A Survey on Conditional Computation

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Abstract

Using large-scale models has proven to be an effective approach to enhancing model performance and enabling various applications. However, such models come at a significant computation cost. To address this issue, conditional computation has been proposed to dynamically adjust the model scale based on input via dynamic dropout and an additional gate network. The gate network partitions the original network (called backbone network) into multiple sub-networks and selects a specific sub-network for each input. In this paper, we present a novel classification not from model structure to discuss the sub-network granularity and the training methods of this framework from a new perspective, namely the definition and learning of decision sequence respectively, and summarize the latest approaches in conditional computation.

1 Introduction

In recent years, large-scale models have gained widespread success in a wide range of tasks (Krizhevsky et al., 2012; Vaswani et al., 2017). However, with the increasing capacity of these models, like constructing the pre-trained models or large language models (Devlin et al., 2019; Raffel et al., 2020), the computation cost associated with training and inference has become a significant bottleneck. As such, further increasing model capacity through expanding model parameters is prohibitively expensive and inefficient in terms of performance gains.

An appropriate method to address the challenges associated with model efficiency and adaptability is conditional computation, in which the core idea is that instead of dropping out paths independently and at random, drop them in a learned and optimized way. We can mainly categorize the conditional computation methods into four types based on the structure: Early Exit (Teerapittayanon et al., 2016), Mixture of Expert (Shazeer et al., 2017), Skip (Wu et al., 2018), Cascade (Li et al., 2021a), and Adaptive Computation Time (Graves, 2016).

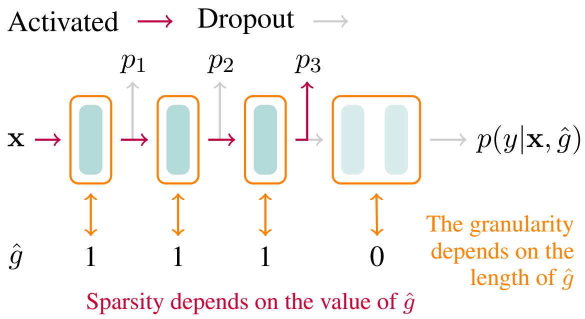

Figure 1: Decision sequences in conditional computation. Taking early exit as an example, the length of $\hat{g}$ corresponds to the granularity of the network structure, while its value determines the sparsity of the network when computed for different samples, p_i represents the early exit prediction.

Early conditional computation. Mixture of expert, also called the ME method in the early stage, focuses on dividing the entire system and the training set(corresponding to tasks to multiple subtasks) into several parts by the Divide-and-Conquer principle from an implicit (learn by loss function) or explicit (partition the training set directly) perspective (Jacobs et al., 1991; Masoudnia and Ebrahimpour, 2014). Each part is composed of an "expert" network, which is responsible for the Corresponding part in the training set(subtasks). While many works in this research line try to optimize the MoE network, these structures are often very simple, like based on fully connected networks. Also, this attempt based on simple structures occurs in some structures Other than EM (Bengio et al., 2013, 2015).

Modern conditional computation. As deep neural network gradually show its advantage, the dynamic depth approach started to emerge, where the early exit and skip methods attempt to dynamically adjust the used layers during the inference phase based on a fixed model structure, while cascade and act by adaptively selecting one of the sub-networks in a potentially infinitely deep network structure. Furthermore, the Mixture of Expert (MoE) has also been applied to transformer models recently, which learn the activation of experts implicitly by the loss function, meanwhile utilizing an additional loss term to reduce the competition between experts (load imbalance). Although this approach is highly similar to the ME approach in structure and training, MoE is more concerned with obtaining a larger model capacity while maintaining a lower computational cost rather than decomposing the target task. The activation pattern between experts forms a distributed instead of mutually exclusive, making the moe approach more consistent with the definition of conditional computation.

To achieve the above dynamic structure, conditional computation methods commonly add a crucial component gate network to a static network. For ease of understanding, we call the static network as backbone network.

- Backbone network: Like the foundation model, the backbone network projects the input to the prediction, such as the Transformer(Vaswani et al., 2017) model, and so on. The new structure added for conditional computation is not included.

- Gate network: Partitions the backbone network into multiple sub-networks and selects sub-networks for each input (Kaya et al., 2019; Zhang et al., 2021), which may be completely independent (Wu et al., 2018; Roller et al., 2021) or shared part parameters with the backbone network (Teerapittayanon et al., 2016; Elbayad et al., 2020; Shazeer et al., 2017).

