

DRIVERLESSAI

Introduction to AutoML and Machine Learning Interpretability



Jan GAMEC

@JanGamec

Senior SW/ML Engineer



- Violin enthusiast
- I like hiking, climbing and generally sporting
- I like discovering new (sometimes also old) technologies

AGENDA

- H2O.ai – company and people
- Intro to DriverlessAI
- Feature engineering with DriverlessAI
- Machine Learning Interpretability with DriverlessAI
- DEMO

Company Overview

Founded	2012, Series C in Nov, 2017
Products	<ul style="list-style-type: none">• Driverless AI - Automated Machine Learning• H2O - Open Source Machine Learning Platform• H2O4GPU - Lightning Fast Machine Learning on GPUs• Sparkling Water - Integration of H2O and Apache Spark
Mission	Democratize AI. Do Good.
Team	<ul style="list-style-type: none">~130 employees• Distributed Systems Engineers doing Machine Learning• World-class visualization designers
Offices	Mountain View, London, Prague



Scientific Advisory Council



Dr. Trevor Hastie

- John A. Overdeck Professor of Mathematics, Stanford University
- PhD in Statistics, Stanford University
- Co-author, *The Elements of Statistical Learning: Prediction, Inference and Data Mining*
- Co-author with John Chambers, *Statistical Models in S*
- Co-author, *Generalized Additive Models*



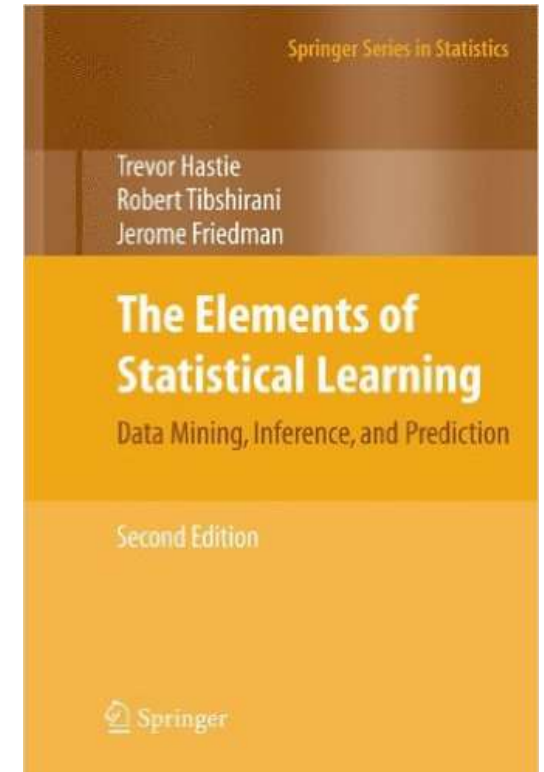
Dr. Robert Tibshirani

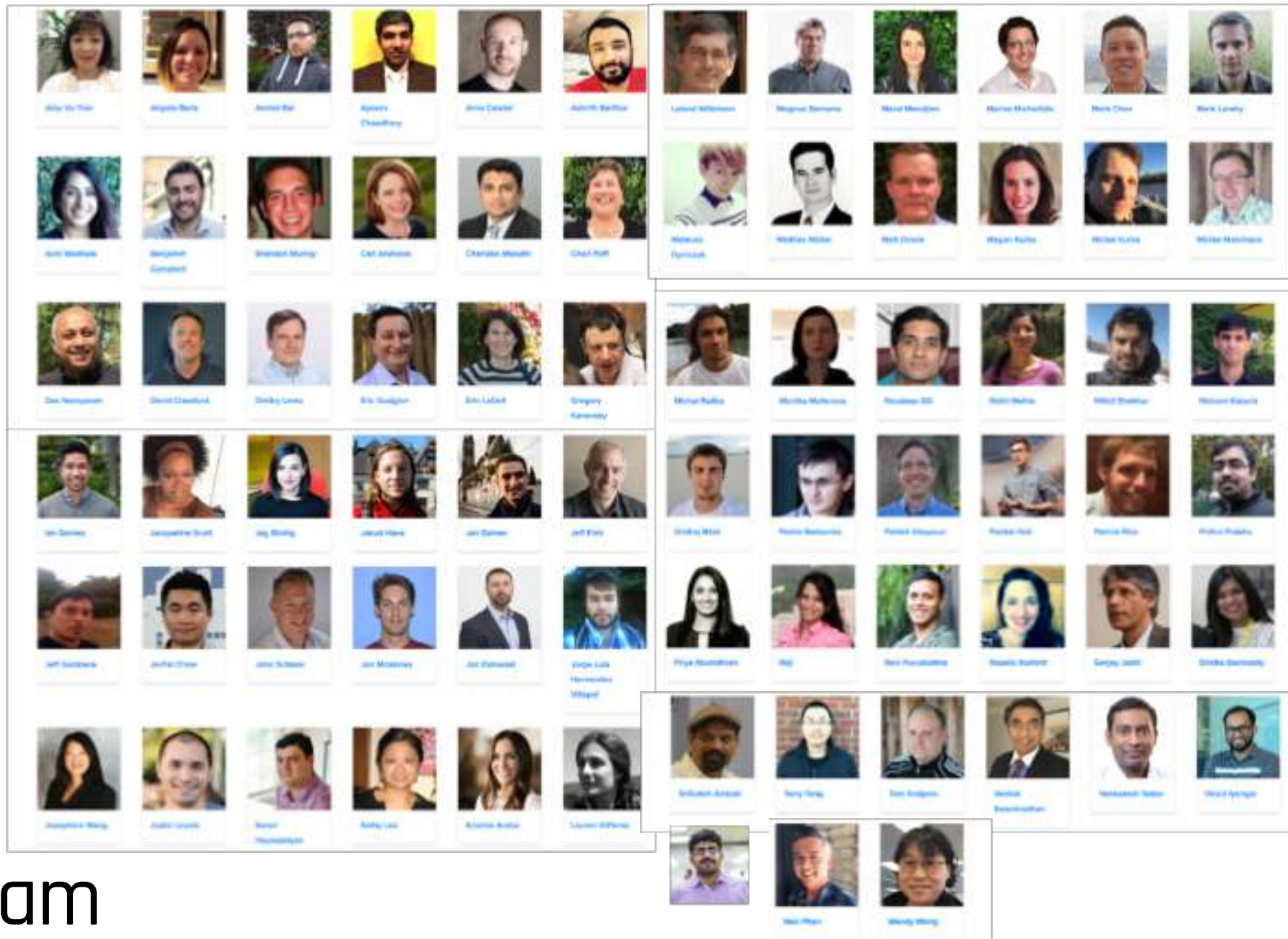
- Professor of Statistics and Health Research and Policy, Stanford University
- PhD in Statistics, Stanford University
- Co-author, *The Elements of Statistical Learning: Prediction, Inference and Data Mining*
- Author, *Regression Shrinkage and Selection via the Lasso*
- Co-author, *An Introduction to the Bootstrap*



