step02-prudential-kaggle-160124

January 30, 2016

In [22]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from ml_metrics import quadratic_weighted_kappa
import xgboost as xgb
import datetime as dt
import sklearn
from sklearn.cross_validation import train_test_split
from sklearn.cross_validation import KFold
import functools
from sklearn.metrics import confusion_matrix
```

In [2]:
```
data = pd.read_csv('data_imputed.csv')
pd.options.display.max_columns = None
print(data['Response'].dtype)
data.head()
```

```
float64
```

Out[2]:

	BMI	Employment_Info_1	Employment_Info_2	Employment_Info_3	Employment_Info_4	Employment_Info_5	Employment_Info_6	Family_Hist_1	Family_Hist_2	Family_Hist_3	Family_Hist_4	Family_Hist_5	Ht	Id	Ins_Age	Insurance_History_1	Insurance_History_2	Insurance_History_3
0	0.323008	0.028	12	1	0	3	-1.0000	2	-1.000000	0.598039	-1.000000	0.526786	0.581818	2	0.641791	1	1	3
1	0.272288	0.000	1	3	0	2	0.0018	2	0.188406	-1.000000	0.084507	-1.000000	0.600000	5	0.059701	2	1	3
2	0.428780	0.030	9	1	0	2	0.0300	3	0.304348	-1.000000	0.225352	-1.000000	0.745455	6				
3	0.352438	0.042	9	1	0	3	0.2000	3	0.420290	-1.000000	0.352113	-1.000000	0.672727	7				
4	0.424046	0.027	9	1	0	2	0.0500	2	0.463768	-1.000000	0.408451	-1.000000	0.654545	8				

```
2  0.029851                   2                    1                    1
3  0.164179                   2                    1                    1
4  0.417910                   2                    1                    1

   Insurance_History_4  Insurance_History_5  Insurance_History_7  \
0                    1             0.000667                    1
1                    1             0.000133                    1
2                    3            -1.000000                    3
3                    3            -1.000000                    3
4                    3            -1.000000                    3

   Insurance_History_8  Insurance_History_9  InsuredInfo_1  InsuredInfo_2  \
0                    1                    2              1              2
1                    3                    2              1              2
2                    2                    3              1              2
3                    2                    3              2              2
4                    2                    3              1              2

   InsuredInfo_3  InsuredInfo_4  InsuredInfo_5  InsuredInfo_6  InsuredInfo_7  \
0              6              3              1              2              1
1              6              3              1              2              1
2              8              3              1              1              1
3              8              3              1              2              1
4              6              3              1              2              1

   Medical_History_1  Medical_History_10  Medical_History_11  \
0                  4                  -1                   3
1                  5                  -1                   3
2                 10                  -1                   3
3                  0                  -1                   3
4                 -1                  -1                   3

   Medical_History_12  Medical_History_13  Medical_History_14  \
0                   2                   3                   3
1                   2                   3                   3
2                   2                   3                   3
3                   2                   3                   3
4                   2                   3                   3

   Medical_History_15  Medical_History_16  Medical_History_17  \
0                 240                   3                   3
1                   0                   1                   3
2                  -1                   1                   3
3                  -1                   1                   3
4                  -1                   1                   3

   Medical_History_18  Medical_History_19  Medical_History_2  \
0                   1                   1                112
1                   1                   1                412
2                   1                   1                  3
3                   1                   1                350
4                   1                   1                162

   Medical_History_20  Medical_History_21  Medical_History_22  \
```

```
0                   2                   1                   2
1                   2                   1                   2
2                   2                   1                   2
3                   2                   2                   2
4                   2                   1                   2

   Medical_History_23  Medical_History_24  Medical_History_25  \
0                   3                  -1                   1
1                   3                  -1                   1
2                   3                  -1                   2
3                   3                  -1                   1
4                   3                  -1                   2

   Medical_History_26  Medical_History_27  Medical_History_28  \
0                   3                   3                   1
1                   3                   3                   1
2                   2                   3                   1
3                   3                   3                   1
4                   2                   3                   1

   Medical_History_29  Medical_History_3  Medical_History_30  \
0                   3                  2                   2
1                   3                  2                   2
2                   3                  2                   2
3                   3                  2                   2
4                   3                  2                   2

   Medical_History_31  Medical_History_32  Medical_History_33  \
0                   3                  -1                   1
1                   3                  -1                   3
2                   3                  -1                   3
3                   3                  -1                   3
4                   3                  -1                   3

   Medical_History_34  Medical_History_35  Medical_History_36  \
0                   3                   1                   2
1                   1                   1                   2
2                   3                   1                   3
3                   3                   1                   2
4                   3                   1                   3

   Medical_History_37  Medical_History_38  Medical_History_39  \
0                   2                   1                   3
1                   2                   1                   3
2                   2                   1                   3
3                   2                   1                   3
4                   2                   1                   3

   Medical_History_4  Medical_History_40  Medical_History_41  \
0                  1                   3                   3
1                  1                   3                   1
2                  2                   3                   1
3                  2                   3                   1
4                  2                   3                   1
```

	Medical_History_5	Medical_History_6	Medical_History_7	Medical_History_8	\
0	1	3	2	2	
1	1	3	2	2	
2	1	3	2	2	
3	1	3	2	2	
4	1	3	2	2	

	Medical_History_9	Medical_Keyword_1	Medical_Keyword_10	\
0	1	0	0	
1	1	0	0	
2	2	0	0	
3	2	0	0	
4	2	0	0	

	Medical_Keyword_11	Medical_Keyword_12	Medical_Keyword_13	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Medical_Keyword_14	Medical_Keyword_15	Medical_Keyword_16	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Medical_Keyword_17	Medical_Keyword_18	Medical_Keyword_19	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Medical_Keyword_2	Medical_Keyword_20	Medical_Keyword_21	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Medical_Keyword_22	Medical_Keyword_23	Medical_Keyword_24	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Medical_Keyword_25	Medical_Keyword_26	Medical_Keyword_27	\
0	0	0	0	
1	0	0	0	
2	0	0	0	

```
3                    0                    0                    0
4                    0                    0                    0

   Medical_Keyword_28  Medical_Keyword_29  Medical_Keyword_3  \
0                    0                    0                  0
1                    0                    0                  0
2                    0                    0                  0
3                    0                    0                  0
4                    0                    0                  0

   Medical_Keyword_30  Medical_Keyword_31  Medical_Keyword_32  \
0                    0                    0                   0
1                    0                    0                   0
2                    0                    0                   0
3                    0                    0                   1
4                    0                    0                   0

   Medical_Keyword_33  Medical_Keyword_34  Medical_Keyword_35  \
0                    0                    0                   0
1                    0                    0                   0
2                    0                    0                   0
3                    0                    0                   0
4                    0                    0                   0

   Medical_Keyword_36  Medical_Keyword_37  Medical_Keyword_38  \
0                    0                    0                   0
1                    0                    0                   0
2                    0                    0                   0
3                    0                    0                   0
4                    0                    0                   0

   Medical_Keyword_39  Medical_Keyword_4  Medical_Keyword_40  \
0                    0                  0                   0
1                    0                  0                   0
2                    0                  0                   0
3                    0                  0                   0
4                    0                  0                   0

   Medical_Keyword_41  Medical_Keyword_42  Medical_Keyword_43  \
0                    0                    0                   0
1                    0                    0                   0
2                    0                    0                   0
3                    0                    0                   0
4                    0                    0                   0

   Medical_Keyword_44  Medical_Keyword_45  Medical_Keyword_46  \
0                    0                    0                   0
1                    0                    0                   0
2                    0                    0                   0
3                    0                    0                   0
4                    0                    0                   0

   Medical_Keyword_47  Medical_Keyword_48  Medical_Keyword_5  \
0                    0                    0                  0
```

```
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_6  Medical_Keyword_7  Medical_Keyword_8  Medical_Keyword_9  \
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  0                  0
4                  0                  0                  0                  0

   Product_Info_1  Product_Info_3  Product_Info_4  Product_Info_5  \
0               1              10        0.076923               2
1               1              26        0.076923               2
2               1              26        0.076923               2
3               1              10        0.487179               2
4               1              26        0.230769               2

   Product_Info_6  Product_Info_7        Wt  A1  A2  A3  A4  A5  A6  A7  A8  \
0               1               1  0.148536   0   0   0   0   0   0   0   0
1               3               1  0.131799   1   0   0   0   0   0   0   0
2               3               1  0.288703   0   0   0   0   0   0   0   0
3               3               1  0.205021   0   0   0   0   0   0   0   0
4               3               1  0.234310   0   0   0   0   0   0   0   0

   B1  B2  C1  C2  C3  C4  D1  D2  D3  D4  E1  Response train?
0   0   0   0   0   0   0   0   0   1   0   0         8   True
1   0   0   0   0   0   0   0   0   0   0   0         4   True
2   0   0   0   0   0   0   0   0   0   0   1         8   True
3   0   0   0   0   0   0   0   0   0   1   0         8   True
4   0   0   0   0   0   0   0   1   0   0   0         8   True
```

In [3]:
```
train_features = data[data['train?'] == True].drop(['train?', 'Id', 'Response'], axis=1)
train_labels = data[data['train?'] == True]['Response'] -1

print(train_labels.value_counts().sort_index())
print()
print(len(train_labels.value_counts()))
print(len(train_features))
print(len(train_labels))
train_features.head()
```

```
0     6207
1     6552
2     1013
3     1428
4     5432
5    11233
6     8027
7    19489
Name: Response, dtype: int64

8
59381
```

59381

Out[3]:

	BMI	Employment_Info_1	Employment_Info_2	Employment_Info_3	\
0	0.323008	0.028	12	1	
1	0.272288	0.000	1	3	
2	0.428780	0.030	9	1	
3	0.352438	0.042	9	1	
4	0.424046	0.027	9	1	

	Employment_Info_4	Employment_Info_5	Employment_Info_6	Family_Hist_1	\
0	0	3	-1.0000	2	
1	0	2	0.0018	2	
2	0	2	0.0300	3	
3	0	3	0.2000	3	
4	0	2	0.0500	2	

	Family_Hist_2	Family_Hist_3	Family_Hist_4	Family_Hist_5	Ht	\
0	-1.000000	0.598039	-1.000000	0.526786	0.581818	
1	0.188406	-1.000000	0.084507	-1.000000	0.600000	
2	0.304348	-1.000000	0.225352	-1.000000	0.745455	
3	0.420290	-1.000000	0.352113	-1.000000	0.672727	
4	0.463768	-1.000000	0.408451	-1.000000	0.654545	

	Ins_Age	Insurance_History_1	Insurance_History_2	Insurance_History_3	\
0	0.641791	1	1	3	
1	0.059701	2	1	3	
2	0.029851	2	1	1	
3	0.164179	2	1	1	
4	0.417910	2	1	1	

	Insurance_History_4	Insurance_History_5	Insurance_History_7	\
0	1	0.000667	1	
1	1	0.000133	1	
2	3	-1.000000	3	
3	3	-1.000000	3	
4	3	-1.000000	3	

	Insurance_History_8	Insurance_History_9	InsuredInfo_1	InsuredInfo_2	\
0	1	2	1	2	
1	3	2	1	2	
2	2	3	1	2	
3	2	3	2	2	
4	2	3	1	2	

	InsuredInfo_3	InsuredInfo_4	InsuredInfo_5	InsuredInfo_6	InsuredInfo_7	\
0	6	3	1	2	1	
1	6	3	1	2	1	
2	8	3	1	1	1	
3	8	3	1	2	1	
4	6	3	1	2	1	

	Medical_History_1	Medical_History_10	Medical_History_11	\
0	4	-1	3	
1	5	-1	3	

