Analyzing Residential Single Family Properties

The Question / Problem

You have been hired as an indepedent auditor by Colorado's Boulder County Assessors Office to help with the following problems.

Problem 1: Annual Report Insights

The Accessors Office is set to release their annual report on the valuation of residential single family properties. They have asked you to explore the data and produce at least 2 key findings they can share in their annual report to the public.

Problem 2: Estimate Home Values

The Assessors Office needs help improving their valuation process for residential single family properties. They have asked you to write a KNN alogorithm to value new homes based on similar home sales. By law, residential properties must be valued by using a "market approach". This predicts the price a property would bring on the open market in a transaction between a willing, informed, and knowledgeable buyer and seller. A property can be valued through the process of analyzing comparable sales. A comparable sale is any qualified sale in the last 5 years (January 2015 - December 2020).

The central factors used by the Assessors for property valuation are:

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

Problem 3: Ethics Review

Fairness and accuracy are vitally important. If the assessed values are too high, the property owners will overpay in taxes. If the assessed values are too low then we may fall short of the capital needed to cover the budget approved by legislators. As such, thinking through the impact of how we predict home prices is vitial.

Problem 1: EDA for the Annual Report Insights

Goal

Perform EDA on the property valuations for "1-Story" and "2-3 Story" single family residential buildings. Identify at least 2 key insights and/or graphs that tell a story about the valuations for these properties for the annual report.

1.0 Get the Data

Tasks:

1. Read in the following data:
    - buildings.csv

- land.csv
- values.csv
- owner_addresses.csv

2. Adjust the structure of our data as necessary (joins, drop unneeded columns, add features, etc).
3. Inspect and handle missing values as necessary.

```
# Your Code Here

import pandas as pd
import numpy as np

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

pd.set_option('display.max_columns', None)

buildings = pd.read_csv('buildings.csv')
land = pd.read_csv('land.csv')
values = pd.read_csv('values.csv')
addresses = pd.read_csv('owner_address.csv')
```

```
buildings.head()
len(buildings)
len(buildings.strap.unique())
```

	strap	bld_num	section_num	designCode	designCodeDscr	qualityCode	qualityCodeDscr	bldgClass	bldgClassDscr	ConstCode	ConstCodeDscr	builtYea
0	R0000005	1	1	10	1 Story - Ranch	30	AVERAGE	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	195
1	R0000006	1	1	20	2-3 Story	32	AVERAGE ++	1212	SINGLE FAM RES IMPROVEMENTS	310	Frame	192
2	R0000008	1	1	10	1 Story - Ranch	31	AVERAGE +	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	195
3	R0000009	1	1	10	1 Story - Ranch	50	VERY GOOD	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	196
4	R0000013	1	1	10	1 Story - Ranch	50	VERY GOOD	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	197

```
4196141961
```

```
land.head()
len(land)
```

```
len(land.strap.unique())
```

	strap	landUnitValue	landUnitType	landClass	landClassDscr	GIS_sqft	GIS_acreage	status_cd
0	R0000005	7958.0	SF	1112.0	SINGLE FAM.RES.-LAND	7958	0.183	A
1	R0000006	8995.0	SF	1112.0	SINGLE FAM.RES.-LAND	8995	0.206	A
2	R0000008	6801.0	SF	1112.0	SINGLE FAM.RES.-LAND	6801	0.156	A
3	R0000009	6308.0	SF	1112.0	SINGLE FAM.RES.-LAND	6308	0.145	A
4	R0000013	29023.0	SF	1112.0	SINGLE FAM.RES.-LAND	29023	0.666	A

```
4196141961
```

```
values.head()
len(values)
len(values.strap.unique())
```

