Big Data Project, Summer 2021

Course Title: Big Data

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Section-B, 4 Batch

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Contents:

In [ ]:
```
from google.colab import drive
```

```
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
import numpy as np
import gzip
import os
import sys
import struct
import numpy as np

def read_image(fi):
    magic, n, rows, columns = struct.unpack(">IIII", fi.read(16))
    assert magic == 0x00000803
    assert rows == 28
    assert columns == 28
    rawbuffer = fi.read()
    assert len(rawbuffer) == n * rows * columns
    rawdata = np.frombuffer(rawbuffer, dtype='>u1', count=n*rows*columns)
    return rawdata.reshape(n, rows, columns).astype(np.float32)

def read_label(fi):
    magic, n = struct.unpack(">II", fi.read(8))
    assert magic == 0x00000801
    rawbuffer = fi.read()
    assert len(rawbuffer) == n
    return np.frombuffer(rawbuffer, dtype='>u1', count=n)



train_x = '/content/drive/MyDrive/Dataset/mnist/train-images-idx3-ubyte.gz'
train_y = "/content/drive/MyDrive/Dataset/mnist/train-labels-idx1-ubyte.gz"
test_x = "/content/drive/MyDrive/Dataset/mnist/t10k-images-idx3-ubyte.gz"
test_y = "/content/drive/MyDrive/Dataset/mnist/t10k-labels-idx1-ubyte.gz"

np.savez_compressed(
    'mnist',
     train_x=read_image(gzip.open(train_x,'rb')),
     train_y=read_label(gzip.open(train_y, 'rb')),
     test_x=read_image(gzip.open(test_x, 'rb')),
     test_y=read_label(gzip.open(test_y, 'rb'))
  )
```

In [ ]:

```
data = np.load('mnist.npz')

print(data['train_x'].shape, data['train_x'].dtype)
print(data['train_y'].shape, data['train_y'].dtype)
print(data['test_x'].shape, data['test_x'].dtype)
print(data['test_y'].shape, data['test_y'].dtype)
#print(data['train_x'])
#j = data['train_x']
#print(j[1])
```

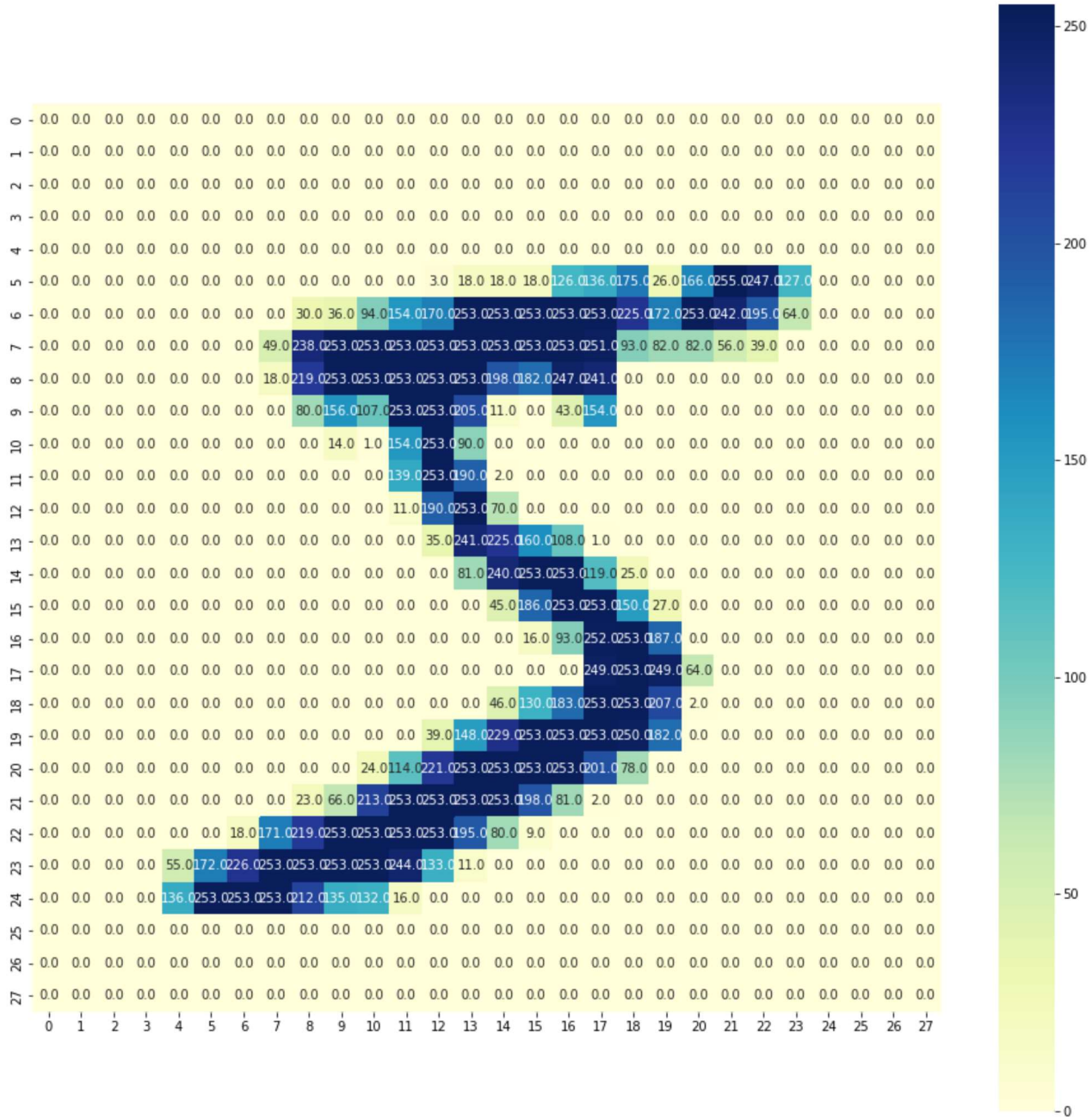
```
(60000, 28, 28) float32
(60000,) uint8
(10000, 28, 28) float32
(10000,) uint8
```

Visualize the dataset

In [ ]:

```
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# Index number of an instance (change this to view another instance).
i = 0

data = np.load('mnist.npz')
image = data['train_x'][i]
label = data['train_y'][i]

print(label)
f, ax = plt.subplots(figsize=(16, 16))
sns.heatmap(image, annot=True, fmt='.1f', square=True, cmap="YlGnBu")
plt.show()
```

```
5
```

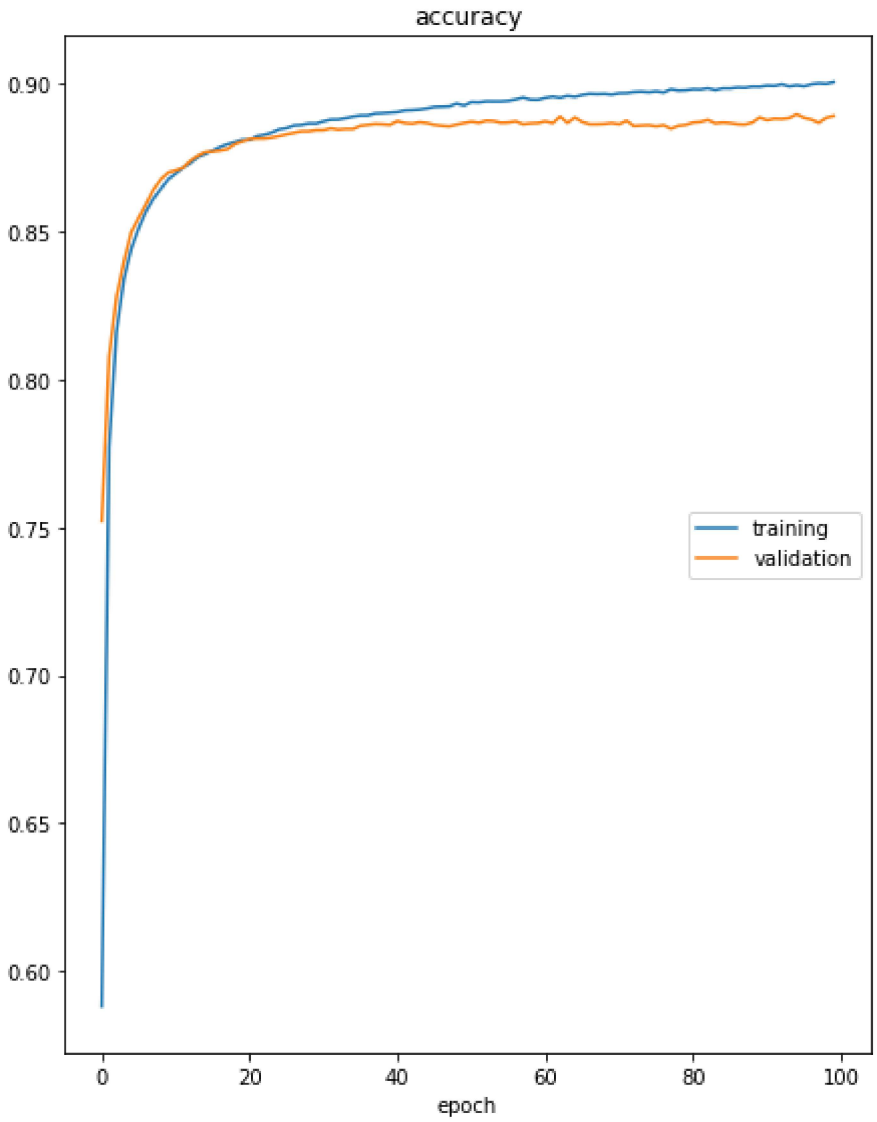


In [ ]:
```
!pip install livelossplot
```

Perceptron algorithm for single-layer neural network

In [ ]:
```
import numpy as np
from livelossplot import PlotLosses

def image_to_vector(X):
    X = np.reshape(X, (len(X), -1))      # Flatten: (N x 28 x 28) -> (N x 784)
    return np.c_[X, np.ones(len(X))]     # Append 1: (N x 784) -> (N x 785)

data = np.load('mnist.npz')
Xtrain = image_to_vector(data['train_x'])
Ytrain = data['train_y']
Xtest = image_to_vector(data['test_x'])
Ytest = data['test_y']
```

```
W = np.random.randn(10, 28*28+1)

eta = 0.001
liveloss = PlotLosses()
for t in range(100):
    # Structured perceptron for updating weights.
    num_correct_train = 0
    for x, y in zip(Xtrain, Ytrain):
        y_pred = np.argmax(np.dot(W, x))
        if y_pred != y:
            W[y] += x * eta
            W[y_pred] -= x * eta
        else:
            num_correct_train += 1

    # Evaluate and store the accuracy on the test set.
    num_correct_test = 0
    for x, y in zip(Xtest, Ytest):
        y_pred = np.argmax(np.dot(W, x))
        if y_pred == y:
            num_correct_test += 1

    # Visualize accuracy values on the training and test sets.
    liveloss.update({
        'accuracy': float(num_correct_train) / len(Ytrain),
        'val_accuracy': float(num_correct_test) / len(Ytest)
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(
    float(num_correct_test) / len(Ytest),
    float(num_correct_train) / len(Ytrain)
    ))
```



