617) and* has been carried out under our supervision.

Dr. Deepak Bhardwaj
(Project Supervisor)

Mr. Neeraj Kumar
(Head of department)

Signature of External Examiner: …………………

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We express our deep gratitude to **Dr.Deepak Bhardwaj**, Associate Professor, Department of Mechanical and Automation Engineering for his valuable guidance and suggestion throughout our project work.

We would like to extend our sincere thanks to **Dr.Deepak Bhardwaj** for his time to time suggestion to complete our project work. We are also thankful to **Prof. (Dr.) Sanjay Kumar (Director)** for providing us the facilities to carry out our project work.

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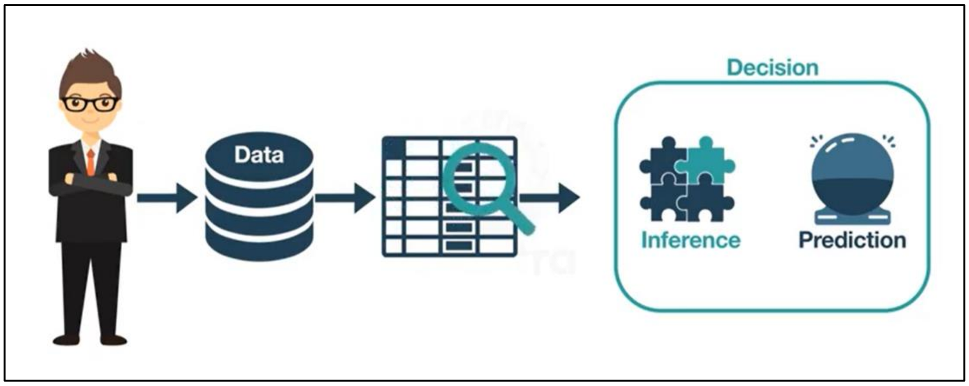
Table of Content

INTRODUCTION

Data science is all about using data to solve problems. The problem could be decision making such as identifying which email is spam and which is not.



Data Science is a blend of various tools, algorithms, and machine learning principles with the goal to discover hidden patterns from the raw data. Data Science is primarily used to make decisions and predictions making use of predictive causal analytics, prescriptive analytics (predictive plus decision science) and machine learning.

- **Predictive causal analytics** – If you want a model that can predict the possibilities of a particular event in the future, you need to apply predictive causal analytics.

- **Prescriptive analytics** – If you want a model that has the intelligence of taking its own decisions and the ability to modify it with dynamic parameters, you certainly need prescriptive analytics for it. This relatively new field is all about providing advice.

- **Machine learning for making predictions** — If you have transactional data of a finance company and need to build a model to determine the future trend, then machine learning algorithms are the best bet.
- **Machine learning for pattern discovery** — If you don't have the parameters based on which you can make predictions, then you need to find out the hidden patterns within the dataset to be able to make meaningful predictions. This is nothing but the unsupervised model as you don't have any predefined labels for grouping.

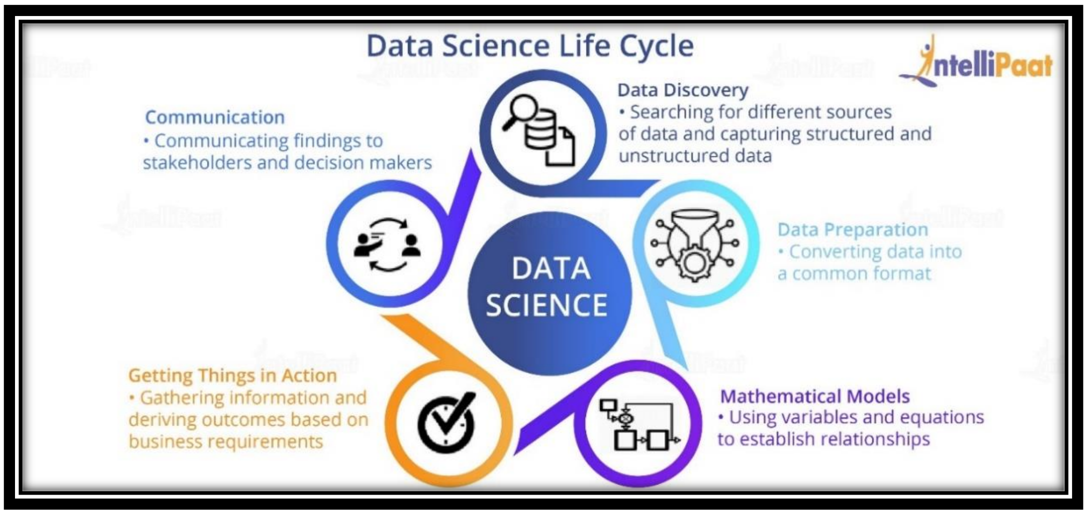
Objective

Predictive analytics is the use of data, statistical algorithms and machine learning techniques to identify the likelihood of future outcomes based on historical data. The goal is to go beyond knowing what has happened to providing a best assessment of what will happen in the future **.**The main objective of data prediction model is to use current and historical data to make predictions about future customer behavior, otherwise unknown events, risks, trends and opportunities**.**

THEORY

- **Data Science**

Data Science is a blend of various tools, algorithms, and machine learning principles with the goal to discover hidden patterns from the raw data.



- **Data Discovery**

The first phase in the Data Science life cycle is data discovery for any Data Science problem. It includes ways to discover data from various sources which could be in an unstructured format like videos or images or in a structured format like in text files, or it could be from relational database systems. Organizations are also peeping into customer social media data, and the like, to understand customer mindset better.

- **Data Preparation**

  Once the data discovery phase is completed, the next stage is data preparation. It includes converting disparate data into a common format in order to work with it seamlessly. This process involves collecting clean data subsets and inserting suitable defaults, and it can also involve more complex methods like identifying missing values by modelling, and so on. Once the data cleaning is done, the next step is to integrate and create a conclusion from the dataset for analysis. This involves the integration of data which includes **merging** two or more tables of the same objects, but storing different information, or summarizing fields in a table using **aggregation**. Here, we would also try to explore and understand what patterns and values our datasets have.

- **Mathematical Models**

  All **Data Science projects** have certain mathematical models driving them. These models are planned and built by the Data Scientists in order to suit the specific need of the business organization. This might involve various areas of the mathematical domain including statistics, logistic and linear regression, differential and integral calculus, etc. Various tools and apparatus used in this regard could be R statistical computing tools, **Python programming language**, **SAS advanced analytical tools**, **SQL**, and various data visualization tools like **Tableau** and **QlikView**.

- **Getting Things in Action**

  Once the data is prepared and the models are built, it is time to get these models working in order to achieve the desired results. There might be various discrepancies and a lot of troubleshooting that might be needed, and thus the model might have to be tweaked. Here, model evaluation explains the performance of the model.

- **Communication**

  Communicating the findings is the last but not the least step in a Data Science endeavour. In this stage, the Data Scientist needs to be a liaison between various teams and should be able to seamlessly communicate his findings to key stakeholders and decision-makers in the organization so that actions can be taken based on the recommendations of the Data Scientist.

Data Science Components

Key components of Data Science, which are:

- **Data (and Its Various Types)**

The raw dataset is the foundation of Data Science, and it can be of various types like structured data (mostly in a tabular form) and unstructured data (images, videos, emails, PDF files, etc.)

- **Programming (Python and R)**

Data management and analysis is done by computer programming. In Data Science, two programming languages are most popular: Python and R.

- **Statistics and Probability**

Data is manipulated to extract information out of it. The mathematical foundation of Data Science is statistics and probability. Without having a clear knowledge of statistics and probability, there is a high possibility of misinterpreting data and reaching at incorrect conclusions. That's the reason why statistics and probability play a crucial role in Data Science.

- **Machine Learning**

As a Data Scientist, every day, you will be using Machine Learning algorithms such as regression and classification methods. It is very important for a Data Scientist to know Machine learning as a part of their job so that they can predict valuable insights from available data.

METHODOLOGY

Multiple linear regression (MLR), also known simply as multiple regression, is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of multiple linear regression (MLR) is to model the linear relationship between the explanatory (independent) variables and response (dependent) variable.

$$yi = \beta 0 + \beta 1xi1 + \beta 2xi2 + \ldots + \beta pxip + \epsilon$$

where, for **i=n** observations:

y_i = dependent variable

x_i = explanatory variables

β_o = y-intercept (constant term)

β_p = slope coefficients for each explanatory variable

ϵ = the model's error term (also known as the residuals)

In a Data Science model, Multiple Linear Regression attempts to model the relationship between two or more features and a response by fitting a linear equation to observed data.

PROGRAMS

1. Cars Price Prediction:-

The goal of this notebook is to predict the prices of used cars in India. Three important steps involved in this notebook are: Data cleaning/ Feature engineering. Exploratory Data Analysis. Predicting the price of car using price using Machine Learning.

Source of Data - www.kaggle.com

Kaggle, a subsidiary of Google LLC, is an online community of data scientists and machine learning practitioners. Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges

Read dataset

I'll read the dataset and get information about it

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import style
import sklearn
from pandas import Series
from pandas import DataFrame
import matplotlib.pyplot as plt
```

In [2]:
```
data = pd.read_csv("C:\\Users\mohdf\OneDrive\Desktop\Automobile.csv")
```

In [3]:
```
data.head(5)
```

Out[3]:

	car	price	body	mileage	engV	engType	registration	year	model	drive
0	Ford	15500.0	crossover	68	2.5	Gas	yes	2010	Kuga	full
1	Mercedes-Benz	20500.0	sedan	173	1.8	Gas	yes	2011	E-Class	rear
2	Mercedes-Benz	35000.0	other	135	5.5	Petrol	yes	2008	CL 550	rear
3	Mercedes-Benz	17800.0	van	162	1.8	Diesel	yes	2012	B 180	front
4	Mercedes-Benz	33000.0	vagon	91	NaN	Other	yes	2013	E-Class	NaN

CHECKING TO NUMBER OF UNIQUE VALUES

In [4]:
```
data.nunique()
```

Out[4]:
```
car             87
price         1353
body             6
mileage        442
engV           117
engType          4
registration     2
year            56
model          888
drive            3
dtype: int64
```

CONVERTING TEXT DATA INTO NUMERIC FORM USING LABEL ENCODER AND ONEHOT ENCODER

In [5]:
```
from sklearn import reprocessing
le = reprocessing.LabelEncoder()
 data['registration'] = le.fit_transform(data['registration'])
 print(le.classes_)
 ['no' 'yes']
```

In [6]:
```
data.columns
```

Out[6]:
```
Index(['car', 'price', 'body', 'mileage', 'engV', 'engType',
       'registration', 'year', 'model', 'drive'],
      dtype='object')
```

In [7]:
```
data = pd.get_dummies(data,columns = ["body","engType","drive"])
```

In [8]:
```
data.head(10)
```

Out[8]:

	car	price	mileage	engV	registration	year	model	body_crossover	body_hatch
0	Ford	15500.0	68	2.5	1	2010	Kuga	1	0
1	Mercedes-Benz	20500.0	173	1.8	1	2011	E-Class	0	0
2	Mercedes-Benz	35000.0	135	5.5	1	2008	CL 550	0	0
3	Mercedes-Benz	17800.0	162	1.8	1	2012	B 180	0	0
4	Mercedes-Benz	33000.0	91	NaN	1	2013	E-Class	0	0
5	Nissan	16600.0	83	2.0	1	2013	X-Trail	1	0
6	Honda	6500.0	199	2.0	1	2003	Accord	0	0
7	Renault	10500.0	185	1.5	1	2011	Megane	0	0
8	Mercedes-Benz	21500.0	146	1.8	1	2012	E-Class	0	0
9	Mercedes-Benz	22700.0	125	2.2	1	2010	E-Class	0	0

CHECKING TOTAL NUMBER OF NAN VALUES IN A GIVEN DATA SET

In [9]:
```
data.isnull().head(10)
```

Out[9]:

	car	price	mileage	engV	registration	year	model	body_crossover	body_hatch	body_o
0	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	F
4	False	False	False	True	False	False	False	False	False	F
5	False	False	False	False	False	False	False	False	False	F
6	False	False	False	False	False	False	False	False	False	F
7	False	False	False	False	False	False	False	False	False	F
8	False	False	False	False	False	False	False	False	False	F
9	False	False	False	False	False	False	False	False	False	F

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
car                  0
price                0
mileage              0
engV               434
registration         0
year                 0
model                0
body_crossover       0
body_hatch           0
body_other           0
body_sedan           0
body_vagon           0
body_van             0
engType_Diesel       0
engType_Gas          0
engType_Other        0
engType_Petrol       0
drive_front          0
drive_full           0
drive_rear           0
dtype: int64
```

DROPPING ALL ROWS HAVING NAN VALUES

In [11]:
```
data =data.dropna()
```

IMPORTING OUR CLEAN DATA SET

In [12]:
```
data32= data.to_csv("C:\\Users\mohdf\OneDrive\Documents\data32.csv")
```

In [13]:
```
data32
```

GETTING MORE INFORMATION FROM OUR DATA SET

In [14]:
```
data.head(10)
```

Out[14]:

	car	price	mileage	engV	registration	year	model	body_crossover body_hat
0	Ford	15500.000	68	2.5	1	2010	Kuga	1
1	Mercedes-Benz	20500.000	173	1.8	1	2011	E-Class	0
2	Mercedes-Benz	35000.000	135	5.5	1	2008	CL 550	0
3	Mercedes-Benz	17800.000	162	1.8	1	2012	B 180	0
5	Nissan	16600.000	83	2.0	1	2013	X-Trail	1
6	Honda	6500.000	199	2.0	1	2003	Accord	0
7	Renault	10500.000	185	1.5	1	2011	Megane	0
8	Mercedes-Benz	21500.000	146	1.8	1	2012	E-Class	0
9	Mercedes-Benz	22700.000	125	2.2	1	2010	E-Class	0
10	Nissan	20447.154	0	1.2	1	2016	Qashqai	1

In [15]:
```
data.isnull().sum()
```

Out[15]:
```
car                0
price              0
mileage            0
engV               0
registration       0
year               0
model              0
body_crossover     0
body_hatch         0
body_other         0
body_sedan         0
body_vagon         0
body_van           0
engType_Diesel     0
engType_Gas        0
engType_Other      0
engType_Petrol     0
drive_front        0
drive_full         0
drive_rear         0
dtype: int64
```

In [16]:
```
data.shape
```

Out[16]:
```
(9142, 20)
```

In [17]:
```
data.size
```

Out[17]:
```
182840
```

In [18]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9142 entries, 0 to 9575
Data columns (total 20 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   car              9142 non-null   object
 1   price            9142 non-null   float64
 2   mileage          9142 non-null   int64
 3   engV             9142 non-null   float64
 4   registration     9142 non-null   int32
 5   year             9142 non-null   int64
 6   model            9142 non-null   object
 7   body_crossover   9142 non-null   uint8
 8   body_hatch       9142 non-null   uint8
 9   body_other       9142 non-null   uint8
 10  body_sedan       9142 non-null   uint8
 11  body_vagon       9142 non-null   uint8
 12  body_van         9142 non-null   uint8
 13  engType_Diesel   9142 non-null   uint8
 14  engType_Gas      9142 non-null   uint8
 15  engType_Other    9142 non-null   uint8
 16  engType_Petrol   9142 non-null   uint8
 17  drive_front      9142 non-null   uint8
 18  drive_full       9142 non-null   uint8
 19  drive_rear       9142 non-null   uint8
dtypes: float64(2), int32(1), int64(2), object(2), uint8(13)
memory usage: 651.7+ KB
```

In [19]:
```
data.describe()
```

Out[19]:

	price	mileage	engV	registration	year	body_crossover	body_hatch	body_other	body_sedan	bc
count	9142.000000	9142.000000	9142.000000	9142.000000	9142.000000	9142.000000	9142.000000	9142.000000	9142.000000	91
mean	15606.644973	139.887005	2.646344	0.942135	2006.602932	0.219646	0.125902	0.085758	0.380333	
std	24060.337206	97.881736	5.927699	0.233500	6.975465	0.414029	0.331758	0.280022	0.485495	
min	0.000000	0.000000	0.100000	0.000000	1959.000000	0.000000	0.000000	0.000000	0.000000	
25%	4999.250000	70.000000	1.600000	1.000000	2004.000000	0.000000	0.000000	0.000000	0.000000	
50%	9200.000000	129.000000	2.000000	1.000000	2008.000000	0.000000	0.000000	0.000000	0.000000	
75%	16737.500000	195.000000	2.500000	1.000000	2012.000000	0.000000	0.000000	0.000000	1.000000	
max	547800.000000	999.000000	99.990000	1.000000	2016.000000	1.000000	1.000000	1.000000	1.000000	

IMPLEMENTING MACHINE LEARNING ALGORITHM FOR PREDICTION

In [20]:
```
data.head()
```

Out[20]:

	car	price	mileage	engV	registration	year	model	body_crossover	body_hatch	body_other	body_sedan	body_vagon
0	Ford	15500.0	68	2.5	1	2010	Kuga	1	0	0	0	0
1	Mercedes-Benz	20500.0	173	1.8	1	2011	E-Class	0	0	0	1	0
2	Mercedes-Benz	35000.0	135	5.5	1	2008	CL 550	0	0	1	0	0
3	Mercedes-Benz	17800.0	162	1.8	1	2012	B 180	0	0	0	0	0
5	Nissan	16600.0	83	2.0	1	2013	X-Trail	1	0	0	0	0

In [21]:
```
data.nunique()
```

Out[21]:
```
car                  84
price              1307
mileage             438
engV                117
registration          2
year                 54
model               869
body_crossover        2
body_hatch            2
body_other            2
body_sedan            2
body_vagon            2
body_van              2
engType_Diesel        2
engType_Gas           2
engType_Other         2
engType_Petrol        2
drive_front           2
drive_full            2
drive_rear            2
dtype: int64
```

In [22]:
```
X = data.iloc[:,[2,3,4,5,7,8,9,10,11,12,13,14,15,16,17,18,19]].values
```

In [23]:
```
y = data.iloc[:,1].values
```

In [24]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=7)
```

In [25]:
```
from sklearn import linear_model
model = linear_model.LinearRegression()
```

In [26]:
```
model.fit(X_train, y_train)
```

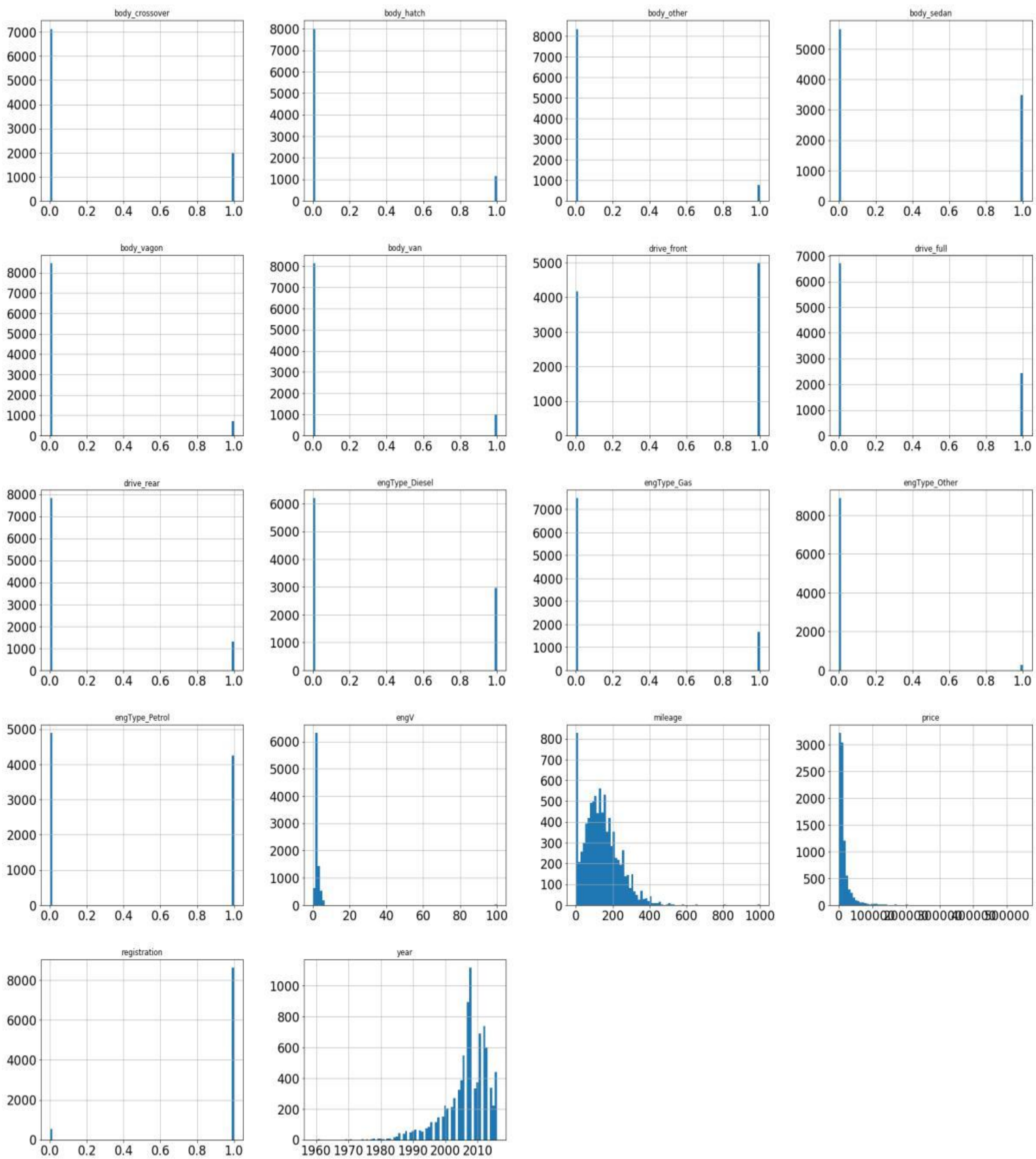
Out[26]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [27]:
```
y_pred = model.predict(X_test)
```

```
In [28]: y_pred

Out[28]: array([16084.23537558, 15067.23625772, 13413.79582567, ...,
                11707.20724146, 35488.81731419,  9277.12466026])

In [29]: y_test

Out[29]: array([ 6600., 14200., 10800., ...,  7300., 25999.,  1150.])

In [30]: print("Accuracy --> ", model.score(X_test, y_test)*100)

         Accuracy -->  29.185165421709037

In [31]: y_pred

Out[31]: array([16084.23537558, 15067.23625772, 13413.79582567, ...,
                11707.20724146, 35488.81731419,  9277.12466026])

In [32]: y_test

Out[32]: array([ 6600., 14200., 10800., ...,  7300., 25999.,  1150.])

In [33]: y_test.mean()

Out[33]: 15145.536953973751

In [34]: y_pred.mean()

Out[34]: 15985.251753044835

In [35]: y_pred = y_pred.astype(float)

In [36]: y_test = y_test.astype(float)
```

