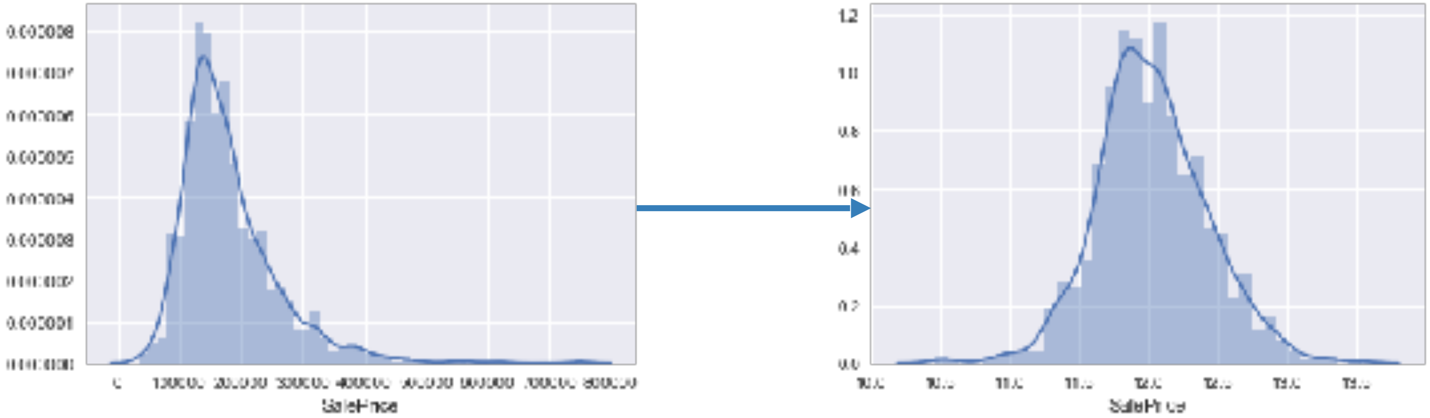
# ML Presentation

# Summary:

- EDA
- Pre-processing
  - Imputing Missing Values
  - - Categorical
  - - Numeric
  - Encoding Categorical Features
  - Feature Engineering
  - - New Features
- Modeling
  - Model Performance
  - Model Tuning
  - Model Ensembling
- Results
- - RMSLE score using CV on training set
- - Kaggle score

# Pre-Processing: Skewness




We discovered the Target Variable (SalePrice) was skewed, so we perform a log transformation to normalize its distribution. We then investigated the skewness of the predictor variables to understand if further transformation was necessary.

# Pre-Processing: Skewness

| Variable Name | Positive Skewness |
|---|---|
| Fireplaces | 0.725277917 |
| TotRmsAbvGrd | 0.74923209 |
| ExterGrade | 0.782428205 |
| ExterQual | 0.783456143 |
| 2ndFlrSF | 0.861555523 |
| BsmtUnfSF | 0.919688213 |
| AvgRoomSize | 0.931703531 |
| BsmtFinSF1 | 0.980644589 |
| TotLivArea | 1.009156621 |
| GrLivArea | 1.06875039 |
| LotFrontage | 1.103038596 |
| BsmtExposure | 1.119066336 |
| 1stFlrSF | 1.257285977 |
| ExterCond | 1.315069293 |
| Fence | 1.753731433 |
| WoodDeckSF | 1.844791628 |
| Overallscore | 1.907677233 |
| AllPorchSF | 2.244499743 |
| OpenPorchSF | 2.529358203 |
| MasVnrArea | 2.621719301 |
| BsmtFinType2 | 3.150951371 |
| BsmtHalfBath | 3.929995969 |
| ScreenPorch | 3.945101226 |
| EnclosedPorch | 4.002344092 |
| BsmtFinSF2 | 4.14450336 |
| KitchenAbvGr | 4.300550114 |
| 3SsnPorch | 11.37207993 |
| LowQualFinSF | [illegible] |
| LotArea | [illegible] |
| PoolArea | 17.68866449 |
| PoolQC | [illegible] |
| MiscVal | 21.93967217 |

