Ideas on Machine Learning Interpretability

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February 2017

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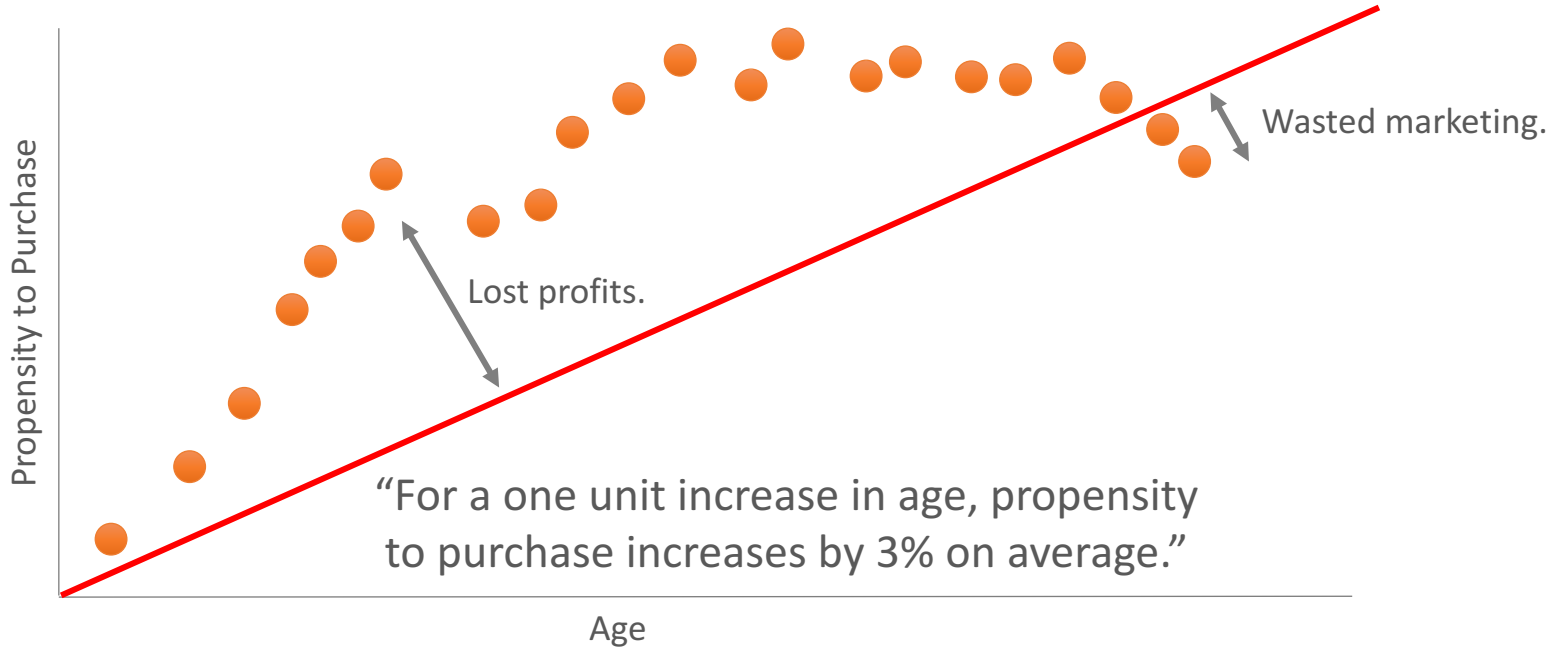
Big Ideas

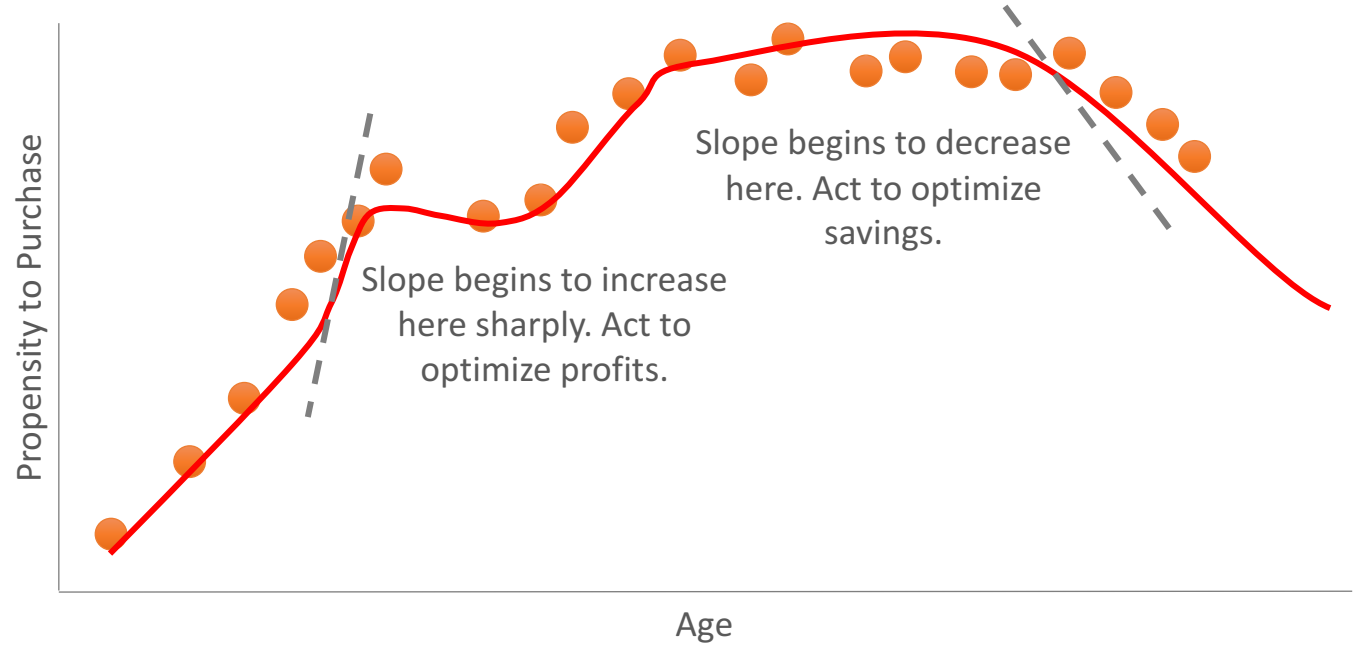
Linear Models

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



Machine Learning

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



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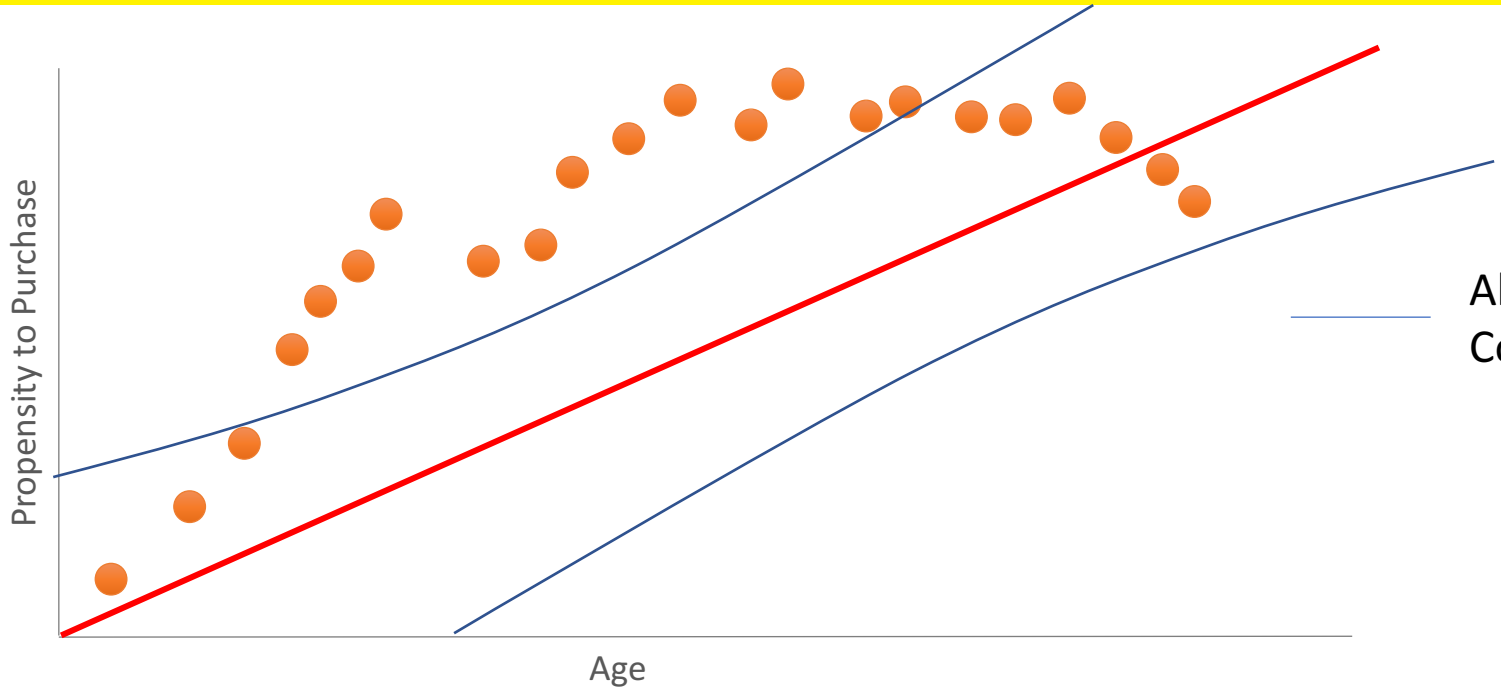
Linear Models

