FIT5196-S2-2020 Assessment 3

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Introduction

The .zip files contains various datasets from the purpose of developing an linear model to predict various attributes related to properties located in Victoria, Australia. specification to know about :

- Defualts values has been provided for various attributes in the event of NAN value
- Harvesine distance have been used in kilometers all across the project.
- Only trip departed on weekdays (Monday - Friday) between 07:00 - 09:00 has been considered
- Transfer flag of `0` means direct trip to flinders street station. Transfer flag of `1` means indirect trip

In [1]:

```
#---------------------------------------- Importing required libraries --------------
------------------------------------
import os
from zipfile import ZipFile
from distutils.dir_util import copy_tree
import pandas as pd
import numpy as np

import json   #------------------------------------------- Opening json --------------
--------------
import xlrd
import geopandas as gpd #---------------------------------- Opening Shapefile ---------
--------------
#%pip install shapely
import shapely
from shapely.geometry import Point
from shapely.geometry import shape
from shapely.geometry import Polygon
import xml.etree.ElementTree as ET

#%pip install tabula-py
import tabula  #------------------------------------------- Opening pdf --------------
--------------

from math import sin, cos, sqrt, atan2, radians  #---------- for Harvesine distance ---
--------------

import warnings #----------------------------------------- supressing warnings ------
--------------
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt  #------------------------- For Plotting -------------
--------------
import seaborn as sns

import statsmodels.formula.api as sm  #-------------------- For Linear Modelling -----
--------------
from sklearn import preprocessing
```

Task1 : Data Integration

In Real life even if an company manage to extract important data, changes are it will come from different sources . Data might even be in various formats such as .csv, .json, .txt, etc. The Company needs to combine data from different sources for operational actions or analytical needs. Data integration is not a small task for data engineers if the big data is used.

Importing Data

In [2]:

```
def zip_extract(file_name):
    #---------------------------------------- opening the zip file --------------------
-------------
    with ZipFile(file_name, 'r') as zip:
        #----------------------- extracting all the contents of the zip file ----------
--------------
        zip.extractall()

#------------------------------------------- Zipping various file ----------------------
-----------------------------------
filename = "31337406.zip"
zip_extract(filename)

filename = "Vic_suburb_boundary.zip"
zip_extract(filename)

filename = "GTFS_Melbourne_Train_Information.zip"
zip_extract(filename)
```

Findings

- file named `31337406.zip` contained 5 files all in different formats
- file named `Vic_suburb_boundary.zip` contained shape files .
- file named `GTFS_Melbourne_Train_Information.zip` contained another folder. Upon further exploring it was found that 8 .txt files were contained inside the folder. These datasets needs to exported out to main directory

Extracting data from inner folders

In [3]:

```
#--------------------- opening and copying contents inside few folders to main director
y ---------------------------------
path1 = os.path.abspath("1. GTFS - Melbourne Train Information - From PTV (9 Oct 2015)"
)

path2 = os.getcwd() #-------------------------------- Path of main directory ----------
----------------
copy_tree(path1, path2)  #----------------- Copy all the file in path to main directory
---------------
path3 = os.path.abspath("GTFS - Melbourne Train Information")

copy_tree(path3, path2)  #----------------- Copy all the file in path to main directory
---------------
```

Out[3]:

```
['C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\agency.tx
t',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\calendar.t
xt',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\calendar_d
ates.txt',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\routes.tx
t',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\shapes.tx
t',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\stops.tx
t',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\stop_time
s.txt',
 'C:\\Users\\hitan\\Documents\\Jupyter\\Wrangling\\Assignment3\\trips.tx
t']
```

Result

All files are now exported to main directory for ease of use

Converting data to dataframes

In [4]:

```
#---------------- Reading various format file such as json, shape file, pdf (using tabu
la) --------------------
real = pd.read_json (r'real_state.json')
victoria = gpd.read_file('VIC_LOCALITY_POLYGON_shp.shp')
dataframe = tabula.read_pdf("supermarkets.pdf", pages='all')

agency_data=pd.read_csv('agency.txt', sep=",", header=0)  #--------------- Reading vari
ous .txt files --------------------
calendar_data=pd.read_csv('calendar.txt', sep=",", header=0)
calendar_dates_data=pd.read_csv('calendar_dates.txt', sep=",", header=0)
routes_data=pd.read_csv('routes.txt', sep=",", header=0)
shapes_data=pd.read_csv('shapes.txt', sep=",", header=0)
stop_times_data=pd.read_csv('stop_times.txt', sep=",", header=0)
stops_data=pd.read_csv('stops.txt', sep=",", header=0)
trips_data=pd.read_csv('trips.txt', sep=",", header=0)

#--------- supermarket data after reading, pdf made the index as a separate coloumn , d
eleting this column -------------
supermarket_df = pd.concat(dataframe)
supermarket_df = supermarket_df.drop(['Unnamed: 0'],axis=1)

#--------- shopping cart data after reading, html made the index as a separate coloumn
 , deleting this column -------------
shopingcenters = pd.read_html("shopingcenters.html")[0]
shopingcenters = shopingcenters.drop(['Unnamed: 0'], axis=1)
```

Function Definition: xmltodataframe()

The function xmltodataframe accepts string input extracted from .xml file as an input and convert it to xml type dataset. Function extract the attributes inside the string and values inside those attributes to form an dataset

In [5]:

```
def xmltodataframe(xml_data):
    #----------------------------------------- Reading data --------------------------
-------------
    data = ET.XML(xml_data)

    #--------------------------------------- Recording in dictionary ------------------
-------------
    xmlrecord = {}

    #--------------------------------- for getting inside the root--------------------
-------------
    for child in data:

        #-------- for getting the value of data inside various values of root ---------
----
        xmlrecord[child.tag] = [grandchild.text for grandchild in child]
    return xmlrecord
```

.XML file is read and converted to pandas dataframe with column used in xml and json file

In [6]:

```
#-------------------------------------- Opening and reading .xml file -----------------
------------------------------
with open('real_state.xml', 'r', encoding ="UTF-8") as f:
    real_s = f.read()
#------------------------ Deleting first 2 and last character, might be addded by mista
ke -------------------------------
real_s = real_s[2:-1]

#--------------------------------------------- Calling function -----------------------
--------------------------------
real_state = xmltodataframe(real_s)

# --------------------------- Defining coloumn and converting to dataframe -----------
---------------------------------
cols = ['property_id','lat','lng','addr_street','price','property_type','year','bedroom
s','bathrooms','parking_space']
real_state_df = pd.DataFrame(real_state, columns = cols)
```

Result

- Different techniques were used to read and convert many datasets to pandas dataframe.
- Textual errors in .xml file were found by viewing syntax and then adjustments were made for reading the data as an .xml file.

Combining main datasets

Dataframes made using `real_state.json` and `real_state.xml` were selected as main dataset. Both needs to be combined and then other datasets needs to be joined with this combined dataset according to the business rules

In [7]:

```
#-------------------------- Concatinate xml and json values, Dropping duplicates if an
y --------------------------------
Comb_real_state = pd.concat([real_state_df,real])
Comb_real_state.reset_index(drop=True,inplace=True)
Comb_real_state['property_id'] = Comb_real_state['property_id'].astype(int)
Comb_real_state.drop_duplicates(subset='property_id',inplace=True,keep='first')
Comb_real_state.reset_index(drop=True,inplace=True)
```

Result

- Combined dataset is formed and duplicated rows were deleted using the key `property_id`

Adding Suburbs information to main dataset

After exploring the dataset extracted from the shapefiles, we found that suburbs/locality were defined along with there borders in the form of polygon. We are able to find which property is located in which suburb if we could find in which border polygon does the property lies in.

In [8]:

```
victoria.head(2).iloc[:,[6,12]]
```

Out[8]:

	VIC_LOCA_2	geometry
0	UNDERBOOL	POLYGON ((141.74552 -35.07229, 141.74552 -35.0...
1	NURRAN	POLYGON ((148.66877 -37.39571, 148.66876 -37.3...

To check if property lies in an perticular suburb, latitude and longitude of the property is converted into geopandas point which is then checked using `contained` function in geopandas. If an particular suburb containes an property (point), Its corresponding suburb will be assigned

In [9]:

```
#---------------- converting latitude and longitude to point function of geopandas in m
ain database --------------------
Comb_real_state["lat"] = Comb_real_state['lat'].apply(lambda x: float(x))
Comb_real_state["lng"] = Comb_real_state['lng'].apply(lambda x: float(x))
geometry = [Point(xy) for xy in zip(Comb_real_state["lng"],Comb_real_state["lat"])]
geo_df = gpd.GeoDataFrame(Comb_real_state,geometry=geometry)

#------------------------------ Adding suburb coloumn with defualt value -------------
----------------------------------
geo_df["suburb"] = "not available"
geo_df.reset_index(drop=True,inplace=True)
```

In [10]:

```
%%time
#-------------------- checking to see in which suburb's polygon house location is cont
ained ------------------------------
for i in range(len(geo_df)):
    for k in range(len(victoria)):
        if victoria.geometry[k].contains(geo_df.geometry[i]): #----------------- house
 is contained in this suburb
            geo_df.suburb[i] = victoria.VIC_LOCA_2[k]
```

```
Wall time: 6min 1s
```

Result

Suburb Data is added to with respest to property locations

Adding Supermarket information to main dataset

From dataset extracted from the supermarket file, we'll check the closed supermarket to a particular property. As specified by the business rules, closest supermarket will be mentioned with respect to the property along with the distance to said supermarket. Harvesine method of distance calculation is used to get the distance in kilometers (km).