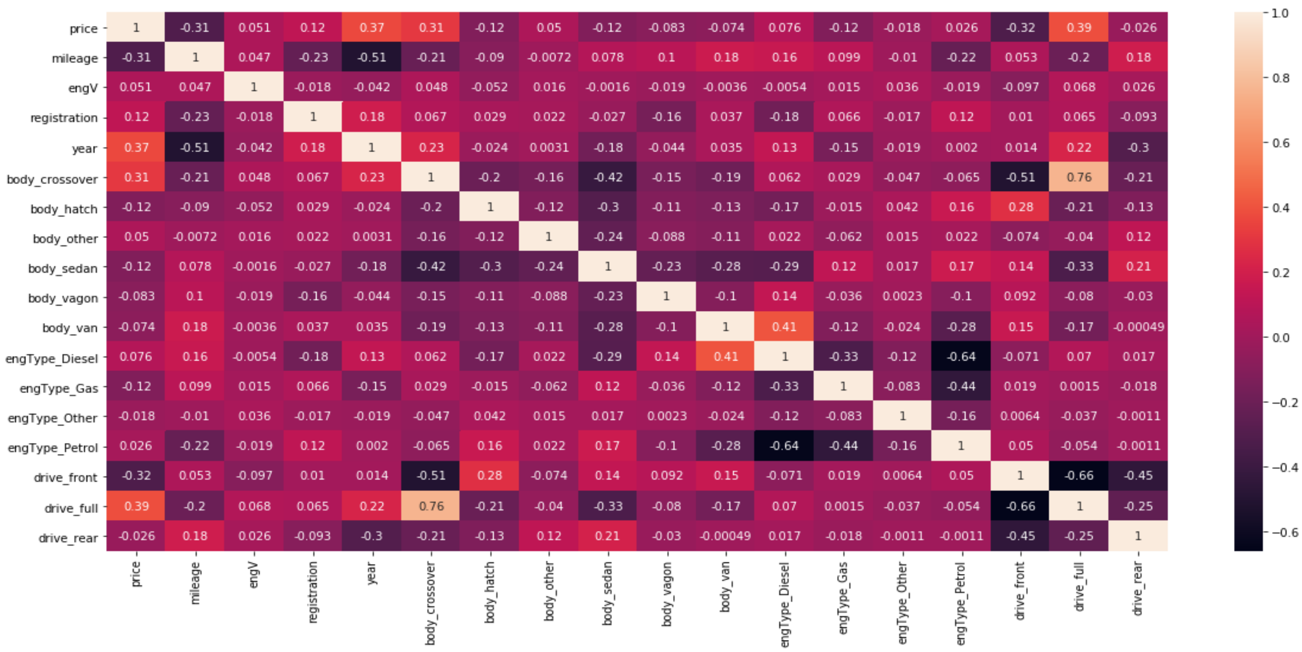
VISUALISATION THROUGH MATPLOTLIB AND SEABORN

In [37]:
```
import matplotlib.pyplot as plt
data.hist(bins=80,
figsize=(30,30),xlabelsize=20,ylabelsize=20,grid=True)
plt.show()
```



Checking Correlation using heatmap

In [38]:
```
corr = data.corr()
plt.subplots(figsize=(20,9))
sns.heatmap(corr, annot=True)
plt.show()
```



In [28]:
```
y_pred
```
Out[28]:
```
array([16084.23537558, 15067.23625772, 13413.79582567, ...,
       11707.20724146, 35488.81731419,  9277.12466026])
```

In [29]:
```
y_test
```
Out[29]:
```
array([ 6600., 14200., 10800., ...,  7300., 25999.,  1150.])
```

In [30]:
```
print("Accuracy --> ", model.score(X_test, y_test)*100)
```
```
Accuracy -->  29.185165421709037
```

In [31]:
```
y_pred
```
Out[31]:
```
array([16084.23537558, 15067.23625772, 13413.79582567, ...,
       11707.20724146, 35488.81731419,  9277.12466026])
```

In [32]:
```
y_test
```
Out[32]:
```
array([ 6600., 14200., 10800., ...,  7300., 25999.,  1150.])
```

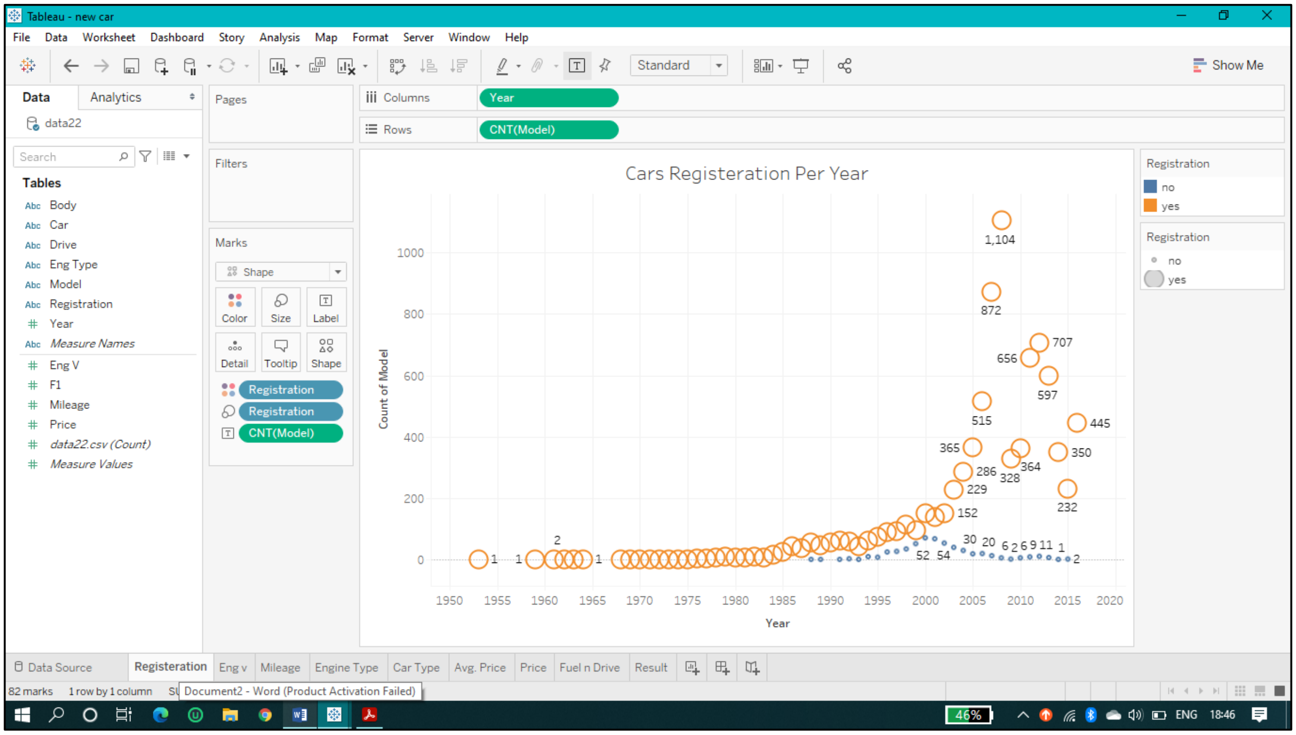
In [33]:
```
y_test.mean()
```
Out[33]:
```
15145.536953973751
```

