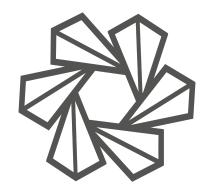
Universidad Autónoma de Querétaro

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Reporte 10 Regularización de sobreajuste

Maestría en Ciencias en Inteligencia Artificial Optativa de especialidad II - Deep Learning

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1. Introducción

En la presente práctica, se utilizaran técnicas de sobreajuste de entrenamiento para evitar que el modelo se memorice los datos de entrenamiento y al momento de validar no se obtenga un valor tan bajo. Se utilizará la red LeNet5 como modelo para disminuir el sobreajuste y por lo tanto observar si una red tan sencilla es capaz de poder aumentar su exactitud del modelo. Todo esto con la base de datos de perros y gatos.

2. Marco Teórico

2.1. Base de datos

La base de datos consta de imágenes que contienen perros y gatos, de diferentes razas en diferentes posiciones, paisajes, etc. Por lo que todas las imagenes contienen una dimensión diferente (véase Figura 1).



Figura 1: Imágenes de la base de datos.

2.2. Sobreajuste

Es un efecto al sobreentrenar un algoritmo de aprendizaje [1] con los datos de entrenamiento. Teniendo el problema de que no puede generalizar el problema y cuando lleguen nuevos datos para validación y test, habrá malos resultados (véase Figura 2).

Otro indicador se encuentra en las perdidas del modelo al momento de entrenar y validar, pues al ir ajustándose el modelo a los datos de entrenamiento, puede ir incrementando la perdida de la validación (véase Figura 3) [2].

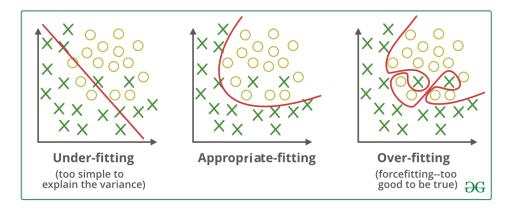


Figura 2: Representación del sobreajuste.

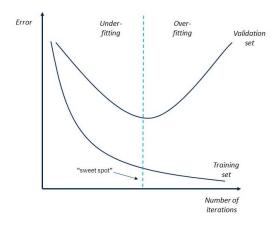


Figura 3: Representación de la perdida en función de las épocas del modelo con sobreajuste.

Por lo que se requieren técnicas que eviten estos comportamientos como se muestran a continuación:

2.2.1. Regularizadores L1 y L2

Esta técnica de regularización consiste en minimizar la complejidad y se obtienen modelos más simples que tienden a generalizar mejor [3].

Partiendo de la función de coste J como un error cuadrático medio MSE tenemos que:

$$J = MSE J = MSE + (\alpha C) (1)$$

Donde:

- \bullet α es un hiperparámetro que indica la importancia de la regularización.
- ullet C es la medida de complejidad del modelo.

El regularizador L_1 Lasso la complejidad C se mide como la media del valor absoluto de los coeficientes del modelo. Esto se puede aplicar a regresiones lineales, polinómicas, regresión logística, redes neuronales, máquinas de vectores de soporte, etc. Se define como:

$$L_1 = C = \frac{1}{N} \sum_{i=1}^{N} |\omega_i|$$
 (2)

Lasso nos va a servir de ayuda cuando sospechemos que varios de los atributos de entrada (features) sean irrelevantes. Al usar Lasso, estamos fomentando que la solución sea poco densa. Es decir, favorecemos que algunos de los coeficientes acaben valiendo 0. Esto puede ser útil para descubrir cuáles de los atributos de entrada son relevantes y, en general, para obtener un modelo que generalice mejor. Lasso nos puede ayudar, en este sentido, a hacer la selección de atributos de entrada. Lasso funciona mejor cuando los atributos no están muy correlados entre ellos.

Por otro lado se tiene la regularización L_2 Ridge medida en la que los coeficientes son más pequeños. Minimizando el efecto de la correlación entre los atributos de los datos. Se define como:

$$L_2 = C = \frac{1}{2N} \sum_{j=1}^{N} \omega_i^2 \tag{3}$$

Finalmente se tiene la regularización ElasticNet L_1L_2 . Combinando las dos caracteristicas con otro hiperparámetro r que permite indicar la importancia de cada uno de los regularizadores, esta dada por:

$$L_1 L_2 = C = rL_1 + (1 - r)L_2 \tag{4}$$

Teniendo como principal característica cuando se tienen un gran numero de atributos. Teniendo algunos irrelevantes y otros si tienen correlación.

2.2.2. Dropout

Consiste en remover de manera aleatoria y temporalmente unidades de neuronas de las capas ocultas de la red en una probabilidad dada p. Al tener una p baja p(<0.4) el error del modelo aumentará por lo que requerirá de más épocas para poder aprender y si es alto, se observará el sobreajuste (over fittinq).

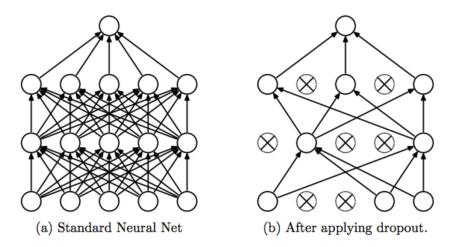


Figura 4: Representación de la técnica de Dropout.

2.2.3. BatchNormalization

Consiste en la normalización de lotes de información (batch) y básicamente lo que hace es normalizar las entradas y reescalar a la salida de cada capa. Existiendo los siguientes, tomando en cuenta el batch como $B = [x_1...m]$ y los hiperparámetros γ, β [4].

Mini-batch:

$$\mu_B = \frac{1}{m} \sum_{i=1}^{m} x_i \tag{5}$$

Mini-Batch con varianza:

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2 \tag{6}$$

Normalización:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{7}$$

Escalación y cambio:

$$y_i = \gamma \hat{x}_i + \beta \equiv BN_{\gamma,\beta}(x_i) \tag{8}$$

2.2.4. Data Augmentation

Consiste en el incremento de los datos para poder obtener mas datos de entrenamiento, existen muchas técnicas que *keras* nos incluye como son [5, 6]:

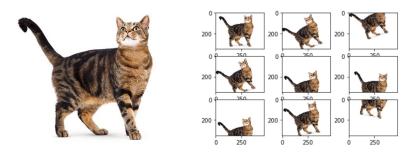


Figura 5: Representación de la técnica de Dropout.

- class CategoryEncoding: A preprocessing layer which encodes integer features.
- class CenterCrop: A preprocessing layer which crops images.
- class Discretization: A preprocessing layer which buckets continuous features by ranges.
- class HashedCrossing: A preprocessing layer which crosses features using the "hashing trick".
- class Hashing: A preprocessing layer which hashes and bins categorical features.
- class IntegerLookup: A preprocessing layer which maps integer features to contiguous ranges.
- class Normalization: A preprocessing layer which normalizes continuous features.
- class PreprocessingLayer: Base class for Preprocessing Layers.
- class RandomContrast: A preprocessing layer which randomly adjusts contrast during training.
- class RandomCrop: A preprocessing layer which randomly crops images during training.
- class RandomFlip: A preprocessing layer which randomly flips images during training.
- class RandomHeight: A preprocessing layer which randomly varies image height during training.
- class RandomRotation: A preprocessing layer which randomly rotates images during training.
- class RandomTranslation: A preprocessing layer which randomly translates images during training.
- class RandomWidth: A preprocessing layer which randomly varies image width during training.
- class RandomZoom: A preprocessing layer which randomly zooms images during training.
- class Rescaling: A preprocessing layer which rescales input values to a new range.
- class Resizing: A preprocessing layer which resizes images.
- class StringLookup: A preprocessing layer which maps string features to integer indices.
- class TextVectorization: A preprocessing layer which maps text features to integer sequences.

2.3. Convoluciones

Las convoluciones constan de kernels que permiten modificar la imagen píxel a píxel, generalmente dichos kernels representan una matriz de valores, los cuales interactúan con la cantidad de datos en igual forma para realizar la convolución (véase Figura 6) [7, 8].

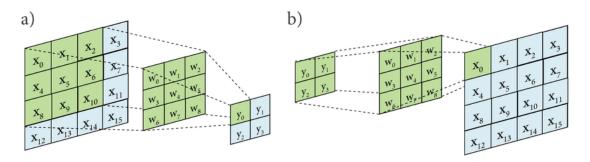


Figura 6: Paleta cúbica de colores RGB.

2.4. Pooling

Como sabemos, las convoluciones permiten resaltar partes de la imagen que nos podrían interesar, siempre conservando prácticamente en su totalidad la imagen. Por otro lado, la capa de pooling nos asegura que los patrones detectados en la capa convolucional se mantengan [9].

Además de que las capas de pooling no requieren de ningún parámetro de aprendizaje. Existen principalmente 3 tipos de Pooling: el maxpool, el minpool y el averagepool. El primero indica que el minímo de los valores de la sección de la matriz de pooling sera el seleccionado como resultado, mismo caso para el máximo y para el promedio del conjunto de valores (véase Figura 7).

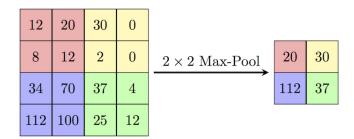


Figura 7: Ejemplo de Maxpool.

2.5. Red Convolucional

Consiste en en algoritmo que al igual que una red neuronal, asigna y actualiza pesos a los valores de la función y por lo tanto se optimizan los valores de los kernels (convoluciones) para poder reconocer patrones de siluetas, curvas, lineas, rostros, etc [10].

2.5.1. Red LeNet-5

Consiste en un arreglo de 7 capas propuesta por Yann LeCun en 1998, tiene como principal objetivo, resolver problemas con imágenes. Dichas capas se van alternando entre convoluciones y Pooling, en donde las capas de convolución son resultado de la multipliación de un kernel por la imagen, por lo que, dichos valores de la matriz del kernel, serán definidas como pesos de la red, el punto es ir disminuyendo el tamaño de la imagen y aplanarla para que pueda entrar a una red neuronal (véase Figura 8).

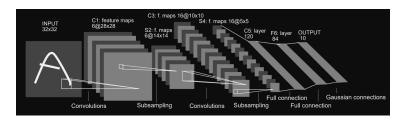


Figura 8: Estructura de red convolucional LeNet5.

3. Justificación

El uso de regularizadores es muy útil para poder incrementar el porcentaje de exactitud de nuestras pruebas y tener más fiabilidad de las mismas, sin la necesidad de tener que depender del resultado del entrenamiento. Además de tener la posibilidad de poder almacenar los resultlados del modelo y sus pesos

4. Resultados

Se observó que el uso de los regularizadores disminuye abruptamente el porcentaje de exactitud del entrenamiento, evitando el sobreajuste y por lo tanto, mostrando de una manera más realista el desempeño de la red. Se observó que algunos regularizadores usados de manera individual funcionan de una mejor manera que todos juntos, así como también su aplicación en sus capas.

Prueba	Características	Optimizador	Épocas	Batch	% de entrenamiento	% de validación	% de test
1	LeNet5 básica	SGD	80	64	100	62.25	59.625
2	LeNet5 con L_1L_2 en las capas flatten	SGD	120	64	100	59.38	58.75
3	LeNet5 con Dropout en $c_4(0.3)$, $c_5(0.5)$, $c_6(0.6)$	SGD	120	64	62	52	52.875
4	LeNet5 con BatchNormalization	SGD	80	64	100	59.38	59.625
5	LeNet5 con Data Augmentation RandomCrop	SGD	80	64	98.04	59.25	58.75
6	LeNet5 con: • con L_1L_2 en las capas flatten • $Dropout$ en todas las capas • BatchNormalization en todas las capas • RandomCrop • Reducción de factor de aprendizaje • EarlyStopper	Adam	138	32	50	50	50

Tabla 1: Resultados de LeNet5.

5. Conclusiones

- 1. El uso de la red LeNet5 ya se puede considerar como un poco obsoleta para su uso en imagenes complejas y debido a su redimensionamiento a una imagen de baja resolución como 32x32x1.
- 2. El uso de regularizadores permite disminuir el porcentaje de exactitud del entrenamiento y por lo tanto, también hacen dar cuenta que será necesaria una red más compleja.
- 3. El uso del aumento de imagenes genera datos sinteticos de una manera fiable y útil para poder tener más datos de entrenamiento en casos en los que se cuenten con pocos datos.
- 4. La red LeNet5 debe ser utilizada para únicamente imagenes en blanco y negro (escala de grises), puesto que el uso de un solo filtro pudo haber afectado los resultados del desempeño de la red.
- 5. El uso de redes más complejas pueden ir mejorando el desempeño del modelo, sin embargo, es mejor comenzar con un modelo sencillo como este y continuar abstrayendo el problema.
- 6. Tambien es posible observar el sobreajuste en las funciones de perdida cuando se cruzan y toman rumbos distintos, puesto que si decrece la perdida del entrenamiento, tambien deberia disminuir tambien la perdida de la validación, no incrementar.

