Ahmad_Sayeb_Assignment_1

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0.1 AIDI 1002 ASSIGNMENT 1

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0.2.1 Question1

[1]:
```
import pandas as pd
import numpy as np
from scipy.stats import shapiro
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn import preprocessing
```

[139]:
```
def load_csv(path: str) -> 'dataframe':
    '''
    Loads csv into a dataframe

    Args:
        path: path to the csv file

    Returns:
        dataframe, loaded csv file
    '''
    df = pd.read_csv(path)
    print('description: \n', df.describe)
    print('data types: \n', df.dtypes)
    print('size of data: \n', df.shape)
    return pd.read_csv(path)


def imputer(df: 'dataframe', col: str):
    '''
    Imputes nan values with the mean of the column

    Args:
        df: dataframe
        col: targeted column
```

```python
    '''
    print(f'imputing {col}...')
    col_mean = df[col].mean()
    df[col].fillna(col_mean, inplace=True)


def shapiro_normality_test(
    df: 'dataframe',
    col: str,
    alpha: float
) -> float:
    '''
    provides shapiro normality test

    Args:
        df: dataframe
        col: targeted column

    Returns:
        W: calculated shapiro test value
        p: p-value

    '''
    W, p = shapiro(df[col].values)
    if p > alpha:
        print('Failed to reject Null Hypothesis. Sample is Guassian')
    else:
        print('Rejected Null Hypothesis. Sample is not Guassian')

    return W,p


def dist_plot_test(df: 'dataframe'):
    '''
    Histogram of all the numerical columns

    Args:
        df: dataframe

    '''
    temp_df = df.select_dtypes('float')
    length = len(temp_df.columns.to_list())
    fig, axes = plt.subplots(1, length, figsize=(8, 4), sharey=True)
    fig.suptitle('Column Distributions')
    for i, col in enumerate(temp_df.columns):
        if df[col].dtypes == 'float64':
            print(col)
```

```
            sns.histplot(ax=axes[i], data=df[col])
            axes[i].set_title(col)


def qq_plot_test(df: 'dataframe'):
    '''
    Q-Q plot of all numerical columns

    Args:
        df: dataframe

    '''
    temp_df = df.select_dtypes('float')
    length = len(temp_df.columns.to_list())
    fig, axes = plt.subplots(1, length, figsize=(8, 4), sharey=True)
    fig.suptitle('Columns Q-Q Plot')
    for i, col in enumerate(temp_df.columns):
        if df[col].dtypes == 'float64':
            sm.qqplot(ax=axes[i], line='q',data=df[col])
            axes[i].set_title(col)


def cat_encoding(df: 'dataframe', col: str):
    '''
     Applies label encoding for the categorical column

     Args:
         df: dataframe
         col: target column
    '''
    print(f'lable encoding {col}...')
    label_encoder = preprocessing.LabelEncoder()
    df[col] = df[[col]].apply(label_encoder.fit_transform)


def normalize(df: 'dataframe', col: str):
    '''
    Normalizes the independent columns

    Args:
        df: dataframe
        col: target column
    '''

    print(f'normalizing {col}...')
    values = df[col].values
    min_max_scaler = preprocessing.MinMaxScaler()
```

```
    values_scaled = min_max_scaler.fit_transform(values.reshape(-1,1))
    df[col] = values_scaled
```

[146]:
```
df = load_csv("noisy_data.csv")
```

```
description:
 <bound method NDFrame.describe of    Region   Age   Income Online Shopper
0   India  49.0  86400.0             No
1  Brazil  32.0  57600.0            Yes
2     USA  35.0  64800.0             No
3  Brazil  43.0  73200.0             No
4     USA  45.0      NaN            Yes
5   India  40.0  69600.0            Yes
6  Brazil   NaN  62400.0             No
7   India  53.0  94800.0            Yes
8     USA  55.0  99600.0             No
9   India  42.0  80400.0            Yes>
data types:
 Region             object
Age               float64
Income            float64
Online Shopper     object
dtype: object
size of data:
 (10, 4)
```

[147]:
```
df
```

[147]:

	Region	Age	Income	Online Shopper
0	India	49.0	86400.0	No
1	Brazil	32.0	57600.0	Yes
2	USA	35.0	64800.0	No
3	Brazil	43.0	73200.0	No
4	USA	45.0	NaN	Yes
5	India	40.0	69600.0	Yes
6	Brazil	NaN	62400.0	No
7	India	53.0	94800.0	Yes
8	USA	55.0	99600.0	No
9	India	42.0	80400.0	Yes

Handling missing values. this function replaces missing values with Mean. This is peformed on columns that are numerical and contains Nan

[149]:
```
# performing imputation for columns that contains Nan
# This functions
imputer(df, 'Age')
imputer(df, 'Income')
```

```
df
```

```
imputing Age…
imputing Income…
```

[149]:

	Region	Age	Income	Online Shopper
0	India	49.000000	86400.000000	No
1	Brazil	32.000000	57600.000000	Yes
2	USA	35.000000	64800.000000	No
3	Brazil	43.000000	73200.000000	No
4	USA	45.000000	76533.333333	Yes
5	India	40.000000	69600.000000	Yes
6	Brazil	43.777778	62400.000000	No
7	India	53.000000	94800.000000	Yes
8	USA	55.000000	99600.000000	No
9	India	42.000000	80400.000000	Yes

Applying normality tests. For this I have used Shapiro Normality Test as its suitable for samples less than 50. The null hypothesis is that the distribution is Normal. In other words there is no difference between our distribution and a normal distribution. We use Shapiro score and p-value to decide that. If we have desired p-value but Shapiro score is below a cretain thresold, we may reject the hypothesis without refering to p-value. We also performed some visualizing tests like Q-Q plot and Distribution Plot. The sample is very small hence Distribution Plot is not that helpful. However from Q-Q plot we can see that most of the data are around mean hence we say "Failed to Reject Null Hypothesis"

