Assignment 1 Report

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This report is about the result from using my implementation of the multi-layers perceptron on Rust language to solve 2 problems given on 261456 - INTRO COMP INTEL FOR CPE class. If you are interested to know how I implement the multi-layers perceptron and trained a model to solve these problems , you can see the source code for all models that have been shown in this report on my Github repository or in this document appendix on page 14.

Flood Dataset

Problem

We want to predict water level at 7 hours ahead given station 1 and station 2 data at present, 1 hour before, 2 hours before, and 3 hours before.

	A	B	C	D	E	F	G	H	I
1	s1_t3	s1_t2	s1_t1	s1_t0	s2_t3	s2_t2	s2_t1	s2_t0	t7
2	95	95	95	95	148	149	150	150	153
3	95	95	95	95	149	150	150	150	153
4	95	95	95	95	150	150	150	150	153
5	95	95	95	95	150	150	150	150	153
6	95	95	95	95	150	150	150	152	153
7	95	95	95	95	150	150	152	152	153
8	95	95	95	96	150	152	152	153	153
9	95	95	96	97	152	152	153	153	153
10	95	96	97	98	152	153	153	153	153
11	96	97	98	100	153	153	153	153	154
12	97	98	100	100	153	153	153	153	155
13	98	100	100	100	153	153	153	153	156
14	100	100	100	101	153	153	153	153	156

Figure 1: Examples of given data where s1_t3 is water level from 3 hours before at station 1, and so on. t7 is water level at 7 hours ahead.

Parameters Setting

- All nodes use *sigmoid* as an activation function except output node that use *linear* function.
- Weights are random number that is in range $[-1, 1]$
- Each layer's bias is 1
- Use MSE (Mean Squared Error) as a loss function.

Training Method

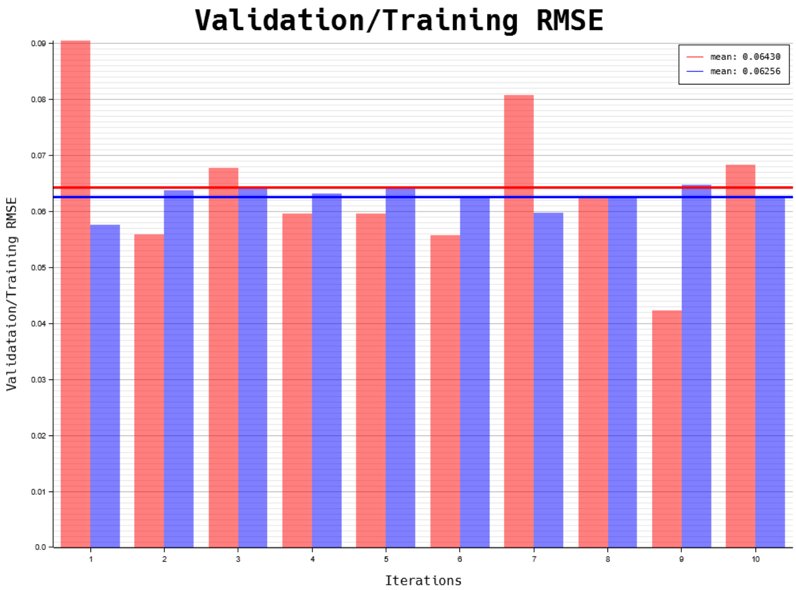
Use 10% cross-validation, and preprocess our data by using training set *mean* and *std* to standardize (For each data point x we calculate new $x' = \frac{x - mean}{std}$) both training set and validation set before training with SGD (Stochastic Gradient Descent) algorithm. Then, we train each cross-validation set for 1000 epochs.

We will create one base model that should perform good enough and create a variations base on that model. For this problem we will introduce these variations i.e. train with no *momentum*, train with smaller *learning rate*, train with no data preprocessing and add more layers or hidden nodes to see that if we introduce those variations, will the model perform better, converge faster, or have no improvement at all?

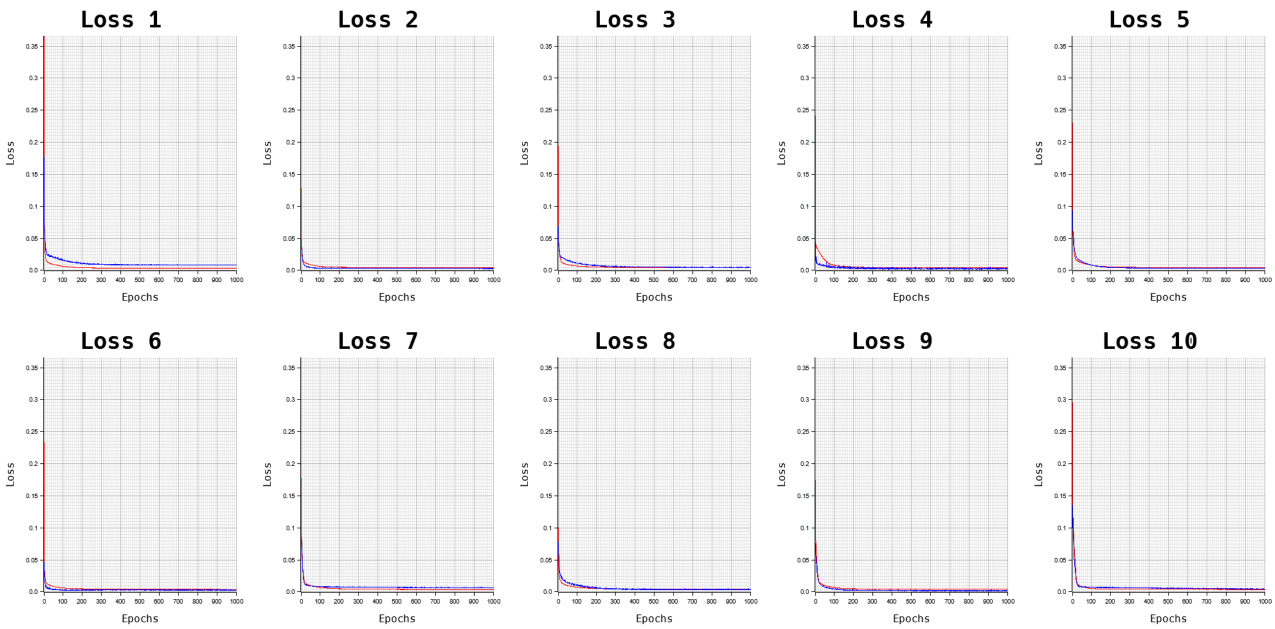
Training Result

Flood-8-4-1

Our base model that contains only 8 input nodes, 1 hidden layer with 4 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process takes about 54 seconds. Below are the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) RMSE at last epoch

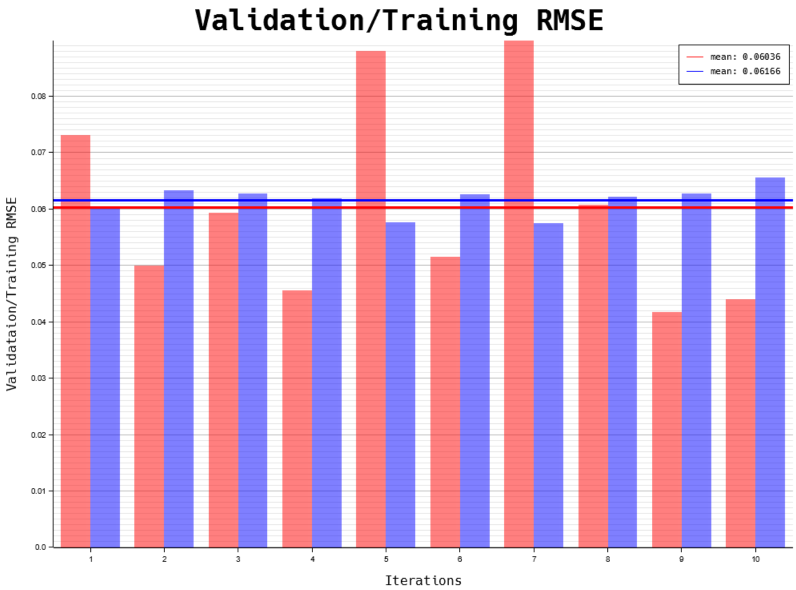


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

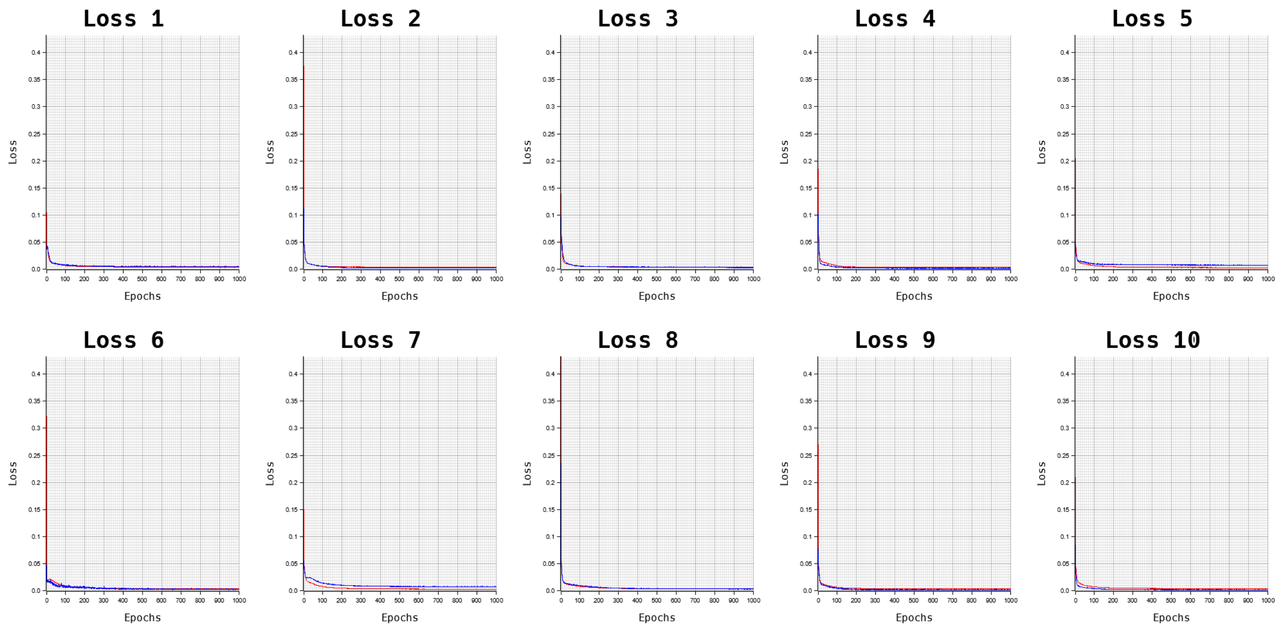
Figure 2: Training result of Flood-8-4-1.

