

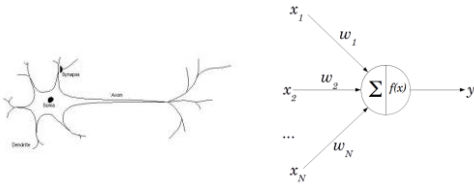
Handwritten Digit Recognition using Convolutional Neural Networks in Python with Keras

Dr. Petra Kralj Novak
10.1.2019

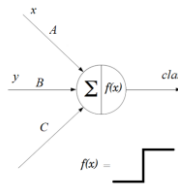
<https://machinelearningmastery.com/handwritten-digit-recognition-using-convolutional-neural-networks-python-keras/>

Neural networks

Neuron, perceptron



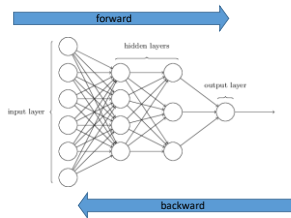
The **perceptron** is a mathematical model of a biological neuron



- A single perceptron can separate linearly.

$$\text{Output of } P = \begin{cases} 1 & \text{if } Ax + By > C \\ 0 & \text{if } Ax + By \leq C \end{cases}$$

Neural network



Predictive model

- Architecture
 - Define
 - Compile
- Train (fit)
 - Forward
 - Backward
 - Optimize
- Predict (evaluate)
 - Forward

Train

- **Forward propagation** (check performance)
 - **loss function** is an error metric between actual and predicted
 - absolute error, sum of squares
- **Backpropagation** (direction of parameter/weight change)
 - how much the total error will change if we change the internal weight of the neural network with a certain small value Δw (**gradient**)
 - backpropagate the errors using the derivatives of these functions: auto-differentiation
- **Optimization** (change weights based on learning rate, gradient descent)
 - New weight = old weight - Derivative Rate * learning rate
 - **Batch size** is a hyperparameter that controls the number of training samples to work through before the model's internal parameters are updated.
 - The number of **epochs** is a hyperparameter that controls the number of complete passes through the training dataset.

[Neural networks and back-propagation explained in a simple way](#)

Keras: The Python Deep Learning library

- Keras is a high-level neural networks API, written in Python and capable of running on top of [TensorFlow](#), [CNTK](#), or [Theano](#).
- Google's Tensorflow: is a low-level framework that can be used with Python and C++.
- Install packages: tensorflow, keras

MNIST – handwritten digits

- Each image is a 28 by 28 pixel square (784 pixels total).
- Normalized in size and centered
- A standard split of the dataset is used to evaluate and compare models, where 60,000 images are used to train a model and a separate set of 10,000 images are used to test it.

From the MNIST Database of Hand-written Digits



Exercise

- Load the MNIST dataset in Keras.
- Train and evaluate a **baseline neural network** model for the MNIST problem.
- Train and evaluate a simple **Convolutional Neural Network** for MNIST.
- Implement a **close to state-of-the-art deep learning** model for MNIST.

Load the data: 9_neural_nets-0-load_data.py

```
from keras.datasets import mnist
import matplotlib.pyplot as plt

# Plot ad hoc mnist instances
(X_train, y_train), (X_test, y_test) = mnist.load_data() # Dataset of 60,000 28x28
grayscale images of the 10 digits, along with a test set of 10,000 images.
# plot 4 images as gray scale
plt.subplot(222)
plt.imshow(X_train[0], cmap=plt.get_cmap('gray'))
plt.subplot(222)
plt.imshow(X_train[1], cmap=plt.get_cmap('gray'))
plt.subplot(223)
plt.imshow(X_train[2], cmap=plt.get_cmap('gray'))
plt.subplot(224)
plt.imshow(X_train[3], cmap=plt.get_cmap('gray'))
# show the plot
plt.show()
```

Prepare data: 9_neural_nets-1-perceptron.py

```
# fix random seed for reproducibility
seed = 7
numpy.random.seed(seed)

# load data
(X_train, y_train), (X_test, y_test) = mnist.load_data()

# flatten 28*28 images to a 784 vector for each image
num_pixels = X_train.shape[1] * X_train.shape[2]
X_train = X_train.reshape(X_train.shape[0], num_pixels).astype('float32')
X_test = X_test.reshape(X_test.shape[0], num_pixels).astype('float32')

# train-validation split
X_train, X_validation, y_train, y_validation = train_test_split(X_train, y_train, test_size=0.1, random_state=42)

# normalize inputs from 0-255 to 0-1
X_train = X_train / 255
X_test = X_test / 255

# one hot encode outputs
y_train = np_utils.to_categorical(y_train)
y_validation = np_utils.to_categorical(y_validation)
y_test = np_utils.to_categorical(y_test)
num_classes = y_test.shape[1]
```

One-hot Encoding for Multi-label and multi-target prediction

```
# one-hot encoding class labels
from keras.utils import np_utils

y_train[:10]
array([5, 0, 4, 1, 9, 2, 1, 3, 1, 4], dtype=int8)

y_train_onehotencoding = np_utils.to_categorical(y_train)
y_train_onehotencoding[:10]
array([[0., 0., 0., 0., 0., 1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 1., 0.],
       [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.]])
    0 1 2 3 4 5 6 7 8 9
```

Define + compile, fit, predict: 9_neural_nets-1-perceptron.py

```
# Define baseline model
def baseline_model():
    # create model
    model = Sequential()
    model.add(Dense(num_pixels, input_dim=num_pixels, kernel_initializer='normal', activation='relu'))
    model.add(Dense(num_classes, kernel_initializer='normal', activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

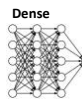
# Build the model
model = baseline_model()
# Fit the model
model.fit(X_train, y_train, validation_data=(X_validation, y_validation), epochs=10, batch_size=200)

# Final evaluation of the model
print("Final evaluation of the model")
score = model.evaluate(X_test, y_test, verbose=1)
print("Baseline Error: %.2f%%" % (100 - score[1] * 100))
```

Architecture

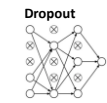
- Layers: type, initialization, regularization
 - Dense
 - Convolutional
 - Pooling
 - Dropout – for regularization
 - Recurrent
 - Embedding
- Activation functions
 - relu
 - softmax (output layer)
- Loss function
 - Classification
 - categorical_crossentropy, categorical_hinge, sparse_categorical_crossentropy, binary_crossentropy, ...
 - Numeric prediction
 - mean_squared_error, mean_absolute_error, mean_absolute_percentage_error, mean_squared_logarithmic_error, cosine_proximity, ...
- Model compile

Types of layers (1)



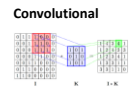
Dense

Fully connected.



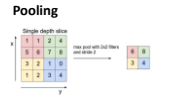
Dropout

During training, some neurons on a particular layer will be deactivated. This improves generalization because it forces the layer to learn with different neurons the same "concept".



Convolutional

The convolution layer comprises of a set of independent filters. Each filter is independently convolved with the image.
Example: [link](#)

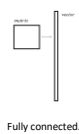


Pooling

A max-pooling layer takes the maximum of features over small blocks of a previous layer.

Types of layers (2)

Flatten



- LAYERS
- About Keras layers
- Core Layers
- Convolutional Layers
- Pooling Layers
- Locally connected Layers
- Recurrent Layers
- Embedding Layers
- Merge Layers
- Advanced Activation Layers
- Normalization Layers
- Noise layers
- Layer wrappers
- Writing your own Keras layers

Convolutional model

```
def baseline_model():
    # create model
    model = Sequential()
    model.add(Conv2D(32, (5, 5), input_shape=(1, 28, 28), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.2))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```