Proyecto Final - CAPSNETS

Descripción de la Evidencia: El proyecto de aprendizaje profundo consiste en la solución del problema de clasificación de prendas de vestir utilizando el conjunto de datos Fashion MNIST. Éste código implementa un modelo de red neuronal CAPSNETS (*no visto en clase*) que resuelva el problema de clasificación.

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```
# Librerías

import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.python.framework import ops
from keras.utils import to_categorical
import os

from __future__ import division, print_function, unicode_literals
```

```
# Cargar los datos de fashion_mnist desde TF Keras

(X_train, Y_train), (X_test, Y_test) = tf.keras.datasets.fashion_mnist.load_data()
X_train = X_train.reshape(-1, 28, 28, 1).astype('float32') / 255.
X_test = X_test.reshape(-1, 28, 28, 1).astype('float32') / 255.
```

```
# Verificar que se han cargado los datos correctamente
X_train.shape
```

```
(60000, 28, 28, 1)
```

```
# Ver algunos ejemplos del dataset

n_samples = 5

plt.figure(figsize=(n_samples * 2, 3))
for index in range(n_samples):
    plt.subplot(1, n_samples, index + 1)
    sample_image = X_train[index].reshape(28, 28)
    plt.imshow(sample_image, cmap="binary")
    plt.axis("off")

plt.show()
```

```
# Etiquetas del ejemplo
Y_train[:n_samples]
```

```
array([9, 0, 0, 3, 0], dtype=uint8)
```

Input de las imagenes

Creamos un molde para las imagenes (28×28 pixeles, 1 color = grayscale).

```
tf.compat.v1.disable_eager_execution()
X = tf.compat.v1.placeholder(shape=[None, 28, 28, 1], dtype=tf.float32, name="X")
```

Capsulas primarias

```
# La primera capa estará compuesta por 32 mapas de 6×6 cápsulas cada uno, donde cada cápsula generará un vector de activación 8D:
caps1_n_maps = 32
caps1_n_caps = caps1_n_maps * 6 * 6  # 1152 primary capsules
caps1_n_dims = 8


# Para calcular sus resultados, primero aplicamos dos capas convolucionales normales:
conv1_params = {
    "filters": 256,
    "kernel_size": 9,
    "strides": 1,
    "padding": "valid",
    "activation": tf.nn.relu, #Funcion de activación relu
}

conv2_params = {
    "filters": caps1_n_maps * caps1_n_dims, # 256 filtros convolucionales
    "kernel_size": 9,
    "strides": 2,
    "padding": "valid",
    "activation": tf.nn.relu #Funcion de activación relu
}


# Cargar los paramatros a la red convolucional normal

conv1 = tf.compat.v1.layers.conv2d(X, name="conv1", **conv1_params)
conv2 = tf.compat.v1.layers.conv2d(conv1, name="conv2", **conv2_params)
```

```
<ipython-input-9-442f536f4182>:3: UserWarning: `tf.layers.conv2d` is deprecated and will be removed in a future version. Please Use `tf.
  conv1 = tf.compat.v1.layers.conv2d(X, name="conv1", **conv1_params)
<ipython-input-9-442f536f4182>:4: UserWarning: `tf.layers.conv2d` is deprecated and will be removed in a future version. Please Use `tf.
  conv2 = tf.compat.v1.layers.conv2d(conv1, name="conv2", **conv2_params)
```

Nota: puesto que usamos un tamaño de kernel de 9, la imagen se redujo en 9-1=8 píxeles después de cada capa convolucional (28×28 a 20×20, luego 20 × 20 a 12 × 12), y como usamos un paso de 2 en la segunda capa convolucional, el tamaño de la imagen se dividió por 2. Así es como terminamos con mapas de características de 6 × 6.

Con esto en mente, luego modificamos la salida para obtener un conjunto de vectores 8D que representan las salidas de las cápsulas primarias. La salida de conv2 es una matriz que contiene 32 × 8 = 256 mapas de características para cada instancia, donde cada mapa de características es 6 × 6. Entonces, la forma de esta salida es (tamaño de lote, 6, 6, 256). Queremos dividir el 256 en 32 vectores de 8 dimensiones cada uno. Podríamos hacer esto remodelando a (tamaño de lote, 6, 6, 32, 8). Sin embargo, dado que esta primera capa de cápsula estará completamente conectada a la siguiente capa de cápsula, podemos simplemente aplanar las grids de 6×6. Esto significa que al final serán (tamaño de lote, 6×6×32, 8).

```
caps1_raw = tf.reshape(conv2, [-1, caps1_n_caps, caps1_n_dims],
                       name="caps1_raw")


# La función squash() aplastará todos los vectores en la matriz dada dentro de 0 a 1, a lo largo del eje dado (por defecto, el último eje).
# Es importante mencionar que no podemos usar una normalizacion la derivada de ‖s‖ no está definida cuando ‖s‖=0: si un vector es cero, los gr
# Este dato no lo conocíamos hasta revisar otras implementaciones del método

def squash(s, axis=-1, epsilon=1e-7, name=None):
    #with tf.name_scope(name, default_name="squash"):
    with tf.name_scope(name):
        #squared_norm = tf.reduce_sum(tf.square(s), axis=axis,
        #                              keep_dims=True)
        squared_norm = tf.reduce_sum(tf.square(s), axis=axis,
                                     keepdims=True)
        safe_norm = tf.sqrt(squared_norm + epsilon)
        squash_factor = squared_norm / (1. + squared_norm)
        unit_vector = s / safe_norm
        return squash_factor * unit_vector
```

```
caps1_output = squash(caps1_raw, name="caps1_output")
```

Cápsulas Digitales

Calcular los vectores de salida previstos

```
caps2_n_caps = 10
caps2_n_dims = 16
```

```
init_sigma = 0.1

#W_init = tf.random_normal(
W_init = tf.random.normal(
    shape=(1, caps1_n_caps, caps2_n_caps, caps2_n_dims, caps1_n_dims),
    stddev=init_sigma, dtype=tf.float32, name="W_init")
W = tf.Variable(W_init, name="W")
```

```
batch_size = tf.shape(X)[0]
W_tiled = tf.tile(W, [batch_size, 1, 1, 1, 1], name="W_tiled")
```

```
caps1_output_expanded = tf.expand_dims(caps1_output, -1,
                                       name="caps1_output_expanded")
caps1_output_tile = tf.expand_dims(caps1_output_expanded, 2,
                                   name="caps1_output_tile")
caps1_output_tiled = tf.tile(caps1_output_tile, [1, 1, caps2_n_caps, 1, 1],
                             name="caps1_output_tiled")
```

```
W_tiled
```

```
<tf.Tensor 'W_tiled:0' shape=(None, 1152, 10, 16, 8) dtype=float32>
```

```
caps2_predicted = tf.matmul(W_tiled, caps1_output_tiled,
                            name="caps2_predicted")
```

```
caps2_predicted
```

```
<tf.Tensor 'caps2_predicted:0' shape=(None, 1152, 10, 16, 1) dtype=float32>
```

Ruteo por aceptación

```
raw_weights = tf.zeros([batch_size, caps1_n_caps, caps2_n_caps, 1, 1],
                       dtype=np.float32, name="raw_weights")
```

Round 1

```
routing_weights = tf.nn.softmax(raw_weights, name="routing_weights")
```

```
weighted_predictions = tf.multiply(routing_weights, caps2_predicted,
                                   name="weighted_predictions")
weighted_sum = tf.reduce_sum(weighted_predictions, axis=1, keepdims=True,
                             name="weighted_sum")
```

```
caps2_output_round_1 = squash(weighted_sum, axis=-2,
                              name="caps2_output_round_1")
```

```
caps2_output_round_1
```

```
<tf.Tensor 'caps2_output_round_1/mul:0' shape=(None, 1, 10, 16, 1) dtype=float32>
```

Round 2

```
caps2_predicted
```

```
<tf.Tensor 'caps2_predicted:0' shape=(None, 1152, 10, 16, 1) dtype=float32>
```

```
caps2_output_round_1
```

```
<tf.Tensor 'caps2_output_round_1/mul:0' shape=(None, 1, 10, 16, 1) dtype=float32>
```

```
caps2_output_round_1_tiled = tf.tile(
    caps2_output_round_1, [1, caps1_n_caps, 1, 1, 1],
    name="caps2_output_round_1_tiled")
```

```
agreement = tf.matmul(caps2_predicted, caps2_output_round_1_tiled,
                      transpose_a=True, name="agreement")
```

```
raw_weights_round_2 = tf.add(raw_weights, agreement,
                             name="raw_weights_round_2")
```

```
routing_weights_round_2 = tf.nn.softmax(raw_weights_round_2,
                                        name="routing_weights_round_2")
weighted_predictions_round_2 = tf.multiply(routing_weights_round_2,
                                           caps2_predicted,
                                           name="weighted_predictions_round_2")
weighted_sum_round_2 = tf.reduce_sum(weighted_predictions_round_2,
                                     axis=1, keepdims=True,
                                     name="weighted_sum_round_2")
caps2_output_round_2 = squash(weighted_sum_round_2,
                              axis=-2,
                              name="caps2_output_round_2")
```

```
caps2_output = caps2_output_round_2
```

Loop dinámico o estático

```
def condition(input, counter):
    return tf.less(counter, 100)

def loop_body(input, counter):
    output = tf.add(input, tf.square(counter))
    return output, tf.add(counter, 1)

with tf.name_scope("compute_sum_of_squares"):
    counter = tf.constant(1)
    sum_of_squares = tf.constant(0)

    result = tf.while_loop(condition, loop_body, [sum_of_squares, counter])
```

```
with tf.compat.v1.Session() as sess:
    print(sess.run(result))
```

```
[328350, 100]
```

```
sum([i**2 for i in range(1, 100 + 1)])
```

```
338350
```

Probabilidades estimadas de cada clase (longitud)

```
def safe_norm(s, axis=-1, epsilon=1e-7, keep_dims=False, name=None):
    with tf.name_scope(name):
        squared_norm = tf.reduce_sum(tf.square(s), axis=axis,
                                     keepdims=keep_dims)
        return tf.sqrt(squared_norm + epsilon)
```

```
y_proba = safe_norm(caps2_output, axis=-2, name="y_proba")
```

```
y_proba_argmax = tf.argmax(y_proba, axis=2, name="y_proba")
y_proba_argmax
```

```
<tf.Tensor 'y_proba_1:0' shape=(None, 1, 1) dtype=int64>
```

```
y_pred = tf.squeeze(y_proba_argmax, axis=[1,2], name="y_pred")
y_pred
```

```
<tf.Tensor 'y_pred:0' shape=(None,) dtype=int64>
```

Labels

```
y = tf.compat.v1.placeholder(shape=[None], dtype=tf.int64, name="y")
```

Margin Loss

```
m_plus = 0.9
m_minus = 0.1
lambda_ = 0.5
```

```
T = tf.one_hot(y, depth=caps2_n_caps, name="T")
```

```
with tf.compat.v1.Session():
    print(T.eval(feed_dict={y: np.array([0, 1, 2, 3, 9])}))
```

```
[[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]]
```

```
caps2_output
```

```
<tf.Tensor 'caps2_output_round_2/mul:0' shape=(None, 1, 10, 16, 1) dtype=float32>
```

```
caps2_output_norm = safe_norm(caps2_output, axis=-2, keep_dims=True,
                              name="caps2_output_norm")
```

```
present_error_raw = tf.square(tf.maximum(0., m_plus - caps2_output_norm),
                              name="present_error_raw")
present_error = tf.reshape(present_error_raw, shape=(-1, 10),
                           name="present_error")
```

```
absent_error_raw = tf.square(tf.maximum(0., caps2_output_norm - m_minus),
                             name="absent_error_raw")
absent_error = tf.reshape(absent_error_raw, shape=(-1, 10),
                          name="absent_error")
```

```
L = tf.add(T * present_error, lambda_ * (1.0 - T) * absent_error,
           name="L")
```

```
margin_loss = tf.reduce_mean(tf.reduce_sum(L, axis=1), name="margin_loss")
```

Reconstruccion

Mask

```
mask_with_labels = tf.compat.v1.placeholder_with_default(False, shape=(),
                                                         name="mask_with_labels")
```

```
reconstruction_targets = tf.cond(mask_with_labels, # condition
                                 lambda: y,        # if True
```

```
                                 lambda: y_pred,   # if False
                                 name="reconstruction_targets")
```

```
reconstruction_mask = tf.one_hot(reconstruction_targets,
                                 depth=caps2_n_caps,
                                 name="reconstruction_mask")
reconstruction_mask
```

```
<tf.Tensor 'reconstruction_mask:0' shape=(None, 10) dtype=float32>
```

```
caps2_output
```

```
<tf.Tensor 'caps2_output_round_2/mul:0' shape=(None, 1, 10, 16, 1) dtype=float32>
```

```
reconstruction_mask_reshaped = tf.reshape(
    reconstruction_mask, [-1, 1, caps2_n_caps, 1, 1],
    name="reconstruction_mask_reshaped")
```

```
caps2_output_masked = tf.multiply(
    caps2_output, reconstruction_mask_reshaped,
    name="caps2_output_masked")

caps2_output_masked
```

```
<tf.Tensor 'caps2_output_masked:0' shape=(None, 1, 10, 16, 1) dtype=float32>
```

```
decoder_input = tf.reshape(caps2_output_masked,
                           [-1, caps2_n_caps * caps2_n_dims],
                           name="decoder_input")
```

Decoder

```
n_hidden1 = 512
n_hidden2 = 1024
n_output = 28 * 28
```

```
with tf.name_scope("decoder"):
    hidden1 = tf.compat.v1.layers.dense(decoder_input, n_hidden1,
                              activation=tf.nn.relu,
                                        name="hidden1")
    hidden2 = tf.compat.v1.layers.dense(hidden1, n_hidden2,
                                        activation=tf.nn.relu,
                                        name="hidden2")
    decoder_output = tf.compat.v1.layers.dense(hidden2, n_output,
                                               activation=tf.nn.sigmoid,
                                               name="decoder_output")
```

```
<ipython-input-56-2867c9c81853>:2: UserWarning: `tf.layers.dense` is deprecated and will be removed in a future version. Please use `tf.
  hidden1 = tf.compat.v1.layers.dense(decoder_input, n_hidden1,
<ipython-input-56-2867c9c81853>:5: UserWarning: `tf.layers.dense` is deprecated and will be removed in a future version. Please use `tf.
  hidden2 = tf.compat.v1.layers.dense(hidden1, n_hidden2,
<ipython-input-56-2867c9c81853>:8: UserWarning: `tf.layers.dense` is deprecated and will be removed in a future version. Please use `tf.
  decoder_output = tf.compat.v1.layers.dense(hidden2, n_output,
```

Reconstruction Loss

```
X_flat = tf.reshape(X, [-1, n_output], name="X_flat")
squared_difference = tf.square(X_flat - decoder_output,
                               name="squared_difference")
reconstruction_loss = tf.reduce_mean(squared_difference,
                                    name="reconstruction_loss")
```

Final Loss

```
alpha = 0.0005

loss = tf.add(margin_loss, alpha * reconstruction_loss, name="loss")
```

Accuracy

```
correct = tf.equal(y, y_pred, name="correct")
accuracy = tf.reduce_mean(tf.cast(correct, tf.float32), name="accuracy")
```

Training Operators

```
optimizer = tf.compat.v1.train.AdamOptimizer()
training_op = optimizer.minimize(loss, name="training_op")
```

Init and Saver

```
init = tf.compat.v1.global_variables_initializer()
saver = tf.compat.v1.train.Saver()
```

```
len(X_train)
```

```
60000
```

```
X_train[0:0+50]
```

```
array([[[[0.],
         [0.],
         [0.],
         ...,
         [0.],
         [0.],
         [0.]],

        [[0.],
         [0.],
         [0.],
         ...,
         [0.],
         [0.],
         [0.]],

        [[0.],
         [0.],
         [0.],
         ...,
         [0.],
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         [0.]],

        ...,

        [[0.],
         [0.],
         [0.],
         ...,
         [0.],
         [0.],
         [0.]],

        [[0.],
         [0.],
         [0.],
         ...,
         [0.],
         [0.],
         [0.]],

        [[0.],
         [0.],
         [0.],
         ...,
         [0.],
         [0.],
         [0.]]],
```

```
[[[0.],
  [0.],
  [0.],
  ...,
  [0.],
  [0.],
  [0.]],
```

```
from sklearn.model_selection import train_test_split
X_train, X_val, Y_train, Y_val = train_test_split(X_train, Y_train, test_size=0.08, random_state=42)
```

```
len(X_train)
```

```
55200
```

```
len(X_val)
```

```
4800
```

```
X_val.shape
```

```
(4800, 28, 28, 1)
```

```
Y_val.shape
```

```
(4800,)
```

```
n_epochs = 12
batch_size = 18
restore_checkpoint = True

n_iterations_per_epoch = len(X_train) // batch_size
n_iterations_validation = len(X_val) // batch_size
best_loss_val = np.infty
checkpoint_path = "./my_capsule_network"

with tf.compat.v1.Session() as sess:
    if restore_checkpoint and tf.compat.v1.train.checkpoint_exists(checkpoint_path):
        saver.restore(sess, checkpoint_path)
    else:
        init.run()

    for epoch in range(n_epochs):
        b0 = 0
        c0 = 0
        for iteration in range(1, n_iterations_per_epoch + 1):
            X_batch, y_batch = X_train[b0:b0+batch_size], Y_train[b0:b0+batch_size]
            # Run the training operation and measure the loss:
            _, loss_train = sess.run(
                [training_op, loss],
                feed_dict={X: X_batch.reshape([-1, 28, 28, 1]),
                           y: y_batch,
                           mask_with_labels: True})
            print("\rIteration: {}/{} ({:.1f}%)  Loss: {:.5f}".format(
                      iteration, n_iterations_per_epoch,
                      iteration * 100 / n_iterations_per_epoch,
                      loss_train),
                  end="")
            b0+=batch_size

        # At the end of each epoch,
        # measure the validation loss and accuracy:
        loss_vals = []
        acc_vals = []
        for iteration in range(1, n_iterations_validation + 1):
            X_batch, y_batch = X_val[c0:c0+batch_size], Y_val[c0:c0+batch_size]
            loss_val, acc_val = sess.run(
                    [loss, accuracy],
                    feed_dict={X: X_batch.reshape([-1, 28, 28, 1]),
                               y: y_batch})
            loss_vals.append(loss_val)
            acc_vals.append(acc_val)
            print("\rEvaluating the model: {}/{} ({:.1f}%) {}".format(
```

```
                    iteration, n_iterations_validation,
                    iteration * 100 / n_iterations_validation, c0),
                end=" " * 10)
            c0+=batch_size
        loss_val = np.mean(loss_vals)
        acc_val = np.mean(acc_vals)
        print("\rEpoch: {}  Val accuracy: {:.4f}%  Loss: {:.6f}{}".format(
            epoch + 1, acc_val * 100, loss_val,
            " (improved)" if loss_val < best_loss_val else ""))

        # And save the model if it improved:
        if loss_val < best_loss_val:
            save_path = saver.save(sess, checkpoint_path)
            best_loss_val = loss_val
```

```
WARNING:tensorflow:From <ipython-input-69-c89486f5d11c>:11: checkpoint_exists (from tensorflow.python.checkpoint.checkpoint_management)
Instructions for updating:
Use standard file APIs to check for files with this prefix.
Epoch: 1  Val accuracy: 86.4870%  Loss: 0.097451 (improved)
Epoch: 2  Val accuracy: 87.8864%  Loss: 0.092859 (improved)
Epoch: 3  Val accuracy: 87.9073%  Loss: 0.090345 (improved)
Epoch: 4  Val accuracy: 88.4294%  Loss: 0.091095
Epoch: 5  Val accuracy: 88.3250%  Loss: 0.092442
Epoch: 6  Val accuracy: 88.0326%  Loss: 0.098845
Epoch: 7  Val accuracy: 88.0535%  Loss: 0.095083
Epoch: 8  Val accuracy: 88.0535%  Loss: 0.097473
Epoch: 9  Val accuracy: 87.9908%  Loss: 0.099547
Epoch: 10  Val accuracy: 88.1370%  Loss: 0.099193
Epoch: 11  Val accuracy: 87.9908%  Loss: 0.102342
Epoch: 12  Val accuracy: 87.5104%  Loss: 0.105535
```

Predictions

```
n_samples = 10

sample_images = X_test[:n_samples].reshape([-1, 28, 28, 1])

with tf.compat.v1.Session() as sess:
    saver.restore(sess, checkpoint_path)
    caps2_output_value, decoder_output_value, y_pred_value = sess.run(
            [caps2_output, decoder_output, y_pred],
            feed_dict={X: sample_images,
                       y: np.array([], dtype=np.int64)})
```

```
sample_images.shape
```

```
(10, 28, 28, 1)
```

```
decoder_output_value.reshape([-1, 28, 28]).shape
```

```
(10, 28, 28)
```

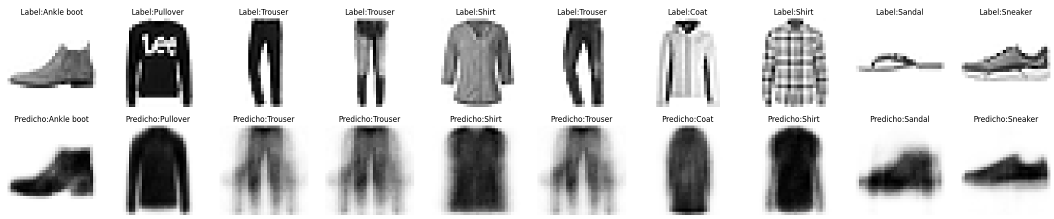
```
clothes_name = ["T-shirt/top", "Trouser", "Pullover", "Dress", "Coat", "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"]
label_dict = dict(zip(list(range(len(clothes_name))), clothes_name, ))
```

```
label_dict[0]
```

```
'T-shirt/top'
```

```
sample_images = sample_images.reshape(-1, 28, 28)
reconstructions = decoder_output_value.reshape([-1, 28, 28])

plt.figure(figsize=(n_samples * 3, 5))
for index in range(n_samples):
    plt.subplot(1, n_samples, index + 1)
    plt.imshow(sample_images[index], cmap="binary")
    plt.title("Label:" + label_dict[Y_test[index]])
    plt.axis("off")

plt.show()

plt.figure(figsize=(n_samples * 3, 5))
for index in range(n_samples):
```

```
    plt.subplot(1, n_samples, index + 1)
    plt.title("Predicho:" + label_dict[y_pred_value[index]])
    plt.imshow(reconstructions[index], cmap="binary")
    plt.axis("off")

plt.show()
```



Interpretacion de los vectores de output

```
caps2_output_value.shape
```

```
(10, 1, 10, 16, 1)
```

```
def tweak_pose_parameters(output_vectors, min=-0.5, max=0.5, n_steps=11):
    steps = np.linspace(min, max, n_steps) # -0.25, -0.15, ..., +0.25
    pose_parameters = np.arange(caps2_n_dims) # 0, 1, ..., 15
    tweaks = np.zeros([caps2_n_dims, n_steps, 1, 1, 1, caps2_n_dims, 1])
    tweaks[pose_parameters, :, 0, 0, 0, pose_parameters, 0] = steps
    output_vectors_expanded = output_vectors[np.newaxis, np.newaxis]
    return tweaks + output_vectors_expanded
```

```
n_steps = 11

tweaked_vectors = tweak_pose_parameters(caps2_output_value, n_steps=n_steps)
tweaked_vectors_reshaped = tweaked_vectors.reshape(
    [-1, 1, caps2_n_caps, caps2_n_dims, 1])
```

```
n_steps = 11

tweaked_vectors = tweak_pose_parameters(caps2_output_value, n_steps=n_steps)
tweaked_vectors_reshaped = tweaked_vectors.reshape(
    [-1, 1, caps2_n_caps, caps2_n_dims, 1])
```

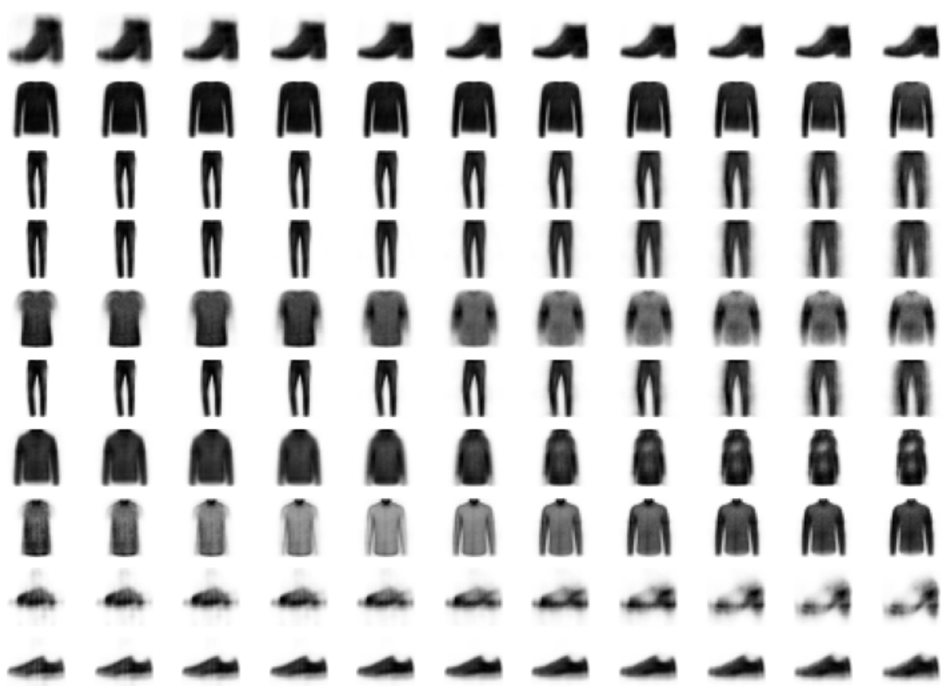
```
tweak_labels = np.tile(Y_test[:n_samples], caps2_n_dims * n_steps)

with tf.compat.v1.Session() as sess:
    saver.restore(sess, checkpoint_path)
    decoder_output_value = sess.run(
            decoder_output,
            feed_dict={caps2_output: tweaked_vectors_reshaped,
                       mask_with_labels: True,
                       y: tweak_labels})
```

```
tweak_reconstructions = decoder_output_value.reshape(
        [caps2_n_dims, n_steps, n_samples, 28, 28])
```

```
for dim in range(3):
    print("Ajustando la dimensión de salida #{}".format(dim))
    plt.figure(figsize=(n_steps / 1.2, n_samples / 1.5))
    for row in range(n_samples):
        for col in range(n_steps):
            plt.subplot(n_samples, n_steps, row * n_steps + col + 1)
            plt.imshow(tweak_reconstructions[dim, col, row], cmap="binary")
            plt.axis("off")
    plt.show()
```

```
Ajustando la dimensión de salida #0
```

```
Ajustando la dimensión de salida #1
```



```
Ajustando la dimensión de salida #2
```