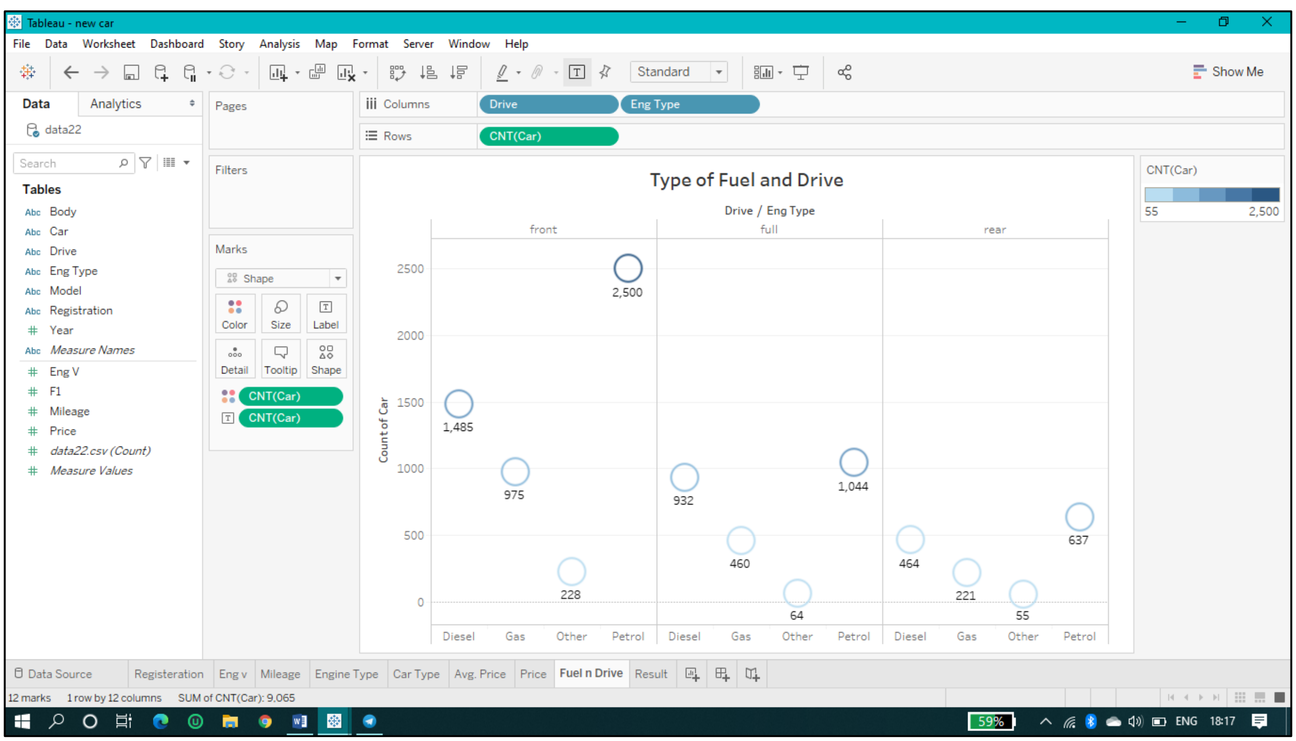
In [34]:
```
y_pred.mean()
```
Out[34]:
```
15985.251753044835
```

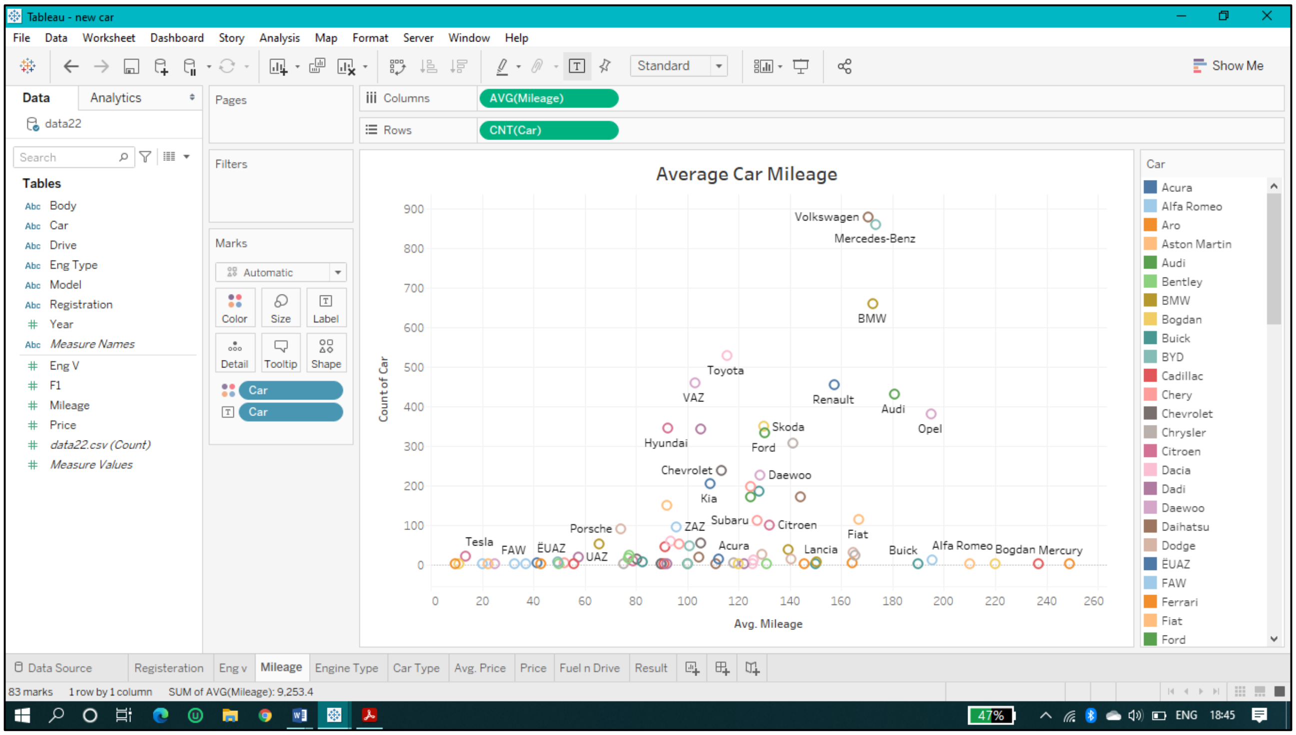
In [35]:
```
y_pred = y_pred.astype(float)
```

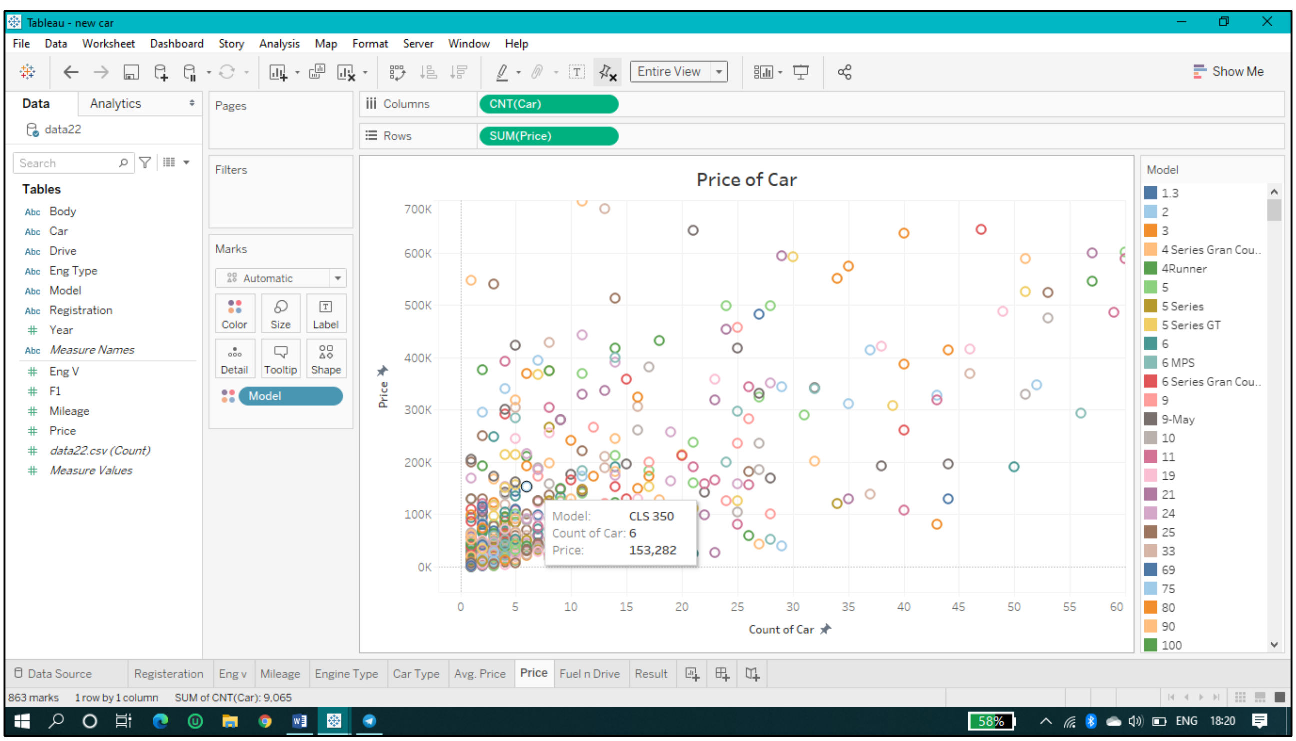
In [36]:
```
y_test = y_test.astype(float)
```

VISUALIZATION ON TABLEAU






Average Car Mileage
Avg. Mileage
Count of Car


Price of Car
Count of Car
Price

CARS LIST

- Fisker
- Ford
- GAZ
- Geely
- GMC
- Great Wall
- Groz
- Hafei
- Honda
- Huanghai
- Hummer
- Hyundai
- Infiniti
- Isuzu
- JAC
- Jaguar
- Jeep
- Kia
- Lamborghini
- Lancia
- Land Rover
- Lexus
- Lifan
- Lincoln
- Maserati
- Mazda
- Mercedes-Benz
- Mercury
- MG
- MINI
- Mitsubishi
- Moskvich-AZLK
- Moskvich-Izh
- Nissan
- Opel
- Other-Retro
- Peugeot
- Porsche
- Renault
- Rolls-Royce
- Rover
- Saab
- Samand
- Samsung
- Seat
- Skoda
- SMA
- Smart
- SsangYong
- Subaru
- Peugeot
- Porsche
- Renault
- Rolls-Royce
- Rover
- Saab
- Samand
- Samsung
- Seat
- Skoda
- SMA
- Smart
- SsangYong
- Subaru
- Suzuki
- TATA
- Tesla
- Toyota
- UAZ
- VAZ
- Volkswagen
- Volvo
- Wartburg
- ZAZ
- ZX
- Alfa Romeo
- Aro
- Aston Martin
- Audi
- Barkas
- Bentley
- BMW
- Bogdan
- Buick
- BYD
- Cadillac
- Changan
- Chery
- Chevrolet
- Chrysler
- Citroen
- Dacia
- Dadi
- Daewoo
- Daihatsu
- Dodge
- ËUAZ
- FAW
- Ferrari
- Fiat

