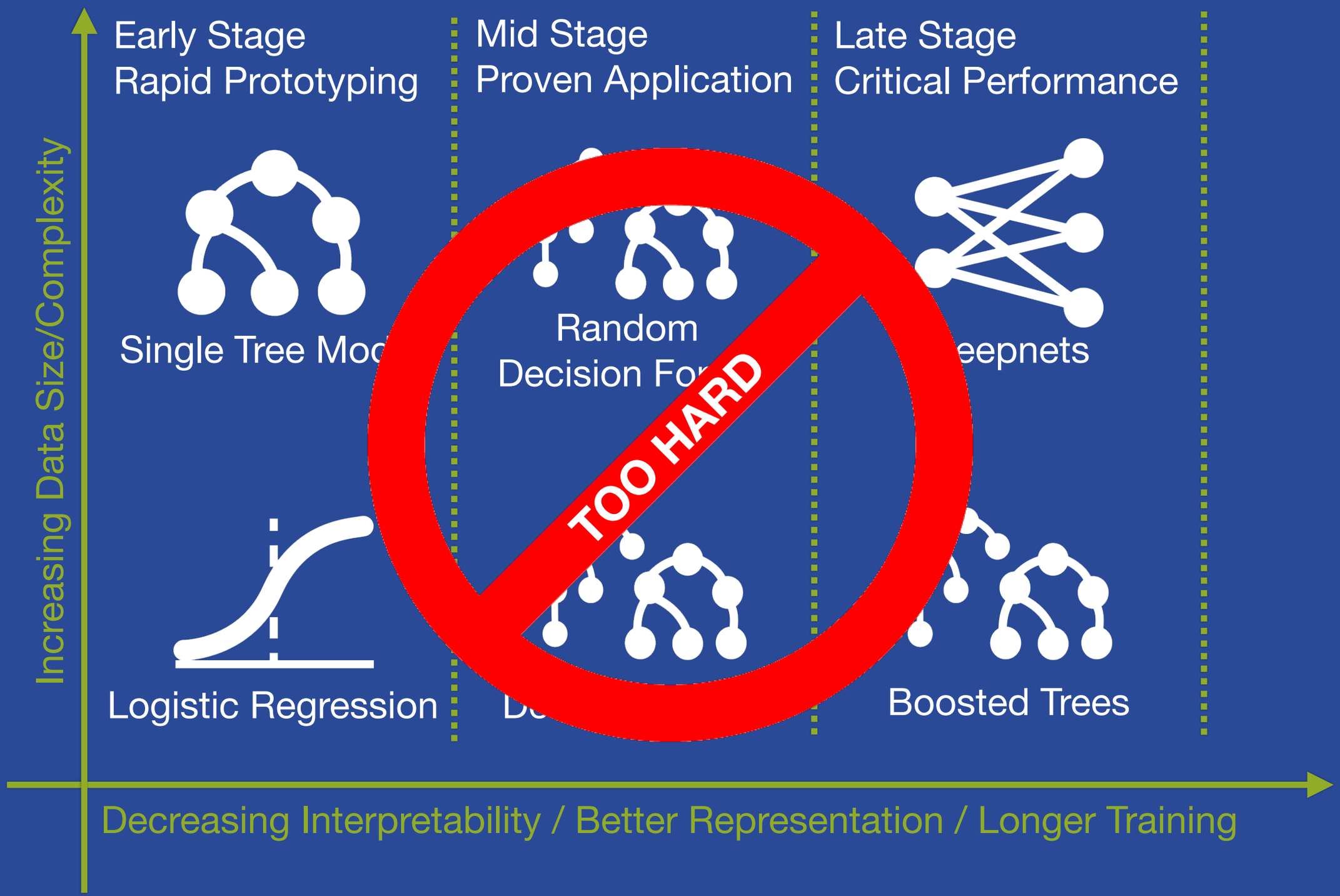
OptiML and Fusions

Automating Machine Learning

Charles Parker

VP ML Algorithms, BigML, Inc

Model Choices



BigML Deepnets

Remember this?