	strap	tax_yr	bldAcutalVal	LandAcutalVal	xfActualVal	totalActualVal	landAssessedVal	bldAssessedVal	xfAssessedVal	totalAssessedVal	status_cd
0	R0000005	2021	73140	658260	NaN	731400	47066.0	5230.0	NaN	52296	A
1	R0000006	2021	354100	724400	NaN	1078500	51795.0	25318.0	NaN	77113	A
2	R0000008	2021	222700	668300	NaN	891000	47783.0	15923.0	NaN	63706	A
3	R0000009	2021	719800	986400	NaN	1706200	70528.0	51466.0	NaN	121994	A
4	R0000013	2021	1054300	783700	NaN	1838000	56035.0	75382.0	NaN	131417	A

```
4196141961
```

```
addresses.head()
len(addresses)
len(addresses.strap.unique())
```

	strap	str_pfx	str_num	str	str_sfx	city	sub_code	sub_dscr	section	township	range	nh	mill_levy
0	R0000005	NaN	3030.0	DOVER	DR	BOULDER	3459.0	HIGHLAND PARK 5 - BO	5.0	1S	70.0	160.0	87.045
1	R0000006	NaN	1310.0	HAWTHORN	AVE	BOULDER	6255.0	PARSONS PARK - BO	19.0	1N	70.0	115.0	87.045
2	R0000008	NaN	2002.0	COLUMBINE	AVE	BOULDER	3822.0	INTERURBAN PARK - BO	6.0	1S	70.0	102.0	87.045
3	R0000009	NaN	3100.0	6TH	ST	BOULDER	5709.0	NEWLANDS - BO	24.0	1N	71.0	170.0	87.045
4	R0000013	NaN	3640.0	19TH	ST	BOULDER	1227.0	CAROLYN HEIGHTS - BO	19.0	1N	70.0	120.0	87.045

```
4196141961
```

```
#creating master dataframe
from functools import reduce
dfs = [buildings, land, values, addresses]
master = reduce(lambda left,right: pd.merge(left,right,on='strap'), dfs)
len(master.strap.unique())
master.head()
master.section.unique()
```

```
41961
```

	strap	bld_num	section_num	designCode	designCodeDscr	qualityCode	qualityCodeDscr	bldgClass	bldgClassDscr	ConstCode	ConstCodeDscr	builtYear
0	R0000005	1	1	10	1 Story - Ranch	30	AVERAGE	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	195
1	R0000006	1	1	20	2-3 Story	32	AVERAGE ++	1212	SINGLE FAM RES IMPROVEMENTS	310	Frame	192
2	R0000008	1	1	10	1 Story - Ranch	31	AVERAGE +	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	195
3	R0000009	1	1	10	1 Story - Ranch	50	VERY GOOD	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	196
4	R0000013	1	1	10	1 Story - Ranch	50	VERY GOOD	1212	SINGLE FAM RES IMPROVEMENTS	320	Masonry	197

```
array([ 5., 19.,  6., 24., 30., 36., 31., 29., 13., 25., 32., 18., 20.,
        1., 17.,  8., 33.,  9.,  7.,  4.,  2., 34.,  3., 35., 11., 10.,
       15., 26., 28., 21., 14., 12., 22., 16., 27., 23.])
```

```
#since problem is asking for the report on the valuation I will only be keeping the central factors
#used by the Assessors for property valuation

#Location - for location I will be using city, since there are more options than in township
#Living Area (SQFT) - for living area I will be using TotalFinishedSF since it is already calculated into the intended measure (has the finshed living area which i
#Age of the Home - for the age of the home I will be basing it off effective year instead of year built, since I believe a lot can change when rennovating a house,
#Finished Basement - going to use column bsmtTypeDscr

valuation_df = master[['strap','city','TotalFinishedSF','EffectiveYear','bsmtTypeDscr', 'designCodeDscr','totalActualVal', 'totalAssessedVal']]

#we will be removing all homes listed as unincorporated since it is a region not governed by a local municipal corporation, and is only 20% of the data.
sum(valuation_df.city == 'UNINCORPORATED')/len(valuation_df)
valuation_df = valuation_df[valuation_df.city != 'UNINCORPORATED']

#will be making new column to indicate whether or not basement is finished, 1 = finished and 0 = not finished
valuation_df['finished_basement'] = np.where(valuation_df.bsmtTypeDscr.str.lower().str.strip().str.contains(r'\bfinished') == True, 1,0)
#valuation_df.head()

valuation_df = valuation_df.drop('bsmtTypeDscr', axis=1)

#next will be making an age column based off 2022 - effective year. Chose 2022 since that is most recent year in dataset. Assuming that the building isn't done yet

valuation_df['age'] = 2022 - valuation_df['EffectiveYear']
valuation_df = valuation_df.drop('EffectiveYear', axis=1)

#create column indicating whether or not building is greater than 1 story
valuation_df['large'] = np.where(valuation_df.designCodeDscr.str.lower().str.strip().str.contains(r'\b1') == True, 0,1)
valuation_df = valuation_df.drop('designCodeDscr', axis=1)
```

```
#setting the index as strap

valuation_df = valuation_df.set_index('strap')
valuation_df.head()
```

```
0.2092419151116513
```