In [11]:

```
# making supermarket coloumn in main data and converting latitude and longitude to poin
t function of geopandas of supermarket
geo_df["Supermarket_id"] = "not available"
geometry = [Point(xy) for xy in zip(supermarket_df["lng"],supermarket_df["lat"])]
supermarket_df = gpd.GeoDataFrame(supermarket_df,geometry=geometry)
supermarket_df.reset_index(drop=True,inplace=True)
```

Function Definition: Harvesine()

The function Harvesine accepts two geopandas points as an input and return haversine distance in kilometers between these two points. Function is basically an mathematical formula function with output as distance

Function Definition: nearest_distance_super()

The function nearest_distance_super accepts one geopandas point and supermerket's dataset as an input and return supermarket closest to inputted point and distance in kilometers between them. Function runs of looping the dataset to find distance of each supermarket to input point and then sorting to find the closest distance supermarket.

- nearest_distance_super() functin can work for dataset related to hospital

In [12]:

```
#------------------------------- function to get harvesine of two geopandas points ----
------------------------------------
def Harvesine(point1, point2):

    R = 6378.0
    #---------------------- Convert latitude and longitude to radians -----------------
-----------
    lat1 = radians(float(point1.y))
    lon1 = radians(float(point1.x))
    lat2 = radians(float(point2.y))
    lon2 = radians(float(point2.x))

    #---------------------- Formula used to find Harvesine function in km -------------
------------
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))
    distance = R * c
    return(distance)

#----------------- function which return closest supermarket and Harvesine distance to
location in kilometer -------------
def nearest_distance_super(point,df):
    #--------------------------------- temp coloumn to store distance -----------------
--------------------
    df['have_distance'] = float(0)

    #---- Looping to get distance of each supermarket to location and then sorting to f
ind closest ----------
    for i in range(len(df)):
        df.have_distance[i] = float(Harvesine(point,df.geometry[i]))
    df.sort_values(by=['have_distance'],ascending=True, inplace=True)

    #--------------------- first row's id and distance is returned --------------------
--------------
    data_id = df["id"].iloc[0]
    test_distance = df["have_distance"].iloc[0]
    test_distance = round(test_distance, 3)
    return data_id,test_distance
```

In [13]:

```
%%time
#-------------------------------- coloumn to store distance and supermerket id --------
----------------------------------
geo_df["Supermarket_id"] = "not available"
geo_df["Distance_to_supermaket"] = float(0)

#------------------------------ Looping to get distance of closest supermarket to locat
ion ------------------------------
for i in range(len(geo_df)):
    point = geo_df.geometry[i]
    answer = nearest_distance_super(point,supermarket_df)

    #----------------------- setting supermarket_id and distance ----------------------
------
    geo_df.Supermarket_id[i] = answer[0]
    geo_df.Distance_to_supermaket[i] = answer[1]
```

```
Wall time: 2min 34s
```

Result

Closest Supermarket id and distance Data is added to with respest to property locations

Adding Shopping center information to main dataset

From dataset extracted from the shoppingcenter file, we'll check the closed Shopping center to a particular property. As specified by the business rules, closest Shopping center will be mentioned with respect to the property along with the distance to said Shopping center. Harvesine method of distance calculation is used to get the distance in kilometers (km).

In [14]:

```
#------------ Reading shoping cart data and converting latitude and longitude to point
 function of geopandas -----------
geometry = [Point(xy) for xy in zip(shopingcenters["lng"],shopingcenters["lat"])]
shopingcenters = gpd.GeoDataFrame(shopingcenters,geometry=geometry)
shopingcenters.reset_index(drop=True,inplace=True)
```

Function Definition: nearest_distance_shop()

The function nearest_distance_super accepts one geopandas point and shopping center's dataset as an input and return shopping center closest to inputted point and distance in kilometers between them. Function runs of looping the dataset to find distance of each shopping center to input point and then sorting to find the closest distance supermarket

In [15]:

```
%%time
#--------------- function which return closest shopping center and Harvesine distance t
o location in kilometer -------------
def nearest_distance_shop(point,df):
    #-------------------------------- temp coloumn to store distance ------------------
----------------
    df['have_distance'] = float(0)

    #------------------ Looping to get distance of closest shopping ceter to location -
-----------------
    for i in range(len(df)):
        df.have_distance[i] = float(Harvesine(point,df.geometry[i]))
    df.sort_values(by=['have_distance'],ascending=True, inplace=True)

    #---------------------------- first row's id and distance is returned -------------
------------------
    data_id = df["sc_id"].iloc[0]
    test_distance = df["have_distance"].iloc[0]
    test_distance = round(test_distance, 3)
    return data_id,test_distance

#---------------------------- coloumn to store distance and shopping center id -------
------------------------------------
geo_df["Shopping_center_id"] = "not available"
geo_df["Distance_to_sc"] = float(0)

#---------------------------- Looping to get distance of closest shopping center to loc
ation ------------------------------
for i in range(len(geo_df)):
    point = geo_df.geometry[i]
    answer = nearest_distance_shop(point,shopingcenters)

    #------------------- setting supermarket_id and distance --------------------------
------
    geo_df.Shopping_center_id[i] = answer[0]
    geo_df.Distance_to_sc[i] = answer[1]
```

```
Wall time: 1min 17s
```

Result

Closest Shopping_center id and distance is added to with respest to property locations

Adding Hospital information to main dataset

From dataset extracted from the hospital file, we'll check the closed hospital to a particular property. As specified by the business rules, closest hospital will be mentioned with respect to the property along with the distance to said hospital. Harvesine method of distance calculation is used to get the distance in kilometers (km).

In [16]:

```
#- making hospital coloumn in main data and converting latitude and longitude to point
 function of geopandas of hospitals --
hospitals = pd.read_excel("hospitals.xlsx")
hospitals = hospitals.drop(['Unnamed: 0'], axis=1)
geometry = [Point(xy) for xy in zip(hospitals["lng"],hospitals["lat"])]
hospitals = gpd.GeoDataFrame(hospitals,geometry=geometry)
hospitals.reset_index(drop=True,inplace=True)
```

In [17]:

```
%%time
#---------------------------------- coloumn to store distance and hospital id ----------
-----------------------------------
geo_df["Hospital_id"] = "not available"
geo_df["Distance_to_hospital"] = float(0)

#--------------------------- looping to get distance of closest hospital to location -
------------------------------------
for i in range(len(geo_df)):
    point = geo_df.geometry[i]
    answer = nearest_distance_super(point,hospitals)
    #------------------------- setting hospital_id and distance ----------------------
-------
    geo_df.Hospital_id[i] = answer[0]
    geo_df.Distance_to_hospital[i] = answer[1]
```

```
Wall time: 2min 5s
```

Result

closest Hospital id and distance is added to with respest to property locations

Adding train stop information to main dataset

From dataset extracted from the stops file, we'll check the closed train stop to a particular property. As specified by the business rules, closest train stop will be mentioned with respect to the property along with the distance to said train stop. Harvesine method of distance calculation is used to get the distance in kilometers (km).

In [18]:

```
#----------------- converting latitude and longitude to point function of geopandas of
 stops ------------------------------
geometry = [Point(xy) for xy in zip(stops_data["stop_lon"],stops_data["stop_lat"])]
stops_data = gpd.GeoDataFrame(stops_data,geometry=geometry)
stops_data.reset_index(drop=True,inplace=True)
```

In [19]:

```
%%time
#----------- function which return closest train stop and Harvesine distance to locatio
n in kilometer ------------------
def nearest_distance_stop(point,df):
    #--------------------------- temp coloumn to store distance -----------------------
------------
    df['have_distance'] = float(0)

    #------------------ Looping to get distance of closest train stop to location -----
---------
    for i in range(len(df)):
        df.have_distance[i] = float(Harvesine(point,df.geometry[i]))
    df.sort_values(by=['have_distance'],ascending=True, inplace=True)

    #--------------------------- first row's id and distance is returned --------------
--------------
    data_id = df["stop_id"].iloc[0]
    test_distance = df["have_distance"].iloc[0]
    test_distance = round(test_distance, 3)
    return data_id,test_distance

#---------------------------- coloumn to store distance and train stop id -----------
-------------------------------
geo_df["Train_station_id"] = 0
geo_df["Distance_to_train_station"] = float(0)

#-------------------------- Looping to get distance of closest train stop to location -
--------------------------------
for i in range(len(geo_df)):
    point = geo_df.geometry[i]
    answer = nearest_distance_stop(point,stops_data)

    #--------------------------- setting train stop_id and distance-------------------
----------
    geo_df.Train_station_id[i] = answer[0]
    geo_df.Distance_to_train_station[i] = answer[1]
```

```
Wall time: 2min 21s
```

Result

closest Train_station id and distance is added to with respest to property locations

Filtering trips

Business rules states that in order for trip to be accounted, respected train needs to run on all weekdays (Mon-Fri) and trip inbetween 07:00 to 09:00 will be measures. Therfore to check the services which run on all weekdays. We'll need to extract information from dataset extracted from calender.txt.

