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T3 - Análise e Síntese de Emoções em Conteúdo Multimídia

Atividade 6 - Tutorial: Emotion Recognition using Facial Landmarks, Python, DLib and OpenCV

Este jupyter notebook contém os passos realizados para reproduzir o tutorial de van Gent, P. (2016). Emotion Recognition Using Facial Landmarks, Python, DLib and OpenCV. Disponível em http://www.paulvangent.com/2016/08/05/emotion-recognition-using-facial-landmarks/ (http://www.paulvangent.com/2016/08/05/emotion-recognition-using-facial-landmarks/)

Para realizar o tutorial é necessário preparar o ambiente. Desta forma, os softwares abaixo foram instalados:

- Python (anaconda + jupyter notebook)
- DLib
- OpenCV
- SKLearn (já instalado com anaconda)

1. Preparação do ambiente

O sistema operacional utilizado para realizar o tutorial foi o Windows 10.

1.1 Instalação do Anaconda, Jupyter Notebook e Python

Para instalar o Anaconda, Jupyter Notebook e Python foi utilizado o tutorial:

https://medium.com/@neuralnets/beginners-quick-guide-for-handling-issues-launching-jupyter-notebook-for-python-using-anaconda-8be3d57a209b (https://medium.com/@neuralnets/beginners-quick-guide-for-handling-issues-launching-jupyter-notebook-for-python-using-anaconda-8be3d57a209b)

1.2 Instalação da biblioteca DLib para extrair marcos faciais

Ao realizar uma pesquisa pela internet foi encontrado um pacote com a biblioteca DLib para Anaconda em Windows. Para instalar a biblioteca foi utilizado o comando:

$ conda install -c conda-forge dlib=19.4

1.3 Instalação da biblioteca OpenCV

Para Python 3.6 foi feito o download do binário opencv_python-3.4.3+contrib-cp36-cp36m-win_amd64.whl do site https://www.lfd.uci.edu/~gohlke/pythonlibs/#opencv (https://www.lfd.uci.edu/~gohlke/pythonlibs/#opencv) e instalado manualmente.

$ pip install opencv_python-3.4.3+contrib-cp36-cp36m-win_amd64.whl

In [18]:
```
# Testes para verificar a instalação do Anaconda, Jupyter Notebook, Python, DLib e
OpenCV

# Anaconda, Python e Jupyter Notebook
print("Versão do Anaconda, Python e Jupyter Notebook: ")
!python --version
!conda list ipython

# DLib
print("Versão da biblioteca DLib: ")
import dlib
print(dlib.__version__)

# OpenCV
print("Versão da biblioteca OpenCV: ")
import cv2
print(cv2.__version__)
```

```
Versão do Anaconda, Python e Jupyter Notebook:

Python 3.6.5 :: Anaconda, Inc.

# packages in environment at C:\ProgramData\Anaconda3:
#
# Name                    Version                   Build  Channel
ipython                   6.4.0                  py36_0
ipython_genutils          0.2.0            py36h3c5d0ee_0
Versão da biblioteca DLib:
19.4.0
Versão da biblioteca OpenCV:
3.4.3
```

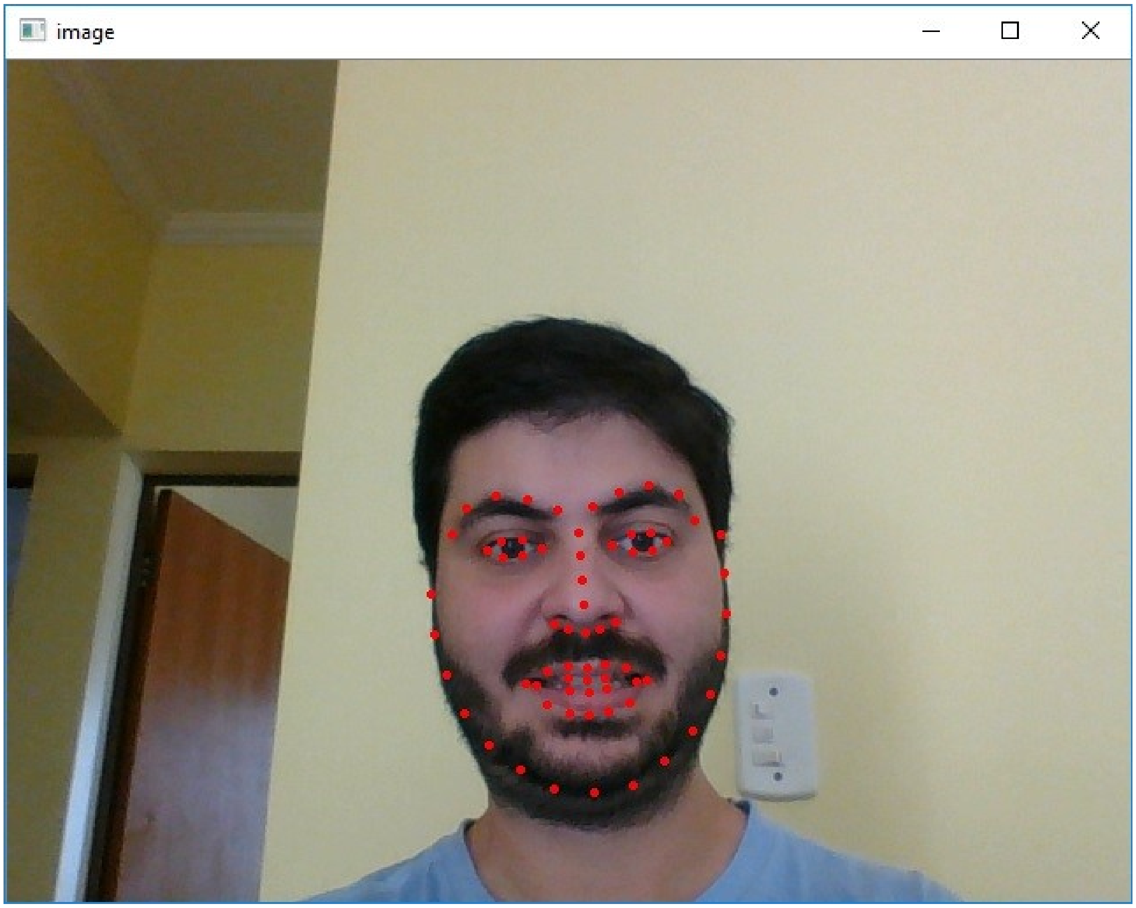
2. Detecção e captura de face via webcam