strap	city	TotalFinishedSF	totalActualVal	totalAssessedVal	finished_basement	age	large
R0000005	BOULDER	1282	731400	52296	1	65	0
R0000006	BOULDER	2130	1078500	77113	0	37	1
R0000008	BOULDER	1558	891000	63706	0	68	0
R0000009	BOULDER	1604	1706200	121994	1	27	0
R0000013	BOULDER	3111	1838000	131417	0	27	0

1.1 Explore the Data

Tasks:

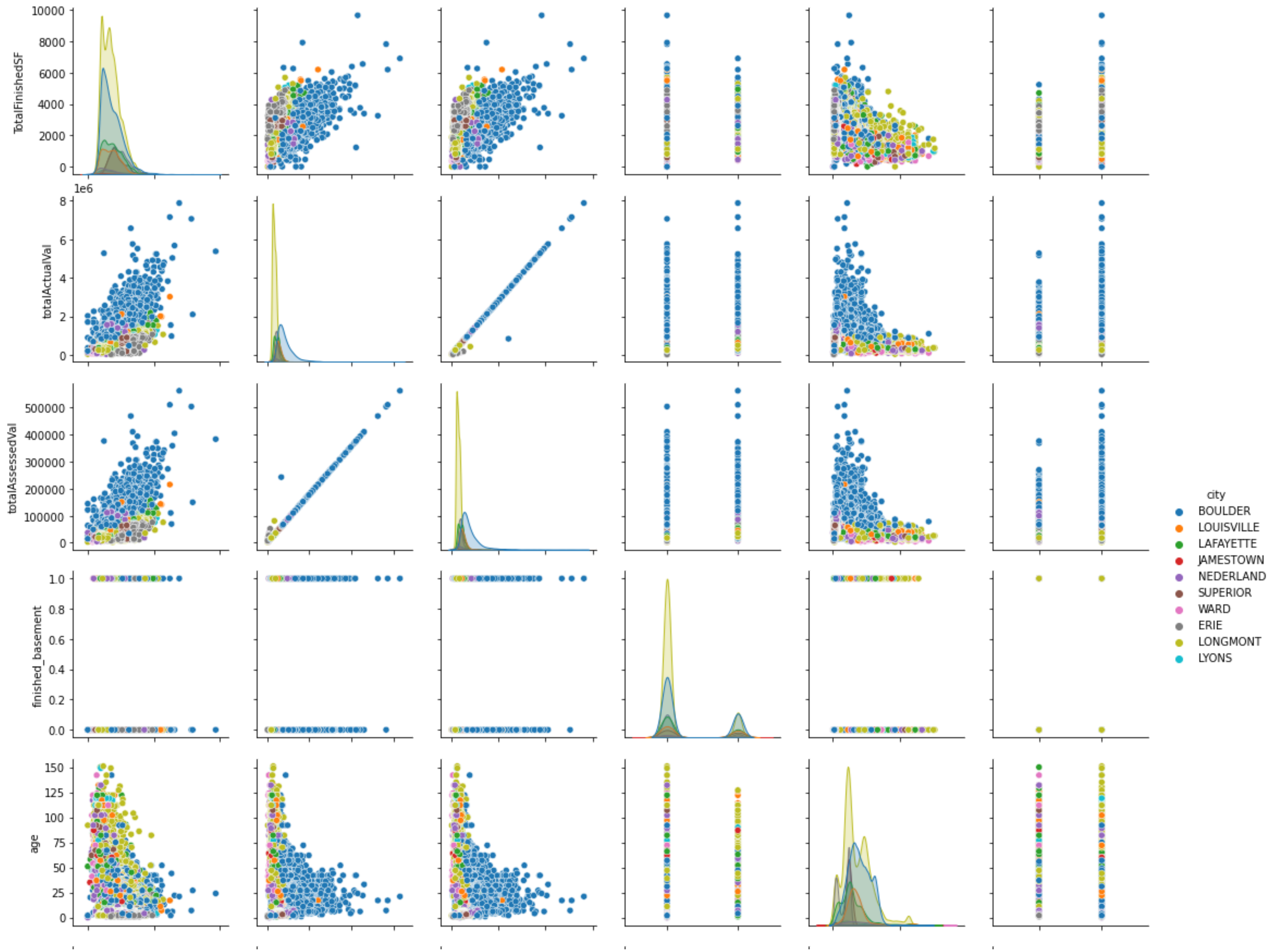
- Explore the relationships in the data (univariate, bivariate, etc)
- Explore outliers
- Provide a summary of your findings.
    - Highlight at least 2 key findings and/or graphs that you feel would be interesting to share in the Annual Report to Homeowners.

```
# Your Code Here
import seaborn as sns

sns.pairplot(data=valuation_df, hue = 'city')

#between 1 story and multiple story single family residential buildings it seems that multiple stories have more
#living area and value which obviously makes sense since these homes are bigger. It also seems that the larger
#the living area and the newer the building both increase the value of the building. It also seems that the
#average age of these buildings in boulder county are around 25 years old. There seems to be some outliers in
