

# Introduction to Big Data Analytics

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# 1. DataSet & Goal Description





Celeb A : <https://www.kaggle.com/jessicali9530/celeba-dataset>

This dataset consists of two kinds of data.

01

## Features of images (Extracted by human)

There are many attributes describe each image using Boolean value. For example, there are features such as Big\_Nose, Bangs ...

image_id	# 5_o_Clock_Shadow	# Arched_Eyebrows	# Attractive	# Bags_Under_Eyes
202599 unique values				
000001.jpg	-1	1	1	-1
000002.jpg	-1	-1	-1	1
000003.jpg	-1	-1	-1	-1
000004.jpg	-1	-1	1	-1
000005.jpg	-1	1	1	-1
000006.jpg	-1	1	1	-1

02

## Raw Image

Images of men and women



# 1. DataSet & Goal Description

## Goal

### Gender Classification

My project goal is to classify each data as Male or Female

By Kernel SVM Algorithm

Using

1. Features of images (only)
2. Raw Images (only)

And Compare their results with the other

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# 2. Feature Data Kernel SVM

(This experiment uses only Feature data)



01

I made SVM classification objects with given linear and RBF kernel

01

## Linear kernel

```
clf = svm.SVC(kernel='linear', verbose=True, gamma='scale')
```

Python code for making SVM object (Sklearn library)

$$k(x_1, x_2) = x_1^T x_2$$

kernel function of 'linear' object.

02

## RBF kernel

```
clf = svm.SVC(kernel='rbf', verbose=True, gamma='scale')
```

$$k(x_1, x_2) = \exp\left(-\gamma \|x_1 - x_2\|^2\right)$$

kernel function of 'rbf' object.

# 2. Feature Data Kernel SVM



## 02 I customized SVM's kernel function

I changed SVM's kernel function so that it can calculate the vector's distance. Hamming Distance and Cosine Distance are known as good metrics for Boolean Encoded vectors' distance.

(I made following kernels so that they calculate values inversely proportional to their distances)

### 01 Hamming Distance kernel

```
def get_Hamming_Dist(x1,x2):  
    ret = np.zeros(shape=(len(x1), len(x2)), dtype=np.float)  
    for idx1, _x1 in enumerate(x1):  
        for idx2, _x2 in enumerate(x2):  
            ret[idx1][idx2]=np.sum(_x1==_x2)  
    return ret
```

### 02 Cosine Distance kernel

```
def ret_Cosine_Dist(x1,x2):  
    ret = np.zeros(shape=(len(x1), len(x2)), dtype=np.float)  
    for idx1, _x1 in enumerate(x1):  
        for idx2, _x2 in enumerate(x2):  
            ret[idx1][idx2]=distance.cosine(_x1,_x2)  
    return 1-ret
```

I Used scipy.spatial.cosine function

# 2. Feature Data Kernel SVM



## 02 I customized SVM's kernel function

### 03 Interpolation Hamming Distance & Cosine Distance

```
def interpolation_HAM_COS(prac=0.5):  
    def ret_interpolation(x1,x2):  
        return prac*get_Hamming_Dist(x1,x2)+(1-prac)*ret_Cosine_Dist(x1,x2)  
    return ret_interpolation
```

This kernel return interpolated value between Hamming Distance and Cosine Distance Using given ratio(prac value).

Below are python codes making SVM objects

```
clf = svm.SVC(kernel=get_Hamming_Dist)
```

```
clf = svm.SVC(kernel=ret_Cosine_Dist)
```

```
clf = svm.SVC(kernel=interpolation_HAM_COS(prac=0.5))
```

# 2. Feature Data Kernel SVM

Comparing Results (1,400 Training Data & 600 Test Data)

01

01

**Linear kernel**

ACC: 0.9217  
F1 score: 0.9069  
Precision: 0.8808  
Recall: 0.9347

Confusion  
TP : 229 FP : 31  
FN : 16 TN : 324

02

**RBF kernel**

ACC: 0.9133  
F1score: 0.9008  
Precision: 0.8459  
Recall: 0.9633

Confusion  
TP : 236 FP : 43  
FN : 9 TN : 312

02

01

**Hamming Dist**

ACC: 0.9150  
F1score: 0.9006  
Precision: 0.8619  
Recall: 0.9429

Confusion  
TP : 231 FP : 37  
FN : 14 TN : 318

02

**Cosine Dist**

ACC: 0.9067  
F1score: 0.8943  
Precision: 0.8316  
Recall: 0.9673

Confusion  
TP : 237 FP : 48  
FN : 8 TN : 307

03

**InterPolation**

ACC: 0.9250  
F1score: 0.9112  
Precision: 0.8817  
Recall: 0.9429

Confusion  
TP : 231 FP : 31  
FN : 14 TN : 324

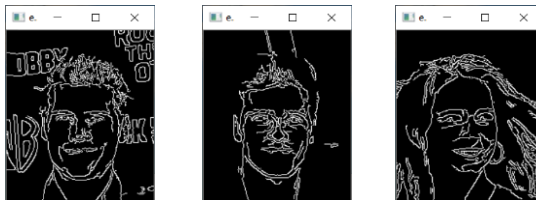
## Conclusion

InterPolation  
Kernel  
Showed  
Best  
ACC & F1

# 3. Raw Image Data Kernel SVM

## 01 Preprocessing

### 01 Edge Detection



```
img = cv2.imread('./img_files/img_align_celeba/'+img_idx+'.jpg', cv2.IMREAD_GRAYSCALE)
img = cv2.Canny(img, 50, 200)
```

**Read Image as gray scale  
& Detect Edge  
Using OpenCV Lib.**

### 02 PCA

**Reduced Image Dimension from 38,804 to 1,000  
PCA object was fitted using 20,000 Images**

```
pca = PCA(n_components=1000)
pca.fit(train_img)
```



# 3. Raw Image Data Kernel SVM



02

**Kernel SVM Classification Result**

**(1,400 Training Data & 600 Test Data)**

01

**Linear kernel**

ACC: 0.5850  
F1score: nan  
Precision: nan  
Recall: 0.0000

Confusion  
TP : 0 FP : 0  
FN : 166 TN : 234

02

**RBF kernel**

ACC: 0.5850  
F1score: nan  
Precision: nan  
Recall: 0.0000

Confusion  
TP : 0 FP : 0  
FN : 166 TN : 234

# 4. Conclusion



1. **Raw Image Data Kernel SVM Model almost didn't get fitted to the data.  
I guess this is because the raw image data is too confusing to classify gender.**
2. **When the data is encoded as Boolean values,  
Cosine Distance, Hamming Distance Calculation can work as SVM Kernel function.**