2. California Housing Prediction :-

Read dataset

I'll read the dataset and get information about it

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
housing = pd.read_csv("D:\\housing.csv")
```

In [3]:
```
housing1 = housing.copy()
```

In [4]:
```
housing.head()
```

Out[4]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0

CHECKING TO NUMBER OF UNIQUE VALUES

In [5]:
```
housing.nunique()
```

Out[5]:
```
longitude                844
latitude                 862
housing_median_age        52
total_rooms             5926
total_bedrooms          1923
population              3888
households              1815
median_income          12928
median_house_value      3842
ocean_proximity            5
dtype: int64
```

In [6]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [7]:
```
housing.isnull()
```

Out[7]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	house
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
...	...	...	...	...	...	...	
20635	False	False	False	False	False	False	
20636	False	False	False	False	False	False	
20637	False	False	False	False	False	False	
20638	False	False	False	False	False	False	
20639	False	False	False	False	False	False	

20640 rows × 10 columns

In [8]:

```
housing.isnull
```

Out[8]:

```
<bound method DataFrame.isnull of        longitude  latitude housing_median_
age  total_rooms  total_bedrooms  \
0        -122.23     37.88                41.0        880.0           129.0
1        -122.22     37.86                21.0       7099.0          1106.0
2        -122.24     37.85                52.0       1467.0           190.0
3        -122.25     37.85                52.0       1274.0           235.0
4        -122.25     37.85                52.0       1627.0           280.0
...          ...       ...                 ...          ...             ...
20635    -121.09     39.48                25.0       1665.0           374.0
20636    -121.21     39.49                18.0        697.0           150.0
20637    -121.22     39.43                17.0       2254.0           485.0
20638    -121.32     39.43                18.0       1860.0           409.0
20639    -121.24     39.37                16.0       2785.0           616.0

       population  households  median_income  median_house_value  \
0           322.0       126.0         8.3252            452600.0
1          2401.0      1138.0         8.3014            358500.0
2           496.0       177.0         7.2574            352100.0
3           558.0       219.0         5.6431            341300.0
4           565.0       259.0         3.8462            342200.0
...           ...         ...            ...                 ...
20635       845.0       330.0         1.5603             78100.0
20636       356.0       114.0         2.5568             77100.0
20637      1007.0       433.0         1.7000             92300.0
20638       741.0       349.0         1.8672             84700.0
20639      1387.0       530.0         2.3886             89400.0

      ocean_proximity
0            NEAR BAY
1            NEAR BAY
2            NEAR BAY
3            NEAR BAY
4            NEAR BAY
...               ...
20635          INLAND
20636          INLAND
20637          INLAND
20638          INLAND
20639          INLAND

[20640 rows x 10 columns]>
```

In [9]:
```
housing.isnull().sum()
```

Out[9]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

In [10]:
```
housing.columns
```

Out[10]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

In [11]:
```
housing["ocean_proximity"].value_counts()
```

Out[11]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

In [12]:
```
housing["housing_median_age"].value_counts().head(5)
```

Out[12]:
```
52.0    1273
36.0     862
35.0     824
16.0     771
17.0     698
Name: housing_median_age, dtype: int64
```

In [13]:
```
housing["housing_median_age"].value_counts().head(5)
```

Out[13]:
```
52.0    1273
36.0     862
35.0     824
16.0     771
17.0     698
Name: housing_median_age, dtype: int64
```

In [14]:
```
housing.shape
```

Out[14]:
```
(20640, 10)
```

```
In [15]: housing.size
```

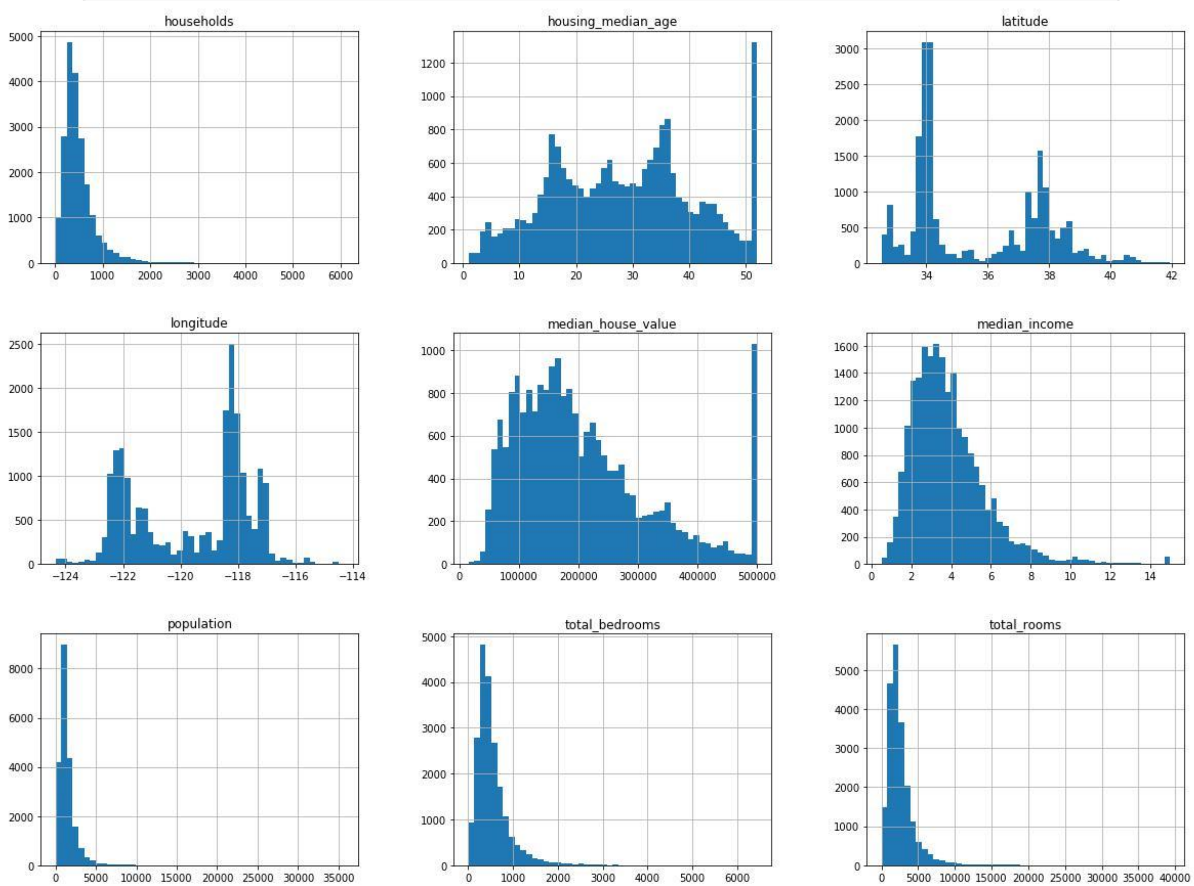
```
Out[15]: 206400
```

```
In [16]: housing.describe()
```

Out[16]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popul
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.00
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.47
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.46
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.00
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.00
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.00
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.00
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.00

```
In [17]: import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
plt.show()
```



In [18]:
```
housing.head(5)
```

Out[18]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0

In [19]:
```
housing["households"].value_counts()
```

Out[19]:
```
306.0     57
386.0     56
335.0     56
282.0     55
429.0     54
          ..
1506.0     1
1765.0     1
1338.0     1
2333.0     1
1455.0     1
Name: households, Length: 1815, dtype: int64
```

In [20]:
```
housing.size
```

Out[20]:
```
206400
```

In [21]:
```
data = housing.dropna()
```

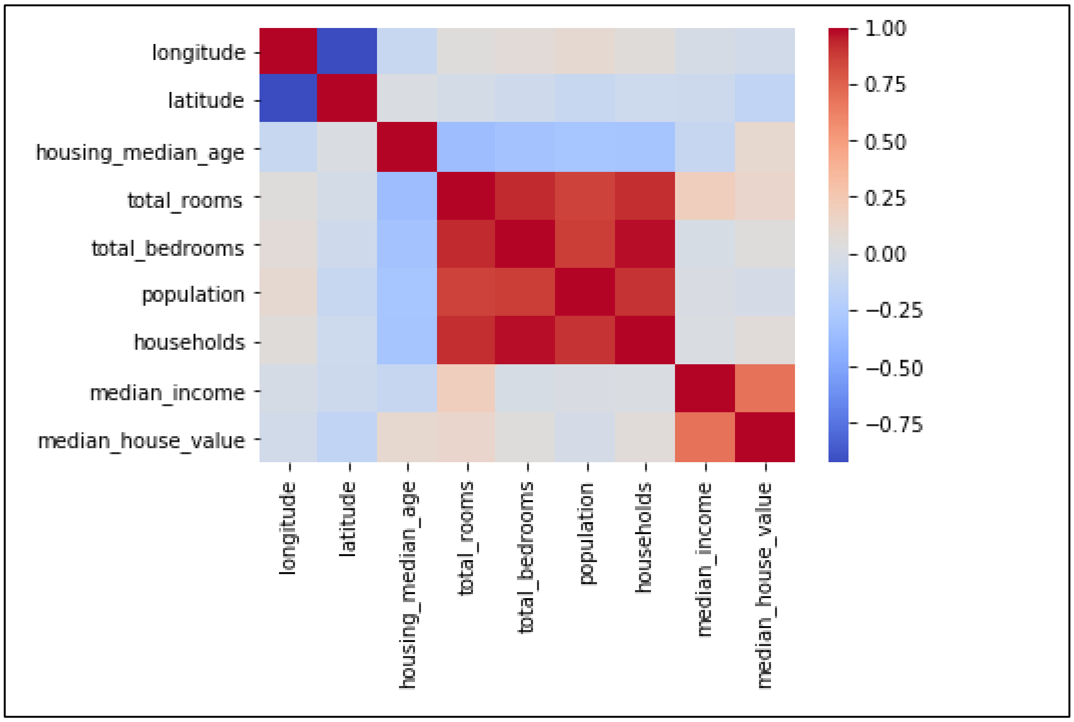
In [22]:
```
data.size
```

Out[22]:
```
204330
```

Checking Correlation

In [23]:
```
sns.heatmap(data.corr(),cmap='coolwarm')
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1d337f43808>



In [24]:
```
data.columns
```

Out[24]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

In [25]:
```
data.head(4)
```

Out[25]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0

In [26]:
```
del housing['total_bedrooms']
```

In [27]:
```
housing.head(4)
```
Out[27]:

	longitude	latitude	housing_median_age	total_rooms	population	households	median_income
0	-122.23	37.88	41.0	880.0	322.0	126.0	8.3252
1	-122.22	37.86	21.0	7099.0	2401.0	1138.0	8.3014
2	-122.24	37.85	52.0	1467.0	496.0	177.0	7.2574
3	-122.25	37.85	52.0	1274.0	558.0	219.0	5.6431

