

Problem Statement - Part II

Q1. You have determined the optimal value of lambda for ridge and lasso regression during the assignment. Now, which one will you choose to apply and why?

Ans: It is crucial to apply regularization to coefficients to enhance prediction accuracy, reduce variance, and improve model interpretability.

Ridge regression employs a tuning parameter, lambda, to introduce a penalty that is the square of the magnitude of coefficients, determined through cross-validation. The penalty, lambda times the sum of squares of coefficients, penalizes coefficients with larger values. Increasing lambda reduces the model's variance while keeping bias constant. Ridge regression includes all variables in the final model, unlike Lasso Regression.

Lasso regression also utilizes a tuning parameter, lambda, with a penalty represented by the absolute value of the magnitude of coefficients, identified through cross-validation. As lambda increases, Lasso shrinks coefficients toward zero, causing some variables to become exactly zero. Lasso performs variable selection, behaving as simple linear regression with a small lambda and gradually neglecting variables with a lambda-induced increase in shrinkage.

Q2. After building the model, you realized that the five most important predictor variables in the lasso model are not available in the incoming data. You will now have to create another model excluding the five most important predictor variables. Which are the five most important predictor variables now?

Ans: Those 5 most important predictor variables that will be excluded are:-

1. GrLivArea
2. OverallQual
3. OverallCond
4. TotalBsmtSF
5. GarageArea

Q3. How can you make sure that a model is robust and generalizable? What are the implications of the same for the accuracy of the model and why?

- A model is **robust** when any variation in the data does not affect its performance much.
- A **generalizable** model is able to adapt properly to new, previously unseen data, drawn from the same distribution as the one used to create the model.
- To make sure a model is robust and generalizable, we have to **take care it doesn't overfit**. This is because an overfitting model has very high variance and a smallest change in data affects the

model prediction heavily. Such a model will identify all the patterns of a training data, but fail to pick up the patterns in unseen test data.

- In other words, the model should not be too complex in order to be robust and generalizable.
- If we look at it from the perspective of **Accuracy**, a too complex model will have a very high accuracy. So, to make our model more robust and generalizable, we will have to decrease variance which will lead to some bias. Addition of bias means that accuracy will decrease.
- In general, we have to find strike some balance between model accuracy and complexity. This can be achieved by Regularization techniques like Ridge Regression and Lasso.

Q4. What is the optimal value of alpha for ridge and lasso regression? What will be the changes in the model if you choose double the value of alpha for both ridge and lasso? What will be the most important predictor variables after the change is implemented?

- **Ans:** Optimal value of lambda for Ridge Regression = **10**
- Optimal value of lambda for Lasso = **0.001**

In [80]:

```
## Let us build the ridge regression model with double value of alpha i.e. 20
```

```
ridge = Ridge(alpha=20)
```

```
# Fit the model on training data
```

```
ridge.fit(X_train, y_train)
```

Out [80]:

```
Ridge(alpha=20)
```

In [81]:

```
## Make predictions
```

```
y_train_pred = ridge.predict(X_train)
```

```
y_pred = ridge.predict(X_test)
```

In [82]:

```
## Check metrics
```

```
ridge_metrics = show_metrics(y_train, y_train_pred, y_test, y_pred)
```

```
R-Squared (Train) = 0.93
```

```
R-Squared (Test) = 0.93
```

```
RSS (Train) = 9.37
```

```
RSS (Test) = 2.82
```

```
MSE (Train) = 0.01
```

```
MSE (Test) = 0.01
```

```
RMSE (Train) = 0.09
```

```
RMSE (Test) = 0.10
```

In [83]:

```
## Now we will build the lasso model with double value of alpha i.e. 0.002
```

```
lasso = Lasso(alpha=0.002)
```

```
# Fit the model on training data
```

```
lasso.fit(X_train, y_train)
```

Out[83]:

```
Lasso(alpha=0.002)
```

In [84]:

```
## Make predictions
```

```
y_train_pred = lasso.predict(X_train)
```

```
y_pred = lasso.predict(X_test)
```

In [85]:

```
## Check metrics
```

```
lasso_metrics = show_metrics(y_train, y_train_pred, y_test, y_pred)
```

```
R-Squared (Train) = 0.91
```

```
R-Squared (Test) = 0.91
```

```
RSS (Train) = 13.49
```

```
RSS (Test) = 3.45
```

```
MSE (Train) = 0.01
```

```
MSE (Test) = 0.01
```

```
RMSE (Train) = 0.11
```

```
RMSE (Test) = 0.11
```

