Ideas on Machine Learning Interpretability

Navdeep Gill, H2O.ai

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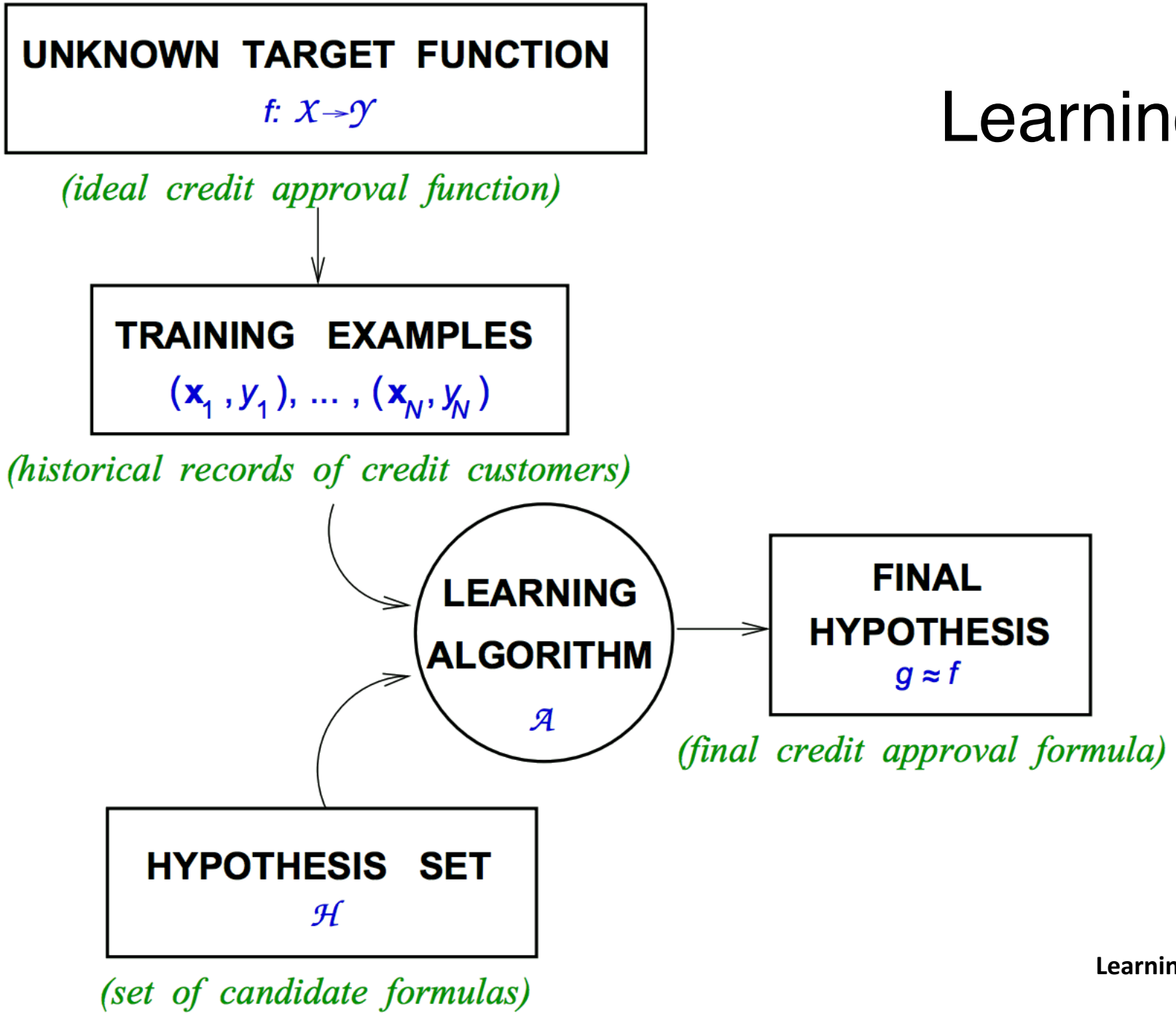
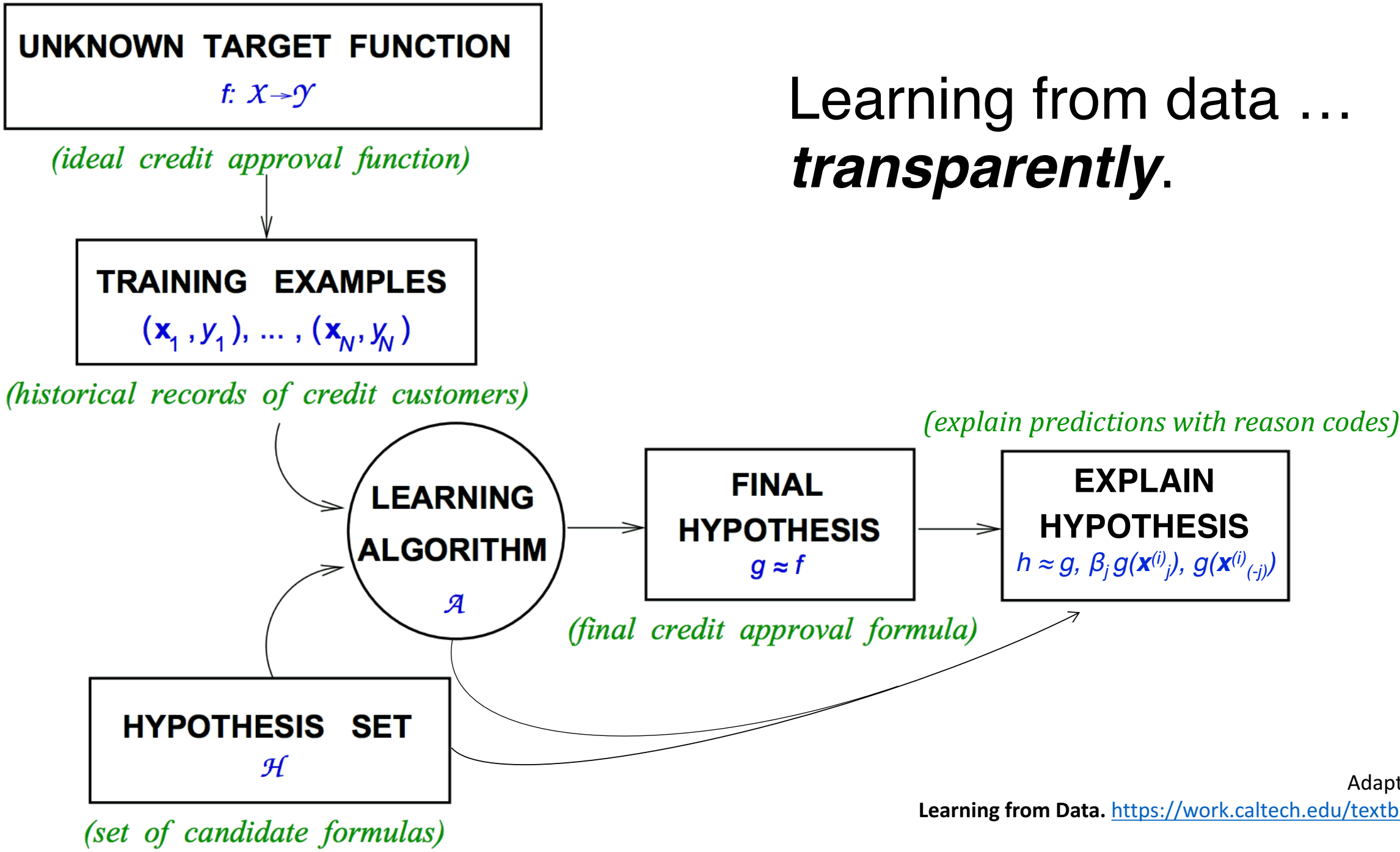
Big Ideas

