Create your own neural network with Keras

CSRG Talks

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Machine Learning

The objective of **machine learning** is to create algorithms that **learn**:

> "A computer program is said to learn from experience [...] if its performance at tasks in T, as measured by P, improves with experience E."
> -- Tom Mitchell (1997)

T may be **classification**, **regression**, **clustering**, etc.
E usually comes in the form of **data**.

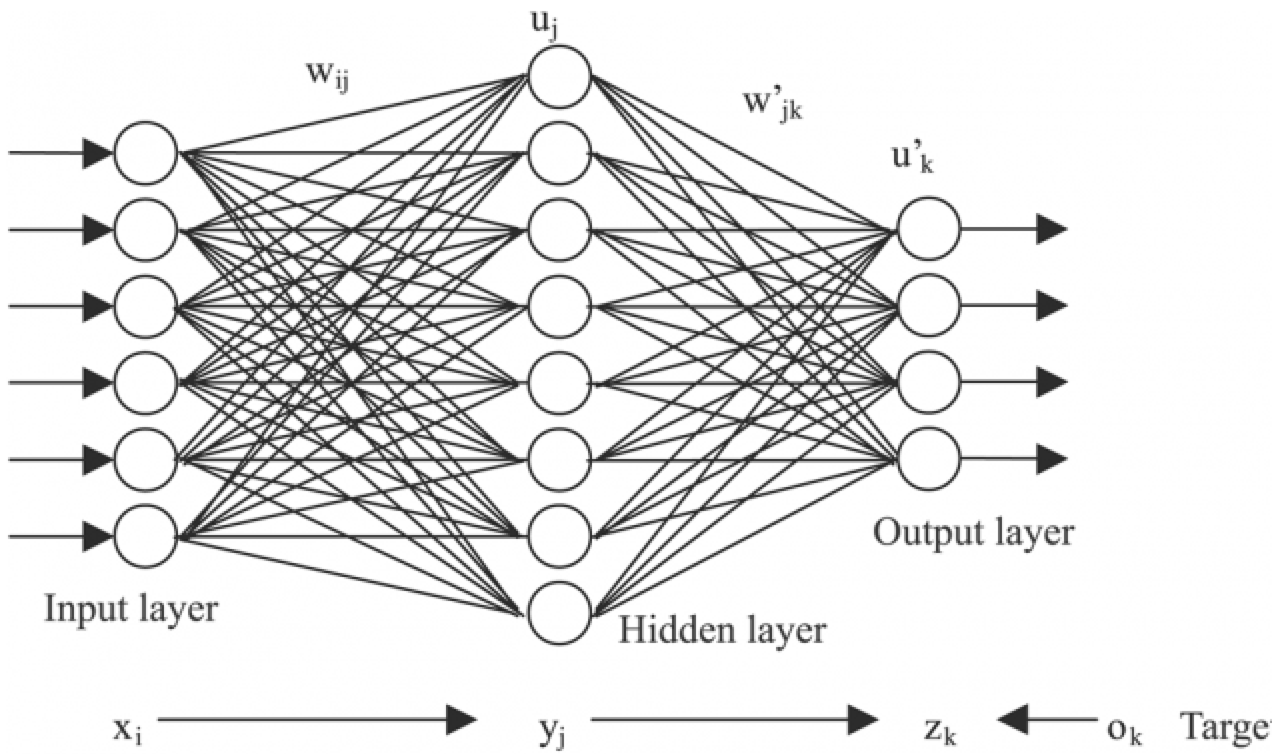
Artificial Neural Networks

- An **ANN** is a collection of connected units (artificial neurons).
- Each connection transmits a signal.
- An artificial neuron receives signals and processes them to signal additional artificial neurons.

They are usually useful for multivariate problems with strong correlations between the variables and with complex distributions.

Artificial Neural Networks

A feed forward neural network:

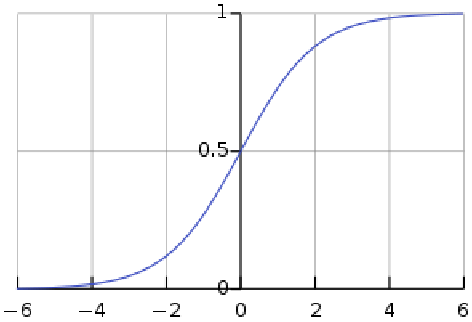


Artificial Neural Networks

Typical activation for a neuron:

$$u_j = \sigma\left(\sum_i w_{ij} x_i + b_j\right)$$

where x_i are the activations from input neurons and σ is the sigmoid activation function.



Weights w_{ij} and biases b_j are parameters to be trained.

Artificial Neural Networks

- When we train an ANN we calibrate them to approximate an **unknown** function $X \to Y$.
- We take the input features x_i and try to predict y_i for each sample i.
- We minimize an error function like the **mean square error**:

$$L = \sum_i (y_i - \hat{y}_i)^2$$

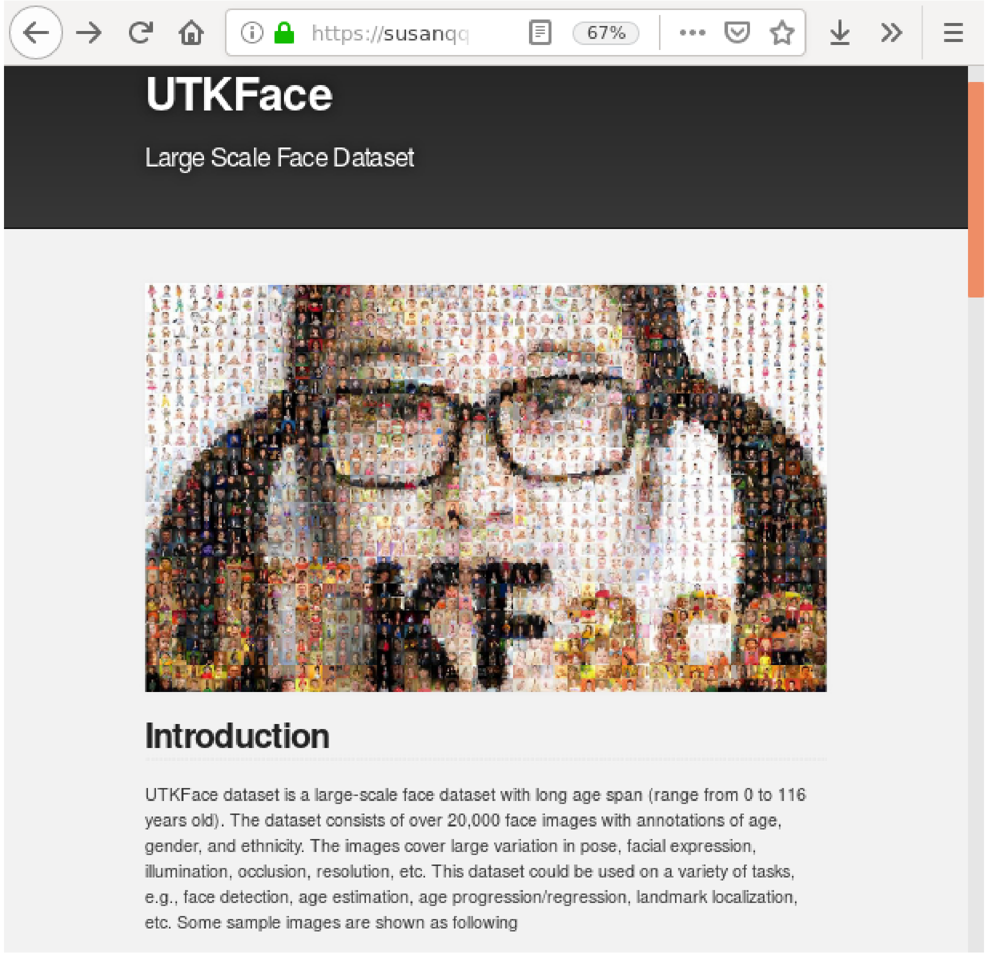
where $\hat{y}_i$ is the network prediction for x_i.
Mainstream learning algorithms use the gradient of this function to adjust the w's and b's as each $\hat{y}_i$ depends of them.

