ML Presentation

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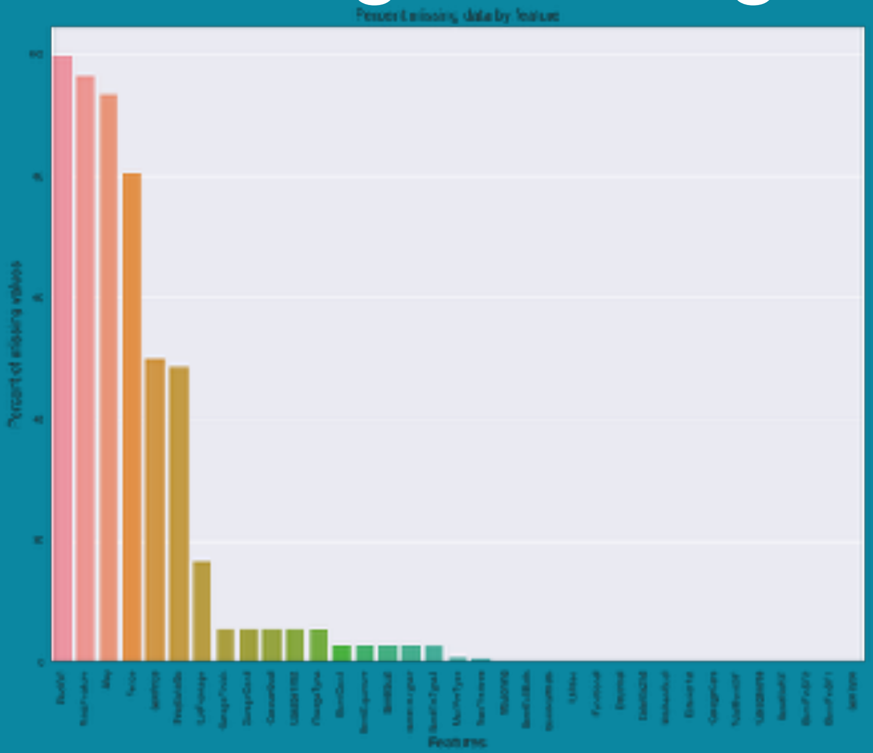
Summary:

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

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)
```

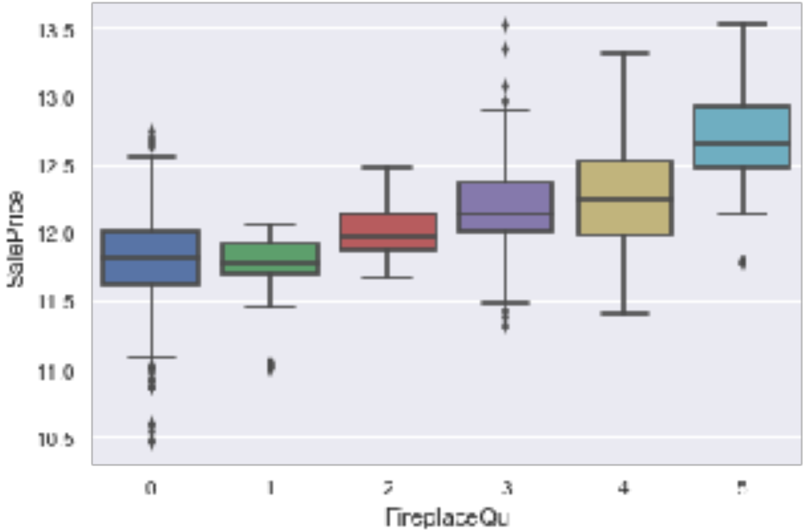
Pre-Processing: Encoding

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)
```

