Evolutionary Algorithm with Phenotype Diversity for Virtual Network Embedding

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Virtual Network Embedding

- Network virtualization technologies that allocate network resources flexibly are in demand for various Internet-based applications.
- Virtual network embedding maps a virtual network onto a physical network to meet per-application requirements, but this is often done approximately with heuristics due to the complexity of the optimization problem.
- Dynamic virtual network embedding is necessary to continuously monitor and reconfigure the virtual network in response to changes in the physical network or application conditions.

Recalculation Problem

- Changes in the physical network or application conditions can result in the mismatch of virtual network embedding and the need for reconfiguration.
- To reduce the time required for recalculation, **multiple solution candidates can be prepared in advance and switched between depending on the situation**.
- However, it can be challenging to determine which solution candidates to keep, and updating the candidates may be necessary when there are large environmental changes.

Genotype and Phenotype

- The process of selecting solution candidates and updating them is similar to the relationship between phenotype and genotype in biological evolution.
- Phenotypic plasticity allows for multiple different phenotypes in response to different environments, and genotypic evolution can change this plasticity.
- The Baldwin effect suggests that phenotypic plasticity can promote learning in individuals.
- Biological evolution has successfully adapted to environmental variation through the interplay between **genotype and phenotype**.

Approach

- A dynamic virtual network embedding method is proposed that updates solution candidates based on the evolution of genotype and phenotype.
- The proposed method encodes candidate solutions as genotypes and decodes them as phenotypes through attractor selection using noise-induced fluctuations.
- Short-term search with noise is effective for virtual network embedding due to the dynamic nature of the environment.
- Long-term search with evolution is also effective due to the drastic environmental change.

Dynamic Search and Selection

1. Initialize the random **genotype (attractor structure)** of each individual.
2. **Each individual selects a solution suitable for the environment from a set of attractors** by attractor selection with activity in a simulation of virtual network embedding.
3. Evaluate novelty and fitness for each individual choice, then select surviving individuals.
4. Move to the next generation and repeat the procedure from Step 2.

Candidates as Genotype

- In attractor selection, the structure of the Hopfield network influences the selection process.
- The coupling structure of the Hopfield network can be used as the genotype of an individual in this process.
- The weights of the couplings between nodes of the Hopfield network form the genotype.
- Mutation of the genotype is achieved by adding a random number to the weights.

$$\vec{w} = (w_{01}, w_{02}, \cdots, w_{n-1,n})$$

Phenotype Adaptive to Environment

- Attractor selection updates the state of the individual at each time based on the Hopfield network, the activity representing the goodness of the state, and a noise term.
- The state determines the output of the individual and incorporates feedback from the environment through the activity.
- Different phenotypes may be obtained for the same genotype and environment due to the noise term in attractor selection.

$$\frac{d\vec{x}_t}{dt} = \alpha_t F_{\vec{w}}(\vec{x}_t) + \vec{\eta}_t$$

Genotype Evolution

- Evolutionary updates of the candidates themselves in response to environmental changes that cannot be handled by the prepared candidates.
- The genotype that maximizes the next fitness function is obtained by evolutionary computation.
- The balance is determined by λ, where R is the amount of surplus resources and P is the penalty for resource constraints.

$$F(\vec{x}_t) = R(\vec{x}_t) - \lambda P(\vec{x}_t)$$

Novelty Search

- Novelty search uses the uniqueness of individuals as the objective function for evolution instead of fitness.
- In novelty search, individuals with higher novelty survive to the next generation based on their average distance from other solutions.

$$\rho(x) = \frac{1}{n}\sum_{k=1}^{n} dist(x, \mu_i)$$

Fitness of Local Competition

- Local competition is a method used to limit competition by a fitness to a local range in order to maintain diversity in the population.
- The survival of each individual is determined by the weighted sum of their novelty and competitiveness in their local neighborhood.

$$E(\vec{x_t^i}) = (1 - w)\bar{\rho}(\vec{x_t^i}) + wF^i(\vec{x_t^i})$$

$$F_i(\vec{x_t^i}) = (F(\vec{x_t^i}) - \min_{j \in \mathscr{O}_i} F(\vec{x_t^j}))/(\max_{j \in \mathscr{O}_i} F(\vec{x_t^j}) - \min_{j \in \mathscr{O}_i} F(\vec{x_t^j}))$$

Definition of Behavior

- In novelty search, the phenotype of individuals is represented as behavior, and the search for diverse individuals is carried out by maximizing the distance between behaviors over generations.
- The behavior can be a summary of the output series or the series itself.
- In attractor selection, the appropriate solution is searched for within a generation, and the state at the time of convergence is used as the behavior.

$$\vec{b}_i = \vec{x}^{\,i}_f$$

Simulation Setting

- 5-node virtual network is embedded into a 30-node physical network by attractor selection.
- The number of individuals is 100.
- State updates are performed for 20-time slots in each generation.
- The size of the population that defines the neighborhood of an individual is set to $k = 15$.
- The weights of fitness and novelty are set to $w = 0.5$.
- The resource requirements of the virtual network are randomly changed every 40 generations.

Metrics

- Max Fitness
  - maximum fitness among individuals

$$F_{max}(t) = \max_{x_t} F(\vec{x}_t)$$

- Solution Diversity
  - Jensen-Shannon divergence between solution distribution P and uniform distribution Q.

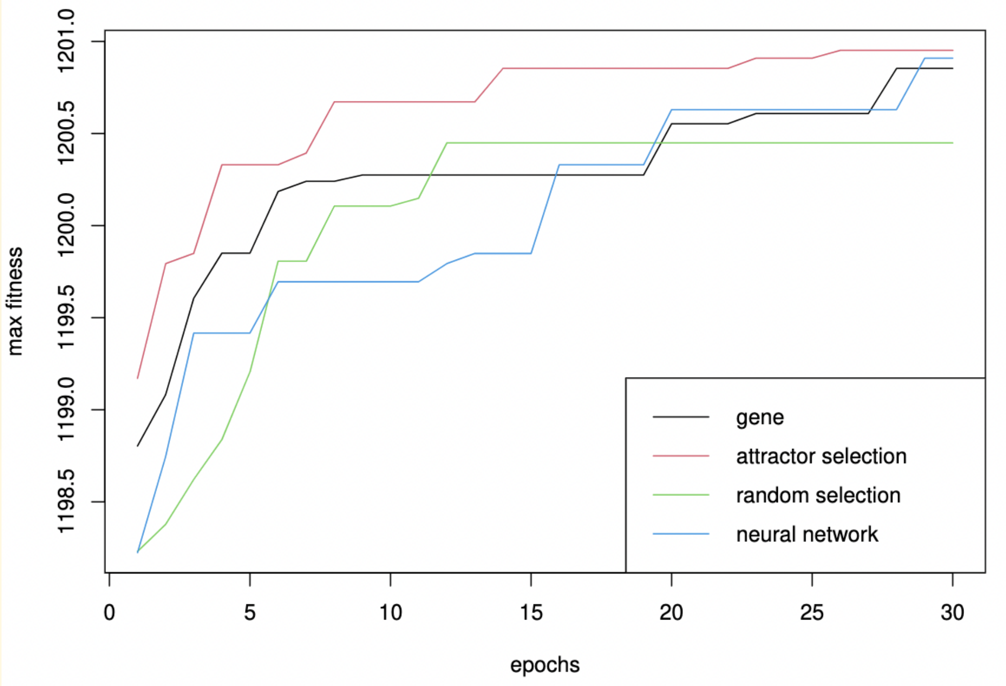
$$D_{JS}(P, Q) = (D_{KL}(P, M) + D_{KJ}(Q, M))/2$$
$$M = (P + Q)/2$$

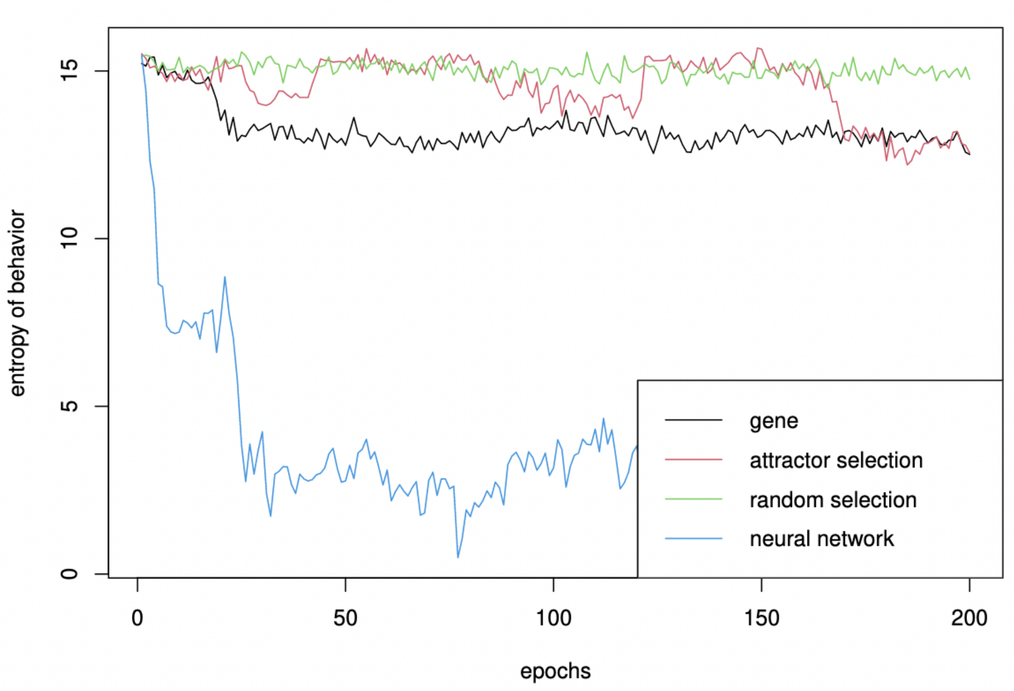
Other Individual Types

- Neural Network
  - Neural network determines phenotype from the environment.
  - The inputs to the neural network are the resource requirements and the residual resources.
- Random Selection
  - Individual randomly selects one of the multiple solutions as phenotype.
- Direct Gene Encoring
  - Solution is directly encoded into genotype.

Results

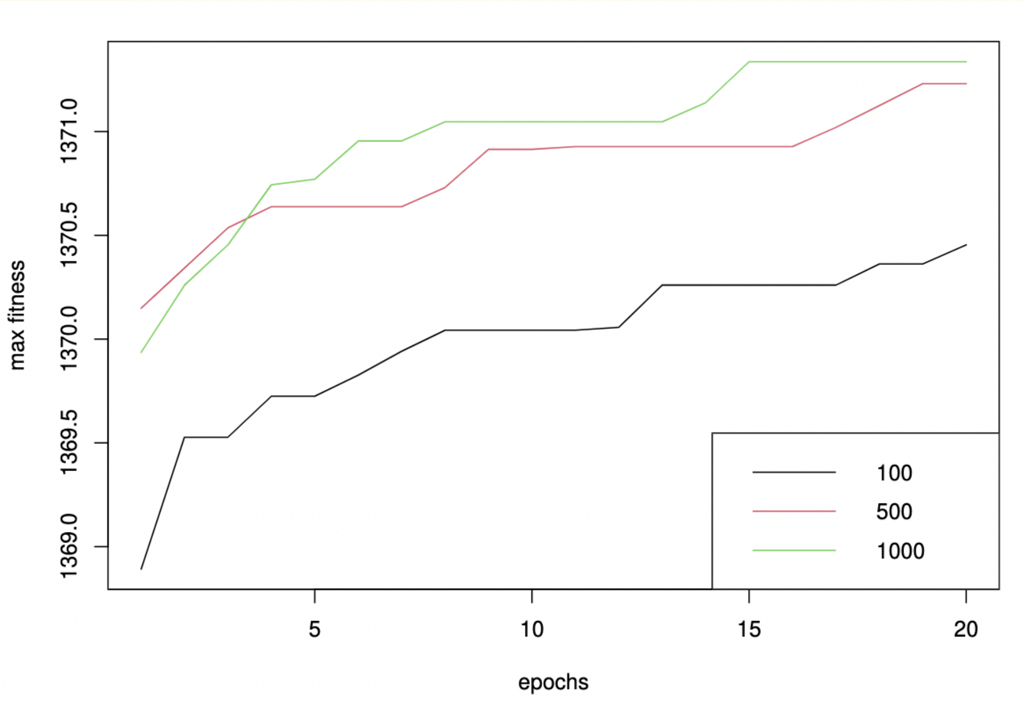
- The use of attractor selection allows individuals to search for solutions within a generation, resulting in the faster discovery of solutions with higher fitness.
- Diversity in the population can be improved by allowing multiple phenotypes to appear from a single genotype, as in the case of attractor selection and random selection.





Population Size

- As population size increases, the better solution is found in fewer generations
- The increase in maximum fitness is larger when the number of individuals increases from 100 to 500 than from 500 to 1000, possibly because the novelty search allows individuals of about 500 to cover a wide range of the solution space



Summary

- Proposed a dynamic virtual network embedding method that can adapt to environmental changes through genotype and phenotype search
- Genotypes evolved through novelty search to maintain diversity and promote adaptation in both genotype and phenotype
- Simulation results showed that the method using attractor selection can find better solutions faster than novelty search alone
- Future work includes investigating the adaptive limits of the method under different environmental change scenarios

Thank you for your attention

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