- The success of a Deepnet is dependent on getting the right network structure for the dataset
- But, there are too many parameters:
  - Nodes, layers, activation function, learning rate, etc…
- And setting them takes significant expert knowledge
- Solution:
  - Metalearning (a good initial guess)
  - Network search (try a bunch)

OptiML

*Key Insight: We can solve **any** parameter selection problem in a similar way.*

- Each resource has several parameters that impact quality
  - Number of trees, missing splits, nodes, weight
- Rather than trial and error, we can use ML to find ideal parameters
- Why not make the model type, Decision Tree, Boosted Tree, etc, a parameter as well?
- Similar to Deepnet network search, but finds the optimum machine learning **algorithm** and **parameters** for your data **automatically**

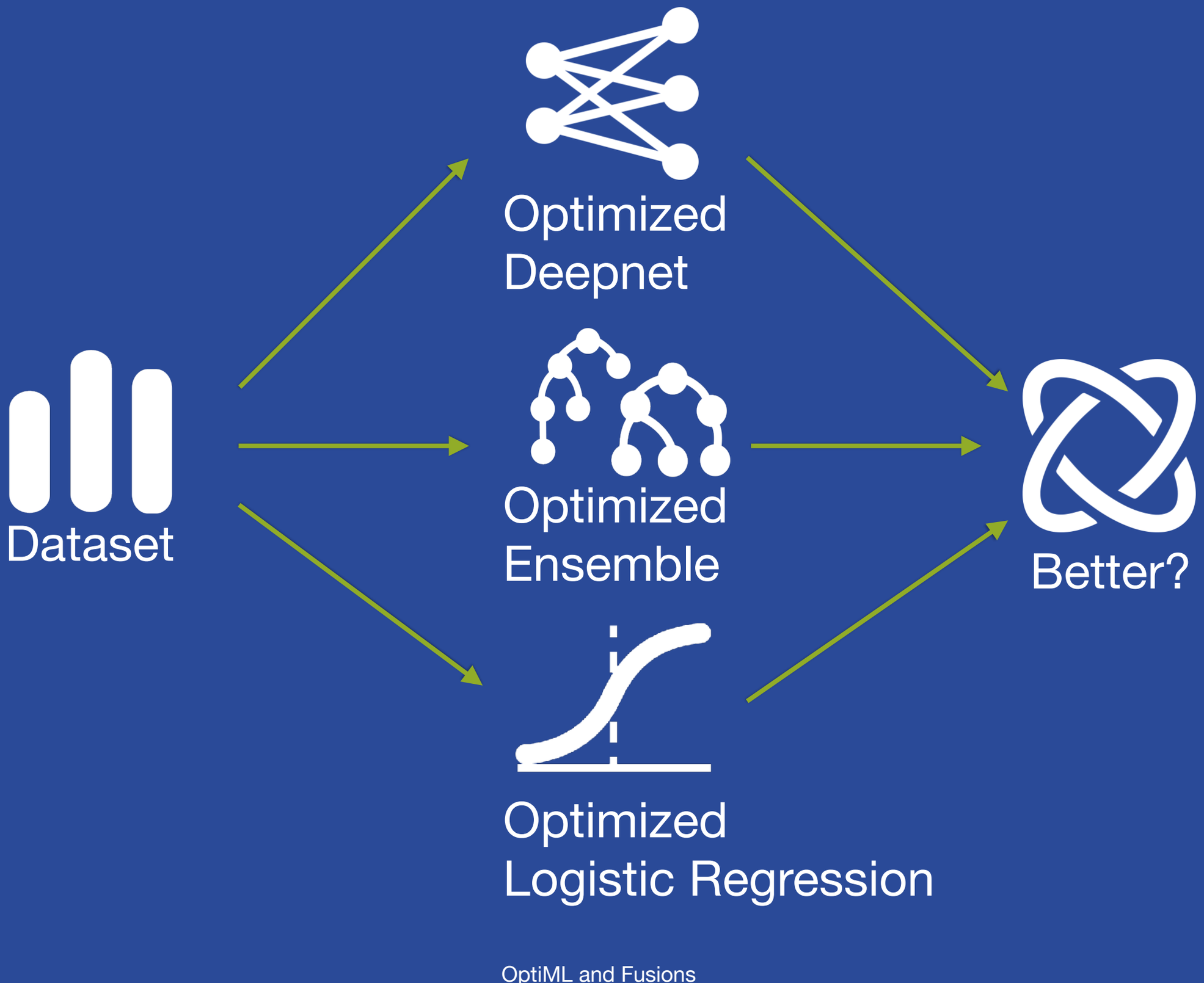
OptiML Demo

Fusions Inside

Key Insight: ML algorithms each have unique strengths and weaknesses

- Fuse any set of models into a new “fusion”
  - Must have the same objective type
  - Inputs and feature space **can** differ
- Weights can be added
  - Give more importance to individual models
- Fusions can be fused as well
- Especially useful for fusing OptiML models