In [28]:
```
del housing['population']
```
In [29]:
```
housing.head(4)
```
Out[29]:

	longitude	latitude	housing_median_age	total_rooms	households	median_income	median_h
0	-122.23	37.88	41.0	880.0	126.0	8.3252	
1	-122.22	37.86	21.0	7099.0	1138.0	8.3014	
2	-122.24	37.85	52.0	1467.0	177.0	7.2574	
3	-122.25	37.85	52.0	1274.0	219.0	5.6431	

In [30]:
```
del housing['households']
```
In [31]:
```
housing1.nunique()
```
Out[31]:
```
longitude               844
latitude                862
housing_median_age       52
total_rooms            5926
total_bedrooms         1923
population             3888
households             1815
median_income         12928
median_house_value     3842
ocean_proximity           5
dtype: int64
```

In [32]:
```
housing.head()
```

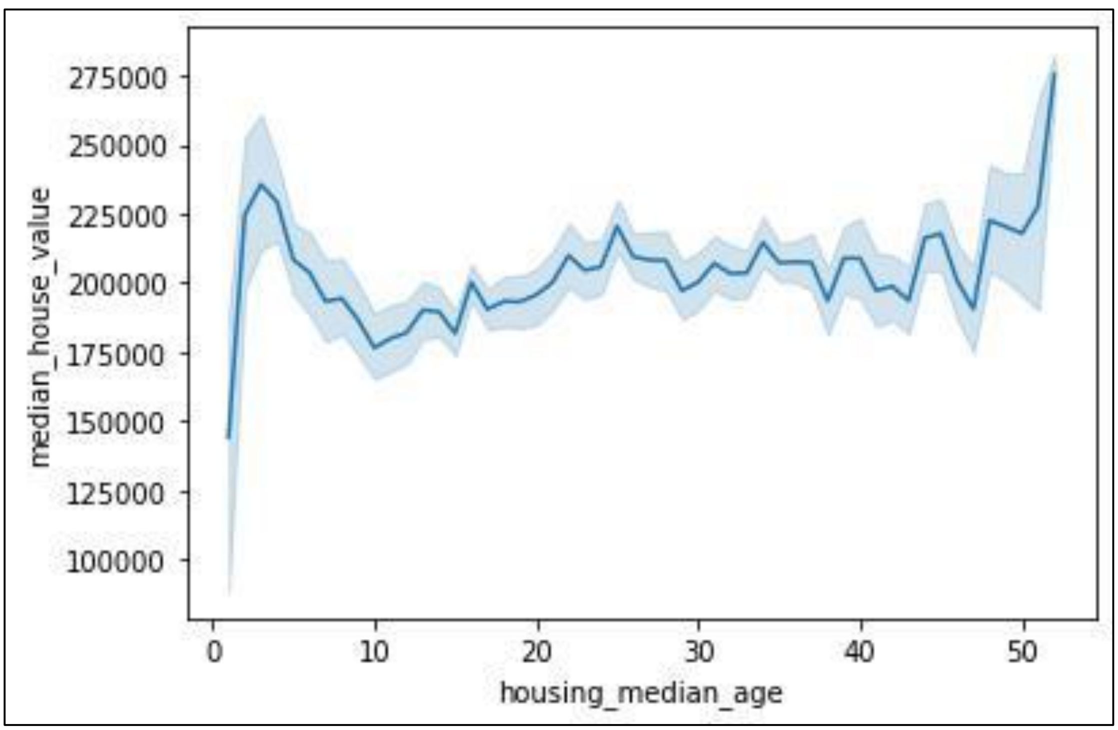
Out[32]:

	longitude	latitude	housing_median_age	total_rooms	median_income	median_house_value	o
0	-122.23	37.88	41.0	880.0	8.3252	452600.0	
1	-122.22	37.86	21.0	7099.0	8.3014	358500.0	
2	-122.24	37.85	52.0	1467.0	7.2574	352100.0	
3	-122.25	37.85	52.0	1274.0	5.6431	341300.0	
4	-122.25	37.85	52.0	1627.0	3.8462	342200.0	

In [33]:
```
del housing["ocean_proximity"]
```

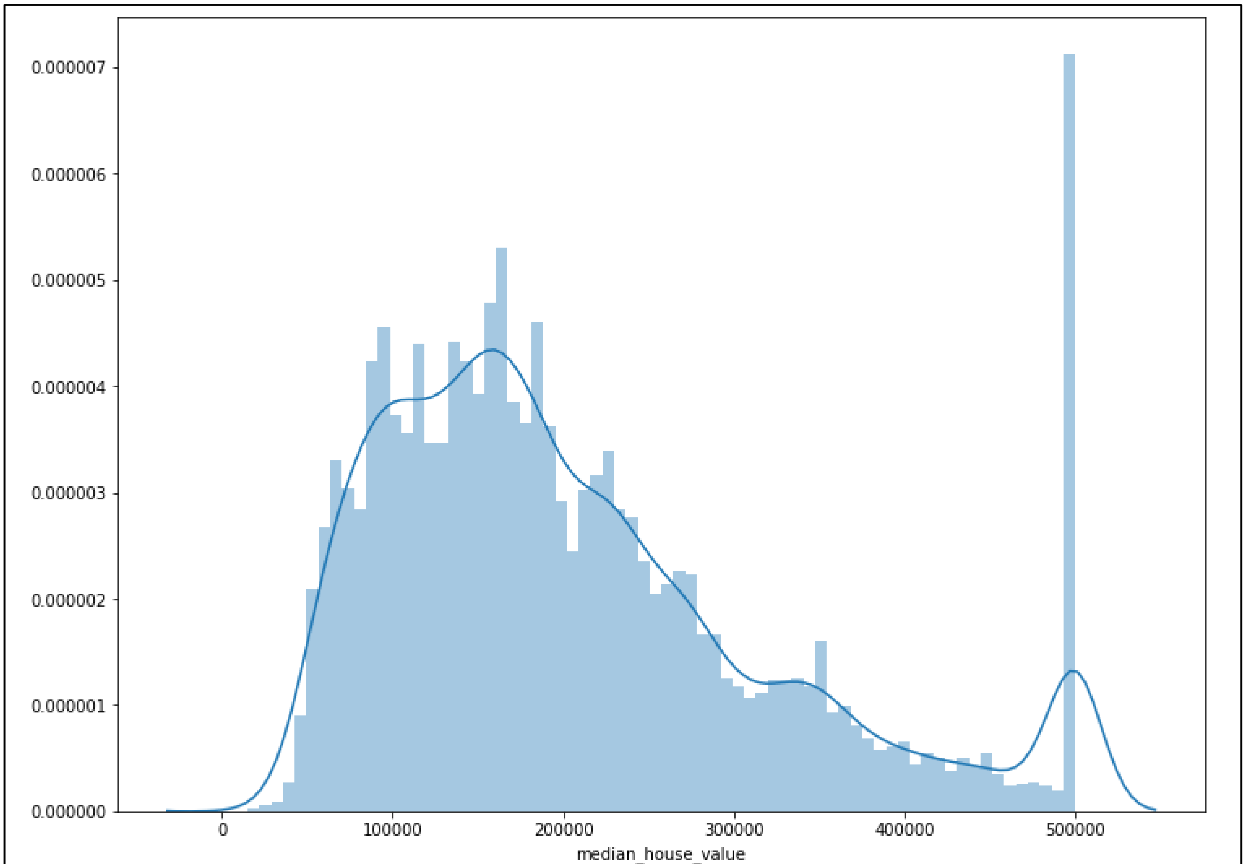
Visualization

In [34]:
```
sns.lineplot(housing["housing_median_age"],housing["median_house_value"])
plt.show()
```



In [35]:
```
plt.subplots(figsize=(12,9))
sns.distplot(housing['median_house_value'],bins = 70)
```

Out[35]: `<matplotlib.axes._subplots.AxesSubplot at 0x1d3399c5a48>`



In [36]:
```
corr = housing.corr()
plt.subplots(figsize=(20,9))
sns.heatmap(corr, annot=True)
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1d338ceb6c8>

In [37]:
```
y = housing["median_house_value"]
```

In [38]:
```
del housing["median_house_value"]
```

In [39]:
```
X = housing.values
```

In [40]:
```
y = y.values
```

In [41]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando m_state=7)
```

In [42]:
```
from sklearn import linear_model
model = linear_model.LinearRegression()
```

In [43]:
```
model.fit(X_train, y_train)
```

Out[43]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

In [44]:
```
y_pred = model.predict(X_test)
```

In [45]:
```
print("Predict value " + str(model.predict([X_test[600]])))
print("Real value " + str(y_test[600]))
```

```
Predict value [312985.97547473]
Real value 410500.0
```

In [46]:
```
y_pred
```

Out[46]:
```
array([153526.02420419, 244917.16207568, 249089.2341909 , ...,
       202145.21045608, 237283.07582104, 397578.96788946])
```

In [47]:
```
y_test
```

Out[47]:
```
array([360000., 336000., 269900., ..., 200000., 406500., 413700.])
```

In [48]:
```
print("Accuracy --> ", model.score(X_test, y_test)*100)
```

```
Accuracy -->  59.415290009731415
```

