Tutorial: Automated Recommender System

KDD 2020 | Virtual Conference

By Quanming Yao, Yong Li, Chen Gao, Huan Zhao, Yongqi Zhang

2020/08/24

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Tutorial outline

1. What is Automated machine learning (AutoML) - A retrospective view
   - Dr. Quanming Yao (4Paradigm) – 50mins talk + 10min break
2. Recommender System: Basic and Why AutoML is Needed?
   - Prof. Yong Li (Tsinghua) – 35mins + 5 mins break
3. Recent Advances in Automated Recommender System
   - Mr. Chen Gao (Tsinghua) – 35mins + 5 mins break
4. Automated Graph Neural Network for Recommender System
   - Dr. Huan Zhao (4Paradigm) – 35mins + 5 mins break
5. Automated Knowledge Graph Embedding
   - Dr. Yongqi Zhang (4Paradigm) – 35mins + 5 mins break

Slides: https://github.com/AutoML-4Paradigm/KDD-2020-Tutor

Automated Machine Learning (AutoML)

– A Retrospective Review

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2020/08/24

My Wechat

Outline

- What is Machine Learning (ML)
- What is Automated Machine Learning (AutoML)
- Is AutoML Really New
- What Should We Focus Next

Summary of 1st Stage

Proposal of 2nd Stage

What is Machine Learning (ML)?

Definition 1 [1,2,3]. A computer program is said to learn from experience E with respect to some classes of task T and performance measure P if its performance can improve with E on T measured by P.

Experience Task Measurement

Computer Program

Improve performance ↑

Image Classification

Cat / Dog / Car?

- Experience: Images
- Task: Classification
- Measurement: Accuracy

In short: A computer program specified by E, T and P.

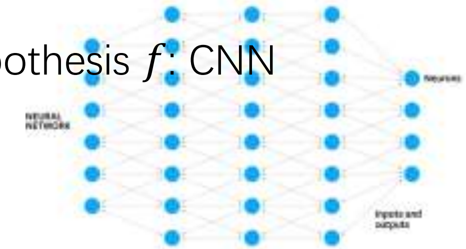
[1]. T. Mitchell. Machine learning. 1997.
[2]. M. Mohri, A. Rostamizadeh, A. Talwalkar. Foundations of machine learning. 2018
[3]. 周志华. 机器学习. 2016

What are Core Issues in ML?

Image Classification

Optimization

Hypothesis f: CNN



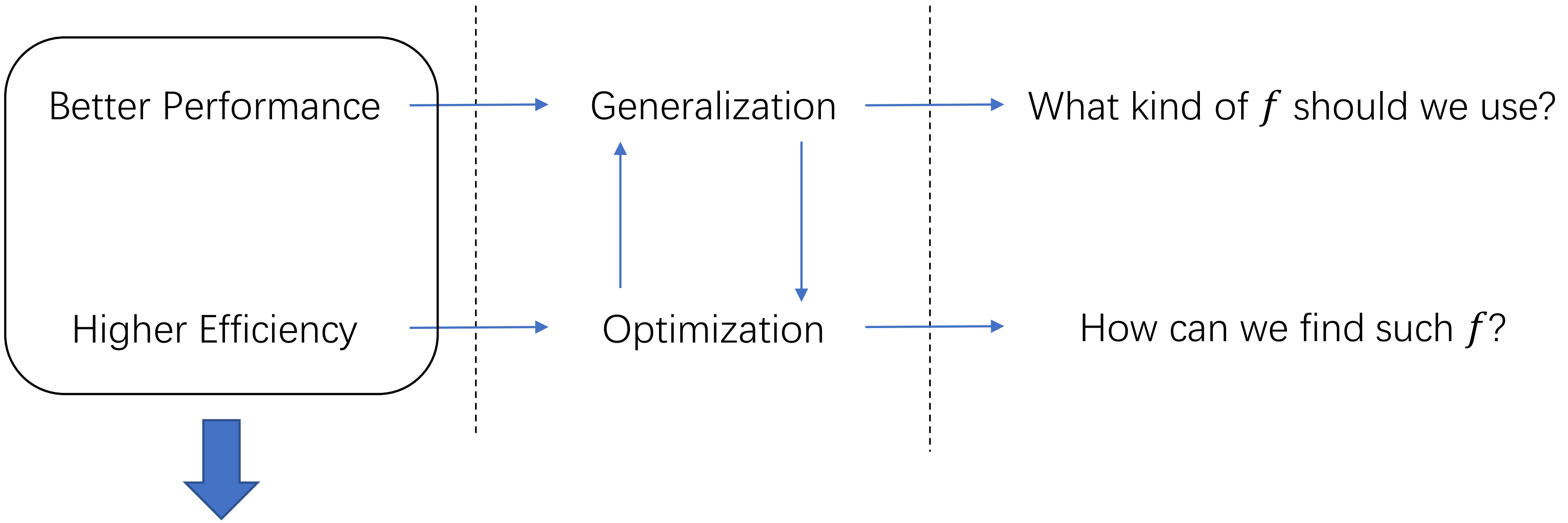
Generalization

Accuracy

Usually, we need to find a **hypothesis (function) f** to perform the learning task

Target	Term	Issue
Better Performance (more important)	Generalization	What kind of f should we use?
Higher Efficiency	Optimization	How can we find such f?

Not Everything can be Learnt



PAC-Learning (Definition 2.3 in [1]): What kind of problems can be solved in polynomial time

No Free Lunch Theorem (Appendix B [2]): No single algorithm can be good on all problems

[1]. M. Mohri, A. Rostamizadeh, A. Talwalkar. Foundations of machine learning. 2018
[2]. O. Bousquet, et.al. Introduction to Statistical Learning Theory. 2016

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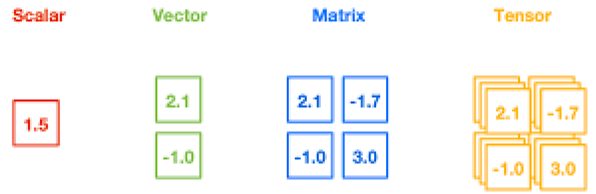
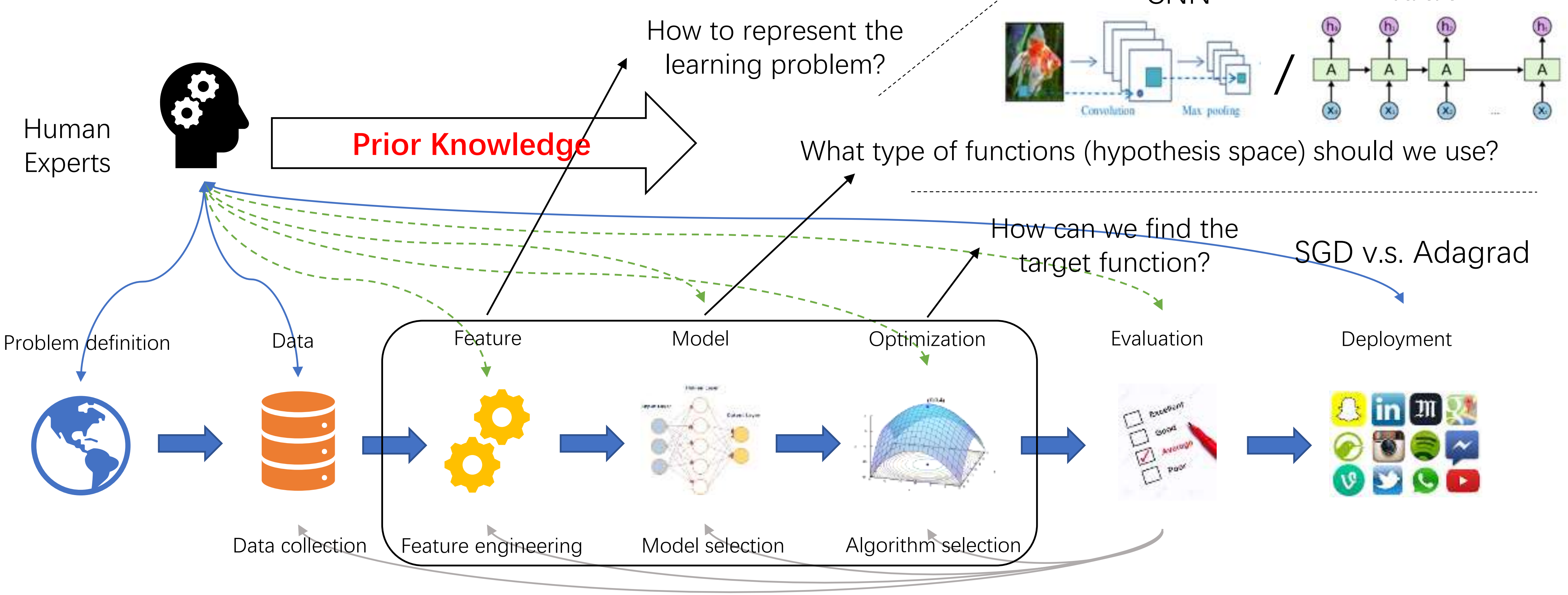
How to use ML?





A trial-and-error process

Also see. T. Mitchell. Machine learning. 1997 (Chapter 1.3.1)

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ML = Data + Knowledge

Given a learning problem: human's understanding on target concept $c \in C$

Prior knowledge on unseen data

Generalization

What kind of f should we use?

Determine hypothesis space H (hyper-parameters*)

From seen to unseen

How can we find such f?

