The Validation Experiment

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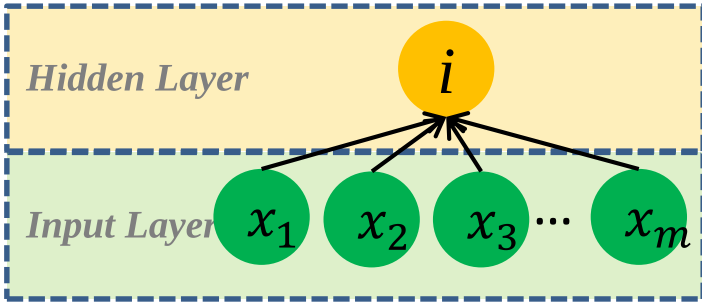
Present your learning mechanism

1. The SLFN model with notations
2. The learning goal
3. The learning mechanism
4. The detailed arrangement of each module
   - the initializing
   - the obtaining
   - the selecting
   - the weight-tuning
   - the cramming
   - the reorganizing
   - …

Where we are now...

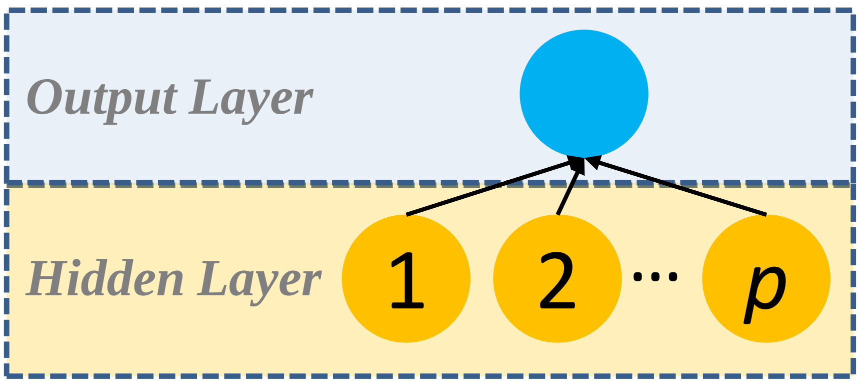
The SLFN with one output node



The hidden layer:

$$a_i^c \equiv ReLU\left(w_{i0}^H + \sum_{j=1}^{m} w_{ij}^H x_j^c\right)$$

$$\mathbf{a} \equiv ReLU(\mathbf{W}^H\mathbf{x} + \mathbf{w}_0^H)$$



The output layer:

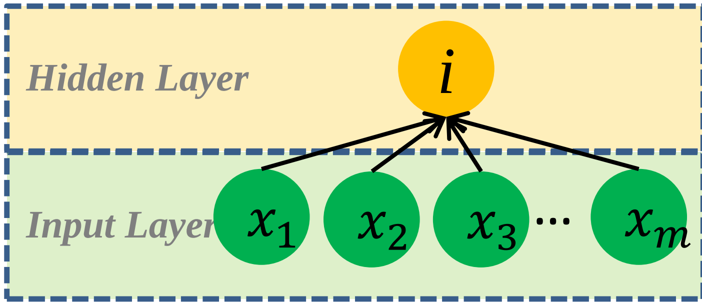
$$f(\mathbf{x}^c,\mathbf{w}) \equiv w_0^o + \sum_{i=1}^{p} w_i^o a_i^c$$

$$\boldsymbol{f}(\mathbf{x}^c,\mathbf{w}) \equiv \mathbf{W}^o\mathbf{a} + \mathbf{w}_0^o$$

$E_N(\mathbf{w}) \equiv \frac{1}{N}\sum_{c\in\mathbf{I}}(f(\mathbf{x}^c,\mathbf{w})-y^c)^2$: the loss function;

$E_N(\mathbf{w}) \equiv \frac{1}{N}\sum_{c\in\mathbf{I}}(f(\mathbf{x}^c,\mathbf{w})-y^c)^2 + \lambda(\sum_{i=0}^{p}(w_i^o)^2 + \sum_{i=1}^{p}\sum_{j=0}^{m}(w_{ij}^H)^2)$: the loss function with the regularization term.

The SLFN with multiple output nodes



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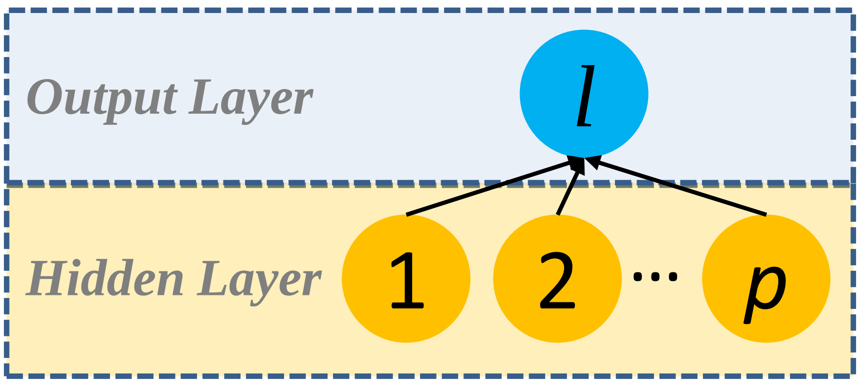


The output layer:

$$f_l(\mathbf{x}^c,\mathbf{w}) \equiv w_{l0}^o + \sum_{i=1}^{p} w_{li}^o a_i^c$$

$$\boldsymbol{f}(\mathbf{x}^c, \mathbf{w}) \equiv \mathbf{W}^o\mathbf{a} + \mathbf{w}_0^o$$

$E_N(\mathbf{w}) \equiv \frac{1}{N}\sum_{c\in\mathbf{I}}\sum_{l=1}^{q}(f_l(\mathbf{x}^c,\mathbf{w})-y_l^c)^2$: the loss function;

$E_N(\mathbf{w}) \equiv \frac{1}{N}\sum_{c\in\mathbf{I}}\sum_{l=1}^{q}(f_l(\mathbf{x}^c,\mathbf{w})-y_l^c)^2 + \lambda(\sum_{l=1}^{q}\sum_{i=0}^{p}(w_{li}^o)^2 + \sum_{i=1}^{p}\sum_{j=0}^{m}(w_{ij}^H)^2)$: the loss function with the regularization term.

Where we are now...

Two-layer nets / SLFN with one output node

The notations and indexes

- $ReLU(x) \equiv max(0, x)$;
- N: the number of data;
- m: the number of input nodes;
- $\mathbf{x}^c \equiv (x_1^c, x_2^c, \ldots, x_m^c)^{\mathrm{T}}$: the c^{th} input;
- p: the number of adopted hidden nodes; p is adaptable within the training phase;
- $w_{i,0}^{\mathrm{H}}$: the bias value of i^{th} hidden node;
- $w_{i,j}^{\mathrm{H}}$: the weight between the j^{th} input node and the i^{th} hidden node, j = 1, 2, ..., m;
- $\mathbf{w}_i^{\mathrm{H}} \equiv (w_{i,1}^{\mathrm{H}}, w_{i,2}^{\mathrm{H}}, \ldots, w_{i,m}^{\mathrm{H}})^{\mathrm{T}}, i=1, 2, \ldots, p$;
- $\mathbf{w}^H \equiv (\mathbf{w}_1^H, \mathbf{w}_2^H, \ldots, \mathbf{w}_p^H)^{\mathrm{T}}$;
- $\mathbf{w}_0^H \equiv (w_{1,0}^H, w_{2,0}^H, \ldots, w_{p,0}^H)^{\mathrm{T}}$;
- w_0^o: the bias value of output node;
- w_i^o: the weight between the i^{th} hidden node and the output node;
- $\mathbf{w}^o \equiv \left(w_1^o, w_2^o, \ldots, w_p^o\right)^{\mathrm{T}}$;
- $\mathbf{w} \equiv \{\mathbf{w}^H, \mathbf{w}_0^H, \mathbf{w}^o, w_0^o\}$;
- a_i^c: the activation value of i^{th} hidden node corresponding to $\mathbf{x}^c$;
- $\mathbf{a}^c \equiv \left(a_1^c, a_2^c, \ldots, a_p^c\right)^{\mathrm{T}}$;
- $f(\mathbf{x}^c, \mathbf{w}) \in \mathrm{R}$: the output value of SLFN corresponding to $\mathbf{x}^c$;
- y^c: the desired output value corresponding to $\mathbf{x}^c$;
- $e^c \equiv f(\mathbf{x}^c, \mathbf{w}) - y^c$.

Should specify (binary or real numbers)

The adaptive SLFN, if you adopt the new learning mechanism

Depend on the application!

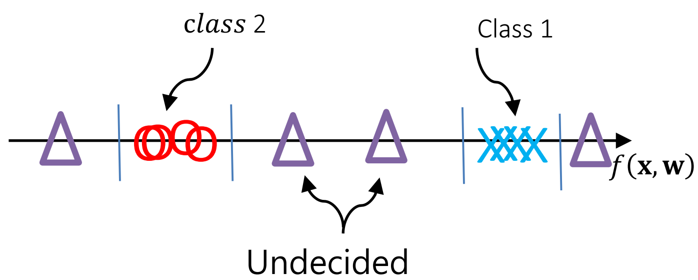
Different stopping criteria result in different length of training time and different model.

Should specify (binary or real numbers)

Where we are now…

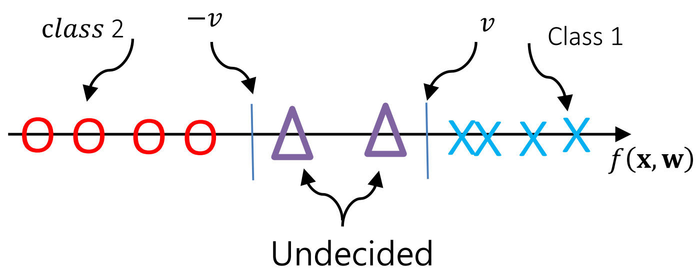
The learning goals for the SLFN with each output node whose output values are real numbers for the two-class classification application

$y^c = 1\ \forall\ c \in \mathbf{I}_1;\ y^c = 0\ \forall\ c \in \mathbf{I}_2$ X : $f(\mathbf{x}^c, \mathbf{w}),\ \forall\ c \in \mathbf{I}_1$ O : $f(\mathbf{x}^c, \mathbf{w}),\ \forall\ c \in \mathbf{I}_2$



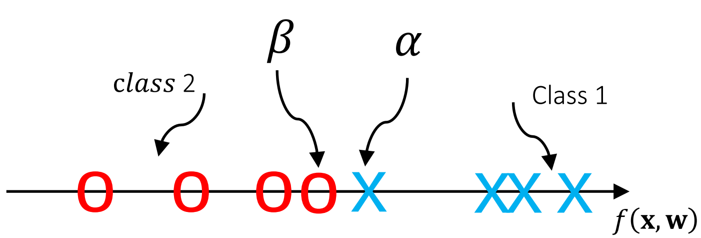
learning goal type 1
(also inferencing mechanism):
$|f(\mathbf{x}^c, \mathbf{w}) - y^c| \le \varepsilon\ \forall\ c \in \mathbf{I}_1;$
$|f(\mathbf{x}^c, \mathbf{w}) + y^c| \le \varepsilon\ \forall\ c \in \mathbf{I}_2$

ε Is a hyperparameter regarding the learning!



learning goal type 2
(also inferencing mechanism):
$f(\mathbf{x}^c, \mathbf{w}) \ge \nu\ \forall\ c \in \mathbf{I}_1;$
$f(\mathbf{x}^c, \mathbf{w}) \le -\nu\ \forall\ c \in \mathbf{I}_2$

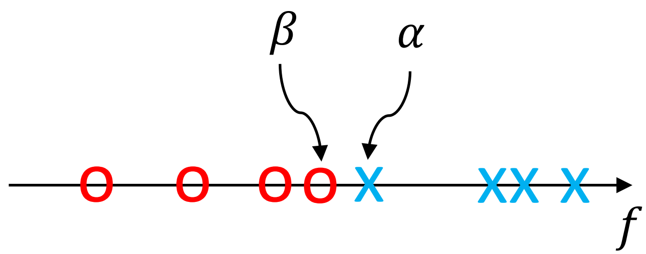
ν Is a hyperparameter regarding the learning and the inferencing!



learning goal type 3: LSC
inferencing mechanism:
$f(\mathbf{x}^c, \mathbf{w}) \ge \nu\ \forall\ c \in \mathbf{I}_1;$
$f(\mathbf{x}^c, \mathbf{w}) \le -\nu\ \forall\ c \in \mathbf{I}_2$

ν Is a hyperparameter regarding the learning!

