

Using H2O AutoML for Kaggle Competitions

- AutoML? Does it work?
- About H₂O AutoML
- Q & A

H₂O.ai

Jo-fai (Joe) Chow
Data Scientist at H2O.ai
joe@h2o.ai

About Me

- Civil (Water) Engineer

- 2010 – 2015

- Consultant (UK)

- Utilities

- Asset Management

- Constrained Optimization

- EngD (Industrial PhD) (UK)

- Infrastructure Design Optimization

- Machine Learning +
Water Engineering

- Discovered H₂O in 2014

- Data Scientist

- 2015 – 2016

- Virgin Media (UK)

- Domino Data Lab (Silicon Valley)

- 2016 – Present

- H₂O.ai (Silicon Valley)

- How?

- bit.ly/joe_kaggle_story

H₂O AutoML: Does it work?

4	▲3	Juan Zhai 卷宅		0.06335...	53	2d
5	▲14	Trottefox		0.06359...	86	18h
6	▲319	cmanning		0.06362...	11	7d
7	▲90	Benchmark		0.06362...	324	13h
8	▼7	R2		0.06366...	352	2d
9	▲2	Zidmie & Kostadinov & L		0.06378...	273	9h
10	▼8	Nima Shahbazi mcha...		0.06378...	251	12h
11	▲454	FF		0.06383...	14	9h
12	▼7	Zensemble		0.06384...	253	1d
13	▼4	KFP		0.06387...	349	18h
14	▲369	raytrace		0.06388...	47	16h
15	▲46	To Train Them Is My C...		0.06390...	66	1d
16	▲154	Batangas		0.06393...	75	13h
17	▲265	Thomas Hoffmann		0.06394...	67	13h
18	▼5	Ivonik		0.06394...	118	9h
19	▼13	Belinda Trotta		0.06394...	47	3d
20	▼5	Thomas H. Thoresen ...		0.06397...	113	9h
21	▼1	Bierkom		0.06398...	72	20h
22	▲23	Gough		0.06398...	56	9h
23	▼13	Alpha 60		0.06400...	180	18h
24	▼12	The Slippery Appraisal...		0.06400...	363	2d
25	▼8	Dmitry Kulagin		0.06400...	27	2d
26	▲1476	Bin		0.06400...	7	1d
27	▲241	Bram Boroson		0.06400...	99	9h
28	—	ys		0.06401...	81	10h
29	new	no one		0.06401...	25	15h
30	▼9	双鸭山数据科学RUA小分...		0.06401...	175	10h
31	▲6	VincaPiggy		0.06401...	101	13h
32	▲6	Comment Allez-Vous		0.06401...	186	13h
33	▲88	m1in		0.06401...	28	9h
34	▲19	...		0.06402...	135	1d
35	▲35	proof by adverb		0.06402...	45	13h
36	▼7	Helgi		0.06402...	197	9h
37	▲90	Deal or No Deal		0.06402...	79	9h

Your Best Entry ↑
Your submission scored 0.0640257, which is an improvement of your previous score of 0.0640259. Great

[Competitions](#)
[Datasets](#)
[Kernels](#)
[Discussion](#)
[Jobs](#)
[...](#)

Featured Prediction Competition

Zillow

3,839 teams

3 months to go

Zillow Prize: Zillow's Home Value Prediction (Zestimate)

Can you improve the algorithm that changed the world of real estate?

\$1,200,000

Prize Money

Some of the H₂O Kagglers

Marios Michailidis (KazAnova)
Mathias Müller (Faron)

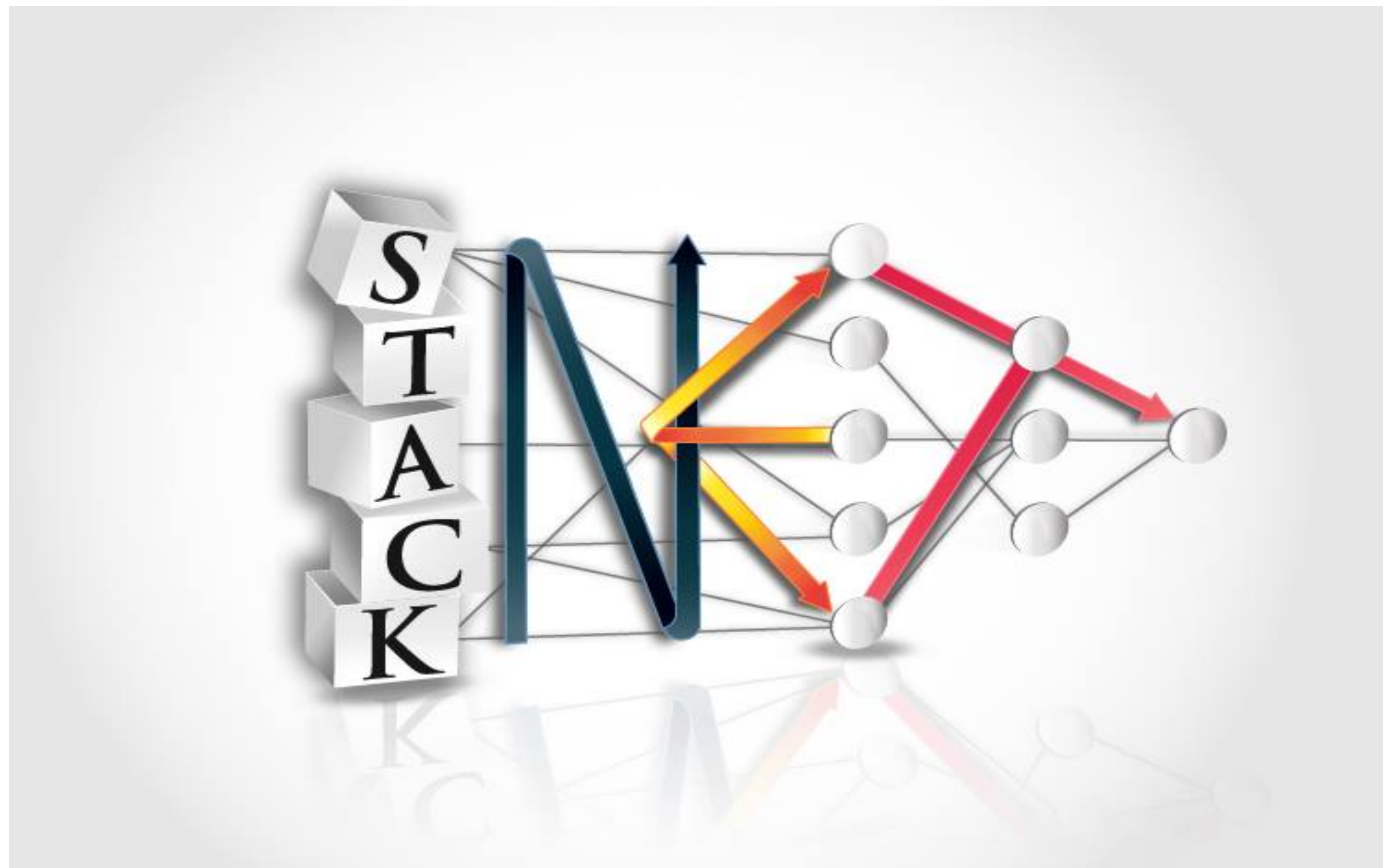
Dmitry Larko
... and his father

Joe ... trying to catch up ...
Used AutoML a lot to save time
37 out of 3839 (Top 1%)

Does it work with other tools?

Does it work with other tools?

YES – I used H₂O and StackNet together



Introducing StackNet Meta-Modelling Framework

Marios Michaildis

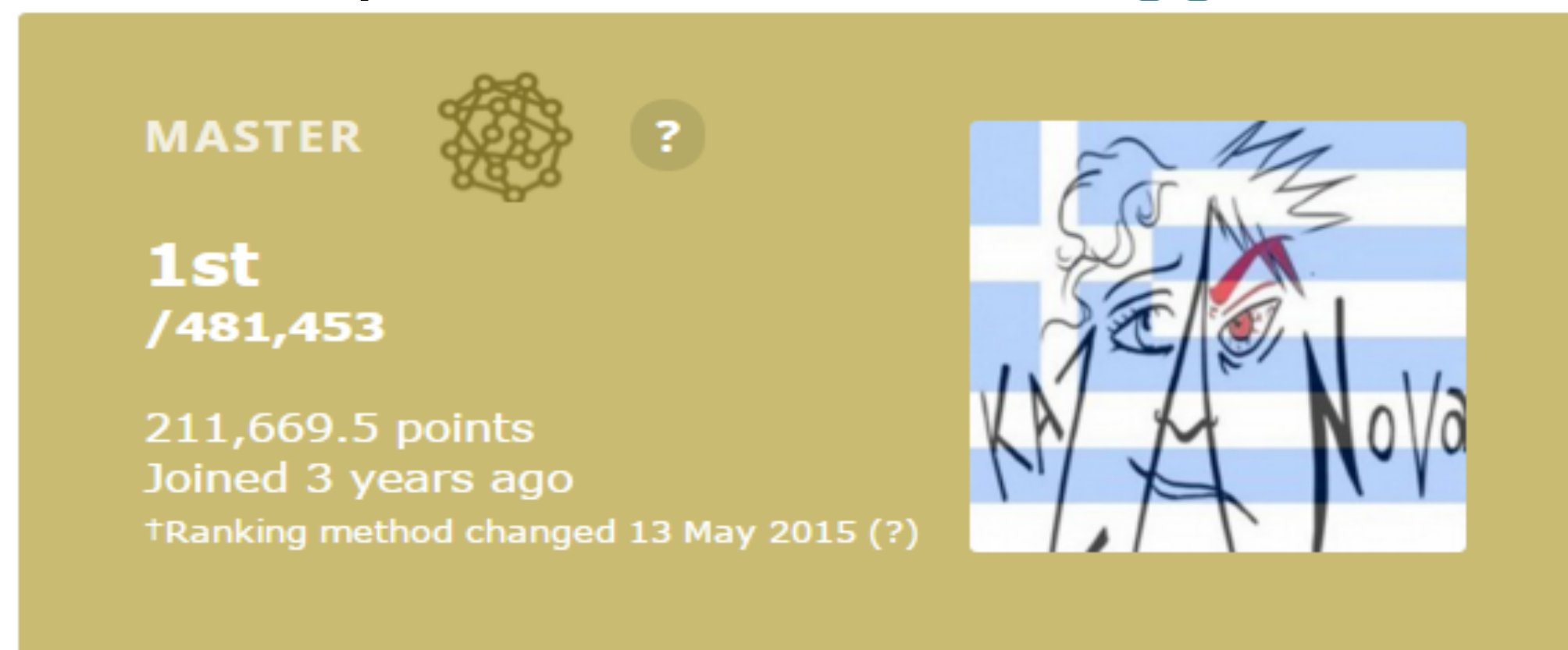
Research Data Scientist at

Email: marios@h2o.ai



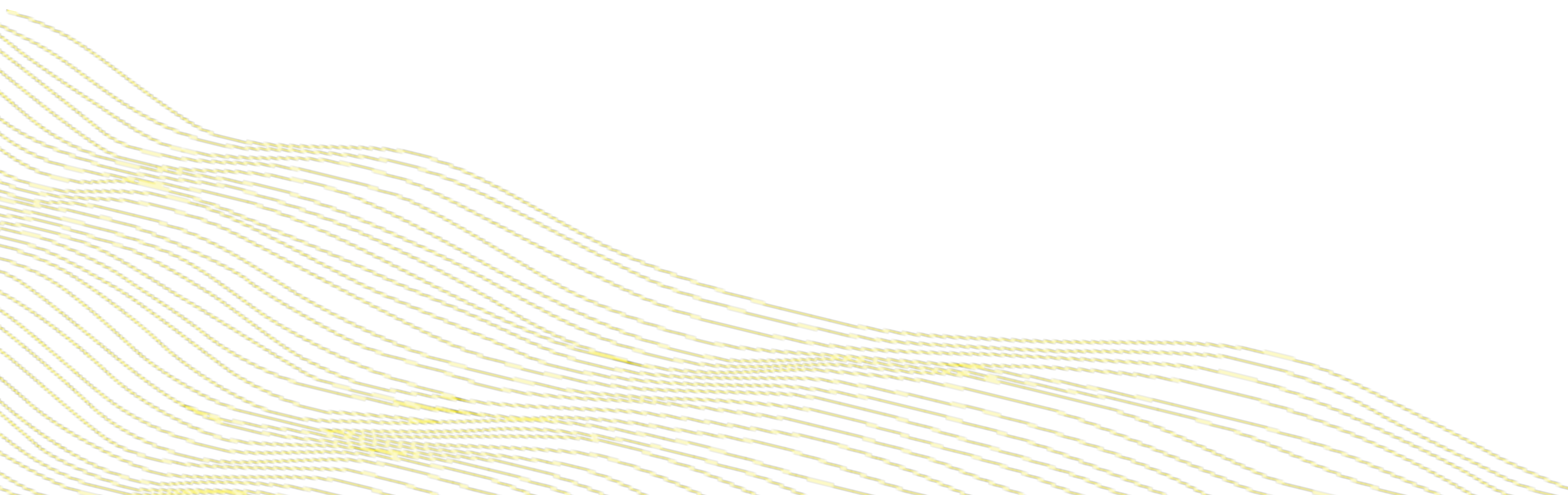
Why bother learning more about StackNet?

