assignment01-regression

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1 CSAL4243: Introduction to Machine Learning

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2 Assignment 1: Linear Regression

In this assignment you are going to learn how Linear Regression works by using the code for linear regression and gradient descent we have been looking at in the class. You are also going to use linear regression from scikit-learn library for machine learning. You are going to learn how to download data from kaggle (a website for datasets and machine learning) and upload submissions to kaggle competitions. And you will be able to compete with the world.

2.0.1 Overview

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3 Pseudocode

3.1 Linear Regressio with Gradient Descent

- Load training data into X_train and y_train
- [Optionally] normalize features X_train using $x^i = \frac{x^i - \mu^i}{\rho^i}$ where μ^i is mean and ρ^i is standard deviation of feature i
- Initialize hyperparameters
  - iterations
  - learning rate α
- Initialize θ_s
- At each iteration
  - Compute cost using $J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h(x^i) - y^i)^2$ where $h(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 .... + \theta_n x_n$
  - Update θ_s using
  - [Optionally] Break if cost $J(\theta)$ does not change.

4 Tasks

1. Effect of Learning Rate α
2. Predict test data output and submit it to Kaggle
3. Use scikit-learn for Linear Regression
4. Multivariate Linear Regression

4.1 Load and analyze data

```
In [4]: %matplotlib inline
        import pandas as pd
        import numpy as np
        import seaborn as sns
        from sklearn import linear_model
        import matplotlib.pyplot as plt
        import matplotlib as mpl

        # read house_train.csv data in pandas dataframe df_train using pandas read_
        df_train = pd.read_csv('datasets/house_price/train.csv', encoding='utf-8')
```

```
In [5]: # check data by printing first few rows
        df_train.head()
```

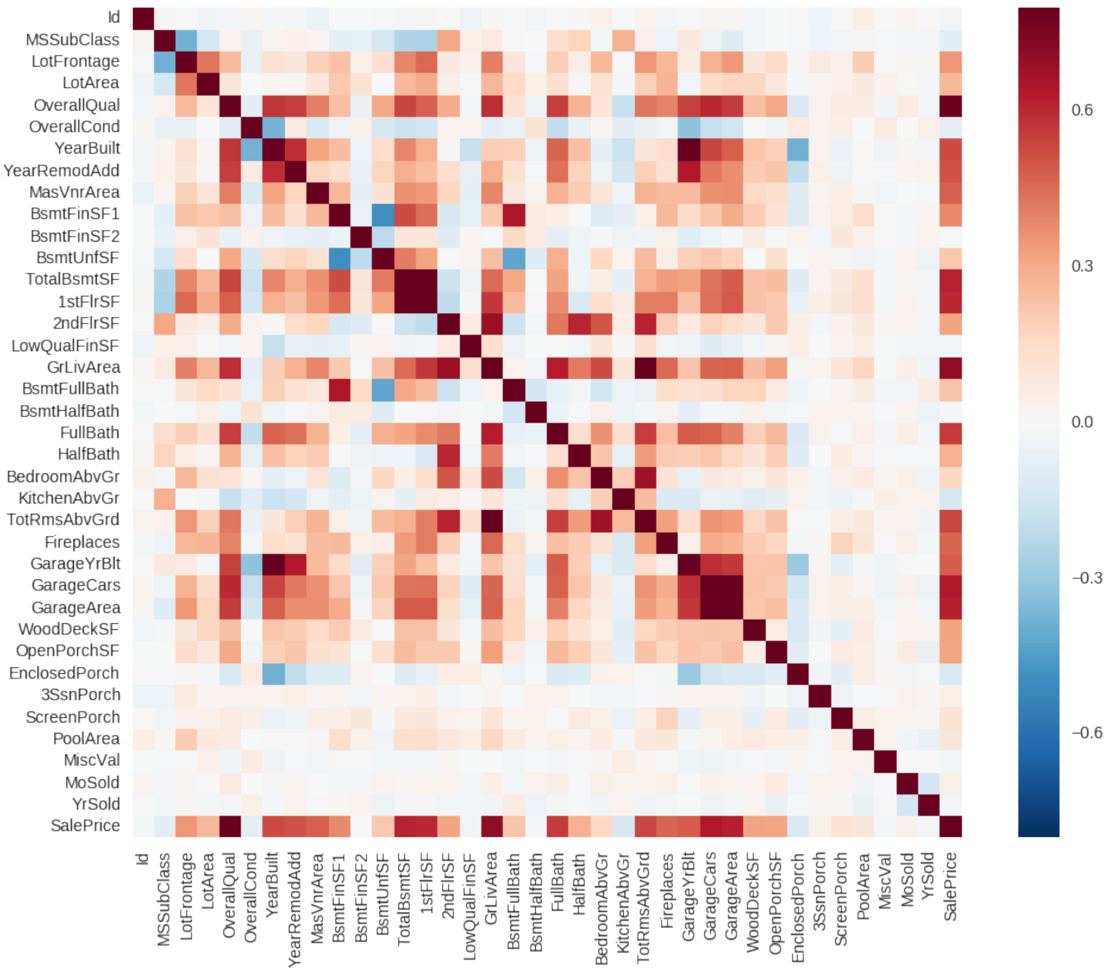
```
Out[5]:    Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
        0   1          60       RL         65.0     8450   Pave   NaN      Reg
        1   2          20       RL         80.0     9600   Pave   NaN      Reg
        2   3          60       RL         68.0    11250   Pave   NaN      IR1
        3   4          70       RL         60.0     9550   Pave   NaN      IR1
        4   5          60       RL         84.0    14260   Pave   NaN      IR1
```

```
  LandContour Utilities    ...     PoolArea PoolQC Fence MiscFeature MiscVa
0         Lvl    AllPub    ...            0    NaN   NaN         NaN
1         Lvl    AllPub    ...            0    NaN   NaN         NaN
2         Lvl    AllPub    ...            0    NaN   NaN         NaN
3         Lvl    AllPub    ...            0    NaN   NaN         NaN
4         Lvl    AllPub    ...            0    NaN   NaN         NaN

  MoSold YrSold  SaleType  SaleCondition  SalePrice
0      2   2008        WD         Normal     208500
1      5   2007        WD         Normal     181500
2      9   2008        WD         Normal     223500
3      2   2006        WD        Abnorml     140000
4     12   2008        WD         Normal     250000

[5 rows x 81 columns]
```

