ml-ex2

August 4, 2017

0.1 Logistic regression

This exercise is described in ex2.pdf.

```
In [25]: import numpy as np
         import matplotlib.pyplot as plt

         from matplotlib import colors
         from sklearn.linear_model import LogisticRegression
         from sklearn.pipeline import Pipeline
         from sklearn.preprocessing import PolynomialFeatures, StandardScaler

         %matplotlib inline
```

0.1.1 Unregularized logistic regression

```
In [26]: # Admission data:
         # - exam 1 score (x1)
         # - exam 2 score (x2)
         # - admitted (y)
         data = np.loadtxt('data/ml-ex2/ex2data1.txt', delimiter=',')
```

```
In [27]: # Separate features (x1, x2) from target (y)
         X, y = np.hsplit(data, np.array([2]))
```

```
In [28]: # LogisticRegression estimator expect an y row vector
         y = y.ravel()
```

```
In [29]: # Use 'lbfgs' solver for logistic regression as this is what Octave fminunc does.
         # Parameter C ist the inverse regularization strength (high values = low regularization
         clf = LogisticRegression(C=1e9, solver='lbfgs')
         clf.fit(X, y)
```

```
Out[29]: LogisticRegression(C=1000000000.0, class_weight=None, dual=False,
                   fit_intercept=True, intercept_scaling=1, max_iter=100,
                   multi_class='ovr', n_jobs=1, penalty='l2', random_state=None,
                   solver='lbfgs', tol=0.0001, verbose=0, warm_start=False)
```

In [30]:
```python
theta0 = clf.intercept_[0]
theta1 = clf.coef_[0,0]
theta2 = clf.coef_[0,1]
```

In [31]:
```python
# Computes x2 at y=0.5 from x1 and model parameters
# (used for computing the linear decision boundary)
def x2(x1):
    return (0.5 - theta0 - theta1*x1) / theta2
```

In [32]:
```python
x1_min = X[:,0].min()
x1_max = X[:,0].max()
```

In [33]:
```python
# x1 and x2 data of linear decision boundary
x1_plot = np.array([x1_min, x1_max])
x2_plot = x2(x1_plot)
```

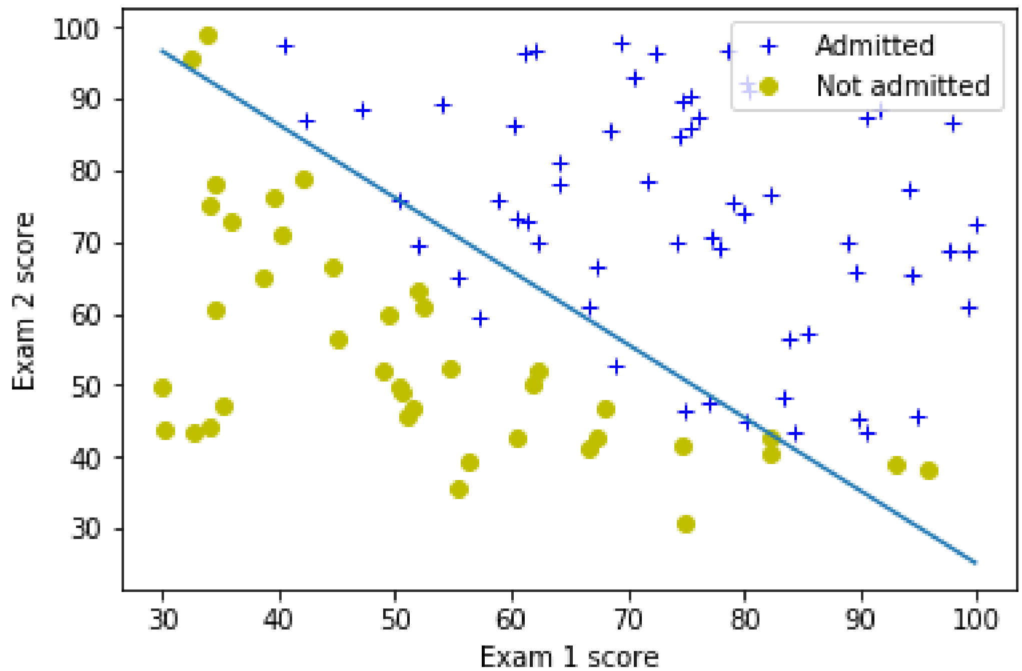
In [34]:
```python
fig, ax = plt.subplots()

# Mask for selecting positive and negative samples
y_pos = y == 1
y_neg = y == 0

# Plot samples and decision boundary
ax.plot(X[y_pos,0], X[y_pos,1], 'b+', label='Admitted')
ax.plot(X[y_neg,0], X[y_neg,1], 'yo', label='Not admitted')
ax.set_xlabel('Exam 1 score')
ax.set_ylabel('Exam 2 score')
ax.legend(loc='upper right')

# Plot decision boundary
ax.plot(x1_plot, x2_plot)
```

Out[34]:
```
[<matplotlib.lines.Line2D at 0x117d5a6a0>]
```




```
In [35]: X_test = np.array([
             [45., 85.],
             [50., 50.],
             [80., 80.]
         ])
```

```
In [36]: # Predict class
         clf.predict(X_test)
```

```
Out[36]: array([ 1.,  0.,  1.])
```

```
In [37]: # Predict class probabilities
         clf.predict_proba(X_test)
```

```
Out[37]: array([[  2.23709868e-01,   7.76290132e-01],
                [  9.91642300e-01,   8.35769979e-03],
                [  5.78239123e-04,   9.99421761e-01]])
```

```
In [38]: theta0 = clf.intercept_[0]
         theta1 = clf.coef_[0,0]
         theta2 = clf.coef_[0,1]
```

```
In [39]: theta0, theta1, theta2
```

```
Out[39]: (-25.161385671019783, 0.20623222395628091, 0.20147190519771876)
```

```
In [40]: # Classification accuracy on training set
         clf.score(X, y)
```

```
Out[40]: 0.8900000000000001
```

0.1.2 Regularized logistic regression

In [41]:
```
# Microchip test:
# - test 1 (x1)
# - test 2 (x2)
# - accepted=1, rejected=0 (y)
data = np.loadtxt('data/ml-ex2/ex2data2.txt', delimiter=',')
```

In [42]:
```
# LogisticRegression estimator expect an y row vector
X, y = np.hsplit(data, np.array([2]))
```

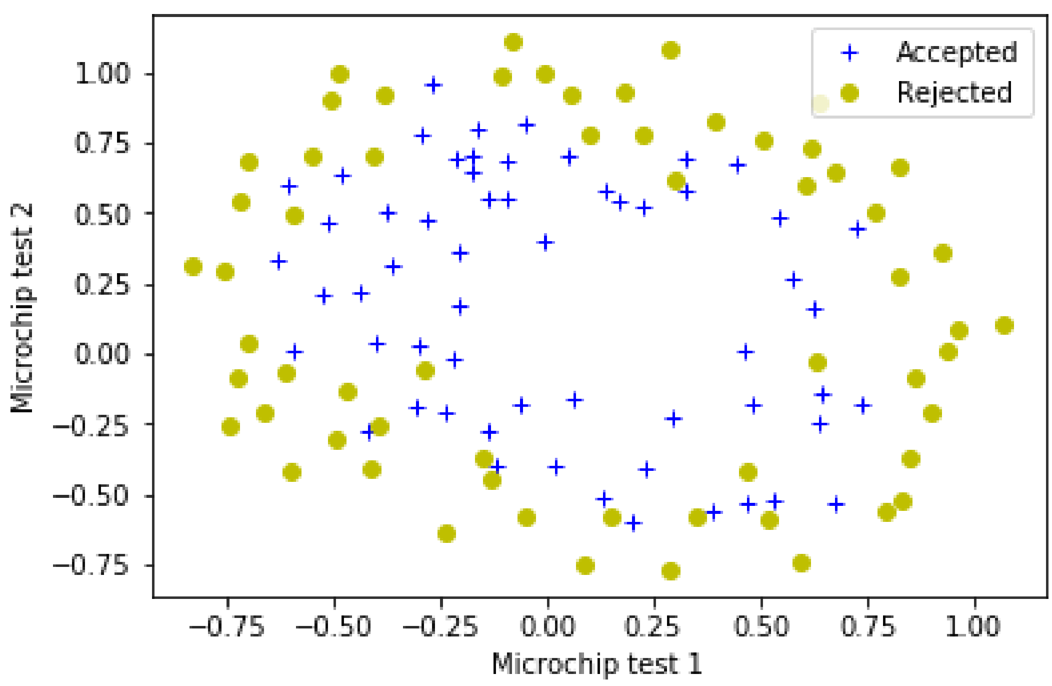
In [43]:
```
# Logistic regression estimator requires an y row vector
y = y.ravel()
```