The learning goals for the SLFN with each output node whose output values are real numbers for the two-class classification application



$$\alpha \equiv \min_{c \in \mathbf{I}_1} f(\mathbf{x}^c, \mathbf{w})\,;\;\; \beta \equiv \max_{c \in \mathbf{I}_2} f(\mathbf{x}^c, \mathbf{w})$$

learning goal type 3: LSC

When LSC $(\alpha > \beta)$ is true, the inferencing mechanism

$$f(\mathbf{x}^c, \mathbf{w}) \geq v \;\; \forall\, c \in \mathbf{I}_1 \text{ and } f(\mathbf{x}^c, \mathbf{w}) \leq -v \;\forall\, c \in \mathbf{I}_2$$

can be set by directly adjusting $\mathbf{w}^o$ according to the following formula:

$$\frac{2v}{\alpha - \beta} w_i^o \to w_i^o \;\; \forall\, i,$$

The weight vector between the hidden layer and the output node

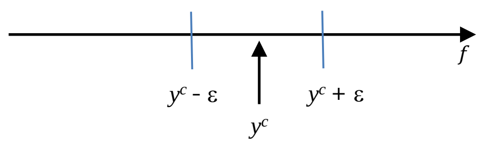
then $v - \min_{c \in \mathbf{I}_1} \sum_{i=1}^{p} w_i^o a_i^c \to w_0^o$

The threshold of the output node

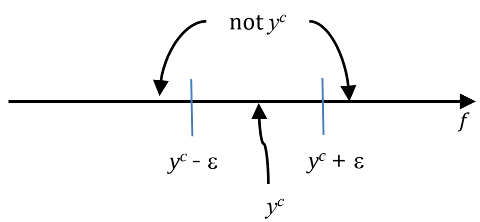
The regression applications

The learning goal

$$|f(\mathbf{x}^c, \mathbf{w}) - y^c| \leq \varepsilon \ \forall \ c \in \mathbf{I}$$



The inferencing mechanism

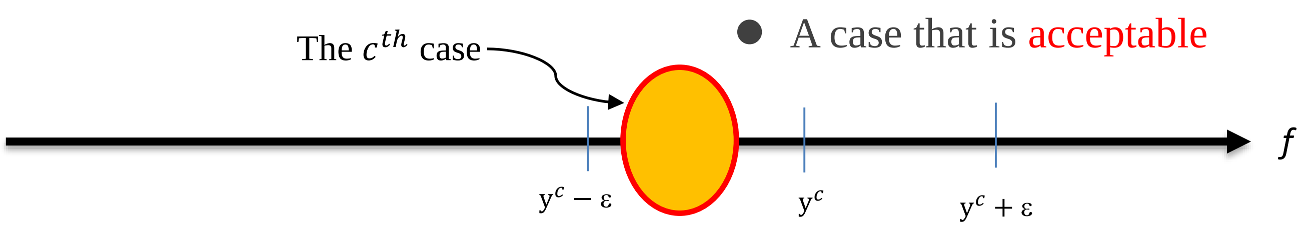


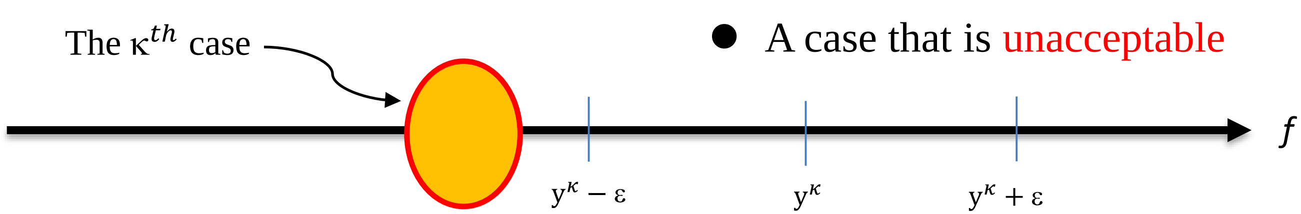
This learning goal and the associated inferencing mechanism is similar to LGT1:
$|f(\mathbf{x}^c, \mathbf{w}) - 1| \leq \varepsilon \ \forall \ c \in \mathbf{I}_1$ and $|f(\mathbf{x}^c, \mathbf{w})| \leq \varepsilon \ \forall \ c \in \mathbf{I}_2$

The unacceptable case

The acceptability of each case is related with the learning goal.

For example, the learning goal is $(f(\mathbf{x}^c, \mathbf{w}) - y^c)^2 \le \varepsilon^2 \ \forall \ c \in$





Your new learning mechanism which is made like playing with Lego – lots of (pre-built or self-built) modules

For the AI application, some AI framework (e.g., PyTorch or TensorFlow) is used to implement the new learning mechanism. Thus, the module concept is recommended.

Neural Network

Linear classifiers

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The module list

- ✓ Weight-tuning
- ✓ Regularizing
- ✓ Reorganizing

Optimization mechanisms: much harder to be proved by mathematical proofs, but much easier to be approved by CS code.

- ✓ Cramming
- ✓ Initializing
- ✓ Obtaining
- ✓ Selecting
- ✓ …

Rule-based mechanisms: much easier to be proved by mathematical proofs, but the code approval is still required.

Validate the new mechanism

- Cannot validate the new learning mechanism through the **mathematical proof**.
- To validate the new learning mechanism, you need to make it and then to set up an AI application experiment with the real-world data, the proposed learning mechanism, and the computation capability.
- Within the experiment, explore two kinds of issues:

1. The AI fundamental study issue regarding the learning mechanism. For example, whether the corresponding learning process does display the proposed ideas/concepts.
2. The AI application study issue regarding the AI system. For example, whether the proposed learning mechanism does lead to good application performances (in terms of efficiency and effectiveness).

Objectives of the experiment

The experiment results should provide evidences for examining whether

1. the corresponding learning process does display the proposed ideas/concepts (e.g., the LTS module, the cramming module, and the reorganizing module can help cope with the encountered undesired attractors and alleviate the overfitting tendency.)
2. the proposed learning mechanism does lead to good application performances in terms of efficiency and effectiveness (e.g., the total training time is acceptable and the proposed learning mechanism can have better accuracy than other tools in the literature.)

Derive insights from the experiment result

- Insights regarding the proposed learning mechanism for the AI professionals.
- Insights regarding the AI application for the domain professionals.

Present your AI application

1. 描述核心問題：AI 應用研究要處理之核心問題是什麼？ (e.g., p. 16 or p. 17)
2. 描述自變數**x**和因變數***y***。
3. 描述實際使用的資料。 (e.g., p. 16 or p. 17)
4. 描述解決核心問題所採用的新型學習演算法。(Your HW#4)
5. 描述新型學習演算法的電腦實作環境。
6. 描述實驗目的：如何驗證此新型學習演算法的優點。 (e.g., p. 13 or p. 21)
7. 描述新型學習演算法之對照組。 (e.g., p. 22)
8. 描述實驗結果。 (e.g., p. 30 ~ p. 52)
9. 結論與討論。 (e.g., p. 14)

The AI Application Problem

- Single Proton Emission Computed Tomography (SPECT) heart diagnosis data set (Kurgan, et al., 2001; UCI Machine Learning)
- 267 instances (55 normal samples and 212 abnormal samples)
- 23 attributes
  (x: 22 (binary) attributes,
  y: 1 (binary) attribute)
- y: Binary (normal: 0, abnormal: 1)
- Randomly generate 20 sets of training and testing data.

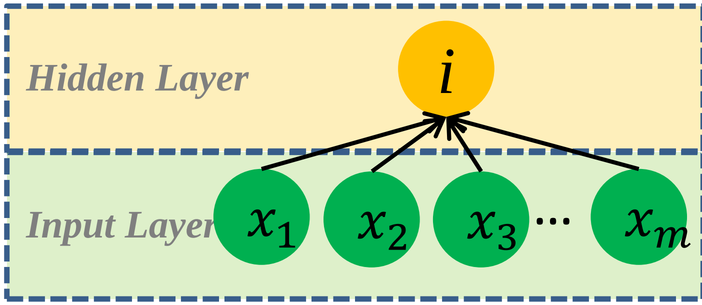
Training data set	Amount of normal samples	40
	Amount of abnormal samples	40
Testing data set	Amount of normal samples	15
	Amount of abnormal samples	172
Total amount of samples		267

The AI Application Problem (2nd version)

- Single Proton Emission Computed Tomography (SPECT) heart diagnosis data set (Kurgan, et al., 2001; UCI Machine Learning)
- 267 instances (55 normal samples and 212 abnormal samples)
- 23 attributes
  (x: 22 (binary) attributes,
  y: 1 (binary) attribute)
- y: Binary (normal: 0, abnormal: 1)
- The SPECT dataset has a total of 267 instances, and the ratio of normal to abnormal instances is approximately 1:4.
- After cleaning the data, there are a total of 250 instances, with 52 normal instances and 198 abnormal instances.
- Randomly generate 20 sets of training and testing data.