- It helps to **improve predictions** given the same input data
- Its is **educational** in its own way, especially in understanding Stacking.
- Compiles the **pinnacle of machine learning** into one framework-and-library.
- Has **won 2 kaggle competitions** ([link A](#) and [Link B](#))
- Has helped many people **get top 10** results in kaggle.
- It has helped me become **kaggle #1**



About H2O AutoML

Scalable Automatic Machine Learning

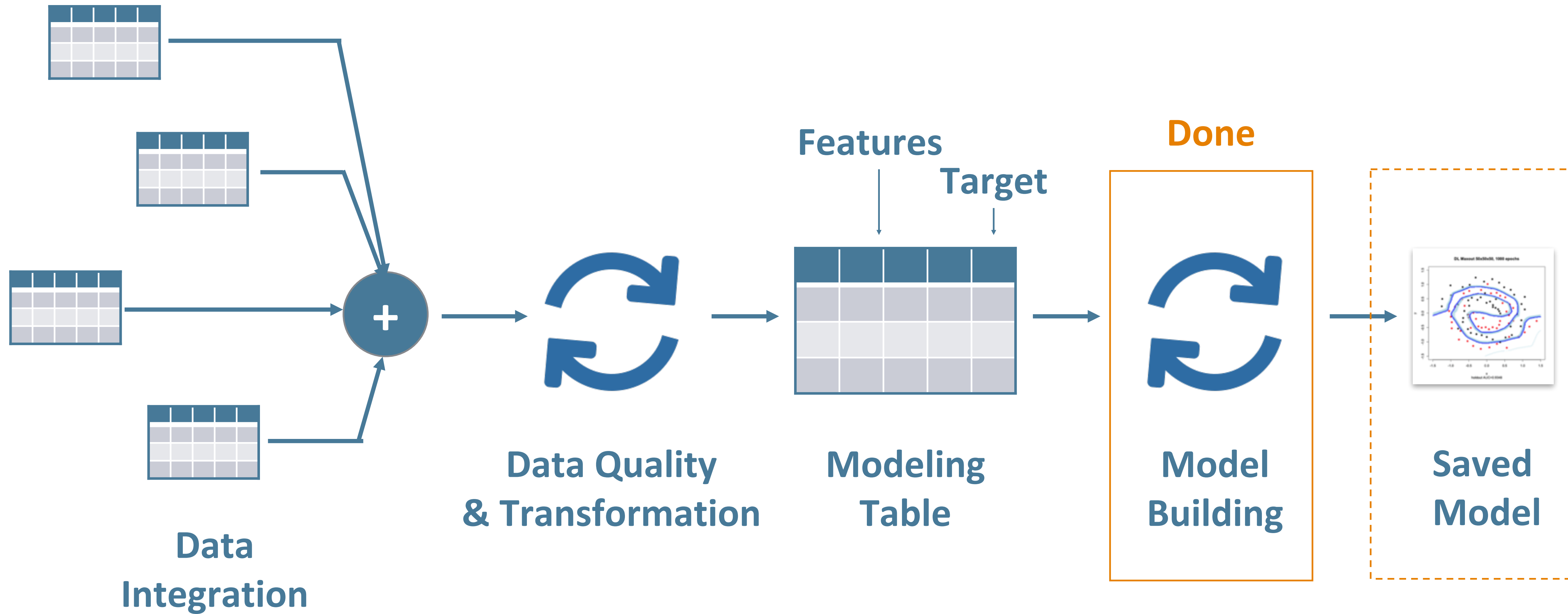


Why Use AutoML?

Automates Model Building Workflow

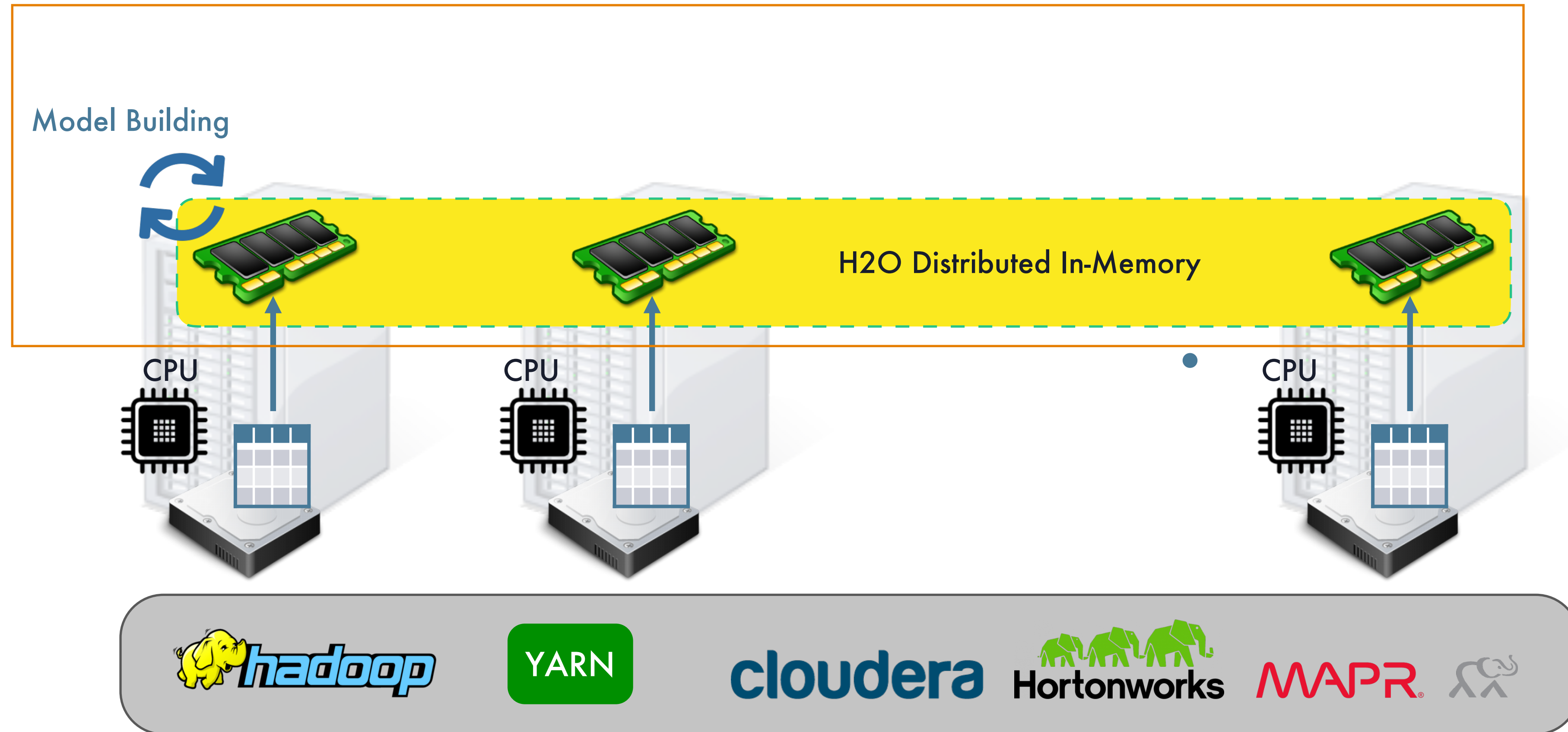
- Includes **Automatic training & tuning** of a large selection of candidate models
- Allows for user-specified performance metric-based **Stopping criterion** or time-limit
- Provides **Real-time monitoring** of model building progress
- Includes highly predictive **Stacked Ensembles** trained on collection of models

What is Completed?

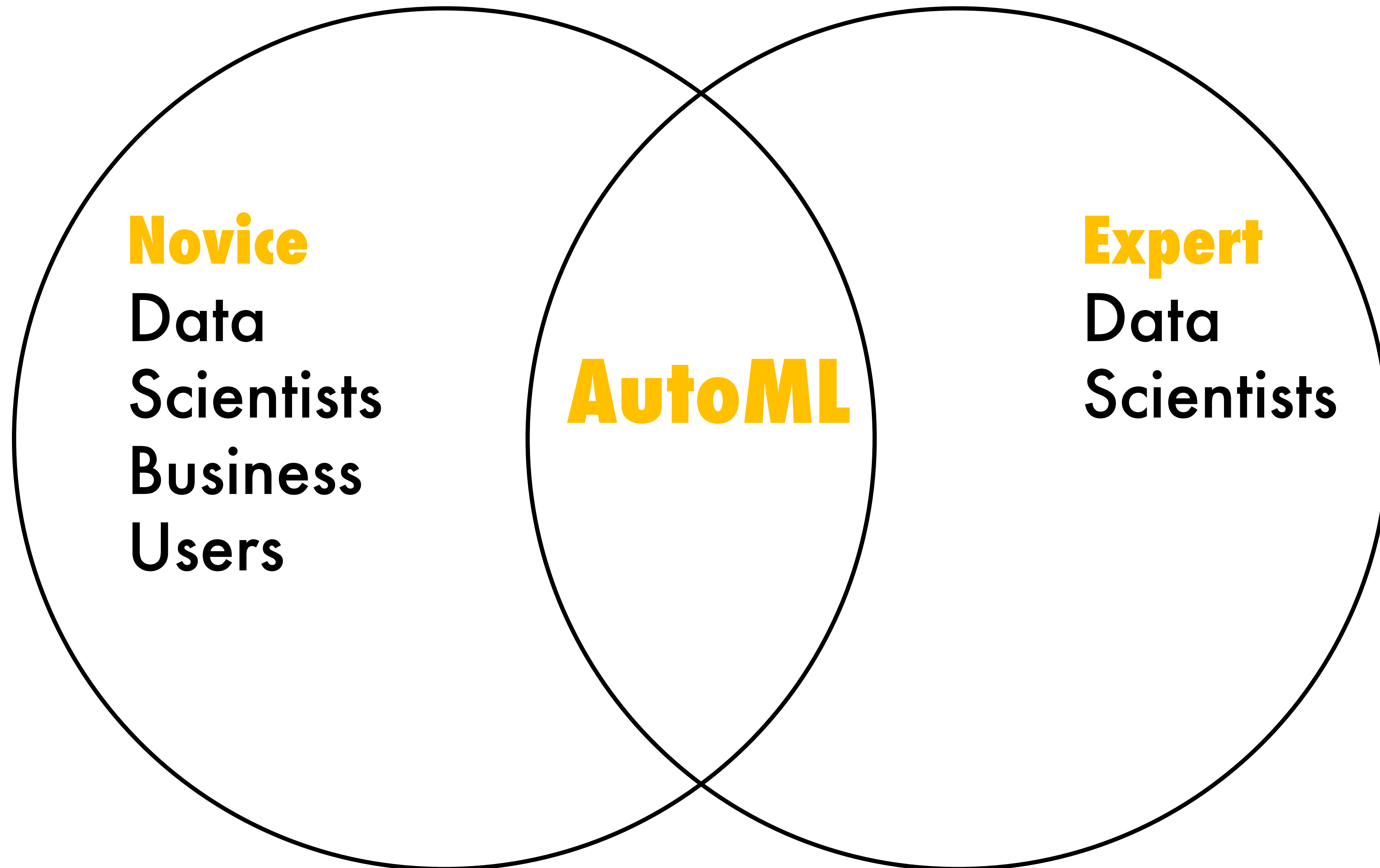


Fast: Distributed & In-Memory

AutoML



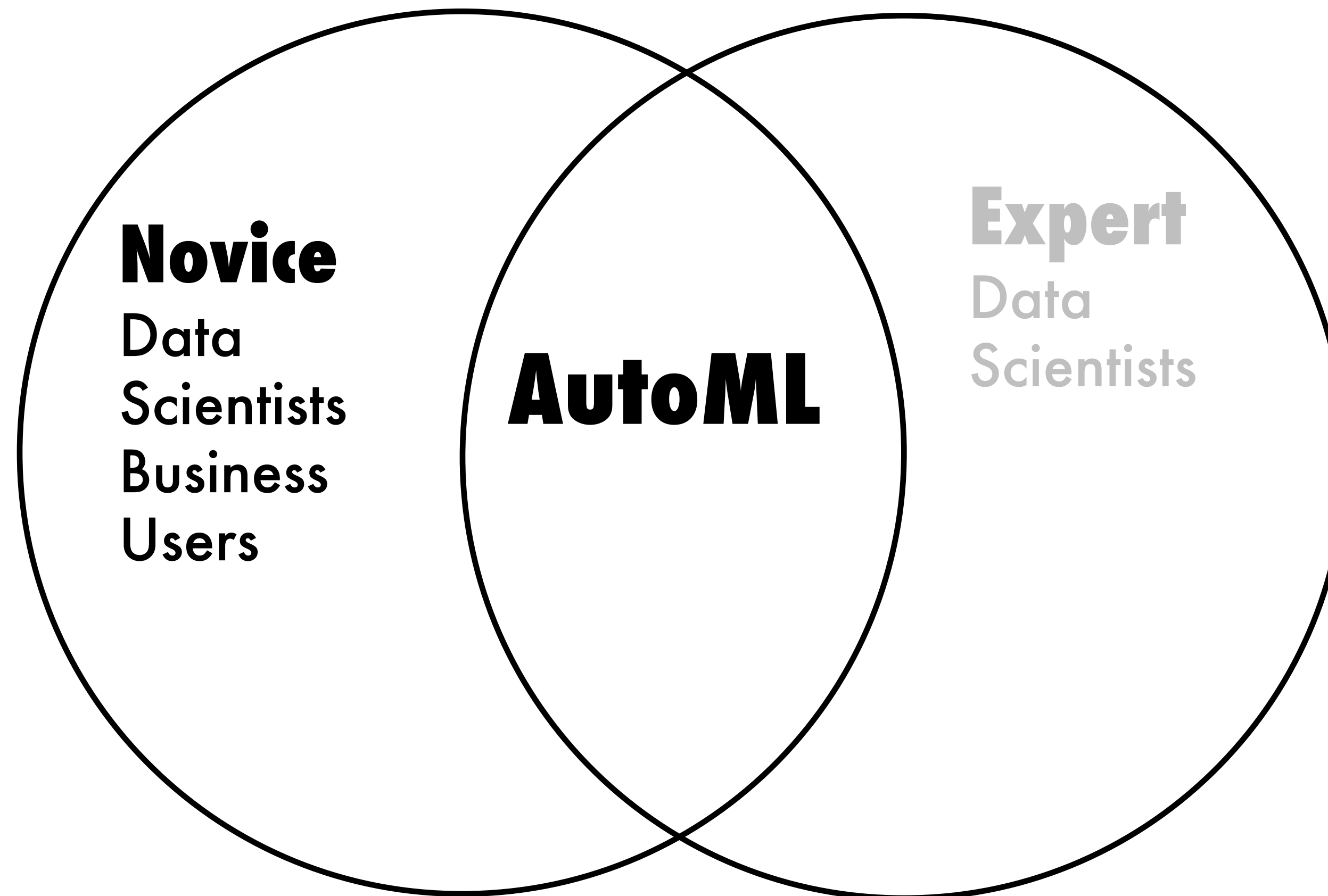
Who is it For?



Who is it For?