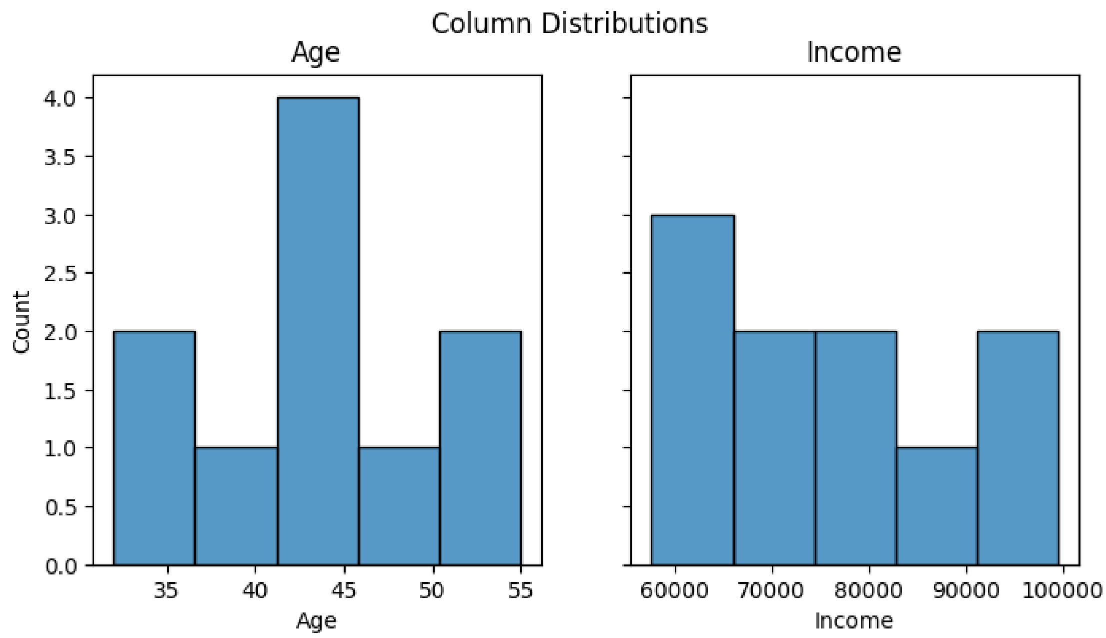
[155]:
```
print('Shapiro test for age')
print(shapiro_normality_test(df, 'Age', 0.05))
print('-----'*10)
print(shapiro_normality_test(df, 'Income', 0.05))
```

```
Shapiro test for age
Failed to reject Null Hypothesis. Sample is Guassian
(0.9711921811103821, 0.9016733765602112)
--------------------------------------------------
Failed to reject Null Hypothesis. Sample is Guassian
(0.9625768661499023, 0.8148096203804016)
```

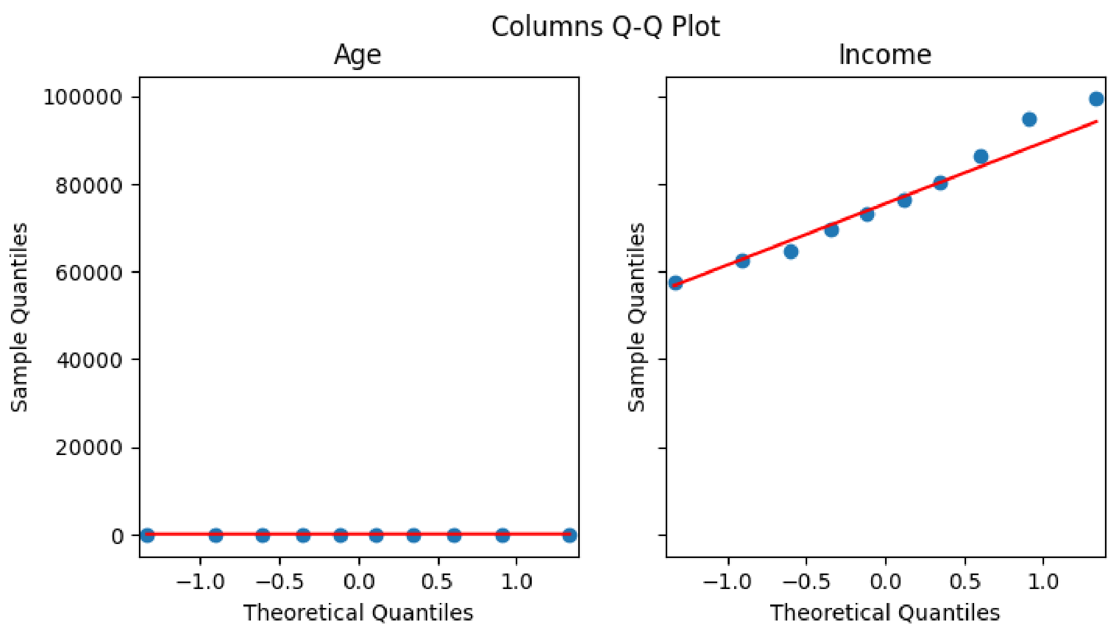
Q-Q and distribution plots. These functions detect the numerical columns and plot them!

[159]:
```
dist_plot_test(df)
```

```
Age
Income
```



[160]:
```
qq_plot_test(df)
```



Applying Label encoding to categorical columns and normalizing numerical data

[163]:
```
cat_encoding(df, 'Region')
cat_encoding(df, 'Online Shopper')
normalize(df, 'Age')
normalize(df, 'Income')
```

```
lable encoding Region…
lable encoding Online Shopper…
normalizing Age…
normalizing Income…
```

[164]:
```
df
```

[164]:

	Region	Age	Income	Online Shopper
0	1	0.739130	0.685714	0
1	0	0.000000	0.000000	1
2	2	0.130435	0.171429	0
3	0	0.478261	0.371429	0
4	2	0.565217	0.450794	1
5	1	0.347826	0.285714	1
6	0	0.512077	0.114286	0
7	1	0.913043	0.885714	1
8	2	1.000000	1.000000	0
9	1	0.434783	0.542857	1

0.2.2 Question 2

[103]:
```
import re
import nltk
from nltk.tokenize import word_tokenize
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords
# from nltk.corpus import wordnet
# from nltk.corpus import words
# from collections import Counter
```

[134]:
```
def read_txt(path: str) -> str:
    '''
    Reads the text file and returns the value in one string

    Args:
        path: path to the file

    Returns: a string that contains text from file
    '''

    print('loading the file...')
    with open(path, 'r') as file:
```

```python
        data = file.read().replace('\n', '')
    return data


def lower_case(text: str) -> str:
    '''
    changes the words to lower case

    Args:
        text: targeted string

    Returns: lowered case string
    '''

    print('applying lower case functions...')
    return text.lower()


def remove_punc(text: str) -> str:
    '''
    Removes punctuations using Regex

    Args:
        text: targeted string

    Returns: text withtout punctuations
    '''

    print('removing punctuations...')
    return re.sub(r'[^\w\s]', '', text)


def tokenize_word_tok(text: str) -> list:
    '''
    Tokenize your text using word_tokenize

    Args:
        text: targeted string

    Returns: array of tokenized words

    '''

    return word_tokenize(text)


# Note: regexpression was used from the follwoing link
```

```python
# https://www.nltk.org/_modules/nltk/tokenize/regexp.html
def tokenize_regexp(text: str) -> list:
    '''
    Tokenize your text using regexp

    Args:
        text: targeted string

    Returns: arrya of tokenized words
    '''
    return RegexpTokenizer('\s+', gaps=True).tokenize(text)

def remove_stop(text: str):
    '''
    Removes stops words, excluding negative words like
    don't, doesn't, can't and ... .

    Args:
        text: targeted string

    Returns: text without stop words

    '''

    ##words we remove from stop_words list
    negative_words = [
            "doesn't",
            "doesn",
            "aren",
            "shant",
            "neednt",
            "shouldn",
            "mustn",
            "aren't",
            "needn't",
            "shouldnt'",
            "wouldn't",
            "don't",
            "isn't",
            "didn't",
            "couldn't",
            "mustn't",
            "haven't",
            "hasn't",
            "aren't",
        ]
```

```
    stop_words = set(stopwords.words('english')) - set(negative_words)
    no_stop_word = []
    for word in text:
        if word not in stop_words:
            no_stop_word.append(word)
    return no_stop_word


def extract_year(text: str) -> list:
    '''
    Extracts years from the text

    Args:
        text: targeted text

    Returns: list of extracted years

    '''

    return re.findall('(\d{4})', text)
```