Training data set	Amount of normal samples	21
	Amount of abnormal samples	59
Testing data set	Amount of normal samples	31
	Amount of abnormal samples	139
Total amount of samples		250

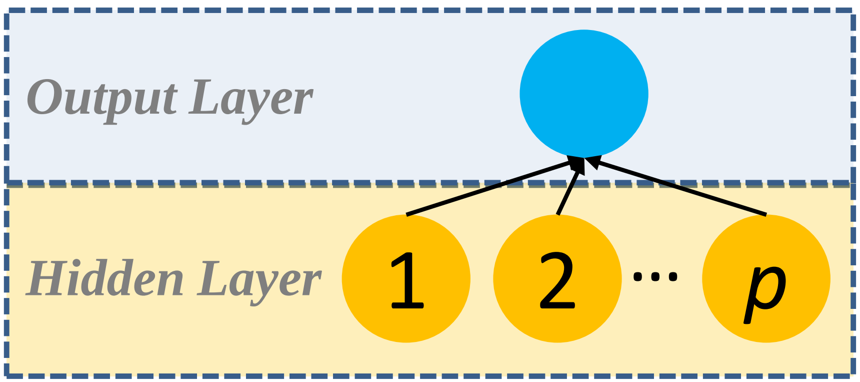
The SLFN with one output node



The hidden layer:

$$a_i^c \equiv ReLU\left(w_{i0}^H + \sum_{j=1}^{m} w_{ij}^H x_j^c\right)$$

$$\mathbf{a} \equiv ReLU(\mathbf{W}^H\mathbf{x} + \mathbf{w}_0^H)$$



The output layer:

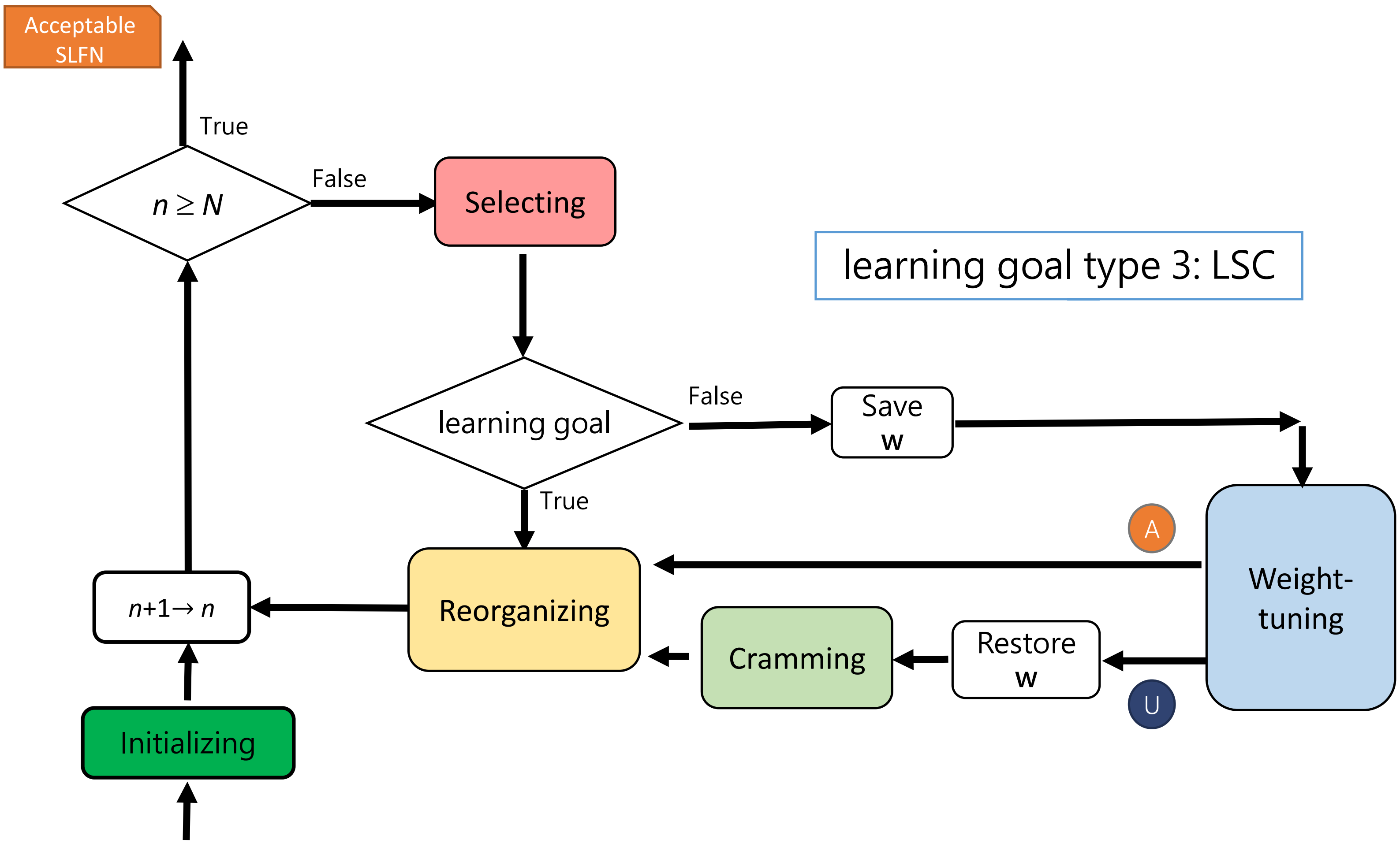
$$f(\mathbf{x}^c, \mathbf{w}) \equiv w_0^o + \sum_{i=1}^{p} w_i^o a_i^c$$

$$\boldsymbol{f}(\mathbf{x}^c, \mathbf{w}) \equiv \mathbf{W}^o\mathbf{a} + \mathbf{w}_0^o$$

$E_N(\mathbf{w}) \equiv \frac{1}{N}\sum_{c\in\mathbf{I}}(f(\mathbf{x}^c,\mathbf{w}) - y^c)^2$: the loss function;

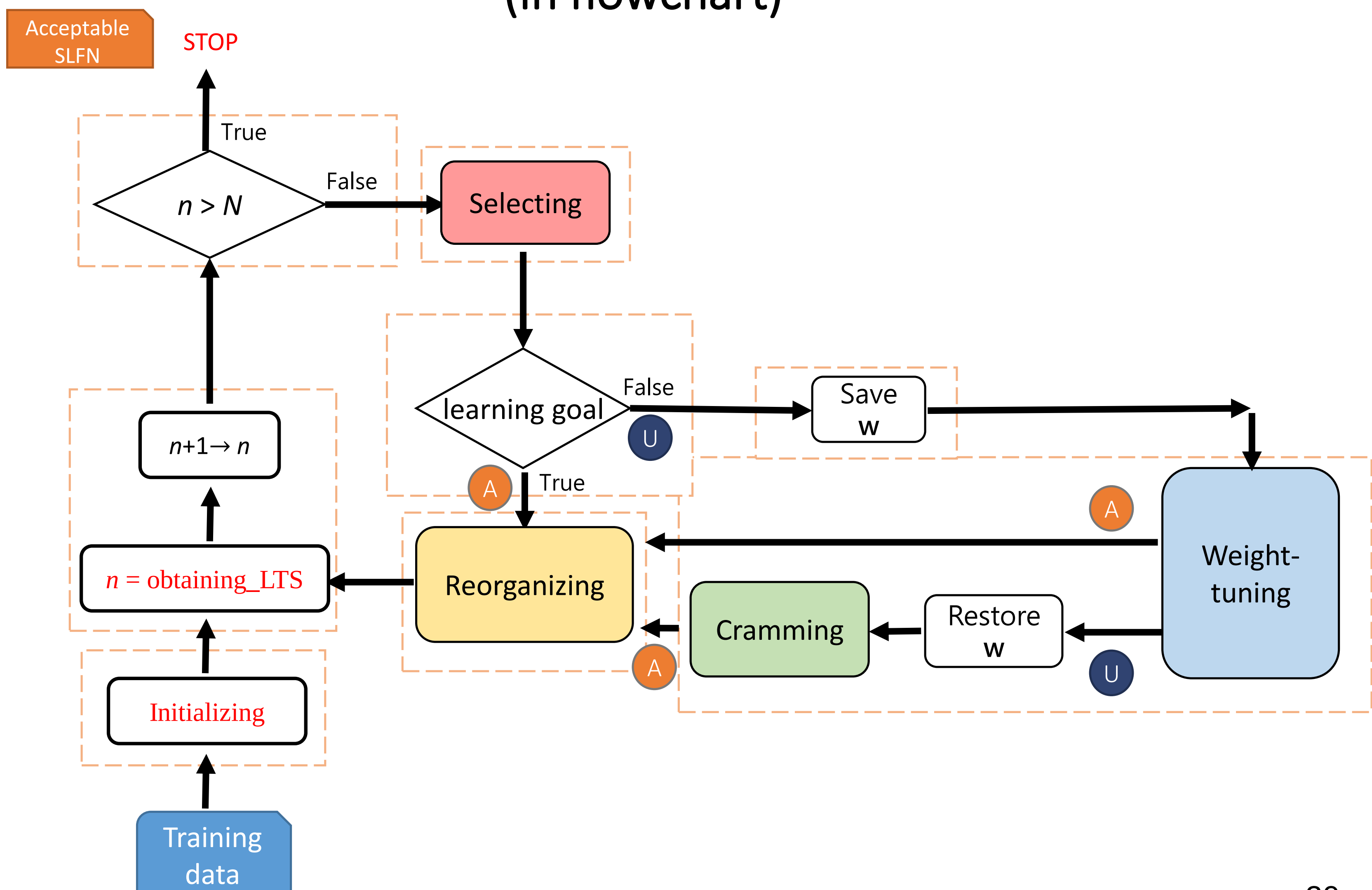
$E_N(\mathbf{w}) \equiv \frac{1}{N}\sum_{c\in\mathbf{I}}(f(\mathbf{x}^c,\mathbf{w}) - y^c)^2 + \lambda(\sum_{i=0}^{p}(w_i^o)^2 + \sum_{i=1}^{p}\sum_{j=0}^{m}(w_{ij}^H)^2)$: the loss function with the regularization term.

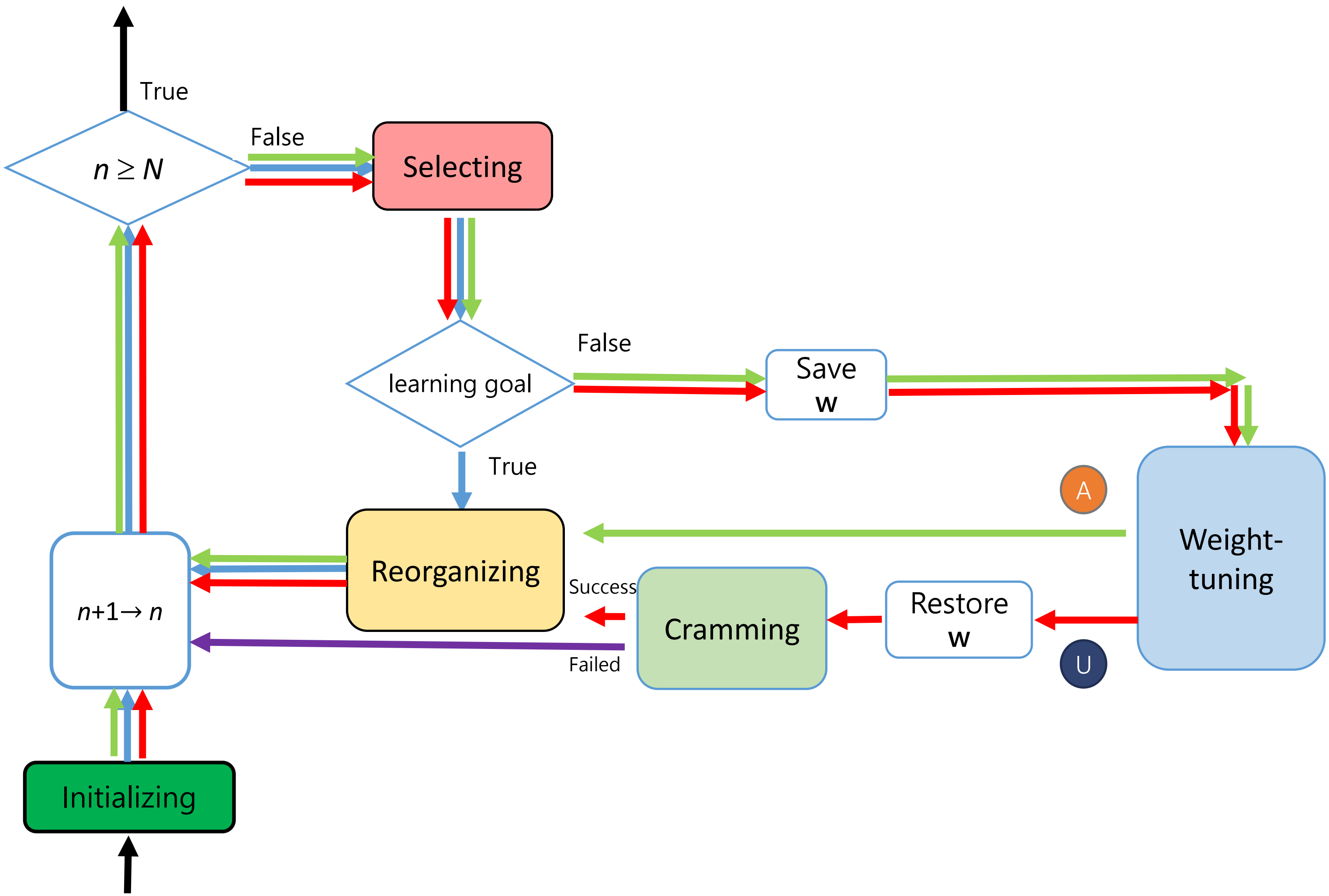
The proposed learning mechanism
(in flowchart)



The third new learning mechanism

(in flowchart)





True
$n \geq N$
False
Selecting
learning goal
False
Save
w
True
Reorganizing
A
Weight-
tuning
n+1→ n
Success
Cramming
Restore
w
Failed
U
Initializing

Four versions

For the validation purpose, there are four versions of the proposed learning mechanism (i.e., four different module arrangements).

