babaahmadi-niloufar-610398103

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1 House price prediction

The data of the houses sold are given and we are requested to predict the price of houses accordingly.

2 The given Data Discription

ID: a unique number given to each property

MSSubClass: The building class

MSZoning: The general zoning classification

LotArea: Lot size in square feet

SaleCondition: Condition of sale

Sale Price: Dependent Variable

3 Import Libraries

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
import sklearn.metrics as metrics
from sklearn import linear_model
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
```

4 Read the Data

[4]:
```
train = pd.read_csv("train.csv")
train.head()
```

[4]:

	Id	MSSubClass	MSZoning	LotArea	SaleCondition	SalePrice
0	1	60	RL	8450	Normal	208500
1	2	20	RL	9600	Normal	181500
2	3	60	RL	11250	Normal	223500
3	4	70	RL	9550	Abnorml	140000
4	5	60	RL	14260	Normal	250000

5 Determind the Data type

[5]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotArea        1460 non-null   int64
 4   SaleCondition  1460 non-null   object
 5   SalePrice      1460 non-null   int64
dtypes: int64(4), object(2)
memory usage: 68.6+ KB
```

6 Data Describtion

We can see the general information of our data which includes min, max, first quarter, second quarter, third quarter and the mean.

[6]:
```
train.describe()
```

[6]:

	Id	MSSubClass	LotArea	SalePrice
count	1460.000000	1460.000000	1460.000000	1460.000000
mean	730.500000	56.897260	10516.828082	180921.195890
std	421.610009	42.300571	9981.264932	79442.502883
min	1.000000	20.000000	1300.000000	34900.000000
25%	365.750000	20.000000	7553.500000	129975.000000
50%	730.500000	50.000000	9478.500000	163000.000000

```
75%    1095.250000   70.000000   11601.500000  214000.000000
max    1460.000000  190.000000  215245.000000  755000.000000
```

6.0.1 To make our job easier, we will print out the column's names

[7]:
```
train.columns
```

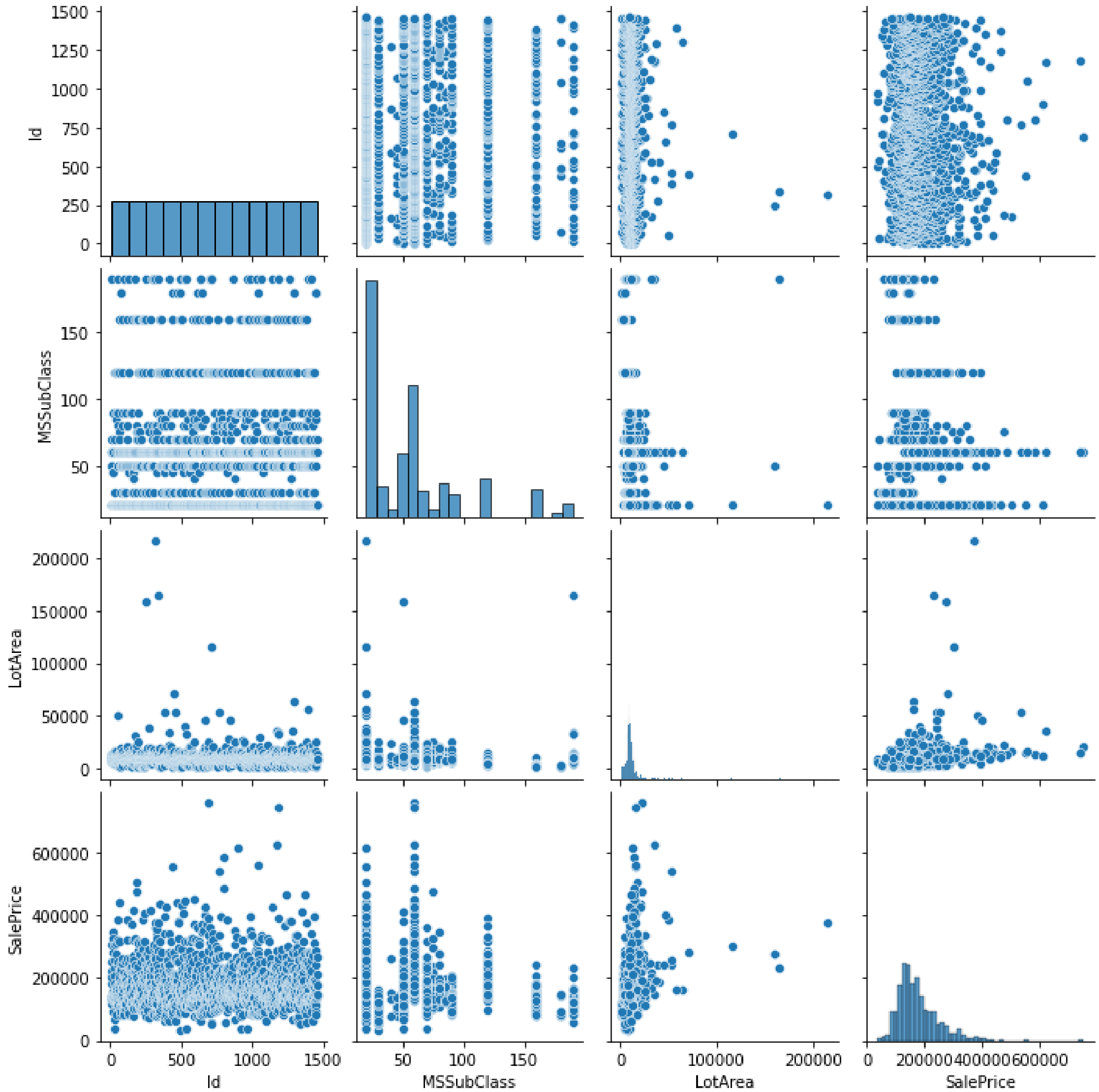
[7]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotArea', 'SaleCondition',
       'SalePrice'],
      dtype='object')
```

7 Illustrate the plot of the data

Using the function bellow we can get the plot of our data in pairs. The important pairs are those including the SalePrice. According to the given plots we can determine the outlier data and delete it.

[8]:
```
sns.pairplot(train)
```

[8]:
```
<seaborn.axisgrid.PairGrid at 0x7faf044008d0>
```



8 Determind the outliers

Multiplying the interquartile range (IQR) by 3 will give us a way to determine whether a certain value is a strong outlier. If we subtract 3 x IQR from the first quartile, any data values that are less than this number are considered strong outliers. Similarly, if we add 3 x IQR to the third quartile, any data values that are greater than this number are considered strong outliers. With the help of the pair plot we can see that the SalePrice seem to have outlier data.

8.0.1 Which means the data over 466 075 must be deleted from the SalesPrice, however it will lower our accuracy; so we will ignore the data over 566 075 instead.

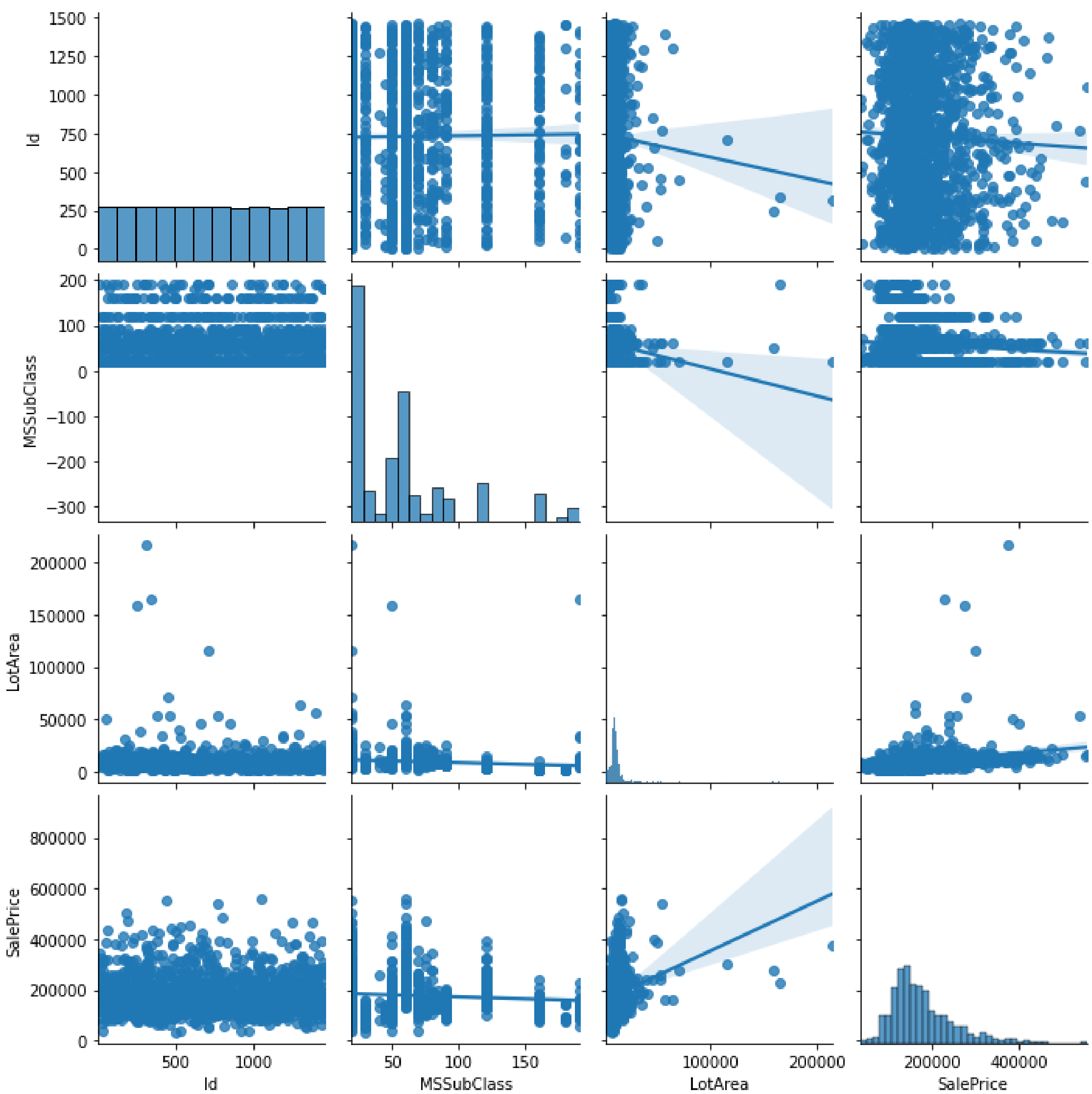
[9]:
```python
train = train[train.SalePrice < 566075]
```

9 Check the reg plot

This method is used to plot data and a linear regression model fit. As you see this data is not a good candidate for linear regression and using the linear regression method woul probably give us an unaccurate prediction.

[10]:
```python
sns.pairplot(train,kind="reg")
```

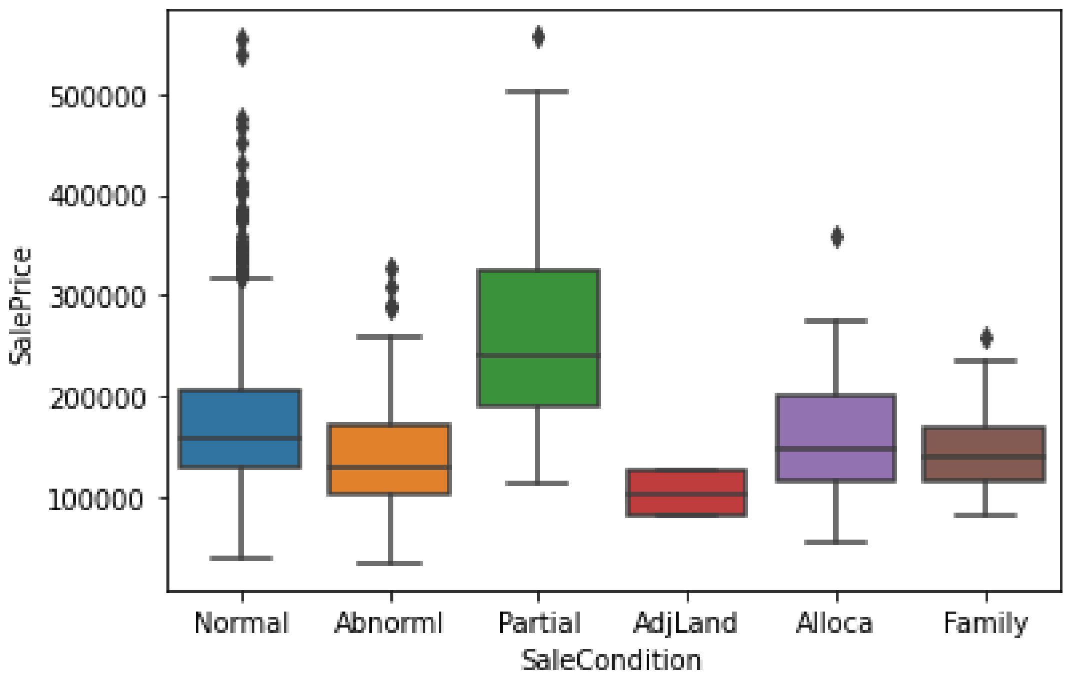
[10]:
```
<seaborn.axisgrid.PairGrid at 0x7faeb619cb90>
```



9.1 Now we will check the plot of the data with object data type.

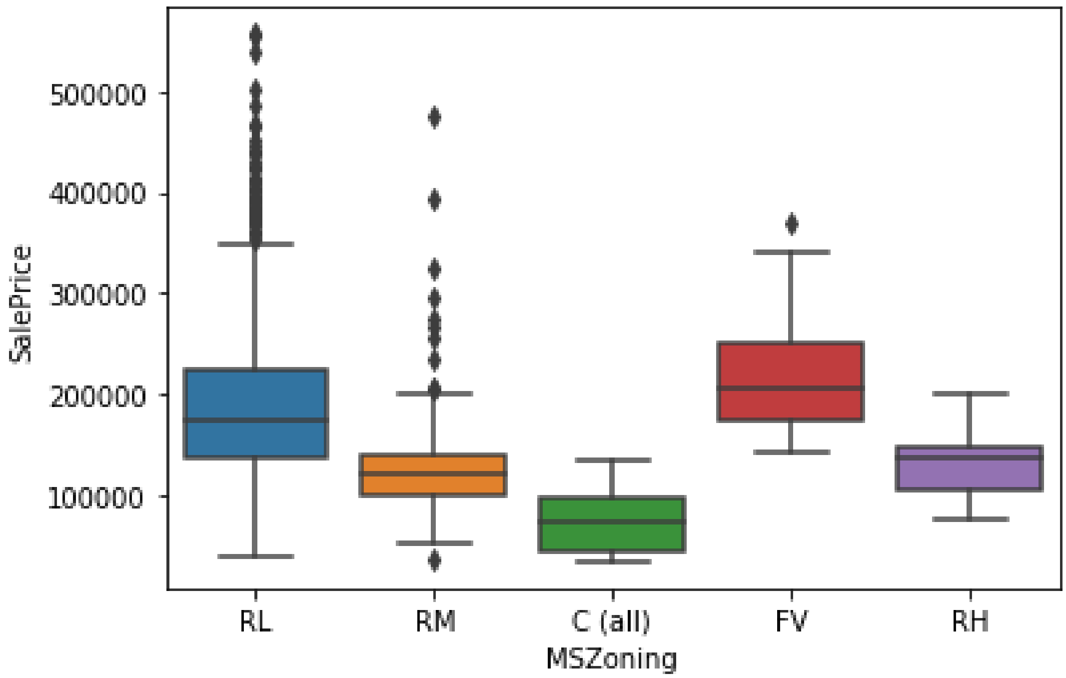
As you see, the 'Partial' SaleCondition seem to have the highest 'SalePrice' and the 'Normal' SaleCondition have a higher 'SalePrice' than the 'Abnormal' one. 'AdjLand' holds the lowest SalePrice and the 'Alloca' and 'Family' are almost similar, however 'Alloca' has a wider range.

[11]:
```
ax = sns.boxplot(x='SaleCondition', y='SalePrice', data=train)
```



The 'RL' MSZoning seem to have a higher 'SalePrice' than the 'RM' MSZoning and the 'FV' have a higher 'SalePrice' than the 'RH' one. 'C (all)' seems to hold the lowest SalePrice.

[12]:
```
ax = sns.boxplot(x= 'MSZoning', y='SalePrice', data=train)
```

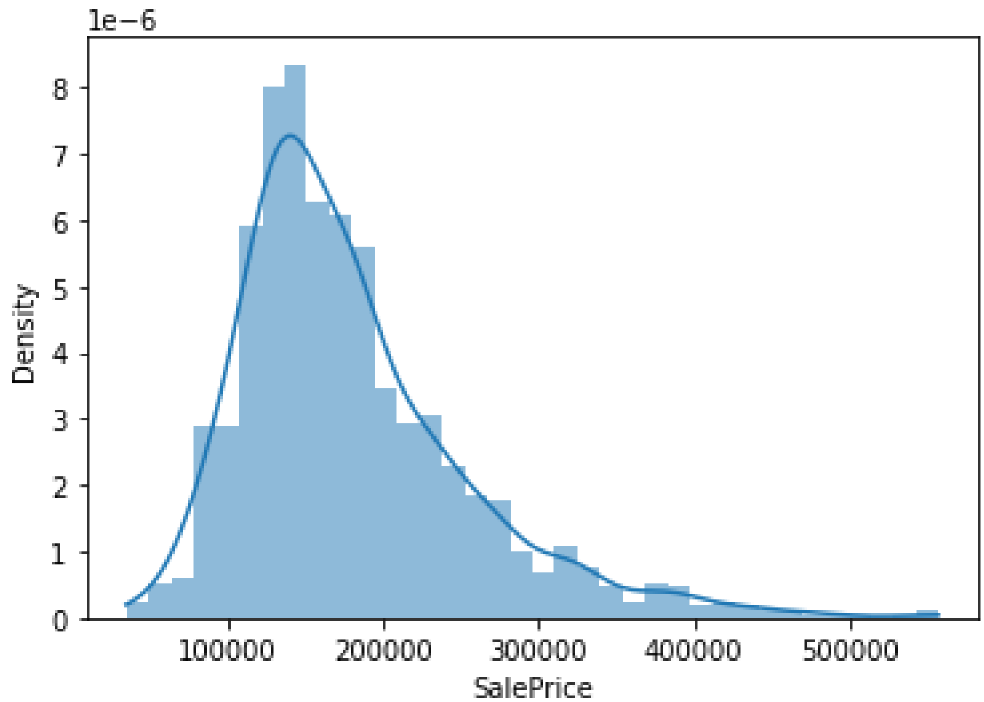


10 Distribution of data

We can see that the SalePrice is more dense between the range 100 000 to 200 000 and most prices are in this range.

[13]:
```
sns.histplot(train['SalePrice'], kde=True, stat="density", linewidth=0)
```

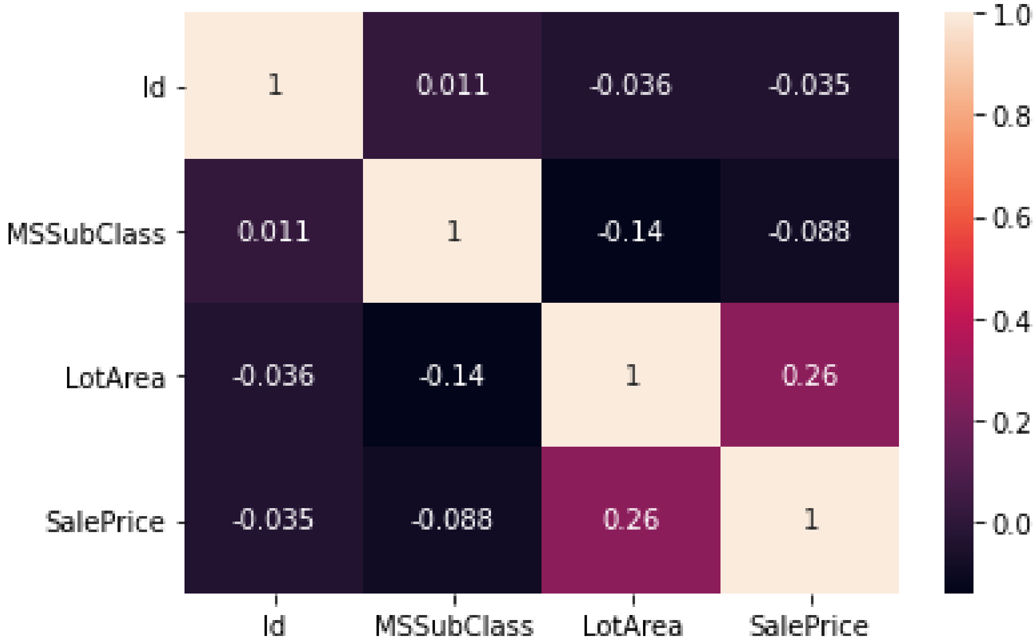
[13]: <AxesSubplot:xlabel='SalePrice', ylabel='Density'>



10.0.1 With the help of the heatmap we can, once again, see that our data can't be modeled using the Linear regression, because the numbers calculated seem to be much less than 1.

[14]:
```
sns.heatmap(train.corr(), annot=True)
```

[14]: <AxesSubplot:>



10.0.2 To make sure that we deleted a column we will print the number of columns before and after deletation.

[15]:
```
train.shape
```

[15]: (1455, 6)

10.0.3 The 'Id' column hold no significance for the prediction and so it must get deleted

[16]:
```
del train['Id']
```

[17]:
```
train.shape
```

[17]: (1455, 5)

11 Handle the object data types

Categorical data must be converted to numbers. A one hot encoding is a representation of categorical variables as binary vectors. This first requires that the categorical values be mapped to integer values. Then, each integer value is represented as a binary vector that is all zero values except the index of the integer, which is marked with a 1.

[18]:
```
one_hot = pd.get_dummies(train['MSZoning'])
train = train.drop('MSZoning',axis = 1)
train = train.join(one_hot)
second_hot = pd.get_dummies(train['SaleCondition'])
train = train.drop('SaleCondition',axis = 1)
train = train.join(second_hot)
```

12 X and Y arrays of the train

[19]:
```
y_train = train['SalePrice']
del train['SalePrice']
x_train = train.values
```

13 Read the test

[20]:
```
test = pd.read_csv("test1.csv")
test.head()
```

[20]:

	Id	MSSubClass	MSZoning	LotArea	SaleCondition	SalePrice
0	16	45	RM	6120	Normal	132000
1	23	20	RL	9742	Normal	230000
2	25	20	RL	8246	Normal	154000
3	30	30	RM	6324	Normal	68500
4	35	120	RL	7313	Normal	277500

14 Determind the data type

[21]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 191 entries, 0 to 190
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             191 non-null    int64
 1   MSSubClass     191 non-null    int64
 2   MSZoning       191 non-null    object
 3   LotArea        191 non-null    int64
 4   SaleCondition  191 non-null    object
 5   SalePrice      191 non-null    int64
```

```
dtypes: int64(4), object(2)
memory usage: 9.1+ KB
```

14.0.1 To make sure that we deleted a column we will print the number of columns before and after deletation.

[22]:
```
test.shape
```

[22]:
```
(191, 6)
```

14.0.2 The 'Id' column hold no significance for the prediction and so it must get deleted

[23]:
```
del test['Id']
```

[24]:
```
test.shape
```

[24]:
```
(191, 5)
```

15 Handle the object data types

Categorical data must be converted to numbers. A one hot encoding is a representation of categorical variables as binary vectors. This first requires that the categorical values be mapped to integer values. Then, each integer value is represented as a binary vector that is all zero values except the index of the integer, which is marked with a 1.

[25]:
```
one_hot = pd.get_dummies(test['MSZoning'])
test = test.drop('MSZoning',axis = 1)
test = test.join(one_hot)
second_hot = pd.get_dummies(test['SaleCondition'])
test = test.drop('SaleCondition',axis = 1)
test = test.join(second_hot)
```

16 X and Y arrays of the test

[26]:
```
y_test = test['SalePrice']
del test['SalePrice']
x_test = test.values
```

17 Linear Regression

As mentioned above, the Linear Regression won't be a good model and here you can see the accuracy is not adequate.

[27]:
```
model = linear_model.LinearRegression()
model.fit(x_train, y_train)
```

[27]:
```
LinearRegression()
```

[28]:
```
y_predict = model.predict(x_test)
```

[29]:
```
df = pd.DataFrame({'data': y_test, 'prediction': y_predict})
df
```

[29]:
```
       data     prediction
0    132000  125171.093163
1    230000  179817.375383
2    154000  177443.342006
3     68500  124871.213115
4    277500  180120.157467
..      …              …
186  394617  267628.193648
187  310000  192975.807191
188  121000  178823.931043
189   92000   97960.616746
190  145000  126903.578884

[191 rows x 2 columns]
```

[30]:
```
MSE = metrics.mean_squared_error(y_test, y_predict)
MSE_SQRT = np.sqrt(MSE)
print("test accuracy:", MSE_SQRT)
y_predict = model.predict(x_train)
MSE = metrics.mean_squared_error(y_train, y_predict)
MSE_SQRT = np.sqrt(MSE)
print("train accuracy:", MSE_SQRT)
```

```
test accuracy: 66941.21823805536
train accuracy: 63256.70750635694
```

18 Decision Tree

Since Linear Regression proved to be useless, we must seek nonlinear regressions. Decision trees is a non-linear classifier. It is generally used for classifying non-linearly separable data. A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.

[31]:
```
model = DecisionTreeRegressor(random_state = 0)
model.fit(x_train,y_train)
```

[31]:
```
DecisionTreeRegressor(random_state=0)
```

[32]:
```
y_predict = model.predict(x_test)
```

[33]:
```
prediction = pd.DataFrame(y_predict, columns=['SalePrice']).to_csv('prediction.
↪csv')
```

[34]:
```
MSE = metrics.mean_squared_error(y_test, y_predict)
MSE_SQRT = np.sqrt(MSE)
print("test accuracy:", MSE_SQRT)
y_predict = model.predict(x_train)
MSE = metrics.mean_squared_error(y_train, y_predict)
MSE_SQRT = np.sqrt(MSE)
print("train accuracy:", MSE_SQRT)
```

```
test accuracy: 9650.22344618717
train accuracy: 10042.93811149797
```

19 Conclusions

The data given was nonlinear and therefore the nonlinear regression model Decision Tree worked and successfully predicted the outcomes.

the accuracy is estimated as 9650.2

20 References

pbpython.com seaborn.pydata.org machinelearningmastery.com datascience.stackexchange.com wikipedia.org scikit-learn.org journaldev.com geeksforgeeks.org datacamp.com kaggle.com programmersought.com