

▼ MÁSTER BIG DATA Y DATA SCIENCE

Mapas de atención visual basados en redes neuronales para la búsqueda de predicciones

- Curso: Trabajo fin de máster
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- Fecha entrega: 30/09/21

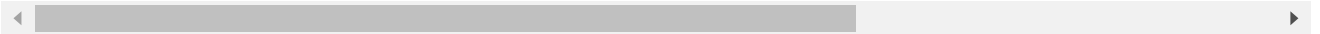
```
# Se importa la función de drive que es donde se encuentra el dataset
from google.colab import drive
```

```
# Esto provocará la autorización
drive.mount('/content/drive')
```

```
# Se cambia el directorio
import os
os.chdir('/content/drive/My Drive/MASTER/TFM/TFM_CNN_training')
```



Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount('/content/drive').



▼ Librerías

```
pip install multimatch-gaze
```

```
Requirement already satisfied: multimatch-gaze in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from multimatch-gaze)
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from multimatch-gaze)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from multimatch-gaze)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas->multimatch-gaze)
Requirement already satisfied: python-dateutil>=2.5.0 in /usr/local/lib/python3.6/dist-packages (from pandas->multimatch-gaze)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil->multimatch-gaze)
```



```
import numpy as np
import matplotlib.pyplot as plt
import cv2 as cv # Importa opencv
plt.style.use('default')
from os import listdir
from keras import backend as K
import tensorflow as tf
```

```
from scipy.io import loadmat
from scipy.ndimage import gaussian_filter
from scipy import ndimage
from imageio import imread
```

```
from imageio import imread
```

```
import skimage.io as io          # Importa skimage necesario para leer imágenes como array
from skimage.transform import rescale
from skimage import color
from skimage.measure import label
from skimage.morphology import extrema
from skimage import exposure
```

```
import multimatch_gaze as m
```

▼ Funciones

```
def normalize_map(s_map):
    # Normaliza el mapa de prominencia
    norm_s_map = (s_map - np.min(s_map))/((np.max(s_map)-np.min(s_map))*1.0)
    return norm_s_map

# Determina los peaks necesarios
def peaks():
    a = np.arange(3,13,1) # El resultado es un array [3 a 12]
    # Asigna probabilidades a cada número
    p = np.asarray([9, 89, 405, 1098, 1952, 2466, 2461, 1256, 252, 12], dtype= np.float16 )
    p[:] = [x / 10000 for x in p]
    result = np.random.choice(a, p=p)
    return result
```

▼ Variables globales

```
# Tamaño de entrada a la CNN
in_rows = 240
in_cols = 320

# Tamaño de salida a la CNN
out_rows = 240
out_cols = 320

# Rutas
path_imgs = "/content/drive/My Drive/MASTER/TFM/SALICON/images/train2014/"
path_maps = "/content/drive/My Drive/MASTER/TFM/SALICON/maps/train/"
path_imgs_test = "/content/drive/My Drive/MASTER/TFM/SALICON/images/val2014/"
path_maps_test = "/content/drive/My Drive/MASTER/TFM/SALICON/maps/val/"

path_fixs = "/content/drive/My Drive/MASTER/TFM/SALICON/fix_maps/train/"
path_fixs_test = "/content/drive/My Drive/MASTER/TFM/SALICON/fix_maps/val/"

path_predic = "/content/drive/My Drive/MASTER/TFM/predictions/test/"
path_pred_val = "/content/drive/My Drive/MASTER/TFM/predictions/val/"
#path_weights= "/content/drive/My Drive/MASTER/TFM/tmp2"
weights_filename = 'imagenet-vgg-m.mat'
```

```
font = cv.FONT_HERSHEY_SIMPLEX
```

PREPROCESAMIENTO

▼ Función que procesa previamente las imágenes antes de introducirlas en la arquitectura de CNN

```
def preprocess_images(paths, in_rows, in_cols):

    for i, path in enumerate(paths):
        original_image = io.imread(path)
        ims = np.zeros((len(paths), in_rows, in_cols, 3))
        ims[i] = rescale(original_image, 1.0 / 2.0, anti_aliasing=False)

        ims[:, :, :, 0] -= 126.763/255      #103.939/255
        ims[:, :, :, 1] -= 121.651/255      #116.779/255
        ims[:, :, :, 2] -= 114.519/255      #123.68/255

    return ims
```

