Home Value Analysis

Introduction

In real estate, accurate property valuation is crucial for both buyers and sellers. This project leverages historical sales data to estimate the value of single-family homes using a K-Nearest Neighbors (KNN) regression algorithm. Our objective is to predict the value of a new property by analyzing recent sales of comparable homes in the same neighborhood.

To achieve this, we have processed and filtered sales data to focus on recent transactions, ensuring that our model reflects current market conditions. We then employ KNN regression to find the most similar properties based on key features—such as living space, age, and basement condition—and compute the average price of these similar homes to estimate the value of the new property.

This project addresses important ethical considerations in addition to technical implementation. We explore potential biases in the dataset, algorithm sensitivity's impact, and normalization's importance. Furthermore, we emphasize the need for an appeal process to ensure fairness and accuracy in property valuation. By combining advanced data analytics with a thorough ethical review, this project aims to deliver a robust and equitable approach to property valuation.

In [ ]:

```
# Import Pandas, Matplotlib, and Seaborn and allow for inline plotting

import pandas as pd
import numpy as np
import seaborn as sns
from scipy.stats import zscore

%matplotlib inline

# import matplotlib as mpl # for non-interactive, pure object-oriented plotting
from matplotlib import pyplot as plt
import matplotlib.style as style
# plt.style.use('ggplot')

# Set to None to display all columns
pd.set_option('display.max_columns', None)
```

In [ ]:

```
# Load Buildings
buildings = pd.read_csv("/buildings.csv")

# Check columns for data types and identify any missing values
#buildings.info()

# Check columns for missing values
#buildings.isnull().sum().sort_values(ascending=False)

# Columns with missing values
# Stories 41954 | UnitCount 41939 | ExtWallDscrSec 30821 | ExtWallSec 30821 | AcDscr 236
# Roof_Cover 19525 | HeatingDscr 1134 | Heating 1097 | IntWallDscr 216 | IntWall 215 | C
# ExtWallDscrPrim 29 | ExtWallPrim 7

# Drop NA rows and verify
buildings.dropna(subset=['ExtWallDscrPrim'], inplace=True)
```

```
# I am dropping the following columns for the reasons after the description
# Stories - this field is only used for commercial properties
# UnitCount - the number of residential units in the building specified. This is mostly
#   because they also state "we generally do not have apartment unit numbers delineated
#   one account"
# ExtWallSec, ExtWallDscrSec - code and description of the secondary material used on th
# Ac, AcDscr - we have a lot of null values and this column is for if an air conditioner
# Roof_CoverDscr, Roof_Cover Dropping to to the number of null values
# Heating, HeatingDscr - we have null values and this column is for if a heater exists
# IntWallDscr, IntWall - describes the primary material used for the interior walls of t
#   not crucial to my analysis
# ConstCodeDscr - Description of the construction code assoc with bldg/section
# ConstCode - identifies what the main type of construction material for the bldg
# ExtWallPrim - I don't believe this info is not crucial to my analysis
# status_cd - whether the account is currently active "A" or has been deactivated "D". -
# CompCode - The Building's % complete for the current year I don't believe this info is
# section_num - Building section number - particularly for commercial properties, I don'

# dropping anything related to codes as long as we have the description - designCode, qu


# Drop Columns Formatted for readability
columns_to_drop = [
    'ConstCodeDscr', 'section_num', 'carStorageType',
    'bldgClass', 'CompCode', 'qualityCode', 'status_cd', 'ConstCode',
    'Heating', 'HeatingDscr', 'Ac', 'AcDscr', 'Stories', 'UnitCount',
    'ExtWallSec', 'ExtWallDscrSec', 'Roof_CoverDscr', 'Roof_Cover',
    'IntWallDscr', 'IntWall', 'ExtWallPrim', 'designCode'
]
# Drop Columns
buildings.drop(columns_to_drop, axis=1, inplace=True)


# Convert basement type to either unfinished (0) or finished(1)
buildings['bsmtCond'] = buildings['bsmtTypeDscr'].apply(lambda x: 1 if 'FINISHED' in x e

# Create a new column calculating the age of the home based on builtYear
buildings['age'] = 2021 - buildings['builtYear']

# Rename the column designCodeDscr to 'homeDesign' to better describe our column
buildings.rename(columns={'designCodeDscr': 'homeDesign'}, inplace=True)

# Rename the column TotalFinishedSF to 'livingSpaceSqft' to better describe our column
buildings.rename(columns={'TotalFinishedSF': 'livingSpaceSqft'}, inplace=True)
```

In [ ]:

```
# Load Land
land = pd.read_csv('/land.csv')

# Check columns for data types and identify any missing values
#land.isnull().sum()
# landClass 1 and landClassDscr 1 - we will drop these rows since they are one apiece

# Drop NA rows and verified
land.dropna(subset=['landClass', 'landClassDscr', 'landUnitValue'], inplace=True)

# I am dropping the following columns for the reasons after the description
# status_cd - whether the account is currently active "A" or has been deactivated "D". -
# GIS_acreage, GIS_sqft - this is not survey quality sqft measurements
# landClass - classification code, we have the description column as well
```

```
land.drop(['status_cd', 'GIS_acreage', 'GIS_sqft', 'landClass'], axis=1, inplace=True)
```

In [ ]:
```
# Load Owner Info
owner_address = pd.read_csv('/owner_address.csv')

# Check columns for data types and identify any missing values
#owner_address.info()
# owner_address.isnull().sum()
# str_pfx 37950
# str_sfx 616

# I am dropping the following columns for the reasons after the description
# str_pfx - Instead of imputing default values I am going to drop this, the missing valu
 # and I don't believe this info is not crucial to my analysis
# str_sfx - I don't believe this info is not crucial to my analysis
# sub_code subdivision code, we have the description column as well
owner_address.drop(['str_pfx', 'str_sfx', 'sub_code'], axis=1, inplace=True)
```

In [ ]:
```
# Load Values Info
values = pd.read_csv('/values.csv')
values

# Check columns for data types and identify any missing values
# values.info()
# values.isnull().sum()


# I am dropping the following columns for the reasons after the description
# xfAssessedVal - Assessed value for extra features associated with the account - all of
# status_cd - whether the account is currently active “A” or has been deactivated “D”. -
# xfActualVal - value attributed to extra features, generally on commercial properties

# bldAssessedVal column will not help this analysis but I am leaving

values.drop(['xfAssessedVal', 'status_cd', 'xfActualVal'], axis=1, inplace=True)
```

In [ ]:
```
values.isnull().sum()
```

Out[ ]:
```
strap               0
tax_yr              0
bldAcutalVal        0
LandAcutalVal       0
totalActualVal      0
landAssessedVal     0
bldAssessedVal     24
totalAssessedVal    0
dtype: int64
```

In [ ]:
```
# Merge buildings with land using 'strap' as the common key

buildings_land = pd.merge(buildings, land, on='strap', how='left')

# Merge buildings_land with owner_address
buildings_land_owner = pd.merge(buildings_land, owner_address, on='strap', how='left')

# Merge buildings_land_owner with value
buildings_land_owner_value = pd.merge(buildings_land_owner, values, on='strap', how='lef
```