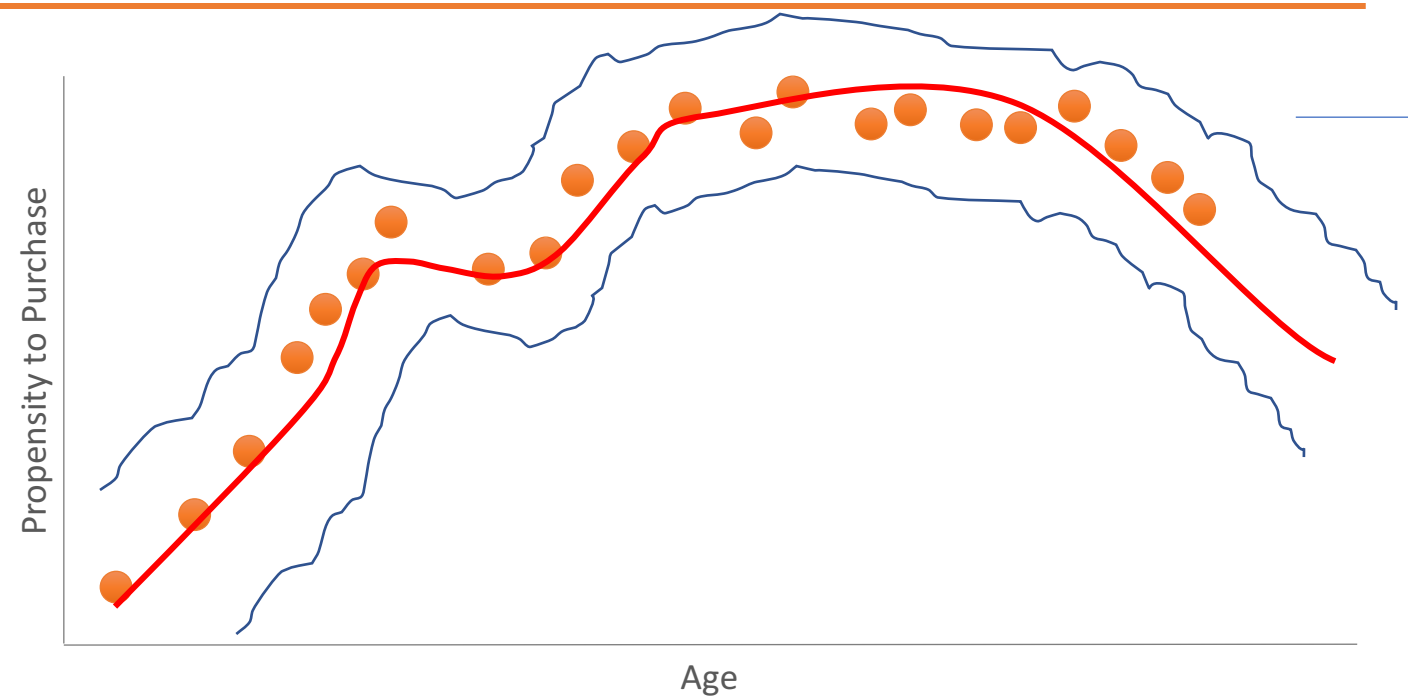
Risk is well defined ...
Theoretically ...
Based on **strong assumptions**.



Alpha = 0.05
Confidence Bands

Machine Learning

Risk is **empirically quantifiable** ...
But it's **hard work**.



Empirically Derived
Prediction Bands

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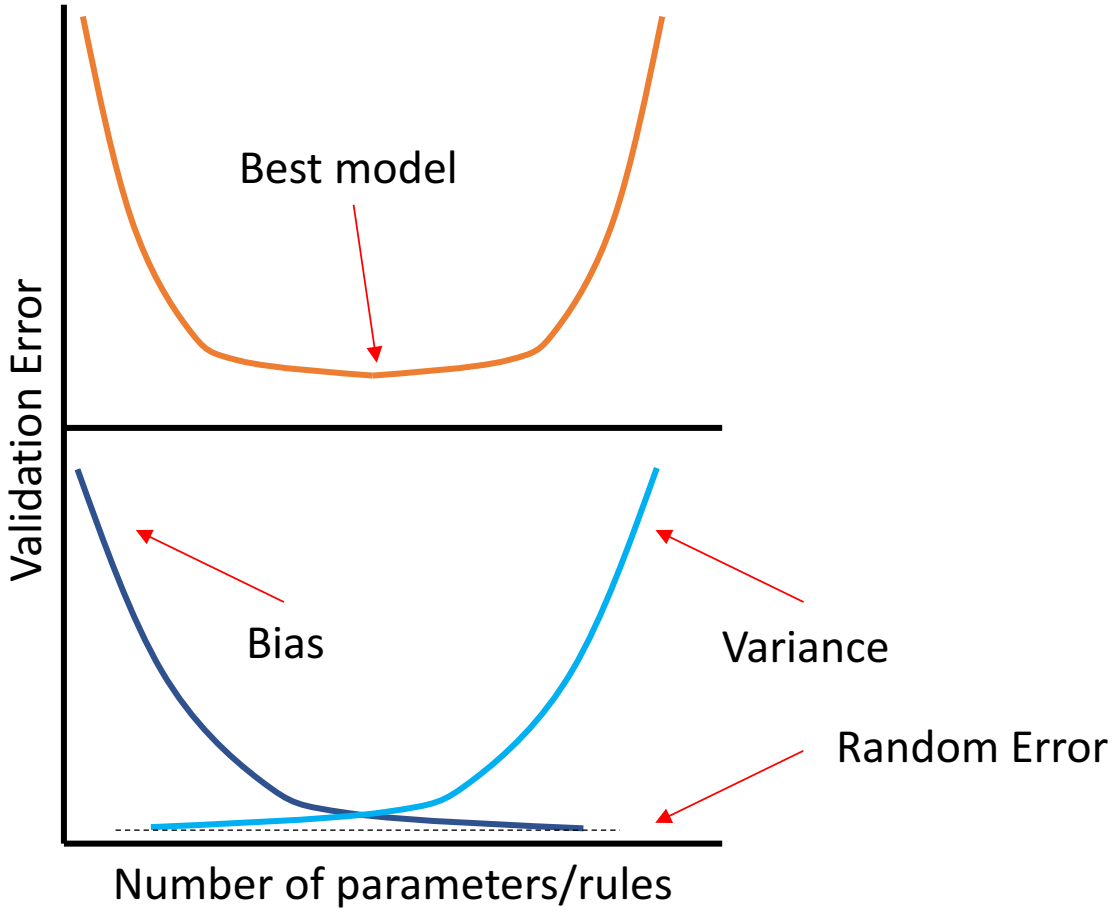
Risk from Unwanted Bias and Prediction Variance

Total Error = Bias + Variance + Random Error =
$(\hat{f}(x) - f(x))^2$



Bias = $E[\hat{f}(x)] - f(x)$ or the error that arises from a model's inability to replicate the fundamental phenomena represented by a data set.

Variance = $(\hat{f}(x) - E[\hat{f}(x)])^2$ or the error that arises from a model's ability to produce differing predictions from the values in a new data set.

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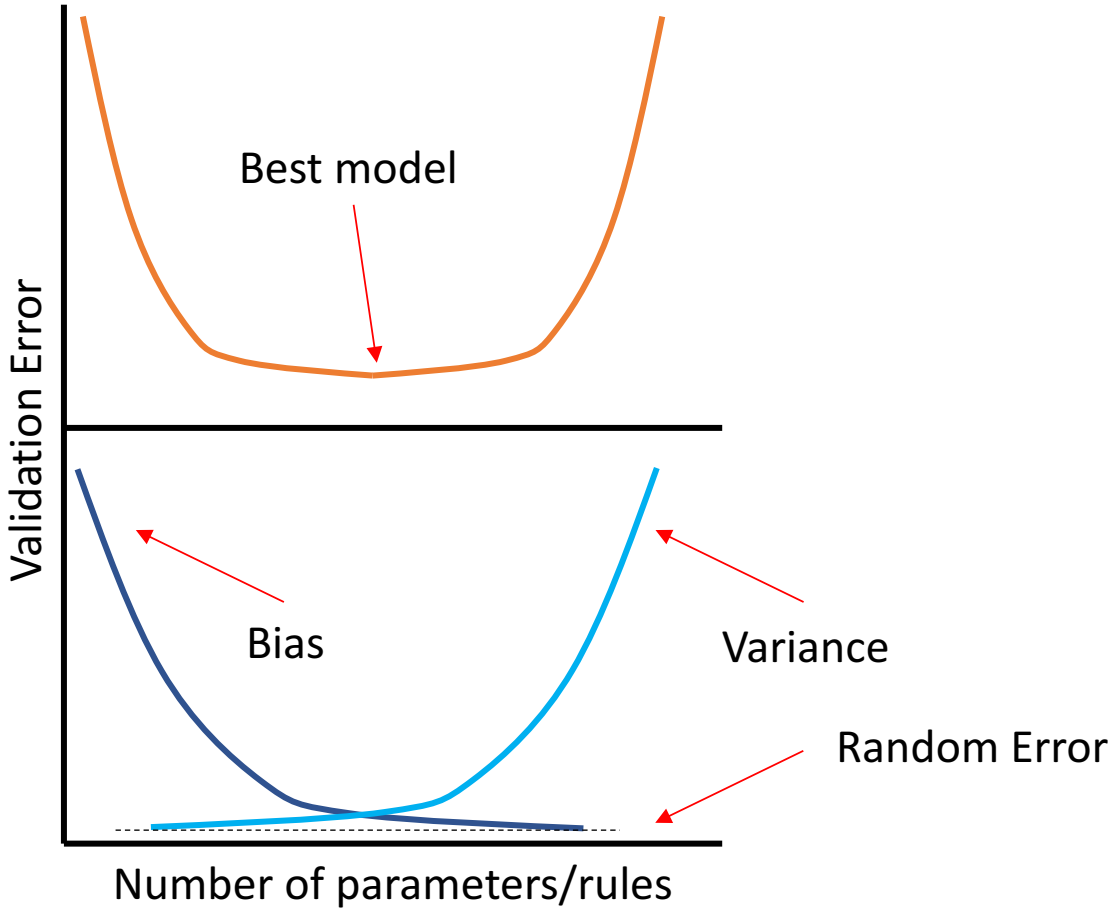
Risk from Unwanted Bias and Prediction Variance

Total Error = Bias + Variance + Random Error =

$$(\hat{f}(x) - f(x))^2$$



Risk from Unwanted Bias: Your model includes contributions from race, gender, disability status, marital status, or other unwanted latent features.

