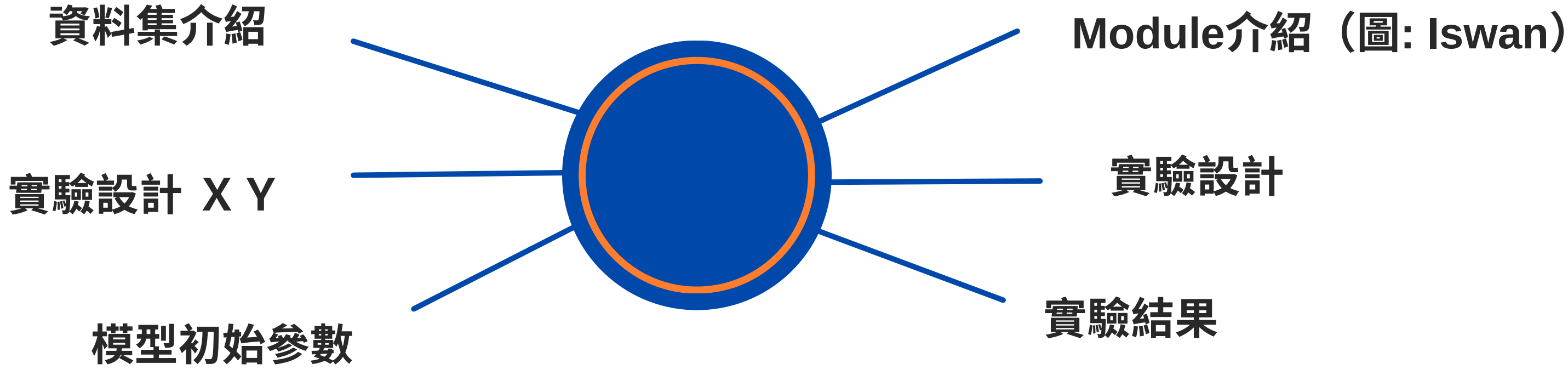


# 新型學習演算法 心臟病健康預測

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# 報告架構



# 資料集介紹

主題: 心臟疾病預測

來源: **KAGGLE**

X: 21個attributes  
(Numerical)

BMI, Smoker, Alcohol,  
Edcuation, Income...

Y: 1個attribute  
(Binary)

training data set	normal sample	80%	80%
	abnormal sample	20%	
testing data set	normal sample	80%	20%
	abnormal sample	20%	