AUTOMATES

- **basic preprocessing**
- **model training**
- **hyperparameter tuning**
- **stacking**
- **model results table**



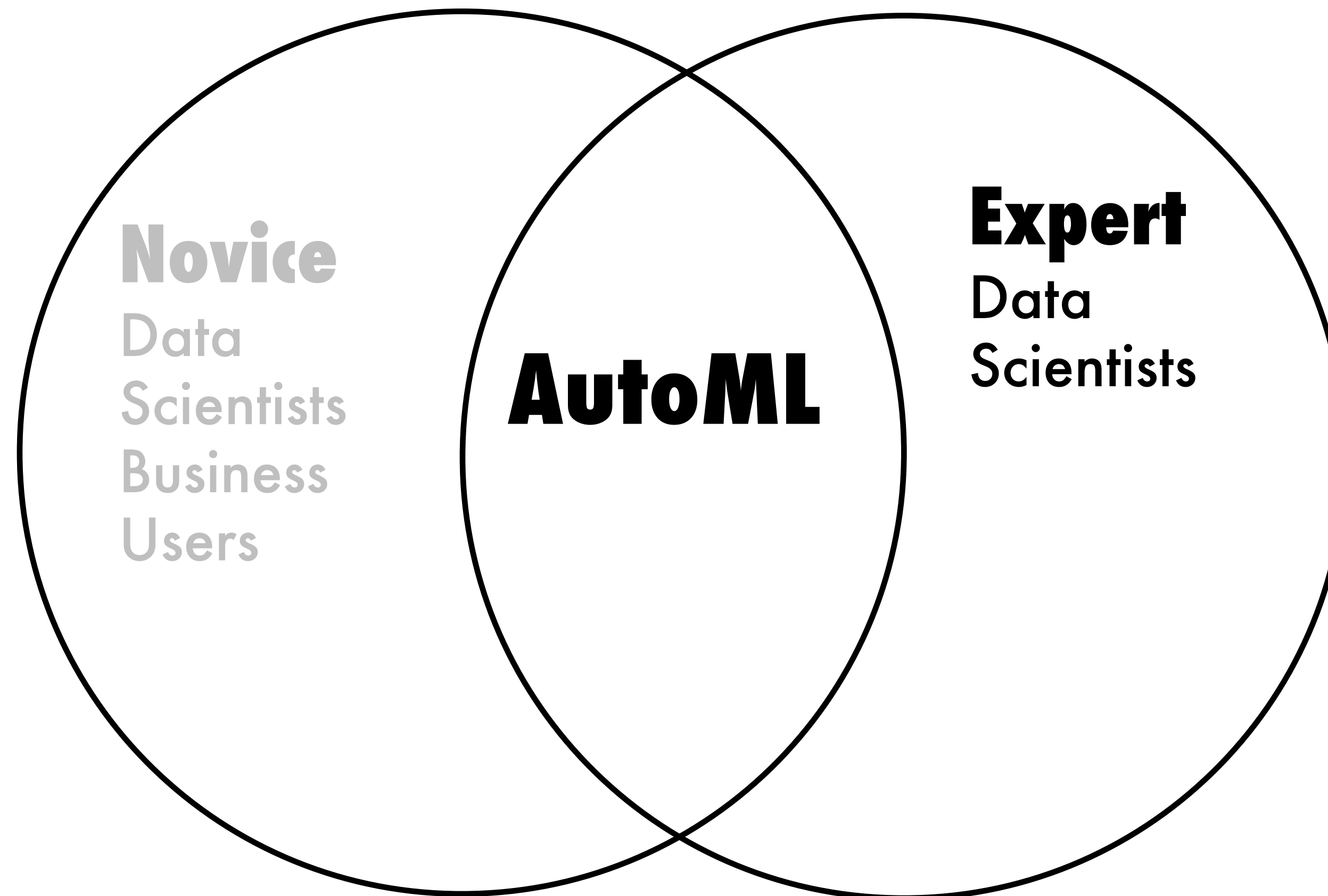
FREES TIME FOR

- data-preprocessing
- feature engineering
- model deployment

Who is it For?

AUTOMATES

- basic preprocessing
- model training
- tuning with validation
- stacking
- model results table



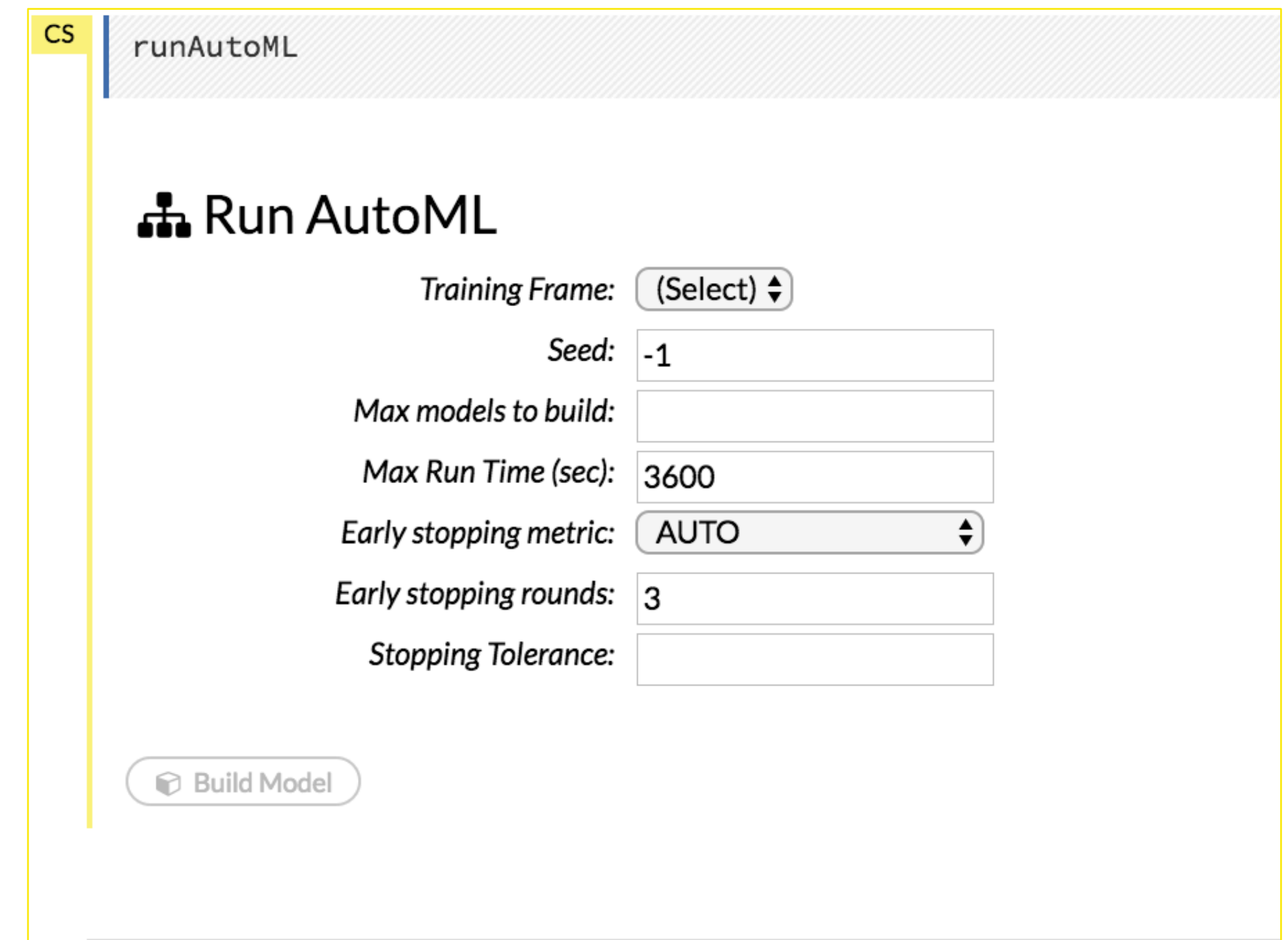
FREES TIME FOR

- data-preprocessing
- feature engineering
- model deployment

The Interface

Simplify Machine Learning

2 Required parameters
training frame & response



The screenshot shows the 'Run AutoML' interface in the H2O.ai environment. The interface is titled 'runAutoML' and features a sidebar with a 'CS' tab. The main area contains the 'Run AutoML' section with the following parameters:

- Training Frame: (Select) ▾
- Seed: -1
- Max models to build:
- Max Run Time (sec): 3600
- Early stopping metric: AUTO ▾
- Early stopping rounds: 3
- Stopping Tolerance:

At the bottom of the interface, there is a 'Build Model' button.

The Interface

R

```
# Identify predictors and response
y <- "response"
x <- setdiff(names(train), y)

aml <- h2o.automl(x = x, y = y,
                 training_frame = train,
                 leaderboard_frame = test,
                 max_runtime_secs = 30)

# View the AutoML Leaderboard
lb <- aml@leaderboard
lb
```

PYTHON

```
# Identify predictors and response
x = train.columns
y = "response"
x.remove(y)

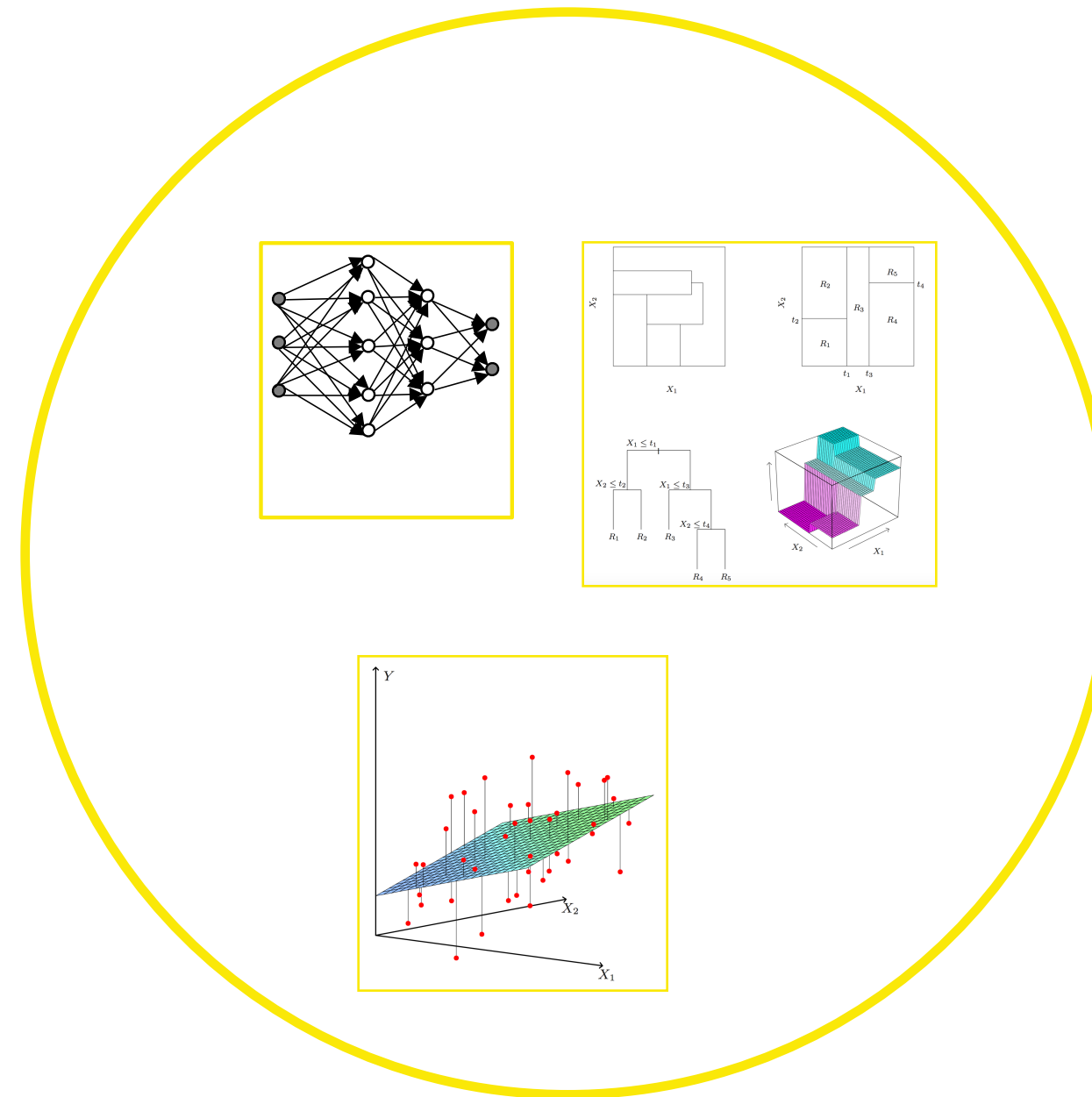
# Run AutoML for 30 seconds
aml = H2OAutoML(max_runtime_secs = 30)
aml.train(x = x, y = y,
          training_frame = train,
          leaderboard_frame = test)

# View the AutoML Leaderboard
lb = aml.leaderboard
lb
```