O código abaixo disponível no tutorial foi utilizado para detectar e capturar uma face via webcam.

In [7]:

```
#Import required modules
import cv2
import dlib

#Set up some required objects
video_capture = cv2.VideoCapture(0) #Webcam object
detector = dlib.get_frontal_face_detector() #Face detector
predictor = dlib.shape_predictor("shape_predictor_68_face_landmarks.dat") #Landmark
identifier. Set the filename to whatever you named the downloaded file

while True:
    ret, frame = video_capture.read()
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8,8))
    clahe_image = clahe.apply(gray)

    detections = detector(clahe_image, 1) #Detect the faces in the image

    for k,d in enumerate(detections): #For each detected face

        shape = predictor(clahe_image, d) #Get coordinates
        for i in range(1,68): #There are 68 landmark points on each face
            cv2.circle(frame, (shape.part(i).x, shape.part(i).y), 1, (0,0,255), thi
ckness=2) #For each point, draw a red circle with thickness2 on the original frame

    cv2.imshow("image", frame) #Display the frame

    if cv2.waitKey(1) & 0xFF == ord('q'): #Exit program when the user presses 'q'
        break
```

In [2]:
```
# Imagem de minha face detectada e capturada
from IPython.display import Image, display
display(Image(filename='face-detect-capture-elb.jpg', embed=True))
```



3. Extração de features de faces

O código para detecção e captura de face foi então modificado conforme tutorial para extrair as coordenadas dos marcos faciais (features) através da função get_landmarks().