▼ Funciones que preprocesan los mapas de la verdad y el mapa de fijaciones antes de introducirlos en la arquitectura de CNN

```
def preprocess_maps(paths, in_rows, in_cols):
    ims = np.zeros((len(paths), in_rows, in_cols, 1))

    for i, path in enumerate(paths):
        original_map = io.imread(path)
        ims[i, :, :, 0] = rescale(original_map.astype(np.float32), 1.0 / 2.0, anti_aliasing=F)
        ims[i, :, :, 0] /= 255.0

    return ims

def preprocess_fixs(paths, in_rows, in_cols):
    ims = np.zeros((len(paths), in_rows, in_cols, 1))

    for i, path in enumerate(paths):
        original_map = color.rgb2gray(io.imread(path))
        ims[i, :, :, 0] = rescale(original_map.astype(np.float32), 1.0 / 2.0, anti_aliasing=F)
        ims[i, :, :, 0] = normalize_map(ims[i, :, :, 0])
        r, c = np.nonzero(ims[i, :, :, 0])
        # Después de cambiar la escala, los valores de intensidad cambian -> Conversión de
        for j in range(len(r)):
            ims[i, r[j], c[j], 0] = 1

    return ims
```

Función que define el generador que será utilizado por la función `fit_generator` para leer imágenes durante el proceso de entrenamiento.

```
def generator(b_s, phase_gen='train'):

    list_images = [path_imgs + f for f in os.listdir(path_imgs)
                    if f.endswith(('.jpg', '.jpeg', '.png'))]
    list_maps = [path_maps + f for f in os.listdir(path_maps)
                 if f.endswith(('.jpg', '.jpeg', '.png'))]

    # Hace correspondencia entre imágenes y mapas
    list_images.sort()
    list_maps.sort()

    if phase_gen == 'train':
        images = list_images[0:9000]
        maps = list_maps[0:9000]
    elif phase_gen == 'val':
        images = list_images[9000:]
        maps = list_maps[9000:]
    else:
        raise NotImplementedError

    counter = 0
    while True:
        Y = preprocess_maps(maps[counter:counter+b_s], out_rows, out_cols)
        yield preprocess_images(images[counter:counter+b_s], in_rows, in_cols), Y
        counter = (counter + b_s) % len(images)
```

Función que define el generador que leerá imágenes de prueba para probar el desempeño de la arquitectura CNN

```
def generator_test(b_s, path_imgs_test):
    images = [path_imgs_test + f for f in os.listdir(path_imgs_test) if f.endswith(('.jpg',
maps = [path_maps_test + f for f in os.listdir(path_maps_test) if f.endswith(('.jpg',
fixs = [path_fixs_test + f for f in os.listdir(path_fixs_test) if f.endswith(('.jpg',
images.sort()
maps.sort()
fixs.sort()

    counter = 0
    while True:
        Y = preprocess_maps(maps[counter:counter+b_s], out_rows, out_cols)
        F = preprocess_fixs(fixs[counter:counter+b_s], out_rows, out_cols)
        return preprocess_images(images[counter:counter + b_s], in_rows, in_cols), Y, F
        counter = (counter + b_s) % len(images)
```

Función que nos permite replicar elementos mediante tensorflow

```
def repeat_elements(x, rep, axis):
    x_shape = x.get_shape().as_list()
    reps = np.ones(len(x_shape))
    reps[axis] = rep
    x_rep = tf.tile(x, reps)
    return x_rep
```