Behind the Scenes

Grid Search

- Large selection of models
- Hyperparameter tuning
- Early Stopping

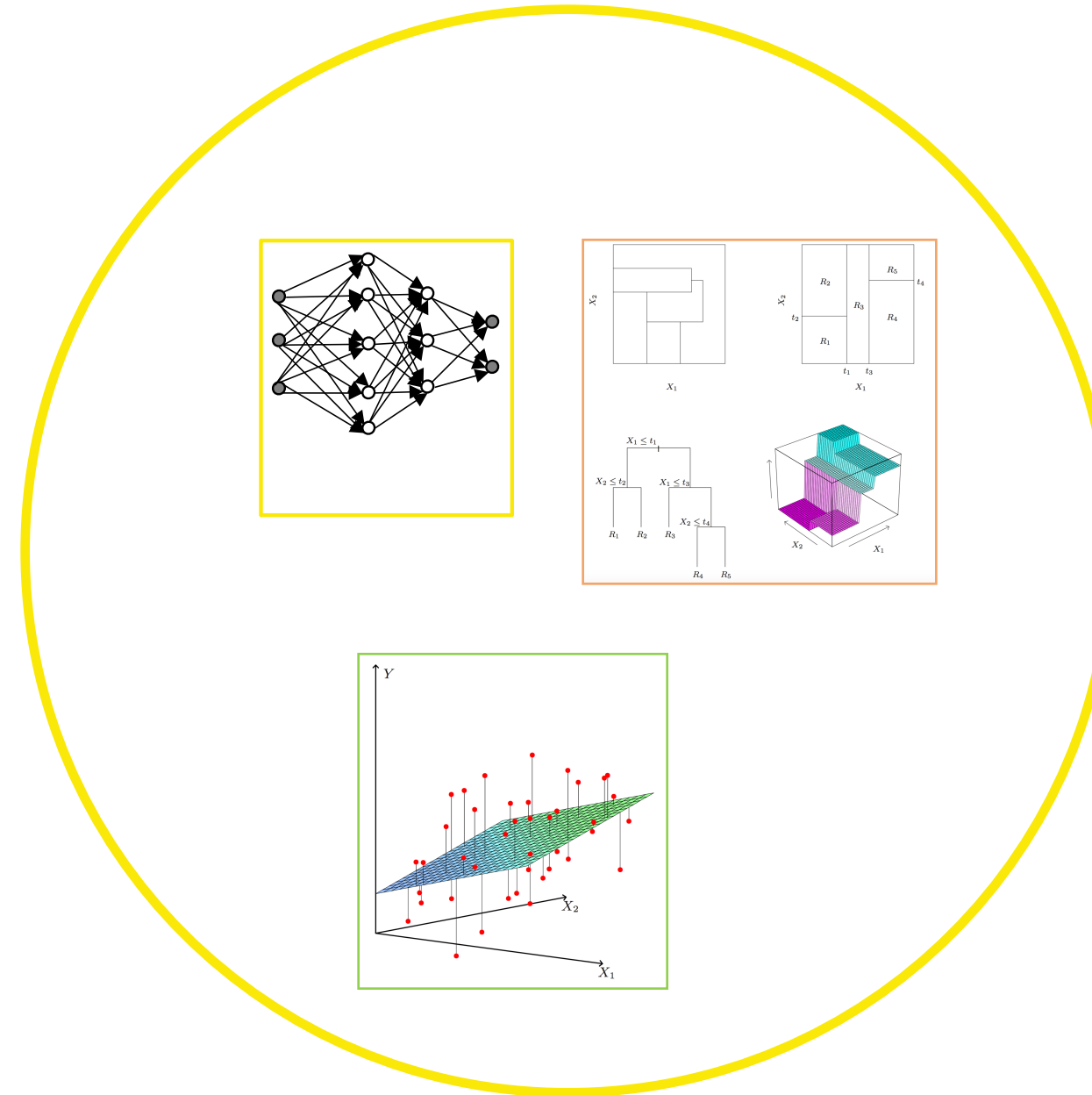


Behind the Scenes

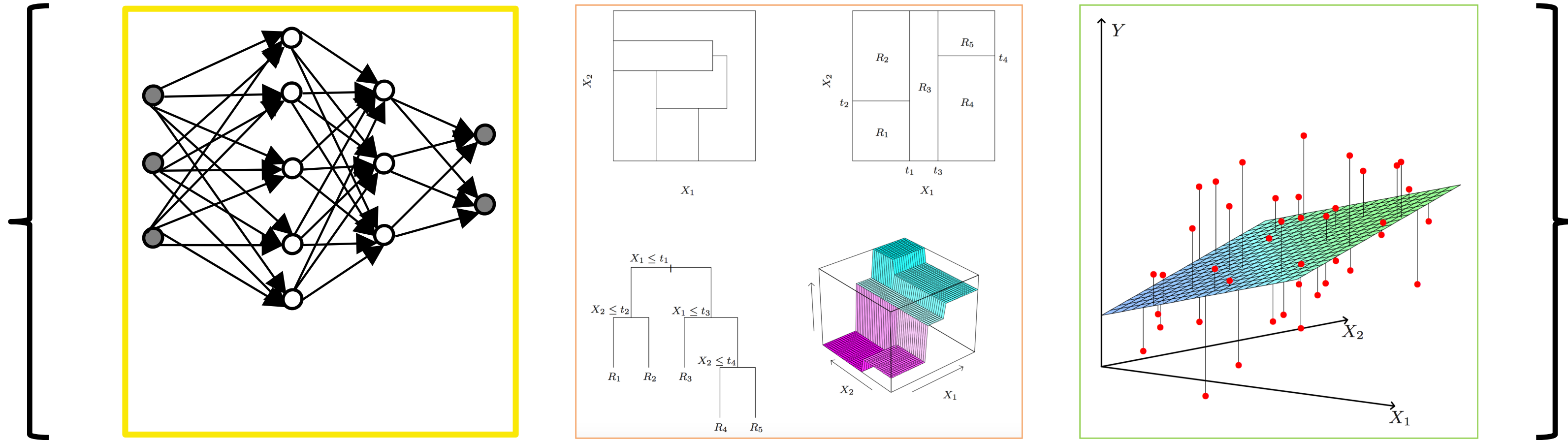
Stacked Ensemble



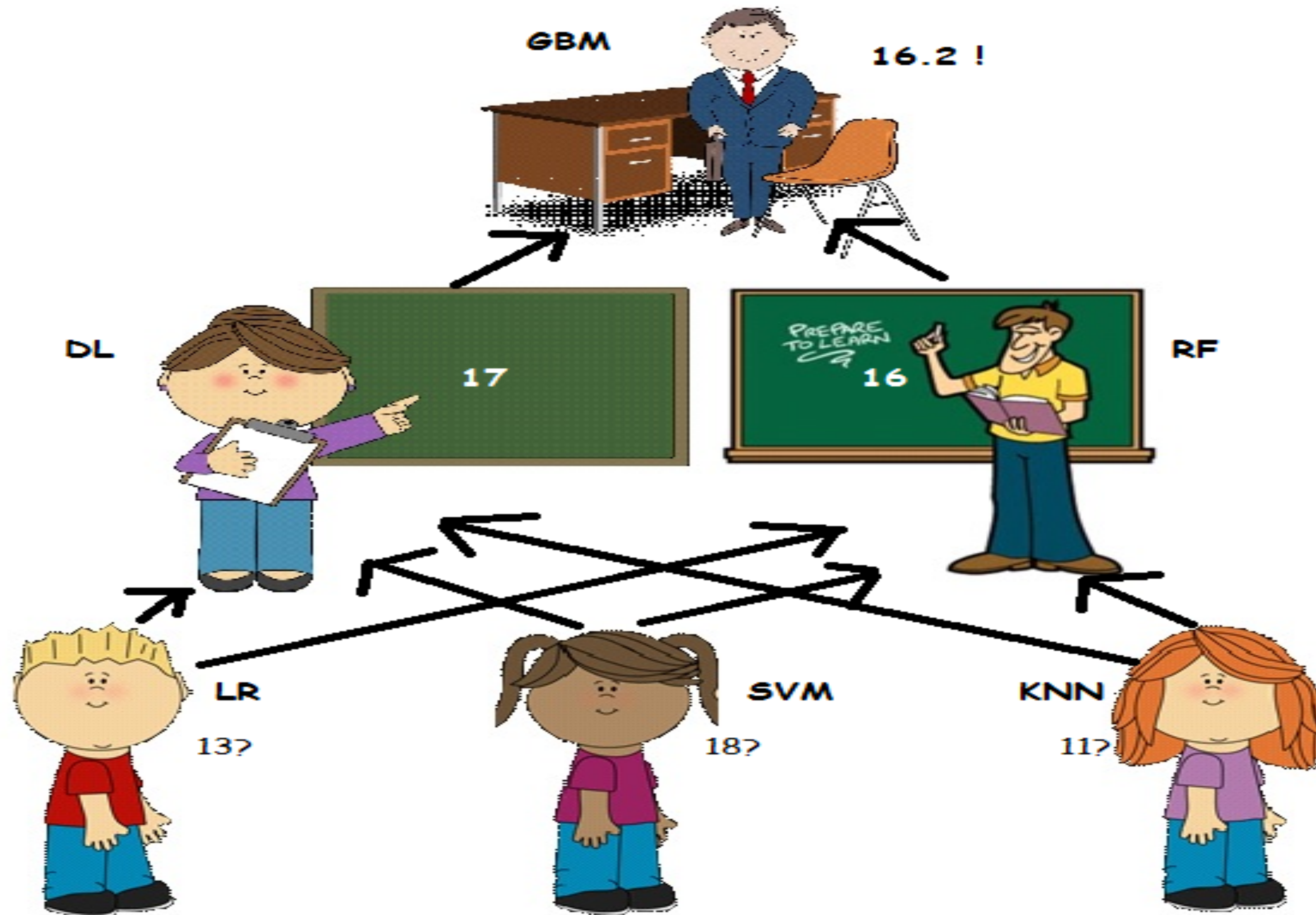
- Highly predictive ensemble trains on all the models



Stacking Base Learners

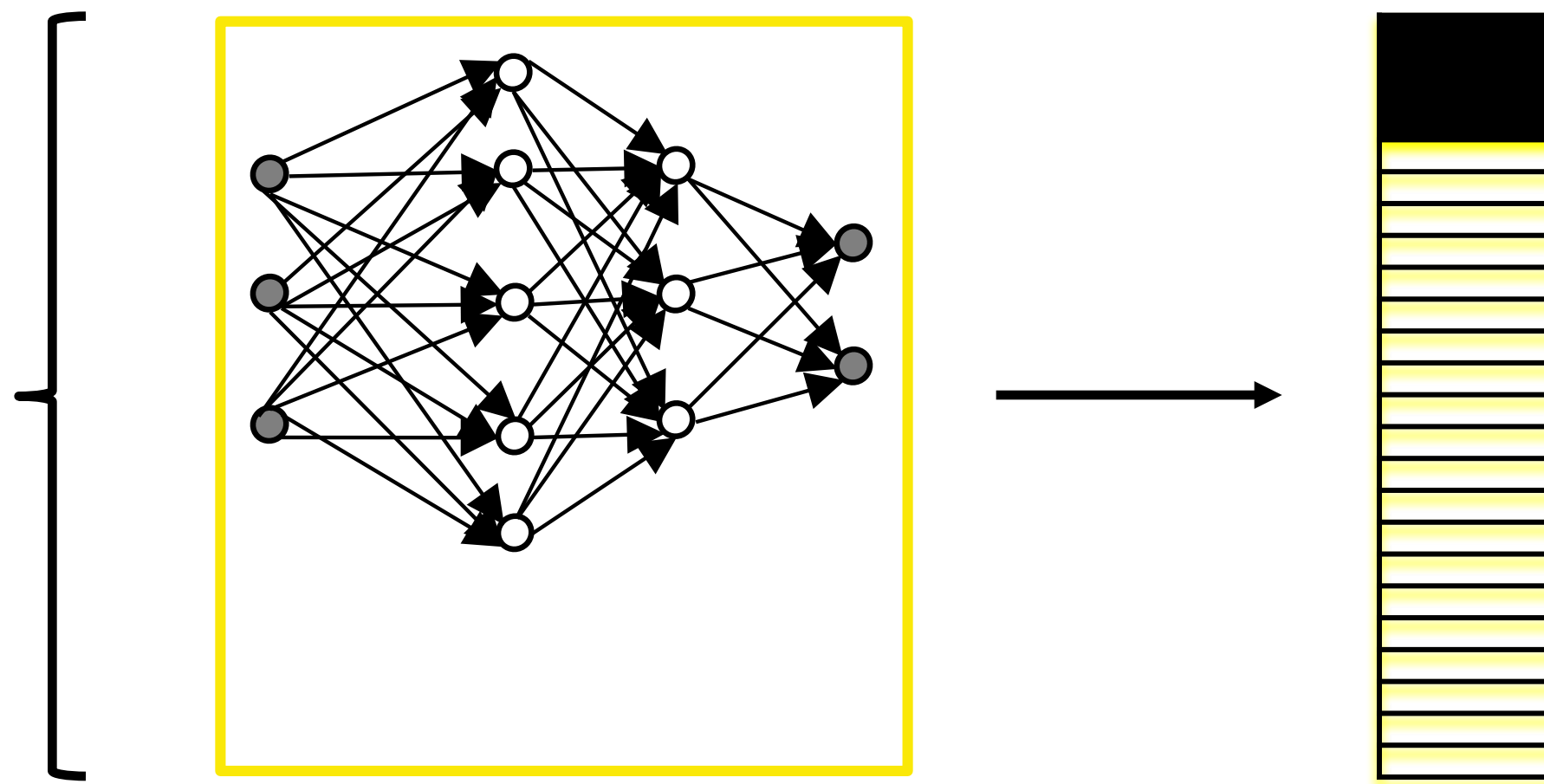


Why meta modelling?



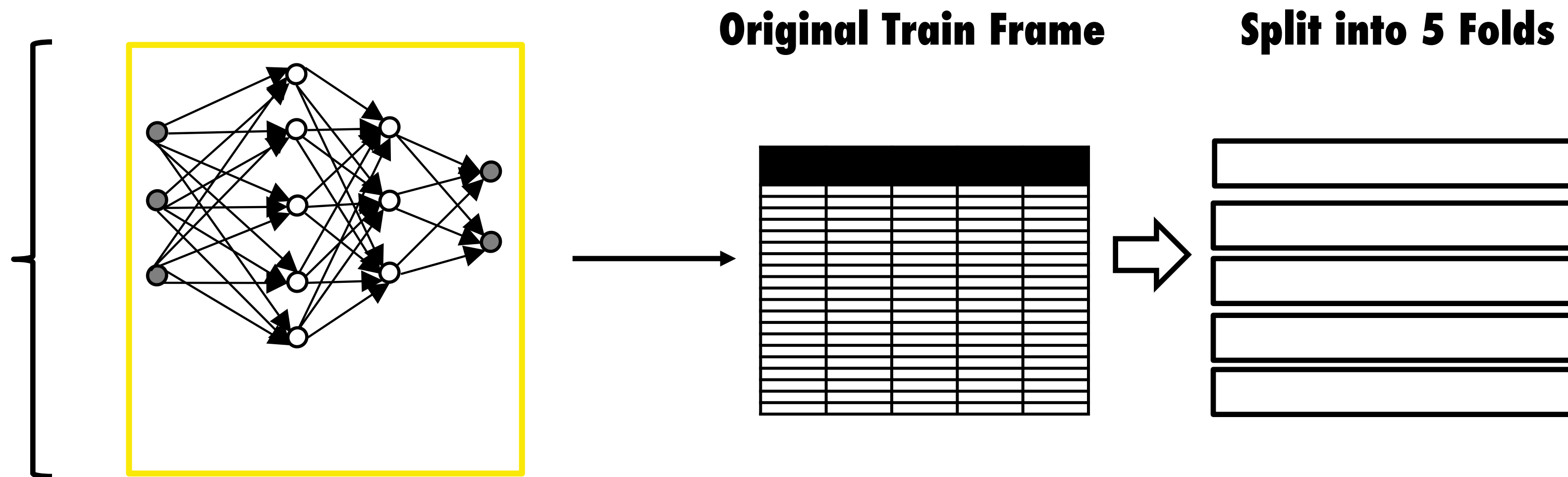
Base Learner Results

CV Prediction Results Column



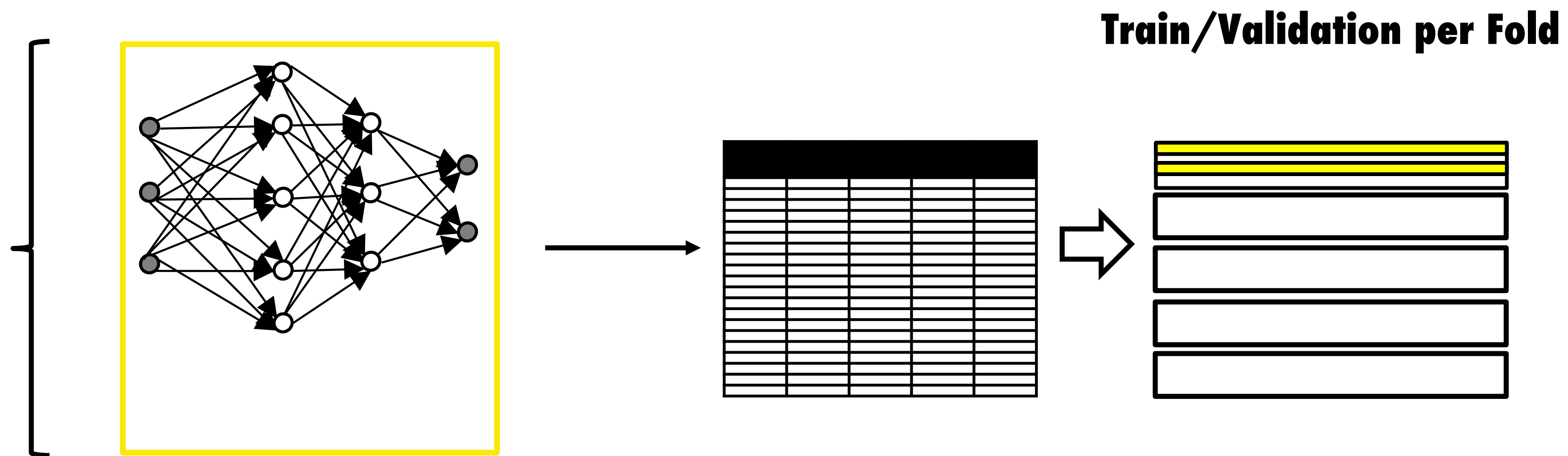
Get CV Prediction Column

Split Dataset



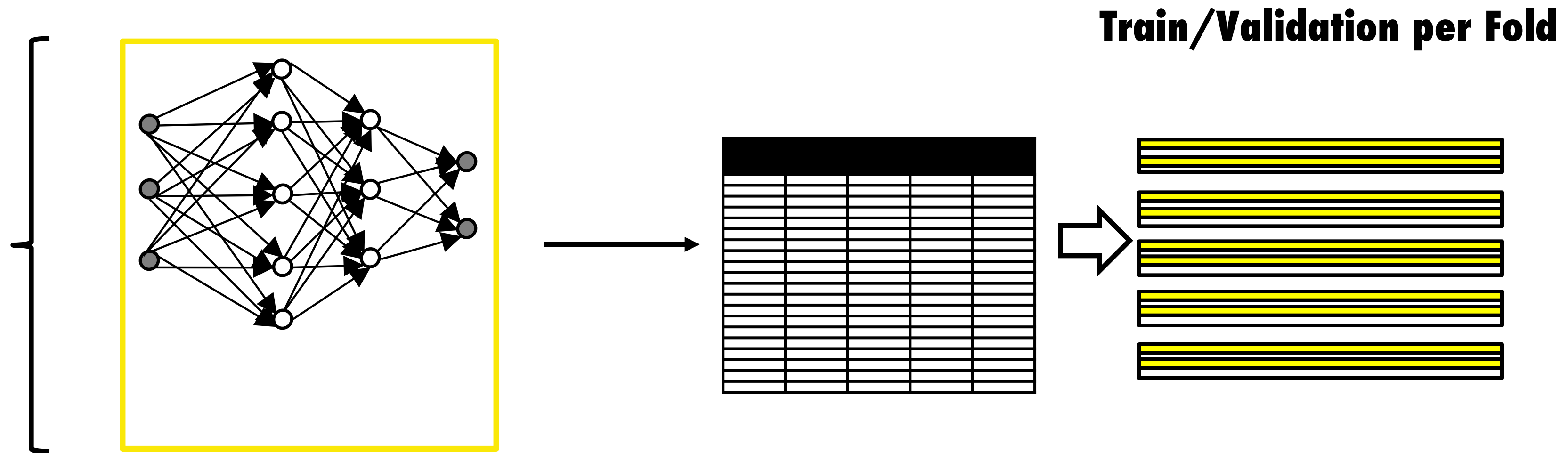
Behind the Scenes

Split into Train and Valid



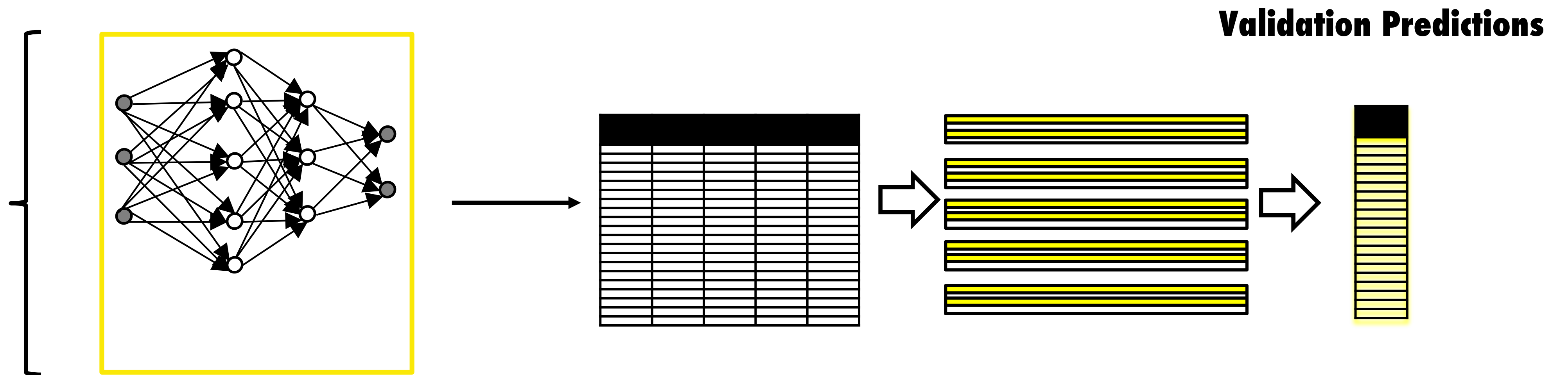
Behind the Scenes

Split into Train and Valid per Fold



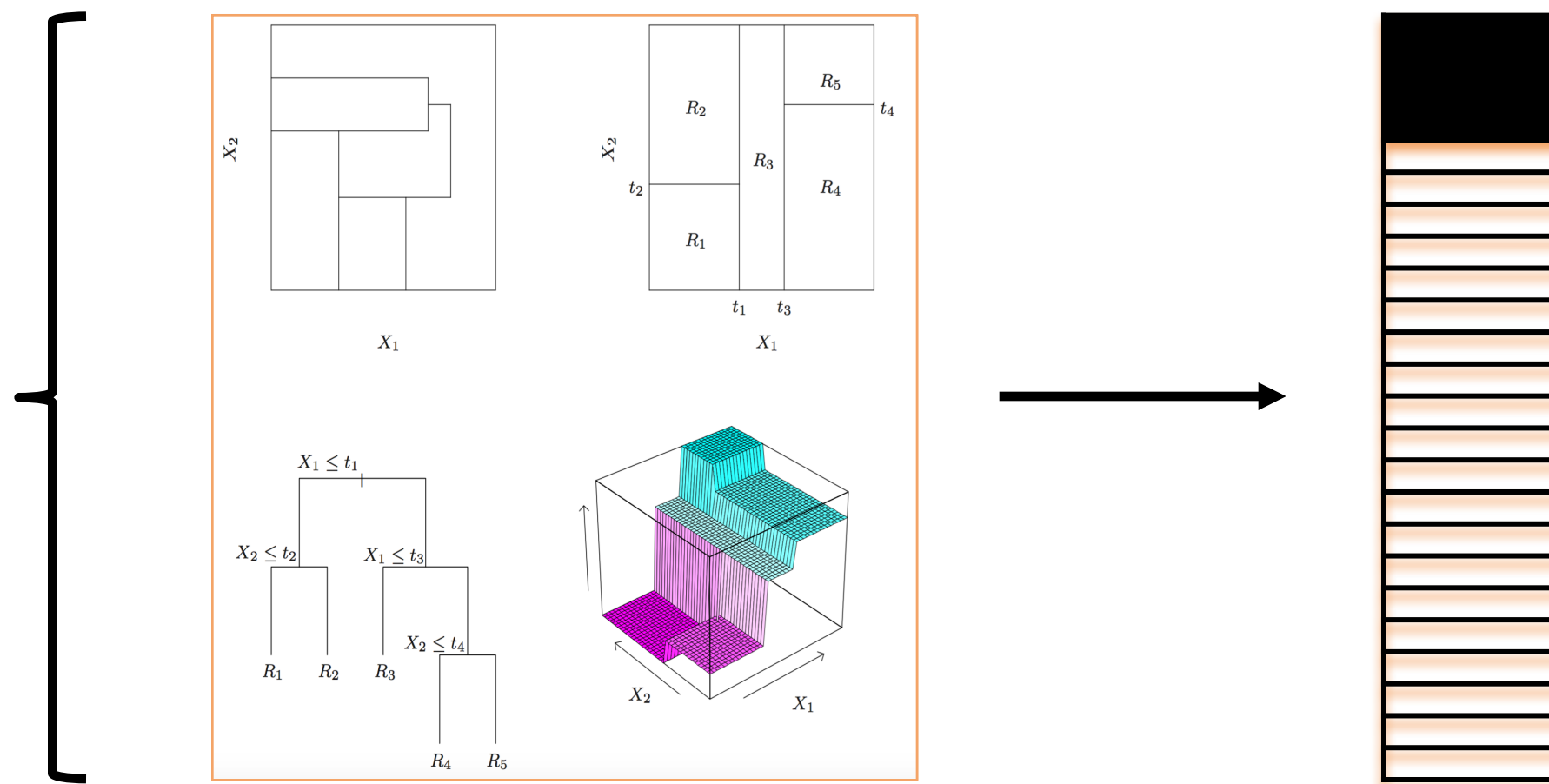
Behind the Scenes

Form Prediction Column

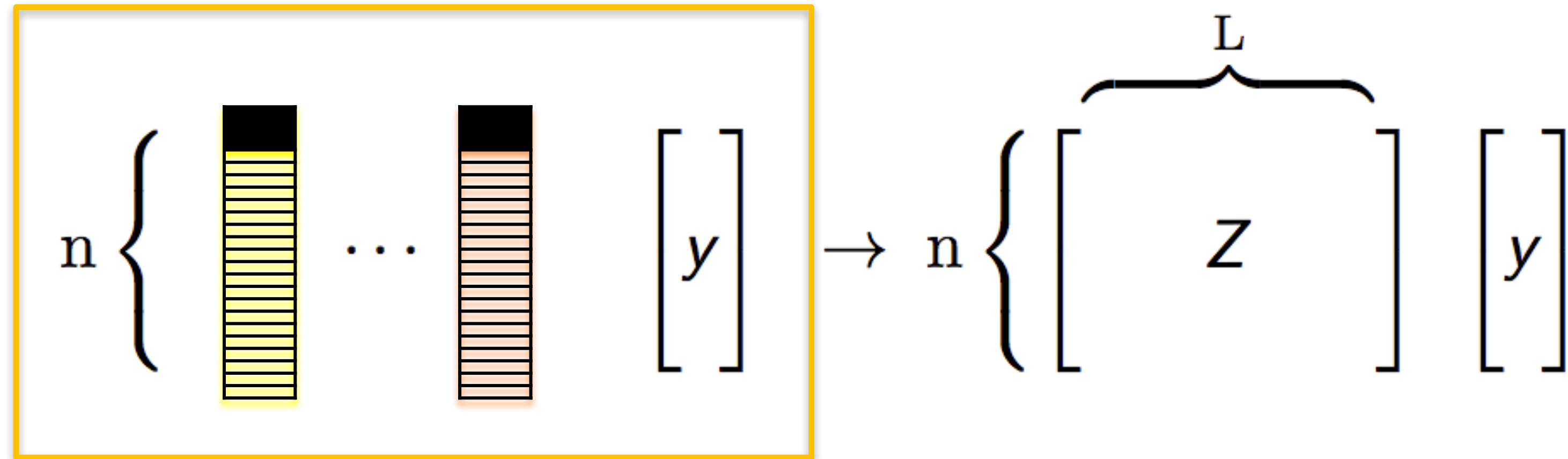


Base Learner Results

Prediction Results Column



Stacking: Level-One Data



- Collect the predicted values from k -fold CV that was performed on each of the L base learners

Stacking: Level-One Data

$$n \left\{ \begin{bmatrix} p_1 \end{bmatrix} \cdots \begin{bmatrix} p_L \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\} \rightarrow n \left\{ \begin{bmatrix} \overbrace{\quad\quad\quad}^L \\ z \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\}$$

- Collect the predicted values from k -fold CV that was performed on each of the L base learners

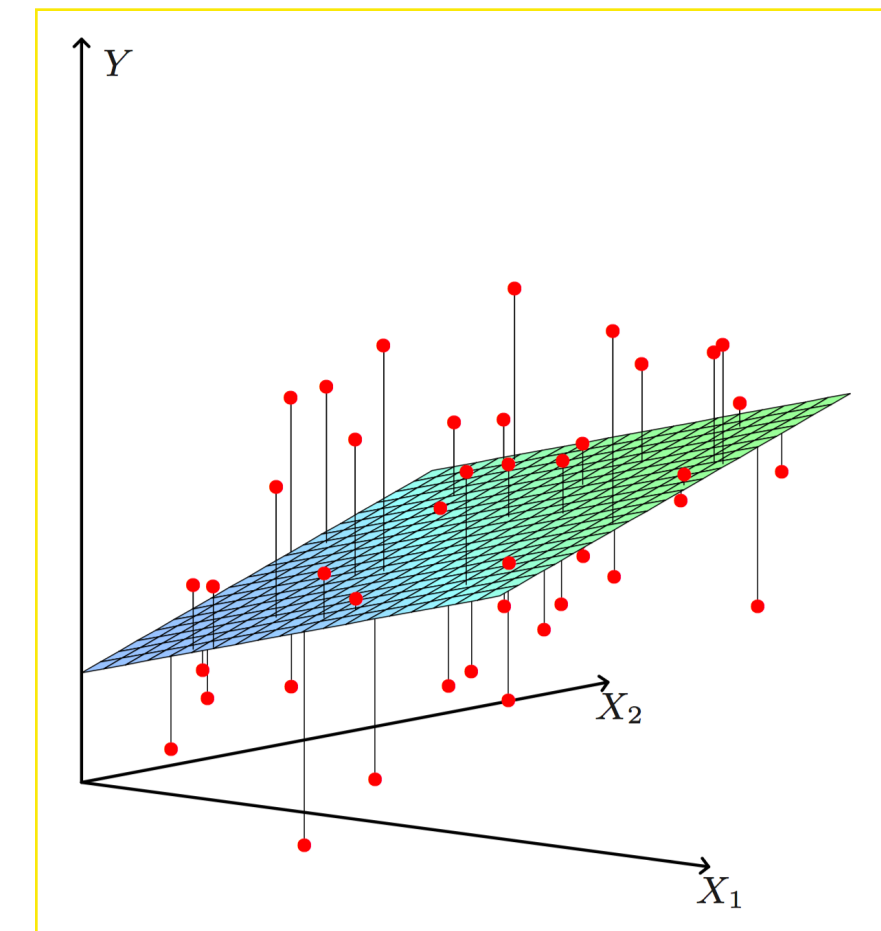
Stacking: Level-One Data

$$n \left\{ \begin{bmatrix} p_1 \end{bmatrix} \cdots \begin{bmatrix} p_L \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\} \rightarrow n \left\{ \begin{bmatrix} \overbrace{\hspace{1.5cm}}^L \\ Z \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\}$$

- Collect the predicted values from k -fold CV that was performed on each of the L base learners
- Column-bind (“stack”) these prediction vectors together to form a new design matrix, Z