In [20]:

```
# ----------------------------------- information about services run -----------------
----------------------------------
calendar_data
```

Out[20]:

	service_id	monday	tuesday	wednesday	thursday	friday	saturday	sunday	start_date
0	T2	0	0	0	0	0	1	0	20151009
1	UJ	0	0	0	0	0	0	1	20151009
2	T6	0	0	0	0	1	0	0	20151009
3	T5	1	1	1	1	0	0	0	20151012
4	T2_1	0	0	0	0	0	1	0	20151016
5	UJ_1	0	0	0	0	0	0	1	20151016
6	T6_1	0	0	0	0	1	0	0	20151016
7	T5_1	1	1	1	1	0	0	0	20151019
8	T0	1	1	1	1	1	0	0	20151023
9	T2_2	0	0	0	0	0	1	0	20151023
10	UJ_2	0	0	0	0	0	0	1	20151023
11	T0+a6	0	0	0	0	1	0	0	20151023
12	T0+a5	1	1	1	1	0	0	0	20151023
13	T5+tg	1	1	0	0	0	0	0	20151012
14	T5+ph	0	0	1	1	0	0	0	20151012
15	T5+tg_1	1	1	0	0	0	0	0	20151019
16	T5+ph_1	0	0	1	1	0	0	0	20151019
17	T5+ao	1	0	0	0	0	0	0	20151012
18	T5+ta	0	1	1	1	0	0	0	20151012

In [21]:

```
#------------------ Filtering for only 'Flinders Street Railway Station' station ------
-----------------------------------
finder_stops_data = stops_data.loc[(stops_data['stop_name'] == 'Flinders Street Railway
Station')]
finder_stops_data
```

Out[21]:

	stop_id	stop_name	stop_short_name	stop_lat	stop_lon	geometry	have_distance
29	19854	Flinders Street Railway Station	Melbourne City	-37.818305	144.966964	POINT (144.96696 -37.81831)	27.7294

Result

From above data we'll conclude that only Service_id `T0` runs on all 5 weekdays and the stop_id for flinders street is 19854. In future we'll consider only this Service_id and this stop_id as destination.

Filtering trips

Filtering trips by service T0

In [22]:

```
#---------------------- Filtering for only service_id "T0" as only "T0" work on all wee
kdays ------------------------------
trips_data = trips_data[(trips_data['service_id'] == 'T0')]
trip_list = list(trips_data['trip_id'])
stop_times_data = stop_times_data[stop_times_data['trip_id'].isin(trip_list)]
stop_times_data.reset_index(drop=True,inplace=True)
```

Filtering trips by destination as Flinders Station and merging with all data

In [23]:

```
#----------------------- Filtering for only 'Flinders Street Railway Station' station -
-----------------------------------
flinder_stop_times=stop_times_data[stop_times_data['stop_id']==19854]
flinder_stop_times.reset_index(drop=True,inplace=True)

#-------------------- Merging only flinder data and all data, taking key as trip_id --
------------------------------------
train_to_flinder = stop_times_data.merge(flinder_stop_times, on='trip_id', how='inner')
train_to_flinder.reset_index(drop=True,inplace=True)
```

Filtering trips by time

In [24]:

```
temp_list = []
#---------------- Looping to remove all departure time other than between 7:00am to 9:0
0am --------------------------------
for i in train_to_flinder.index:
    departure = int(train_to_flinder['departure_time_x'][i].split(':',1)[0])

    #----------- index which satisfy condition is appended in list to be used to drop r
ows -------------
    if (departure >= 7):
        if (departure < 9):
            temp_list.append(True)
        else:
            temp_list.append(False)
    else:
        temp_list.append(False)


train_to_flinder =train_to_flinder[(temp_list)]
```

Result

With the help of above algorithm data is now filtered and ready to be worked on to find time taken by train to reach destination

Finding the time taken

In the data we got the time of train's arrival to different station and the train' arrival to its destination i.e. flinders. These datetime values can now be subtracted to get time taken. further data can be grouped according to train stops and mean time taken can be found.

In [25]:

```
train_to_flinder.reset_index(drop=True,inplace=True)
#--------------- Converting departure(location) and arrival(flinders) time to datetime
 format ---------------------------
train_to_flinder['departure_time_x']=pd.to_datetime(train_to_flinder['departure_time_x'
],format='%H:%M:%S')
train_to_flinder['arrival_time_y']=pd.to_datetime(train_to_flinder['arrival_time_y'],fo
rmat='%H:%M:%S')

# ------------------------ finding time difference between arrival(flinders) and depart
ure ----------------------------
train_to_flinder['time_taken'] =(train_to_flinder['arrival_time_y']-train_to_flinder['d
eparture_time_x'])
train_to_flinder['time_taken']=train_to_flinder['time_taken'].astype('timedelta64[m]')

# ----------------------------- filtering to drop rows where trip which start from flin
ders ------------------------------
train_to_flinder1 = train_to_flinder[train_to_flinder['time_taken'] > 0]
```

In [26]:

```
train_to_flinder1.reset_index(drop=True,inplace=True)

#--------------------------- Finding the mean of various trip from a stop -------------------------------------------------
train_to_flinder2 = train_to_flinder1.groupby('stop_id_x', as_index=False).mean()
train_to_flinder2.reset_index(drop=True,inplace=True)

#------------------------- dropping useless coloumns and renaming coloumns ----------------------------------------------------
train_to_flinder3 = train_to_flinder2[['stop_id_x','time_taken']]
train_to_flinder3.rename(columns={"stop_id_x":"Train_station_id"}, inplace = True)
train_to_flinder3.rename(columns={"time_taken":"travel_min_to_CBD"}, inplace = True)
```

Result

Mean time taken by train from various train stop are calculated

Merging and inputting transfer flags

Mean time taken data is now merged with combined main dataset. Accordingly train station not present in mean time taken data doesn't have direct train to flinders street therefore must be flagged `1` and stations with direct train must be be flgged a `0` according to business rules

In [27]:

```
#-------------------- Merging main dataframe with average time to flinders data --------------------------------------------
combined = geo_df.merge(train_to_flinder3, on='Train_station_id', how='left').fillna(0)
```

In [28]:

```
#--------------------------------------------------- Defualt value -----------------------------------------------------------
combined['Transfer_flag'] = '-1'

#------- train stops which are not present in direct transfer database(dataframe gotten in previous set)
#------- is considered non-direct, therefore will be given value of 1 ----------------------------------------------------
for ind in range(len(combined)):
    if combined['travel_min_to_CBD'][ind] > 0:
        combined['Transfer_flag'][ind] = '0'
    else:
        combined['Transfer_flag'][ind] = '1'
```

Rearranging Dataframe coloumns and generating CSV file

In [29]:

```
#--------------------------- Rearranging the main dataframe's coloumns to specification
-----------------------------------
combined = combined[['property_id', 'lat', 'lng', 'addr_street',
                     'suburb', 'price', 'property_type', 'year',
                     'bedrooms', 'bathrooms', 'parking_space',
                     'Shopping_center_id', 'Distance_to_sc',
                     'Train_station_id', 'Distance_to_train_station',
                     'travel_min_to_CBD', 'Transfer_flag', 'Hospital_id',
                     'Distance_to_hospital', 'Supermarket_id', 'Distance_to_supermaket'
]]
```

In [30]:

```
#---------------------------------- Main dataframe is converted to .CSV file ----------
------------------------------------
combined.reset_index(drop=True, inplace=True)
combined.to_csv('31337406_A3_solution.csv',index=False)
```

Task2 : Data Reshaping

Normaization process entails to reshaping range of numerical values using mathematical function

Plotting the graphs

For normalization process we need to first get a sense of the data. the best way is to plot the data on graphs. to check for any linearity relation between dependent variable (price) and independent variables (Distance_to_sc, travel_min_to_CBD, Distance_to_hospital) scatterplot can be used.