This results in a natural structural summary (Han et al., 2022; Xu and McAuley, 2022), discussing the problems faced by conditional computation models under specific structures.

An important feature of conditional computational methods is the sparsity of the conditional computational model, such as extending the model capacity by an extremely sparse MoE layer (Shazeer et al., 2017; Lepikhin et al., 2021; Fedus et al., 2021), or obtaining a denser model by early exit (Teerapittayanon et al., 2016). The different sparsity is not only determined by the model structure, but the output of the gate network also plays a crucial role. In addition, by a time-step related gate function, the conditional computational model can also obtain a model beyond a predefined structure similar to Neural Architecture Search(NAS) (Zoph and Le, 2017). However, unlike NAS, the structure of the conditional computational model is dynamic for different inputs.

This motivates us to propose a new taxonomy that a novel taxonomy that encompasses both structural and sparsity considerations, defined as the decision sequence, namely the definition and learning of decision sequence, which is more concerned with the output of the gate network and the training of the whole model respectively. This taxonomy provides a more in-depth perspective on the design and training of such methods and characterizes the design of structure-specific gate networks as a particular instance of a more general gate network. We hope this survey can provide insights into developing more versatile gate networks.

This survey is organized as follows: In Section 2, we differentiate between conditional computation and dynamic algorithms and propose a novel taxonomy perspective based on the decision sequence represented by the output of the gate network. Then, the classical model structure of conditional computation is introduced in Section 3. Section 4 summarizes the current state-of-the-art work in the field, including the definition and realization of the decision sequence. Finally, Section 5 examines the existing challenges and outlines potential avenues for future research.

2 Basic Framework of Conditional Computation

2.1 Definition of Conditional Computation

Conditional computation can be categorized as a subset of adaptive algorithms that design a learnable method for dynamic dropout (Bengio, 2013). It is motivated by the hypothesis that most samples do not require a full high-capacity model but can be fully inferred using a smaller sub-model while ensuring inference accuracy (Panda et al., 2016; Bolukbasi et al., 2017; Shazeer et al., 2017). Recent studies find that layers or branches decompose the solution space of the original problem in some interpretable way (Jawahar et al., 2019). This makes it possible to specify a specialized sub-network for different samples through an additional gate network.

Introducing a gate network (function) to a back-

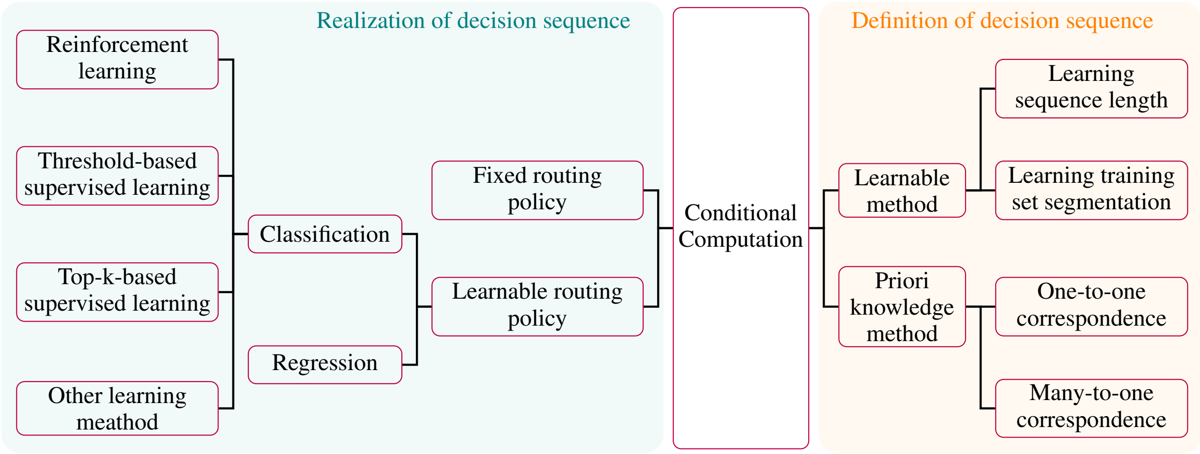

Figure 2: Typology of conditional computation.

