HW2 TA hours

TAs
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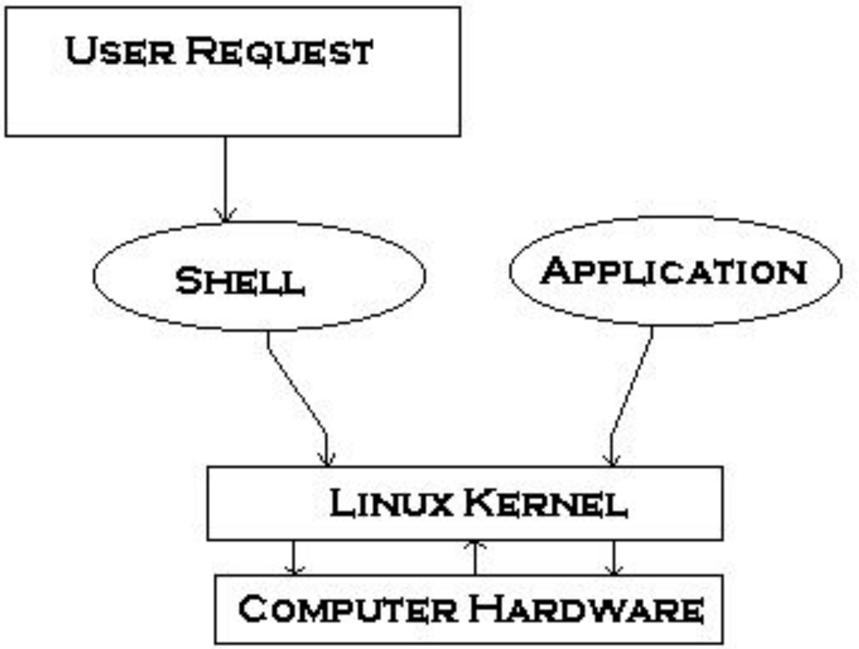
Outline

1. 如何在shell scripts與python檔中接收arguments
2. Logistic Regresion
3. Generative model

Shell Scripts

1. What is Linux Shell?

Shell accepts your instruction or commands (usually in English) and pass it to kernel.



Shell Scripts

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... 把很多指令寫成一個檔案，可以一次做很多事情。

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Script Tutorial and Example

Shell Script Tutorial:
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Example:

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Passing Arguments

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$0 $1 $2

2. 在terminal或cmd中的輸入與.py中變數對應關係：
/path/to/pythonfile /path/to/data /path/to/output
sys.argv[0] sys.argv[1] sys.argv[2]

Passing Arguments

script:

```
echo 'script_arg1 is : '$0''
echo 'script_arg2 is : '$1''
echo 'script_arg3 is : '$2''
echo 'Start to run Python'
python test.py $1 $2
```

python:

```
import sys
a = sys.argv[0]
b = sys.argv[1]
c = sys.argv[2]
print 'python_arg1 is : %s' % a
print 'python_arg2 is : %s' % b
print 'python_arg3 is : %s' % c
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Passing Arguments

Let's run...

```
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script_arg1 is : ./test.sh
script_arg2 is : path1
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Start to run Python
python_arg1 is : test.py
python_arg2 is : path1
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- 絕對路徑 : 相對於**根目錄**的路徑。
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- 相對路徑 : 相對於**目前資料夾**的路徑。
  - Ex: ./hw2/logistic.py、../hw1/linear_regression.py

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★ 並在 ML2017/hw2資料夾執行程式(Ex : hw2_best.sh)

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Logistic Regression

Implementation:

1. feature normalization
2. logistic regression using gradient descent with batch

Code Example:

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If we let batch_size=25...

Logistic Regression

```
X.shape=(25, 106)
w.shape=(106,)
b.sahpe=(1,)
z.shape=(25,)
y.shape=(25,)
Y.shape=(25,)
```

Logistic Regression

Step 1: $f_{w,b}(x) = \sigma\left(\sum_i w_i x_i + b\right)$

```
z = np.dot(X, np.transpose(w)) + b
y = sigmoid(z)
```

Step 2: $\boxed{\hat{y}^n\text{: 1 for class 1, 0 for class 2}}$

$$L(f) = \sum_n C(f(x^n), \hat{y}^n)$$

```
cross_entropy = -(np.dot(Y, np.log(y)) + np.dot((1 - Y), np.log(1 - y)))
```

$$C(f(x^n), \hat{y}^n) = -\left[\hat{y}^n lnf(x^n) + (1 - \hat{y}^n) ln\left(1 - f(x^n)\right)\right]$$

Logistic Regression

Step 3: Find the best function

$$\frac{-lnL(w,b)}{\partial w_i} = \sum_n -\left[\hat{y}^n \underbrace{\boxed{\frac{ln f_{w,b}(x^n)}{\partial w_i}}}_{} + (1-\hat{y}^n)\boxed{\frac{ln\left(1-f_{w,b}(x^n)\right)}{\partial w_i}}\right]$$

$$\left(1-f_{w,b}(x^n)\right)x_i^n \qquad -f_{w,b}(x^n)x_i^n$$

$$= \sum_n -\left[\hat{y}^n\left(1-f_{w,b}(x^n)\right)x_i^n - (1-\hat{y}^n)f_{w,b}(x^n)x_i^n\right]$$

```
w_grad = np.sum(-1 * X * (Y - y).reshape((batch_size,1)), axis=0)
b_grad = np.sum(-1 * (Y - y))
```

$$= \sum_n -\left(\hat{y}^n - f_{w,b}(x^n)\right)x_i^n$$

```
w = w - l_rate * w_grad
b = b - l_rate * b_grad
```

Larger difference, larger update

$$w_i \leftarrow w_i - \eta\sum_n -\left(\hat{y}^n - f_{w,b}(x^n)\right)x_i^n$$

Gaussian Distribution-Training(mean)

$$\mu^* = \frac{1}{79}\sum_{n=1}^{79} x^n$$

average

```
#calclulate mu1 and mu2
mu1 = np.zeros((dim,))
mu2 = np.zeros((dim,))
for i in range(train_data_size):
    if Y_train[i] == 1:
        mu1 += X_train[i]
        cnt1 += 1
    else:
        mu2 += X_train[i]
        cnt2 += 1
mu1 /= cnt1
mu2 /= cnt2
```

Gaussian Distribution-Training(sigma)

$$\Sigma^* = \frac{1}{79}\sum_{n=1}^{79}(x^n - \mu^*)(x^n - \mu^*)^T$$

```
#calculate sigma1 and sigma2
sigma1 = np.zeros((dim,dim))
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for i in range(train_data_size):
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Gaussian Distribution-Training(sigma)

Shared sigma: $$\Sigma = \frac{79}{140}\Sigma^1 + \frac{61}{140}\Sigma^2$$

```
shared_sigma = (float(cnt1) / train_data_size) * sigma1 \
             + (float(cnt2) / train_data_size) * sigma2
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Gaussian Distribution-predict

$$\Sigma_1 = \Sigma_2 = \Sigma$$

$$z = \underbrace{(\mu^1 - \mu^2)^T \Sigma^{-1}}_{\boldsymbol{w}^T} x \underbrace{- \frac{1}{2}(\mu^1)^T \Sigma^{-1} \mu^1 + \frac{1}{2}(\mu^2)^T \Sigma^{-1} \mu^2 + ln \frac{N_1}{N_2}}_{b}$$

$$P(C_1|x) = \sigma(w \cdot x + b)$$

How about directly find ***w*** and b?

```
def predict(X_test, mu1, mu2, shared_sigma, N1, N2):
    sigma_inverse = np.linalg.inv(shared_sigma)
    w = np.dot( (mu1-mu2), sigma_inverse)
    x = X_test.T
    b = (-0.5) * np.dot(np.dot([mu1], sigma_inverse), mu1) \
        + (0.5) * np.dot(np.dot([mu2], sigma_inverse), mu2) + np.log(float(N1)/N2)
    a = np.dot(w, x) + b
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Gaussian Distribution-sigmoid

```
def sigmoid(z):
    res = 1 / (1.0 + np.exp(-z))
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使用np.clip() 避免數值太小或太大而overflow

Generative model -Naive Bayes Classifier

1. Calculate the probability in each category
2. P(C1 | X) = 連乘P(C1 | X in each category)
3. log(P(C1 | X)) = sigma(log(P(C1 | X_i)))
4. 比較 log(P(C1 | X)) 和 log(P(C2 | X_i))

$$\begin{bmatrix} \text{白人} \\ \text{黑人} \\ \text{黃人} \end{bmatrix}$$

P(C1 ｜ 白人) = N(白人, C1) / N(白人)

P(C2 ｜ 白人) = N(白人, C2) / N(白人)

P(? ｜ C1) = N(C1) / N(total)

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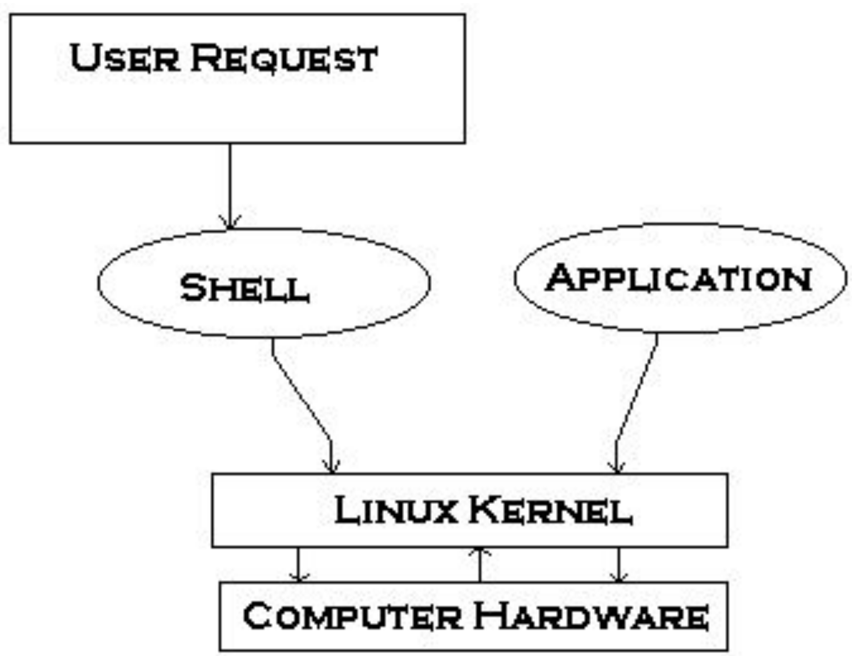

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白人

黑人

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P(C2 | 白人) = N(白人, C2) / N(白人)

P(? | C1) = N(C1) / N(total)

code

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