```
2                 10                  -1                   3
3                  0                  -1                   3
4                 -1                  -1                   3

   Medical_History_12  Medical_History_13  Medical_History_14  \
0                   2                   3                   3
1                   2                   3                   3
2                   2                   3                   3
3                   2                   3                   3
4                   2                   3                   3

   Medical_History_15  Medical_History_16  Medical_History_17  \
0                 240                   3                   3
1                   0                   1                   3
2                  -1                   1                   3
3                  -1                   1                   3
4                  -1                   1                   3

   Medical_History_18  Medical_History_19  Medical_History_2  \
0                   1                   1                112
1                   1                   1                412
2                   1                   1                  3
3                   1                   1                350
4                   1                   1                162

   Medical_History_20  Medical_History_21  Medical_History_22  \
0                   2                   1                   2
1                   2                   1                   2
2                   2                   1                   2
3                   2                   2                   2
4                   2                   1                   2

   Medical_History_23  Medical_History_24  Medical_History_25  \
0                   3                  -1                   1
1                   3                  -1                   1
2                   3                  -1                   2
3                   3                  -1                   1
4                   3                  -1                   2

   Medical_History_26  Medical_History_27  Medical_History_28  \
0                   3                   3                   1
1                   3                   3                   1
2                   2                   3                   1
3                   3                   3                   1
4                   2                   3                   1

   Medical_History_29  Medical_History_3  Medical_History_30  \
0                   3                  2                   2
1                   3                  2                   2
2                   3                  2                   2
3                   3                  2                   2
4                   3                  2                   2

   Medical_History_31  Medical_History_32  Medical_History_33  \
```

```
0                   3                  -1                   1
1                   3                  -1                   3
2                   3                  -1                   3
3                   3                  -1                   3
4                   3                  -1                   3

   Medical_History_34  Medical_History_35  Medical_History_36  \
0                   3                   1                   2
1                   1                   1                   2
2                   3                   1                   3
3                   3                   1                   2
4                   3                   1                   3

   Medical_History_37  Medical_History_38  Medical_History_39  \
0                   2                   1                   3
1                   2                   1                   3
2                   2                   1                   3
3                   2                   1                   3
4                   2                   1                   3

   Medical_History_4  Medical_History_40  Medical_History_41  \
0                  1                   3                   3
1                  1                   3                   1
2                  2                   3                   1
3                  2                   3                   1
4                  2                   3                   1

   Medical_History_5  Medical_History_6  Medical_History_7  Medical_History_8  \
0                  1                  3                  2                  2
1                  1                  3                  2                  2
2                  1                  3                  2                  2
3                  1                  3                  2                  2
4                  1                  3                  2                  2

   Medical_History_9  Medical_Keyword_1  Medical_Keyword_10  \
0                  1                  0                   0
1                  1                  0                   0
2                  2                  0                   0
3                  2                  0                   0
4                  2                  0                   0

   Medical_Keyword_11  Medical_Keyword_12  Medical_Keyword_13  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_14  Medical_Keyword_15  Medical_Keyword_16  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0
```

```
   Medical_Keyword_17  Medical_Keyword_18  Medical_Keyword_19  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_2  Medical_Keyword_20  Medical_Keyword_21  \
0                  0                   0                   0
1                  0                   0                   0
2                  0                   0                   0
3                  0                   0                   0
4                  0                   0                   0

   Medical_Keyword_22  Medical_Keyword_23  Medical_Keyword_24  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_25  Medical_Keyword_26  Medical_Keyword_27  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_28  Medical_Keyword_29  Medical_Keyword_3  \
0                   0                   0                  0
1                   0                   0                  0
2                   0                   0                  0
3                   0                   0                  0
4                   0                   0                  0

   Medical_Keyword_30  Medical_Keyword_31  Medical_Keyword_32  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   1
4                   0                   0                   0

   Medical_Keyword_33  Medical_Keyword_34  Medical_Keyword_35  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_36  Medical_Keyword_37  Medical_Keyword_38  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
```

```
3                    0                    0                    0
4                    0                    0                    0

   Medical_Keyword_39  Medical_Keyword_4  Medical_Keyword_40  \
0                   0                  0                   0
1                   0                  0                   0
2                   0                  0                   0
3                   0                  0                   0
4                   0                  0                   0

   Medical_Keyword_41  Medical_Keyword_42  Medical_Keyword_43  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_44  Medical_Keyword_45  Medical_Keyword_46  \
0                   0                   0                   0
1                   0                   0                   0
2                   0                   0                   0
3                   0                   0                   0
4                   0                   0                   0

   Medical_Keyword_47  Medical_Keyword_48  Medical_Keyword_5  \
0                   0                   0                  0
1                   0                   0                  0
2                   0                   0                  0
3                   0                   0                  0
4                   0                   0                  0

   Medical_Keyword_6  Medical_Keyword_7  Medical_Keyword_8  Medical_Keyword_9  \
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  0                  0
4                  0                  0                  0                  0

   Product_Info_1  Product_Info_3  Product_Info_4  Product_Info_5  \
0               1              10        0.076923               2
1               1              26        0.076923               2
2               1              26        0.076923               2
3               1              10        0.487179               2
4               1              26        0.230769               2

   Product_Info_6  Product_Info_7        Wt  A1  A2  A3  A4  A5  A6  A7  A8  \
0               1               1  0.148536   0   0   0   0   0   0   0   0
1               3               1  0.131799   1   0   0   0   0   0   0   0
2               3               1  0.288703   0   0   0   0   0   0   0   0
3               3               1  0.205021   0   0   0   0   0   0   0   0
4               3               1  0.234310   0   0   0   0   0   0   0   0

   B1  B2  C1  C2  C3  C4  D1  D2  D3  D4  E1
0   0   0   0   0   0   0   0   0   1   0   0
```

```
1   0   0   0   0   0   0   0   0   0   0   0
2   0   0   0   0   0   0   0   0   0   0   1
3   0   0   0   0   0   0   0   0   0   1   0
4   0   0   0   0   0   0   0   1   0   0   0
```

1 Define functions to train a model with xgboost

```
In [72]: def xg_eval_pred(features, labels, test_features, test_labels, param, num_round):

             features = np.asarray(features)
             labels = np.asarray(labels)

             test_features = np.asarray(test_features)
             test_labels = np.asarray(test_labels)


             xg_train = xgb.DMatrix(features, labels)
             xg_test = xgb.DMatrix(test_features, test_labels)

             watchlist = [(xg_train,'train'), (xg_test, 'test')]
             bst = xgb.train(param, xg_train, num_round)

             train_prediction = bst.predict(xg_train)
             test_prediction = bst.predict(xg_test)

             return (bst,
                     quadratic_weighted_kappa(labels,np.array(train_prediction)),
                     quadratic_weighted_kappa(test_labels,np.array(test_prediction)), test_labels, test_


         def make_plot_eval(y, yhat, text, kappa_text):
             fig,ax = plt.subplots(1,2, figsize=(9., 4.))

             y = pd.Series(y)
             yhat = pd.Series(yhat)

             yhist = y.value_counts()
             yhathist = yhat.value_counts()

             ax[0].scatter(yhist.index, yhist.values, s=40, c='blue', alpha=0.5, label='response')
             ax[0].scatter(yhathist.index-0.1, yhathist.values, s=40, c='green', alpha=0.5, label='predi

             ax[0].legend(loc='upper left', prop={'size':10})
             ax[0].set_xlabel('classification')
             ax[0].set_ylabel('frequency')



             ax[0].text(0.99, 1.01, text, fontsize=9,
                     ha='right', va='bottom', transform=ax[0].transAxes)

             cm = confusion_matrix(y, yhat)
             print(cm)
```

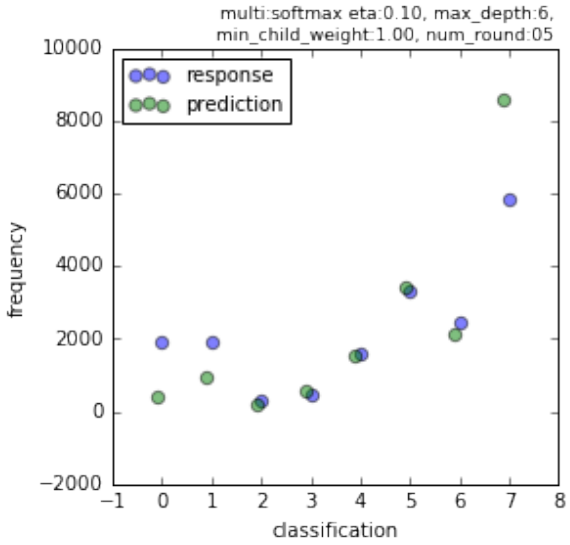
```
    im = ax[1].imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    ax[1].set_xlabel('true label')
    ax[1].set_ylabel('predicted label')
    plt.colorbar(im)

    ax[1].text(0.99, 1.01, kappa_text, fontsize=12,
            ha='right', va='bottom', transform=ax[1].transAxes)

    fname = 'plots/classification_' + text.replace(':', '').replace(', ', '_').replace(' ','')
    fig.savefig(fname, dpi=150)


def learning(data, eval_function, xgbparam, num_round, nsamples=[10000, 25000]):

    features = data[data['train?'] == True].drop(['train?', 'Id', 'Response'], axis=1)
    labels = data[data['train?'] == True]['Response'].astype('int') -1

    text = "{} eta:{:0.2f}, max_depth:{:d},\nmin_child_weight:{:0.2f}, num_round:{:02d}".forma
        xgbparam['objective'],
        xgbparam['eta'], xgbparam['max_depth'], xgbparam['min_child_weight'], num_round)

    # Xtest, ytest will be saved for evaluating over a constant sized set:
    Xtrain, Xtest, ytrain, ytest = train_test_split(features, labels, train_size=0.70, random_


