# FLEXIBLE UPDATING OF ATTRACTORS IN VIRTUAL NETWORK TOPOLOGY CONTROL WITH BAYESIAN ATTRACTOR MODEL

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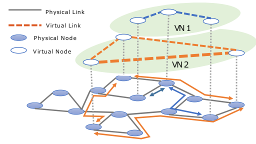
## Software-Defined Infrastructure(SDI)

- Virtual allocation of communication and computing resources according to requirements
  - Flexible use of physical resources through virtualization
    - FW, LB, communication bandwidth, CPU, memory, etc.
  - Enabling the provision of services that respond immediately to market changes



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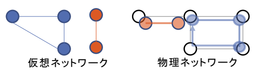
## Resource allocation issues

- Virtual Network Embedding (VNE)
  - Mapping between virtual and physical networks
    - Virtual node → Physical node
    - Virtual link → Physical path




- Challenges
  - Computational complexity is huge due to combinatorial optimization
    - Heuristic solutions are available, but performance is degraded.
    - Solving offline using predictions, etc., may not match the real situation.
  - Variation in resource availability includes noise
    - Possibility of incorrect response due to noise in the variation



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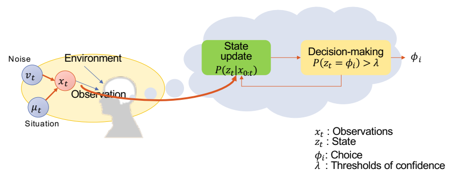
## Bayesian Attractor Model(BAM)[2]

- A cognitive model for decision making under uncertainty
- Confidence is accumulated with noisy input
- A category is expressed by a representative value




[2] S. Bitzer (number),J. Bruineberg, and S. J. Kiebel (singer), "A bayesian attractor model for perceptual decision making," *PLOS Computingal Biology*, vol. 11, no. 8, p. e1004442, Aug. 2015.



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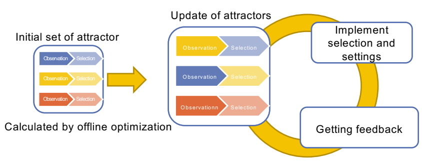
## Approach

- BAM-based cognition and feedback mechanisms to make correctable choices
  - Recognition by BAM based on noisy observations
    - Balance between noise and change point detection with BAM parameters
  - Corrects deviations from prior assumptions using a feedback mechanism



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## Learning through BAM feedback

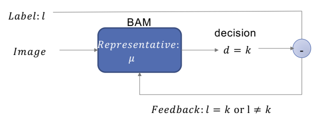
- Feedback on the correctness of BAM selection results
- Estimate distribution of representative values by Bayesian estimation

$$p(z|data) \propto p(data|z)p(z)$$
$$d = k \quad \text{if } p(z = \phi_k) > \lambda$$

BAM Decision Making

$$p(\mu|l = k, d = k, data) \propto p(l = k|d = k, data, \mu)p(\mu)$$
$$p(\mu|l \neq k, d = k, data) \propto p(l \neq k|d = k, data, \mu)p(\mu)$$

Learning through feedback



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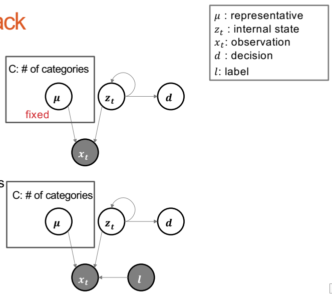
## Model including feedback

- Original Model
  - Input the observed value
  - Update internal state
- Proposal Model
  - Input observation values and labels
  - Update the representative value

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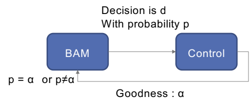
## Non-explicit feedback

- Rarely do we get accurate labels as feedback
- It is realistic to use the "goodness" of the classification as feedback
  - Feedback on the results of "BAM recognition → control"
- Modify the model by comparing the confidence level and the goodness of the results
  - Difficult to compare in terms of confidence as probability density
  - It's easy to handle if you define the confidence level to fit between 0 and 1.

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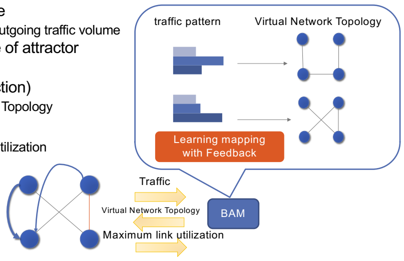
## Application of BAM to Network Topology Control

- Observed value
  - Incoming and outgoing traffic volume
- Representative of attractor
  - traffic pattern
- Attractor (selection)
  - Virtual Network Topology
- Feedback
  - Maximum link utilization

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## Simulation Environment

- Comparison method
  - random search
    - Randomly switch to another attractor when congestion is occurring in the current selection without recognition by BAM
  - Optimum(minimize link utilization)
    - Select the attractor that minimizes the maximum link utilization in an ideal situation where traffic is known in advance.
- Evaluation Environment
  - Give 10 unknown patterns of traffic every 20 timeslots.
    - Add noise at each time for each pattern.
    - $x_t = \mu_i + \epsilon_t$

      $\mu_i$ : i-th pattern
      $\epsilon_t$: Noise at each time (normally distributed)
  - Run by changing the initial 20 attractors.
- Adjusting parameters
  - Change the BAM parameters s and q in the range of 0.1 to 1 in increments of 0.1.
  - Select the most appropriate parameters from the results

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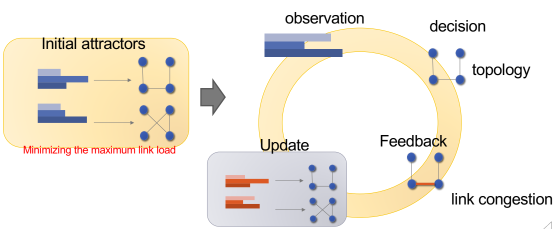
## Simulation Flow

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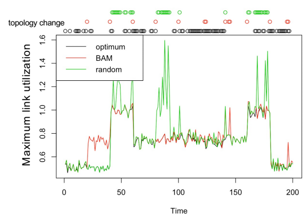
## Time series of link utilization and topology change

- BAM can avoid the overshoot of link utilization with few topology changes
- Minimizing link utilization requires too many topology changes

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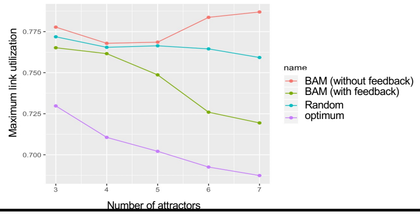
## Maximum link utilization

- BAM with feedback will be selected to reduce the maximum link utilization.
- As the number of attractors increases, the optimal link utilization decreases, and BAM with feedback will have a correspondingly low link utilization.



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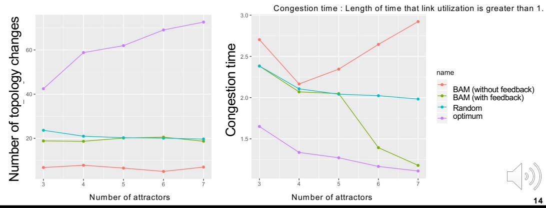
## Number of topology changes and congestion generation time

- The choice to minimize link utilization results in many topology changes due to the response to noise
- BAM with feedback gets closer to optimum as the number of attractors increases.



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## Summary

- Summary
  - Proposed an extended model of BAM that automatically learns attractors in a dynamic environment
  - Application of extended models to virtual network topology reconfiguration
  - Achieve appropriate control even in fluctuating environments with few control changes
- Future Work
  - Policy for setting appropriate BAM parameters
  - Automatic acquisition of attractor numbers



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