#the data however, none of them seems to stray to far off from what's expected, since this is the case I won't
#be removing any.
```

```
<seaborn.axisgrid.PairGrid at 0x7fd01ded7bb0>
```

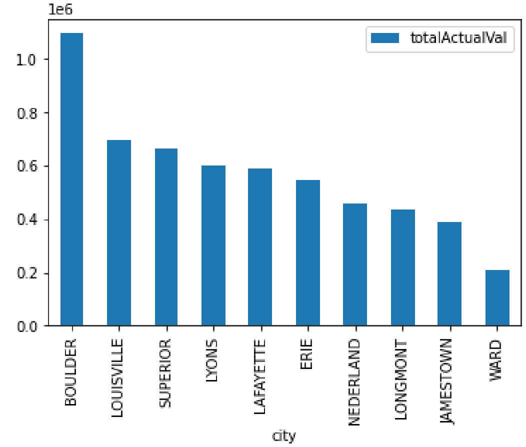



```
#looking at if location has an effect on valuation

valuation_df.pivot_table(index = 'city', values = 'totalActualVal', aggfunc = 'mean').sort_values(by='totalActualVal', ascending=False).plot(kind = 'bar')

#as can be shown in the bar chart below, Boulder on average has the highest valued homes while, Ward, has the least
#valuable homes. All the other cities listed in the dataset are also listed below as well.
```

```
<AxesSubplot:xlabel='city'>
```



Part II: Algorithmic Thinking

Objective

Our goal is to predict the value of a new single-family property given comparable sales data. One way we might estimate the value of a home is to look at the value of *k*-similar nearby homes that have recently sold. The average sales price of those *k* homes could then be used as the predicted valuation for our new home. This process is effectively how the K-Nearest Neighbor Algorithm (KNN) works for regression problems.