bone network provides an implementation path for conditional computation, resulting in a better dynamic property and the ability to find the accuracy speed balance automatically. Therefore, the core objective of achieving an efficient conditional computation model is learning an ideal decision sequence $\hat{g} = \{\hat{g}_1, \hat{g}_2, \ldots, \hat{g}_n\}$ with n elements shown in Figure 1. On the one hand, it can provide sufficient adaptability for the backbone network, both during training and inference procedures. On the other hand, it needs to have certain stability to ensure the performance of the backbone network. At this point, the backbone network $F(\cdot)$ predicts y based on the input vector $\mathbf{x}$ and the output $\hat{g}$ of gate function $G(\cdot)$ can be formulated as:

$$p(y|\mathbf{x}, \hat{g}) = c(G(\mathbf{x}, \delta) \cdot F(\mathbf{x}, \theta)) \tag{1}$$

where c is the classifier, δ and θ is the trainable parameters in the network. Based on Eq. 1, we expand our taxonomy based on these two key issues in conditional computation.

- **How to partition the network**. The key issue decides the specific form of the network $F(\cdot)$ and $G(\cdot)$, and the correspondence of each part $f_i(\cdot)$ in $F(\cdot)$ with each element $\hat{g}_k$ in $\hat{g}$, which determines the minimum granularity of the conditional computation model when executing the routing policy. We summarize this as the *definition of decision sequence*.

- **How to train the conditional computation model**. The key issue decides the value of parameters δ and θ. More importantly, it determines the value of ideal decision sequence $\hat{g}$, which determines the sparsity of the network and the optimization problems that the network may face under different sparsity. We summarize this as the *realization of decision sequence*.

2.2 Definition of Decision Sequence

When the sample activates a certain sub-network in a conditional computation model with a stable $\hat{g}$, its discarded forever by the other sub-networks, this is decided at the time of network partition. So it can be found that the correspondence between $f_i(\cdot)$ and $\hat{g}_i$ and their specific forms not only determines the minimum granularity, but also assigns the training set to different sub-network, which partitions the solution space of the task and assigns different subtasks to different sub-networks potentially. We classify the learning of this correspondence into the following two categories:

- Prior knowledge method. Directly define $\hat{g}$ with fixed length by hyper-parameters associated with the model structure or external constraints such as computational budgets (Panda et al., 2016) and experience (Teerapittayanon et al., 2016).

- Learnable method. Learn $\hat{g}$ with variable-length based on the model hidden layer state (Graves, 2016; Zhang et al., 2021).

2.3 Realization of Decision Sequence

The difficulty in training a conditional computation model stems from the lack of a tangible target in the decision sequence, this makes $\hat{g}$ unknowable, and leading to instability during training and hindering the training process of the backbone network, *e.g.*, load imbalance (Eigen et al., 2014). Furthermore, when seeking a sparse network, the discrete nature of the decision sequence exacerbates the training problem by introducing a discrete decision sequence. To mitigate this issue, we suggest utilizing a fixed or learnable approximation of the decision sequence, denoted as g^*, to approximate the target $\hat{g}$.

- Fixed routing policy. Based on prior knowledge (Liu et al., 2021), clustering method (Zhang et al., 2021) or hash method (Roller et al., 2021), training samples are assigned to different sub-networks. This results in a fixed pseudo-label for decision sequence on each sample.
- Learnable routing policy. Approximate $\hat{g}$ by maximum the task-relevant metrics, such as g^* that allows the maximum correct rate of the model prediction or g^* that maximizes the likelihood of the loss function (Elbayad et al., 2020). Although the correct rate is not available at testing stage, g^* based on maximum correct rate is often used to measure the upper bound of performance and provide a pseudo-label for optimization.

During the test phase, for fixed routing policy, we can use the pseudo-label directly (Liu et al., 2021). While for the learnable routing policy, the computation of g^* relies on true labels, so using g to learn the distribution of g^* during training is a common choice (Elbayad et al., 2020).