Risk from Prediction Variance: Your model is unpredictable outside of the training domain.

A framework for 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

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Contents

Part 1: Seeing your data

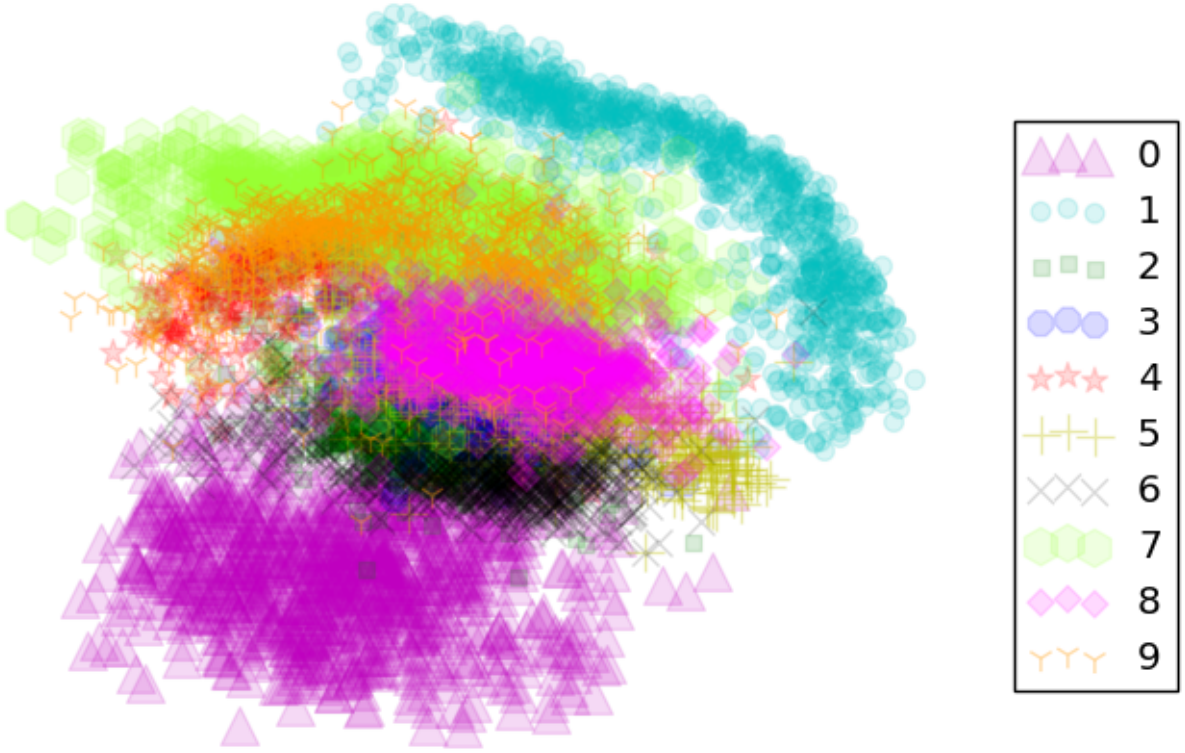
- Glyphs
- Correlation graphs
- 2-D projections
- Partial dependence plots
- Residual analysis

Part 2: Using machine learning in regulated industry

- OLS regression alternatives
- Build toward ML model benchmarks
- ML in traditional analytics processes
- Small, interpretable ensembles
- Monotonicity constraints
- Rule-Based Models

Part 3: Understanding complex ML models

- Surrogate models
- LIME
- Maximum activation analysis
- Sensitivity analysis
- Variable importance measures
- TreeInterpreter

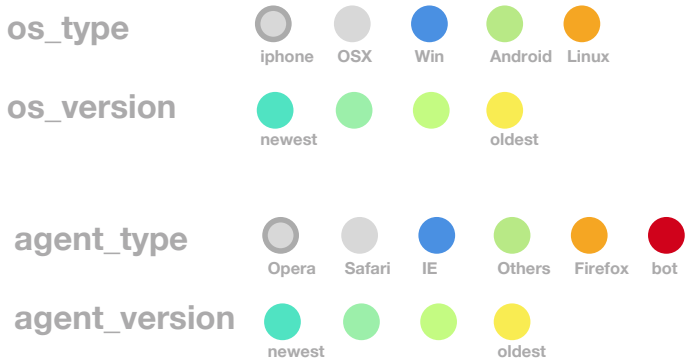


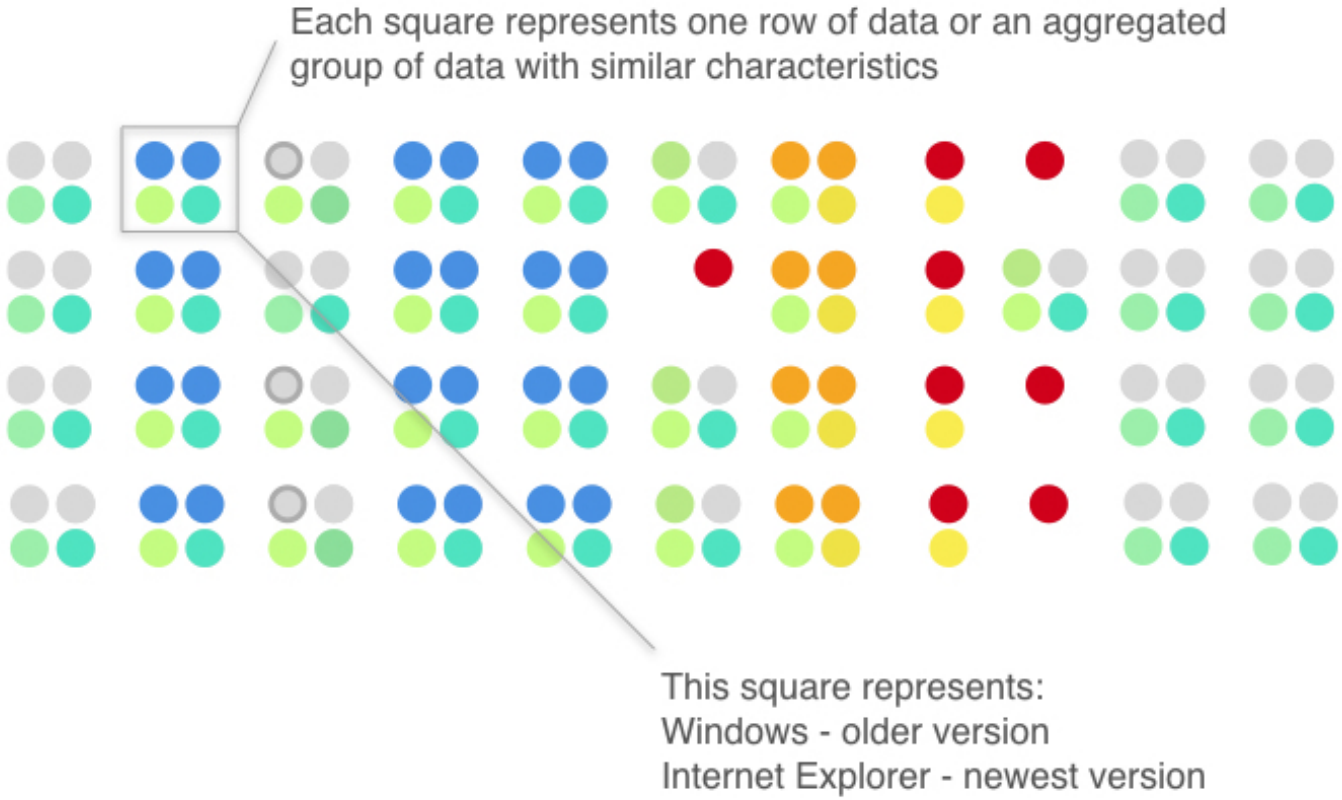
Part 1: Seeing your data

Glyphs

Variables and their values can be represented by small pictures with certain attributes, called “glyphs”.