- Función que implementa la métrica de divergencia Kullback Leibler en 2D que mide la
- ▼ diferencia entre dos distribuciones de probabilidad (mapas gaussianos y mapas de predicción).

```
# KL-Divergence Loss
def kl_divergence_2d(y_true, y_pred):
    min_y_true = repeat_elements(K.expand_dims(repeat_elements(K.expand_dims(K.min(K.min(y_true,
                                                                                               in_rows, axis=1)), in_c
                                                                                               in_rows, axis=1)), in_c
    min_y_pred = repeat_elements(K.expand_dims(repeat_elements(K.expand_dims(K.min(K.min(y_pred,
                                                                                               in_rows, axis=1)), in_c
                                                                                               in_rows, axis=1)), in_c
    max_y_true = repeat_elements(K.expand_dims(repeat_elements(K.expand_dims(K.max(K.max(y_true,
                                                                                               in_rows, axis=1)), in_c
                                                                                               in_rows, axis=1)), in_c
    max_y_pred = repeat_elements(K.expand_dims(repeat_elements(K.expand_dims(K.max(K.max(y_pred,
                                                                                               in_rows, axis=1)), in_c
                                                                                               in_rows, axis=1)), in_c

    y_true = (y_true - min_y_true) / (max_y_true - min_y_true + K.epsilon())
    y_pred = (y_pred - min_y_pred) / (max_y_pred - min_y_pred + K.epsilon())

    sum_y_true = repeat_elements(K.expand_dims(repeat_elements(K.expand_dims(K.sum(K.sum(y_true,
                                                                                               out_rows, axis=1)), out_c
                                                                                               out_rows, axis=1)), out_c
    sum_y_pred = repeat_elements(K.expand_dims(repeat_elements(K.expand_dims(K.sum(K.sum(y_pred,
                                                                                               out_rows, axis=1)), out_c
                                                                                               out_rows, axis=1)), out_c

    y_true = K.clip(y_true / (sum_y_true + K.epsilon()), K.epsilon(), 1)
    y_pred = K.clip(y_pred / (sum_y_pred + K.epsilon()), K.epsilon(), 1)

    return K.sum(K.sum(y_true * K.log(y_true / y_pred), axis=2), axis=1)
```

- ▼ Función que carga pesos

```
def load_matconvnet_weights(model, weights_filename, idx_layers=[0,4,8]):
    data = loadmat(weights_filename, matlab_compatible=False, struct_as_record=False)

    layers = data['layers'][0]

    for i in idx_layers:
        weights = layers[i][0][0].weights[0,0]
        bias = np.squeeze(layers[i][0][0].weights[0,1])
        model.get_layer(layers[i][0][0].name[0]).set_weights([weights, bias])

    return model
```