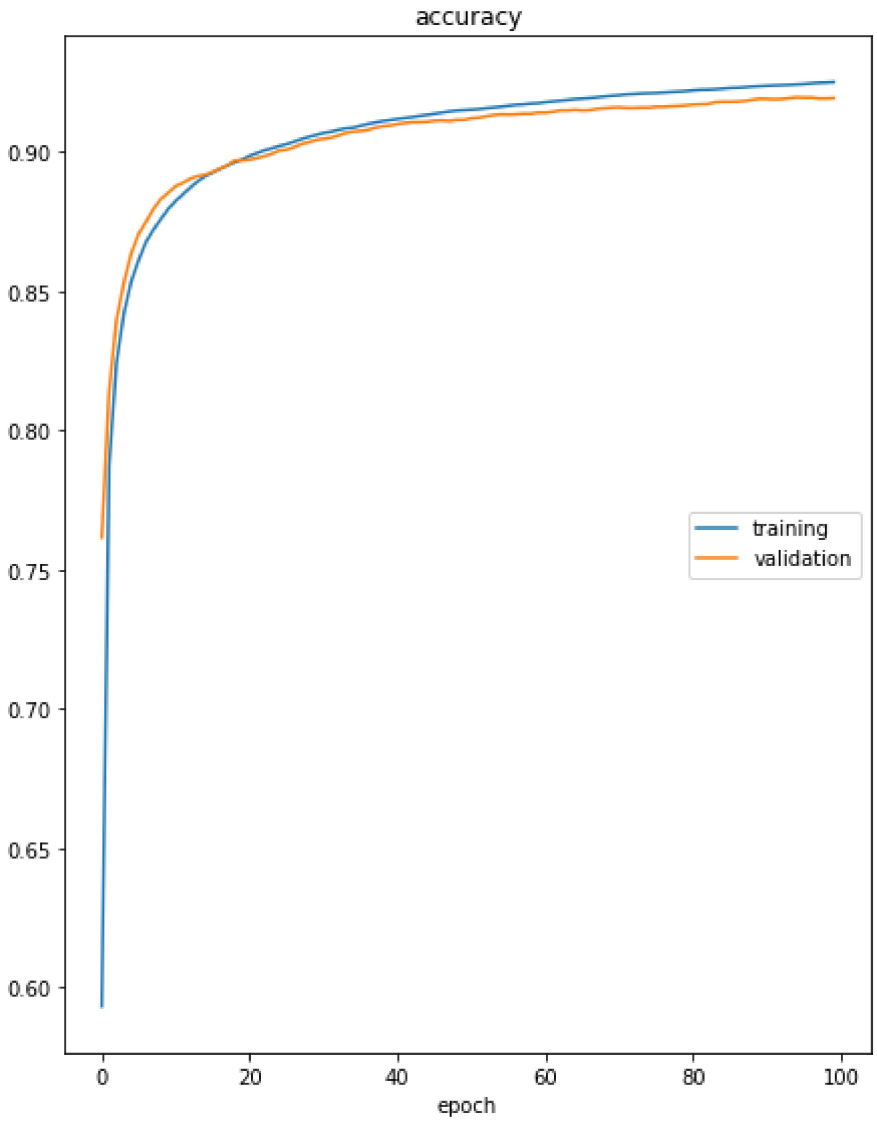

```
accuracy
        training                 (min:    0.588, max:    0.900, cur:    0.900)
        validation               (min:    0.752, max:    0.890, cur:    0.889)
Accuracy: 0.8890 (test), 0.9004 (train)
```

Stochastic gradient descent for single-layer neural network

In [ ]:

```
import numpy as np
from livelossplot import PlotLosses

def softmax(x):
    # Result of softmax are invariant even if we add/subtract a constant.
    ex = np.exp(x - np.max(x))  # Subtract such that the maximum value is one.
    return ex / ex.sum(axis=0)

def image_to_vector(X):
    X = np.reshape(X, (len(X), -1))      # Flatten: (N x 28 x 28) -> (N x 784)
    return np.c_[X, np.ones(len(X))]     # Append 1: (N x 784) -> (N x 785)

def label_to_onehot(Y, K):
    return np.eye(K)[Y]                  # e.g., 3 -> [0, 0, 0, 1, 0, 0, 0, 0, 0]
```

```
data = np.load('mnist.npz')
Xtrain = image_to_vector(data['train_x'])
Ytrain = label_to_onehot(data['train_y'], 10)
Xtest = image_to_vector(data['test_x'])
Ytest = data['test_y']

W = np.random.randn(10, 28*28+1)

eta = 0.001
liveloss = PlotLosses()
for t in range(100):
    num_correct_train = 0

    # Stochastic gradient descent.
    for x, y in zip(Xtrain, Ytrain):
        y_pred = softmax(np.dot(W, x))
        W += np.outer(eta * (y - y_pred), x)
        if  np.argmax(y_pred) == np.argmax(y):
            num_correct_train += 1

    # Evaluate and store the accuracy on the test set.
    num_correct_test = 0
    for x, y in zip(Xtest, Ytest):
        y_pred = np.argmax(np.dot(W, x))
        if y_pred == y:
            num_correct_test += 1

    # Visualize accuracy values on the training and test sets.
    liveloss.update({
        'accuracy': float(num_correct_train) / len(Ytrain),
        'val_accuracy': float(num_correct_test) / len(Ytest)
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(
    float(num_correct_test) / len(Ytest),
    float(num_correct_train) / len(Ytrain)
    ))
```




```
accuracy
        training                 (min:    0.593, max:    0.925, cur:    0.925)
        validation               (min:    0.761, max:    0.920, cur:    0.919)
Accuracy: 0.9193 (test), 0.9251 (train)
```

Training with pytorch

Convert the numpy arrays into pytorch tensor

In [ ]:

```
def create_dataset(x, y, flatten=False):
    if flatten:
        # Convert it into a matrix (N [samples], 28*28 [dims])
        xt = torch.from_numpy(x).view(len(x), -1)
    else:
        # Convert it into a 4D tensor (N [samples], 1 [ch], 28 [px], 28 [px])
        xt = torch.from_numpy(x).unsqueeze(1)
    yt = torch.from_numpy(y).long()
    return TensorDataset(xt, yt)
```

```
def test_model(model, loss_fn, test_loader, device):
    model.eval()

    loss = 0.
    num_correct = 0.
    for batch_idx, (x, y) in enumerate(test_loader):
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        loss += loss_fn(y_pred, y).item()
        _, predicted = torch.max(y_pred.data, 1)
        num_correct += (predicted == y).sum().item()

    model.train()
    loss /= len(test_loader.dataset)
    num_correct /= len(test_loader.dataset)
    return loss, num_correct
```

Single-layer neural network

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

def create_dataset(x, y):
    xt = torch.from_numpy(x).view(len(x), -1)
    yt = torch.from_numpy(y).long()
    return TensorDataset(xt, yt)

model = nn.Sequential()
model.add_module('fc1', nn.Linear(784, 10, bias=True))
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.SGD(model.parameters(), lr=0.001)

for t in range(100):
    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)

        # Compute the loss value.
        loss = loss_fn(y_pred, y)

        # Update the parameters.
        optimizer.zero_grad()
```

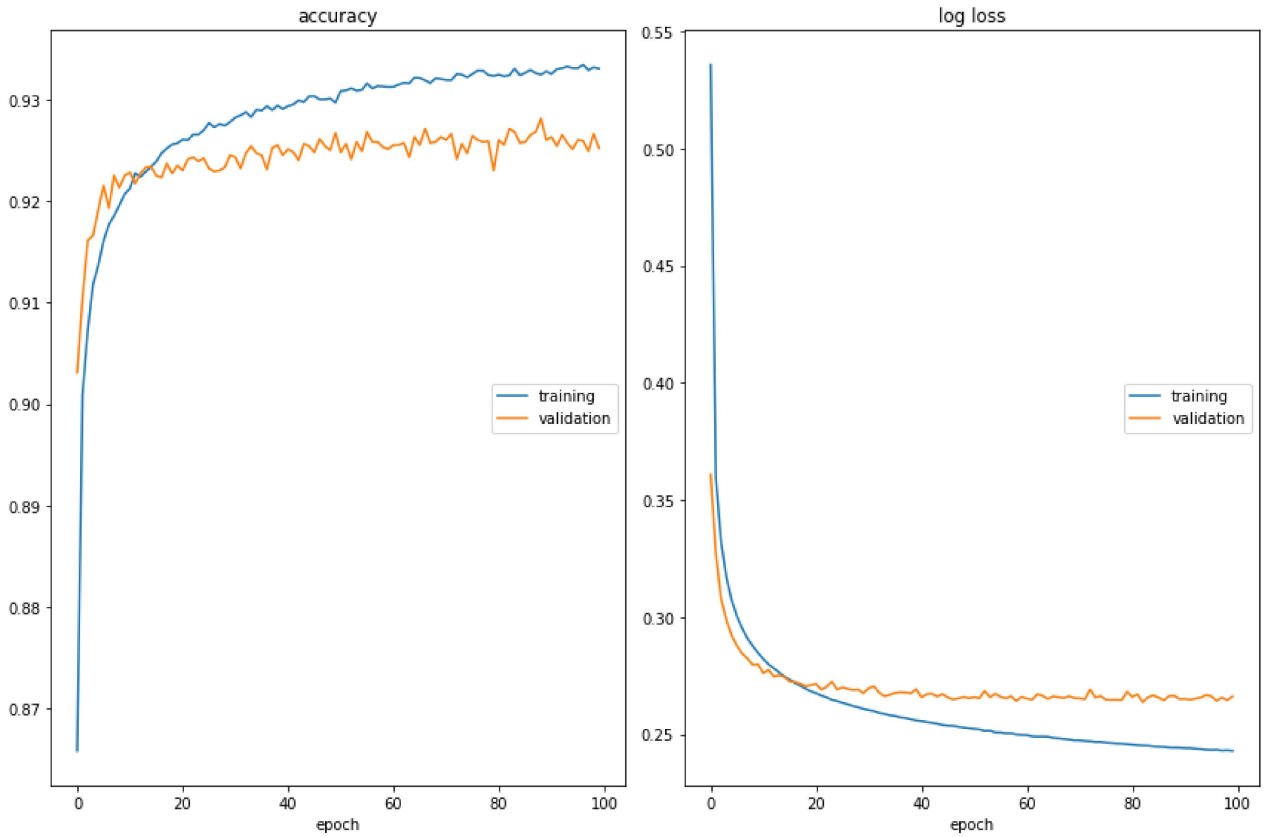
```
        loss.backward()
        optimizer.step()
```

```
/usr/local/lib/python3.7/dist-packages/torch/nn/_reduction.py:42: UserWarning: size_aver
age and reduce args will be deprecated, please use reduction='sum' instead.
  warnings.warn(warning.format(ret))
```

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1', nn.Linear(784, 10, bias=True))
print(model)
model.to(device)


data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.SGD(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)
```

```
    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                (min:    0.866, max:    0.933, cur:    0.933)
        validation              (min:    0.903, max:    0.928, cur:    0.925)
log loss
        training                (min:    0.243, max:    0.536, cur:    0.243)
        validation              (min:    0.264, max:    0.361, cur:    0.266)
Accuracy: 0.9252 (test), 0.9330 (train)
```