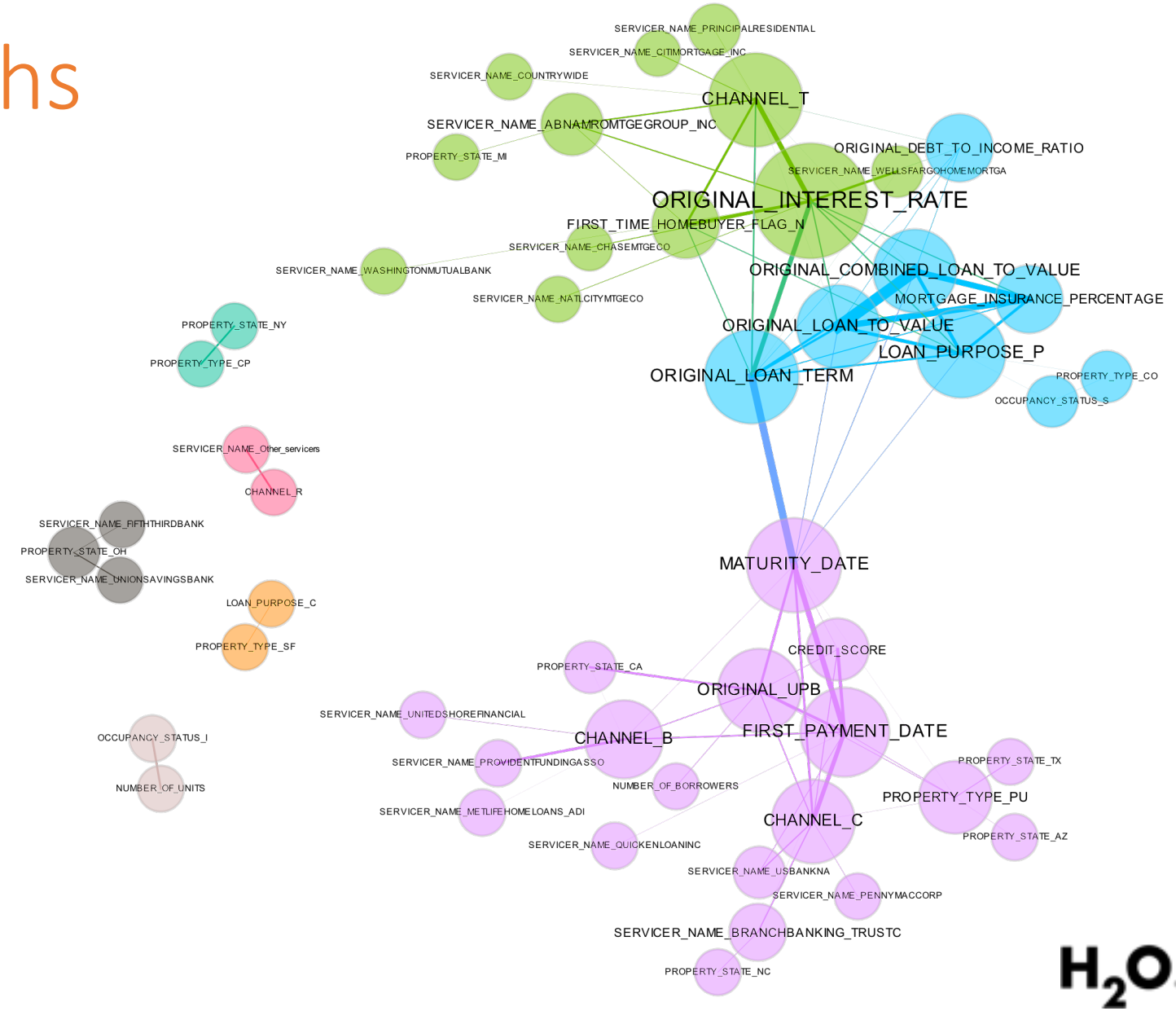
Here the four variables are represented by their position in a square and their values are represented by a color.



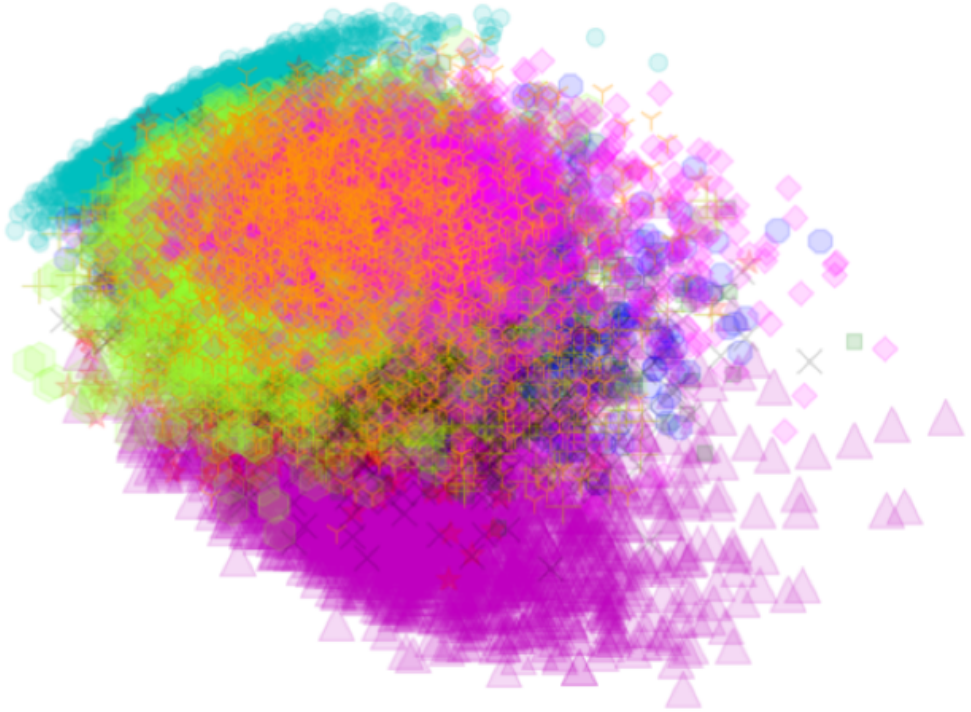


Correlation graphs

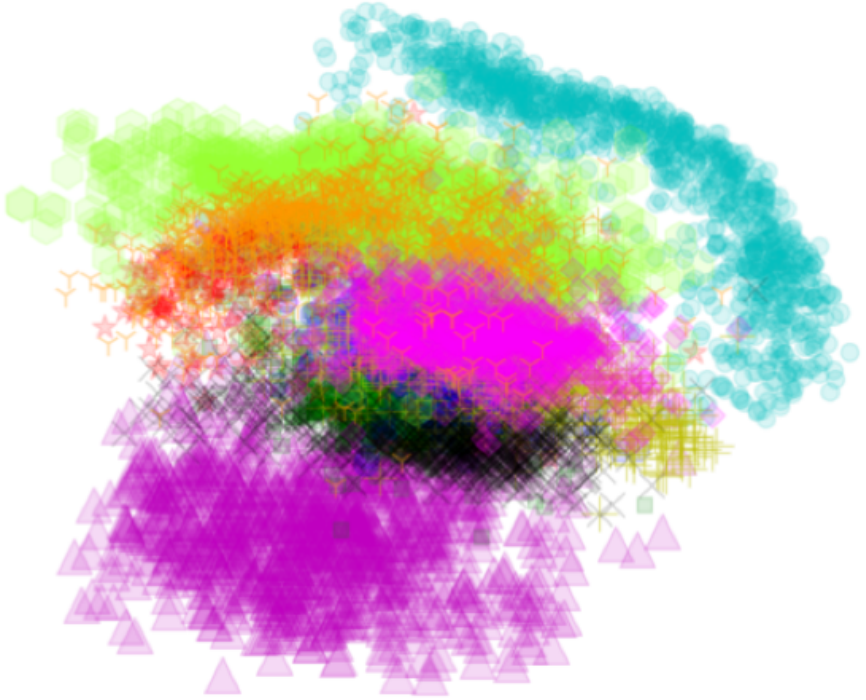
The nodes of this graph are the variables in a data set. The weights between the nodes are defined by the absolute value of their pairwise Pearson correlation.



2-D projections



784 dimensions to 2 dimensions with PCA



784 dimensions to 2 dimensions with autoencoder network

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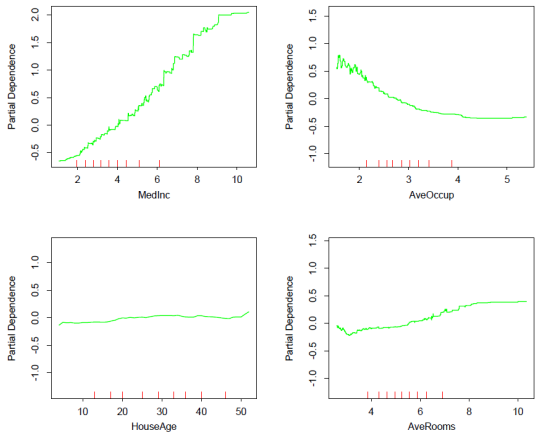
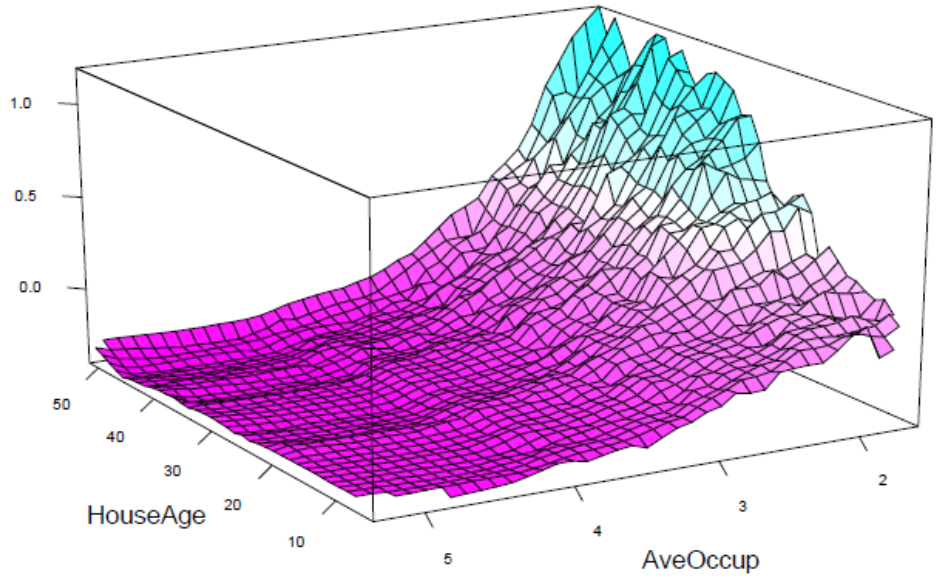
Partial dependence plots