In [ ]:
```
buildings_land_owner_value.shape
```

```
# buildings (41932, 20)
# land (41960, 4)
# owner_address(41961, 10)
# values(41961, 8)
# buildings_land_owner_value.shape(41932, 41)

# We maintained our row counts for building and our column count increased
```

Out[ ]: (41932, 41)

In [ ]:

```
#  Check and count the number of missing (null or NaN) values in each column of the Data

buildings_land_owner_value.isnull().sum().sort_values(ascending=False)

# I dropped these previously but will drop again
buildings_land_owner_value.drop(['landUnitValue', 'landUnitType', 'landClassDscr'], axis
```

In [ ]:

```
# Descriptive statistics for numerical columns
buildings_land_owner_value.describe()
```

Out[ ]:

	bld_num	builtYear	EffectiveYear	bsmtSF	carStorageSF	nbrBedRoom	nbr
count	41932.000000	41932.000000	41932.000000	41932.000000	41932.000000	41932.000000	
mean	1.001049	1977.195149	1987.054612	696.512902	444.909926	3.213417	
std	0.032377	27.965244	20.641085	634.201216	253.740562	0.938945	
min	1.000000	1860.000000	1871.000000	0.000000	0.000000	0.000000	
25%	1.000000	1963.000000	1976.000000	0.000000	312.000000	3.000000	
50%	1.000000	1981.000000	1991.000000	728.000000	448.000000	3.000000	
75%	1.000000	1998.000000	2000.000000	1134.000000	592.000000	4.000000	
max	2.000000	2021.000000	2021.000000	4743.000000	4800.000000	10.000000	

Descriptive statistics overview

The dataset comprises information on 41,932 buildings with construction years from 1860 to 2021. The total living space in sqft exhibits a broad range, from a minimum of 0 to a maximum of 19044 square feet, with a mean of 1862.25. We will need to investigate this further.

In [ ]:

```
buildings_land_owner_value[buildings_land_owner_value['livingSpaceSqft'] <5]
```

Out[ ]:

	strap	bld_num	homeDesign	qualityCodeDscr	bldgClassDscr	builtYear	EffectiveYear
173	R0000448	1	2-3 Story	VERY GOOD +	SINGLE FAM RES IMPROVEMENTS	2021	2021
6656	R0020955	2	1 Story - Ranch	AVERAGE	SINGLE FAM RES IMPROVEMENTS	1971	1971
9004	R0029599	2	1 Story - Ranch	AVERAGE	SINGLE FAM RES IMPROVEMENTS	1987	1987
41922	R0612986	1	2-3 Story	GOOD +	SINGLE FAM RES IMPROVEMENTS	2020	2020

In [ ]:

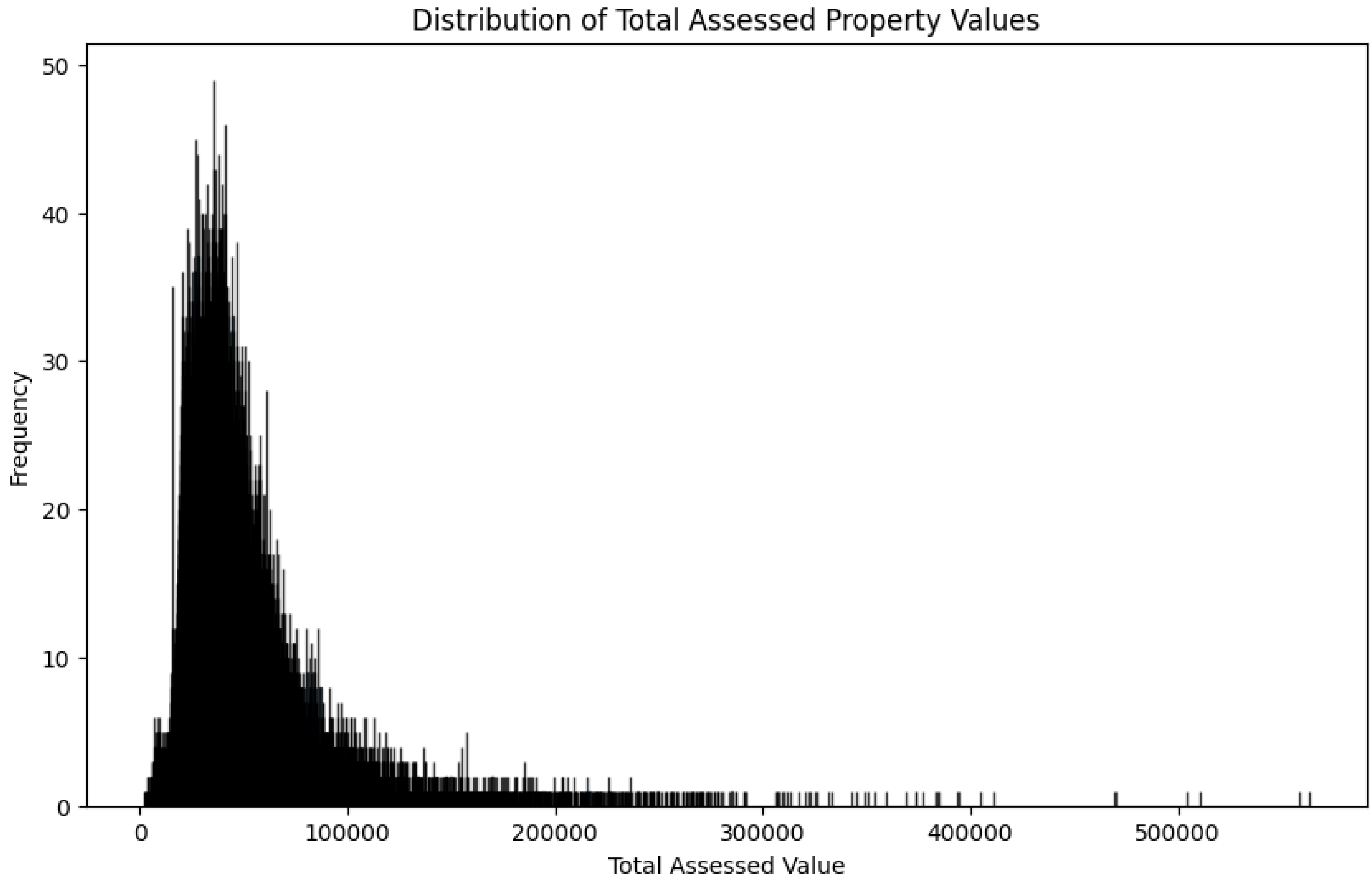
```
# We filtered our results to < 5
# buildings_land_owner_value[buildings_land_owner_value['livingSpaceSqft'] <5]

# we also looked <100 and Zillow confirmed sqft
# we also spot checked a few more < 500 and all were confirmed on zillow




# We have 2 rows with null values and 2 rows with 1 for livingSpaceSqft. looking at some
# confirmed sqft on zillow
buildings_land_owner_value.loc[173, 'livingSpaceSqft'] = 3236
buildings_land_owner_value.loc[6656, 'livingSpaceSqft'] = 924
buildings_land_owner_value.loc[9004, 'livingSpaceSqft'] = 1246
buildings_land_owner_value.loc[41922, 'livingSpaceSqft'] = 6332
```