Dr. Steven Boyd

- Professor of Electrical Engineering and Computer Science, Stanford University
- PhD in Electrical Engineering and Computer Science, UC Berkeley
- Co-author, *Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers*
- Co-author, *Linear Matrix Inequalities in System and Control Theory*
- Co-author, *Convex Optimization*





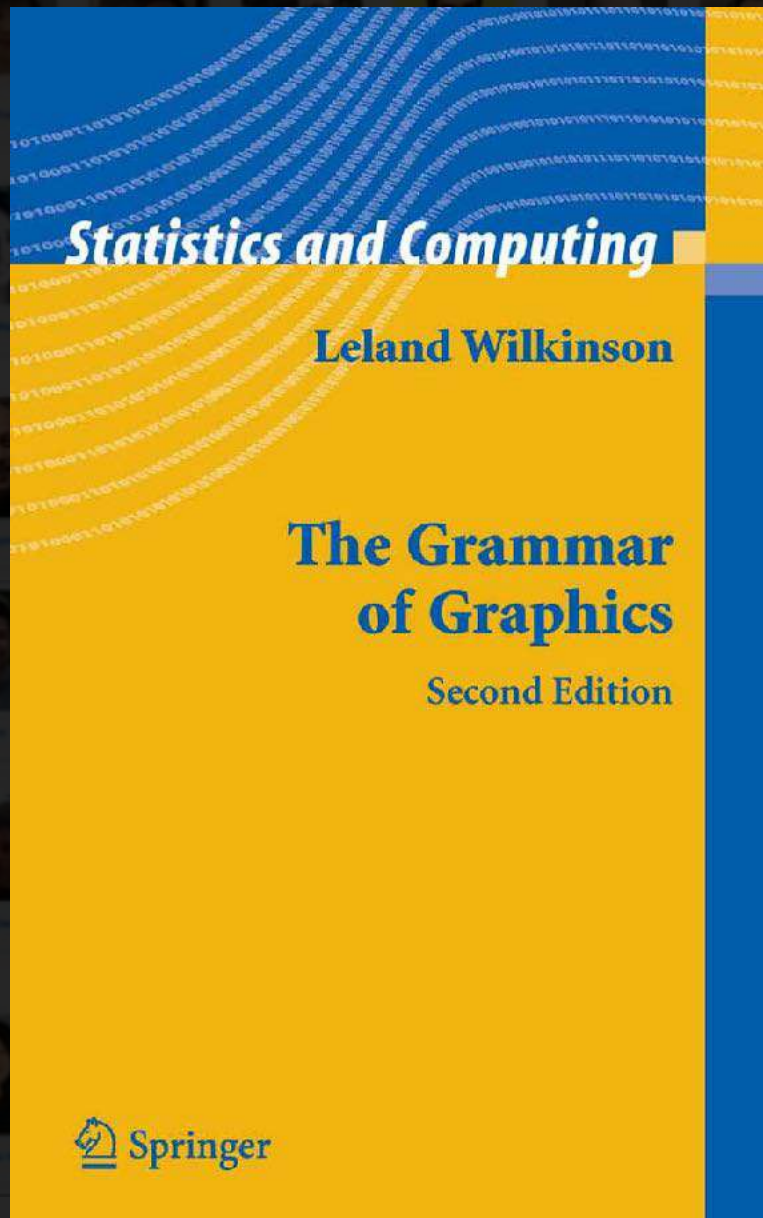
H₂O Team

Arno Candel, CTO
Fortune's 2014 Big Data All-Star

