W207 Final Project

Predicting Sale Price

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Overview of our process

EDA

What does our data look like? Missing values?

Data Cleaning

How to deal with missing values? Outliers?

Feature Engineering

Which features are most relevant? How to deal with categorical and numerical features?

Create Train/ Dev Data

How to split? Use CV?

Model Setup

How does each model perform? Should we use a blended model?

Model Analysis

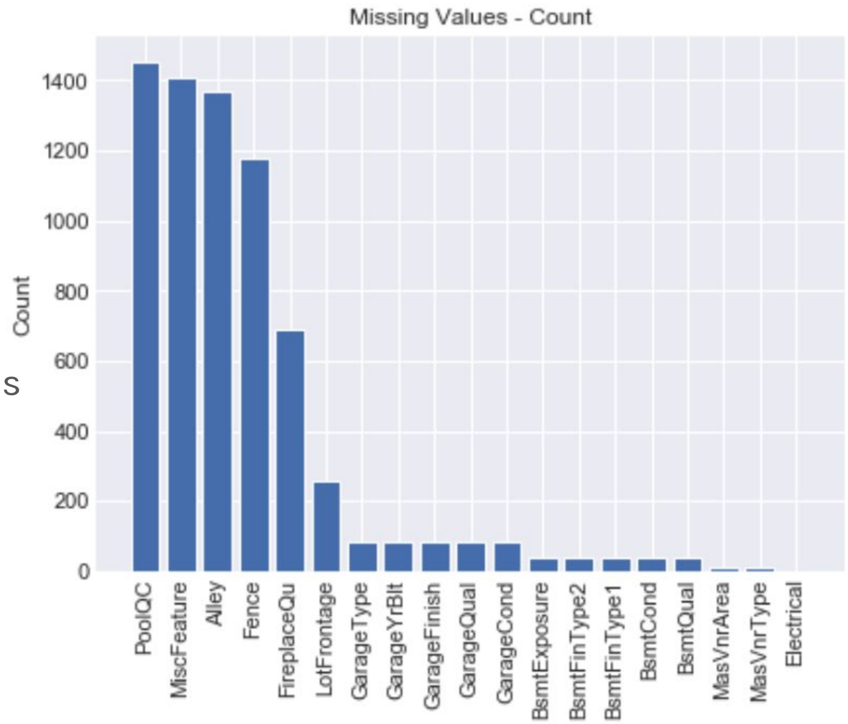
Which model is best? How do we measure this?

Final Submission

Base on the best performing model's RMSE

EDA and Data Cleaning: General Approach

- Look at shape of data
  - Train (80 features, 1,460 examples)
  - Test (79 features, 1,459 examples)
- Missing Values
  - See histogram
- Look at data structure
  - Mix of categorical and quantitative features
- Use Median for Outliers
  - GrLivArea > 4000 and SalePrice < 200000
  - Total_sf > 60000 and SalePrice < 200000
  - LotFrontage > 200
  - GarageArea > 1200 and SalePrice < 300000