In [ ]:

```
# Key Finding 1: Distribution of Assessed Property Values

# Column we want to create a histogram
assessed_values = buildings_land_owner_value['totalAssessedVal']

# Plot the histogram
figure, axes= plt.subplots(figsize=(10, 6))
axes.hist(assessed_values, bins=assessed_values.nunique(), edgecolor='black', alpha=0.75
axes.set_xlabel('Total Assessed Value')
axes.set_ylabel('Frequency')
axes.set_title('Distribution of Total Assessed Property Values')
```

Out[ ]:

```
Text(0.5, 1.0, 'Distribution of Total Assessed Property Values')
```



In [ ]:
```
# Look at the underlying data
data = buildings_land_owner_value['totalAssessedVal'].dropna()

# Display basic statistics of the data
data_description = data.describe()

data_description
```

Out[ ]:
```
count     41932.000000
mean      48883.762711
std       31292.942565
min        2352.000000
25%       30180.000000
50%       41298.000000
75%       57565.000000
max      562874.000000
Name: totalAssessedVal, dtype: float64
```

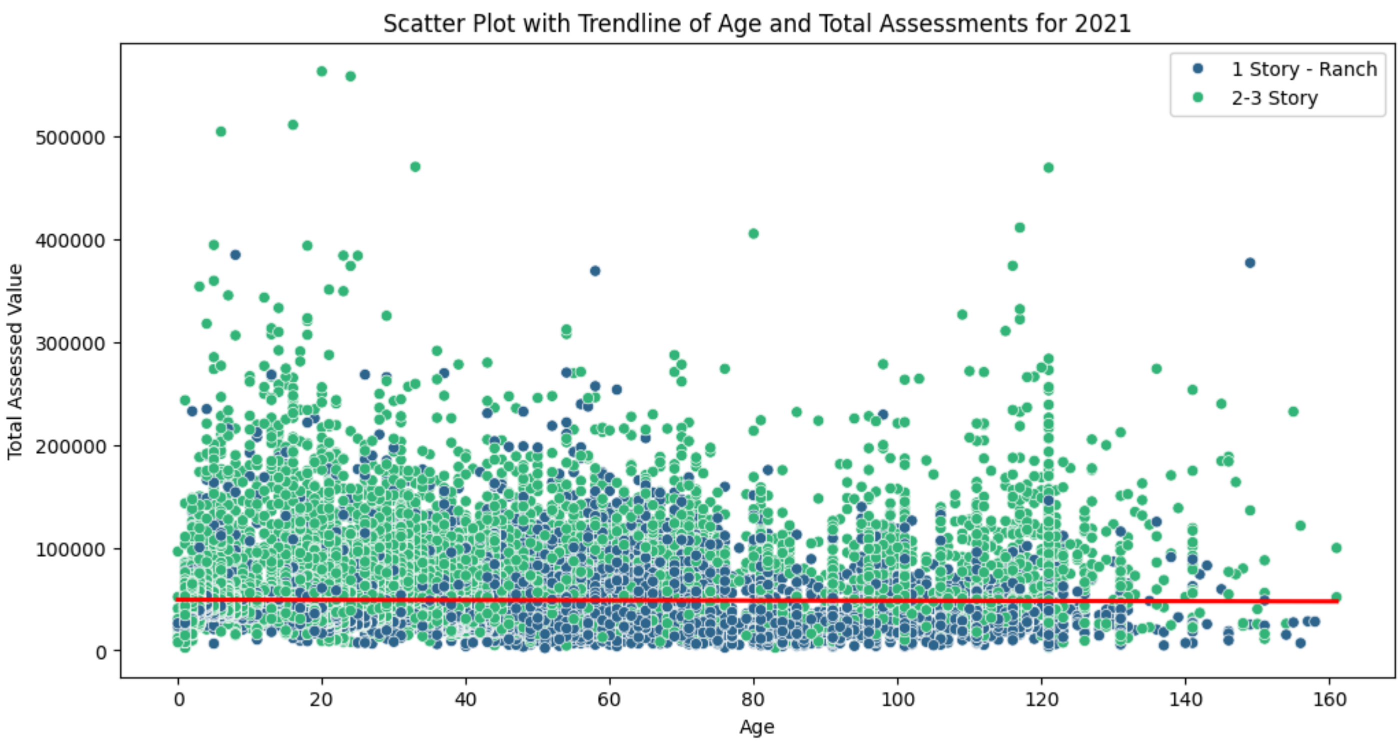
Key Finding 1: Distribution of Assessed Property Values

Our initial analysis focused on the Total Assessed Property Values, uncovering valuable insights through graphical representation and descriptive statistics. The mean total assessed property value stands at approximately 48,884, highlighting the average value in our dataset. The associated standard deviation of 31,293 signifies considerable variability, underscoring the diverse range of assessed property values. Examining the extremes, we observe a minimum value of 2,352, indicating the presence of lower-valued properties. In contrast, the dataset's maximum assessed value reaches 562,874, suggesting the inclusion of high-valued properties.

In [ ]:
```
# Scatter Plot with Trendlines
fig, ax = plt.subplots(figsize=(12, 6))
```

```
# Scatter Plot
sns.scatterplot(x='age', y='totalAssessedVal', hue='homeDesign', data=buildings_land_own

# Add Trendline
sns.regplot(x='age', y='totalAssessedVal', data=buildings_land_owner_value, scatter=Fals

ax.set_xlabel('Age')
ax.set_ylabel('Total Assessed Value')
ax.set_title('Scatter Plot with Trendline of Age and Total Assessments for 2021')
ax.legend()
```

