TMVA Implementation

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2020.02.04

Summary & Overview

- We decided to try TMVA in C and Python
- I implemented MNIST classifier in kDL/kPyKeras for exercise.
- Today, I'll explain how to implement DL with TMVA.
  - All codes are available on my github.
  - https://github.com/physmlee/DLStudy

List of Codes

- MNISTtoROOT.py
- MNISTTMVA.py
- MNISTTMVA.C
- MNISTTMVAApplication.C
- MNISTTMVAApplication.py
- MNIST_PyMVA_CNN.py
- MNIST_TMVA_CNN.C

MNISTtoROOT.py

```
# Load MNIST Data Set
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

Download data.
It is written in .npz format.

```
# Make Tree
nb_classes = 10
treelist = []

for i in range(nb_classes):
    treelist.append( TTree( 'train%d' %(i), 'MNIST_train%d' %(i) ) )
    treelist.append( TTree( 'test%d'  %(i), 'MNIST_test%d'  %(i) ) )
```

MNISTtoROOT.py

```
# Load MNIST Data Set
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# Make Tree
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```

Declare trees.

MNISTtoROOT.py

```
# Set Branch
imagelist = []
for tree in treelist:
    for j in range( 28 * 28 ):
        imagelist.append( np.empty( (1), dtype="float32" ) )
        tree.Branch( 'image%d' %(j), imagelist[j], 'image%d/F' %(j) )
```

Link each pixel to one branch.
There will be 784 branches.

```
# Fill Tree
for i in tqdm( range( X_train.shape[0] ), desc='Writing Training Data' ):
    for j in range( 28 * 28 ):
        imagelist[j][0] = X_train[i][j]
    treelist[ 2*y_train[i] ].Fill()

for i in tqdm( range( X_test.shape[0] ),  desc='Writing   Test   Data' ): #
    for j in range( 28 * 28 ):
        imagelist[j][0] = X_test[i][j]
    treelist[ 2*y_test[i] + 1 ].Fill()
```

MNISTtoROOT.py

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# Fill Tree
for i in tqdm( range( X_train.shape[0] ), desc='Writing Training Data' ):
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    treelist[ 2*y_test[i] + 1 ].Fill()
```

Fill in the tree.

List of Codes

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- MNISTTMVAApplication.C
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- MNIST_PyMVA_CNN.py
- MNIST_TMVA_CNN.C

Train. Today's topic.

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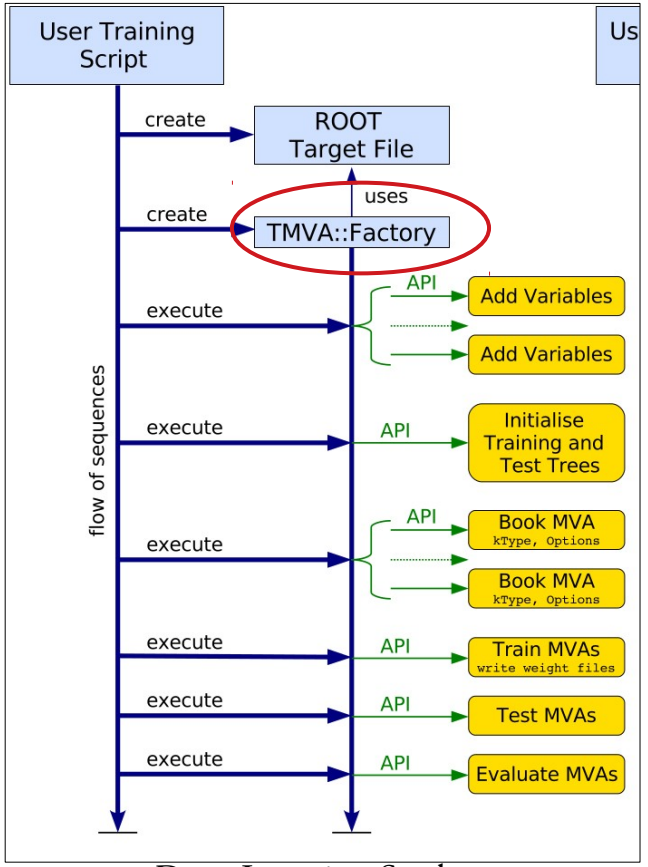
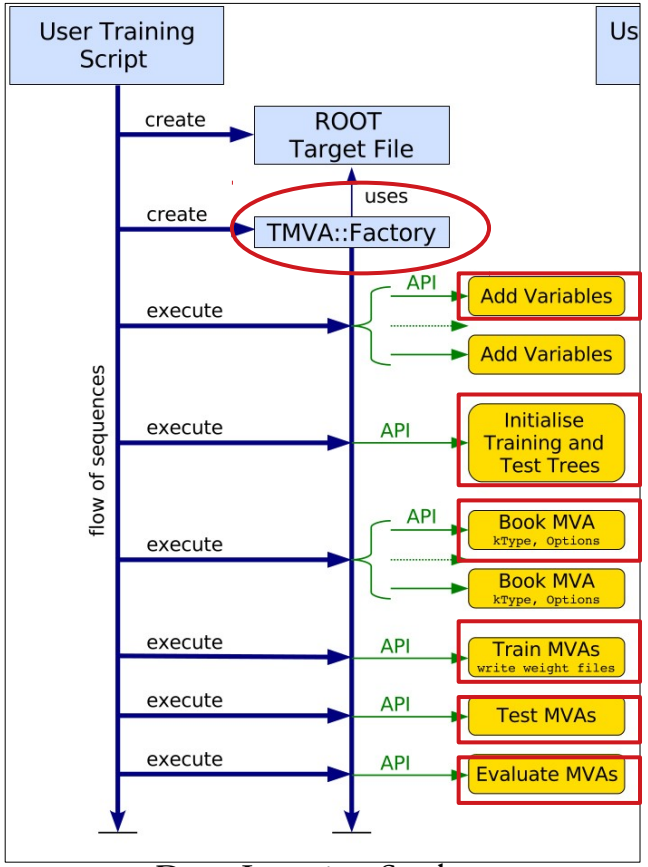
Application. Not on today.
You can find the codes in github.

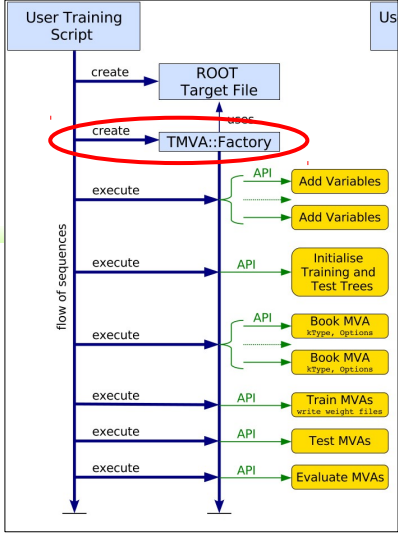
TMVA Flow Chart



TMVA Flow Chart



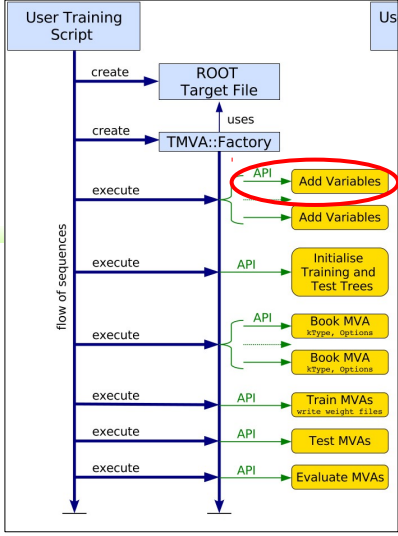
MNISTTMVA.py