KNN is considered a supervised machine learning algorithm that can be used to solve both classification and regression problems. As shown above, we can be used to solve nonparametric regression problems such as predicting the price of a new home based on *similar* nearby homes.

Recall the central factors used for property valuation:

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

2.0 Read and Prepare the Sales Data

Tasks:

- Load the sales.csv
- Keep only qualified sales (sales.sales_cd == 'Q') and sales.price > 0.
- Keep only sales in the last 5 years (01/01/2015 and 12/31/2020)
- Join "sales" with the necessary data frames to add the following columns
  - nh, this is the neighborhood number that must be used to identify comparable sales by location.
  - totalActualVal
  - builtYear

- EffectiveYear
- TotalFinishedSF
- A boolean flag (1/0) for if the basement is finished that you will need to create

```
sales
```

	strap	deedNum	Tdate	sales_cd	deed_type	price	status_cd	nh	builtYear	EffectiveYear	TotalFinishedSF	bsmtTypeDscr	totalActualVal
0	R0000013	3490566	2015-12-14	Q	WJ	1315000.0	A	120.0	1973	1995	3111	SUBTERRANEAN BASEMENT UNFINISHED AREA	1838000
1	R0000017	3686840	2018-11-20	Q	WD	728500.0	A	120.0	1968	1985	1213	SUBTERRANEAN BASEMENT FINISHED AREA	876000
2	R0000026	3575976	2017-02-15	Q	WD	1240000.0	A	102.0	1891	1983	3022	SUBTERRANEAN BASEMENT FINISHED AREA	1715000
3	R0000028	3672204	2018-08-15	Q	WD	2350000.0	A	103.0	1945	1985	1905	WALK-OUT BASEMENT FINISHED AREA	2225500
4	R0000038	3458700	2015-06-15	Q	WD	569900.0	A	109.0	1900	1960	660	0	668000
...	...	...	...	...	...	...	...	...	...	...	...	...	...
11754	R0612351	3804136	2020-08-03	Q	SJ	915000.0	A	157.0	2019	2019	2582	0	870300
11755	R0612352	3768876	2020-02-28	Q	SJ	1013500.0	A	157.0	2019	2019	2946	0	903600
11756	R0612879	3796977	2020-06-25	Q	WD	360000.0	A	960.0	1944	1980	902	0	410600
11757	R0612880	3794829	2020-06-17	Q	WJ	363000.0	A	960.0	1958	1980	1230	0	471700
11758	R0612917	3754820	2019-12-13	Q	WJ	545000.0	A	144.0	1955	1960	1359	0	636140

11759 rows × 14 columns

```
# Your Code Here

#keeping only qualified sales
sales = pd.read_csv('sales.csv', parse_dates=['Tdate'])
sales = sales[(sales['sales_cd'] == 'Q') & (sales['price'] > 0)]

#Keep only sales in the last 5 years (01/01/2015 and 12/31/2020)
mask = (sales['Tdate'] >= '2015-01-01') & (sales['Tdate'] <= '2020-12-31')
sales = sales.loc[mask]
```

```
sales.info()
addresses.info()


#creating data frame
add = addresses[['strap','nh']]
build = buildings[['strap','builtYear','EffectiveYear','TotalFinishedSF','bsmtTypeDscr']]
val = values[['strap','totalActualVal']]


sales = sales.merge(add, on = 'strap')
sales = sales.merge(build, on = 'strap')
sales = sales.merge(val, on = 'strap')

#creating boolean column for if basement is finished
sales['finished_basement'] = np.where(sales.bsmtTypeDscr.str.lower().str.strip().str.contains(r'\bfinished') == True, 1,0)
sales = sales.drop('bsmtTypeDscr', axis = 1)
sales.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11759 entries, 26 to 221106
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   strap      11759 non-null  object
 1   deedNum    11759 non-null  object
 2   Tdate      11759 non-null  datetime64[ns]
```

2.1 Property Valuation using KNN

Tasks:

- Complete the below function **predict_knn()** so that it finds the k-most similar sales properties in the appraisal neighborhood (nh) and returns the average sale price for those *k* properties as the predicted value (y_hat).

