

# Week11

November 10, 2024

## 1 STOR 320 Introduction to Data Science

### 1.1 Week 10: Cross validation

```
[ ]: 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
```

#### 1.1.1 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

```

[ ]:

```

[ ]: ames = pd.read_csv('cleaned_Ames.csv')
      ames.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2765 entries, 0 to 2764
Columns: 105 entries, Unnamed: 0 to YearsSince1950GarageBuilt
dtypes: float64(21), int64(45), object(39)
memory usage: 2.2+ MB

```

```

[ ]: ames = pd.read_feather('cleaned_ames.feather')
      ames

```

```

[ ]:
      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
...      ...      ...      ...      ...      ...      ...
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	...	PreCast	Stone	Stucco	VinylSd	WdSdng	\
0	IR1	Lvl	AllPub	...	0	0	0	0	0	
1	Reg	Lvl	AllPub	...	0	0	0	1	0	
2	IR1	Lvl	AllPub	...	0	0	0	0	1	
3	Reg	Lvl	AllPub	...	0	0	0	0	0	
4	IR1	Lvl	AllPub	...	0	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	...
2924	Reg	Lvl	AllPub	...	0	0	0	1	0	
2925	IR1	Lvl	AllPub	...	0	0	0	0	0	
2926	IR1	Low	AllPub	...	0	0	0	0	0	
2928	Reg	Lvl	AllPub	...	0	0	0	0	0	
2929	Reg	Lvl	AllPub	...	0	0	0	0	0	

	WdShing	WdShng	YearsSince1950Built	YearsSince1950Remod	\
0	0	0	10	10	
1	0	0	11	11	
2	0	0	8	8	
3	0	0	18	18	
4	0	0	47	48	
...	...	...	...	...	...
2924	0	0	10	46	
2925	0	0	34	34	
2926	0	0	33	33	
2928	0	0	24	25	
2929	0	0	43	44	

	YearsSince1950GarageBuilt
0	10.0
1	11.0
2	8.0
3	18.0
4	47.0
...	...
2924	10.0
2925	34.0
2926	33.0
2928	25.0
2929	43.0

[2765 rows x 105 columns]

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

```
<class 'pandas.core.frame.DataFrame'>
Index: 2765 entries, 0 to 2929
```

Columns: 105 entries, LogSalePrice to YearsSince1950GarageBuilt  
dtypes: category(53), float64(21), int64(31)  
memory usage: 1.3 MB

```
[ ]: import warnings
warnings.filterwarnings('ignore')
```

```
[ ]: 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'])

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

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

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

### 1.1.2 Simple Linear model with higher-order Variables

```
[ ]: 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+BsmtCond+BsmtExposure+BsmtFinSF1+BsmtFinSF1\_p2+BsmtFinSF2+BsmtFinSF2\_p2+BsmtFinType1+BsmtFinType2+BsmtFullBath+BsmtHalfBath+BsmtQual+BsmtUnfSF+BsmtUnfSF\_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+RoofM

atl+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:                   Wed, 06 Nov 2024 Prob (F-statistic):       0.00
Time:                   18:17:35         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[Grvl]                  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.Othr]	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

```
[ ]: from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
```

## 1.2 Tuning parameters for LASSO

```
[ ]: 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)
```

```
[ ]: 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)

```
[ ]:
```

```
[ ]: alpha = 0.1
      lasso = Lasso(alpha=alpha, random_state=88)
      lasso.fit(X_train_lasso, y_train)
      print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
                    ↪flag_log_sale_price = True)
      print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
                    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

Training R2 0.8434328276296639  
Training MAE 0.10512146274745086  
Training RMSE 0.15315995785273875  
Out-of-sample R2 0.8272606660089641  
Out-of-sample MAE 0.11098188208314018  
Out-of-sample RMSE 0.1646121748477917

Metrics for Sale Price:

Training R2 0.8771753803277366  
Training MAE 18703.62412014218  
Training RMSE 27378.546173438564  
Out-of-sample R2 0.8763647003108185  
Out-of-sample MAE 19243.304403735783  
Out-of-sample RMSE 27558.870499831355

```
[ ]: alpha = 1e-2
      lasso = Lasso(alpha=alpha, random_state=88)
      lasso.fit(X_train_lasso, y_train)
      print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
                    ↪flag_log_sale_price = True)
      print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
                    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

Training R2 0.8499429858739374  
Training MAE 0.10300561266815048

Training RMSE 0.1499419084810546  
Out-of-sample R2 0.8220062230158947  
Out-of-sample MAE 0.11032085223765256  
Out-of-sample RMSE 0.16709703425025807

Metrics for Sale Price:

Training R2 0.8817688305547458  
Training MAE 18354.387859038405  
Training RMSE 26861.71033834519  
Out-of-sample R2 0.8640371155817245  
Out-of-sample MAE 19243.388183114424  
Out-of-sample RMSE 28900.16723185019

```
[ ]: alpha = 1e-3
lasso = Lasso(alpha=alpha, random_state=88)
lasso.fit(X_train_lasso, y_train)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = True)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

Training R2 0.930121322344742  
Training MAE 0.0693863840072313  
Training RMSE 0.10232157655865007  
Out-of-sample R2 0.8874024847675652  
Out-of-sample MAE 0.08314147804623102  
Out-of-sample RMSE 0.13290176107494575

Metrics for Sale Price:

Training R2 0.9414769024277362  
Training MAE 12459.409164012955  
Training RMSE 18898.673470545342  
Out-of-sample R2 0.9194885352942028  
Out-of-sample MAE 14287.152645232196  
Out-of-sample RMSE 22239.193567377857

```
[ ]: alpha = 1e-4
lasso = Lasso(alpha=alpha, random_state=88)
lasso.fit(X_train_lasso, y_train)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = True)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

Training R2 0.9591387227010627  
Training MAE 0.05679795053144252  
Training RMSE 0.07824396555230513  
Out-of-sample R2 0.8989936623088266  
Out-of-sample MAE 0.07800037399372267  
Out-of-sample RMSE 0.12587533655731084

Metrics for Sale Price:

Training R2 0.9611684976129613  
Training MAE 10369.737135417017  
Training RMSE 15394.293622412848  
Out-of-sample R2 0.9310061238902255  
Out-of-sample MAE 13389.285161194184  
Out-of-sample RMSE 20587.112764707137

```
[ ]: alpha = 1e-5
lasso = Lasso(alpha=alpha, random_state=88)
lasso.fit(X_train_lasso, y_train)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = True)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
    ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

Training R2 0.9622832237041625  
Training MAE 0.05457420034317798  
Training RMSE 0.0751730492656569  
Out-of-sample R2 0.8881083316233747  
Out-of-sample MAE 0.07994225740632856  
Out-of-sample RMSE 0.13248454152958558

Metrics for Sale Price:

Training R2 0.9638757207480595  
Training MAE 10010.81646880421  
Training RMSE 14847.976256226326  
Out-of-sample R2 0.9272909790616876  
Out-of-sample MAE 13681.307280622397  
Out-of-sample RMSE 21134.127319826755

```
[ ]: alpha = 1e-6
lasso = Lasso(alpha=alpha, random_state=88)
```



```

lasso.fit(X_train_lasso, y_train)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
↳flag_log_sale_price = True)
print_metrics(lasso, X_train_lasso, y_train, X_test_lasso, y_test,
↳flag_log_sale_price = False)

```

Metrics for Log(Sale Price):

```

Training R2 0.9624088075098128
Training MAE 0.05432119722133529
Training RMSE 0.07504779480251142
Out-of-sample R2 0.887174332291282
Out-of-sample MAE 0.08045121076601408
Out-of-sample RMSE 0.13303634007223722

```

Metrics for Sale Price:

```

Training R2 0.9640275202363419
Training MAE 9965.285133817228
Training RMSE 14816.7467334153
Out-of-sample R2 0.9267533208150691
Out-of-sample MAE 13751.7824584604
Out-of-sample RMSE 21212.12320497363

```

```

[ ]: MAE_list = []
candidate_values = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1]

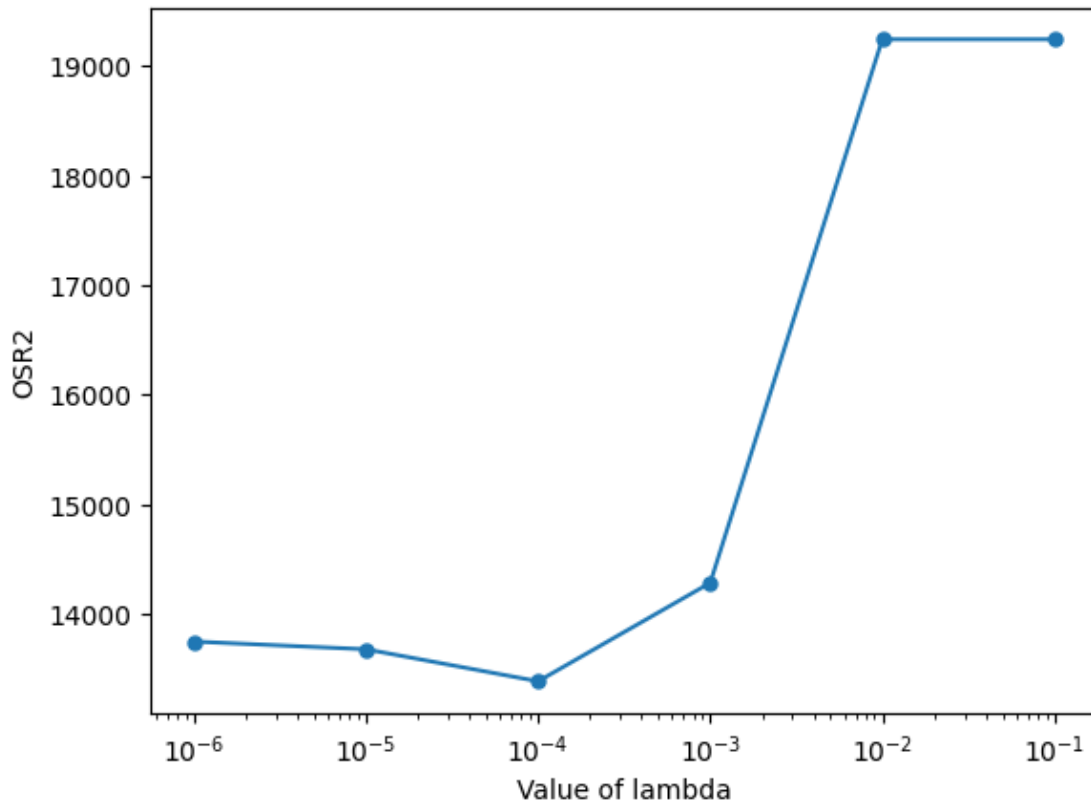
for alpha in candidate_values:
    lasso = Lasso(alpha=alpha, random_state=88)
    lasso.fit(X_train_lasso, y_train)
    y_pred_test = pd.Series(lasso.predict(X_test_lasso)).apply(np.exp).
↳reset_index(drop=True)
    y_train_exp = y_train.copy().apply(np.exp).reset_index(drop=True)
    y_test_exp = y_test.copy().apply(np.exp).reset_index(drop=True)
    MAE_list.append(MAE(y_test_exp, y_pred_test))

```

```

[ ]: plt.plot(candidate_values, MAE_list, 'o-', markersize = 5)
plt.xlabel('Value of lambda')
plt.ylabel('OSR2')
plt.xscale('log')

```



**1.3 In-class activity 1:** Create a similar plot for Ridge regression. The candidate value for labmda is [ 1e-1, 1, 10, 1e2, 1e3, 1e4 ]. Y-axis is the OSR2 and X-axis is the value of lambda.

```
[ ]: OSR2_list = []
candidate = [ 1e-1, 1, 10, 1e2, 1e3, 1e4 ]

for alpha in candidate:
    ridge = Ridge(alpha=alpha, random_state=88)
    ridge.fit(X_train_lasso, y_train)
    y_pred_test = pd.Series(ridge.predict(X_test_lasso)).apply(np.exp).
    ↪reset_index(drop=True)
    y_train_exp = y_train.copy().apply(np.exp).reset_index(drop=True)
    y_test_exp = y_test.copy().apply(np.exp).reset_index(drop=True)
    MAE_list.append(MAE(y_test_exp, y_pred_test))
```

Add Training set performance to the graph.

```
[ ]: TrainingMAE_list = []
candidate_values = [1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1]
```

```

for alpha in candidate_values:
    lasso = Lasso(alpha=alpha, random_state=88)
    lasso.fit(X_train_lasso, y_train)
    y_pred_train = pd.Series(lasso.predict(X_train_lasso)).apply(np.exp).
    ↪reset_index(drop=True)
    y_train_exp = y_train.copy().apply(np.exp).reset_index(drop=True)
    y_test_exp = y_test.copy().apply(np.exp).reset_index(drop=True)
    TrainingMAE_list.append(MAE(y_train_exp, y_pred_train))

```

```

[ ]: plt.plot(candidate_values, MAE_list, 'o-', markersize = 5, label = '
    ↪'Out-of-sample')
plt.plot(candidate_values, TrainingMAE_list, 'o-', markersize = 5, label = '
    ↪'In-sample')
plt.xlabel('Value of lambda')
plt.ylabel('')
plt.xscale('log')
plt.legend();

```

-----  
ValueError Traceback (most recent call last)

Cell In[78], line 1

----> 1

```

    ↪plt.plot(candidate_values, MAE_list, 'o-', markersize = 5, label = 'Out-of-sample')
    2 plt.plot(candidate_values, TrainingMAE_list, 'o-', markersize = 5, label,
    ↪= 'In-sample')
    3 plt.xlabel('Value of lambda')

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/

```

    ↪site-packages/matplotlib/pyplot.py:3794, in plot(scalex, scaley, data, *args,
    ↪**kwargs)

```

```

    3786 @_copy_docstring_and_deprecators(Axes.plot)

```

```

    3787 def plot(

```

```

    3788     *args: float | ArrayLike | str,
    (...)

```

```

    3792     **kwargs,

```

```

    3793 ) -> list[Line2D]:

```

```

-> 3794     return gca().plot(

```

```

    3795         *args,

```

```

    3796         scalex=scalex,

```

```

    3797         scaley=scaley,

```

```

    3798         **({"data": data} if data is not None else {}),

```

```

    3799         **kwargs,

```

```

    3800     )

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/

```

    ↪site-packages/matplotlib/axes/_axes.py:1779, in Axes.plot(self, scalex,
    ↪scaley, data, *args, **kwargs)

```

```

1536 """
1537 Plot y versus x as lines and/or markers.
1538 (...)
1776 (``'green'``) or hex strings (``'#008000'``).
1777 """
1778 kwargs = cbook.normalize_kwargs(kwargs, mlines.Line2D)
-> 1779 lines = [*self._get_lines(self, *args, data=data, **kwargs)]
1780 for line in lines:
1781     self.add_line(line)

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
↳ site-packages/matplotlib/axes/_base.py:296, in _process_plot_var_args.
↳ __call__(self, axes, data, *args, **kwargs)
    294     this += args[0],
    295     args = args[1:]
--> 296 yield from self._plot_args(
    297     axes, this, kwargs, ambiguous_fmt_datakey=ambiguous_fmt_datakey)

```

```

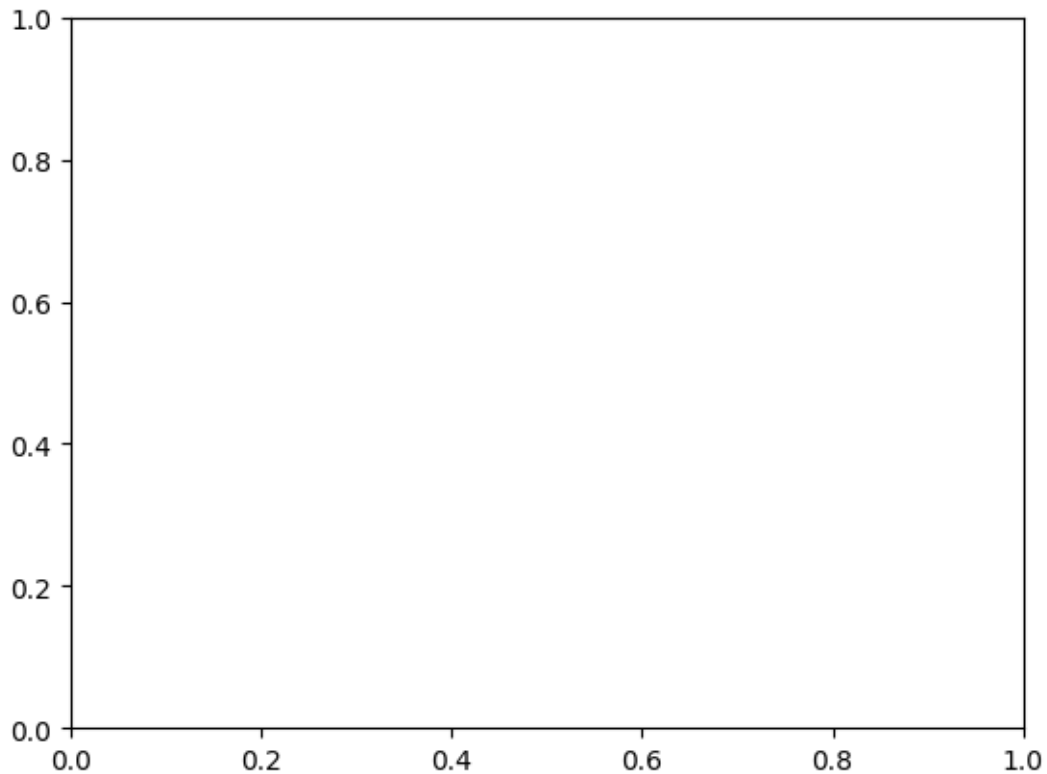
File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
↳ site-packages/matplotlib/axes/_base.py:486, in _process_plot_var_args.
↳ _plot_args(self, axes, tup, kwargs, return_kwargs, ambiguous_fmt_datakey)
    483     axes.yaxis.update_units(y)
    485 if x.shape[0] != y.shape[0]:
--> 486     raise ValueError(f"x and y must have same first dimension, but "
    487                       f"have shapes {x.shape} and {y.shape}")
    488 if x.ndim > 2 or y.ndim > 2:
    489     raise ValueError(f"x and y can be no greater than 2D, but have "
    490                       f"shapes {x.shape} and {y.shape}")

```

```

ValueError: x and y must have same first dimension, but have shapes (6,) and
↳ (12,)

```



### 1.3.1 K-fold cross validation

```
[ ]: from sklearn.model_selection import GridSearchCV
```

```
alpha_grid = {'alpha': np.logspace(-8, -1, num=10, base=10)}
```

```
lasso_cv = GridSearchCV(lasso, param_grid = alpha_grid,
```

```
    scoring='neg_mean_squared_error', cv=10, verbose=1)
```

```
lasso_cv.fit(X_train_lasso, y_train)
```

Fitting 10 folds for each of 10 candidates, totalling 100 fits

```
[ ]: GridSearchCV(cv=10, estimator=Lasso(alpha=0.1, random_state=88),  
    param_grid={'alpha': array([1.00000000e-08, 5.99484250e-08,  
    3.59381366e-07, 2.15443469e-06,  
    1.29154967e-05, 7.74263683e-05, 4.64158883e-04, 2.78255940e-03,  
    1.66810054e-02, 1.00000000e-01])},  
    scoring='neg_mean_squared_error', verbose=1)
```

```
[ ]: lasso_cv.cv_results_
```

```
[ ]: {'mean_fit_time': array([0.74864337, 0.74456458, 0.75606918, 0.73773813,
0.74517162,
0.62181613, 0.51850934, 0.35173864, 0.2392029 , 0.24281828]),
'std_fit_time': array([0.04160104, 0.05409118, 0.07124824, 0.03803379,
0.05941938,
0.00888817, 0.01800875, 0.01517724, 0.01328081, 0.0157893 ]),
'mean_score_time': array([0.00316212, 0.00462024, 0.00691543, 0.00376642,
0.00333533,
0.00310757, 0.0040307 , 0.00296528, 0.00315723, 0.00292087]),
'std_score_time': array([0.00066263, 0.00237882, 0.00603587, 0.00131657,
0.00151474,
0.00073947, 0.00188376, 0.00093391, 0.00169379, 0.00095648]),
'param_alpha': masked_array(data=[1e-08, 5.99484250318941e-08,
3.5938136638046254e-07,
2.1544346900318865e-06, 1.2915496650148827e-05,
7.742636826811278e-05, 0.0004641588833612782,
0.0027825594022071257, 0.016681005372000592, 0.1],
mask=[False, False, False, False, False, False, False, False,
False, False],
fill_value=1e+20),
'params': [{'alpha': 1e-08},
{'alpha': 5.99484250318941e-08},
{'alpha': 3.5938136638046254e-07},
{'alpha': 2.1544346900318865e-06},
{'alpha': 1.2915496650148827e-05},
{'alpha': 7.742636826811278e-05},
{'alpha': 0.0004641588833612782},
{'alpha': 0.0027825594022071257},
{'alpha': 0.016681005372000592},
{'alpha': 0.1}],
'split0_test_score': array([-0.00787318, -0.00787117, -0.00785983, -0.00779085,
-0.00757535,
-0.00735782, -0.00761434, -0.0105296 , -0.01173297, -0.01166006]),
'split1_test_score': array([-0.01815299, -0.01778185, -0.01597704, -0.01470858,
-0.01397911,
-0.01117959, -0.01165344, -0.01702969, -0.02329114, -0.02158746]),
'split2_test_score': array([-0.0254296 , -0.02436969, -0.02344383, -0.02317906,
-0.02275288,
-0.02615171, -0.02970623, -0.03616987, -0.04693504, -0.04688338]),
'split3_test_score': array([-0.00790345, -0.00787734, -0.00787569, -0.00787901,
-0.00800425,
-0.0079026 , -0.00748859, -0.0101973 , -0.01401935, -0.01400183]),
'split4_test_score': array([-0.02904953, -0.02900245, -0.0287643 , -0.02792024,
-0.0238768 ,
-0.00986928, -0.01259665, -0.01794151, -0.03566135, -0.03559733]),
'split5_test_score': array([-0.0155111 , -0.01513605, -0.01498391, -0.01480683,
-0.01465653,
```

```

        -0.01424154, -0.01478704, -0.01855934, -0.02740716, -0.02776815]),
'split6_test_score': array([-0.01502746, -0.01501102, -0.01497681, -0.01488101,
-0.01448217,
        -0.01287819, -0.01325205, -0.02035065, -0.03199917, -0.03186222]),
'split7_test_score': array([-0.008832 , -0.00873671, -0.00841158, -0.00825042,
-0.00775649,
        -0.00641255, -0.00612379, -0.00853876, -0.01248738, -0.01208519]),
'split8_test_score': array([-0.01122054, -0.01138903, -0.01146731, -0.01147103,
-0.01126702,
        -0.01001889, -0.01098486, -0.01832119, -0.03018501, -0.03030998]),
'split9_test_score': array([-0.0268892 , -0.02685823, -0.02667113, -0.02610903,
-0.0232181 ,
        -0.0162867 , -0.01412417, -0.02621292, -0.03973004, -0.03953425]),
'mean_test_score': array([-0.0165889 , -0.01640335, -0.01604314, -0.01569961,
-0.01475687,
        -0.01222989, -0.01283312, -0.01838508, -0.02734486, -0.02712898]),
'std_test_score': array([0.00765478, 0.0075257 , 0.00738017, 0.00716361,
0.00614612,
        0.005501 , 0.00629317, 0.00780515, 0.0113778 , 0.01147782]),
'rank_test_score': array([ 7,  6,  5,  4,  3,  1,  2,  8, 10,  9],
dtype=int32)}

```

```

[ ]: from sklearn.model_selection import GridSearchCV

def one_standard_error_rule(model, results, param_grid, n_splits,
    ↪neg_mean_squared_error=True):

    assert neg_mean_squared_error == True # function is defined specifically
    ↪for neg_mean_squared_error

    range_x = param_grid # results['param_'+list(param_grid.keys())[0]].data
    std_vs_x = pd.Series(results['std_test_score'], index = range_x)
    sem_vs_x = std_vs_x/np.sqrt(n_splits)

    mean_vs_x = pd.Series(results['mean_test_score'], index = range_x)
    mean_vs_x = mean_vs_x*(-1)

    x_min = mean_vs_x.idxmin()
    sem = sem_vs_x[x_min]

    if (model=='pcr'):
        x_1se = mean_vs_x[mean_vs_x <= min(mean_vs_x) + sem].index.min()
    elif (model=='ridge') | (model=='lasso'):
        x_1se = mean_vs_x[mean_vs_x <= min(mean_vs_x) + sem].index.max()

    #x_1se_idx = int(np.argwhere(range_x == x_1se)[0])

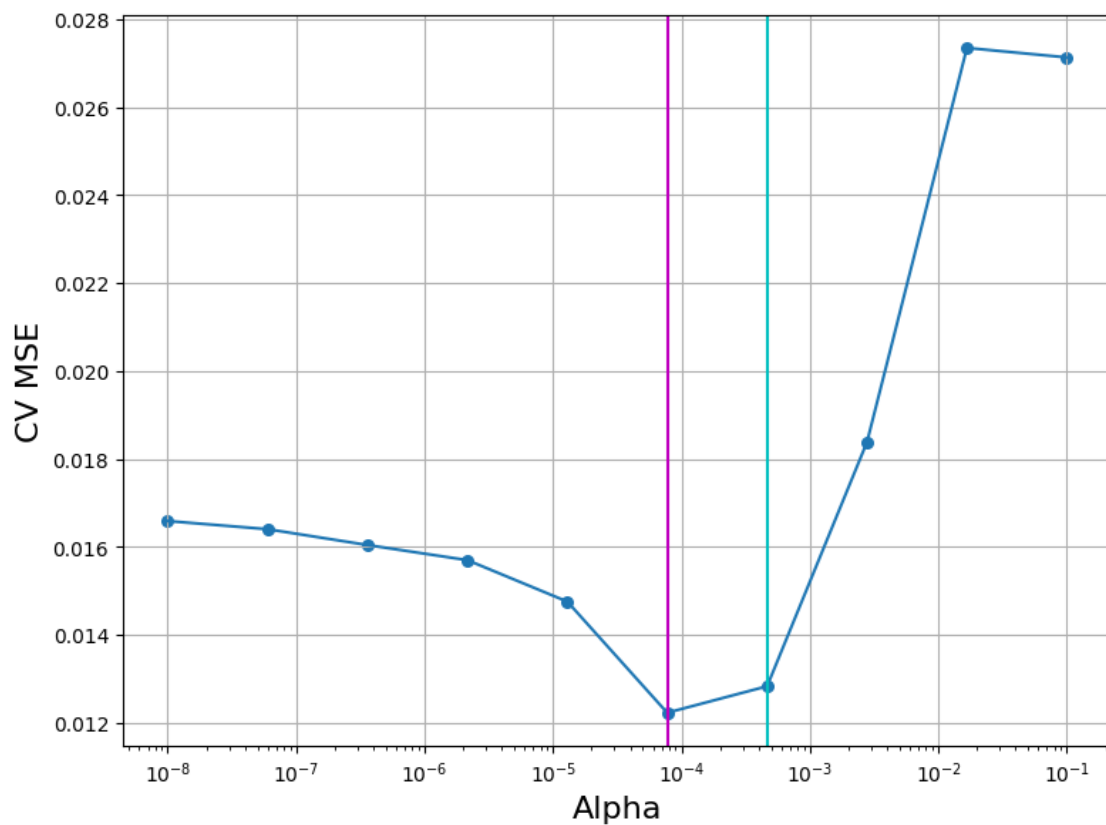
```

```
return x_min, x_1se
```

```
[ ]: range_alpha = lasso_cv.cv_results_['param_alpha'].data
MSE_scores = lasso_cv.cv_results_['mean_test_score']*(-1)
x_min, x_1se = one_standard_error_rule(model='lasso',
                                       results=lasso_cv.cv_results_,
                                       param_grid=range_alpha,
                                       n_splits=10,
                                       neg_mean_squared_error=True)

plt.figure(figsize=(8, 6))
ax = plt.gca()
ax.set_xscale('log')
plt.xlabel('Alpha', fontsize=16)
plt.ylabel('CV MSE', fontsize=16)
plt.scatter(range_alpha, MSE_scores, s=30)
plt.plot(range_alpha, MSE_scores)
plt.axvline(x=x_min, color='m')
plt.axvline(x=x_1se, color='c')
plt.grid()

plt.tight_layout()
plt.show()
```





Magenta vertical line is the minimizer, the cyan vertical line is the “1 Standard Error” selection.

```
[ ]: acc = lasso_cv.cv_results_['mean_test_score'] # what sklearn calls
      ↪mean_test_score is the holdout set, i.e. the validation set.
ccp = lasso_cv.cv_results_['param_alpha'].data

pd.DataFrame({'ccp alpha' : ccp, 'Validation Accuracy': acc})
```

```
[ ]:      ccp alpha  Validation Accuracy
0  1.000000e-08      -0.016589
1  5.994843e-08      -0.016403
2  3.593814e-07      -0.016043
3  2.154435e-06      -0.015700
4  1.291550e-05      -0.014757
5  7.742637e-05      -0.012230
6  4.641589e-04      -0.012833
7  2.782559e-03      -0.018385
8  1.668101e-02      -0.027345
9  1.000000e-01      -0.027129
```

```
[ ]: print('Alpha one standard error rule:', x_1se)
```

Alpha one standard error rule: 0.0004641588833612782

### 1.3.2 Lasso Refit with One Standard Error Rule

```
[ ]: lasso_cv = GridSearchCV(lasso, {'alpha': [x_1se]},
      ↪scoring='neg_mean_squared_error', cv=10)
lasso_cv.fit(X_train_lasso, y_train)

print_metrics(lasso_cv, X_train_lasso, y_train, X_test_lasso, y_test,
      ↪flag_log_sale_price = True)
print_metrics(lasso_cv, X_train_lasso, y_train, X_test_lasso, y_test,
      ↪flag_log_sale_price = False)
```

Metrics for Log(Sale Price):

Training R2 0.9467465562233576  
Training MAE 0.06238524036959335  
Training RMSE 0.08932411725332272  
Out-of-sample R2 0.9007191016790816  
Out-of-sample MAE 0.07862128213660351  
Out-of-sample RMSE 0.1247955735851673

Metrics for Sale Price:

Training R2 0.9526034800011082  
Training MAE 11250.968361557421  
Training RMSE 17007.516334830016  
Out-of-sample R2 0.9325057084639106  
Out-of-sample MAE 13461.47428911071  
Out-of-sample RMSE 20362.152823875873

## 1.4 Shuffle the dataset for k-fold cross validation

```
[ ]: from sklearn.model_selection import KFold

alpha_grid = {'alpha': np.logspace(-8, -1, num=15, base=10)}
cv = KFold(n_splits = 10, random_state = 1, shuffle = True)
lasso_cv = GridSearchCV(lasso, param_grid = alpha_grid,
    scoring='neg_mean_squared_error', cv=cv, verbose=2)
lasso_cv.fit(X_train_lasso, y_train)
```

Fitting 10 folds for each of 15 candidates, totalling 150 fits

```
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.8s
[CV] END ...alpha=1e-08; total time= 0.8s
[CV] END ...alpha=1e-08; total time= 0.8s
[CV] END ...alpha=1e-08; total time= 0.8s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.7s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.7s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.7s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.7s
[CV] END ...alpha=3.162277660168379e-08; total time= 0.8s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.8s
[CV] END ...alpha=1e-07; total time= 0.7s
[CV] END ...alpha=1e-07; total time= 0.7s
```



[illegible]

```

[CV] END ...alpha=0.01; total time= 0.4s
[CV] END ...alpha=0.01; total time= 0.3s
[CV] END ...alpha=0.01; total time= 0.3s
[CV] END ...alpha=0.01; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.2s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.03162277660168379; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s
[CV] END ...alpha=0.1; total time= 0.3s

```

```

[ ]: GridSearchCV(cv=KFold(n_splits=10, random_state=1, shuffle=True),
                  estimator=Lasso(alpha=0.1, random_state=88),
                  param_grid={'alpha': array([1.00000000e-08, 3.16227766e-08,
1.00000000e-07, 3.16227766e-07,
1.00000000e-06, 3.16227766e-06, 1.00000000e-05, 3.16227766e-05,
1.00000000e-04, 3.16227766e-04, 1.00000000e-03, 3.16227766e-03,
1.00000000e-02, 3.16227766e-02, 1.00000000e-01])},
                  scoring='neg_mean_squared_error', verbose=2)

```

```

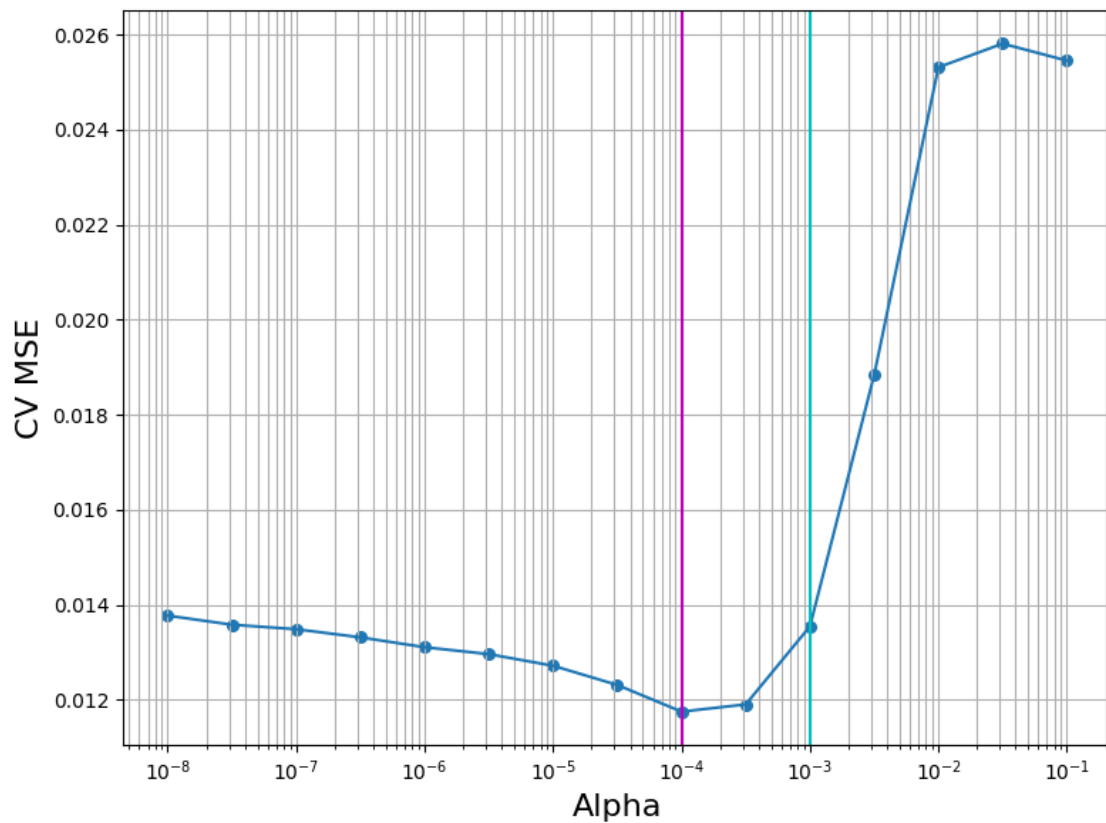
[ ]: range_alpha = lasso_cv.cv_results_['param_alpha'].data
MSE_scores = lasso_cv.cv_results_['mean_test_score']*(-1)
x_min, x_1se = one_standard_error_rule(model='lasso',
                                       results=lasso_cv.cv_results_,
                                       param_grid=range_alpha,
                                       n_splits=10,
                                       neg_mean_squared_error=True)

plt.figure(figsize=(8, 6))
ax = plt.gca()
ax.set_xscale('log')
plt.xlabel('Alpha', fontsize=16)
plt.ylabel('CV MSE', fontsize=16)
plt.scatter(range_alpha, MSE_scores, s=30)