In [86]:

```
# Again creating a table which contain all the metrics
```

```
lr_table = {'Metric': ['R2 Score (Train)', 'R2 Score (Test)', 'RSS (Train)', 'RSS (Test)',  
                      'MSE (Train)', 'MSE (Test)', 'RMSE (Train)', 'RMSE (Test)'],  
            'Ridge Regression': ridge_metrics,  
            'Lasso Regression': lasso_metrics  
            }
```

```
final_metric = pd.DataFrame(lr_table, columns = ['Metric', 'Ridge Regression', 'Lasso Regression'])
```

```
final_metric.set_index('Metric')
```

Out[86]:

	Ridge Regression	Lasso Regression
Metric		
R2 Score (Train)	0.93	0.91
R2 Score (Test)	0.93	0.91
RSS (Train)	9.37	13.49
RSS (Test)	2.82	3.45
MSE (Train)	0.01	0.01
MSE (Test)	0.01	0.01

	Ridge Regression	Lasso Regression
Metric		
RMSE (Train)	0.09	0.11
RMSE (Test)	0.10	0.11

Changes in Ridge Regression metrics:

- R2 score of train set decreased from 0.94 to 0.93
- R2 score of test set remained same at 0.93

Changes in Lasso metrics:

- R2 score of train set decreased from 0.92 to 0.91
- R2 score of test set decreased from 0.93 to 0.91

In [87]:

Now we see the changes in coefficients after regularization

First create empty dataframe with all the independent variables as indices

```
betas = pd.DataFrame(index=X.columns)
betas.rows = X.columns
betas
```

Out[87]:

LotFrontage
LotArea
YearRemodAdd
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF

GrLivArea
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageCars
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
PoolArea
MiscVal
MoSold
Age
MSSubClass_30
MSSubClass_40
MSSubClass_45
MSSubClass_50
MSSubClass_60
MSSubClass_70
MSSubClass_75

MSSubClass_80
MSSubClass_85
MSSubClass_90
MSSubClass_120
MSSubClass_160
MSSubClass_180
MSSubClass_190
MSZoning_FV
MSZoning_RH
MSZoning_RL
MSZoning_RM
Street_Pave
Alley_None
Alley_Pave
LotShape_IR2
LotShape_IR3
LotShape_Reg
LandContour_HLS
LandContour_Low
LandContour_Lvl
Utilities_NoSeWa
LotConfig_CulDSac
LotConfig_FR2
LotConfig_FR3
LotConfig_Inside
LandSlope_Mod
LandSlope_Sev

Neighborhood_Blueste

Neighborhood_BrDale

Neighborhood_BrkSide

Neighborhood_ClearCr

Neighborhood_CollgCr

Neighborhood_Crawfor

Neighborhood_Edwards

Neighborhood_Gilbert

Neighborhood_IDOTRR

Neighborhood_MeadowV

Neighborhood_Mitchel

Neighborhood_NAms

Neighborhood_NPkVill

Neighborhood_NWAms

Neighborhood_NoRidge

Neighborhood_NridgHt

Neighborhood_OldTown

Neighborhood_SWISU

Neighborhood_Sawyer

Neighborhood_SawyerW

Neighborhood_Somerst

Neighborhood_StoneBr

Neighborhood_Timber

Neighborhood_Veenker

Condition1_Feedr

Condition1_Norm

Condition1_PosA

Condition1_PosN
Condition1_RRAe
Condition1_RRAn
Condition1_RRNe
Condition1_RRNn
Condition2_Feedr
Condition2_Norm
Condition2_PosA
Condition2_PosN
Condition2_RRAe
Condition2_RRAn
Condition2_RRNn
BldgType_2fmCon
BldgType_Duplex
BldgType_Twnhs
BldgType_TwnhsE
HouseStyle_1.5Unf
HouseStyle_1Story
HouseStyle_2.5Fin
HouseStyle_2.5Unf
HouseStyle_2Story
HouseStyle_SFoyer
HouseStyle_SLvl
OverallQual_2
OverallQual_3
OverallQual_4
OverallQual_5

OverallQual_6
OverallQual_7
OverallQual_8
OverallQual_9
OverallQual_10
OverallCond_2
OverallCond_3
OverallCond_4
OverallCond_5
OverallCond_6
OverallCond_7
OverallCond_8
OverallCond_9
RoofStyle_Gable
RoofStyle_Gambrel
RoofStyle_Hip
RoofStyle_Mansard
RoofStyle_Shed
RoofMatl_CompShg
RoofMatl_Membran
RoofMatl_Metal
RoofMatl_Roll
RoofMatl_Tar&Grv
RoofMatl_WdShake
RoofMatl_WdShngl
Exterior1st_AsphShn
Exterior1st_BrkComm