Out[ ]: <matplotlib.legend.Legend at 0x13424cef0>



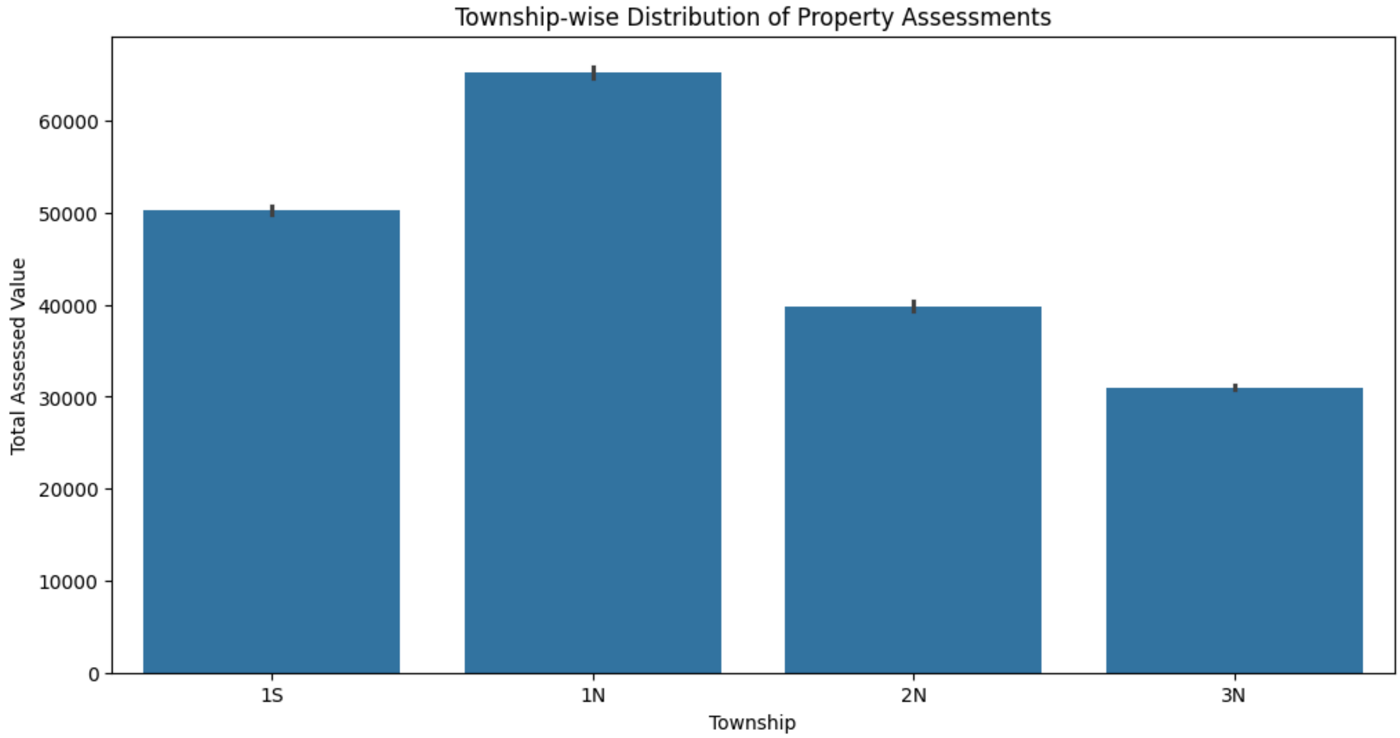
Looking at a secondary plot

Looking at our graph it appears that we have a very weak linear relationship between the two variables. We calculated the correlation coefficient at -0.0094; this small magnitude suggests that there is little to no linear relationship between the age of the properties and their total assessed values. We should note that a low correlation coefficient does not necessarily mean there is no relationship; it simply means that a linear model does not well capture any relationship.

In [ ]:

```
# Key Finding 2: Township-wise Distribution of Property Assessments

# Create a bar chart to visualize the distribution of property assessments for each town
figure, axes = plt.subplots(figsize=(12, 6))
sns.barplot(x='township', y='totalAssessedVal', data=buildings_land_owner_value)
axes.set_xlabel('Township')
axes.set_ylabel('Total Assessed Value')
axes.set_title('Township-wise Distribution of Property Assessments')
```

Out[ ]: Text(0.5, 1.0, 'Township-wise Distribution of Property Assessments')



Key Finding 2: Township-wise Distribution of Property Assessments

Our second key finding was uncovered when we explored the distribution of property assessments across different townships within Denver County. The bar chart illustrates each township's average total assessed values, providing helpful insights into the economic landscape of residential properties. Notably, Township 1N emerges with the highest average total assessed value at approximately 65,266, followed by Township 1S with an average of 50,337: township 2N and 3N exhibit slightly lower average values at approximately 39,872 and 31,034, respectively.

Estimate Home Values

A K-Nearest Neighbors (KNN) algorithm is being developed to estimate the value of new homes based on recent comparable sales to improve the valuation process for residential single-family properties. By law, residential properties must be valued using the "market approach," which estimates a property's value based on what it would fetch in a transaction between a knowledgeable buyer and seller in the open market. This approach involves analyzing sales of comparable properties, defined as any qualified sale from the past five years (January 2015 - December 2020).

Key factors considered in the valuation process include:

- Location
- Living Area (SQFT)
- Age of the Home
- Finished Basement

In [ ]:

```
# Load Sales Info not sure if I need it for the KNN
sales = pd.read_csv('/sales.csv')


# Convert 'tdate' to datetime format
sales['date_of_sale'] = pd.to_datetime(sales['Tdate'])
```

```python
# Filter the data to the specified timeframe
sales = sales[(sales['date_of_sale'] >= '2015-01-01') & (sales['date_of_sale'] <= '2020-


sales.info()
```

```
/var/folders/16/wq4_bln96mqg5s2nfgwdsgp40000gn/T/ipykernel_8392/1959366679.py:6: UserWarn
ing: Could not infer format, so each element will be parsed individually, falling back to
`dateutil`. To ensure parsing is consistent and as-expected, please specify a format.
  sales['date_of_sale'] = pd.to_datetime(sales['Tdate'])
<class 'pandas.core.frame.DataFrame'>
Index: 31624 entries, 21 to 221134
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   strap         31624 non-null  object
 1   deedNum       31624 non-null  object
 2   Tdate         31624 non-null  object
 3   sales_cd      31624 non-null  object
 4   deed_type     31624 non-null  object
 5   price         31601 non-null  float64
 6   status_cd     31624 non-null  object
 7   date_of_sale  31624 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(1), object(6)
memory usage: 2.2+ MB
```

In [ ]:

```python
# Simplified KNN?

# Merge the datasets on 'strap' to combine building information with sale dates
merged_data = pd.merge(buildings_land_owner_value, sales, on='strap', how='inner')

def knn_2d_specific_x(merged_data, k, nh, builtYear, livingSpaceSqft, bsmtCond, visualiz

    """
    To demonstrate how the KNN algorithm produces a prediction in a 2D case

    Input:

        df - DataFrame with x, y columns
        k  - number of neighbors to consider
        x_pt - value of x where we want to make prediction

    Output:
        Prediction
    """

    df_temp = merged_data.copy()
    df_temp['distance'] = np.sqrt(
        (df_temp.nh - nh)**2 +
        (df_temp.builtYear - builtYear)**2 +
        (df_temp.livingSpaceSqft - livingSpaceSqft)**2 +
        (df_temp.bsmtCond - bsmtCond)**2
    )
    y_pred = df_temp.loc[df_temp.distance.nsmallest(k).index].price.mean()
    df_knn = df_temp.loc[df_temp.distance.nsmallest(k).index]


    return y_pred
```

In [ ]:
```
# Test the function
knn_2d_specific_x(merged_data, k=3, nh=120, builtYear=2000, livingSpaceSqft=2500, bsmtCo
```

Out[ ]:
```
627333.3333333334
```

In [ ]:
```
# Get unique values to use in the KNN Test Function

# Display unique values for 'nh'
unique_values_nh = buildings_land_owner_value['nh'].unique().tolist()
print("Unique values for column 'nh':")
print(unique_values_nh)
```

```
Unique values for column 'nh':
[160.0, 115.0, 102.0, 170.0, 120.0, 109.0, 105.0, 103.0, 101.0, 162.0, 166.0, 174.0, 107.
0, 126.0, 140.0, 122.0, 158.0, 148.0, 164.0, 142.0, 146.0, 150.0, 401.0, 405.0, 430.0, 41
0.0, 460.0, 465.0, 472.0, 820.0, 480.0, 940.0, 178.0, 901.0, 910.0, 903.0, 930.0, 172.0,
920.0, 911.0, 157.0, 830.0, 124.0, 145.0, 152.0, 154.0, 159.0, 420.0, 155.0, 415.0, 450.
0, 440.0, 132.0, 144.0, 490820.0, 425.0, 156.0, 129.0, 451.0, 136.0, 133.0, 130.0, 201.0,
203.0, 202.0, 204.0, 256.0, 255.0, 205.0, 223.0, 240.0, 241.0, 962.0, 257.0, 960.0, 825.
0, 501.0, 242.0, 243.0, 137.0, 134.0, 470.0, 135.0, 128.0, 455.0, 445.0, 187101.0, 29320
1.0, 291201.0, 293204.0, 298201.0, 298204.0, 495405.0, 990901.0, 495401.0]
```

Ethics Review

Fairness and accuracy are crucial in property valuation. Overestimated values can lead to property owners paying excessive taxes, while undervalued properties might result in insufficient capital to meet budget requirements. Therefore, carefully considering the impact of our price prediction methods is vital.

Building and deploying a predictive model like KNN requires attention to ethical considerations and model performance. Ensuring transparency and accountability throughout the model-building process is essential. This includes regularly reviewing and updating the model and documenting features, methodologies, and assumptions to maintain ethical standards. Key considerations involve addressing potential biases from unrepresentative training data, managing the risk of overfitting or underfitting based on the choice of K and evaluating the impact of irrelevant features and missing or incorrect data. To ensure fairness, it is important to use a diverse and unbiased dataset, select an appropriate K, and focus on relevant features. Transparency about the model’s limitations and conducting regular audits are crucial for upholding fairness and accuracy.

EDA Property Valuations

We conducted exploratory data analysis (EDA) on property valuations for "1-Story" and "2-3 Story" single-family residential buildings to uncover trends and insights. This involves investigating relationships within the data through univariate and bivariate analyses, examining outliers, and summarizing key findings.

In [ ]:
```
pd.set_option('display.float_format', lambda x: '%.2f' % x)
# qualified_sales_5yrs['price']
# print(qualified_sales_5yrs['price'].dtype)
qualified_sales_5yrs[['livingSpaceSqft', 'price']].describe()
```

Out[ ]:

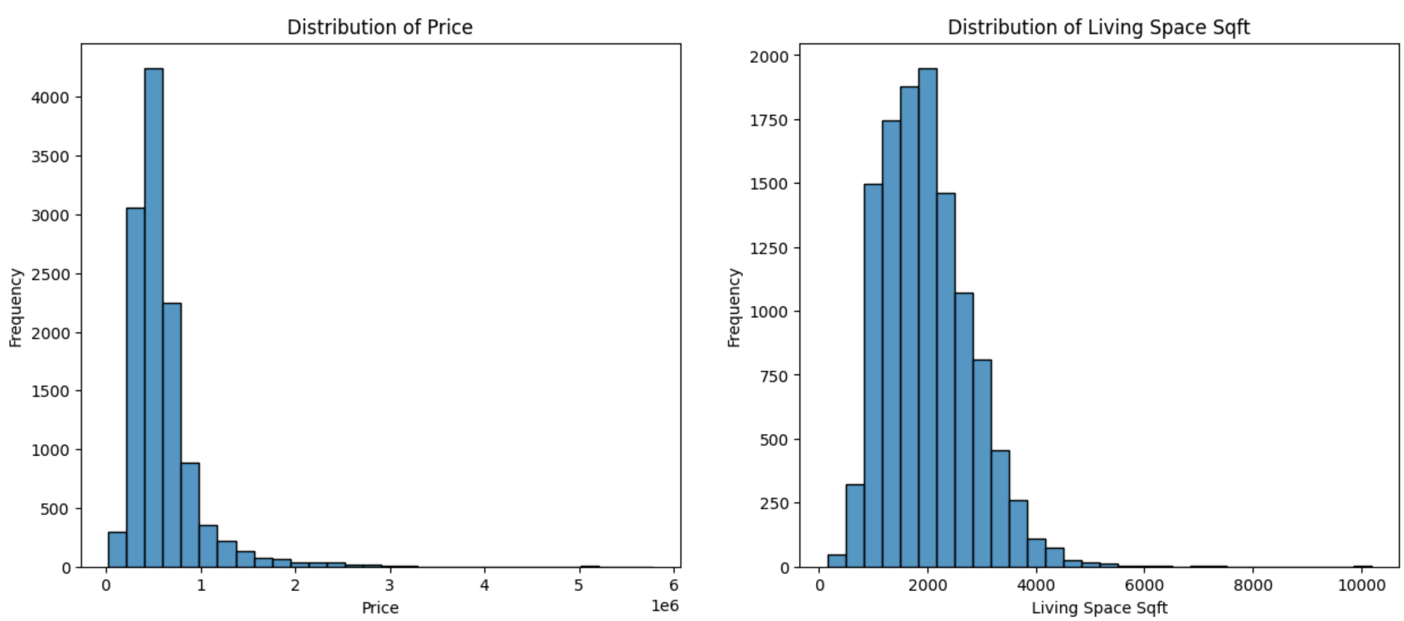
	livingSpaceSqft	price
count	11751.00	11751.00
mean	1979.18	602946.30
std	811.19	375476.52
min	150.00	29000.00
25%	1364.50	395000.00
50%	1891.00	522000.00
75%	2473.00	687000.00
max	10188.00	5779000.00

In [ ]:

```
# Set up grid
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 6))

# Plot histogram for 'price'
sns.histplot(data=qualified_sales_5yrs, x='price', bins=30, ax=axes[0])
axes[0].set_xlabel('Price')
axes[0].set_ylabel('Frequency')
axes[0].set_title('Distribution of Price')

# Plot histogram for 'livingSpaceSqft'
sns.histplot(data=qualified_sales_5yrs, x='livingSpaceSqft', bins=30, ax=axes[1])
axes[1].set_xlabel('Living Space Sqft')
axes[1].set_ylabel('Frequency')
axes[1].set_title('Distribution of Living Space Sqft')
```

Out[ ]:

```
Text(0.5, 1.0, 'Distribution of Living Space Sqft')
```



In [ ]:

```
# Scatter plot with a regression line for 'price' versus 'livingSpaceSqft'
sns.regplot(data=qualified_sales_5yrs, x='livingSpaceSqft', y='price')
plt.xlabel('Living Space Sqft')
plt.ylabel('Price')
plt.title('Scatter Plot with Regression Line: Price vs Living Space Sqft')
```

Out[ ]:

```
Text(0.5, 1.0, 'Scatter Plot with Regression Line: Price vs Living Space Sqft')
```

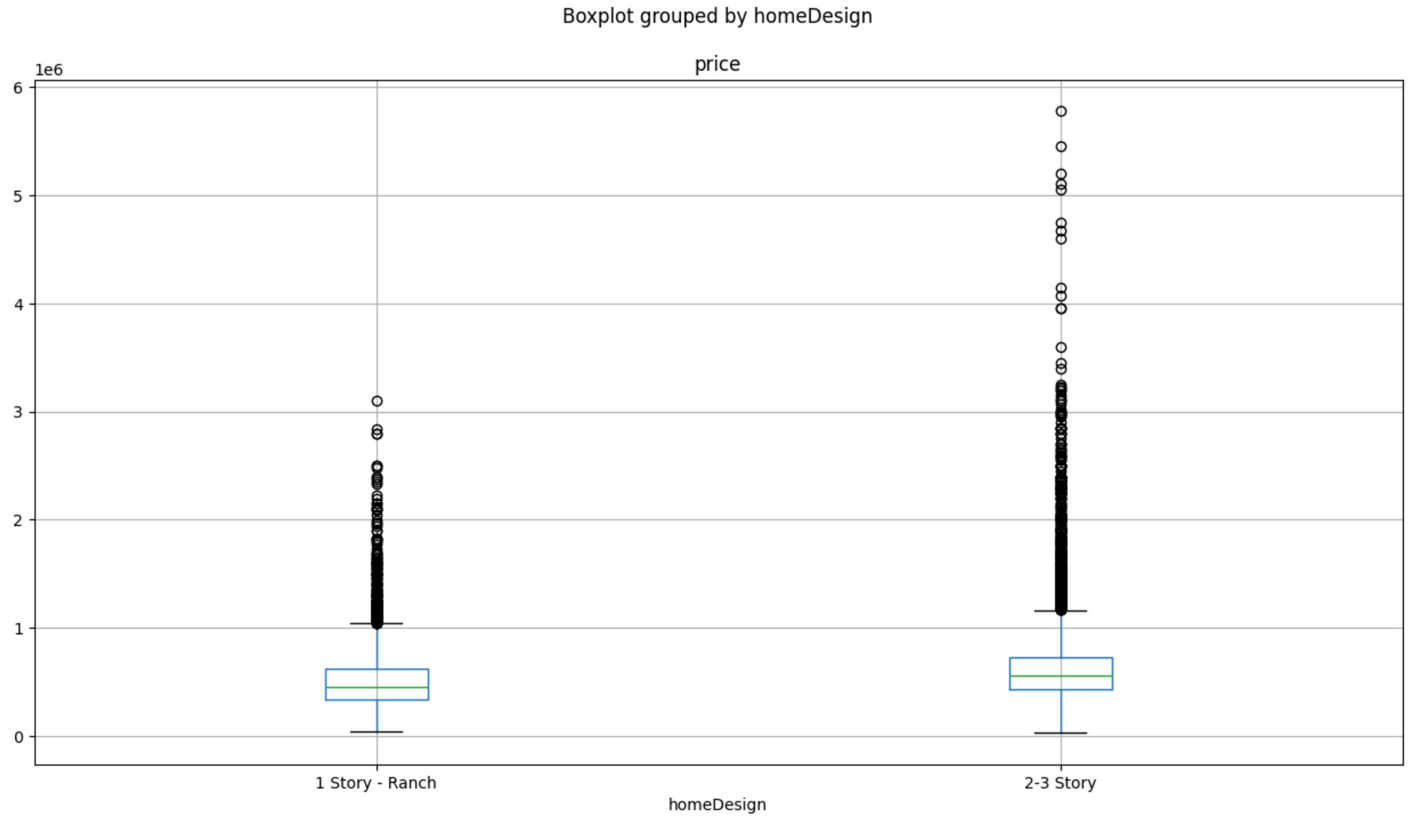
Observations

The mean living space size is approximately 1979 sqft, with a standard deviation of 811.19, indicating a notable spread in the sizes of homes. For 'price,' the mean is 602,946.30, with a standard deviation of 375,476.52, highlighting substantial variability in home prices. The minimum and maximum values indicate a wide price range, with the smallest home priced at 29,000 and the largest at 5,779,000.

The scatter plot reinforces these observations, revealing a dense concentration of points in the 0 - 4000 sqft range for living area, suggesting considerable price variability among homes of similar sizes. A few high-value homes further emphasize the right skewness, contributing to the average price being significantly influenced. In summary, the dataset is characterized by most homes in the lower price range. In contrast, a handful of high-value homes substantially impact the average, introducing the right skewness to the distribution. These findings underscore the importance of considering outliers in the analysis to understand the housing market better, which we see in the next graph.

In [ ]:
```
qualified_sales_5yrs.boxplot(column = 'price', by = 'homeDesign', figsize = (15,8))
```

Out[ ]:
```
<Axes: title={'center': 'price'}, xlabel='homeDesign'>
```



In [ ]:
```
# Calculate z-scores for the 'price' column
z_scores = zscore(qualified_sales_5yrs['price'])

# Mask for identifying outliers based on z-scores
outliers_z = (z_scores > 3) | (z_scores < -3)

# Results
outliers_df_z = qualified_sales_5yrs[outliers_z]

outliers_df_z.sample(5)

# Looking at these on zillow they appear to be legit outliers
```

Obervation

To investigate these outliers further, we employed z-scores as a statistical measure to identify potential anomalies within the price column. We chose this methodology because the z-score provides a standardized approach for comparing and quantifying deviations from the mean. It is independent of the scale of the data and offers clear interpretability. A z-score threshold greater than three or less than -3 was applied, following the standard convention for detecting extreme values. The identified outliers were then extracted into a new DataFrame named 'outliers_df_z,' allowing for targeted examination and analysis. A random sample of five rows from this DataFrame was selected to offer a brief snapshot for closer inspection. During our examination, we cross-referenced this sample with data from Zillow.com and observed some anomalies in the property details. However, it is important to note that the data set we were provided may have been the accurate record of this property as of 2021, and any recent remodels or changes in the property will not be reflected. Additionally, we observed that the prices were close to or well below the 2023 pricing.

In [ ]:
```
# What proportion of homes in the data are smaller than 1979 square foot and cost more t
filt1 = (qualified_sales_5yrs['price']> 602946) & (qualified_sales_5yrs['livingSpaceSqft
print(filt1.mean().round(3))
```

```
# What proportion of homes in the data are smaller than 1979 square foot and cost less t
filt2 = (qualified_sales_5yrs['price']< 602946) & (qualified_sales_5yrs['livingSpaceSqft
print(filt2.mean().round(3))
```

```
0.114
0.44
```

Oberservations

When we look at price and square footage, the data reveals some intriguing insights into the relationship between home size and pricing. Approximately 11.4% of the homes (filt1) are smaller than the average size of 1979 square feet, yet command prices higher than the dataset's average of 602,946. This phenomenon may be attributed to factors such as a prime location, upscale amenities, or recent renovations, which contribute to the elevated pricing despite the smaller size. These homes could appeal to buyers, prioritizing features and location over sheer square footage.

On the other hand, a substantial 44% of the homes (filt2) are smaller in size and priced below the dataset's average. This segment might attract first-time homebuyers, individuals on a more constrained budget, or those who appreciate the charm of smaller residences. The prevalence of such homes in the dataset suggests a diverse range of preferences among buyers, emphasizing that size alone does not dictate the perceived value of a property.

In [ ]:

```
# Create correlation matrix between variables

qualified_sales_5yrs[['price', 'livingSpaceSqft', 'age', 'nbrBedRoom']].corr()
```

Out[ ]:

	price	livingSpaceSqft	age	nbrBedRoom
price	1.00	0.49	0.02	0.32
livingSpaceSqft	0.49	1.00	-0.45	0.57
age	0.02	-0.45	1.00	-0.27
nbrBedRoom	0.32	0.57	-0.27	1.00

Obervations

Firstly, the correlation between price and living area indicates a weak positive connection. While larger homes generally command higher prices, this relationship is not absolute, suggesting other factors play a role in determining property values. Conversely, the negative correlation between price and age suggests that, on average, older homes tend to be more affordable. However, exceptions exist, and this trend is not uniformly applicable. The correlation between price and the number of bedrooms is very weak, suggesting that the number of bedrooms alone does not dictate property prices.

Interestingly, a moderate positive correlation between living area and number of bedrooms implies that larger homes tend to have more bedrooms, contributing to their overall size and potentially influencing pricing. Moreover, the moderate negative correlation between living area and age suggests that newer properties tend to boast larger living spaces. In contrast, the weak negative correlation between number of bedrooms and age hints that newer homes, on average, may have fewer bedrooms.

In summary, exploring older properties might yield favorable options for those seeking large, affordable homes. On the other hand, individuals in search of spacious, modern homes with fewer bedrooms may find newer properties more aligned with their preferences. The data underscores the complexity of property valuation, emphasizing the need to consider multiple factors when navigating the real estate landscape.

Algorithmic Thinking

Objective

Our goal is to predict the value of a new single-family property using the K-Nearest Neighbors (KNN) algorithm. This approach estimates property values by averaging the sales prices of k-similar nearby homes. To do this, we will work with data from sales.csv, focusing on qualified sales where sales.sales_cd == 'Q' and sales.price > 0, and include only sales from the past 5 years (01/01/2015 to 12/31/2020). We will enhance our dataset by adding columns such as nh (neighborhood number), totalActualVal, builtYear, EffectiveYear, TotalFinishedSF, and a boolean flag indicating whether the basement is finished (1 for yes, 0 for no).

KNN is a supervised machine learning algorithm suitable for regression problems. It predicts the price of a new home by finding similar properties in the dataset, based on factors such as location, living area (SQFT), age of the home, and the presence of a finished basement.

In [ ]:

```
# Filter qualified sales with price > 0 and sales_cd == 'Q'
qualified_sales = merged_data[(merged_data['sales_cd'] == 'Q') & (merged_data['price'] >

# Keep only sales in the last 5 years (01/01/2015 to 12/31/2020)
qualified_sales_5yrs = qualified_sales[(qualified_sales['date_of_sale'] >= '2015-01-01')

# Load the necessary data frames

# Display the resulting DataFrame
simplified = ['builtYear', 'EffectiveYear', 'nbrBedRoom', 'livingSpaceSqft', 'age', 'nh'
qualified_sales_5yrs[simplified].head()
```

Out[ ]:

	builtYear	EffectiveYear	nbrBedRoom	livingSpaceSqft	age	nh	totalActualVal	totalAssessed
1	1973	1995	4.00	3111	48	120.00	1838000	131
2	1968	1985	4.00	1213	53	120.00	876000	62(
4	1891	1983	4.00	3022	130	102.00	1715000	122(
5	1945	1985	4.00	1905	76	103.00	2225500	159
6	1900	1960	2.00	660	121	109.00	668000	47

In [ ]:

```
def predict_knn(qualified_sales_5yrs, k=3, nh=201, livingSpaceSqft=1500, age=5, bsmtCond

    # Create a copy of the DataFrame to avoid modifying the original.
    data = qualified_sales_5yrs.copy()

    # Filter down to sales data for the provided neighborhood number, nh.
    data = data[data['nh'] == nh]

    # Calculate Euclidean Distance for finished_sqft, home_age, and finished_basement fo
    features = ['livingSpaceSqft', 'age', 'bsmtCond']
    data['distance'] = np.sqrt(
    np.sum((data[features] - np.array([livingSpaceSqft, age, int(bsmtCond)])) ** 2, axis
```

```
    )

    # Keep only the k closest rows and take the mean of our target variable "price".
    k_closest = data.nsmallest(k, 'distance')
    y_hat = k_closest['price'].mean()
    # y_hat = pd.Series([100000,110000,150000]).mean()

    return y_hat
```

In [ ]:
```
# Validate your function works for a new home in nh 201 that is 1500 sqft, 5 years old,
predict_knn(qualified_sales_5yrs, k=3, nh=201, livingSpaceSqft=1500, age=5, bsmtCond=0)
```

Out[ ]: 595000.0

In [ ]:
```
# I though this was an unreasonable number so did a search for similar properties, gener
# to validate against and I am off by 200k

similar_properties = qualified_sales_5yrs[(qualified_sales_5yrs['livingSpaceSqft'] > 140
                                          (qualified_sales_5yrs['livingSpaceSqft'] < 160
                                          (qualified_sales_5yrs['age'] > 0) &
                                          (qualified_sales_5yrs['age'] < 5) &
                                          (qualified_sales_5yrs['bsmtCond'] == 0)]

similar_properties['price'].mean()
```

Out[ ]: 395372.3333333333

Test your KNN function

Select 10 or more existing home valuations at random and compare the results of predict_knn() to the Accessors's provided valuation (In values.csv, the totalActualVal column). How do your predictions perform relative to the Accessor's valuation as you try different values of *k*?

In [ ]:
```
# Done after the after the fact to simplify the PDF display
columns_to_show = ['homeDesign', 'builtYear', 'nbrBedRoom', 'livingSpaceSqft', 'bsmtCond


# sample
random_homes = qualified_sales_5yrs.sample(10)
random_homes[columns_to_show]
```

Out[ ]:

	homeDesign	builtYear	nbrBedRoom	livingSpaceSqft	bsmtCond	age	str_num	str
3558	2-3 Story	1920	3.00	1503	0	101	315.00	BASELINE
9160	1 Story - Ranch	1910	3.00	962	0	111	140.00	SAINT CLAIR
371	1 Story - Ranch	1957	4.00	1204	1	64	2992.00	23RD
2291	1 Story - Ranch	1970	3.00	960	0	51	1276.00	AIKINS
7793	1 Story - Ranch	1910	3.00	1985	1	111	516.00	BROSS
24183	2-3 Story	2014	5.00	4140	1	7	2257.00	FRONT RANGE
20490	2-3 Story	1999	4.00	2203	1	22	1245.00	FALL RIVER
23748	2-3 Story	2013	4.00	2763	1	8	681.00	FOSSIL BED
12888	2-3 Story	1976	4.00	1680	0	45	411.00	VERDANT
10228	1 Story - Ranch	1974	3.00	1910	1	47	2425.00	JEWEL

In [ ]:

```
# extracts the values from the 'totalActualVal' column and covert to a list
sample_actual_valuations = random_homes['totalActualVal'].tolist()
sample_actual_valuations
```

Out[ ]:

```
[417600,
 368800,
 935700,
 613900,
 604100,
 820100,
 426500,
 607600,
 362500,
 381500]
```

In [ ]:

```
predictions = []
for index, home in random_homes.iterrows():
    nh = home['nh']
    livingSpaceSqft = home['livingSpaceSqft']
    age = home['age']
    bsmtCond = home['bsmtCond']
    prediction = predict_knn(qualified_sales_5yrs, k=3, nh=nh, livingSpaceSqft=livingSpa
    predictions.append(prediction)

    print(predictions)
```

```
[441333.3333333333]
[441333.3333333333, 276500.0]
[441333.3333333333, 276500.0, 692833.3333333334]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0, 518833.3333333333]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0, 518833.3333333333, 634033.3333
333334]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0, 518833.3333333333, 634033.3333
333334, 389000.0]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0, 518833.3333333333, 634033.3333
333334, 389000.0, 501966.6666666667]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0, 518833.3333333333, 634033.3333
333334, 389000.0, 501966.6666666667, 368666.6666666667]
[441333.3333333333, 276500.0, 692833.3333333334, 595000.0, 518833.3333333333, 634033.3333
333334, 389000.0, 501966.6666666667, 368666.6666666667, 385666.6666666667]
```

