Multiple Linear Regression

Week of November 14th, 2020

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In this session, we will learn the following points :

```
- Data pre-processing: Missing Values
- Plotting : Seaborn library
- Impact of outliers : Simple Linear Regression as example
- Practical Example of Multiple Linear Regression on house_price data -
 jupyter notebook
- Practical Example of Multiple Linear Regression on house_price data -
 Spyder
```

1 - How do we handle Missing Values :

it is very common to find a lot of values missing in your data due to many factors not in your direct control.

Sometimes due to the ways the data was captured: collecting data via surveys, some users don't fill the whole inputs.

In some cases the values are not available at all for observation.

Anyway, you will need to handle those missing values before you move further on your analysis

There are a few techniques which can help you deal with missing values in your dataset:

- **Drop missing values/columns/rows**
- **Imputation**

In [1]:
```python
import pandas as pd
df = pd.read_csv("house_price_data.csv")
```

In [2]:
```python
dataset = df.copy()
```

In [3]:
```
dataset.head()
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPu

5 rows × 81 columns

In [13]:
```
dataset.isnull().sum()
```

Out[13]:
```
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

Drop :

In [14]:
```
dataset["Alley"].unique()
```

Out[14]:
```
array([nan, 'Grvl', 'Pave'], dtype=object)
```

In [7]:
```
#dropna function in Pandas removes all the rows with missing values
dataset.dropna(inplace=True)

#Putting axis=1 removes the columns with missing values
dataset.dropna(inplace=True, axis=1)
```

Imputation :

Replace or fill the missing data with some value.

There are lot of ways to impute the data.

- A constant value that belongs to the set of possible values of that variable, such as 0, distinct from all other values
- A mean, median or mode value for the column
- A value estimated by another predictive model
- Multiple Imputation

In [15]:
```
dataset['LotFrontage'].fillna(dataset['LotFrontage'].mean(), inplace=True)
dataset.head()
```

Out[15]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPu

5 rows × 81 columns

In [ ]:
```
dataset.fillna() # hit shift+tab on the keyboard to learn more about fillna() met
```

Mmultiple imputation:

In [10]:
```
#### You might get errors running this cell
## you need to instant fancyimpute package, to do that, use the command line : ec
## MICE stands for : Multivariate Imputation by Chained Equations

from fancyimpute import IterativeImputer as MICE

dataset["LotFrontage"] = pd.DataFrame(MICE().fit_transform(dataset[["LotFrontage"

# To apply this method to the whole dataframe, We need to select only the columns
# it doesn't apply to the categorical values
```

In [ ]:

Please visit this link to learn more about missing values imputation

: https://scikit-learn.org/stable/modules/impute.html (https://scikit-learn.org/stable/modules/impute.html)

2 - Plotting : Seaborn library

In [3]:
```
import seaborn as sns
```

In [5]:
```
dataset.head()
```

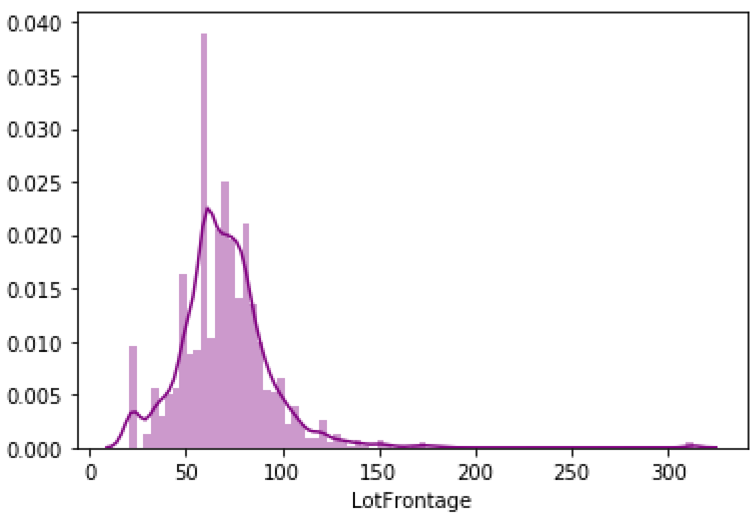
Out[5]:

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

vs × 81 columns

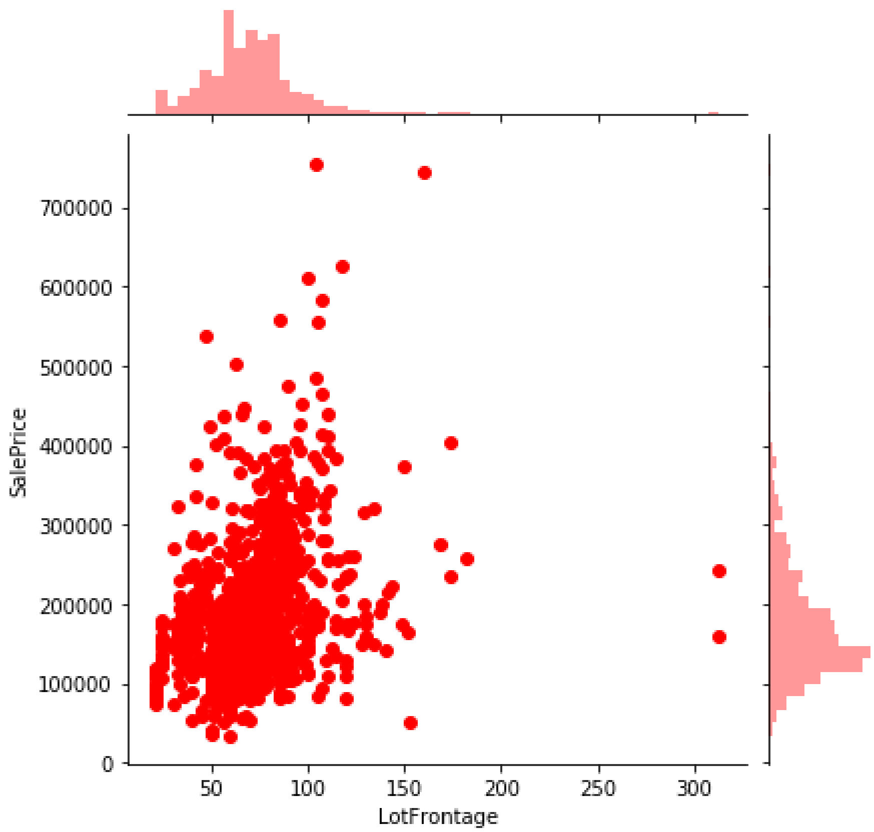
In [19]:
```
sns.distplot(dataset["LotFrontage"], kde = True, bins = 80, color = "purple")
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0xc595048>



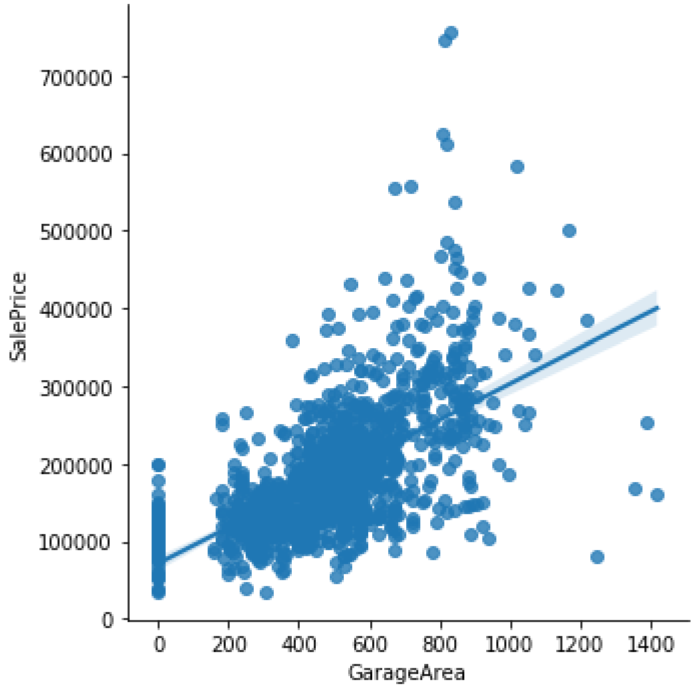
In [27]:
```
# we can use kind as  Kind = reg to plot the regression line

sns.jointplot(x = "LotFrontage" , y = "SalePrice" , data = dataset, kind = "scatt
```

Out[27]: <seaborn.axisgrid.JointGrid at 0x4cf45748>



In [131]:
```
# another way to use regression plot is (scatter plot with a linear fit on top of
sns.lmplot(x= "GarageArea", y = "SalePrice", data = dataset)
```

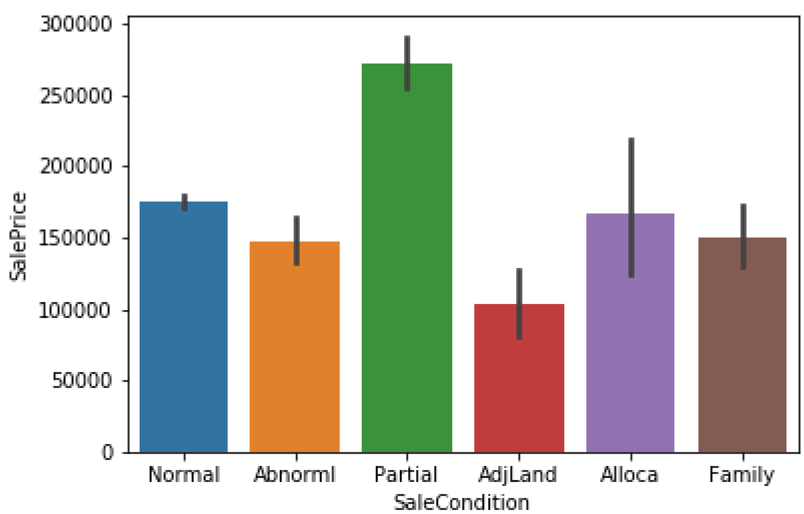
Out[131]:
```
<seaborn.axisgrid.FacetGrid at 0xea45a48>
```



In [39]:
```
#sns.pairplot(dataset)
```

In [29]:
```
sns.barplot(x = "SaleCondition" , y ="SalePrice" , data = dataset)
```

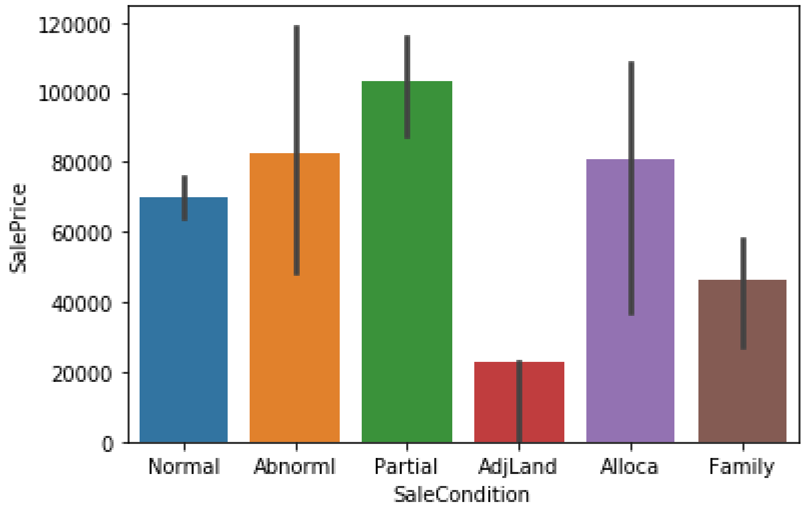
Out[29]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x4dcb1288>
```



In [31]:
```
import numpy as np
```

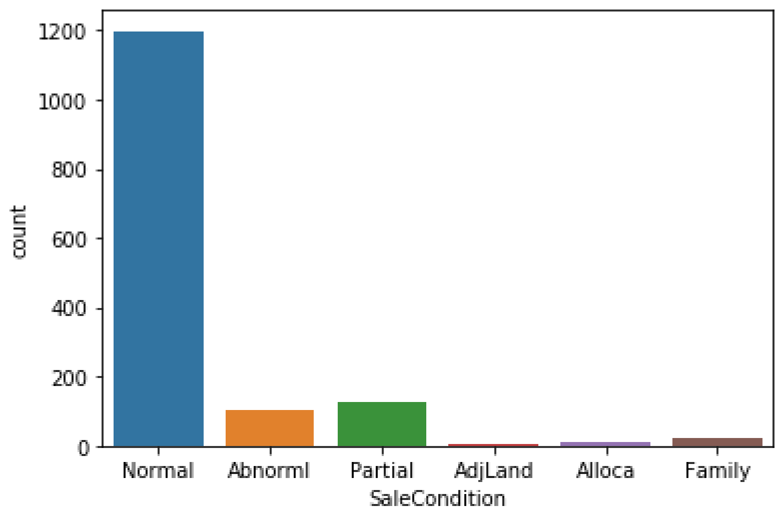
In [32]:
```
sns.barplot(x = "SaleCondition" , y ="SalePrice" , data = dataset, estimator = np
```

Out[32]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x59274c48>
```



In [33]:
```
sns.countplot(x = "SaleCondition", data = dataset)
```

Out[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x4dca0b08>
```



In [34]:
```
#dataset.corr()
```

Out[34]:

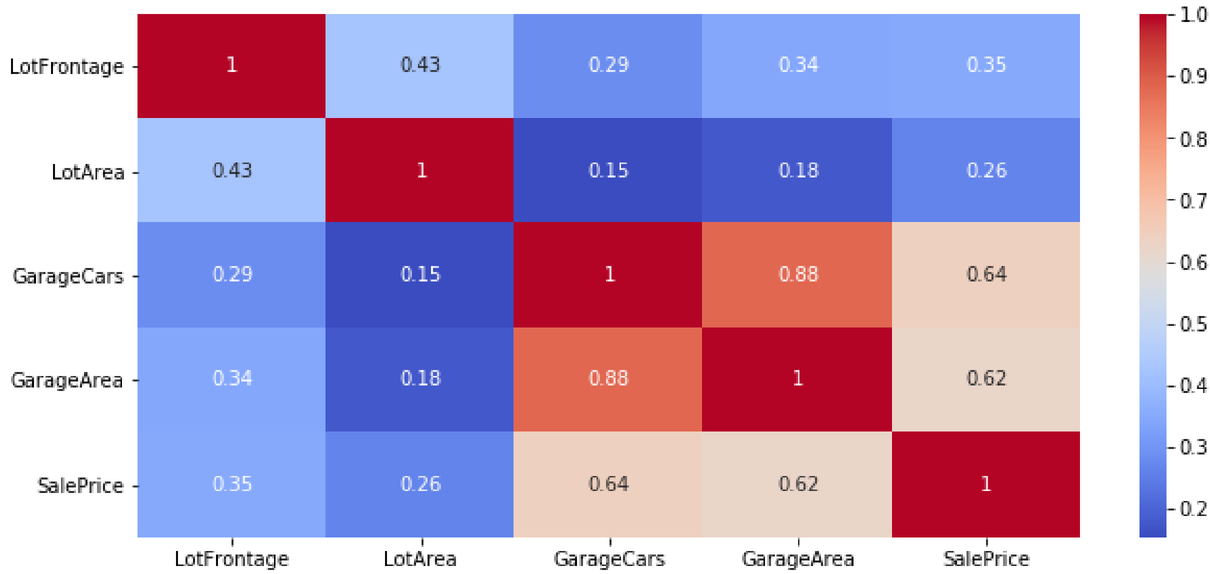
	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBui
Id	1.000000	0.011156	-0.010601	-0.033226	-0.028365	0.012609	-0.01271
MSSubClass	0.011156	1.000000	-0.386347	-0.139781	0.032628	-0.059316	0.02785
LotFrontage	-0.010601	-0.386347	1.000000	0.426095	0.251646	-0.059213	0.12334
LotArea	-0.033226	-0.139781	0.426095	1.000000	0.105806	-0.005636	0.01422
OverallQual	-0.028365	0.032628	0.251646	0.105806	1.000000	-0.091932	0.57232
OverallCond	0.012609	-0.059316	-0.059213	-0.005636	-0.091932	1.000000	-0.37598
YearBuilt	-0.012713	0.027850	0.123349	0.014228	0.572323	-0.375983	1.00000
YearRemodAdd	-0.021998	0.040581	0.088866	0.013788	0.550684	0.073741	0.59285
MasVnrArea	-0.050298	0.022936	0.193458	0.104160	0.411876	-0.128101	0.31570
BsmtFinSF1	-0.005024	-0.069836	0.233633	0.214103	0.239666	-0.046231	0.24950
BsmtFinSF2	-0.005968	-0.065649	0.049900	0.111170	-0.059119	0.040229	-0.04910
BsmtUnfSF	-0.007940	-0.140759	0.132644	-0.002618	0.308159	-0.136841	0.14904
TotalBsmtSF	-0.015415	-0.238518	0.392075	0.260833	0.537808	-0.171098	0.39145
1stFlrSF	0.010496	-0.251758	0.457181	0.299475	0.476224	-0.144203	0.28198
2ndFlrSF	0.005590	0.307886	0.080177	0.050986	0.295493	0.028942	0.01030
LowQualFinSF	-0.044230	0.046474	0.038469	0.004779	-0.030429	0.025494	-0.18378
GrLivArea	0.008273	0.074853	0.402797	0.263116	0.593007	-0.079686	0.19901
BsmtFullBath	0.002289	0.003491	0.100949	0.158155	0.111098	-0.054942	0.18759
BsmtHalfBath	-0.020155	-0.002333	-0.007234	0.048046	-0.040150	0.117821	-0.03816
FullBath	0.005587	0.131608	0.198769	0.126031	0.550600	-0.194149	0.46827
HalfBath	0.006784	0.177354	0.053532	0.014259	0.273458	-0.060769	0.24265
BedroomAbvGr	0.037719	-0.023438	0.263170	0.119690	0.101676	0.012980	-0.07065
KitchenAbvGr	0.002951	0.281721	-0.006069	-0.017784	-0.183882	-0.087001	-0.17480
TotRmsAbvGrd	0.027239	0.040380	0.352096	0.190015	0.427452	-0.057583	0.09558
Fireplaces	-0.019772	-0.045569	0.266639	0.271364	0.396765	-0.023820	0.14771
GarageYrBlt	0.000072	0.085072	0.070250	-0.024947	0.547766	-0.324297	0.82566
GarageCars	0.016570	-0.040110	0.285691	0.154871	0.600671	-0.185758	0.53785
GarageArea	0.017634	-0.098672	0.344997	0.180403	0.562022	-0.151521	0.47895
WoodDeckSF	-0.029643	-0.012579	0.088521	0.171698	0.238923	-0.003334	0.22488
OpenPorchSF	-0.000477	-0.006100	0.151972	0.084774	0.308819	-0.032589	0.18868
EnclosedPorch	0.002889	-0.012037	0.010700	-0.018340	-0.113937	0.070356	-0.38726
3SsnPorch	-0.046635	-0.043825	0.070029	0.020423	0.030371	0.025504	0.03135
ScreenPorch	0.001330	-0.026030	0.041383	0.043160	0.064886	0.054811	-0.05036
PoolArea	0.057044	0.008283	0.206167	0.077672	0.065166	-0.001985	0.00495
MiscVal	-0.006242	-0.007683	0.003368	0.038068	-0.031406	0.068777	-0.03438

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBui
MoSold	0.021172	-0.013585	0.011200	0.001205	0.070815	-0.003511	0.01239
YrSold	0.000712	-0.021407	0.007450	-0.014261	-0.027347	0.043950	-0.01361
SalePrice	-0.021917	-0.084284	0.351799	0.263843	0.790982	-0.077856	0.52289

38 rows × 38 columns

In [189]:
```
plt.figure(figsize = (11,5))
sns.heatmap(dataset.corr(), annot = True, cmap = "coolwarm")
```

Out[189]: <matplotlib.axes._subplots.AxesSubplot at 0x15b7e088>

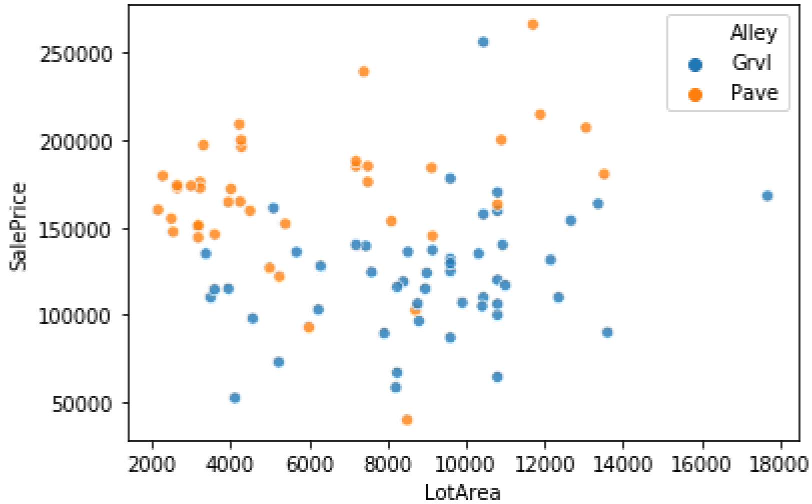


In [ ]:

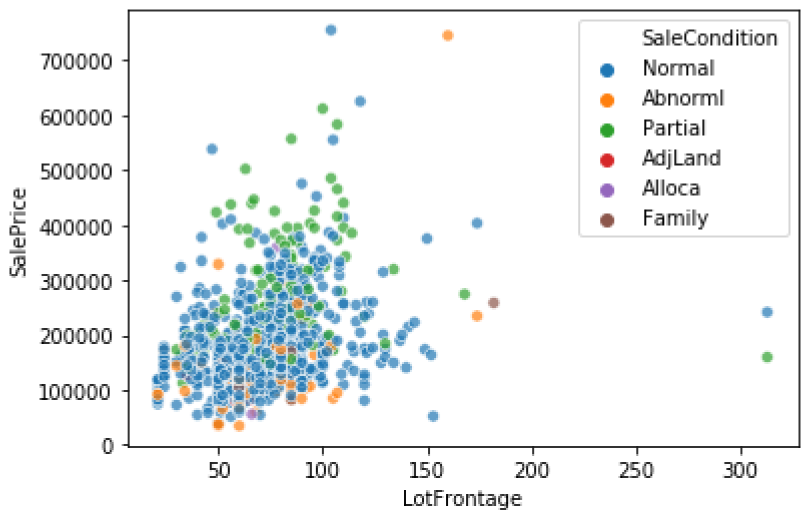
In [ ]:

In [7]:
```
# Plot
sns.scatterplot(data=dataset, x='LotArea', y='SalePrice', hue = "Alley", alpha=0.
```

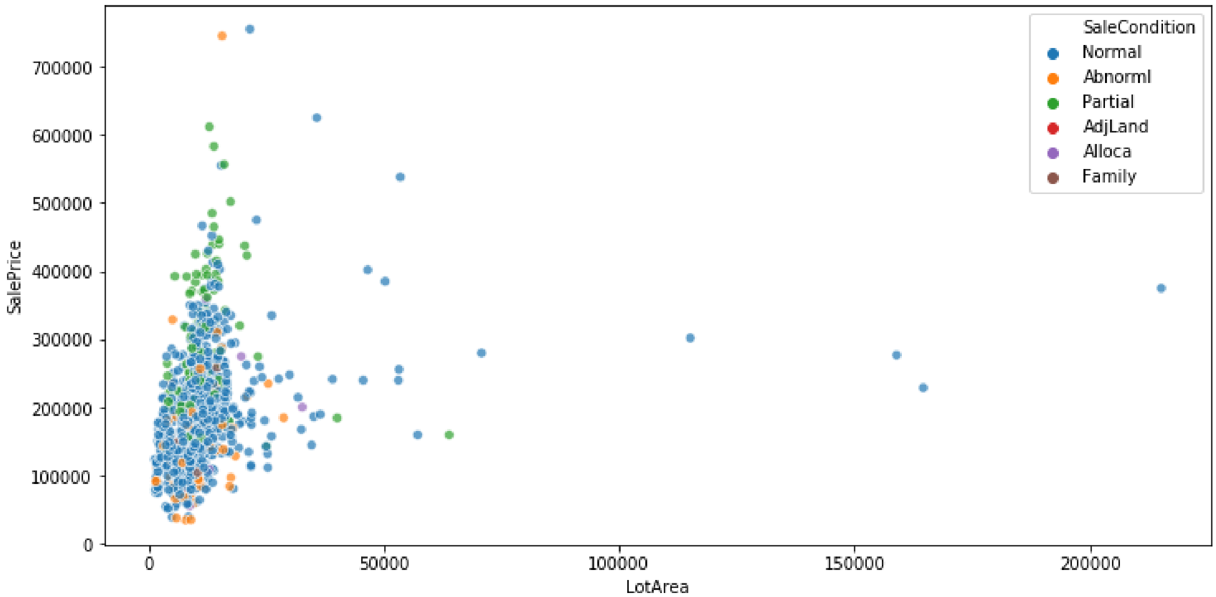
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x9d2b448>



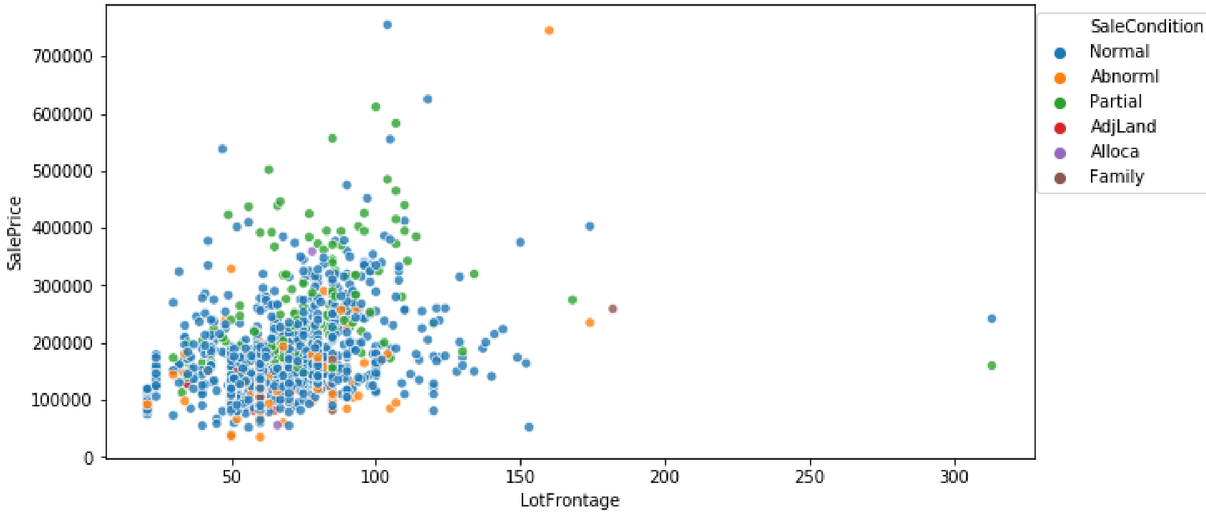
In [33]:
```
# Plot
sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.7, hue='SaleCondi
```



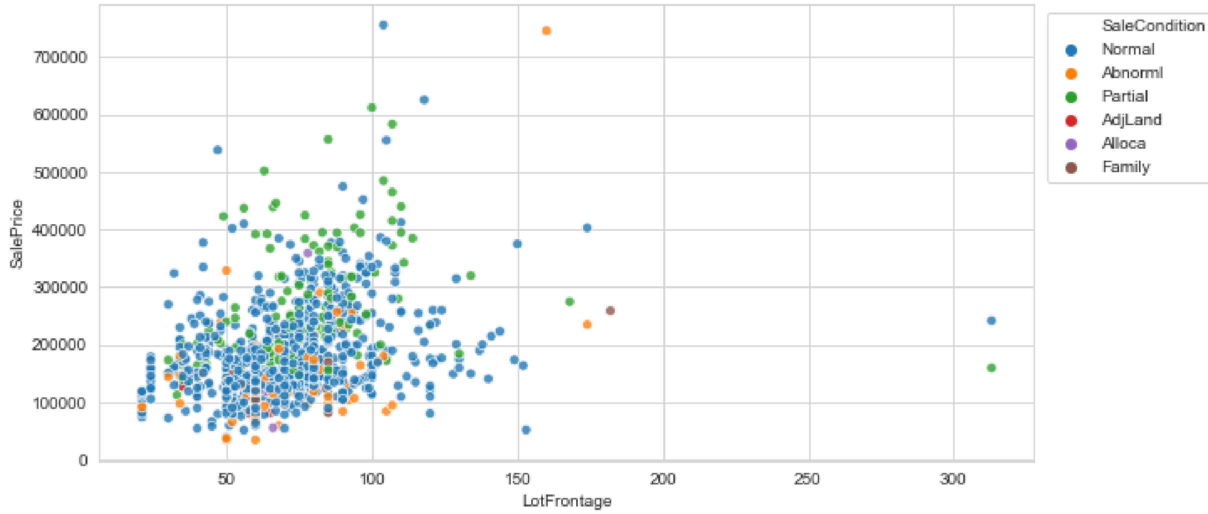
In [40]:
```
#If we want to resize the figure , this is how we do it:
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))

sns.scatterplot(data=df, x='LotArea', y='SalePrice',alpha=0.7, hue='SaleConditior
```



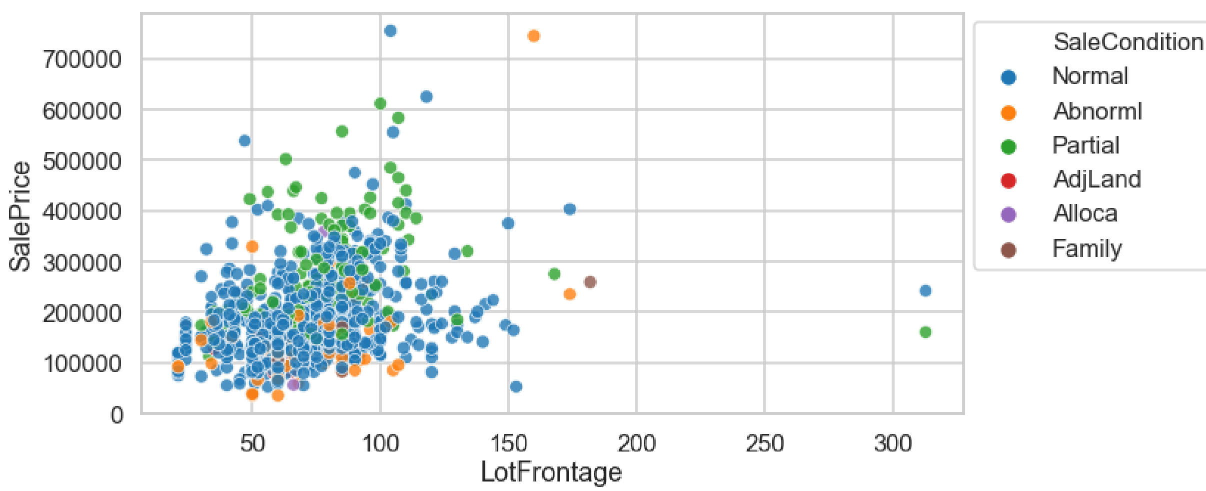
In [43]:
```
plt.figure(figsize=(10, 5))

sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.8, hue='SaleCondi

plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1));
```



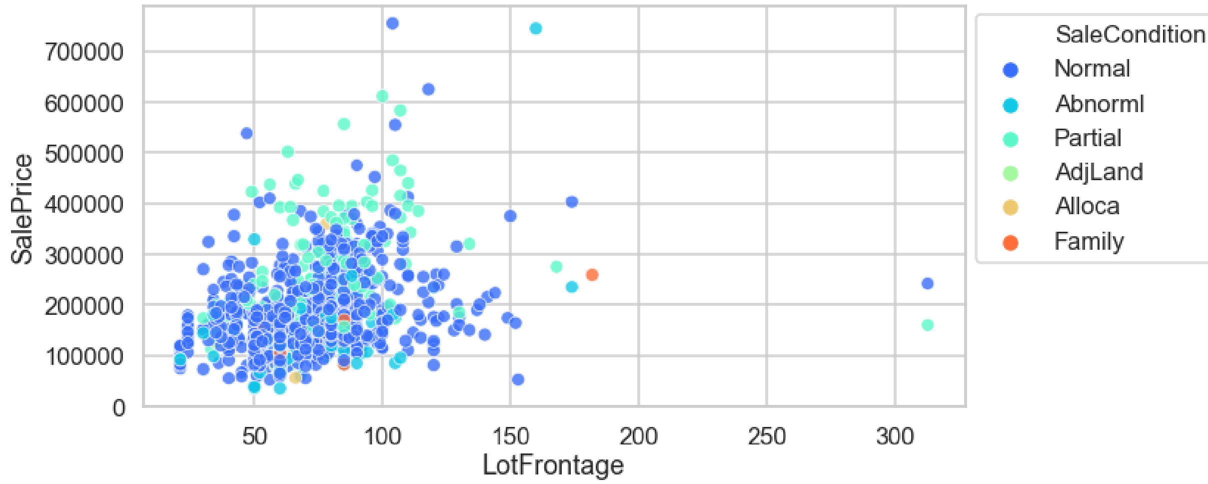
In [48]:
```
# To Change default style
sns.set_style('whitegrid')


plt.figure(figsize=(10, 5))

sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.8, hue='SaleCondi

plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1));
```



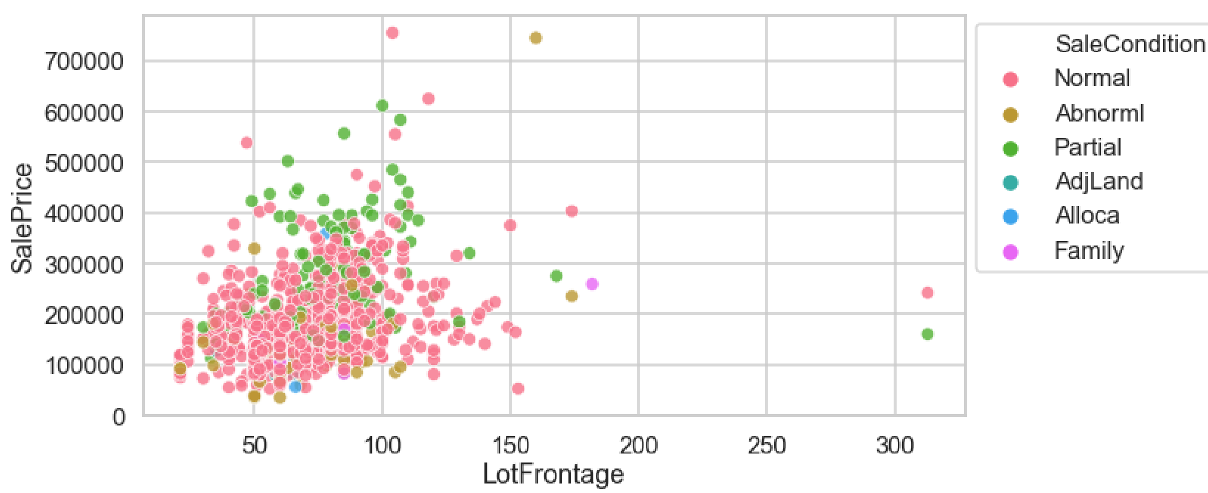
In [56]:
```
#Change default context
sns.set_context('talk')

plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.8, hue='SaleCondi
plt.legend(loc='upper right', bbox_to_anchor=(1.32, 1.007));
```



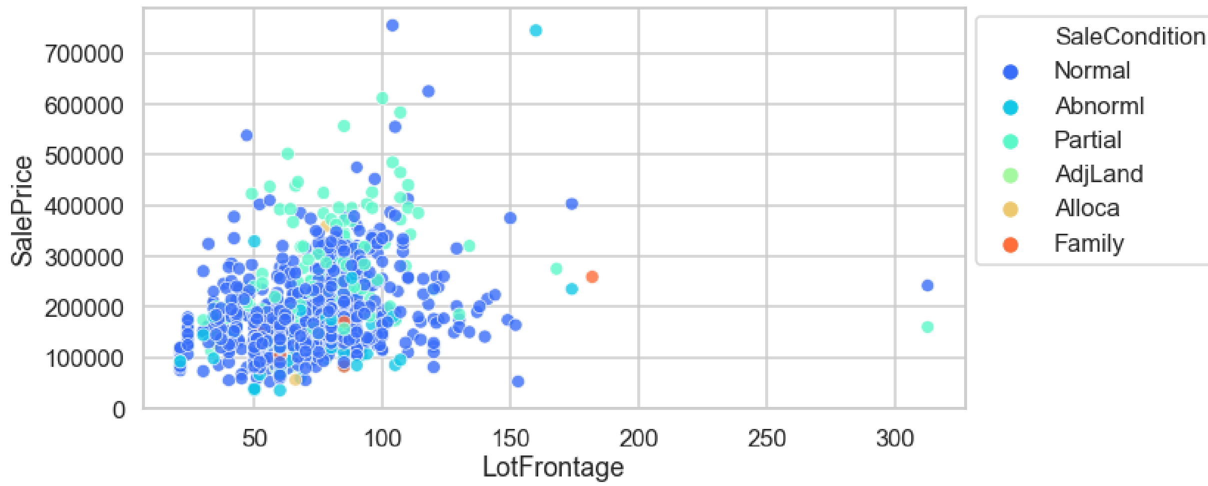
In [57]:
```
# Change default palette
sns.set_palette('rainbow')

plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.8, hue='SaleCondi
plt.legend(loc='upper right', bbox_to_anchor=(1.32, 1.007));
```



In [58]:
```
# Change default palette
sns.set_palette(['green', 'purple', 'red'])

# or by using colors codes :
# sns.set_palette(['#62C370', '#FFD166', '#EF476F'])

plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.8, hue='SaleCondi
plt.legend(loc='upper right', bbox_to_anchor=(1.32, 1.007));
```



In [59]:
```
# Or we can do all above as following :

# Change defaults
sns.set(style='whitegrid', context='talk', palette='rainbow')

plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='LotFrontage', y='SalePrice',alpha=0.8, hue='SaleCondi
plt.legend(loc='upper right', bbox_to_anchor=(1.32, 1.007));
```



In [ ]:

3 - Impact of outliers : Simple Linear Regression as example

We will see this example at the end of this tutorial: Simple Linear Regression on GarageArea and SalePrice

4 - Practical Example of Multiple Linear Regression on house_price data - Jupypter notebook

Introduction : Linear Regression can be classified into 2 categories:

- Simple Linear Regression: when there is a single input variable for the output variable

- Multiple Linear Regression: when there are 2 or more features.

STEP 1 : Libraries

In [5]:
```python
import numpy as np  # library for scientific computing
import pandas as pd # data structures and data analysis package
import matplotlib.pyplot as plt # 2D plotting library
```

STEP 2 : Dataset - Import, Visualize and Process

In [160]:
```python
df = pd.read_csv('house_price_data.csv')
dataset = df.copy() # We take a copy of our raw data, In order to avoid any loss
                    # and we try to cancel and go back)
```

In [161]:
```python
dataset.head()
```

Out[161]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPu

5 rows × 81 columns

In [162]:
```python
dataset.columns
```

Out[162]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [163]:
```python
dataset = dataset[["LotFrontage","LotArea","GarageCars","GarageArea","SalePrice"]
```

In [164]:
```
dataset
```

Out[164]:

	LotFrontage	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	8450	2	548	208500
1	80.0	9600	2	460	181500
2	68.0	11250	2	608	223500
3	60.0	9550	3	642	140000
4	84.0	14260	3	836	250000
...	...	...	...	...	...
1455	62.0	7917	2	460	175000
1456	85.0	13175	2	500	210000
1457	66.0	9042	1	252	266500
1458	68.0	9717	1	240	142125
1459	75.0	9937	1	276	147500

1460 rows × 5 columns

In [84]:
```
dataset.isnull().values.any()
```

Out[84]:
```
True
```

In [85]:
```
dataset.isnull().sum()
```

Out[85]:
```
LotFrontage    259
LotArea          0
GarageCars       0
GarageArea       0
SalePrice        0
dtype: int64
```

In [86]:
```
dataset.fillna(value=dataset["LotFrontage"].mean(), inplace = True)
# impute the NaN with the column's mean
# If you don't force inplace to True, the modification won't take place
```

In [87]:
```
dataset.isnull().sum()
```

Out[87]:
```
LotFrontage    0
LotArea        0
GarageCars     0
GarageArea     0
SalePrice      0
dtype: int64
```

In [88]:
```
dataset.head(5)
```

Out[88]:

	LotFrontage	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	8450	2	548	208500
1	80.0	9600	2	460	181500
2	68.0	11250	2	608	223500
3	60.0	9550	3	642	140000
4	84.0	14260	3	836	250000

In [ ]:
```

```

In [89]:
```
dataset.describe() # Shows the statistics of the dataset
```

Out[89]:

	LotFrontage	LotArea	GarageCars	GarageArea	SalePrice
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	70.049958	10516.828082	1.767123	472.980137	180921.195890
std	22.024023	9981.264932	0.747315	213.804841	79442.502883
min	21.000000	1300.000000	0.000000	0.000000	34900.000000
25%	60.000000	7553.500000	1.000000	334.500000	129975.000000
50%	70.049958	9478.500000	2.000000	480.000000	163000.000000
75%	79.000000	11601.500000	2.000000	576.000000	214000.000000
max	313.000000	215245.000000	4.000000	1418.000000	755000.000000

In [90]:
```
#Checking the shape of our dataset
dataset.shape
```

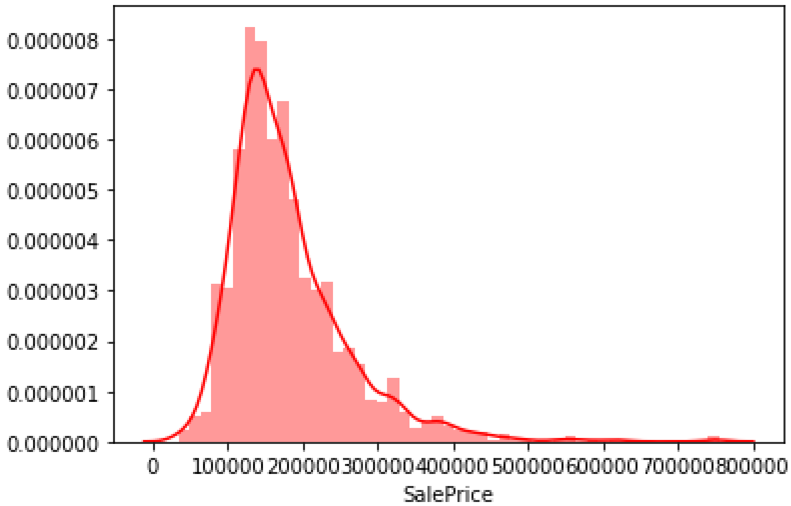
Out[90]:
```
(1460, 5)
```

In [91]:
```
dataset.columns
```

Out[91]:
```
Index(['LotFrontage', 'LotArea', 'GarageCars', 'GarageArea', 'SalePrice'], dtyp
e='object')
```

In [127]:
```
sns.distplot(dataset["SalePrice"], color = "red")
```

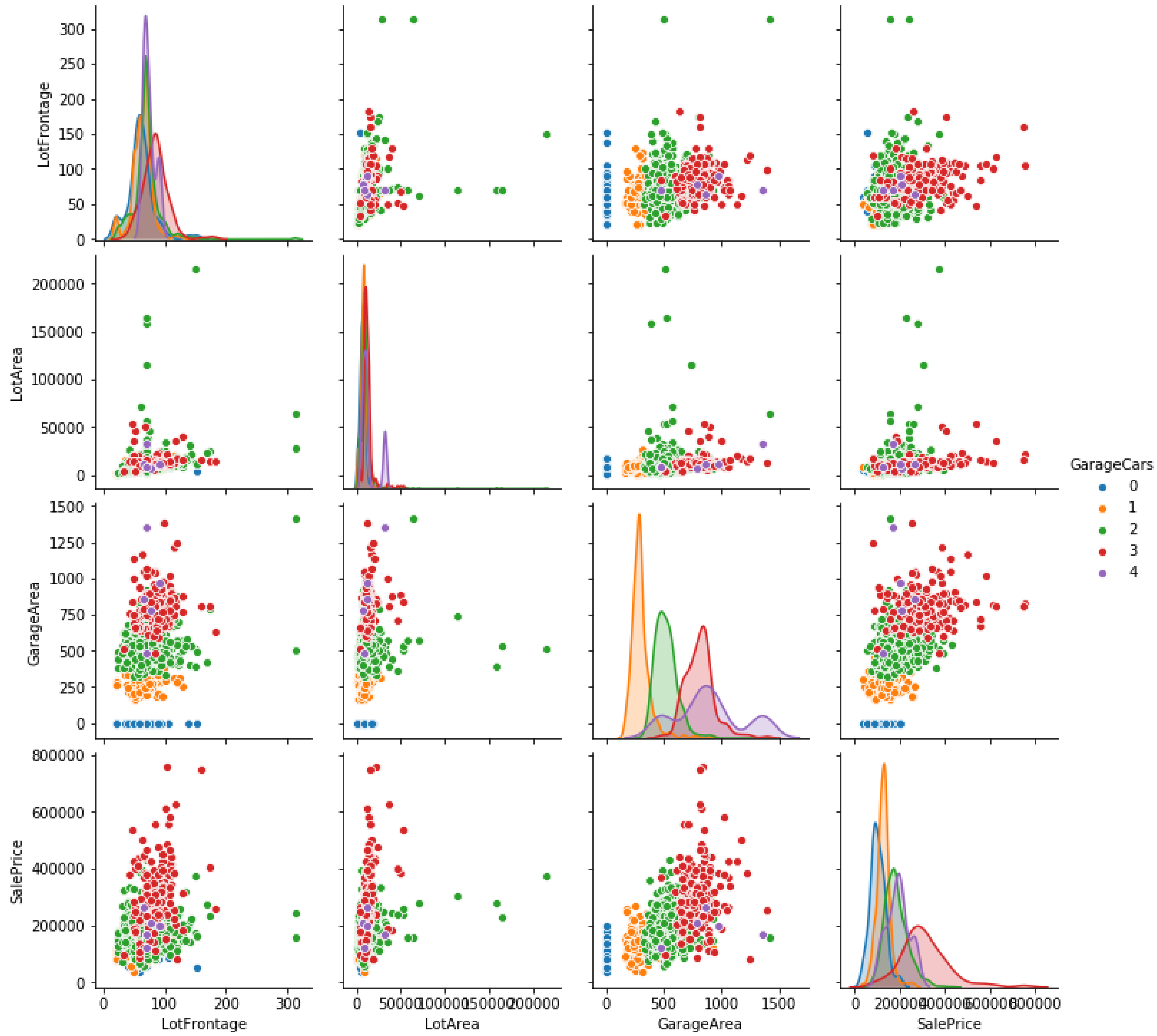
Out[127]: <matplotlib.axes._subplots.AxesSubplot at 0xde37fc8>



In [126]:
```
sns.pairplot(dataset, hue = "GarageCars")
```

```
C:\Users\pc\anaconda3\lib\site-packages\seaborn\distributions.py:288: UserWarni
ng: Data must have variance to compute a kernel density estimate.
  warnings.warn(msg, UserWarning)
```

Out[126]: <seaborn.axisgrid.PairGrid at 0x19122908>



In [ ]:

In [ ]:

In [92]:
```
# Define X and y.
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

In [ ]:

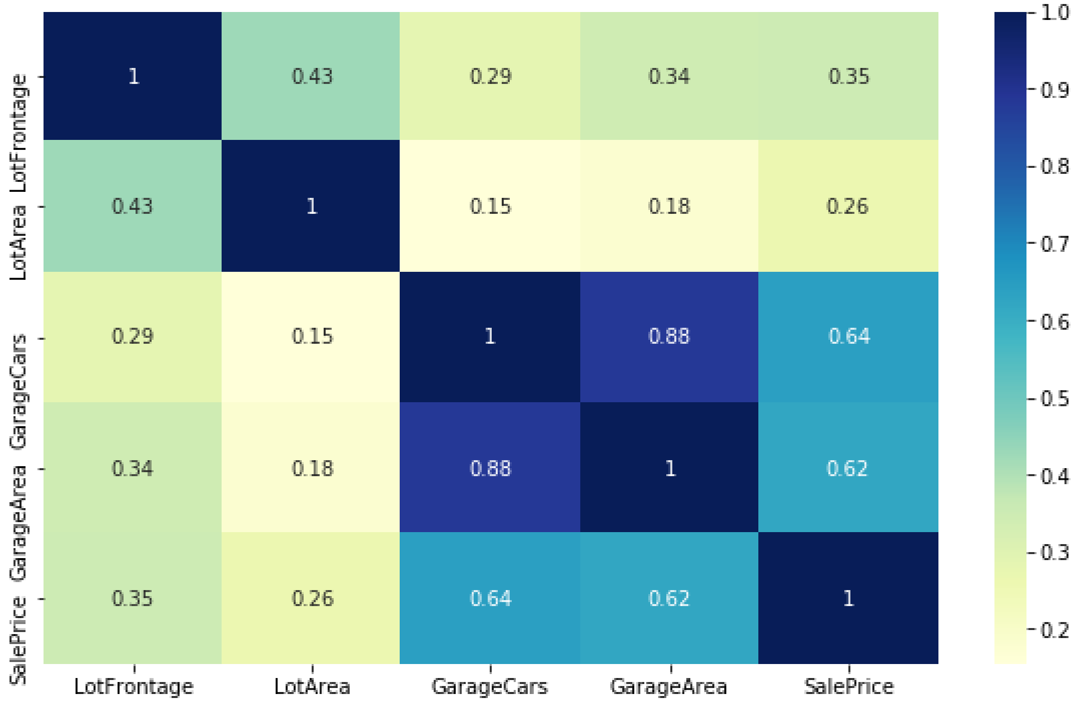
In [93]:
```
dataset.corr()
```

Out[93]:

	LotFrontage	LotArea	GarageCars	GarageArea	SalePrice
LotFrontage	1.000000	0.306795	0.269729	0.323663	0.334901
LotArea	0.306795	1.000000	0.154871	0.180403	0.263843
GarageCars	0.269729	0.154871	1.000000	0.882475	0.640409
GarageArea	0.323663	0.180403	0.882475	1.000000	0.623431
SalePrice	0.334901	0.263843	0.640409	0.623431	1.000000

In [193]:
```
import seaborn as sns
plt.figure(figsize = (10,6))
sns.heatmap(dataset.corr(), annot=True, cmap = "YlGnBu")
```

Out[193]: <matplotlib.axes._subplots.AxesSubplot at 0xea88c48>



Scale / Standardize the features:

In [95]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)
```

In [ ]:
```
```

STEP 3 : Training set and Test set

In [96]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, randon
```

In [ ]:

STEP 4 : Create and Train the Model

In [97]:
```
from sklearn.linear_model import LinearRegression

#Create the model :
regressor = LinearRegression()

#Train the model :
regressor.fit(X_train, y_train)
```

Out[97]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Trainig the model: model has to find the most optimal coefficients for all the features.

In [98]:
```
L = regressor.coef_
L
```

Out[98]:
```
array([ 9460.22036732,  9311.4149111 , 31943.47298982, 19110.63841026])
```

In [ ]:

In [99]:
```
coeff_X = pd.DataFrame(regressor.coef_, index = dataset.columns[:-1], columns=['C
coeff_X
```

Out[99]:

	Coefficient
LotFrontage	9460.220367
LotArea	9311.414911
GarageCars	31943.472990
GarageArea	19110.638410

In [100]:
```
regressor.intercept_
```

Out[100]:
```
180652.846374314
```

In [106]:
```
print("Price = {:.2f} + {:.2f}*LotFrontage + {:.2f}*LotArea + {:.2f}*GarageCars +
      format(regressor.intercept_,L[0], L[1], L[2] ,L[3]))
```

```
Price = 180652.85 + 9460.22*LotFrontage + 9311.41*LotArea + 31943.47*GarageCars
+ 19110.64*GarageArea
```

STEP 5 : Evaluate the Model - Predict X_test

In [107]:
```
y_pred = regressor.predict(X_test)
```

To check the difference between the **predicted value - y_pred** and **actual value - y_test**

In [110]:
```
df_results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df_results.head(20)
```

Out[110]:

	Actual	Predicted
0	200624	212267.417292
1	133000	129907.198531
2	110000	133766.168706
3	192000	198560.281273
4	88000	99842.864054
5	85000	123182.642602
6	282922	253874.264233
7	141000	144170.882931
8	745000	307187.575065
9	148800	186187.723287
10	208900	174215.072591
11	136905	196447.475355
12	225000	192361.027994
13	123000	127930.848698
14	119200	123771.919624
15	145000	129851.173566
16	190000	214317.145133
17	123600	56199.594017
18	149350	127950.495820
19	155000	104127.633162

In [ ]:

In [121]:
```
# Root Mean Squared Error:

from sklearn.metrics import mean_squared_error , r2_score

mse = mean_squared_error(y_test, y_pred)

# Root Mean Squared Error:
root_mse = np.sqrt(mse)

#R_squared :
R_squared = r2_score(y_test, y_pred)

print("Intercept:              ", regressor.intercept_)
print("Root Mean Square Error: ", root_mse)
print("R^2 Value in %:              ", R_squared*100)
```

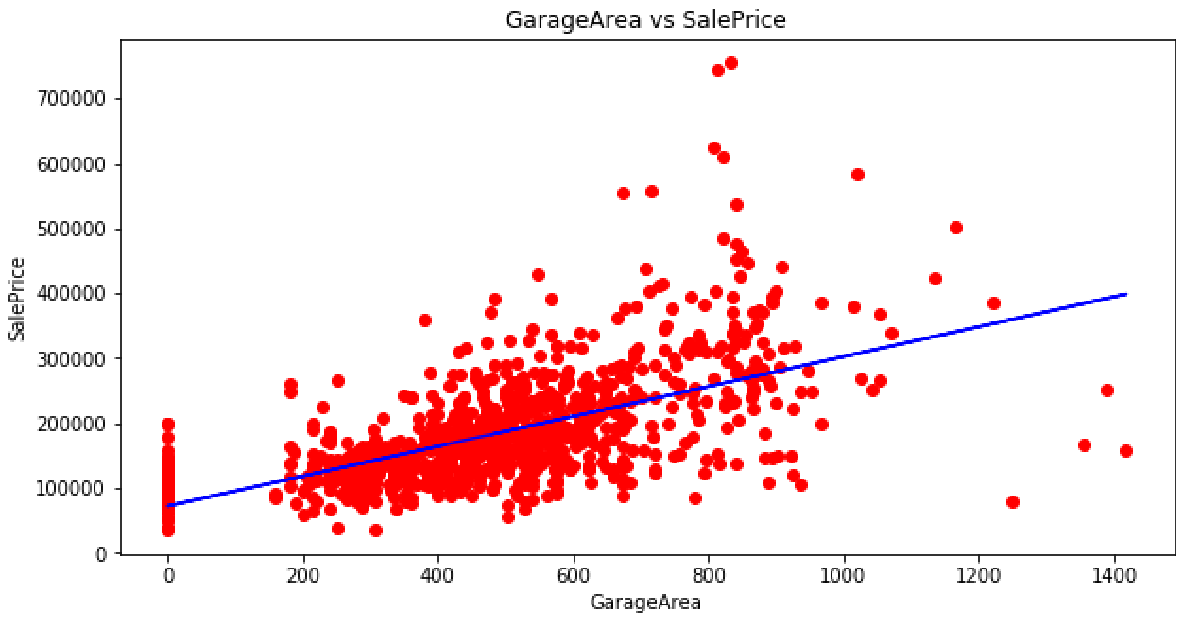
```
Intercept:               180652.846374314
Root Mean Square Error:  66317.21692703411
R^2 Value in %:               36.31525034758156
```

STEP 6 : How to improve the Model ?

- Using more training data,
- choosing more appropriate features which have high correlation to the output.

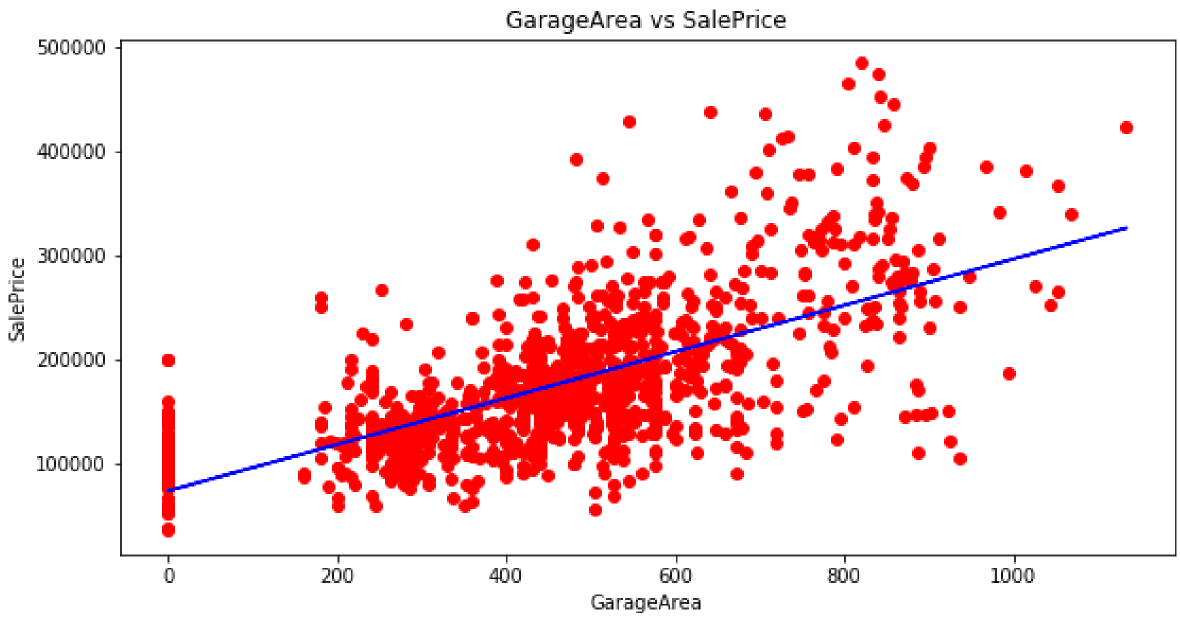
3 - Impact of outliers : Simple Linear Regression on GarageArea and SalePrice as example

In [181]:
```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# Importing the dataset : Define X and y
# dataset = pd.read_csv('house_price_data.csv') # already imported above

X_s = dataset["GarageArea"].values # .values convert dataframe into numpy array
y_s = dataset["SalePrice"].values # dataset.to_numpy()

# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_s, y_s, test_size = 0.2)

# Training the Simple Linear Regression model on the whole dataset
# import linear_model from sklearn
from sklearn.linear_model import LinearRegression

simple_regressor = LinearRegression() # created our model
simple_regressor.fit(X_train.reshape(-1,1), y_train.reshape(-1,1)) # Train the mo

# Predicting the Test set results
simple_y_pred = simple_regressor.predict(X_test.reshape(-1,1))

# Visualising the Training set results

plt.figure(figsize=(10, 5))
plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, simple_regressor.predict(X_train.reshape(-1,1)), color = 'blue'
plt.title('GarageArea vs SalePrice')
plt.xlabel('GarageArea')
plt.ylabel('SalePrice')
plt.show()

# R-squared
r_squared = simple_regressor.score(X_s.reshape(-1,1), y_s.reshape(-1,1))
print ("R_squared in % is: ", "{:.2f}".format(r_squared*100))
```




```
R_squared in % is:  38.86
```

In [180]:
```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# Importing the dataset : Define X and y
# dataset = pd.read_csv('house_price_data.csv') # already imported above


# This line removes the outliers:
dataset2 = dataset[(dataset["SalePrice"]<500000)& (dataset["GarageArea"]<1200)]

#Define X and y
X_s = dataset2["GarageArea"].values # .values convert dataframe into numpy array
y_s = dataset2["SalePrice"].values # dataset.to_numpy()

# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_s, y_s, test_size = 0.2)

# Training the Simple Linear Regression model on the whole dataset
# import linear_model from sklearn
from sklearn.linear_model import LinearRegression

simple_regressor = LinearRegression() # created our model
simple_regressor.fit(X_train.reshape(-1,1), y_train.reshape(-1,1)) # Train the mo

# Predicting the Test set results
simple_y_pred = simple_regressor.predict(X_test.reshape(-1,1))

# Visualising the Training set results
plt.figure(figsize=(10, 5))
plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, simple_regressor.predict(X_train.reshape(-1,1)), color = 'blue'
plt.title('GarageArea vs SalePrice')
plt.xlabel('GarageArea')
plt.ylabel('SalePrice')
plt.show()

# R-squared
r_squared = simple_regressor.score(X_s.reshape(-1,1), y_s.reshape(-1,1))
print ("R_squared in % is: ", "{:.2f}".format(r_squared*100))
```




```
R_squared in % is:  42.14
```

In [ ]:

5 - Practical Example of Multiple Linear Regression on house_price data - Spyder

See you in spyder application!

In [ ]: