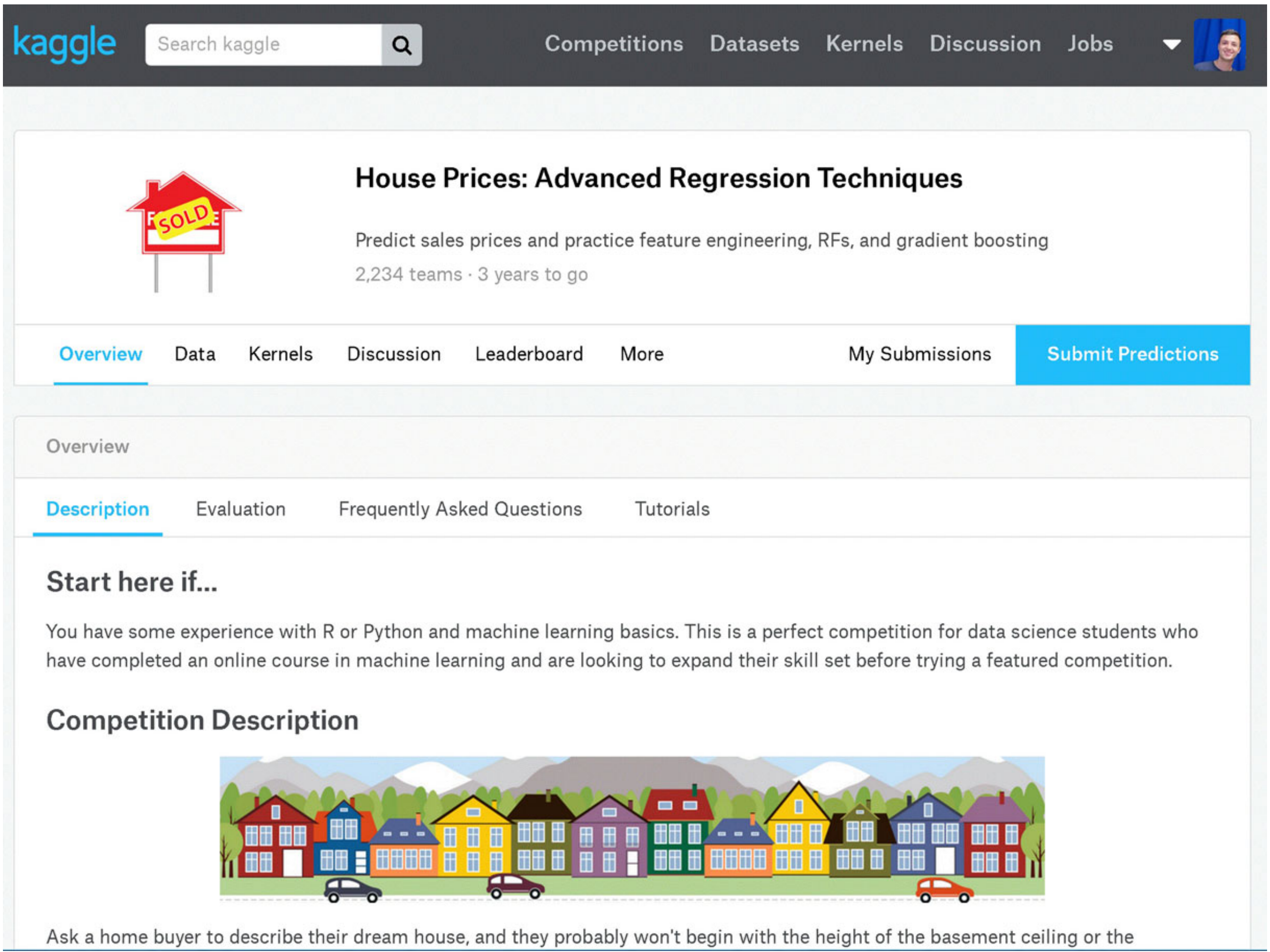
Getting Started with Kaggle: House Prices Competition

Adam Massachi | 05 MAY 2017 in tutorials, python, and kaggle

Founded in 2010, Kaggle is a Data Science platform where users can share, collaborate, and compete. One key feature of Kaggle is "Competitions", which offers users the ability to practice on real world data and to test their skills with, and against, an international community.

This guide will teach you how to approach and enter a Kaggle competition, including exploring the data, creating and engineering features, building models, and submitting predictions. We'll use Python 3 and Jupyter Notebook.



The Competition

We'll work through the House Prices: Advanced Regression Techniques competition.

We'll follow these steps to a successful Kaggle Competition submission:

- Acquire the data
- Explore the data
- Engineer and transform the features and the target variable
- Build a model
- Make and submit predictions

Step 1: Acquire the data and create our environment

We need to acquire the data for the competition. The descriptions of the features and some other helpful information are contained in a file with an obvious name, `data_description.txt`.

Download the data and save it into a folder where you'll keep everything you need for the competition.

We will first look at the `train.csv` data. After we've trained a model, we'll make predictions using the `test.csv` data.

First, import Pandas, a fantastic library for working with data in Python. Next we'll import Numpy.

```
import pandas as pd
import numpy as np
```

We can use Pandas to read in csv files. The `pd.read_csv()` method creates a DataFrame from a csv file.

```
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

Let's check out the size of the data.

```
print ("Train data shape:", train.shape)
print ("Test data shape:", test.shape)
```

```
Train data shape: (1460, 81)
Test data shape: (1459, 80)
```

We see that `test` has only 80 columns, while `train` has 81. This is due to, of course, the fact that the test data do not include the final sale price information!

Next, we'll look at a few rows using the `DataFrame.head()` method.

```
train.head()
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley
0	1	60	RL	65.0	8450	Pave	NaN
1	2	20	RL	80.0	9600	Pave	NaN
2	3	60	RL	68.0	11250	Pave	NaN
3	4	70	RL	60.0	9550	Pave	NaN
4	5	60	RL	84.0	14260	Pave	NaN

We should have the `data dictionary` available in our folder for the competition. You can also find it here.

Here's a brief version of what you'll find in the data description file:

- `SalePrice` – the property's sale price in dollars. This is the target variable that you're trying to predict.
- `MSSubClass` – The building class
- `MSZoning` – The general zoning classification
- `LotFrontage` – Linear feet of street connected to property
- `LotArea` – Lot size in square feet
- `Street` – Type of road access
- `Alley` – Type of alley access
- `LotShape` – General shape of property
- `LandContour` – Flatness of the property
- `Utilities` – Type of utilities available
- `LotConfig` – Lot configuration

And so on.

The competition challenges you to predict the final price of each home. At this point, we should start to think about what we know about housing prices, Ames, Iowa, and what we might expect to see in this dataset.

Looking at the data, we see features we expected, like `YrSold` (the year the home was last sold) and `SalePrice`. Others we might not have anticipated, such as `LandSlope` (the slope of the land the home is built upon) and `RoofMatl` (the materials used to construct the roof). Later, we'll have to make decisions about how we'll approach these and other features.

We want to do some plotting during the exploration stage of our project, and we'll need to import that functionality into our environment as well. Plotting allows us to visualize the distribution of the data, check for outliers, and see other patterns that we might miss otherwise. We'll use Matplotlib, a popular visualization library.

```
import matplotlib.pyplot as plt
plt.style.use(style='ggplot')
plt.rcParams['figure.figsize'] = (10, 6)
```

Step 2: Explore the data and engineer Features

The challenge is to predict the final sale price of the homes. This information is stored in the `SalePrice` column. The value we are trying to predict is often called the **target variable**.