KNN Regression Pseudo Code

Given a new data point:

1. Calculate the Euclidean distance between the new data point and all known datapoints in the dataset.
2. Select the *k* closest datapoints.
3. Average the target variable for the *k* closest data points.

Euclidean Distance formula for 3-dimenstions where p_1 and q_1 is finished_sqft, p2 and q_2 is home_age, and p3 and q_3 is finished_basement:

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2}$$

.

```
memory usage: 4.2+ MB
```

```
#creating age with subtracting effective year from 2022 since that is the most recent effective year in entire data set
sales['age'] = 2020 - sales.EffectiveYear
```

	strap	deedNum	Tdate	sales_cd	deed_type	price	status_cd	nh	builtYear	EffectiveYear	TotalFinishedSF	totalActualVal	finished_basemen
1625	R0026982	3662269	2018-06-18	Q	WD	80000.0	A	903.0	1961	1961	150	80301	
778	R0011305	03803922	2020-07-29	Q	WJ	849000.0	A	146.0	2002	2002	193	809800	
			08-15										

```
# This function is incomplete, fix it!
def predict_knn(sales, k=3, nh=200, finished_sqft=1500, home_age=5, finished_basement=False):

    # Filter down to our sales data to the provided neighborhood number, nh.
    if sum(sales.nh == nh) > 0:
        sales = sales[sales.nh == float(nh)]

    # Calculate the Euclidean Distance for finished_sqft, home_age, and finished_basement for every sale in our nh.

        sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
    # Keep only the *k* closeset rows and take the mean of our target variable "price"
        sales = sales.nsmallest(k, 'euc_dis')
```

```
        y_hat = sales['price'].mean()


        return y_hat
    else:
        print('Not a valid neighborhood number')


# Validate your function works for a new home in nh 200 that is 1500 sqft, 5 years old, and does not have a finished basement.
predict_knn(sales, k=3, nh=200, finished_sqft=1500, home_age=5, finished_basement=0)
```

```
Not a valid neighborhood number
```

2.2 Test your KNN function.

Selecting 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 our predictions perform relative to the Accessor's valuation as we try different values of *k*?

```
#ten random
sales.sample(n = 10, random_state=23)
```