[94]:

```
# Loading text
text = read_txt("wiki.txt")
print(text)
```

```
loading the file…
The history of NLP generally started in the 1950s, although work can be found
from earlier periods. In 1950, Alan Turing published an article titled
"Computing Machinery and Intelligence" which proposed what is now called the
Turing test as a criterion of intelligence.The Georgetown experiment in 1954
involved fully automatic translation of more than sixty Russian sentences into
English. The authors claimed that within three or five years, machine
translation would be a solved problem.[2] However, real progress was much
slower, and after the ALPAC report in 1966, which found that ten-year-long
research had failed to fulfill the expectations, funding for machine translation
was dramatically reduced. Little further research in machine translation was
conducted until the late 1980s, when the first statistical machine translation
systems were developed.Some notably successful NLP systems developed in the
1960s were SHRDLU, a natural-language system working in restricted "blocks
worlds" with restricted vocabularies, and ELIZA, a simulation of a Rogerian
psychotherapist, written by Joseph Weizenbaum between 1964 and 1966. Using
almost no information about human thought or emotion, ELIZA sometimes provided a
startlingly human-like interaction. When the "patient" exceeded the very small
knowledge base, ELIZA might provide a generic response, for example, responding
to "My head hurts" with "Why do you say your head hurts?".
```

[97]:
```
# changing to lower case and
# removing punctuations
txt_lowerd = lower_case(text)
txt_lwrd_punc_rmvd = remove_punc(txt_lowerd)
print('------' * 10)
print(txt_lwrd_punc_rmvd)
print('------' * 10)
```

```
applying lower case functions…
removing punctuations…
------------------------------------------------------------
the history of nlp generally started in the 1950s although work can be found
from earlier periods in 1950 alan turing published an article titled computing
machinery and intelligence which proposed what is now called the turing test as
a criterion of intelligencethe georgetown experiment in 1954 involved fully
automatic translation of more than sixty russian sentences into english the
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system working in restricted blocks worlds with restricted vocabularies and
eliza a simulation of a rogerian psychotherapist written by joseph weizenbaum
between 1964 and 1966 using almost no information about human thought or emotion
eliza sometimes provided a startlingly humanlike interaction when the patient
exceeded the very small knowledge base eliza might provide a generic response
for example responding to my head hurts with why do you say your head hurts
------------------------------------------------------------
```

Applying word_tokenizer and stop words removal

[135]:
```
txt_wrd_tknzer = tokenize_word_tok(txt_lwrd_punc_rmvd)
txt_wrd_tknzer_stpwords_rmvd = remove_stop(txt_wrd_tknzer)
print('------' * 10)
print(txt_wrd_tknzer_stpwords_rmvd)
print('------' * 10)
```

```
------------------------------------------------------------
['history', 'nlp', 'generally', 'started', '1950s', 'although', 'work', 'found',
'earlier', 'periods', '1950', 'alan', 'turing', 'published', 'article',
'titled', 'computing', 'machinery', 'intelligence', 'proposed', 'called',
'turing', 'test', 'criterion', 'intelligencethe', 'georgetown', 'experiment',
'1954', 'involved', 'fully', 'automatic', 'translation', 'sixty', 'russian',
'sentences', 'english', 'authors', 'claimed', 'within', 'three', 'five',
'years', 'machine', 'translation', 'would', 'solved', 'problem2', 'however',
'real', 'progress', 'much', 'slower', 'alpac', 'report', '1966', 'found',
```

```
'tenyearlong', 'research', 'failed', 'fulfill', 'expectations', 'funding',
'machine', 'translation', 'dramatically', 'reduced', 'little', 'research',
'machine', 'translation', 'conducted', 'late', '1980s', 'first', 'statistical',
'machine', 'translation', 'systems', 'developedsome', 'notably', 'successful',
'nlp', 'systems', 'developed', '1960s', 'shrdlu', 'naturallanguage', 'system',
'working', 'restricted', 'blocks', 'worlds', 'restricted', 'vocabularies',
'eliza', 'simulation', 'rogerian', 'psychotherapist', 'written', 'joseph',
'weizenbaum', '1964', '1966', 'using', 'almost', 'information', 'human',
'thought', 'emotion', 'eliza', 'sometimes', 'provided', 'startlingly',
'humanlike', 'interaction', 'patient', 'exceeded', 'small', 'knowledge', 'base',
'eliza', 'might', 'provide', 'generic', 'response', 'example', 'responding',
'head', 'hurts', 'say', 'head', 'hurts']
------------------------------------------------------------
```

Applying RegexpTokenizer and stop words removal

[136]:
```python
txt_rgx_tknzer = tokenize_regexp(txt_lwrd_punc_rmvd)
txt_rgx_tknzer_stopwords_rmvd = remove_stop(txt_rgx_tknzer)
print('------' * 10)
print(txt_rgx_tknzer_stopwords_rmvd)
print('------' * 10)
```

```
------------------------------------------------------------
['history', 'nlp', 'generally', 'started', '1950s', 'although', 'work', 'found',
'earlier', 'periods', '1950', 'alan', 'turing', 'published', 'article',
'titled', 'computing', 'machinery', 'intelligence', 'proposed', 'called',
'turing', 'test', 'criterion', 'intelligencethe', 'georgetown', 'experiment',
'1954', 'involved', 'fully', 'automatic', 'translation', 'sixty', 'russian',
'sentences', 'english', 'authors', 'claimed', 'within', 'three', 'five',
'years', 'machine', 'translation', 'would', 'solved', 'problem2', 'however',
'real', 'progress', 'much', 'slower', 'alpac', 'report', '1966', 'found',
'tenyearlong', 'research', 'failed', 'fulfill', 'expectations', 'funding',
'machine', 'translation', 'dramatically', 'reduced', 'little', 'research',
'machine', 'translation', 'conducted', 'late', '1980s', 'first', 'statistical',
'machine', 'translation', 'systems', 'developedsome', 'notably', 'successful',
'nlp', 'systems', 'developed', '1960s', 'shrdlu', 'naturallanguage', 'system',
'working', 'restricted', 'blocks', 'worlds', 'restricted', 'vocabularies',
'eliza', 'simulation', 'rogerian', 'psychotherapist', 'written', 'joseph',
'weizenbaum', '1964', '1966', 'using', 'almost', 'information', 'human',
'thought', 'emotion', 'eliza', 'sometimes', 'provided', 'startlingly',
'humanlike', 'interaction', 'patient', 'exceeded', 'small', 'knowledge', 'base',
'eliza', 'might', 'provide', 'generic', 'response', 'example', 'responding',
'head', 'hurts', 'say', 'head', 'hurts']
------------------------------------------------------------
```

Extract years using regex

[118]:
```python
years = extract_year(text)
print('------' * 10)
```

```
print(years)
print('------' * 10)
```

```
------------------------------------------------------------
['1950', '1950', '1954', '1966', '1980', '1960', '1964', '1966']
------------------------------------------------------------
```

What is the difference

[137]:
```
txt_rgx_tknzer_stopwords_rmvd == txt_wrd_tknzer_stpwords_rmvd
```

[137]:
```
True
```

In my case the pattern that I chose for my regex exactly matches that of the word tokenizer. Both results are the same. However RegexpTokenizer is a dynamic tokenizer meaning that you have the freedom to choose the regex pattern and tokenize accordingly.