```
# Setup TMVA
TMVA.Tools.Instance()
TMVA.PyMethodBase.PyInitialize()
output = TFile.Open('./data/MNISTTMVA.root', 'RECREATE')

factory = TMVA.Factory( 'TMVAClassification', output,
                        '!V:Color:DrawProgressBar:'
                        '!Silent:'
                        'Transformations=:'
                        'AnalysisType=multiclass' )
```

MNISTTMVA.py



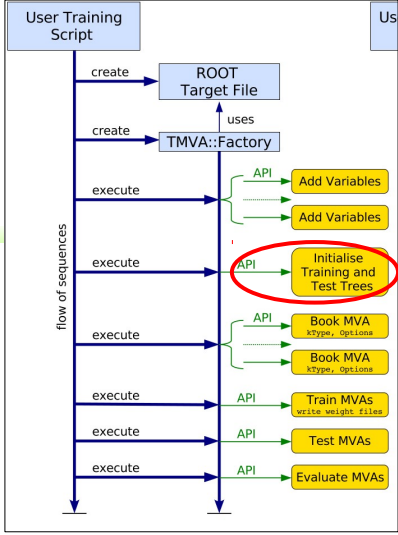

```
dataloader = TMVA.DataLoader( 'dataset' )
for branch in traintree[0].GetListOfBranches():
    dataloader.AddVariable( branch.GetName() )

for i in range( nb_classes ):
    dataloader.AddTree( traintree[i], '%d' %(i), weight, cut, TMVA.Types.kTraining )
    dataloader.AddTree( testtree[i] , '%d' %(i), weight, cut, TMVA.Types.kTesting  )

dataloader.PrepareTrainingAndTestTree(cut, '!CalcCorrelations:NormMode=None:!V')
```

Add variables

MNISTTMVA.py

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for i in range( nb_classes ):
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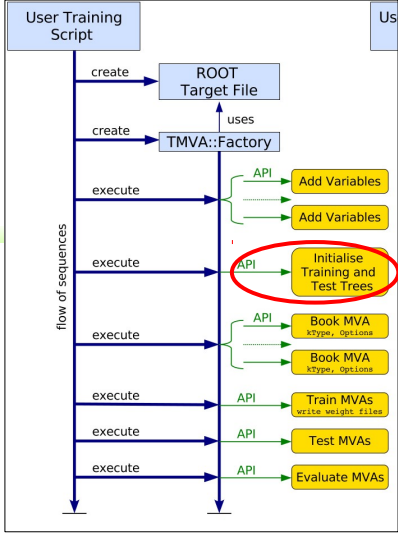
    dataloader.AddTree( testtree[i] , '%d' %(i), weight, cut, TMVA.Types.kTesting  )
```

Initialize

```
dataloader.PrepareTrainingAndTestTree(cut, '!CalcCorrelations:NormMode=None:!V')
```

MNISTTMVA.py

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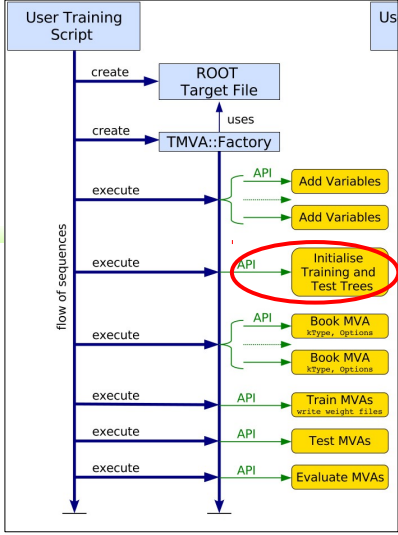
    dataloader.AddVariable( branch.GetName() )


for i in range( nb_classes ):
    dataloader.AddTree( traintree[i], '%d' %(i), weight, cut, TMVA.Types.kTraining )
    dataloader.AddTree( testtree[i] , '%d' %(i), weight, cut, TMVA.Types.kTesting  )
```

It calculates correlation matrix of input variables as default, which is time consuming!

```
dataloader.PrepareTrainingAndTestTree(cut, '!CalcCorrelations:NormMode=None:!V')
```

MNISTTMVA.py

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for branch in traintree[0].GetListOfBranches():
    dataloader.AddVariable( branch.GetName() )


for i in range( nb_classes ):
    dataloader.AddTree( traintree[i], '%d' %(i), weight, cut, TMVA.Types.kTraining )
    dataloader.AddTree( testtree[i] , '%d' %(i), weight, cut, TMVA.Types.kTesting  )
```

One can apply some normalization technique to the event numbers of each classes.

```
dataloader.PrepareTrainingAndTestTree(cut, '!CalcCorrelations:NormMode=None:!V')
```

MNISTTMVA.py

```
# Model generating start
model = Sequential()

model.add(Dense(512, input_shape=(784,)))
model.add(Activation('relu'))
model.add(Dropout(0.2))

model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.2))

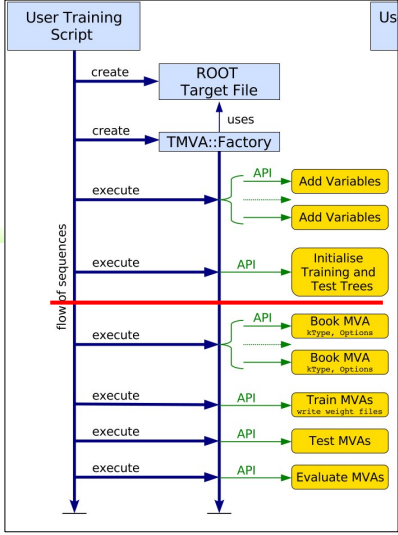
model.add(Dense(10))
model.add(Activation('softmax'))

# Compile and set loss and optimizer
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.save('PyKerasMNIST.h5')
```

1st layer. 512 neurons. RELU activation.

2nd layer. 512 neurons. RELU activation.

Final layer. 10 neurons. SOFTMAX activation.