Learning from data …



Adapted from:
Learning from Data. https://work.caltech.edu/textbook.html



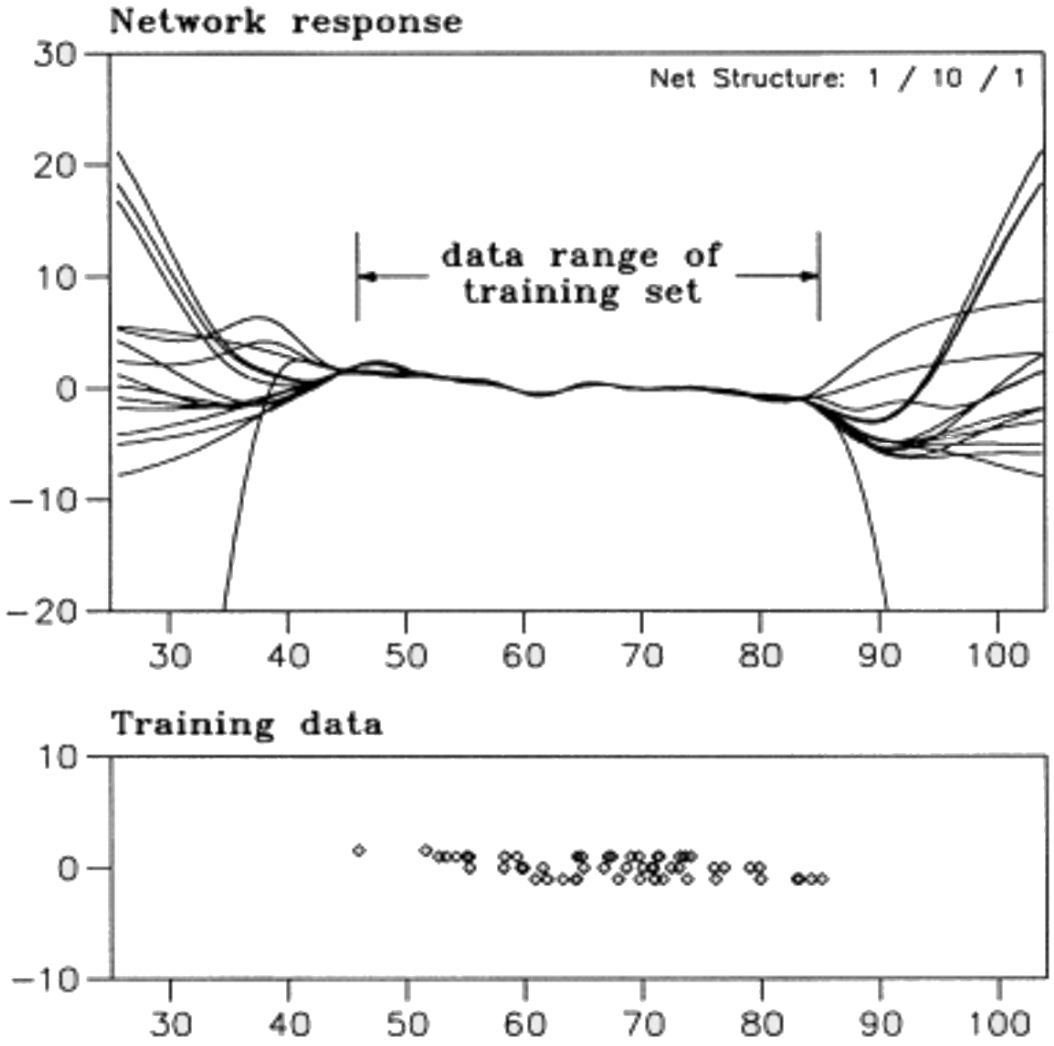
Learning from data … ***transparently***.

Adapted from:
Learning from Data. https://work.caltech.edu/textbook.html

Increasing fairness, accountability, and trust by decreasing unwanted sociological biases

Source: http://money.cnn.com/, Apple Computers

Increasing trust by quantifying prediction variance



Source: http://www.vias.org/tmdatanaleng/

A framework for interpretability

Complexity of learned functions:
- Linear, monotonic
- Nonlinear, monotonic
- Nonlinear, non-monotonic

(~ Number of parameters/VC dimension)

Scope of interpretability:
Global vs. local

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

Understanding ~ transparency
Trust ~ fairness and accountability

Application domain:
Model-agnostic vs. model-specific

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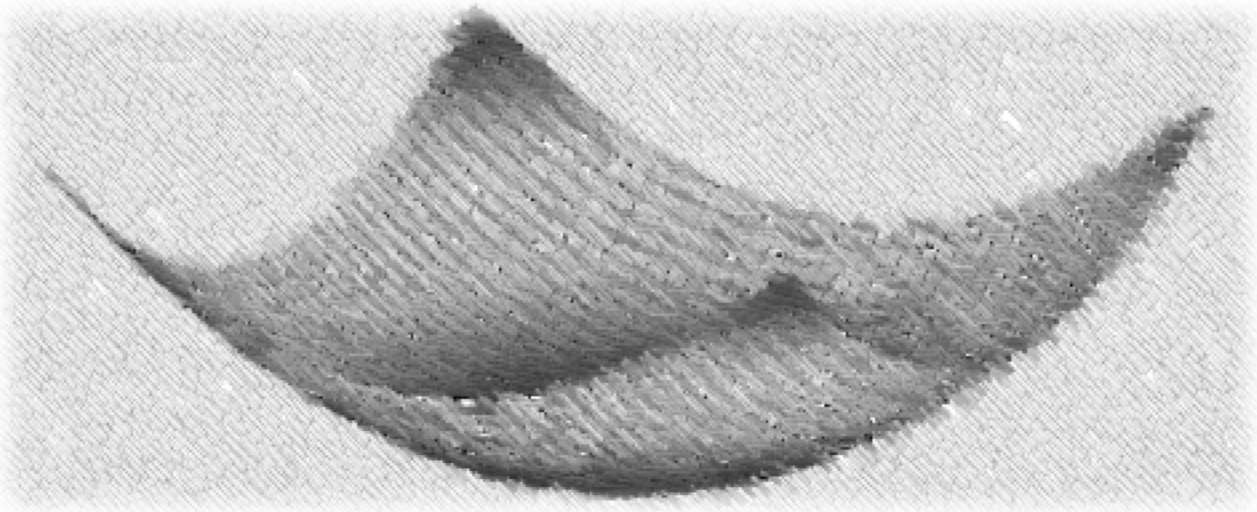
Big Challenges