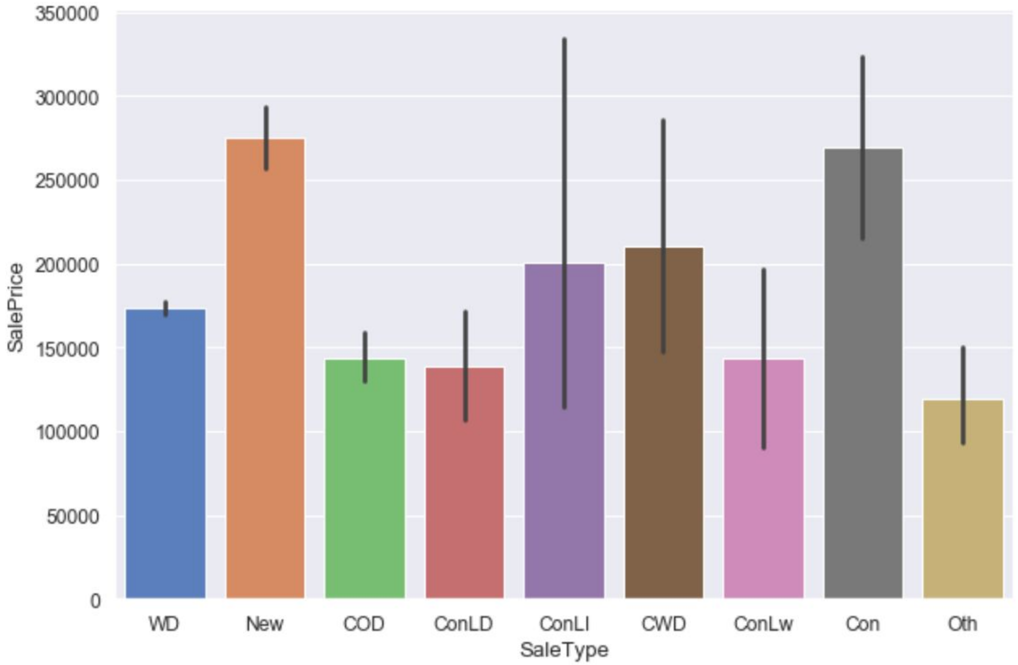
An iterative process…

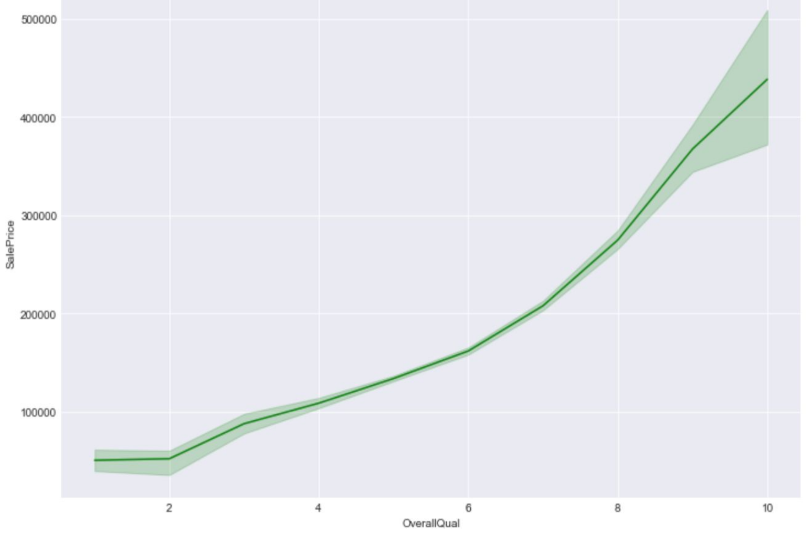
Dealing with Missing Values	*Encoding Non-Numerical Variables*	*Feature Selection*	*Selecting Models*		*Other*
Exclude all columns with > 10% missing values	LabelEncoder()	No manual feature selection	Adaboost (base estimator = LR	Random Forest	Find and label duplicates
Fill missing categorical values with NA	Hot_encode()	Take 20 most correlated features	Bayesian Ridge	Xgboost (base estimator = BR)	Use log scale for Sale Price
Fill missing categorical values with the most common category	Convert_ordinals()	Add and delete features and evaluate RMSE	Lasso Lars	Linear	Use log scale for skewed features
Fill missing numerical values with 0		Use L1 and L2 for model feature selection	Thielsen	ARD	Use 5-fold cross validation instead of 80-20 split
Fill all missing numerical values with the median value		Remove multicollinear variables	Passive Aggressive	Blended Model	Tuning Hyperparameters for each model through CV
Fill select features' missing values with median or mode		Include features with Spearman Rank > abs(0.05)			Manually sift through data points whose predictions are most off & adjust features