Referencias

- [1] A. Rubiales, "¿qué es underfitting y overfitting?— medium." https://rubialesalberto.medium.com/qu%C3%A9-es-underfitting-y-overfitting-c73d51ffd3f9. (Accessed on 10/22/2022).
- [2] "What is overfitting? ibm." https://www.ibm.com/cloud/learn/overfitting. (Accessed on 11/22/2022).
- [3] "Regularización lasso l1, ridge l2 y elasticnet iartificial.net." https://www.iartificial.net/regularizacion-lasso-l1-ridge-l2-y-elasticnet/. (Accessed on 11/22/2022).
- [4] "Implementing batch normalization in python by tracy chang towards data science." https://towardsdatascience.com/implementing-batch-normalization-in-python-a044b0369567. (Accessed on 11/22/2022).
- [5] "Image augmentation for deep learning with keras machinelearningmastery.com." https://machinelearningmastery.com/image-augmentation-deep-learning-keras/. (Accessed on 11/22/2022).
- [6] "Module: tf.keras.layers.experimental.preprocessing tensorflow v2.11.0." https://www.tensorflow.org/api_docs/python/tf/keras/layers/experimental/preprocessing. (Accessed on 11/22/2022).

- [7] "2d convolution using python & numpy by samrat sahoo analytics vidhya medium." https://medium.com/analytics-vidhya/2d-convolution-using-python-numpy-43442ff5f381. (Accessed on 09/17/2022).
- [8] "5.2. imágenes rgb introducción a la programación." https://cupi2-ip.github.io/IPBook/nivel4/seccion4-4.html. (Accessed on 09/17/2022).
- [9] "Cómo crear red convolucional en keras ander fernández." https://anderfernandez.com/blog/que-es-una-red-neuronal-convolucional-y-como-crearlaen-keras/. (Accessed on 09/26/2022).
- [10] "Intro a las redes neuronales convolucionales by bootcamp ai medium." https://bootcampai.medium.com/redes-neuronales-convolucionales-5e0ce960caf8. (Accessed on 09/26/2022).

P10 eliminación de sobre ajuste

November 21, 2022

1 Eliminación de sobreajuste

Se utilizará la base de datos de perros y gatos.

```
[2]: ## Primeramente se descarga la base de datos que será la de perros y gatos
import cv2
import numpy as np
import os
import zipfile
from matplotlib import image

files=zipfile.ZipFile('cats_and_dogs_small.zip','r')
files.extractall('')

x_dog=[]
x_cat=[]
```

```
[3]: from PIL import Image
     x_size=32
     y_size=32
     for name in files.namelist():
         if '/dogs/' in name and '.jpg' in name:
             a=cv2.imread(name)
             a=cv2.resize(a,(x_size,y_size)) # Dimensión de la imagen
             img = cv2.cvtColor(a, cv2.COLOR_BGR2RGB)
             #imq2=imq.resize(200,200) # Mobilenet (224,224,3)
             x_dog.append(img)
         elif '/cats/' in name and '.jpg' in name:
             a=cv2.imread(name)
             a=cv2.resize(a,(x_size,y_size)) # Dimensión de la imagen
             img = cv2.cvtColor(a, cv2.COLOR_BGR2RGB)
             x_cat.append(img)
     print(len(x_dog),len(x_cat))
     x_dog=np.stack(x_dog,axis=0)
     x_cat=np.stack(x_cat,axis=0)
```

2000 2000

1.1 Normalización y One Hot

```
[4]: print(type(x_dog),x_dog.shape)
     print(type(x_cat),x_cat.shape)
     print('Valores minimos y maximos sin normalizar')
     print(x_dog.min(),x_dog.max())
     print(x_cat.min(),x_cat.max())
     x_dog=x_dog.astype('float32')
     x,y,z,w=x_dog.shape
     y_dog=np.zeros((x,1),dtype=int)
     x_cat=x_cat.astype('float32')
     x,y,z,w=x_{cat.shape}
     y_cat=np.ones((x,1),dtype=int)
     x_dog/=255 \# (x_dog/127.5) - 1 \# x_dog/=255
     x_cat/=255 \# (x_cat/127.5) - 1 \# x_cat/=255
     ## Conjunto combinado de perros y gatos
     x_comb=np.vstack((x_dog,x_cat))
     y_comb=np.vstack((y_dog,y_cat))
     print(x_comb.ndim,x_comb.shape)
     print('Valores minimos y maximos normalizados')
     print(x_comb.min(),x_comb.max())
     #print(y_dog)
     ### ONE HOT
     from keras.utils import to_categorical
     y_dog_oh=to_categorical(y_dog,y_dog.max()+2)
     y_cat_oh=to_categorical(y_cat,y_cat.max()+1)
     print(y_comb[3455])
     y_comb_oh=to_categorical(y_comb,y_comb.max()+1)
     print(y_comb_oh[3455])
     print(type(y_comb_oh),y_comb_oh.shape)
     #print(y_cat_oh.shape)
     #print(y_dog_oh.shape)
     #print(y_dog_oh)
     #print(y_cat_oh)
    <class 'numpy.ndarray'> (2000, 32, 32, 3)
    <class 'numpy.ndarray'> (2000, 32, 32, 3)
    Valores minimos y maximos sin normalizar
    0 255
    0 255
    4 (4000, 32, 32, 3)
    Valores minimos y maximos normalizados
    0.0 1.0
    [1]
    [0. 1.]
    <class 'numpy.ndarray'> (4000, 2)
```

1.2 Division de datos 60 20 20

0.0 1.0

1.3 Red LeNet-5

```
[5]: import tensorflow as tf
    from keras.models import Model, load_model
    #from tensorflow.keras.applications.resnet50 import preprocess_input,
     \rightarrow decode_predictions
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense, Flatten, Dropout, Input
    from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, u
     → ReduceLROnPlateau
    lr_reduce = ReduceLROnPlateau(monitor='val_accuracy', factor=0.6, patience=8,_
     →verbose=1, mode='max', min_lr=5e-5)
    checkpoint = ModelCheckpoint('vgg16_finetune.h5', monitor= 'val_accuracy', u
     →mode= 'max', save_best_only = True, verbose= 1)
    earlystopper = EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 10, __
     →verbose = 1, restore_best_weights = True)
     #"""
     #"""
    model=Sequential()
    model.add(tf.keras.layers.
     \hookrightarrow #C1
    model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #S2
    model.add(tf.keras.layers.
     →Conv2D(16,(5,5),activation='tanh',padding='valid',strides=1)) #c3
```

```
model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #s4
model.add(tf.keras.layers.Flatten())
model.add(Dense(120,activation='tanh')) #c5
model.add(Dense(84,activation='tanh')) #c6
from keras.layers import Layer
from keras import backend as K
class RBFLayer(Layer):
    def __init__(self, units, gamma, **kwargs):
       super(RBFLayer, self).__init__(**kwargs)
       self.units = units
       self.gamma = K.cast_to_floatx(gamma)
    def build(self, input_shape):
       self.mu = self.add_weight(name='mu',
                              shape=(int(input_shape[1]), self.units),
                              initializer='uniform',
                              trainable=True)
       super(RBFLayer, self).build(input_shape)
    def call(self, inputs):
       diff = K.expand_dims(inputs) - self.mu
       12 = K.sum(K.pow(diff,2), axis=1)
       res = K.exp(-1 * self.gamma * 12)
       return res
    def compute_output_shape(self, input_shape):
       return (input_shape[0], self.units)
model.add(RBFLayer(2,0.5)) #c7
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.
 →SGD(learning_rate=0.25),metrics=['accuracy'])
hist_1=model.fit(x_train,y_train,verbose=1,_
 ⇒batch_size=64,epochs=80,validation_data=(x_val,y_val))
Epoch 1/80
0.5063 - val_loss: 0.6925 - val_accuracy: 0.5150
```

0.5367 - val_loss: 0.6893 - val_accuracy: 0.5437

0.5542 - val_loss: 0.6863 - val_accuracy: 0.5638

```
Epoch 4/80
0.5646 - val_loss: 0.6921 - val_accuracy: 0.5175
Epoch 5/80
0.5537 - val_loss: 0.6846 - val_accuracy: 0.5425
Epoch 6/80
0.5750 - val_loss: 0.6920 - val_accuracy: 0.5288
Epoch 7/80
0.5858 - val_loss: 0.6864 - val_accuracy: 0.5537
Epoch 8/80
0.5688 - val_loss: 0.6889 - val_accuracy: 0.5475
Epoch 9/80
0.5733 - val_loss: 0.6913 - val_accuracy: 0.5462
Epoch 10/80
0.5750 - val_loss: 0.6922 - val_accuracy: 0.5350
Epoch 11/80
0.5833 - val_loss: 0.6896 - val_accuracy: 0.5763
Epoch 12/80
0.5846 - val_loss: 0.6959 - val_accuracy: 0.5362
Epoch 13/80
0.5796 - val_loss: 0.6881 - val_accuracy: 0.5512
Epoch 14/80
0.5792 - val_loss: 0.6994 - val_accuracy: 0.5325
Epoch 15/80
38/38 [============== ] - 2s 47ms/step - loss: 0.6710 - accuracy:
0.5921 - val_loss: 0.6925 - val_accuracy: 0.5362
Epoch 16/80
0.5863 - val_loss: 0.6932 - val_accuracy: 0.5625
Epoch 17/80
0.5987 - val_loss: 0.6976 - val_accuracy: 0.5400
38/38 [=================== ] - 2s 53ms/step - loss: 0.6657 - accuracy:
0.5950 - val_loss: 0.6916 - val_accuracy: 0.5113
Epoch 19/80
0.5858 - val_loss: 0.7013 - val_accuracy: 0.5213
```

```
Epoch 20/80
0.5962 - val_loss: 0.6891 - val_accuracy: 0.5575
Epoch 21/80
0.5987 - val_loss: 0.6861 - val_accuracy: 0.5775
Epoch 22/80
0.6050 - val_loss: 0.6814 - val_accuracy: 0.5575
Epoch 23/80
0.6075 - val_loss: 0.6847 - val_accuracy: 0.5763
Epoch 24/80
0.6046 - val_loss: 0.6829 - val_accuracy: 0.5800
Epoch 25/80
0.6142 - val_loss: 0.6850 - val_accuracy: 0.5913
Epoch 26/80
0.6292 - val_loss: 0.6828 - val_accuracy: 0.5525
Epoch 27/80
0.6167 - val_loss: 0.7054 - val_accuracy: 0.5387
Epoch 28/80
0.6313 - val_loss: 0.6972 - val_accuracy: 0.5688
Epoch 29/80
0.6317 - val_loss: 0.6718 - val_accuracy: 0.5888
Epoch 30/80
0.6263 - val_loss: 0.6731 - val_accuracy: 0.5987
Epoch 31/80
0.6267 - val_loss: 0.6863 - val_accuracy: 0.5638
Epoch 32/80
0.6325 - val_loss: 0.6650 - val_accuracy: 0.6125
Epoch 33/80
0.6363 - val_loss: 0.6768 - val_accuracy: 0.5962
0.6279 - val_loss: 0.6881 - val_accuracy: 0.5900
Epoch 35/80
0.6421 - val_loss: 0.6680 - val_accuracy: 0.5987
```

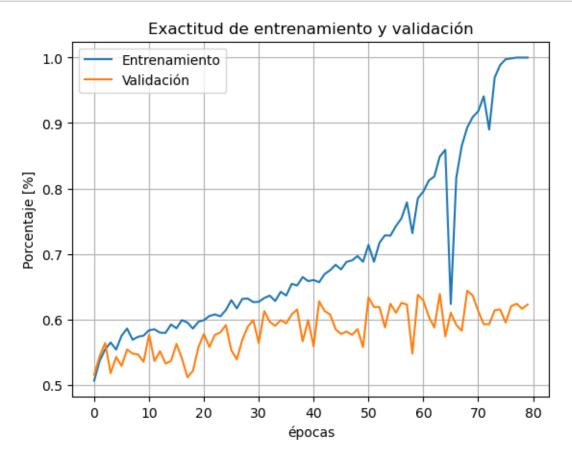
```
Epoch 36/80
0.6363 - val_loss: 0.6739 - val_accuracy: 0.5938
Epoch 37/80
0.6542 - val_loss: 0.6757 - val_accuracy: 0.6075
Epoch 38/80
0.6517 - val_loss: 0.6752 - val_accuracy: 0.6150
Epoch 39/80
0.6646 - val_loss: 0.6824 - val_accuracy: 0.5663
Epoch 40/80
0.6583 - val_loss: 0.6717 - val_accuracy: 0.5987
Epoch 41/80
0.6600 - val_loss: 0.7221 - val_accuracy: 0.5587
Epoch 42/80
0.6567 - val_loss: 0.6651 - val_accuracy: 0.6275
Epoch 43/80
0.6692 - val_loss: 0.6575 - val_accuracy: 0.6125
Epoch 44/80
0.6750 - val_loss: 0.6931 - val_accuracy: 0.6075
Epoch 45/80
0.6833 - val_loss: 0.6767 - val_accuracy: 0.5850
Epoch 46/80
0.6762 - val_loss: 0.7112 - val_accuracy: 0.5775
Epoch 47/80
0.6879 - val_loss: 0.7275 - val_accuracy: 0.5813
Epoch 48/80
0.6900 - val_loss: 0.7209 - val_accuracy: 0.5763
Epoch 49/80
0.6967 - val_loss: 0.7552 - val_accuracy: 0.5850
0.6879 - val_loss: 0.7411 - val_accuracy: 0.5575
Epoch 51/80
0.7138 - val_loss: 0.6524 - val_accuracy: 0.6338
```

```
Epoch 52/80
0.6879 - val_loss: 0.6717 - val_accuracy: 0.6187
Epoch 53/80
0.7171 - val_loss: 0.6901 - val_accuracy: 0.6187
Epoch 54/80
0.7283 - val_loss: 0.7934 - val_accuracy: 0.5875
Epoch 55/80
0.7279 - val_loss: 0.6977 - val_accuracy: 0.6237
Epoch 56/80
0.7425 - val_loss: 0.7346 - val_accuracy: 0.6100
Epoch 57/80
0.7542 - val_loss: 0.7602 - val_accuracy: 0.6250
Epoch 58/80
0.7788 - val_loss: 0.7551 - val_accuracy: 0.6225
Epoch 59/80
0.7317 - val_loss: 0.8334 - val_accuracy: 0.5475
Epoch 60/80
0.7850 - val_loss: 0.7002 - val_accuracy: 0.6375
Epoch 61/80
0.7954 - val_loss: 0.7570 - val_accuracy: 0.6288
Epoch 62/80
0.8121 - val_loss: 0.8416 - val_accuracy: 0.6037
Epoch 63/80
0.8183 - val_loss: 0.8887 - val_accuracy: 0.5875
Epoch 64/80
0.8487 - val_loss: 0.7774 - val_accuracy: 0.6388
Epoch 65/80
0.8592 - val_loss: 1.0568 - val_accuracy: 0.5738
0.6233 - val_loss: 0.7428 - val_accuracy: 0.6100
Epoch 67/80
0.8167 - val_loss: 0.8173 - val_accuracy: 0.5913
```

