

nn

March 16, 2023

# 1 Neural Networks

## 1.1 Introduction

popular

### 1.1.1 Setup

neurons w/ weights  $w$  (+ biases  $b$ ) and nonlinearity/activation  $\phi$

$$\phi(\sum_i x_i w_i + b_i)$$

In layers w/ weights  $W \in \mathbb{R}^{n_l \times n_{l+1}}$  and biases  $b_l \in \mathbb{R}^{n_k}$  w/  $n_l$  neurons in layer  $l$ :

$$\phi(W_l x_l + b_l)$$

(abuse of notation w/  $\phi$ )

(if input points are  $x \in \mathbb{R}^d$ , then  $n_l = d$ )

Do this for all layers to get some output values in your final layer (*forward pass*)

set initial weights  $W_l$  randomly

*Tons* of different shapes/types of NNs

split data into train and test (80/20ish is good)

### 1.1.2 Backpropagation

Loss  $L(y)$  is a function of the output  $y$  and the target  $t$ , e.g.:

$$L(y) = (t - y)^2$$

Calculate derivative wrt each weight  $D_n = \frac{\partial L(y)}{\partial w_n}$  and use gradient descent to update weights:

$$w_n \leftarrow w_n - \eta D_n$$

for learning rate  $\eta > 0$

```
[ ]: from sklearn.datasets import load_iris
X, y = load_iris(as_frame = True, return_X_y=True)
```

```
[ ]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=42)
```

```
[ ]: import tensorflow as tf
train = tf.data.Dataset.from_tensor_slices((X_train, y_train))
test = tf.data.Dataset.from_tensor_slices((X_test, y_test))
```

```
[ ]: train = train.repeat(20).shuffle(1000).batch(32)
test = test.batch(1)
```

```
[ ]: model = tf.keras.Sequential([
    tf.keras.layers.Dense(10, activation=tf.nn.relu),  # hidden layer
    # tf.keras.layers.Dense(10, activation=tf.nn.relu),  # hidden layer
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(3, activation=tf.nn.softmax) # output layer
])

model.compile(
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"],
)

model.fit(
    train,
    validation_data=test,
    epochs=10,
)
```

Epoch 1/10

75/75 [=====] - 1s 3ms/step - loss: 1.2829 - accuracy: 0.3292 - val\_loss: 1.1317 - val\_accuracy: 0.3667

Epoch 2/10

75/75 [=====] - 0s 2ms/step - loss: 1.1326 - accuracy: 0.2912 - val\_loss: 1.0770 - val\_accuracy: 0.3333

Epoch 3/10

75/75 [=====] - 0s 2ms/step - loss: 1.0597 - accuracy: 0.3508 - val\_loss: 1.0327 - val\_accuracy: 0.4333

Epoch 4/10

75/75 [=====] - 0s 2ms/step - loss: 1.0013 - accuracy: 0.5467 - val\_loss: 0.9714 - val\_accuracy: 0.6333

Epoch 5/10

75/75 [=====] - 0s 2ms/step - loss: 0.9382 - accuracy: 0.6058 - val\_loss: 0.9125 - val\_accuracy: 0.6333

Epoch 6/10

75/75 [=====] - 0s 2ms/step - loss: 0.8886 - accuracy: 0.6029 - val\_loss: 0.8520 - val\_accuracy: 0.6333

Epoch 7/10

```

75/75 [=====] - 0s 3ms/step - loss: 0.8368 - accuracy:
0.6071 - val_loss: 0.7963 - val_accuracy: 0.6333
Epoch 8/10
75/75 [=====] - 0s 2ms/step - loss: 0.8034 - accuracy:
0.6075 - val_loss: 0.7507 - val_accuracy: 0.6333
Epoch 9/10
75/75 [=====] - 0s 2ms/step - loss: 0.7824 - accuracy:
0.6029 - val_loss: 0.7095 - val_accuracy: 0.6333
Epoch 10/10
75/75 [=====] - 0s 3ms/step - loss: 0.7626 - accuracy:
0.6017 - val_loss: 0.6747 - val_accuracy: 0.6333

```

```
[ ]: <keras.callbacks.History at 0x7f00181a6740>
```

```
[ ]: for pred_dict, expected in zip(predictions, ["setosa", "versicolor", "virginica"]):
    predicted_index = pred_dict.argmax()
    predicted = load_iris().target_names[predicted_index]
    probability = pred_dict.max()
    tick_cross = " " if predicted == expected else " "
    print(f"{tick_cross} Prediction is '{predicted}' ({100 * probability:.1f}%), expected '{expected}'")
```

```

Prediction is 'setosa' (100.0%), expected 'setosa'
Prediction is 'versicolor' (99.8%), expected 'versicolor'
Prediction is 'virginica' (91.9%), expected 'virginica'

```

## 1.2 Convolutional Neural Networks (CNNs)

### 1.2.1 Image Kernel Convolutions

images are matrices of pixel values use kernel to convolve over image to get new image (using padding at edges maybe so output image is same size as input image—e.g. zero padding (add a border of zeros) or mirror padding (add a border of identical pixels to the edge pixels))

e.g. for kernel  $w$  and image w/ pixel coords  $f(x, y)$  we get pixel value  $g(x, y)$  where:

$$g(x, y) = w * f(x, y) = \sum_{dx=-a}^a \sum_{dy=-b}^b w(dx, dy) f(x - dx, y - dy)$$

e.g. for a 3x3 kernel:

$$w = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$$

( $\sim$ directional edge detection kernel (I think?))

### 1.2.2 CNNs

**Convolutional Layers** We'll make an NN learn the convolution kernels for us! (i.e. learn the weights  $w_{x,y}(dx, dy)$ —i.e. the weights of the kernel depend on the pixels being convolved over.) And we can stack these layers to get more complex kernels.

**Pooling Layers** We can also use pooling layers to reduce the size of the image (e.g. max pooling). These just take a window of pixels and output the max value (or average value or something), meaning we can reduce the size of the image without losing too much information (downsampling).

**Fully Connected Layers (FC/Dense Layers)** Fully connected layers are just like the ones we've seen before (i.e. in non-convolution-land), but we flatten the image first (i.e. we take the image and turn it into a vector of pixel values).

```
[ ]: model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(
        filters=16,
        kernel_size=5,
        padding="same",
        activation=tf.nn.relu
    ),
    tf.keras.layers.MaxPool2D((2, 2), (2, 2), padding="same"),
    tf.keras.layers.Conv2D(
        filters=32,
        kernel_size=5,
        padding="same",
        activation=tf.nn.relu
    ),
    tf.keras.layers.MaxPool2D((2, 2), (2, 2), padding="same"),
    tf.keras.layers.Conv2D(
        filters=64,
        kernel_size=5,
        padding="same",
        activation=tf.nn.relu
    ),
    tf.keras.layers.MaxPool2D((2, 2), (2, 2), padding="same"),
    tf.keras.layers.Conv2D(
        filters=128,
        kernel_size=5,
        padding="same",
        activation=tf.nn.relu
    ),
    tf.keras.layers.MaxPool2D((2, 2), (2, 2), padding="same"),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dropout(0.4),
    tf.keras.layers.Dense(10, activation="softmax")
])
```

```
model.compile(
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"],
)
```

```
[ ]: import tensorflow_datasets as tfds
```

```
ds_train, ds_test = tfds.load(
    "mnist",
    split=["train", "test"],
    as_supervised=True,
)
```

```
[ ]: ds_train.element_spec
```

```
[ ]: (TensorSpec(shape=(28, 28, 1), dtype=tf.uint8, name=None),
      TensorSpec(shape=(), dtype=tf.int64, name=None))
```

```
[ ]: def normalize_img(image, label):
      return tf.cast(image, tf.float32) / 255., label
```

```
ds_train = ds_train.map(normalize_img)
```

```
ds_train = ds_train.shuffle(1000)
```

```
ds_train = ds_train.batch(128)
```

```
ds_test = ds_test.map(normalize_img)
```

```
ds_test = ds_test.batch(128)
```

```
[ ]: model.fit(
    ds_train,
    validation_data=ds_test,
    epochs=20,
)
```

Epoch 1/20

469/469 [=====] - 19s 41ms/step - loss: 0.0046 - accuracy: 0.9987 - val\_loss: 0.0366 - val\_accuracy: 0.9935

Epoch 2/20

469/469 [=====] - 19s 41ms/step - loss: 0.0040 - accuracy: 0.9988 - val\_loss: 0.0478 - val\_accuracy: 0.9932

Epoch 3/20

469/469 [=====] - 20s 42ms/step - loss: 0.0031 - accuracy: 0.9992 - val\_loss: 0.0496 - val\_accuracy: 0.9928

Epoch 4/20

469/469 [=====] - 19s 41ms/step - loss: 0.0036 - accuracy: 0.9990 - val\_loss: 0.0611 - val\_accuracy: 0.9921

Epoch 5/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0035 - accuracy: 0.9990 - val\_loss: 0.0441 - val\_accuracy: 0.9925

Epoch 6/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0036 - accuracy: 0.9990 - val\_loss: 0.0510 - val\_accuracy: 0.9925

Epoch 7/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0023 - accuracy: 0.9994 - val\_loss: 0.0825 - val\_accuracy: 0.9900

Epoch 8/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0023 - accuracy: 0.9994 - val\_loss: 0.0604 - val\_accuracy: 0.9918

Epoch 9/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0034 - accuracy: 0.9993 - val\_loss: 0.0536 - val\_accuracy: 0.9928

Epoch 10/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0023 - accuracy: 0.9995 - val\_loss: 0.0600 - val\_accuracy: 0.9919

Epoch 11/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0022 - accuracy: 0.9995 - val\_loss: 0.0515 - val\_accuracy: 0.9928

Epoch 12/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0030 - accuracy: 0.9993 - val\_loss: 0.0688 - val\_accuracy: 0.9926

Epoch 13/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0019 - accuracy: 0.9995 - val\_loss: 0.0709 - val\_accuracy: 0.9923

Epoch 14/20  
469/469 [=====] - 19s 40ms/step - loss: 0.0021 - accuracy: 0.9995 - val\_loss: 0.0554 - val\_accuracy: 0.9933

Epoch 15/20  
469/469 [=====] - 19s 40ms/step - loss: 0.0027 - accuracy: 0.9994 - val\_loss: 0.0607 - val\_accuracy: 0.9932

Epoch 16/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0020 - accuracy: 0.9995 - val\_loss: 0.0698 - val\_accuracy: 0.9920

Epoch 17/20  
469/469 [=====] - 19s 40ms/step - loss: 0.0018 - accuracy: 0.9995 - val\_loss: 0.0553 - val\_accuracy: 0.9943

Epoch 18/20  
469/469 [=====] - 19s 40ms/step - loss: 0.0019 - accuracy: 0.9995 - val\_loss: 0.0640 - val\_accuracy: 0.9934

Epoch 19/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0013 - accuracy: 0.9997 - val\_loss: 0.0624 - val\_accuracy: 0.9926

Epoch 20/20  
469/469 [=====] - 19s 41ms/step - loss: 0.0022 - accuracy: 0.9996 - val\_loss: 0.0649 - val\_accuracy: 0.9923

```
[ ]: <keras.callbacks.History at 0x7eff9b45e920>
```

```
[ ]: from urllib.request import urlretrieve

for i in list(range(1,10)) + ["dog"]:
    urlretrieve(f"https://github.com/milliams/intro_deep_learning/raw/master/
↳{i}.png", f"{i}.png")
```

```
[ ]: import numpy as np
from skimage.io import imread

images = []
for i in list(range(1,10)) + ["dog"]:
    images.append(np.array(imread(f"{i}.png")/255.0, dtype="float32"))
images = np.array(images)[:,:,:,:np.newaxis]
images.shape
```

```
[ ]: (10, 28, 28, 1)
```

```
[ ]: probabilities = model.predict(images)
```

```
1/1 [=====] - 0s 32ms/step
```

```
1/1 [=====] - 0s 32ms/step
```

```
[ ]: truths = list(range(1, 10)) + ["dog"]

table = []
for truth, probs in zip(truths, probabilities):
    prediction = probs.argmax()
    if truth == 'dog':
        print(f"{truth}. CNN thinks it's a {prediction} ({probs[prediction]*100:
↳.1f}%)")
    else:
        print(f"{truth} at {probs[truth]*100:4.1f}%. CNN thinks it's a
↳{prediction} ({probs[prediction]*100:4.1f}%)")
    table.append((truth, probs))
```

```
1 at 51.3%. CNN thinks it's a 1 (51.3%)
2 at 84.8%. CNN thinks it's a 2 (84.8%)
3 at 91.2%. CNN thinks it's a 3 (91.2%)
4 at 0.1%. CNN thinks it's a 5 (41.7%)
5 at 100.0%. CNN thinks it's a 5 (100.0%)
6 at 0.0%. CNN thinks it's a 3 (99.9%)
7 at 99.7%. CNN thinks it's a 7 (99.7%)
8 at 4.7%. CNN thinks it's a 1 (21.8%)
9 at 15.2%. CNN thinks it's a 8 (64.3%)
dog. CNN thinks it's a 8 (17.0%)
```

### 1.2.3 Data Augmentation

add inveted images to training data to make the NN more robust to different images (could also do rotated images, &c.)

```
[ ]: def invert_img(image, label):  
      return 1.-image, label  
  
ds_train = ds_train.map(normalize_img)  
ds_train = ds_train.concatenate(ds_train.map(invert_img)) # new line  
ds_train = ds_train.shuffle(1000)  
ds_train = ds_train.batch(128)  
  
ds_test = ds_test.map(normalize_img)  
ds_test = ds_test.concatenate(ds_test.map(invert_img)) # new line  
ds_test = ds_test.batch(128)  
  
model.fit(  
    ds_train,  
    validation_data=ds_test,  
    epochs=2,  
)
```

Epoch 1/2

```
-----  
ValueError                                Traceback (most recent call last)  
Cell In[169], line 14  
    11 ds_test = ds_test.concatenate(ds_test.map(invert_img)) # new line  
    12 ds_test = ds_test.batch(128)  
----> 14 model.fit(  
    15     ds_train,  
    16     validation_data=ds_test,  
    17     epochs=2,  
    18 )  
  
File ~/Documents/Compass/SC2/lec7/.conda/lib/python3.10/site-packages/keras/  
↳ utils/traceback_utils.py:70, in filter_traceback.<locals>.error_handler(*args,   
↳ **kwargs)  
    67     filtered_tb = _process_traceback_frames(e.__traceback__)  
    68     # To get the full stack trace, call:  
    69     # `tf.debugging.disable_traceback_filtering()`  
----> 70     raise e.with_traceback(filtered_tb) from None  
    71 finally:  
    72     del filtered_tb  
  
File /tmp/_autograph_generated_filec1w5pftg.py:15, in outer_factory.<locals>.  
↳ inner_factory.<locals>.tf__train_function(iterator)
```



```

13 try:
14     do_return = True
----> 15     retval_ = ag__.converted_call(ag__.ld(step_function), (ag__.
↳ld(self), ag__.ld(iterator)), None, fscope)
16 except:
17     do_return = False

```

ValueError: in user code:

```

File "/home/dg22309/Documents/Compass/SC2/lec7/.conda/lib/python3.10/
↳site-packages/keras/engine/training.py", line 1249, in train_function *
    return step_function(self, iterator)

```

```

File "/home/dg22309/Documents/Compass/SC2/lec7/.conda/lib/python3.10/
↳site-packages/keras/engine/training.py", line 1233, in step_function **
    outputs = model.distribute_strategy.run(run_step, args=(data,))

```

```

File "/home/dg22309/Documents/Compass/SC2/lec7/.conda/lib/python3.10/
↳site-packages/keras/engine/training.py", line 1222, in run_step **
    outputs = model.train_step(data)

```

```

File "/home/dg22309/Documents/Compass/SC2/lec7/.conda/lib/python3.10/
↳site-packages/keras/engine/training.py", line 1023, in train_step
    y_pred = self(x, training=True)

```

```

File "/home/dg22309/Documents/Compass/SC2/lec7/.conda/lib/python3.10/
↳site-packages/keras/utils/traceback_utils.py", line 70, in error_handler
    raise e.with_traceback(filtered_tb) from None

```

```

ValueError: Exception encountered when calling layer 'sequential_24' (type_
↳Sequential).

```

Cannot iterate over a shape with unknown rank.

Call arguments received by layer 'sequential\_24' (type Sequential):

- inputs=tf.Tensor(shape=<unknown>, dtype=float32)
- training=True
- mask=None

```
[ ]: probabilities = model.predict(images)
```

```
[ ]: truths = list(range(1, 10)) + ["dog"]
```

```

table = []
for truth, probs in zip(truths, probabilities):
    prediction = probs.argmax()
    if truth == 'dog':
        print(f"{truth}. CNN thinks it's a {prediction} ({probs[prediction]*100:
↳.1f}%)")

```

```
    else:
        print(f"{truth} at {probs[truth]*100:4.1f}%. CNN thinks it's a_
↪{prediction} ({probs[prediction]*100:4.1f}%)")
        table.append((truth, probs))
```