A relatively simple case is to take the learning of g as a regression task, which can produce a normalized probability $g_i \in [0, 1]$ or a real value $g_i \in R$ sequence (Collobert et al., 2003), but leading to a dense model and an ensemble model corresponding to a soft gate. In order to enlarge the sparsity, the learning of g is often modeled as a classification task, which can be classified as binary classification and multi-classification according to the number of g_i can be taken (Shazeer et al., 2017; Bolukbasi et al., 2017). At this time, g is like the output of indicator function $g_i \in \{0, 1\}$, which is a discrete sequence and leads a serious indifferentiable problem. We classify the training methods for learnable routing policy under the classification task into the following four categories:

- Reinforcement learning. Use g as an active function and computational cost as a reward, and find the optimal discrete sequence g by observing the effect of random perturbations on the reward (Wang et al., 2018; Wu et al., 2018).
- Threshold-based supervised learning. Since g^* is an indifferentiable value, the threshold-based approach optimizes a continuous g while maintaining a predetermined threshold τ, generates a discrete sequence based on the magnitude[1] of g with respect to τ. Here τ is used as a pseudo-label (Teerapittayanon et al., 2016; Elbayad et al., 2020).
- Top-k-based supervised learning. Like MoE structure, when the output of the gate network is very relevant to the hidden state, a more reasonable choice is to optimize the gate network using task-dependent supervisory signals. Here the gate function also faces the problem of discontinuity, but a straight-through gradient (Bengio et al., 2013) is commonly used to optimize the selected top-k expert (Shazeer et al., 2017; Lepikhin et al., 2021; Fedus et al., 2021).
- Other learning methods. Learning the gate function from a regularization perspective or using the EM algorithm (Zuo et al., 2022; Shen et al., 2019).

Based on the above descriptions, we classify conditional computation methods from the definition of decision sequence and the realization of decision sequence. The overall structure of our taxonomy is as shown in Figure 2.

3 Main Structure of the Conditional Computation

To facilitate understanding, we briefly introduce several main structures of conditional computation from the width and the depth, respectively. Here we are based on a network composed of a stack of layers. The final output of the backbone network (omitting the gate network for simplification) is

$$\begin{aligned} p(y|\mathbf{x}) &= c(\mathbf{h}_{final}) \\ \mathbf{h}_k &= f_k(\mathbf{h}_{k-1}) \end{aligned} \tag{2}$$

where $\mathbf{h}_k$ is the hidden state that is output by k-th layer $f_k(\cdot)$, $c(\cdot)$ is the final classifier of the backbone network, and we omit skip-connections for brevity.

[1]Output 1 for g_i^* if $g_i > \tau_i$, 0 otherwise.

When constructing a conditional computation model with a gate network that outputs a decision sequence g with length N, we briefly summarize the main structures of the conditional computation model as shown in Figure 3, where $g_k = 1$.

3.1 Depth Adaptive

Based on the conclusion that low-dimensional and high-dimensional features are extracted from the bottom and up layer of the model (Jawahar et al., 2019), the depth adaptive model regards a layer as the most fundamental unit. The depth adaptive models can be classified into four categories, namely Early Exit, Cascade, Adaptive Computation Time (ACT), and Skip according to the dynamic activation of a subset of its layers.

Early Exit The early exit involves utilizing the first k layers of a neural network model for the purpose of sample prediction. In order to achieve exit at the k-th layer, an intermediate classifier $c_k(\cdot)$ needs to be added at the exit position (Panda et al., 2016), the output $p_k(y|\mathbf{x}, g)$ can be described formally as

$$p(y|\mathbf{x}, g) = c_k(g_k \cdot \mathbf{h}_k) \quad when\ g_{k+1} \neq 1 \tag{3}$$

Cascade Cascade do not require an intermediate classifier since they only exit at the final classifier $c^k(\cdot)$ in the k-th model based on its final hidden state $\mathbf{h}^k_{final}$ (Li et al., 2021a; Wang et al., 2021).

$$p(y|\mathbf{x}, g) = c^k(g_k \cdot \mathbf{h}^k_{final}) \quad when\ g_{k+1} \neq 1 \tag{4}$$

ACT ACT selects a suitable model from the super-network based on a common unit with shared parameters, and obtain the final prediction by a linear weighting of all continuous representation based on hidden states (Graves, 2016; Dehghani et al., 2019).

$$p(y|\mathbf{x}, g) = c(\sum_{k=1}^{N} g_k \cdot \mathbf{h}_k) \tag{5}$$

Skip Skip is premised on the notion that each layer in a neural network operates to effect targeted transformations on the input features. This methodology assumes that it is feasible to omit layers that are inconsequential to the input, thereby preserving computational efficiency, akin to a residual layer with learnable parameters (Wu et al., 2018; Wang et al., 2018).

$$p(y|\mathbf{x}, g) \;=\; c(\mathbf{h}_{final}) \tag{6}$$

$$\mathbf{h}_k \;=\; \begin{cases} f_k(\mathbf{h}_{k-1}), & \text{when } \mathrm{g}_k = 1 \\ \mathbf{h}_{k-1}, & \text{when } \mathrm{g}_k = 0 \end{cases}$$

3.2 Width Adaptive

The most representative method of width-adaptive method is the Mixture of experts (MoE) (Jacobs et al., 1991), which is considered as a data-dependent trainable combining method (Masoudnia and Ebrahimpour, 2014).

