In [197]:
```
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn import linear_model
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
from math import sqrt
import tensorflow as tf
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from sklearn.utils import resample
```

1-1. Fit the data using linear (1st order) regression model (matrix form, gradient descent method).

Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE).

In [198]:
```
data1 = pd.read_csv("ex2data1.csv")
X_1 = data1.as_matrix(columns=data1.columns[0:1])
Y_1 = data1.as_matrix(columns=data1.columns[1:])
X_1_coloumn_added = np.c_[np.ones((data1.shape[0], 1)), X_1]
```

In [199]:
```
def weight_optimizer(data,degree,Label,learn_rate = .01,epochs = 100000,
regularisation_alpha=0):
    theta_1 = np.random.randn(degree+1,1)
    for epoch in range(epochs):
        gradients = (2/data.shape[0])* (data.T.dot(data.dot(theta_1)- La
bel)+regularisation_alpha*theta_1)
        theta_1 = theta_1 - learn_rate * gradients
    return theta_1
```

In [200]:
```
def rmse_calculator(data,weights,actual_label):
    predict_y = data.dot(weights)
    rms = sqrt(mean_squared_error(actual_label, predict_y))
    return rms
```

In [201]:
```
# Please input sorted data
def graph_plotter(X_1_poly_dn_scaled_coloumn_added,weights,actual_label,
graph_label=None):
    X_1_poly_dn_scaled_coloumn_added_sorted = X_1_poly_dn_scaled_coloumn
_added [X_1_poly_dn_scaled_coloumn_added [:,1].argsort()]
    plt.plot(X_1_poly_dn_scaled_coloumn_added_sorted[:,1:2], actual_labe
l, 'bo')
    y_1_dn_plot = X_1_poly_dn_scaled_coloumn_added_sorted.dot(weights)
    plt.plot(X_1_poly_dn_scaled_coloumn_added_sorted[:,1:2], y_1_dn_plot
,label=graph_label)
    legend = plt.legend(loc='upper right', shadow=True)
```

In [202]:
```
scaler = StandardScaler()
```

In [203]:
```
def polynomial_adder(data,degree):
    poly_features = PolynomialFeatures(degree=degree, include_bias=False
)
    X_1_poly_dn = poly_features.fit_transform(data)
    X_1_poly_dn_scaled = scaler.fit_transform(X_1_poly_dn)
    X_1_poly_dn_scaled_coloumn_added = np.c_[np.ones((data.shape[0], 1
)), X_1_poly_dn_scaled]
    ## Sorting for graph plotting
    #X_1_poly_dn_scaled_coloumn_added = X_1_poly_dn_scaled_coloumn_added
 [X_1_poly_dn_scaled_coloumn_added [:,1].argsort()]
    return X_1_poly_dn_scaled_coloumn_added
```

Optimized Weight - Deg1

In [204]:
```
theta_1 = weight_optimizer(X_1_coloumn_added,1,Y_1)
print (theta_1)
```

```
[[ 1.07581132]
 [-1.1887203 ]]
```

RMSE - Deg1

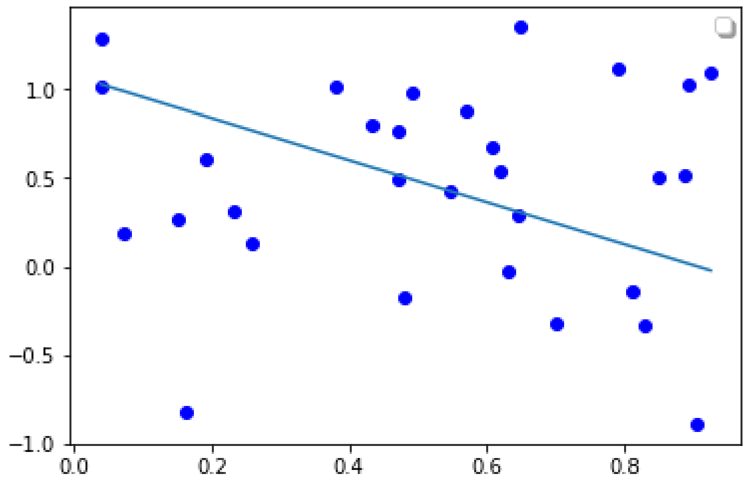
In [205]:
```
rms_1 = rmse_calculator(X_1_coloumn_added,theta_1,Y_1)
print (rms_1)
```

```
0.47624021947640577
```

Plot - Deg1

In [206]:
```
graph_plotter(X_1_coloumn_added,theta_1,Y_1)
```

```
No handles with labels found to put in legend.
```



1-2. Fit the data using 2nd order polynomial regression model (matrix form, gradient descent method).

In [207]:
```
X_1_poly_d2_scaled_coloumn_added = polynomial_adder(X_1,2)
```

Optimized Weight - deg2

In [208]:
```
theta_1_d2 = weight_optimizer(X_1_poly_d2_scaled_coloumn_added,2,Y_1,epo
chs=1000000)
print (theta_1_d2)
```

```
[[ 0.45269151]
 [ 1.13735736]
 [-1.51236155]]
```

RMSE

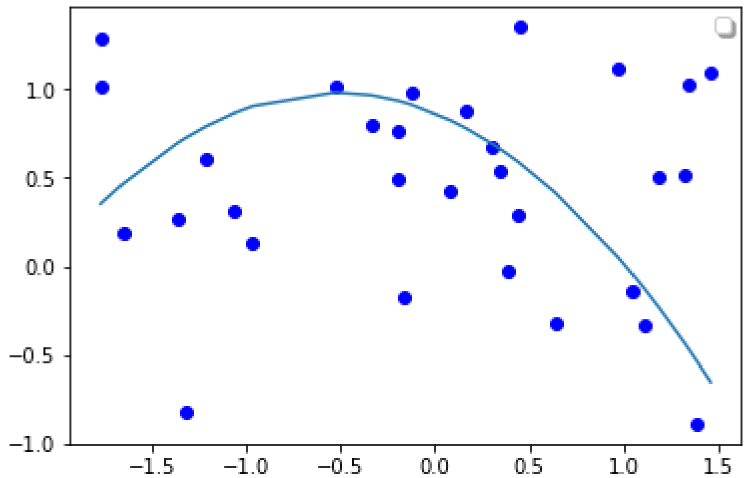
In [209]:
```
rms_1_d2 = rmse_calculator(X_1_poly_d2_scaled_coloumn_added,theta_1_d2,Y
_1)
print (rms_1_d2)
```

```
0.2856992946970416
```

Plot - deg2

In [210]:
```
graph_plotter(X_1_poly_d2_scaled_coloumn_added,theta_1_d2,Y_1)
```

```
No handles with labels found to put in legend.
```



1-3. Fit the data using 4th order polynomial regression model (matrix form, gradient descent method).

In [211]:
```
X_1_poly_d4_scaled_coloumn_added = polynomial_adder(X_1,4)
```

Optimized Weight - deg4

In [212]:
```
theta_1_d4 = weight_optimizer(X_1_poly_d4_scaled_coloumn_added,4,Y_1,epo
chs=1000000)
print (theta_1_d4)
```

```
[[ 0.45269151]
 [ 1.29328167]
 [-1.97124121]
 [ 0.40758024]
 [-0.09772327]]
```

RMSE Deg-4

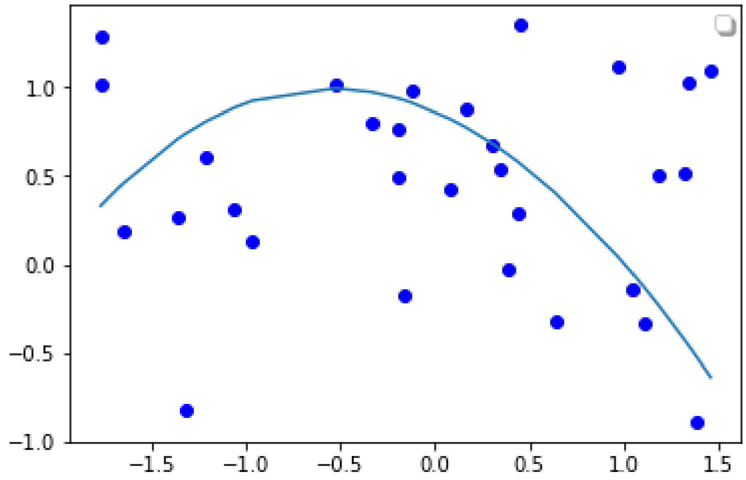
In [213]:
```
rms_1_d4 = rmse_calculator(X_1_poly_d4_scaled_coloumn_added,theta_1_d4,Y
_1)
print (rms_1_d4)
```

```
0.2853539310798953
```

Graph_Deg 4

In [214]:
```
graph_plotter(X_1_poly_d4_scaled_coloumn_added,theta_1_d4,Y_1)
```

```
No handles with labels found to put in legend.
```



1-4. Fit the data using 16th order polynomial regression model (matrix form, gradient descent method).

