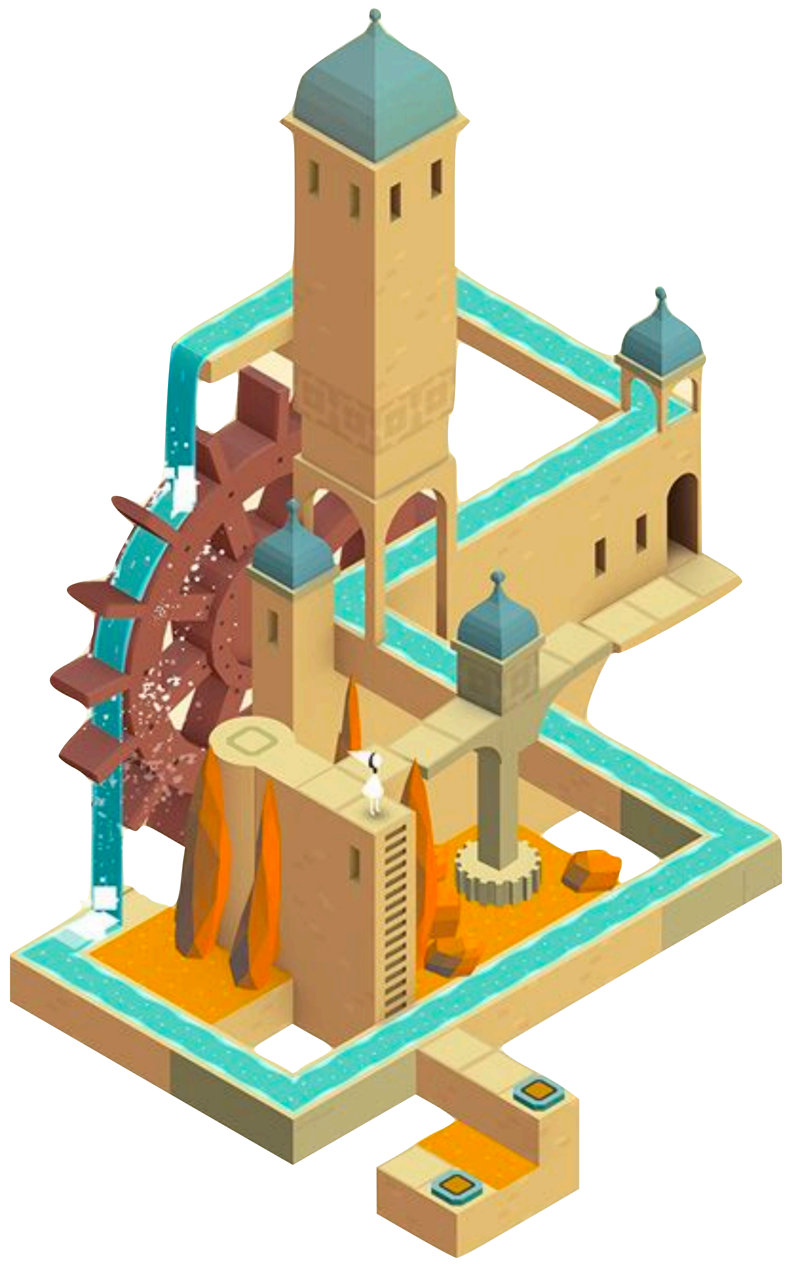


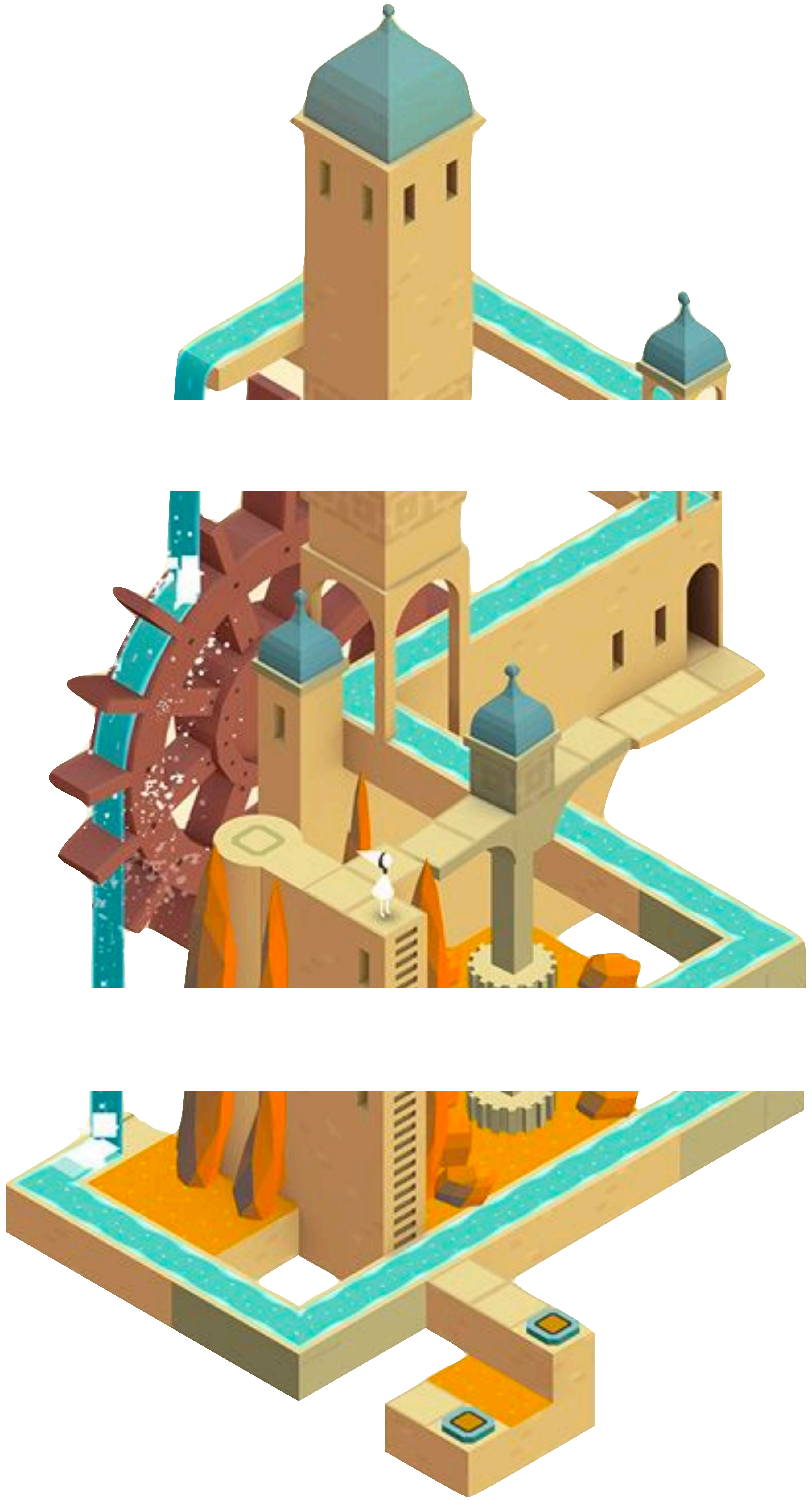
Automated Machine Learning

Open Data Science Conference
March 30th, 2021

Joaquin Vanschoren & Pieter Gijsbers
Eindhoven University of Technology

image credit: ustwo

Overview



Part 1: *Why* automate machine learning?

High-level goals

Part 2: *How* AutoML works

The machinery

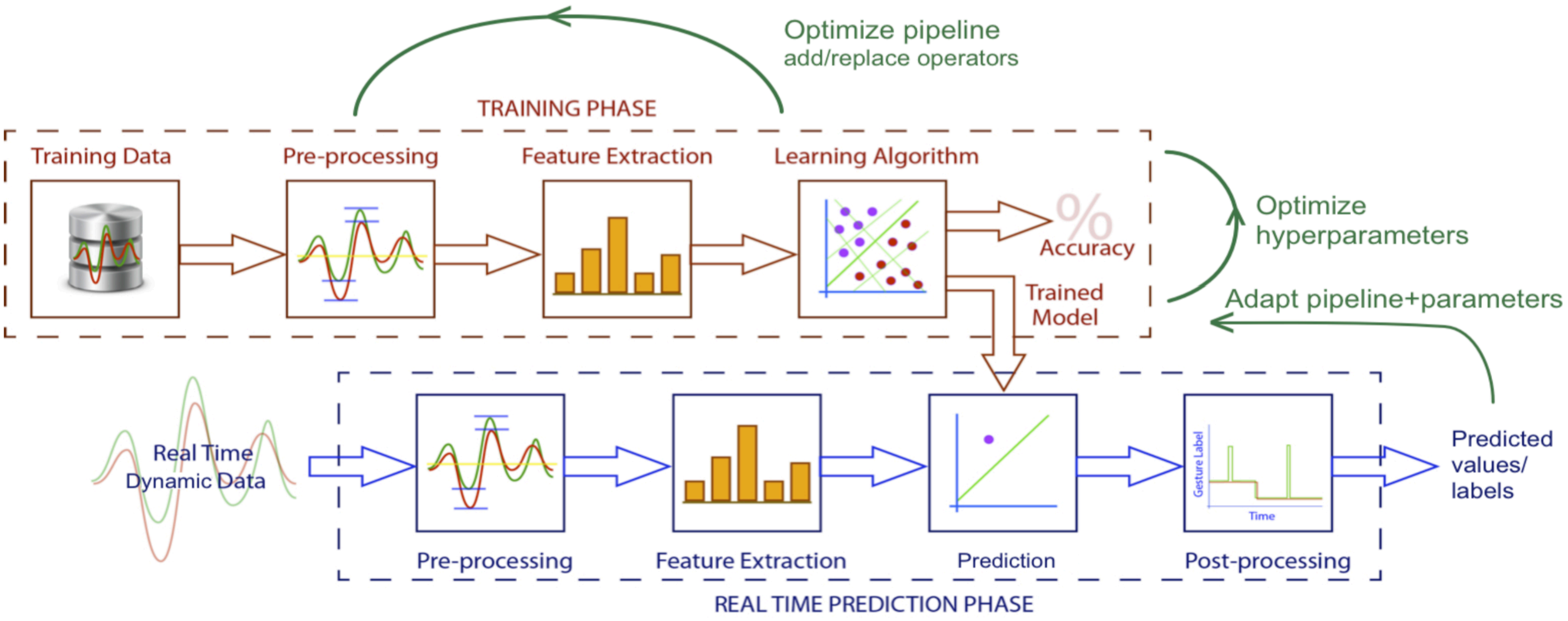
Part 3: Learning how to do AutoML

Closing the loop

Part 1: *Why* automate machine learning?

High-level goals

Doing machine learning requires lots of expertise and exploration



Cleaning, preprocessing, feature selection/engineering features, model selection, hyperparameter tuning, adapting to concept drift,…

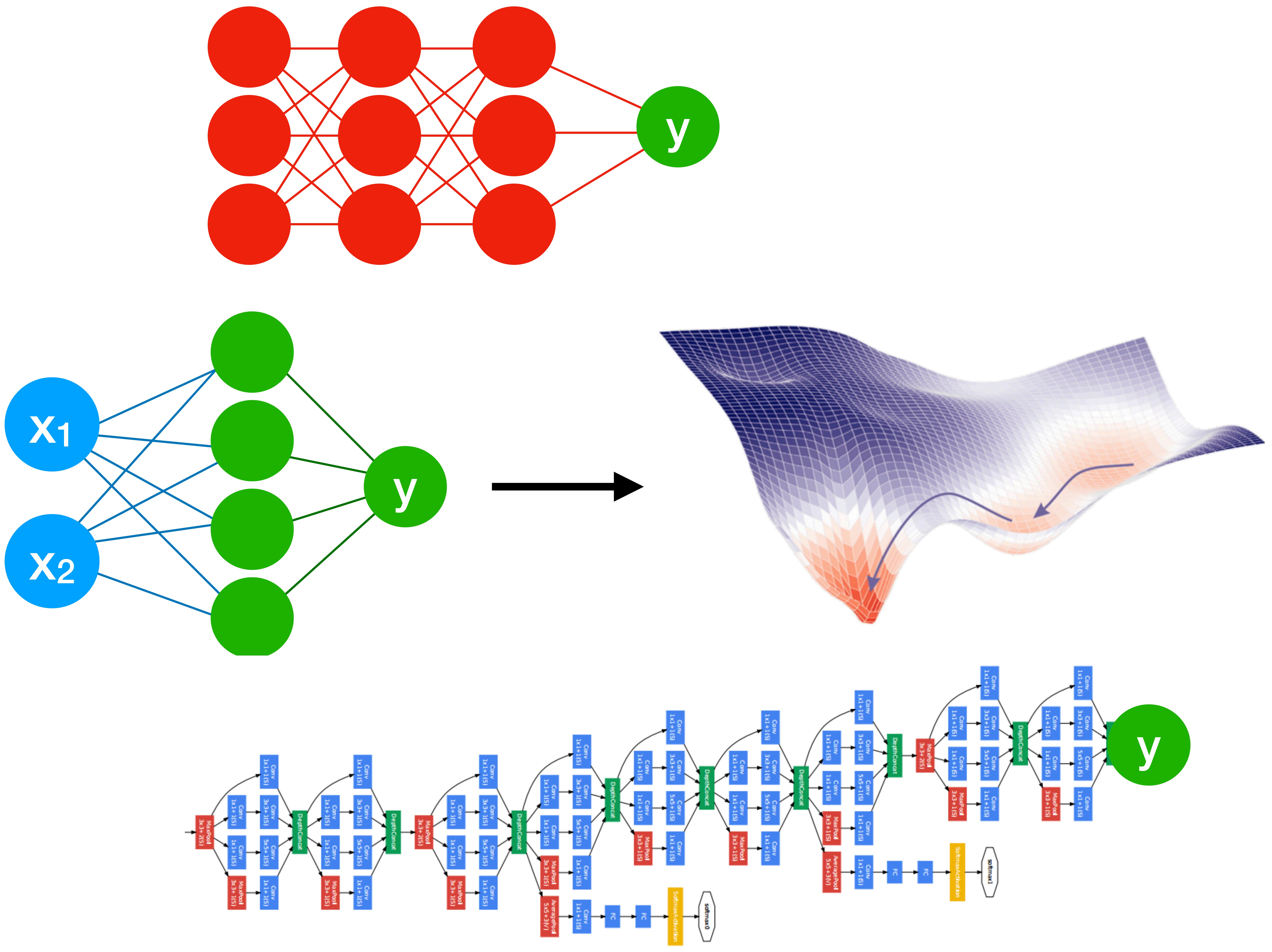
Doing machine learning requires lots of expertise and exploration

Architecture:

- Type of operators
- Size of layers
- Filter sizes
- Skip connections
- Pre-trained layers
- Transformers
- …

Optimization:

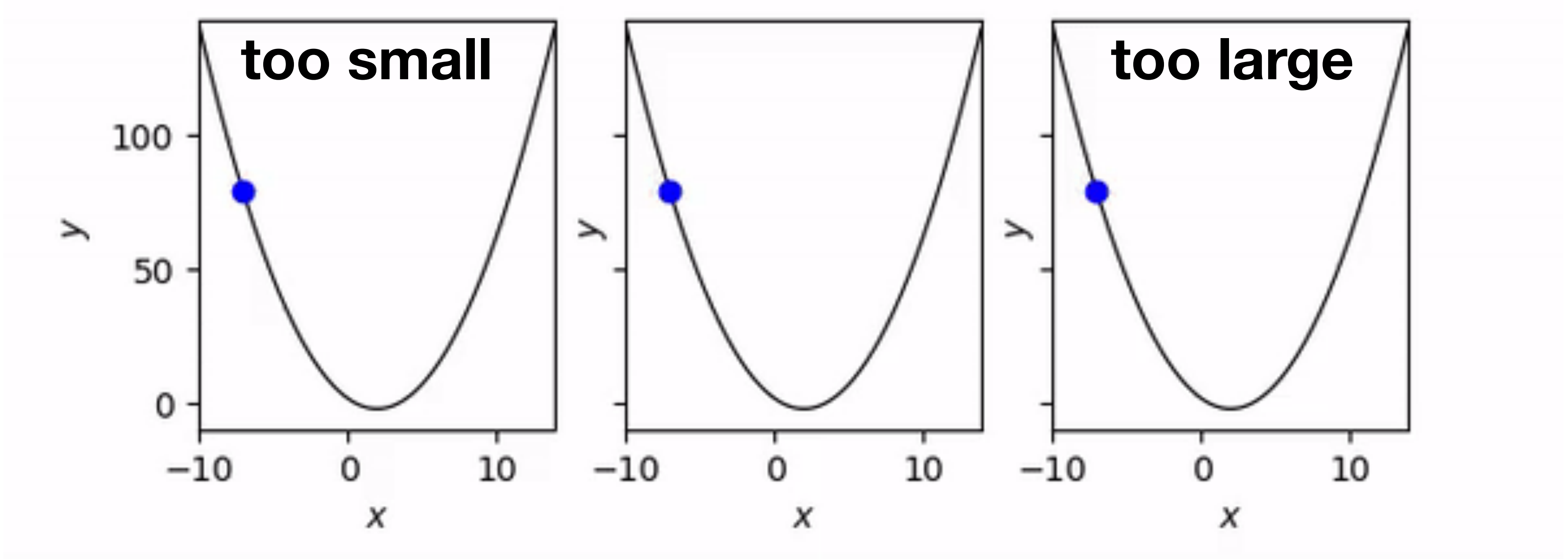
- Gradient descent hyperparameters
- Regularization
- …



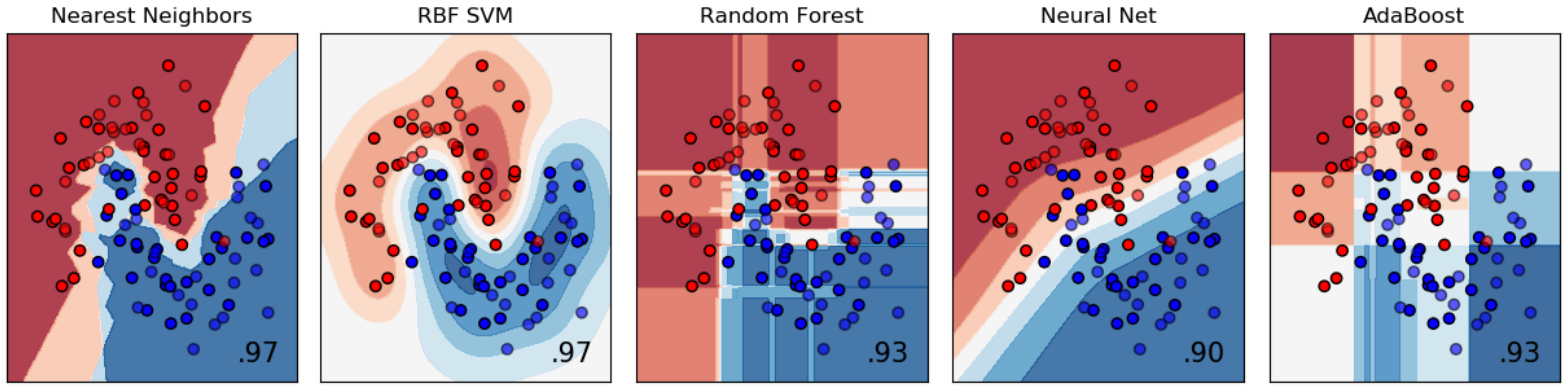
Hyperparameters

Every design decision usually made by the *user (architecture, operators, tuning,…)*

- Numeric
  - e.g. learning rate

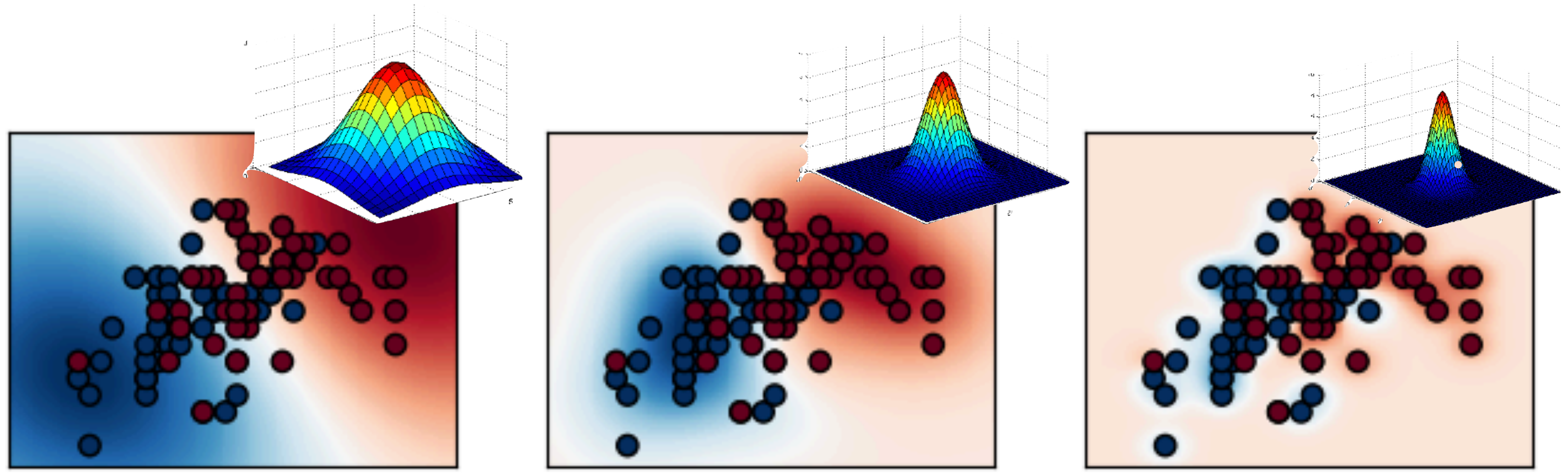


- Categorical
  - e.g. classifier



- Conditional
  - SVM -> kernel?

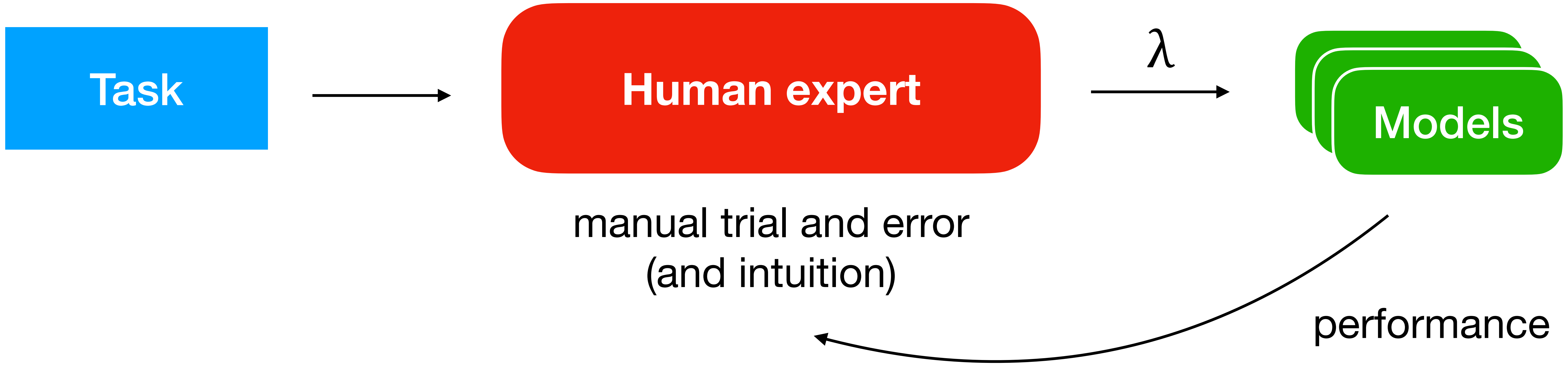
    RBF kernel -> gamma?



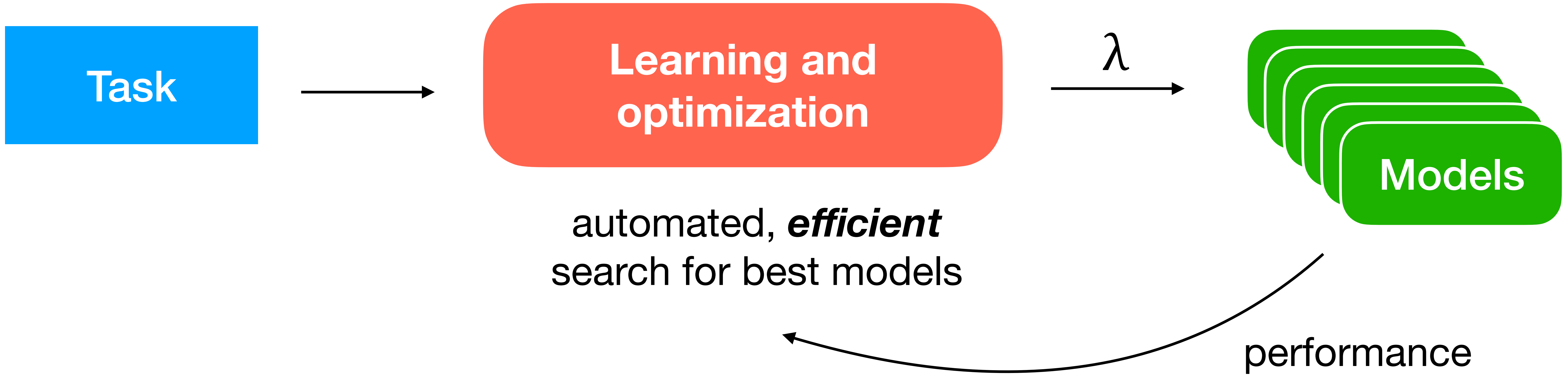
Hutter et al. 2019

Automatic Machine Learning (AutoML)

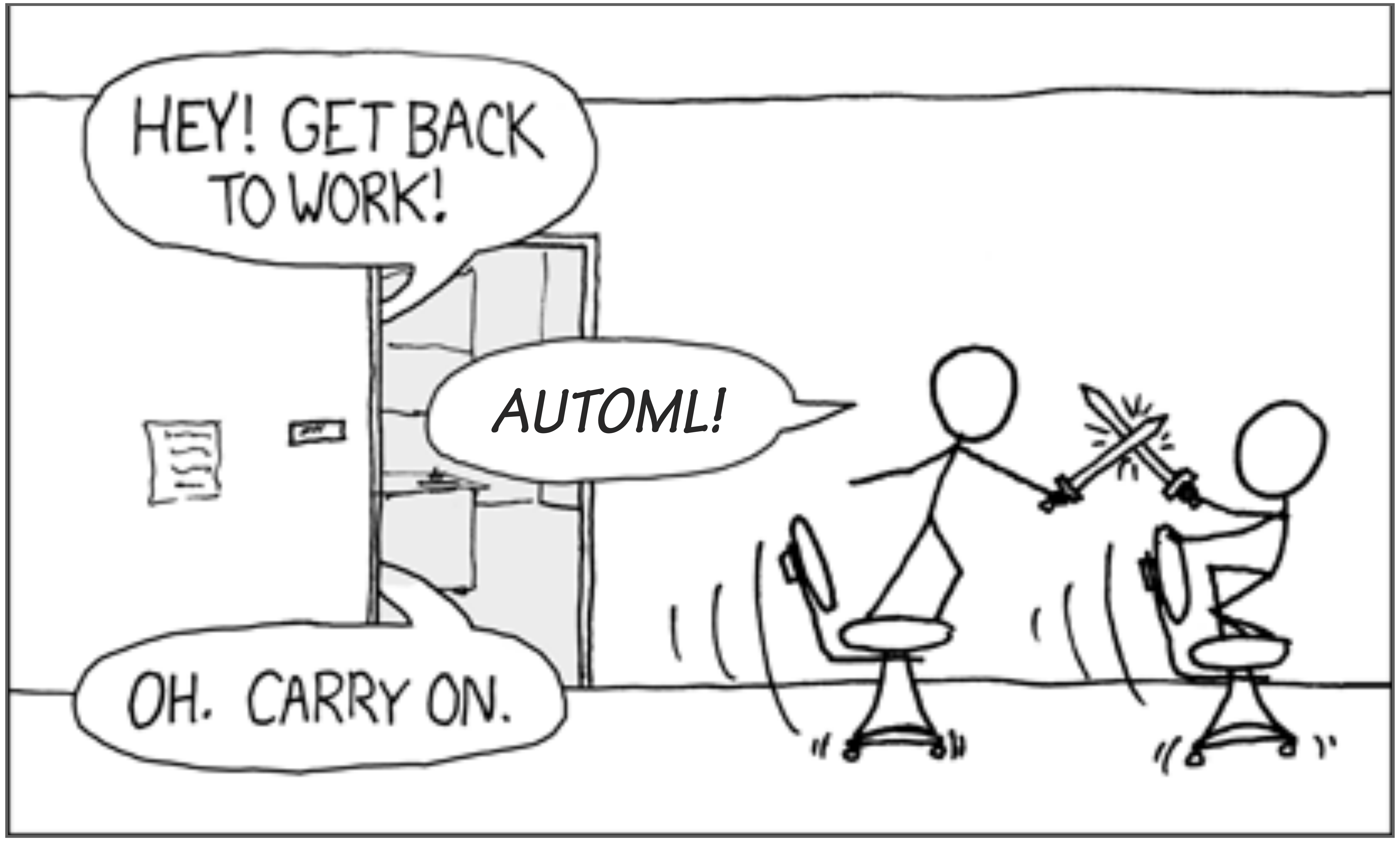
Manual machine learning



AutoML: build models in a *data-driven, intelligent, purposeful* way



THE DATA SCIENTIST'S #1 EXCUSE FOR LEGITIMATELY SLACKING OFF:
"THE AUTOML TOOL IS OPTIMIZING MY MODELS!"



Adapted from XKCD (Randall Munroe)


> Antenna broken. No communication with Earth.
*Sigh. I’m going to have to AutoML the s*** out of this*

Many open challenges in AutoML!

