adaboost_solution

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0.1 Boosting Decision Stumps

In this notebook, you will use scikit-learn's decision trees and implement the AdaBoost algorithm for binary classification. In particular, you will

1. Implement AdaBoost and evaluate its performance on a toy dataset
2. Investigate the effect of number of iterations/tree depth

The exercise is mostly based on the lecture and the following book:
T. Hastie, R. Tibshirani, and J. Friedman: *The Elements for Statistical Learning*, 2001
As usual, some setup first:

```
In [1]: import sklearn.datasets
        import sklearn.tree
        import sklearn.base
        import sklearn.metrics
        import sklearn.ensemble

        import numpy as np

        import matplotlib.pyplot as plt
```

```
/home/eggenspk/anaconda3/envs/general_36/lib/python3.6/site-packages/sklearn/ensemble/weight_b
  from numpy.core.umath_tests import inner1d
```

The data set is an example from scikit-learn's datasets submodule which was introduced by [Hastie, Tibshirani and Friedman]. It has 10 features, which are standard independent Gaussian. The deterministic target Y is defined with:

```
y[i] = 1 if np.sum(X[i] ** 2) > 9.34 else -1
```

```
In [2]: # Create a binary classification dataset
        def create_dataset():
            num_samples=12000
            n_train = 2000

            X, y = sklearn.datasets.make_hastie_10_2(n_samples=num_samples,
                                                     random_state=1)
            X_train = X[:n_train]
```

```
    y_train = y[:n_train]
    X_test = X[n_train:]
    y_test = y[n_train:]
    return X_train, y_train, X_test, y_test
```

In [3]:
```
class AdaBooster(object):

    def __init__(self, weak_learner, iterations):
        '''
        weak_learner: sklearn classifier - G_m
        iterations: number of iteration to train - M
        '''
        self.weak_learner = weak_learner
        self.iterations = iterations

        # 1. Initialize some more lists
        self.classifiers = list() # trained classifiers G_m
        self.alphas = list()      # classifier weights

    def fit(self, X, y):
        # YOUR TURN
        # 1. initialize the observation weights
        w = np.ones_like(y) / X.shape[0]

        # 2. For m=1 to M
        for it in range(self.iterations):
            # hint: Use sklearn.base.clone method to copy the
            #       classifier in each iteration. Only 'clones'
            #       the class, not the model.

            # (a) Fit a classifier
            tmp_learner = sklearn.base.clone(self.weak_learner)
            tmp_learner.fit(X, y, sample_weight=w)
            self.classifiers.append(tmp_learner)

            # (b) Compute error
            y_pred = tmp_learner.predict(X)
            error = np.sum(w * (y != y_pred))
            error /= np.sum(w)

            # (c) Compute classifier weight
            alpha = np.log((1 - error) / error)
            self.alphas.append(alpha)

            # (d) Update observation weights
            w *= np.exp(alpha * (y != y_pred))

    def predict(self, X):
```

```
            # Compute predictions by looping over all classifiers
            # and adding weighted predictions.
            # The actual output should be
            # -1 if y_i <= 0 and 1 otherwise

            # YOUR TURN
            pred = np.zeros(X.shape[0])
            for alpha, c in zip(self.alphas, self.classifiers):
                tmp_pred = c.predict(X)
                pred += alpha * tmp_pred
            pred[pred > 0] = 1
            pred[pred <= 0] = -1
            return pred

        def staged_predict(self, X):
            # returns predictions for X for all iterations
            # this is for convenience to simplify computing
            # train/test error for all iterations

            staged_predictions = []
            pred = np.zeros(X.shape[0])
            for alpha, c in zip(self.alphas, self.classifiers):
                tmp_pred = c.predict(X)
                pred += alpha * tmp_pred

                staged_prediction = pred.copy()
                staged_prediction[staged_prediction > 0] = 1
                staged_prediction[staged_prediction <= 0] = -1
                staged_predictions.append(staged_prediction)

            return staged_predictions
```