Flood-8-4-1 with no momentum

Same base model but train with $lr = 0.01$ and $momentum = 0$. The training process takes about 54 seconds. Below are the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) RMSE at last epoch

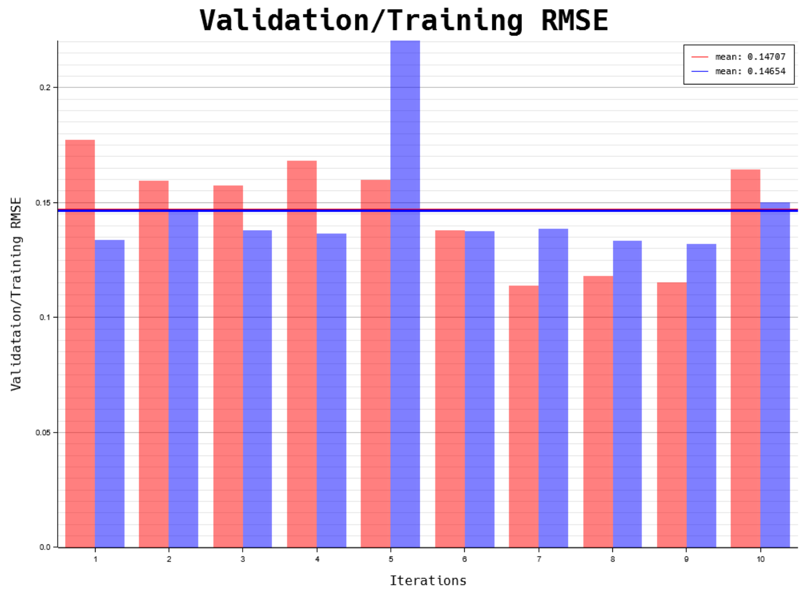


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

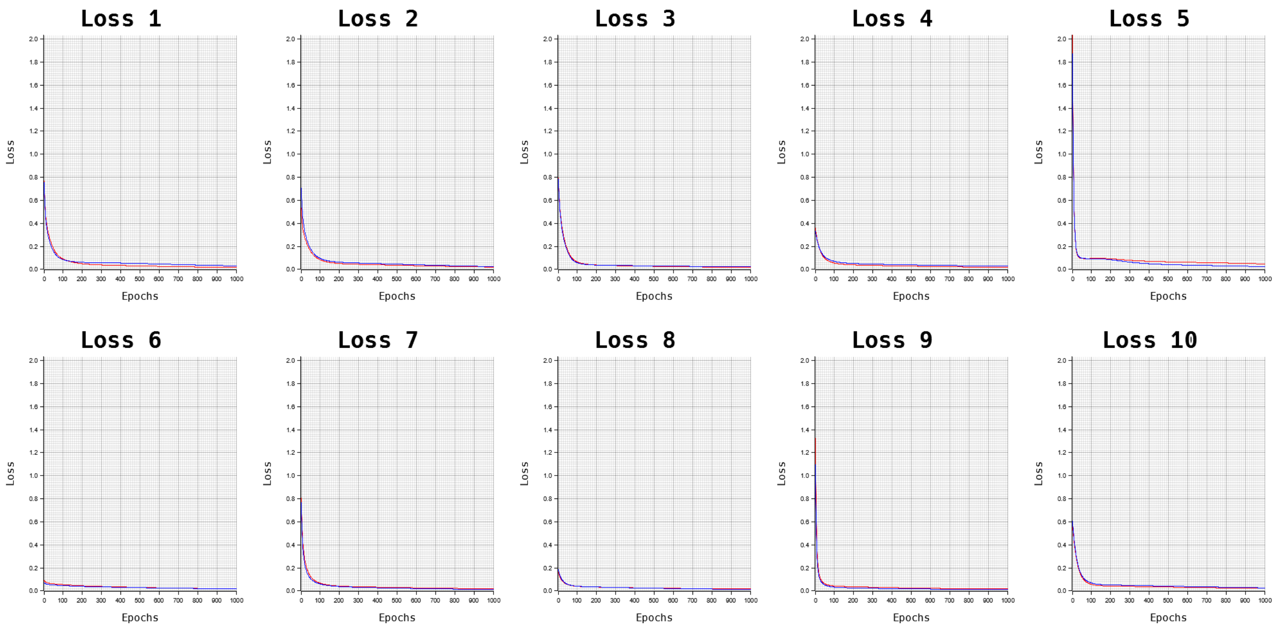
Figure 3: Training result of Flood-8-4-1 with no momentum.

Flood-8-4-1 with small learning rate

Same base model but train with $lr = 0.0001$ and $momentum = 0.01$. The training process takes about 54 seconds. Below are the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) RMSE at last epoch

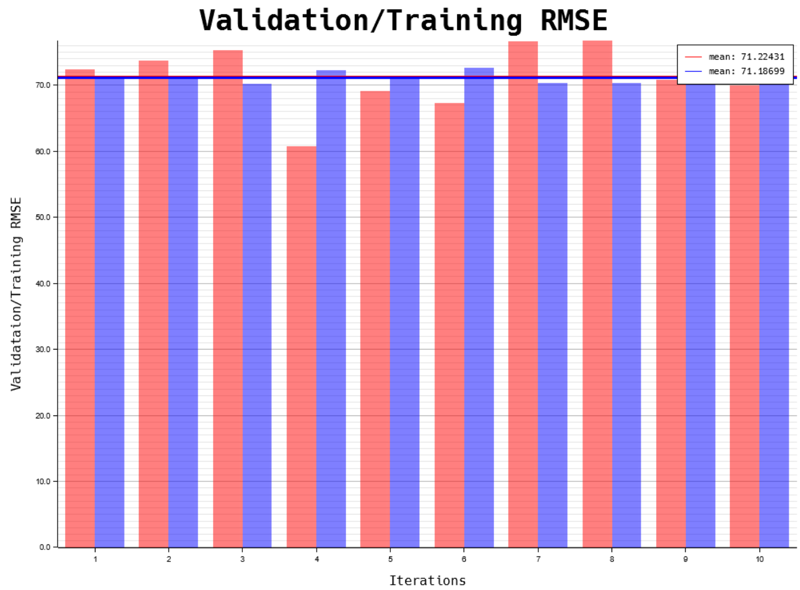


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

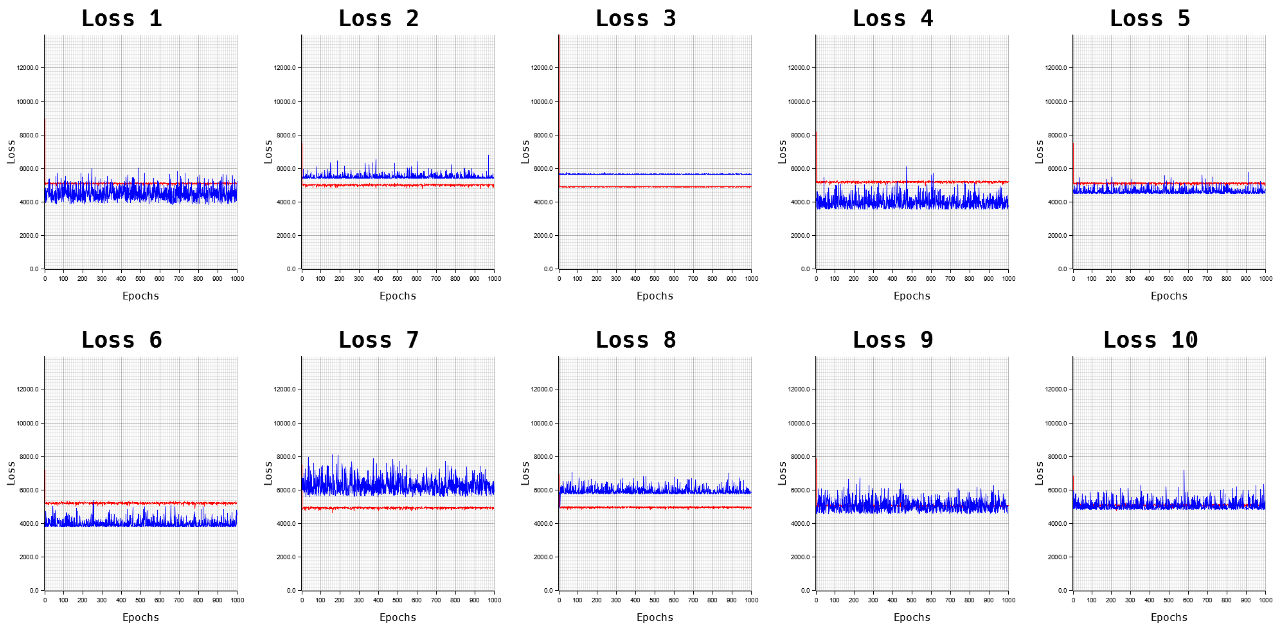
Figure 4: Training result of Flood-8-4-1 with smaller learning rate.

Flood-8-4-1 with no data preprocessing

Same base model train with $lr = 0.01$ and $momentum = 0.01$ but it is the only model with no data preprocessing. The training process takes about 57 seconds. Below are the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) RMSE at last epoch

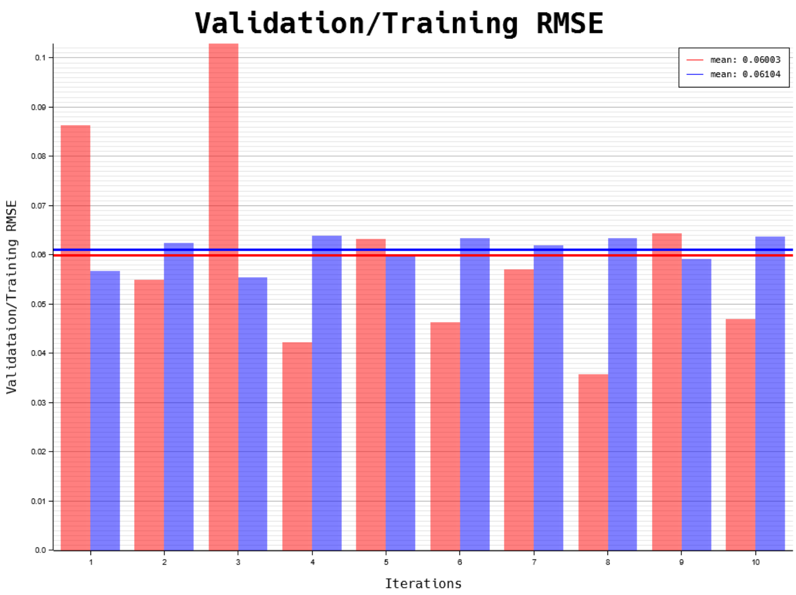


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

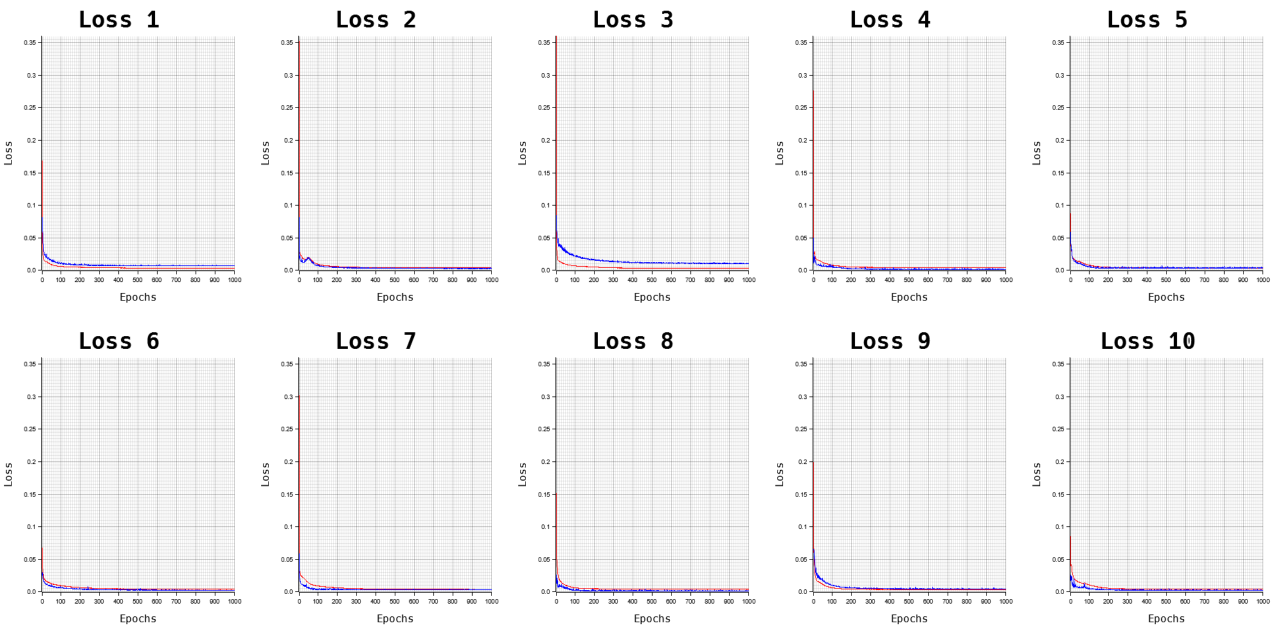
Figure 5: Training result of Flood-8-4-1 with no data preprocessing.

Flood-8-8-1

Bigger model that contains 8 input nodes, 1 hidden layer with 8 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process takes about 104 seconds. Below are the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) RMSE at last epoch



(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

Figure 6: Training result of Flood-8-8-1.

Analysis

From table 1, we can see that models with the same size will use around the same amount of training time, but with the bigger model, the training time gets longer. And, we can see that the best performing model in terms of validation set mean RMSE is Flood-8-8-1 which has mean RMSE at 6.003×10^{-2} thus we anticipate that the more hidden nodes in the model may make the model better.

Model	Training Time (seconds)	Validation Set Mean RMSE (10^{-2})
Flood-8-4-1	54	6.430
Flood-8-4-1 with no momentum	54	6.036
Flood-8-4-1 with small learning rate	54	14.707
Flood-8-4-1 with no data preprocessing	57	7122.431
Flood-8-8-1	104	6.003

Table 1: Training time and validation set mean RMSE (red line on fig. 2a, fig. 3a, fig. 4a, fig. 5a, and fig. 6a) of each Flood model.

We can also see a similar pattern on all of our Flood models in fig. 2b, fig. 3b fig. 4b, and fig. 6b the MSE is decreasing very fast at the first 100 epochs and seems to be stuck at a certain level of MSE or very slow in MSE reduction. But, there is one model that does not follow this pattern which is Flood-8-4-1 with no data preprocessing as we can see in fig. 5b, the training MSE seems to be flickering a lot and there is no sign of the training MSE converging indicating that the model is struggling to learn with big error that comes from not standardized data e.g. we are training a model with not standardized data; the result from forward pass is 170, the desired value is 150, we'll get MSE $= (170 - 150)^2 = 400$ compared with standardized data; imagine the training set $mean = 340$, $std = 120$ the desired value will be $\frac{(150-mean)}{std} \approx -1.58$ and suppose that the result from forward pass will be $\frac{(170-mean)}{std} \approx -1.42$, we will get MSE $= (-1.42 - (-1.58))^2 = 0.0256$ which is much smaller than not standardized data MSE (note that there is no need for the result from forward pass to be exactly like that, I use that conversion to only point out that in standardized data the MSE is much smaller).

CrossPat Dataset

Problem

We want to predict the class (1 of possible 2 classes) that belongs to our inputs (or features).

```
p0
0.0902 0.2690
1 0
p1
0.8143 0.5887
0 1
p2
0.2962 0.0697
1 0
p3
0.5533 0.5493
0 1
p4
0.1472 0.1856
1 0
p5
0.4653 0.6214
0 1
```

Figure 7: Examples of given data where px is an object and the first line after it is its features, the second line is its class

Parameters Setting

- All nodes use *sigmoid* as an activation function.
- Weights are random number that is in range $[-1, 1]$
- Each layer's bias is 1
- Use MSE (Mean Squared Error) as a loss function.

Training Method

Use 10% cross-validation with no data preprocessing, and train with SGD (Stochastic Gradient Descent) algorithm. Then, we train each cross-validation set for 7500 epochs.

We will create one base model that should perform good enough and create a variations base on that model, that is train with no *momentum*, train with smaller *learning rate*, and add more layers or hidden nodes to see that if we introduce those variations, will the model perform better, converge faster, or have no improvement?

Training Result

We use only 1 output node in all models because this is a binary classification task so we can just map a pair $(1, 0) \rightarrow 1$ and $(0, 1) \rightarrow 0$. We then have a threshold at 0.5 if output is more than 0.5 then it is 1 else it is 0. Accuracy is then calculated by using this equation $\frac{TP+TN}{TP+TN+FN+FP}$ where TP, TN, FN, FP come from confusion matrix.

Cross-2-4-1

Our base model with 2 input nodes, 1 hidden layer with 4 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process takes about 163 seconds..

Cross-2-4-1 with no momentum

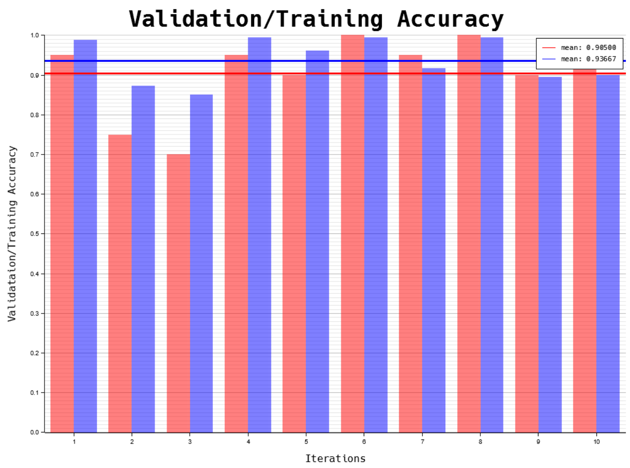
Same base model train with $lr = 0.01$ and $momentum = 0.0$. The training process takes about 167 seconds.

Cross-2-4-1 with smaller learning rate

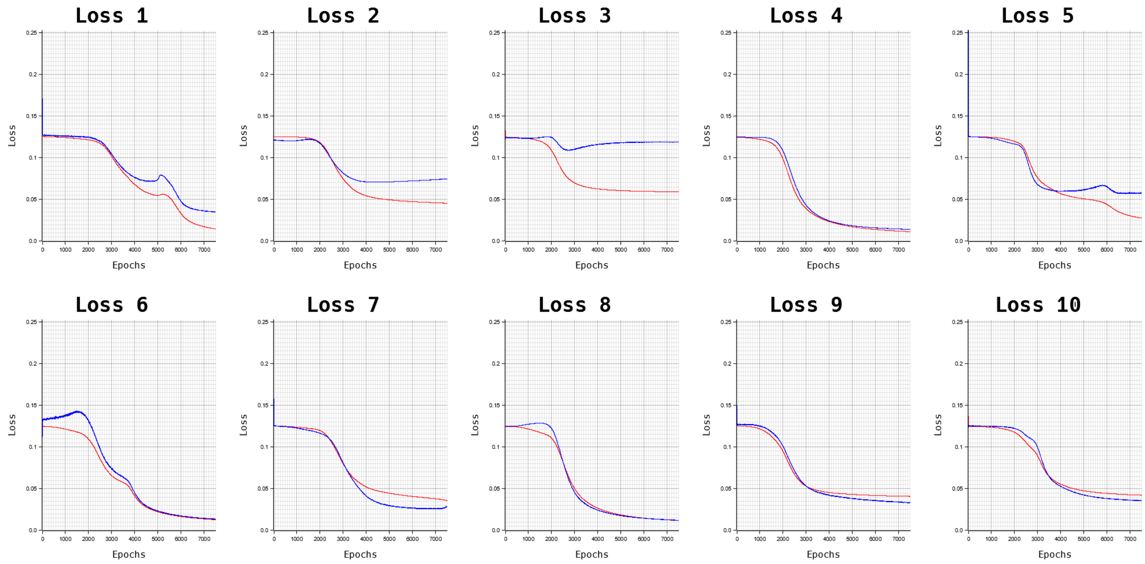
Same base model train with $lr = 0.0001$ and $momentum = 0.01$. The training process takes about 162 seconds.

Cross-2-8-1

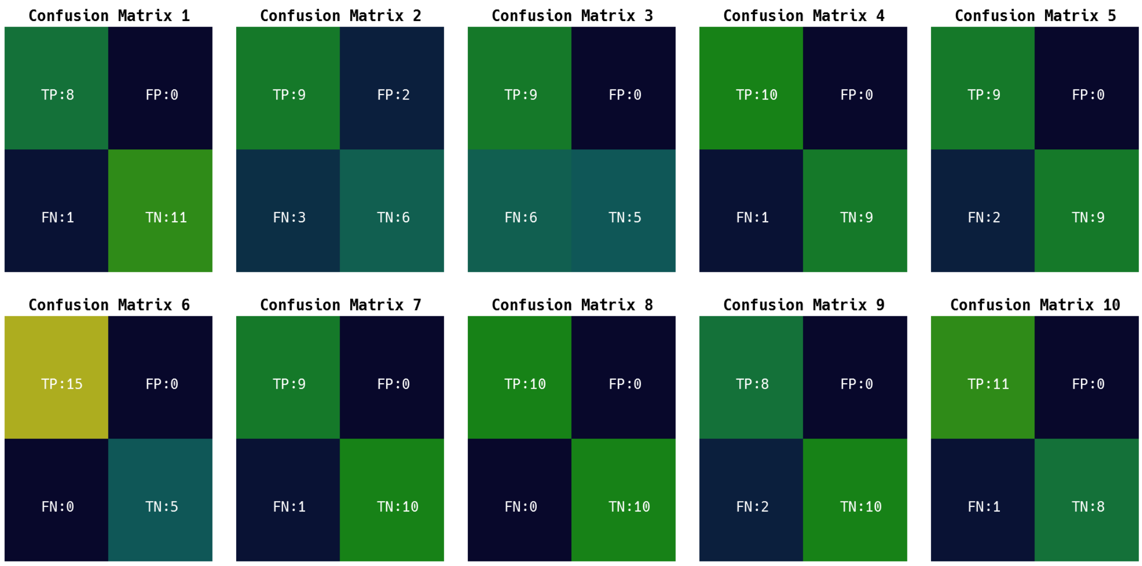
Bigger model that contains 2 input nodes, 1 hidden layer with 4 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process takes about 311 seconds.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch

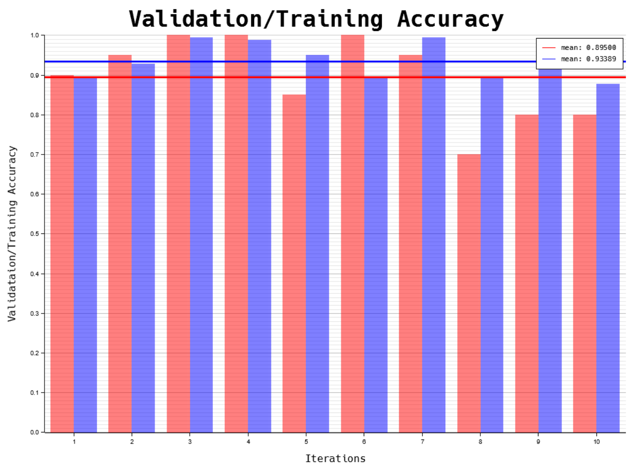


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

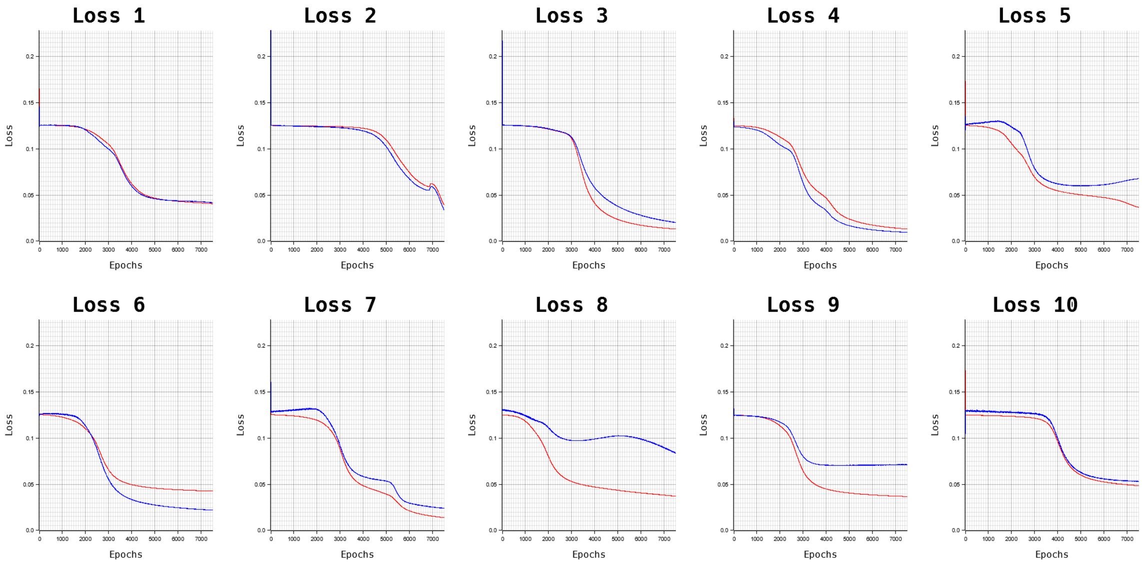


(c) Each iterations validation set confusion matrix where y-axis is an actual class $1, 0$ top to bottom and x-axis is predicted class $1, 0$ left to right.

