# MO444 – Aprendizado de Máquina

Edgar Rodolfo Quispe Condori - RA 192617 June 17, 2017

### 1 Dataset

The original dataset is ex6-train.csv but in order to test the algorithms we create a new dataset small\_7000.csv that contains 7000 random elements from the original dataset. This let us test the algorithms in smallest time and have and intuition of which algorithm would be better in ex6-train.csv.

The algorithms where tested in ex-train.csv in ascending order of its MAE obtained in small\_7000.csv and the final classifier is the one with best MAE in the complete dataset. Note that some methods did not end to train in the complete dataset because of the high number data.

## 2 Preprocessing

For the preprocessing we consider normalization. Results with and without normalization are compared.

# 3 Regressors

The list of regressors and the list of hyperparameters tested is shown below.

Regressors	hyperparameter		
	kernel: linear, rbf		
Support Vector Machine (SVM)	$C: 2^{-5}, 2^0, 2^5, 2^{10}$		
	gamma: $2^{-15}, 2^{-10}, 2^{-5}, 2^0, 2^5$		
Random Forest (RF)	n_estimators: 100, 200, 400, 800		
	max_features: 8, 10, 30, 32		
Multi Layer Perceptron (MLP)	hidden_layer_sizes: 3, 7, 10, 20		
	solver : lbfgs		
Gradient Boosting Machine (GBM)	n_estimators: 30, 70, 100, 400, 800		
	learning_rate: 0.1, 0.05		
	max_depth: 5, 10		
Bagging Regressor Machine (BRM)	base_estimator: $KNeighborsRegressor(n\_neighbors = 1)$ ,		
	$MLPRegressor(solver = 'lbfgs', hidden_layer_sizes = (20,))$		
	n_estimators: 100, 400, 800		
	max_features : 5,10, 30,40		

Table 1: Algorithm and hyperparameters tested.

### 4 Evaluation

Because of the quantities of data, the evaluation was made with a 3-fold, a grid search is run for each fold and the score of an algorithm is the best score in the folds.

#### 5 Results

The results are show in the tables below. Note that some algorithm results are not included for the complete dataset because of computer power and time limitations.

Dogwoodow	small_7000.csv		ex6-train.csv	
Regressor	hyperparameters	MAE	hyperparameters	MAE
SVM	kernel: linear		-	-
	C: 0.03125	0.08919	-	-
	gamma: $3.0517578125e - 05$		-	_
RF	n_estimators : 200	0.08165	n_estimators: 800	0.08820
	max_features : 10	0.06103	max_features : 8	
MLP	hidden_layer_sizes : 3	0.08575	hidden_layer_sizes: 7	0.11058
	solver : lbfgs	0.00373	solver : lbfgs	
GBM	n_estimators : 70		n_estimators: 800	
	learning_rate : 0.1	0.08616	learning_rate : 0.05,	0.09554
	max_depth: 5		max_depth: 5	
BRM	base_estimator: <i>MLP</i>		base_estimator: MLP	
	n_estimators : 800	0.07394	n_estimators: 800	0.08382
	max_features : 40		max_features : 40	

Table 2: Results for data without normalization.

Родиоссои	small_7000.csv		ex6-train.csv	
Regressor	hyperparameters	MAE	hyperparameters	MAE
SVM	kernel: linear		-	-
	C: 0.03125	0.08949	-	-
	gamma: $3.0517578125e - 05$		-	-
RF	n_estimators : 400	0.08182	n_estimators: 800	0.08866
	max_features : 10	0.00102	max_features: 10	
MLP	hidden_layer_sizes : 3	0.08755	hidden_layer_sizes: 7	0.11058
	solver : lbfgs	0.08733	solver : lbfgs	
GBM	n_estimators : 70		n_estimators: 800	
	learning_rate : 0.1	0.08646	learning_rate : 0.05,	0.09554
	max_depth: 5		max_depth: 5	
BRM	base_estimator: MLP		base_estimator: MLP	
	n_estimators : 800	0.07418	n_estimators: 800	0.08322
	max_features : 40		max_features : 40	

Table 3: Results for data with normalization.

From the results we can see that the hyperparameter does not change to much from small\_7000.csv and ex6-train.csv, the same happens for the results with and without normalization. The best regressor is the Bagging Regressor Machine with a Multilayer Perceptron as base estimator, it gets a MAE of 0.08382 with normalization and 0.08322 without normalization.

