

Overcoming the Barriers to Production-Ready Machine Learning Workflows

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wise.io



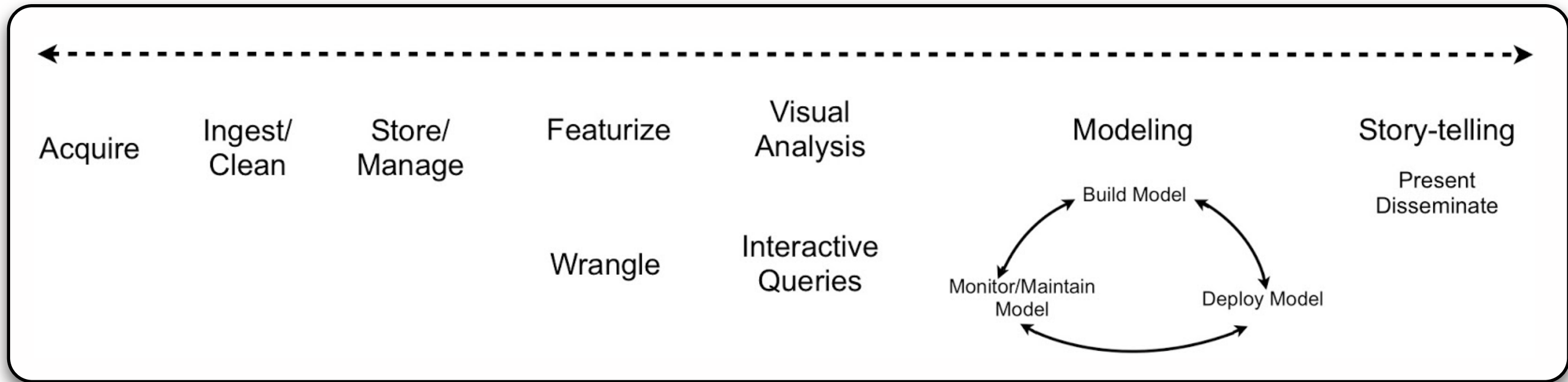
@profjsb

@brinkar

@wiseio

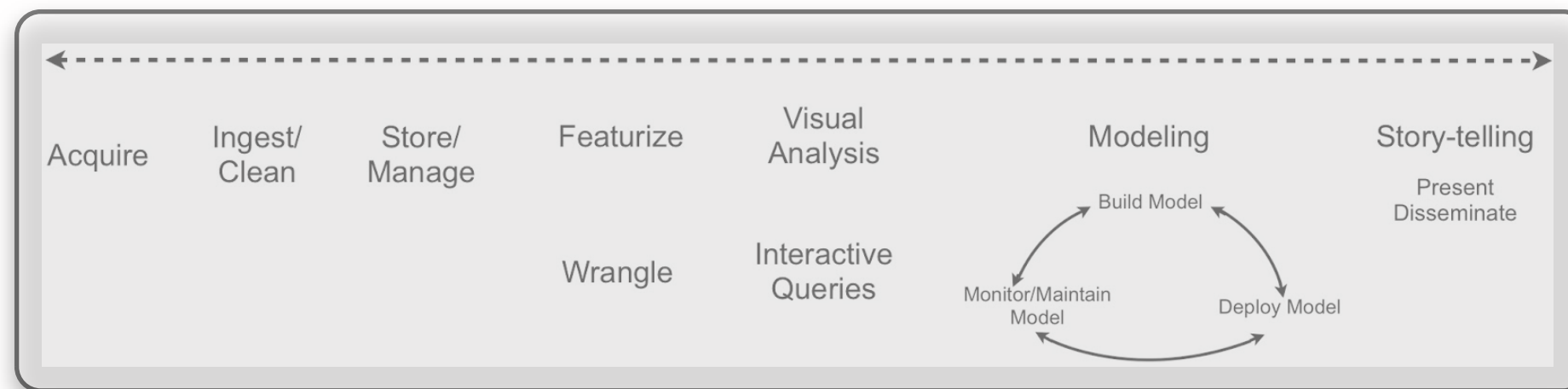


University of
