Dynamic Deep Neural Networks:
Optimizing Accuracy-Efficiency Trade-offs by Selective Execution
AAAI 2018

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2019.10.14

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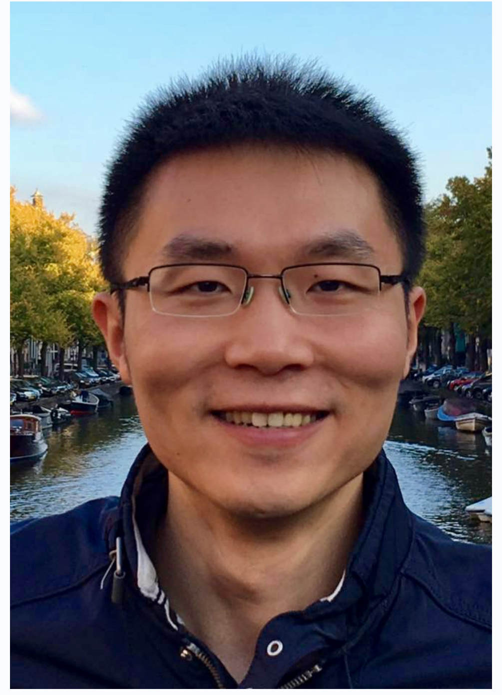
International Conference on Computer Vision(ICCV), 2019



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European Conference on Computer Vision(ECCV), 2018

Abstract

- **Introduce Dynamic Deep Neural Networks** D^2NN
  - A new type of feed-forward deep neural network that allows selective execution
  - Given an input, only a subset of D^2NN neurons are executed, D^2NN provide a way to improve computational efficiency
- D^2NN augments a feed-forward deep neural-network with control node.
- Training is achieved by integrating backpropagation with reinforcement learning (Q-Learning)
- As a result,
  - They demonstrate that D^2NN are general and flexible, and can optimize accuracy - efficiency trade-offs.

Introduction

- **Motivation**
  - The need for computational efficiency, by need to deploy deep networks on mobile devices & data centers.
    - Mobile : constrained by energy and power, limiting the amount of computation that can be executed.
    - Data centers : need energy efficiency to scale to higher throughput and to save operating cost.

Introduction

- **Advantages**
  - Improve computational efficiency by selective execution
    - Pruning unnecessary computation depending on input.
  - It makes possible to use a bigger network under a computation budget by executing only a subset of the neurons each time.

Definition and Semantics of D^2NN

D^2NN definition

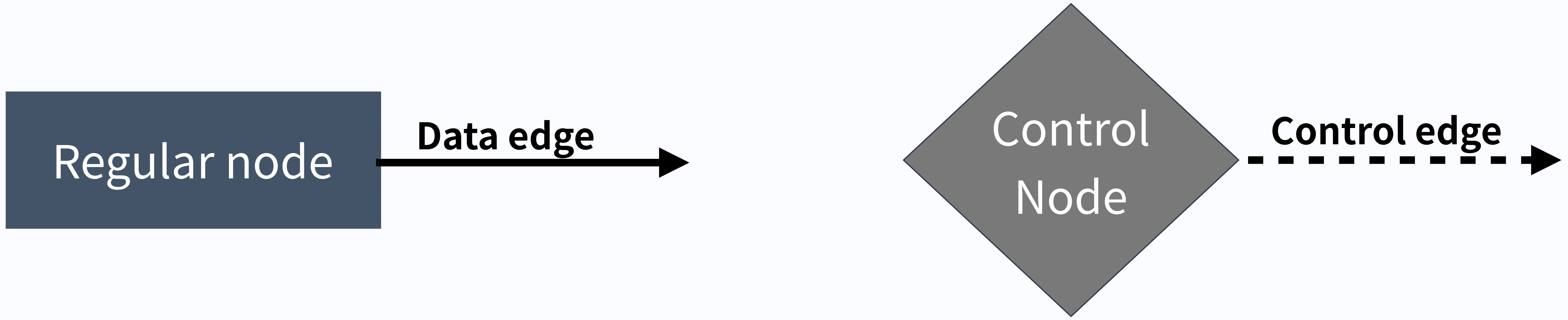
- **Node**
  - Input nodes & Output nodes
    - = input or output networks
  - Function nodes
    - = control node or data edge (depending on outgoing edge)
  - Dummy nodes
    - It is possible for a function node to take no data input and output a constant value.
- **Edge**
  - Data edge
    - A vector sent from one node to another, same as conventional DNN
    - optionally have a user-defined “default value”, representing the output will still be sent even if the function node does not execute.
  - Control edge
    - Control signal, a scalar, sent from one node to another

Definition and Semantics of D^2NN

Restrictions

- **The Outgoing edges from a node are either all data edges or all control edges.**
    - Cannot be a mix of data edges or all control edges

- **If a node has an incoming control edge, outgoing edge cannot be a control edge.**



Definition and Semantics of D^2NN

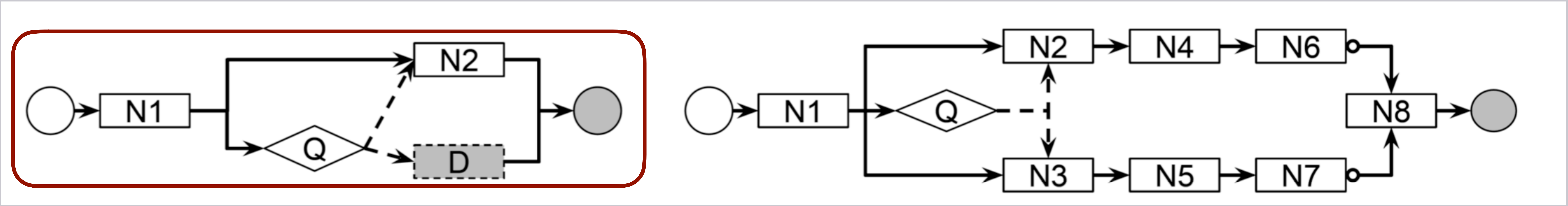
D^2NN Semantics

- Perform inference by traversing the graph starting from the input nodes
- Same as conventional DNNs except that the control nodes can cause the computation of One nodes to be skipped.
- After execute a Control node,
  - Output is a set of control scores, one for each of its outgoing control edges
  - **Highest score is "activated" -> allowed to execute**
- D^2NN can be though of as a program with conditional statements.
  - D^2NN introduces conditional statements with the conditions themselves generated by learnable functions.

Definition and Semantics of D^2NN

D^2NN Semantics

- **Control node**
  - Output is a decision that control whether other modules can execute.



- Q : control node
- N : regular module
- D : dummy node

——> : data edge
- - -> : control edge

- Simple D^2NN with one control module (Q)
  - Q outputs a binary decision on whether module N2 executes
  - If Q decide that N2 is unnecessary , execute Dummy node(D) to save on computation.

- As an example, used for binary classification of images
  - Can be rapidly classified as negative after only a small amount of computation.

Definition and Semantics of D^2NN

D^2NN Semantics

- **Control node**
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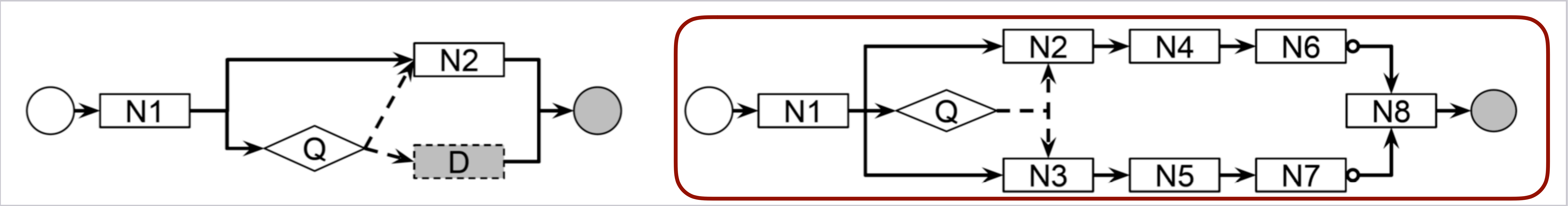


- Q : control ode
- N : regular module
- D : dummy node

——> : data edge
- - -> : control edge

- The node Q controls N2 and N3.
  - N2 or N3 - execute depending on which has the higher control score.
- If one of the node is skipped, its output will be default or null.
  - If output is default value, subsequent execution will continue as usual.
  - If output is null, any downstream nodes that depend on this output will be skipped.

D^2NN Learning

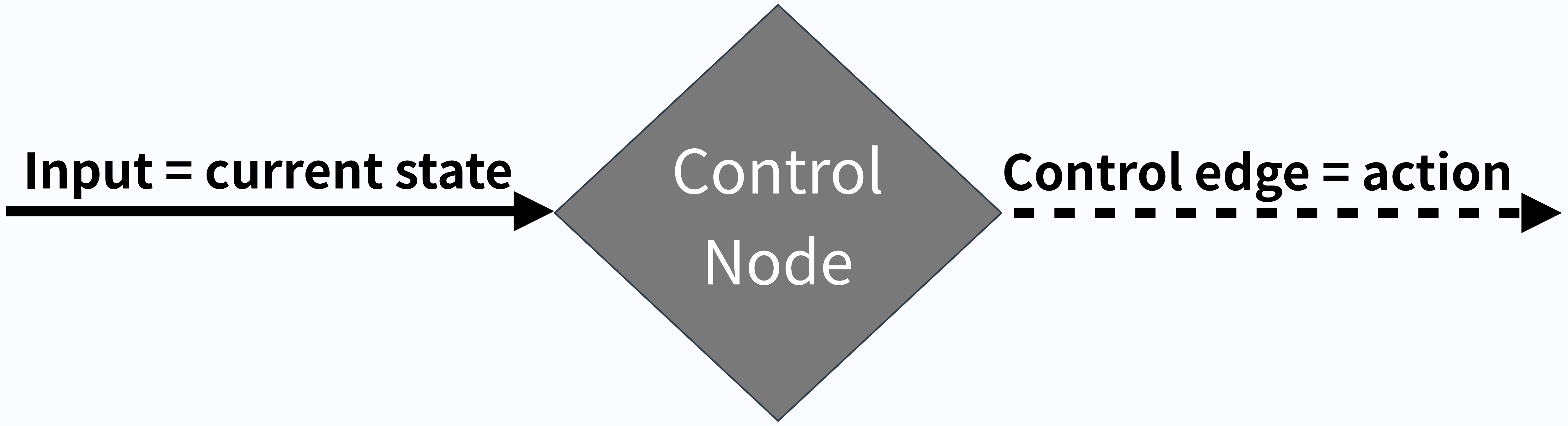
- D^2NN cannot be trained same way as a conventional DNN.
  - Back propagation cannot be directly applied.
  - Used Q-Learning(reinforcement learning) to discretized control node.

D^2NN Learning

Learning a Single Control Node

Learning a Single Control Node

- Start with one control node
  - The goal is to learn the parameters of the control node to maximize a user-defined reward.
    - User-defined reward == combination of accuracy and efficiency = $\lambda A + (1 - \lambda)E$
  - Learning a control policy to take actions so as to maximize reward
    - Method on Q-Learning (one of reinforcement learning)
- Outgoing control edge = action
- Control node approximate the action-value (Q) function
  - Each control node only executes once.