We can use `Series.describe()` to get more information.

```
train.SalePrice.describe()
```

```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

`Series.describe()` gives you more information about any series. `count` displays the total number of rows in the series. For numerical data, `Series.describe()` also gives the `mean`, `std`, `min` and `max` values as well.

The average sale price of a house in our dataset is close to `$180,000`, with most of the values falling within the `$130,000` to `$215,000` range.

Next, we'll check for skewness, which is a measure of the shape of the distribution of values.

When performing regression, sometimes it makes sense to log-transform the target variable when it is skewed. One reason for this is to improve the linearity of the data. Although the justification is beyond the scope of this tutorial, more information can be found here.

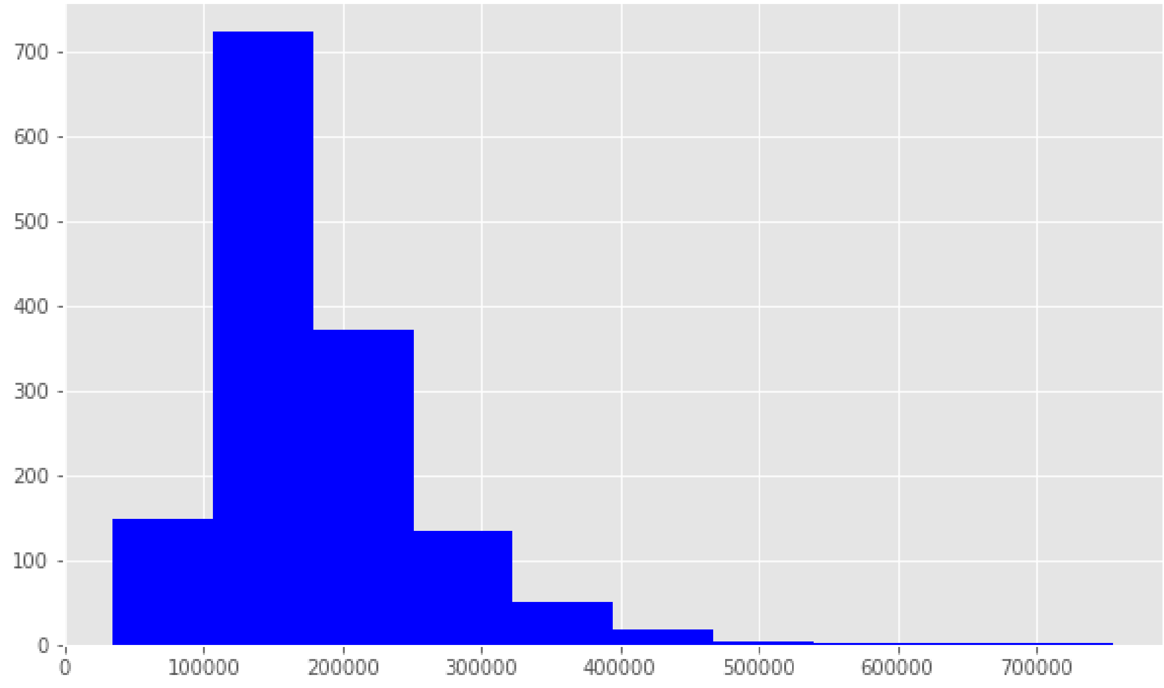
Importantly, the predictions generated by the final model will also be log-transformed, so we'll need to convert these predictions back to their original form later.

`np.log()` will transform the variable, and `np.exp()` will reverse the transformation.

We use `plt.hist()` to plot a histogram of `SalePrice`. Notice that the distribution has a longer tail on the right. The distribution is positively skewed.

```
print ("Skew is:", train.SalePrice.skew())
plt.hist(train.SalePrice, color='blue')
plt.show()
```

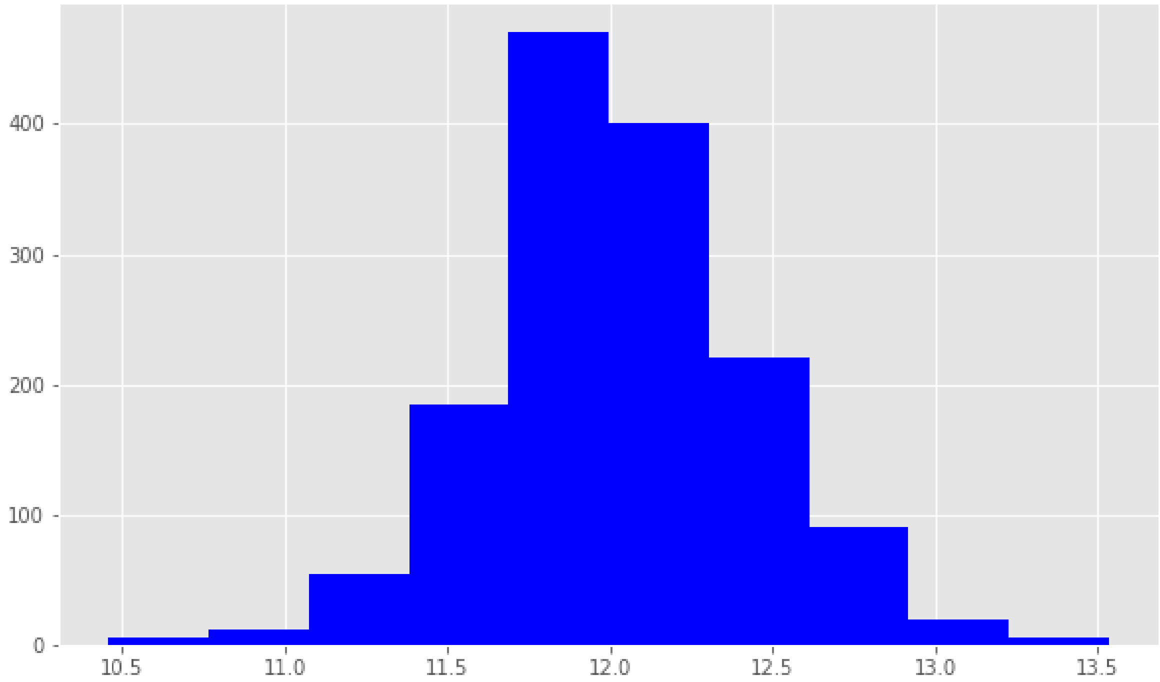
```
Skew is: 1.88287575977
```



Now we use `np.log()` to transform `train.SalePric` and calculate the skewness a second time, as well as re-plot the data. A value closer to 0 means that we have improved the skewness of the data. We can see visually that the data will more resembles a normal distribution.

```
target = np.log(train.SalePrice)
print ("Skew is:", target.skew())
plt.hist(target, color='blue')
plt.show()
```

```
Skew is: 0.121335062205
```



Now that we've transformed the target variable, let's consider our features. First, we'll check out the numerical features and make some plots. The `.select_dtypes()` method will return a subset of columns matching the specified data types.

Working with Numeric Features

```
numeric_features = train.select_dtypes(include=[np.num
numeric_features.dtypes
```

```
Id                 int64
MSSubClass         int64
LotFrontage      float64
LotArea            int64
OverallQual        int64
OverallCond        int64
YearBuilt          int64
YearRemodAdd       int64
MasVnrArea       float64
BsmtFinSF1         int64
BsmtFinSF2         int64
BsmtUnfSF          int64
TotalBsmtSF        int64
1stFlrSF           int64
2ndFlrSF           int64
LowQualFinSF       int64
GrLivArea          int64
BsmtFullBath       int64
BsmtHalfBath       int64
FullBath           int64
HalfBath           int64
BedroomAbvGr       int64
KitchenAbvGr       int64
TotRmsAbvGrd       int64
Fireplaces         int64
GarageYrBlt      float64
GarageCars         int64
GarageArea         int64
WoodDeckSF         int64
OpenPorchSF        int64
EnclosedPorch      int64
3SsnPorch          int64
ScreenPorch        int64
PoolArea           int64
MiscVal            int64
MoSold             int64
YrSold             int64
SalePrice          int64
dtype: object
```

The `DataFrame.corr()` method displays the correlation (or relationship) between the columns. We'll examine the correlations between the features and the target.

```
corr = numeric_features.corr()

print (corr['SalePrice'].sort_values(ascending=False)[
print (corr['SalePrice'].sort_values(ascending=False)[
```

```
SalePrice      1.000000
OverallQual    0.790982
GrLivArea      0.708624
GarageCars     0.640409
GarageArea     0.623431
Name: SalePrice, dtype: float64

YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

The first five features are the most positively correlated with `SalePrice`, while the next five are the most negatively correlated.

Let's dig deeper on `OverallQual`. We can use the `.unique()` method to get the unique values.

```
train.OverallQual.unique()
```

```
array([ 7,  6,  8,  5,  9,  4, 10,  3,  1,  2])
```

The `OverallQual` data are integer values in the interval 1 to 10 inclusive.

We can create a pivot table to further investigate the relationship between `OverallQual` and `SalePrice`. The Pandas docs demonstrate how to accomplish this task. We set `index='OverallQual'` and `values='SalePrice'`. We chose to look at the `median` here.