0.1.1 Test your implementation

Now, you have a working implementation of the AdaBoost algorithm. To test your algorithm for correctness you can compare to sklearns AdaBoost implementation which should yield the same output as your implementation:

In [10]:
```
# Use this cell to test whether your implementation is correct

weak_learner = sklearn.tree.DecisionTreeClassifier(max_depth=1)
adaboost = AdaBooster(weak_learner=weak_learner, iterations=400)
sk_adaboost = sklearn.ensemble.AdaBoostClassifier(weak_learner,
                                                  algorithm="SAMME",
                                                  n_estimators=400)

# Get data
X_train, y_train, X_test, y_test = create_dataset()
```

```
        # Fit model
        adaboost.fit(X_train, y_train)
        sk_adaboost.fit(X_train, y_train)

        # Predict
        pred = adaboost.predict(X_test)
        pred_sk = sk_adaboost.predict(X_test)

        print("Difference: %d" % np.sum([pred != pred_sk]))
```

```
Difference: 0
```

0.1.2 Playground

Next, you can play around with AdaBoost's hyperparameters. Here are some suggestions:

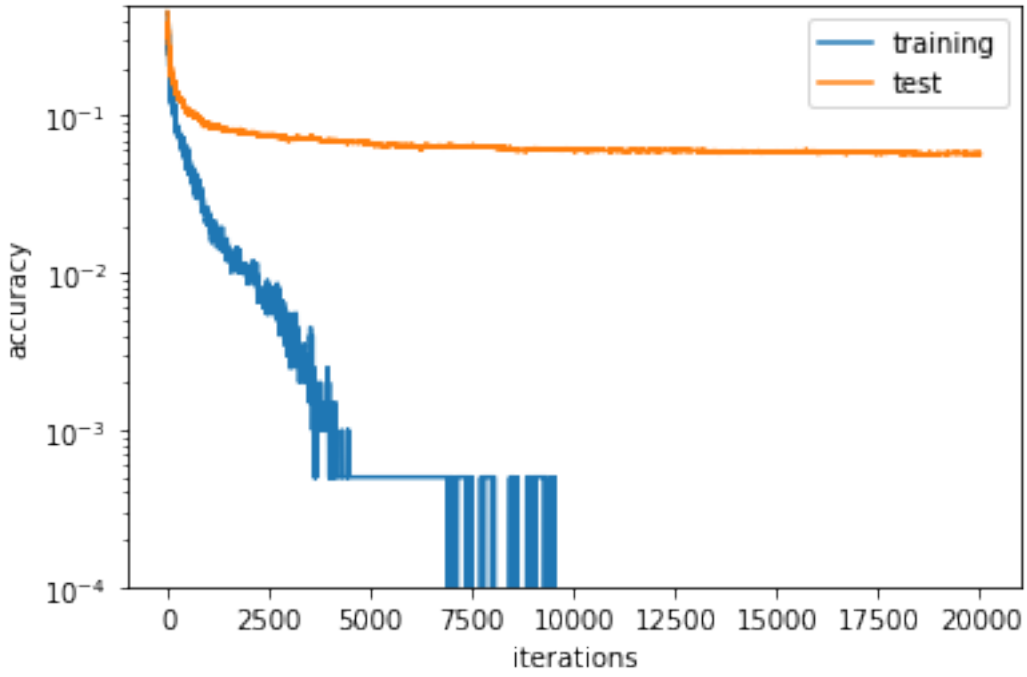
- Investigate the number of iterations that are needed to start overfitting.
- Add some noise on the targets and try again.
- Investigate the effect of the tree depth.