Three-layer neural network

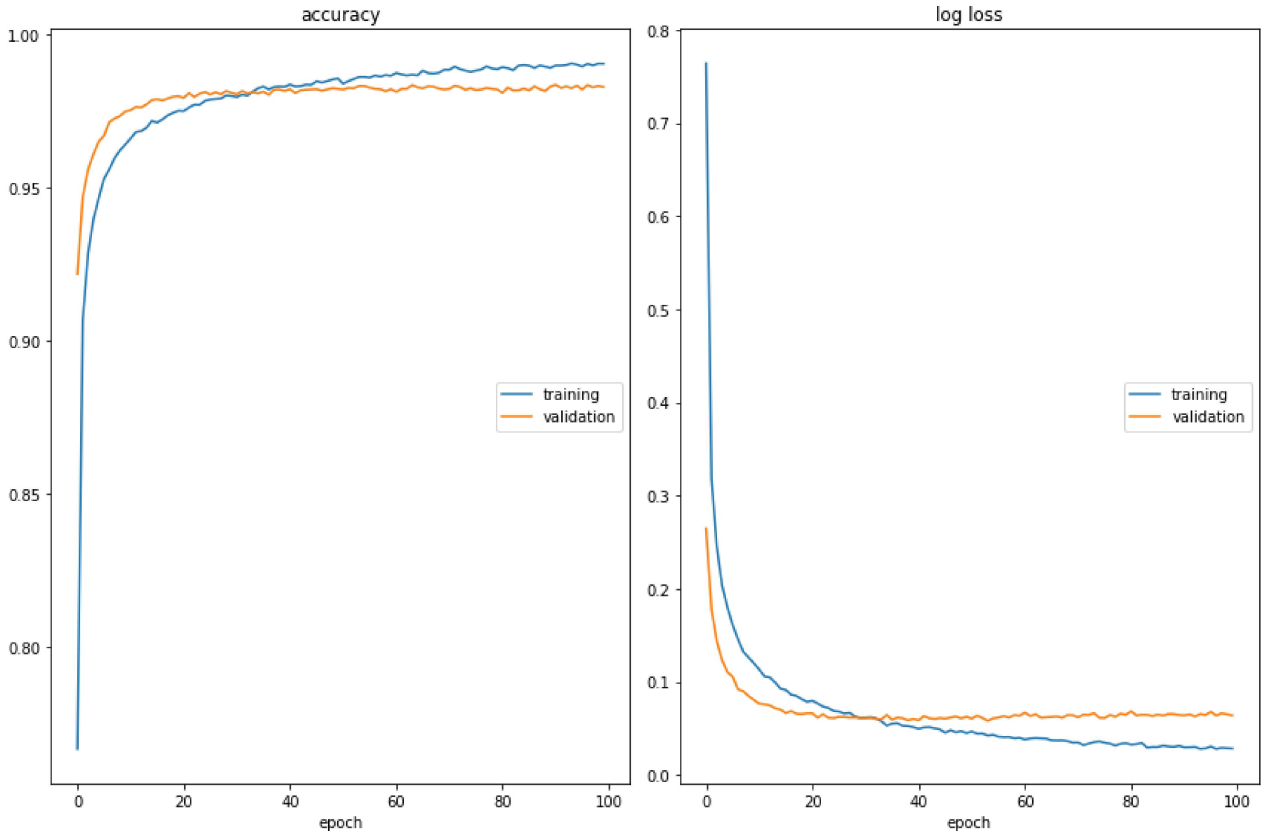
For Stochastic Gradient Descent (SGD) and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
```

```
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.SGD(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
```

```
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



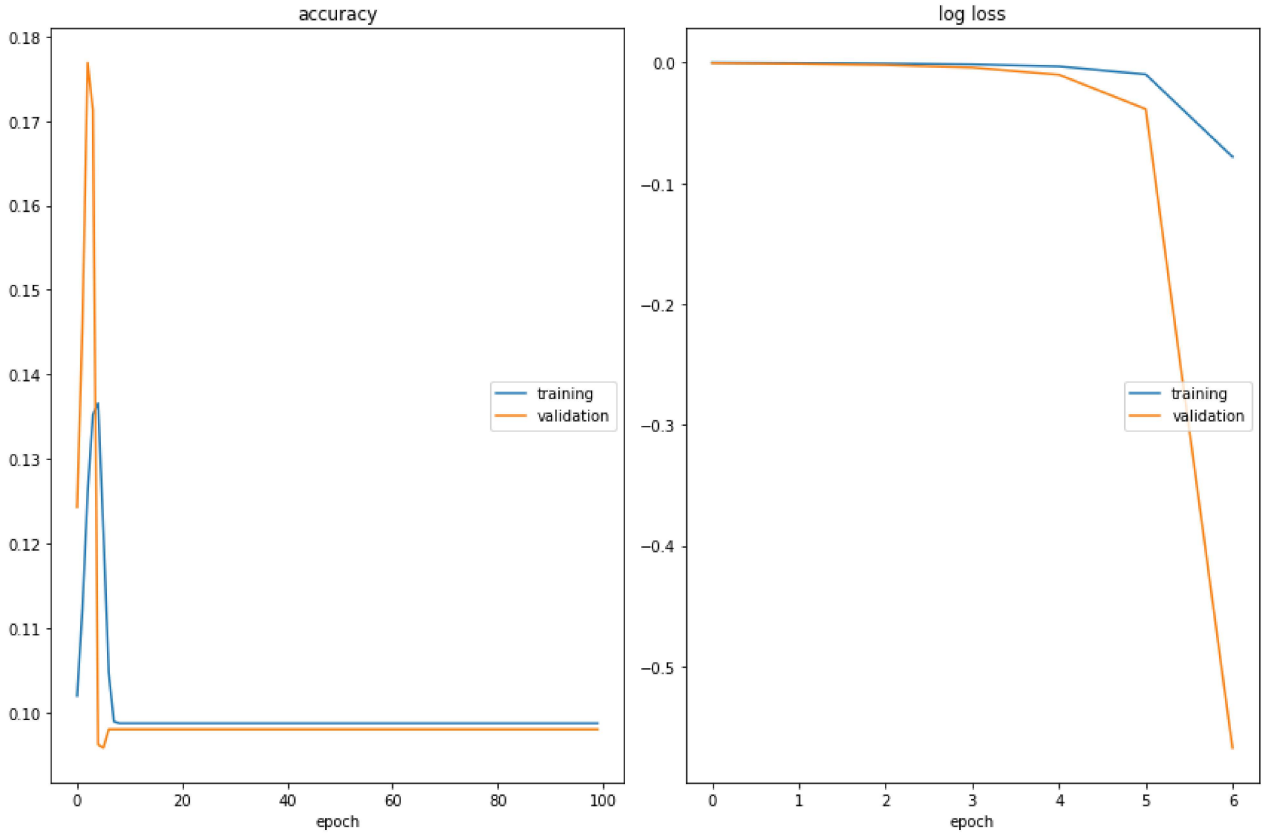

```
accuracy
        training                 (min:    0.767, max:    0.991, cur:    0.991)
        validation               (min:    0.922, max:    0.984, cur:    0.983)
log loss
        training                 (min:    0.028, max:    0.764, cur:    0.028)
        validation               (min:    0.058, max:    0.265, cur:    0.064)
Accuracy: 0.9830 (test), 0.9906 (train)
```

For Stochastic Gradient Descent (SGD) and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
```

```
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.SGD(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



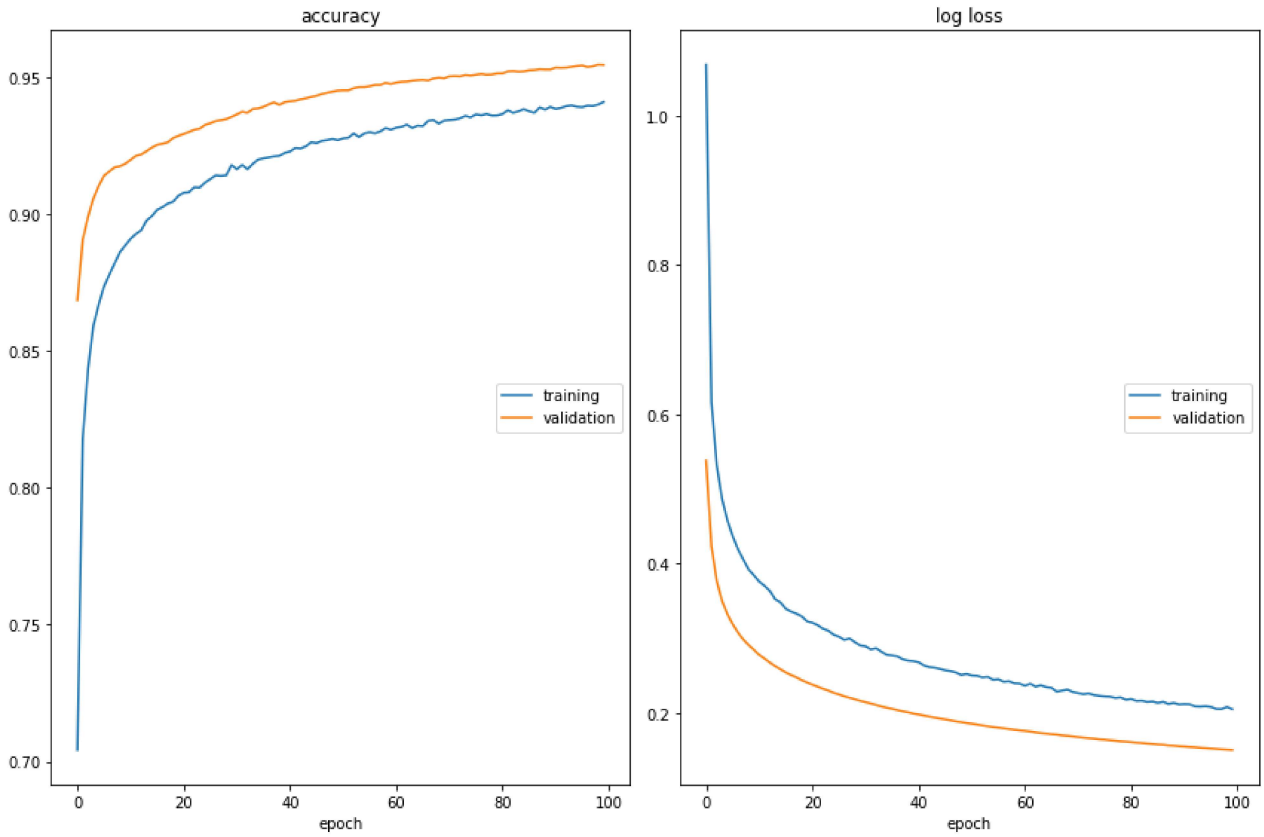

```
accuracy
        training                 (min:    0.099, max:    0.137, cur:    0.099)
        validation               (min:    0.096, max:    0.177, cur:    0.098)
log loss
        training                 (min:   -0.078, max:   -0.000, cur:      nan)
        validation               (min:   -0.568, max:   -0.000, cur:      nan)
Accuracy: 0.0980 (test), 0.0987 (train)
```

For Adagrad and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)
```

```
data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.Adagrad(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



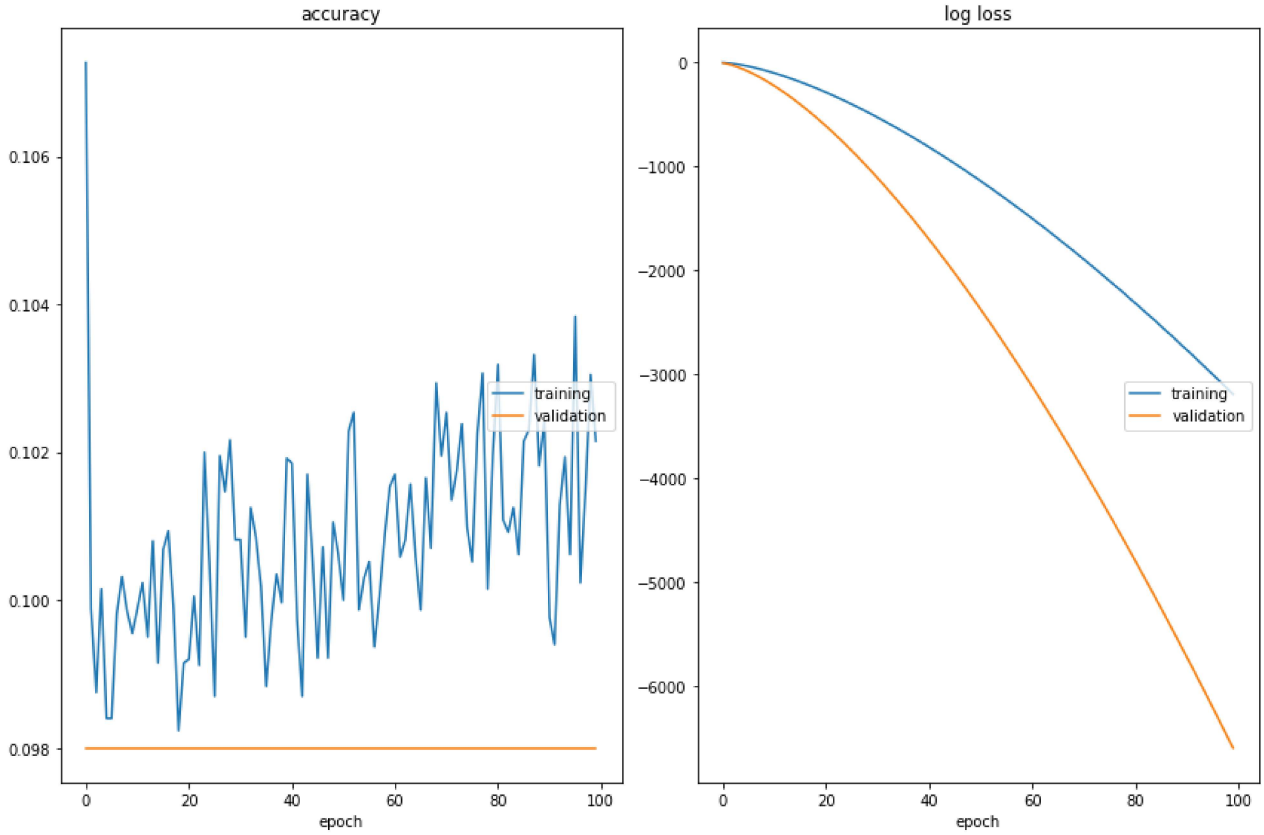

```
accuracy
        training                 (min:    0.704, max:    0.941, cur:    0.941)
        validation               (min:    0.869, max:    0.955, cur:    0.954)
log loss
        training                 (min:    0.205, max:    1.068, cur:    0.205)
        validation               (min:    0.150, max:    0.538, cur:    0.150)
Accuracy: 0.9544 (test), 0.9408 (train)
```

For Adagrad and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)
```

```
data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.Adagrad(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



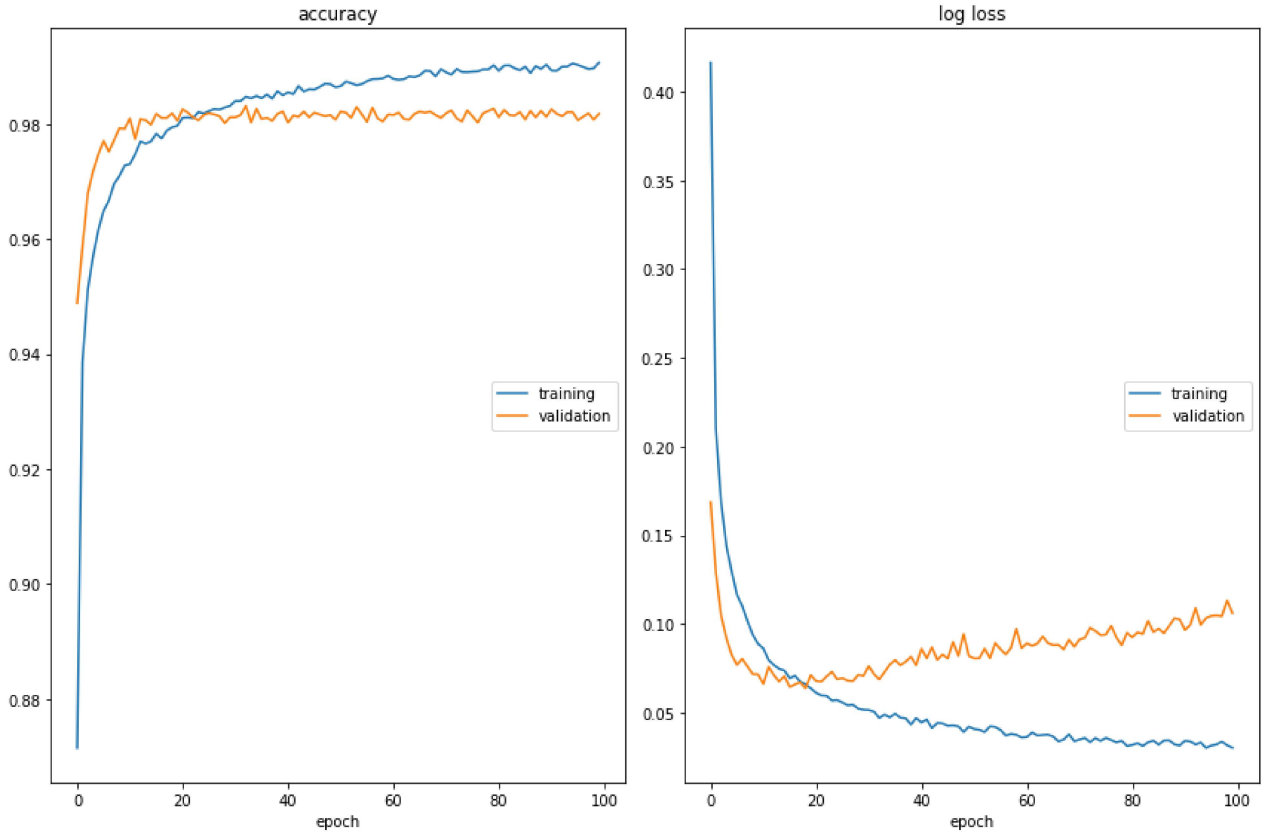

```
accuracy
        training                 (min:    0.098, max:    0.107, cur:    0.102)
        validation               (min:    0.098, max:    0.098, cur:    0.098)
log loss
        training                 (min: -3193.990, max:   -0.883, cur: -3193.990)
        validation               (min: -6598.251, max:   -4.964, cur: -6598.251)
Accuracy: 0.0980 (test), 0.1022 (train)
```

For RMSPROP and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)
```

```
data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.RMSprop(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



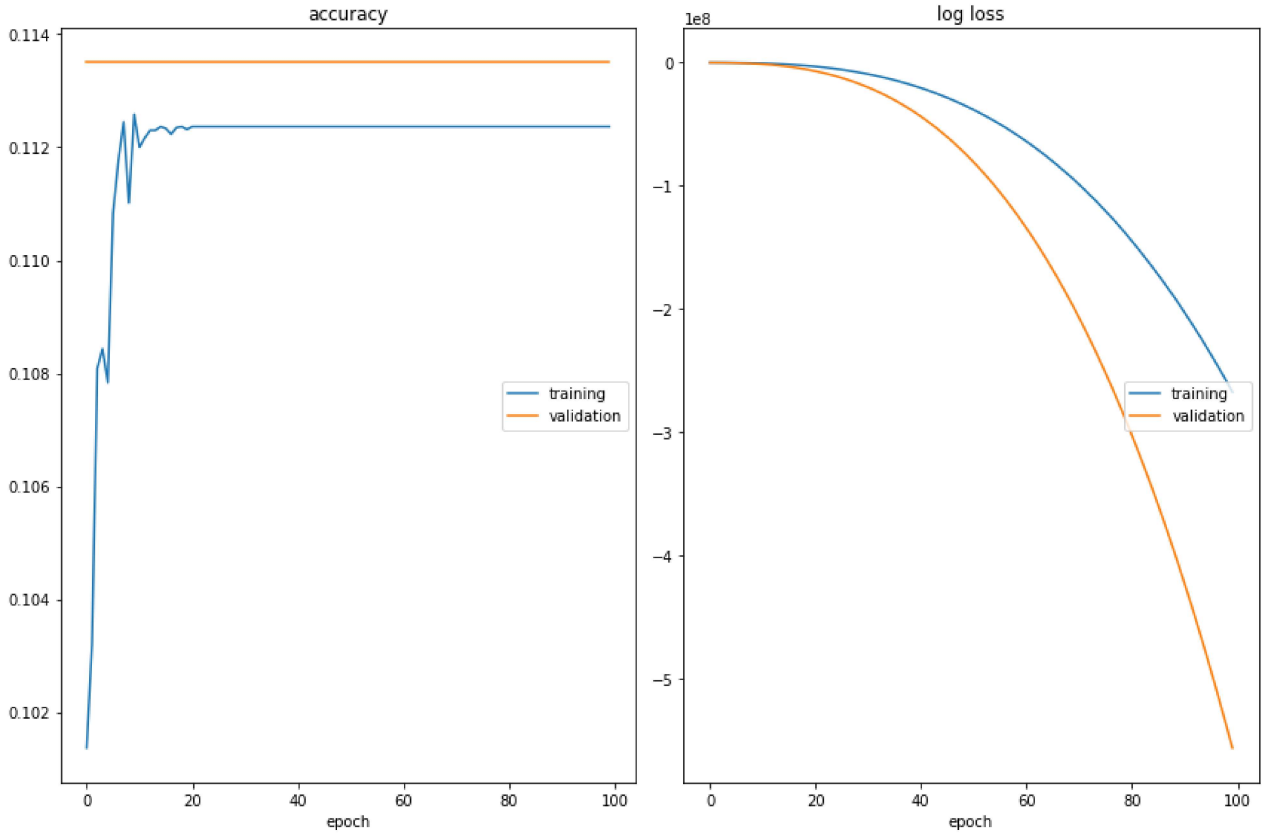

```
accuracy
        training                 (min:    0.871, max:    0.991, cur:    0.991)
        validation               (min:    0.949, max:    0.983, cur:    0.982)
log loss
        training                 (min:    0.030, max:    0.416, cur:    0.030)
        validation               (min:    0.064, max:    0.169, cur:    0.106)
Accuracy: 0.9818 (test), 0.9907 (train)
```

For RMSprop and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)
```

```
data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.RMSprop(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



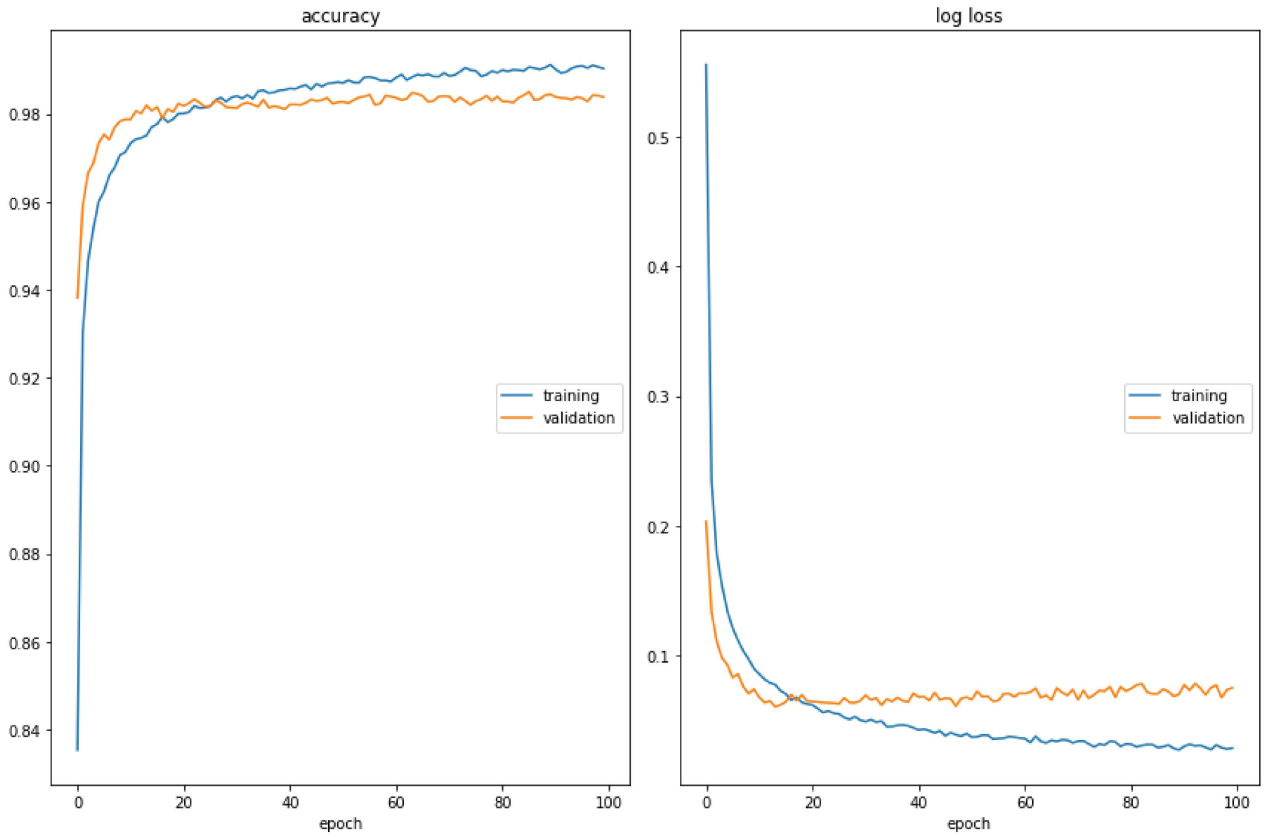

```
accuracy
        training                 (min:    0.101, max:    0.113, cur:    0.112)
        validation               (min:    0.114, max:    0.114, cur:    0.114)
log loss
        training                 (min: -267166984.329, max: -1136.229, cur: -267166984.3
29)
        validation               (min: -555961161.318, max: -6648.717, cur: -555961161.3
18)
Accuracy: 0.1135 (test), 0.1124 (train)
```

For Adam and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)
```

```
data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.Adam(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



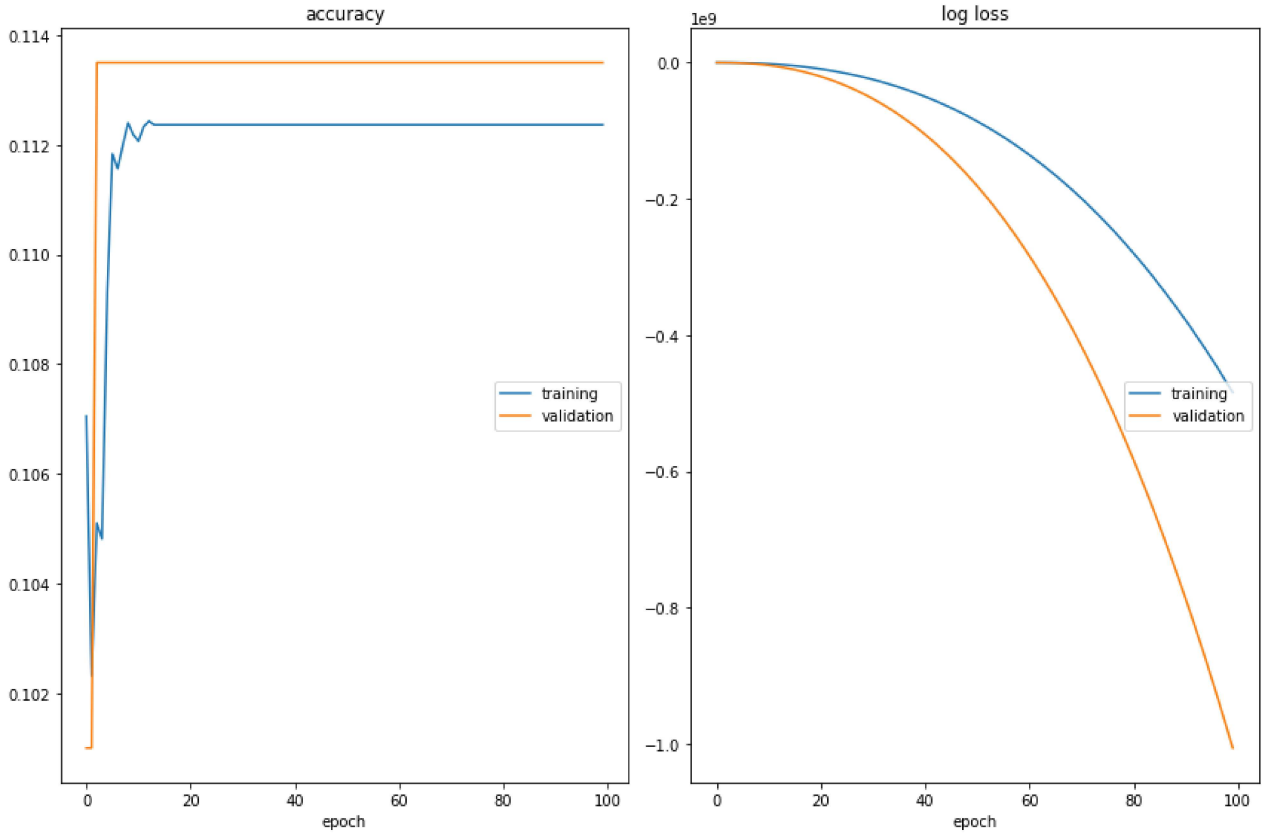

```
accuracy
        training                 (min:    0.835, max:    0.991, cur:    0.990)
        validation               (min:    0.938, max:    0.985, cur:    0.984)
log loss
        training                 (min:    0.027, max:    0.555, cur:    0.029)
        validation               (min:    0.061, max:    0.203, cur:    0.075)
Accuracy: 0.9838 (test), 0.9903 (train)
```

For Adam and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

model = nn.Sequential()
model.add_module('fc1',      nn.Linear(784, 256))
model.add_module('relu1',    nn.ReLU())
model.add_module('dropout1', nn.Dropout())
model.add_module('fc2',      nn.Linear(256, 256))
model.add_module('relu2',    nn.ReLU())
model.add_module('dropout2', nn.Dropout())
model.add_module('fc3',      nn.Linear(256, 10))
print(model)
model.to(device)
```

```
data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'], flatten=True)
test_set = create_dataset(data['test_x'], data['test_y'], flatten=True)
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                (min:    0.102, max:    0.112, cur:    0.112)
        validation              (min:    0.101, max:    0.114, cur:    0.114)
log loss
        training                (min: -483891027.149, max: -307.360, cur: -483891027.14
9)
        validation              (min: -1005867514.266, max: -2963.845, cur: -100586751
4.266)
Accuracy: 0.1135 (test), 0.1124 (train)
```

Comparison table for ANN using differents Optimizers and Loss Function

Optimizer	Loss Function	Training Accuracy	Testing Accuracy
Stochastic Gradient Descent (SGD)	Multi-Class Cross-Entropy Loss	0.9906	0.9830
Stochastic Gradient Descent (SGD)	Negative Log-Likelihood Loss Function	0.0987	0.0980
Adagrad	Multi-Class Cross-Entropy Loss	0.9408	0.9544
Adagrad	Negative Log-Likelihood Loss Function	0.1022	0.0980
RMSPROP	Multi-Class Cross-Entropy Loss	0.9907	0.9818
RMSPROP	Negative Log-Likelihood Loss Function	0.1124	0.1135
Adam	Multi-Class Cross-Entropy Loss	0.9903	0.9838
Adam	Negative Log-Likelihood Loss Function	0.1124	0.1135

We got better results by using RMSPROP & Multi-Class Cross-Entropy Loss Function and Adam & Multi-Class Cross-Entropy Loss Function in ANN.

Convolutional Neural Network (CNN)

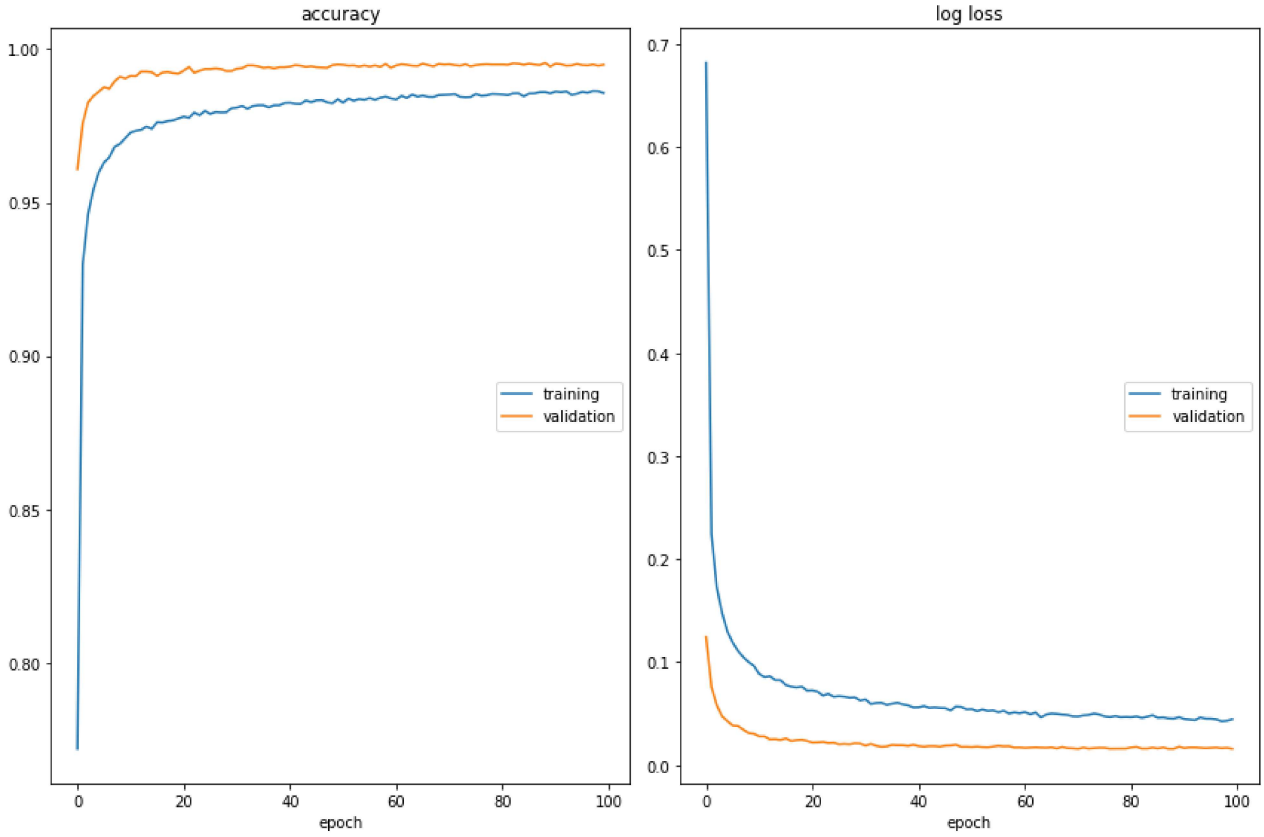
For Stochastic Gradient Descent (SGD) and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU
```

```
class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.SGD(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))
```

```
    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                 (min:    0.772, max:    0.986, cur:    0.986)
        validation               (min:    0.961, max:    0.996, cur:    0.995)
log loss
        training                 (min:    0.043, max:    0.682, cur:    0.045)
        validation               (min:    0.016, max:    0.124, cur:    0.016)
Accuracy: 0.9949 (test), 0.9857 (train)
```

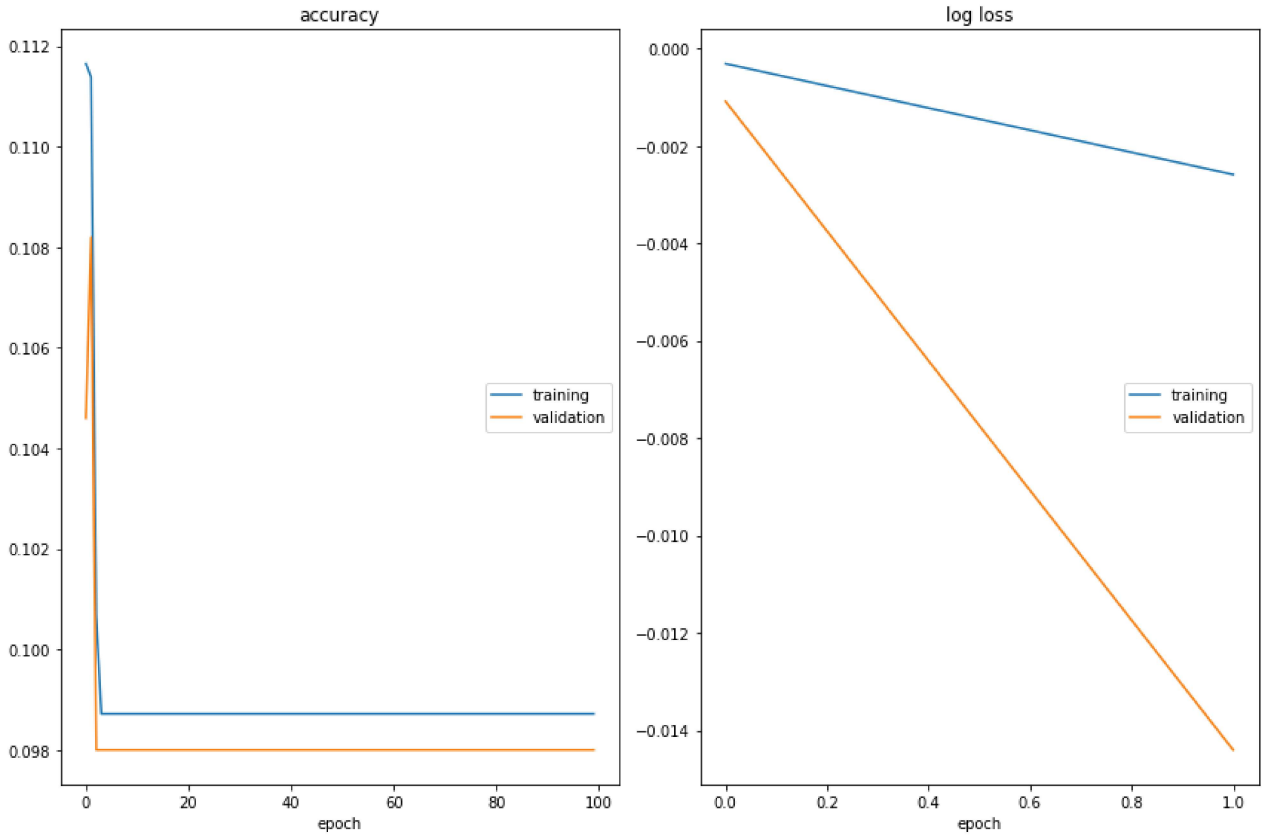
For Stochastic Gradient Descent (SGD) and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses
```

```
device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.SGD(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
```

```
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                 (min:    0.099, max:    0.112, cur:    0.099)
        validation               (min:    0.098, max:    0.108, cur:    0.098)
log loss
        training                 (min:   -0.003, max:   -0.000, cur:      nan)
        validation               (min:   -0.014, max:   -0.001, cur:      nan)
Accuracy: 0.0980 (test), 0.0987 (train)
```

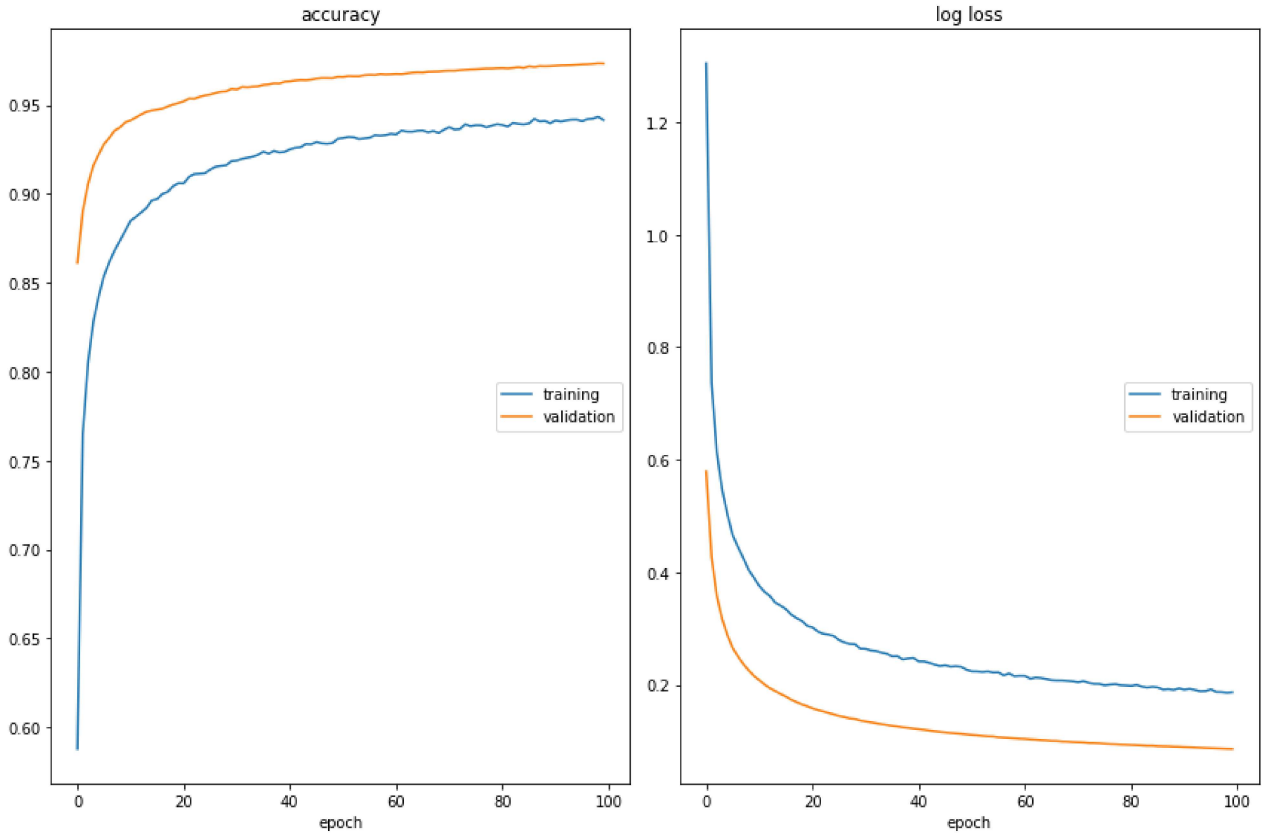
For Adagrad and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
```

```
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.Adagrad(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
```

```
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



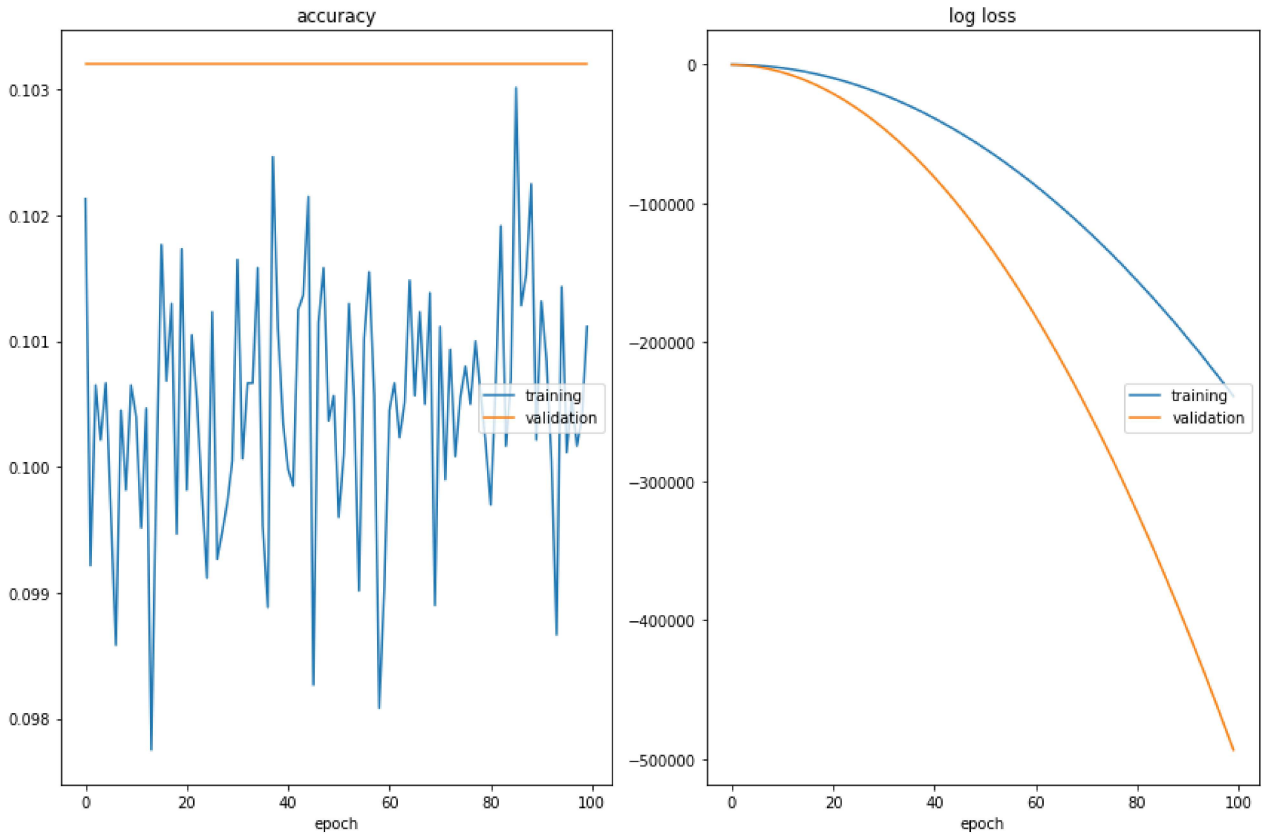

```
accuracy
        training                (min:    0.588, max:    0.943, cur:    0.942)
        validation              (min:    0.861, max:    0.974, cur:    0.973)
log loss
        training                (min:    0.186, max:    1.304, cur:    0.187)
        validation              (min:    0.086, max:    0.579, cur:    0.086)
Accuracy: 0.9734 (test), 0.9416 (train)
```

For Adagrad and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.Adagrad(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()
```

```
            # Update the parameters.
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        # Compute the average loss and accuracy.
        train_loss /= len(train_loader.dataset)
        train_correct /= float(len(train_loader.dataset))

        # Evaluate the model on the test set.
        test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

        # Visualize the loss and accuracy values.
        liveloss.update({
            'log loss': train_loss,
            'val_log loss': test_loss,
            'accuracy': train_correct,
            'val_accuracy': test_correct,
        })
        liveloss.draw()

    print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                (min:    0.098, max:    0.103, cur:    0.101)
        validation              (min:    0.103, max:    0.103, cur:    0.103)
log loss
        training                (min: -238921.400, max:   -6.397, cur: -238921.400)
        validation              (min: -493492.724, max:  -40.992, cur: -493492.724)
Accuracy: 0.1032 (test), 0.1011 (train)
```

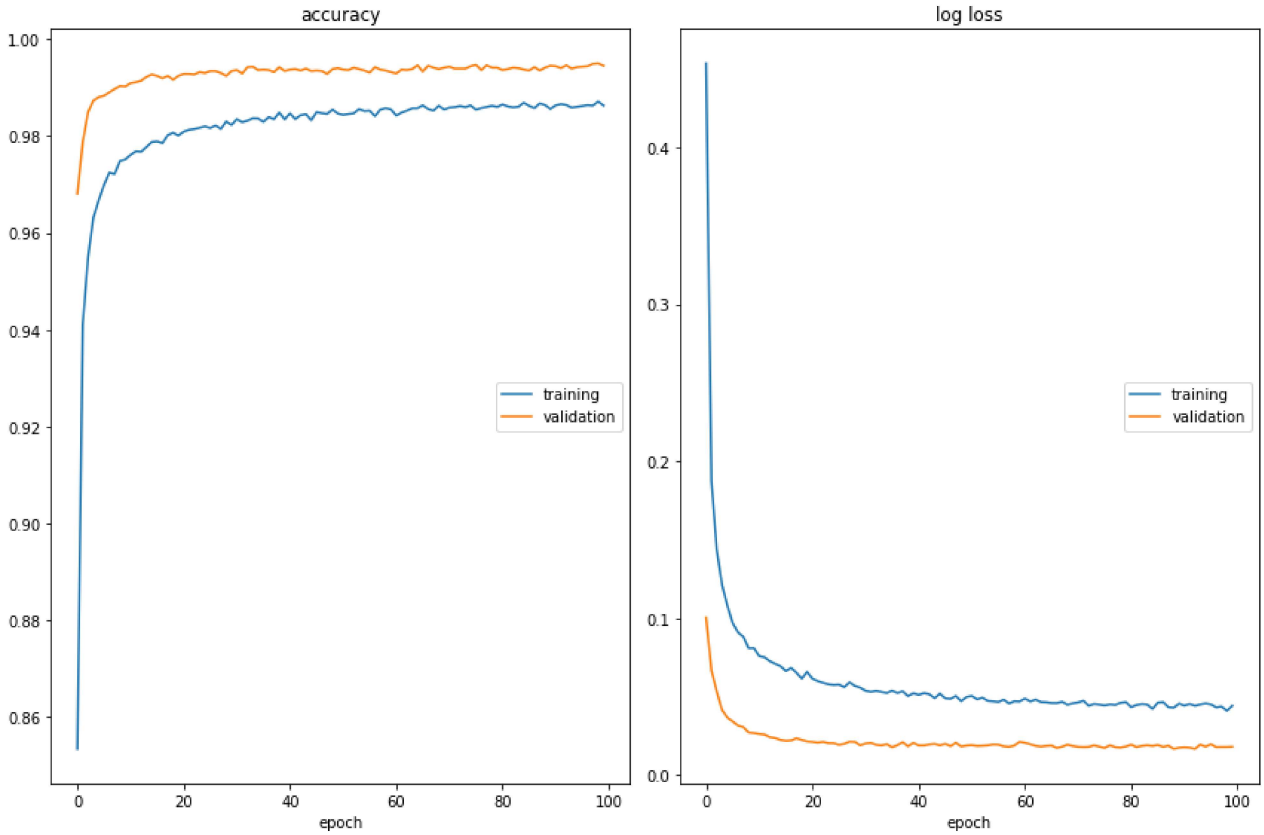
For RMSPROP and Multi-Class Cross-Entropy

Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.RMSprop(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()
```

```
            # Compute the loss value.
            loss = loss_fn(y_pred, y)
            train_loss += loss.item()

            # Update the parameters.
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        # Compute the average loss and accuracy.
        train_loss /= len(train_loader.dataset)
        train_correct /= float(len(train_loader.dataset))

        # Evaluate the model on the test set.
        test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

        # Visualize the loss and accuracy values.
        liveloss.update({
            'log loss': train_loss,
            'val_log loss': test_loss,
            'accuracy': train_correct,
            'val_accuracy': test_correct,
        })
        liveloss.draw()

    print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```



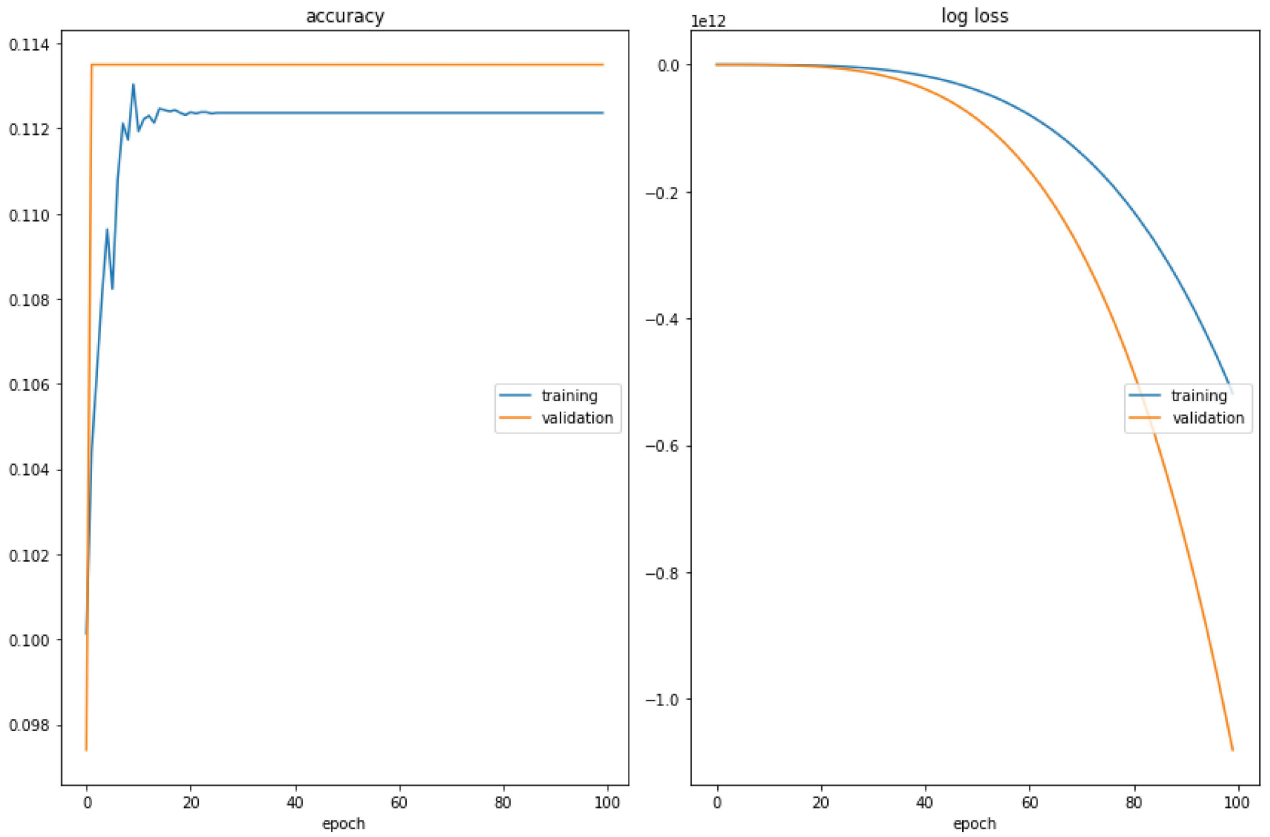

```
accuracy
        training                (min:    0.853, max:    0.987, cur:    0.986)
        validation              (min:    0.968, max:    0.995, cur:    0.995)
log loss
        training                (min:    0.041, max:    0.454, cur:    0.044)
        validation              (min:    0.017, max:    0.100, cur:    0.018)
Accuracy: 0.9945 (test), 0.9863 (train)
```

For RMSprop and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.RMSprop(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
```

```
            train_correct += (predicted == y).sum().item()

            # Compute the loss value.
            loss = loss_fn(y_pred, y)
            train_loss += loss.item()

            # Update the parameters.
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        # Compute the average loss and accuracy.
        train_loss /= len(train_loader.dataset)
        train_correct /= float(len(train_loader.dataset))

        # Evaluate the model on the test set.
        test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

        # Visualize the loss and accuracy values.
        liveloss.update({
            'log loss': train_loss,
            'val_log loss': test_loss,
            'accuracy': train_correct,
            'val_accuracy': test_correct,
        })
        liveloss.draw()

    print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                 (min:    0.100, max:    0.113, cur:    0.112)
        validation               (min:    0.097, max:    0.114, cur:    0.114)
log loss
        training                 (min: -518730874215.902, max: -68505.597, cur: -5187308
```

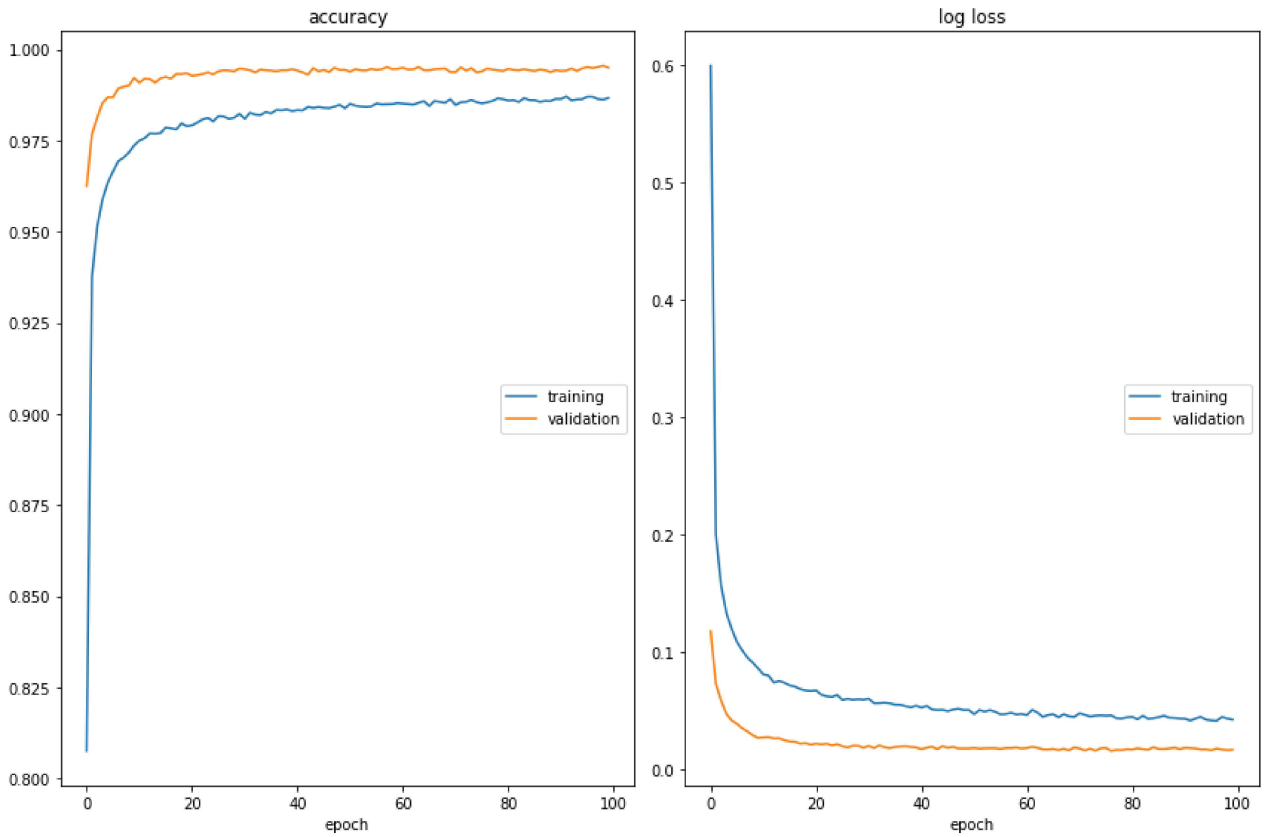
```
74215.902)
        validation             (min: -1080895272386.560, max: -480433.920, cur: -10808
95272386.560)
Accuracy: 0.1135 (test), 0.1124 (train)
```

For Adam and Multi-Class Cross-Entropy Loss

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.CrossEntropyLoss(size_average=False)
optimizer = optim.Adam(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0

    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
```

```
            x, y = x.to(device), y.to(device)
            y_pred = model(x)
            _, predicted = torch.max(y_pred.data, 1)
            train_correct += (predicted == y).sum().item()

            # Compute the loss value.
            loss = loss_fn(y_pred, y)
            train_loss += loss.item()

            # Update the parameters.
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        # Compute the average loss and accuracy.
        train_loss /= len(train_loader.dataset)
        train_correct /= float(len(train_loader.dataset))

        # Evaluate the model on the test set.
        test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

        # Visualize the loss and accuracy values.
        liveloss.update({
            'log loss': train_loss,
            'val_log loss': test_loss,
            'accuracy': train_correct,
            'val_accuracy': test_correct,
        })
        liveloss.draw()

    print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```




```
accuracy
        training                 (min:    0.808, max:    0.987, cur:    0.987)
```

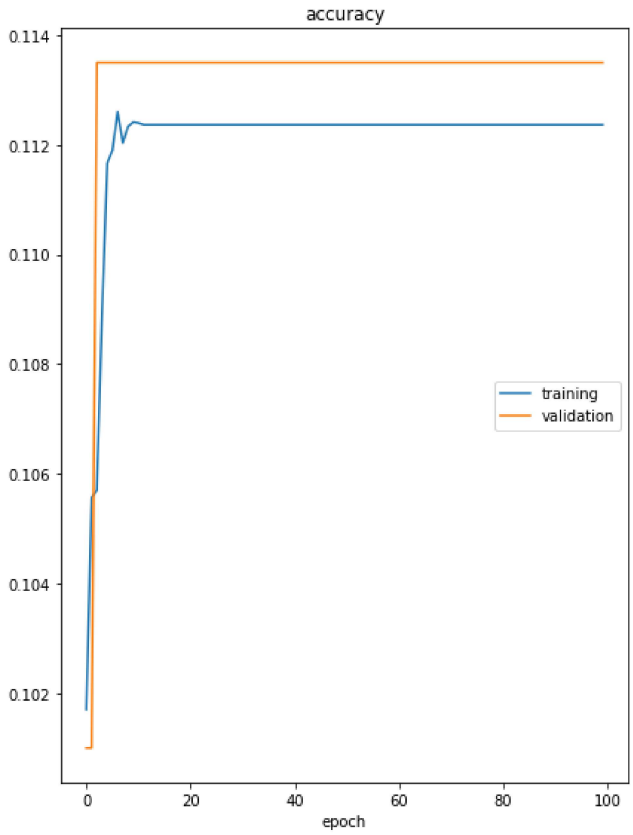
```
	validation             (min:    0.963, max:    0.996, cur:    0.995)
log loss
	training               (min:    0.041, max:    0.600, cur:    0.042)
	validation             (min:    0.015, max:    0.117, cur:    0.016)
Accuracy: 0.9950 (test), 0.9867 (train)
```

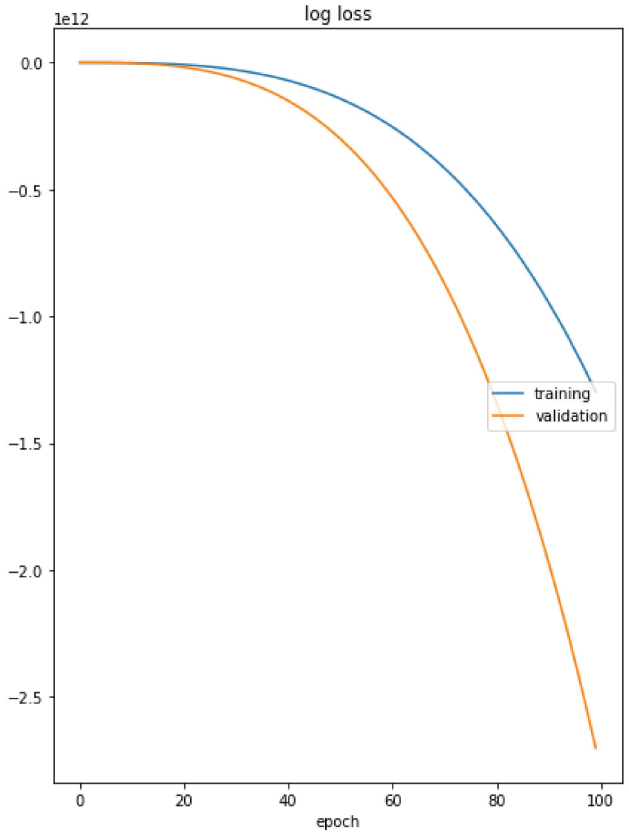
For Adam and Negative Log-Likelihood Loss Function

In [ ]:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
import numpy as np
from livelossplot import PlotLosses

device = torch.device("cpu") # Uncomment this to run on CPU
#device = torch.device("cuda:0") # Uncomment this to run on GPU

class Flatten(torch.nn.Module):
    def __init__(self):
        super(Flatten, self).__init__()

    def forward(self, x):
        return x.view(-1, 512)

model = torch.nn.Sequential(
    torch.nn.Conv2d(1, 16, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Conv2d(16, 32, (5, 5)),
    torch.nn.MaxPool2d(2),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    Flatten(),
    torch.nn.Linear(512, 256),
    torch.nn.ReLU(),
    torch.nn.Dropout(),
    torch.nn.Linear(256, 10),
)
print(model)
model.to(device)

data = np.load('mnist.npz')
train_set = create_dataset(data['train_x'], data['train_y'])
test_set = create_dataset(data['test_x'], data['test_y'])
train_loader = DataLoader(train_set, batch_size=256, shuffle=True)
test_loader = DataLoader(test_set, batch_size=128)

loss_fn = nn.NLLLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

liveloss = PlotLosses()
for t in range(100):
    train_loss = 0.
    train_correct = 0
```

```
    # Training loop for mini-batches
    for batch_idx, (x, y) in enumerate(train_loader):
        # Make predictions with the current parameters.
        x, y = x.to(device), y.to(device)
        y_pred = model(x)
        _, predicted = torch.max(y_pred.data, 1)
        train_correct += (predicted == y).sum().item()

        # Compute the loss value.
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # Update the parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    # Compute the average loss and accuracy.
    train_loss /= len(train_loader.dataset)
    train_correct /= float(len(train_loader.dataset))

    # Evaluate the model on the test set.
    test_loss, test_correct = test_model(model, loss_fn, test_loader, device)

    # Visualize the loss and accuracy values.
    liveloss.update({
        'log loss': train_loss,
        'val_log loss': test_loss,
        'accuracy': train_correct,
        'val_accuracy': test_correct,
    })
    liveloss.draw()

print('Accuracy: {:.4f} (test), {:.4f} (train)'.format(test_correct, train_correct))
```






```
accuracy
        training                 (min:    0.102, max:    0.113, cur:    0.112)
        validation               (min:    0.101, max:    0.114, cur:    0.114)
log loss
        training                 (min: -1298036947034.658, max: -10999.907, cur: -129803
6947034.658)
        validation               (min: -2701167147404.493, max: -136078.734, cur: -27011
67147404.493)
Accuracy: 0.1135 (test), 0.1124 (train)
```

In [ ]:

Comparison table for ANN using differents Optimizers and Loss Function

Optimizer	Loss Function	Training Accuracy	Testing Accuracy
Stochastic Gradient Descent (SGD)	Multi-Class Cross-Entropy Loss	0.1124	0.1135
Stochastic Gradient Descent (SGD)	Negative Log-Likelihood Loss Function	0.0987	0.0980
Adagrad	Multi-Class Cross-Entropy Loss	0.9416	0.9734
Adagrad	Negative Log-Likelihood Loss Function	0.1011	0.1032
RMSPROP	Multi-Class Cross-Entropy Loss	0.9863	0.9945
RMSPROP	Negative Log-Likelihood Loss Function	0.1124	0.1135
Adam	Multi-Class Cross-Entropy Loss	0.9867	0.9950
Adam	Negative Log-Likelihood Loss Function	0.1124	0.1135

We got better results by using RMSPROP & Multi-Class Cross-Entropy Loss Function and Adam & Multi-Class Cross-Entropy Loss Function in CNN.