Human in the loop

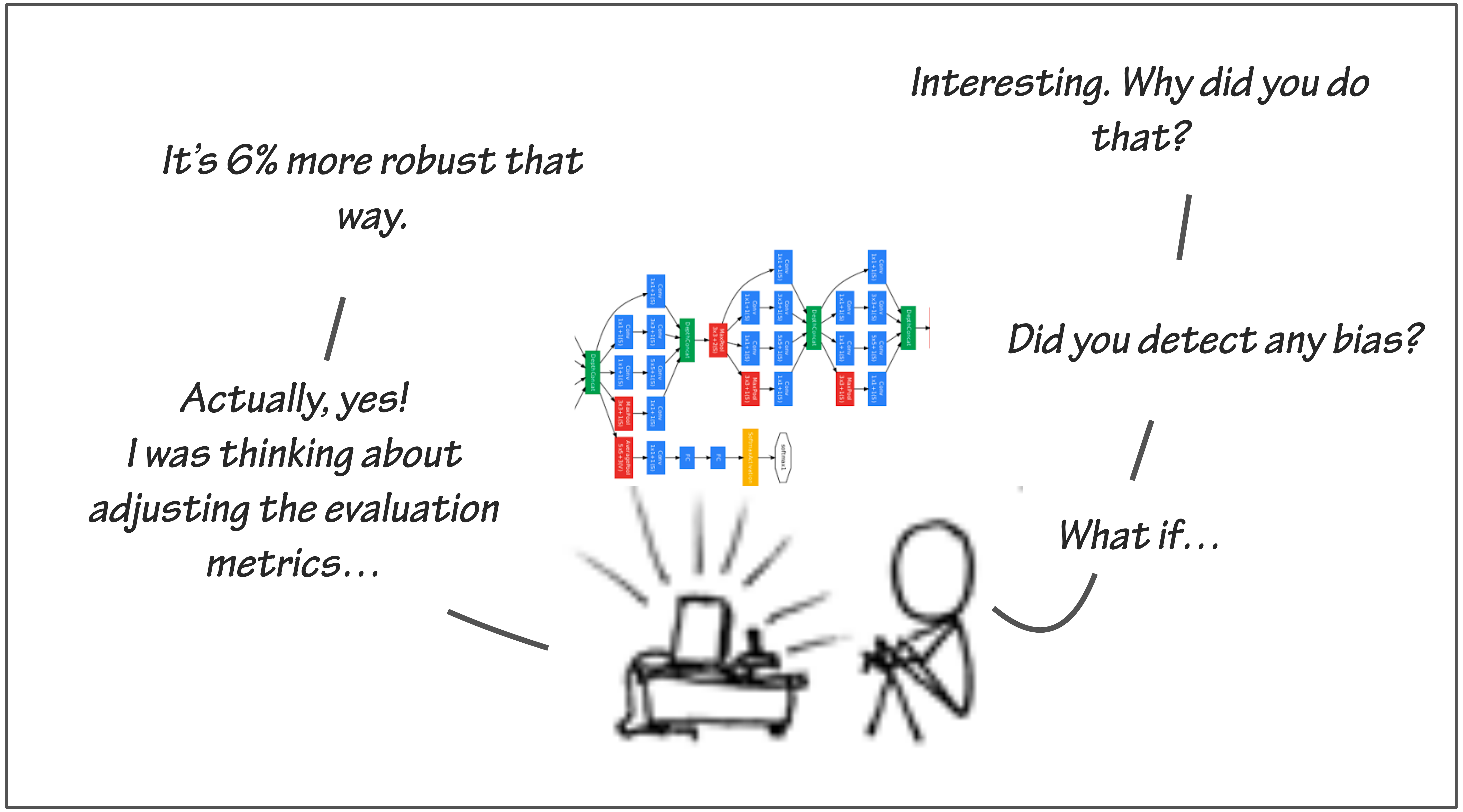
Explainable process/models

Ask for help/data

Self-assess trustworthiness

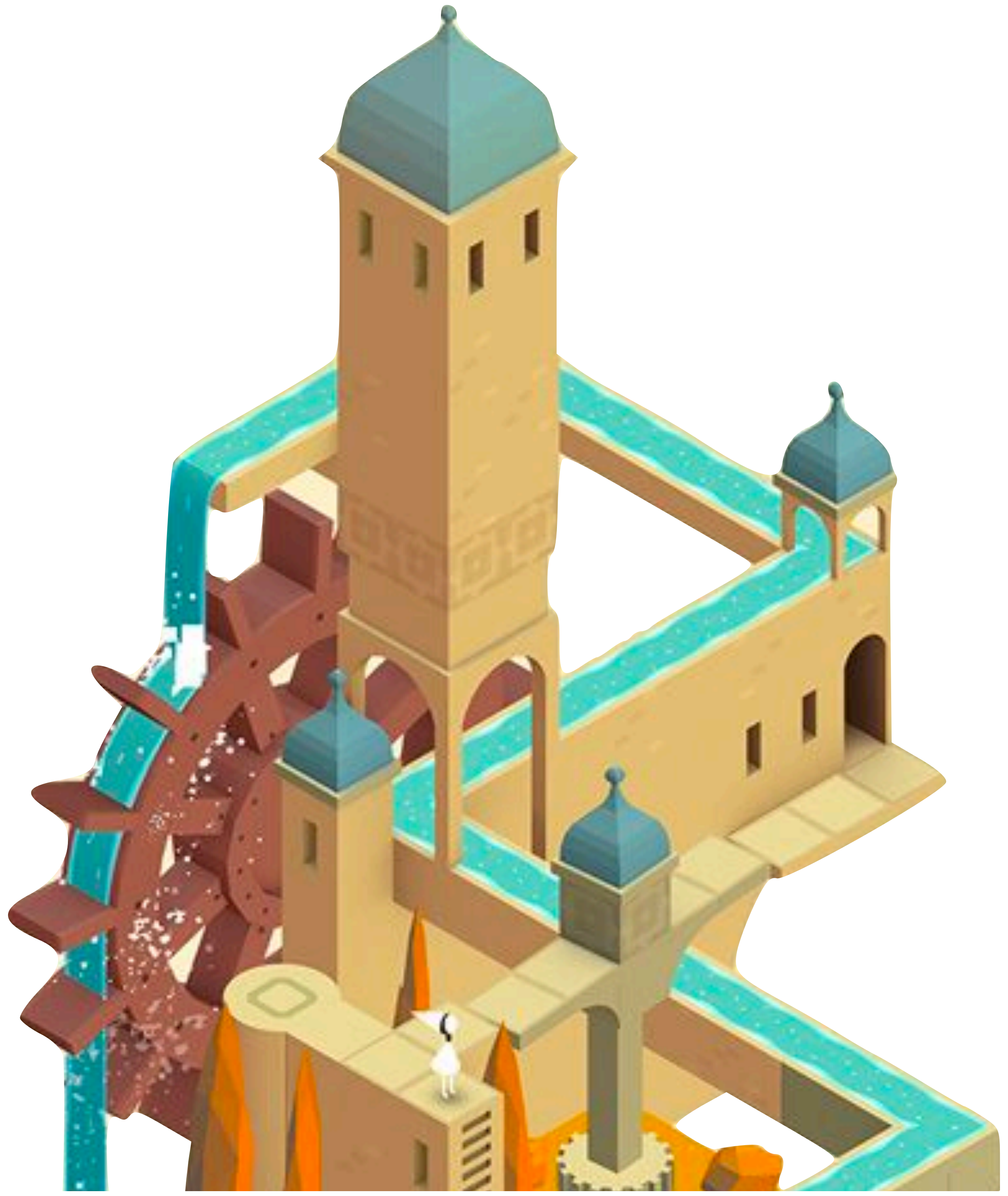
Real-world constraints

Meta-learning



Adapted from XKCD (Randall Munroe)

Overview

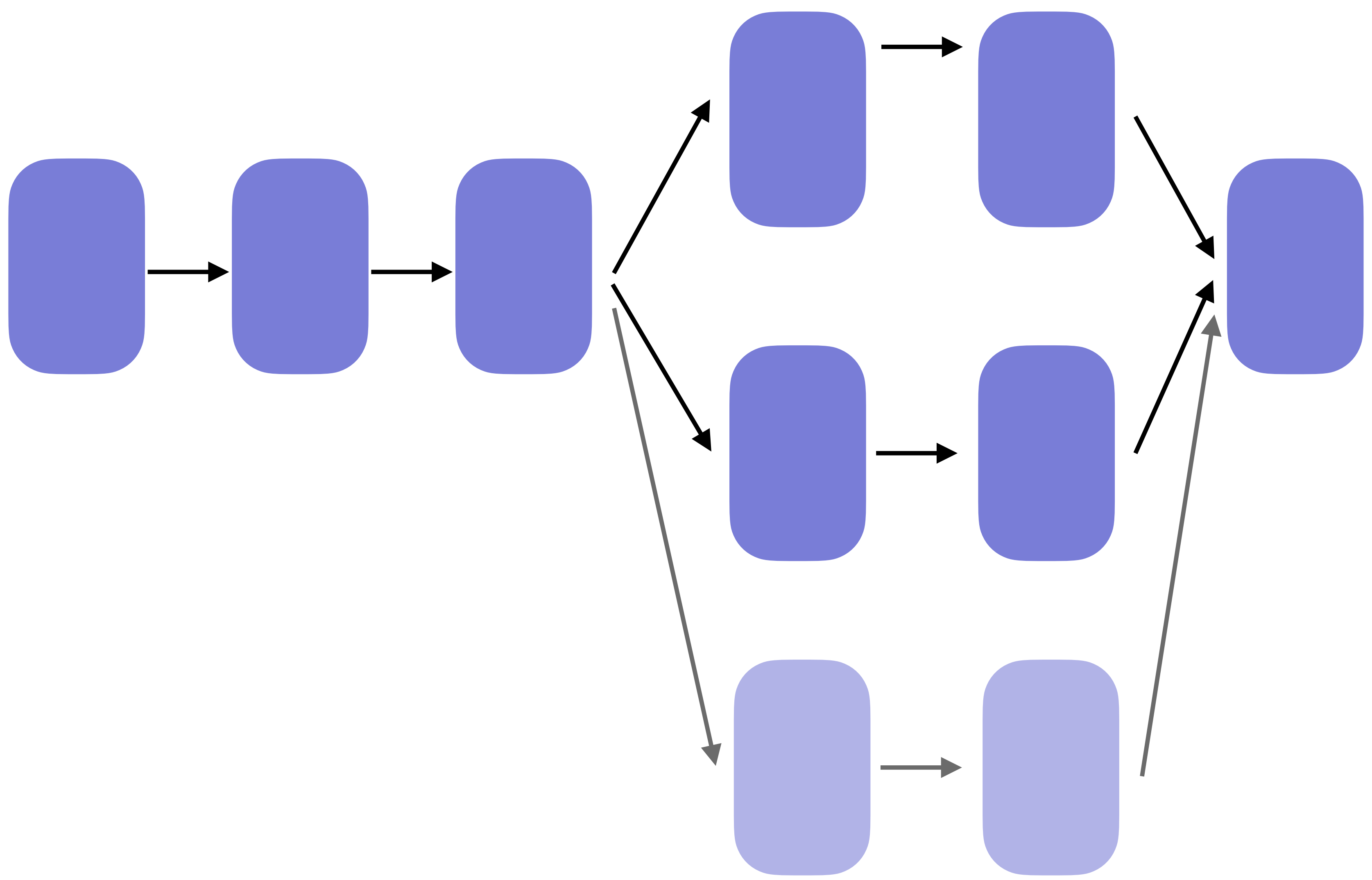


Part 2: *How* AutoML works

The machinery

AutoML: subproblems

- **Architecture search space**: *represent* all pipelines or neural architectures
  - Pipeline operators, neural layers, interconnections,…
  - Defines a (complex) search space

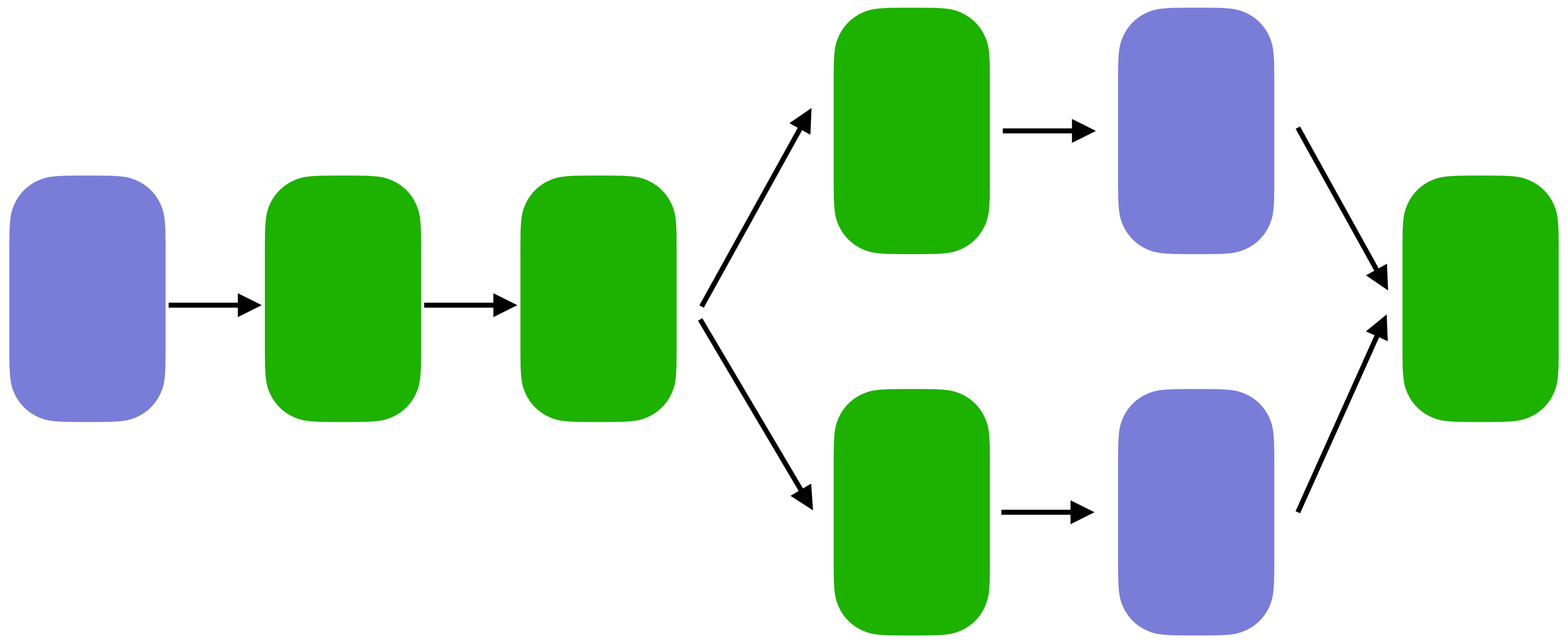


```
make_pipeline(
 OneHotEncoder(),
 Imputer(),
 StandardScaler(),
 SVC())
```

```
model.add(Conv2D(32, (3, 3))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3))
```

AutoML: subproblems

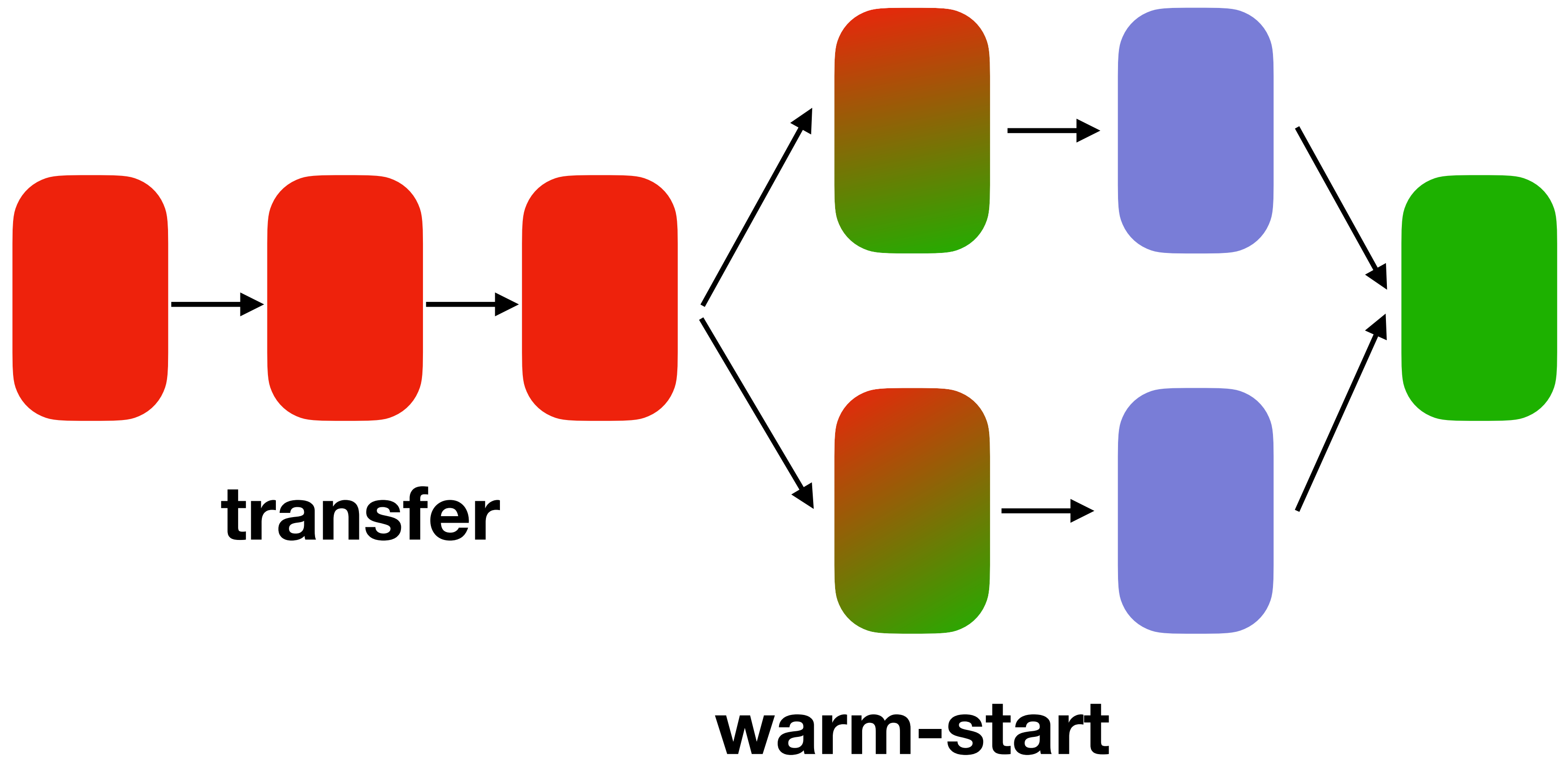
- **Architecture search space**: *represent* all possible architectures
- **Optimization**:
  - What is the best architecture? Which hyperparameters are important?
  - How to optimize them? What is the (multi-) objective function?



```
hyper_space = {'SVC__C': expon(scale=100),
               'SVC__gamma': expon(scale=.1)}
RandomizedSearchCV(pipe, param_distributions=hyper_space, n_iter=200)
```

AutoML: subproblems

- **Architecture search space**: *represent* all possible architectures
- **Optimization**: *optimize* architecture and hyperparameters
- **Meta-learning**: how can we transfer *experience* from previous tasks?
  - Don't start from scratch (search space is too large)
  - Transfer learning: reuse good architectures/configurations/weights
  - Warm starting: start from promising architectures/configurations/initializations

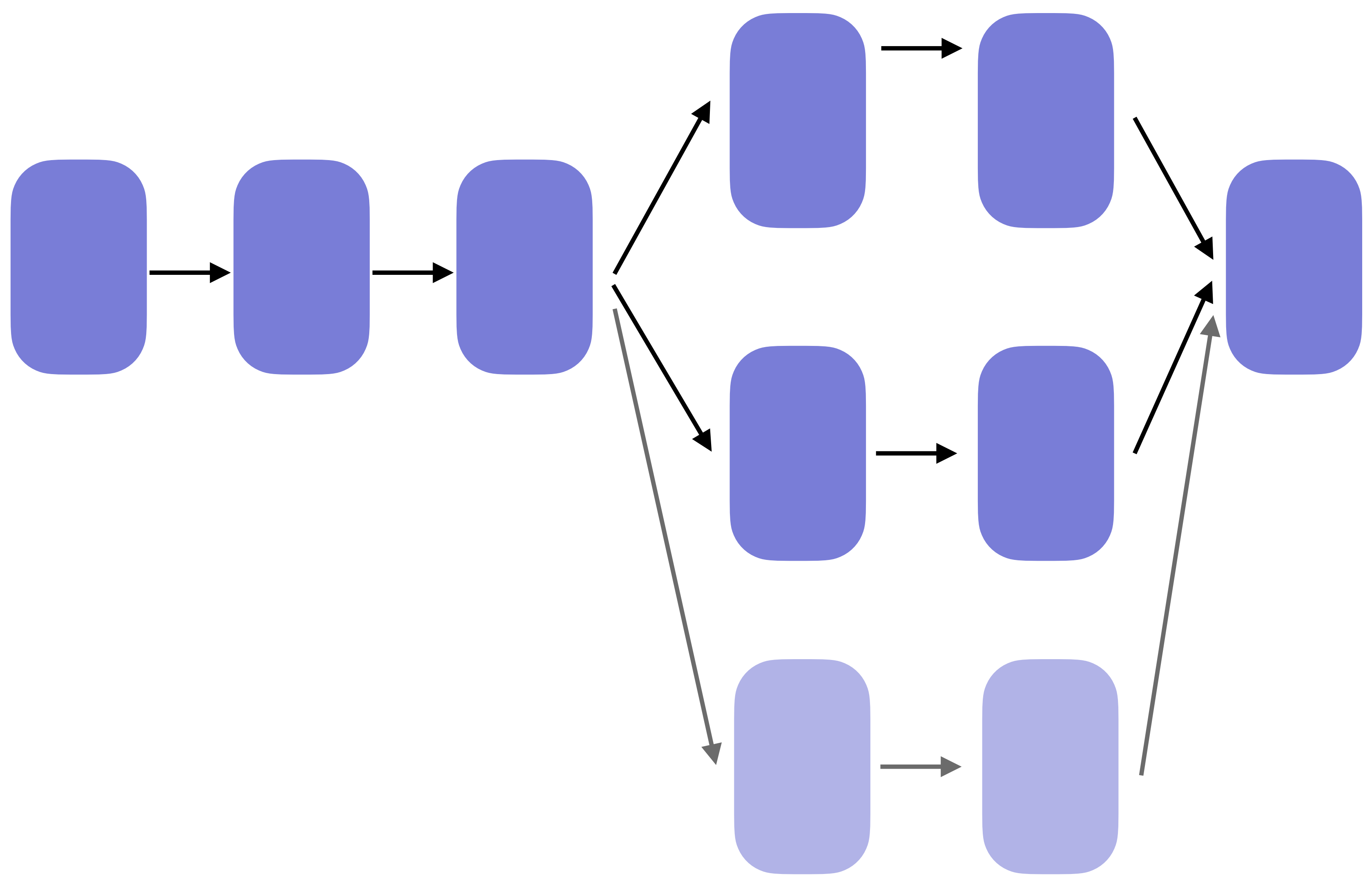


AutoML: subproblems

- **Architecture search**: *represent* all possible architectures
- **Optimization**: *optimize* architecture and hyperparameters
- **Meta-learning**: how can we transfer experience from previous tasks?

Many combinations are possible!
They can be done *consecutively*, *simultaneously* or *interleaved*

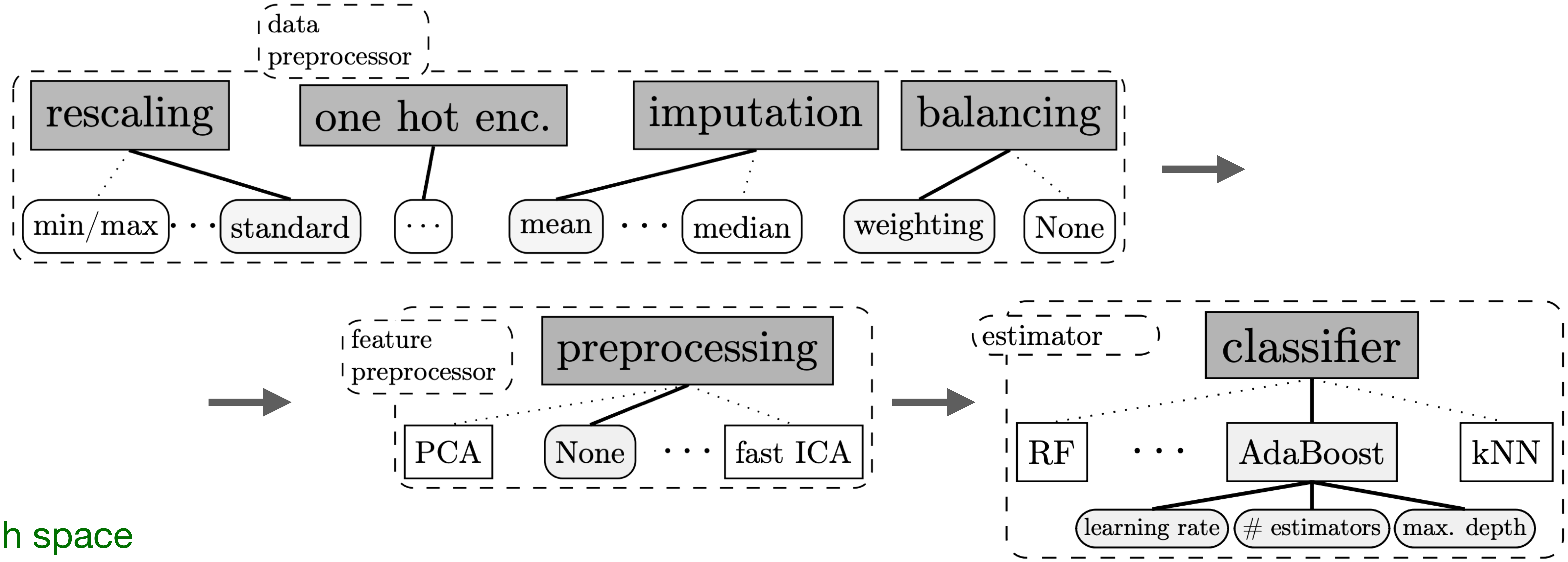
Architecture search space



Parameterized architectures

autosklearn *Feurer et al. 2015*
autoWEKA *Thornton et al. 2013*
hyperopt-sklearn *Komer et al. 2014*

- Manual bias: most successful pipelines have a similar structure
- Fix architecture, encode ***all*** choices as extra hyperparameters
    - *Architecture search becomes hyperparameter optimization*

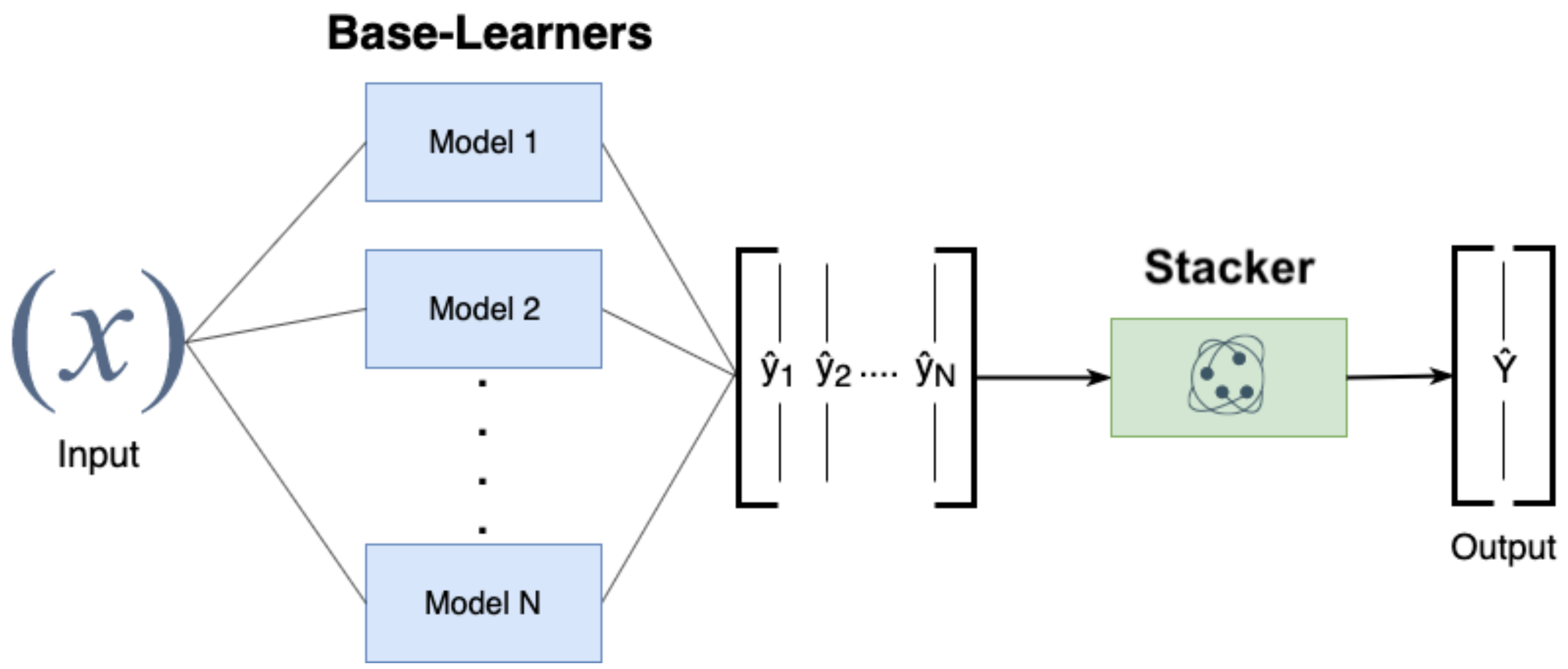


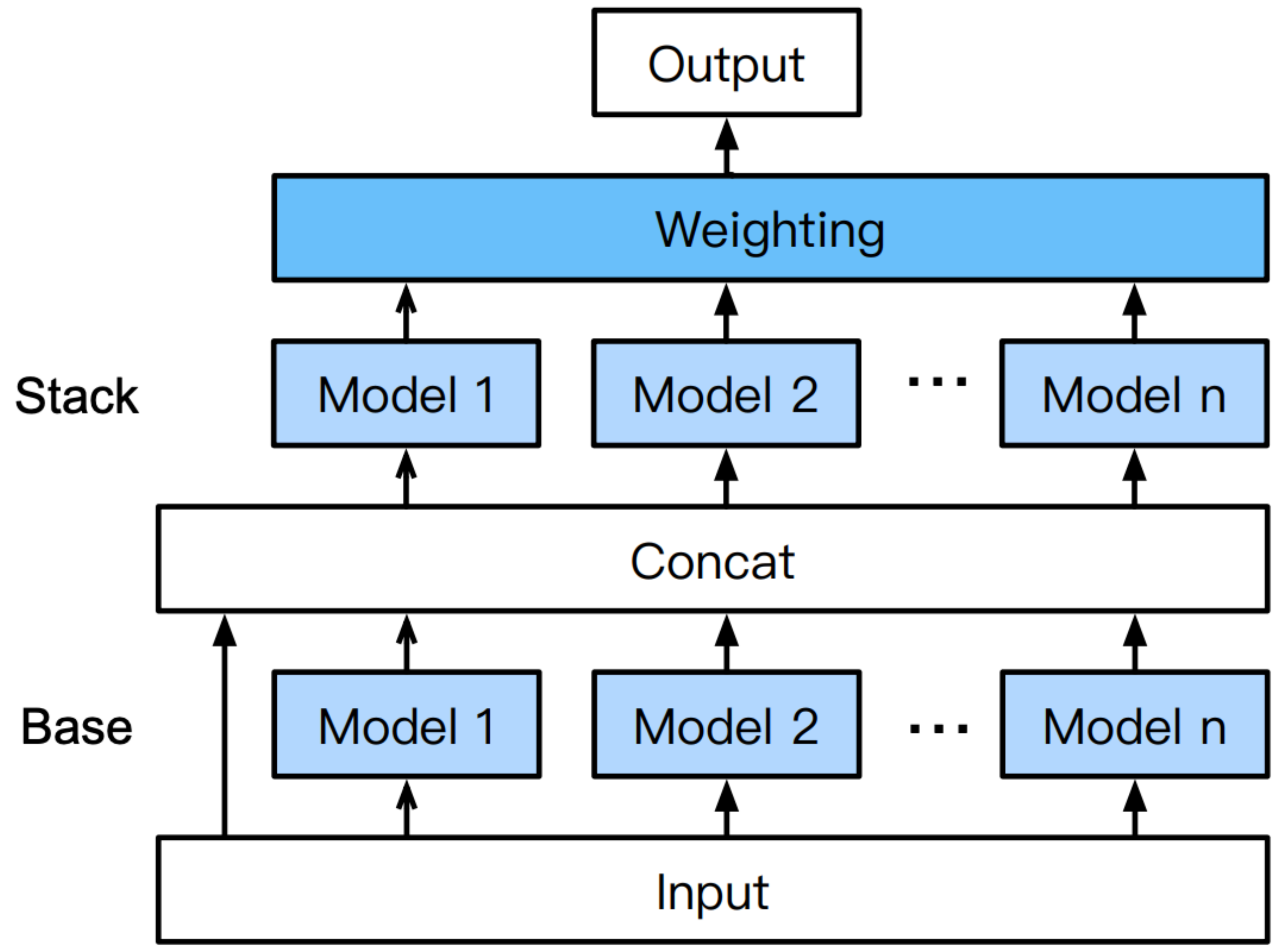
+ smaller search space
- you can't learn entirely new architectures

Ensembling

autosklearn Feurer et al. 2015
GAMA Gijsbers & Vanschoren, 2020
AutoGluon-Tabular, Erikson et al. 2020
H2O AutoML, LeDell et al.

- Build ensembles of multiple pipelines to avoid overfitting
  - RandomForests (Auto-sklearn, GAMA,…)
  - Stacking (AutoGluon-Tabular, H2O AutoML,…)





Multi-level stacking

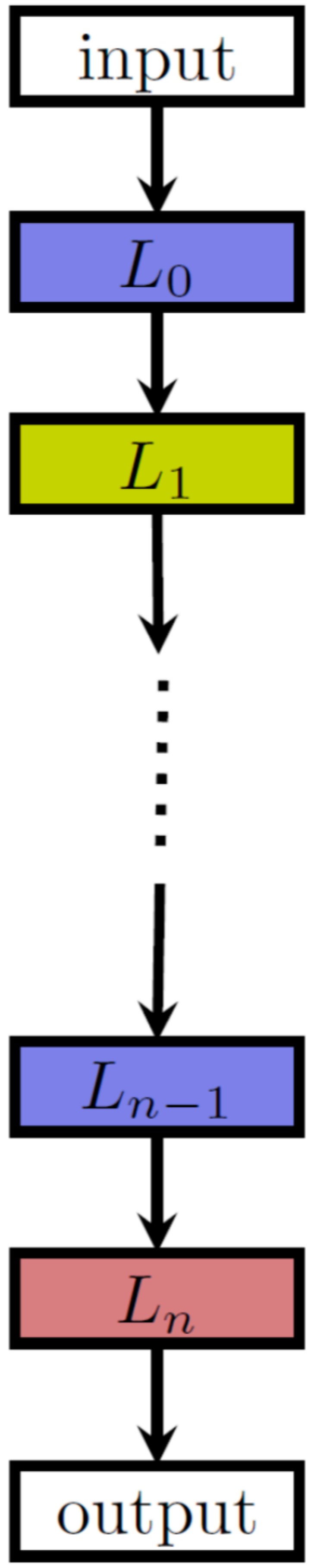
Elsken et al. 2019

Parameterized neural architectures

Parameterized Sequential

Choose:
- number of layers
- type of layers
  - dense
  - convolutional
  - max-pooling
  - …
- hyperparameters of layers

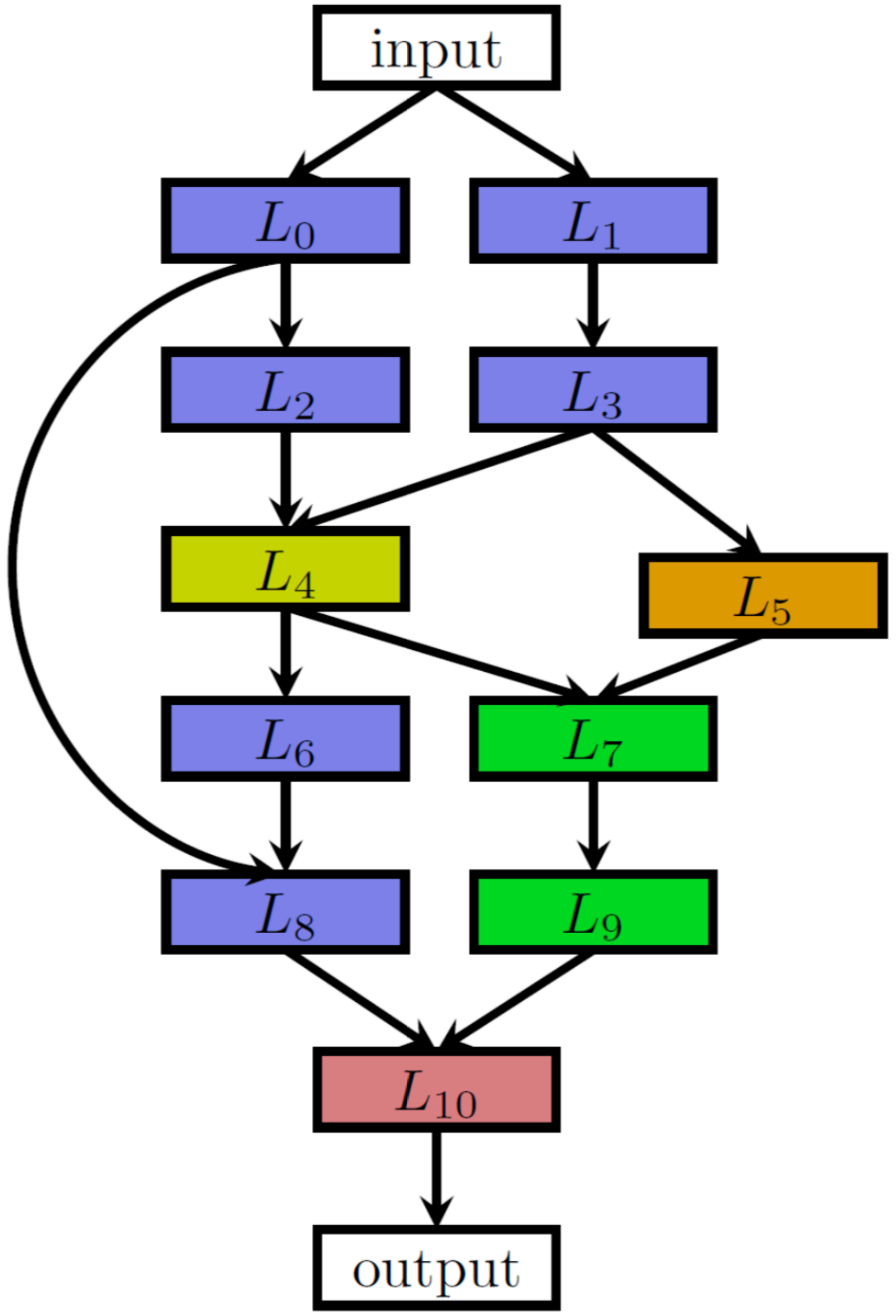
+ easier to search
- sometimes too simple



Parameterized Graph

Choose:
- branching
- joins
- skip connections
- types of layers
- hyperparameters of layers

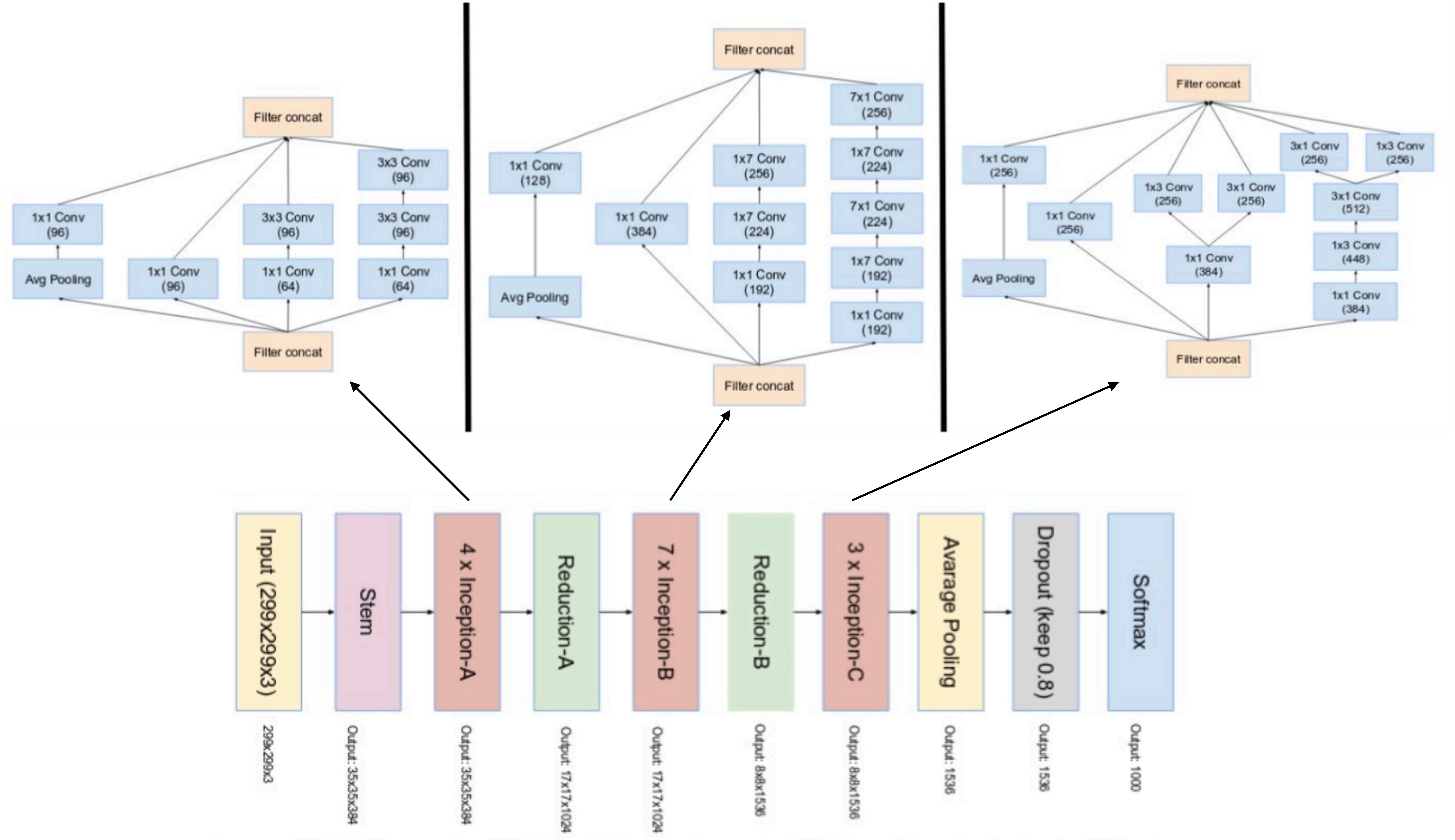
+ more flexible
- much harder to search



Cell search spaces

Manual bias: successful deep networks have repeated motifs (cells)

e.g. Inception v4:



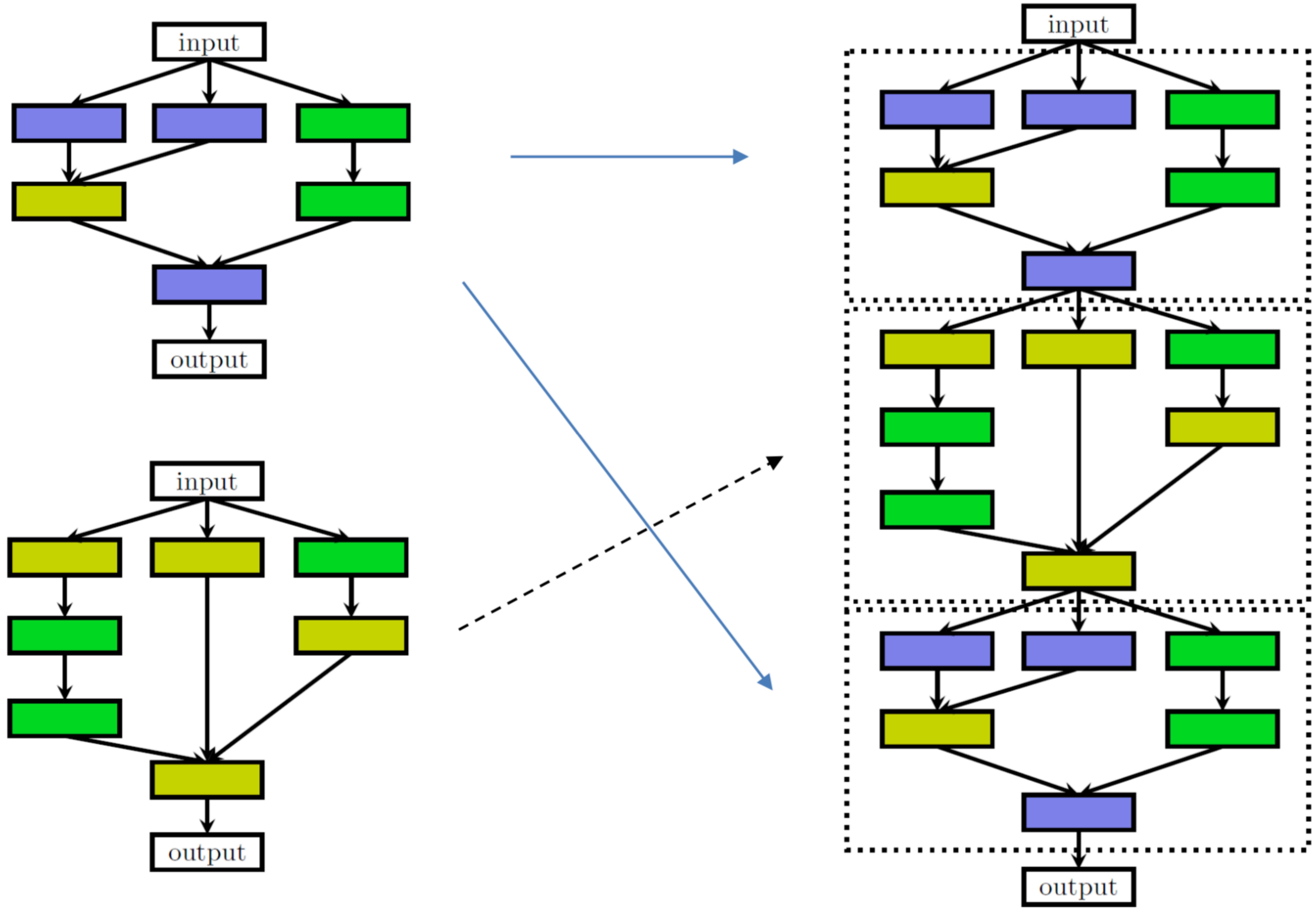
Cell search spaces

Google NASNet [Zoph et al 2018](#)

Compositionality: learn hierarchical building blocks to simplify the task

Cell search space

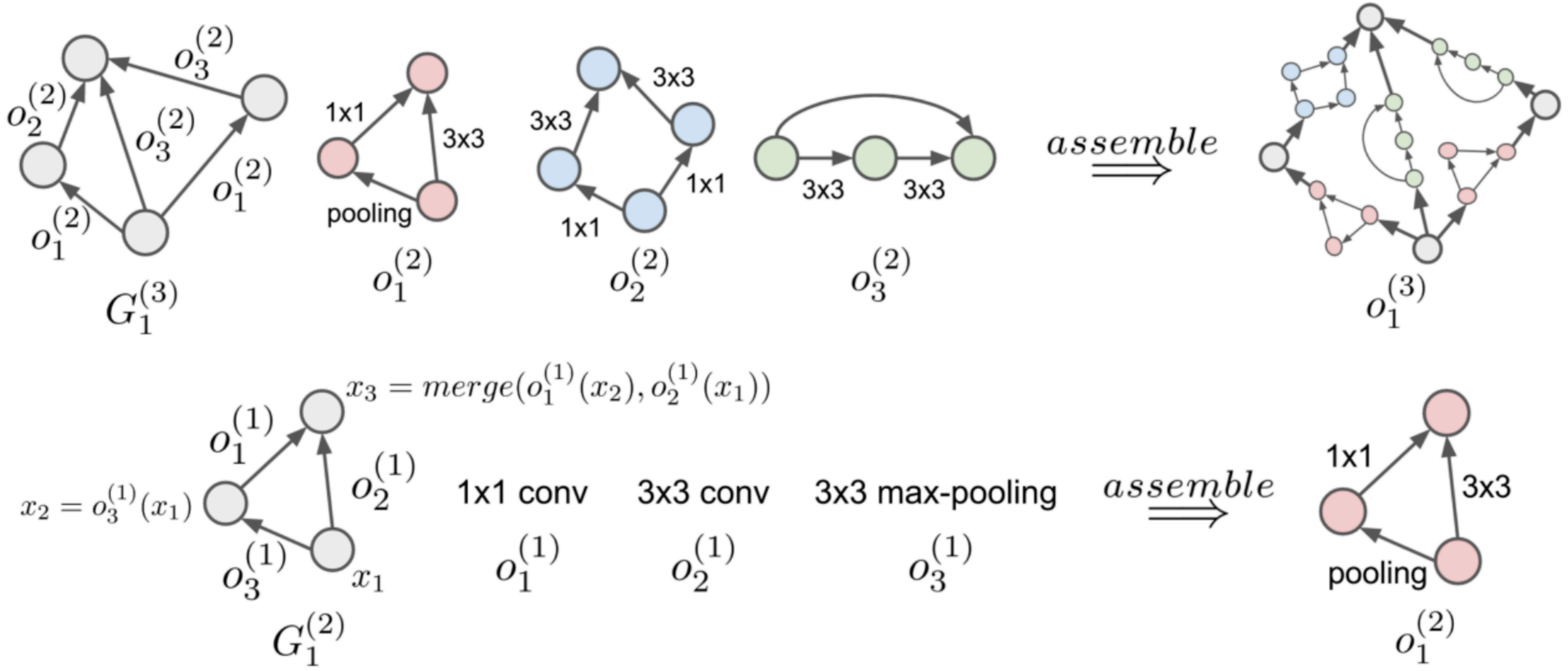
- learn parameterized building blocks *(cells)*
- stack cells together in macro-architecture



\+ smaller search space
\+ cells can be learned on a small dataset & transferred
\- strong domain priors, doesn't generalize well

Hierarchical Search Spaces

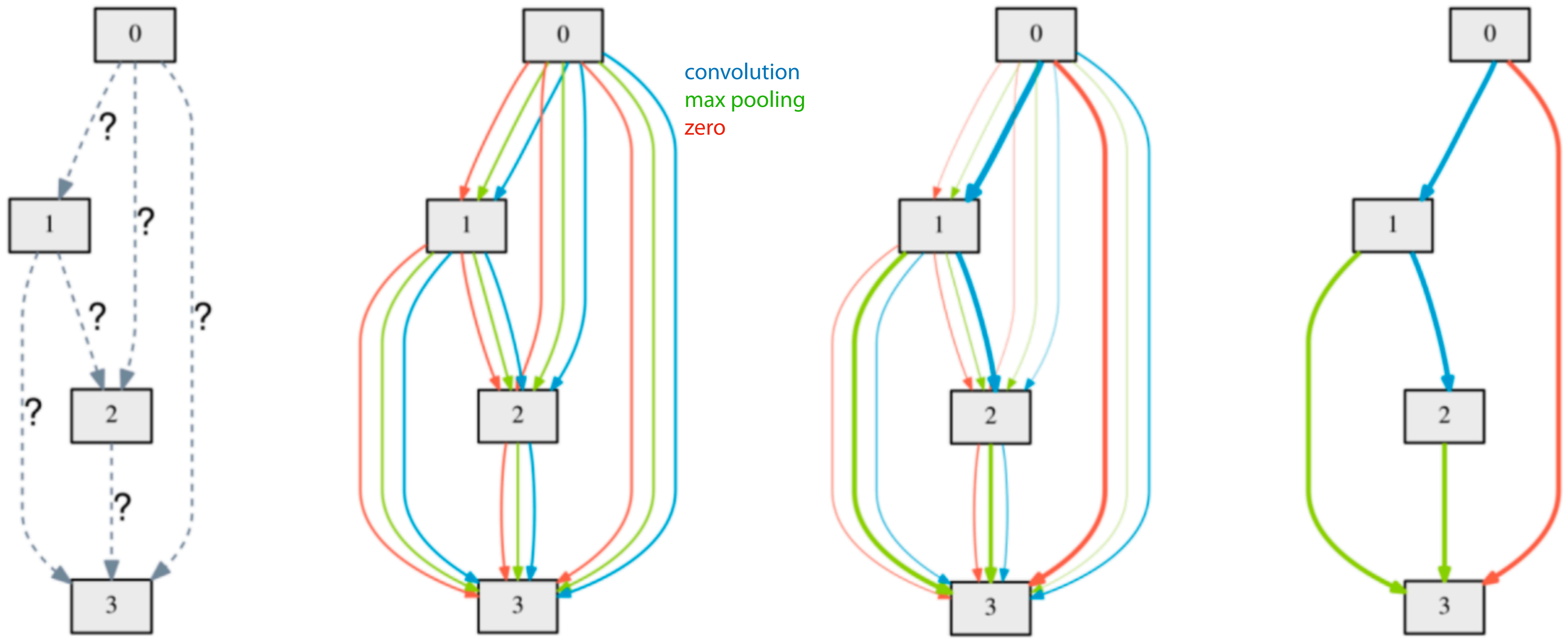
- Define a number of primitive operations (e.g. convolution, max-pooling,…)
- Build small motifs of primitives (o_1, o_2, o_3,…)
- Choose a graph structure G_i, replace edges with motifs, repeat



Differentiable Search Spaces (DARTS)

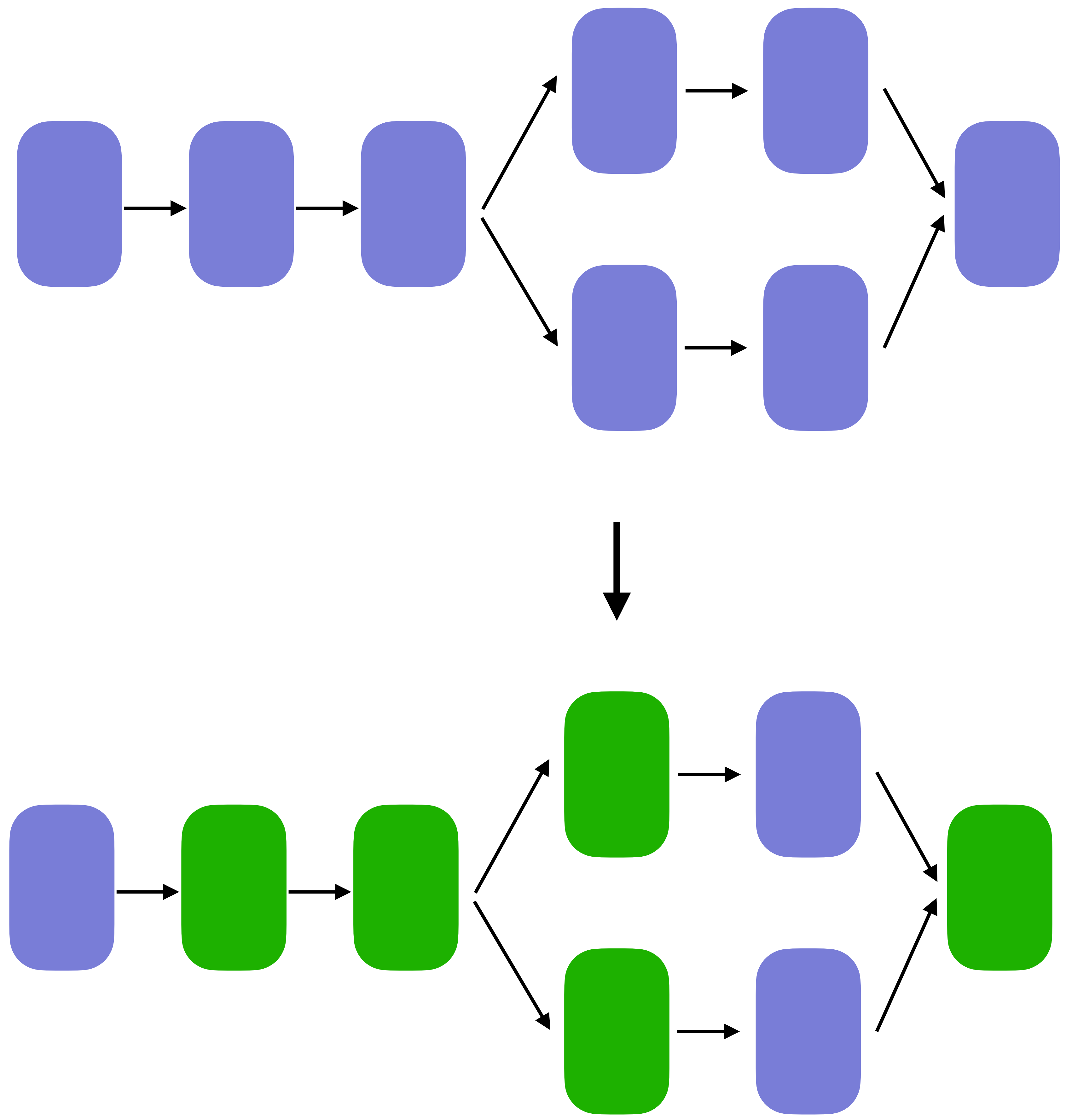
Liu et al. 2018

- Fixed (one-shot) structure, each edge can be any primitive operation
- Give all operators a weight α_i ,
- Optimize α_i and model weights ω_j using bilevel programming



One-shot model **operator weights α_i** **interleaved optimization of α_i and ω_j with SGD** **argmax α_i**

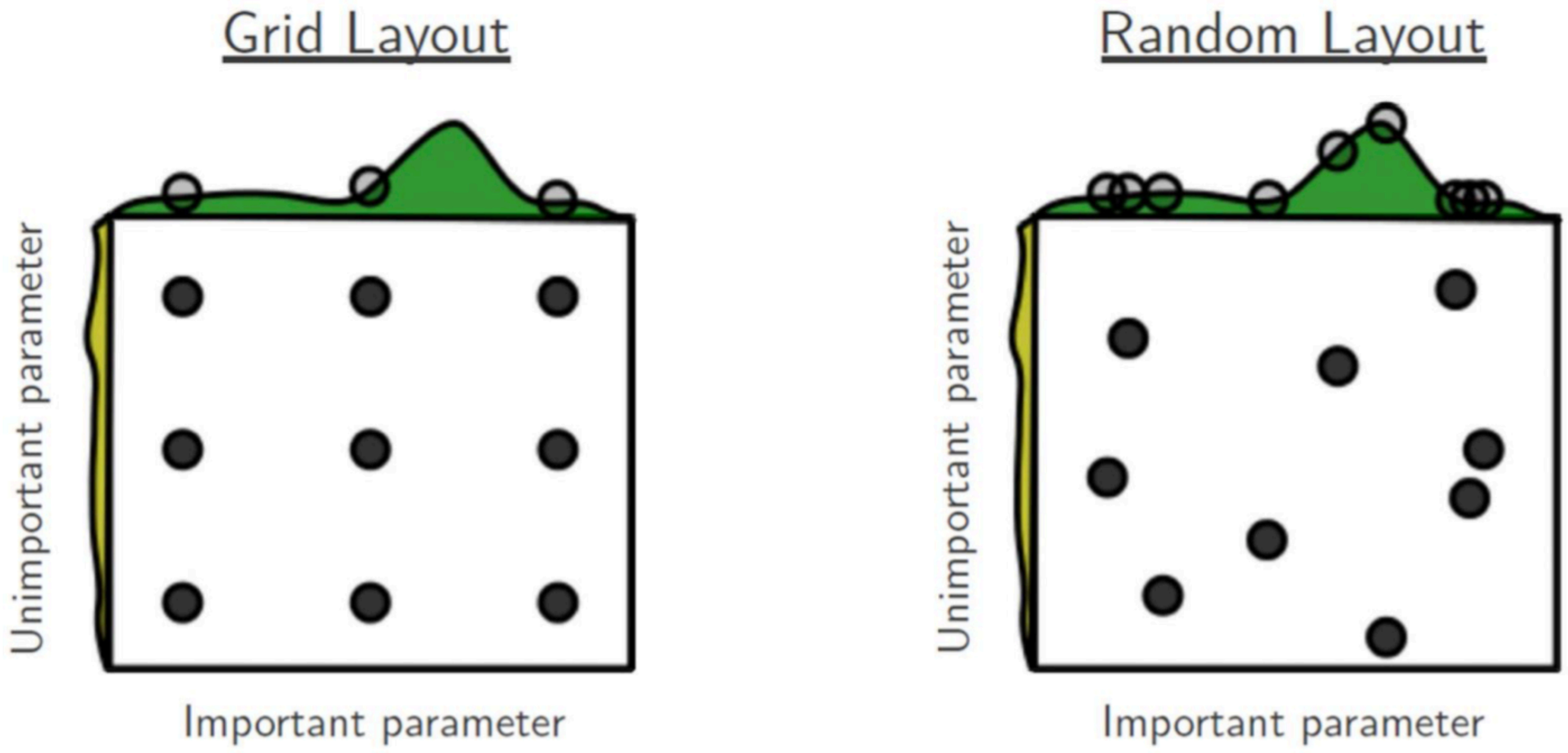
Optimization



Bergstra & Bengio, JMLR 2012

Random search

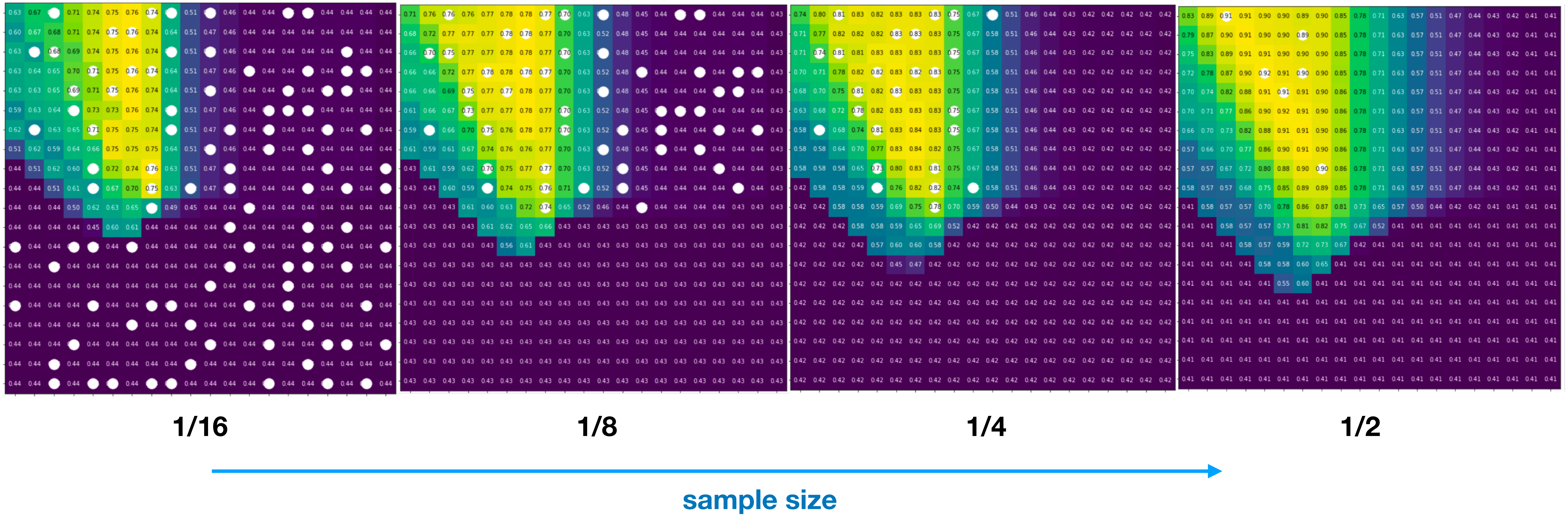
- Handles unimportant dimensions better than grid search
- Easily parallelizable, but uninformed (no learning)



Jamieson & Talwalkar 2016

Successive Halving

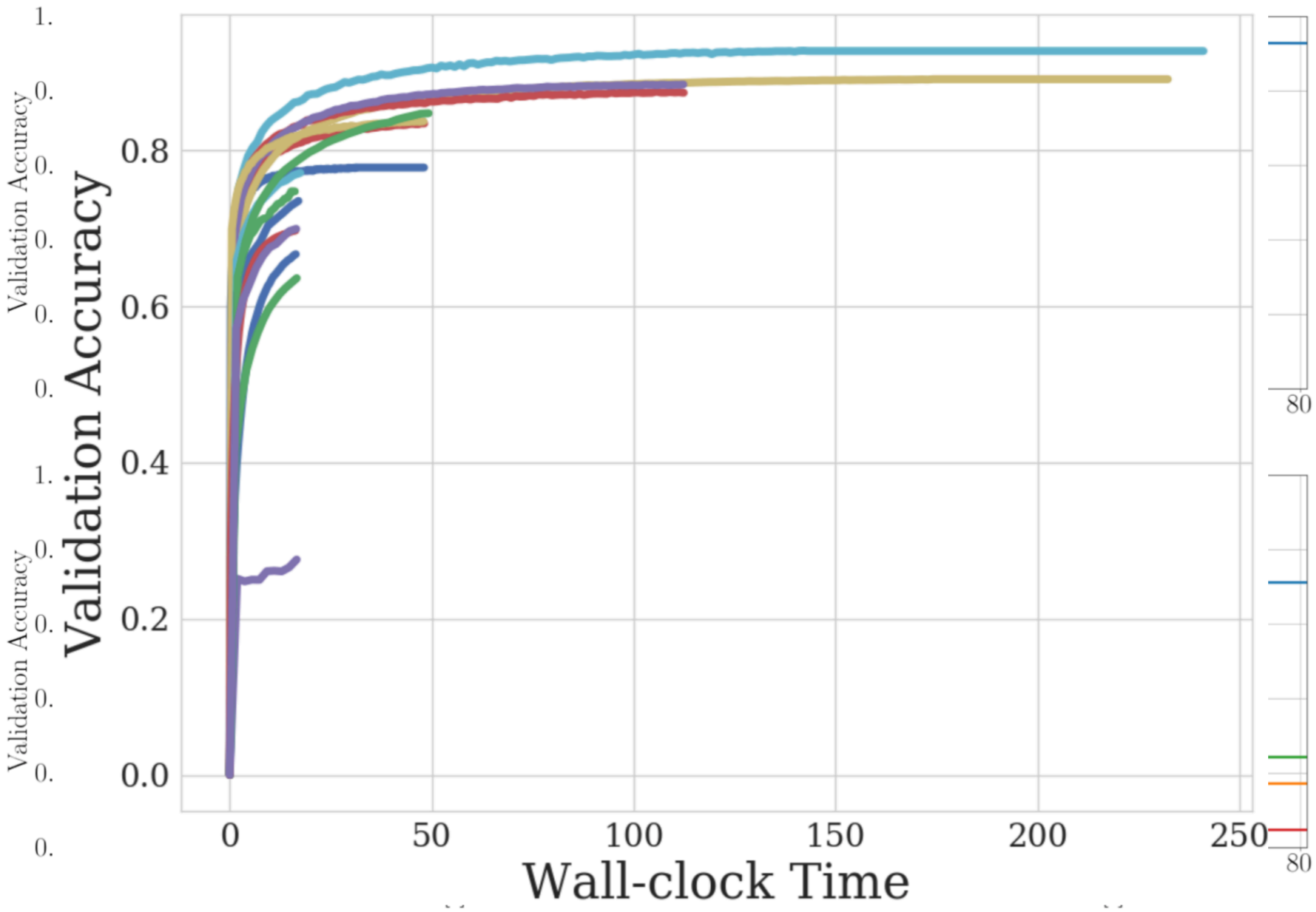
- Train on small data subsets, infer which regions may be interesting to evaluate in more depth
  - Randomly sample candidates and evaluate on a small data sample
  - Retrain the 50% best candidates on twice the data, repeat



Hyperband

Successive halving risks killing good models too early

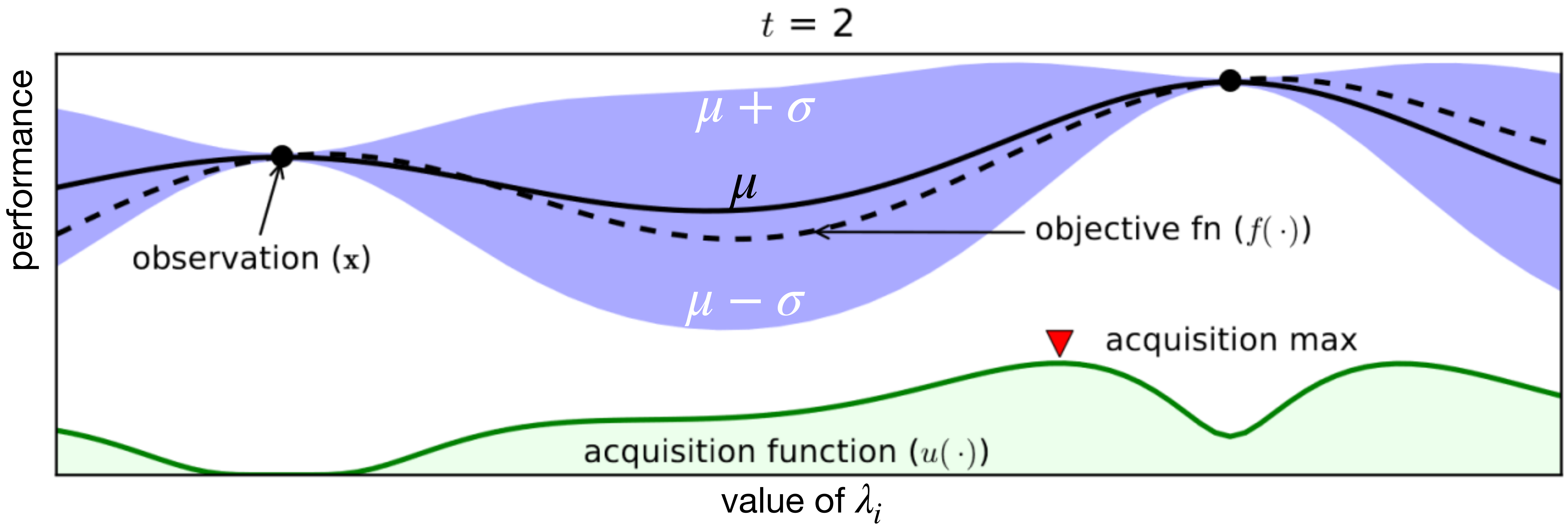
- Repeat in multiple, decreasingly aggressive iterations (brackets)
- Strong anytime performance, easy to implement, scalable, parallelizable



Bayesian Optimization

Mockus [1974]

- Start with a few (random) hyperparameter configurations
- Fit a ***surrogate model*** to predict other configurations
- Probabilistic regression (e.g. Gaussian Processes): mean μ and standard deviation σ (blue band)
- Use an ***acquisition function*** to trade off exploration and exploitation, e.g. Expected Improvement (EI)
- Sample for the best configuration under that function



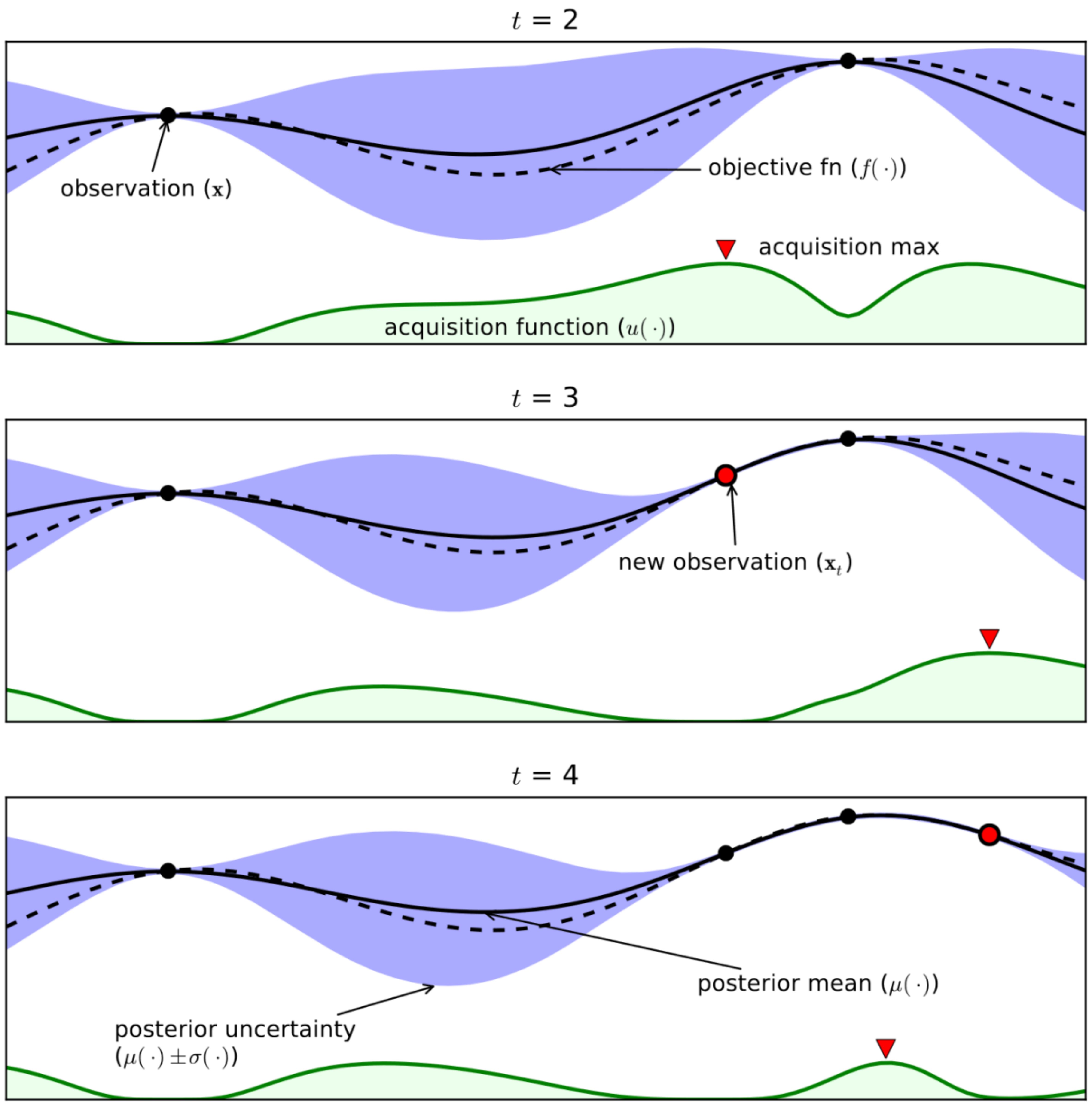
Bayesian Optimization

- Repeat until some stopping criterion:
  - Fixed budget
  - Convergence
  - EI threshold

- Theoretical guarantees

  [Srinivas et al. 2010](), [Freitas et al. 2012](), [Kawaguchi et al. 2016]()

- Also works for non-convex, noisy data
- Used in AlphaGo

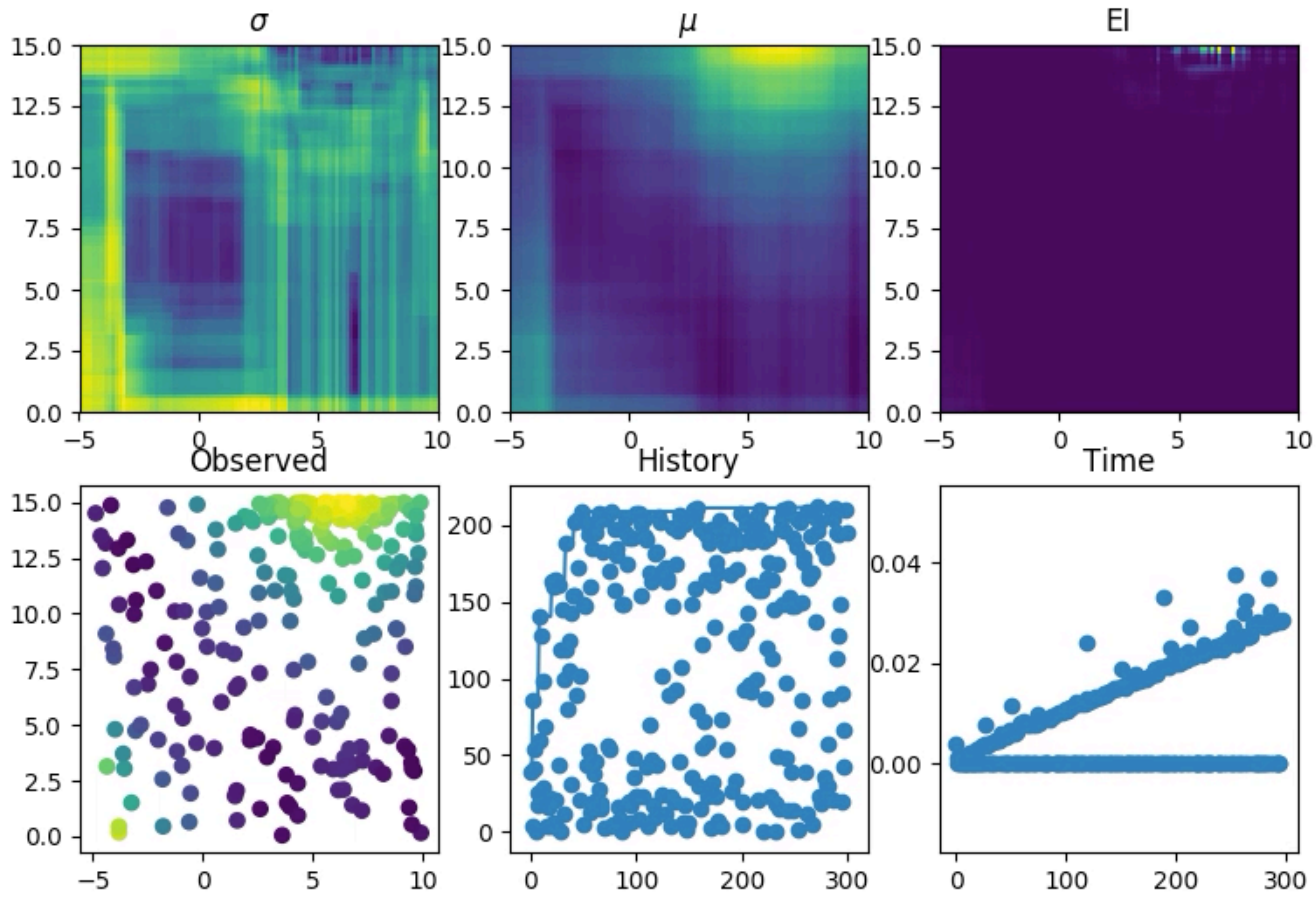


Bayesian Optimization (surrogate: random forests)

Hutter et al. 2011

Feurer et al. 2015

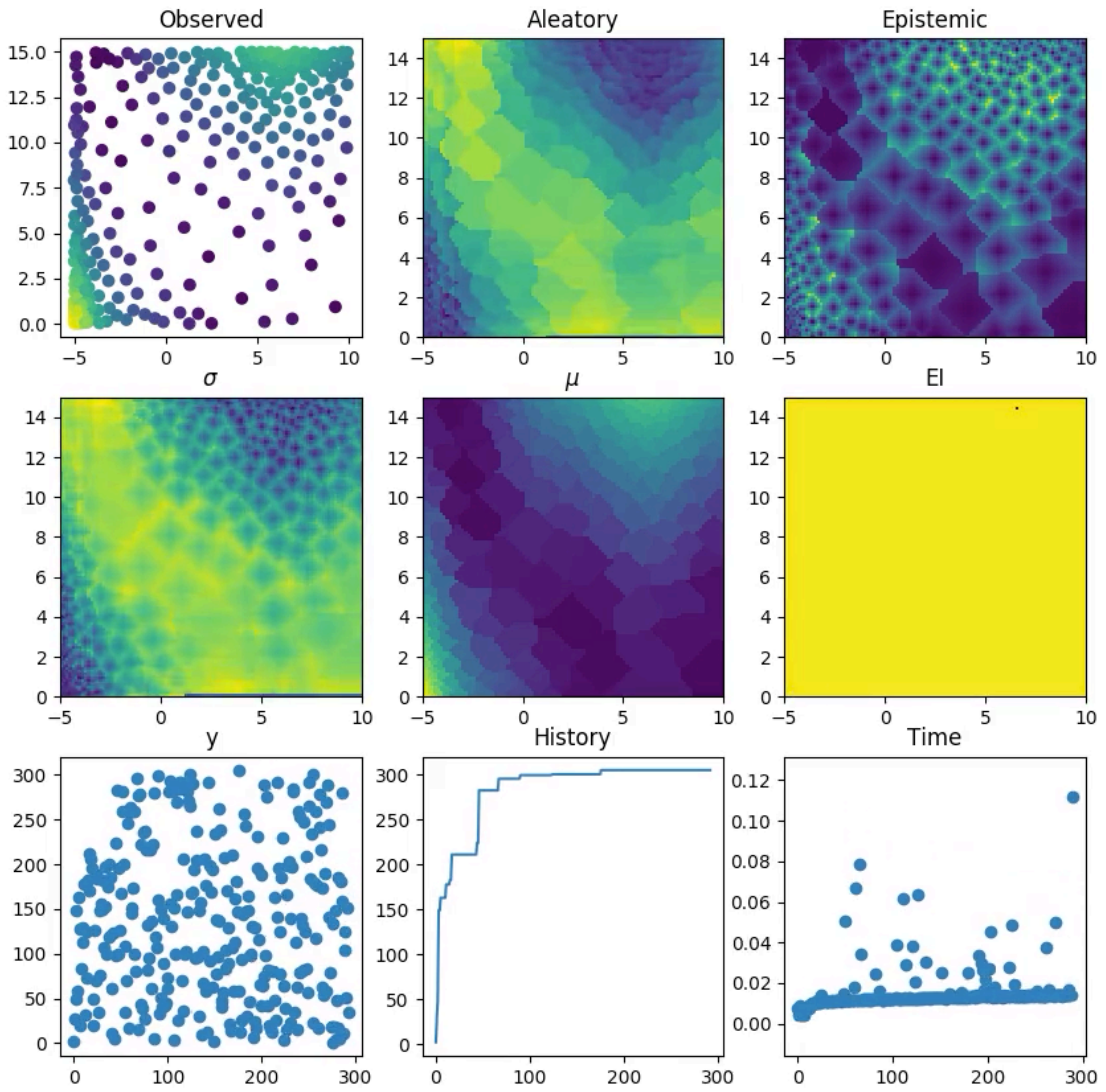
- Use random forest variance
- Scales well to many hyperparameters
- Used in Auto-sklearn

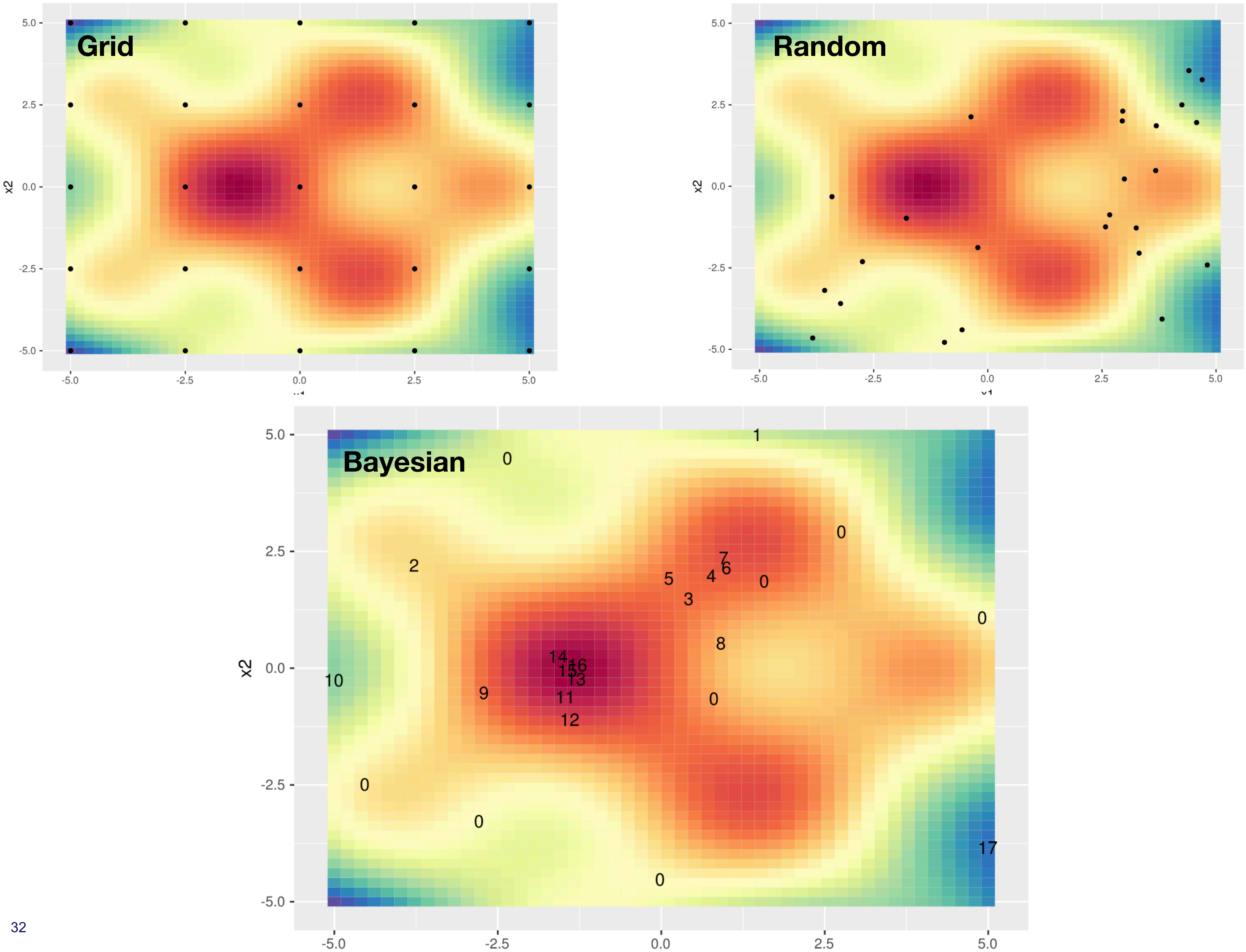


animation by Jeroen van Hoof

Bayesian Optimization (surrogate: gradient boosting)

- Let gradient boosting predict the mean + upper and lower quantile
  - Faster
  - More robust to concept drift

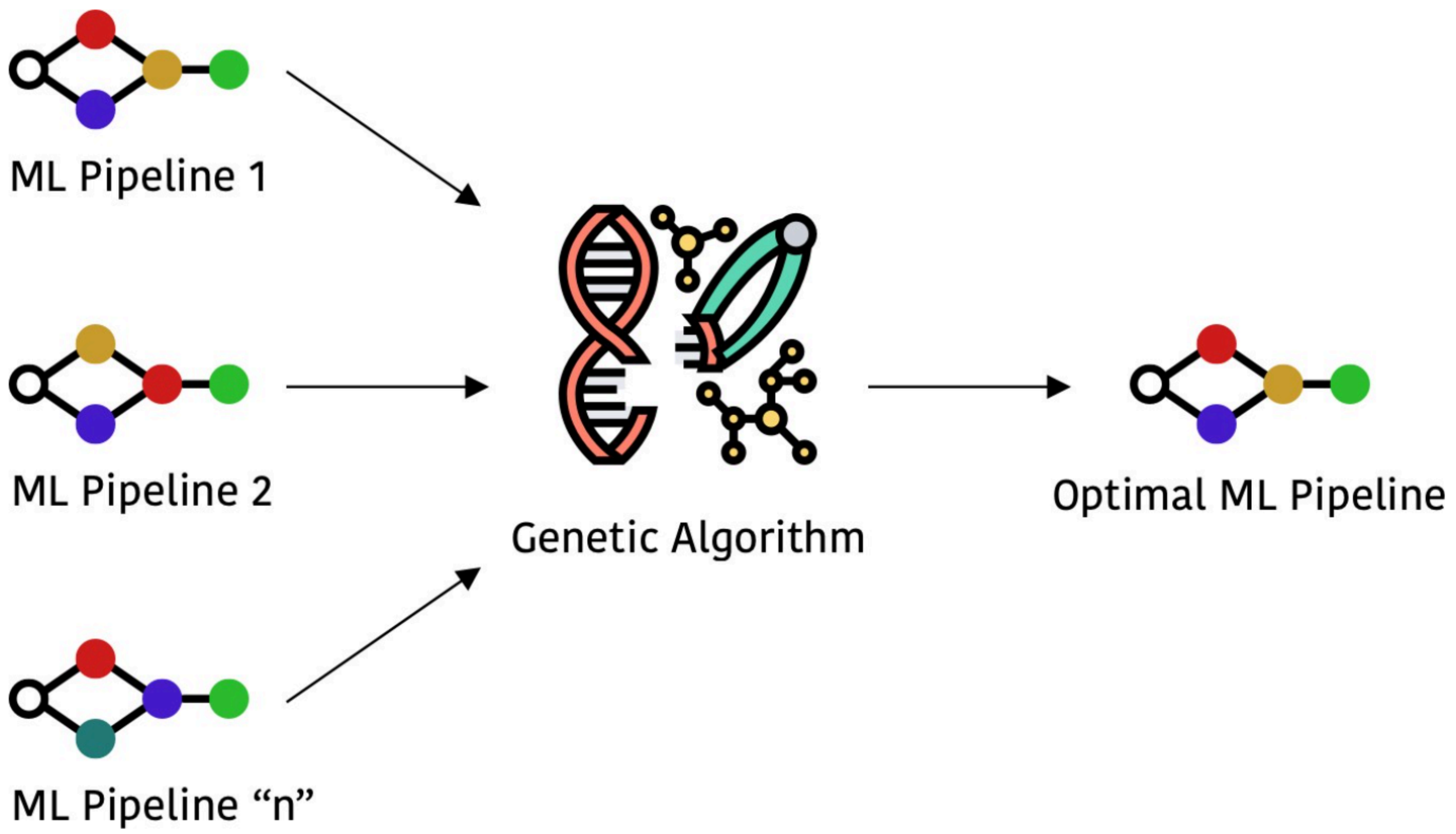



Grid
Random
Bayesian
x2
5.0
2.5
0.0
-2.5
-5.0

Evolution

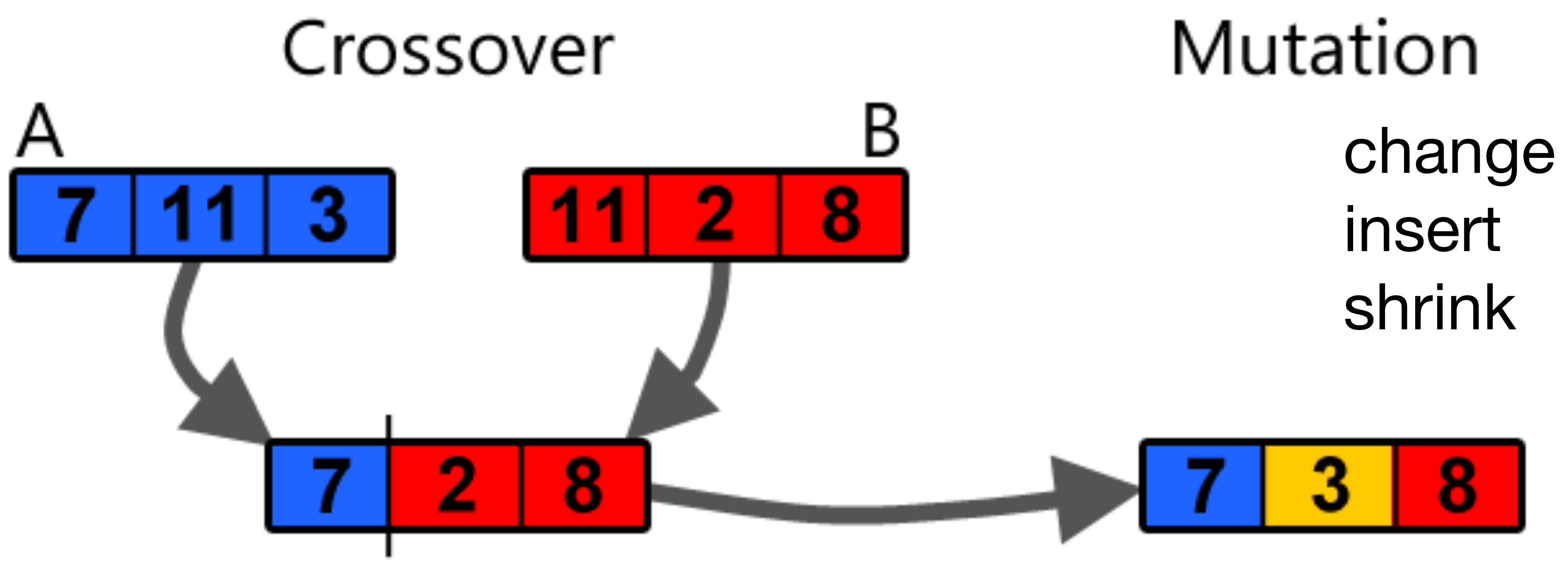
TPOT - Olson & Moore 2016
GAMA - Gijsbers & Vanschoren 2018

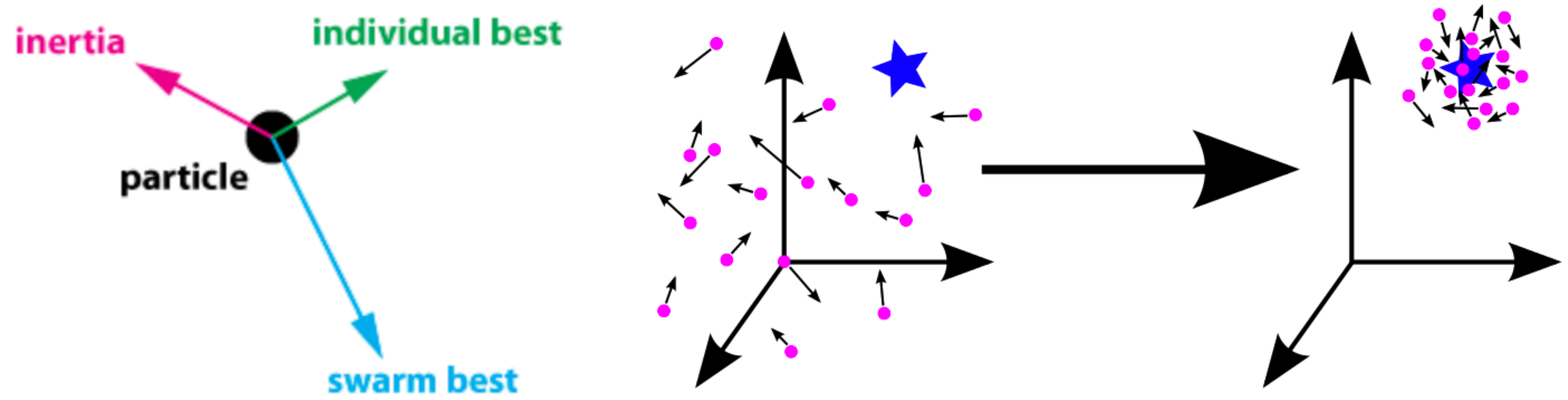
- Start with initial pipeline
- Best pipelines *evolve*: cross-over or mutation
- No fixed pipeline length: adapts to complexity of the problem
- Used in GAMA, TPOT,…



Evolution

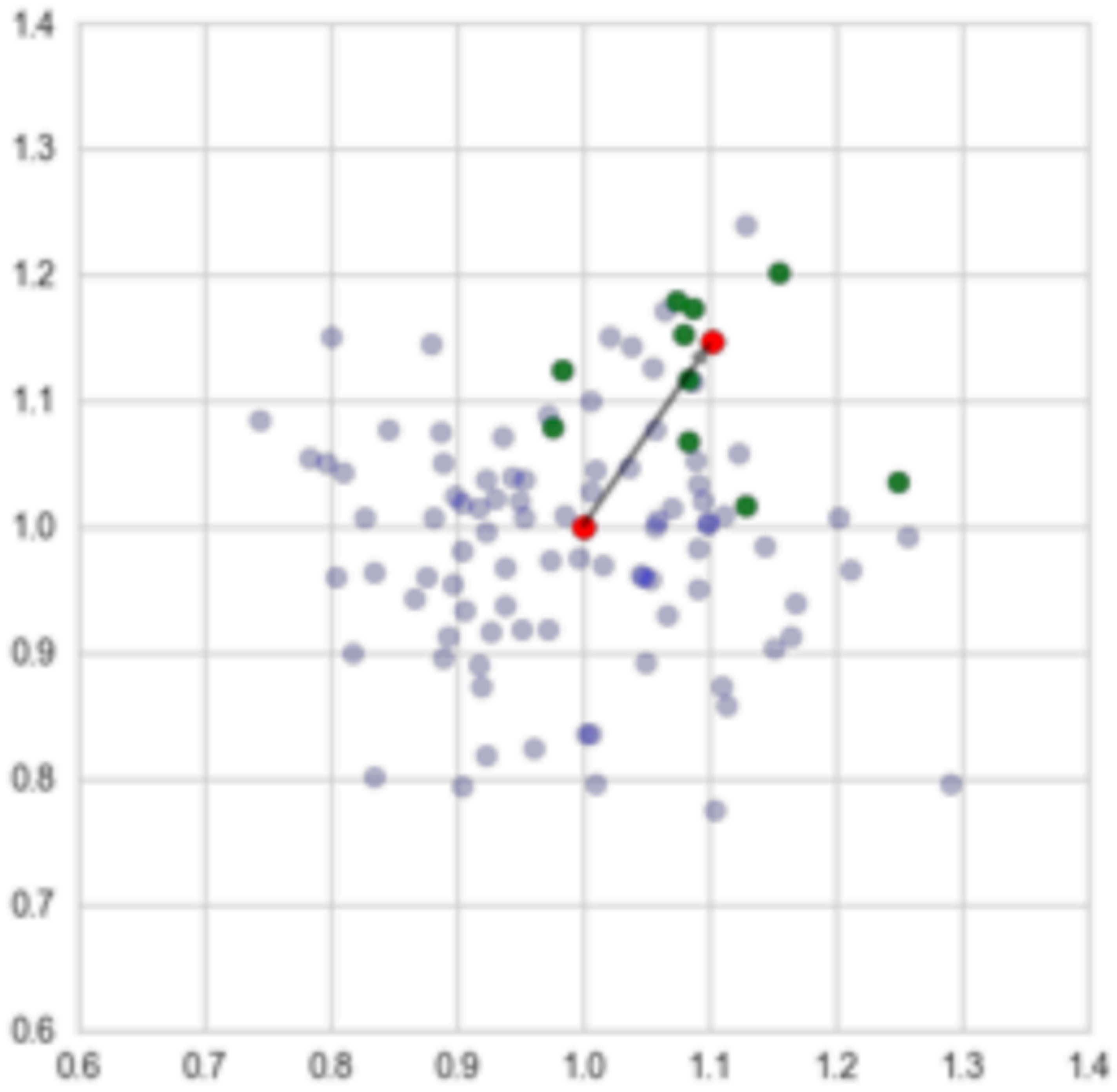
- Genetic programming [Olson, Moore 2016, 2019]
  - Mutations: add, mutate/tune, remove HP
- Particle swarm optimization [Mantovani et al 2015]





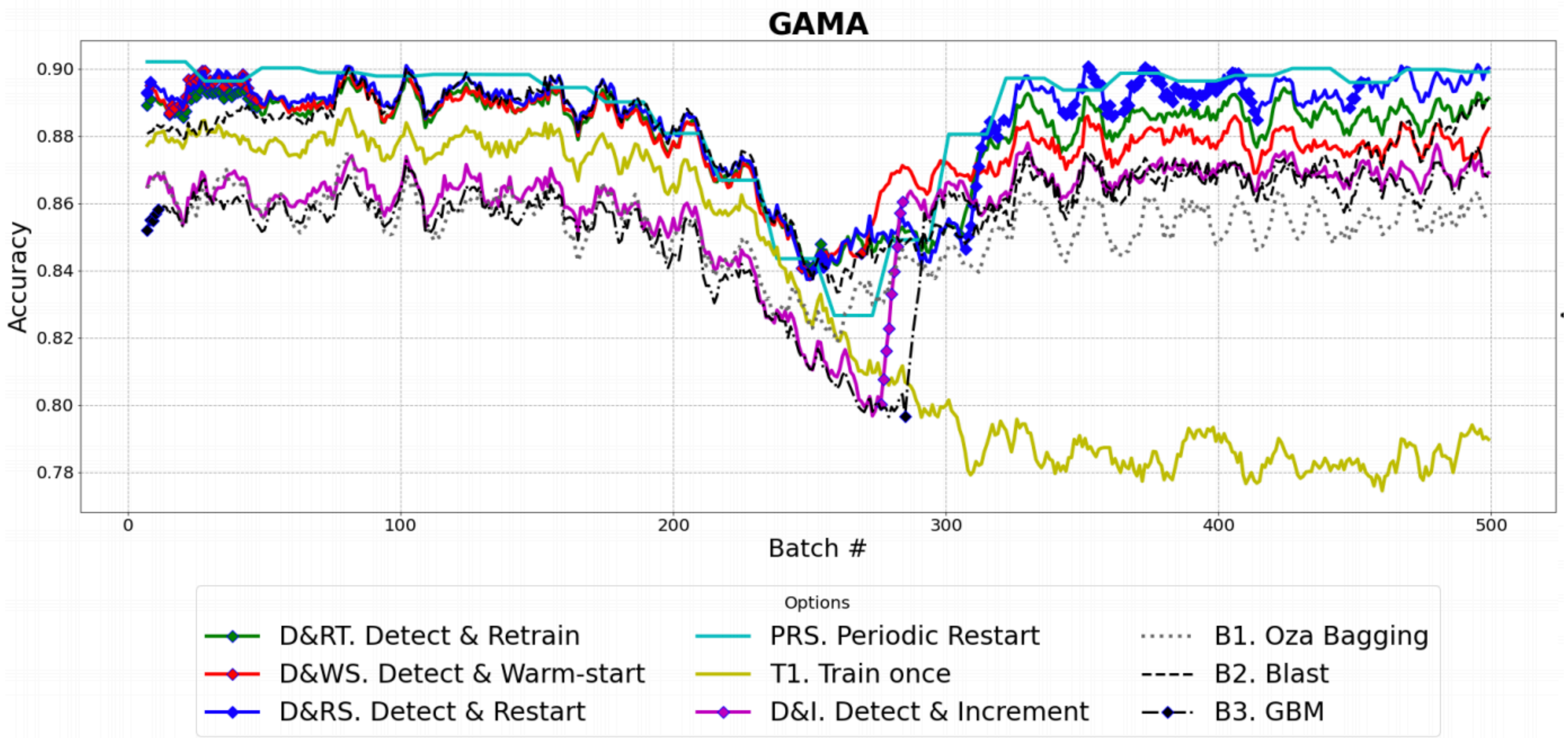
- Covariance matrix adaptation evolution (CMA-ES) [Hansen 2015]
  - Purely continuous, expensive
  - Competitive to optimize deep neural nets

[Loshilov, Hutter 2016]



Evolution

- Less sample efficient, but easy to parallelize, and quickly adapts to changes in the data
  - Allows warm-starting: if the data changes, re-start AutoML but start with best prior pipelines

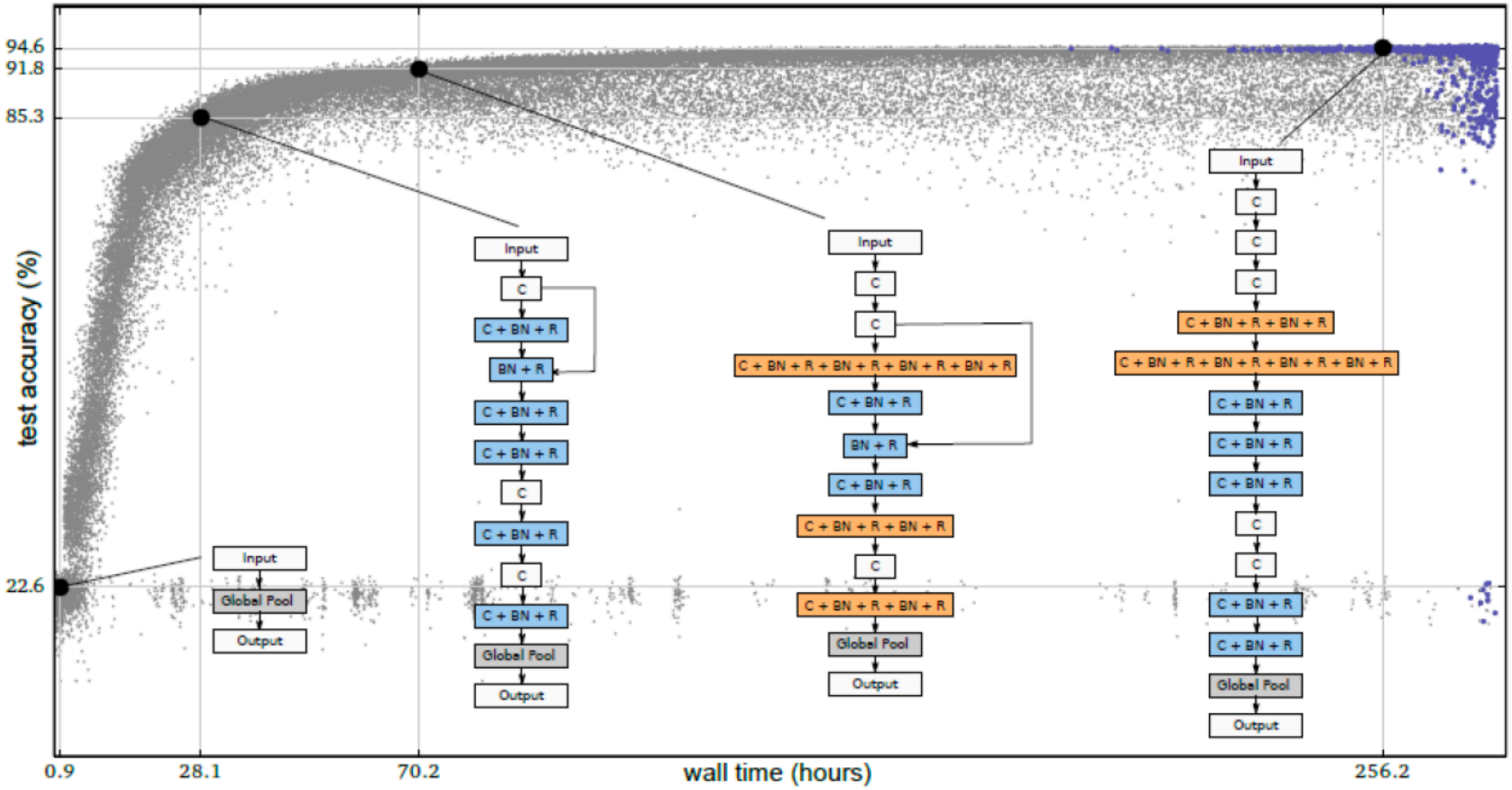


Neuro-evolution

Real et al 2017
Miikkulainen et al 2017
Wistuba et al 2018

- learn the neural architecture through evolution
- mutations: add, change, remove layer

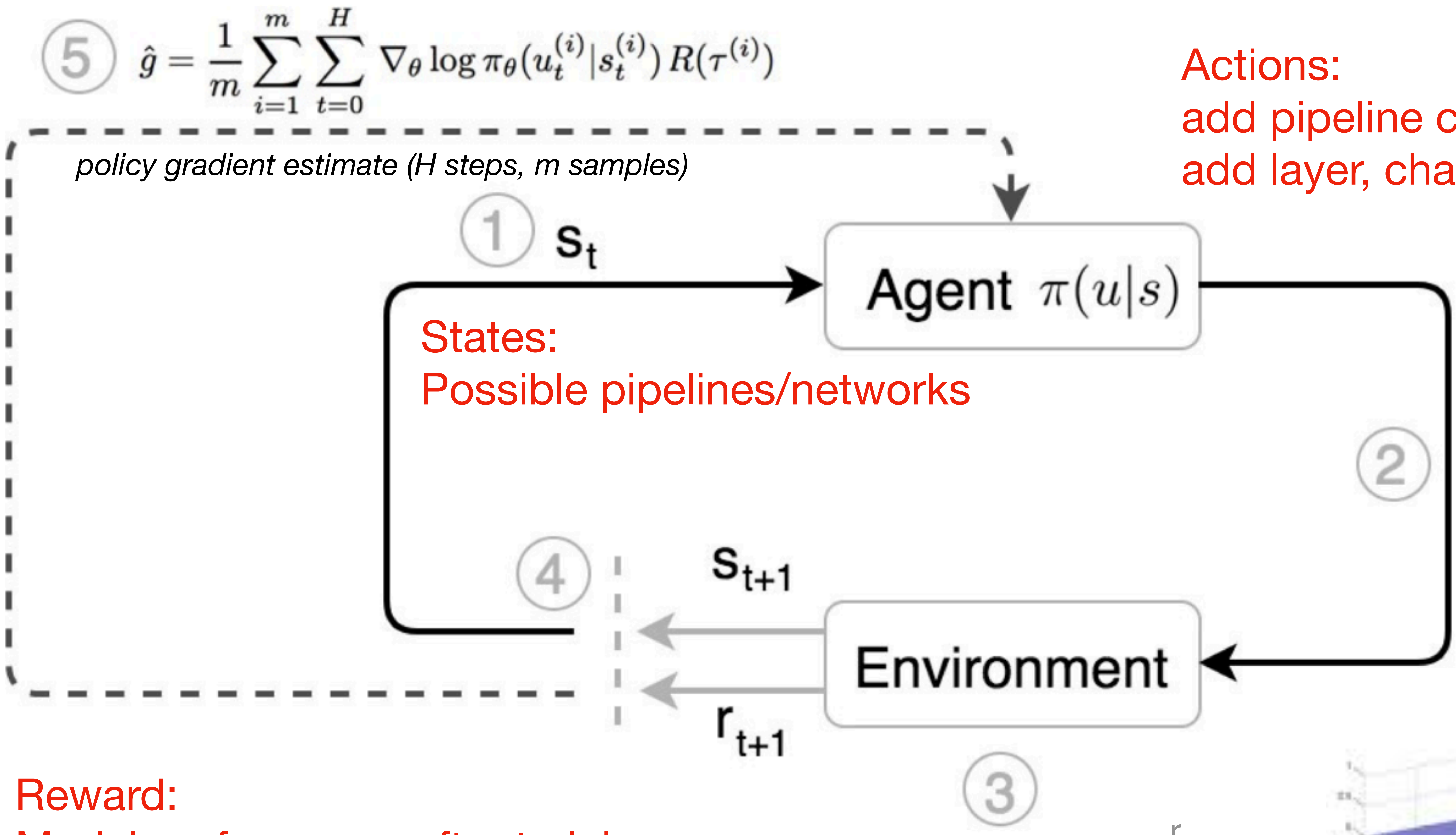
alive, killed



[Zoph & Le 2017](#)
[Levine 2018](#)

Optimization: Reinforcement learning

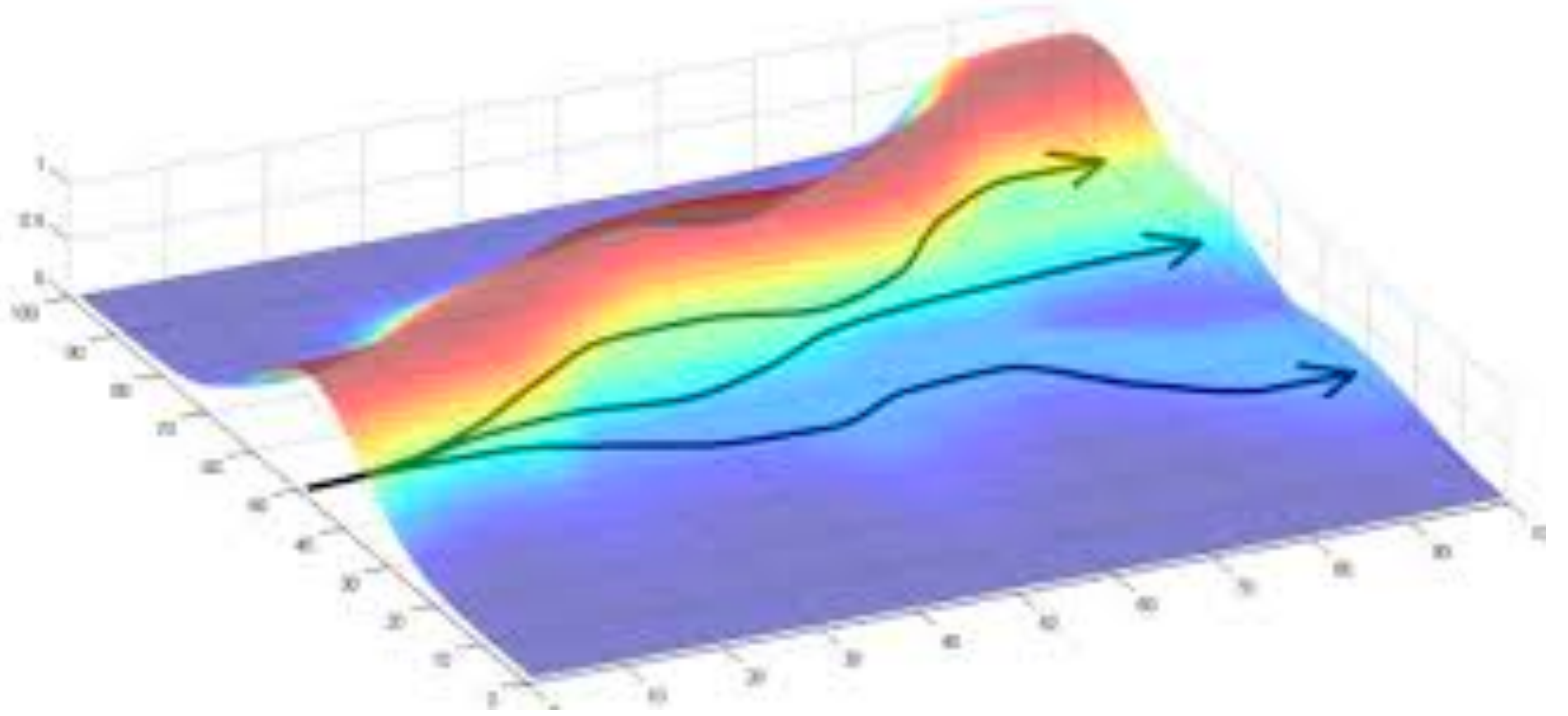
Build pipeline or network step-by-step, learn general strategy (policy)



Actions:
add pipeline component, tune,…
add layer, change filter size,…

States:
Possible pipelines/networks

Reward:
Model performance after training
After trajectory τ of actions, adjust policy based on total reward $R(\tau)$



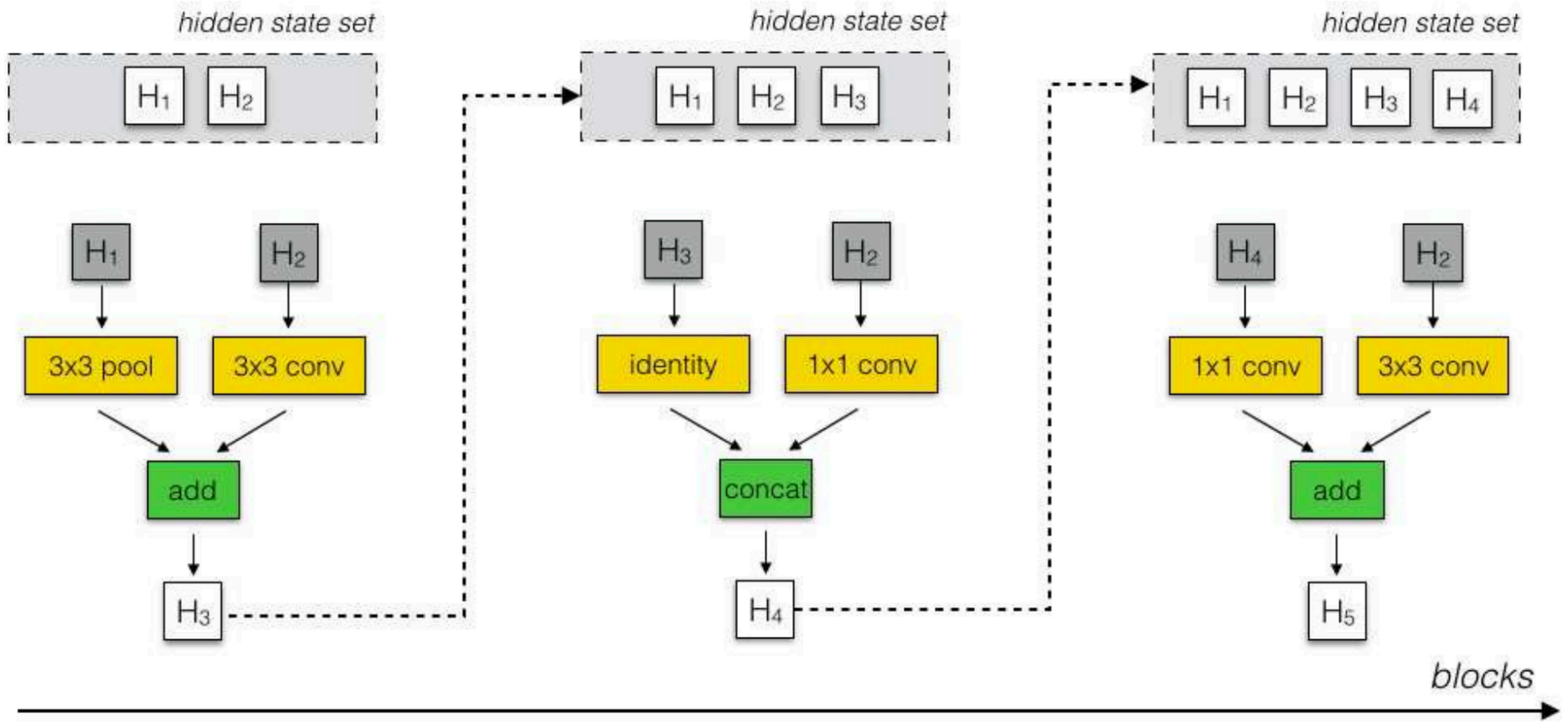
NAS with Reinforcement learning

Zoph et al 2018

1-layer LSTM (PPO), cell space search

- State of the art on ImageNet
- 450 GPUs, 3-4 days, 20000 architectures

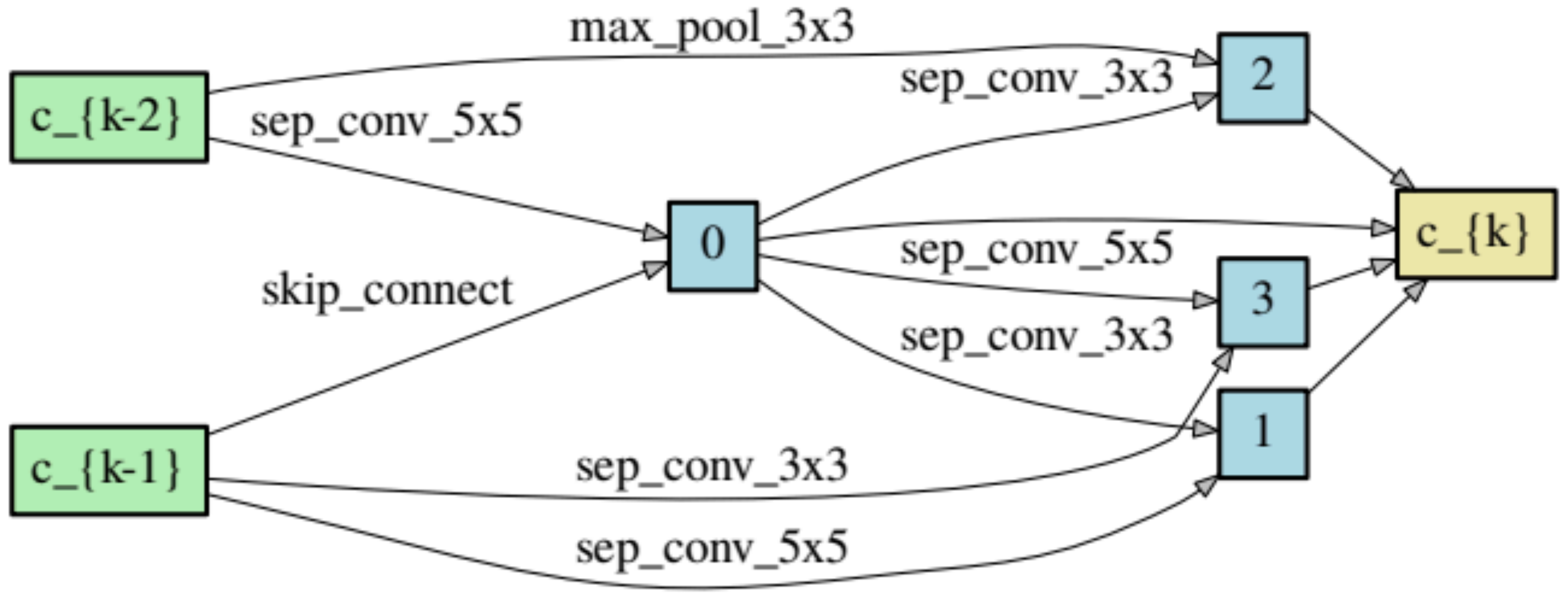
- Cell construction:
  - Select existing layers (hidden states, e.g. cell input) H_i to build on
  - Add operation (e.g. 3x3conv) on H_i
  - Combine into new hidden state (e.g. concat, add,…)
  - Iterate over *B* blocks



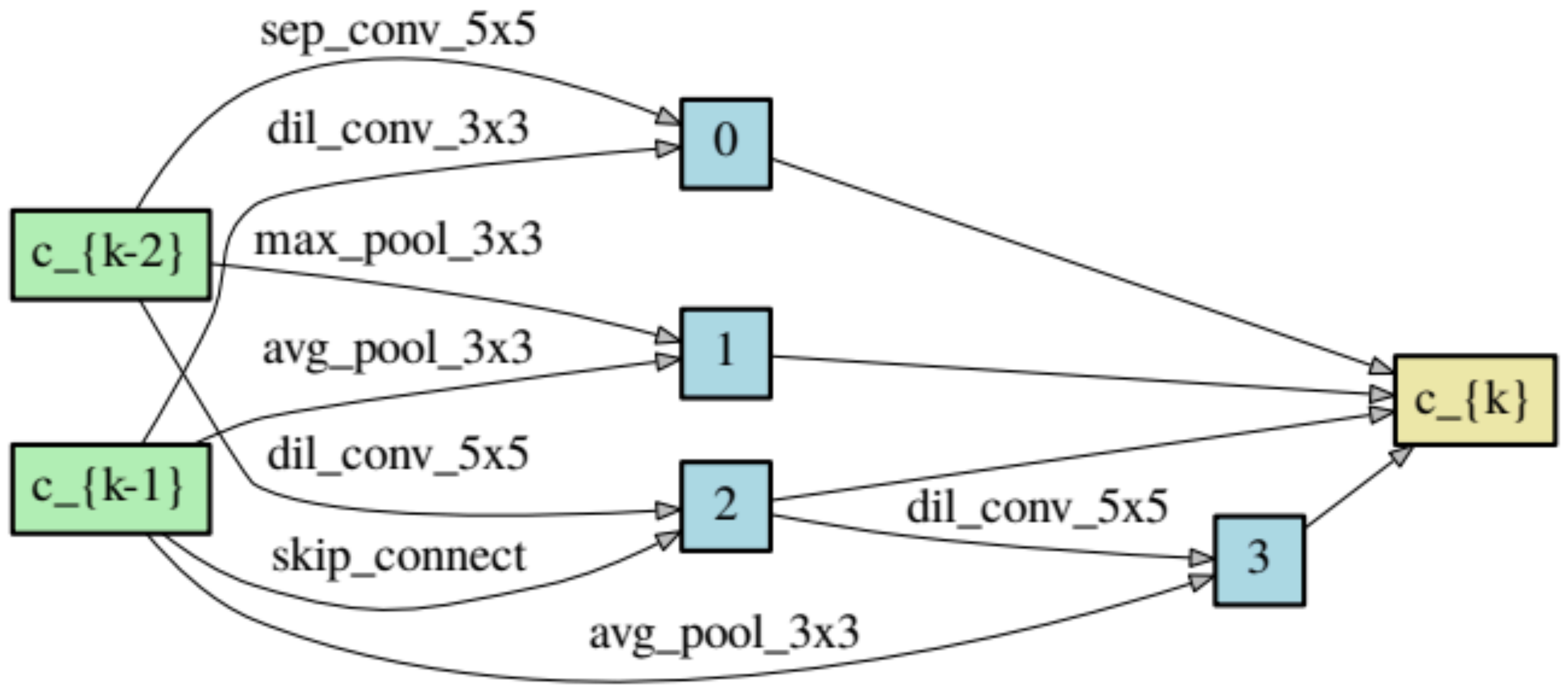
Li & Talwalkar 2019
Yu et al. 2019
Real et al. 2019

Sidenote: NAS with random search?

If you constrain the search space enough, you can get SOTA results with random search!



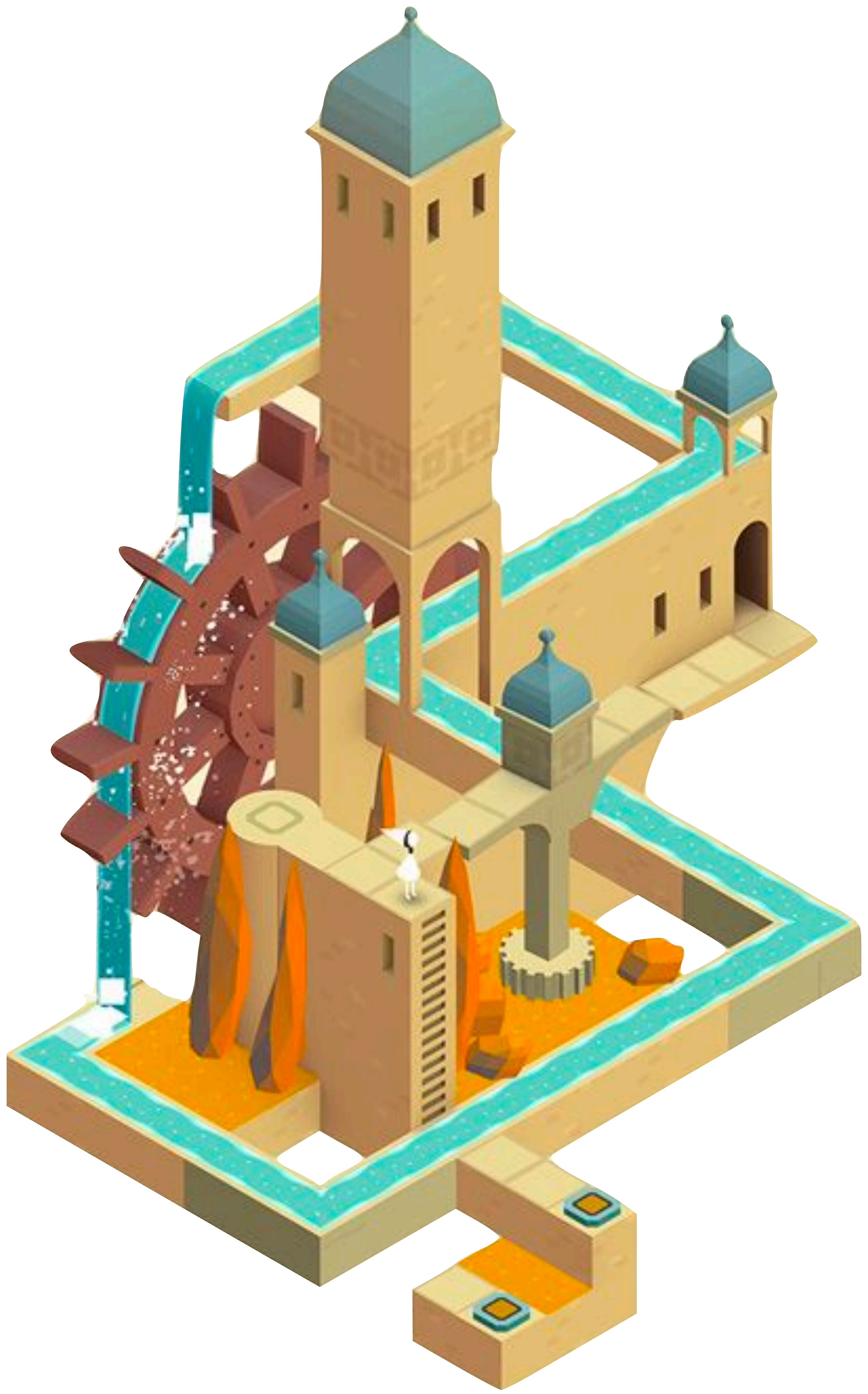
(a) Normal Cell



(b) Reduction Cell

Convolutional Cells on CIFAR-10 Benchmark: Best architecture found by random search with weight-sharing.

Overview



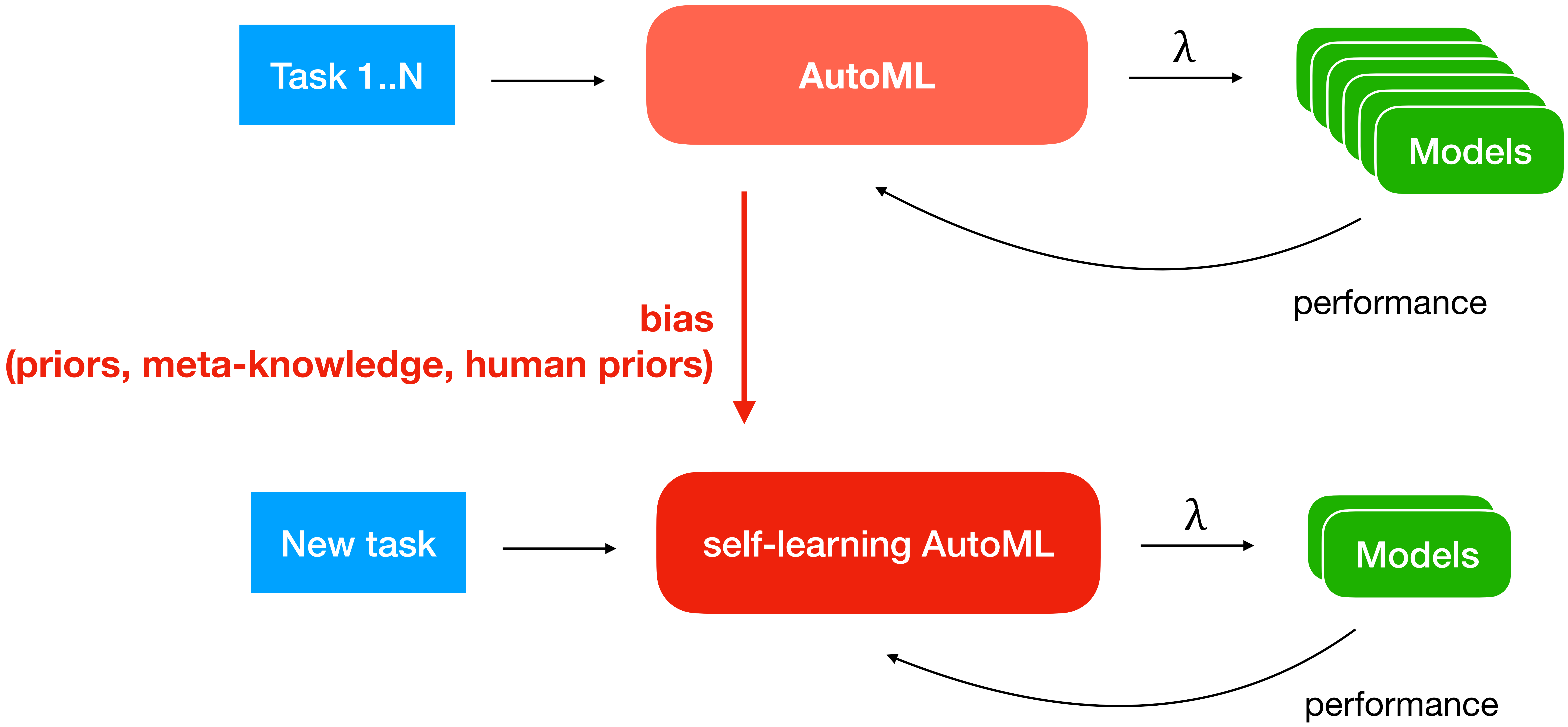
Part 3: Learning how to do AutoML

Closing the loop

AutoML + meta-learning

Meta-learn how to design architectures/pipelines and tune hyper parameters

Human data scientists also learn from experience



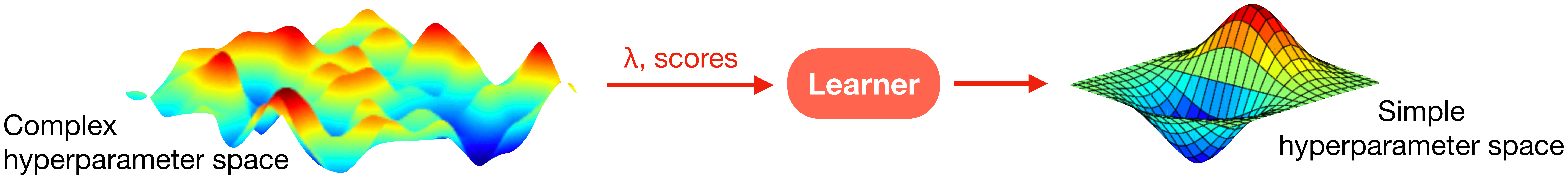
Search space can be huge!

Meta-learning for AutoML: how?

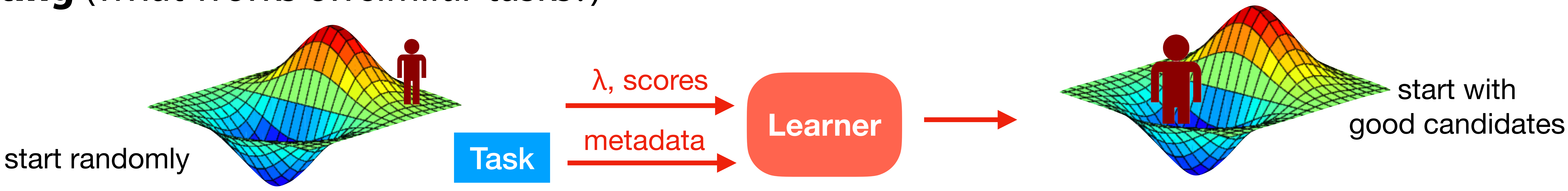
Vanschoren 2018

hyperparameters = architecture + hyperparameters

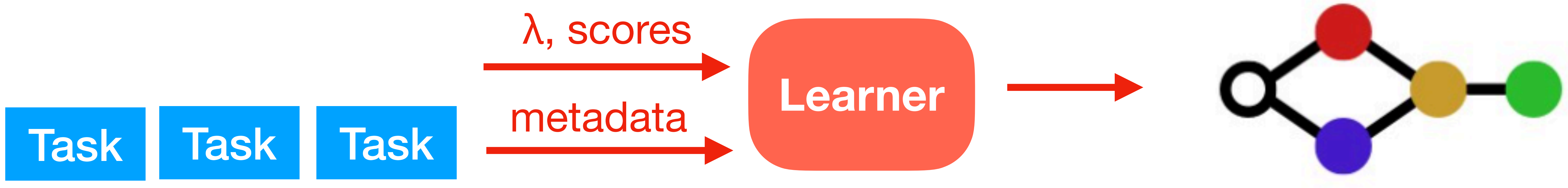
Learning hyperparameter priors



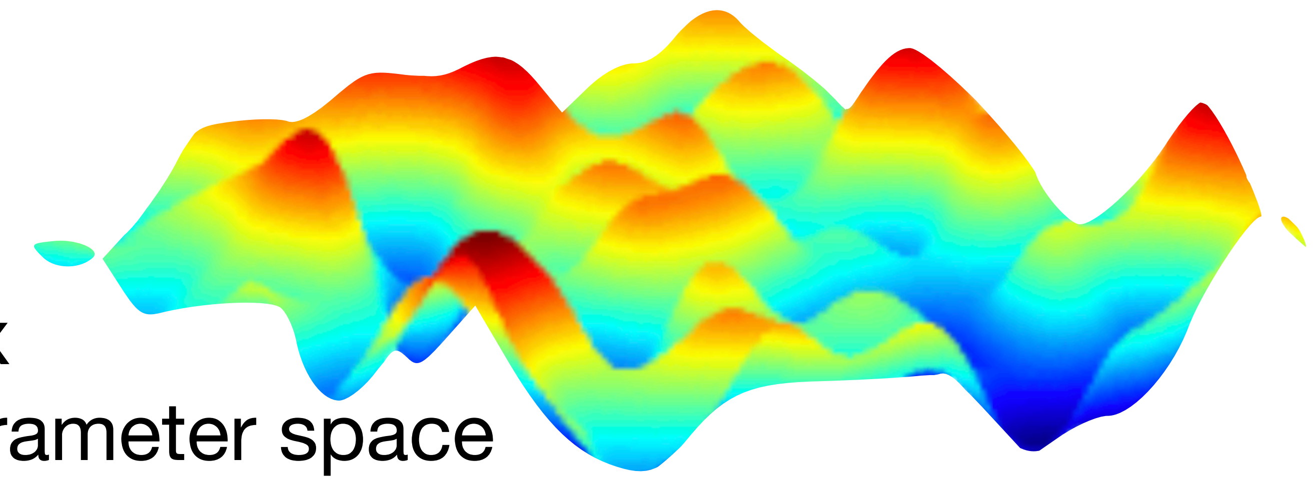
Warm starting (what works on *similar* tasks?)



Meta-models (learn how to build models/components)

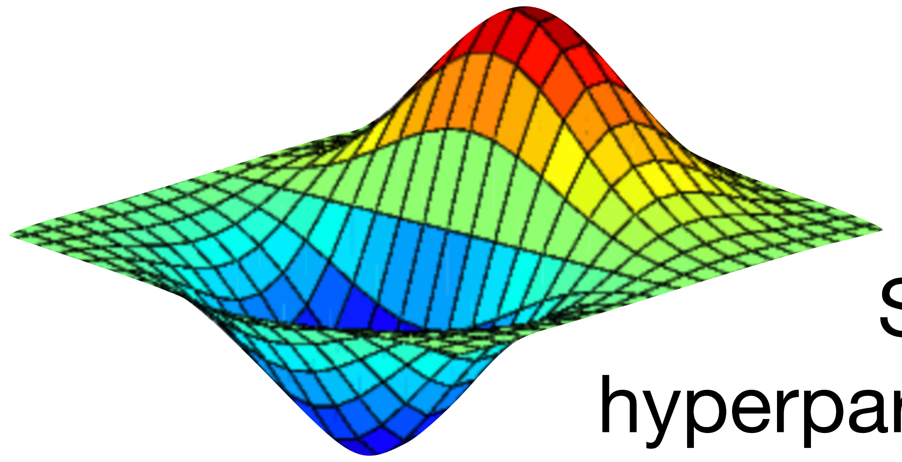


Observation:
current AutoML strongly depends on learned priors

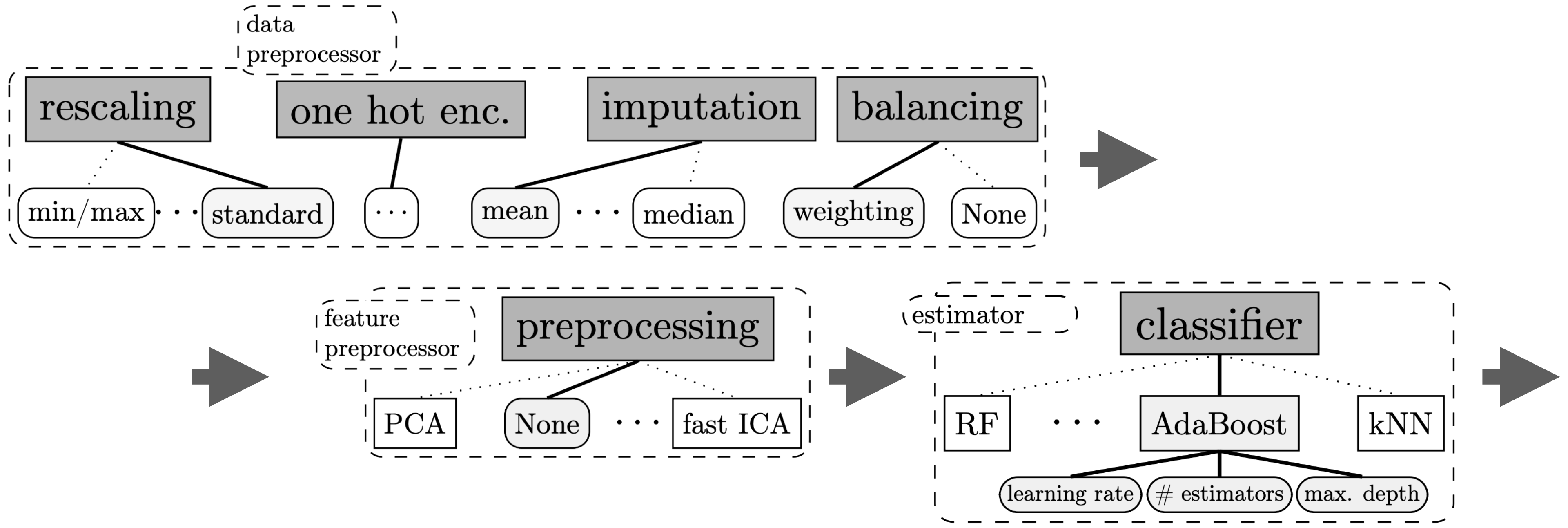


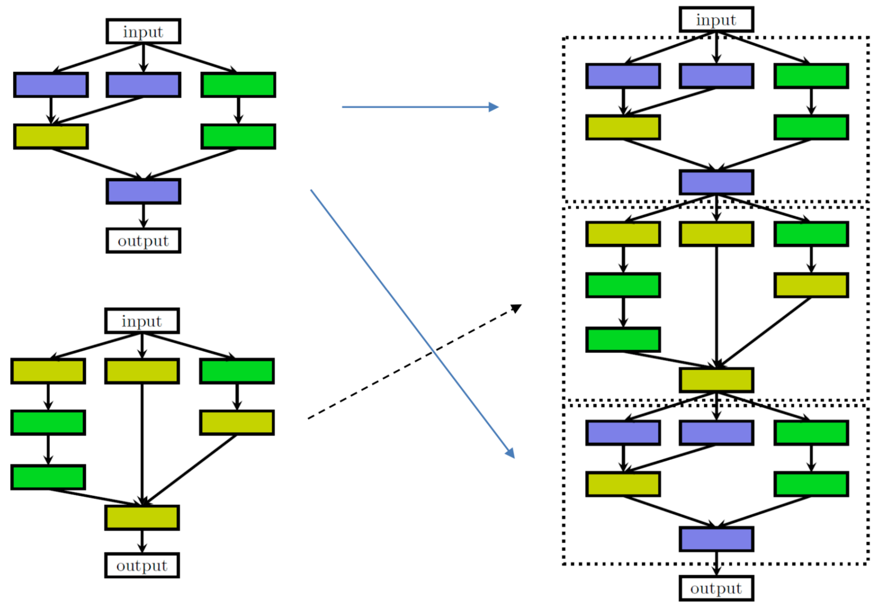
Complex
hyperparameter space

observation

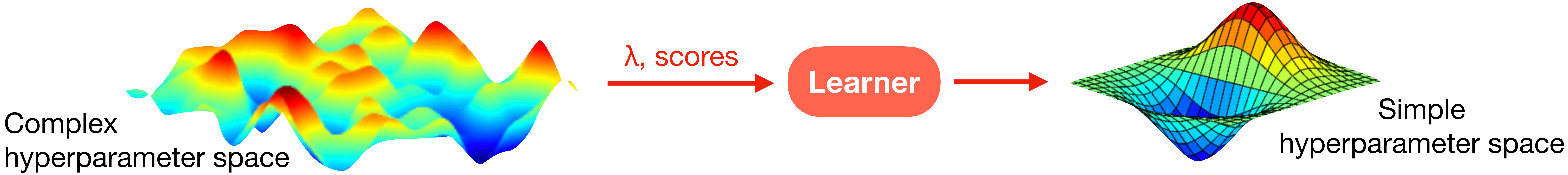


Simple
hyperparameter space





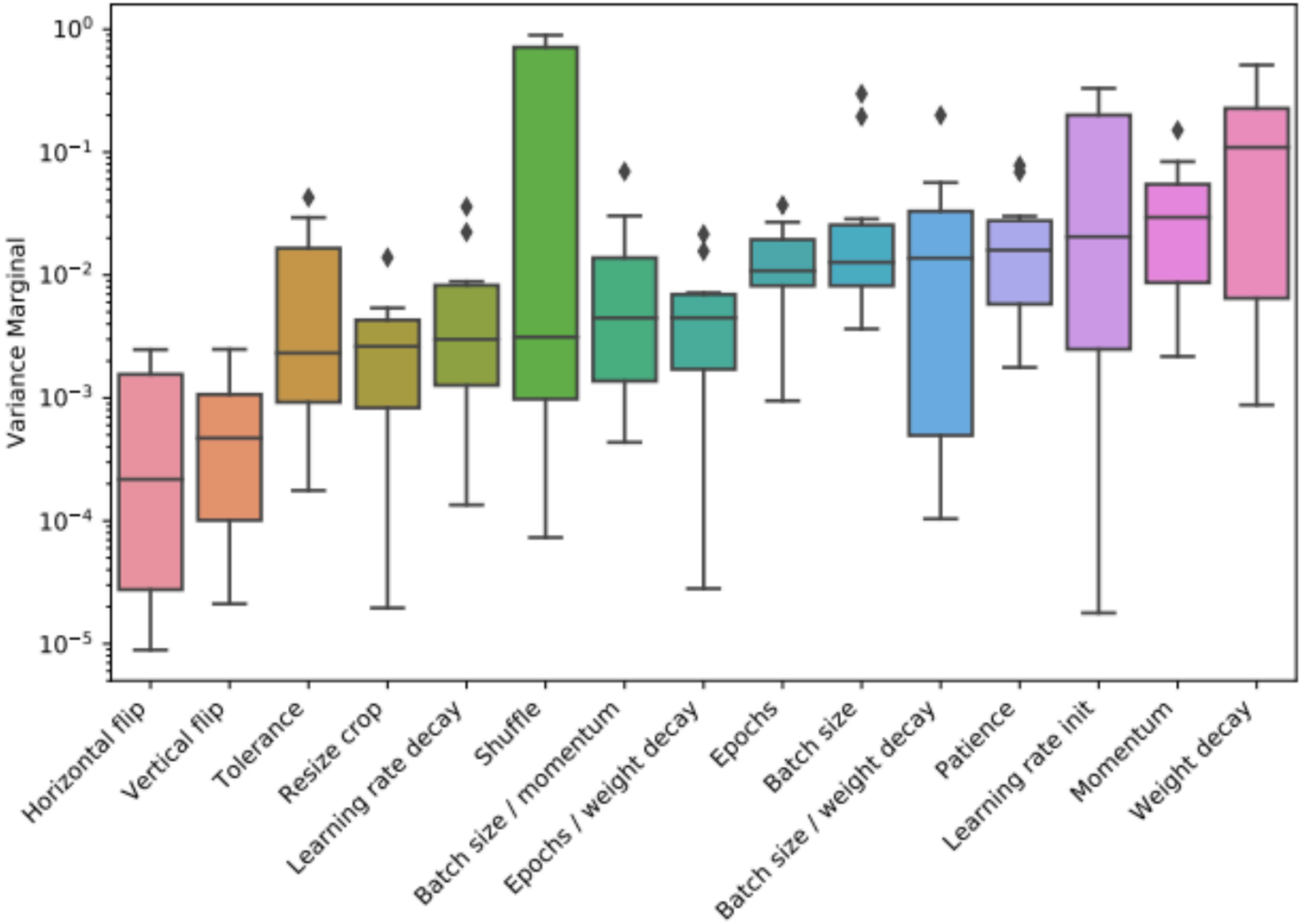
Can we *learn* good hyperparameter priors?



[1] van Rijn & Hutter 2018

Learn hyperparameter importance

- **Functional ANOVA** [1]
  - Select hyperparameters that cause variance in the evaluations.
  - Useful to speed up black-box optimization techniques



ResNets for image classification

Figure source: van Rijn & Hutter, 2018

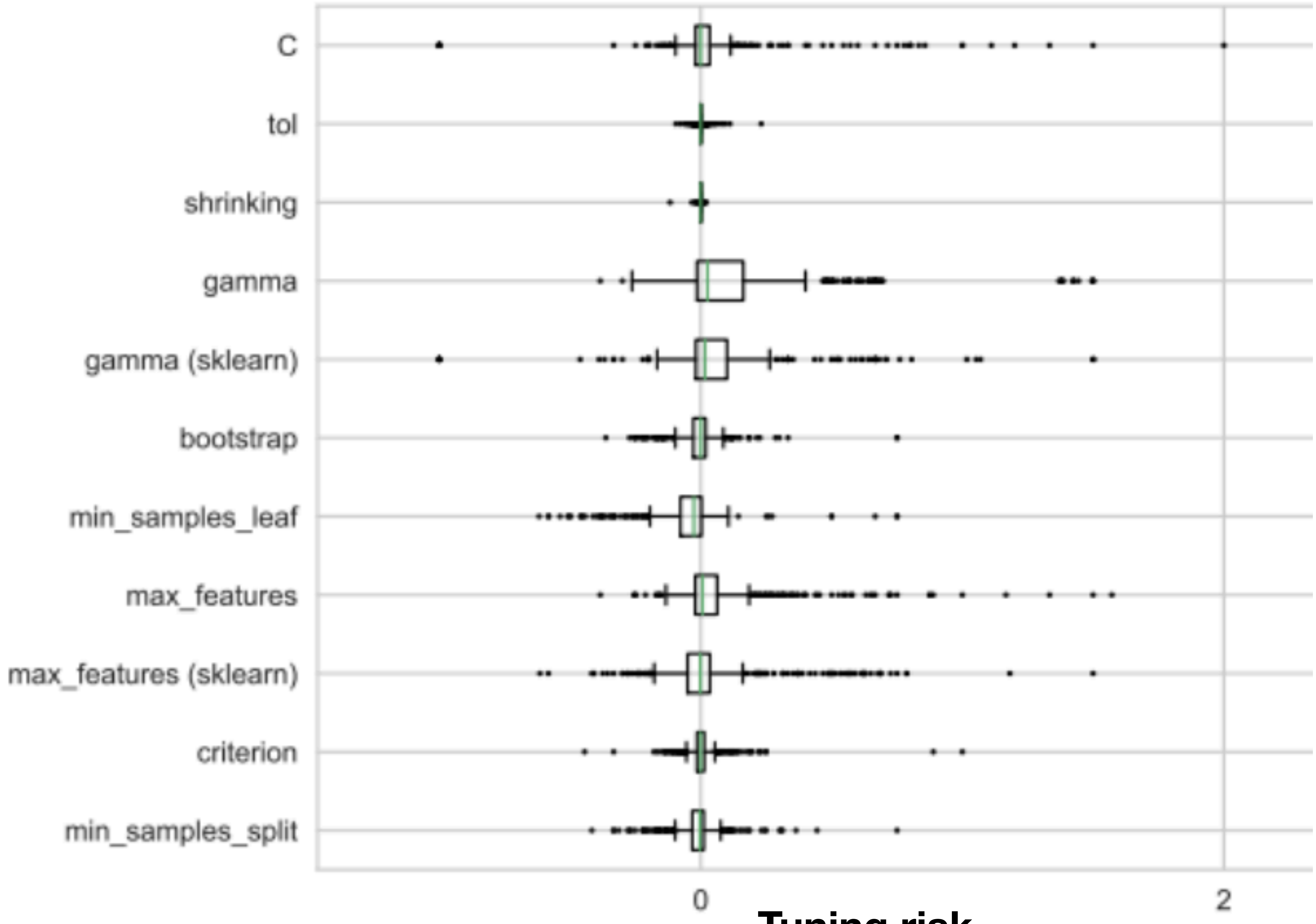
Learn defaults + hyperparameter importance

[1] Probst et al. 2018
[2] Weerts et al. 2018
[3] van Rijn et al. 2018

- **Tunability** [1,2,3]
  Learn good defaults, measure importance as improvement via tuning

function
max_features
m = 0.16*p
m = p ^0.74
m = 1.15^sqrt(p)
m = sqrt(p)
gamma
m = 0.00574*p
m = 1/p
m = 0.006

Learned defaults

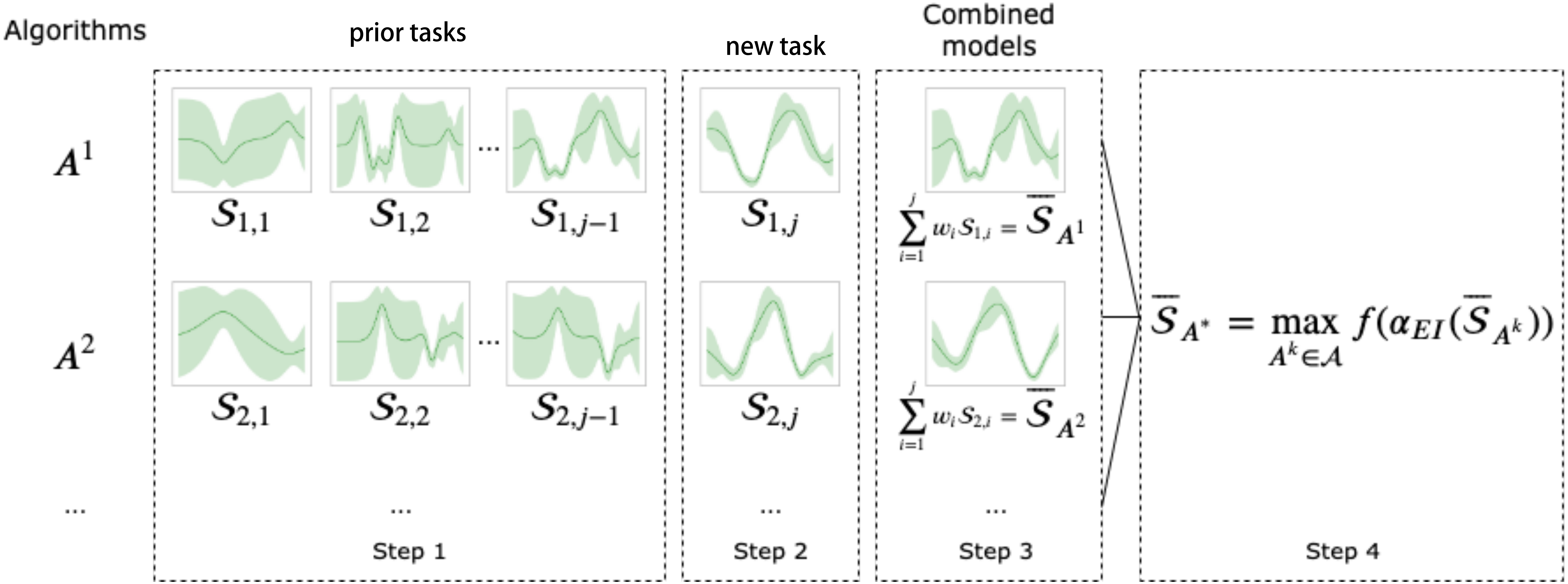


Tuning risk

Manolache & Vanschoren 2019

Surrogate model transfer

- If task j is *similar* to the new task, its surrogate model S_j will likely transfer well
- Sum up all S_j predictions, weighted by task similarity
- Build combined surrogate, *weighted by current performance* on new task[2]



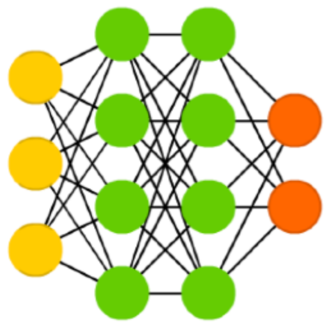
Perrone et al. 2018

Learn basis expansions for hyperparameters

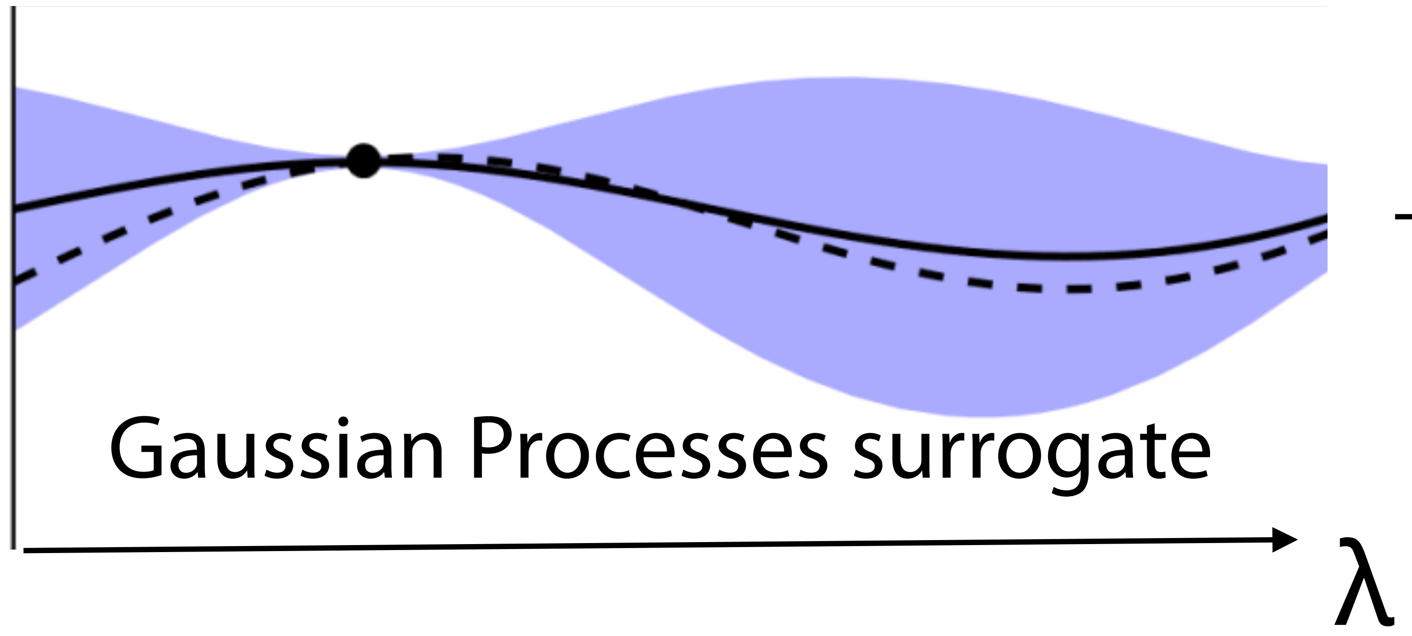
- Hyperparameters can interact in very non-linear ways
- Use a neural net to learn a suitable transform $\phi_z(\lambda)$ so that they behave linearly
- Used in SageMaker AutoML

Learn basis expansion on lots of data (e.g. OpenML)

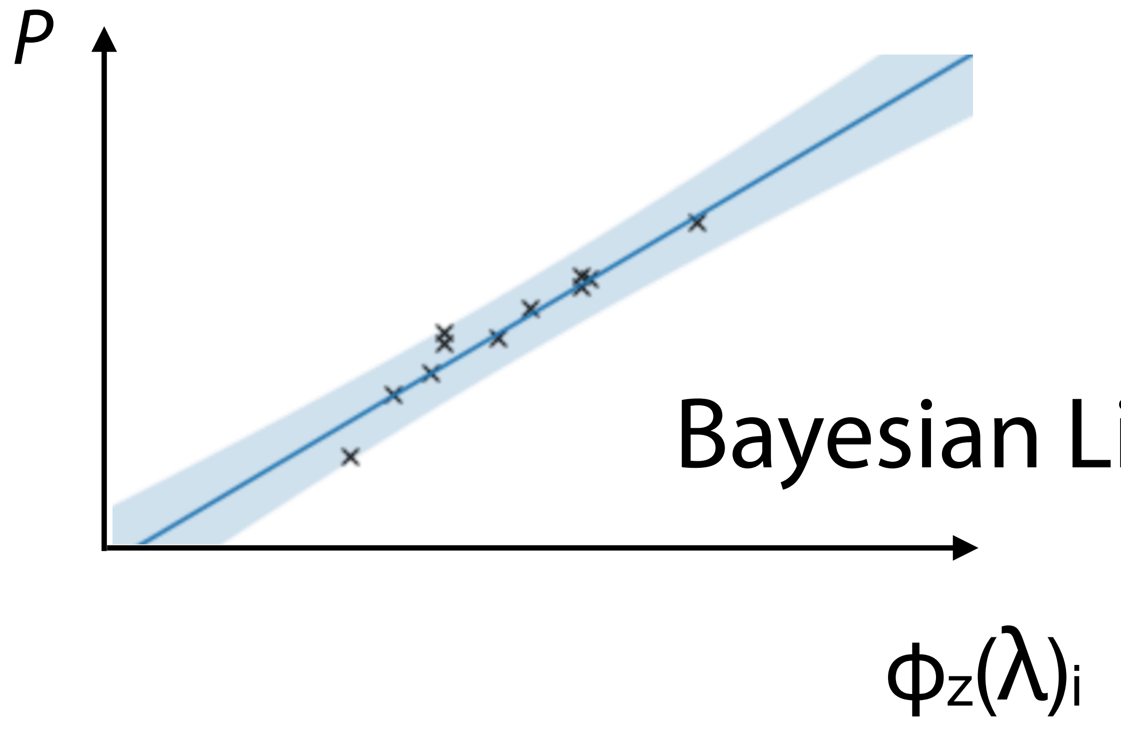
λ_i, scores →



→ $\phi_z(\lambda)$



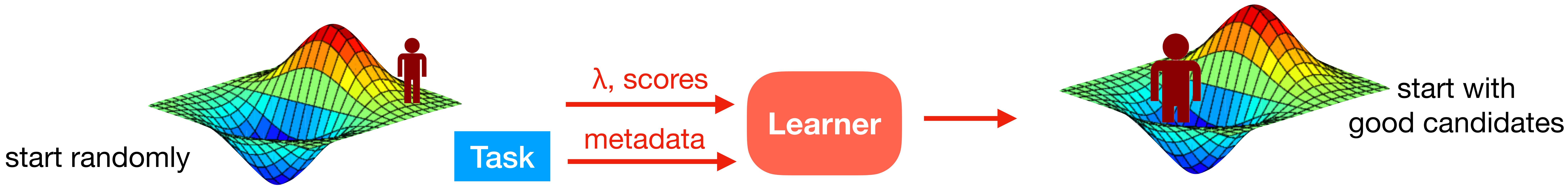
→ $\phi_z(\lambda)$ →



Bayesian Linear surrogate

Warm starting

(what works on *similar* tasks?)



How to measure task similarity?

[1] Vanschoren 2018
[2] Achille et al. 2019
[3] Alvarez-Melis et al. 2020
[4] Drori et al. 2019
[5] Jooma et al. 2020
[6] de Bie et al. 2020

- Hand-designed (statistical) meta-features that describe (tabular) datasets [1]
- Task2Vec: task embedding for image data [2]
- Optimal transport: similarity measure based on comparing probability distributions [3]
- Metadata embedding based on textual dataset description [4]
- Dataset2Vec: compares batches of datasets [5]
- Distribution-based invariant deep networks [6]

Figure source: Alvarez-Melis et al. 2020

Warm-starting with kNN

Feurer et al. 2015

- Find k most similar tasks, warm-start search with best λ_i
  - Auto-sklearn: Bayesian optimization (SMAC)
    - Meta-learning yield better models, faster
    - Winner of several AutoML Challenges

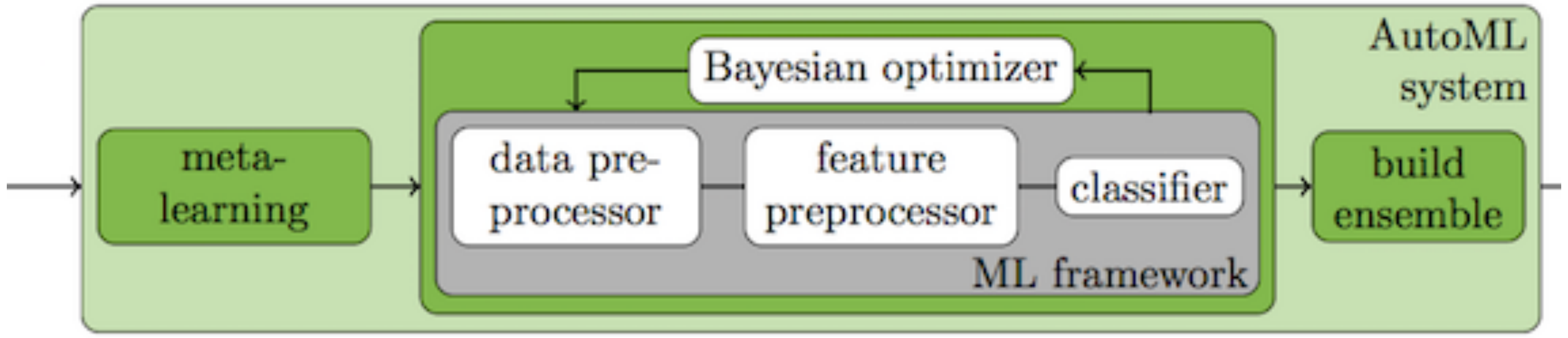
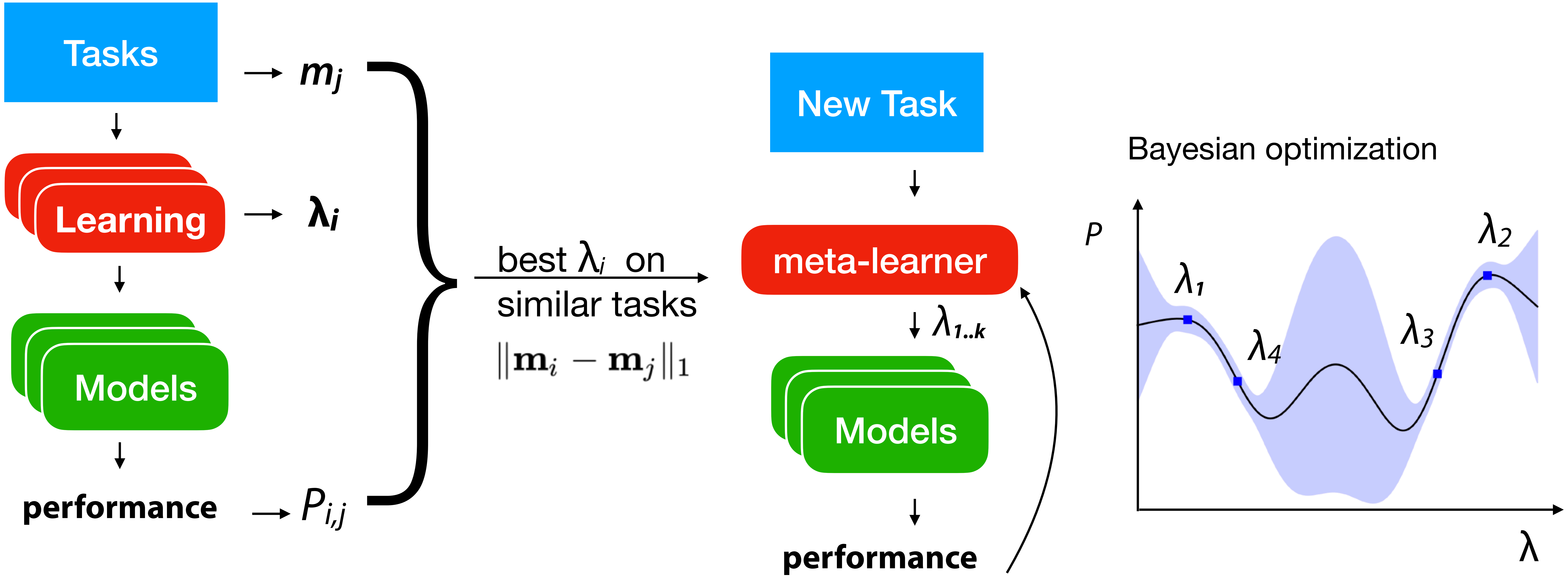


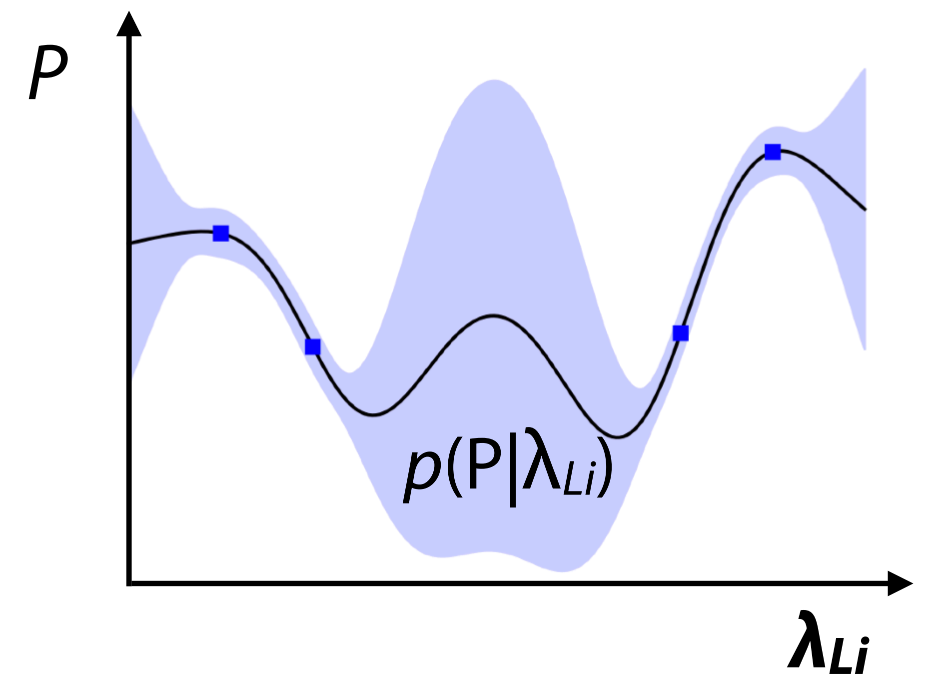
Figure source: Feurer et al., 2015



Probabilistic Matrix Factorization

- Collaborative filtering: configurations λ_i are `rated' by tasks t_j

- Learn latent representation for tasks T and configurations λ
- Use meta-features to warm-start on new task
- Returns probabilistic predictions for Bayesian optitmization
- Used in Azure AutoML



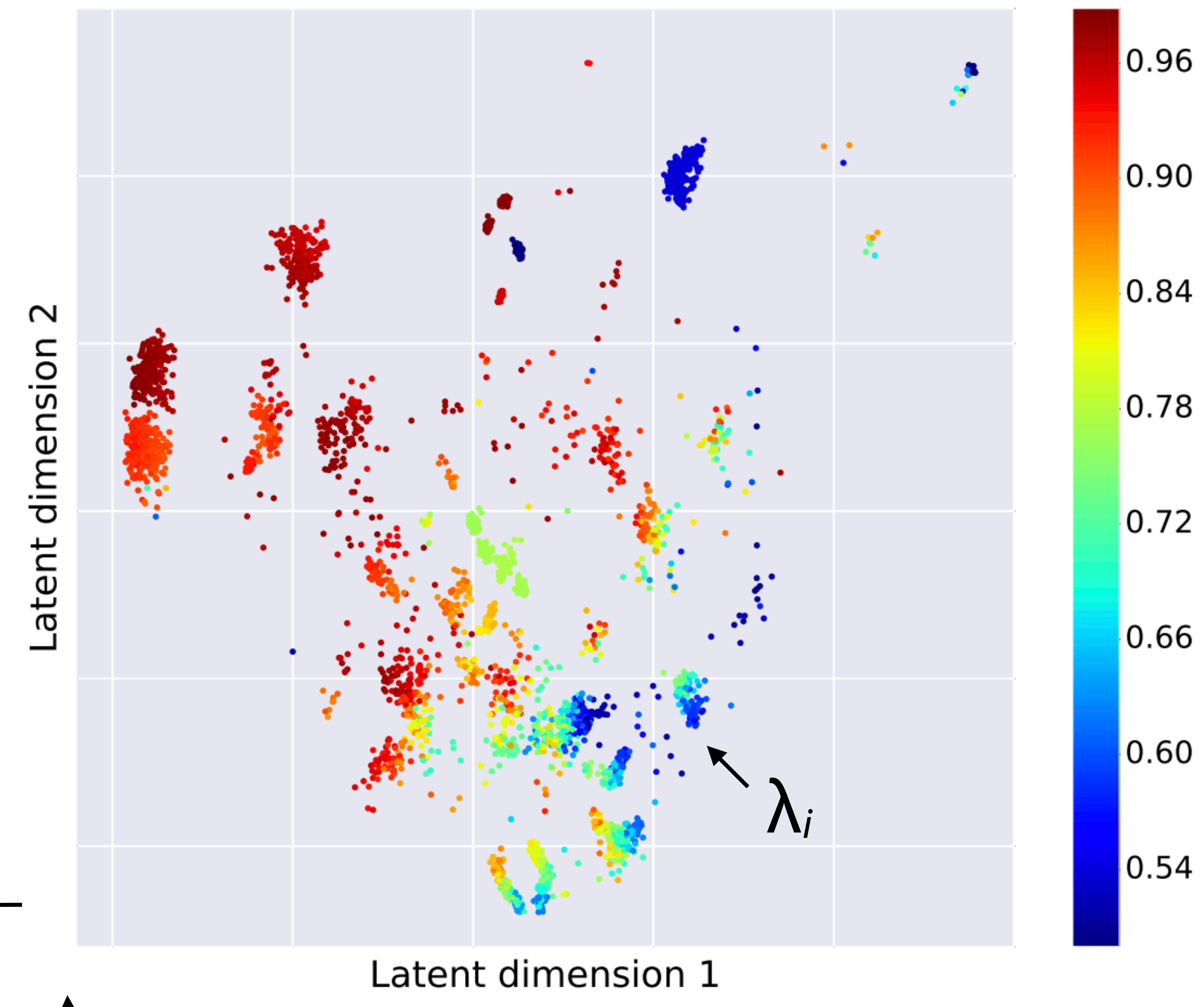
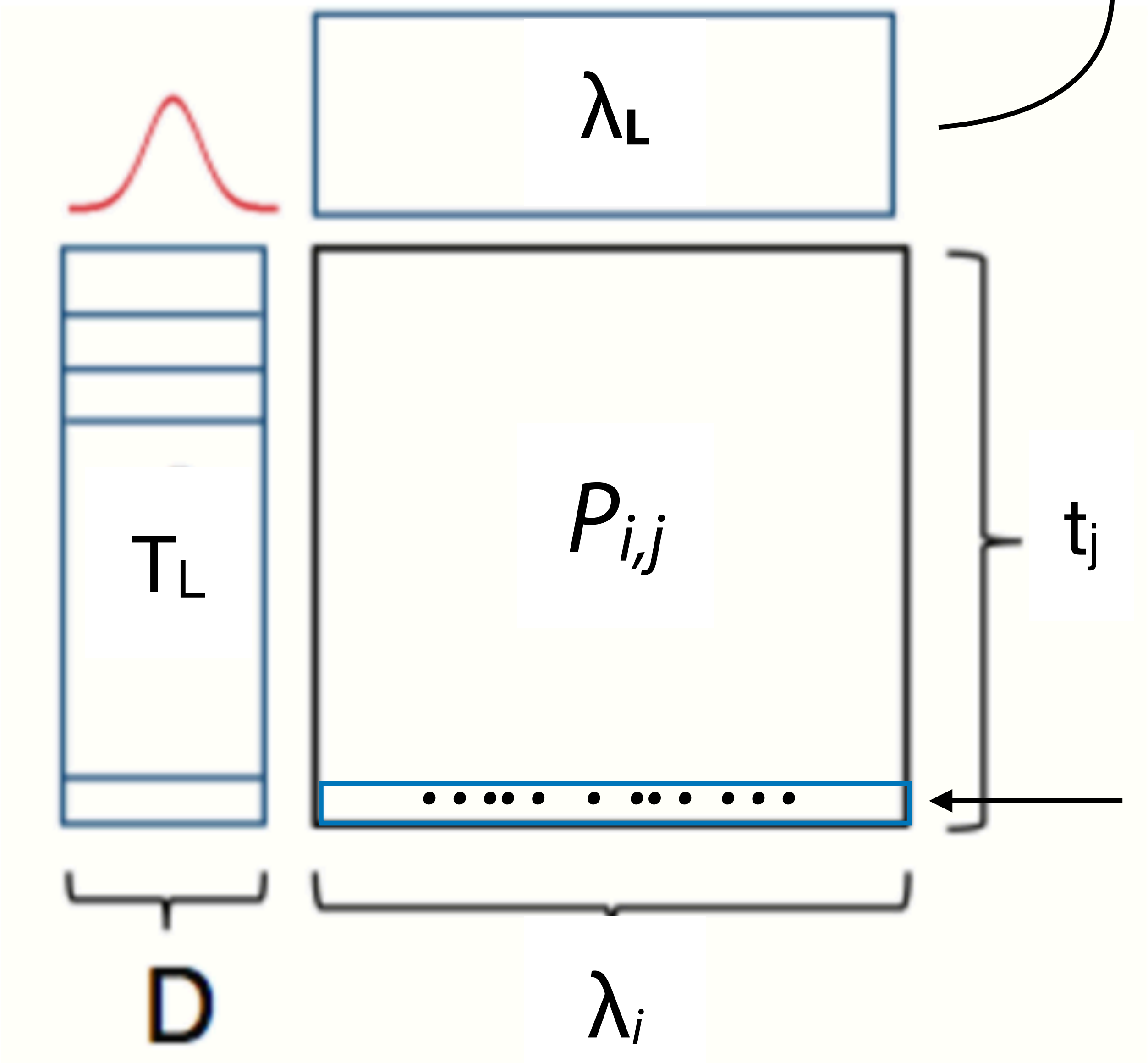


Figure source: Fusi et al., 2017

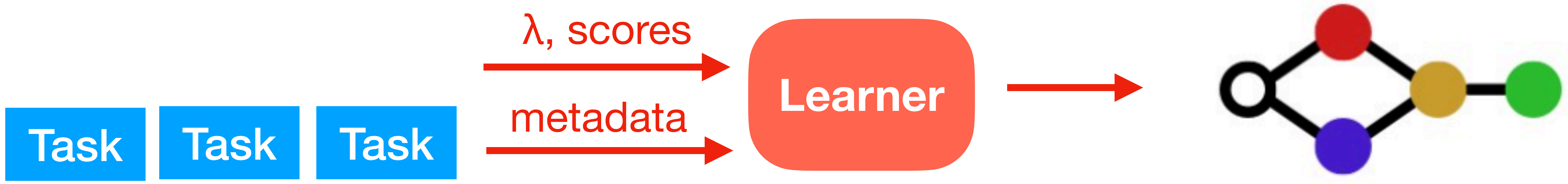


latent representation

t_{new} warm-started with $\lambda_{1..k}$

Meta-models

(learn how to build models/components)



[1] Brazdil et al. 2009, Lemke et al. 2015

[2] Sun and Pfahringer 2013, Pinto et al. 2017

[3] Sanders and C. Giraud-Carrier 2017

[4] Yang et al. 2018

Algorithm selection models

- *Learn* direct mapping between meta-features and $P_{i,j}$
  - Zero-shot meta-models: predict best λ_i given meta-features [1]

    $\boldsymbol{m_j} \longrightarrow$ meta-learner $\longrightarrow \lambda_{best}$

  - Ranking models: return ranking $\lambda_{1..k}$ [2]

    $\boldsymbol{m_j} \longrightarrow$ meta-learner $\longrightarrow \lambda_{1..k}$

  - Predict which algorithms / configurations to consider / tune [3]

    $\boldsymbol{m_j} \longrightarrow$ meta-learner $\longrightarrow \boldsymbol{\Lambda}$

  - Predict performance / runtime for given Θ_i and task [4]

    $\boldsymbol{m_j}, \lambda_i \longrightarrow$ meta-learner $\longrightarrow P_{ij}$

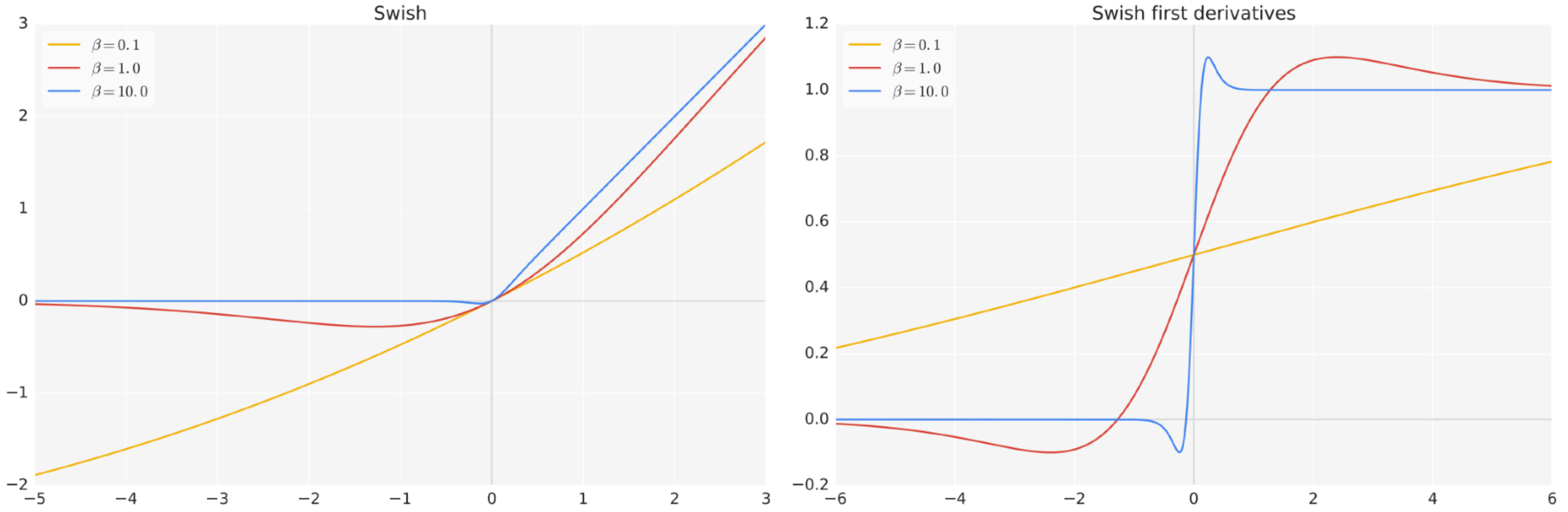
- Can be integrated in larger AutoML systems: warm start, guide search,…

Learning model components

[1] Ramachandran et al. 2017
[2] Bello et al. 2017
[3] Volpp et al. 2020

- Learn nonlinearities: RL-based search of space of likely useful activation functions [1]
  - E.g. *Swish* can outperform ReLU

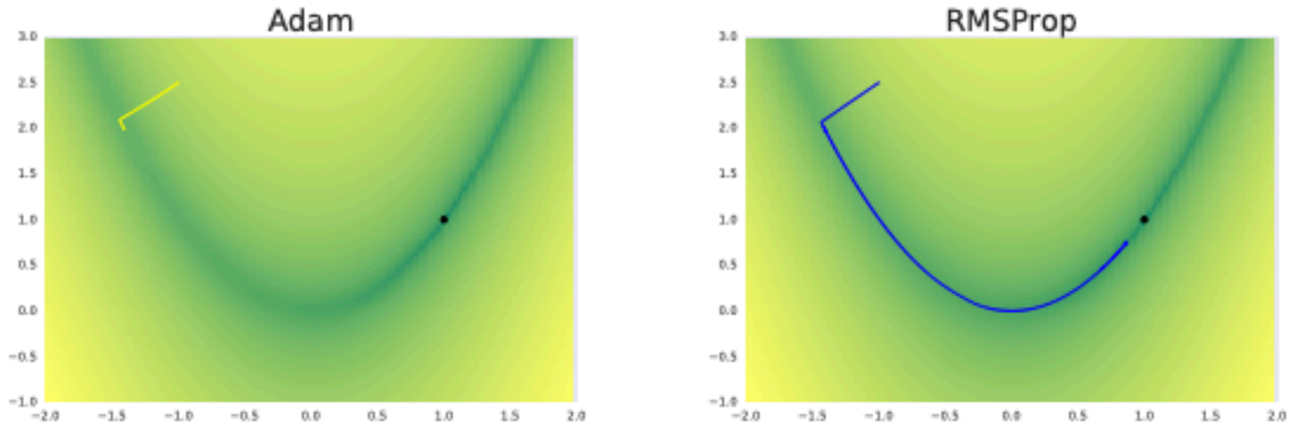
$$Swish : \frac{x}{1 + e^{-\beta x}}$$

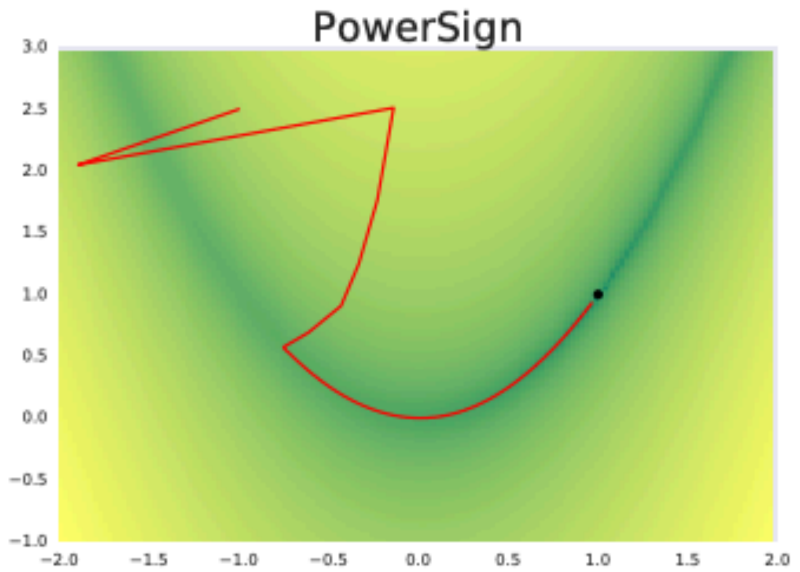


- Learn optimizers: RL-based search of space of likely useful update rules [2]
  - E.g. PowerSign can outperform Adam, RMPprop

$$PowerSign : e^{sign(g)sign(m)} g$$

g: gradient, m:moving average





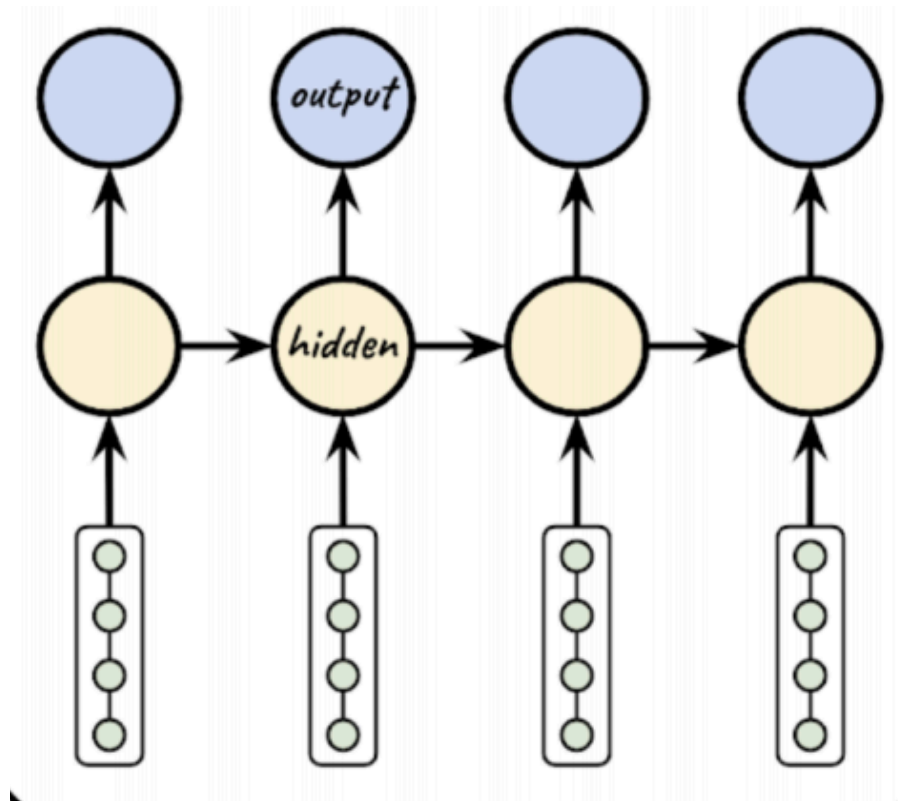
- Learn acquisition functions for Bayesian optimization [3]

