

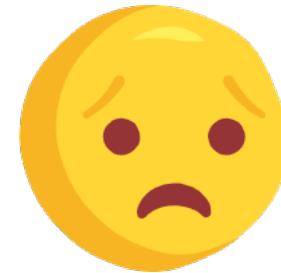
AutoML: From Methodology to Application

**Yaliang Li, Zhen Wang, Yuexiang Xie, Bolin Ding,
Kai Zeng, Ce Zhang, and Rong Zhu**

Alibaba Group, ETH Zürich



Machine Learning Pipeline



So **MANY** choices

- Which feature transformation?
- Which model architecture?
- Which hyperparameters?

Machine Learning Pipeline

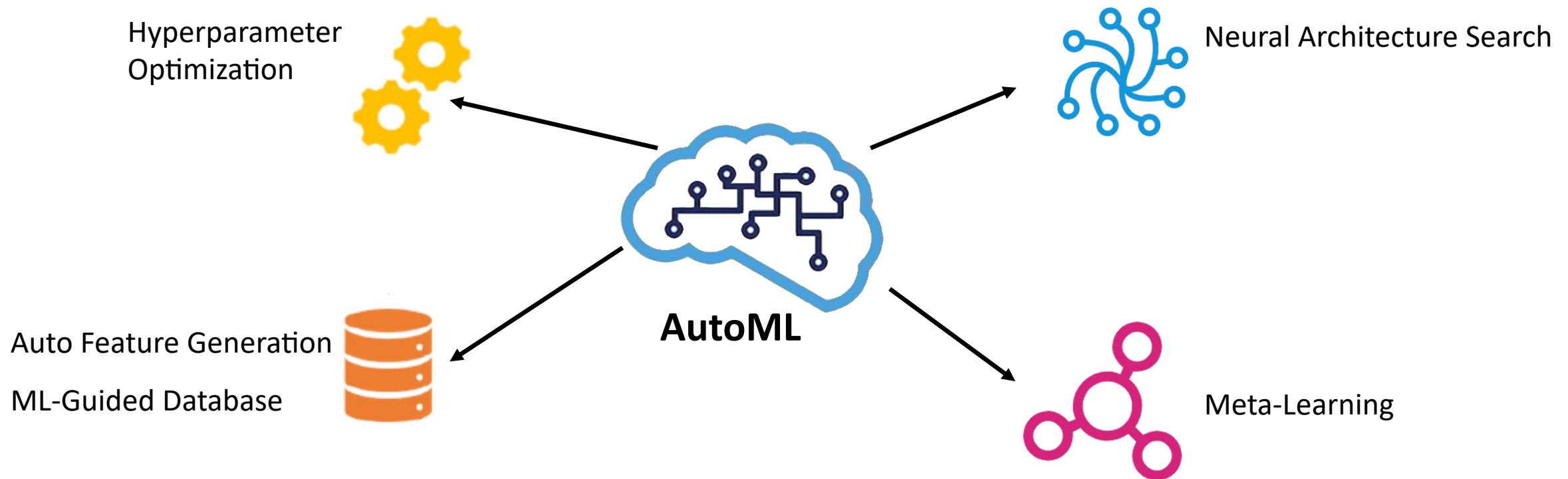


AutoML

- Auto Feature Generation
- Neural Architecture Search
- Hyperparameters Optimization
- Meta Learning



Automated Machine Learning



AutoML: How to automate the process of applying machine learning components to various real-world tasks?

Automated Machine Learning

Inductive bias (prior α): how we represent data, which kinds of models to be considered, how to tune hyper-parameter, how to transfer knowledge across tasks, etc...

Traditional ML:

$$\theta^* = \operatorname{argmax}_{\theta} P(D|\theta) \cdot P(\theta|\alpha)$$

where α is given by experts

AutoML : bilevel optimization

$$\theta^* = \operatorname{argmax}_{\theta} P(D|\theta) \cdot P(\theta|\alpha^*)$$

where $\alpha^* = \operatorname{argmax}_{\alpha} f(D', \theta^*)$

$D' = D$ for HPO,

D' is validation data for NAS, AutoFeature,

D' is data of other tasks for Meta-learning.

Tutorial Schedule



Yaliang Li, Background and Overview of AutoML
Hyperparameter Optimization



Zhen Wang, Neural Architecture Search
Meta-Learning



Yuexiang Xie, Automatic Feature Generation



Ce Zhang, VolcanoML: End-to-End AutoML via
Scalable Search Space Decomposition

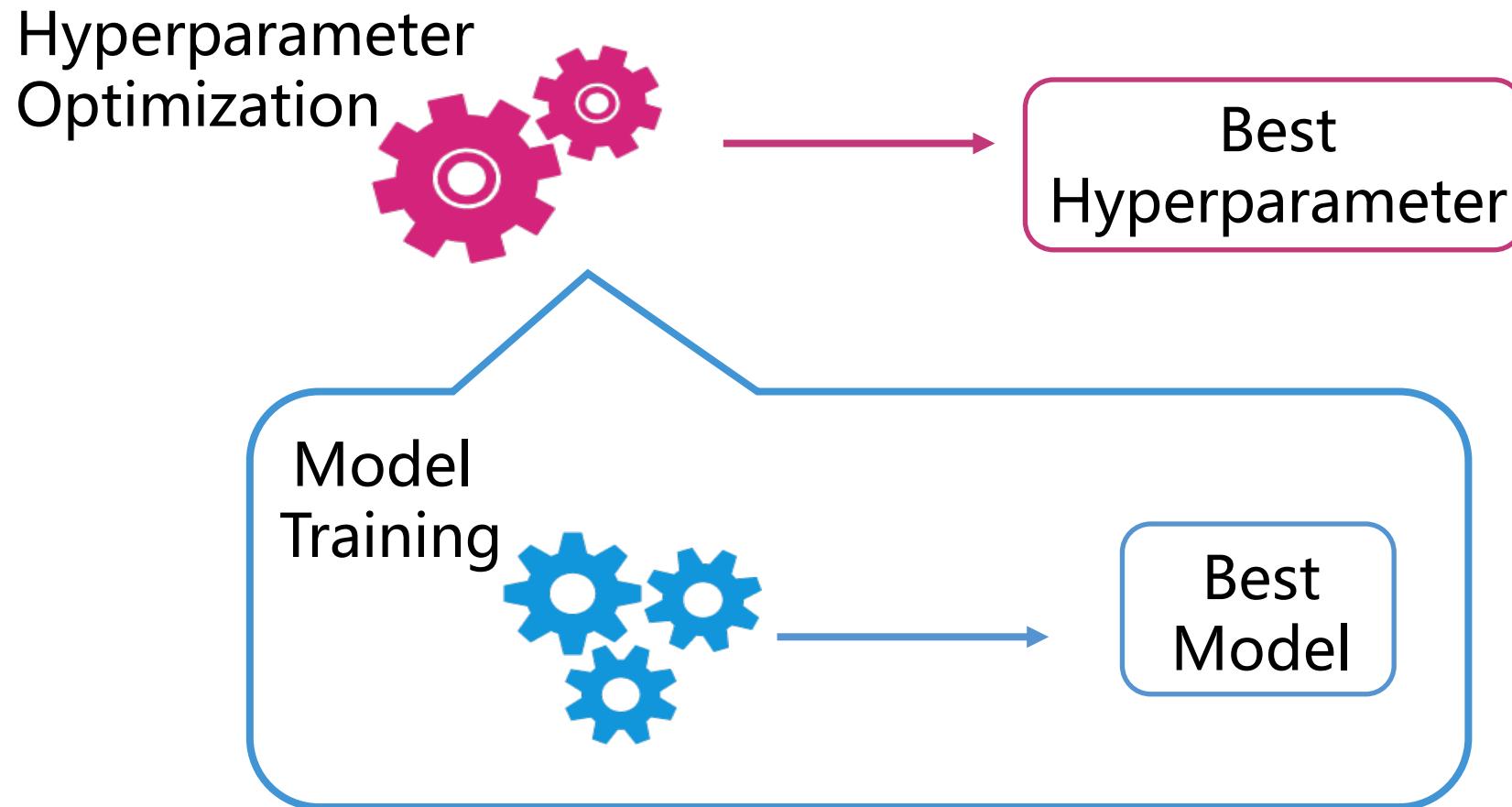


Bolin Ding, Kai Zeng, and Rong Zhu
Machine Learning Guided Database

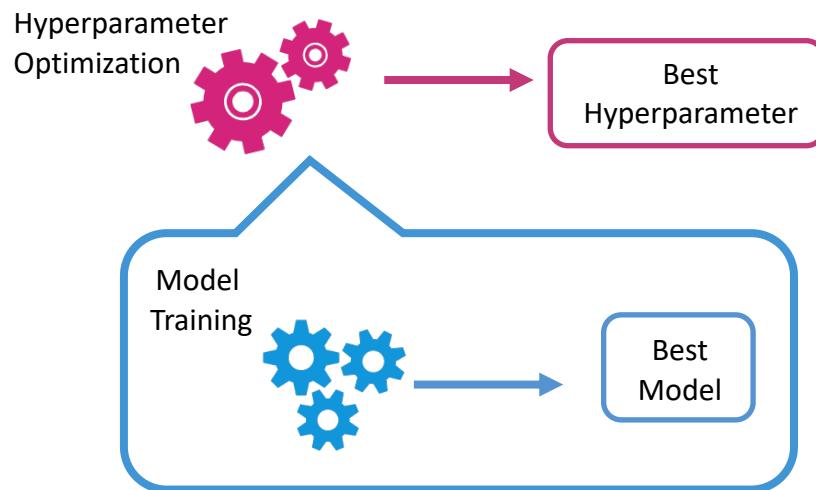
Hyperparameter Optimization (HPO)



Hyperparameter Optimization

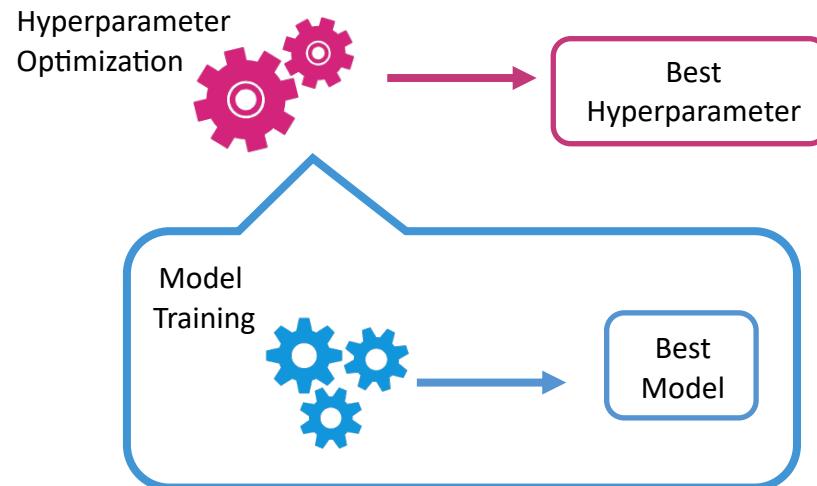


Hyperparameter Configuration v.s. Schedule



- Hyperparameter **configuration** search methods find a **fixed** hyperparameter setting to maximize the model performance.
- Hyperparameter **schedule** search methods seek a **dynamic** hyperparameter schedule in the model training process.

Hyperparameter Optimization



❑ Hyperparameter Configuration

- Random search, Grid Search
- Successive-halving, Hyperband
- Bayesian optimization

❑ Hyperparameter Schedule

- Population-based training
- Hypergradient

Search Methods

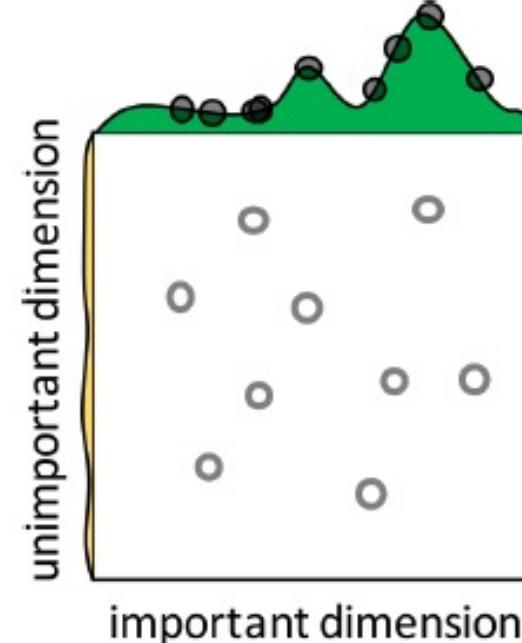
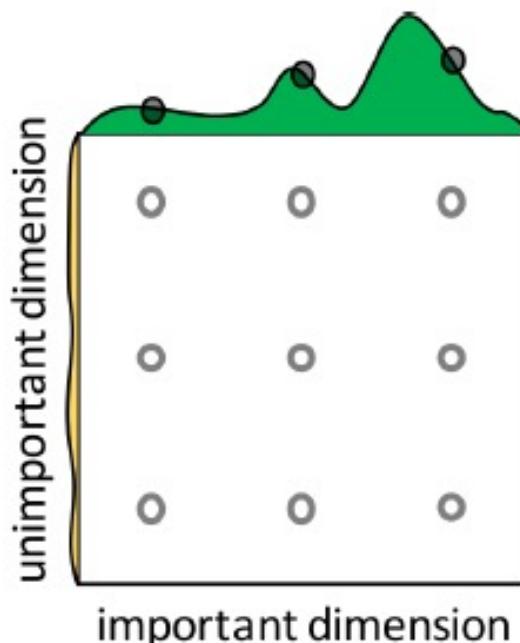
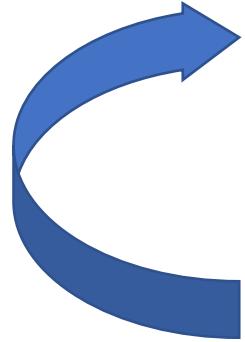


Image source: Bergstra & Bengio. *JMLR*, 2012.

Successive-Halving

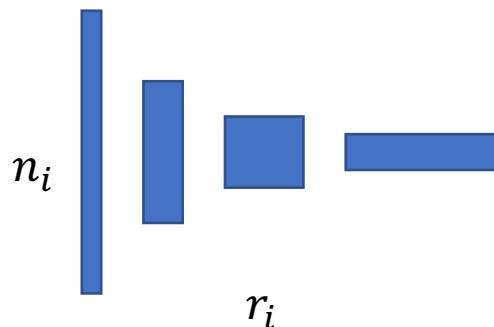


- Uniformly allocate *a budget* to a set of hyperparameter configurations
- Evaluate the performance of all configurations
- Throw out the worst half

Repeat until one configuration remains

Hyperband

- Successive-Halving needs to determine the number of configurations (i.e., n)
- Outer loop
 - Grid search for different n
- Inner loop
 - Successive-Halving for given n configs
 - s.t. at least one config is trained for R



Algorithm 1: HYPERBAND algorithm for hyperparameter optimization

```
input      :  $R, \eta$  (default  $\eta = 3$ )
initialization:  $s_{\max} = \lfloor \log_{\eta}(R) \rfloor, B = (s_{\max} + 1)R$ 
1 for  $s \in \{s_{\max}, s_{\max} - 1, \dots, 0\}$  do
2    $n = \lceil \frac{B}{R} \frac{\eta^s}{(s+1)} \rceil, r = R\eta^{-s}$ 
   // begin SUCCESSIVEHALVING with  $(n, r)$  inner loop
3    $T = \text{get\_hyperparameter\_configuration}(n)$ 
4   for  $i \in \{0, \dots, s\}$  do
5      $n_i = \lfloor n\eta^{-i} \rfloor$ 
6      $r_i = r\eta^i$ 
7      $L = \{\text{run\_then\_return\_val\_loss}(t, r_i) : t \in T\}$ 
8      $T = \text{top\_k}(T, L, \lfloor n_i/\eta \rfloor)$ 
9   end
10 end
11 return Configuration with the smallest intermediate loss seen so far.
```

Bayesian Optimization



Given some tried {hyperparameter, performance} pairs,
which hyperparameter should be the next one to try?

Bayesian Optimization



Given some tried {hyperparameter, performance} pairs,
which hyperparameter should be the next one to try?

Independence assumption

Follow a certain distribution

Bayesian Optimization

Bayesian Optimization

Fit a probabilistic function $f(x)$ to model $\{x=\text{hyperparameter}, f(x)=\text{performance}\}$

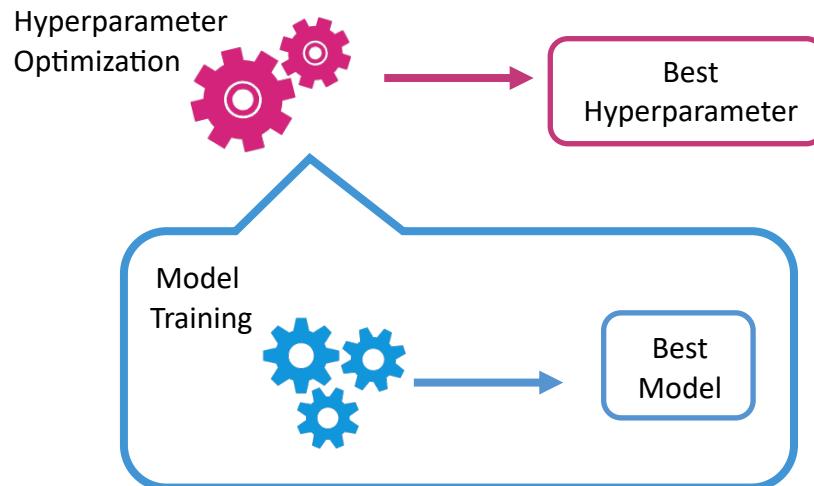


- Function $f(x)$ isn't required to be convex, differentiable
- Rich theoretical results: convergence, sync v.s. async, various model choices



- Exploration-exploitation trade-off
- Costly

Hyperparameter Optimization



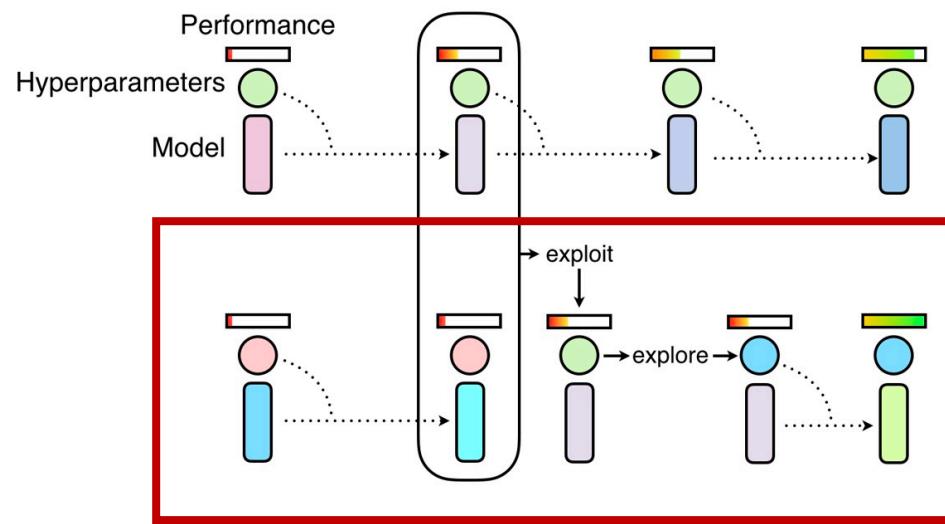
❑ Hyperparameter Configuration

- Random search, Grid Search
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❑ Hyperparameter Schedule

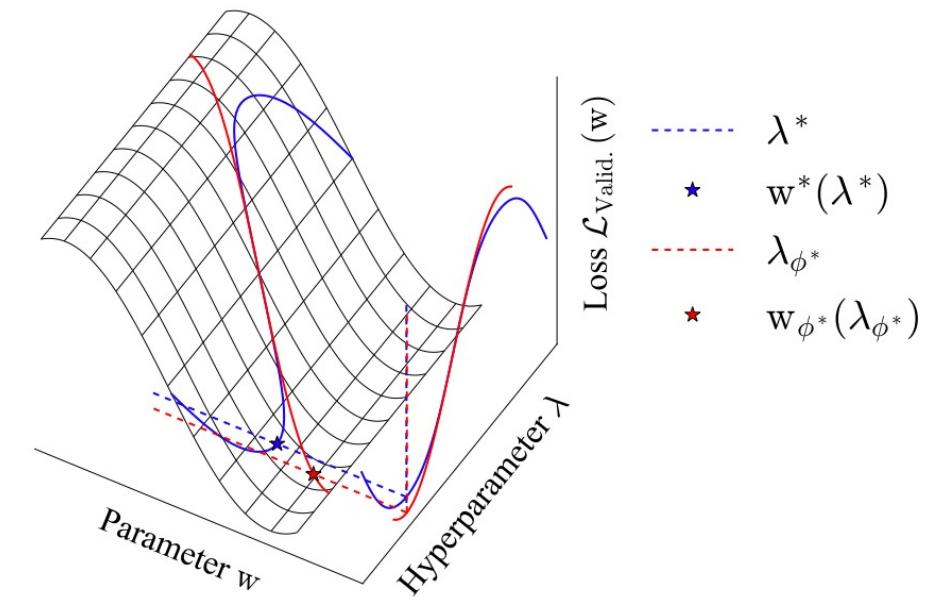
- Population-based training
- Hypergradient

Hyperparameter Schedule



Population-based training

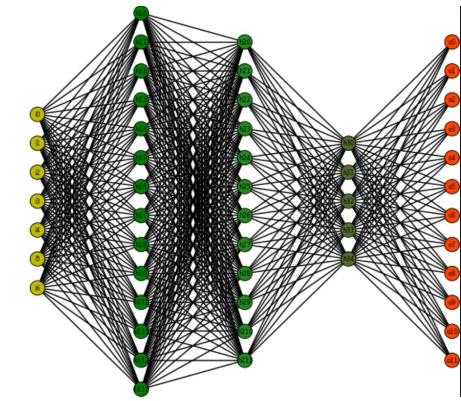
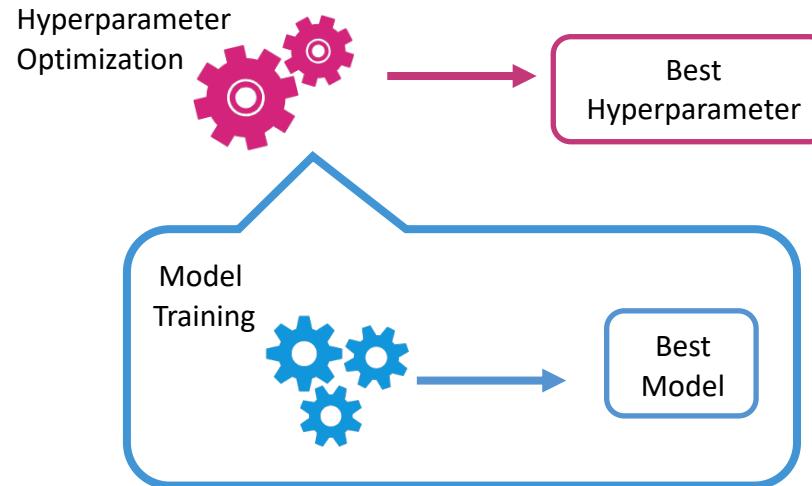
A generalized framework for population based training. *KDD*, 2019.



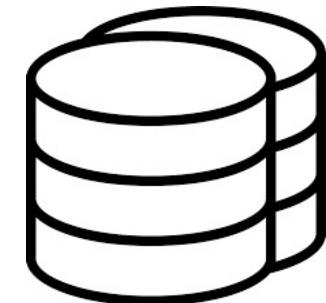
Hypergradient

Self-tuning networks: Bilevel optimization of hyperparameters using structured best-response functions. *ICLR*, 2019.

Practical Challenge (1)

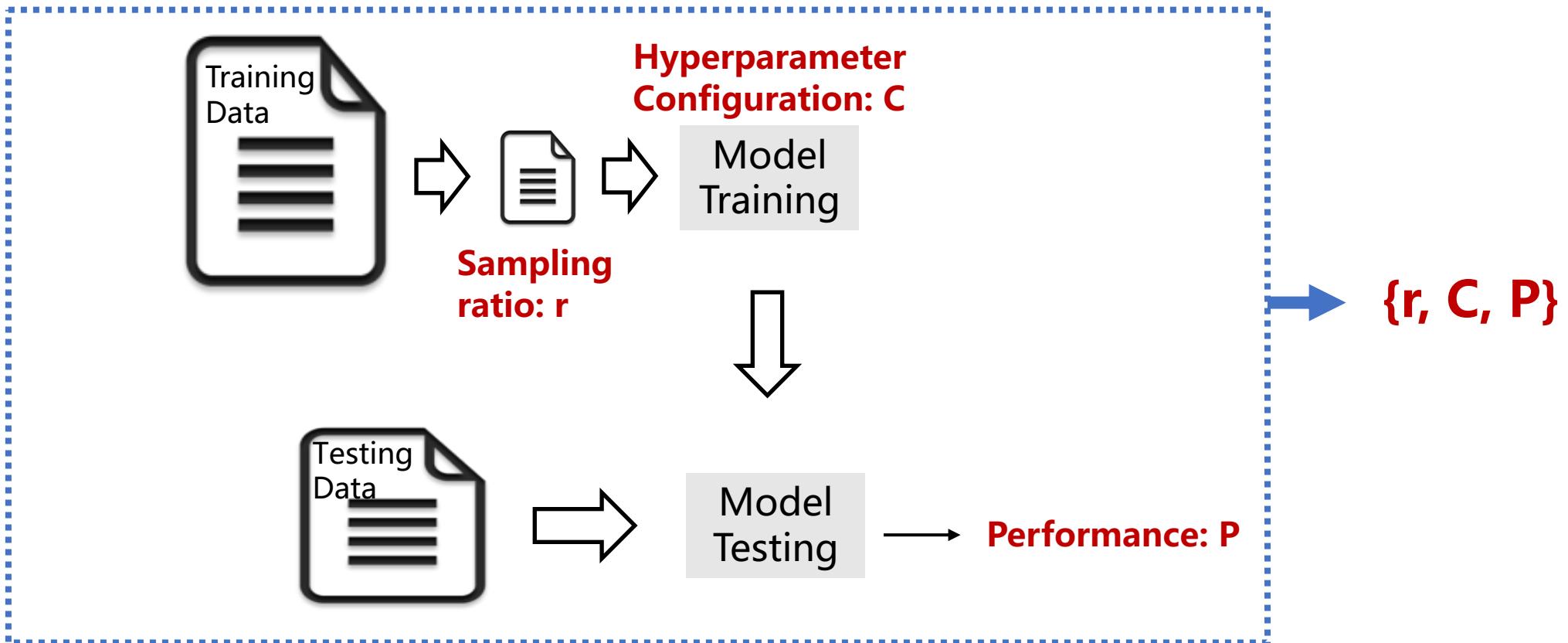


Model Size



Data Size

ABC: Sampling



A New Method: ε GE

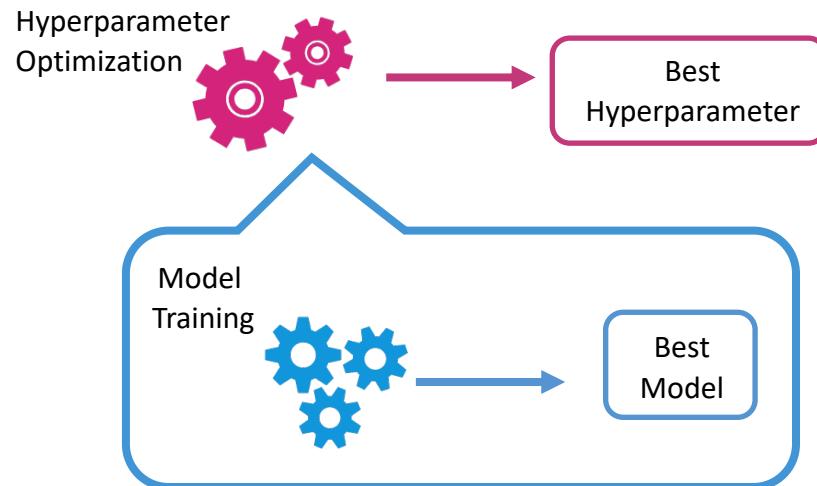


Illustration of Hyperparameter optimization

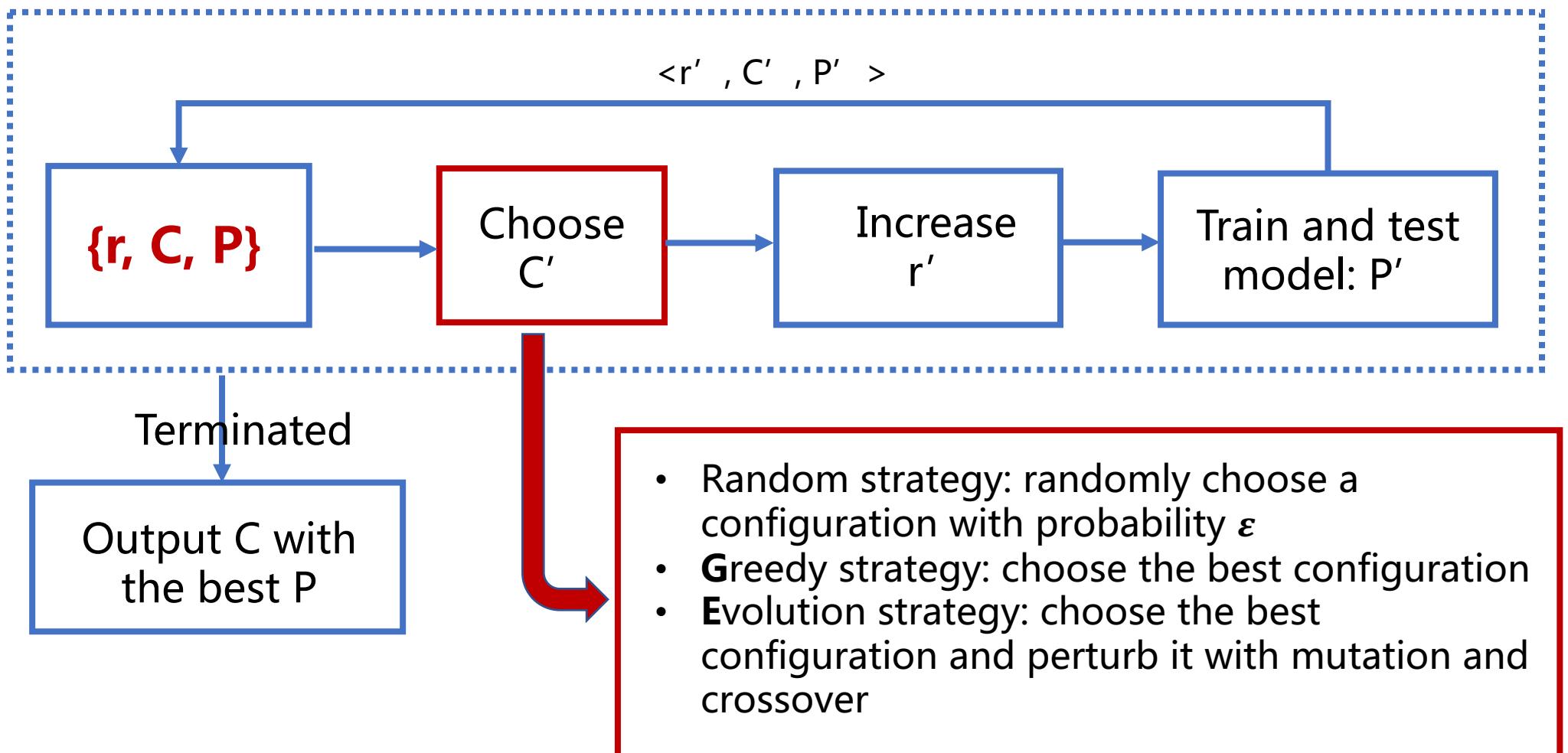
❑ Existing methods

- Search-strategy based: Successive-halving, Hyperband, etc.
- Evolutionary algorithm: Population Based Training, etc.
- Bayesian optimization

Each category of hyperparameter optimization methods has its advantages and disadvantages. Can we **adaptively** combine them and utilize their advantages for different tasks?

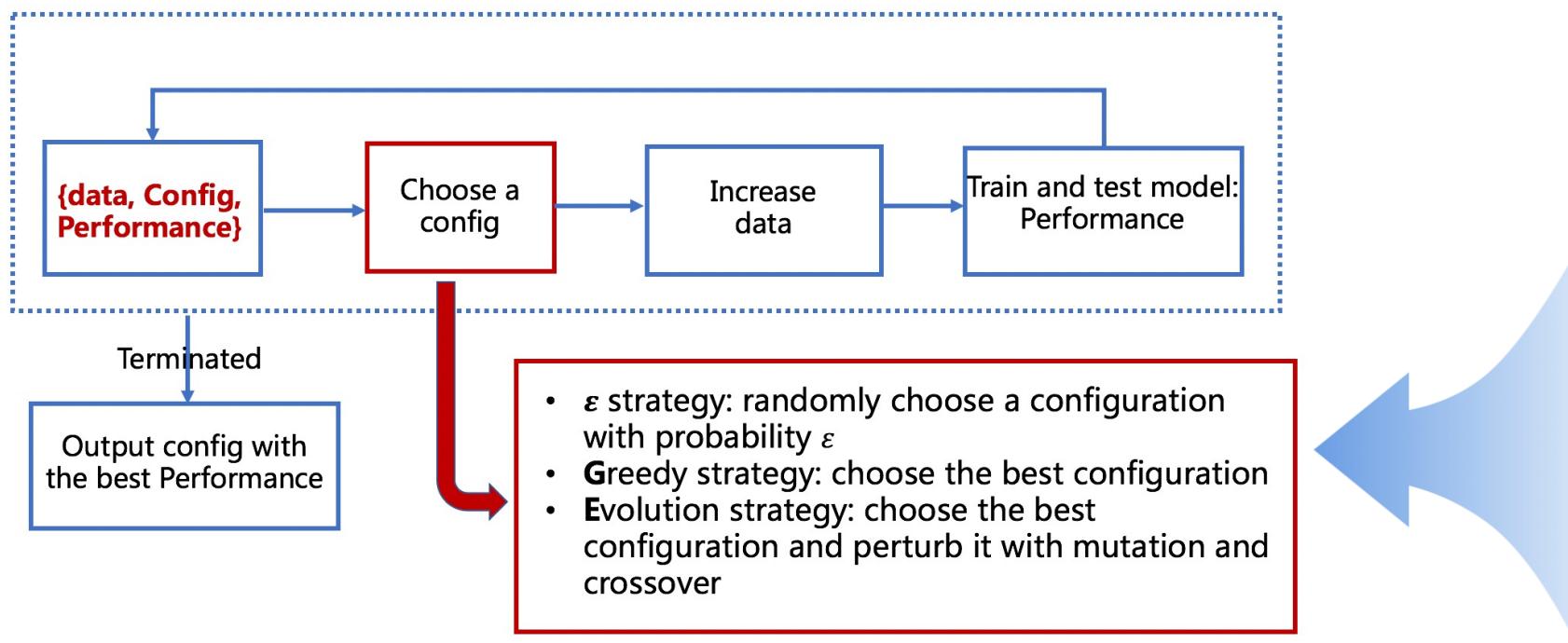


A New Method: ε GE



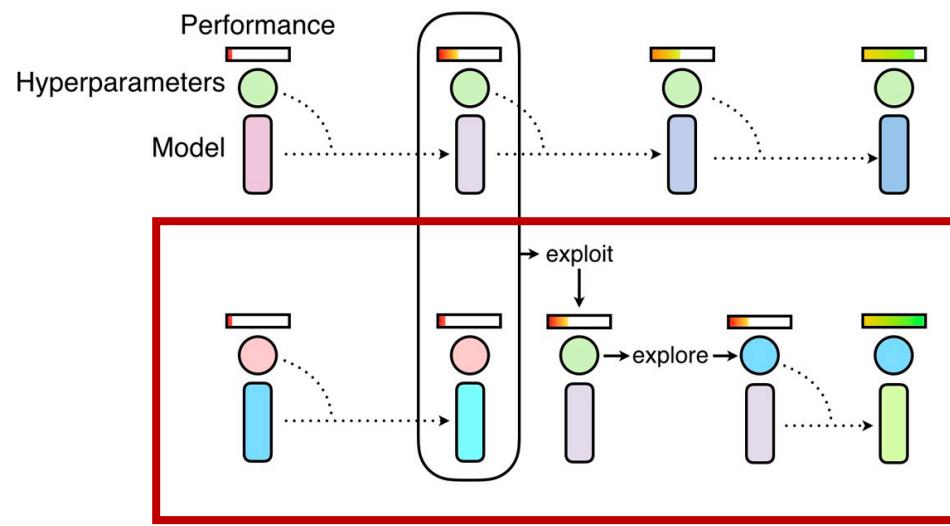
HPO: Sampling method- ε GE

The task-adaptively combination of different hyperparameter optimization methods leads to faster solutions!

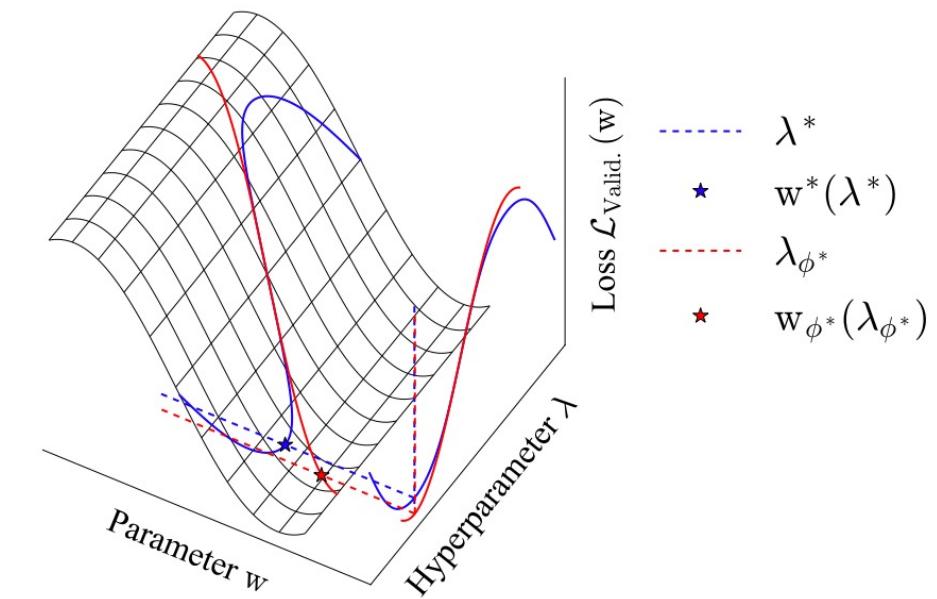


- A soft version of Hyperband
- Evolutionary operation
- A simplified version of Bayesian optimization (i.e., local smoothness assumption)

Practical Challenge (2)

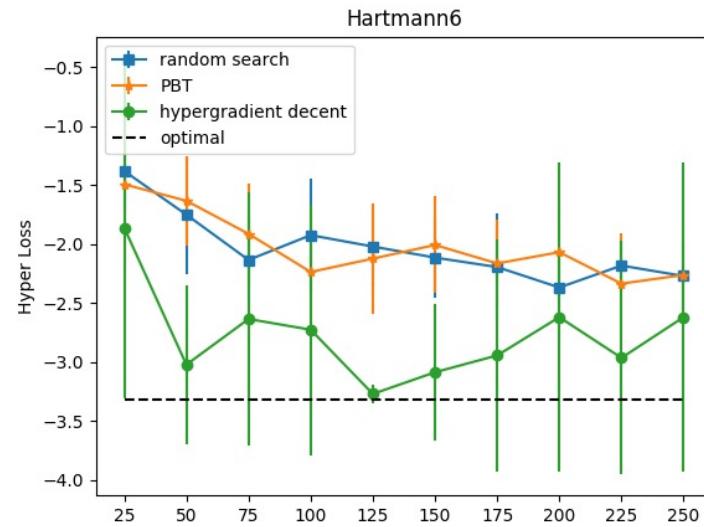


Mutation-driven **global** search
PBT, KDD2019

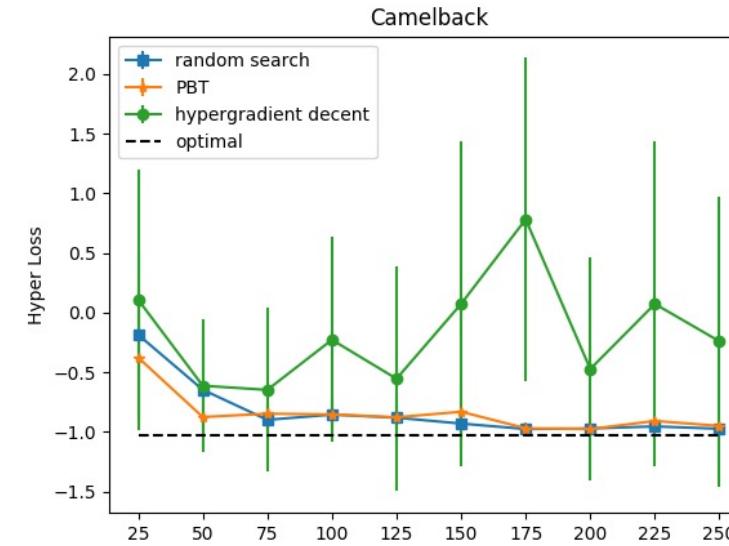


Hypergradient-guided **local** search
STN, ICLR2019

Hyperparameter Schedule



A smooth optimization problem



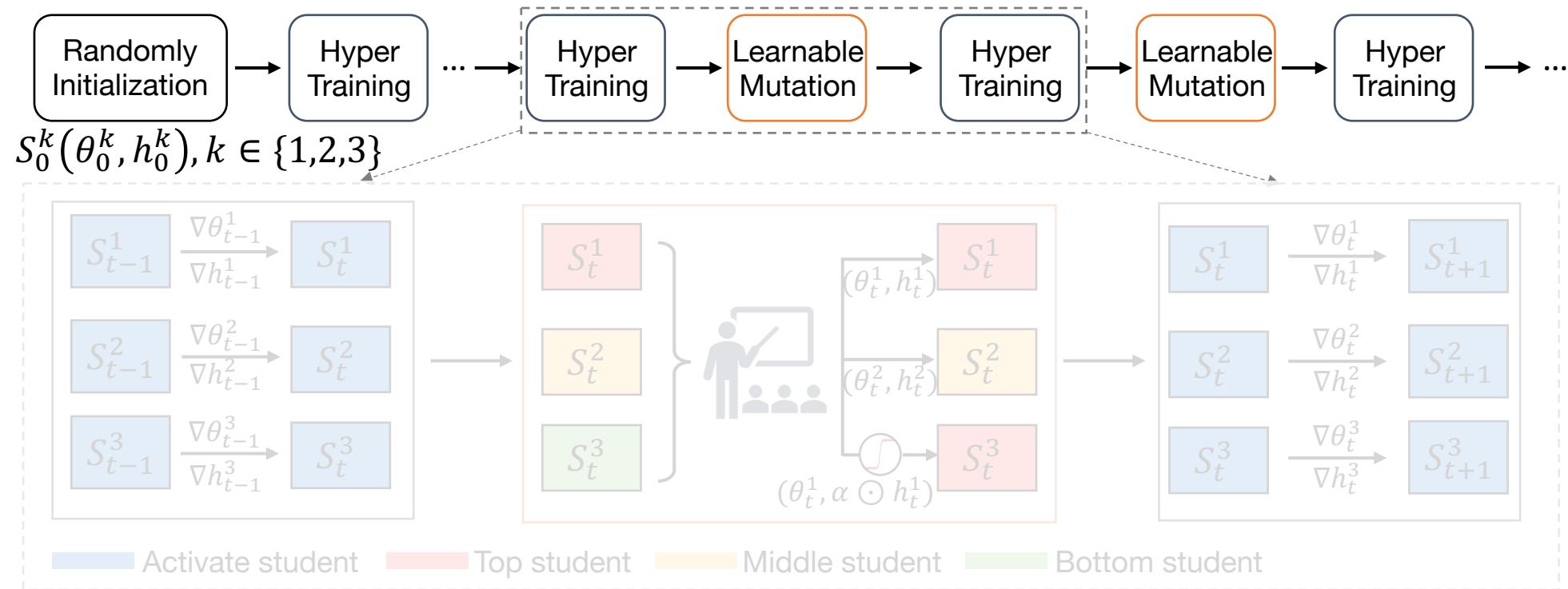
A non-smooth optimization problem

Trade-off between Evolutionary algorithm (PBT) and Hyper-gradient based method:

- Hyper-gradient based method performs better than PBT on the smooth optimization problems.
- Hyper-gradient based method performs worse than PBT on the cases of many local minima (non-smooth).

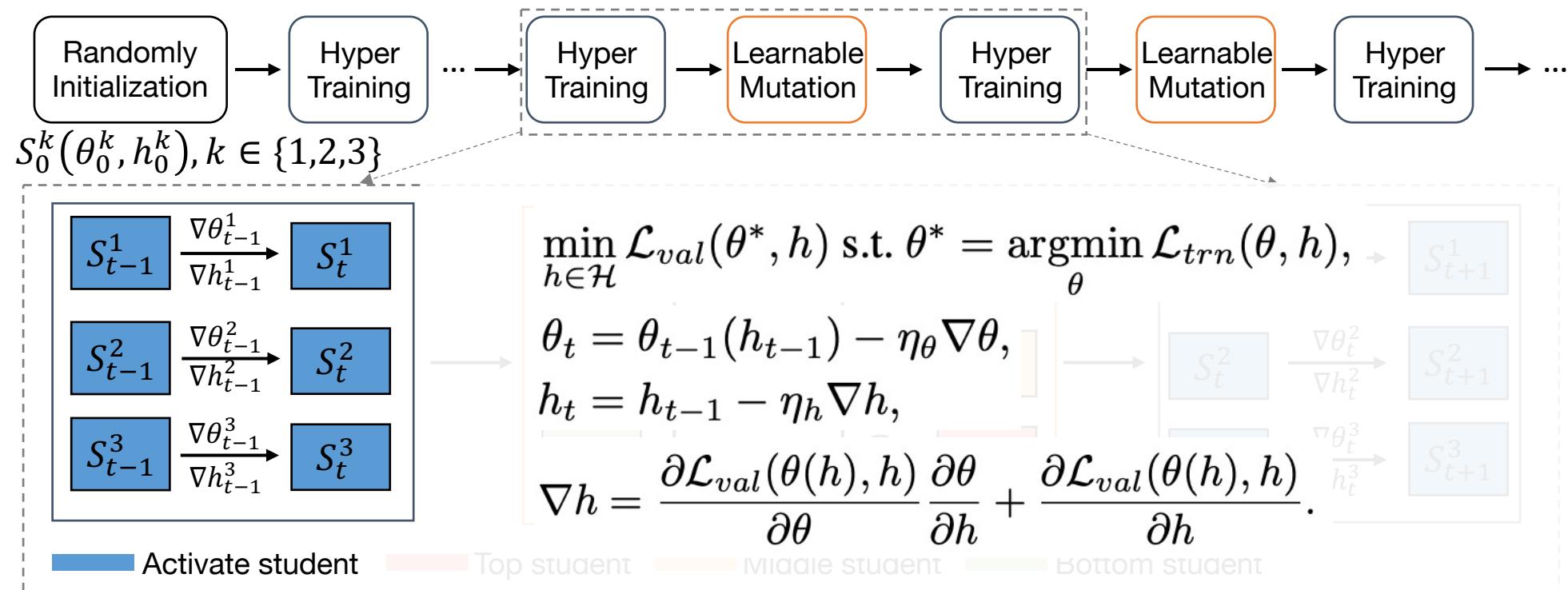
How to learn a good trade-off between the global search and local search?

HyperMutation (HPM)

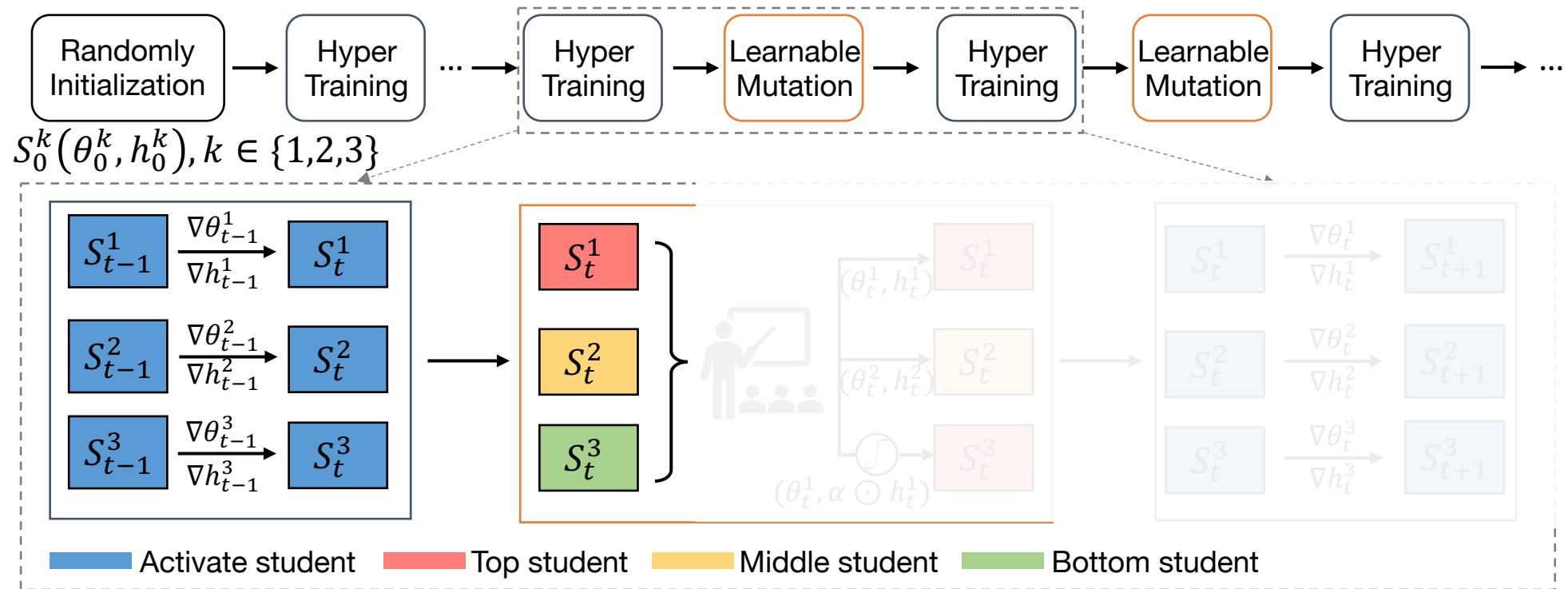


Learning to Mutate with Hypergradient Guided Population. *NeurIPS*, 2020.

