1. Introduction

Problem

We are interest in know the sales price of residential homes in Ames, Iowa giving the homes attributes.

And with that we could know which neighborhood has more offers for a price range of 100,000 to 250,000.

2. Data acquisition

Data source

For this project we need the following data that we could get from kaggle in this link, which contains all base data that we need.

Data structure

Here's a brief version of the data description files.

- `SalePrice` - the property's sale price in dollars. This is the target variable that you're trying to predict.
- `MSSubClass` - The building class
- `MSZoning` - The general zoning classification
- `LotArea` - Lot size in square feet
- `LotShape` - General shape of property
- `LandContour` - Flatness of the property
- `Utilities` - Type of utilities available
- `LotConfig` - Lot configuration
- `LandSlope` - Slope of property
- `Neighborhood` - Physical locations within Ames city limits
- `Condition1` - Proximity to main road or railroad
- `Condition2` - Proximity to main road or railroad (if a second is present)
- `BldgType` - Type of dwelling
- `HouseStyle` - Style of dwelling
- `OverallQual` - Overall material and finish quality
- `OverallCond` - Overall condition rating
- `YearBuilt` - Original construction date
- `YearRemodAdd` - Remodel date
- `RoofStyle` - Type of roof
- `RoofMatl` - Roof material
- `Exterior1st` - Exterior covering on house
- `Exterior2nd` - Exterior covering on house (if more than one material)
- `MasVnrType` - Masonry veneer type
- `MasVnrArea` - Masonry veneer area in square feet
- `ExterQual` - Exterior material quality
- `ExterCond` - Present condition of the material on the exterior
- `Foundation` - Type of foundation
- `BsmtQual` - Height of the basement
- `BsmtCond` - General condition of the basement
- `BsmtExposure` - Walkout or garden level basement walls
- `BsmtFinType1` - Quality of basement finished area
- `BsmtFinSF1` - Type 1 finished square feet
- `BsmtFinType2` - Quality of second finished area (if present)
- `BsmtFinSF2` - Type 2 finished square feet
- `BsmtUnfSF` - Unfinished square feet of basement area
- `TotalBsmtSF` - Total square feet of basement area
- `Heating` - Type of heating
- `HeatingQC` - Heating quality and condition
- `CentralAir` - Central air conditioning
- `Electrical` - Electrical system
- `1stFlrSF` - First Floor square feet
- `2ndFlrSF` - Second floor square feet
- `LowQualFinSF` - Low quality finished square feet (all floors)
- `GrLivArea` - Above grade (ground) living area square feet
- `BsmtFullBath` - Basement full bathrooms
- `BsmtHalfBath` - Basement half bathrooms
- `FullBath` - Full bathrooms above grade
- `HalfBath` - Half baths above grade
- `Bedroom` - Number of bedrooms above basement level
- `Kitchen` - Number of kitchens
- `KitchenQual` - Kitchen quality
- `TotRmsAbvGrd` - Total rooms above grade (does not include bathrooms)
- `Functional` - Home functionality rating
- `Fireplaces` - Number of fireplaces
- `FireplaceQu` - Fireplace quality
- `GarageType` - Garage location
- `GarageYrBlt` - Year garage was built
- `GarageFinish` - Interior finish of the garage
- `GarageCars` - Size of garage in car capacity
- `GarageArea` - Size of garage in square feet
- `GarageQual` - Garage quality
- `GarageCond` - Garage condition
- `PavedDrive` - Paved driveway
- `WoodDeckSF` - Wood deck area in square feet
- `OpenPorchSF` - Open porch area in square feet
- `EnclosedPorch` - Enclosed porch area in square feet
- `3SsnPorch` - Three season porch area in square feet
- `ScreenPorch` - Screen porch area in square feet
- `PoolArea` - Pool area in square feet
- `MiscFeature` - Miscellaneous feature not covered in other categories
- `MiscVal` - $Value of miscellaneous feature
- `MoSold` - Month Sold
- `YrSold` - Year Sold
- `SaleType` - Type of sale
- `SaleCondition` - Condition of sale

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor
```

In [2]:
```
test_df_path = "test.csv"
test_df = pd.read_csv(test_df_path)
test_df.head()
```

Out[2]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	ScreenPorch	PoolArea	PoolQC
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	AllPub	...	120	0	NaN
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl	AllPub	...	0	0	NaN
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS	AllPub	...	144	0	NaN

5 rows × 80 columns

In [3]:
```
train_df_path = "train.csv"
train_df = pd.read_csv(train_df_path)
train_df.head()
```

Out[3]:

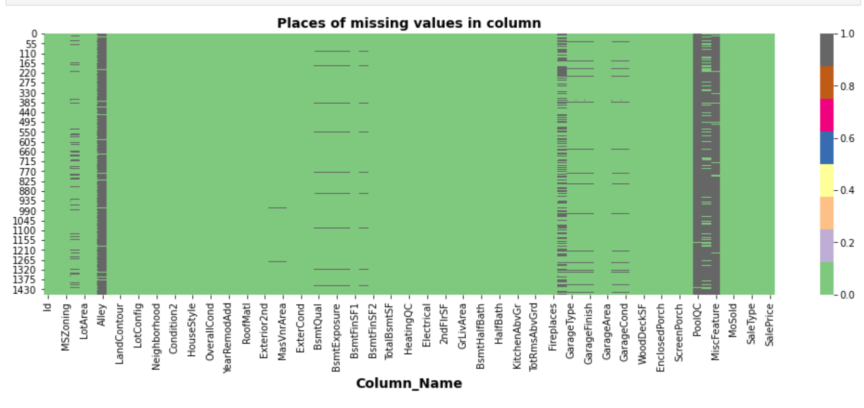
	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFe
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	

5 rows × 81 columns

Methodology

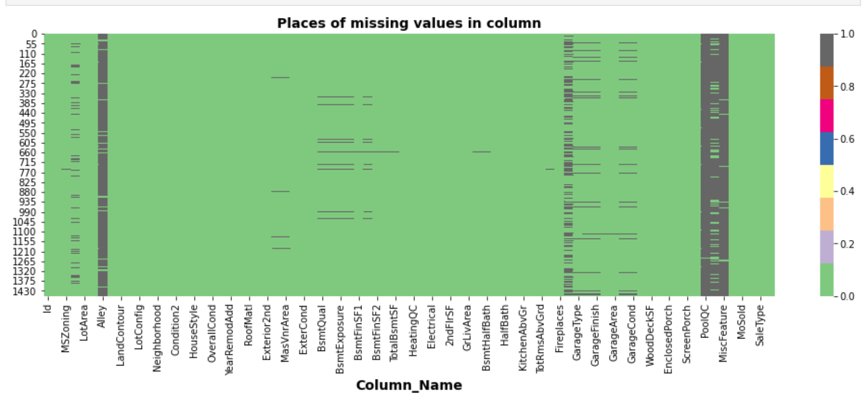
Building a heatmap to see where the missing values are focus, in the train data frame

In [4]:
```
#Plotting heatmap of missing values
plt.figure(figsize=(17, 5))
sns.heatmap(train_df.isnull(), cmap='Accent')
plt.xlabel("Column_Name", size=14, weight="bold")
plt.title("Places of missing values in column",fontweight="bold",size=14)
plt.show()
```



Building a heatmap to see where the missing values are focus, in the test data frame

In [5]:
```
#Plotting heatmap of missing values
plt.figure(figsize=(17, 5))
sns.heatmap(test_df.isnull(), cmap='Accent')
plt.xlabel("Column_Name", size=14, weight="bold")
plt.title("Places of missing values in column",fontweight="bold",size=14)
plt.show()
```



Changing missing data to 0

In [6]:
```
train_df = train_df.fillna(0)
test_df = test_df.fillna(0)
```

In [7]:
```
#Lets plot histogram for prices
# train_df["SalePrice"].hist()
```

Since the values of price after 400,000 look so small, making an other histogram to see that espectrum to

In [8]:
```
# train_df["SalePrice"][train_df["SalePrice"]>400000].hist()
```

Remove of unneeded columns

In [9]:
```
# Cloumns to remove
drop_colum = ['Id', 'PoolQC', 'Fence','MSZoning','MiscFeature','Alley', 'RoofStyle'
    ,'Condition2','HouseStyle','RoofMatl','Exterior1st','KitchenQual','Functional'
    ,'GarageQual','MiscFeature','SaleType','Electrical','Exterior2nd','Heating'
    ,'Utilities']
test_df = test_df.drop(columns=drop_colum, axis=1)
train_df = train_df.drop(columns=drop_colum, axis=1)
```

Removing random row since test set is missing one row

In [10]:
```
remove_n = 1
drop_indices = np.random.choice(train_df.index, remove_n, replace=False)
train_df = train_df.drop(drop_indices)
y_train_df = train_df[['SalePrice']]
train_df = train_df.drop('SalePrice', axis='columns')
```

Finding all columns with Categorical

In [11]:
```
cat_train=[cat for cat in train_df.columns if train_df[cat].dtype=='object']
cat_test=[cat for cat in test_df.columns if test_df[cat].dtype=='object']
```

Handling Categorical Data using Get_Dummies()

In [13]:
```
train_cat_dumm= pd.get_dummies(train_df, columns=cat_train, drop_first= True)
test_cat_dumm= pd.get_dummies(test_df, columns=cat_test, drop_first= True)
```

Concatenating the Original Dataset & the One after creating Dummies(get_dummies() creates a new DF containing JUST the dummies

In [14]:
```
train_df_clean=pd.concat([train_df,train_cat_dumm],axis=1)
test_df_clean=pd.concat([test_df,test_cat_dumm],axis=1)
```

Dropping the columns already concatenated after Get_Dummies()

In [15]:
```
train_df_clean=train_df_clean.drop(cat_train,axis=1)
test_df_clean=test_df_clean.drop(cat_test,axis=1)
```

Splitting data frames in independent x and dependent y

In [17]:
```
x_train_df=train_df_clean