0.3 Question 3

Some of the codes are copied from **My lab works**

[187]:
```
from sklearn.feature_selection import SelectKBest, mutual_info_regression, chi2
from sklearn.feature_selection import VarianceThreshold
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from sklearn.preprocessing import OrdinalEncoder
from sklearn.feature_selection import SelectFromModel
```

[336]:
```
def corr_analysis(df: 'dataframe'):
    '''

    Description: generates a correlation heatmap and suggests
    columns that can be dropped based on correlation
    Args
        df: dataframe, should only have numeric data
    '''

    df_indep = df.loc[:, df.columns!='Price']
    corr = df_indep.corr(method='pearson')
    for col in corr.columns:
        for ind in corr.index:
            if (col != ind) and (corr[col][ind] > 0.5):
                print(f'{col} and {ind} are correlated. you can drop one!')
    f,ax = plt.subplots(figsize=(15, 12))
    ax = sns.heatmap(corr,cmap="YlGnBu", annot=True)
    return corr


def mutual_info(df:'dataframe'):
```

```python
    '''

    Description: applies mutual information technique for
    feature selection
    Args:
        df: dataframe, should only have numeric data
    '''
    target = df['Price']
    df_indep = df.loc[:, df.columns != 'Price']
    selector = SelectKBest(mutual_info_regression, k=10)
    new_data = selector.fit_transform(df_indep, target)
    mask = selector.get_support()
    new_features = df_indep.columns[mask]
    scores = selector.scores_
    zipped = list(zip(new_features, scores))
    zipped_sort = sorted(zipped, key=lambda x: x[1], reverse=True)
    #ploting the columns and scores
    plt.figure(figsize=(12, 8), dpi=80)
    plt.bar([x[0] for x in zipped_sort], [x[1] for x in zipped_sort])
    plt.title('Mutual Info Importance Graph')
    plt.xlabel('Columns')
    plt.ylabel('Scores')
    plt.show()
    return new_features


def chi_squared(df:'dataframe'):
    '''
    Description: applies mutual information technique for
    feature selection
    input
        df: dataframe, should only have numeric data
    '''
    target = df['Price']
    df_indep = df.loc[:, df.columns != 'Price']
    selector = SelectKBest(chi2, k=10)
    new_data = selector.fit_transform(df_indep, target)
    mask = selector.get_support()
    scores = selector.scores_
    new_features = df_indep.columns[mask]
    zipped = list(zip(new_features, scores))
    zipped_sort = sorted(zipped, key=lambda x: x[1], reverse=True)
    #ploting the columns and scores
    plt.figure(figsize=(12, 8), dpi=80)
    plt.bar([x[0] for x in zipped_sort], [x[1] for x in zipped_sort])
    plt.title('Chi2 Importance Graph')
    plt.xlabel('Columns')
```

```python
    plt.ylabel('Scores')
    plt.show()
    return new_features

def random_forest(df: 'dataframe'):
    '''
    Using Random Forest feature selection

    Args:
        df: dataframe

    '''
    clf = RandomForestRegressor(n_estimators=100)
    df_indep = df.loc[:, df.columns!='Price']
    target = df['Price']
    clf.fit(df_indep, target)
    scores = clf.feature_importances_[:10]
    features = df_indep.columns[:10]
    zipped = list(zip(features, scores))
    zipped_sort = sorted(zipped, key=lambda x: x[1], reverse=True)
    # zipped_sort = zipped.sort(key=lambda x:x[1])
    plt.figure(figsize=(12, 8), dpi=80)
    plt.bar([x[0] for x in zipped_sort], [x[1] for x in zipped_sort])
    plt.title('Random Forest Importance Graph')
    plt.xlabel('Columns')
    plt.ylabel('Scores')
    plt.show()
```

[198]:
```python
df_q3 = load_csv('melb_data.csv')
```

```
description:
 <bound method NDFrame.describe of              Suburb          Address  Rooms
Type      Price Method  \
0          Abbotsford      85 Turner St      2     h  1480000.0      S
1          Abbotsford   25 Bloomburg St      2     h  1035000.0      S
2          Abbotsford      5 Charles St      3     h  1465000.0     SP
3          Abbotsford  40 Federation La      3     h   850000.0     PI
4          Abbotsford       55a Park St      4     h  1600000.0     VB
…               …                …     …   …         …    …
13575   Wheelers Hill      12 Strada Cr      4     h  1245000.0      S
13576    Williamstown     77 Merrett Dr      3     h  1031000.0     SP
13577    Williamstown       83 Power St      3     h  1170000.0      S
13578    Williamstown      96 Verdon St      4     h  2500000.0     PI
13579      Yarraville        6 Agnes St      4     h  1285000.0     SP

        SellerG       Date  Distance  Postcode  …  Bathroom  Car  Landsize  \
0        Biggin  3/12/2016       2.5    3067.0  …       1.0  1.0     202.0
```

```
1        Biggin   4/02/2016       2.5    3067.0  …       1.0  0.0     156.0
2        Biggin   4/03/2017       2.5    3067.0  …       2.0  0.0     134.0
3        Biggin   4/03/2017       2.5    3067.0  …       2.0  1.0      94.0
4        Nelson   4/06/2016       2.5    3067.0  …       1.0  2.0     120.0
…          …         …         …       …   …       …  …        …
13575     Barry  26/08/2017      16.7    3150.0  …       2.0  2.0     652.0
13576  Williams  26/08/2017       6.8    3016.0  …       2.0  2.0     333.0
13577     Raine  26/08/2017       6.8    3016.0  …       2.0  4.0     436.0
13578   Sweeney  26/08/2017       6.8    3016.0  …       1.0  5.0     866.0
13579   Village  26/08/2017       6.3    3013.0  …       1.0  1.0     362.0

       BuildingArea  YearBuilt  CouncilArea Lattitude  Longtitude  \
0               NaN        NaN        Yarra -37.79960   144.99840
1              79.0     1900.0        Yarra -37.80790   144.99340
2             150.0     1900.0        Yarra -37.80930   144.99440
3               NaN        NaN        Yarra -37.79690   144.99690
4             142.0     2014.0        Yarra -37.80720   144.99410
…               …          …          …         …           …
13575           NaN     1981.0          NaN -37.90562   145.16761
13576         133.0     1995.0          NaN -37.85927   144.87904
13577           NaN     1997.0          NaN -37.85274   144.88738
13578         157.0     1920.0          NaN -37.85908   144.89299
13579         112.0     1920.0          NaN -37.81188   144.88449

                       Regionname Propertycount
0           Northern Metropolitan        4019.0
1           Northern Metropolitan        4019.0
2           Northern Metropolitan        4019.0
3           Northern Metropolitan        4019.0
4           Northern Metropolitan        4019.0
…                             …            …
13575  South-Eastern Metropolitan        7392.0
13576        Western Metropolitan        6380.0
13577        Western Metropolitan        6380.0
13578        Western Metropolitan        6380.0
13579        Western Metropolitan        6543.0

[13580 rows x 21 columns]>
data types:
 Suburb            object
Address           object
Rooms              int64
Type              object
Price            float64
Method            object
SellerG           object
Date              object
Distance         float64
```

```
Postcode          float64
Bedroom2          float64
Bathroom          float64
Car               float64
Landsize          float64
BuildingArea      float64
YearBuilt         float64
CouncilArea        object
Lattitude         float64
Longtitude        float64
Regionname         object
Propertycount     float64
dtype: object
size of data:
 (13580, 21)
```