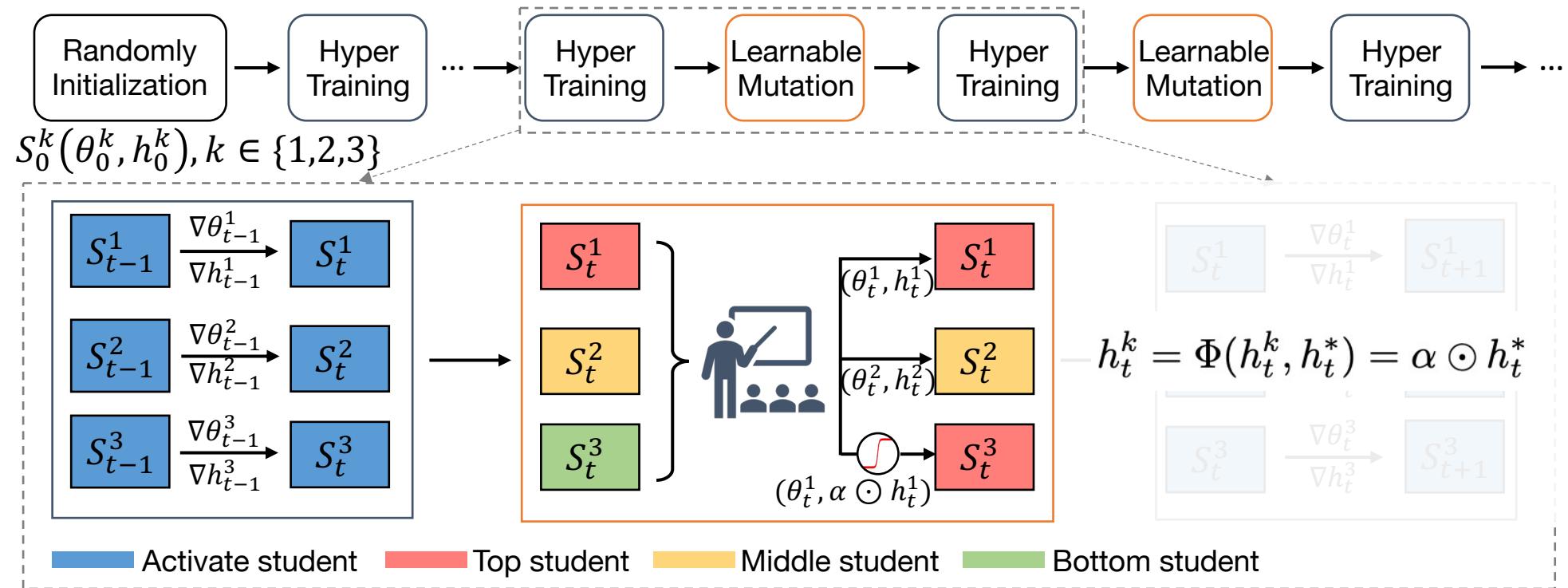
Hypertraining: a joint optimization over θ and h



Exploit by a truncation selection

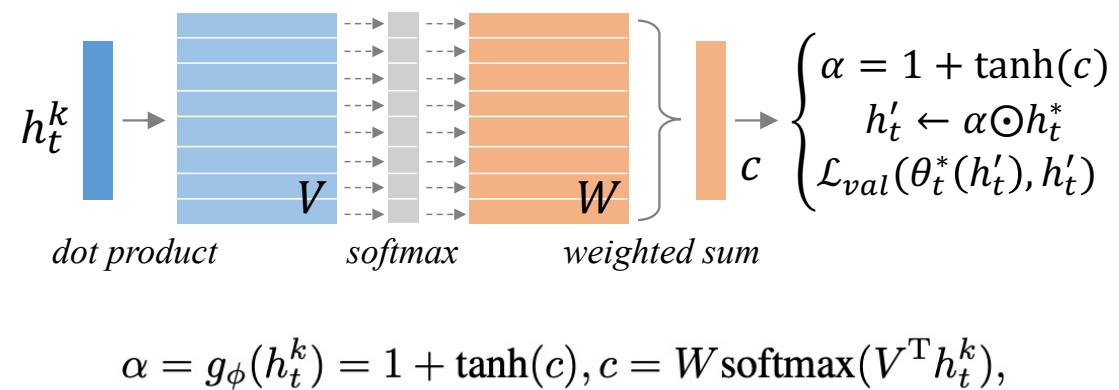
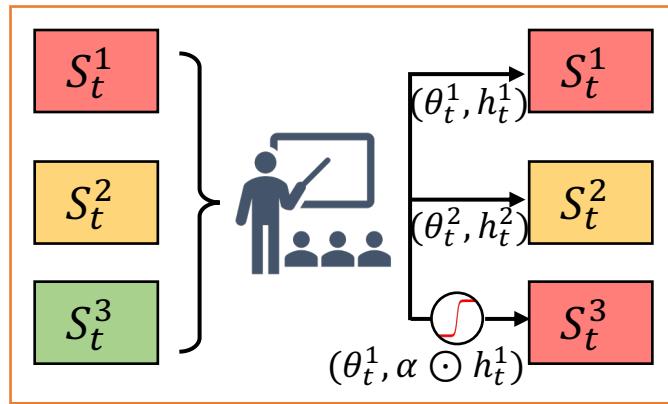


Explore by the learnable mutation

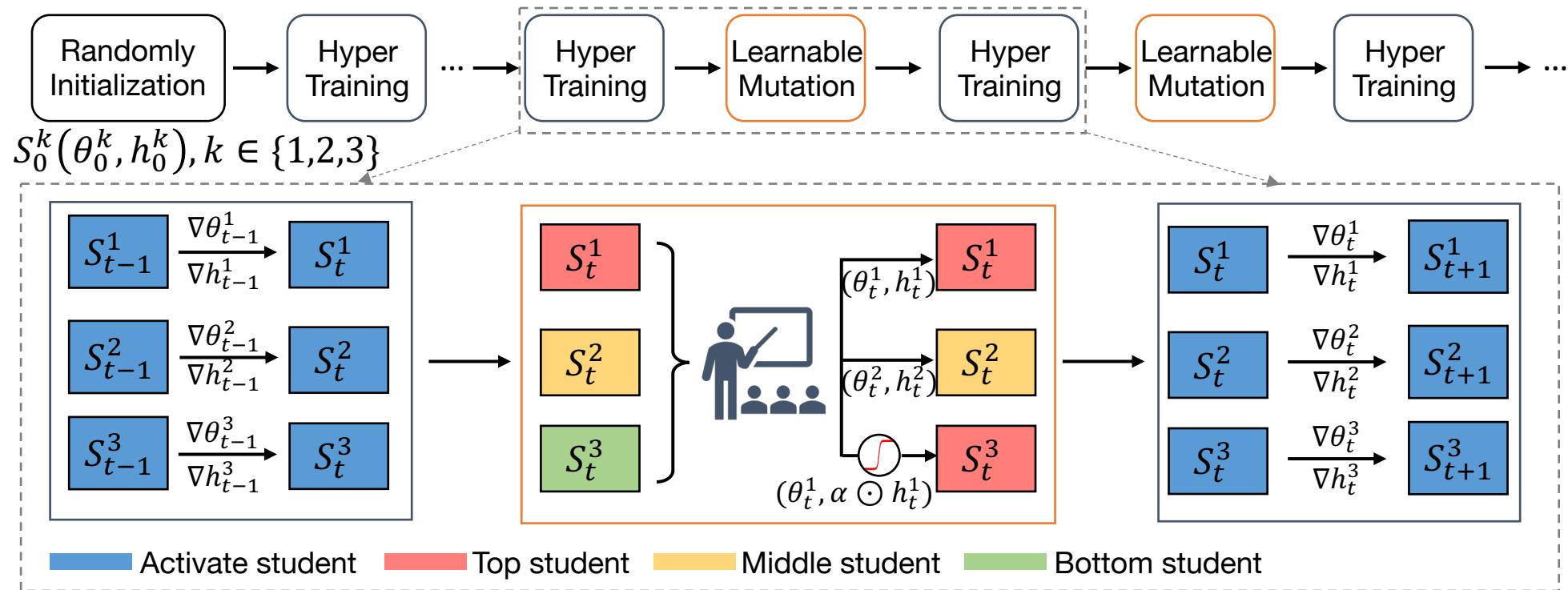


Learning mutations with a teacher network

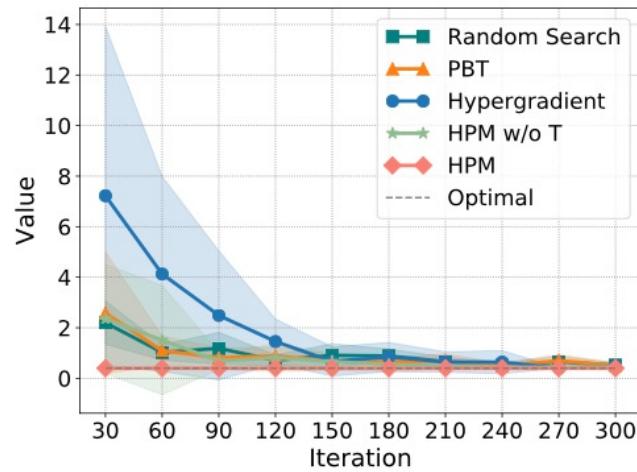
- Student-teaching schema
- Teacher model with attention networks



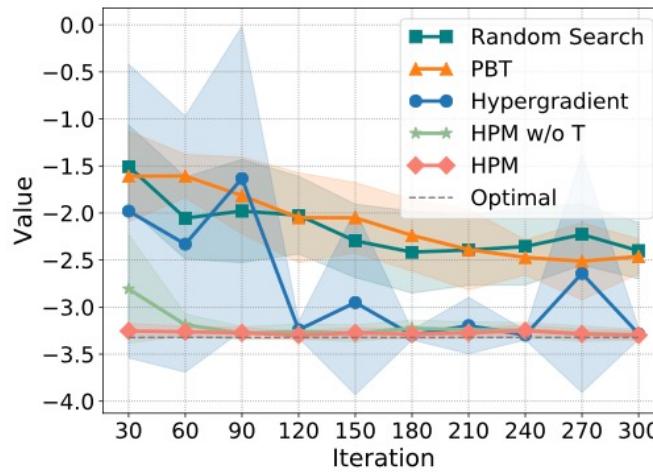
Continue hypertraining after exploit & explore



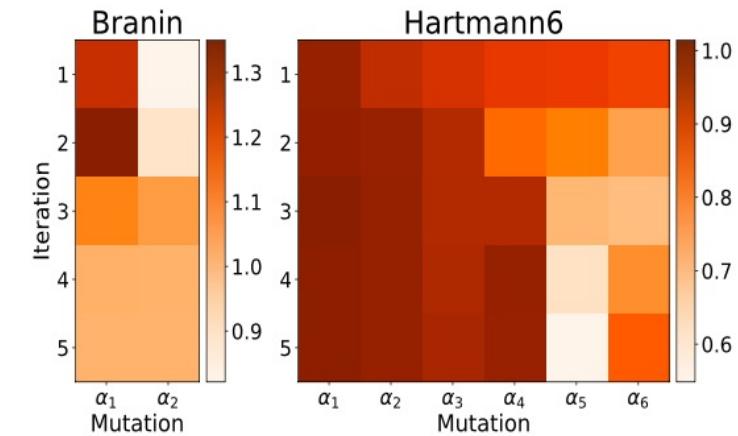
Experiments on test functions



(a) Branin



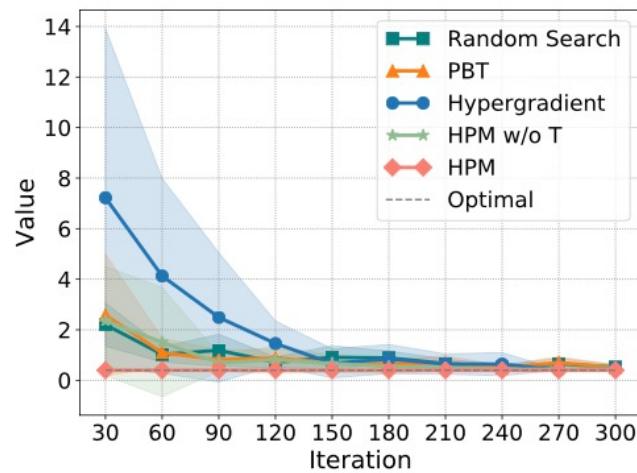
(b) Hartmann6D



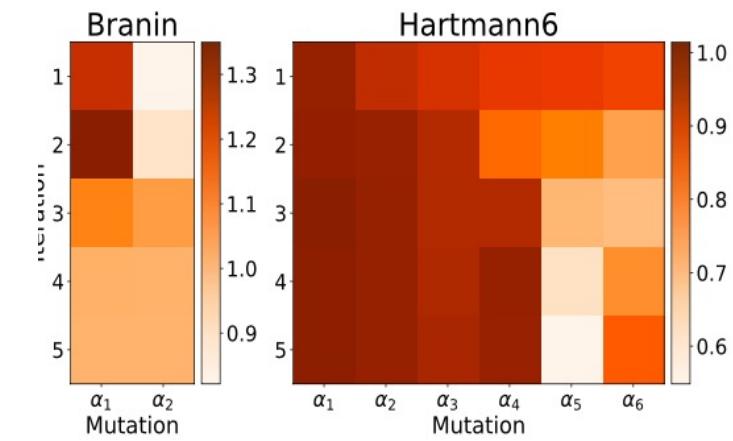
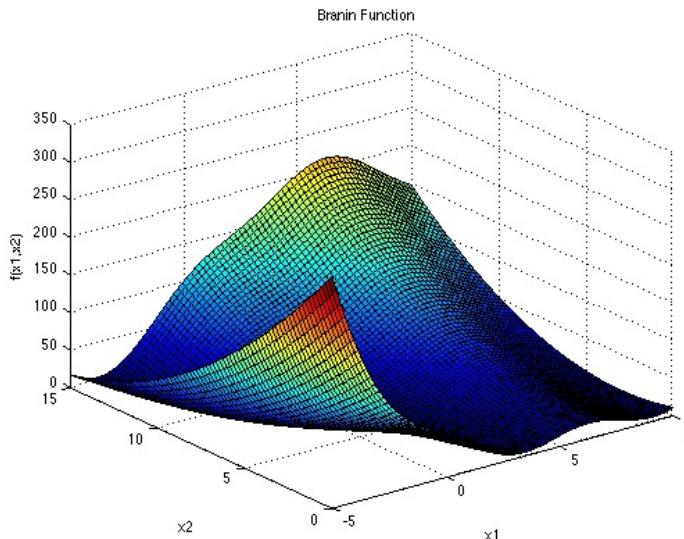
(c) Learned Mutations

Figure: (a)-(b) The mean performance computed by different methods along with the standard deviation over 10 trials, in terms of different given budget of iterations. (c) The average mutation values learned by HPM over 10 trials. In each trial, HPM runs 30 iterations in total with a population size of 5, resulting in 6 training steps and 5 mutations.

Experiments on test functions



(a) Branin



(c) Learned Mutations

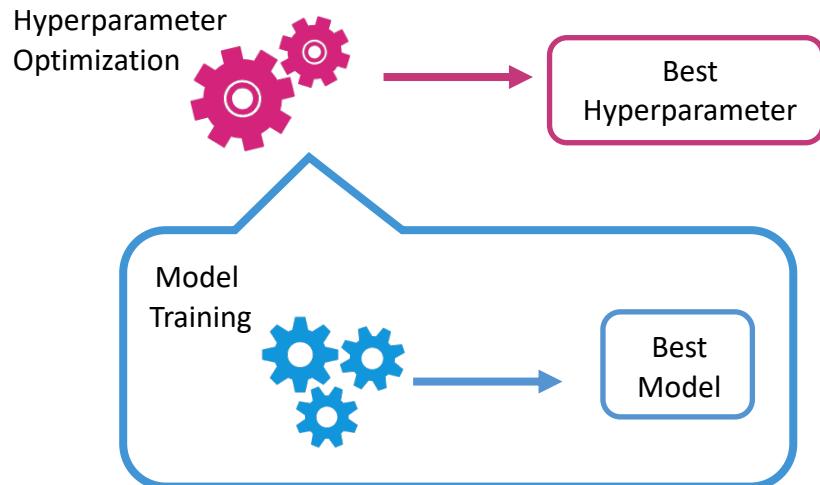
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Experiments on benchmark datasets

Table 1: Performance comparison for the image classification task on the CIFAR10 dataset by validation/test loss and the language modeling task on the PTB corpus dataset by perplexity (PPL).

Method	CIFAR10		PTB		
	Val Loss	Test Loss	Val PPL	Test PPL	
Fixed	Grid Search	0.7940	0.8090	97.32	94.58
	Random Search	0.9210	0.7520	84.81	81.86
	Bayesian Optimization	0.6360	0.6510	72.13	69.29
	Hyperband [20]	0.7156	0.7491	71.25	68.39
Schedule	PBT [15]	0.6253	0.6437	72.07	69.33
	STN [23]	0.5892	0.5878	71.49	68.29
	HPM w/o T	0.5724	0.5802	73.18	70.48
	HPM	0.5636	0.5649	70.49	67.88

Takeaways



❑ Hyperparameter Configuration

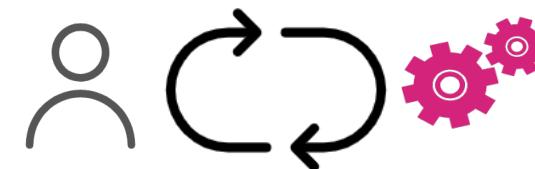
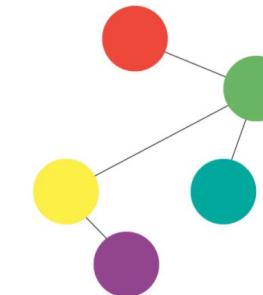
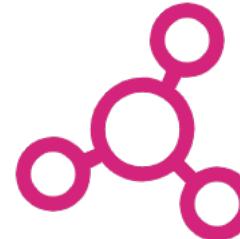
- Random search, Grid Search
- Successive-halving, Hyperband
- Bayesian optimization

❑ Hyperparameter Schedule

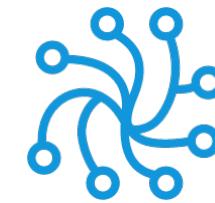
- Population-based training
- Hypergradient
- HyperMutation (HPM)

Future Directions

- Faster, Green
 - HPO via Meta-Learning
- HPO for a specific domain
 - a group of algorithm, e.g. Graph-related
- Interactive, Human-in-the-loop



Neural Architecture Search (NAS)



Neural Architecture Search

□ What is neural architecture search (NAS)? □ Why NAS?

- To find the optimal topology and/or size configuration for the neural network.
 - E.g., select a filter from $\{\text{CNN}_{3 \times 3}, \text{CNN}_{5 \times 5}, \text{DilatedCNN}_{5 \times 5}\}$.
 - E.g., determine the depth and width of a neural network.

- Architecture matters a lot on the performance!
- The choices cannot be exhausted.
- Useful prior knowledge, e.g., the invariance possessed by the task, has been exploited.

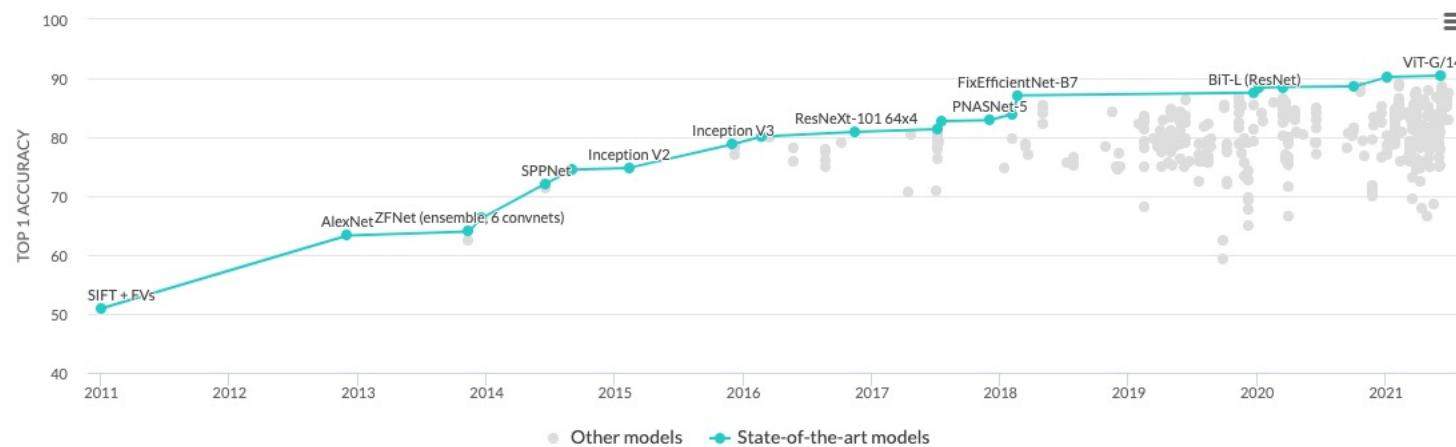


Figure: Image classification on ImageNet (source: <https://paperswithcode.com/sota/image-classification-on-imagenet>).

Elements of NAS

❑ Search space

- All the possible configurations.
- E.g., filter size, activation functions, depth, etc.

❑ Search strategy

- How to utilize experience?
- How to propose new configuration to try?
- E.g., RL, ES, and differentiable search.

❑ Performance estimation strategy

- How to evaluate a configuration?
- E.g., standard training and surrogate objective.

And the Theme of NAS

❑ Search space

- All the possible configurations.
- E.g., filter size, activation functions, depth, etc.

Exploitation v.s. Exploration

Incorporating prior knowledge reduces search space but makes it constrained to some extent, e.g., Inception-v2/3 → stacked cells [Zoph et al. 2018].

❑ Search strategy

- How to utilize experience?
- How to propose new configuration to try?
- E.g., RL, ES, and differentiable search.

Instead of asymptotic regret, practitioners balance the exploitation and exploration to achieve best solution under *a given finite horizon*.

❑ Performance estimation strategy

- How to evaluate a configuration?
- E.g., standard training and surrogate objective.

Standard training&validation is expensive but accurate. The proposed surrogate objectives are efficient but less correlated.

Pioneer Works of NAS

❑ Search space

- Consider both CNN and RNN cells.
- The configuration of each layer can be determined respectively.

❑ Search strategy

- RL with the policy parameterized by a RNN.

❑ Performance estimation strategy

- Standard train&validation

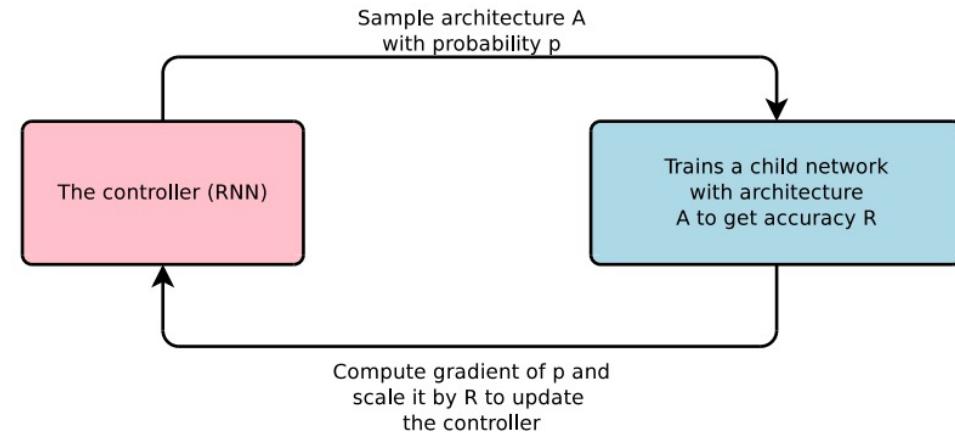


Figure: An overview of the trial-and-error process of NAS.

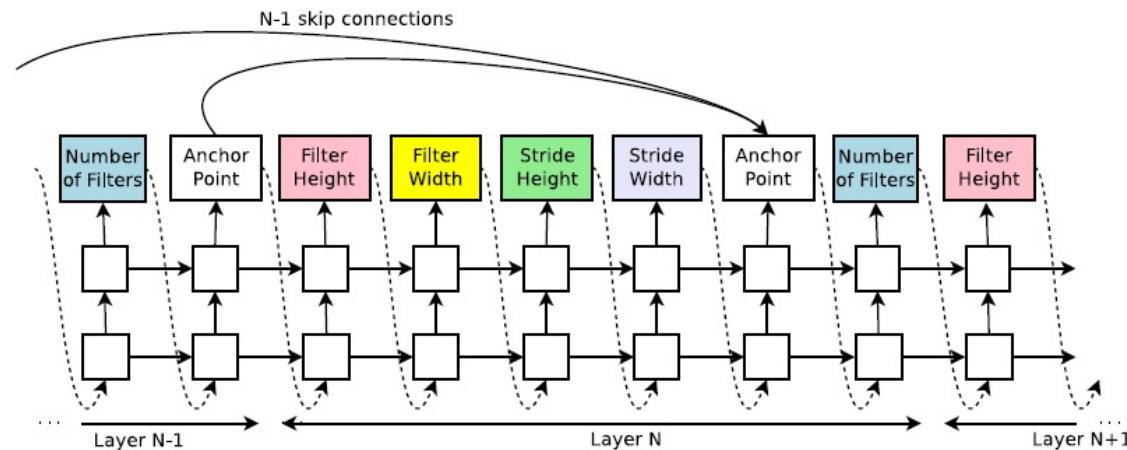


Figure: How the controller (i.e., a RNN) samples a CNN with skip connection.

Pioneer Works of NAS

❑ Search space

- Consider both CNN and RNN cells.
- The configuration of each layer can be determined respectively.

❑ Search strategy

- RL with the policy parameterized by a RNN.

❑ Performance estimation strategy

- Standard train&validation

❑ Unfold the gain of NAS 😊 and also its pain 😕

- Searched CNN and RNN cells achieve competitive performances against manually designed architectures on CIFAR-10 and PTB respectively.
- Searched architecture can be transferred to other tasks.
- Trained 12,800 models in total on 800 GPUs.

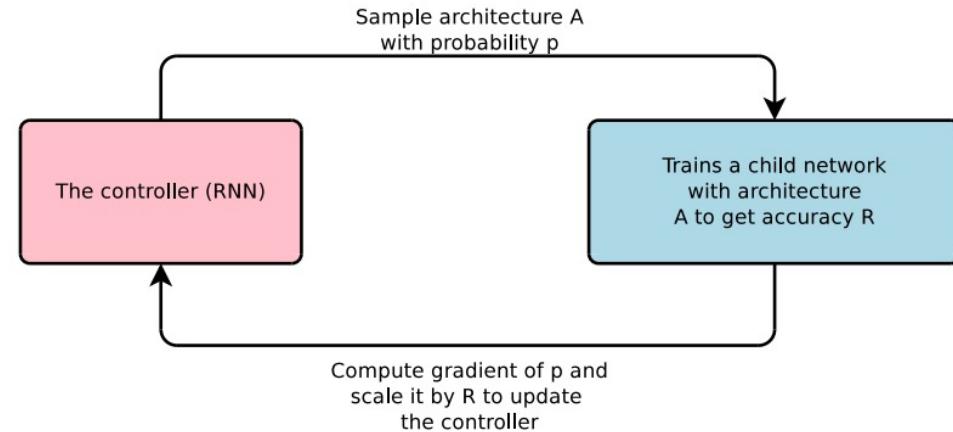


Figure: An overview of the trial-and-error process of NAS.

Weight Sharing for One-shot NAS

□ Weight sharing

- Represent NAS's search space using a single DAG.
- An architecture can be realized by taking a subgraph.
- E.g., deducing a RNN cell as follow:

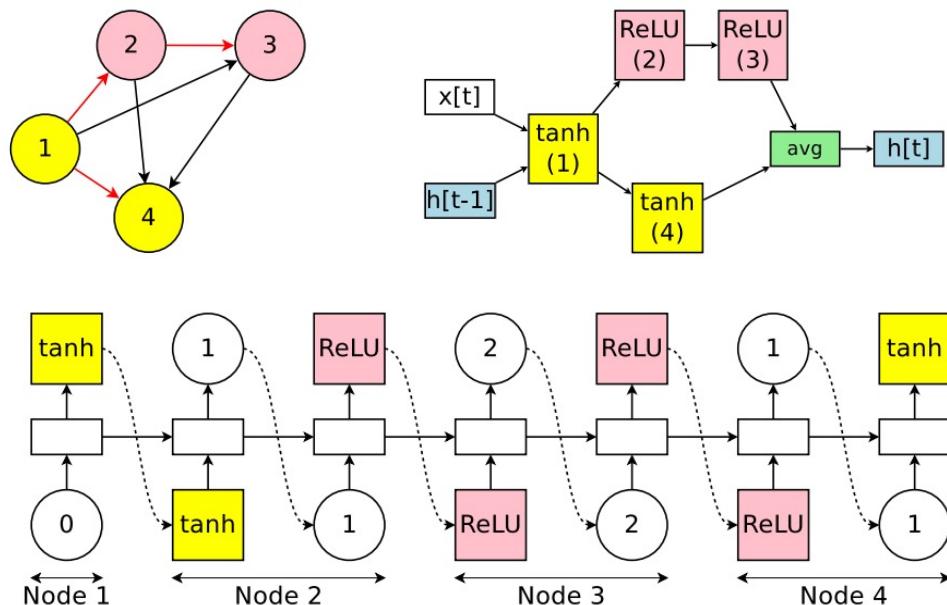


Figure: How a RNN cell (i.e., highlighted subgraph) inherits the shared parameters.

□ One-shot NAS

- Each architecture (i.e., subgraph) is evaluated by inheriting the shared parameters.
- Shared parameters are trained with sampled architecture.
- Parameters and the controller are updated alternatively.

□ Advantage and concern

- ENAS [Pham and Guan et al., 2018] uses 10h of one GTX1080Ti, which is *1000x faster* than [Zoph et al., 2017].
- *Does the performance of a stand-alone training correlate with that of one-shot NAS [Bender et al., 2018, Zhang et al., 2020]?*

Differentiable NAS

□ Continuous relaxation

- Each edge denotes a mixture of ops in $O = \{\text{CNN}_{3 \times 3}, \text{DilatedCNN}_{3 \times 3}, \text{Zero}, \text{Identity}, \dots\}$.
- For each edge (i, j) , they parameterize the weights of ops by architecture parameter $\alpha^{(i,j)}$.
- Suppose the tensor at node i is x , then the tensor propagated to node j will be:

$$\bar{o}^{(i,j)}(x) = \sum_{o \in \mathcal{O}} \frac{\exp(\alpha_o^{(i,j)})}{\sum_{o' \in \mathcal{O}} \exp(\alpha_{o'}^{(i,j)})} o(x)$$

□ Differentiable learning

- Formulated as a bilevel optimization problem:

$$\min_{\alpha} \mathcal{L}_{val}(w^*(\alpha), \alpha)$$

$$\text{s.t. } w^*(\alpha) = \operatorname{argmin}_w \mathcal{L}_{train}(w, \alpha)$$

- Regarded as a Stackelberg game
 - Architecture parameters as leader
 - Model parameters as follower

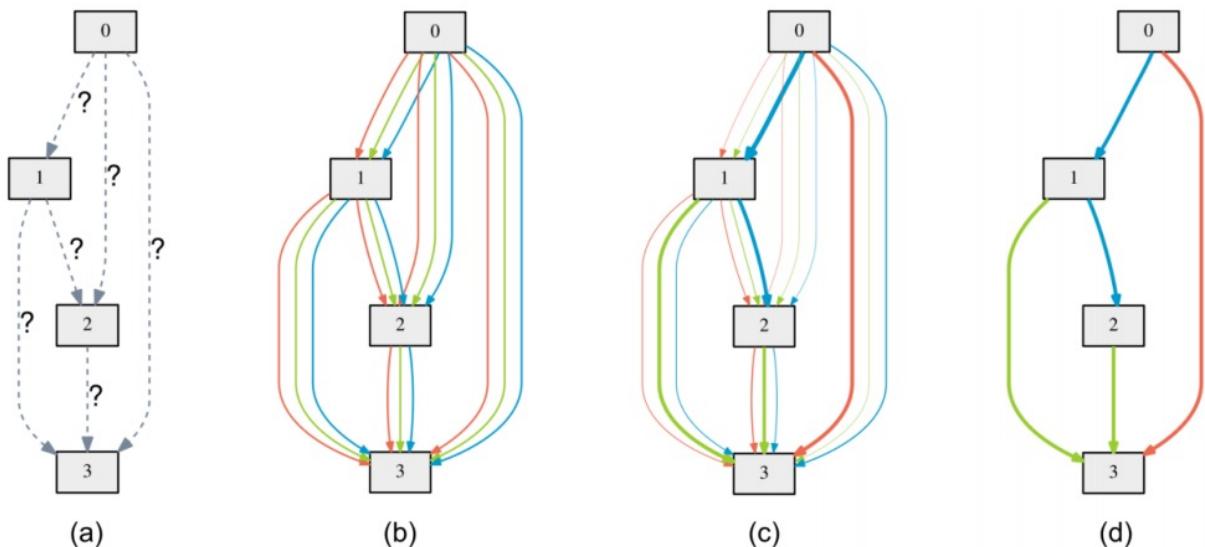


Figure: An overview of DARTS. (a) Operations are initially unknown. (b) Continuous relaxation. (c) architecture parameters are optimized jointly. (d) Inducing the final architecture.

Differentiable NAS

□ Differentiable learning (contd')

$$\begin{aligned} \min_{\alpha} \quad & \mathcal{L}_{val}(w^*(\alpha), \alpha) \\ \text{s.t.} \quad & w^*(\alpha) = \operatorname{argmin}_w \mathcal{L}_{train}(w, \alpha) \end{aligned}$$

- No way to estimate the $\nabla_{\alpha} \mathcal{L}_{val}(w^*(\alpha), \alpha)$ exactly.
- DARTS approximates the gradient by looking ahead one-step for ω like meta-learning.
- It is further simplified by treating the parameters equally [Li et al., 2021].

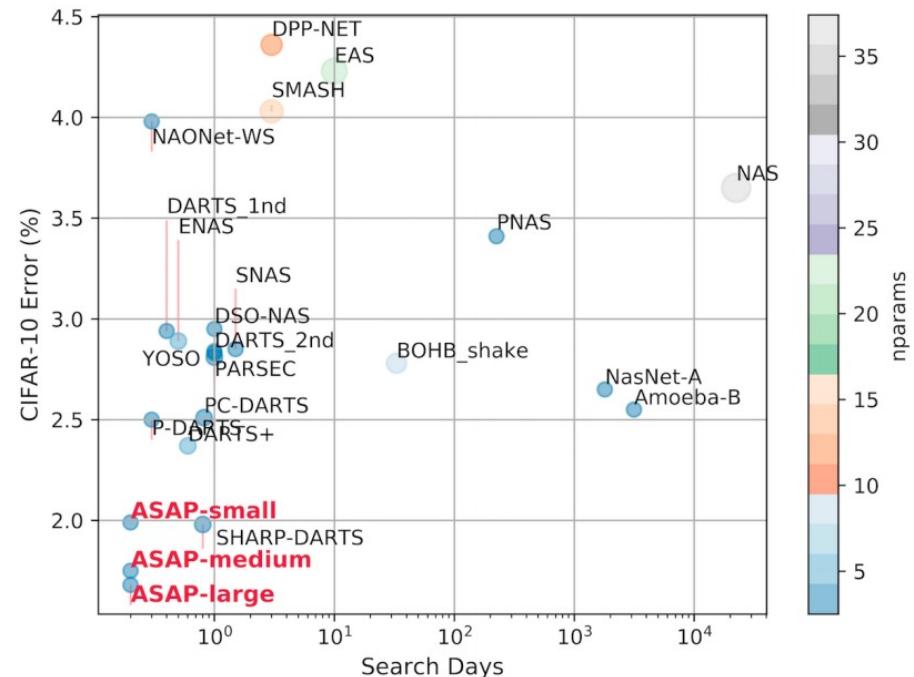
□ Deriving discrete architecture

- Retain the top-k strongest predecessors for each node j where strength of (i, j) is defined as: $\operatorname{argmax}_{o \in \mathcal{O}} \frac{\exp\{\alpha_o^{(i,j)}\}}{\sum_{o' \in \mathcal{O}} \exp\{\alpha_{o'}^{(i,j)}\}}$.

- Replace each edge by the most likely op: $\alpha^{(i,j)} = \operatorname{argmax}_{o \in \mathcal{O}} \alpha_o^{(i,j)}$

□ Improve DARTS by annealing and pruning

$$\Phi_o(\alpha^{(i,j)}; T) = \frac{\exp\left\{\frac{\alpha_o^{(i,j)}}{T}\right\}}{\sum_{o' \in \mathcal{O}} \exp\left\{\frac{\alpha_{o'}^{(i,j)}}{T}\right\}}$$



Dealing with Scalability Issue

❑ Horrible memory occupation of one-shot NAS

- The supergraph cannot fit into GPU memory for large datasets.
- Usually search architecture on CIFAR-10 and transfer to ImageNet.



Figure: ProxylessNAS directly optimizes neural architecture on target task and hardware.

❑ Binarized architecture

- Transform real-valued path weights to binary gates.
- Only one path is active in memory at runtime.

```
y_hard = tf.cast(tf.equal(y, tf.reduce_max(y, 0, keep_dims=True)),  
                 y.dtype)  
y_soft = tf.stop_gradient(y_hard - y) + y
```

Figure: Note the straight-through estimator (STE) trick.

Rethinking the Search Space of NAS

❑ Explore less constrained search spaces

[Xie et al. 19]

- Consider stochastic network generator, e.g., ER, BA, and WS.
- All yield $>73\%$ mean accuracy on ImageNet with a low variance!
- Presented graph damage ablation.

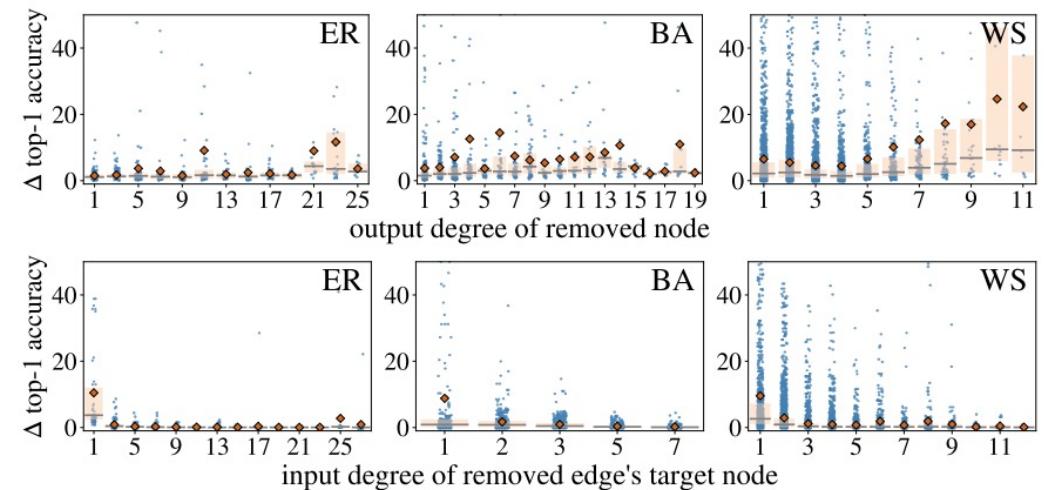


Figure: randomly remove one node/edge.

❑ Design search space [Radosavovic et al. 20]

- Evaluate a search space by its error distribution.
- Input a search space and output a refined one.

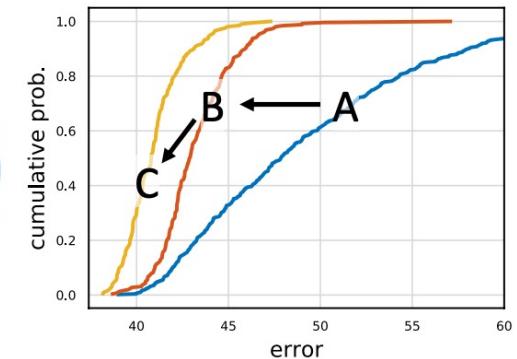
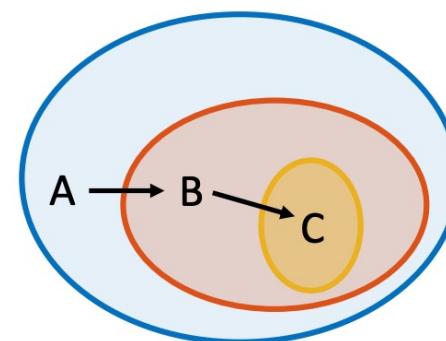


Figure: two steps of refinement with the error distribution constantly improved.

Rethinking the Search Space of NAS

□ From the view of graph structure [You et al. 20a]

- From DAG to relational graph.
- Sweet spots are consistent across different datasets and architectures.

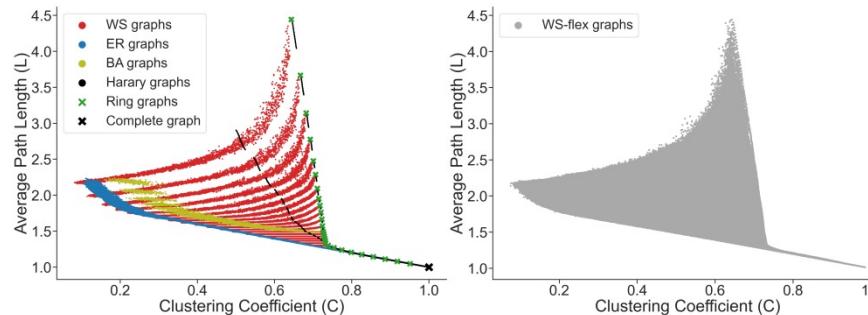


Figure: proposed WS-flex provides a larger search space.

Rethinking the Search Space of NAS

□ From the view of graph structure [You et al. 20a]

- From DAG to relational graph.
- Sweet spots are consistent across different datasets and architectures.

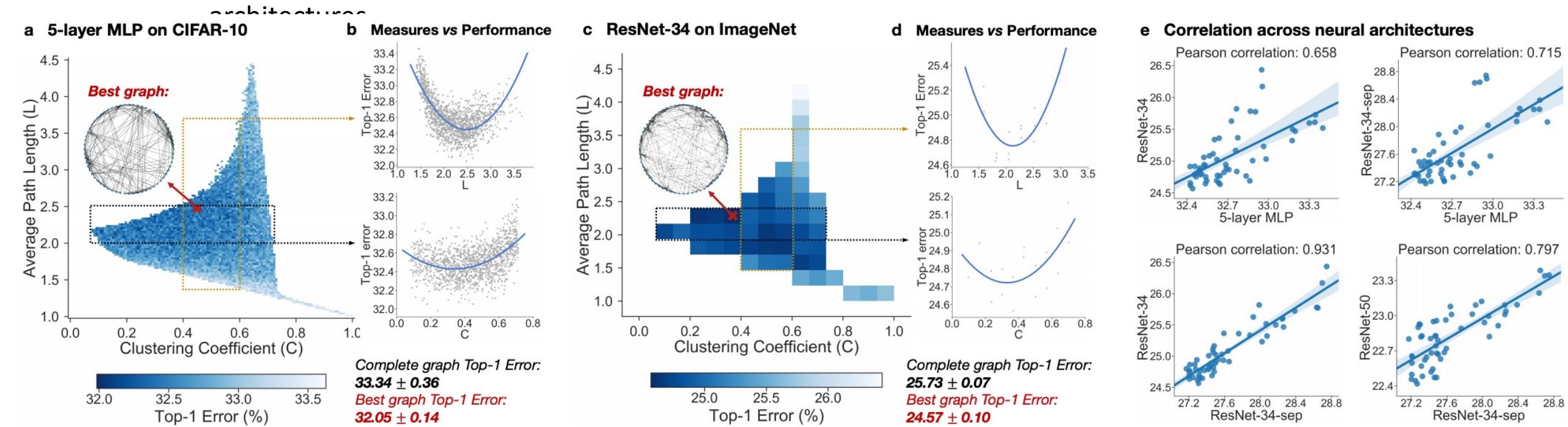


Figure: Key results.

Size Search Space

❑ Model scaling

- Keep the architecture but adjust the size:
 - Depth L
 - Width C
 - And resolution H, W
- Maximize the performance w.r.t. the size.

❑ EfficientNet [Tan et al. 19]

$$\max_{d, w, r} \text{Accuracy}(\mathcal{N}(d, w, r))$$

$$s.t. \quad \mathcal{N}(d, w, r) = \bigodot_{i=1 \dots s} \hat{\mathcal{F}}_i^{d \cdot \hat{L}_i} (X_{(r \cdot \hat{H}_i, r \cdot \hat{W}_i, w \cdot \hat{C}_i)})$$

$$\text{Memory}(\mathcal{N}) \leq \text{target_memory}$$

$$\text{FLOPS}(\mathcal{N}) \leq \text{target_flops}$$

- Compound scaling method: $d = \alpha^\phi, w = \beta^\phi, r = \gamma^\phi$ where $\alpha \times \beta^2 \times \gamma^2 \approx 2, \alpha \geq 1, \beta \geq 1, \gamma \geq 1$.
- Step1: Fix $\phi = 1$ and do a small grid search for α, β, γ . Step2: Fix α, β, γ and scale up ϕ .

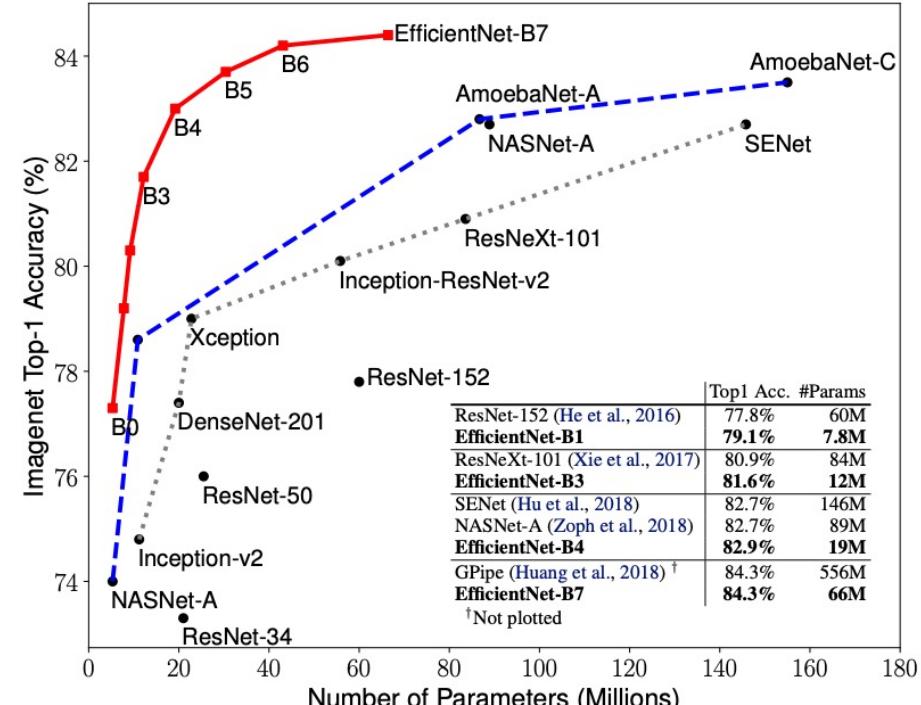


Figure: Model size v.s. ImageNet accuracy.

From CNN/RNN to GNN

❑ Uniqueness in search space

- More dimensions of choices:
 - Micro: mainly aggregation and combine functions.
 - Macro: how node embeddings in each layer produce the final one.
- Nodes are not independent, so how about in a node-wise manner?

$$\mathbf{m}_i^{(l)} = \text{AGG}^{(l)} \left(\left\{ a_{ij}^{(l)} \mathbf{W}^{(l)} \mathbf{h}_i^{(l)}, \forall j \in \mathcal{N}(i) \right\} \right)$$

$$\mathbf{h}_i^{(l+1)} = \sigma \left(\text{COMBINE}^{(l)} \left[\mathbf{m}_i^{(l)}, \mathbf{h}_i^{(l)} \right] \right),$$

Figure: General message passing.

❑ Challenges of weight-sharing one-shot NAS

- Different options lead to quite different output statistics [Zhou et al. 19].

❑ Transfer across datasets and tasks [You et al. 20b]

- Collect 32 (diverse) tasks.
- Use anchor models to calculate task similarities.

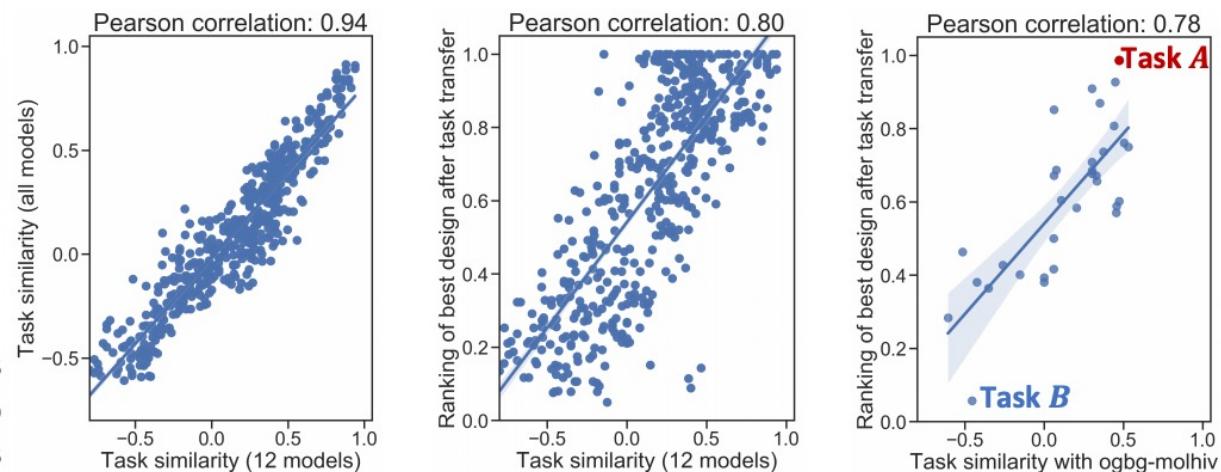


Figure: Comparing the correlations.

Beyond Accuracy: Efficiency and Robustness

□ Making latency differentiable [Cai et al. 19]

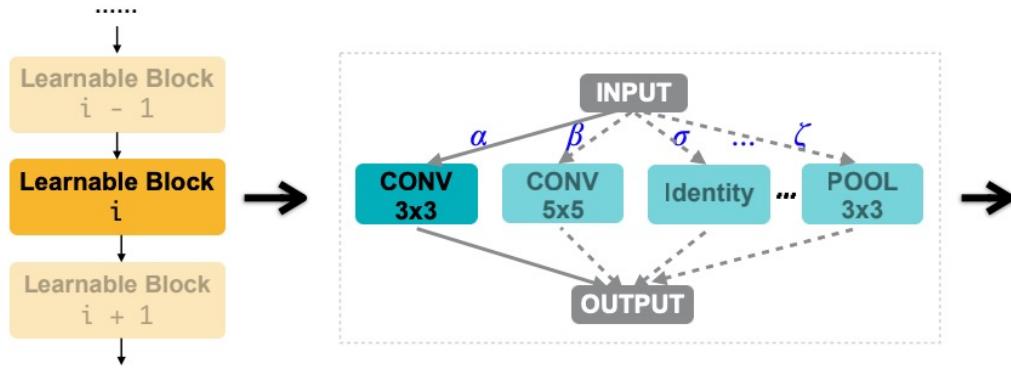


Figure: Introducing latency regularization loss.

□ Searching robust architecture [Guo et al. 20]

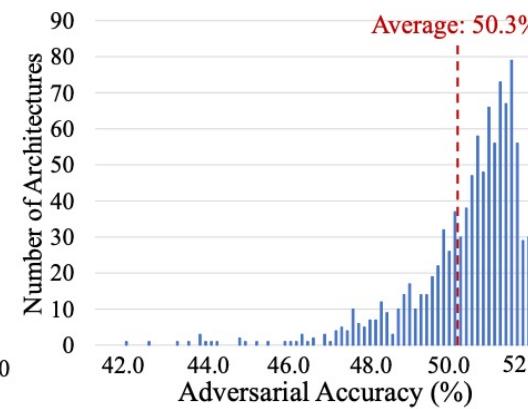
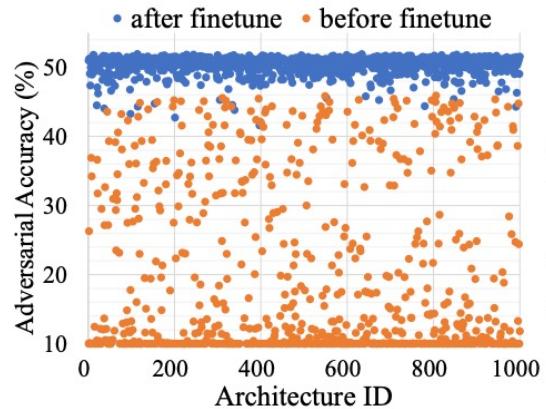


Figure: Performance of 1k sampled architecture.

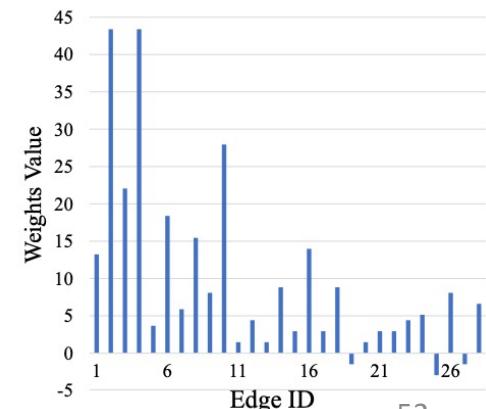
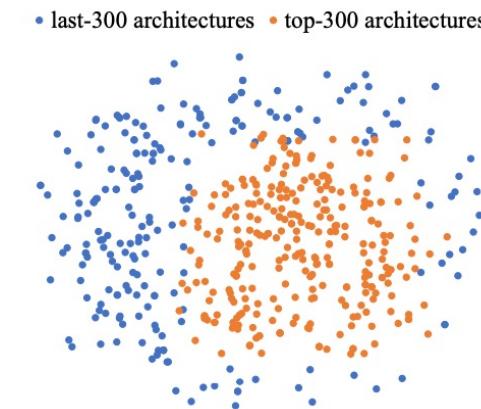
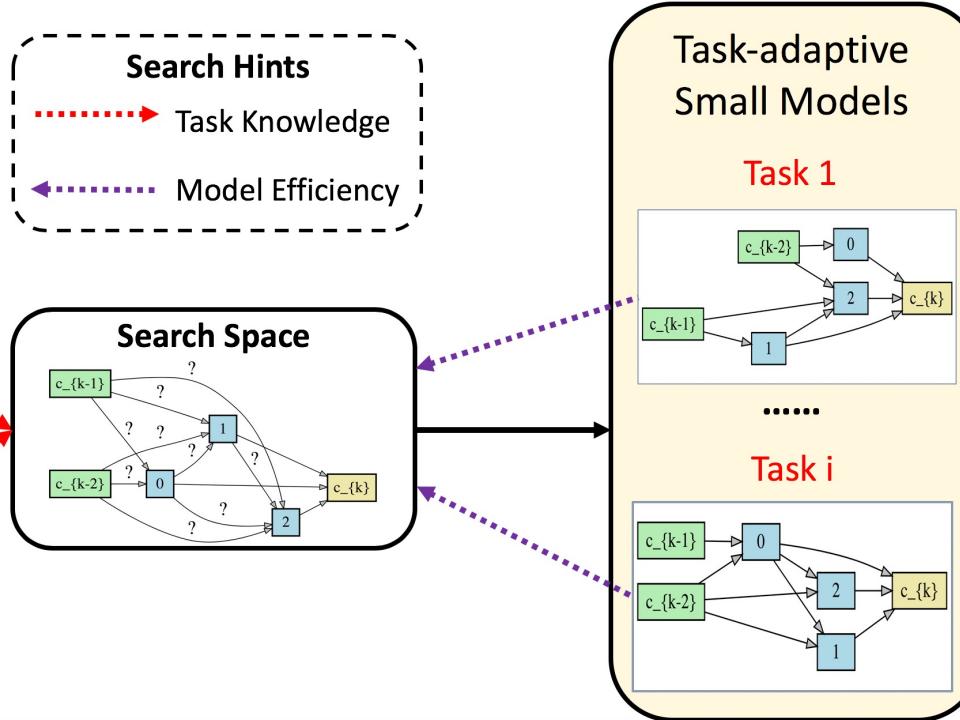


Figure: Analysis of top 300 robust v.s. non-robust architectures.

Beyond Accuracy: Compressed Model Search

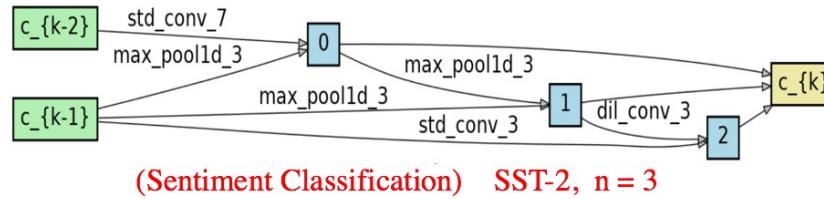
- Pre-trained language model such as BERT achieves great performance on various tasks, but it is difficult to be deployed to real-time applications.
- Can we **task-adaptively** compresses original BERT for different tasks?



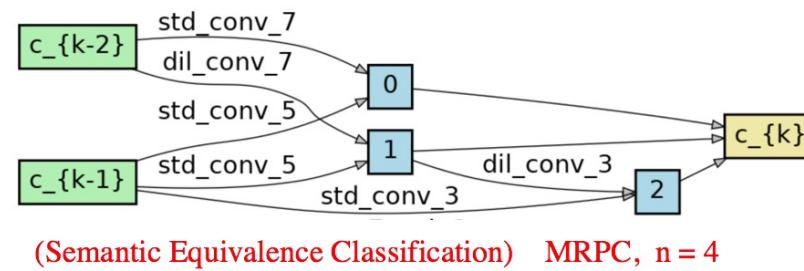
Method	Averaged Performance	Inference Speed
BERT	82.5	1x
BERT-PKD	80.6	1.9x
DistillBERT	76.8	3.0x
TinyBERT	80.6	9.4x
AdaBERT	80.1	12.7x ~ 29.3x

The proposed AdaBERT achieves significant speedup in inference time while maintaining comparable performance compared to uncompressed model.

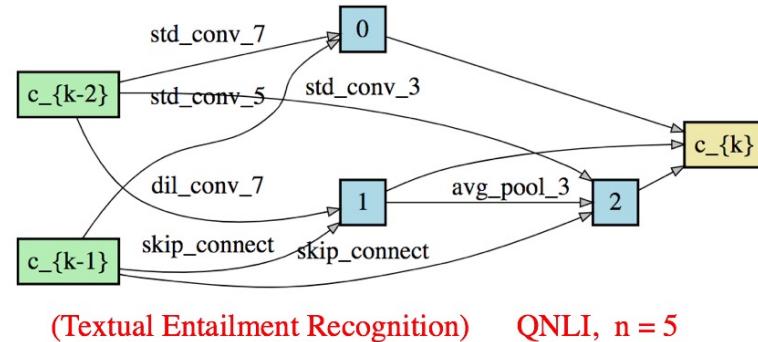
Beyond Accuracy: Compressed Model Search



(Sentiment Classification) SST-2, n = 3



(Semantic Equivalence Classification) MRPC, n = 4



(Textual Entailment Recognition) QNLI, n = 5

Models \ Tasks	SST-2	MRPC	QQP	MNLI	QNLI	RTE
SST-2	91.9	78.1	58.6	63.7	74.1	53.8
MRPC	81.5	84.7	68.9	75.7	82.2	60.3
QQP	81.9	84.1	70.5	76.2	82.5	60.5
MNLI	82.1	81.5	66.8	80.4	86.1	63.2
QNLI	81.6	82.3	67.7	79.1	87.2	62.9
RTE	82.9	81.1	66.5	79.6	86.0	64.1

Table: Performance of searched structures across different tasks

These results demonstrate that the proposed AdaBERT compresses original BERT adaptively for different downstream tasks.

Figure: Searched structures of compressed models for different tasks

NAS Benchmarks

❑ NAS-Bench-101 [Ying et al. 19]

- Provides a lookup table for the 423k architectures.
- Including their train/valid/test accuracies, number of parameters, and training time.

❑ NATS-Bench [Dong et al. 21]

- Search space considers both size and topology factors.