Other kinds of ANNs

- Convolutional Neural Networks (CNNs).
- Generative Adversarial Networks (GANs).
- Recurrent networks (RNN, LSTM).
- Many more.

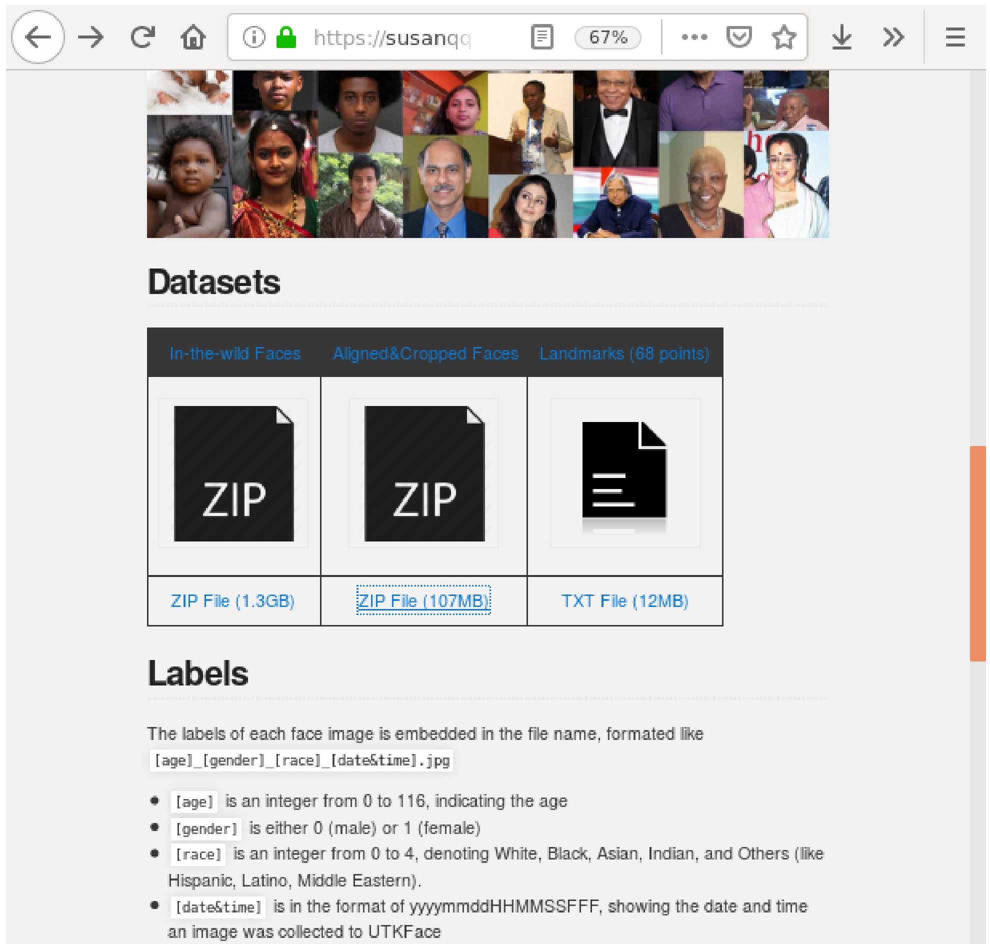
Our example problem

We will take images from the UTKFace dataset:



Our example problem

We will use the automatically cropped face images:



Our example problem

We will try to predict the **race** of a person from:

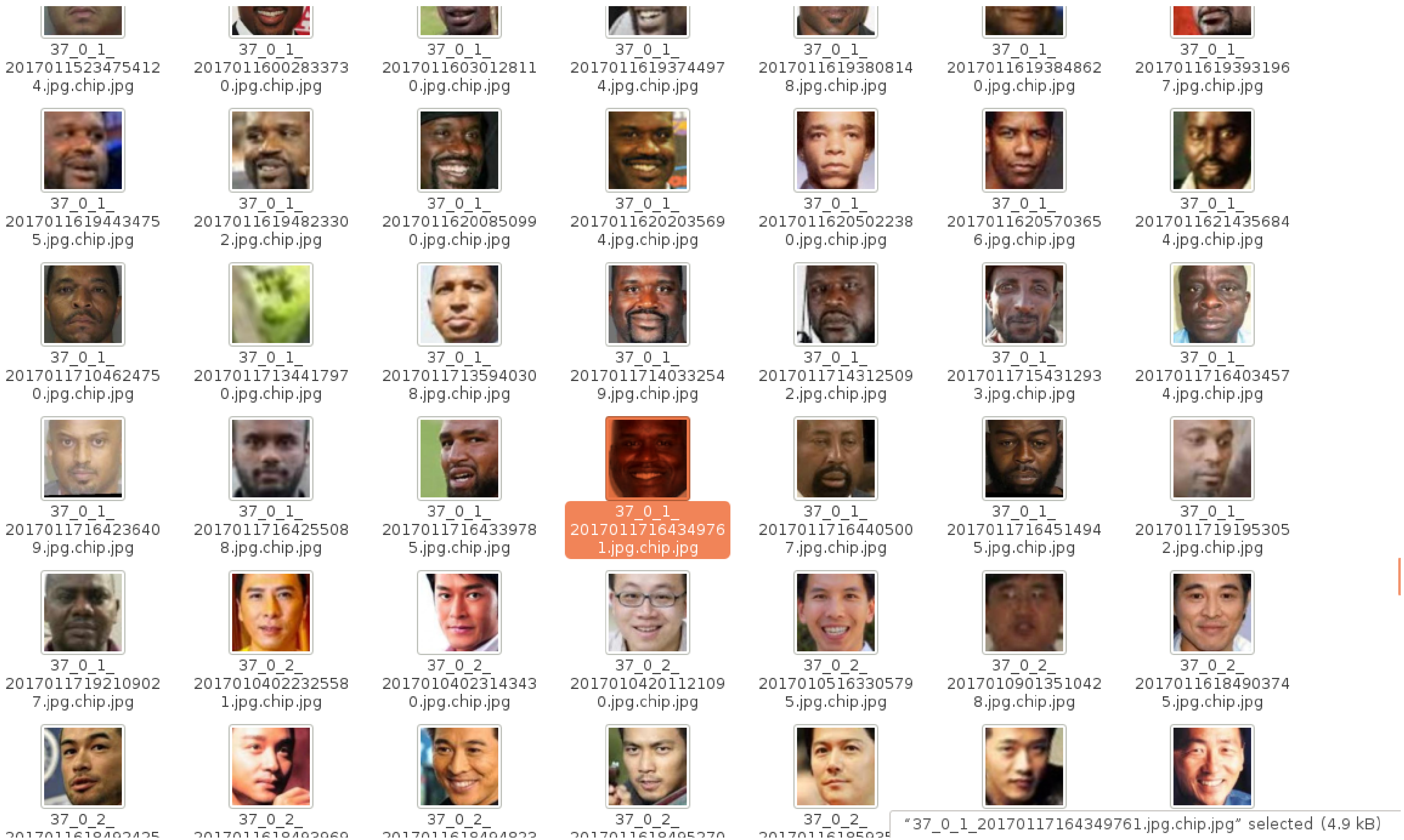
- The **photo**, which will be rescaled to 48x48 pixels

We may then expand our model to include the following inputs:

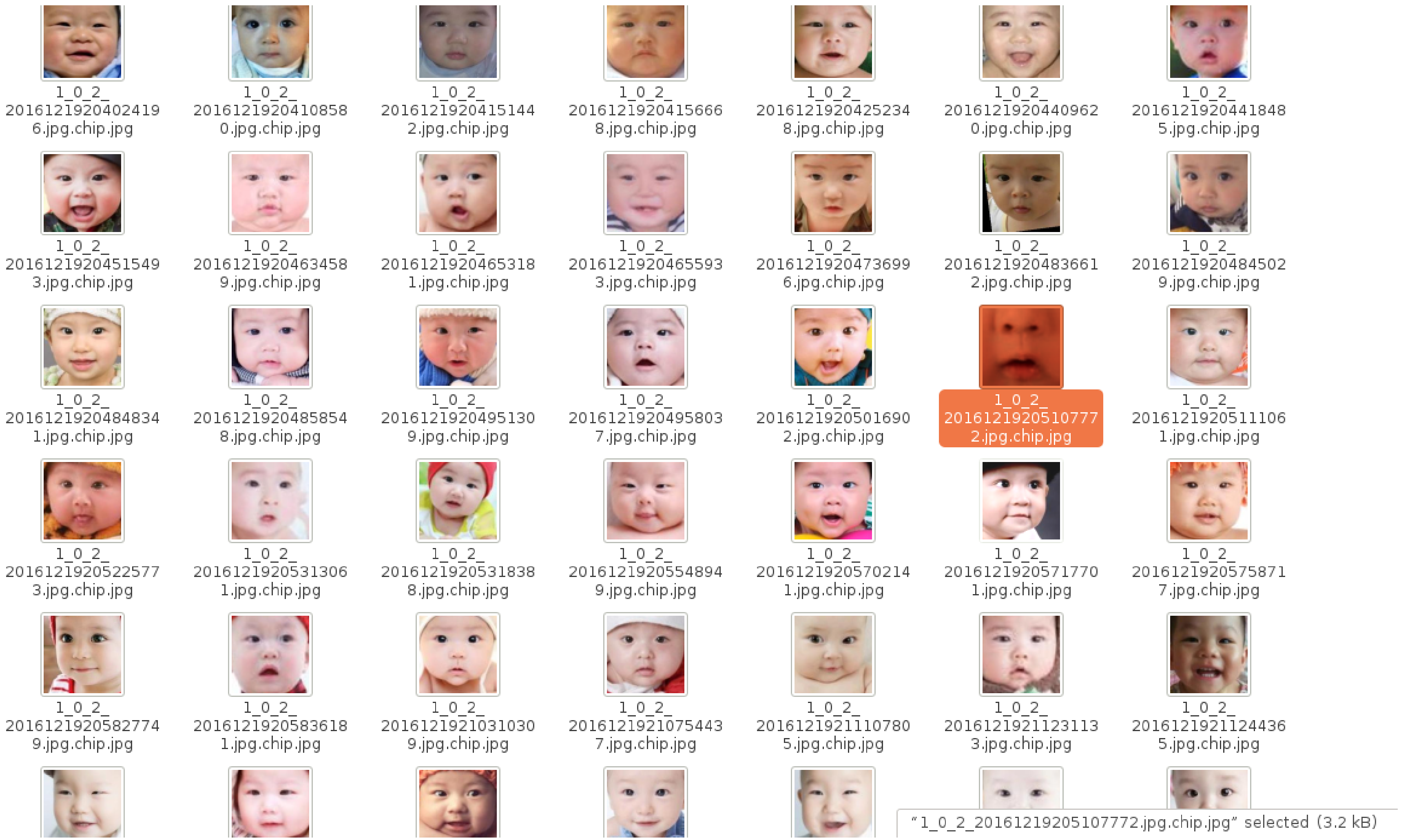
- The **age**
- The **gender**

For this purpose we will build **CNNs**!

Inspecting the data



Inspecting the data



Preprocessing the data

```python
import os
import re

import numpy as np

from PIL import Image

# Get the file names:
DIR = './UTKFace'
fnames = list(os.listdir(DIR))

# Data arrays
x_img = []
x_age = []
x_gender = []
y_race = []
```

Preprocessing the data

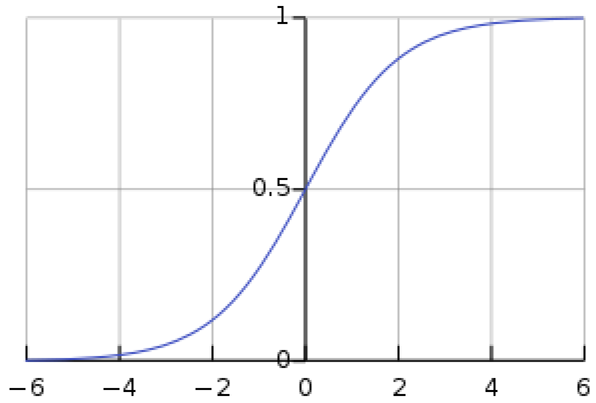
```
# Regular expression to parse the parts of the name
regex = re.compile('(\d+)_(\d+)_(\d+)_.*\.jpg')

# Process each file:
for fname in fnames:
    match = regex.match(fname)
    if match:
        age,gender,race = match.groups()
    else:
        print("Bad match: \"%s\""%fname)
        continue
    x_age.append(int(age))
    x_gender.append(int(gender))
    y_race.append(int(race))
    # Read the image and scale it
    img = Image.open(os.path.join(DIR,fname))
    img = img.convert('RGB').resize((48,48))
    x_img.append(np.array(img,dtype='float')/255.0)
    # Notice the normalization here         ^^^^^^
```

Preprocessing the data

Normalizing the data is important

- The **weight initializers** (that determinate the starting point of our optimization), assume input activations around 1.
- Depending on our **activations**, it may be very necessary to avoid learning problems.



If our initial activations are too **big** we may have a **saturated gradient**.

Preprocessing the data

```
np.save('x_img.npy',np.array(x_img,dtype='float'))
np.save('x_age.npy',np.array(x_age,dtype='int'))
np.save('x_gender.npy',np.array(x_gender,dtype='int'))
np.save('y_race.npy',np.array(y_race,dtype='int'))
```

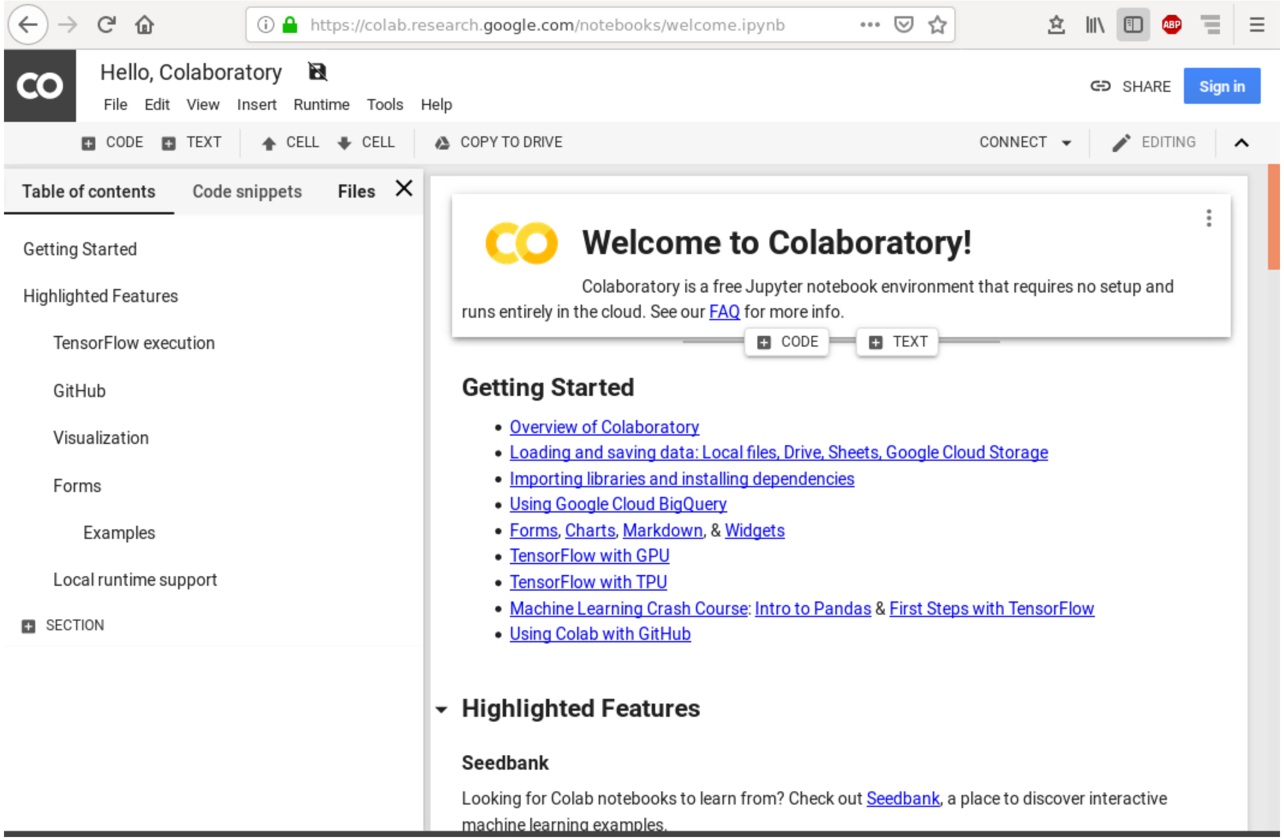
Output:

```
$ python3 preproc.py
Bad match: "61_1_20170109150557335.jpg.chip.jpg"
Bad match: "61_1_20170109142408075.jpg.chip.jpg"
Bad match: "39_1_20170116174525125.jpg.chip.jpg"
```

There were bad labeled samples too!

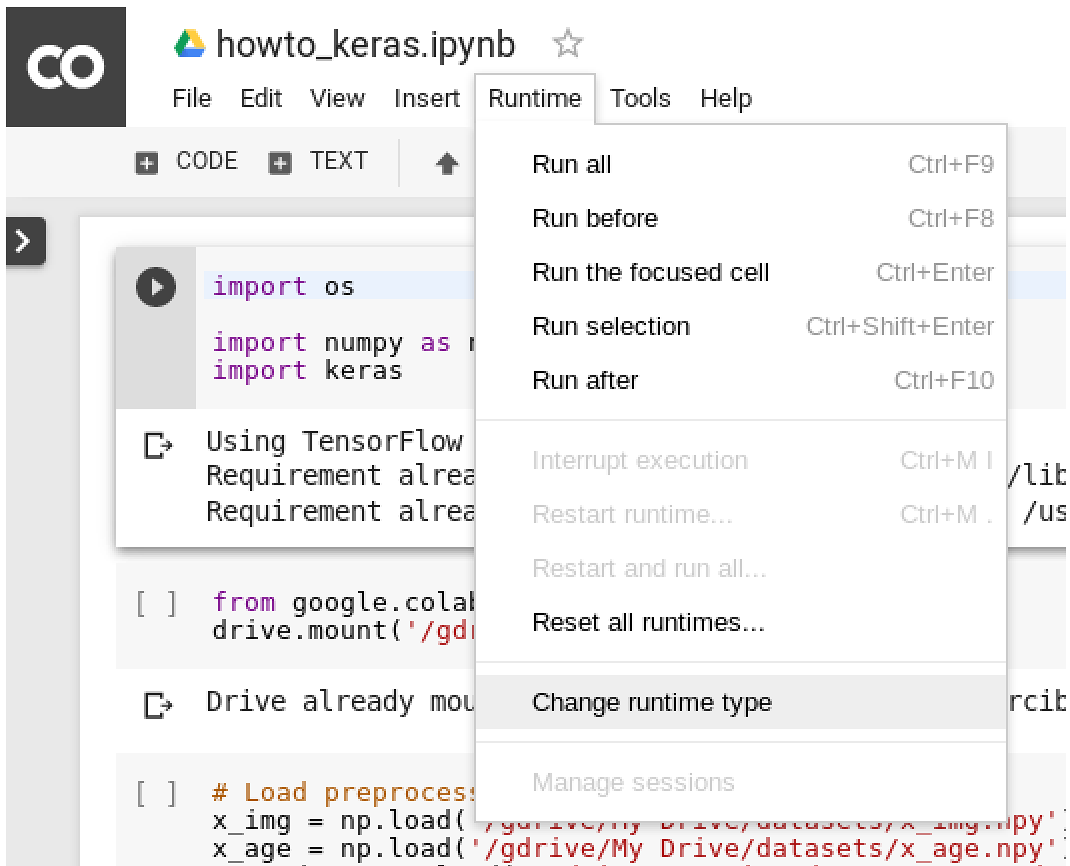
Google Colaboratory

We will work on Google Colaboratory, it allows us to create collaborative **jupyter notebooks** and use remote **GPUs**.
It also has all the python packages we need, already installed.

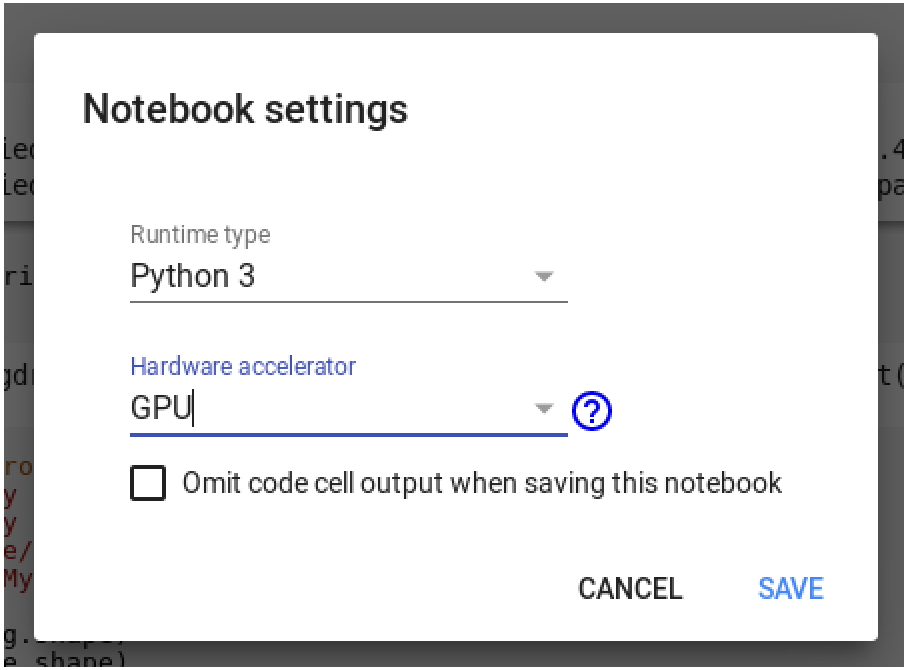


Google Colaboratory

We need to change the *runtime type* to one with **GPU** support



Google Colaboratory



- Link to the Colaboratory notebook

Shuffle the data

```
# Shuffle the data
indexes = np.arange(x_img.shape[0])
np.random.shuffle(indexes)
x_img    = x_img[indexes]
y_race   = y_race[indexes]
```

Shapes:

```
x_img.shape      (23705, 48, 48, 3)
y_race.shape     (23705,)
```

Separate the data

```
# Separate data for testing
N_TEST = x_img.shape[0]//4 # 25% of data for testing
x_img_test  = x_img[:N_TEST]
x_img_trai  = x_img[N_TEST:]
y_race_test = y_race[:N_TEST]
y_race_trai = y_race[N_TEST:]
```

Shapes:

```
x_img_trai.shape         (17779, 48, 48, 3)
x_img_test.shape         (5926, 48, 48, 3)
y_race_trai.shape        (17779,)
y_race_test.shape        (5926,)
```

Convolutional Neural Networks

Networks that have **convolutional layers**:

- Train several filters that are multiplied over the image.
- Ideal for *images* or other data with *spacial locality* as they exploit **local connectivity**.

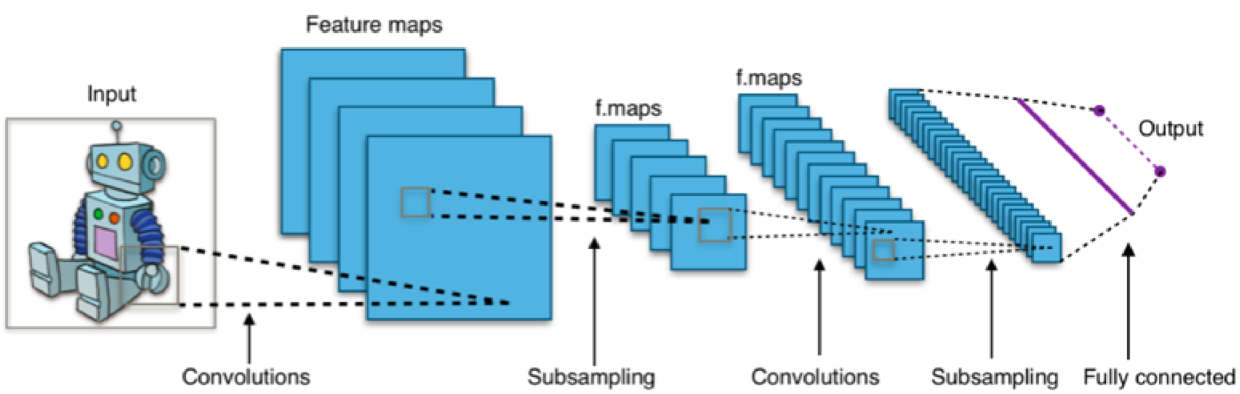


Image source

Convolutional Layers

- Each filter receives t^2k values (where $t \times t$ is the kernel size and k is the number of channels).
- The resulting tensor will have one channel for each filter.

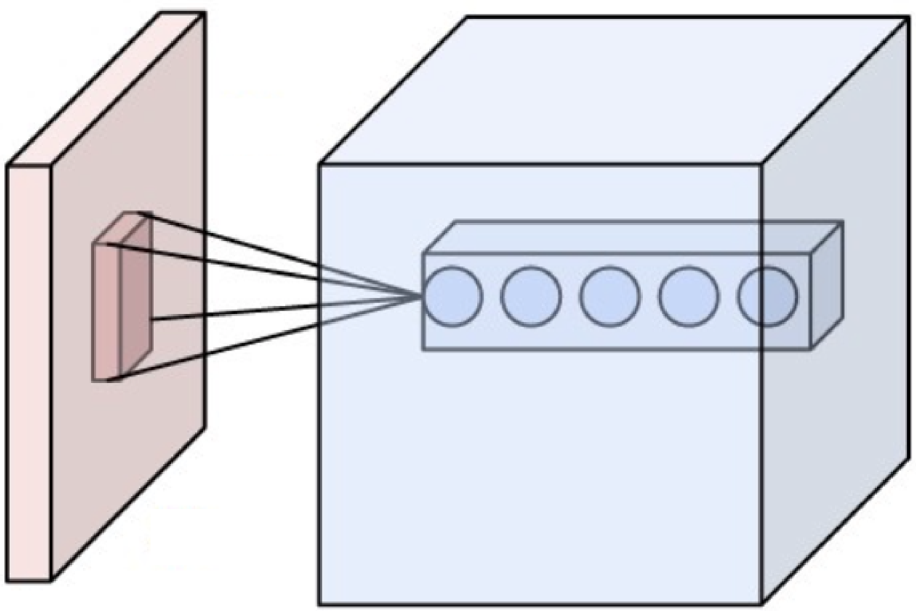


Image source

Max pooling layers

- Generally used **after** convolutional layers.
- It reduces tensor dimensions.
- For each pool of size $t \times t$, it only takes the maximum values.

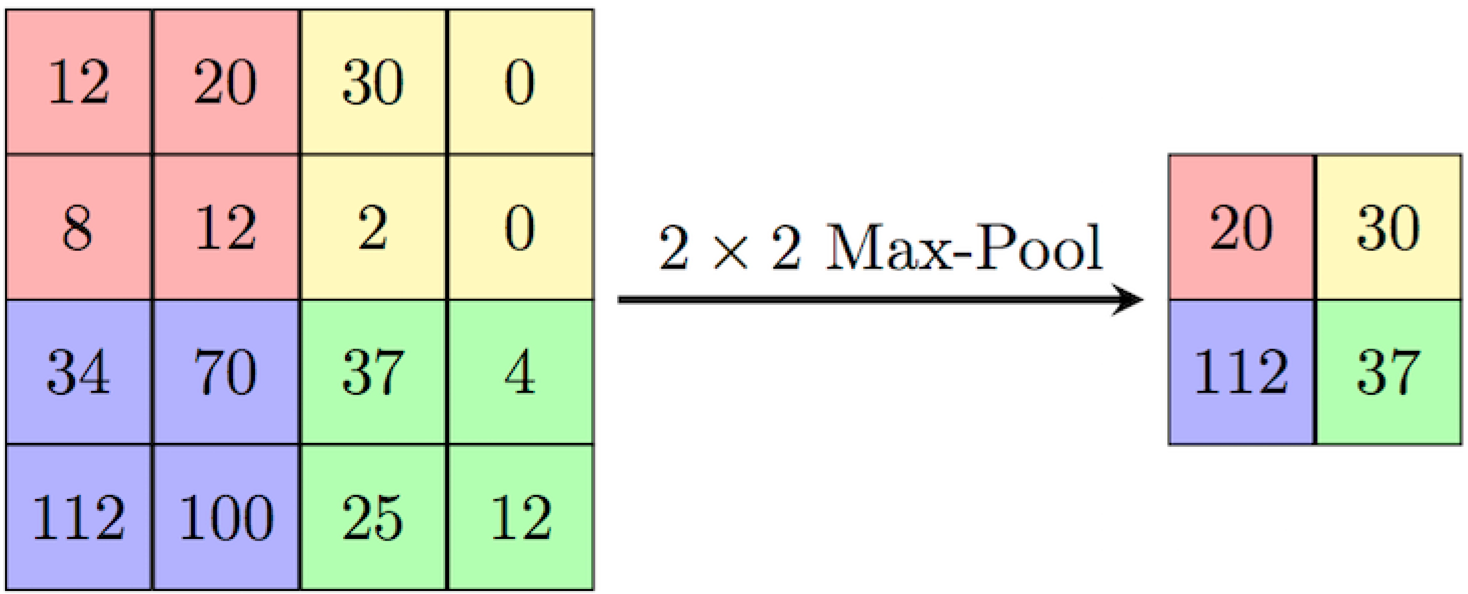


Image source

Keras

Keras

Keras is a **high-level** open source neural networks API in **Python**.

Keras delegates low-level operations such as tensor products and convolutions to a specialized tensor manipulation library to do so.

The available **backend engines** are:

- **TensorFlow**
- **Theano**
- **CNTK**

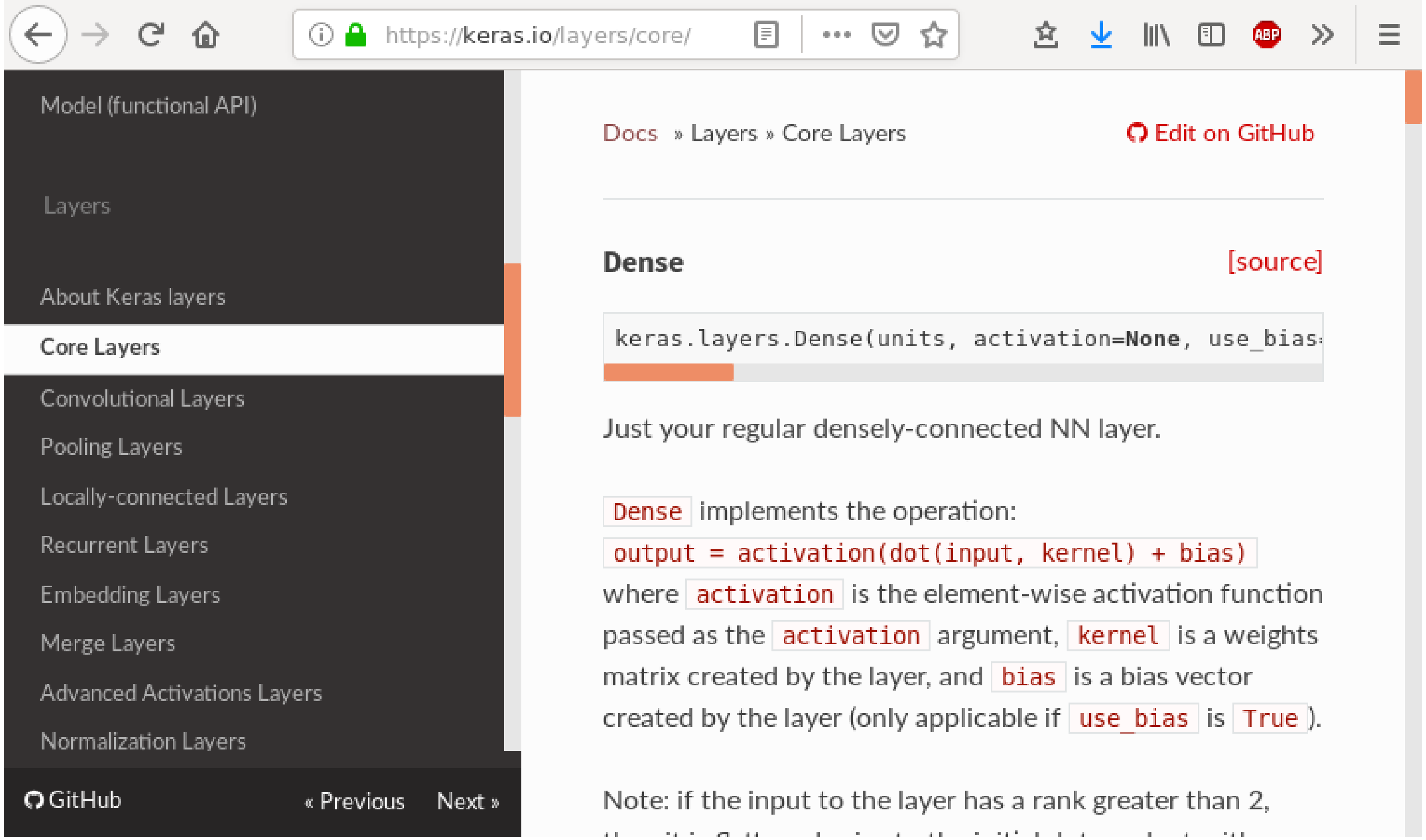
Creating a Keras Model

Keras provides two ways to create a model.

- If our model is simple, only composed of several layers in sequence, we can create an instance of `Sequential`.
- If our model is more complex, e.g. multiple inputs, we'll have to use the **functional API**.

Keras documentation

For any question that we may have, we should use the Keras documentation.

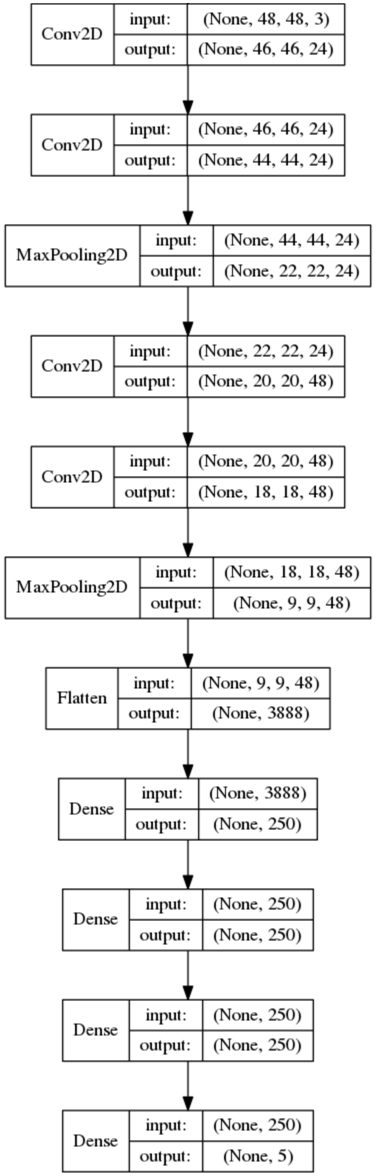


Building our model

```
# Create a sequential model:
model = keras.models.Sequential()
# 1st convolutional layer:
model.add(keras.layers.Conv2D(
    input_shape=(48,48,3), # Notice input_shape!
    filters=24,
    kernel_size=(3,3),
    activation='relu'))
# Convolutional layer:
model.add(keras.layers.Conv2D(
    filters=24,
    kernel_size=(3,3),
    activation='relu'))
# Max pooling
model.add(keras.layers.MaxPooling2D(
    pool_size=(2,2)))
# ...
```

```python
# 2 more convolutional layers:
model.add(keras.layers.Conv2D(
    filters=48,
    kernel_size=(3,3),
    activation='relu'))
model.add(keras.layers.Conv2D(
    filters=48,
    kernel_size=(3,3),
    activation='relu'))
# Max pooling
model.add(keras.layers.MaxPooling2D(
    pool_size=(2,2)))
# Flatten the last image
model.add(keras.layers.Flatten())
# 3 dense layers:
for i in range(3):
  model.add(keras.layers.Dense(
      units=250,
      activation='relu'))
# Last layer
model.add(keras.layers.Dense(
    units=5,
    activation='softmax'))
```

Building our model



The batch dimension

- We must fit in memory a parallel version of the model for **each sample**!
- As this is often not possible, we take a subset of them.
- This is known as the **batch**.

The size of this dimension is the **batch size**. We have to choose it.

The **batch size** affects the training!

ReLU activations

- We used **ReLU** activations instead of **sigmoids**.
- They are often better for **deep** architectures, as long as we initialize the weights right.

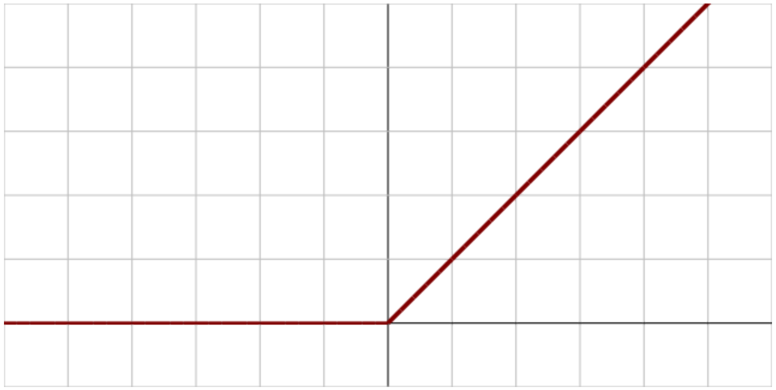


Image source

Final dense layer (softmax activation)

- Our model will have with 5 **output neurons**.
- Each **neuron** will represent a probability for each class.
- Probabilities must be **normalized**.
- As we will measure the performance of the network by its **accuracy**, we only care about the **max**.

We use **softmax** as the last activation:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

> We can't just set the **maximum** to 1 and the **others** to 0, as we need it to be differentiable.

Loss function

For our **Loss** function we could use:

- The **mean squared error** against a **one-hot** vector.
- The **cross entropy**: ideal for comparing **probability distributions**:

$$L = -\sum_i p(y=i)\log(\sigma(z)_i)$$

we make $p(y{=}i){=}1$ for the right class and 0 for the others:

$$L = -\log(\sigma(z)_y)$$

Compiling our model

We have to choose an optimizer and our loss function:

```
model = cnn_model()
model.compile(optimizer='sgd',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

- **SGD** or Stochastic Gradient Descent, is just to use the Gradient Descent on the batch samples at a constant rate.
- We can pass a more customized `Optimizer` if we want.
- We use `sparse_categorical_crossentropy` if our **targets** are encoded as an integer instead of an **one-hot** vectors.
- We also want to measure the `accuracy`.

Training our model

```
EPOCHS = 50
history = model.fit(x_img_trai,y_race_trai,
        validation_data=(x_img_test,y_race_test),
        epochs=EPOCHS,batch_size=128)
```

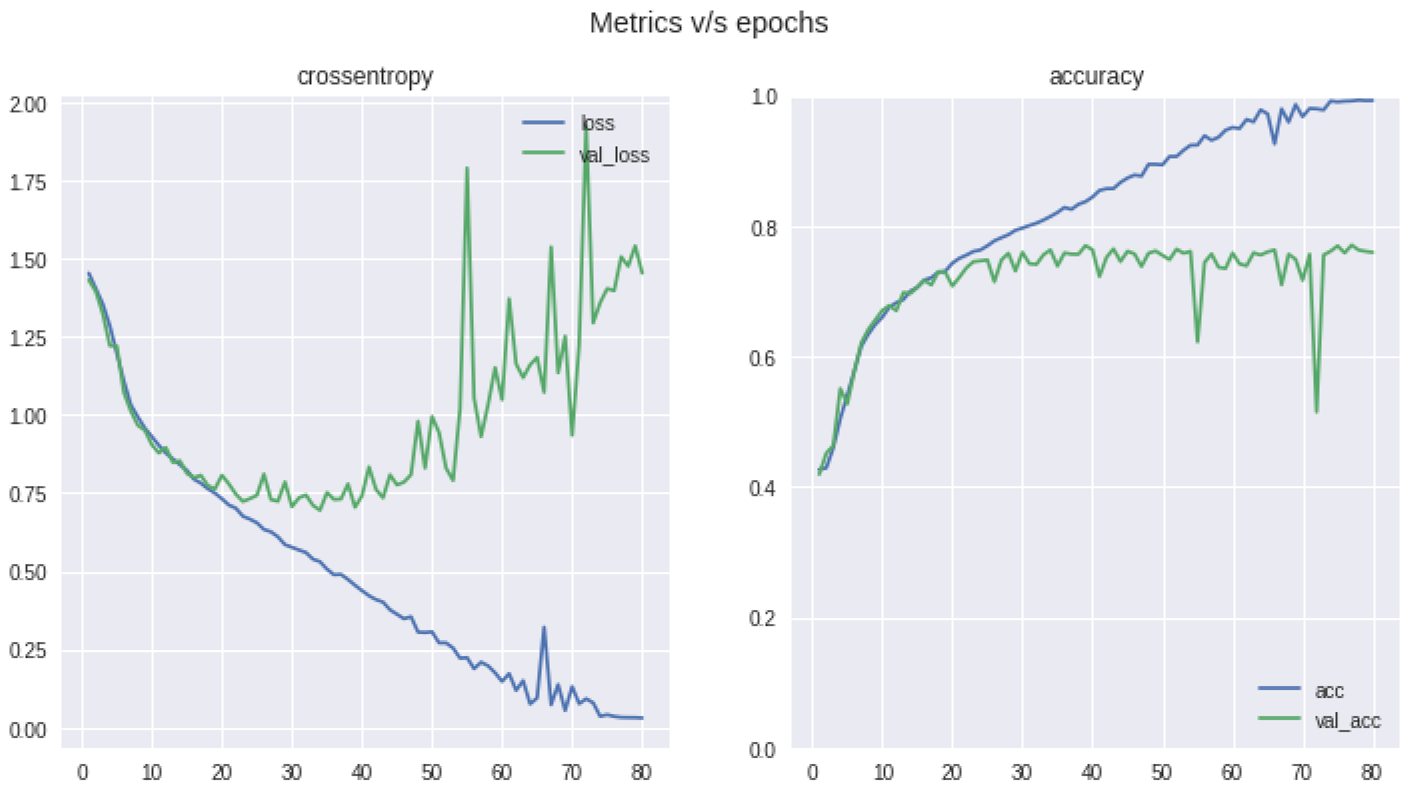
- The **epochs** are the times we will feed the whole training dataset.
- The **validation data** is used to measure the *validation loss* and *accuracy*.
- We also save the `History` object in order to plot the this measures.

Training our model

```
EPOCHS = 50
history = model.fit(x_img_trai,y_race_trai,validation_data=(x_img_test,y_race_test),
          epochs=EPOCHS,batch_size=128)
```

```
Train on 17779 samples, validate on 5926 samples
Epoch 1/50
17779/17779 [==============================] - 6s 347us/step - loss: 0.6819 - acc: 0.7597 - val_loss: 0.7332 - val_ac
Epoch 2/50
17779/17779 [==============================] - 6s 340us/step - loss: 0.6761 - acc: 0.7632 - val_loss: 0.7193 - val_ac
Epoch 3/50
17779/17779 [==============================] - 6s 339us/step - loss: 0.6592 - acc: 0.7688 - val_loss: 0.7271 - val_ac
Epoch 4/50
17779/17779 [==============================] - 6s 341us/step - loss: 0.6476 - acc: 0.7728 - val_loss: 0.7073 - val_ac
Epoch 5/50
17779/17779 [==============================] - 6s 344us/step - loss: 0.6354 - acc: 0.7758 - val_loss: 0.7084 - val_ac
Epoch 6/50
17779/17779 [==============================] - 6s 340us/step - loss: 0.6232 - acc: 0.7809 - val_loss: 0.7030 - val_ac
Epoch 7/50
17779/17779 [==============================] - 6s 342us/step - loss: 0.6070 - acc: 0.7837 - val_loss: 0.6964 - val_ac
Epoch 8/50
 6528/17779 [==========>...................] - ETA: 3s - loss: 0.5890 - acc: 0.7937
```

Learning over epochs



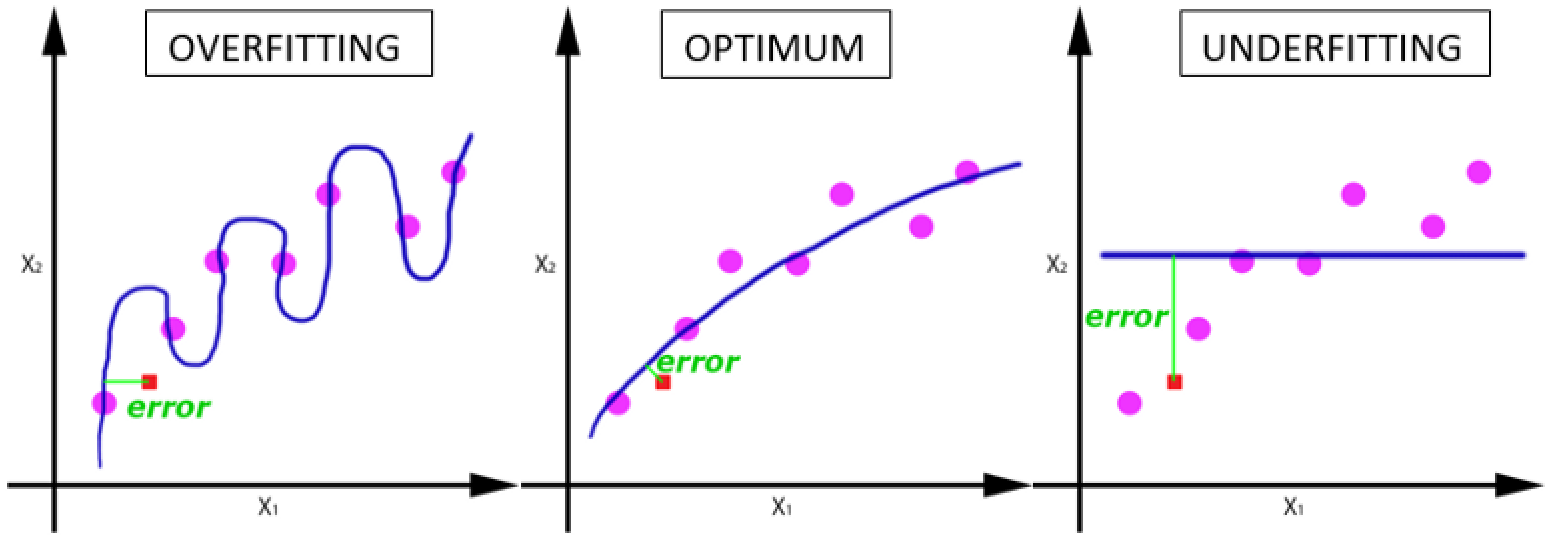
Saving and loading our model

```
# Save model
model.save('/gdrive/My Drive/datasets/race_model.h5')
```

```
# Load model
loaded_model = keras.models.load_model(
        '/gdrive/My Drive/datasets/race_model.h5')
```

Overfitting

When the model **overadjust** to the samples instead of learning the real distribution.

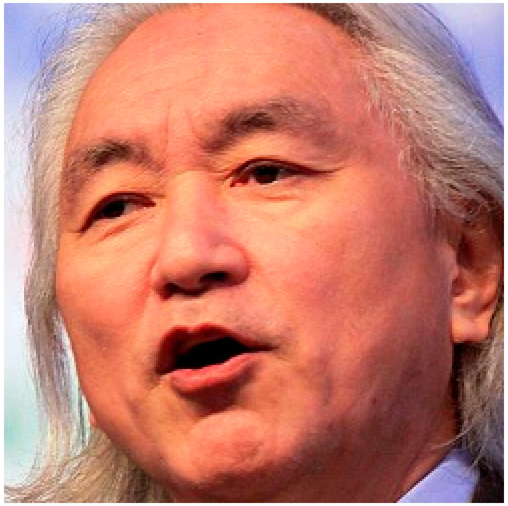


Its like **memorizing** the training dataset.

Predicting with our model

We will test the model on 4 images outside the dataset:

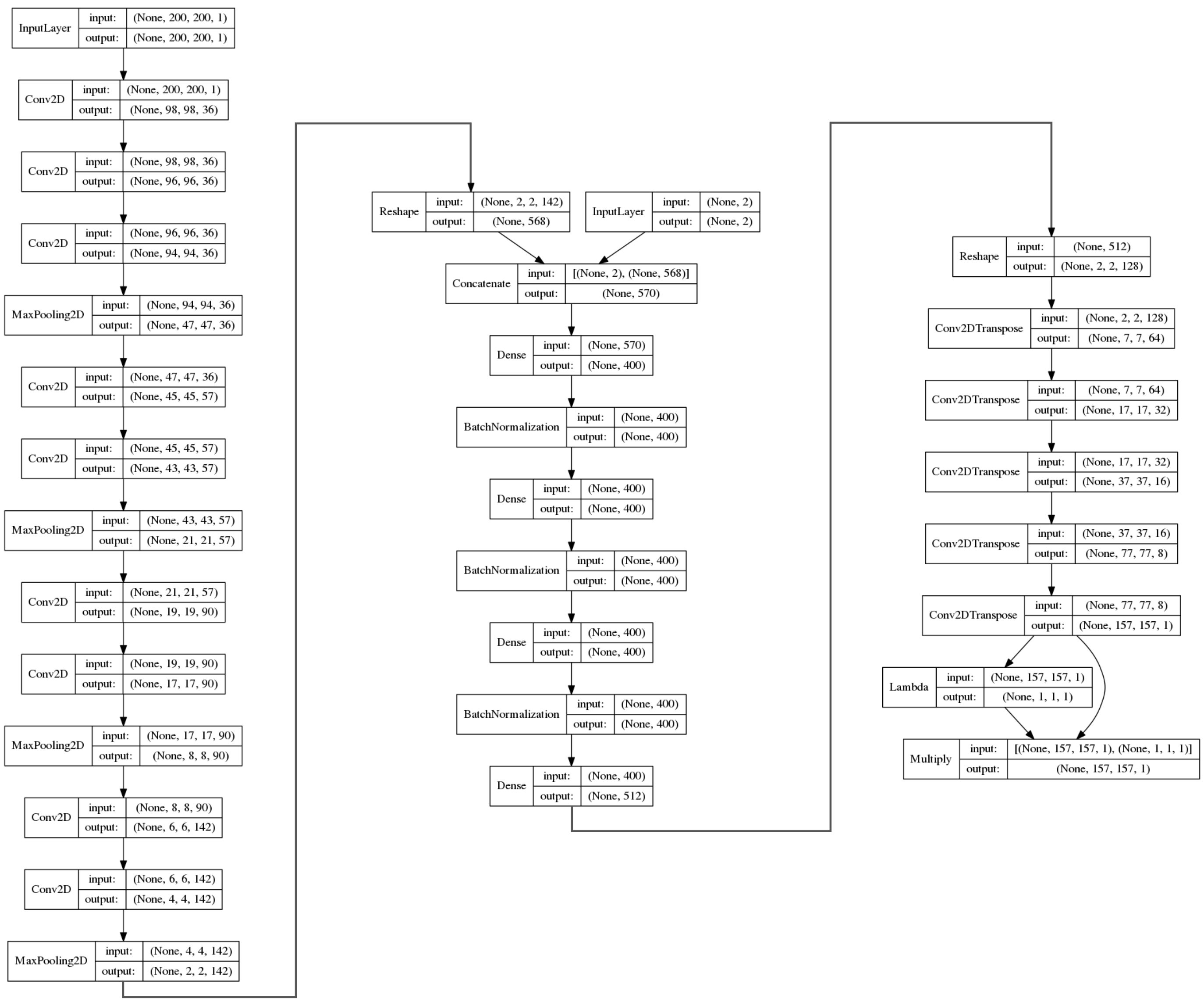


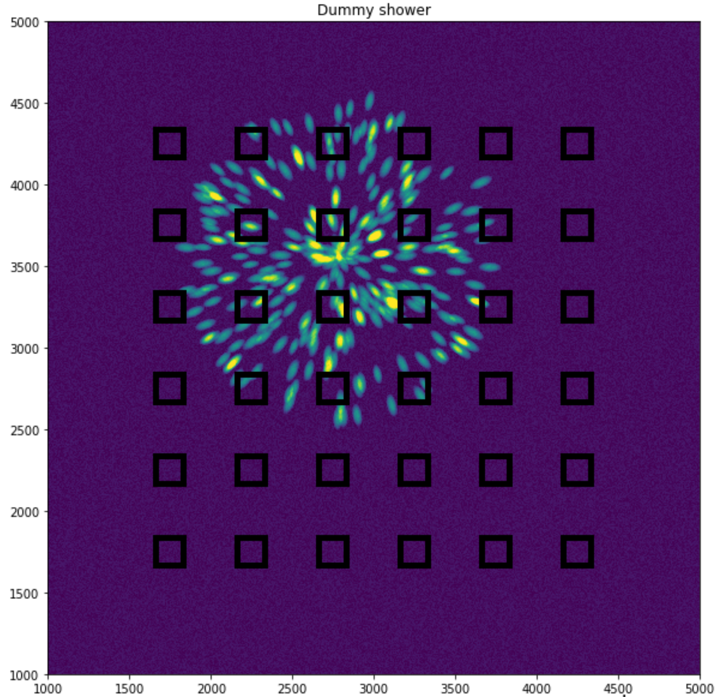
How we may enhance our model

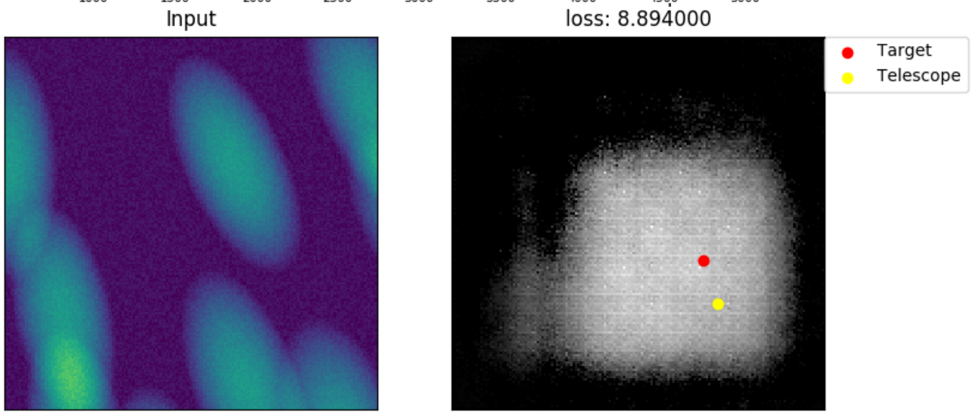
- Reduce overfitting using **regularizers** like **Dropout** or **Batch normalization**.
- Using the right **Kernel initializers**, e.g. `he_uniform` for `relu` activations.
- Test several architectures using **cross validation**.
- Using the **Functional API** to create multi-input model that also recieves the **age** and **gender** and **concatenate** them in the first dense layer.

A more complex model: UMONNA



A more complex model: UMONNA





Artificial Neural Networks drawbacks

- They need a lot of **data**.
- Acceptable training and execution times usually require **GPU**.
- They are **black-boxes**, getting insight of how they solve the task from inspection is hard. *What are they learning?*
- As they have a lot of parameters, **overfitting** is an issue.

Artificial Neural Networks drawbacks

A lot of ML problems can be solved using simpler strategies, e.g.:

- Decisions trees
- Less squares regression
- Principal component analysis
- k-nearest neighbors

Recommended references

- 3Blue1Brown Deep learning video series.
- The Deep Learning book.