    # The number of samples taken out of X for training will be varied
    nsamples.append(len(Xtrain))

    results = []
    for n in nsamples:
        print("Working on n = {:05d}  at {:%H:%M:%S}".format(n, dt.datetime.now()))
        if n < len(Xtrain):
            Xsample, _, ysample, _ = train_test_split(Xtrain, ytrain, test_size=n, random_stat
        else:
            Xsample, ysample = Xtrain, ytrain

        model, train_qwk, test_qwk, y, yhat = eval_function(Xsample, ysample, Xtest, ytest, xg
        results.append([n, train_qwk, test_qwk])

        print("num categories = {:d}".format(len(np.unique(yhat))))

        print("train_qwk: {:0.4f}, test_qwk: {:0.4f}".format(train_qwk, test_qwk))

        if n == len(Xtrain):
            kappa_text = '$\kappa_{{q,\mathrm{{train}}}} = {:0.4f}$, '.format(train_qwk) + \
            '$\kappa_{{q,\mathrm{{test}}}} = {:0.4f}$'.format(test_qwk)
            make_plot_eval(y, yhat, text, kappa_text)



    df = pd.DataFrame(results, columns=['num_samples', 'train_qwk', 'test_qwk'])
```

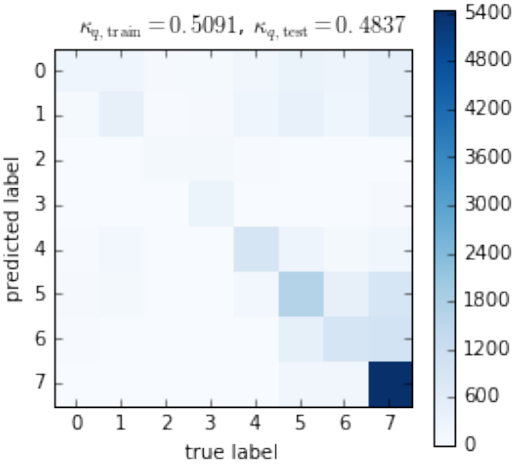
```
            if len(nsamples) > 1:
                make_plot_learning(df, text, num_round)

            return model, df


        def make_plot_learning(df, text, num_round):
            fig,ax = plt.subplots(1,1)

            ax.scatter(df['num_samples'], df['train_qwk'], s=40, c='blue', alpha=0.5, label='train set
            ax.scatter(df['num_samples'], df['test_qwk'], s=40, c='green', alpha=0.5, label='test set'

            ax.legend(loc='upper left', prop={'size':10})
            ax.set_xlabel('number of training samples')
            ax.set_ylabel('quadratic weighted kappa')


            ax.text(0.99, 1.01, text, fontsize=9,
                    ha='right', va='bottom', transform=ax.transAxes)

            fname = 'plots/learning_' + text.replace(':', '').replace(', ', '_').replace(' ','') + '.pn
            fig.savefig(fname, dpi=150)
```

In [62]:
```
data = pd.read_csv('data_imputed.csv')

# xgboost parameters:
param = {}

# use softmax multi-class classification
param['objective'] = 'multi:softmax'

# scale weight of positive examples
param['eta'] = 0.1
param['max_depth'] = 6
param['min_child_weight'] = 1

param['silent'] = 1
param['nthread'] = 1
param['num_class'] = len(pd.Series(data['Response']).value_counts())

print(param['num_class'])

results = []
for num_round in [5]:
    print("\n" + "-"*40)
    print("num boosting rounds = ", num_round)
    results.append(learning(data, xg_eval_pred, param, num_round, nsamples=[]))
```

```
8

----------------------------------------
num boosting rounds =  5
Working on n = 41566  at 13:13:09
num categories = 8
```

```
train_qwk: 0.5091, test_qwk: 0.4837
[[ 222  250   43   75  180  360  266  493]
 [  84  433   29   51  239  401  215  483]
 [   8    8  112  119   31   18    7   18]
 [   6    0   13  338    0   19   13   54]
 [  26  136    0    0  902  270   91  192]
 [  60   95    1    7  168 1677  426  864]
 [  23   11    0    0   15  468  934 1008]
 [   6    5    0    4   13  185  189 5451]]
```



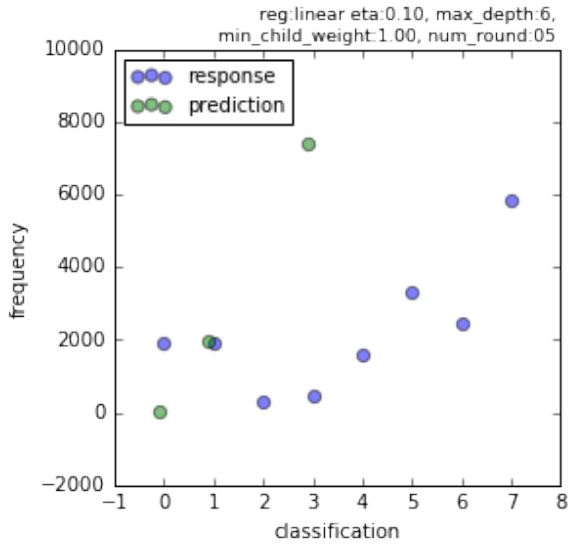


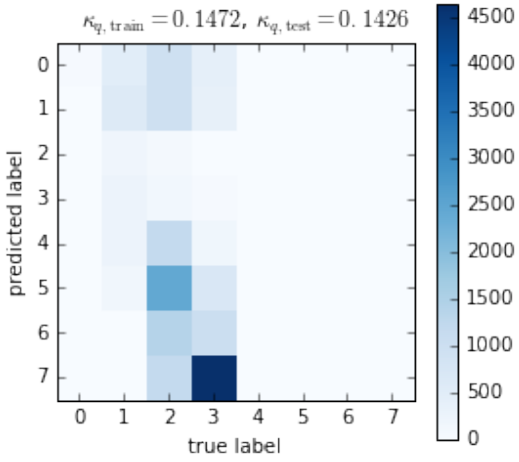
1.0.1 Define a function that will use a reg:linear objective (as opposed to the multi:softmax typically used for classification in xgboost

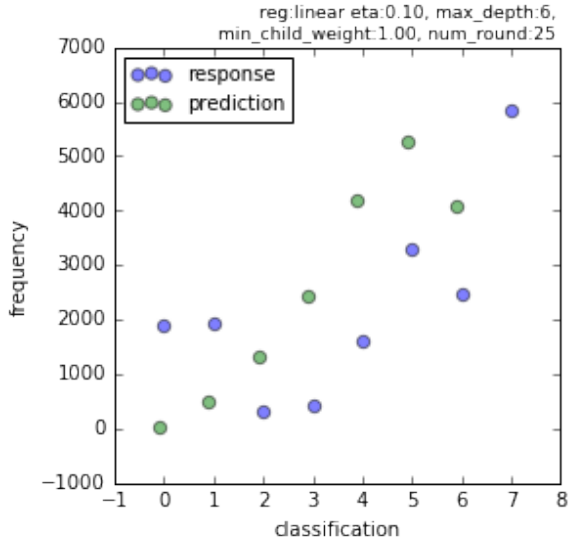
```
In [63]: def xg_eval_linear_pred(features, labels, test_features, test_labels, param, num_round, classi

             features = np.asarray(features)
             labels = np.asarray(labels)

             test_features = np.asarray(test_features)
             test_labels = np.asarray(test_labels)


             xg_train = xgb.DMatrix(features, labels)
             xg_test = xgb.DMatrix(test_features, test_labels)

             bst = xgb.train(param, xg_train, num_round)

             train_prediction = classify_function(bst.predict(xg_train))
             test_prediction = classify_function(bst.predict(xg_test))

             return (bst,
                     quadratic_weighted_kappa(labels,np.array(train_prediction)),
                     quadratic_weighted_kappa(test_labels,np.array(test_prediction)), test_labels, test
```

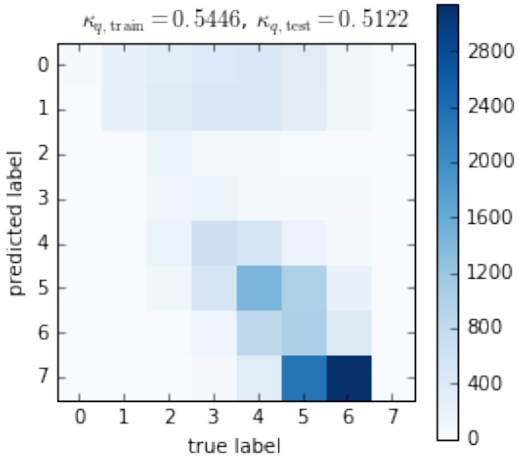
```
In [64]: data = pd.read_csv('data_imputed.csv')

         # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         # scale weight of positive examples
         param['eta'] = 0.1
         param['max_depth'] = 6
         param['min_child_weight'] = 1

         param['silent'] = 1
         param['nthread'] = 1


         def classify(score):
             return np.rint(np.clip(score, -0.49, 7.49))

         evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

         results = []
         for num_round in [5, 25, 125]:
             print("\n" + "-"*40)
             print("num boosting rounds = ", num_round)
             results.append(learning(data, evalfun, param, num_round, nsamples=[]))

----------------------------------------
num boosting rounds =  5
Working on n = 41566  at 13:13:48
num categories = 4
train_qwk: 0.1472, test_qwk: 0.1426
[[  40  497  948  404    0    0    0    0]
 [  10  610  946  369    0    0    0    0]
 [   1  195  108   17    0    0    0    0]
 [   2  256  138   47    0    0    0    0]
 [   0  255 1190  172    0    0    0    0]
 [   0  154 2449  695    0    0    0    0]
 [   0   18 1401 1040    0    0    0    0]
 [   0    3 1194 4656    0    0    0    0]]

----------------------------------------
num boosting rounds =  25
Working on n = 41566  at 13:13:50
num categories = 7
train_qwk: 0.5446, test_qwk: 0.5122
[[  25  215  338  425  436  345  105    0]
 [   3  227  372  452  457  325   99    0]
 [   1   20  169   72   37   13    9    0]
 [   0    6  136  167   68   39   27    0]
 [   0   20  187  665  518  180   47    0]
 [   0   12  111  494 1459 1011  211    0]
 [   0    1   14  151  847 1030  416    0]
```

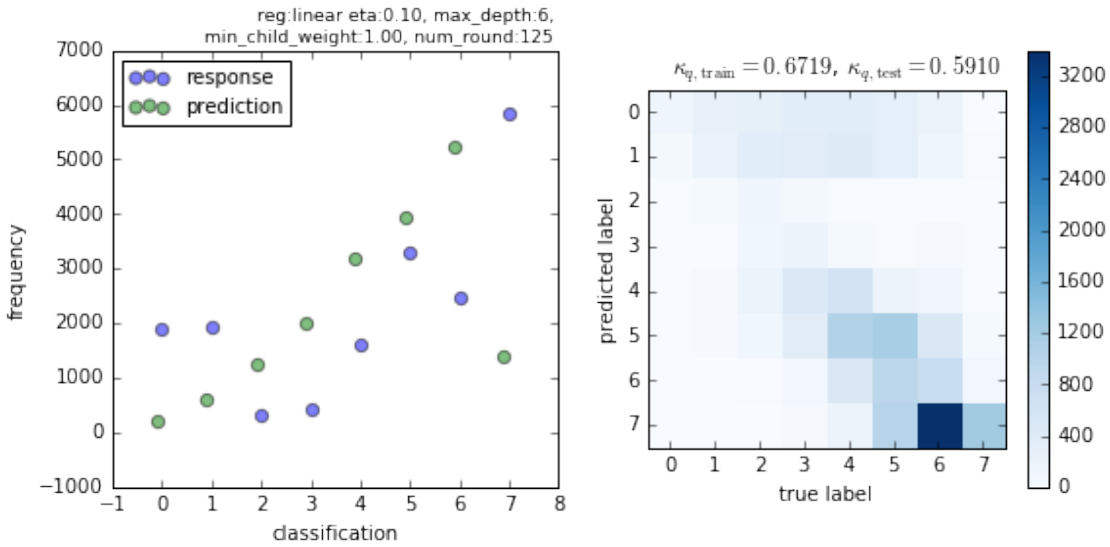
```
 [   0    0    0   25  358 2319 3151    0]]