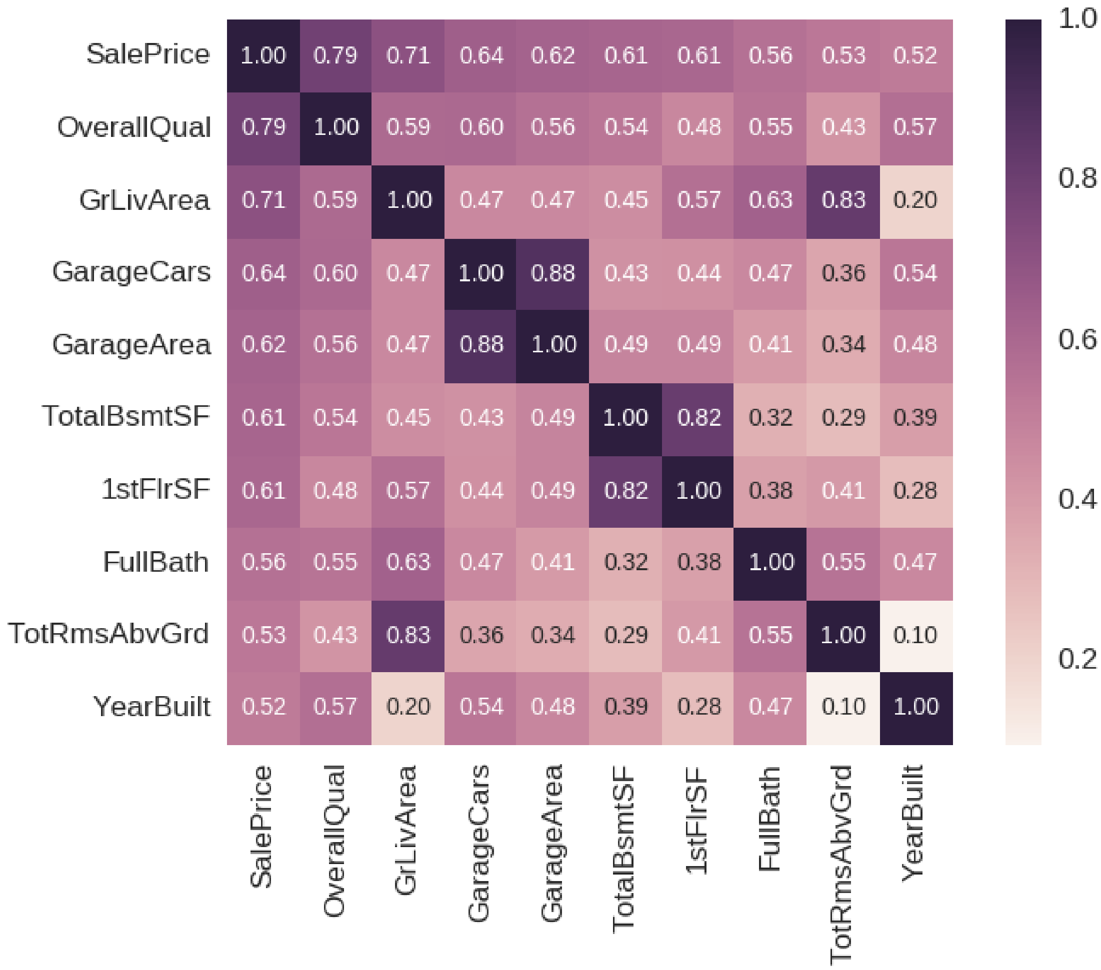
In [6]:
```
# check columns in dataset
df_train.columns
```

