FIT5196 Assessment 3

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Environment: Python 3 and Jupyter notebook

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1. Introduction

- This assignment revolves around integrating several datasets into one standard form, calculating the different additional columns and performing data normalizations and data transformations!
- We have been given 7 datasets and it's about the housing information in Victoria.

Assumptions

- The following files are in the current directory:
  - hospitals.xlsx
  - real_state.json
  - real_state.xml
  - shopingcenters.html
  - supermarkets.pdf
  - Melbourne Train Information Files
  - vic_suburb_boudary file

2. Methodology

Importing Libraries

In [1]:

```
# Handling Dataframes
import pandas as pd

# Numeric Calculations
import numpy as np

# For mathematical calculations
import math

# For regular expressions in order to extract the xml data
import re

# For reading the json data
import json

# For reading in the xml data
import bs4
from bs4 import BeautifulSoup

# For reading in the pdf data
import tabula

# For performing box-cox transformation
from scipy import stats

# For plotting functions
import matplotlib as mpl
import matplotlib.pyplot as plt

# For z transform and min max tranformations
from sklearn import preprocessing

# For splitting the dataset into training and testing data
from sklearn.model_selection import train_test_split

# In order to calculate the mean squared error
from sklearn.metrics import mean_squared_error, r2_score

# In order to train the linear model
from sklearn.linear_model import LinearRegression
```

In [2]:

```
# For reading in the shape files


# import shapefile
# #import geopandas
# from shapely.geometry import Point, Polygon
```

2.1 Task 1 : Data Integration : Part A : Reading Data

- This section revolves around reading in the various datasets present in various formats such as json data, xml data, html data, pdf data, and excel data.
- After reading in the data, this section then covers merging the data into one integrated format which has been named as integrated_data.

- We would be reading the various data-formats in the following manner:
  - **json data** using read_json function
  - **xml data** using regular expressions
  - **html data** using read_html function
  - **pdf data** using tabula
  - **excel data** using read_excel function

2.1.1 Data : real_state.json (Property Data 1)

In [3]:

```
# Reading in the json_data
real_state_json_data = pd.read_json('real_state.json')
real_state_json_data.to_csv ('real_state.csv', index = None)
```

In [4]:

```
# Displaying the json_data
real_state_json_data.head(2)
```

Out[4]:

	property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	39345	-37.694100	145.056091	1/40 McLeans Road	5753000	house	2011	3
1	58362	-37.826197	145.153935	8 Wellington Avenue	15680000	house	2015	3

In [5]:

```
# Renaming the property id column as per the specification
real_state_json_data.rename(columns = {'property_id': 'Property_id'}, inplace = True)
real_state_json_data.head(2)
```

Out[5]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	39345	-37.694100	145.056091	1/40 McLeans Road	5753000	house	2011	3
1	58362	-37.826197	145.153935	8 Wellington Avenue	15680000	house	2015	3

2.1.2 Data : real_state.xml (Property Data 2)

In [6]:

```
# Opening the XML File
real_state_xml = open("real_state.xml", "r")

# Reading in the xml data
real_state = BeautifulSoup(real_state_xml, "html.parser")

# Converting into a string format
real_state_combined = str(real_state)
```

In [7]:

```
# Creating the regex
property_id_regex = '<property_id type="dict">(.*?)</property_id>'
lat_regex = '<lat type="dict">(.*?)</lat>'
lng_regex = '<lng type="dict">(.*?)</lng>'
addr_street_regex = '<addr_street type="dict">(.*?)</addr_street>'
price_regex = '<price type="dict">(.*?)</price>'
property_type_regex = '<property_type type="dict">(.*?)</property_type>'
bedrooms_regex = '<bedrooms type="dict">(.*?)</bedrooms>'
year_regex = '<year type="dict">(.*?)</year>'
bathrooms_regex = '<bathrooms type="dict">(.*?)</bathrooms>'
parking_space_regex = '<parking_space type="dict">(.*?)</parking_space>'


# Finding and Extracting using regex
# for property_id
find_property_id = re.findall(property_id_regex,real_state_combined,re.DOTALL)
for i in find_property_id:
    id_regex = "<n[\d]+ type=\"int\">(.*?)</n[0-9]+>"
    property_id_list =  re.findall(id_regex,i,re.DOTALL)

# for lat
find_lat = re.findall(lat_regex,real_state_combined,re.DOTALL)
for i in find_lat:
    lat_regex = "<n[\d]+ type=\"float\">(.*?)</n[0-9]+>"
    lat_list =  re.findall(lat_regex,i,re.DOTALL)

# for lng
find_lng = re.findall(lng_regex,real_state_combined,re.DOTALL)
for i in find_lng:
    lng_regex = "<n[\d]+ type=\"float\">(.*?)</n[0-9]+>"
    lng_list =  re.findall(lng_regex,i,re.DOTALL)

# for address street
find_addr_street = re.findall(addr_street_regex,real_state_combined,re.DOTALL)
for i in find_addr_street:
    adress_regex = "<n[\d]+ type=\"str\">(.*?)</n[0-9]+>"
    adress_list =  re.findall(adress_regex,i,re.DOTALL)

# for price
find_price = re.findall(price_regex,real_state_combined,re.DOTALL)
for i in find_price:
    price_regex = "<n[\d]+ type=\"int\">(.*?)</n[0-9]+>"
    price_list =  re.findall(price_regex,i,re.DOTALL)

# for property
find_property = re.findall(property_type_regex,real_state_combined,re.DOTALL)
for i in find_property:
    type_regex = "<n[\d]+ type=\"str\">(.*?)</n[0-9]+>"
    type_list =  re.findall(type_regex,i,re.DOTALL)

# for year
find_year = re.findall(year_regex,real_state_combined,re.DOTALL)
for i in find_year:
    year_regex = "<n[\d]+ type=\"int\">(.*?)</n[0-9]+>"
    year_list =  re.findall(year_regex,i,re.DOTALL)

# for bedrooms
find_bedrooms = re.findall(bedrooms_regex,real_state_combined,re.DOTALL)
for i in find_bedrooms:
```

```
    bedrooms_regex = "<n[\d]+ type=\"int\">(.*?)</n[0-9]+>"
    bedrooms_list =  re.findall(bedrooms_regex,i,re.DOTALL)

# for bathrooms
find_bathrooms = re.findall(bathrooms_regex,real_state_combined,re.DOTALL)
for i in find_bathrooms:
    bathrooms_regex = "<n[\d]+ type=\"int\">(.*?)</n[0-9]+>"
    bathrooms_list =  re.findall(bathrooms_regex,i,re.DOTALL)

# for parking space
find_parking_space = re.findall(parking_space_regex,real_state_combined,re.DOTALL)
for i in find_parking_space:
    parking_space_regex = "<n[\d]+ type=\"int\">(.*?)</n[0-9]+>"
    parking_space_list =  re.findall(parking_space_regex,i,re.DOTALL)
```

In [8]:

```
# Creating a df from the combined xml data
df_realstate_xml = pd.DataFrame(list(zip(property_id_list, lat_list,lng_list,adress_list,pr
               columns =['Property_id', 'lat','lng','addr_street','price','property_type','
```

In [9]:

```
# Displaying the xml real_state
df_realstate_xml.head(2)
```

Out[9]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	:
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	:

In [10]:

```
# Converting the json data into a dataframe
df_realstate_json = pd.read_csv('real_state.csv', )
```

In [11]:

```
# Displaying the json real_state
df_realstate_json.head(2)
```

Out[11]:

	property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	39345	-37.694100	145.056091	1/40 McLeans Road	5753000	house	2011	3
1	58362	-37.826197	145.153935	8 Wellington Avenue	15680000	house	2015	3

In [12]:

```
# Renaming column name for the json dataframe
df_realstate_json.rename(columns = {'property_id':'Property_id'}, inplace = True)
```

In [13]:

```
df_realstate_json.head(2)
```

Out[13]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	39345	-37.694100	145.056091	1/40 McLeans Road	5753000	house	2011	3
1	58362	-37.826197	145.153935	8 Wellington Avenue	15680000	house	2015	3

In [14]:

```
# Shape of real_state json
df_realstate_json.shape
```

Out[14]:

```
(1010, 10)
```

In [15]:

```
# Shape of real_state xml
df_realstate_xml.shape
```

Out[15]:

```
(1001, 10)
```

In [16]:

```
# Creating a list of both the dataframes
df_xml_and_json = [df_realstate_xml, df_realstate_json]
```

In [17]:

```
# Join the data
integrated_data = pd.concat(df_xml_and_json, sort = False)
```

In [18]:

```
integrated_data.head(2)
```

Out[18]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	:
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	:

In [19]:

```
# Shape of our first version of integrated data
integrated_data.shape
```

Out[19]:

```
(2011, 10)
```

In [20]:

```
# Dropping the duplicated data
integrated_data.drop_duplicates(subset ="Property_id", keep = False, inplace = True)
```

In [21]:

```
# Shaoe after dropping duplicates
integrated_data.shape
```

Out[21]:

```
(2003, 10)
```

2.1.3 Data : shopingcenters.html

In [22]:

```
# Reading in the html data
html_data = r"shopingcenters.html"

# Opening the html file
shopingcenter_data = open(html_data, 'r')

# Reading the shopping centre data file
html_data_read = shopingcenter_data.read()

# Reading the html data as a dataframe
html_data_df = pd.read_html(html_data_read)

# Converting the html data into a csv format
for i, table in enumerate(html_data_df):
    table.to_csv('shopingcenters.csv'.format(i))
```

In [23]:

```
# Reading in the csv data
shopingcenter_data = pd.read_csv("shopingcenters.csv")
shopingcenter_data.head(2)
```

Out[23]:

	Unnamed: 0	Unnamed: 0.1	sc_id	lat	lng
0	0	0	SC_001	-37.767915	145.041790
1	1	1	SC_002	-37.819375	145.171472

In [24]:

```
# Deleting unwanted columns
del shopingcenter_data['Unnamed: 0']
del shopingcenter_data['Unnamed: 0.1']
```

In [25]:

```
# Displaying the shopingcenter data
shopingcenter_data.head(2)
```

Out[25]:

	sc_id	lat	lng
0	SC_001	-37.767915	145.041790
1	SC_002	-37.819375	145.171472

2.1.4 Data : supermarkets.pdf

In [26]:

```
# Converting into csv
tabula.convert_into("supermarkets.pdf","supermarkets.csv", pages='all')

# Reading in the csv data
supermarkets_data = pd.read_csv("supermarkets.csv")
supermarkets_data.head(2)
```

Out[26]:

	Unnamed: 0	id	lat	lng	type
0	0.0	S_001	-37.883978	144.735287	Woolworths
1	1.0	S_002	-41.161591	147.514797	Woolworths

In [27]:

```
# Deleting unwanted columns
del supermarkets_data['Unnamed: 0']
```

In [28]:

```
# Displaying the supermarket data
supermarkets_data.head(2)
```

Out[28]:

	id	lat	lng	type
0	S_001	-37.883978	144.735287	Woolworths
1	S_002	-41.161591	147.514797	Woolworths