EVALUACIÓN DE LAS MÉTRICAS

▼ Función que calcula el área bajo la curva

```
def sAUC_Zhang(smap,gt,other_map,splits=100,stepsize=0.01):
    # smap es el mapa de prominencia o saliency map
    # gt es el mapa de fijación humana (matriz binaria)
    # other_map es un mapa de fijación binario tomando la unión de
    # fijaciones de M otras imágenes aleatorias
    # splits es el número de divisiones aleatorias
    # stepsize sirve para recorrer el mapa de prominencia

    eps = np.finfo(float).eps

    # Se normaliza el saliency map
    smap = (smap-np.min(smap))/(np.max(smap)-np.min(smap)+eps)
    smap=np.nan_to_num(smap)
    other_map = (other_map-np.min(other_map))/(np.max(other_map)-np.min(other_map)+eps)
    other_map=np.nan_to_num(other_map)

    # Hace del mapa de prominencia, otro mapa del tamaño del mapa de fijación
    S = np.reshape(smap,-1)
    F = np.reshape(gt,-1)
    Oth = np.reshape(other_map,-1)

    Sth = S[F>0];
    Nfixations = len(Sth)

    # Para cada fijación, se muestra los valores de Nsplits del mapa en ubicaciones
    # especificadas por otherMap
    ind = np.where(Oth>0)[0] # Encuentra ubicaciones de fijación en las imágenes
    pind = Oth[ind]
    pind = pind/(np.sum(pind)+eps)
    if np.sum(np.isnan(pind)) == np.size(pind):
        pind = (1.0/np.size(pind))*np.ones(np.shape(pind))

    Nfixations_oth = np.minimum(Nfixations,len(ind))
    randfix = [];

    for i in np.arange(splits):
        randind = np.random.choice(ind,Nfixations_oth,p=pind)
        randfix.append(S[randind])

    # Calcula el área bajo la curva por random split (aleatorias)
    if Nfixations > 0:
        auc = [] # nan(1,Nsplits);
        for s in np.arange(splits):

            curfix = randfix[s]

            allthreshe = np.flip(np.arange(0,np.double(np.max([Sth,curfix]))+stepsize,ste
            tn = np.zeros(len(allthreshe)+2)
```

```

tp = np.zeros((len(allthreses)+2),
fp = np.zeros((len(allthreses)+2))
tp[0]=0; tp[-1] = 1
fp[0]=0; fp[-1] = 1

for i in np.arange(len(allthreses)):
    thresh = allthreses[i]
    tp[i+1] = np.sum((Sth >= thresh))/Nfixations
    fp[i+1] = np.sum((curfix >= thresh))/Nfixations_oth

auc.append(np.trapz(tp,fp)) # Media sobre el área bajo la curva

score = np.mean(auc)
if np.isnan(score):
    score = 0
else:
    score = np.nan
    tp = []
    fp = []

return score

def nss(smap,gt):
    # smap es el mapa de prominencia o saliency map
    # gt es el mapa de fijación humana (matriz binaria)

    # Hace que el saliency map sea del tamaño del mapa de fijación
    if np.shape(smap)[0]!=np.shape(gt)[0] or np.shape(smap)[1]!=np.shape(gt)[1]:
        smap = rescale(smap, np.shape(gt),anti_aliasing='False')

    # Normaliza el saliency map
    smap = (smap-np.min(smap))/(np.max(smap)-np.min(smap))
    smap=np.nan_to_num(smap)

    S = np.reshape(smap,-1)
    F = np.reshape(gt,-1)

    Sth = S[F>0];
    Sth_norm = (Sth - np.mean(smap))/np.std(smap)

    NSSscore = np.mean(Sth_norm)

    return NSSscore

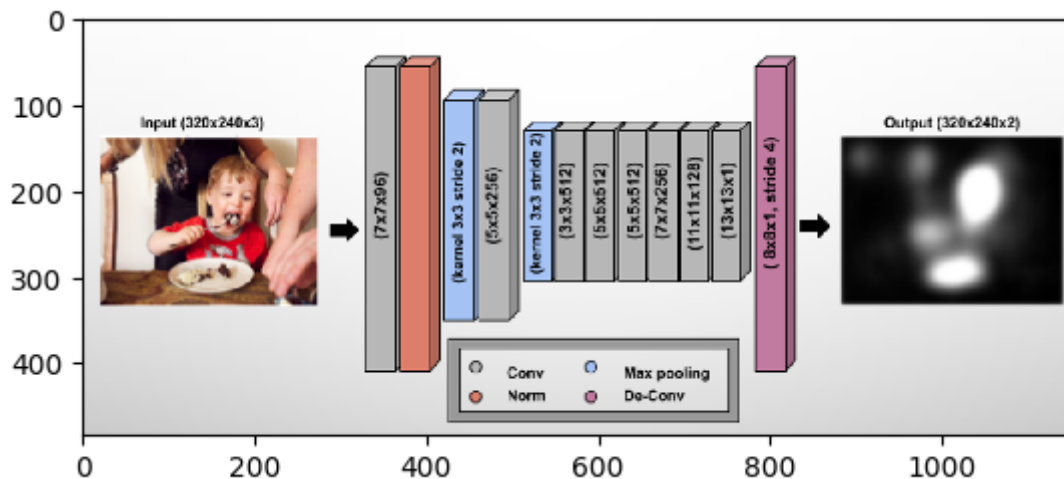
def kldiv(s_map,gt):
    s_map = normalize_map(s_map)
    s_map /= (np.sum(s_map)*1.0)
    gt = gt/(np.sum(gt)*1.0)
    eps = 2.2204e-16
    res = gt * np.log(eps + gt/(s_map + eps))
    return np.sum(res)

```

Arquitectura redes neuronales (CNN)

▼ Arquitectura inicial

```
arch = io.imread('CNN_Architecture.PNG')
plt.imshow(arch)
plt.show()
```



▼ Función que define LNR para implementar la capa de normalización en Keras

```
def LRN(x):
    import tensorflow as tf
    return tf.nn.local_response_normalization(x)
```