Out[6]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodA
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBa
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageTy
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQu
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

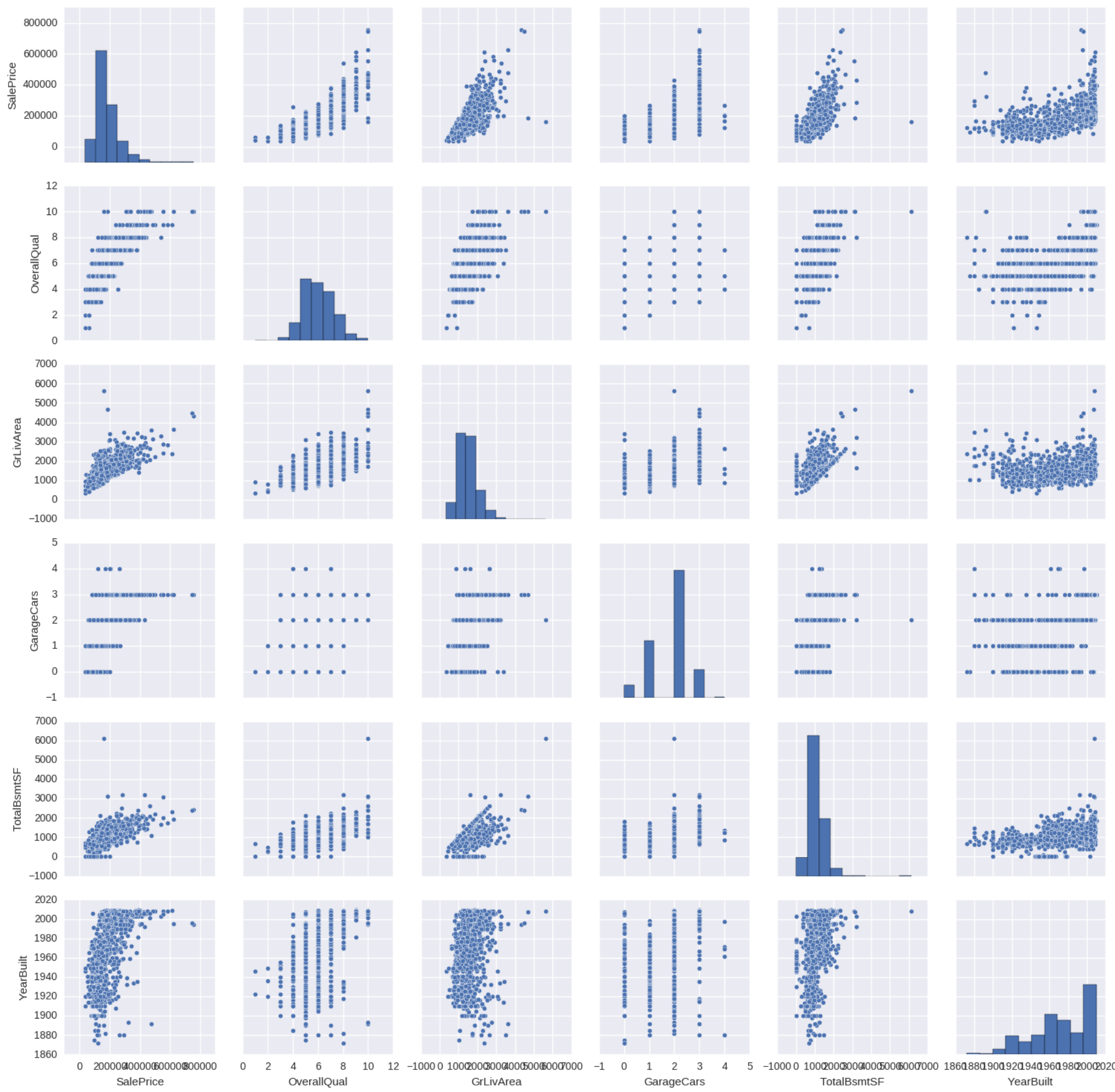
In [7]:
```
# check correlation matrix, darker means more correlation
corrmat = df_train.corr()
f, aX_train= plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
```