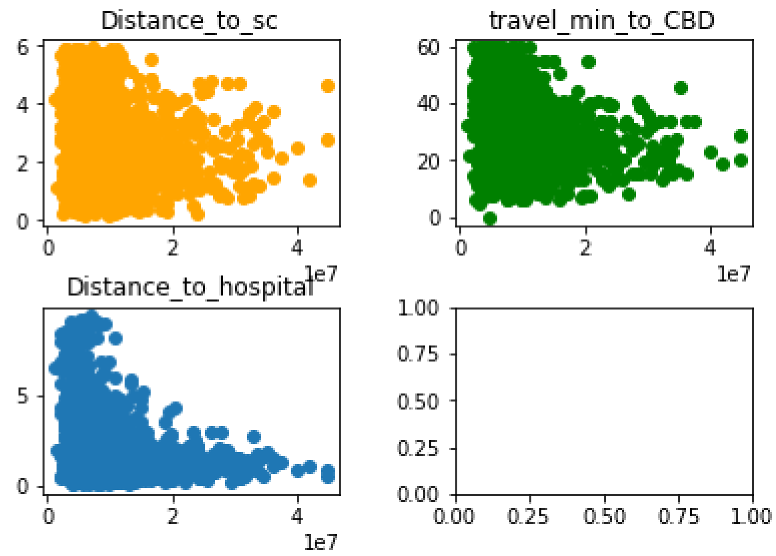
In [31]:

```
#---------------------- Subplot to show 3 attributes as intructed by business rules --
------------------------------------
combined['price'] = combined['price'].astype(int)
fig, axs = plt.subplots(2, 2)
fig.tight_layout(pad=2.0)

#---------------------- Scatter plot of attributes  -----------------------------------
---
axs[0, 0].scatter(combined['price'], combined['Distance_to_sc'], c = 'orange')
axs[0, 0].set_title('Distance_to_sc')
axs[0, 1].scatter(combined['price'], combined['travel_min_to_CBD'], c = 'green')
axs[0, 1].set_title('travel_min_to_CBD')
axs[1, 0].scatter(combined['price'], combined['Distance_to_hospital'])
axs[1, 0].set_title('Distance_to_hospital')
```

Out[31]:

```
Text(0.5, 1, 'Distance_to_hospital')
```

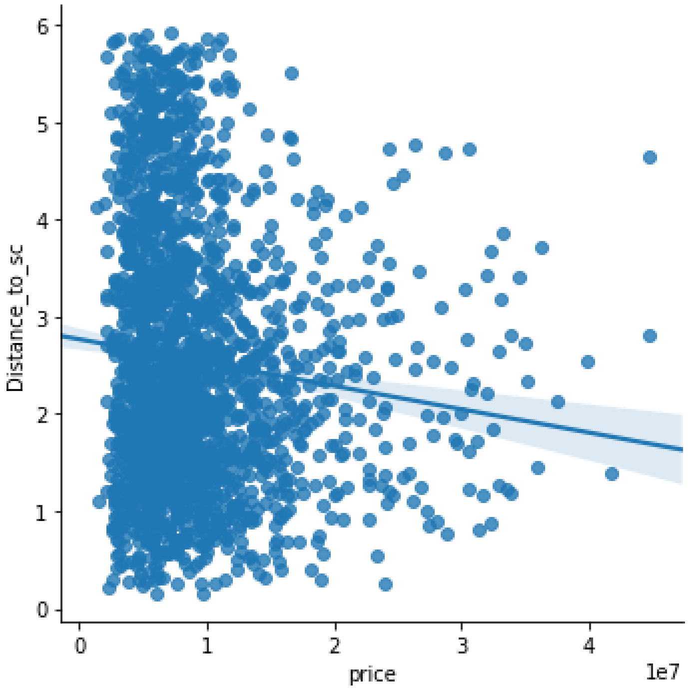


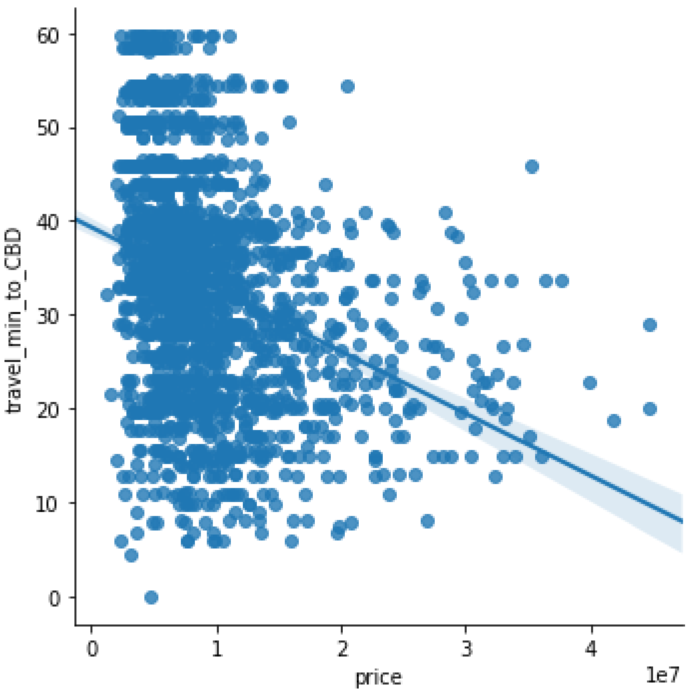
Result

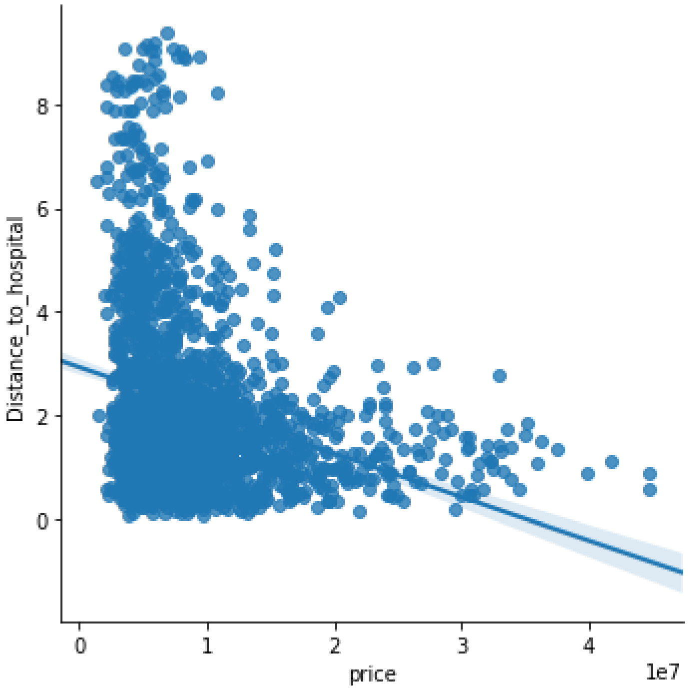
As visually no linear relation can not observed in above graphs, we'll use lmplot to further explot the data

In [32]:

```
#---------------------- linear model graph to show 3 attributes -----------------------
---------------
g0 = sns.lmplot(x = "price", y = "Distance_to_sc", data = combined)
g1 = sns.lmplot(x = "price", y = "travel_min_to_CBD", data = combined)
g2 = sns.lmplot(x = "price", y = "Distance_to_hospital", data = combined)
```


Distance_to_sc
price
1e7
0
1
2
3
4
5
6


travel_min_to_CBD
price
1e7
0
10
20
30
40
50
60



Result

After carefully evaluating scatterplot and lmplot , we can confirm that their may be some form of linear relation between dependent and independent variables. The key in getting an good accuracy and r-sqaure value is transformation of variables. From initial look Distance_to_hospital may require an log transformation. however more experiment is neccesary

Transformation

In [33]:

```
combined['new_price'] = combined["price"].apply(lambda x: np.log(x+1))
combined['new_Distance_to_sc'] = combined["Distance_to_sc"].apply(sqrt)
combined['new_travel_min_to_CBD'] = combined["travel_min_to_CBD"].apply(lambda x: np.lo
g(x+1))
combined['new_Distance_to_hospital'] = combined['Distance_to_hospital'].apply(lambda x:
np.log(x+1))
```

Result

After going through various transformation, above non- linear transformation resulted in best possible accuracy.