# 模型初始參數(環境)

環境: Jupyter notebook

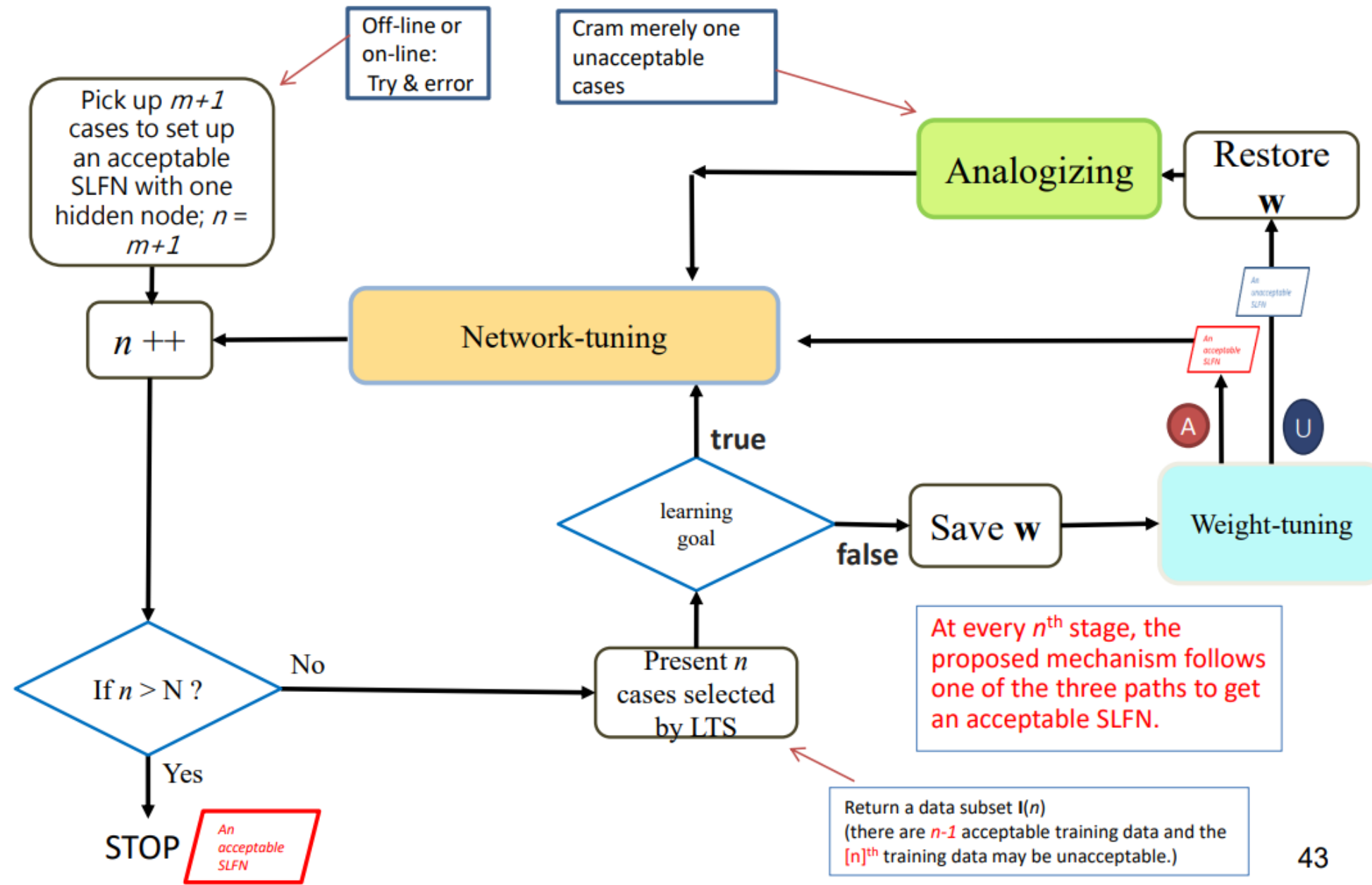
語言: Pytorch

模型初始設定:

- Sequential model
- Two layer nenural, one hidden node
- Activation Funtion: Relu
- Optimizer: Adam
- Loss: BCELoss

# MODULE(ISWAN)

## The ISWAN algorithm



43

Why: k值很多個

Initializing\_1\_WT

Weight\_Tuning\_LG\_UA

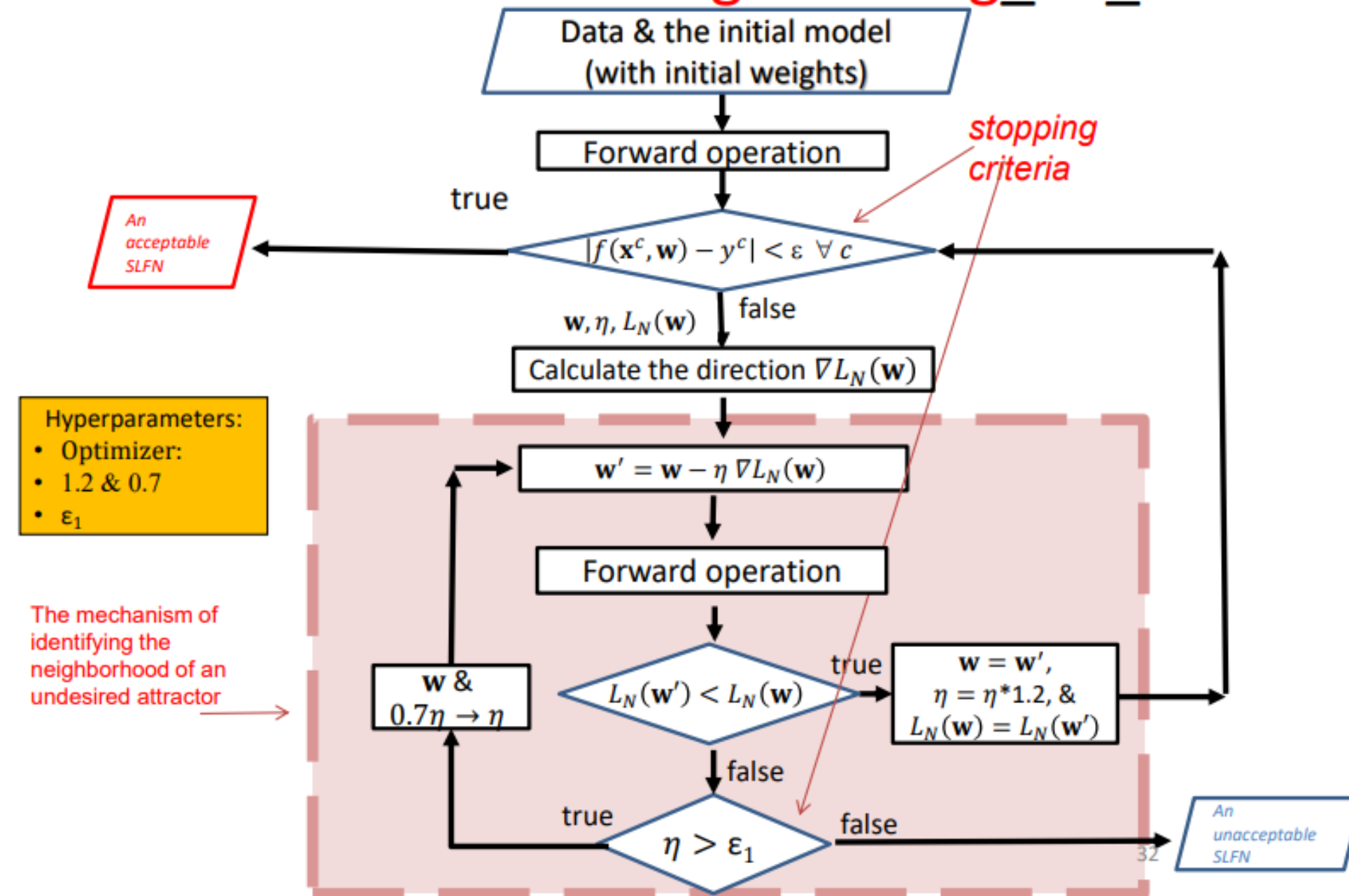
Isolating\_Ri\_ZG

Analogizing\_Ri\_LG1

Network\_tuning\_4

# MODULE(ISWAN)

The flowchart of **weight-tuning\_LG\_UA**



Weight\_Tuning\_LG\_UA

重要參數:

epsilon(實驗設計)

learning rate(\*1.05, \*0.95)