----------------------------------------
num boosting rounds =  125
Working on n = 41566  at 13:13:55
num categories = 8
train_qwk: 0.6719, test_qwk: 0.5910
[[ 133  246  285  359  370  305  178   13]
 [  63  230  368  385  414  301  159   15]
 [   8   45  139   77   25   14   12    1]
 [   2   13  123  181   53   26   38    7]
 [   5   30  184  470  614  192  116    6]
 [   4   29  125  383 1054 1173  488   42]
 [   0    5   20  102  488  944  820   80]
 [   1    0    4   33  186  997 3402 1230]]
```











The reg:linear objective is better for this problem, since the evaluation metric is the quadratic weighted kappa, which takes into account the relative distance between categories. From now on we will stick to the reg:linear objective.

1.0.2 Tuning:

If model has high variance (large diff in test-train at full dataset):

- decrease eta
- decrease max depth
- increase min child weight

If model has high bias (small diff in test-train at full dataset):

- increase eta
- increase max depth
- decrease min child weight

2 Try to tune parameters by hand

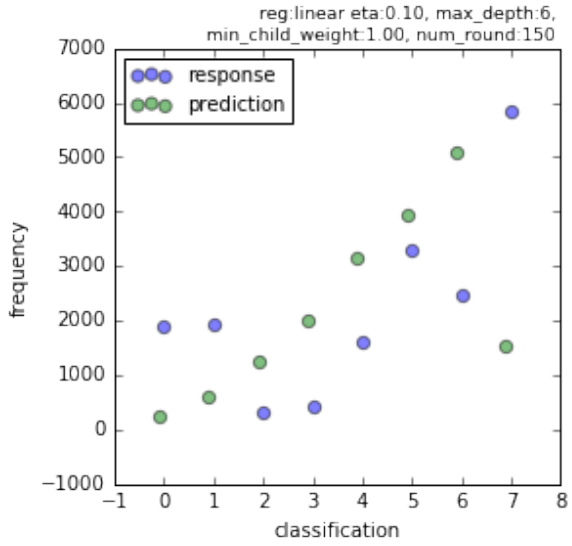
Increase min child weight by two orders of magnitude:

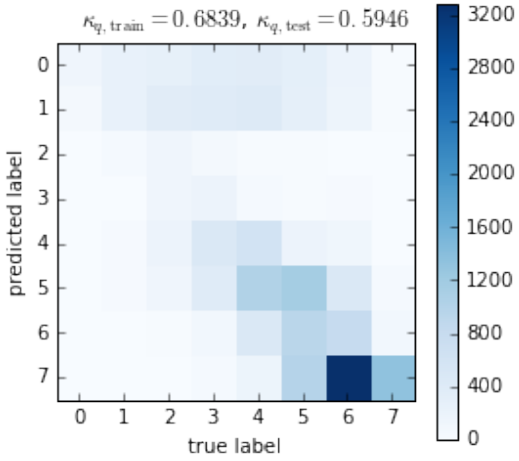
```
In [65]: # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         # scale weight of positive examples
         param['eta'] = 0.1
         param['max_depth'] = 6
```

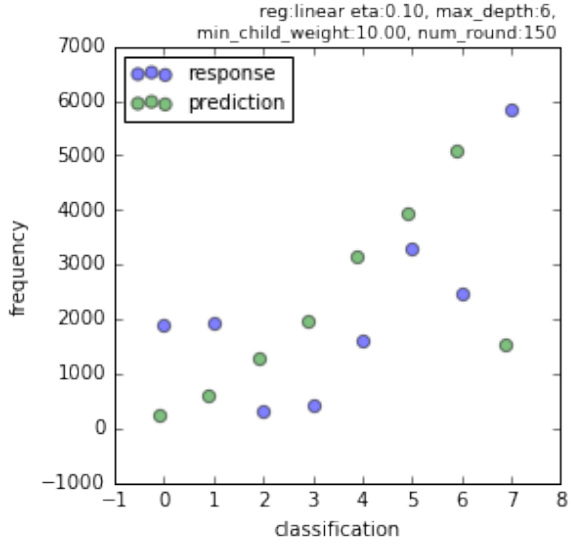
```
    param['min_child_weight'] = 1

    param['silent'] = 1
    param['nthread'] = 1


    def classify(score):
        return np.rint(np.clip(score, -0.49, 7.49))

    evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

    results = []
    num_round = 150

    for val in [1, 10, 100]:
        param['min_child_weight'] = val
        print("\n" + "-"*40)
        print("min_child_weight = {}".format(val))
        results.append(learning(data, evalfun, param, num_round, nsamples=[]))
```

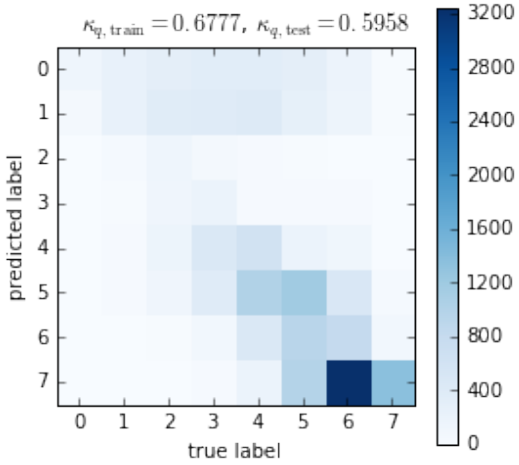
```
----------------------------------------
min_child_weight = 1
Working on n = 41566  at 13:20:48
num categories = 8
train_qwk: 0.6839, test_qwk: 0.5946
[[ 141  254  281  351  361  305  181   15]
 [  66  236  369  386  412  292  156   18]
 [  11   48  139   76   20   15   11    1]
 [   3   11  136  183   40   25   38    7]
 [   6   33  184  473  611  185  119    6]
 [   4   32  130  388 1039 1169  487   49]
 [   0    5   24  100  473  942  815  100]
 [   1    0    5   39  179  999 3291 1339]]

----------------------------------------
min_child_weight = 10
Working on n = 41566  at 13:21:12
num categories = 8
train_qwk: 0.6777, test_qwk: 0.5958
[[ 141  243  306  343  350  305  186   15]
 [  69  229  375  389  420  279  156   18]
 [  10   47  141   69   27   15   11    1]
 [   3   13  129  191   37   26   36    8]
 [   5   34  173  459  632  191  118    5]
 [   5   29  133  389 1018 1187  495   42]
 [   0    5   24   93  476  951  817   93]
 [   0    2    3   31  199 1000 3251 1367]]

----------------------------------------
min_child_weight = 100
Working on n = 41566  at 13:21:38
num categories = 8
train_qwk: 0.6486, test_qwk: 0.5965
[[ 148  232  306  349  351  305  184   14]
```

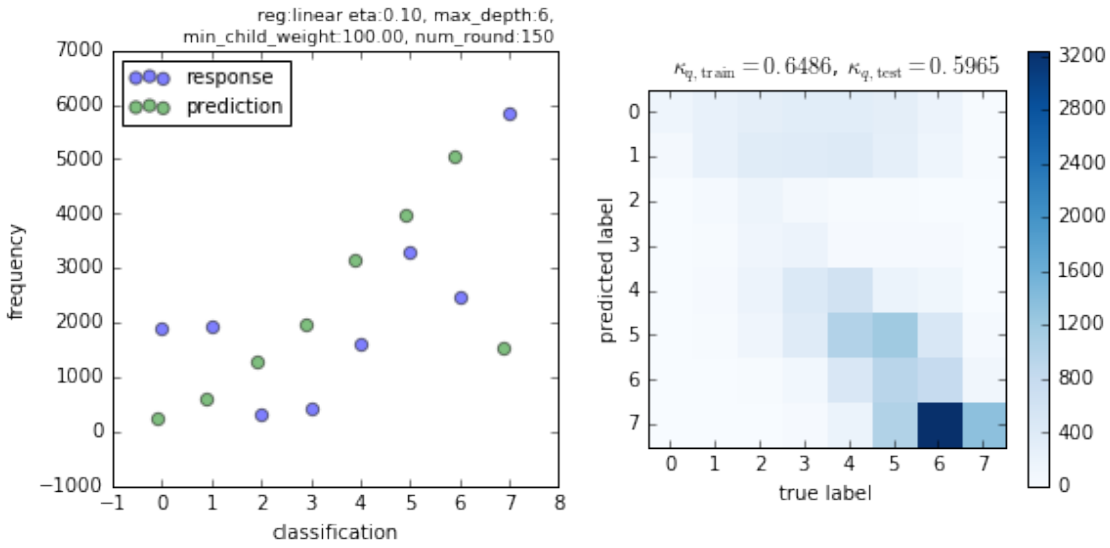
```
[  67  237  369  387  417  287  152   19]
[  10   47  153   62   22   15   10    2]
[   1   15  137  187   33   27   35    8]
[   4   35  180  455  629  193  115    6]
[   5   25  135  389 1009 1197  495   43]
[   0    5   17  101  484  939  807  106]
[   0    0    4   31  202 1015 3245 1356]]
```









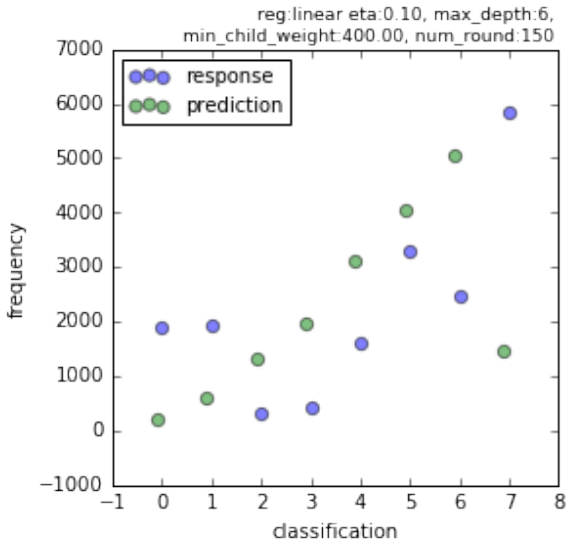


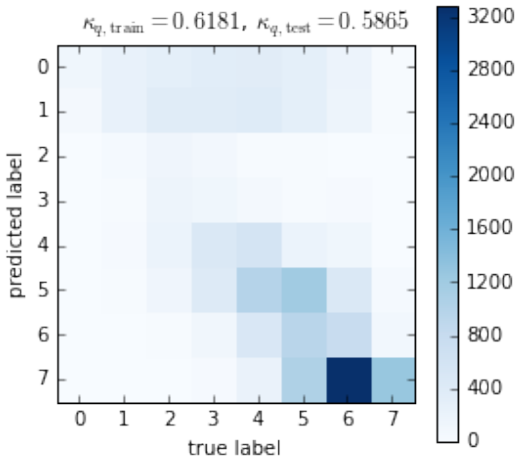
Variance is getting better, so try even larger values of min_child_weight

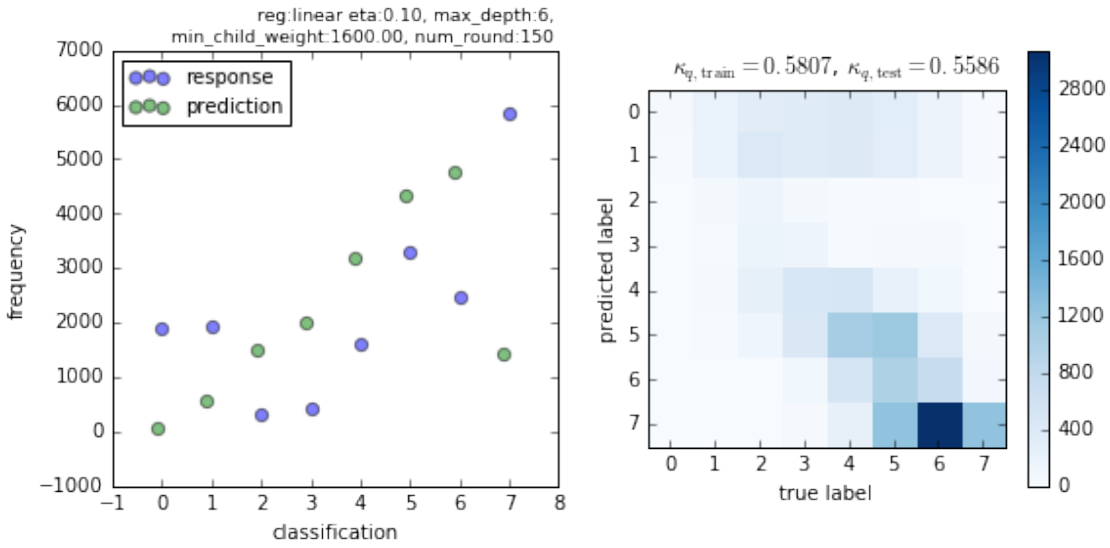
In [66]:
```
# xgboost parameters:
param = {}