Price is taken as the Target variable

[178]:
```
df_q3.head(10)
```

[178]:
```
       Suburb             Address  Rooms Type      Price Method SellerG  \
0  Abbotsford        85 Turner St      2    h  1480000.0      S  Biggin
1  Abbotsford     25 Bloomburg St      2    h  1035000.0      S  Biggin
2  Abbotsford        5 Charles St      3    h  1465000.0     SP  Biggin
3  Abbotsford    40 Federation La      3    h   850000.0     PI  Biggin
4  Abbotsford         55a Park St      4    h  1600000.0     VB  Nelson
5  Abbotsford      129 Charles St      2    h   941000.0      S  Jellis
6  Abbotsford        124 Yarra St      3    h  1876000.0      S  Nelson
7  Abbotsford       98 Charles St      2    h  1636000.0      S  Nelson
8  Abbotsford  6/241 Nicholson St      1    u   300000.0      S  Biggin
9  Abbotsford       10 Valiant St      2    h  1097000.0      S  Biggin

        Date  Distance  Postcode  …  Bathroom  Car  Landsize  BuildingArea  \
0  3/12/2016       2.5    3067.0  …       1.0  1.0     202.0           NaN
1  4/02/2016       2.5    3067.0  …       1.0  0.0     156.0          79.0
2  4/03/2017       2.5    3067.0  …       2.0  0.0     134.0         150.0
3  4/03/2017       2.5    3067.0  …       2.0  1.0      94.0           NaN
4  4/06/2016       2.5    3067.0  …       1.0  2.0     120.0         142.0
5  7/05/2016       2.5    3067.0  …       1.0  0.0     181.0           NaN
6  7/05/2016       2.5    3067.0  …       2.0  0.0     245.0         210.0
7  8/10/2016       2.5    3067.0  …       1.0  2.0     256.0         107.0
8  8/10/2016       2.5    3067.0  …       1.0  1.0       0.0           NaN
9  8/10/2016       2.5    3067.0  …       1.0  2.0     220.0          75.0

   YearBuilt  CouncilArea Lattitude  Longtitude             Regionname  \
0        NaN        Yarra  -37.7996    144.9984  Northern Metropolitan
1     1900.0        Yarra  -37.8079    144.9934  Northern Metropolitan
2     1900.0        Yarra  -37.8093    144.9944  Northern Metropolitan
```

```
3         NaN        Yarra  -37.7969    144.9969  Northern Metropolitan
4      2014.0        Yarra  -37.8072    144.9941  Northern Metropolitan
5         NaN        Yarra  -37.8041    144.9953  Northern Metropolitan
6      1910.0        Yarra  -37.8024    144.9993  Northern Metropolitan
7      1890.0        Yarra  -37.8060    144.9954  Northern Metropolitan
8         NaN        Yarra  -37.8008    144.9973  Northern Metropolitan
9      1900.0        Yarra  -37.8010    144.9989  Northern Metropolitan

   Propertycount
0         4019.0
1         4019.0
2         4019.0
3         4019.0
4         4019.0
5         4019.0
6         4019.0
7         4019.0
8         4019.0
9         4019.0

[10 rows x 21 columns]
```

Removing Nulls and replacing them with mean of column for numerical columns. Using Label Encoder for categorical data

[199]:
```
# Extracting numerical columns
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
num_df_q3 = df_q3.select_dtypes(include=numerics)
cat_df_q3 = df_q3.select_dtypes(exclude=numerics)
print('numerical data columns:\n', num_df_q3.dtypes)
print('------' * 10)
print('categorical data columns:\n', cat_df_q3.dtypes)
print('------' * 10)
# Applying imputer for numerical columns
for col in num_df_q3.columns:
    imputer(df_q3, col)
# Also normalizing numerical columns
for col in num_df_q3.columns:
    if col != 'Price':
        normalize(df_q3, col)
# Applying label encoder for categorical columns
for col in cat_df_q3.columns:
    cat_encoding(df_q3, col)
# printing head
df_q3.head(10)
```

```
numerical data columns:
 Rooms              int64
```

```
Price           float64
Distance        float64
Postcode        float64
Bedroom2        float64
Bathroom        float64
Car             float64
Landsize        float64
BuildingArea    float64
YearBuilt       float64
Lattitude       float64
Longtitude      float64
Propertycount   float64
dtype: object
------------------------------------------------------------
categorical data columns:
 Suburb         object
Address        object
Type           object
Method         object
SellerG        object
Date           object
CouncilArea    object
Regionname     object
dtype: object
------------------------------------------------------------
imputing Rooms…
imputing Price…
imputing Distance…
imputing Postcode…
imputing Bedroom2…
imputing Bathroom…
imputing Car…
imputing Landsize…
imputing BuildingArea…
imputing YearBuilt…
imputing Lattitude…
imputing Longtitude…
imputing Propertycount…
normalizing Rooms…
normalizing Distance…
normalizing Postcode…
normalizing Bedroom2…
normalizing Bathroom…
normalizing Car…
normalizing Landsize…
normalizing BuildingArea…
normalizing YearBuilt…
normalizing Lattitude…
```

```
normalizing Longtitude…
normalizing Propertycount…
lable encoding Suburb…
lable encoding Address…
lable encoding Type…
lable encoding Method…
lable encoding SellerG…
lable encoding Date…
lable encoding CouncilArea…
lable encoding Regionname…
```

[199]:

```
   Suburb  Address     Rooms  Type      Price  Method  SellerG  Date  \
0       0    12794  0.111111     0  1480000.0       1       23    45
1       0     5943  0.111111     0  1035000.0       1       23    47
2       0     9814  0.222222     0  1465000.0       3       23    48
3       0     9004  0.222222     0   850000.0       0       23    48
4       0    10589  0.333333     0  1600000.0       4      155    49
5       0     2195  0.111111     0   941000.0       1      106    52
6       0     2142  0.222222     0  1876000.0       1      155    52
7       0    13335  0.111111     0  1636000.0       1      155    56
8       0    11082  0.000000     2   300000.0       1       23    56
9       0     1090  0.111111     0  1097000.0       1       23    56

   Distance  Postcode  …  Bathroom  Car  Landsize  BuildingArea  YearBuilt  \
0  0.051975  0.068577  …     0.125  0.1  0.000466      0.003414   0.935139
1  0.051975  0.068577  …     0.125  0.0  0.000360      0.001775   0.856448
2  0.051975  0.068577  …     0.250  0.0  0.000309      0.003370   0.856448
3  0.051975  0.068577  …     0.250  0.1  0.000217      0.003414   0.935139
4  0.051975  0.068577  …     0.125  0.2  0.000277      0.003190   0.995134
5  0.051975  0.068577  …     0.125  0.0  0.000418      0.003414   0.935139
6  0.051975  0.068577  …     0.250  0.0  0.000566      0.004718   0.868613
7  0.051975  0.068577  …     0.125  0.2  0.000591      0.002404   0.844282
8  0.051975  0.068577  …     0.125  0.1  0.000000      0.003414   0.935139
9  0.051975  0.068577  …     0.125  0.2  0.000508      0.001685   0.856448

   CouncilArea  Lattitude  Longtitude  Regionname  Propertycount
0           31   0.494755    0.517651           2        0.17616
1           31   0.484031    0.513083           2        0.17616
2           31   0.482223    0.513997           2        0.17616
3           31   0.498243    0.516281           2        0.17616
4           31   0.484936    0.513723           2        0.17616
5           31   0.488941    0.514819           2        0.17616
6           31   0.491137    0.518474           2        0.17616
7           31   0.486486    0.514910           2        0.17616
8           31   0.493204    0.516646           2        0.17616
9           31   0.492946    0.518108           2        0.17616
```

[10 rows x 21 columns]

CORRELATION ANALYSIS

[322]:
```
corr_analysis(df_q3)
```

```
Rooms and Bedroom2 are correlated. you can drop one!
Rooms and Bathroom are correlated. you can drop one!
Bedroom2 and Rooms are correlated. you can drop one!
Bedroom2 and Bathroom are correlated. you can drop one!
Bathroom and Rooms are correlated. you can drop one!
Bathroom and Bedroom2 are correlated. you can drop one!
```

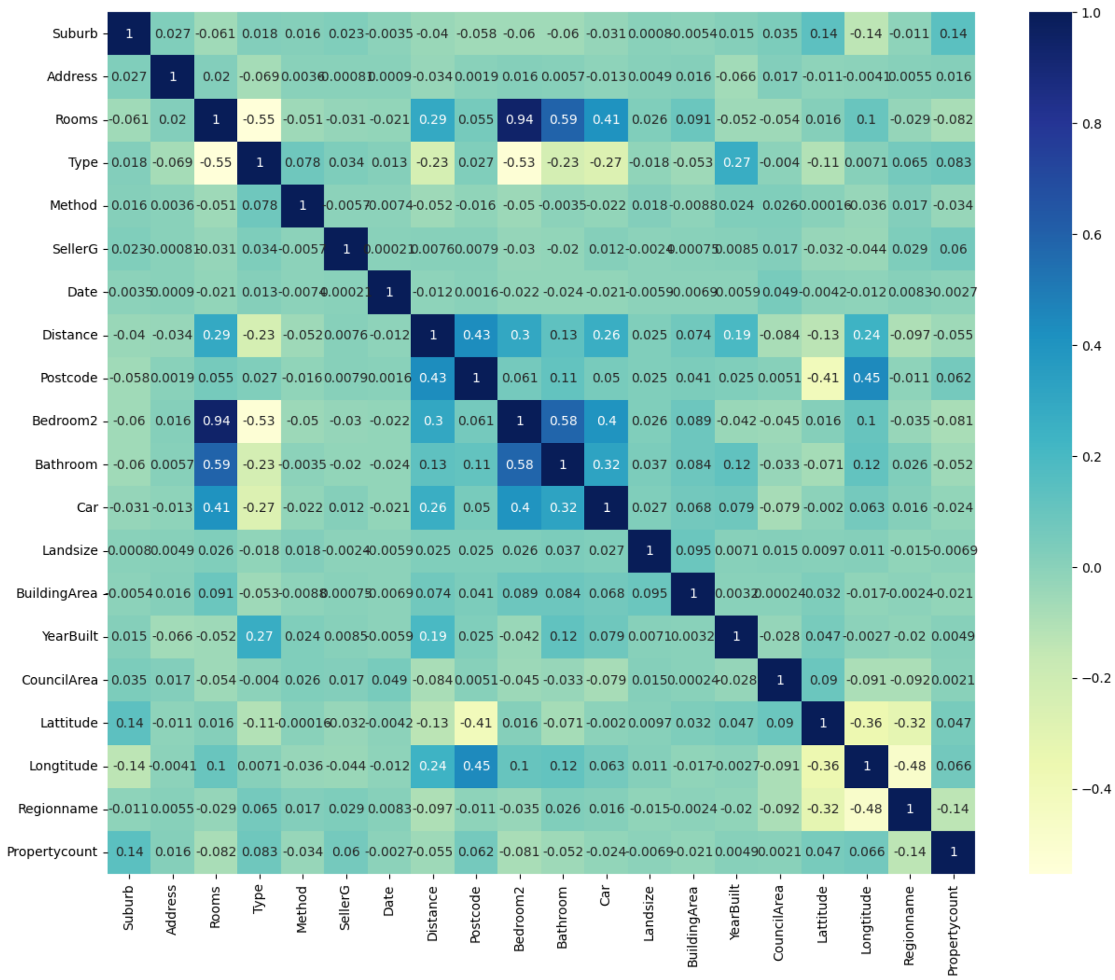
[322]:
```
                 Suburb   Address     Rooms      Type    Method   SellerG  \
Suburb         1.000000  0.027335 -0.060510  0.018195  0.016421  0.023240
Address        0.027335  1.000000  0.020016 -0.069483  0.003562 -0.000806
Rooms         -0.060510  0.020016  1.000000 -0.554141 -0.051368 -0.031054
Type           0.018195 -0.069483 -0.554141  1.000000  0.078432  0.034045
Method         0.016421  0.003562 -0.051368  0.078432  1.000000 -0.005728
SellerG        0.023240 -0.000806 -0.031054  0.034045 -0.005728  1.000000
Date          -0.003511  0.000900 -0.020722  0.012903 -0.007378  0.000208
Distance      -0.039550 -0.034019  0.294203 -0.234845 -0.052316  0.007584
Postcode      -0.057947  0.001943  0.055303  0.027420 -0.016321  0.007928
Bedroom2      -0.059578  0.015854  0.944190 -0.533994 -0.049553 -0.030165
Bathroom      -0.059516  0.005659  0.592934 -0.231465 -0.003509 -0.020390
Car           -0.031209 -0.013062  0.407843 -0.273001 -0.022423  0.011620
Landsize       0.000796  0.004874  0.025678 -0.017725  0.018041 -0.002397
BuildingArea  -0.005351  0.016078  0.091373 -0.052744 -0.008783  0.000748
YearBuilt      0.014673 -0.065673 -0.052112  0.270223  0.024497  0.008517
CouncilArea    0.035157  0.016941 -0.054428 -0.004047  0.025644  0.016838
Lattitude      0.137892 -0.010896  0.015948 -0.105827 -0.000157 -0.032291
Longtitude    -0.140629 -0.004079  0.100771  0.007094 -0.036409 -0.043861
Regionname    -0.010919  0.005517 -0.028661  0.065048  0.016837  0.028686
Propertycount  0.142738  0.016331 -0.081530  0.082663 -0.034055  0.060338

                   Date  Distance  Postcode  Bedroom2  Bathroom       Car  \
Suburb        -0.003511 -0.039550 -0.057947 -0.059578 -0.059516 -0.031209
Address        0.000900 -0.034019  0.001943  0.015854  0.005659 -0.013062
Rooms         -0.020722  0.294203  0.055303  0.944190  0.592934  0.407843
Type           0.012903 -0.234845  0.027420 -0.533994 -0.231465 -0.273001
Method        -0.007378 -0.052316 -0.016321 -0.049553 -0.003509 -0.022423
SellerG        0.000208  0.007584  0.007928 -0.030165 -0.020390  0.011620
Date           1.000000 -0.011740  0.001577 -0.021638 -0.024481 -0.021369
Distance      -0.011740  1.000000  0.431514  0.295927  0.127155  0.262074
Postcode       0.001577  0.431514  1.000000  0.060584  0.113664  0.050201
Bedroom2      -0.021638  0.295927  0.060584  1.000000  0.584685  0.404721
Bathroom      -0.024481  0.127155  0.113664  0.584685  1.000000  0.321788
Car           -0.021369  0.262074  0.050201  0.404721  0.321788  1.000000
```