Linear Models

Strong model locality

Usually stable models and explanations

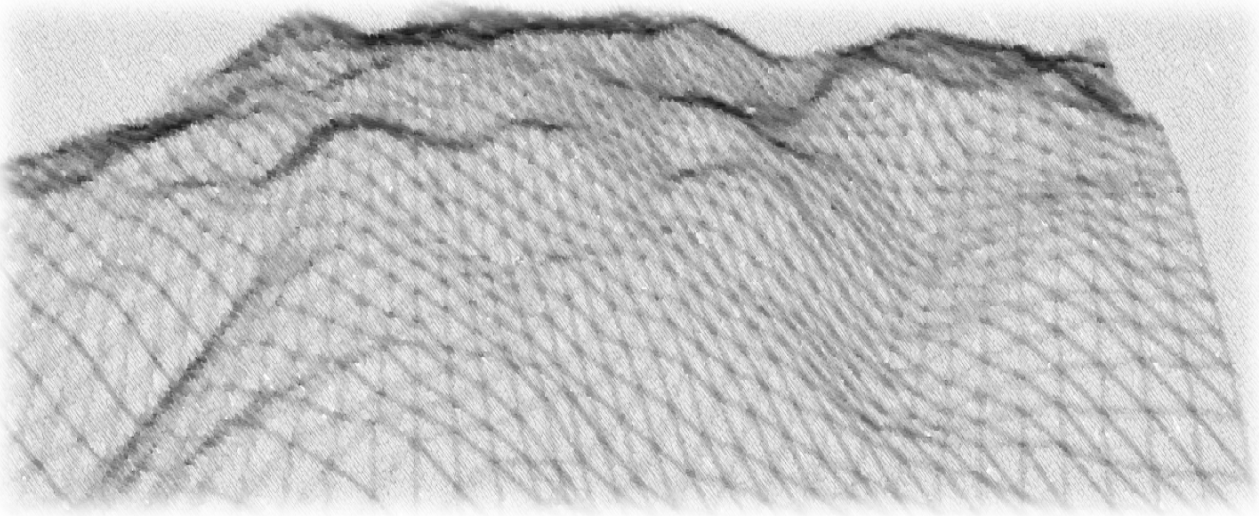


Machine Learning

Weak model locality

Sometimes unstable models and explanations

(a.k.a. The Multiplicity of Good Models)



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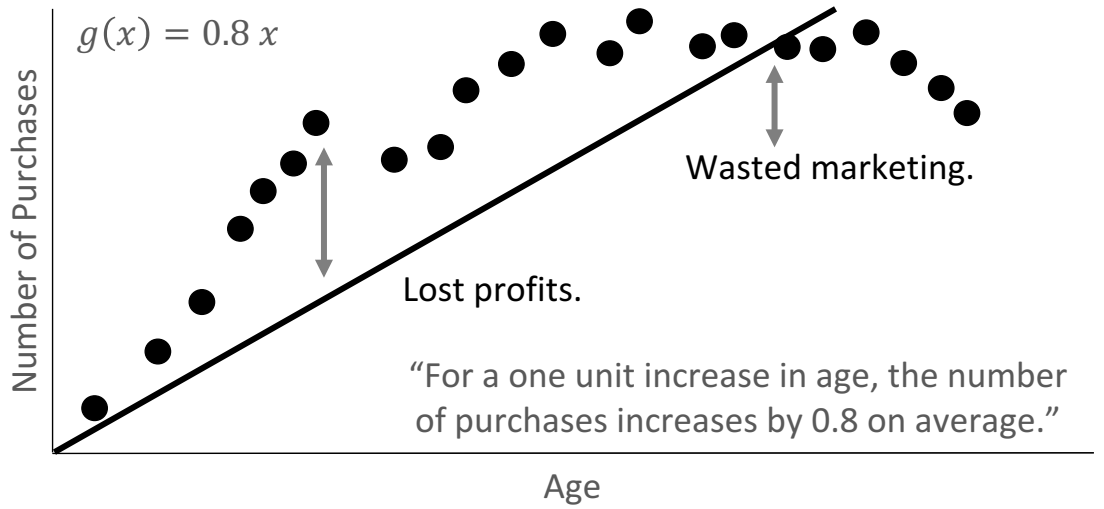
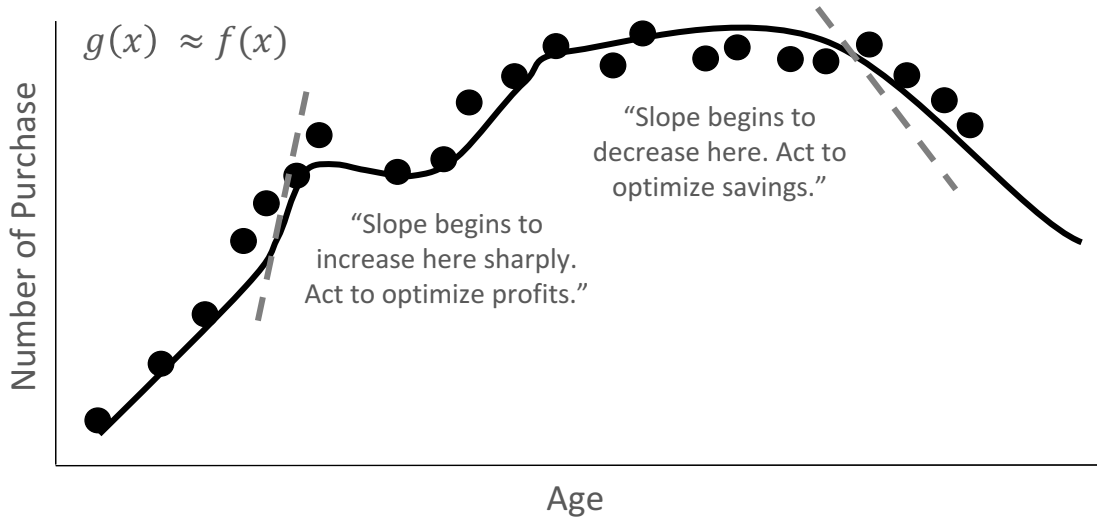
Linear Models

Exact explanations for ***approximate*** models.



Machine Learning

Approximate explanations for ***exact*** models.



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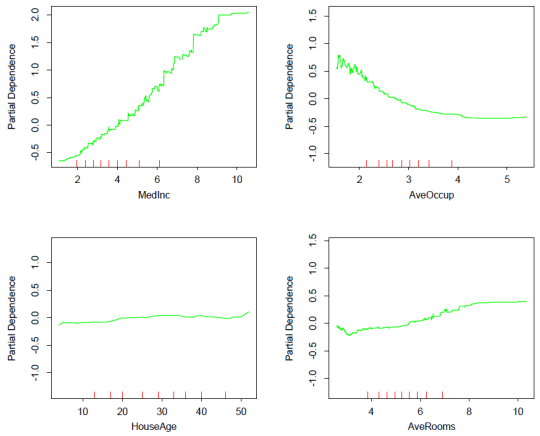
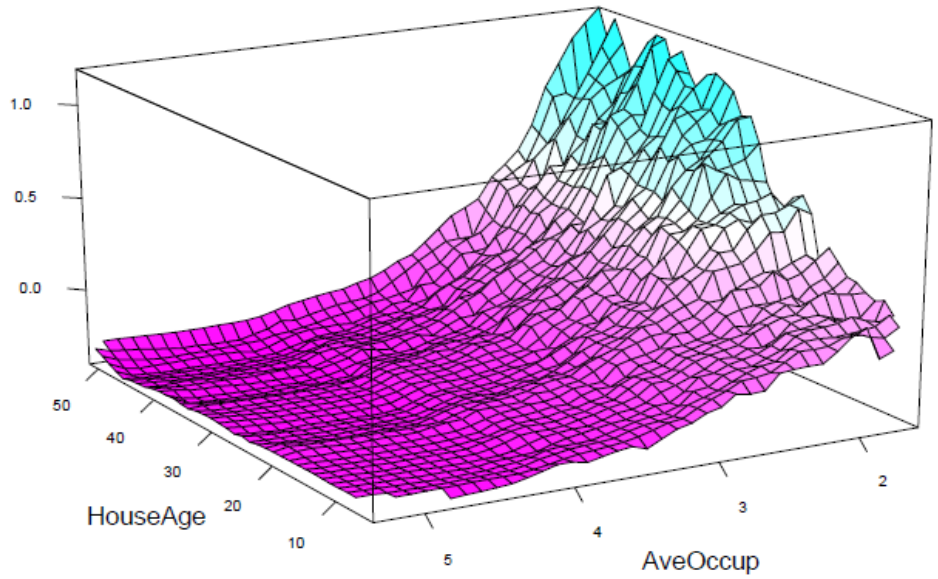
A Few of Our Favorite Things