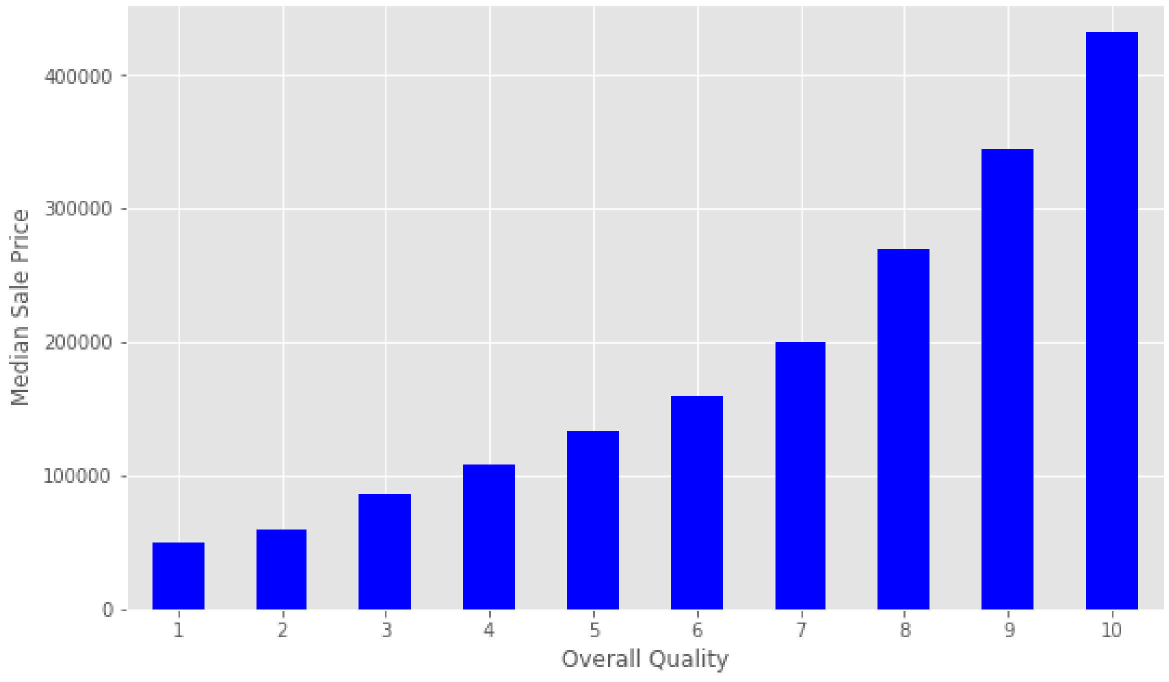
```
quality_pivot = train.pivot_table(index='OverallQual',
                                  values='SalePrice',
```

```
quality_pivot
```

```
OverallQual
1      50150
2      60000
3      86250
4     108000
5     133000
6     160000
7     200141
8     269750
9     345000
10    432390
Name: SalePrice, dtype: int64
```

To help us visualize this pivot table more easily, we can create a bar plot using the `Series.plot()` method.

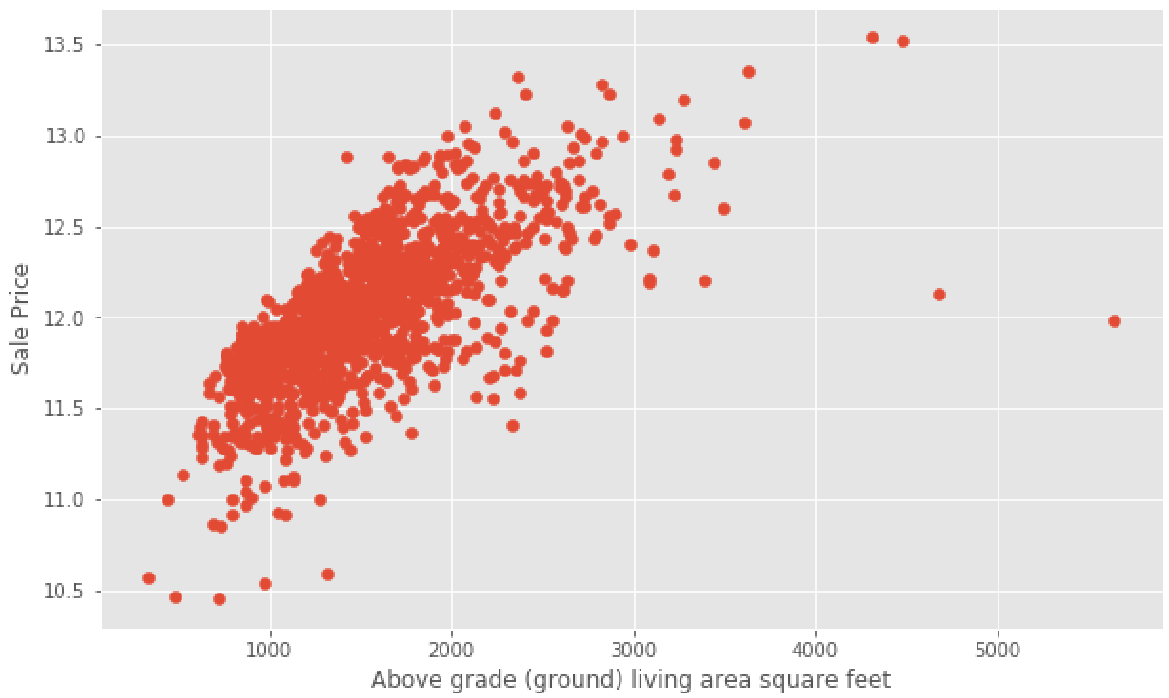
```
quality_pivot.plot(kind='bar', color='blue')
plt.xlabel('Overall Quality')
plt.ylabel('Median Sale Price')
plt.xticks(rotation=0)
plt.show()
```



Notice that the median sales price strictly increases as Overall Quality increases.

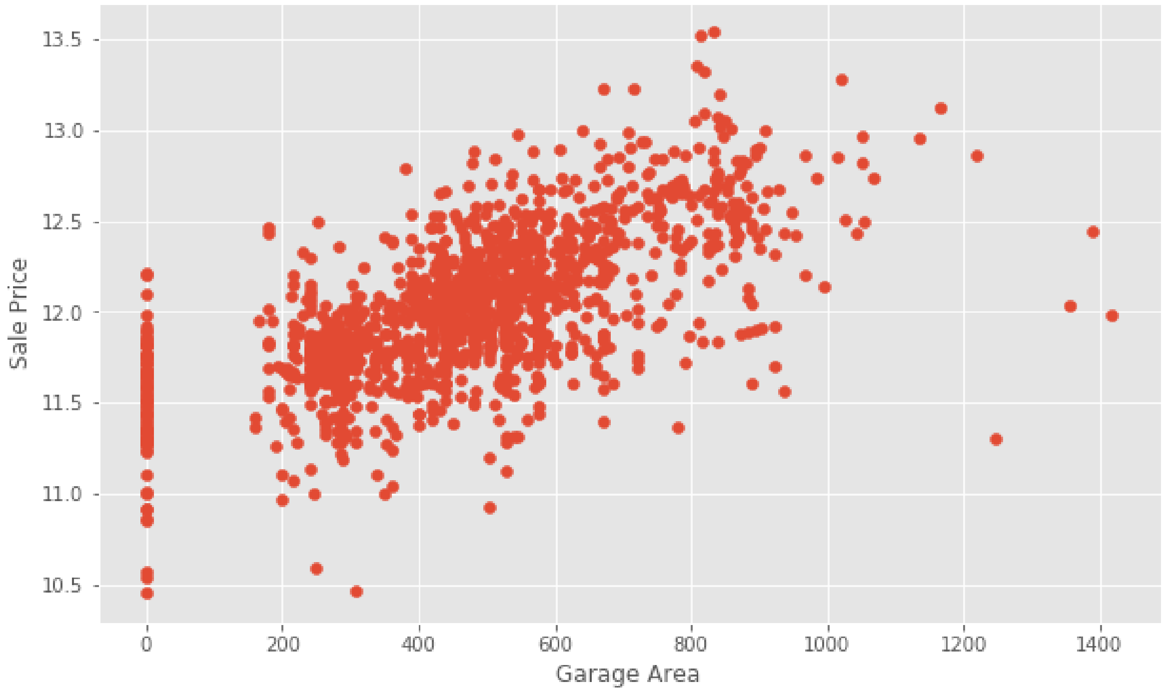
Next, let's use `plt.scatter()` to generate some scatter plots and visualize the relationship between the Ground Living Area `GrLivArea` and `SalePrice`.

```
plt.scatter(x=train['GrLivArea'], y=target)
plt.ylabel('Sale Price')
plt.xlabel('Above grade (ground) living area square fe
plt.show()
```