The motivation for this approach arises from the challenge of processing complex tasks, such as multi-task learning, where strong interference effects can degrade the performance of a single network. To mitigate these effects, if the training data can be logically partitioned into distinct subsets corresponding to each subtask, the system can be decomposed into several components, each consisting of an "expert" network. This expert network is designed to fit a portion of the input, thereby reducing the mutual interference between the components. It can be formulated as:

$$\mathbf{h}_k = \sum_{i=1}^{N} g^i_k e^i_k(\mathbf{h}_{k-1}) \tag{7}$$

where the $e^i_k(\mathbf{h}_{k-1})$ denotes the i-th expert in layer k, and g^i_k is the gate function to control i-th expert behavior depend on the input in layer k.

The advent of deep Mixture of Experts (MoE) architecture as proposed in (Eigen et al., 2014) has led to its widespread use as a mechanism for augmenting the capacity of deep models (Shazeer et al., 2017; Gross et al., 2017; Xue et al., 2022), which replace feed-forward layer with the MoE architecture. Moreover, The MoE approach has been demonstrated to achieve superior computational efficiency compared to dense models (Lepikhin et al., 2021; Fedus et al., 2021), and has especially advantageous in multi-task learning scenarios, such as multilingual translation (Lepikhin et al., 2021; Fedus et al., 2021).

4 Taxonomy

4.1 Definition of Decision Sequence

Priori Knowledge Method Priori knowledge method follows an assumption that there is some kind of nature consistency between the network structure and the ideal discrete sequence. Most conditional computation methods consider this consistency as a one-to-one relationship, and define the length of the decision sequence N directly equal

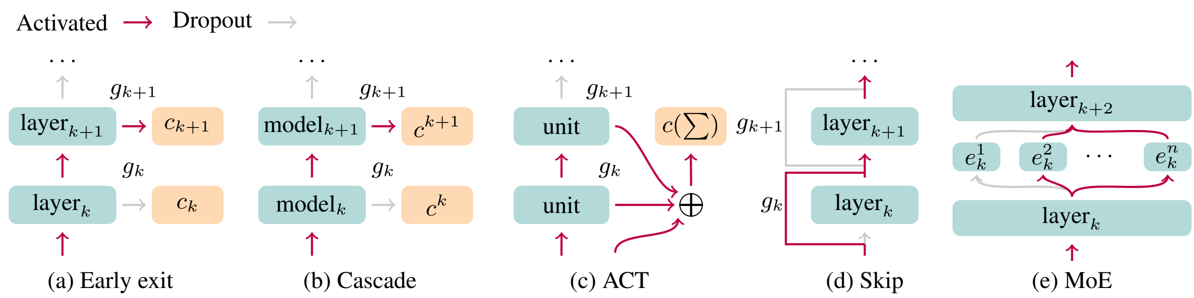

Figure 3: Main structures of the conditional computation. Where g_k is the k-th element in g, and e_k^i is the i-th expert in k-th layer.

to a hyper-parameter related to the model structure, such as the layers in skip (Wang et al., 2018; Wu et al., 2018), early exit (Huang et al., 2018; Elbayad et al., 2020), the models in cascade (Li et al., 2021a), and the expert number in MoE (Lepikhin et al., 2021; Fedus et al., 2021).

Since the early exit model requires adding $N-1$ intermediate classifiers, a natural idea is to obtain N satisfying $N < L$ according to the number of layers L. The consistency is then modeled as a many-to-one relationship, which multiple layers correspond to an intermediate classifier, and the position of the intermediate classifier can be determined by the computational cost (Kaya et al., 2019) or experience (Teerapittayanon et al., 2016).

Learnable Method Learnable method can be divided into two types. One is learning the length of decision sequence based on the assumption of one-to-one correspondence between the model structure and the decision sequence. The other is learning the correspondence between the network structure and decision sequence based on a fixed sequence length.