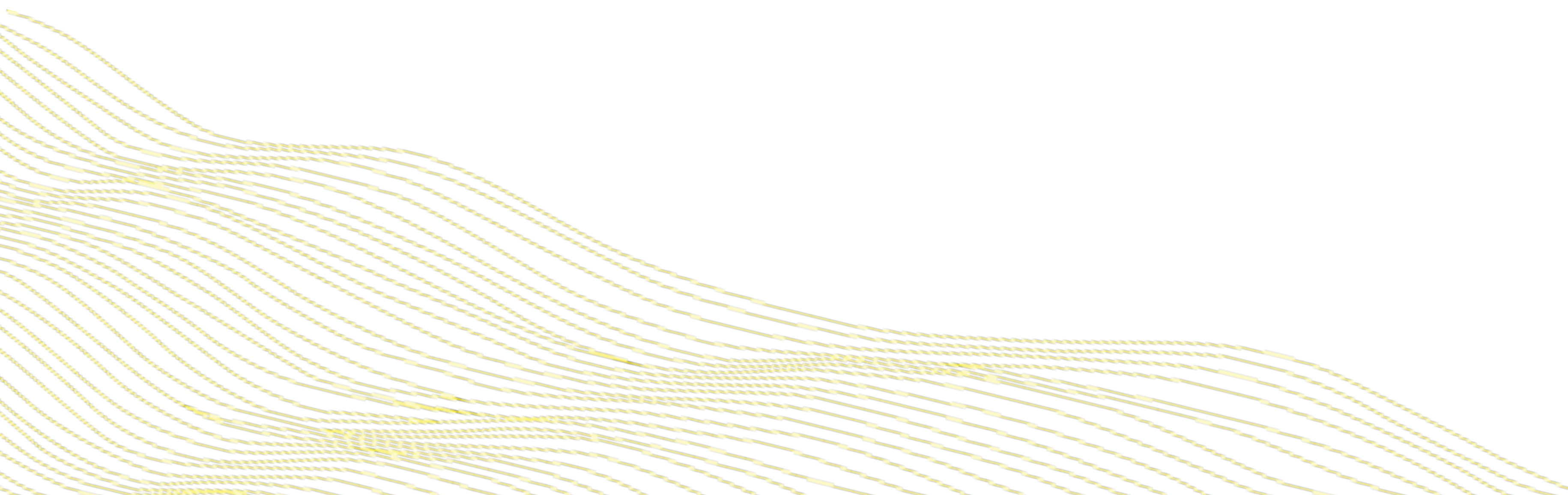
Stacking: Level-One Data

$$n \left\{ \begin{bmatrix} p_1 \end{bmatrix} \cdots \begin{bmatrix} p_L \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\} \rightarrow n \left\{ \begin{bmatrix} \overbrace{\hspace{1cm}}^L \\ Z \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\}$$



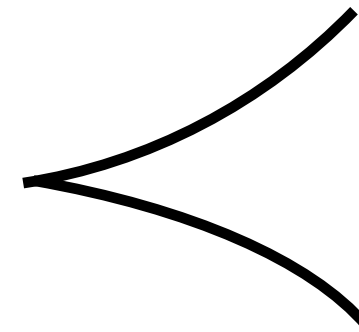
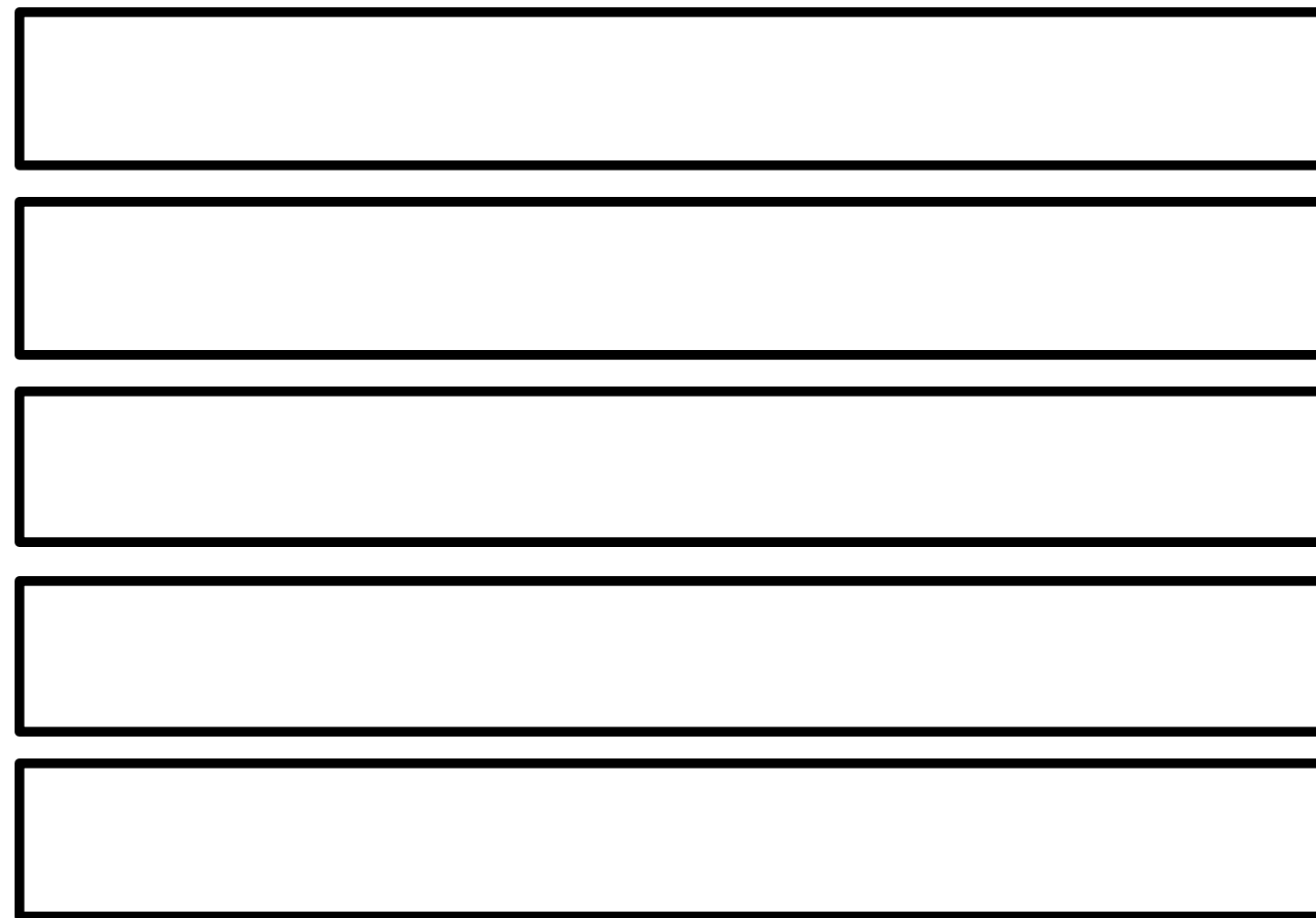
- Collect the predicted values from k -fold CV that was performed on each of the L base learners
- Column-bind (“stack”) these prediction vectors together to form a new design matrix, Z
- Train the metalearner (currently a GLM) using Z, y

Appendix

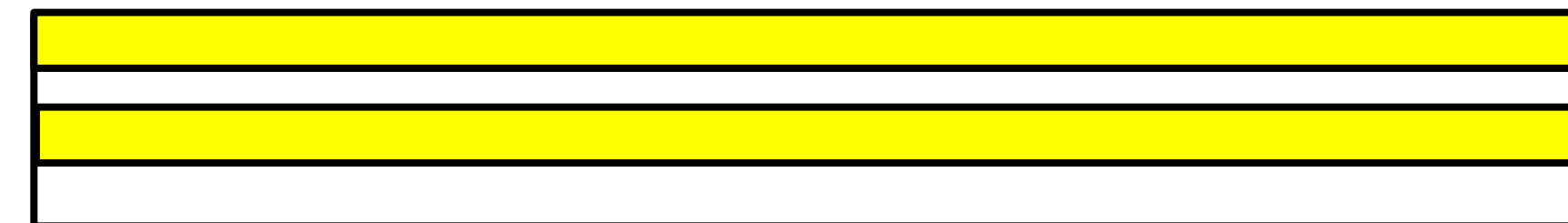


5-fold Cross Validation

Full Data Set



Each Fold



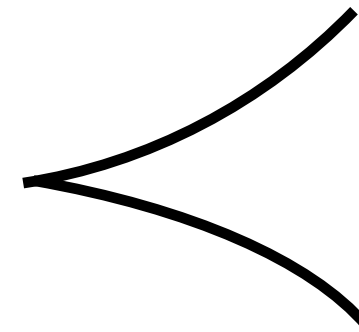
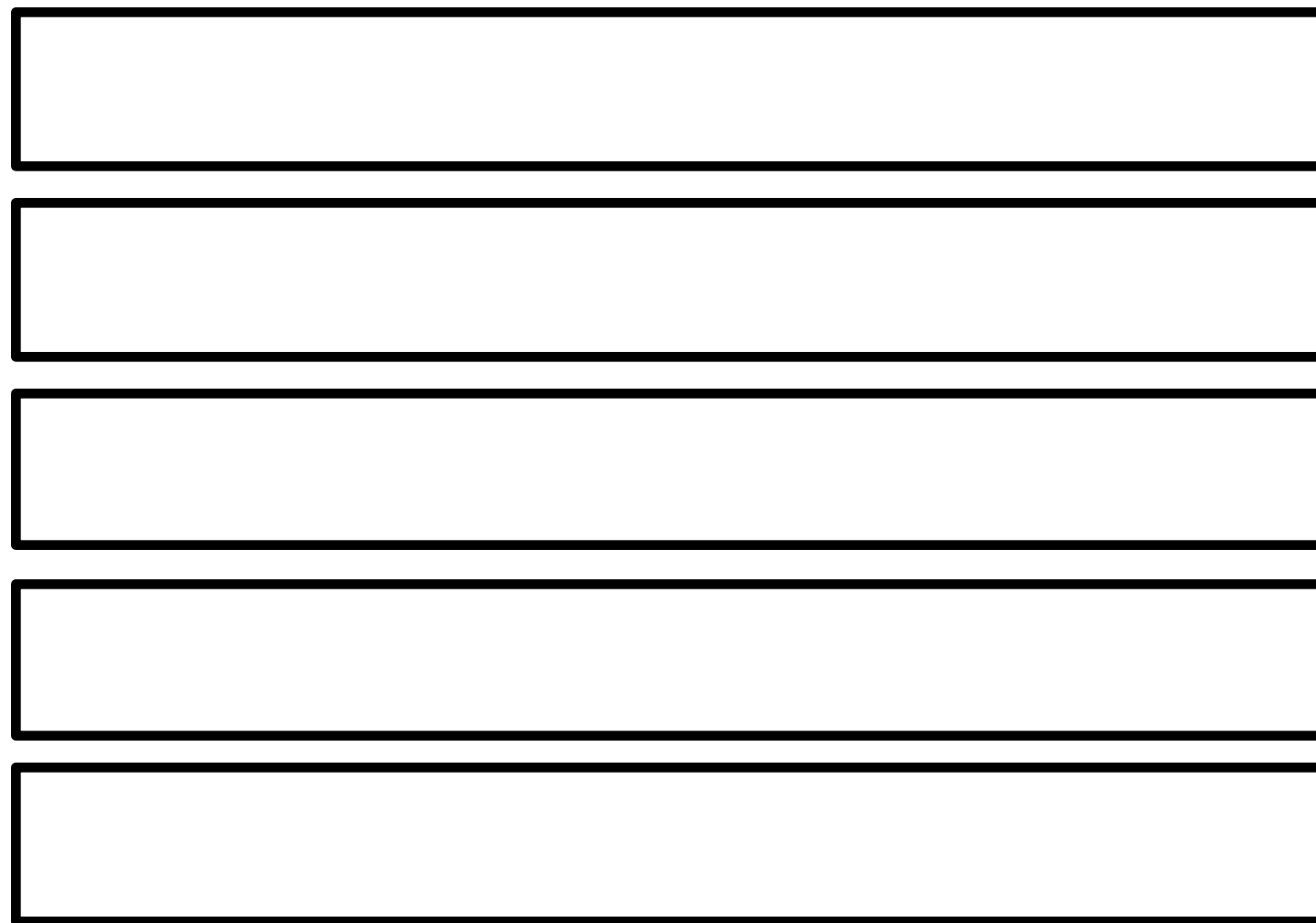
Validation Rows



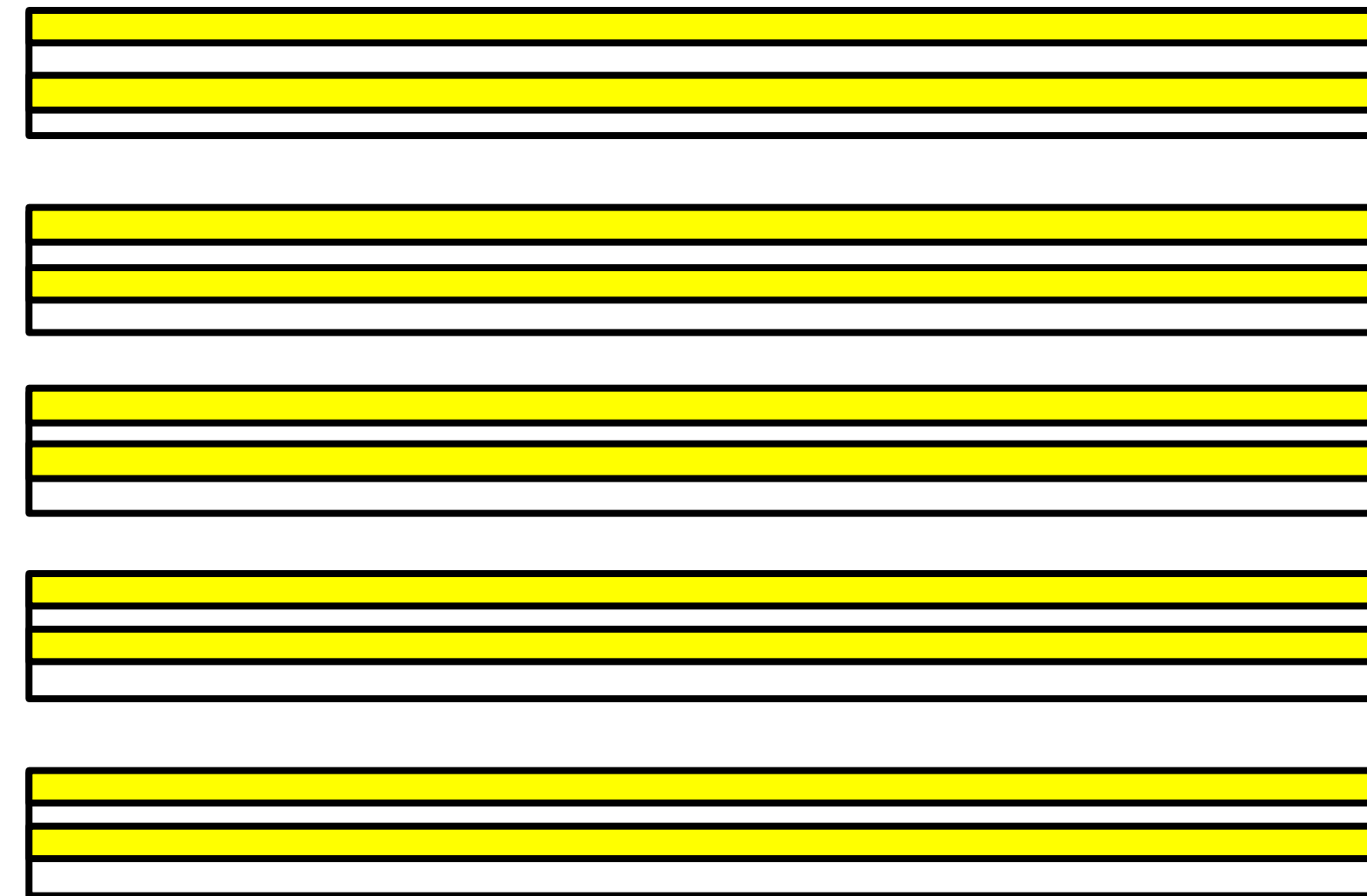
Training Rows

5-fold Cross Validation

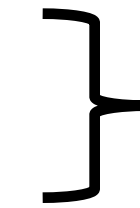
Full Data Set



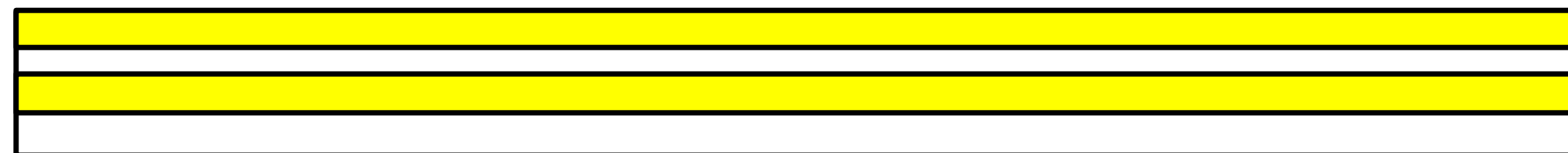
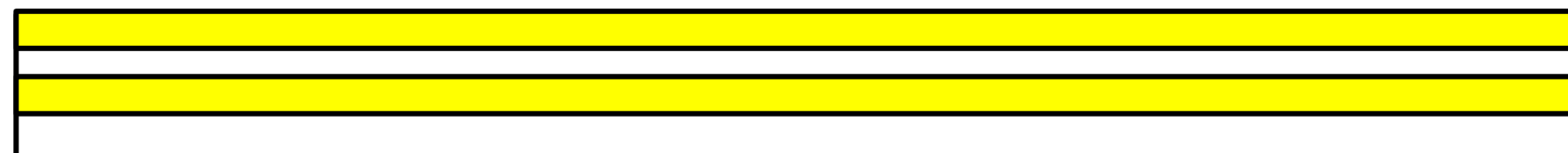
5 Folds