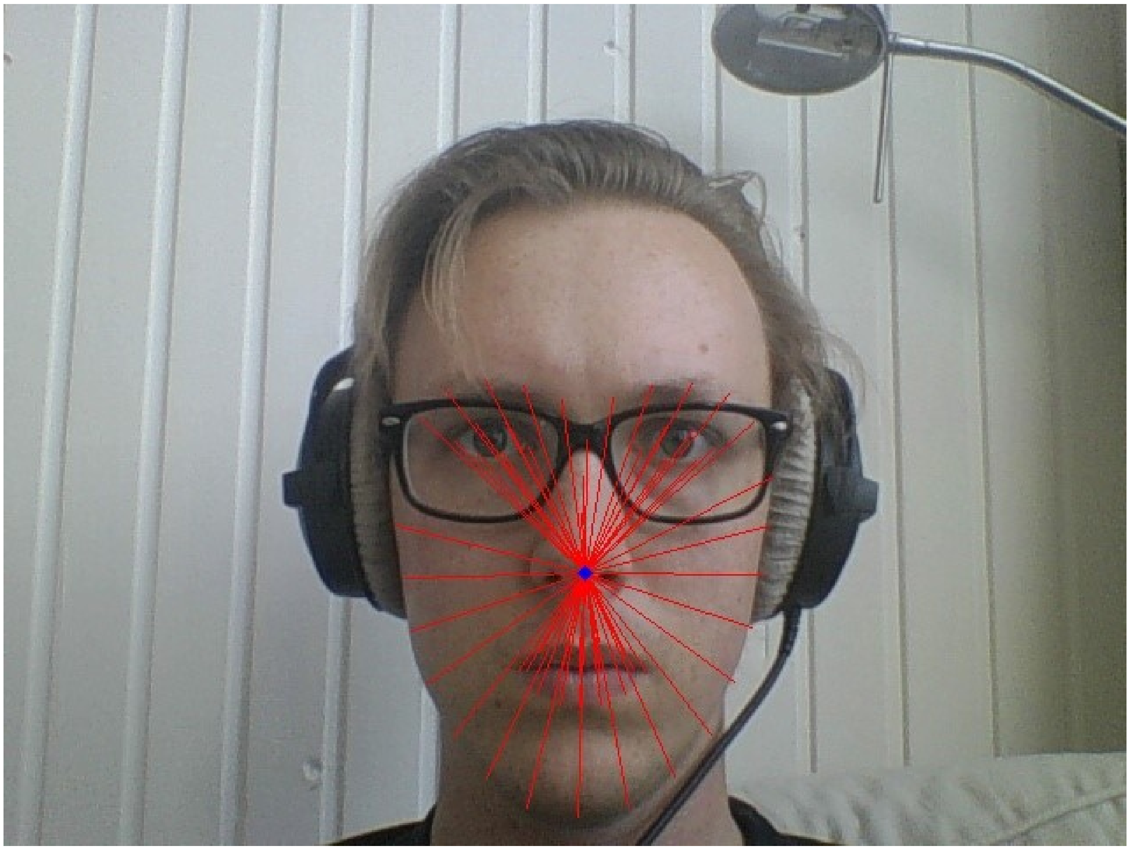
In [3]:
```
import cv2
import dlib

detector = dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor("shape_predictor_68_face_landmarks.dat")

def get_landmarks(image):
    detections = detector(image, 1)
    for k,d in enumerate(detections): #For all detected face instances individually
        shape = predictor(image, d) #Draw Facial Landmarks with the predictor class
        xlist = []
        ylist = []
        for i in range(1,68): #Store X and Y coordinates in two lists
            xlist.append(float(shape.part(i).x))
            ylist.append(float(shape.part(i).y))

        for x, y in zip(xlist, ylist): #Store all landmarks in one list in the form
at x1,y1,x2,y2,etc.
            landmarks.append(x)
            landmarks.append(y)
    if len(detections) > 0:
        return landmarks
    else: #If no faces are detected, return error message to other function to hand
le
        landmarks = "error"
        return landmarks
```

Devido a movimentação ou inclinação da face a extração dos marcos faciais (features) pode ser um problema. Desta forma, o autor propõe normalizar as coordenadas dos marcos:

```
xnorm = [(i-min(xlist))/(max(xlist)-min(xlist)) for i in xlist]
ynorm = [(i-min(ylist))/(max(ylist)-min(ylist)) for i in ylist]
```

Como esas abordagem provoca perda de informação ao comparar duas fotos muito similares, uma alternativa seria calcular a posição dos pontos em relação a um centro de gravidade facial, conforme ilustrado abaixo no tutorial.

In [4]:
```python
# Imagem dos pontos calculados em relação a um centro de gravidade facial
from IPython.display import Image, display
display(Image(filename='face-center-gravity.jpg', embed=True))
```



O autor descreve em seu tutorial algumas razões para utilizar o centro de gravidade da face ao invés da ponta do nariz como centro dos pontos, tais como:

1) Tipos diferentes de nariz introduziriam variância nos dados.

2) A distância ou inclinação da cabeça pode confundir o classificador.

Desta forma, a função get_landmarks() foi modificada para tratar o centro de gravidade das coordenadas.

In [5]:
```
def get_landmarks(image):
    detections = detector(image, 1)
    for k,d in enumerate(detections): #For all detected face instances individually
        shape = predictor(image, d) #Draw Facial Landmarks with the predictor class
        xlist = []
        ylist = []
        for i in range(1,68): #Store X and Y coordinates in two lists
            xlist.append(float(shape.part(i).x))
            ylist.append(float(shape.part(i).y))

        xmean = np.mean(xlist) #Find both coordinates of centre of gravity
        ymean = np.mean(ylist)
        xcentral = [(x-xmean) for x in xlist] #Calculate distance centre <-> other
points in both axes
        ycentral = [(y-ymean) for y in ylist]

        landmarks_vectorised = []
        for x, y, w, z in zip(xcentral, ycentral, xlist, ylist):
            landmarks_vectorised.append(w)
            landmarks_vectorised.append(z)
            meannp = np.asarray((ymean,xmean))
            coornp = np.asarray((z,w))
            dist = np.linalg.norm(coornp-meannp)
            landmarks_vectorised.append(dist)
            landmarks_vectorised.append((math.atan2(y, x)*360)/(2*math.pi))

        data['landmarks_vectorised'] = landmarks_vectorised
    if len(detections) < 1:
        data['landmarks_vestorised'] = "error"
```

4. Classificação de emoções do dataset Cohn-Kanade

O último passo do tutorial trata da classificação de emoções de um dataset usando marcos faciais.