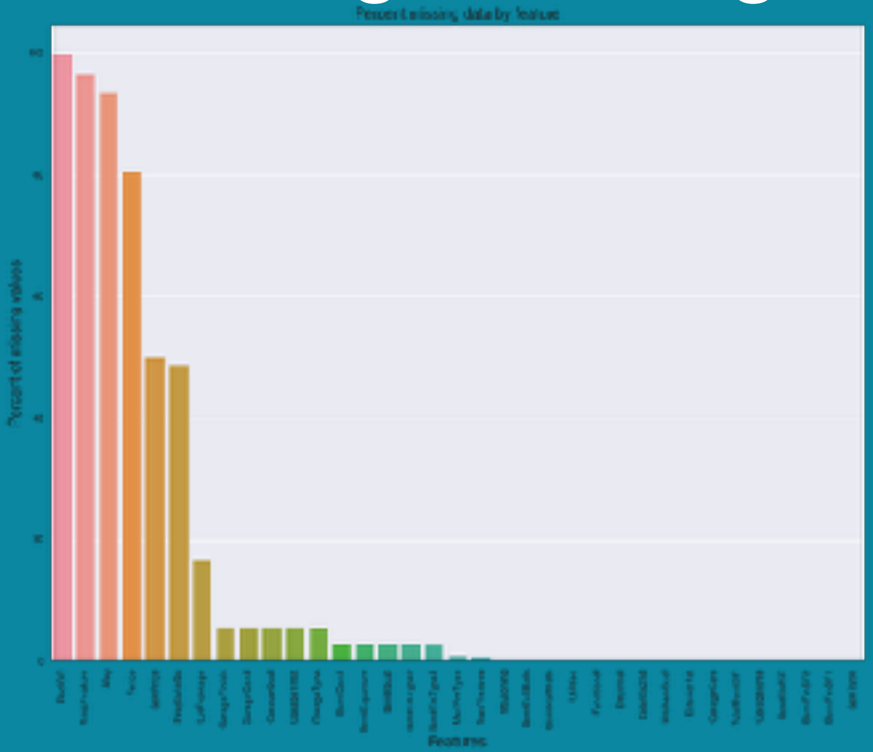
| Variable Name | Negative Skewness |
|---|---|
| Street | -15.49475602 |
| LandSlope | -4.973253614 |
| Functional | -4.961674871 |
| GarageYrBlt | -3.904632328 |
| BsmtCond | -3.602661074 |
| CentralAir | -3.45755483 |
| GarageCond | -3.381673401 |
| GarageQual | -3.262259968 |
| PavedDrive | -2.977741053 |
| BsmtQual | -1.271610943 |
| LotShape | -1.247972934 |

We found 43 features to exhibit skewness > 0.7. Therefore, we performed a boxcox transformation to normalize each of them.

We also found 6 features with skewness <0.3. However, upon further inspection we found that only dropping the “Utilities” variable would result in a minimal loss of predictive power.

| **Variables with <0.3 skewness** |
|---|
| Condition2 |
| Heating |
| PoolQC |
| RoofMatl |
| Street |
| Utilities |

# Pre-Processing: Missing Values




There is a substantial amount of missing data. We differentiate columns on a categorical/numeric basis.