At first glance, we see that increases in living area correspond to increases in price. We will do the same for `GarageArea`.

```
plt.scatter(x=train['GarageArea'], y=target)
plt.ylabel('Sale Price')
plt.xlabel('Garage Area')
plt.show()
```



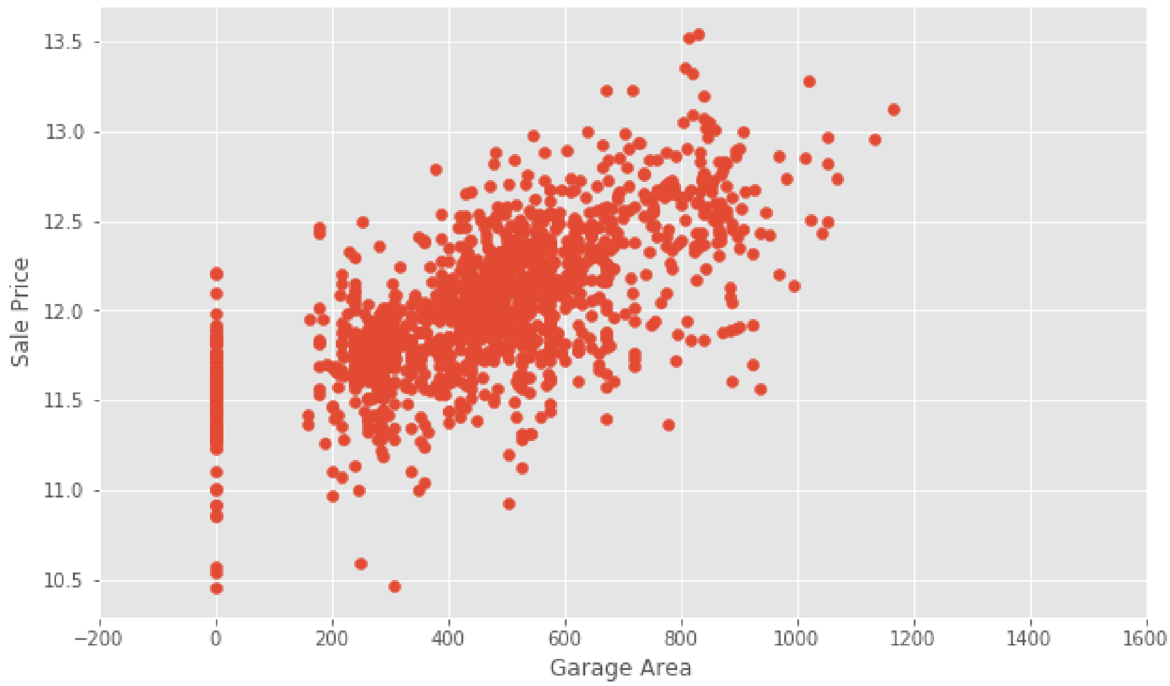
Notice that there are many homes with `0` for `Garage Area`, indicating that they don't have a garage. We'll transform other features later to reflect this assumption. There are a few outliers as well. Outliers can affect a regression model by pulling our estimated regression line further away from the true population regression line. So, we'll remove those observations from our data. Removing outliers is an art and a science. There are many techniques for dealing with outliers.

We will create a new dataframe with some outliers removed.

```
train = train[train['GarageArea'] < 1200]
```

Let's take another look.

```
plt.scatter(x=train['GarageArea'], y=np.log(train.Sale
plt.xlim(-200,1600) # This forces the same scale as be
plt.ylabel('Sale Price')
plt.xlabel('Garage Area')
plt.show()
```



Handling Null Values

Next, we'll examine the null or missing values.

We will create a DataFrame to view the top null columns. Chaining together the `train.isnull().sum()` methods, we return a Series of the counts of the null values in each column.

```python
nulls = pd.DataFrame(train.isnull().sum().sort_values(
nulls.columns = ['Null Count']
nulls.index.name = 'Feature'
nulls
```

	Null Count
Feature	
PoolQC	1449
MiscFeature	1402
Alley	1364
Fence	1174
FireplaceQu	689
LotFrontage	258
GarageCond	81
GarageType	81
GarageYrBlt	81
GarageFinish	81
GarageQual	81
BsmtExposure	38
BsmtFinType2	38
BsmtFinType1	37
BsmtCond	37
BsmtQual	37
MasVnrArea	8
MasVnrType	8
Electrical	1
Utilities	0
YearRemodAdd	0
MSSubClass	0
Foundation	0
ExterCond	0
ExterQual	0

The documentation can help us understand the missing values. In the case of `PoolQC`, the column refers to Pool Quality. Pool quality is `NaN` when `PoolArea` is `0`, or there is no pool. We can find a similar relationship between many of the Garage-related columns.

Let's take a look at one of the other columns, `MiscFeature`. We'll use the `Series.unique()` method to return a list of the unique values.

```
print ("Unique values are:", train.MiscFeature.unique(
```

```
Unique values are: [nan 'Shed' 'Gar2' 'Othr' 'TenC']
```

We can use the documentation to find out what these values indicate:

```
MiscFeature: Miscellaneous feature not covered in other ca

   Elev Elevator
   Gar2 2nd Garage (if not described in garage section)
   Othr Other
   Shed Shed (over 100 SF)
   TenC Tennis Court
   NA   None
```

These values describe whether or not the house has a shed over 100 sqft, a second garage, and so on. We might want to use this information later. It's important to gather domain knowledge in order to make the best decisions when dealing with missing data.

Wrangling the non-numeric Features

Let's now consider the non-numeric features.

```
categoricals = train.select_dtypes(exclude=[np.number]
categoricals.describe()
```

	MSZoning	Street	Alley	LotShape	LandContour	Utilities
count	1455	1455	91	1455	1455	1455
unique	5	2	2	4	4	2
top	RL	Pave	Grvl	Reg	Lvl	AllPub
freq	1147	1450	50	921	1309	1454

The `count` column indicates the count of non-null observations, while `unique` counts the number of unique values. `top` is the most commonly occurring value, with the frequency of the top value shown by `freq`.

For many of these features, we might want to use one-hot encoding to make use of the information for modeling. One-hot encoding is a technique which will transform categorical data into numbers so the model can understand whether or not a particular observation falls into one category or another.

Transforming and engineering features

When transforming features, it's important to remember that any transformations that you've applied to the training data before fitting the model *must* be applied to the test data.

Our model expects that the shape of the features from the `train` set match those from the `test` set. This means that any feature engineering that occurred while working on the `train` data should be applied again on the `test` set.

To demonstrate how this works, consider the `Street` data, which indicates whether there is `Gravel` or `Paved` road access to the property.

```
print ("Original: \n")
print (train.Street.value_counts(), "\n")
```

```
Original:

Pave    1450
Grvl       5
Name: Street, dtype: int64
```

In the `Street` column, the unique values are `Pave` and `Grvl`, which describe the type of road access to the property. In the training set, only 5 homes have gravel access. Our model needs numerical data, so we will use one-hot encoding to transform the data into a Boolean column.

We create a new column called `enc_street`. The `pd.get_dummies()` method will handle this for us.

As mentioned earlier, we need to do this on both the `train` and `test` data.

```
train['enc_street'] = pd.get_dummies(train.Street, dro
test['enc_street'] = pd.get_dummies(train.Street, drop
```