4.1 Preparação do dataset Cohn-Kanade

- A classificação foi feita no dataset Cohn-Kanade (Kanade, T., Cohn, J. F., & Tian, Y. (2000)).
- Foi feito o download do dataset CK+ disponível em http://www.consortium.ri.cmu.edu/ckagree/ (http://www.consortium.ri.cmu.edu/ckagree/)
- O dataset foi preparado conforme tutorial anterior do mesmo autor disponível em http://www.paulvangent.com/2016/04/01/emotion-recognition-with-python-opencv-and-a-face-dataset/ (http://www.paulvangent.com/2016/04/01/emotion-recognition-with-python-opencv-and-a-face-dataset/)

O dataset CK+ consiste de uma sequência de imagens com progressão de neutro para a emoção rotulada em cada uma das pastas de imagem. Veja abaixo.

In [17]:
```
# Imagem de uma amostra do dataset CK+
from IPython.display import Image, display
display(Image(filename='ckp-dataset.jpg', embed=True))
```

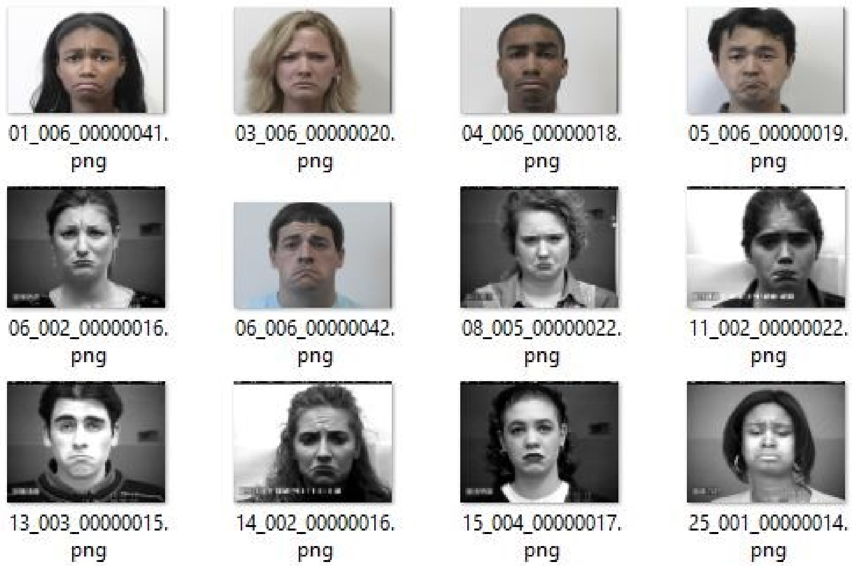
Para realizar a classificação é necessário apenas a imagem com a emoção final das progressões. Por isso, um script que seleciona essas imagens de acordo com o rótulo emocional e coloca as mesmas numa nova estrutura de diretórios agrupados por rótulo emocional será executado.

A seguinte estrutura de diretórios foi criada:

- source_emotion - contém os arquivos .txt com as emoções das imagens do dataset ck+;
- source_images - contém as imagens do dataset ck+;
- sorted_set - contém os diretórios com as emoções ("neutral", "anger", "contempt", "disgust", "fear", "happy", "sadness", "surprise"), onde o script colocará as imagens agrupadas pelas emoções.

In [1]:
```
import glob
from shutil import copyfile

emotions = ["neutral", "anger", "contempt", "disgust", "fear", "happy", "sadness", "surprise"] #Define emotion order
participants = glob.glob("source_emotion\\*") #Returns a list of all folders with participant numbers

for x in participants:
    part = "%s" %x[-4:] #store current participant number
    for sessions in glob.glob("%s\\*" %x): #Store list of sessions for current participant
        for files in glob.glob("%s\\*" %sessions):
            current_session = files[20:-30]
            file = open(files, 'r')

            emotion = int(float(file.readline())) #emotions are encoded as a float, readline as float, then convert to integer.

            sourcefile_emotion = glob.glob("source_images\\%s\\%s\\*" %(part, current_session))[-1] #get path for last image in sequence, which contains the emotion
            sourcefile_neutral = glob.glob("source_images\\%s\\%s\\*" %(part, current_session))[0] #do same for neutral image

            dest_neut = "sorted_set\\neutral\\%s" %sourcefile_neutral[25:] #Generate path to put neutral image
            dest_emot = "sorted_set\\%s\\%s" %(emotions[emotion], sourcefile_emotion[25:]) #Do same for emotion containing image

            copyfile(sourcefile_neutral, dest_neut) #Copy file
            copyfile(sourcefile_emotion, dest_emot) #Copy file
```

In [9]:
```python
# Imagem de uma amostra de tristeza
from IPython.display import Image, display
display(Image(filename='sorted-sadness.jpg', embed=True))
```



Para maximizar o desempenho do classificador é necessário realizar um pré-processamento das imagens. Foi criado um diretório chamado dataset e dentro desse diretório foram criados diretórios para as emoções ("neutral", "anger", "contempt", "disgust", "fear", "happy", "sadness", "surprise").