In [29]:

```
supermarkets_data.shape
```

Out[29]:

```
(243, 4)
```

In [30]:

```
# Correcting some mistakes
mistakes = supermarkets_data[( supermarkets_data['lat'] == 'lat') | (supermarkets_data['lng
supermarkets_data = supermarkets_data.drop(mistakes.index, axis = 0)

supermarkets_data.shape
```

Out[30]:

```
(239, 4)
```

In [31]:

```
supermarkets_data['lat_long'] = list(zip(supermarkets_data.lat, supermarkets_data.lng))
supermarkets_lat_long = supermarkets_data['lat_long'].to_list()
supermarkets_data.head(2)
```

Out[31]:

	id	lat	lng	type	lat_long
0	S_001	-37.883978	144.735287	Woolworths	(-37.883978, 144.735287)
1	S_002	-41.161591	147.514797	Woolworths	(-41.161591, 147.514797)

In [32]:

```
supermarkets_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 239 entries, 0 to 242
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   id        239 non-null    object
 1   lat       239 non-null    object
 2   lng       239 non-null    object
 3   type      239 non-null    object
 4   lat_long  239 non-null    object
dtypes: object(5)
memory usage: 11.2+ KB
```

In [33]:

```
# Converting the datatype for distance calculation
supermarkets_data['lat_long'] = pd.to_numeric(supermarkets_data['lat_long'], errors='coerce
supermarkets_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 239 entries, 0 to 242
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   id        239 non-null    object 
 1   lat       239 non-null    object 
 2   lng       239 non-null    object 
 3   type      239 non-null    object 
 4   lat_long  239 non-null    float64
dtypes: float64(1), object(4)
memory usage: 11.2+ KB
```

2.1.5 Data : hospitals.xlsx

In [34]:

```
# Reading in the excel data
hospital_data = pd.read_excel('hospitals.xlsx')
hospital_data.head(2)
```

Out[34]:

	Unnamed: 0	id	lat	lng	name
0	0	hospital_001	-37.990622	145.072836	Como Private Hospital
1	1	hospital_002	-37.855469	145.268183	Mountain District Private Hospital

In [35]:

```
# Structure of the hospital data
hospital_data.shape
```

Out[35]:

```
(199, 5)
```

In [36]:

```
# General information about the hospital data
hospital_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 199 entries, 0 to 198
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  199 non-null    int64
 1   id          199 non-null    object
 2   lat         199 non-null    float64
 3   lng         199 non-null    float64
 4   name        199 non-null    object
dtypes: float64(2), int64(1), object(2)
memory usage: 7.9+ KB
```

In [37]:

```
# Deleting unwanted columns
del hospital_data['Unnamed: 0']
hospital_data.head(2)
```

Out[37]:

	id	lat	lng	name
0	hospital_001	-37.990622	145.072836	Como Private Hospital
1	hospital_002	-37.855469	145.268183	Mountain District Private Hospital

2.1.6 Data : GTFS - Melbourne Train Information : Individual Text Files

In [38]:

```
# Reading in the GTFS data
agency_data = pd.read_csv("GTFS - Melbourne Train Information/agency.txt")
calendar_data = pd.read_csv("GTFS - Melbourne Train Information/calendar.txt")
calendar_dates_data = pd.read_csv("GTFS - Melbourne Train Information/calendar_dates.txt")
routes_data = pd.read_csv("GTFS - Melbourne Train Information/routes.txt")
shapes_data = pd.read_csv("GTFS - Melbourne Train Information/shapes.txt")
stop_times_data = pd.read_csv("GTFS - Melbourne Train Information/stop_times.txt")
stops_data = pd.read_csv("GTFS - Melbourne Train Information/stops.txt")
trips_data = pd.read_csv("GTFS - Melbourne Train Information/trips.txt")
```

2.1.7 Data : VIC Suburb Boundary

In [39]:

```
# # # For reading in the shape files
# # import geos

# import shapefile
# import geopandas
# from shapely.geometry import Point, Polygon
```

In [40]:

```
# gdf = geopandas.read_file("vic_suburb_boundary/VIC_LOCALITY_POLYGON_shp.shp")
```

In [41]:

```
# print("Shape of the Suburb File:", gdf.shape)
# gdf.head()
```

2.2 Part B : Additional Computed Columns

- This section revolves around computing the following additional columns!
  - Suburb in which the property is present
  - Distance to the nearest shopping center
  - Nearest shopping center ID
  - Distance to the nearest hospital
  - Nearest hospital ID
  - Distance to the nearest supermarket
  - Nearest supermarket ID
  - Distance to the nearest train-station
  - Nearest train-station ID
  - Minimum time taken to reach the CBD
  - Transfer Flag indicating if there is a direct route
- The various distances have been calculated using the haversine distance.
- I have even defined various functions to compute the distances and the IDS.

Suburb

- This specifies the suburb of the property.

In [42]:

```
# Creating a new empty column for Suburb
integrated_data['Suburb'] = 'not available'
```

In [43]:

```
integrated_data.head()
```

Out[43]:

	Property_id	lat	lng	addr_street	price	property_type	year
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009
2	20162	-37.800715999999994	144.973143	37 Owen Street	12870000	house	2011
3	52140	-37.814572999999996	144.994122	11 Leeds Street	6314000	house	2015
4	81404	-37.978701	145.199705	6 Campbell Street	4914000	house	2010

In [44]:

```
# # Creating a dictionary for suburb from the above shape files
# suburbs_dictionary = dict(zip(list(gdf['VIC_LOCA_2']),list(gdf['geometry'])))
```

In [45]:

```
# # This function returns the Suburb from the shape file data frame
# def return_suburb(lng, lat):

#     # Dimensions of the given point
#     given_point = Point(lng, lat)

#     # Iterating through the suburb dictionary
#     for key,values in suburbs_dictionary.items():

#         # Creating the suburb based on values
#         suburb = Polygon(values)

#         # Checking if the given point is contained in the suburb
#         if suburb.contains(given_point):
#             # Return the particular suburb
#             return key
#     return "not available"
```

In [46]:

```
# integrated_data['Suburb'] = integrated_data.apply(lambda row: return_suburb(row["lng"], r
```

In [47]:

```
integrated_data.head()
```

Out[47]:

	Property_id	lat	lng	addr_street	price	property_type	year
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009
2	20162	-37.800715999999994	144.973143	37 Owen Street	12870000	house	2011
3	52140	-37.814572999999996	144.994122	11 Leeds Street	6314000	house	2015
4	81404	-37.978701	145.199705	6 Campbell Street	4914000	house	2010

2.2.1 Distance_to_sc

- This gives is the Euclidean distance from the nearest shopping center to the given property.
- Default Value:0

In [48]:

```
# Function to calculate the distance between two geological locations
def haversine_distance(lat1, lon1, lat2, lon2):
    # As per the specification provided
    r = 6378

    # Calculating the phi values
    phi1 = np.radians(lat1)
    phi2 = np.radians(lat2)

    # Calculating the delta and lambda values
    delta_phi = np.radians(lat2 - lat1)
    delta_lambda = np.radians(lon2 - lon1)

    # Distance calculated as per the haversine distance formula
    a = np.sin(delta_phi / 2)**2 + np.cos(phi1) * np.cos(phi2) *   np.sin(delta_lambda / 2)*
    hav_distance = r * (2 * np.arctan2(np.sqrt(a), np.sqrt(1 - a)))
    return np.round(hav_distance, 4)
```

In [49]:

```
# In order to later extract the id in an easier manner
shopingcenter_data['lat_long_id'] = list(zip(shopingcenter_data.lat, shopingcenter_data.lng
shopingcenter_data_lat_long_id = shopingcenter_data['lat_long_id'].to_list()
shopingcenter_data.head(2)
```

Out[49]:

	sc_id	lat	lng	lat_long_id
0	SC_001	-37.767915	145.041790	(-37.767915, 145.04179, SC_001)
1	SC_002	-37.819375	145.171472	(-37.819375, 145.171472, SC_002)

In [50]:

```
# Function to calculate the nearest shoping center distance
def nearest_shopingcenter_distance(row):

    # Getting the property coordinates
    prop_lng = float(row.lng)
    prop_lat = float(row.lat)

    # Initializing dictionaries to store the distance values
    distance_dict = dict()

    # Iterating through the list
    for location in shopingcenter_data_lat_long_id:
        super_lat = float(location[0])
        super_lng = float(location[1])

        # Calculating the distance using the function
        calc_distance = haversine_distance(prop_lat, prop_lng, super_lat, super_lng)
        distance_dict[location] = calc_distance

    # Storing all the values
    all_values = distance_dict.values()

    # Calculating the min value
    nearest_distance = min(all_values)

    # Returning the least distance
    return nearest_distance
```

In [51]:

```
# Nearest Shopping Centre distance
integrated_data['Distance_to_sc'] = integrated_data.apply(lambda x: nearest_shopingcenter_c
integrated_data.head(2)
```

Out[51]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	[illegible]
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	[illegible]

In [52]:

```
integrated_data.head(2)
```

Out[52]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	

2.2.2 Shopping_center_id

- This gives us the id of the closest shopping center to the property.
- Default Value: 0

In [53]:

```
# Function to calculate the nearest shoping center ID
def nearest_shopingcenter_id(row):

    # Property Coordinates
    prop_lng = float(row.lng)
    prop_lat = float(row.lat)

    # Dictionary to store the IDs
    distance_id_dict = dict()

    # Iterating through the list
    for location in shopingcenter_data_lat_long_id:
        sc_lat = float(location[0])
        sc_lng = float(location[1])
        sc_ID = location[2]

        # Calculating the distance
        calc_distance = haversine_distance(prop_lat, prop_lng, sc_lat, sc_lng)
        distance_id_dict[sc_ID] = calc_distance

    # Sorting the distance dictionary
    distance_id_dict = sorted(distance_id_dict.items(), key = lambda x: x[1])

    nearest_id = distance_id_dict[0][0]

    # Returning the nearest ID
    return nearest_id
```

In [54]:

```
# Nearest Shopping Centre ID
integrated_data['Shopping_center_id'] = integrated_data.apply(lambda x: nearest_shopingcent
integrated_data.head(2)
```

Out[54]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	:
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	:

2.2.3 Distance_to_hospital

- This is the Euclidean distance of the property to the closest hospital.