▼ Función que define las Convolution layers

```
def conv2D(filters, k_s, n_conv, act='relu'):

    conv_layer = Conv2D(filters,(k_s,k_s),padding='same',activation=act,
                        kernel_initializer=RandomNormal(mean=0.0, stddev=0.01, seed=2),
                        bias_initializer=Constant(value=0.1), name=n_conv)

    return conv_layer

from keras.models import Sequential, load_model
from keras.layers import Conv2D, MaxPooling2D, Conv2DTranspose, Lambda, UpSampling2D
from keras.optimizers import Adam
from keras.initializers import RandomNormal, Constant
from keras.callbacks import EarlyStopping, ModelCheckpoint

b_s = 32
epochs = 25

# Función seed () aleatoria (para los pesos)
#seed(3)
```



```

model = Sequential()
model.add(Conv2D(96,(7,7),padding='same',activation='relu',
                kernel_initializer=RandomNormal(mean=0.0, stddev=0.01,seed=2),
                bias_initializer=Constant(value=0.1), name='conv1',
                input_shape=(240,320,3)))
model.add(Lambda(LRN))
model.add(MaxPooling2D(pool_size=(3,3),strides=2,padding='same'))
model.add(conv2D(256, 5, n_conv='conv2'))
model.add(MaxPooling2D(pool_size=(3,3),strides=2,padding='same'))
model.add(conv2D(512, 3, n_conv='conv3'))
model.add(conv2D(512, 5, n_conv='conv4'))
model.add(conv2D(512, 5, n_conv='conv5'))
model.add(conv2D(256, 7, n_conv='conv6'))
model.add(conv2D(128, 11, n_conv='conv7'))
model.add(conv2D(1, 13, n_conv='conv8'))
#model.add(UpSampling2D(size=(16, 16)))
#model.add(Conv2D(1,(8,8),strides=(4,4),padding='same',activation='relu',
#                kernel_initializer=RandomNormal(mean=0.0, stddev=0.01,seed=2),
#                bias_initializer=Constant(value=0.1), name='convOut'))
model.add(Conv2DTranspose(1,(8,8),strides=4,padding='same',activation=None,
                        kernel_initializer=RandomNormal(mean=0.0, stddev=0.01,seed=2),
                        bias_initializer=Constant(value=0.1)))

# Carga los pesos de un fichero de matlab
load_matconvnet_weights(model, weights_filename)

model.load_weights(filepath='tmp2/weights.24.hdf5')
model.compile(loss=kl_divergence_2d, optimizer=Adam(lr=0.00001)) #metrics=[kl_divergence_2
                        # Default lr parameter = 0.001

# ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=False, save_weig
checkpointer = ModelCheckpoint(filepath='tmp4/weights.{epoch:02d}.hdf5', verbose=1, save_b

# EarlyStopping(monitor='val_loss', min_delta=0, patience=0, verbose=0, mode='auto', base
earlyStop = EarlyStopping(monitor='val_loss', patience=5, verbose=1, restore_best_weights=

```

WARNING: Logging before flag parsing goes to stderr.

W0716 12:09:25.216133 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

W0716 12:09:25.272207 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

W0716 12:09:25.280038 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

W0716 12:09:25.313764 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

W0716 12:09:32.221543 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

W0716 12:09:32.223237 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

W0716 12:09:37.960326 139787602458496 deprecation_wrapper.py:119] From /usr/local/lib

```

# Entrena el modelo en datos generados por un generador de Python lr = 0.00001
record = model.fit_generator(generator(b_s, phase_gen='train'),

```

```

steps_per_epoch=np.around(9000/b_s), epochs=epochs, verbose=1,
validation_data=generator(b_s, phase_gen='val'),
validation_steps=np.around(999/b_s),
callbacks=[checkpointer, earlyStop])

```

Epoch 1/25

```

/usr/local/lib/python3.6/dist-packages/skimage/transform/_warps.py:23: UserWarning
warn('The default multichannel argument (None) is deprecated. Please '
281/281 [=====] - 4776s 17s/step - loss: 1.0722 - val_loss:

```

Epoch 00001: val_loss improved from inf to 0.93052, saving model to tmp2/weights.0

Epoch 2/25

```

281/281 [=====] - 871s 3s/step - loss: 0.8420 - val_loss:

```

Epoch 00002: val_loss improved from 0.93052 to 0.72501, saving model to tmp2/weights.0