In [215]:
```
X_1_poly_d16_scaled_coloumn_added = polynomial_adder(X_1,16)
```

Optimized Weight - deg16

In [216]:
```
theta_1_d16 = weight_optimizer(X_1_poly_d16_scaled_coloumn_added,16,Y_1,
epochs=1000000)
print (theta_1_d16)
```

```
[[ 0.45269151]
 [ 0.90569215]
 [-0.63905604]
 [ 0.58174172]
 [-2.18981068]
 [-0.36381962]
 [-0.48679136]
 [ 0.03242304]
 [ 1.22399681]
 [ 1.3783914 ]
 [ 0.51790883]
 [ 0.54350124]
 [-1.12891568]
 [ 0.26915691]
 [ 0.5333662 ]
 [-0.19490954]
 [-1.39357019]]
```

RMSE - Deg4

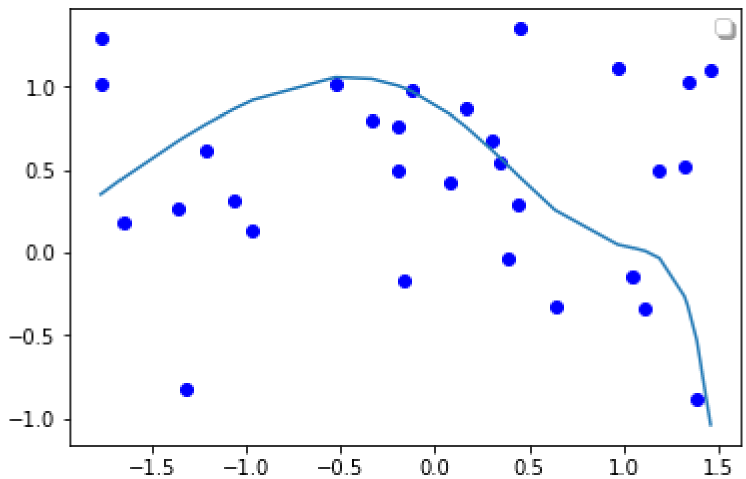
In [217]:
```
rms_1_d16 = rmse_calculator(X_1_poly_d16_scaled_coloumn_added,theta_1_d1
6,Y_1)
print (rms_1_d16)
```

```
0.2625062559634639
```

Graph_Deg 16

In [218]:
```
graph_plotter(X_1_poly_d16_scaled_coloumn_added,theta_1_d16,Y_1)
```

```
No handles with labels found to put in legend.
```



1-5. Fit the data using 16th order polynomial regression model with ridge (L2 penalty) regularization (matrix form, gradient descent method).

You need to try at least 3 different L2 penalty (for example, λ = 0.1, 1, 10).

λ = 0.1

Optimized weights λ = 0.1

In [219]:
```
theta_1_d16_regularised_1 = weight_optimizer(X_1_poly_d16_scaled_coloumn
_added,16,Y_1,regularisation_alpha=0.1)
print (theta_1_d16_regularised_1)
```

```
[[ 0.45118755]
 [ 0.78496938]
 [-0.41986364]
 [-0.64770631]
 [-0.48516438]
 [-0.22691241]
 [ 0.00677979]
 [ 0.17744631]
 [ 0.27520327]
 [ 0.30862102]
 [ 0.28991242]
 [ 0.22673522]
 [ 0.12928467]
 [ 0.01020639]
 [-0.12850398]
 [-0.27605485]
 [-0.43514748]]
```

RMSE - λ = 0.1

In [220]:
```
rms_1_d16_regularised_1 = rmse_calculator(X_1_poly_d16_scaled_coloumn_ad
ded,theta_1_d16_regularised_1,Y_1)
print (rms_1_d16_regularised_1)
```

```
0.2693872247572115
```

λ = 1

Optimized weights λ = 1

In [221]:
```
theta_1_d16_regularised_2 = weight_optimizer(X_1_poly_d16_scaled_coloumn
_added,16,Y_1,regularisation_alpha=1)
print (theta_1_d16_regularised_2)
```

```
[[ 0.43808856]
 [ 0.30532714]
 [-0.11714469]
 [-0.21555533]
 [-0.18959658]
 [-0.12931817]
 [-0.06945018]
 [-0.02187918]
 [ 0.01069068]
 [ 0.02911397]
 [ 0.03545038]
 [ 0.03198174]
 [ 0.02082246]
 [ 0.00379041]
 [-0.01760999]
 [-0.04215991]
 [-0.06888419]]
```

RMSE - λ = 1

In [222]:
```
rms_1_d16_regularised_2 = rmse_calculator(X_1_poly_d16_scaled_coloumn_ad
ded,theta_1_d16_regularised_2,Y_1)
print (rms_1_d16_regularised_2)
```

```
0.30190806311237905
```

λ = 10

Optimized weights λ = 10

In [223]:
```
theta_1_d16_regularised_3 = weight_optimizer(X_1_poly_d16_scaled_coloumn
_added,16,Y_1,regularisation_alpha=10)
print (theta_1_d16_regularised_3)
```

```
[[ 0.33951863]
 [ 0.05560105]
 [-0.02707079]
 [-0.0564417 ]
 [-0.06173571]
 [-0.05764355]
 [-0.05057775]
 [-0.04323712]
 [-0.03668487]
 [-0.03126116]
 [-0.02699188]
 [-0.02377544]
 [-0.02146823]
 [-0.01992273]
 [-0.01900323]
 [-0.01859114]
 [-0.01858551]]
```

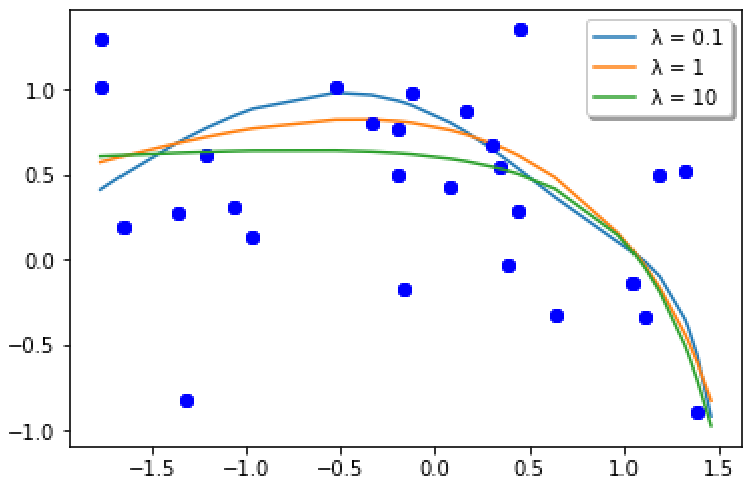
RMSE - λ = 10

In [224]:
```
rms_1_d16_regularised_3 = rmse_calculator(X_1_poly_d16_scaled_coloumn_ad
ded,theta_1_d16_regularised_3,Y_1)
print (rms_1_d16_regularised_3)
```

```
0.34575123097106086
```

Graph Plot λ = 0.1,1,10

In [225]:
```
graph_plotter(X_1_poly_d16_scaled_coloumn_added,theta_1_d16_regularised_
1,Y_1,graph_label="λ = 0.1")
graph_plotter(X_1_poly_d16_scaled_coloumn_added,theta_1_d16_regularised_
2,Y_1,graph_label= "λ = 1")
graph_plotter(X_1_poly_d16_scaled_coloumn_added,theta_1_d16_regularised_
3,Y_1,graph_label= "λ = 10")
```



1-6. Fit the data using 16th order polynomial regression model with scikit-learn Ridge model.

You need to try at least 3 different L2 penalty (for example, λ = 0.1, 1, 10).

In [226]:
```
alpha = [0.1, 1, 10]
```

In [227]:
```
def ridge_optimized_weight(data,label,alpha=0.1):
    ridge_reg = Ridge(alpha=alpha, solver="cholesky")
    ridge_model = ridge_reg.fit(data[:,1:], label)
    print ("Model-Intercept",ridge_model.intercept_)
    print ("Model-Co-ef",ridge_model.coef_.T)
    return ridge_model
```

In [228]:
```
def ridge_lasso_graph_plotter(data,actual_label,ridge_model,graph_label=
None):
    X_1_poly_dn_scaled_coloumn_added_sorted = data[data[:,1].argsort()]
    Y_ridge_model_1_predict = ridge_model.predict(X_1_poly_dn_scaled_col
oumn_added_sorted[:,1:])
    plt.plot(X_1_poly_dn_scaled_coloumn_added_sorted[:,1:2], actual_labe
l, 'bo')
    plt.plot(X_1_poly_dn_scaled_coloumn_added_sorted[:,1:2], Y_ridge_mod
el_1_predict,label=graph_label)
    legend = plt.legend(loc='upper right', shadow=True)
```

In [229]:
```
def ridge_lasso_rmse(data,actual_label,ridge_model):
    Y_ridge_mode1_1_predict = ridge_model.predict(data[:,1:])
    rms = sqrt(mean_squared_error(actual_label, Y_ridge_mode1_1_predict
))
    return rms
```

Optimized_Weights ridge λ = 0.1

In [230]:
```
ridge_mode1_1 = ridge_optimized_weight(X_1_poly_d16_scaled_coloumn_added
,Y_1,0.1)
```

```
Model-Intercept [0.45269151]
Model-Co-ef [[ 0.78485691]
 [-0.41980483]
 [-0.6474652 ]
 [-0.48475686]
 [-0.22708056]
 [ 0.00646183]
 [ 0.17607267]
 [ 0.27503508]
 [ 0.30951311]
 [ 0.28986803]
 [ 0.22699526]
 [ 0.13087521]
 [ 0.01010497]
 [-0.12814542]
 [-0.27800671]
 [-0.43473061]]
```

RMSE ridge λ = 0.1

In [231]:
```
rms_ridge_1 = ridge_lasso_rmse(X_1_poly_d16_scaled_coloumn_added,Y_1,rid
ge_mode1_1)
print(rms_ridge_1)
```

```
0.2693814634185468
```

Optimized Weights Ridge λ = 1

In [232]:
```
ridge_model_2 = ridge_optimized_weight(X_1_poly_d16_scaled_coloumn_added
,Y_1,1)
```

```
Model-Intercept [0.45269151]
Model-Co-ef [[ 0.30532714]
 [-0.11714469]
 [-0.21555533]
 [-0.18959658]
 [-0.12931817]
 [-0.06945018]
 [-0.02187918]
 [ 0.01069068]
 [ 0.02911397]
 [ 0.03545038]
 [ 0.03198174]
 [ 0.02082246]
 [ 0.00379041]
 [-0.01760999]
 [-0.04215991]
 [-0.06888419]]
```

RMSE ridge λ = 1

In [233]:
```
rms_ridge_2 = ridge_lasso_rmse(X_1_poly_d16_scaled_coloumn_added,Y_1,rid
ge_model_2)
print(rms_ridge_2)
```

```
0.3015546921663988
```