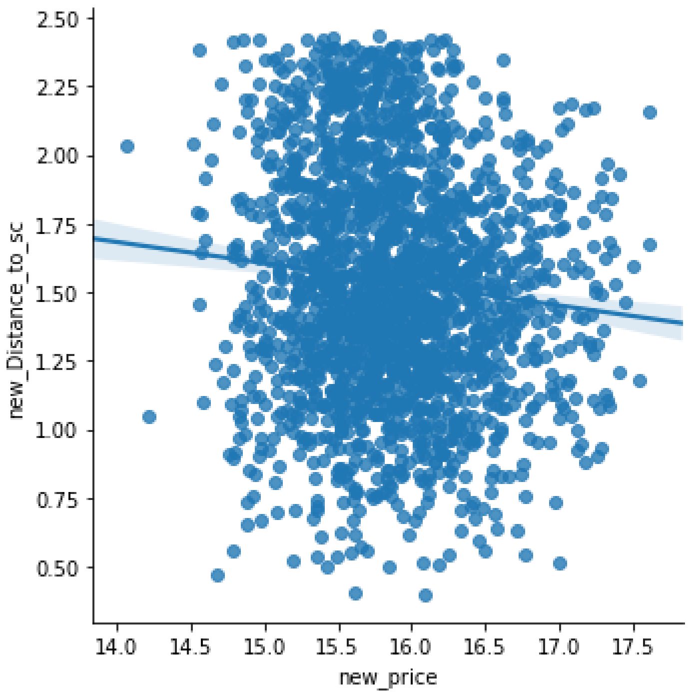
Plotting the transformed graphs

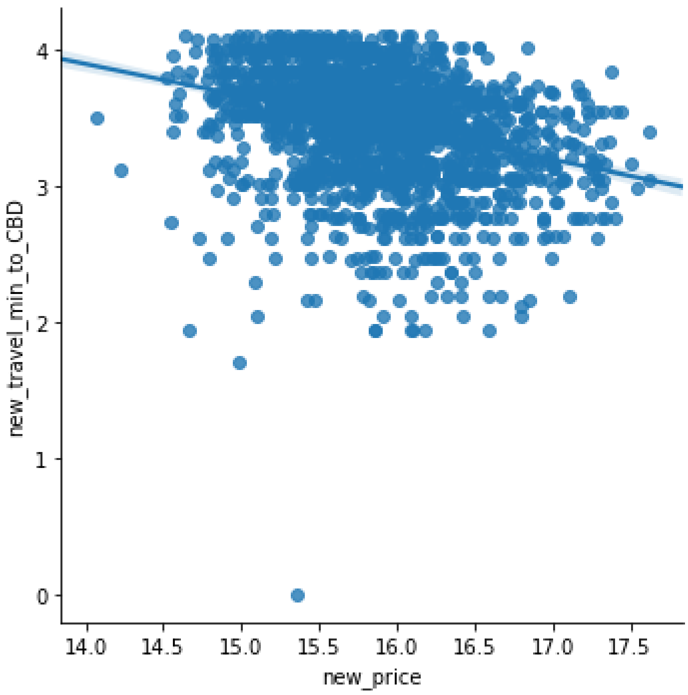
In [34]:

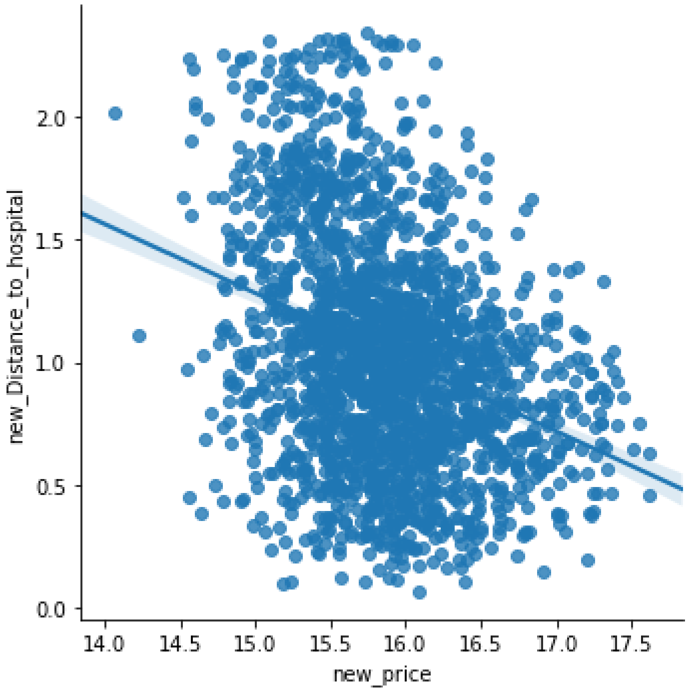
```
sns.lmplot(x = "new_price", y = "new_Distance_to_sc", data = combined)
sns.lmplot(x = "new_price", y = "new_travel_min_to_CBD", data = combined)
sns.lmplot(x = "new_price", y = "new_Distance_to_hospital", data = combined)
```

Out[34]:

<seaborn.axisgrid.FacetGrid at 0x1e5163ea208>





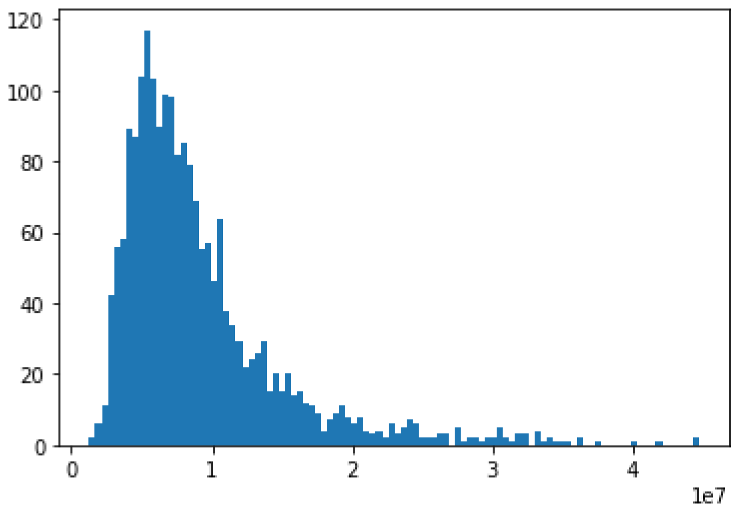

new_Distance_to_hospital
2.0
1.5
1.0
0.5
0.0
14.0
14.5
15.0
15.5
16.0
16.5
17.0
17.5
new_price

In [35]:

```
plt.hist(data = combined, x = "price", bins=100)
```

Out[35]:

```
(array([  2.,   6.,  11.,  42.,  56.,  58.,  89.,  87., 104., 117., 103.,
         90.,  99.,  98.,  82.,  85.,  79.,  69.,  55.,  57.,  46.,  64.,
         38.,  34.,  29.,  22.,  24.,  26.,  29.,  15.,  20.,  15.,  20.,
         14.,  15.,  12.,  11.,   9.,   4.,   7.,   9.,  11.,   8.,   6.,
          8.,   4.,   3.,   4.,   2.,   6.,   3.,   5.,   7.,   6.,   2.,
          2.,   2.,   3.,   3.,   0.,   5.,   1.,   2.,   2.,   1.,   2.,
          2.,   5.,   2.,   1.,   3.,   3.,   0.,   4.,   1.,   2.,   1.,
          1.,   1.,   0.,   2.,   0.,   0.,   1.,   0.,   0.,   0.,   0.,
          0.,   1.,   0.,   0.,   0.,   1.,   0.,   0.,   0.,   0.,   0.,
          2.]),
 array([ 1281500.,  1715785.,  2150070.,  2584355.,  3018640.,  3452925.,
         3887210.,  4321495.,  4755780.,  5190065.,  5624350.,  6058635.,
         6492920.,  6927205.,  7361490.,  7795775.,  8230060.,  8664345.,
         9098630.,  9532915.,  9967200., 10401485., 10835770., 11270055.,
        11704340., 12138625., 12572910., 13007195., 13441480., 13875765.,
        14310050., 14744335., 15178620., 15612905., 16047190., 16481475.,
        16915760., 17350045., 17784330., 18218615., 18652900., 19087185.,
        19521470., 19955755., 20390040., 20824325., 21258610., 21692895.,
        22127180., 22561465., 22995750., 23430035., 23864320., 24298605.,
        24732890., 25167175., 25601460., 26035745., 26470030., 26904315.,
        27338600., 27772885., 28207170., 28641455., 29075740., 29510025.,
        29944310., 30378595., 30812880., 31247165., 31681450., 32115735.,
        32550020., 32984305., 33418590., 33852875., 34287160., 34721445.,
        35155730., 35590015., 36024300., 36458585., 36892870., 37327155.,
        37761440., 38195725., 38630010., 39064295., 39498580., 39932865.,
        40367150., 40801435., 41235720., 41670005., 42104290., 42538575.,
        42972860., 43407145., 43841430., 44275715., 44710000.]),
 <a list of 100 Patch objects>)
```