Após, duas etapas foram realizadas:

1) Crop - foi utilizado o filtro HAAR da biblioteca OpenCV para assegurar que apenas as imagens das faces sejam selecionadas.

2) Conversão das imagens para escala de cinza.

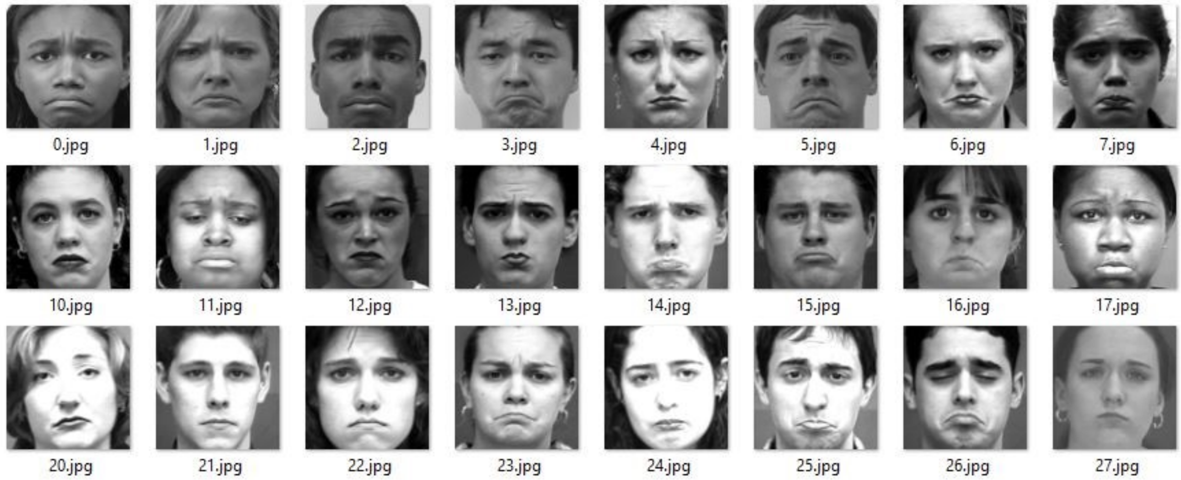
Conforme tutorial, quatro classificadores pré-treinados fornecidos pela OpenCV em http://www.paulvangent.com/wp-content/uploads/2016/04/OpenCV_FaceCascade.zip (http://www.paulvangent.com/wp-content/uploads/2016/04/OpenCV_FaceCascade.zip) foram baixados e utilizados.

Para realizar esse tratamento nas imagens script abaixo foi executado.

In [3]:
```
import cv2
import glob

faceDet = cv2.CascadeClassifier("haarcascade_frontalface_default.xml")
faceDet_two = cv2.CascadeClassifier("haarcascade_frontalface_alt2.xml")
faceDet_three = cv2.CascadeClassifier("haarcascade_frontalface_alt.xml")
faceDet_four = cv2.CascadeClassifier("haarcascade_frontalface_alt_tree.xml")

emotions = ["neutral", "anger", "contempt", "disgust", "fear", "happy", "sadness",
"surprise"] #Define emotions

def detect_faces(emotion):
    files = glob.glob("sorted_set\\%s\\*" %emotion) #Get list of all images with em
otion

    filenumber = 0
    for f in files:
        frame = cv2.imread(f) #Open image
        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY) #Convert image to grayscale

        #Detect face using 4 different classifiers
        face = faceDet.detectMultiScale(gray, scaleFactor=1.1, minNeighbors=10, min
Size=(5, 5), flags=cv2.CASCADE_SCALE_IMAGE)
        face_two = faceDet_two.detectMultiScale(gray, scaleFactor=1.1, minNeighbors
=10, minSize=(5, 5), flags=cv2.CASCADE_SCALE_IMAGE)
        face_three = faceDet_three.detectMultiScale(gray, scaleFactor=1.1, minNeigh
bors=10, minSize=(5, 5), flags=cv2.CASCADE_SCALE_IMAGE)
        face_four = faceDet_four.detectMultiScale(gray, scaleFactor=1.1, minNeighbo
rs=10, minSize=(5, 5), flags=cv2.CASCADE_SCALE_IMAGE)

        #Go over detected faces, stop at first detected face, return empty if no fa
ce.
        if len(face) == 1:
            facefeatures = face
        elif len(face_two) == 1:
            facefeatures = face_two
        elif len(face_three) == 1:
            facefeatures = face_three
        elif len(face_four) == 1:
            facefeatures = face_four
        else:
            facefeatures = ""

        #Cut and save face
        for (x, y, w, h) in facefeatures: #get coordinates and size of rectangle co
ntaining face
            print("face found in file: %s" %f)
            gray = gray[y:y+h, x:x+w] #Cut the frame to size

            try:
                out = cv2.resize(gray, (350, 350)) #Resize face so all images have
same size
                cv2.imwrite("dataset\\%s\\%s.jpg" %(emotion, filenumber), out) #Wri
te image
            except:
               pass #If error, pass file
        filenumber += 1 #Increment image number

for emotion in emotions:
    detect_faces(emotion) #Call functions
```

```
face found in file: sorted_set\neutral\00_002_00000001.png
face found in file: sorted_set\neutral\00_005_00000001.png
face found in file: sorted_set\neutral\00_006_00000001.png
face found in file: sorted_set\neutral\01_001_00000001.png
face found in file: sorted_set\neutral\01_002_00000001.png
face found in file: sorted_set\neutral\01_004_00000001.png
face found in file: sorted_set\neutral\01_006_00000001.png
face found in file: sorted_set\neutral\02_001_00000001.png
face found in file: sorted_set\neutral\02_002_00000001.png
face found in file: sorted_set\neutral\02_003_00000001.png
face found in file: sorted_set\neutral\02_004_00000001.png
face found in file: sorted_set\neutral\02_009_00000001.png
face found in file: sorted_set\neutral\03_001_00000001.png
face found in file: sorted_set\neutral\03_002_00000001.png
face found in file: sorted_set\neutral\03_006_00000001.png
face found in file: sorted_set\neutral\04_001_00000001.png
face found in file: sorted_set\neutral\04_002_00000001.png
face found in file: sorted_set\neutral\04_004_00000001.png
face found in file: sorted_set\neutral\04_006_00000001.png
face found in file: sorted_set\neutral\05_001_00000001.png
face found in file: sorted_set\neutral\05_002_00000001.png
face found in file: sorted_set\neutral\05_006_00000001.png
face found in file: sorted_set\neutral\05_008_00000001.png
face found in file: sorted_set\neutral\06_001_00000001.png
face found in file: sorted_set\neutral\06_002_00000001.png
face found in file: sorted_set\neutral\06_004_00000001.png
face found in file: sorted_set\neutral\06_006_00000001.png
face found in file: sorted_set\neutral\07_001_00000001.png
face found in file: sorted_set\neutral\07_005_00000001.png
face found in file: sorted_set\neutral\08_005_00000001.png
face found in file: sorted_set\neutral\08_006_00000001.png
face found in file: sorted_set\neutral\08_008_00000001.png
face found in file: sorted_set\neutral\09_003_00000001.png
face found in file: sorted_set\neutral\09_005_00000001.png
face found in file: sorted_set\neutral\09_006_00000001.png
face found in file: sorted_set\neutral\10_001_00000001.png
face found in file: sorted_set\neutral\10_002_00000001.png
face found in file: sorted_set\neutral\10_004_00000001.png
face found in file: sorted_set\neutral\10_006_00000001.png
face found in file: sorted_set\neutral\11_001_00000001.png
face found in file: sorted_set\neutral\11_002_00000001.png
face found in file: sorted_set\neutral\11_003_00000001.png
face found in file: sorted_set\neutral\11_004_00000001.png
face found in file: sorted_set\neutral\11_005_00000001.png
face found in file: sorted_set\neutral\11_006_00000001.png
face found in file: sorted_set\neutral\11_007_00000001.png
face found in file: sorted_set\neutral\12_005_00000001.png
face found in file: sorted_set\neutral\13_001_00000001.png
face found in file: sorted_set\neutral\13_003_00000001.png
face found in file: sorted_set\neutral\13_008_00000001.png
face found in file: sorted_set\neutral\14_001_00000001.png
face found in file: sorted_set\neutral\14_002_00000001.png
face found in file: sorted_set\neutral\14_003_00000001.png
face found in file: sorted_set\neutral\14_005_00000001.png
face found in file: sorted_set\neutral\14_006_00000001.png
face found in file: sorted_set\neutral\15_001_00000001.png
face found in file: sorted_set\neutral\15_004_00000001.png
face found in file: sorted_set\neutral\15_008_00000001.png
face found in file: sorted_set\neutral\16_001_00000001.png
face found in file: sorted_set\neutral\16_006_00000001.png
face found in file: sorted_set\neutral\16_007_00000001.png
face found in file: sorted_set\neutral\17_001_00000001.png
face found in file: sorted_set\neutral\17_003_00000001.png
face found in file: sorted_set\neutral\17_006_00000001.png
```

In [13]:
```
# Resultado, após executar o script de tratamento do dataset ck+ para obter o crop
e grayscale
from IPython.display import Image, display
display(Image(filename='crop-grayscale-sadness.jpg', embed=True))
```



4.2 Execução do Classificador Fisher Face

Após preparar o dataset foi realizado uma divisão aleatória do mesmo, 80% para treinamento e 20% para teste. A classificação foi então executada pelo script 10 vezes para derivar uma média do desempenho do classificador. O script com o classificador fisher face está disponível no tuturial http://www.paulvangent.com/2016/04/01/emotion-recognition-with-python-opencv-and-a-face-dataset/ (http://www.paulvangent.com/2016/04/01/emotion-recognition-with-python-opencv-and-a-face-dataset/)

In [14]:
```
import cv2
import glob
import random
import numpy as np
emotions = ["neutral", "anger", "contempt", "disgust", "fear", "happy", "sadness",
"surprise"] #Emotion list
fishface = cv2.face.FisherFaceRecognizer_create() #Initialize fisher face classifie
r

data = {}
def get_files(emotion): #Define function to get file list, randomly shuffle it and
split 80/20
    files = glob.glob("dataset\\%s\\*" %emotion)
    random.shuffle(files)
    training = files[:int(len(files)*0.8)] #get first 80% of file list
    prediction = files[-int(len(files)*0.2):] #get last 20% of file list
    return training, prediction
def make_sets():
    training_data = []
    training_labels = []
    prediction_data = []
    prediction_labels = []
    for emotion in emotions:
        training, prediction = get_files(emotion)
        #Append data to training and prediction list, and generate labels 0-7
        for item in training:
            image = cv2.imread(item) #open image
            gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY) #convert to grayscale
            training_data.append(gray) #append image array to training data list
            training_labels.append(emotions.index(emotion))
        for item in prediction: #repeat above process for prediction set
            image = cv2.imread(item)
            gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
            prediction_data.append(gray)
            prediction_labels.append(emotions.index(emotion))
    return training_data, training_labels, prediction_data, prediction_labels
def run_recognizer():
    training_data, training_labels, prediction_data, prediction_labels = make_sets(
)
    print("training fisher face classifier")
    print("size of training set is:", len(training_labels), "images")
    fishface.train(training_data, np.asarray(training_labels))
    print("predicting classification set")
    cnt = 0
    correct = 0
    incorrect = 0
    for image in prediction_data:
        pred, conf = fishface.predict(image)
        if pred == prediction_labels[cnt]:
            correct += 1
            cnt += 1
        else:
            incorrect += 1
            cnt += 1
    return ((100*correct)/(correct + incorrect))
#Now run it
metascore = []
for i in range(0,10):
    correct = run_recognizer()
    print("got", correct, "percent correct!")
    metascore.append(correct)
print("\n\nend score:", np.mean(metascore), "percent correct!")
```

```
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 73.33333333333333 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 75.55555555555556 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 74.44444444444444 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 73.33333333333333 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 71.11111111111111 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 76.66666666666667 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 75.55555555555556 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 72.22222222222223 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 72.22222222222223 percent correct!
training fisher face classifier
size of training set is: 371 images
predicting classification set
got 76.66666666666667 percent correct!


end score: 74.1111111111111 percent correct!
```

4.3 Execução do Classificador Linear SVM

Após preparar o dataset foi realizado uma divisão aleatória do mesmo, 80% para treinamento e 20% para teste. A classificação foi então executada pelo script 10 vezes para derivar uma média do desempenho do classificador.

In [16]:

```
import cv2
import glob
import random
import math
import numpy as np
import dlib
import itertools
from sklearn.svm import SVC

emotions = ["anger", "contempt", "disgust", "fear", "happiness", "neutral", "sadnes
s", "surprise"] #Emotion list
clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8,8))
detector = dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor("shape_predictor_68_face_landmarks.dat") #Or set t
his to whatever you named the downloaded file
clf = SVC(kernel='linear', probability=True, tol=1e-3)#, verbose = True) #Set the c
lassifier as a support vector machines with polynomial kernel

data = {} #Make dictionary for all values
#data['landmarks_vectorised'] = []

def get_files(emotion): #Define function to get file list, randomly shuffle it and
split 80/20
    files = glob.glob("dataset\\%s\\*" %emotion)
    random.shuffle(files)
    training = files[:int(len(files)*0.8)] #get first 80% of file list
    prediction = files[-int(len(files)*0.2):] #get last 20% of file list
    return training, prediction

def get_landmarks(image):
    detections = detector(image, 1)
    for k,d in enumerate(detections): #For all detected face instances individually
        shape = predictor(image, d) #Draw Facial Landmarks with the predictor class
        xlist = []
        ylist = []
        for i in range(1,68): #Store X and Y coordinates in two lists
            xlist.append(float(shape.part(i).x))
            ylist.append(float(shape.part(i).y))

        xmean = np.mean(xlist)
        ymean = np.mean(ylist)
        xcentral = [(x-xmean) for x in xlist]
        ycentral = [(y-ymean) for y in ylist]

        landmarks_vectorised = []
        for x, y, w, z in zip(xcentral, ycentral, xlist, ylist):
            landmarks_vectorised.append(w)
            landmarks_vectorised.append(z)
            meannp = np.asarray((ymean,xmean))
            coornp = np.asarray((z,w))
            dist = np.linalg.norm(coornp-meannp)
            landmarks_vectorised.append(dist)
            landmarks_vectorised.append((math.atan2(y, x)*360)/(2*math.pi))

        data['landmarks_vectorised'] = landmarks_vectorised
    if len(detections) < 1:
        data['landmarks_vestorised'] = "error"

def make_sets():
    training_data = []
    training_labels = []
    prediction_data = []
    prediction_labels = []
    for emotion in emotions:
```

```
Making sets 0
 working on anger
 working on contempt
 working on disgust
 working on fear
 working on happiness
 working on neutral
 working on sadness
 working on surprise
training SVM linear 0
getting accuracies 0
linear:  0.7662337662337663
Making sets 1
 working on anger
 working on contempt
 working on disgust
 working on fear
 working on happiness
 working on neutral
 working on sadness
 working on surprise
training SVM linear 1
getting accuracies 1
linear:  0.8571428571428571
Making sets 2
 working on anger
 working on contempt
 working on disgust
 working on fear
 working on happiness
 working on neutral
 working on sadness
 working on surprise
training SVM linear 2
getting accuracies 2
linear:  0.7662337662337663
Making sets 3
 working on anger
 working on contempt
 working on disgust
 working on fear
 working on happiness
 working on neutral
 working on sadness
 working on surprise
training SVM linear 3
getting accuracies 3
linear:  0.7402597402597403
Making sets 4
 working on anger
 working on contempt
 working on disgust
 working on fear
 working on happiness
 working on neutral
 working on sadness
 working on surprise
training SVM linear 4
getting accuracies 4
linear:  0.7662337662337663
Making sets 5
 working on anger
 working on contempt
 working on disgust
```

5. Conclusões

Comparando o resultado dos classificadores: Fisher Face sem o uso de marcos faciais e Linear SVM com o uso de marcos faciais, nota-se que o desempenho do classificador Linear SVM com o uso de marcos faciais foi superior.

O tutorial compara o desempenho de outros classificadores, mostrando que o SVM linear possui melhor desempenho para vários casos com uso de marcos faciais (features).

A utilização de outras features, tais como: (vetorização, centro de gravidade) não aumentou o desempenho do classificador.

O tutorial é muito interessante para introduzir o uso da bibliotecas Python para a detecção e captura de emoções em imagens rotuladas com o usu de modelos de aprendizado de máquina.

O algoritmo SVM Linear mostrou-se mais eficiante e portanto mais apropriado para a classificação.

6. Referências

- van Gent, P. (2016). Emotion Recognition Using Facial Landmarks, Python, DLib and OpenCV. A tech blog about fun things with Python and embedded electronics - http://www.paulvangent.com/2016/08/05/emotion-recognition-using-facial-landmarks/ (http://www.paulvangent.com/2016/08/05/emotion-recognition-using-facial-landmarks/)
- van Gent, P. (2016). Emotion Recognition With Python, OpenCV and a Face Dataset - http://www.paulvangent.com/2016/04/01/emotion-recognition-with-python-opencv-and-a-face-dataset/ (http://www.paulvangent.com/2016/04/01/emotion-recognition-with-python-opencv-and-a-face-dataset/)
- Kanade, T., Cohn, J. F., & Tian, Y. (2000). Comprehensive database for facial expression analysis. Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition (FG'00), Grenoble, France, 46-53.
- Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., & Matthews, I. (2010). The Extended Cohn-Kanade Dataset (CK+): A complete expression dataset for action unit and emotion-specified expression. Proceedings of the Third International Workshop on CVPR for Human Communicative Behavior Analysis (CVPR4HB 2010), San Francisco, USA, 94-101.
- Cohn-Kanade (CK and CK+) database Download Site - http://www.consortium.ri.cmu.edu/ckagree/ (http://www.consortium.ri.cmu.edu/ckagree/)
- Beginner’s Guide for installing Jupyter Notebook using Anaconda Distribution - https://medium.com/@neuralnets/beginners-quick-guide-for-handling-issues-launching-jupyter-notebook-for-python-using-anaconda-8be3d57a209b (https://medium.com/@neuralnets/beginners-quick-guide-for-handling-issues-launching-jupyter-notebook-for-python-using-anaconda-8be3d57a209b)
- Unofficial Windows Binaries for Python Extension Packages - https://www.lfd.uci.edu/~gohlke/pythonlibs/ (https://www.lfd.uci.edu/~gohlke/pythonlibs/)