Before you investigate the model it will be helpful to prepare a function that generates a plot showing test/train performance over number of iterations:

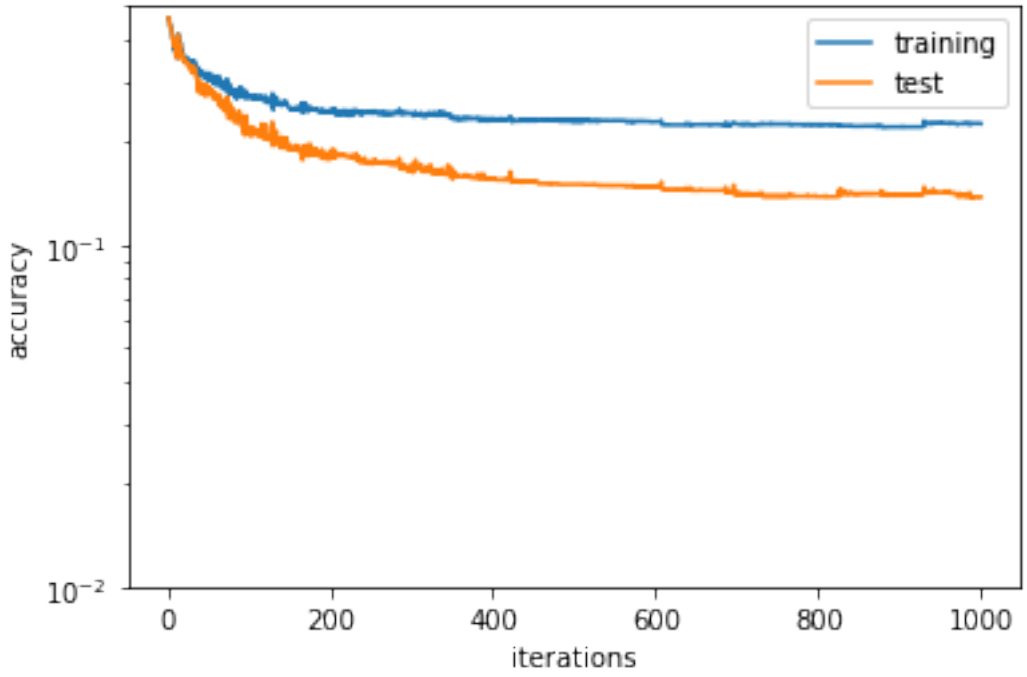
```
In [5]: def plot_train_test_error(model, X_train, y_train, X_test, y_test):
            ''' Shows a plot with train/test error over iterations

            model (AdaBooster): trained AdaBoost algorithm
            X_train (array): [#samples, #features]
            y_train (array): [#samples, ]
            X_test (array): [#samples, #features]
            y_test (array): [#samples, ]
            '''
            # Loop over all predictions and compute accuracy
            y_pred_train = model.staged_predict(X_train)
            training_errors = [1-sklearn.metrics.accuracy_score(y_train, y_pred)
                               for y_pred in y_pred_train]

            y_pred_test = model.staged_predict(X_test)
            test_errors = [1-sklearn.metrics.accuracy_score(y_test, y_pred)
                           for y_pred in y_pred_test]

            # Plot results
            x_values = np.arange(1, len(training_errors) + 1)

            plt.plot(x_values, training_errors, label="training")
            plt.plot(x_values, test_errors, label="test")
            plt.xlabel("iterations")
```

```
    plt.ylabel("accuracy")
    plt.legend(loc="best")
    plt.ylim([0, 1.1])

    #plt.show()
```