In [55]:

```
hospital_data.head(2)
```

Out[55]:

	id	lat	lng	name
0	hospital_001	-37.990622	145.072836	Como Private Hospital
1	hospital_002	-37.855469	145.268183	Mountain District Private Hospital

In [56]:

```
# For easier data retrieval
hospital_data['lat_long_id'] = list(zip(hospital_data.lat, hospital_data.lng, hospital_data
hospital_data_lat_long_id = hospital_data['lat_long_id'].to_list()
hospital_data.head(2)
```

Out[56]:

	id	lat	lng	name	lat_long_id
0	hospital_001	-37.990622	145.072836	Como Private Hospital	(-37.99062199999999, 145.072836, hospital_001)
1	hospital_002	-37.855469	145.268183	Mountain District Private Hospital	(-37.8554685, 145.2681831, hospital_002)

In [57]:

```
# Function to calculate the nearest hospital distance
def nearest_hospital_distance(row):

    # Coordinates of the property
    prop_lng = float(row.lng)
    prop_lat = float(row.lat)

    # Dictionary to store the various distance values
    distance_dict = dict()

    # Iterating through the dataset
    for location in hospital_data_lat_long_id:
        hospital_lat = float(location[0])
        hospital_lng = float(location[1])

        # Calculating the distance
        calc_distance = haversine_distance(prop_lat, prop_lng, hospital_lat, hospital_lng)
        distance_dict[location] = calc_distance

    # Getting all the values to calculate the minimum value
    all_values = distance_dict.values()
    nearest_distance = min(all_values)

    return nearest_distance
```

In [58]:

```
# Nearest Hospital distance
integrated_data['Distance_to_hospital'] = integrated_data.apply(lambda x: nearest_hospital_
integrated_data.head(2)
```

Out[58]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedroom
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	[illegible]
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	[illegible]

2.2.4 Hospital_id

- This is the hospital id which is closest to the property.

In [59]:

```
# Function to return the nearest hospital ID
def nearest_hospital_id(row):

    # Property Coordinates
    prop_lng = float(row.lng)
    prop_lat = float(row.lat)

    # Dictionary to store the values
    distance_id_dict = dict()

    # Iterating through the dataset
    for location in hospital_data_lat_long_id:
        hospital_lat = float(location[0])
        hospital_lng = float(location[1])
        hospital_ID = location[2]

        # Distance calculation
        calc_distance = haversine_distance(prop_lat, prop_lng, hospital_lat, hospital_lng)
        distance_id_dict[hospital_ID] = calc_distance

    # Sorting the distance dictionary
    distance_id_dict = sorted(distance_id_dict.items(), key = lambda x: x[1])

    nearest_id = distance_id_dict[0][0]

    # Returning the nearest ID
    return nearest_id
```

In [60]:

```
# Nearest Hospital ID
integrated_data['Hospital_id'] = integrated_data.apply(lambda x: nearest_hospital_id(x), ax
integrated_data.head(2)
```

Out[60]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	[illegible]
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	[illegible]

2.2.5 Distance_to_supermarket

- This corresponds to the distance to the supermarket which is present closest to the property.

In [61]:

```
supermarkets_data.head(2)
```

Out[61]:

	id	lat	lng	type	lat_long
0	S_001	-37.883978	144.735287	Woolworths	0.0
1	S_002	-41.161591	147.514797	Woolworths	0.0

In [62]:

```
# For easier data retrieval
supermarkets_data['lat_long_id'] = list(zip(supermarkets_data.lat, supermarkets_data.lng, s
supermarkets_data_lat_long_id = supermarkets_data['lat_long_id'].to_list()
supermarkets_data.head(2)
```

Out[62]:

	id	lat	lng	type	lat_long	lat_long_id
0	S_001	-37.883978	144.735287	Woolworths	0.0	(-37.883978, 144.735287, S_001)
1	S_002	-41.161591	147.514797	Woolworths	0.0	(-41.161591, 147.514797, S_002)

In [63]:

```
# Function to get the distance to the nearest super_market
def nearest_supermarket_distance(row):

    # Getting property coordinates
    prop_lng = float(row.lng)
    prop_lat = float(row.lat)

    # Dictionary to store the values
    distance_dict = dict()

    # Iterating through the dataset
    for location in supermarkets_data_lat_long_id:
        super_lat = float(location[0])
        super_lng = float(location[1])

        # Distance calculations
        calc_distance = haversine_distance(prop_lat, prop_lng, super_lat, super_lng)
        distance_dict[location] = calc_distance

    # Getting the least distance
    all_values = distance_dict.values()
    nearest_distance = min(all_values)

    return nearest_distance
```

In [64]:

```
# Nearest Hospital distance
integrated_data['Distance_to_supermarket'] = integrated_data.apply(lambda x: nearest_superm
integrated_data.head(2)
```

Out[64]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	:
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	:

2.2.6 Supermarket_id

- This corresponds to the id of the supermarket which is closest to the property.

In [65]:

```
# Function to return the nearest supermarket ID
def nearest_supermarket_id(row):

    # Property Coordinates
    prop_lng = float(row.lng)
    prop_lat = float(row.lat)

    # Dictionary to hold the distance values
    distance_id_dict = dict()

    # Iterating through the list
    for location in supermarkets_data_lat_long_id:
        super_lat = float(location[0])
        super_lng = float(location[1])
        super_ID = location[2]

        # Distance calculation
        calc_distance = haversine_distance(prop_lat, prop_lng, super_lat, super_lng)
        distance_id_dict[super_ID] = calc_distance

    # Sorting the distance dictionary
    distance_id_dict = sorted(distance_id_dict.items(), key = lambda x: x[1])

    nearest_id = distance_id_dict[0][0]
    # Returning the nearest ID
    return nearest_id
```

In [66]:

```
# Nearest Hospital ID
integrated_data['Supermarket_id'] = integrated_data.apply(lambda x: nearest_supermarket_id(
integrated_data.head(2)
```

Out[66]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	:
1	3979	-37.81578064	144.8942719	96 Stephen Street	7136000	house	2009	:

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In [67]:

```
# Understaning the general structure
print("Agency Data:",agency_data.shape)
print("Calendar Data:",calendar_data.shape)
print("Calendar Dates Data:",calendar_dates_data.shape)
print("Routes Data:",routes_data.shape)
print("Shapes Data:",shapes_data.shape)
print("Stop Times Data:", stop_times_data.shape)
print("Stops Data:", stops_data.shape)
print("Trips Data:",trips_data.shape)
```

```
Agency Data: (1, 5)
Calendar Data: (19, 10)
Calendar Dates Data: (2, 3)
Routes Data: (81, 5)
Shapes Data: (339711, 5)
Stop Times Data: (390305, 9)
Stops Data: (218, 5)
Trips Data: (23809, 6)
```

In [68]:

```
agency_data.head()
```

Out[68]:

	agency_id	agency_name	agency_url	agency_timezone	agency_lang
0	1	PTV	http://www.ptv.vic.gov.au	Australia/Melbourne	EN

In [69]:

```
calendar_dates_data.head()
```

Out[69]:

	service_id	date	exception_type
0	T0	20151103	2
1	T0+a5	20151103	2

In [70]:

```
shapes_data.head()
```

Out[70]:

	shape_id	shape_pt_lat	shape_pt_lon	shape_pt_sequence	shape_dist_traveled
0	2-ain-mjp-1.1.H	-37.818631	144.951994	1	0.000000
1	2-ain-mjp-1.1.H	-37.817425	144.951050	2	157.543645
2	2-ain-mjp-1.1.H	-37.817241	144.950828	3	185.827916
3	2-ain-mjp-1.1.H	-37.816327	144.950047	4	308.469671
4	2-ain-mjp-1.1.H	-37.816127	144.949950	5	332.239399

In [71]:

```
trips_data.head()
```

Out[71]:

	route_id	service_id	trip_id	shape_id	trip_headsign	direction_id
0	2-ALM-F-mjp-1	T0	17067982.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0
1	2-ALM-F-mjp-1	T0	17067988.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0
2	2-ALM-F-mjp-1	T0	17067992.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0
3	2-ALM-F-mjp-1	T0	17067999.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0
4	2-ALM-F-mjp-1	T0	17068003.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0

In [72]:

```
routes_data.head()
```

Out[72]:

	route_id	agency_id	route_short_name	route_long_name	route_type
0	2-ALM-B-mjp-1	1	Alamein	Alamein - City (Flinders Street)	2
1	2-ALM-C-mjp-1	1	Alamein	Alamein - City (Flinders Street)	2
2	2-ALM-D-mjp-1	1	Alamein	Alamein - City (Flinders Street)	2
3	2-ALM-E-mjp-1	1	Alamein	Alamein - City (Flinders Street)	2
4	2-ALM-F-mjp-1	1	Alamein	Alamein - City (Flinders Street)	2

In [73]:

```
# Merging trips and routes on route_id
merge1 = trips_data.merge(routes_data, on = "route_id")
merge1.head()
```

Out[73]:

	route_id	service_id	trip_id	shape_id	trip_headsign	direction_id	agency_id	route_
0	2-ALM-F-mjp-1	T0	17067982.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
1	2-ALM-F-mjp-1	T0	17067988.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
2	2-ALM-F-mjp-1	T0	17067992.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
3	2-ALM-F-mjp-1	T0	17067999.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
4	2-ALM-F-mjp-1	T0	17068003.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	

In [74]:

```
calendar_data.head()
```

Out[74]:

	service_id	monday	tuesday	wednesday	thursday	friday	saturday	sunday	start_date	er
0	T2	0	0	0	0	0	1	0	20151009	2(
1	UJ	0	0	0	0	0	0	1	20151009	2(
2	T6	0	0	0	0	1	0	0	20151009	2(
3	T5	1	1	1	1	0	0	0	20151012	2(
4	T2_1	0	0	0	0	0	1	0	20151016	2(

In [75]:

```
# merging with calendar on service_id
merge2 = merge1.merge(calendar_data, on = "service_id")
merge2.head()
```

Out[75]:

	route_id	service_id	trip_id	shape_id	trip_headsign	direction_id	agency_id	route_
0	2-ALM-F-mjp-1	T0	17067982.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
1	2-ALM-F-mjp-1	T0	17067988.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
2	2-ALM-F-mjp-1	T0	17067992.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
3	2-ALM-F-mjp-1	T0	17067999.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
4	2-ALM-F-mjp-1	T0	17068003.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	

In [76]:

```
stop_times_data.head()
```

Out[76]:

	trip_id	arrival_time	departure_time	stop_id	stop_sequence	stop_headsign	pickup_
0	17182517.T2.2-ALM-B-mjp-1.1.H	04:57:00	04:57:00	19847	1	NaN	
1	17182517.T2.2-ALM-B-mjp-1.1.H	04:58:00	04:58:00	19848	2	NaN	
2	17182517.T2.2-ALM-B-mjp-1.1.H	05:00:00	05:00:00	19849	3	NaN	
3	17182517.T2.2-ALM-B-mjp-1.1.H	05:02:00	05:02:00	19850	4	NaN	
4	17182517.T2.2-ALM-B-mjp-1.1.H	05:04:00	05:04:00	19851	5	NaN	

In [77]:

```
# Merging with stop times on trip_id
merge3 = merge2.merge(stop_times_data, on = "trip_id")
```

In [78]:

```
stops_data.head()
```

Out[78]:

	stop_id	stop_name	stop_short_name	stop_lat	stop_lon
0	15351	Sunbury Railway Station	Sunbury	-37.579091	144.727319
1	15353	Diggers Rest Railway Station	Diggers Rest	-37.627017	144.719922
2	19827	Stony Point Railway Station	Crib Point	-38.374235	145.221837
3	19828	Crib Point Railway Station	Crib Point	-38.366123	145.204043
4	19829	Morradoo Railway Station	Crib Point	-38.354033	145.189602

In [79]:

```
# Merging with stops data on stop_id
merge4 = merge3.merge(stops_data, on = "stop_id")
print("Merged Data Shape:", merge4.shape)
```

```
Merged Data Shape: (390305, 31)
```