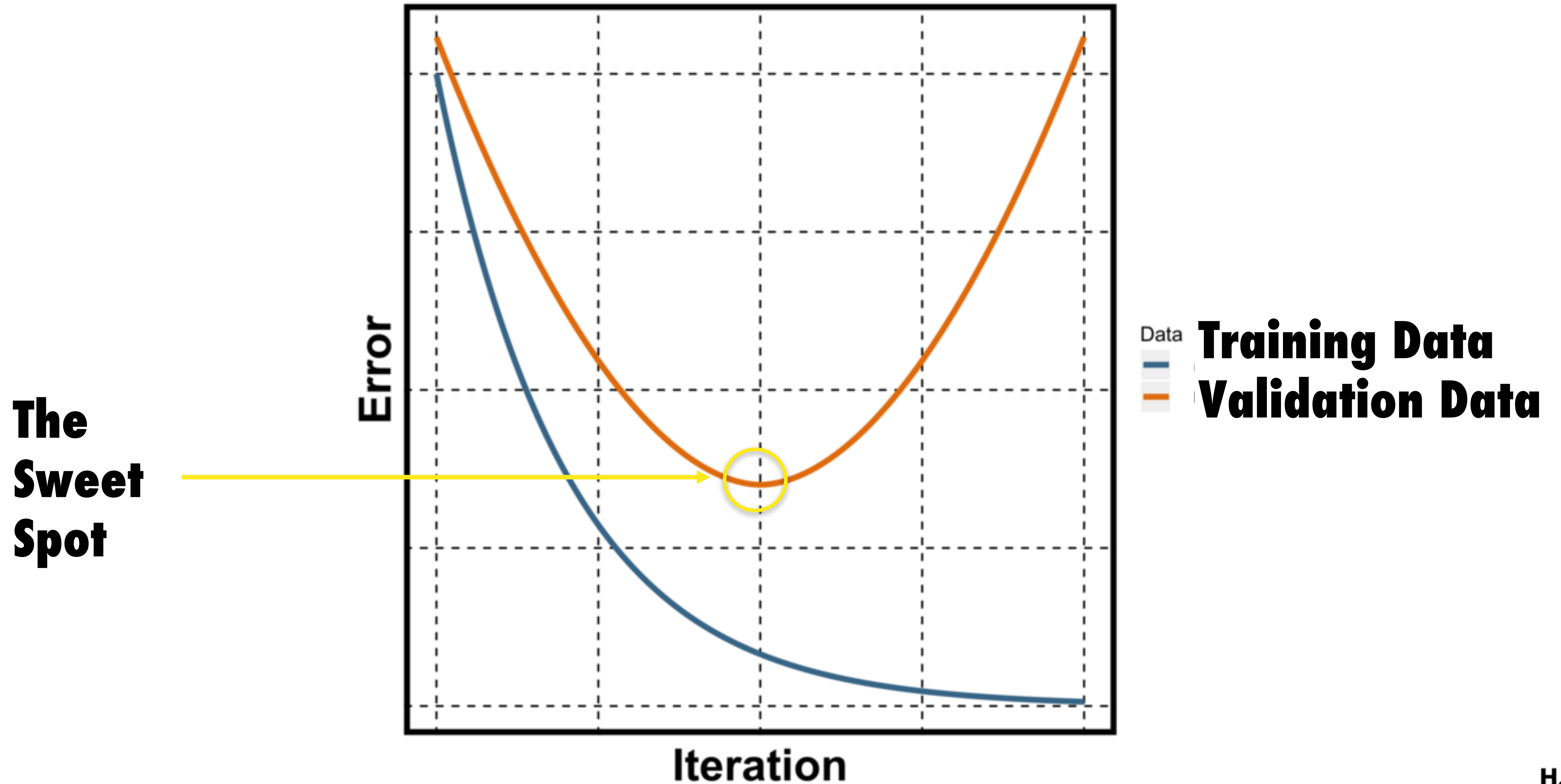
5-fold Cross Validation



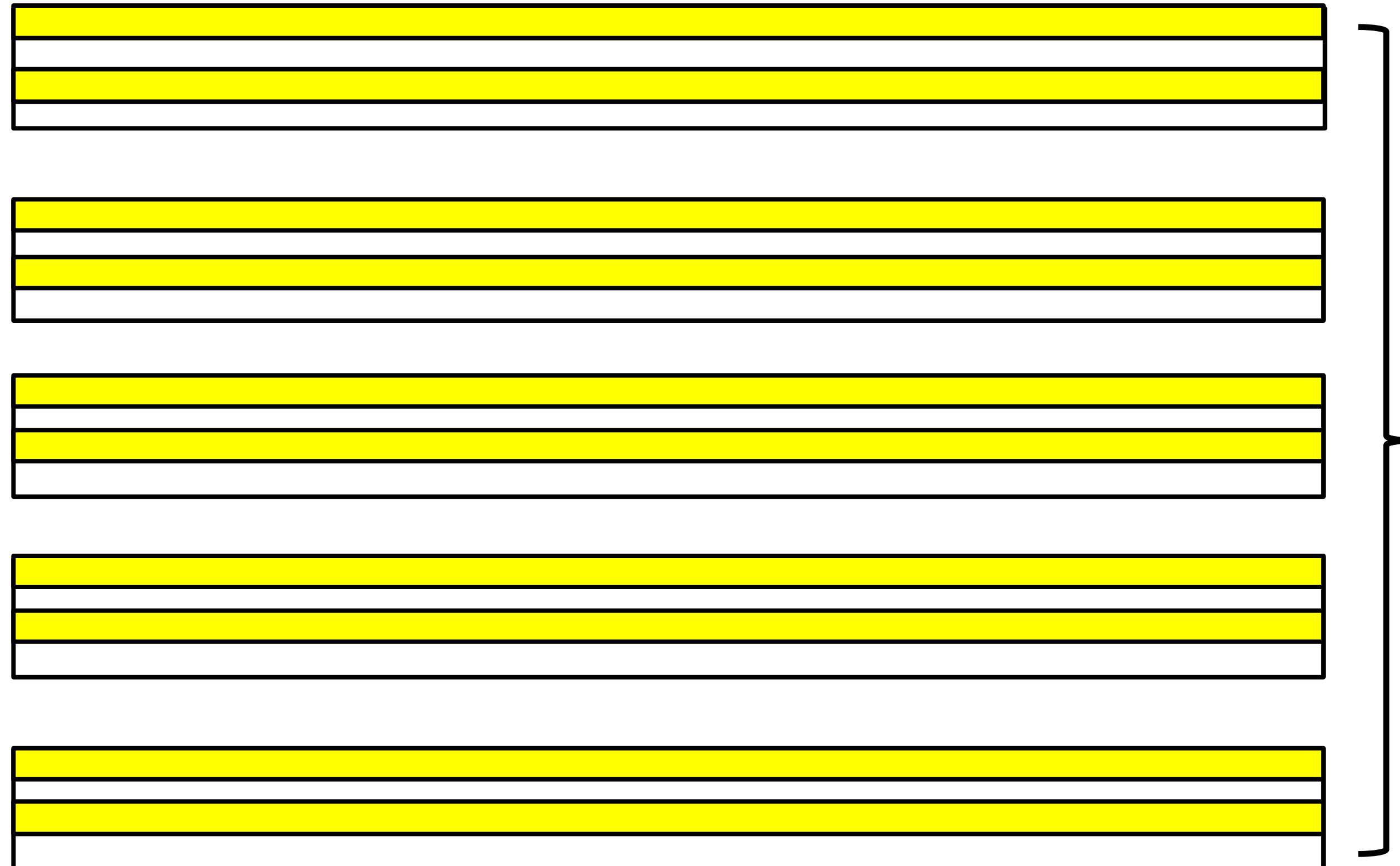
Early stopping happens within each fold



Early Stopping



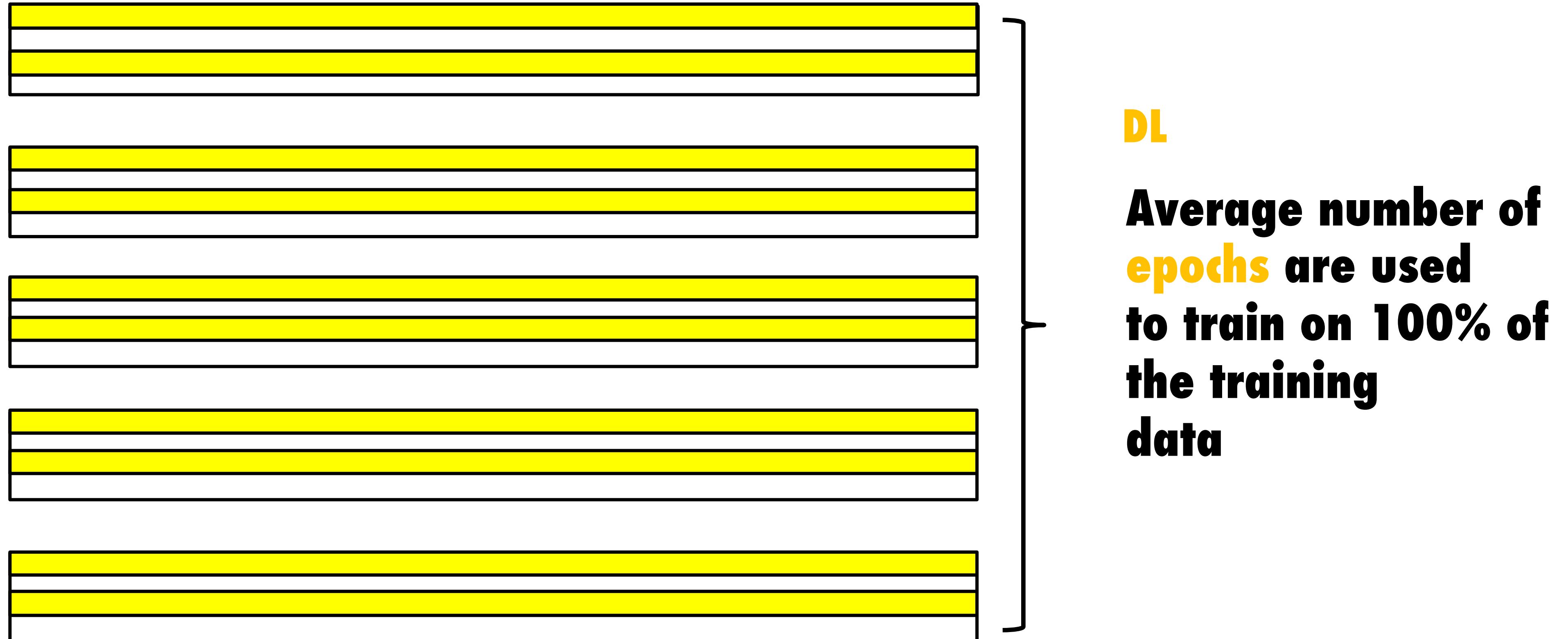
5-fold Cross Validation



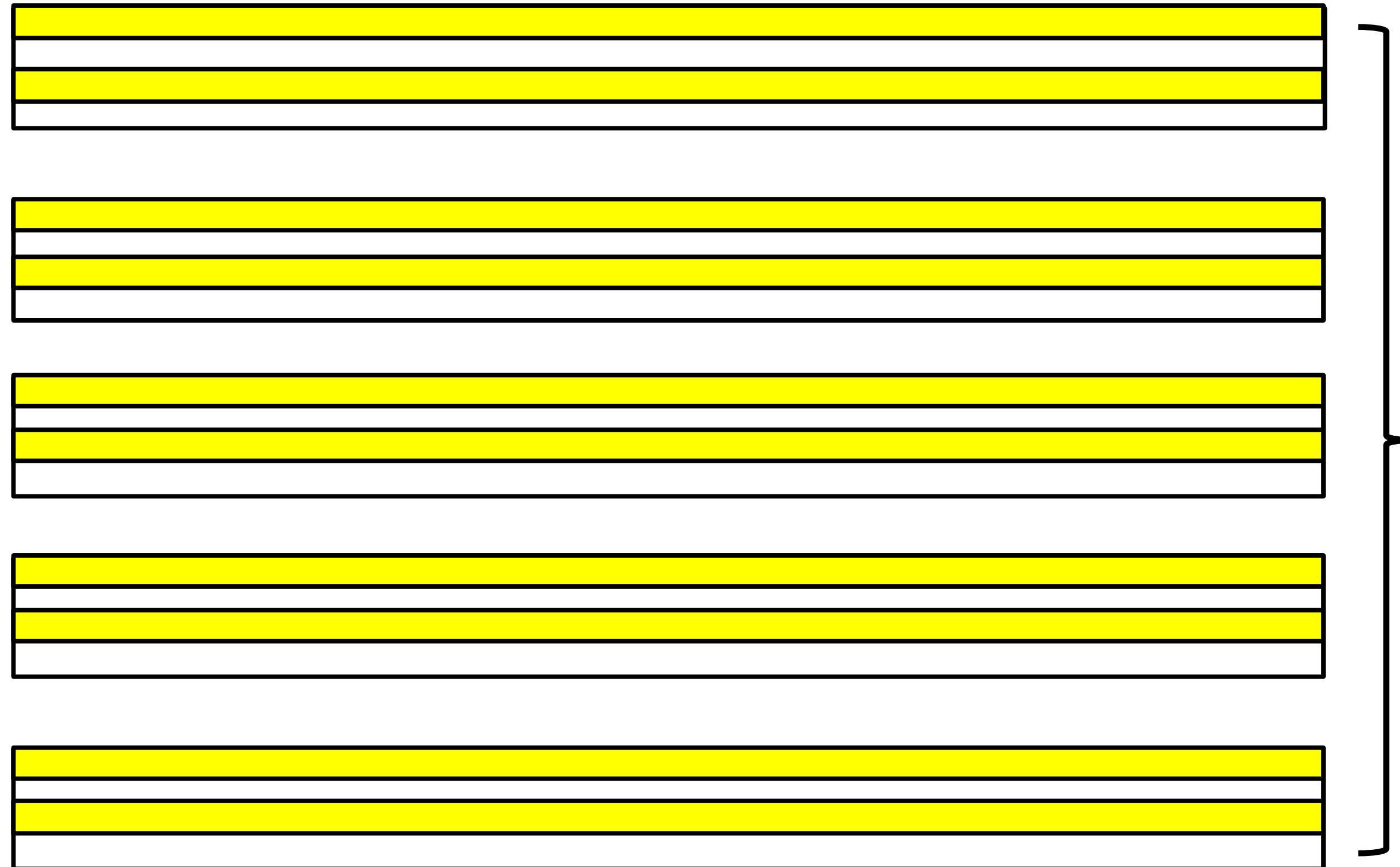
GBM

**Average number of
trees are used
to train on 100% of
the training
data**

5-fold Cross Validation



5-fold Cross Validation

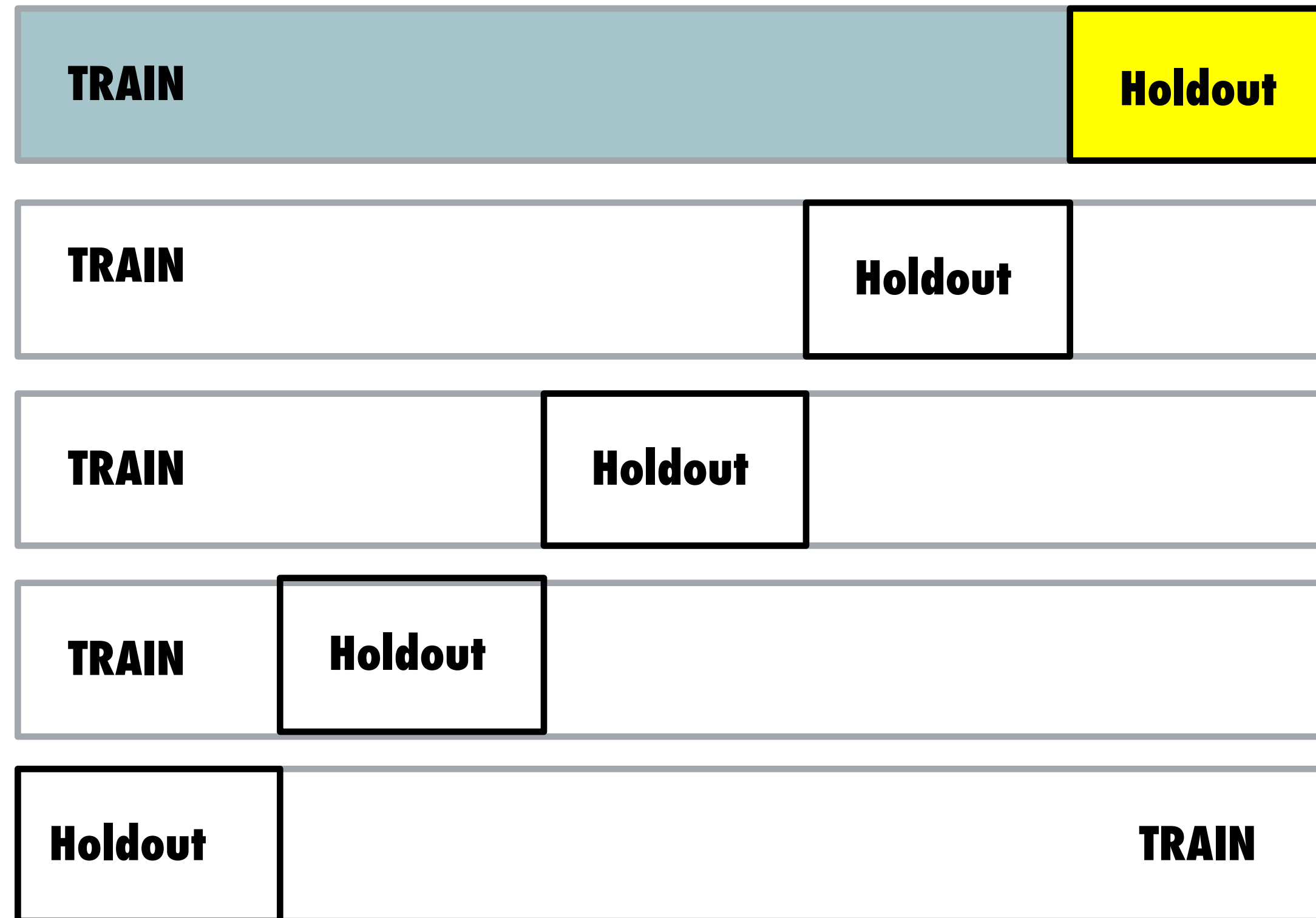


GLM

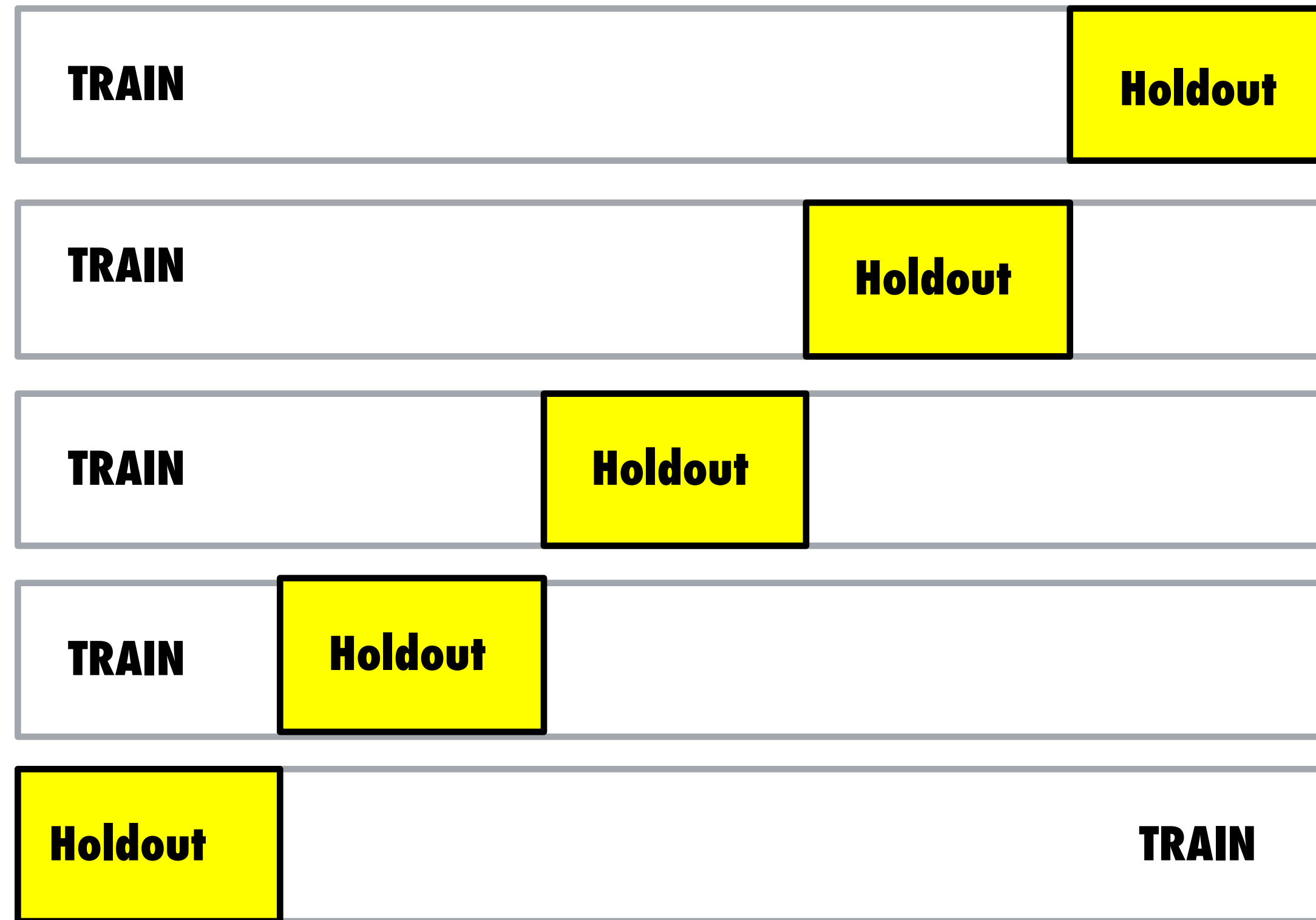
Best **Lambda from all folds is used to train on 100% of the training data**

5-fold Cross Validation

Each Fold Uses its Holdout for Early Stopping

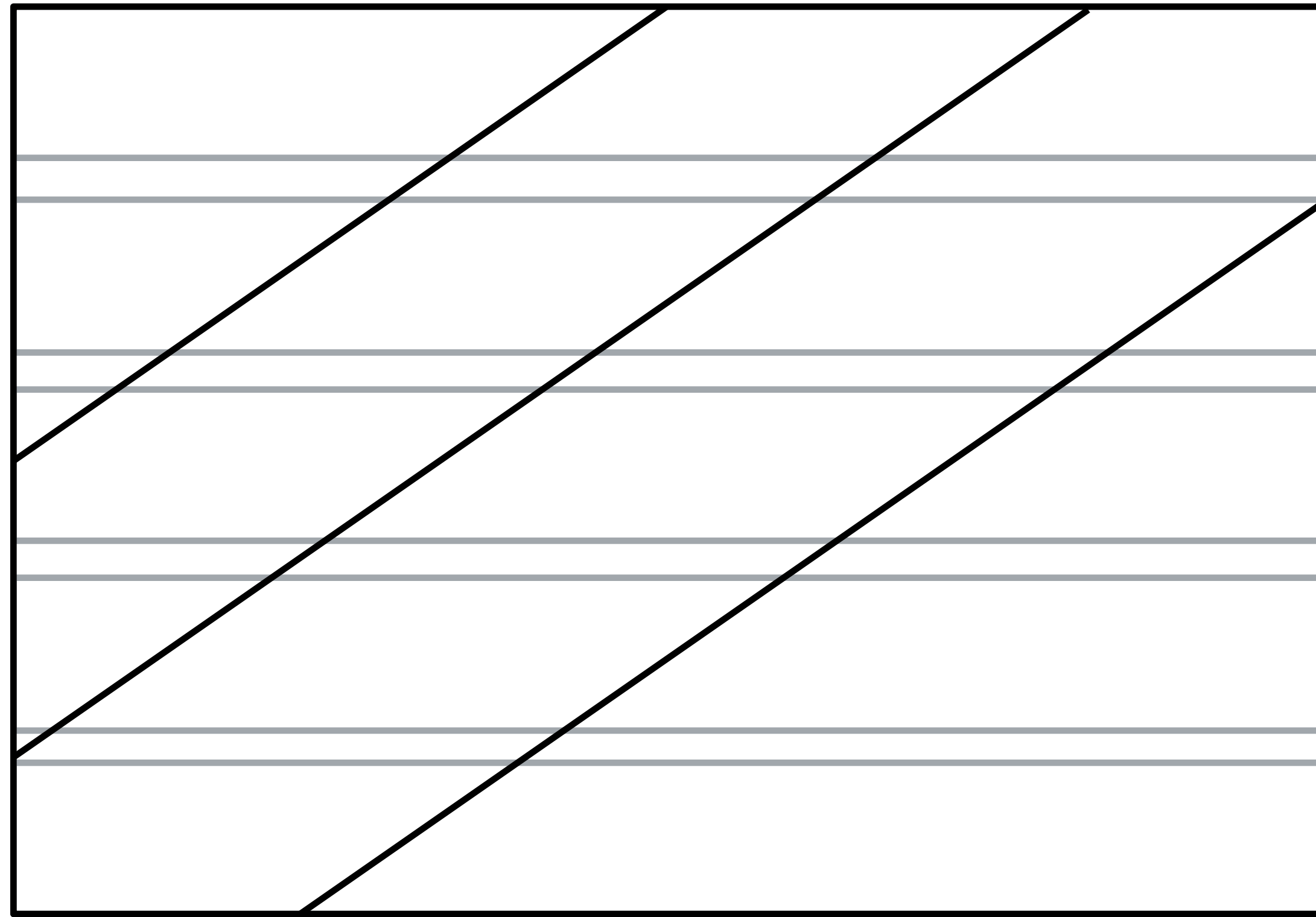


5-fold Cross Validation



**Average number of trees are used
to train on 100% of the training
data**

5-fold Cross Validation



Average number of trees are used
to train on 100% of the training
data – **The Model You Get Back**

Auto-Splits

User provides: **Training Frame**

Train is Split: **70%** Train, **15%** Valid, **15%** Leaderboard

Auto-Splits

User provides: **Training** & **Validation Frames**

Valid is Split: **50%** Valid, **50%** Leaderboard

Auto Splits

User provides: **Training**, **Validation** & **Leaderboard Frames**

Data is Left as is