Epoch 3/25

```

281/281 [=====] - 881s 3s/step - loss: 0.6799 - val_loss:

```

Epoch 00003: val_loss improved from 0.72501 to 0.61139, saving model to tmp2/weights.0

Epoch 4/25

```

281/281 [=====] - 889s 3s/step - loss: 0.5950 - val_loss:

```

Epoch 00004: val_loss improved from 0.61139 to 0.56670, saving model to tmp2/weights.0

Epoch 5/25

```

281/281 [=====] - 871s 3s/step - loss: 0.5610 - val_loss:

```

Epoch 00005: val_loss improved from 0.56670 to 0.54476, saving model to tmp2/weights.0

Epoch 6/25

```

281/281 [=====] - 863s 3s/step - loss: 0.5435 - val_loss:

```

Epoch 00006: val_loss improved from 0.54476 to 0.53404, saving model to tmp2/weights.0

Epoch 7/25

```

281/281 [=====] - 866s 3s/step - loss: 0.5286 - val_loss:

```

Epoch 00007: val_loss improved from 0.53404 to 0.52392, saving model to tmp2/weights.0

Epoch 8/25

```

281/281 [=====] - 868s 3s/step - loss: 0.5178 - val_loss:

```

Epoch 00008: val_loss improved from 0.52392 to 0.50830, saving model to tmp2/weights.0

Epoch 9/25

```

281/281 [=====] - 866s 3s/step - loss: 0.5075 - val_loss:

```

Epoch 00009: val_loss improved from 0.50830 to 0.50222, saving model to tmp2/weights.0

Epoch 10/25

```

281/281 [=====] - 868s 3s/step - loss: 0.4994 - val_loss:

```

Epoch 00010: val_loss improved from 0.50222 to 0.49905, saving model to tmp2/weights.0

Epoch 11/25

```

281/281 [=====] - 862s 3s/step - loss: 0.4928 - val_loss:

```

Epoch 00011: val_loss improved from 0.49905 to 0.49385, saving model to tmp2/weights.0

Epoch 12/25

```

281/281 [=====] - 865s 3s/step - loss: 0.4844 - val_loss:

```

Epoch 00012: val_loss improved from 0.49385 to 0.48934, saving model to tmp2/weights.0

Epoch 13/25

```

281/281 [=====] - 867s 3s/step - loss: 0.4798 - val_loss:

```

Epoch 00013: val_loss improved from 0.48934 to 0.48318, saving model to tmp2/weights.0

Epoch 14/25

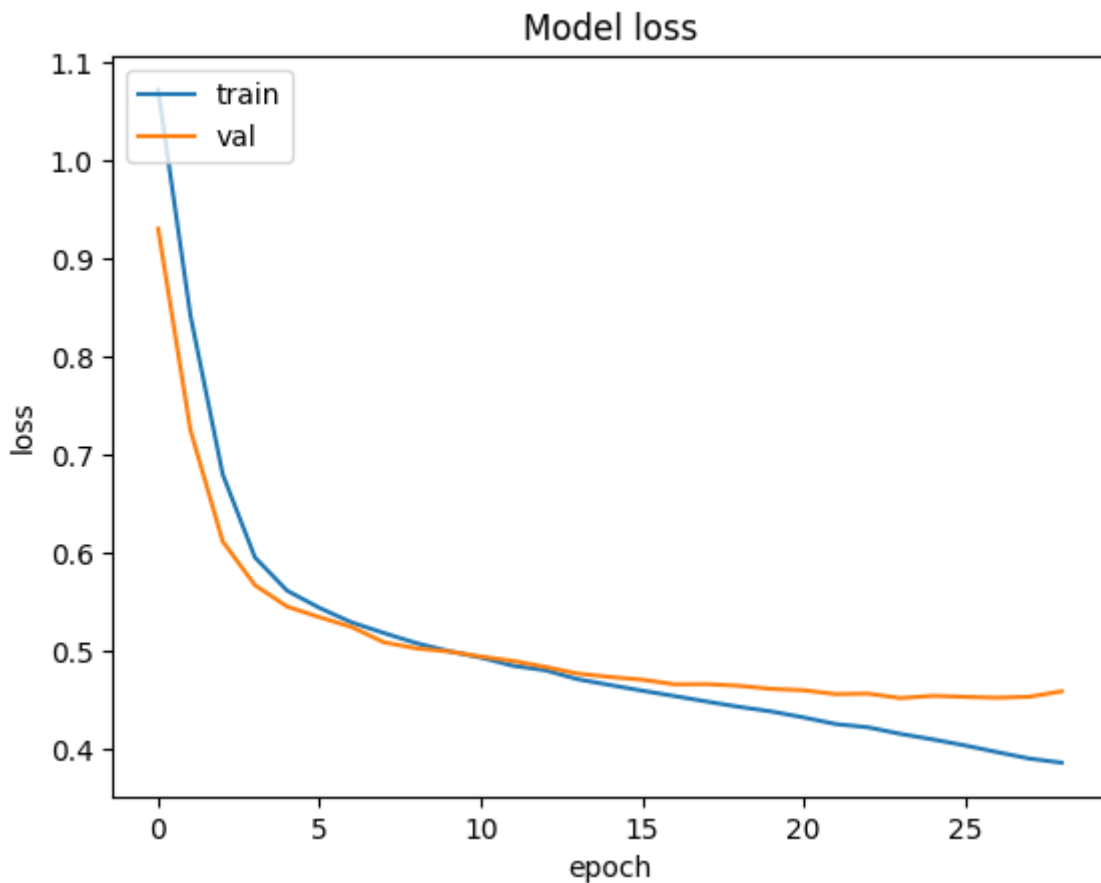
```

281/281 [=====] - 866s 3s/step - loss: 0.4707 - val_loss:

```

Epoch 00014: val_loss improved from 0.48318 to 0.47636, saving model to tmp2/weight

```
# Model loss con lr = 0.00001
plt.plot([1.0722, 0.8420, 0.6799, 0.5950, 0.5610, 0.5435, 0.5286, 0.5178,
          0.5075, 0.4994, 0.4928, 0.4844, 0.4798, 0.4707, 0.4648, 0.4590,
          0.4535, 0.4479, 0.4425, 0.4378, 0.4317, 0.4249, 0.4216, 0.4149,
          0.4093, 0.4031, 0.3963, 0.3897, 0.3855])
plt.plot([0.9305, 0.7250, 0.6114, 0.5667, 0.5448, 0.5340, 0.5239, 0.5083,
          0.5022, 0.4990, 0.4938, 0.4893, 0.4832, 0.4764, 0.4730, 0.4702,
          0.4655, 0.4657, 0.4640, 0.4608, 0.4594, 0.4555, 0.4560, 0.4514,
          0.4537, 0.4527, 0.4518, 0.4528, 0.4583])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



'\n281/281 [=====] - 877s 3s/step - loss: 0.4031 - val_loss

▼ Lectura shuffled map para la implementación del área bajo de curva**

```
# Leer y preprocesar el mapa de fijación -----
other_map = color.rgb2gray(io.imread("sAUC/other_map_gauss.png"))

plt.subplot(2,1,1)
```

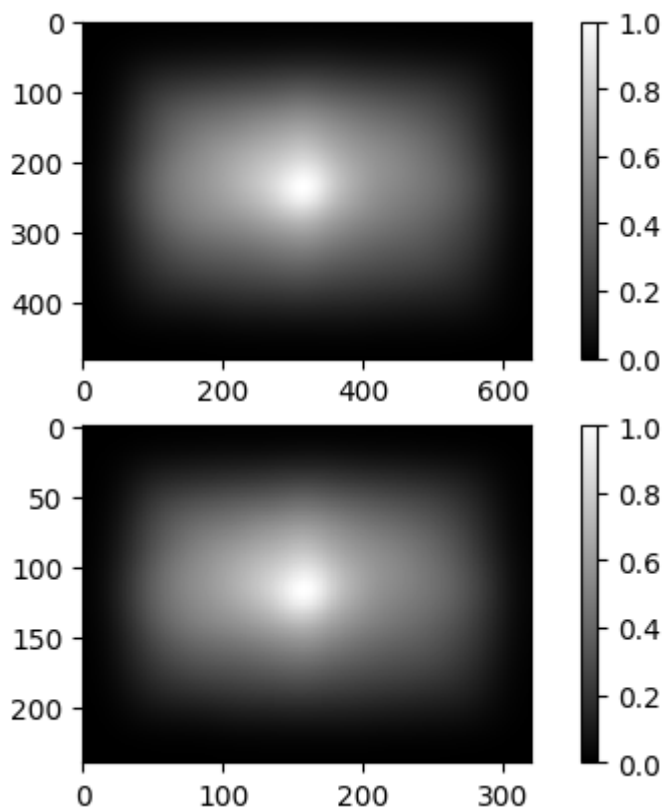
```
plt.imshow(other_map, cmap='gray')
plt.colorbar()
```