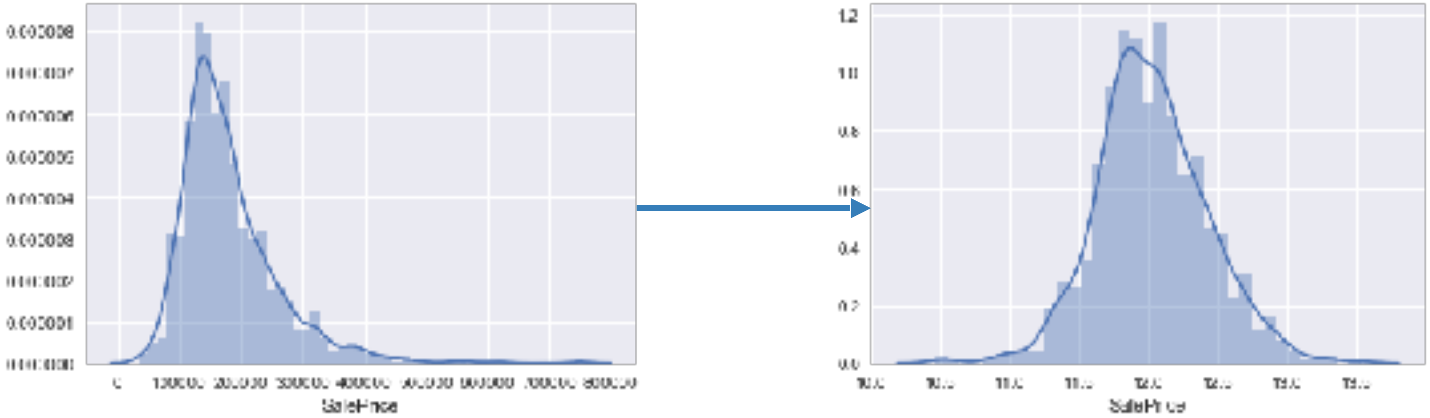
The LabelEncoder function performs one-hot encoding within the listed columns

```
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: 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	12.[illegible]
LotArea	13.[illegible]469
PoolArea	17.68866449
PoolQC	20.[illegible]42409
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: Feature Engineering

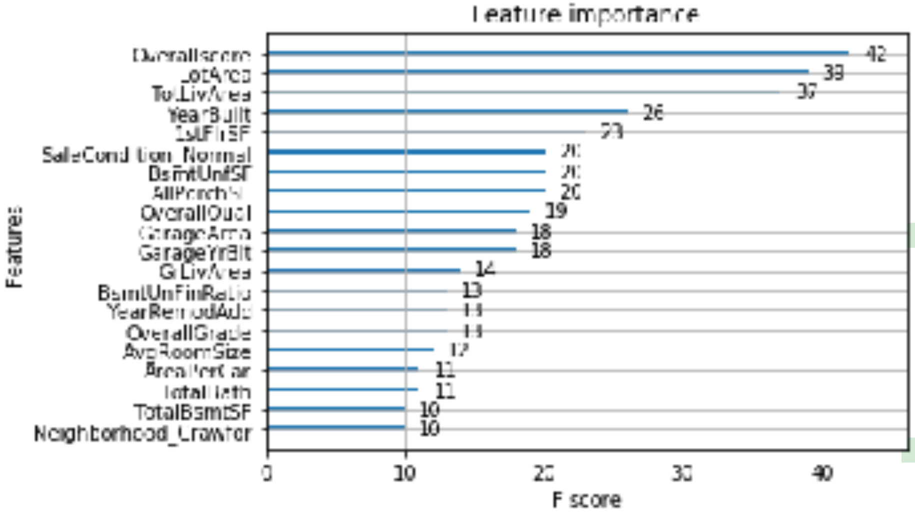
Feature Engineering: Created 11 new variables based off of feature interactions

```
# 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['GarageScore'] = 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.

Model Feature Importance:

Lasso Coefficients (most important variables)



Xgboost – most important features

Parameter Tuning:

- Grid Search
- Bayesian Optimization

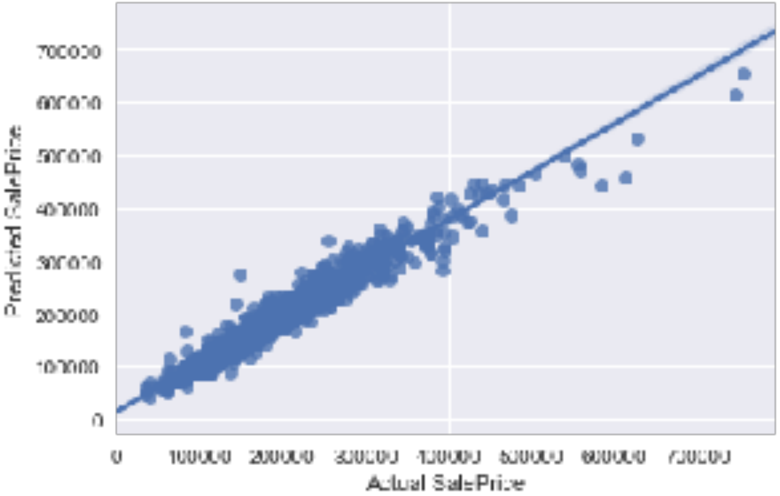
Modeling: Parameter Tuning

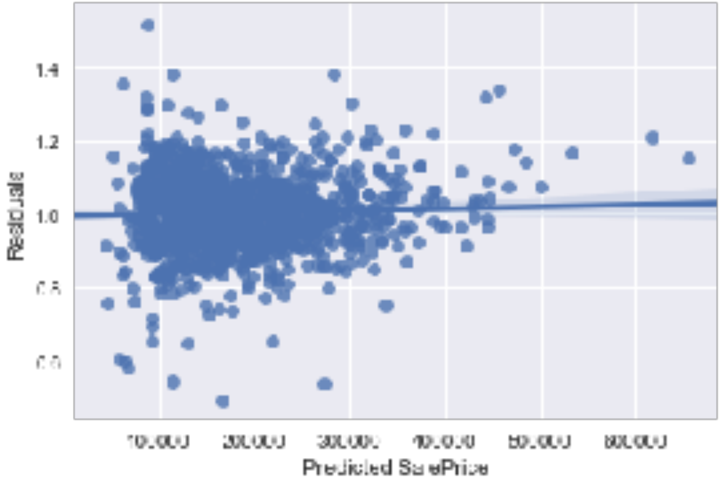
Linear Models: After running 5000 fits through GridSearchCV, optimal parameters are below:

```
Results for ridge:
Best parameters:  {'alpha': 5.774615152359814, '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:  0.112621644646
```

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.

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.

Tuned Model Performances:

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

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

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

```
Random Forest Aggressive:
Mean RMSLE:  0.113899715187
Min RMSLE:  0.096376429415
Max RMSLE:  0.13121484438
Std RMSLE:  0.0143629567948
```

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

```
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

Thank You!