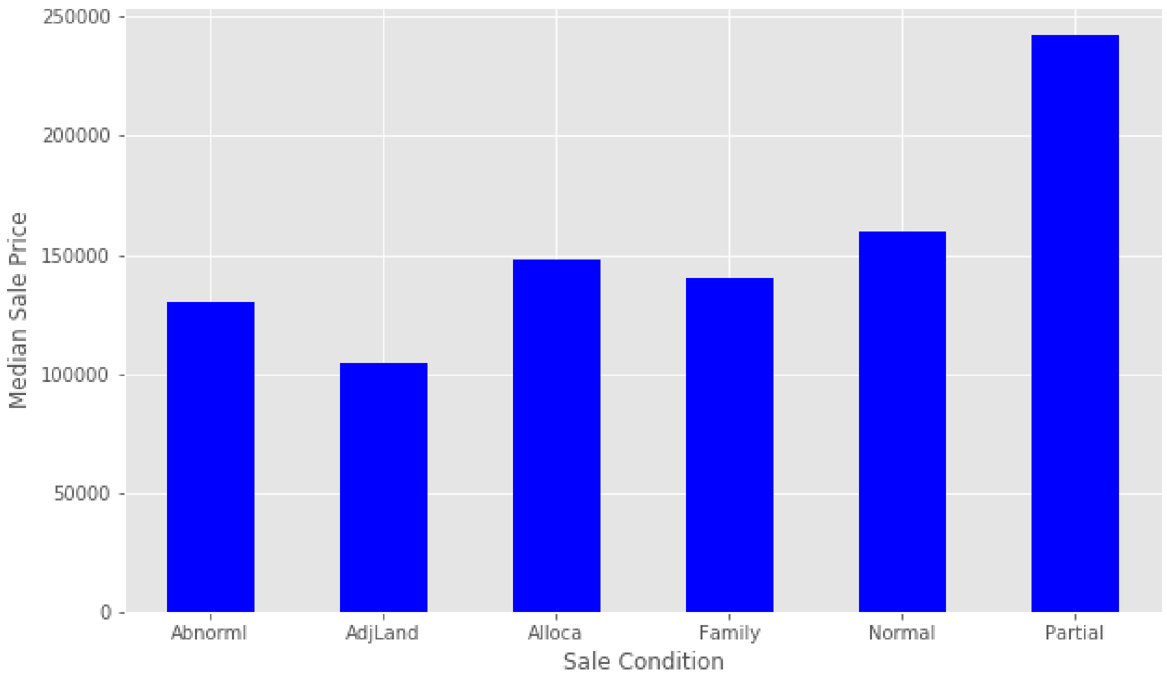
```
print ('Encoded: \n')
print (train.enc_street.value_counts())
```

```
Encoded:

1    1450
0       5
Name: enc_street, dtype: int64
```

The values agree. We've engineered our first feature! Feature Engineering is the process of making features of the data suitable for use in machine learning and modelling. When we encoded the `Street` feature into a column of Boolean values, we engineered a feature.

Let's try engineering another feature. We'll look at `SaleCondition` by constructing and plotting a pivot table, as we did above for `OverallQual`.

```
condition_pivot = train.pivot_table(index='SaleConditi
                                    values='SalePrice'
condition_pivot.plot(kind='bar', color='blue')
plt.xlabel('Sale Condition')
plt.ylabel('Median Sale Price')
plt.xticks(rotation=0)
plt.show()
```



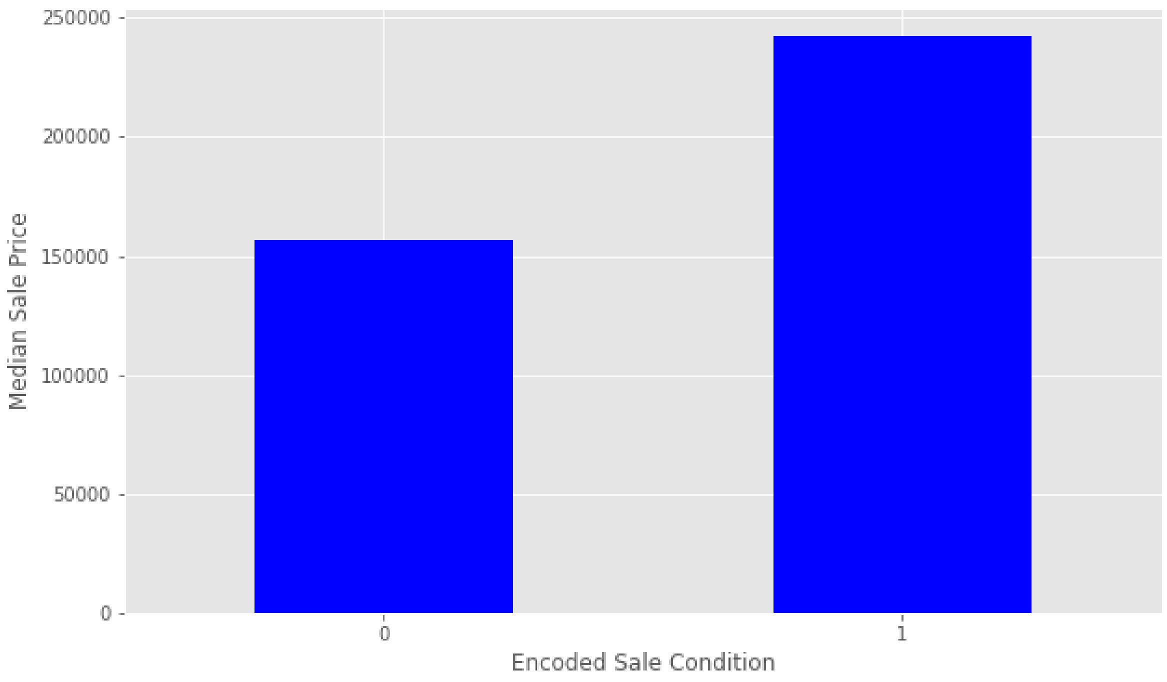
Notice that `Partial` has a significantly higher Median Sale Price than the others. We will encode this as a new feature. We select all of the houses where `SaleCondition` is equal to `Patrial` and assign the value `1`, otherwise assign `0`.

Follow a similar method that we used for `Street` above.

```
def encode(x): return 1 if x == 'Partial' else 0
train['enc_condition'] = train.SaleCondition.apply(enc
test['enc_condition'] = test.SaleCondition.apply(encod
```

Let's explore this new feature as a plot.

```
condition_pivot = train.pivot_table(index='enc_conditi
condition_pivot.plot(kind='bar', color='blue')
plt.xlabel('Encoded Sale Condition')
plt.ylabel('Median Sale Price')
plt.xticks(rotation=0)
plt.show()
```



This looks great. You can continue to work with more features to improve the ultimate performance of your model.

Before we prepare the data for modeling, we need to deal with the missing data. We'll the missing values with an average value and then assign the results to `data`. This is a method of interpolation. The `DataFrame.interpolate()` method makes this simple.

This is a quick and simple method of dealing with missing values, and might not lead to the best performance of the model on new data. Handling missing values is an important part of the modeling process, where creativity and insight can make a big difference. This is another area where you can extend on this tutorial.

```
data = train.select_dtypes(include=[np.number]).interp
```

Check if the all of the columns have 0 null values.

```
sum(data.isnull().sum() != 0)
```

```
0
```

Step 3 : Build a linear model

Let's perform the final steps to prepare our data for modeling. We'll separate the features and the target variable for modeling. We will assign the features to `X` and the target variable to `y`. We use `np.log()` as explained above to transform the y variable for the model. `data.drop([features], axis=1)` tells pandas which columns we want to exclude. We won't include `SalePrice` for obvious reasons, and `Id` is just an index with no relationship to `SalePrice`.

```
y = np.log(train.SalePrice)
X = data.drop(['SalePrice', 'Id'], axis=1)
```

Let's partition the data and start modeling. We will use the `train_test_split()` function from scikit-learn to create a training set and a hold-out set. Partitioning the data in this way allows us to evaluate how our model might perform on data that it has never seen before. If we train the model on all of the test data, it will be difficult to tell if overfitting has taken place.

`train_test_split()` returns four objects:

- `X_train` is the subset of our features used for training.

- `X_test` is the subset which will be our 'hold-out' set – what we'll use to test the model.
- `y_train` is the target variable `SalePrice` which corresponds to `X_train`.
- `y_test` is the target variable `SalePrice` which corresponds to `X_test`.

The first parameter value `X` denotes the set of predictor data, and `y` is the target variable. Next, we set `random_state=42`. This provides for reproducible results, since sci-kit learn's `train_test_split` will randomly partition the data. The `test_size` parameter tells the function what proportion of the data should be in the `test` partition. In this example, about 33% of the data is devoted to the hold-out set.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
                                    X, y, random_state
```

Begin modelling

We will first create a Linear Regression model. First, we instantiate the model.

```
from sklearn import linear_model
lr = linear_model.LinearRegression()
```

Next, we need to fit the model. First instantiate the model and next fit the model. Model fitting is a procedure that varies for different types of models. Put simply, we are estimating the relationship between our predictors and the target variable so we can make accurate predictions on new data.

We fit the model using `X_train` and `y_train`, and we'll score with `X_test` and `y_test`. The `lr.fit()` method will fit the linear regression on the features and target variable that we pass.

```
model = lr.fit(X_train, y_train)
```

Evaluate the performance and visualize results

Now, we want to evaluate the performance of the model. Each competition might evaluate the submissions differently. In this competition, Kaggle will evaluate our submission using root-mean-squared-error (RMSE). We'll also look at The r-squared value. The r-squared value is a measure of how close the data are to the fitted regression line. It takes a value between 0 and 1, 1 meaning that all of the variance in the target is explained by the data. In general, a higher r-squared value means a better fit.

The `model.score()` method returns the r-squared value by default.