```
other_map = rescale(other_map, (1.0 / 2.0), anti_aliasing=False) #Reducción a la mitad
print("Shape of other_map", other_map.shape)
```

```
plt.subplot(2,1,2)
plt.imshow(other_map, cmap='gray')
plt.colorbar()
plt.show()
```

```
#-----
```

```
/usr/local/lib/python3.6/dist-packages/skimage/transform/_warps.py:23: UserWarning: 1
warn('The default multichannel argument (None) is deprecated. Please '
Shape of other_map (240, 320)
```



```
# Se evalúan todas las predicciones en el conjunto TEST
```

```
NSS_m = 0
KL_m = 0
sAUC_m = 0
```

```
# Se obtienen los mapas de predicción y se guardan
```

```
smaps = [path_predic + f for f in os.listdir(path_predic) if f.endswith(('jpg', 'jpeg',
maps = [path_maps_test + f for f in os.listdir(path_maps_test) if f.endswith(('jpg', '.jp
fixs = [path_fixs_test + f for f in os.listdir(path_fixs_test) if f.endswith(('jpg', '.jp
smaps.sort()
maps.sort()
fixs.sort()
```

```
matrix = np.zeros((len(smaps),3))
```

```
for i in range(len(smaps)):
```

```

# Y = mapas preprocesados
Y = io.imread(maps[i])
Y = rescale(Y.astype(np.float32), 1.0 / 2.0, anti_aliasing=False) #Se reduce a la mita
Y /= 255.0

# F = fijaciones preprocesadas
F = color.rgb2gray(io.imread(fixs[i]))
F = rescale(F.astype(np.float32), 1.0 / 2.0, anti_aliasing=False) #Se reducen a la mit
F = normalize_map(F)
r,c = np.nonzero(F)
# Después de cambiar la escala, los valores de intensidad cambian -> Conversión de image
for j in range (len(r)):
    F[ r[j],c[j] ] = 1

# smap = saliency maps preprocesados
smap = color.rgb2gray(io.imread(smmaps[i]))
#smap = gaussian_filter(smap, 2)

#Evaluación
NSS = nss(smap,F)
KL = kldiv(smap,Y)
sAUC = sAUC_Zhang(smap, F, other_map )

NSS_m += NSS
KL_m += KL
sAUC_m += sAUC

#Se guardan las evaluaciones en una matriz
matrix[i,0] = NSS
matrix[i,1] = KL
matrix[i,2] = sAUC

if (i % 500) == 0:
    print(matrix[i],"i= ", i)

print(NSS_m/len(smmaps))
print(KL_m/len(smmaps))
print(sAUC_m/len(smmaps))

```

```

/usr/local/lib/python3.6/dist-packages/skimimage/transform/_warps.py:23: UserWarning: 1
warn('The default multichannel argument (None) is deprecated. Please '

```

```

[0.64544645 0.36084673 0.57275945] i= 0
[0.90005471 0.21054957 0.5582323 ] i= 500
[1.38024385 0.52610878 0.68101264] i= 1000
[2.65842231 0.41204342 0.88819501] i= 1500
[2.13936794 0.5427667 0.82809775] i= 2000
[2.26171187 0.58664693 0.83218463] i= 2500
[1.92056956 0.42200336 0.83691156] i= 3000
[0.88428327 0.17356954 0.56445114] i= 3500
[2.01352144 0.6427048 0.81679825] i= 4000
[1.46240938 0.86032607 0.88831019] i= 4500
1.465567440559221
0.4373982788587102
0.7134179984184019

```