MNISTTMVA.py

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# Model generating start
model = Sequential()

model.add(Dense(512, i
model.add(Activation('re
model.add(Dropout(0.2)

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model.add(Activation('re
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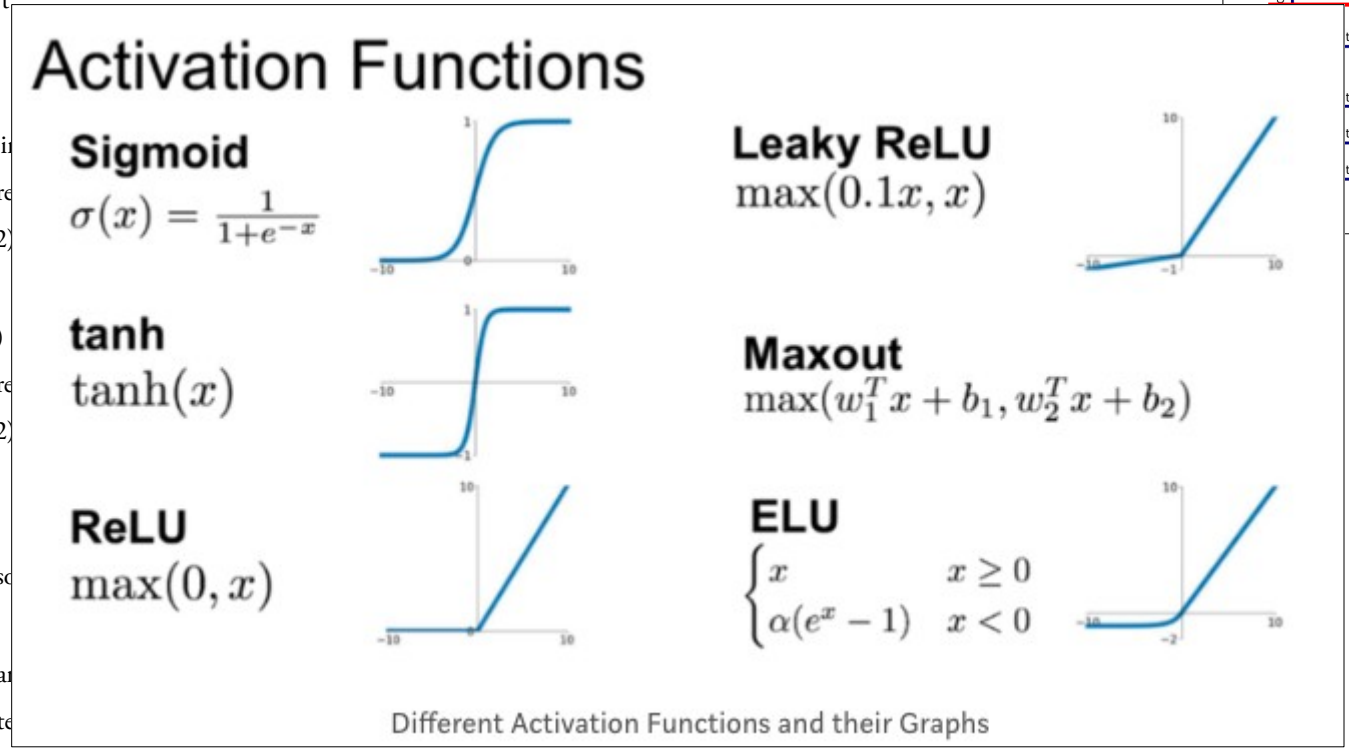
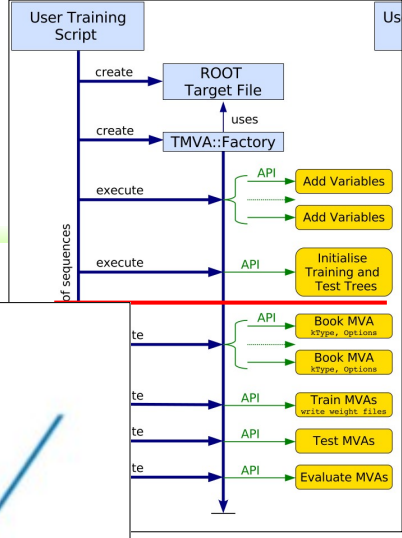
model.add(Dense(10))
model.add(Activation('so

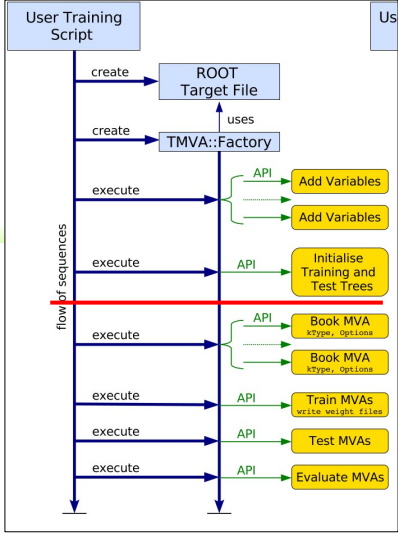
# Compile and set loss a
model.compile(loss='cate
model.save('PyKerasMNIST.h5')
```



Different Activation Functions and their Graphs



MNISTTMVA.py




```
# Model generating start
model = Sequential()

model.add(Dense(512, input_shape=(784,)))
model.add(Activation('relu'))
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model.add(Dense(512))
model.add(Activation('relu'))
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model.add(Dense(10))
model.add(Activation('softmax'))

# Compile and set loss and optimizer
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.save('PyKerasMNIST.h5')
```

Use CROSS ENTROPY loss function and ADAM optimizer.

MNISTTMVA.py

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# Model generating start
model = Sequential()

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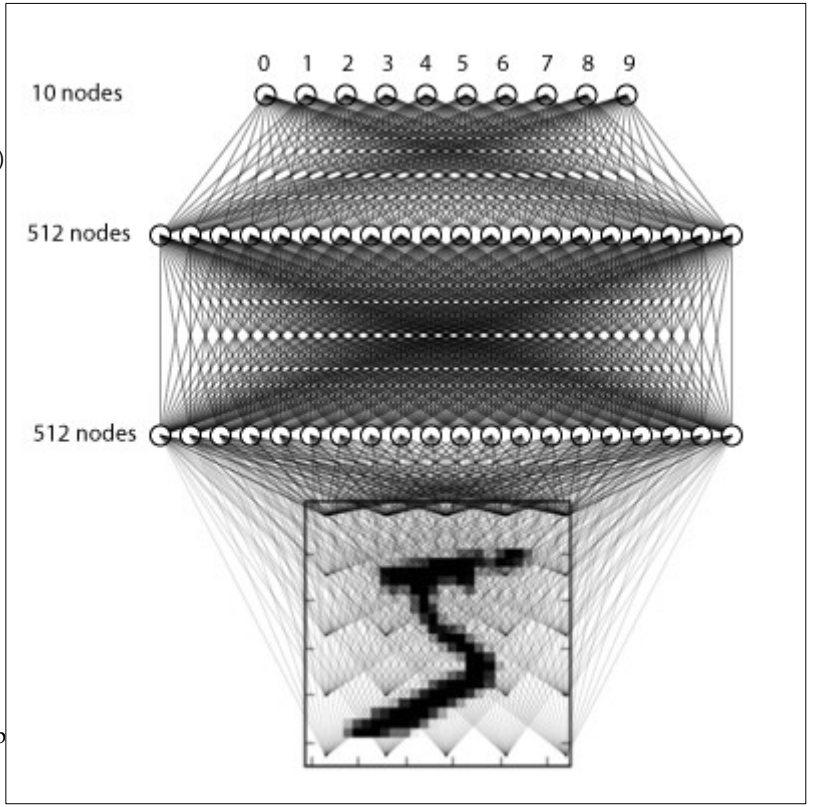
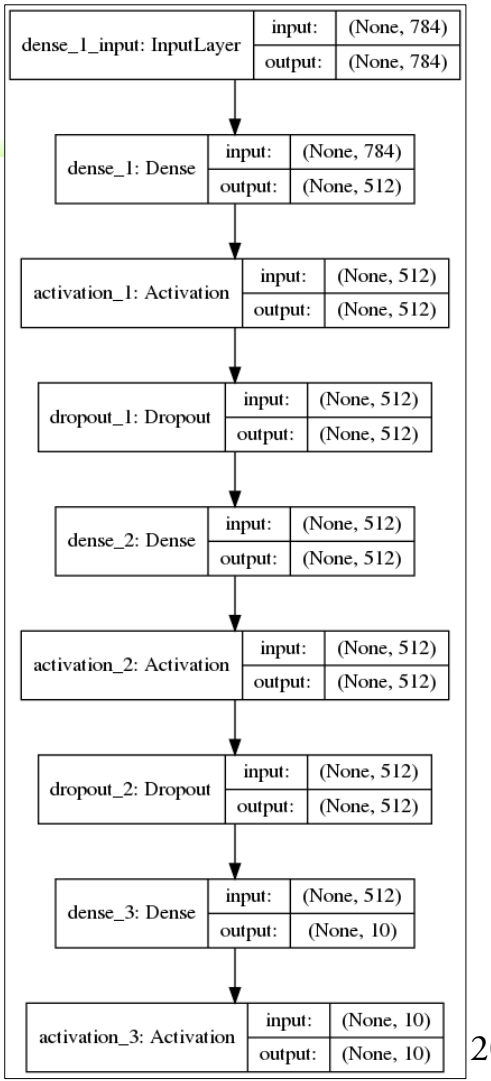
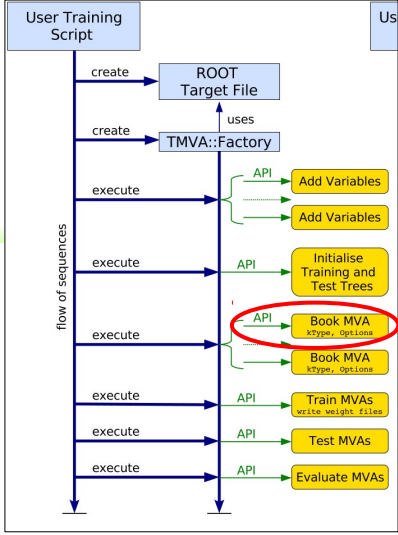




MNISTTMVA.py



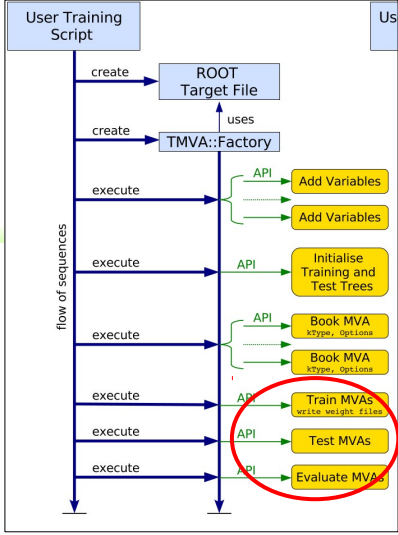