Optimized Weights Ridge λ = 10

In [234]:
```
ridge_model_3 = ridge_optimized_weight(X_1_poly_d16_scaled_coloumn_added
,Y_1,10)
```

```
Model-Intercept [0.45269151]
Model-Co-ef [[ 0.05560105]
 [-0.02707079]
 [-0.0564417 ]
 [-0.06173571]
 [-0.05764355]
 [-0.05057775]
 [-0.04323712]
 [-0.03668487]
 [-0.03126116]
 [-0.02699188]
 [-0.02377544]
 [-0.02146823]
 [-0.01992273]
 [-0.01900323]
 [-0.01859114]
 [-0.01858551]]
```

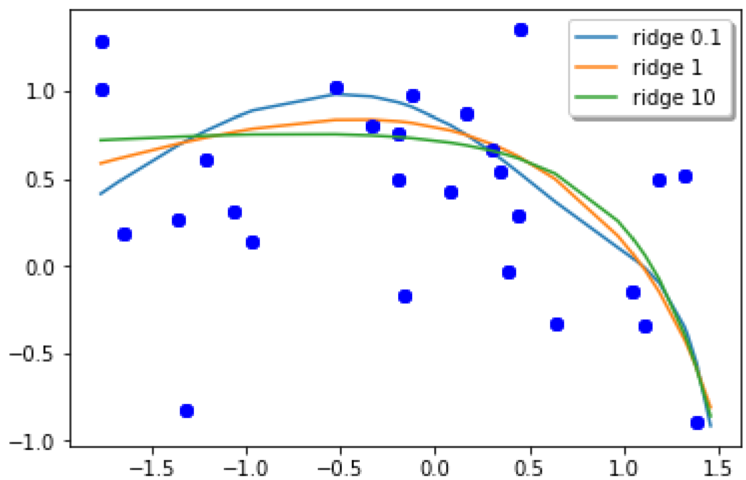
RMSE ridge λ = 10

In [235]:
```
rms_ridge_3 = ridge_lasso_rmse(X_1_poly_d16_scaled_coloumn_added,Y_1,rid
ge_model_3)
print(rms_ridge_3)
```

```
0.3267044743318329
```

Graph Plot Ridge λ = 0.1,1,10

In [236]:
```
ridge_lasso_graph_plotter(X_1_poly_d16_scaled_coloumn_added,Y_1,ridge_mo
del_1,graph_label="ridge 0.1")
ridge_lasso_graph_plotter(X_1_poly_d16_scaled_coloumn_added,Y_1,ridge_mo
del_2,graph_label="ridge 1")
ridge_lasso_graph_plotter(X_1_poly_d16_scaled_coloumn_added,Y_1,ridge_mo
del_3,graph_label="ridge 10")
```



1-7. Fit the data using 16th order polynomial regression model with scikit-learn Lasso model.

In [237]:
```
def lasso_optimized_weight(data,label,alpha=0.1):
    lasso_reg = Lasso(alpha)
    lasso_model = lasso_reg.fit(data[:,1:], label)
    print ("Model-Intercept",lasso_model.intercept_)
    print ("Model-Co-ef",lasso_model.coef_.T)
    return lasso_model
```

Optimized_Weights lasso λ = 0.1

In [238]:
```
lasso_mode1_1 = lasso_optimized_weight(X_1_poly_d16_scaled_coloumn_added
,Y_1,0.1)
```

```
Model-Intercept [0.45269151]
Model-Co-ef [-0.         -0.         -0.         -0.         -0.
  -0.37373874
 -0.         -0.         -0.         -0.         -0.         -0.
 -0.         -0.         -0.         -0.         ]
```

RMSE lasso λ = 0.1

In [239]:
```
rms_lasso_1 = ridge_lasso_rmse(X_1_poly_d16_scaled_coloumn_added,Y_1,las
so_mode1_1)
print(rms_lasso_1)
```

```
0.34466712593964577
```

Optimized_Weights lasso λ = 1

In [240]:
```
lasso_mode1_2 = lasso_optimized_weight(X_1_poly_d16_scaled_coloumn_added
,Y_1,1)
```

```
Model-Intercept [0.45269151]
Model-Co-ef [-0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -
0. -0.]
```

RMSE lasso λ = 1

In [241]:
```
rms_lasso_2 = ridge_lasso_rmse(X_1_poly_d16_scaled_coloumn_added,Y_1,las
so_mode1_2)
print(rms_lasso_2)
```

```
0.5772554182087681
```

Optimized_Weights lasso λ = 10

In [242]:
```
lasso_mode1_3 = lasso_optimized_weight(X_1_poly_d16_scaled_coloumn_added
,Y_1,10)
```

```
Model-Intercept [0.45269151]
Model-Co-ef [-0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -0. -
0. -0.]
```

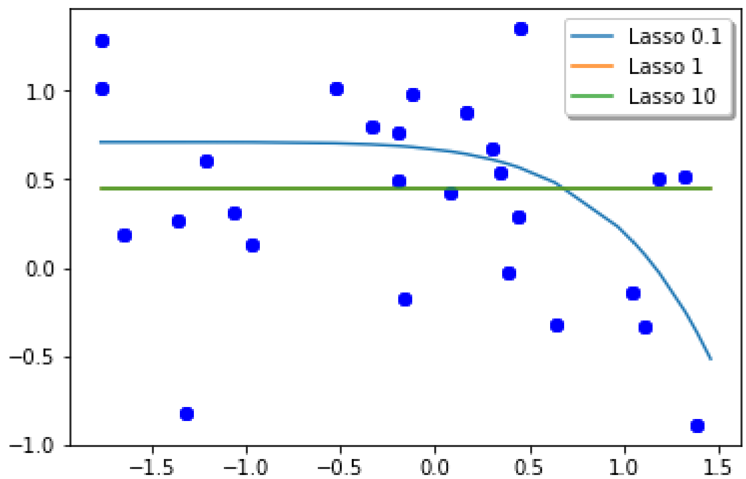
RMSE lasso λ = 10

In [243]:
```
rms_lasso_3 = ridge_lasso_rmse(X_1_poly_d16_scaled_coloumn_added,Y_1,las
so_mode1_3)
print(rms_lasso_3)
```

```
0.5772554182087681
```

Graph Plot Lasso λ = 0.1,1,10

In [244]:
```
ridge_lasso_graph_plotter(X_1_poly_d16_scaled_coloumn_added,Y_1,lasso_mo
de1_1,graph_label="Lasso 0.1")
ridge_lasso_graph_plotter(X_1_poly_d16_scaled_coloumn_added,Y_1,lasso_mo
de1_2,graph_label="Lasso 1")
ridge_lasso_graph_plotter(X_1_poly_d16_scaled_coloumn_added,Y_1,lasso_mo
de1_3,graph_label="Lasso 10")
```



2.Polynomial regression with train/validation/test

You need to split the data into training/validation/testing data set as 60% / 20% / 20%.

Please use np.random.seed(1) to have consistent data for evaluation

2-1. Fit the data using linear (1st order) regression model (matrix form, gradient descent method).

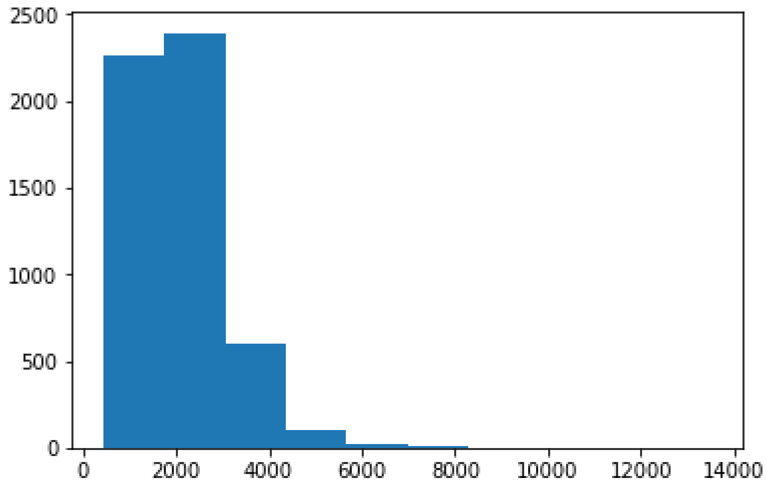
In [245]:
```
# def plot_learning_curves(model, X, y):
#     X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=
0.2)
#     train_errors, val_errors = [], []
#     for m in range(1, len(X_train)):
#         model.fit(X_train[:m], y_train[:m])
#         y_train_predict = model.predict(X_train[:m])
#         y_val_predict = model.predict(X_val)
#         train_errors.append(mean_squared_error(y_train_predict, y_trai
n[:m]))
#         val_errors.append(mean_squared_error(y_val_predict, y_val))
#     plt.plot(np.sqrt(train_errors), "r-+", linewidth=2, label="train")
#     plt.plot(np.sqrt(val_errors), "b-", linewidth=3, label="val")

# lin_reg = LinearRegression()
# plot_learning_curves(lin_reg, X, y)

# from sklearn.pipeline import Pipeline

# polynomial_regression = Pipeline([
#         ("poly_features", PolynomialFeatures(degree=10, include_bias=F
alse)),
#         ("lin_reg", LinearRegression()),
#     ])

# plot_learning_curves(polynomial_regression, X, y)
```