In [49]:
```
df1 =pd.DataFrame({"y_pred": y_pred})
```

In [50]:
```
df2 = pd.DataFrame({"y_test": y_test})
```

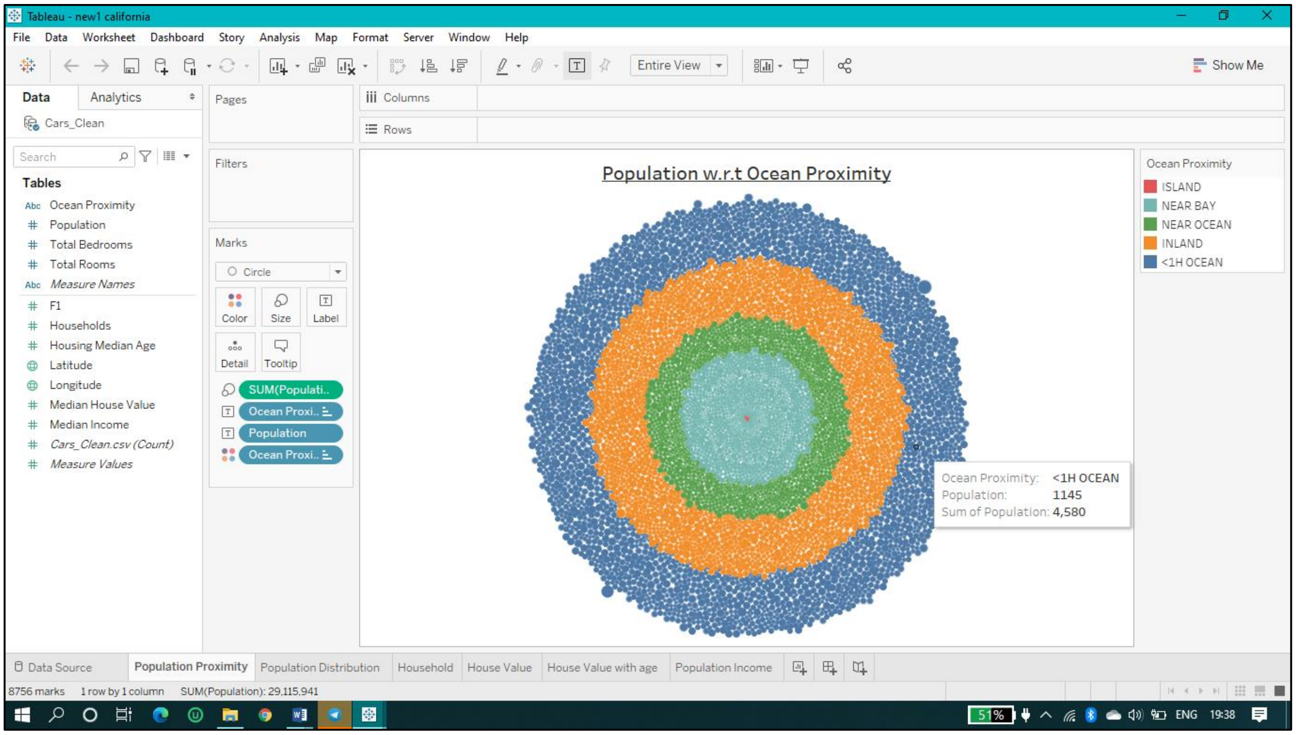
In [51]:
```
df1 = df1.loc[0:500].astype(float)
```

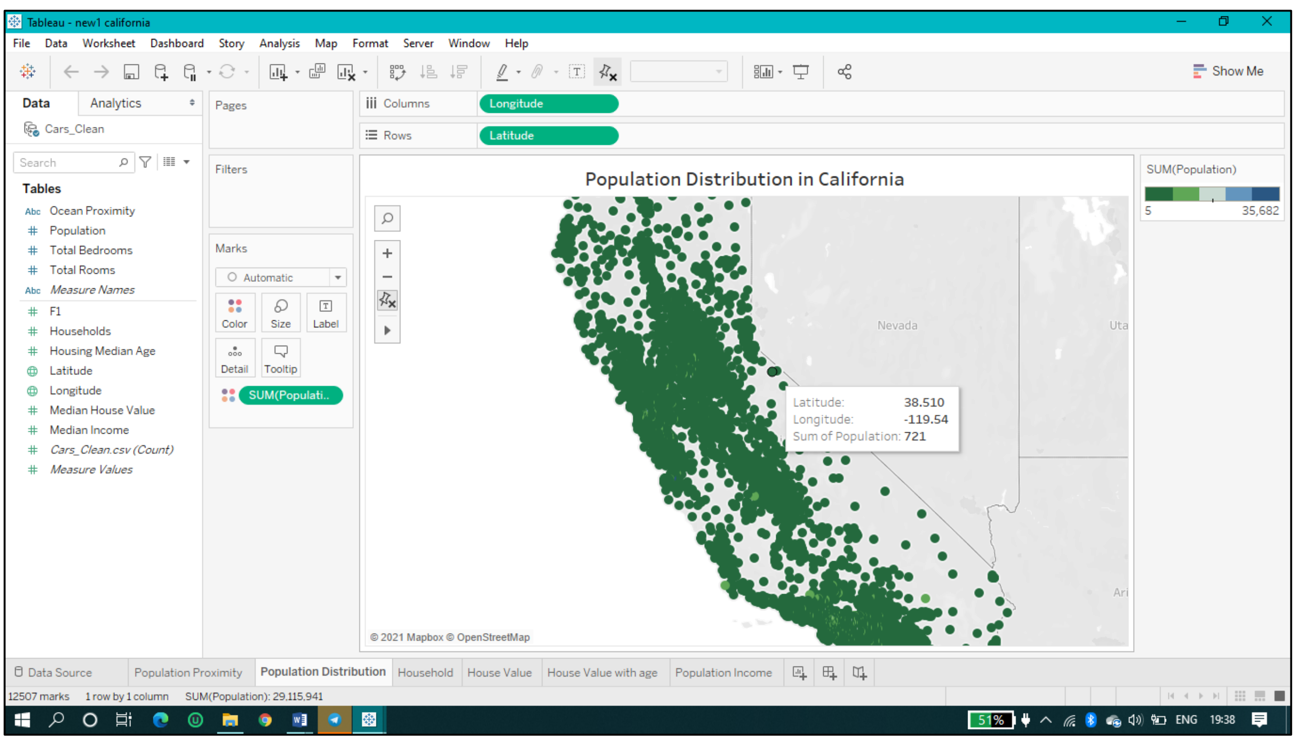
In [52]:
```
df2 = df2.loc[0:500].astype(float)
```

In [53]:
```
df1.to_csv("D:\y_pred.csv")
```

In [54]:
```
df2.to_csv("D:\y_test.csv"
```

Visualization on Tableau





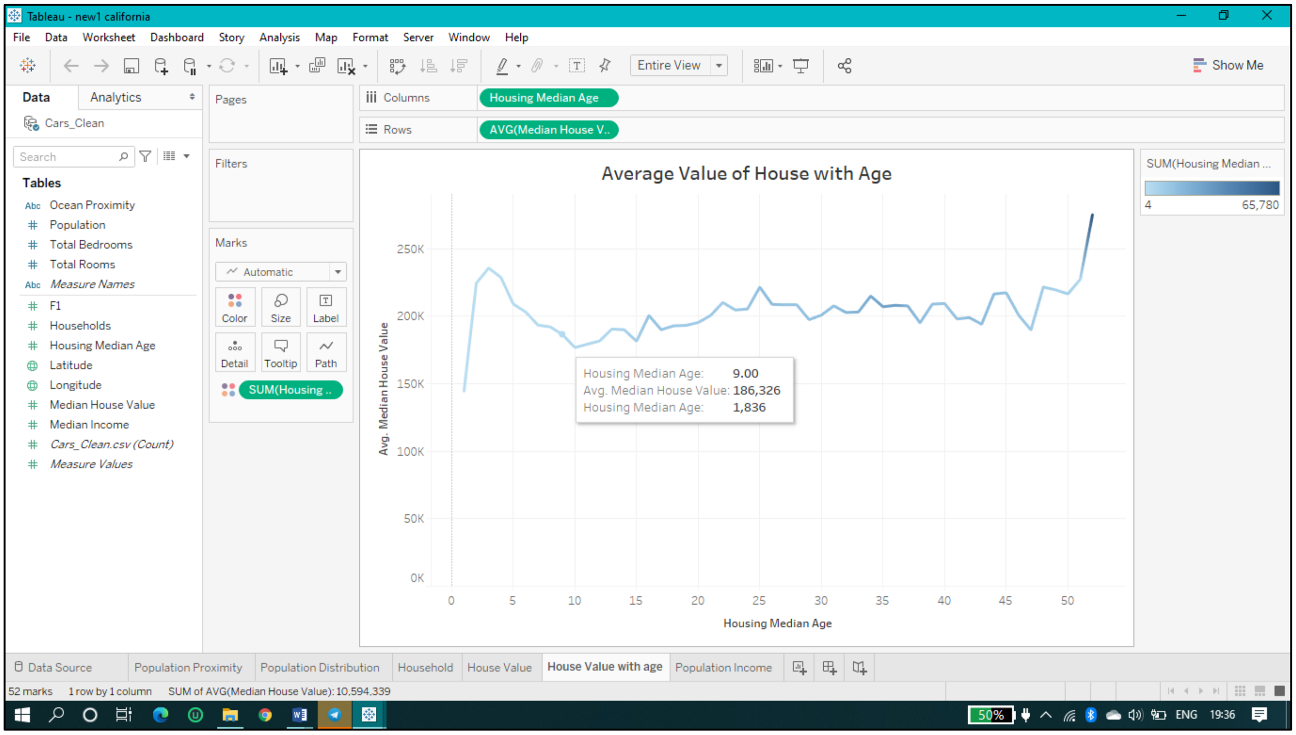


Tableau - new1 california
Columns: Housing Median Age
Rows: AVG(Median House V..
Average Value of House with Age
SUM(Housing Median ...
4
65,780
Housing Median Age: 9.00
Avg. Median House Value: 186,326
Housing Median Age: 1,836
Avg. Median House Value
Housing Median Age
Data Source
Population Proximity
Population Distribution
Household
House Value
House Value with age
Population Income
52 marks
1 row by 1 column
SUM of AVG(Median House Value): 10,594,339