```
print ("R^2 is: \n", model.score(X_test, y_test))
```

```
R^2 is:
 0.888247770926
```

This means that our features explain approximately 89% of the variance in our target variable. Follow the link above to learn more.

Next, we'll consider `rmse`. To do so, use the model we have built to make predictions on the test data set.

```
predictions = model.predict(X_test)
```

The `model.predict()` method will return a list of predictions given a set of predictors. Use `model.predict()` after fitting the model.

The `mean_squared_error` function takes two arrays and calculates the `rmse`.

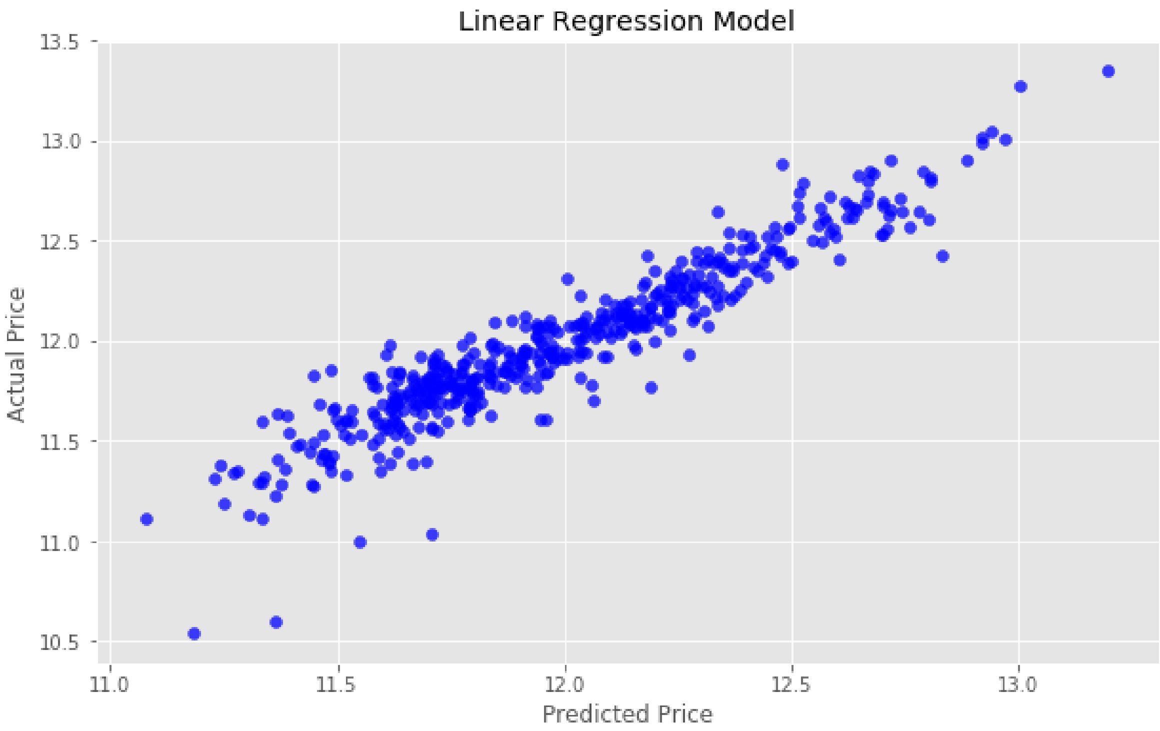
```
from sklearn.metrics import mean_squared_error
print ('RMSE is: \n', mean_squared_error(y_test, predi
```

```
RMSE is:
 0.0178417945196
```

Interpreting this value is somewhat more intuitive that the r-squared value. The RMSE measures the distance between our predicted values and actual values.

We can view this relationship graphically with a scatter plot.

