EE-613: Machine Learning for Engineers
Practical session 11
(Multi-layer perceptron)

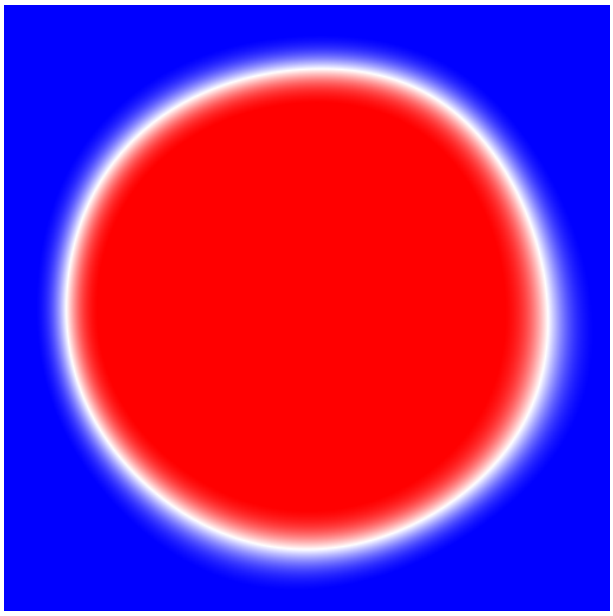
1 Download and test

```
wget http://www.idiap.ch/~fleuret/files/EE613/EE613-pw11.tgz
tar zxvf EE613-pw11.tgz
cd EE613/pw11
./do.sh example
```

after a few seconds, you should have obtained at the bottom of the console

```
LOSS 33 375.619
LOSS 34 375.594
TRAIN_LOSS 727.659
TEST_LOSS 719.488
Writing MLP activation image ... done. Wrote "example.png".
```

and the following image should be displayed



2 Programming

2.1 Compilation

You can compile the source code with `make`. Running the `do.sh` script will always recompile the source if the executable is not up-to-date.

It is suggested to implement each question its corresponding function

```
void function_question1() {
  ...
}
```

so that the `do.sh` script can run it and call the appropriate visualizing tools.

2.2 Classes

A **DataSet** Contains the input and output vectors corresponding to a set of samples.

```
class DataSet {
public:
  int input_dim, output_dim;
  int nb_samples;
  scalar_t **input_activations;
  scalar_t **output_activations;

  DataSet(int input_dim, int output_dim, int nb_samples);
  ~DataSet();
};
```

A **MLP** is a simple implementation of a multi-layer perceptron.

```
class MLP {
public:

  MLP(TransferFunction *transfer_function,
      LossFunction *loss_function,
```

```
6         int input_dim, int nb_layers, const int *layer_dim);
7
8     ~MLP();
9
10    void randomize_weights_and_biases(scalar_t epsilon);
11
12    void train(DataSet *train_set);
13
14    void test(scalar_t *input_activations,
15              scalar_t *output_activations);
16  };
```

3 Questions

Question 1: XOR with and without hidden layer

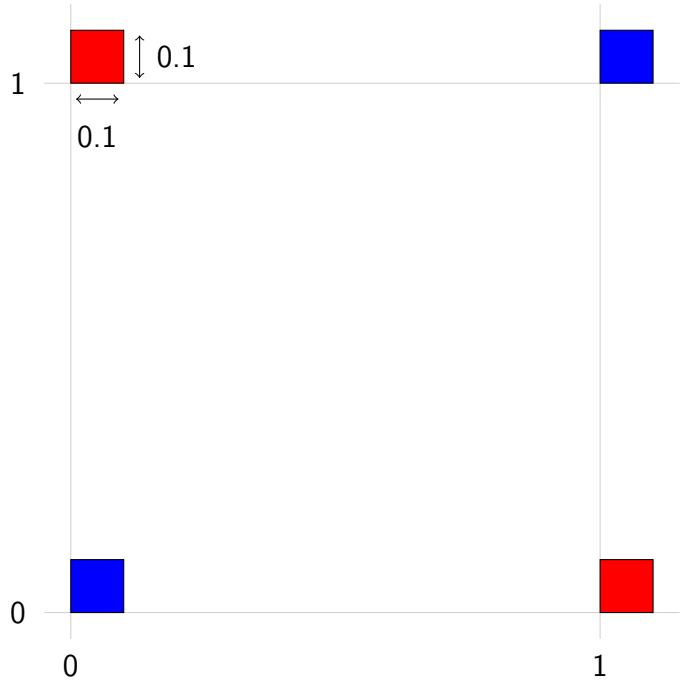
Generate a training set

$$(x_n, y_n) \in \mathbb{R}^2 \times \{-1, 1\}, \ n = 1, \dots, 1000$$

with

$$P(Y = 1) = P(Y = -1) = \frac{1}{2}$$

and $X|Y=1$ (resp. $X|Y=-1$) uniform over the two blue squares (resp. red squares) on the scheme below.



Train a MLP with no hidden layer, and a MLP with two hidden units, print the train loss in both cases.

Help:

Use the `random_0_1()` function to generate scalar uniformly distributed in $[0, 1]$.

Question 2: Real function regression

Generate a training set

$$(x_n, y_n) \in \mathbb{R}^2, \ n = 1, \dots, 1000$$

with $x_n \simeq \mathcal{U}[-\pi, \pi]$ and $y_n = sin(x_n)$.

Train a MLP with 100 hidden units, compute the prediction for all the values

$$x = \pi \left(\frac{n-1}{500} - 1 \right), \ n = 1, \dots, 1000$$

and write in a file `prediction.dat` the pairs of test xs and ys, one pair per line, separated by a space.

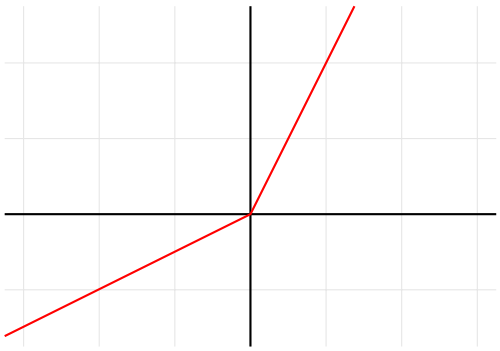
Question 3: Different transfer function and loss

Create two classes

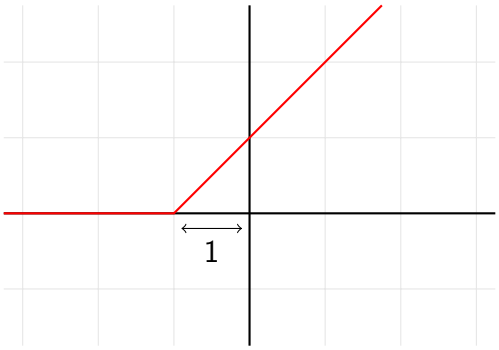
```
class TransferFunctionDoubleRectified : public TransferFunction {
...
}

class LossFunctionHinge : public LossFunction {
...
}
```

that implement respectively the double rectified transfer function and the hinge loss



Double rectified transfer



Hinge loss

Run an experiments similar to the example one with a MLP using these two classes.