In [8]:
```
# SalePrice correlation matrix with top k variables
k = 10 #number of variables for heatmap
cols = corrmat.nlargest(k, 'SalePrice')['SalePrice'].index
cm = np.corrcoef(df_train[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_k
plt.show()
```




```
In [9]: #scatterplot with some important variables
        cols = ['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF
        sns.set()
        sns.pairplot(df_train[cols], size = 2.5)
        plt.show();
```



Task 1: Effect of Learning Rate α Use Linear Regression code below using X="GrLivArea" as input variable and y="SalePrice" as target variable. Use different values of α given in table below and comment on why they are useful or not and which one is a good choice.

- $\alpha = 0.000001$:
- $\alpha = 0.00000001$:
- $\alpha = 0.000000001$:

Load X and y

```
In [10]: # Load X and y variables from pandas dataframe df_train
         cols = ['GrLivArea']
         X_train = np.array(df_train[cols])
         y_train = np.array(df_train[["SalePrice"]])
```

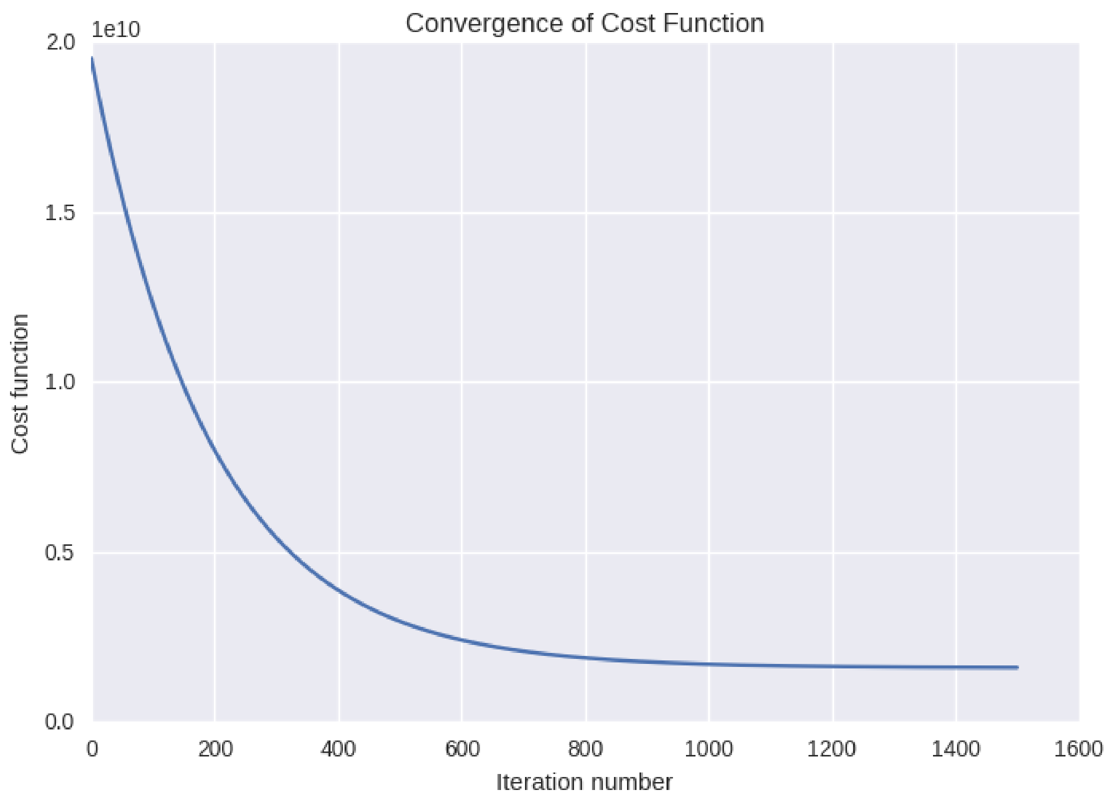
```
# Get m = number of samples and n = number of features
m = X_train.shape[0]
n = X_train.shape[1]

# append a column of 1's to X for theta_0
X_train = np.insert(X_train,0,1,axis=1)
```