In [ ]:

```
# Step 1: Create a list of actual valuations
actual_valuations = random_homes['totalActualVal'].tolist()

# Step 2: Calculate differences between predicted and actual values
differences = [actual - predicted for actual, predicted in zip(actual_valuations, predic

# Step 3: Calculate the average error
average_error = sum(differences) / len(differences)

# Step 4: Round predicted values and differences to 2 decimal places
rounded_predictions = [round(prediction, 2) for prediction in predictions]
rounded_differences = [round(difference, 2) for difference in differences]

# Print the results
print("Actual Valuations:", actual_valuations)
print("Predicted Values:", rounded_predictions)
print("Differences:", rounded_differences)
print("Average Error:", round(average_error, 2))
```

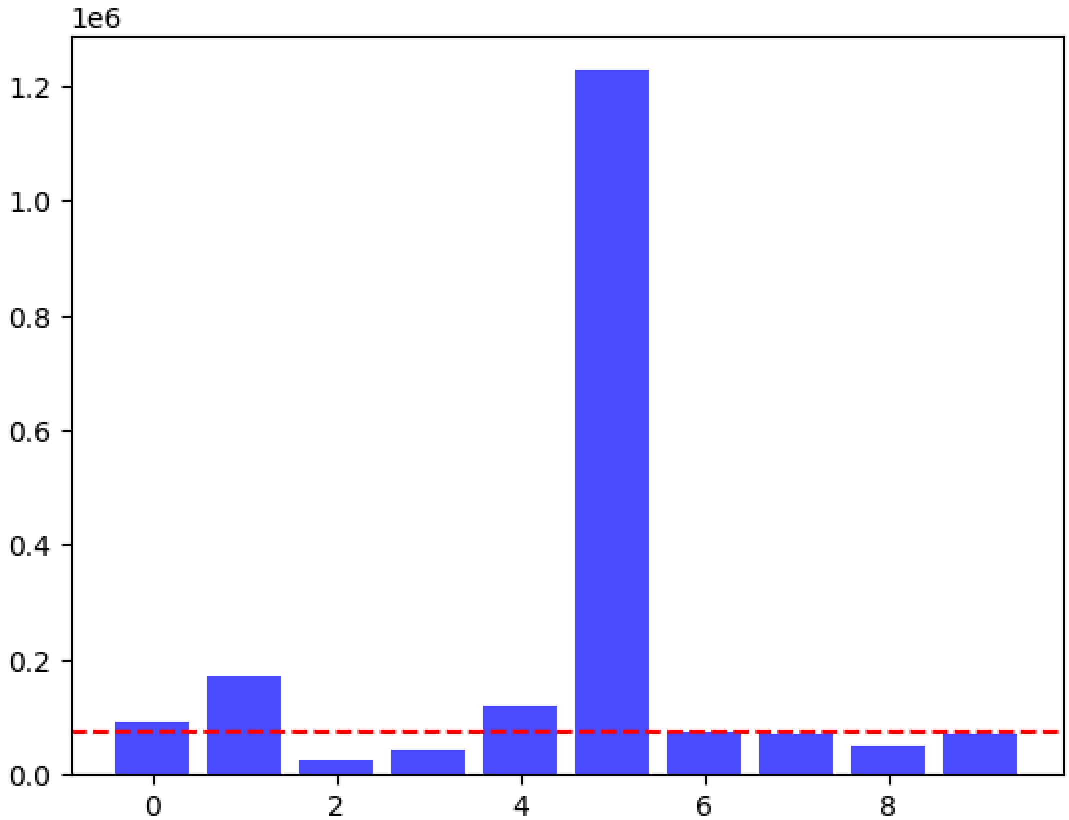
```
Actual Valuations: [417600, 368800, 935700, 613900, 604100, 820100, 426500, 607600, 36250
0, 381500]
Predicted Values: [441333.33, 276500.0, 692833.33, 595000.0, 518833.33, 634033.33, 38900
0.0, 501966.67, 368666.67, 385666.67]
Differences: [-23733.33, 92300.0, 242866.67, 18900.0, 85266.67, 186066.67, 37500.0, 10563
3.33, -6166.67, -4166.67]
Average Error: 73446.67
```

In [ ]:

```
# Create a scatterplot to visually see how my model performed

# Actual and predicted values
actual_valuations = [557000, 668300, 473000, 470100, 646800, 2256700, 499700, 465600, 45
predicted_values = [465000.0, 496666.67, 448566.67, 428800.0, 527500.0, 1030000.0, 42550
differences = [92000.0, 171633.33, 24433.33, 41300.0, 119300.0, 1226700.0, 74200.0, 7106

# Bar positions
positions = np.arange(len(actual_valuations))

# Create a bar plot
plt.bar(positions, differences, color='blue', alpha=0.7, label='Differences')

plt.axhline(y=average_error, color='red', linestyle='--', label=f'Average Error: {round(
```

Out[ ]:

```
<matplotlib.lines.Line2D at 0x135bd18b0>
```



In [ ]:

```
# Alternate way of calculating that I found

# Step 1: Create a list of actual valuations
actual_valuations = random_homes['totalActualVal'].tolist()

# Step 2: Calculate differences between predicted and actual values
differences = [actual - predicted for actual, predicted in zip(actual_valuations, predic

# Step 3: Square each difference.
squared_differences = [difference ** 2 for difference in differences]


squared_differences
```

Out[ ]:

```
[563271111.1111102,
 8519290000.0,
 58984217777.777756,
 357210000.0,
 7270404444.4444475,
 34620804444.44443,
 1406250000.0,
 11158401111.111107,
 38027777.777778015,
 17361111.111111272]
```

Ethics Review

1. When modeling data, it is crucial to consider the impact that algorithms can have on people's lives. One possible source of bias in this dataset could be socioeconomic factors. If the dataset predominantly includes homes from specific income brackets or neighborhoods, it might not represent the full diversity of the housing market. This bias could lead to inaccuracies in property

valuations, either underestimating or overestimating values in areas with different socioeconomic characteristics, thus affecting the fairness and reliability of the valuations.

2. When using the KNN regression algorithm, several potential harms must be considered. The performance of KNN can be sensitive to the choice of k. If k is too low, the model may be influenced too heavily by a few data points, leading to erratic predictions. Conversely, a high k can smooth out the model too much, potentially overlooking important local patterns. Outliers can disproportionately affect predictions, acting as misleading influences within this collective decision-making process. Normalizing data, such as standardizing features between 0 and 1, can help mitigate these issues by reducing sensitivity to varying scales and improving stability. However, this normalization process also introduces its own trade-offs that need to be carefully managed.
3. Implementing an appeal process is essential to address potential harm from the model’s results. Such a process ensures fairness by allowing individuals to challenge and review the outcomes, accounting for factors that may not be explicitly captured in the data. This adds a layer of accountability and human judgment, recognizing that automated models have limitations in reflecting the full complexity of real-world situations. By including an appeal mechanism, we acknowledge these limitations and provide a pathway for addressing and rectifying any potential issues, thus promoting fairness and transparency in the model's application.