	strap	deedNum	Tdate	sales_cd	deed_type	price	status_cd	nh	builtYear	EffectiveYear	TotalFinishedSF	totalActualVal	finished_basemen
9856	R0603285	3524231	2016-06-13	Q	SW	417400.0	A	205.0	2015	2015	2265	506400	(
2451	R0040838	3759861	2019-12-17	Q	WJ	380000.0	A	203.0	1965	1965	1556	339300	(
2777	R0043115	3582008	2017-03-22	Q	WJ	322000.0	A	205.0	1965	1998	1631	369100	(
3741	R0052754	3629350	2017-12-01	Q	WJ	714000.0	A	825.0	1979	1987	2240	743090	(
5344	R0096250	3762840	2020-01-23	Q	SJ	610000.0	A	223.0	1992	1994	3320	625100	
2969	R0044539	3539652	2016-08-24	Q	WJ	282500.0	A	203.0	1943	2001	848	350800	(
5032	R0087326	3838018	2020-[illegible]	Q	WD	345000.0	A	202.0	1983	1996	896	363500	(

```
# Your code here and thoughts here.

predict_knn(sales, k=1, nh=205, finished_sqft=2265, home_age=5, finished_basement=0) - 506400 #off by -186400.0

predict_knn(sales, k=2, nh=203, finished_sqft=1556, home_age=55, finished_basement=0) - 339300 #off by 172550.0

predict_knn(sales, k=3, nh=205, finished_sqft=1631, home_age=22, finished_basement=0) - 369100 #off by 476233.33

predict_knn(sales, k=4, nh=825, finished_sqft=2240, home_age=33, finished_basement=0) - 743090 #off by 88160.0

predict_knn(sales, k=5, nh=223, finished_sqft=3320, home_age=26, finished_basement=1) - 625100 #off by -341500.0
```

```
predict_knn(sales, k=6, nh=203, finished_sqft=848, home_age=19, finished_basement=0) - 350800 #off by 178116.67

predict_knn(sales, k=7, nh=202, finished_sqft=896, home_age=24, finished_basement=0) - 363500 #off by 57471.43

predict_knn(sales, k=8, nh=410, finished_sqft=1192, home_age=33, finished_basement=0) - 471000 #off by 376375.0

predict_knn(sales, k=9, nh=440, finished_sqft=2358, home_age=14, finished_basement=0) - 600400 #off by 313833.33

predict_knn(sales, k=10, nh=155, finished_sqft=2602, home_age=18, finished_basement=1) - 818300 #off by -308260.0

#it seems that there is a sweet spot for each of these predictions when picking a value of K.
#when playing around with it I couldn't seem to find a common trend between different values of K
#and the accuracy of the predictor. You would think that the more values of K the more accurate it is
#however, it's more based off of the amount of houses in the neighborhood, becuase if you have a lot of houses
#in the same nh then there will be more variation, leading to most likely a more off prediction.
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
-186400.0<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
172550.0<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
476233.3333333334<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
88160.0<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
-341500.0<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
178116.66666666663<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
376375.0<ipython-input-84-b35196fde511>:12: 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
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
313833.3333333334<ipython-input-84-b35196fde511>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
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See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  sales['euc_dis'] = ((sales.TotalFinishedSF - finished_sqft)^2 + (sales.age - home_age)^2 + (sales.finished_basement - finished_basement)^2)**1/2
-308260.0
```

Part III: Ethics Review

Whenever we are modeling our data, it's critical that we take time to consider the impact our algorithms have on people's lives.

3.0

Writing a short paragraph that addresses the following questions.

1. Describe one possible source of bias that exist might exist in this dataset and impact our estimated valuation?
2. What potential harm could arise due to how our knn regression algorithm works? For example, what if *k* is too low or too high? What impact can outliers have? Would it make sense to normalize (e.g. standardize our values between 0 and 1) for our data points (sqft, age, basement) before calculating Euclidean Distance?
3. Should we have an appeal process for people that may be harmed by the results of our model?

Answer

https://www.bloomberg.com/news/articles/2021-03-03/appraisers-acknowledge-bias-in-home-valuations

When researching on potential biases on home evaluations one I kept stumbling upon was racial bias. Our dataset didn't have a race of the families living in the household or the race of the apraiser, and research shows that this can actually impact the value of a house positvely or negatively. The link to this article is above. A potential harm of how our knn regression alogrithim is due to the number of homes in nh and the value of K. I mentioned this in the previous problem, but each nh has differing number of homes, so you could potentially have a higher K than the number of homes in the same nh, which could lead to an error or a miscalculation. Also if there are outliers this could really screw up our calculation, especially if K is small, and an outlier is in the selected K. This would make our prediction a lot smaller or even larger than expected.Normalizing the data could potentially fix this problem, however in my opinion that's not how it works in the real world, and in my opionion outliers should be included unless they are very extreme in order to capture a more realistic value. However, if you wanted a close prediction with only including non-outliers, that would work for a small sample in specific situations. Also you couldn't scale having a finished basement since it's a value of 0 or 1, and it would just return 0 and 1 of what it was already. I think having an appeal process would be a great idea, especially if we are considering ethics. It would be a lot more work on our end but would make us look a lot more reliable and trustworthy, therefore leading to more people coming to us for home valuations.