x_test_df=test_df_clean
```

Splitting the data frane into test and training data

In [18]:
```
X_train, X_test, y_train, y_test = train_test_split(x_train_df, y_train_df, test_size=0.25)
# y_train
```

Building a regression model

In [19]:
```
reg=GradientBoostingRegressor(random_state=0)
reg.fit(X_train,y_train)
```

```
D:\Users\Dante\anaconda3\envs\pythonProject\lib\site-packages\sklearn\utils\validation.py:72: DataConversion
Warning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_sampl
es, ), for example using ravel().
  return f(**kwargs)
```

Out[19]:
```
GradientBoostingRegressor(random_state=0)
```

Checking the variance score of the model

In [20]:
```
print('Variance score: %.2f' % reg.score(X_test, y_test))
```

```
Variance score: 0.87
```

Fit the complete train dateset in the model to get the prediction for the test dataset

In [21]:
```
reg=GradientBoostingRegressor(random_state=0)
reg.fit(x_train_df,y_train_df)
```

```
D:\Users\Dante\anaconda3\envs\pythonProject\lib\site-packages\sklearn\utils\validation.py:72: DataConversion
Warning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_sampl
es, ), for example using ravel().
  return f(**kwargs)
```

Out[21]:
```
GradientBoostingRegressor(random_state=0)
```

Getting the prediction of the prices for the test dataframe

In [23]:
```
predictions= reg.predict(x_test_df)
```

Checking the variance score of the model with the test dataset

In [24]:
```
print('Variance score: %.2f' % reg.score(x_test_df, predictions))
```