# use softmax multi-class classification
param['objective'] = 'reg:linear'

# scale weight of positive examples
param['eta'] = 0.1
param['max_depth'] = 6
param['min_child_weight'] = 1

param['silent'] = 1
param['nthread'] = 1


def classify(score):
    return np.rint(np.clip(score, -0.49, 7.49))

evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

results = []
num_round = 150

for val in [400, 1600]:
    param['min_child_weight'] = val
    print("\n" + "-"*40)
    print("min_child_weight = {}".format(val))
    results.append(learning(data, evalfun, param, num_round, nsamples=[]))
```

```
----------------------------------------
min_child_weight = 400
Working on n = 41566  at 13:23:50
```

```
num categories = 8
train_qwk: 0.6181, test_qwk: 0.5865
[[ 118  247  303  357  360  303  183   18]
 [  61  238  373  376  402  297  166   22]
 [   7   44  132   87   25   15    9    2]
 [   3   19  163  127   62   24   36    9]
 [   4   33  205  474  577  201  117    6]
 [   3   24  135  416 1002 1200  475   43]
 [   0    1   19  105  494  953  792   95]
 [   0    0    2   28  206 1056 3289 1272]]

----------------------------------------
min_child_weight = 1600
Working on n = 41566  at 13:24:14
num categories = 8
train_qwk: 0.5807, test_qwk: 0.5586
[[  48  210  344  366  387  332  180   22]
 [  21  205  423  364  399  325  174   24]
 [   4   68  146   59   21   14    7    2]
 [   0   19  188  147   20   26   38    5]
 [   0   38  253  470  496  239  118    3]
 [   0   15  133  435 1078 1162  426   49]
 [   0    1    8  115  527  988  726   94]
 [   0    0    1   31  252 1242 3083 1244]]
```





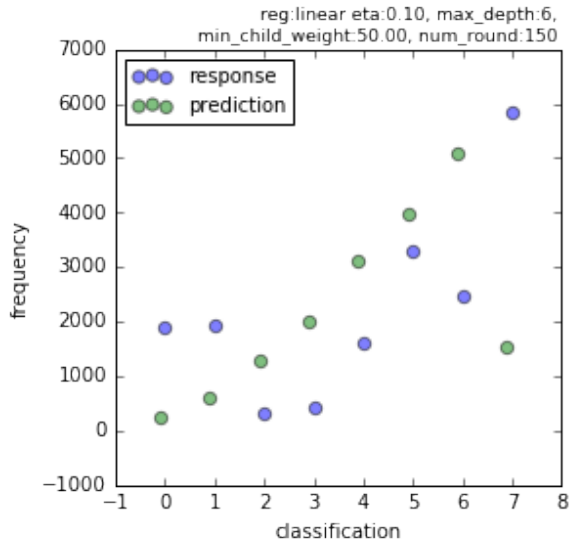


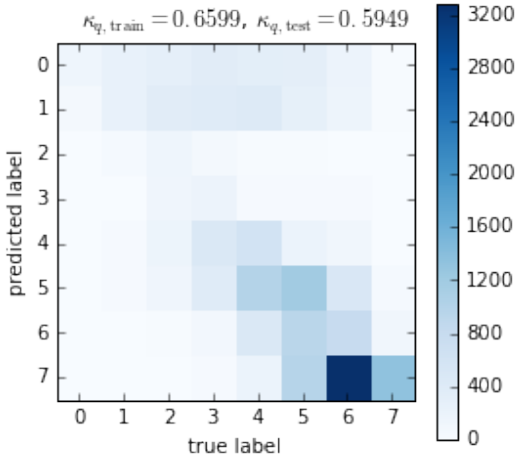
In going from 100 to 400 for min_child weight, the model started loosing some predictive power. Will fill in the blanks around that neighborhood:

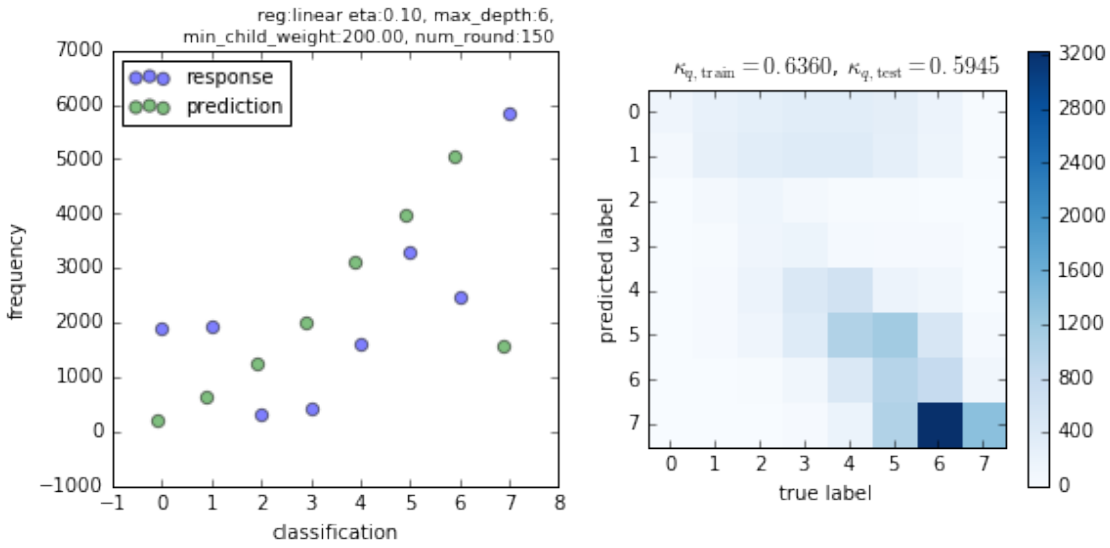
```
In [67]: # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         # scale weight of positive examples
         param['eta'] = 0.1
         param['max_depth'] = 6
         param['min_child_weight'] = 1

         param['silent'] = 1
         param['nthread'] = 1


         def classify(score):
             return np.rint(np.clip(score, -0.49, 7.49))

         evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

         results = []
         num_round = 150

         for val in [50, 200]:
             param['min_child_weight'] = val
             print("\n" + "-"*40)
             print("min_child_weight = {}".format(val))
             results.append(learning(data, evalfun, param, num_round, nsamples=[]))
```

```
----------------------------------------
min_child_weight = 50
```

```
Working on n = 41566  at 13:26:13
num categories = 8
train_qwk: 0.6599, test_qwk: 0.5949
[[ 143  244  287  368  331  313  186   17]
 [  67  233  369  388  428  275  155   20]
 [  11   46  147   68   22   14   11    2]
 [   3   10  135  189   36   27   35    8]
 [   4   37  178  476  605  201  110    6]
 [   5   27  131  390 1012 1194  490   49]
 [   0    6   20   89  481  951  803  109]
 [   0    0    7   32  201  983 3290 1340]]

----------------------------------------
min_child_weight = 200
Working on n = 41566  at 13:26:38
num categories = 8
train_qwk: 0.6360, test_qwk: 0.5945
[[ 138  244  293  352  353  305  187   17]
 [  63  255  348  404  402  290  152   21]
 [   9   55  141   67   22   15   10    2]
 [   2   16  139  173   44   26   34    9]
 [   3   35  185  476  616  187  110    5]
 [   4   26  130  392 1018 1172  507   49]
 [   0    1   16  111  460  963  806  102]
 [   0    0    3   35  201 1023 3237 1354]]
```







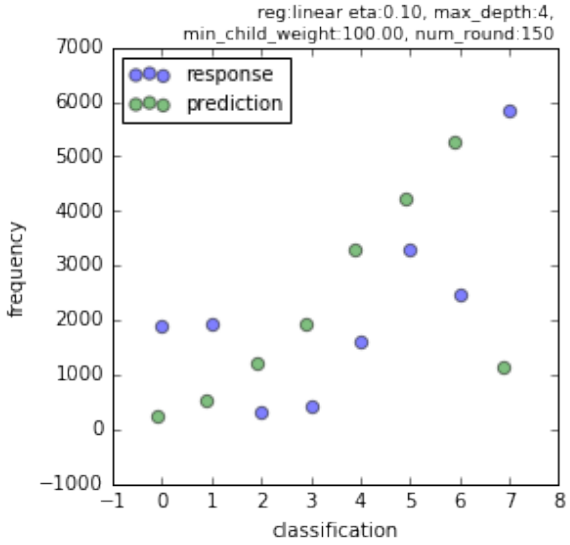
The value of min_child_weight that maximizes kappa for the test set is 100. Will now experiment with max_depth

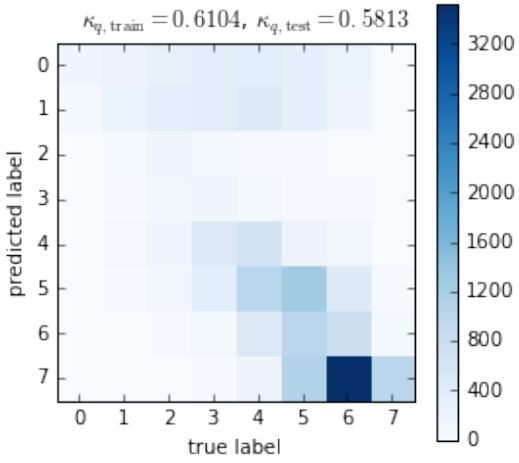
```
In [68]: # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         # scale weight of positive examples
         param['eta'] = 0.1
         param['min_child_weight'] = 100

