ML_Coursework_2

November 27, 2018

1 Machine Learning - Practical 2: Generative and Discriminative Models

Import Libraries

```
In [5]: %matplotlib inline

        import numpy as np
        import math
        import matplotlib.pyplot as plt
        from sklearn.datasets import load_iris
        from sklearn.linear_model import LogisticRegression
        import pickle as cp
```

```
In [6]: class NBC:
            # feature_types: 'b' -> binary, 'r' -> real
            def __init__(self, feature_types, num_classes):
                self.features = feature_types
                self.num_classes = num_classes
                self.separated_means = []
                self.separated_std = []
                self.frequency = []
                self.bernoulli_p = []

            def fit(self, Xtrain, ytrain):
                separated = self.separateByClass(Xtrain,ytrain)

                if self.features == 'r':
                    for i in range(len(separated)):
                        self.frequency.append(separated[i].shape[0] / Xtrain.shape[0])
                        self.separated_means.append(self.get_feature_means(separated[i]))
                        self.separated_std.append(self.get_feature_std_dev(
                            separated[i], self.separated_means[-1]))
                else:
                    for i in range(len(separated)):
                        self.frequency.append(separated[i].shape[0] / Xtrain.shape[0])
                        curr_class_frequencies = [0 for _ in range(Xtrain.shape[1])]
```

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                for j in range(len(separated[i])):
                    curr_class_frequencies += separated[i][j]

                self.bernoulli_p.append(curr_class_frequencies / separated[i].shape[0]

    def predict(self, Xtest):
        N,D = Xtest.shape

        predicted_classes = []
        for curr_data in range(N):
            classes_prob = [1 for _ in range(self.num_classes)]
            for curr_class in range(self.num_classes):
                    for curr_attr in range(D):
                        if self.features == 'r':
                            classes_prob[curr_class] *= self.calculateGaussian(
                                Xtest[curr_data][curr_attr],
                                self.separated_means[curr_class][curr_attr],
                                self.separated_std[curr_class][curr_attr])
                        else:
                            classes_prob[curr_class] *= self.calculateBernoulli(
                                Xtest[curr_data][curr_attr],
                                self.bernoulli_p[curr_class][curr_attr])

                    classes_prob[curr_class] *= self.frequency[curr_class]

            predicted_classes.append(classes_prob.index(max(classes_prob)))

        return predicted_classes

    def separateByClass(self, X, y):
        separated = [[] for _ in range(self.num_classes)]
        for i in range(len(y)):
            separated[int(y[i])].append(X[i])

        for i in range(len(separated)):
            if(len(separated[i]) > 0):
                separated[i] = np.vstack(separated[i])
            else:
                separated[i] = np.zeros(shape=(1,X.shape[1]))

        return separated

    def get_feature_means(self, X):
        N, D = X.shape
        feature_means = []
        for col in range(D):
            feature_means.append(float(0))
            for row in range(N):
```

```
                feature_means[-1] += X[row][col]
            feature_means[-1] = feature_means[-1] / N
        return feature_means

    def get_feature_std_dev(self, X, means):
        N, D = X.shape
        feature_std_dev = []
        for col in range(D):
            feature_std_dev.append(float(0))
            for row in range(N):
                feature_std_dev[-1] += (X[row][col] - means[col])**2
            feature_std_dev[-1] = max(np.sqrt(feature_std_dev[-1] / N), 1e-6)
        return feature_std_dev

    def calculateGaussianProbability(self, x, mean, stdev):
        exponent = math.exp(-math.pow((x - mean) / stdev, 2) / 2)
        return(1 / (math.sqrt(2*math.pi) * stdev)) * exponent

    def calculateBernoulliProbability(self, k, p):
        if k == 0:
            return 1 - p
        return p
```

2 Handin 1

In the lectures, we only formulated the negative log-likelihood for logistic regression without adding any regularization term. As per the formulation used in the lectures, if you wanted to add wTwwTw as a regularization to the negative log-likelihood of observing the data, and set =0.1=0.1, what value of C would you set in the sklearn implementation?

C is the inverse of the regularization. We then have to specify C = 5

3 Handin 2

```
In [12]: iris = load_iris()
         #X,y = iris['data'], iris['target']
         X, y = cp.load(open('voting.pickle', 'rb'))

         N,D = X.shape
         Ntrain = int(0.8 * N)
         Xtrain = X[:Ntrain]
         ytrain = y[:Ntrain]
         Xtest = X[Ntrain:]
         ytest = y[Ntrain:]

         def learning_curve (title, X, y, min_perc, max_perc, step):
             plt.figure()
             plt.title(title)
```

