第一周机器学习

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[*Mathjax开源项目地址*]

线性回归(Linear regression)

cost function:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{m}(y^{(i)} - \theta^T x^{(i)})^2$$

来源于假设误差 ε_i 服从正态分布，然后对参数θ进行极大似然估计，经过运算后得出$J(\theta)$取最小时，似然函数最大，从而推出这个式子。
此外，对这个$J(\theta)$求偏导，令其偏导数为0（这里涉及到矩阵偏导数计算），即可得到正规方程(normal equation)。

梯度下降法的Python实现

参考代码，自己就一些细节进行优化
(https://www.cnblogs.com/focusonepoint/p/6394339.html)

```
#!/usr/bin/python
# -*- coding: UTF-8 -*-

import numpy as np
from numpy import linalg



def gradientDescent(x, y, theta, m, alpha, maxIteration):
        '''
        使用批处理梯度下降算法计算theta
        '''
        # 得到x的转置
        # 即 x的第一行为x1 第二行为x2 第三行全部初始化为1
        xTrains = x.transpose()
        # theta 是一个列向量
        for i in xrange(0,maxIteration):
                # x矩阵(10*3)与theta(3*1)矩阵相乘
                # hypothesis(i) = x1(i)*theta1(i) + x2(i)*theta2(2) + 1*theta0(i)
                hypothesis = np.dot(x, theta)
                # 作差
                loss = hypothesis - y
                # 当loss的范数在我们的误差允许范围内 就停止循环
                if (linalg.norm(loss) < 1e-5):
                        break
```

```
                # xTrains (3*10) * loss(10*1) = gradient(3*1)
                # 计算代价函数
                gradient = (1.0/m) * np.dot(xTrains, loss)
                theta = theta - alpha * gradient
        print('the number of iteration is %d' % i);
        return theta


# define the prepared 训练集
# the meaning of column : x1,x2,y
dataSet = np.array([
        [1.1,1.5,2.5],
        [1.3,1.9,3.2],
        [1.5,2.3,3.9],
        [1.7,2.7,4.6],
        [1.9,3.1,5.3],
        [2.1,3.5,6.0],
        [2.3,3.9,6.7],
        [2.5,4.3,7.4],
        [2.7,4.7,8.1],
        [2.9,5.1,8.8],
])


# print(dataSet)
m,n = np.shape(dataSet)
# print(m,n)
trainData = np.ones((m,n))
# 截取dataSet的前N-1列
trainData[:,:-1] = dataSet[:,:-1]
# 获取dataSet的最后一列
trainLabel = dataSet[:,-1]

# print(m,n)
theta = np.ones(n)
# print(theta)
alpha = 0.001

# the max time of iteration 这个值定义的尽量大(考虑计算机的性能)
maxIteration = 10000000
theta = gradientDescent(trainData, trainLabel, theta, m, alpha, maxIteration)
print('thec value of theta is:')
print(np.round(theta,2))


# a test for the algorithm
x = np.array([
        [3.1, 5.5],
        [3.3, 5.9],
        [3.5, 6.3],
        [3.7, 6.7],
        [3.9, 7.1]
])


# define a predict function used to test
def predict(x,theta):
        m, n = np.shape(x)
        xTest = np.ones((m, n+1))
        xTest[:, :-1] = x
        yPre = np.dot(xTest,theta)
        return yPre

print('the predicted value is')
yP = predict(x, theta)
print(np.round(yP,2))
```

运行结果

```
the number of iteration is 114575
thec value of theta is:
[ 0.71  1.39 -0.38]
the predicted value is
[ 9.5 10.2 10.9 11.6 12.3]
[Finished in 2.2s]
```

优化技巧

- Feature Scaling（特征缩放）
    - 归一化
        1. 线性归一化
            - $$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$
        2. 标准差归一化
            - $$x^* = \frac{x - \overline{x}}{s}$$
        3. 非线性归一化
- 多项式回归
    - $$h_\theta(x) = \theta_0 + \theta_1 x + \theta_2 x^2$$
    - $$h_\theta(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3$$
    - $$h_\theta(x) = \theta_0 + \theta_1 x + \theta_2 \sqrt{x}$$
    - 上面的举例只是为了说明，x_i的取值可以不是x的一次多项式，但是这里要注意的是特征缩放在这里显得尤为重要
- α选取技巧
    - 如果J（θ)的值随着θ的取值单调递增或者出现震荡，那么α应该选的小一点