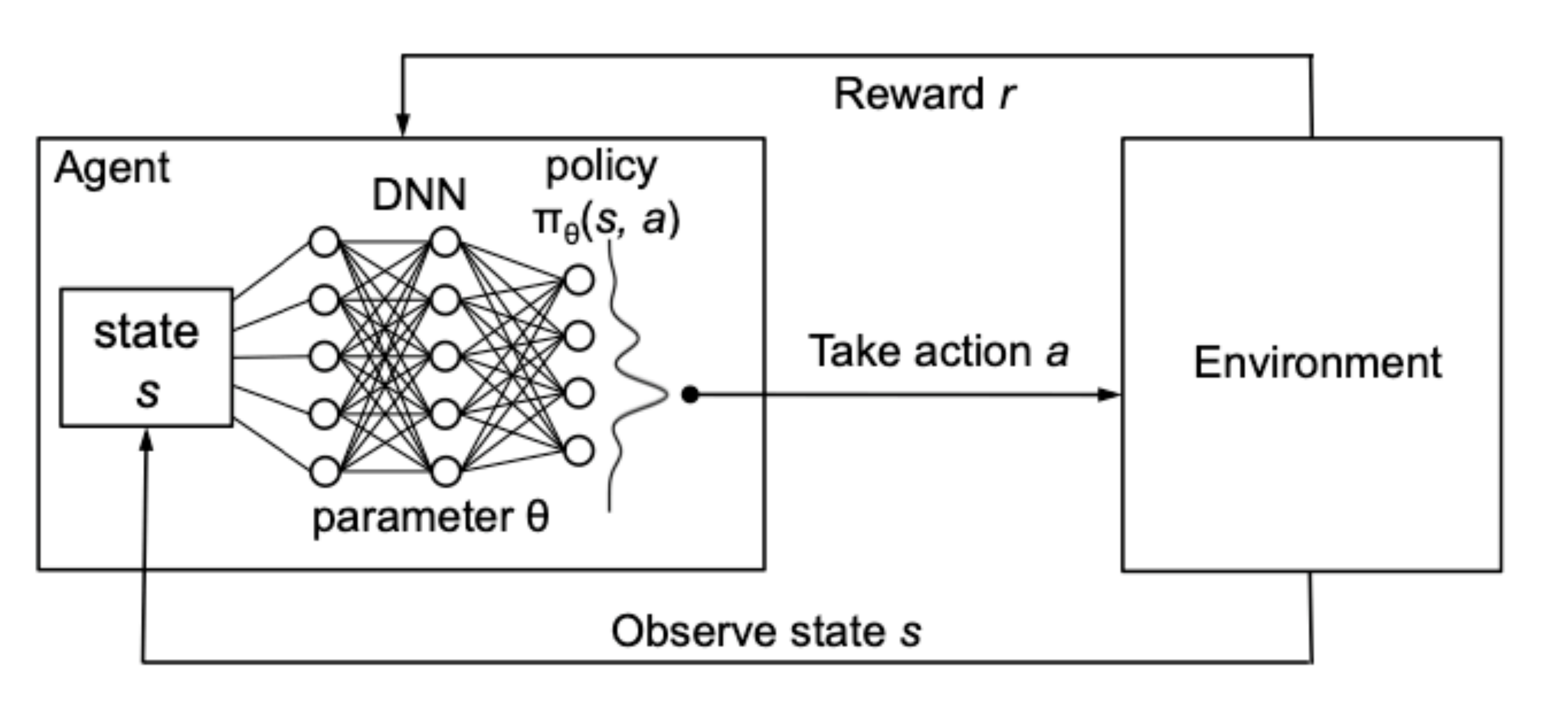


D^2NN Learning

Q-Learning

Q - Learning

- seeks to find the best action to take given the current state
- seeks to learn a policy that maximizes the total reward.



D^2NN Learning

Q-Learning

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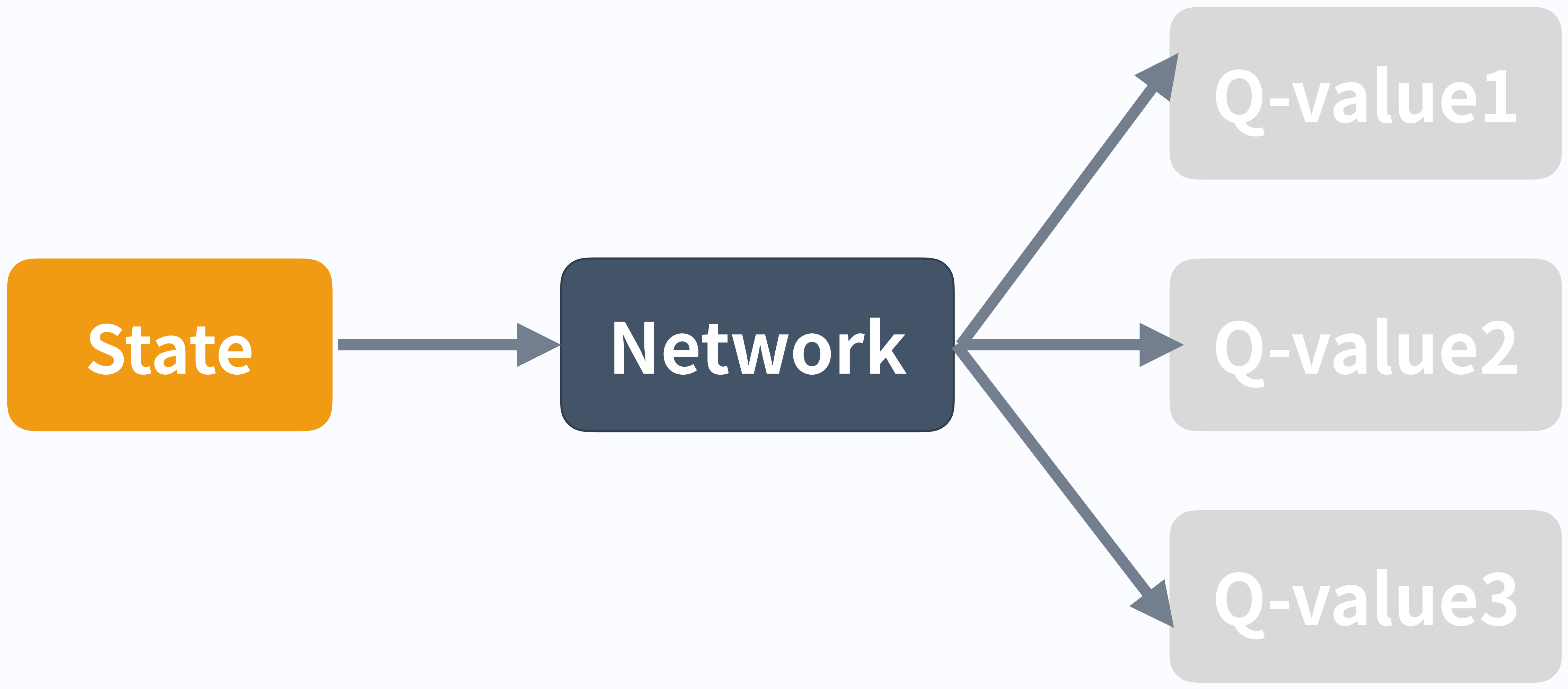


D^2NN Learning

Learning a Single Control Node

Learning a Single Control Node

- An action take on one input has no effect on another input.

$$\boxed{L = (Q(s,a) - r)^2}$$

- **r** = user-defined reward
- **a** = action
- **s** = input to control node
- **Q** = computed by control node
- Predict the reward for each action under an **L2** loss

D^2NN Learning

Learning a Single Control Node

Learning a Single Control Node

- During training we also perform $\epsilon - greedy\ exploration$ instead of always choosing with the best Q- value
- The hyperparameter ϵ is initialized to 1 and decreases over time.
  - A = accuracy (F-score)
  - E = efficiency (inverse of number of multiplications)
  - Reward = $\lambda A + (1 - \lambda)E$

D^2NN Learning

Mini-Bags for Set-Based Metrics

Mini-Bags for Set-Based Metrics

- Set of inputs = Mini-bag
  - With a mini-bag of images, any set-based metric can be computed and can be used to directly define a reward.
  - Mini-bag =! Mini-batch
- Calculate gradients using a mini-batch of mini-bags.
- Mini-bag $s = (s_1, \ldots, s_m)$
- Joint action $a = (a_1, \ldots, a_m)$

$$\boxed{Q = \sum_{i=1}^{m} Q(s_i, a_i)}$$

- $Q(s_i, a_i)$ is a score given by the control node when choosing the action a_i for example s_i

D^2NN Learning

Mini-Bags for Set-Based Metrics

Mini-Bags for Set-Based Metrics

- Then define new learning objective on a **mini-bag of size** m as where r is the **reward** observed by choosing the joint **action** a on **mini-bag** s.

$$\boxed{L = (r - Q(s, a))^2 = \sum_{i=1}^{m} (r - Q(s_i, a_i))^2}$$

- Control node predicts an action value for each example such that their sum approximates the reward defined on the whole mini-bag

- $Q(s, a)$ is simply the concatenation of the best actions for individual examples

$$\boxed{a_i^* = argmax_{a_i} Q(s_i, a_i) \qquad i = 1,2,\ldots,m\,.}$$

  - Because maximizing optimal a is equivalent to maximizing the individual summands.

D^2NN Learning

Mini-Bags for Set-Based Metrics

Mini-Bags for Set-Based Metrics

- Then define new learning objective on a mini-bag of size m as where r is the reward observed by choosing the joint action a on mini-bag s.

$$\boxed{\frac{\delta L}{\delta x_i} = 2\left(r - \sum_{j=1}^{m} Q(s_j, a_j)\right)\frac{\delta Q(s_i, a_i)}{\delta x_i}}$$

  - x_i is the output of any internal neuron for example i in the mini-bag.
  - Shows that there is no change to the implementation of back propagation except that we scale the gradient using the difference between the mini-bag Q-value Q and reward r.

DNN Learning

Joint Training of All Nodes

Joint Training of All Nodes

- When D^2NN has multiple control nodes, simply train them together.
- For each mini-bag, perform back propagation for multiple losses together.
  - observe a reward for the whole network, then use the same reward (which is a result of the actions of all control nodes) to back propagate for each control node.
- Important detail
  - The losses on regular nodes need to be properly weighted against the losses on the control nodes. ***
    - To eliminate this problem use Q-learning losses on regular nodes
      - For example treat the classification scores as action-values ——> an estimated reward for each classification decision.

Experiments

- **Experiment four D^2NN structures**
  - motivated by different demands of efficient network design to show its flexibility and effectiveness.

< 4 typed of D^2NN model >

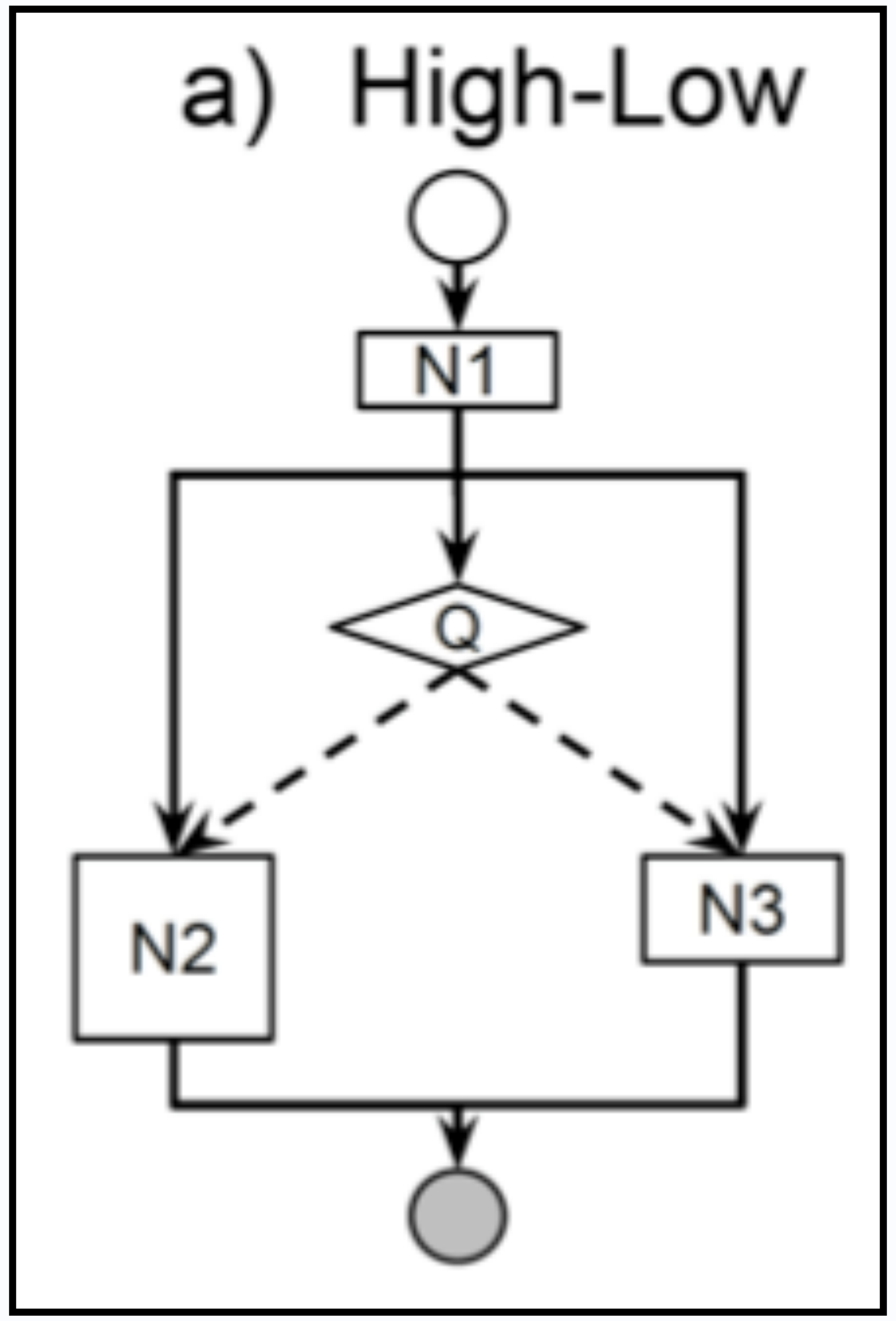
- High - Low
- Cascade
- Chain
- Hierarchy

Experiments

High-Low Capacity DNN

- Motivated by that can save computation by choosing a low-capacity subnetwork for easy examples.
  - High-capacity : N2
  - Low-capacity : N3

- Test with binary classification task
  - Input image : Labeled Faces in the Wild dataset
  - Accuracy : F1-score
  - Efficiency : Computational cost - number of multiplications
  - Reward : $\lambda A + (1 - \lambda)E$



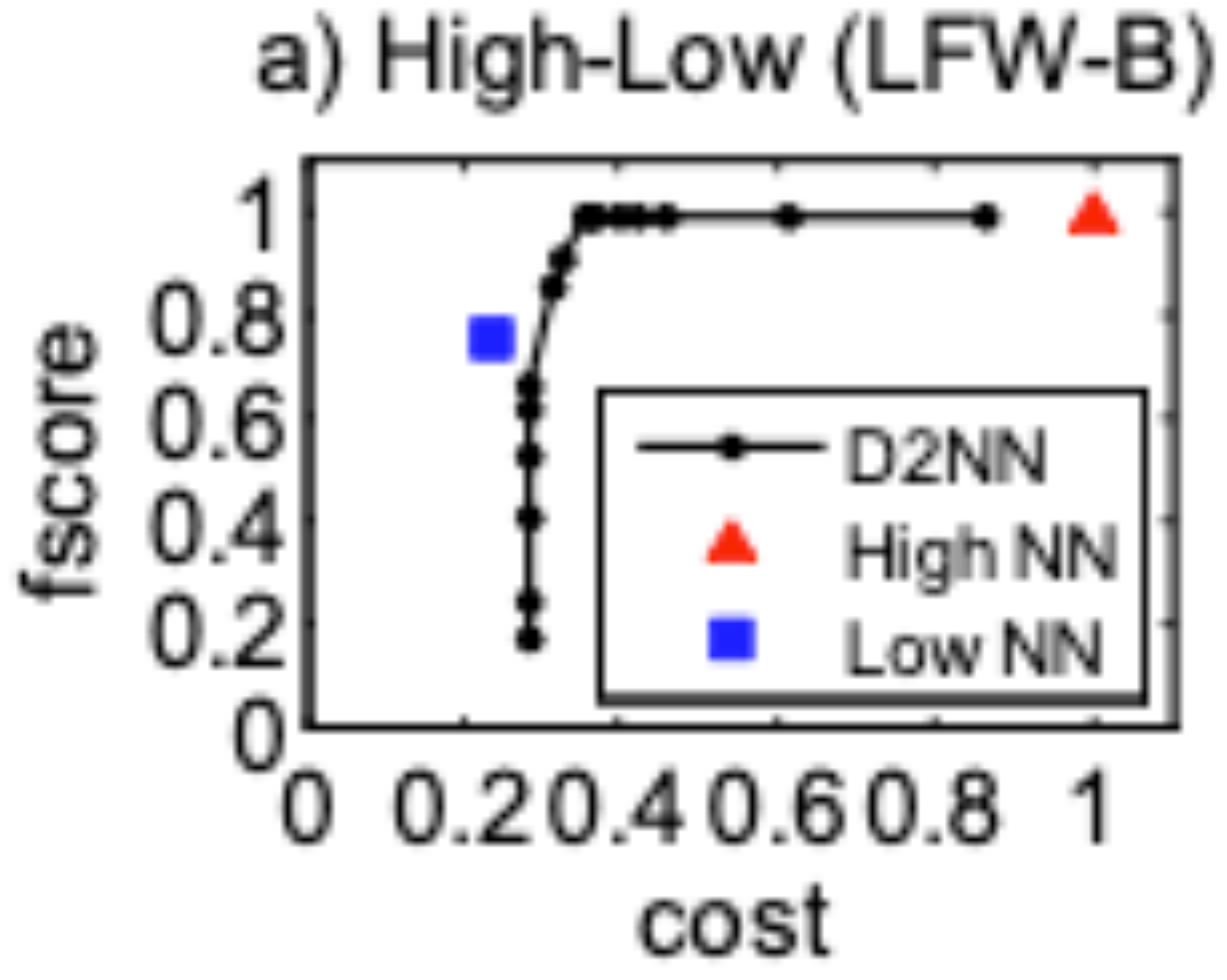
- N1 : **conv** (filter size = (3,3), filters = 8, stride = 2) + **max_pooling**(3x3, stride = 2)
- N2 : **conv** (filter size = (3,3), filters = 16) + **max_pooling**(3x3, stride = 2) + **reshape + fully_connected**(512) **+ fully_connected**(2-class output)
- N3 : **max_pooling**(3x3, stride = 2) + **fully_connected**(32) **+ fully_connected**(2-class output)
- Q1 : **conv** (filter size = (3,3), filters = 2) + **max_pooling**(3x3, stride = 2) + **reshape + fully_connected**(128) **+ fully_connected**(2-action output)

Experiments

High-Low Capacity DNN

- As λ increases, the learned D^2NN trades off efficiency for accuracy.
- This example suggest that this learning algorithm is effective for networks with a single control Node.
- With low NN, it achieves 0.2 cost and 0.8 accuracy.
- With high NN, it achieves 1 cost and 1.0 accuracy.

accuracy-cost graph



Experiments

High-Low Capacity DNN

- Fig 5 plots the distribution of examples going through different execution path.
  - It shows that as λ increases, accuracy becomes more important and more examples go through the high-capacity node.
- This example suggest that this learning algorithm is effective for networks with a single control Node.

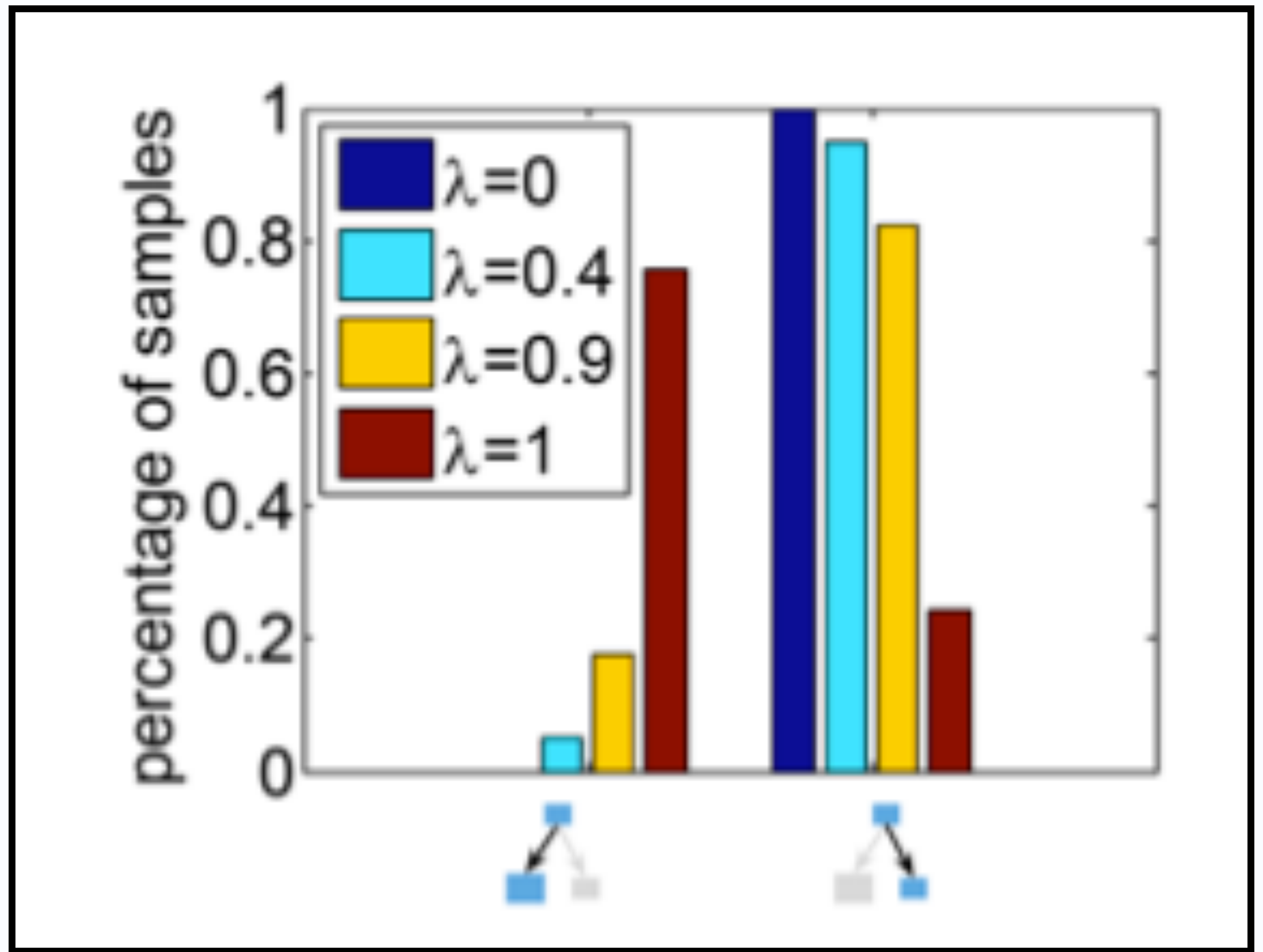
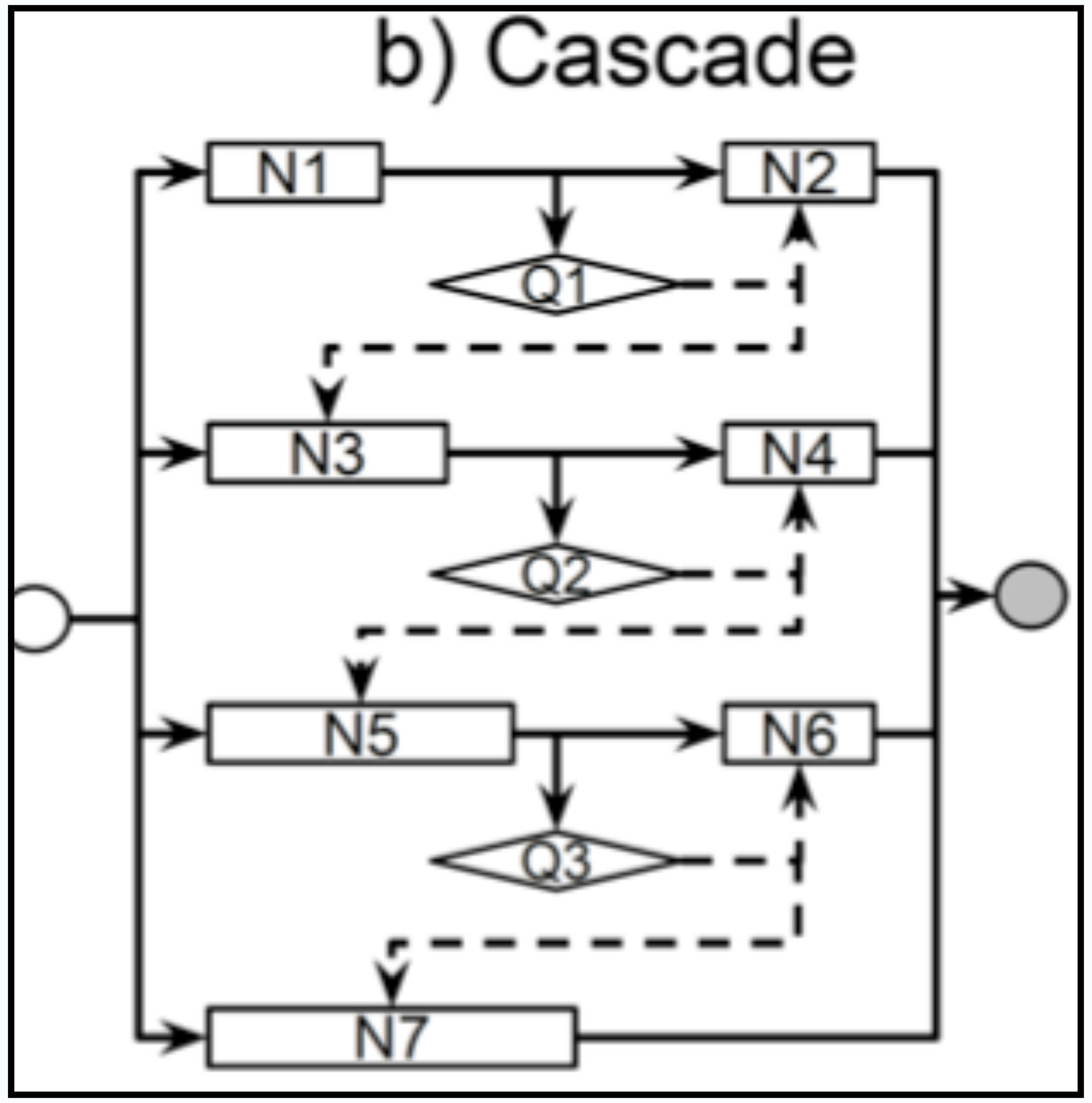