Search a function $f \in H$ on seen data (parameters)

Optimization

*Hyper-parameters: Free parameters that are not determined by the learning algorithm, but rather specified as inputs to the learning algorithm [Page 4. M. Mohri, A. Rostamizadeh, A. Talwalkar. Foundations of machine learning. 2018]

Trade-off underneath ML

Theorem 2.13 (Learning bound — finite $\mathcal{H}$, inconsistent case) *Let $\mathcal{H}$ be a finite hypothesis set. Then, for any $\delta > 0$, with probability at least $1-\delta$, the following inequality holds:*

$$\forall h \in \mathcal{H}, \quad R(h) \leq \widehat{R}_S(h) + \sqrt{\frac{\log|\mathcal{H}| + \log\frac{2}{\delta}}{2m}}. \tag{2.20}$$

Definition 2.1 (Generalization error) *Given a hypothesis $h \in \mathcal{H}$, a target concept $c \in \mathcal{C}$, and an underlying distribution $\mathcal{D}$, the* generalization error *or* risk *of h is defined by*

$$R(h) = \mathop{\mathbb{P}}_{x\sim\mathcal{D}}[h(x) \neq c(x)] = \mathop{\mathbb{E}}_{x\sim\mathcal{D}}\left[1_{h(x)\neq c(x)}\right], \tag{2.1}$$

where 1_ω is the indicator function of the event ω.[2]

Definition 2.2 (Empirical error) *Given a hypothesis $h \in \mathcal{H}$, a target concept $c \in \mathcal{C}$, and a sample $S = (x_1, \ldots, x_m)$, the* empirical error *or* empirical risk *of h is defined by*

$$\widehat{R}_S(h) = \frac{1}{m}\sum_{i=1}^{m} 1_{h(x_i)\neq c(x_i)}. \tag{2.2}$$

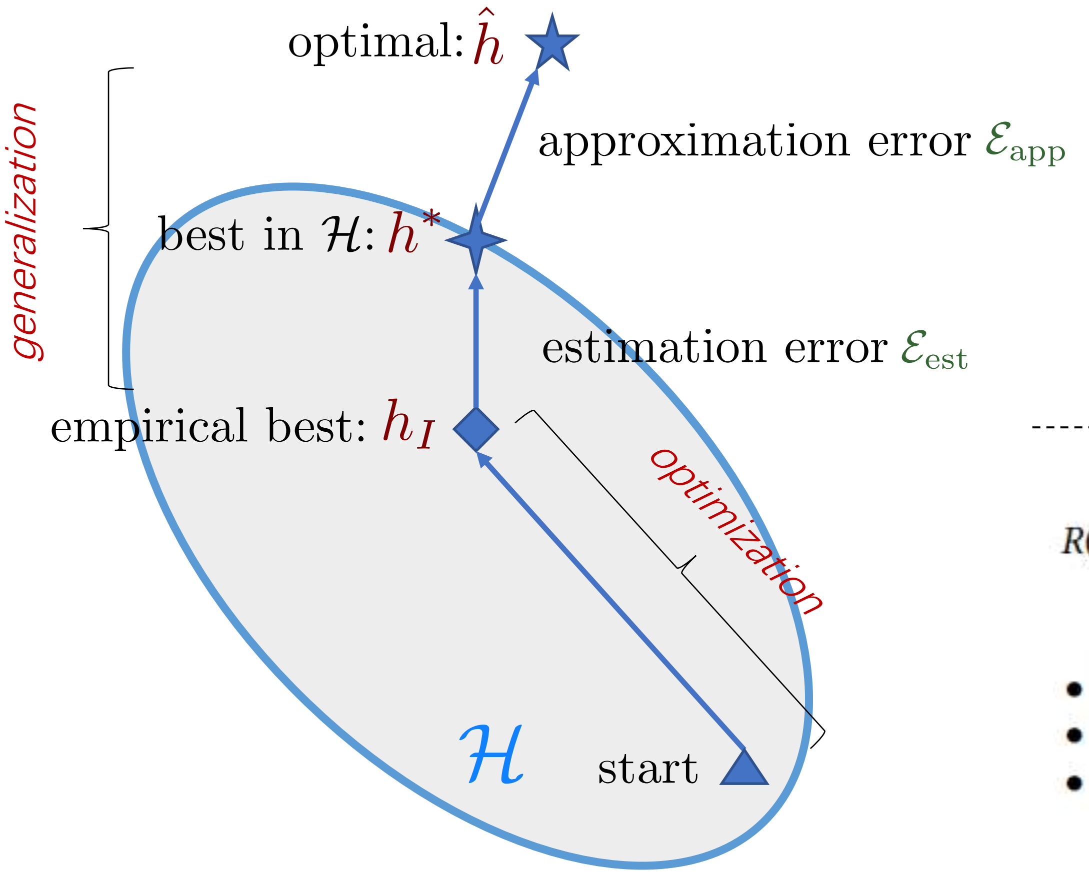
M. Mohri, A. Rostamizadeh, A. Talwalkar. Foundations of machine learning. 2018

Fundamental Trade-off

- Independent of distribution and algorithms

- More training samples are always desired
- In order to approximate target concept c, empirically we prefer using more complex, i.e., larger H

Error Decomposition in ML



Fundamental error decomposition:

$$\mathbb{E}[R(h_I) - R(\hat{h})] = \underbrace{\mathbb{E}[R(h^*) - R(\hat{h})]}_{\mathcal{E}_{\text{app}}(\mathcal{H})} + \underbrace{\mathbb{E}[R(h_I) - R(h^*)]}_{\mathcal{E}_{\text{est}}(\mathcal{H}, I)},$$

Determine by prior knowledge | Determine by training data

$$R(h) = \int \ell(h(x), y)\, dp(x, y) = \mathbb{E}[\ell(h(x), y)]. \qquad R_I(h) = \frac{1}{I}\sum_{i=1}^{I} \ell(h(x_i), y_i),$$

- $\hat{h} = \arg\min_h R(h)$ be the function that minimizes the expected risk;
- $h^* = \arg\min_{h \in \mathcal{H}} R(h)$ be the function in $\mathcal{H}$ that minimizes the expected risk;
- $h_I = \arg\min_{h \in \mathcal{H}} R_I(h)$ be the function in $\mathcal{H}$ that minimizes the empirical risk.

L. Bottou, O. Bousquet. The tradeoffs of large scale learning. NIPS 2008
Y. Wang et.al. Generalizing from a Few Examples: A Survey on Few-Shot Learning. CSUR 2020 (Section 2.3)

Recent Trends

Computers being getting more powerful allowing collections of more samples

Rule-based
Association rules mining
1970s

Statistics-based
Support vector machine
1990s

Deep Learning-based
Convolutional neural networks
2010s

Better performance →

Trends

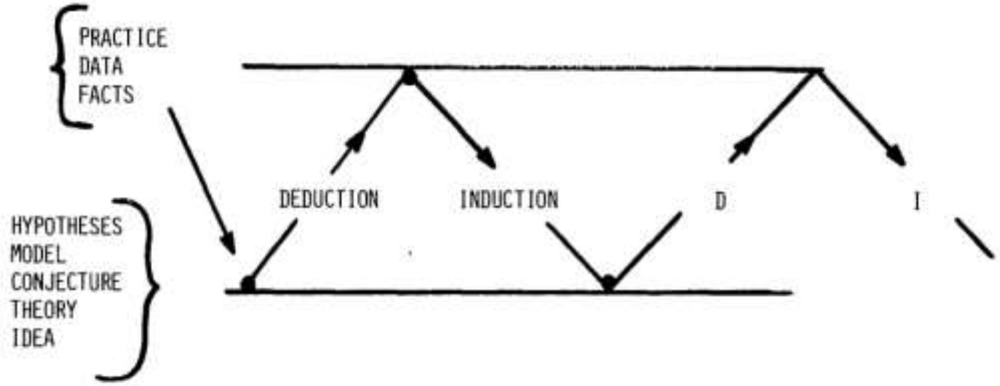
- Larger hypothesis (more complex models) are being used
- Optimization is getting complex (even mixed up with generalization)
- The prior knowledge is imposed on more abstract level

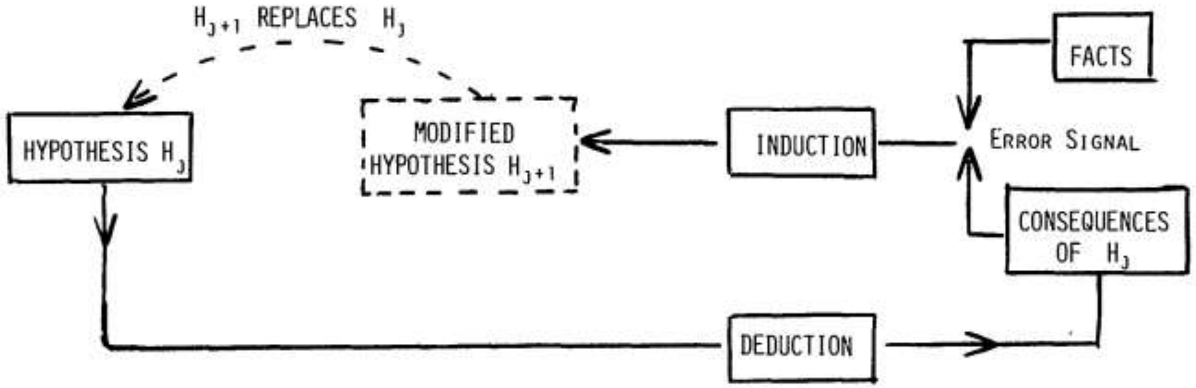
See Chapter 1 in " V. Vapnik. The nature of Statistical Learning Theory (second edition). 2000" for another older story

Principles underneath Trends

Ronald Fisher

"a genius who almost single-handedly created the foundations for modern statistical science"[2]





The Advancement of Learning

- Left: an iteration between theory and practice
- Right: a feedback loop

Better hypothesis (better performance) on the real data

Prior knowledge

"All models are wrong, but some are useful"[1]

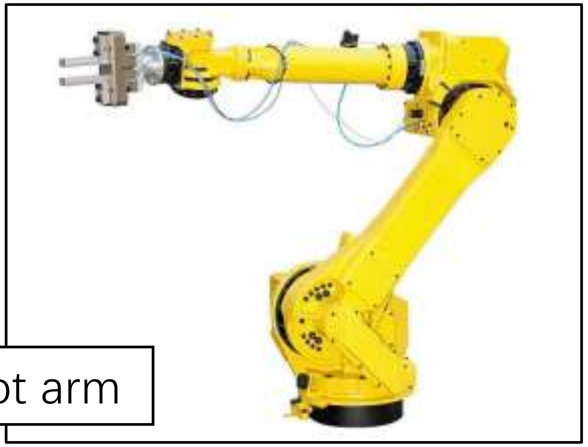
[1] Figures are taken from 'G. Box, Science and statistics, JASA 1976 '
[2] https://en.wikipedia.org/wiki/Ronald_Fisher

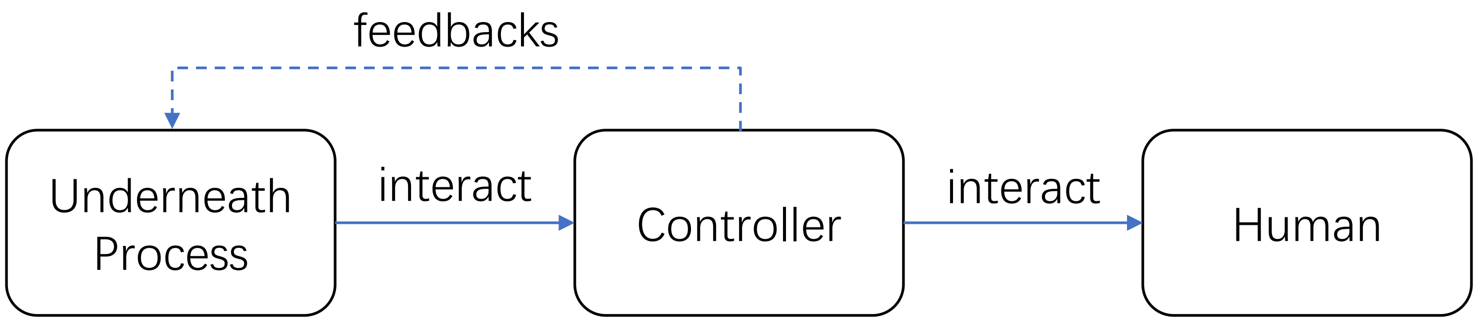
Outline

- What is Machine Learning
- What is Automated Machine Learning (AutoML)
- Is AutoML Really New
- What Should We Focus Next

What is Automation?