         param['silent'] = 1
         param['nthread'] = 1


         def classify(score):
             return np.rint(np.clip(score, -0.49, 7.49))

         evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

         results = []
         num_round = 150

         for val in [4, 6, 8, 10, 12]:
             name = 'max_depth'
             param[name] = val
             print("\n" + "-"*40)
             print("{} = {}".format(name, val))
             results.append(learning(data, evalfun, param, num_round, nsamples=[]))
```

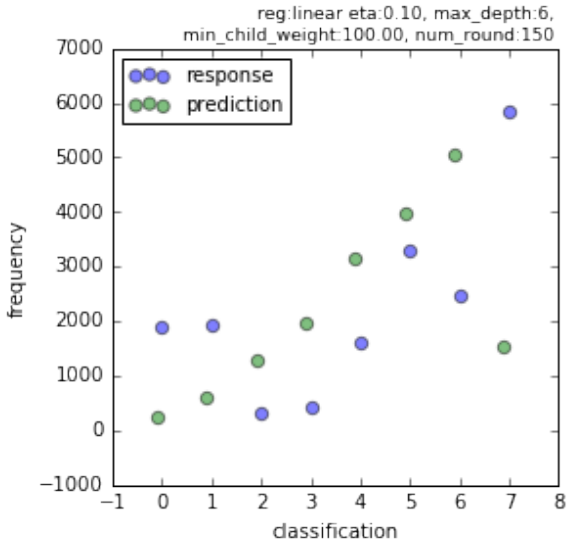
```
----------------------------------------
max_depth = 4
```

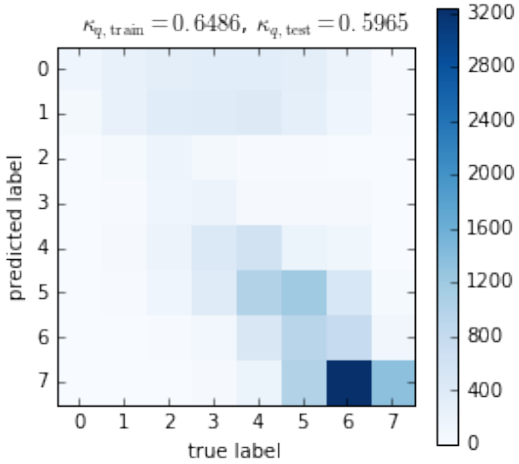
```
Working on n = 41566  at 13:30:28
num categories = 8
train_qwk: 0.6104, test_qwk: 0.5813
[[ 147  197  299  360  375  313  189    9]
 [  69  208  346  391  447  304  158   12]
 [  11   46  140   63   33   16   10    2]
 [   2   15  122  163   71   27   36    7]
 [   3   33  163  464  643  194  113    4]
 [   5   25  122  374 1008 1271  461   32]
 [   0    2   14   83  506 1004  786   64]
 [   0    0    2   24  198 1093 3528 1008]]

----------------------------------------
max_depth = 6
Working on n = 41566  at 13:30:46
num categories = 8
train_qwk: 0.6486, test_qwk: 0.5965
[[ 148  232  306  349  351  305  184   14]
 [  67  237  369  387  417  287  152   19]
 [  10   47  153   62   22   15   10    2]
 [   1   15  137  187   33   27   35    8]
 [   4   35  180  455  629  193  115    6]
 [   5   25  135  389 1009 1197  495   43]
 [   0    5   17  101  484  939  807  106]
 [   0    0    4   31  202 1015 3245 1356]]

----------------------------------------
max_depth = 8
Working on n = 41566  at 13:31:11
num categories = 8
train_qwk: 0.6826, test_qwk: 0.6000
[[ 145  244  321  338  354  282  185   20]
 [  60  253  358  420  379  279  164   22]
 [   5   51  145   79   14   16    9    2]
 [   2   14  161  173   24   24   34   11]
 [   1   40  187  496  585  185  115    8]
 [   3   27  162  374 1002 1178  492   60]
 [   0    8   21  113  471  903  805  138]
 [   0    0    7   35  212  958 3096 1545]]

----------------------------------------
max_depth = 10
Working on n = 41566  at 13:31:44
num categories = 8
train_qwk: 0.7080, test_qwk: 0.6040
[[ 139  267  315  347  336  280  177   28]
 [  60  257  374  402  389  277  149   27]
 [   8   56  143   71   17   16    8    2]
 [   2   16  168  173   14   22   35   13]
 [   2   40  202  481  574  194  111   13]
 [   2   30  154  403  966 1185  491   67]
 [   0    6   24  125  446  893  813  152]
 [   0    0    8   48  222  930 2940 1705]]
```

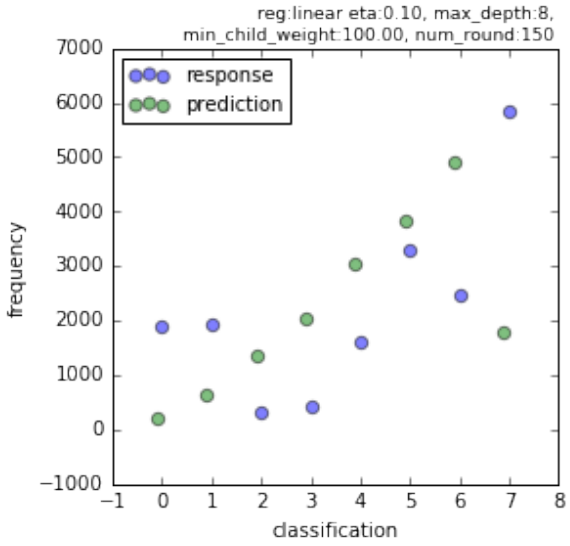
```
----------------------------------------
max_depth = 12
Working on n = 41566  at 13:32:26
num categories = 8
train_qwk: 0.7303, test_qwk: 0.6040
[[ 120  293  310  336  347  272  182   29]
 [  65  252  387  416  371  261  151   32]
 [   6   64  149   57   20   13   10    2]
 [   2   21  177  161   16   22   33   11]
 [   1   34  207  497  556  200  110   12]
 [   1   35  161  404  950 1179  493   75]
 [   0    7   26  126  445  891  795  169]
 [   0    0    5   45  259  925 2848 1771]]
```

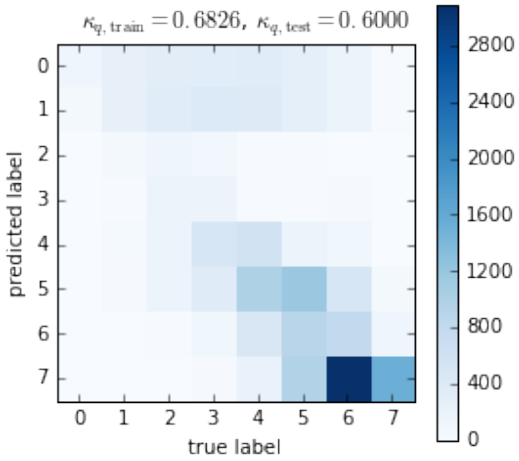


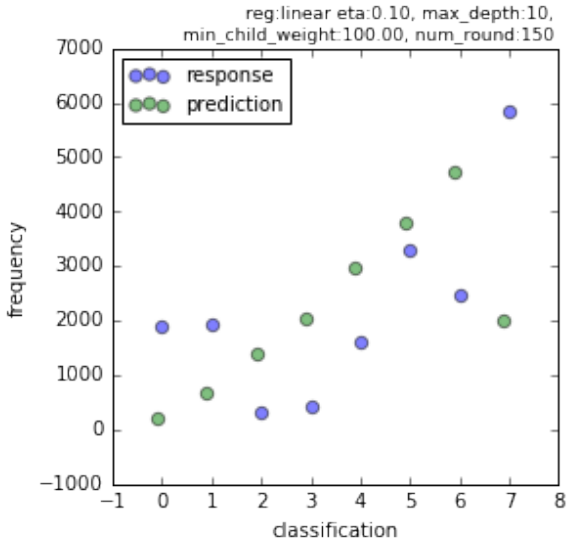


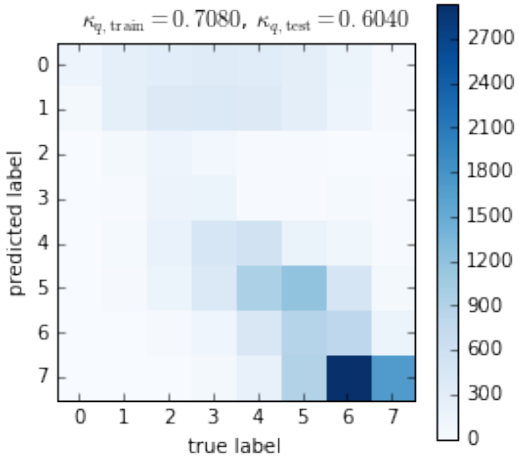


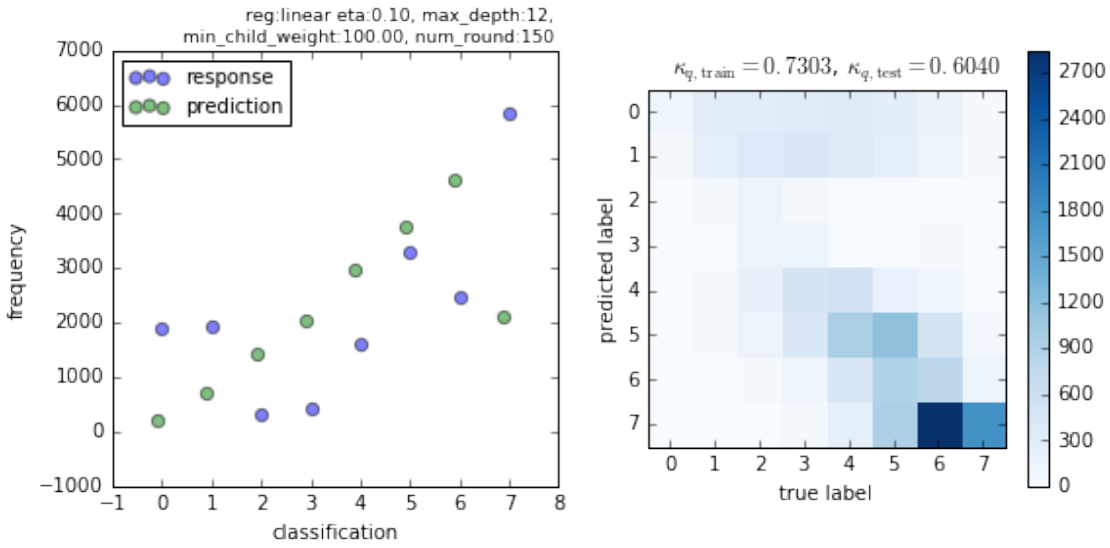



reg:linear eta:0.10, max_depth:8,
min_child_weight:100.00, num_round:150
response
prediction
frequency
classification


$\kappa_{q,\,\mathrm{train}} = 0.6826,\ \kappa_{q,\,\mathrm{test}} = 0.6000$
predicted label
true label


reg:linear eta:0.10, max_depth:10,
min_child_weight:100.00, num_round:150
response
prediction
frequency
classification


$\kappa_{q,\,\mathrm{train}} = 0.7080,\ \kappa_{q,\,\mathrm{test}} = 0.6040$
predicted label
true label

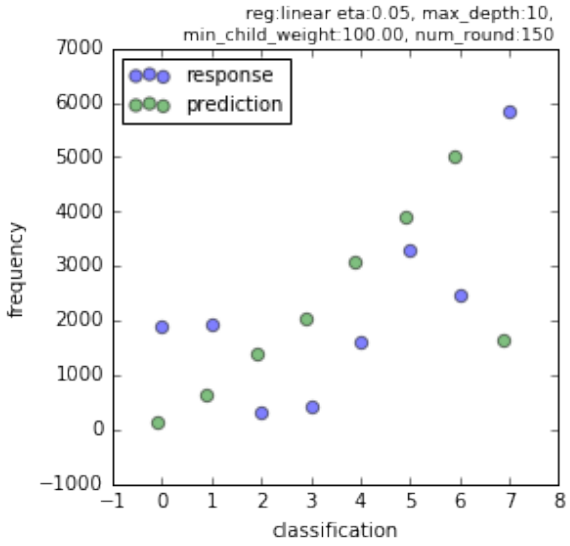


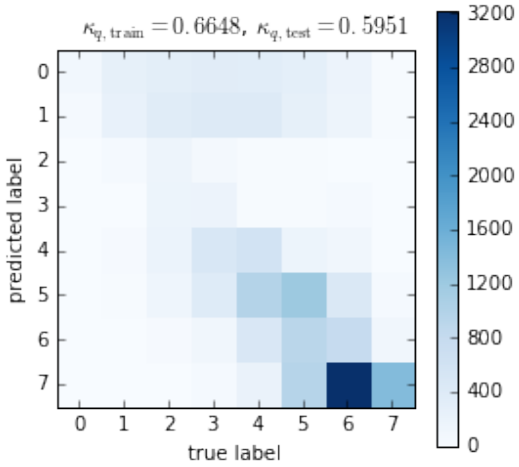
At a max_depth of 10, I will now vary eta:

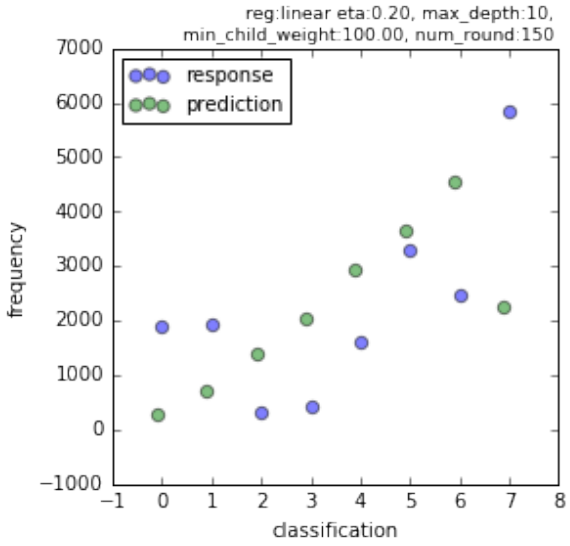
```
In [69]: # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         param['max_depth'] = 10
         param['min_child_weight'] = 100