# Pre-Processing: Missing Values

- Categorical Features:
  - Impute Missing with “None”
  - Imputed with mode of feature
    - MSZoning, Functional, Exterior1st

**Categorical features**

```
list_none = ['PoolQC', 'GarageType', 'GarageFinish', 'GarageCond', 'GarageQual', 'BsmtQual', 'BsmtCond', 'KitchenQual',
             'BsmtExposure', 'BsmtFinType2', 'BsmtFinType1', 'MasVnrType', 'Alley', 'Fence', 'FireplaceQu', 'MiscFeature

# Replace with "None"
df_all[list_none] = df_all[list_none].fillna('None')

# replace with the mode
df_all['MSZoning'] = df_all['MSZoning'].fillna(df_all['MSZoning'].mode()[0])
df_all['Functional'] = df_all['Functional'].fillna(df_all['Functional'].mode()[0])
df_all['Exterior1st'] = df_all['Exterior1st'].fillna(df_all['Exterior1st'].mode()[0])
```

- Numeric Features:
  - Impute Missing with “0”
  - Impute with Median of feature
    - LotFrontage

**Numeric features**

```
list_null = ['GarageYrBlt', 'GarageArea', 'GarageCars', 'BsmtFinSF1' , 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
             'BsmtFullBath', 'BsmtHalfBath', 'MasVnrArea', 'Exterior2nd', 'SaleType' , 'Electrical']

# Replace with 0
df_all[list_null] = df_all[list_null].fillna(0)

# Replace with the median of the neighborhood
df_all['LotFrontage'] = df_all.groupby('Neighborhood')['LotFrontage'].transform(lambda x: x.fillna(x.median()))
df_all.loc[df_all.LotFrontage.isnull(), 'LotFrontage'] = np.sqrt(df_all.loc[df_all.LotFrontage.isnull()].LotArea)
```

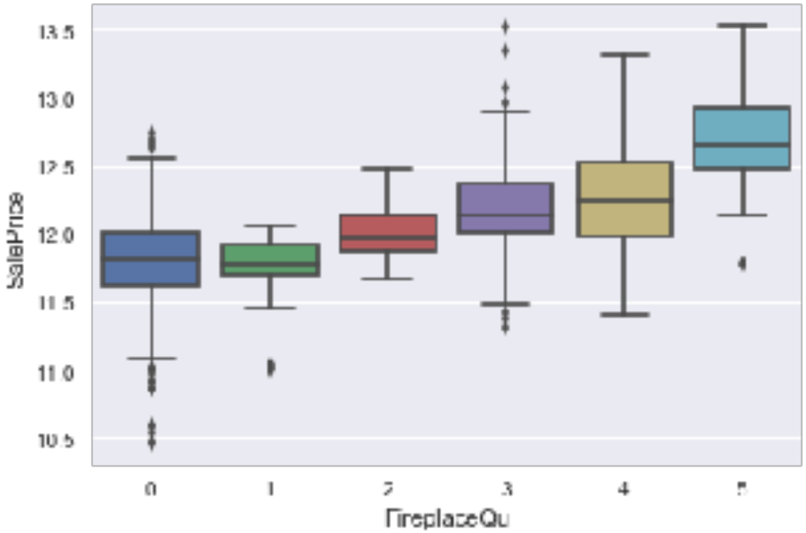
# Pre-Processing: Encoding

**Ordinal Categorical Features:** Converted to numeric based on scale:

```
qual_dict = {"None": 0, "Po": 1, "Fa": 2, "TA": 3, "Gd": 4, "Ex": 5}
df_all["ExterCond"] = df_all["ExterCond"].map(qual_dict).astype(int)
df_all["ExterQual"] = df_all["ExterQual"].map(qual_dict).astype(int)
df_all["BsmtQual"] = df_all["BsmtQual"].map(qual_dict).astype(int)
df_all["BsmtCond"] = df_all["BsmtCond"].map(qual_dict).astype(int)
df_all["HeatingQC"] = df_all["HeatingQC"].map(qual_dict).astype(int)
df_all["KitchenQual"] = df_all["KitchenQual"].map(qual_dict).astype(int)
df_all["GarageQual"] = df_all["GarageQual"].map(qual_dict).astype(int)
df_all["GarageCond"] = df_all["GarageCond"].map(qual_dict).astype(int)
df_all["FireplaceQu"] = df_all["FireplaceQu"].map(qual_dict).astype(int)
```

9 other variables received this treatment but had different scales.