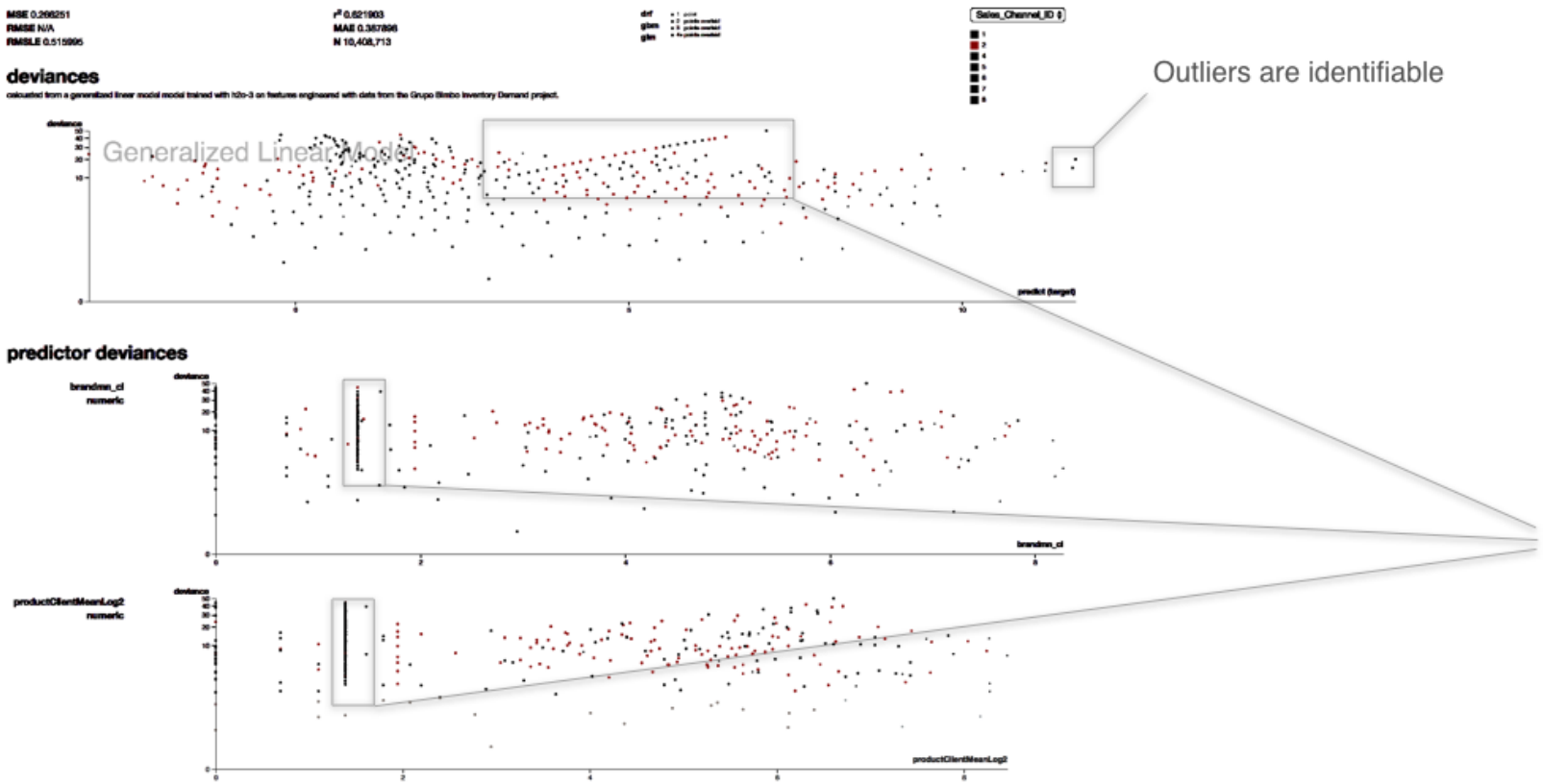




HomeValue ~ MedInc + AveOccup + HouseAge + AveRooms

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

Residual analysis

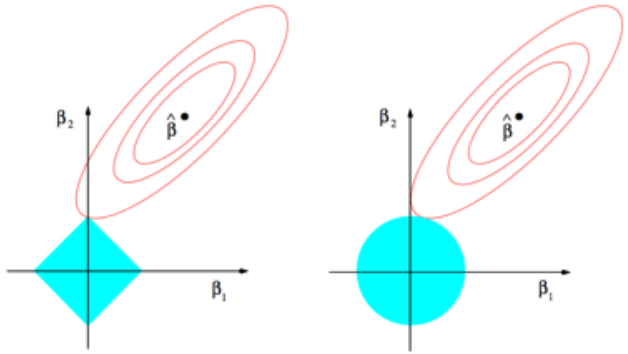


Residuals from a machine learning model should be randomly distributed

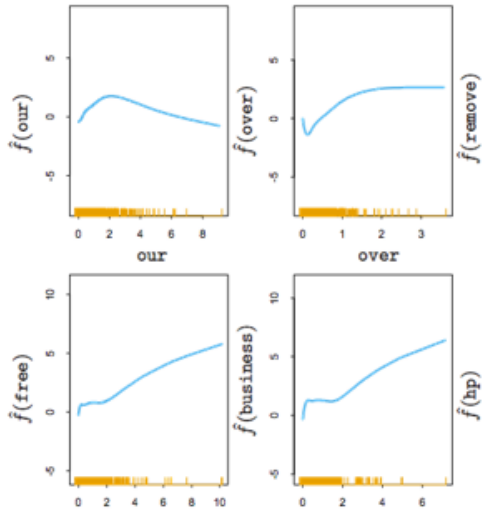
obvious patterns in residuals can indicate problems with data preparation or model specification