In [44]:
```
fig, ax = plt.subplots()

# Mask for selecting positive and negative samples
y_pos = y == 1
y_neg = y == 0

# Plot samples
ax.plot(X[y_pos,0], X[y_pos,1], 'b+', label='Accepted')
ax.plot(X[y_neg,0], X[y_neg,1], 'yo', label='Rejected')
ax.set_xlabel('Microchip test 1')
ax.set_ylabel('Microchip test 2')
ax.legend(loc='upper right')
```

Out[44]:
```
<matplotlib.legend.Legend at 0x117dec2b0>
```



In [45]:
```
# Preprocessor to include polynomial features up to degree 6
poly = PolynomialFeatures(6, include_bias=False)

# Mean and standard deviation scaler
scaler = StandardScaler()

# Logistic regression classifier.
# - C=1.0 will result in good fit
# - C=1e4 will result in overfit (to little regularization)
# - C=1e-2 will result in underfit (to much regularization)
clf = LogisticRegression(C=1.0, solver='lbfgs')

# Pipeline of polynomial feature generator, feature scaler and linear regressor
model = Pipeline([('poly', poly), ('scaler', scaler), ('clf', clf)])

# Fit data to model
model.fit(X, y)
```

Out[45]:
```
Pipeline(steps=[('poly', PolynomialFeatures(degree=6, include_bias=False, interaction_o
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='lbfgs', tol=0.0001,
          verbose=0, warm_start=False))])
```

In [46]:
```
# Classification accuracy on training set
model.score(X, y)
```

Out[46]:
```
0.83050847457627119
```

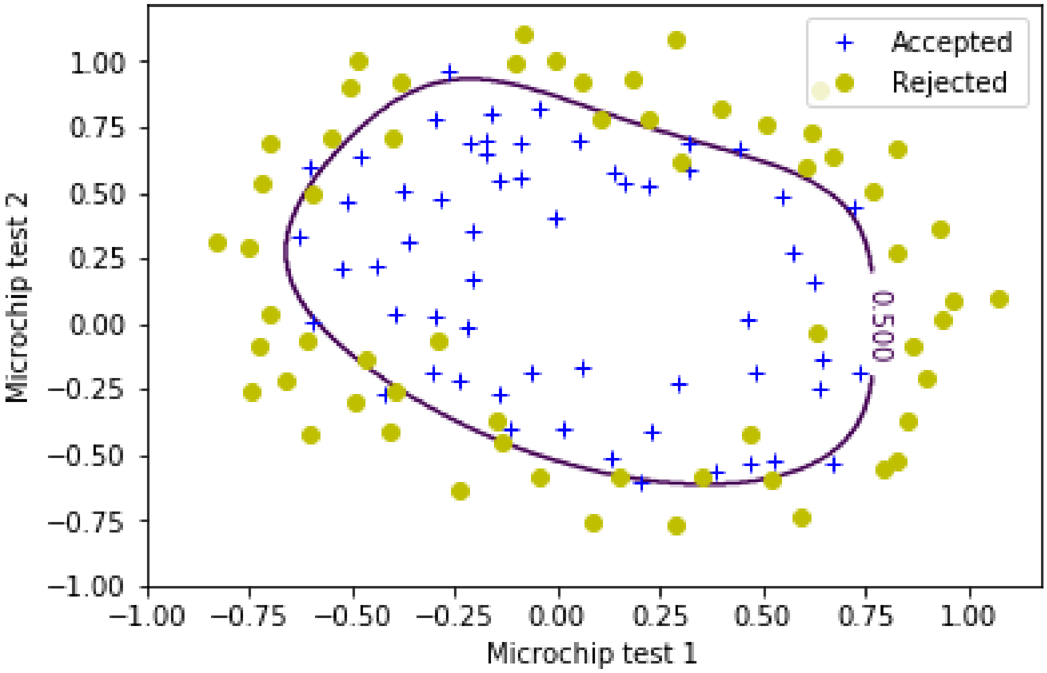
In [47]:
```
grid = np.mgrid[-1:1:500j, -1:1:500j]

# Compute acceptance probabilities on 500*500 grid
X_grid = np.c_[grid[0].ravel(), grid[1].ravel()]
y_grid = model.predict(X_grid).reshape(grid[0].shape)

# Plot decision boundary on previous figure
cs = ax.contour(grid[0], grid[1], y_grid, 'g-', levels=[0.5])
ax.clabel(cs)

# Show previous figure with decision boundary
fig
```

Out[47]:



Accepted
Rejected
0.500
Microchip test 1
Microchip test 2
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00