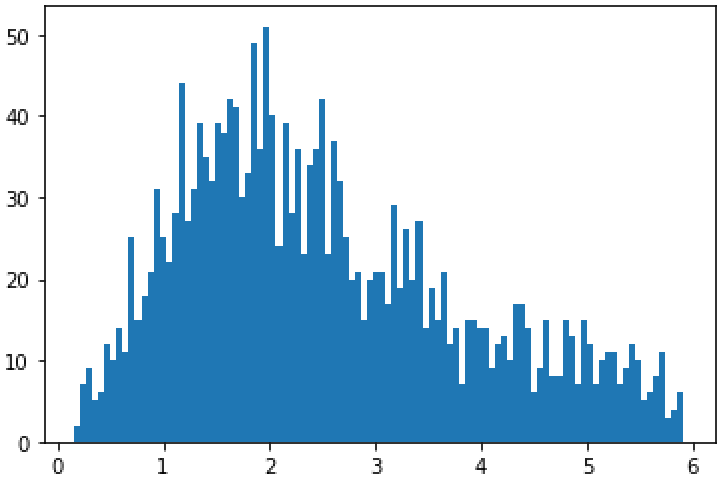


In [36]:

```
plt.hist(data = combined, x = "Distance_to_sc", bins=100)
```

Out[36]:

```
(array([ 2.,  7.,  9.,  5.,  6., 12., 10., 14., 11., 25., 15., 18., 21.,
        31., 25., 22., 28., 44., 27., 31., 39., 35., 32., 39., 38., 42.,
        41., 30., 33., 49., 36., 51., 40., 24., 39., 28., 36., 23., 34.,
        36., 42., 23., 37., 32., 25., 20., 21., 15., 20., 21., 21., 17.,
        29., 19., 26., 20., 27., 14., 19., 15., 21., 12., 14.,  7., 15.,
        15., 14., 14.,  9., 12., 13., 10., 17., 17., 14.,  6.,  9., 15.,
         8.,  8., 15., 13.,  7., 15., 12.,  7., 10., 11., 11.,  7.,  9.,
        12., 10.,  5.,  6.,  8., 11.,  3.,  4.,  6.]),
 array([0.159  , 0.21657, 0.27414, 0.33171, 0.38928, 0.44685, 0.50442,
        0.56199, 0.61956, 0.67713, 0.7347 , 0.79227, 0.84984, 0.90741,
        0.96498, 1.02255, 1.08012, 1.13769, 1.19526, 1.25283, 1.3104 ,
        1.36797, 1.42554, 1.48311, 1.54068, 1.59825, 1.65582, 1.71339,
        1.77096, 1.82853, 1.8861 , 1.94367, 2.00124, 2.05881, 2.11638,
        2.17395, 2.23152, 2.28909, 2.34666, 2.40423, 2.4618 , 2.51937,
        2.57694, 2.63451, 2.69208, 2.74965, 2.80722, 2.86479, 2.92236,
        2.97993, 3.0375 , 3.09507, 3.15264, 3.21021, 3.26778, 3.32535,
        3.38292, 3.44049, 3.49806, 3.55563, 3.6132 , 3.67077, 3.72834,
        3.78591, 3.84348, 3.90105, 3.95862, 4.01619, 4.07376, 4.13133,
        4.1889 , 4.24647, 4.30404, 4.36161, 4.41918, 4.47675, 4.53432,
        4.59189, 4.64946, 4.70703, 4.7646 , 4.82217, 4.87974, 4.93731,
        4.99488, 5.05245, 5.11002, 5.16759, 5.22516, 5.28273, 5.3403 ,
        5.39787, 5.45544, 5.51301, 5.57058, 5.62815, 5.68572, 5.74329,
        5.80086, 5.85843, 5.916  ]),
 <a list of 100 Patch objects>)
```

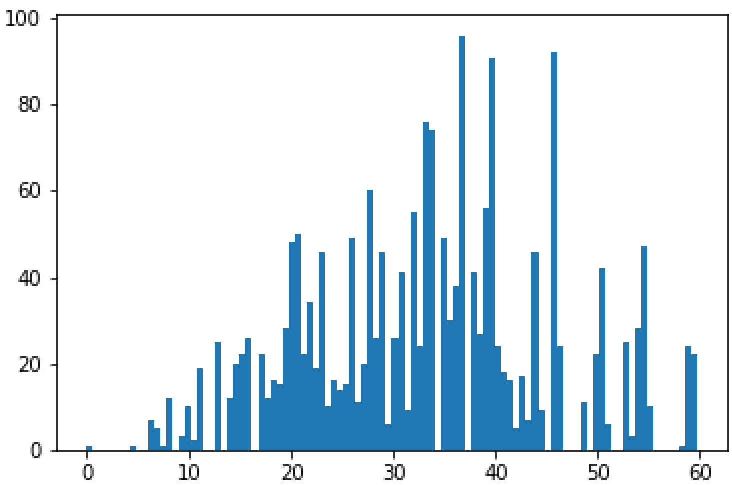


In [37]:

```
plt.hist(data = combined, x = "travel_min_to_CBD", bins=100)
```

Out[37]:

```
(array([ 1.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  7.,  5.,  1.,
        12.,  0.,  3., 10.,  2., 19.,  0.,  0., 25.,  0., 12., 20., 22.,
        26.,  0., 22., 12., 16., 15., 28., 48., 50., 22., 34., 19., 46.,
        10., 16., 14., 15., 49., 11., 20., 60., 26., 46.,  6., 26., 41.,
         9., 55., 24., 76., 74.,  0., 49., 30., 38., 96.,  0., 41., 27.,
        56., 91., 24., 18., 16.,  5., 17.,  7., 46.,  9.,  0., 92., 24.,
         0.,  0.,  0., 11.,  0., 22., 42.,  6.,  0.,  0., 25.,  3., 28.,
        47., 10.,  0.,  0.,  0.,  0.,  1., 24., 22.]),
 array([ 0.        ,  0.59666667,  1.19333333,  1.79      ,  2.38666667,
         2.98333333,  3.58      ,  4.17666667,  4.77333333,  5.37      ,
         5.96666667,  6.56333333,  7.16      ,  7.75666667,  8.35333333,
         8.95      ,  9.54666667, 10.14333333, 10.74      , 11.33666667,
        11.93333333, 12.53      , 13.12666667, 13.72333333, 14.32      ,
        14.91666667, 15.51333333, 16.11      , 16.70666667, 17.30333333,
        17.9       , 18.49666667, 19.09333333, 19.69      , 20.28666667,
        20.88333333, 21.48      , 22.07666667, 22.67333333, 23.27      ,
        23.86666667, 24.46333333, 25.06      , 25.65666667, 26.25333333,
        26.85      , 27.44666667, 28.04333333, 28.64      , 29.23666667,
        29.83333333, 30.43      , 31.02666667, 31.62333333, 32.22      ,
        32.81666667, 33.41333333, 34.01      , 34.60666667, 35.20333333,
        35.8       , 36.39666667, 36.99333333, 37.59      , 38.18666667,
        38.78333333, 39.38      , 39.97666667, 40.57333333, 41.17      ,
        41.76666667, 42.36333333, 42.96      , 43.55666667, 44.15333333,
        44.75      , 45.34666667, 45.94333333, 46.54      , 47.13666667,
        47.73333333, 48.33      , 48.92666667, 49.52333333, 50.12      ,
        50.71666667, 51.31333333, 51.91      , 52.50666667, 53.10333333,
        53.7       , 54.29666667, 54.89333333, 55.49      , 56.08666667,
        56.68333333, 57.28      , 57.87666667, 58.47333333, 59.07      ,
        59.66666667]),
 <a list of 100 Patch objects>)
```

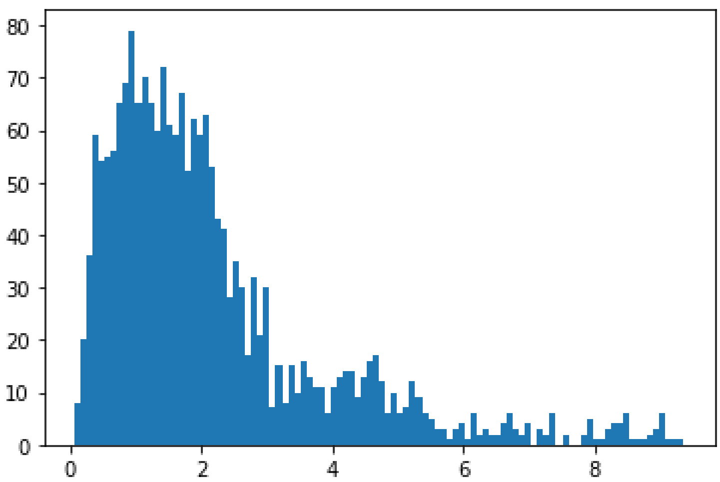


In [38]:

```
plt.hist(data = combined, x = "Distance_to_hospital", bins=100)
```

Out[38]:

```
(array([ 8., 20., 36., 59., 54., 55., 56., 65., 69., 79., 65., 70., 65.,
        60., 72., 61., 59., 67., 52., 62., 59., 63., 53., 43., 41., 28.,
        35., 30., 17., 32., 21., 30.,  7., 15.,  8., 15., 10., 16., 13.,
        11., 11.,  6., 11., 13., 14., 14.,  9., 13., 16., 17., 12.,  6.,
        10.,  6.,  7., 12.,  9.,  6.,  5.,  3.,  3.,  1.,  3.,  4.,  1.,
         6.,  2.,  3.,  2.,  2.,  4.,  6.,  3.,  2.,  4.,  0.,  3.,  2.,
         6.,  0.,  2.,  0.,  0.,  2.,  5.,  1.,  1.,  3.,  4.,  4.,  6.,
         1.,  1.,  1.,  2.,  3.,  6.,  1.,  1.,  1.]),
 array([0.07   , 0.16294, 0.25588, 0.34882, 0.44176, 0.5347 , 0.62764,
        0.72058, 0.81352, 0.90646, 0.9994 , 1.09234, 1.18528, 1.27822,
        1.37116, 1.4641 , 1.55704, 1.64998, 1.74292, 1.83586, 1.9288 ,
        2.02174, 2.11468, 2.20762, 2.30056, 2.3935 , 2.48644, 2.57938,
        2.67232, 2.76526, 2.8582 , 2.95114, 3.04408, 3.13702, 3.22996,
        3.3229 , 3.41584, 3.50878, 3.60172, 3.69466, 3.7876 , 3.88054,
        3.97348, 4.06642, 4.15936, 4.2523 , 4.34524, 4.43818, 4.53112,
        4.62406, 4.717  , 4.80994, 4.90288, 4.99582, 5.08876, 5.1817 ,
        5.27464, 5.36758, 5.46052, 5.55346, 5.6464 , 5.73934, 5.83228,
        5.92522, 6.01816, 6.1111 , 6.20404, 6.29698, 6.38992, 6.48286,
        6.5758 , 6.66874, 6.76168, 6.85462, 6.94756, 7.0405 , 7.13344,
        7.22638, 7.31932, 7.41226, 7.5052 , 7.59814, 7.69108, 7.78402,
        7.87696, 7.9699 , 8.06284, 8.15578, 8.24872, 8.34166, 8.4346 ,
        8.52754, 8.62048, 8.71342, 8.80636, 8.8993 , 8.99224, 9.08518,
        9.17812, 9.27106, 9.364  ]),
 <a list of 100 Patch objects>)
```