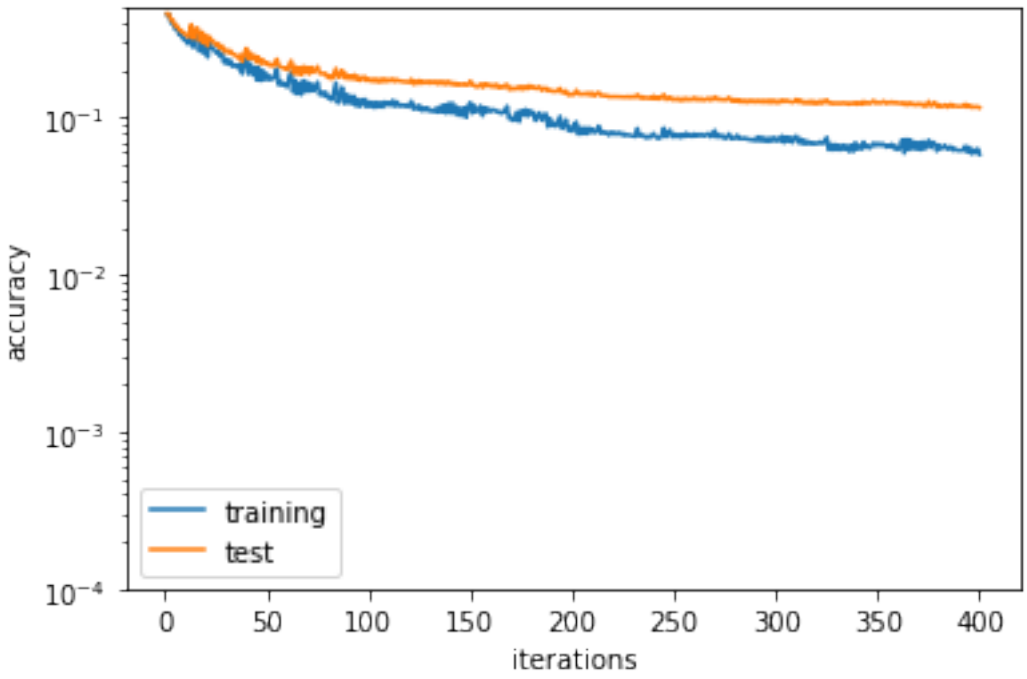
In [17]:
```
# Investigate overfitting and find out number of iterations
# needed to overfit
# --> The train and test error diverge after roughly ~100
# iterations. While the training error goes down to 0
# (after ~2000 iterations), the test accuracy does not decrease anymore.

# YOUR TURN

# Get data
X_train, y_train, X_test, y_test = create_dataset()

# Instantiate model
weak_learner = sklearn.tree.DecisionTreeClassifier(max_depth=1)
adaboost = AdaBooster(weak_learner=weak_learner, iterations=20000)

# Fit model
adaboost.fit(X_train, y_train)
pred = adaboost.predict(X_test)

# Evaluate model
plot_train_test_error(adaboost, X_train, y_train, X_test, y_test)
plt.ylim([0.0001, 0.5])
plt.yscale('log')
```



In [22]:
```
# Add some noise on the data and try again
# --> Changing 0.01 of all y-values does not harm the prediction,
# a higher noise decreases training accuracy

# Get data
X_train, y_train, X_test, y_test = create_dataset()
swap_ratio = 0.2
swap_idx = list(range(0, y_train.shape[0]))
np.random.shuffle(swap_idx)
y_train[swap_idx[:int(y_train.shape[0]*swap_ratio)]] *= -1

# Instantiate model
weak_learner = sklearn.tree.DecisionTreeClassifier(max_depth=1)
adaboost = AdaBooster(weak_learner=weak_learner, iterations=1000)

# Fit model
adaboost.fit(X_train, y_train)
pred = adaboost.predict(X_test)

# Evaluate model
plot_train_test_error(adaboost, X_train, y_train, X_test, y_test)
plt.ylim([0.01, 0.5])
plt.yscale('log')
```



In [23]:
```
# Investigate the effect of the tree depth
# Outcome: Using simple learners allow to still learn a complex function.
# Using a stronger base model increases the gap between train/test
# performance

# Get data
X_train, y_train, X_test, y_test = create_dataset()

# Instantiate model
weak_learner = sklearn.tree.DecisionTreeClassifier(max_depth=1)
adaboost = AdaBooster(weak_learner=weak_learner, iterations=400)

# Fit model
adaboost.fit(X_train, y_train)
pred = adaboost.predict(X_test)

# Evaluate model
plot_train_test_error(adaboost, X_train, y_train, X_test, y_test)
plt.ylim([0.0001, 0.5])
plt.yscale('log')
```


accuracy
10^{-1}
10^{-2}
10^{-3}
10^{-4}
training
test
0
50
100
150
200
250
300
350
400
iterations