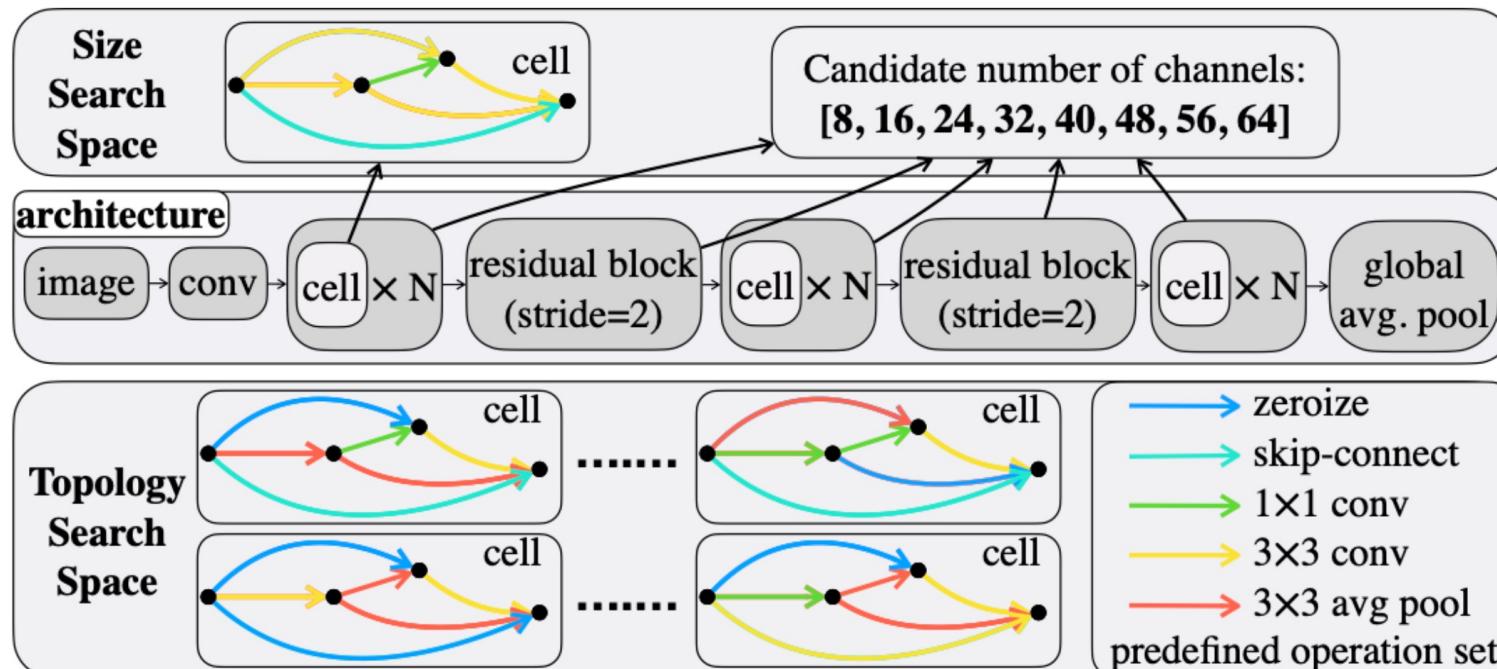


Figure: The search space of NATS-Bench.

NAS Benchmarks

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- Search space considers both size and topology factors.

	#Unique Architectures	#Datasets	Diagnostic Information	Search Space
NAS-Bench-101	423K	1	X	topology
St in NATS-Bench	6.5K	3	fine-grained information	topology
Ss in NATS-Bench	32.8K	3	fine-grained information	size

Figure: Comparison the benchmarks.

Takeaways

❑ Search space

- Layer by layer
- Pre-defined restricted design space
- Pre-defined size

- Repeated normal&reduction cell
- Search for design space
- Also search for optimal size

❑ Search strategy

- Trial-and-error, e.g., RL and ES

- One-shot NAS
- Differentiable (+sampling ops)

❑ Performance estimation strategy

- Stand training&validation
- Single objective

- With weight-sharing
- Multiple objectives

Future Directions

□ Reduce the variance of one-shot NAS

- The interference between child models is a main factor [Zhang et al. 2020].
- E.g., sharing unless some condition(s) are satisfied.

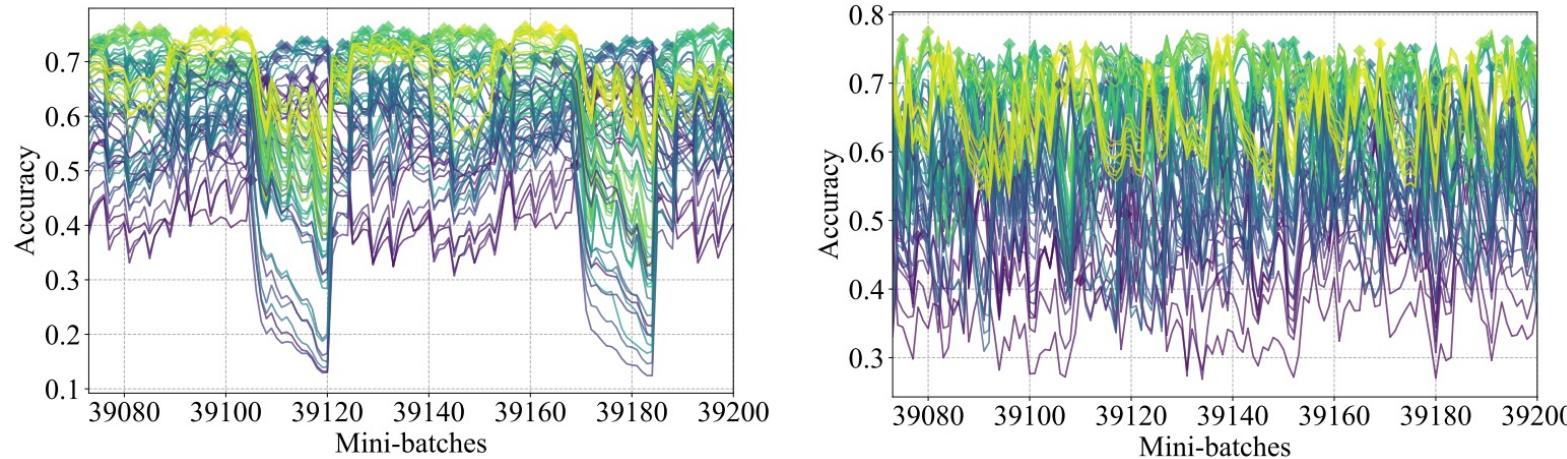
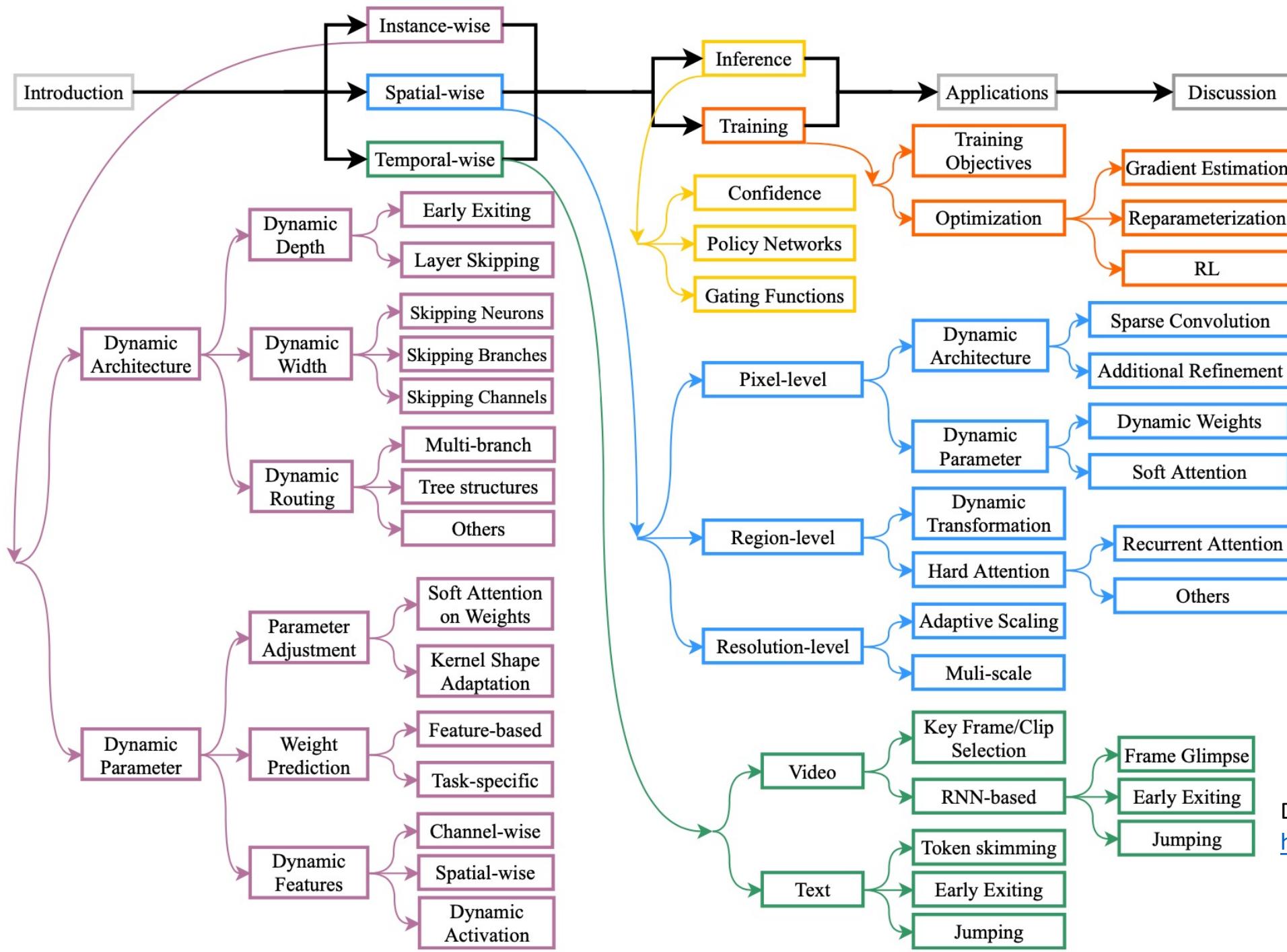


Figure: Validation performance of each child model during the last 120 steps.

□ Select the truly useful architecture

- The magnitude of architecture parameters does not necessarily indicate how much the operation contributes to the supernet's performance [Wang and Cheng et al. 2021].



❑ Beyond NAS: From static to dynamic neural architecture.

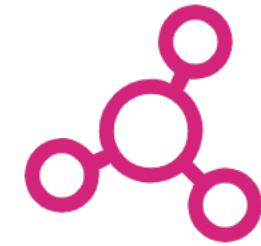
- Fine-grained tuning.
- Mainly focusing on CNNs and efficiency issue now.

Dynamic Neural Networks: A Survey,
<https://arxiv.org/pdf/2102.04906.pdf>

References of NAS

- [Zoph et al. 2017] Neural Architecture Search with Reinforcement Learning. ICLR. 2017.
- [Zoph et al. 2018] Learning Transferable Architectures for Scalable Image Recognition. CVPR. 2018.
- [Bender et al. 2018] Understanding and Simplifying One-Shot Architecture Search. ICML. 2018.
- [Zhang et al. 2020] Deeper Insights into Weight Sharing in Neural Architecture Search. arXiv. 2020.
- [Li et al. 2021] Geometry-aware Gradient Algorithms for Neural Architecture Search. ICLR. 2021.
- [Xie et al. 2019] Exploring Randomly Wired Neural Networks for Image Recognition. ICCV. 2019.
- [Radosavovic et al. 2020] Designing Network Design Spaces. CVPR. 2020.
- [You et al. 2020a] Graph Structure of Neural Networks. ICML. 2020a.
- [Zhou et al. 2019] Auto-GNN: Neural Architecture Search of Graph Neural Networks. Arxiv. 2019.
- [You et al. 2020b] Design Space for Graph Neural Networks. NeurIPS. 2020b.
- [Cai et al. 2019] ProxylessNAS: Direct Neural Architecture Search on Target Task and Hardware. ICLR. 2019.
- [Guo et al. 2020] When NAS Meets Robustness: In Search of Robust Architectures against Adversarial Attacks. CVPR. 2020.
- [Ying et al. 2019] NAS-Bench-101: Towards Reproducible Neural Architecture Search. ICML. 2019.
- [Dong et al. 2021] NATS-Bench: Benchmarking NAS Algorithms for Architecture Topology and Size. TPAMI. 2021.
- [Tan et al. 2019] EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. ICML. 2019.
- [Wang and Cheng et al. 2021] Rethinking Architecture Selection in Differentiable NAS. ICLR. 2021.

Meta-Learning



Meta-learning

□ What is meta-learning?

- Training on a meta-dataset consisting of many datasets, where each is a different task.
- Extract prior knowledge from it that accelerates the learning of new tasks.



Figure: Example of how meta-learning works (source: https://cs330.stanford.edu/slides/cs330_metalearning_bbox_2020.pdf).

When Meta-learning Meets AutoML

□ AutoML as a service

- What if users do not have a large dataset for training a deep model?
- What if users want to quickly learn a new task?

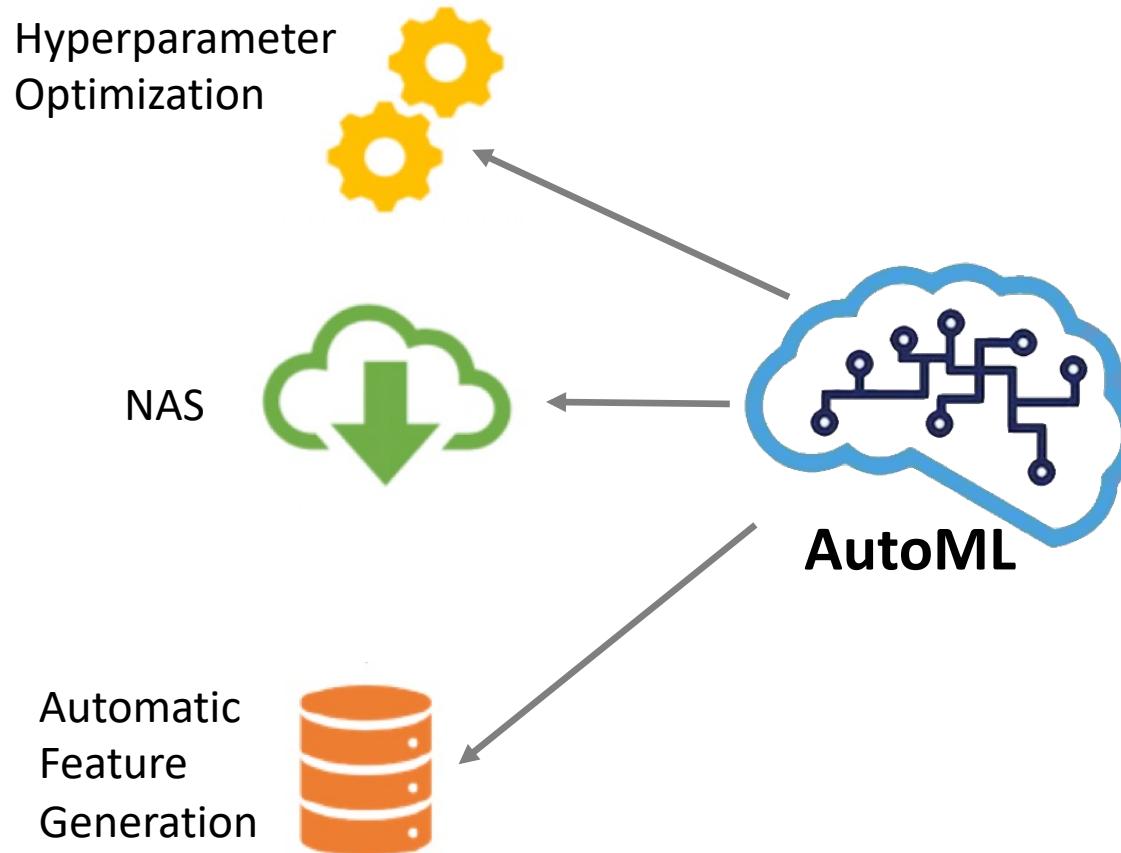


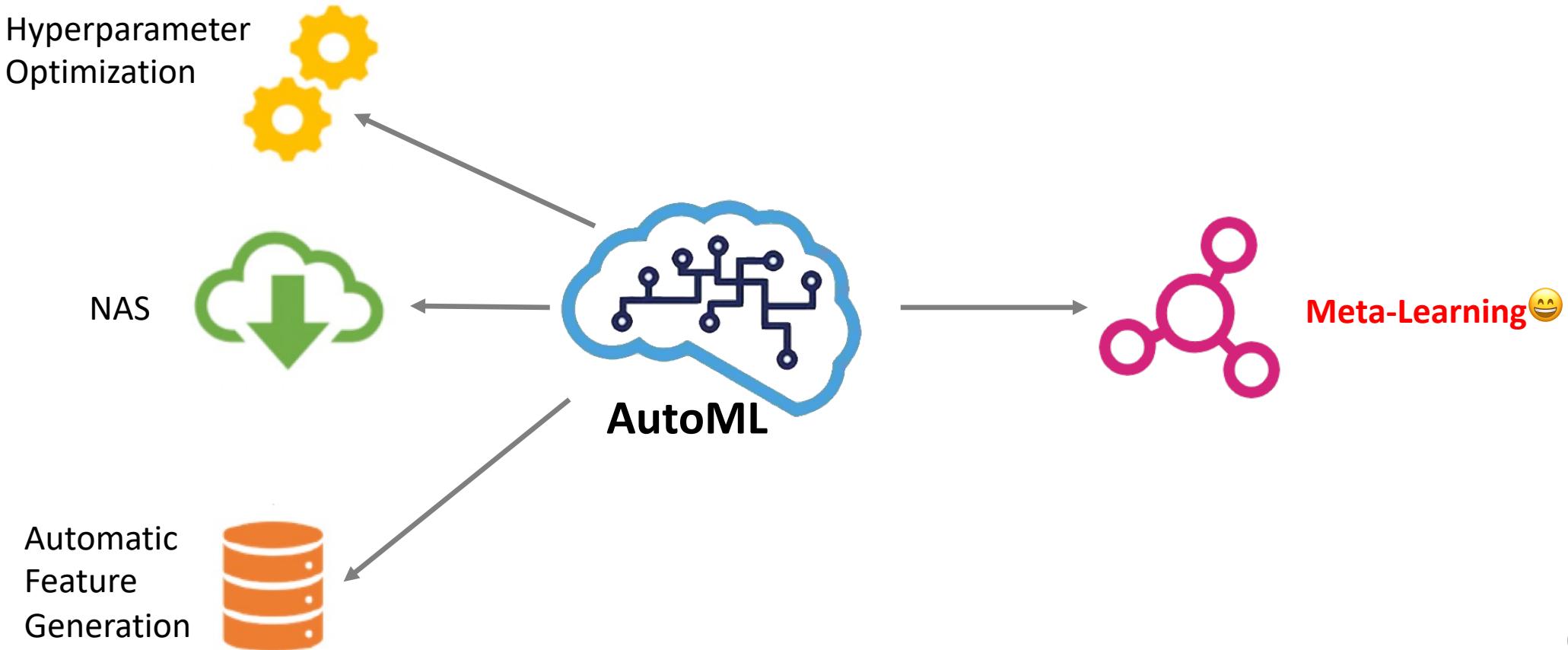
Figure: The distribution of the scales of datasets. (source: <https://cs330.stanford.edu/>).



When Meta-learning Meets AutoML

❑ AutoML as a service

- Assume different tasks share some common principles.
- Can we exploit the cumulated experience?



Meta-learning Basics

❑ Exploit the meta-dataset

- Conventional ML: $\arg \max_{\phi} \log p(\phi | \mathcal{D})$
- Meta-learning: $\arg \max_{\phi} \log p(\phi | \mathcal{D}, \mathcal{D}_{\text{meta-train}})$

❑ Replace the meta-dataset by meta-parameters

- Sufficient to represent the meta-dataset.

learn *meta-parameters* θ : $p(\theta | \mathcal{D}_{\text{meta-train}})$

whatever we need to know about $\mathcal{D}_{\text{meta-train}}$ to solve new tasks

$$\begin{aligned}\log p(\phi | \mathcal{D}, \mathcal{D}_{\text{meta-train}}) &= \log \int_{\Theta} p(\phi | \mathcal{D}, \theta) p(\theta | \mathcal{D}_{\text{meta-train}}) d\theta \\ &\approx \log p(\phi | \mathcal{D}, \theta^*) + \log p(\theta^* | \mathcal{D}_{\text{meta-train}})\end{aligned}$$

$$\arg \max_{\phi} \log p(\phi | \mathcal{D}, \mathcal{D}_{\text{meta-train}}) \approx \arg \max_{\phi} \log p(\phi | \mathcal{D}, \theta^*)$$

this is the meta-learning problem

assume $\phi \perp\!\!\!\perp \mathcal{D}_{\text{meta-train}} | \theta$

$$\theta^* = \arg \max_{\theta} \log p(\theta | \mathcal{D}_{\text{meta-train}})$$

this is the adaptation problem

Optimization-based Meta-learning

□ Adaptation problem

- Acquire ϕ_i via optimization $\phi_i = \operatorname{argmax}_\phi \log p(D_i^{tr}|\phi) + \log p(\phi|\theta)$.
- θ serves as a prior.

□ Which form of prior to take?

- Initialization and fine-tuning!

Fine-tuning
$$\phi \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}^{tr})$$
 pre-trained parameters
 training data for new task
 (typically for many gradient steps)

Meta-learning
$$\min_{\theta} \sum_{\text{task } i} \mathcal{L}(\theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{tr}), \mathcal{D}_i^{\text{ts}})$$

$$\begin{aligned} g_{\text{MAML}} &= \bar{g}_2 - \alpha \bar{H}_2 \bar{g}_1 - \alpha \bar{H}_1 \bar{g}_2 + O(\alpha^2) \\ g_{\text{FOMAML}} = g_2 &= \bar{g}_2 - \alpha \bar{H}_2 \bar{g}_1 + O(\alpha^2) \\ g_{\text{Reptile}} = g_1 + g_2 &= \bar{g}_1 + \bar{g}_2 - \alpha \bar{H}_2 \bar{g}_1 + O(\alpha^2) \end{aligned}$$

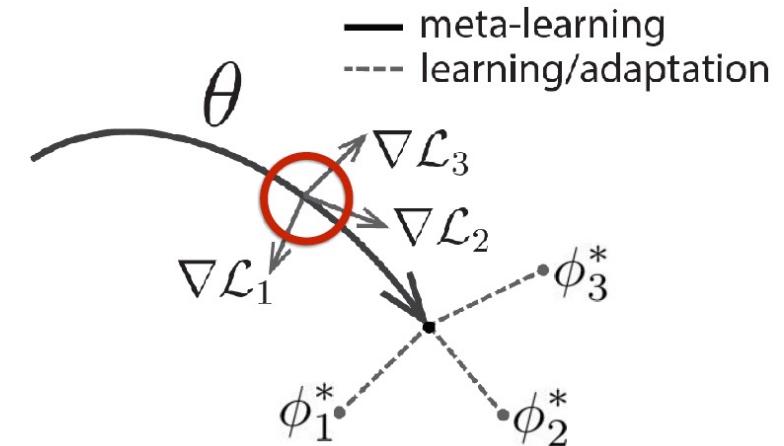


Figure: Illustrating the idea of optimization-based meta-learning (source: <https://arxiv.org/pdf/1703.03400.pdf>).

Where $g_i = \frac{\partial}{\partial \theta_i} L(\theta_i, D^{tr})$, $\bar{g}_i = \frac{\partial}{\partial \theta_1} L(\theta_i, D^{tr})$,
 $\bar{H}_i = \frac{\partial}{\partial \theta_1} \bar{g}_i$ (Hessian w.r.t. θ_1)

Optimization-based Meta-learning

❑ Probabilistic interpretation

- Maximize a posterior (MAP) with θ as the prior.

❑ MAML [Finn et al. 17] approximates hierarchical Bayesian inference!

- Gradient descent with early stop = MAP inference under Gaussian prior with mean at initial parameters.
- Other forms, e.g.,

$$\phi \leftarrow \min_{\phi'} \mathcal{L}(\phi', \mathcal{D}^{\text{tr}}) + \frac{\lambda}{2} \|\theta - \phi'\|^2$$

😊 Model-agnostic

😊 Maximally expressive with sufficiently deep neural networks

😢 Typically requires second-order computation/memory intensive

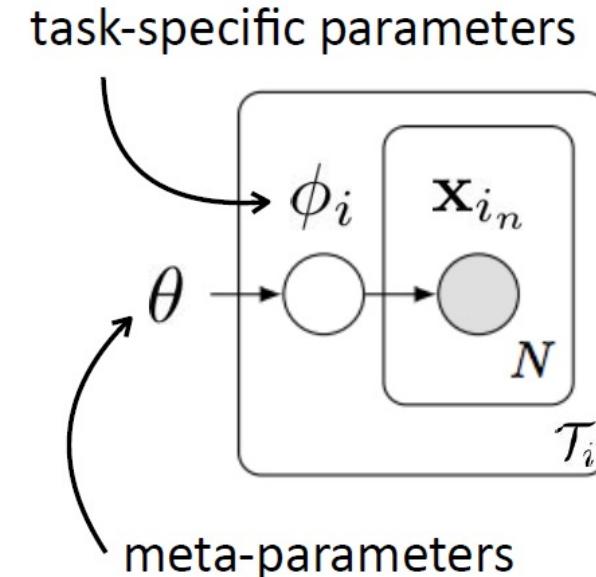


Figure: Probabilistic interpretation of optimization-based meta-learning (source: <https://cs330.stanford.edu/>).

Model-based Meta-learning

□ Adaptation problem

- From solving optimization problem to black-box adaptation $\phi_i = f_\theta(D_i^{tr}) = \text{argmax}_\phi \log p(\phi|D_i^{tr}, \theta)$
- Train a neural networks to represent $p(\phi_i|D_i^{tr}, \theta)$
 - E.g., RNN, Neural Turing Machine, memory-augmented NN [Santoro et al. 16], etc.

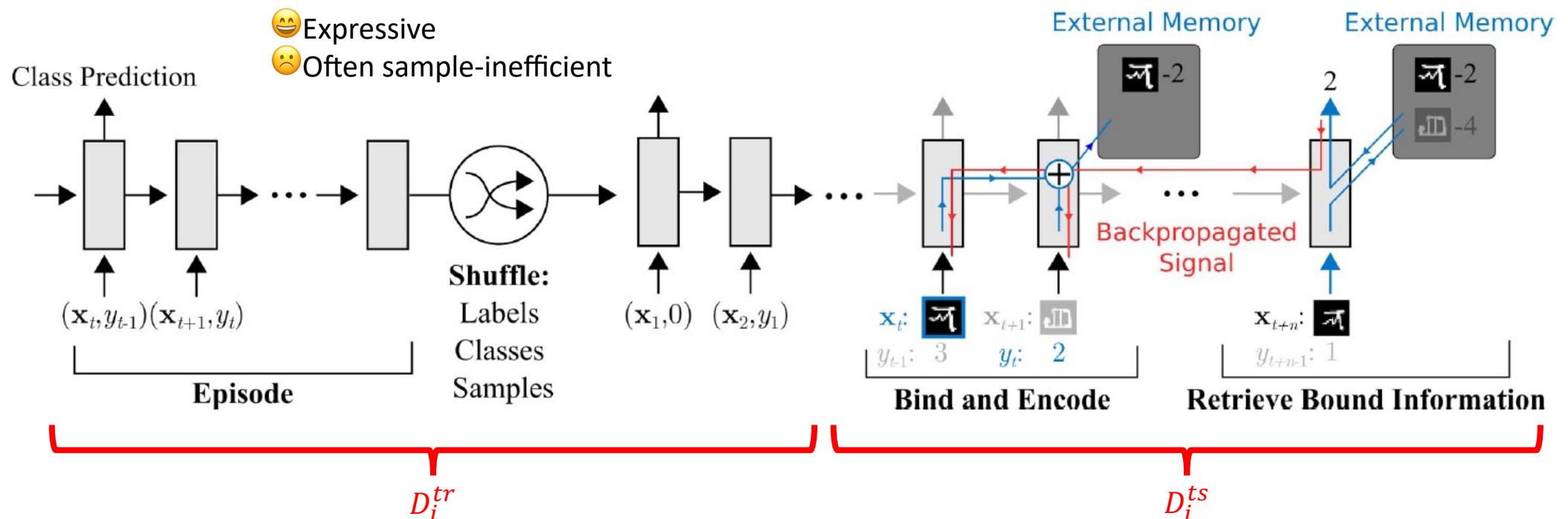
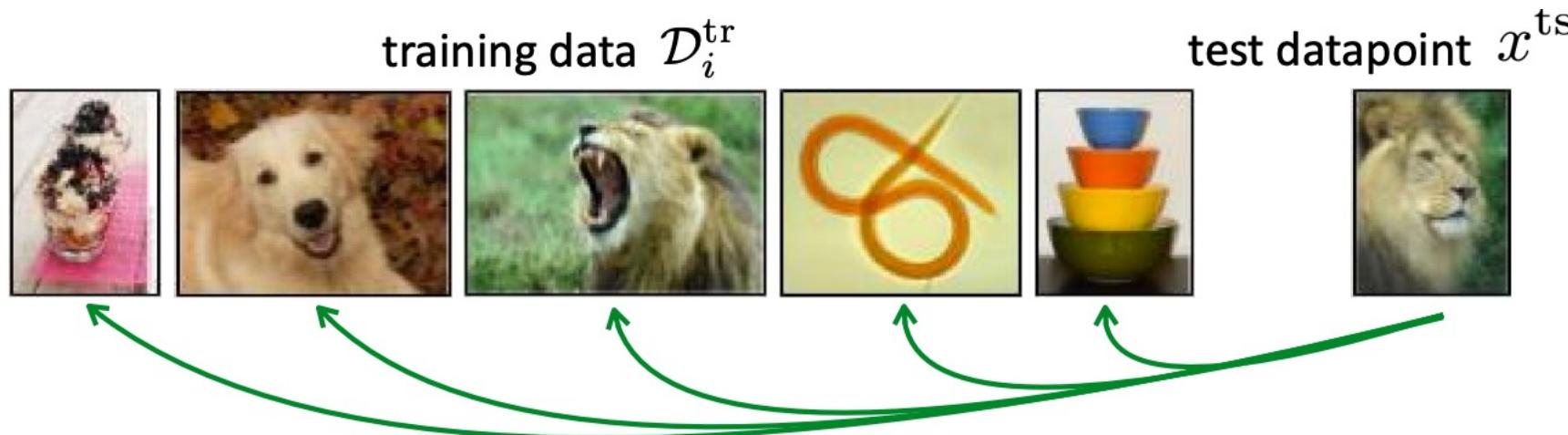


Figure: Memory-augmented neural networks (source: <https://proceedings.mlr.press/v48/santoro16.pdf>).

Metric-based Meta-learning

- ❑ Use Non-parametric learner



In what space do you compare? With what distance metric?

~~pixel space, ℓ_2 distance?~~

Learn to compare using meta-training data!

- 😊 Entirely feedforward
- 😊 Easy to optimize
- 😢 Harder to generalize to varying k-ways (especially for very large k)

Figure: The idea of metric-based meta-learning (source: https://cs330.stanford.edu/slides/cs330_nonparametric_2020.pdf).

Metric-based Meta-learning

□ Use Siamese neural networks

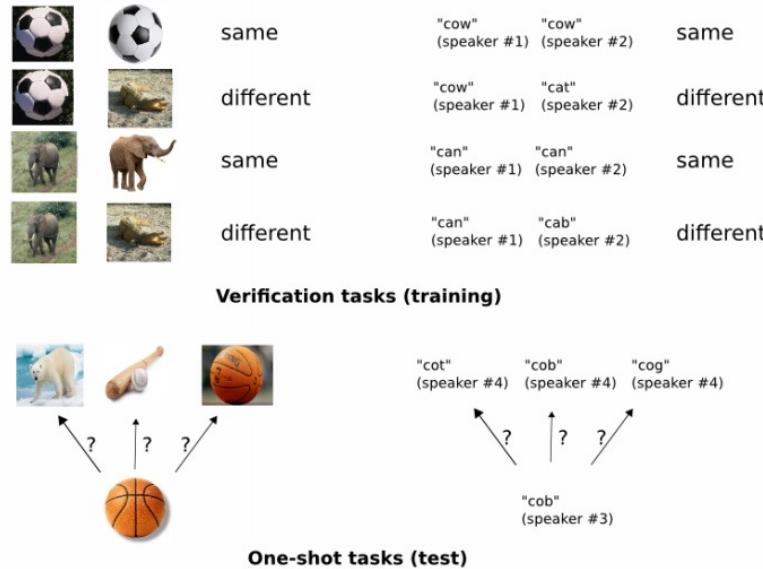
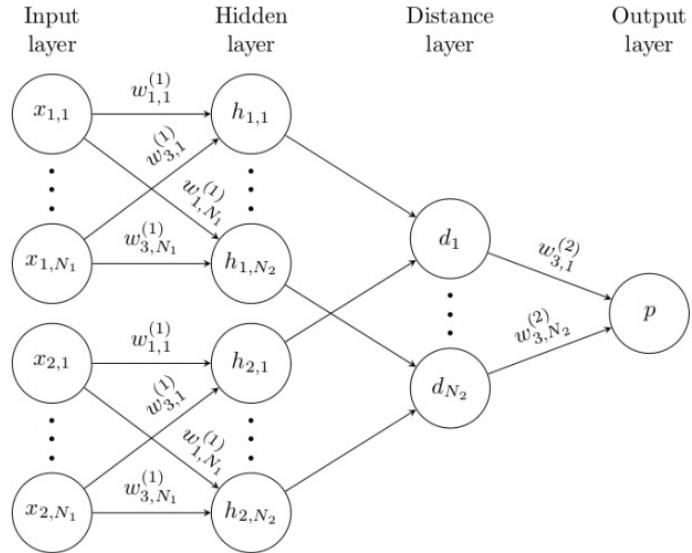


Figure: Architecture of Siamese neural networks and its application to one-shot learning.

- Meta-training: binary classification.
- Meta-test: k-way classification.

Metric-based Meta-learning

□ Match the train&test phases by Matching networks

- Fix the mismatch between meta-training and meta-test.
- Map a (support) set $S = \{(x_i, y_i)\}$ to a classifier:

$$P(\hat{y}|\hat{x}, S) = \sum_{i=1}^k a(\hat{x}, x_i) y_i$$

- The attention mechanism $a(\cdot, \cdot)$ fully specifies the classifier.

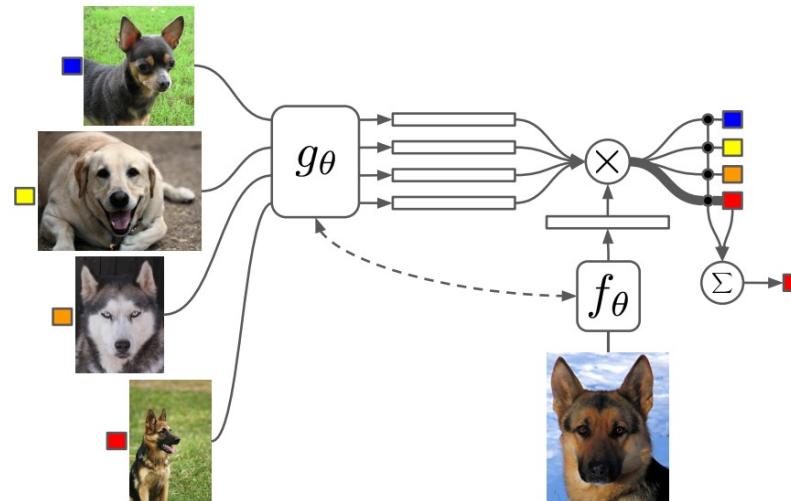


Figure: Architecture of Matching network.

GPT-3: meta-learning as pre-training

❑ What's the meta-dataset?

- Crawled text corpora.
- D_i^{tr} : sequence of characters, D_i^{ts} : the following sequence of characters.

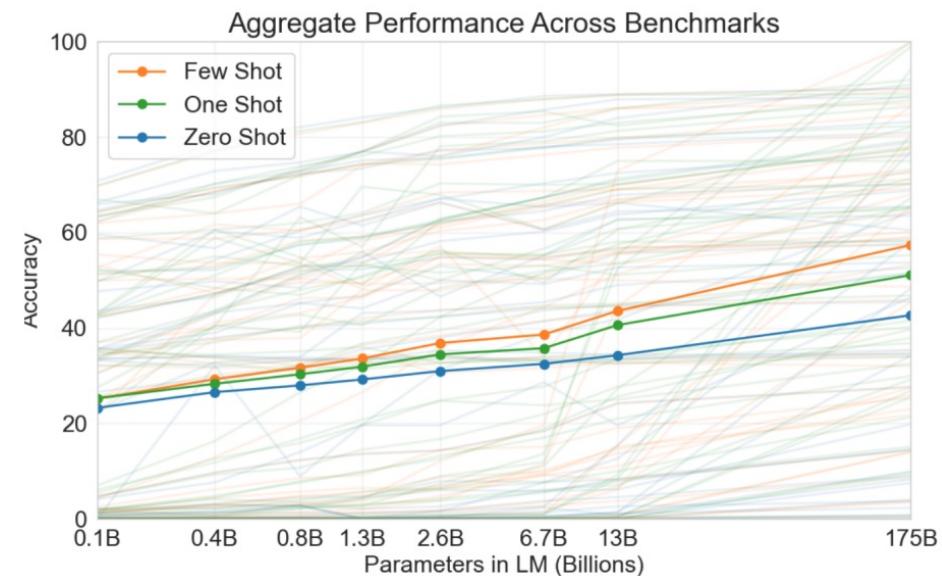
❑ What's the meta-learning problem?

- Put different tasks all in the form of text.
- Thus trained on language generation tasks.

❑ What's the extracted prior knowledge?

- A “Transformer” model as the initialization.

Figure: The model is far from perfect (source: <https://github.com/shreyashankar/gpt3-sandbox/blob/master/docs/priming.md>).



Generalization v.s. Customization

☐ Key assumption of meta-learning

- Meta-training and meta-test tasks are drawn i.i.d. from the same task distribution.
 - E.g., Omniglot:
 - 1623 characters from 50 different alphabets.
 - 20 instances for each character.

Hebrew					
וּ	כְּ	בְּ	לְ	כְּ	בְּ
לְ	אֵ	יְ	הָ	מְ	אֵ
לְ	חָ	גָּ	לְ	אָ	לְ
לְ	לָ	לְ	לְ	לְ	לְ
בְּ	רְ				

Greek					
Ψ	Λ	Β	Δ	Ζ	Λ
Η	Α	Κ	Χ	Υ	Υ
Ω	Θ	Υ	Ι	Ω	Ω
Ω	Π	Η	Ο	Ε	Ε
Ρ	Ξ	Ζ	Ψ		

• • •

Figure: Characters of different alphabets (source: <https://omniglot.com/>).

Generalization v.s. Customization

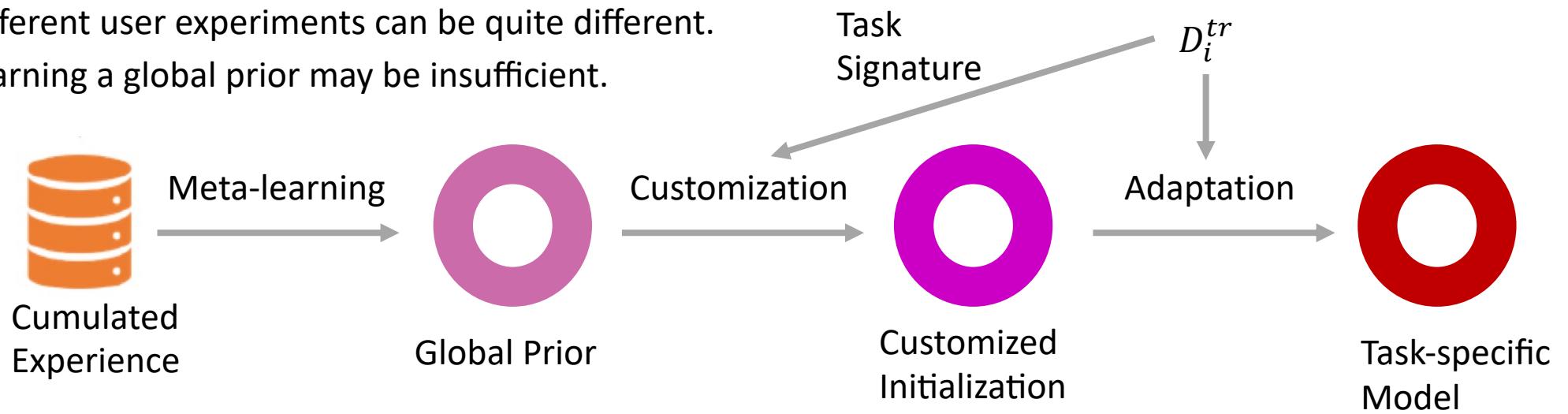
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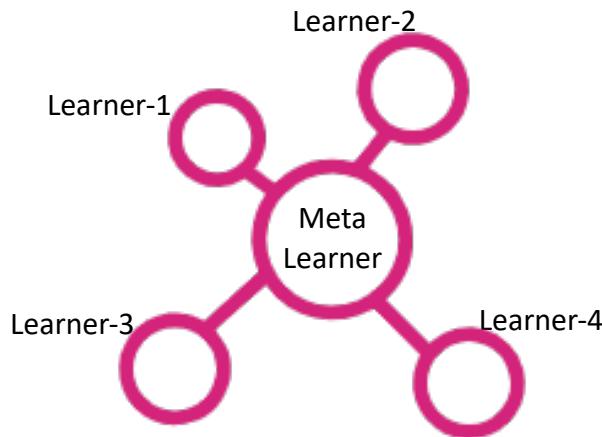
:(Can NOT be strictly satisfied!

❑ Experience cumulated on the cloud

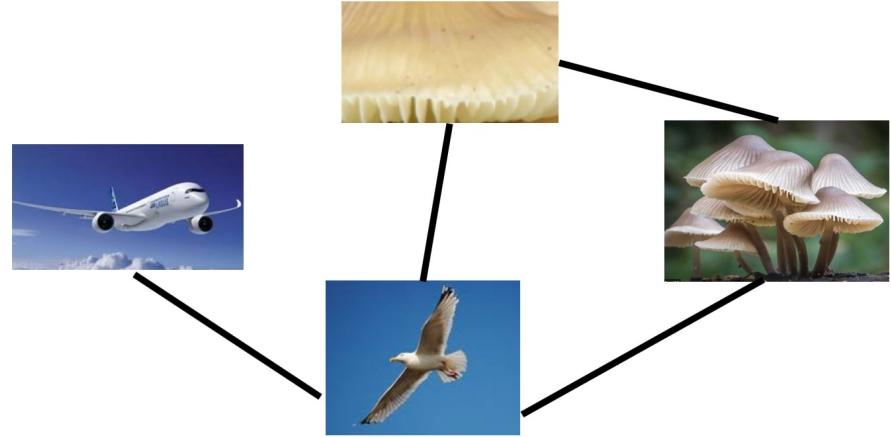
- Different user experiments can be quite different.
- Learning a global prior may be insufficient.



Relational Meta-Learning



Most Meta-learning methods don't capture the relations among tasks/learners.



Algorithms	Data: Bird	Data: Texture	Data: Aircraft	Data: Fungi
MAML	$53.94 \pm 1.45\%$	$31.66 \pm 1.31\%$	$51.37 \pm 1.38\%$	$42.12 \pm 1.36\%$
MetaSGD	$55.58 \pm 1.43\%$	$32.38 \pm 1.32\%$	$52.99 \pm 1.36\%$	$41.74 \pm 1.34\%$
MT-Net	$58.72 \pm 1.43\%$	$32.80 \pm 1.35\%$	$47.72 \pm 1.46\%$	$43.11 \pm 1.42\%$
MUMOMAML	$56.82 \pm 1.49\%$	$33.81 \pm 1.36\%$	$53.14 \pm 1.39\%$	$42.22 \pm 1.40\%$
HSML	$60.98 \pm 1.50\%$	$35.01 \pm 1.36\%$	$57.38 \pm 1.40\%$	$44.02 \pm 1.39\%$
ProtoNet	$54.11 \pm 1.38\%$	$32.52 \pm 1.28\%$	$50.63 \pm 1.35\%$	$41.05 \pm 1.37\%$
TADAM	$56.58 \pm 1.34\%$	$33.34 \pm 1.27\%$	$53.24 \pm 1.33\%$	$43.06 \pm 1.33\%$
ARML	$62.33 \pm 1.47\%$	$35.65 \pm 1.40\%$	$58.56 \pm 1.41\%$	$44.82 \pm 1.38\%$

The proposed relational meta-learning method can capture the relations among different tasks, which enhances the effectiveness of meta-learners.

Summary and Future Directions

❑ How to utilize existing experience---meta-learning

- Learn a meta-parameter, so that we can quickly transfer to new task.
- Optimization-based, model-based, metric-based

❑ What if tasks are heterogeneous?

- Trade-off between generalization v.s. customization

❑ Use meta-learning for improving real-world services

- AutoML as a service has cumulated a lot of experience.
- Learning tasks on different domains and/or with different models share some intrinsic patterns of machine learning.
- What kinds of features are transferable? How to represent a task, a model, and a objective?

References of Meta-learning

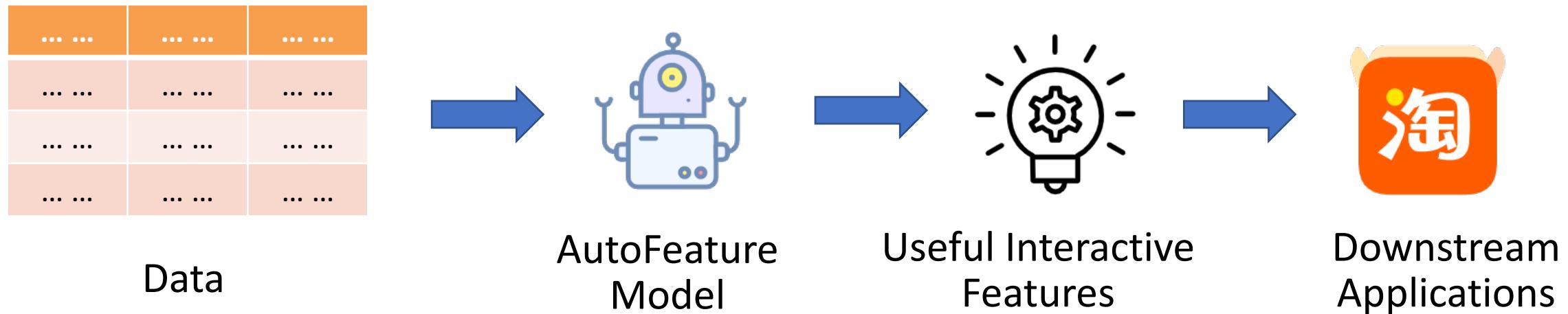
- [Santoro et al. 2016] Meta-Learning with Memory-Augmented Neural Networks. ICML. 2016.
- [Finn et al. 2017] Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. ICML. 2017.
- [Nichol et al. 2018] On First-Order Meta-Learning Algorithm. arXiv. 2018.
- [Koch et al. 2015] Siamese Neural Networks for One-shot Image Recognition. ICML. 2015.
- [Vinyals et al. 2016] Matching Networks for One Shot Learning. NeurIPS. 2016.

Auto Feature Generation



Automatic Feature Generation

- In practice, many data scientists search for useful interactive features in a trial-and-error manner, which has occupied a lot of their workloads.
- Therefore, automatic feature generation (AutoFeature), as one major topic of automated machine learning (AutoML), has received a lot of attention from both academia and industry.



Automatic Feature Generation

Feature Interpretability



- Industries such as healthcare and finance need interpretability
- Can be applied to train lightweight models for real-time requirement

Search Efficiency



- The number of possible interactive features is too large to be traversed ($O(2^m)$ for m original features)

Automatic Feature Generation

□ The related works on automatic feature generation can be roughly divided into two categories:

- DNN-based methods
- Search-based methods

DNN-based methods design specific neural architectures to express the interactions among different features.

- Implicit feature generation
- One-shot training course
- Lack of interpretable rules for feature interactions

Search-based methods focus on designing different search strategies that prune as much of the candidates to be evaluated as possible, while aiming to keep the most useful interactive features.

- Explicit feature generation
- Trial-and-error training manner
- Need lots of time and computing resource

AutoInt

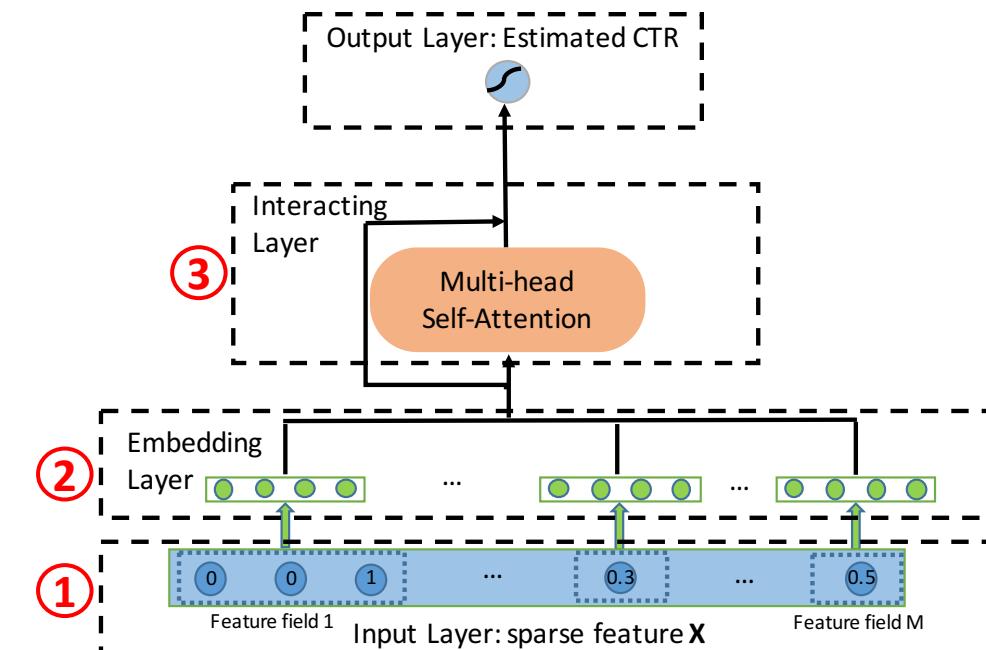
- Map the original features into low-dimensional feature space and model the high-order feature interactions via self-attention.

① Input Layer:

Each feature field is represented as an one-hot vector (for categorical feature) or a scalar value (for numerical feature).

② Embedding Layer:

To transform the sparse and high-dimension features into a low-dimensional feature space via a learnable embedding matrix.



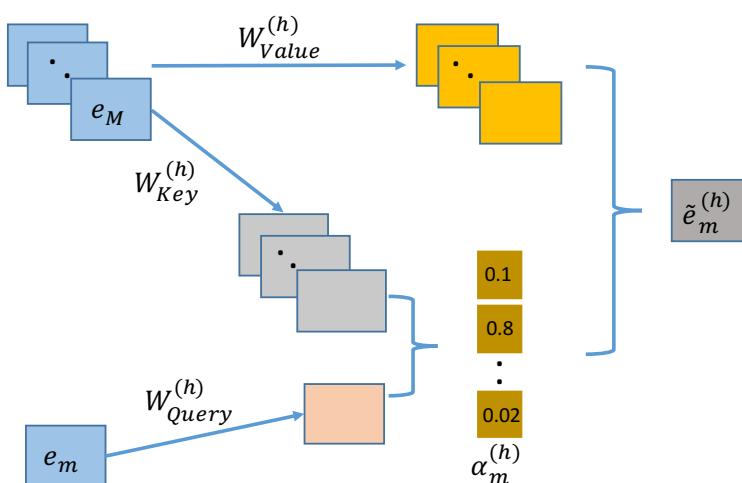
Overview of the proposed model AutoInt.

AutoInt

- Map the original features into low-dimensional feature space and model the high-order feature interactions via self-attention.

③ Interacting Layer:

- The multi-head key-value attention mechanism is adopted to capture the interactions between different features.

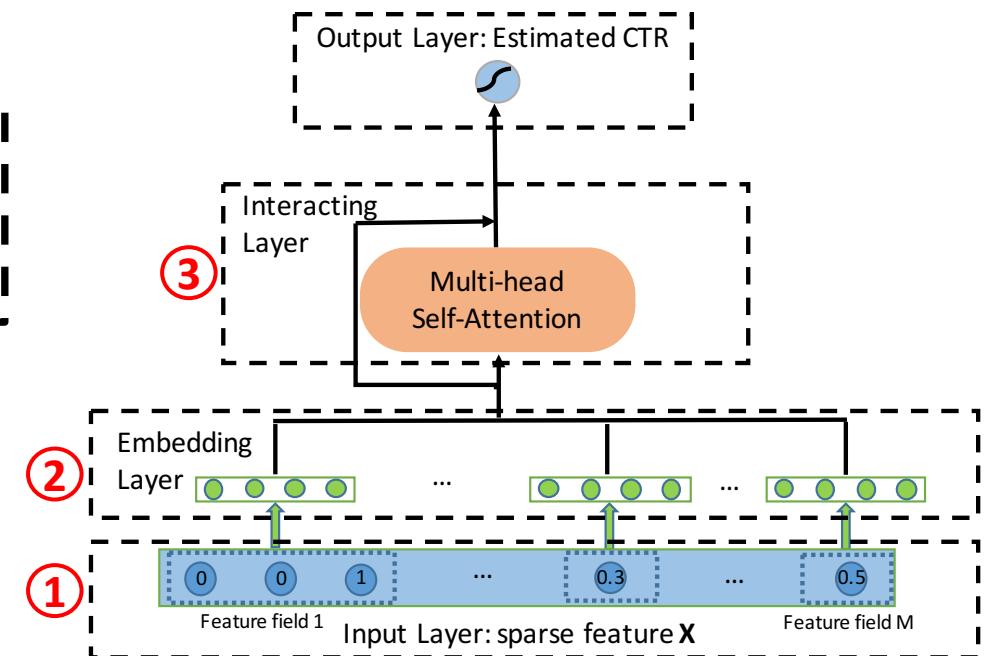


$$\alpha_{m,k}^{(h)} = \frac{\exp(\psi^{(h)}(e_m, e_k))}{\sum_{l=1}^M \exp(\psi^{(h)}(e_m, e_l))},$$

$$\psi^{(h)}(e_m, e_k) = \langle W_{\text{Query}}^{(h)} e_m, W_{\text{Key}}^{(h)} e_k \rangle,$$

$$\tilde{e}_m^{(h)} = \sum_{k=1}^M \alpha_{m,k}^{(h)} (W_{\text{Value}}^{(h)} e_k),$$

The architecture of interacting layer.

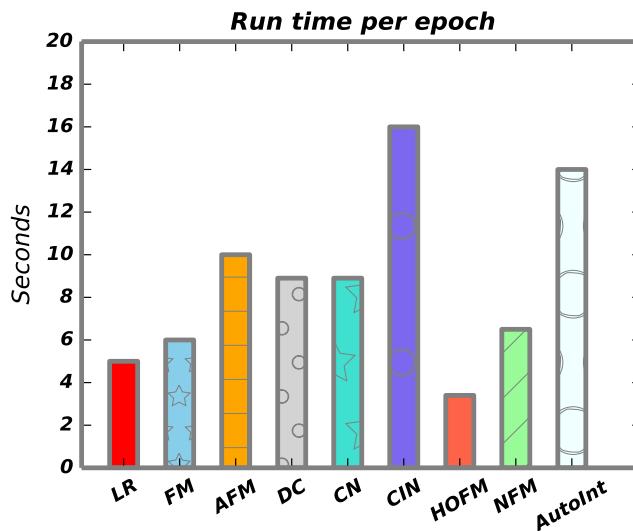


Overview of the proposed model AutoInt.