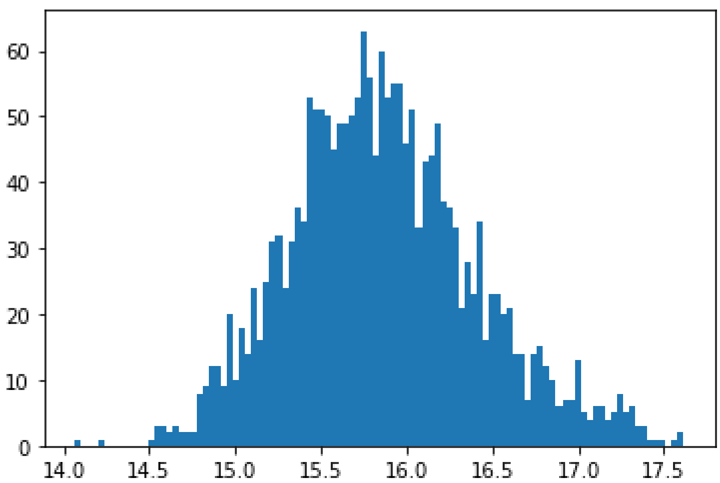


In [39]:

```
plt.hist(data = combined, x = "new_price", bins=100)
```

Out[39]:

```
(array([ 1.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,
         3.,  3.,  2.,  3.,  2.,  2.,  2.,  8.,  9., 12., 12.,  9., 20.,
        10., 18., 14., 24., 16., 25., 31., 32., 24., 31., 36., 34., 53.,
        51., 51., 50., 45., 49., 49., 50., 53., 63., 56., 44., 60., 53.,
        55., 55., 46., 51., 33., 43., 44., 49., 37., 36., 33., 21., 28.,
        23., 34., 16., 23., 23., 20., 21., 14., 14.,  7., 14., 15., 12.,
        10.,  6.,  7.,  7., 13.,  5.,  4.,  6.,  6.,  4.,  5.,  8.,  5.,
         6.,  3.,  3.,  1.,  1.,  1.,  0.,  1.,  2.]),
 array([14.06354261, 14.09906426, 14.13458591, 14.17010756, 14.20562921,
        14.24115086, 14.27667252, 14.31219417, 14.34771582, 14.38323747,
        14.41875912, 14.45428077, 14.48980242, 14.52532408, 14.56084573,
        14.59636738, 14.63188903, 14.66741068, 14.70293233, 14.73845399,
        14.77397564, 14.80949729, 14.84501894, 14.88054059, 14.91606224,
        14.9515839 , 14.98710555, 15.0226272 , 15.05814885, 15.0936705 ,
        15.12919215, 15.16471381, 15.20023546, 15.23575711, 15.27127876,
        15.30680041, 15.34232206, 15.37784372, 15.41336537, 15.44888702,
        15.48440867, 15.51993032, 15.55545197, 15.59097363, 15.62649528,
        15.66201693, 15.69753858, 15.73306023, 15.76858188, 15.80410354,
        15.83962519, 15.87514684, 15.91066849, 15.94619014, 15.98171179,
        16.01723345, 16.0527551 , 16.08827675, 16.1237984 , 16.15932005,
        16.1948417 , 16.23036336, 16.26588501, 16.30140666, 16.33692831,
        16.37244996, 16.40797161, 16.44349327, 16.47901492, 16.51453657,
        16.55005822, 16.58557987, 16.62110152, 16.65662318, 16.69214483,
        16.72766648, 16.76318813, 16.79870978, 16.83423143, 16.86975309,
        16.90527474, 16.94079639, 16.97631804, 17.01183969, 17.04736134,
        17.082883  , 17.11840465, 17.1539263 , 17.18944795, 17.2249696 ,
        17.26049125, 17.29601291, 17.33153456, 17.36705621, 17.40257786,
        17.43809951, 17.47362116, 17.50914282, 17.54466447, 17.58018612,
        17.61570777]),
 <a list of 100 Patch objects>)
```

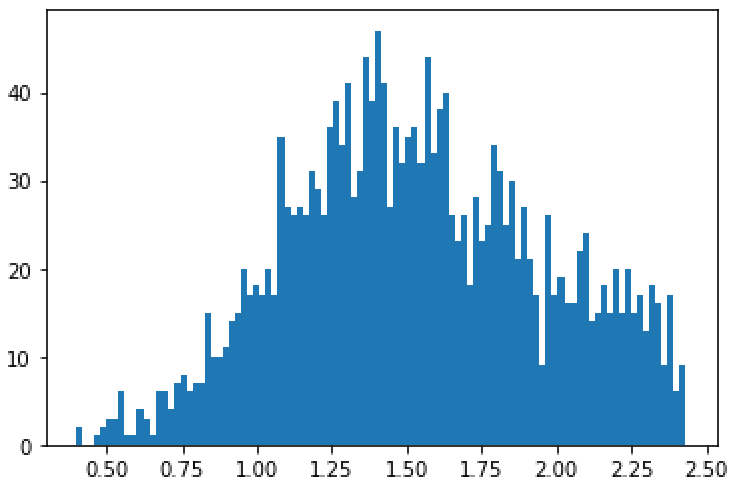


In [40]:

```
plt.hist(data = combined, x = "new_Distance_to_sc", bins=100)
```

Out[40]:

```
(array([ 2.,  0.,  0.,  1.,  2.,  3.,  3.,  6.,  1.,  1.,  4.,  3.,  1.,
         6.,  6.,  4.,  7.,  8.,  6.,  7.,  7., 15., 10., 10., 11., 14.,
        15., 20., 17., 18., 17., 20., 17., 35., 27., 26., 27., 26., 31.,
        29., 26., 36., 39., 34., 41., 28., 31., 44., 39., 47., 41., 27.,
        36., 32., 35., 36., 32., 44., 33., 38., 40., 26., 23., 26., 18.,
        28., 23., 25., 34., 31., 25., 30., 21., 27., 21., 17.,  9., 26.,
        17., 19., 16., 16., 22., 24., 14., 15., 18., 15., 20., 15., 20.,
        15., 17., 13., 18., 16.,  9., 17.,  6.,  9.]),
 array([0.39874804, 0.41908339, 0.43941874, 0.45975409, 0.48008943,
        0.50042478, 0.52076013, 0.54109548, 0.56143083, 0.58176618,
        0.60210152, 0.62243687, 0.64277222, 0.66310757, 0.68344292,
        0.70377827, 0.72411361, 0.74444896, 0.76478431, 0.78511966,
        0.80545501, 0.82579036, 0.84612571, 0.86646105, 0.8867964 ,
        0.90713175, 0.9274671 , 0.94780245, 0.9681378 , 0.98847314,
        1.00880849, 1.02914384, 1.04947919, 1.06981454, 1.09014989,
        1.11048523, 1.13082058, 1.15115593, 1.17149128, 1.19182663,
        1.21216198, 1.23249732, 1.25283267, 1.27316802, 1.29350337,
        1.31383872, 1.33417407, 1.35450941, 1.37484476, 1.39518011,
        1.41551546, 1.43585081, 1.45618616, 1.4765215 , 1.49685685,
        1.5171922 , 1.53752755, 1.5578629 , 1.57819825, 1.59853359,
        1.61886894, 1.63920429, 1.65953964, 1.67987499, 1.70021034,
        1.72054569, 1.74088103, 1.76121638, 1.78155173, 1.80188708,
        1.82222243, 1.84255778, 1.86289312, 1.88322847, 1.90356382,
        1.92389917, 1.94423452, 1.96456987, 1.98490521, 2.00524056,
        2.02557591, 2.04591126, 2.06624661, 2.08658196, 2.1069173 ,
        2.12725265, 2.147588  , 2.16792335, 2.1882587 , 2.20859405,
        2.22892939, 2.24926474, 2.26960009, 2.28993544, 2.31027079,
        2.33060614, 2.35094148, 2.37127683, 2.39161218, 2.41194753,
        2.43228288]),
 <a list of 100 Patch objects>)
```