Automation is the technology by which a process or procedure is performed with minimal human assistance





Automation (control with feedbacks):

- Fewer and more understandable interface exposed to **human**
- The **controller** interacts with underneath process in a more robust and stable way

F. Golnaraghi and B. Kuo. Automatic control systems. (tenth edition) 2018 (Chapter 1)

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What can be Automated in ML?

Reduce the usage of humans **(low-level) prior knowledge** in the trial-and-error process of machine learning

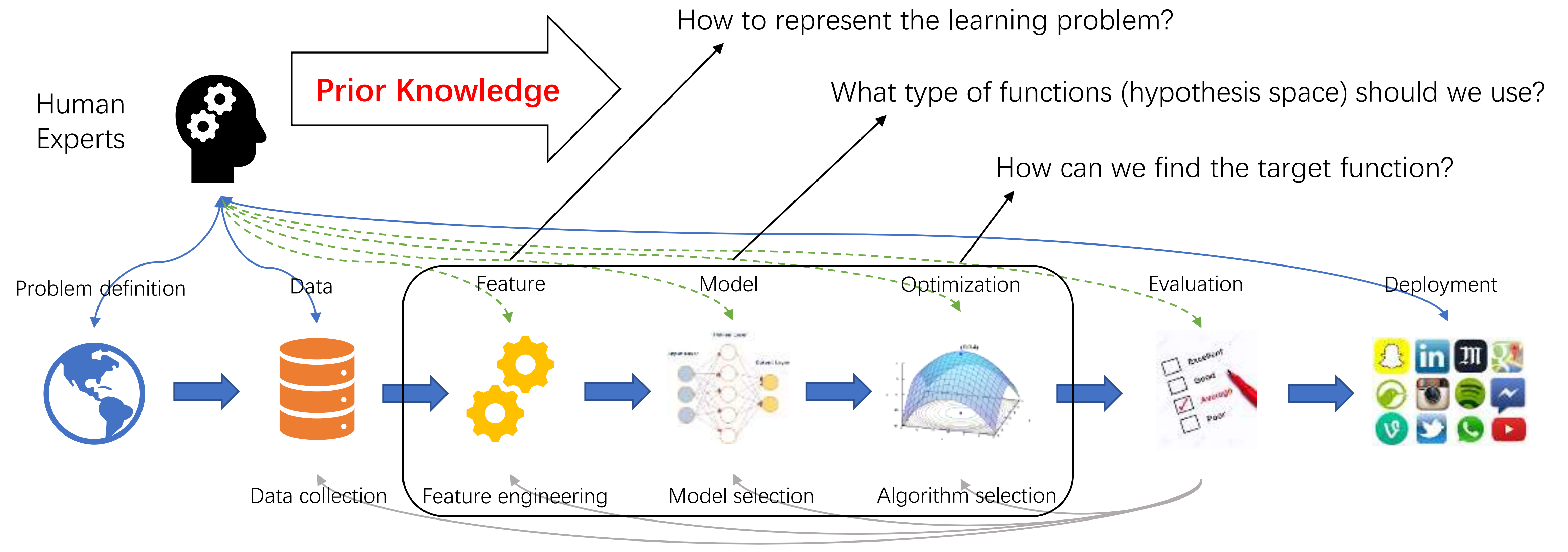
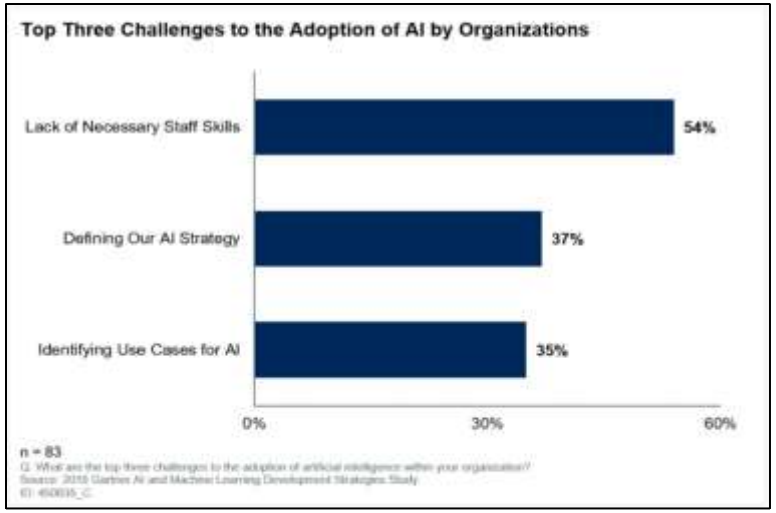


Figure is from "Q. Yao et.al. Taking Human out of Learning Applications: A Survey on Automated Machine Learning. arXiv 2019"

Why We need AutoML?

Investment in AI industry



- **Industry** – reduce the expense, increase usage coverage – huge market value [1]
- **Academy** – understanding data science on a higher level – great intelligence value [2,3]

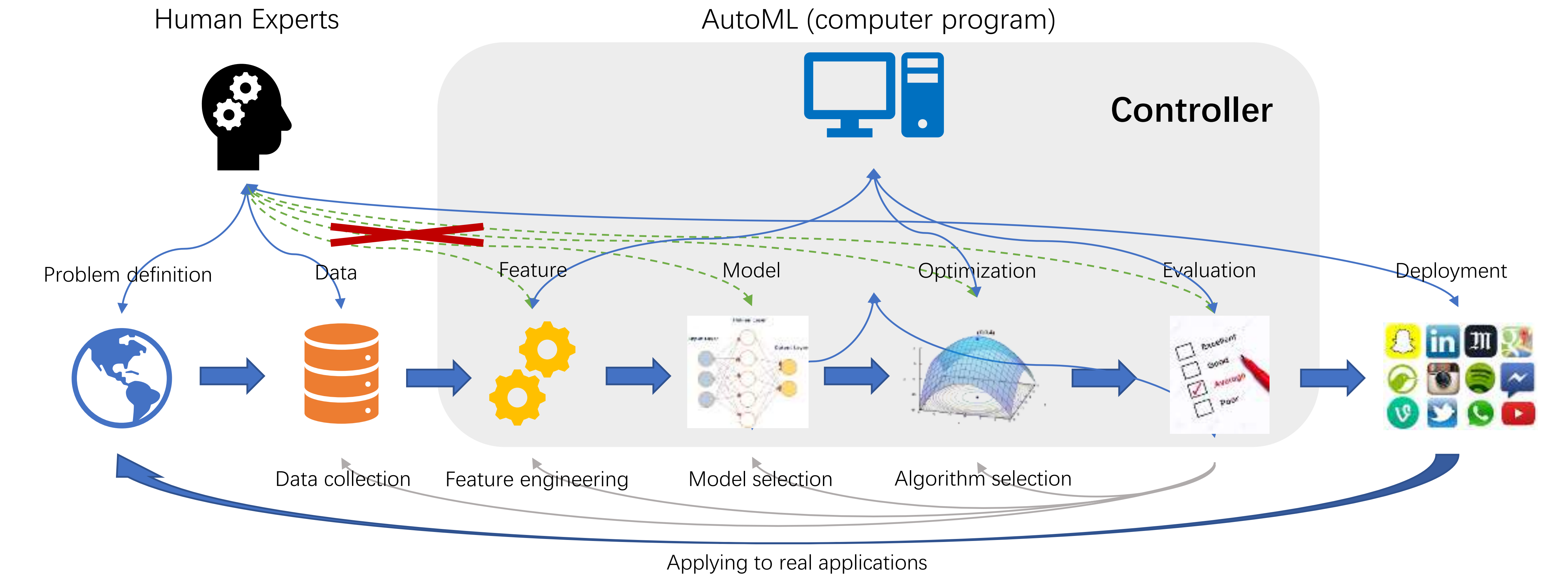
[1]. Gartner: https://www.forbes.com/sites/janakirammsv/2020/03/02/key-takeaways-from-the-gartner-magic-quadrant-for-ai-developer-services/#a95b99ee3e5e

[2]. Y. Bengio: From System 1 Deep Learning to System 2 Deep Learning | NeurIPS 2019

[3]. F Hutter, L Kotthoff, J Vanschoren. Automated machine learning: methods, systems, challenges. Book 2019

AutoML – Industrial view

Taking machine learning as a black box – simply its exposed interface



AutoML – Commercialized examples

AutoSklearn

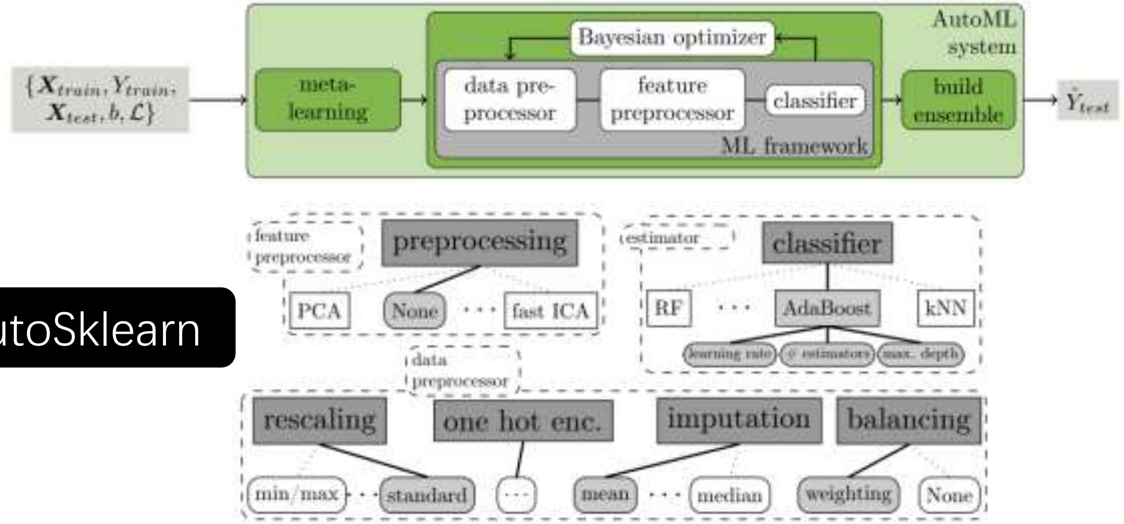
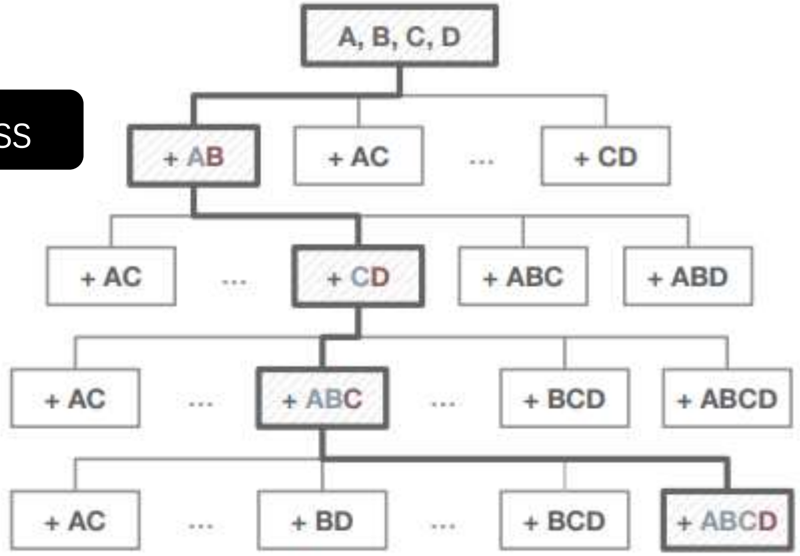


Figure 2: Structured configuration space. Squared boxes denote parent hyperparameters whereas boxes with rounded edges are leaf hyperparameters. Grey colored boxes mark active hyperparameters which form an example configuration and machine learning pipeline. Each pipeline comprises one *feature preprocessor*, *classifier* and up to three *data preprocessor* methods plus respective hyperparameters.

Tuning few hyper-parameters [1]

AutoCross

$$\mathbf{c}_{i,j,\cdots,k} = \text{vec}\left(\mathbf{f}_i \otimes \mathbf{f}_j \otimes \cdots \otimes \mathbf{f}_k\right),$$



Cross-product feature generation [2]

[1]. F. Matthias et.al. Efficient and Robust Automated Machine Learning. NIPS 2015
[2]. Y. Luo, et.al. AutoCross: Automatic Feature Crossing for Tabular Data in Real-World Applications. KDD 2019

AutoML – Commercialized examples

A brief list of AutoML products in the industrials, and "——" indicated no official announcements are found.

	company	AutoML products	customer
public company	Google	Deployed in Google's Cloud	Disney, ZSL, URBN
	Microsoft	Deployed in Azure	——
	IBM	IBM Watson Studio	——
startup	H2O.ai	H2O AutoML Package	AWS, databricks, IBM, NVIDIA
	Feature Labs	Feature Labs' platform	NASA, MONSANTO, MIT, KOHL'S
	4Paradigm	AutoML platform	Bank of China, PICC, Zhihu

Some popular open-source research projects on Github (up to Nov. 2018). More stars indicates greater popularity.

Project	stars	Project	stars
TPOT	4326	hyperopt	2302
autokeras	3728	adanet	1802
H2O AutoML	3262	darts	1547
Auto-sklearn	2367	ENAS-pytorch	1297
MOE	1077	Spearmint	1124

Azure No-Code AutoML

H_2O AutoML

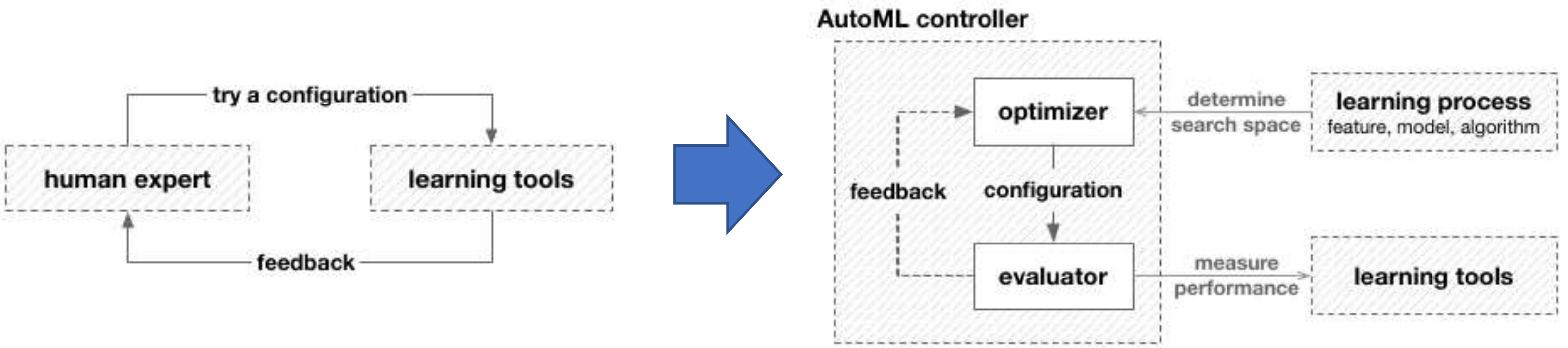
Google's AutoML

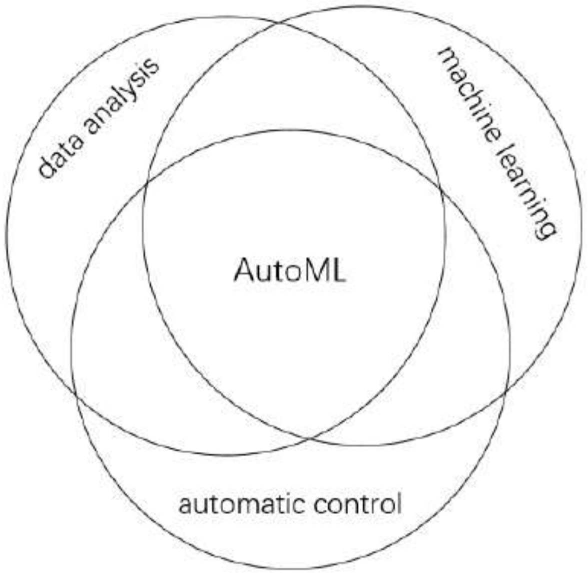
4Paradigm 第四范式

IBM Watson

Automated ML (AutoML) - Definition

Definition 2. AutoML attempts to minimize the assistance from human on designing proper machine learning computer programs (specified by E, T and P in Definition 1) which can satisfy certain requirements.

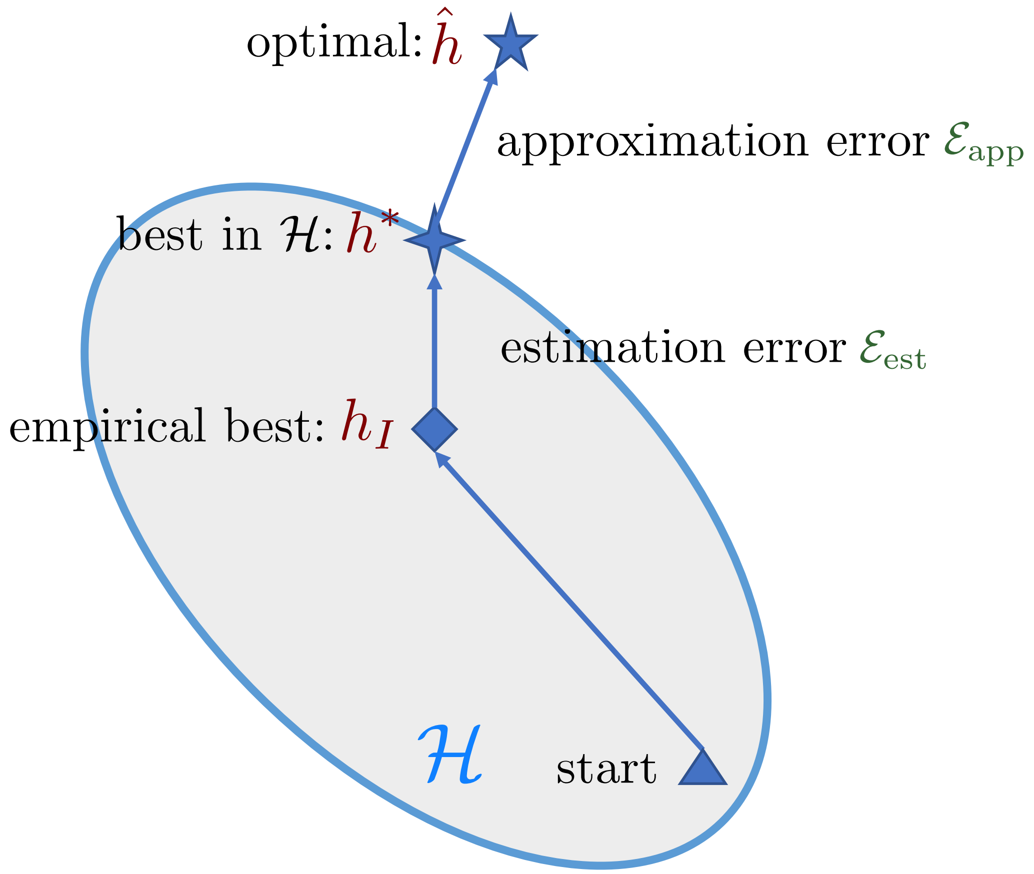




	classical machine learning	AutoML
feature engineering	humans design and construct features from data	automated by the computer program
	humans process features making them more informative	
model selection	humans design or pick up some machine learning tools based on professional knowledge	
	humans adjust hyper-parameters of machine learning tools based on performance evaluation	
algorithm selection	humans pick up some optimization algorithms to find parameters	
summary	human are involved in every aspect of learning applications	the program can be directly reused on other learning problems

Q. Yao. et.al. Taking Human out of Learning Applications: A Survey on Automated Machine Learning. Arvix 2019

AutoML – Academic view



AutoML directly minimizes the **total error**

- Approximation error
  - Which classifier to be used
  - What are their hyper-parameters
- Estimation error
  - How to represent your training data
- Optimization error
  - Which algorithm to be used
  - How to tune its step-size

AutoML – Academic view

Parameterized the prior knowledge that help meet needs of ML programs, e.g.,

- minimize the total error
- reduce parameter numbers

Perform efficient search in the designed (new) space

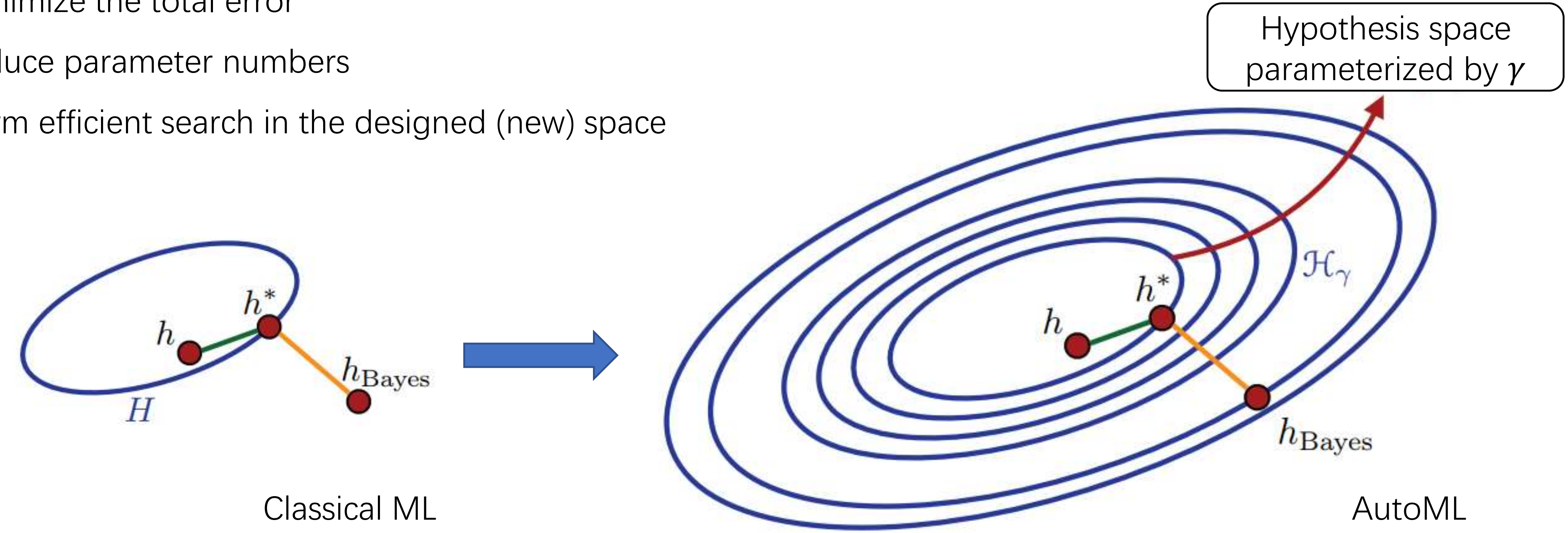


Figure 4.1 & 4.2. M. Mohri, A. Rostamizadeh, A. Talwalkar. Foundations of machine learning. 2018

AutoML – Successor of ML's trend

- Core Issue in Machine Learning: Improving learning performance (with higher efficiency)
- AutoML: an evolving way to improve learning performance

Rule-based	Statistics-based	Deep Learning-based	AutoML-based
Association rules mining	Support vector machine	Convolutional neural networks	Neural architecture search
1970s	1990s	2010s	2017

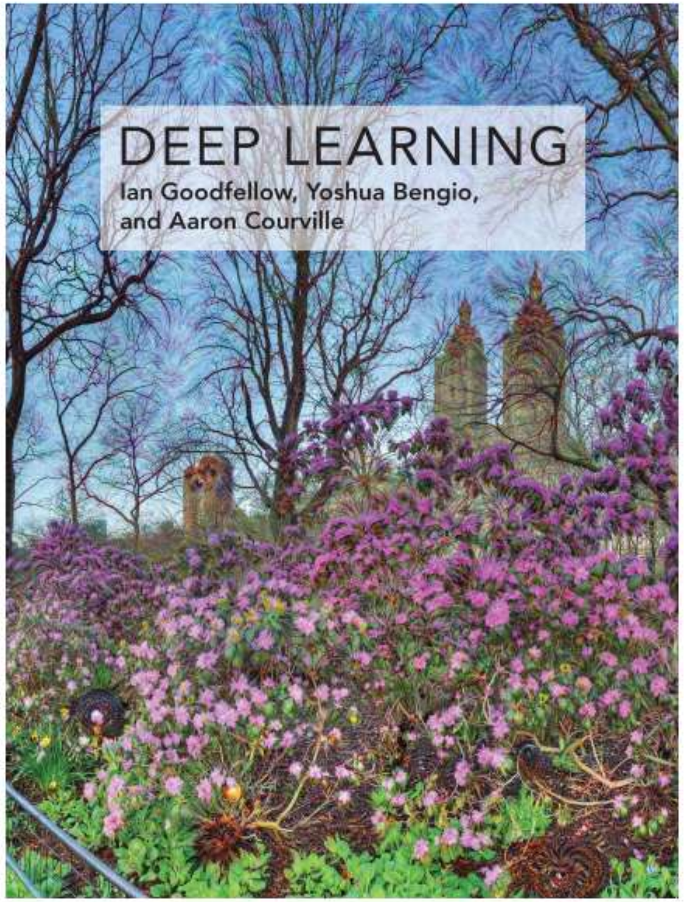
Better performance →

Continue the trends

- Larger hypothesis (more complex models) are being used
- Optimization is getting complex (even mixed up with generalization)
- The prior knowledge is imposed on more abstract level

Low-level human knowledge on data / model are replacing by computation power

AutoML – Successor of ML's trend



DEEP LEARNING FOR SYSTEM 2 PROCESSING

YOSHUA BENGIO

AAAI'2019 Invited Talk
February 9th, 2020, New York City

Mila

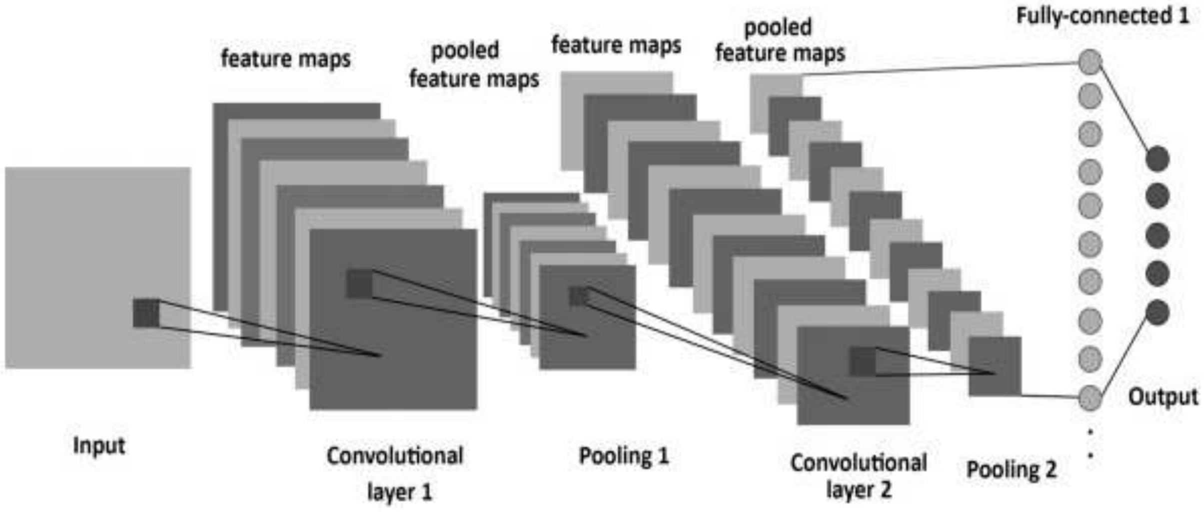
Université de Montréal

CIFAR CANADIAN INSTITUTE FOR ADVANCED RESEARCH | ICRA INSTITUT CANADIEN DE RECHERCHES AVANCÉES

Parameterized prior knowledge on a higher level

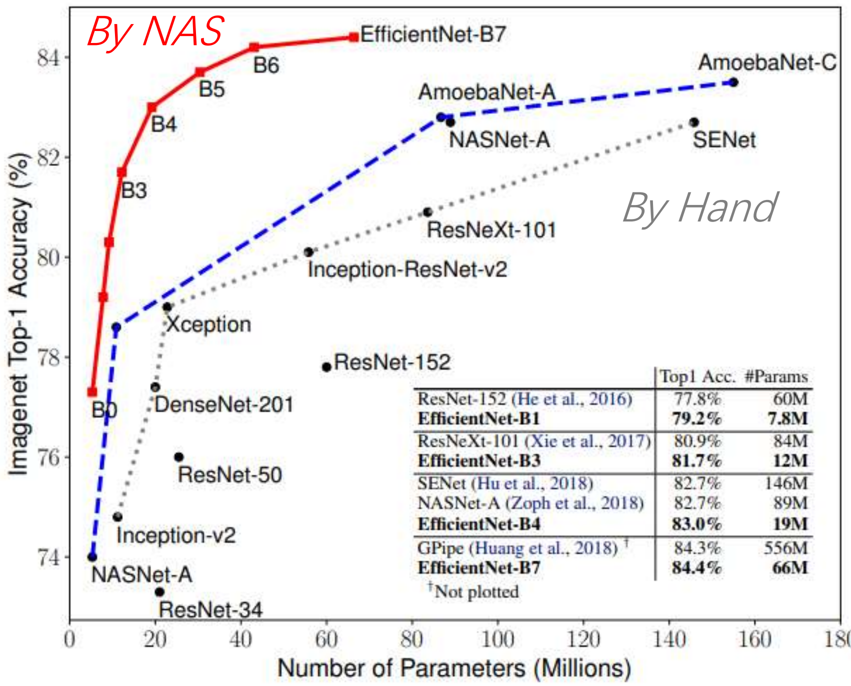
AutoML – Research examples

Architecture of networks are critical to deep learning's performance but hard to fine-tune



Design choice in each layer

- number of filters
- filter height
- filter width
- stride height
- stride width
- skip connections



Much better than hand-designed ones

Neural Architecture Search (**NAS**) tries to directly optimize network architecture using validation data sets

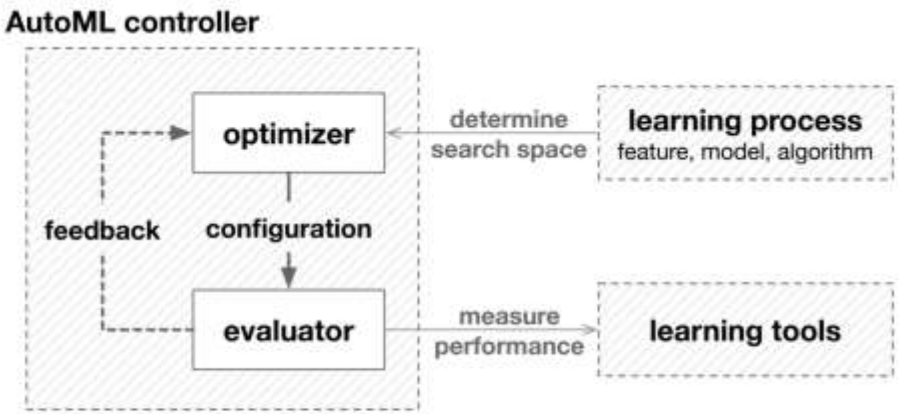
Right figure: EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. ICML 2019
Left figure: Gradient-based learning applied to document recognition. 1998

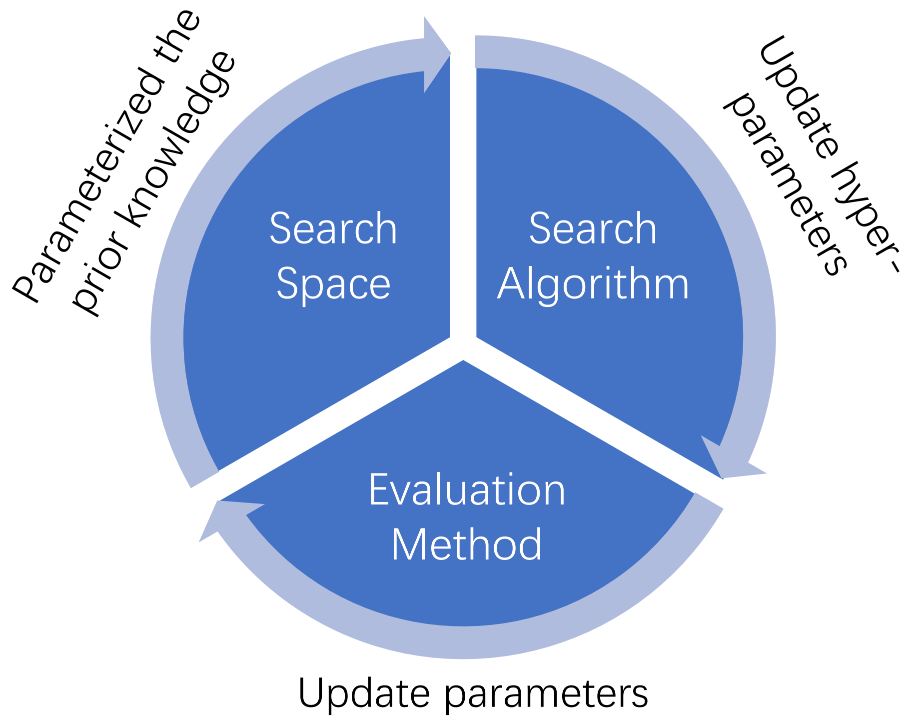
NAS – Brief review

Core issue: *effectiveness v.s. efficiency*

- 2016.12 — Born of NAS [1,2]
- 2017.02 — Block and Cell [3]: *reduce search space*
- 2018.05 — One-shot in super-net [4]:
- 2018.05 — Parameter-sharing in super-net [5]: *fast evaluation*
- 2018.12 — Differentiable architecture search [6]: *fast search algorithm* → NASP [8]: faster
- 2019.05 — Scaleup base networks [7]: *better structured search space*

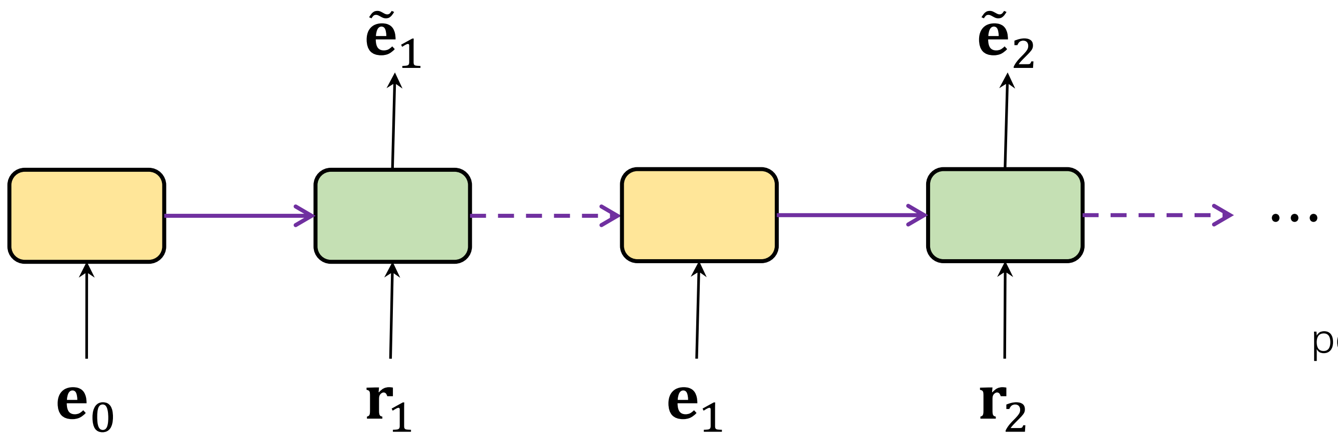
[1] Neural architecture search with reinforcement learning. ICLR 2017 (1785 cites)
[2] Designing neural network architectures using reinforcement learning. ICLR 2017 (599 cites)
[3] Learning transferable architectures for scalable image recognition. CVPR 2017 (1736 cites)
[4] Efficient Neural Architecture Search via Parameter Sharing. ICML 2018 (785 cites)
[5] Understanding and Simplifying One-Shot Architecture Search. ICML 2018 (206 cites)
[6] DARTS: Differentiable Architecture Search. ICLR 2019 (820 cites)
[7] EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. ICML 2019 (683 cites)
[8] Efficient Neural Architecture Search via Proximal Iterations. AAAI 2020 (16 cites)
See more in " Neural architecture search: A survey. JMLR 2018" (431 cites)

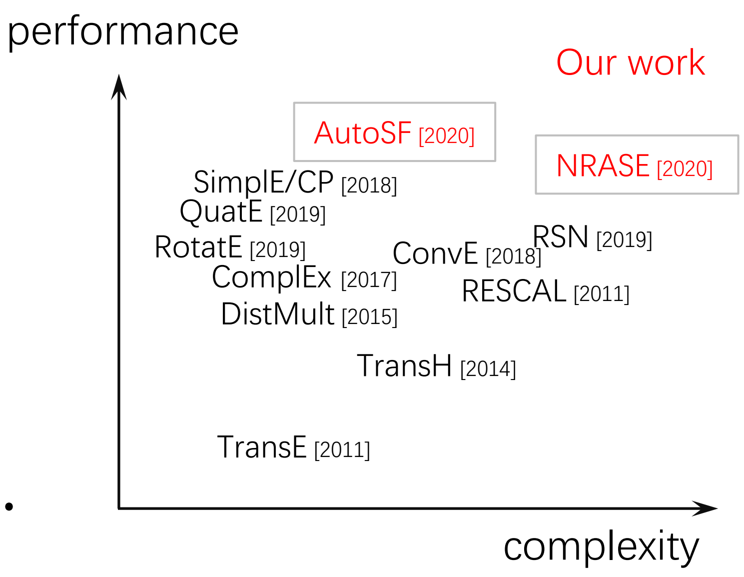




AutoML – Usage in KG

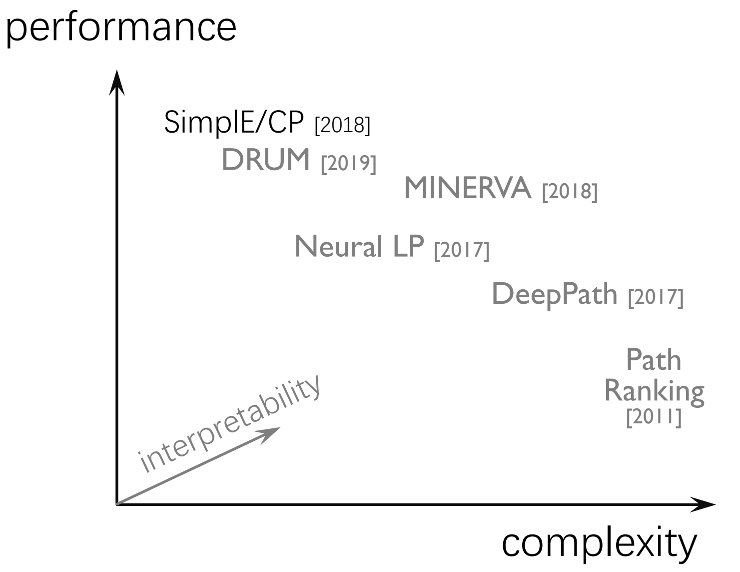
- **Knowledge Graph Embedding learning**





- **Knowledge Graph Rule learning**

$$e_0 \xrightarrow{r_1} e_1 \xrightarrow{r_2} \cdots \xrightarrow{r_L} e_L \quad \text{infer/support} \quad (e_0, r, e_L)$$



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- What is Machine Learning
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Is AutoML really New? – No

Feature generation

[PDF] Genetic Algorithms as a Tool for Feature Selection in Machine Lear

H Vafaie, KA De Jong - ICTAI, 1992 - researchgate.net

This paper describes an approach being explored to improve the usefulness of machine learning techniques for generating classification rules for complex, real world data. The approach involves the use of genetic algorithms as a" front end" to traditional rule induction ...

Cited by 288 Related articles All 15 versions

Bi-level optimization

An overview of **bilevel optimization**

B Colson, P Marcotte, G Savard - Annals of operations research, 2007 - Springer

This paper is devoted to **bilevel optimization**, a branch of mathematical programming of both practical and theoretical interest. Starting with a simple example, we proceed towards a general formulation. We then present fields of application, focus on solution approaches ...

Cited by 1034 Related articles All 19 versions

Model selection

[BOOK] **Model selection**.

H Linhart, W Zucchini - 1986 - psycnet.apa.org

Model selection. Citation. Linhart, H., & Zucchini, W. (1986). Wiley series in probability and mathematical statistics. **Model selection**. Oxford, England: John Wiley & Sons. Abstract. This book describes a systematic way of selecting between competing statistical models ...

Cited by 999 Related articles All 3 versions

Meta-learning

A perspective view and survey of **meta-learning**

R Vilalta, Y Drissi - Artificial intelligence review, 2002 - Springer

Different researchers hold different views of what the term **meta-learning** exactlymeans. The first part of this paper provides our own perspective view in which the goal isto build self-adaptive learners (ie learning algorithms that improve their bias dynamicallythrough ...

Cited by 658 Related articles All 22 versions

Hyper-parameter optimization

Gradient-based optimization of hyperparameters

Y Bengio - Neural computation, 2000 - MIT Press

Many machine learning algorithms can be formulated as the minimization of a training criterion that involves a hyperparameter. This hyperparameter is usually chosen by trial and error with a model selection criterion. In this article we present a methodology to optimize several hyper-parameters, based on the computation of the gradient of a model selection criterion with respect to the hyperparameters. In the case of a quadratic training criterion, the gradient of the selection criterion with respect to the hyperparameters is efficiently computed ...

Cited by 265 Related articles All 15 versions

Neural architecture search

Constructive algorithms for structure learning in feedforward neural netw regression problems

TY Kwok, DY Yeung - IEEE transactions on neural networks, 1997 - ieeexplore.ieee.org

In this survey paper, we review the constructive algorithms for structure learning in feedforward neural networks for regression problems. The basic idea is to start with a small network, then add hidden units and weights incrementally until a satisfactory solution is found. By formulating the whole problem as a state-space search, we first describe the general issues in constructive algorithms, with special emphasis on the search strategy. A taxonomy, based on the differences in the state transition mapping, the training algorithm ...

Cited by 588 Related articles All 21 versions

AutoML v.s. Meta-Learning - Examples

Definition 2 (CASH). *Let $\mathcal{A} = \{A^{(1)}, \ldots, A^{(R)}\}$ be a set of algorithms, and let the hyperparameters of each algorithm $A^{(j)}$ have domain $\Lambda^{(j)}$. Further, let $D_{train} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$ be a training set which is split into K cross-validation folds $\{D^{(1)}_{valid}, \ldots, D^{(K)}_{valid}\}$ and $\{D^{(1)}_{train}, \ldots, D^{(K)}_{train}\}$ such that $D^{(i)}_{train} = D_{train} \backslash D^{(i)}_{valid}$ for $i = 1, \ldots, K$. Finally, let $\mathcal{L}(A^{(j)}_{\boldsymbol{\lambda}}, D^{(i)}_{train}, D^{(i)}_{valid})$ denote the loss that algorithm $A^{(j)}$ achieves on $D^{(i)}_{valid}$ when trained on $D^{(i)}_{train}$ with hyperparameters $\boldsymbol{\lambda}$. Then, the* Combined Algorithm Selection and Hyperparameter optimization (CASH) *problem is to find the joint algorithm and hyperparameter setting that minimizes this loss:*

$$A^*, \boldsymbol{\lambda}_* \in \underset{A^{(j)} \in \mathcal{A}, \boldsymbol{\lambda} \in \Lambda^{(j)}}{\operatorname{argmin}} \frac{1}{K} \sum_{i=1}^{K} \mathcal{L}(A^{(j)}_{\boldsymbol{\lambda}}, D^{(i)}_{train}, D^{(i)}_{valid}). \quad (1)$$

Auto-sklearn [1]

This implies a bilevel optimization problem (Anandalingam & Friesz, 1992; Colson et al., 2007) with α as the upper-level variable and w as the lower-level variable:

$$\min_{\alpha} \ \mathcal{L}_{val}(w^*(\alpha), \alpha) \quad (3)$$
$$\text{s.t.} \ \ w^*(\alpha) = \operatorname{argmin}_w \ \mathcal{L}_{train}(w, \alpha) \quad (4)$$

DARTS [2]

Definition 1 (AutoML Problem). *Let $F(\boldsymbol{P}; g)$ be a KGE model (with indexed embeddings $\boldsymbol{P} = \{\boldsymbol{h}, \boldsymbol{r}, \boldsymbol{t}\}$ and structure g), $\mathcal{M}(F(\boldsymbol{P}; g), \mathcal{S})$ measures the performance (the higher the better) of a KGE model F on a set of triplets $\mathcal{S}$. The problem of searching the SF is formulated as:*

$$g^* \in \arg\max_{g \in \mathcal{G}} \mathcal{M}(F(\boldsymbol{P}^*; g), \mathcal{S}_{val}) \quad (1)$$
$$\text{s.t.} \ \ \boldsymbol{P}^* = \arg\max_{\boldsymbol{P}} \mathcal{M}(F(\boldsymbol{P}; g), \mathcal{S}_{tra}), \quad (2)$$

where $\mathcal{G}$ contains all possible choices of g, $\mathcal{S}_{tra}$ and $\mathcal{S}_{val}$ denote training and validation data sets.

AutoSF [3]

In standard training, we aim to minimize the expected loss for the training set: $\frac{1}{N}\sum_{i=1}^{N} C(\hat{y}_i, y_i) = \frac{1}{N}\sum_{i=1}^{N} f_i(\theta)$, where each input example is weighted equally, and $f_i(\theta)$ stands for the loss function associating with data x_i. Here we aim to learn a reweighting of the inputs, where we minimize a weighted loss:

$$\theta^*(w) = \arg\min_{\theta} \sum_{i=1}^{N} w_i f_i(\theta), \quad (1)$$

with w_i unknown upon beginning. Note that $\{w_i\}_{i=1}^{N}$ can be understood as training hyperparameters, and the optimal selection of w is based on its validation performance:

$$w^* = \arg\min_{w, w \geq 0} \frac{1}{M} \sum_{i=1}^{M} f_i^v(\theta^*(w)). \quad (2)$$

It is necessary that $w_i \geq 0$ for all i, since minimizing the negative training loss can usually result in unstable behavior.

Noisy Label Learning [4]

1. Efficient and robust automated machine learning. NIPS 2015
2. DARTS: Differentiable Architecture Search. ICLR 2019
3. AutoSF: Searching Scoring Functions for Knowledge Graph Embedding. ICDE 2020
4. Learning to Reweight Examples for Robust Deep Learning. ICML 2018

See more in" Bilevel programming for hyperparameter optimization and meta-learning. ICML 2018"

What's Meta-Learning?

In the 1990s, the term metalearning started to appear in machine learning research, although the concept itself dates back to the mid-1970s (Rice 1976). A number of definitions of metalearning have been given, the following list cites the main review papers and books from the last decade:

1. Metalearning studies how learning systems can increase in efficiency through experience; the goal is to understand how learning itself can become flexible according to the domain or task under study (Vilalta and Drissi 2002a).
2. The primary goal of metalearning is the understanding of the interaction between the mechanism of learning and the concrete contexts in which that mechanism is applicable (Giraud-Carrier 2008).
3. Metalearning is the study of principled methods that exploit metaknowledge to obtain efficient models and solutions by adapting machine learning and data mining processes (Brazdil et al. 2009).
4. Metalearning monitors the automatic learning process itself, in the context of the learning problems it encounters, and tries to adapt its behaviour to perform better (Vanschoren 2010).

Definition 1 1. A metalearning system must include a learning subsystem, which adapts with experience.
2. Experience is gained by exploiting metaknowledge extracted
   (a) …in a previous learning episode on a single dataset, and/or
   (b) …from different domains or problems.

Metalearning: a survey of trends and technologies. AIJ 2015

DARTS

This implies a bilevel optimization problem (Anandalingam & Friesz, 1992; Colson et al., 2007) with α as the upper-level variable and w as the lower-level variable:

$$\min_{\alpha} \quad \mathcal{L}_{val}(w^*(\alpha), \alpha) \tag{3}$$

$$\text{s.t.} \quad w^*(\alpha) = \text{argmin}_w \; \mathcal{L}_{train}(w, \alpha) \tag{4}$$

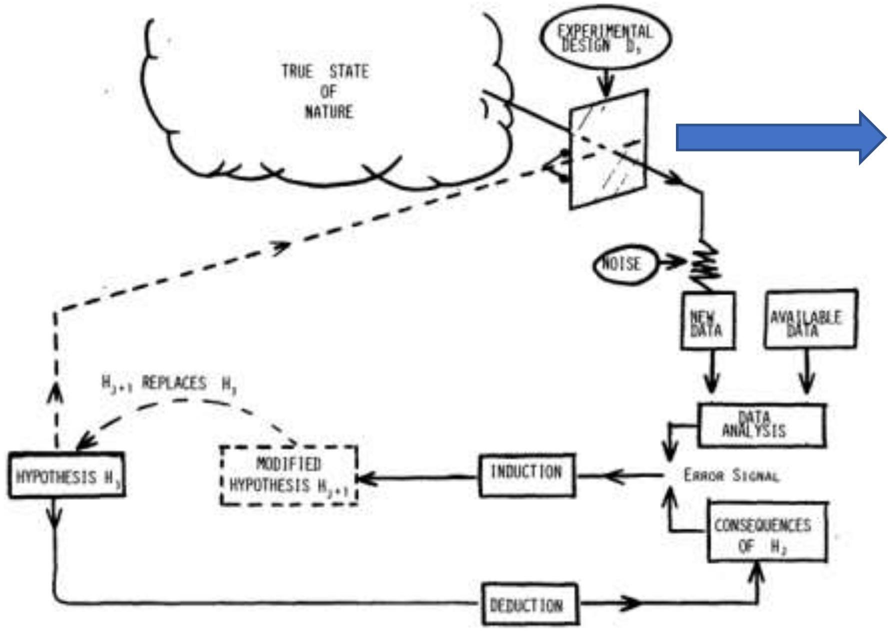
Meta-learner   Base-learner

Just an application of meta-learning?

Model selection?

Bilevel programming?

Is AutoML New? – Yes!

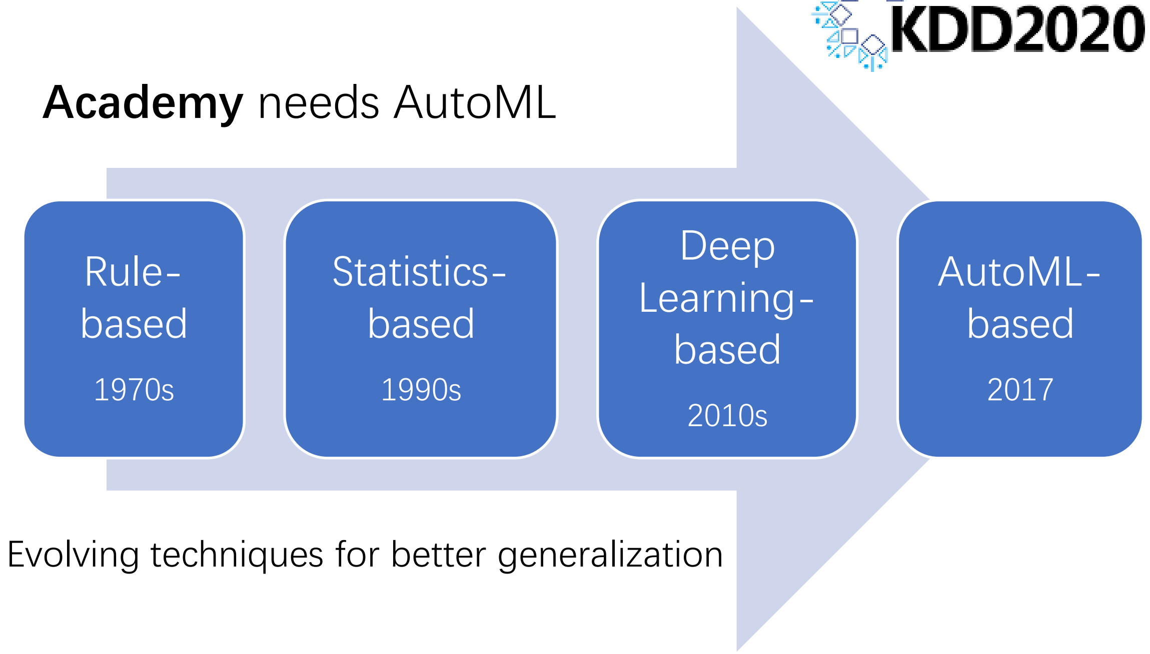


The moving window

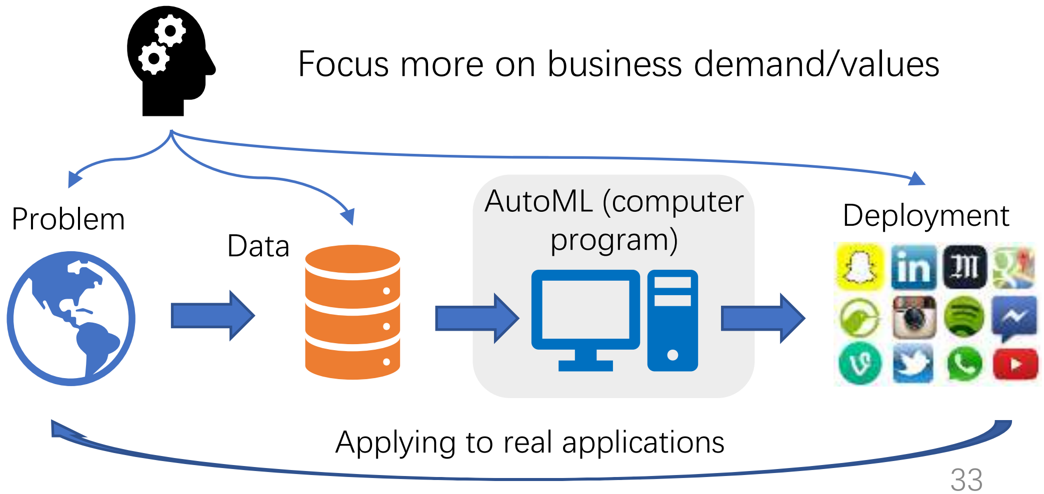
The experimental design is here shown as a movable window looking onto the true state of nature. Its positioning at each stage is motivated by current beliefs, hopes, and fears [1]

[1] G. Box, Science and statistics, JASA 1976

Academy needs AutoML



Industry needs AutoML

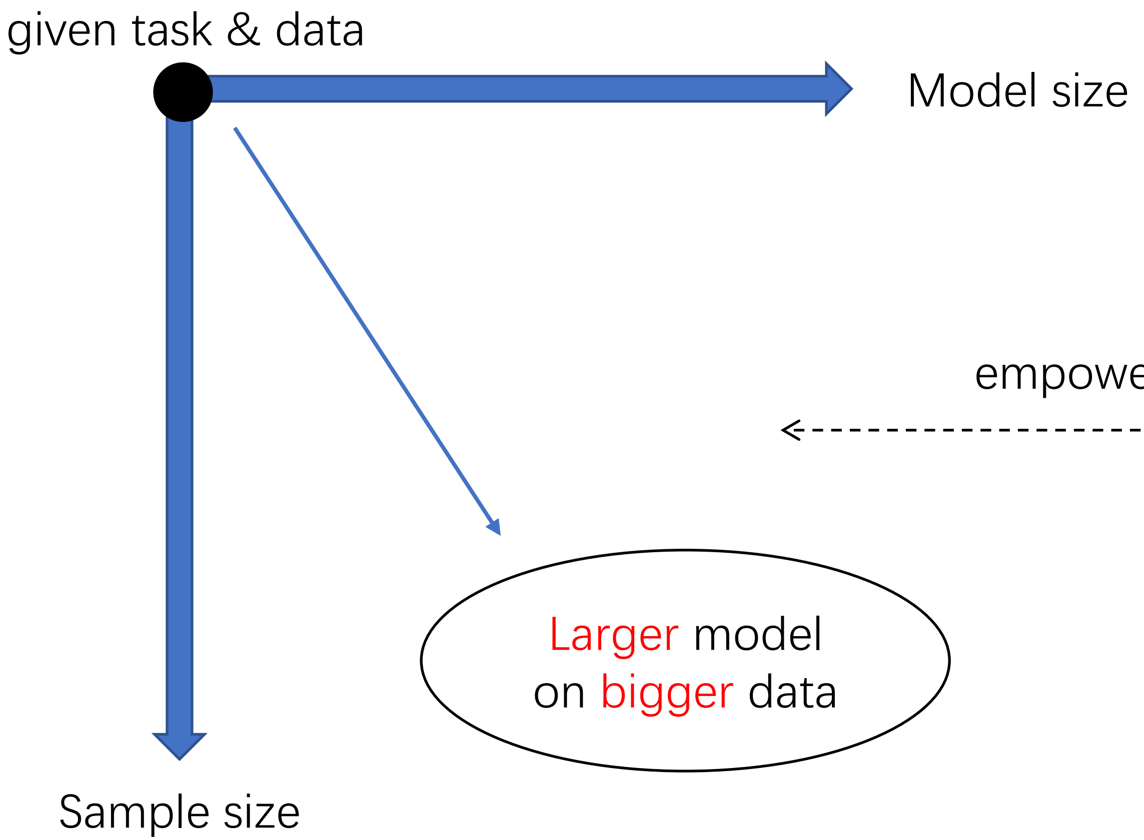


Outline

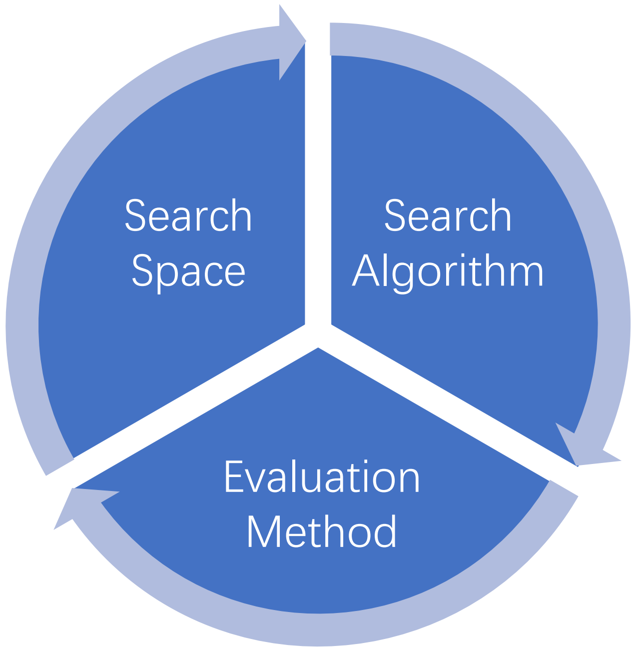
- What is Machine Learning
- What is Automated Machine Learning (AutoML)
- Is AutoML Really New
- What Should We Focus Next

Proposal of 2nd Stage

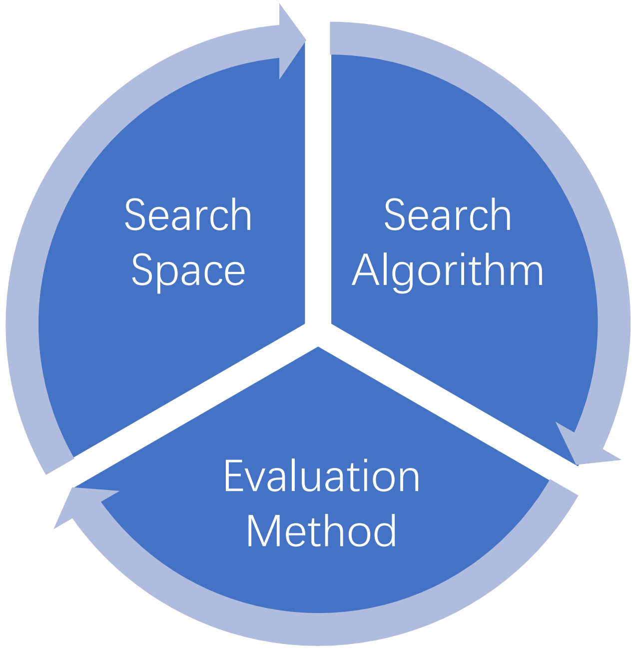
AutoML – Research landscape



empower



AutoML – Next focus



AUTOML

- **SPACE**
  - Old task
    - Scaleup small model to large one
    - Transfer model from small data to large data
  - New task
    - Design new space for important tasks (match company's demand)
- **ALGORITHM**
  - Applicability
    - Handling various search constraint
  - Convergence
    - Faster convergence
- **EVALUATION**
  - Parameter-sharing
    - make sense of it

Thanks!

Please send questions/discussions to

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