AutoInt

□ Experimental results on four real-world datasets show the advantages of AutoInt

- Performance comparison in offline AUC evaluation for click-through rate (CTR) prediction
- Efficiency comparison
- Explainable recommendations



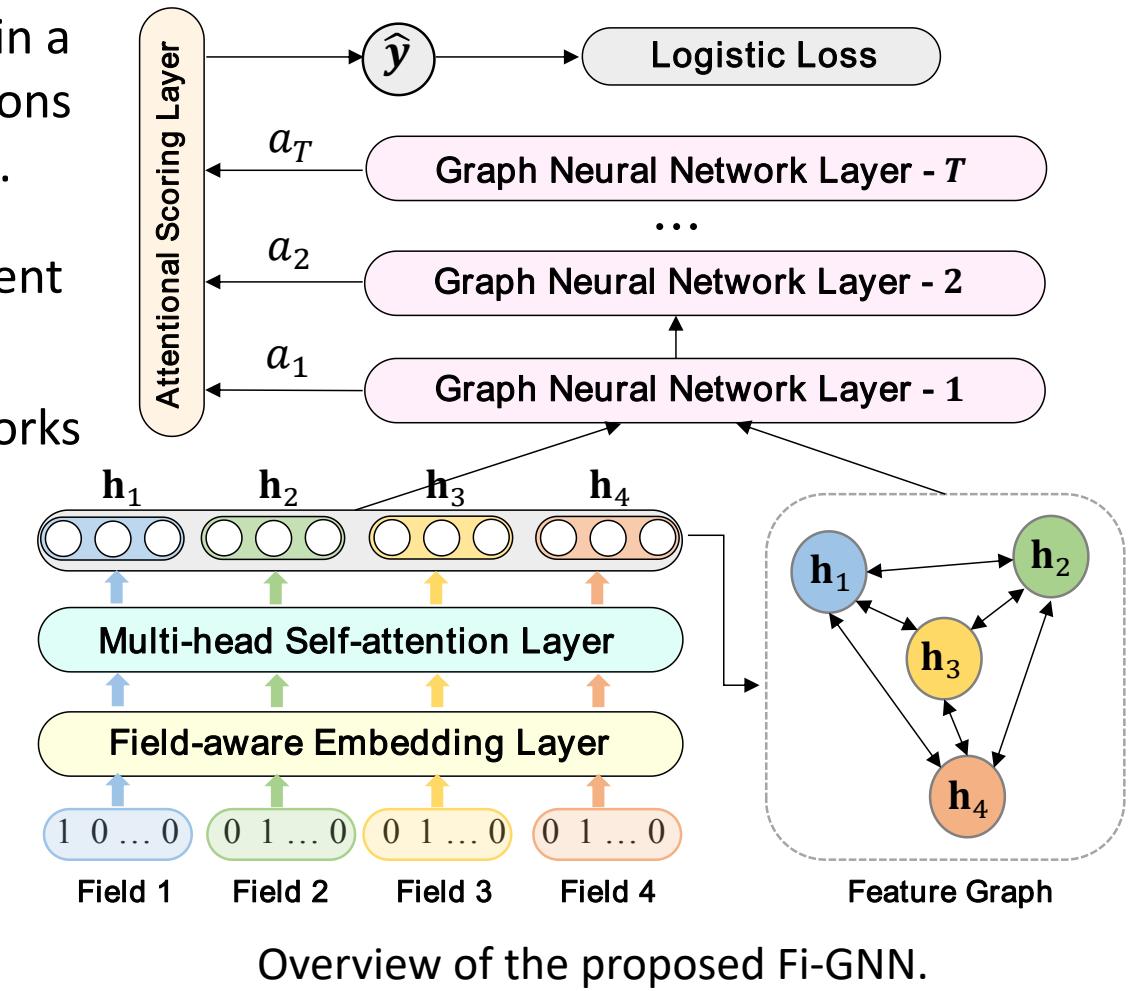
Efficiency comparison on *MovieLens-1M*.



An instance of attention weights for feature interactions on *MovieLens-1M*.

Fi-GNN

- Fi-GNN proposes to represent multi-field features in a graph structure, and captures the feature interactions through node representation learning in the graph.
- Feature interaction via a graph view: nodes represent features and edges denote their interactions
- Model feature interactions via Graph Neural Networks (GNN)
- Attentional scoring for predictions



Overview of the proposed Fi-GNN.

Fi-GNN

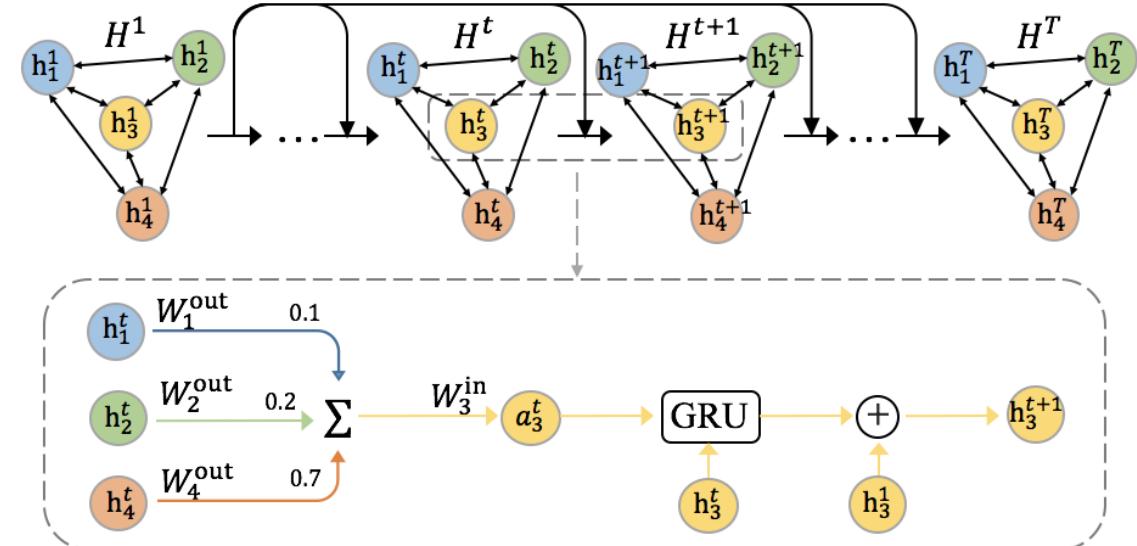
- Feature interaction in Fi-GNN: The nodes interact with neighbors and update their states in a recurrent fashion.

Feature Graph:

The edge weights reflect the importance of interactions between the connected nodes (features), which are learned via an attention mechanism.

Node Aggregation:

The node aggregates the transformed information from neighbors and update its state according to the aggregated information and history via GRU and residual connection.

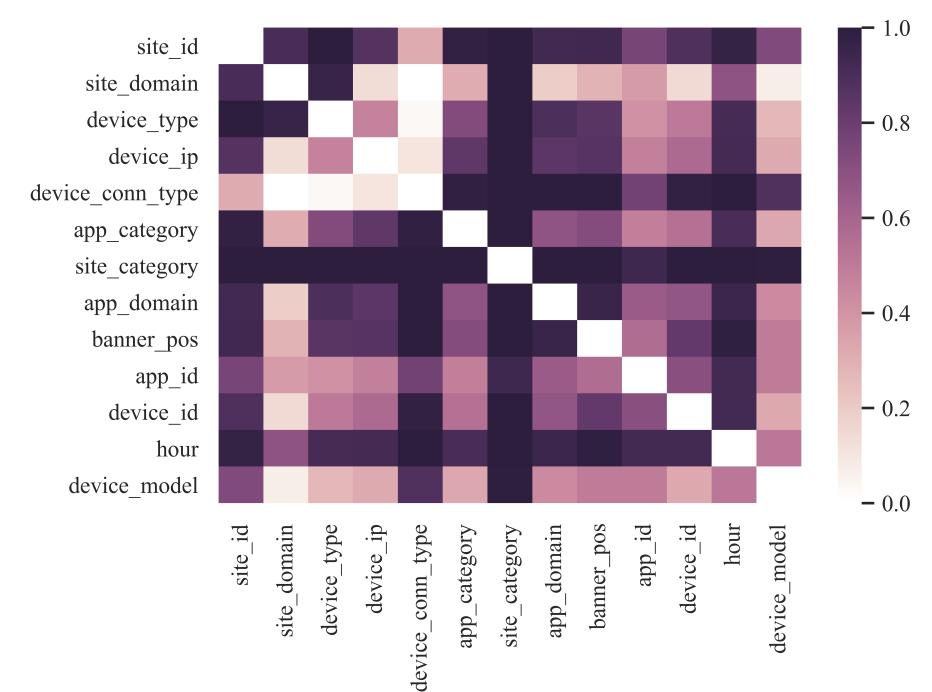


Fi-GNN

- Taking advantage of the strong representative power of graphs, Fi-GNN captures high-order feature interaction in an efficient way.
- Fi-GNN also provides good model explanations for CTR prediction.

Model Type	Model	Criteo			
		AUC	RI-AUC	Logloss	RI-Logloss
First-order	LR	0.7820	3.00%	0.4695	5.43%
Second-order	FM [23]	0.7836	2.80%	0.4700	5.55%
	AFM[34]	0.7938	1.54%	0.4584	2.94%
High-order	DeepCrossing [25]	0.8009	0.66%	0.4513	1.35%
	NFM [8]	0.7957	1.57%	0.4562	2.45%
	CrossNet [31]	0.7907	1.92%	0.4591	3.10%
	CIN [15]	0.8009	0.63%	0.4517	1.44%
	Fi-GNN (ours)	0.8062	0.00%	0.4453	0.00%

Performance comparison.



Heat map of attentional edge weights.

Automatic Feature Generation

□ The related works on automatic feature generation can be roughly divided into two categories:

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- Search-based methods

DNN-based methods design specific neural architectures to express the interactions among different features.

- Implicit feature generation
- One-shot training course
- Lack of interpretable rules for feature interactions

Search-based methods focus on designing different search strategies that prune as much of the candidates to be evaluated as possible, while aiming to keep the most useful interactive features.

- Explicit feature generation
- Trial-and-error training manner
- Need lots of time and computing resource

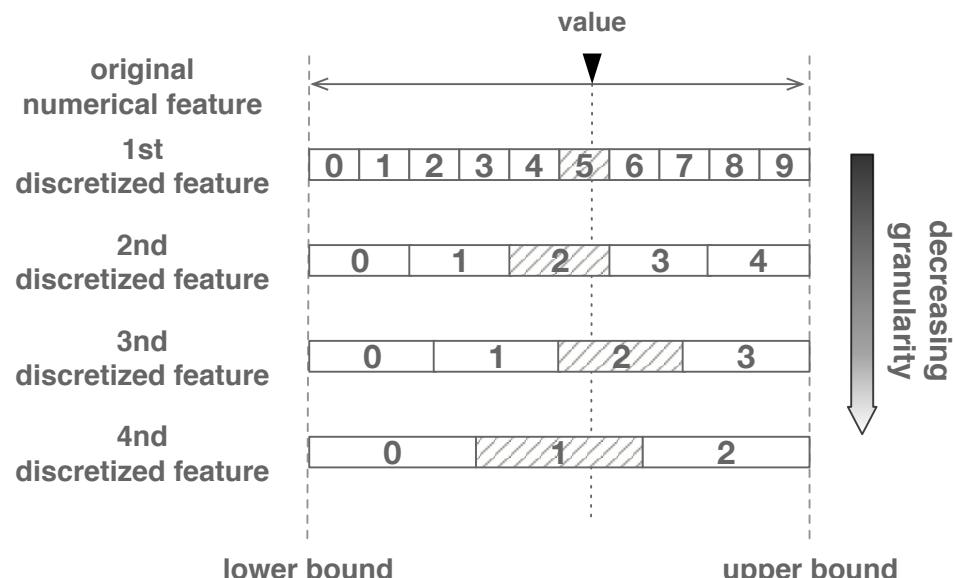
AutoCross

- AutoCross searches useful feature interactions in the high-order interactive feature space by incrementally constructing local optimal feature set

- Multi-granularity discretization
 - Greedy & beam search
 - Field-wise logistic regression
 - Successive mini-batch gradient descent

Multi-granularity discretization:

- For automatic discretization, each numerical feature is discretized into several categorical features with different granularities.



An illustration of multi-granularity discretization.

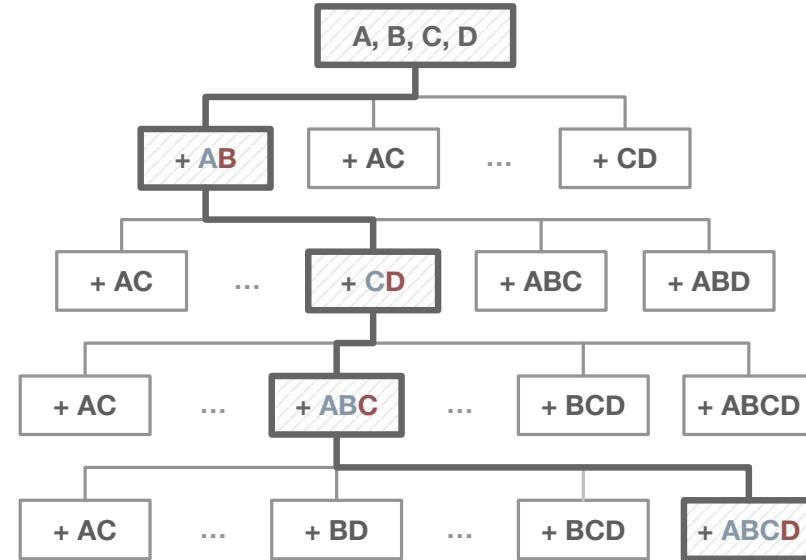
AutoCross

- AutoCross searches useful feature interactions in the high-order interactive feature space by incrementally constructing local optimal feature set

- Multi-granularity discretization
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- Field-wise logistic regression
- Successive mini-batch gradient descent

Greedy & beam search:

- Tree-structured space with the original features as the root.
- The children are generated by added one pair-wise crossing to the parent.
- Only the most promising child will be expanded during the search



An illustration of the search space and beam search strategy.

AutoCross

- AutoCross searches useful feature interactions in the high-order interactive feature space by incrementally constructing local optimal feature set

- Multi-granularity discretization
- Greedy & beam search
- Field-wise logistic regression
- Successive mini-batch gradient descent

Field-wise logistic regression :

- For each node, the weights of the newly added interactive features are updated during training, while other weights are inherited from the parent and fixed.

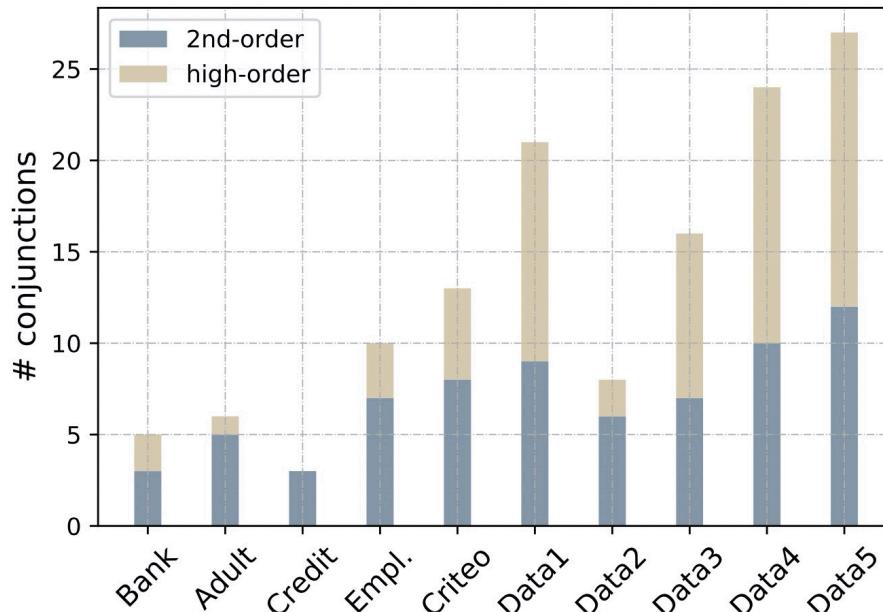
Successive mini-batch gradient descent :

- The data are split into several blocks, and gradually added into the training process along with narrowing the candidate interactive features.

AutoCross

□ The advantages of AutoCross:

- Explicit high-order feature generation
- Fast inference
- Interpretability



The number of second/high-order interactive features.

Method	Benchmark Datasets				
	Bank	Adult	Credit	Employee	Criteo
AC+LR	0.00048	0.00048	0.00062	0.00073	0.00156
AC+W&D	0.01697	0.01493	0.00974	0.02807	0.02698
Deep	0.01413	0.01142	0.00726	0.02166	0.01941
xDeepFM	0.08828	0.05522	0.04466	0.06467	0.18985

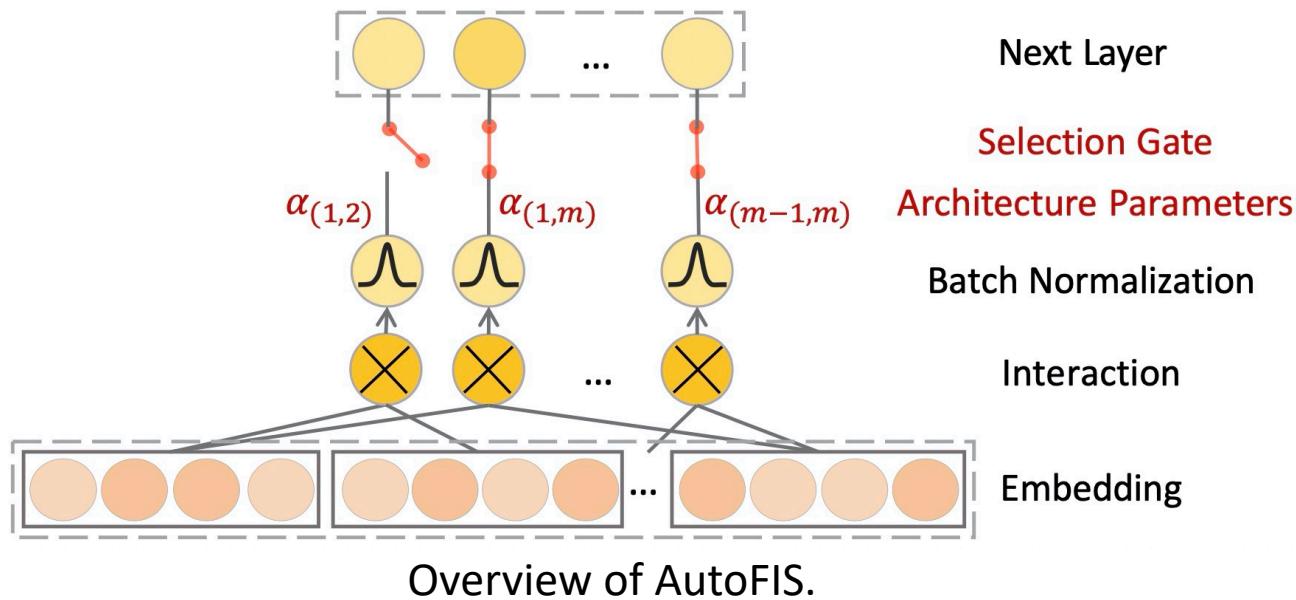
Method	Real-World Business Datasets				
	Data1	Data2	Data3	Data4	Data5
AC+LR	0.00367	0.00111	0.00185	0.00393	0.00279
AC+W&D	0.03537	0.01706	0.04042	0.02434	0.02582
Deep	0.02616	0.01348	0.03150	0.01414	0.01406
xDeepFM	0.32435	0.11415	0.40746	0.12467	0.13235

Inference latency comparison.

AutoFIS

- AutoFIS automatically identifies important feature interactions for Factorization Models (FM).

- *Search Stage*: Learn the relative importance of each feature interaction via architecture parameters within one full training process.
- *Re-train Stage*: Remove the unimportance interactions and re-train the resulting neural networks.

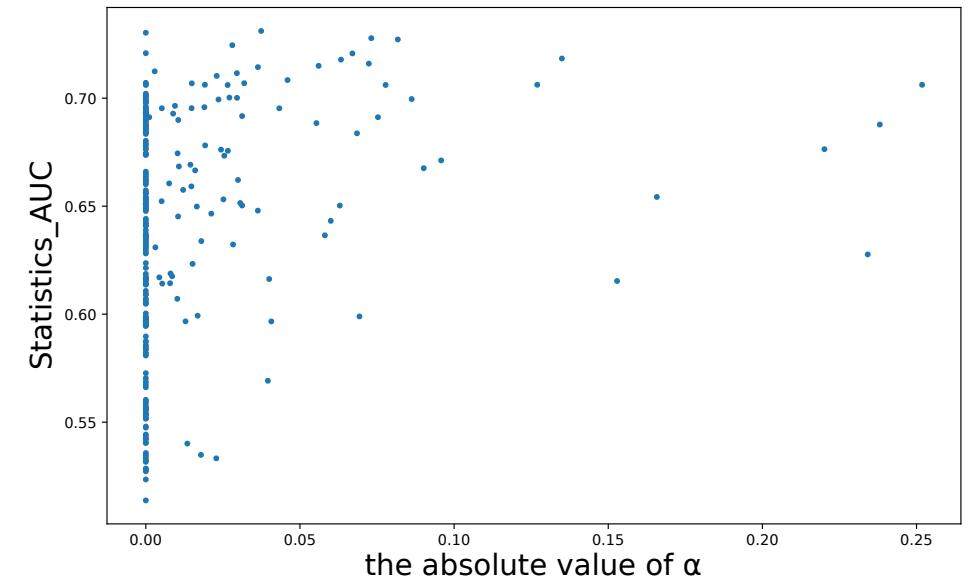


AutoFIS

- Experiments on large-scale datasets demonstrate that AutoFIS can improve various FM based models in CTR prediction tasks.

Model	AUC	log loss	top	ReI. Impr
FM	0.8880	0.08881	100%	0
FwFM	0.8897	0.08826	100%	0.19%
AFM	0.8915	0.08772	100%	0.39%
FFM	0.8921	0.08816	100%	0.46%
DeepFM	0.8948	0.08735	100%	0.77%
AutoFM(2nd)	0.8944*	0.08665*	37%	0.72%
AutoDeepFM(2nd)	0.8979*	0.08560*	15%	1.11%

Performance comparison.



Correlations between the architecture parameters α and AUC.

FIVES

- To possess both feature interpretability and search efficiency, the proposed method FIVES formulates the task of interactive feature generation as searching for edges on the defined feature graph.

1. Search Strategy

PROPOSITION 1. Let X_1, X_2 and Y be Bernoulli random variables with a joint conditional probability mass function, $p_{x_1, x_2 | y} := \mathbb{P}(X_1 = x_1, X_2 = x_2 | Y = y)$ such that $x_1, x_2, y \in \{0, 1\}$. Suppose further that mutual information between X_i and Y satisfies $\mathcal{I}(X_i; Y) < L$ where $i \in \{1, 2\}$ and L is a non-negative constant. If X_1 and X_2 are weakly correlated given $y \in \{0, 1\}$, that is, $\left| \frac{\text{Cov}(X_1, X_2 | Y=y)}{\sigma_{X_1|Y=y} \sigma_{X_2|Y=y}} \right| \leq \rho$, we have

$$\mathcal{I}(X_1 X_2; Y) < 2L + \log(2\rho^2 + 1). \quad (1)$$

Theoretical support for the search strategy.

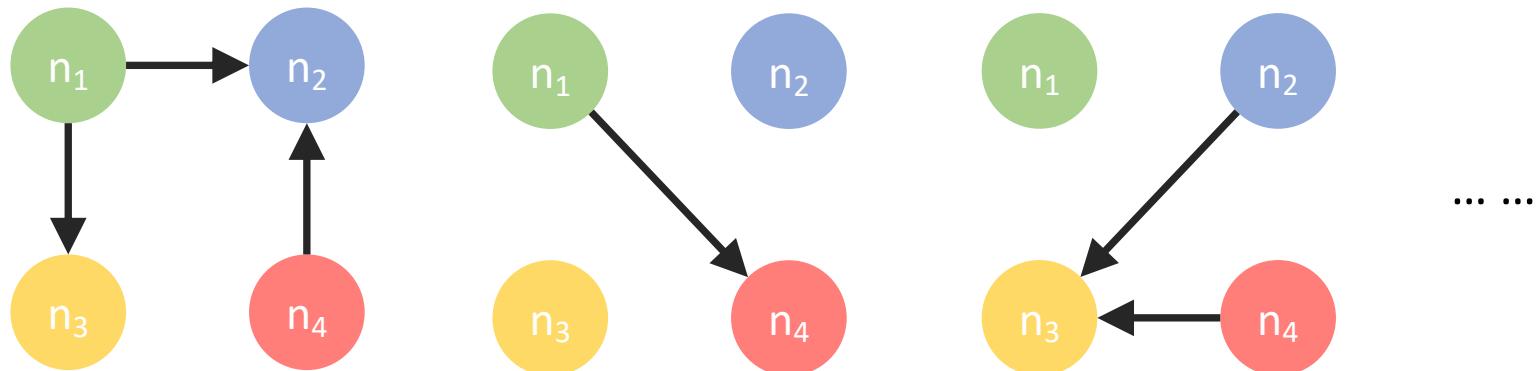
- This proposition states that informative interactive features unlikely come from the uninformative lower-order ones.
- The theory motivates the bottom-up search strategy in FIVES: Searching for a group of informative k -order features from the interactions between original features and the group of $(k - 1)$ -order features.

FIVES

- To possess both feature interpretability and search efficiency, the proposed method FIVES formulates the task of interactive feature generation as searching for edges on the defined feature graph.

2. Feature Graph

- To instantiate the proposed search strategy, the original features are conceptually regarded as a *feature graph* and their interactions are modeled by a designed GNN.
- Each node n_i corresponds to a feature f_i . Each edge $e_{i,j}$ indicates an interaction between n_i and n_j .



The constructed feature graph to represent high-order feature interactions.

FIVES

- To possess both feature interpretability and search efficiency, the proposed method FIVES formulates the task of interactive feature generation as searching for edges on the defined feature graph.

2. Feature Graph

- The feature graph consists of K subgraphs to represent high-order interactive feature. Each subgraph indicates a layer-wise interaction between features, represented by an adjacency matrix $A^{(k)} \in \{0,1\}^{m \times m}$. The graph convolutional operator for aggregation are defined as:

$$n_i^{(k)} = p_i^{(k)} \odot n_i^{(k-1)}, \quad \text{where } p_i^{(k)} = \text{MEAN}_{j|A_{i,j}^{(k)}=1} \{W_j n_j^{(0)}\} \quad (1)$$

- The node representation at k -th layer corresponds to the generated features:

$$n_i^{(k)} = \text{MEAN}_{j|A_{i,j}^{(k)}=1} \{W_j n_j^{(0)}\} \odot n_i^{(k-1)} \approx \text{MEAN}_{(c_1, \dots, c_k)|A_{i,c_j}^{(j)}=1, j=1, \dots, k} \{f_{c_1} \otimes \dots \otimes f_{c_k} \otimes f_i\} \quad (2)$$

FIVES

- To possess both feature interpretability and search efficiency, the proposed method FIVES formulates the task of interactive feature generation as searching for edges on the defined feature graph.

3. Differentiable Edge Search

- The task of generating useful interactive features is equivalent to learning an optimal adjacency tensor A , so-called *edge search*.

$$\begin{aligned} & \min_A \mathcal{L}(\mathcal{D}_{\text{val}} | A, \Theta(A)) \\ \text{s. t.} \quad & \Theta(A) = \arg \min_{\Theta} \mathcal{L}(\mathcal{D}_{\text{train}} | A, \Theta) \end{aligned} \tag{3}$$

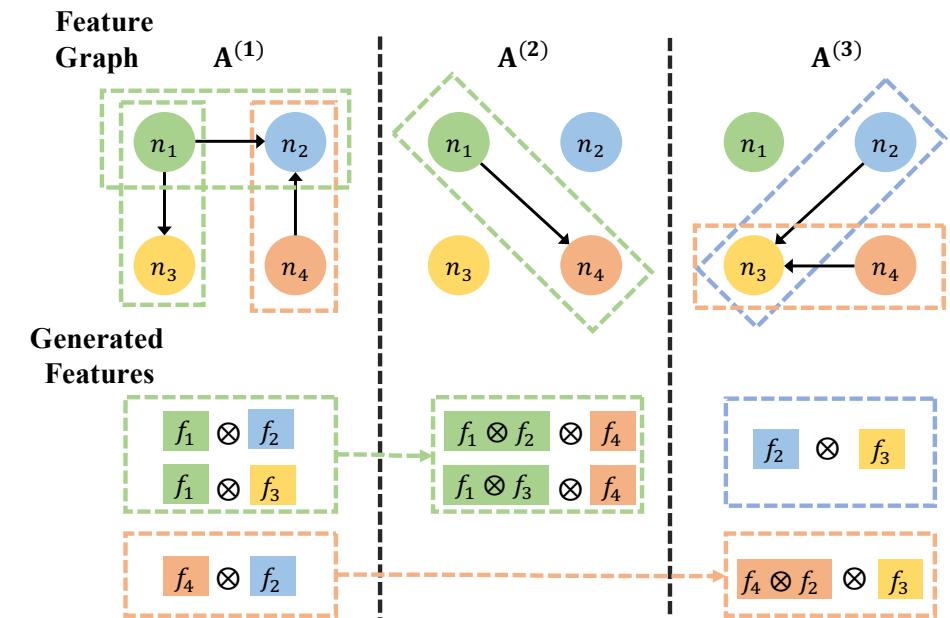
- To make the optimization more efficient, A is regraded as Bernoulli random variables parameterized by $H \in [0,1]^{K \times m \times m}$, and a soft $A^{(k)}$ is allowed to be used for propagation at the k -th layer.

FIVES

- To possess both feature interpretability and search efficiency, the proposed method FIVES formulates the task of interactive feature generation as searching for edges on the defined feature graph.

4. Interactive Feature Derivation

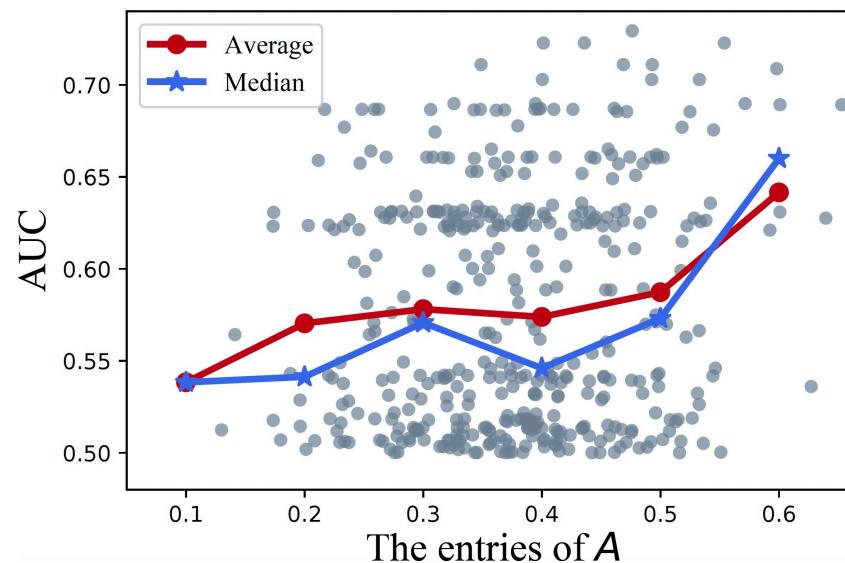
- The learned adjacency tensor can explicitly indicate which interactive features are useful.
- One can inductively derive useful high-order interactive features by specify layer-wise thresholds for binarizing the learned A .
- FIVES serves as a feature generator for lightweight models to meet the requirement of inference speed.



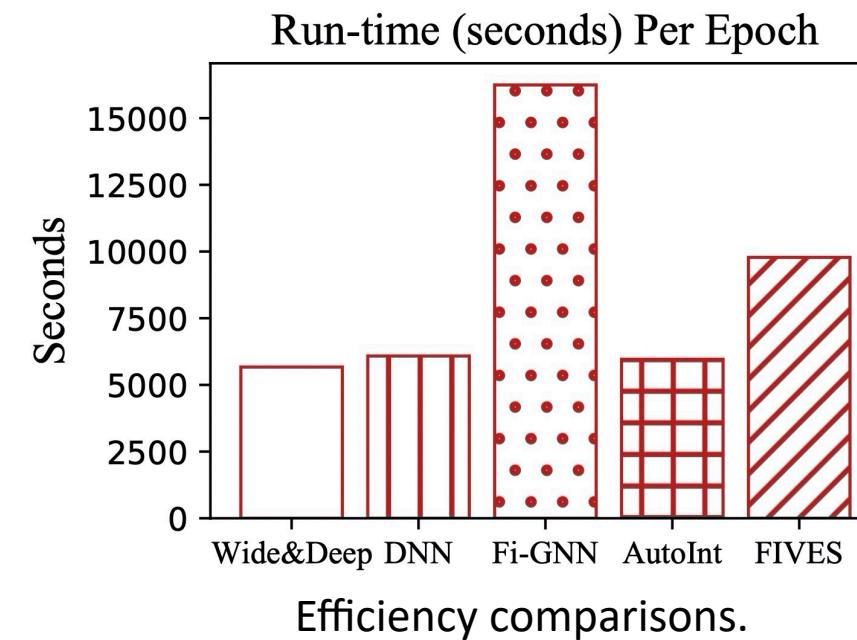
An example of interactive feature derivation.

FIVES

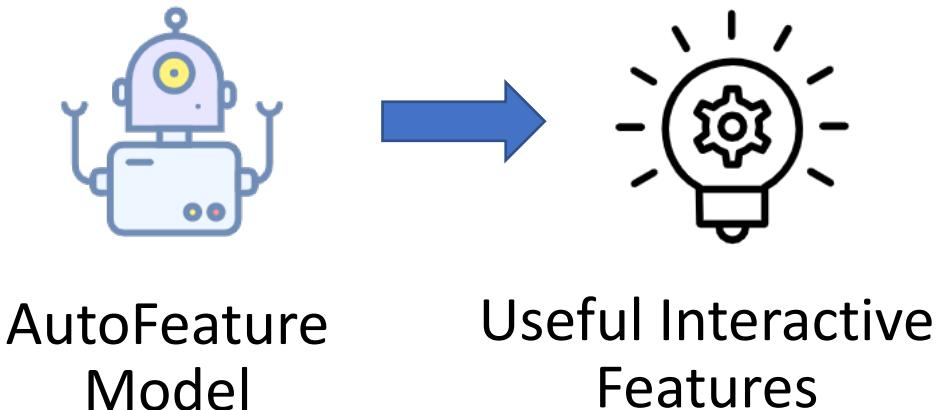
- Extensive experiments on five public datasets and two business datasets confirm that FIVES can generate useful interactive features.
 - FIVES as a predictive model for downstream tasks, such as CTR prediction
 - FIVES as the feature generator for lightweight models to meet the requirement of inference speed



Correlation between the entries of A and the AUC of the corresponding indicated feature.



Takeaways



- ✓ Feature Interpretability
- ✓ Search Efficiency

DNN-based methods

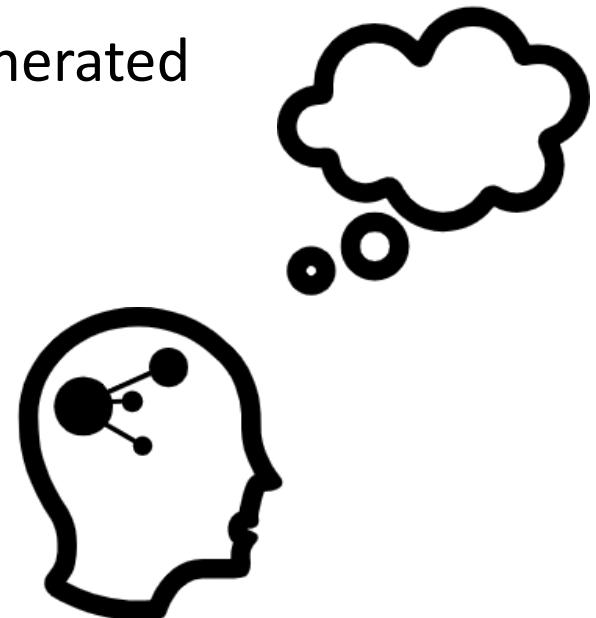
- Implicit feature generation
- One-shot training course
- Lack of interpretable rules for feature interactions

Search-based methods

- Explicit feature generation
- Trial-and-error training manner
- Need lots of time and computing resource

Future Directions

- ❑ How to introduce human experience as prior knowledge for AutoFeature?
- ❑ Causal features or spurious correlations?
- ❑ How to balance the trade-off between the usefulness of generated features and the completeness of them?



References of AutoFeature

- [1] AutoInt: Automatic Feature Interaction Learning via Self-Attentive Neural Networks. In CIKM 2019.
- [2] Fi-GNN: Modeling Feature Interactions via Graph Neural Networks for CTR Prediction. In CIKM 2019.
- [3] AutoCross: Automatic Feature Crossing for Tabular Data in Real-World Applications. In KDD 2019.
- [4] AutoFIS: Automatic Feature Interaction Selection in Factorization Models for Click-Through Rate Prediction. In KDD 2020.
- [5] FIVES: Feature Interaction Via Edge Search for Large-Scale Tabular Data. In KDD 2021.

VolcanoML: End-to-End AutoML via Scalable Search Space Decomposition

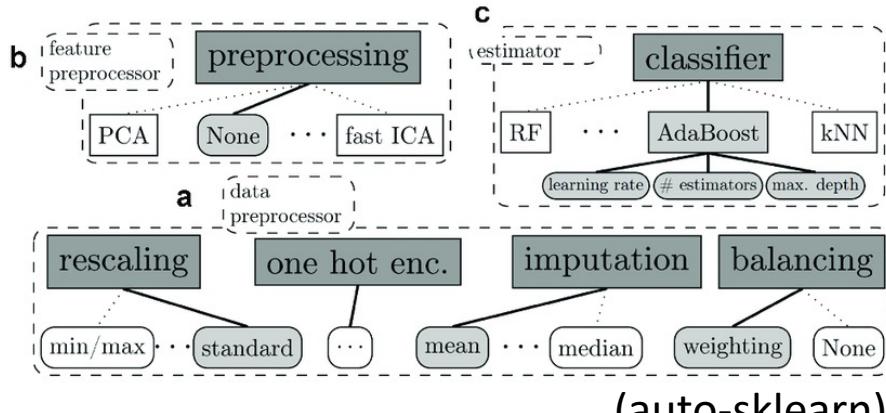
Two Complications of AutoML going E2E

AutoML

$$\alpha^* = \underset{\alpha}{\operatorname{argmax}} f(D', \theta_\alpha^*)$$
$$\text{s.t. } \theta_\alpha^* = \underset{\theta}{\operatorname{argmax}} P(D|\theta)P(\theta|\alpha)$$

Two Complications

1. α is not a homogenous space, it is rather heterogenous

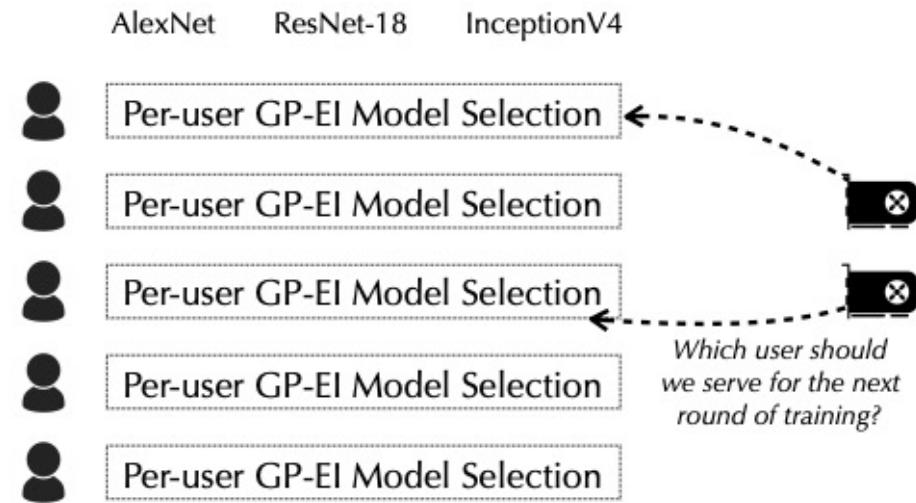


$$\alpha \in Feature \times HP \times Model$$

Personal perspectives, from our past experiences

- VolcanoML: Speeding up End-to-End AutoML via Scalable Search Space Decomposition. *VLDB 2021*.
- AutoML from Service Provider's Perspective: Multi-device, Multi-tenant Model Selection with GP-EI. *AISTATS 2019*.
- Ease.ml: Towards Multi-tenant Resource Sharing for Machine Learning Workloads. *VLDB 2018*.

2. From single-tenant to multi-tenant scenarios

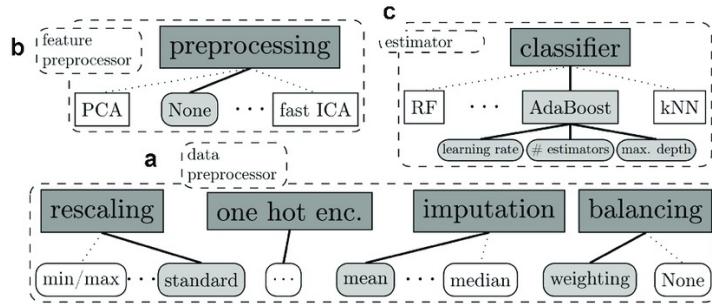


Disclaimer

This segment of the tutorial is more opinioned and closer to our own experience than previous segments

It is less about how much we know about these two problems, but more about discussing some observations and preliminary explorations to show you what we don't know and a “cry for help”.

Heterogenous Search Space



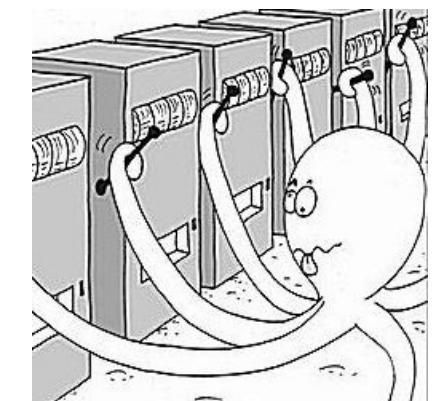
- **Feature \times HP \times Model**
- **A strong baseline**: Treat the heterogenous space as a single joint space.
 - Model it with a single Bayesian optimization problem, a single genetic algorithm, or a single hyperband problem
 - Good? Very powerful approach, yet simple.
 - Could be improved?
 - “The curse of dimensionality”: often it is not easy to scale up when the dimensionality of the space is high.
 - Heterogeneity in algorithm: Different subspaces might benefit from different algorithms.
- **Can we do better?**

Heterogenous Search Space

- **Different ways to conduct search. Let's take for example the space $\alpha \in X \times Y$**
- **Strategy 1. Joint**
 - Treating the space $X \times Y$ as a single search space
 - (If you are doing BO) Create a surrogate model M to approximate $f(\alpha)$
 - Use M to select $\bar{\alpha}$
 - Evaluate $f(\bar{\alpha})$ and update the surrogate model M
- One can implement such a strategy using methods beyond BO.

Heterogenous Search Space

- Different ways to conduct search. Let's take for example the space $\alpha \in X \times Y$
- Strategy 2. Conditioning
 - Idea: decompose $X \times Y$ into multiple subspaces, e.g., one for each value of X
 - $\min_{x,y} f(x, y) \Rightarrow \min_{x \in X} \min_y g_x(y)$
 - Then treating each $x \in X$ as a subproblem $\min_y g_x(y)$
 - Can be modeled as a Multi-armed bandit problem – each arm corresponds to a possible value of $x \in X$, playing an arm means optimizing $\min_y g_x(y)$ one step
- For example, think about X as Algorithm and Y as Feature – For each Algorithm, search for the best feature, and pick the best Algorithm



Heterogenous Search Space

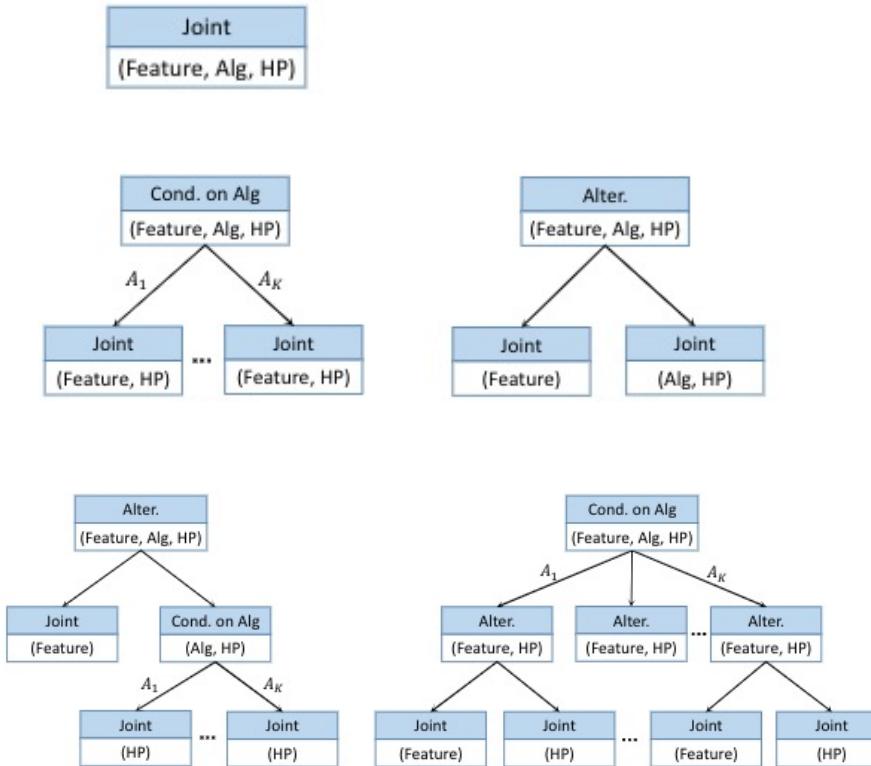
- **Different ways to conduct search. Let's take for example the space $\alpha \in X \times Y$**
- **Strategy 3. Alternating**
 - Idea: decompose $X \times Y$ into two subspaces, X and Y
 - Solve two problems alternatively:
 - $\min_x g_{\bar{y}}(x)$, where \bar{y} is the current best value for subspace Y
 - $\min_y g_{\bar{x}}(y)$, where \bar{x} is the current best value for subspace X
 - Each subproblem can be solved either jointly or via some conditioning strategy
 - At each iteration, pick the subproblem with the largest expected improvement
- For example, think about X as Feature and Y as HP – Alternating the process of search for feature and search for HP

Heterogenous Search Space

- **Different ways to conduct search**
- **Strategy 1. Joint**
 - **Pros:** Simple, works well when dimensionality is low
 - **Cons:** Might suffer when the dimensionality is high
- **Strategy 2. Conditioning**
 - **Pros:** Effective when some dimension is categorical variable with small cardinality
 - **Cons:** Might not be applicable to other scenarios.
- **Strategy 3. Alternating**
 - **Pros:** Very effective in reducing dimensions
 - **Cons:** Assuming conditional independence of two subspaces

Heterogenous Search Space

- A single search space can be decomposed in different ways.



Dataset	Plan 1	Plan 2	Plan 3	Plan 4	Plan 5
puma8NH	0.8275	0.8312	0.8271	0.8280	0.8303
kin8nm	0.8808	0.8886	0.8886	0.8654	0.8910
cpu_csmall	0.9122	0.9126	0.9126	0.9027	0.9127
puma32H	0.8849	0.8864	0.8848	0.8835	0.8894
cpu_act	0.9303	0.9315	0.9305	0.9302	0.9309
bank32nh	0.7896	0.7889	0.7838	0.7891	0.7957
mc1	0.8796	0.8904	0.8722	0.8721	0.8975
delta_elevators	0.8763	0.8760	0.8779	0.8766	0.8790
jm1	0.6718	0.6721	0.6581	0.6473	0.6692
pendigits	0.9932	0.9936	0.9929	0.9945	0.9937
delta_ilerons	0.9235	0.9240	0.9242	0.9225	0.9259
wind	0.8587	0.8589	0.8566	0.8583	0.8593
satimage	0.8961	0.8954	0.8965	0.8946	0.8981
optdigits	0.9889	0.9889	0.9883	0.9889	0.9889
phoneme	0.8799	0.8832	0.8808	0.8791	0.8866
spambase	0.9401	0.9406	0.9379	0.9387	0.9386
abalone	0.6688	0.6679	0.6618	0.6614	0.6680
mammography	0.8740	0.8783	0.8577	0.8755	0.8787
waveform	0.8948	0.8961	0.8900	0.8835	0.8952
pollen	0.4934	0.5013	0.5012	0.5013	0.5013
Average Rank	3.28	2.33	3.80	3.98	1.63

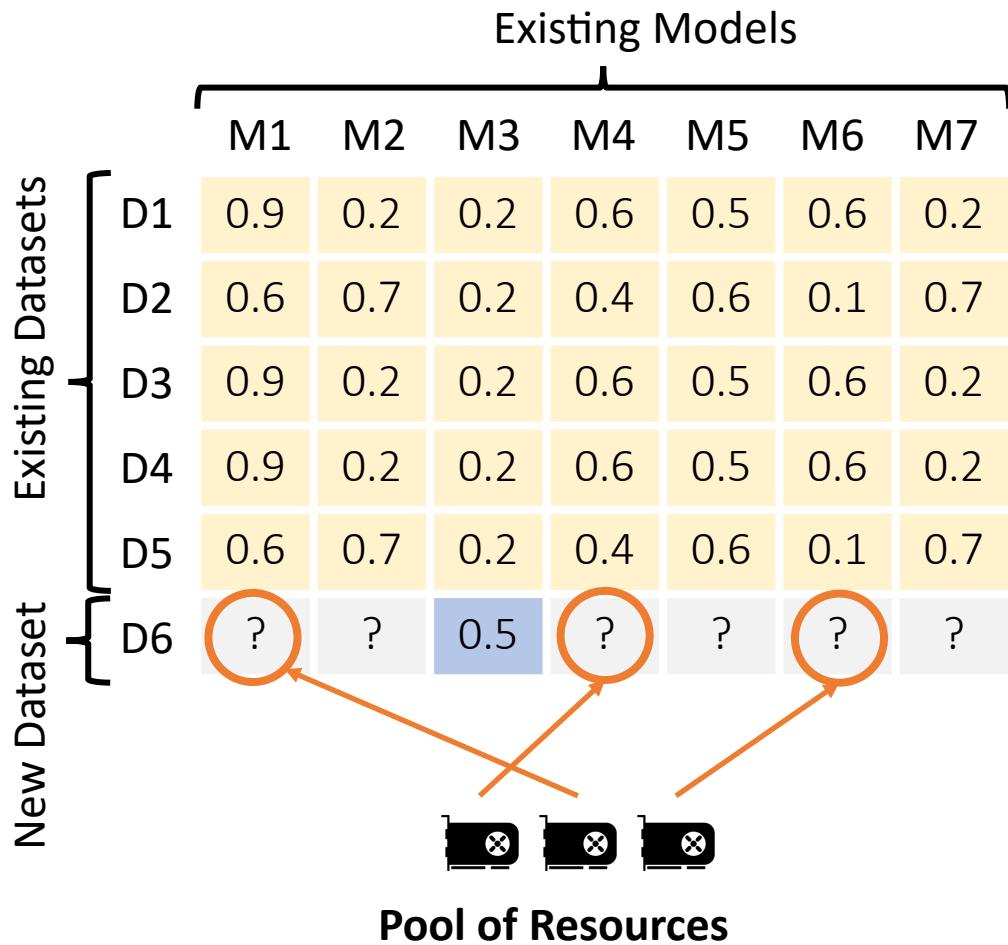
Different plans have different performance

Potentially, can learn to decompose given a target workload

Heterogenous Search Space

- **Moving Forward**
 - Build up a suite of different building blocks – what is the unified framework to talk about different search algorithms?
 - How to automatically construct search space decomposition?
 - How to automatically conduct building block selection?
AutoML for AutoML?

AutoML: From Single-tenant to Multi-tenant

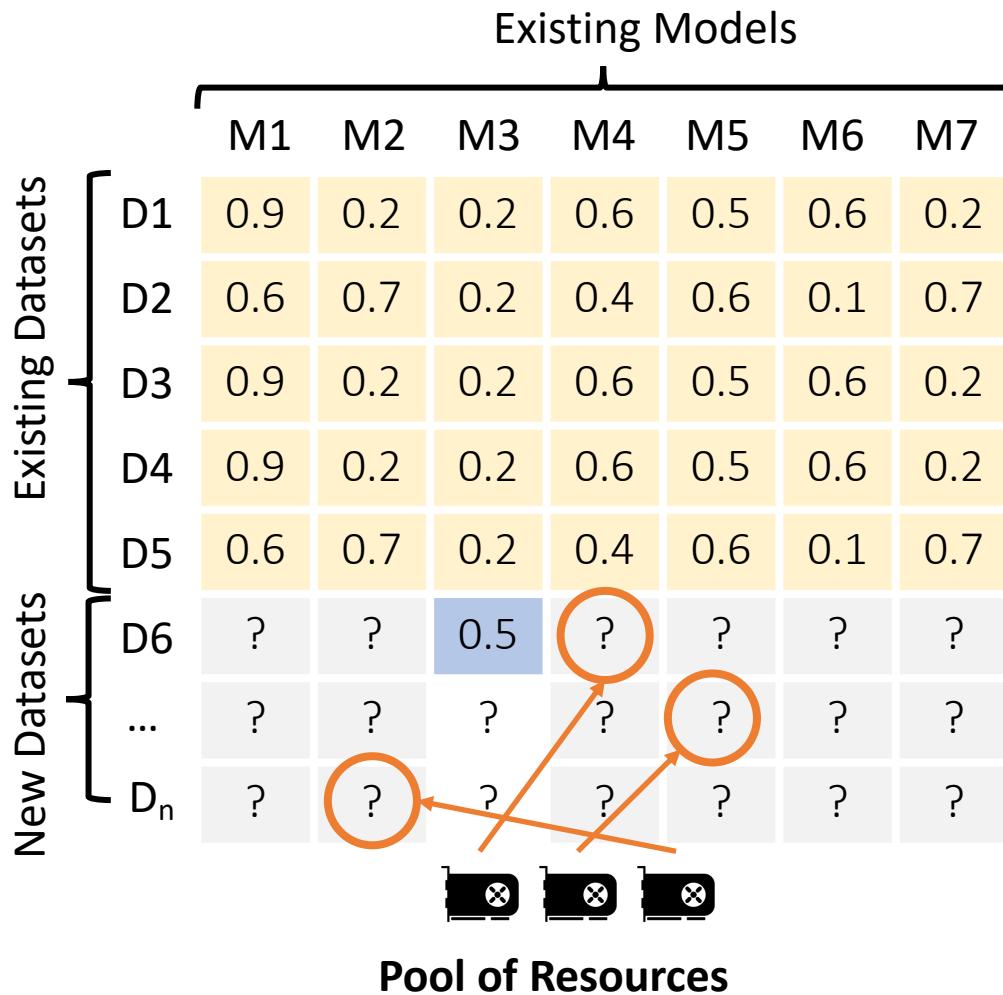


Single-tenant Scenario: One target dataset

What if multiple users running their own AutoML workload over a shared infrastructure?

Interesting problem especially when AutoML as a service becomes more and more popular.

AutoML: From Single-tenant to Multi-tenant

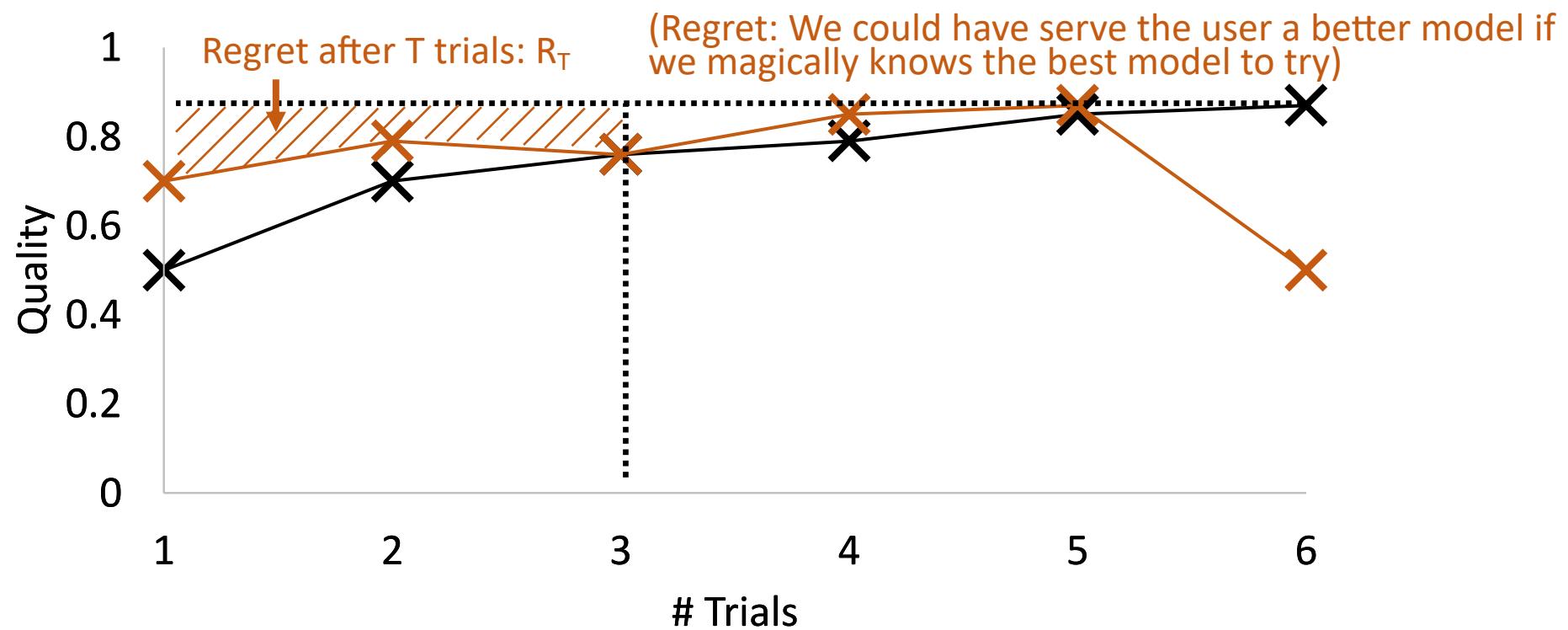


How to balance resource allocations to different users?

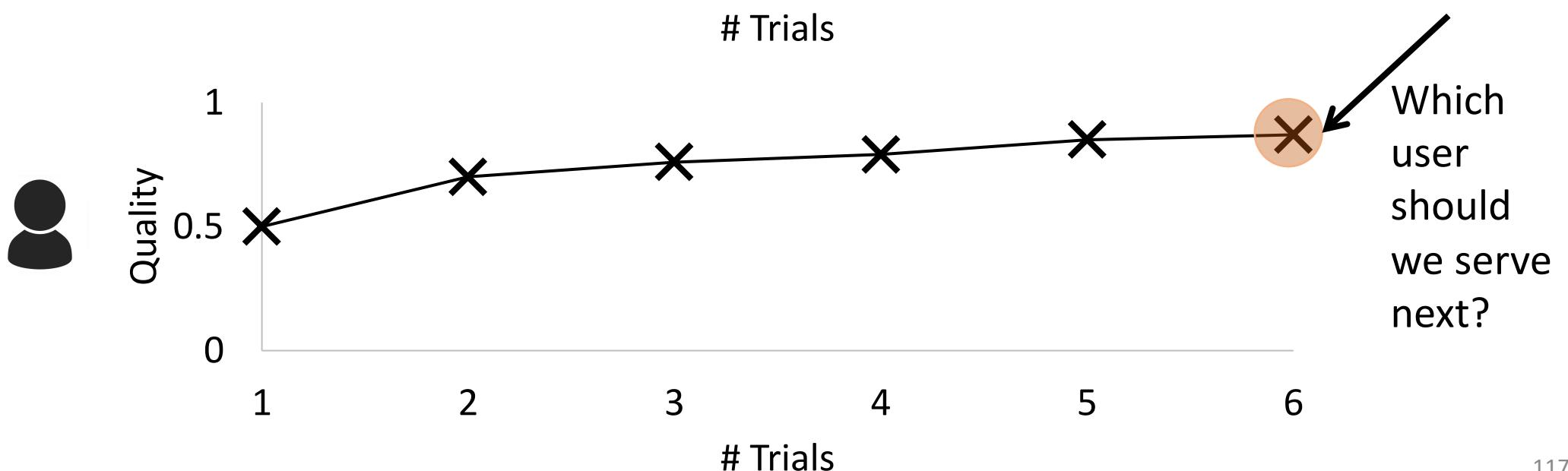
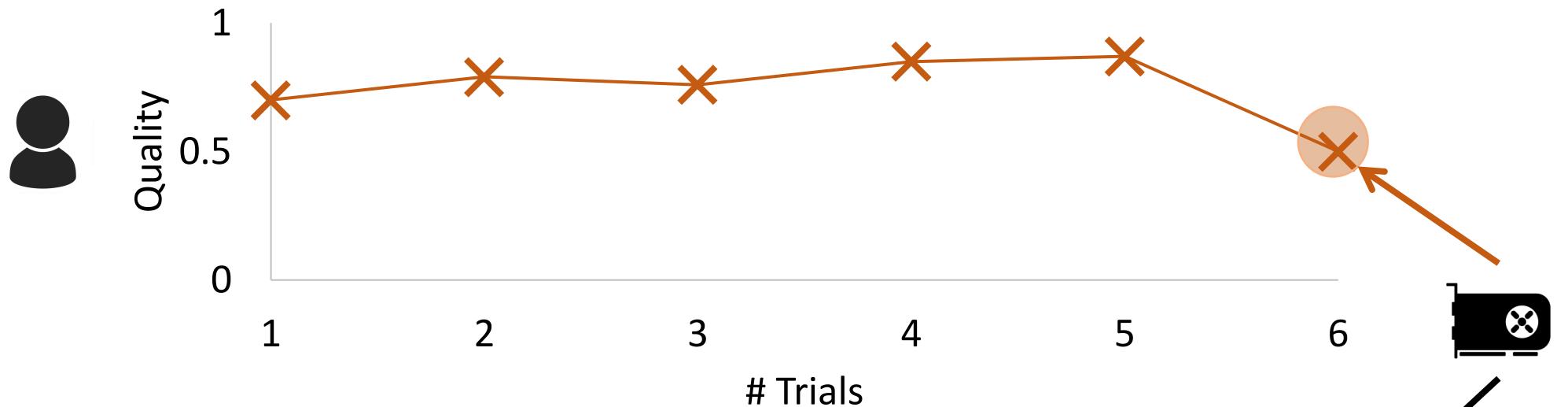
AutoML: From Single-tenant to Multi-tenant

- **Regret: A Single User's Unhappiness**

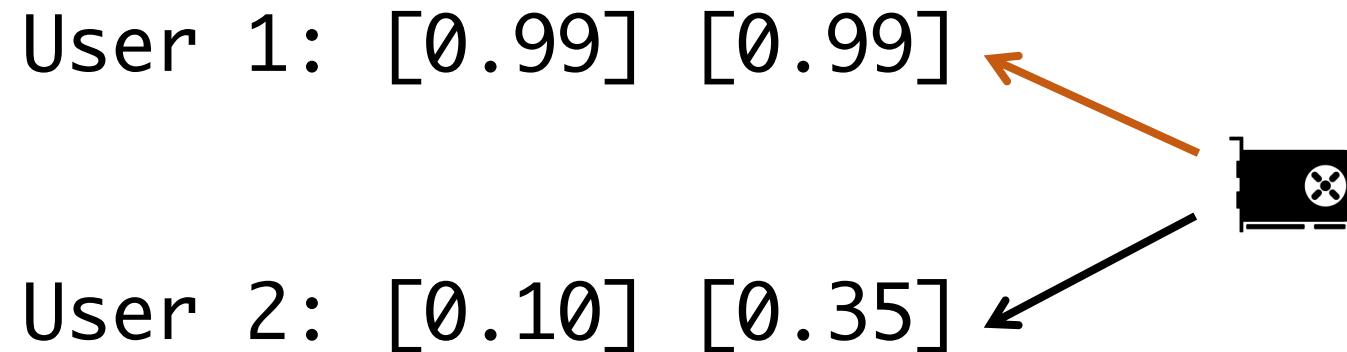
Decisions	Quality
M1	0.5
M2	0.7
M3	0.76
M4	0.79
M5	0.85
M6	0.87



AutoML: From Single-tenant to Multi-tenant



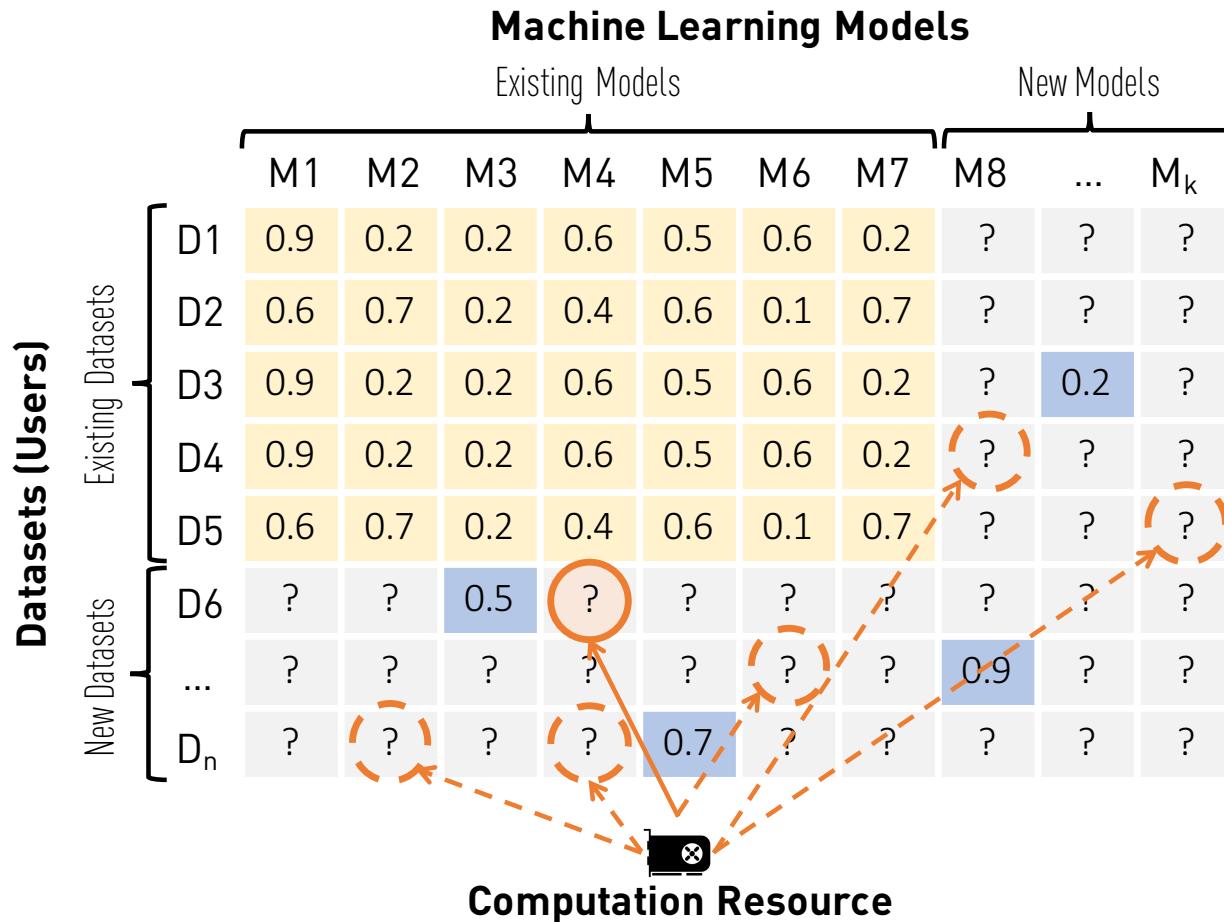
AutoML: From Single-tenant to Multi-tenant



Extreme Case: User 1 is not worth serving any more

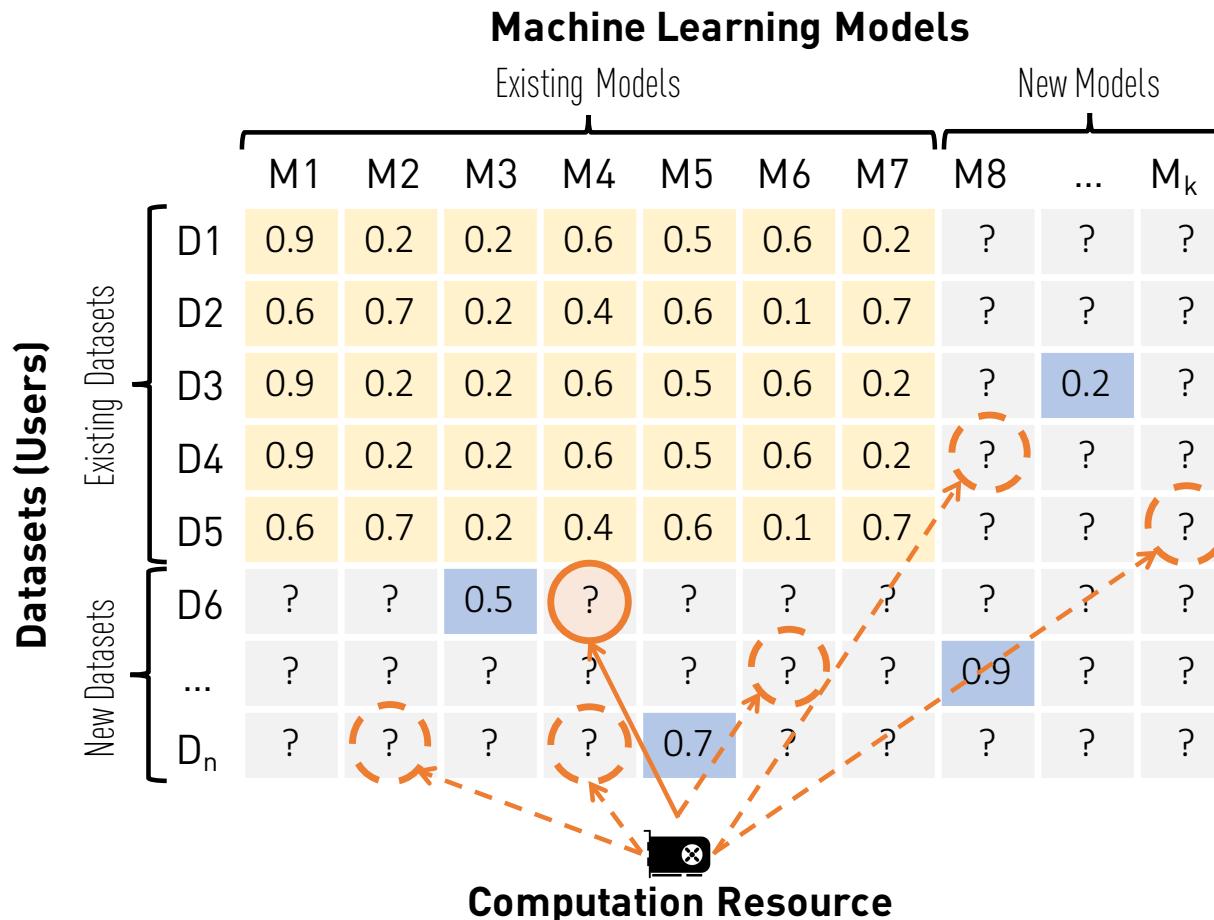
How about more general case?

AutoML: From Single-tenant to Multi-tenant



- 01 *Each user runs their own GP-EI model selection*
 - 02 *Serve the user with highest expected improvement.*
- Informal Theorem.** *If the performance of all models is a linear combination of a finite, shared set of hidden Gaussian variables, the global regret converges to 0 with rate $O(1 / \text{runtime})$.*

AutoML: From Single-tenant to Multi-tenant



01

Each user runs their own GP-UCB algorithm

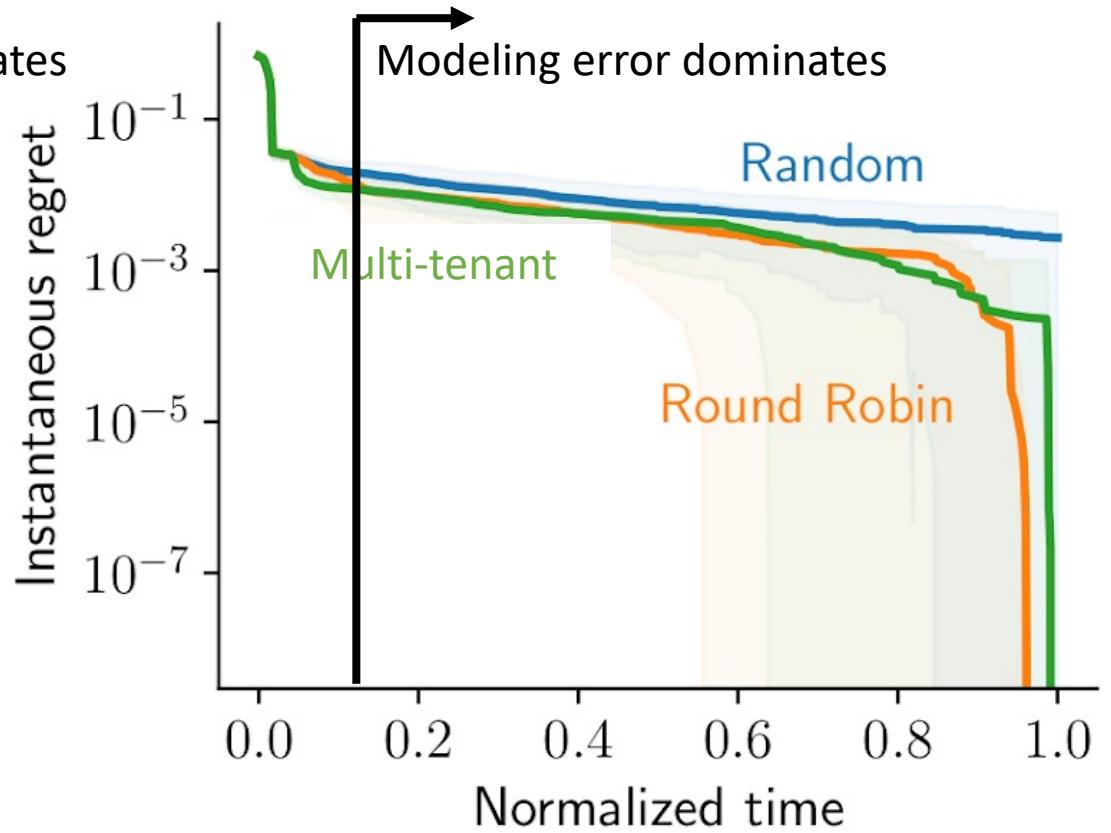
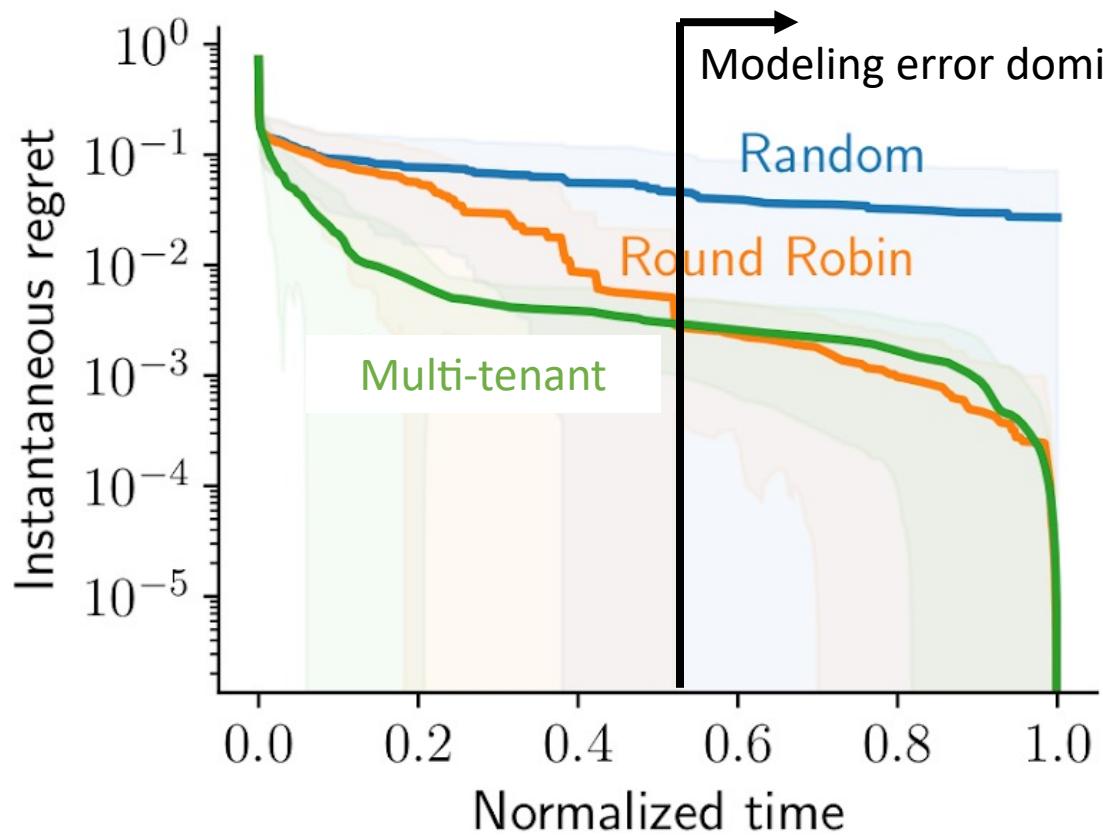
02

Serve the user with a factor that is very similar to expected improvement (directly comparing each user's UCB does not work, for obvious reason)

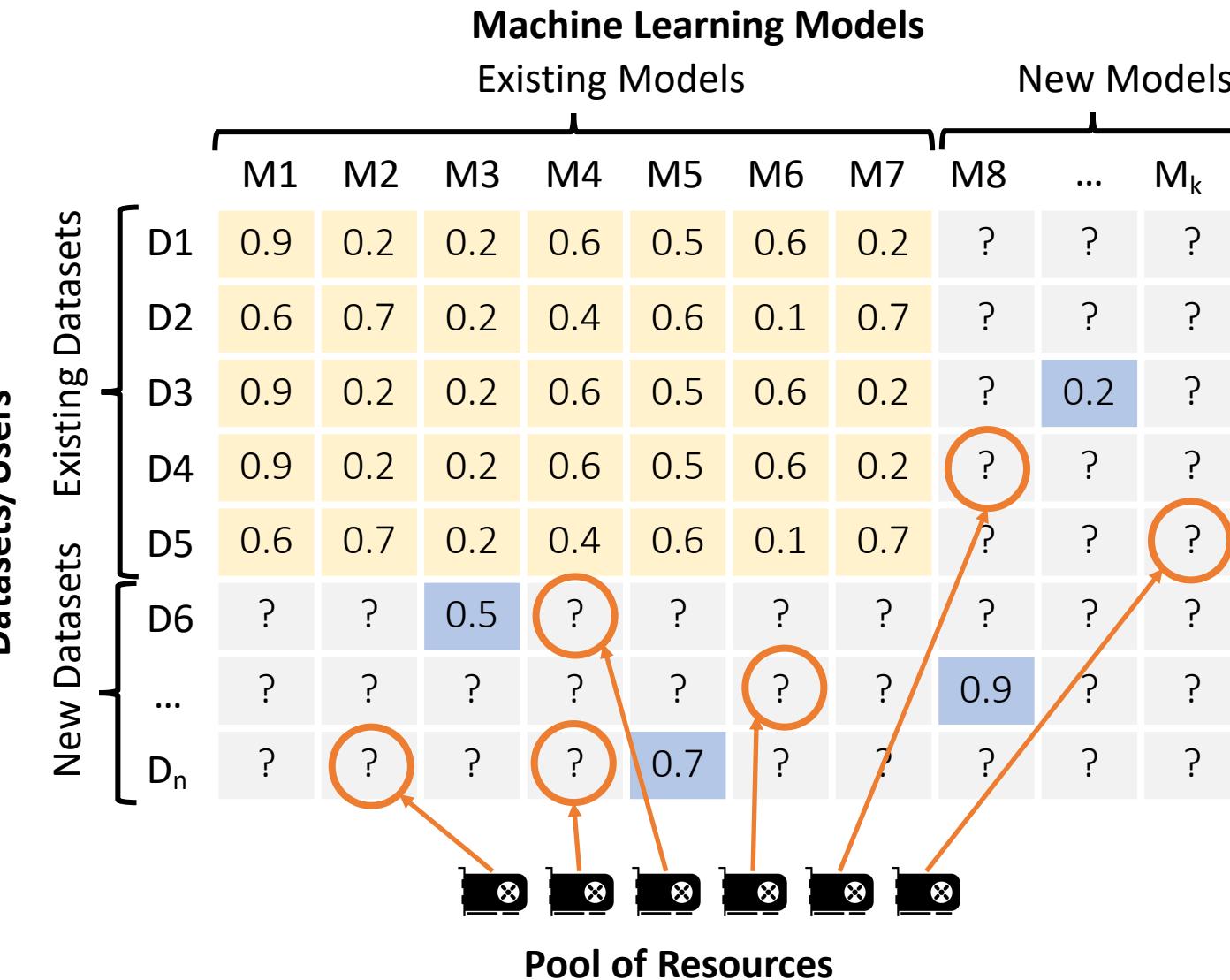
In this case, the total regret is bounded (up to some constant) by

$$n^{3/2} \sqrt{\beta * T \sum_{i=1}^n \log(|T(i)|)} \leq n^{3/2} \underbrace{\sqrt{\beta * T \log \left(\frac{T}{n} \right)}}_{\text{the regret for RR, see (1)}}.$$

AutoML: From Single-tenant to Multi-tenant



AutoML: From Single-tenant to Multi-tenant



Need some special care on the diversity: don't put all GPUs on a single user.

Theorem. Near linear speed up with respect to the number of devices when # devices << # users.

AutoML: From Single-tenant to Multi-tenant

- **Moving Forward**

- In my opinion, it is exciting future direction to try to understand resource allocation and scheduling for AutoML workloads
- What's the unified way to talk about and think about different AutoML workloads, e.g., those we have been talking about over the last two hours
- Fairness? Efficiency? How should we aggregate unhappiness from multiple users?

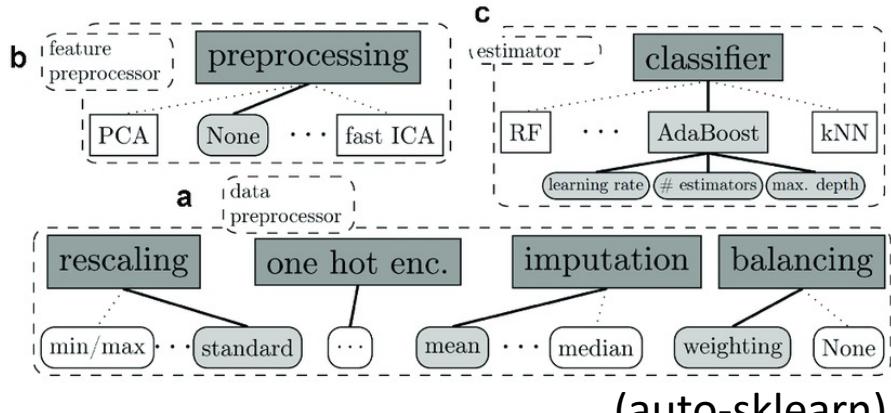
Two Complications of AutoML going E2E

AutoML

$$\begin{aligned}\alpha^* &= \underset{\alpha}{\operatorname{argmax}} f(D', \theta_\alpha^*) \\ \text{s.t. } \theta_\alpha^* &= \underset{\theta}{\operatorname{argmax}} P(D|\theta)P(\theta|\alpha)\end{aligned}$$

Two Complications

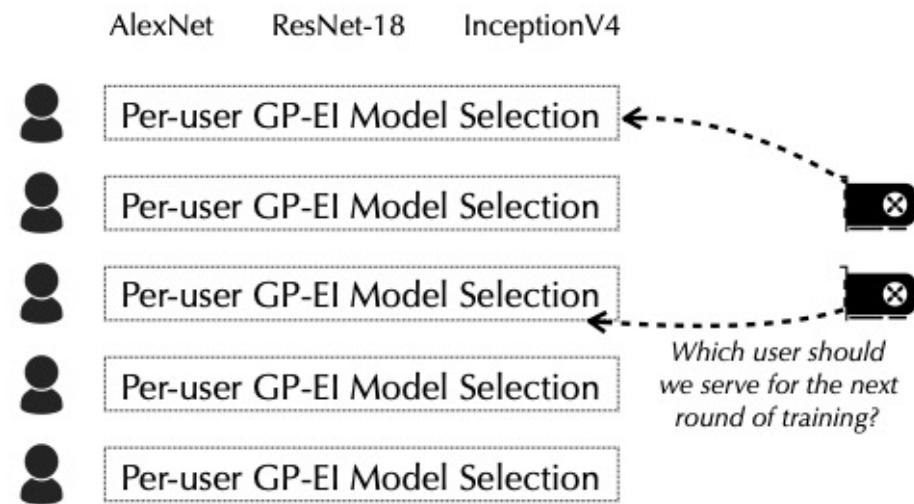
1. α is not a homogenous space, it is rather heterogenous



$$\alpha \in Feature \times HP \times Model$$

A lot of challenges and exciting opportunities when bring AutoML to and end-to-end production scenario!

2. From single-tenant to multi-tenant scenarios

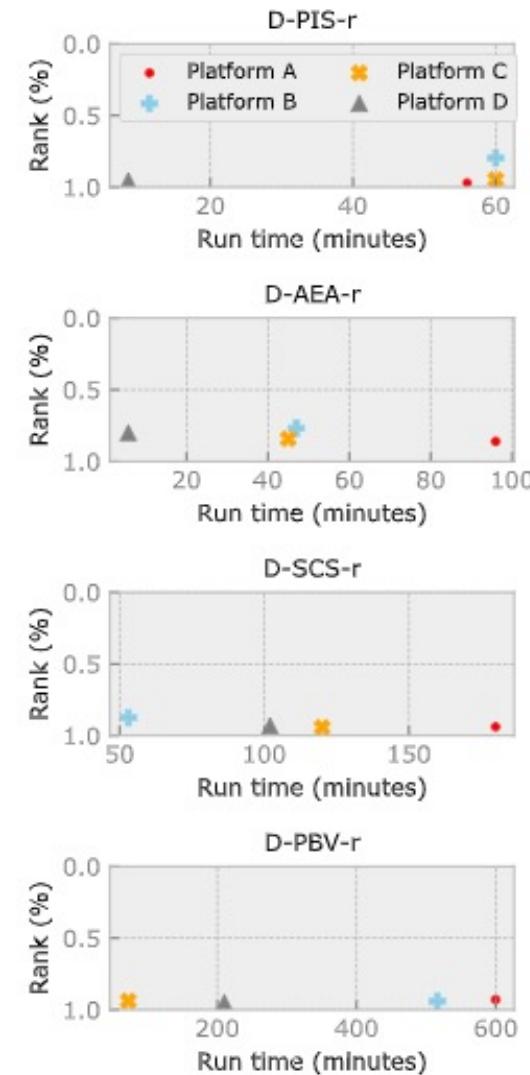


AutoML: A Small Personal Remark

ML today is now a Data Problem

- For many tasks, given the raw features from Kaggle, most AutoML platforms rank in the bottom 50%.
- It is the data that we need to improve, and knowledge that we need to integrate, to build better ML applications.
- To improve data, we need to first understand them.

Moving from a Model-driven development to a Data-driven development.



MLBench

VLDB (2018)

<http://www.vldb.org/pvldb/vol11/p1220-liu.pdf>

ML-Guided Database: Learned Index



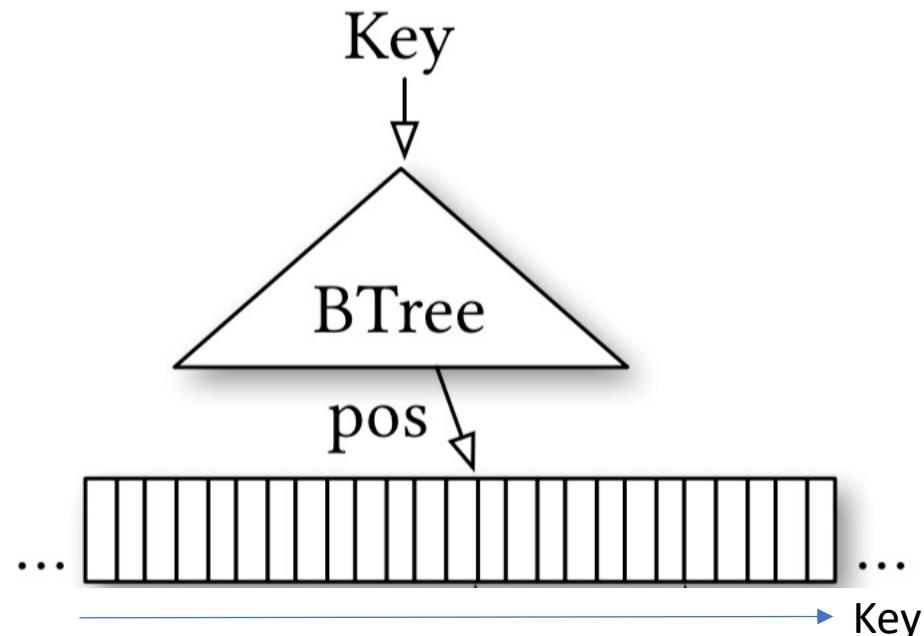
Where DB Meets ML

- Human involved in research/engineering/analyzing/administrating:
 - Building and maintaining indexes
 - Query optimization
 - Physical design tuning
 - Optimizing view materialization
- Learning to automatically designing/optimizing/tuning?

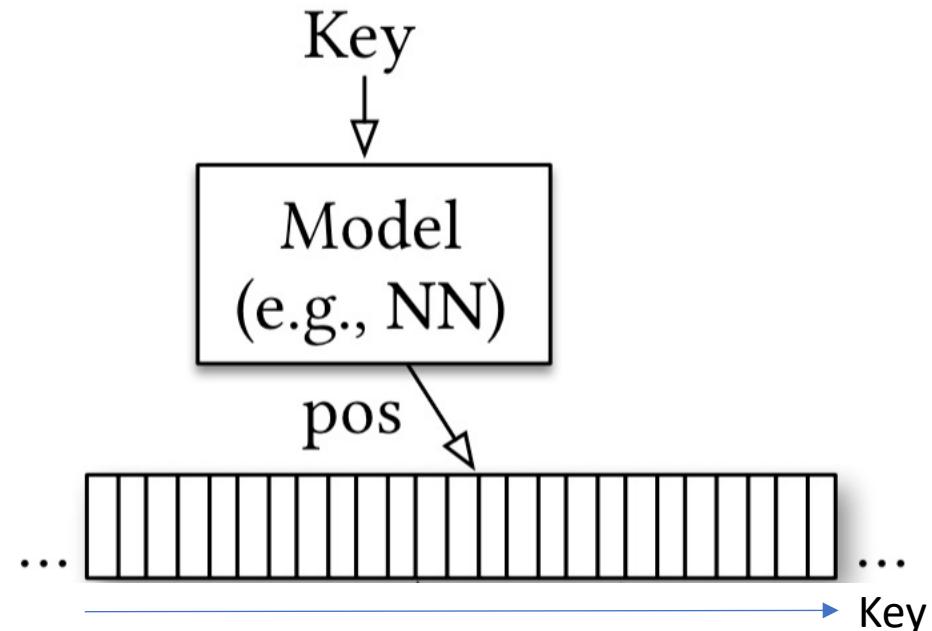
Where DB Meets ML: Learning to Index

- Human involved in research/engineering/analyzing/administrating:
 - **Building and maintaining indexes**
 - Query optimization
 - Physical design tuning
 - Optimizing view materialization
- **Learning to automatically designing/optimizing/tuning?**

B-Tree Index from Learning Perspective



Input: Key
Output: Position
B-Tree Index: position = **B-tree**(Key)

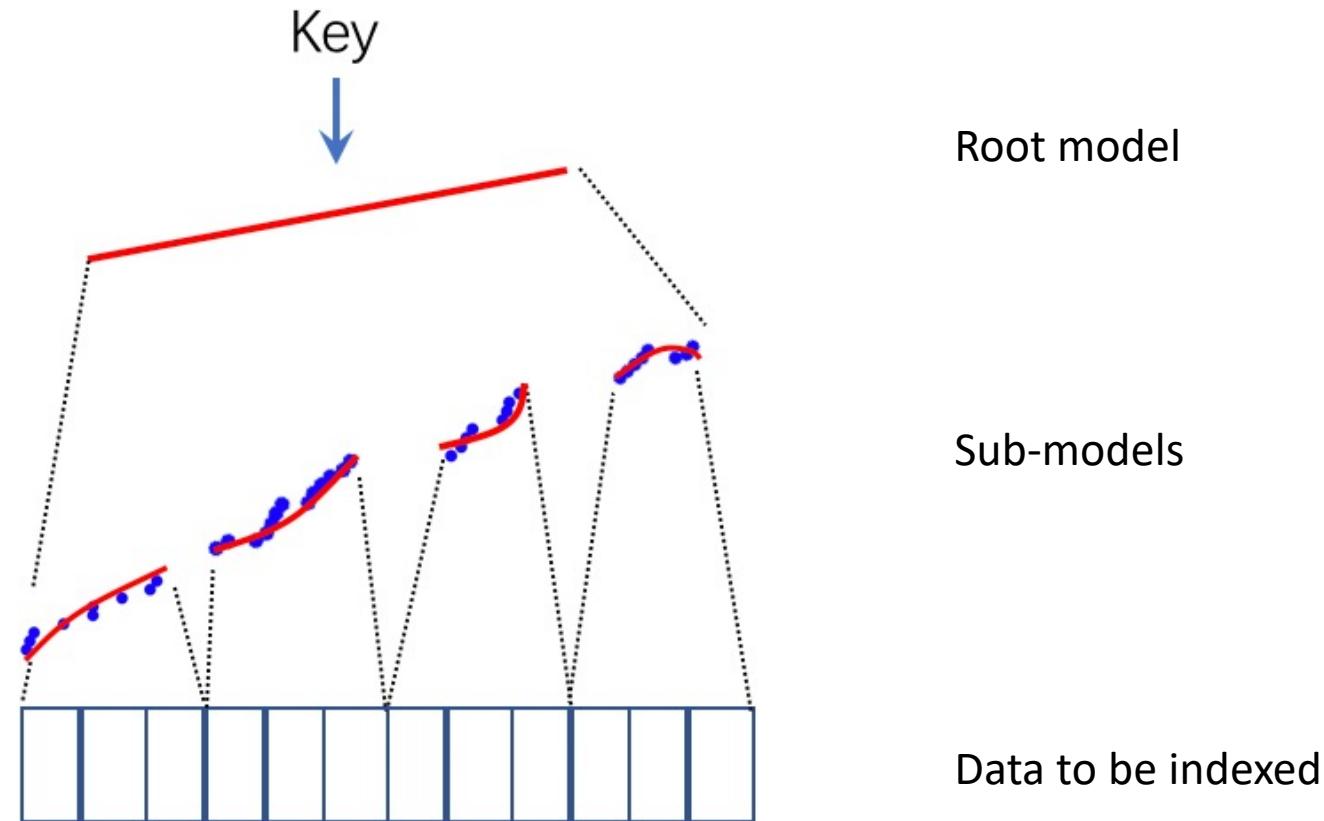


Input: Key
Output: Position
Learned Index: position = **function**(Key)

Why Learning Index from Data?

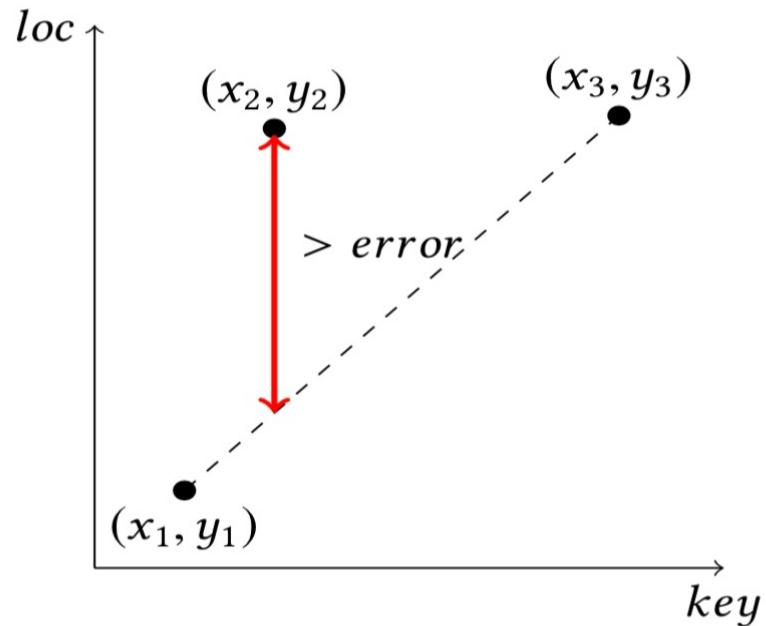
- Consider this (ideal) case: build an index to store and query over a table of n rows with continuous integer keys, *i.e.*, Keys = [11, 12, 13, 14, 15, ...] and Pos = [0, 1, 2, 3, 4, ...]
 - B-Tree: seeking **Pos** in time $O(\log n)$
 - a learned function **Pos = M(Key) = Key + offset** : $O(1)$
- Main motivation: the **hidden yet useful distribution information** about the data to be indexed has not been fully explored and utilized in the classic index techniques
 - learned index: an **automatic** way to explore and utilize such information

Recursive-Model Index (RMI)

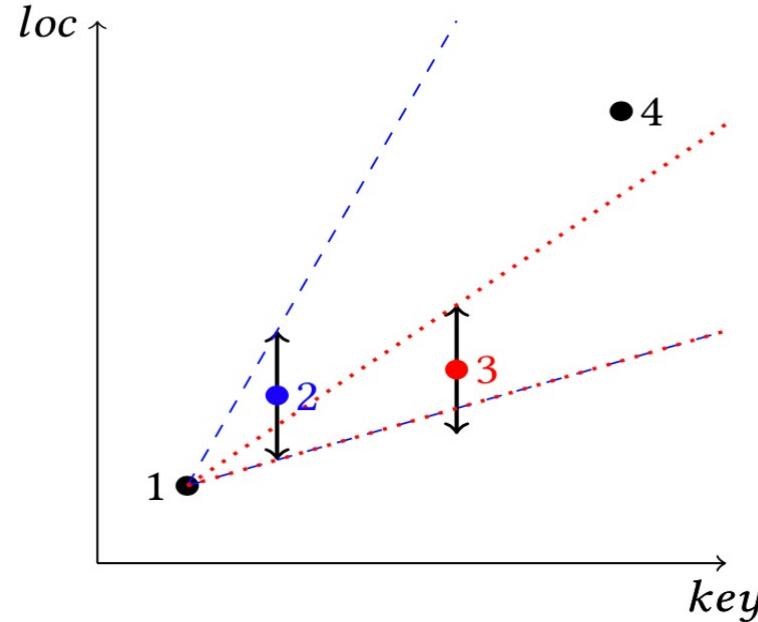


[Image source] Kraska et al., The case for learned index structures. *SIGMOD*, 2018

FITing-Tree

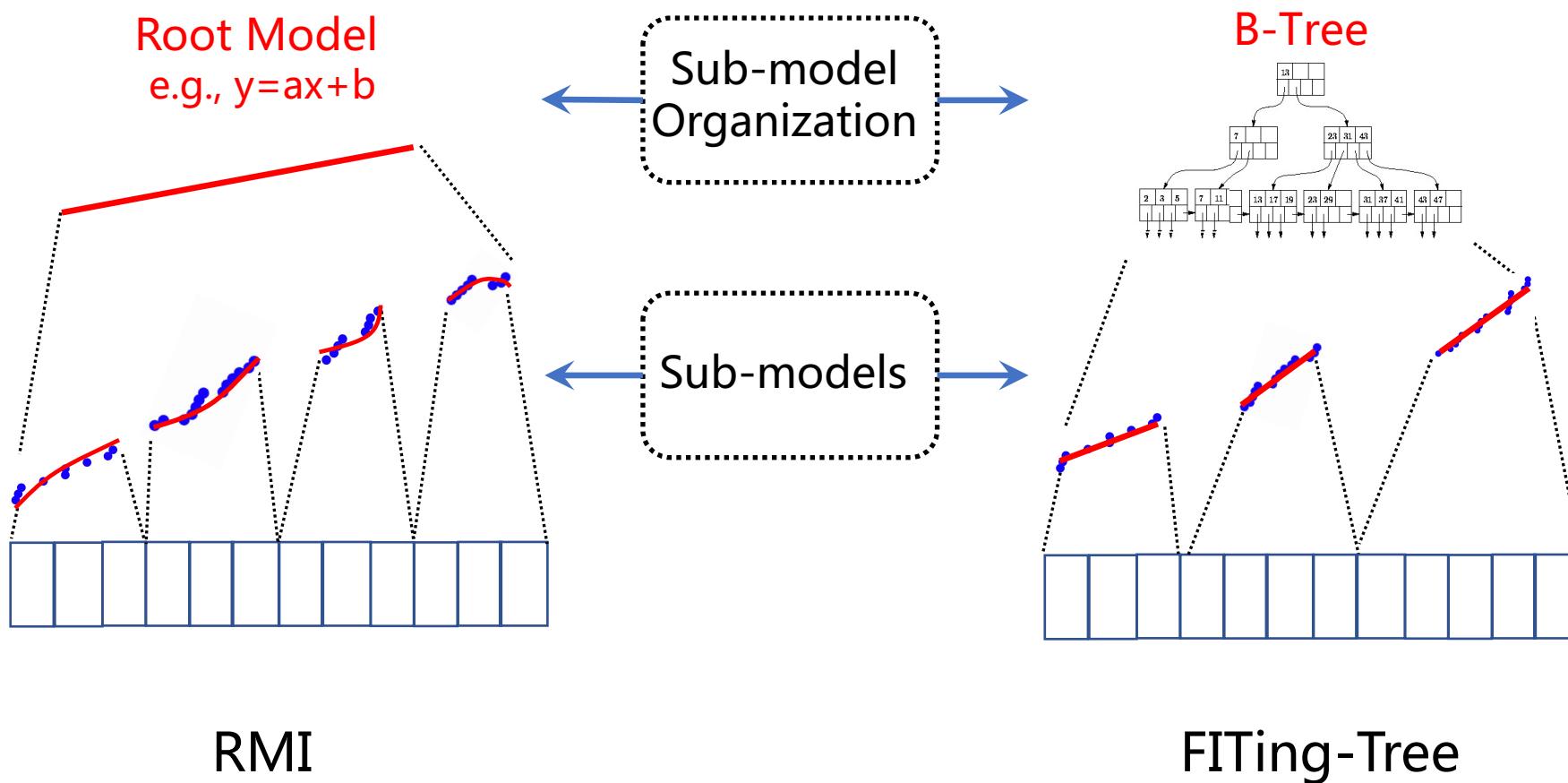


Error-Bounded Linear Segment: Given threshold *error*, a segment from (x_1, y_1) to (x_3, y_3) is *not valid* if (x_2, y_2) is further than *error* from the interpolated line.



ShrinkingCone (building a segment): Point 1 is the origin of the cone. Point 2 is then added, resulting in the dashed cone. Point 3 is added next, yielding in the dotted cone. Point 4 is outside the dotted cone and therefore starts a new segment.

RMI v.s. FITing-Tree



RMI

FITing-Tree

More Learned Index Methods

- PGM [1] improves FITing-Tree by finding the optimal number of learned segments given an error bound.
- ALEX [2] proposes an adaptive RMI with workload-specific optimization, achieving high performance on dynamic workloads.
- RadixSpline [3] gains competitive performance with a radix structure while using a single-pass training.
- Multi-dimensional indexes: NEIST [4], Flood [5], Tsunami [6] and LISA [7].

More Learned Index Methods

- [1] The PGM-Index: A Fully-Dynamic Compressed Learned Index with Provable Worst-Case Bounds. *VLDB*, 2020.
- [2] ALEX: An Updatable Adaptive Learned Index. *SIGMOD*, 2020.
- [3] RadixSpline: A Single-Pass Learned Index. *In aiDM Workshop on SIGMOD*, 2020.
- [4] NEIST: a Neural-Enhanced Index for Spatio-Temporal Queries. *TKDE*, 2019.
- [5] Learning Multi-dimensional Indexes. *SIGMOD*, 2020.
- [6] Tsunami: A Learned Multi-dimensional Index for Correlated Data and Skewed Workloads. *VLDB*, 2020.
- [7] LISA: A Learned Index Structure for Spatial Data. *SIGMOD*, 2020.

Questions about Learned Indexes



How to systematically analyze and design
machine learning based indexing methods?

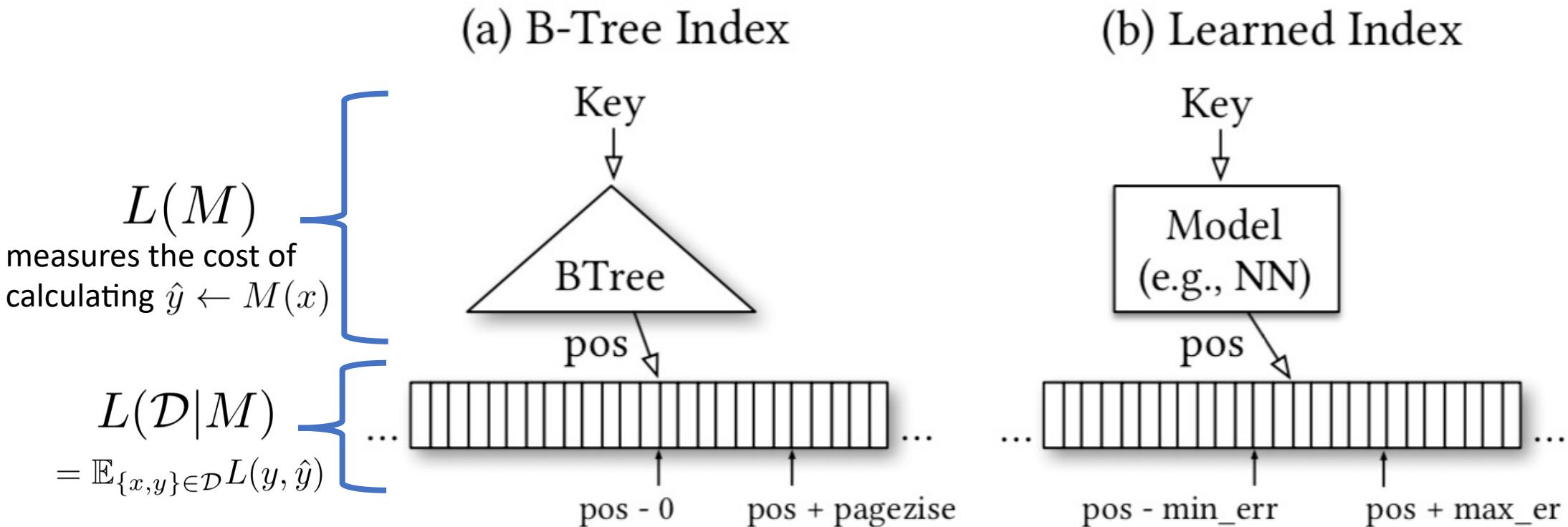
More scalable index learning methods?

Which class of models suffice?

Task Definition

- Given a database \mathcal{D} with n records (rows), let's assume that a *range index* structure will be built on a specific column x . For each record $i \in [n]$, the value of this column, x_i , is adopted as the *key*, and y_i is the *position* where the record is stored.
- We want to learn a *mechanism* M with the key x as input and outputs a *predicated position* $\hat{y} \leftarrow M(x)$ for accessing data.

Learning Index: A Machine Learning Task



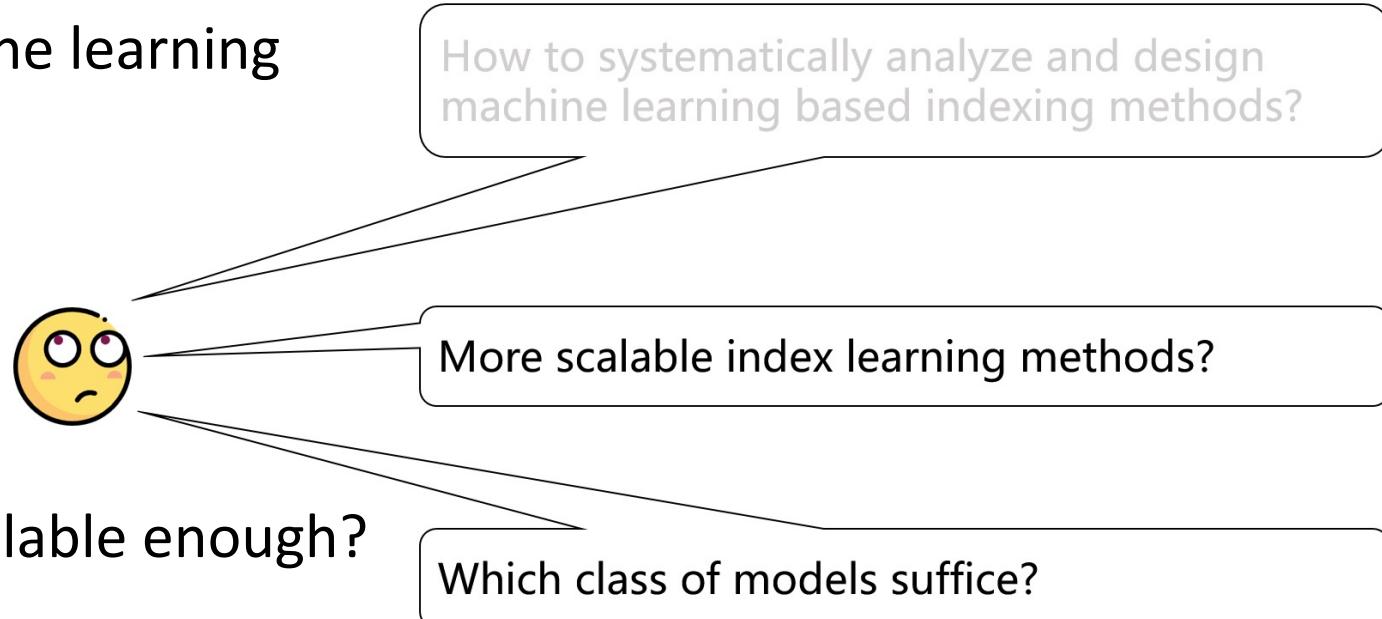
Learning Index: A Machine Learning Task

$$\begin{aligned} M^* &= \arg \min_{M \in \mathcal{M}} \text{MDL}(M, \mathcal{D}) \\ &= \arg \min_{M \in \mathcal{M}} (L(M) + \alpha L(\mathcal{D}|M)) \\ &= \arg \min_{M \in \mathcal{M}} (L(M) + \alpha \mathbb{E}_{\{x,y\} \in \mathcal{D}} L(y, \hat{y})) \end{aligned}$$

The diagram shows the objective function J as a red horizontal line segment. A blue bracket labeled "regularization" is positioned above the left part of the line. A blue bracket labeled "training loss" is positioned above the right part of the line. A vertical blue arrow labeled "trade-off" points downwards from the center of the line, indicating the balance between the two components.