```

```
plt.plot(range_alpha, MSE_scores)
plt.axvline(x=x_min, color='m')
plt.axvline(x=x_1se, color='c')
plt.grid(True, which='both')

plt.tight_layout()
plt.show()
```



## 1.5 Custom loss function

```
[ ]: def large_prediction_error_count(y_test, y_pred, threshold = 2000):
    y_pred_test = pd.Series(y_pred).copy().apply(np.exp).reset_index(drop=True)
    y_test_exp = pd.Series(y_test).copy().apply(np.exp).reset_index(drop=True)
    count = [(y_pred_test - y_test_exp) > threshold]
    return np.sum(count)
```

```
[ ]: from sklearn.metrics import make_scorer
```

```
alpha_grid = {'alpha': np.logspace(-8, -1, num=10, base=10)}
cv = KFold(n_splits = 10, random_state = 1, shuffle = True)
```

```
lasso_cv = GridSearchCV(lasso, param_grid = alpha_grid,
    ↳scoring=make_scorer(large_prediction_error_count, greater_is_better=False),
    ↳cv=cv, verbose=2)
lasso_cv.fit(X_train_lasso, y_train)
```

Fitting 10 folds for each of 10 candidates, totalling 100 fits

```
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.8s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.8s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=1e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.8s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.8s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=5.99484250318941e-08; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=3.5938136638046254e-07; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.8s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.8s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.8s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.8s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=2.1544346900318865e-06; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
```

```
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.8s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
[CV] END ...alpha=1.2915496650148827e-05; total time= 0.7s
```

```
-----
KeyboardInterrupt                                Traceback (most recent call last)
Cell In[89], line 6
      4 cv = KFold(n_splits = 10, random_state = 1, shuffle = True)
      5 lasso_cv = GridSearchCV(lasso, param_grid = alpha_grid,
    ↪ scoring=make_scorer(large_prediction_error_count, greater_is_better=False),
    ↪ cv=cv, verbose=2)
----> 6 lasso_cv.fit(X_train_lasso, y_train)

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
    ↪ site-packages/sklearn/base.py:1473, in _fit_context.<locals>.decorator.
    ↪ <locals>.wrapper(estimator, *args, **kwargs)
    1466     estimator._validate_params()
    1468 with config_context(
    1469     skip_parameter_validation=(
    1470         prefer_skip_nested_validation or global_skip_validation
    1471     )
    1472 ):
-> 1473     return fit_method(estimator, *args, **kwargs)

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
    ↪ site-packages/sklearn/model_selection/_search.py:1019, in BaseSearchCV.
    ↪ fit(self, X, y, **params)
    1013     results = self._format_results(
    1014         all_candidate_params, n_splits, all_out, all_more_results
    1015     )
    1017     return results
-> 1019 self._run_search(evaluate_candidates)
    1021 # multimetric is determined here because in the case of a callable
    1022 # self.scoring the return type is only known after calling
    1023 first_test_score = all_out[0]["test_scores"]

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
    ↪ site-packages/sklearn/model_selection/_search.py:1573, in GridSearchCV.
    ↪ _run_search(self, evaluate_candidates)
    1571 def _run_search(self, evaluate_candidates):
    1572     """Search all candidates in param_grid"""
-> 1573     evaluate_candidates(ParameterGrid(self.param_grid))
```



```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/sklearn/model_selection/_search.py:965, in BaseSearchCV.fit.
<locals>.evaluate_candidates(candidate_params, cv, more_results)
    957 if self.verbose > 0:
    958     print(
    959         "Fitting {0} folds for each of {1} candidates,"
    960         " totalling {2} fits".format(
    961             n_splits, n_candidates, n_candidates * n_splits
    962         )
    963     )
--> 965 out = parallel(
    966     delayed(_fit_and_score)(
    967         clone(base_estimator),
    968         X,
    969         y,
    970         train=train,
    971         test=test,
    972         parameters=parameters,
    973         split_progress=(split_idx, n_splits),
    974         candidate_progress=(cand_idx, n_candidates),
    975         **fit_and_score_kwargs,
    976     )
    977     for (cand_idx, parameters), (split_idx, (train, test)) in product(
    978         enumerate(candidate_params),
    979         enumerate(cv.split(X, y, **routed_params.splitter.split)),
    980     )
    981 )
    983 if len(out) < 1:
    984     raise ValueError(
    985         "No fits were performed. "
    986         "Was the CV iterator empty? "
    987         "Were there no candidates?"
    988     )

```

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/sklearn/utils/parallel.py:74, in Parallel.__call__(self,
iterable)
    69 config = get_config()
    70 iterable_with_config = (
    71     _with_config(delayed_func, config), args, kwargs)
    72     for delayed_func, args, kwargs in iterable
    73 )
---> 74 return super().__call__(iterable_with_config)

```

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/joblib/parallel.py:1918, in Parallel.__call__(self, iterable)
    1916 output = self._get_sequential_output(iterable)
    1917 next(output)

```

```

-> 1918     return output if self.return_generator else list(output)
    1920 # Let's create an ID that uniquely identifies the current call. If the
    1921 # call is interrupted early and that the same instance is immediately
    1922 # re-used, this id will be used to prevent workers that were
    1923 # concurrently finalizing a task from the previous call to run the
    1924 # callback.
    1925 with self._lock:

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/

↳ site-packages/joblib/parallel.py:1847, in Parallel.

↳ \_get\_sequential\_output(self, iterable)

```

    1845 self.n_dispatched_batches += 1
    1846 self.n_dispatched_tasks += 1
-> 1847 res = func(*args, **kwargs)
    1848 self.n_completed_tasks += 1
    1849 self.print_progress()

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/

↳ site-packages/sklearn/utils/parallel.py:136, in \_FuncWrapper.\_\_call\_\_(self, \*

↳ args, \*\*kwargs)

```

    134     config = {}
    135     with config_context(**config):
--> 136     return self.function(*args, **kwargs)

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/

↳ site-packages/sklearn/model\_selection/\_validation.py:888, in \*

↳ fit\_and\_score(estimator, X, y, scorer, train, test, verbose, parameters, \*

↳ fit\_params, score\_params, return\_train\_score, return\_parameters, \*

↳ return\_n\_test\_samples, return\_times, return\_estimator, split\_progress, \*

```

    886     estimator.fit(X_train, **fit_params)
    887     else:
--> 888     estimator.fit(X_train, y_train, **fit_params)
    890 except Exception:
    891     # Note fit time as time until error
    892     fit_time = time.time() - start_time

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/

↳ site-packages/sklearn/base.py:1473, in \_fit\_context.<locals>.decorator.

↳ <locals>.wrapper(estimator, \*args, \*\*kwargs)

```

    1466     estimator._validate_params()
    1468     with config_context(
    1469         skip_parameter_validation=(
    1470             prefer_skip_nested_validation or global_skip_validation
    1471         )
    1472     ):
-> 1473     return fit_method(estimator, *args, **kwargs)

```

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
↳ site-packages/sklearn/linear_model/_coordinate_descent.py:1077, in ElasticNet
↳ fit(self, X, y, sample_weight, check_input)
    1075 else:
    1076     this_Xy = None
-> 1077 _, this_coef, this_dual_gap, this_iter = self.path(
    1078     X,
    1079     y[:, k],
    1080     l1_ratio=self.l1_ratio,
    1081     eps=None,
    1082     n_alphas=None,
    1083     alphas=[alpha],
    1084     precompute=precompute,
    1085     Xy=this_Xy,
    1086     copy_X=True,
    1087     coef_init=coef_[k],
    1088     verbose=False,
    1089     return_n_iter=True,
    1090     positive=self.positive,
    1091     check_input=False,
    1092     # from here on **params
    1093     tol=self.tol,
    1094     X_offset=X_offset,
    1095     X_scale=X_scale,
    1096     max_iter=self.max_iter,
    1097     random_state=self.random_state,
    1098     selection=self.selection,
    1099     sample_weight=sample_weight,
    1100 )
    1101 coef_[k] = this_coef[:, 0]
    1102 dual_gaps_[k] = this_dual_gap[0]

```

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
↳ site-packages/sklearn/utils/_param_validation.py:186, in validate_params.
↳ <locals>.decorator.<locals>.wrapper(*args, **kwargs)
    184 global_skip_validation = get_config()["skip_parameter_validation"]
    185 if global_skip_validation:
--> 186     return func(*args, **kwargs)
    188 func_sig = signature(func)
    190 # Map *args/**kwargs to the function signature

```

```

File /Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
↳ site-packages/sklearn/linear_model/_coordinate_descent.py:697, in enet_path(X,
↳ y, l1_ratio, eps, n_alphas, alphas, precompute, Xy, copy_X, coef_init,
↳ verbose, return_n_iter, positive, check_input, **params)
    683     model = cd_fast.enet_coordinate_descent_gram(
    684         coef_,
    685         l1_reg,
    (...)