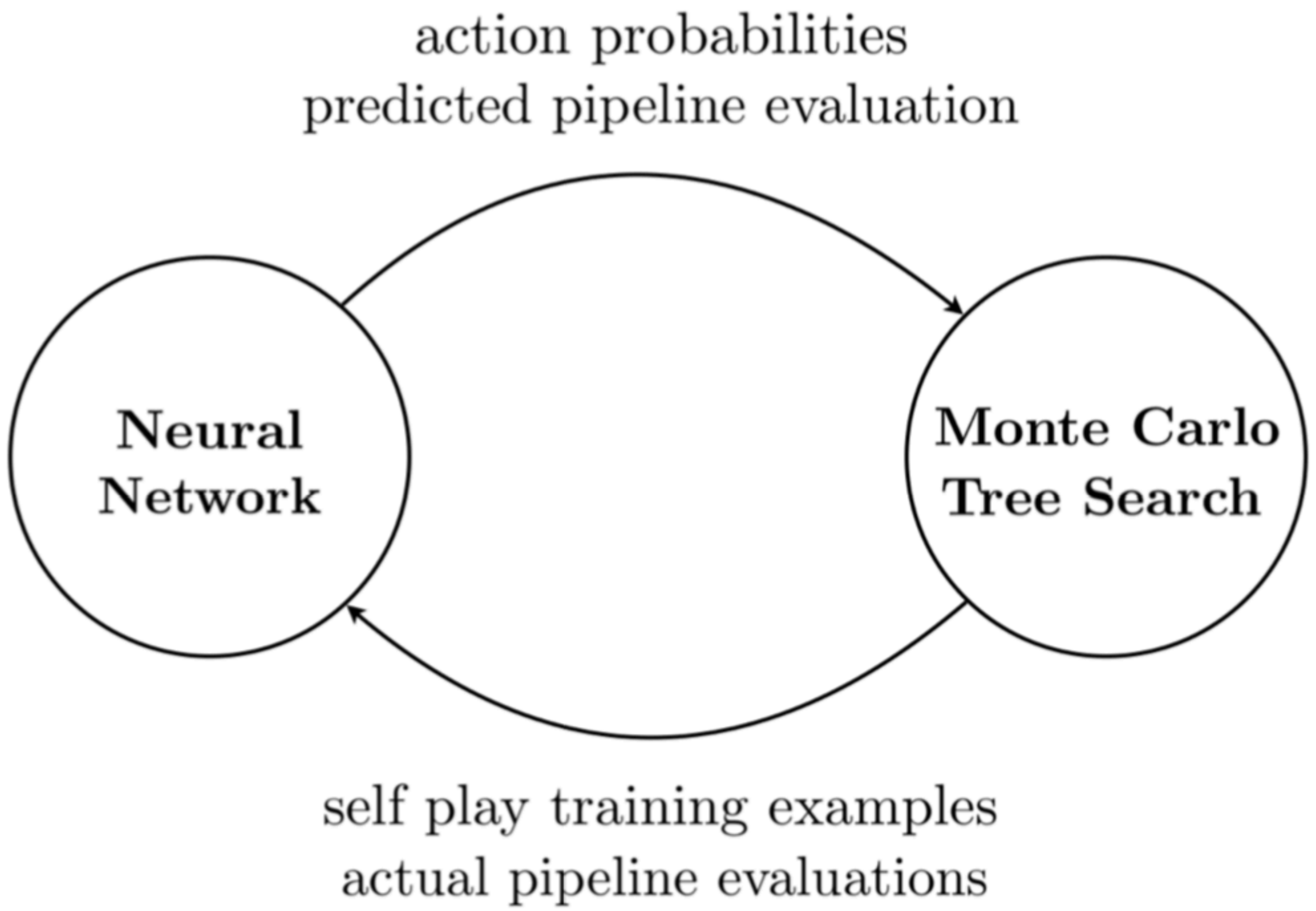
Figure source: Ramachandran et al., 2017 (top), Bello et al. 2017 (bottom)

MOSAIC *[Rakotoarison et al. 2019]*
AlphaD3M *[Drori et al. 2019]*

Monte Carlo Tree Search + reinforcement learning

- ***Self-play:***
    - Game actions: insert, delete, replace components in a pipeline
    - Monte Carlo Tree Search builds pipelines given action probabilities
    - Neural network (LSTM) Predicts pipeline performance





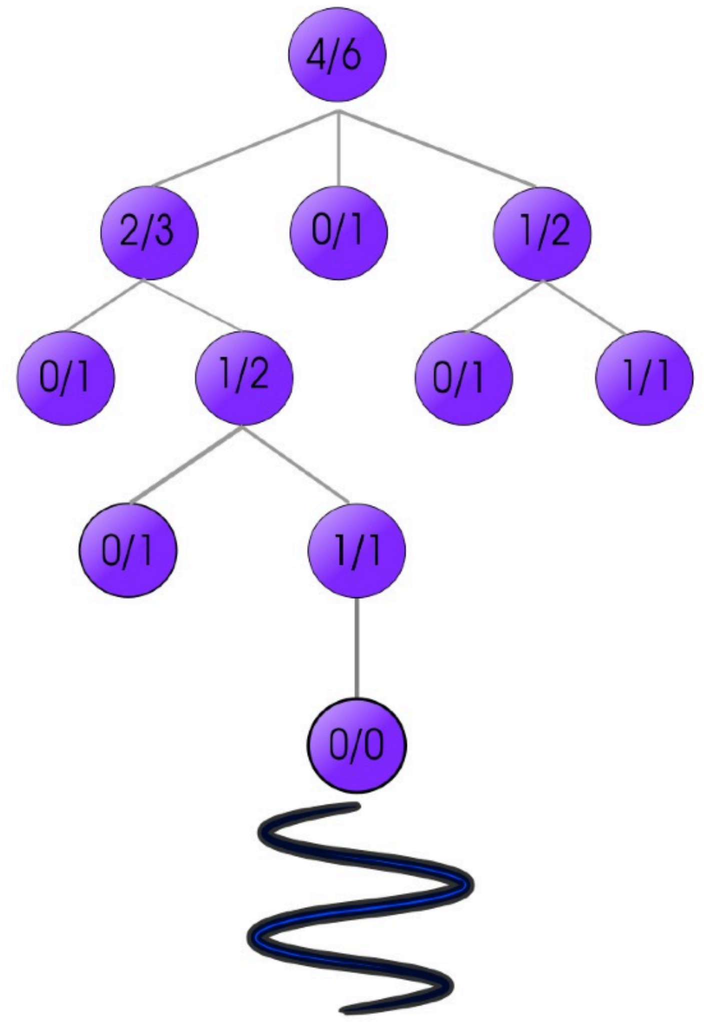
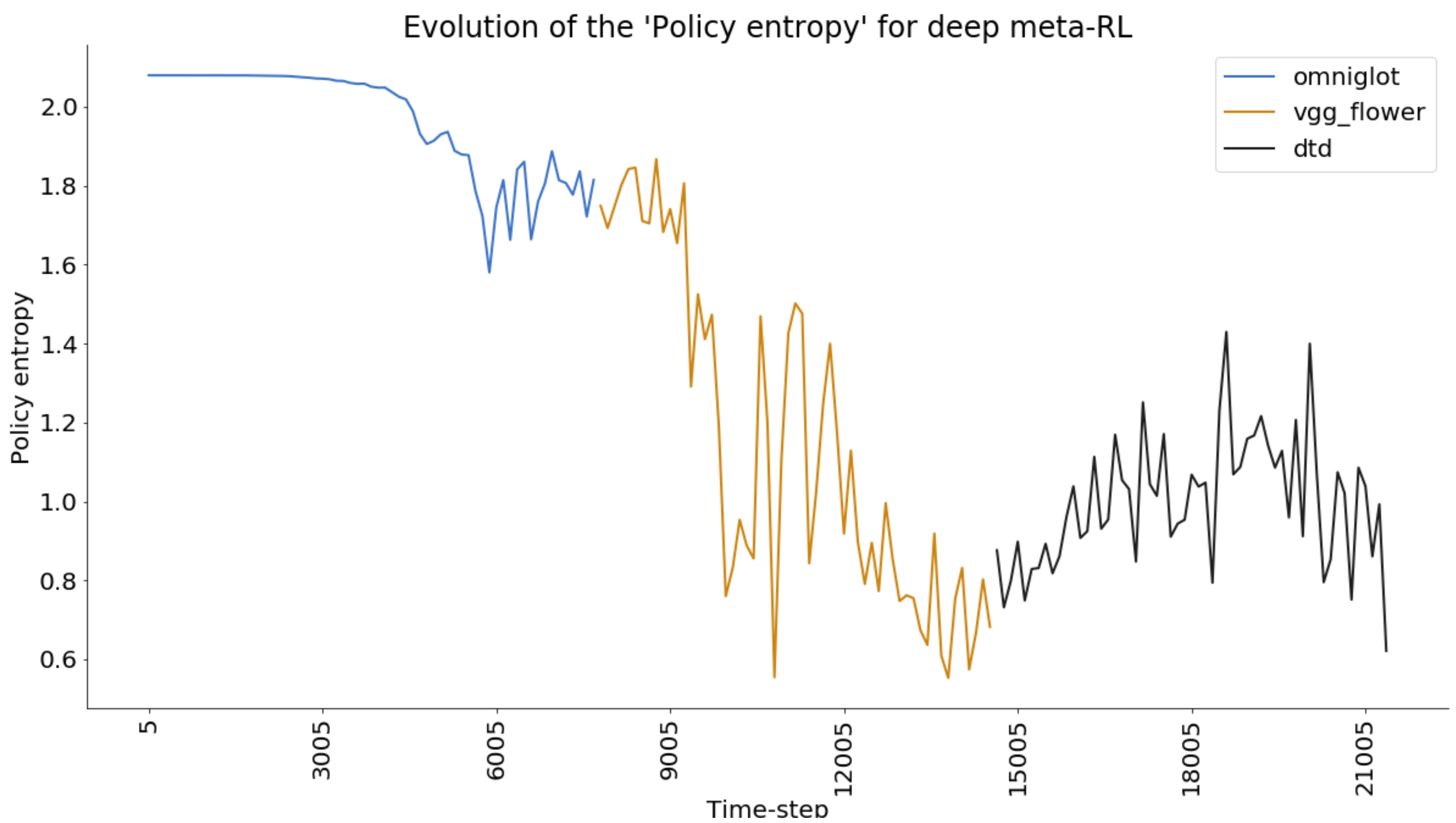


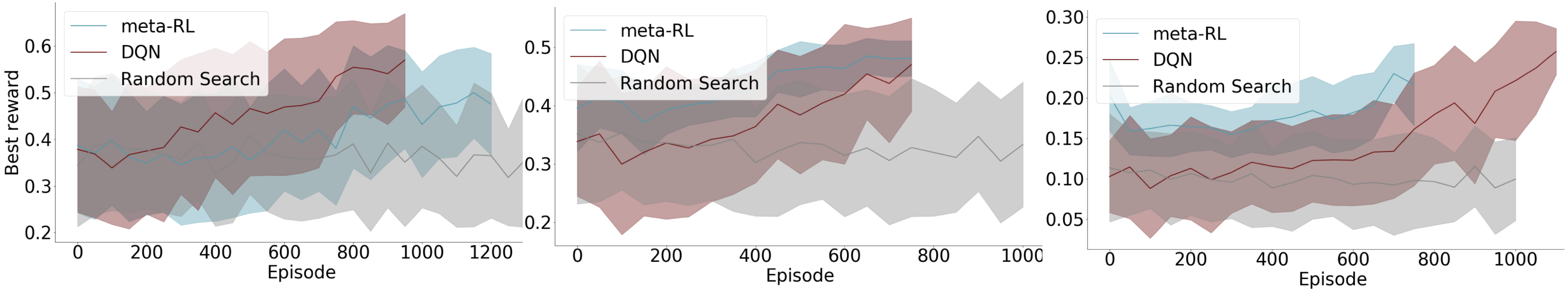
Figure source: Drori et al., 2019

Meta-Reinforcement Learning for NAS

Results on increasingly difficult tasks:

- Initially slower than DQN, but faster after a few tasks
- Policy entropy shows learning/re-learning



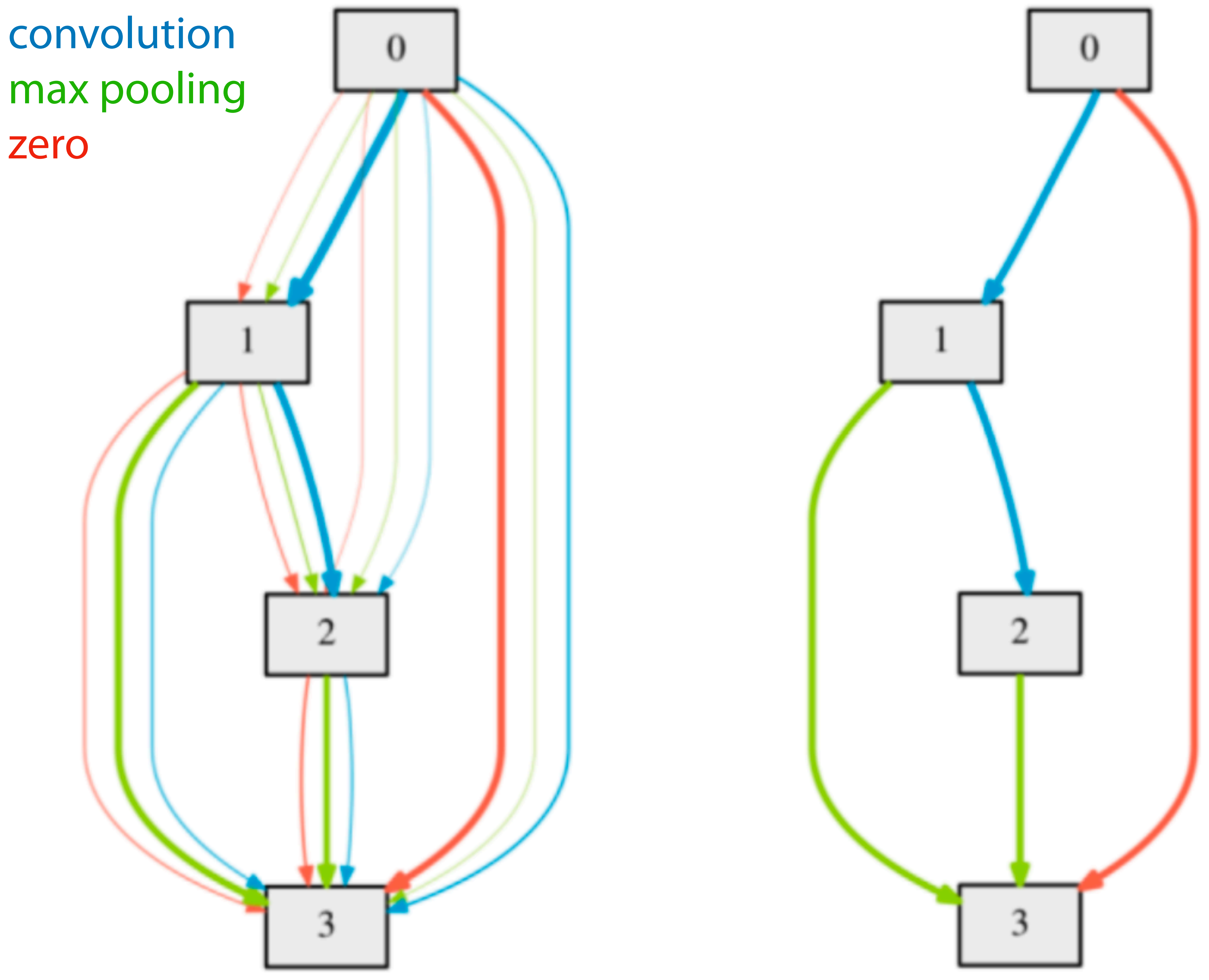


omniglot　vgg_flower　dtd

MetaNAS: meta-learning + NAS

- Use meta-learning (MAML) to learn a good weight initialization for the network

Meta-learn initial operator weights α_i from previous tasks

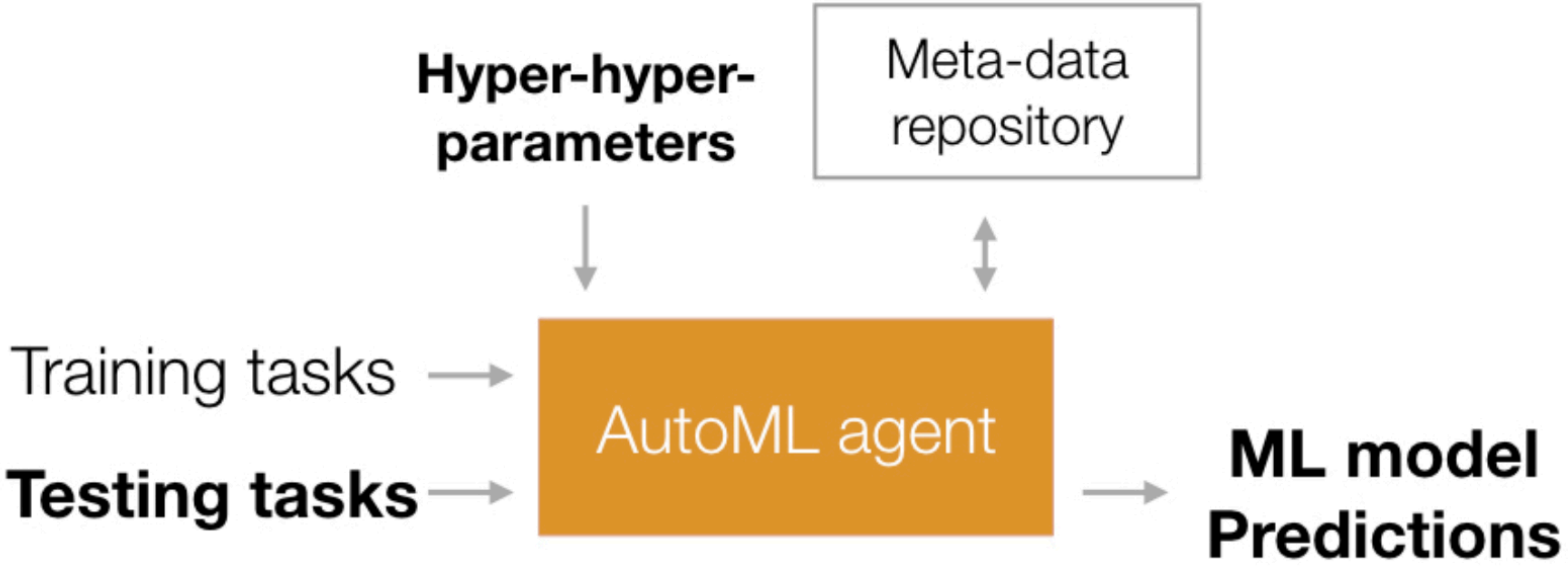


interleaved optimization of α_i and ω_j with SGD

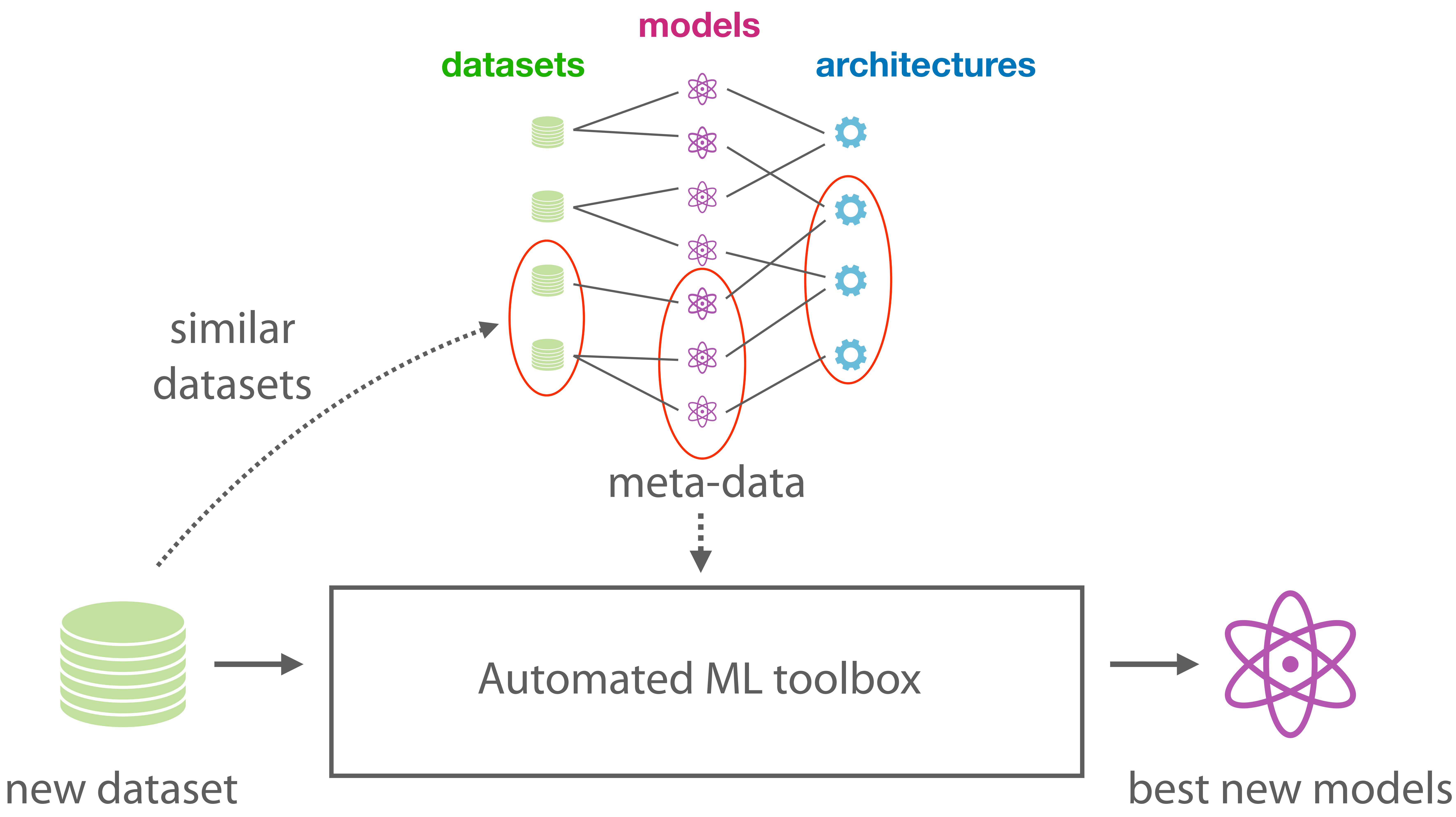
argmax α_i

Meta-learning AutoML in practice

- We need a meta-data repository of prior machine learning datasets (tasks) and experiments
  - e.g. OpenML.org
- Ideally, a *shared* memory that all AutoML tools can access



Meta-learning with OpenML



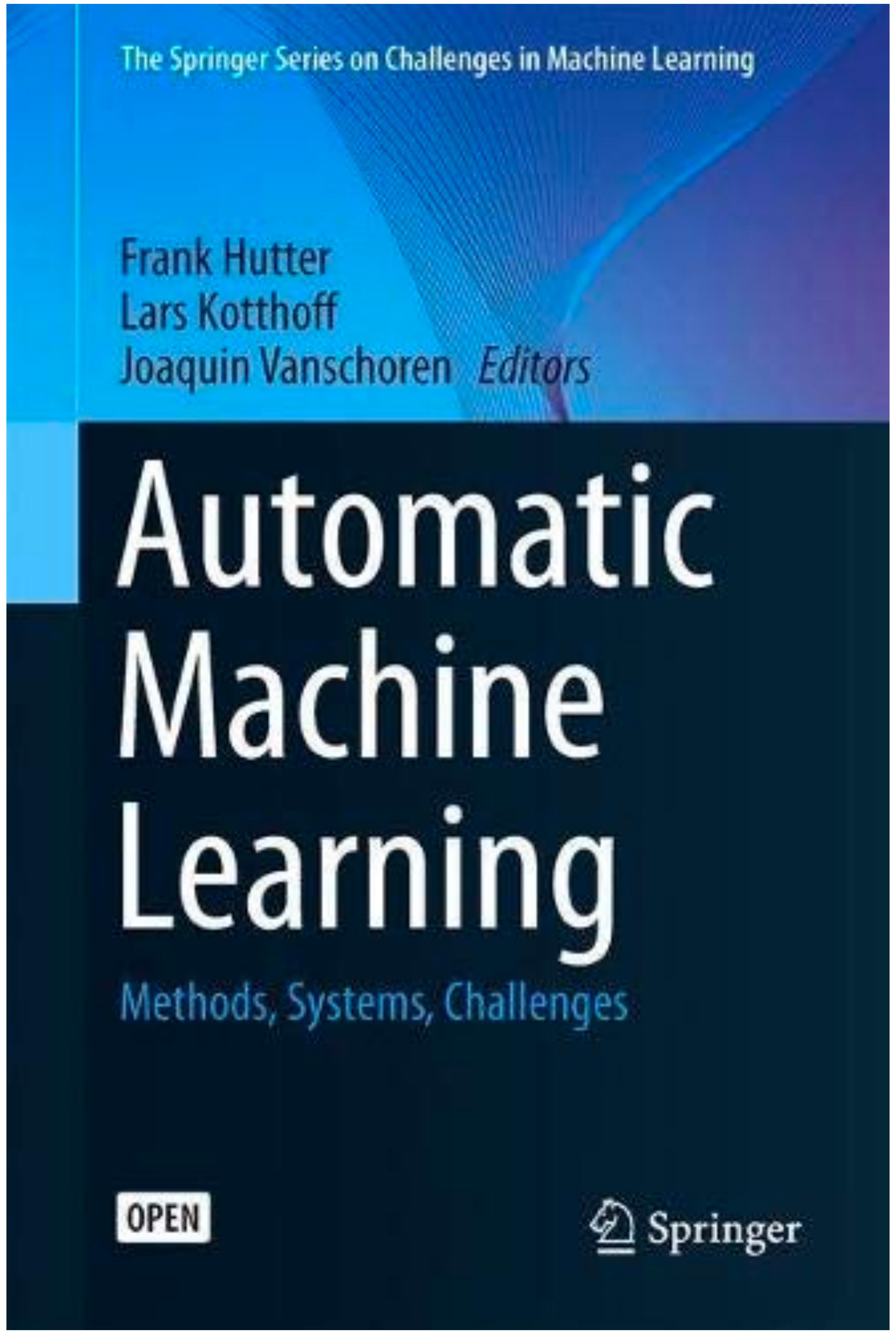
AutoML *open source* tools

	Architect. search	Operators	Hyperpar. search	Improvements	Metalearning
Auto-WEKA	Param. pipeline	WEKA	Bayesian Opt. (RF)		
auto-sklearn	Param. pipeline	sklearn	Bayesian Opt. (RF)	Ensemble	warm-start
mlr-mbo	Param. pipeline	mlr	Bayesian Opt.	multi-obj.	
BO-HB	Param. pipeline	sklearn	Tree of Parzen Estim.	Ensemble, HB	
hyperopt-sklearn	Param. pipeline	sklearn	Tree of Parzen Estim.		
skopt	Param. pipeline	sklearn	Bayesian Opt. (GP)		
TPOT	Evolving pipelines	sklearn	Population-based		
GAMA	Evolving pipelines	sklearn	Population-based	Ensemble, ASHA	
H2O AutoML	Param. pipeline	H2O	Random search	Stacking	
AutoGluon-Tabular	Param. pipeline	Sagemaker	Random search	multi-level Stacking	
OBOE	Single algorithms	sklearn	Low rank approx.	Ensembling	runtime pred
Auto-Keras	Param. NAS	keras	Bayesian Opt.	Net Morphisms	
Auto-pyTorch	Param. pipeline	pyTorch	BO-HB		
TensorFlow 2	/	keras	RS or HB		
Talos	/	keras	RS variants		

Many other tools for hyperparameter optimization alone

Further reading

Open access book
PDF (free): www.automl.org/book
www.amazon.de/dp/3030053172



Thank you!

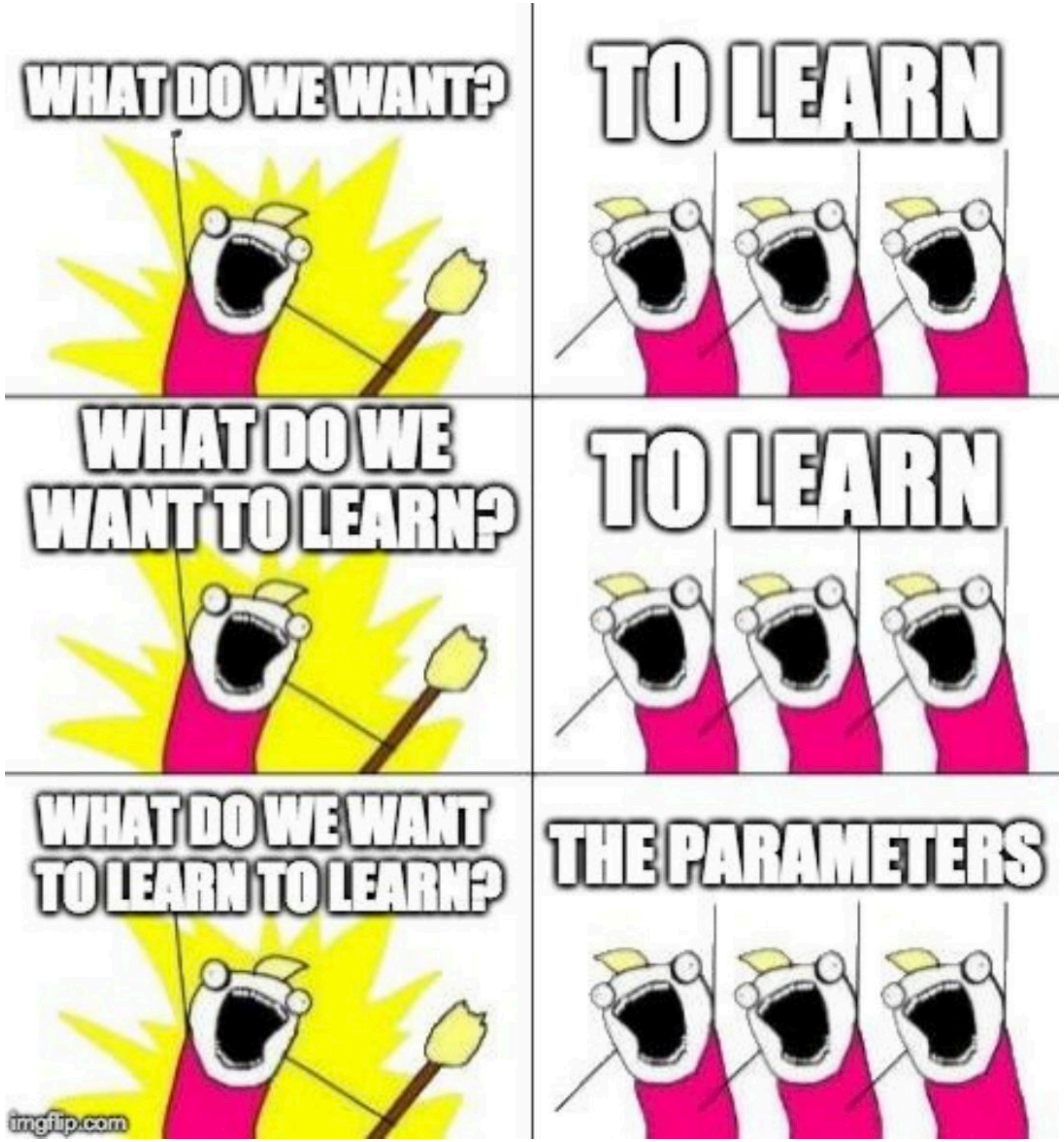


Image: Pesah et al. 2018