17

```
Epoch 68/80
  0.8650 - val_loss: 0.9714 - val_accuracy: 0.5825
  Epoch 69/80
  0.8933 - val_loss: 0.9960 - val_accuracy: 0.6438
  Epoch 70/80
  0.9092 - val_loss: 0.9471 - val_accuracy: 0.6363
  Epoch 71/80
  0.9179 - val_loss: 1.0612 - val_accuracy: 0.6125
  Epoch 72/80
  0.9408 - val_loss: 1.3412 - val_accuracy: 0.5925
  Epoch 73/80
  0.8900 - val_loss: 1.0773 - val_accuracy: 0.5925
  Epoch 74/80
  0.9696 - val_loss: 1.1497 - val_accuracy: 0.6137
  Epoch 75/80
  0.9887 - val_loss: 1.2386 - val_accuracy: 0.6150
  Epoch 76/80
  0.9975 - val_loss: 1.3674 - val_accuracy: 0.5950
  Epoch 77/80
  0.9987 - val_loss: 1.3315 - val_accuracy: 0.6200
  Epoch 78/80
  1.0000 - val_loss: 1.3965 - val_accuracy: 0.6237
  Epoch 79/80
  1.0000 - val_loss: 1.4764 - val_accuracy: 0.6162
  Epoch 80/80
  1.0000 - val_loss: 1.4847 - val_accuracy: 0.6225
[6]: type(hist_1.history['loss'])
  import matplotlib.pyplot as plt
  plt.plot(hist_1.history['accuracy'])
  plt.plot(hist_1.history['val_accuracy'])
  plt.title('Exactitud de entrenamiento y validación')
  plt.xlabel('épocas')
  plt.ylabel('Porcentaje [%]')
```

```
plt.legend(['Entrenamiento','Validación'])
plt.grid()
```



1.4 Test de al red LeNet5 v1

2 1) Red LeNet5 con regularización mediante L1oL2

l1 o l2

```
[8]: import tensorflow as tf
     from keras.models import Model, load_model
     #from tensorflow.keras.applications.resnet50 import preprocess_input,
     \rightarrow decode_predictions
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense,Flatten,Dropout,Input
     from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, u
      → ReduceLROnPlateau
     from tensorflow.keras import regularizers
     lr_reduce = ReduceLROnPlateau(monitor='val_accuracy', factor=0.6, patience=8,_
      →verbose=1, mode='max', min_lr=5e-5)
     checkpoint = ModelCheckpoint('vgg16_finetune.h5', monitor= 'val_accuracy', u
     →mode= 'max', save_best_only = True, verbose= 1)
     earlystopper = EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 10, __
      →verbose = 1, restore_best_weights = True)
     #"""
     #"""
     k_r=tf.keras.regularizers.L1L2(l1=1e-5,12=1e-4)
     b_r=tf.keras.regularizers.L2(12=1e-4)
     a_r=tf.keras.regularizers.L2(12=1e-5)
     model=Sequential()
     model.add(tf.keras.layers.
      →Conv2D(6,(5,5),input_shape=(x_size,y_size,1),activation='tanh',padding='valid',strides=1))
      \hookrightarrow \#C1
     model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #S2
     model.add(tf.keras.layers.
      \hookrightarrowConv2D(16,(5,5),activation='tanh',padding='valid',strides=1)) #c3
     model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #s4
     model.add(tf.keras.layers.Flatten())
      →add(Dense(120,activation='tanh',kernel_regularizer=k_r,bias_regularizer=b_r,activity_regularizer
     →#c5
      →add(Dense(84,activation='tanh',kernel_regularizer=k_r,bias_regularizer=b_r,activity_regulariz
      →#c6
     from keras.layers import Layer
```

```
from keras import backend as K
class RBFLayer(Layer):
   def __init__(self, units, gamma, **kwargs):
      super(RBFLayer, self).__init__(**kwargs)
      self.units = units
      self.gamma = K.cast_to_floatx(gamma)
   def build(self, input_shape):
      self.mu = self.add_weight(name='mu',
                        shape=(int(input_shape[1]), self.units),
                        initializer='uniform',
                        trainable=True)
      super(RBFLayer, self).build(input_shape)
   def call(self, inputs):
      diff = K.expand_dims(inputs) - self.mu
      12 = K.sum(K.pow(diff,2), axis=1)
      res = K.exp(-1 * self.gamma * 12)
      return res
   def compute_output_shape(self, input_shape):
      return (input_shape[0], self.units)
model.add(RBFLayer(2,0.5)) #c7
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.
→SGD(learning_rate=0.23),metrics=['accuracy'])
hist_2=model.fit(x_train,y_train,verbose=1,_
 ⇒batch_size=64,epochs=120,validation_data=(x_val,y_val))
Epoch 1/120
0.5088 - val_loss: 0.7535 - val_accuracy: 0.5063
Epoch 2/120
0.5371 - val_loss: 0.7547 - val_accuracy: 0.5138
Epoch 3/120
0.5437 - val_loss: 0.7486 - val_accuracy: 0.5400
Epoch 4/120
0.5512 - val_loss: 0.7482 - val_accuracy: 0.5450
Epoch 5/120
0.5592 - val_loss: 0.7492 - val_accuracy: 0.5550
Epoch 6/120
```

```
0.5663 - val_loss: 0.7493 - val_accuracy: 0.5537
Epoch 7/120
0.5654 - val_loss: 0.7511 - val_accuracy: 0.5213
Epoch 8/120
0.5800 - val_loss: 0.7573 - val_accuracy: 0.5362
Epoch 9/120
0.5742 - val_loss: 0.7483 - val_accuracy: 0.5450
Epoch 10/120
0.5692 - val_loss: 0.7506 - val_accuracy: 0.5525
Epoch 11/120
0.5729 - val_loss: 0.7546 - val_accuracy: 0.5475
Epoch 12/120
0.5717 - val_loss: 0.7519 - val_accuracy: 0.5800
Epoch 13/120
0.5742 - val_loss: 0.7529 - val_accuracy: 0.5625
Epoch 14/120
0.5700 - val_loss: 0.7662 - val_accuracy: 0.5325
Epoch 15/120
0.5771 - val_loss: 0.7541 - val_accuracy: 0.5575
Epoch 16/120
0.5792 - val_loss: 0.7515 - val_accuracy: 0.5475
Epoch 17/120
0.5788 - val_loss: 0.7562 - val_accuracy: 0.5550
Epoch 18/120
0.5792 - val_loss: 0.7578 - val_accuracy: 0.5250
Epoch 19/120
0.5967 - val_loss: 0.7492 - val_accuracy: 0.5550
Epoch 20/120
0.5946 - val_loss: 0.7517 - val_accuracy: 0.5525
Epoch 21/120
0.5871 - val_loss: 0.7533 - val_accuracy: 0.5750
Epoch 22/120
22
```

```
0.5804 - val_loss: 0.7547 - val_accuracy: 0.5462
Epoch 23/120
0.5938 - val_loss: 0.7574 - val_accuracy: 0.5375
Epoch 24/120
0.5992 - val_loss: 0.7584 - val_accuracy: 0.5250
Epoch 25/120
0.5992 - val_loss: 0.7709 - val_accuracy: 0.5200
Epoch 26/120
0.5908 - val_loss: 0.7888 - val_accuracy: 0.5362
Epoch 27/120
0.6000 - val_loss: 0.7586 - val_accuracy: 0.5425
Epoch 28/120
0.5992 - val_loss: 0.7563 - val_accuracy: 0.5288
Epoch 29/120
0.5938 - val_loss: 0.7886 - val_accuracy: 0.5263
Epoch 30/120
0.5946 - val_loss: 0.7460 - val_accuracy: 0.5813
Epoch 31/120
0.6075 - val_loss: 0.7902 - val_accuracy: 0.5375
Epoch 32/120
0.6021 - val_loss: 0.7550 - val_accuracy: 0.5663
Epoch 33/120
0.6067 - val_loss: 0.7431 - val_accuracy: 0.5713
Epoch 34/120
0.6142 - val_loss: 0.7488 - val_accuracy: 0.5625
Epoch 35/120
38/38 [================== ] - 2s 55ms/step - loss: 0.7028 - accuracy:
0.6196 - val_loss: 0.7621 - val_accuracy: 0.5587
Epoch 36/120
0.6208 - val_loss: 0.7492 - val_accuracy: 0.5875
Epoch 37/120
0.6229 - val_loss: 0.7477 - val_accuracy: 0.5650
Epoch 38/120
```

```
0.6242 - val_loss: 0.7892 - val_accuracy: 0.5263
Epoch 39/120
0.6162 - val_loss: 0.7581 - val_accuracy: 0.5688
Epoch 40/120
0.6408 - val_loss: 0.7506 - val_accuracy: 0.5575
Epoch 41/120
0.6375 - val_loss: 0.7421 - val_accuracy: 0.5975
Epoch 42/120
0.6388 - val_loss: 0.7176 - val_accuracy: 0.6062
Epoch 43/120
0.6546 - val_loss: 0.7492 - val_accuracy: 0.5900
Epoch 44/120
0.6525 - val_loss: 0.7202 - val_accuracy: 0.6175
Epoch 45/120
0.6533 - val_loss: 0.7177 - val_accuracy: 0.6125
Epoch 46/120
0.6521 - val_loss: 0.7126 - val_accuracy: 0.6200
Epoch 47/120
0.6608 - val_loss: 0.7485 - val_accuracy: 0.5775
0.6625 - val_loss: 0.7326 - val_accuracy: 0.5938
Epoch 49/120
0.6771 - val_loss: 0.7380 - val_accuracy: 0.6012
Epoch 50/120
0.6792 - val_loss: 0.7344 - val_accuracy: 0.5913
Epoch 51/120
0.6992 - val_loss: 0.7460 - val_accuracy: 0.6112
Epoch 52/120
0.6808 - val_loss: 0.7399 - val_accuracy: 0.6037
Epoch 53/120
0.6954 - val_loss: 0.7421 - val_accuracy: 0.6075
Epoch 54/120
24
```

```
0.7063 - val_loss: 0.7205 - val_accuracy: 0.6112
Epoch 55/120
0.7008 - val_loss: 0.7352 - val_accuracy: 0.6025
Epoch 56/120
0.7154 - val_loss: 0.7781 - val_accuracy: 0.6075
Epoch 57/120
0.7158 - val_loss: 0.7957 - val_accuracy: 0.5987
Epoch 58/120
0.7200 - val_loss: 0.7884 - val_accuracy: 0.5875
Epoch 59/120
0.7342 - val_loss: 0.8338 - val_accuracy: 0.5825
Epoch 60/120
0.7117 - val_loss: 0.7538 - val_accuracy: 0.6125
Epoch 61/120
0.7483 - val_loss: 0.8078 - val_accuracy: 0.5863
Epoch 62/120
0.7379 - val_loss: 0.7869 - val_accuracy: 0.6187
Epoch 63/120
0.7538 - val_loss: 0.7697 - val_accuracy: 0.6338
0.7717 - val_loss: 0.8061 - val_accuracy: 0.6125
Epoch 65/120
0.7713 - val_loss: 0.9101 - val_accuracy: 0.5925
Epoch 66/120
0.7808 - val_loss: 0.7729 - val_accuracy: 0.6263
Epoch 67/120
0.7742 - val_loss: 0.8514 - val_accuracy: 0.6237
Epoch 68/120
0.8104 - val_loss: 0.8769 - val_accuracy: 0.5962
Epoch 69/120
0.8046 - val_loss: 0.8688 - val_accuracy: 0.6062
Epoch 70/120
38/38 [=================== ] - 2s 55ms/step - loss: 0.4397 - accuracy:
                  25
```

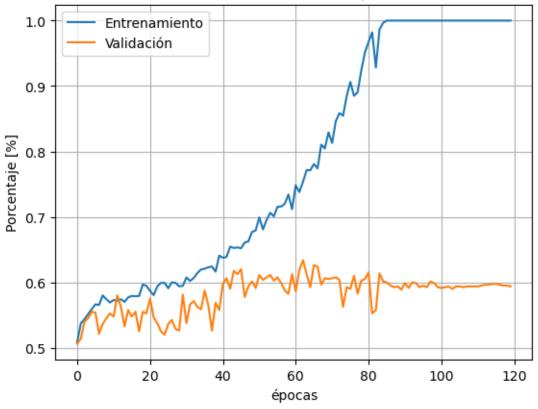
```
0.8292 - val_loss: 0.9179 - val_accuracy: 0.6050
Epoch 71/120
0.8129 - val_loss: 0.8935 - val_accuracy: 0.6062
Epoch 72/120
0.8462 - val_loss: 0.9802 - val_accuracy: 0.6075
Epoch 73/120
0.8587 - val_loss: 1.0266 - val_accuracy: 0.6037
Epoch 74/120
0.8546 - val_loss: 1.1803 - val_accuracy: 0.5625
Epoch 75/120
0.8846 - val_loss: 1.2253 - val_accuracy: 0.5925
Epoch 76/120
0.9062 - val_loss: 1.3348 - val_accuracy: 0.5900
Epoch 77/120
0.8850 - val_loss: 1.1808 - val_accuracy: 0.6100
Epoch 78/120
0.8904 - val_loss: 1.3240 - val_accuracy: 0.5825
Epoch 79/120
0.9237 - val_loss: 1.3487 - val_accuracy: 0.6025
0.9513 - val_loss: 1.3461 - val_accuracy: 0.6050
Epoch 81/120
0.9675 - val_loss: 1.4385 - val_accuracy: 0.6150
Epoch 82/120
0.9821 - val_loss: 1.7675 - val_accuracy: 0.5525
Epoch 83/120
0.9283 - val_loss: 1.5848 - val_accuracy: 0.5575
Epoch 84/120
0.9862 - val_loss: 1.3888 - val_accuracy: 0.6137
Epoch 85/120
0.9967 - val_loss: 1.4930 - val_accuracy: 0.6012
Epoch 86/120
26
```

```
1.0000 - val_loss: 1.6005 - val_accuracy: 0.6000
Epoch 87/120
1.0000 - val_loss: 1.5837 - val_accuracy: 0.5950
Epoch 88/120
1.0000 - val_loss: 1.6472 - val_accuracy: 0.5925
Epoch 89/120
38/38 [============= ] - 3599s 97s/step - loss: 0.0681 -
accuracy: 1.0000 - val_loss: 1.6897 - val_accuracy: 0.5938
Epoch 90/120
1.0000 - val_loss: 1.7287 - val_accuracy: 0.5888
Epoch 91/120
1.0000 - val_loss: 1.7681 - val_accuracy: 0.5987
Epoch 92/120
1.0000 - val_loss: 1.7874 - val_accuracy: 0.5913
Epoch 93/120
1.0000 - val_loss: 1.8215 - val_accuracy: 0.6000
Epoch 94/120
1.0000 - val_loss: 1.8431 - val_accuracy: 0.5987
Epoch 95/120
1.0000 - val_loss: 1.8722 - val_accuracy: 0.5925
1.0000 - val_loss: 1.8845 - val_accuracy: 0.5950
Epoch 97/120
38/38 [================= ] - 34s 905ms/step - loss: 0.0621 -
accuracy: 1.0000 - val_loss: 1.9033 - val_accuracy: 0.5925
Epoch 98/120
1.0000 - val_loss: 1.9307 - val_accuracy: 0.6012
Epoch 99/120
1.0000 - val_loss: 1.9421 - val_accuracy: 0.5987
Epoch 100/120
1.0000 - val_loss: 1.9677 - val_accuracy: 0.5925
Epoch 101/120
1.0000 - val_loss: 1.9803 - val_accuracy: 0.5913
Epoch 102/120
```

```
1.0000 - val_loss: 1.9894 - val_accuracy: 0.5925
Epoch 103/120
1.0000 - val_loss: 2.0127 - val_accuracy: 0.5938
Epoch 104/120
1.0000 - val_loss: 2.0277 - val_accuracy: 0.5900
Epoch 105/120
1.0000 - val_loss: 2.0362 - val_accuracy: 0.5938
Epoch 106/120
1.0000 - val_loss: 2.0486 - val_accuracy: 0.5938
Epoch 107/120
1.0000 - val_loss: 2.0630 - val_accuracy: 0.5925
Epoch 108/120
1.0000 - val_loss: 2.0725 - val_accuracy: 0.5938
Epoch 109/120
1.0000 - val_loss: 2.0844 - val_accuracy: 0.5938
Epoch 110/120
1.0000 - val_loss: 2.1003 - val_accuracy: 0.5938
Epoch 111/120
1.0000 - val_loss: 2.1042 - val_accuracy: 0.5938
Epoch 112/120
1.0000 - val_loss: 2.1151 - val_accuracy: 0.5950
Epoch 113/120
38/38 [=================== ] - 2s 46ms/step - loss: 0.0570 - accuracy:
1.0000 - val_loss: 2.1294 - val_accuracy: 0.5962
Epoch 114/120
1.0000 - val_loss: 2.1402 - val_accuracy: 0.5962
Epoch 115/120
1.0000 - val_loss: 2.1437 - val_accuracy: 0.5975
Epoch 116/120
1.0000 - val_loss: 2.1603 - val_accuracy: 0.5975
Epoch 117/120
1.0000 - val_loss: 2.1665 - val_accuracy: 0.5962
Epoch 118/120
28
```

```
1.0000 - val_loss: 2.1736 - val_accuracy: 0.5950
   Epoch 119/120
   1.0000 - val_loss: 2.1805 - val_accuracy: 0.5950
   Epoch 120/120
   1.0000 - val_loss: 2.1901 - val_accuracy: 0.5938
[9]: type(hist_2.history['loss'])
   import matplotlib.pyplot as plt
   plt.plot(hist_2.history['accuracy'])
   plt.plot(hist_2.history['val_accuracy'])
   plt.title('Exactitud de entrenamiento y validación')
   plt.xlabel('épocas')
   plt.ylabel('Porcentaje [%]')
   plt.legend(['Entrenamiento', 'Validación'])
   plt.grid()
```

Exactitud de entrenamiento y validación



```
[10]: pred=model.predict(x_test)
pred=np.argmax(pred,axis=1)
```

3 2) Regularización con Dropout

Uso de Dropout para capas flatten y convolucionales.

```
[11]: import tensorflow as tf
      from keras.models import Model, load_model
      #from tensorflow.keras.applications.resnet50 import preprocess_input,_
      \rightarrow decode_predictions
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense,Flatten,Dropout,Input
      from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, u
       → ReduceLROnPlateau
      lr_reduce = ReduceLROnPlateau(monitor='val_accuracy', factor=0.6, patience=8,__
       →verbose=1, mode='max', min_lr=5e-5)
      checkpoint = ModelCheckpoint('vgg16_finetune.h5', monitor= 'val_accuracy',
      →mode= 'max', save_best_only = True, verbose= 1)
      earlystopper = EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 10,__
       →verbose = 1, restore_best_weights = True)
      #"""
      # 11 11 11
      model=Sequential()
      model.add(tf.keras.layers.
       →Conv2D(6,(5,5),input_shape=(x_size,y_size,1),activation='tanh',padding='valid',strides=1))
       \hookrightarrow #C1
      model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #S2
      model.add(tf.keras.layers.
       →Conv2D(16,(5,5),activation='tanh',padding='valid',strides=1)) #c3
      model.add(Dropout(0.3))
```

model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #s4

```
model.add(tf.keras.layers.Flatten())
model.add(Dense(120,activation='tanh')) #c5
model.add(Dropout(0.5))
model.add(Dense(84,activation='tanh')) #c6
model.add(Dropout(0.6))
from keras.layers import Layer
from keras import backend as K
class RBFLayer(Layer):
   def __init__(self, units, gamma, **kwargs):
       super(RBFLayer, self).__init__(**kwargs)
       self.units = units
       self.gamma = K.cast_to_floatx(gamma)
   def build(self, input_shape):
       self.mu = self.add_weight(name='mu',
                             shape=(int(input_shape[1]), self.units),
                             initializer='uniform',
                             trainable=True)
       super(RBFLayer, self).build(input_shape)
   def call(self, inputs):
       diff = K.expand_dims(inputs) - self.mu
       12 = K.sum(K.pow(diff,2), axis=1)
       res = K.exp(-1 * self.gamma * 12)
       return res
   def compute_output_shape(self, input_shape):
       return (input_shape[0], self.units)
model.add(RBFLayer(2,0.5)) #c7
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.
 →SGD(learning_rate=0.25),metrics=['accuracy'])
hist_3=model.fit(x_train,y_train,verbose=1,_
 →batch_size=64,epochs=120,validation_data=(x_val,y_val))
Epoch 1/120
0.4971 - val_loss: 0.6926 - val_accuracy: 0.5013
Epoch 2/120
0.5108 - val_loss: 0.6927 - val_accuracy: 0.5000
Epoch 3/120
0.5188 - val_loss: 0.6958 - val_accuracy: 0.5050
Epoch 4/120
```

```
0.5179 - val_loss: 0.6889 - val_accuracy: 0.5638
Epoch 5/120
0.5396 - val_loss: 0.6957 - val_accuracy: 0.4950
Epoch 6/120
0.5350 - val_loss: 0.6921 - val_accuracy: 0.5238
Epoch 7/120
0.5471 - val_loss: 0.6917 - val_accuracy: 0.5188
Epoch 8/120
0.5242 - val_loss: 0.6895 - val_accuracy: 0.5550
Epoch 9/120
0.5429 - val_loss: 0.6901 - val_accuracy: 0.5288
Epoch 10/120
0.5713 - val_loss: 0.6879 - val_accuracy: 0.5387
Epoch 11/120
0.5483 - val_loss: 0.6849 - val_accuracy: 0.5625
Epoch 12/120
0.5562 - val_loss: 0.6939 - val_accuracy: 0.5425
Epoch 13/120
0.5654 - val_loss: 0.6876 - val_accuracy: 0.5575
Epoch 14/120
0.5604 - val_loss: 0.7033 - val_accuracy: 0.5238
Epoch 15/120
0.5537 - val_loss: 0.6947 - val_accuracy: 0.5188
Epoch 16/120
0.5558 - val_loss: 0.6923 - val_accuracy: 0.5325
Epoch 17/120
0.5654 - val_loss: 0.6895 - val_accuracy: 0.5487
Epoch 18/120
0.5733 - val_loss: 0.6928 - val_accuracy: 0.5525
Epoch 19/120
0.5742 - val_loss: 0.7072 - val_accuracy: 0.5213
Epoch 20/120
```

```
0.5646 - val_loss: 0.6861 - val_accuracy: 0.5512
Epoch 21/120
0.5717 - val_loss: 0.6910 - val_accuracy: 0.5638
Epoch 22/120
0.5675 - val_loss: 0.6957 - val_accuracy: 0.5450
Epoch 23/120
0.5775 - val_loss: 0.6904 - val_accuracy: 0.5462
Epoch 24/120
0.5604 - val_loss: 0.6971 - val_accuracy: 0.5350
Epoch 25/120
0.5788 - val_loss: 0.6891 - val_accuracy: 0.5638
Epoch 26/120
0.5692 - val_loss: 0.6963 - val_accuracy: 0.5238
Epoch 27/120
0.5658 - val_loss: 0.6913 - val_accuracy: 0.5312
Epoch 28/120
0.5571 - val_loss: 0.6913 - val_accuracy: 0.5487
Epoch 29/120
0.5658 - val_loss: 0.6990 - val_accuracy: 0.5213
Epoch 30/120
0.5783 - val_loss: 0.6910 - val_accuracy: 0.5750
Epoch 31/120
0.5763 - val_loss: 0.6887 - val_accuracy: 0.5650
Epoch 32/120
0.5729 - val_loss: 0.6905 - val_accuracy: 0.5675
Epoch 33/120
0.5717 - val_loss: 0.6917 - val_accuracy: 0.5900
Epoch 34/120
0.5725 - val_loss: 0.6892 - val_accuracy: 0.5638
Epoch 35/120
0.5788 - val_loss: 0.6919 - val_accuracy: 0.5550
Epoch 36/120
```

```
0.5717 - val_loss: 0.6914 - val_accuracy: 0.5813
Epoch 37/120
0.5671 - val_loss: 0.6903 - val_accuracy: 0.5562
Epoch 38/120
0.5733 - val_loss: 0.6972 - val_accuracy: 0.5638
Epoch 39/120
0.5717 - val_loss: 0.6962 - val_accuracy: 0.5475
Epoch 40/120
0.5800 - val_loss: 0.6995 - val_accuracy: 0.5562
Epoch 41/120
0.5717 - val_loss: 0.6859 - val_accuracy: 0.5888
Epoch 42/120
0.5833 - val_loss: 0.7044 - val_accuracy: 0.5562
Epoch 43/120
0.5821 - val_loss: 0.7103 - val_accuracy: 0.5675
Epoch 44/120
0.5938 - val_loss: 0.6979 - val_accuracy: 0.5400
Epoch 45/120
0.5779 - val_loss: 0.6925 - val_accuracy: 0.5525
Epoch 46/120
0.5775 - val_loss: 0.6932 - val_accuracy: 0.5625
Epoch 47/120
0.5858 - val_loss: 0.6929 - val_accuracy: 0.5700
Epoch 48/120
0.5729 - val_loss: 0.6902 - val_accuracy: 0.5475
Epoch 49/120
0.5700 - val_loss: 0.6985 - val_accuracy: 0.5562
Epoch 50/120
0.5879 - val_loss: 0.7154 - val_accuracy: 0.5175
Epoch 51/120
0.5771 - val_loss: 0.6995 - val_accuracy: 0.5638
Epoch 52/120
```