```

```

694         positive,
695     )
696 elif precompute is False:
--> 697     model = cd_fast.enet_coordinate_descent(
698         coef_, l1_reg, l2_reg, X, y, max_iter, tol, rng, random, positive
699     )
700 else:
701     raise ValueError(
702         "Precompute should be one of True, False, 'auto' or array-like.,
↳ Got %r"
703         % precompute
704     )

```

File \_cd\_fast.pyx:262, in sklearn.linear\_model.\_cd\_fast.enet\_coordinate\_descent )

File ~/Library/Python/3.12/lib/python/site-packages/numpy/core/getlimits.py:484 ,

```

↳ in finfo.__new__(cls, dtype)
380 """
381 finfo(dtype)
382
383 (...)
479
480 """
482 _finfo_cache = {}
--> 484 def __new__(cls, dtype):
485     try:
486         obj = cls._finfo_cache.get(dtype) # most common path

```

KeyboardInterrupt:

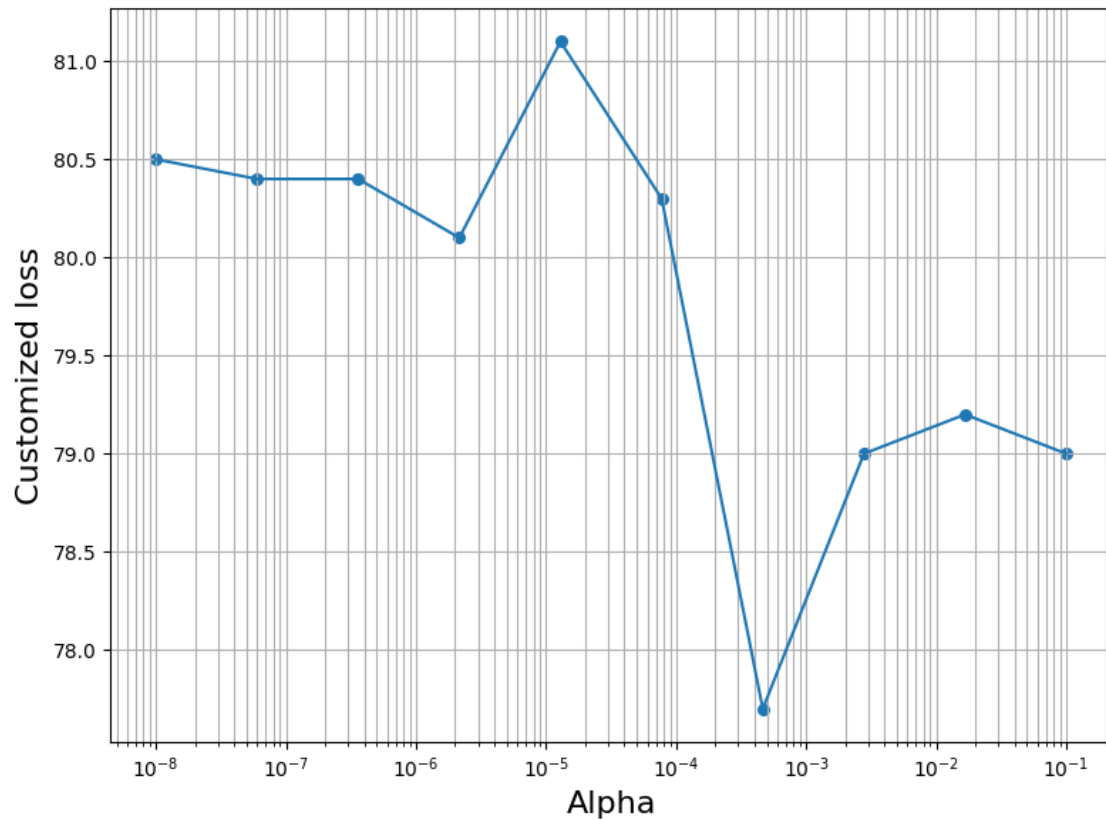
```

[ ]: range_alpha = lasso_cv.cv_results_['param_alpha'].data
new_scores = lasso_cv.cv_results_['mean_test_score']*(-1)

plt.figure(figsize=(8, 6))
ax = plt.gca()
ax.set_xscale('log')
plt.xlabel('Alpha', fontsize=16)
plt.ylabel('Customized loss', fontsize=16)
plt.scatter(range_alpha, new_scores, s=30)
plt.plot(range_alpha, new_scores)
plt.grid(True, which='both')

plt.tight_layout()
plt.show()

```



[ ]:

## 1.6 Cross validation for Principal Components Regression

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

     X_train_pcr = X_train_poly_wide
     X_test_pcr = X_test_poly_wide

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

(1828, 397) (1828, 397)

(937, 397) (937, 397)

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

```
[ ]: from sklearn.pipeline import Pipeline
     scaler = StandardScaler()
     pca = PCA(random_state=88)
```

```
lr = LinearRegression()
pipe = Pipeline(steps=[('scaler', scaler), ('pca', pca), ('lr', lr)])
```

Basic PCR

```
[ ]: pipe.set_params(pca__n_components=5)
pipe.fit(X_train_pcr, y_train)
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 0.8669860382703731
Training MAE 0.09962977875968801
Training RMSE 0.14117035228048616
Out-of-sample R2 0.8396729663435233
Out-of-sample MAE 0.10399547659855168
Out-of-sample RMSE 0.15858777688396108
```

Metrics for Sale Price:

```
Training R2 0.897132348091005
Training MAE 17529.924419135274
Training RMSE 25055.73125787469
Out-of-sample R2 0.9018033283445104
Out-of-sample MAE 17377.607979840453
Out-of-sample RMSE 24560.576408359433
```

**2 In-class activity 2: For PCR, do a 5 fold cross validation value for `n_components` in terms of the R-squared. The potential `n_components` is between 1 and 300.**

- What are the best R2 value and its corresponding `n_components`?
- What is the value of `n_components` according to the one standard error rule?
- Refit the model using the `n_components` selected by the one standard error rule.

```
[ ]: param_grid = {'pca__n_components': np.linspace(1, 300, 35).astype('int')}

pcr_cv = GridSearchCV(pipe, # model
    param_grid, # candidate value
    scoring='r2',
    cv=5,
    verbose = 2)
pcr_cv.fit(X_train_pcr, y_train)
```

Fitting 5 folds for each of 35 candidates, totalling 175 fits

[illegible]

[illegible]



[illegible]

```

[CV] END ...pca__n_components=247; total time= 0.2s
[CV] END ...pca__n_components=247; total time= 0.2s
[CV] END ...pca__n_components=256; total time= 0.2s
[CV] END ...pca__n_components=256; total time= 0.3s
[CV] END ...pca__n_components=256; total time= 0.2s
[CV] END ...pca__n_components=256; total time= 0.3s
[CV] END ...pca__n_components=256; total time= 0.3s
[CV] END ...pca__n_components=264; total time= 0.3s
[CV] END ...pca__n_components=264; total time= 0.7s
[CV] END ...pca__n_components=264; total time= 0.4s
[CV] END ...pca__n_components=264; total time= 0.3s
[CV] END ...pca__n_components=264; total time= 0.3s
[CV] END ...pca__n_components=273; total time= 0.3s
[CV] END ...pca__n_components=273; total time= 0.4s
[CV] END ...pca__n_components=273; total time= 0.3s
[CV] END ...pca__n_components=273; total time= 0.3s
[CV] END ...pca__n_components=273; total time= 0.4s
[CV] END ...pca__n_components=282; total time= 0.4s
[CV] END ...pca__n_components=282; total time= 0.3s
[CV] END ...pca__n_components=282; total time= 0.3s
[CV] END ...pca__n_components=282; total time= 0.2s
[CV] END ...pca__n_components=282; total time= 0.2s
[CV] END ...pca__n_components=291; total time= 0.3s
[CV] END ...pca__n_components=291; total time= 0.5s
[CV] END ...pca__n_components=291; total time= 0.3s
[CV] END ...pca__n_components=291; total time= 0.2s
[CV] END ...pca__n_components=291; total time= 0.3s
[CV] END ...pca__n_components=300; total time= 0.3s
[CV] END ...pca__n_components=300; total time= 0.2s
[CV] END ...pca__n_components=300; total time= 0.4s
[CV] END ...pca__n_components=300; total time= 0.2s
[CV] END ...pca__n_components=300; total time= 0.3s

```

```

[ ]: GridSearchCV(cv=5,
                  estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                             ('pca',
                                              PCA(n_components=5, random_state=88)),
                                             ('lr', LinearRegression())]),
                  param_grid={'pca__n_components': array([ 1,  9, 18, 27, 36,
44, 53, 62, 71, 80, 88, 97, 106,
115, 124, 132, 141, 150, 159, 168, 176, 185, 194, 203, 212, 220,
229, 238, 247, 256, 264, 273, 282, 291, 300])},
                  scoring='r2', verbose=2)