In [80]:

```
# Final merged data : merge4
merge4.head()
```

Out[80]:

	route_id	service_id	trip_id	shape_id	trip_headsign	direction_id	agency_id	route_
0	2-ALM-F-mjp-1	T0	17067982.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
1	2-ALM-F-mjp-1	T0	17067988.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
2	2-ALM-F-mjp-1	T0	17067992.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
3	2-ALM-F-mjp-1	T0	17067999.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	
4	2-ALM-F-mjp-1	T0	17068003.T0.2-ALM-F-mjp-1.1.H	2-ALM-F-mjp-1.1.H	City (Flinders Street)	0	1	

5 rows × 31 columns

In [81]:

```
# General Information about the merged data
merge4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 390305 entries, 0 to 390304
Data columns (total 31 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   route_id            390305 non-null  object 
 1   service_id          390305 non-null  object 
 2   trip_id             390305 non-null  object 
 3   shape_id            390275 non-null  object 
 4   trip_headsign       390305 non-null  object 
 5   direction_id        390305 non-null  int64  
 6   agency_id           390305 non-null  int64  
 7   route_short_name    390305 non-null  object 
 8   route_long_name     390305 non-null  object 
 9   route_type          390305 non-null  int64  
 10  monday              390305 non-null  int64  
 11  tuesday             390305 non-null  int64  
 12  wednesday           390305 non-null  int64  
 13  thursday            390305 non-null  int64  
 14  friday              390305 non-null  int64  
 15  saturday            390305 non-null  int64  
 16  sunday              390305 non-null  int64  
 17  start_date          390305 non-null  int64  
 18  end_date            390305 non-null  int64  
 19  arrival_time        390305 non-null  object 
 20  departure_time      390305 non-null  object 
 21  stop_id             390305 non-null  int64  
 22  stop_sequence       390305 non-null  int64  
 23  stop_headsign       0 non-null       float64
 24  pickup_type         390305 non-null  int64  
 25  drop_off_type       390305 non-null  int64  
 26  shape_dist_traveled 390217 non-null  float64
 27  stop_name           390305 non-null  object 
 28  stop_short_name     390305 non-null  object 
 29  stop_lat            390305 non-null  float64
 30  stop_lon            390305 non-null  float64
dtypes: float64(4), int64(16), object(11)
memory usage: 95.3+ MB
```

2.2.7 Transfer_flag

- This is a Boolean attribute.
- This indicates whether there is a direct trip to Flinders Street Station from the closest station between 7 am - 9 am on weekdays.
- **Flag = 0** : If there is a direct trip (i.e there is no transfer is required between the closest station and Flinders Street Station)
- **Flag = 1** : Otherwise

In [82]:

```
#Function for transfer flag
def transfer_flag_function(row):
    if row['monday'] == 1 and row['tuesday'] == 1 and \
    row['wednesday'] == 1 and row['thursday'] == 1 and \
    row['friday'] == 1 and row['departure_time'] >= "07:00:00" \
    and row['departure_time'] <= "09:00:00":
        return 0
    else:
        return 1
```

In [83]:

```
# Defining the transfer flag using the above functions
merge4['Transfer_flag'] = merge4.apply(lambda row: \
                                       transfer_flag_function(row),
                                       axis = 1)
```

2.2.8 Train_station_id, travel_min_to_CBD, Distance_to_train_station

In [84]:

```
# Initializing the new columns
integrated_data['Train_station_id'] = 0
integrated_data['Distance_to_train_station'] = 0
integrated_data['travel_min_to_CBD'] = 0
#integrated_data.head()
```

In [85]:

```
# Station ID for Flinder's Street
flinders_id = list(merge4[merge4['stop_name'].str.contains\
                          ('Flinders Street Railway Station')]\
                   ['stop_id'].unique())
print(flinders_id)
```

```
[19854]
```

In [86]:

```
# Dataframe containing Flinders Street Railway Station as the stop
flinders_df = merge4[(merge4['stop_id'].isin(flinders_id))]
print("Flinders Data Shape:", flinders_df.shape)
```

```
Flinders Data Shape: (17850, 32)
```

In [87]:

```
# Fetch data with flag 0 which indicates a direct trip
flinders_df = flinders_df[flinders_df['Transfer_flag'] == 0]
print("Flinders Data Direct Trips Shape:", flinders_df.shape)
```

```
Flinders Data Direct Trips Shape: (381, 32)
```

In [88]:

```
# When stop_sequence = 1, it means Flinders is the source
flinders_df = flinders_df[flinders_df['stop_sequence'] != 1]
print("Flinders Data after adjusting stop sequence:", flinders_df.shape)
```

```
Flinders Data after adjusting stop sequence: (297, 32)
```

In [89]:

```
# Function that gives us distance dataframe of a given property from all stations
def distance_to_station(lat1, lon1):

    # Creating a new dataframe
    stops_distance = pd.DataFrame(columns = ['stop_id', 'distance'])

    # Iterating through the stops data
    for index, row in stops_data.iterrows():
        distance = haversine_distance(lat1, lon1, \
                                      row['stop_lat'], row['stop_lon'])
        stops_distance.loc[index, 'stop_id'] = row['stop_id']
        stops_distance.loc[index, 'distance'] = distance

    # Sorting it through the distance values
    stops_distance.sort_values(by = ['distance'], inplace = True)

    # Returning the distance dataframe
    return stops_distance
```

def travel_time():

- The below function checks whether there exists a trip between the given station and Flinders.
    - It returns a Boolean Value:
        - True: If the Trip exists
        - False: If there is no Trip
    - It also returns the minimum time taken to travel to CBD

In [90]:

```
# Function to calculate the travel time to CBD
def travel_time(id):

    # Takes in the information for the required stop
    stop_df = merge4[merge4['stop_id'] == id]

    # Merge this stop data with the Flinders data using trip_id
    flinders_stop = flinders_df.merge(stop_df, on ='trip_id')

    # Assigning the number of rows and columns using the shape function
    rows1, columns1 = flinders_stop.shape

    # Considering only when you have non-zero rows
    if rows1 > 0:
        flinders_stop['travel_time'] = ((pd.to_datetime(flinders_stop['arrival_time_x']) -
                                       pd.to_datetime(flinders_stop['arrival_time_y'])))/ np.timede

        # Considering only positive travel time
        flinders_stop = flinders_stop[flinders_stop['travel_time'] >= 0]

        rows2, columns2 = flinders_stop.shape
        # Considering only when you have non-zero rows
        if rows2 > 0:
            # As per the assignment specification provided, when you find the average
            return True, flinders_stop['travel_time'].mean()
        else:
            return False, 0
    else:
        return False, 0
```

In [91]:

```
# Converting to numeric datatype for calculations
integrated_data['lat'] = pd.to_numeric(integrated_data['lat'], errors='coerce').fillna(0)
integrated_data['lng'] = pd.to_numeric(integrated_data['lng'], errors='coerce').fillna(0)
#integrated_data.info()
```

In [92]:

```
# Iterating through the integrated data df
for index1, row1 in integrated_data.iterrows():

    # Assigning the given property latitude to property_lat
    property_lat = row1['lat']

    # Assigning the given property longitude to property_lng
    property_lon = row1['lng']

    # Generating the distance df
    distance_df = distance_to_station(property_lat, property_lon)

    # Iterating through the distance df
    for index2, row2 in distance_df.iterrows():

        # Calling the function in order to calculate the travel time to CBD
        trip_exists, average_time = travel_time(row2['stop_id'])

        # If the value of trip_exists is True
        if trip_exists:

            # Assigning the nearest station stop id as the Nearest Train Station ID
            integrated_data.loc[index1, 'Train_station_id'] = row2['stop_id']

            # Assigning the distance of the nearest stop as the nearest station distance
            integrated_data.loc[index1, 'Distance_to_train_station'] = row2['distance']

            # Assigning the average time taken as the minimum time taken to reach CBD
            integrated_data.loc[index1, 'travel_min_to_CBD'] = average_time


            # We need to come out of this loop as soon as these assignments are made
            break
```

In [93]:

```
integrated_data.head()
```

Out[93]:

	Property_id	lat	lng	addr_street	price	property_type	year	bedrooms
0	53425	-37.813198	145.002348	50 Lambert Street	5984000	house	2010	3
1	3979	-37.815781	144.894272	96 Stephen Street	7136000	house	2009	2
2	20162	-37.800716	144.973143	37 Owen Street	12870000	house	2011	2
3	52140	-37.814573	144.994122	11 Leeds Street	6314000	house	2015	1
4	81404	-37.978701	145.199705	6 Campbell Street	4914000	house	2010	3

In [94]:

```
# In order to generate the transfer flag, we rename the column first
merge4.rename(columns = {'stop_id': 'Train_station_id'}, inplace = True)

# We consider only the required columns for merging
x = ['Train_station_id','Transfer_flag']
final_merge = merge4[x]
```

In [95]:

```
# Merging the data in order to get the transfer flag
final_integrated_data = integrated_data.merge(final_merge, on = "Train_station_id")
```

In [96]:

```
final_integrated_data.head()
final_integrated_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3346562 entries, 0 to 3346561
Data columns (total 21 columns):
 #   Column                    Dtype
---  ------                    -----
 0   Property_id               object
 1   lat                       float64
 2   lng                       float64
 3   addr_street               object
 4   price                     object
 5   property_type             object
 6   year                      object
 7   bedrooms                  object
 8   bathrooms                 object
 9   parking_space             object
 10  Suburb                    object
 11  Distance_to_sc            float64
 12  Shopping_center_id        object
 13  Distance_to_hospital      float64
 14  Hospital_id               object
 15  Distance_to_supermarket   float64
 16  Supermarket_id            object
 17  Train_station_id          int64
 18  Distance_to_train_station float64
 19  travel_min_to_CBD         float64
 20  Transfer_flag             int64
dtypes: float64(7), int64(2), object(12)
memory usage: 561.7+ MB
```

In [97]:

```
final_integrated_data.shape
```

Out[97]:

```
(3346562, 21)
```

In [148]:

```
# Write to output file
final_integrated_data.to_csv('30945305_A3_solution.csv', index=False)
```

2.3 Task 2 : Data Reshaping

- This task revolved around studying the various effects of the following methods.
- **Normalization methods** such as:
  - standardization
  - minmax normalization
- **transformation methods** such as:
  - log transformation
  - power transformation
  - box-cox transformation
- Our target variable is "price".
- Our predictor variables are:
  - “Distance_to_sc”
  - “travel_min_to_CBD”
  - “Distance_to_hospital”
- We are interested in developing a **Linear Model** in order to predict the price using these factors.
- Finally, our focus will be on two main linear regression assumptions:
  - Normality
  - Linearity

In [99]:

```
# Predictors as per the specification
columns = ['Distance_to_sc', 'travel_min_to_CBD', 'Distance_to_hospital']
```

In [100]:

```
predictors = final_integrated_data[columns]
print("Structure of the predictors:",predictors.shape)
predictors.head()
```

```
Structure of the predictors: (3346562, 3)
```

Out[100]:

	Distance_to_sc	travel_min_to_CBD	Distance_to_hospital
0	2.6713	33.866667	0.2982
1	2.6713	33.866667	0.2982
2	2.6713	33.866667	0.2982
3	2.6713	33.866667	0.2982
4	2.6713	33.866667	0.2982

In [101]:

```
# Creating a copy of the final integrated data to measure the performance
data_df = final_integrated_data.copy()
```

In [102]:

```
# Initializing the linear regression variable
lm = LinearRegression()

# Splitting the final integrated data into training and testing data
# test_size : 25% of the data proportion to be used as test sample
# random_state : In order to control the random number generated. Popular seeds are 0 and 4
x_train, x_test, y_train, y_test = train_test_split(predictors, data_df['price'], test_size
```

In [103]:

```
# Using the training data to fit the linear model
lm.fit(x_train, y_train)

# Using the trained model to predict the model on the test data
predicted_model = lm.predict(x_test)

# Generating the R-Squared value
print("R-squared Value : ", lm.score(x_test, y_test))

# Generating the Mean Squared Error value
print("Mean Squared Error (MSE) Value : ", mean_squared_error(y_test, predicted_model))

# Generating the Root Mean Squared Error value
print("Root Mean Squared Error (RMSE) Value : ", math.sqrt(mean_squared_error(y_test, predi
```

```
R-squared Value :  0.09698062245079553
Mean Squared Error (MSE) Value :  27957646295379.98
Root Mean Squared Error (RMSE) Value :  5287499.05866469
```

In [104]:

```
# In order to view the different statistics of the predictors
predictors.describe()
```

Out[104]:

	Distance_to_sc	travel_min_to_CBD	Distance_to_hospital
count	3.346562e+06	3.346562e+06	3.346562e+06
mean	2.452747e+00	3.190144e+01	2.135016e+00
std	1.344631e+00	1.323753e+01	1.775434e+00
min	1.037000e-01	0.000000e+00	4.740000e-02
25%	1.415900e+00	2.180000e+01	9.445000e-01
50%	2.166500e+00	3.341667e+01	1.636000e+00
75%	3.321200e+00	4.042857e+01	2.635600e+00
max	5.959700e+00	6.000000e+01	9.369100e+00

2.3.1 Data Transformation (Log, Power and Box-Cox)

- Data transformation revolves around re-expressing data so that it's present in a form which is more suitable for analysis.
- Following are the advantages of this transformation:
  - It improves Data Visualisation
  - Data can be interpreted in a better manner.
  - It solves the problem of any skewness in the data.
- In this section, we plot the various predictors and then apply log, power and box-plot transformations on them.
- We then plot the variables both before and after transformation.

Log Transformation

- This makes any highly skewed data less skewed!

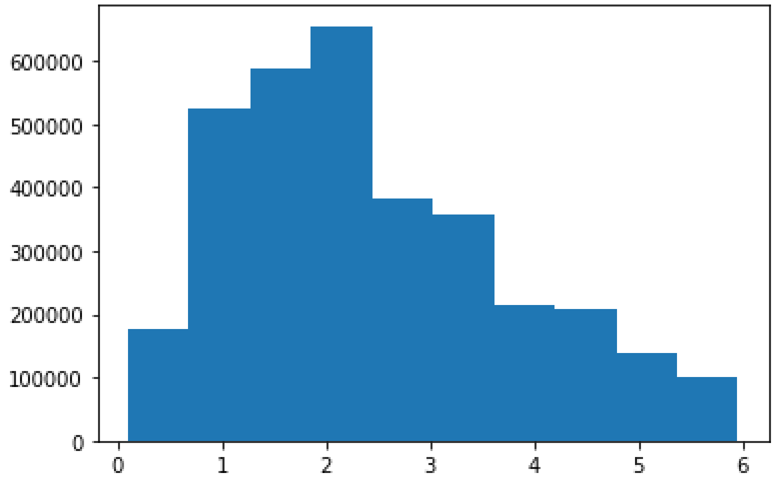
Predictor 1 : Distance_to_sc

In [105]:

```
# Histogram of predictor 1 : Distance_to_sc
plt.hist(predictors['Distance_to_sc'])
```

Out[105]:

```
(array([176692., 523680., 586908., 655347., 381613., 357394., 215078.,
        208529., 139279., 102042.]),
 array([0.1037, 0.6893, 1.2749, 1.8605, 2.4461, 3.0317, 3.6173, 4.2029,
        4.7885, 5.3741, 5.9597]),
 <a list of 10 Patch objects>)
```



Observations:

- This data looks skewed to the left.
- Now, one of the main assumptions of Linear Regression is that the features have to be normally distributed!
- Thus we apply **LOG TRANSFORMATION** to make it normal.

In [106]:

```
# Applying a log transformation
predictors['Distance_to_sc_log'] = predictors['Distance_to_sc'].apply(math.log)
```

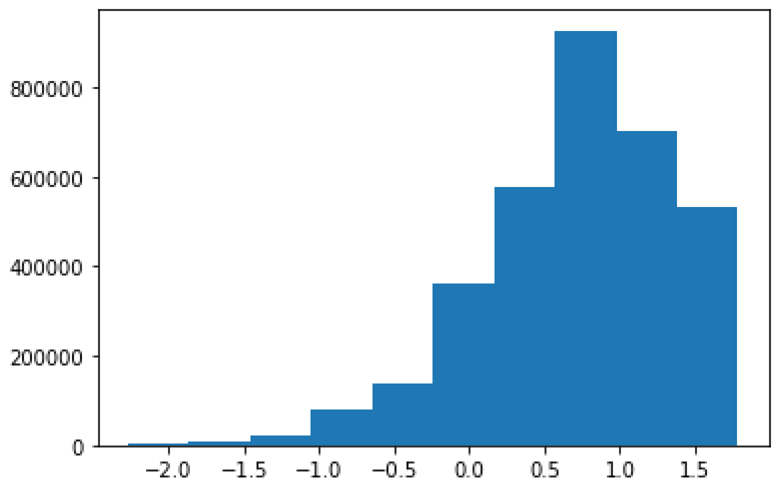
```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
```

In [107]:

```
# Histogram of predictor 1 : Distance_to_sc after log transformation
plt.hist(predictors['Distance_to_sc_log'])
```

Out[107]:

```
(array([  3426.,   5898.,  22065.,  79733., 138538., 359676., 577360.,
        926789., 701928., 531149.]),
 array([-2.26625316, -1.86112583, -1.4559985 , -1.05087117, -0.64574384,
        -0.24061651,  0.16451082,  0.56963815,  0.97476548,  1.37989281,
         1.78502014]),
 <a list of 10 Patch objects>)
```



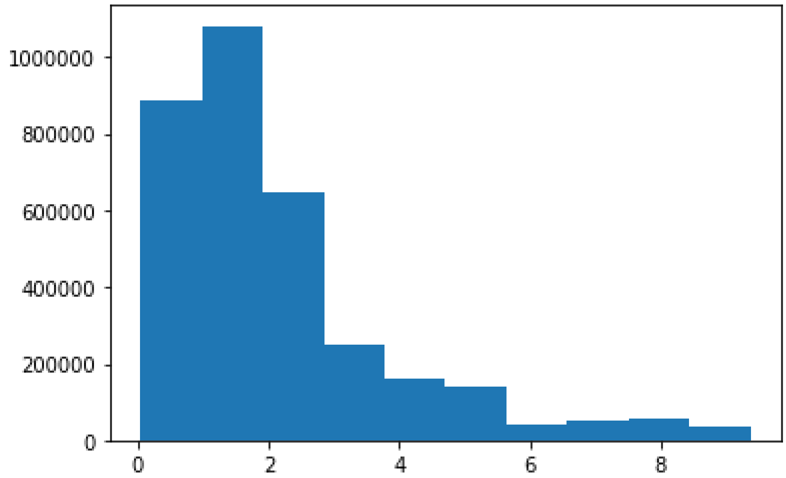
Predictor 2 : Distance_to_hospital

In [108]:

```
plt.hist(predictors['Distance_to_hospital'])
```

Out[108]:

```
(array([ 886692., 1081767.,  644313.,  247240.,  158374.,  141669.,
          41716.,   49877.,   56967.,   37947.]),
 array([0.0474 , 0.97957, 1.91174, 2.84391, 3.77608, 4.70825, 5.64042,
        6.57259, 7.50476, 8.43693, 9.3691 ]),
 <a list of 10 Patch objects>)
```



Observations:

- Thus, similar to the above, this is also slighlt skewed to the left.
- Hence, we apply a log transformation on this one too!

In [109]:

```
# Applying a log transformation
predictors['Distance_to_hospital_log'] = predictors['Distance_to_hospital'].apply(math.log)
```

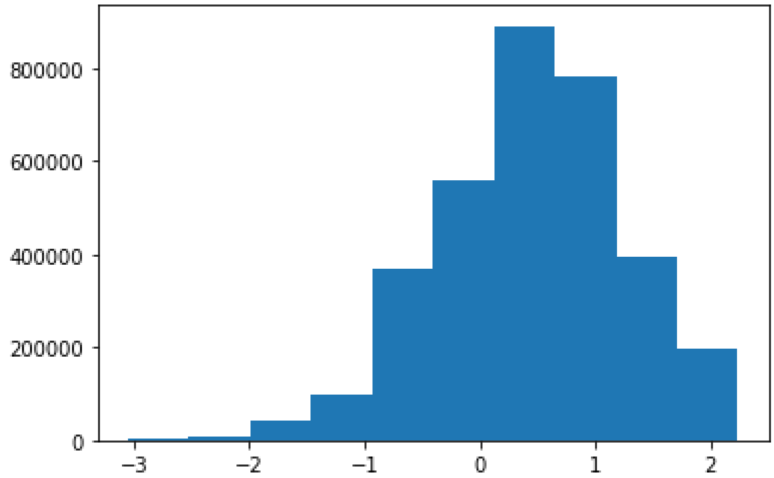
```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
```

In [110]:

```
# Plotting after the transformation
plt.hist(predictors['Distance_to_hospital_log'])
```

Out[110]:

```
(array([  3498.,   9777.,  42717.,  99639., 367395., 557604., 891737.,
        782934., 394973., 196288.]),
 array([-3.04913305, -2.52047804, -1.99182303, -1.46316802, -0.93451301,
        -0.405858  ,  0.122797  ,  0.65145201,  1.18010702,  1.70876203,
         2.23741704]),
 <a list of 10 Patch objects>)
```



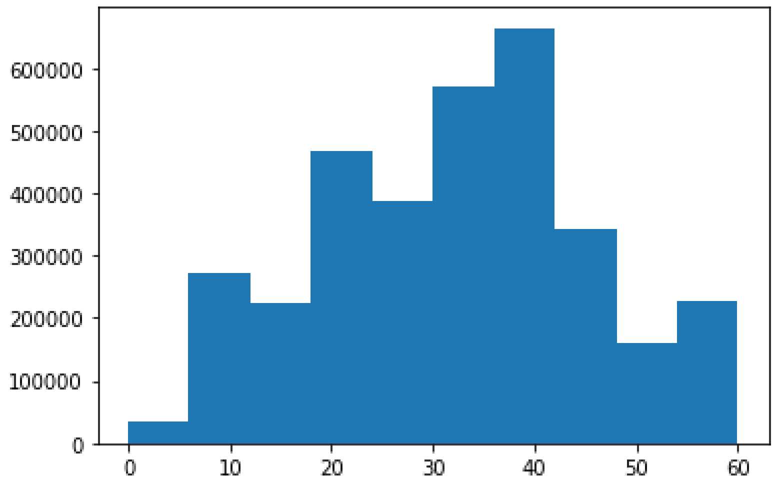
Predictor 3 : travel_min_to_CBD

In [111]:

```
# Plotting the histogram on the original data
plt.hist(predictors['travel_min_to_CBD'])
```

Out[111]:

```
(array([ 35700., 271187., 223667., 468269., 387840., 569063., 664252.,
        341368., 159628., 225588.]),
 array([ 0.,  6., 12., 18., 24., 30., 36., 42., 48., 54., 60.]),
 <a list of 10 Patch objects>)
```



Observations:

- This distribution looks almost Normal.
- Hence, we can do some scaling to it!