In [246]:
```
data2 = pd.read_csv("ex2data2.csv")
X_2 = data2.as_matrix(columns=data2.columns[0:1])
Y_2 = data2.as_matrix(columns=data2.columns[1:])
X_2_poly_d1_scaled = scaler.fit_transform(X_2)
X_2_coloumn_added = np.c_[np.ones((data2.shape[0], 1)), X_2]
X_2_poly_d1_scaled_coloumn_added = np.c_[np.ones((data2.shape[0], 1)), X
_2_poly_d1_scaled]
```

```
/anaconda2/envs/carnd-term1/lib/python3.5/site-packages/sklearn/utils/v
alidation.py:475: DataConversionWarning: Data with input dtype int64 wa
s converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

In [247]:
```
plt.hist(X_2)
```

Out[247]:
```
(array([2.266e+03, 2.393e+03, 6.040e+02, 1.050e+02, 2.100e+01, 1.200e+0
1,
        1.000e+00, 0.000e+00, 1.000e+00, 1.000e+00]),
 array([  430.,  1741.,  3052.,  4363.,  5674.,  6985.,  8296.,  9607.,
        10918., 12229., 13540.]),
 <a list of 10 Patch objects>)
```



In [248]:
```
X_2_train_val, X_2_test, y_2_train_val, y_2_test = train_test_split(X_2_
poly_d1_scaled_coloumn_added , Y_2, test_size=0.2,random_state=1)
X_2_train, X_2_val, y_2_train, y_2_val = train_test_split(X_2_train_val,
 y_2_train_val, test_size=0.25,random_state=1)
print (X_2_coloumn_added.shape)
print (X_2_train_val.shape)
print (X_2_train.shape)
```

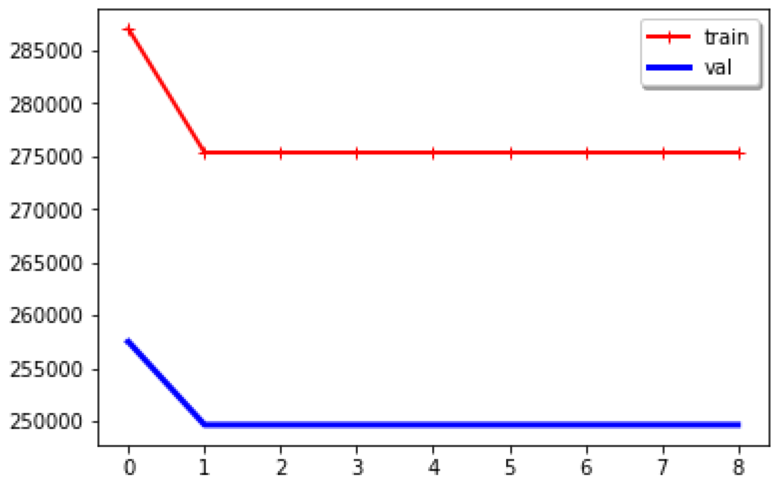
```
(5404, 2)
(4323, 2)
(3242, 2)
```

In [249]:
```
def Mean_Square_Error_calculator(data,weights,actual_label):
    predict_y = data.dot(weights)
    rms = mean_squared_error(actual_label, predict_y)
    return rms
```

In [250]:
```
def train_val_best_model(X_train, X_val, y_train, y_val,degree):
    epochs = [1000,10000,100000]
    learning_rate = [.001,.01,.1]
    train_errors, val_errors = [], []
    counter = 1
    combination = {}
    for epoch in epochs:
        for rate in learning_rate:
            weights = weight_optimizer(X_train,degree,y_train,learn_rate
 = rate,epochs = epoch,regularisation_alpha=0)
            rmse_train = rmse_calculator(X_train,weights,y_train)
            rmse_val = rmse_calculator(X_val,weights,y_val)
            train_errors.append(rmse_train)
            val_errors.append(rmse_val)
            combination[counter] = (epoch,rate)
            counter += 1
    plt.plot(train_errors, "r-+", linewidth=2, label="train")
    plt.plot(val_errors, "b-", linewidth=3, label="val")
    legend = plt.legend(loc='upper right', shadow=True)
    ## Find the lowest validation error
    counter_val_error = list(enumerate(val_errors, 1))
    counter_val_error_sorted = sorted(counter_val_error, key=lambda x:x[
1])
    best_model = combination[(counter_val_error_sorted[0][0])]
    print(counter_val_error)
    print("Epoch and Learning Rate Combination",counter_val_error_sorted
[0][0],best_model)
    return best_model
```

In [251]:
```
best_model_2 = train_val_best_model(X_2_train, X_2_val, y_2_train, y_2_v
al,1)
weights_best_model_2 = weight_optimizer(X_2_train,1,y_2_train,learn_rate
 = best_model_2 [1],epochs = best_model_2 [0],regularisation_alpha=0)
```

```
[(1, 257488.04094283126), (2, 249622.42769314421), (3, 249622.427705436
3), (4, 249622.4276900577), (5, 249622.42770543642), (6, 249622.4277054
363), (7, 249622.42770543747), (8, 249622.42770543642), (9, 249622.4277
054363)]
Epoch and Learning Rate Combination 4 (10000, 0.001)
```



RMSE - Train,test Deg -1

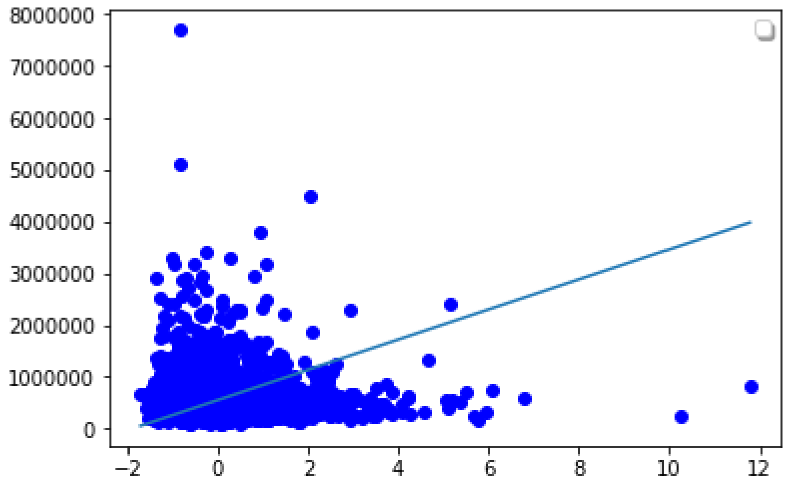
In [252]:
```
rmse_train_2 = rmse_calculator(X_2_train,weights_best_model_2,y_2_train)
rmse_test_2 = rmse_calculator(X_2_test,weights_best_model_2,y_2_test)
print("rmse_train",rmse_train_2)
print("rmse_test",rmse_test_2)
```

```
rmse_train 275355.0256953383
rmse_test 264311.94247884274
```

Graph Train Deg-1

In [253]:
```
graph_plotter(X_2_train,weights_best_model_2,y_2_train,graph_label=None)
```

```
No handles with labels found to put in legend.
```



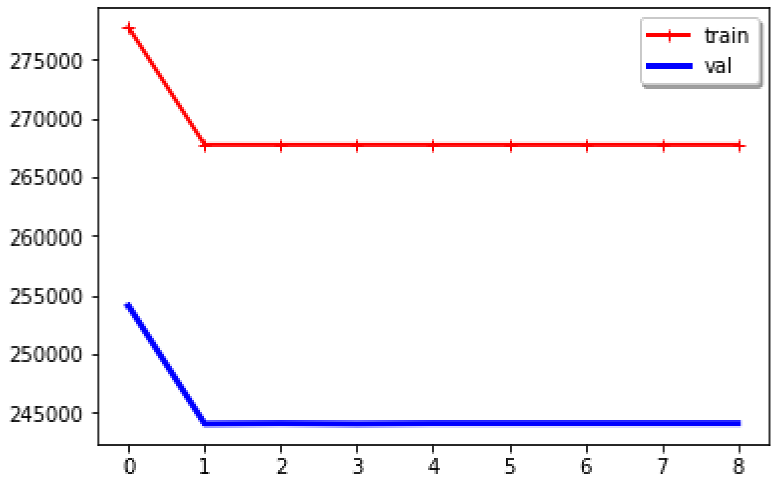
2-2. Fit the data using 2nd order polynomial regression model (matrix form, gradient descent method).

In [254]:
```
X_2_poly_d2_scaled_coloumn_added = polynomial_adder(X_2,2)
```

In [255]:
```
X_22_train_val, X_22_test, y_22_train_val, y_22_test = train_test_split(
X_2_poly_d2_scaled_coloumn_added, Y_2, test_size=0.2,random_state=1)
X_22_train, X_22_val, y_22_train, y_22_val = train_test_split(X_22_train
_val, y_22_train_val, test_size=0.25,random_state=1)
```

In [256]:
```
best_model_22 = train_val_best_model(X_22_train, X_22_val, y_22_train, y
_22_val,2)
weights_best_model_22 = weight_optimizer(X_22_train,2,y_22_train,learn_r
ate = best_model_22 [1],epochs = best_model_22 [0],regularisation_alpha=
0)
```

```
[(1, 254082.7389780978), (2, 244029.3535573043), (3, 244071.5963589443
7), (4, 244029.2686895008), (5, 244071.5963589144), (6, 244071.59635907
054), (7, 244071.59635891087), (8, 244071.59635907042), (9, 244071.5963
5907054)]
Epoch and Learning Rate Combination 4 (10000, 0.001)
```



RMSE - Train,test Deg -2

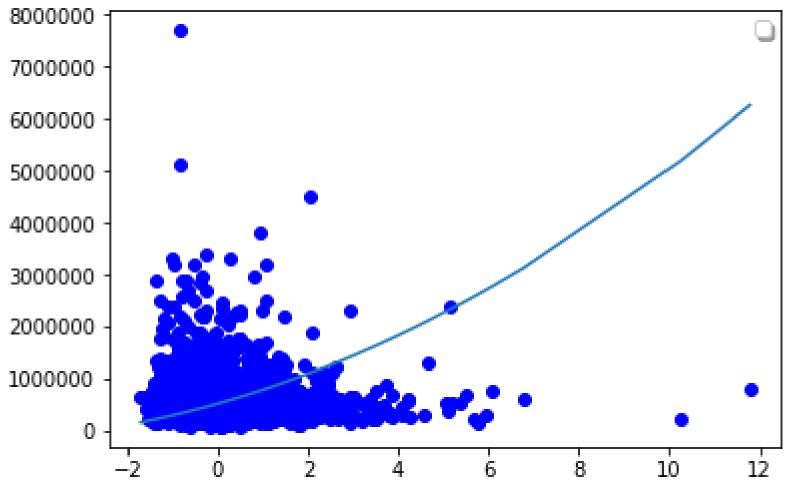
In [257]:
```
rmse_train_22 = rmse_calculator(X_22_train,weights_best_model_22,y_22_tr
ain)
rmse_test_22 = rmse_calculator(X_22_test,weights_best_model_22,y_22_test
)
print("rmse_train",rmse_train_22)
print("rmse_test",rmse_test_22)
```