Normal Equation（正规方程法）

思想

$$J_\theta(x) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x) - y)^2$$

$$= a\theta^2 + b\theta + c$$

微积分思想：求导后令导数为零解方程可以求出极值点θ
对于θ是一个n维向量的情况，可以利用多元函数取极值的必要条件，即偏导数为0

结论

$$\theta = (X^T X)^{-1} X^T y$$

Note

1. No need to do feature scaling
2. 只适用于线性模型，不适合逻辑回归模型等其他模型
3. the pseudo inverse of matrix
    - redundant features (x中存在线性相关的量)
    - too many features (eg. m <= n 数据个数小于特征参数)

Code

这里我使用上一个梯度下降法的例子作为对比,采用相同的数据对比运行结果

```python
#!/usr/bin/python
# -*- coding: UTF-8 -*-

import numpy as np

def normalEqation(x, y):
        '''
        使用正规方程法算法计算theta
        '''
        # 得到x的转置
        xTrains = x.transpose()
        m,n = np.shape(x)
        # theta 为 n维列向量
        theta = np.linalg.pinv(np.dot(xTrains,x))
        theta = np.dot(theta,xTrains)
        theta = np.dot(theta,y)
        return theta


# define the prepared 训练集
# the meaning of column : x1,x2,y
dataSet = np.array([
        [1.1,1.5,2.5],
        [1.3,1.9,3.2],
        [1.5,2.3,3.9],
        [1.7,2.7,4.6],
        [1.9,3.1,5.3],
        [2.1,3.5,6.0],
        [2.3,3.9,6.7],
        [2.5,4.3,7.4],
        [2.7,4.7,8.1],
        [2.9,5.1,8.8],
])


# print(dataSet)
m,n = np.shape(dataSet)
# print(m,n)
trainData = np.ones((m,n))
```

```python
# 截取dataSet的前N-1列
trainData[:,:-1] = dataSet[:,:-1]
# 获取dataSet的最后一列
trainLabel = dataSet[:,-1]



theta = normalEqation(trainData, trainLabel)
print('thec value of theta is:')
print(np.round(theta,2))


# a test for the algorithm
x = np.array([
        [3.1, 5.5],
        [3.3, 5.9],
        [3.5, 6.3],
        [3.7, 6.7],
        [3.9, 7.1]
])


# define a predict function used to test
def predict(x,theta):
        m, n = np.shape(x)
        xTest = np.ones((m, n+1))
        xTest[:, :-1] = x
        yPre = np.dot(xTest,theta)
        return yPre

print('the predicted value is')
yP = predict(x, theta)
print(np.round(yP,2))
```

运行结果：

```
thec value of theta is:
[ 0.61  1.45 -0.34]
the predicted value is
[ 9.5 10.2 10.9 11.6 12.3]
[Finished in 0.2s]
```

由此可以知道，在特征矩阵维度不是太大情况下，对于线性回归模型，normal equation 是一个优先选用的方法。

Logistic Regression

logistic function

由于线性回归的假设函数不再适用于分类问题，因此我们需要一个函数来应用于分类问题的拟合。一般来说，回归不用在分类问题上，因为回归是连续型模型，而且受噪声影响比较大。如果非要应用进入，可以使用logistic回归。

我们可以使用logistic regression解决分类问题，Logistic回归是二分类任务的首选方法，下面讨论二分类的问题。

$$h_\theta(x) = g(\theta^T x)$$

logistic function(sigmoid function):

$$g(z)=\frac{1}{1+e^{-z}}$$

这里

$$h_\theta(x)=P(y=1|x;\theta)$$

含义是在x已知条件下，给定参数θ，事件*y=1*发生的概率

logistic回归本质上是线性回归，只是在特征到结果的映射中加入了一层函数映射，即先把特征线性求和，然后使用函数g(z)将最为假设函数来预测。g(z)可以将连续值映射到0和1上。

对g(z)的解释：将任意的输入映射到[0,1]区间上，我们在线性回归中可以得到一个预测值，再将该值映射到Sigmoid函数，这样我们就实现了由值到概率的转换，也就是分类任务。