In [112]:

```
# Assingning a min max value of 1, 10
scaler = preprocessing.MinMaxScaler(feature_range =(1, 10))
predictors['travel_min_to_CBD_minmax'] = scaler.fit_transform(predictors[['travel_min_to_CB
```

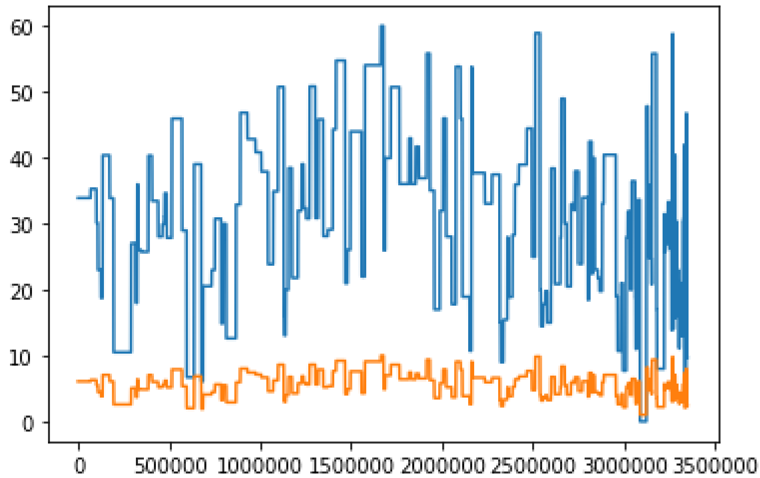
```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  This is separate from the ipykernel package so we can avoid doing imports
 until
```

In [113]:

```
# Plotting both the original data and min-max data
predictors["travel_min_to_CBD"].plot(), predictors["travel_min_to_CBD_minmax"].plot()
```

Out[113]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b04ea0908>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b04ea0908>)
```



In [114]:

```
# Initializing the linear regression variable
lm = LinearRegression()

# Splitting the final integrated data into training and testing data
# test_size : 25% of the data proportion to be used as test sample
# random_state : In order to control the random number generated. Popular seeds are 0 and 4
x_train, x_test, y_train, y_test = train_test_split(predictors[['travel_min_to_CBD','Distar

# Using the training data to fit the linear model
lm.fit(x_train, y_train)

# Using the trained model to predict the model on the test data
predicted_model = lm.predict(x_test)

# Generating the R-Squared value
print("R-squared Value : ", lm.score(x_test, y_test))

# Generating the Mean Squared Error value
print("Mean Squared Error (MSE) Value : ", mean_squared_error(y_test, predicted_model))

# Generating the Root Mean Squared Error value
print("Root Mean Squared Error (RMSE) Value : ", math.sqrt(mean_squared_error(y_test, predi
```

```
R-squared Value :  0.08006149558368458
Mean Squared Error (MSE) Value :  28481465580256.375
Root Mean Squared Error (RMSE) Value :  5336802.936239671
```

Observations:

- Thus, after applying the log-transformations, the R-Suared value has slightly increased.
- At the same time, we have been able to reduce the Mean Squared and Root Mean Squared Error values.

Power Transformation

- This follows the idea that we transform both the target and predictor variables using some functions.

In [115]:

```
# Applying the power raised to 2 transformations
predictors['Distance_to_sc_power'] = np.power(predictors.Distance_to_sc,2)
predictors['Distance_to_hospital_power'] = np.power(predictors.Distance_to_hospital,2)
predictors['travel_min_to_CBD_power'] = np.power(predictors.travel_min_to_CBD,2)
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)

C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  This is separate from the ipykernel package so we can avoid doing imports
 until
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [116]:

```
# Initializing the linear regression variable
lm = LinearRegression()

# Splitting the final integrated data into training and testing data
# test_size : 25% of the data proportion to be used as test sample
# random_state : In order to control the random number generated. Popular seeds are 0 and 4
x_train, x_test, y_train, y_test = train_test_split(predictors[['travel_min_to_CBD_power','

# Using the training data to fit the linear model
lm.fit(x_train, y_train)

# Using the trained model to predict the model on the test data
predicted_model = lm.predict(x_test)

# Generating the R-Squared value
print("R-squared Value : ", lm.score(x_test, y_test))

# Generating the Mean Squared Error value
print("Mean Squared Error (MSE) Value : ", mean_squared_error(y_test, predicted_model))

# Generating the Root Mean Squared Error value
print("Root Mean Squared Error (RMSE) Value : ", math.sqrt(mean_squared_error(y_test, predi
```

```
R-squared Value :  0.08530446526649615
Mean Squared Error (MSE) Value :  28319142272945.664
Root Mean Squared Error (RMSE) Value :  5321573.289258136
```

Box-Cox Transformation

- This transforms the continuous variables into an almost normal distribution!

In [118]:

```
# Applying the box-cox transformations
predictors['Distance_to_sc_boxcox'],_ = stats.boxcox(predictors['Distance_to_sc'])
predictors['Distance_to_hospital_boxcox'],_ = stats.boxcox(predictors['Distance_to_hospital
#predictors['travel_min_to_CBD_boxcox'],_ = stats.boxcox(predictors['travel_min_to_CBD'])
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)

C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  This is separate from the ipykernel package so we can avoid doing imports
 until
```

In [120]:

```
# Initializing the linear regression variable
lm = LinearRegression()

# Splitting the final integrated data into training and testing data
# test_size : 25% of the data proportion to be used as test sample
# random_state : In order to control the random number generated. Popular seeds are 0 and 4
x_train, x_test, y_train, y_test = train_test_split(predictors[['travel_min_to_CBD','Distar

# Using the training data to fit the linear model
lm.fit(x_train, y_train)

# Using the trained model to predict the model on the test data
predicted_model = lm.predict(x_test)

# Generating the R-Squared value
print("R-squared Value : ", lm.score(x_test, y_test))

# Generating the Mean Squared Error value
print("Mean Squared Error (MSE) Value : ", mean_squared_error(y_test, predicted_model))

# Generating the Root Mean Squared Error value
print("Root Mean Squared Error (RMSE) Value : ", math.sqrt(mean_squared_error(y_test, predi
```

```
R-squared Value :  0.08457854018613786
Mean Squared Error (MSE) Value :  28341617047173.305
Root Mean Squared Error (RMSE) Value :  5323684.536782144
```

2.3.2 Data Normalization :- Z Transform and Min-Max

Z-Score Normalization (standardization):

- Here, the focus is on shifting the distribution of the data.
- We fix the data such that it's mean is 0 and standard deviation is 1
- Thus, we aim to rescale the variables and features so that they have the properties of a standard normal distribution!
- travel_min_to_CBD is measured on a different scale - minutes.
- Distance_to_sc and Distance_to_hospital - Haversine Distance in km.

In [121]:

```
# Performing the z tranformation scaling
std_scale = preprocessing.StandardScaler().fit(predictors[['Distance_to_sc', 'travel_min_to
df_std = std_scale.transform(predictors[['Distance_to_sc', 'travel_min_to_CBD']]) # an arra
```

In [122]:

```
# Assigning the values to new generated columns
predictors['Distance_to_sc_scaled'] = df_std[:,0]
predictors['travel_min_to_CBD_scaled'] = df_std[:,1]
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)

C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  This is separate from the ipykernel package so we can avoid doing imports
 until
```

In [123]:

```
predictors.describe()
```

Out[123]:

	Distance_to_sc	travel_min_to_CBD	Distance_to_hospital	Distance_to_sc_log	Distance_tc
count	3.346562e+06	3.346562e+06	3.346562e+06	3.346562e+06	
mean	2.452747e+00	3.190144e+01	2.135016e+00	7.238818e-01	
std	1.344631e+00	1.323753e+01	1.775434e+00	6.311831e-01	
min	1.037000e-01	0.000000e+00	4.740000e-02	-2.266253e+00	
25%	1.415900e+00	2.180000e+01	9.445000e-01	3.477654e-01	
50%	2.166500e+00	3.341667e+01	1.636000e+00	7.731130e-01	
75%	3.321200e+00	4.042857e+01	2.635600e+00	1.200326e+00	
max	5.959700e+00	6.000000e+01	9.369100e+00	1.785020e+00	

Mean and Standard Deviation Values:

In [124]:

```
# Printing out the mean value after Standardisation
print("Mean after standardisation")
print("Distance_to_sc = {:.2f}, travel_min_to_CBD = {:.2f}"
      .format(df_std[:,0].mean(), df_std[:,1].mean()))

print("\n")
# Printing out the standard deviation value after Standardisation
print("Standard deviation after standardisation:")
print("Distance_to_sc = {:.2f}, travel_min_to_CBD = {:.2f}"
      .format(df_std[:,0].std(), df_std[:,1].std()))
```

```
Mean after standardisation
Distance_to_sc = -0.00, travel_min_to_CBD = 0.00


Standard deviation after standardisation:
Distance_to_sc = 1.00, travel_min_to_CBD = 1.00
```

Observations:

- Thus, we can see that the values of mean and standard deviation after the z transformation are 0 and 1 respectively!