```
rmse_train 267719.7117411374
rmse_test 254533.92847752557
```

Graph Train Deg-2

In [258]:
```
graph_plotter(X_22_train,weights_best_model_22,y_22_train,graph_label=No
ne)
```

```
No handles with labels found to put in legend.
```



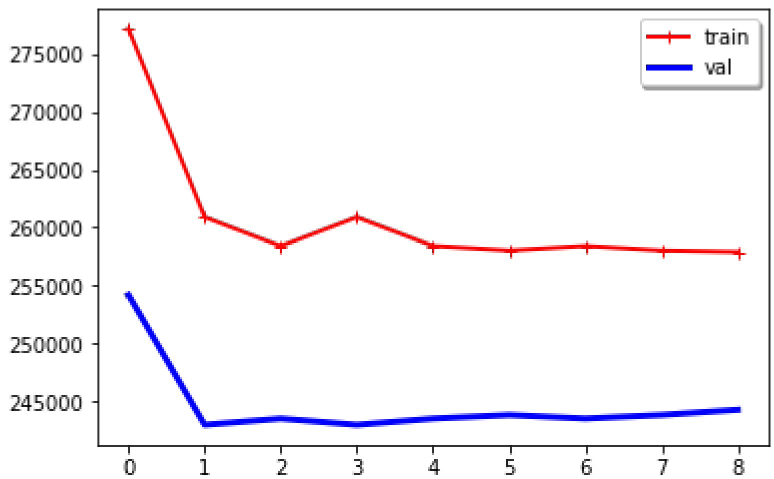
2-3. Fit the data using 4th order polynomial regression model (matrix form, gradient descent method).

In [259]:
```
X_2_poly_d4_scaled_coloumn_added = polynomial_adder(X_2,4)
```

In [260]:
```
X_24_train_val, X_24_test, y_24_train_val, y_24_test = train_test_split(
X_2_poly_d4_scaled_coloumn_added, Y_2, test_size=0.2,random_state=1)
X_24_train, X_24_val, y_24_train, y_24_val = train_test_split(X_24_train
_val, y_24_train_val, test_size=0.25,random_state=1)
```

In [261]:
```
best_model_24 = train_val_best_model(X_24_train, X_24_val, y_24_train, y
_24_val,4)
weights_best_model_24 = weight_optimizer(X_24_train,4,y_24_train,learn_r
ate = best_model_24 [1],epochs = best_model_24 [0],regularisation_alpha=
0)
```

```
[(1, 254205.33656847285), (2, 243001.66458493247), (3, 243544.853181655
7), (4, 243001.8240493743), (5, 243544.6655575537), (6, 243854.62292422
46), (7, 243544.64619277278), (8, 243854.612717776), (9, 244304.6967645
9354)]
Epoch and Learning Rate Combination 2 (1000, 0.01)
```



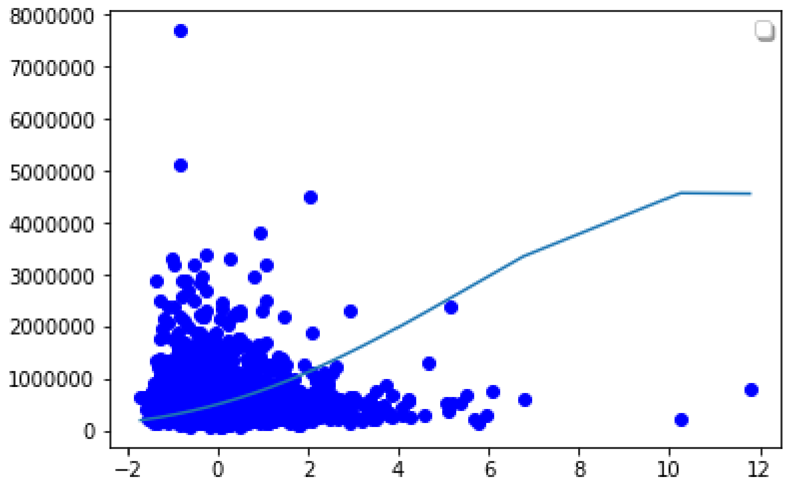
RMSE - Train,test Deg -4

In [262]:
```
rmse_train_24 = rmse_calculator(X_24_train,weights_best_model_24,y_24_tr
ain)
rmse_test_24 = rmse_calculator(X_24_test,weights_best_model_24,y_24_test
)
print("rmse_train",rmse_train_24)
print("rmse_test",rmse_test_24)
```

```
rmse_train 260919.45768952757
rmse_test 251751.42950903866
```

In [263]:
```
graph_plotter(X_24_train,weights_best_model_24,y_24_train,graph_label=None)
```

No handles with labels found to put in legend.



2-4. Fit the data using 16th order polynomial regression model (matrix form, gradient descent method).

In [357]:
```
def weight_optimizer_stoc_batch(data,degree,Label,learn_rate = .01,epochs = 100000,regularisation_alpha=0):
    theta_1 = np.random.randn(degree+1,1)
    data_size = data.shape[0]
    print (data_size)
    batch_size = data_size // 16
    print (batch_size)
    for epoch in range(epochs):
        for batch in range(batch_size):
            X_batch, y_batch = resample(data, Label, n_samples=16, random_state=0,replace=False)
            gradients = (2/X_batch.shape[0])* (X_batch.T.dot(X_batch.dot(theta_1)- y_batch)+ \
                                                                regularisation_alpha*theta_1)
            theta_1 = theta_1 - learn_rate * gradients
    return theta_1
```

In [370]:
```
def train_val_best_model_stoc_batch(X_train, X_val, y_train, y_val,degre
e):
    epochs = [10000]
    learning_rate = [.001,.01,.1]
    train_errors, val_errors = [], []
    counter = 1
    combination = {}
    for epoch in epochs:
        for rate in learning_rate:
            weights = weight_optimizer_stoc_batch(X_train,degree,y_train
,learn_rate = rate,epochs = epoch,regularisation_alpha=0)
            rmse_train = rmse_calculator(X_train,weights,y_train)
            rmse_val = rmse_calculator(X_val,weights,y_val)
            train_errors.append(rmse_train)
            val_errors.append(rmse_val)
            combination[counter] = (epoch,rate)
            counter += 1
    plt.plot(train_errors, "r-+", linewidth=2, label="train")
    plt.plot(val_errors, "b-", linewidth=3, label="val")
    legend = plt.legend(loc='upper right', shadow=True)
    ## Find the lowest validation error
    counter_val_error = list(enumerate(val_errors, 1))
    counter_val_error_sorted = sorted(counter_val_error, key=lambda x:x[
1])
    best_model = combination[(counter_val_error_sorted[0][0])]
    print(counter_val_error)
    print("Epoch and Learning Rate Combination",counter_val_error_sorted
[0][0],best_model)
    return best_model
```

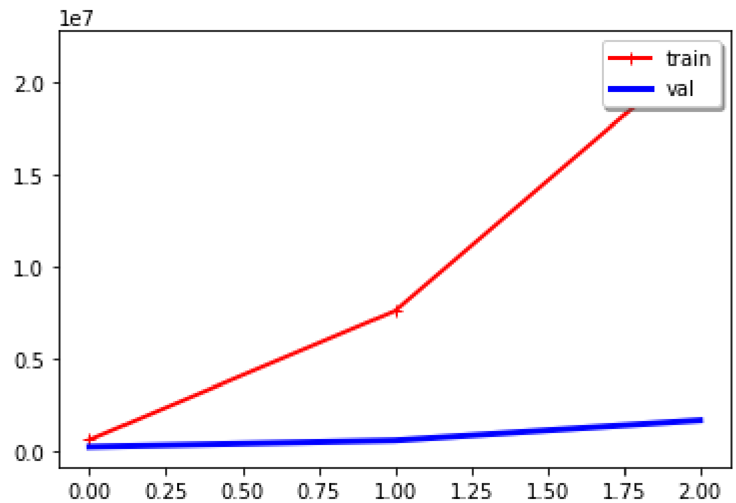
In [371]:
```
X_2_poly_d16_scaled_coloumn_added = polynomial_adder(X_2,16)
```

In [372]:
```
X_216_train_val, X_216_test, y_216_train_val, y_216_test = train_test_sp
lit(X_2_poly_d16_scaled_coloumn_added, Y_2, test_size=0.2,random_state=1
)
X_216_train, X_216_val, y_216_train, y_216_val = train_test_split(X_216_
train_val, y_216_train_val, test_size=0.25,random_state=1)
```

Implemented Mini-batch Gradient Descent as I was getting error with full batch

In [373]:
```
best_model_216 = train_val_best_model_stoc_batch(X_216_train, X_216_val,
 y_216_train, y_216_val,16)
weights_best_model_216 = weight_optimizer_stoc_batch(X_216_train,16,y_21
6_train,learn_rate = best_model_216 [1],epochs = best_model_216 [0],regu
larisation_alpha=0)
```

```
3242
202
3242
202
3242
202
[(1, 271431.84548393165), (2, 621086.9719878328), (3, 1715299.115724269
3)]
Epoch and Learning Rate Combination 1 (10000, 0.001)
3242
202
```

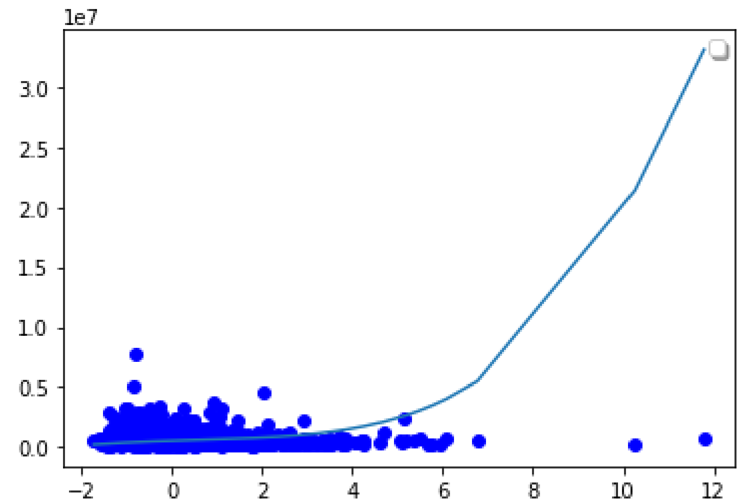


In [374]:
```
rmse_train_216 = rmse_calculator(X_216_train,weights_best_model_216,y_21
6_train)
rmse_test_216 = rmse_calculator(X_216_test,weights_best_model_216,y_216_
test)
print("rmse_train",rmse_train_216)
print("rmse_test",rmse_test_216)
```

```
rmse_train 656156.7479793766
rmse_test 274794.112255375
```

In [375]:
```
graph_plotter(X_216_train,weights_best_model_216,y_216_train,graph_label
=None)
```

```
WARNING:matplotlib.legend:No handles with labels found to put in legen
d.
```



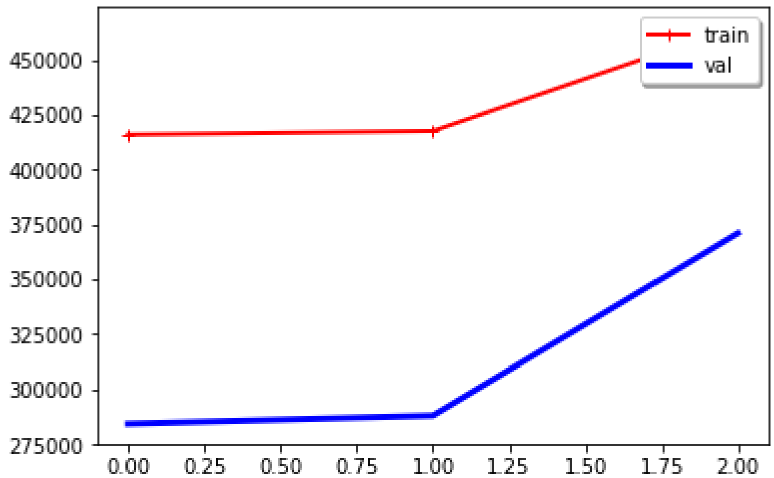
2-5. Fit the data using 16th order polynomial regression model with ridge (L2 penalty) regularization.

In [379]:
```
def train_val_best_model_ridge_stoc_batch(X_train, X_val, y_train, y_val
,degree):
    epochs = [10000]
    learning_rate = [.01]
    regularisation_alpa = [.1,1,10]
    train_errors, val_errors = [], []
    counter = 1
    combination = {}
    for epoch in epochs:
        for rate in learning_rate:
            for alpha in regularisation_alpa:
                weights = weight_optimizer_stoc_batch(X_train,degree,y_t
rain,learn_rate = rate,epochs = epoch, \
                                             regularisation_alpha=alpha)
                rmse_train = rmse_calculator(X_train,weights,y_train)
                rmse_val = rmse_calculator(X_val,weights,y_val)
                train_errors.append(rmse_train)
                val_errors.append(rmse_val)
                combination[counter] = (epoch,rate,alpha)
                counter += 1
    plt.plot(train_errors, "r-+", linewidth=2, label="train")
    plt.plot(val_errors, "b-", linewidth=3, label="val")
    legend = plt.legend(loc='upper right', shadow=True)
    ## Find the lowest validation error
    counter_val_error = list(enumerate(val_errors, 1))
    counter_val_error_sorted = sorted(counter_val_error, key=lambda x:x[
1])
    best_model = combination[(counter_val_error_sorted[0][0])]
    print(best_model)
    return best_model
```

Implemented Mini-batch Gradient Descent as I was getting error with full batch

In [380]:
```
best_model_216_ridge = train_val_best_model_ridge_stoc_batch(X_216_train
, X_216_val, y_216_train, y_216_val,16)
weights_best_model_216_ridge = weight_optimizer_stoc_batch(X_216_train,1
6,y_216_train,learn_rate = best_model_216_ridge [1],epochs = best_model_
216_ridge [0],regularisation_alpha=best_model_216_ridge [2])
```

```
3242
202
3242
202
3242
202
(10000, 0.01, 0.1)
3242
202
```

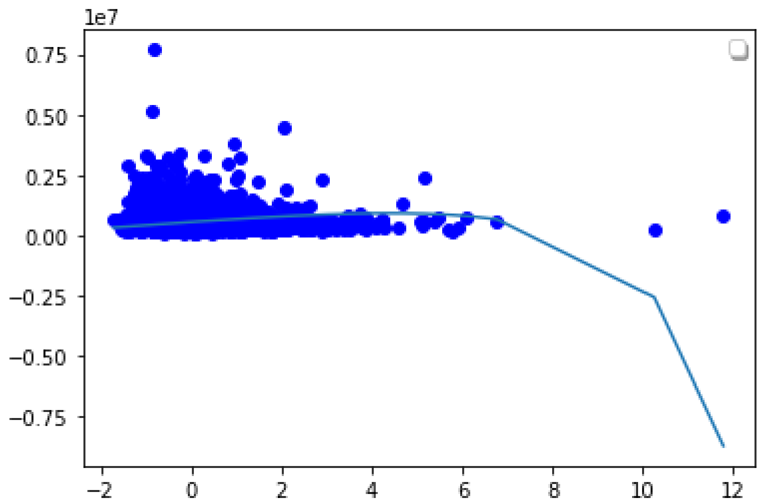


In [383]:
```
rmse_train_216_ridge = rmse_calculator(X_216_train,weights_best_model_21
6_ridge,y_216_train)
rmse_test_216_ridge = rmse_calculator(X_216_test,weights_best_model_216_
ridge,y_216_test)
print("rmse_train",rmse_train_216_ridge)
print("rmse_test",rmse_test_216_ridge)
```

```
rmse_train 415963.5773494703
rmse_test 321415.22175827075
```

In [385]:
```
graph_plotter(X_216_train,weights_best_model_216_ridge,y_216_train,graph
_label=None)
```

```
WARNING:matplotlib.legend:No handles with labels found to put in legen
d.
```

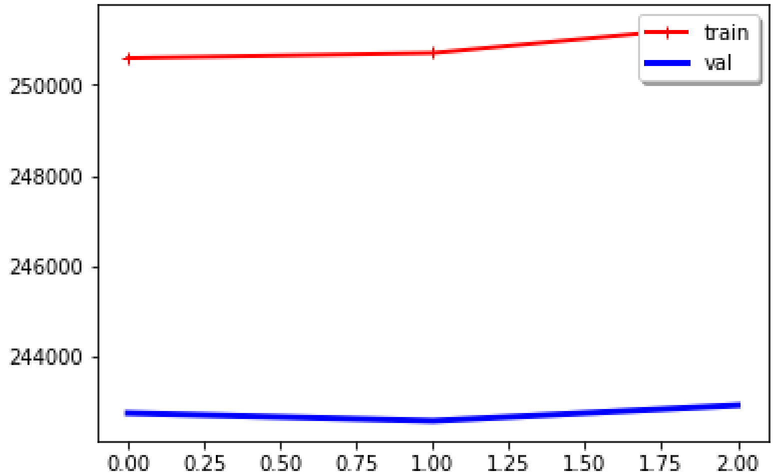


2-6. Fit the data using 16th order polynomial regression model with scikit-learn Ridge model.

In [268]:
```
def train_val_best_model_scikit_ridge(X_train, X_val, y_train, y_val):
    regularisation_alpa = [0.1,1,10]
    train_errors, val_errors = [], []
    counter = 1
    combination = {}
    for alpha in regularisation_alpa:
        ridge_model = ridge_optimized_weight(X_train,y_train,alpha)
        rmse_train = ridge_lasso_rmse(X_train,y_train,ridge_model)
        rmse_val = ridge_lasso_rmse(X_val,y_val,ridge_model)
        train_errors.append(rmse_train)
        val_errors.append(rmse_val)
        combination[counter] = (alpha,ridge_model)
        counter += 1
    plt.plot(train_errors, "r-+", linewidth=2, label="train")
    plt.plot(val_errors, "b-", linewidth=3, label="val")
    legend = plt.legend(loc='upper right', shadow=True)
    ## Find the lowest validation error
    counter_val_error = list(enumerate(val_errors, 1))
    counter_val_error_sorted = sorted(counter_val_error, key=lambda x:x[
1])
    best_model = combination[(counter_val_error_sorted[0][0])]
    print("alpha",best_model[0])
    return best_model[1]
```

In [269]:
```
best_model_216_scikit_ridge = train_val_best_model_scikit_ridge(X_216_tr
ain, X_216_val, y_216_train, y_216_val)
```

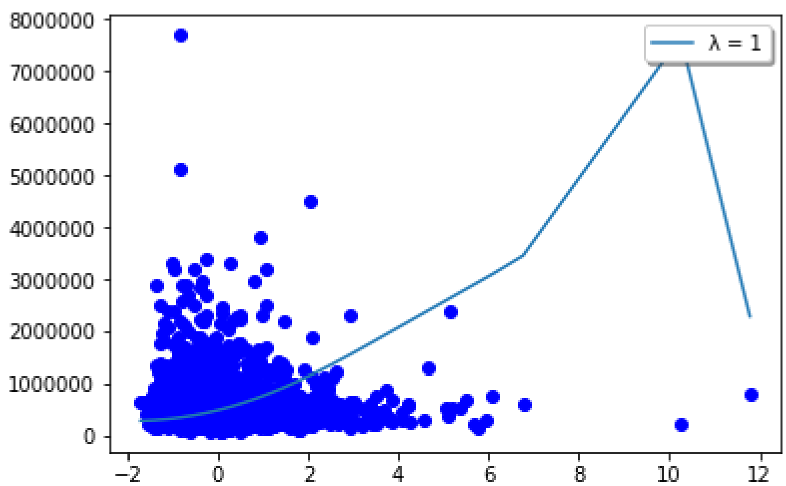
```
Model-Intercept [547704.506878]
Model-Co-ef [[  47149.02303585]
 [  97806.15914125]
 [ 494262.89050946]
 [-227237.60901432]
 [-422132.21976636]
 [-199882.87630559]
 [  64994.59063826]
 [ 230729.38940244]
 [ 287757.59283936]
 [ 265072.70818138]
 [ 193352.45983527]
 [  95486.86500499]
 [ -13592.57195474]
 [-124860.40617845]
 [-233169.41195629]
 [-335762.59926058]]
Model-Intercept [547718.99272249]
Model-Co-ef [[ -16344.34115262]
 [ 320155.60757134]
 [ 172666.68142153]
 [-173831.65937522]
 [-211992.23283438]
 [ -77256.72585303]
 [  64972.77614043]
 [ 152621.76687899]
 [ 180680.13409481]
 [ 162984.49861422]
 [ 115562.95467406]
 [  51361.29686543]
 [ -20522.80095625]
 [ -94191.55415056]
 [-166059.86068628]
 [-234099.56514392]]
Model-Intercept [547547.03238267]
Model-Co-ef [[  36166.43778387]
 [ 269023.40114305]
 [  77631.40011951]
 [ -81988.69738317]
 [ -71553.92749472]
 [  -5369.60495591]
 [  48807.03808062]
 [  74843.22643076]
 [  76275.4587262 ]
 [  60869.18534266]
 [  35528.32733298]
 [   5236.22544228]
 [ -26747.06366153]
 [ -58427.80688802]
 [ -88665.61666554]
 [-116867.58253742]]
alpha 1
```



In [270]:
```
rmse_train_216_scikit_ridge = ridge_lasso_rmse(X_216_train, y_216_train,
best_model_216_scikit_ridge)
rmse_test_216_scikit_ridge = ridge_lasso_rmse(X_216_test,y_216_test,best
_model_216_scikit_ridge)
print("rmse_train",rmse_train_216_scikit_ridge)
print("rmse_test",rmse_test_216_scikit_ridge)
```

```
rmse_train 250700.05033093243
rmse_test 251065.74316573926
```

In [271]:
```
ridge_lasso_graph_plotter(X_216_train,y_216_train,best_model_216_scikit_
ridge,graph_label="λ = 1")
```



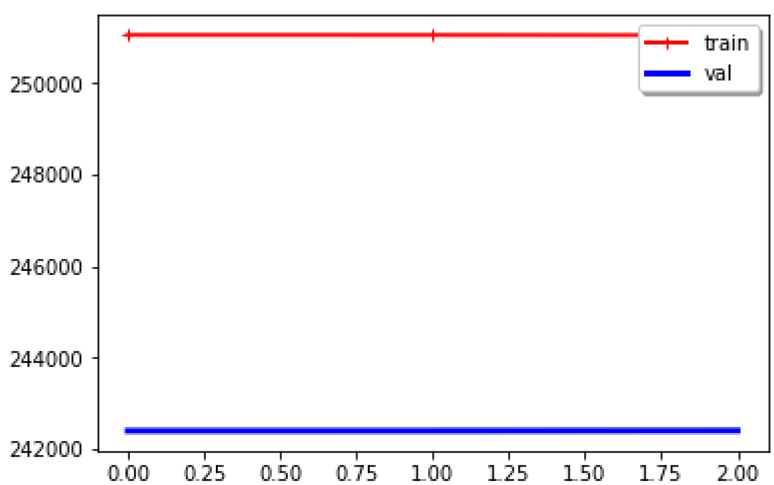
2-7. Fit the data using 16th order polynomial regression model with scikit-learn Lasso model.

In [272]:
```
def train_val_best_model_scikit_lasso(X_train, X_val, y_train, y_val):
    regularisation_alpa = [0.1,1,10]
    train_errors, val_errors = [], []
    counter = 1
    combination = {}
    for alpha in regularisation_alpa:
        lasso_model = lasso_optimized_weight(X_train,y_train,alpha)
        rmse_train = ridge_lasso_rmse(X_train,y_train,lasso_model)
        rmse_val = ridge_lasso_rmse(X_val,y_val,lasso_model)
        train_errors.append(rmse_train)
        val_errors.append(rmse_val)
        combination[counter] = (alpha,lasso_model)
        counter += 1
    plt.plot(train_errors, "r-+", linewidth=2, label="train")
    plt.plot(val_errors, "b-", linewidth=3, label="val")
    legend = plt.legend(loc='upper right', shadow=True)
    ## Find the lowest validation error
    counter_val_error = list(enumerate(val_errors, 1))
    counter_val_error_sorted = sorted(counter_val_error, key=lambda x:x[
1])
    best_model = combination[(counter_val_error_sorted[0][0])]
    print("alpha",best_model[0])
    return best_model[1]
```

In [273]:
```
best_model_216_scikit_lasso = train_val_best_model_scikit_lasso(X_216_tr
ain, X_216_val, y_216_train, y_216_val)
```

```
/anaconda2/envs/carnd-term1/lib/python3.5/site-packages/sklearn/linear_
model/coordinate_descent.py:491: ConvergenceWarning: Objective did not
converge. You might want to increase the number of iterations. Fitting
data with very small alpha may cause precision problems.
  ConvergenceWarning)
```

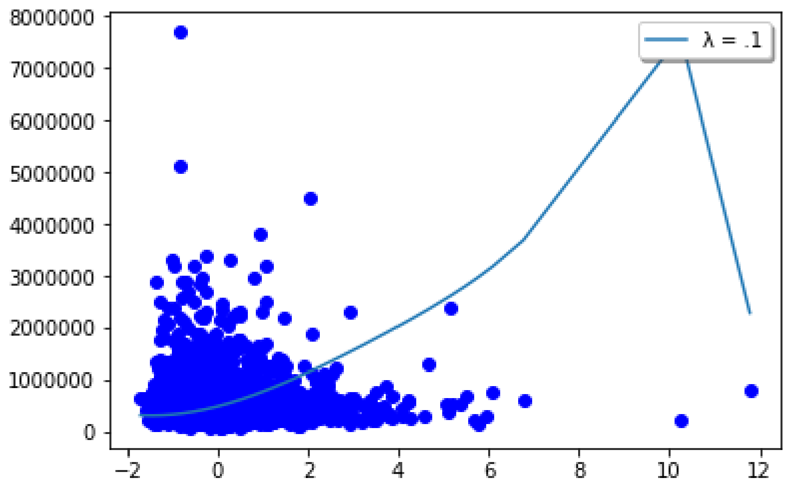
```
Model-Intercept [547780.08000696]
Model-Co-ef [-125318.97003623  666197.50707237 -261841.01303223 -18730
9.44448817
   77160.31260774  155957.01757717  125786.49836694   69160.91493416
   19708.08956119  -14840.20562329  -36093.17315681  -47445.45636661
  -52259.47895543  -52993.40874272  -51325.09359054  -48343.58909978]
Model-Intercept [547779.73592156]
Model-Co-ef [-124992.36217718  665263.70260852 -260753.01353071 -18734
0.17063375
   76345.133887    155967.41656718  125762.63818031   69164.76212111
   19900.84319741  -14276.41829556  -36175.49317507  -47521.03245514
  -52327.97275879  -53055.02152518  -51380.27127648  -48392.87104231]
Model-Intercept [547776.26865725]
Model-Co-ef [-121721.55990706  655932.64030426 -249919.8823818  -18760
2.71597435
   68214.49580173  156107.22185177  125530.49711011   69166.91275706
   21367.94806767   -8139.49732978  -37011.24562008  -48290.1479555
  -53026.14960449  -53683.77064736  -51943.80255891  -48896.47767207]
alpha 0.1
```



In [274]:
```
rmse_train_216_scikit_lasso = ridge_lasso_rmse(X_216_train, y_216_train,
best_model_216_scikit_lasso)
rmse_test_216_scikit_lasso = ridge_lasso_rmse(X_216_test,y_216_test,best
_model_216_scikit_lasso)
print("rmse_train",rmse_train_216_scikit_lasso)
print("rmse_test",rmse_test_216_scikit_lasso)
```

```
rmse_train 251063.94309086326
rmse_test 250161.4085909059
```

In [275]:
```
ridge_lasso_graph_plotter(X_216_train,y_216_train,best_model_216_scikit_
lasso,graph_label="λ = .1")
```



3-1. Fit the training data using regression model with ridge (L2 penalty) regularization with scikit-learn Ridge model.

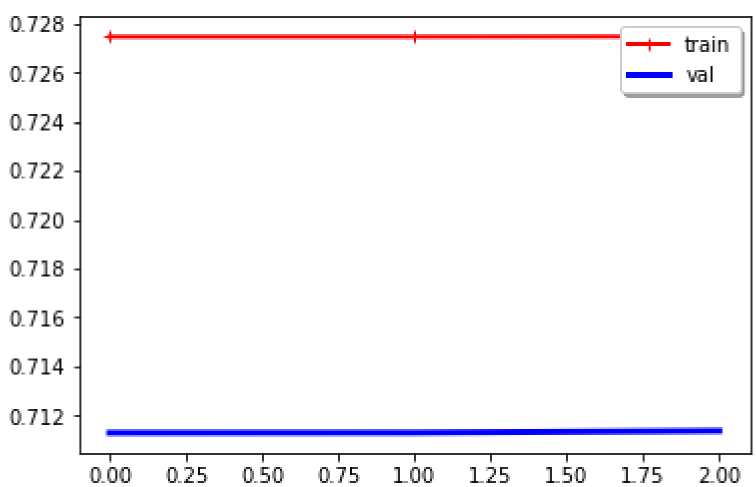
In [276]:
```
data3 = pd.read_csv("ex2data3.csv")
del data3['Unnamed: 0']
```

In [277]:
```
X_3 = data3.as_matrix(columns=data3.columns[0:8])
Y_3 = data3.as_matrix(columns=data3.columns[8:])
X_3_scaled = scaler.fit_transform(X_3)
X_3_scaled_coloumn_added = np.c_[np.ones((data3.shape[0], 1)), X_3_scale
d]
```

In [278]:
```
X_3_train_val, X_3_test, y_3_train_val, y_3_test = train_test_split(X_3_
scaled_coloumn_added, Y_3, test_size=0.2,random_state=1)
X_3_train, X_3_val, y_3_train, y_3_val = train_test_split(X_3_train_val,
 y_3_train_val, test_size=0.25,random_state=1)
```

In [279]:
```
best_model_3_scikit_ridge = train_val_best_model_scikit_ridge(X_3_train,
 X_3_val, y_3_train, y_3_val)
```