# MODULE(ISWAN)

A rule-based mechanism

## The analogizing\_Ri\_LG1\_SO\_SU module

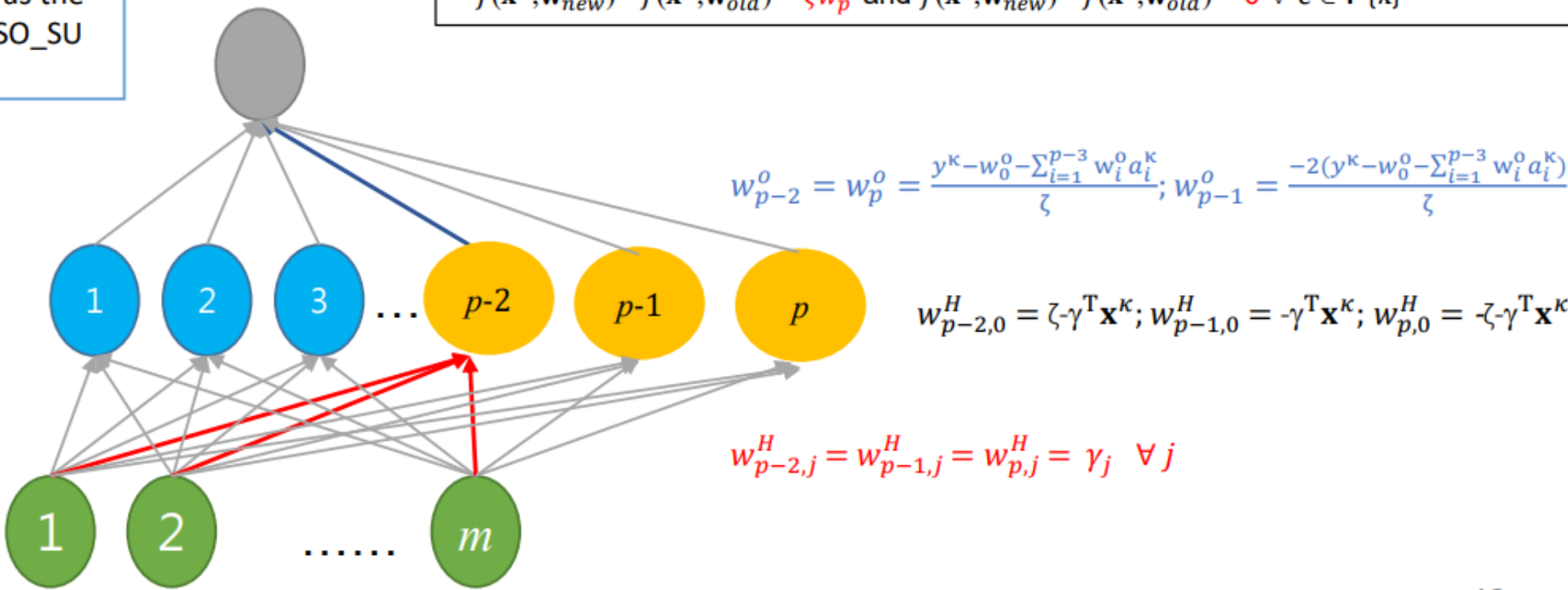
Step 1: Use the isolating\_Ri\_ZG module to obtain a small number  $\zeta$  and an  $m$ -vector  $\gamma$  of length one such that  $\gamma^T(\mathbf{x}^c - \mathbf{x}^k) \neq 0 \forall c \in I - \{k\}$  AND  $(\zeta + \gamma^T(\mathbf{x}^c - \mathbf{x}^k)) * (\zeta - \gamma^T(\mathbf{x}^c - \mathbf{x}^k)) < 0 \forall c \in I - \{k\}$ .

Step 2: Let  $p+3 \rightarrow p$ , add three new hidden nodes  $p-2^{\text{th}}$ ,  $p-1^{\text{th}}$  and  $p^{\text{th}}$  to the existing SLFN, and then assign their associated weights in the following way:

- $\mathbf{w}_{p-2}^H = \mathbf{w}_{p-2}^H = \mathbf{w}_{p-2}^H = \gamma$
- $w_{p-2,0}^H = \zeta - \gamma^T \mathbf{x}^k, w_{p-1,0}^H = -\gamma^T \mathbf{x}^k, w_{p,0}^H = -\zeta - \gamma^T \mathbf{x}^k$
- $w_{p-2}^o = w_p^o = \frac{y^k - w_0^o - \sum_{i=1}^{p-3} w_i^o a_i^k}{\zeta}; w_{p-1}^o = \frac{-2(y^k - w_0^o - \sum_{i=1}^{p-3} w_i^o a_i^k)}{\zeta}$

Note that the analogizing\_Ri\_LG1\_SO\_SU module is the same as the analogizing\_Ri\_RE\_SO\_SU module.

- $f(\mathbf{x}^k, \mathbf{w}_{old}) = w_0^o + \sum_{i=1}^{p-3} w_i^o a_i^k$
- $f(\mathbf{x}^c, \mathbf{w}_{new}) = f(\mathbf{x}^c, \mathbf{w}_{old}) + w_p^{o*} [\text{ReLU}(\gamma^T(\mathbf{x}^c - \mathbf{x}^k) + \zeta) - 2\text{ReLU}(\gamma^T(\mathbf{x}^c - \mathbf{x}^k)) + \text{ReLU}(\gamma^T(\mathbf{x}^c - \mathbf{x}^k) - \zeta)]$
- $f(\mathbf{x}^k, \mathbf{w}_{new}) - f(\mathbf{x}^k, \mathbf{w}_{old}) = \zeta w_p^o$  and  $f(\mathbf{x}^c, \mathbf{w}_{new}) - f(\mathbf{x}^c, \mathbf{w}_{old}) = 0 \forall c \in I - \{k\}$