Partial dependence plots





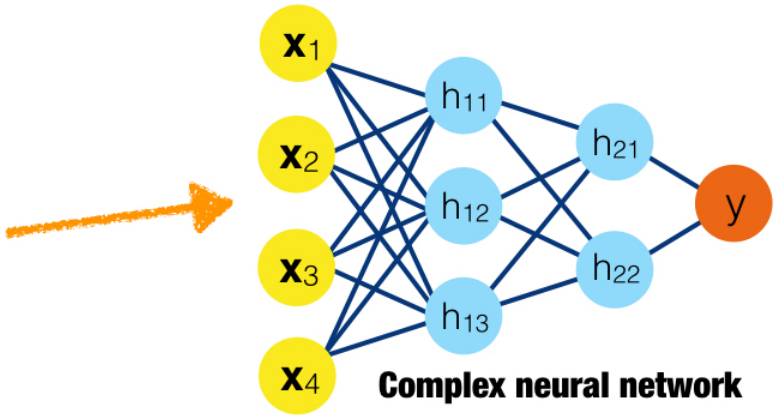
HomeValue ~ MedInc + AveOccup + HouseAge + AveRooms

Source: http://statweb.stanford.edu/~tibs/ElemStatLearn/printings/ESLII_print10.pdf

Surrogate models

BAD	CUSTOMER_DTI	LOAN_PURPOSE	CHANNEL
0	0.18	MORT	7
1	0.42	HELOC	10
0	0.11	MORT	10
0	0.21	MORT	1

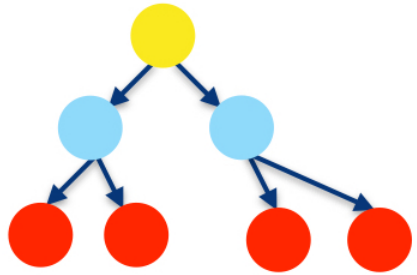
1. Train a complex machine learning model



Complex neural network

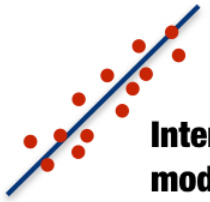
BAD	PREDICTED_BAD	CUSTOMER_DTI	LOAN_PURPOSE	CHANNEL
0	0.47	0.18	MORT	7
1	0.82	0.42	HELOC	10
0	0.18	0.11	MORT	10
0	0.12	0.21	MORT	1

2. Train an interpretable model on the original inputs and the predicted target values of the complex model



Interpretable decision tree

Or



Interpretable linear model

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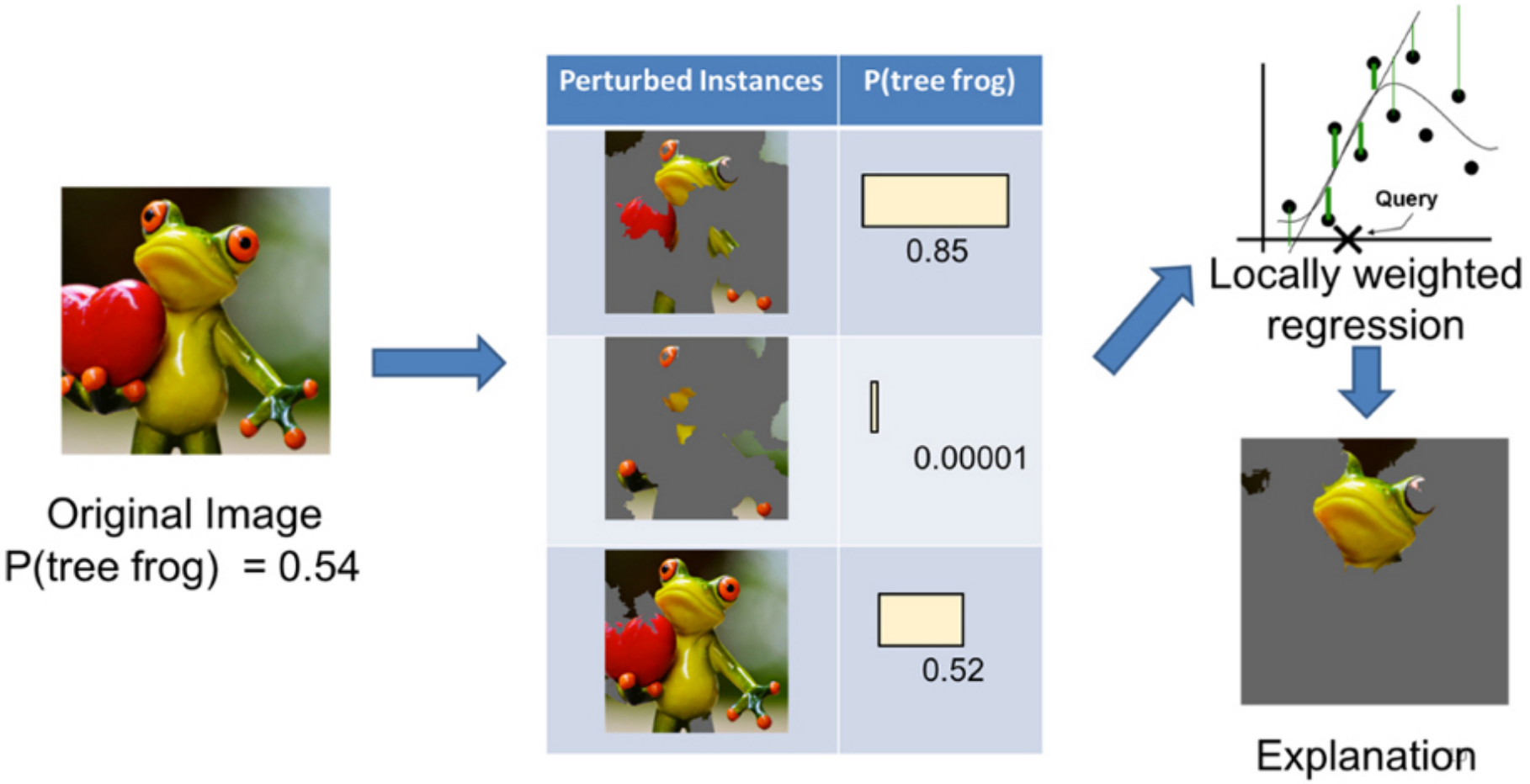
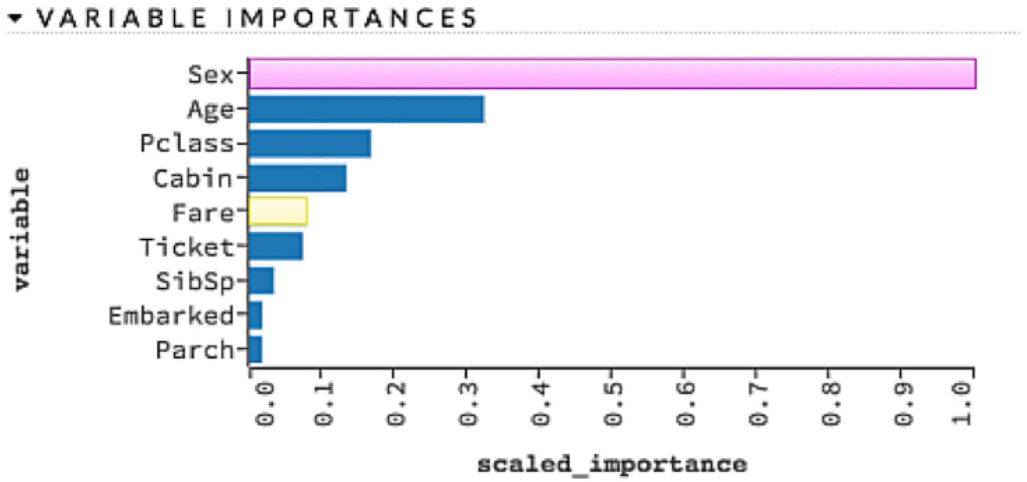
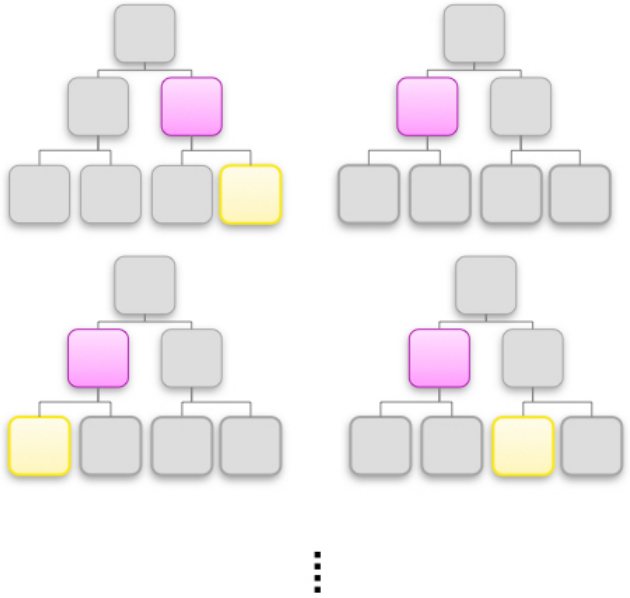
Local interpretable model-agnostic explanations



