# **Introduction to Machine Learning**

# Hyperparameter Tuning Pipelines and AutoML



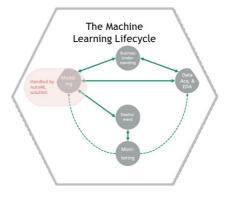


#### Learning goals

- Pipelines as connected steps of learnable operations
- Sequential pipeline
- Pipelines and DAGs

#### **CASE FOR AUTOML**

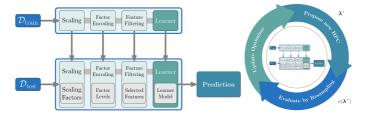
- More and more tasks are approached via data driven methods.
- Data scientists often rely on trial-and-error.
- The process is especially tedious for similar, recurring tasks.
- Not the entire machine learning lifecycle can be automated.





#### PIPELINES AND AUTOML

- ML typically has several data transformation steps before model fit
- If steps are in succession, data flows through sequential pipeline
- NB: Each node has a train and predict step and learns params
- And usually has HPs

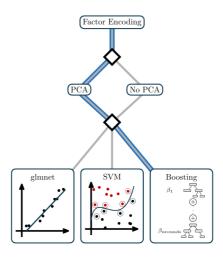


Pipelines are required to embed full model building into CV to avoid overfitting and biased evaluation!



# **PIPELINES AND AUTOML**

- Further flexibility by representing pipeline as DAG
- Single source accepts D<sub>train</sub>, single sink returns predictions
- Each node represents a preprocessing operation, a learner, a postprocessing operation or controls data flow
- Can be used to implement ensembles, operator selection,





## PIPELINES AND AUTOML

 HPs of pipeline are the joint set of all HPs of its contained nodes:

$$\boldsymbol{\tilde{\Lambda}} = \boldsymbol{\tilde{\Lambda}}_{\text{op},1} \times \cdots \times \boldsymbol{\tilde{\Lambda}}_{\text{op},k} \times \boldsymbol{\tilde{\Lambda}}_{\mathcal{I}}$$

 HP space of a DAG is more complex: Depending on branching / selection different nodes and HPs are active

 $\rightarrow$  hierarchical search space

Name	Type	Bounds/Values	Trafo
encoding	C	one-hot, impact	
♦ pca	C	PCA, no PCA	
♦ learner	C	glmnet, SVM,	
		Boosting	
if learner =	glmnet		
s	R	[-12, 12]	$2^x$
alpha	$\mathbf{R}$	[0, 1]	-
if learner =	SVM		
cost	R	[-12, 12]	$2^x$
gamma	R	[-12, 12]	$2^x$
if learner = Boosting			
eta	R	[-4, 0]	$10^x$
nrounds	I	$\{1, \dots, 5000\}$	_
$max\_depth$	I	$\{1, \dots, 20\}$	-

Search Space A



A graph that includes many preprocessing steps and learner types can be flexible enough to work on a large number of data sets

Combining such graph with an efficient tuner is key in AutoML

### **AUTOML – CHALLENGES**

- Most efficient approach?
- How to integrate human a-priori knowledge?
- How can we best (computationally) transfer "experience" into AutoML? Warmstarts, learned search spaces, etc.
- Multi-Objective goals, including model intepretability
- AutoML as a process is too much of a black-box, hurts adoption.