#### 6 Code

```
import numpy as np
import csv
import pandas as pd
from sklearn import preprocessing
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn.metrics import mean_absolute_error
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.decomposition import PCA
from sklearn.externals import joblib
from sklearn import discriminant_analysis
def read_data():
 file_name = "ex6-train.csv"
  data = pd.read_csv(file_name)
  data = np.array(data).astype(np.float)
  labels = data[:, -1]
 data = data[:, 0:-1]
  return data, labels
def preprocess_data(x, standardize = True, pca = True):
 #standardize data
  if standardize:
     x = preprocessing.StandardScaler().fit_transform(x)
     x = PCA(n\_components = 0.9999). fit_transform(x)
  return x
def three\_validation(x, y, clf\_name, params, name\_metada = "", cnt = 1):
    clfs = { 'knn': KNeighborsRegressor, 'svm': SVR, 'mlp': MLPRegressor,
    'rf': RandomForestRegressor, 'gbm': GradientBoostingRegressor, 'brm': BaggingRegressor}
    gridSearch = GridSearchCV(clfs[clf_name](), params, cv = 3,
    scoring = 'neg_mean_absolute_error', n_jobs = 5)
    gridSearch.fit(x, y)
   name = clf_name + str(gridSearch.best_params_) + str(gridSearch.best_score_) + name_metada
if clf_name != 'brm':
        joblib.dump(gridSearch, name + '_GS.pkl')
    else:
        print name
        joblib.dump(gridSearch, str(cnt) + name_metada + '_GS.pkl')
    clf_eval = clfs[clf_name](**gridSearch.best_params_).fit(x, y)
    if clf_name != 'brm':
        joblib.dump(clf_eval, name + '_REG.pkl')
    else:
        joblib.dump(clf_eval, str(cnt) + name_metada + '_REG.pkl')
def svm_evaluation(x, y, model = "five_three", name_metada = ""):
    print "Support Vector Machine"

params = {'kernel': ['linear', 'rbf'], 'C' : [2**(-5), 2**(0), 2**(5), 2**(10)],
    'gamma': [2**(-15), 2**(-10), 2**(-5), 2**(0), 2**(5)]
    if model == "five_three":
        five_three_validation(x, y, 'svm', params)
    if model == "three":
        three_validation(x, y, 'svm', params, name_metada)
def mlp_evaluation(x, y, model = "five_three", name_metada = ""):
    print "Multi Layer Perceptron"
    params = {'hidden_layer_sizes' : [(3,), (7, ), (10, ), (20, )], 'solver' : ['lbfgs']} if model == "five_three":
        five_three_validation(x, y, 'mlp', params)
    if model == "three":
        three_validation(x, y, 'mlp', params, name_metada)
def rf_evaluation(x, y, model = "five_three", name_metada = ""):
```

```
print "Random Forest"
    params = {'n_estimators': [100, 200, 400, 800], 'max_features': [8, 10, 30, 32]}
    if model == "five three":
         five_three_validation(x, y, 'rf', params)
    if model == "three":
        three\_validation\,(x\,,\ y\,,\ 'rf'\ ,\ params\,,\ name\_metada\,)
def gb_evaluation(x, y, model = "five_three", name_metada = ""):
    print "Gradient Boosting Machine"

narams = {'n_estimators': [30, 70, 100, 400, 800], 'learning_rate': [0.1, 0.05],
    if model == "five_three":
        five_three_validation(x, y, 'gbm', params)
    if model == "three":
        three_validation(x, y, 'gbm', params, name_metada)
def brm_evaluation(x, y, model_evaluation = "five_three", name_metada = ""):
    models = [PRegressor(solver = 'lbfgs', hidden_layer_sizes = (20,)),
               KNeighborsRegressor(n_neighbors = 1)]
    cnt = 666
    for model in models:
        print "Bagging Regressor Machine"
         params = {'base_estimator': [model], 'n_estimators': [100, 400, 800],
        'max_features': [5,10, 30,40]}
if model_evaluation == "five_three":
             five_three_validation(x, y, 'brm', params)
         if model_evaluation == "three":
             three_validation(x, y, 'brm', params, name_metada, cnt)
        cnt += 1
def evaluate_finalRegressor():
    reg = joblib.load('models/big/666_1_0_REG.pkl')
    data = pd.read_csv('ex6-test.csv')
    data = np.array(data).astype(np.float)
    print data.shape
    pred = reg.predict(data)
    df = pd. DataFrame (pred)
    df.to_csv("solutions.csv", header = False, index = False)
if __name__ == "__main__":
    x, y = read_data()
    print "standardize = False, pca = False ========== "
   mlp_evaluation(x, y, "three", name_metada = "_0_0")
svm_evaluation(x, y, "three", name_metada = "_0_0")
rf_evaluation(x, y, "three", name_metada = "_0_0")
brm_evaluation(x, y, "three", name_metada = "_0_0")
gb_evaluation(x, y, "three", name_metada = "_0_0")
    xx = preprocess_data(x.copy(), standardize = True, pca = False)
    print "standardize = True, pca = False ========= "
    evaluate_finalRegressor()
```