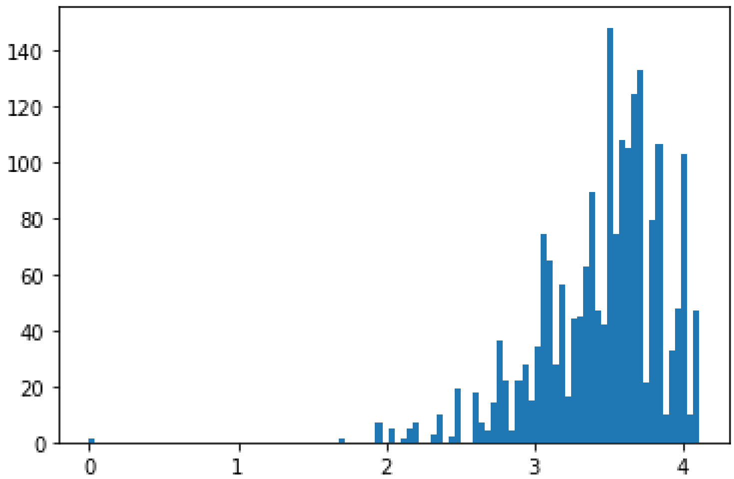


In [41]:

```
plt.hist(data = combined, x = "new_travel_min_to_CBD", bins=100)
```

Out[41]:

```
(array([  1.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,
          0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,
          0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,
          0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   1.,   0.,   0.,
          0.,   0.,   0.,   7.,   0.,   5.,   0.,   1.,   5.,   7.,   0.,
          0.,   3.,  10.,   0.,   2.,  19.,   0.,   0.,  18.,   7.,   4.,
         14.,  36.,  22.,   4.,  22.,  28.,  15.,  34.,  74.,  65.,  28.,
         56.,  16.,  44.,  45.,  63.,  89.,  47.,  42., 148.,  74., 108.,
        105., 124., 133.,  21.,  79., 106.,  10.,  33.,  48., 103.,  10.,
         47.]),
 array([0.        , 0.04105394, 0.08210789, 0.12316183, 0.16421578,
        0.20526972, 0.24632366, 0.28737761, 0.32843155, 0.3694855 ,
        0.41053944, 0.45159338, 0.49264733, 0.53370127, 0.57475522,
        0.61580916, 0.6568631 , 0.69791705, 0.73897099, 0.78002494,
        0.82107888, 0.86213282, 0.90318677, 0.94424071, 0.98529466,
        1.0263486 , 1.06740254, 1.10845649, 1.14951043, 1.19056438,
        1.23161832, 1.27267226, 1.31372621, 1.35478015, 1.3958341 ,
        1.43688804, 1.47794198, 1.51899593, 1.56004987, 1.60110382,
        1.64215776, 1.6832117 , 1.72426565, 1.76531959, 1.80637354,
        1.84742748, 1.88848142, 1.92953537, 1.97058931, 2.01164326,
        2.0526972 , 2.09375114, 2.13480509, 2.17585903, 2.21691298,
        2.25796692, 2.29902086, 2.34007481, 2.38112875, 2.4221827 ,
        2.46323664, 2.50429058, 2.54534453, 2.58639847, 2.62745241,
        2.66850636, 2.7095603 , 2.75061425, 2.79166819, 2.83272213,
        2.87377608, 2.91483002, 2.95588397, 2.99693791, 3.03799185,
        3.0790458 , 3.12009974, 3.16115369, 3.20220763, 3.24326157,
        3.28431552, 3.32536946, 3.36642341, 3.40747735, 3.44853129,
        3.48958524, 3.53063918, 3.57169313, 3.61274707, 3.65380101,
        3.69485496, 3.7359089 , 3.77696285, 3.81801679, 3.85907073,
        3.90012468, 3.94117862, 3.98223257, 4.02328651, 4.06434045,
        4.1053944 ]),
 <a list of 100 Patch objects>)
```

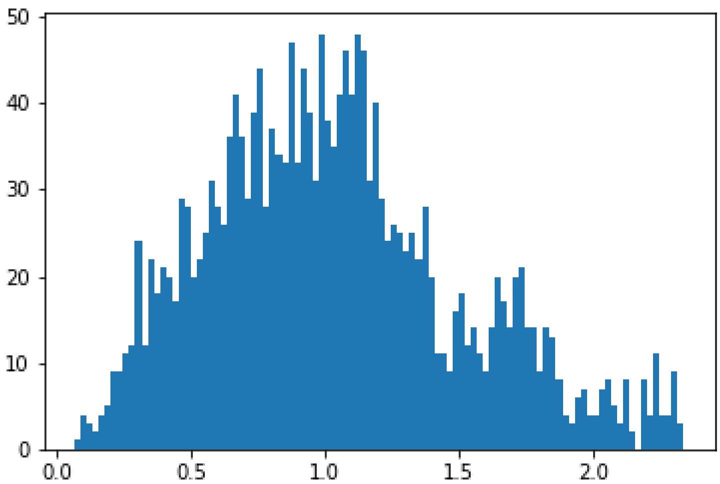


In [42]:

```
plt.hist(data = combined, x = "new_Distance_to_hospital", bins=100)
```

Out[42]:

```
(array([ 1.,  4.,  3.,  2.,  4.,  5.,  9.,  9., 11., 12., 24., 12., 22.,
        18., 21., 20., 17., 29., 28., 20., 22., 25., 31., 28., 26., 36.,
        41., 36., 29., 39., 44., 28., 37., 34., 33., 47., 33., 44., 39.,
        31., 48., 38., 35., 41., 46., 41., 48., 46., 31., 40., 29., 24.,
        26., 25., 23., 25., 22., 28., 20., 11., 11.,  9., 16., 18., 12.,
        14., 11.,  9., 14., 20., 17., 14., 20., 21., 14., 14.,  9., 14.,
        13.,  8.,  4.,  3.,  6.,  7.,  4.,  4.,  7.,  8.,  5.,  3.,  8.,
         2.,  0.,  8.,  4., 11.,  4.,  4.,  9.,  3.]),
 array([0.06765865, 0.09036544, 0.11307224, 0.13577904, 0.15848583,
        0.18119263, 0.20389943, 0.22660622, 0.24931302, 0.27201981,
        0.29472661, 0.31743341, 0.3401402 , 0.362847  , 0.38555379,
        0.40826059, 0.43096739, 0.45367418, 0.47638098, 0.49908778,
        0.52179457, 0.54450137, 0.56720816, 0.58991496, 0.61262176,
        0.63532855, 0.65803535, 0.68074214, 0.70344894, 0.72615574,
        0.74886253, 0.77156933, 0.79427613, 0.81698292, 0.83968972,
        0.86239651, 0.88510331, 0.90781011, 0.9305169 , 0.9532237 ,
        0.97593049, 0.99863729, 1.02134409, 1.04405088, 1.06675768,
        1.08946447, 1.11217127, 1.13487807, 1.15758486, 1.18029166,
        1.20299846, 1.22570525, 1.24841205, 1.27111884, 1.29382564,
        1.31653244, 1.33923923, 1.36194603, 1.38465282, 1.40735962,
        1.43006642, 1.45277321, 1.47548001, 1.49818681, 1.5208936 ,
        1.5436004 , 1.56630719, 1.58901399, 1.61172079, 1.63442758,
        1.65713438, 1.67984117, 1.70254797, 1.72525477, 1.74796156,
        1.77066836, 1.79337516, 1.81608195, 1.83878875, 1.86149554,
        1.88420234, 1.90690914, 1.92961593, 1.95232273, 1.97502952,
        1.99773632, 2.02044312, 2.04314991, 2.06585671, 2.08856351,
        2.1112703 , 2.1339771 , 2.15668389, 2.17939069, 2.20209749,
        2.22480428, 2.24751108, 2.27021787, 2.29292467, 2.31563147,
        2.33833826]),
 <a list of 100 Patch objects>)
```



Linear Modelling

In [43]:

```
#---------------------- linear model graph to show 3 attributes ----------------------
---------------
datavsprice = sm.ols(formula="price ~ Distance_to_hospital+travel_min_to_CBD+Distance_t
o_sc", data=combined).fit()

#---------------------- model accuracy and r-square -----------------------------------
---
print(datavsprice.rsquared, datavsprice.rsquared_adj)
```

```
0.136268235413339 0.13495888963579483
```

In [44]:

```
standard_scale = preprocessing.StandardScaler().fit(combined[['price', 'Distance_to_hos
pital','travel_min_to_CBD','Distance_to_sc']])

col_int = combined[['price', 'Distance_to_hospital','travel_min_to_CBD','Distance_to_s
c']]

arr_standard = standard_scale.transform(combined[['price', 'Distance_to_hospital','trav
el_min_to_CBD','Distance_to_sc']]) # an array not a df
features = pd.DataFrame(arr_standard, index=col_int.index, columns=col_int .columns)

features.head()
```

Out[44]:

	price	Distance_to_hospital	travel_min_to_CBD	Distance_to_sc
0	-0.533692	-0.370627	-0.981816	-0.933662
1	-0.075486	-0.557128	0.046261	-0.517321
2	-1.005970	-0.853912	-1.149640	-0.086083
3	0.040352	0.568805	1.778889	0.133632
4	0.434203	-1.151851	0.469862	-0.288668

Result

After exploring normalization and linearity graph (z-standard transform) are acceptable for transformed data and their may not be any need to perform standard scaler transformation. Therefore concluding that applying above transformation to linear model is acceptable will be accurate

In [ ]: