

Week10

November 3, 2024

1 STOR 320 Introduction to Data Science

1.1 Week 10: Regularization

2 Part 1

2.0.1 Let's first revisit the Ames housing dataset

```
[ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

```
[ ]: ames = pd.read_csv('Ames.csv')

pd.set_option('display.max_rows', 200)
pd.set_option('display.max_columns', 200)
ames.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2930 entries, 0 to 2929
Data columns (total 80 columns):
#   Column                Non-Null Count  Dtype  
---  -
0   MSSubClass             2930 non-null  int64  
1   MSZoning               2930 non-null  object  
2   LotFrontage           2440 non-null  float64 
3   LotArea               2930 non-null  float64 
4   Street                2930 non-null  object  
5   Alley                 2930 non-null  object  
6   LotShape              2930 non-null  object  
7   LandContour           2930 non-null  object  
8   Utilities             2930 non-null  object  
9   LotConfig             2930 non-null  object  
10  LandSlope              2930 non-null  object  
11  Neighborhood           2930 non-null  object
```

12	Condition1	2930	non-null	object
13	Condition2	2930	non-null	object
14	BldgType	2930	non-null	object
15	HouseStyle	2930	non-null	object
16	OverallQual	2930	non-null	int64
17	OverallCond	2930	non-null	int64
18	YearBuilt	2930	non-null	float64
19	YearRemod.Add	2930	non-null	float64
20	RoofStyle	2930	non-null	object
21	RoofMatl	2930	non-null	object
22	Exterior1st	2930	non-null	object
23	Exterior2nd	2930	non-null	object
24	MasVnrType	1155	non-null	object
25	MasVnrArea	2907	non-null	float64
26	ExterQual	2930	non-null	object
27	ExterCond	2930	non-null	object
28	Foundation	2930	non-null	object
29	BsmtQual	2929	non-null	object
30	BsmtCond	2929	non-null	object
31	BsmtExposure	2926	non-null	object
32	BsmtFinType1	2929	non-null	object
33	BsmtFinSF1	2929	non-null	float64
34	BsmtFinType2	2928	non-null	object
35	BsmtFinSF2	2929	non-null	float64
36	BsmtUnfSF	2929	non-null	float64
37	TotalBsmtSF	2929	non-null	float64
38	Heating	2930	non-null	object
39	HeatingQC	2930	non-null	object
40	CentralAir	2930	non-null	object
41	Electrical	2929	non-null	object
42	X1stFlrSF	2930	non-null	float64
43	X2ndFlrSF	2930	non-null	float64
44	LowQualFinSF	2930	non-null	float64
45	GrLivArea	2930	non-null	float64
46	BsmtFullBath	2928	non-null	float64
47	BsmtHalfBath	2928	non-null	float64
48	FullBath	2930	non-null	float64
49	HalfBath	2930	non-null	float64
50	BedroomAbvGr	2930	non-null	float64
51	KitchenAbvGr	2930	non-null	float64
52	KitchenQual	2930	non-null	object
53	TotRmsAbvGrd	2930	non-null	float64
54	Functional	2930	non-null	object
55	Fireplaces	2930	non-null	float64
56	FireplaceQu	2930	non-null	object
57	GarageType	2930	non-null	object
58	GarageYrBlt	2771	non-null	float64
59	GarageFinish	2928	non-null	object

```

60 GarageCars      2929 non-null float64
61 GarageArea      2929 non-null float64
62 GarageQual      2929 non-null object
63 GarageCond      2929 non-null object
64 PavedDrive      2930 non-null object
65 WoodDeckSF      2930 non-null float64
66 OpenPorchSF     2930 non-null float64
67 EnclosedPorch   2930 non-null float64
68 X3SsnPorch      2930 non-null float64
69 ScreenPorch     2930 non-null float64
70 PoolArea        2930 non-null float64
71 PoolQC          2930 non-null object
72 Fence           2930 non-null object
73 MiscFeature     106 non-null object
74 MiscVal         2930 non-null float64
75 MoSold          2930 non-null float64
76 YrSold          2930 non-null float64
77 SaleType        2930 non-null object
78 SaleCondition   2930 non-null object
79 SalePrice       2930 non-null float64
dtypes: float64(34), int64(3), object(43)
memory usage: 1.8+ MB

```

2.0.2 Basic data cleaning and EDA

1.1.1 Dependent Variable

a) A quick visualization of the dependent variable

```

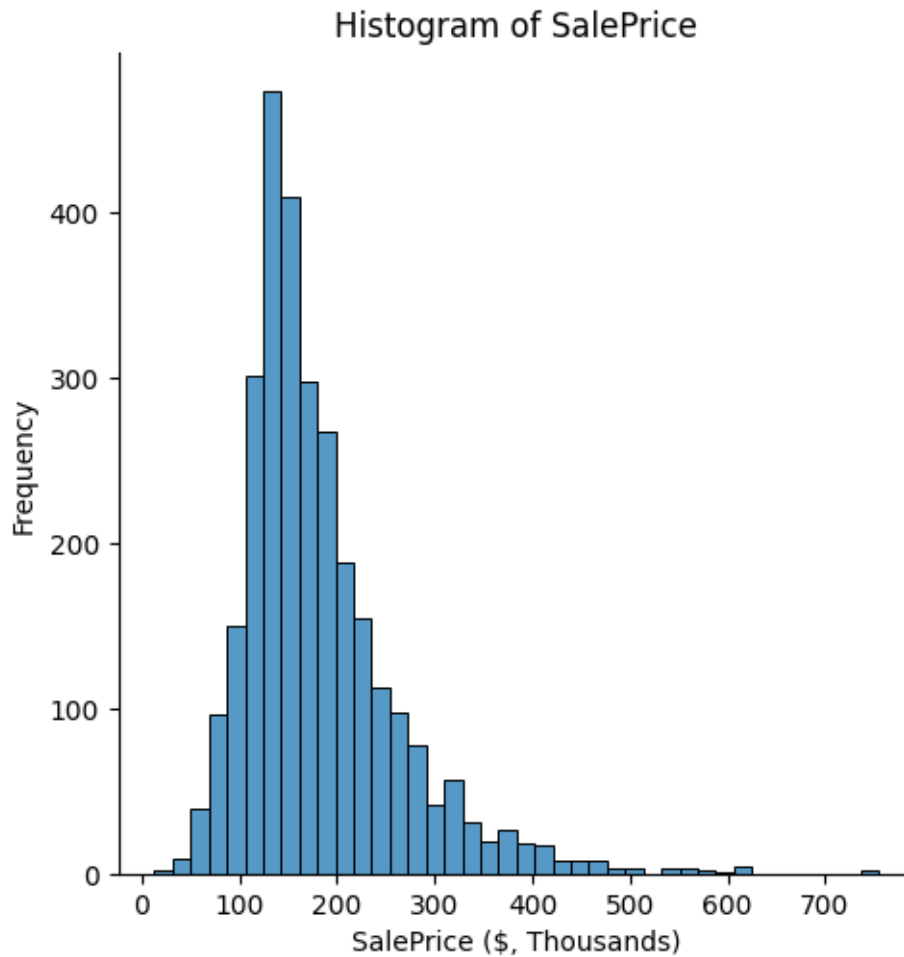
[ ]: plt.figure(figsize=(8,6))
    ax = sns.displot(ames['SalePrice']/1000, bins=40)

    plt.xlabel('SalePrice ($, Thousands)')
    plt.ylabel('Frequency')
    plt.title('Histogram of SalePrice')

    plt.show()
    ames['SalePrice'].describe()

```

<Figure size 800x600 with 0 Axes>



```
[ ]: count      2930.000000
     mean      180796.060068
     std       79886.692357
     min       12789.000000
     25%      129500.000000
     50%      160000.000000
     75%      213500.000000
     max       755000.000000
     Name: SalePrice, dtype: float64
```

b. Log transformation: Let's take log to be more fair in comparing high vs. low price homes.

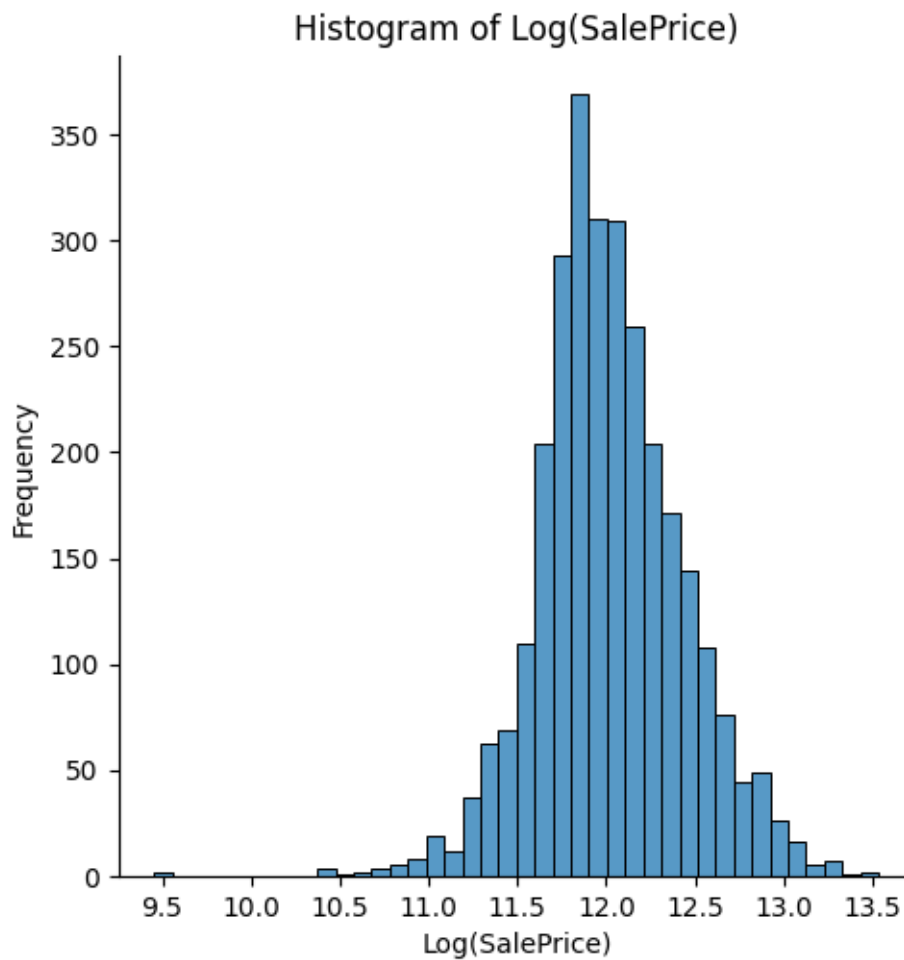
```
[ ]: ames['LogSalePrice'] = ames['SalePrice'].apply(np.log)
     ames.drop(columns='SalePrice', inplace=True)
```

```
[ ]: plt.figure(figsize=(8,6))
     ax = sns.displot(ames['LogSalePrice'], bins=40)
```

```
plt.xlabel('Log(SalePrice)')
plt.ylabel('Frequency')
plt.title('Histogram of Log(SalePrice)')

plt.show()
ames['LogSalePrice'].describe()
```

<Figure size 800x600 with 0 Axes>



```
[ ]: count    2930.000000
     mean      12.020969
     std        0.407587
     min        9.456341
     25%       11.771436
     50%       11.982929
     75%       12.271392
```

```
max          13.534473
Name: LogSalePrice, dtype: float64
```

1.1.2 Independent Variables

a) Column Names: One of the column names contains a dot. We rename it to avoid any problem:

```
[ ]: ames.rename(columns={'YearRemod.Add': 'YearRemodAdd'}, inplace=True)
```

b) Move the new dependent variable (LogSalePrice) to the first column

```
[ ]: ames = ames[[ames.columns[-1]] + list(ames.columns[:-1]) ]
ames
```

```
[ ]:
```

	LogSalePrice	MSSubClass	MSZoning	LotFrontage	LotArea	Street	\
0	12.278393	20	RL	141.0	31770.0	Pave	
1	11.561716	20	RH	80.0	11622.0	Pave	
2	12.055250	20	RL	81.0	14267.0	Pave	
3	12.404924	20	RL	93.0	11160.0	Pave	
4	12.154253	60	RL	74.0	13830.0	Pave	
...	
2925	11.867097	80	RL	37.0	7937.0	Pave	
2926	11.782953	20	RL	NaN	8885.0	Pave	
2927	11.790557	85	RL	62.0	10441.0	Pave	
2928	12.043554	20	RL	77.0	10010.0	Pave	
2929	12.144197	60	RL	74.0	9627.0	Pave	

	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	\
0	NoAccess	IR1	Lvl	AllPub	Corner	Gtl	
1	NoAccess	Reg	Lvl	AllPub	Inside	Gtl	
2	NoAccess	IR1	Lvl	AllPub	Corner	Gtl	
3	NoAccess	Reg	Lvl	AllPub	Corner	Gtl	
4	NoAccess	IR1	Lvl	AllPub	Inside	Gtl	
...	
2925	NoAccess	IR1	Lvl	AllPub	CulDSac	Gtl	
2926	NoAccess	IR1	Low	AllPub	Inside	Mod	
2927	NoAccess	Reg	Lvl	AllPub	Inside	Gtl	
2928	NoAccess	Reg	Lvl	AllPub	Inside	Mod	
2929	NoAccess	Reg	Lvl	AllPub	Inside	Mod	

	Neighborhood	Condition1	Condition2	BldgType	HouseStyle	OverallQual	\
0	NAmes	Norm	Norm	1Fam	1Story	6	
1	NAmes	Feedr	Norm	1Fam	1Story	5	
2	NAmes	Norm	Norm	1Fam	1Story	6	
3	NAmes	Norm	Norm	1Fam	1Story	7	
4	Gilbert	Norm	Norm	1Fam	2Story	5	
...	
2925	Mitchel	Norm	Norm	1Fam	SLvl	6	

2926	Mitchel	Norm	Norm	1Fam	1Story	5
2927	Mitchel	Norm	Norm	1Fam	SFoyer	5
2928	Mitchel	Norm	Norm	1Fam	1Story	5
2929	Mitchel	Norm	Norm	1Fam	2Story	7

	OverallCond	YearBuilt	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	\
0	5	1960.0	1960.0	Hip	CompShg	BrkFace	
1	6	1961.0	1961.0	Gable	CompShg	VinylSd	
2	6	1958.0	1958.0	Hip	CompShg	Wd Sdng	
3	5	1968.0	1968.0	Hip	CompShg	BrkFace	
4	5	1997.0	1998.0	Gable	CompShg	VinylSd	
...	
2925	6	1984.0	1984.0	Gable	CompShg	HdBoard	
2926	5	1983.0	1983.0	Gable	CompShg	HdBoard	
2927	5	1992.0	1992.0	Gable	CompShg	HdBoard	
2928	5	1974.0	1975.0	Gable	CompShg	HdBoard	
2929	5	1993.0	1994.0	Gable	CompShg	HdBoard	

	Exterior2nd	MasVnrType	MasVnrArea	ExterQual	ExterCond	Foundation	\
0	Plywood	Stone	112.0	TA	TA	CBlock	
1	VinylSd	NaN	0.0	TA	TA	CBlock	
2	Wd Sdng	BrkFace	108.0	TA	TA	CBlock	
3	BrkFace	NaN	0.0	Gd	TA	CBlock	
4	VinylSd	NaN	0.0	TA	TA	PConc	
...	
2925	HdBoard	NaN	0.0	TA	TA	CBlock	
2926	HdBoard	NaN	0.0	TA	TA	CBlock	
2927	Wd Shng	NaN	0.0	TA	TA	PConc	
2928	HdBoard	NaN	0.0	TA	TA	CBlock	
2929	HdBoard	BrkFace	94.0	TA	TA	PConc	

	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	\
0	TA	Gd	Gd	BLQ	639.0	Unf	
1	TA	TA	No	Rec	468.0	LwQ	
2	TA	TA	No	ALQ	923.0	Unf	
3	TA	TA	No	ALQ	1065.0	Unf	
4	Gd	TA	No	GLQ	791.0	Unf	
...	
2925	TA	TA	Av	GLQ	819.0	Unf	
2926	Gd	TA	Av	BLQ	301.0	ALQ	
2927	Gd	TA	Av	GLQ	337.0	Unf	
2928	Gd	TA	Av	ALQ	1071.0	LwQ	
2929	Gd	TA	Av	LwQ	758.0	Unf	

	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	\
0	0.0	441.0	1080.0	GasA	Fa	Y	
1	144.0	270.0	882.0	GasA	TA	Y	

2	0.0	406.0	1329.0	GasA	TA	Y
3	0.0	1045.0	2110.0	GasA	Ex	Y
4	0.0	137.0	928.0	GasA	Gd	Y
...
2925	0.0	184.0	1003.0	GasA	TA	Y
2926	324.0	239.0	864.0	GasA	TA	Y
2927	0.0	575.0	912.0	GasA	TA	Y
2928	123.0	195.0	1389.0	GasA	Gd	Y
2929	0.0	238.0	996.0	GasA	Ex	Y

	Electrical	X1stFlrSF	X2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	\
0	SBrkr	1656.0	0.0	0.0	1656.0	1.0	
1	SBrkr	896.0	0.0	0.0	896.0	0.0	
2	SBrkr	1329.0	0.0	0.0	1329.0	0.0	
3	SBrkr	2110.0	0.0	0.0	2110.0	1.0	
4	SBrkr	928.0	701.0	0.0	1629.0	0.0	
...	
2925	SBrkr	1003.0	0.0	0.0	1003.0	1.0	
2926	SBrkr	902.0	0.0	0.0	902.0	1.0	
2927	SBrkr	970.0	0.0	0.0	970.0	0.0	
2928	SBrkr	1389.0	0.0	0.0	1389.0	1.0	
2929	SBrkr	996.0	1004.0	0.0	2000.0	0.0	

	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	\
0	0.0	1.0	0.0	3.0	1.0	
1	0.0	1.0	0.0	2.0	1.0	
2	0.0	1.0	1.0	3.0	1.0	
3	0.0	2.0	1.0	3.0	1.0	
4	0.0	2.0	1.0	3.0	1.0	
...	
2925	0.0	1.0	0.0	3.0	1.0	
2926	0.0	1.0	0.0	2.0	1.0	
2927	1.0	1.0	0.0	3.0	1.0	
2928	0.0	1.0	0.0	2.0	1.0	
2929	0.0	2.0	1.0	3.0	1.0	

	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType	\
0	TA	7.0	Typ	2.0	Gd	Attchd	
1	TA	5.0	Typ	0.0	NoFirePlace	Attchd	
2	Gd	6.0	Typ	0.0	NoFirePlace	Attchd	
3	Ex	8.0	Typ	2.0	TA	Attchd	
4	TA	6.0	Typ	1.0	TA	Attchd	
...	
2925	TA	6.0	Typ	0.0	NoFirePlace	Detchd	
2926	TA	5.0	Typ	0.0	NoFirePlace	Attchd	
2927	TA	6.0	Typ	0.0	NoFirePlace	NoGarage	
2928	TA	6.0	Typ	1.0	TA	Attchd	

2929	TA	9.0	Typ	1.0	TA	Attchd
	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond \
0	1960.0	Fin	2.0	528.0	TA	TA
1	1961.0	Unf	1.0	730.0	TA	TA
2	1958.0	Unf	1.0	312.0	TA	TA
3	1968.0	Fin	2.0	522.0	TA	TA
4	1997.0	Fin	2.0	482.0	TA	TA
...
2925	1984.0	Unf	2.0	588.0	TA	TA
2926	1983.0	Unf	2.0	484.0	TA	TA
2927	NaN	NoGarage	0.0	0.0	NoGarage	NoGarage
2928	1975.0	RFn	2.0	418.0	TA	TA
2929	1993.0	Fin	3.0	650.0	TA	TA

	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	X3SsnPorch \
0	P	210.0	62.0	0.0	0.0
1	Y	140.0	0.0	0.0	0.0
2	Y	393.0	36.0	0.0	0.0
3	Y	0.0	0.0	0.0	0.0
4	Y	212.0	34.0	0.0	0.0
...
2925	Y	120.0	0.0	0.0	0.0
2926	Y	164.0	0.0	0.0	0.0
2927	Y	80.0	32.0	0.0	0.0
2928	Y	240.0	38.0	0.0	0.0
2929	Y	190.0	48.0	0.0	0.0

	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold \
0	0.0	0.0	NoPool	NoFence	NaN	0.0	5.0
1	120.0	0.0	NoPool	MnPrv	NaN	0.0	6.0
2	0.0	0.0	NoPool	NoFence	Gar2	12500.0	6.0
3	0.0	0.0	NoPool	NoFence	NaN	0.0	4.0
4	0.0	0.0	NoPool	MnPrv	NaN	0.0	3.0
...
2925	0.0	0.0	NoPool	GdPrv	NaN	0.0	3.0
2926	0.0	0.0	NoPool	MnPrv	NaN	0.0	6.0
2927	0.0	0.0	NoPool	MnPrv	Shed	700.0	7.0
2928	0.0	0.0	NoPool	NoFence	NaN	0.0	4.0
2929	0.0	0.0	NoPool	NoFence	NaN	0.0	11.0

	YrSold	SaleType	SaleCondition
0	2010.0	WD	Normal
1	2010.0	WD	Normal
2	2010.0	WD	Normal
3	2010.0	WD	Normal
4	2010.0	WD	Normal

```

...      ...      ...
2925  2006.0      WD      Normal
2926  2006.0      WD      Normal
2927  2006.0      WD      Normal
2928  2006.0      WD      Normal
2929  2006.0      WD      Normal

```

[2930 rows x 80 columns]

2.0.3 1.2 More cleaning: Combine the information from two columns

1.2.1 Fix Condition variables Convert condition variables into dummy variables. We look at both Condition1 or Condition2 to decide which conditions each home belongs to.

```
[ ]: print(np.unique(ames['Condition1']))
      print(np.unique(ames['Condition2']))
```

```
['Artery' 'Feedr' 'Norm' 'PosA' 'PosN' 'RRAe' 'RRAn' 'RRNe' 'RRNn']
['Artery' 'Feedr' 'Norm' 'PosA' 'PosN' 'RRAe' 'RRAn' 'RRNn']
```

```
[ ]: condition_dummy=np.unique(ames['Condition1'])
      # In the line above, we implicitly treat 'Norm' as the reference level
      ames[condition_dummy]=0

      for i in condition_dummy:
          print(i)
          ames.loc[(ames['Condition1']==i) | (ames['Condition2']==i), i]=1

      ames.drop(columns=['Condition1', 'Condition2'], inplace=True)
```

```

Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNe
RRNn

```

```
[ ]: ames.loc[:,['Artery', 'Feedr', 'Norm']]
```

```
[ ]:
      Artery  Feedr  Norm
0         0      0      1
1         0      1      1
2         0      0      1
3         0      0      1
4         0      0      1
...      ...      ...      ...
```

2925	0	0	1
2926	0	0	1
2927	0	0	1
2928	0	0	1
2929	0	0	1

[2930 rows x 3 columns]

1.2.2 Encode Exterior Variables Same treatment as with condition variables

```
[ ]: print(np.unique(ames['Exterior1st']))
print(np.unique(ames['Exterior2nd']))
```

```
['AsbShng' 'AsphShn' 'BrkComm' 'BrkFace' 'CBlock' 'CemntBd' 'HdBoard'
 'ImStucc' 'MetalSd' 'Plywood' 'PreCast' 'Stone' 'Stucco' 'VinylSd'
 'Wd Sdng' 'WdShng']
['AsbShng' 'AsphShn' 'Brk Cmn' 'BrkFace' 'CBlock' 'CmentBd' 'HdBoard'
 'ImStucc' 'MetalSd' 'Other' 'Plywood' 'PreCast' 'Stone' 'Stucco'
 'VinylSd' 'Wd Sdng' 'Wd Shng']
```

```
[ ]: # Remove the space in each level to avoid errors in column names later on.
ames['Exterior1st'] = ames['Exterior1st'].str.replace(' ', '')
ames['Exterior2nd'] = ames['Exterior2nd'].str.replace(' ', '')
print(np.unique(ames['Exterior1st']))
print(np.unique(ames['Exterior2nd']))
```

```
['AsbShng' 'AsphShn' 'BrkComm' 'BrkFace' 'CBlock' 'CemntBd' 'HdBoard'
 'ImStucc' 'MetalSd' 'Plywood' 'PreCast' 'Stone' 'Stucco' 'VinylSd'
 'WdSdng' 'WdShng']
['AsbShng' 'AsphShn' 'BrkCmn' 'BrkFace' 'CBlock' 'CmentBd' 'HdBoard'
 'ImStucc' 'MetalSd' 'Other' 'Plywood' 'PreCast' 'Stone' 'Stucco'
 'VinylSd' 'WdSdng' 'WdShng']
```

```
[ ]: np.unique(np.concatenate((np.unique(ames['Exterior1st']),np.
    ↪unique(ames['Exterior2nd'])), axis=0 ))
```

```
[ ]: array(['AsbShng', 'AsphShn', 'BrkCmn', 'BrkComm', 'BrkFace', 'CBlock',
        'CemntBd', 'CmentBd', 'HdBoard', 'ImStucc', 'MetalSd', 'Other',
        'Plywood', 'PreCast', 'Stone', 'Stucco', 'VinylSd', 'WdSdng',
        'WdShng', 'WdShng'], dtype=object)
```

```
[ ]: exterior_dummy=np.unique(np.concatenate((np.unique(ames['Exterior1st']),np.
    ↪unique(ames['Exterior2nd'])), axis=0 ))
ames[exterior_dummy]=0

for i in exterior_dummy:
    print(i)
    ames.loc[(ames['Exterior1st']==i) | (ames['Exterior2nd']==i), i]=1
```

```
ames.drop(columns=['Exterior1st', 'Exterior2nd'], inplace=True)
```

AsbShng
AsphShn
BrkCmn
BrkComm
BrkFace
CBlock
CemntBd
CmentBd
HdBoard
ImStucc
MetalSd
Other
Plywood
PreCast
Stone
Stucco
VinylSd
WdSdng
WdShing
WdShng

2.0.4 1.3 Create New Features for Year Built & Year Remodeled

Let's see how sale price is affected by the year built and the year remodeled.

```
[ ]: print(ames['YearBuilt'].describe(), '\n')  
      print(ames['YearRemodAdd'].describe())
```

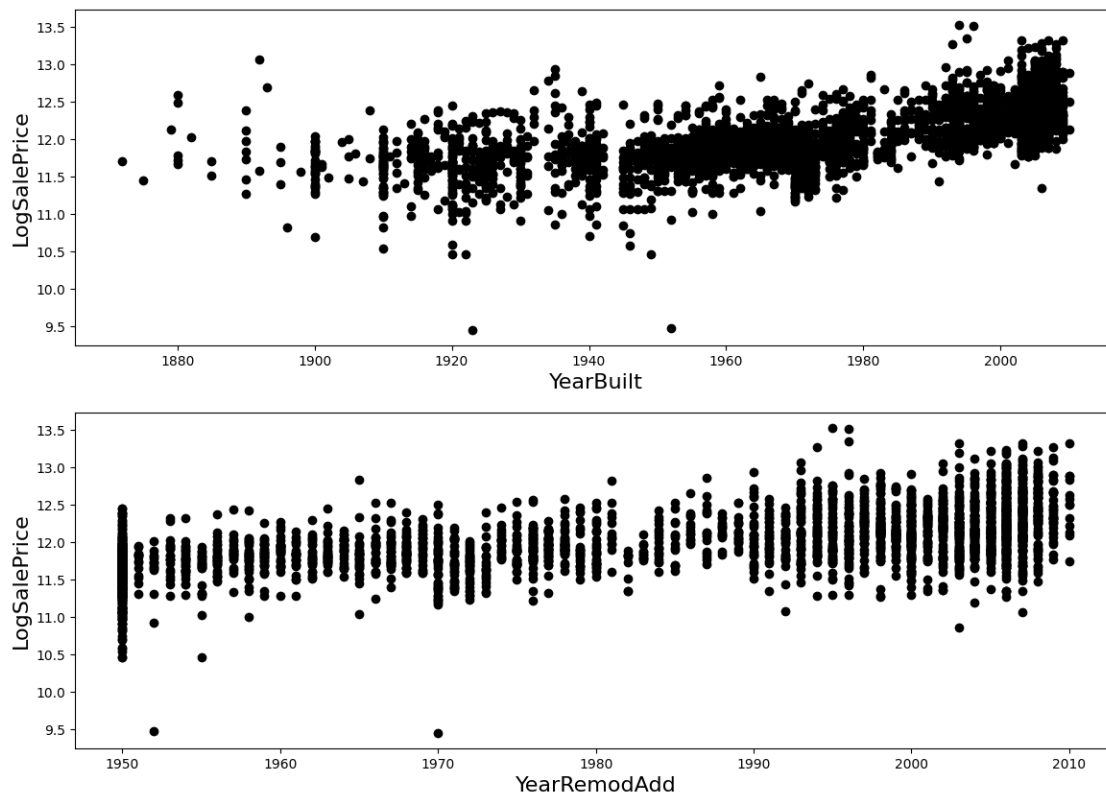
```
count    2930.000000  
mean      1971.356314  
std        30.245361  
min       1872.000000  
25%       1954.000000  
50%       1973.000000  
75%       2001.000000  
max       2010.000000  
Name: YearBuilt, dtype: float64
```

```
count    2930.000000  
mean      1984.266553  
std        20.860286  
min       1950.000000  
25%       1965.000000  
50%       1993.000000  
75%       2004.000000  
max       2010.000000
```

Name: YearRemodAdd, dtype: float64

```
[ ]: plt.figure(figsize=(14, 10))
plt.subplot(2,1,1)
plt.scatter(ames['YearBuilt'].to_numpy(), ames['LogSalePrice'].to_numpy(),
            color='black')
plt.xlabel('YearBuilt', fontsize=16)
plt.ylabel('LogSalePrice', fontsize=16)

plt.subplot(2,1,2)
plt.scatter(ames['YearRemodAdd'].to_numpy(), ames['LogSalePrice'].to_numpy(),
            color='black')
plt.xlabel('YearRemodAdd', fontsize=16)
plt.ylabel('LogSalePrice', fontsize=16)
plt.show()
```



Let's add features:

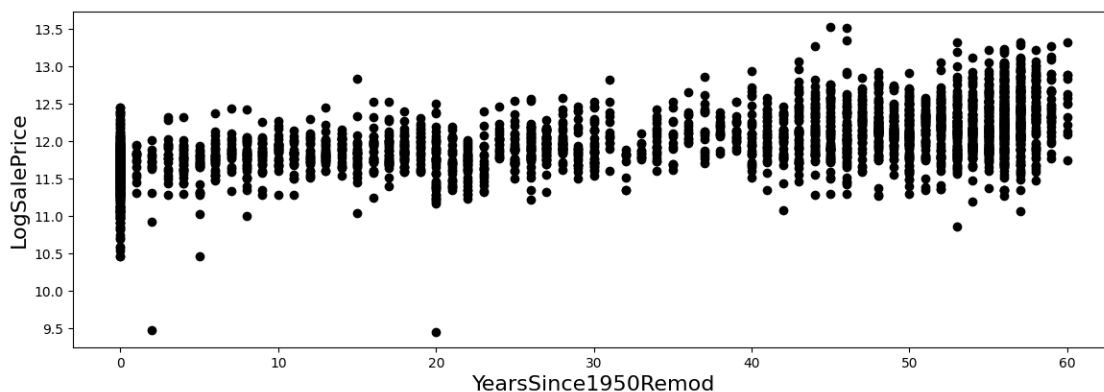
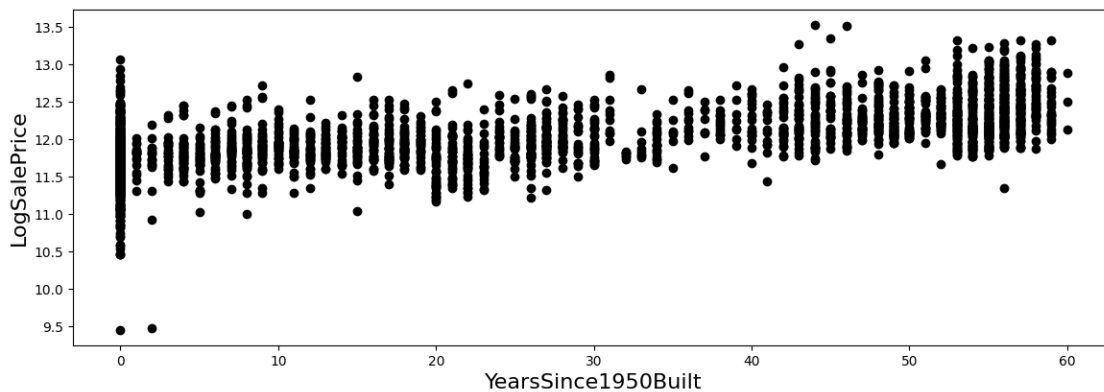
- **YearsSince1950Built** – number of years after 1950 that the home was built (if before 1950, set to 0)
- **YearsSince1950Remod** – number of years after 1950 that the home was remodeled

```
[ ]: ames['YearsSince1950Built'] = (np.clip(ames['YearBuilt']-1950,0,np.nan)).
      ↳astype('int')
ames['YearsSince1950Remod'] = (np.clip(ames['YearRemodAdd']-1950,0,np.nan)).
      ↳astype('int')

ames.drop(columns=['YearBuilt', 'YearRemodAdd'], inplace=True)
```

```
[ ]: plt.figure(figsize=(14, 10))
plt.subplot(2,1,1)
plt.scatter(ames['YearsSince1950Built'].to_numpy(), ames['LogSalePrice'].
      ↳to_numpy(), color='black')
plt.xlabel('YearsSince1950Built', fontsize=16)
plt.ylabel('LogSalePrice', fontsize=16)

plt.subplot(2,1,2)
plt.scatter(ames['YearsSince1950Remod'].to_numpy(), ames['LogSalePrice'].
      ↳to_numpy(), color='black')
plt.xlabel('YearsSince1950Remod', fontsize=16)
plt.ylabel('LogSalePrice', fontsize=16)
plt.show()
```

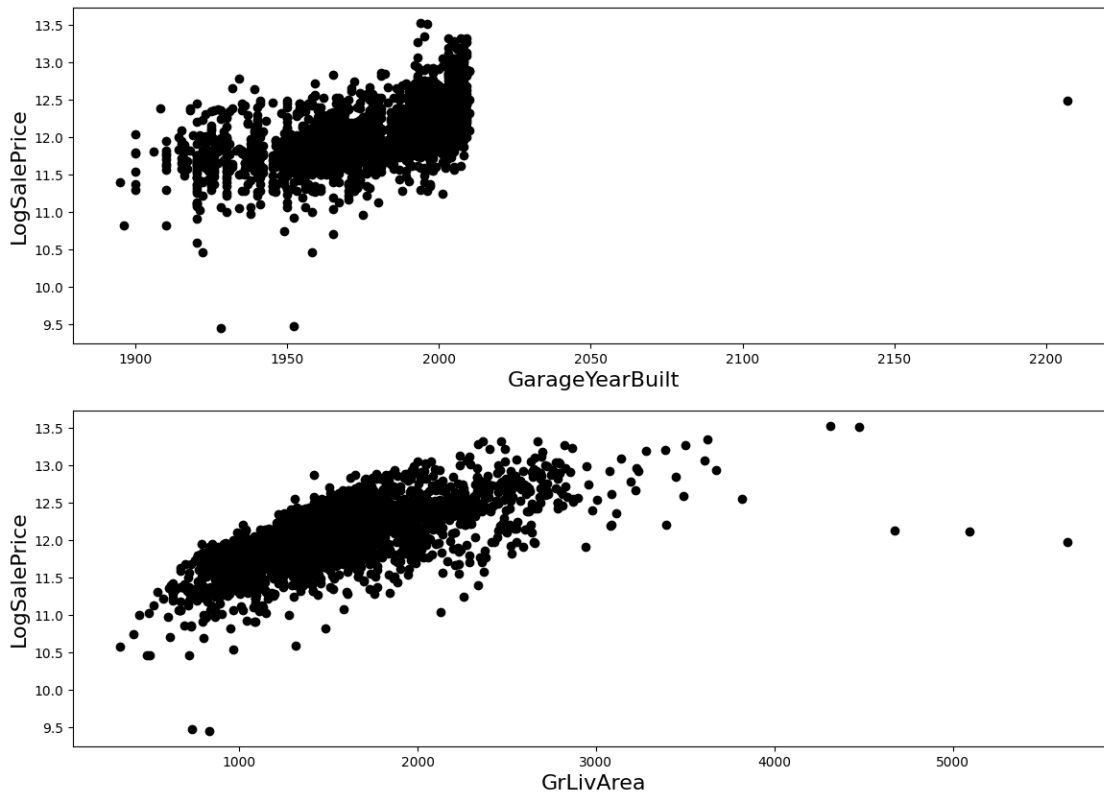


2.0.5 1.4 Remove Outliers and Mistakes

```
[ ]: plt.figure(figsize=(14, 10))
plt.subplot(2,1,1)
plt.scatter(ames['GarageYrBlt'].to_numpy(), ames['LogSalePrice'].to_numpy(),
            color='black')
plt.xlabel('GarageYearBuilt', fontsize=16)
plt.ylabel('LogSalePrice', fontsize=16)

plt.subplot(2,1,2)
plt.scatter(ames['GrLivArea'].to_numpy(), ames['LogSalePrice'].to_numpy(),
            color='black')
plt.xlabel('GrLivArea', fontsize=16)
plt.ylabel('LogSalePrice', fontsize=16)
```

```
[ ]: Text(0, 0.5, 'LogSalePrice')
```



a) Throw away outliers and mistakes:

```
[ ]: ames
```

[]:	LogSalePrice	MSSubClass	MSZoning	LotFrontage	LotArea	Street	\
0	12.278393	20	RL	141.0	31770.0	Pave	
1	11.561716	20	RH	80.0	11622.0	Pave	
2	12.055250	20	RL	81.0	14267.0	Pave	
3	12.404924	20	RL	93.0	11160.0	Pave	
4	12.154253	60	RL	74.0	13830.0	Pave	
...	
2925	11.867097	80	RL	37.0	7937.0	Pave	
2926	11.782953	20	RL	NaN	8885.0	Pave	
2927	11.790557	85	RL	62.0	10441.0	Pave	
2928	12.043554	20	RL	77.0	10010.0	Pave	
2929	12.144197	60	RL	74.0	9627.0	Pave	

	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	\
0	NoAccess	IR1	Lvl	AllPub	Corner	Gtl	
1	NoAccess	Reg	Lvl	AllPub	Inside	Gtl	
2	NoAccess	IR1	Lvl	AllPub	Corner	Gtl	
3	NoAccess	Reg	Lvl	AllPub	Corner	Gtl	
4	NoAccess	IR1	Lvl	AllPub	Inside	Gtl	
...	
2925	NoAccess	IR1	Lvl	AllPub	CulDSac	Gtl	
2926	NoAccess	IR1	Low	AllPub	Inside	Mod	
2927	NoAccess	Reg	Lvl	AllPub	Inside	Gtl	
2928	NoAccess	Reg	Lvl	AllPub	Inside	Mod	
2929	NoAccess	Reg	Lvl	AllPub	Inside	Mod	

	Neighborhood	BldgType	HouseStyle	OverallQual	OverallCond	RoofStyle	\
0	NAMES	1Fam	1Story	6	5	Hip	
1	NAMES	1Fam	1Story	5	6	Gable	
2	NAMES	1Fam	1Story	6	6	Hip	
3	NAMES	1Fam	1Story	7	5	Hip	
4	Gilbert	1Fam	2Story	5	5	Gable	
...	
2925	Mitchel	1Fam	SLvl	6	6	Gable	
2926	Mitchel	1Fam	1Story	5	5	Gable	
2927	Mitchel	1Fam	SFoyer	5	5	Gable	
2928	Mitchel	1Fam	1Story	5	5	Gable	
2929	Mitchel	1Fam	2Story	7	5	Gable	

	RoofMatl	MasVnrType	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	\
0	CompShg	Stone	112.0	TA	TA	CBlock	TA	
1	CompShg	NaN	0.0	TA	TA	CBlock	TA	
2	CompShg	BrkFace	108.0	TA	TA	CBlock	TA	
3	CompShg	NaN	0.0	Gd	TA	CBlock	TA	
4	CompShg	NaN	0.0	TA	TA	PConc	Gd	
...	
2925	CompShg	NaN	0.0	TA	TA	CBlock	TA	

2926	CompShg	NaN	0.0	TA	TA	CBlock	Gd
2927	CompShg	NaN	0.0	TA	TA	PConc	Gd
2928	CompShg	NaN	0.0	TA	TA	CBlock	Gd
2929	CompShg	BrkFace	94.0	TA	TA	PConc	Gd

	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
0	Gd	Gd	BLQ	639.0	Unf	0.0	
1	TA	No	Rec	468.0	LwQ	144.0	
2	TA	No	ALQ	923.0	Unf	0.0	
3	TA	No	ALQ	1065.0	Unf	0.0	
4	TA	No	GLQ	791.0	Unf	0.0	
...	
2925	TA	Av	GLQ	819.0	Unf	0.0	
2926	TA	Av	BLQ	301.0	ALQ	324.0	
2927	TA	Av	GLQ	337.0	Unf	0.0	
2928	TA	Av	ALQ	1071.0	LwQ	123.0	
2929	TA	Av	LwQ	758.0	Unf	0.0	

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	Electrical	\
0	441.0	1080.0	GasA	Fa	Y	SBrkr	
1	270.0	882.0	GasA	TA	Y	SBrkr	
2	406.0	1329.0	GasA	TA	Y	SBrkr	
3	1045.0	2110.0	GasA	Ex	Y	SBrkr	
4	137.0	928.0	GasA	Gd	Y	SBrkr	
...	
2925	184.0	1003.0	GasA	TA	Y	SBrkr	
2926	239.0	864.0	GasA	TA	Y	SBrkr	
2927	575.0	912.0	GasA	TA	Y	SBrkr	
2928	195.0	1389.0	GasA	Gd	Y	SBrkr	
2929	238.0	996.0	GasA	Ex	Y	SBrkr	

	X1stFlrSF	X2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	\
0	1656.0	0.0	0.0	1656.0	1.0	
1	896.0	0.0	0.0	896.0	0.0	
2	1329.0	0.0	0.0	1329.0	0.0	
3	2110.0	0.0	0.0	2110.0	1.0	
4	928.0	701.0	0.0	1629.0	0.0	
...	
2925	1003.0	0.0	0.0	1003.0	1.0	
2926	902.0	0.0	0.0	902.0	1.0	
2927	970.0	0.0	0.0	970.0	0.0	
2928	1389.0	0.0	0.0	1389.0	1.0	
2929	996.0	1004.0	0.0	2000.0	0.0	

	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	\
0	0.0	1.0	0.0	3.0	1.0	
1	0.0	1.0	0.0	2.0	1.0	

2	0.0	1.0	1.0	3.0	1.0
3	0.0	2.0	1.0	3.0	1.0
4	0.0	2.0	1.0	3.0	1.0
...
2925	0.0	1.0	0.0	3.0	1.0
2926	0.0	1.0	0.0	2.0	1.0
2927	1.0	1.0	0.0	3.0	1.0
2928	0.0	1.0	0.0	2.0	1.0
2929	0.0	2.0	1.0	3.0	1.0

	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType	\
0	TA	7.0	Typ	2.0	Gd	Attchd	
1	TA	5.0	Typ	0.0	NoFirePlace	Attchd	
2	Gd	6.0	Typ	0.0	NoFirePlace	Attchd	
3	Ex	8.0	Typ	2.0	TA	Attchd	
4	TA	6.0	Typ	1.0	TA	Attchd	
...	
2925	TA	6.0	Typ	0.0	NoFirePlace	Detchd	
2926	TA	5.0	Typ	0.0	NoFirePlace	Attchd	
2927	TA	6.0	Typ	0.0	NoFirePlace	NoGarage	
2928	TA	6.0	Typ	1.0	TA	Attchd	
2929	TA	9.0	Typ	1.0	TA	Attchd	

	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond	\
0	1960.0	Fin	2.0	528.0	TA	TA	
1	1961.0	Unf	1.0	730.0	TA	TA	
2	1958.0	Unf	1.0	312.0	TA	TA	
3	1968.0	Fin	2.0	522.0	TA	TA	
4	1997.0	Fin	2.0	482.0	TA	TA	
...	
2925	1984.0	Unf	2.0	588.0	TA	TA	
2926	1983.0	Unf	2.0	484.0	TA	TA	
2927	NaN	NoGarage	0.0	0.0	NoGarage	NoGarage	
2928	1975.0	RFn	2.0	418.0	TA	TA	
2929	1993.0	Fin	3.0	650.0	TA	TA	

	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	X3SsnPorch	\
0	P	210.0	62.0	0.0	0.0	
1	Y	140.0	0.0	0.0	0.0	
2	Y	393.0	36.0	0.0	0.0	
3	Y	0.0	0.0	0.0	0.0	
4	Y	212.0	34.0	0.0	0.0	
...	
2925	Y	120.0	0.0	0.0	0.0	
2926	Y	164.0	0.0	0.0	0.0	
2927	Y	80.0	32.0	0.0	0.0	
2928	Y	240.0	38.0	0.0	0.0	

2929	Y	190.0	48.0	0.0	0.0
------	---	-------	------	-----	-----

	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	\
0	0.0	0.0	NoPool	NoFence	NaN	0.0	5.0	
1	120.0	0.0	NoPool	MnPrv	NaN	0.0	6.0	
2	0.0	0.0	NoPool	NoFence	Gar2	12500.0	6.0	
3	0.0	0.0	NoPool	NoFence	NaN	0.0	4.0	
4	0.0	0.0	NoPool	MnPrv	NaN	0.0	3.0	
...	
2925	0.0	0.0	NoPool	GdPrv	NaN	0.0	3.0	
2926	0.0	0.0	NoPool	MnPrv	NaN	0.0	6.0	
2927	0.0	0.0	NoPool	MnPrv	Shed	700.0	7.0	
2928	0.0	0.0	NoPool	NoFence	NaN	0.0	4.0	
2929	0.0	0.0	NoPool	NoFence	NaN	0.0	11.0	

	YrSold	SaleType	SaleCondition	Artery	Feedr	Norm	PosA	PosN	RR Ae	\
0	2010.0	WD	Normal	0	0	1	0	0	0	
1	2010.0	WD	Normal	0	1	1	0	0	0	
2	2010.0	WD	Normal	0	0	1	0	0	0	
3	2010.0	WD	Normal	0	0	1	0	0	0	
4	2010.0	WD	Normal	0	0	1	0	0	0	
...	
2925	2006.0	WD	Normal	0	0	1	0	0	0	
2926	2006.0	WD	Normal	0	0	1	0	0	0	
2927	2006.0	WD	Normal	0	0	1	0	0	0	
2928	2006.0	WD	Normal	0	0	1	0	0	0	
2929	2006.0	WD	Normal	0	0	1	0	0	0	

	RRAn	RRNe	RRNn	AsbShng	AsphShn	BrkCmn	BrkComm	BrkFace	CBlock	\
0	0	0	0	0	0	0	0	1	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	1	0	
4	0	0	0	0	0	0	0	0	0	
...	
2925	0	0	0	0	0	0	0	0	0	
2926	0	0	0	0	0	0	0	0	0	
2927	0	0	0	0	0	0	0	0	0	
2928	0	0	0	0	0	0	0	0	0	
2929	0	0	0	0	0	0	0	0	0	

	CemntBd	CmentBd	HdBoard	ImStucc	MetalSd	Other	Plywood	PreCast	\
0	0	0	0	0	0	0	1	0	
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	

...
2925	0	0	1	0	0	0	0	0	0
2926	0	0	1	0	0	0	0	0	0
2927	0	0	1	0	0	0	0	0	0
2928	0	0	1	0	0	0	0	0	0
2929	0	0	1	0	0	0	0	0	0

	Stone	Stucco	VinylSd	WdSdng	WdShng	WdShng	YearsSince1950Built	\
0	0	0	0	0	0	0	10	
1	0	0	1	0	0	0	11	
2	0	0	0	1	0	0	8	
3	0	0	0	0	0	0	18	
4	0	0	1	0	0	0	47	

...
2925	0	0	0	0	0	0	34	
2926	0	0	0	0	0	0	33	
2927	0	0	0	0	0	1	42	
2928	0	0	0	0	0	0	24	
2929	0	0	0	0	0	0	43	

	YearsSince1950Remod
0	10
1	11
2	8
3	18
4	48
...	...
2925	34
2926	33
2927	42
2928	25
2929	44

[2930 rows x 105 columns]

```
[ ]: ames.loc[~(ames['GrLivArea']>4000)] # drop 5 obs
```

[]:	LogSalePrice	MSSubClass	MSZoning	LotFrontage	LotArea	Street	\
0	12.278393	20	RL	141.0	31770.0	Pave	
1	11.561716	20	RH	80.0	11622.0	Pave	
2	12.055250	20	RL	81.0	14267.0	Pave	
3	12.404924	20	RL	93.0	11160.0	Pave	
4	12.154253	60	RL	74.0	13830.0	Pave	
...	
2925	11.867097	80	RL	37.0	7937.0	Pave	
2926	11.782953	20	RL	NaN	8885.0	Pave	
2927	11.790557	85	RL	62.0	10441.0	Pave	

2928	12.043554	20	RL	77.0	10010.0	Pave
2929	12.144197	60	RL	74.0	9627.0	Pave

	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	\
0	NoAccess	IR1	Lvl	AllPub	Corner	Gtl	
1	NoAccess	Reg	Lvl	AllPub	Inside	Gtl	
2	NoAccess	IR1	Lvl	AllPub	Corner	Gtl	
3	NoAccess	Reg	Lvl	AllPub	Corner	Gtl	
4	NoAccess	IR1	Lvl	AllPub	Inside	Gtl	
...	
2925	NoAccess	IR1	Lvl	AllPub	CulDSac	Gtl	
2926	NoAccess	IR1	Low	AllPub	Inside	Mod	
2927	NoAccess	Reg	Lvl	AllPub	Inside	Gtl	
2928	NoAccess	Reg	Lvl	AllPub	Inside	Mod	
2929	NoAccess	Reg	Lvl	AllPub	Inside	Mod	

	Neighborhood	BldgType	HouseStyle	OverallQual	OverallCond	RoofStyle	\
0	NAMES	1Fam	1Story	6	5	Hip	
1	NAMES	1Fam	1Story	5	6	Gable	
2	NAMES	1Fam	1Story	6	6	Hip	
3	NAMES	1Fam	1Story	7	5	Hip	
4	Gilbert	1Fam	2Story	5	5	Gable	
...	
2925	Mitchel	1Fam	SLvl	6	6	Gable	
2926	Mitchel	1Fam	1Story	5	5	Gable	
2927	Mitchel	1Fam	SFoyer	5	5	Gable	
2928	Mitchel	1Fam	1Story	5	5	Gable	
2929	Mitchel	1Fam	2Story	7	5	Gable	

	RoofMatl	MasVnrType	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	\
0	CompShg	Stone	112.0	TA	TA	CBlock	TA	
1	CompShg	NaN	0.0	TA	TA	CBlock	TA	
2	CompShg	BrkFace	108.0	TA	TA	CBlock	TA	
3	CompShg	NaN	0.0	Gd	TA	CBlock	TA	
4	CompShg	NaN	0.0	TA	TA	PConc	Gd	
...	
2925	CompShg	NaN	0.0	TA	TA	CBlock	TA	
2926	CompShg	NaN	0.0	TA	TA	CBlock	Gd	
2927	CompShg	NaN	0.0	TA	TA	PConc	Gd	
2928	CompShg	NaN	0.0	TA	TA	CBlock	Gd	
2929	CompShg	BrkFace	94.0	TA	TA	PConc	Gd	

	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
0	Gd	Gd	BLQ	639.0	Unf	0.0	
1	TA	No	Rec	468.0	LwQ	144.0	
2	TA	No	ALQ	923.0	Unf	0.0	
3	TA	No	ALQ	1065.0	Unf	0.0	

4	TA	No	GLQ	791.0	Unf	0.0
...
2925	TA	Av	GLQ	819.0	Unf	0.0
2926	TA	Av	BLQ	301.0	ALQ	324.0
2927	TA	Av	GLQ	337.0	Unf	0.0
2928	TA	Av	ALQ	1071.0	LwQ	123.0
2929	TA	Av	LwQ	758.0	Unf	0.0

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	Electrical	\
0	441.0	1080.0	GasA	Fa	Y	SBrkr	
1	270.0	882.0	GasA	TA	Y	SBrkr	
2	406.0	1329.0	GasA	TA	Y	SBrkr	
3	1045.0	2110.0	GasA	Ex	Y	SBrkr	
4	137.0	928.0	GasA	Gd	Y	SBrkr	
...	
2925	184.0	1003.0	GasA	TA	Y	SBrkr	
2926	239.0	864.0	GasA	TA	Y	SBrkr	
2927	575.0	912.0	GasA	TA	Y	SBrkr	
2928	195.0	1389.0	GasA	Gd	Y	SBrkr	
2929	238.0	996.0	GasA	Ex	Y	SBrkr	

	X1stFlrSF	X2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	\
0	1656.0	0.0	0.0	1656.0	1.0	
1	896.0	0.0	0.0	896.0	0.0	
2	1329.0	0.0	0.0	1329.0	0.0	
3	2110.0	0.0	0.0	2110.0	1.0	
4	928.0	701.0	0.0	1629.0	0.0	
...	
2925	1003.0	0.0	0.0	1003.0	1.0	
2926	902.0	0.0	0.0	902.0	1.0	
2927	970.0	0.0	0.0	970.0	0.0	
2928	1389.0	0.0	0.0	1389.0	1.0	
2929	996.0	1004.0	0.0	2000.0	0.0	

	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	\
0	0.0	1.0	0.0	3.0	1.0	
1	0.0	1.0	0.0	2.0	1.0	
2	0.0	1.0	1.0	3.0	1.0	
3	0.0	2.0	1.0	3.0	1.0	
4	0.0	2.0	1.0	3.0	1.0	
...	
2925	0.0	1.0	0.0	3.0	1.0	
2926	0.0	1.0	0.0	2.0	1.0	
2927	1.0	1.0	0.0	3.0	1.0	
2928	0.0	1.0	0.0	2.0	1.0	
2929	0.0	2.0	1.0	3.0	1.0	

	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType	\
0	TA	7.0	Typ	2.0	Gd	Attchd	
1	TA	5.0	Typ	0.0	NoFirePlace	Attchd	
2	Gd	6.0	Typ	0.0	NoFirePlace	Attchd	
3	Ex	8.0	Typ	2.0	TA	Attchd	
4	TA	6.0	Typ	1.0	TA	Attchd	
...	
2925	TA	6.0	Typ	0.0	NoFirePlace	Detchd	
2926	TA	5.0	Typ	0.0	NoFirePlace	Attchd	
2927	TA	6.0	Typ	0.0	NoFirePlace	NoGarage	
2928	TA	6.0	Typ	1.0	TA	Attchd	
2929	TA	9.0	Typ	1.0	TA	Attchd	

	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond	\
0	1960.0	Fin	2.0	528.0	TA	TA	
1	1961.0	Unf	1.0	730.0	TA	TA	
2	1958.0	Unf	1.0	312.0	TA	TA	
3	1968.0	Fin	2.0	522.0	TA	TA	
4	1997.0	Fin	2.0	482.0	TA	TA	
...	
2925	1984.0	Unf	2.0	588.0	TA	TA	
2926	1983.0	Unf	2.0	484.0	TA	TA	
2927	NaN	NoGarage	0.0	0.0	NoGarage	NoGarage	
2928	1975.0	RFn	2.0	418.0	TA	TA	
2929	1993.0	Fin	3.0	650.0	TA	TA	

	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	X3SsnPorch	\
0	P	210.0	62.0	0.0	0.0	
1	Y	140.0	0.0	0.0	0.0	
2	Y	393.0	36.0	0.0	0.0	
3	Y	0.0	0.0	0.0	0.0	
4	Y	212.0	34.0	0.0	0.0	
...	
2925	Y	120.0	0.0	0.0	0.0	
2926	Y	164.0	0.0	0.0	0.0	
2927	Y	80.0	32.0	0.0	0.0	
2928	Y	240.0	38.0	0.0	0.0	
2929	Y	190.0	48.0	0.0	0.0	

	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	\
0	0.0	0.0	NoPool	NoFence	NaN	0.0	5.0	
1	120.0	0.0	NoPool	MnPrv	NaN	0.0	6.0	
2	0.0	0.0	NoPool	NoFence	Gar2	12500.0	6.0	
3	0.0	0.0	NoPool	NoFence	NaN	0.0	4.0	
4	0.0	0.0	NoPool	MnPrv	NaN	0.0	3.0	
...	
2925	0.0	0.0	NoPool	GdPrv	NaN	0.0	3.0	

2926	0.0	0.0	NoPool	MnPrv	NaN	0.0	6.0
2927	0.0	0.0	NoPool	MnPrv	Shed	700.0	7.0
2928	0.0	0.0	NoPool	NoFence	NaN	0.0	4.0
2929	0.0	0.0	NoPool	NoFence	NaN	0.0	11.0

	YrSold	SaleType	SaleCondition	Artery	Feedr	Norm	PosA	PosN	RR Ae	\
0	2010.0	WD	Normal	0	0	1	0	0	0	
1	2010.0	WD	Normal	0	1	1	0	0	0	
2	2010.0	WD	Normal	0	0	1	0	0	0	
3	2010.0	WD	Normal	0	0	1	0	0	0	
4	2010.0	WD	Normal	0	0	1	0	0	0	
...	
2925	2006.0	WD	Normal	0	0	1	0	0	0	
2926	2006.0	WD	Normal	0	0	1	0	0	0	
2927	2006.0	WD	Normal	0	0	1	0	0	0	
2928	2006.0	WD	Normal	0	0	1	0	0	0	
2929	2006.0	WD	Normal	0	0	1	0	0	0	

	RRAn	RRNe	RRNn	AsbShng	AsphShn	BrkCmn	BrkComm	BrkFace	CBlock	\
0	0	0	0	0	0	0	0	1	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	1	0	
4	0	0	0	0	0	0	0	0	0	
...	
2925	0	0	0	0	0	0	0	0	0	
2926	0	0	0	0	0	0	0	0	0	
2927	0	0	0	0	0	0	0	0	0	
2928	0	0	0	0	0	0	0	0	0	
2929	0	0	0	0	0	0	0	0	0	

	CemntBd	CmentBd	HdBoard	ImStucc	MetalSd	Other	Plywood	PreCast	\
0	0	0	0	0	0	0	1	0	
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	
...	
2925	0	0	1	0	0	0	0	0	
2926	0	0	1	0	0	0	0	0	
2927	0	0	1	0	0	0	0	0	
2928	0	0	1	0	0	0	0	0	
2929	0	0	1	0	0	0	0	0	

	Stone	Stucco	VinylSd	WdSdng	WdShing	WdShng	YearsSince1950Built	\
0	0	0	0	0	0	0	10	
1	0	0	1	0	0	0	11	

2	0	0	0	1	0	0	8
3	0	0	0	0	0	0	18
4	0	0	1	0	0	0	47
...
2925	0	0	0	0	0	0	34
2926	0	0	0	0	0	0	33
2927	0	0	0	0	0	1	42
2928	0	0	0	0	0	0	24
2929	0	0	0	0	0	0	43

YearsSince1950Remod	
0	10
1	11
2	8
3	18
4	48
...	...
2925	34
2926	33
2927	42
2928	25
2929	44

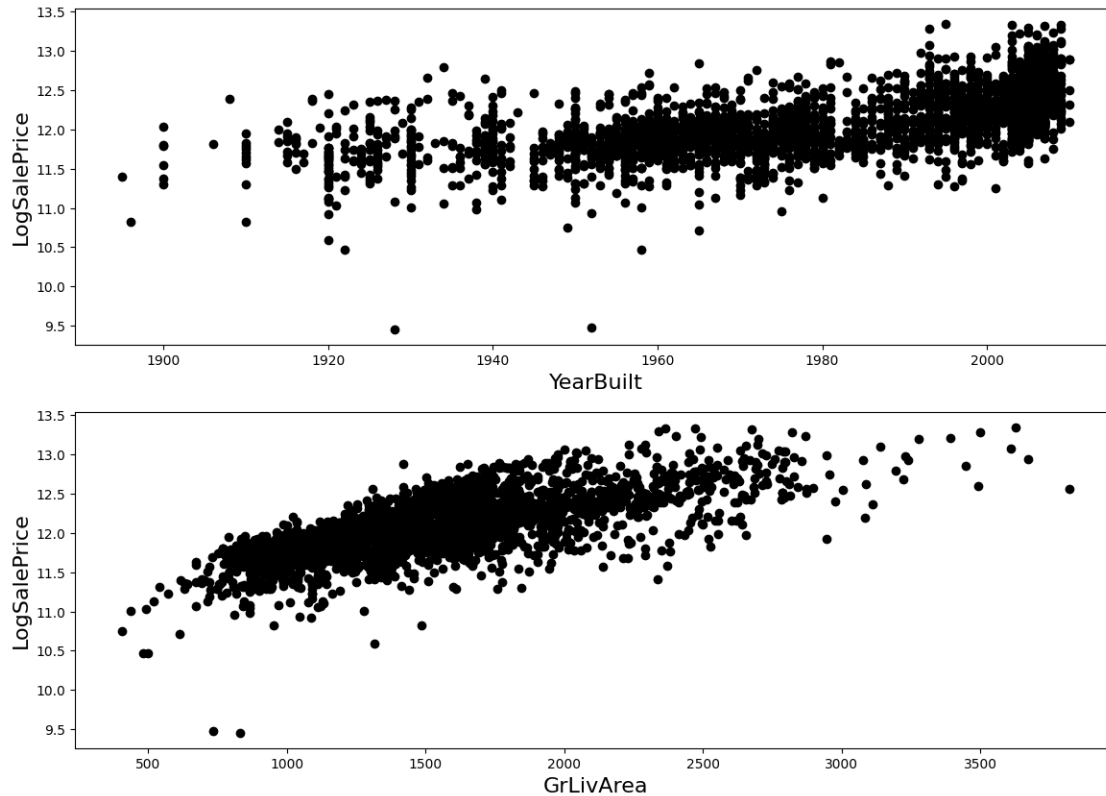
[2925 rows x 105 columns]

```
[ ]: ames = ames.loc[(ames['GarageYrBlt']<=2015)] # drop 1 obs
      ames = ames.loc[~(ames['GrLivArea']>4000)] # drop 4 additional obs
```

```
[ ]: plt.figure(figsize=(14, 10))
      plt.subplot(2,1,1)
      plt.scatter(ames['GarageYrBlt'].to_numpy(), ames['LogSalePrice'].to_numpy(),
                  color='black')
      plt.xlabel('YearBuilt', fontsize=16)
      plt.ylabel('LogSalePrice', fontsize=16)

      plt.subplot(2,1,2)
      plt.scatter(ames['GrLivArea'].to_numpy(), ames['LogSalePrice'].to_numpy(),
                  color='black')
      plt.xlabel('GrLivArea', fontsize=16)
      plt.ylabel('LogSalePrice', fontsize=16)
```

```
[ ]: Text(0, 0.5, 'LogSalePrice')
```



b) Let's apply the same 1950 transformation to GarageYrBlt.

```
[ ]: ames['YearsSince1950GarageBuilt'] = (np.clip(ames['GarageYrBlt']-1950,0,np.nan))
      ames.drop(columns=['GarageYrBlt'], inplace=True)
```

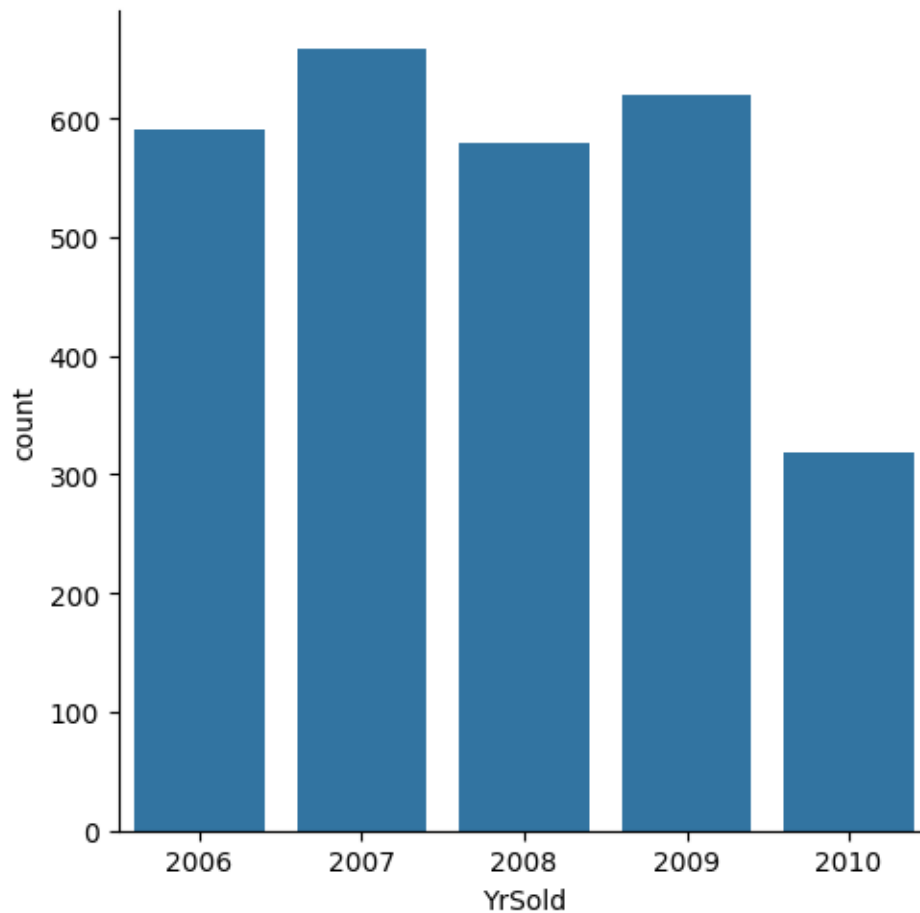
2.0.6 1.5 Numerical variables to categorical variables (Time Sold and Quality Score)

1.5.1 Time Sold: Investigate further the time when the house was sold:

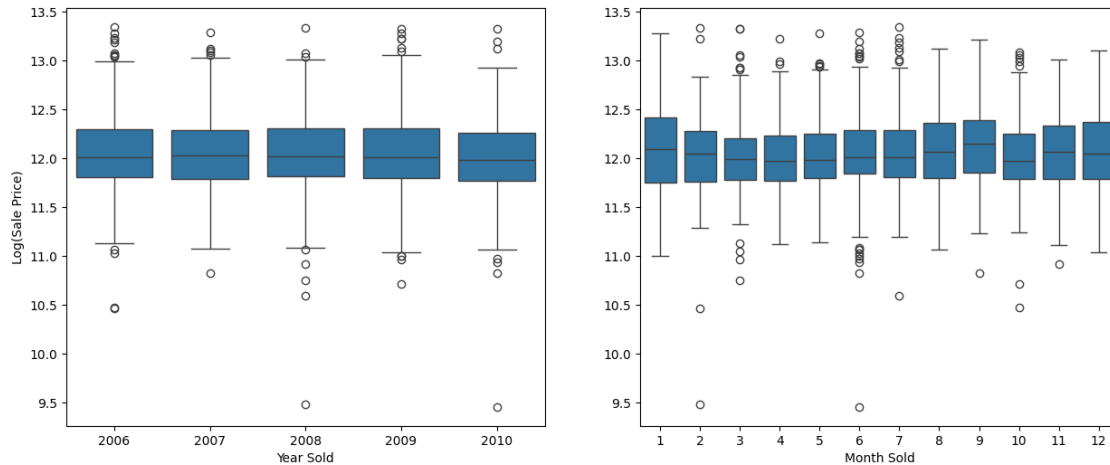
```
[ ]: ames[['YrSold', 'MoSold']] = ames[['YrSold', 'MoSold']].astype('int')
```

```
[ ]: plt.figure(figsize=(6,4))
      sns.catplot(x="YrSold", kind="count", data=ames);
```

<Figure size 600x400 with 0 Axes>



```
[ ]: fig, axs=plt.subplots(1,2, figsize=(15,6))
sns.boxplot(x="YrSold", y="LogSalePrice", data=ames, ax= axs[0])
sns.boxplot(x="MoSold", y="LogSalePrice", data=ames, ax= axs[1])
axs[0].set_xlabel('Year Sold')
axs[1].set_xlabel('Month Sold')
axs[0].set_ylabel('Log(Sale Price)')
axs[1].set_ylabel('')
plt.show()
```

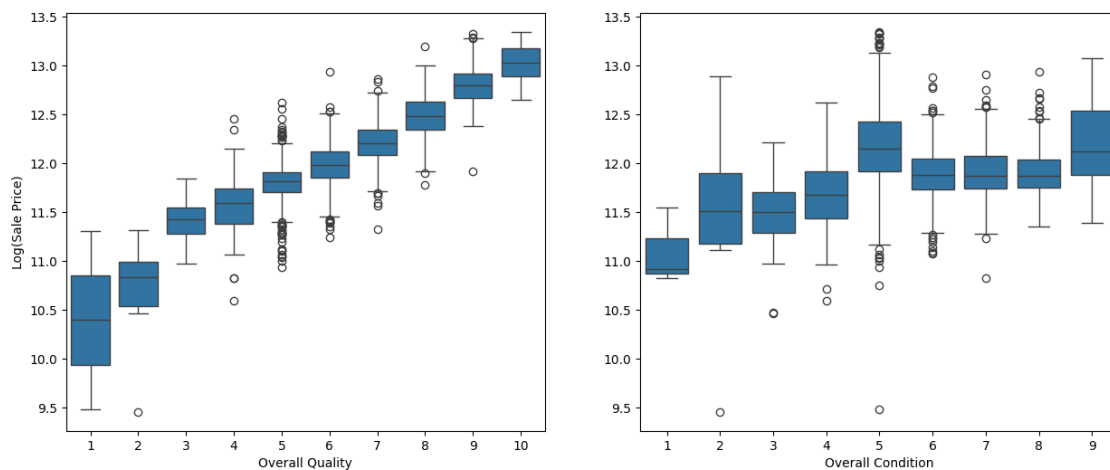


Convert YrSold and MoSold to categorical variables:

```
[ ]: ames[['YrSold', 'MoSold']] = ames[['YrSold', 'MoSold']].astype('category')
```

1.5.2 Quality Variables Let's look at the overall quality/condition variables.

```
[ ]: fig, axs=plt.subplots(1,2, figsize=(15,6))
sns.boxplot(x="OverallQual", y="LogSalePrice", data=ames, ax= axs[0])
sns.boxplot(x="OverallCond", y="LogSalePrice", data=ames, ax= axs[1])
axs[0].set_xlabel('Overall Quality')
axs[1].set_xlabel('Overall Condition')
axs[0].set_ylabel('Log(Sale Price)')
axs[1].set_ylabel('')
plt.show()
```



Let's encode them to categorical:

```
[ ]: ames[['OverallQual', 'OverallCond']] = ames[['OverallQual', 'OverallCond']].  
      ↪astype('category')
```

2.0.7 1.6 Handling NaN Values

```
[ ]: np.sum(ames.isnull(), axis=0)
```

```
[ ]: LogSalePrice           0  
     MSSubClass             0  
     MSZoning               0  
     LotFrontage           479  
     LotArea                0  
     Street                 0  
     Alley                  0  
     LotShape               0  
     LandContour            0  
     Utilities              0  
     LotConfig              0  
     LandSlope              0  
     Neighborhood           0  
     BldgType               0  
     HouseStyle             0  
     OverallQual            0  
     OverallCond            0  
     RoofStyle              0  
     RoofMatl               0  
     MasVnrType             1629  
     MasVnrArea             21  
     ExterQual              0  
     ExterCond              0  
     Foundation             0  
     BsmtQual               1  
     BsmtCond               1  
     BsmtExposure           4  
     BsmtFinType1           1  
     BsmtFinSF1             1  
     BsmtFinType2           2  
     BsmtFinSF2             1  
     BsmtUnfSF              1  
     TotalBsmtSF            1  
     Heating                0  
     HeatingQC              0  
     CentralAir             0  
     Electrical             1  
     X1stFlrSF              0
```

X2ndFlrSF	0
LowQualFinSF	0
GrLivArea	0
BsmtFullBath	2
BsmtHalfBath	2
FullBath	0
HalfBath	0
BedroomAbvGr	0
KitchenAbvGr	0
KitchenQual	0
TotRmsAbvGrd	0
Functional	0
Fireplaces	0
FireplaceQu	0
GarageType	0
GarageFinish	0
GarageCars	0
GarageArea	0
GarageQual	0
GarageCond	0
PavedDrive	0
WoodDeckSF	0
OpenPorchSF	0
EnclosedPorch	0
X3SsnPorch	0
ScreenPorch	0
PoolArea	0
PoolQC	0
Fence	0
MiscFeature	2668
MiscVal	0
MoSold	0
YrSold	0
SaleType	0
SaleCondition	0
Artery	0
Feedr	0
Norm	0
PosA	0
PosN	0
RR Ae	0
RR An	0
RR Ne	0
RR Nn	0
AsbShng	0
AsphShn	0
BrkCmn	0

BrkComm	0
BrkFace	0
CBlock	0
CemntBd	0
CmentBd	0
HdBoard	0
ImStucc	0
MetalSd	0
Other	0
Plywood	0
PreCast	0
Stone	0
Stucco	0
VinylSd	0
WdSdng	0
WdShing	0
WdShng	0
YearsSince1950Built	0
YearsSince1950Remod	0
YearsSince1950GarageBuilt	0

dtype: int64

3 In-class activity 1: Only display the column names with missing values

```
[ ]: missing_columns = ames.columns[ames.isnull().any()]
      print(missing_columns)
```

```
Index(['LotFrontage', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond',
      'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
      'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Electrical', 'BsmtFullBath',
      'BsmtHalfBath', 'MiscFeature'],
      dtype='object')
```

Dealing with NA columns:

- For numerical variables, NAs arise because some factor has already been set to 0 (e.g., there is no basement), so we convert NAs to 0.
- For categorical variables, we add a new level corresponding to whether the variable is missing from that observation. We'll do this via dummy encoding as usual.

```
[ ]: # numerical ones:
numerical_cols = ['LotFrontage', 'MasVnrArea', 'BsmtFinSF1',
                  'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath',
                  'BsmtHalfBath', 'GarageCars', 'GarageArea',
                  'GrLivArea', 'YearsSince1950GarageBuilt']
for var in numerical_cols:
```

```
print(var, ames[var].dtype)
ames.loc[np.isnan(ames[var]), [var]] = 0
```

```
LotFrontage float64
MasVnrArea float64
BsmtFinSF1 float64
BsmtFinSF2 float64
BsmtUnfSF float64
TotalBsmtSF float64
BsmtFullBath float64
BsmtHalfBath float64
GarageCars float64
GarageArea float64
GrLivArea float64
YearsSince1950GarageBuilt float64
```

```
[ ]: ames['MasVnrType'].dtype
```

```
[ ]: dtype('O')
```

```
[ ]: # categorical ones:
categorical_cols = ['MasVnrType', 'BsmtQual', 'BsmtCond', 'BsmtExposure',
                    ↪ 'BsmtFinType1',
                    'BsmtFinType2', 'Electrical', 'GarageFinish', 'GarageQual',
                    ↪ 'GarageCond', 'MiscFeature']

for var in categorical_cols:
    print(var, ames[var].dtype)
    ames.loc[(ames[var]).isna(), [var]] = 'NaN'

ames[categorical_cols]=ames[categorical_cols].astype('category')
```

```
MasVnrType object
BsmtQual object
BsmtCond object
BsmtExposure object
BsmtFinType1 object
BsmtFinType2 object
Electrical object
GarageFinish object
GarageQual object
GarageCond object
MiscFeature object
```

```
[ ]: # check again:
print(np.sum(ames.isnull().any()))
```

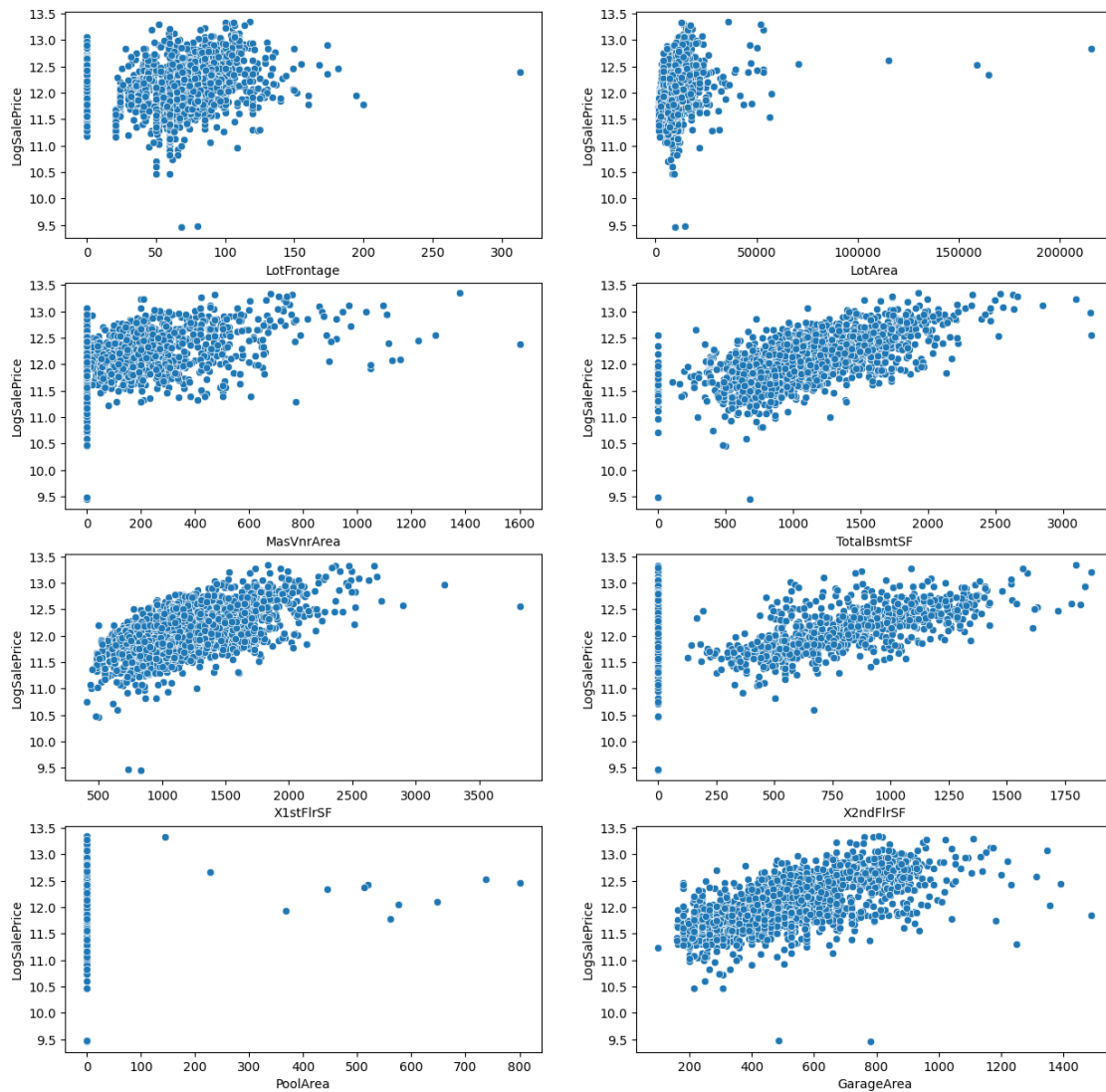
0

3.0.1 1.7 Some More EDA

3.0.2 1.7.1 Continuous variables

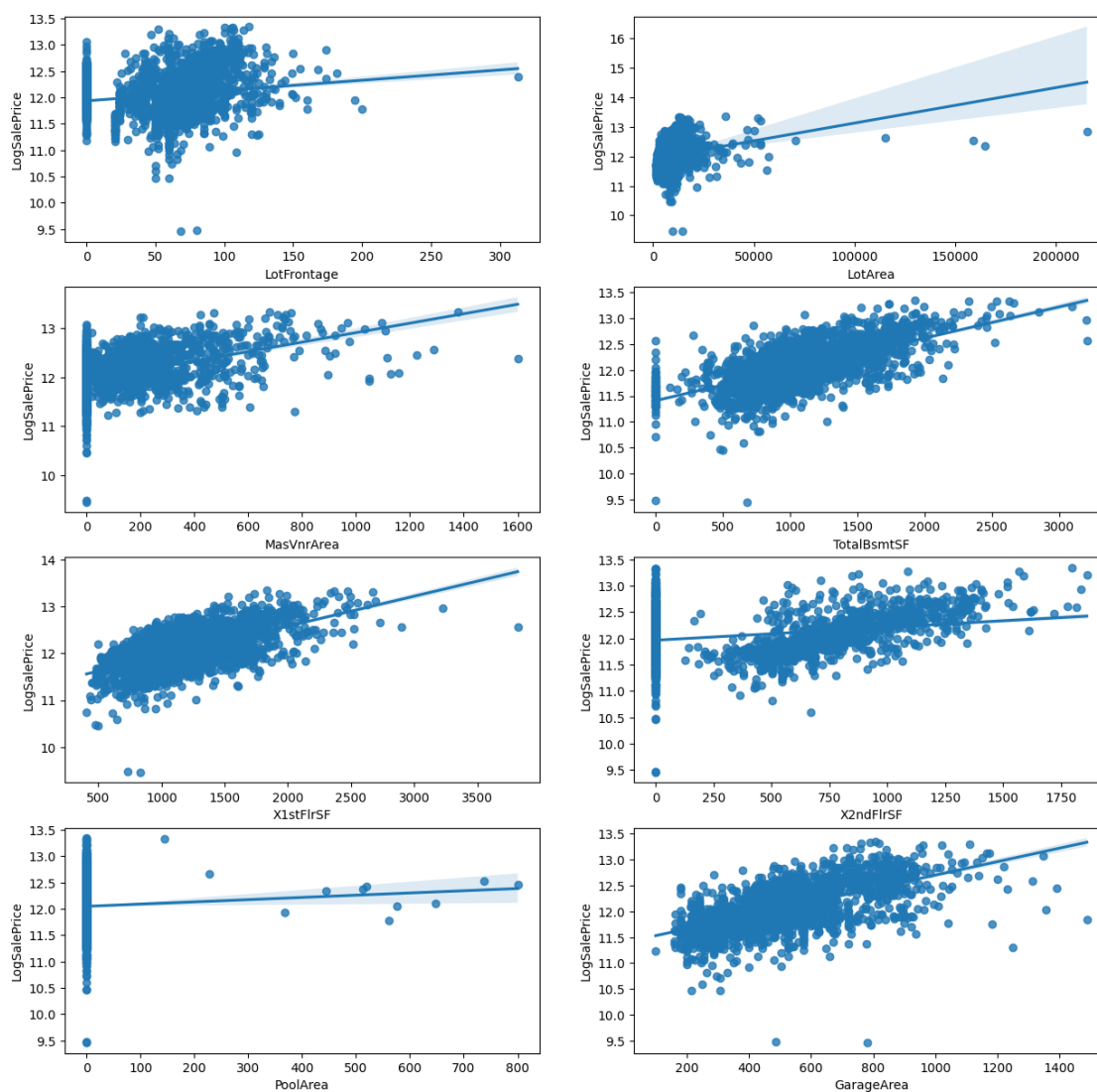
```
[ ]: # a) Scattered plots
fig, axs=plt.subplots(4,2, figsize=(15,15))
sns.scatterplot(data=ames, x="LotFrontage", y="LogSalePrice", ax= axs[0,0])
sns.scatterplot(data=ames, x="LotArea", y="LogSalePrice", ax= axs[0,1])
sns.scatterplot(data=ames, x="MasVnrArea", y="LogSalePrice", ax= axs[1,0])
sns.scatterplot(data=ames, x="TotalBsmtSF", y="LogSalePrice", ax= axs[1,1])
sns.scatterplot(data=ames, x="X1stFlrSF", y="LogSalePrice", ax= axs[2,0])
sns.scatterplot(data=ames, x="X2ndFlrSF", y="LogSalePrice", ax= axs[2,1])
sns.scatterplot(data=ames, x="PoolArea", y="LogSalePrice", ax= axs[3,0])
sns.scatterplot(data=ames, x="GarageArea", y="LogSalePrice", ax= axs[3,1])
```

```
[ ]: <Axes: xlabel='GarageArea', ylabel='LogSalePrice'>
```



```
[ ]: # b) Smoothed versions of those plots (with a trend line).
fig, axs=plt.subplots(4,2, figsize=(15,15))
sns.regplot(data=ames, x="LotFrontage", y="LogSalePrice", ax= axs[0,0])
sns.regplot(data=ames, x="LotArea", y="LogSalePrice", ax= axs[0,1])
sns.regplot(data=ames, x="MasVnrArea", y="LogSalePrice", ax= axs[1,0])
sns.regplot(data=ames, x="TotalBsmtSF", y="LogSalePrice", ax= axs[1,1])
sns.regplot(data=ames, x="X1stFlrSF", y="LogSalePrice", ax= axs[2,0])
sns.regplot(data=ames, x="X2ndFlrSF", y="LogSalePrice", ax= axs[2,1])
sns.regplot(data=ames, x="PoolArea", y="LogSalePrice", ax= axs[3,0])
sns.regplot(data=ames, x="GarageArea", y="LogSalePrice", ax= axs[3,1])
```

```
[ ]: <Axes: xlabel='GarageArea', ylabel='LogSalePrice'>
```



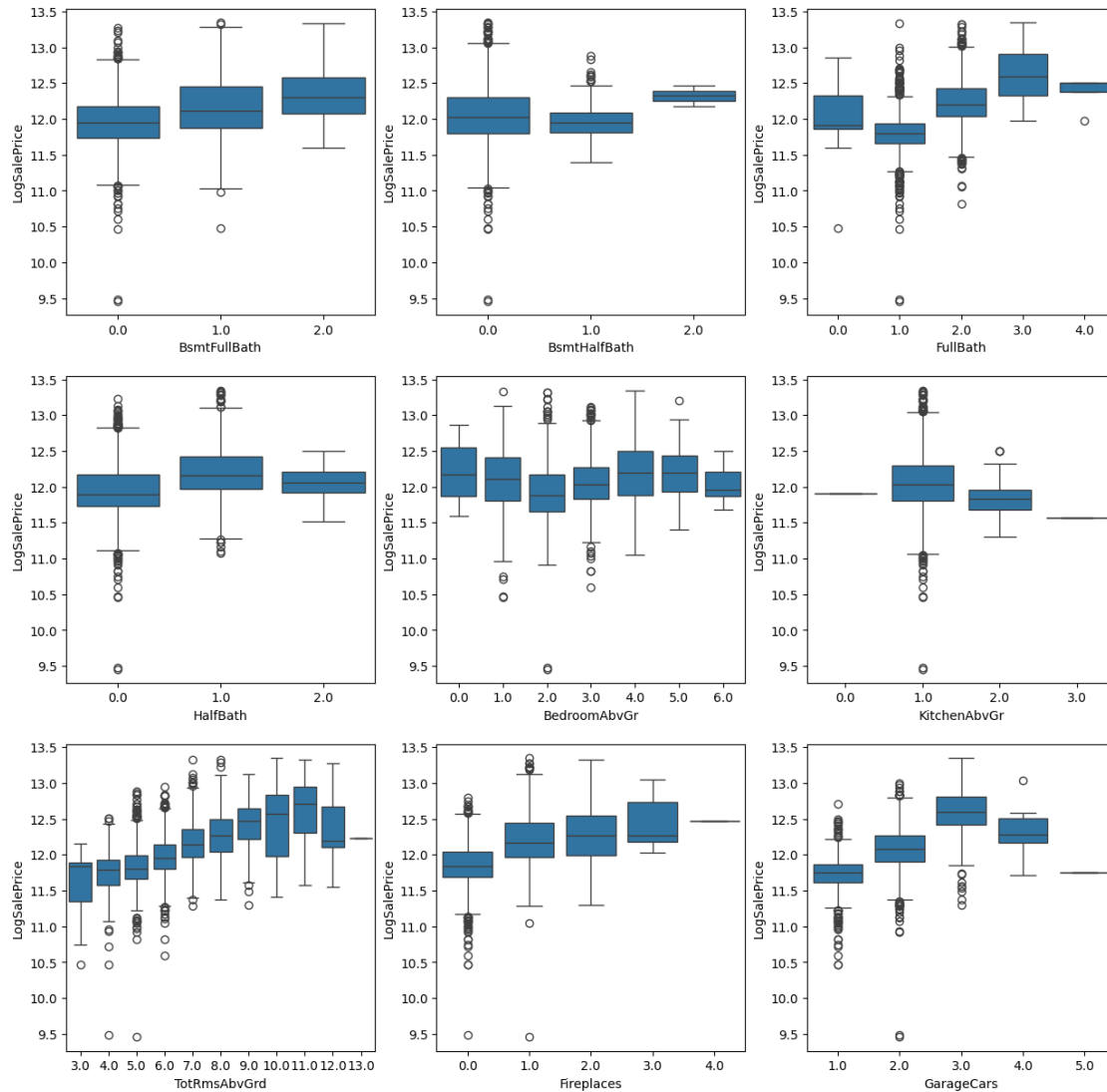
Note: It appears that there are nonlinear relationships. Later, we will use polynomials to enhance our models.

3.0.3 1.7.2 Discrete Variables

Let's look at discrete variables now.

```
[ ]: fig, axs=plt.subplots(3,3, figsize=(15,15))
sns.boxplot(data=ames, x="BsmtFullBath", y="LogSalePrice", ax= axs[0,0])
sns.boxplot(data=ames, x="BsmtHalfBath", y="LogSalePrice", ax= axs[0,1])
sns.boxplot(data=ames, x="FullBath", y="LogSalePrice", ax= axs[0,2])
sns.boxplot(data=ames, x="HalfBath", y="LogSalePrice", ax= axs[1,0])
sns.boxplot(data=ames, x="BedroomAbvGr", y="LogSalePrice", ax= axs[1,1])
sns.boxplot(data=ames, x="KitchenAbvGr", y="LogSalePrice", ax= axs[1,2])
sns.boxplot(data=ames, x="TotRmsAbvGrd", y="LogSalePrice", ax= axs[2,0])
sns.boxplot(data=ames, x="Fireplaces", y="LogSalePrice", ax= axs[2,1])
sns.boxplot(data=ames, x="GarageCars", y="LogSalePrice", ax= axs[2,2])

[ ]: <Axes: xlabel='GarageCars', ylabel='LogSalePrice'>
```



Let's convert those all to factors.

```
[ ]: discrete_cols = ['BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
    ↪ 'BedroomAbvGr',
    ↪ 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageCars',
    ↪ 'MSSubClass']
ames[discrete_cols] = ames[discrete_cols].astype('int').astype('category')
```

3.0.4 1.7.3 Other Categorical Variables

We still have many columns that are categorical. We must encode them before passing them to our models

```
[ ]: still_categorical = ames.columns[ames.dtypes == 'object']
for col in still_categorical:
    print(col, ':\n', ames[col].unique())
```

```
MSZoning :
['RL' 'RH' 'FV' 'RM' 'C' 'I' 'A']
Street :
['Pave' 'Grvl']
Alley :
['NoAccess' 'Pave' 'Grvl']
LotShape :
['IR1' 'Reg' 'IR2' 'IR3']
LandContour :
['Lvl' 'HLS' 'Bnk' 'Low']
Utilities :
['AllPub' 'NoSewr' 'NoSeWa']
LotConfig :
['Corner' 'Inside' 'CulDSac' 'FR2' 'FR3']
LandSlope :
['Gtl' 'Mod' 'Sev']
Neighborhood :
['NAMES' 'Gilbert' 'StoneBr' 'NWAmes' 'Somerst' 'BrDale' 'NPkVill'
'NridgHt' 'Blmngtn' 'NoRidge' 'SawyerW' 'Sawyer' 'Greens' 'OldTown'
'BrkSide' 'IDOTRR' 'ClearCr' 'SWISU' 'Edwards' 'CollgCr' 'Crawfor'
'Blueste' 'Mitchel' 'Timber' 'MeadowV' 'Veenker' 'GrnHill' 'Landmrk']
BldgType :
['1Fam' 'TwnhsE' 'Twnhs' 'Duplex' '2fmCon']
HouseStyle :
['1Story' '2Story' '1.5Fin' 'SFoyer' 'SLvl' '2.5Unf' '1.5Unf' '2.5Fin']
RoofStyle :
['Hip' 'Gable' 'Mansard' 'Gambrel' 'Shed' 'Flat']
RoofMatl :
['CompShg' 'WdShake' 'WdShngl' 'Tar&Grv' 'Membran' 'Roll' 'Metal']
ExterQual :
['TA' 'Gd' 'Ex' 'Fa']
ExterCond :
['TA' 'Gd' 'Fa' 'Po' 'Ex']
Foundation :
['CBlock' 'PConc' 'Wood' 'BrkTil' 'Slab' 'Stone']
Heating :
['GasA' 'GasW' 'Grav' 'Wall' 'Floor' 'OthW']
HeatingQC :
['Fa' 'TA' 'Ex' 'Gd' 'Po']
CentralAir :
['Y' 'N']
KitchenQual :
['TA' 'Gd' 'Ex' 'Fa' 'Po']
Functional :
```

```

['Typ' 'Mod' 'Min1' 'Min2' 'Maj1' 'Maj2' 'Sal' 'Sev']
FireplaceQu :
['Gd' 'NoFirePlace' 'TA' 'Po' 'Ex' 'Fa']
GarageType :
['Attchd' 'BuiltIn' 'Basment' 'Detchd' 'CarPort' '2Types']
PavedDrive :
['P' 'Y' 'N']
PoolQC :
['NoPool' 'Ex' 'Gd' 'TA' 'Fa']
Fence :
['NoFence' 'MnPrv' 'GdPrv' 'GdWo' 'MnWw']
SaleType :
['WD' 'New' 'COD' 'Con' 'ConLD' 'Oth' 'ConLw' 'ConLI' 'CWD' 'VWD']
SaleCondition :
['Normal' 'Partial' 'Family' 'Abnorml' 'Alloca' 'AdjLand']

```

```
[ ]: ames[still_categorical] = ames[still_categorical].astype('category')
```

```
[ ]: ames.head()
```

```
[ ]:
LogSalePrice MSSubClass MSZoning LotFrontage LotArea Street Alley \
0 12.278393 20 RL 141.0 31770.0 Pave NoAccess
1 11.561716 20 RH 80.0 11622.0 Pave NoAccess
2 12.055250 20 RL 81.0 14267.0 Pave NoAccess
3 12.404924 20 RL 93.0 11160.0 Pave NoAccess
4 12.154253 60 RL 74.0 13830.0 Pave NoAccess
```

```

LotShape LandContour Utilities LotConfig LandSlope Neighborhood BldgType \
0 IR1 Lvl AllPub Corner Gtl NAmes 1Fam
1 Reg Lvl AllPub Inside Gtl NAmes 1Fam
2 IR1 Lvl AllPub Corner Gtl NAmes 1Fam
3 Reg Lvl AllPub Corner Gtl NAmes 1Fam
4 IR1 Lvl AllPub Inside Gtl Gilbert 1Fam

```

```

HouseStyle OverallQual OverallCond RoofStyle RoofMatl MasVnrType \
0 1Story 6 5 Hip CompShg Stone
1 1Story 5 6 Gable CompShg NaN
2 1Story 6 6 Hip CompShg BrkFace
3 1Story 7 5 Hip CompShg NaN
4 2Story 5 5 Gable CompShg NaN

```

```

MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure \
0 112.0 TA TA CBlock TA Gd Gd
1 0.0 TA TA CBlock TA TA No
2 108.0 TA TA CBlock TA TA No
3 0.0 Gd TA CBlock TA TA No
4 0.0 TA TA PConc Gd TA No

```

	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	\
0	BLQ	639.0	Unf	0.0	441.0	1080.0	
1	Rec	468.0	LwQ	144.0	270.0	882.0	
2	ALQ	923.0	Unf	0.0	406.0	1329.0	
3	ALQ	1065.0	Unf	0.0	1045.0	2110.0	
4	GLQ	791.0	Unf	0.0	137.0	928.0	

	Heating	HeatingQC	CentralAir	Electrical	X1stFlrSF	X2ndFlrSF	LowQualFinSF	\
0	GasA	Fa	Y	SBrkr	1656.0	0.0	0.0	
1	GasA	TA	Y	SBrkr	896.0	0.0	0.0	
2	GasA	TA	Y	SBrkr	1329.0	0.0	0.0	
3	GasA	Ex	Y	SBrkr	2110.0	0.0	0.0	
4	GasA	Gd	Y	SBrkr	928.0	701.0	0.0	

	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	\
0	1656.0	1	0	1	0	3	
1	896.0	0	0	1	0	2	
2	1329.0	0	0	1	1	3	
3	2110.0	1	0	2	1	3	
4	1629.0	0	0	2	1	3	

	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	\
0	1	TA	7	Typ	2	Gd	
1	1	TA	5	Typ	0	NoFirePlace	
2	1	Gd	6	Typ	0	NoFirePlace	
3	1	Ex	8	Typ	2	TA	
4	1	TA	6	Typ	1	TA	

	GarageType	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond	\
0	Attchd	Fin	2	528.0	TA	TA	
1	Attchd	Unf	1	730.0	TA	TA	
2	Attchd	Unf	1	312.0	TA	TA	
3	Attchd	Fin	2	522.0	TA	TA	
4	Attchd	Fin	2	482.0	TA	TA	

	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	X3SsnPorch	ScreenPorch	\
0	P	210.0	62.0	0.0	0.0	0.0	
1	Y	140.0	0.0	0.0	0.0	120.0	
2	Y	393.0	36.0	0.0	0.0	0.0	
3	Y	0.0	0.0	0.0	0.0	0.0	
4	Y	212.0	34.0	0.0	0.0	0.0	

	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	\
0	0.0	NoPool	NoFence	NaN	0.0	5	2010	WD	
1	0.0	NoPool	MnPrv	NaN	0.0	6	2010	WD	
2	0.0	NoPool	NoFence	Gar2	12500.0	6	2010	WD	

3	0.0	NoPool	NoFence		NaN	0.0	4	2010	WD
4	0.0	NoPool	MnPrv		NaN	0.0	3	2010	WD

	SaleCondition	Artery	Feedr	Norm	PosA	PosN	RRAe	RRAn	RRNe	RRNn	\
0	Normal	0	0	1	0	0	0	0	0	0	
1	Normal	0	1	1	0	0	0	0	0	0	
2	Normal	0	0	1	0	0	0	0	0	0	
3	Normal	0	0	1	0	0	0	0	0	0	
4	Normal	0	0	1	0	0	0	0	0	0	

	AsbShng	AsphShn	BrkCmn	BrkComm	BrkFace	CBlock	CemntBd	CmentBd	\
0	0	0	0	0	1	0	0	0	
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	1	0	0	0	
4	0	0	0	0	0	0	0	0	

	HdBoard	ImStucc	MetalSd	Other	Plywood	PreCast	Stone	Stucco	VinylSd	\
0	0	0	0	0	1	0	0	0	0	
1	0	0	0	0	0	0	0	0	1	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	1	

	WdSdng	WdShing	WdShng	YearsSince1950Built	YearsSince1950Remod	\
0	0	0	0	10	10	
1	0	0	0	11	11	
2	1	0	0	8	8	
3	0	0	0	18	18	
4	0	0	0	47	48	

	YearsSince1950GarageBuilt
0	10.0
1	11.0
2	8.0
3	18.0
4	47.0

```
[ ]:
```

3.1 2. Regression Analysis and Regularization Methods

3.1.1 Helper Functions

```
[ ]: def OSR2(y_train, y_test, y_pred):
    SSE = np.sum((y_test - y_pred)**2)
```



```
SST = np.sum((y_test - np.mean(y_train))**2)

return (1 - SSE/SST)
```

```
[ ]: def MAE(y_test, y_pred):

    return (np.mean(abs(y_test - y_pred)))
```

```
[ ]: def RMSE(y_test, y_pred):

    return np.sqrt(np.mean((y_test - y_pred)**2))
```

```
[ ]: def print_metrics(model, X_train, y_train, X_test, y_test,
    ↪flag_log_sale_price=False):

    if (flag_log_sale_price == True):

        y_pred_train = pd.Series(model.predict(X_train)).reset_index(drop=True)
        y_pred_test = pd.Series(model.predict(X_test)).reset_index(drop=True)
        y_train = y_train.copy().reset_index(drop=True)
        y_test = y_test.copy().reset_index(drop=True)

        print("\nMetrics for Log(Sale Price):\n")

    elif (flag_log_sale_price == False):

        y_pred_train = pd.Series(model.predict(X_train)).apply(np.exp).
    ↪reset_index(drop=True)
        y_pred_test = pd.Series(model.predict(X_test)).apply(np.exp).
    ↪reset_index(drop=True)
        y_train = y_train.copy().apply(np.exp).reset_index(drop=True)
        y_test = y_test.copy().apply(np.exp).reset_index(drop=True)

        print("\nMetrics for Sale Price:\n")

    print('Training R2', OSR2(y_train, y_train, y_pred_train))
    print('Training MAE', MAE(y_train, y_pred_train))
    print('Training RMSE', RMSE(y_train, y_pred_train))

    print('Out-of-sample R2', OSR2(y_train, y_test, y_pred_test))
    print('Out-of-sample MAE', MAE(y_test, y_pred_test))
    print('Out-of-sample RMSE', RMSE(y_test, y_pred_test))

    return None
```

4 In-class activity 2: Randomly select 30% rows as the testing set and the other 70% as the training set

```
[ ]: test_df = ames.sample(n=int(len(ames) * 0.3), random_state=42)
train_df = ames.drop(test_df.index)
test_df.shape
```

```
[ ]: (829, 105)
```

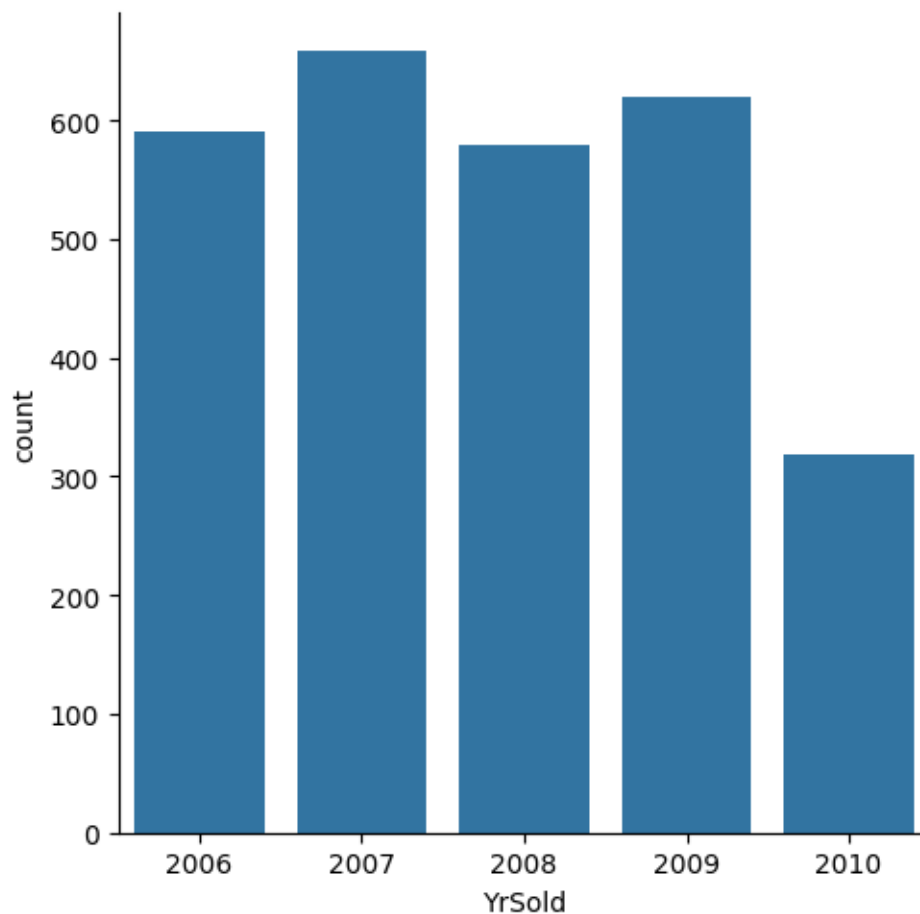
```
[ ]: train_df.shape
```

```
[ ]: (1936, 105)
```

4.0.1 Sequential Split

```
[ ]: sns.catplot(x="YrSold", kind="count", data=ames)
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x16a7be240>
```



```
[ ]: ames.loc[ames['YrSold'].isin([2006, 2007, 2008])]
```

```
[ ]:      LogSalePrice MSSubClass MSZoning  LotFrontage  LotArea Street  Alley \
989      12.081076      20      RL      87.0  11029.0  Pave  NoAccess
990      12.377923      20      RL      0.0  12925.0  Pave  NoAccess
991      12.239991      60      RL      85.0  11075.0  Pave  NoAccess
992      12.141534      60      RL      72.0   8702.0  Pave  NoAccess
993      12.013701      60      RL      65.0   8139.0  Pave  NoAccess
...      ...      ...      ...      ...      ...      ...
2924     11.782953      20      RL     160.0  20000.0  Pave  NoAccess
2925     11.867097      80      RL      37.0   7937.0  Pave  NoAccess
2926     11.782953      20      RL      0.0   8885.0  Pave  NoAccess
2928     12.043554      20      RL      77.0  10010.0  Pave  NoAccess
2929     12.144197      60      RL      74.0   9627.0  Pave  NoAccess
```

```
      LotShape LandContour Utilities LotConfig LandSlope Neighborhood BldgType \
989      IR1      Lvl      AllPub      Corner      Gtl      Names      1Fam
990      IR1      Lvl      AllPub      Corner      Gtl      Names      1Fam
991      Reg      Lvl      AllPub      Inside      Gtl      Names      1Fam
992      IR1      Lvl      AllPub      Inside      Gtl      Gilbert      1Fam
993      Reg      Lvl      AllPub      Inside      Gtl      Gilbert      1Fam
...      ...      ...      ...      ...      ...      ...
2924      Reg      Lvl      AllPub      Inside      Gtl      Mitchel      1Fam
2925      IR1      Lvl      AllPub      CulDSac      Gtl      Mitchel      1Fam
2926      IR1      Low      AllPub      Inside      Mod      Mitchel      1Fam
2928      Reg      Lvl      AllPub      Inside      Mod      Mitchel      1Fam
2929      Reg      Lvl      AllPub      Inside      Mod      Mitchel      1Fam
```

```
      HouseStyle OverallQual OverallCond RoofStyle RoofMatl MasVnrType \
989      1Story      6      8      Hip      CompShg      NaN
990      1Story      6      7      Gable      CompShg      NaN
991      2Story      6      5      Gable      CompShg      NaN
992      2Story      6      5      Gable      CompShg      NaN
993      2Story      6      5      Gable      CompShg      BrkFace
...      ...      ...      ...      ...      ...
2924      1Story      5      7      Gable      CompShg      NaN
2925      SLvl      6      6      Gable      CompShg      NaN
2926      1Story      5      5      Gable      CompShg      NaN
2928      1Story      5      5      Gable      CompShg      NaN
2929      2Story      7      5      Gable      CompShg      BrkFace
```

```
      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond \
989      0.0      Ex      TA      CBlock      Gd      TA
990      0.0      TA      TA      CBlock      TA      TA
991      0.0      TA      TA      CBlock      Fa      TA
992      0.0      TA      TA      PConc      TA      TA
993      119.0      TA      TA      PConc      Gd      TA
```

...
2924	0.0	TA	TA	CBlock	TA	TA
2925	0.0	TA	TA	CBlock	TA	TA
2926	0.0	TA	TA	CBlock	Gd	TA
2928	0.0	TA	TA	CBlock	Gd	TA
2929	94.0	TA	TA	PConc	Gd	TA

	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
989	No	ALQ	528.0	BLQ	411.0	
990	Mn	BLQ	865.0	Unf	0.0	
991	Mn	ALQ	500.0	LwQ	276.0	
992	No	BLQ	706.0	Unf	0.0	
993	No	ALQ	476.0	Unf	0.0	
...	
2924	No	ALQ	1224.0	Unf	0.0	
2925	Av	GLQ	819.0	Unf	0.0	
2926	Av	BLQ	301.0	ALQ	324.0	
2928	Av	ALQ	1071.0	LwQ	123.0	
2929	Av	LwQ	758.0	Unf	0.0	

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	Electrical	\
989	245.0	1184.0	GasA	Ex	Y	SBrkr	
990	340.0	1205.0	GasA	Ex	Y	SBrkr	
991	176.0	952.0	GasA	TA	Y	SBrkr	
992	220.0	926.0	GasA	Ex	Y	SBrkr	
993	204.0	680.0	GasA	Gd	Y	SBrkr	
...	
2924	0.0	1224.0	GasA	Ex	Y	SBrkr	
2925	184.0	1003.0	GasA	TA	Y	SBrkr	
2926	239.0	864.0	GasA	TA	Y	SBrkr	
2928	195.0	1389.0	GasA	Gd	Y	SBrkr	
2929	238.0	996.0	GasA	Ex	Y	SBrkr	

	X1stFlrSF	X2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	\
989	1414.0	0.0	0.0	1414.0	1	0	
990	2117.0	0.0	0.0	2117.0	0	0	
991	1092.0	1020.0	0.0	2112.0	0	0	
992	926.0	678.0	0.0	1604.0	0	0	
993	680.0	790.0	0.0	1470.0	0	0	
...	
2924	1224.0	0.0	0.0	1224.0	1	0	
2925	1003.0	0.0	0.0	1003.0	1	0	
2926	902.0	0.0	0.0	902.0	1	0	
2928	1389.0	0.0	0.0	1389.0	1	0	
2929	996.0	1004.0	0.0	2000.0	0	0	

FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	\
----------	----------	--------------	--------------	-------------	--------------	---

989	1	0	3	1	TA	6
990	2	1	4	1	TA	7
991	2	1	4	1	TA	9
992	2	1	3	1	TA	7
993	2	1	3	1	TA	7
...
2924	1	0	4	1	TA	7
2925	1	0	3	1	TA	6
2926	1	0	2	1	TA	5
2928	1	0	2	1	TA	6
2929	2	1	3	1	TA	9

	Functional	Fireplaces	FireplaceQu	GarageType	GarageFinish	GarageCars	\
989	Min1	1	TA	Attchd	Unf	2	
990	Typ	2	Gd	Attchd	Fin	2	
991	Typ	2	Gd	Attchd	Unf	2	
992	Typ	1	TA	Attchd	Fin	2	
993	Typ	1	TA	BuiltIn	Fin	2	
...	
2924	Typ	1	TA	Detchd	Unf	2	
2925	Typ	0	NoFirePlace	Detchd	Unf	2	
2926	Typ	0	NoFirePlace	Attchd	Unf	2	
2928	Typ	1	TA	Attchd	RFn	2	
2929	Typ	1	TA	Attchd	Fin	3	

	GarageArea	GarageQual	GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	\
989	601.0	TA	TA	Y	0.0	51.0	
990	550.0	TA	TA	Y	0.0	42.0	
991	576.0	TA	TA	Y	280.0	0.0	
992	470.0	TA	TA	Y	0.0	36.0	
993	420.0	TA	TA	Y	192.0	49.0	
...	
2924	576.0	TA	TA	Y	474.0	0.0	
2925	588.0	TA	TA	Y	120.0	0.0	
2926	484.0	TA	TA	Y	164.0	0.0	
2928	418.0	TA	TA	Y	240.0	38.0	
2929	650.0	TA	TA	Y	190.0	48.0	

	EnclosedPorch	X3SsnPorch	ScreenPorch	PoolArea	PoolQC	Fence	\
989	0.0	0.0	190.0	0.0	NoPool	NoFence	
990	0.0	0.0	0.0	0.0	NoPool	NoFence	
991	0.0	0.0	0.0	0.0	NoPool	NoFence	
992	0.0	0.0	0.0	0.0	NoPool	NoFence	
993	0.0	0.0	0.0	0.0	NoPool	NoFence	
...	
2924	0.0	0.0	0.0	0.0	NoPool	NoFence	
2925	0.0	0.0	0.0	0.0	NoPool	GdPrv	

2926	0.0	0.0	0.0	0.0	NoPool	MnPrv
2928	0.0	0.0	0.0	0.0	NoPool	NoFence
2929	0.0	0.0	0.0	0.0	NoPool	NoFence

	MiscFeature	MiscVal	MoSold	YrSold	SaleType	SaleCondition	Artery	Feedr	\
989	NaN	0.0	5	2008	WD	Normal	0	0	
990	NaN	0.0	5	2008	WD	Normal	0	0	
991	NaN	0.0	6	2008	WD	Normal	0	0	
992	NaN	0.0	4	2008	WD	Normal	0	0	
993	NaN	0.0	10	2008	WD	Normal	0	0	
...	
2924	NaN	0.0	9	2006	WD	Abnorml	0	0	
2925	NaN	0.0	3	2006	WD	Normal	0	0	
2926	NaN	0.0	6	2006	WD	Normal	0	0	
2928	NaN	0.0	4	2006	WD	Normal	0	0	
2929	NaN	0.0	11	2006	WD	Normal	0	0	

	Norm	PosA	PosN	RR Ae	RR An	RR Ne	RR Nn	AsbShng	AsphShn	BrkCmn	\
989	1	0	0	0	0	0	0	0	0	0	
990	1	0	0	0	0	0	0	0	0	0	
991	1	0	0	0	0	0	0	0	0	0	
992	1	0	0	0	0	0	0	0	0	0	
993	1	0	0	0	0	0	0	0	0	0	
...	
2924	1	0	0	0	0	0	0	0	0	0	
2925	1	0	0	0	0	0	0	0	0	0	
2926	1	0	0	0	0	0	0	0	0	0	
2928	1	0	0	0	0	0	0	0	0	0	
2929	1	0	0	0	0	0	0	0	0	0	

	BrkComm	BrkFace	CBlock	CemntBd	CmentBd	HdBoard	ImStucc	MetalSd	\
989	0	0	0	0	0	0	0	1	
990	0	1	0	0	0	0	0	0	
991	0	0	0	0	0	1	0	0	
992	0	0	0	0	0	0	0	0	
993	0	0	0	0	0	0	0	0	
...	
2924	0	0	0	0	0	0	0	0	
2925	0	0	0	0	0	1	0	0	
2926	0	0	0	0	0	1	0	0	
2928	0	0	0	0	0	1	0	0	
2929	0	0	0	0	0	1	0	0	

	Other	Plywood	PreCast	Stone	Stucco	VinylSd	WdSdng	WdShing	\
989	0	0	0	0	0	0	0	0	
990	0	1	0	0	0	0	0	0	
991	0	0	0	0	0	0	0	0	

992	0	0	0	0	0	1	0	0
993	0	0	0	0	0	1	0	0
...
2924	0	0	0	0	0	1	0	0
2925	0	0	0	0	0	0	0	0
2926	0	0	0	0	0	0	0	0
2928	0	0	0	0	0	0	0	0
2929	0	0	0	0	0	0	0	0

	WdShng	YearsSince1950Built	YearsSince1950Remod	\
989	0	8	52	
990	0	20	20	
991	0	19	19	
992	0	47	48	
993	0	45	46	
...	
2924	0	10	46	
2925	0	34	34	
2926	0	33	33	
2928	0	24	25	
2929	0	43	44	

	YearsSince1950GarageBuilt
989	40.0
990	20.0
991	19.0
992	47.0
993	45.0
...	...
2924	10.0
2925	34.0
2926	33.0
2928	25.0
2929	43.0

[1828 rows x 105 columns]

5 In-class activity 3: If we use a categorical variable (for example, YrSold), to split the training set and testing set, can we use this categorical variable as a predictor? Why?

We could not bec

```
[ ]: ames_train = ames.loc[ames['YrSold'].isin([2006, 2007, 2008])]
      ames_test = ames.loc[ames['YrSold'].isin([2009, 2010])]
```

```
ames = ames.drop(columns = ['YrSold'])
ames_train = ames_train.drop(columns = ['YrSold'])
ames_test = ames_test.drop(columns = ['YrSold'])

print(ames.shape, ames_train.shape, ames_test.shape)
```

(2765, 104) (1828, 104) (937, 104)

5.1 2.1 Naive Linear Regression

a) with only original features (without polynomial features)

```
[ ]: print(ames_train.shape)
all_columns = "+".join(ames_train.columns.difference(["LogSalePrice"]))
my_formula = "LogSalePrice~" + all_columns + '-1'
print(my_formula)

mod_naive = smf.ols(my_formula, data=ames_train)
nlr = mod_naive.fit()

print(nlr.summary())
```

(1828, 104)

LogSalePrice~Alley+Artery+AsbShng+AsphShn+BedroomAbvGr+BldgType+BrkCmn+BrkComm+BrkFace+BsmCond+BsmExposure+BsmFinSF1+BsmFinSF2+BsmFinType1+BsmFinType2+BsmFullBath+BsmHalfBath+BsmQual+BsmUnfSF+CBlock+CemntBd+CentralAir+CmentBd+Electrical+EnclosedPorch+ExterCond+ExterQual+Feedr+Fence+FireplaceQu+Fireplaces+Foundation+FullBath+Functional+GarageArea+GarageCars+GarageCond+GarageFinish+GarageQual+GarageType+GrLivArea+HalfBath+HdBoard+Heating+HeatingQC+HouseStyle+ImStucc+KitchenAbvGr+KitchenQual+LandContour+LandSlope+LotArea+LotConfig+LotFrontage+LotShape+LowQualFinSF+MSSubClass+MSZoning+MasVnrArea+MasVnrType+MetalSd+MiscFeature+MiscVal+MoSold+Neighborhood+Norm+OpenPorchSF+Other+OverallCond+OverallQual+PavedDrive+Plywood+PoolArea+PoolQC+PosA+PosN+PreCast+RR Ae+RRAn+RRNe+RRNn+RoofMatl+RoofStyle+SaleCondition+SaleType+ScreenPorch+Stone+Street+Stucco+TotRmsAbvGrd+TotalBsmSF+Utilities+VinylSd+WdSdng+WdShng+WdShng+WoodDeckSF+X1stFlrSF+X2ndFlrSF+X3SsnPorch+YearsSince1950Built+YearsSince1950GarageBuilt+YearsSince1950Remod-1

OLS Regression Results

```
=====
Dep. Variable:          LogSalePrice    R-squared:                0.960
Model:                  OLS             Adj. R-squared:           0.952
Method:                 Least Squares    F-statistic:             121.8
Date:                   Fri, 01 Nov 2024  Prob (F-statistic):       0.00
Time:                   18:18:55         Log-Likelihood:          2091.0
No. Observations:      1828             AIC:                    -3574.
Df Residuals:          1524             BIC:                    -1899.
Df Model:               303
Covariance Type:        nonrobust
=====
=====
```


[0.025 0.975]		coef	std err	t	P> t

Alley[Grvl]		4.9744	0.139	35.709	0.000
4.701	5.248				
Alley[NoAccess]		4.9924	0.139	36.001	0.000
4.720	5.264				
Alley[Pave]		5.0001	0.140	35.839	0.000
4.726	5.274				
BedroomAbvGr[T.1]		-0.0148	0.075	-0.198	0.843
-0.162	0.132				
BedroomAbvGr[T.2]		-0.0141	0.075	-0.187	0.851
-0.161	0.133				
BedroomAbvGr[T.3]		-0.0177	0.075	-0.235	0.814
-0.166	0.130				
BedroomAbvGr[T.4]		-0.0183	0.076	-0.241	0.809
-0.167	0.131				
BedroomAbvGr[T.5]		-0.0721	0.078	-0.923	0.356
-0.225	0.081				
BedroomAbvGr[T.6]		0.0336	0.089	0.376	0.707
-0.141	0.208				
BldgType[T.2fmCon]		-0.0799	0.107	-0.744	0.457
-0.290	0.131				
BldgType[T.Duplex]		-0.0301	0.017	-1.810	0.070
-0.063	0.003				
BldgType[T.Twnhs]		-0.0176	0.043	-0.412	0.680
-0.101	0.066				
BldgType[T.TwnhsE]		0.0228	0.039	0.580	0.562
-0.054	0.100				
BsmtCond[T.Fa]		0.0222	0.055	0.402	0.688
-0.086	0.131				
BsmtCond[T.Gd]		0.0333	0.054	0.611	0.541
-0.074	0.140				
BsmtCond[T.NaN]		-0.7664	0.043	-17.786	0.000
-0.851	-0.682				
BsmtCond[T.NoBasement]		-0.0102	0.014	-0.746	0.456
-0.037	0.017				
BsmtCond[T.Po]		-0.0901	0.090	-0.998	0.318
-0.267	0.087				
BsmtCond[T.TA]		0.0265	0.054	0.494	0.621
-0.079	0.132				
BsmtExposure[T.Gd]		0.0226	0.010	2.366	0.018
0.004	0.041				
BsmtExposure[T.Mn]		-0.0276	0.010	-2.822	0.005
-0.047	-0.008				
BsmtExposure[T.NaN]		0.0241	0.062	0.389	0.697
-0.098	0.146				

BsmtExposure[T.No]	-0.0255	0.007	-3.460	0.001
-0.040 -0.011				
BsmtExposure[T.NoBasement]	-0.0102	0.014	-0.746	0.456
-0.037 0.017				
BsmtFinType1[T.BLQ]	-0.0109	0.010	-1.144	0.253
-0.030 0.008				
BsmtFinType1[T.GLQ]	0.0034	0.008	0.405	0.686
-0.013 0.020				
BsmtFinType1[T.LwQ]	-0.0366	0.012	-3.063	0.002
-0.060 -0.013				
BsmtFinType1[T.NaN]	-0.7664	0.043	-17.786	0.000
-0.851 -0.682				
BsmtFinType1[T.NoBasement]	-0.0102	0.014	-0.746	0.456
-0.037 0.017				
BsmtFinType1[T.Rec]	-0.0323	0.009	-3.440	0.001
-0.051 -0.014				
BsmtFinType1[T.Unf]	-0.0240	0.010	-2.465	0.014
-0.043 -0.005				
BsmtFinType2[T.BLQ]	-0.0292	0.024	-1.240	0.215
-0.075 0.017				
BsmtFinType2[T.GLQ]	0.0084	0.027	0.307	0.759
-0.045 0.062				
BsmtFinType2[T.LwQ]	-0.0238	0.022	-1.070	0.285
-0.067 0.020				
BsmtFinType2[T.NaN]	-0.7664	0.043	-17.786	0.000
-0.851 -0.682				
BsmtFinType2[T.NoBasement]	-0.0102	0.014	-0.746	0.456
-0.037 0.017				
BsmtFinType2[T.Rec]	-0.0297	0.021	-1.392	0.164
-0.071 0.012				
BsmtFinType2[T.Unf]	-0.0142	0.023	-0.623	0.533
-0.059 0.030				
BsmtFullBath[T.1]	0.0172	0.007	2.569	0.010
0.004 0.030				
BsmtFullBath[T.2]	0.0504	0.031	1.613	0.107
-0.011 0.112				
BsmtHalfBath[T.1]	0.0138	0.010	1.363	0.173
-0.006 0.034				
BsmtHalfBath[T.2]	0.1116	0.122	0.918	0.359
-0.127 0.350				
BsmtQual[T.Fa]	-0.0526	0.020	-2.586	0.010
-0.093 -0.013				
BsmtQual[T.Gd]	-0.0187	0.011	-1.736	0.083
-0.040 0.002				
BsmtQual[T.NaN]	-0.7664	0.043	-17.786	0.000
-0.851 -0.682				
BsmtQual[T.NoBasement]	-0.0102	0.014	-0.746	0.456
-0.037 0.017				

BsmtQual[T.Po]	0.0953	0.090	1.061	0.289
-0.081 0.271				
BsmtQual[T.TA]	-0.0110	0.014	-0.795	0.427
-0.038 0.016				
CentralAir[T.Y]	0.0243	0.013	1.810	0.070
-0.002 0.051				
Electrical[T.FuseF]	-0.0061	0.022	-0.273	0.785
-0.050 0.038				
Electrical[T.FuseP]	0.0010	0.057	0.017	0.987
-0.111 0.113				
Electrical[T.Mix]	-0.0901	0.090	-0.998	0.318
-0.267 0.087				
Electrical[T.NaN]	0.0457	0.089	0.514	0.608
-0.129 0.220				
Electrical[T.SBrkr]	-0.0067	0.010	-0.650	0.516
-0.027 0.014				
ExterCond[T.Fa]	-0.0101	0.042	-0.241	0.809
-0.092 0.072				
ExterCond[T.Gd]	0.0033	0.036	0.091	0.928
-0.068 0.075				
ExterCond[T.Po]	1.3374	0.234	5.710	0.000
0.878 1.797				
ExterCond[T.TA]	0.0161	0.036	0.445	0.656
-0.055 0.087				
ExterQual[T.Fa]	-0.0161	0.040	-0.406	0.685
-0.094 0.062				
ExterQual[T.Gd]	-0.0087	0.017	-0.500	0.617
-0.043 0.026				
ExterQual[T.TA]	-0.0180	0.019	-0.933	0.351
-0.056 0.020				
Fence[T.GdWo]	0.0092	0.017	0.554	0.580
-0.023 0.042				
Fence[T.MnPrv]	-0.0056	0.013	-0.422	0.673
-0.032 0.020				
Fence[T.MnWw]	-0.0097	0.031	-0.310	0.756
-0.071 0.051				
Fence[T.NoFence]	0.0035	0.012	0.290	0.772
-0.020 0.027				
FireplaceQu[T.Fa]	0.0037	0.023	0.161	0.872
-0.042 0.049				
FireplaceQu[T.Gd]	0.0167	0.019	0.897	0.370
-0.020 0.053				
FireplaceQu[T.NoFirePlace]	3.0216	0.081	37.211	0.000
2.862 3.181				
FireplaceQu[T.Po]	-0.0041	0.026	-0.159	0.874
-0.054 0.046				
FireplaceQu[T.TA]	0.0043	0.019	0.225	0.822
-0.033 0.042				

Fireplaces[T.1]	3.0427	0.081	37.341	0.000
2.883 3.203				
Fireplaces[T.2]	3.0773	0.082	37.468	0.000
2.916 3.238				
Fireplaces[T.3]	3.0624	0.087	35.371	0.000
2.893 3.232				
Fireplaces[T.4]	2.7628	0.186	14.833	0.000
2.397 3.128				
Foundation[T.CBlock]	0.0217	0.011	1.940	0.053
-0.000 0.044				
Foundation[T.PConc]	0.0283	0.012	2.389	0.017
0.005 0.052				
Foundation[T.Slab]	0.0086	0.036	0.239	0.811
-0.062 0.079				
Foundation[T.Stone]	-0.0132	0.047	-0.281	0.779
-0.106 0.079				
Foundation[T.Wood]	0.0412	0.065	0.631	0.528
-0.087 0.169				
FullBath[T.1]	0.0299	0.077	0.390	0.696
-0.120 0.180				
FullBath[T.2]	0.0518	0.077	0.669	0.504
-0.100 0.204				
FullBath[T.3]	0.0972	0.079	1.228	0.220
-0.058 0.252				
FullBath[T.4]	-2.134e-14	2.17e-15	-9.849	0.000
-2.56e-14 -1.71e-14				
Functional[T.Maj2]	0.0490	0.067	0.728	0.467
-0.083 0.181				
Functional[T.Min1]	0.0595	0.033	1.803	0.072
-0.005 0.124				
Functional[T.Min2]	0.0302	0.034	0.895	0.371
-0.036 0.097				
Functional[T.Mod]	0.0383	0.037	1.045	0.296
-0.034 0.110				
Functional[T.Sal]	-0.3892	0.151	-2.584	0.010
-0.685 -0.094				
Functional[T.Sev]	-0.2305	0.110	-2.092	0.037
-0.447 -0.014				
Functional[T.Typ]	0.0765	0.029	2.619	0.009
0.019 0.134				
GarageCars[T.2]	0.0191	0.009	2.184	0.029
0.002 0.036				
GarageCars[T.3]	0.0485	0.016	3.051	0.002
0.017 0.080				
GarageCars[T.4]	0.0719	0.039	1.846	0.065
-0.005 0.148				
GarageCars[T.5]	-4.547e-15	7.02e-16	-6.478	0.000
-5.92e-15 -3.17e-15				

GarageCond[T.Fa]	0.0644	0.083	0.777	0.437
-0.098 0.227				
GarageCond[T.Gd]	0.0810	0.084	0.964	0.335
-0.084 0.246				
GarageCond[T.Po]	0.2043	0.092	2.216	0.027
0.023 0.385				
GarageCond[T.TA]	0.0797	0.081	0.981	0.327
-0.080 0.239				
GarageFinish[T.RFn]	-0.0012	0.006	-0.193	0.847
-0.014 0.011				
GarageFinish[T.Unf]	-0.0023	0.008	-0.297	0.767
-0.017 0.013				
GarageQual[T.Fa]	-0.1674	0.097	-1.723	0.085
-0.358 0.023				
GarageQual[T.Gd]	-0.1324	0.095	-1.391	0.165
-0.319 0.054				
GarageQual[T.Po]	-0.1549	0.129	-1.199	0.231
-0.408 0.099				
GarageQual[T.TA]	-0.1370	0.096	-1.426	0.154
-0.325 0.051				
GarageType[T.Attchd]	0.0362	0.024	1.517	0.130
-0.011 0.083				
GarageType[T.Basment]	0.0238	0.033	0.712	0.477
-0.042 0.089				
GarageType[T.BuiltIn]	0.0293	0.026	1.125	0.261
-0.022 0.080				
GarageType[T.CarPort]	-0.0188	0.040	-0.469	0.639
-0.097 0.060				
GarageType[T.Detchd]	0.0412	0.024	1.734	0.083
-0.005 0.088				
HalfBath[T.1]	0.0253	0.007	3.429	0.001
0.011 0.040				
HalfBath[T.2]	-0.0831	0.033	-2.519	0.012
-0.148 -0.018				
Heating[T.GasA]	0.1503	0.098	1.528	0.127
-0.043 0.343				
Heating[T.GasW]	0.1526	0.101	1.505	0.133
-0.046 0.352				
Heating[T.Grav]	-0.0518	0.161	-0.323	0.747
-0.367 0.263				
Heating[T.OthW]	0.0894	0.137	0.651	0.515
-0.180 0.358				
Heating[T.Wall]	0.2007	0.121	1.665	0.096
-0.036 0.437				
HeatingQC[T.Fa]	-0.0535	0.016	-3.360	0.001
-0.085 -0.022				
HeatingQC[T.Gd]	-0.0112	0.007	-1.649	0.099
-0.024 0.002				

HeatingQC[T.Po]	-0.1209	0.071	-1.713	0.087
-0.259 0.018				
HeatingQC[T.TA]	-0.0324	0.007	-4.686	0.000
-0.046 -0.019				
HouseStyle[T.1.5Unf]	0.0142	0.074	0.191	0.849
-0.132 0.160				
HouseStyle[T.1Story]	0.0423	0.031	1.361	0.174
-0.019 0.103				
HouseStyle[T.2.5Fin]	-0.0686	0.068	-1.012	0.312
-0.202 0.064				
HouseStyle[T.2.5Unf]	0.0433	0.047	0.930	0.352
-0.048 0.134				
HouseStyle[T.2Story]	0.0134	0.032	0.421	0.674
-0.049 0.076				
HouseStyle[T.SFoyer]	0.0520	0.043	1.196	0.232
-0.033 0.137				
HouseStyle[T.SLvl]	0.0719	0.047	1.536	0.125
-0.020 0.164				
KitchenAbvGr[T.1]	-0.1077	0.092	-1.165	0.244
-0.289 0.074				
KitchenAbvGr[T.2]	-0.1499	0.098	-1.536	0.125
-0.341 0.041				
KitchenAbvGr[T.3]	-2.938e-15	1.15e-15	-2.562	0.011
-5.19e-15 -6.88e-16				
KitchenQual[T.Fa]	-0.0536	0.023	-2.374	0.018
-0.098 -0.009				
KitchenQual[T.Gd]	-0.0429	0.012	-3.497	0.000
-0.067 -0.019				
KitchenQual[T.Po]	-1.77e-15	1.11e-15	-1.602	0.109
-3.94e-15 3.97e-16				
KitchenQual[T.TA]	-0.0546	0.014	-3.984	0.000
-0.081 -0.028				
LandContour[T.HLS]	0.0102	0.017	0.600	0.549
-0.023 0.044				
LandContour[T.Low]	0.0204	0.024	0.852	0.395
-0.027 0.068				
LandContour[T.Lvl]	0.0004	0.013	0.030	0.976
-0.025 0.026				
LandSlope[T.Mod]	0.0243	0.014	1.753	0.080
-0.003 0.051				
LandSlope[T.Sev]	-0.0545	0.041	-1.345	0.179
-0.134 0.025				
LotConfig[T.CulDSac]	0.0148	0.011	1.345	0.179
-0.007 0.036				
LotConfig[T.FR2]	-0.0202	0.014	-1.406	0.160
-0.048 0.008				
LotConfig[T.FR3]	-0.0075	0.028	-0.264	0.792
-0.063 0.048				

LotConfig[T.Inside]	-0.0019	0.006	-0.311	0.756
-0.014 0.010				
LotShape[T.IR2]	0.0056	0.013	0.418	0.676
-0.021 0.032				
LotShape[T.IR3]	0.0151	0.028	0.541	0.588
-0.040 0.070				
LotShape[T.Reg]	-0.0023	0.005	-0.413	0.679
-0.013 0.008				
MSSubClass[T.30]	-0.0601	0.017	-3.623	0.000
-0.093 -0.028				
MSSubClass[T.40]	-0.0257	0.049	-0.521	0.603
-0.123 0.071				
MSSubClass[T.45]	0.0233	0.077	0.301	0.764
-0.128 0.175				
MSSubClass[T.50]	0.0297	0.032	0.941	0.347
-0.032 0.092				
MSSubClass[T.60]	-0.0211	0.032	-0.671	0.502
-0.083 0.041				
MSSubClass[T.70]	0.0259	0.034	0.771	0.441
-0.040 0.092				
MSSubClass[T.75]	0.0056	0.050	0.113	0.910
-0.092 0.103				
MSSubClass[T.80]	-0.0516	0.044	-1.185	0.236
-0.137 0.034				
MSSubClass[T.85]	0.0059	0.039	0.152	0.879
-0.070 0.082				
MSSubClass[T.90]	-0.0301	0.017	-1.810	0.070
-0.063 0.003				
MSSubClass[T.120]	-0.0634	0.040	-1.599	0.110
-0.141 0.014				
MSSubClass[T.150]	-0.1852	0.113	-1.637	0.102
-0.407 0.037				
MSSubClass[T.160]	-0.1437	0.053	-2.732	0.006
-0.247 -0.041				
MSSubClass[T.180]	-0.0974	0.062	-1.559	0.119
-0.220 0.025				
MSSubClass[T.190]	0.0401	0.105	0.383	0.702
-0.165 0.246				
MSZoning[T.C]	1.4675	0.059	24.738	0.000
1.351 1.584				
MSZoning[T.FV]	1.7801	0.051	34.822	0.000
1.680 1.880				
MSZoning[T.I]	1.5664	0.143	10.990	0.000
1.287 1.846				
MSZoning[T.RH]	1.7555	0.053	32.836	0.000
1.651 1.860				
MSZoning[T.RL]	1.7681	0.048	36.754	0.000
1.674 1.862				

MSZoning[T.RM]	1.7220	0.049	35.389	0.000
1.627 1.817				
MasVnrType[T.BrkJace]	0.0338	0.023	1.468	0.142
-0.011 0.079				
MasVnrType[T.CBlock]	-0.2792	0.119	-2.354	0.019
-0.512 -0.047				
MasVnrType[T.NaN]	0.0329	0.023	1.416	0.157
-0.013 0.078				
MasVnrType[T.Stone]	0.0311	0.024	1.278	0.202
-0.017 0.079				
MiscFeature[T.NaN]	-0.0020	0.079	-0.025	0.980
-0.156 0.152				
MiscFeature[T.Othr]	0.0943	0.087	1.087	0.277
-0.076 0.265				
MiscFeature[T.Shed]	-0.0210	0.075	-0.280	0.779
-0.168 0.126				
MiscFeature[T.TenC]	-0.3765	0.160	-2.349	0.019
-0.691 -0.062				
MoSold[T.2]	-0.0380	0.016	-2.444	0.015
-0.069 -0.008				
MoSold[T.3]	-0.0227	0.014	-1.610	0.108
-0.050 0.005				
MoSold[T.4]	-0.0055	0.014	-0.397	0.691
-0.033 0.022				
MoSold[T.5]	0.0027	0.013	0.208	0.835
-0.023 0.028				
MoSold[T.6]	-0.0031	0.013	-0.245	0.806
-0.028 0.022				
MoSold[T.7]	0.0042	0.013	0.332	0.740
-0.020 0.029				
MoSold[T.8]	-0.0159	0.013	-1.188	0.235
-0.042 0.010				
MoSold[T.9]	0.0052	0.015	0.359	0.720
-0.023 0.034				
MoSold[T.10]	-0.0245	0.014	-1.710	0.088
-0.053 0.004				
MoSold[T.11]	-0.0103	0.015	-0.709	0.479
-0.039 0.018				
MoSold[T.12]	-0.0091	0.016	-0.586	0.558
-0.040 0.021				
Neighborhood[T.Blueste]	0.1140	0.055	2.073	0.038
0.006 0.222				
Neighborhood[T.BrDale]	-0.0058	0.039	-0.149	0.882
-0.082 0.070				
Neighborhood[T.BrkJSide]	0.0175	0.032	0.546	0.585
-0.045 0.080				
Neighborhood[T.ClearCr]	0.0283	0.033	0.857	0.392
-0.037 0.093				

Neighborhood[T.CollgCr]	-0.0253	0.025	-1.007	0.314
-0.075 0.024				
Neighborhood[T.Crawfor]	0.0907	0.029	3.156	0.002
0.034 0.147				
Neighborhood[T.Edwards]	-0.0473	0.028	-1.720	0.086
-0.101 0.007				
Neighborhood[T.Gilbert]	-0.0187	0.026	-0.717	0.473
-0.070 0.032				
Neighborhood[T.Greens]	0.0641	0.052	1.238	0.216
-0.037 0.166				
Neighborhood[T.GrnHill]	0.5099	0.069	7.345	0.000
0.374 0.646				
Neighborhood[T.IDOTRR]	0.0109	0.035	0.313	0.754
-0.057 0.079				
Neighborhood[T.Landmrk]	0.0180	0.096	0.188	0.851
-0.170 0.206				
Neighborhood[T.MeadowV]	-0.0757	0.041	-1.864	0.063
-0.155 0.004				
Neighborhood[T.Mitchel]	-0.0382	0.028	-1.366	0.172
-0.093 0.017				
Neighborhood[T.NAmes]	-0.0173	0.027	-0.644	0.520
-0.070 0.035				
Neighborhood[T.NPkVill]	-0.0036	0.058	-0.062	0.951
-0.117 0.110				
Neighborhood[T.NWAmes]	-0.0222	0.028	-0.805	0.421
-0.076 0.032				
Neighborhood[T.NoRidge]	0.0219	0.029	0.745	0.457
-0.036 0.079				
Neighborhood[T.NridgHt]	0.0425	0.026	1.635	0.102
-0.008 0.094				
Neighborhood[T.OldTown]	-0.0168	0.032	-0.525	0.600
-0.080 0.046				
Neighborhood[T.SWISU]	-0.0345	0.035	-0.994	0.320
-0.102 0.034				
Neighborhood[T.Sawyer]	0.0097	0.028	0.353	0.724
-0.044 0.064				
Neighborhood[T.SawyerW]	-0.0302	0.027	-1.106	0.269
-0.084 0.023				
Neighborhood[T.Somerst]	0.0297	0.030	1.003	0.316
-0.028 0.088				
Neighborhood[T.StoneBr]	0.0852	0.029	2.892	0.004
0.027 0.143				
Neighborhood[T.Timber]	-0.0036	0.027	-0.131	0.896
-0.057 0.050				
Neighborhood[T.Veenker]	-0.0013	0.033	-0.038	0.970
-0.066 0.064				
OverallCond[T.2]	-0.0162	0.161	-0.101	0.920
-0.332 0.299				

OverallCond[T.3]	-0.0028	0.124	-0.022	0.982
-0.246 0.240				
OverallCond[T.4]	0.1160	0.124	0.937	0.349
-0.127 0.359				
OverallCond[T.5]	0.1937	0.124	1.565	0.118
-0.049 0.436				
OverallCond[T.6]	0.2207	0.124	1.777	0.076
-0.023 0.464				
OverallCond[T.7]	0.2577	0.124	2.072	0.038
0.014 0.502				
OverallCond[T.8]	0.2761	0.124	2.221	0.026
0.032 0.520				
OverallCond[T.9]	0.3119	0.127	2.465	0.014
0.064 0.560				
OverallQual[T.2]	0.7215	0.058	12.501	0.000
0.608 0.835				
OverallQual[T.3]	1.0120	0.037	27.387	0.000
0.939 1.084				
OverallQual[T.4]	1.0524	0.031	34.025	0.000
0.992 1.113				
OverallQual[T.5]	1.1148	0.030	36.559	0.000
1.055 1.175				
OverallQual[T.6]	1.1438	0.031	37.296	0.000
1.084 1.204				
OverallQual[T.7]	1.1785	0.031	38.189	0.000
1.118 1.239				
OverallQual[T.8]	1.2299	0.032	39.034	0.000
1.168 1.292				
OverallQual[T.9]	1.2885	0.034	38.340	0.000
1.223 1.354				
OverallQual[T.10]	1.3182	0.038	34.393	0.000
1.243 1.393				
PavedDrive[T.P]	0.0081	0.018	0.448	0.654
-0.027 0.044				
PavedDrive[T.Y]	0.0247	0.013	1.957	0.051
-5.44e-05 0.049				
PoolQC[T.Fa]	0.2286	0.162	1.412	0.158
-0.089 0.546				
PoolQC[T.Gd]	0.3563	0.151	2.365	0.018
0.061 0.652				
PoolQC[T.NoPool]	-0.1255	0.107	-1.176	0.240
-0.335 0.084				
PoolQC[T.TA]	0.1469	0.099	1.486	0.137
-0.047 0.341				
RoofMatl[T.Membran]	0.1658	0.114	1.450	0.147
-0.059 0.390				
RoofMatl[T.Metal]	0.0680	0.111	0.615	0.539
-0.149 0.285				

RoofMatl[T.Roll]	0.0973	0.097	1.001	0.317
-0.093 0.288				
RoofMatl[T.Tar&Grv]	0.0010	0.046	0.021	0.983
-0.088 0.090				
RoofMatl[T.WdShake]	-0.0359	0.039	-0.931	0.352
-0.111 0.040				
RoofMatl[T.WdShngl]	0.0876	0.052	1.694	0.090
-0.014 0.189				
RoofStyle[T.Gable]	-0.0135	0.052	-0.261	0.794
-0.115 0.088				
RoofStyle[T.Gambrel]	-0.0645	0.058	-1.116	0.265
-0.178 0.049				
RoofStyle[T.Hip]	-0.0050	0.052	-0.096	0.924
-0.107 0.097				
RoofStyle[T.Mansard]	-0.1087	0.065	-1.682	0.093
-0.236 0.018				
RoofStyle[T.Shed]	-0.0190	0.081	-0.234	0.815
-0.179 0.141				
SaleCondition[T.AdjLand]	0.1867	0.044	4.285	0.000
0.101 0.272				
SaleCondition[T.Alloca]	0.0750	0.034	2.174	0.030
0.007 0.143				
SaleCondition[T.Family]	0.0209	0.019	1.119	0.263
-0.016 0.058				
SaleCondition[T.Normal]	0.0367	0.010	3.607	0.000
0.017 0.057				
SaleCondition[T.Partial]	0.0842	0.047	1.791	0.073
-0.008 0.176				
SaleType[T.CWD]	0.0224	0.029	0.763	0.445
-0.035 0.080				
SaleType[T.Con]	0.0588	0.055	1.073	0.284
-0.049 0.166				
SaleType[T.ConLD]	0.0498	0.031	1.597	0.110
-0.011 0.111				
SaleType[T.ConLI]	-0.1998	0.058	-3.430	0.001
-0.314 -0.086				
SaleType[T.ConLw]	-0.0918	0.049	-1.880	0.060
-0.188 0.004				
SaleType[T.New]	-0.0053	0.049	-0.108	0.914
-0.101 0.091				
SaleType[T.Oth]	0.1280	0.089	1.446	0.149
-0.046 0.302				
SaleType[T.VWD]	-0.0075	0.092	-0.082	0.935
-0.187 0.172				
SaleType[T.WD]	0.0094	0.014	0.661	0.509
-0.018 0.037				
Street[T.Pave]	0.0534	0.045	1.200	0.230
-0.034 0.141				

TotRmsAbvGrd[T.4]	0.0256	0.032	0.810	0.418
-0.036 0.088				
TotRmsAbvGrd[T.5]	0.0200	0.032	0.635	0.526
-0.042 0.082				
TotRmsAbvGrd[T.6]	0.0315	0.032	0.983	0.326
-0.031 0.094				
TotRmsAbvGrd[T.7]	0.0267	0.033	0.807	0.420
-0.038 0.091				
TotRmsAbvGrd[T.8]	0.0291	0.034	0.851	0.395
-0.038 0.096				
TotRmsAbvGrd[T.9]	0.0087	0.036	0.241	0.810
-0.062 0.079				
TotRmsAbvGrd[T.10]	-0.0115	0.039	-0.297	0.766
-0.088 0.064				
TotRmsAbvGrd[T.11]	-0.0404	0.043	-0.947	0.344
-0.124 0.043				
TotRmsAbvGrd[T.12]	0.0872	0.077	1.139	0.255
-0.063 0.237				
TotRmsAbvGrd[T.13]	4.001e-16	9.21e-17	4.346	0.000
2.2e-16 5.81e-16				
Utilities[T.NoSeWa]	1.151e-16	6.26e-17	1.838	0.066
-7.74e-18 2.38e-16				
Utilities[T.NoSewr]	-0.0517	0.139	-0.372	0.710
-0.324 0.221				
Artery	-0.0877	0.015	-5.813	0.000
-0.117 -0.058				
AsbShng	-0.0202	0.025	-0.823	0.411
-0.068 0.028				
AsphShn	0.1446	0.068	2.120	0.034
0.011 0.278				
BrkCmn	0.0401	0.063	0.637	0.524
-0.083 0.163				
BrkComm	0.2073	0.067	3.112	0.002
0.077 0.338				
BrkFace	0.0524	0.015	3.577	0.000
0.024 0.081				
BsmtFinSF1	5.092e-05	9.19e-06	5.540	0.000
3.29e-05 6.9e-05				
BsmtFinSF2	4.314e-05	1.86e-05	2.317	0.021
6.62e-06 7.97e-05				
BsmtUnfSF	-1.353e-05	8.5e-06	-1.592	0.112
-3.02e-05 3.14e-06				
CBlock	2.8036	0.111	25.216	0.000
2.585 3.022				
CemntBd	-0.0711	0.066	-1.077	0.282
-0.201 0.058				
CmentBd	0.0901	0.066	1.361	0.174
-0.040 0.220				

EnclosedPorch		7.145e-05	4.04e-05	1.767	0.077
-7.86e-06	0.000				
Feedr		-0.0541	0.011	-5.062	0.000
-0.075	-0.033				
GarageArea		8.381e-05	2.65e-05	3.158	0.002
3.18e-05	0.000				
GrLivArea		0.0002	2.25e-05	8.326	0.000
0.000	0.000				
HdBoard		-0.0063	0.012	-0.528	0.597
-0.030	0.017				
ImStucc		-0.0304	0.030	-1.019	0.308
-0.089	0.028				
LotArea		2.117e-06	4.41e-07	4.798	0.000
1.25e-06	2.98e-06				
LotFrontage		9.516e-05	7.7e-05	1.236	0.217
-5.58e-05	0.000				
LowQualFinSF		-3.663e-06	5.66e-05	-0.065	0.948
-0.000	0.000				
MasVnrArea		3.583e-05	1.91e-05	1.878	0.061
-1.59e-06	7.33e-05				
MetalSd		0.0177	0.012	1.420	0.156
-0.007	0.042				
MiscVal		7.798e-06	7.97e-06	0.978	0.328
-7.84e-06	2.34e-05				
Norm		0.0444	0.026	1.684	0.092
-0.007	0.096				
OpenPorchSF		0.0001	3.74e-05	3.211	0.001
4.67e-05	0.000				
Other		-0.0695	0.088	-0.786	0.432
-0.243	0.104				
Plywood		-0.0009	0.012	-0.082	0.934
-0.024	0.022				
PoolArea		-0.0004	0.000	-1.284	0.199
-0.001	0.000				
PosA		0.0615	0.027	2.317	0.021
0.009	0.114				
PosN		0.0239	0.021	1.160	0.246
-0.017	0.064				
PreCast		0	0	nan	nan
0	0				
RR Ae		-0.0580	0.023	-2.543	0.011
-0.103	-0.013				
RR An		-0.0188	0.016	-1.144	0.253
-0.051	0.013				
RR Ne		-0.0223	0.047	-0.474	0.635
-0.114	0.070				
RR Nn		0.0497	0.042	1.193	0.233
-0.032	0.131				

ScreenPorch		0.0002	4.06e-05	4.759	0.000
0.000	0.000				
Stone		-0.0193	0.048	-0.405	0.686
-0.113	0.074				
Stucco		0.0211	0.019	1.131	0.258
-0.015	0.058				
TotalBsmtSF		8.053e-05	1.24e-05	6.511	0.000
5.63e-05	0.000				
VinylSd		0.0061	0.013	0.478	0.633
-0.019	0.031				
WdSdng		0.0120	0.012	0.981	0.327
-0.012	0.036				
WdShng		0.0059	0.022	0.266	0.790
-0.037	0.049				
WdShng		-0.0026	0.018	-0.143	0.887
-0.038	0.033				
WoodDeckSF		4.619e-05	1.96e-05	2.352	0.019
7.67e-06	8.47e-05				
X1stFlrSF		8.927e-05	2.26e-05	3.950	0.000
4.49e-05	0.000				
X2ndFlrSF		0.0001	2.12e-05	4.812	0.000
6.04e-05	0.000				
X3SsnPorch		0.0002	9.51e-05	2.141	0.032
1.7e-05	0.000				
YearsSince1950Built		0.0031	0.001	6.064	0.000
0.002	0.004				
YearsSince1950GarageBuilt		-0.0003	0.000	-1.110	0.267
-0.001	0.000				
YearsSince1950Remod		0.0005	0.000	2.464	0.014
9.94e-05	0.001				
=====					
Omnibus:		266.117	Durbin-Watson:		1.943
Prob(Omnibus):		0.000	Jarque-Bera (JB):		1925.093
Skew:		-0.463	Prob(JB):		0.00
Kurtosis:		7.941	Cond. No.		3.80e+16
=====					

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 2.19e-22. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
[ ]: y_train = ames_train['LogSalePrice']
      y_test = ames_test['LogSalePrice']
```

```
[ ]: print_metrics(nlr, ames_train, y_train, ames_test, y_test, flag_log_sale_price_
      ↪= True)
      print_metrics(nlr, ames_train, y_train, ames_test, y_test, flag_log_sale_price_
      ↪= False)
```

Metrics for Log(Sale Price):

```
Training R2 0.9603376376378353
Training MAE 0.056296645864186146
Training RMSE 0.07708753756375215
Out-of-sample R2 0.84160608337568
Out-of-sample MAE 0.08310808994525071
Out-of-sample RMSE 0.15762880434009238
```

Metrics for Sale Price:

```
Training R2 0.9617308456634752
Training MAE 10352.437245152909
Training RMSE 15282.418966032086
Out-of-sample R2 0.3685202291723365
Out-of-sample MAE 15719.441358572112
Out-of-sample RMSE 62283.05295821487
```

6 In-class activity 4: Remove some predictors of the linear regression model based on the output. Does the out-of-sample performance get better?

```
[ ]: 
```

b) with polynomial features

```
[ ]: 
```

6.0.1 Higher-order Variables

We can construct new features using a polynomial transformation. This is necessary because the regression plots we generated with ‘LogSalePrice ~ [single independent variable]’ exhibits some non-linear relationship. In the function below, you can choose the highest degree of the polynomial features. A higher degree polynomial might cause overfitting concern, but we will later use ‘regularization’ to mitigate this issue.

```
[ ]: def create_polynomial_features(df, n_degree):
      new_df = None
      for i in range(2, n_degree+1):
```

```

tmp = df.pow(i)

affix = '_p'+str(i)
tmp.columns = list(map(lambda x: x + affix, df.columns))

if new_df is not None:
    new_df = pd.concat([new_df, tmp], axis=1)
else:
    new_df = tmp

return new_df

```

NOTE: An important consideration when creating higher-order variables is that the resulting features will tend to have some degree of linear dependence amongst themselves. This is normal as several new features are based on their zero-th power peer. Such correlation can also yield a high degree of multicollinearity in the regression models. The `sklearn` implementations that we will be using do not automatically account for this phenomenon, therefore we must be careful in selection the `n_degree`, and analyzing the model fit.

```

[ ]: # We only choose a select list of variables to do polynomial transformation.
poly_cols = ['LotFrontage', 'LotArea', 'MasVnrArea', 'BsmtFinSF1',
↳ 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
            'X1stFlrSF', 'X2ndFlrSF', 'LowQualFinSF', 'GrLivArea',
↳ 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
            'EnclosedPorch', 'X3SsnPorch', 'ScreenPorch', 'MiscVal',
↳ 'YearsSince1950Built',
            'YearsSince1950Remod', 'YearsSince1950GarageBuilt']

```

```

[ ]: n_degree = 2

train_poly_temp = create_polynomial_features(ames_train[poly_cols], n_degree)
test_poly_temp = create_polynomial_features(ames_test[poly_cols], n_degree)

ames_train_poly = pd.concat([ames_train, train_poly_temp], axis=1)
ames_test_poly = pd.concat([ames_test, test_poly_temp], axis=1)

print(ames_train.shape, ames_test.shape)
print(train_poly_temp.shape, test_poly_temp.shape)
print(ames_train_poly.shape, ames_test_poly.shape)

```

```

(1828, 104) (937, 104)
(1828, 21) (937, 21)
(1828, 125) (937, 125)

```

```

[ ]: print(ames_train_poly.shape)
all_columns = "+".join(ames_train_poly.columns.difference(["LogSalePrice"]))
my_formula = "LogSalePrice~" + all_columns + "-1"

```



```
print(my_formula)

mod_naive_poly = smf.ols(my_formula, data=ames_train_poly)
nlr_poly = mod_naive_poly.fit()

print(nlr_poly.summary())
```

(1828, 125)

LogSalePrice~Alley+Artery+AsbShng+AsphShn+BedroomAbvGr+BldgType+BrkCmn+BrkComm+BrkFace+BsmCond+BsmExposure+BsmFinSF1+BsmFinSF1_p2+BsmFinSF2+BsmFinSF2_p2+BsmFinType1+BsmFinType2+BsmFullBath+BsmHalfBath+BsmQual+BsmUnfSF+BsmUnfSF_p2+CBlock+CemntBd+CentralAir+CmentBd+Electrical+EnclosedPorch+EnclosedPorch_p2+ExterCond+ExterQual+Feedr+Fence+FireplaceQu+Fireplaces+Foundation+FullBath+Functional+GarageArea+GarageArea_p2+GarageCars+GarageCond+GarageFinish+GarageQual+GarageType+GrLivArea+GrLivArea_p2+HalfBath+HdBoard+Heating+HeatingQC+HouseStyle+ImStucc+KitchenAbvGr+KitchenQual+LandContour+LandSlope+LotArea+LotArea_p2+LotConfig+LotFrontage+LotFrontage_p2+LotShape+LowQualFinSF+LowQualFinSF_p2+MSSubClass+MSZoning+MasVnrArea+MasVnrArea_p2+MasVnrType+MetalSd+MiscFeature+MiscVal+MiscVal_p2+MoSold+Neighborhood+Norm+OpenPorchSF+OpenPorchSF_p2+Other+OverallCond+OverallQual+PavedDrive+Plywood+PoolArea+PoolQC+PosA+PosN+PreCast+RR Ae+RRAn+RRNe+RRNn+RoofMatl+RoofStyle+SaleCondition+SaleType+ScreenPorch+ScreenPorch_p2+Stone+Street+Stucco+TotRmsAbvGrd+TotalBsmtSF+TotalBsmtSF_p2+Utilities+VinylSd+WdSdng+WdShing+WdShng+WoodDeckSF+WoodDeckSF_p2+X1stFlrSF+X1stFlrSF_p2+X2ndFlrSF+X2ndFlrSF_p2+X3SsnPorch+X3SsnPorch_p2+YearsSince1950Built+YearsSince1950Built_p2+YearsSince1950GarageBuilt+YearsSince1950GarageBuilt_p2+YearsSince1950Remod+YearsSince1950Remod_p2-1

OLS Regression Results

```
=====
Dep. Variable:          LogSalePrice    R-squared:                0.962
Model:                  OLS             Adj. R-squared:          0.954
Method:                 Least Squares   F-statistic:            118.8
Date:                  Fri, 01 Nov 2024 Prob (F-statistic):      0.00
Time:                  18:18:57         Log-Likelihood:         2140.1
No. Observations:      1828            AIC:                   -3630.
Df Residuals:          1503            BIC:                   -1839.
Df Model:               324
Covariance Type:       nonrobust
=====
```

```
=====
coef      std err        t    P>|t|
-----
[0.025    0.975]
-----
Alley[Grv1]          4.9635    0.140    35.451    0.000
4.689      5.238
Alley[NoAccess]      4.9859    0.139    35.754    0.000
4.712      5.259
```

Alley[Pave]	4.9939	0.140	35.609	0.000
4.719 5.269				
BedroomAbvGr[T.1]	-0.0107	0.074	-0.145	0.885
-0.155 0.134				
BedroomAbvGr[T.2]	-0.0093	0.074	-0.126	0.900
-0.154 0.136				
BedroomAbvGr[T.3]	-0.0123	0.074	-0.165	0.869
-0.158 0.133				
BedroomAbvGr[T.4]	-0.0144	0.075	-0.193	0.847
-0.161 0.132				
BedroomAbvGr[T.5]	-0.0677	0.077	-0.880	0.379
-0.218 0.083				
BedroomAbvGr[T.6]	0.0342	0.088	0.389	0.697
-0.138 0.206				
BldgType[T.2fmCon]	-0.1128	0.106	-1.061	0.289
-0.321 0.096				
BldgType[T.Duplex]	-0.0287	0.017	-1.726	0.085
-0.061 0.004				
BldgType[T.Twnhs]	-0.0321	0.042	-0.764	0.445
-0.115 0.050				
BldgType[T.TwnhsE]	0.0022	0.039	0.057	0.954
-0.074 0.079				
BsmtCond[T.Fa]	0.0069	0.055	0.127	0.899
-0.100 0.114				
BsmtCond[T.Gd]	0.0116	0.054	0.215	0.830
-0.094 0.117				
BsmtCond[T.NaN]	-0.7545	0.043	-17.473	0.000
-0.839 -0.670				
BsmtCond[T.NoBasement]	-0.0166	0.014	-1.153	0.249
-0.045 0.012				
BsmtCond[T.Po]	-0.1085	0.089	-1.216	0.224
-0.284 0.067				
BsmtCond[T.TA]	0.0084	0.053	0.158	0.875
-0.096 0.112				
BsmtExposure[T.Gd]	0.0269	0.010	2.826	0.005
0.008 0.046				
BsmtExposure[T.Mn]	-0.0260	0.010	-2.672	0.008
-0.045 -0.007				
BsmtExposure[T.NaN]	0.0131	0.061	0.215	0.830
-0.107 0.133				
BsmtExposure[T.No]	-0.0217	0.007	-2.959	0.003
-0.036 -0.007				
BsmtExposure[T.NoBasement]	-0.0166	0.014	-1.153	0.249
-0.045 0.012				
BsmtFinType1[T.BLQ]	-0.0129	0.009	-1.366	0.172
-0.031 0.006				
BsmtFinType1[T.GLQ]	0.0008	0.008	0.095	0.924
-0.016 0.017				

BsmtFinType1[T.LwQ]	-0.0370	0.012	-3.138	0.002
-0.060 -0.014				
BsmtFinType1[T.NaN]	-0.7545	0.043	-17.473	0.000
-0.839 -0.670				
BsmtFinType1[T.NoBasement]	-0.0166	0.014	-1.153	0.249
-0.045 0.012				
BsmtFinType1[T.Rec]	-0.0333	0.009	-3.594	0.000
-0.052 -0.015				
BsmtFinType1[T.Unf]	-0.0155	0.011	-1.378	0.168
-0.037 0.007				
BsmtFinType2[T.BLQ]	-0.0291	0.023	-1.248	0.212
-0.075 0.017				
BsmtFinType2[T.GLQ]	-0.0021	0.027	-0.078	0.938
-0.056 0.051				
BsmtFinType2[T.LwQ]	-0.0309	0.022	-1.406	0.160
-0.074 0.012				
BsmtFinType2[T.NaN]	-0.7545	0.043	-17.473	0.000
-0.839 -0.670				
BsmtFinType2[T.NoBasement]	-0.0166	0.014	-1.153	0.249
-0.045 0.012				
BsmtFinType2[T.Rec]	-0.0371	0.021	-1.762	0.078
-0.078 0.004				
BsmtFinType2[T.Unf]	-0.0284	0.025	-1.138	0.255
-0.077 0.021				
BsmtFullBath[T.1]	0.0120	0.007	1.798	0.072
-0.001 0.025				
BsmtFullBath[T.2]	0.0812	0.033	2.465	0.014
0.017 0.146				
BsmtHalfBath[T.1]	0.0145	0.010	1.454	0.146
-0.005 0.034				
BsmtHalfBath[T.2]	0.1422	0.120	1.187	0.235
-0.093 0.377				
BsmtQual[T.Fa]	-0.0543	0.020	-2.696	0.007
-0.094 -0.015				
BsmtQual[T.Gd]	-0.0198	0.011	-1.860	0.063
-0.041 0.001				
BsmtQual[T.NaN]	-0.7545	0.043	-17.473	0.000
-0.839 -0.670				
BsmtQual[T.NoBasement]	-0.0166	0.014	-1.153	0.249
-0.045 0.012				
BsmtQual[T.Po]	0.0744	0.089	0.836	0.403
-0.100 0.249				
BsmtQual[T.TA]	-0.0123	0.014	-0.900	0.368
-0.039 0.015				
CentralAir[T.Y]	0.0222	0.013	1.661	0.097
-0.004 0.048				
Electrical[T.FuseF]	-0.0063	0.022	-0.288	0.774
-0.049 0.037				

Electrical[T.FuseP]	0.0237	0.056	0.420	0.674
-0.087 0.134				
Electrical[T.Mix]	-0.1085	0.089	-1.216	0.224
-0.284 0.067				
Electrical[T.NaN]	0.0382	0.088	0.434	0.664
-0.135 0.211				
Electrical[T.SBrkr]	-0.0080	0.010	-0.786	0.432
-0.028 0.012				
ExterCond[T.Fa]	-0.0025	0.041	-0.060	0.952
-0.084 0.079				
ExterCond[T.Gd]	0.0187	0.036	0.516	0.606
-0.052 0.090				
ExterCond[T.Po]	1.4030	0.234	6.000	0.000
0.944 1.862				
ExterCond[T.TA]	0.0310	0.036	0.861	0.390
-0.040 0.102				
ExterQual[T.Fa]	-0.0100	0.039	-0.256	0.798
-0.087 0.067				
ExterQual[T.Gd]	-0.0005	0.018	-0.030	0.976
-0.035 0.034				
ExterQual[T.TA]	-0.0108	0.019	-0.554	0.580
-0.049 0.027				
Fence[T.GdWo]	0.0020	0.016	0.119	0.905
-0.030 0.034				
Fence[T.MnPrv]	-0.0081	0.013	-0.613	0.540
-0.034 0.018				
Fence[T.MnWw]	-0.0169	0.031	-0.549	0.583
-0.077 0.043				
Fence[T.NoFence]	-0.0032	0.012	-0.273	0.785
-0.026 0.020				
FireplaceQu[T.Fa]	-0.0012	0.023	-0.052	0.958
-0.046 0.044				
FireplaceQu[T.Gd]	0.0051	0.018	0.278	0.781
-0.031 0.041				
FireplaceQu[T.NoFirePlace]	2.9952	0.082	36.637	0.000
2.835 3.156				
FireplaceQu[T.Po]	-0.0172	0.025	-0.677	0.499
-0.067 0.033				
FireplaceQu[T.TA]	-0.0043	0.019	-0.223	0.824
-0.042 0.033				
Fireplaces[T.1]	3.0216	0.082	36.907	0.000
2.861 3.182				
Fireplaces[T.2]	3.0565	0.082	37.086	0.000
2.895 3.218				
Fireplaces[T.3]	3.0135	0.087	34.716	0.000
2.843 3.184				
Fireplaces[T.4]	2.8565	0.186	15.394	0.000
2.493 3.220				

Foundation[T.CBlock]	0.0216	0.011	1.943	0.052
-0.000 0.043				
Foundation[T.PConc]	0.0242	0.012	2.056	0.040
0.001 0.047				
Foundation[T.Slab]	0.0018	0.036	0.049	0.961
-0.068 0.072				
Foundation[T.Stone]	-0.0180	0.047	-0.387	0.698
-0.109 0.073				
Foundation[T.Wood]	0.0413	0.064	0.641	0.521
-0.085 0.168				
FullBath[T.1]	0.0427	0.076	0.565	0.572
-0.105 0.191				
FullBath[T.2]	0.0605	0.076	0.792	0.429
-0.089 0.210				
FullBath[T.3]	0.1131	0.078	1.448	0.148
-0.040 0.266				
FullBath[T.4]	2.24e-14	1.46e-15	15.327	0.000
1.95e-14 2.53e-14				
Functional[T.Maj2]	0.0230	0.069	0.334	0.739
-0.112 0.158				
Functional[T.Min1]	0.0628	0.033	1.920	0.055
-0.001 0.127				
Functional[T.Min2]	0.0276	0.034	0.821	0.412
-0.038 0.094				
Functional[T.Mod]	0.0274	0.037	0.749	0.454
-0.044 0.099				
Functional[T.Sal]	-0.3687	0.152	-2.433	0.015
-0.666 -0.071				
Functional[T.Sev]	-0.2319	0.109	-2.126	0.034
-0.446 -0.018				
Functional[T.Typ]	0.0875	0.029	3.020	0.003
0.031 0.144				
GarageCars[T.2]	0.0186	0.010	1.856	0.064
-0.001 0.038				
GarageCars[T.3]	0.0462	0.016	2.849	0.004
0.014 0.078				
GarageCars[T.4]	0.0584	0.040	1.466	0.143
-0.020 0.137				
GarageCars[T.5]	2.698e-15	1.03e-15	2.622	0.009
6.79e-16 4.72e-15				
GarageCond[T.Fa]	0.0675	0.082	0.822	0.411
-0.094 0.229				
GarageCond[T.Gd]	0.0868	0.083	1.043	0.297
-0.076 0.250				
GarageCond[T.Po]	0.1992	0.091	2.185	0.029
0.020 0.378				
GarageCond[T.TA]	0.0833	0.081	1.033	0.302
-0.075 0.241				

GarageFinish[T.RFn]	-0.0010	0.006	-0.156	0.876
-0.013 0.011				
GarageFinish[T.Unf]	-0.0060	0.008	-0.781	0.435
-0.021 0.009				
GarageQual[T.Fa]	-0.1885	0.098	-1.923	0.055
-0.381 0.004				
GarageQual[T.Gd]	-0.1530	0.096	-1.597	0.110
-0.341 0.035				
GarageQual[T.Po]	-0.1660	0.129	-1.284	0.199
-0.420 0.088				
GarageQual[T.TA]	-0.1662	0.097	-1.715	0.086
-0.356 0.024				
GarageType[T.Attchd]	0.0432	0.024	1.821	0.069
-0.003 0.090				
GarageType[T.Basment]	0.0214	0.033	0.643	0.520
-0.044 0.087				
GarageType[T.BuiltIn]	0.0358	0.026	1.378	0.168
-0.015 0.087				
GarageType[T.CarPort]	-0.0107	0.040	-0.271	0.786
-0.088 0.067				
GarageType[T.Detchd]	0.0555	0.024	2.343	0.019
0.009 0.102				
HalfBath[T.1]	0.0209	0.007	2.830	0.005
0.006 0.035				
HalfBath[T.2]	-0.0971	0.033	-2.970	0.003
-0.161 -0.033				
Heating[T.GasA]	0.1664	0.097	1.716	0.086
-0.024 0.357				
Heating[T.GasW]	0.1591	0.100	1.593	0.111
-0.037 0.355				
Heating[T.Grav]	-0.0336	0.158	-0.213	0.831
-0.343 0.276				
Heating[T.OthW]	0.1002	0.135	0.742	0.458
-0.165 0.365				
Heating[T.Wall]	0.1925	0.119	1.624	0.105
-0.040 0.425				
HeatingQC[T.Fa]	-0.0532	0.016	-3.393	0.001
-0.084 -0.022				
HeatingQC[T.Gd]	-0.0075	0.007	-1.114	0.265
-0.021 0.006				
HeatingQC[T.Po]	-0.1181	0.069	-1.702	0.089
-0.254 0.018				
HeatingQC[T.TA]	-0.0306	0.007	-4.461	0.000
-0.044 -0.017				
HouseStyle[T.1.5Unf]	-0.0012	0.074	-0.016	0.987
-0.146 0.144				
HouseStyle[T.1Story]	0.0209	0.033	0.636	0.525
-0.044 0.085				

HouseStyle[T.2.5Fin]	-0.0739	0.070	-1.055	0.292
-0.211 0.063				
HouseStyle[T.2.5Unf]	0.0440	0.046	0.957	0.339
-0.046 0.134				
HouseStyle[T.2Story]	0.0046	0.031	0.146	0.884
-0.057 0.066				
HouseStyle[T.SFoyer]	0.0292	0.045	0.652	0.515
-0.059 0.117				
HouseStyle[T.SLvl]	0.0588	0.047	1.262	0.207
-0.033 0.150				
KitchenAbvGr[T.1]	-0.1250	0.091	-1.367	0.172
-0.304 0.054				
KitchenAbvGr[T.2]	-0.1718	0.097	-1.778	0.076
-0.361 0.018				
KitchenAbvGr[T.3]	-4.375e-15	1.12e-15	-3.897	0.000
-6.58e-15 -2.17e-15				
KitchenQual[T.Fa]	-0.0534	0.022	-2.404	0.016
-0.097 -0.010				
KitchenQual[T.Gd]	-0.0446	0.012	-3.674	0.000
-0.068 -0.021				
KitchenQual[T.Po]	-5.42e-16	1.14e-15	-0.477	0.634
-2.77e-15 1.69e-15				
KitchenQual[T.TA]	-0.0542	0.014	-3.990	0.000
-0.081 -0.028				
LandContour[T.HLS]	0.0213	0.017	1.256	0.209
-0.012 0.055				
LandContour[T.Low]	0.0109	0.024	0.454	0.650
-0.036 0.058				
LandContour[T.Lvl]	0.0052	0.013	0.402	0.688
-0.020 0.030				
LandSlope[T.Mod]	0.0163	0.014	1.191	0.234
-0.011 0.043				
LandSlope[T.Sev]	0.0025	0.042	0.060	0.952
-0.081 0.086				
LotConfig[T.CulDSac]	0.0096	0.011	0.874	0.382
-0.012 0.031				
LotConfig[T.FR2]	-0.0247	0.014	-1.741	0.082
-0.053 0.003				
LotConfig[T.FR3]	-0.0092	0.028	-0.329	0.742
-0.064 0.046				
LotConfig[T.Inside]	-0.0009	0.006	-0.150	0.880
-0.013 0.011				
LotShape[T.IR2]	-0.0044	0.013	-0.329	0.742
-0.031 0.022				
LotShape[T.IR3]	0.0037	0.028	0.132	0.895
-0.051 0.059				
LotShape[T.Reg]	0.0005	0.005	0.093	0.926
-0.010 0.011				

MSSubClass[T.30]	-0.0582	0.017	-3.491	0.000
-0.091 -0.026				
MSSubClass[T.40]	-0.0310	0.049	-0.626	0.531
-0.128 0.066				
MSSubClass[T.45]	0.0251	0.076	0.330	0.742
-0.124 0.175				
MSSubClass[T.50]	0.0112	0.031	0.357	0.721
-0.050 0.073				
MSSubClass[T.60]	-0.0209	0.031	-0.665	0.506
-0.082 0.041				
MSSubClass[T.70]	0.0243	0.033	0.733	0.464
-0.041 0.090				
MSSubClass[T.75]	0.0014	0.049	0.028	0.978
-0.095 0.098				
MSSubClass[T.80]	-0.0559	0.043	-1.305	0.192
-0.140 0.028				
MSSubClass[T.85]	0.0159	0.039	0.412	0.680
-0.060 0.092				
MSSubClass[T.90]	-0.0287	0.017	-1.726	0.085
-0.061 0.004				
MSSubClass[T.120]	-0.0302	0.039	-0.766	0.444
-0.108 0.047				
MSSubClass[T.150]	-0.1521	0.118	-1.284	0.199
-0.384 0.080				
MSSubClass[T.160]	-0.1089	0.053	-2.065	0.039
-0.212 -0.005				
MSSubClass[T.180]	-0.0694	0.062	-1.116	0.265
-0.192 0.053				
MSSubClass[T.190]	0.0679	0.104	0.652	0.514
-0.136 0.272				
MSZoning[T.C]	1.4713	0.059	24.956	0.000
1.356 1.587				
MSZoning[T.FV]	1.7984	0.051	35.292	0.000
1.698 1.898				
MSZoning[T.I]	1.4924	0.141	10.608	0.000
1.216 1.768				
MSZoning[T.RH]	1.7684	0.053	33.281	0.000
1.664 1.873				
MSZoning[T.RL]	1.7799	0.048	37.131	0.000
1.686 1.874				
MSZoning[T.RM]	1.7332	0.049	35.721	0.000
1.638 1.828				
MasVnrType[T.BrkFace]	0.0196	0.023	0.862	0.389
-0.025 0.064				
MasVnrType[T.CBlock]	-0.3480	0.117	-2.965	0.003
-0.578 -0.118				
MasVnrType[T.NaN]	0.0277	0.024	1.180	0.238
-0.018 0.074				

MasVnrType[T.Stone]	0.0157	0.024	0.651	0.515
-0.032 0.063				
MiscFeature[T.NaN]	0.0236	0.087	0.272	0.786
-0.147 0.194				
MiscFeature[T.0thr]	0.0872	0.087	0.999	0.318
-0.084 0.258				
MiscFeature[T.Shed]	-0.0027	0.079	-0.034	0.973
-0.157 0.151				
MiscFeature[T.TenC]	-0.3784	0.162	-2.341	0.019
-0.695 -0.061				
MoSold[T.2]	-0.0384	0.015	-2.507	0.012
-0.068 -0.008				
MoSold[T.3]	-0.0219	0.014	-1.577	0.115
-0.049 0.005				
MoSold[T.4]	-0.0083	0.014	-0.610	0.542
-0.035 0.018				
MoSold[T.5]	0.0011	0.013	0.086	0.932
-0.024 0.026				
MoSold[T.6]	-0.0017	0.012	-0.139	0.890
-0.026 0.023				
MoSold[T.7]	0.0033	0.012	0.266	0.790
-0.021 0.028				
MoSold[T.8]	-0.0147	0.013	-1.112	0.266
-0.041 0.011				
MoSold[T.9]	0.0037	0.014	0.257	0.798
-0.024 0.032				
MoSold[T.10]	-0.0216	0.014	-1.533	0.126
-0.049 0.006				
MoSold[T.11]	-0.0103	0.014	-0.714	0.475
-0.038 0.018				
MoSold[T.12]	-0.0104	0.015	-0.677	0.499
-0.040 0.020				
Neighborhood[T.Blueste]	0.1267	0.054	2.326	0.020
0.020 0.234				
Neighborhood[T.BrDale]	0.0042	0.039	0.107	0.915
-0.073 0.081				
Neighborhood[T.BrkSide]	0.0211	0.032	0.657	0.511
-0.042 0.084				
Neighborhood[T.ClearCr]	0.0209	0.034	0.621	0.534
-0.045 0.087				
Neighborhood[T.CollgCr]	-0.0314	0.025	-1.238	0.216
-0.081 0.018				
Neighborhood[T.Crawfor]	0.0772	0.029	2.663	0.008
0.020 0.134				
Neighborhood[T.Edwards]	-0.0495	0.028	-1.789	0.074
-0.104 0.005				
Neighborhood[T.Gilbert]	-0.0302	0.026	-1.154	0.249
-0.082 0.021				

Neighborhood[T.Greens]	0.0771	0.052	1.483	0.138
-0.025 0.179				
Neighborhood[T.GrnHill]	0.4596	0.069	6.657	0.000
0.324 0.595				
Neighborhood[T.IDOTRR]	0.0129	0.035	0.367	0.714
-0.056 0.082				
Neighborhood[T.Landmrk]	0.0131	0.094	0.139	0.890
-0.172 0.198				
Neighborhood[T.MeadowV]	-0.0561	0.041	-1.361	0.174
-0.137 0.025				
Neighborhood[T.Mitchel]	-0.0392	0.028	-1.384	0.166
-0.095 0.016				
Neighborhood[T.NAmes]	-0.0209	0.027	-0.773	0.440
-0.074 0.032				
Neighborhood[T.NPkVill]	0.0059	0.057	0.103	0.918
-0.106 0.118				
Neighborhood[T.NWAmes]	-0.0254	0.028	-0.901	0.368
-0.081 0.030				
Neighborhood[T.NoRidge]	0.0299	0.030	1.001	0.317
-0.029 0.089				
Neighborhood[T.NridgHt]	0.0288	0.026	1.104	0.270
-0.022 0.080				
Neighborhood[T.OldTown]	-0.0178	0.032	-0.551	0.581
-0.081 0.046				
Neighborhood[T.SWISU]	-0.0364	0.035	-1.046	0.296
-0.105 0.032				
Neighborhood[T.Sawyer]	0.0084	0.028	0.302	0.762
-0.046 0.063				
Neighborhood[T.SawyerW]	-0.0412	0.028	-1.487	0.137
-0.096 0.013				
Neighborhood[T.Somerst]	0.0144	0.030	0.488	0.626
-0.044 0.073				
Neighborhood[T.StoneBr]	0.0710	0.030	2.367	0.018
0.012 0.130				
Neighborhood[T.Timber]	-0.0154	0.027	-0.563	0.574
-0.069 0.038				
Neighborhood[T.Veenker]	-0.0114	0.034	-0.341	0.733
-0.077 0.054				
OverallCond[T.2]	0.0450	0.158	0.284	0.776
-0.266 0.356				
OverallCond[T.3]	0.0153	0.122	0.126	0.900
-0.224 0.255				
OverallCond[T.4]	0.1183	0.122	0.971	0.332
-0.121 0.357				
OverallCond[T.5]	0.2038	0.122	1.673	0.094
-0.035 0.443				
OverallCond[T.6]	0.2354	0.122	1.926	0.054
-0.004 0.475				

OverallCond[T.7]	0.2765	0.122	2.259	0.024
0.036 0.517				
OverallCond[T.8]	0.2983	0.122	2.438	0.015
0.058 0.538				
OverallCond[T.9]	0.3423	0.125	2.748	0.006
0.098 0.587				
OverallQual[T.2]	0.7610	0.058	13.213	0.000
0.648 0.874				
OverallQual[T.3]	1.0193	0.037	27.679	0.000
0.947 1.092				
OverallQual[T.4]	1.0455	0.031	33.832	0.000
0.985 1.106				
OverallQual[T.5]	1.1034	0.030	36.215	0.000
1.044 1.163				
OverallQual[T.6]	1.1296	0.031	36.839	0.000
1.069 1.190				
OverallQual[T.7]	1.1648	0.031	37.683	0.000
1.104 1.225				
OverallQual[T.8]	1.2162	0.032	38.586	0.000
1.154 1.278				
OverallQual[T.9]	1.2776	0.034	38.117	0.000
1.212 1.343				
OverallQual[T.10]	1.3260	0.038	34.507	0.000
1.251 1.401				
PavedDrive[T.P]	0.0032	0.018	0.177	0.859
-0.032 0.039				
PavedDrive[T.Y]	0.0293	0.013	2.332	0.020
0.005 0.054				
PoolQC[T.Fa]	0.3093	0.167	1.852	0.064
-0.018 0.637				
PoolQC[T.Gd]	0.4395	0.156	2.824	0.005
0.134 0.745				
PoolQC[T.NoPool]	-0.2178	0.108	-2.012	0.044
-0.430 -0.005				
PoolQC[T.TA]	0.0348	0.104	0.333	0.739
-0.170 0.239				
RoofMatl[T.Membran]	0.0795	0.115	0.689	0.491
-0.147 0.306				
RoofMatl[T.Metal]	0.0230	0.112	0.206	0.837
-0.197 0.243				
RoofMatl[T.Roll]	0.0743	0.096	0.774	0.439
-0.114 0.262				
RoofMatl[T.Tar&Grv]	-0.0012	0.045	-0.026	0.979
-0.090 0.087				
RoofMatl[T.WdShake]	-0.0181	0.038	-0.472	0.637
-0.093 0.057				
RoofMatl[T.WdShngl]	0.0631	0.051	1.227	0.220
-0.038 0.164				

RoofStyle[T.Gable]	-0.0082	0.052	-0.158	0.874
-0.110 0.093				
RoofStyle[T.Gambrel]	-0.0521	0.058	-0.904	0.366
-0.165 0.061				
RoofStyle[T.Hip]	-0.0008	0.052	-0.015	0.988
-0.103 0.101				
RoofStyle[T.Mansard]	-0.1099	0.064	-1.711	0.087
-0.236 0.016				
RoofStyle[T.Shed]	-0.0457	0.081	-0.563	0.574
-0.205 0.113				
SaleCondition[T.AdjLand]	0.2002	0.043	4.658	0.000
0.116 0.285				
SaleCondition[T.Alloca]	0.0725	0.034	2.127	0.034
0.006 0.139				
SaleCondition[T.Family]	0.0227	0.018	1.233	0.218
-0.013 0.059				
SaleCondition[T.Normal]	0.0390	0.010	3.881	0.000
0.019 0.059				
SaleCondition[T.Partial]	0.0961	0.046	2.077	0.038
0.005 0.187				
SaleType[T.CWD]	0.0156	0.029	0.539	0.590
-0.041 0.072				
SaleType[T.Con]	0.0544	0.054	1.007	0.314
-0.052 0.160				
SaleType[T.ConLD]	0.0277	0.031	0.898	0.369
-0.033 0.088				
SaleType[T.ConLI]	-0.2024	0.057	-3.531	0.000
-0.315 -0.090				
SaleType[T.ConLw]	-0.1059	0.048	-2.196	0.028
-0.201 -0.011				
SaleType[T.New]	-0.0274	0.048	-0.567	0.571
-0.122 0.067				
SaleType[T.Oth]	0.1478	0.088	1.678	0.094
-0.025 0.321				
SaleType[T.VWD]	-0.0313	0.090	-0.348	0.728
-0.208 0.145				
SaleType[T.WD]	0.0034	0.014	0.245	0.806
-0.024 0.031				
Street[T.Pave]	0.0204	0.044	0.460	0.645
-0.067 0.107				
TotRmsAbvGrd[T.4]	0.0211	0.032	0.670	0.503
-0.041 0.083				
TotRmsAbvGrd[T.5]	0.0158	0.032	0.497	0.619
-0.046 0.078				
TotRmsAbvGrd[T.6]	0.0185	0.033	0.568	0.570
-0.045 0.082				
TotRmsAbvGrd[T.7]	0.0113	0.034	0.337	0.736
-0.055 0.077				

TotRmsAbvGrd[T.8]	0.0164	0.035	0.474	0.636
-0.052 0.084				
TotRmsAbvGrd[T.9]	-0.0057	0.036	-0.158	0.874
-0.077 0.065				
TotRmsAbvGrd[T.10]	-0.0178	0.039	-0.462	0.644
-0.093 0.058				
TotRmsAbvGrd[T.11]	-0.0326	0.042	-0.768	0.443
-0.116 0.051				
TotRmsAbvGrd[T.12]	0.0897	0.076	1.180	0.238
-0.059 0.239				
TotRmsAbvGrd[T.13]	-3.155e-16	9.89e-17	-3.189	0.001
-5.1e-16 -1.21e-16				
Utilities[T.NoSeWa]	2.269e-16	1.48e-16	1.532	0.126
-6.37e-17 5.17e-16				
Utilities[T.NoSewr]	-0.1244	0.137	-0.907	0.364
-0.394 0.145				
Artery	-0.0918	0.015	-6.155	0.000
-0.121 -0.063				
AsbShng	-0.0204	0.024	-0.844	0.399
-0.068 0.027				
AsphShn	0.1508	0.068	2.231	0.026
0.018 0.283				
BrkCmn	0.0462	0.062	0.747	0.455
-0.075 0.167				
BrkComm	0.1891	0.066	2.877	0.004
0.060 0.318				
BrkFace	0.0648	0.015	4.445	0.000
0.036 0.093				
BsmtFinSF1	9.94e-05	2.54e-05	3.915	0.000
4.96e-05 0.000				
BsmtFinSF1_p2	-3.784e-08	1.73e-08	-2.187	0.029
-7.18e-08 -3.89e-09				
BsmtFinSF2	-1.364e-06	5.17e-05	-0.026	0.979
-0.000 0.000				
BsmtFinSF2_p2	4.068e-08	5.78e-08	0.704	0.481
-7.26e-08 1.54e-07				
BsmtUnfSF	-3.462e-05	2.4e-05	-1.444	0.149
-8.17e-05 1.24e-05				
BsmtUnfSF_p2	8.152e-09	1.12e-08	0.729	0.466
-1.38e-08 3.01e-08				
CBlock	2.7422	0.110	24.878	0.000
2.526 2.958				
CemntBd	-0.0743	0.065	-1.142	0.254
-0.202 0.053				
CmentBd	0.0959	0.065	1.470	0.142
-0.032 0.224				
EnclosedPorch	-9.118e-05	6.25e-05	-1.458	0.145
-0.000 3.15e-05				

EnclosedPorch_p2	4.909e-07	1.46e-07	3.369	0.001
2.05e-07 7.77e-07				
Feedr	-0.0555	0.011	-5.251	0.000
-0.076 -0.035				
GarageArea	-4.593e-06	8.08e-05	-0.057	0.955
-0.000 0.000				
GarageArea_p2	5.741e-08	5.91e-08	0.971	0.332
-5.86e-08 1.73e-07				
GrLivArea	0.0003	7.98e-05	3.686	0.000
0.000 0.000				
GrLivArea_p2	-3.041e-08	1.26e-08	-2.421	0.016
-5.5e-08 -5.77e-09				
HdBoard	0.0004	0.012	0.034	0.973
-0.023 0.024				
ImStucc	-0.0246	0.030	-0.834	0.404
-0.083 0.033				
LotArea	6.268e-06	8.91e-07	7.035	0.000
4.52e-06 8.02e-06				
LotArea_p2	-3.289e-11	6.34e-12	-5.186	0.000
-4.53e-11 -2.05e-11				
LotFrontage	-7.06e-06	0.000	-0.047	0.962
-0.000 0.000				
LotFrontage_p2	5.364e-07	1.16e-06	0.464	0.643
-1.73e-06 2.81e-06				
LowQualFinSF	2.652e-05	0.000	0.119	0.905
-0.000 0.000				
LowQualFinSF_p2	-7.349e-08	5.25e-07	-0.140	0.889
-1.1e-06 9.57e-07				
MasVnrArea	9.059e-05	4.38e-05	2.069	0.039
4.73e-06 0.000				
MasVnrArea_p2	-4.991e-08	4e-08	-1.249	0.212
-1.28e-07 2.85e-08				
MetalSd	0.0174	0.012	1.416	0.157
-0.007 0.042				
MiscVal	2.305e-05	2.05e-05	1.126	0.260
-1.71e-05 6.32e-05				
MiscVal_p2	-9.851e-10	1.21e-09	-0.814	0.416
-3.36e-09 1.39e-09				
Norm	0.0571	0.026	2.196	0.028
0.006 0.108				
OpenPorchSF	8.498e-05	7.67e-05	1.108	0.268
-6.55e-05 0.000				
OpenPorchSF_p2	1.204e-07	2.54e-07	0.474	0.636
-3.78e-07 6.19e-07				
Other	-0.0595	0.087	-0.683	0.494
-0.230 0.111				
Plywood	0.0006	0.011	0.052	0.959
-0.022 0.023				

PoolArea		-0.0007	0.000	-2.091	0.037
-0.001	-4.32e-05				
PosA		0.0471	0.027	1.773	0.076
-0.005	0.099				
PosN		0.0237	0.020	1.164	0.245
-0.016	0.064				
PreCast		-3.194e-19	1.39e-17	-0.023	0.982
-2.75e-17	2.69e-17				
RR Ae		-0.0554	0.023	-2.460	0.014
-0.100	-0.011				
RR An		-0.0160	0.016	-0.989	0.323
-0.048	0.016				
RR Ne		-0.0211	0.046	-0.456	0.649
-0.112	0.070				
RR Nn		0.0639	0.041	1.559	0.119
-0.016	0.144				
ScreenPorch		0.0003	9.24e-05	3.149	0.002
0.000	0.000				
ScreenPorch_p2		-4.331e-07	3.31e-07	-1.310	0.190
-1.08e-06	2.16e-07				
Stone		-0.0021	0.047	-0.044	0.965
-0.095	0.091				
Stucco		0.0205	0.019	1.108	0.268
-0.016	0.057				
TotalBsmtSF		6.341e-05	3.41e-05	1.859	0.063
-3.49e-06	0.000				
TotalBsmtSF_p2		3.152e-09	1.53e-08	0.206	0.837
-2.69e-08	3.32e-08				
VinylSd		0.0059	0.013	0.457	0.648
-0.019	0.031				
WdSdng		0.0088	0.012	0.727	0.467
-0.015	0.033				
WdShng		0.0061	0.022	0.278	0.781
-0.037	0.049				
WdShng		0.0041	0.018	0.231	0.818
-0.031	0.039				
WoodDeckSF		8.018e-05	3.14e-05	2.550	0.011
1.85e-05	0.000				
WoodDeckSF_p2		-7.926e-08	5.42e-08	-1.462	0.144
-1.86e-07	2.71e-08				
X1stFlrSF		0.0002	8.13e-05	2.313	0.021
2.86e-05	0.000				
X1stFlrSF_p2		-2.878e-08	1.4e-08	-2.059	0.040
-5.62e-08	-1.37e-09				
X2ndFlrSF		7.968e-05	7.94e-05	1.004	0.315
-7.6e-05	0.000				
X2ndFlrSF_p2		1.574e-08	2.92e-08	0.540	0.589
-4.15e-08	7.29e-08				

X3SsnPorch	8.546e-05	0.000	0.292	0.770
-0.000 0.001				
X3SsnPorch_p2	4.591e-07	1.04e-06	0.443	0.658
-1.57e-06 2.49e-06				
YearsSince1950Built	5.089e-05	0.001	0.036	0.972
-0.003 0.003				
YearsSince1950Built_p2	6.621e-05	2.77e-05	2.393	0.017
1.19e-05 0.000				
YearsSince1950GarageBuilt	0.0006	0.001	0.528	0.597
-0.002 0.003				
YearsSince1950GarageBuilt_p2	-1.493e-05	2.13e-05	-0.700	0.484
-5.68e-05 2.69e-05				
YearsSince1950Remod	0.0015	0.001	1.889	0.059
-5.77e-05 0.003				
YearsSince1950Remod_p2	-2.076e-05	1.44e-05	-1.444	0.149
-4.9e-05 7.45e-06				
=====				
Omnibus:	303.264	Durbin-Watson:	1.912	
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2249.910	
Skew:	-0.564	Prob(JB):	0.00	
Kurtosis:	8.317	Cond. No.	4.48e+17	
=====				

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 8.45e-15. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
[ ]: print_metrics(nlr_poly, ames_train_poly, y_train, ames_test_poly, y_test,
    ↪flag_log_sale_price = True)
print_metrics(nlr_poly, ames_train_poly, y_train, ames_test_poly, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

```
Training R2 0.9624105774575185
Training MAE 0.05428713187831344
Training RMSE 0.07504602800253764
Out-of-sample R2 0.8389618470389943
Out-of-sample MAE 0.08377525015006256
Out-of-sample RMSE 0.15893909023513655
```

Metrics for Sale Price:

```
Training R2 0.9640398351503799
Training MAE 9959.9415261308
```


Training RMSE 14814.210314147367
 Out-of-sample R2 0.42824990275266905
 Out-of-sample MAE 15888.470959526549
 Out-of-sample RMSE 59264.318499926754

Pay attention to the test set performance.

6.1 2.2 “Common Sense” Linear Regression

We want to perform linear regression with only some of the variables which could be chosen using common sense

```
[ ]: ames_train[['MSSubClass',  
               ↪ 'OverallQual', 'YearsSince1950Built', 'GrLivArea', 'TotRmsAbvGrd', 'FullBath', 'SaleCondition']]
```

```
[ ]:      MSSubClass OverallQual  YearsSince1950Built  GrLivArea TotRmsAbvGrd \  
989          20           6              8      1414.0           6  
990          20           6             20      2117.0           7  
991          60           6             19      2112.0           9  
992          60           6             47      1604.0           7  
993          60           6             45      1470.0           7  
...          ...           ...             ...          ...  
2924         20           5             10      1224.0           7  
2925         80           6             34      1003.0           6  
2926         20           5             33       902.0           5  
2928         20           5             24      1389.0           6  
2929         60           7             43      2000.0           9
```

```
      FullBath SaleCondition  
989          1      Normal  
990          2      Normal  
991          2      Normal  
992          2      Normal  
993          2      Normal  
...          ...           ...  
2924         1  Abnorml  
2925         1      Normal  
2926         1      Normal  
2928         1      Normal  
2929         2      Normal
```

[1828 rows x 7 columns]

```
[ ]: ames_train_cs = ames_train[['LogSalePrice', 'MSSubClass',  
               ↪ 'OverallQual', 'YearsSince1950Built', 'GrLivArea', 'TotRmsAbvGrd', 'FullBath', 'SaleCondition']]  
ames_train_cs = ames_train_cs.copy()  
ames_train_cs['OverallQual'] = ames_train_cs['OverallQual'].astype('float')  
ames_train_cs['TotRmsAbvGrd'] = ames_train_cs['TotRmsAbvGrd'].astype('int')
```

```

ames_train_cs['FullBath'] = ames_train_cs['FullBath'].astype('int')

ames_test_cs = ames_test[['LogSalePrice', 'MSSubClass', '
↳ 'OverallQual', 'YearsSince1950Built', 'GrLivArea', 'TotRmsAbvGrd', 'FullBath', 'SaleCondition']]
ames_test_cs = ames_test_cs.copy()
ames_test_cs['OverallQual'] = ames_test_cs['OverallQual'].astype('float')
ames_test_cs['TotRmsAbvGrd'] = ames_test_cs['TotRmsAbvGrd'].astype('int')
ames_test_cs['FullBath'] = ames_test_cs['FullBath'].astype('int')

print(ames_train_cs.shape)

```

(1828, 8)

```

[ ]: all_columns = "+".join(ames_train_cs.columns.difference(["LogSalePrice"]))
my_formula = "LogSalePrice~" + all_columns + "-1"
print(my_formula)

mod_commonsense = smf.ols(my_formula, data=ames_train_cs)
lr_cs = mod_commonsense.fit()

print(lr_cs.summary())

```

LogSalePrice~FullBath+GrLivArea+MSSubClass+OverallQual+SaleCondition+TotRmsAbvGrd+YearsSince1950Built-1

OLS Regression Results

```

=====
Dep. Variable:          LogSalePrice    R-squared:                0.859
Model:                  OLS             Adj. R-squared:           0.857
Method:                 Least Squares   F-statistic:              437.4
Date:                   Fri, 01 Nov 2024 Prob (F-statistic):       0.00
Time:                   18:18:57        Log-Likelihood:          928.68
No. Observations:      1828            AIC:                    -1805.
Df Residuals:           1802            BIC:                    -1662.
Df Model:                25
Covariance Type:        nonrobust
=====
=====

```

	coef	std err	t	P> t	[0.025
0.975]					
MSSubClass[20]	10.7050	0.027	400.469	0.000	10.653
10.757					
MSSubClass[30]	10.5387	0.031	342.113	0.000	10.478
10.599					
MSSubClass[40]	10.5311	0.078	134.816	0.000	10.378

10.684					
MSSubClass[45]	10.6019	0.051	207.974	0.000	10.502
10.702					
MSSubClass[50]	10.5715	0.030	352.890	0.000	10.513
10.630					
MSSubClass[60]	10.5596	0.031	342.320	0.000	10.499
10.620					
MSSubClass[70]	10.5422	0.034	309.101	0.000	10.475
10.609					
MSSubClass[75]	10.4234	0.048	216.125	0.000	10.329
10.518					
MSSubClass[80]	10.6874	0.032	338.392	0.000	10.625
10.749					
MSSubClass[85]	10.7808	0.038	285.581	0.000	10.707
10.855					
MSSubClass[90]	10.5422	0.037	286.747	0.000	10.470
10.614					
MSSubClass[120]	10.6443	0.030	355.652	0.000	10.586
10.703					
MSSubClass[150]	10.3006	0.150	68.787	0.000	10.007
10.594					
MSSubClass[160]	10.3885	0.031	338.192	0.000	10.328
10.449					
MSSubClass[180]	10.5393	0.057	186.112	0.000	10.428
10.650					
MSSubClass[190]	10.5839	0.037	282.665	0.000	10.510
10.657					
SaleCondition[T.AdjLand]	0.0346	0.063	0.553	0.581	-0.088
0.157					
SaleCondition[T.Alloca]	0.1598	0.047	3.403	0.001	0.068
0.252					
SaleCondition[T.Family]	0.0338	0.029	1.153	0.249	-0.024
0.091					
SaleCondition[T.Normal]	0.0990	0.015	6.711	0.000	0.070
0.128					
SaleCondition[T.Partial]	0.1320	0.019	6.869	0.000	0.094
0.170					
FullBath	-0.0231	0.010	-2.403	0.016	-0.042
-0.004					
GrLivArea	0.0004	1.53e-05	28.971	0.000	0.000
0.000					
OverallQual	0.1159	0.004	27.329	0.000	0.108
0.124					
TotRmsAbvGrd	-0.0163	0.004	-3.792	0.000	-0.025
-0.008					
YearsSince1950Built	0.0034	0.000	10.515	0.000	0.003
0.004					

=====

Omnibus:	633.662	Durbin-Watson:	1.749
Prob(Omnibus):	0.000	Jarque-Bera (JB):	8959.171
Skew:	-1.225	Prob(JB):	0.00
Kurtosis:	13.565	Cond. No.	7.09e+04

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 7.09e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
[ ]: print_metrics(lr_cs, ames_train_cs, y_train, ames_test_cs, y_test,
    ↪flag_log_sale_price = True)
print_metrics(lr_cs, ames_train_cs, y_train, ames_test_cs, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

```
Training R2 0.8585288469181491
Training MAE 0.10592319141717338
Training RMSE 0.14558908973890214
Out-of-sample R2 0.8347117625903195
Out-of-sample MAE 0.11370443708303558
Out-of-sample RMSE 0.1610227749435649
```

Metrics for Sale Price:

```
Training R2 0.8752645912586368
Training MAE 19392.02270765631
Training RMSE 27590.689019810863
Out-of-sample R2 0.8672838314855108
Out-of-sample MAE 19917.235925224228
Out-of-sample RMSE 28553.022575248742
```

```
[ ]:
```

```
[ ]:
```

7 Part 2: Model refinement

7.1 1. Principal Components Regression

We first remove columns that are nearly constant, i.e., have small standard deviation. Then we use sklearn grid-search for cross validation and finally retrain the final model.

```
[ ]: X_train_poly = ames_train_poly.drop(columns='LogSalePrice')
X_test_poly = ames_test_poly.drop(columns='LogSalePrice')

X_train_poly_wide = pd.get_dummies(X_train_poly)
X_test_poly_wide = pd.get_dummies(X_test_poly)

[ ]: y_train = ames_train['LogSalePrice']
y_test = ames_test['LogSalePrice']

X_train_pcr = X_train_poly_wide.loc[:, X_train_poly_wide.std() > 0.1]
X_test_pcr = X_test_poly_wide[X_train_pcr.columns]

print(X_train_poly_wide.shape, X_train_pcr.shape)
print(X_test_poly_wide.shape, X_test_pcr.shape)

(1828, 397) (1828, 275)
(937, 397) (937, 275)
```

We also standardize the data before feeding it to the PCA step, as recommended by good practice.

```
[ ]: from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV

scaler = StandardScaler()
pca = PCA(n_components=5, random_state=88)
lr = LinearRegression()
pipe = Pipeline(steps=[('scaler', scaler), ('pca', pca), ('lr', lr)])

pipe.fit(X_train_pcr, y_train)

[ ]: Pipeline(steps=[('scaler', StandardScaler()),
                    ('pca', PCA(n_components=5, random_state=88)),
                    ('lr', LinearRegression())])

[ ]: print_metrics(pipe, X_train_pcr, y_train, X_test_pcr, y_test,
    ↪flag_log_sale_price = True)
print_metrics(pipe, X_train_pcr, y_train, X_test_pcr, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

```
Training R2 0.8567244094773699
Training MAE 0.10108699422106086
Training RMSE 0.14651462829012946
Out-of-sample R2 0.8355568543382658
```

```
Out-of-sample MAE 0.10530967892420574
Out-of-sample RMSE 0.16061060586244827
```

Metrics for Sale Price:

```
Training R2 0.8927975509686596
Training MAE 17757.429598137704
Training RMSE 25578.202564553925
Out-of-sample R2 0.8987227159041019
Out-of-sample MAE 17636.54874599874
Out-of-sample RMSE 24942.856856990882
```

```
[ ]:
```

7.2 2. Ridge Regression

We can choose `alpha_max` so as the value that makes all coefficients zero, and then construct a log sequence of `alpha` values trending smaller, decreasing the degree of regularization.

For the case of Ridge Regression, `alpha` value that would make all coefficients zero would be `Inf`, however we can be satisfied with sufficiently small numbers, and work from there.

```
[ ]: X_train_rr = X_train_poly_wide
      X_test_rr = X_test_poly_wide

      print(X_train_rr.shape, X_test_rr.shape)
```

```
(1828, 397) (937, 397)
```

7.2.1 Determine 'alpha_max'

```
[ ]: from sklearn.linear_model import Ridge

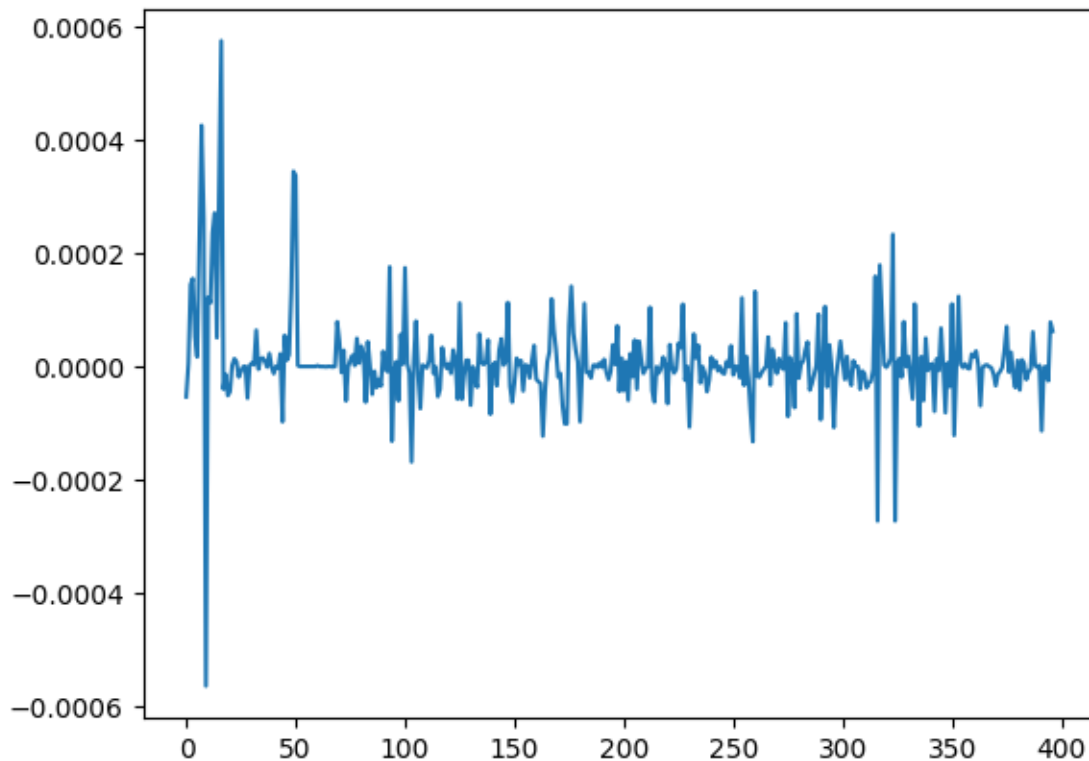
      alpha_max = 10**5
      rr = Ridge(alpha=alpha_max, random_state=88)
      rr.fit(X_train_rr, y_train)
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned
matrix (rcond=5.87405e-17): result may not be accurate.
```

```
    return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

```
[ ]: Ridge(alpha=100000, random_state=88)
```

```
[ ]: plt.plot(rr.coef_)
      plt.show()
      print(max(abs(rr.coef_)))
```



0.0005755966628195446

```
[ ]: print_metrics(rr, X_train_rr, y_train, X_test_rr, y_test, flag_log_sale_price =
      ↪True)
      print_metrics(rr, X_train_rr, y_train, X_test_rr, y_test, flag_log_sale_price =
      ↪False)
```

Metrics for Log(Sale Price):

```
Training R2 0.8452590849089253
Training MAE 0.10467969125067748
Training RMSE 0.1522640805932089
Out-of-sample R2 0.8229399441245389
Out-of-sample MAE 0.11151022706827869
Out-of-sample RMSE 0.16665817850890513
```

Metrics for Sale Price:

```
Training R2 0.878237976891266
Training MAE 18648.76164916895
Training RMSE 27259.85846771404
Out-of-sample R2 0.8695106549025007
```

Out-of-sample MAE 19389.607748338716
Out-of-sample RMSE 28312.465936142868

```
[ ]:
```

7.3 3. Lasso Regression

```
[ ]: from sklearn.linear_model import Lasso
```

```
[ ]: X_train_lasso = X_train_poly_wide  
X_test_lasso = X_test_poly_wide  
  
print(X_train_lasso.shape, X_test_lasso.shape)
```

(1828, 397) (937, 397)

7.3.1 Lasso Coefficients vs. Degree of Regularization

```
[ ]: # Question: What is the best value of lambda in Lasso?
```

7.3.2 Lasso Hyper-parameter Tuning

```
[ ]: alphas = np.logspace(-5, 1 , num=50, base=10)  
coefs = []
```

```
[ ]: from sklearn.linear_model import Lasso  
  
for a in alphas:  
    lasso = Lasso(alpha=a, random_state=88)  
    lasso.fit(X_train_lasso, y_train)  
    coefs.append(lasso.coef_)  
  
plt.figure(figsize=(12, 10))  
ax = plt.gca()  
ax.plot(alphas, coefs)  
ax.set_xscale('log')  
plt.xlabel('Alpha')  
plt.ylabel('Coefficients')  
plt.title('Lasso coefficients as a function of the regularization')  
plt.show()
```

/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 5.418e+00, tolerance: 2.739e-02

```
    model = cd_fast.enet_coordinate_descent(  
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
```



```

packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.499e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.600e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.727e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 5.885e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 6.079e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 6.317e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 6.609e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 6.965e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-

```

```

packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 7.397e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 7.914e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 8.532e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 9.266e+00, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.012e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.106e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.209e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.317e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-

```

```

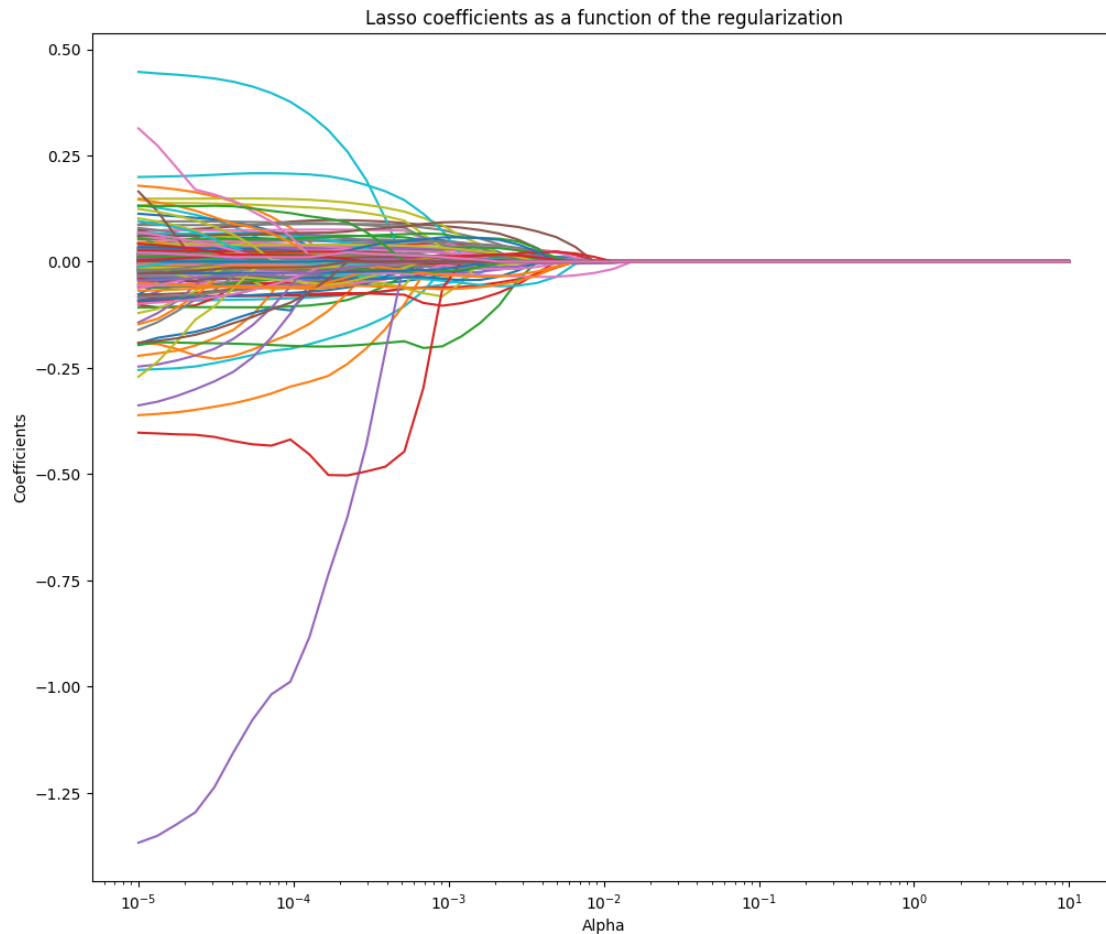
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.431e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.548e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.491e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.354e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 1.889e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.145e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.127e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 3.411e-01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-

```

```

packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.100e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.168e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.190e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.220e+01, tolerance: 2.739e-02
    model = cd_fast.enet_coordinate_descent(

```



7.3.3 Selected Variables

Let's look at some of the variables selected by lasso

```
[ ]: lasso = Lasso(alpha=0.1, random_state=88)
lasso.fit(X_train_lasso, y_train)
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/sklearn/linear_model/_coordinate_descent.py:697: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.157e+01, tolerance: 2.739e-02
model = cd_fast.enet_coordinate_descent(
```

```
[ ]: Lasso(alpha=0.1, random_state=88)
```

```
[ ]: cols = X_train_lasso.columns
      coefs = lasso.coef_
      sorted(zip(abs(coefs), cols))
```

```

[ ]: [(0.0, 'Alley_Grvl'),
      (0.0, 'Alley_NoAccess'),
      (0.0, 'Alley_Pave'),
      (0.0, 'Artery'),
      (0.0, 'AsbShng'),
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      (0.0, 'BsmtFinType2_NaN'),

```

```

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(0.0, 'FireplaceQu_Fa'),
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```

```

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```

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```

```

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[ ]: print_metrics(rr, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = True)
print_metrics(rr, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

```
Training R2 0.8452590849089253
Training MAE 0.10467969125067748
Training RMSE 0.1522640805932089
Out-of-sample R2 0.8229399441245389
Out-of-sample MAE 0.11151022706827869
Out-of-sample RMSE 0.16665817850890513
```

Metrics for Sale Price:

```
Training R2 0.878237976891266
Training MAE 18648.76164916895
Training RMSE 27259.85846771404
Out-of-sample R2 0.8695106549025007
Out-of-sample MAE 19389.607748338716
Out-of-sample RMSE 28312.465936142868
```

```
[ ]:
```

[]: