Neural Network Meets DCN: Traffic-driven Topology Adaptation with Deep Learning

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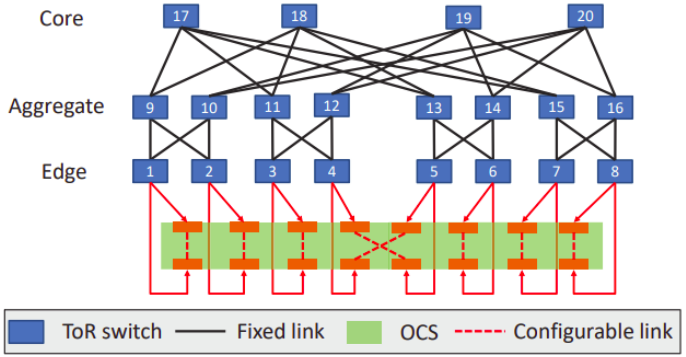
Introduction

Conventional wired data centers generally adopt a static network topology (e.g. Clos networks) leading to over-provisioning to handle worst case scenarios

Topology-reconfigurable DCNs use network components such as Optical Circuit Switches(OCS) or Wireless Radio to build agile links that can be quickly reconfigured

Modeling the global interactions between traffic and topology in a reconfigurable network is non-trivial, especially while considering user defined performance metrics



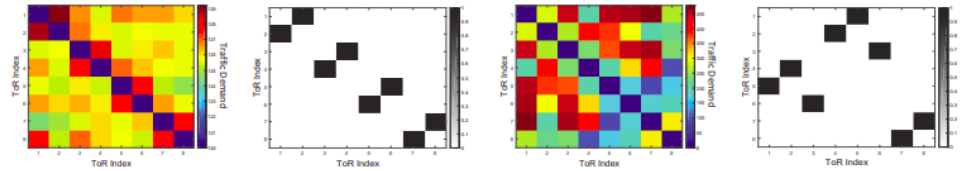
Reconfigurable Topology for 4-port fat tree

xWeaver

- A traffic-driven deep learning system for learning the topology configuration in DCNs
- Uses deep learning to perform 2 tasks:
  a. Learn network traffic in DCNs
  b. Learn global interactions between traffic and topology
- Design Features:
  a. Can support optimization over conventional flow-level performance metrics and application level performance metrics
  b. Uses SCNN to automatically label high-score topologies with corresponding traffic demands
  c. Uses FPNN to capture interaction between traffic and topology configurations

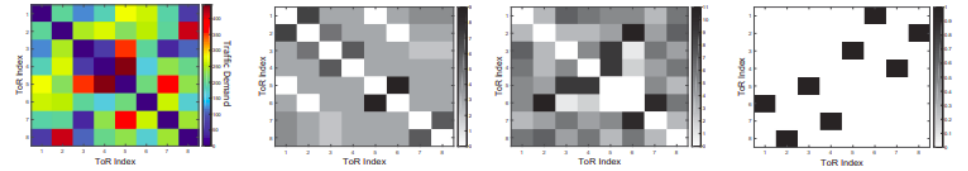
Why Deep Learning?

- Heuristic approaches do not consider interactions between fixed and configurable parts of the network
- High performance topologies for a given traffic demand share a set of critical links
- CNNs are good at feature extraction, in this case, the critical links in the network



(a) Sum of a class of traffic demand matrices $\mathbf{D}$ (b) Topology P_0 that optimally supports the demand class $\mathbf{D}$ (c) One sample demand $d \in \mathbf{D}$ (d) Weight-matching topology P_1 for demand d

Fig. 2. An example of traffic pattern attached to a specific topology configuration.

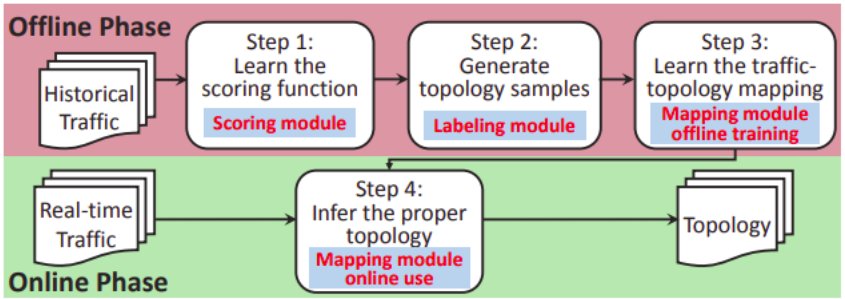


(a) One sample demand $d' \in \mathbf{D}$ (b) Sum of high-score topologies for demand d' (c) Sum of low-score topologies for demand d' (d) Weight-matching topology P_2 for demand d'

System Modules

Offline phase:

- **Scoring module**: Takes traffic-topology score as input and gives performance score based on optimization criteria
- **Labeling module**: Label historic traffic traces with corresponding high score topologies
- **Mapping module**: Learn the high-dimensional global mapping between traffic and topology



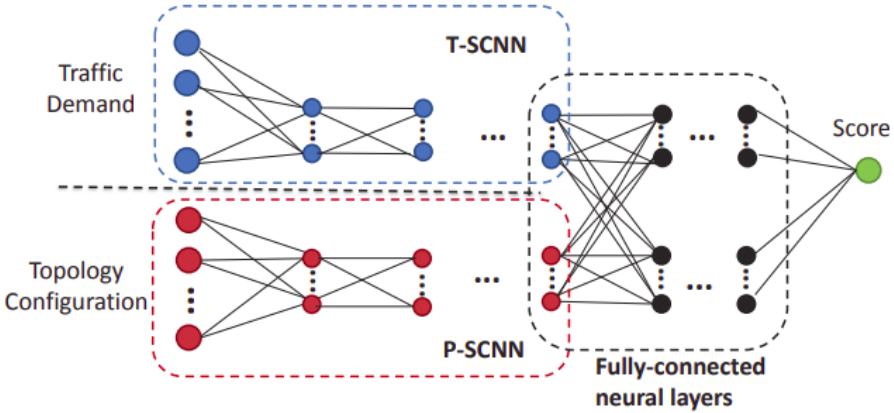
Online phase:

- Controller uses mapping module to periodically update OCS switch configuration

Traffic-driven training sample generation

Topology performance scoring:

- Objective is to learn a scoring function **Score(f,p)** that maps topologies to scores based on a user-specified metric (for traffic trace f and topology configuration p)
- Neural networks can be used to learn an **approximate scoring function** with tolerable accuracy loss
- **Separate CNNs** can be used to extract features from traffic and topology since their patterns are unrelated



High score topology sample generation

- Candidate topologies can be exponentially large for even small scale DCN
- Using high score topologies to learn traffic to topology mapping leads to better accuracy
- Use a heuristic search algorithm to generate high score topology samples

$$p_t = \arg\max_{p \in N\delta\ (pt-1)} \text{Score}(f_t, p)$$

- Can lead to a local optimal score since topologies can have similar scores
- Beam search and random start to get out of local optimum

Traffic topology mapping learning

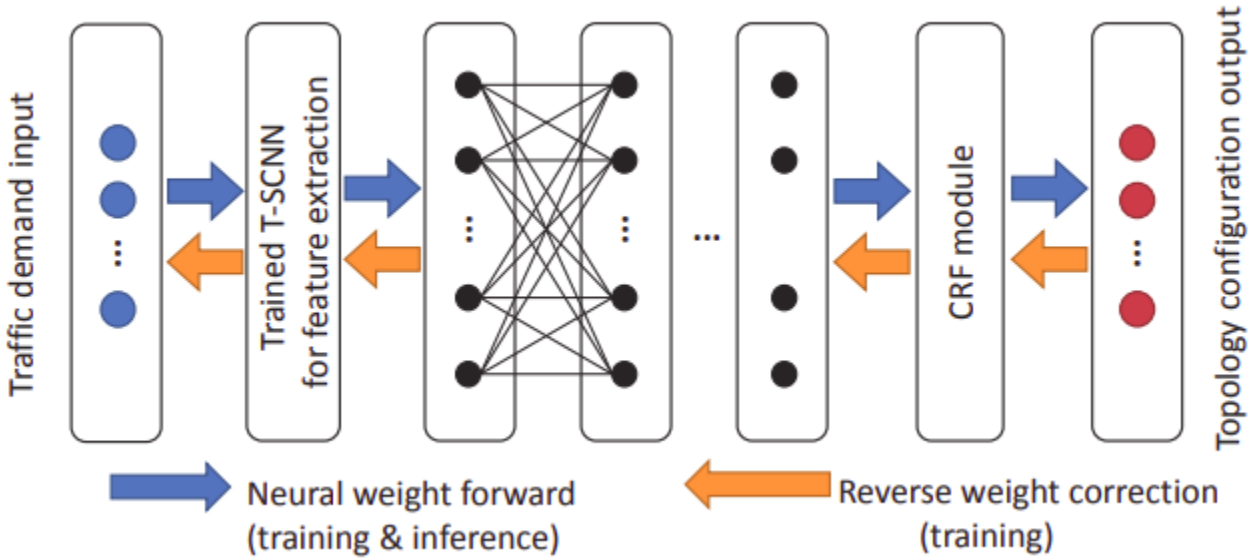
- Objective is to learn the mapping between input traffic demands and output topology configurations
- Input feature extraction can be done using the already trained SCNN
- Prior human knowledge embedding can be done using Conditional Random Fields
- CRF input is the original output of the FPNN, while the CRF output is a new topology that is corrected by the prior human knowledge

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{\mathbb{Z}(\mathbf{x})} \prod_{c \in \mathbf{C}} \phi(\mathbf{x}, \mathbf{y}|_c)$$

$$\phi(x, y|_c) = \prod_{c \in \mathbf{C}} \exp\left(\sum_k \lambda_{k,c} f_{k,c}(\mathbf{x}, \mathbf{y}|_c)\right)$$

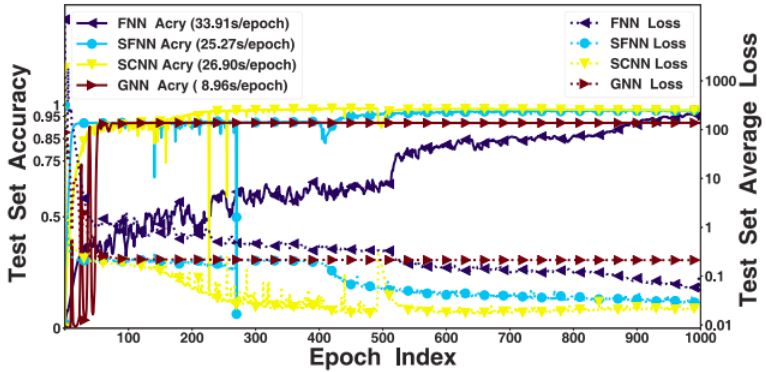
- Uses MLE to find the topology y to maximize P(y|x) given the observed FPNN output x that satisfies all feature functions.

Traffic topology mapping learning

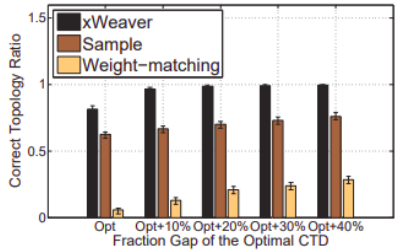


Performance Evaluation

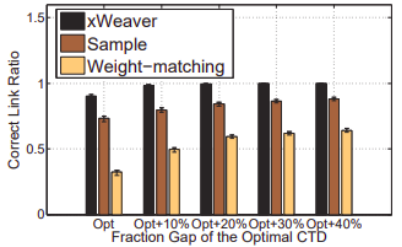
Scoring module



Traffic-topology learning

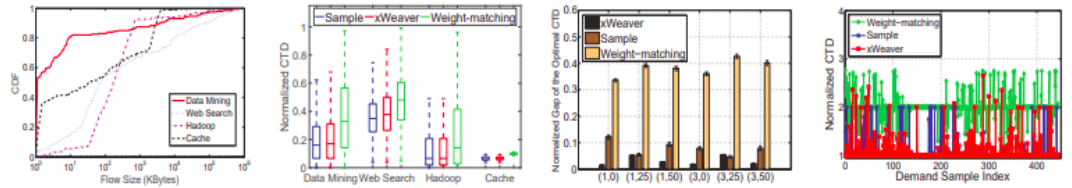


(a) Learning performance of the optimal topologies



(b) Learning performance of the critical topology links

Performance Evaluation



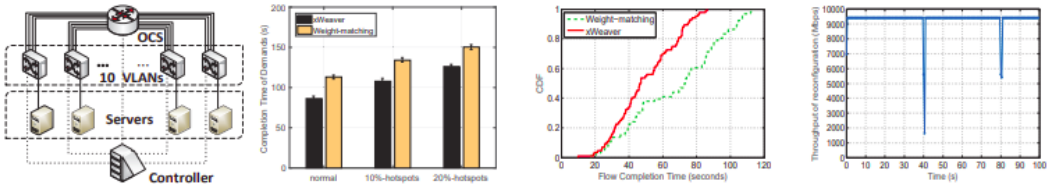
(a) CDF of flow size over application traffic patterns

(b) Normalized CTD over application traffic patterns

(c) Optimality gaps for hot-spot traffic patterns

(d) CDF of normalized CTD over real data center traces

Fig. 10. Learning performance for different traffic patterns.



(a) OCS Testbed

(b) CTD of different traffic patterns

(c) CDF of flow completion time

(d) Throughput of reconfiguration

Fig. 11. Performance evaluation in an OCS-based testbed.

Scalability and Adapting to New Traffic Patterns

Independent Learning: FPNN is re-trained for every new traffic pattern

Adaptive Learning: FPNN is initialized for the first pattern and then keep updating the parameters for later traffic patterns

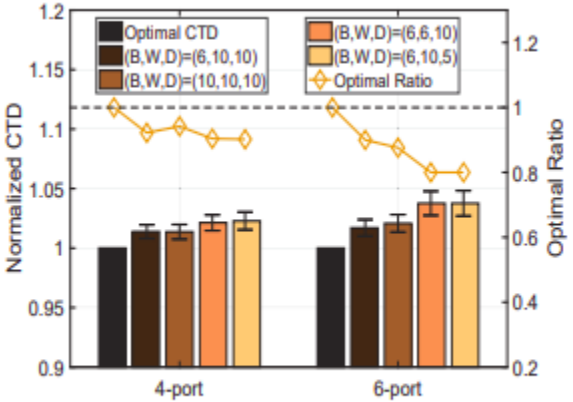
Table 1. Comparison of iterations required for different training processes.

Traffic pattern	(3, 50)	(3, 25)	(3, 0)	(1, 50)	(1, 25)	(1, 0)
Independent training (iter.)	23369	35783	20739	21502	20032	19341
Adaptive training (iter.)	23369	2431	2678	1440	2343	2536

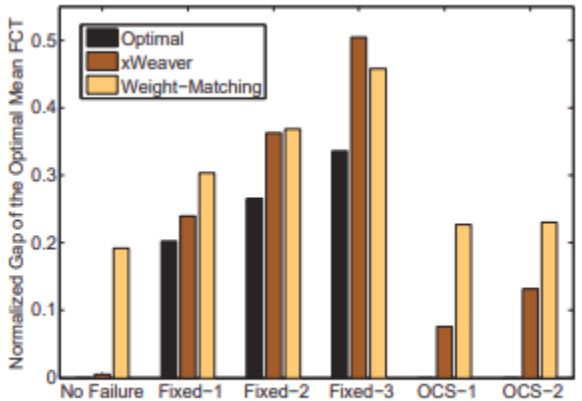
Table 2. Comparison of online running time over different network scales.

Number of racks	10	100	200	500
Running time of FPNN (CPU) (ms)	0.02	0.29	1.56	10.4
Running time of FPNN (GPU) (ms)	0.09	0.18	0.48	2.37
Running time of Weight-matching (ms)	0.02	0.15	0.94	24

Sensitivity and Robustness Analysis



(a) Sensitivity of labeling module with dif-



(b) Robustness with different numbers

Thoughts

Pros:

- Auto-labeling for training data
- Support for application level performance metrics
- Separate CNN modeling

Doubts:

- Can it optimize for multiple performance metrics at once? What if they are contradictory?
- Significant drop in throughput during reconfiguration (for about 300ms)