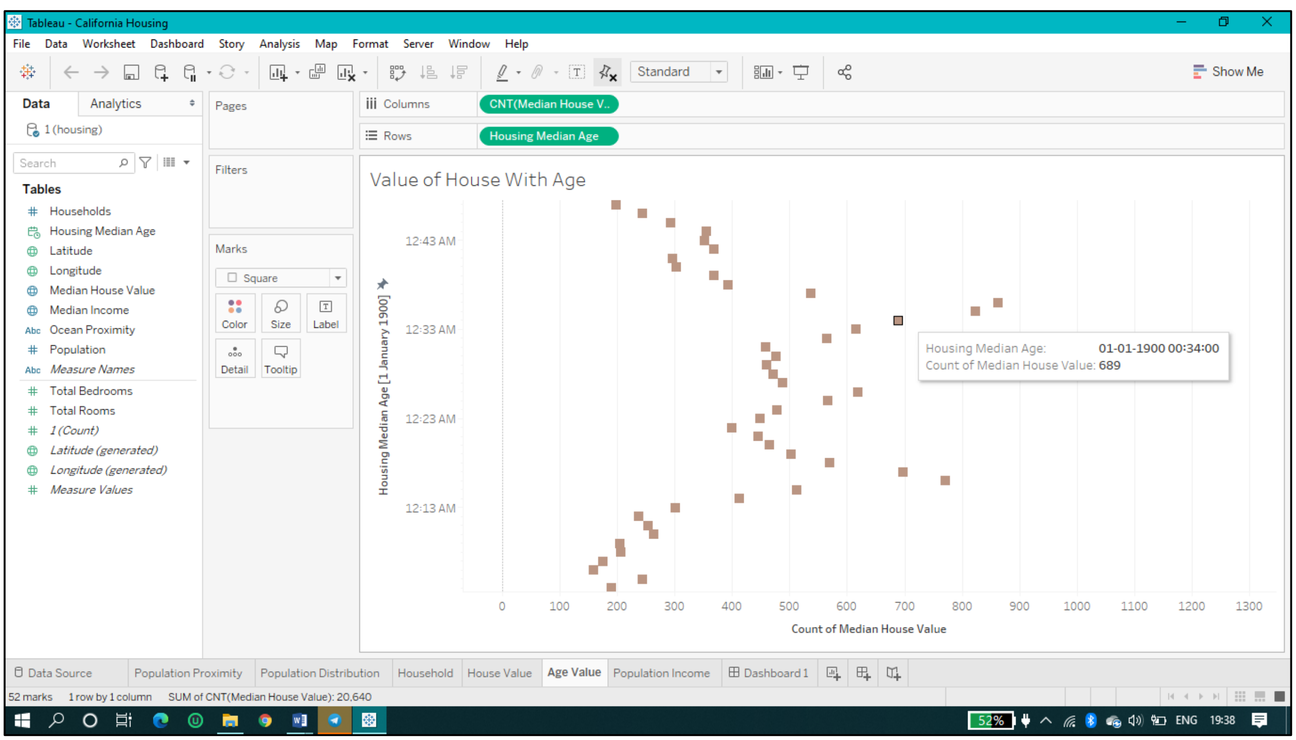


Tableau - California Housing
Columns: CNT(Median House V..
Rows: Housing Median Age
Value of House With Age
Housing Median Age: 01-01-1900 00:34:00
Count of Median House Value: 689
Housing Median Age [1 January 1900]
Count of Median House Value
Data Source
Population Proximity
Population Distribution
Household
House Value
Age Value
Population Income
Dashboard 1
52 marks
1 row by 1 column
SUM of CNT(Median House Value): 20,640

Advantages and disadvantages

Advantages

- Smarter detection
- Prioritize workloads
- Monitor progress
- Detect patterns to initiate action
- Aggregate and correlate information
- Optimize processes and performance
- Identity insights and relationships insights
- Catch suspicious trends before loss occurs
- Achieve improved collaboration and control
- Embed logic into case management systems

Disadvantages

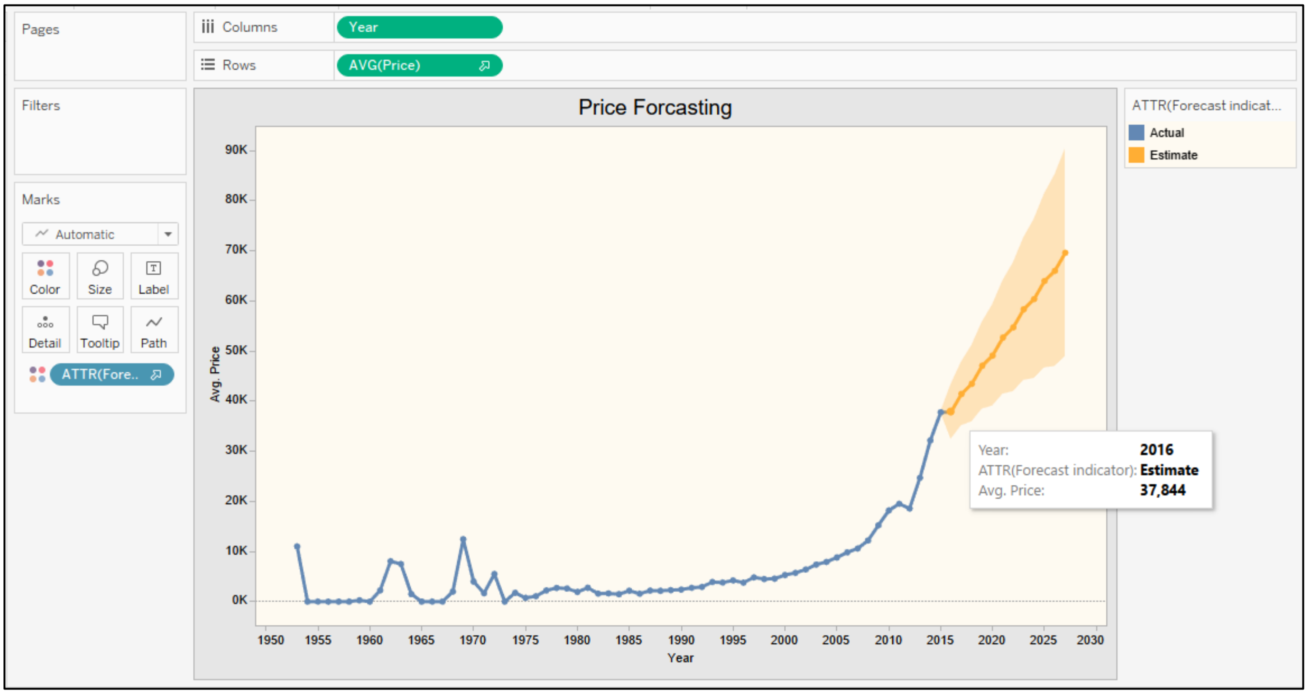
- The data could be incomplete. Missing values, even the lack of a section or a substantial part of the data, could limit its usability.
- If you're using data from surveys, keep in mind that people don't always provide accurate information.
- Data collected from different sources can vary in quality and format. Data collected from such diverse sources as surveys, e-mails, data-entry forms, and the company website will have different attributes and structures.

APPLICATIONS OF DATA PREDICTION MODEL:

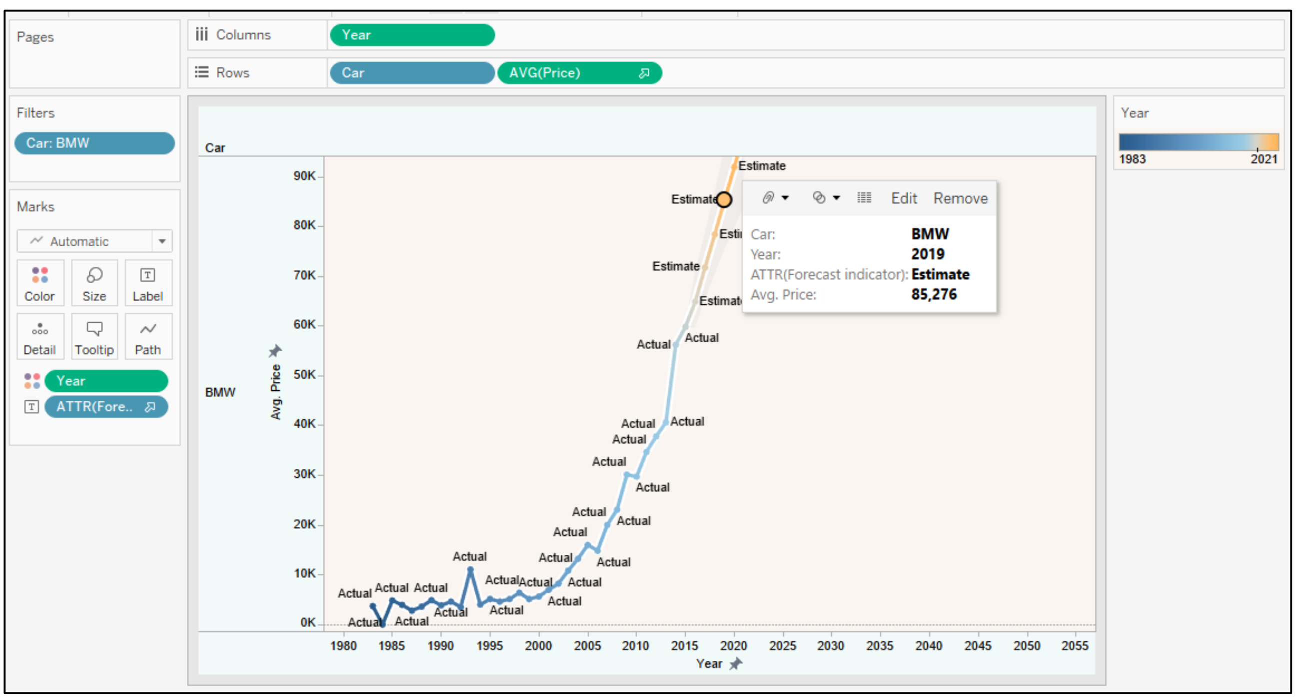
- Actuarial science
- Marketing
- Financial services
- Insurance
- Telecommunications
- Travel
- Healthcare
- Mobility

Result

Forecasting



(Year vs Average Price)



[Year vs Average Price (BMW)]

Forecasting the estimated price of the cars using our data prediction model based on Python and Machine Learning using raw data.

CONCLUSION:

This paper has presented the Report of our Minor Project, i.e.. DATA PREDICTION MODEL. It has shown all the required information about the introduction, objective, plan, advantages and application of the project. It can make a positive contribution to society. Data science can give you some pretty super superpowers. One of them is reshaping industries like healthcare, business. The amount of data produced about patients and illnesses rises by the second, opening new opportunities for better structured and more informed healthcare. The challenge is to carefully analyze the data in order to be able to recognize problems quickly and accurately – like deepsense.ai did in diagnosing diabetic retinopathy with deep learning.

We made a predictive model using Multi-Linear Regression technique for predicting the sales of automobile company and forecast the estimated value of their respective models w.r.t year.

FUTURE SCOPE

The market is witnessing an unprecedented shift in business intelligence (BI), largely because of technological innovation and increasing business needs. The latest shift in the BI market is the move from traditional analytics to predictive analytics. Although predictive analytics belongs to the BI family, it is emerging as a new distinct software sector.

Analytical tools enable greater transparency, and can find and analyze past and present trends, as well as the hidden nature of data. However, past and present insight and trend information are not enough to be competitive in business. Business organizations need to know more about the future, and in particular, about future trends, patterns, and customer behavior in order to understand the market better. To meet this demand, many BI vendors developed predictive analytics to forecast future trends in customer behavior, buying patterns, and who is coming into and leaving the market and why.

Traditional analytical tools claim to have a real 360° view of the enterprise or business, but they analyze only historical data—data about what has already happened. Traditional analytics help gain insight for what was right and what went wrong in decision-making. Today's tools merely provide rear view analysis.

However, one cannot change the past, but one can prepare better for the future and decision makers want to see the predictable future, control it, and take actions today to attain tomorrow's goals.

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