The first type of method learning sequence length does not use hyper-parameters to define the length N, but is dependent on the hidden state, which allows the model to go beyond a pre-defined structure and automatically select a suitable structure from super-network based on the rnn unit (Graves, 2016) or block unit (Dehghani et al., 2019).

The second type of method appears in the MoE, unlike the clear boundary between layers in depth adaptive model, since each expert in MoE is equivalent to some of the parameters in the original FFN layer, there is no explicit boundary between experts. Zhang et al. proposes to establish the correspondence by leveraging the co-activation graph and parameter clustering, and to construct the expert based on the inherent sparse structure in pre-trained model.

4.2 Realization of Decision Sequence

Fixed Routing Policy As aforementioned mentioned, although the cost of the gate network tends to be lightweight, the additional computational cost imposed by the gate network increases with the length of the decision sequence, which can offset the computation gain from the conditional computation. Thus, a fixed routing policy can be decided during the pre-processing phase by the mutual information (Liu et al., 2021) or a hash function (Roller et al., 2021) according to the training set. The above methods do not require any additional parameters, thus alleviating the problem of gate network scale and the training cost it introduces.

Other work proposes to get the fixed routing policy by the hidden state during training. One way is selecting the routing by cosine similarity between the input representation and the center of the expert parameter (Zhang et al., 2021). Dai et al. propose a two-stage training approach, in which a learnable routing mechanism is trained in an initial phase, followed by the fine-tuning of the remaining components of the conditional computation model utilizing a distilled, fixed routing strategy derived from the learnable routing. Although the fixed routing policy results in the model's inability to adapt to external constraints, it can mitigate instability during training caused by gate network not fully trained, such as routing fluctuation (Dai et al., 2022).

Learnable Routing Policy Based on the previous description, we will summarize the learnable routing policy from two perspectives: regression task, and classification task. Since the classification task is plagued by a discontinuity problem, which prompts the exploration of various learning methods beyond conventional reinforcement learning, such as threshold-based supervised learning, regularization learning, and others, in order to expand the scope of the classification task.

- Regression task. A representative work of defining the learning of gate function as a regression task was MoE in the early stage, mainly concerned with constructing a network from a divide-and-conquer perspective. Each expert fits a different sub-problem while choosing an efficient combination of experts, benefiting from the ensemble and sparse structure. The output of the gate network was often a probability distribution (Jacobs et al., 1991; Eigen et al., 2014) or real-valued weights (Wang et al., 2019), which brought the advantage of easy optimization. Since there is no constraint on the gate function, it is still relatively dense and could not achieve significant speedup. Another type of work is ACT, which is the only one that defines the learning of gate function as a regression task in the depth adaptive model, the gate network generates a probability distribution with sum of 1 for each layer, and the final model output is a dense connection of every layer (Graves, 2016; Dehghani et al., 2019).

- Classification task. The advantage of defining the learning of the gate function as a classification task is that it allows the gate network to output a discrete sequence, lead $g_i \in \{0, 1, \cdots, C\}$, and C is the class number of the classification task. Under the classification task, the most straightforward way to learn the gate function is to build a pseudo-label based on the hidden state. Mullapudi et al. utilizes clustering of hidden states to allocate all classes in the task to each sub-network. While Zhang et al. assigns a label to each sub-network based on the activation ratio of the parameters in the sub-network, trying to maximize leverage the inherent sparsity in the pre-trained model.

  Moreover, although this discrete sequence increases the sparse degree of the network, some methods realize a very sparse structure under the constraints in loss function related to the norm of g and thus achieve remarkable computational speedup. However, this discrete sequence makes model optimization difficult.

Reinforcement Learning The application of Reinforcement Learning (RL) provides a solution for the optimization of discrete sequences. The BlockDrop approach (Wu et al., 2018) leverages a policy network that behaves as a k-dimensional Bernoulli distribution as the gate function, similar to the policy described by Bengio et al.. The reward function is about the percentage of parameters utilized, wherein the expected gradient is approximated via Monte-Carlo sampling. In contrast, the SkipNet methodology implements a hybrid reinforcement learning approach where the probabilistic gate function, which operates as the action function, is separated from the backbone network. The input to the gate network is the original input and the output is the optimal value of g^*. The reward function is the total computational savings of the skip layer and the optimization process utilizes supervised learning for the backbone network and RL for the optimization of the gate network (Wang et al., 2018).