```

```

[ ]: from scipy import stats

n_components = pcr_cv.cv_results_['param_pca__n_components'].data

```

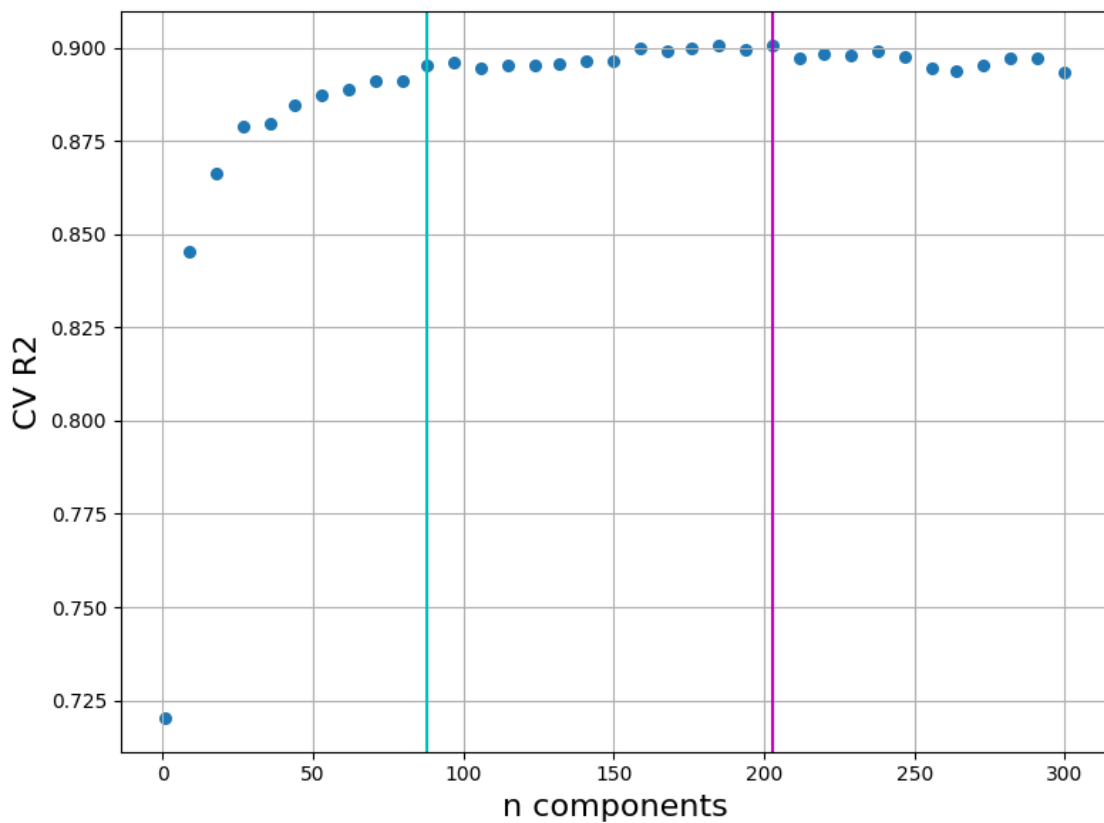
```

R2_scores = pcr_cv.cv_results_['mean_test_score']
x_min, x_1se = one_standard_error_rule(model='pcr',
                                       results=pcr_cv.cv_results_,
                                       param_grid=n_components,
                                       n_splits=10,
                                       neg_mean_squared_error=True)

plt.figure(figsize=(8, 6))
plt.xlabel('n components', fontsize=16)
plt.ylabel('CV R2', fontsize=16)
plt.scatter(n_components, R2_scores, s=30)
plt.axvline(x=x_min, color='m')
plt.axvline(x=x_1se, color='c')
plt.grid(True, which='both')

plt.tight_layout()
plt.show()

```



```

[ ]: best_r2_score = pcr_cv.best_score_
print("Best R2 Score from Cross-Validation:", best_r2_score)

```

```
best_n_components = pcr_cv.best_params_['pca__n_components']
print("Best n_components value:", best_n_components)
```

Best R2 Score from Cross-Validation: 0.9007477824665224

Best n\_components value: 203

```
[ ]: print('pca n_components', x_1se)
      index_x_1se = np.where(n_components == x_1se)[0][0]

      # Get the corresponding R2 score
      R2_score_x_1se = R2_scores[index_x_1se]
      print("R2 Score corresponding to x_1se:", R2_score_x_1se)
```

pca n\_components 88

R2 Score corresponding to x\_1se: 0.8954299553618595

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

Metrics for Log(Sale Price):

Training R2 0.9470509309926725  
Training MAE 0.06613921430190121  
Training RMSE 0.08906848150530083  
Out-of-sample R2 0.8909564729172067  
Out-of-sample MAE 0.08577621657861301  
Out-of-sample RMSE 0.13078751186261808

Metrics for Sale Price:

Training R2 0.9498759628436522  
Training MAE 12080.226374617378  
Training RMSE 17490.035484096694  
Out-of-sample R2 0.9208510195464497  
Out-of-sample MAE 14744.142116330762  
Out-of-sample RMSE 22050.215262039193

**Refit the model with the selected parameter**

```
[ ]: pipe.set_params(pca__n_components=x_1se)
      pipe.fit(X_train_lasso, y_train)
      pipe.get_params()
```

```
[ ]: {'memory': None,
      'steps': [('scaler', StandardScaler()),
                ('pca', PCA(n_components=88, random_state=88)),
```

```

    ('lr', LinearRegression())],
    'verbose': False,
    'scaler': StandardScaler(),
    'pca': PCA(n_components=88, random_state=88),
    'lr': LinearRegression(),
    'scaler__copy': True,
    'scaler__with_mean': True,
    'scaler__with_std': True,
    'pca__copy': True,
    'pca__iterated_power': 'auto',
    'pca__n_components': 88,
    'pca__n_oversamples': 10,
    'pca__power_iteration_normalizer': 'auto',
    'pca__random_state': 88,
    'pca__svd_solver': 'auto',
    'pca__tol': 0.0,
    'pca__whiten': False,
    'lr__copy_X': True,
    'lr__fit_intercept': True,
    'lr__n_jobs': None,
    'lr__positive': False}

```

```

[ ]: 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 0.9307885562259678
Training MAE 0.07523869573417481
Training RMSE 0.10183189800532155
Out-of-sample R2 0.8867156269855305
Out-of-sample MAE 0.09027393060383741
Out-of-sample RMSE 0.13330650277813924

```

Metrics for Sale Price:

```

Training R2 0.93768977143283
Training MAE 13632.105577276641
Training RMSE 19500.5715801474
Out-of-sample R2 0.9217227150903017
Out-of-sample MAE 15441.372024002116
Out-of-sample RMSE 21928.455702831296

```

## 2.1 Cross validation for 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)
```

### 2.1.1 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)
```

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

### 2.1.2 Ridge Hyper-parameter Tuning

```
[ ]: alpha_grid = {'alpha': np.logspace(-1, 5, num=50, base=10)}

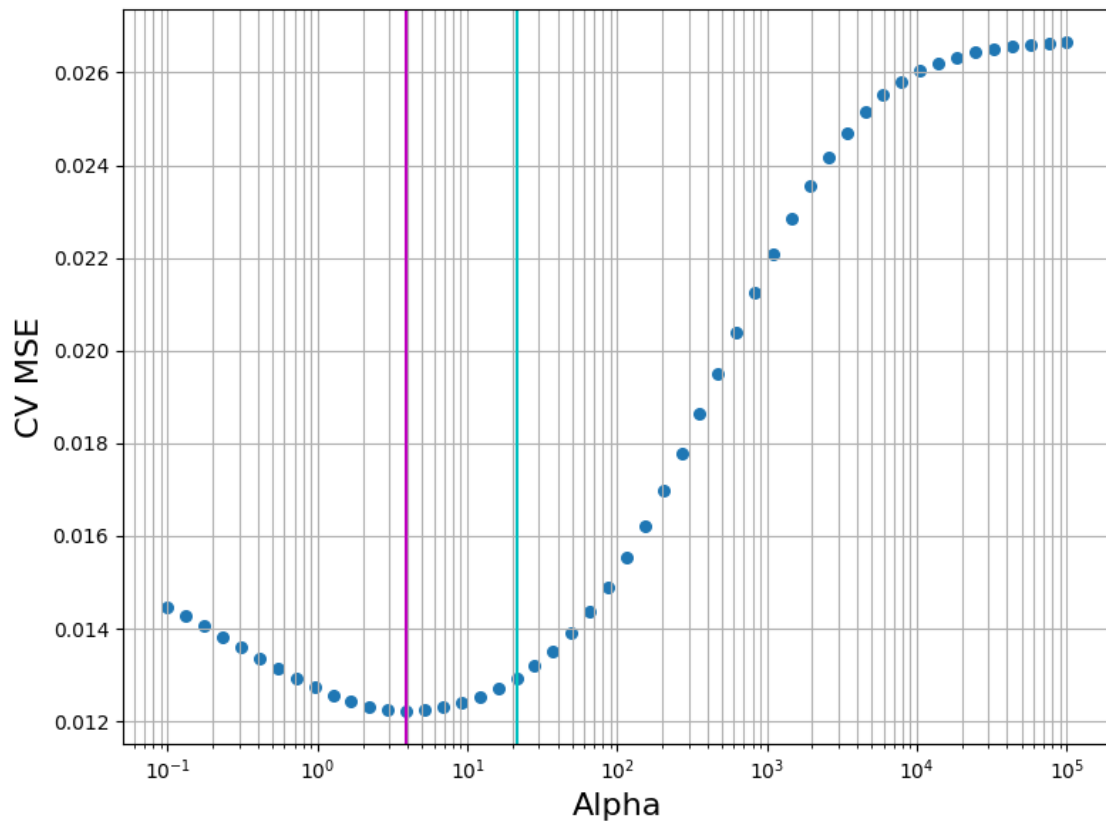
      rr = Ridge(random_state=88)
      rr_cv = GridSearchCV(rr, alpha_grid, scoring='neg_mean_squared_error', cv=5)
      rr_cv.fit(X_train_rr, y_train)
```

```
[ ]: GridSearchCV(cv=5, estimator=Ridge(random_state=88),
                  param_grid={'alpha': array([1.00000000e-01, 1.32571137e-01,
1.75751062e-01, 2.32995181e-01,
3.08884360e-01, 4.09491506e-01, 5.42867544e-01, 7.19685673e-01,
9.54095476e-01, 1.26485522e+00, 1.67683294e+00, 2.22299648e+00,
2.94705170e+00, 3.90693994e+00, 5.17947468e+00, 6.86648845e+00,
9.10298178e+00, 1.20679264e+01, 1...
2.68269580e+02, 3.55648031e+02, 4.71486636e+02, 6.25055193e+02,
8.28642773e+02, 1.09854114e+03, 1.45634848e+03, 1.93069773e+03,
2.55954792e+03, 3.39322177e+03, 4.49843267e+03, 5.96362332e+03,
7.90604321e+03, 1.04811313e+04, 1.38949549e+04, 1.84206997e+04,
2.44205309e+04, 3.23745754e+04, 4.29193426e+04, 5.68986603e+04,
7.54312006e+04, 1.00000000e+05])},
                  scoring='neg_mean_squared_error')
```

```
[ ]: range_alpha = rr_cv.cv_results_['param_alpha'].data
MSE_scores = rr_cv.cv_results_['mean_test_score']*(-1)
x_min, x_1se = one_standard_error_rule(model='ridge',
                                       results=rr_cv.cv_results_,
                                       param_grid=range_alpha,
                                       n_splits=10,
                                       neg_mean_squared_error=True)

plt.figure(figsize=(8, 6))
ax = plt.gca()
ax.set_xscale('log')
plt.xlabel('Alpha', fontsize=16)
plt.ylabel('CV MSE', fontsize=16)
plt.scatter(range_alpha, MSE_scores, s=30)
plt.axvline(x=x_min, color='m')
plt.axvline(x=x_1se, color='c')
plt.grid(True, which='both')

plt.tight_layout()
plt.show()
```



```
[ ]: print('Alpha one standard error rule:', x_1se)
```

Alpha one standard error rule: 21.209508879201906

### 2.1.3 Ridge Refit with One Standard Error Rule

```
[ ]: rr.set_params(alpha=x_1se)
     rr.fit(X_train_lasso, y_train)
     rr.get_params()
```

```
[ ]: {'alpha': 21.209508879201906,
      'copy_X': True,
      'fit_intercept': True,
      'max_iter': None,
      'positive': False,
      'random_state': 88,
      'solver': 'auto',
      'tol': 0.0001}
```

```
[ ]: 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 0.9459931437852581  
Training MAE 0.06235134218698391  
Training RMSE 0.0899537623805996  
Out-of-sample R2 0.893481603642305  
Out-of-sample MAE 0.08065342198667663  
Out-of-sample RMSE 0.1292643129340068

Metrics for Sale Price:

Training R2 0.9537554772032324  
Training MAE 11195.688008014222  
Training RMSE 16799.55663050555  
Out-of-sample R2 0.9209438962794584  
Out-of-sample MAE 13888.3660977596  
Out-of-sample RMSE 22037.2741408468

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



Metrics for Log(Sale Price):

```
Training R2 0.9566658840031975
Training MAE 0.0576670905483711
Training RMSE 0.08057677009982724
Out-of-sample R2 0.9003061738445208
Out-of-sample MAE 0.07877099524934432
Out-of-sample RMSE 0.12505482836437523
```

Metrics for Sale Price:

```
Training R2 0.9605502868413793
Training MAE 10432.00812852822
Training RMSE 15516.350946475923
Out-of-sample R2 0.9277610608337501
Out-of-sample MAE 13581.237490221118
Out-of-sample RMSE 21065.697861595443
```

### 3 In-class activity 3: Do a cross validation for Ridge regression using custom loss function `large_prediction_error_count`. What do you observe from the result?

```
[ ]: 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)

alpha_grid = {'alpha': np.logspace(-1, 5, num=50, base=10)}

rr = Ridge(random_state=88)
rr_cv = GridSearchCV(rr, alpha_grid,
    ↳scoring=make_scorer(large_prediction_error_count, greater_is_better=False),
    ↳cv=5)
rr_cv.fit(X_train_rr, y_train)

range_alpha = rr_cv.cv_results_['param_alpha'].data
MSE_scores = rr_cv.cv_results_['mean_test_score']*(-1)
x_min, x_1se = one_standard_error_rule(model='ridge',
    results=rr_cv.cv_results_,
    param_grid=range_alpha,
    n_splits=10,
    neg_mean_squared_error=True)

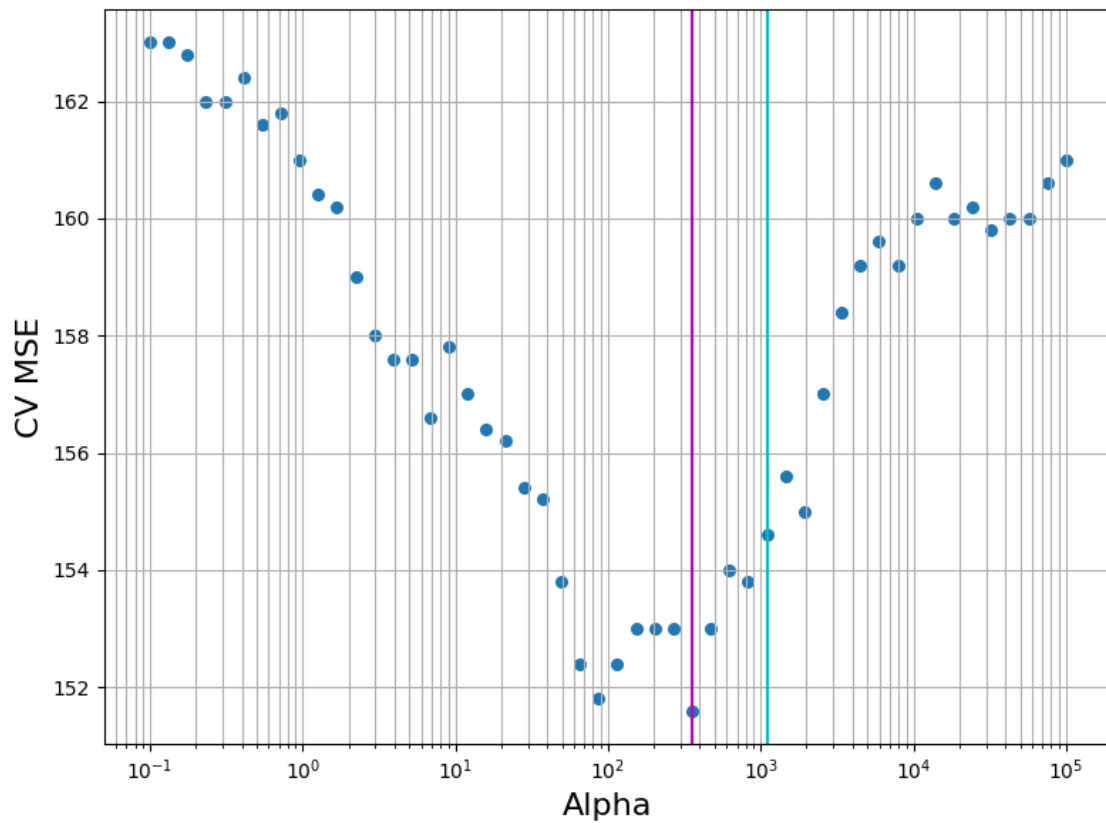
plt.figure(figsize=(8, 6))
ax = plt.gca()
```

```

ax.set_xscale('log')
plt.xlabel('Alpha', fontsize=16)
plt.ylabel('CV MSE', fontsize=16)
plt.scatter(range_alpha, MSE_scores, s=30)
plt.axvline(x=x_min, color='m')
plt.axvline(x=x_1se, color='c')
plt.grid(True, which='both')

plt.tight_layout()
plt.show()

```



```

[ ]: print('Alpha one standard error rule:', x_1se)

```

Alpha one standard error rule: 1098.5411419875572