Import biblioteki **TensorFlow** (https://www.tensorflow.org/) z której będziemy korzystali w uczeniu maszynowym:

```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np

import keras
from keras.models import Sequential
from keras.layers import Dense
```

Numbers recognition - dataset MNIST

```
Download dataset
```

train_data[0]

```
0,
       0],
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[ 0,
             0,
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                                      0, 80, 156, 107, 253, 253,
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205,
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241, 225, 160, 108,
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                     0]], dtype=uint8)
train_labels[0]
One-hot encoding
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
train_data.shape,train_labels.shape
     ((60000, 28, 28), (60000, 10))
test_data.shape,test_labels.shape
     ((10000, 28, 28), (10000, 10))
train_labels[0]
     array([0., 0., 0., 0., 0., 1., 0., 0., 0., 0.], dtype=float32)
```

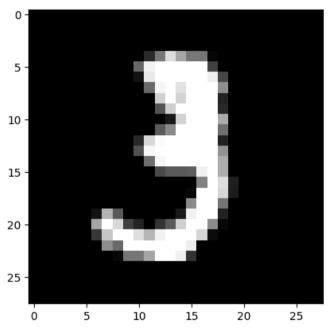
Visulization

5

```
def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)
```

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



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_27"

Layer (type)	Output Shape	Param #
dense_64 (Dense)	(None, 128)	100480
dense_65 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)
Trainable params: 101770 (397.54 KB)
Non-trainable params: 0 (0.00 Byte)

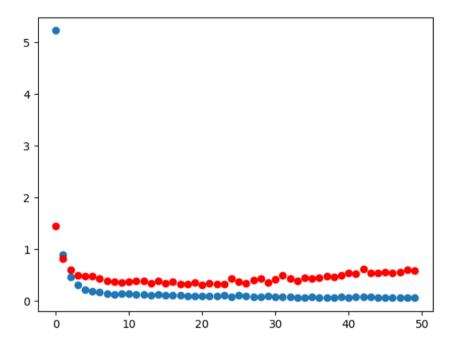
batch_size = 128
epochs = 50

h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs,validation_split=0.2)

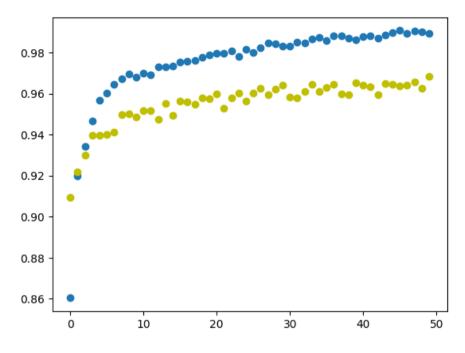
plt.show()

```
Epoch 38/50
Epoch 39/50
Epoch 40/50
Fnoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
```

```
https://colab.research.google.com/drive/1jjlx7otWe0l5SrZeJp6qu5jHEUHhbff_#scrollTo=HPsjpZOyA_2S&printMode=true
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

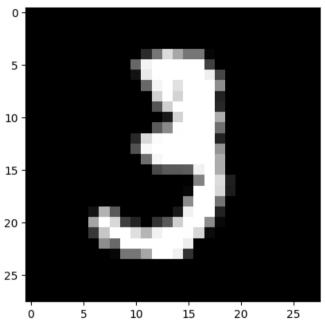
    Test loss: 0.6038411259651184
    Test accuracy: 0.96670001745224

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```



Import biblioteki **TensorFlow** (https://www.tensorflow.org/) z której będziemy korzystali w uczeniu maszynowym:

```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import keras
```

import keras
from keras.models import Sequential
from keras.layers import Dense

Numbers recognition - dataset MNIST

Download dataset

```
(train_data, train_labels), (test_data, test_labels) = tf.keras.datasets.mnist.load_data()
(train_data, train_labels), (test_data, test_labels) = tf.keras.datasets.mnist.load_data()
data = np.concatenate([train_data, test_data])
data.shape
    (70000, 28, 28)
label = np.concatenate([train_labels,test_labels])
label.shape
    (70000,)
Informations about dataset
train_data.shape,train_labels.shape
    ((60000, 28, 28), (60000,))
test_data.shape,test_labels.shape
    ((10000, 28, 28), (10000,))
train_data[0]
```

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         0]], dtype=uint8)
```

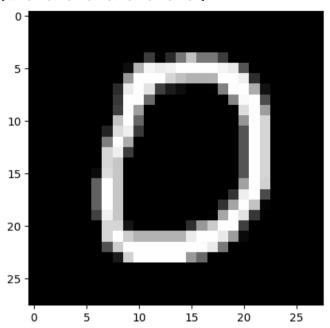
train_labels[0]

5

One-hot encoding

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((60000, 28, 28), (60000, 10))
test data.shape,test labels.shape
    ((10000, 28, 28), (10000, 10))
train_labels[0]
    array([0., 0., 0., 0., 0., 1., 0., 0., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label_index = test_labels[img_index]
   plt.imshow(test_data[img_index]/255, cmap = 'gray')
   print(label_index)
img index = 10
plot image(img index)
```

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



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)

model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_28"

Layer (type)	Output Shape	Param #
dense_66 (Dense)	(None, 128)	100480
dense_67 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

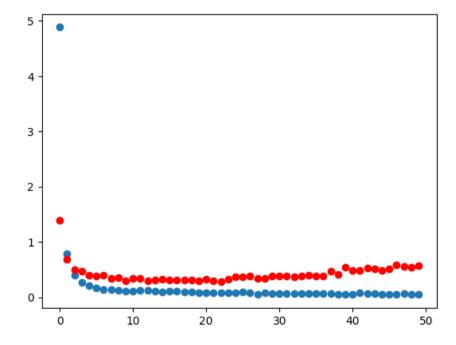
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

```
batch_size = 128
epochs = 50
```

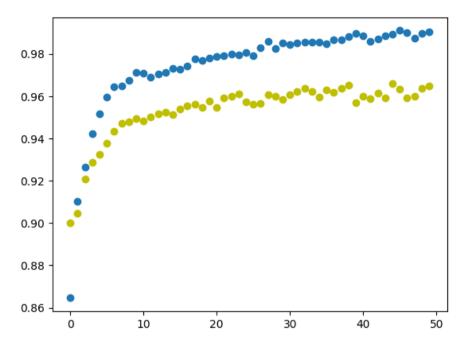
h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs, validation_split=0.2)

```
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

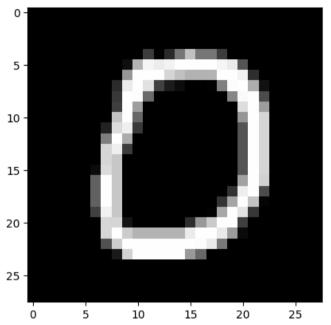
    Test loss: 0.506654679775238
    Test accuracy: 0.9695000052452087

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = test_data[img_index].reshape(-1,784)

model.predict(picture)
```



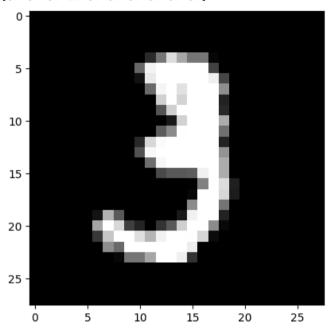
Regularyzacja - metoda 1

Zwiększamy zbiór treningowy z 60000 do 65000 (20% to zbiór walidacyjny)

One-hot coding

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((5000, 28, 28), (5000, 10))
test data.shape,test labels.shape
    ((65000, 28, 28), (65000, 10))
train_labels[0]
    array([0., 0., 0., 1., 0., 0., 0., 0., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
   label index = test labels[img index]
   plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label index)
img_index = 10
plot_image(img_index)
```

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



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_29"

Layer (type)	Output Shape	Param #
dense_68 (Dense)	(None, 128)	100480
dense_69 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

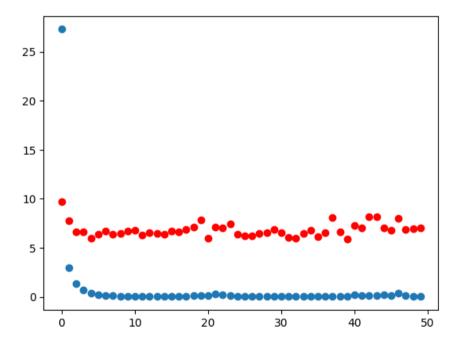
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

```
batch_size = 128
epochs = 50
```

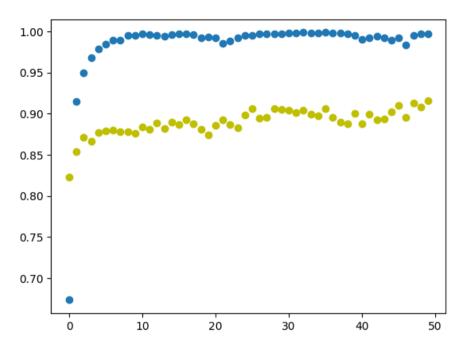
h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs, validation_split=0.2)

```
- M2 OHI2/216b - 1022: M.1371 - ACCRIACA: M.3873 - AGT 1022: 1.M300 - AGT GCCRIACA: M.0888
    32/32 [=====
    Epoch 43/50
    32/32 [=====
                                     - 0s 4ms/step - loss: 0.0903 - accuracy: 0.9942 - val loss: 8.1261 - val accuracy: 0.8920
    Epoch 44/50
    32/32 [======
                                     - 0s 3ms/step - loss: 0.1175 - accuracy: 0.9923 - val loss: 8.1469 - val accuracy: 0.8930
    Epoch 45/50
    32/32 [========================== ] - 0s 3ms/step - loss: 0.2243 - accuracy: 0.9895 - val loss: 6.9922 - val accuracy: 0.9020
    Epoch 46/50
    32/32 [=========================== ] - 0s 4ms/step - loss: 0.1407 - accuracy: 0.9918 - val loss: 6.7552 - val accuracy: 0.9100
    Epoch 47/50
    32/32 [============== ] - 0s 3ms/step - loss: 0.4111 - accuracy: 0.9835 - val loss: 7.9961 - val accuracy: 0.8950
    Epoch 48/50
    32/32 [=======
                                     - 0s 4ms/step - loss: 0.1410 - accuracy: 0.9952 - val loss: 6.8934 - val accuracy: 0.9130
    Epoch 49/50
    32/32 [========
                      ===========] - 0s 4ms/step - loss: 0.0619 - accuracy: 0.9973 - val loss: 6.9808 - val accuracy: 0.9080
    Epoch 50/50
    plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
```

```
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

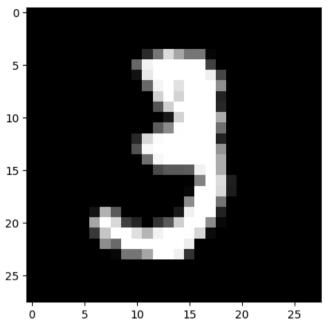
    Test loss: 8.388226509094238
    Test accuracy: 0.883384644985199

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = test_data[img_index].reshape(-1,784)

model.predict(picture)
```

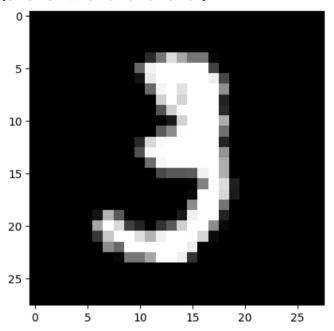


Zwiększamy zbiór treningowy z 60000 do 68000 (20% to zbiór walidacyjny)

One-hot coding

```
train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test labels = tf.keras.utils.to categorical(test labels, 10)
train_data.shape,train_labels.shape
    ((2000, 28, 28), (2000, 10))
test data.shape,test labels.shape
    ((68000, 28, 28), (68000, 10))
train_labels[0]
    array([0., 0., 0., 0., 1., 0., 0., 0., 0., 0.], dtype=float32)
Visulization
def plot_image(img_index):
    label index = test labels[img index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)
img\_index = 10
plot_image(img_index)
```

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



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_30"

Layer (type)	Output Shape	Param #
dense_70 (Dense)	(None, 128)	100480
dense_71 (Dense)	(None, 10)	1290

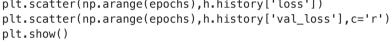
Total params: 101770 (397.54 KB)

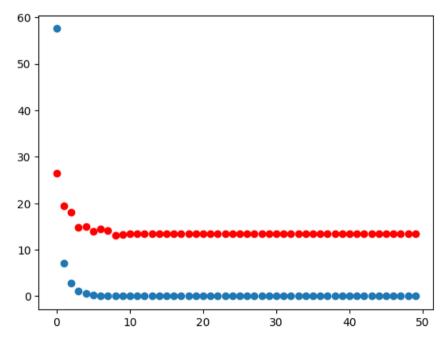
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

```
batch_size = 128
epochs = 50
```

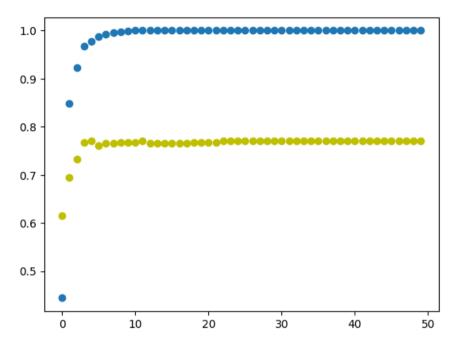
h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs, validation_split=0.2)

```
- WS DMS/Step - toss: /.W8Z0e-W/ - dccurdcy: 1.WWW - Vdt toss: 13.40Z0 - Vdt dccurdcy: W.//WW
   13/13 [======
   Epoch 43/50
   13/13 [=======
                             - 0s 6ms/step - loss: 6.7333e-07 - accuracy: 1.0000 - val loss: 13.4622 - val accuracy: 0.7700
   Epoch 44/50
   13/13 [=======
                             - 0s 5ms/step - loss: 6.5470e-07 - accuracy: 1.0000 - val loss: 13.4616 - val accuracy: 0.7700
   Epoch 45/50
   Fnoch 46/50
   13/13 [=========]
                            - 0s 6ms/step - loss: 6.1343e-07 - accuracy: 1.0000 - val loss: 13.4605 - val accuracy: 0.7700
   Epoch 47/50
   Epoch 48/50
   13/13 [========
                             - 0s 5ms/step - loss: 5.7671e-07 - accuracy: 1.0000 - val loss: 13.4596 - val accuracy: 0.7700
   Epoch 49/50
   13/13 [========
                 =============== ] - 0s 6ms/step - loss: 5.6173e-07 - accuracy: 1.0000 - val loss: 13.4591 - val accuracy: 0.7700
   Epoch 50/50
   plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
```





```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

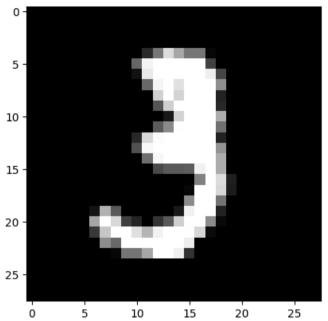
    Test loss: 10.958120346069336
    Test accuracy: 0.8068529367446899

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = test_data[img_index].reshape(-1,784)

model.predict(picture)
```



v Opis:

batch_size = 128

epochs = 50

Zwiększony zbiór treningowy z **60000** do **68000** (20% to zbiór walidacyjny)

opt = keras.optimizers.Adam(learning_rate=0.001)

model.summary()

Model: "sequential_30"

Layer (type)	Output Shape	Param #
dense_70 (Dense)	(None, 128)	100480
dense 71 (Dense)	(None, 10)	1290

```
______
```

```
Total params: 101770 (397.54 KB)
Trainable params: 101770 (397.54 KB)
Non-trainable params: 0 (0.00 Byte)
```

Wnioski i komentarz

Model uczy się do około 4 epoki, potem praktycznie się nie uczy, wykres błędu (treningowego i walidacyjnego) jest praktycznie na stałym poziomie.

Regularyzacja - metoda 2

Zmniejszamy wielkość modelu:

```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 64, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_31"

Layer (type)	Output Shape	Param #
dense_72 (Dense)	(None, 64)	50240
dense_73 (Dense)	(None, 10)	650

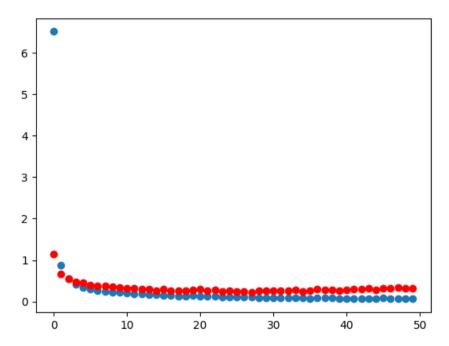
Total params: 50890 (198.79 KB)
Trainable params: 50890 (198.79 KB)
Non-trainable params: 0 (0.00 Byte)

```
batch_size = 128
epochs = 50
```

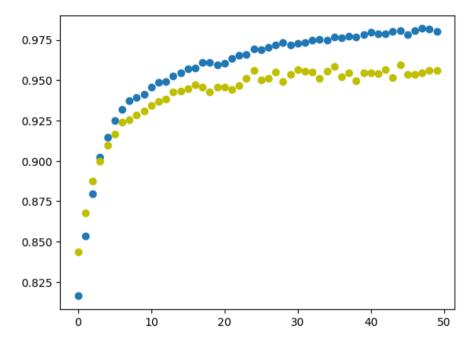
h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs, validation_split=0.2)

plt.show()

```
בטטכוו באַן ש
Epoch 30/50
Fnoch 31/50
Epoch 32/50
Fnoch 33/50
Epoch 34/50
Epoch 35/50
Epoch 36/50
Epoch 37/50
Epoch 38/50
Epoch 39/50
Epoch 40/50
Epoch 41/50
Epoch 42/50
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

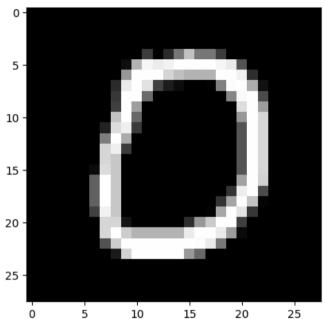
    Test loss: 0.3401225507259369
    Test accuracy: 0.9570000171661377

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = test_data[img_index].reshape(-1,784)

model.predict(picture)
```



Opis:

```
batch_size = 128
epochs = 50
Zbiór treningowy 60000 (20% to zbiór walidacyjny)
opt = keras.optimizers.Adam(learning_rate=0.001)
model.summary()
```

Model: "sequential_31"

Layer (type)	Output Shape	Param #
dense_72 (Dense)	(None, 64)	50240
dense_73 (Dense)	(None, 10)	650
Total params: 50890 (198.79 KB) Trainable params: 50890 (198.79 KB) Non-trainable params: 0 (0.00 Byte)		

Wnioski i komentarz

Model uczy się, mniewięcej do 35 epoki, poźniej następuje lekkie niewielkie przeuczeniem wykresy błędu (treningowego i walidacyjnego) się obijają

Regularyzacja - metoda 3

```
Import normy L2:

from keras.regularizers import l2

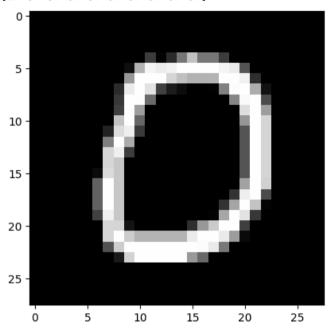
Danie regularyzacji L2 do warstw:

Visulization

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)
```

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



```
train_images = train_data.reshape((-1, 784))

test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128,kernel_regularizer=12(0.01), use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dense(units = 10,kernel_regularizer=12(0.01), use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential 32"

Layer (type)	Output Shape	Param #
dense_74 (Dense)	(None, 128)	100480
dense_75 (Dense)	(None, 10)	1290

Total params: 101770 (397.54 KB)

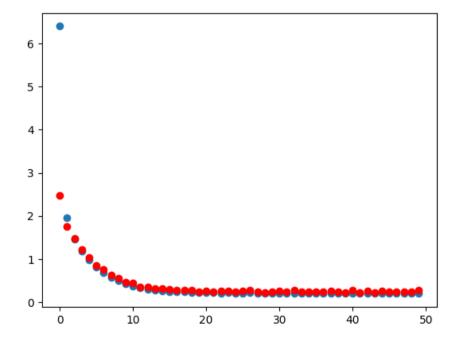
```
Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)
```

```
batch_size = 128
epochs = 50
```

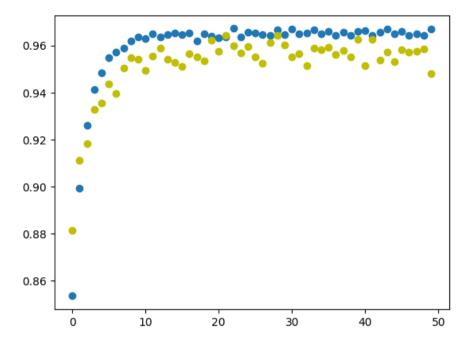
h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs, validation_split=0.2)

```
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
```

```
plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

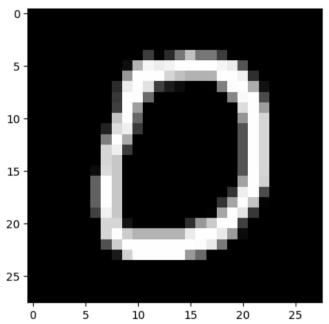
    Test loss: 0.2521417737007141
    Test accuracy: 0.9491999745368958

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = test_data[img_index].reshape(-1,784)

model.predict(picture)
```



```
batch_size = 128
epochs = 50

Zwiększony zbiór treningowy z 60000 do 68000 (20% to zbiór walidacyjny)
opt = keras.optimizers.Adam(learning_rate=0.001)
kernel_regularizer=I2(0.01) (we wszystkich warstwach)

model.summary()
```

Model: "sequential_32"

Layer (type)	Output Shape	Param #
dense_74 (Dense)	(None, 128)	100480
dense_75 (Dense)	(None, 10)	1290
Total narams: 101770 (30	======================================	

Total params: 101770 (397.54 KB) Trainable params: 101770 (397.54 KB) Non-trainable params: 0 (0.00 Byte)

·

Wnioski i komentarz

Model uczy się do około 30 epoki potem się praktycznie nie uczy, ale się nie przeucza, wykresy błędu (treningowego i walidacyjnego)są podobne przy czym błędy cały czas spadają, ale od około 30 epoki spada bardzo wolno wręcz są stałe. Dokładność modelu dla danych treningowych i walidacyjnych praktycznie cały czas rośnie, ale po 30 epoce mniej.

Regularyzacja - metoda 4

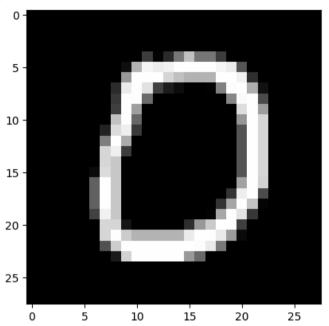
from keras.layers import Dropout

Visulization

```
def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)
```

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



```
train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

model = Sequential()
model.add(Dense(units = 128, use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dropout(0.4))
model.add(Dense(units = 10, use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_33"

Layer (type)	Output Shape	Param #
dense_76 (Dense)	(None, 128)	100480
dropout_26 (Dropout)	(None, 128)	0
dense_77 (Dense)	(None, 10)	1290

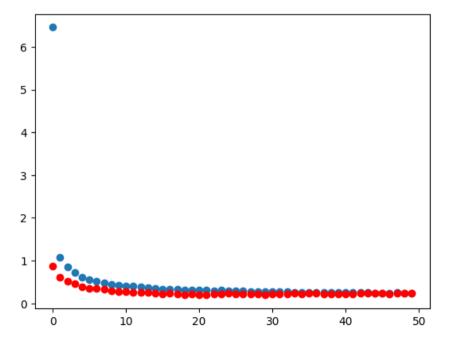
Total params: 101770 (397.54 KB)
Trainable params: 101770 (397.54 KB)
Non-trainable params: 0 (0.00 Byte)

batch_size = 128
epochs = 50

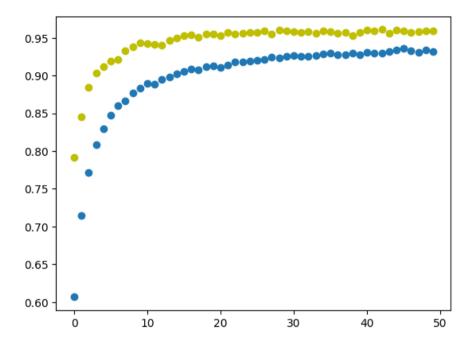
h = model.fit(train_images, train_labels, batch_size=batch_size, epochs=epochs, validation_split=0.2)

```
EDOCII 41/00
Epoch 42/50
375/375 [============] - 1s 4ms/step - loss: 0.2472 - accuracy: 0.9301 - val loss: 0.2253 - val accuracy: 0.9596
Epoch 43/50
Epoch 44/50
Epoch 45/50
Epoch 46/50
Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
```

plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()



```
plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()
```



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

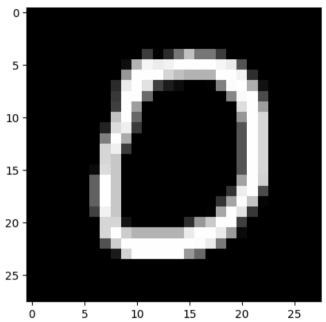
    Test loss: 0.2699497938156128
    Test accuracy: 0.9580000042915344

def plot_image(img_index):
    label_index = test_labels[img_index]
    plt.imshow(test_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = test_data[img_index].reshape(-1,784)

model.predict(picture)
```



```
batch_size = 128
epochs = 50

Zbiór treningowy 60000 (20% to zbiór walidacyjny)
opt = keras.optimizers.Adam(learning_rate=0.001)
model.add(Dropout(0.4))

model.summary()
    Model: "sequential_33"
```

dense_76 (Dense)	(None, 128)	100480
dropout_26 (Dropout)	(None, 128)	0
dense_77 (Dense)	(None, 10)	1290
Total params: 101770 (397.54 Trainable params: 101770 (397 Non-trainable params: 0 (0.00	7.54 KB)	======

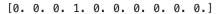
Wnioski i komentarz

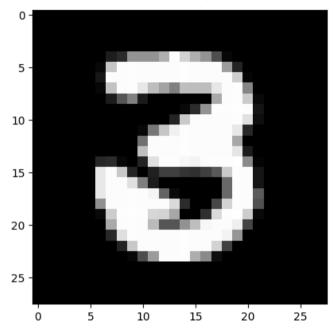
Model uczy się do samego końca i się nie przeucza, wykresy błędu (treningowego i walidacyjnego)są podobne przy czym błędy cały czas spadają. Dokładność modelu dla danych treningowych i walidacyjnych praktycznie cały czas rośnie.

Regularyzacja all in one #1

Zwiększamy zbiór treningowy z 60000 do 68000 (20% to zbiór walidacyjny)

One-hot coding





Danie **regularyzacji L2** do warstw:

Adding dropout layer

Resizing model

```
model = Sequential()
model.add(Dense(units = 64, kernel_regularizer=l2(0.01), use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dropout(0.4))
model.add(Dense(units = 10, kernel_regularizer=l2(0.01), use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_34"

Layer (type)	Output Shape	Param #
dense_78 (Dense)	(None, 64)	50240
dropout_27 (Dropout)	(None, 64)	0
dense_79 (Dense)	(None, 10)	650

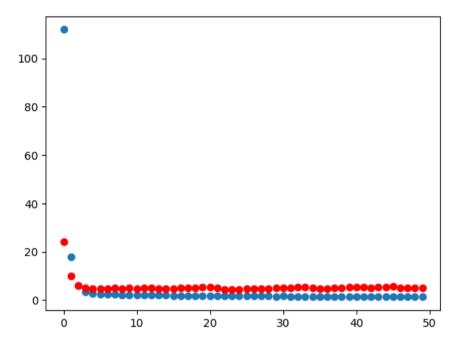
Total params: 50890 (198.79 KB) Trainable params: 50890 (198.79 KB) Non-trainable params: 0 (0.00 Byte)

```
batch_size = 128
epochs = 50
```

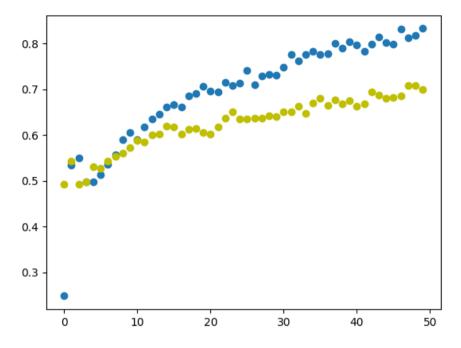
h = model.fit(train images, train labels, batch size=batch size, epochs=epochs, validation split=0.2)

```
Epoch 31/50
  Epoch 32/50
  Epoch 33/50
  Fnoch 34/50
  13/13 [============================ ] - 0s 5ms/step - loss: 1.4906 - accuracy: 0.7763 - val loss: 5.3286 - val accuracy: 0.6475
  Epoch 35/50
  13/13 [============================== ] - 0s 5ms/step - loss: 1.4734 - accuracy: 0.7831 - val loss: 5.1145 - val accuracy: 0.6700
  Epoch 36/50
  13/13 [============================== ] - 0s 4ms/step - loss: 1.4990 - accuracy: 0.7756 - val loss: 4.7616 - val accuracy: 0.6800
  Epoch 37/50
  Epoch 38/50
  13/13 [============================= ] - 0s 5ms/step - loss: 1.4053 - accuracy: 0.8006 - val loss: 4.9413 - val accuracy: 0.6775
  Epoch 39/50
  Epoch 40/50
  Epoch 41/50
  Epoch 42/50
  Epoch 43/50
  Epoch 44/50
  13/13 [============================== ] - 0s 5ms/step - loss: 1.3751 - accuracy: 0.8144 - val loss: 5.2944 - val accuracy: 0.6875
  Epoch 45/50
  13/13 [=========================== ] - 0s 5ms/step - loss: 1.3511 - accuracy: 0.8019 - val loss: 5.5340 - val accuracy: 0.6800
  Epoch 46/50
  13/13 [============================= ] - 0s 4ms/step - loss: 1.3905 - accuracy: 0.7994 - val loss: 5.6892 - val accuracy: 0.6825
  Epoch 47/50
  13/13 [============================= ] - 0s 4ms/step - loss: 1.3428 - accuracy: 0.8319 - val loss: 5.1355 - val accuracy: 0.6850
  Epoch 48/50
  Epoch 49/50
  Epoch 50/50
  plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```

```
https://colab.research.google.com/drive/1jjlx7otWe0l5SrZeJp6qu5jHEUHhbff_#scrollTo=HPsjpZOyA_2S&printMode=true
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

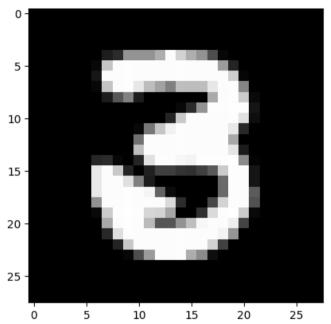
    Test loss: 4.359646797180176
    Test accuracy: 0.747735321521759

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```



```
batch_size = 128
epochs = 50
```

Zbiór treningowy zwiększony z 60000 do *68000 (20% to zbiór walidacyjny)

opt = keras.optimizers.Adam(learning_rate=0.001)

kernel_regularizer=I2(0.01) we wszystkich warstwach

model.add(Dropout(0.4))

model.summary()

Model: "sequential 34"

Layer (type)	Output Shape	Param #
dense_78 (Dense)	(None, 64)	50240
dropout_27 (Dropout)	(None, 64)	0
dense_79 (Dense)	(None, 10)	650

Total params: 50890 (198.79 KB) Trainable params: 50890 (198.79 KB) Non-trainable params: 0 (0.00 Byte)

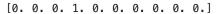
Wnioski i komentarz

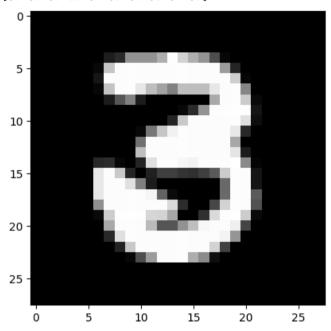
Model uczy się do samego końca i się nie przeucza, wykresy błędu (treningowego i walidacyjnego)są podobne przy czym błędy cały czas, ale od 5 epoki dużo wolniej. Dokładność modelu dla danych treningowych i walidacyjnych praktycznie cały czas rośnie.

Regularyzacja all in one #2

Zwiększamy zbiór treningowy z 60000 do 68000 (20% to zbiór walidacyjny)

One-hot coding





train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

Danie **regularyzacji L2** do warstw:

Adding dropout layer

Resizing model

```
model = Sequential()
model.add(Dense(units = 64, kernel_regularizer=l2(0.01), use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dropout(0.4))
model.add(Dense(units = 10, kernel_regularizer=l2(0.01), use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.001)
#opt = keras.optimizers.SGD(learning_rate=0.001)
model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential_35"

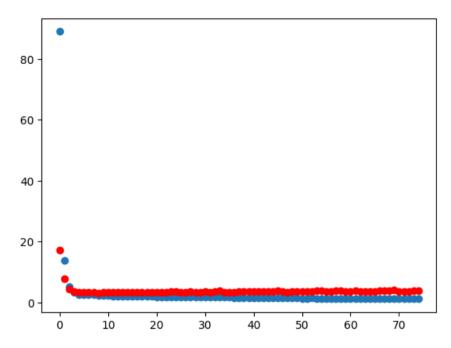
Layer (type)	Output Shape	Param #
dense_80 (Dense)	(None, 64)	50240
dropout_28 (Dropout)	(None, 64)	0
dense_81 (Dense)	(None, 10)	650

Total params: 50890 (198.79 KB) Trainable params: 50890 (198.79 KB) Non-trainable params: 0 (0.00 Byte)

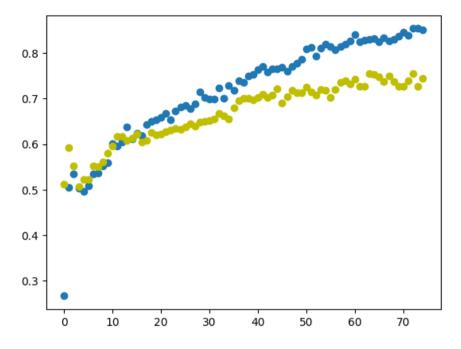
```
batch_size = 128
epochs = 75
```

h = model.fit(train images, train labels, batch size=batch size, epochs=epochs, validation split=0.2)

```
Epoch 56/75
  Epoch 57/75
  Epoch 58/75
  Fnoch 59/75
  13/13 [============================= ] - 0s 4ms/step - loss: 1.2735 - accuracy: 0.8200 - val loss: 3.8605 - val accuracy: 0.7400
  Epoch 60/75
  Epoch 61/75
  13/13 [============================== ] - 0s 4ms/step - loss: 1.2399 - accuracy: 0.8413 - val loss: 3.6363 - val accuracy: 0.7425
  Epoch 62/75
  13/13 [============================== ] - 0s 4ms/step - loss: 1.2620 - accuracy: 0.8256 - val loss: 3.8278 - val accuracy: 0.7275
  Epoch 63/75
  13/13 [============================== ] - 0s 4ms/step - loss: 1.2392 - accuracy: 0.8281 - val loss: 3.6231 - val accuracy: 0.7275
  Epoch 64/75
  Epoch 65/75
  Epoch 66/75
  Epoch 67/75
  13/13 [============================== ] - 0s 5ms/step - loss: 1.2244 - accuracy: 0.8331 - val loss: 3.8716 - val accuracy: 0.7375
  Epoch 68/75
  13/13 [============================== ] - 0s 4ms/step - loss: 1.2266 - accuracy: 0.8263 - val loss: 3.7557 - val accuracy: 0.7500
  Epoch 69/75
  13/13 [============================== ] - 0s 5ms/step - loss: 1.2315 - accuracy: 0.8300 - val loss: 3.9692 - val accuracy: 0.7375
  Epoch 70/75
  13/13 [============================== ] - 0s 5ms/step - loss: 1.1914 - accuracy: 0.8369 - val loss: 4.0792 - val accuracy: 0.7275
  Epoch 71/75
  13/13 [============================= ] - 0s 6ms/step - loss: 1.1636 - accuracy: 0.8450 - val loss: 3.6859 - val accuracy: 0.7275
  Epoch 72/75
  13/13 [============================== ] - 0s 5ms/step - loss: 1.2058 - accuracy: 0.8381 - val loss: 3.5828 - val accuracy: 0.7400
  Epoch 73/75
  Epoch 74/75
  Epoch 75/75
  plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

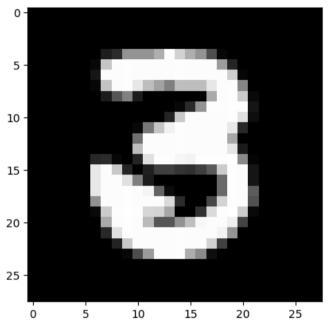
    Test loss: 3.6267483234405518
    Test accuracy: 0.7762647271156311

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```



```
batch_size = 128
epochs = 75
Zbiór treningowy zwiększony z 60000 do *68000 (20% to zbiór walidacyjny)
opt = keras.optimizers.Adam(learning_rate=0.001)
kernel_regularizer=l2(0.01) we wszystkich warstwach
model.add(Dropout(0.4))
```

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Model: "sequential_35"

Layer (type)	Output Shape	Param #
dense_80 (Dense)	(None, 64)	50240
dropout_28 (Dropout)	(None, 64)	0
dense_81 (Dense)	(None, 10)	650
=======================================	============	

Total params: 50890 (198.79 KB)

Trainable params: 50890 (198.79 KB) Non-trainable params: 0 (0.00 Byte)

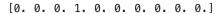
Wnioski i komentarz

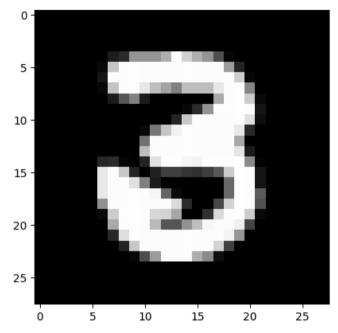
Model uczy się do około 30 epoki potem deliktanie się przeucza, wykresy błędu (treningowego i walidacyjnego) są podobne przy czym po 30 epoce błąd validacyjny rośnie dalej, a błąd treningowy spada. Dokładność modelu dla danych treningowych i walidacyjnych praktycznie cały czas rośnie.

Regularyzacja all in one #3

Zwiększamy zbiór treningowy z 60000 do 68000 (20% to zbiór walidacyjny)

One-hot coding





train_images = train_data.reshape((-1, 784))
test_images = test_data.reshape((-1, 784))

Danie **regularyzacji L2** do warstw:

Adding dropout layer

Resizing model

```
model = Sequential()
model.add(Dense(units = 64, kernel_regularizer=l2(0.01), use_bias=True, input_shape=(784,), activation = "relu"))
model.add(Dropout(0.3))
model.add(Dense(units = 10, kernel_regularizer=l2(0.01), use_bias=True, activation = "softmax"))

opt = keras.optimizers.Adam(learning_rate=0.002)
#opt = keras.optimizers.SGD(learning_rate=0.001)

model.compile(loss='categorical_crossentropy',optimizer=opt,metrics=['accuracy'])
model.summary()
```

Model: "sequential 36"

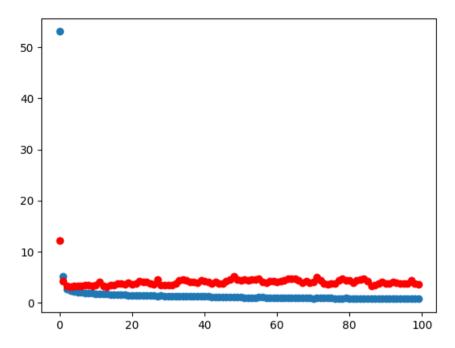
Layer (type)	Output Shape	Param #
dense_82 (Dense)	(None, 64)	50240
dropout_29 (Dropout)	(None, 64)	0
dense_83 (Dense)	(None, 10)	650
dense_83 (Dense)	(None, 10)	650

Total params: 50890 (198.79 KB) Trainable params: 50890 (198.79 KB) Non-trainable params: 0 (0.00 Byte)

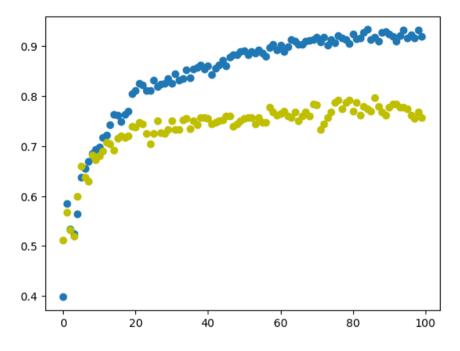
batch_size = 128
epochs = 100

h = model.fit(train images, train labels, batch size=batch size, epochs=epochs, validation split=0.2)

```
Epoch 81/100
  Epoch 82/100
  Epoch 83/100
  Fnoch 84/100
  13/13 [============================== ] - 0s 6ms/step - loss: 0.7616 - accuracy: 0.9269 - val loss: 4.4429 - val accuracy: 0.7800
  Epoch 85/100
  Epoch 86/100
  13/13 [============================== ] - 0s 4ms/step - loss: 0.7900 - accuracy: 0.9131 - val loss: 4.1504 - val accuracy: 0.7700
  Epoch 87/100
  Epoch 88/100
  13/13 [============================ ] - 0s 5ms/step - loss: 0.7633 - accuracy: 0.9106 - val loss: 3.3430 - val accuracy: 0.7800
  Epoch 89/100
  Epoch 90/100
  13/13 [============================== ] - 0s 5ms/step - loss: 0.7152 - accuracy: 0.9294 - val loss: 4.0196 - val accuracy: 0.7625
  Epoch 91/100
  Epoch 92/100
  13/13 [============================== ] - 0s 4ms/step - loss: 0.7302 - accuracy: 0.9200 - val loss: 3.6781 - val accuracy: 0.7850
  Epoch 93/100
  13/13 [============================== ] - 0s 4ms/step - loss: 0.7435 - accuracy: 0.9106 - val loss: 3.9936 - val accuracy: 0.7850
  Fnoch 94/100
  13/13 [=============================== ] - 0s 4ms/step - loss: 0.7386 - accuracy: 0.9212 - val loss: 3.9131 - val accuracy: 0.7775
  Epoch 95/100
  13/13 [============================== ] - 0s 4ms/step - loss: 0.7052 - accuracy: 0.9325 - val loss: 3.7564 - val accuracy: 0.7775
  Epoch 96/100
  13/13 [============================ ] - 0s 4ms/step - loss: 0.7170 - accuracy: 0.9156 - val loss: 3.6580 - val accuracy: 0.7750
  Epoch 97/100
  13/13 [============================== ] - 0s 4ms/step - loss: 0.7417 - accuracy: 0.9231 - val loss: 3.7504 - val accuracy: 0.7625
  Epoch 98/100
  Epoch 99/100
  Epoch 100/100
  plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val loss'],c='r')
plt.show()
```



plt.scatter(np.arange(epochs),h.history['accuracy'])
plt.scatter(np.arange(epochs),h.history['val_accuracy'],c='y')
plt.show()



```
score = model.evaluate(test_images, test_labels, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])

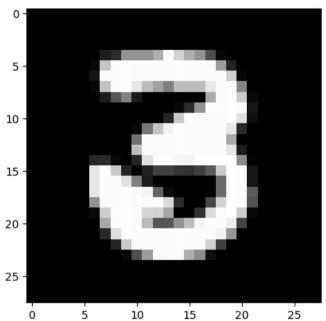
    Test loss: 2.8622798919677734
    Test accuracy: 0.8228235244750977

def plot_image(img_index):
    label_index = train_labels[img_index]
    plt.imshow(train_data[img_index]/255, cmap = 'gray')
    print(label_index)

img_index = 10
plot_image(img_index)

picture = train_data[img_index].reshape(-1,784)

model.predict(picture)
```



```
batch_size = 128
epochs = 100
Zbiór treningowy zwiększony z 60000 do *68000 (20% to zbiór walidacyjny)
opt = keras.optimizers.Adam(learning_rate=0.002)
kernel_regularizer=I2(0.01) we wszystkich warstwach
model.add(Dropout(0.3))
```

model.summary()

Model: "sequential_36"

Layer (type)	Output Shape	Param #
dense_82 (Dense)	(None, 64)	50240
dropout_29 (Dropout)	(None, 64)	0
dense_83 (Dense)	(None, 10)	650
=======================================	=======================================	=======================================

Total params: 50890 (198.79 KB)