Inspecting the boxplot distribution for ‘FireplaceQu’ shows that retaining ordinality is important.



# Pre-Processing: Encoding

**Non-ordinal Categorical Features:** :

```
df_all = df_all.replace({"MSSubClass" : {20 : "SC20", 30 : "SC30", 40 :
                                        50 : "SC50", 60 : "SC60", 70 : "
                                        80 : "SC80", 85 : "SC85", 90 : "
                                        150 : "SC150", 160 : "SC160", 18
                         "MoSold" : {1 : "Jan", 2 : "Feb", 3 : "Mar", 4 :
                                     7 : "Jul", 8 : "Aug", 9 : "Sep", 10
                        })

df_all['YrSold'] = df_all['YrSold'].astype(str)
```

MSSubClass, MoSold, and YrSold were initially numeric features but actually hold categorical data

```
# Label encoding non-order categorical features
from sklearn.preprocessing import LabelEncoder
columns = ('PavedDrive', 'Alley', 'Street', 'CentralAir', 'MSSubClass'
for column in columns:
    lbl = LabelEncoder()
    lbl.fit(list(df_all[column].values))
    df_all[column] = lbl.transform(list(df_all[column].values))
print(df_all.shape)
```

(2917, 80)

The LabelEncoder function performs one-hot encoding within the listed columns

```
df_all = pd.get_dummies(df_all, drop_first = True)
print(df_all.shape)
```

(2917, 239)

Performing one-hot encoding on the remaining dataset then yields additional columns, resulting in 237 total columns.

# Pre-Processing: Feature Engineering

**Feature Engineering:** Created 11 new variables based off of feature interactions

```
# 1: Total square feet
df_all['TotLivArea'] = df_all.TotalBsmtSF + df_all['1stFlrSF'] + df_all['2ndFlrSF']

# 2: # Total number of bathrooms
df_all['TotalBath'] = df_all['BsmtFullBath'] + (0.5 * df_all['BsmtHalfBath']) + \
df_all['FullBath'] + (0.5 * df_all['HalfBath'])

# 3: BsmtUnFinRatio
df_all['BsmtUnFinRatio'] = df_all.BsmtUnfSF / df_all.TotalBsmtSF
df_all['BsmtUnFinRatio'] = df_all['BsmtUnFinRatio'].fillna(0)

# 4: AreaPerCar
df_all['AreaPerCar'] = df_all.GarageArea / df_all.GarageCars
df_all['AreaPerCar'] = df_all['AreaPerCar'].fillna(0)

# 5: AvgRoomSize
df_all['AvgRoomSize'] = df_all.GrLivArea / df_all.TotRmsAbvGrd

# 6: GarageScore
df_all['GarageSocre'] = df_all.GarageCond * df_all.GarageType

# 7: OverallGrade
df_all["OverallGrade"] = df_all["OverallQual"] * df_all["OverallCond"]

# 8: Overallscore
df_all["Overallscore"] = df_all["OverallGrade"] * df_all['GrLivArea']

#9: Exterior Grae
df_all["ExterGrade"] = df_all["ExterQual"] * df_all["ExterCond"]

#10: All Porch SF
df_all["AllPorchSF"] = df_all["OpenPorchSF"] + df_all["EnclosedPorch"] + \
df_all["3SsnPorch"] + df_all["ScreenPorch"]

#11: Age
df_all['Age'] = 2010 - df_all['YearBuilt']
```

Age is the only variable that can be considered as a feature representation rather than an interaction. Room to explore creating further indicator/categorical features.

# Modeling: Parameter Tuning

**Linear Models:** After running 5000 fits through GridSearchCV, optimal parameters are below:

```
Results for ridge:
Best parameters:  {'alpha': 5.774615152359814 4, 'random_state': 42}
Fitted MSE:  0.0126834105009
Fitted RMSE:  0.112620648644
------------------------------------------------------------------------
Results for lasso:
Best parameters:  {'alpha': 0.00020923834803969769, 'random_state': 42}
Fitted MSE:  0.0123602338342
Fitted RMSE: 0.111176508516
------------------------------------------------------------------------
Results for elastic net:
Best parameters:  {'alpha': 0.0043178797273320212, 'l1_ratio': 0, 'random_state': 42}
Fitted MSE:  0.0126836348432
Fitted RMSE:  0.112621644640
```

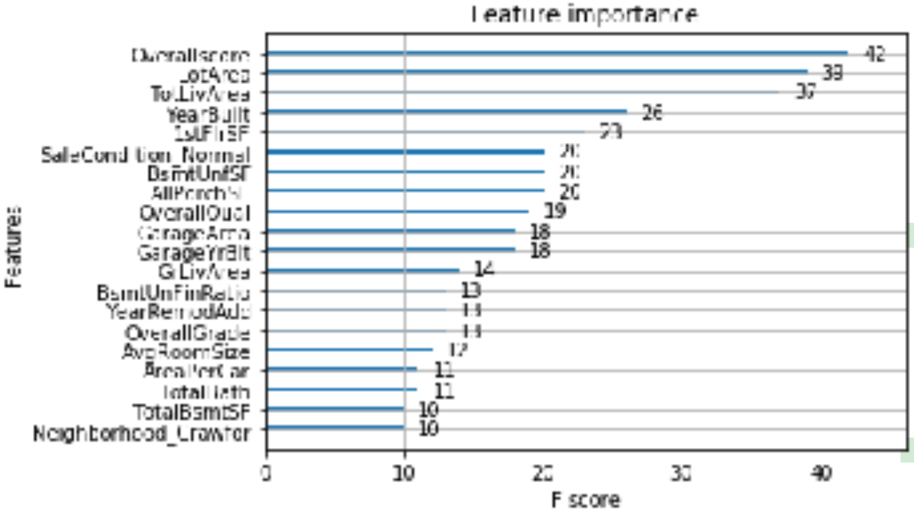
With an Elastic Net l1_ratio of 0, this means that that the ridge regression may yield the best results over a Lasso. The Lasso's near 0 alpha result also shows that a straightforward linear regression may also produce positive results.

# Modeling: Parameter Tuning

**Tree-based Models:** After running 5000 fits through GridSearchCV and Bayesian Optimizaiton

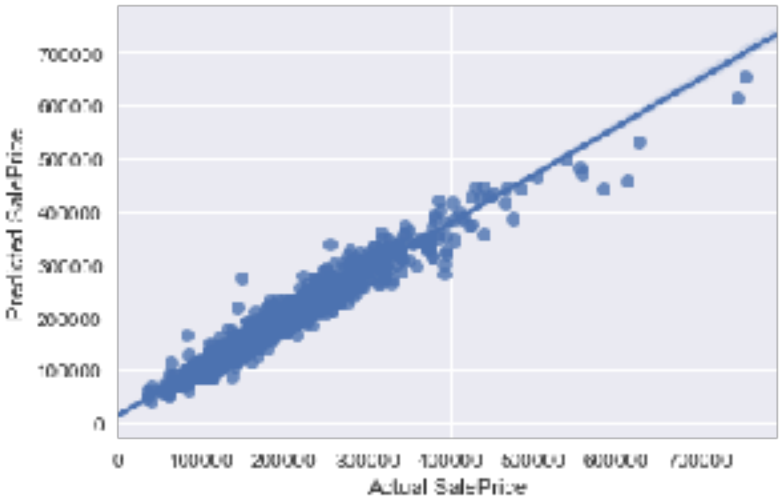
# Model Feature Importance:

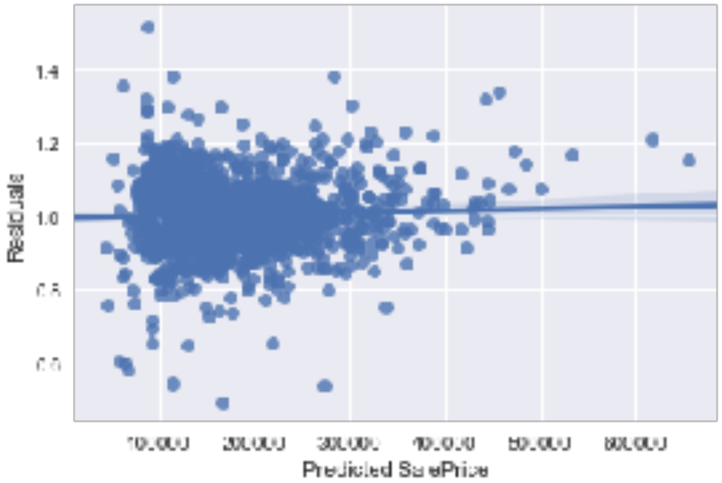
Lasso Coefficients (most important variables)




Xgboost – most important features

# Model Evaluation:




Y_hat VS. actual SalePrice (lasso model):

We observe a strong linear trend in the results

Residual Plot (lasso) Y_hat vs. Residuals

We do not observe any significant outliers.

# Parameter Tuning:

- Grid Search
- Bayesian Optimization

## Tuned Model Performances:

```
Ridge:
Mean RMSLE:   0.111579632589
Min RMSLE:   0.0956569591734
Max RMSLE:   0.137629970056
Std RMSLE:   0.0134479803353
```

```
Lasso:
Mean RMSLE:   0.110223352332
Min RMSLE:   0.0960129858893
Max RMSLE:   0.13684855486
Std RMSLE:   0.0133668504869
```

```
Xgboost:
Mean RMSLE:   0.115406681482
Min RMSLE:   0.100213833837
Max RMSLE:   0.135809223636
Std RMSLE:   0.0137285687266
```

```
Xgboost Alternative:
Mean RMSLE:   0.121502812757
Min RMSLE:   0.101831128608
Max RMSLE:   0.142983312984
Std RMSLE:   0.0155486014157
```

```
Random Forest Aggressive:
Mean RMSLE:   0.113899715187
Min RMSLE:   0.096376429415
Max RMSLE:   0.133121484438
Std RMSLE:   0.0143629567948
```

```
Random Forest Conservative:
Mean RMSLE:   0.132577372561
Min RMSLE:   0.111758666571
Max RMSLE:   0.158920830563
Std RMSLE:   0.014566172841
```

## RESULTS

ridge, model_xgb, RForest: **0.1151**

ENet, lasso, ridge, model_xgb: **0.1086**

lasso, ridge, model_xgb: **0.1082**

lasso ridge, model_xgb, RForest: **0.1115**

ENet, lasso, rdige, model_xgb (all new features): **0.1087**

ENet, lasso, ridge, model_xgb (excluded last new variables): **0.1088**

ENet, lasso, ridge, model_xgb (exluded PoolQC and Street): **0.1089**

lasso, model_xgb (exluded PoolQC and Street): **0.1089**

lasso, model_xgb (all new features): **0.1085**

lasso, model_xgb (exluded low variance variables): **0.1087**

lasso, model_xgb (lower lambda for box-cox): **0.1086**

lasso, model_xgb (with two new derived features): **0.1084**

lasso, model_xgb (ex. levels not in test set): **0.1086** - best on Kaggle leaderbord (0.11763)

lasso, model_xgb (ex. levels not in test set and "Age"): **0.1088**

lasso, model_xgb, RForest_agg (ex. levels not in test set): **0.1117**

lasso, model_xgb, RForest_agg, RForest_con (ex. levels not in test set): **0.1155**

lasso, model_xgb, model_lgb: **0.1086**

lasso, model_lgb: **0.1076**

lasso, model_xgb_al (gridsearchCV parameters): **0.1108**

lasso, model_xgb (with new variable "SoldYr"): **0.1085**

# Results:

**0.11774 RMSLE ON PUBLIC TEST**