```
    plt.xlabel("Training examples")
    plt.ylabel("Score")

    N, D = X.shape
    Ntrain = int(0.8 * N)

    errors_nbc = [0 for _ in range(10)]
    errors_linear = [0 for _ in range(10)]

    num_iterations = 1000

    for _ in range(num_iterations):
        shuffler = np.random.permutation(N)
        Xtrain = X[shuffler[:Ntrain]]
        ytrain = y[shuffler[:Ntrain]]
        Xtest = X[shuffler[Ntrain:]]
        ytest = y[shuffler[Ntrain:]]

        pos = 0
        for i in range (min_perc, max_perc + 1, step):
            X_train = Xtrain[:int(len(Xtrain) / 100 * i)]
            y_train = ytrain[:int(len(ytrain) / 100 * i)]

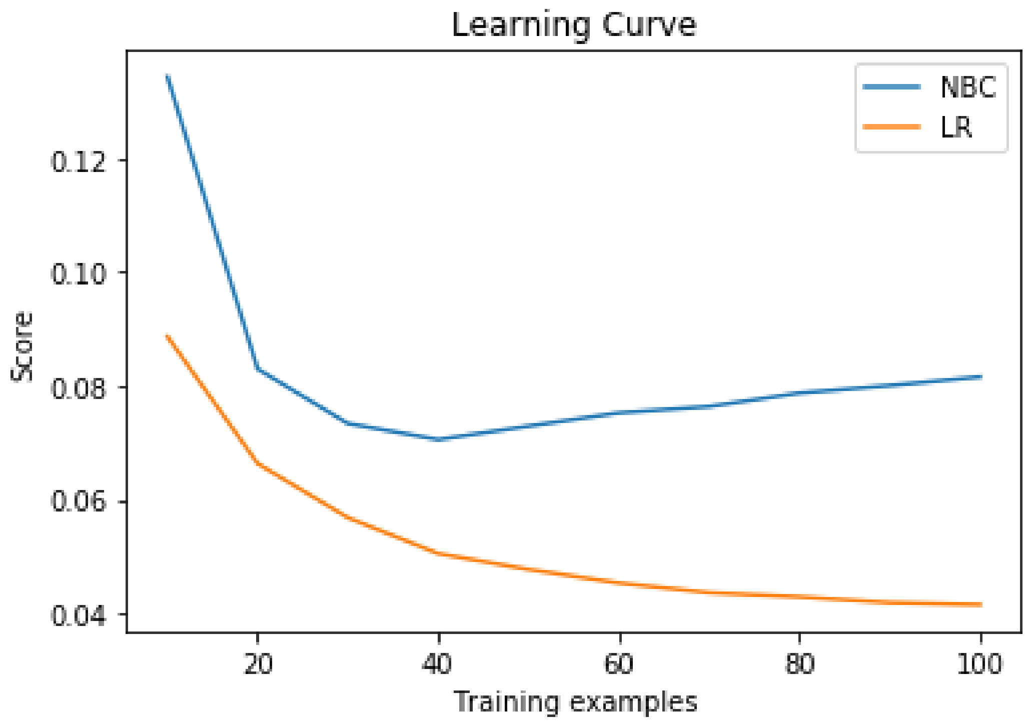
            # Naive Bayes
            nbc = NBC('b',2)
            nbc.fit(X_train, y_train)
            yhat = nbc.predict(Xtest)
            mean_nbc = 1 - np.mean(yhat == ytest)

            # Logistic
            clf = LogisticRegression(random_state=0, solver='newton-cg',
                                     multi_class='multinomial').fit(
                                     X_train, y_train)
            mean_linear = 1 - clf.score(Xtest,ytest)

            errors_nbc[pos] += (mean_nbc / num_iterations)
            errors_linear[pos] += (mean_linear/ num_iterations)
            pos += 1

    plt.plot(np.linspace(10,100, num=10), errors_nbc, label='NBC')
    plt.plot(np.linspace(10,100, num=10), errors_linear, label='LR')
    plt.legend()
    plt.show()

learning_curve('Learning Curve', X, y, 10, 100, 10)
```



In [15]:
```
iris = load_iris()
X,y = iris['data'], iris['target']