4.2 Linear Regression with Gradient Descent code

```
In [11]: iterations = 1500
         alpha = 0.000000001 # change it and find what happens

         def h(X, theta): #Linear hypothesis function
             hx = np.dot(X,theta)
             return hx


         def computeCost(theta,X,y): #Cost function
             """
             theta is an n- dimensional vector, X is matrix with n- columns and m-
             y is a matrix with m- rows and 1 column
             """
             #note to self: *.shape is (rows, columns)
             return float((1./(2*m)) * np.dot((h(X,theta)-y).T,(h(X,theta)-y)))

         #Actual gradient descent minimizing routine
         def gradientDescent(X,y, theta_start = np.zeros((n+1,1))):
             """
             theta_start is an n- dimensional vector of initial theta guess
             X is input variable matrix with n- columns and m- rows. y is a matrix
             """
             theta = theta_start
             j_history = [] #Used to plot cost as function of iteration
             theta_history = [] #Used to visualize the minimization path later on
             for meaninglessvariable in range(iterations):
                 tmptheta = theta
                 # append for plotting
                 j_history.append(computeCost(theta,X,y))
                 theta_history.append(list(theta[:,0]))
                 #Simultaneously updating theta values
                 for j in range(len(tmptheta)):
                     tmptheta[j] = theta[j] - (alpha/m)*np.sum((h(X,theta) - y)*np.
                 theta = tmptheta
             return theta, theta_history, j_history
```

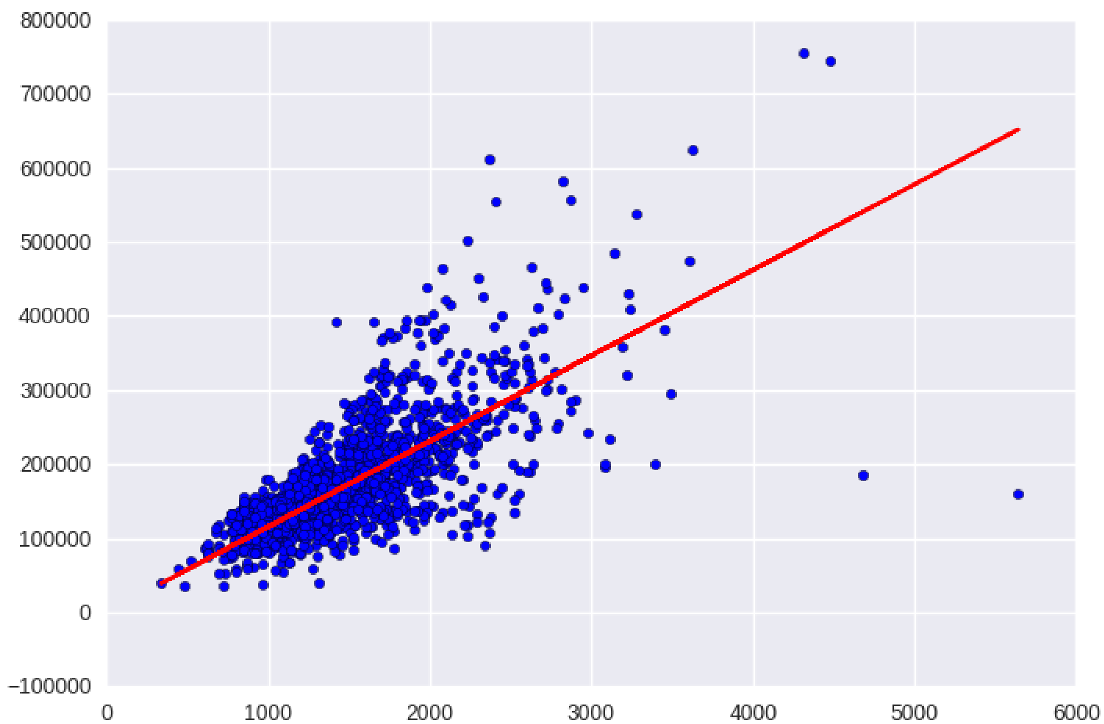
4.3 Run Gradient Descent on training data

In [12]:
```
#Actually run gradient descent to get the best-fit theta values
initial_theta = np.zeros((n+1,1));
theta, theta_history, j_history = gradientDescent(X_train,y_train,initial_

plt.plot(j_history)
plt.title("Convergence of Cost Function")
plt.xlabel("Iteration number")
plt.ylabel("Cost function")
plt.show()
```



4.4 Plot trained line on data

In [13]:
```
# predict output for training data
hx_train= h(X_train, theta)

# plot it
plt.scatter(X_train[:,1],y_train)
plt.plot(X_train[:,1],hx_train[:,0], color='red')
plt.show()
```



Task 2: Predict test data output and submit it to Kaggle In this task we will use the model trained above to predict "SalePrice" on test data. Test data has all the input variables/features but no target variable. Out aim is to use the trained model to predict the target variable for test data. This is called generalization i.e. how good your model works on unseen data. The output in the form "Id","SalePrice" in a .csv file should be submitted to kaggle. Please provide your score on kaggle after this step as an image. It will be compared to the 5 feature Linear Regression later.