```
actual_values = y_test
plt.scatter(predictions, actual_values, alpha=.75,
            color='b') #alpha helps to show overlappin
plt.xlabel('Predicted Price')
plt.ylabel('Actual Price')
plt.title('Linear Regression Model')
plt.show()
```



If our predicted values were identical to the actual values, this graph would be the straight line `y=x` because each predicted value `x` would be equal to each actual value `y`.

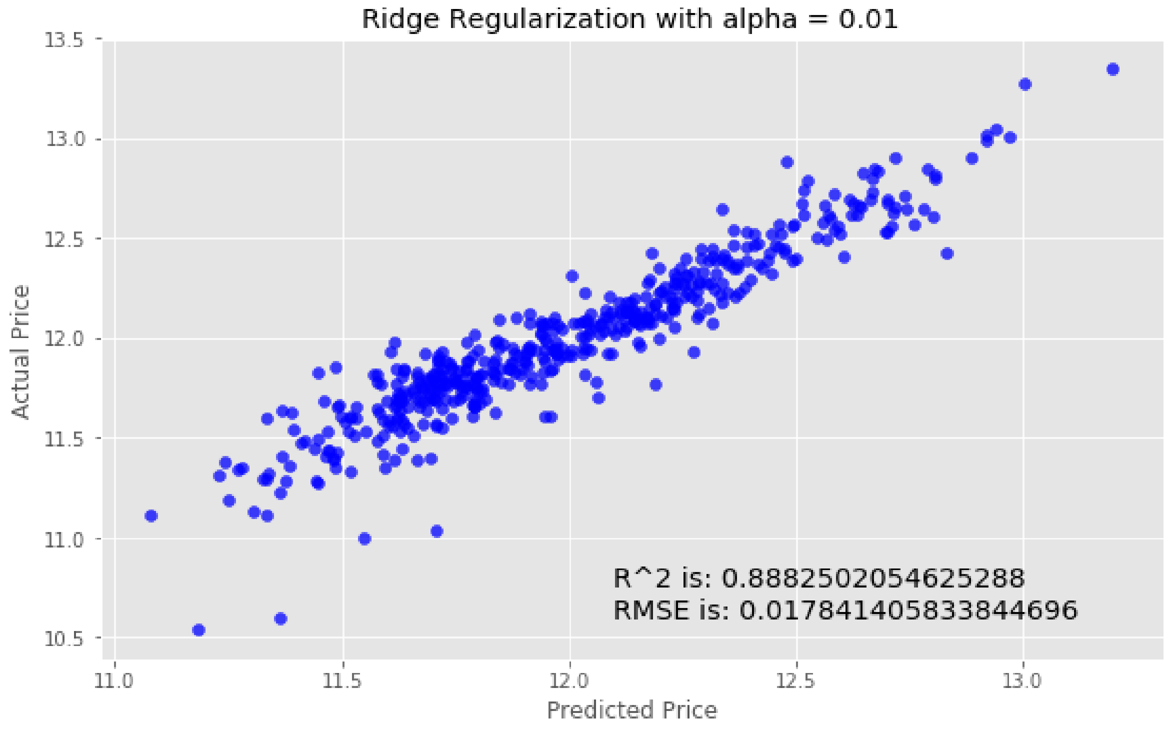
Try to improve the model

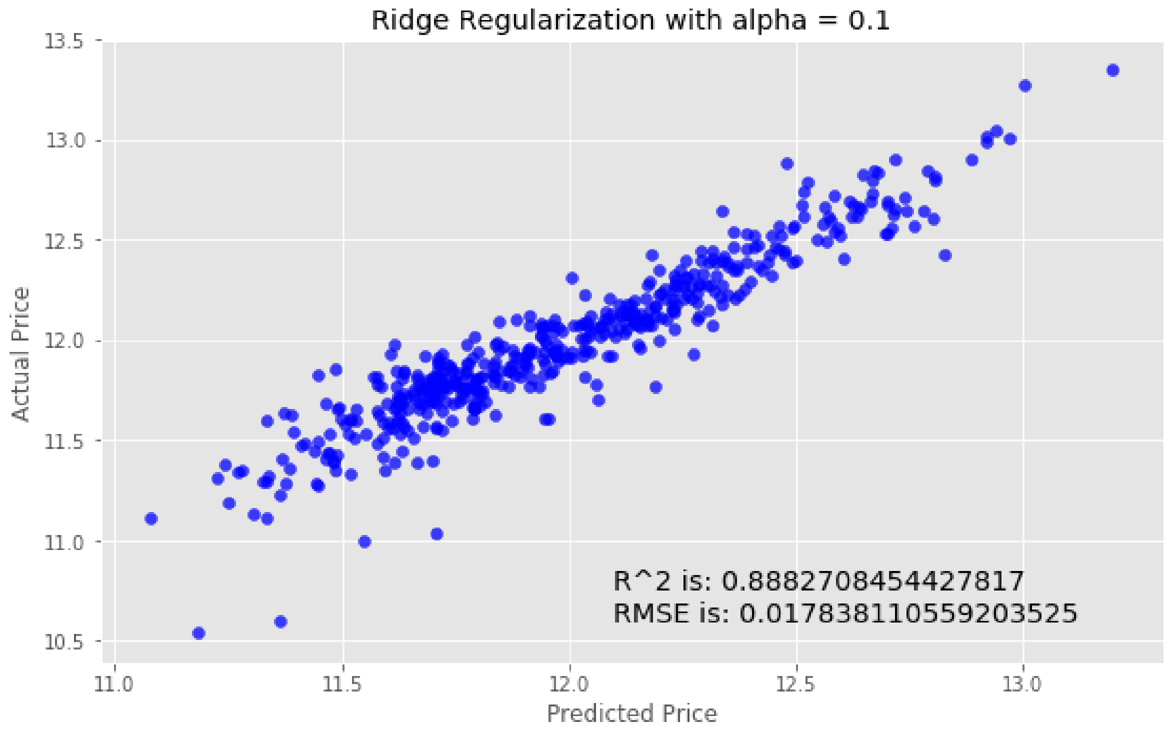
We'll next try using Ridge Regularization to decrease the influence of less important features. Ridge Regularization is a process which shrinks the regression coefficients of less important features.

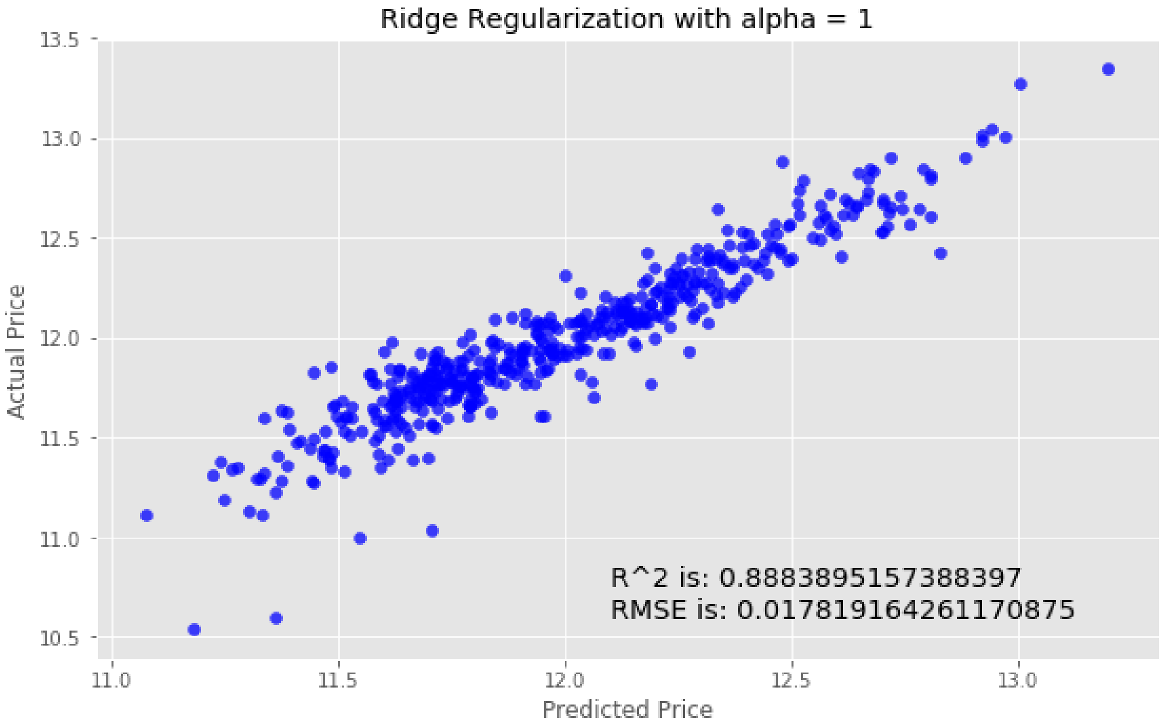
We'll once again instantiate the model. The Ridge Regularization model takes a parameter, `alpha` , which controls the strength of the regularization.

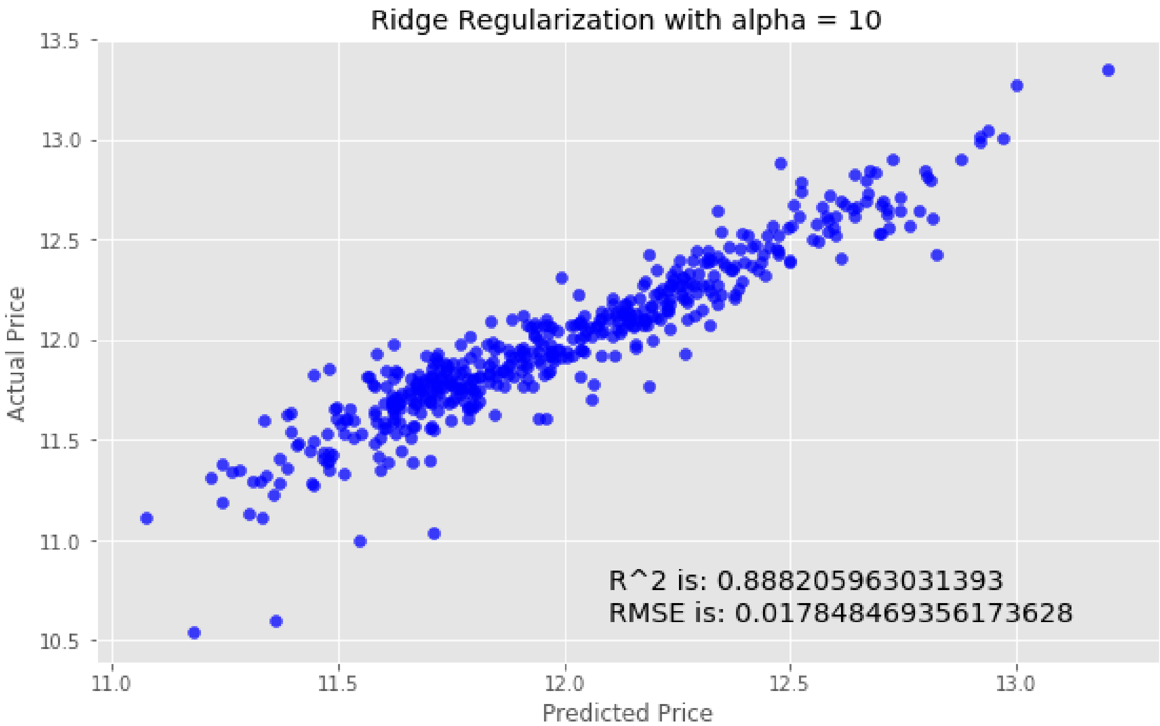
We'll experiment by looping through a few different values of alpha, and see how this changes our results.

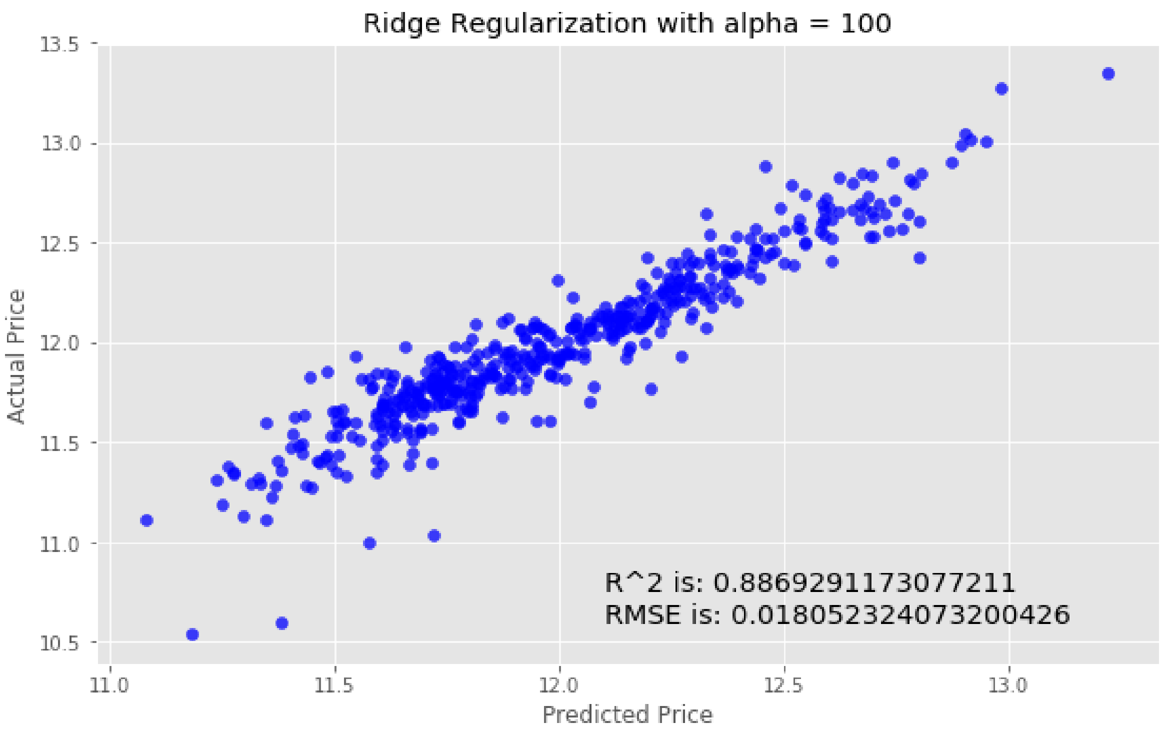
```
for i in range (-2, 3):
    alpha = 10**i
    rm = linear_model.Ridge(alpha=alpha)
    ridge_model = rm.fit(X_train, y_train)
    preds_ridge = ridge_model.predict(X_test)