California,
Berkeley



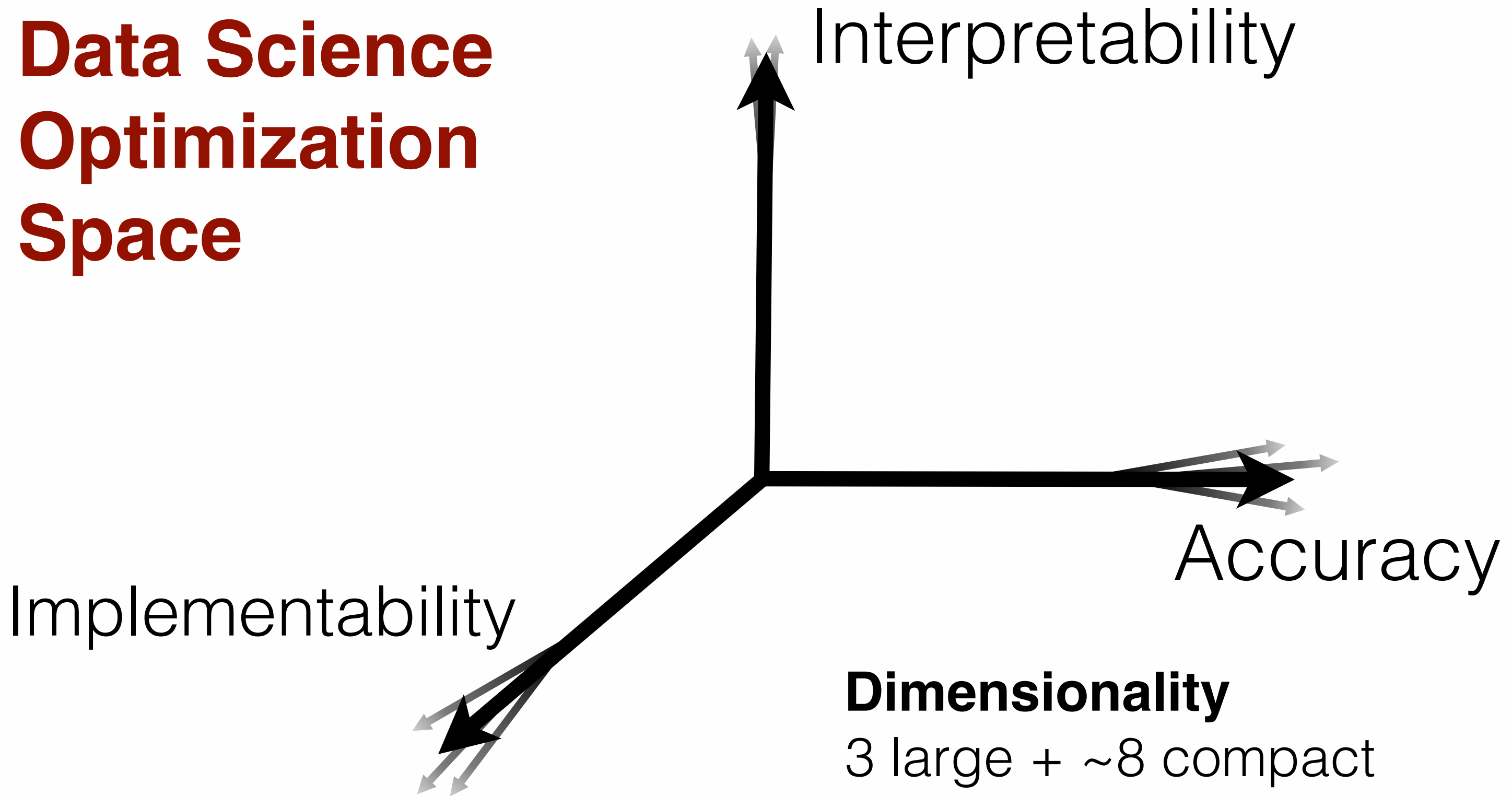
Lorica's "Data Science Workflow"

Real-World Data Science = *Optimization* over this *full* Workflow



Lorica's "Data Science Workflow"

Data Science Optimization Space



Our Background ...

