Fault Tolerance in Feed-Forward Neural Networks

Course Seminar
Neural Networks (CS623)

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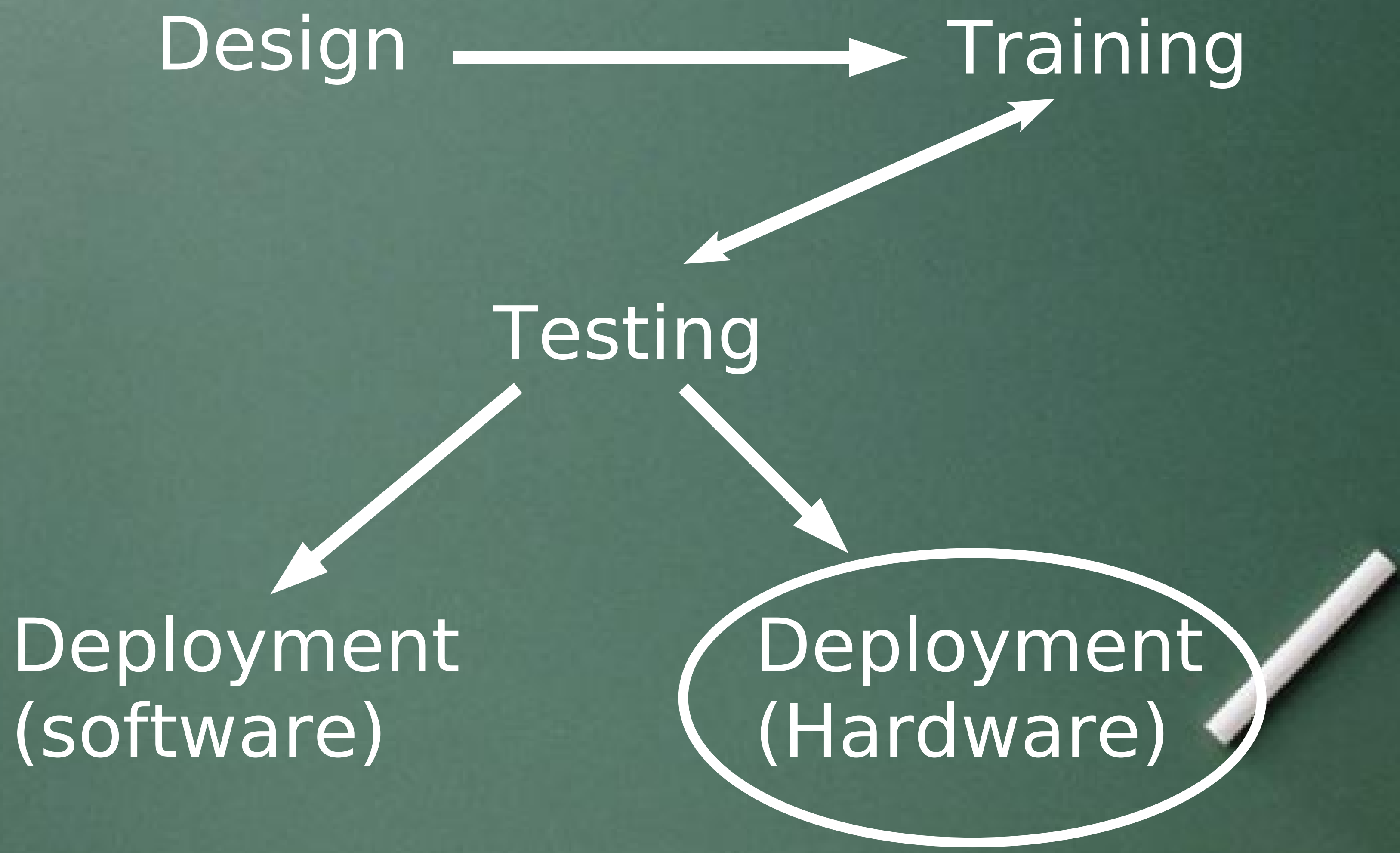
Development Cycle of ANN



Motivation

- NN Hardware is faster due to inherent hardware-level parallelism
  - Portable devices for speech recognition / biometrics / image-processing / control systems for safety-critical devices
- On-field deployment requires ***transparent*** resilience to component failure
- Not possible to plug-in and modify network hardware on the fly
- **For Neural Networks**, fault tolerance in s/w design is much cheaper than h/w redundancy

Agenda

- Great Expectations
- Ground Realities
- Defining Fault Tolerance
- Training to improve Fault Tolerance
  - Training with Injected Faults
  - Addition/Deletion Procedure (ADP)
  - Constraint Back-propagation (CBP)
- Conclusion & References

Great Expectations

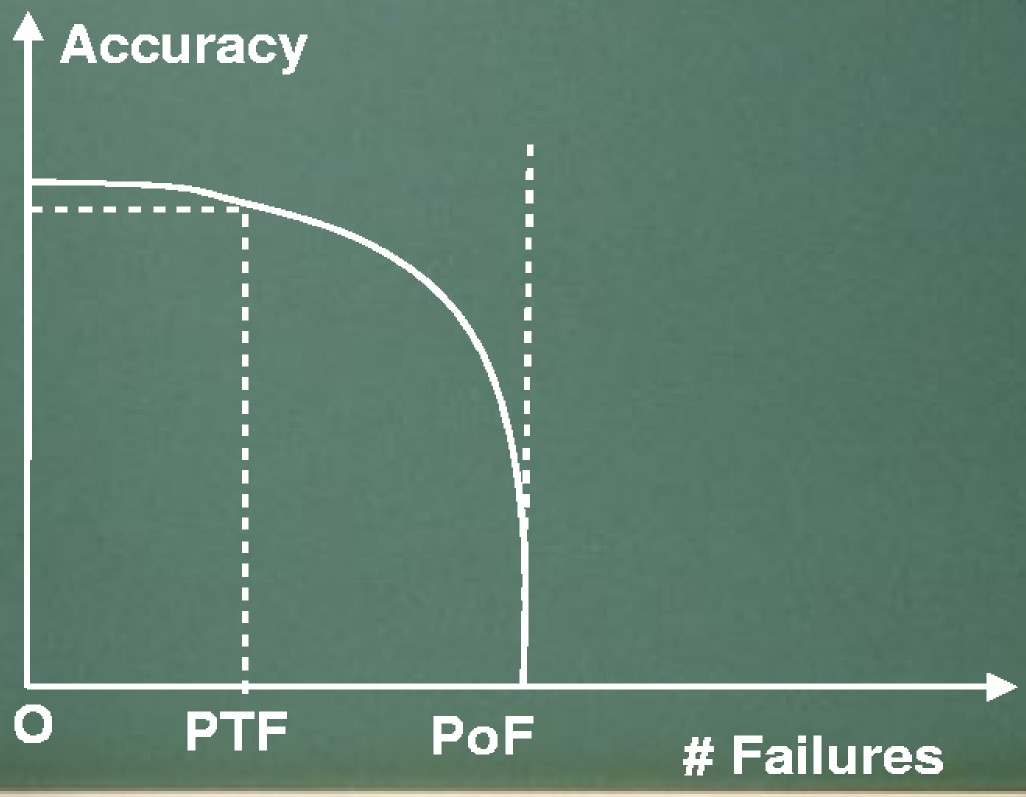
- ANN are widely considered fault-tolerant
- By virtue of Biological heritage
- Empirical data does **NOT** always support
- **Potentially** fault tolerant
- Redundancy != Fault Tolerance

Ground Realities

- Few proven mathematical model exist...
- Most results based on heuristics and experimental observations
- Training procedures need to be modified