```
factory.BookMethod(dataloader, TMVA.Types.kPyKeras,
                   "PyKerasMNIST",
                   '!H:!V:VarTransform=:'
                   'FilenameModel=PyKerasMNIST.h5:'
                   'ValidationSize=1:'   # At least one data must be given to validation dataset.
                   '!SaveBestOnly:'      # Save the last result, not the best one.
                   'NumEpochs=5:'        # Train 5 times
                   'BatchSize=128')      # Calculate gradient descent using 128 samples
```

MNISTTMVA.py

factory.TrainAllMethods()

factory.TestAllMethods()

factory.EvaluateAllMethods()



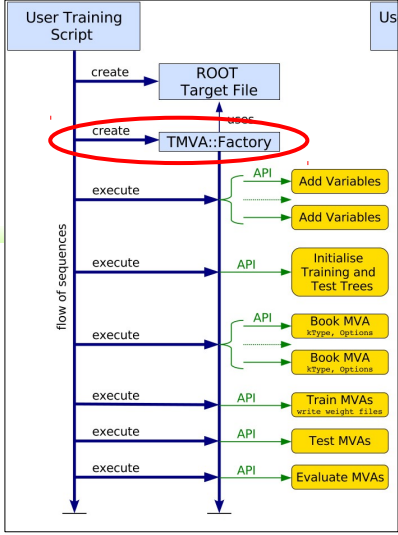
MNISTTMVA.py - Training

Epoch 1/5
59999/59999 [==============================] - **5s 84us**/step - **loss: 0.2476** - accuracy: 0.9253
Epoch 2/5
59999/59999 [==============================] - **5s 83us**/step - **loss: 0.1019** - accuracy: 0.9686
Epoch 3/5
59999/59999 [==============================] - **5s 80us**/step - **loss: 0.0729** - accuracy: 0.9772
Epoch 4/5
59999/59999 [==============================] - **5s 77us**/step - **loss: 0.0565** - accuracy: 0.9819
Epoch 5/5
59999/59999 [==============================] - **5s 78us**/step - **loss: 0.0454** - accuracy: 0.9857

MNISTTMVA.C

- It has the same structure with MNISTTMVA.py.
- Only some option form / grammar issues exists.

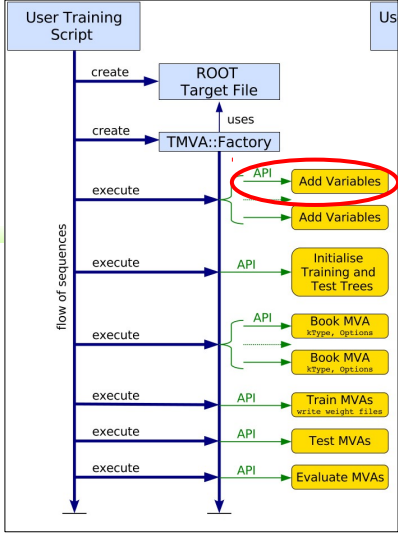
MNISTTMVA.C




```
TMVA::Tools::Instance();
TString outfileName = "./data/MNISTTMVA.root";
TFile *output = TFile::Open(outfileName, "RECREATE");

TMVA::Factory *factory = new TMVA::Factory("TMVAMulticlass", output,
   "!V:Color:DrawProgressBar:!Silent:"
   "Transformations=:"            // No preprocessing for input variable
   "AnalysisType=multiclass"); // It is a multiclass classification example
```

MNISTTMVA.C

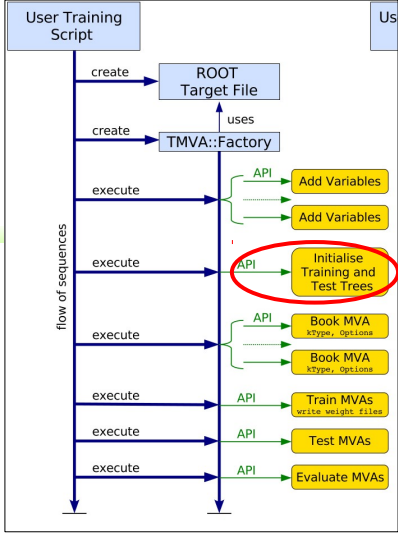