In [14]:
```
# read data in pandas frame df_test and check first few rows
    # write code here

df_test.head()
```

Out[14]:

```
     Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0  1461          20       RH         80.0    11622   Pave   NaN      Reg
1  1462          20       RL         81.0    14267   Pave   NaN      IR1
2  1463          60       RL         74.0    13830   Pave   NaN      IR1
3  1464          60       RL         78.0     9978   Pave   NaN      IR1
4  1465         120       RL         43.0     5005   Pave   NaN      IR1

  LandContour Utilities    ...     ScreenPorch PoolArea PoolQC  Fence  \
0         Lvl    AllPub    ...             120        0    NaN  MnPrv
1         Lvl    AllPub    ...               0        0    NaN    NaN
2         Lvl    AllPub    ...               0        0    NaN  MnPrv
3         Lvl    AllPub    ...               0        0    NaN    NaN
4         HLS    AllPub    ...             144        0    NaN    NaN
```

```
  MiscFeature MiscVal MoSold  YrSold  SaleType  SaleCondition
0         NaN       0      6    2010        WD         Normal
1        Gar2   12500      6    2010        WD         Normal
2         NaN       0      3    2010        WD         Normal
3         NaN       0      6    2010        WD         Normal
4         NaN       0      1    2010        WD         Normal

[5 rows x 80 columns]
```

In [15]:
```python
# check statistics of test data, make sure no data is missing.
print(df_test.shape)
df_test[cols].describe()
```

```
(1459, 80)
```

Out[15]:
```
          GrLivArea
count  1459.000000
mean   1486.045922
std     485.566099
min     407.000000
25%    1117.500000
50%    1432.000000
75%    1721.000000
max    5095.000000
```

In [16]:
```python
# Get X_test, no target variable (SalePrice) provided in test data. It is
X_test = np.array(df_test[cols])

#Insert the usual column of 1's into the "X" matrix
X_test = np.insert(X_test,0,1,axis=1)
```

In [17]:
```python
# predict test data labels i.e. y_test
predict = h(X_test, theta)
```

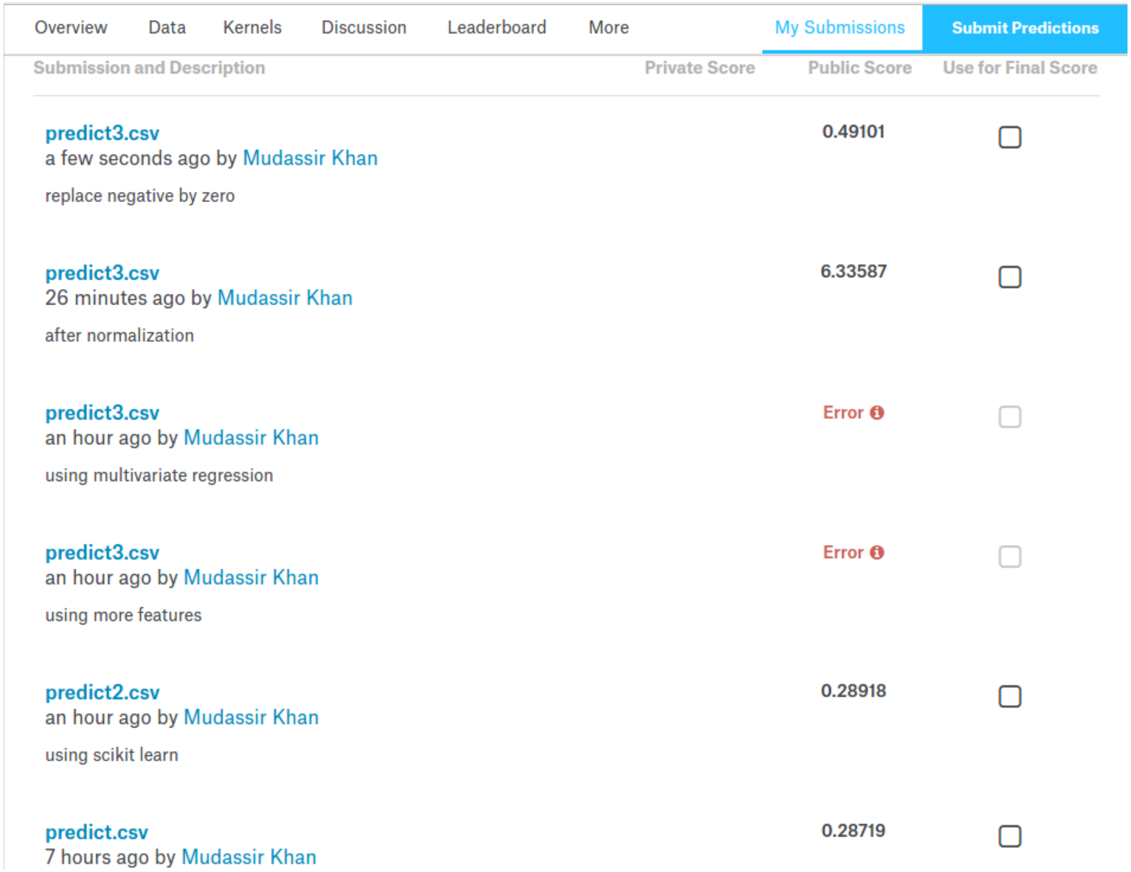
In [18]:
```python
# save prediction as .csv file
pd.DataFrame({'Id': df_test.Id, 'SalePrice': predict[:,0]}).to_csv("predic
```