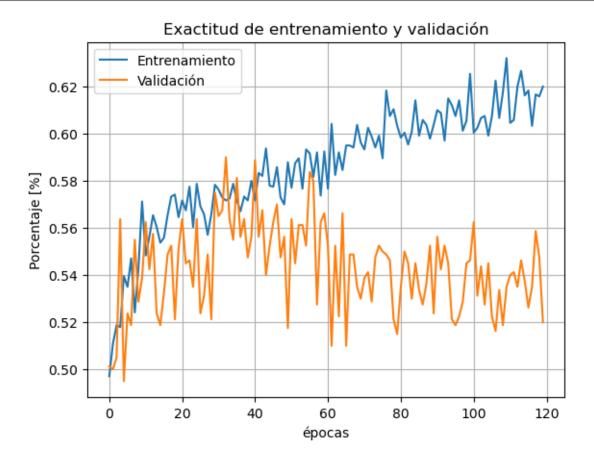
```
0.5875 - val_loss: 0.7116 - val_accuracy: 0.5450
Epoch 53/120
0.5896 - val_loss: 0.6905 - val_accuracy: 0.5612
Epoch 54/120
0.5767 - val_loss: 0.6988 - val_accuracy: 0.5612
Epoch 55/120
0.5933 - val_loss: 0.6952 - val_accuracy: 0.5525
Epoch 56/120
0.5917 - val_loss: 0.7114 - val_accuracy: 0.5838
Epoch 57/120
0.5817 - val_loss: 0.7044 - val_accuracy: 0.5800
Epoch 58/120
0.5921 - val_loss: 0.6929 - val_accuracy: 0.5275
Epoch 59/120
0.5738 - val_loss: 0.6963 - val_accuracy: 0.5625
Epoch 60/120
0.5925 - val_loss: 0.7099 - val_accuracy: 0.5663
Epoch 61/120
0.5767 - val_loss: 0.6983 - val_accuracy: 0.5525
Epoch 62/120
0.6042 - val_loss: 0.7046 - val_accuracy: 0.5100
Epoch 63/120
0.5825 - val_loss: 0.6942 - val_accuracy: 0.5525
Epoch 64/120
0.5921 - val_loss: 0.7072 - val_accuracy: 0.5225
Epoch 65/120
0.5846 - val_loss: 0.7100 - val_accuracy: 0.5663
Epoch 66/120
0.5950 - val_loss: 0.7043 - val_accuracy: 0.5100
Epoch 67/120
0.5950 - val_loss: 0.7003 - val_accuracy: 0.5487
Epoch 68/120
```

```
0.5942 - val_loss: 0.7047 - val_accuracy: 0.5487
Epoch 69/120
0.6037 - val_loss: 0.6992 - val_accuracy: 0.5350
Epoch 70/120
0.5962 - val_loss: 0.7189 - val_accuracy: 0.5300
Epoch 71/120
0.5933 - val_loss: 0.6967 - val_accuracy: 0.5387
Epoch 72/120
0.6025 - val_loss: 0.7004 - val_accuracy: 0.5412
Epoch 73/120
0.5987 - val_loss: 0.7072 - val_accuracy: 0.5288
Epoch 74/120
0.5942 - val_loss: 0.7035 - val_accuracy: 0.5475
Epoch 75/120
0.5992 - val_loss: 0.7099 - val_accuracy: 0.5525
Epoch 76/120
0.5896 - val_loss: 0.6928 - val_accuracy: 0.5500
Epoch 77/120
0.6183 - val_loss: 0.7057 - val_accuracy: 0.5487
Epoch 78/120
0.6075 - val_loss: 0.7087 - val_accuracy: 0.5462
Epoch 79/120
0.6104 - val_loss: 0.7073 - val_accuracy: 0.5213
Epoch 80/120
0.6033 - val_loss: 0.7038 - val_accuracy: 0.5150
Epoch 81/120
0.5983 - val_loss: 0.6996 - val_accuracy: 0.5350
Epoch 82/120
0.6004 - val_loss: 0.6945 - val_accuracy: 0.5500
Epoch 83/120
0.5954 - val_loss: 0.7009 - val_accuracy: 0.5450
Epoch 84/120
```

```
0.6008 - val_loss: 0.7003 - val_accuracy: 0.5300
Epoch 85/120
0.6142 - val_loss: 0.7067 - val_accuracy: 0.5450
Epoch 86/120
0.5992 - val_loss: 0.7026 - val_accuracy: 0.5337
Epoch 87/120
0.6058 - val_loss: 0.6970 - val_accuracy: 0.5275
Epoch 88/120
0.6037 - val_loss: 0.6980 - val_accuracy: 0.5362
Epoch 89/120
0.5979 - val_loss: 0.6940 - val_accuracy: 0.5525
Epoch 90/120
0.6037 - val_loss: 0.6990 - val_accuracy: 0.5238
Epoch 91/120
0.6100 - val_loss: 0.6967 - val_accuracy: 0.5562
Epoch 92/120
0.6087 - val_loss: 0.7133 - val_accuracy: 0.5425
Epoch 93/120
0.5971 - val_loss: 0.7172 - val_accuracy: 0.5525
Epoch 94/120
0.6150 - val_loss: 0.6990 - val_accuracy: 0.5450
Epoch 95/120
0.6121 - val_loss: 0.6991 - val_accuracy: 0.5213
Epoch 96/120
0.6075 - val_loss: 0.7305 - val_accuracy: 0.5188
Epoch 97/120
0.6142 - val_loss: 0.7003 - val_accuracy: 0.5225
Epoch 98/120
0.6012 - val_loss: 0.7004 - val_accuracy: 0.5288
Epoch 99/120
0.6054 - val_loss: 0.7102 - val_accuracy: 0.5450
Epoch 100/120
```

```
0.6254 - val_loss: 0.7139 - val_accuracy: 0.5462
Epoch 101/120
0.6004 - val_loss: 0.6976 - val_accuracy: 0.5625
Epoch 102/120
0.6025 - val_loss: 0.7050 - val_accuracy: 0.5312
Epoch 103/120
0.6067 - val_loss: 0.7095 - val_accuracy: 0.5437
Epoch 104/120
0.6075 - val_loss: 0.6970 - val_accuracy: 0.5275
Epoch 105/120
0.5992 - val_loss: 0.7038 - val_accuracy: 0.5450
Epoch 106/120
0.6075 - val_loss: 0.7199 - val_accuracy: 0.5225
Epoch 107/120
0.6225 - val_loss: 0.7063 - val_accuracy: 0.5163
Epoch 108/120
0.6067 - val_loss: 0.7124 - val_accuracy: 0.5337
Epoch 109/120
0.6175 - val_loss: 0.7274 - val_accuracy: 0.5188
Epoch 110/120
0.6321 - val_loss: 0.7154 - val_accuracy: 0.5350
Epoch 111/120
0.6046 - val_loss: 0.7061 - val_accuracy: 0.5400
Epoch 112/120
0.6058 - val_loss: 0.7130 - val_accuracy: 0.5412
Epoch 113/120
0.6200 - val_loss: 0.6980 - val_accuracy: 0.5350
Epoch 114/120
0.6267 - val_loss: 0.7021 - val_accuracy: 0.5462
Epoch 115/120
0.6162 - val_loss: 0.7089 - val_accuracy: 0.5375
Epoch 116/120
```

```
0.6183 - val_loss: 0.6989 - val_accuracy: 0.5263
   Epoch 117/120
   0.6033 - val_loss: 0.7087 - val_accuracy: 0.5350
   Epoch 118/120
   0.6167 - val_loss: 0.6956 - val_accuracy: 0.5587
   Epoch 119/120
   0.6158 - val_loss: 0.7353 - val_accuracy: 0.5475
   Epoch 120/120
   0.6200 - val_loss: 0.7456 - val_accuracy: 0.5200
[12]: type(hist_3.history['loss'])
   import matplotlib.pyplot as plt
   plt.plot(hist_3.history['accuracy'])
   plt.plot(hist_3.history['val_accuracy'])
   plt.title('Exactitud de entrenamiento y validación')
   plt.xlabel('épocas')
   plt.ylabel('Porcentaje [%]')
   plt.legend(['Entrenamiento','Validación'])
   plt.grid()
```



4 3) Regularización por BatchNormalization

exactitud de la prueba= 52.875 %

```
[14]: import tensorflow as tf from keras.models import Model, load_model
```

```
#from tensorflow.keras.applications.resnet50 import preprocess_input,_
\rightarrow decode_predictions
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Flatten,Dropout,Input
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, u
→ ReduceLROnPlateau
lr_reduce = ReduceLROnPlateau(monitor='val_accuracy', factor=0.6, patience=8,__
→verbose=1, mode='max', min_lr=5e-5)
checkpoint = ModelCheckpoint('vgg16_finetune.h5', monitor= 'val_accuracy',
→mode= 'max', save_best_only = True, verbose= 1)
earlystopper = EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 10, __
→verbose = 1, restore_best_weights = True)
#"""
#"""
model=Sequential()
model.add(tf.keras.layers.
→Conv2D(6,(5,5),input_shape=(x_size,y_size,1),activation='tanh',padding='valid',strides=1))
model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #S2
model.add(tf.keras.layers.
→Conv2D(16,(5,5),activation='tanh',padding='valid',strides=1)) #c3
model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #s4
model.add(tf.keras.layers.Flatten())
model.add(Dense(120,activation='tanh')) #c5
model.add(tf.keras.layers.BatchNormalization())
model.add(Dense(84,activation='tanh')) #c6
from keras.layers import Layer
from keras import backend as K
class RBFLayer(Layer):
    def __init__(self, units, gamma, **kwargs):
        super(RBFLayer, self).__init__(**kwargs)
        self.units = units
        self.gamma = K.cast_to_floatx(gamma)
    def build(self, input_shape):
        self.mu = self.add_weight(name='mu',
```

```
shape=(int(input_shape[1]), self.units),
                       initializer='uniform',
                       trainable=True)
     super(RBFLayer, self).build(input_shape)
   def call(self, inputs):
     diff = K.expand_dims(inputs) - self.mu
     12 = K.sum(K.pow(diff,2), axis=1)
     res = K.exp(-1 * self.gamma * 12)
     return res
   def compute_output_shape(self, input_shape):
     return (input_shape[0], self.units)
model.add(RBFLayer(2,0.5)) #c7
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.
 →SGD(learning_rate=0.25),metrics=['accuracy'])
hist_4=model.fit(x_train,y_train,verbose=1,_
 ⇒batch_size=64,epochs=80,validation_data=(x_val,y_val))
Epoch 1/80
38/38 [============= ] - 3s 56ms/step - loss: 0.7120 - accuracy:
0.5288 - val_loss: 0.7166 - val_accuracy: 0.5000
Epoch 2/80
0.5683 - val_loss: 0.7424 - val_accuracy: 0.5000
Epoch 3/80
0.5708 - val_loss: 0.7696 - val_accuracy: 0.5000
Epoch 4/80
0.5917 - val_loss: 0.6992 - val_accuracy: 0.5437
Epoch 5/80
0.6342 - val_loss: 0.7333 - val_accuracy: 0.5400
Epoch 6/80
0.6283 - val_loss: 0.7636 - val_accuracy: 0.5437
Epoch 7/80
0.6708 - val_loss: 0.8907 - val_accuracy: 0.5350
Epoch 8/80
38/38 [================== ] - 3s 67ms/step - loss: 0.6059 - accuracy:
0.6704 - val_loss: 0.9825 - val_accuracy: 0.5288
0.7163 - val_loss: 0.8699 - val_accuracy: 0.5238
```

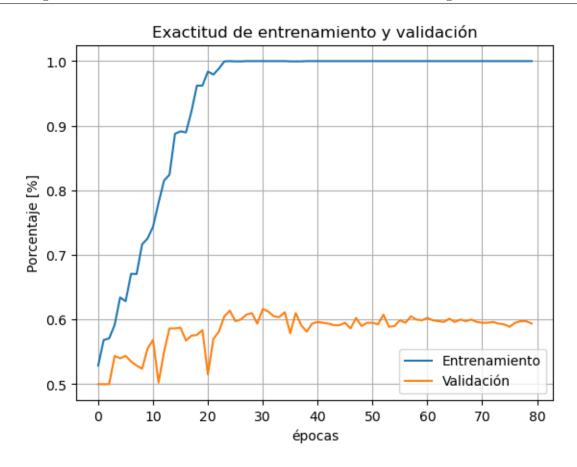
```
Epoch 10/80
0.7254 - val_loss: 0.9009 - val_accuracy: 0.5550
Epoch 11/80
0.7437 - val_loss: 0.9155 - val_accuracy: 0.5688
Epoch 12/80
accuracy: 0.7804 - val_loss: 1.0378 - val_accuracy: 0.5025
Epoch 13/80
0.8150 - val_loss: 1.0041 - val_accuracy: 0.5500
Epoch 14/80
0.8242 - val_loss: 1.0038 - val_accuracy: 0.5863
Epoch 15/80
0.8875 - val_loss: 0.9602 - val_accuracy: 0.5863
Epoch 16/80
0.8913 - val_loss: 1.3475 - val_accuracy: 0.5875
Epoch 17/80
0.8896 - val_loss: 1.1469 - val_accuracy: 0.5675
Epoch 18/80
0.9221 - val_loss: 1.1957 - val_accuracy: 0.5750
Epoch 19/80
0.9621 - val_loss: 1.5078 - val_accuracy: 0.5763
Epoch 20/80
0.9621 - val_loss: 1.3711 - val_accuracy: 0.5838
Epoch 21/80
0.9837 - val_loss: 1.3791 - val_accuracy: 0.5150
Epoch 22/80
0.9792 - val_loss: 1.6888 - val_accuracy: 0.5700
Epoch 23/80
0.9883 - val_loss: 1.5643 - val_accuracy: 0.5813
Epoch 24/80
0.9996 - val_loss: 1.4825 - val_accuracy: 0.6050
Epoch 25/80
1.0000 - val_loss: 1.4487 - val_accuracy: 0.6137
```

```
Epoch 26/80
0.9996 - val_loss: 1.5791 - val_accuracy: 0.5975
Epoch 27/80
0.9996 - val_loss: 1.5545 - val_accuracy: 0.6000
Epoch 28/80
1.0000 - val_loss: 1.5737 - val_accuracy: 0.6075
Epoch 29/80
1.0000 - val_loss: 1.5825 - val_accuracy: 0.6100
Epoch 30/80
1.0000 - val_loss: 1.6074 - val_accuracy: 0.5938
Epoch 31/80
1.0000 - val_loss: 1.6409 - val_accuracy: 0.6162
Epoch 32/80
1.0000 - val_loss: 1.6501 - val_accuracy: 0.6125
Epoch 33/80
1.0000 - val_loss: 1.6706 - val_accuracy: 0.6050
Epoch 34/80
1.0000 - val_loss: 1.6834 - val_accuracy: 0.6037
Epoch 35/80
1.0000 - val_loss: 1.7002 - val_accuracy: 0.6112
Epoch 36/80
0.9996 - val_loss: 1.9191 - val_accuracy: 0.5788
Epoch 37/80
0.9996 - val_loss: 1.7785 - val_accuracy: 0.6100
Epoch 38/80
0.9996 - val_loss: 1.8215 - val_accuracy: 0.5913
Epoch 39/80
1.0000 - val_loss: 1.8219 - val_accuracy: 0.5813
1.0000 - val_loss: 1.8098 - val_accuracy: 0.5938
Epoch 41/80
1.0000 - val_loss: 1.8260 - val_accuracy: 0.5962
```

```
Epoch 42/80
1.0000 - val_loss: 1.8139 - val_accuracy: 0.5950
Epoch 43/80
1.0000 - val_loss: 1.8372 - val_accuracy: 0.5938
Epoch 44/80
1.0000 - val_loss: 1.8522 - val_accuracy: 0.5913
Epoch 45/80
1.0000 - val_loss: 1.8719 - val_accuracy: 0.5913
Epoch 46/80
38/38 [============= ] - 2s 51ms/step - loss: 0.0010 - accuracy:
1.0000 - val_loss: 1.8726 - val_accuracy: 0.5950
Epoch 47/80
1.0000 - val_loss: 1.9762 - val_accuracy: 0.5863
Epoch 48/80
1.0000 - val_loss: 1.8778 - val_accuracy: 0.6025
Epoch 49/80
38/38 [============= ] - 2s 50ms/step - loss: 9.5201e-04 -
accuracy: 1.0000 - val_loss: 1.8924 - val_accuracy: 0.5900
Epoch 50/80
38/38 [============== ] - 2s 50ms/step - loss: 9.5213e-04 -
accuracy: 1.0000 - val_loss: 1.9279 - val_accuracy: 0.5950
Epoch 51/80
38/38 [============== ] - 2s 47ms/step - loss: 8.7523e-04 -
accuracy: 1.0000 - val_loss: 1.9240 - val_accuracy: 0.5950
Epoch 52/80
38/38 [=============== ] - 2s 49ms/step - loss: 8.2130e-04 -
accuracy: 1.0000 - val_loss: 1.9334 - val_accuracy: 0.5925
Epoch 53/80
38/38 [================ ] - 2s 50ms/step - loss: 8.4788e-04 -
accuracy: 1.0000 - val_loss: 1.9385 - val_accuracy: 0.6075
Epoch 54/80
1.0000 - val_loss: 1.9257 - val_accuracy: 0.5888
Epoch 55/80
38/38 [============== ] - 2s 48ms/step - loss: 9.2246e-04 -
accuracy: 1.0000 - val_loss: 1.8946 - val_accuracy: 0.5900
accuracy: 1.0000 - val_loss: 1.9038 - val_accuracy: 0.5987
Epoch 57/80
38/38 [=============== ] - 2s 52ms/step - loss: 6.9166e-04 -
accuracy: 1.0000 - val_loss: 1.9016 - val_accuracy: 0.5950
```

```
Epoch 58/80
38/38 [============== ] - 2s 48ms/step - loss: 8.1271e-04 -
accuracy: 1.0000 - val_loss: 1.9278 - val_accuracy: 0.6050
Epoch 59/80
38/38 [============== ] - 2s 50ms/step - loss: 6.1350e-04 -
accuracy: 1.0000 - val_loss: 1.9234 - val_accuracy: 0.6000
38/38 [=============== ] - 2s 49ms/step - loss: 5.1931e-04 -
accuracy: 1.0000 - val_loss: 1.9381 - val_accuracy: 0.5987
Epoch 61/80
38/38 [============== ] - 2s 46ms/step - loss: 6.1753e-04 -
accuracy: 1.0000 - val_loss: 1.9629 - val_accuracy: 0.6025
Epoch 62/80
accuracy: 1.0000 - val_loss: 1.9713 - val_accuracy: 0.5987
Epoch 63/80
38/38 [============== ] - 2s 47ms/step - loss: 6.3513e-04 -
accuracy: 1.0000 - val_loss: 1.9782 - val_accuracy: 0.5975
Epoch 64/80
38/38 [=============== ] - 2s 46ms/step - loss: 6.2630e-04 -
accuracy: 1.0000 - val_loss: 1.9958 - val_accuracy: 0.5962
Epoch 65/80
38/38 [============= ] - 2s 48ms/step - loss: 6.1119e-04 -
accuracy: 1.0000 - val_loss: 1.9905 - val_accuracy: 0.6012
Epoch 66/80
accuracy: 1.0000 - val_loss: 1.9949 - val_accuracy: 0.5962
Epoch 67/80
38/38 [============= ] - 2s 48ms/step - loss: 5.5764e-04 -
accuracy: 1.0000 - val_loss: 1.9995 - val_accuracy: 0.6000
Epoch 68/80
38/38 [============== ] - 2s 42ms/step - loss: 7.3648e-04 -
accuracy: 1.0000 - val_loss: 1.9913 - val_accuracy: 0.5975
Epoch 69/80
38/38 [=============== ] - 2s 46ms/step - loss: 6.4903e-04 -
accuracy: 1.0000 - val_loss: 1.9932 - val_accuracy: 0.6000
Epoch 70/80
accuracy: 1.0000 - val_loss: 2.0138 - val_accuracy: 0.5962
Epoch 71/80
38/38 [=============== ] - 2s 45ms/step - loss: 4.0495e-04 -
accuracy: 1.0000 - val_loss: 2.0220 - val_accuracy: 0.5950
38/38 [============= ] - 2s 48ms/step - loss: 7.0355e-04 -
accuracy: 1.0000 - val_loss: 2.0194 - val_accuracy: 0.5950
Epoch 73/80
38/38 [=============== ] - 2s 50ms/step - loss: 4.1989e-04 -
accuracy: 1.0000 - val_loss: 2.0188 - val_accuracy: 0.5962
```

```
Epoch 74/80
    38/38 [============== ] - 2s 47ms/step - loss: 4.9727e-04 -
    accuracy: 1.0000 - val_loss: 2.0216 - val_accuracy: 0.5938
    Epoch 75/80
    38/38 [============== ] - 2s 51ms/step - loss: 4.2023e-04 -
    accuracy: 1.0000 - val_loss: 2.0304 - val_accuracy: 0.5925
    38/38 [================ ] - 2s 51ms/step - loss: 5.1811e-04 -
    accuracy: 1.0000 - val_loss: 2.0789 - val_accuracy: 0.5888
    Epoch 77/80
    38/38 [============== ] - 2s 51ms/step - loss: 5.3157e-04 -
    accuracy: 1.0000 - val_loss: 2.0467 - val_accuracy: 0.5950
    Epoch 78/80
    accuracy: 1.0000 - val_loss: 2.0541 - val_accuracy: 0.5975
    Epoch 79/80
    38/38 [============== ] - 2s 52ms/step - loss: 4.2673e-04 -
    accuracy: 1.0000 - val_loss: 2.0540 - val_accuracy: 0.5975
    Epoch 80/80
    38/38 [=============== ] - 2s 46ms/step - loss: 3.3516e-04 -
    accuracy: 1.0000 - val_loss: 2.0545 - val_accuracy: 0.5938
[15]: type(hist_4.history['loss'])
     import matplotlib.pyplot as plt
     plt.plot(hist_4.history['accuracy'])
     plt.plot(hist_4.history['val_accuracy'])
     plt.title('Exactitud de entrenamiento y validación')
     plt.xlabel('épocas')
     plt.ylabel('Porcentaje [%]')
     plt.legend(['Entrenamiento','Validación'])
     plt.grid()
```



5 4) Regularización por data augmentation

exactitud de la prueba= 59.625 %

```
[17]: import tensorflow as tf from keras.models import Model, load_model
```

```
#from tensorflow.keras.applications.resnet50 import preprocess_input,_
\rightarrow decode_predictions
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Flatten,Dropout,Input
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, u
→ ReduceLROnPlateau
lr_reduce = ReduceLROnPlateau(monitor='val_accuracy', factor=0.6, patience=8,_
→verbose=1, mode='max', min_lr=5e-5)
checkpoint = ModelCheckpoint('vgg16_finetune.h5', monitor= 'val_accuracy',
→mode= 'max', save_best_only = True, verbose= 1)
earlystopper = EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 10, __
→verbose = 1, restore_best_weights = True)
#"""
#"""
## Uso de RandomCrop
\#tf.keras.layers.experimental.preprocessing.RandomCrop()
#tf.keras.layers.CenterCrop(x_size,y_size,1)
tf.keras.layers.RandomCrop(x_size,y_size,1)
model=Sequential()
model.add(tf.keras.layers.
→Conv2D(6,(5,5),input_shape=(x_size,y_size,1),activation='tanh',padding='valid',strides=1))
\hookrightarrow #C1
model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #S2
model.add(tf.keras.layers.
→Conv2D(16,(5,5),activation='tanh',padding='valid',strides=1)) #c3
model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #s4
model.add(tf.keras.layers.Flatten())
model.add(Dense(120,activation='tanh')) #c5
model.add(Dense(84,activation='tanh')) #c6
from keras.layers import Layer
from keras import backend as K
class RBFLayer(Layer):
    def __init__(self, units, gamma, **kwargs):
        super(RBFLayer, self).__init__(**kwargs)
        self.units = units
        self.gamma = K.cast_to_floatx(gamma)
```

```
def build(self, input_shape):
     self.mu = self.add_weight(name='mu',
                      shape=(int(input_shape[1]), self.units),
                      initializer='uniform',
                      trainable=True)
     super(RBFLayer, self).build(input_shape)
   def call(self, inputs):
     diff = K.expand_dims(inputs) - self.mu
     12 = K.sum(K.pow(diff,2), axis=1)
     res = K.exp(-1 * self.gamma * 12)
     return res
   def compute_output_shape(self, input_shape):
     return (input_shape[0], self.units)
model.add(RBFLayer(2,0.5)) #c7
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.
→SGD(learning_rate=0.25),metrics=['accuracy'])
hist_5=model.fit(x_train,y_train,verbose=1,_
 ⇒batch_size=64,epochs=80,validation_data=(x_val,y_val))
Epoch 1/80
0.5096 - val_loss: 0.6918 - val_accuracy: 0.5350
Epoch 2/80
0.5412 - val_loss: 0.6905 - val_accuracy: 0.5163
Epoch 3/80
0.5446 - val_loss: 0.6869 - val_accuracy: 0.5600
Epoch 4/80
0.5542 - val_loss: 0.6850 - val_accuracy: 0.5450
Epoch 5/80
0.5546 - val_loss: 0.6993 - val_accuracy: 0.5437
Epoch 6/80
0.5675 - val_loss: 0.6945 - val_accuracy: 0.5425
Epoch 7/80
0.5571 - val_loss: 0.6897 - val_accuracy: 0.5300
0.5775 - val_loss: 0.7113 - val_accuracy: 0.5225
```

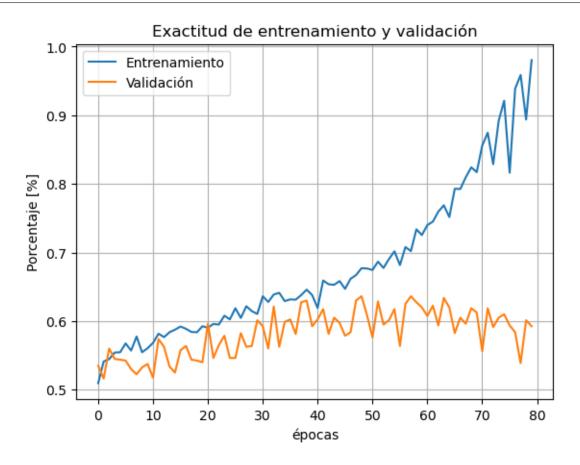
```
Epoch 9/80
0.5546 - val_loss: 0.6963 - val_accuracy: 0.5325
Epoch 10/80
0.5604 - val_loss: 0.6939 - val_accuracy: 0.5375
Epoch 11/80
0.5683 - val_loss: 0.6917 - val_accuracy: 0.5175
Epoch 12/80
0.5817 - val_loss: 0.6889 - val_accuracy: 0.5738
Epoch 13/80
0.5767 - val_loss: 0.6898 - val_accuracy: 0.5625
Epoch 14/80
0.5838 - val_loss: 0.6952 - val_accuracy: 0.5337
Epoch 15/80
0.5875 - val_loss: 0.7017 - val_accuracy: 0.5250
Epoch 16/80
0.5921 - val_loss: 0.6949 - val_accuracy: 0.5575
Epoch 17/80
0.5888 - val_loss: 0.6916 - val_accuracy: 0.5638
Epoch 18/80
0.5842 - val_loss: 0.7011 - val_accuracy: 0.5437
Epoch 19/80
0.5838 - val_loss: 0.6956 - val_accuracy: 0.5425
Epoch 20/80
0.5925 - val_loss: 0.7027 - val_accuracy: 0.5400
Epoch 21/80
0.5904 - val_loss: 0.6919 - val_accuracy: 0.5962
Epoch 22/80
0.5958 - val_loss: 0.6889 - val_accuracy: 0.5462
0.5950 - val_loss: 0.6840 - val_accuracy: 0.5650
Epoch 24/80
0.6079 - val_loss: 0.6867 - val_accuracy: 0.5788
```

```
Epoch 25/80
0.6025 - val_loss: 0.7047 - val_accuracy: 0.5462
Epoch 26/80
0.6187 - val_loss: 0.6906 - val_accuracy: 0.5462
Epoch 27/80
0.6046 - val_loss: 0.6789 - val_accuracy: 0.5825
Epoch 28/80
0.6217 - val_loss: 0.6895 - val_accuracy: 0.5625
Epoch 29/80
0.6146 - val_loss: 0.6882 - val_accuracy: 0.5638
Epoch 30/80
38/38 [============== ] - 2s 53ms/step - loss: 0.6520 - accuracy:
0.6104 - val_loss: 0.6692 - val_accuracy: 0.6012
Epoch 31/80
0.6363 - val_loss: 0.6714 - val_accuracy: 0.5925
Epoch 32/80
0.6279 - val_loss: 0.7016 - val_accuracy: 0.5600
Epoch 33/80
0.6388 - val_loss: 0.6633 - val_accuracy: 0.6212
Epoch 34/80
0.6413 - val_loss: 0.7096 - val_accuracy: 0.5625
Epoch 35/80
0.6292 - val_loss: 0.6635 - val_accuracy: 0.5987
Epoch 36/80
0.6317 - val_loss: 0.6760 - val_accuracy: 0.6025
Epoch 37/80
0.6313 - val_loss: 0.6810 - val_accuracy: 0.5813
Epoch 38/80
0.6379 - val_loss: 0.6672 - val_accuracy: 0.6275
0.6458 - val_loss: 0.6618 - val_accuracy: 0.6300
Epoch 40/80
0.6379 - val_loss: 0.6745 - val_accuracy: 0.5925
```

```
Epoch 41/80
0.6192 - val_loss: 0.6639 - val_accuracy: 0.6025
Epoch 42/80
0.6592 - val_loss: 0.6691 - val_accuracy: 0.6175
Epoch 43/80
0.6538 - val_loss: 0.6966 - val_accuracy: 0.5813
Epoch 44/80
0.6529 - val_loss: 0.6748 - val_accuracy: 0.6050
Epoch 45/80
0.6583 - val_loss: 0.6752 - val_accuracy: 0.5975
Epoch 46/80
0.6471 - val_loss: 0.6898 - val_accuracy: 0.5788
Epoch 47/80
0.6617 - val_loss: 0.6754 - val_accuracy: 0.5838
Epoch 48/80
0.6671 - val_loss: 0.6636 - val_accuracy: 0.6300
Epoch 49/80
0.6771 - val_loss: 0.6460 - val_accuracy: 0.6363
Epoch 50/80
0.6767 - val_loss: 0.6630 - val_accuracy: 0.6087
Epoch 51/80
38/38 [============== ] - 2s 53ms/step - loss: 0.5938 - accuracy:
0.6746 - val_loss: 0.7744 - val_accuracy: 0.5763
Epoch 52/80
0.6867 - val_loss: 0.6661 - val_accuracy: 0.6288
Epoch 53/80
0.6775 - val_loss: 0.6812 - val_accuracy: 0.5950
Epoch 54/80
0.6904 - val_loss: 0.7030 - val_accuracy: 0.6012
0.7017 - val_loss: 0.6994 - val_accuracy: 0.6175
Epoch 56/80
0.6817 - val_loss: 0.7332 - val_accuracy: 0.5638
```

```
Epoch 57/80
0.7079 - val_loss: 0.7062 - val_accuracy: 0.6250
Epoch 58/80
0.7021 - val_loss: 0.6963 - val_accuracy: 0.6363
Epoch 59/80
0.7337 - val_loss: 0.6935 - val_accuracy: 0.6275
Epoch 60/80
0.7254 - val_loss: 0.7741 - val_accuracy: 0.6200
Epoch 61/80
0.7400 - val_loss: 0.7360 - val_accuracy: 0.6075
Epoch 62/80
0.7450 - val_loss: 0.7299 - val_accuracy: 0.6225
Epoch 63/80
0.7596 - val_loss: 0.8021 - val_accuracy: 0.5938
Epoch 64/80
0.7688 - val_loss: 0.7543 - val_accuracy: 0.6338
Epoch 65/80
0.7517 - val_loss: 0.7544 - val_accuracy: 0.6200
Epoch 66/80
0.7929 - val_loss: 0.8374 - val_accuracy: 0.5825
Epoch 67/80
0.7925 - val_loss: 0.8420 - val_accuracy: 0.6050
Epoch 68/80
0.8096 - val_loss: 0.9198 - val_accuracy: 0.5962
Epoch 69/80
0.8242 - val_loss: 0.8238 - val_accuracy: 0.6187
Epoch 70/80
0.8171 - val_loss: 0.8654 - val_accuracy: 0.6125
0.8558 - val_loss: 1.0697 - val_accuracy: 0.5562
Epoch 72/80
0.8746 - val_loss: 0.9811 - val_accuracy: 0.6187
```

```
Epoch 73/80
   0.8288 - val_loss: 0.9229 - val_accuracy: 0.5913
   Epoch 74/80
   0.8921 - val_loss: 0.9998 - val_accuracy: 0.6050
   Epoch 75/80
   0.9212 - val_loss: 1.1522 - val_accuracy: 0.6100
   Epoch 76/80
   0.8163 - val_loss: 1.0370 - val_accuracy: 0.5938
   Epoch 77/80
   0.9388 - val_loss: 1.1654 - val_accuracy: 0.5838
   Epoch 78/80
   0.9588 - val_loss: 1.5540 - val_accuracy: 0.5387
   Epoch 79/80
   0.8938 - val_loss: 1.1374 - val_accuracy: 0.6012
   Epoch 80/80
   0.9804 - val_loss: 1.1905 - val_accuracy: 0.5925
[18]: type(hist_5.history['loss'])
   import matplotlib.pyplot as plt
   plt.plot(hist_5.history['accuracy'])
   plt.plot(hist_5.history['val_accuracy'])
   plt.title('Exactitud de entrenamiento y validación')
   plt.xlabel('épocas')
   plt.ylabel('Porcentaje [%]')
   plt.legend(['Entrenamiento', 'Validación'])
   plt.grid()
```



```
pred=model.predict(x_test)
pred=np.argmax(pred,axis=1)
y1=np.argmax(y_test,axis=1)

#label=np.argmax(yp_oh)
exactitud_test=0
for a in range(len(pred)):
    if pred[a] == y1[a]:
        exactitud_test+=1
print('exactitud_de la prueba= ',100*exactitud_test/len(pred),'%')
```

6 5) Regularización con todos los métodos

25/25 [========] - Os 1ms/step

• L1 o norma L1 Lasso

exactitud de la prueba= 58.75 %

- Dropout
- Normalización por lotes (BatchNormalization)

• Aumento de los datos (Data augmentation)

Extra: También se usarán los Callbacks de reducción de factor de aprendizaje y el "EarlyStopper".

```
[14]: import tensorflow as tf
      from keras.models import Model, load_model
      #from tensorflow.keras.applications.resnet50 import preprocess_input,_
      \rightarrow decode_predictions
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense, Flatten, Dropout, Input
      from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, u
       → ReduceLROnPlateau
      lr_reduce = ReduceLROnPlateau(monitor='val_accuracy', factor=0.6, patience=8,_
      →verbose=1, mode='max', min_lr=5e-5)
      #checkpoint = ModelCheckpoint('vgq16_finetune.h5', monitor= 'val_accuracy',_
      →mode= 'max', save_best_only = True, verbose= 1)
      earlystopper = EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 10, __
       →verbose = 1, restore_best_weights = True)
      k_r=tf.keras.regularizers.L1L2(l1=1e-5,12=1e-4)
      b_r=tf.keras.regularizers.L2(12=1e-4)
      a_r=tf.keras.regularizers.L2(12=1e-5)
      #111111
      #"""
      # Data Augmentation con RandomCrop
      tf.keras.layers.RandomCrop(x_size,y_size,1)
      model=Sequential()
      model.add(tf.keras.layers.
       →Conv2D(6,(5,5),input_shape=(x_size,y_size,1),activation='tanh',padding='valid',strides=1))
       \hookrightarrow #C1
      model.add(Dropout(0.2)) #Dropout
      model.add(tf.keras.layers.BatchNormalization()) # BatchNormalization
      model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #S2
      model.add(Dropout(0.9)) #Dropout
      model.add(tf.keras.layers.BatchNormalization()) # BatchNormalization
      model.add(tf.keras.layers.
       →Conv2D(16,(5,5),activation='tanh',padding='valid',strides=1)) #c3
      model.add(Dropout(0.6)) #Dropout
      model.add(tf.keras.layers.BatchNormalization()) # BatchNormalization
      model.add(tf.keras.layers.AveragePooling2D(pool_size=(2,2))) #s4
      model.add(Dropout(0.5)) #Dropout
      model.add(tf.keras.layers.BatchNormalization()) # BatchNormalization
      model.add(tf.keras.layers.Flatten())
```

```
model.
 →add(Dense(120,activation='tanh',kernel_regularizer=k_r,bias_regularizer=b_r,activity_regularizer
model.add(Dropout(0.6)) #Dropout
model.add(tf.keras.layers.BatchNormalization()) # BatchNormalization
 -add(Dense(84,activation='tanh',kernel_regularizer=k_r,bias_regularizer=b_r,activity_regularizer=b_r
model.add(Dropout(0.7)) #Dropout
model.add(tf.keras.layers.BatchNormalization()) # BatchNormalization
from keras.layers import Layer
from keras import backend as K
class RBFLayer(Layer):
    def __init__(self, units, gamma, **kwargs):
        super(RBFLayer, self).__init__(**kwargs)
        self.units = units
        self.gamma = K.cast_to_floatx(gamma)
    def build(self, input_shape):
        self.mu = self.add_weight(name='mu',
                                 shape=(int(input_shape[1]), self.units),
                                 initializer='uniform',
                                 trainable=True)
        super(RBFLayer, self).build(input_shape)
    def call(self, inputs):
        diff = K.expand_dims(inputs) - self.mu
        12 = K.sum(K.pow(diff,2), axis=1)
        res = K.exp(-1 * self.gamma * 12)
        return res
    def compute_output_shape(self, input_shape):
        return (input_shape[0], self.units)
model.add(RBFLayer(2,0.5)) #c7
model.compile(loss='categorical_crossentropy',optimizer=tf.keras.optimizers.
 →Adam(learning_rate=0.25), metrics=['accuracy'])
hist_final=model.fit(x_train,y_train,verbose=1,_
 →batch_size=32,epochs=150,validation_data=(x_val,y_val),callbacks=[lr_reduce,earlystopper])
Epoch 1/150
0.5013 - val_loss: 6.2067 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 2/150
```

```
0.5096 - val_loss: 2.6703 - val_accuracy: 0.5000 - 1r: 0.2500
Epoch 3/150
0.5029 - val_loss: 1.5981 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 4/150
0.5221 - val_loss: 1.3449 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 5/150
75/75 [============= ] - 3s 36ms/step - loss: 1.5869 - accuracy:
0.5075 - val_loss: 1.1648 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 6/150
0.4808 - val_loss: 1.2436 - val_accuracy: 0.5000 - lr: 0.2500
0.4946 - val_loss: 1.1519 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 8/150
0.4979 - val_loss: 0.9882 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 9: ReduceLROnPlateau reducing learning rate to 0.15.
0.5017 - val_loss: 2.2968 - val_accuracy: 0.5000 - lr: 0.2500
Epoch 10/150
0.5071 - val_loss: 1.0017 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 11/150
0.4958 - val_loss: 0.8342 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 12/150
0.5142 - val_loss: 0.7735 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 13/150
0.4971 - val_loss: 0.7905 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 14/150
0.4996 - val_loss: 0.8091 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 15/150
0.4958 - val_loss: 0.8324 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 16/150
0.5083 - val_loss: 0.8397 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 17/150
```

```
0.4916
Epoch 17: ReduceLROnPlateau reducing learning rate to 0.09000000357627869.
0.4917 - val_loss: 0.9981 - val_accuracy: 0.5000 - lr: 0.1500
Epoch 18/150
0.5192 - val_loss: 0.8746 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 19/150
0.4988 - val_loss: 0.7295 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 20/150
75/75 [============] - 2s 26ms/step - loss: 0.7605 - accuracy:
0.4804 - val_loss: 0.7241 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 21/150
0.4967 - val_loss: 0.7234 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 22/150
75/75 [============] - 2s 26ms/step - loss: 0.7491 - accuracy:
0.4825 - val_loss: 0.7507 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 23/150
0.5046 - val_loss: 0.7708 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 24/150
0.5129 - val_loss: 1.0622 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 25/150
Epoch 25: ReduceLROnPlateau reducing learning rate to 0.05400000214576721.
0.4917 - val_loss: 0.7505 - val_accuracy: 0.5000 - lr: 0.0900
Epoch 26/150
0.5108 - val_loss: 0.7404 - val_accuracy: 0.5000 - lr: 0.0540
Epoch 27/150
75/75 [============] - 3s 47ms/step - loss: 0.7310 - accuracy:
0.5092 - val_loss: 0.7311 - val_accuracy: 0.5000 - lr: 0.0540
Epoch 28/150
0.4892 - val_loss: 0.7402 - val_accuracy: 0.5000 - 1r: 0.0540
Epoch 29/150
0.4975 - val_loss: 0.7119 - val_accuracy: 0.5000 - lr: 0.0540
Epoch 30/150
0.4904 - val_loss: 0.6996 - val_accuracy: 0.5000 - lr: 0.0540
Epoch 31/150
```

```
0.5083 - val_loss: 0.8238 - val_accuracy: 0.5000 - 1r: 0.0540
Epoch 32/150
0.4879 - val_loss: 0.7550 - val_accuracy: 0.5000 - lr: 0.0540
Epoch 33/150
0.4945
Epoch 33: ReduceLROnPlateau reducing learning rate to 0.03240000084042549.
0.4954 - val_loss: 0.7323 - val_accuracy: 0.5000 - lr: 0.0540
Epoch 34/150
75/75 [============] - 2s 28ms/step - loss: 0.7233 - accuracy:
0.4900 - val_loss: 0.7059 - val_accuracy: 0.5000 - lr: 0.0324
0.4958 - val_loss: 0.7026 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 36/150
0.5171 - val_loss: 0.7490 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 37/150
0.5208 - val_loss: 0.7080 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 38/150
0.5033 - val_loss: 0.7015 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 39/150
0.4888 - val_loss: 0.6982 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 40/150
0.4867 - val_loss: 0.6952 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 41/150
0.5101
Epoch 41: ReduceLROnPlateau reducing learning rate to 0.019440000504255293.
0.5104 - val_loss: 0.6971 - val_accuracy: 0.5000 - lr: 0.0324
Epoch 42/150
75/75 [=============] - 3s 37ms/step - loss: 0.6973 - accuracy:
0.4950 - val_loss: 0.6960 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 43/150
0.4908 - val_loss: 0.7145 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 44/150
0.4942 - val_loss: 0.7028 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 45/150
```

```
0.4963 - val_loss: 0.7037 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 46/150
0.4875 - val_loss: 0.6964 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 47/150
0.4871 - val_loss: 0.6952 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 48/150
75/75 [============] - 3s 45ms/step - loss: 0.6959 - accuracy:
0.4950 - val_loss: 0.6949 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 49/150
0.4987
Epoch 49: ReduceLROnPlateau reducing learning rate to 0.011664000526070594.
0.4979 - val_loss: 0.6946 - val_accuracy: 0.5000 - lr: 0.0194
Epoch 50/150
0.5167 - val_loss: 0.6940 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 51/150
0.5167 - val_loss: 0.6963 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 52/150
0.4812 - val_loss: 0.6939 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 53/150
0.4929 - val_loss: 0.6936 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 54/150
0.5008 - val_loss: 0.6936 - val_accuracy: 0.4863 - lr: 0.0117
Epoch 55/150
0.5050 - val_loss: 0.6934 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 56/150
0.4825 - val_loss: 0.6936 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 57/150
0.5079
Epoch 57: ReduceLROnPlateau reducing learning rate to 0.006998400203883648.
0.5079 - val_loss: 0.6936 - val_accuracy: 0.5000 - lr: 0.0117
Epoch 58/150
75/75 [============] - 3s 44ms/step - loss: 0.6941 - accuracy:
0.5021 - val_loss: 0.6935 - val_accuracy: 0.5000 - lr: 0.0070
Epoch 59/150
```

```
75/75 [===========] - 3s 40ms/step - loss: 0.6933 - accuracy:
0.4929 - val_loss: 0.6933 - val_accuracy: 0.5000 - 1r: 0.0070
Epoch 60/150
0.4929 - val_loss: 0.6933 - val_accuracy: 0.5000 - lr: 0.0070
Epoch 61/150
0.5042 - val_loss: 0.6933 - val_accuracy: 0.5000 - lr: 0.0070
Epoch 62/150
75/75 [============] - 3s 34ms/step - loss: 0.6933 - accuracy:
0.4808 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0070
Epoch 63/150
75/75 [============] - 3s 43ms/step - loss: 0.6933 - accuracy:
0.4842 - val_loss: 0.6933 - val_accuracy: 0.5000 - lr: 0.0070
0.5042 - val_loss: 0.6936 - val_accuracy: 0.5000 - lr: 0.0070
Epoch 65/150
75/75 [============ ] - ETA: Os - loss: 0.6933 - accuracy:
0.4908
Epoch 65: ReduceLROnPlateau reducing learning rate to 0.004199040122330189.
0.4908 - val_loss: 0.6933 - val_accuracy: 0.5000 - lr: 0.0070
Epoch 66/150
75/75 [============] - 3s 42ms/step - loss: 0.6932 - accuracy:
0.4967 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0042
Epoch 67/150
0.4921 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0042
Epoch 68/150
0.4971 - val_loss: 0.6932 - val_accuracy: 0.5000 - 1r: 0.0042
Epoch 69/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0042
Epoch 70/150
0.4942 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0042
Epoch 71/150
0.5067 - val_loss: 0.6932 - val_accuracy: 0.5000 - 1r: 0.0042
Epoch 72/150
75/75 [=============] - 3s 37ms/step - loss: 0.6932 - accuracy:
0.4979 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0042
Epoch 73/150
0.5093
Epoch 73: ReduceLROnPlateau reducing learning rate to 0.0025194240733981133.
```

```
0.5104 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0042
Epoch 74/150
0.5113 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 75/150
0.4746 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 76/150
75/75 [============] - 3s 37ms/step - loss: 0.6932 - accuracy:
0.4992 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 77/150
0.4967 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
0.4979 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 79/150
0.4967 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 80/150
75/75 [============] - 3s 42ms/step - loss: 0.6932 - accuracy:
0.5033 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 81/150
0.4992
Epoch 81: ReduceLROnPlateau reducing learning rate to 0.0015116544440388678.
0.5004 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0025
Epoch 82/150
0.4850 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 83/150
75/75 [============] - 3s 34ms/step - loss: 0.6932 - accuracy:
0.5063 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 84/150
0.4900 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 85/150
0.4942 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 86/150
75/75 [=============] - 3s 36ms/step - loss: 0.6932 - accuracy:
0.5038 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 87/150
75/75 [============] - 3s 41ms/step - loss: 0.6932 - accuracy:
0.4908 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 88/150
```

```
75/75 [============] - 3s 39ms/step - loss: 0.6932 - accuracy:
0.4850 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 89/150
0.4983
Epoch 89: ReduceLROnPlateau reducing learning rate to 0.0009069926803931594.
0.4996 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 0.0015
Epoch 90/150
0.4992 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 91/150
0.4996 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 93/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 94/150
0.5013 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 95/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 96/150
0.4979 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 97/150
Epoch 97: ReduceLROnPlateau reducing learning rate to 0.0005441956222057342.
75/75 [============] - 3s 35ms/step - loss: 0.6932 - accuracy:
0.5004 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 9.0699e-04
Epoch 98/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - 1r: 5.4420e-04
Epoch 99/150
75/75 [============] - 3s 43ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 5.4420e-04
Epoch 100/150
75/75 [=============] - 3s 36ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - 1r: 5.4420e-04
Epoch 101/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 5.4420e-04
Epoch 102/150
```

```
75/75 [===========] - 3s 34ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 5.4420e-04
Epoch 103/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 5.4420e-04
Epoch 104/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 5.4420e-04
Epoch 105/150
0.5008
Epoch 105: ReduceLROnPlateau reducing learning rate to 0.00032651738729327917.
75/75 [============] - 2s 31ms/step - loss: 0.6932 - accuracy:
0.5008 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 5.4420e-04
Epoch 106/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 107/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 108/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 109/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 110/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 111/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 112/150
0.4992 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 113/150
Epoch 113: ReduceLROnPlateau reducing learning rate to 0.0001959104323759675.
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 3.2652e-04
Epoch 114/150
75/75 [=============] - 3s 34ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 115/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 116/150
```

```
75/75 [===========] - 3s 41ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 117/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 118/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 119/150
75/75 [============] - 3s 35ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 120/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 121/150
0.5000
Epoch 121: ReduceLROnPlateau reducing learning rate to 0.00011754625593312084.
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.9591e-04
Epoch 122/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 123/150
75/75 [============] - 3s 38ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 124/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 125/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 126/150
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 127/150
75/75 [============] - 3s 43ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 128/150
75/75 [=============] - 3s 34ms/step - loss: 0.6932 - accuracy:
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 129/150
0.4991
Epoch 129: ReduceLROnPlateau reducing learning rate to 7.052775181364268e-05.
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 1.1755e-04
Epoch 130/150
```

```
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 131/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 132/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 133/150
75/75 [============] - 3s 35ms/step - loss: 0.6931 - accuracy:
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 134/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 136/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 137/150
Epoch 137: ReduceLROnPlateau reducing learning rate to 5e-05.
0.5000 - val_loss: 0.6932 - val_accuracy: 0.5000 - lr: 7.0528e-05
Epoch 138/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 139/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 140/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 141/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 142/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 143/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 144/150
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
Epoch 145/150
```

```
0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
   Epoch 146/150
   0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
   Epoch 147/150
   0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
   Epoch 148/150
   0.5000Restoring model weights from the end of the best epoch: 138.
   0.5000 - val_loss: 0.6931 - val_accuracy: 0.5000 - lr: 5.0000e-05
   Epoch 148: early stopping
[15]: type(hist_final.history['loss'])
   import matplotlib.pyplot as plt
   plt.plot(hist_final.history['accuracy'])
   plt.plot(hist_final.history['val_accuracy'])
   plt.title('Exactitud de entrenamiento y validación')
   plt.xlabel('épocas')
   plt.ylabel('Porcentaje [%]')
   plt.legend(['Entrenamiento','Validación'])
   plt.grid()
```