         param['silent'] = 1
         param['nthread'] = 1


         def classify(score):
             return np.rint(np.clip(score, -0.49, 7.49))

         evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

         results = []
         num_round = 150

         for val in [0.05, 0.2, 0.4]:
             name = 'eta'
             param[name] = val
             print("\n" + "-"*40)
             print("{} = {}".format(name, val))
             results.append(learning(data, evalfun, param, num_round, nsamples=[]))
```

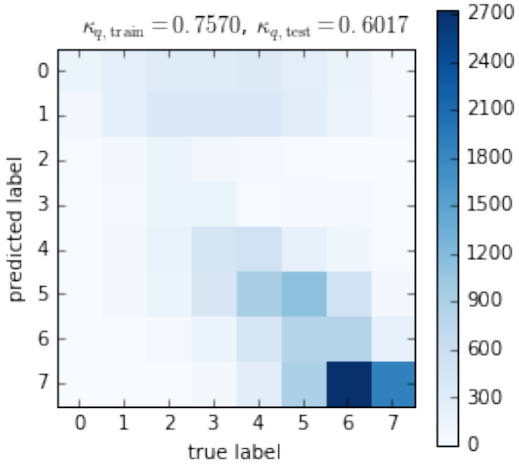
```
----------------------------------------
eta = 0.05
Working on n = 41566  at 13:35:21
num categories = 8
```

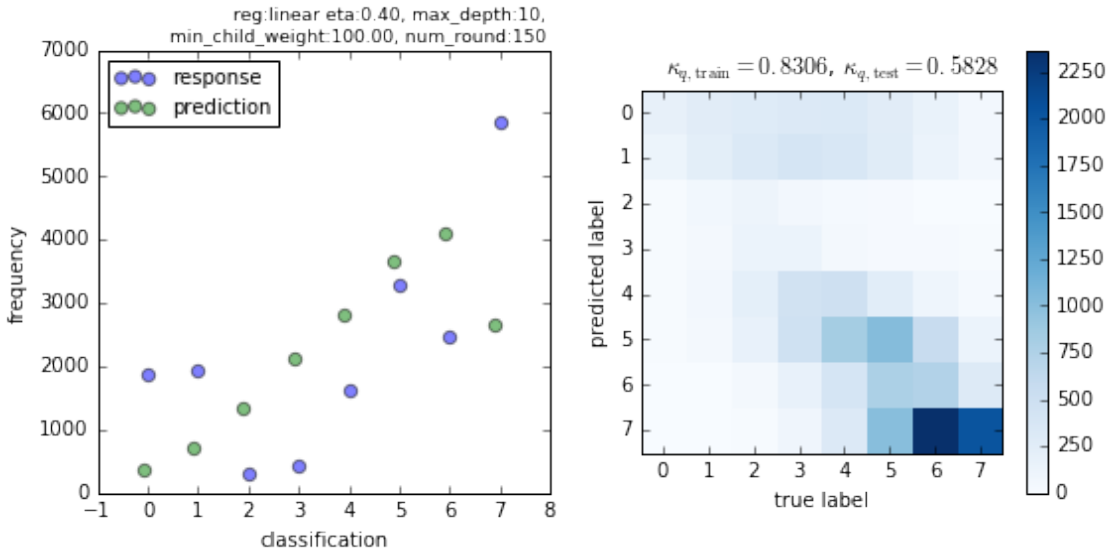
```
train_qwk: 0.6648, test_qwk: 0.5951
[[  89  272  325  358  352  296  177   20]
 [  41  247  377  405  410  275  160   20]
 [   3   45  162   67   18   15    9    2]
 [   1    9  173  178   13   21   39    9]
 [   0   35  194  498  595  174  113    8]
 [   1   23  147  399  990 1219  472   47]
 [   0    0   27  107  488  929  802  106]
 [   0    0    4   39  204  961 3226 1419]]

----------------------------------------
eta = 0.2
Working on n = 41566  at 13:36:04
num categories = 8
train_qwk: 0.7570, test_qwk: 0.6017
[[ 160  256  329  320  342  272  180   30]
 [  84  248  378  383  376  280  153   33]
 [  11   57  144   60   24   15    8    2]
 [   4   28  161  164   19   22   33   12]
 [   5   59  189  490  540  216  100   18]
 [   3   43  170  414  924 1137  523   84]
 [   0    6   32  139  429  820  835  198]
 [   0    2    9   55  282  904 2730 1871]]

----------------------------------------
eta = 0.4
Working on n = 41566  at 13:36:46
num categories = 8
train_qwk: 0.8306, test_qwk: 0.5828
[[ 191  266  294  320  325  265  164   64]
 [ 129  234  330  406  361  269  147   59]
 [  17   67  117   60   31   20    7    2]
 [  11   37  147  142   41   21   27   17]
 [  11   59  220  444  491  254  107   31]
 [  16   46  184  477  840 1029  562  144]
 [   5    7   52  183  401  781  732  298]
 [   0    4   12   95  323 1013 2366 2040]]
```


reg:linear eta:0.05, max_depth:10,
min_child_weight:100.00, num_round:150
response
prediction
frequency
classification


$\kappa_{q,\,\mathrm{train}} = 0.6648,\ \kappa_{q,\,\mathrm{test}} = 0.5951$
predicted label
true label


reg:linear eta:0.20, max_depth:10,
min_child_weight:100.00, num_round:150
response
prediction
frequency
classification


$\kappa_{q,\,\mathrm{train}} = 0.7570,\ \kappa_{q,\,\mathrm{test}} = 0.6017$
predicted label
true label

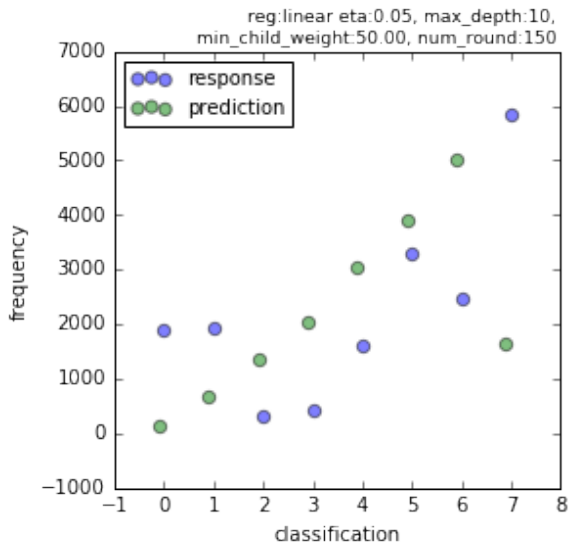


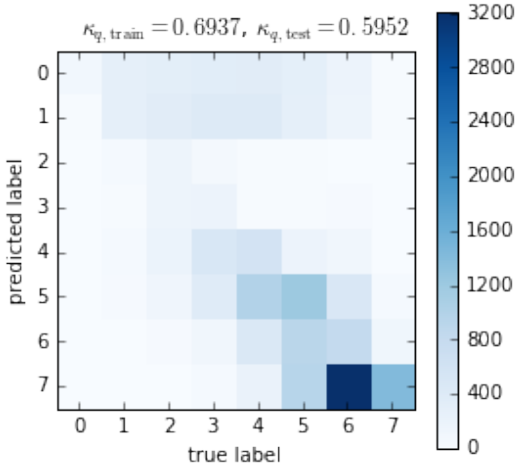
Let's keep a small eta and decrease the min child weight:

```
In [70]: # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         param['eta'] = 0.05
         param['max_depth'] = 10
         param['min_child_weight'] = 50

         param['silent'] = 1
         param['nthread'] = 1


         def classify(score):
             return np.rint(np.clip(score, -0.49, 7.49))

         evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

         results = []
         num_round = 150

         results.append(learning(data, evalfun, param, num_round, nsamples=[]))
```

```
Working on n = 41566  at 13:40:34
num categories = 8
train_qwk: 0.6937, test_qwk: 0.5952
[[  94  282  317  348  353  295  181   19]
 [  25  281  357  409  406  278  160   19]
 [   4   43  153   74   20   14   11    2]
 [   2   14  154  187   17   24   35   10]
 [   0   40  195  491  589  183  112    7]
```

```
[   2   29  136  388  995 1216  483   49]
[   0    3   26  101  469  927  819  114]
[   0    0    5   47  210  949 3216 1426]]
```

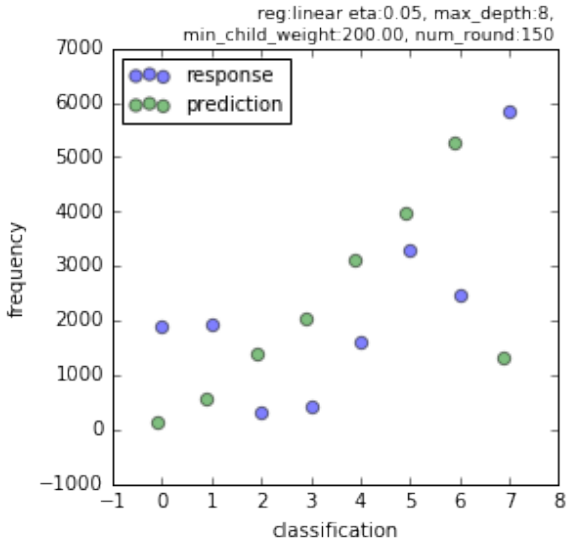


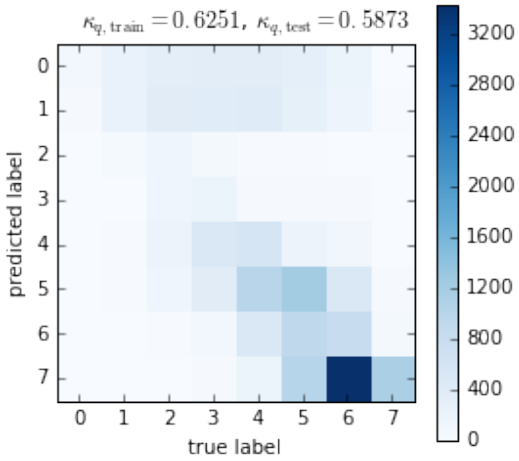


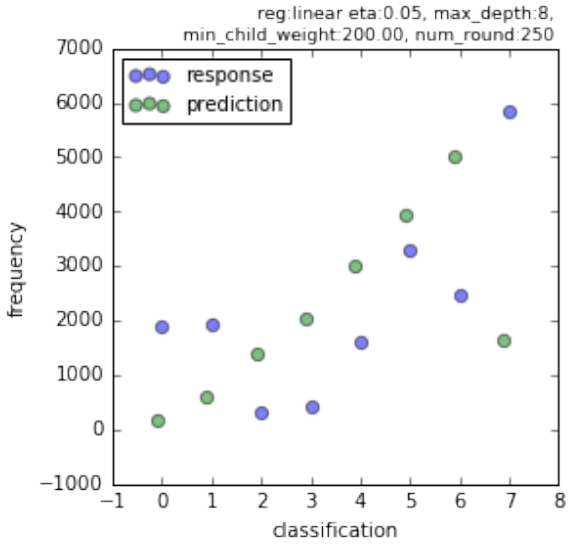
I want to increase the number of rounds, but for that I need to set the parameters to have a model with less variance:

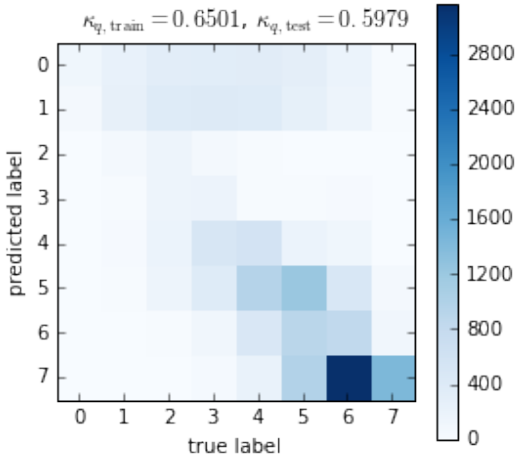
```
In [71]: # xgboost parameters:
         param = {}

         # use softmax multi-class classification
         param['objective'] = 'reg:linear'

         param['eta'] = 0.05
         param['max_depth'] = 8
         param['min_child_weight'] = 200

         param['silent'] = 1
         param['nthread'] = 1


         def classify(score):
             return np.rint(np.clip(score, -0.49, 7.49))

         evalfun = functools.partial(xg_eval_linear_pred, classify_function=classify)

         results = []
         for num_round in [150, 250, 500]:
             print("\n" + "-"*40)
             print("{} = {}".format("num_round", num_round))
             results.append(learning(data, evalfun, param, num_round, nsamples=[]))

----------------------------------------
num_round = 150
```

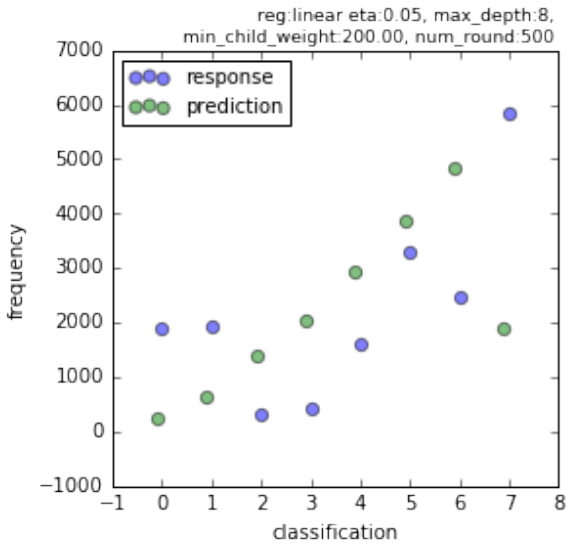
```
Working on n = 41566  at 13:45:41
num categories = 8
train_qwk: 0.6251, test_qwk: 0.5873
[[  92  240  342  358  352  306  188   11]
 [  31  241  387  398  414  283  163   18]
 [   3   44  153   74   20   14   11    2]
 [   1   10  151  183   29   27   34    8]
 [   0   25  196  501  588  190  114    3]
 [   1   18  151  387  997 1223  484   37]
 [   0    0   17  101  505  928  831   77]
 [   0    0    0   36  205 1018 3439 1155]]

----------------------------------------
num_round = 250
Working on n = 41566  at 13:46:13
num categories = 8
train_qwk: 0.6501, test_qwk: 0.5979
[[ 120  246  332  341  347  302  186   15]
 [  51  249  385  403  395  272  159   21]
 [   5   52  150   69   22   11   10    2]
 [   2   18  153  185   16   23   37    9]
 [   1   31  196  503  573  193  114    6]
 [   4   21  159  394  956 1221  492   51]
 [   0    0   19  110  479  913  830  108]
 [   0    0    2   39  212  987 3170 1443]]

----------------------------------------
num_round = 500
Working on n = 41566  at 13:47:10
num categories = 8
train_qwk: 0.6823, test_qwk: 0.6034
[[ 147  251  311  346  344  289  180   21]
 [  68  237  393  412  373  275  143   34]
 [   9   62  138   67   19   16    8    2]
 [   3   18  167  172   14   26   33   10]
 [   2   34  199  487  576  196  113   10]
 [   5   28  164  389  934 1211  507   60]
 [   0    2   22  118  451  896  836  134]
 [   0    0    3   42  234  958 3005 1611]]
```

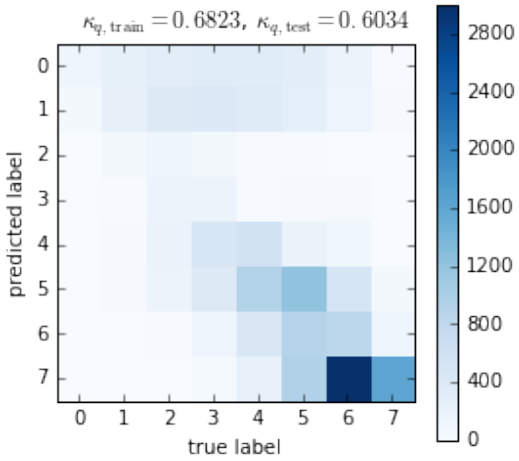

reg:linear eta:0.05, max_depth:8,
min_child_weight:200.00, num_round:150
response
prediction
frequency
classification


$\kappa_{q,\,\mathrm{train}} = 0.6251,\ \kappa_{q,\,\mathrm{test}} = 0.5873$
predicted label
true label


reg:linear eta:0.05, max_depth:8,
min_child_weight:200.00, num_round:250
response
prediction
frequency
classification


$\kappa_{q,\,\mathrm{train}} = 0.6501,\ \kappa_{q,\,\mathrm{test}} = 0.5979$
predicted label
true label





2.1 Conclusion of this step:

A model with eta=0.05, max_depth=8, min_child_weight=200 and num_round=150 provides a good bias-variance balance and is fast enough that I can go ahead and start trying to do other explorations.

The next thing I will explore is the optimization of the cutoff points that are used to classify the continuous output of this model into categories.

2.2 Submission

In [81]:
```
data = pd.read_csv('data_imputed.csv')

features = data[data['train?'] == True].drop(['train?', 'Id', 'Response'], axis=1)
labels = data[data['train?'] == True]['Response'].astype('int') -1
submission_features = data[data['train?'] == False].drop(['train?', 'Id', 'Response'], axis=1)


# xgboost parameters:
param = {}

# use softmax multi-class classification
param['objective'] = 'reg:linear'

param['eta'] = 0.05
param['max_depth'] = 8
param['min_child_weight'] = 200

param['silent'] = 1
param['nthread'] = 1

def classify(score):
    return np.rint(np.clip(score, -0.49, 7.49))
```

```
        num_round = 150
        xg_train = xgb.DMatrix(features, labels)
        print("\n" + "-"*40)
        print("{} = {}".format("num_round", num_round))
        model = xgb.train(param, xg_train, num_round)


        xg_submission = xgb.DMatrix(submission_features)
        submission_prediction = model.predict(xg_submission)
        submission = classify(submission_prediction)

----------------------------------------
num_round = 150

In [84]: submission_ids = data[data['train?'] == False]['Id']

         submission_df = pd.DataFrame({"Id": submission_ids, "Response": submission.astype('int') + 1})
         submission_df = submission_df.set_index('Id')
         submission_df.to_csv('step02_submission.csv')

In [86]: submission_df.describe()

Out[86]:            Response
         count  19765.000000
         mean       5.619833
         std        1.583783
         min        1.000000
         25%        5.000000
         50%        6.000000
         75%        7.000000
         max        8.000000

In [ ]:
```