4.5 Upload .csv file to Kaggle.com

- Create an account at https://www.kaggle.com
- Go to https://www.kaggle.com/c/house-prices-advanced-regression-techniques/submit
- Upload "predict1.csv" file created above.
- Upload your score as an image below.

In [19]:
```python
from IPython.display import Image
Image(filename='images/asgn_01.png', width=500)
```

Out[19]:



Task 3: Use scikit-learn for Linear Regression

In this task we are going to use Linear Regression class from scikit-learn library to train the same model. The aim is to move from understanding algorithm to using an exisiting well established library. There is a Linear Regression example available on scikit-learn website as well.

- Use the scikit-learn linear regression class to train the model on df_train
- Compare the parameters from scikit-learn linear_model.LinearRegression.coef_ to the θ_s from earlier.
- Use the linear_model.LinearRegression.predict on test data and upload it to kaggle. See if your score improves. Provide screenshot.
- Note: no need to append 1's to X_train. Scitkit linear regression has parameter called fit_intercept that is by defauly enabled.

In [20]:
```
# import scikit-learn linear model
from sklearn import linear_model

# get X and y
    # write code here


# Create linear regression object
```

```
 # write code here check link above for example

# Train the model using the training sets. Use fit(X,y) command
  # write code here

# The coefficients
print('Intercept: \n', regr.intercept_)
print('Coefficients: \n', regr.coef_)
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((regr.predict(X_train) - y_train) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % regr.score(X_train, y_train))
```

```
Intercept:
 [ 18569.02585649]
Coefficients:
 [[ 107.13035897]]
Mean squared error: 3139843209.67
Variance score: 0.50
```

```
In [21]: # read test X without 1's
           # write code here
```

```
In [22]: # predict output for test data. Use predict(X) command.
         predict2 = # write code here
```

```
In [23]: # remove negative sales by replacing them with zeros
         predict2[predict2<0] = 0
```

```
In [24]: # save prediction as predict2.csv file
            # write code here
```

Task 4: Multivariate Linear Regression

Lastly use columns ['OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF', 'YearBuilt'] and scikit-learn or the code given above to predict output on test data. Upload it to kaggle like earlier and see how much it improves your score.

- Everything remains same except dimensions of X changes.
- There might be some data missing from the test or train data that you can check using pandas.DataFrame.describe() function. Below we provide some helping functions for removing that data.

```
In [25]: # define columns ['OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF',
             # write code here

         # check features range and statistics. Training dataset looks fine as all
         df_train[cols].describe()
```

Out[25]:

	OverallQual	GrLivArea	GarageCars	TotalBsmtSF	YearBuilt
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	6.099315	1515.463699	1.767123	1057.429452	1971.267808
std	1.382997	525.480383	0.747315	438.705324	30.202904
min	1.000000	334.000000	0.000000	0.000000	1872.000000
25%	5.000000	1129.500000	1.000000	795.750000	1954.000000
50%	6.000000	1464.000000	2.000000	991.500000	1973.000000
75%	7.000000	1776.750000	2.000000	1298.250000	2000.000000
max	10.000000	5642.000000	4.000000	6110.000000	2010.000000