Figure 5. Examples with different paths in a high-low D^2NN (left) and a hierarchical D^2NN (right).

Experiments

Cascade DNN

- Cascade design
  - Inspired by the standard cascade design commonly used in computer vision.
  - The intuition is that many negative examples may be rejected early using simple functions.
  - Regular node N1-N7 form 4 cascade stages
    - N1 + N2
    - N3 + N4
    - N5 + N6
    - N7

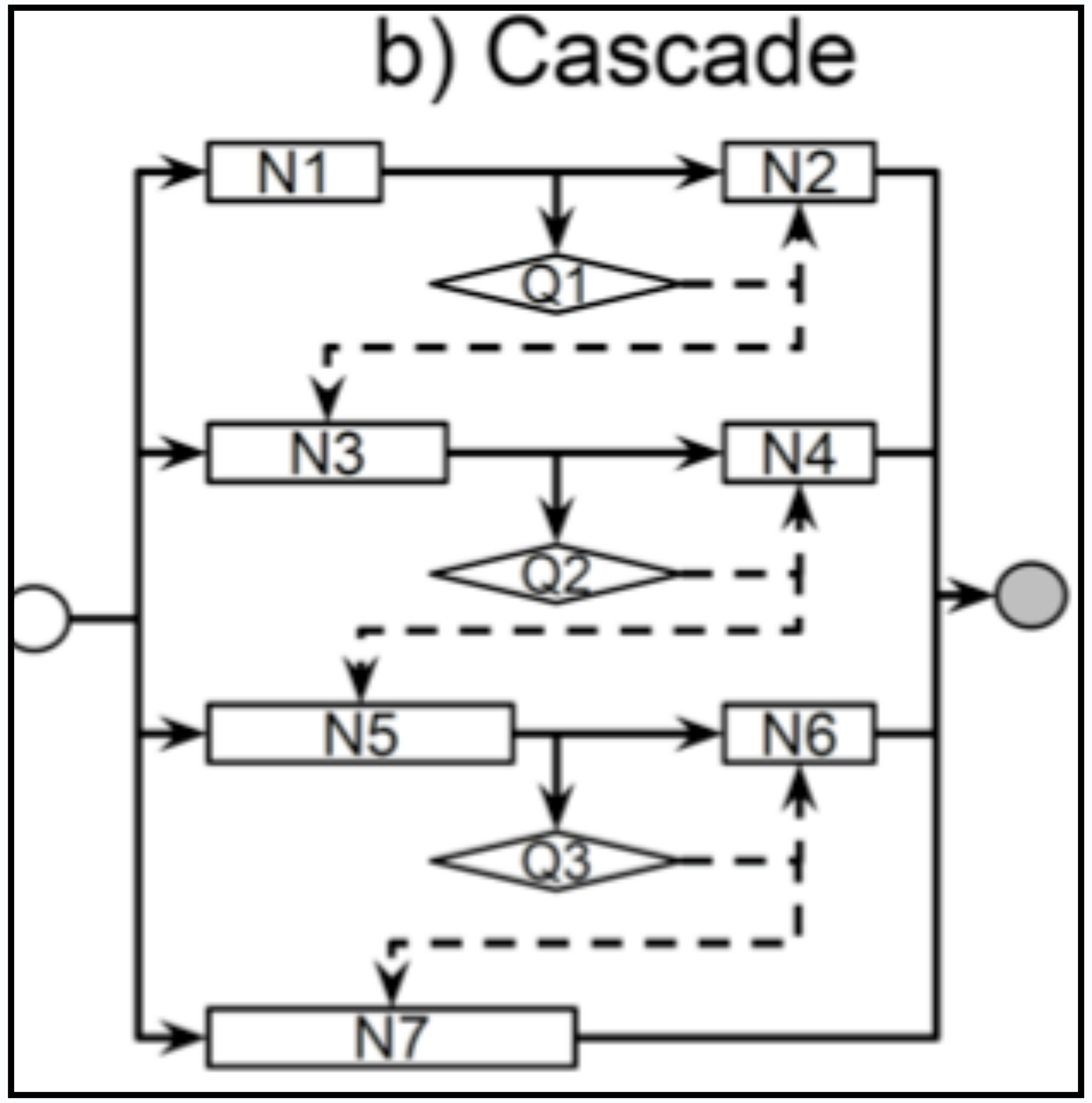


- N1 : **conv** (filter size = (3,3), filters = 2, stride = 2) + **max_pooling**(3x3, stride = 2)
- N2 : **conv** (filter size = (3,3), filters = 16) + **max_pooling**(3x3, stride = 2) + **fully_connected**(2-class output)
- N3 : **conv** (filter size = (3,3), filters = 2, stride = 2)+ **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 8, stride = 2) + **max_pooling**(3x3, stride = 2)
- N4, N6 : **max_pooling**(3x3, stride = 2) + **max_pooling**(3x3, stride = 2) + **fully_connected**(2-class output)
- N5 : **conv** (filter size = (3,3), filters = 4, stride = 2)+ **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 16, stride = 2) + **max_pooling**(3x3, stride = 2)
- N7 : **conv** (filter size = (3,3), filters = 2, stride = 2)+ **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 8, stride = 2) + **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,32), filters = 2, stride = 2) + **conv** (filter size = (3,3), filters = 32, stride = 2)+ **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 64, stride = 2) + **fully_connected**(512) + **fully_connected**(2-class output)
- Q1, Q2, Q3 : **fully_connected**(2-action output)

Experiments

Cascade DNN

- Cascade design
  - Regular node N1-N7 form 4 cascade stages
    - N1 + N2
    - N3 + N4
    - N5 + N6
    - N7
  - Each control node decide whether to execute the next cascade stage or not.

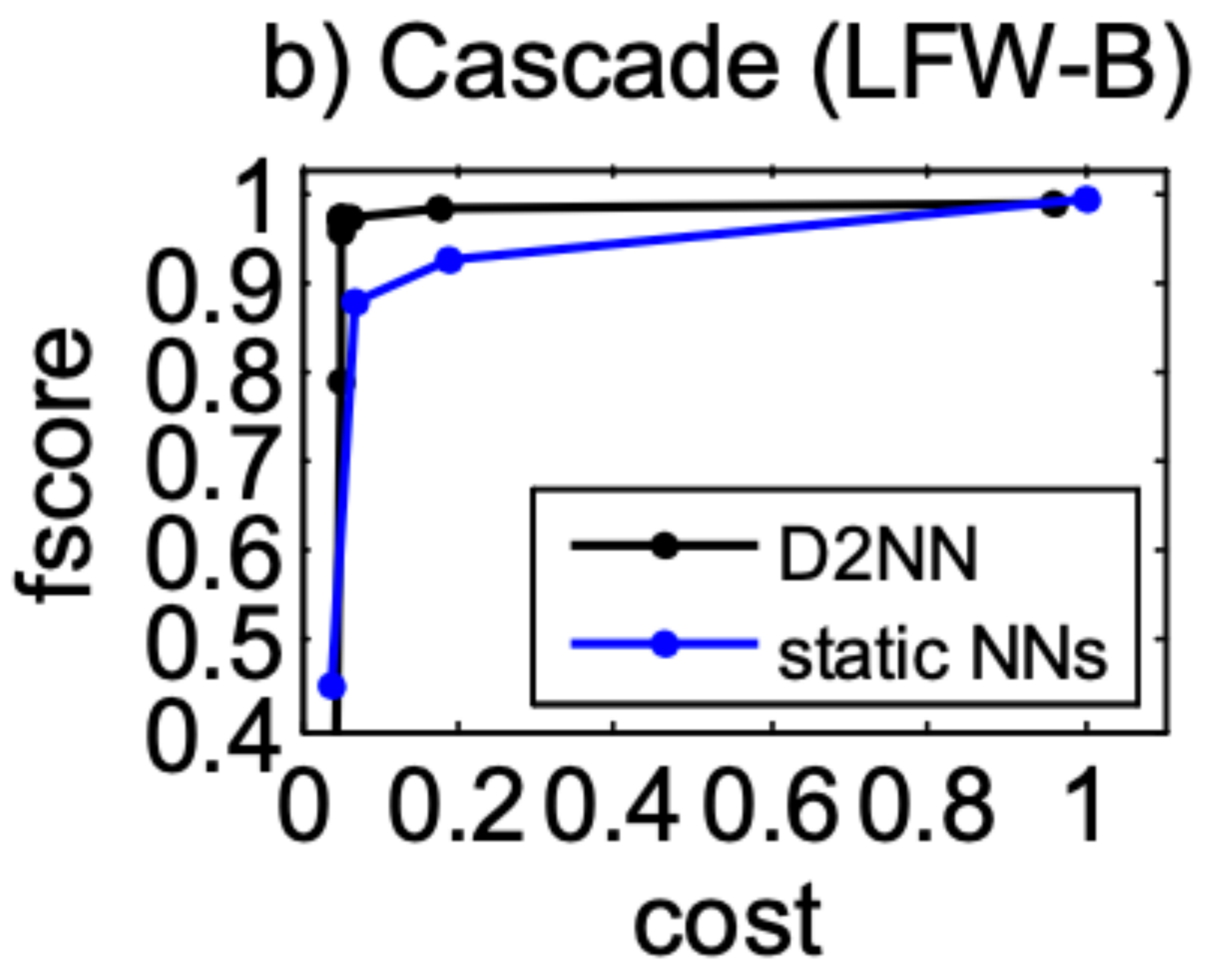


Experiments

Cascade DNN

- Cascade design
  - achieve a close to optimal trade-off, reducing computation significantly with negligible loss of accuracy.
  - This result demonstrates that our algorithm is successful for jointly training multiple control nodes.

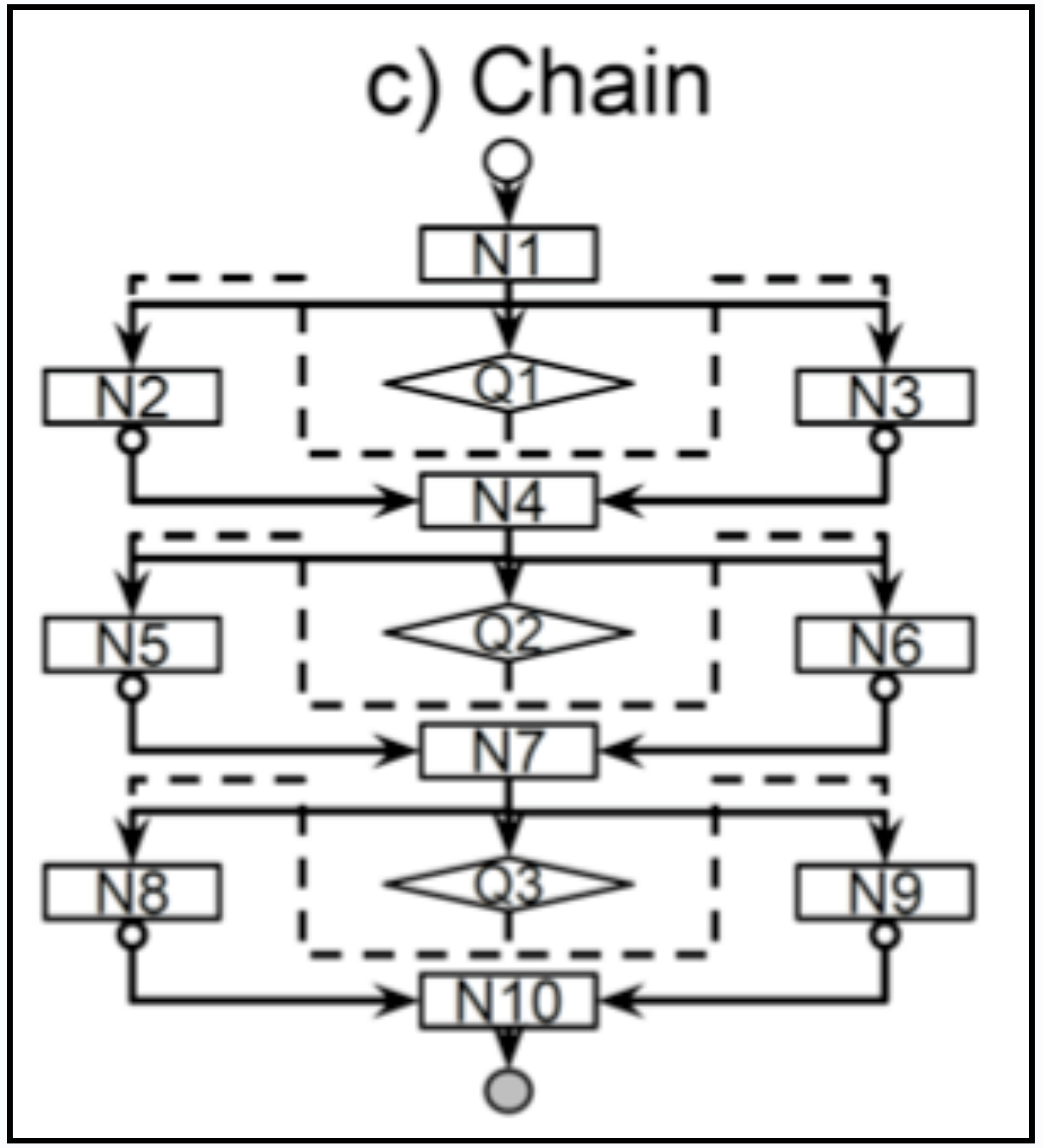
accuracy-cost graph



Experiments

Chain DNN

- Chain design ,
  - Tree-shaped data graph and it allows two divergent data paths to merge again.
  - Number of possible execution paths can be exponential to the number of nodes.



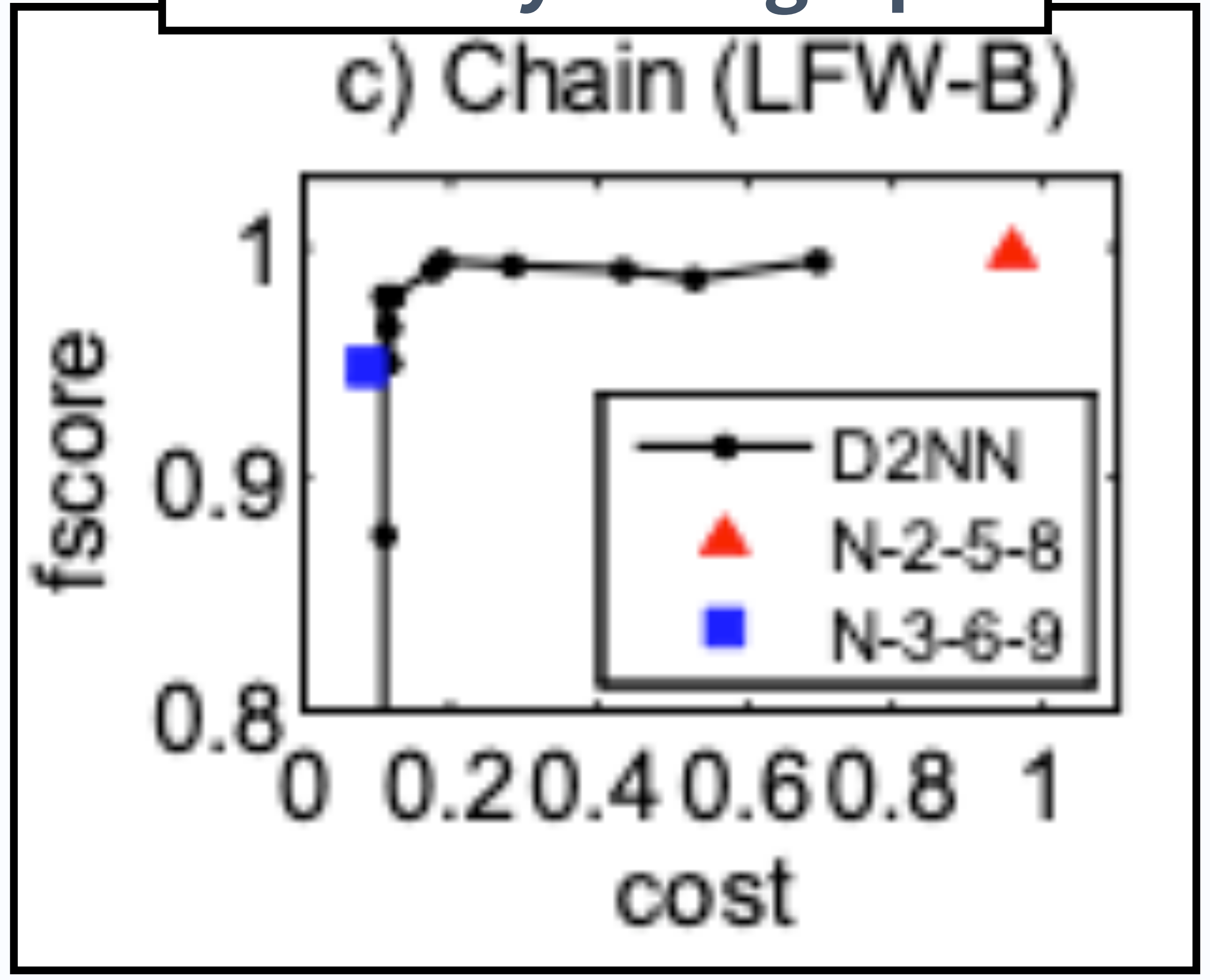
- N1 : **conv** (filter size = (3,3), filters = 2, stride = 2) + **max_pooling**(3x3, stride = 2)
- N2 : **conv** (filter size = (1,1), filters = 16)
- N3 : **conv** (filter size = (3,3), filters = 16)
- N4 ,N7: **max_pooling**(3x3, stride = 2)
- N5 : **conv** (filter size = (1,1), filters = 32)
- N6 : **conv** (filter size = (3,3), filters = 32) + **conv** (filter size = (3,3), filters = 32)
- N8 : **conv** (filter size = (1,1), filters = 32)+ **max_pooling**(3x3, stride = 2) + **fully_connected**(256)
- N9 : **conv** (filter size = (3,3), filters = 64) + **fully_connected**(256)
- N10 : **fully_connected**(2-class output)
- Q1 : **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 8) + **max_pooling**(3x3, stride = 2) + **fully_connected**(64) + **fully_connected**(2-action output)
- Q2 : **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 4) + **fully_connected**(64) + **fully_connected**(2-action output)
- Q3 : **conv** (filter size = (3,3), filters = 2) + **fully_connected**(64) + **fully_connected**(2-action output)

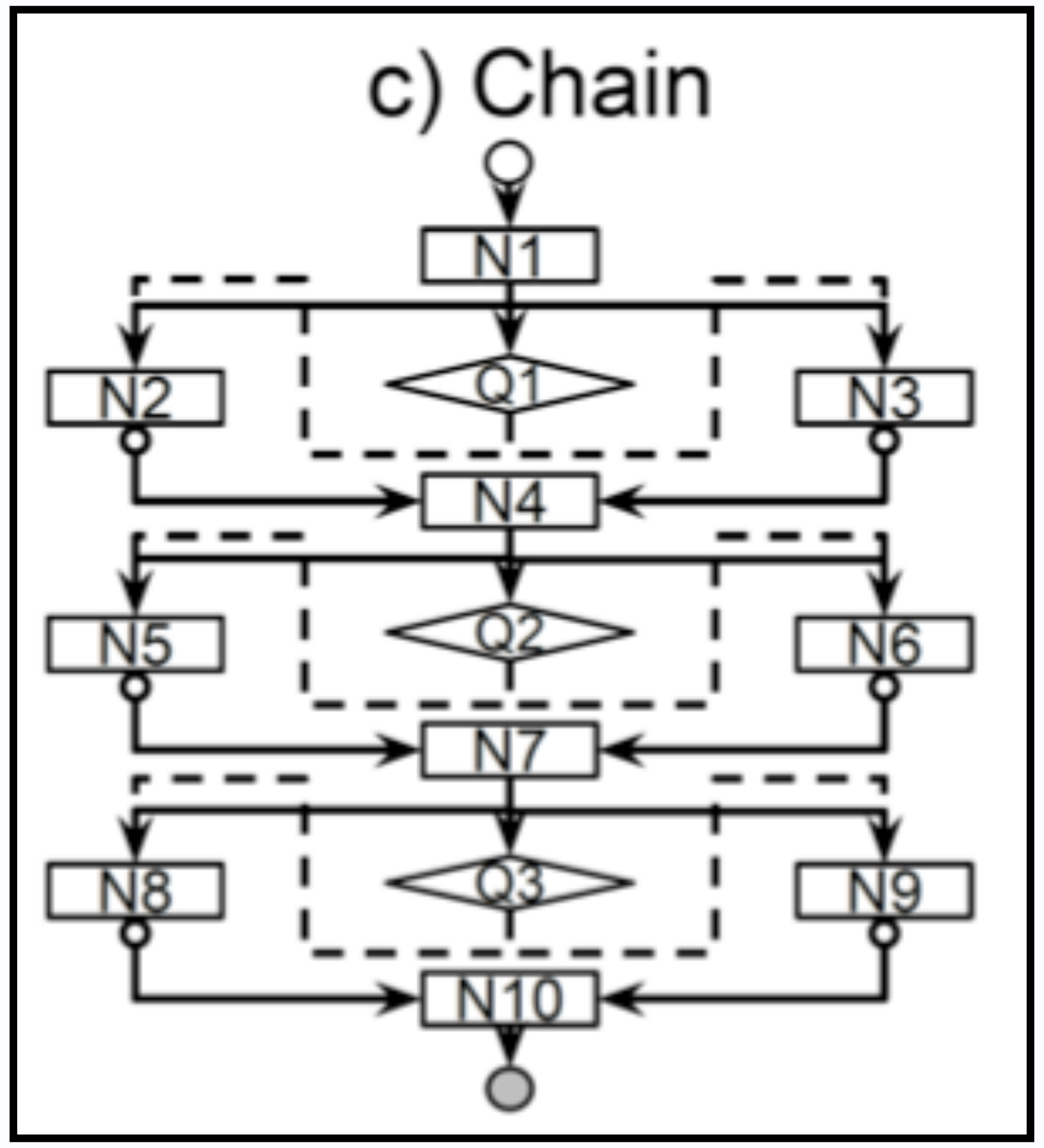
Experiments

Chain DNN

- Q1 chooses low-capacity N2 or high-capacity N3
  - One of them chosen and the other will output a default value zero.
- Path
  - Lowest capacity : N1-N2-N5-N8-N10
  - Highest capacity : N1-N3-N6-N9-N10
- The chain DNN achieves trade-off curve close to optimal and can speed up computation significantly with little accuracy loss.

accuracy-cost graph





Experiments

Hierarchical DNN

- Hierarchical multi class classification
- The idea is to first classify images to coarse categories and then to fine categories.
    - Data : ILSVRC-10, a subset of the ILSVRC-65
        - D^2NN mirrors the semantic hierarchy in ILSVRC-10.
        - 10classes are organized into a 3-layer hierarchy
            - 2 superclasses, 5 coarse classes and 10 leaf classes.

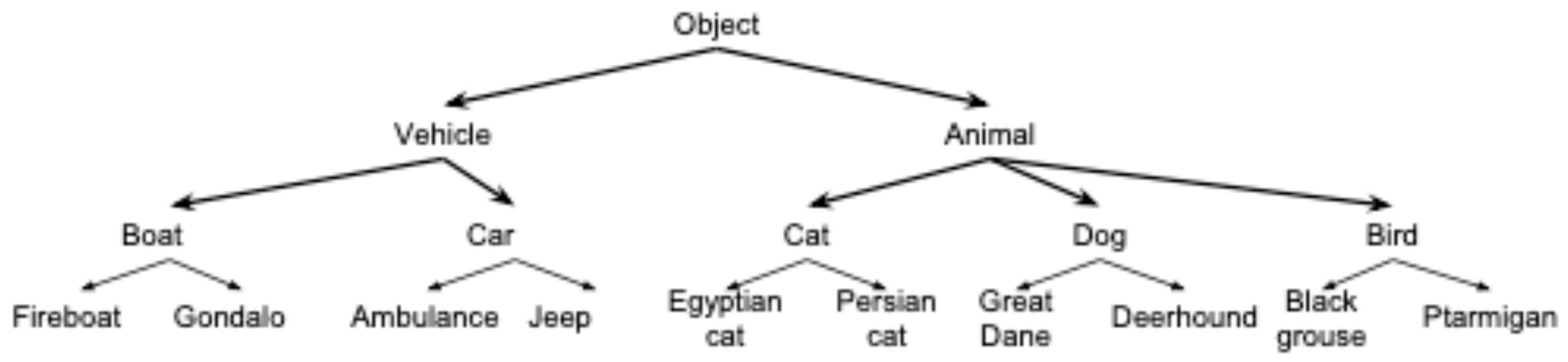
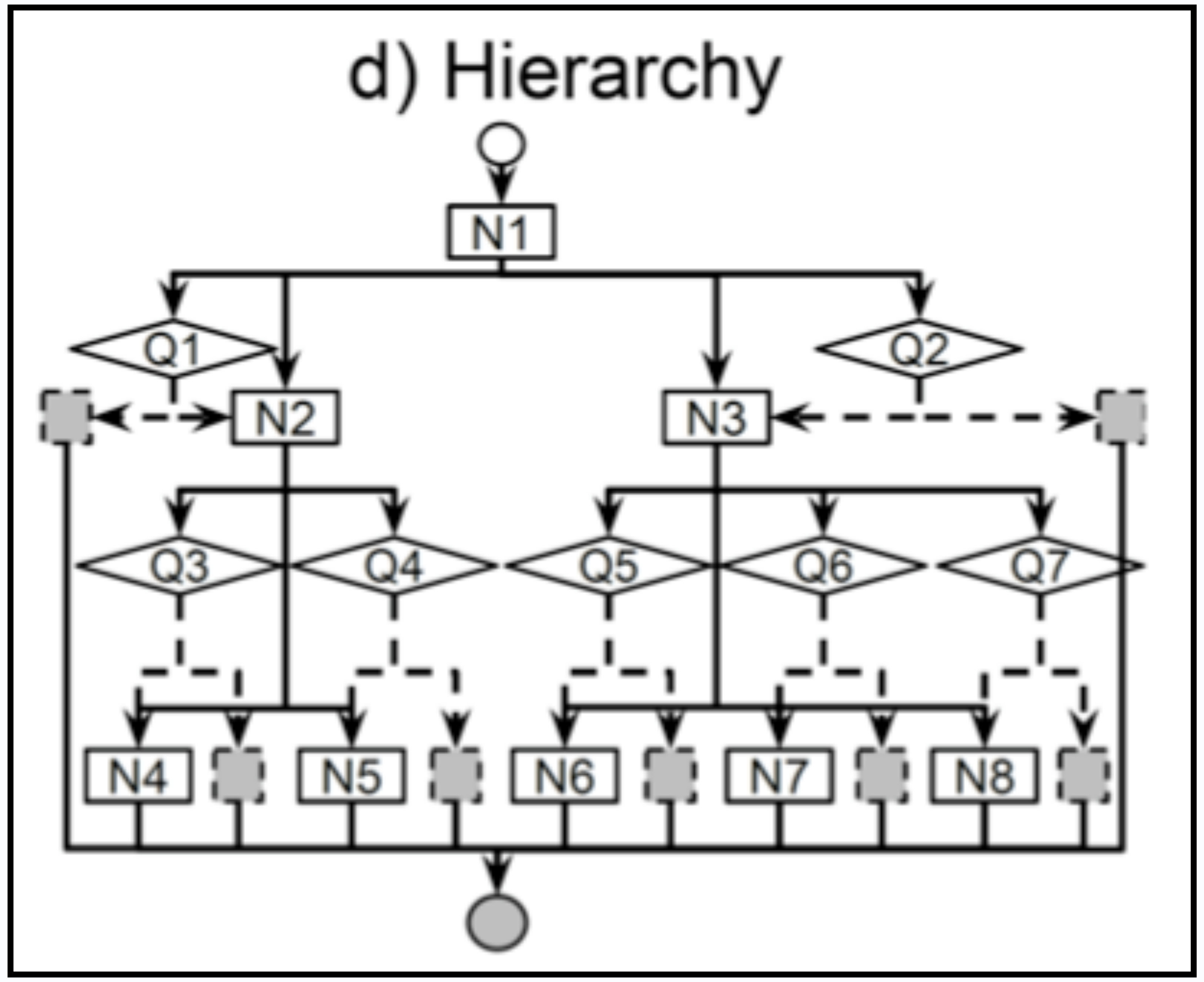


Figure 7. The semantic class hierarchy of the ILSVRC-10 dataset.

Experiments

Hierarchical DNN

- Start with root N1
- Q1 decides where to descend the N2 or children
- Q2 decides where to descend the N3 or children
- Leaf nodes N4-N8 are each responsible for classifying two fine-grained leaf classes.
- (***)Input image can go down parallel paths in the hierarchy descending left & right together.
    - Because Q1 and Q2 make separate decisions.
- “Multi-threading” allows the network to avoid committing to a single path prematurely if an input is ambiguous.



- N1 : **conv** (filter size = (11,11), filters = 64, stride = 24, 2x2padding) + **max_pooling**(3x3, stride = 2)
- N2, N3 : **conv** (filter size = (5,5), filters = 96, 2x2padding)
- N4 ~ N8 : **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters =160) + **conv** (filter size = (3,3), filters =128) + **conv** (filter size = (3,3), filters =128) + **max_pooling**(3x3, stride = 2) + **fully_connected**(2048) + **fully_connected**(2048) + **fully_connected**(2 fine-class output)
- Q1, Q2 : **conv** (filter size = (5,5), filters = 16, 2x2padding) + **max_pooling**(3x3, stride = 2) + **conv** (filter size = (5,5), filters = 32) + **max_pooling**(3x3, stride = 2) + **fully_connected**(1024) + **fully_connected**(1024) + **fully_connected**(2-action output)
- Q3 ~ Q7 : **conv** (filter size = (5,5), filters = 16, 2x2padding) + **max_pooling**(3x3, stride = 2) + **conv** (filter size = (3,3), filters = 32) + **max_pooling**(3x3, stride = 2) + **fully_connected**(1024) + **fully_connected**(1024) + **fully_connected**(2-action output)

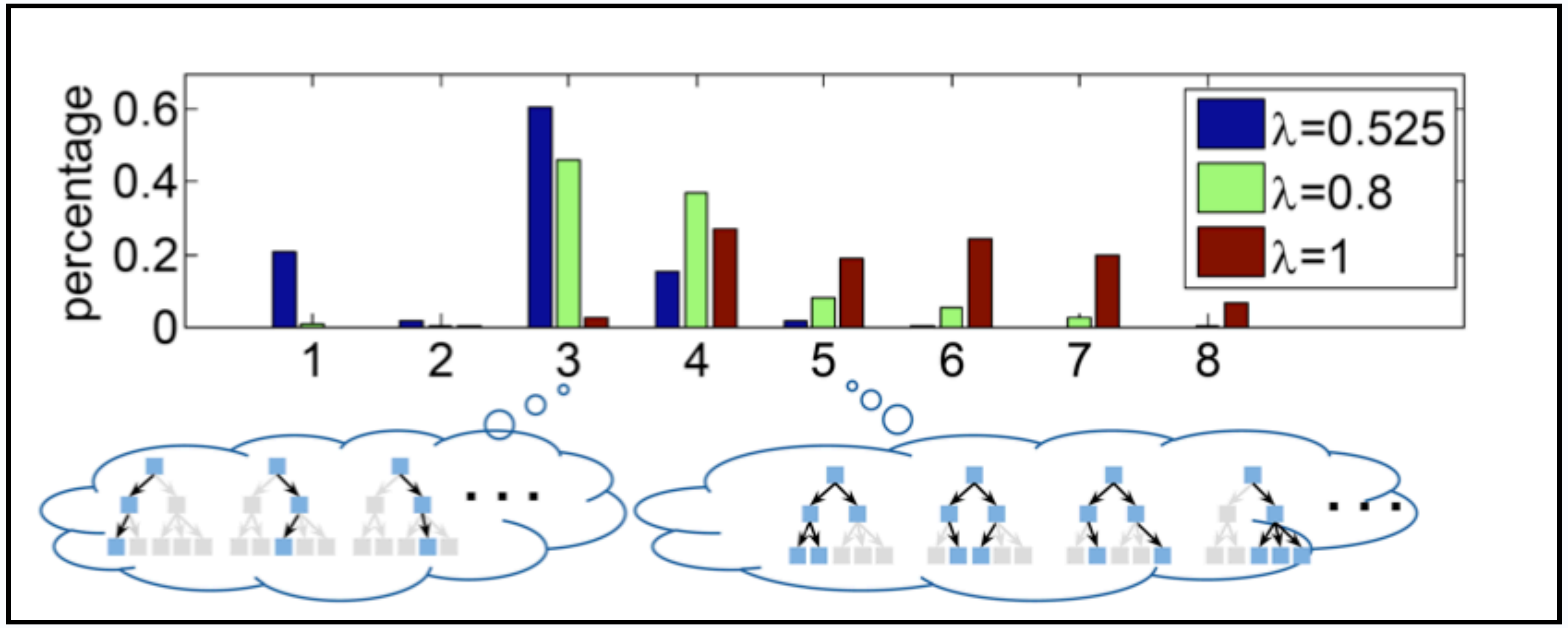
Experiments

Hierarchical DNN

- In **accuracy-cost graph**,
  - We can see the hierarchy D^2NN can match the accuracy of the full network with about half of the computational cost.

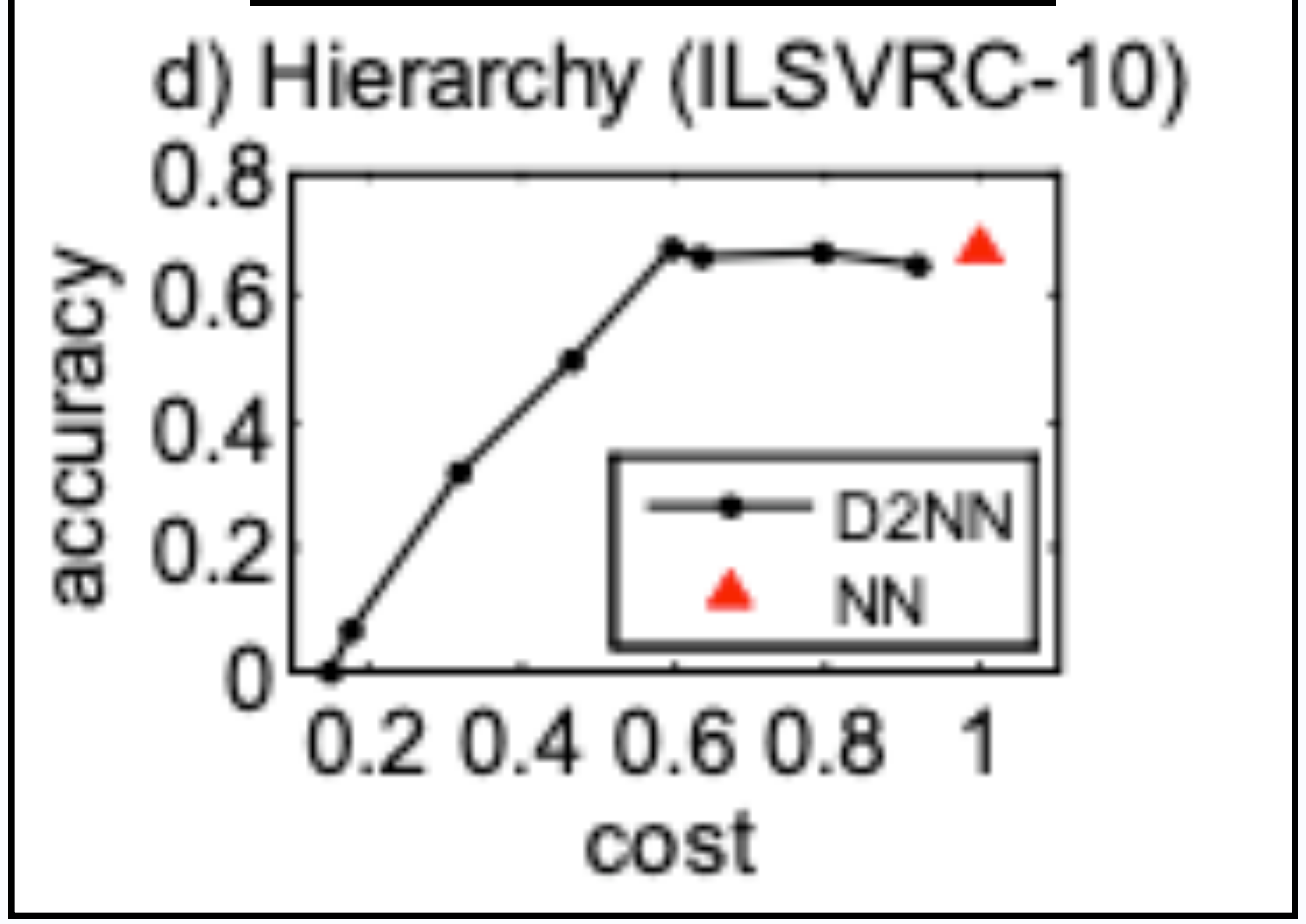
- **Fig 4.** plots for the distribution of examples going through execution sequences with different numbers of nodes activated.
- Due to the parallelism, there can be many execution sequences.
- λ increases, accuracy is given more weight and more nodes are activated.

Fig 4. (right)



- x-axis = number of nodes activated

accuracy-cost graph



- Accuracy : proportion of correctly classified test examples.
- Cost : number of multiplication

Experiments

Comparison with Dynamic Capacity Networks

- Compare D^2NN (Chain design D^2NN)with Dynamic Capacity Networks(DCN)
  - Efficiency measurement = absolute number of multiplications
  - Dataset : Cluttered MNIST
- DCN applies additional high capacity subnetwork for certain image
  - Idea is that more intensive processing is only necessary for certain image regions.

- Achievement :
  - DCN
    - Accuracy : 0.9861
    - Efficiency : 2.77 **x** 10^7
  - D^2NN
    - Accuracy : 0.9698
    - Efficiency : 2.66 **x** 10^7

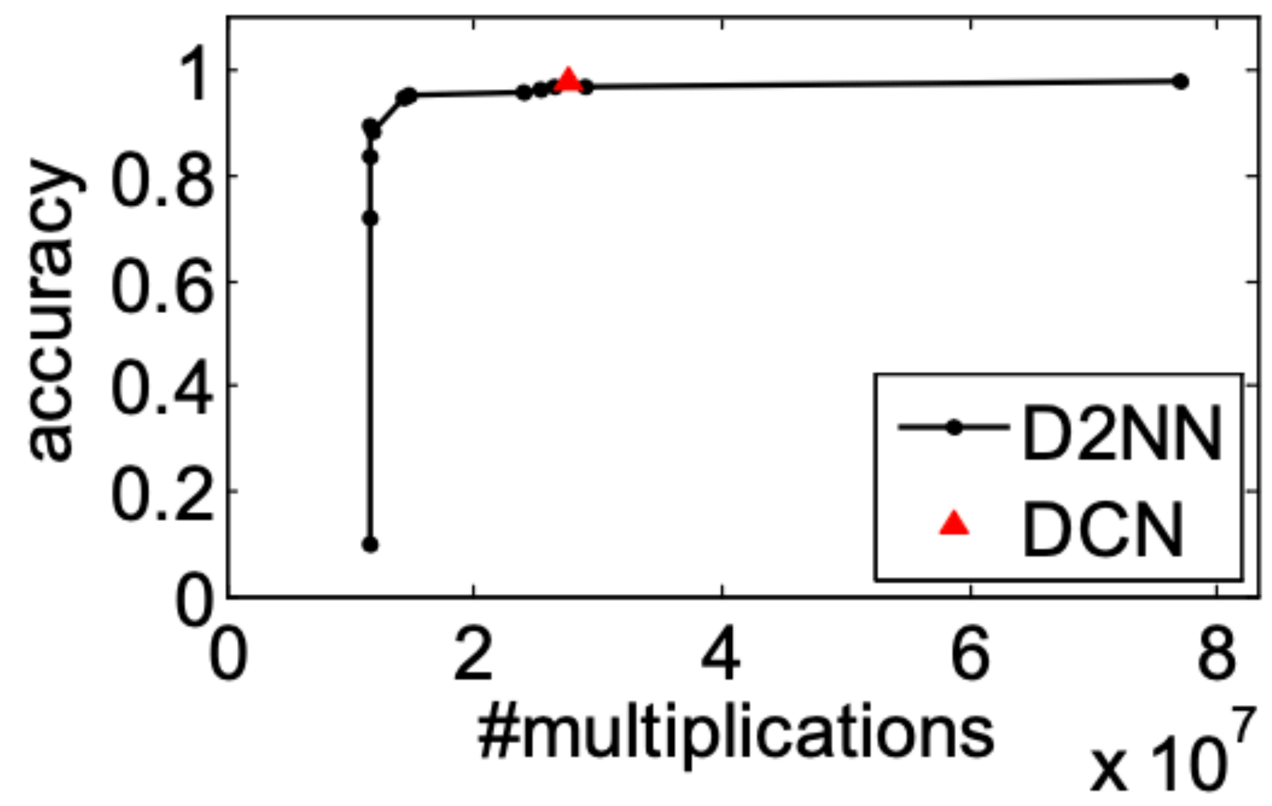


Figure 6. Accuracy-cost curve for a chain D^2NN on the CMNIST task compared to DCN [2].

Experiments

Visualization of Examples in Different Paths

- **LEFT** image = face examples in the high-low D^2NN for
  - Examples in low-capacity path are more frontal than high-capacity path
- **RIGHT** image = car examples in the hierarchical D^2NN with
  1. Single path executed
  2. Full graph executed ($\lambda = 1$)

→ Show single path executed should be easier to classify than full graph executed.

Figure 5. Examples with different paths in a high-low D^{2}NN (left) and a hierarchical D^{2}NN (right).

Experiments

Cifar-10 Results

- Train a cascade D^2NN on CIFAR-10
- Initialize this D^2NN with pre-trained ResNet-110weights, apply cross-entropy losses on regular nodes, and tune the mixed-loss weight as explained in Sec 4.
  - Result
    - **30% reduction** of cost with **2% loss** on accuracy
    - **62% reduction** of cost with **7% loss** on accuracy
- In CIFAR-10, all images are low resolution(32x32) few images are significantly easier to classify.
- As a result,
  - The efficiency improvement is **modest** compared to other datasets.