```
Variance score: 1.00
```

Now that we have the prediction of the prices we can add them to the dataset

In [25]:
```
neighborhood_df = test_df.loc[:]
neighborhood_df['SalePrice'] = predictions
neighborhood_df.head()
```

Out[25]:

	MSSubClass	LotFrontage	LotArea	Street	LotShape	LandContour	LotConfig	LandSlope	Neighborhood	Condition1	...	OpenPorchSF
0	20	80.0	11622	Pave	Reg	Lvl	Inside	Gtl	NAmes	Feedr	...	0
1	20	81.0	14267	Pave	IR1	Lvl	Corner	Gtl	NAmes	Norm	...	36
2	60	74.0	13830	Pave	IR1	Lvl	Inside	Gtl	Gilbert	Norm	...	34
3	60	78.0	9978	Pave	IR1	Lvl	Inside	Gtl	Gilbert	Norm	...	36
4	120	43.0	5005	Pave	IR1	HLS	Inside	Gtl	StoneBr	Norm	...	82

5 rows × 62 columns

Filtering the dataset in the price range

In [26]:
```
range_price_df = neighborhood_df[(neighborhood_df['SalePrice']<=250000) & (neighborhood_df['SalePrice']>=100
range_price_df.shape
```

Out[26]:
```
(1145, 62)
```

Making a dataframe with the count of each Neighborhood

In [27]:
```
neighborhood_homes_price = pd.DataFrame(data=range_price_df.groupby(['Neighborhood'])['Neighborhood'].count(
```

Out[27]:

	Neighborhood
Neighborhood	
Blmngtn	11
Blueste	8
BrDale	9
BrkSide	42
ClearCr	15

In [28]:
```
neighborhood_homes_price['Offers'] = neighborhood_homes_price[['Neighborhood']]
neighborhood_homes_price = neighborhood_homes_price.drop(['Neighborhood'],axis=1)
```

Sorting the dataframe by the count of offers on the Neighborhood

In [29]:
```
neighborhood_homes_price.sort_values(ascending=False,by=['Offers']).head()
```

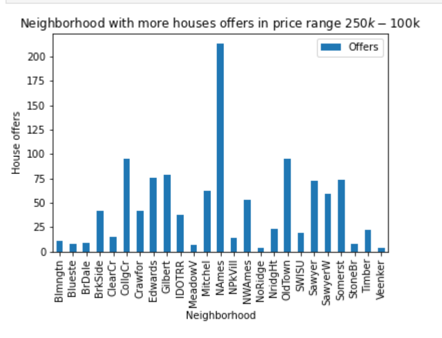
Out[29]:

	Offers
Neighborhood	
NAmes	213
CollgCr	95
OldTown	95
Gilbert	79
Edwards	76

Display of a visual graphic for the previews dataframe

In [30]:
```
neighborhood_homes_price.plot(kind='bar')

plt.title("Neighborhood with more houses offers in price range $250k-$100k")
plt.xlabel("Neighborhood")
plt.ylabel("House offers")
plt.show()
```



Code	Neighborhood Name
Blmngtn	Bloomington Heights
Blueste	Bluestem
BrDale	Briardale
BrkSide	Brookside
ClearCr	Clear Creek
CollgCr	College Creek
Crawfor	Crawford
Edwards	Edwards
Gilbert	Gilbert
IDOTRR	Iowa DOT and Rail Road
MeadowV	Meadow Village
Mitchel	Mitchell
Names	North Ames
NoRidge	Northridge
NPkVill	Northpark Villa
NridgHt	Northridge Heights
NWAmes	Northwest Ames
OldTown	Old Town
SWISU	South & West of Iowa State University
Sawyer	Sawyer
SawyerW	Sawyer West
Somerst	Somerset
StoneBr	Stone Brook
Timber	Timberland
Veenker	Veenker

Results

As we can see on the result the best neighborhood to look for houses offers at price range 250k-100k is **North Ames**, since it has **214** offers.

Conclusion

In this study, we manage to predict the prices of a set of house offerted and form there we were able to focus on a neighborhood that have more offers in our price range. section where you conclude the report.