Part 2: Using ML in regulated industry

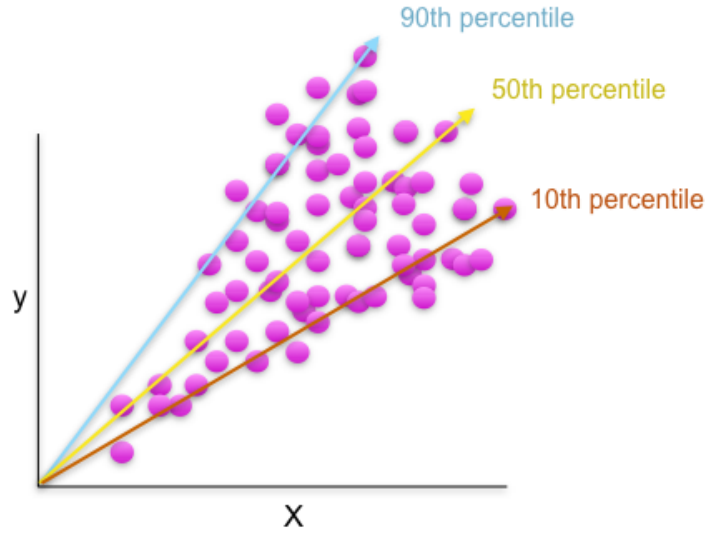
OLS regression alternatives



Penalized Regression



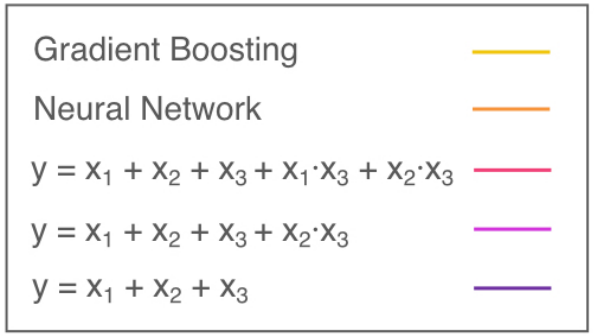
Generalized Additive Models

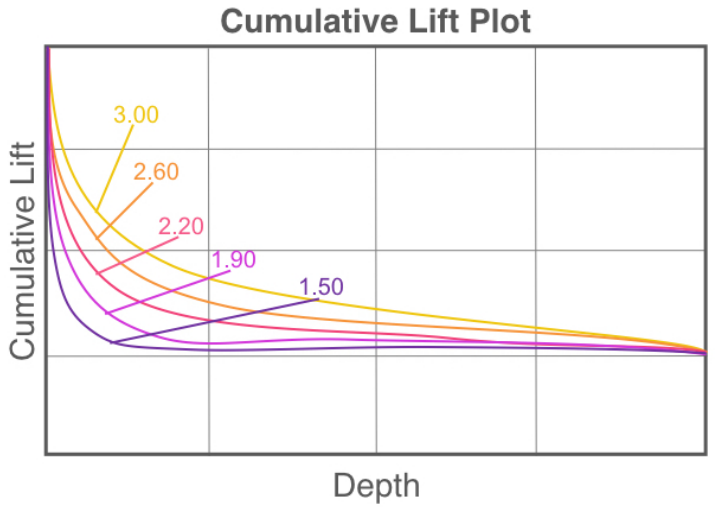


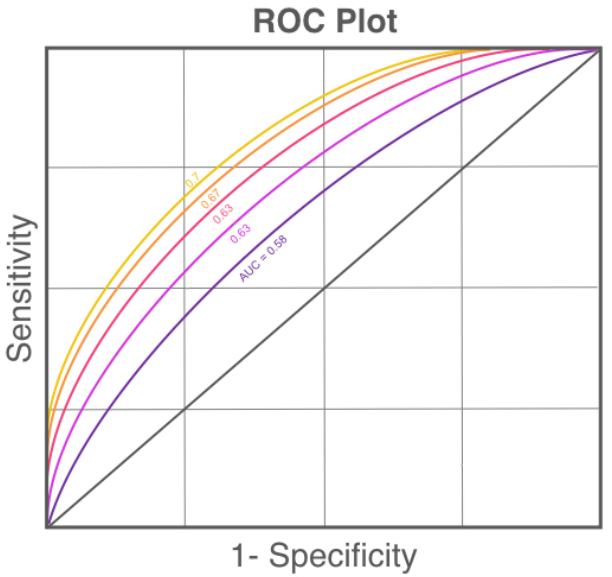
Quantile Regression

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

Build toward ML model benchmarks

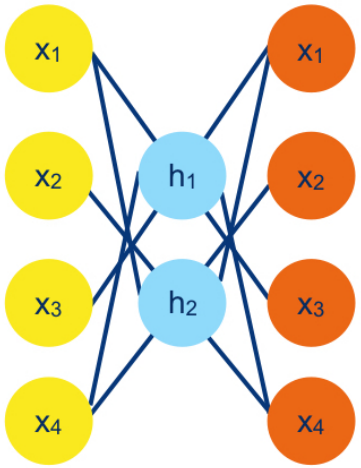




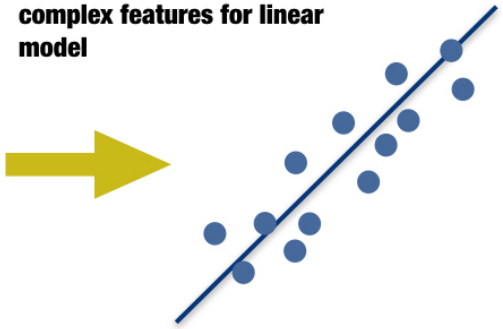


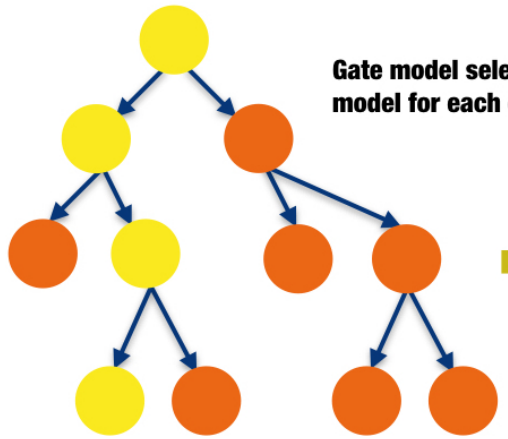
Incorporate interactions and piecewise linear components to increase the accuracy of linear models relative to machine learning models.

Machine learning in traditional analytics processes

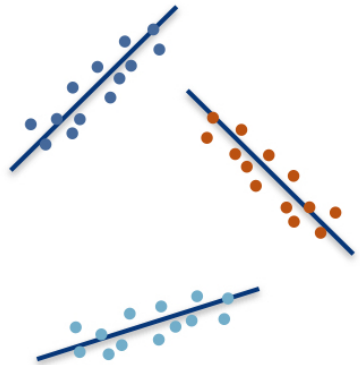


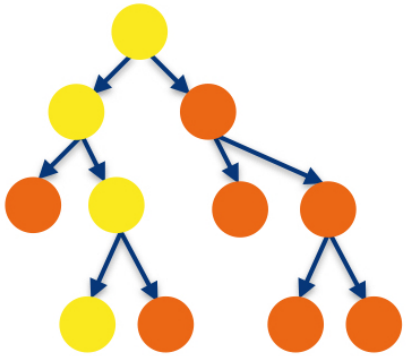
Autoencoder extracts complex features for linear model

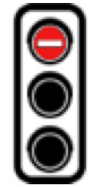




Gate model selects best linear model for each observation







Machine learning forecasts degradation of deployed linear model

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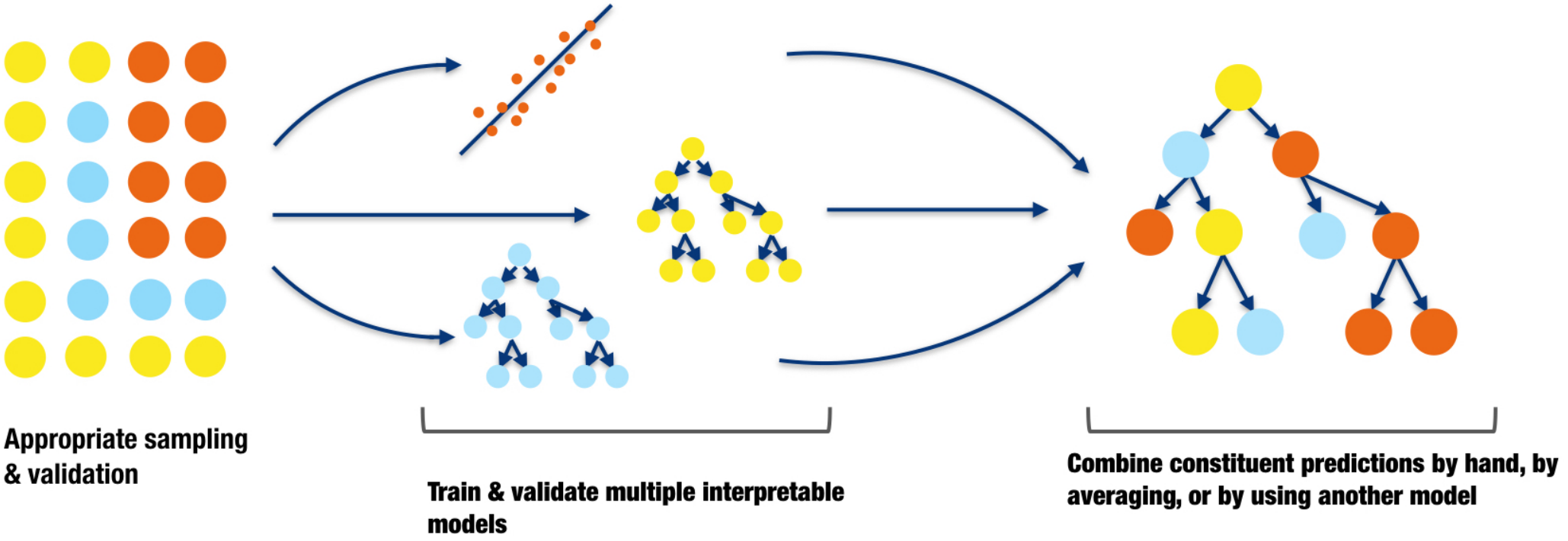
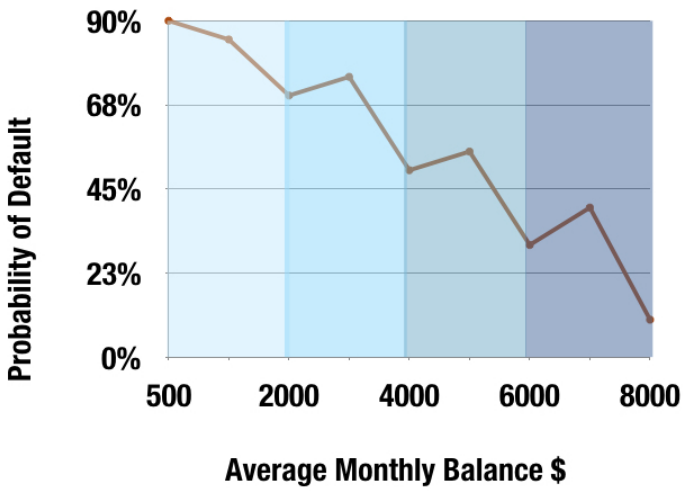
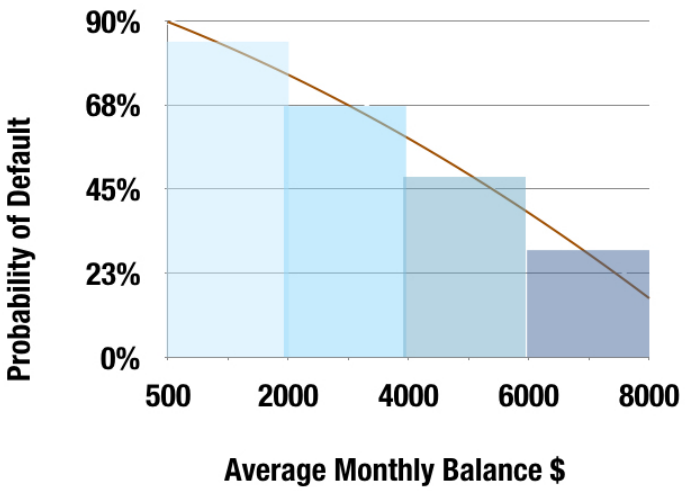
Small, interpretable ensembles



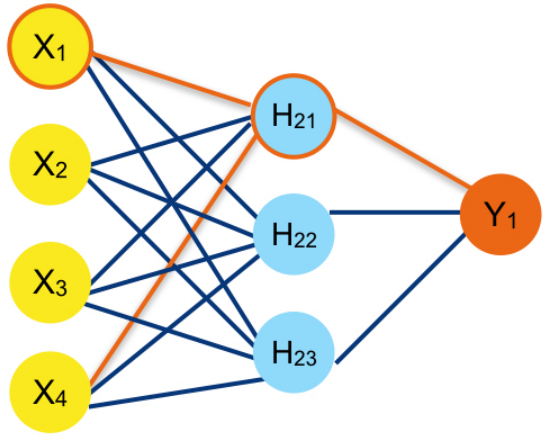
Monotonicity constraints



Average Monthly Balance is a nonnegative quantity, but is not monotonic with respect to Probability of Default.