Threshold-based Supervised Learning To obtain the discrete sequence g^*, some work uses a threshold that converts the non-differentiable problem into a pre-defined threshold τ. Here, we optimize only a continuous value g, which represents the output certainty of the model based on the subnetwork i. A straightforward idea to obtain g is to leverage the information from the classifier, such as the confidence of classifier (Kaya et al., 2019), or the entropy of the distribution output by classifier (Xin et al., 2020; Liao et al., 2021; Teerapittayanon et al., 2016). Furthermore, it has also been suggested that the hidden state contains the estimates of how certain the model for its output, thus some works have employed transformations based on the hidden state as g (Xin et al., 2021; Li et al., 2021b; Elbayad et al., 2020).

The threshold τ is typically established by a set of pre-defined values (Teerapittayanon et al., 2016) that can be manually adjusted subject to computational resource constraints. In particular, Huang et al. determine τ by the relationship between the computational cost of the model and the predefined computational budget. Recently, adjusting τ by conformal prediction can guarantee the intermediate classifier similar to the final classifier to some extent (Schuster et al., 2021, 2022).

Top-k-based Supervised Learning Transform the continuous output of the gate network into a discrete sequence by Top-k approach is often used in MoE architecture. Since MoE separates the model capacity and computational cost, Top-k-based supervised learning can obtain a higher degree of sparsity with a tendency towards smaller k (Shazeer et al., 2017; Fedus et al., 2021; Lepikhin et al., 2021). For the in-differentiable problem posed by the sampling methods in Top-k, a common approach is to use a straight-through estimator (Bengio et al., 2013).

Other Learning Methods A fixed routing policy generates a stable routing but can not response to external constrains, while a learnable route has more adaptability but generates routing fluctuation and load imbalance problems in MoE, which interfere with training the backbone network. One approach that combines the advantages of both routing policy is use a consistency regularizer (Zuo et al., 2022), which minimizes the Kullback–Leibler divergence between the two feedforward outputs based on a random gate function. In addition, Shen et al. propose to model the each expert in MoE as a latent variable, and optimized by the EM algorithm from the perspective of an latent variable model.

5 Challenges

In this section, we summarize the challenges in conditional computation methods from the perspective of its application.

5.1 Granularity of the Input

In sequence-to-sequence tasks, the token-level method is commonly discussed. It achieves higher speedup ratios by routing for the smallest input unit. However, it overlooks the information between input units and incurs a high computational cost for the gate network (Elbayad et al., 2020; Fedus et al., 2021). Exploring the sequence-level method in early exit, it is found that although it performs similarly to the token-level method on shorter sequences, it yields worse results as the sequence length increases due to a coarser routing policy (Li et al., 2021b; Elbayad et al., 2020). Similar conclusions apply to the MoE model (Kudugunta et al., 2021). The task-level method is proposed, leading to significant results such as higher peak throughput and reduced communication cost across devices compared to the token-level method in the MoE model (Kudugunta et al., 2021). Furthermore, a cascade model with varying input granularity is realized by increasing the number of patches in a vision Transformer model. While no dynamic window method for determining input granularity was found, the window confidence-based approach demonstrates potential in this regard (Li et al., 2021b).

5.2 Modeling

Conditional computation models commonly employ a gate network and backbone network. However, recent research on MoE introduces new modeling approaches. One idea is to replace the gate function with random dropout or utilize the inherent sparsity in the model to construct the expert (Zuo et al., 2022; Zhang et al., 2021). Additionally, the MoE model based on the FFN layer has attracted attention, prompting exploration of experts beyond the FFN layer, including the attention-based MoE model (Peng et al., 2020; Zhang and Feng, 2021). Furthermore, it has been demonstrated that utilizing MoE for multi-task learning outperforms parameter-dense single models (Gupta et al., 2022; Kudugunta et al., 2021).

5.3 Training Paradigm

The main challenge in optimizing the conditional computation model is the joint training of the backbone and gate network. Unlike the MoE model, which utilizes ensemble learning, the depth adaptive model relies on a single sub-network for generating predictions. As a result, the gate function training follows a layer-wise approach, progressively augmenting and training intermediate classifiers as the final classifier (Panda et al., 2016).

In comparison to a step-wise training procedure, Joint Optimization is deemed to offer a regularization benefit to each classifier, as the losses of all classifiers are integrated into the final loss function (Teerapittayanon et al., 2016; Kaya et al., 2019). Based on the success of the joint optimization approach and pre-trained model, many early exit model use the pre-training and joint optimization to train depth adaptive model, by inserting intermediate classifiers on pre-train model and fine-tuning intermediate classifiers has also become an option (Zhou et al., 2020; Li et al., 2021b).