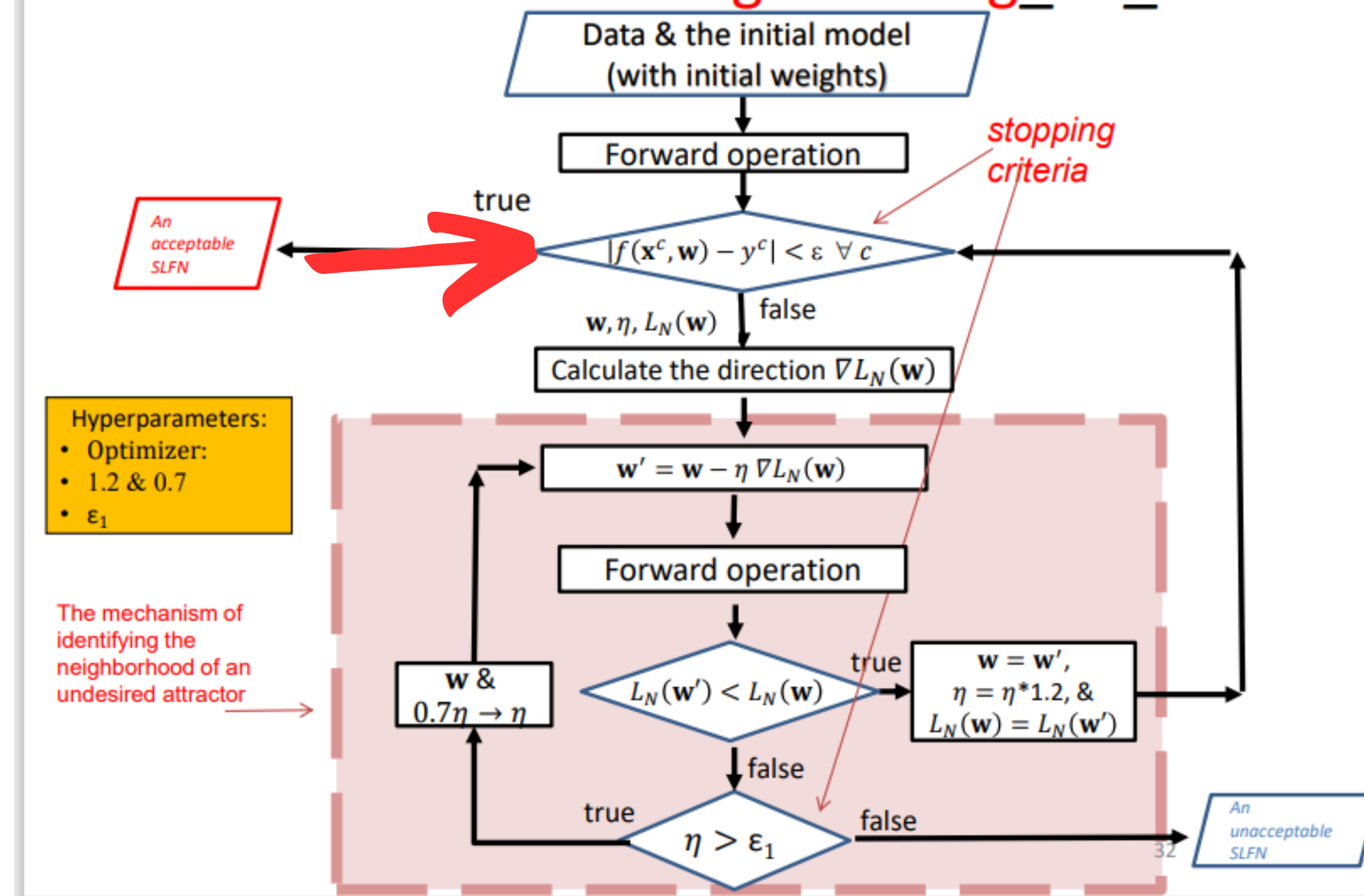
Isolating\_Ri\_ZG

新增:

Hidden node的數量限制

# 實驗設計

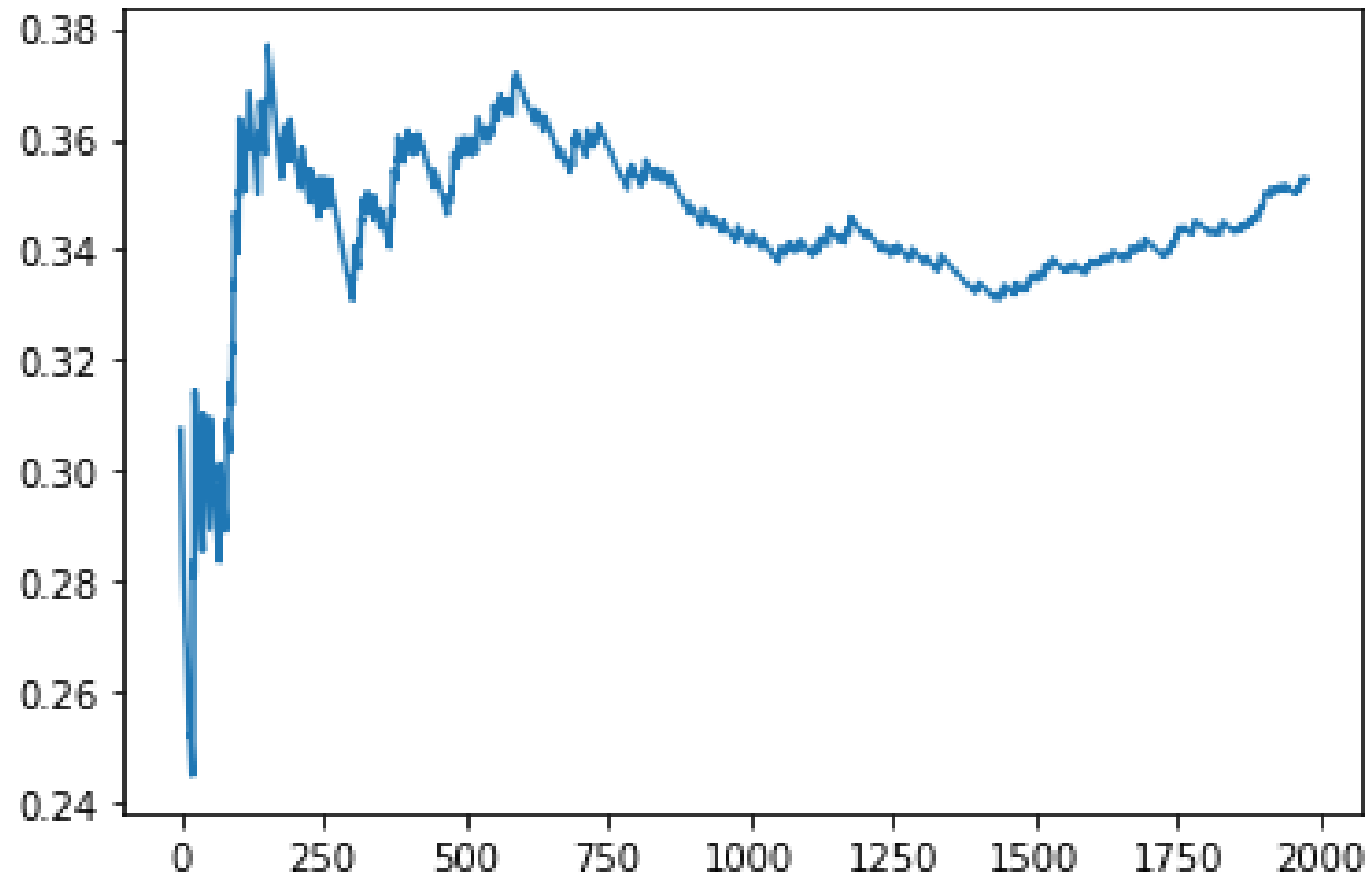
## The flowchart of **weight-tuning\_LG\_UA**