    plt.scatter(preds_ridge, actual_values, alpha=.75,
    plt.xlabel('Predicted Price')
    plt.ylabel('Actual Price')
    plt.title('Ridge Regularization with alpha = {}'.f
    overlay = 'R^2 is: {}\nRMSE is: {}'.format(
                    ridge_model.score(X_test, y_test),
                    mean_squared_error(y_test, preds_r
    plt.annotate(s=overlay,xy=(12.1,10.6),size='x-larg
    plt.show()
```


Ridge Regularization with alpha = 0.01
Actual Price
Predicted Price
R^2 is: 0.8882502054625288
RMSE is: 0.017841405833844696
13.5
13.0
12.5
12.0
11.5
11.0
10.5
11.0
11.5
12.0
12.5
13.0


Ridge Regularization with alpha = 0.1
Actual Price
Predicted Price
R^2 is: 0.8882708454427817
RMSE is: 0.017838110559203525
13.5
13.0
12.5
12.0
11.5
11.0
10.5
11.0
11.5
12.0
12.5
13.0


Ridge Regularization with alpha = 1
Actual Price
Predicted Price
R^2 is: 0.8883895157388397
RMSE is: 0.017819164261170875


Ridge Regularization with alpha = 10
Actual Price
Predicted Price
R^2 is: 0.888205963031393
RMSE is: 0.017848469356173628



These models perform almost identically to the first model. In our case, adjusting the alpha did not substantially improve our model. As you add more features, regularization can be helpful. Repeat this step after you've added more features.

Step 4: Make a submission

We'll need to create a `csv` that contains the predicted `SalePrice` for each observation in the `test.csv` dataset.

We'll log in to our Kaggle account and go to the submission page to make a submission. We will use the `DataFrame.to_csv()` to create a csv to submit. The first column must the contain the ID from the test data.

```
submission = pd.DataFrame()
submission['Id'] = test.Id
```

Now, select the features from the test data for the model as we did above.

```
feats = test.select_dtypes(
        include=[np.number]).drop(['Id'], axis=1).inte
```

Next, we generate our predictions.

```
predictions = model.predict(feats)
```

Now we'll transform the predictions to the correct form. Remember that to reverse `log()` we do `exp()`. So we will apply `np.exp()` to our predictions becasuse we have taken the logarithm previously.

```
final_predictions = np.exp(predictions)
```

Look at the difference.

```
print ("Original predictions are: \n", predictions[:5]
print ("Final predictions are: \n", final_predictions[
```

```
Original predictions are:
 [ 11.76725362  11.71929504  12.07656074  12.20632678

Final predictions are:
 [ 128959.49172586  122920.74024358  175704.82598102
  182075.46986405]
```

Lets assign these predictions and check that everything looks good.

```
submission['SalePrice'] = final_predictions
submission.head()
```

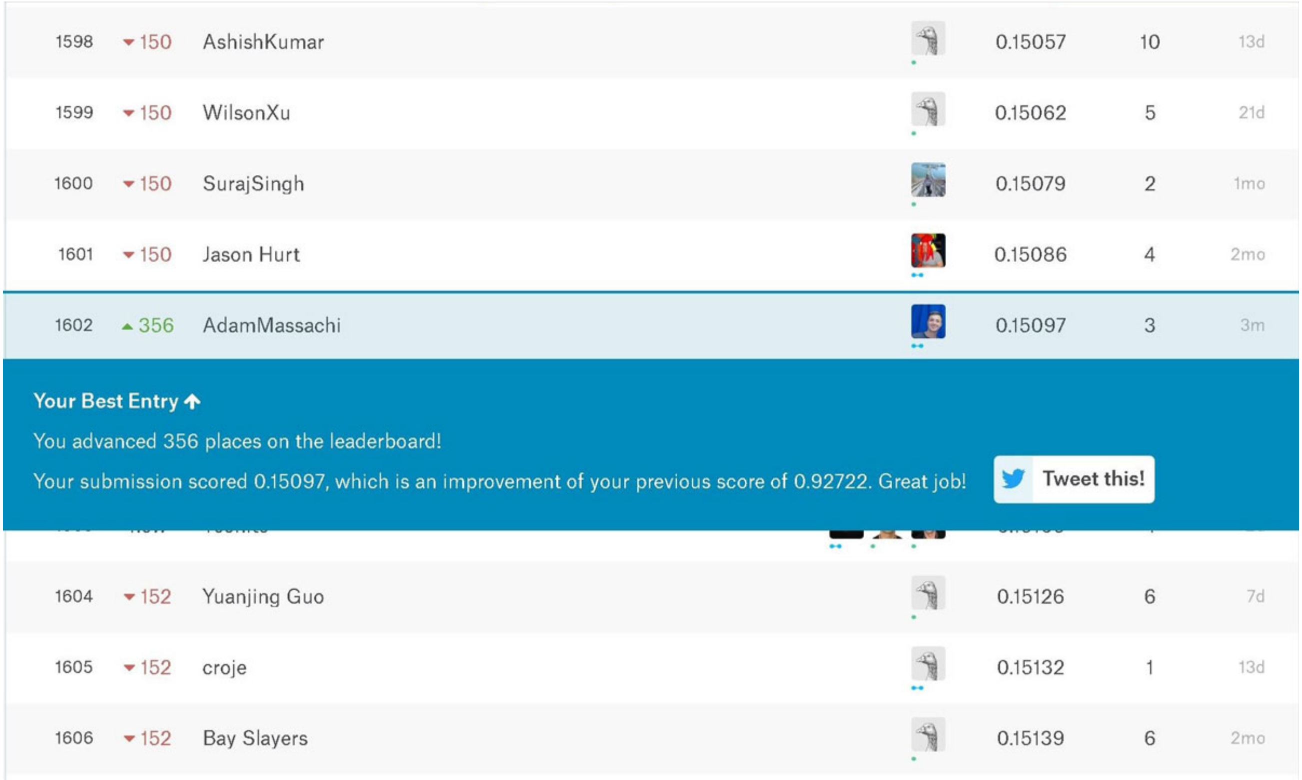
	Id	SalePrice
0	1461	128959.491726
1	1462	122920.740244
2	1463	175704.825981
3	1464	200050.832638
4	1465	182075.469864

One we're confident that we've got the data arranged in the proper format, we can export to a `.csv file` as Kaggle expects. We pass `index=False` because Pandas otherwise would create a new index for us.

```
submission.to_csv('submission1.csv', index=False)
```

Submit our results

We've created a file called `submission1.csv` in our working directory that conforms to the correct format. Go to the submission page to make a submission.



Our Submission!

We placed 1602 out of about 2400 competitors. Almost middle of the pack, not bad! Notice that our score here is `.15097`, which is better than the score we observed on the test data. That's a good result, but will not always be the case.

Next steps

You can extend this tutorial and improve your results by:

- Working with and transforming other features in the training set
- Experimenting with different modeling techniques, such as Random Forest Regressors or Gradient Boosting
- Using ensembling models

We created a set of categorical features called `categoricals` that were not all included in the final model. Go back and try to include these features. There are other methods that might help with categorical data,