N,D = X.shape
Ntrain = int(0.8 * N)
Xtrain = X[:Ntrain]
ytrain = y[:Ntrain]
Xtest = X[Ntrain:]
ytest = y[Ntrain:]

def learning_curve (title, X, y, min_perc, max_perc, step):
    plt.figure()
    plt.title(title)
    plt.xlabel("Training examples")
    plt.ylabel("Score")

    N, D = X.shape
    Ntrain = int(0.8 * N)

    errors_nbc = [0 for _ in range(10)]
    errors_linear = [0 for _ in range(10)]

    num_iterations = 1000
```

```
    for _ in range(num_iterations):
        shuffler = np.random.permutation(N)
        Xtrain = X[shuffler[:Ntrain]]
        ytrain = y[shuffler[:Ntrain]]
        Xtest = X[shuffler[Ntrain:]]
        ytest = y[shuffler[Ntrain:]]

        pos = 0
        for i in range (min_perc, max_perc + 1, step):
            X_train = Xtrain[:int(len(Xtrain) / 100 * i)]
            y_train = ytrain[:int(len(ytrain) / 100 * i)]

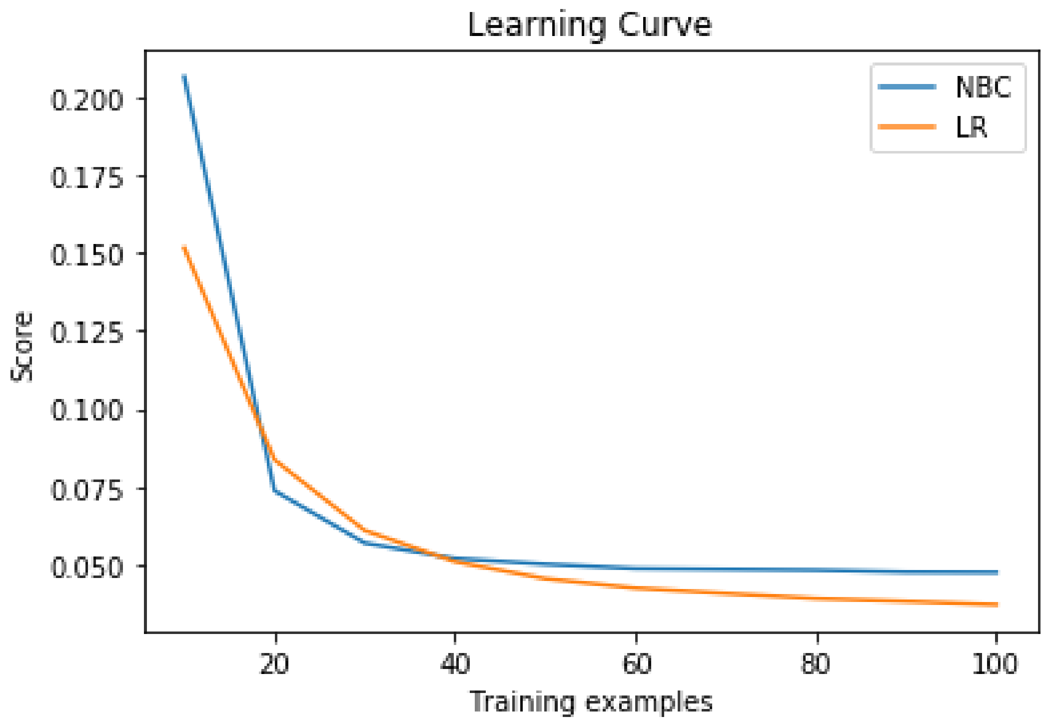
            # Naive Bayes
            nbc = NBC('r',3)
            nbc.fit(X_train, y_train)
            yhat = nbc.predict(Xtest)
            mean_nbc = 1 - np.mean(yhat == ytest)

            # Logistic Regression
            clf = LogisticRegression(random_state=0, solver='newton-cg',
                                     multi_class='multinomial').fit(X_train, y_train)
            mean_linear = 1 - clf.score(Xtest,ytest)

            errors_nbc[pos] += (mean_nbc / num_iterations)
            errors_linear[pos] += (mean_linear/ num_iterations)
            pos += 1

    plt.plot(np.linspace(10,100, num=10), errors_nbc, label='NBC')
    plt.plot(np.linspace(10,100, num=10), errors_linear, label='LR')
    plt.legend()
    plt.show()

learning_curve('Learning Curve', X, y, 10, 100, 10)
```


Learning Curve
NBC
LR
Score
0.200
0.175
0.150
0.125
0.100
0.075
0.050
20
40
60
80
100
Training examples