By discretization, the Average Monthly Balance can be transformed to be monotonic with respect to the target.



When all inputs are nonnegative and monotonic with respect to the target, and model weights are constrained to be nonnegative, it's easier understand the impact of individual features and to find interactions.

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Rule-based models

IF Age: 30 <= 40 …

AND Income: 70K <= 80K …

AND Zip Code == 20009 …

AND Marital Status == SINGLE …

AND Loyalty Status == SILVER …

THEN Probability = 0.7463

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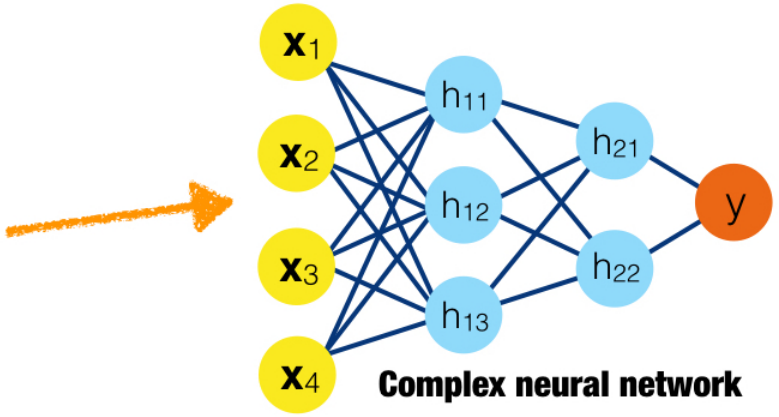
Part 3: Understanding complex machine learning models

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

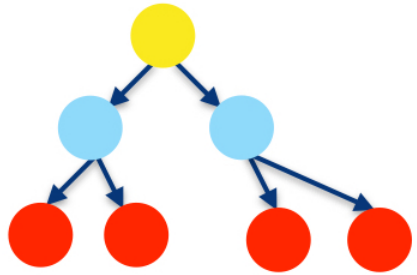
1. Train a complex machine learning model



Complex neural network

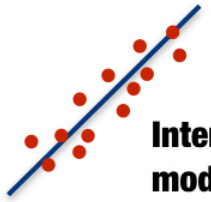
BAD	PREDICTED_BAD	CUSTOMER_DTI	LOAN_PURPOSE	CHANNEL
0	0.47	0.18	MORT	7
1	0.82	0.42	HELOC	10
0	0.18	0.11	MORT	10
0	0.12	0.21	MORT	1