Landsize	-0.005921	0.025004	0.024558	0.025646	0.037130	0.026759
BuildingArea	-0.006940	0.073990	0.040714	0.089102	0.084462	0.068389
YearBuilt	-0.005850	0.193183	0.025406	-0.041894	0.120910	0.078563
CouncilArea	0.048890	-0.084354	0.005085	-0.045426	-0.033186	-0.079393
Lattitude	-0.004169	-0.130723	-0.406104	0.015925	-0.070594	-0.001961
Longtitude	-0.011994	0.239425	0.445357	0.102238	0.118971	0.063304
Regionname	0.008289	-0.096808	-0.010656	-0.034797	0.025680	0.015959
Propertycount	-0.002676	-0.054910	0.062304	-0.081350	-0.052201	-0.024255

	Landsize	BuildingArea	YearBuilt	CouncilArea	Lattitude \
Suburb	0.000796	-0.005351	0.014673	0.035157	0.137892
Address	0.004874	0.016078	-0.065673	0.016941	-0.010896
Rooms	0.025678	0.091373	-0.052112	-0.054428	0.015948
Type	-0.017725	-0.052744	0.270223	-0.004047	-0.105827
Method	0.018041	-0.008783	0.024497	0.025644	-0.000157
SellerG	-0.002397	0.000748	0.008517	0.016838	-0.032291
Date	-0.005921	-0.006940	-0.005850	0.048890	-0.004169
Distance	0.025004	0.073990	0.193183	-0.084354	-0.130723
Postcode	0.024558	0.040714	0.025406	0.005085	-0.406104
Bedroom2	0.025646	0.089102	-0.041894	-0.045426	0.015925
Bathroom	0.037130	0.084462	0.120910	-0.033186	-0.070594
Car	0.026759	0.068389	0.078563	-0.079393	-0.001961
Landsize	1.000000	0.094659	0.007052	0.014835	0.009695
BuildingArea	0.094659	1.000000	0.003155	0.000244	0.031799
YearBuilt	0.007052	0.003155	1.000000	-0.027893	0.046938
CouncilArea	0.014835	0.000244	-0.027893	1.000000	0.089898
Lattitude	0.009695	0.031799	0.046938	0.089898	1.000000
Longtitude	0.010833	-0.017441	-0.002672	-0.090586	-0.357634
Regionname	-0.014822	-0.002351	-0.019536	-0.092248	-0.316136
Propertycount	-0.006854	-0.020736	0.004909	0.002072	0.047086

	Longtitude	Regionname	Propertycount
Suburb	-0.140629	-0.010919	0.142738
Address	-0.004079	0.005517	0.016331
Rooms	0.100771	-0.028661	-0.081530
Type	0.007094	0.065048	0.082663
Method	-0.036409	0.016837	-0.034055
SellerG	-0.043861	0.028686	0.060338
Date	-0.011994	0.008289	-0.002676
Distance	0.239425	-0.096808	-0.054910
Postcode	0.445357	-0.010656	0.062304
Bedroom2	0.102238	-0.034797	-0.081350
Bathroom	0.118971	0.025680	-0.052201
Car	0.063304	0.015959	-0.024255
Landsize	0.010833	-0.014822	-0.006854
BuildingArea	-0.017441	-0.002351	-0.020736
YearBuilt	-0.002672	-0.019536	0.004909

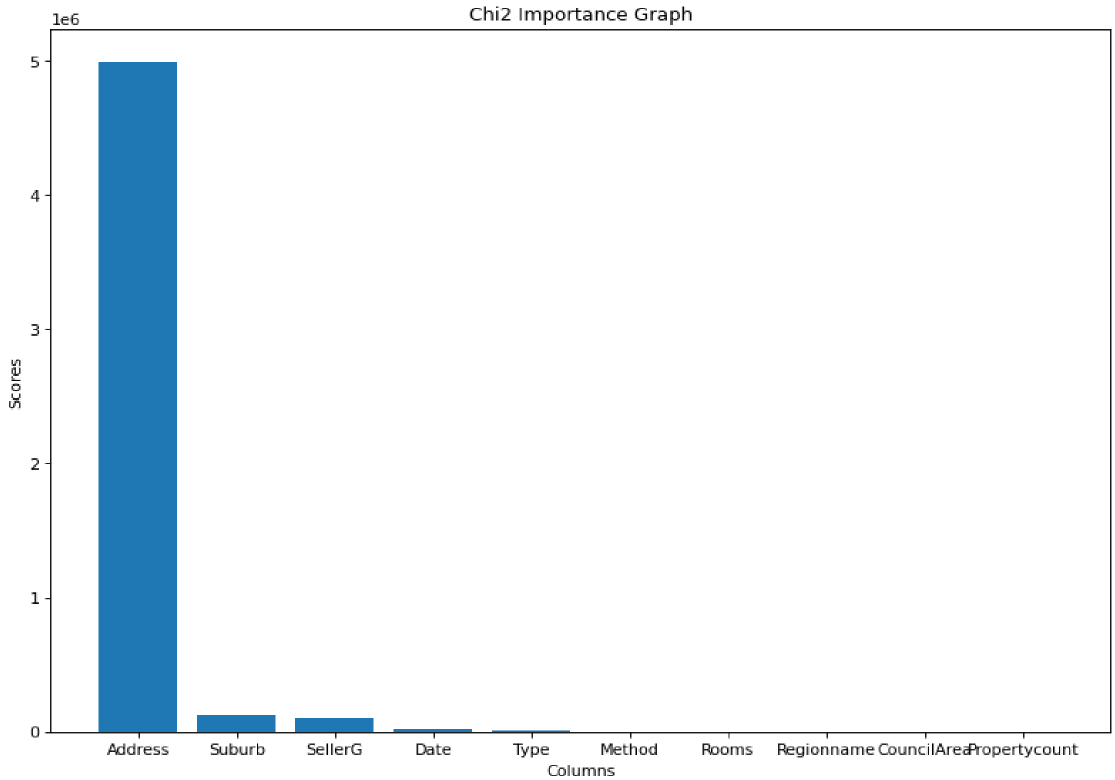
```
CouncilArea     -0.090586   -0.092248       0.002072
Lattitude       -0.357634   -0.316136       0.047086
Longtitude       1.000000   -0.477740       0.065988
Regionname      -0.477740    1.000000      -0.135754
Propertycount    0.065988   -0.135754       1.000000
```