Benefits of Learned Index

- Smaller Size
- Faster Index Seek
- Better Handling Index Update
 - Generalization ability of machine learning
 - Incremental learning
- Question Mark
 - Is model training/inference scalable enough?



Learned Index with Sampling

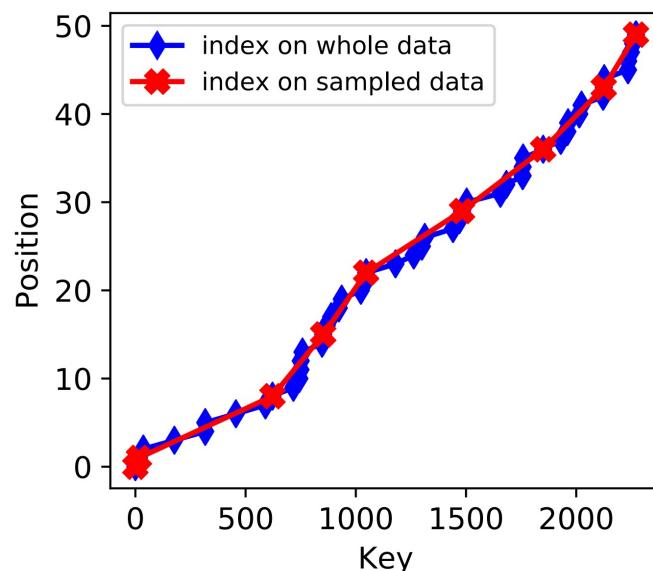


Fig: Illustration of sampling

- How large the sample needs to be?
 - n is the data size
 - M^* is fully optimized

THEOREM 1. Consider the optimization problem:

$$M^* = \arg \min_{M \in \mathcal{M}} \text{MDL}(M, \mathcal{D}) = \arg \min_{M \in \mathcal{M}} (L(M) + \alpha L(\mathcal{D}|M)).$$

We can solve it on a random sample D_s with size $s = O(\alpha^2 \log^2 n)$ as

$$\hat{M}^* = \arg \min_{M \in \mathcal{M}} \text{MDL}(M, \mathcal{D}_s)$$

s.t., $\text{MDL}(\hat{M}^*, \mathcal{D}) \leq \text{MDL}(M^*, \mathcal{D}) + O(1)$ with high probability.

$$\begin{aligned} M^* &= \arg \min_{M \in \mathcal{M}} \text{MDL}(M, \mathcal{D}) \\ &= \arg \min_{M \in \mathcal{M}} (L(M) + \alpha L(\mathcal{D}|M)) \\ &= \arg \min_{M \in \mathcal{M}} (L(M) + \alpha \mathbb{E}_{\{x,y\} \in \mathcal{D}} L(y, \hat{y})) \end{aligned}$$

regularization trade-off training loss

objective function

Learned Index with Sampling

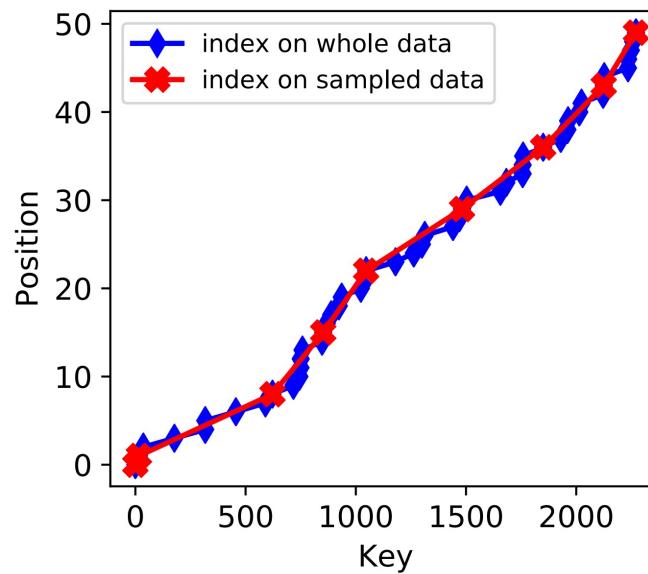
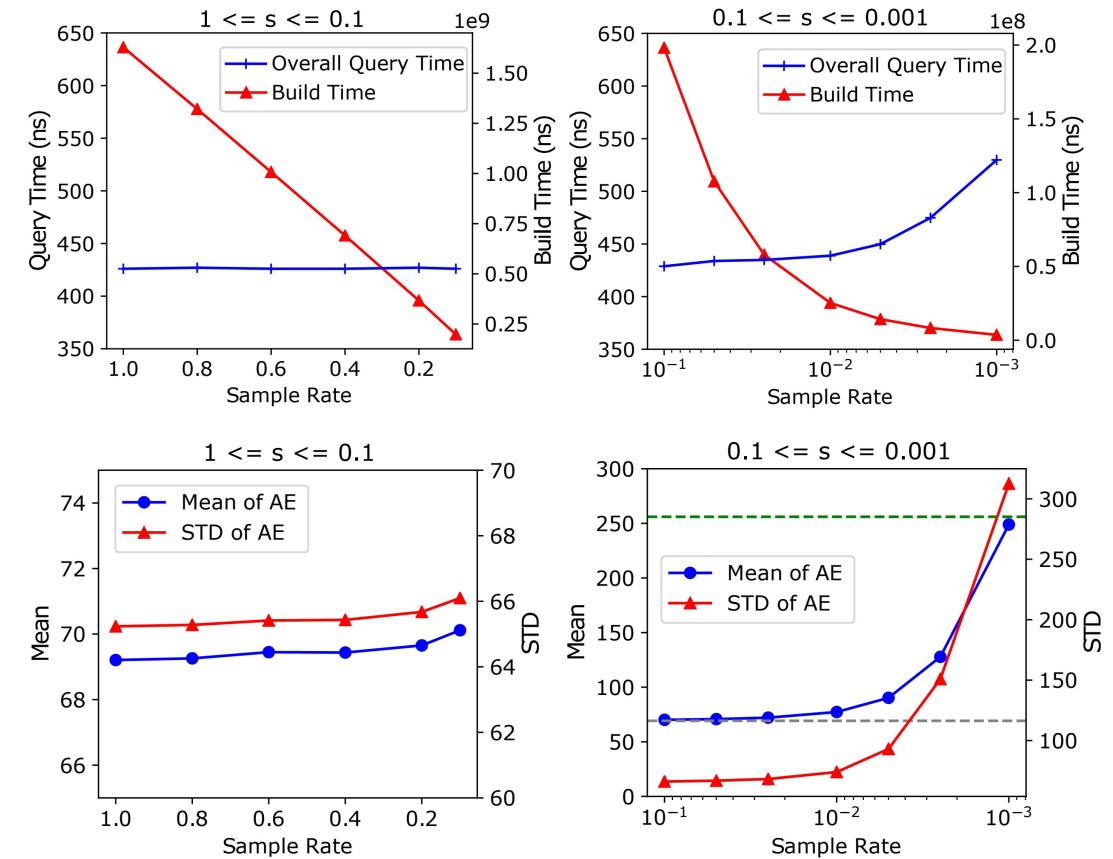


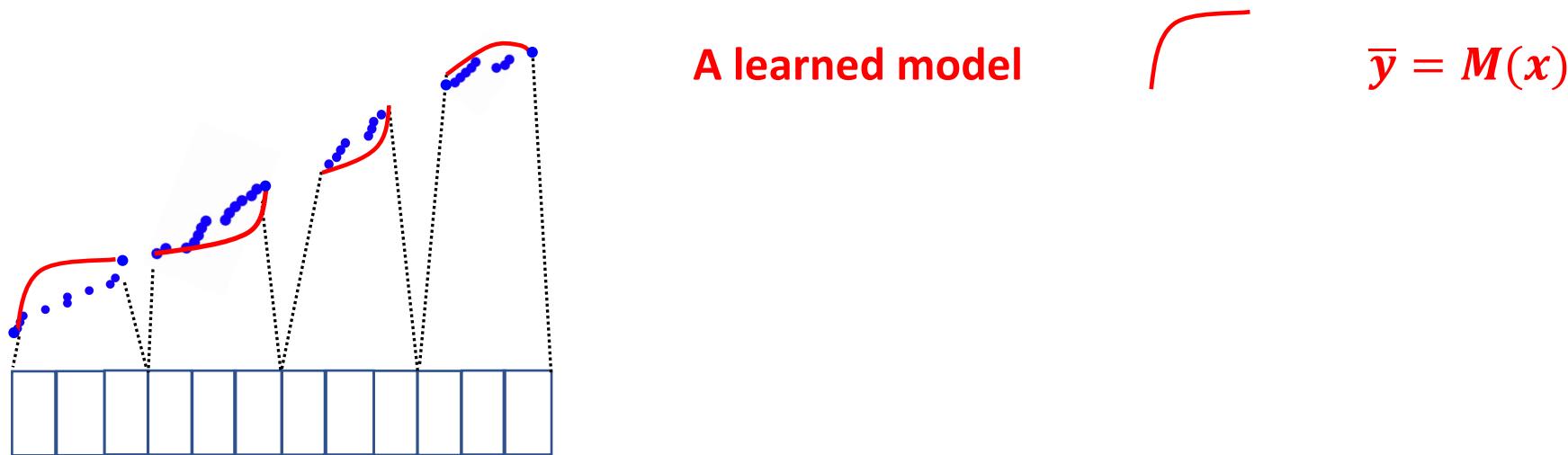
Fig: Illustration of sampling

- Up to **78x** building speedup
- **Non-degraded performance** in terms of query time and prediction error)



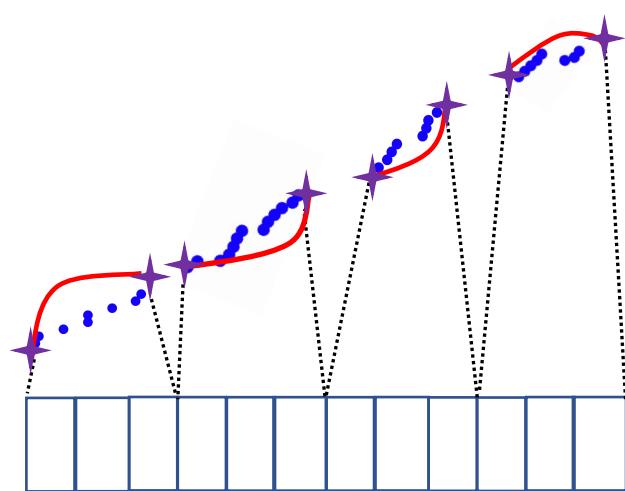
Is Linear Model Sufficient?

- Linearization of a learned model



Is Linear Model Sufficient?

- Linearization of a learned model



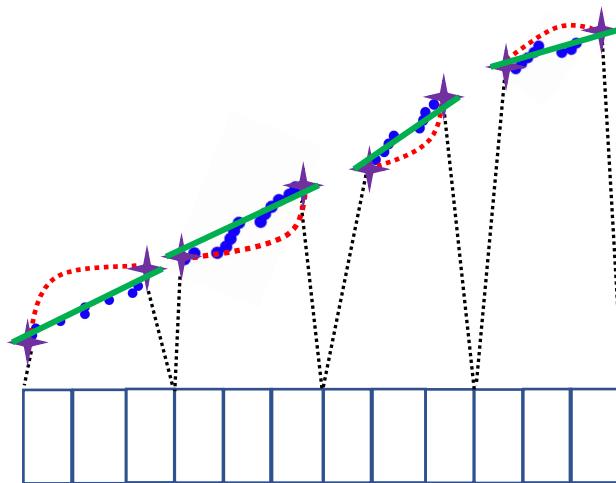
A learned model
Landmark points



$\bar{y} = M(x)$
 $\dots, (x_l, y_l), (x_r, y_r), \dots$

Is Linear Model Sufficient?

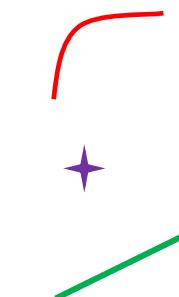
- Linearization of a learned model



A learned model

Landmark points

Linearized model



$$\bar{y} = M(x)$$

$\dots, (x_l, y_l), (x_r, y_r), \dots$

$$\hat{y} = M_L(x)$$

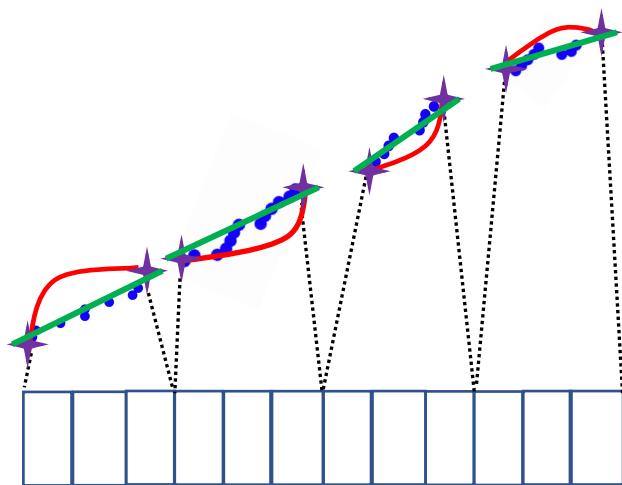
connecting $(x_l, \bar{y}_l = M(x_l))$ to $(x_r, \bar{y}_r = M(x_r))$

Is Linear Model Sufficient?



Yes! As long as landmark points are dense enough

- Linearization of a learned model



A learned model

Landmark points

Linearized model

$$\bar{y} = M(x)$$

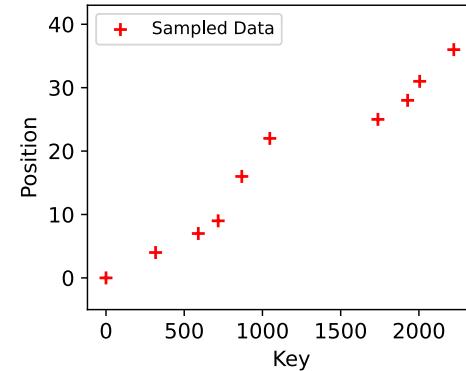
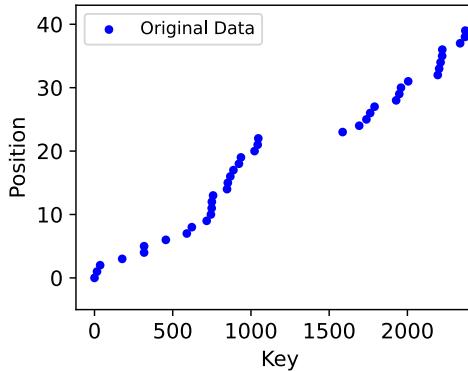
$$\dots, (x_l, y_l), (x_r, y_r), \dots$$

$$\hat{y} = M_L(x)$$

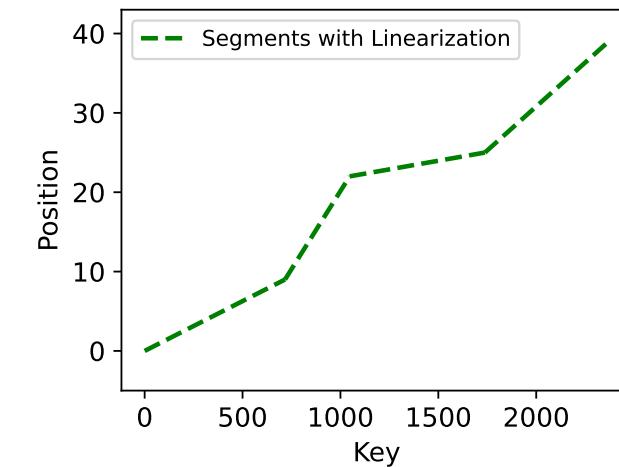
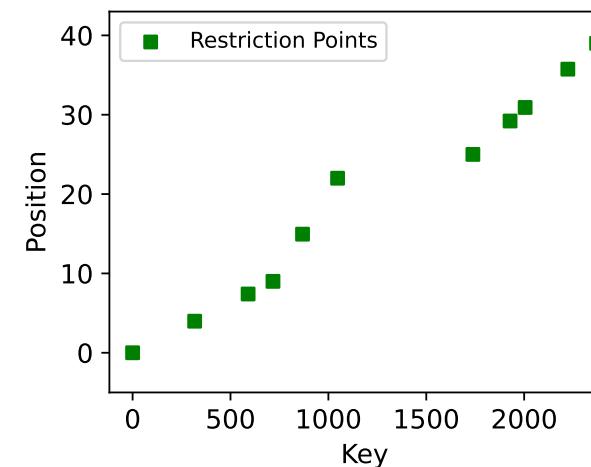
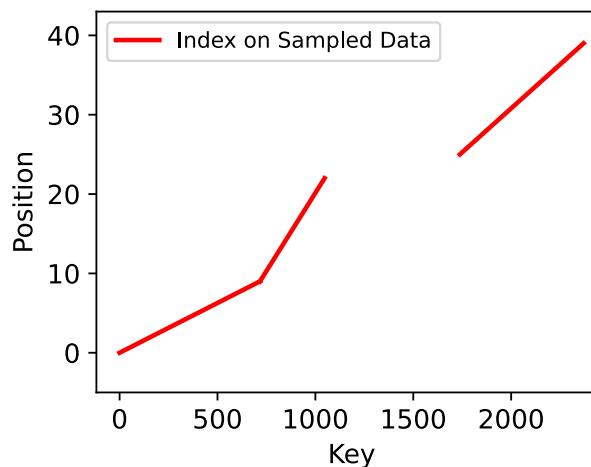
connecting $(x_l, \bar{y}_l = M(x_l))$ to $(x_r, \bar{y}_r = M(x_r))$

Theorem 2. Suppose $\forall x, |\bar{y} - y| \leq \epsilon$, after linearization, we have $\forall x, |\hat{y} - y| \leq 3\epsilon + 2(y_r - y_l)$.

Sampling-Restriction-Linearization



Sampled data points as landmark points:
 $\dots, (x_l, y_l), (x_r, y_r), \dots$



Learned Index on Sampled Data



Restriction



Linearization

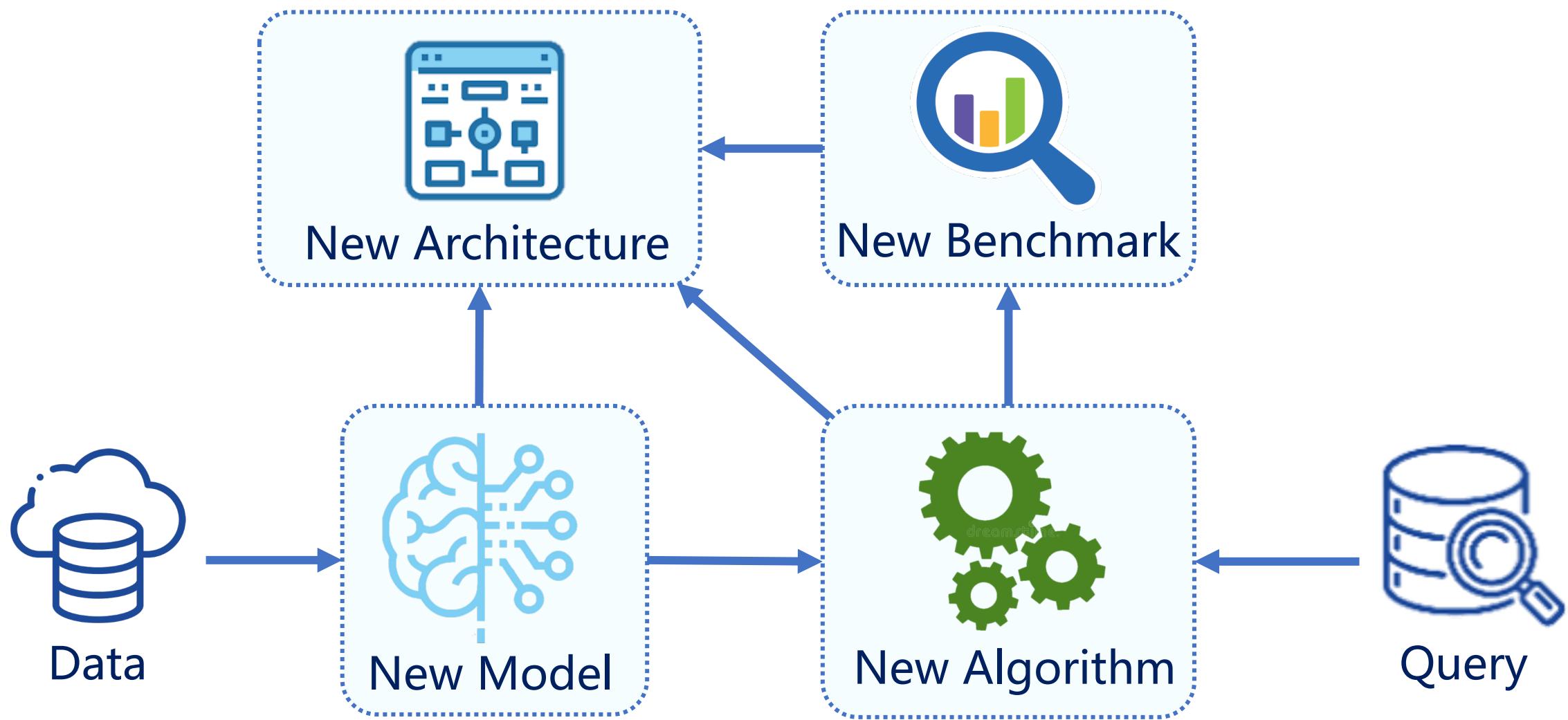
Open Questions

- How to handle extremely outlier keys?
- How to maintain index on updating data? [2]
- How to handle multi-dim data? [5, 6, 7]
- How to build it into real DB systems?
 - without too much modification to the current system

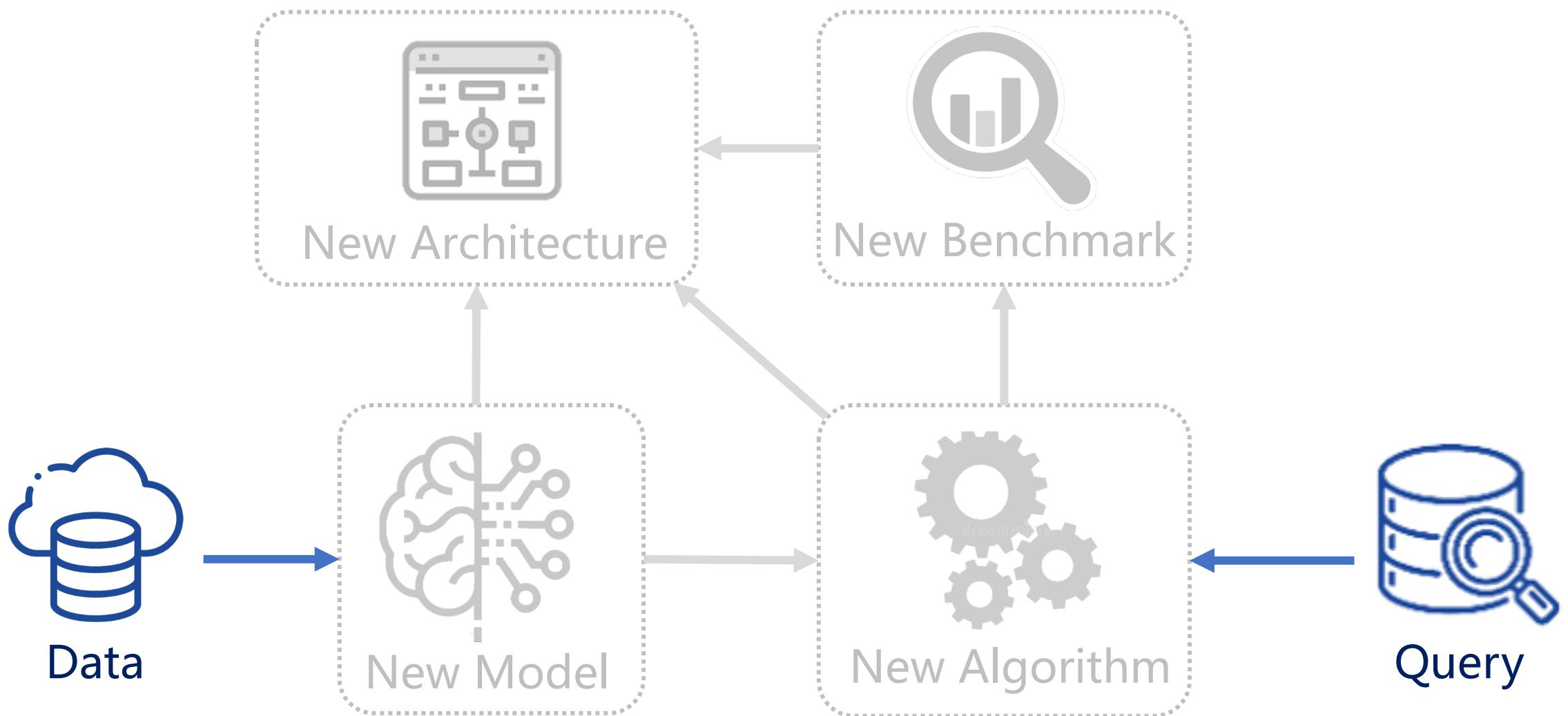
ML-Guided Database: Cardinality Estimation and Query Optimizer



Overview



Part 0: Background and Preliminaries



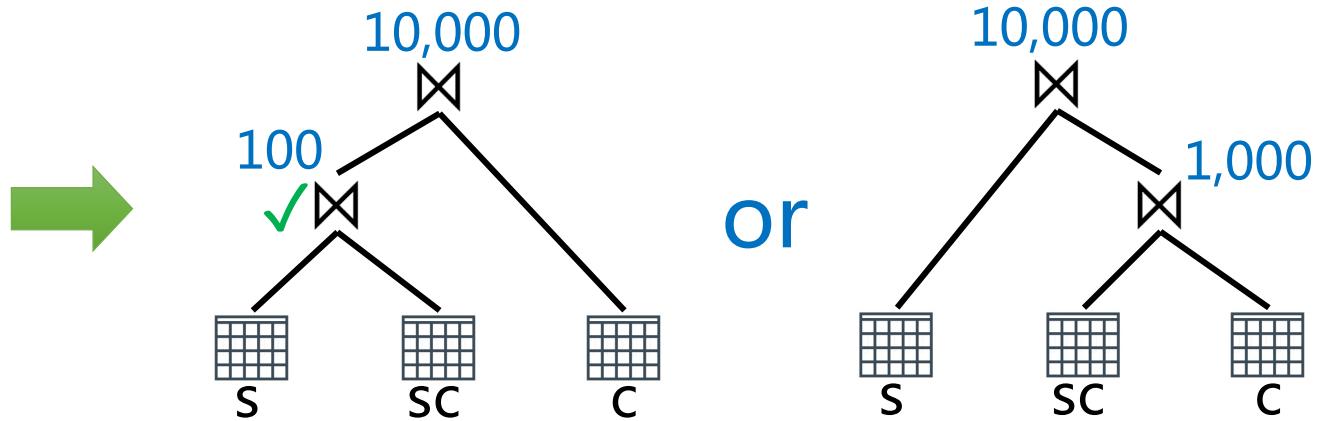
Outline

- Cardinality Estimation (CardEst) in Query Optimizer (QO)
- Existing CardEst Methods
- Motivation for New CardEst Methods

CardEst in QO

- CardEst: estimate the result size $C(Q)$ of the query Q without actual execution

```
SELECT COUNT(*)  
FROM s, sc, c  
WHERE s.sid = sc.sid AND sc.cid = c.cid  
AND s.year < 2009 AND c.credit >= 3
```



- Lay foundations for join ordering decision and cost estimation
- A key component in QO and decides the query plan quality

Existing CardEst Methods

- Statistical models to summarize data/query information
- Supervised methods: $\Pr(C(Q) \mid Q)$ mapping Q to $C(Q)$
 - High training cost: requiring lots of executed queries
 - Poor generalization: Q' must be similar to Q
- Unsupervised methods: $\Pr(A)$ of table T having attributes A
 - $C(Q) = \Pr(Q) \cdot |T|$
 - Low training cost and easy to generalize: model data directly

Unsupervised CardEst Methods

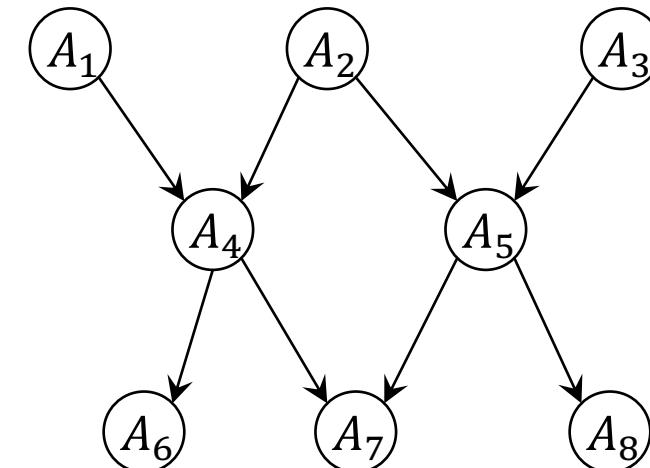
- Full Joint: store each entry in $\Pr(A)$
 - High space cost: grow exponentially w.r.t. $|A|$
- Sampling: fetch samples to estimate $\Pr(Q)$ on the fly
 - Model free, low space cost
 - Efficiency and accuracy decreases significantly w.r.t. $|A|$
- Factorization: use multiple $\Pr(A')$ to approximate $\Pr(A)$
 - $|A'| \ll |A|$ and $\Pr(A')$ is easy to model and store
 - A suitable aggregation function s.t. $f(\Pr(A')) \approx \Pr(A)$

Unsupervised CardEst Methods: Factorization

- 1-D Histogram: $\Pr(A) \approx \prod_i \Pr(A_i)$
 - Fast inference and low storage cost
 - Strong independence assumption: high estimation error
- M-D Histogram: $\Pr(A) \approx \prod_{S \subseteq A} \Pr(A_S)$
 - High space cost and lossy decomposition
- Deep Auto-Regression (DAR): $\Pr(A) = \prod_i \Pr(A_i | A_{<i})$
 - No independence assumption: high accuracy
 - Low inference: need sampling for range query
 - Large model size: use DNN to model each $\Pr(A_i | A_{<i})$

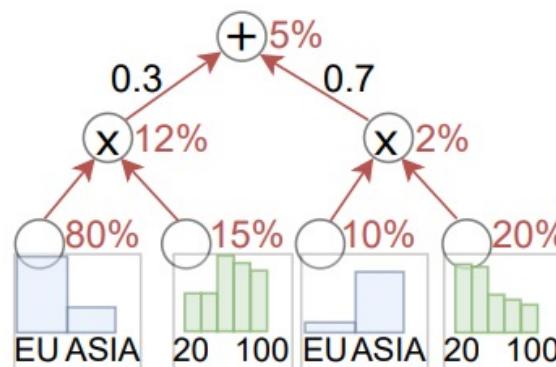
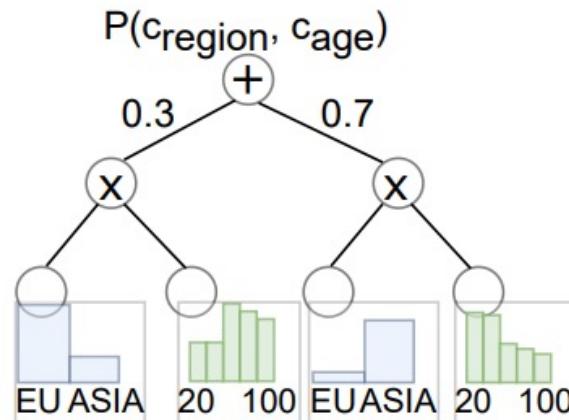
Unsupervised CardEst Methods: PGM Factorization

- Factorization using probabilistic graphical models (PGMs)
- Bayesian Network (BN): $\Pr(A) = \prod_i \Pr(A_i | A_{\text{pa}(i)})$
 - Conditional independence assumption: high accuracy
 - Explainable and compact model
 - Difficult in structure learning (NP-Hard)
 - Low inference (NP-Hard)



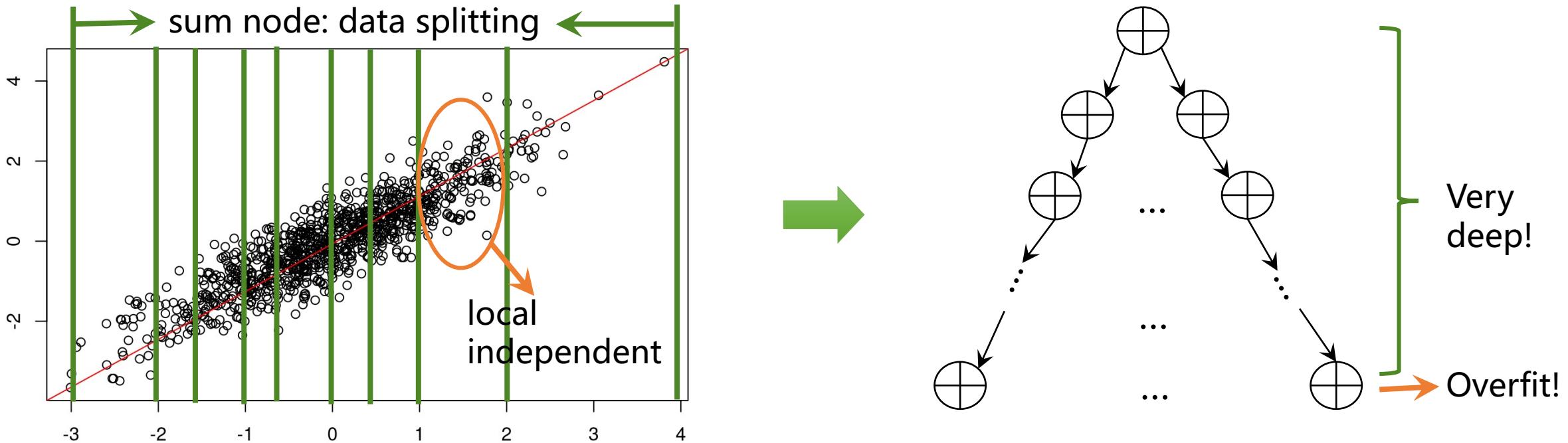
Unsupervised CardEst Methods: SPN

- Sum-Product Network (SPN): split $\Pr(A)$ on data or attributes
 - Sum node: $\Pr(A) = \sum_i \Pr_i(A) \cdot w_i$, $\Pr_i(A)$ is a sub-model on some data
 - Product node: $\Pr(A) = \prod_S \Pr(A_S)$, $A_S \subseteq A$ is a subset of attributes
 - Leaf node: model $\Pr(A_i)$ of one attribute A_i on some data
- Inference/Space cost \propto node size
- Local independence assumption: performance is data relevant



Unsupervised CardEst Methods: SPN

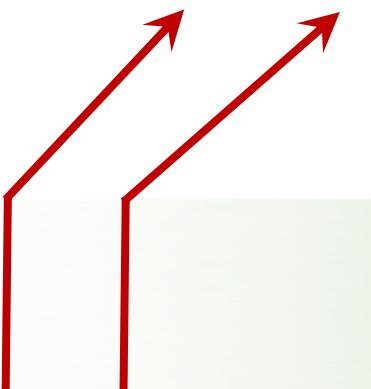
- When SPN can't perform well?
 - Some attributes are globally strongly correlated, e.g. $Y = 2X$
 - Splitting data into extremely small cluster to attain local independence



Unsupervised CardEst Methods: Summary

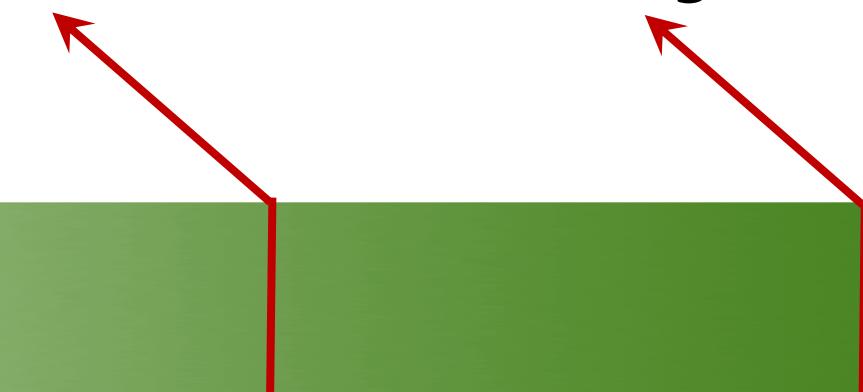
Conditional Decomposition
 $\Pr(XY) = \Pr(X)\Pr(Y|X)$

DAR BN



Independent Decomposition
 $\Pr(XY) = \Pr(X)\Pr(Y)$

SPN 1/M-D Histogram



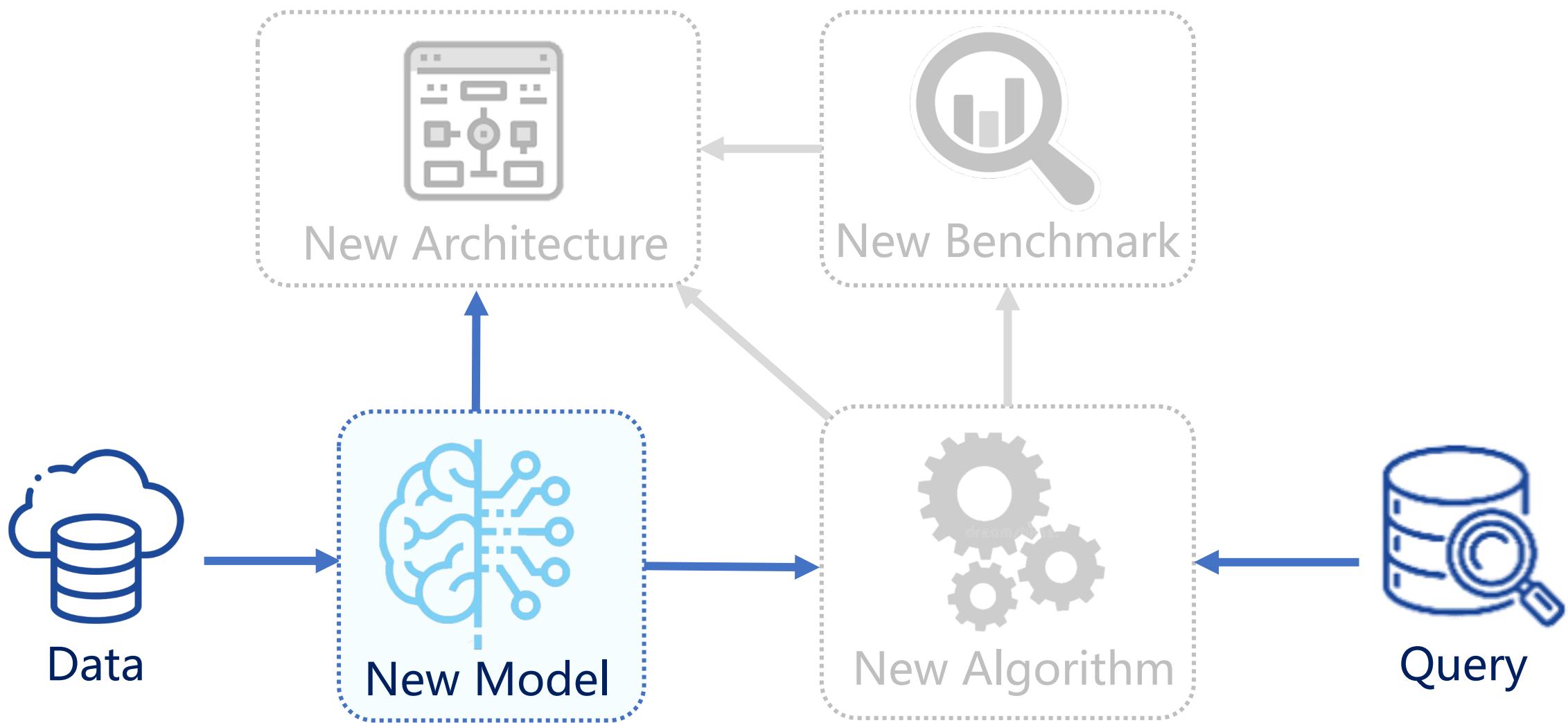
Attribute Independence Assumption : Weak \rightarrow Strong

Unsupervised CardEst Methods: Motivation

- No model achieves desirable performance in all aspects at the same time

Model	Independence Assumption	Inference Speed	Estimation Accuracy	Model Size
1-D Histogram	Strong	✓	✗	✓
M-D Histogram	Strong	✓	✗	✗
DAR	No	✗	✓	✗
BN	Conditional	✗	✓	✓
SPN	Local	✓ ✗	Data relevant	
?	No	✓	✓	✓

Part 1: The New FSPN Model



Outline

□ FSPN Model

- Ideas, definitions and theory analysis
- Structure learning, inference and update
- Empirical evaluation

Reference

- Ziniu Wu[#], Rong Zhu^{#, *}, Andreas Pladler, Yuxing Han, Jiangneng Li, Zhengping Qian, Kai Zeng, Jingren Zhou. *FSPN: A New Class of Probabilistic Graphical Model*, ArXiv, 2020.
<https://arxiv.org/abs/2011.09020>

FSPN: Basic Idea

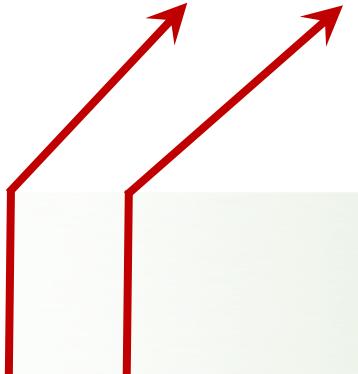
Adaptively use by different attribute dependence level

Accurate, Slow inference

Conditional Decomposition

$$\Pr(XY) = \Pr(X)\Pr(Y|X)$$

DAR BN

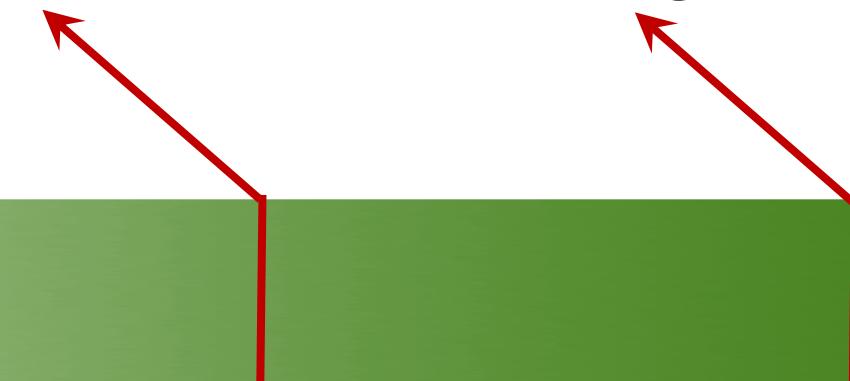


Fast inference, Not accurate

Independent Decomposition

$$\Pr(XY) = \Pr(X)\Pr(Y)$$

SPN 1/M-D Histogram

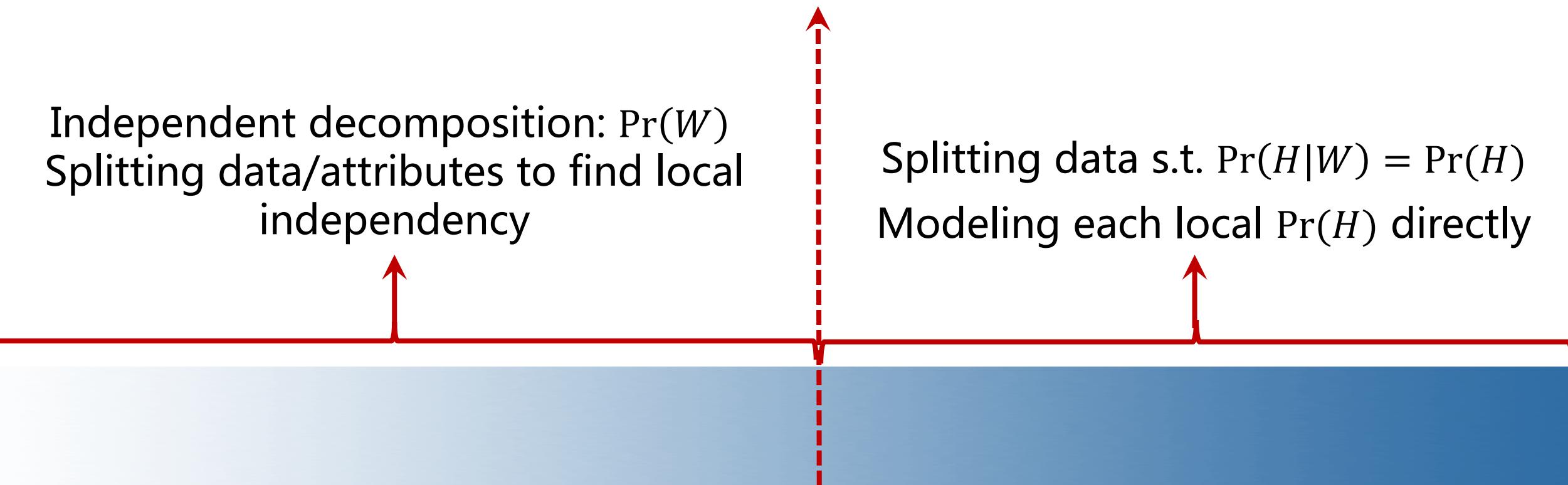


Attribute Independence Assumption : Weak \rightarrow Strong

FSPN: Basic Idea

Independent decomposition: $\Pr(W)$
Splitting data/attributes to find local
independency

Conditional decomposition: $\Pr(A) = \Pr(W) \cdot \Pr(H|W)$
Splitting strong and weak correlated attributes losslessly



Attribute Dependence Level : Weak \rightarrow Strong

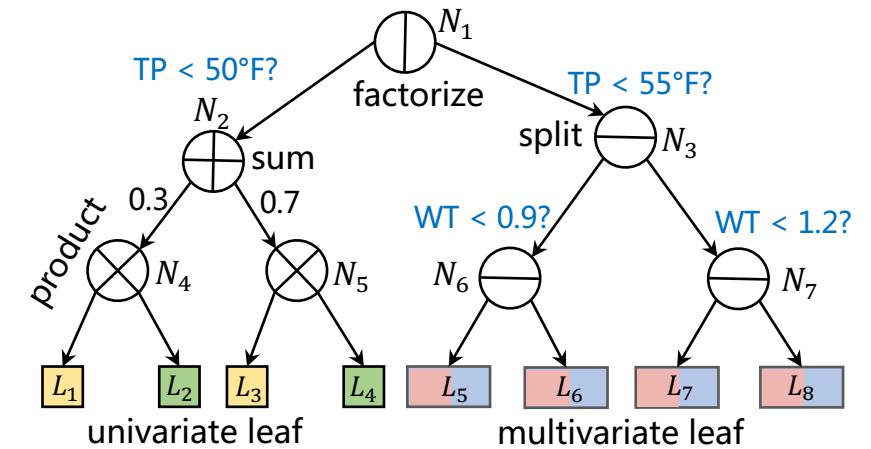
FSPN: Definition

- FSPN: Factorize-Sum-Split-Product Network
- A hierarchical tree structure
- A new type of PGM

$W = \{ WT, TP \}$ weakly correlated		$H = \{ WH, WF \}$ highly correlated	
WT (NTU)	TP (°F)	WH (m)	WF (m/s)
1.27	43.7	0.9	5.5
0.63	46.3	3.7	16.2
0.55	51.6	3.2	14.9
...
2.61	62.8	1.5	8.9
1.18	60.5	4.7	18.9
0.97	73.6	2.1	11.7

UCI Ocean Observation Data

- WT: water turbidity
- TP: temperature
- WH: wave height
- WF: wind force



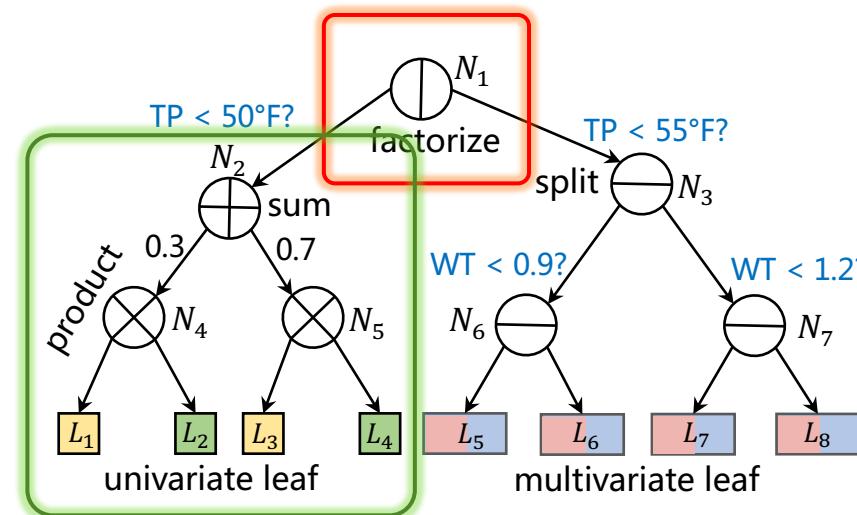
The FSPN Structure

FSPN: Definition

- **Factorize Node:** splitting $\Pr(A) = \Pr(W) \cdot \Pr(H|W)$, could be used multiple times
- **Left branch:** modeling $\Pr(W)$ with Sum/Product/Uni-leaf nodes

$W = \{ WT, TP \}$ weakly correlated $H = \{ WH, WF \}$ highly correlated

WT (NTU)		TP (°F)		WH (m)		WF (m/s)	
1.27	43.7	0.9	5.5				
0.63	46.3	3.7	16.2				
0.55	51.6	3.2	14.9				
...				
2.61	62.8	1.5	8.9				
1.18	60.5	4.7	18.9				
0.97	73.6	2.1	11.7				

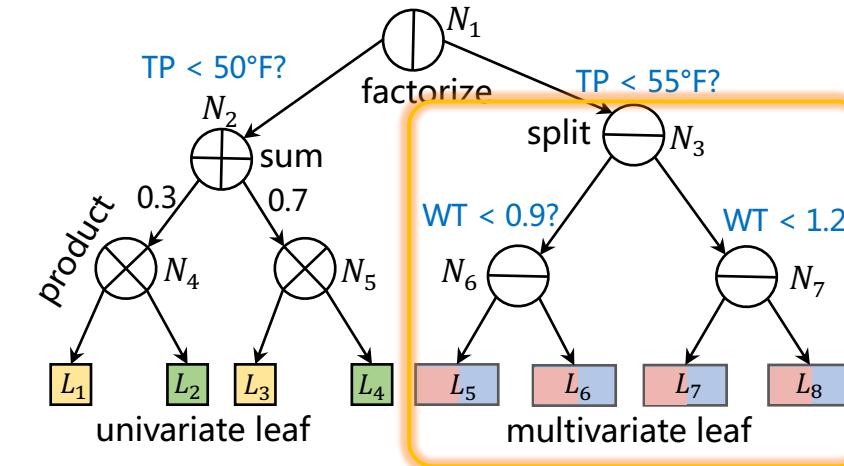


The FSPN Structure

FSPN: Definition

- Right branch: modeling $\Pr(H|W)$
 - Split Node: splitting data s.t. $\Pr(H|W) = \Pr(H)$ in each part
 - Multi-Leaf Node: modeling $\Pr(H)$ as a multivariate PDF

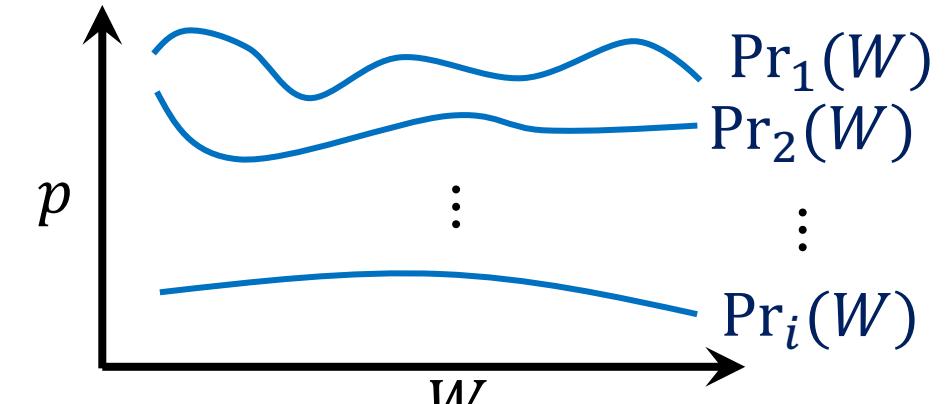
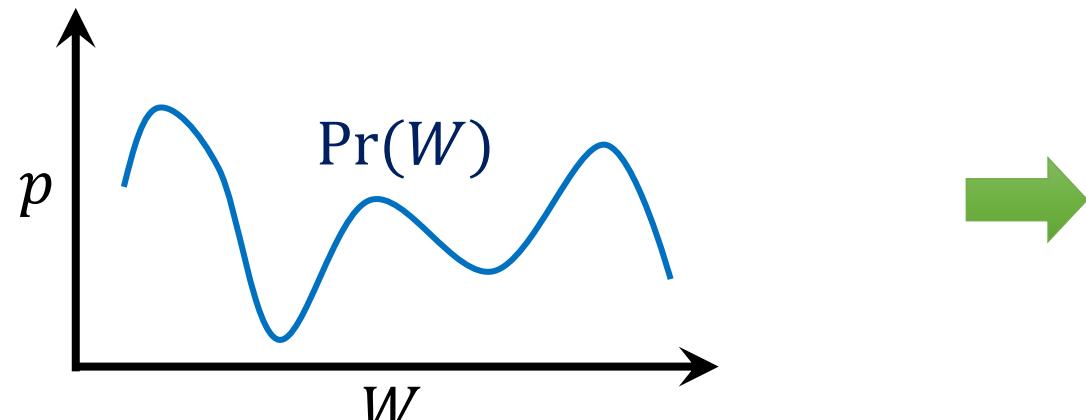
$W = \{ WT, TP \}$ weakly correlated		$H = \{ WH, WF \}$ highly correlated	
WT (NTU)	TP (°F)	WH (m)	WF (m/s)
1.27	43.7	0.9	5.5
0.63	46.3	3.7	16.2
0.55	51.6	3.2	14.9
...
2.61	62.8	1.5	8.9
1.18	60.5	4.7	18.9
0.97	73.6	2.1	11.7