Version	The selection module	The reorganizing module
CSI-100	PO_n^N	Reorganizing(100)
CSI-LTS-0	LTS_n^N	Reorganizing(0)
CSI-LTS-100	LTS_n^N	Reorganizing(100)
CSI-LTS-500	LTS_n^N	Reorganizing(500)

LTS_n^N: the module that follows the least trimmed squares principle to pick up *n* training data from *N* training data.

PO_n^N: the module that follows the pre-order principle to pick up first *n* training data from *N* training data.

Reorganizing(100): the module that helps further regularize weights one hundred epochs as well as identify and remove the potentially irrelevant hidden node.

Reorganizing(500): the module that helps further regularize weights five hundred epochs as well as identify and remove the potentially irrelevant hidden node.

Reorganizing(0): the module that helps merely identify and remove the potentially irrelevant hidden node.

Where we are now…

An optimization mechanism

The reorganizing_ALL_r_EU_LG_UA_w_EU_LG_UA

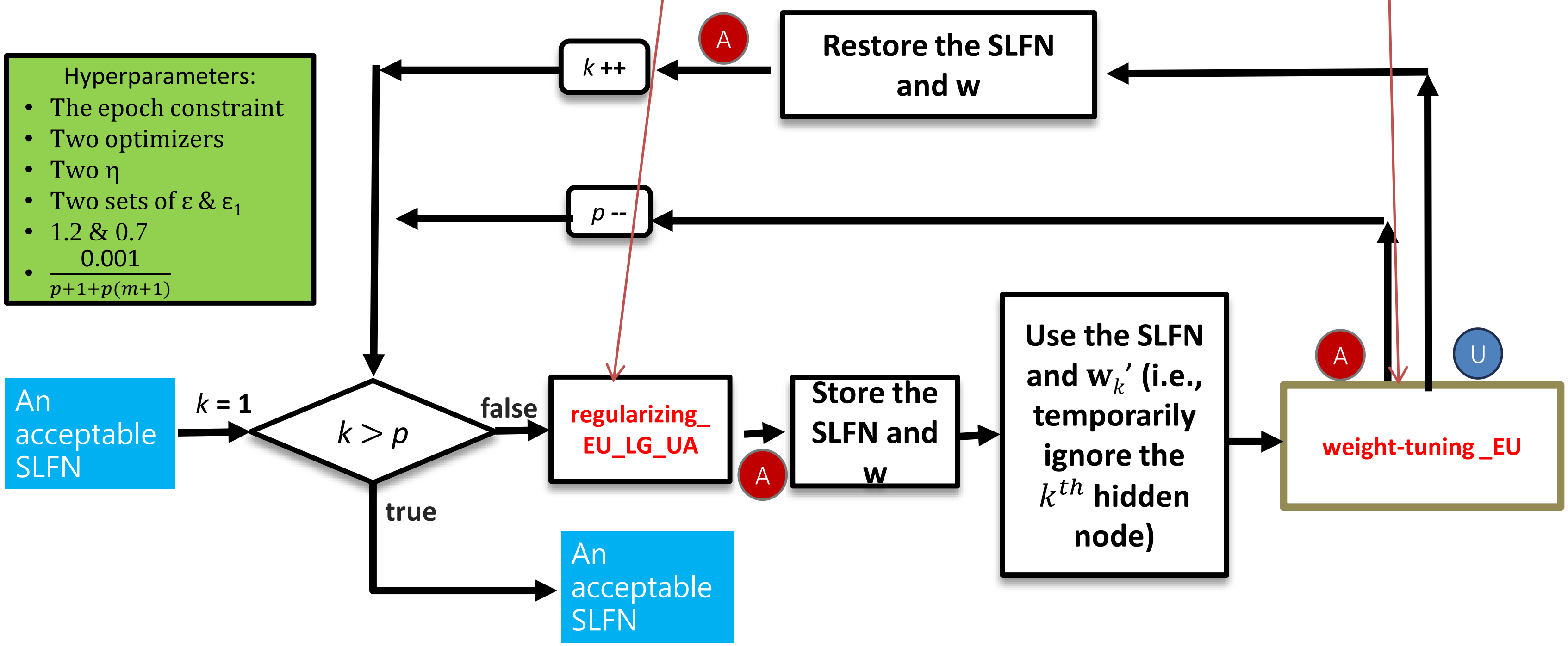
Note that there are two optimizers:

$$L_N(\mathbf{w}) \equiv \frac{\sum_c (f(\mathbf{x}^c, \mathbf{w}) - y^c)^2}{N} + \frac{0.001}{p+1+p(m+1)} \left(\sum_{i=0}^{p} (w_i^o)^2 + \sum_{i=1}^{p} \sum_{j=0}^{m} (w_{ij}^H)^2 \right)$$

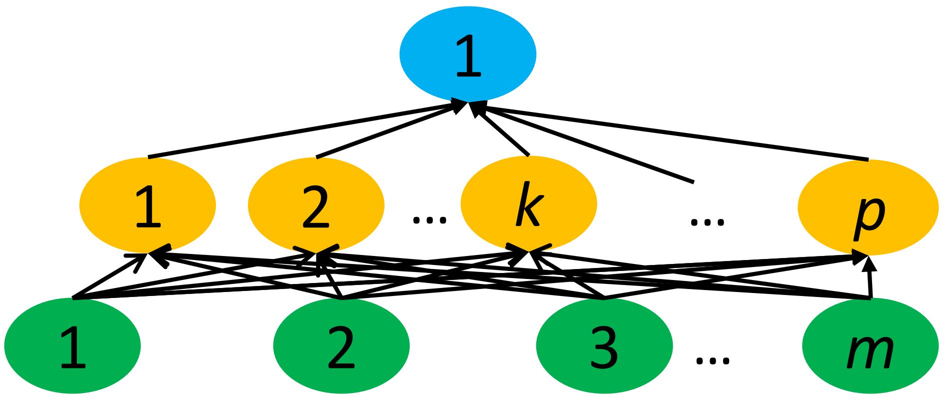
One for the regularizing purpose

$$L_N(\mathbf{w}) \equiv \frac{\sum_c (f(\mathbf{x}^c, \mathbf{w}) - y^c)^2}{N}$$

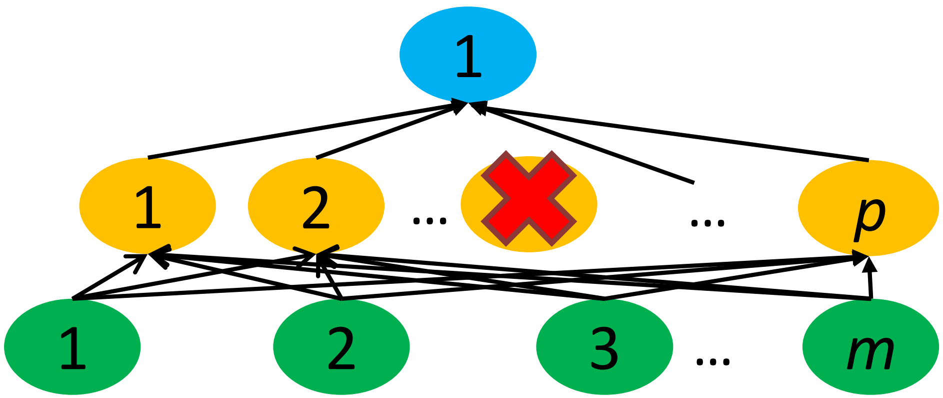
Another for the pruning purpose



Where we are now...



$$\mathbf{w}$$



$$\mathbf{w}_k' \equiv \mathbf{w} - \left\{w_k^o, w_{k0}^H, \mathbf{w}_k^H\right\}$$

Where we are now...