0.3.1 CHI-SQUARE

Selecting 10 Best Features

[333]:
```
chi_squared(df_q3)
```

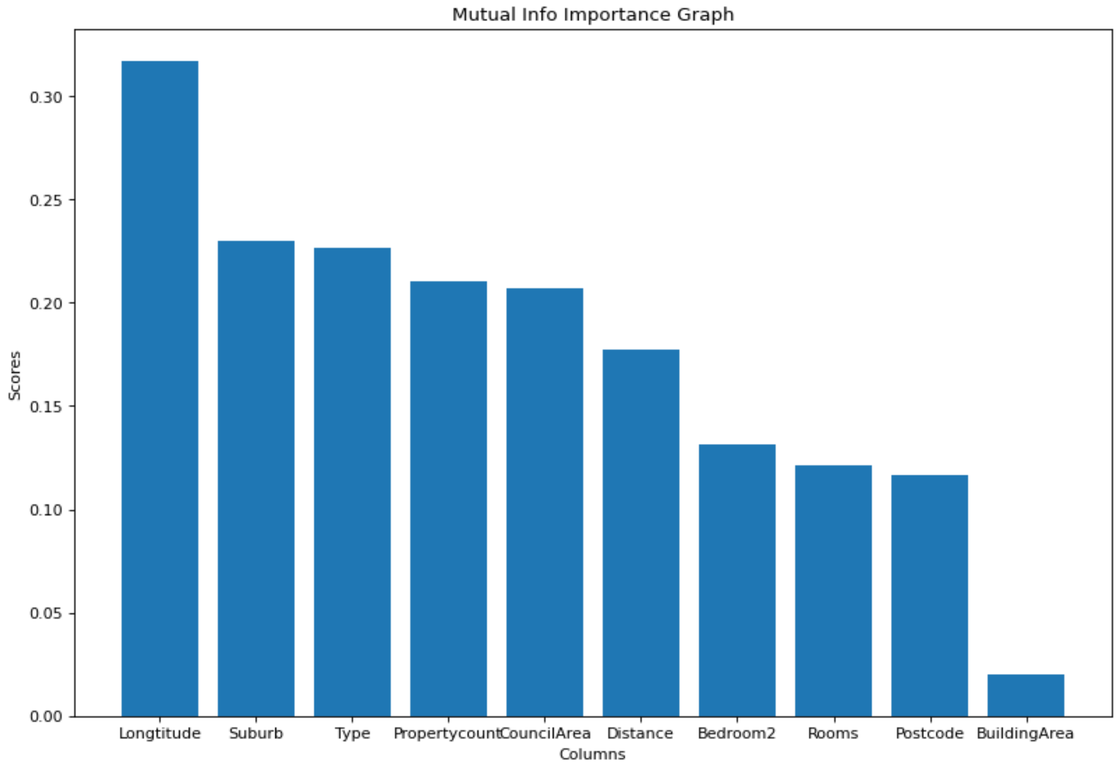



```
[333]: Index(['Suburb', 'Address', 'Rooms', 'Type', 'Method', 'SellerG', 'Date',
              'CouncilArea', 'Regionname', 'Propertycount'],
             dtype='object')
```

0.3.2 MUTUAL-INFORMATION

Selecting 10 Best Features

```
[334]: mutual_info(df_q3)
```

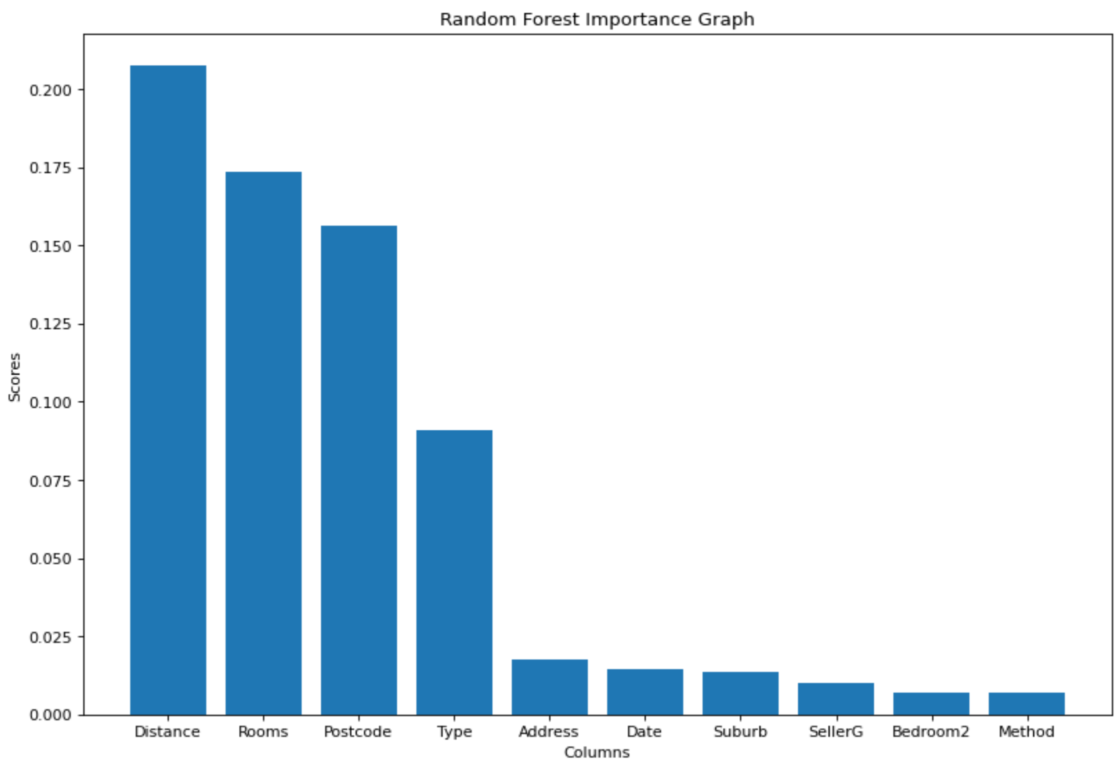


[334]:
```
Index(['Suburb', 'Rooms', 'Type', 'Distance', 'Postcode', 'Bedroom2',
       'BuildingArea', 'CouncilArea', 'Longtitude', 'Propertycount'],
      dtype='object')
```

0.3.3 RANDOM-FOREST

Selecting 10 Best Features

[337]:
```
random_forest(df_q3)
```



0.3.4 Comments

Comments for different feature selection method: Correlation: We have 20 columns in our data and there is not a high correlation for most of the features. We can only remove at most 2 columns with this method, Hence its not very helpful

Chi-Sqaure: This method selects only one column over-emphasizes on that column while completely ignoring importance of other features. This is not a very helpful method to select features from this data-set

Mutual-Information and Random Forest: These two methods are most suitable for this dataset. We can perform further analysis like model accuracy to select one of these two methods. We are given multiple columns with different scores which is helpful for model training