```
Model-Intercept [2.07192364]
Model-Co-ef [[ 0.82501033]
 [ 0.12438917]
 [-0.23245061]
 [ 0.2778601 ]
 [-0.00178963]
 [-0.03738571]
 [-0.9098153 ]
 [-0.88498937]]
Model-Intercept [2.07192619]
Model-Co-ef [[ 0.82499755]
 [ 0.12448827]
 [-0.23231252]
 [ 0.27766071]
 [-0.0017563 ]
 [-0.03738623]
 [-0.90885179]
 [-0.88401781]]
Model-Intercept [2.07195156]
Model-Co-ef [[ 0.82484941]
 [ 0.12546401]
 [-0.23091504]
 [ 0.27566139]
 [-0.00142815]
 [-0.03739063]
 [-0.89934824]
 [-0.87443278]]
alpha 0.1
```



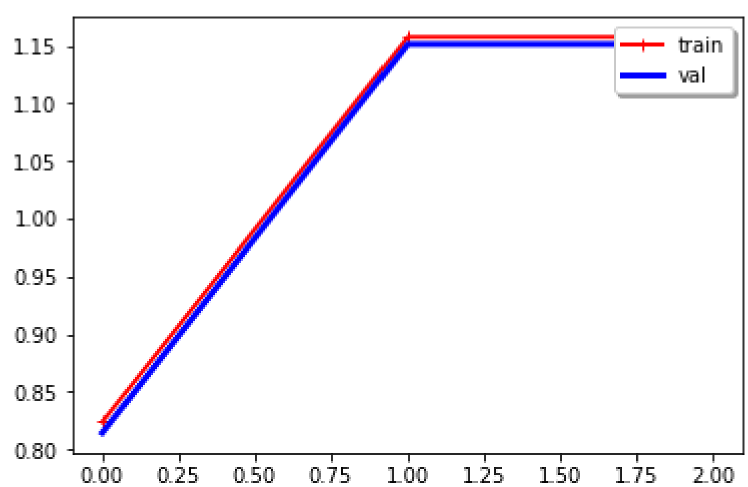
In [280]:
```
rmse_train_3_scikit_ridge = ridge_lasso_rmse(X_3_train, y_3_train,best_m
odel_3_scikit_ridge)
rmse_test_3_scikit_ridge = ridge_lasso_rmse(X_3_test,y_3_test,best_model
_3_scikit_ridge)
print("rmse_train",rmse_train_3_scikit_ridge)
print("rmse_test",rmse_test_3_scikit_ridge)
```

```
rmse_train 0.7274577804827311
rmse_test 0.7276608037847032
```

3-2. Fit the training data using regression model with lasso (L1 penalty) regularization with scikit-learn Lasso model.

In [281]:
```
best_model_3_scikit_lasso = train_val_best_model_scikit_lasso(X_3_train,
 X_3_val, y_3_train, y_3_val)
```

```
Model-Intercept [2.07432847]
Model-Co-ef [ 0.71386457  0.11001596 -0.          0.         -0.
  -0.
 -0.00645422 -0.        ]
Model-Intercept [2.07444727]
Model-Co-ef [ 0.  0.  0. -0. -0. -0. -0. -0.]
Model-Intercept [2.07444727]
Model-Co-ef [ 0.  0.  0. -0. -0. -0. -0. -0.]
alpha 0.1
```



In [282]:
```
rmse_train_3_scikit_lasso = ridge_lasso_rmse(X_3_train, y_3_train,best_m
odel_3_scikit_lasso)
rmse_test_3_scikit_lasso = ridge_lasso_rmse(X_3_test,y_3_test,best_model
_3_scikit_lasso)
print("rmse_train",rmse_train_3_scikit_lasso)
print("rmse_test",rmse_test_3_scikit_lasso)
```

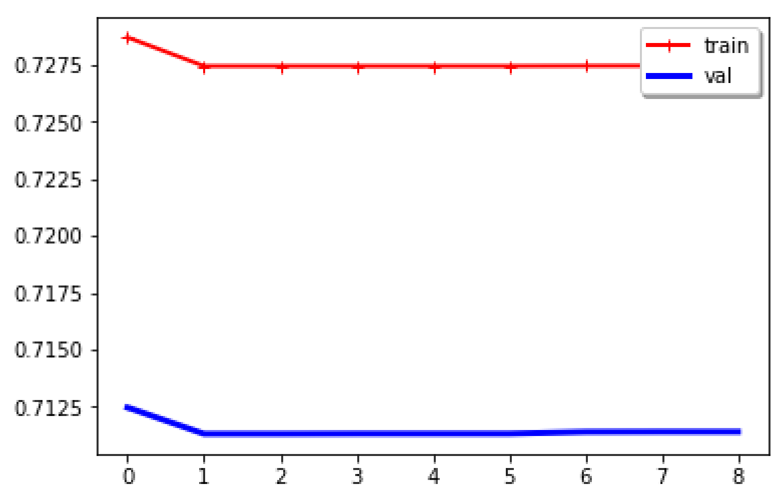
```
rmse_train 0.8239579515519808
rmse_test 0.8147268457966831
```

3-3. Fit the training data using regression model with ridge (L2 penalty) regularization using TensorFlow.

In [345]:
```
epochs_list = [10000]
alpha_list = [.1,1,10]
learning_rate_list = [.001,.01,.1]

#n_epochs = 10000
#learning_rate = 0.01
#alpha = 0.1

tf.reset_default_graph()

X_3 = tf.placeholder(tf.float64)
Y_3 = tf.placeholder(tf.float64)
theta = tf.Variable(tf.random_uniform([data3.shape[1], 1], -1.0, 1.0, dt
ype=tf.float64, name="theta"))
learning_rate = tf.placeholder(dtype=tf.float64)
alpha = tf.placeholder(dtype=tf.float64)
train_errors = []
val_errors = []
counter = 1
combination = {}


y_pred_3 = tf.matmul(X_3, theta, name="predictions")
error = y_pred_3 - Y_3
mse = tf.sqrt(tf.reduce_mean(tf.square(error), name="mse"))
gradients = 2/tf.shape(X_3)[0] * (tf.matmul(tf.transpose(X_3), error)+al
pha*theta)
training_op = tf.assign(theta, theta - learning_rate * gradients)

init = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init)
    for n_epochs in epochs_list:
        for alpha_value in alpha_list:
            for learning_rate_value in learning_rate_list:
                    for epoch in range(n_epochs):
                                sess.run(training_op,feed_dict={X_3: X_3
_train, Y_3: y_3_train, \
                                                                learning
_rate: learning_rate_value,alpha: alpha_value})
                    train_errors.append(sess.run(mse,feed_dict={X_3: X_3
_train, Y_3: y_3_train, \
                                                               learning_
rate: learning_rate_value,alpha: alpha_value}))
                    val_errors.append(sess.run(mse,feed_dict={X_3: X_3_v
al, Y_3: y_3_val, \
                                                             learning_ra
te: learning_rate_value,alpha: alpha_value}))
                    combination[counter] = (n_epochs,learning_rate_value
```

```
,alpha_value)
                    counter += 1
        ## Find the lowest validation error
    plt.plot(train_errors, "r-+", linewidth=2, label="train")
    plt.plot(val_errors, "b-", linewidth=3, label="val")
    legend = plt.legend(loc='upper right', shadow=True)
    counter_val_error = list(enumerate(val_errors, 1))
    counter_val_error_sorted = sorted(counter_val_error, key=lambda x:x[
1])
    best_model = combination[(counter_val_error_sorted[0][0])]
    print(counter_val_error)
    print("Epoch ,Learning Rate and alpha Combination",best_model)
    ##print train,test error
    print("train_error",sess.run(mse,feed_dict={X_3: X_3_train, Y_3: y_3
_train, \
                                                                learning_
rate: best_model[1],alpha: best_model[2]}))
    print("test_error",sess.run(mse,feed_dict={X_3: X_3_test, Y_3: y_3_t
est, \
                                                            learning_rate
: best_model[1],alpha: best_model[2]}))
```

```
[(1, 0.712454827014997), (2, 0.7112967432688554), (3, 0.711296818273914
8), (4, 0.7113039267849257), (5, 0.711304166648072), (6, 0.711304166488
7844), (7, 0.7113825753435046), (8, 0.7113889004585454), (9, 0.71138889
92949285)]
Epoch ,Learning Rate and alpha Combination (10000, 0.01, 0.1)
train_error 0.7274706274995454
test_error 0.7275337175750082

Exception ignored in: <generator object get_controller at 0x11bd75f10>
Traceback (most recent call last):
  File "/anaconda2/envs/carnd-term1/lib/python3.5/site-packages/tensorf
low/python/framework/ops.py", line 3523, in get_controller
    % type(default))
AssertionError: Nesting violated for default stack of <class 'tensorflo
w.python.framework.ops.Graph'> objects
```



3-4. Fit the training data using regression model with lasso (L1 penalty) regularization using TensorFlow.