Note：

```
当y等于1时，假设函数计算出的概率应该大于0.5，即θ的转置乘以x需要大于等于0
当y等于0时，假设函数计算出的概率应该小于0.5，即θ的转置乘以x需要小于0
另外需要注意的是阈值0.5在一些情况下是可以改变的，从而获得我们所希望的特征
```

cost function

$$J_\theta(x)=\frac{1}{m}\sum_{i=1}^{m}cost(h_\theta(x^{(i)}),y^{(i)})$$

这里我们将 cost function 定义为

$$cost(h_\theta(x),y)=\begin{cases}-\log(h_\theta(x)) & y=1\\ -\log(1-h_\theta(x)) & y=0\end{cases}$$

例如，y = 1时 $h_\theta(x)\to 1$,cost = 0 表示误差很小。 此时，若 $h_\theta(x)\to 0$,$cost\to\infty$表示误差很大

Simple Classification(简单分类算法)

```
Note: y=0 or 1
```

这里对cost function进行优化，表示为：

$$cost(h_\theta(x),y)=-y\log(h_\theta(x))-(1-y)\log(1-h_\theta(x))$$

```
这里的cost function 实际上也是由对θ的极大似然估计推导出来的。
```

by the way,remind:

$$J_\theta(x)=\frac{1}{m}\sum_{i=1}^{m}cost(h_\theta(x^{(i)}),y^{(i)})$$

$$h_\theta(x) = \frac{1}{1+e^{-\theta^T x}}$$

ok,接着我们对 $J_\theta(x)$ 计算偏微分

$$\begin{aligned} \frac{\partial}{\partial\theta_j}J(\theta) &= \frac{1}{m}\sum_{i=1}^{m}\frac{\partial}{\partial\theta_j}cost(h_\theta(x^{(i)}), y^{(i)}) \\ &= \frac{1}{m}\sum_{i=1}^{m}(-y\frac{1}{h_\theta(x)}\frac{\partial}{\partial\theta_j}h_\theta(x) - (1-y)\frac{1}{1-h_\theta(x)}(-1)\frac{\partial}{\partial\theta_j}h_\theta(x)) \end{aligned}$$

其中

$$\frac{1}{h_\theta(x)} = 1+e^{-\theta^T x}$$

$$\begin{aligned} \frac{1}{1-h_\theta(x)} &= \frac{1}{1-\frac{1}{1+e^{-\theta^T x}}} \\ &= \frac{1+e^{-\theta^T x}}{e^{-\theta^T x}} \\ &= 1+e^{\theta^T x} \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial\theta_j}h_\theta(x) &= -(1+e^{-\theta^T x})^{-2}(e^{-\theta^T x})(-x_j) \\ &= (h_\theta(x))^2 x_j e^{-\theta^T x} \end{aligned}$$

将上面式子代入 $\frac{\partial}{\partial\theta_j}J(\theta)$ 得

$$\begin{aligned} \frac{\partial}{\partial\theta_j}J(\theta) =& \frac{1}{m}\sum_{i=1}^{m}(-y(1+e^{-\theta^T x})(h_\theta(x))^2 x_j e^{-\theta^T x} + \\ & (1-y)(1+e^{\theta^T x})(h_\theta(x))^2 x_j e^{-\theta^T x}) \\ =& \frac{1}{m}\sum_{i=1}^{m} -y h_\theta(x) x_j e^{-\theta^T x} + (1-y)h_\theta(x)x_j \\ =& \frac{1}{m}\sum_{i=1}^{m} -y(1-h_\theta(x))x_j + h_\theta(x)x_j - y h_\theta(x) x_j \\ =& \frac{1}{m}\sum_{i=1}^{m} -y x_j + h_\theta(x) x_j \\ =& \frac{1}{m}\sum_{i=1}^{m}(h_\theta(x) - y)x_j \end{aligned}$$

这里我们推出一个重要的结论

$$\frac{\partial}{\partial\theta_j}J(\theta) = \frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j$$

$$\theta_j := \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta) = \theta_j - \alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j$$

Note: 这里的$h_\theta(x^{(i)})$ 与 线性回归模型中的 $h_\theta(x^{(i)})$ 定义不一样，尽管计算出来的 $\frac{\partial}{\partial\theta_j}J(\theta)$形式相同