In [125]:

```
%matplotlib inline
```

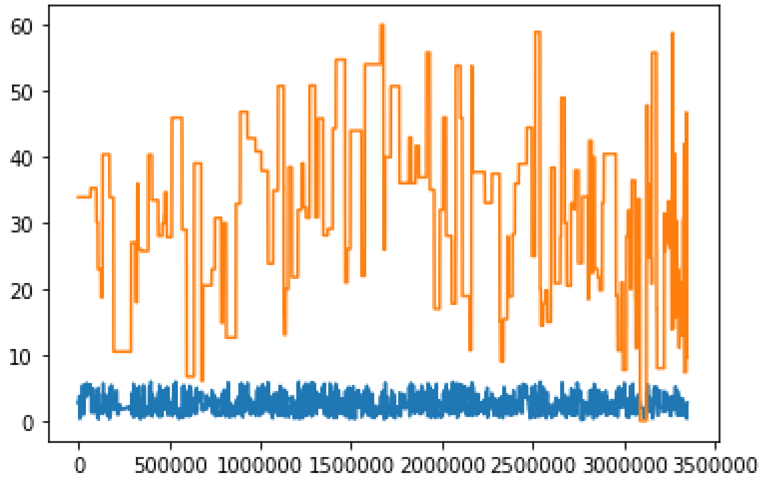
Data before Normalization:

In [126]:

```
# Plotting the data before Normalisation
predictors["Distance_to_sc"].plot(), predictors["travel_min_to_CBD"].plot()
```

Out[126]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b04f1cdd8>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b04f1cdd8>)
```



Data after Normalization:

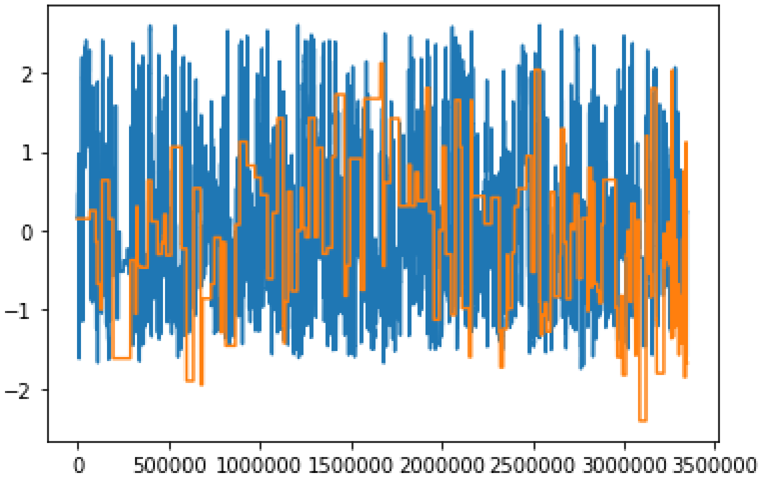
- Here, we observe the range and the centre of the distribution for the new features which have been standardised.
- Thus from the two plots we can see that the original and the standardised data are in the same shape but are shifted!

In [127]:

```
# Plotting the scaled data
predictors["Distance_to_sc_scaled"].plot(), predictors["travel_min_to_CBD_scaled"].plot()
```

Out[127]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b050f9978>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b050f9978>)
```

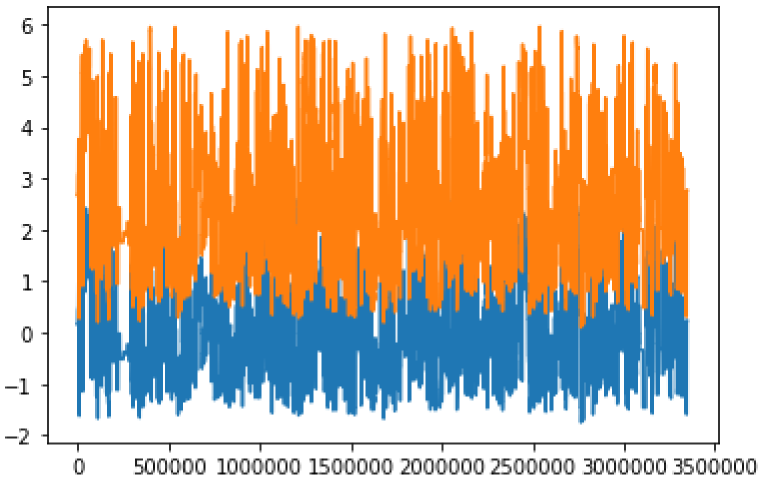


In [128]:

```
# Plotting the scaled and original data to compare
predictors["Distance_to_sc_scaled"].plot(), predictors["Distance_to_sc"].plot()
```

Out[128]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b051557f0>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b051557f0>)
```

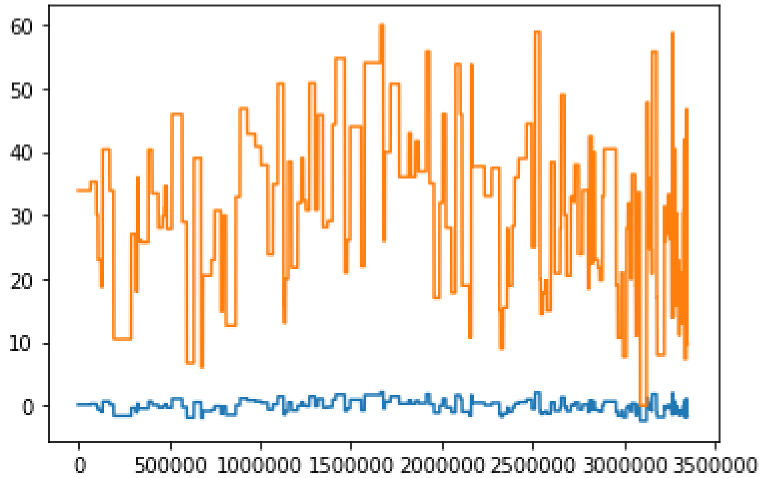


In [129]:

```
# Plotting the scaled and original data to compare
predictors["travel_min_to_CBD_scaled"].plot(), predictors["travel_min_to_CBD"].plot()
```

Out[129]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b0519e438>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b0519e438>)
```



Z-Tranformations: One predictor at a time!

- From the above viualisations, we can see the behaviour of the parameters when we take them two at a time.
- We would now be considering them one at a time!

In [130]:

```
# Z_tranform on Distance_to_sc
std_scale = preprocessing.StandardScaler().fit(predictors[['Distance_to_sc']])
df_std = std_scale.transform(predictors[['Distance_to_sc']])
predictors['Distance_to_sc_z_transform'] = df_std[:,0]
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [131]:

```
# Z_tranform on Distance_to_hospital
std_scale = preprocessing.StandardScaler().fit(predictors[['Distance_to_hospital']])
df_std = std_scale.transform(predictors[['Distance_to_hospital']])
predictors['Distance_to_hospital_z_transform'] = df_std[:,0]
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [132]:

```
# Z_tranform on travel_min_to_CBD
std_scale = preprocessing.StandardScaler().fit(predictors[['travel_min_to_CBD']])
df_std = std_scale.transform(predictors[['travel_min_to_CBD']])
predictors['travel_min_to_CBD_z_transform'] = df_std[:,0]
```

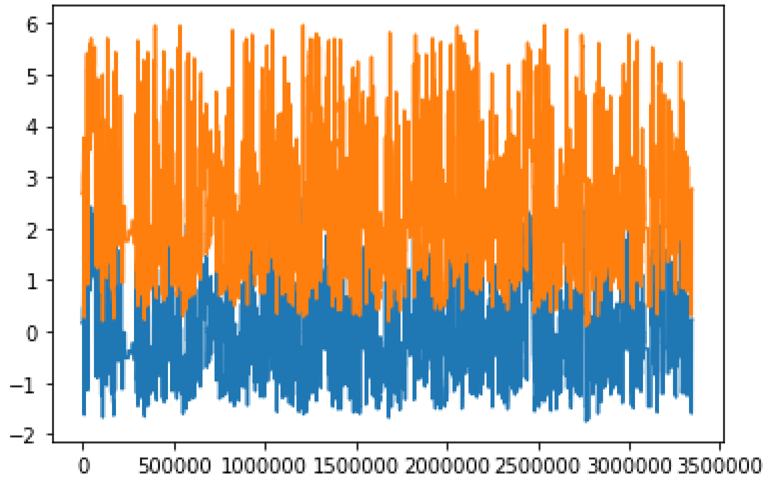
```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [133]:

```
# Plotting the z_transformed data for Distance_to_sc
predictors["Distance_to_sc_z_transform"].plot(), predictors["Distance_to_sc"].plot()
```

Out[133]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b052295c0>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b052295c0>)
```

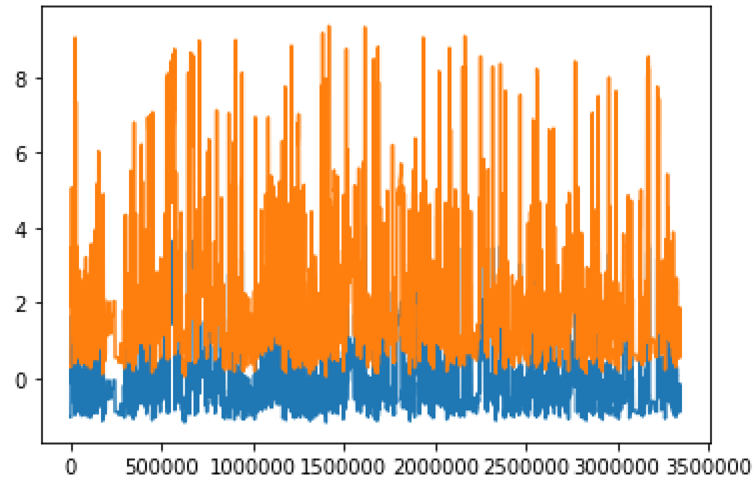


In [134]:

```
# Plotting the z_transformed data to Distance_to_hospital
predictors["Distance_to_hospital_z_transform"].plot(), predictors["Distance_to_hospital"].p
```

Out[134]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b053fca20>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b053fca20>)
```

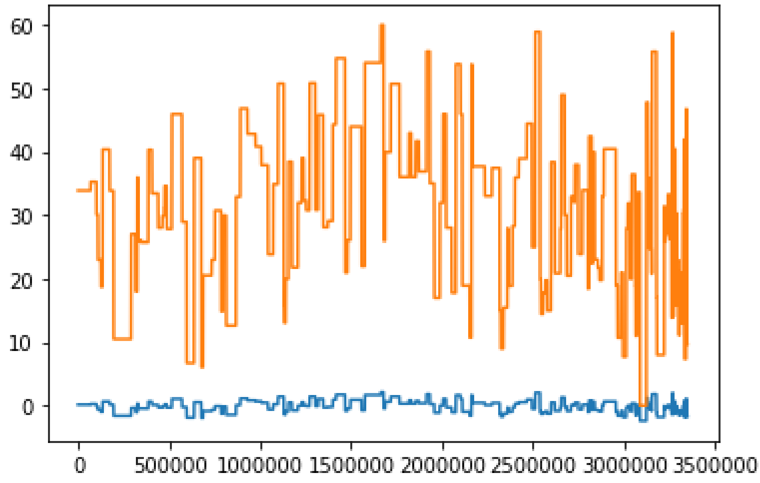


In [135]:

```
# Plotting the z_transformed data for travel_min_to_CBD
predictors["travel_min_to_CBD_z_transform"].plot(), predictors["travel_min_to_CBD"].plot()
```

Out[135]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b05461be0>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b05461be0>)
```



2. MinMax Normalisation:

- In Min-Max Normalisation, we rescale the features or variables such that their values come in a specific range.