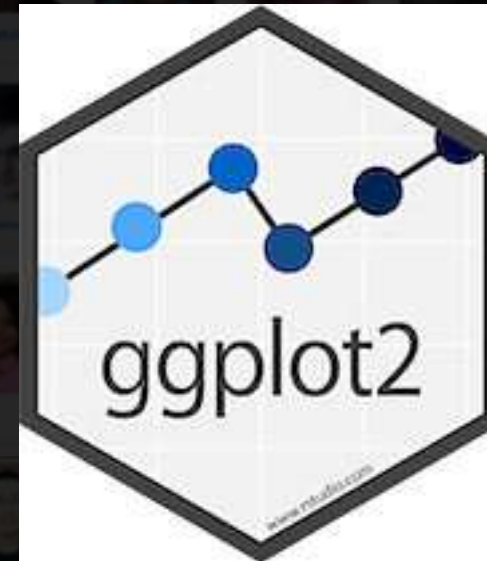
Sri Ambati, Co-founder & CEO

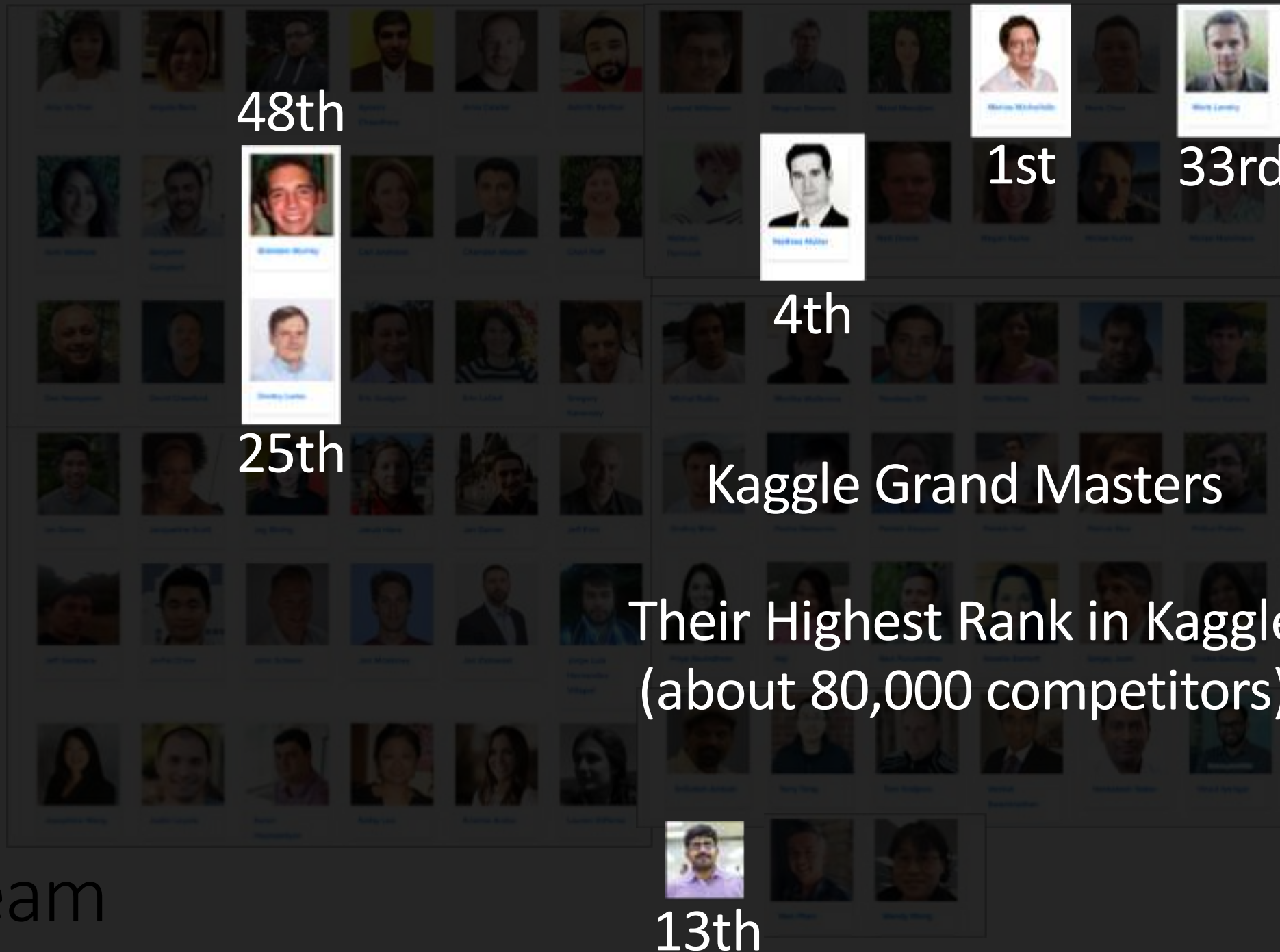
H₂O Team

H₂O.ai



Origin of R Package `ggplot2`





H₂O Team

H₂O Products



In-Memory, Distributed
Machine Learning Algorithms
with H2O Flow GUI



H2O AI Open Source Engine
Integration with Spark



Lightning Fast machine
learning on GPUs

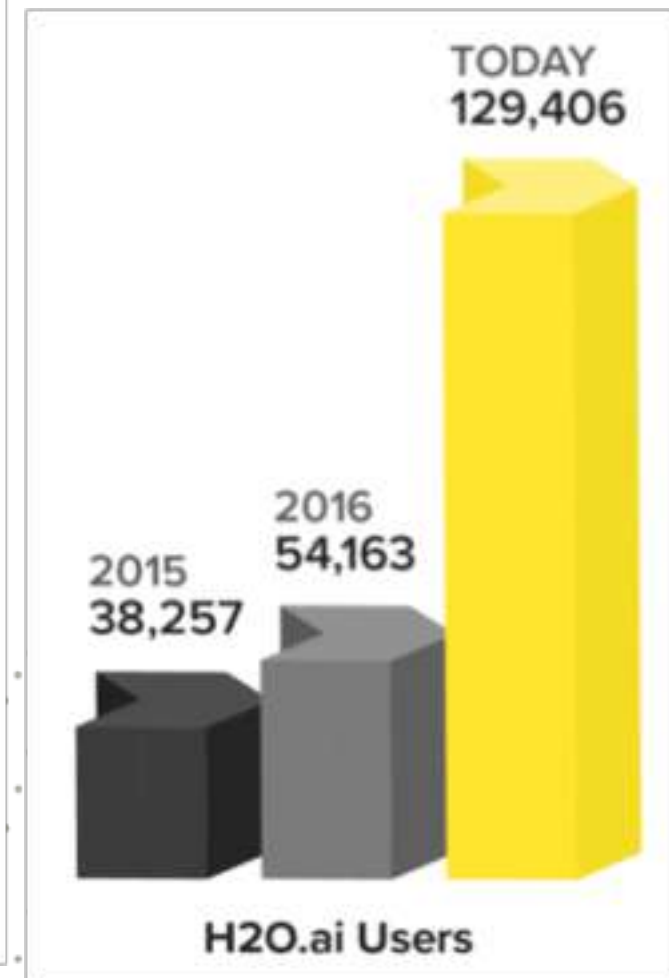
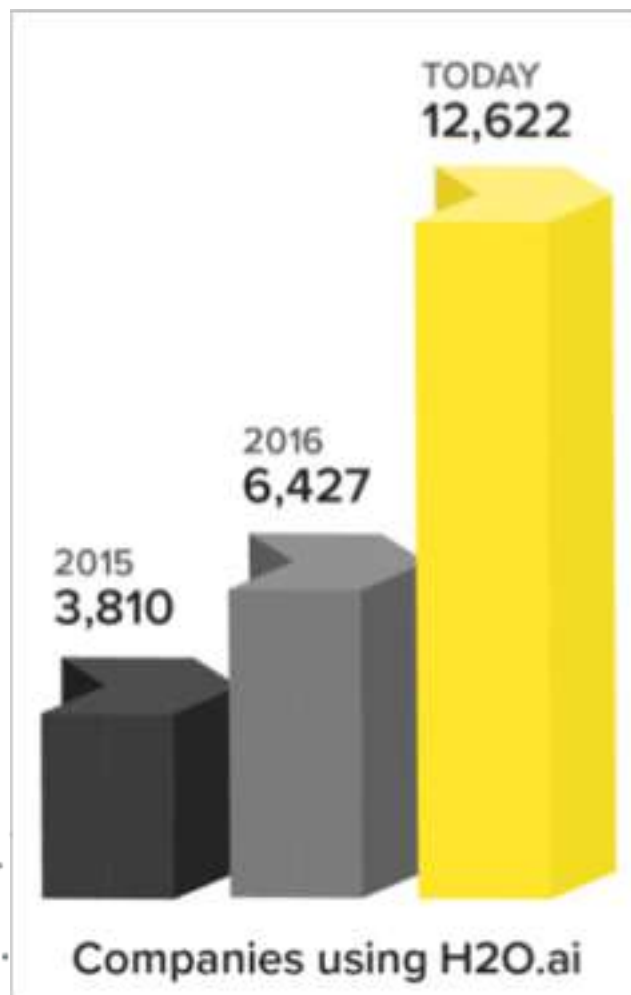
DRIVERLESSAI

Automatic feature
engineering, machine learning
and interpretability

Steam

Secure multi-tenant H2O clusters

Worldwide Community Adoption



* DATA FROM GOOGLE ANALYTICS EMBEDDED IN THE END USER PRODUCT

H2O.ai Solution Leadership Across Verticals



DRIVERLESSAI

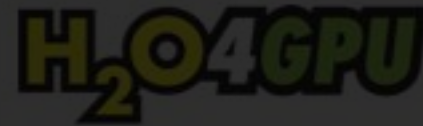
Driverless AI Overview



In-Memory, Distributed
Machine Learning Algorithms
with H2O Flow GUI



H2O AI Open Source Engine
Integration with Spark



Lightning Fast machine
learning on GPUs

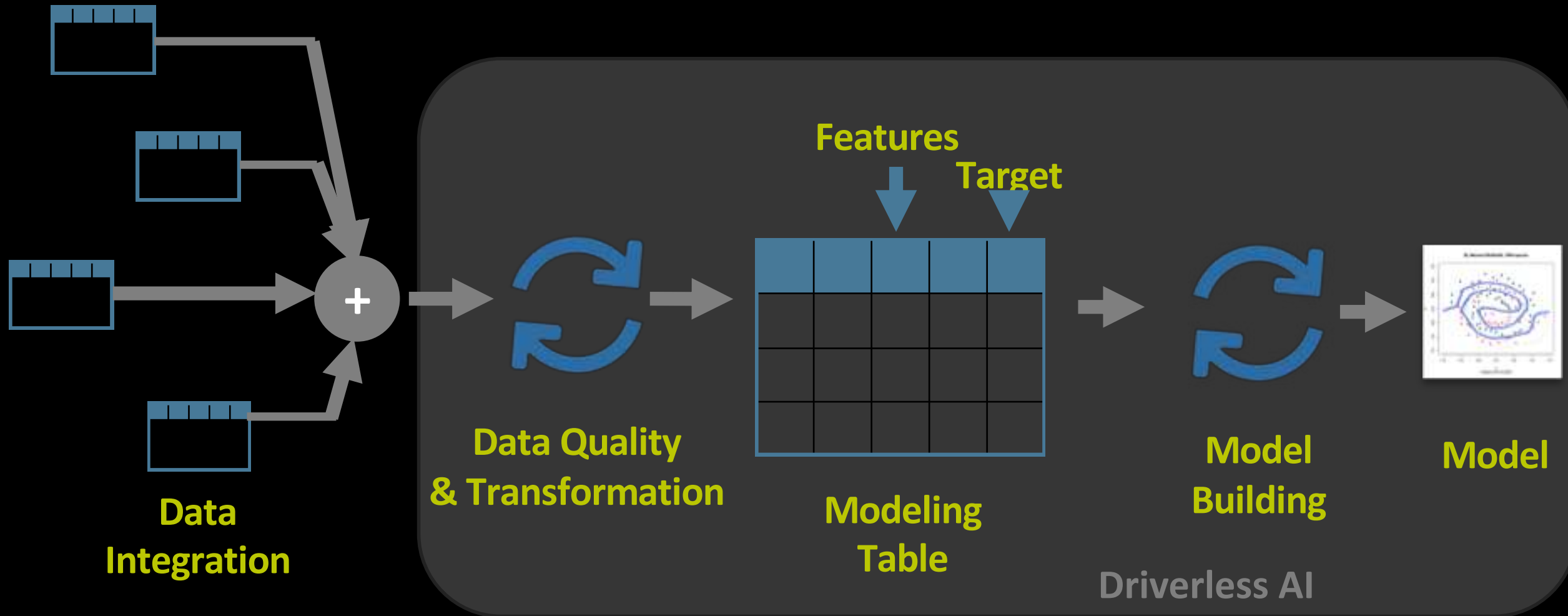


Automatic feature
engineering, machine
learning and interpretability