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



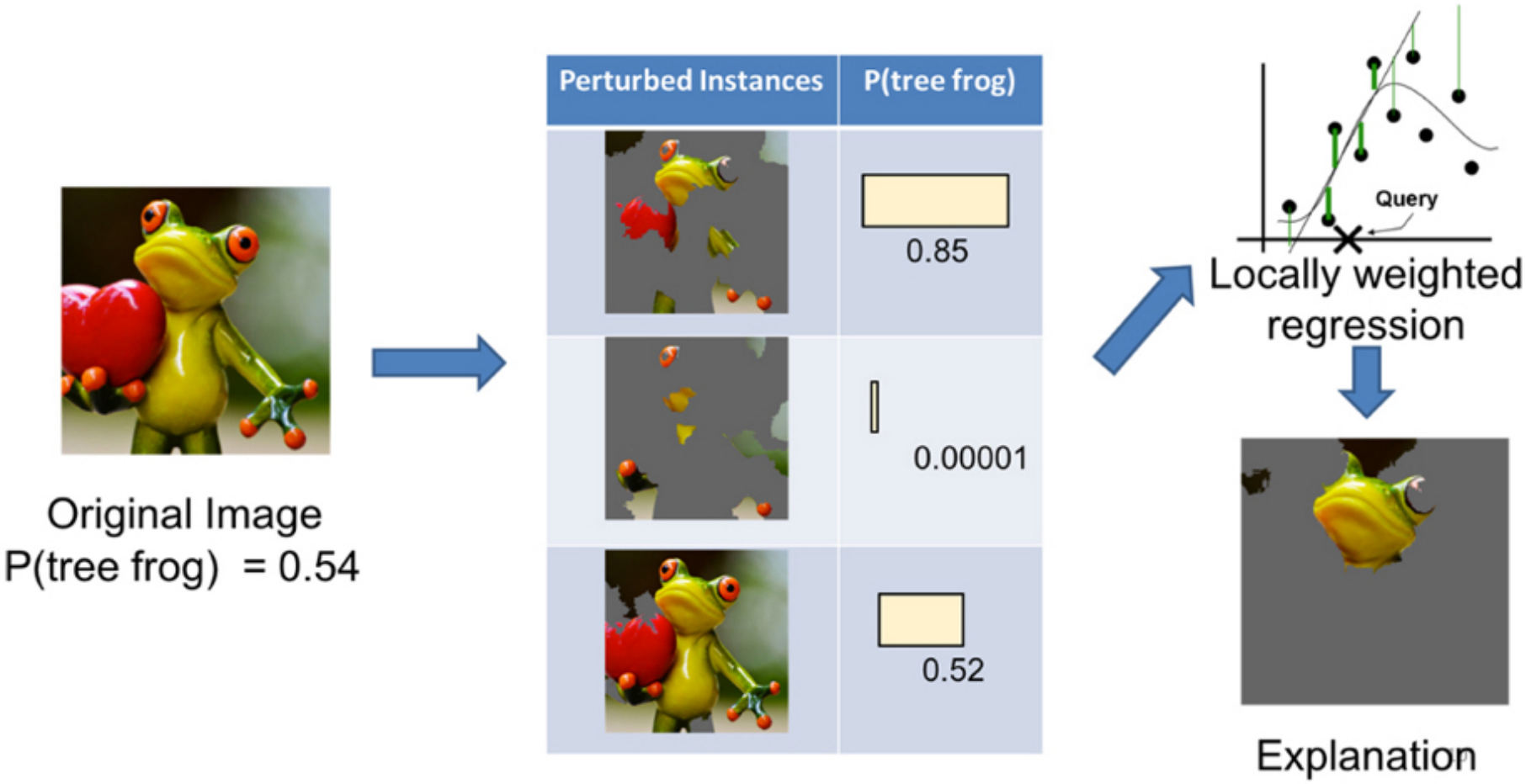
Interpretable decision tree

Or



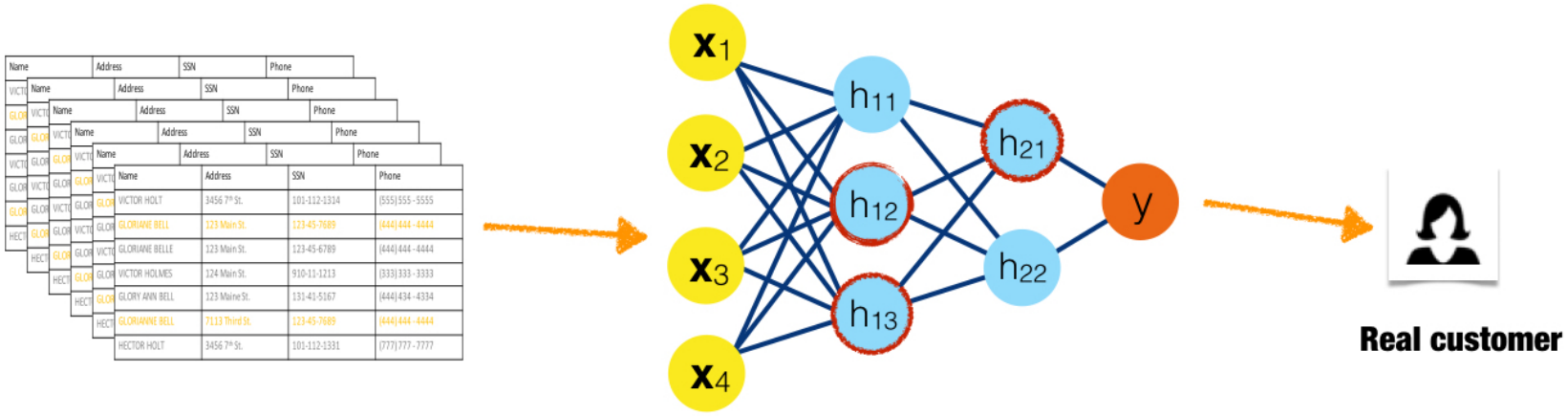
Interpretable linear model

Local interpretable model-agnostic explanations

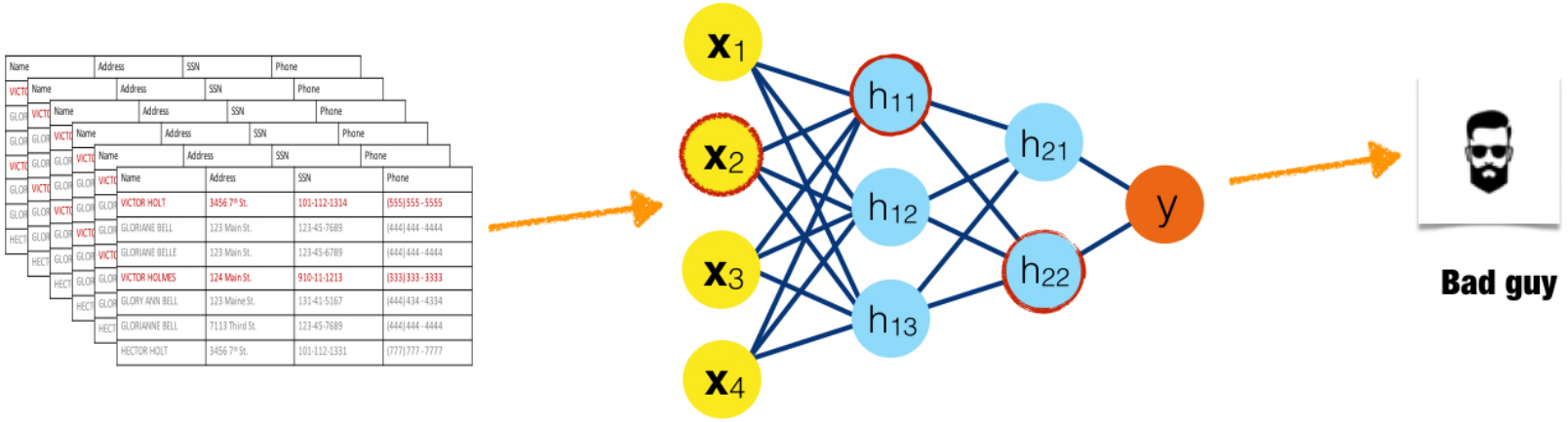


Source: https://www.oreilly.com/learning/introduction-to-local-interpretable-model-agnostic-explanations-lime

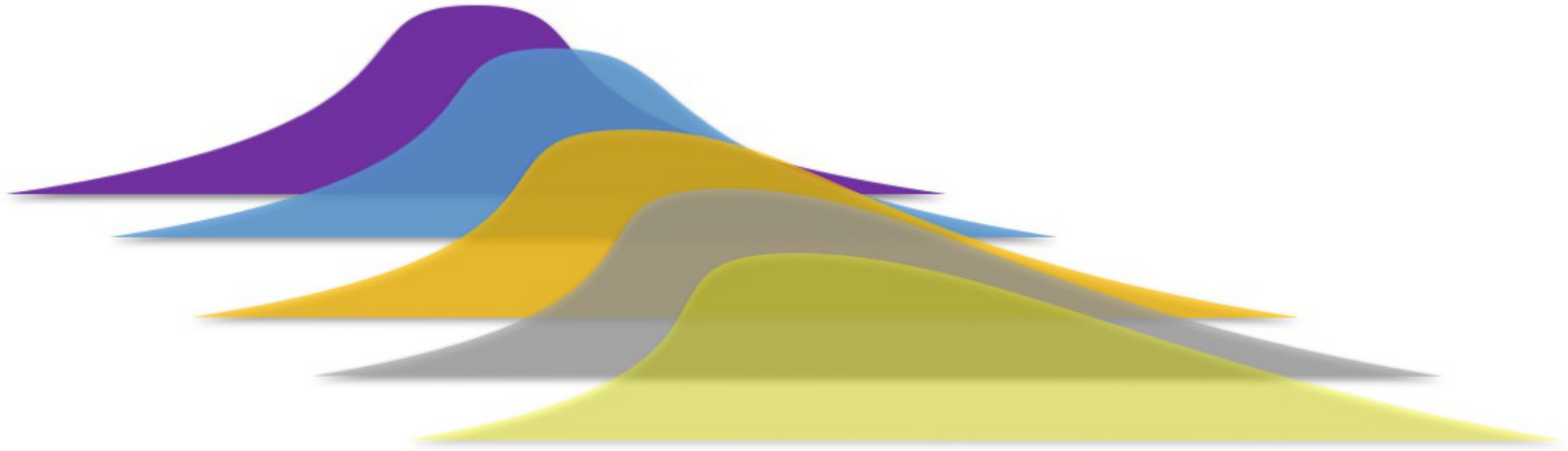
Maximum activation analysis



Different types of customers maximally activate different internal structures

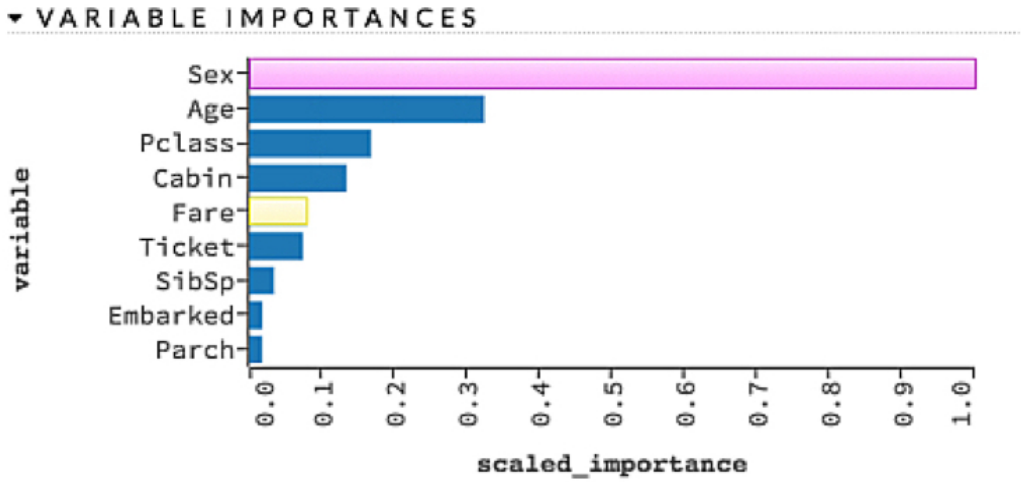


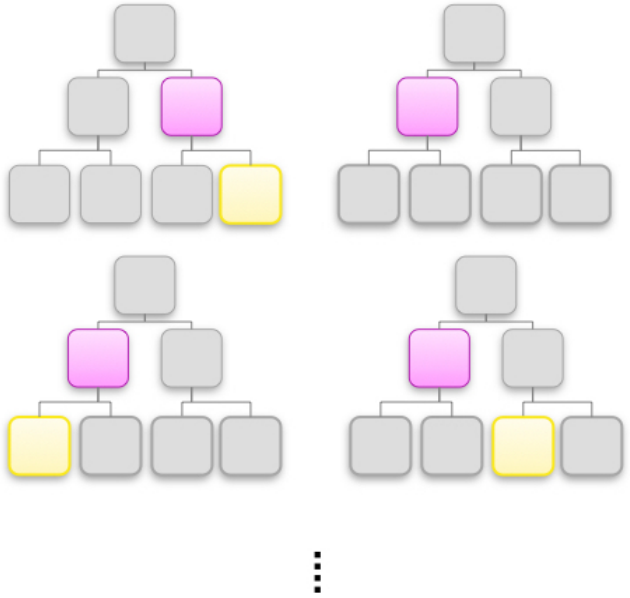
Sensitivity analysis



Data distributions shift over time. How will your model handle these shifts?

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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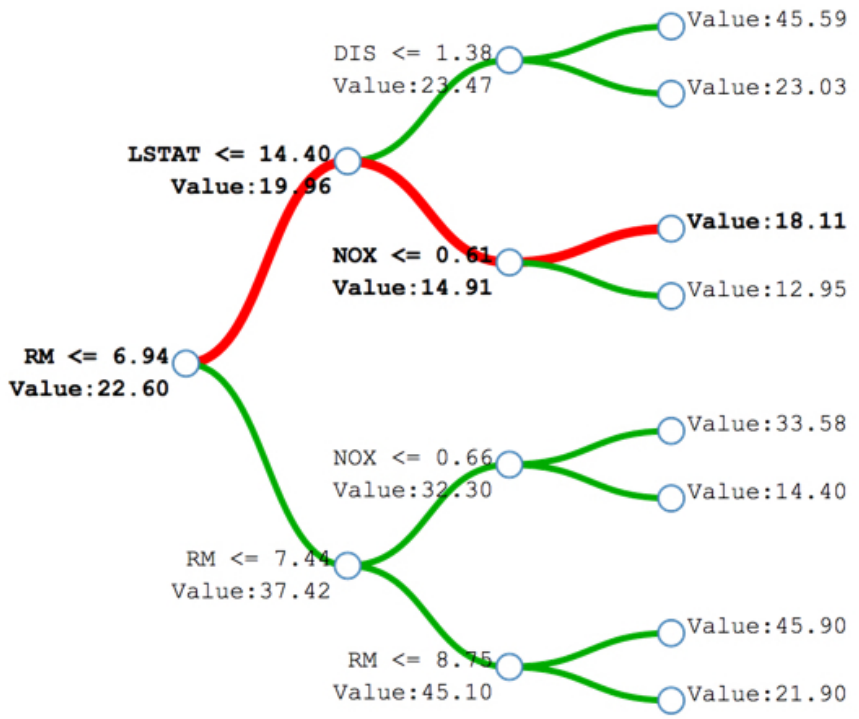
Treeinterpreter

Tree interpreter decomposes decision tree and random forest predictions into bias (overall average) and component terms.

This slide portrays the decomposition of the decision path into bias and individual contributions for a single decision tree - treeinterpreter simply prints a ranked list of the bias and individual contributions for a given prediction.



Prediction: 18.11 ≈ 22.60 (trainset mean) - 2.64(loss from RM) - 5.04(loss from LSTAT) + 3.20(gain from NOX)

Source: http://blog.datadive.net/interpreting-random-forests/