# 實驗設計

loss\_criteria = 0.25, Hidden node限制50顆



路徑次數

Green = 0

Blue = 0

Red = 1978

Green - network

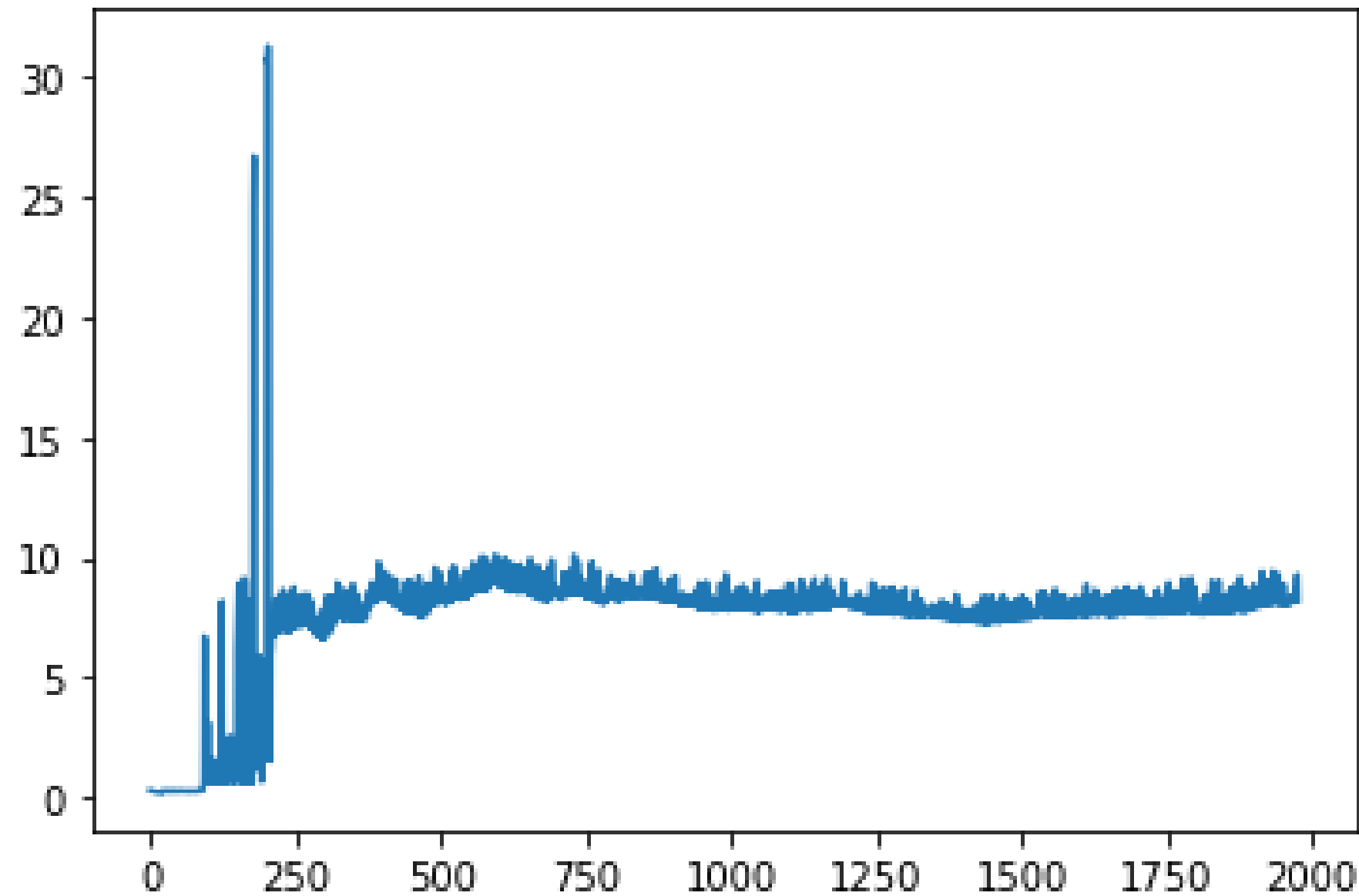
Blue

-Weight - analogizing-network

Red - Weight - network

# 實驗設計

loss\_criteria = 0.14, Hidden node限制50顆



路徑次數

Green = 0

Blue = 1885

Red = 93

Green - network

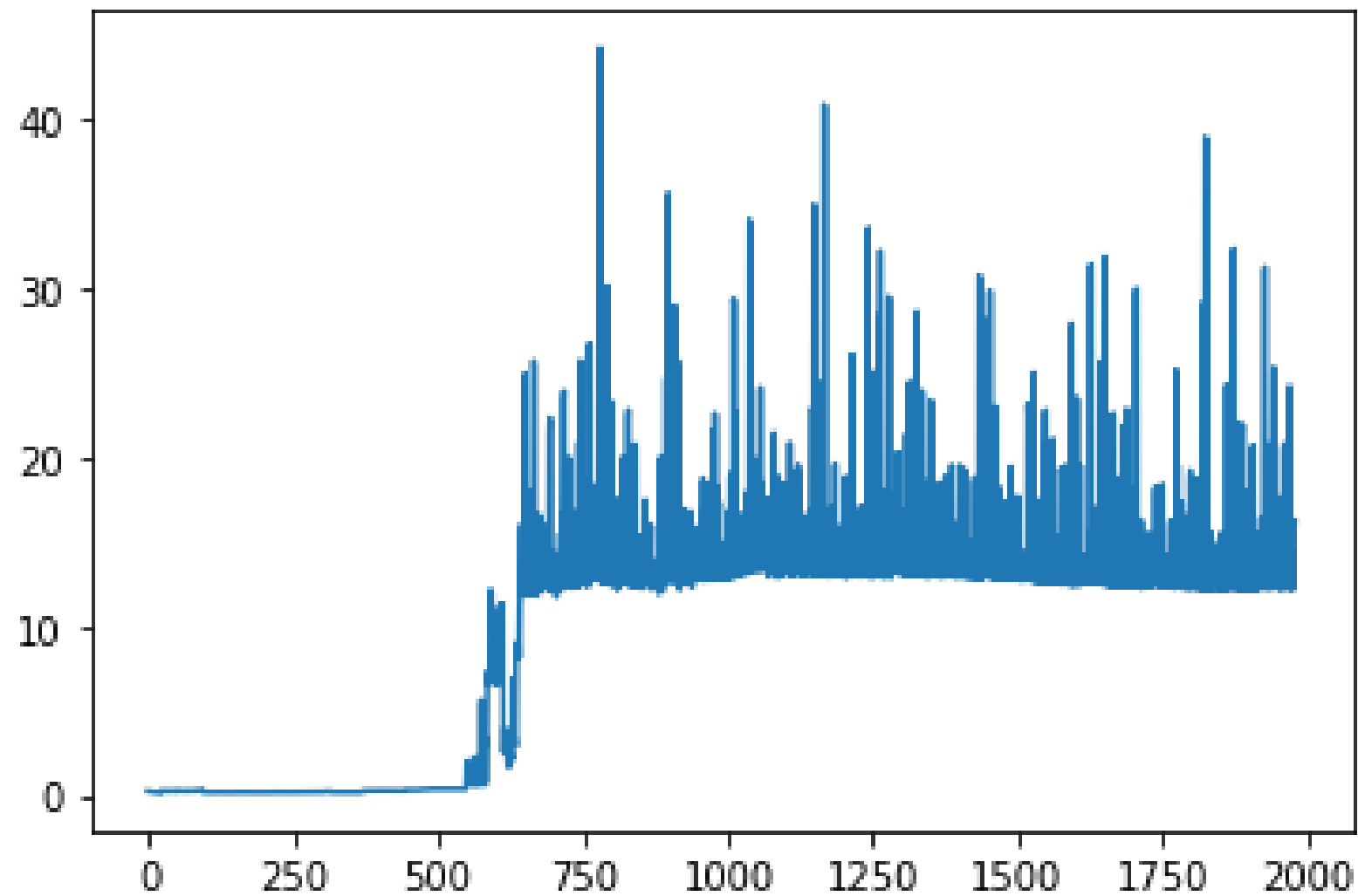
Blue

-Weight - analogizing-network

Red - Weight - network

# 實驗設計

loss\_criteria = 0.12, Hidden node限制50顆



Green = 0

Blue = 1429

Red = 549

Green - network

Blue

- Weight - analogizing - network

Red - Weight - network

# Insight

- 超參數調整
- 資料複雜度
- 模型路徑分析

謝謝大家

# 實驗設計

loss\_criterion = 0.12, Hidden node限制50顆