Exterior1st_BrkFace
Exterior1st_CBlock
Exterior1st_CemntBd
Exterior1st_HdBoard
Exterior1st_ImStucc
Exterior1st_MetalSd
Exterior1st_Plywood
Exterior1st_Stone
Exterior1st_Stucco
Exterior1st_VinylSd
Exterior1st_Wd Sdng
Exterior1st_WdShing
Exterior2nd_AsphShn
Exterior2nd_Brk Cmn
Exterior2nd_BrkFace
Exterior2nd_CBlock
Exterior2nd_CmentBd
Exterior2nd_HdBoard
Exterior2nd_ImStucc
Exterior2nd_MetalSd
Exterior2nd_Other
Exterior2nd_Plywood
Exterior2nd_Stone
Exterior2nd_Stucco
Exterior2nd_VinylSd
Exterior2nd_Wd Sdng
Exterior2nd_Wd Shng

MasVnrType_BrkFace
MasVnrType_NA
MasVnrType_None
MasVnrType_Stone
ExterQual_Fa
ExterQual_Gd
ExterQual_TA
ExterCond_Fa
ExterCond_Gd
ExterCond_Po
ExterCond_TA
Foundation_CBlock
Foundation_PConc
Foundation_Slab
Foundation_Stone
Foundation_Wood
BsmtQual_Fa
BsmtQual_Gd
BsmtQual_None
BsmtQual_TA
BsmtCond_Gd
BsmtCond_None
BsmtCond_Po
BsmtCond_TA
BsmtExposure_Gd
BsmtExposure_Mn
BsmtExposure_No

BsmtExposure_None
BsmtFinType1_BLQ
BsmtFinType1_GLQ
BsmtFinType1_LwQ
BsmtFinType1_None
BsmtFinType1_Rec
BsmtFinType1_Unf
BsmtFinType2_BLQ
BsmtFinType2_GLQ
BsmtFinType2_LwQ
BsmtFinType2_None
BsmtFinType2_Rec
BsmtFinType2_Unf
Heating_GasA
Heating_GasW
Heating_Grav
Heating_OthW
Heating_Wall
HeatingQC_Fa
HeatingQC_Gd
HeatingQC_Po
HeatingQC_TA
CentralAir_Y
Electrical_FuseF
Electrical_FuseP
Electrical_Mix
Electrical_NA

Electrical_SBrkr
KitchenQual_Fa
KitchenQual_Gd
KitchenQual_TA
Functional_Maj2
Functional_Min1
Functional_Min2
Functional_Mod
Functional_Sev
Functional_Typ
FireplaceQu_Fa
FireplaceQu_Gd
FireplaceQu_None
FireplaceQu_Po
FireplaceQu_TA
GarageType_Attchd
GarageType_Basment
GarageType_BuiltIn
GarageType_CarPort
GarageType_Detchd
GarageType_None
GarageYrBlt_1906
GarageYrBlt_1908
GarageYrBlt_1910
GarageYrBlt_1914
GarageYrBlt_1915
GarageYrBlt_1916

GarageYrBlt_1918
GarageYrBlt_1920
GarageYrBlt_1921
GarageYrBlt_1922
GarageYrBlt_1923
GarageYrBlt_1924
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GarageYrBlt_1927
GarageYrBlt_1928
GarageYrBlt_1929
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GarageYrBltn_2001

GarageYrBlt_2002
GarageYrBlt_2003
GarageYrBlt_2004
GarageYrBlt_2005
GarageYrBlt_2006
GarageYrBlt_2007
GarageYrBlt_2008
GarageYrBlt_2009
GarageYrBlt_2010
GarageYrBlt_NA
GarageFinish_None
GarageFinish_RFn
GarageFinish_Unf
GarageQual_Fa
GarageQual_Gd
GarageQual_None
GarageQual_Po
GarageQual_TA
GarageCond_Fa
GarageCond_Gd
GarageCond_None
GarageCond_Po
GarageCond_TA
PavedDrive_P
PavedDrive_Y
PoolQC_Fa
PoolQC_Gd

PoolQC_None
Fence_GdWo
Fence_MnPrv
Fence_MnWw
Fence_None
MiscFeature_None
MiscFeature_Othr
MiscFeature_Shed
MiscFeature_TenC
SaleType_CWD
SaleType_Con
SaleType_ConLD
SaleType_ConLI
SaleType_ConLw
SaleType_New
SaleType_Oth
SaleType_WD
SaleCondition_AdjLand
SaleCondition_Alloca
SaleCondition_Family
SaleCondition_Normal
SaleCondition_Partial

In [88]:

```
## Now fill in the values of betas, one column for ridge coefficients and one for lasso coefficients
betas['Ridge'] = ridge.coef_
betas['Lasso'] = lasso.coef_
```

In [89]:

```
## View the betas/coefficients
betas
```

Out[89]:

	Ridge	Lasso
LotFrontage	0.01	0.00
LotArea	0.02	0.02
YearRemodAdd	0.03	0.04
MasVnrArea	-0.00	-0.00
BsmtFinSF1	0.02	0.03
BsmtFinSF2	0.00	0.00
BsmtUnfSF	-0.01	-0.00
TotalBsmtSF	0.05	0.05
1stFlrSF	0.01	-0.00
2ndFlrSF	0.03	0.01
LowQualFinSF	0.00	0.00
GrLivArea	0.08	0.11
BsmtFullBath	0.01	0.01
BsmtHalfBath	-0.00	0.00
FullBath	0.01	0.00
HalfBath	0.01	0.01
BedroomAbvGr	0.00	-0.00
KitchenAbvGr	0.00	0.00
TotRmsAbvGrd	0.00	-0.00
Fireplaces	0.02	0.03
GarageCars	0.02	0.02
GarageArea	0.02	0.02
WoodDeckSF	0.01	0.01
OpenPorchSF	0.01	0.01
EnclosedPorch	0.00	0.00
3SsnPorch	0.00	0.00
ScreenPorch	0.01	0.01

	Ridge	Lasso
PoolArea	0.00	0.00
MiscVal	0.00	0.00
MoSold	-0.00	-0.00
Age	-0.05	-0.05
MSSubClass_30	-0.03	-0.00
MSSubClass_40	0.00	0.00
MSSubClass_45	0.00	0.00
MSSubClass_50	-0.00	0.00
MSSubClass_60	-0.01	-0.00
MSSubClass_70	0.04	0.01
MSSubClass_75	0.02	0.00
MSSubClass_80	0.00	0.00
MSSubClass_85	0.00	0.00
MSSubClass_90	-0.03	-0.00
MSSubClass_120	0.01	0.00
MSSubClass_160	-0.04	-0.01
MSSubClass_180	-0.01	-0.00
MSSubClass_190	-0.02	-0.00
MSZoning_FV	0.03	0.00
MSZoning_RH	0.01	-0.00
MSZoning_RL	0.01	0.00
MSZoning_RM	-0.03	-0.03
Street_Pave	-0.00	0.00
Alley_None	-0.00	-0.00
Alley_Pave	0.01	0.00
LotShape_IR2	0.01	0.00
LotShape_IR3	-0.02	-0.00

	Ridge	Lasso
LotShape_Reg	-0.00	-0.00
LandContour_HLS	0.03	0.00
LandContour_Low	0.01	0.00
LandContour_Lvl	0.01	-0.00
Utilities_NoSeWa	-0.01	-0.00
LotConfig_CulDSac	0.02	0.00
LotConfig_FR2	-0.01	-0.00
LotConfig_FR3	-0.00	0.00
LotConfig_Inside	0.00	0.00
LandSlope_Mod	-0.00	0.00
LandSlope_Sev	0.02	0.00
Neighborhood_Blueste	-0.00	-0.00
Neighborhood_BrDale	-0.00	-0.00
Neighborhood_BrkSide	0.03	0.00
Neighborhood_ClearCr	0.02	0.00
Neighborhood_CollgCr	-0.01	-0.00
Neighborhood_Crawfor	0.06	0.07
Neighborhood_Edwards	-0.05	-0.03
Neighborhood_Gilbert	-0.01	-0.00
Neighborhood_IDOTRR	0.00	0.00
Neighborhood_MeadowV	-0.05	-0.00
Neighborhood_Mitchel	-0.03	-0.00
Neighborhood_NAmes	-0.02	-0.00
Neighborhood_NPkVill	0.01	0.00
Neighborhood_NWAmes	-0.02	-0.00
Neighborhood_NoRidge	0.00	-0.00
Neighborhood_NridgHt	0.03	0.00

	Ridge	Lasso
Neighborhood_OldTown	-0.02	-0.00
Neighborhood_SWISU	0.00	0.00
Neighborhood_Sawyer	-0.01	-0.00
Neighborhood_SawyerW	-0.02	-0.00
Neighborhood_Somerst	0.03	0.02
Neighborhood_StoneBr	0.04	0.00
Neighborhood_Timber	0.01	0.00
Neighborhood_Veenker	0.02	0.00
Condition1_Feedr	-0.01	-0.00
Condition1_Norm	0.03	0.03
Condition1_PosA	0.00	0.00
Condition1_PosN	0.01	0.00
Condition1_RRAe	-0.02	-0.00
Condition1_RRAn	0.01	0.00
Condition1_RRNe	0.00	0.00
Condition1_RRNn	0.01	0.00
Condition2_Feedr	-0.00	-0.00
Condition2_Norm	0.02	0.00
Condition2_PosA	0.02	0.00
Condition2_PosN	-0.02	-0.00
Condition2_RRAe	-0.00	-0.00
Condition2_RRAn	-0.00	-0.00
Condition2_RRNn	0.00	0.00
BldgType_2fmCon	-0.02	-0.00
BldgType_Duplex	-0.03	-0.02
BldgType_Twnhs	-0.03	-0.00
BldgType_TwnhsE	-0.01	-0.00

	Ridge	Lasso
HouseStyle_1.5Unf	-0.00	0.00
HouseStyle_1Story	0.01	-0.00
HouseStyle_2.5Fin	0.01	0.00
HouseStyle_2.5Unf	-0.00	0.00
HouseStyle_2Story	-0.02	-0.00
HouseStyle_SFoyer	0.01	0.00
HouseStyle_SLvl	0.01	0.00
OverallQual_2	-0.00	-0.00
OverallQual_3	-0.04	-0.00
OverallQual_4	-0.05	-0.05
OverallQual_5	-0.03	-0.02
OverallQual_6	-0.01	0.00
OverallQual_7	0.02	0.03
OverallQual_8	0.07	0.08
OverallQual_9	0.06	0.08
OverallQual_10	-0.02	-0.00
OverallCond_2	-0.02	-0.00
OverallCond_3	-0.05	-0.01
OverallCond_4	-0.05	-0.04
OverallCond_5	-0.02	-0.03
OverallCond_6	0.02	0.00
OverallCond_7	0.04	0.02
OverallCond_8	0.03	0.00
OverallCond_9	0.05	0.00
RoofStyle_Gable	-0.01	-0.00
RoofStyle_Gambrel	0.00	0.00
RoofStyle_Hip	-0.01	-0.00

	Ridge	Lasso
RoofStyle_Mansard	0.01	0.00
RoofStyle_Shed	-0.00	0.00
RoofMatl_CompShg	0.00	-0.00
RoofMatl_Membran	0.00	0.00
RoofMatl_Metal	0.00	0.00
RoofMatl_Roll	0.00	0.00
RoofMatl_Tar&Grv	0.01	0.00
RoofMatl_WdShake	0.00	0.00
RoofMatl_WdShngl	0.02	0.00
Exterior1st_AsphShn	-0.00	-0.00
Exterior1st_BrkComm	-0.01	-0.00
Exterior1st_BrkFace	0.06	0.04
Exterior1st_CBlock	-0.00	-0.00
Exterior1st_CemntBd	-0.01	-0.00
Exterior1st_HdBoard	-0.01	-0.00
Exterior1st_ImStucc	0.00	-0.00
Exterior1st_MetalSd	0.00	0.00
Exterior1st_Plywood	-0.00	-0.00
Exterior1st_Stone	0.00	0.00
Exterior1st_Stucco	0.01	0.00
Exterior1st_VinylSd	0.00	0.00
Exterior1st_Wd Sdng	-0.02	0.00
Exterior1st_WdShing	-0.01	-0.00
Exterior2nd_AsphShn	0.00	0.00
Exterior2nd_Brk Cmn	-0.00	-0.00
Exterior2nd_BrkFace	0.01	0.00
Exterior2nd_CBlock	-0.00	-0.00

	Ridge	Lasso
Exterior2nd_CmentBd	0.00	-0.00
Exterior2nd_HdBoard	-0.00	-0.00
Exterior2nd_ImStucc	0.00	-0.00
Exterior2nd_MetalSd	-0.00	0.00
Exterior2nd_Other	0.00	0.00
Exterior2nd_Plywood	-0.02	-0.00
Exterior2nd_Stone	0.00	0.00
Exterior2nd_Stucco	0.00	-0.00
Exterior2nd_VinylSd	-0.01	-0.00
Exterior2nd_Wd Sdng	0.02	0.00
Exterior2nd_Wd Shng	-0.01	-0.00
MasVnrType_BrkFace	0.01	-0.00
MasVnrType_NA	-0.00	-0.00
MasVnrType_None	0.00	0.00
MasVnrType_Stone	0.02	0.00
ExterQual_Fa	-0.00	-0.00
ExterQual_Gd	0.00	0.00
ExterQual_TA	-0.02	-0.02
ExterCond_Fa	-0.00	-0.00
ExterCond_Gd	-0.01	-0.00
ExterCond_Po	-0.01	-0.00
ExterCond_TA	-0.00	0.00
Foundation_CBlock	-0.00	-0.00
Foundation_PConc	0.02	0.02
Foundation_Slab	-0.01	-0.00
Foundation_Stone	-0.00	0.00
Foundation_Wood	-0.02	-0.00

	Ridge	Lasso
BsmtQual_Fa	-0.01	-0.00
BsmtQual_Gd	-0.01	0.00
BsmtQual_None	-0.01	-0.00
BsmtQual_TA	-0.02	-0.00
BsmtCond_Gd	0.04	0.00
BsmtCond_None	-0.01	-0.00
BsmtCond_Po	-0.00	-0.00
BsmtCond_TA	0.03	0.01
BsmtExposure_Gd	0.02	0.00
BsmtExposure_Mn	0.00	0.00
BsmtExposure_No	-0.01	-0.01
BsmtExposure_None	-0.01	-0.00
BsmtFinType1_BLQ	-0.01	-0.00
BsmtFinType1_GLQ	0.01	0.01
BsmtFinType1_LwQ	-0.02	-0.00
BsmtFinType1_None	-0.01	-0.00
BsmtFinType1_Rec	-0.00	0.00
BsmtFinType1_Unf	-0.01	-0.00
BsmtFinType2_BLQ	-0.01	-0.00
BsmtFinType2_GLQ	0.01	0.00
BsmtFinType2_LwQ	-0.00	0.00
BsmtFinType2_None	-0.01	-0.00
BsmtFinType2_Rec	-0.01	-0.00
BsmtFinType2_Unf	0.01	0.00
Heating_GasA	0.01	0.00
Heating_GasW	0.00	-0.00
Heating_Grav	0.01	0.00

	Ridge	Lasso
Heating_OthW	-0.01	-0.00
Heating_Wall	-0.01	-0.00
HeatingQC_Fa	0.00	-0.00
HeatingQC_Gd	-0.02	-0.00
HeatingQC_Po	-0.00	-0.00
HeatingQC_TA	-0.02	-0.01
CentralAir_Y	0.05	0.04
Electrical_FuseF	-0.00	-0.00
Electrical_FuseP	0.00	-0.00
Electrical_Mix	0.00	0.00
Electrical_NA	0.00	0.00
Electrical_SBrkr	-0.01	0.00
KitchenQual_Fa	-0.01	-0.00
KitchenQual_Gd	-0.02	-0.00
KitchenQual_TA	-0.03	-0.02
Functional_Maj2	-0.02	-0.00
Functional_Min1	0.01	0.00
Functional_Min2	-0.02	-0.00
Functional_Mod	-0.02	-0.00
Functional_Sev	-0.01	-0.00
Functional_Typ	0.06	0.07
FireplaceQu_Fa	-0.01	-0.00
FireplaceQu_Gd	0.01	0.01
FireplaceQu_None	-0.00	-0.00
FireplaceQu_Po	-0.01	-0.00
FireplaceQu_TA	-0.00	-0.00
GarageType_Attchd	0.03	0.02

	Ridge	Lasso
GarageType_Basment	0.00	-0.00
GarageType_BuiltIn	0.01	0.00
GarageType_CarPort	-0.03	-0.00
GarageType_Detchd	0.01	0.00
GarageType_None	-0.00	-0.00
GarageYrBltd_1906	0.00	0.00
GarageYrBltd_1908	0.01	0.00
GarageYrBltd_1910	-0.01	-0.00
GarageYrBltd_1914	-0.00	0.00
GarageYrBltd_1915	-0.00	-0.00
GarageYrBltd_1916	0.01	0.00
GarageYrBltd_1918	0.00	-0.00
GarageYrBltd_1920	-0.01	-0.00
GarageYrBltd_1921	0.00	0.00
GarageYrBltd_1922	0.00	0.00
GarageYrBltd_1923	0.01	0.00
GarageYrBltd_1924	-0.01	-0.00
GarageYrBltd_1925	0.00	0.00
GarageYrBltd_1926	-0.00	0.00
GarageYrBltd_1927	0.00	0.00
GarageYrBltd_1928	0.01	0.00
GarageYrBltd_1929	0.00	0.00
GarageYrBltd_1930	0.02	0.00
GarageYrBltd_1931	-0.00	0.00
GarageYrBltd_1932	0.01	0.00
GarageYrBltd_1933	0.00	0.00
GarageYrBltd_1934	0.01	0.00

	Ridge	Lasso
GarageYrBlt_1935	-0.00	-0.00
GarageYrBlt_1936	0.01	0.00
GarageYrBlt_1937	0.00	0.00
GarageYrBlt_1938	0.00	-0.00
GarageYrBlt_1939	0.00	0.00
GarageYrBlt_1940	0.01	0.00
GarageYrBlt_1941	-0.00	-0.00
GarageYrBlt_1942	-0.00	-0.00
GarageYrBlt_1945	-0.00	-0.00
GarageYrBlt_1946	-0.00	0.00
GarageYrBlt_1947	0.00	0.00
GarageYrBlt_1948	-0.00	-0.00
GarageYrBlt_1949	-0.01	-0.00
GarageYrBlt_1950	0.02	0.00
GarageYrBlt_1951	-0.00	-0.00
GarageYrBlt_1952	-0.00	0.00
GarageYrBlt_1953	-0.01	-0.00
GarageYrBlt_1954	-0.00	-0.00
GarageYrBlt_1955	-0.01	-0.00
GarageYrBlt_1956	-0.00	-0.00
GarageYrBlt_1957	-0.02	-0.00
GarageYrBlt_1958	-0.00	0.00
GarageYrBlt_1959	-0.00	0.00
GarageYrBlt_1960	0.01	0.00
GarageYrBlt_1961	-0.00	-0.00
GarageYrBlt_1962	0.02	0.00
GarageYrBlt_1963	-0.02	-0.00

	Ridge	Lasso
GarageYrBlt_1964	0.01	0.00
GarageYrBlt_1965	-0.02	-0.00
GarageYrBlt_1966	0.01	0.00
GarageYrBlt_1967	-0.02	-0.00
GarageYrBlt_1968	-0.00	-0.00
GarageYrBlt_1969	0.01	0.00
GarageYrBlt_1970	-0.01	-0.00
GarageYrBlt_1971	-0.02	-0.00
GarageYrBlt_1972	0.01	0.00
GarageYrBlt_1973	-0.02	-0.00
GarageYrBlt_1974	0.01	0.00
GarageYrBlt_1975	-0.00	-0.00
GarageYrBlt_1976	0.00	-0.00
GarageYrBlt_1977	-0.02	-0.00
GarageYrBlt_1978	-0.01	-0.00
GarageYrBlt_1979	0.01	-0.00
GarageYrBlt_1980	-0.00	-0.00
GarageYrBlt_1981	-0.01	-0.00
GarageYrBlt_1982	0.00	0.00
GarageYrBlt_1983	0.00	0.00
GarageYrBlt_1984	-0.01	-0.00
GarageYrBlt_1985	-0.01	-0.00
GarageYrBlt_1986	0.00	0.00
GarageYrBlt_1987	0.00	0.00
GarageYrBlt_1988	-0.00	0.00
GarageYrBlt_1989	-0.00	-0.00
GarageYrBlt_1990	-0.00	0.00

	Ridge	Lasso
GarageYrBlt_1991	0.01	0.00
GarageYrBlt_1992	-0.01	-0.00
GarageYrBlt_1993	-0.00	0.00
GarageYrBlt_1994	-0.00	-0.00
GarageYrBlt_1995	0.01	0.00
GarageYrBlt_1996	-0.00	0.00
GarageYrBlt_1997	0.01	0.00
GarageYrBlt_1998	0.01	0.00
GarageYrBlt_1999	0.01	0.00
GarageYrBlt_2000	0.01	0.00
GarageYrBlt_2001	0.01	0.00
GarageYrBlt_2002	-0.02	-0.00
GarageYrBlt_2003	-0.00	0.00
GarageYrBlt_2004	-0.01	-0.00
GarageYrBlt_2005	-0.00	0.00
GarageYrBlt_2006	0.00	0.00
GarageYrBlt_2007	-0.01	-0.00
GarageYrBlt_2008	0.02	0.00
GarageYrBlt_2009	0.02	0.00
GarageYrBlt_2010	0.00	0.00
GarageYrBlt_NA	-0.00	-0.00
GarageFinish_None	-0.00	-0.00
GarageFinish_RFn	-0.00	0.00
GarageFinish_Unf	-0.01	-0.01
GarageQual_Fa	-0.02	-0.00
GarageQual_Gd	0.03	0.00
GarageQual_None	-0.00	-0.00

	Ridge	Lasso
GarageQual_Po	-0.00	-0.00
GarageQual_TA	-0.01	0.00
GarageCond_Fa	-0.01	-0.00
GarageCond_Gd	0.00	0.00
GarageCond_None	-0.00	-0.00
GarageCond_Po	-0.01	-0.00
GarageCond_TA	0.01	0.00
PavedDrive_P	-0.01	-0.00
PavedDrive_Y	0.01	0.00
PoolQC_Fa	0.00	-0.00
PoolQC_Gd	-0.02	-0.00
PoolQC_None	0.02	0.00
Fence_GdWo	-0.00	-0.00
Fence_MnPrv	-0.00	-0.00
Fence_MnWw	-0.01	-0.00
Fence_None	0.00	0.00
MiscFeature_None	-0.00	-0.00
MiscFeature_Othr	0.00	0.00
MiscFeature_Shed	0.00	0.00
MiscFeature_TenC	-0.00	-0.00
SaleType_CWD	0.01	0.00
SaleType_Con	0.01	0.00
SaleType_ConLD	0.01	-0.00
SaleType_ConLI	-0.01	-0.00
SaleType_ConLw	0.00	0.00
SaleType_New	0.01	0.00
SaleType_Oth	0.01	0.00

	Ridge	Lasso
SaleType_WD	-0.00	-0.00
SaleCondition_AdjLand	0.01	0.00
SaleCondition_Alloca	0.04	0.00
SaleCondition_Family	-0.01	-0.00
SaleCondition_Normal	0.03	0.00
SaleCondition_Partial	0.02	0.00

Now, we look at the most important predictor variables after the change is implemented.

In [90]:

```
## View the top 10 coefficients of Ridge regression in descending order
betas['Ridge'].sort_values(ascending=False)[:10]
```

Out[90]:

```
GrLivArea          0.08
OverallQual_8      0.07
OverallQual_9      0.06
Neighborhood_Crawfor 0.06
Functional_Typ     0.06
Exterior1st_BrkFace 0.06
OverallCond_9      0.05
TotalBsmtSF        0.05
CentralAir_Y       0.05
OverallCond_7      0.04
Name: Ridge, dtype: float64
```

In [91]:

```
## To interpret the ridge coefficients in terms of target, we have to take inverse log (i.e. e to the power) of betas
ridge_coeffs = np.exp(betas['Ridge'])
ridge_coeffs.sort_values(ascending=False)[:10]
```

Out[91]:

```
GrLivArea          1.08
OverallQual_8      1.07
OverallQual_9      1.07
Neighborhood_Crawfor 1.07
Functional_Typ     1.06
Exterior1st_BrkFace 1.06
OverallCond_9      1.06
TotalBsmtSF        1.05
CentralAir_Y       1.05
OverallCond_7      1.04
```

```
Name: Ridge, dtype: float64
```

In [92]:

```
## View the top 10 coefficients of Lasso in descending order  
betas['Lasso'].sort_values(ascending=False)[:10]
```

Out [92]:

```
GrLivArea          0.11  
OverallQual_8      0.08  
OverallQual_9      0.08  
Functional_Typ     0.07  
Neighborhood_Crawfor 0.07  
TotalBsmtSF        0.05  
Exterior1st_BrkFace 0.04  
CentralAir_Y       0.04  
YearRemodAdd       0.04  
Condition1_Norm    0.03  
Name: Lasso, dtype: float64
```

In [93]:

```
## To interpret the lasso coefficients in terms of target, we have to take inverse log (i.e. 10 to the power) of beta  
s
```

```
lasso_coeffs = np.exp(betas['Lasso'])  
lasso_coeffs.sort_values(ascending=False)[:10]
```

Out [93]:

```
GrLivArea          1.11  
OverallQual_8      1.09  
OverallQual_9      1.08  
Functional_Typ     1.07  
Neighborhood_Crawfor 1.07  
TotalBsmtSF        1.05  
Exterior1st_BrkFace 1.05  
CentralAir_Y       1.04  
YearRemodAdd       1.04  
Condition1_Norm    1.03  
Name: Lasso, dtype: float64
```

So, the most important predictor variables after we double the alpha values are:-

- GrLivArea
- OverallQual_8
- OverallQual_9
- Functional_Typ

- Neighborhood_Crawfor
- Exterior1st_BrkFace
- TotalBsmtSF
- CentralAir_Y