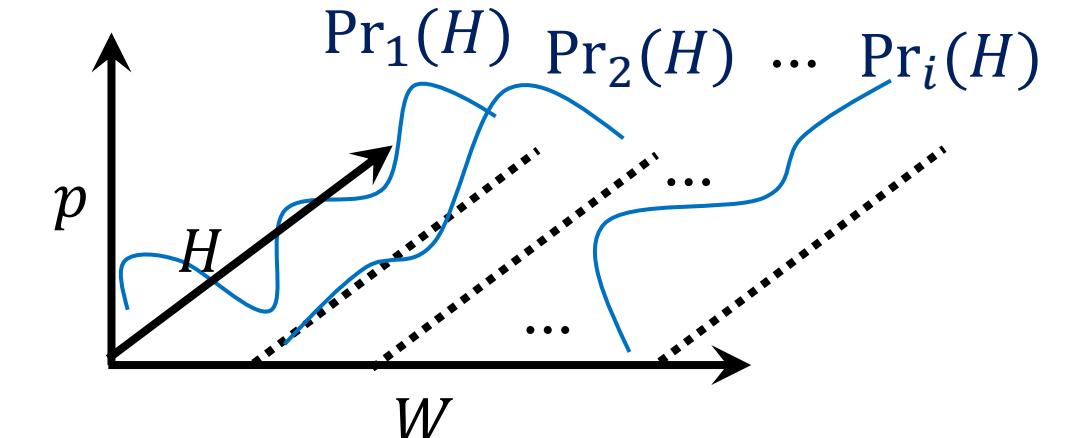
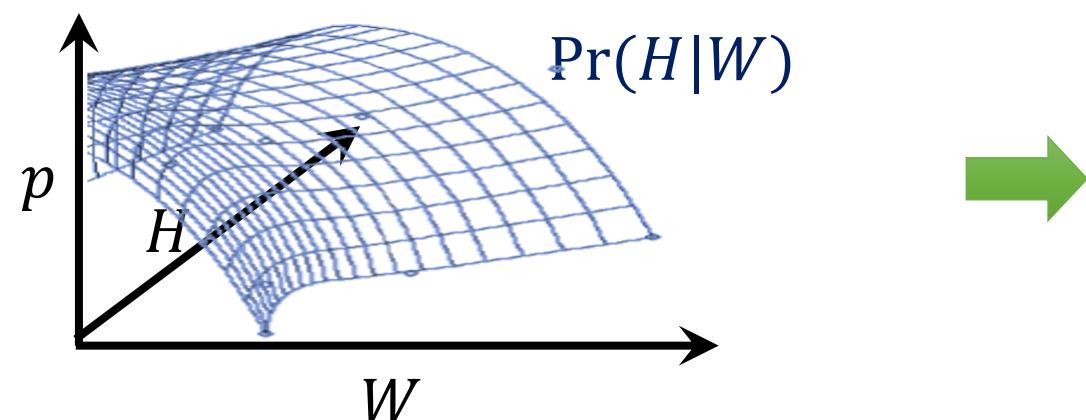
The FSPN Structure

FSPN: Definition

- **Sum Node:** splitting $\Pr(W)$ into small models on space of W

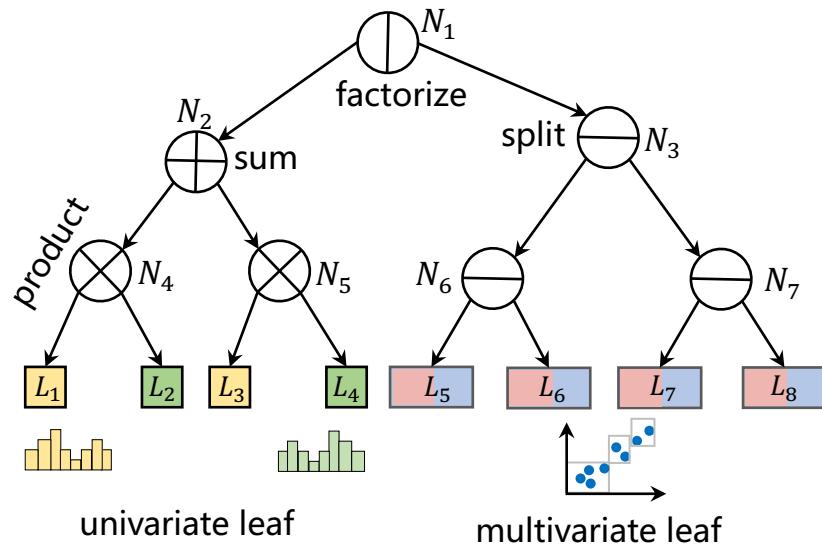


- **Split Node:** splitting $\Pr(H|W)$ into several parts by values of W

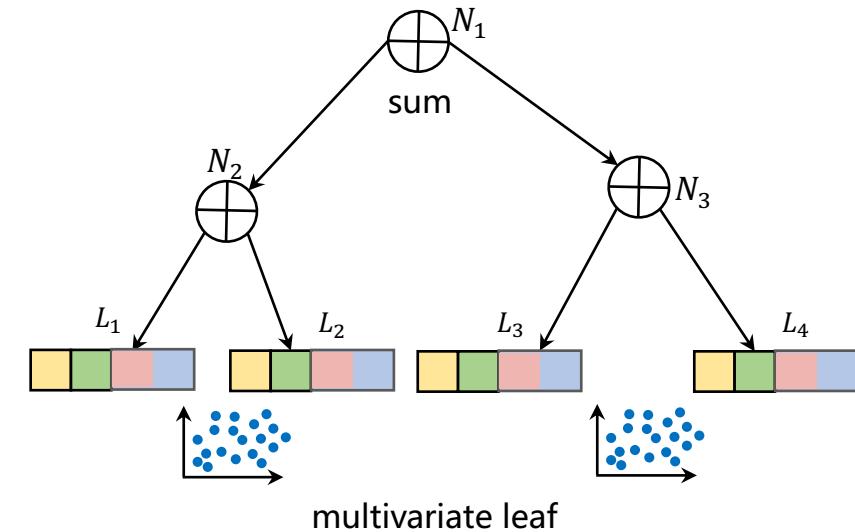


FSPN: Theoretical Advantages

- FSPN makes no independence assumption, overcomes the drawbacks of SPN
- $\text{FSPN} \neq \text{SPN} + \text{Multi-leaf nodes}$



FSPN: Process weakly and highly correlated attributes in different way



SPN + Multi-leaf nodes: Complex high-dimensional multivariate PDF to model

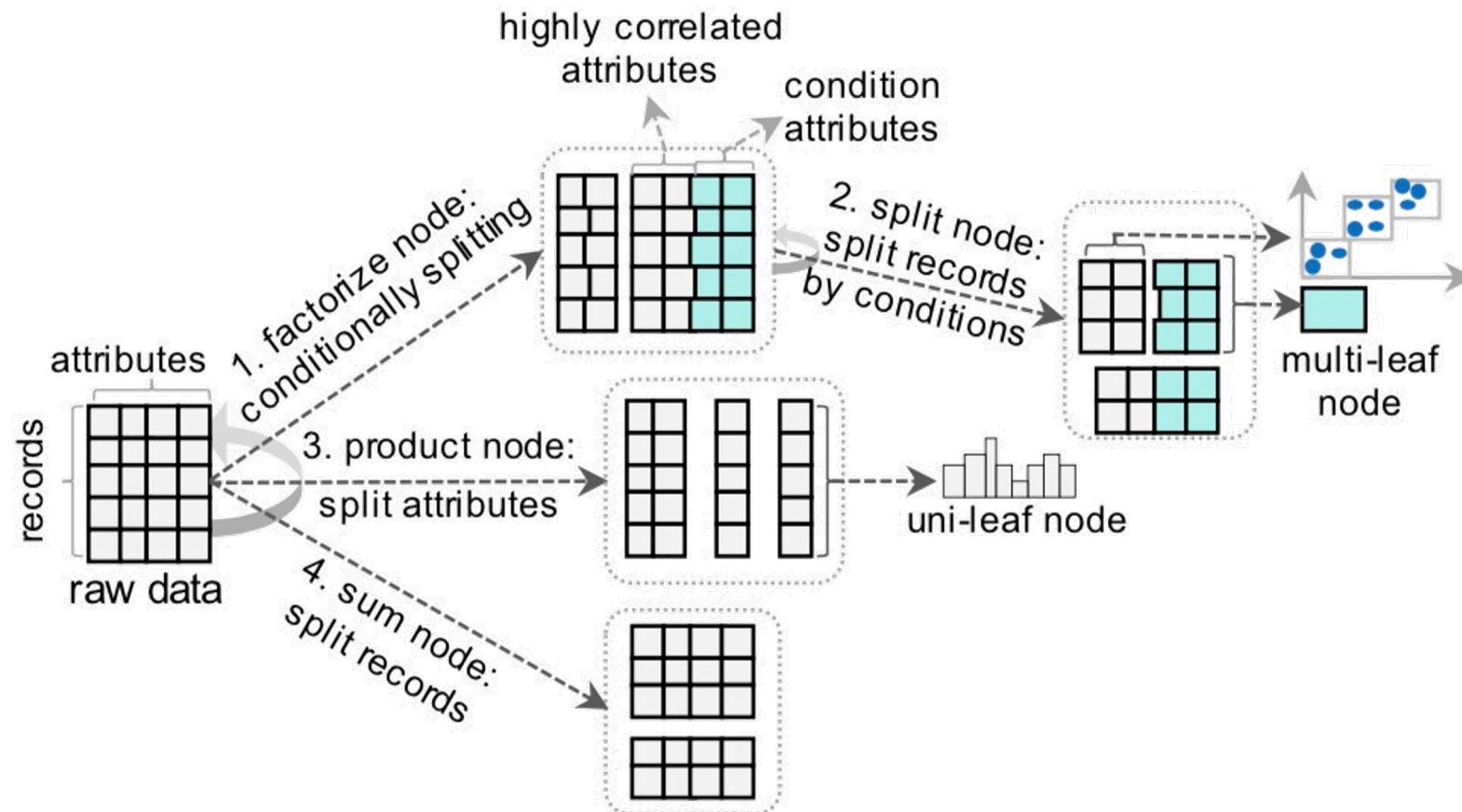
FSPN: Theoretical Advantages

- FSPN is a generalization of DAR, BN and SPN
 - SPN: disable factorize/split/multi-leaf nodes in FSPN
 - BN: iteratively factorize each attribute
 - DAR: a special case of BN
- The model size of FSPN is no larger than others

Lemma 1 *Given a table T with attributes A , if the joint $\text{PDFPr}_T(A)$ is represented by an SPN \mathcal{S} or a BN \mathcal{B} with space cost $O(M)$, then there exists an FSPN \mathcal{F} that can equivalently model $\text{Pr}_T(A)$ with no more than $O(M)$ space.*

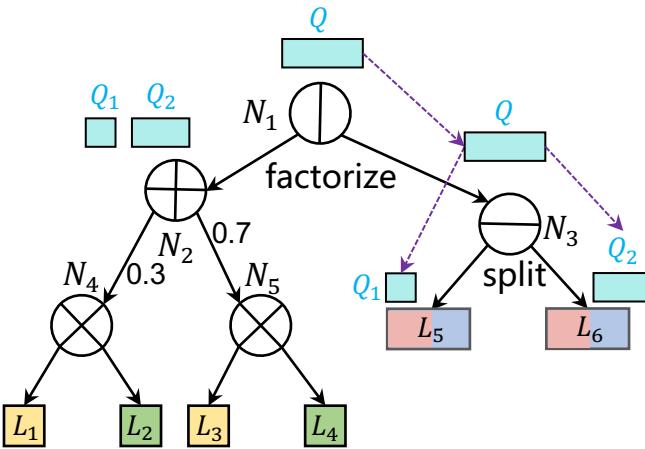
FSPN: Structure Learning

- Iterative operations: factorize → split → product → sum
 - Polynomial time cost

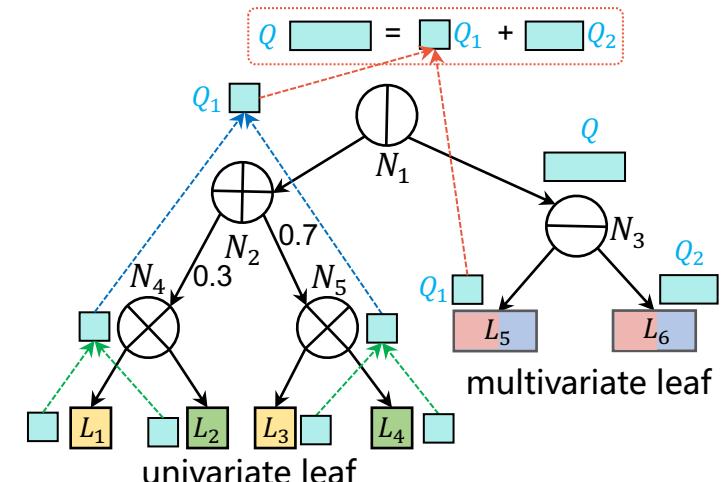


FSPN: Inference

- Top-down space decomposition
 - Iteratively divide the query space Q to Q_i , W and H are locally independent in each Q_i
- Bottom-up probability accumulation
- Time complexity: almost linear w.r.t. node size

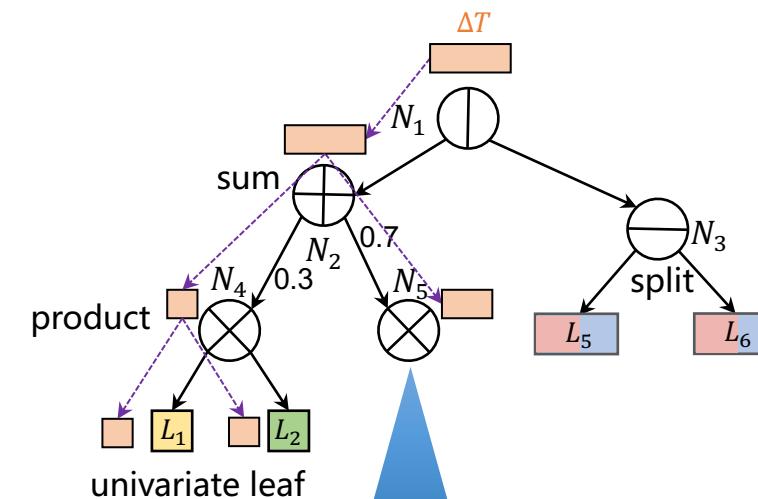
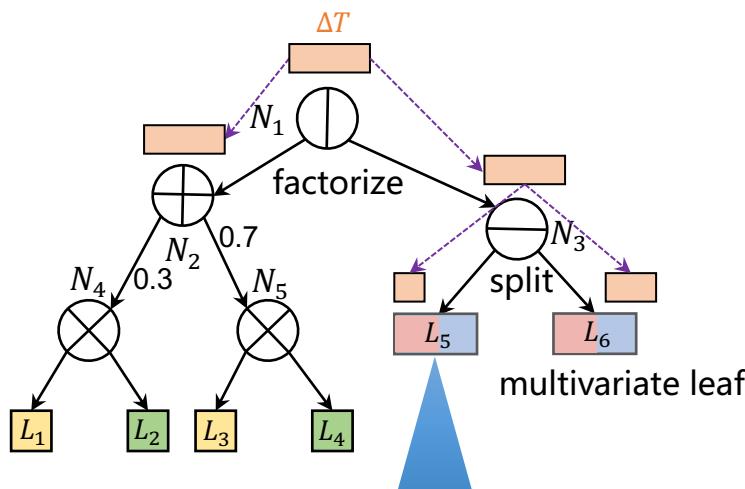


$$\Pr(W, H \in Q) = \sum_i \Pr(W, H \in Q_i) = \sum_i \Pr(W \in Q_i) \cdot \Pr(H \in Q_i)$$



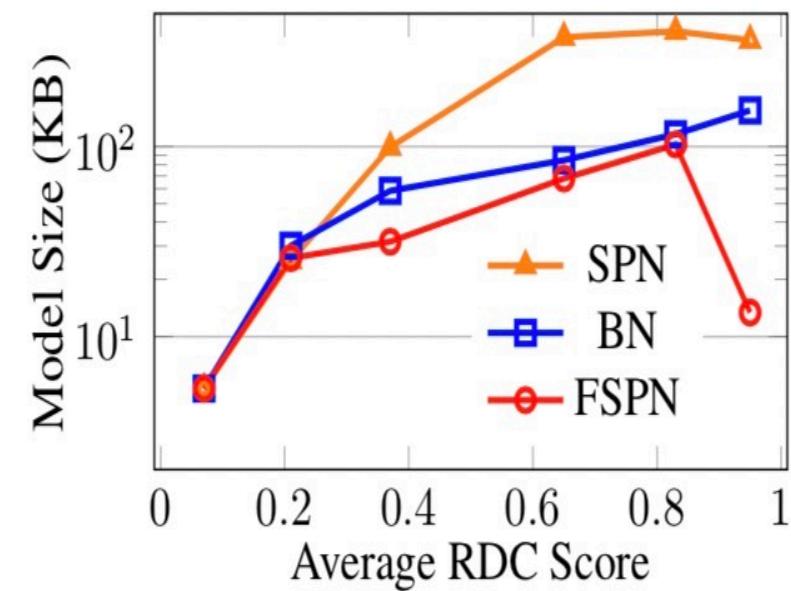
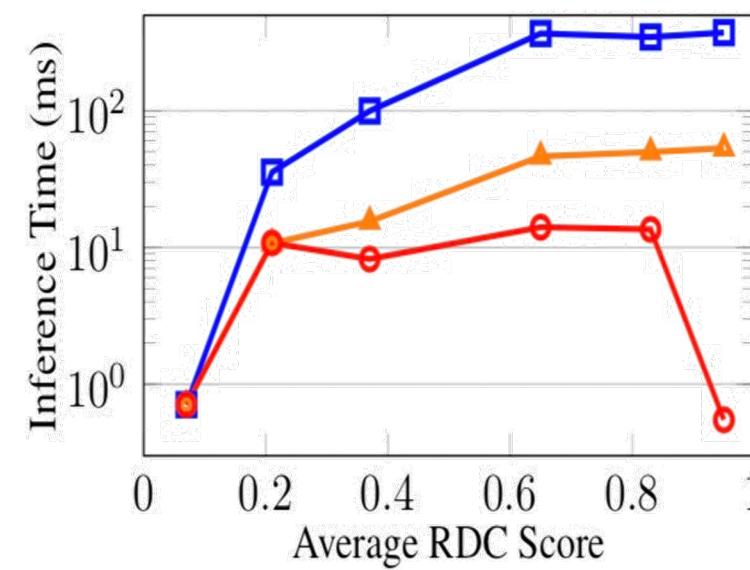
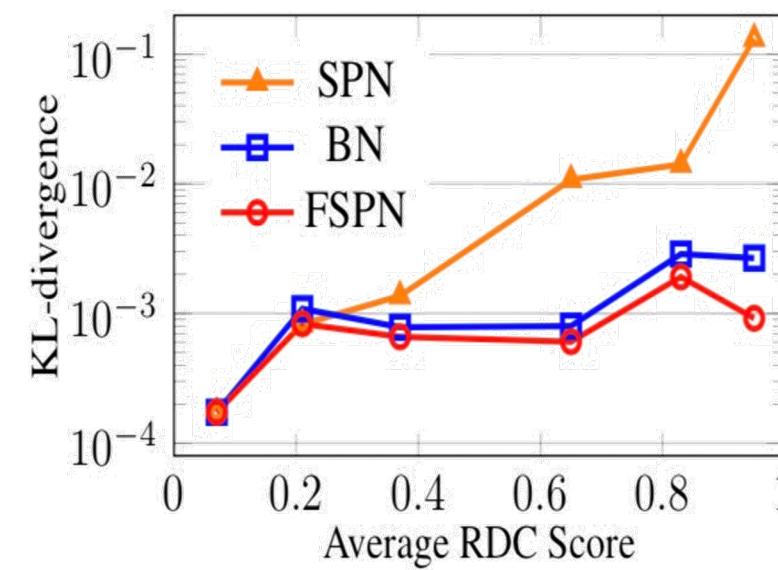
FSPN: Update

- Key idea: top-down incremental update
 - 1. **Factorize node**: losslessly decomposition, push ΔT to children
 - 2. **Left branch**: splitting ΔT and re-split the multi-leaf node if needed
 - 3. **Right branch**: assigning ΔT and re-split the product node if needed
- FSPN keeps the same if the distribution does not change



FSPN: Empirical Evaluation

- FSPN outperforms BN/SPN on synthetic datasets varying in dependency levels
 - Metrics: estimation accuracy, inference speed, model size

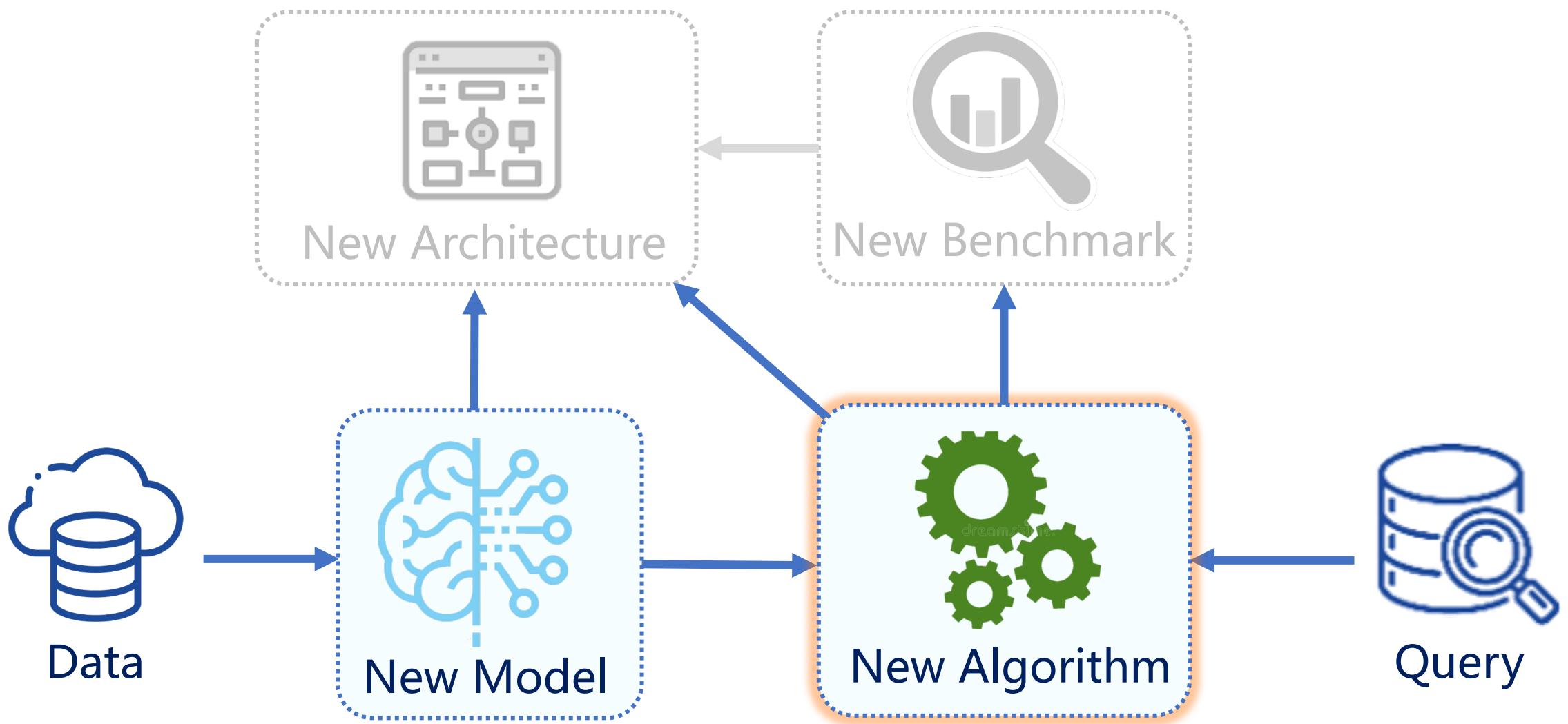


FSPN: Summary

- FSPN achieves our desirable goals

Model	Independence Assumption	Inference Speed	Estimation Accuracy	Model Size
1-D Histogram	Strong	✓	✗	✓
M-D Histogram	Strong	✓	✗	✗
DAR	No	✗	✓	✗
BN	Conditional	✗	✓	✓
SPN	Local	✓	✗ Data relevant	
FSPN	No	✓	✓	✓

Part 2: The New CardEst Algorithm



Outline

- FLAT: New CardEst Algorithm

- Basic idea and challenges
- Key techniques
- Evaluation results

Reference

- Rong Zhu^{#, *}, Ziniu Wu[#], Yuxing Han, Kai Zeng, Andreas Pfadler, Zhengping Qian, Jingren Zhou, Bin Cui. *FLAT: Fast, Lightweight and Accurate Method for Cardinality Estimation*, VLDB, 2021. <https://arxiv.org/abs/2011.09022>

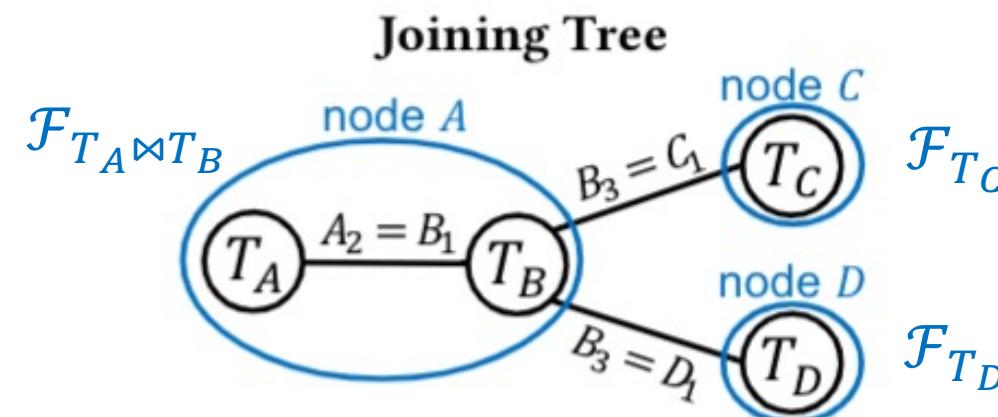
FLAT: Basic Idea

- How to apply FSPN on multiple tables?
- A single model on the full joined table → NeuroCard (DAR)
 - Not efficient: inference on the whole model for any query
 - High training cost: join table size grows exponentially
 - Not flexible: table insertion/deletion
- Multiple models, each represent several tables → DeepDB (SPN)
 - Can't support general join type
 - Key Challenges: how to aggregate local probabilities to global results

FLAT: Main Framework

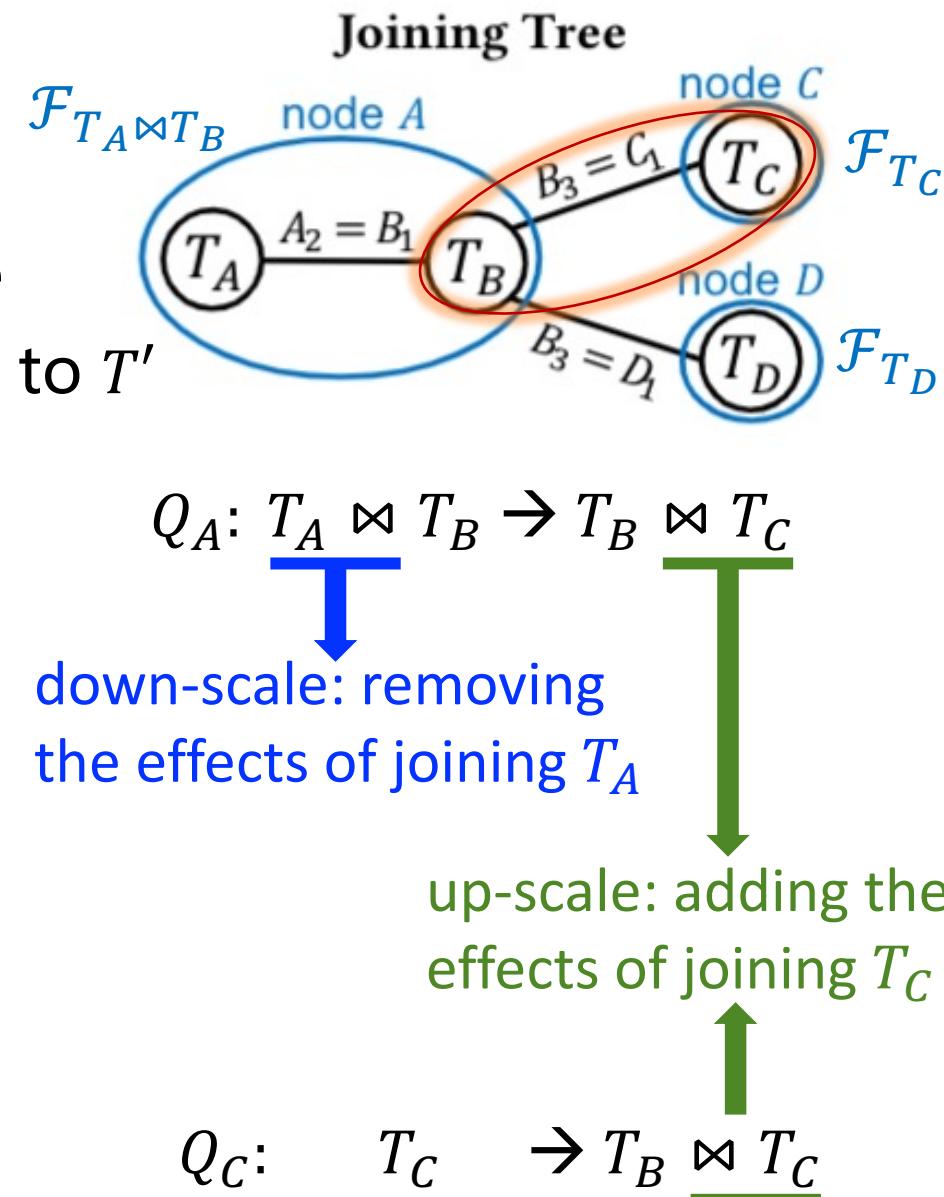
- Offline: join tree construction

- Group correlated tables into one node N_i , builds an FSPN on \mathcal{F}_{T_i} on its joined table T_i
- Probability independence assumption across different nodes
- Balance accuracy and efficiency



FLAT: Main Framework

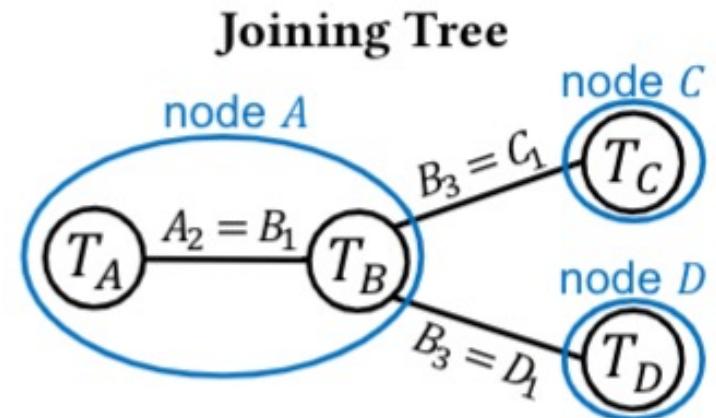
- Online: query Q on joined table T'
 - Decompose Q to sub-query Q_i on each node
 - Compute and **correct the probability** from T_i to T'
 - Global probability $\Pr_{T'}(Q) = \prod_i \Pr_{T'} Q_i$
- Probability correction
 - Intra-node: down-scale tables not in query
 - Inter-node: up-scale tables not in the node



FLAT: Probability Correction

- Scattering columns: support any join type

- $S_{A,O}$: how many tuples can join with A in O
- Intra-node: $S_{A,B}$ for each table B can join with A
- Inter-node: $S_{A,\{T\}}$ for each set of nodes T can join with node A
- Obtained by scanning the rooted join tree in linear time



(a) Table T_A

A_1	A_2
b	0
c	2
b	3
c	4

(b) Table T_B

B_1	B_2	B_3
1	0.32	M
0	0.67	D
3	0.41	D
2	0.79	M
4	0.58	K
3	0.21	K

$S_{A,B} \neq S_{B,A}$

(f) Table $T_A \bowtie T_B$

A_1	A_2	B_1	B_2	B_3	$S_{A,B}$	$S_{B,A}$	$S_{A,\{C\}}$	$S_{A,\{D\}}$	$S_{A,\{C,D\}}$
null	null	1	0.32	M	0	0	1	2	2
b	0	0	0.67	D	1	1	2	2	4
b	3	3	0.41	D	2	1	2	2	4
c	2	2	0.79	M	1	1	1	2	2
c	4	4	0.58	K	1	1	1	1	1
b	3	3	0.21	K	2	1	1	1	1

FLAT: Probability Correction

- Down-scale: use intra-node $S_{A,B}$ columns

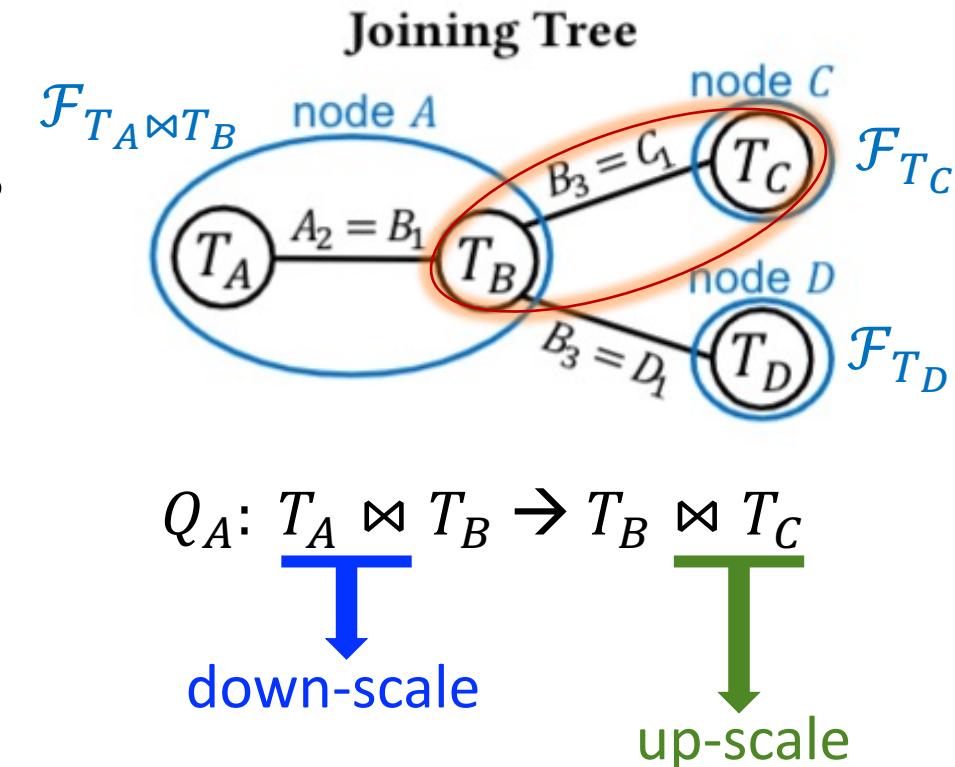
$$\Pr'(Q_i) = \sum_{s \in N} \frac{\Pr(Q_i \text{ and } S_{A,B} = s)}{\max\{s, 1\}}$$

- Up-scale: use inter-node $S_{A,\{C\}}$ columns

$$\Pr'(Q_i) = \sum_{s' \in N} \Pr(Q_i \text{ and } S_{A,\{C\}} = s') \cdot \max\{s', 1\}$$

- Put it together: how to fast compute over the summarization

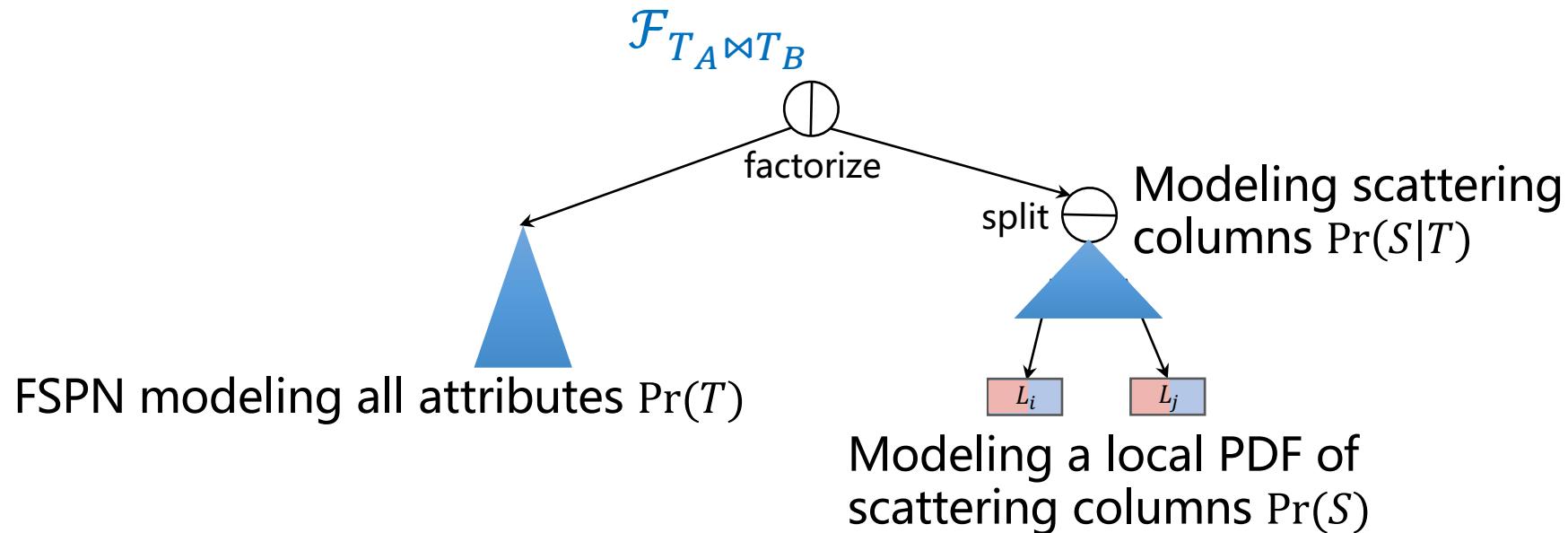
$$\Pr'(Q_i) = \sum_{s,s' \in N} \Pr(Q_i \text{ and } S = s \text{ and } S' = s') \frac{\max\{s', 1\}}{\max\{s, 1\}}$$



FLAT: Fast Probability Computation

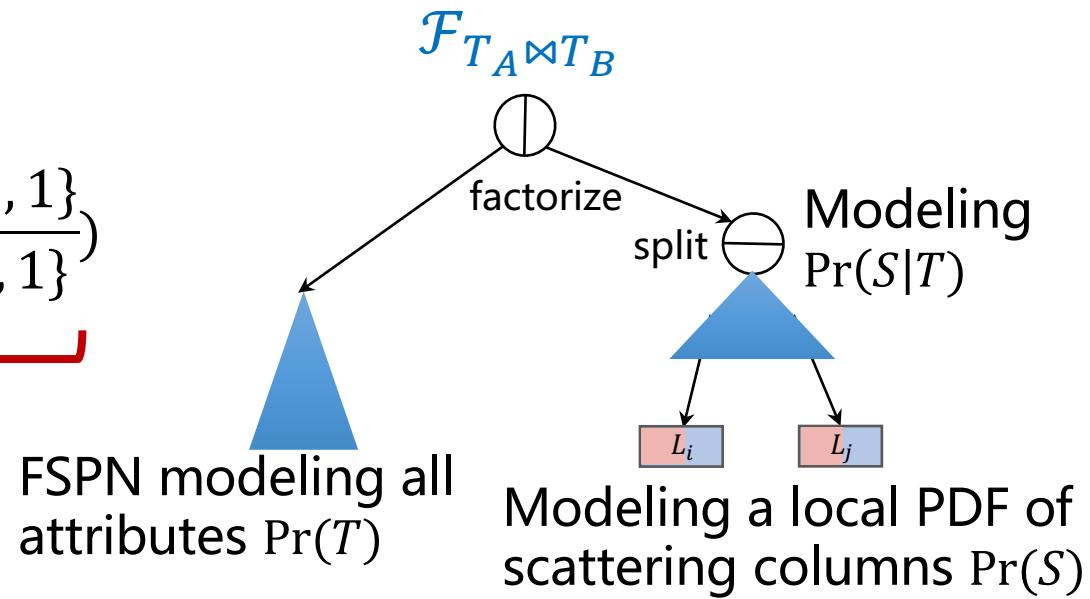
- A special FSPN

- Root factorize node: splitting attributes T with scattering columns S
- Left branch: a common FSPN modeling $\Pr(T)$
- Right branch multi-leaf nodes: a local PDF of scattering columns $\Pr(S)$



FLAT: Fast Probability Computation

$$\begin{aligned}
 \Pr'(Q_i) &= \sum_{s, s' \in N} \Pr(Q_i \text{ and } S = s \text{ and } S' = s') \frac{\max\{s', 1\}}{\max\{s, 1\}} \\
 &= \sum_L \left(\Pr(Q_i) \cdot \sum_{s, s' \in N} \Pr(S = s \text{ and } S' = s') \frac{\max\{s', 1\}}{\max\{s, 1\}} \right) \\
 &\quad \text{Independent on each multi-leaf node } L \\
 &= \sum_L \left(\Pr(Q_i) \cdot \mathbb{E} \left[\frac{\max\{S', 1\}}{\max\{S, 1\}} \right] \right) \\
 &\quad \text{Store as a constant offline}
 \end{aligned}$$



FLAT: Evaluation Results

- IMDB dataset and two query workload
 - State-of-the-art accuracy
 - Reasonable model size
 - Efficient training time

Simple JOB-light

$$Q\text{-Error} = \max\left(\frac{\hat{Q}}{Q}, \frac{Q}{\hat{Q}}\right)$$

Algorithm	50%	90%	95%	99%	Max	Size (KB)
Histogram	8.310	1, 386	6, 955	$8 \cdot 10^5$	$2 \cdot 10^7$	131
NeuroCard	1.580	4.545	5.910	8.480	8.510	7, 076
BN	2.162	28.00	74.60	241.0	306.0	237
DeepDB	1.250	2.891	3.769	25.10	31.50	$3.7 \cdot 10^4$
MaxDiff	32.31	5, 682	$5 \cdot 10^4$	$4 \cdot 10^6$	$4 \cdot 10^7$	$4 \cdot 10^5$
Sample	2.206	65.80	1, 224	$5 \cdot 10^4$	$1 \cdot 10^6$	-
KDE	10.56	563.0	4, 326	$4 \cdot 10^5$	$8 \cdot 10^6$	-
MSCN	2.750	19.70	97.60	622.0	661.0	3, 421
FLAT (Ours)	1.150	1.819	2.247	7.230	10.86	3, 430

Complex JOB-ours

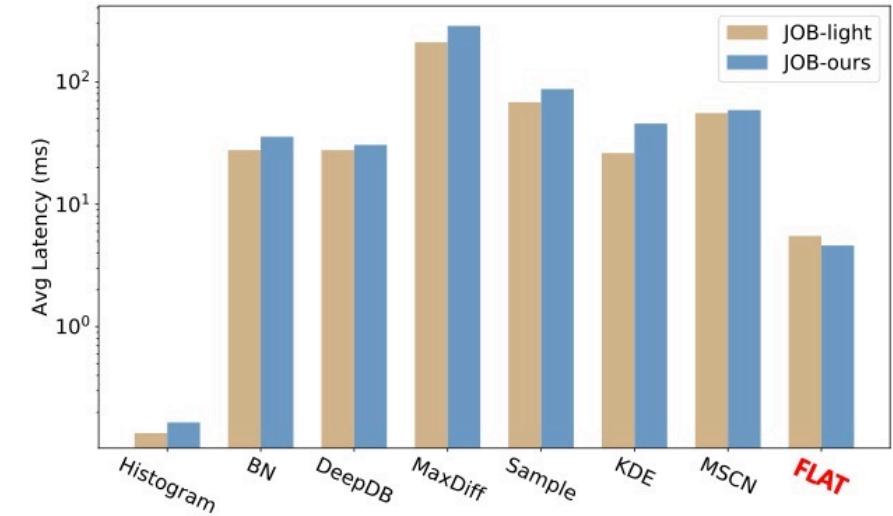
Algorithm	50%	90	95%	99%	Max	Training Time (Min)
Histogram	15.71	7480	$4 \cdot 10^4$	$1 \cdot 10^6$	$4 \cdot 10^8$	2.7
NeuroCard	1.538	9.506	81.23	8012	$1 \cdot 10^5$	173
BN	2.213	25.60	2456	$2 \cdot 10^5$	$7 \cdot 10^6$	7.3
DeepDB	1.930	28.30	248.0	$1 \cdot 10^4$	$1 \cdot 10^5$	68
MaxDiff	45.50	8007	$2 \cdot 10^5$	$9 \cdot 10^6$	$1 \cdot 10^9$	79
Sample	2.862	116.0	3635	$3 \cdot 10^5$	$4 \cdot 10^7$	-
KDE	8.561	1230	$1 \cdot 10^4$	$9 \cdot 10^5$	$2 \cdot 10^8$	15
MSCN	4.961	45.7	447.0	8576	$1 \cdot 10^5$	1, 744
FLAT (Ours)	1.202	6.495	57.23	1120	$1 \cdot 10^4$	53

FLAT: Evaluation Results

- IMDB dataset and JOB query workload
 - 1-2 orders faster inference
 - Efficient and accuracy incremental update

$$Q\text{-Error} = \max\left(\frac{\hat{Q}}{Q}, \frac{Q}{\hat{Q}}\right)$$

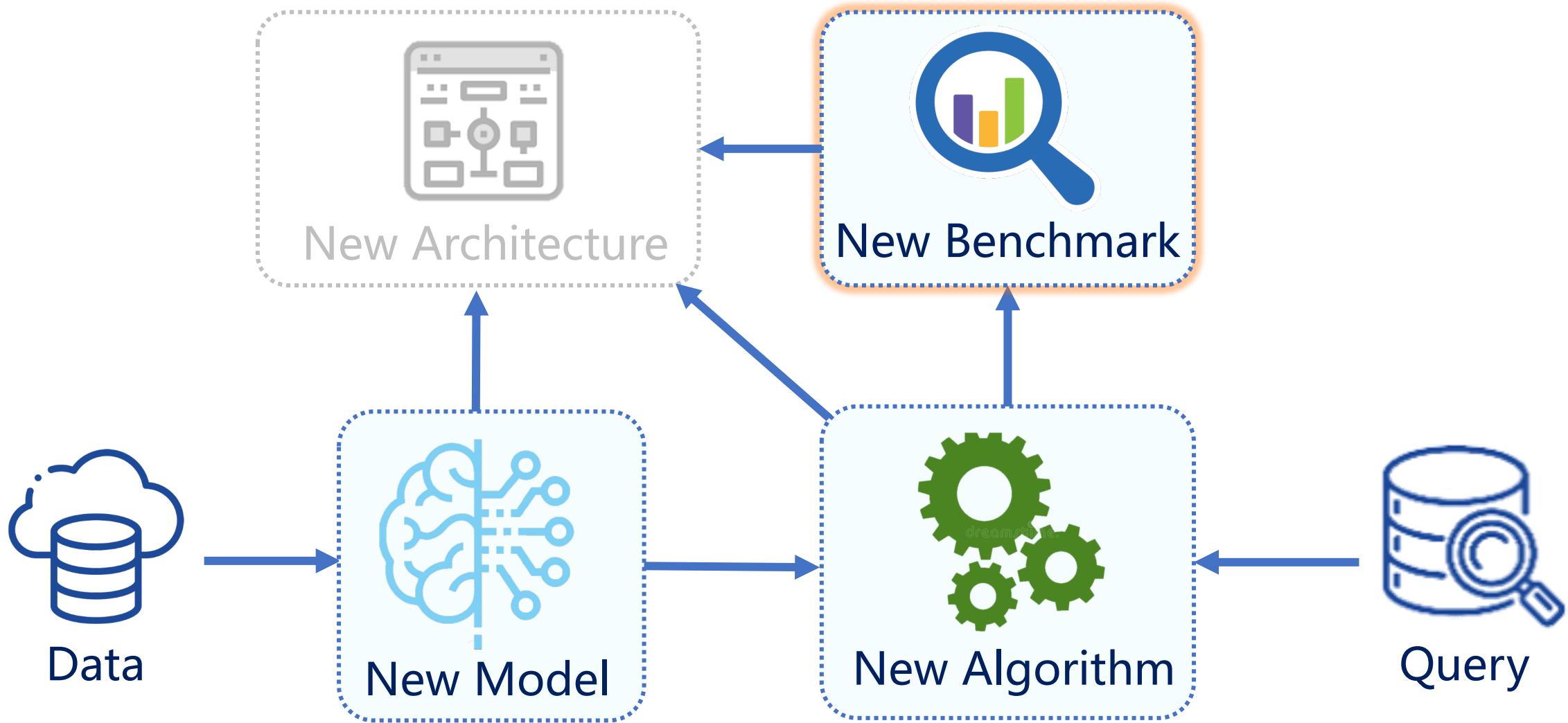
Update	Method	50%	90%	95%	99%	Max	Time (Min)
Insertion	Non-Updated	1.201	2.297	3.862	18.93	47.14	0
	Retrained	1.150	1.819	2.247	7.230	10.86	53
	Our Method	1.153	1.821	2.480	8.914	13.72	1.2
Deletion	Non-Updated	1.218	2.263	3.905	15.47	56.21	0
	Retrained	1.129	1.763	2.253	6.815	15.3	49
	Our Method	1.134	1.791	2.432	8.285	19.78	1.0



FLAT: Summary

- Build on top of the FSPN Model
 - Accurate data modeling
 - Fast inference, small model size
 - Efficient incremental update
- Key techniques: divide and conquer, probability correction
 - Flexible to use, fast to train
 - General to any type of join queries
 - Keep efficiency and accuracy

Part 3: The New CardEst Benchmark



Outline

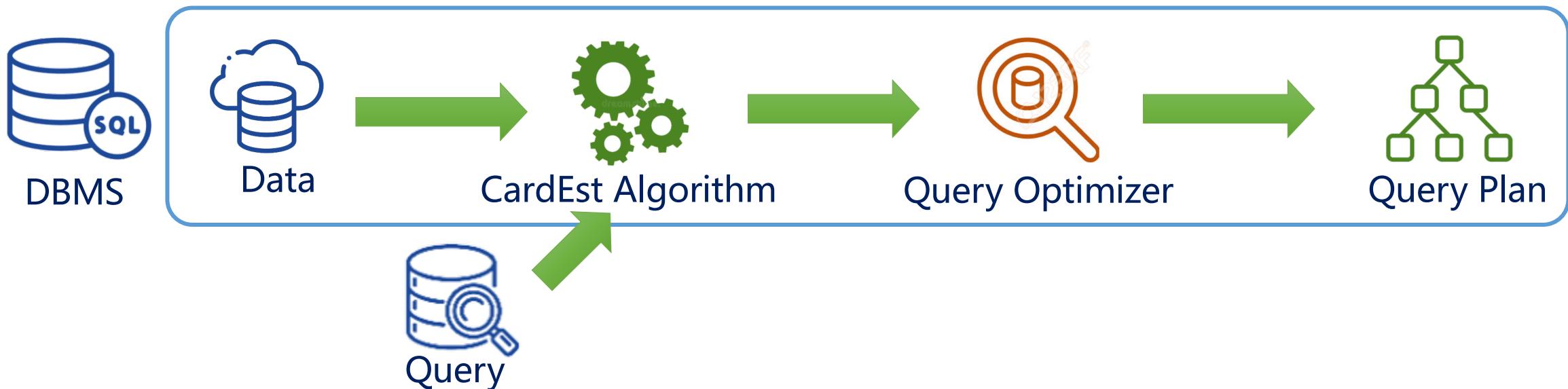
- ❑ CardEst Benchmark Revisit
 - ❑ Settings, principles and shortcomings
- ❑ New CardEst Benchmark
 - ❑ Tool, data/query and metrics
 - ❑ New evaluation findings

Reference

- Yuxing Han[#], Ziniu Wu[#], Peizhi Wu, Rong Zhu^{*}, Jingyi Yang, Liang Wei Tan, Kai Zeng, Gao Cong, Yanzhao Qin, Andreas Pfadler, Zhengping Qian, Jingren Zhou, Jiangneng Li, Bin Cui. *Cardinality Estimation in DBMS: A Comprehensive Benchmark Evaluation*, VLDB, 2022. <https://arxiv.org/abs/2109.05877>

CardEst Benchmark Settings

- The role of CardEst: bridge data/query to high quality plan
- Goal of CardEst Benchmark: reveal the performance of each CardEst algorithm under varied settings



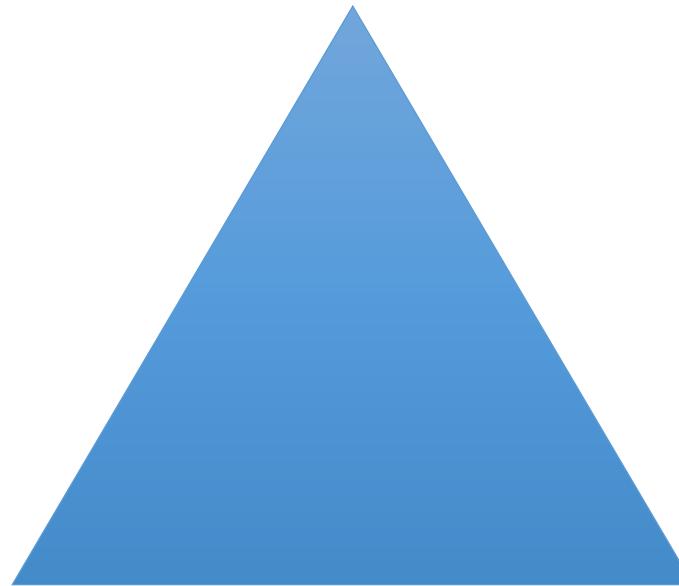
Existing CardEst Benchmark

- Input: the impact on varied settings to output
 - Data/Query/System...
 - [Are we ready for learned cardinality estimation?](#) by Wang et. al. in VLDB' 21
 - Comprehensively answer this question
- Output: the impact on query plan quality and execution time
 - [How good are query optimizers, really?](#) by Leis et. al. in VLDB'15
 - IMDB dataset/JOB-light workload
- Some other evaluations in numerous CardEst papers...

CardEst Benchmark Principle

- What is a good benchmark?
- Real!

metric: reflect the real performance



environment: deployed
in real DBMS

data/query: close to
real-world settings

Existing CardEst Benchmark Shortcomings

- Evaluations are not conducted in real DBMS
 - No tools to easily deploy a CardEst method into a DBMS
- Data/query settings are not complex enough to reflect real-world scenarios
 - Are we ready benchmark: single table
 - IMDB dataset/JOB-light query workload: Only 6 tables form a fixed star join and 8 numerical/categorical(n./c.) attributes

Existing CardEst Benchmark Shortcomings

- Metrics overlook the most important overall end-to-end(e2e) query execution time
 - E2e time improvement is the ultimate goal and influenced by many factors
 - Current metric may distort: higher accuracy by Q-Error \neq higher e2e improvement

end-to-end execution time = plan generation time + plan execution time



inference time



estimation accuracy

$$\text{Q-Error} = \max\left(\frac{\hat{Q}}{Q}, \frac{Q}{\hat{Q}}\right)$$

New CardEst Benchmark Overview

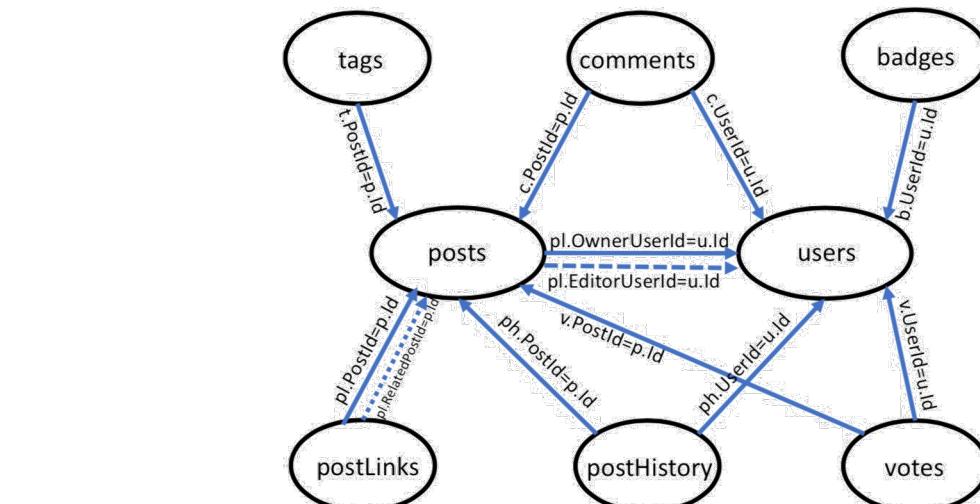
- **Plug-in tool**: easy to integrate any CardEst method into PostgreSQL 13.1 with a docker deployment
- **STATS dataset/STATS-CEB query workload**: more complex and close to real-world settings
- **Comprehensive evaluation**: focus on learned CardEst methods
 - Overall e2e time improvement and detailed analysis
 - A new and distortionless evaluation metric

<https://github.com/Nathaniel-Han/End-to-End-CardEst-Benchmark>

Complex Dataset

- STATS dataset: an anonymized dump of user-contributed content on the Stats Stack Exchange network
- More complex than IMDB: more tables/attributes, skewed distribution, larger scale, more join forms...