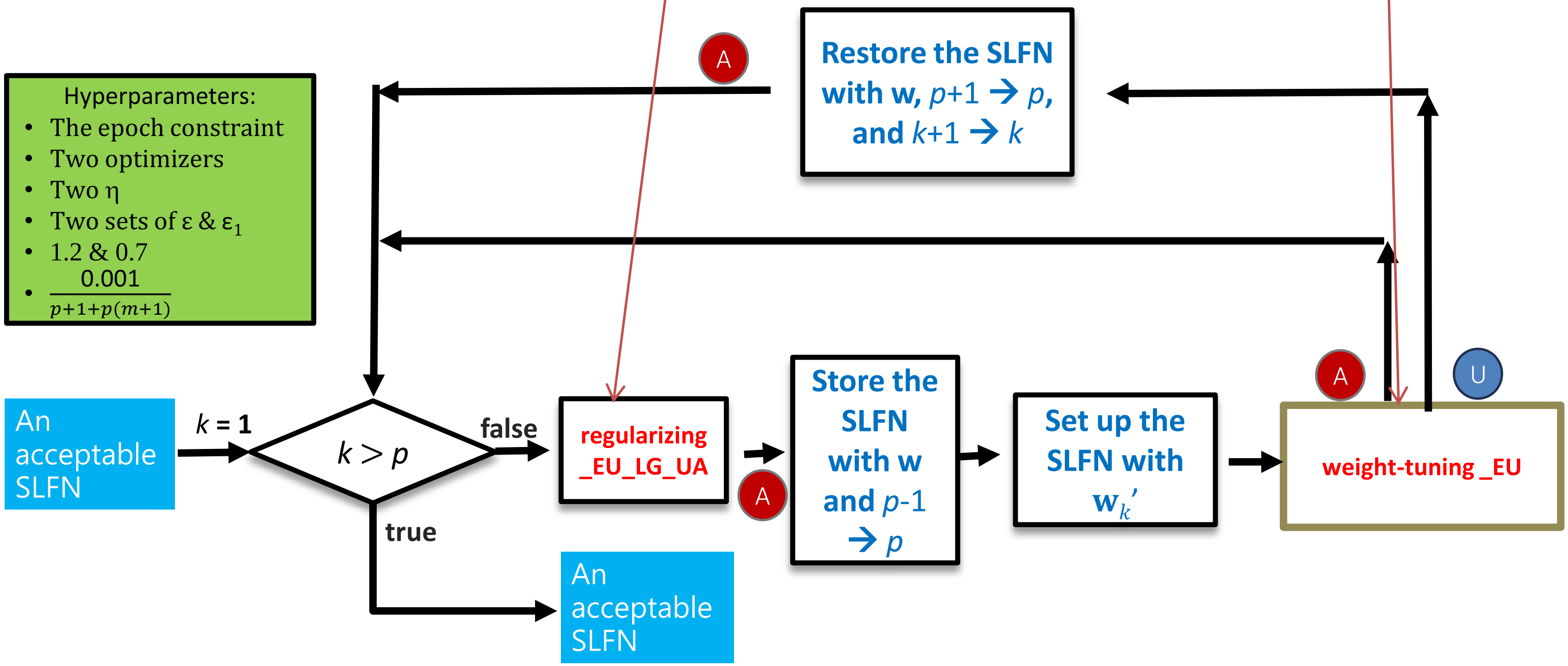
An optimization mechanism

The reorganizing_ALL_r_EU_LG_UA_w_EU_LG_UA

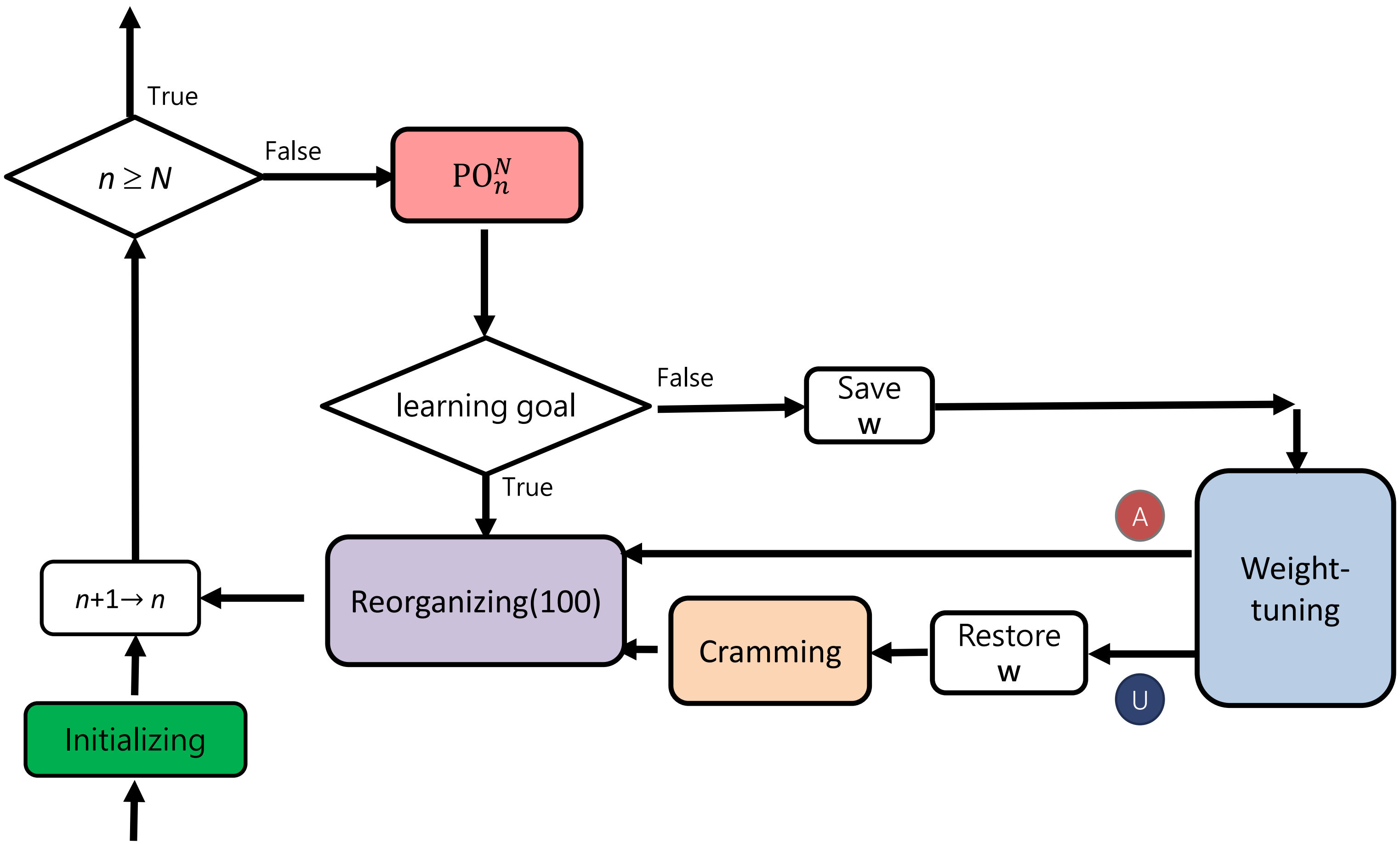
$$L_N(\mathbf{w}) \equiv \frac{\sum_c (f(\mathbf{x}^c, \mathbf{w}) - y^c)^2}{N} + \frac{0.001}{p+1+p(m+1)}\left(\sum_{i=0}^{p} (w_i^o)^2 + \sum_{i=1}^{p}\sum_{j=0}^{m} (w_{ij}^H)^2\right)$$

$$L_N(\mathbf{w}) \equiv \frac{\sum_c (f(\mathbf{x}^c, \mathbf{w}) - y^c)^2}{N}$$

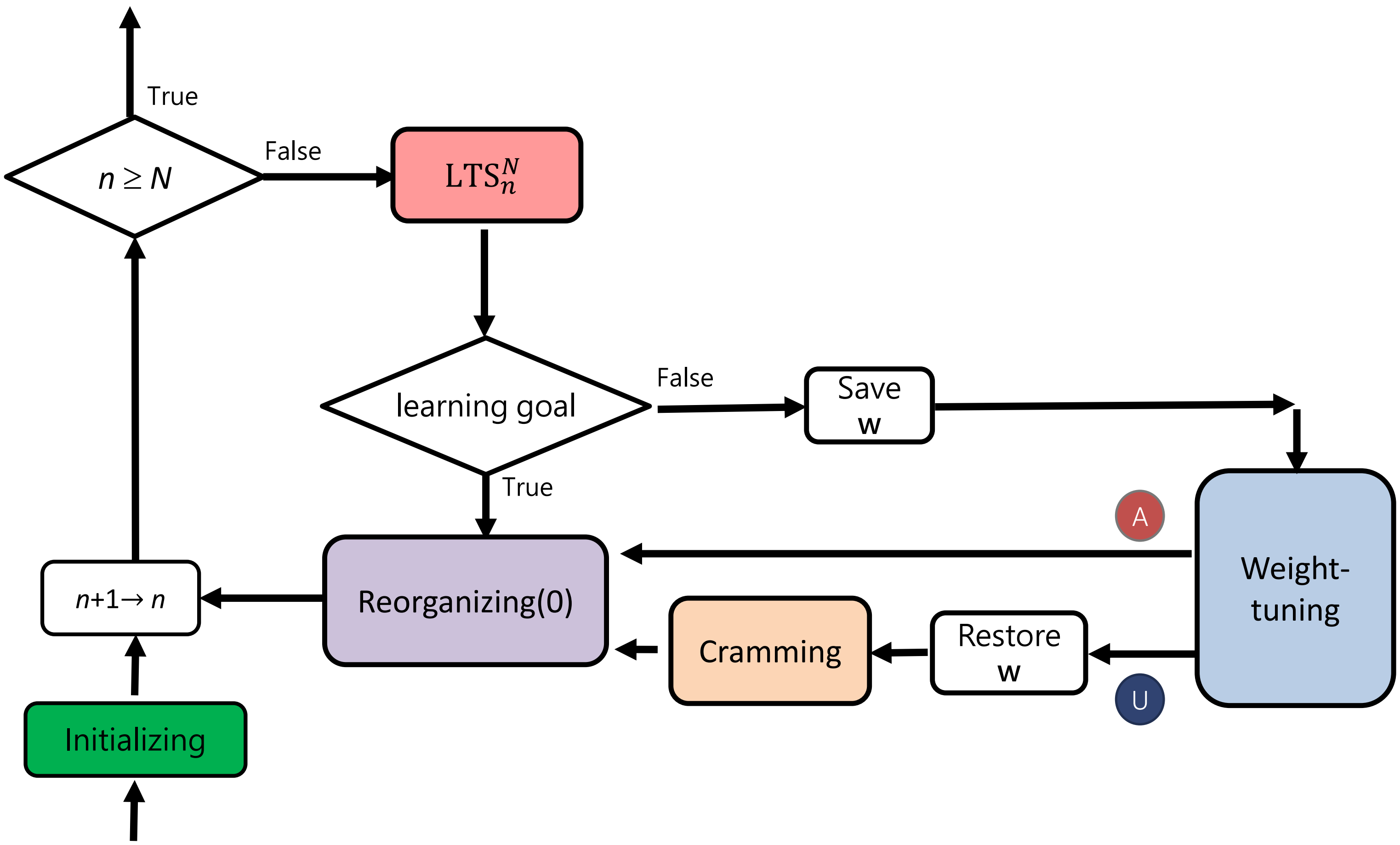
Note that there are two optimizers: One for the regularizing purpose Another for the pruning purpose