Joint Optimization, as opposed to a step-wise training procedure, offers regularization benefits to each classifier by integrating the losses of all classifiers into the final loss function. Building upon the success of joint optimization and pre-trained models, many early exit models incorporate pre-training and joint optimization to train depth adaptive models. This involves inserting intermediate classifiers into pre-trained models and fine-tuning them accordingly.

In addition, direct fine-tuning based on pre-trained model is considered too aggressive, which damages the features obtained during the pre-training period, further, the regularization brought by joint optimization may interfere with the learning of different classifiers. Therefore, Liao et al. propose to fine-tuning with frozen part of parameters, fine-tuning backbone network and intermediate classifier gradually (Xin et al., 2020), or fine-tuning backbone network and intermediate classifiers alternatively (Xin et al., 2021).

5.4 Optimization Problem

The behavior of the optimization problem differs between depth-adaptive and width-adaptive models, as evidenced by the unreliable hidden state in depth-adaptive models and the load imbalance in MoE models.

Unreliable Hidden State Although using different computational costs for samples with different difficulties is an acceptable assumption, the measure of sample difficulty is always ambiguous, so it is uncertain which hidden state should be used to complete the inference, which leads to a discussion on how to provide a reliable hidden state for the classifier.

Intermediate classifiers in depth adaptive model has been widely criticized due to the conflicting requirements for high-dimensional and low-dimensional features. This conflict can be addressed through the implementation of the cascade (Li et al., 2021a; Wang et al., 2021). Alternatively, the multi-scale early exit (Huang et al., 2018; McGill and Perona, 2017) can be utilized to provide the early layer with high-dimensional features. Additionally, the single hidden state has been questioned in its ability to provide sufficient features for intermediate classifiers, leading to the proposal of the patience-based early exit (Zhou et al., 2020), which outputs the final classification result only after it has been confirmed by multiple intermediate classifiers. Another approach is the fusion of both high-level and low-level features through the utilization of high-level and low-level feature estimators (Liao et al., 2021).

Furthermore, the early exit model can be viewed as a multi-branch network comprising a backbone network and several sub-networks, each of which utilizes an intermediate classifier as its final classifier and shares a portion of the parameters via residual connections. Recent studies have adopted an ensemble learning approach, leveraging either the hidden state (Liao et al., 2021) or the intermediate classifier (Sun et al., 2021) to get a more reliable prediction.

Load Imbalance and Training instability When treating the training gate function as a classification task, while it improves the network sparsity, it also amplifies the training instability caused by fluctuating gate function. Sparse activation of training patterns reduces parameters that can be updated every epoch. On the one hand, it enlarges the randomness brought by initialization and leads to the load imbalance problem that often occurs in MoE. On the other hand, it increases the time required for the network to converge and interferes with the learning of the backbone network.

A straightforward way to avoid the load imbalance problem is to renormalize the gate function when it is greater than a threshold based on mean value after multiple epochs (Eigen et al., 2014). Another widely adopted approach is to add a regularization loss term with respect to the gate function to the final loss to encourage a balanced load (Shazeer et al., 2017; Xue et al., 2022). Recently, some methods set the expert capacity for each expert, which provides an upper limit of training samples for each expert and ensures that the frequently selected experts are not over-optimized (Lepikhin et al., 2021; Fedus et al., 2021). In addition, modeling the gate function as a linear assignment problem (Lewis et al., 2021), or use a completely random gate function can also avoid load imbalance (Zuo et al., 2022).

For the training instability problem, a common approach is to adopt a fixed routing policy. Dai et al. propose a two-stage training strategy, which trains the gate network in the first stage while distilling the gate network, and then trains the backbone network using the distilled fixed gate network in the second stage. In addition, using the hash method based on input samples can also provide a stable routing (Roller et al., 2021).

6 Conclusion

In this paper, we present a comprehensive overview of the conditional computation methods. The gate network, a critical aspect of the model, is shown to be contingent on both structural and sparsity considerations. To this end, we suggest a novel taxonomy, derived from the decision sequence output of the gate network, which serves to categorize prevalent issues encountered in varying structures, while simultaneously proffering insightful strategies for the development of more versatile methodologies.

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A Example Appendix

This is a section in the appendix.