Criteria	Item	IMDB	STATS
Scale	# of tables	6	8
	# of n./c. attributes	8	23
	# of n./c. attributes per table	1–2	1–8
	full outer join size	$2 \cdot 10^{12}$	$3 \cdot 10^{16}$
Data	total attribute domain size	369, 563	578, 341
	average distribution skewness	9.159	21.798
	average pairwise correlation	0.149	0.221
Schema	join forms	star	star/chain/mixed
	# of join relations	5	12



<https://relational.fit.cvut.cz/dataset/Stats>

Complex Query Workload

- STATS-CEB query workload: join template enumeration + selection by log data
- More complex than JOB-light: more join schemas, more join types, larger range...

Item	JOB-LIGHT	STATS-CEB
# of queries	70	146
# of joined tables	2-5	2-8
# of join templates	23	70
# of filtering n./c. predicates	1-4	1-16
join type	PK-FK	PK-FK/FK-FK
true cardinality range	$9 - 9 \cdot 10^9$	$200 - 2 \cdot 10^{10}$

Criteria	Item	IMDB	STATS
Scale	# of tables	6	8
	# of n./c. attributes	8	23
	# of n./c. attributes per table	1-2	1-8
	full outer join size	$2 \cdot 10^{12}$	$3 \cdot 10^{16}$
Data	total attribute domain size	369, 563	578, 341
	average distribution skewness	9.159	21.798
	average pairwise correlation	0.149	0.221
Schema	join forms	star	star/chain/mixed
	# of join relations	5	12

Evaluated CardEst Algorithms

Category	Method	Model
Baselines	PostgreSQL	1-D Histogram
	TrueCard (Optimal)	True Cardinality
Traditional	MultiHist	M-D Histogram
	UniSample	Uniformly Sampling
	WJSample	WanderJoin Sampling
	PessEst	Pessimistic Estimator
Query-driven	MSCN	Multi-set Convolutional Network
	LW-XGB	XGBoost
	LW-NN	Deep Neural Network
	UAE-Q	DAR + Gumbel-Softmax
Data-driven	NeuroCard	DAR
	BayesCard	Bayesian Network (Revitalizing)
	DeepDB	SPN
	FLAT	FSPN

Evaluated CardEst Algorithms: BayesCard

- Key Idea: Revitalizing BN with faster structure learning and inference methods
 - Probabilistic programming languages
 - Progressive sampling and compiled variable elimination

Reference

- Ziniu Wu, Amir Shaikhha, Rong Zhu, Yuxing Han, Jingren Zhou. *BayesCard: Revitalizing Bayesian Networks for Cardinality Estimation*, ArXiv, 2021.
<https://arxiv.org/abs/2012.14743>
- Rong Zhu[#], Andreas Pfadler[#], Ziniu Wu^{*}, Yuxing Han, Xiaoke Yang, Feng Ye, Zhengping Qian, Jingren Zhou, Bin Cui. *Efficient and Scalable Structure Learning for Bayesian Networks: Algorithms and Applications*, ICDE, 2021. <https://arxiv.org/abs/2012.03540>

Overall E2E Performance

- Learned CardEst methods have significant improvement

Category	Method	Data / Query Workload			
		IMDB / JOB-LIGHT		STATS / STATS-CEB	
		End-to-End Time	Improvement	End-to-End Time	Improvement
Baseline	PostgreSQL	3.67h	0.0%	11.34h	0.0%
	TrueCard	3.15h	14.2%	5.69h	49.8%
Traditional	MultiHist	3.92h	-6.8%	14.55h	-28.3%
	UniSample	4.87h	-32.6%	> 25h	--
	WJSample	4.15h	-13.1%	19.86h	-75.0%
	PessEst	3.38h	7.9%	6.10h	46.2%
Query-driven	MSCN	3.50h	4.6%	8.13h	28.3%
	LW-XGB	4.31h	-17.4%	> 25h	--
	LW-NN	3.63h	1.1%	11.33h	0.0%
	UAE	3.65h	-1.9%	11.21h	1.1%
Data-driven	NeuroCard	3.41h	6.8%	12.05h	-6.2%
	BayesCard	3.18h	13.3%	7.16h	36.9%
	DeepDB	3.29h	10.3%	6.51h	42.6%
	FLAT	3.21h	12.9%	5.92h	47.8%

PGM-based
methods
improve
near optimal

Overall E2E Performance

- Performance: data-driven > query-driven

Category	Method	Data / Query Workload			
		IMDB / JOB-LIGHT		STATS / STATS-CEB	
		End-to-End Time	Improvement	End-to-End Time	Improvement
Baseline	PostgreSQL	3.67h	0.0%	11.34h	0.0%
	TrueCard	3.15h	14.2%	5.69h	49.8%
Traditional	MultiHist	3.92h	-6.8%	14.55h	-28.3%
	UniSample	4.87h	-32.6%	> 25h	--
	WJSample	4.15h	-13.1%	19.86h	-75.0%
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	LW-XGB	4.31h	-17.4%	> 25h	--
	LW-NN	3.63h	1.1%	11.33h	0.0%
	UAE	3.65h	-1.9%	11.21h	1.1%
Data-driven	NeuroCard	3.41h	6.8%	12.05h	-6.2%
	BayesCard	3.18h	13.3%	7.16h	36.9%
	DeepDB	3.29h	10.3%	6.51h	42.6%
	FLAT	3.21h	12.9%	5.92h	47.8%

not easy to generalize

Overall E2E Performance

- Data-driven methods: multiple small models > a single model

Category	Method	Data / Query Workload			
		IMDB / JOB-LIGHT		STATS / STATS-CEB	
		End-to-End Time	Improvement	End-to-End Time	Improvement
Baseline	PostgreSQL	3.67h	0.0%	11.34h	0.0%
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Traditional	MultiHist	3.92h	-6.8%	14.55h	-28.3%
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	LW-XGB	4.31h	-17.4%	> 25h	--
	LW-NN	3.63h	1.1%	11.33h	0.0%
	UAE	3.65h	-1.9%	11.21h	1.1%
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	BayesCard	3.18h	13.3%	7.16h	36.9%
	DeepDB	3.29h	10.3%	6.51h	42.6%
	FLAT	3.21h	12.9%	5.92h	47.8%

long inference time,
accuracy decrease on
more tables

Estimation Accuracy

- The more accurate, the better
- Q-Error is a distort metric
 - Lower Q-Error \neq Lower e2e time
 - Correct the optimization goal in the long literature
- Different sub-queries matter differently, Q-Error can't distinguish
 - Small/large sub-query: 10/100 vs. 10,000/100,000
 - Overestimation/underestimation: 1,000/100 vs. 1,000/10,000

Method	Execution Time (Descending Order)	STATS / STATS-CEB Workload		
		Q-Error		
		50%	90%	99%
UniSample	> 25h	3.259	135.4	$6 \cdot 10^4$
LW-XGB	> 25h	5.652	453.2	$3 \cdot 10^5$
WJSample	19.86h	3.452	351.4	$8 \cdot 10^4$
NeuroCard	11.85h	951.4	$9 \cdot 10^5$	$6 \cdot 10^8$
PostgreSQL	11.34h	1.439	11.08	$2 \cdot 10^3$
LW-NN	11.33h	15.73	832.9	$2 \cdot 10^4$
UAE	11.03h	2.875	20.613	$1 \cdot 10^4$
MSCN	8.11h	20.92	392.3	$1 \cdot 10^4$
BayesCard	7.16h	1.182	50.40	156.4
DeepDB	6.46h	2.451	22.37	$1 \cdot 10^3$
FLAT	5.80h	1.675	10.44	768.8

0.036 0.037

A New Metric: P-Error

- The actual execution time is best, but expensive to obtain
- Idea: the estimated cost is a good counterpart
 - Cost model in DBMS is optimized to approximate the execution time

the cost computed using true cardinality
= the actual execution cost

the plan generated using
estimated cardinality

$$P\text{-Error} = \frac{\text{Plan Cost}(\text{Est Card Plan}, \text{True Card})}{\text{Plan Cost}(\text{True Card Plan}, \text{True Card})}$$

the possible optimal case using true cardinality

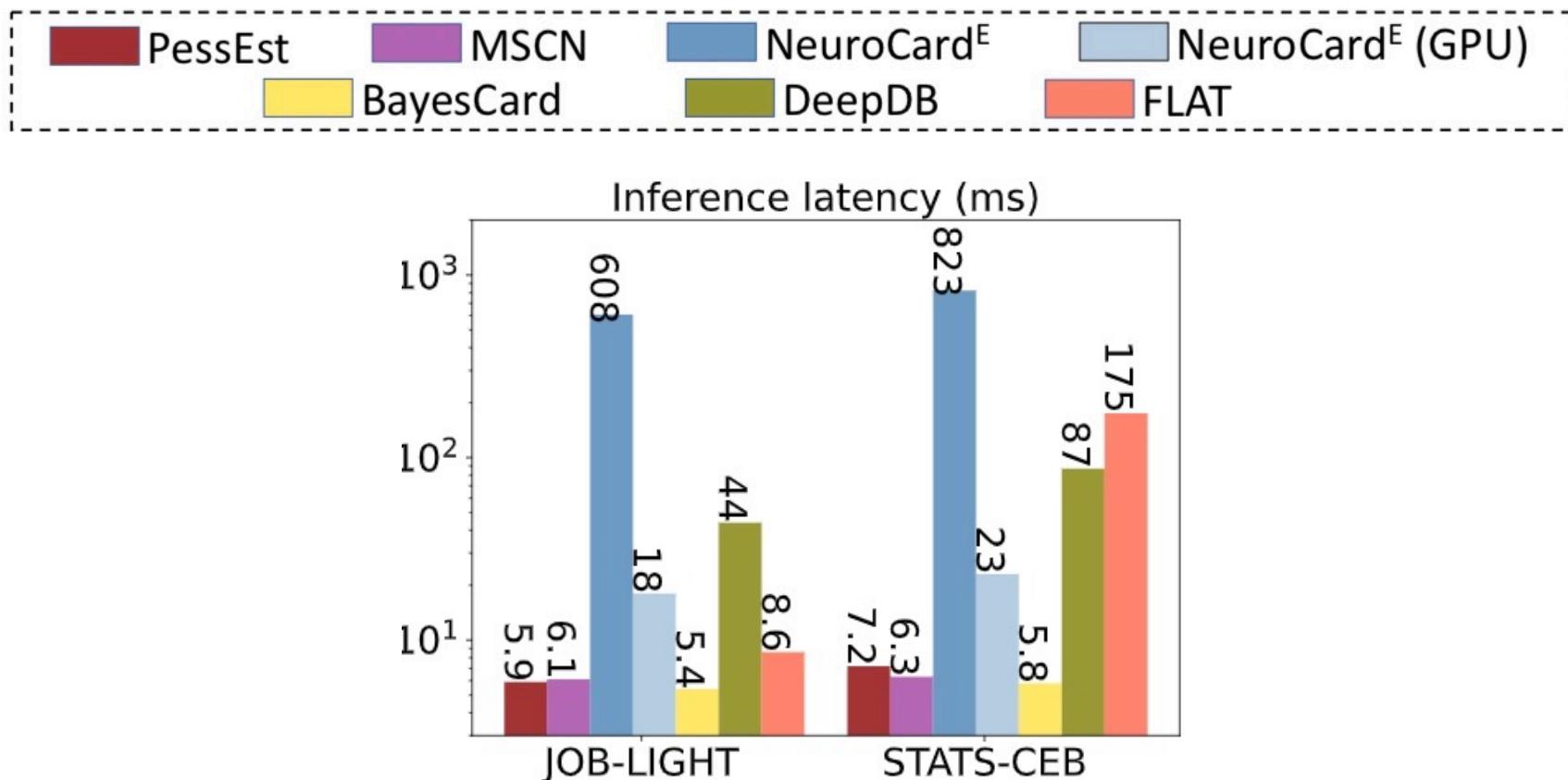
A New Metric: P-Error

- P-Error is a better metric for plan quality/execution time
 - The impact of different sub-queries are considered together
 - New optimization goal
 - FLAT > BayesCard/DeepDB

Method	Execution Time (Descending Order)	Q-Error			P-Error		
		50%	90%	99%	50%	90%	99%
UniSample	> 25h	3.259	135.4	$6 \cdot 10^4$	1.000	1.345	3.593
LW-XGB	> 25h	5.652	453.2	$3 \cdot 10^5$	1.742	6.627	526.2
WJSample	19.86h	3.452	351.4	$8 \cdot 10^4$	1.103	4.954	501.6
NeuroCard	11.85h	951.4	$9 \cdot 10^5$	$6 \cdot 10^8$	1.193	2.844	$1 \cdot 10^3$
PostgreSQL	11.34h	1.439	11.08	$2 \cdot 10^3$	1.000	1.595	12.35
LW-NN	11.33h	15.73	832.9	$2 \cdot 10^4$	1.159	4.651	18.02
UAE	11.03h	2.875	20.613	$1 \cdot 10^4$	1.145	4.001	13.14
MSCN	8.11h	20.92	392.3	$1 \cdot 10^4$	1.138	4.031	11.11
BayesCard	7.16h	1.182	50.40	156.4	1.000	1.582	6.843
DeepDB	6.46h	2.451	22.37	$1 \cdot 10^3$	1.030	1.833	6.819
FLAT	5.80h	1.675	10.44	768.8	1.000	1.346	5.546

Inference Speed

- BayesCard < FLAT/DeepDB < NeuroCard



Inference Speed

- Inference time has significant impact on OLTP, but very little impact on OLAP
 - OLTP: accurate and fast are both important, BayesCard > DeepDB/FLAT
 - OLAP: accurate is more important, FLAT > BayesCard/DeepDB

Methods	TP E2E Time	TP Plan Time	AP E2E Time	AP Plan Time
PostgreSQL	49.5s	4.8s (9.7%)	11.33h	20.3s (0.05%)
TrueCard	13s	4.8s (36.9%)	5.69h	20.3s (0.1%)
PessEst	27.7s	8.4s (30.3%)	6.10h	35.4s (0.16%)
MSCN	23.9s	8.2s (34.3%)	8.12h	38.0s (0.13%)
NeuroCard	99.3s	73s (73.5%)	11.94h	350s (0.81%)
BayesCard	18s	7.3s (40.6%)	7.16h	27.4s (0.11%)
DeepDB	45.1s	33.6s (74.5%)	6.50h	135s (0.58%)
FLAT	55.8s	41.5s (74.4%)	5.91h	396s (1.86%)

Other Aspects

- Model size/training time: BayesCard << FLAT/DeepDB < others
- Updating speed/accuracy: BayesCard << others

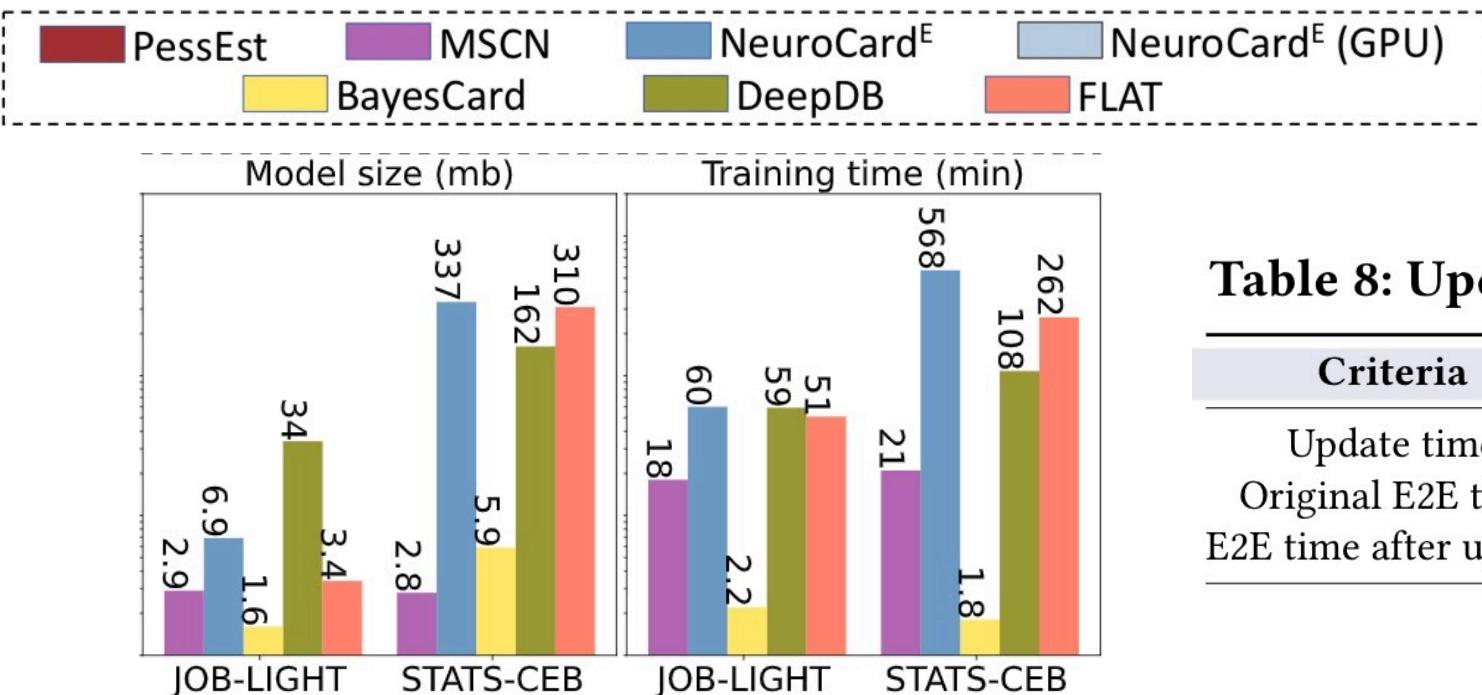


Table 8: Update performance of CardEst algorithms.

Criteria	NeuroCard	BayesCard	DeepDB	FLAT
Update time	5,569s	12s	248s	360s
Original E2E time	11.85h	7.16h	6.46h	5.80h
E2E time after update	13.94h	7.16h	6.72h	7.04h

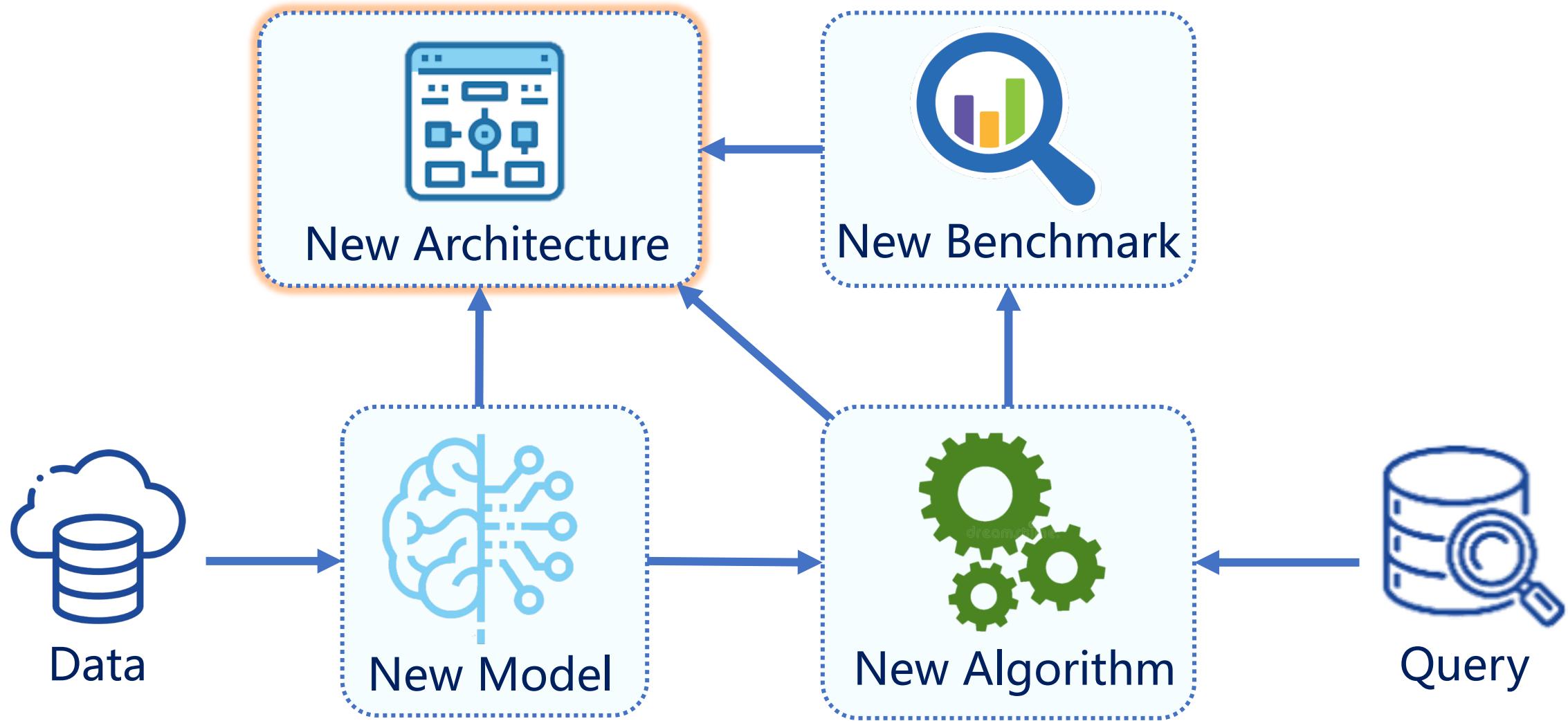
Benchmark: Summary

- New CardEst benchmark
 - Plug-in tool in PostgreSQL
 - Complex STATS dataset/STATS-CEB query workload
 - P-Error evaluation metric: new optimization goal

<https://github.com/Nathaniel-Han/End-to-End-CardEst-Benchmark>

- Take-away information
 - Learned CardEst methods using PGMs could help
 - OLTP: BayesCard exhibits superiority in many aspects
 - OLAP: accuracy is the first priority, FLAT > BayesCard/DeepDB > Others

Part 4: The New Architecture



Outline

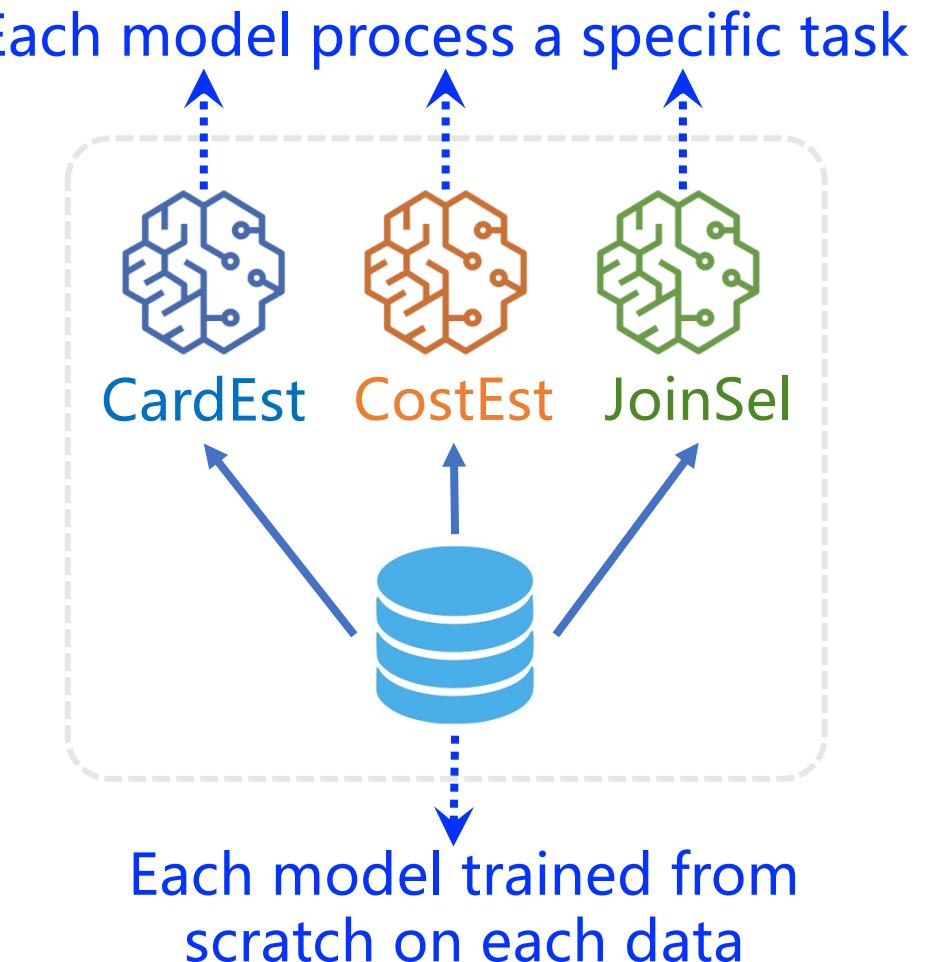
- One Model for All: New Architecture
 - Basic idea, architecture and workflow
 - Query optimizer case study
 - Evaluation results

Reference

- Ziniu Wu, Peilun Yang[#], Pei Yu[#], Rong Zhu, Yuxing Han , Yaliang Li, Defu Lian, Kai Zeng, Jingren Zhou. *A Unified Transferable Model for ML-Enhanced DBMS*, CIDR, 2022.
<https://arxiv.org/abs/2105.02418>

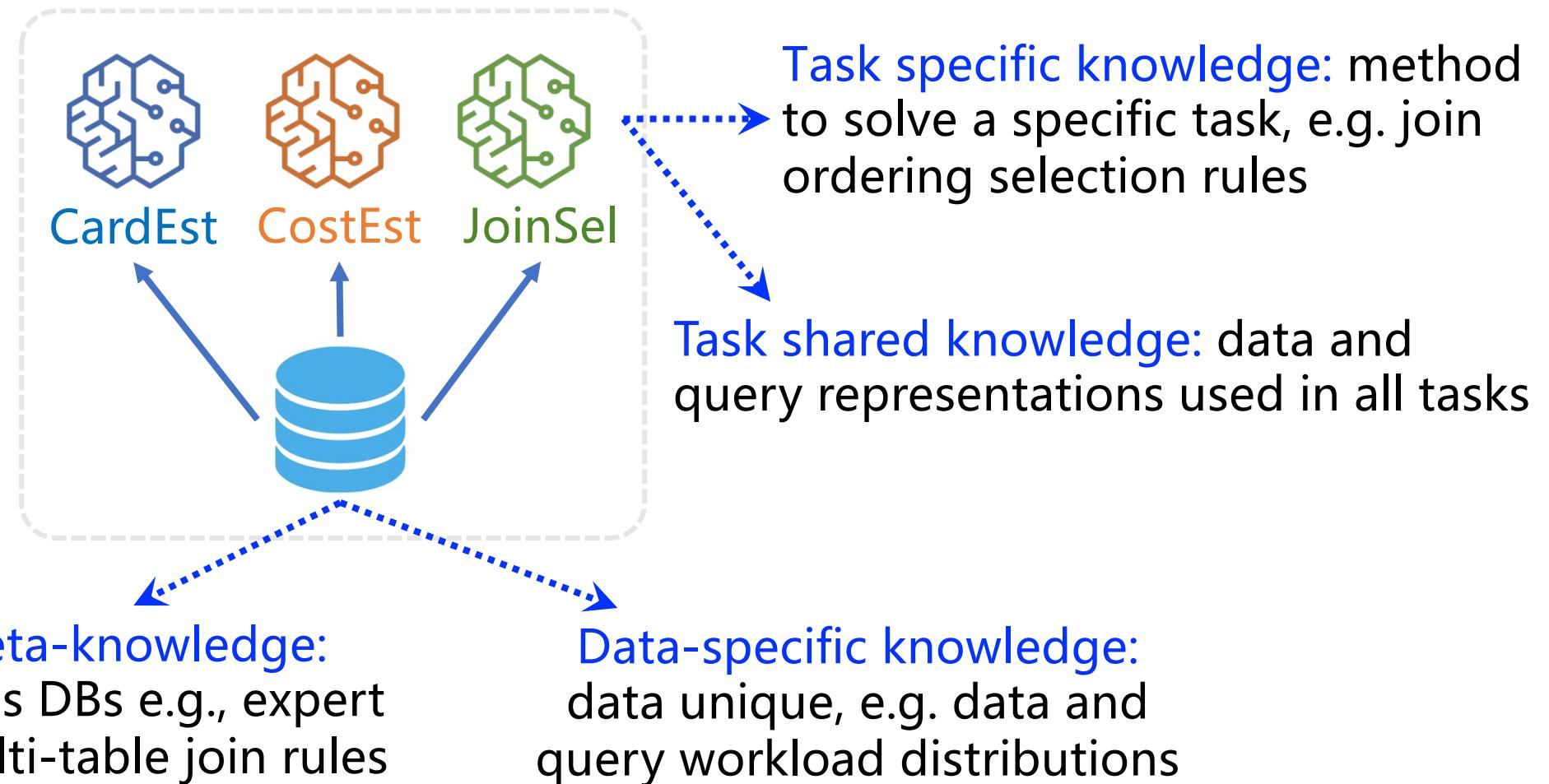
Existing AI4DB Architecture

- Plug-in: one model for one task, one model for one data
- Cold start: not transferrable across data
 - Large training cost on new data
- Ignore intrinsic relations between tasks
 - Redundant learning of common knowledge
 - Not effective without posterior knowledge



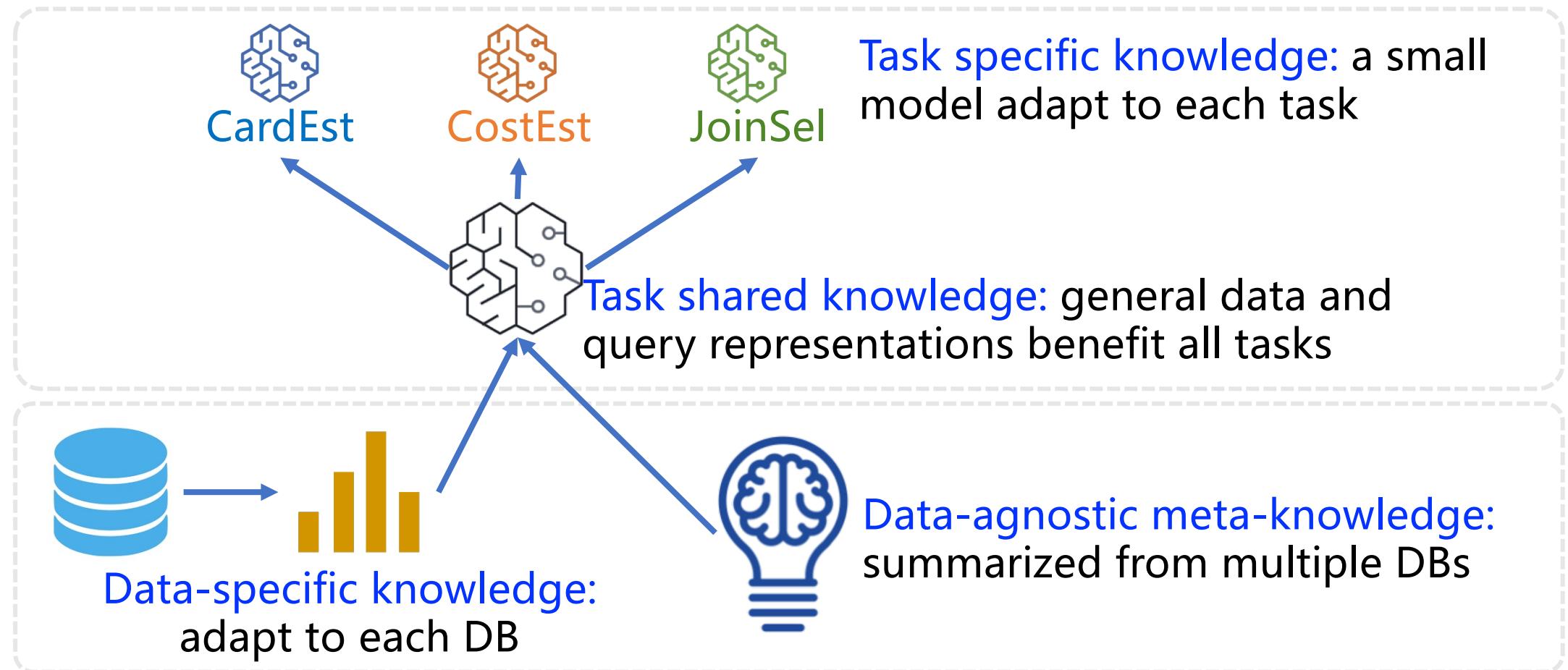
New Architecture: Basic Idea

- Learned data and task knowledge decomposition



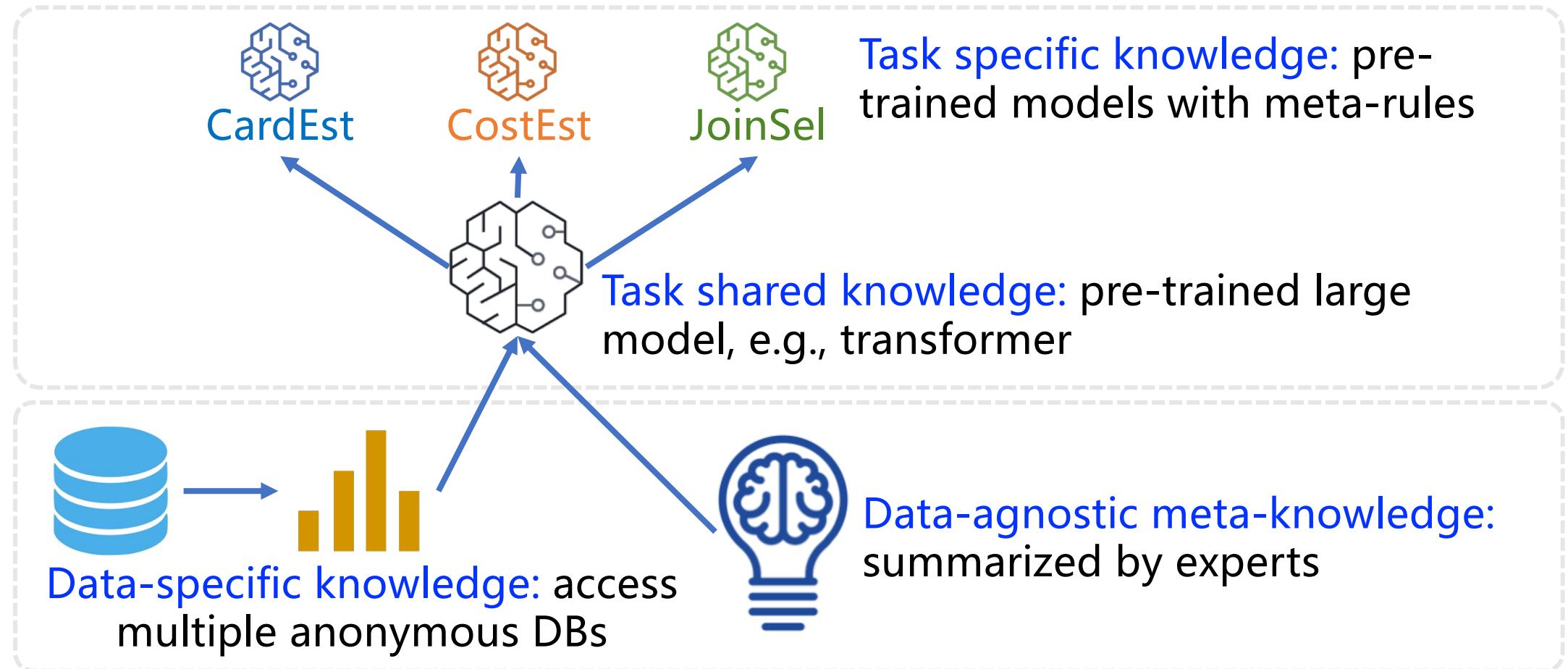
New Architecture: One Model for All

- Shared learning and specific adaption



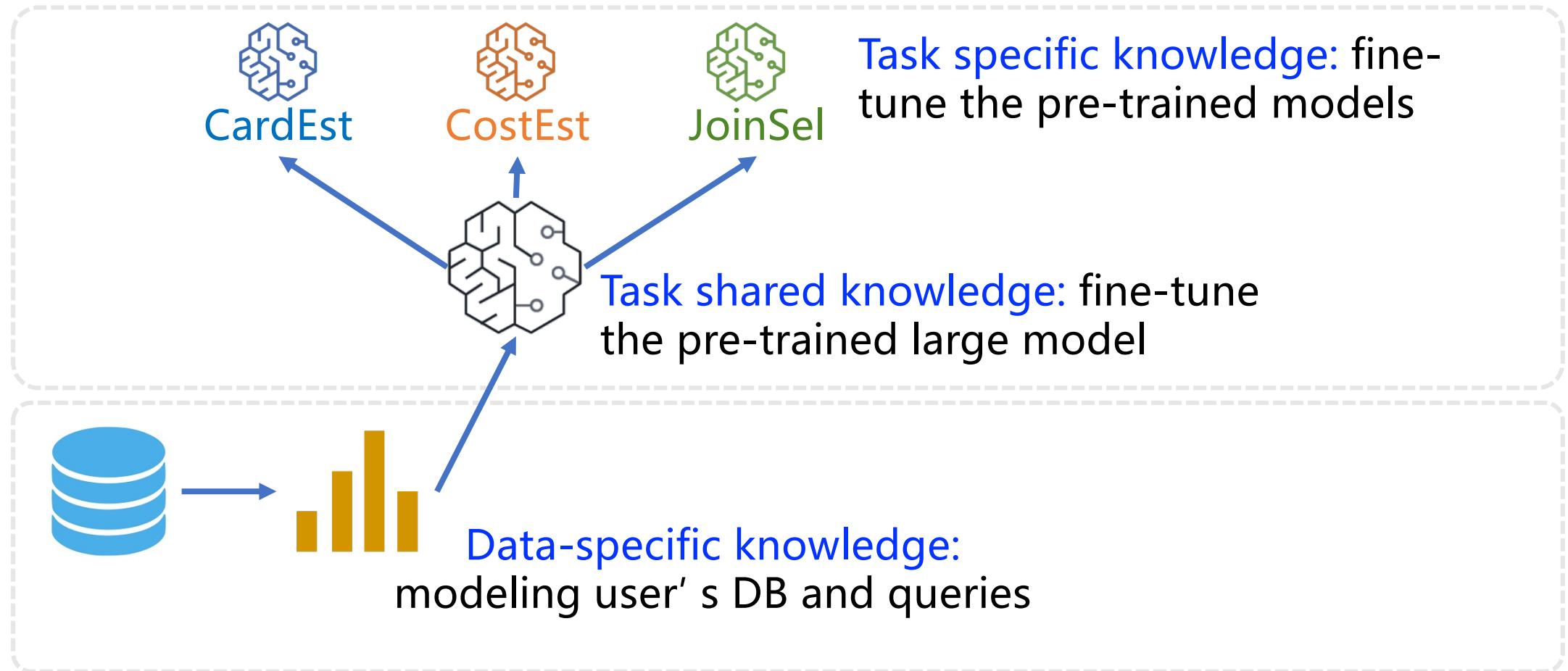
Workflow: Service Provider Side

- Pre-trained large models as services



Workflow: User Side

- Fine-tune pre-trained models to fit user data



One Model for All: Advantages

- **Architecture**

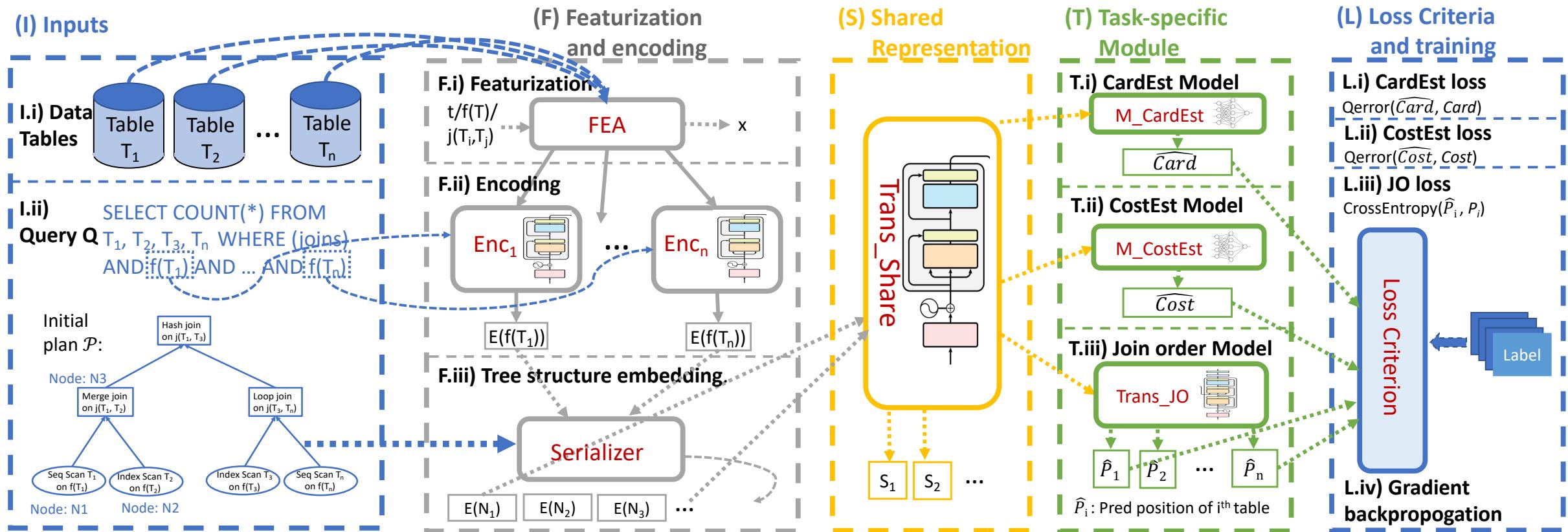
- More efficient without redundant learning
- More effective task modeling with posterior knowledge guidelines, e.g., CostEst to CardEst
- Transferability

- **Workflow**

- More **green** computation: pre-trained large models provided as fundamental tool
- More in-depth optimization: see more data
- Easy to evolve and manage

Query Optimizer: A Case Study

- Jointly learn multiple tasks in QO together



Evaluation Results

- One model for all architecture is more accurate
 - Better than previous plug-in architecture
 - Multi-task learning > separate learning

Method	Cardinality Q-Error			Cost Q-Error		
	median	max	mean	median	max	mean
PostgreSQL	184	670,000	10,416	4.90	4,920	105
Tree-LSTM	8.78	696.29	36.83	4.00	290.35	15.01
Ours-QO	4.48	614.45	28.69	2.10	37.54	4.20
Ours-CardEst	5.12	804.48	36.66	---	---	---
Ours-CostEst	---	---	---	2.06	61.41	4.69

Evaluation Results

- One model for all architecture is effective
- Pre-train/fine-tune is transferable to new DBs

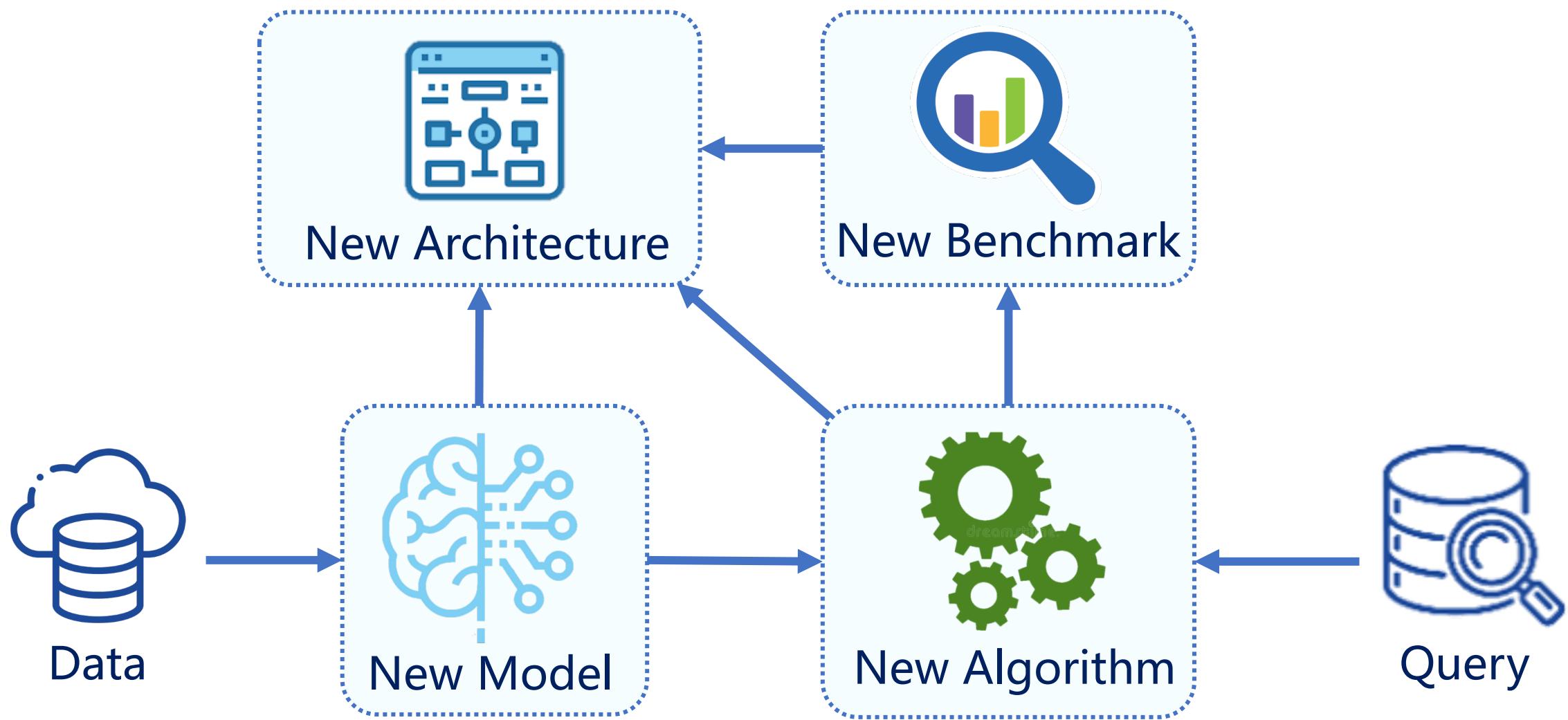
Method	Execution Time (min)	Improvement Ratio
PostgreSQL (Baseline)	1143.2	---
Optimal	209.1	81.7%
Ours-QO	318.3	72.2%
Ours-JoinSel	450.4	60.6%

Method	Execution Time (min)	Improvement Ratio
PostgreSQL (Baseline)	393.3	---
Ours-QO (No Finetune)	234.1	40.6%
Ours-QO (Retrained)	219.5	44.3%

One Model for All: Summary

- A vision for next-generation of ML-enhanced DBMS
 - More efficient and effective for multiple DB tasks
 - Pre-train and fine-tune workflow in cloud services
- A case study in query optimizer
 - The effectiveness of multi-task joint learning
 - The practicality of pre-train/fine-tune meta-learning

Summary



Summary

- ❑ FSPN: A New PGM for PDF Modeling
 - ❑ Accurate, lightweight and fast inference
- ❑ FLAT: A New Learned CardEst Algorithm
 - ❑ Efficient, accurate, flexible and practical
- ❑ A New Comprehensive CardEst Benchmark
 - ❑ Complex data/queries, plug-in tool and distortionless metric
- ❑ One Model for All: A New Architecture using Pre-train/Fine-tune
 - ❑ Effective, transferable and vision for next-G ML-enhanced DBMS

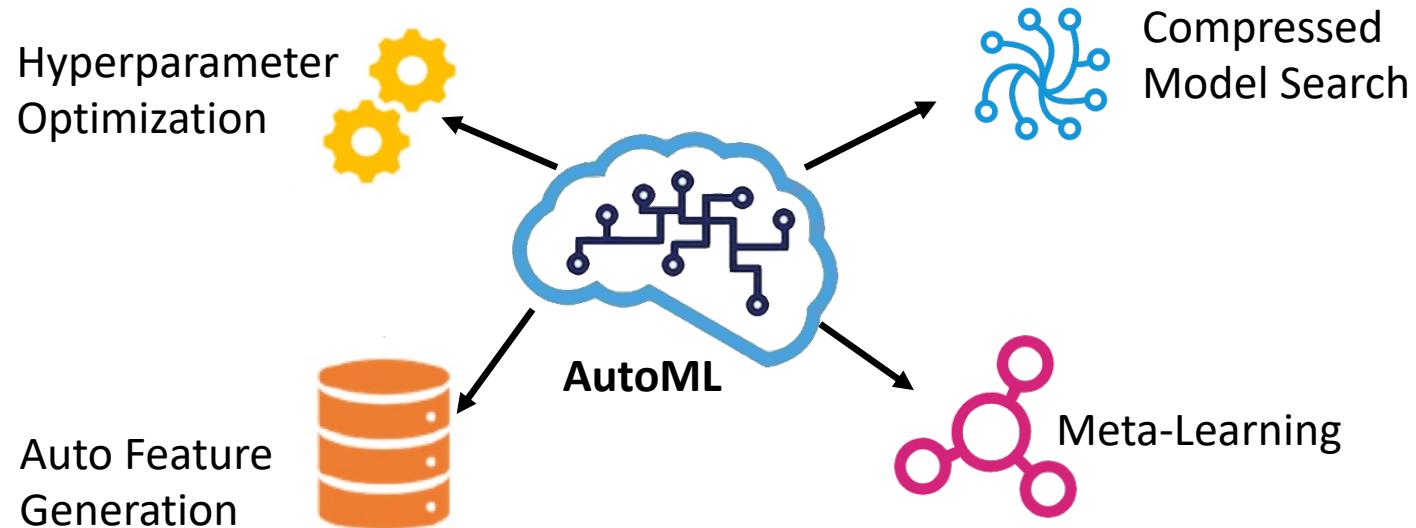
Future Work

- Deep Data Modeling
 - Theory foundation
 - Meta vs. specific knowledge representation
- Deep ML-Enhanced Algorithms
 - More tasks: indexing, scheduling...
 - Multi-task learning
- New Standard for ML-Enhanced DBMS
- From QO to General DBMS
 - Federated learning, practical issues...
 - Fusion of ML + Traditional

AutoML Tools

Availability

Learning to Mutate with Hypergradient Guided Population, NeurIPS 2020.



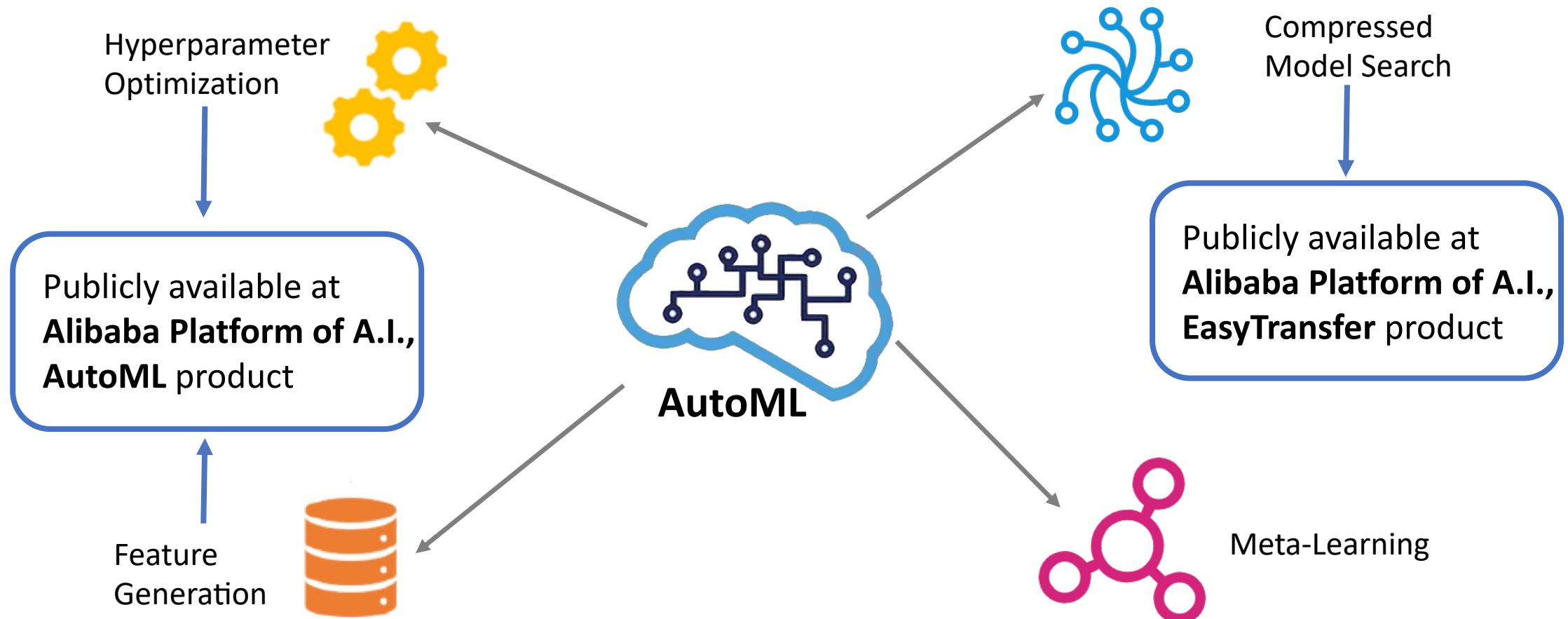
FIVES: Feature Interaction Via Edge Search for Large-Scale Tabular Data, KDD 2021.
<https://arxiv.org/abs/2007.14573>

AdaBERT: Task-Adaptive BERT Compression with D-NAS, IJCAI 2020
<https://arxiv.org/abs/2001.04246>

Compressed Model Search

Automated Relational Meta-learning, ICLR 2020.
<https://arxiv.org/abs/2001.00745>

Availability



A Summary of AutoML Tools

Name	Authors	Functionalities	Algorithms	Language
Auto Tune Models (ATM)	MIT	AutoFeature, Model Selection, HPO	BO and Bandit	Python
AutoKeras	Texas A&M University	NAS	BO	Python
NNI	Microsoft	AutoFeature, HPO, NAS, Model Selection	Comprehensive	Python
emukit	Amazon	HPO	Meta-surrogate model	Python
Ray Tune	Berkeley	HPO	Comprehensive	Python
TPOT	University of Pennsylvania	AutoFeature, Model Selection, HPO	Genetic programming	Python

More AutoML packages include AutoFolio, Auto-sklearn, Auto-PyTorch, Auto-WEKA, etc.

Tutorial Schedule



Yaliang Li, Background and Overview of AutoML
Hyperparameter Optimization



Zhen Wang, Neural Architecture Search
Meta-Learning



Yuexiang Xie, Automatic Feature Generation



Ce Zhang, VolcanoML: End-to-End AutoML via
Scalable Search Space Decomposition



Bolin Ding, Kai Zeng, and Rong Zhu
Machine Learning Guided Database

Thank you!



Yaliang Li, Zhen Wang, Yuexiang Xie, Bolin Ding,
Kai Zeng, Ce Zhang, and Rong Zhu

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Please feel free to contact us if you have any questions,
or you are interested in **full-time** or **research intern** positions.