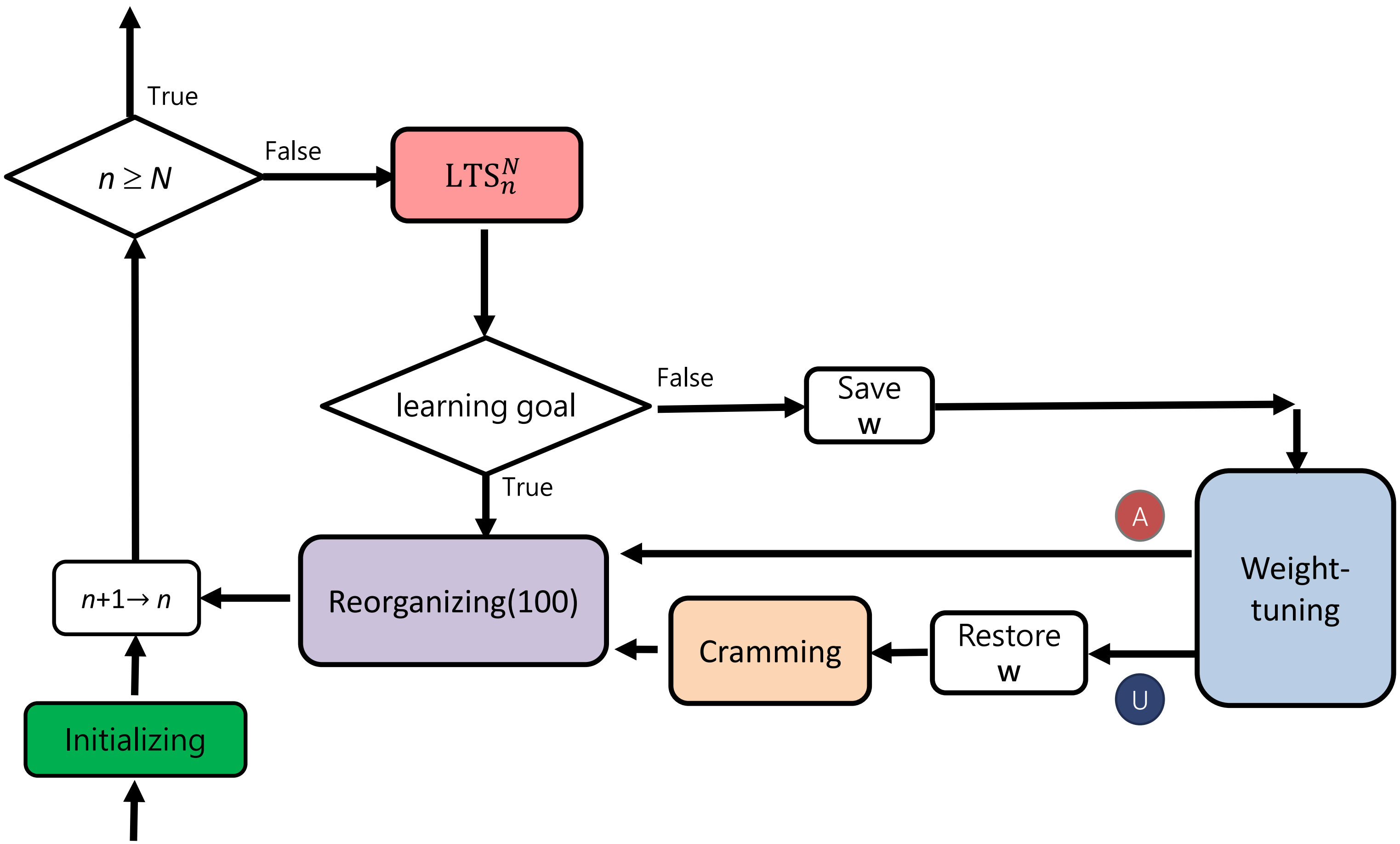
The proposed CSI-100



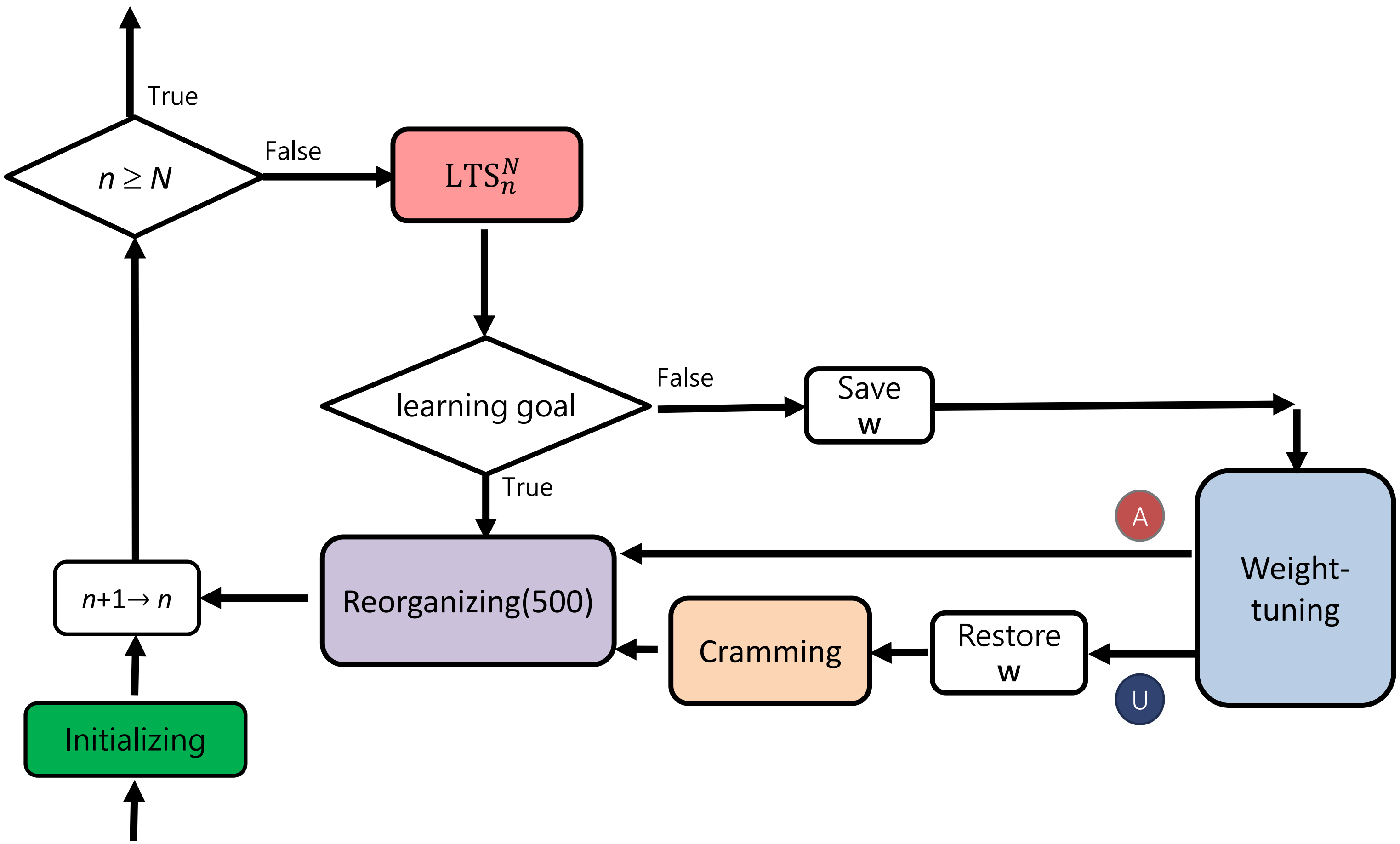
The proposed CSI-LTS-0



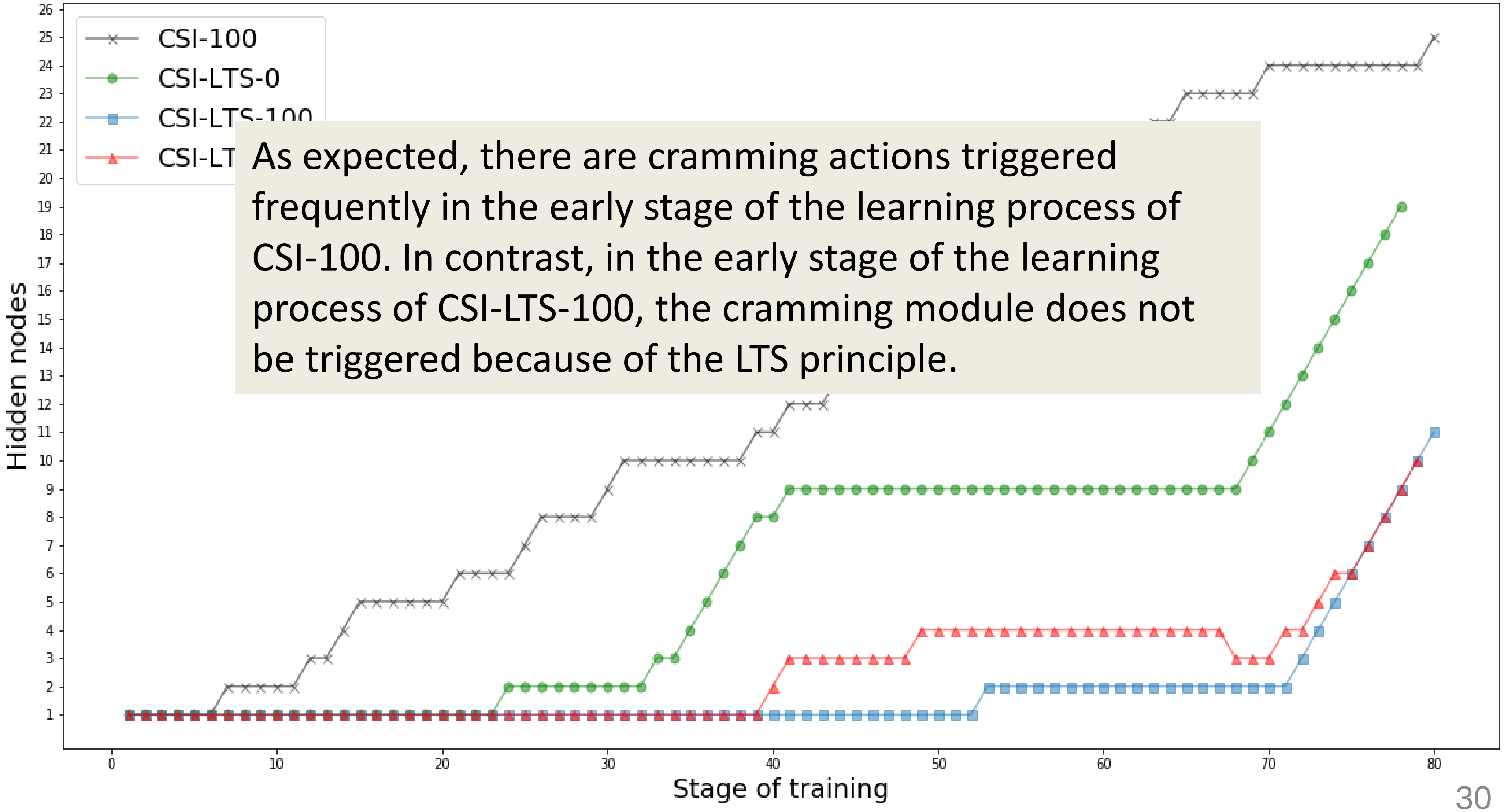
The proposed CSI-LTS-100



The proposed CSI-LTS-500



The evolution of total number of adopted hidden nodes in the learning process of the 1st training data set



As expected, there are cramming actions triggered frequently in the early stage of the learning process of CSI-100. In contrast, in the early stage of the learning process of CSI-LTS-100, the cramming module does not be triggered because of the LTS principle.

Total number of adopted hidden nodes

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	25	19	11	10
2	16			14
3	16			7
4	7			10
5	21			11
6	10			9
7	11	25	13	7
8				
9				
10				
11	13	3	7	11
12	15	12	9	11
13	17	23	10	15
14	7	22	12	12
15	16	9	11	10
16	8	21	9	13
17				
18				
19				
20				
Average	13.85	16.25	9.55	10.20
Standard deviation	5.9	8.1	2.06	2.6

- CSI--100: from 4 to 25.
- CSI-LTS-0: from 3 to 30.
- CSI-LTS-100: from 6 to 12.
- CSI-LTS-500: from 5 to 15.

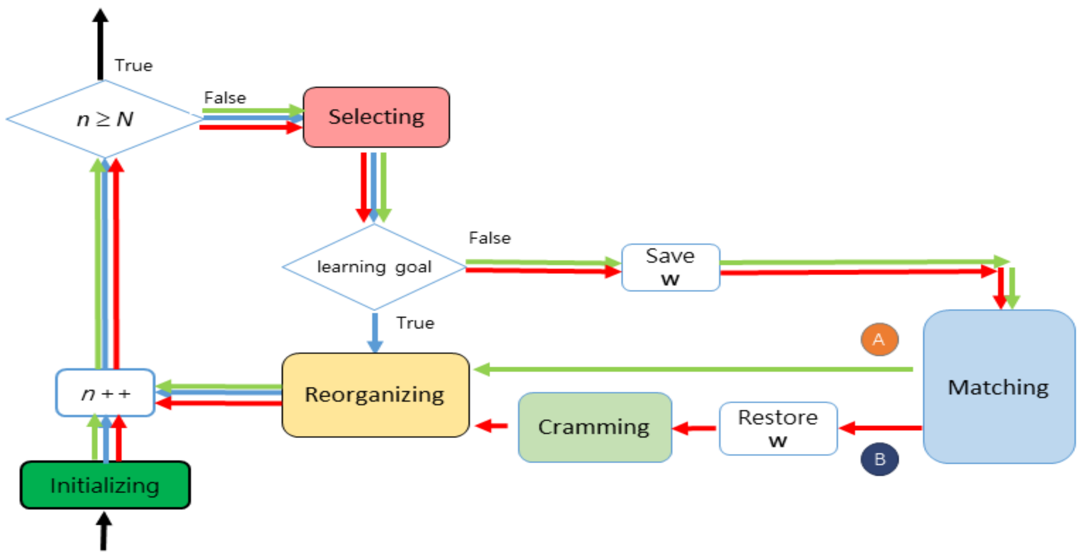
The adoption of LTS and the regularizing module helps reduce the total number of adopted hidden nodes, in average.