Code

```
#!/usr/bin/python
# -*- coding: UTF-8 -*-

'''
本例程是根据学生两门课的成绩判断是否录取
'''


import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

dataStr = '''
34.62365962451697,78.0246928153624,0
30.28671076822607,43.89499752400101,0
35.84740876993872,72.90219802708364,0
60.18259938620976,86.30855209546826,1
79.0327360507101,75.3443764369103,1
45.08327747668339,56.3163717815305,0
61.10666453684766,96.51142588489624,1
75.02474556738889,46.55401354116538,1
76.09878670226257,87.42056971926803,1
84.43281996120035,43.53339331072109,1
95.86155507093572,38.22527805795094,0
75.01365838958247,30.60326323428011,0
82.30705337399482,76.48196330235604,1
69.36458875970939,97.71869196188608,1
39.53833914367223,76.03681085115882,0
53.9710521485623,89.20735013750205,1
69.07014406283025,52.74046973016765,1
67.94685547711617,46.67857410673128,0
70.66150955499435,92.92713789364831,1
76.97878372747498,47.57596364975532,1
67.37202754570876,42.83843832029179,0
89.67677575072079,65.79936592745237,1
50.534788289883,48.85581152764205,0
34.21206097786789,44.20952859866288,0
77.9240914545704,68.9723599933059,1
62.27101367004632,69.95445795447587,1
80.1901807509566,44.82162893218353,1
93.114388797442,38.80067033713209,0
61.83020602312595,50.25610789244621,0
38.78580379679423,64.99568095539578,0
61.379289447425,72.80788731317097,1
85.40451939411645,57.05198397627122,1
52.10797973193984,63.12762376881715,0
52.04540476831827,69.43286012045222,1
40.23689373545111,71.16774802184875,0
54.63510555424817,52.21388588061123,0
33.91550010906887,98.86943574220611,0
64.17698887494485,80.90806058670817,1
74.78925295941542,41.57341522824434,0
```

```
34.1836400264419,75.2377203360134,0
83.90239366249155,56.30804621605327,1
51.54772026906181,46.85629026349976,0
94.44336776917852,65.56892160559052,1
82.36875375713919,40.61825515970618,0
51.04775177128865,45.82270145776001,0
62.22267576120188,52.06099194836679,0
77.19303492601364,70.45820000180959,1
97.77159928000232,86.7278223300282,1
62.07306379667647,96.76882412413983,1
91.56497449807442,88.69629254546599,1
79.94481794066932,74.16311935043758,1
99.2725269292572,60.99903099844988,1
90.54671411399852,43.39060180650027,1
34.52451385320009,60.39634245837173,0
50.2864961189907,49.80453881323059,0
49.58667721632031,59.80895099453265,0
97.64563396007767,68.86157272420604,1
32.57720016809309,95.59854761387875,0
74.24869136721598,69.82457122657193,1
71.79646205863379,78.45356224515052,1
75.3956114656803,85.75993667331619,1
35.28611281526193,47.02051394723416,0
56.25381749711624,39.26147251058019,0
30.05882244669796,49.59297386723685,0
44.66826172480893,66.45008614558913,0
66.56089447242954,41.09209807936973,0
40.45755098375164,97.53518548909936,1
49.07256321908844,51.88321182073966,0
80.27957401466998,92.11606081344084,1
66.74671856944039,60.99139402740988,1
32.72283304060323,43.30717306430063,0
64.0393204150601,78.03168802018232,1
72.34649422579923,96.22759296761404,1
60.45788573918959,73.09499809758037,1
58.84095621726802,75.85844831279042,1
99.82785779692128,72.36925193383885,1
47.26426910848174,88.47586499559782,1
50.45815980285988,75.80985952982456,1
60.45555629271532,42.50840943572217,0
82.22666157785568,42.71987853716458,0
88.9138964166533,69.80378889835472,1
94.83450672430196,45.69430680250754,1
67.31925746917527,66.58935317747915,1
57.23870631569862,59.51428198012956,1
80.36675600171273,90.96014789746954,1
68.46852178591112,85.59430710452014,1
42.0754545384731,78.84478600148043,0
75.47770200533905,90.42453899753964,1
78.63542434898018,96.64742716885644,1
52.34800398794107,60.76950525602592,0
94.09433112516793,77.15910509073893,1
90.44855097096364,87.50879176484702,1