Defining Fault Tolerance

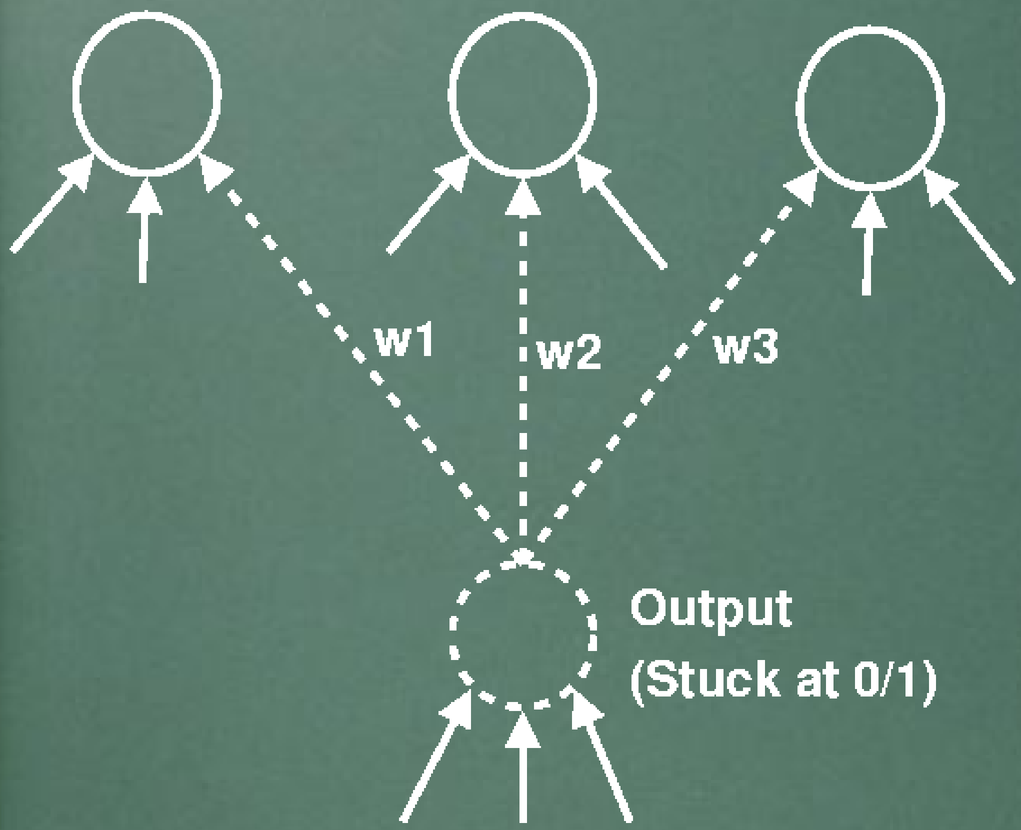
- No single point of failure
- Performance should degrade *gracefully*
- Quantified point of complete breakdown



Types of Failure in ANN

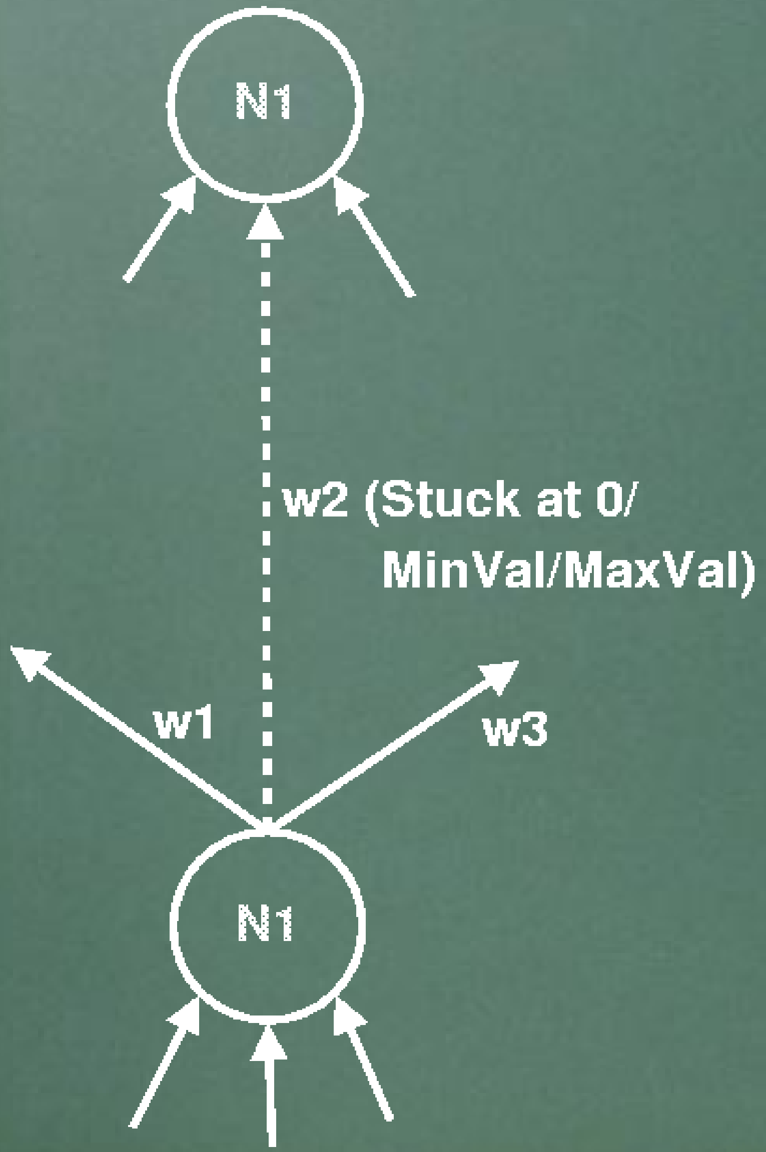
- Neuron Failure
- Link Failure

Types of Failure



- Neuron Failure
  - Stuck at 0
    - Neutral impact on next layer
  - Stuck at 1
    - Maximum activation / inhibition for next layer

Types of Failure



- Link Failure
  - Stuck at MinVal
    - Max Inhibition
  - Stuck at MaxVal
    - Max Activation
  - Stuck at 0
    - Neutral (Missing)

Training Algorithms

1. Training with Injected Faults

Training with Injected Faults

- Brute-force approach
- Assume that all components (links / neurons) have **equal** importance.
- During training, randomly *fail* few neurons/links for few iterations at regular intervals
- Training time increases **drastically**
- Network ***learns*** to be resilient to

  failures (hopefully!!)

Training Algorithms

1. Training with Injected Faults

2. Addition Deletion Procedure

Impact of Failure

- Are there any *hot-spots* in the network?
- Are there any singular point of failure?

- Failure of each neuron/link contributes to an **increase** in system error (MSE/SSE).
- Failure of which neuron/link, contributes the most?
- Concept of Sensitivity ...

Impact of Failure

- Sensitivity: (of a neuron)
  - The impact of failure of that neuron on overall system error
  - Simulate different types of failure of neuron (stuck at 0 / stuck at 1)
  - Calculate **change in network error** for each failure over entire training set
  - Add these and average over types of failures (in our case 2).

Impact of Failure

- W : vector of **all weights**
- E(W) : Sum error over all weights
- $E(W, o(n_j) = \alpha)$: error with neuron n_j stuck at α
- *B :* set of all possible faults (α) = {0, 1}
- Sensitivity:

$$s_n^{\alpha}(n_j) = E(W, o(n_j) = \alpha) - E(W)$$

$$S_n(n_j) = \frac{1}{|B|} \sum_{\alpha \in B} s_n^{\alpha}(n_j)$$

Addition/Deletion Procedure(ADP)

- Smarter approach
- Train network with Back-propagation as usual
- At end of training, different components may have different impact on network
- *But we want them to have equal impact*
- We will use our knowledge of **sensitivity** to distribute load equally across all neurons in a layer

Addition/Deletion Procedure(ADP)

- Rank neurons according to sensitivity
- Eliminate dead-spots by substituting the least sensitive neuron with fresh neuron
- This step **increases** network error within limits
- Eliminate hot-spots by configuring new neuron to share load of most sensitive neuron
- Retrain to remove chinks

  (very few iterations required).

Addition/Deletion Procedure(ADP)

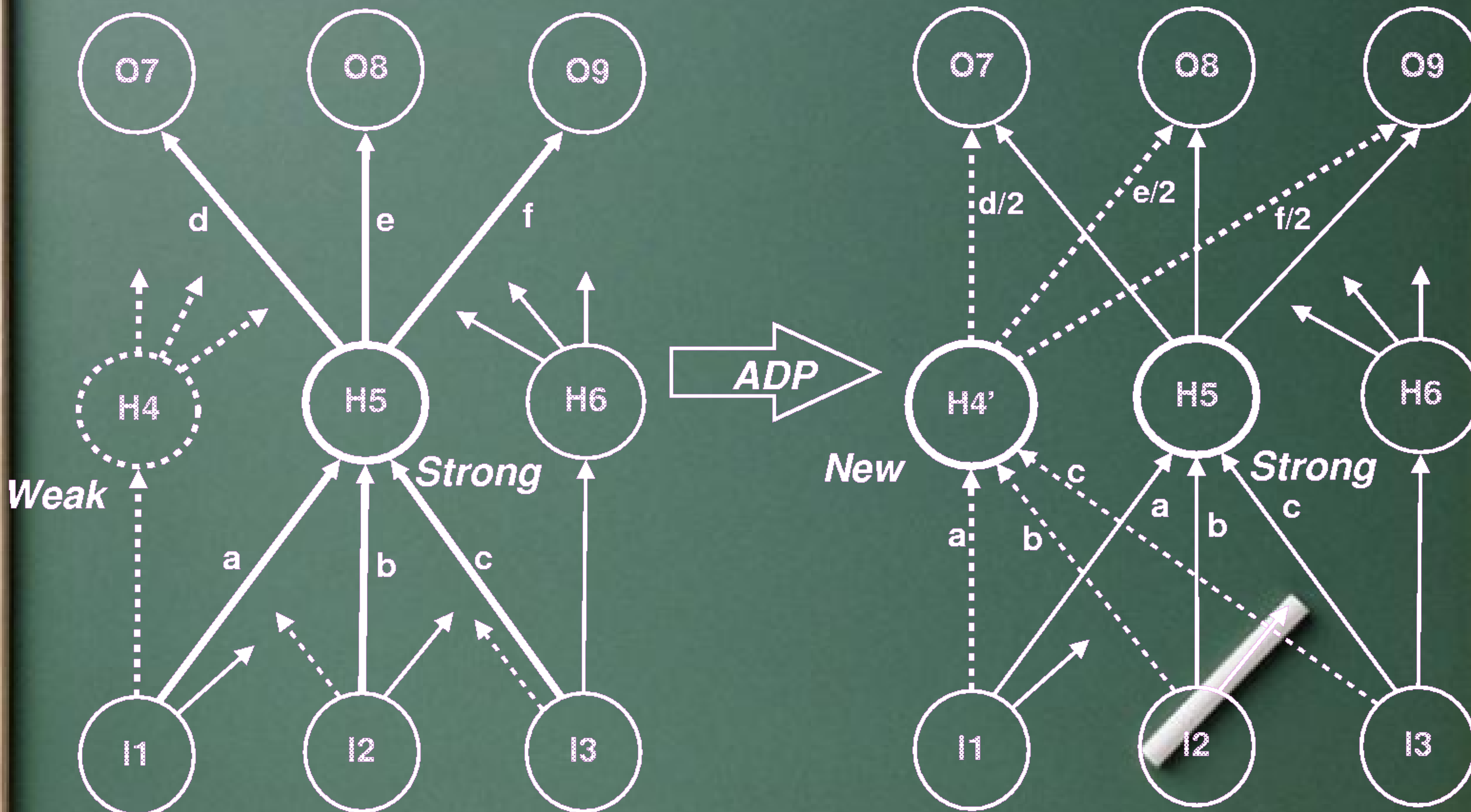
- **<u>Load Sharing algorithm:</u>**
- Let n_max = most sensitive neuron
  n_new = freshly added neuron
- input weights to n_new =

  input weights to n_max
- ouput weights from n_new =

  1/2(output weights from n_max)
- ouput weights from n_max =

  1/2(output weights from n_max)

Addition/Deletion Procedure(ADP)



Training Algorithms

1. Training with Injected Faults
2. Addition Deletion Procedure
3. Constraint Backpropagation

Constraint Backpropagation

- Most sophisticated approach so far
- Fault-tolerance *built-in* into Back-prop
- In each training iteration:
  - minimize Global error (as usual)
  - minimize susceptibility to failure (called Constraint Energy E_c)
- Degree of fault-tolerance can be **quantified**

Constraint Backpropagation

- m : degree of fault tolerance
- R : Set of neurons in hidden layer
- α : type of fault {0, 1}
- $\vec{m}_\alpha$: subset of R of size m with output set to α
- $o(\vec{m}_\alpha)$: net output with elements of $\vec{m}_\alpha$ set to α

Minimize : $E = \frac{1}{2} \sum_{i/p} \sum_{o/p} (t-o)^2$

For $\vec{m}_\alpha$ from R minimize :

$$E_C = \frac{1}{2} \sum_{i/p} \sum_{o/p} (t-o(\vec{m}_\alpha))^2 \quad \ldots\ldots \times \binom{|R|}{m}$$

Constraint Backpropagation

- Trained network **guarantees** fault tolerance of upto m neurons
- Degree of fault tolerance can be varied via training parameter (m)
- We traverse a set of $\binom{|R|}{m}$ error surfaces simultaneously
- What is the effect of varying m?

Constraint Backpropagation

- Smaller m
  - $\binom{|R|}{m}$ is small $\Rightarrow$ fewer error surfaces
  - small variations in error surfaces
- Medium m
  - $\binom{|R|}{m}$ is large $\Rightarrow$ more error surfaces
  - significant variation in error surfaces
- Large m
  - $\binom{|R|}{m}$ is small $\Rightarrow$ fewer error surfaces
  - Large variation across error surfaces
  - CBP may never converge

Conclusion

- Neural networks are **not** inherently fault-tolerant - but potential exists!!
- Training procedures need to be modified
- Sometimes, redundancy helps
- No explicit fault-handling required
- Resilience comes implicitly by clever design and training algorithms
- Guaranteed Fault-tolerance requires extra effort in training stage

References

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