Performance thru Diversity



Fusion Demo #1

Fusions: Under the Hood

Classification

Model	Prediction	Probability	Weight
Ensemble	TRUE	%56	1
Deepnet	FALSE	%67	1
Model	TRUE	%78	2

Fusion

TRUE	%61

P(TRUE) = [56+(100-67)+2*78] / 4

Regression

Model	Prediction	Error	Weight
Ensemble	156.78	12.56	1
Deepnet	139.55	9.88	1
Model	172.10	23.76	2

Fusion

160.13	17.49

Fusions: Like any BigML Model

- Fully accessible thru API and WhizzML
- Bindings have support for local predictions

```
;; WhizzML - create a fusion
(define my-fusion (create-fusion {"models" my-best-models}))
```

```
# Python - create a fusion
fusion = api.create_fusion(["model/5af06df94e17277501000010",
                            "logisticregression/5af06df84e17277502000019",
                            "deepnet/5af06df84e17277502000016",
                            "ensemble/5af06df74e1727750100000d"]})
```

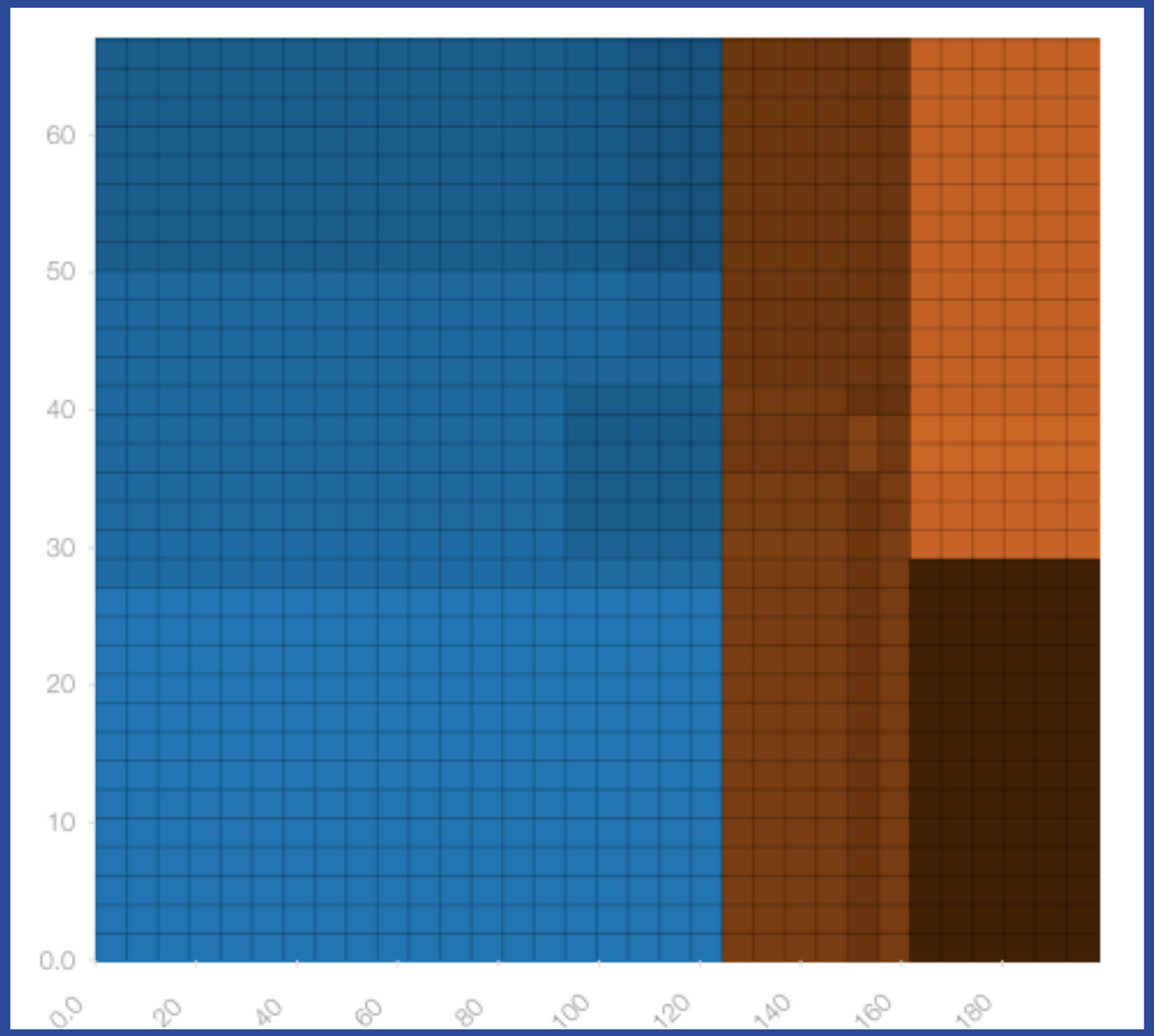
Decision Boundary Smoothness

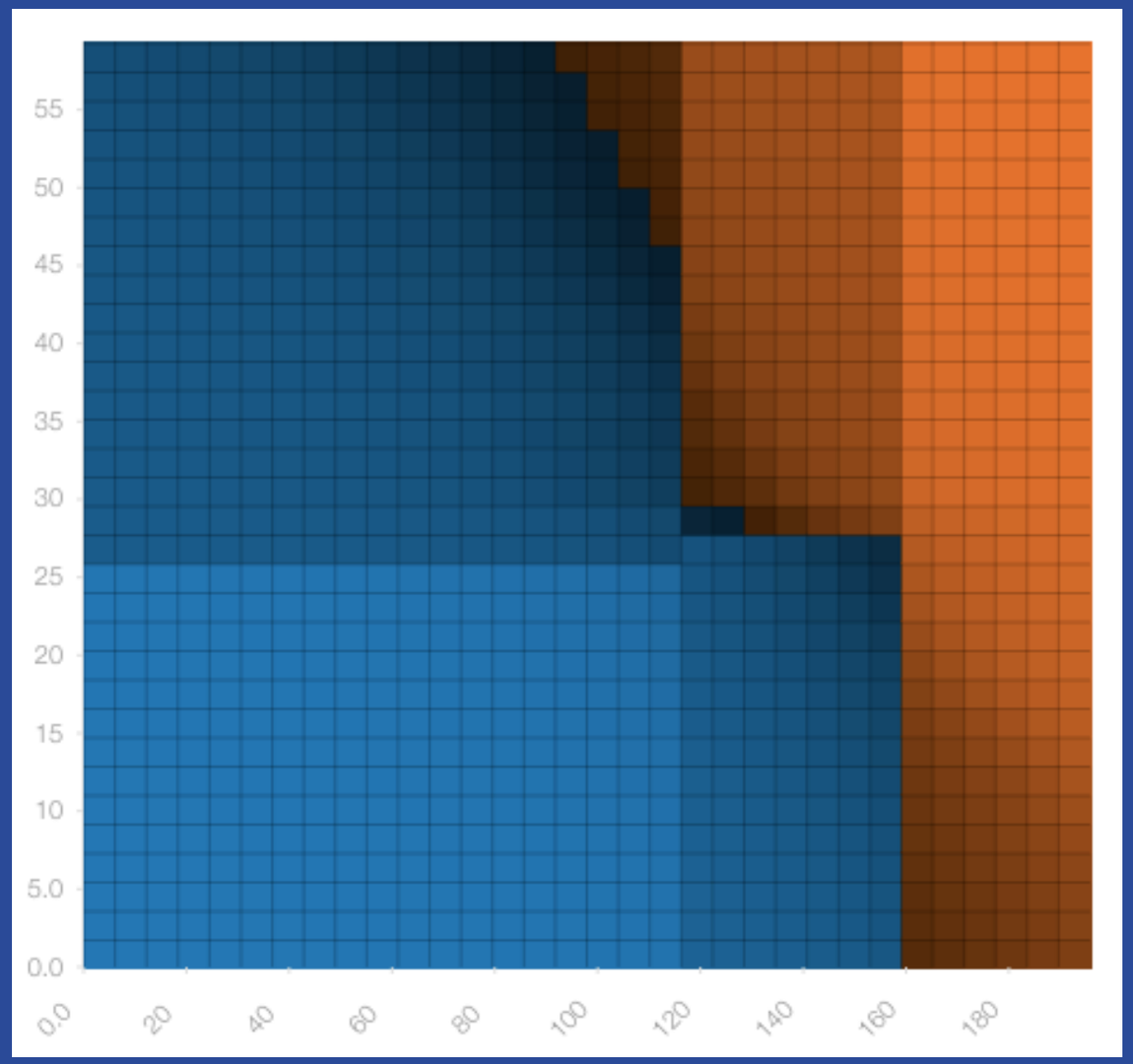
Single Tree:

- Outcome changes abruptly near decision boundary
- And not at all parallel to the boundary
- This can be “surprising”

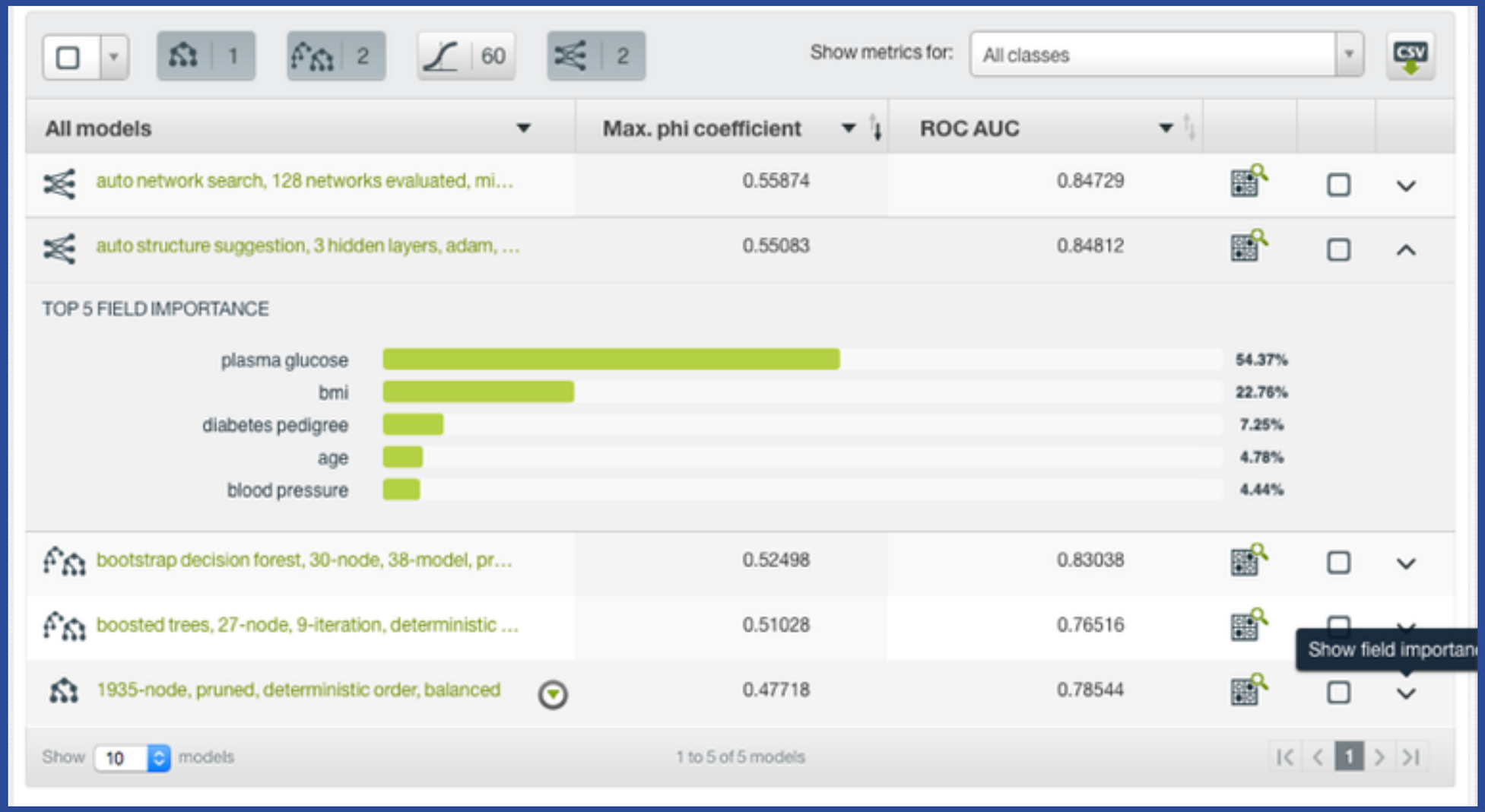
Single Tree + Deepnet:

- Keep the interpretability of the tree
- But with a more nuanced decision boundary





Feature Stability



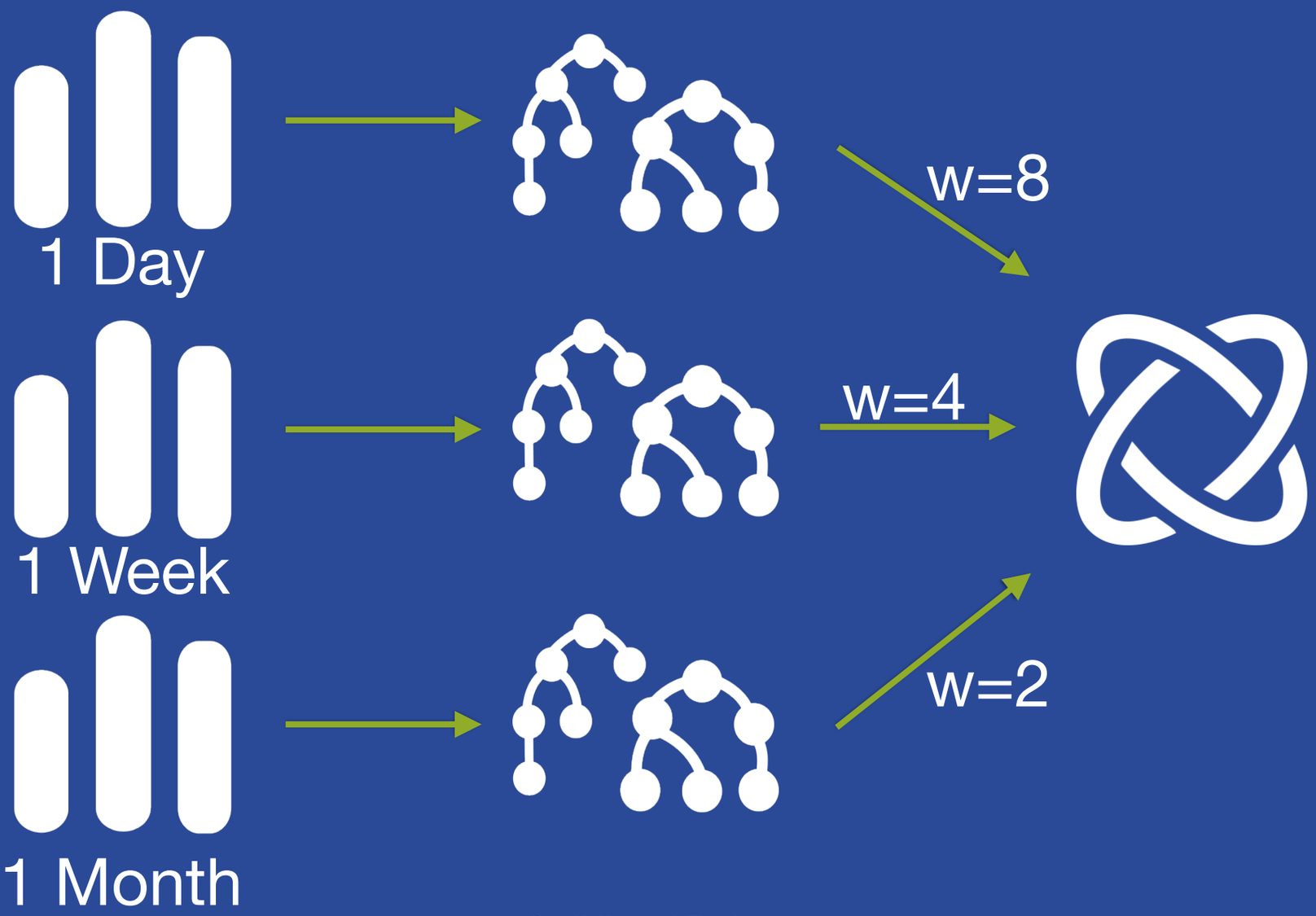
Feature Importance: Different subsets of features may have similar modeling performance