In terms of the total number of adopted hidden nodes, the average and standard deviation of CSI-LTS-100 are the smallest.

The occurrence percentages of blue, green and red paths

At every n^{th} stage, the proposed mechanism follows one of the three paths to get an acceptable SLFN:

- blue path
- green path
- red path



CSI-100

Set No.	blue	green	red	
1	62.50%	2.50%	35.00%	
2	73.75%	3.75%	22.50%	
3	63.75%	15.00%	21.25%	
4	71.25%	18.75%	10.00%	
5	58.75%	11.25%	30.00%	
6	60.00%	25.00%	15.00%	
7	71.25%	12.50%	16.25%	
8	61.25%	6.25%	32.50%	
9	60.00%	2.50%	37.50%	
10	67.50%	26.25%	6.25%	
11	72.50%	7.50%	20.00%	
12	68.75%	8.75%	22.50%	
13	68.75%	3.75%	27.50%	
14	73.75%	15.00%	11.25%	
15	68.75%	5.00%	26.25%	
16	70.00%	16.25%	13.75%	
17	78.75%	10.00%	11.25%	
18	63.75%	20.00%	16.25%	
19	78.75%	7.50%	13.75%	
20	61.25%	5.00%	33.75%	
Average	67.75%	11.13%	21.13%	
Standard deviation	6.13%	7.28%	9.27%	

In average of 20 training datasets, there are approximately 67.75% of 80 learning processes that go through the blue path, 11.13% that go through the green path, and 21.13% that go through the red path.

CSI-LTS-0

In average of 20 training datasets, there are approximately 63.31% of 80 learning processes that go through the blue path, 14.31% that go through the green path, and 22.38% that go through the red path.

Set No.	blue	green	red	
1	61.25%	13.75%	25.00%	
2	62.50%	30.00%	7.50%	
3	60.00%	23.75%	16.25%	
4	63.75%	5.00%	31.25%	
5	52.50%	12.50%	35.00%	
6	62.50%	7.50%	30.00%	
7	61.25%	5.00%	33.75%	
8	71.25%	10.00%	18.75%	
9	65.00%	21.25%	13.75%	
10	72.50%	17.50%	10.00%	
11	83.75%	11.25%	5.00%	
12	62.50%	21.25%	16.25%	
13	58.75%	11.25%	30.00%	
14	53.75%	15.00%	31.25%	
15	60.00%	27.50%	12.50%	
16	61.25%	11.25%	27.50%	
17	57.50%	8.75%	33.75%	
18	73.75%	13.75%	12.50%	
19	65.00%	16.25%	18.75%	
20	57.50%	3.75%	38.75%	
Average	63.31%	14.31%	22.38%	
Standard deviation	7.30%	7.37%	10.36%	

CSI-LTS-100

Set No.	blue	green	red
1	71.25%	11.25%	17.50%
2	73.75%	13.75%	12.50%
3	68.75%	15%	16.25%
4	72.5%	11.25%	16.25%
5	72.5%	10%	17.50%
6	68.75%	13.75%	17.50%
7	71.25%	7.5%	21.25%
8	70%	13.75%	16.25%
9	68.75%	17.5%	13.75%
10	75%	5%	20.00%
11	72.5%	13.75%	13.75%
12	77.5%	8.75%	13.75%
13	71.25%	11.25%	17.50%
14	65%	18.75%	16.25%
15	66.25%	16.25%	17.50%
16	68.75%	15%	16.25%
17	72.5%	16.25%	11.25%
18	63.75%	20%	16.25%
19	76.25%	7.5%	16.25%
20	71.25%	10%	18.75%
Average	70.88%	12.81%	16.31%
Standard deviation	3.51%	3.99%	2.42%

In average of 20 training datasets, there are approximately 70.88% of 80 learning processes that go through the blue path, 12.81% that go through the green path, and 16.31% that go through the red path.

CSI-LTS-500

Set No.	blue	green	red	
1	72.50%	11.25%	16.25%	
2	67.50%	11.25%	21.25%	
3	67.50%	21.25%	11.25%	
4	77.50%	5.00%	17.50%	
5	75.00%	8.75%	16.25%	
6	67.50%	17.50%	15.00%	
7	67.50%	18.75%	13.75%	
8	63.75%	18.75%	17.50%	
9	68.75%	13.75%	17.50%	
10	75.00%	11.25%	13.75%	
11	50.00%	33.75%	16.25%	
12	72.50%	12.50%	15.00%	
13	75.00%	3.75%	21.25%	
14	65.00%	18.75%	16.25%	
15	67.50%	16.25%	16.25%	
16	73.75%	5.00%	21.25%	
17	65.00%	16.25%	18.75%	
18	62.50%	27.50%	10.00%	
19	58.75%	33.75%	7.50%	
20	76.25%	7.50%	16.25%	
Average	68.44%	15.63%	15.94%	
Standard deviation	6.70%	8.63%	3.56%	

In average of 20 training datasets, there are approximately 68.44% of 80 learning processes that go through the blue path, 15.63% that go through the green path, and 15.94% that go through the red path.

The occurrence percentages of blue paths

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	62.50%	61.25%	71.25%	72.50%
2	73.75%	[illegible]	[illegible]	67.50%
3	63.75%	[illegible]	[illegible]	67.50%
4	71.25%	[illegible]	[illegible]	77.50%
5	58.75%	[illegible]	[illegible]	75.00%
6	60.00%	[illegible]	[illegible]	67.50%
7	71.25%	61.25%	71.25%	67.50%
8	61.25%	71.25%	70.00%	63.75%
9	60.00%	65.00%	68.75%	68.75%
10	[illegible]	[illegible]	[illegible]	[illegible]
11	[illegible]	[illegible]	[illegible]	[illegible]
12	[illegible]	[illegible]	[illegible]	[illegible]
13	[illegible]	[illegible]	[illegible]	[illegible]
14	73.75%	53.75%	65.00%	65.00%
15	68.75%	60.00%	66.25%	67.50%
16	70.00%	61.25%	68.75%	73.75%
17	[illegible]	[illegible]	[illegible]	[illegible]
18	[illegible]	[illegible]	[illegible]	[illegible]
19	[illegible]	[illegible]	[illegible]	[illegible]
20	[illegible]	[illegible]	[illegible]	[illegible]
Average	**67.75%**	**63.31%**	**70.88%**	**68.44%**
Standard deviation	6.13%	7.30%	3.51%	6.70%

- CSI-100: from 58.75% to 78.75%.
- CSI-LTS-0: from 52.50% to 83.75%.
- CSI-LTS-100: from 63.75% to 76.25%.
- CSI-LTS-500: from 50.00% to 77.50%.

The average occurrence percentage of blue path over these four versions is 67.59% and the standard deviation is 7%. (???)

In terms of the occurrence percentage of blue path, the average of CSI-LTS-100 is the largest and the standard deviation of CSI-LTS-100 is the smallest.

The occurrence percentages of green path

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	2.50%	13.75%	11.25%	11.25%
2	3.75%			11.25%
3	15.00%			21.25%
4	18.75%			5.00%
5	11.25%			8.75%
6	25.00%			17.50%
7	12.50%	5.00%	7.50%	18.75%
8	6.25%	10.00%	13.75%	18.75%
9	2.50%	21.25%	17.50%	13.75%
10				
11				
12				
13				
14	15.00%	15.00%	18.75%	18.75%
15	5.00%	27.50%	16.25%	16.25%
16	16.25%	11.25%	15.00%	5.00%
17				%
18				%
19				%
20				%
Average	**11.13%**	**14.31%**	**12.81%**	**15.63%**
Standard deviation	7.28%	7.37%	3.99%	8.63%

- CSI-100: from 2.50% to 26.25%.
- CSI-LTS-0: from 3.75% to 30.00%.
- CSI-LTS-100: from 5.00% to 20.00%.
- CSI-LTS-500: from 3.75% to 33.75%.

The average occurrence percentage of green path over these four versions is 13.47% and the standard deviation is 7%.

In terms of the occurrence percentage of green path, the average of CSI-LTS-500 is the largest and the standard deviation of CSI-LTS-100 is the smallest.

The occurrence percentages of red path

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	35.00%	25.00%	17.50%	16.25%
2	22.50%			21.25%
3	21.25%			11.25%
4	10.00%			17.50%
5	30.00%			16.25%
6	15.00%			15.00%
7	16.25%	33.75%	21.25%	13.75%
8	32.50%	18.75%	16.25%	17.50%
9	37.50%	13.75%	13.75%	17.50%
10				
11				
12				
13				
14	11.25%	31.25%	16.25%	16.25%
15	26.25%	12.50%	17.50%	16.25%
16	13.75%	27.50%	16.25%	21.25%
17				
18				
19				
20				
Average	**21.13%**	**22.38%**	**16.31%**	**15.94%**
Standard deviation	9.27%	10.36%	2.42%	3.56%

- CSI-100: from 6.25% to 37.50%.
- CSI-LTS-0: from 7.50% to 38.75%.
- CSI-LTS-100: from 11.25% to 20.00%.
- CSI-LTS-500: from 7.50% to 21.25%.

The average occurrence percentage of red path over these four versions is 18.94% and the standard deviation is 8%.

In terms of the occurrence percentage of red path, the average of CSI-LTS-0 is the largest and the standard deviation of CSI-LTS-100 is the smallest.

Total number of cramming occurrences

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	26	18	12	11
2	16	[illegible]	[illegible]	15
3	15	[illegible]	[illegible]	7
4	6	[illegible]	[illegible]	12
5	22	[illegible]	[illegible]	11
6	10	[illegible]	[illegible]	10
7	11	25	15	9
8	24	13	11	12
9	28	9	9	12
10	3	6	14	9
11	14	2	9	11
12	[illegible]	[illegible]	[illegible]	[illegible]
13	[illegible]	[illegible]	[illegible]	[illegible]
14	[illegible]	[illegible]	[illegible]	[illegible]
15	19	8	12	11
16	9	20	11	15
17	[illegible]	[illegible]	[illegible]	[illegible]
18	[illegible]	[illegible]	[illegible]	[illegible]
19	[illegible]	[illegible]	[illegible]	[illegible]
20	[illegible]	[illegible]	[illegible]	[illegible]
Average	14.90	15.9	11.05	10.75
Standard deviation	7.4	8.3	1.93	2.8

- CSI-100: from 3 to 28.
- CSI-LTS-0: from 2 to 29.
- CSI-LTS-100: from 7 to 14.
- CSI-LTS-500: from 4 to 15.

The adoption of LTS and the regularizing module helps reduce the average total number of cramming occurrences.

In terms of the total number of cramming occurrences, the average of CSI-LTS-500 is the smallest, while the standard deviation of CSI-LTS-100 is the smallest.

Total number of hidden nodes pruned within the learning process

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	2	0	2	2
2				
3				
4				
5				
6				
7				
8	6	2	2	4
9				2
10				2
11				1
12	2	0	1	0
13				1
14				0
15	4	0	2	2
16	2	0	3	3
17				
18				
19				
20	[illegible]	[illegible]	[illegible]	1
Average	2.05	0.65	2.50	1.55
Standard deviation	2.4	0.9	1.76	1.1

The percentage of the reorganizing module that does work
- CSI-100: fourteen out of twenty trials.
- CSI-LTS-0: eight out of twenty trials.
- CSI-LTS-100: seventeen out of twenty trials.
- CSI-LTS-500: sixteen out of twenty trials.

The average total number of hidden nodes pruned over these four versions is 1.69 and the standard deviation is 1.75.