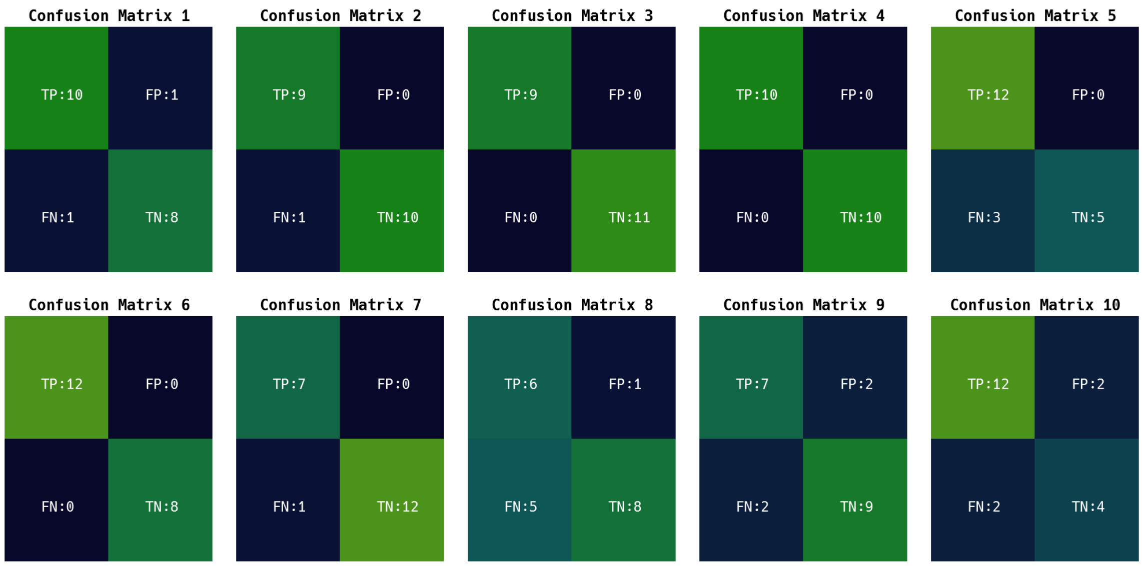
Figure 8: Training result of Cross-2-4-1.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch

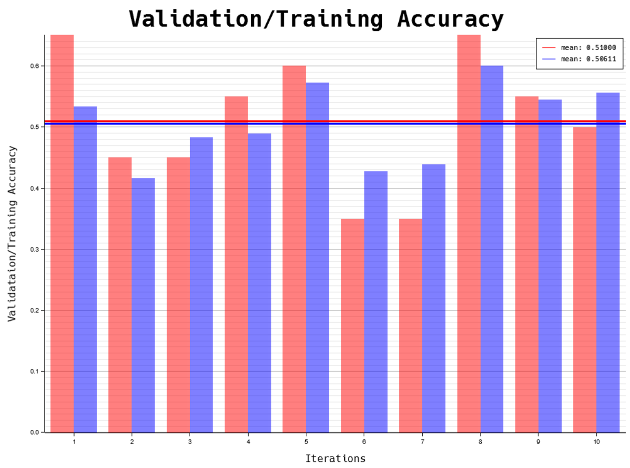


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

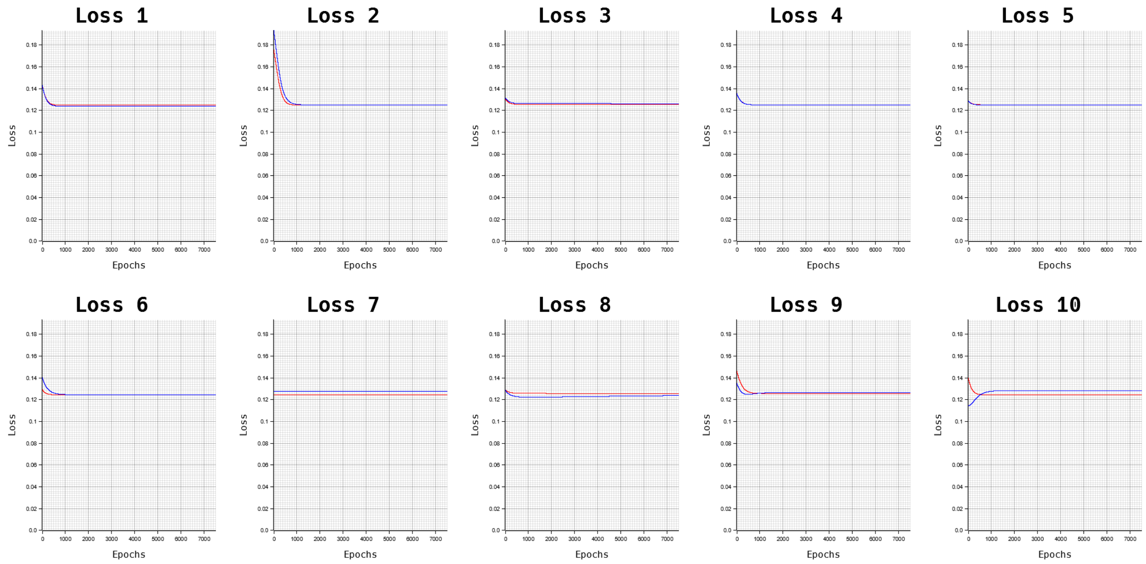


(c) Each iterations validation set confusion matrix where y-axis is an actual class 1, 0 top to bottom and x-axis is predicted class 1, 0 left to right.

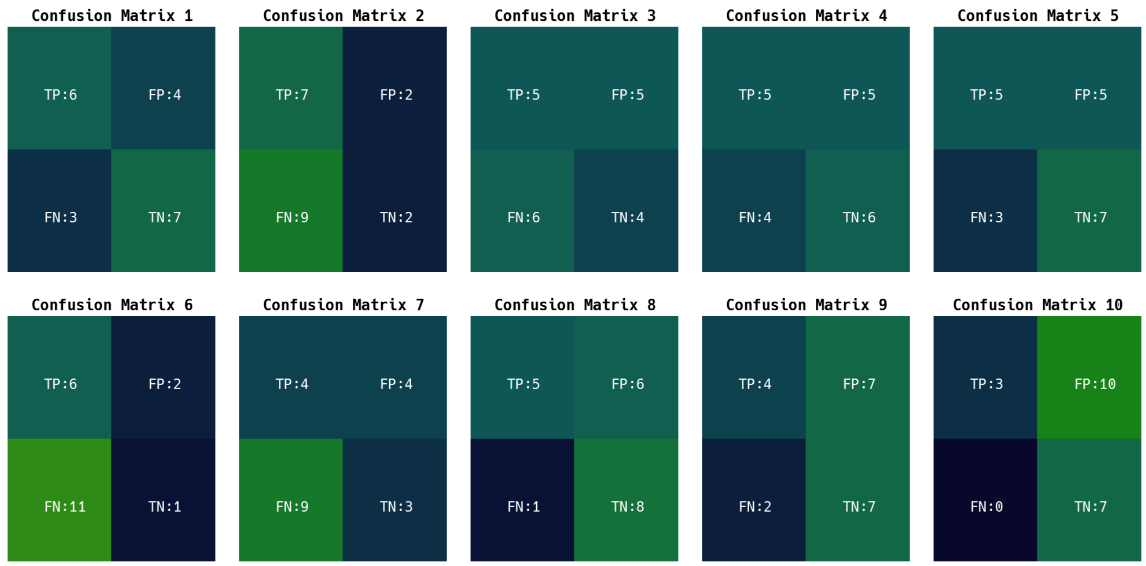
Figure 9: Training result of Cross-2-4-1 with no momentum.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch

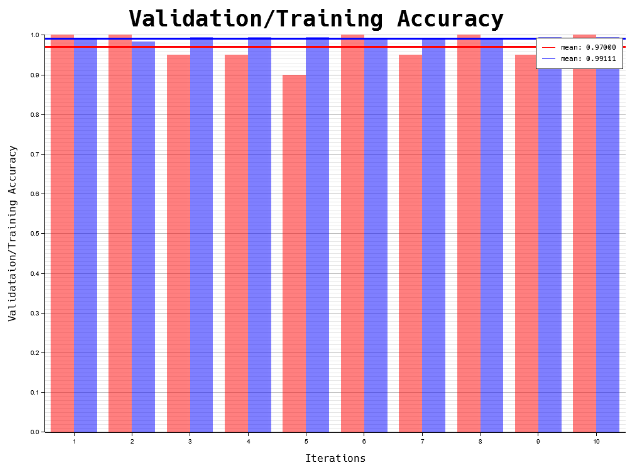


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

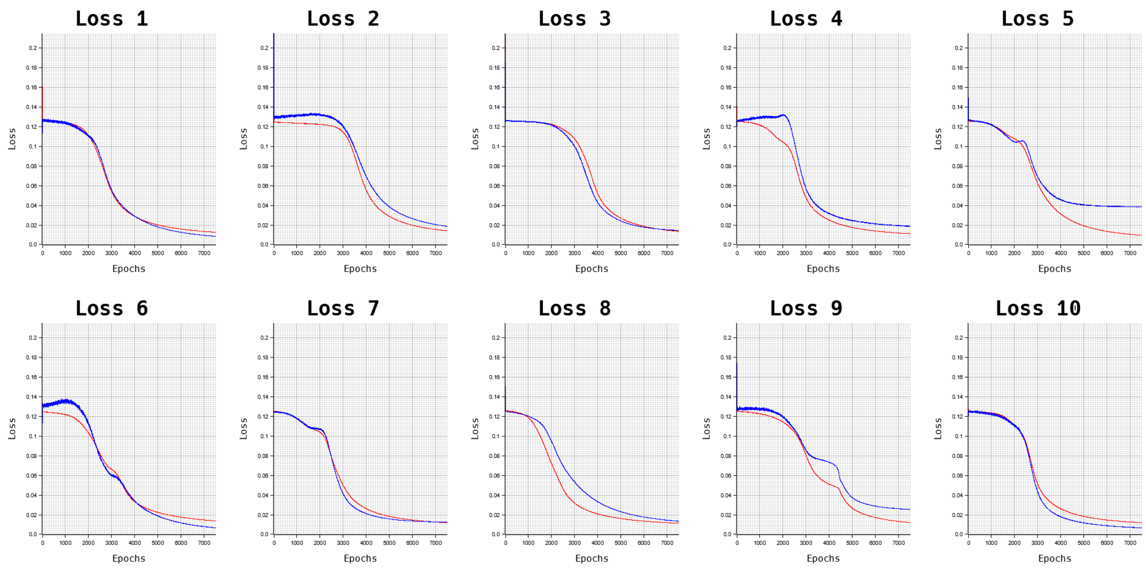


(c) Each iterations validation set confusion matrix where y-axis is an actual class $1, 0$ top to bottom and x-axis is predicted class $1, 0$ left to right.

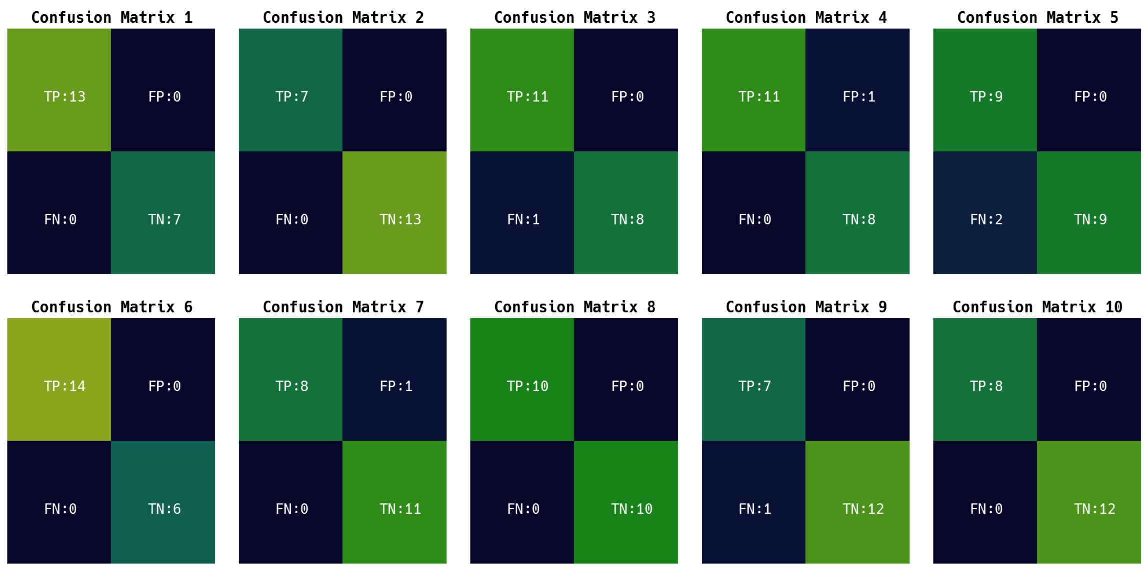
Figure 10: Training result of Cross-2-4-1 with smaller learning rate.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch



(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.



(c) Each iterations validation set confusion matrix where y-axis is an actual class 1, 0 top to bottom and x-axis is predicted class 1, 0 left to right.

Figure 11: Training result of Cross-2-8-1.

Analysis

From table 2, we can see that all Cross-2-4-1 models used around the same amount of training time but only the base model is performing okay in terms of validation set mean accuracy. And the biggest model Cross-2-8-1 is performing much better than others at 97% validation set mean accuracy but the training time used is also around 2 times other models training time.

Model	Training Time (seconds)	Validation Set Mean Accuracy (%)
Cross-2-4-1	163	90.5
Cross-2-4-1 with no momentum	167	89.5
Cross-2-4-1 with small learniing rate	162	51.0
Cross-2-8-1	311	97.0

Table 2: Training time and validation set mean accuracy (red line on fig. 8a, fig. 9a, fig. 10a, and fig. 11) of each Cross model.

From fig. 11b, we can also see that Cross-2-8-1 training is going smoother with a steady decrease in MSE compared with other models as we can see in fig. 8b, fig. 9b, and fig. 10b the graphs overall seem to go down and stop at a certain level indicating that the model stop learning. Confusion matrix of Cross-2-8-1 from fig. 11c also, show that the error is not biased to one specific class indicating that the model learned about the 2 classes equally. On the other hand, the confusion matrix of all Cross-2-4-1 models specifically in fig. 9c and fig. 10c we can see that there're a big number of FP and FN and in some iteration the error is biased to one of FP or FN.

Summary

From both problems, we have learned that an MLP model can solve these problems and the performance of the model is dependent on parameters that we can set for the model such as learning rate, momentum, and size of the model as we can see in the above experimenting result. And, in some datasets, there is a need for data preprocessing so that the model does not struggle to learn with that dataset as we can see in Flood Dataset.

Appendix

main.rs

```
pub mod activator;
pub mod cross;
pub mod flood;
pub mod loss;
pub mod model;
pub mod utills;

use std::error::Error;

fn main() -> Result<(), Box<dyn Error>> {
    // training code
    flood::flood_8_4_1(0.01, 0.01, "flood-8-4-1", true)?; // base
    flood::flood_8_4_1(0.01, 0.0, "flood-8-4-1_2", true)?; // no momentum
    flood::flood_8_4_1(0.0001, 0.01, "flood-8-4-1_3", true)?; // small learning rate
    flood::flood_8_4_1(0.01, 0.01, "flood-8-4-1_4", false)?; // no data preprocessing
    flood::flood_8_8_1(0.01, 0.01, "flood-8-8-1")?;

    cross::cross_2_4_1(0.01, 0.01, "cross-2-4-1")?; // base
    cross::cross_2_4_1(0.01, 0.0, "cross-2-4-1_2")?; // no momentum
    cross::cross_2_4_1(0.0001, 0.01, "cross-2-4-1_3")?; // small learning rate
    cross::cross_2_8_1(0.01, 0.01, "cross-2-8-1")?;

    Ok(())
}
```

flood/mod.rs

```
    //! Contains training code for variations of flood dataset models.
    use super::activator;
    use super::loss;
    use super::model;
    use super::utills;

    use model::{Layer, Net};
    use std::error::Error;
    use std::fs;
    use std::io::Write;
    use std::time::{Duration, Instant};
    use utills::data;
    use utills::graph;
    use utills::io;

    pub fn flood_8_4_1(
        lr: f64,
        momentum: f64,
        folder: &str,
        standardize: bool,
    ) -> Result<(), Box<dyn Error>> {
        fn model() -> Net {
            let mut layers: Vec<model::Layer> = vec![];
            layers.push(Layer::new(8, 4, 1.0, activator::sigmoid()));
            layers.push(Layer::new(4, 1, 1.0, activator::linear()));
            Net::from_layers(layers)
        }

        flood_fit(&model, lr, momentum, folder, standardize)?;
        Ok(())
    }

    pub fn flood_8_8_1(lr: f64, momentum: f64, folder: &str) -> Result<(), Box<dyn Error>> {
        fn model() -> Net {
            let mut layers: Vec<model::Layer> = vec![];
            layers.push(Layer::new(8, 8, 1.0, activator::sigmoid()));
            layers.push(Layer::new(8, 1, 1.0, activator::linear()));
            Net::from_layers(layers)
        }

        flood_fit(&model, lr, momentum, folder, true)?;
        Ok(())
    }

    fn mse_to_rmse(mse: &Vec<f64>) -> Vec<f64> {
```

```
    mse.iter().map(|v| v.sqrt()).collect()
}

pub fn flood_fit(
    model: &dyn Fn() -> Net,
    lr: f64,
    momentum: f64,
    folder: &str,
    standardize: bool,
) -> Result<(), Box<dyn Error>> {
    let (models, img) = utills::io::check_dir(folder)?;

    let dataset = data::flood_dataset()?;
    let mut loss = loss::Loss::mse();
    let epochs = 1000;

    let mut cv_valid_loss: Vec<f64> = vec![];
    let mut cv_train_loss: Vec<f64> = vec![];

    let mut r2_score: Vec<f64> = vec![];
    let mut loss_g = graph::LossGraph::new();
    let start = Instant::now();
    for (j, dt) in dataset.cross_valid_set(0.1).iter().enumerate() {
        // creating a model
        let mut net = model();

        // get training set and validation set
        let training_set = if standardize {
            data::standardization(&dt.0, dt.0.mean(), dt.0.std())
        } else {
            dt.0.clone()
        };

        let validation_set = if standardize {
            data::standardization(&dt.1, dt.0.mean(), dt.0.std())
        } else {
            dt.1.clone()
        };
        //let training_set = data::minmax_norm(&dt.0, dt.0.min(), dt.0.max());
        //let validation_set = data::minmax_norm(&dt.1, dt.1.min(), dt.1.max());

        // training
        let mut loss_vec: Vec<f64> = vec![];
        let mut valid_loss_vec: Vec<f64> = vec![];
        for i in 0..epochs {
            let mut running_loss: f64 = 0.0;

            for data in training_set.get_shuffled() {
                let result = net.forward(&data.inputs);

                running_loss += loss.criterion(&result, &data.labels);
                loss.backward(&mut net.layers);

                net.update(lr, momentum);
            }
            running_loss /= training_set.len() as f64;
            loss_vec.push(running_loss);

            let mut valid_loss: f64 = 0.0;
            for data in validation_set.get_datas() {
                let result = net.forward(&data.inputs);
                valid_loss += loss.criterion(&result, &data.labels);
            }
            valid_loss /= validation_set.get_datas().len() as f64;
            valid_loss_vec.push(valid_loss);

            if i == epochs - 1 {
                // log score
                let label_mean = validation_set.get_datas().iter().fold(0f64, |mean, val| {
                    mean + val.labels[0] / validation_set.len() as f64
                });

                let mut total_sum_sqr = 0f64;
                let mut sum_sqr = 0f64;

                for data in validation_set.get_datas() {
```

```
                    let result = net.forward(&data.inputs);
                    sum_sqr += (data.labels[0] - result[0]).powi(2);
                    total_sum_sqr += (data.labels[0] - label_mean).powi(2);
                }

                r2_score.push(1.0 - (sum_sqr / total_sum_sqr));
                cv_valid_loss.push(valid_loss);
                cv_train_loss.push(running_loss);
            }

            println!(
                "iteration: {}, epoch: {}, loss: {:.6}, valid_loss: {:.6}",
                j, i, running_loss, valid_loss
            );
        }

        loss_g.add_loss(loss_vec, valid_loss_vec);
        io::save(&net.layers, format!("{}/{}.json", models, j))?;
    }
    let duration: Duration = start.elapsed();

    let mut file = fs::File::create(format!("{}/result.txt", models))?;
    file.write_all(
        format!(
            "cv_score: {:?}\n\nr2_score: {:?}\n\ntime used: {:?}",
            cv_valid_loss, r2_score, duration
        )
        .as_bytes(),
    )?;

    loss_g.draw(format!("{}/loss.png", img))?;

    graph::draw_2hist(
        [mse_to_rmse(&cv_valid_loss), mse_to_rmse(&cv_train_loss)],
        "Validation/Training RMSE",
        ("Iterations", "Validataion/Training RMSE"),
        format!("{}/cv_l.png", img),
    )?;

    graph::draw_histogram(
        r2_score,
        "Cross Validation R2 Scores",
        ("Iterations", "R2 Scores"),
        format!("{}/r2_score.png", img),
    )?;
    Ok(())
}
```

cross/mod.rs

```
//! Contains training code for variations of cross.pat dataset models.
use super::activator;
use super::loss;
use super::model;
use super::utills;

use model::{Layer, Net};
use std::error::Error;
use std::fs;
use std::io::Write;
use std::time::{Duration, Instant};
use utills::data;
use utills::graph;
use utills::io;

fn confusion_count(matrix: &mut [[i32; 2]; 2], result: &Vec<f64>, label: &Vec<f64>) {
    let threshold = 0.5;
    if result[0] > threshold {
        // true positive
        if label[0] == 1.0 {
            matrix[0][0] += 1
        } else {
            // false negative
            matrix[1][0] += 1
        }
    } else if result[0] <= threshold {
```

```
        // true negative
        if label[0] == 0.0 {
            matrix[1][1] += 1
        }
        // false positive
        else {
            matrix[0][1] += 1
        }
    }
}

pub fn cross_2_4_1(lr: f64, momentum: f64, folder: &str) -> Result<(), Box<dyn Error>> {
    fn model() -> Net {
        let mut layers: Vec<model::Layer> = vec![];
        layers.push(Layer::new(2, 4, 1.0, activator::sigmoid()));
        layers.push(Layer::new(4, 1, 1.0, activator::sigmoid()));
        Net::from_layers(layers)
    }

    cross_fit(&model, lr, momentum, folder)?;
    Ok(())
}

pub fn cross_2_8_1(lr: f64, momentum: f64, folder: &str) -> Result<(), Box<dyn Error>> {
    fn model() -> Net {
        let mut layers: Vec<model::Layer> = vec![];
        layers.push(Layer::new(2, 8, 1.0, activator::sigmoid()));
        layers.push(Layer::new(8, 1, 1.0, activator::sigmoid()));
        Net::from_layers(layers)
    }

    cross_fit(&model, lr, momentum, folder)?;
    Ok(())
}

pub fn cross_fit(
    model: &dyn Fn() -> Net,
    lr: f64,
    momentum: f64,
    folder: &str,
) -> Result<(), Box<dyn Error>> {
    let (models, img) = utills::io::check_dir(folder)?;

    let dataset = data::cross_dataset()?;
    let mut loss = loss::Loss::mse();
    let epochs = 7500;

    let mut valid_acc: Vec<f64> = vec![];
    let mut train_acc: Vec<f64> = vec![];
    let mut loss_g = graph::LossGraph::new();
    let mut matrix_vec: Vec<[[i32; 2]; 2]> = vec![];

    let start = Instant::now();
    for (j, dt) in dataset.cross_valid_set(0.1).iter().enumerate() {
        // creating a model
        let mut net = model();

        // get training set and validation set
        let training_set = &dt.0;
        let validation_set = &dt.1;

        // training
        let mut loss_vec: Vec<f64> = vec![];
        let mut valid_loss_vec: Vec<f64> = vec![];
        for i in 0..epochs {
            let mut running_loss: f64 = 0.0;

            for data in training_set.get_shuffled() {
                let result = net.forward(&data.inputs);

                running_loss += loss.criterion(&result, &data.labels);
                loss.backward(&mut net.layers);

                net.update(lr, momentum);
            }
            running_loss /= training_set.len() as f64;
```

```
            loss_vec.push(running_loss);

            let mut valid_loss: f64 = 0.0;
            for data in validation_set.get_datas() {
                let result = net.forward(&data.inputs);
                valid_loss += loss.criterion(&result, &data.labels);
            }
            valid_loss /= validation_set.get_datas().len() as f64;
            valid_loss_vec.push(valid_loss);

            if i == epochs - 1 {
                let mut matrix = [[0, 0], [0, 0]];
                for data in validation_set.get_datas() {
                    let result = net.forward(&data.inputs);
                    confusion_count(&mut matrix, &result, &data.labels);
                }

                let mut matrix2 = [[0, 0], [0, 0]];
                for data in training_set.get_datas() {
                    let result = net.forward(&data.inputs);
                    confusion_count(&mut matrix2, &result, &data.labels);
                }
                valid_acc.push((matrix[0][0] + matrix[1][1]) as f64 / validation_set.len() as f64);
                train_acc.push((matrix2[0][0] + matrix2[1][1]) as f64 / training_set.len() as f64);
                matrix_vec.push(matrix);
            }

            println!(
                "iteration: {}, epoch: {}, loss: {:.6}, valid_loss: {:.6}",
                j, i, running_loss, valid_loss
            );
        }

        loss_g.add_loss(loss_vec, valid_loss_vec);
        io::save(&net.layers, format!("{}/{}.json", models, j))?;
    }
    let duration: Duration = start.elapsed();

    let mut file = fs::File::create(format!("{}/result.txt", models))?;
    file.write_all(format!("cv_score: {:?}\n\ntime used: {:?}", valid_acc, duration).as_bytes())?;

    loss_g.draw(format!("{}/loss.png", img))?;

    graph::draw_2hist(
        [valid_acc, train_acc],
        "Validation/Training Accuracy",
        ("Iterations", "Validataion/Training Accuracy"),
        format!("{}/acc.png", img),
    )?;

    graph::draw_confustion(matrix_vec, format!("{}/confusion_matrix.png", img))?;

    Ok(())
}
```

model.rs

```
    use crate::activator;

    #[derive(Debug)]
    pub struct Layer {
        pub inputs: Vec<f64>,
        pub outputs: Vec<f64>, // need to save this for backward pass
        pub w: Vec<Vec<f64>>,
        pub b: Vec<f64>,
        pub grads: Vec<Vec<f64>>,
        pub w_prev_changes: Vec<Vec<f64>>,
        pub local_grads: Vec<f64>,
        pub b_prev_changes: Vec<f64>,
        pub act: activator::ActivationContainer,
    }

    impl Layer {
        pub fn new(
            input_features: u64,
            output_features: u64,
```

```
        bias: f64,
        act: activator::ActivationContainer,
    ) -> Layer {
        // initialize weights matrix
        let mut weights: Vec<Vec<f64>> = vec![];
        let mut inputs: Vec<f64> = vec![];
        let mut outputs: Vec<f64> = vec![];
        let mut grads: Vec<Vec<f64>> = vec![];
        let mut local_grads: Vec<f64> = vec![];
        let mut w_prev_changes: Vec<Vec<f64>> = vec![];
        let mut b_prev_changes: Vec<f64> = vec![];
        let mut b: Vec<f64> = vec![];

        for _ in 0..output_features {
            outputs.push(0.0);
            local_grads.push(0.0);
            b_prev_changes.push(0.0);
            b.push(bias);

            let mut w: Vec<f64> = vec![];
            let mut g: Vec<f64> = vec![];
            for _ in 0..input_features {
                if (inputs.len() as u64) < input_features {
                    inputs.push(0.0);
                }
                g.push(0.0);
                // random both positive and negative weight
                w.push(2f64 * rand::random::<f64>() - 1f64);
            }
            weights.push(w);
            grads.push(g.clone());
            w_prev_changes.push(g);
        }
        Layer {
            inputs,
            outputs,
            w: weights,
            b,
            grads,
            w_prev_changes,
            local_grads,
            b_prev_changes,
            act,
        }
    }

    pub fn forward(&mut self, inputs: &Vec<f64>) -> Vec<f64> {
        if inputs.len() != self.inputs.len() {
            panic!("forward: input size is wrong");
        }
        let mut result: Vec<f64> = vec![];
        for j in 0..self.outputs.len() {
            let mut sum: f64 = 0.0;
            // loop through input and add w*x + b to sum
            for i in 0..inputs.len() {
                sum += self.w[j][i] * inputs[i];
            }
            sum += self.b[j];
            self.outputs[j] = sum;
            result.push((self.act.func)(sum));
        }
        self.inputs = inputs.clone();
        result
    }

    pub fn update(&mut self, lr: f64, momentum: f64) {
        for j in 0..self.w.len() {
            let delta_b = lr * self.local_grads[j] + momentum * self.b_prev_changes[j];
            self.b[j] -= delta_b; // update each neuron bias
            self.b_prev_changes[j] = delta_b;
            for i in 0..self.w[j].len() {
                // update each weights
                let delta_w = lr * self.grads[j][i] + momentum * self.w_prev_changes[j][i];
                self.w[j][i] -= delta_w;
                self.w_prev_changes[j][i] = delta_w;
            }
```

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            }
        }

    pub fn zero_grad(&mut self) {
        for j in 0..self.outputs.len() {
            self.local_grads[j] = 0.0;
            for i in 0..self.grads[j].len() {
                self.grads[j][i] = 0.0;
            }
        }
    }
}

#[derive(Debug)]
pub struct Net {
    pub layers: Vec<Layer>,
}

impl Net {
    pub fn from_layers(layers: Vec<Layer>) -> Net {
        Net { layers }
    }

    pub fn new(architecture: Vec<u64>) -> Net {
        let mut layers: Vec<Layer> = vec![];
        for i in 1..architecture.len() {
            layers.push(Layer::new(
                architecture[i - 1],
                architecture[i],
                1f64,
                activator::sigmoid(),
            ))
        }
        Net { layers }
    }

    pub fn zero_grad(&mut self) {
        for l in 0..self.layers.len() {
            self.layers[l].zero_grad();
        }
    }

    pub fn forward(&mut self, input: &Vec<f64>) -> Vec<f64> {
        let mut result = self.layers[0].forward(input);
        for l in 1..self.layers.len() {
            result = self.layers[l].forward(&result);
        }
        result
    }

    pub fn update(&mut self, lr: f64, momentum: f64) {
        for l in 0..self.layers.len() {
            self.layers[l].update(lr, momentum);
        }
    }
}

#[cfg(test)]
mod tests {
    use super::*;

    #[test]
    fn test_linear_new() {
        let linear = Layer::new(2, 3, 1.0, activator::linear());
        assert_eq!(linear.outputs.len(), 3);
        assert_eq!(linear.inputs.len(), 2);

        assert_eq!(linear.w.len(), 3);
        assert_eq!(linear.w[0].len(), 2);
        assert_eq!(linear.b.len(), 3);

        assert_eq!(linear.grads.len(), 3);
        assert_eq!(linear.w_prev_changes.len(), 3);
        assert_eq!(linear.grads[0].len(), 2);
        assert_eq!(linear.w_prev_changes[0].len(), 2);
        assert_eq!(linear.local_grads.len(), 3);
```

```
            assert_eq!(linear.b_prev_changes.len(), 3);
        }

        #[test]
        fn test_linear_forward1() {
            let mut linear = Layer::new(2, 1, 1.0, activator::sigmoid());

            for j in 0..linear.w.len() {
                for i in 0..linear.w[j].len() {
                    linear.w[j][i] = 1.0;
                }
            }

            assert_eq!(linear.forward(&vec![1.0, 1.0])[0], 0.9525741268224334);
            assert_eq!(linear.outputs[0], 3.0);
        }

        #[test]
        fn test_linear_forward2() {
            let mut linear = Layer::new(2, 2, 1.0, activator::sigmoid());

            for j in 0..linear.w.len() {
                for i in 0..linear.w[j].len() {
                    linear.w[j][i] = (j as f64) + 1.0;
                }
            }
            let result = linear.forward(&vec![0.0, 1.0]);
            assert_eq!(linear.outputs[0], 2.0);
            assert_eq!(linear.outputs[1], 3.0);
            assert_eq!(result[0], 0.8807970779778823);
            assert_eq!(result[1], 0.9525741268224334);
        }
    }
```

activator.rs

```
#[derive(Debug)]
pub struct ActivationContainer {
    pub func: fn(f64) -> f64,
    pub der: fn(f64) -> f64,
    pub name: String,
}

pub fn sigmoid() -> ActivationContainer {
    fn func(input: f64) -> f64 {
        1.0 / (1.0 + (-input).exp())
    }
    fn der(input: f64) -> f64 {
        func(input) * (1.0 - func(input))
    }
    ActivationContainer {
        func,
        der,
        name: "sigmoid".to_string(),
    }
}

pub fn relu() -> ActivationContainer {
    fn func(input: f64) -> f64 {
        return f64::max(0.0, input);
    }
    fn der(input: f64) -> f64 {
        if input > 0.0 {
            return 1.0;
        } else {
            return 0.0;
        }
    }
    ActivationContainer {
        func,
        der,
        name: "relu".to_string(),
    }
}

pub fn linear() -> ActivationContainer {
```

```
    fn func(input: f64) -> f64 {
        input
    }
    fn der(_input: f64) -> f64 {
        1.0
    }
    ActivationContainer {
        func,
        der,
        name: "linear".to_string(),
    }
}

#[cfg(test)]
mod tests {
    use super::*;

    #[test]
    fn test_sigmoid() {
        let act = sigmoid();

        assert_eq!((act.func)(1.0), 0.7310585786300048792512);
        assert_eq!((act.func)(-1.0), 0.2689414213699951207488);
        assert_eq!((act.func)(0.0), 0.5);
        assert_eq!((act.der)(1.0), 0.1966119332414818525374);
        assert_eq!((act.der)(-1.0), 0.1966119332414818525374);
        assert_eq!((act.der)(0.0), 0.25);
    }

    #[test]
    fn test_relu() {
        let act = relu();

        assert_eq!((act.func)(-1.0), 0.0);
        assert_eq!((act.func)(20.0), 20.0);
        assert_eq!((act.der)(-1.0), 0.0);
        assert_eq!((act.der)(20.0), 1.0);
    }
}
```

loss.rs

```
use crate::model;

pub struct Loss {
    outputs: Vec<f64>,
    desired: Vec<f64>,
    pub func: fn(f64, f64) -> f64,
    pub der: fn(f64, f64) -> f64,
}

impl Loss {
    /// Mean Squared Error
    pub fn mse() -> Loss {
        fn func(output: f64, desired: f64) -> f64 {
            0.5 * (output - desired).powi(2)
        }
        fn der(output: f64, desired: f64) -> f64 {
            output - desired
        }

        Loss {
            outputs: vec![],
            desired: vec![],
            func,
            der,
        }
    }

    /// Binary Cross Entropy
    pub fn bce() -> Loss {
        fn func(output: f64, desired: f64) -> f64 {
            -desired * output.ln() + (1.0 - desired) * (1.0 - output).ln()
        }
        fn der(output: f64, desired: f64) -> f64 {
```

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            -(desired / output - (1.0 - desired) / (1.0 - output))
        }

        Loss {
            outputs: vec![],
            desired: vec![],
            func,
            der,
        }
    }

    pub fn criterion(&mut self, outputs: &Vec<f64>, desired: &Vec<f64>) -> f64 {
        if outputs.len() != desired.len() {
            panic!("outputs size is not equal to desired size");
        }

        let mut loss = 0.0;
        for i in 0..outputs.len() {
            loss += (self.func)(outputs[i], desired[i]);
        }
        self.outputs = outputs.clone();
        self.desired = desired.clone();
        loss
    }

    pub fn backward(&self, layers: &mut Vec<model::Layer>) {
        for l in (0..layers.len()).rev() {
            // output layer
            if l == layers.len() - 1 {
                for j in 0..layers[l].outputs.len() {
                    // compute grads
                    let local_grad = (self.der)(self.outputs[j], self.desired[j])
                        * (layers[l].act.der)(layers[l].outputs[j]);

                    layers[l].local_grads[j] = local_grad;

                    // set grads for each weight
                    for k in 0..(layers[l - 1].outputs.len()) {
                        layers[l].grads[j][k] =
                            (layers[l - 1].act.func)(layers[l - 1].outputs[k]) * local_grad;
                    }
                }
                continue;
            }
            // hidden layer
            for j in 0..layers[l].outputs.len() {
                // calculate local_grad based on previous local_grad
                let mut local_grad = 0f64;
                for i in 0..layers[l + 1].w.len() {
                    for k in 0..layers[l + 1].w[i].len() {
                        local_grad += layers[l + 1].w[i][k] * layers[l + 1].local_grads[i];
                    }
                }
                local_grad = (layers[l].act.der)(layers[l].outputs[j]) * local_grad;
                layers[l].local_grads[j] = local_grad;

                // set grads for each weight
                if l == 0 {
                    for k in 0..layers[l].inputs.len() {
                        layers[l].grads[j][k] = layers[l].inputs[k] * local_grad;
                    }
                } else {
                    for k in 0..layers[l - 1].outputs.len() {
                        layers[l].grads[j][k] =
                            (layers[l - 1].act.func)(layers[l - 1].outputs[k]) * local_grad;
                    }
                }
            }
        }
    }
}

#[cfg(test)]
mod tests {
    use super::*;
```

```
    #[test]
    fn test_mse_func() {
        assert_eq!((Loss::mse().func)(2.0, 1.0), 0.5);
        assert_eq!((Loss::mse().func)(5.0, 0.0), 12.5);
    }

    #[test]
    fn test_mse_der() {
        assert_eq!((Loss::mse().der)(2.0, 1.0), 1.0);
        assert_eq!((Loss::mse().der)(5.0, 0.0), 5.0);
    }

    #[test]
    fn test_mse() {
        let mut loss = Loss::mse();

        let l = loss.criterion(&vec![2.0, 1.0, 0.0], &vec![0.0, 1.0, 2.0]);
        assert_eq!(l, 4.0);

        loss.criterion(
            &vec![34.0, 37.0, 44.0, 47.0, 48.0],
            &vec![37.0, 40.0, 46.0, 44.0, 46.0],
        );
        assert_eq!(l, 4.0);
    }

    #[test]
    fn test_bce_func() {
        println!("{}", (Loss::bce().func)(0.9, 0.0));
        println!("{}", (Loss::bce().func)(0.9, 1.0));
    }
}
```

utills/mod.rs

```
pub mod data;
pub mod graph;
pub mod io;
```

utills/data.rs

```
use super::io::read_lines;
use rand::prelude::SliceRandom;
use serde::Deserialize;
use std::error::Error;

#[derive(Debug, Clone)]
pub struct Data {
    pub inputs: Vec<f64>,
    pub labels: Vec<f64>,
}
#[derive(Clone)]
pub struct DataSet {
    datas: Vec<Data>,
}

impl DataSet {
    pub fn new(datas: Vec<Data>) -> DataSet {
        DataSet { datas }
    }

    pub fn cross_valid_set(&self, percent: f64) -> Vec<(DataSet, DataSet)> {
        if percent < 0.0 && percent > 1.0 {
            panic!("argument percent must be in range [0, 1]")
        }
        let k = (percent * (self.datas.len() as f64)).ceil() as usize; // fold size
        let n = (self.datas.len() as f64 / k as f64).ceil() as usize; // number of folds
        let datas = self.get_shuffled().clone(); // shuffled data before slicing it
        let mut set: Vec<(DataSet, DataSet)> = vec![];

        let mut curr: usize = 0;
        for _ in 0..n {
            let r_pt: usize = if curr + k > datas.len() {
                datas.len()
            } else {
```

```
                curr + k
            };

            let validation_set: Vec<Data> = datas[curr..r_pt].to_vec();
            let training_set: Vec<Data> = if curr > 0 {
                let mut temp = datas[0..curr].to_vec();
                temp.append(&mut datas[r_pt..datas.len()].to_vec());
                temp
            } else {
                datas[r_pt..datas.len()].to_vec()
            };

            set.push((DataSet::new(training_set), DataSet::new(validation_set)));
            curr += k
        }
        set
    }

    pub fn data_points(&self) -> Vec<f64> {
        let mut data_points: Vec<f64> = vec![];
        for mut dt in self.datas.clone() {
            data_points.append(&mut dt.inputs);
            data_points.append(&mut dt.labels);
        }
        data_points
    }

    pub fn max(&self) -> f64 {
        self.data_points()
            .iter()
            .fold(f64::NAN, |max, &v| v.max(max))
    }

    pub fn min(&self) -> f64 {
        self.data_points()
            .iter()
            .fold(f64::NAN, |min, &v| v.min(min))
    }

    pub fn std(&self) -> f64 {
        let mean = self.mean();
        let data_points = self.data_points();
        let n = data_points.len() as f64;
        data_points
            .iter()
            .fold(0.0f64, |sum, &val| sum + (val - mean).powi(2) / n)
            .sqrt()
    }

    pub fn mean(&self) -> f64 {
        let data_points = self.data_points();
        let n = data_points.len() as f64;
        data_points.iter().fold(0.0f64, |mean, &val| mean + val / n)
    }

    pub fn len(&self) -> usize {
        self.datas.len()
    }

    pub fn get_datas(&self) -> Vec<Data> {
        self.datas.clone()
    }

    pub fn get_shuffled(&self) -> Vec<Data> {
        let mut shuffled_datas = self.datas.clone();
        shuffled_datas.shuffle(&mut rand::thread_rng());
        shuffled_datas
    }
}

pub fn minmax_norm(dataset: &DataSet, min: f64, max: f64) -> DataSet {
    let datas: Vec<Data> = dataset
        .get_datas()
        .into_iter()
        .map(|dt| {
            let inputs: Vec<f64> = dt.inputs.iter().map(|x| (x - min) / (max - min)).collect();
```

```
            let labels: Vec<f64> = dt.labels.iter().map(|x| (x - min) / (max - min)).collect();
            Data { inputs, labels }
        })
        .collect();
    DataSet::new(datas)
}

pub fn standardization(dataset: &DataSet, mean: f64, std: f64) -> DataSet {
    let datas: Vec<Data> = dataset
        .get_datas()
        .into_iter()
        .map(|dt| {
            let inputs: Vec<f64> = dt.inputs.iter().map(|x| (x - mean) / std).collect();
            let labels: Vec<f64> = dt.labels.iter().map(|x| (x - mean) / std).collect();
            Data { inputs, labels }
        })
        .collect();
    DataSet::new(datas)
}

pub fn un_standardization(value: f64, mean: f64, std: f64) -> f64 {
    value * std + mean
}

pub fn xor_dataset() -> DataSet {
    let inputs = vec![[0.0, 0.0], [0.0, 1.0], [1.0, 0.0], [1.0, 1.0]];
    let labels = vec![[0.0], [1.0], [1.0], [0.0]];
    let mut datas: Vec<Data> = vec![];
    for i in 0..4 {
        datas.push(Data {
            inputs: inputs[i].to_vec(),
            labels: labels[i].to_vec(),
        });
    }

    DataSet::new(datas)
}

pub fn flood_dataset() -> Result<DataSet, Box<dyn Error>> {
    #[derive(Deserialize)]
    struct Record {
        s1_t3: f64,
        s1_t2: f64,
        s1_t1: f64,
        s1_t0: f64,
        s2_t3: f64,
        s2_t2: f64,
        s2_t1: f64,
        s2_t0: f64,
        t7: f64,
    }

    let mut datas: Vec<Data> = vec![];
    let mut reader = csv::Reader::from_path("data/flood_dataset.csv")?;
    for record in reader.deserialize() {
        let record: Record = record?;
        let mut inputs: Vec<f64> = vec![];
        // station 1
        inputs.push(record.s1_t3);
        inputs.push(record.s1_t2);
        inputs.push(record.s1_t1);
        inputs.push(record.s1_t0);
        // station 2
        inputs.push(record.s2_t3);
        inputs.push(record.s2_t2);
        inputs.push(record.s2_t1);
        inputs.push(record.s2_t0);

        let labels: Vec<f64> = vec![f64::from(record.t7)];
        datas.push(Data { inputs, labels });
    }
    Ok(DataSet::new(datas))
}

pub fn cross_dataset() -> Result<DataSet, Box<dyn Error>> {
    let mut datas: Vec<Data> = vec![];
```

```
    let mut lines = read_lines("data/cross.pat")?;
    while let (Some(_), Some(Ok(l1)), Some(Ok(l2))) = (lines.next(), lines.next(), lines.next()) {
        let mut inputs: Vec<f64> = vec![];
        let mut labels: Vec<f64> = vec![];
        for w in l1.split(" ") {
            let v: f64 = w.parse().unwrap();
            inputs.push(v);
        }
        for w in l2.split(" ") {
            let v: f64 = w.parse().unwrap();
            // class 1 0 -> 1
            // class 0 1 -> 0
            labels.push(v);
            break;
        }
        datas.push(Data { inputs, labels });
    }
    Ok(DataSet::new(datas))
}
```

utills/graph.rs

```
use plotters::coord::Shift;
use plotters::prelude::*;
use std::error::Error;

pub struct LossGraph {
    loss: Vec<Vec<f64>>,
    valid_loss: Vec<Vec<f64>>,
}

impl LossGraph {
    pub fn new() -> LossGraph {
        let loss: Vec<Vec<f64>> = vec![];
        let valid_loss: Vec<Vec<f64>> = vec![];
        LossGraph { loss, valid_loss }
    }

    pub fn add_loss(&mut self, training: Vec<f64>, validation: Vec<f64>) {
        self.loss.push(training);
        self.valid_loss.push(validation);
    }
    /// Draw training loss and validation loss at each epoch (x_vec)
    pub fn draw_loss(
        &self,
        idx: u32,
        root: &DrawingArea<BitMapBackend, Shift>,
        loss_vec: &Vec<f64>,
        valid_loss_vec: &Vec<f64>,
        max_loss: f64
    ) -> Result<(), Box<dyn Error>> {
        let min_loss1 = loss_vec.iter().fold(f64::NAN, |min, &val| val.min(min));
        let min_loss2 = valid_loss_vec
            .iter()
            .fold(f64::NAN, |min, &val| val.min(min));
        let min_loss = if min_loss1.min(min_loss2) > 0.0 {
            0.0
        } else {
            min_loss1.min(min_loss2)
        };

        let mut chart = ChartBuilder::on(&root)
            .caption(
                format!("Loss {}", idx),
                ("Hack", 44, FontStyle::Bold).into_font(),
            )
            .margin(20)
            .x_label_area_size(50)
            .y_label_area_size(60)
            .build_cartesian_2d(0..loss_vec.len(), min_loss..max_loss)?;

        chart
            .configure_mesh()
            .y_desc("Loss")
            .x_desc("Epochs")
            .axis_desc_style(("Hack", 20))
```

```
            .draw()?;

        chart.draw_series(LineSeries::new(
            loss_vec.iter().enumerate().map(|(i, x)| (i + 1, *x)),
            &RED,
        ))?;

        chart.draw_series(LineSeries::new(
            valid_loss_vec.iter().enumerate().map(|(i, x)| (i + 1, *x)),
            &BLUE,
        ))?;

        root.present()?;
        Ok(())
    }

    pub fn max_loss(&self) -> f64 {
        f64::max(
            self.loss.iter().fold(f64::NAN, |max, vec| {
                let max_loss = vec.iter().fold(f64::NAN, |max, &val| val.max(max));
                f64::max(max_loss, max)
            }),
            self.valid_loss.iter().fold(f64::NAN, |max, vec| {
                let max_loss = vec.iter().fold(f64::NAN, |max, &val| val.max(max));
                f64::max(max_loss, max)
            })
        )
    }

    pub fn draw(&self, path: String) -> Result<(), Box<dyn Error>> {
        let root = BitMapBackend::new(&path, (2000, 1000)).into_drawing_area();
        root.fill(&WHITE)?;
        // hardcode for 10 iteraions
        let drawing_areas = root.split_evenly((2, 5));

        let mut loss_iter = self.loss.iter();
        let mut valid_loss_iter = self.valid_loss.iter();
        let max_loss = self.max_loss();
        for (drawing_area, idx) in drawing_areas.iter().zip(1..) {
            if let (Some(loss_vec), Some(valid_loss_vec)) =
                (loss_iter.next(), valid_loss_iter.next())
            {
                self.draw_loss(idx, drawing_area, loss_vec, valid_loss_vec, max_loss)?;
            }
        }
        Ok(())
    }
}

/// Draw histogram of given datas
pub fn draw_histogram(
    datas: Vec<f64>,
    title: &str,
    axes_desc: (&str, &str),
    path: String,
) -> Result<(), Box<dyn Error>> {
    let n = datas.len();
    let max_y = datas.iter().fold(f64::NAN, |max, &val| val.max(max));
    let mean = datas
        .iter()
        .fold(0.0f64, |mean, &val| mean + val / n as f64);

    let root = BitMapBackend::new(&path, (1024, 768)).into_drawing_area();
    root.fill(&WHITE)?;

    let mut chart = ChartBuilder::on(&root)
        .caption(title, ("Hack", 44, FontStyle::Bold).into_font())
        .margin(20)
        .x_label_area_size(50)
        .y_label_area_size(60)
        .build_cartesian_2d((1..n).into_segmented(), 0.0..max_y)?
        .set_secondary_coord(1..n, 0.0..max_y);

    chart
        .configure_mesh()
        .disable_x_mesh()
```

```
        .y_desc(axes_desc.1)
        .x_desc(axes_desc.0)
        .axis_desc_style(("Hack", 20))
        .draw()?;

    let hist = Histogram::vertical(&chart)
        .style(RED.mix(0.5).filled())
        .margin(10)
        .data(datas.iter().enumerate().map(|(i, x)| (i + 1, *x)));

    chart.draw_series(hist)?;

    chart
        .draw_secondary_series(LineSeries::new(
            datas.iter().enumerate().map(|(i, _)| (i + 1, mean)),
            BLUE.filled().stroke_width(2),
        ))?
        .label(format!("mean: {:.3}", mean))
        .legend(|(x, y)| PathElement::new(vec![(x, y), (x + 20, y)], &BLUE));

    chart
        .configure_series_labels()
        .label_font(("Hack", 14).into_font())
        .background_style(&WHITE)
        .border_style(&BLACK)
        .draw()?;

    root.present()?;
    Ok(())
}

pub fn draw_2hist(
    datas: [Vec<f64>; 2],
    title: &str,
    axes_desc: (&str, &str),
    path: String,
) -> Result<(), Box<dyn Error>> {
    let n = datas.iter().fold(0f64, |max, l| max.max(l.len() as f64));
    let max_y = datas.iter().fold(0f64, |max, l| {
        max.max(l.iter().fold(f64::NAN, |v_max, &v| v.max(v_max)))
    });
    let mean: Vec<f64> = datas
        .iter()
        .map(|l| {
            l.iter()
                .fold(0f64, |mean, &val| mean + val / l.len() as f64)
        })
        .collect();

    let root = BitMapBackend::new(&path, (1024, 768)).into_drawing_area();
    root.fill(&WHITE)?;

    let mut chart = ChartBuilder::on(&root)
        .caption(title, ("Hack", 44, FontStyle::Bold).into_font())
        .margin(20)
        .x_label_area_size(50)
        .y_label_area_size(60)
        .build_cartesian_2d((1..n as u32).into_segmented(), 0.0..max_y)?
        .set_secondary_coord(0.0..n, 0.0..max_y);

    chart
        .configure_mesh()
        .disable_x_mesh()
        .y_desc(axes_desc.1)
        .x_desc(axes_desc.0)
        .axis_desc_style(("Hack", 20))
        .draw()?;

    let a = datas[0].iter().zip(0..).map(|(y, x)| {
        Rectangle::new(
            [(x as f64 + 0.1, *y), (x as f64 + 0.5, 0f64)],
            Into::<ShapeStyle>::into(&RED.mix(0.5)).filled(),
        )
    });

    let b = datas[1].iter().zip(0..).map(|(y, x)| {
```

```rust
        Rectangle::new(
            [(x as f64 + 0.5, *y), (x as f64 + 0.9, 0f64)],
            Into::<ShapeStyle>::into(&BLUE.mix(0.5)).filled(),
        )
    });

    chart.draw_secondary_series(a)?;
    chart.draw_secondary_series(b)?;

    let v: Vec<usize> = (0..(n + 1.0) as usize).collect();
    chart
        .draw_secondary_series(LineSeries::new(
            v.iter().map(|i| (*i as f64, mean[0])),
            RED.filled().stroke_width(2),
        ))?
        .label(format!("mean: {:.5}", mean[0]))
        .legend(|(x, y)| PathElement::new(vec![(x, y), (x + 20, y)], &RED));

    chart
        .draw_secondary_series(LineSeries::new(
            v.iter().map(|i| (*i as f64, mean[1])),
            BLUE.filled().stroke_width(2),
        ))?
        .label(format!("mean: {:.5}", mean[1]))
        .legend(|(x, y)| PathElement::new(vec![(x, y), (x + 20, y)], &BLUE));

    chart
        .configure_series_labels()
        .position(SeriesLabelPosition::UpperRight)
        .label_font(("Hack", 14).into_font())
        .background_style(&WHITE)
        .border_style(&BLACK)
        .draw()?;

    root.present()?;
    Ok(())
}

/// Draw confusion matrix
pub fn draw_confustion(matrix_vec: Vec<[[i32; 2]; 2]>, path: String) -> Result<(), Box<dyn Error>> {
    let root = BitMapBackend::new(&path, (2000, 1000)).into_drawing_area();
    root.fill(&WHITE)?;
    // hardcode for 10 iteraions
    let drawing_areas = root.split_evenly((2, 5));
    let mut matrix_iter = matrix_vec.iter();

    for (drawing_area, idx) in drawing_areas.iter().zip(1..) {
        if let Some(matrix) = matrix_iter.next() {
            let mut chart = ChartBuilder::on(&drawing_area)
                .caption(
                    format!("Confusion Matrix {}", idx),
                    ("Hack", 32, FontStyle::Bold).into_font(),
                )
                .margin(20)
                .build_cartesian_2d(0i32..2i32, 2i32..0i32)?
                .set_secondary_coord(0f64..2f64, 2f64..0f64);

            chart
                .configure_mesh()
                .disable_axes()
                .max_light_lines(4)
                .disable_x_mesh()
                .disable_y_mesh()
                .label_style(("Hack", 20))
                .draw()?;

            chart.draw_series(
                matrix
                    .iter()
                    .zip(0..)
                    .map(|(l, y)| l.iter().zip(0..).map(move |(v, x)| (x, y, v)))
                    .flatten()
                    .map(|(x, y, v)| {
                        Rectangle::new(
                            [(x, y), (x + 1, y + 1)],
                            HSLColor(
```

```
                                240.0 / 360.0 - 240.0 / 360.0 * (*v as f64 / 20.0),
                                0.7,
                                0.1 + 0.4 * *v as f64 / 20.0,
                            )
                            .filled(),
                        )
                    }),
            )?;

            chart.draw_secondary_series(
                matrix
                    .iter()
                    .zip(0..)
                    .map(|(l, y)| l.iter().zip(0..).map(move |(v, x)| (x, y, v)))
                    .flatten()
                    .map(|(x, y, v)| {
                        let text: String = if x == 0 && y == 0 {
                            format!["TP:{}", v]
                        } else if x == 1 && y == 0 {
                            format!["FP:{}", v]
                        } else if x == 0 && y == 1 {
                            format!["FN:{}", v]
                        } else {
                            format!["TN:{}", v]
                        };

                        Text::new(
                            text,
                            ((2.0 * x as f64 + 0.7) / 2.0, (2.0 * y as f64 + 1.0) / 2.0),
                            "Hack".into_font().resize(30.0).color(&WHITE),
                        )
                    }),
            )?;
        }
    }

    root.present()?;
    Ok(())
}
```

utills/io.rs

```
use crate::activator;
use crate::model;
use serde_json::{json, to_writer_pretty, Value};
use std::error::Error;
use std::fs::create_dir;
use std::fs::File;
use std::io::Read;
use std::io::{self, BufRead};
use std::path::Path;

pub fn save(layers: &Vec<model::Layer>, path: String) -> Result<(), Box<dyn Error>> {
    let mut json: Vec<Value> = vec![];

    for l in layers {
        json.push(json!({
            "inputs": l.inputs.len(),
            "outputs": l.outputs.len(),
            "w": l.w,
            "b": l.b,
            "act": l.act.name
        }));
    }
    let result = json!(json);
    let file = File::create(path)?;
    to_writer_pretty(&file, &result)?;
    Ok(())
}

pub fn read_lines<P>(filename: P) -> io::Result<io::Lines<io::BufReader<File>>>
where
    P: AsRef<Path>,
{
    let file = File::open(filename)?;
    Ok(io::BufReader::new(file).lines())
```

```
}

pub fn read_file<P>(filename: P) -> Result<String, Box<dyn Error>>
where
    P: AsRef<Path>,
{
    let mut file = File::open(filename)?;
    let mut contents = String::new();
    file.read_to_string(&mut contents)?;
    Ok(contents)
}

pub fn load<P>(filename: P) -> Result<model::Net, Box<dyn Error>>
where
    P: AsRef<Path>,
{
    let contents = read_file(filename)?;

    let json: Value = serde_json::from_str(&contents)?;
    let mut layers: Vec<model::Layer> = vec![];

    for l in json.as_array().unwrap() {
        // default layer activation is simeple linear f(x) = x
        let mut layer = model::Layer::new(
            l["inputs"].as_u64().unwrap(),
            l["outputs"].as_u64().unwrap(),
            0.0,
            activator::linear(),
        );
        // setting activation function
        if l["act"] == "sigmoid" {
            layer.act = activator::sigmoid();
        }

        // setting weights and bias
        let w = l["w"].as_array().unwrap();
        let b = l["b"].as_array().unwrap();
        for j in 0..w.len() {
            layer.b[j] = b[j].as_f64().unwrap();
            let w_j = w[j].as_array().unwrap();
            for i in 0..w_j.len() {
                layer.w[j][i] = w_j[i].as_f64().unwrap();
            }
        }

        layers.push(layer);
    }

    Ok(model::Net::from_layers(layers))
}

/// Check if specify folder exists in models and img folder, if not create it
///
/// Return models path and img path
pub fn check_dir(folder: &str) -> Result<(String, String), Box<dyn Error>> {
    let models_path = format!("models/{}", folder);
    if !Path::new(&models_path).exists() {
        create_dir(&models_path)?;
    }
    let img_path = format!("report/images/{}", folder);
    if !Path::new(&img_path).exists() {
        create_dir(&img_path)?;
    }
    Ok((models_path, img_path))
}
```