Experiments

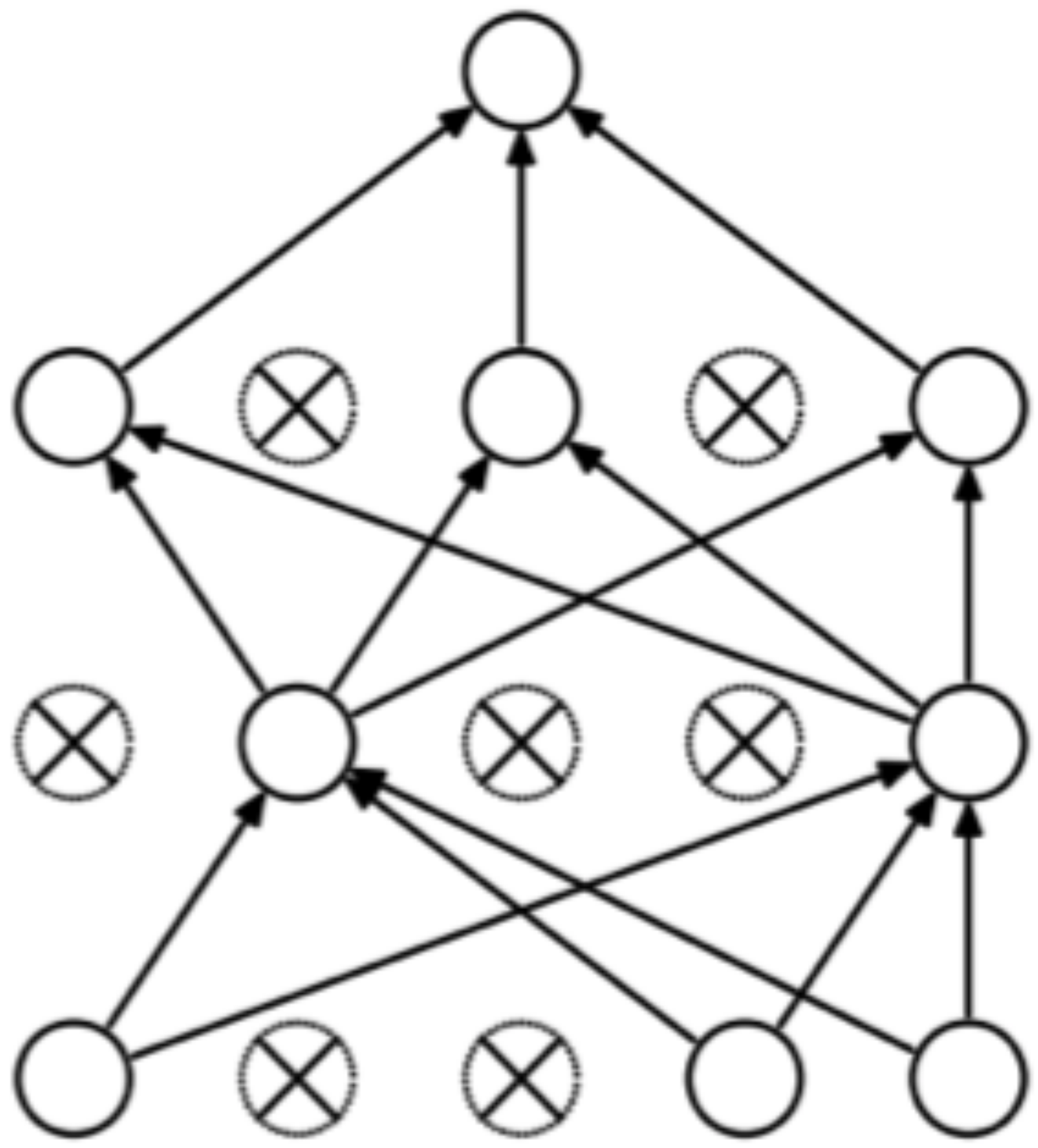
Conclusion

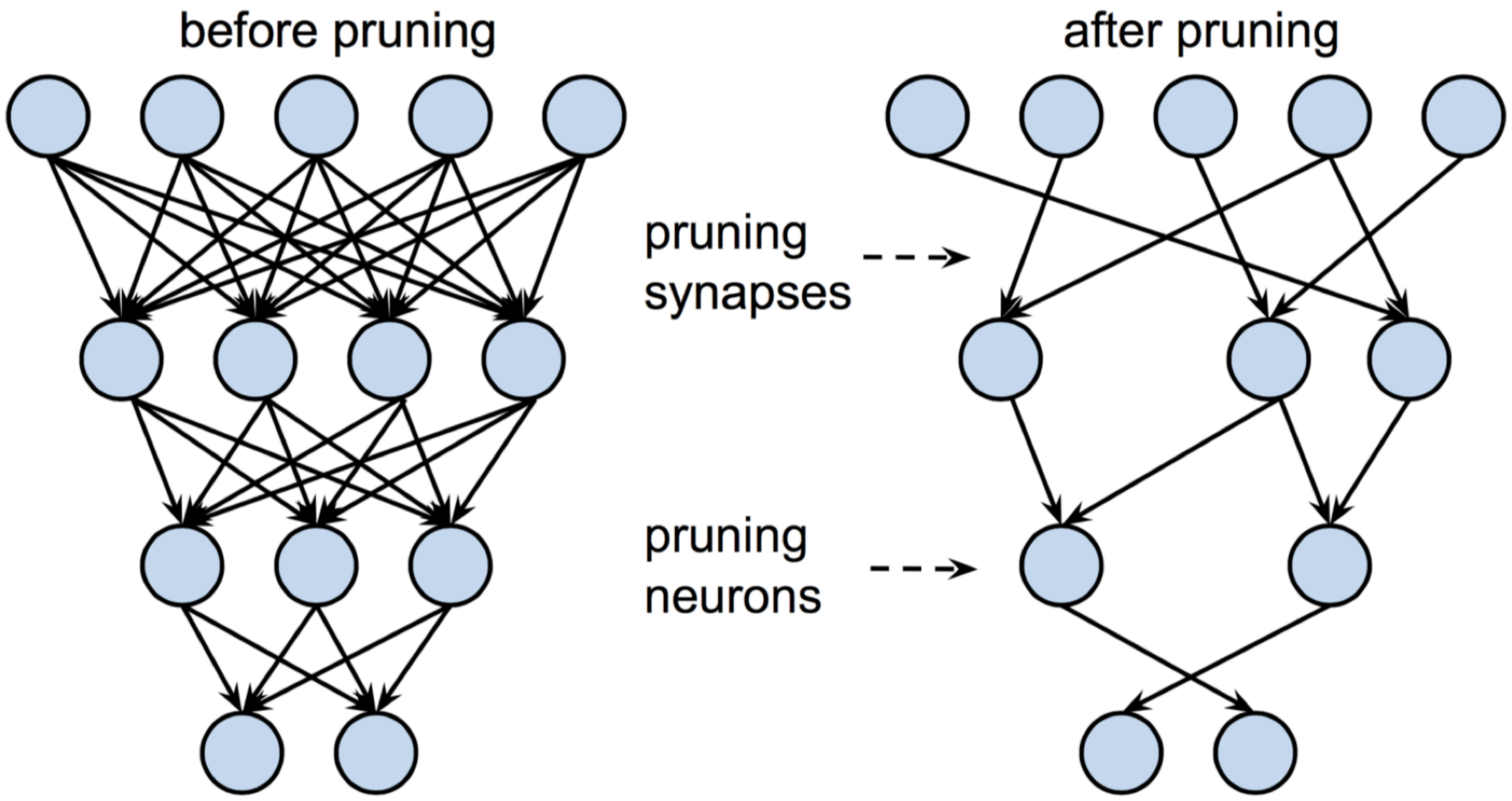
- Introduced Dynamic Deep Neural Networks with **selective execution.**
- Extensive experiments have shown that D^2NN are flexible and effective for optimizing accuracy-efficiency trade-offs.

Thank you.

Backup Slides

Dropout VS Pruning





End-to-end learning

- D^2NN is trained end to end.
  - Optimize the weights by considering the inputs and outputs directly
  - 반대의 의미로 divide-and-train도 있음.
  - Regular models and control modules are jointly trained to optimize both accuracy and efficiency.

- Achieve such training by integrating back propagation with reinforcement learning, necessitated by the non-differentiability of control modules.

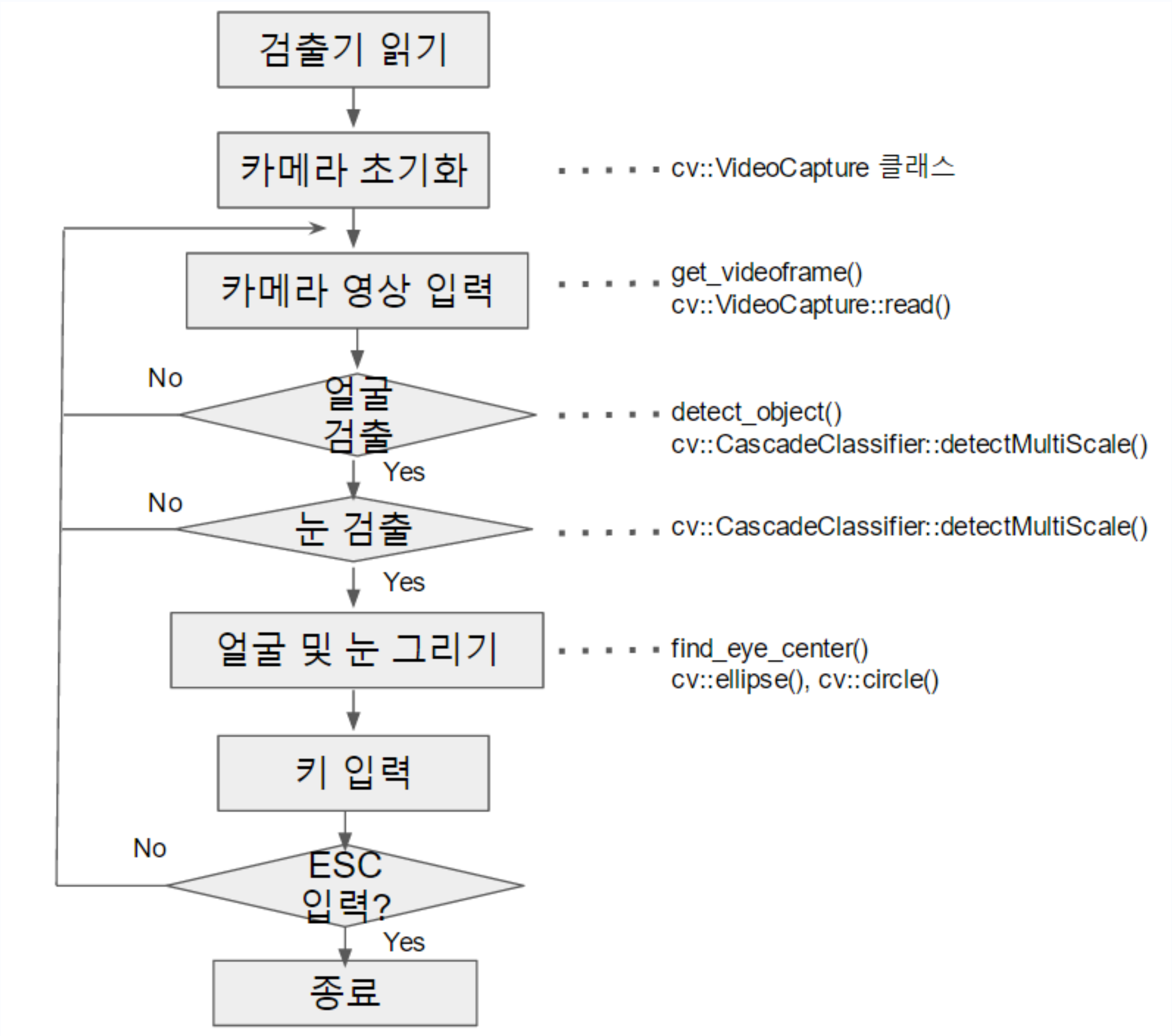
Introduction

- **Main Contribution**
  - Allows user to augment a static feed-forward network with control modules to achieve dynamic selective execution.
  - Provides a new tool for designing and training computationally efficient neural network models.

- **Advantages**
  - Improve computational efficiency by selective execution
    - Pruning unnecessary computation depending on input.
  - It makes possible to use a bigger network under a computation budget by executing only a subset of the neurons each time.

Experiments

Cascade



Experiments

Comparison with Dynamic Capacity Networks

- Compare D^2NN (Chain design D^2NN)with Dynamic Capacity Networks(DCN)
  - E

- Achievement :
  - D