In [136]:

```
# Generating the min_max versions condidering two variables at a time
minmax_scale = preprocessing.MinMaxScaler().fit(predictors[['Distance_to_sc', 'travel_min_t
df_minmax = minmax_scale.transform(predictors[['Distance_to_sc', 'travel_min_to_CBD']])
```

In [141]:

```
print(" Min-value after min-max scaling:")
print(" Distance_to_sc = {:.2f}, travel_min_to_CBD = {:.2f}"
      .format(df_minmax[:,0].min(), df_minmax[:,1].min()))

print("\n")

print(" Max-value after min-max scaling:")
print(" Distance_to_sc = {:.2f}, travel_min_to_CBD = {:.2f}"
      .format(df_minmax[:,0].max(), df_minmax[:,1].max()))
```

```
 Min-value after min-max scaling:
 Distance_to_sc = 0.00, travel_min_to_CBD = 0.00


 Max-value after min-max scaling:
 Distance_to_sc = 1.00, travel_min_to_CBD = 1.00
```

Observations:

- Thus, we can see that the mean and standard deviation values have been normalised!
- They have taken the values of 0 and 1 respectively.

- Thus, we can see that the Minimum and Maximum values after scaling are 0 and 1 respectively.

Min_Max Tranformations: One Variable at a time!

In [142]:

```
# Performing the min-max normalisation for Distance_to_sc
minmax_scale = preprocessing.MinMaxScaler().fit(predictors[['Distance_to_sc']])
df_minmax = minmax_scale.transform(predictors[['Distance_to_sc']])
predictors['Distance_to_sc_minmax'] = df_minmax[:,0]
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [143]:

```
# Performing the min-max normalisation for Distance_to_hospital
minmax_scale = preprocessing.MinMaxScaler().fit(predictors[['Distance_to_hospital']])
df_minmax = minmax_scale.transform(predictors[['Distance_to_hospital']])
predictors['Distance_to_hospital_minmax'] = df_minmax[:,0]
```

```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [144]:

```
# Performing the min-max normalisation for travel_min_to_CBD
minmax_scale = preprocessing.MinMaxScaler().fit(predictors[['travel_min_to_CBD']])
df_minmax = minmax_scale.transform(predictors[['travel_min_to_CBD']])
predictors['travel_min_to_CBD_minmax'] = df_minmax[:,0]
```

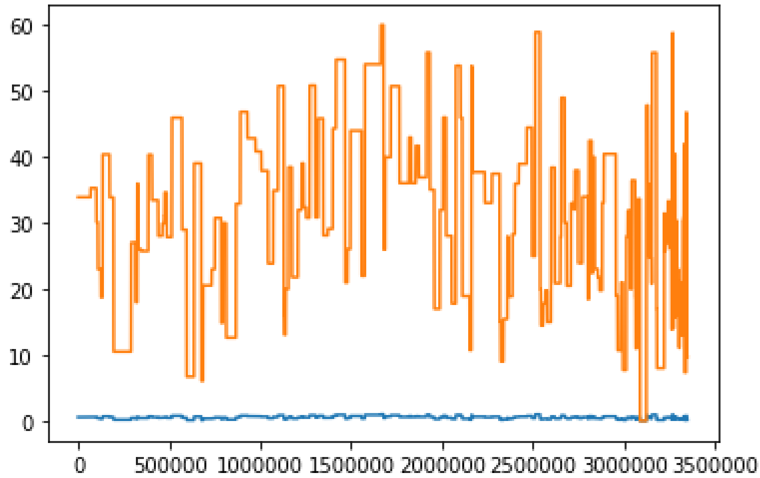
```
C:\Users\Gayatri Aniruddha\Anaconda3\lib\site-packages\ipykernel_launcher.p
y:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  after removing the cwd from sys.path.
```

In [145]:

```
# Plotting the minmax_transformed data for travel_min_to_CBD
predictors["travel_min_to_CBD_minmax"].plot(), predictors["travel_min_to_CBD"].plot()
```

Out[145]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b3defcd30>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b3defcd30>)
```

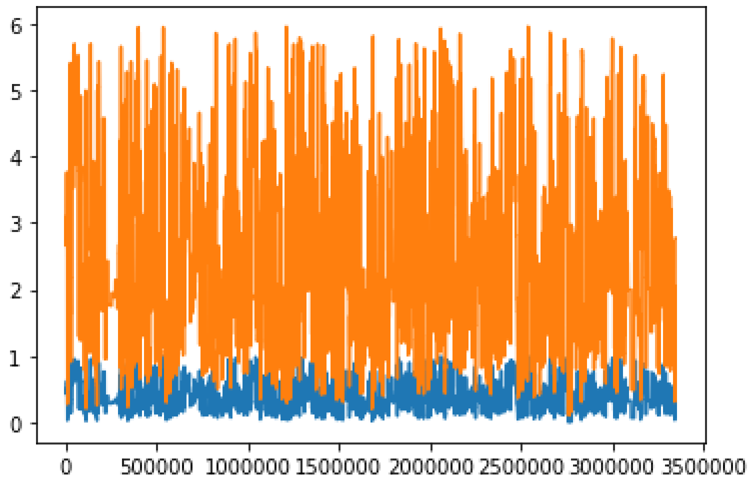


In [146]:

```
# Plotting the minmax_transformed data for Distance_to_sc
predictors["Distance_to_sc_minmax"].plot(), predictors["Distance_to_sc"].plot()
```

Out[146]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b05abc518>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b05abc518>)
```

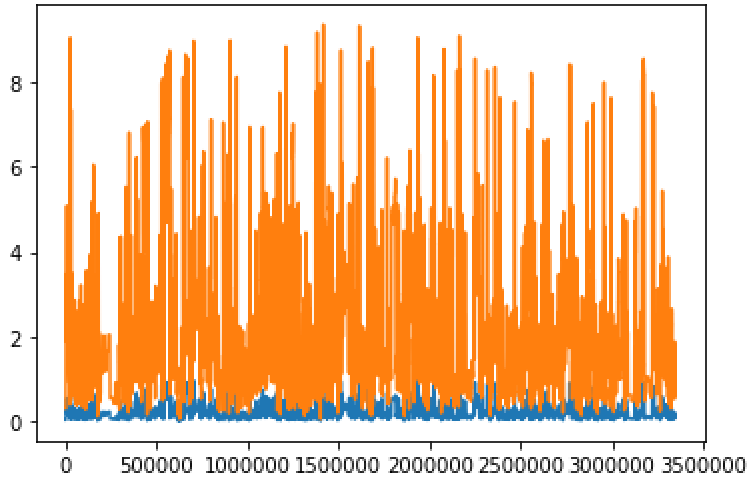


In [147]:

```
# Plotting the minmax_transformed data for Distance_to_hospital
predictors["Distance_to_hospital_minmax"].plot(), predictors["Distance_to_hospital"].plot()
```

Out[147]:

```
(<matplotlib.axes._subplots.AxesSubplot at 0x28b05b2d240>,
 <matplotlib.axes._subplots.AxesSubplot at 0x28b05b2d240>)
```



3. Discussion and Analysis

For Task 1:

After performing the various tasks associated with task 1, I have come to the following analysis and discussions:

- Performing this task of reading and integrating data was really insightful. We are seldom given datasets which are present in the same format. We are often given different data, in different formats and specifications.
- It was comparatively easier to extract and read the data stored in json, html, excel and pdf formats. However, it took significant amount of time to read in the xml data and shape files data using regular expressions and shape files!
- Similarly, using the learnings of assignment 2, it was relatively easier to perform the task of distance calculation in order to calculate the nearest supermarket, shopping center, hospital and train-station.
- However, I had to spend quite a lot of time in order to merge the various Melbourne Train Information datasets, to calculate if there was a direct transfer between a given station and Flinders Street Railway Station.

For Task 2:

After performing the various tasks associated with task 2, I have come to the following analysis and discussions:

- We were given three predictor variables and one target variable and we had to make a linear model using all sorts of normalisations and transformations possible!
- The difficult part was to understand which transformations had to be applied to which predictors in order to make their relationship more and more linear!
- Thus, I realised the importance of these Data Tranformations.
  - Data after transformations became more suitable for analysis.
  - It was able to improve the data visualizations.
  - It was also successful in fixing the skewness of the data.
  - It also improved the readability and interpretability of the data
- The log-transformation was able to make really highly skewed data, less skewed. Hence, this helps in meeting the statistical assumptions!
- Finally, after applying these transformations, viewing the visualizations and normalizing the data, we were able to reduced the errors and increase the R Squared values!

4. Conclusion

In Conclusion, for TASK 1, we were able to perform the following activities as per the document specification

- Thus, we were able to successfully read in all our different data files such as the json data, xml data, html data, pdf data, and excel data as follows!
  - **json data** using read_json function
  - **xml data** using regular expressions
  - **html data** using read_html function
  - **pdf data** using tabula
  - **excel data** using read_excel function
- We were even able to properly integrate the various files into one integrated format.
- Additionally, we were even able to successfully compute the required additional columns of:
  - Suburb in which the property is present
  - Distance to the nearest shopping center
  - Nearest shopping center ID
  - Distance to the nearest hospital
  - Nearest hospital ID
  - Distance to the nearest supermarket
  - Nearest supermarket ID
  - Distance to the nearest train-station
  - Nearest train-station ID
  - Minimum time taken to reach the CBD
  - Transfer Flag indicating if there is a direct route

In Conclusion, for TASK 2, we were able to perform the following activities as per the document specification

- We have successfully understood and the learnt the linear behaviour of the predictors on the target variable!
- Thus, we have been able to successfully able to first get an idea of the predictors without any normalizations or transformations.

- We were able to split the data-set intro training and testing datasets and compute the various statistical values.
- Then, we were even able to perform the various transformations such as log, power and box-cox on the predictors.
- We were even able to visulize the effects of these transformations by plotting plots before and after the required three transformations!
- We observed that on performing these transformations, we were able to:
    - **INCREASE THE VALUE OF R-SQUARED**
    - **DECREASE THE VALUE OF THE Mean Squared and Root Mean Squared Error.**
- Furthermore, we even perfomed z-transformation and min-max transformations on our predictor values.
- We have even been able to visualize these effects before and after performing these normalizations!

5. References

- Devin Jeanpierre(2009, March 5). How do I sort a dictionary by value?
  Retrieved from: [https://stackoverflow.com/questions/613183/how-do-i-sort-a-dictionary-by-value (https://stackoverflow.com/questions/613183/how-do-i-sort-a-dictionary-by-value)](https://stackoverflow.com/questions/613183/how-do-i-sort-a-dictionary-by-value)

- Andrew(2019, August 21). You should (usually) log transform your positive data
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- Bruno Scibilia(2015, March 30). How Could You Benefit from a Box-Cox Transformation?
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  Retrived from: [https://towardsdatascience.com/everything-you-need-to-know-about-min-max-normalization-in-python-b79592732b79 (https://towardsdatascience.com/everything-you-need-to-know-about-min-max-normalization-in-python-b79592732b79)](https://towardsdatascience.com/everything-you-need-to-know-about-min-max-normalization-in-python-b79592732b79)

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  Retrived from: [https://towardsdatascience.com/heres-how-to-calculate-distance-between-2-geolocations-in-python-93ecab5bbba4 (https://towardsdatascience.com/heres-how-to-calculate-distance-between-2-geolocations-in-python-93ecab5bbba4)](https://towardsdatascience.com/heres-how-to-calculate-distance-between-2-geolocations-in-python-93ecab5bbba4)

In [ ]:

```

```