55.48216114069585,35.57070347228866,0
74.49269241843041,84.84513684930135,1
89.84580670720979,45.35828361091658,1
83.48916274498238,48.38028579728175,1
42.2617008099817,87.10385094025457,1
99.31500880510394,68.77540947206617,1
55.34001756003703,64.9319380069486,1
74.77589300092767,89.52981289513276,1
'''

tmpdataList = dataStr.split()
dataList = []
for data in tmpdataList:
        data = data.split(',')
        dataList.append(data)
```

```python
del tmpdataList

# define the prepared 训练集
# the meaning of column : x1,x2,y
dataSet = np.array(dataList)
dataSet = dataSet.astype(np.float64)

def shuffleData(dataSet):
        # 打乱数据
        np.random.shuffle(dataSet)
        m,n = np.shape(dataSet)

        trainData = np.ones((m,n))
        trainData[:,:-1] = dataSet[:,:-1]
        # 获取dataSet的最后一列 并 强制类型转换
        trainLabel = dataSet[:,-1]
        return trainData,trainLabel


# 这里我们使用matplot先看一下数据
negativeData = dataSet[dataSet[:,-1] == 0.0]
positiveData = dataSet[dataSet[:,-1] == 1.0]
trainLabel = dataSet[:,-1].astype(np.float64)


fig,ax = plt.subplots(figsize=(10,5))
ax.scatter(positiveData[:,0],positiveData[:,1],s = 30,c = 'b',marker = 'o',label = 'Admite
ax.scatter(negativeData[:,0],negativeData[:,1],s = 30,c = 'r',marker = 'x',label = 'Not Ad
ax.legend()
ax.set_xlabel('Exam 1 Score')
ax.set_ylabel('Exam 2 Score')
plt.show()

# 下面是逻辑回归算法
def sigmoid(z):
        return (1.0 / (1.0 + np.exp(-z)))


def model(X,theta):
        return sigmoid(np.dot(X,theta))

# x2 x1 x0
# res = model(trainData,theta)
def cost_function(X,y,theta):
        h_x = model(X,theta)
        left = -y*np.log(h_x)
        right = (1-y)*np.log(1-h_x)
        return np.sum(left - right) / (len(X))

# x = cost_function(trainData,trainLabel,theta)
def gradient(X,y,theta):
        grad = np.zeros(theta.shape)
        error = (model(X,theta) - y).ravel()
        for j in xrange(len(theta.ravel())):
                term = np.multiply(error, X[:,j])
                grad[j] = np.sum(term) / len(X)
        return grad
# 3种梯度下降方法  1.批处理 2.小批处理 3.随机处理
# 数据量较小，直接批处理即可
def batchGradientDescent(dataSet, alpha, maxIteration, thresh):
        X,y = shuffleData(dataSet)
        m,n = np.shape(X)
        k = 1.0 / m
        theta = np.zeros((n,))

        trainX = X.transpose()
```

```
        for i in xrange(0,maxIteration):
                error = model(X, theta) - y
                _gradient = k * np.dot(trainX, error)
                if (np.linalg.norm(_gradient) < thresh[0]):
                        print('hit thresh1')
                        break
                # print(gradient(X,y,theta))
                # print(_gradient)
                cost1 = cost_function(X,y,theta)
                theta = theta - alpha * _gradient
                cost2 = cost_function(X,y,theta)
                if  abs(cost2 - cost1) < thresh[1]:
                        print('hit thresh2')
                        break
                # print(theta)
        print('the number of iteration is %d' % (i+1))
        # print(error)
        return theta

# theta = batchGradientDescent(dataSet,alpha =0.001,maxIteration = 1000000,thresh = (1e-6,
# print(theta)

'''
hit thresh2
the number of iteration is 109902
[ 0.04771429  0.04072397 -5.13364014]

这个数据说明当迭代次数为110000次时，cost function下降就跟缓慢了
'''

theta = batchGradientDescent(dataSet,alpha =0.001,maxIteration = 1000000,thresh = (0.05,1e
print(theta)
# theta = batchGradientDescent(dataSet,alpha =0.001,maxIteration = 1000000,thresh = (1e-6,
# print(theta)

'''
hit thresh1
the number of iteration is 40046
[ 0.02721656  0.01899417 -2.37028409]
[Finished in 8.2s]
按照梯度下降停止大概需要40000次迭代
'''
```

这里实际上，如果数据经过预处理以及miniBatch后获得的数据精度比较高

Advanced optimization

Optimization algorithms:

- Gradient descent
- Conjugate gradient
- BFGS
- L-BFGS 后面三种算法不需要给出学习率α，且运算速度较快，但是算法较为复杂，选修。

多类别处理

遇到y的取值不仅仅是0,1情况时，可以将一类与其余类化为两种模型，然后用划分两类的分类算法计算出h(x)，最后每一类都对应一个h(x)，训练出模型后，判断max $h_\theta(x)$对应的类即为最后输出。

关于机器学习的一些概念补充

下采样与上采样

下采样，对于一个不均衡的数据，让目标值(如0和1分类)中的样本数据量相同，且以数据量少的一方的样本数量为准。
上采样就是以数据量多的一方的样本数量为标准，把样本数量较少的类的样本数量生成和样本数量多的一方相同，称为上采样。

交叉验证

交叉验证的基本思想是把在某种意义下将原始数据(dataset)进行分组,一部分做为训练集(train set),另一部分做为验证集(validation set or test set),首先用训练集对分类器进行训练,再利用验证集来测试训练得到的模型(model),以此来做为评价分类器的性能指标。

二分类模型评估方法

以正例（恐怖分子）的识别为例子

真正例（True Positive，TP）：预测值和真实值都为1 假正例（False Positive，FP）：预测值为1，真实值为0(去真) 真负例（True Negative，TN）:预测值与真实值都为0 假负例（False Negative，FN）：预测值为0，真实值为1(存伪)

召回率（也叫查全率）

$$召回率 = \frac{真正例}{真正例 + 假负例}$$

> 正确判为恐怖分子占实际所有恐怖分子的比例。
> 在某些情况中，我们也许需要以牺牲另一个指标为代价来最大化精度或者召回率。
> 比如检测癌症

精确度(precision,也叫查准率)

$$精确度() = \frac{真正例}{真正例 + 假正例}$$

> 在所有判为恐怖分子中，真正的恐怖分子的比例。

准确率（accuracy）

$$accuracy = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN}$$

正则化(Regularization)

欠拟合(underfitting)和过拟合(overfitting)

How to addressing overfitting

1. Reduce number of featrues
2. Regularization
   - keep all the feature,but reduce magnitude/values of feature.
     it works well when we have a lot of features,each of which contributs a bit to predicting y.
3. Regularization used in linear Regression
   - $$J(\theta)=\frac{1}{2m}[\sum_{i=1}^{m}(h_\theta(x^{(i)})-y^{(i)})^2+\lambda\sum_{j=1}^{n}\theta_j^2]$$

   `λ 称为 regularization parameter`

   Note:加上θ^2 是一种形式，有时也可以选择加上$|\theta|$

`3.1 Gradient descent`

$$
\begin{aligned}
&Repeat\quad\{\\
&\qquad \theta_0:=\theta_0-\alpha\frac{1}{m}\sum_{i=1}^{m}(h_{\color{red}{\text{\\thet}}}(x^{(i)})-y^{(i)})x_0^{(i)}\\
&\qquad \theta_j:=\theta_j-\alpha[\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-y^{(i)})x_j^{(i)}+\frac{\lambda}{m}\theta_j]\\
&\qquad (j=1,2,,\dots,n)\\
&\quad\}
\end{aligned}
$$

`* 其中`

$$\theta_j:=\theta_j(1-\alpha\frac{\lambda}{m})-\alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-y^{(i)})x_j^{(i)}$$

`3.2 Normal Equation`

$$\theta=(X^TX+\lambda\begin{bmatrix}0&0&\cdots&0\\0&1&\cdots&0\\\vdots&\vdots&\ddots&\vdots\\0&0&\cdots&1\end{bmatrix}_{n*n})^{-1}X^Ty$$

4. Regularization used in logistic Regression

Neural networks(神经网络)

Typeical Application

待补充

Layer

待补充

Backpropagetion algorithm(反向传播算法)

待补充

Gradient checking(梯度检测)

待补充

Random initialization(随机初始化)

待补充

Summary

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Test and Debug

Debug the ML System

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Machine learning diagnostic

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Evalating your hypothesis

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