```
TMVA::DataLoader *dataloader = new TMVA::DataLoader("dataset");
for (Int_t i = 0; i < pixel; i++) {
    sprintf(branchname, "image%d", i);
    dataloader->AddVariable(branchname, 'F'); // register all the 784 pixels as variable
}

for (Int_t i = 0; i < nb_classes; i++) {
    sprintf(classname, "%d", i);
    dataloader->AddTree(traintree[i], classname, weight, cut, TMVA::Types::kTraining); // Add trees specifying their purpose (Training)
    dataloader->AddTree(testtree[i] , classname, weight, cut, TMVA::Types::kTesting ); // Add trees specifying their purpose (Testing)
}

dataloader→PrepareTrainingAndTestTree(cut, "!CalcCorrelations:NormMode=None:!V");
```

MNISTTMVA.C

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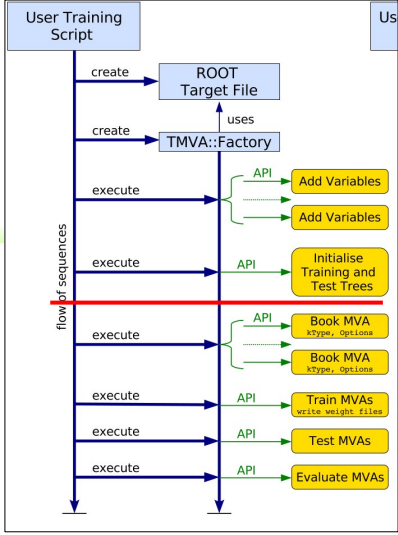
```

MNISTTMVA.C

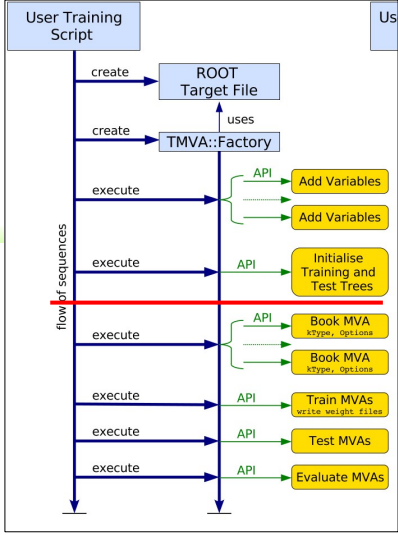



```
// Model generating start
TString layoutString("Layout=RELU|512,"    // First hidden layer with 512 neurons, RELU activation function
                     "RELU|512,"           // Second hidden layer with 512 neurons, RELU activation function
                     "LINEAR|10");         // Final output layer to 10 categories
TString training("Repetitions=1,Regularization=None,Multithreading=True,"
                 "Optimizer=ADAM,LearningRate=0.001,"    // Use Adam optimizer with learning rate 0.001
                 "MaxEpochs=5,BatchSize=128,"            // Batch size 128 and train 5 times
                 "ConvergenceSteps=100,"                 // Do not use Convergence check
                 "TestRepetitions=1,"                    // Show validation result for every epochs
                 "DropConfig=0.2+0.2+0");                // Set dropout. 0.2 for the first and second layers, and 0 for the final layer.

TString nnOptions("!H:!V:VarTransform=:ErrorStrategy=MUTUALEXCLUSIVE:ValidationSize=128");

TString trainingStrategyString("TrainingStrategy=");       trainingStrategyString += training;
nnOptions.Append(":");       nnOptions.Append(layoutString);
nnOptions.Append(":");       nnOptions.Append(trainingStrategyString);
```

MNISTTMVA.C

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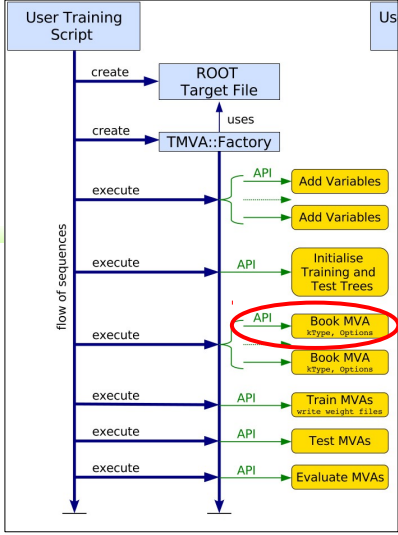
                 "Optimizer=ADAM,LearningRate=0.001,"    // Use Adam optimizer with learning rate 0.001
                 "MaxEpochs=5,BatchSize=128,"            // Batch size 128 and train 5 times
                 "ConvergenceSteps=100,"                 // Do not use Convergence check
                 "TestRepetitions=1,"                    // Show validation result for every epochs
                 "DropConfig=0.2+0.2+0");                // Set dropout. 0.2 for the first and second layers, and 0 for the final layer.

TString nnOptions("!H:!V:VarTransform=:ErrorStrategy=MUTUALEXCLUSIVE:ValidationSize=128");
```

MUTUALEXCLUSIVE=SOFTMAX * CROSS ENTROPY

```
TString trainingStrategyString("TrainingStrategy=");       trainingStrategyString += training;
nnOptions.Append(":");       nnOptions.Append(layoutString);
nnOptions.Append(":");       nnOptions.Append(trainingStrategyString);
```

MNISTTMVA.C



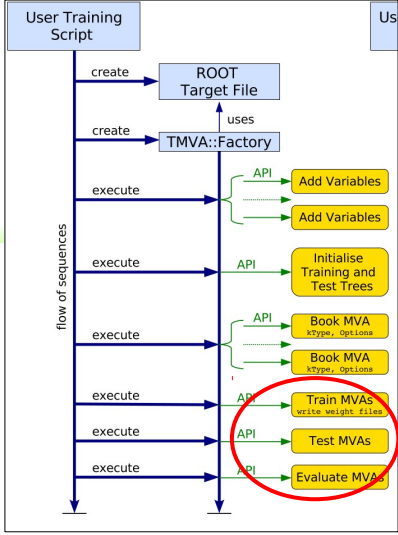

```
factory->BookMethod(dataloader, TMVA::Types::kDL, "MNISTTMVA", nnOptions);


factory->TrainAllMethods();

factory->TestAllMethods();

factory->EvaluateAllMethods();
```

MNISTTMVA.C

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factory->BookMethod(dataloader, TMVA::Types::kDL, "MNISTTMVA", nnOptions);
```

```
factory->TrainAllMethods();
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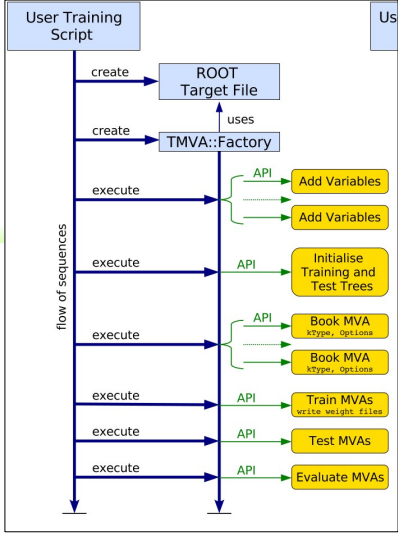
MNISTTMVA.C



We should use kDL method. It has much various functions than kDNN.
Unfortunately, description for kDL is not in the UsersGuide.
We should refer to its source code in the link below;
https://root.cern.ch/doc/master/MethodDL_8cxx_source.html#l00161

```
factory->BookMethod(dataloader, TMVA::Types::kDL, "MNISTTMVA", nnOptions);


factory->TrainAllMethods();

factory->TestAllMethods();

factory->EvaluateAllMethods();
```

MNISTTMVA.C - Training

```
                : *****   Deep Learning Network *****
DEEP NEURAL NETWORK:   Depth = 3  Input = ( 1, 1, 784 )  Batch size = 128  Loss function = S
Layer 0   DENSE Layer:   ( Input =   784 , Width =   512 ) Output = (  1 ,   128 ,   512 )    Activation Function = Relu  Dropout prob. = 0.8
Layer 1   DENSE Layer:   ( Input =   512 , Width =   512 ) Output = (  1 ,   128 ,   512 )    Activation Function = Relu  Dropout prob. = 0.8
Layer 2   DENSE Layer:   ( Input =   512 , Width =    10 ) Output = (  1 ,   128 ,    10 )    Activation Function = Identity
                : Using 59872 events for training and 128 for testing
                : Training phase 1 of 1:  Optimizer ADAM Learning rate = 0.001 regularization 0 minimum error = 2.31272
                : ------------------------------------------------------------
                :     Epoch |   Train Err.   Val. Err.  t(s)/epoch   t(s)/Loss   nEvents/s Conv. Steps
                : ------------------------------------------------------------
                :         1 Minimum Test error found - save the configuration
                :         1 |    0.106914  0.0973637    15.2004    3.28711    5017.61         0
                :         2 Minimum Test error found - save the configuration
                :         2 |   0.0731581  0.0519007    16.2432    3.58274    4721.49         0
                :         3 |   0.0588579  0.0568269     18.624    4.14863     4129.5         1
                :         4 Minimum Test error found - save the configuration
                :         4 |   0.0481715  0.0447528    17.3988    3.14962    4195.04         0
                :         5 |   0.0418479  0.0455728    17.7728    3.76165    4266.32         1
                :
                : Elapsed time for training with 60000 events: 85.3 sec
```

Comparison (DNN) - kPyKeras vs kDL

- The accuracy is consistent as they use exactly the same neural network architecture.
  - Can be checked using '*Application.C/py' macros.
- Training time is quite different.
  - kDL : t / epoch = 17 s
  - kPyKeras : t / epoch = 5 s

Comparison (DNN) - kPyKeras vs kDL

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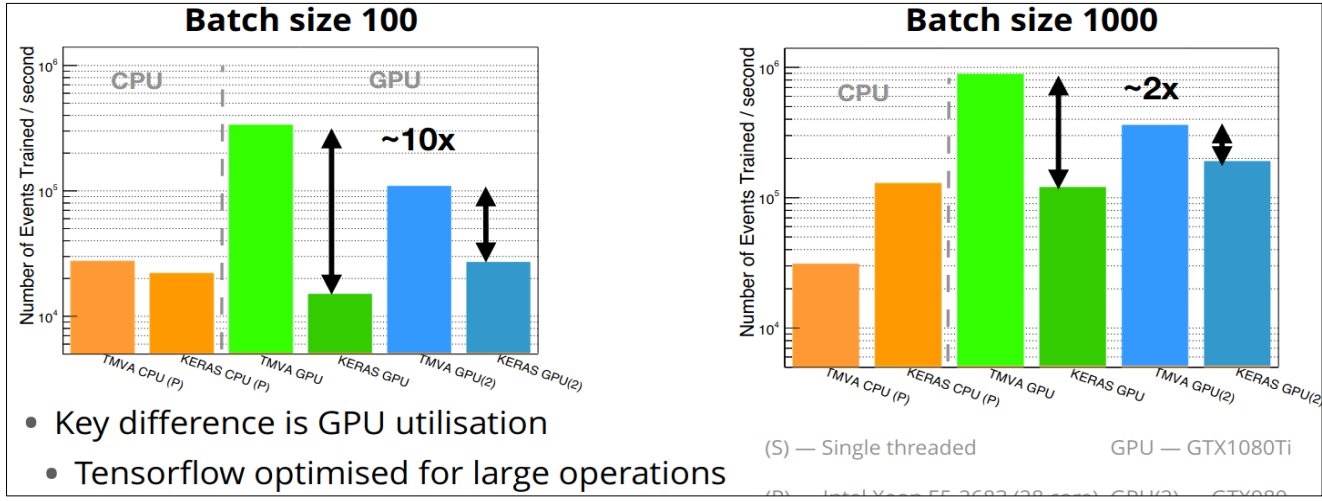
  - Can be checked using '*Application.C/py' macros.
- Training time is quite different.
  - kDL : t / epoch = 17 s
  - kPyKeras : t / epoch = 5 s → 3.4 times faster!

Comparison (DNN) - kPyKeras vs kDL

- TMVA group claims that TMVA is faster than Keras for light network.



https://indico.cern.ch/event/587955/contributions/2937501/attachments/1678682/2705216/tmva-chep2018.pdf

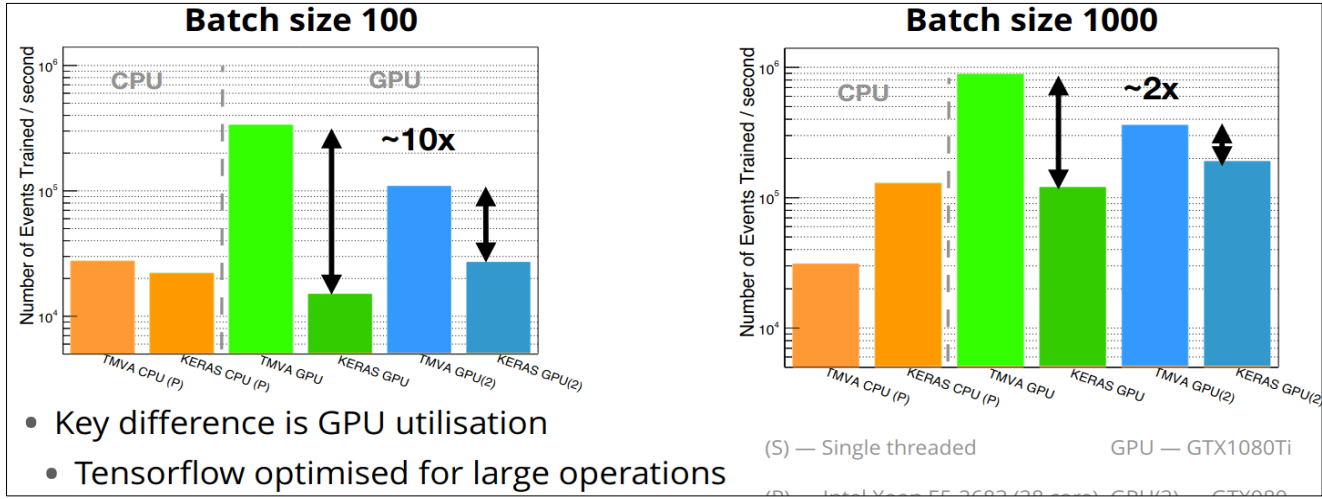
Comparison (DNN) - kPyKeras vs kDL

- TMVA group claims that TMVA is faster than Keras for light network.
- TMVA seems slower than Keras for heavy net.

<Training time>

kDL : t / epoch = 17 s

kPyKeras : t / epoch = 5 s



https://indico.cern.ch/event/587955/contributions/2937501/attachments/1678682/2705216/tmva-chep2018.pdf

List of Codes

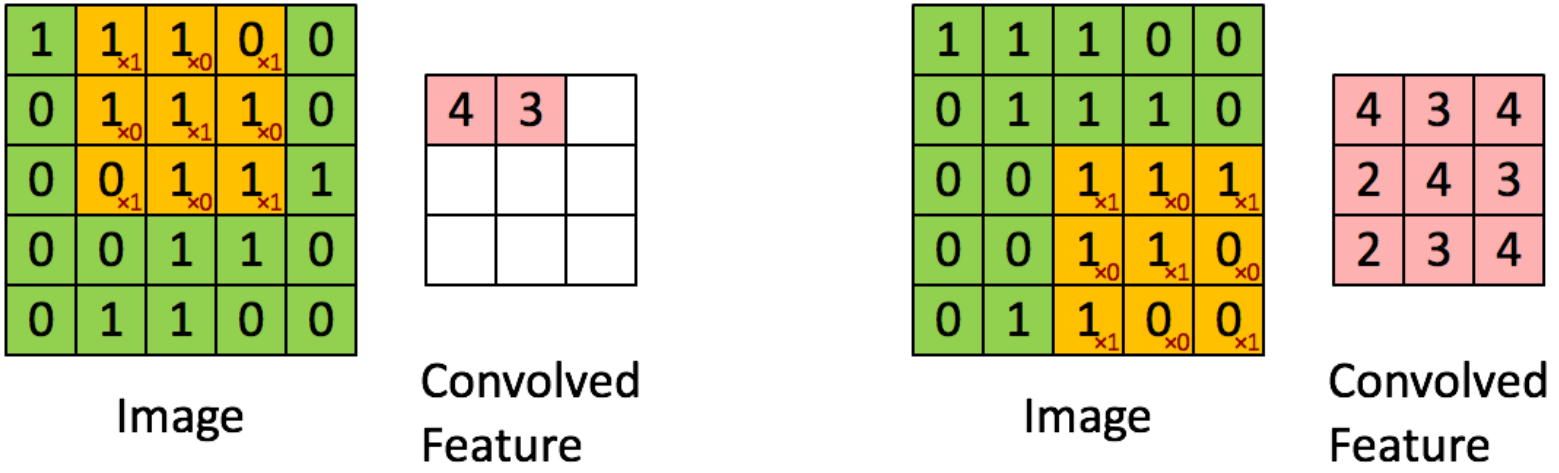
- ~~MNISTtoROOT.py~~
- ~~MNISTTMVA.py~~
- ~~MNISTTMVA.C~~
- ~~MNISTTMVAApplication.C~~
- ~~MNISTTMVAApplication.py~~

Not today's topic

- MNIST_PyMVA_CNN.py
- MNIST_TMVA_CNN.C

Introduction to CNN

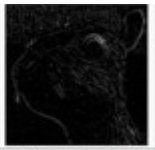
- Convolution applies **kernels** (**filters**) that traverse through each image and generate **feature maps**.



https://colab.research.google.com/github/AviatorMoser/keras-mnist-tutorial/blob/master/MNIST%20in%20Keras.ipynb#scrollTo=mBSu1bGzafJ3

Introduction to CNN

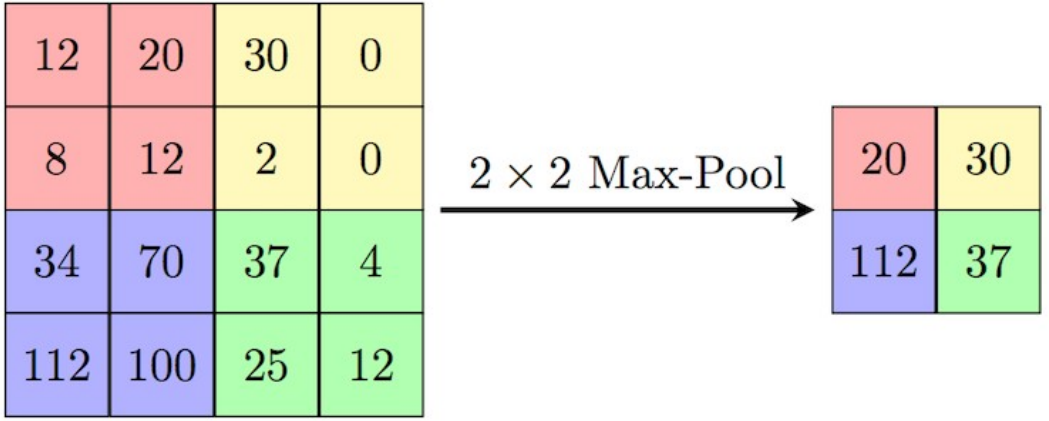
- Convolution was often used in photo-editing software.

Edge detection	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

https://colab.research.google.com/github/AviatorMoser/keras-mnist-tutorial/blob/master/MNIST%20in%20Keras.ipynb#scrollTo=mBSu1bGzafJ3

Introduction to CNN

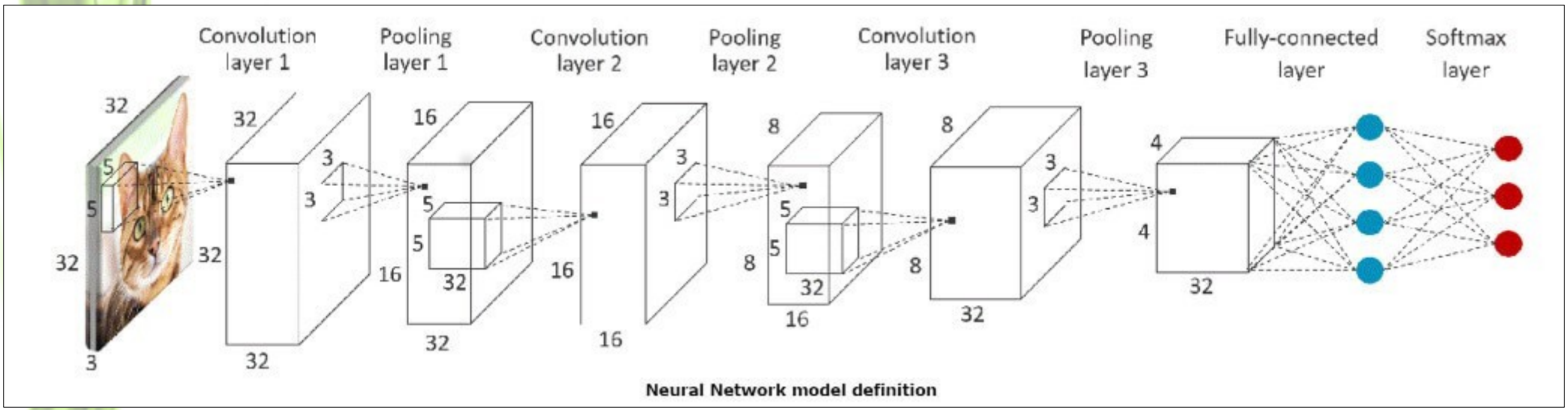
- Max Pooling is applied to discard non-highlighted elements and to cut down on the computational cost.



https://colab.research.google.com/github/AviatorMoser/keras-mnist-tutorial/blob/master/MNIST%20in%20Keras.ipynb#scrollTo=mBSu1bGzafJ3

Introduction to CNN

- Example CNN structure is like this.
  - This is for CIFAR-10. Ours is not this one.

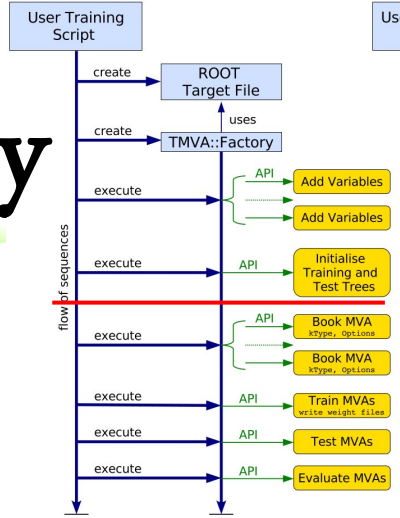


Neural Network model definition

https://community.arm.com/developer/ip-products/processors/b/processors-ip-blog/posts/deploying-convolutional-neural-network-on-cortex-m-with-cmsis-nn

MNIST_PyMVA_CNN.py

- Flow of the code is just the same as before.
- The only change is in ‘model generating’.



MNIST_PyMVA_CNN.py

```
model = Sequential()                        # Linear stacking of layers

# Convolution Layer 1
model.add(Reshape((28,28, 1), input_shape=(784,)))
model.add(Conv2D(32, (3, 3))) # 32 different 3x3 kernels -- so 32 feature maps
model.add(BatchNormalization(axis=-1))          # normalize each feature map before activation
convLayer01 = Activation('relu')                # activation
model.add(convLayer01)

# Convolution Layer 2
model.add(Conv2D(32, (3, 3)))                   # 32 different 3x3 kernels -- so 32 feature maps
model.add(BatchNormalization(axis=-1))          # normalize each feature map before activation
model.add(Activation('relu'))                   # activation
convLayer02 = MaxPooling2D(pool_size=(2,2))     # Pool the max values over a 2x2 kernel
model.add(convLayer02)

# Convolution Layer 3
model.add(Conv2D(64,(3, 3)))                    # 64 different 3x3 kernels -- so 64 feature maps
model.add(BatchNormalization(axis=-1))          # normalize each feature map before activation
convLayer03 = Activation('relu')                # activation
model.add(convLayer03)
```

```
# Convolution Layer 4
model.add(Conv2D(64, (3, 3)))                   # 64 different 3x3 kernels -- so 64 feature maps
model.add(BatchNormalization(axis=-1))          # normalize each feature map before activation
model.add(Activation('relu'))                   # activation
convLayer04 = MaxPooling2D(pool_size=(2,2))     # Pool the max values over a 2x2 kernel
model.add(convLayer04)
model.add(Flatten())                # Flatten final 4x4x64 output matrix into a 1024-length vector

# Fully Connected Layer 5
model.add(Dense(512))                           # 512 FCN nodes
model.add(BatchNormalization())                 # normalization
model.add(Activation('relu'))                   # activation

# Fully Connected Layer 6
model.add(Dropout(0.2))                         # 20% dropout of randomly selected nodes
model.add(Dense(10))                            # final 10 FCN nodes
model.add(Activation('softmax'))                # softmax activation

# we'll use the same optimizer
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

model.save('MNIST_PyMVA_CNN_Model.h5')
model.summary()
```

MNIST_TMVA_CNN.C

```
/***
Reference:
https://github.com/lmoneta/tmva-tutorial/blob/master/notebooks/TMVA_CNN_Classification.C
### Book Convolutional Neural Network in TMVA
For building a CNN one needs to define
- Input Layout : number of channels (in this case = 1) | image height | image width
- Batch Layout : batch size | number of channels | image size = (height*width)

Then one add Convolutional layers and MaxPool layers.
- For Convolutional layer the option string has to be:
  - CONV | number of units | filter height | filter width | stride height | stride width | padding height | paddig width | activation function
  - note in this case we are using a filer 3x3 and padding=1 and stride=1 so we get the output dimension of the conv layer equal to the input
- For the MaxPool layer:
  - MAXPOOL | pool height | pool width | stride height | stride width

The RESHAPE layer is needed to flatten the output before the Dense layer
Note that to run the CNN is required to have CPU or GPU support
***/
```

```
// Generating Model
TString inputLayoutString("InputLayout=1|28|28");
TString batchLayoutString("BatchLayout=128|1|784");

TString convLayer01("CONV|32|3|3|1|1|0|0|RELU");

TString convLayer02("CONV|32|3|3|1|1|0|0|RELU");
TString maxPooling02("MAXPOOL|2|2|2|2");

TString convLayer03("CONV|64|3|3|1|1|0|0|RELU");

TString convLayer04("CONV|64|3|3|1|1|0|0|RELU");
TString maxPooling04("MAXPOOL|2|2|2|2");
TString flatten04("RESHAPE|FLAT");

TString fullyConnLayer05("DENSE|512|RELU");
TString fullyConnLayer06("DENSE|10|LINEAR"); // SOFTMAX is included in the loss function.

TString layoutString("Layout=");
layoutString += "," + convLayer01;
layoutString += "," + convLayer02 + "," + maxPooling02;
layoutString += "," + convLayer03;
layoutString += "," + convLayer04 + "," + maxPooling04 + "," + flatten04;
layoutString += "," + fullyConnLayer05;
layoutString += "," + fullyConnLayer06;
```

MNIST_TMVA_CNN.C

```
/***
   Reference:
https://github.com/lmoneta/tmva-tutorial/blob/master/notebooks/TMVA_CNN_Classification.C
    ### Book Convolutional Neural Network in TMVA
   For building a CNN one needs to define
   -  Input Layout :  number of channels (in this case = 1)  | image height | image width
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    - For the MaxPool layer:
      - MAXPOOL  | pool height | pool width | stride height | stride width

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   Note that to run the CNN is required to have CPU  or GPU support
 ***/
```

```
// Generating Model
TString inputLayoutString("InputLayout=1|28|28");
TString batchLayoutString("BatchLayout=128|1|784");

TString convLayer01("CONV|32|3|3|1|1|0|0|RELU");
TS
TS
TS
TS
TS
TString flatten04("RESHAPE|FLAT");

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TString layoutString("Layout=");
layoutString += "," + convLayer01;
layoutString += "," + convLayer02 + "," + maxPooling02;
layoutString += "," + convLayer03;
layoutString += "," + convLayer04 + "," + maxPooling04 + "," + flatten04;
layoutString += "," + fullyConnLayer05;
layoutString += "," + fullyConnLayer06;
```

Convolutional network having 32 3*3 filters, moving (1, 1), without padding, using activation function RELU.

Comparison - DNN vs CNN

Accuracy	DNN	CNN
Epoch 1	92.53%	97.39%
Epoch 2	96.86%	99.16%
Epoch 3	97.72%	99.33%
Epoch 4	98.19%	99.48%
Epoch 5	98.57%	99.64%
Test	98.20%	99.02%

Comparison (CNN) - kPyKeras vs kDL

- Training using kDL(C++) takes too long time!
  - kDL : t / epoch = 5051 s = 1 h 14 min
  - kPyKeras : t / epoch = 81 s = 1 min

Comparison (CNN) - kPyKeras vs kDL

- Training using kDL(C++) takes too long time!
  - kDL : t / epoch = 5051 s = 1 h 14 min
  - kPyKeras : t / epoch = 81 s = 1 min

→ 62 times faster!

Conclusion

- I've implemented MNIST classifier using DNN / CNN in TMVA(C++) and PyMVA(Python, Keras).
  - All the codes are available in my github.
  - https://github.com/physmlee/DLStudy
- TMVA is much slower (3~60times) than PyMVA when using large network.
- As we are going to try large network, I suggest using PyMVA for our project.