Fusing models gives better resilience against missing values as well as ensuring that all relevant features are utilized.

Weighting over Time

Data significance over time:

- Some data may change significance in different times
- Short-term user behavior versus long-term
- Weights can set to account for significance of time

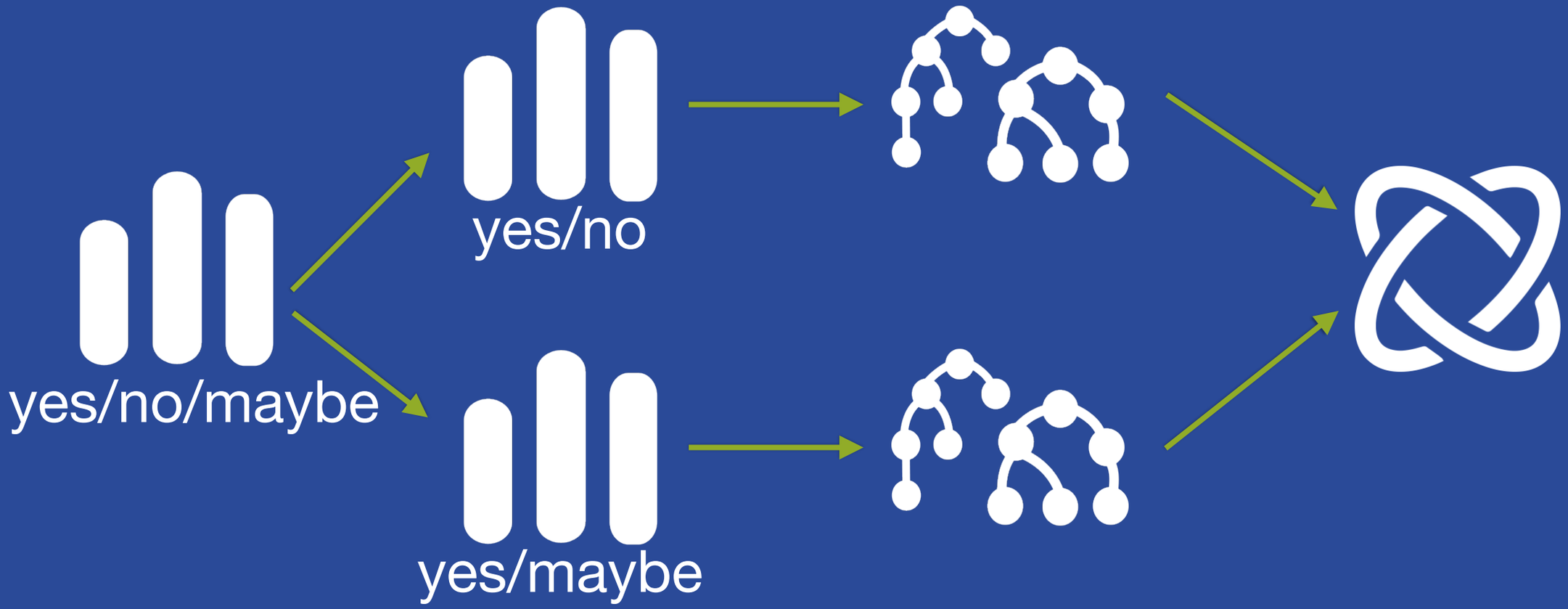


Improved Class Separation

Consider a 3-class objective

Yes	No	Maybe

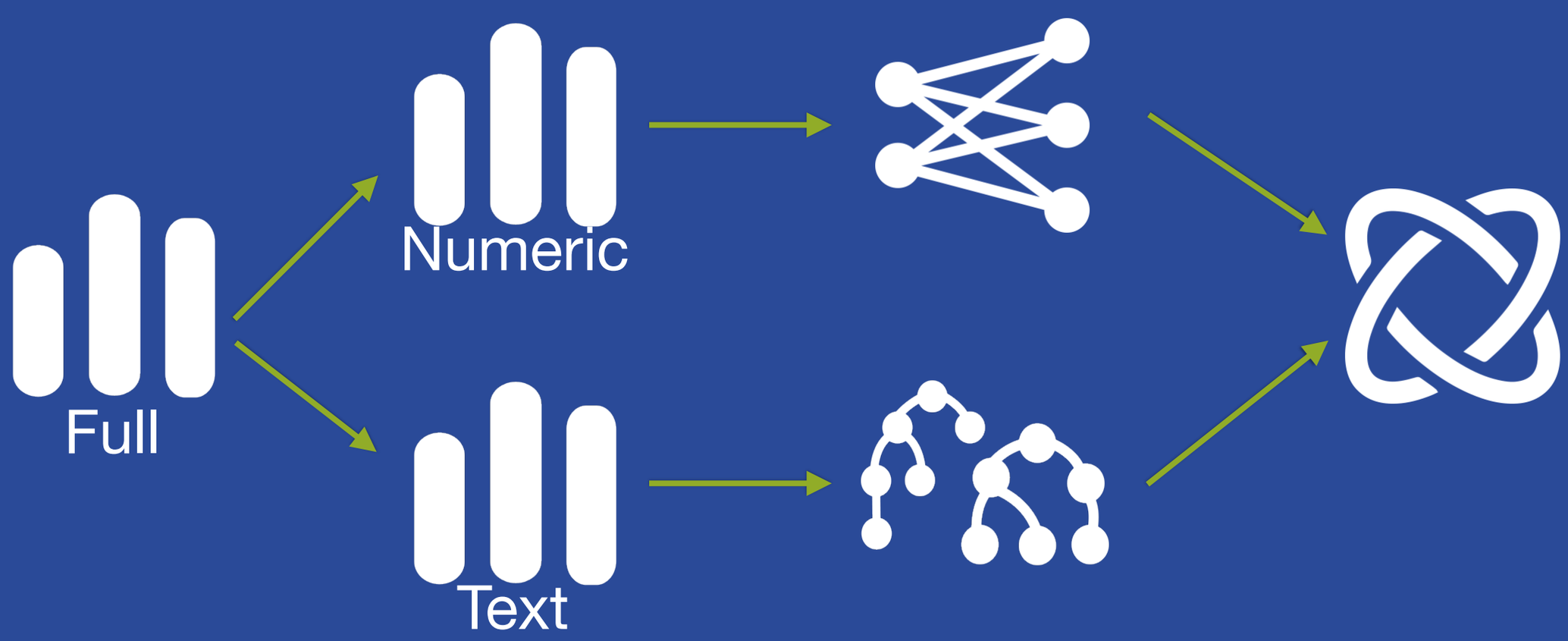
- Really only care about “yes” versus “not yes”
- A single model may struggle to separate the two negative classes



Feature Space Optimization

Model Skills: *Some ML algorithms "generally" do better on some feature types:*

- RDF for sparse text vectors
- LR/Deepnets for numeric features
- Trees for categorical features



Fusions Demo #2

Your Turn!

- *Note*: best to work in groups to limit computation time
- Configure an OptiML of the Diabetes 80%
    - Limit number of model candidates to 10
    - Disable Deepnets from the search
    - Optimize for identifying diabetes
- While the OptiML is running:
    - Build a Fusion from any set of Diabetes 80% models
    - Evaluate the fusion with the 20%
    - How does it compare to previous models?
- Returning to the OptiML
    - Evaluate the top performing model with the 20%
    - How does it perform?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