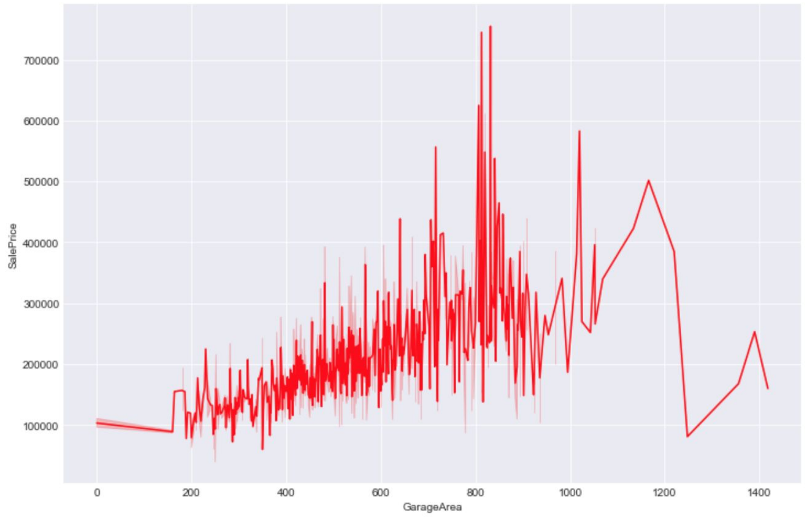
Features Chosen

- 1stFlrSF
- 2ndFlrSF
- BldgType_X
- BsmtExposure
- BsmtFinSF1
- BsmtQual_X
- GarageType_Attc
- SaleType_X
- YrSold_X
- TotalBsmtSF
- ExterQual
- FireplaceQu_Gd
- FireplaceQu_NA
- Fireplaces
- Foundation_X
- FullBath
- Functional
- GarageArea
- GarageCars
- total_porch_sf
- GarageType_Detc
- GrLivArea
- has_fireplace
- HeatingQC
- house_age
- KitchenQual
- LotArea
- LotFrontage
- LotShape
- MasVnrType_Non
- MasVnrType_Ston
- MSSubClass_X
- MSZoning_RM
- Neighborhood_X
- OverallCond
- OverallQual
- SaleCondition_Pa rtial
- SaleType_New
- total_baths
- MasVnrArea
- total_sf
- TotRmsAbvGrd
- WoodDeckSF
- YearBuilt
- YearRemodAdd
- GarageFinish

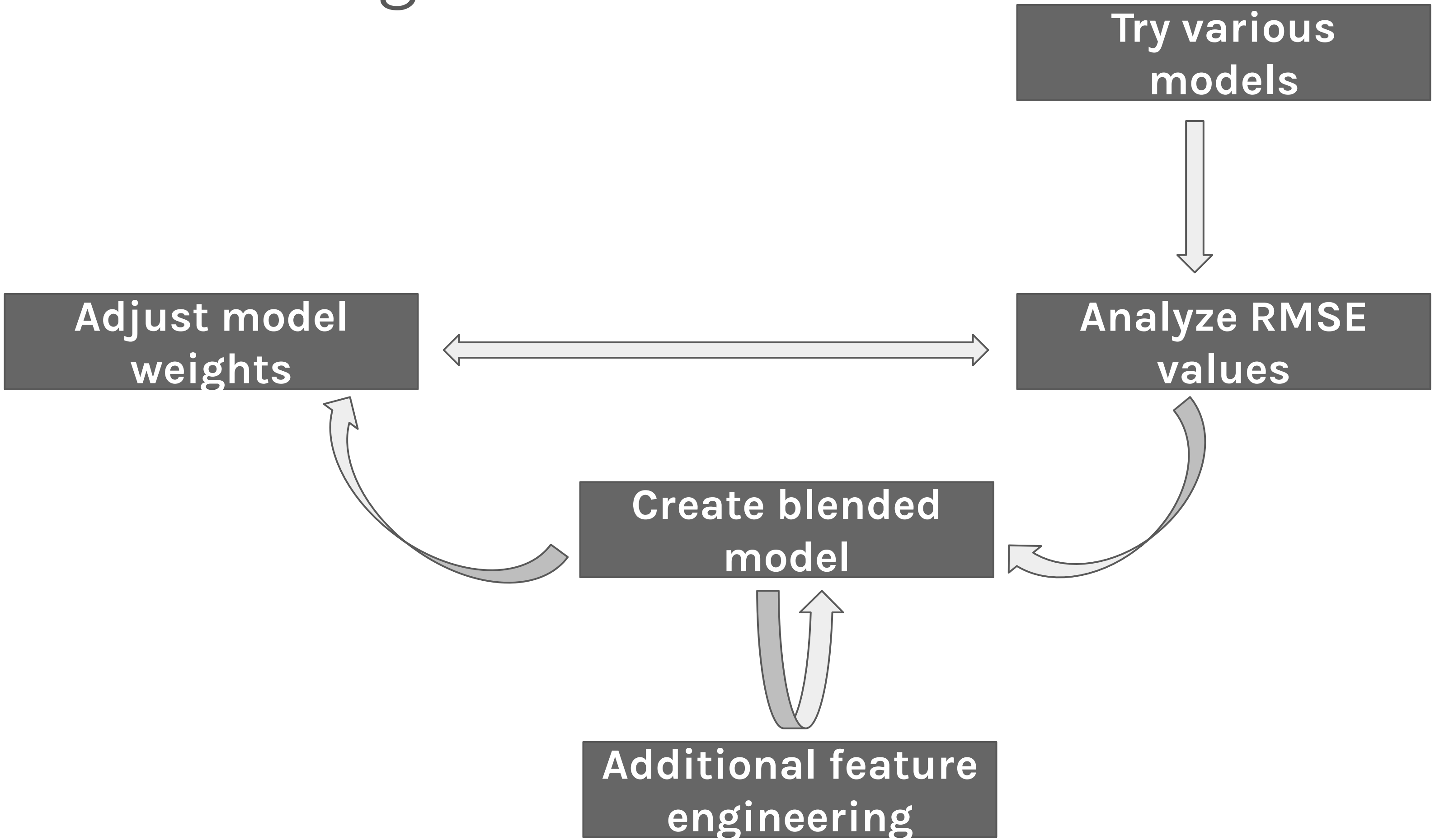
A closer look at specific features







Model Building Process



Converting Categorical/Ordinal Variables

```python
def convert_ordinals(data):
    default_odinal = {
        'Ex': 5,  # Excellent
        'Gd': 4,  # Good
        'TA': 3,  # Average/Typical
        'Fa': 2,  # Fair
        'Po': 1,  # Poor
        'NA': 3
    }

    # LotShape: General shape of property
    lot_shape = {
        'Reg': 4,  # Regular
        'IR1': 3,  # Slightly irregular
        'IR2': 2,  # Moderately Irregular
        'IR3': 1   # Irregular
    }
```

```python
def hot_encode(data):
    categorical_cols = data.select_dtypes(include=
['object'])
    return pd.get_dummies(data, columns = categoric
al_cols.columns)

test_new = hot_encode(test_new)
train_new = hot_encode(train_new)
train_new.head()
```

Using CV and tuning parameters

```
#Validation function
def cross_validation(model):
    kf = KFold(5, shuffle=True, random_state=42).get_n_splits(train_data)
    rmse= np.sqrt(abs(cross_val_score(model, train_data, train_labels, scoring="neg_mean_squared_e
rror", cv = kf)))
    return(rmse)
```

```
def parameter_tuning(model, parameters):
    clf = GridSearchCV(
        model, parameters, cv=5,scoring='neg_mean_squared_error', n_jobs = 5)

    clf.fit(train_data,train_labels)

    print(clf.best_params_)
    print(np.sqrt(-clf.best_score_))
```

