Basic

- There are 4 main parts in a layer program:
    - constants
    - data
    - networks
    - scripts

Constants

- There are three different constants to define (default values):
    - threads: number of threads for parallelization (4)
    - batch size: size of the batch for the network (100)
    - log: log file where some messages are saved (netparser.log)

```
const{
  threads=4
  batch=10
  log="mnist.log"
}
```

Data

- Data can be read in ascii or binary. Data format is the following:

> samples dim output
>
> sample1_1 ... sample1_dim out1_1 .. out1_c
>
> ...
>
> samplen_1 ... samplen_dim outn_1 .. outn_c

- *samples* is the number of samples (int)
- *dim* is the dimensionality of the samples (int)
- *out* is the number of output targets, classes in a classification problem (int)
- each row is a sample (float values)

Note: when samples are color images the channels appear separated, first R, then G and then B and *dim* must be $3 \times rows \times cols$

- An example of a data file (ascii format) with 10 samples. Each sample is represented by a 3-dim vector (feature vector). The targets are vectors of 2-dim values:

```
10 3 2
1.0 0.0 2.4 0.1 0.5
2.3 2.2 1.2 0.5 1.2
-1.2 2.2 0.6 2.1 -1.0
1.0 0.0 2.4 0.1 0.5
2.3 2.2 1.2 0.5 1.2
-1.2 2.2 0.6 2.1 -1.0
1.0 0.0 2.4 0.1 0.5
2.3 2.2 1.2 0.5 1.2
-1.2 2.2 0.6 2.1 -1.0
1.0 0.0 2.4 0.1 0.5
```

- In case of being a classification problem the targets are real values but a unique "1" for the correct class and "0" for the rest:

```
10 3 2
1.0 0.0 2.4 0 1
2.3 2.2 1.2 0 1
1.2 2.2 0.6 1 0
1.0 0.0 2.4 0 1
2.3 2.2 1.2 1 0
1.2 2.2 0.6 0 1
1.0 0.0 2.4 0 1
2.3 2.2 1.2 0 1
1.2 2.2 0.6 1 0
1.0 0.0 2.4 1 0
```

- **Note:** ascii format can be converted to binary format with the **ascii2bin** tool provided

- Data file can be used in layers using a data block. An example of data block:

```
data {
  D1 [filename="../training", binary]
  D2 [filename="../test", binary]
  Dval [filename="../valid", ascii]
}
```

- *D1*, *D2* and *Dval* are the name of the data variables
- Full path to file can be used

Networks

- Networks are the main part of a Layer program
- Networks are composed by three main parts:
    - Data
    - Layers
    - Connections
- The networks are defined like this:

```
network N1 {
    ...
}
```

- where *N1* is the name of the network

Networks - Data

- The Networks have to defined at least a training data set
- Test and validation data sets are optional:

```
network N1 {
  //data
  data tr D1  //mandatory
  data ts D2 //optional
  data va Dval //optional
  ...
}
```

- When test or validation data are provided the error function of the net will be also evaluated for that data sets

Networks - Layers

- There are different layers that can be created:
    - **FI**: Input Fully Connected layer
    - **CI**: Input Convolutional layer
    - **F**: Fully Connected layer
    - **FO**: Output layer
    - **C**: Convolutional layer
    - **MP**: MaxPooling layer

- **CA**: Cat layer

Networks - Layers - FI

- FI has not parameters just serve as a connection with the data

```
//NETWORK
network N1 {
  //data
  data tr D1

  // Fully Connected Input
  FI in
  ...
}
```

- *in* is the name of the layer
- The number of units is the dimensionality of the data

Networks - Layers - CI

- Convolutional input has three mandatory parameters that indicate how the raw data has to be mapped into an input Map
- The parameters are:
  - nz: number of channels
  - nr: image rows
  - nc: image cols

```
//NETWORK
network N1 {
  //data
  data tr D1

  // Convolutional Input for MNIST
  CI in [nz=1, nr=28, nc=28]
  ...
}
```

- *in* is the name of the layer

- Convolutional input has optional parameters:

  - cr: crop rows
  - cc: crop cols

- Images will be randomly cropped on training phase

- Images will be center-cropped in test phase

```
//NETWORK
network N1 {
  //data
  data tr D1

  // Convolutional Input for MNIST
  // Images will be randomly cropped to 24x24
  CI in [nz=1, nr=28, nc=28, cr=24, cc=24]
  ...
}
```

Networks - Layers - F

- A fully connected layer

```
//NETWORK
network N1 {
  //data
  ...

  // Fully connected
  F  f1 [numnodes=1024]
  ...
}
```

- *f1* is the name of the layer
- *numnodes* is a mandatory parameter in regular hidden layers but can be avoided when defining a **reshape** layer after a convolutional layer

Networks - Layers - FO

- FO has a mandatory parameter *{classification,regression}* that define the cost error: cross-entropy or mse respectively
- For regression, optionally, we can define an *autoencoder*

```
network N1 {
   ...
  // Targets are the output in data (one-hot)
  FO  out1 [classification]  // Cross-entropy

  // Targets are the output in data (real values)
  FO  out2 [regression]  // mse over output

  // Targets are the same input in data
  FO  out3 [regression,autoencoder] // mse over input
 ...
}
```

Networks - Layers - C

- Convolutional layers have three mandatory parameters:
  - nk: number of kernels
  - kr: height of kernel
  - kc: width of kernel

```
network N1 {
   ...
  // Convolutional Layer
  C c1 [nk=32, kr=3, kc=3]
   ...
}
```

- *c1* is the name of the layer
- Convolutional layers have the following optional parameters:
  - rpad: indicates if padding is done in the rows (0)
  - cpad: indicates if padding is done in the cols (0)
  - stride: stride value (1)

```
network N1 {
  ...
  // Convolutional Layer with padding
  // To keep the same size of Input Maps
  // use rpad=cpad=1
  C c1 [nk=32, kr=3, kc=3,rpad=1,cpad=1]

  // Stride=2 and only padding in cols
  C c2 [nk=32, kr=3, kc=3,cpad=1,stride=2]
  ...
}
```

Networks - Layers - MP

- MaxPool layers have two mandatory parameters:
  - sizer: height of the pooling region
  - sizec: width of the pooling region

```
network N1 {
  ...
  // Maxpool layer sizer=sizec=2
  MP p1[sizer=2,sizec=2]
  ...
}
```

Networks - Layers - CA

- Cat layers does not require any parameter

```
network N1 {
  ...
  // CAT Layer
  CA cat
  ...
}
```

Networks - Connections

- To connect two layers use the symbols "->"

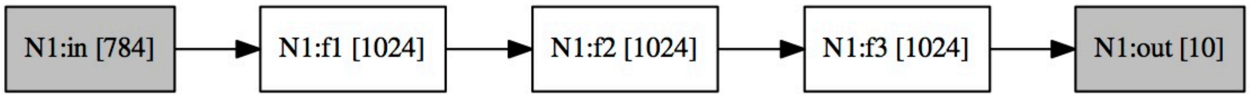
```
network N1 {
  ...
  c1->c2
}
```

Networks - Examples

Example 1 - MLP MNIST

```
// A typical MLP for MNIST
// 784->1024->1024->1024->10

//CONSTANTS
const{
  threads=8
  batch=10
  log="mnist.log"
}

// DATA FILES
data {
  D1 [filename="../training", binary]
  D2 [filename="../test", binary]
}

//NETWORK
network N1 {
  //data
  data tr D1  //mandatory
  data ts D2 //optional

  // Fully Connected Input
  FI in

  // Fully connected
  F  f1 [numnodes=1024]
  F  f2 [numnodes=1024]
  F  f3 [numnodes=1024]

  // Fully Connected Output
  FO  out [classification]

  // Links
  in->f1
  f1->f2
  f2->f3
  f3->out
}
```