More than one hidden nodes may be pruned within a reorganizing occurrence.

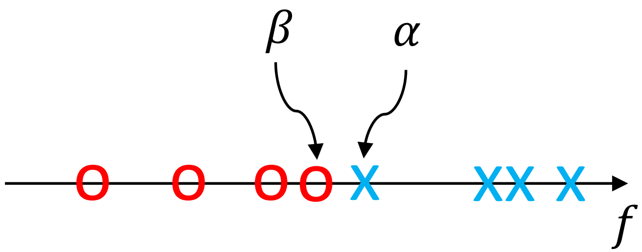
In terms of the number of hidden nodes pruned, the average of CSI-LTS-100 is the largest, while the standard deviation of CSI-LTS-0 is the smallest.

The best case over all training and testing samples

Generating diagnostic rules from cardiac SPECT data (Kurgan at al., 2001). This problem involved database containing cardiac SPECT heart images collected on 267 patients in stress and rest studies. CLIP3 algorithm was applied to generate diagnostic rules for overall diagnosis of the patient's study, by using information of partial, in the predefined regions of the heart muscle, diagnoses. This is a two-classes problem: first class describes normal patients (55 examples), and second patients with coronary artery disease (212 examples). Three diagnostic rules were generated. The rules accuracy was 84%.

Examine an issue in the medical domain: whether the proposed learning mechanism can have better accuracy of diagnoses than other methods in the current literature.

Inferencing mechanism



$$\alpha \equiv \min_{c \in \mathbf{I}_1} f(\mathbf{x}^c, \mathbf{w})\,;\ \beta \equiv \max_{c \in \mathbf{I}_2} f(\mathbf{x}^c, \mathbf{w})$$

learning goal type 3: LSC

When LSC ($\alpha > \beta$) is true, the inferencing mechanism

$$f(\mathbf{x}^c, \mathbf{w}) \geq v \ \ \forall\, c \in \mathbf{I}_1 \text{ and } f(\mathbf{x}^c, \mathbf{w}) \leq -v \ \forall\, c \in \mathbf{I}_2$$

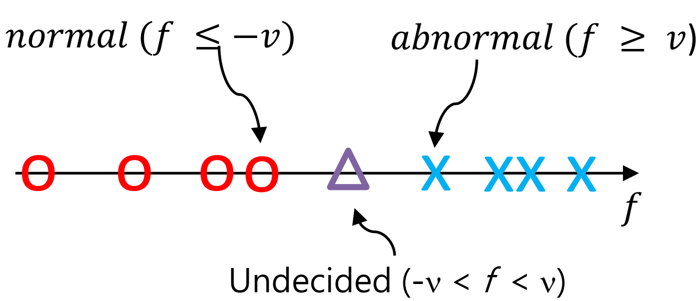
can be set by directly adjusting $\mathbf{w}^o$ according to the following formula:

$$\frac{2v}{\alpha - \beta} w_i^o \rightarrow w_i^o \ \ \forall\, i,$$

The weight vector between the hidden layer and the output node

then $v - \min_{c \in \mathbf{I}_1} \sum_{i=1}^{p} w_i^o a_i^c \rightarrow w_0^o$

The threshold of the output node



Actual / Predicted	Abnormal	Normal
Abnormal	TP	FP
Normal	FN	TN
Undecided	UP	UN

measurement

Predictive Accuracy	(TP+TN) / (TP+TN+FP+FN+UP+UN)
Type 1 error rate	FN / (TP+FN+UP)
Type 2 error rate	FP / (FP+TN+UN)
Sensitivity	TP / (TP+FN+UP)
Specificity	TN / (TF+FP+UN)
Undecided rate	(UP+UN) / (TP+TN+FN+FP+UP+UN)

The accuracy

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	0.417	0.545	0.604	0.626
2	0.358	0.674	0.572	0.524
3	0.342	0.615	0.663	0.722
4	0.695	0.594	0.701	0.636
5	0.321	0.492	0.610	0.684
6	0.701	0.775	0.647	0.706
7	0.813	0.631	0.572	0.765
8	0.321	0.706	0.551	0.599
9	0.246	0.615	0.717	0.690
10	0.711	0.620	0.781	0.535
11	0.417	0.674	0.733	0.786
12	0.428	0.455	0.711	0.578
13	0.299	0.471	0.743	0.690
14	0.706	0.588	0.701	0.663
15	0.444	0.684	0.556	0.588
16	0.717	[illegible]	[illegible]	0.690
17	0.674	[illegible]	[illegible]	0.551
18	0.380	0.722	0.652	0.631
19	0.754	0.695	0.679	0.711
20	0.316	0.374	0.711	0.684
Average	0.503	0.603	0.663	0.653
Standard deviation	0.2	0.1	0.07	0.1

- [80 + (267-80)*66.3%]/267 = 76.4% ← in average
- [80 + (267-80)*78.1%]/267 = 84.6% ← the best case

The accuracy

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	0.417	0.545	0.604	0.626
2	0.358	0.674	0.572	0.524
3	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]
7	[illegible]	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]
9	0.246	0.615	0.717	0.690
10	0.711	[illegible]	[illegible]	0.535
11	0.417	0.674	0.733	0.786
12	0.428	0.455	0.711	0.578
13	0.299	0.471	0.743	0.690
14	0.706	0.588	0.701	0.663
15	0.444	0.684	0.556	0.588
16	0.717	0.561	0.663	0.690
17	0.674	0.578	0.684	0.551
18	0.380	0.722	0.652	0.631
19	[illegible]	[illegible]	[illegible]	0.711
20	[illegible]	[illegible]	[illegible]	0.684
Average	0.503	0.603	0.663	0.653
Standard deviation	0.2	0.1	0.07	0.1

Generating diagnostic rules from cardiac SPECT data (Kurgan at al., 2001). This problem involved database containing cardiac SPECT heart images collected on 267 patients in stress and rest studies. CLIP3 algorithm was applied to generate diagnostic rules for overall diagnosis of the patient's study, by using information of partial, in the predefined regions of the heart muscle, diagnoses. This is a two-classes problem: first class describes normal patients (55 examples), and second patients with coronary artery disease (212 examples). Three diagnostic rules were generated. The rules accuracy was 84%.

The best case over all training and testing samples

- [80 + (267-80)*66.3%]/267 = 76.4% ← in average
- [80 + (267-80)*78.1%]/267 = 84.6% ← the best case

Hyperparameter of the inferencing mechanism

- Above are the results regarding v = 0.9.
- Regarding v = 0, v = 0.8, v = 1.0, what the performance will be?

In ANN, this means more hidden nodes.

- In statistics, **overfitting** is "the production of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore fail to fit additional data or predict future observations reliably."
- An **overfitted model** is a statistical model that contains more parameters than can be justified by the data -- Everitt B.S., Skrondal A. (2010), *Cambridge Dictionary of Statistics*, Cambridge University Press.

whether the proposed learning mechanism can help cope with the encountered undesired attractors and alleviate the overfitting tendency

Total number of adopted hidden nodes & the accuracy

Set No.	CSI-100		CSI-LTS-0		CSI-LTS-100		CSI-LTS-500	
1	25	0.417	19	0.545	11	0.604	10	0.626
2	16	0.358	5	0.674	7	0.572	14	0.524
3	16	0.342	11	0.615	11	0.663	7	0.722
4	7	0.695	24	0.594	7	0.701	10	0.636
5	21	0.321	26	0.492	11	0.610	11	0.684
6	10	0.701	22	0.775	11	0.647	9	0.706
7	11	0.813	25	0.631	13	0.572	7	0.765
8	19	0.321	12	0.706	10	0.551	9	0.599
9	25	0.246	10	0.615	6	0.717	11	0.690
10	4	0.711	5	0.620	11	0.781	8	0.535
11	13	0.417	3	0.674	7	0.733	11	0.786
12	15	0.428	12	0.455	9	0.711	11	0.578
13	17	0.299	23	0.471	10	0.743	15	0.690
14	7	0.706	22	0.588	12	0.701	12	0.663
15	16	0.444	9	0.684	11	0.556	10	0.588
16	8	0.717	21	0.561	9	0.663	13	0.690
17	8	0.674	23	0.578	8	0.684	13	0.551
18	12	0.380	9	0.722	12	0.652	7	0.631
19	10	0.754	14	0.695	8	0.679	5	0.711
20	17	0.316	30	0.374	7	0.711	11	0.684
Average	13.85	0.503	16.25	0.603	9.55	0.663	10.20	0.653
Standard deviation	5.9	0.2	8.1	0.1	2.06	0.07	2.6	0.1

8/20

7/20

m = 22, p = 4 → $p(m+1)+p+1$ = 97 (> 80 but < 267 or 250)

m = 22, p = 10 → $p(m+1)+p+1$ = 241 (> 80 but < 267 or 250)

m = 22, p = 11 → $p(m+1)+p+1$ = 265 (> 80 or 250 but < 267)

Total number of adopted hidden nodes & the accuracy

Set No.	CSI-100		CSI-LTS-0		CSI-LTS-100		CSI-LTS-500	
1	25	0.417	19	0.545	11	0.604	10	0.626
2	16	0.358	5	0.674	7	0.572	14	0.524
9	25	0.246	10	0.615	6	0.717	11	0.690
10	4	0.711	5	0.620	11	0.781	8	0.535
11	13	0.417	3	0.674	7	0.733	11	0.786
12	15	0.428	12	0.455	9	0.711	11	0.578
17	8	0.674	23	0.578	8	0.684	13	0.551
18	12	0.380	9	0.722	12	0.652	7	0.631
19	10	0.754	14	0.695	8	0.679	5	0.711
20	17	0.316	30	0.374	7	0.711	11	0.684
Average	13.85	0.503	16.25	0.603	9.55	0.663	10.20	0.653
Standard deviation	5.9	0.2	8.1	0.1	2.06	0.07	2.6	0.1

It seems that the CSI-LTS-100 mechanism can help cope with the encountered undesired attractors and alleviate the overfitting tendency.

- An **overfitted model** is a statistical model that contains more parameters than can be justified by the data -- Everitt B.S., Skrondal A. (2010), *Cambridge Dictionary of Statistics*, Cambridge University Press.
- The CSI-LTS-100 version has a smallest average number of adopted hidden nodes and a best average accuracy.

It seems that CSI-LTS-100 is better than CSI-100, CSI-LTS-0 and CSI-LTS-500.

Total training Time (Sec.)

Set No.	CSI-100	CSI-LTS-0	CSI-LTS-100	CSI-LTS-500
1	1995	656	76	269
2	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]
7	363	622	486	63
8	1459	78	98	67
9	1926	37	39	174
10	332	94	487	69
11	882	15	356	63
12	1255	576	38	423
13	1139	1612	315	214
14	[illegible]	[illegible]	[illegible]	[illegible]
15	[illegible]	[illegible]	[illegible]	[illegible]
16	1391	145	139	226
17	2290	839	26	130
18	[illegible]	[illegible]	[illegible]	[illegible]
19	[illegible]	[illegible]	[illegible]	[illegible]
20	[illegible]	[illegible]	[illegible]	[illegible]
Average	1250.95	604.55	201.10	149.90
Standard deviation	577.9	722.2	179.41	130.7

- CSI-100: from 332 seconds to 2290 seconds.
- CSI-LTS-0: from 15 seconds to 2702 seconds.
- CSI-LTS-100: from 26 seconds to 487 seconds.
- CSI-LTS-500: from 19 seconds to 452 seconds.

The adoption of LTS and “longer” regularizing module is good for speeding up the learning process.

In terms of the training time, the average and standard deviation of CSI-LTS-500 are the smallest.