In [26]:
```
# Load X and y variables from pandas dataframe df_train
    # write code here

# Get m = number of samples and n = number of features
    # write code here
```

In [27]:
```
#Feature normalizing the columns (subtract mean, divide by standard deviat
#Store the mean and std for later use
#Note don't modify the original X matrix, use a copy
stored_feature_means, stored_feature_stds = [], []
Xnorm = np.array(X_train).copy()
for icol in range(Xnorm.shape[1]):
    stored_feature_means.append(np.mean(Xnorm[:,icol]))
    stored_feature_stds.append(np.std(Xnorm[:,icol]))
    #Skip the first column if 1's
#     if not icol: continue
    #Faster to not recompute the mean and std again, just used stored valu
    Xnorm[:,icol] = (Xnorm[:,icol] - stored_feature_means[-1])/stored_feat

# check data after normalization
pd.DataFrame(data=Xnorm,columns=cols).describe()
```

Out[27]:

	OverallQual	GrLivArea	GarageCars	TotalBsmtSF	YearBuilt
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	0.083562	0.036301	-0.232877	0.069863	0.013014
std	0.655971	0.732612	0.747315	0.717391	0.734330
min	-3.000000	-2.000000	-2.000000	-2.000000	-3.000000
25%	0.000000	0.000000	-1.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	2.000000	7.000000	2.000000	11.000000	1.000000

In [28]:
```
# Run Linear Regression from scikit-learn or code given above.

    # write code here. Repeat from above.
```

```
Intercept:
 [-672030.53248541]
Coefficients:
```

```
[[ 20391.14093374     50.83150559  14510.0032998      29.97787732
     301.43341059]]
Mean squared error: 1463421280.61
Variance score: 0.77
```

In [29]:
```
# To predict output using  ['OverallQual', 'GrLivArea', 'GarageCars', 'Tot
# Check features range and statistics to see if there is any missing data.
# As you can see from count "GarageCars" and "TotalBsmtSF" has 1 missing v
df_test[cols].describe()
```

Out[29]:

	OverallQual	GrLivArea	GarageCars	TotalBsmtSF	YearBuilt
count	1459.000000	1459.000000	1458.000000	1458.000000	1459.000000
mean	6.078821	1486.045922	1.766118	1046.117970	1971.357779
std	1.436812	485.566099	0.775945	442.898624	30.390071
min	1.000000	407.000000	0.000000	0.000000	1879.000000
25%	5.000000	1117.500000	1.000000	784.000000	1953.000000
50%	6.000000	1432.000000	2.000000	988.000000	1973.000000
75%	7.000000	1721.000000	2.000000	1305.000000	2001.000000
max	10.000000	5095.000000	5.000000	5095.000000	2010.000000

In [30]:
```
# Replace missing value with the mean of the feature
df_test['GarageCars'] = df_test['GarageCars'].fillna((df_test['GarageCars'
df_test['TotalBsmtSF'] = df_test['TotalBsmtSF'].fillna((df_test['TotalBsmt
```

In [31]:
```
df_test[cols].describe()
```

Out[31]:

	OverallQual	GrLivArea	GarageCars	TotalBsmtSF	YearBuilt
count	1459.000000	1459.000000	1459.000000	1459.000000	1459.000000
mean	6.078821	1486.045922	1.766118	1046.117970	1971.357779
std	1.436812	485.566099	0.775679	442.746712	30.390071
min	1.000000	407.000000	0.000000	0.000000	1879.000000
25%	5.000000	1117.500000	1.000000	784.000000	1953.000000
50%	6.000000	1432.000000	2.000000	988.000000	1973.000000
75%	7.000000	1721.000000	2.000000	1304.000000	2001.000000
max	10.000000	5095.000000	5.000000	5095.000000	2010.000000

In [32]:
```
# read test X without 1's
  # write code here

# predict using trained model
predict3 = # write code here

# replace any negative predicted saleprice by zero
predict3[predict3<0] = 0
```

In [33]:
```
# predict target/output variable for test data using the trained model and
  # write code to save output as predict3.csv here
```

5 Resources

Course website: https://w4zir.github.io/ml17s/
Course resources

6 Credits

Raschka, Sebastian. Python machine learning. Birmingham, UK: Packt Publishing, 2015. Print.
Andrew Ng, Machine Learning, Coursera
Scikit Learn Linear Regression