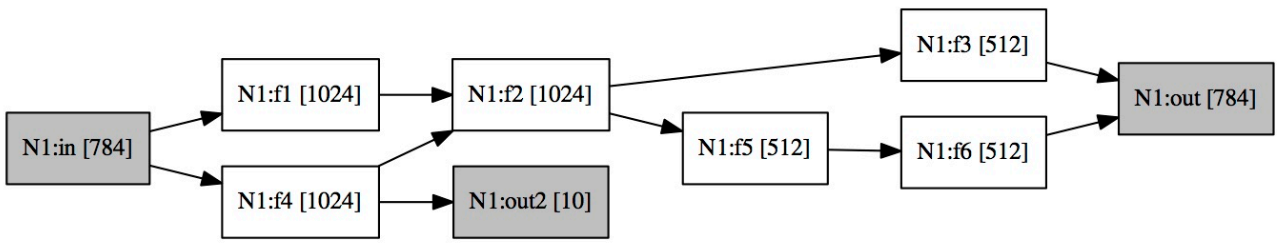
- layers generates a *dot* file with the name of each network
- Use " dot -T pdf N1.dot > N1.pdf" to generate a PDF with the network:



- but yes, more complicated networks can be defined

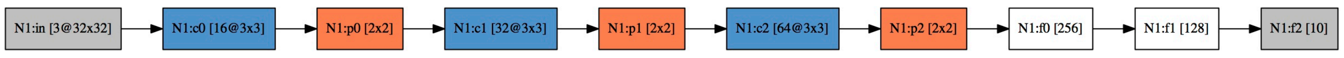
Example 2 - Hybrid MLP MNIST

```
//NETWORK
network N1 {
  //data
  data tr D1
  data ts D2

  // Fully Connected Input
  FI in

  // Fully connected
  F  f1 [numnodes=1024]
  F  f2 [numnodes=1024]
  F  f3 [numnodes=512]

  // Fully connected
  F  f4 [numnodes=1024]
  F  f5 [numnodes=512]
  F  f6 [numnodes=512]


  // Output
  FO  out [regression,autoencoder]
  FO  out2 [classification]

  // Connections
  in->f1
  f1->f2
  f2->f3
  f3->out

  in->f4
  f4->f2
  f4->out2

  f2->f5
  f5->f6
  f6->out

}
```



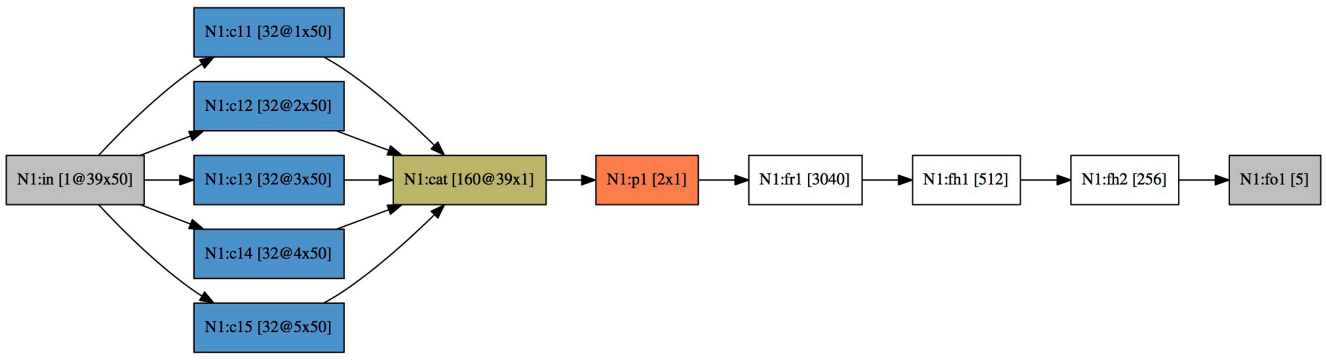
Example 3 - Convolutional CIFAR

```
network N1 {
  data tr D1
  data ts D2

  CI in [nz=3, nr=32, nc=32]

  C c0 [nk=16, kr=3, kc=3]
  MP p0[sizer=2,sizec=2]
  C c1 [nk=32, kr=3, kc=3]
  MP p1 [sizer=2,sizec=2]
  C c2 [nk=64, kr=3, kc=3]
  MP p2 [sizer=2,sizec=2]

  // FC reshape, numnodes is not requiered
  F   f0 []

  // FC hidden
  F  f1 [numnodes=128]

  // FC output
  FO f2 [classification]

  // Connections
  in->c0
  c0->p0
  p0->c1
  c1->p1
  p1->c2
  c2->p2
  //reshape
  p2->f0
  f0->f1
  f1->f2

}
```



Example 4 - CAT layers

```
network N1 {
  data tr D1
  data ts D2

  CI in [nz=1, nr=39, nc=50]

  C c11 [nk=32, kr=1, kc=50,rpad=1]
  C c12 [nk=32, kr=2, kc=50,rpad=1]
  C c13 [nk=32, kr=3, kc=50,rpad=1]
  C c14 [nk=32, kr=4, kc=50,rpad=1]
  C c15 [nk=32, kr=5, kc=50,rpad=1]
  MP p1 [sizer=2,sizec=1]

  CA cat

  // FC reshape
  F   fr1 []

  // FC hidden
  F  fh1 [numnodes=512]
  F  fh2 [numnodes=256]

  // FC output
  FO fo1 [regression]

  // Connections
  in->c11
  in->c12
  in->c13
  in->c14
  in->c15

  c11->cat
  c12->cat
  c13->cat
  c14->cat
  c15->cat

  cat->p1

  p1->fr1
  fr1->fh1
  fh1->fh2
  fh2->fo1

}
```



Scripts

- Script is a block of actions. There are two different types of actions:
  - functions
  - parameters modifications

Scripts Functions

- There are several functions that can be applied to the defined objects:
  - For Data:
    - zscore(): To normalize Data
    - yuv(): to convert RGB Maps to YUV maps
    - center(): To center Data (mean=0)
    - div(x): To div all the data
  - For Networks:
    - train(epochs): to train networks
    - save(fname): to save the network parameters to file
    - load(fname): to load the network parameters from file

      Note that **save** and **load** do not take into account the network structure, only the parameters of the layers (learning rate, dropout,...) and weights (and bias). So in order to load a network the network structure must match the network structure used when it was saved.

    - testout("fname"): writes the output of all the test data in the file. Forward over all data set.
  - For Layers:
    - printkernels("fname"): save the weights of a particular layer in the file.

      For convolutional networks printkernels loop over each filter, then over each map (depth) and then over each pixel (rows and cols). For fully connected layers printkernels loop over each unit and then over each connection to next layer units.

In any case, saving a network with the **save** command provides the weights (and bias) of **all** the layers.

> More functions will be soon implemented

```
script {

  D1.yuv()
  D2.yuv()

  D1.center()
  D2.center(D1)

  D1.div(255.0)
  D2.div(255.0)

  D1.zscore()
  D2.zscore(D1) //normalize D2 with D1 statistics

  N1.train(100)

  N1.save("N1.saved")

  N1.load("N1.saved")

  N1.f1.printkernels("N1f1.txt")

  N1.train(100)

  N1.testout("test_output.txt")

}
```

Scripts Parameters

- There are several parameters that can be modified. Parameter[default value]:
  - mu: learning rate. Scaled by batch size [0.0001/batch_size]
  - mmu: momentum rate [0.9]
  - l2: l2 regularization (weight decay) [0.0]
  - l1: l1 regularization [0.0]
  - maxn: maxnorm regularization [0.0]

    - noiser: noise ratio after activation function [0]
    - noisesd: standard deviation of noise ($N(0.0, \sigma)$) [0]
    - noiseb: ratio of binary noise (only for input layer) [0.0]
    - drop: dropout (0<drop<1) [0.0]
    - bn: batch normalization ({0,1}) [0]
    - act: activation (0 Linear, 1 Relu, 2 Sigmoid, 3 ELU) [1]
    - flip: to flip input images ({1,0}) [0]
    - shift: to shift randomly input images [0]
    - balance: for balancing data classes [0]

- Parameters can be modified for one particular layer or data:

```
script{
...
N1.c2.drop=0.5
N1.in.flip=1
N1.in.shift=2
N1.in.noiseb=0.2
D1.balance=1
...
}
```

- Or, parameters can be modified for all the layers of the same network:

```
script{
...
N1.mu=0.001
N1.l2=0.0005
// noise in all the layers of the network:
N1.noiser=0.5
N1.noisesd=0.3
...
}
```

- Some examples of scripts:

Example 1

```
script {

  D1.yuv()
  D2.yuv()

  D1.zscore()
  D2.zscore(D1)

  N1.in.flip=1
  N1.in.noiser=0.5
  N1.in.noisesd=1.0

  N1.f1.drop=0.5

  N1.l2=0.0005

  N1.bn=1

  // Learning rate annealing every 15 epochs
  N1.mu=0.01
  N1.train(15)

  N1.mu=0.005
  N1.train(15)

  N1.mu=0.0025
  N1.train(15)
}
```

Example 2

```
script {

  D1.zscore()
  D2.zscore(D1)

  N1.noiser=0.0
  N1.noisesd=1.0
  N1.in.noiser=0.5
  N1.mu=0.001
  N1.maxn=3.0

  N1.train(100)

}
```

The whole picture

Example 1

```
// A typical MLP
// 784->1024->1024->1024->10
// Check N1.dot and get a pdf of the net with:
// dot -T pdf N1.dot > N1.pdf

//CONSTANTS
const{
  threads=8
  batch=10
  log="mnist.log"
}

// DATA FILES
data {
  D1 [filename="../training", binary]
  D2 [filename="../test", binary]
}

//NETWORK
network N1 {
  //data
  data tr D1  //mandatory
  data ts D2 //optional

  // Fully Connected Input
  FI in

  // Fully connected
  F  f1 [numnodes=1024]
  F  f2 [numnodes=1024]
  F  f3 [numnodes=1024]

  // Fully Connected Output
  FO  out [regression]

  // Links
  in->f1
  f1->f2
  f2->f3
  f3->out
}
```

```
//RUN SCRIPT
script {

  D1.zscore()
  D2.zscore(D1)


  //N1.noisesd=1.0
  //N1.noiser=0.5
  N1.mu=0.01
  //N1.maxn=3.0

  N1.train(10)

}
```

Example 2

```
const {
threads=4
batch=100
}
data {
  D1 [filename="training", binary]
  D2 [filename="test", binary]
}


network N1 {
  data tr D1
  data ts D2

  // Convolutional Input
  CI in [nz=3, nr=32, nc=32]

  C c0 [nk=16, kr=3, kc=3]
  MP p0[sizer=2,sizec=2]
  C c1 [nk=32, kr=3, kc=3]
  MP p1 [sizer=2,sizec=2]
  C c2 [nk=64, kr=3, kc=3]
  MP p2 [sizer=2,sizec=2]

  // FC reshape
  F   f0 []

  // FC hidden
  F  f1 [numnodes=128]
  // FC output
  FO f2 [classification]

  // Connections
  in->c0
  c0->p0
  p0->c1
  c1->p1
  p1->c2
  c2->p2
  //reshape
  p2->f0
  f0->f1
  f1->f2

}

// RUN
script {

  D1.zscore()
  D2.zscore(D1)

  N1.mu=0.1

  N1.in.noiser=0.5
  N1.in.noisesd=1.0
  //N1.bn=1

  N1.train(1000)
}
```

ADVANCED ISSUES

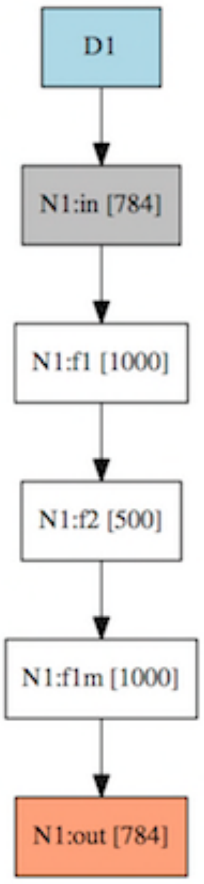
Networks sharing layers

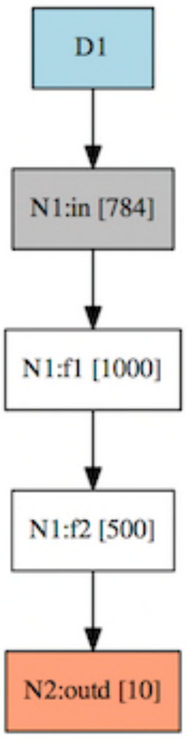
Layers can be shared among networks. For instance one network can train with an unsupervised data set while other net can share the internal representation from this net and fine-tune training with a supervised dataset later. See for instance this example for MNIST:

```
data {
  D1 [filename="training.bin", binary]
  D2 [filename="test.bin", binary]
}
```

```
// Unsupervised
network N1 {
  data tr D1

  // FC de entrada
  FI in

  F  f1 [numnodes=1000]
  F  f2 [numnodes=500]
  F  f1m [numnodes=1000]

  // FC salida
  FO  out [regression,autoencoder]

  // Conexiones
  in->f1
  f1->f2
  f2->f1m
  f1m->out

}

//Supervised
network N2 {
  data tr D1
  data ts D2

  // FC salida
  FO  outd [classification]

  // Conexiones
  N1.in->N1.f1
  N1.f1->N1.f2
  N1.f2->outd

}

script {
  D1.div(255.0)
  D2.div(255.0)

  N1.noiser=1.0
  N1.noisesd=0.3

  // Decoder is clean
  N1.f1m.noiser=0.0
  N1.out.noiser=0.0
  // Training N1
  N1.mu=0.1
  N1.bn=1
  N1.train(100)

  // Training N2
  N2.bn=1
  N2.mu=0.1
  N2.train(100)
}
```

These are the network obtained:





N1 N2

Training several networks

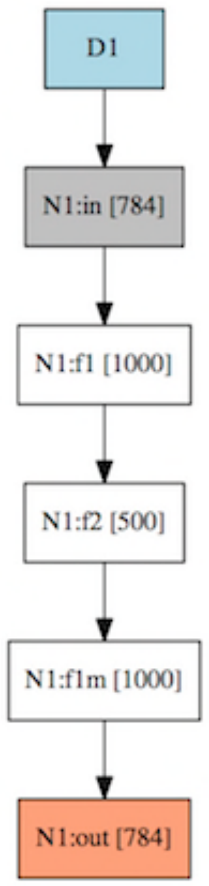
Note that in the previous example, N1 and N2 could be trained with different data sets. For instance the supervised network (N2) can be trained with a small data set while the unsupervised (N1) can be trained with all the available data (with and without labels). In this scenario it could be more interesting to train both netwroks simultaneously, a few bathces each network. To this end we can use a commnand where we specify how many iterations, how many batches per network and a list of networks:

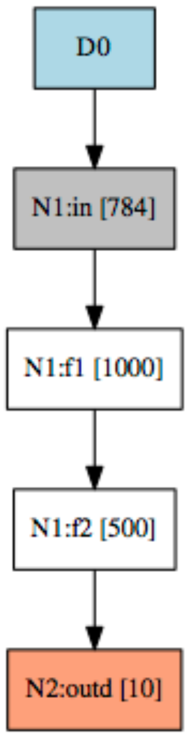
```
train(10,5,N1,N2)
```

the whole picture:

```
data {
  D0 [filename="tinytrain.bin", binary]
  D1 [filename="training.bin", binary]
  D2 [filename="test.bin", binary]
}

// Unsupervised
network N1 {
  data tr D1

  // FC de entrada
  FI in

  F  f1 [numnodes=1000]
  F  f2 [numnodes=500]
  F  f1m [numnodes=1000]

  // FC salida
  FO  out [regression,autoencoder]

  // Conexiones
  in->f1
  f1->f2
  f2->f1m
  f1m->out

}

//Supervised
network N2 {
  data tr D0
  data ts D2

  // FC salida
  FO  outd [classification]

  // Conexiones
  N1.in->N1.f1
  N1.f1->N1.f2
  N1.f2->outd
}

script {
  D0.div(255.0)
  D1.div(255.0)
  D2.div(255.0)

  N1.noiser=1.0
  N1.noisesd=0.3

  // Decoder is clean
  N1.f1m.noiser=0.0
  N1.out.noiser=0.0

  N1.mu=0.1
  N1.bn=1

  // reduce the unsupervised cost part
  N1.out.lambda=0.1

  N2.bn=1
  N2.mu=0.1

  train(10,5,N1,N2)
}
```

Note that there is a new dataset tinytraining.bin that has only 500 supervised samples. Network N2 use oly this samples for the supervised part while network N1 uses the complete data set, 60000 samples. See the networks:





N1 N2

In this example Layers will run 10 iterations with 5 batches processed for each network. When all the command is completed Layers will perform an evaluation of the test set (if any) for each network.