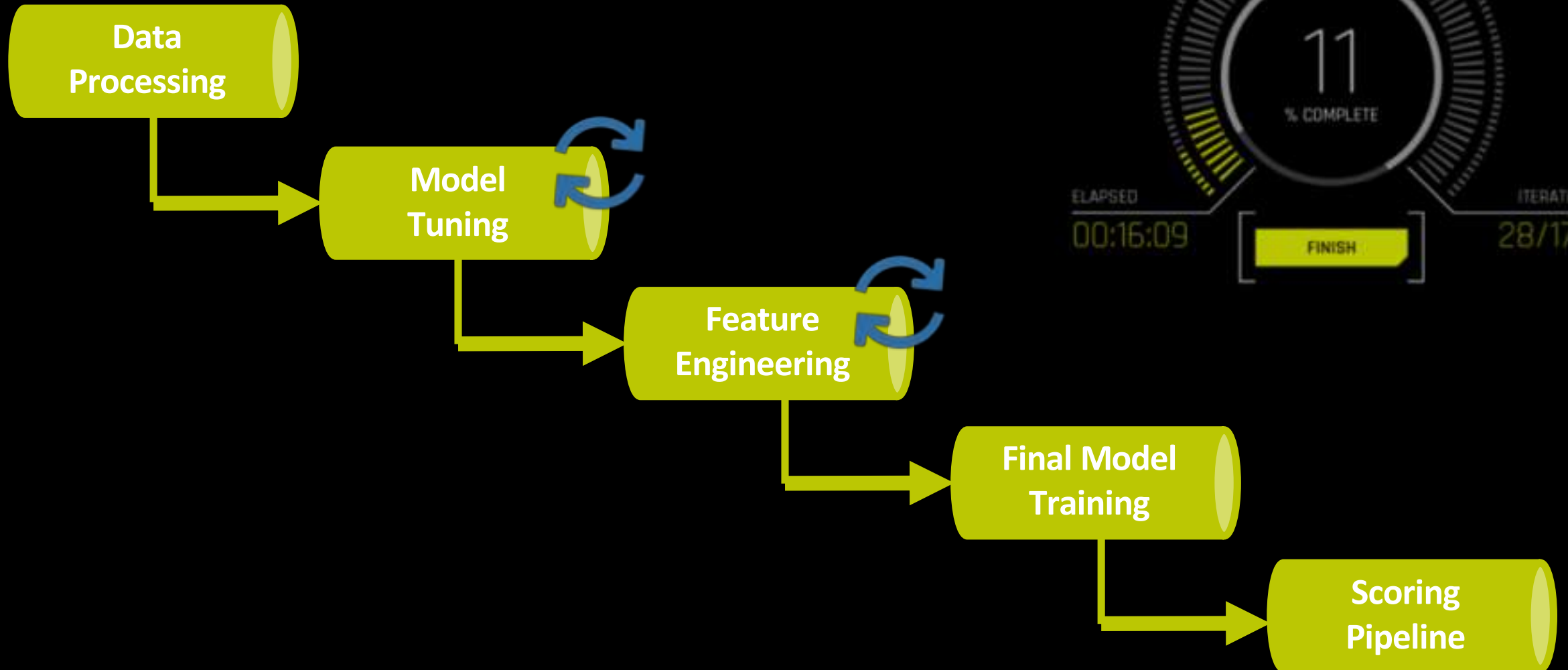
Steam

Secure multi-tenant H2O clusters

Typical Enterprise Machine Learning Workflow



DRIVERLESSAI Workflow



SCORED 72/649 MODELS ON 2299 FEATURES



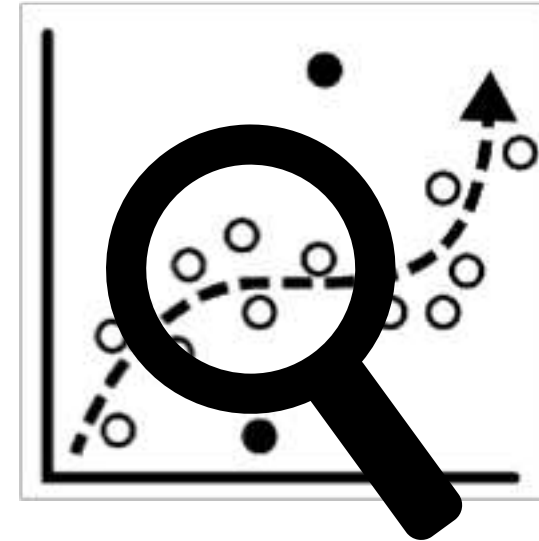
3 Pillars of Driverless AI



Speed



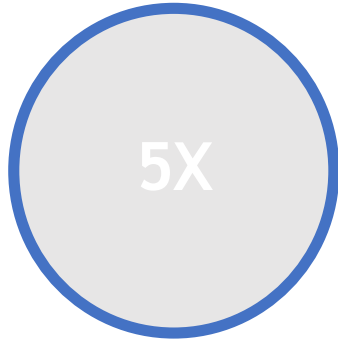
Accuracy



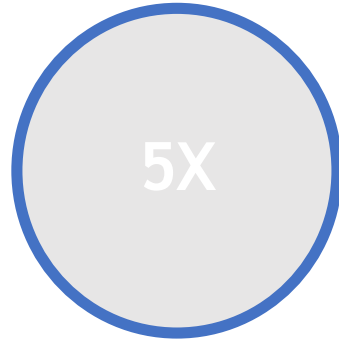
Interpretability



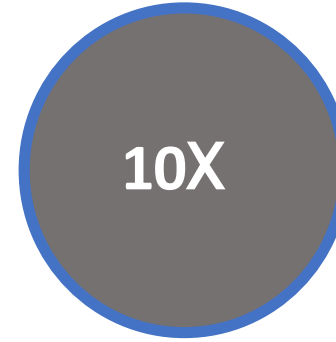
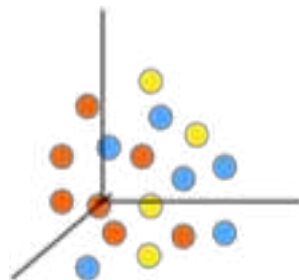
Speed == H2O4GPU Algorithms



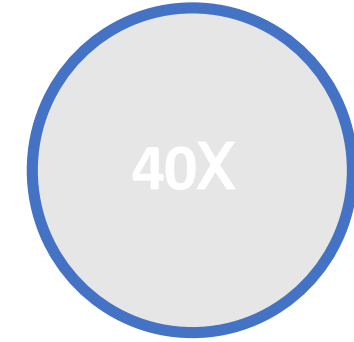
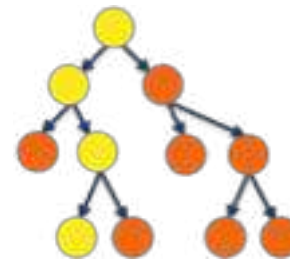
GLM



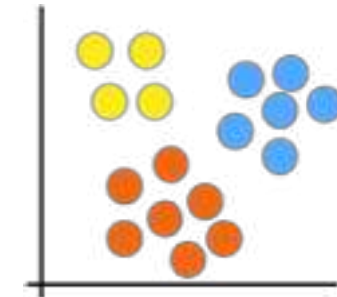
SVD



XGBoost



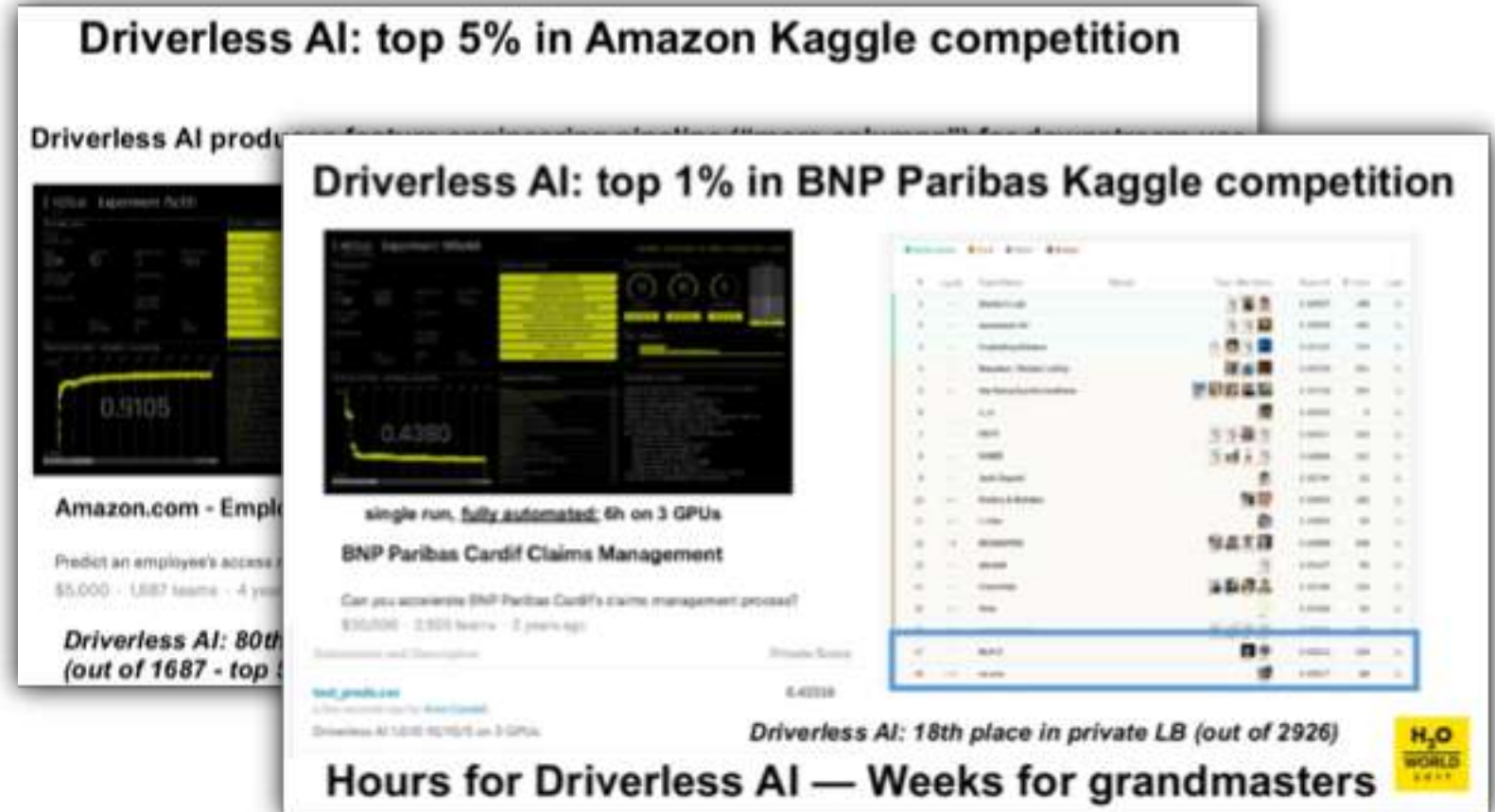
K-means





Accuracy

- Automatic feature engineering to increase accuracy - AlphaGo for AI
- Automatic Kaggle Grandmaster recipes in a box for solving wide variety of use-cases
- Automatic machine learning to find and tune the right ensemble of models



Auto Feature Generation

Kaggle Grand Master Out of the Box

VARIABLE IMPORTANCE	
34_CV_CatNumEnc_PAY_0_PAY_2_mean	1.00
37_CV_TE_PAY_0_PAY_5_0	0.66
36_TruncSVD_PAY_3_PAY_0_0	0.66
44_CV_TE_PAY_2_PAY_5_0	0.51
16_PAY_0	0.33
22_BILL_AMT1	0.31
28_PAY_AMT1	0.28
30_PAY_AMT3	0.26
45_CV_CatNumEnc_PAY_3_LIMIT_BAL_PAY_AMT1_std	0.21
45_CV_CatNumEnc_PAY_3_LIMIT_BAL_BILL_AMT1_std	0.17
4_Freq_AGE	0.17
29_PAY_AMT2	0.16
24_BILL_AMT3	0.15
33_PAY_AMT6	0.14

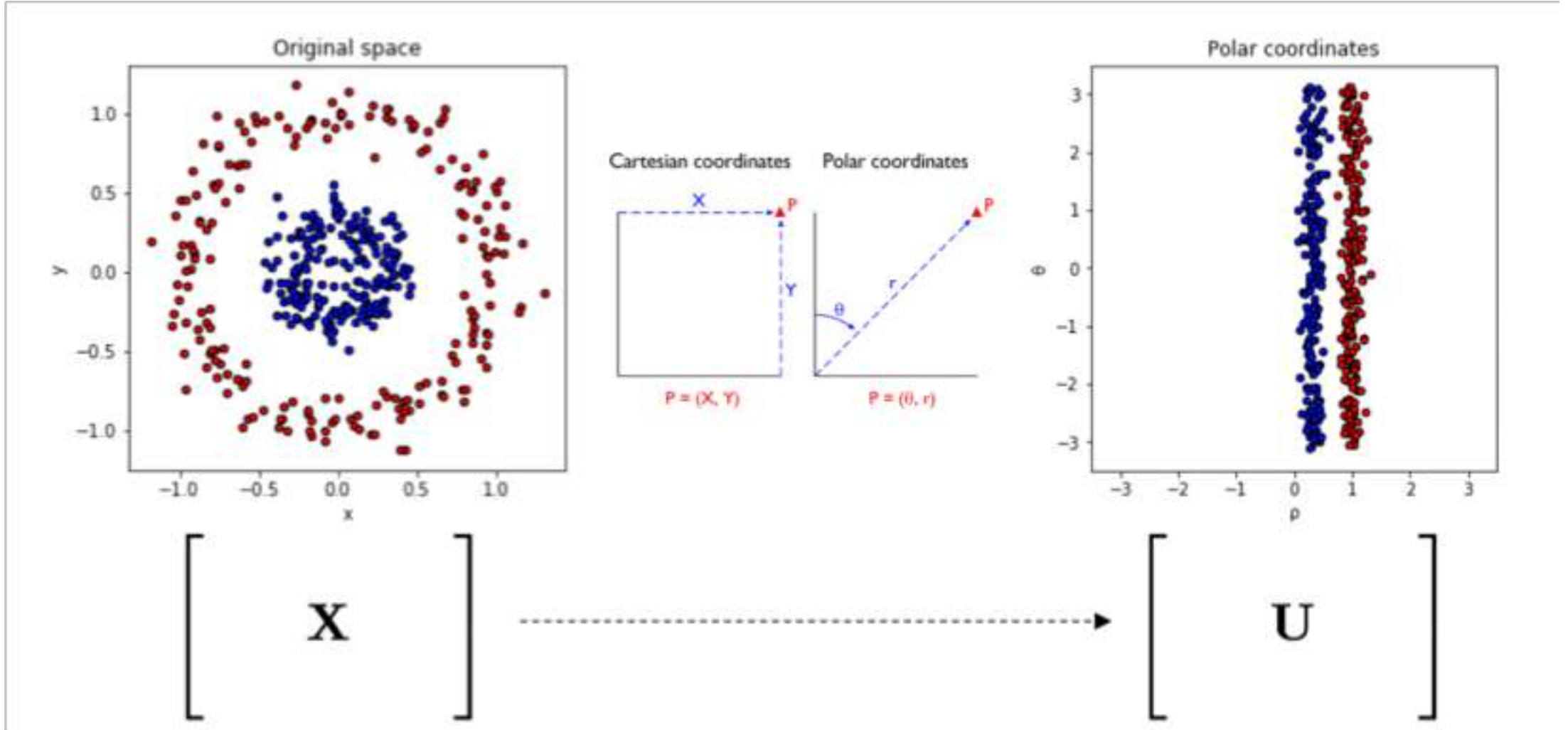
Generated Features

Feature Transformations

- Automatic Text Handling
- Frequency Encoding
- Cross Validation Target Encoding
- Truncated SVD
- Clustering and more

Original Features

Automatic Feature Engineering



Why feature engineering is hard

- Feature transformation (like target encoding) can introduce leakage when applied wrong
- Usually requires domain knowledge
- Time consuming

Key elements of feature engineering

Target transformations:

- Fix skewed distributions and improve model fit
- *Log(y), Sqrt(y), ...*

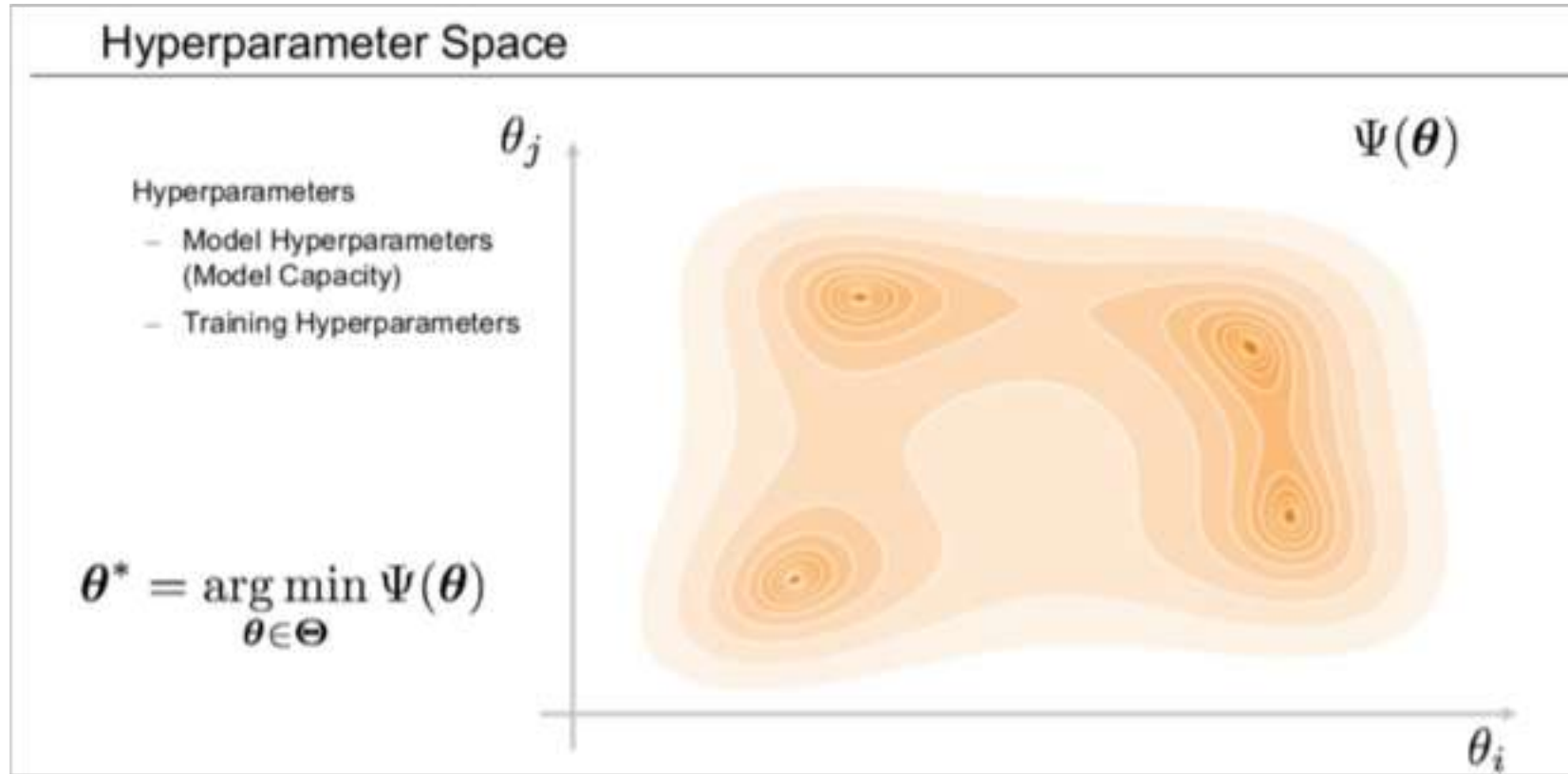
Label encoding:

- Turn categoricals into numerals (most ML tools work with numbers as their input)
- *One-hot encoding, Frequency encoding, Target mean encoding*
- Binning of the numerals
- Dimensionality reduction (*PCA, SVD*) and clustering (*Dist. To cluster mean*)

Feature Interactions & Extraction:

- $y = x_1^2 + x_2^2 - x_1 + 1 \Rightarrow$ Adding x_1^2 and x_2^2 will improve model performance

Automatic finding and tuning of models



- Genetic algorithm based approach
- Grid search



Machine Learning Interpretability

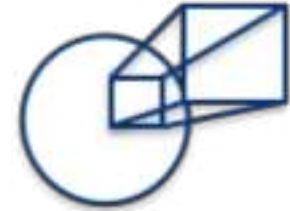
Complexity of learned functions:

- Linear, monotonic
- Nonlinear, monotonic
- Nonlinear, non-monotonic



Scope of interpretability:

Global vs. local

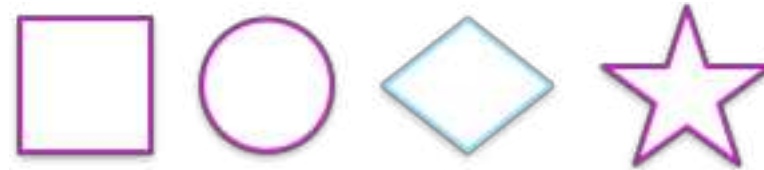


Enhancing trust and understanding: the mechanisms and results of an interpretable model should be both transparent AND dependable.



Application domain:

Model-agnostic vs. model-specific

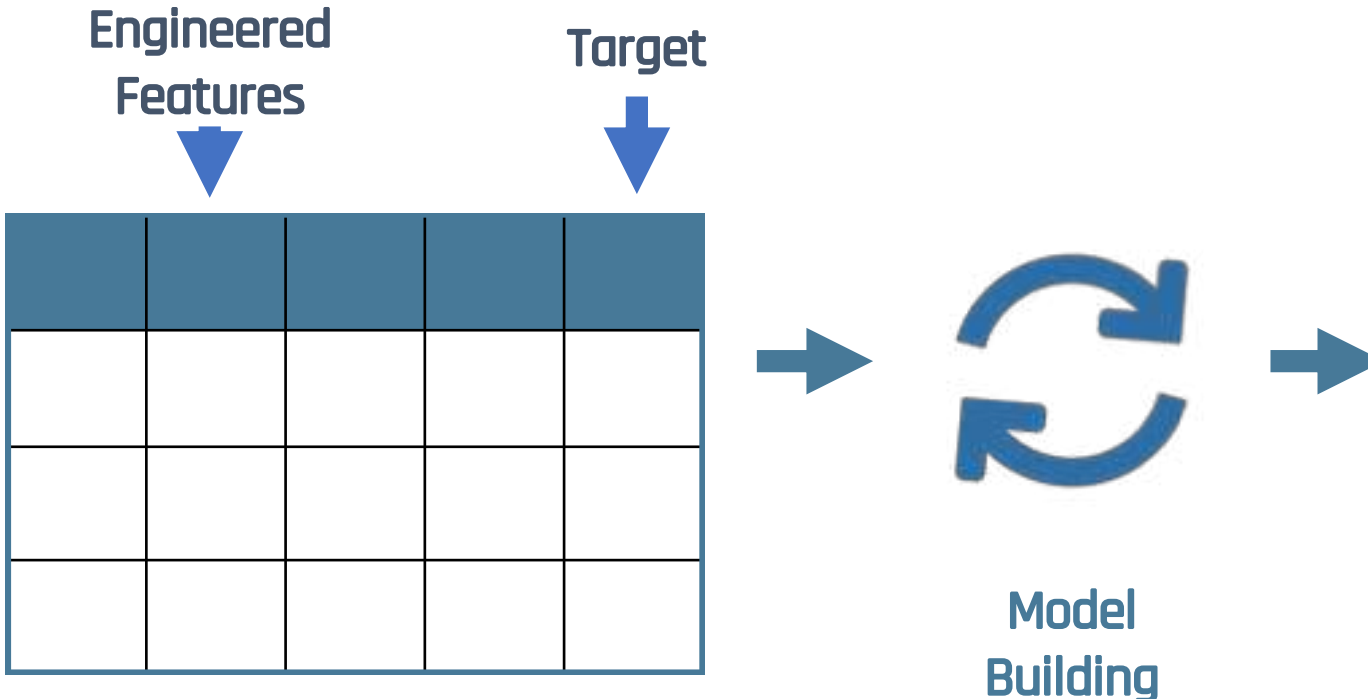


How interpretability works?!

Model Training

Engineered
Features

Target



The diagram illustrates the model training process. On the left, a table with 5 columns and 4 rows is shown. The first four columns are labeled 'Engineered Features' and the fifth column is labeled 'Target'. A blue arrow points from the 'Engineered Features' label to the first four columns, and another blue arrow points from the 'Target' label to the fifth column. A large blue arrow points from this table to a central circular icon representing 'Model Building'. To the right of the circular icon is another large blue arrow pointing to a second table. The circular icon consists of two curved arrows forming a circle, with the text 'Model Building' below it.



Model
Building

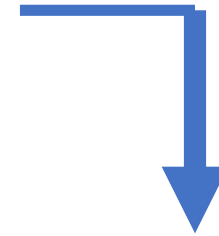
Model Interpretability

Raw
Features

Model
Prediction

The Solution

DEFAULT	TE_PAY_1	LIMIT_BAL	TE_EDUCATION
YES	0.53	\$20,000	0.32
NO	0.19	\$90,000	0.32
NO	0.15	\$50,000	0.19



1. Train a complex machine learning model on generated features

Prob DEFAULT	PAY_1	LIMIT_BAL	EDUCATION
81%	Missed 2 Mo	\$20,000	university
32%	Up to Date	\$90,000	university
21%	Up to Date	\$50,000	graduate

2. Train a complex machine learning model on raw features and the predicted target values of our original model

DEMO

Credit Card Default Dataset

- **USE CASE:**

- Probability of default for Credit Card Loans

- **FEATURES**

- **Default payment next month** (True/False)
- LIMIT_BAL - Credit limit in dollars
- EDUCATION, SEX, MARRIAGE, AGE
- PAY_0 - Was a payment received in current month?
- PAY_2 - Was a payment received 2 months ago?
- ...
- BILL_AMT1 - Amount of bill statement in 1 month ago
- BILL_AMT2 - Amount of bill statement in 2 months ago
- ...
- PAY_AMT1 - Amount of previous payment 1 month ago
- ...

WALMART weekly sales

- **USE CASE:**

- Predict weekly sales of Walmart stores/departments

- **FEATURES**

- **Weekly Sales**
- STORE, DEPT – ID of store/department
- DATE – Time column
- Temperature, Fuel Cost – Characterize the region
- Markdown 1-5 – promotions in stores
- isHoliday – Was the holiday on the date
- ...

Q?

10X