Source: https://www.oreilly.com/learning/introduction-to-local-interpretable-model-agnostic-explanations-lime

Variable importance measures





Global variable importance indicates the impact of a variable on the model for the entire training data set.

Sex	Age	…	Fare	ŷ	ŷ(-Sex)	ŷ(-Age)	…	ŷ(-Fare)
M	11	…	8.45	0.2	0.01	0.1	…	0.21
F	34	…	51.86	0.8	0.6	0.65	…	0.78
M	26	…	21.08	0.5	0.2	0.3	…	0.53
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Local variable importance can indicate the impact of a variable for each decision a model makes – similar to reason codes.

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H20.ai Driverless AI Demo

H2O.ai

H2O.ai Experiment c8b071

0.9.5+LOCAL_584D771

Show Experiments

TRAINING DATA

DATASET
creditcard_cat.csv

ROWS	COLUMNS	DROPPED COLS	TEST DATASET
24K	25	1	--

TARGET COLUMN

default.payment.next.month

TYPE	COUNT	UNIQUE	FREQ
int	23999	2	18630

STATUS: COMPLETE

INTERPRET THIS MODEL

SCORE ON ANOTHER DATASET

DOWNLOAD (HOLDOUT) TRAINING PREDICTIONS

DOWNLOAD TRANSFORMED TRAINING DATA

DOWNLOAD LOGS

DOWNLOAD SCORING PACKAGE

EXPERIMENT SETTINGS

ACCURACY	TIME	INTERPRETABILITY
5	5	5

CLASSIFICATION

SET RAND. SEED

ENABLE GPUS

SCORER

- R2
- MSE
- RMSE
- RMSLE
- MAE
- GINI
- AUC
- LOGLOSS

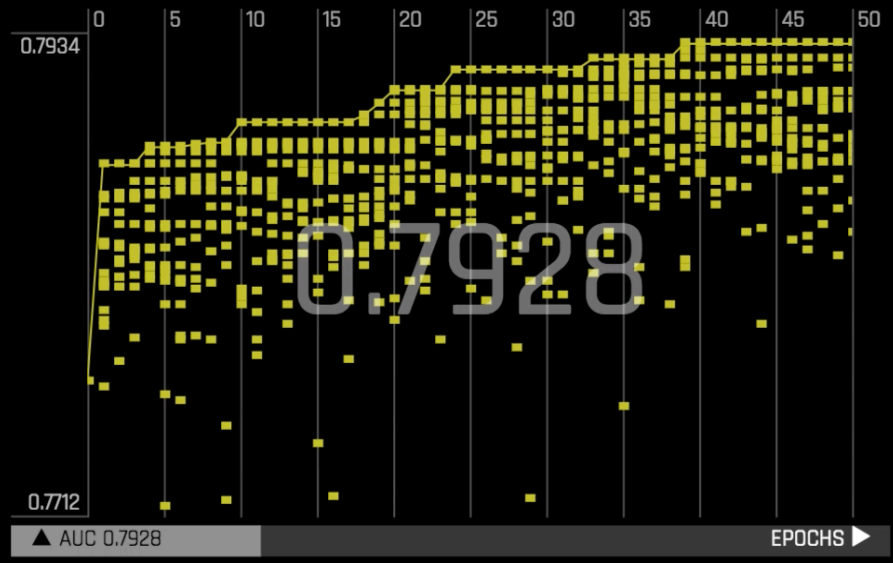
CPU / MEMORY

Trace

CPU

MEM

ITERATION SCORES - INTERNAL VALIDATION



VARIABLE IMPORTANCE

6_Freq__PAY_0	1.00
50_CV_TE_PAY_5_PAY_3_0	0.66
29_TruncSVD_PAY_AMT2_BILL_AMT1_BILL_AMT5_PAY_AMT1...	0.64
32_TruncSVD_BILL_AMT5_PAY_AMT2_LIMIT_BAL_0	0.55
36_TruncSVD_BILL_AMT1_BILL_AMT4_LIMIT_BAL_1	0.43
36_TruncSVD_BILL_AMT1_BILL_AMT4_LIMIT_BAL_0	0.41
46_TruncSVD_PAY_AMT6_BILL_AMT2_0	0.33
23_LIMIT_BAL	0.29
21_BILL_AMT1	0.29
37_TruncSVD_PAY_AMT1_PAY_AMT6_PAY_AMT3_0	0.29
17_PAY_AMT2	0.28
5_CV_TE_PAY_2_0	0.24
16_PAY_AMT1	0.24
44_CV_CatNumEnc_PAY_3__PAY_AMT5_mean	0.23

GPU USAGE

GPU1

GPU2

GPU3

GPU4

GPU5

GPU6

GPU7

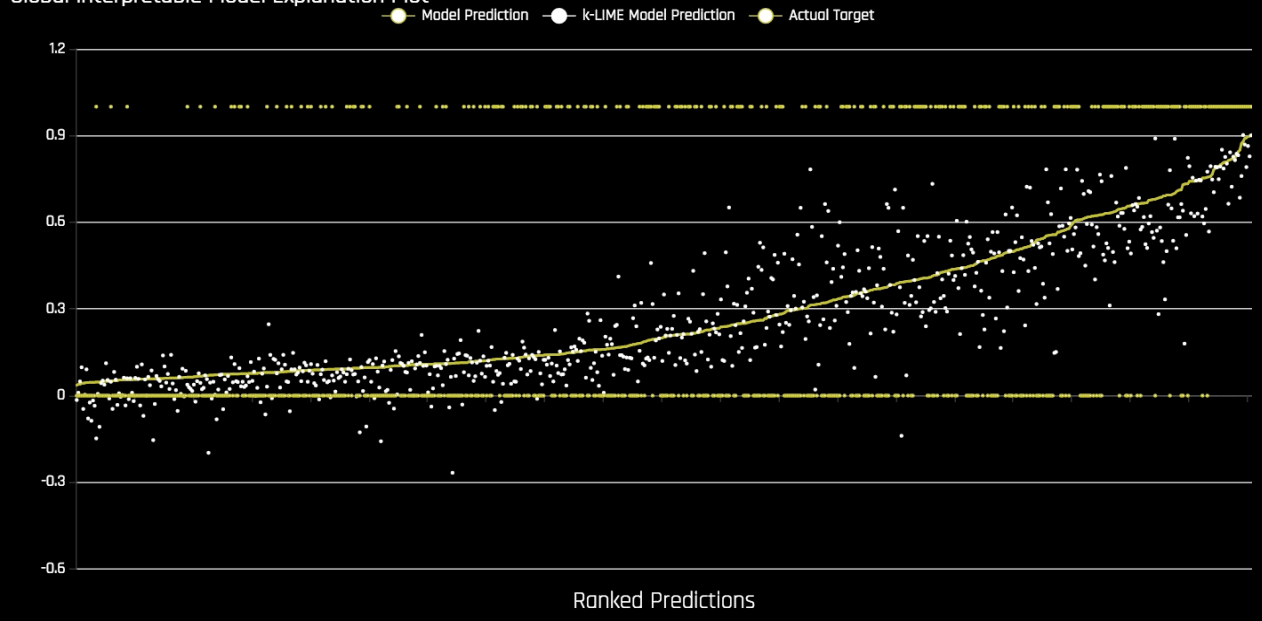
GPU8

Single Row Lookup

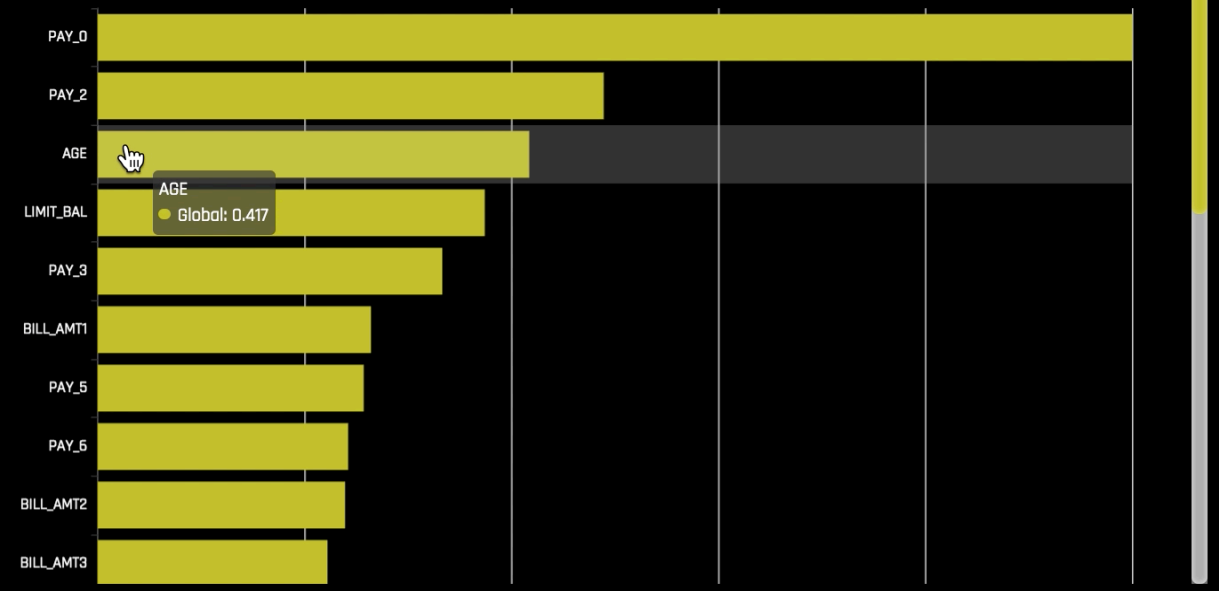
Column: H2O Frame Row # Value: SEARCH Plot: Global

EXPERIMENT EXPLANATIONS

Global Interpretable Model Explanation Plot

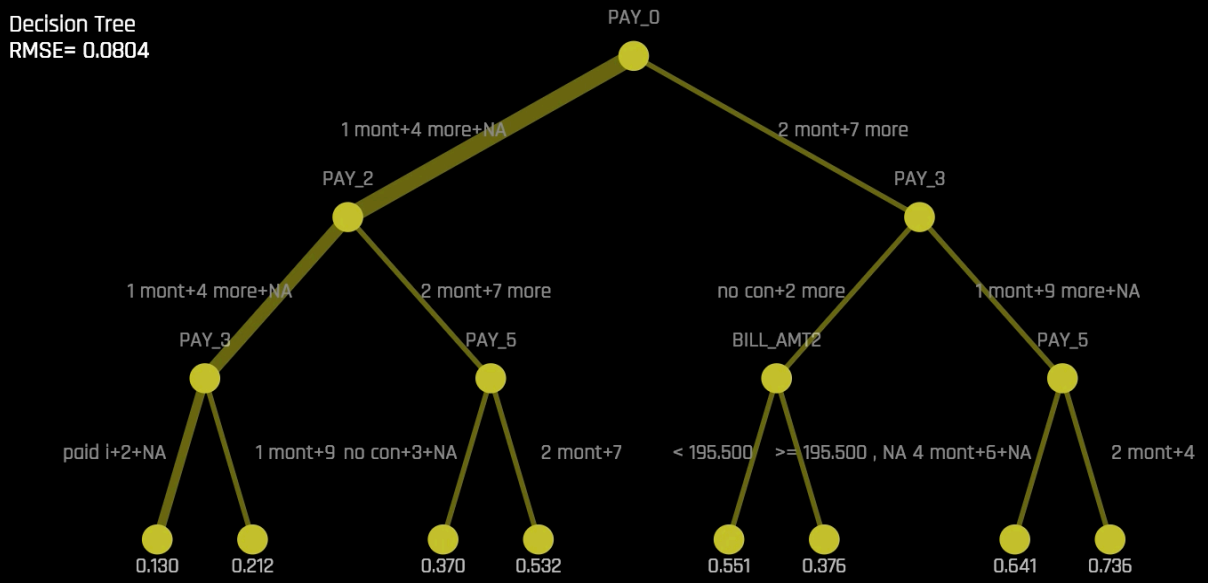


Variable Importance



Decision Tree

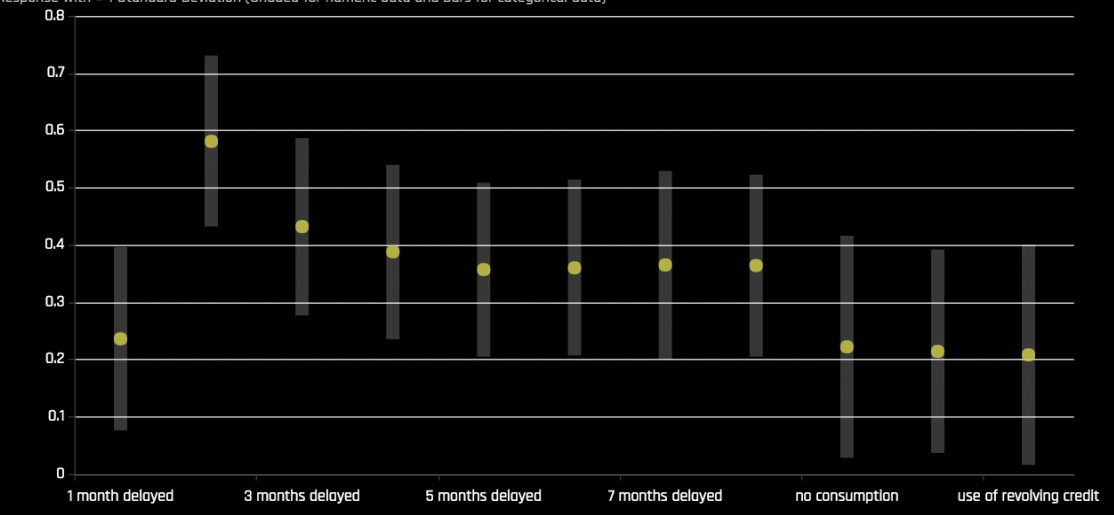
RMSE= 0.0804



Partial Dependence

PAY_0

Mean Response with ± 1 Standard Deviation (Shaded for numeric data and bars for categorical data)

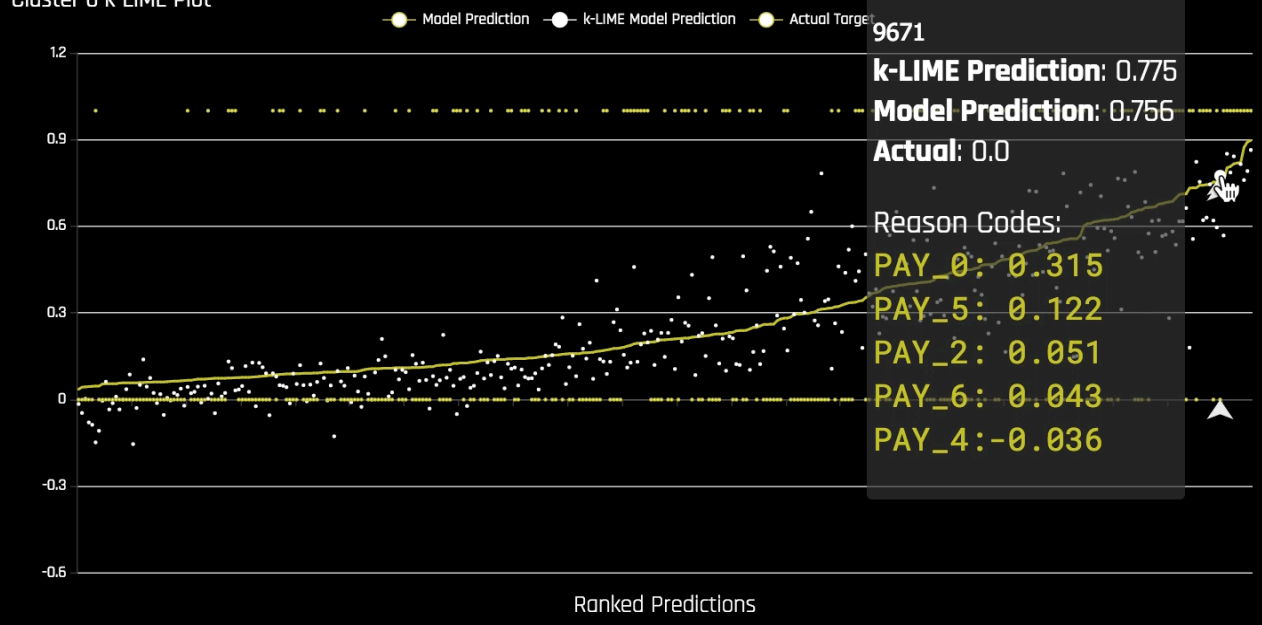


Single Row Lookup

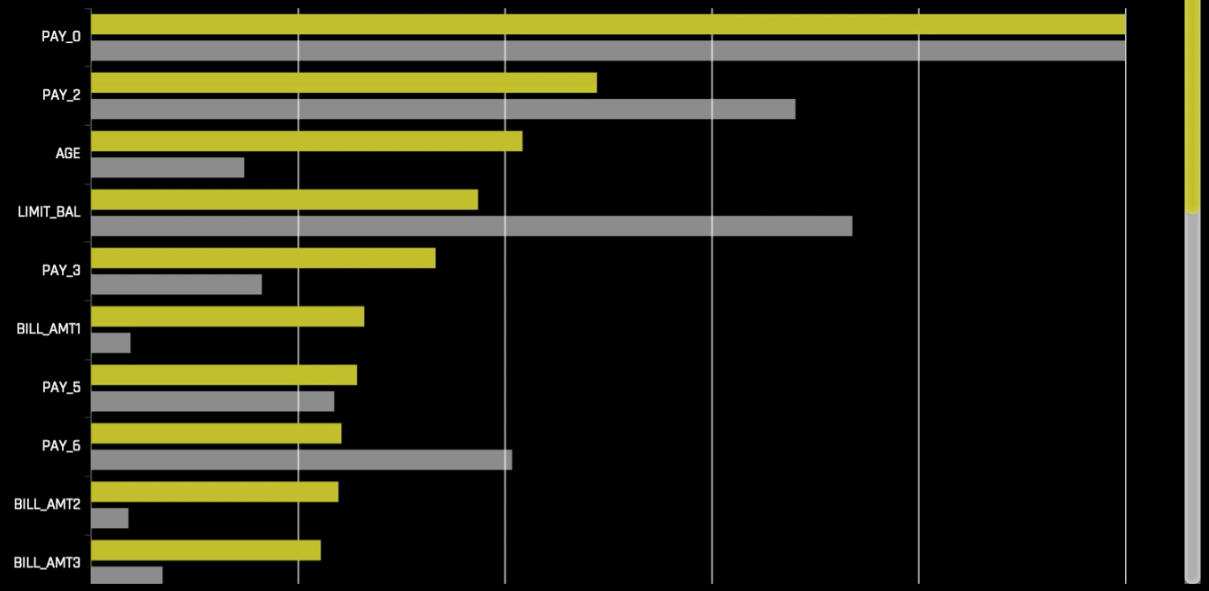
Column: H2O Frame Row # Value: 9671 SEARCH Plot: Cluster0

EXPERIMENT EXPLANATIONS

Cluster 0 k-LIME Plot

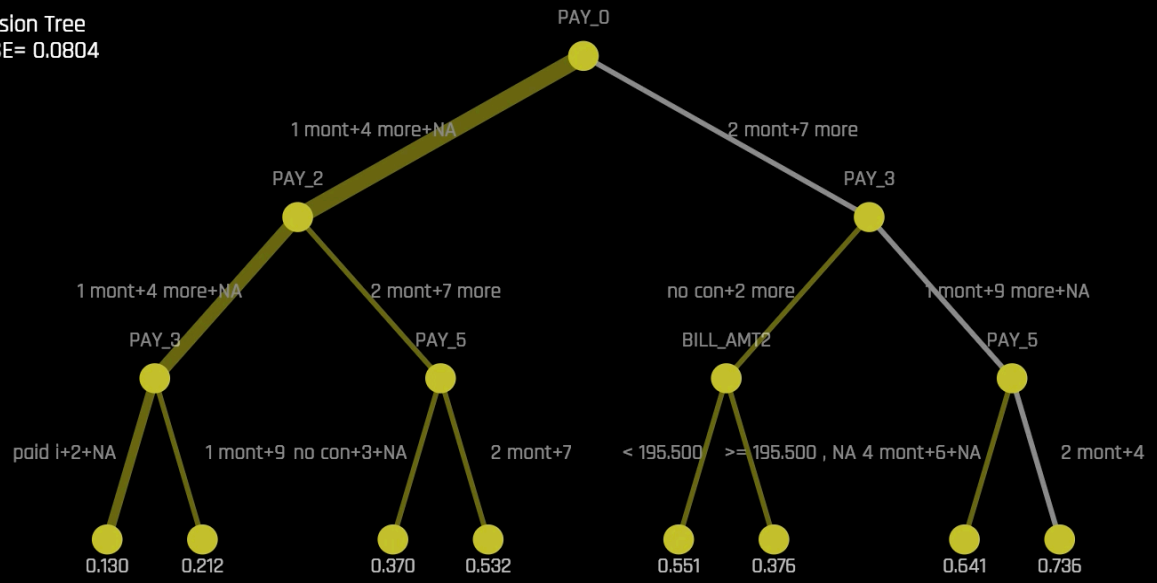


Variable Importance



Decision Tree

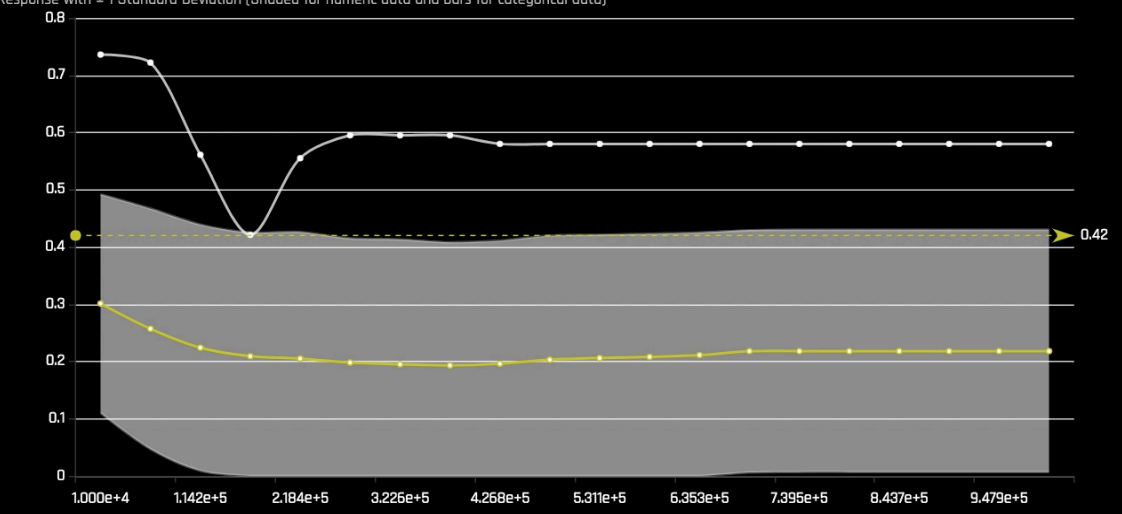
RMSE= 0.0804



Partial Dependence

LIMIT_BAL

Mean Response with ± 1 Standard Deviation (Shaded for numeric data and bars for categorical data)



CLOSE

Actual and Predicted Values

default.payment.next.month (Actual)	0
Model Prediction Value	0.7557
k-LIME Prediction Value	0.7746
k-LIME Prediction Accuracy (%)	97.5%

Local Reason Codes

k-LIME Local Attributions	Variable	with value	is associated with default.payment.next.month	
Top Positive Local Attributions				
	PAY_0	2	increase of	0.32
	PAY_5	7	increase of	0.12
	PAY_2	2	increase of	0.05
Skipped 7 additional attributions, click to view all ...				
Top Negative Local Attributions				
	PAY_4	7	decrease of	0.04
	LIMIT_BAL	170000	decrease of	0.03
	MARRIAGE	NaN	decrease of	0.01
Skipped 10 additional attributions, click to view all ...				
k-LIME Cluster Baseline Attribution				0.2801
k-LIME Prediction (k-LIME Local + Cluster Baseline Attribtions)				0.7746

Cluster 0 Reason Codes

k-LIME explains **89.14%** in **default.payment.next.month** for this cluster.

	Variable	with value	is associated with default.payment.next.month	
Top Positive Cluster Attributions				
	PAY_5	8	increase of	0.413
	PAY_2	6	increase of	0.407
	PAY_0	2	increase of	0.315

Resources

Machine Learning Interpretability with H2O Driverless AI

https://www.h2o.ai/wp-content/uploads/2017/09/MLI.pdf

Ideas on Interpreting Machine Learning

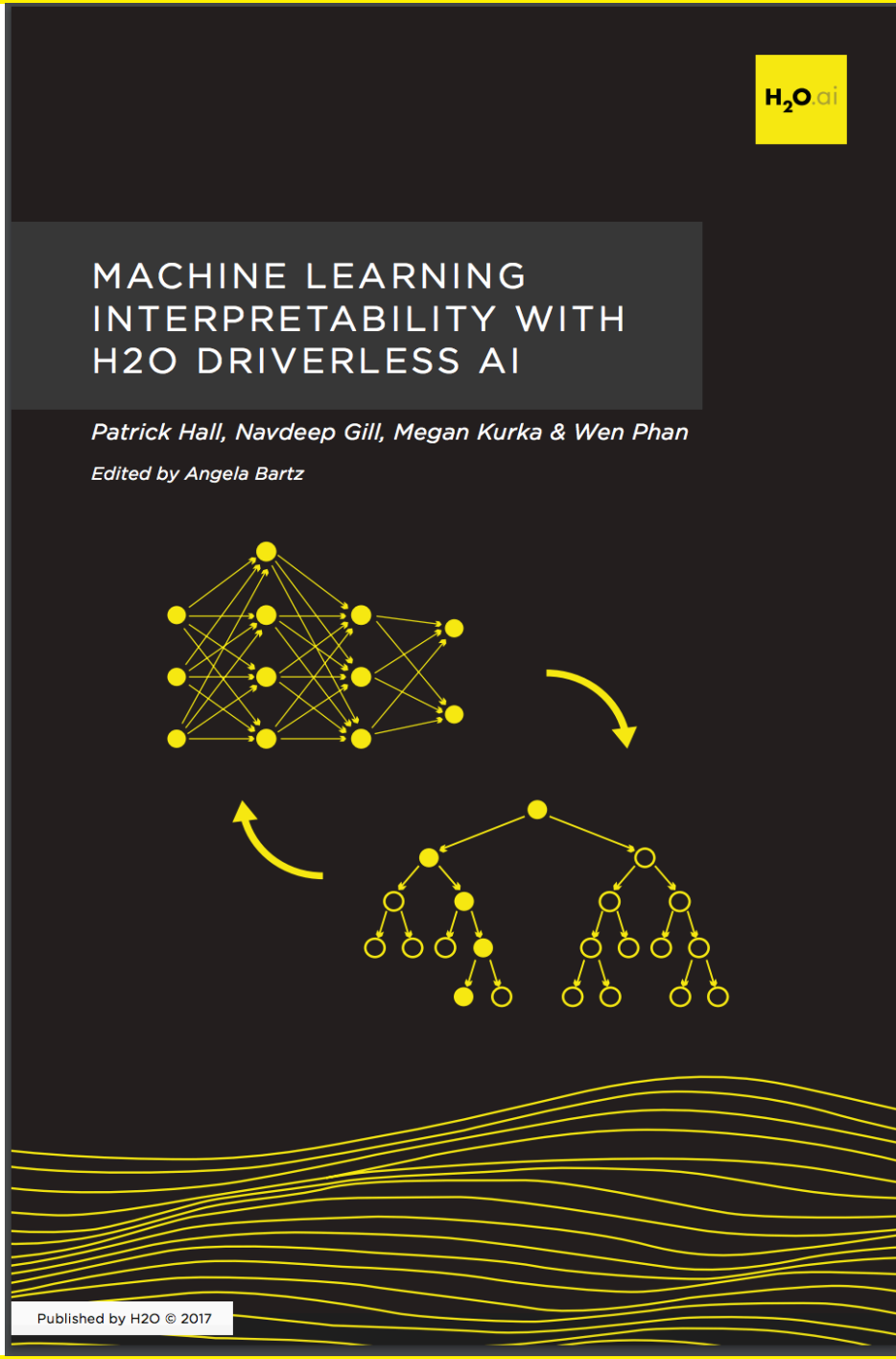
https://www.oreilly.com/ideas/ideas-on-interpreting-machine-learning

FAT/ML

http://www.fatml.org/

MLI Resources

https://github.com/h2oai/mli-resources



Questions?