Choosing the final weights

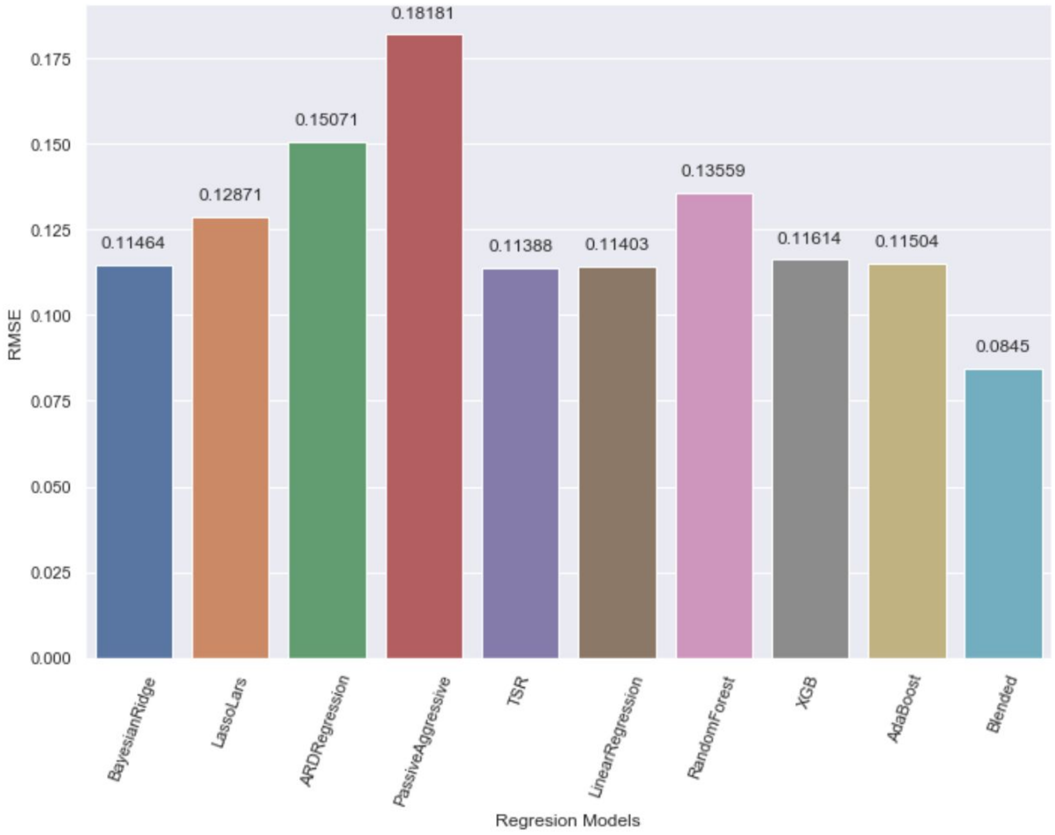
```
sorted_models = sorted(models_rmse.items(), key =
             lambda kv:(kv[1], kv[0]))
for item in sorted_models:
    if item[0] == 'Blended':
        continue
    print ('{:>18}  {:>12}'.format(item[0], item[1]))

regression_models = [
    {'name': 'AdaBoostRegressor', 'weight': 0.14, 'model': ada_model_fit},
    {'name': 'XGBoost', 'weight': 0.14, 'model': xgb_model_fit},
    {'name': 'BayesianRidge', 'weight': 0.14, 'model': br_model_fit},
    {'name': 'Linear', 'weight': 0.14, 'model': lr_model_fit},
    {'name': 'TheilSen', 'weight': 0.16, 'model': trs_model_fit},
    {'name': 'Random Forest', 'weight': 0.14, 'model': rfr_model_fit},
    {'name': 'ARD', 'weight': 0.0, 'model': ardr_model_fit},
    {'name': 'PassiveAggressive', 'weight': 0.0, 'model': par_model_fit},
    {'name': 'LassoLars', 'weight': 0.14, 'model': ll_model_fit},
]
```

Comparing the Models

Lowest RMSE (Blended):
0.0845

While our RMSE decreases with model adjustments, our score in Kaggle stays relatively constant

Are we overfitting our train data?



Final Kaggle Score

RMSE: 0.11743

Place: 525