“Data-Driven Scientists”

- ▶ Built & Deployed Real-time ML framework, discovering >10,000 events in > 10 TB of imaging
→ 50+ journal articles
- ▶ Built Probabilistic Event classification catalogs with innovative active learning
- ▶ Collective over 350 refereed journal articles including ML & timeseries analysis

*Our ML framework found the
Nearest Supernova in 3 Decades ..*



Accuracy

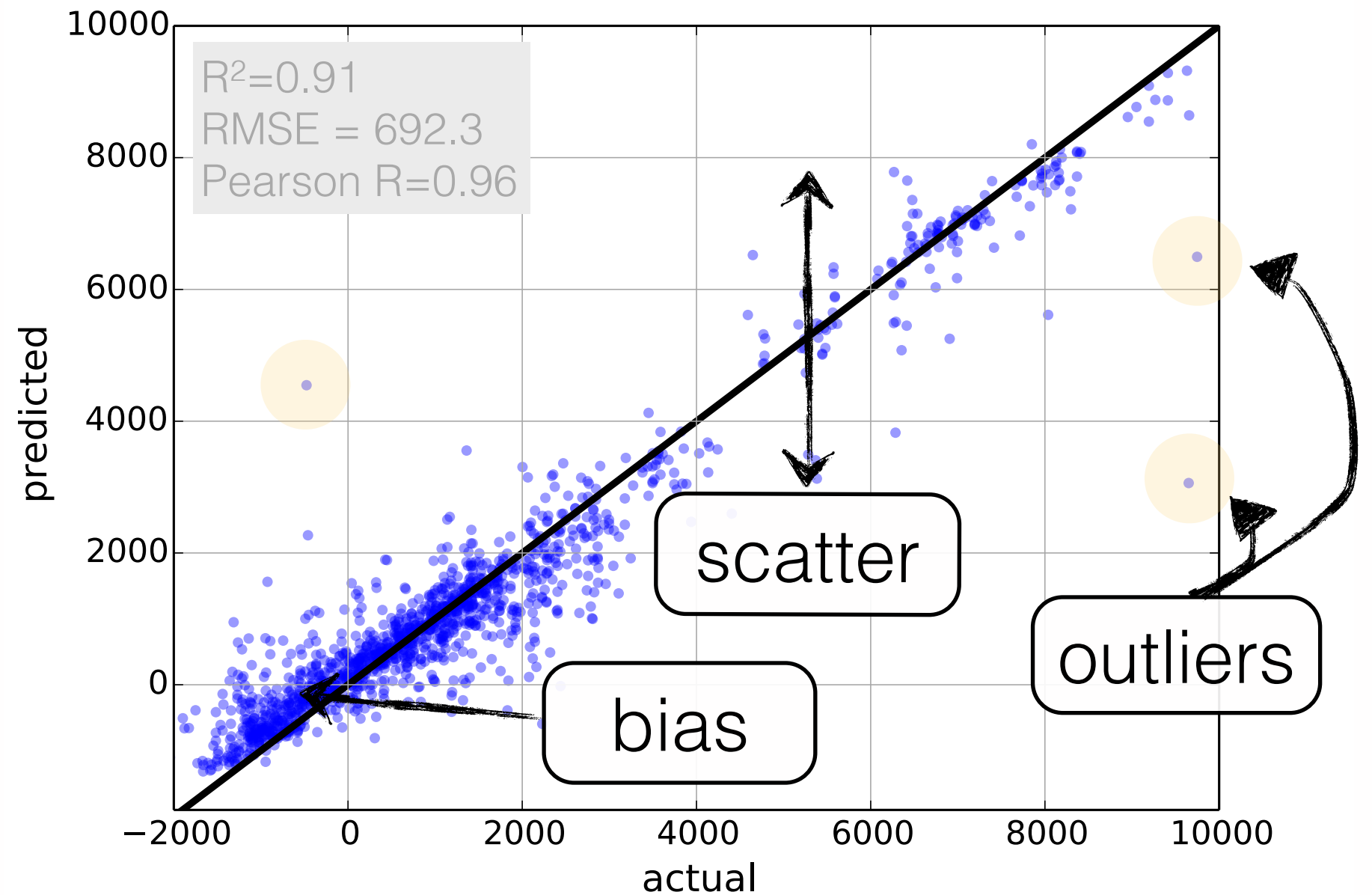


Evaluation Metric: What's the essence of what I care about?

Scalar proxies

- RMSE
- RMSLE
- [adjusted] R^2
- ...

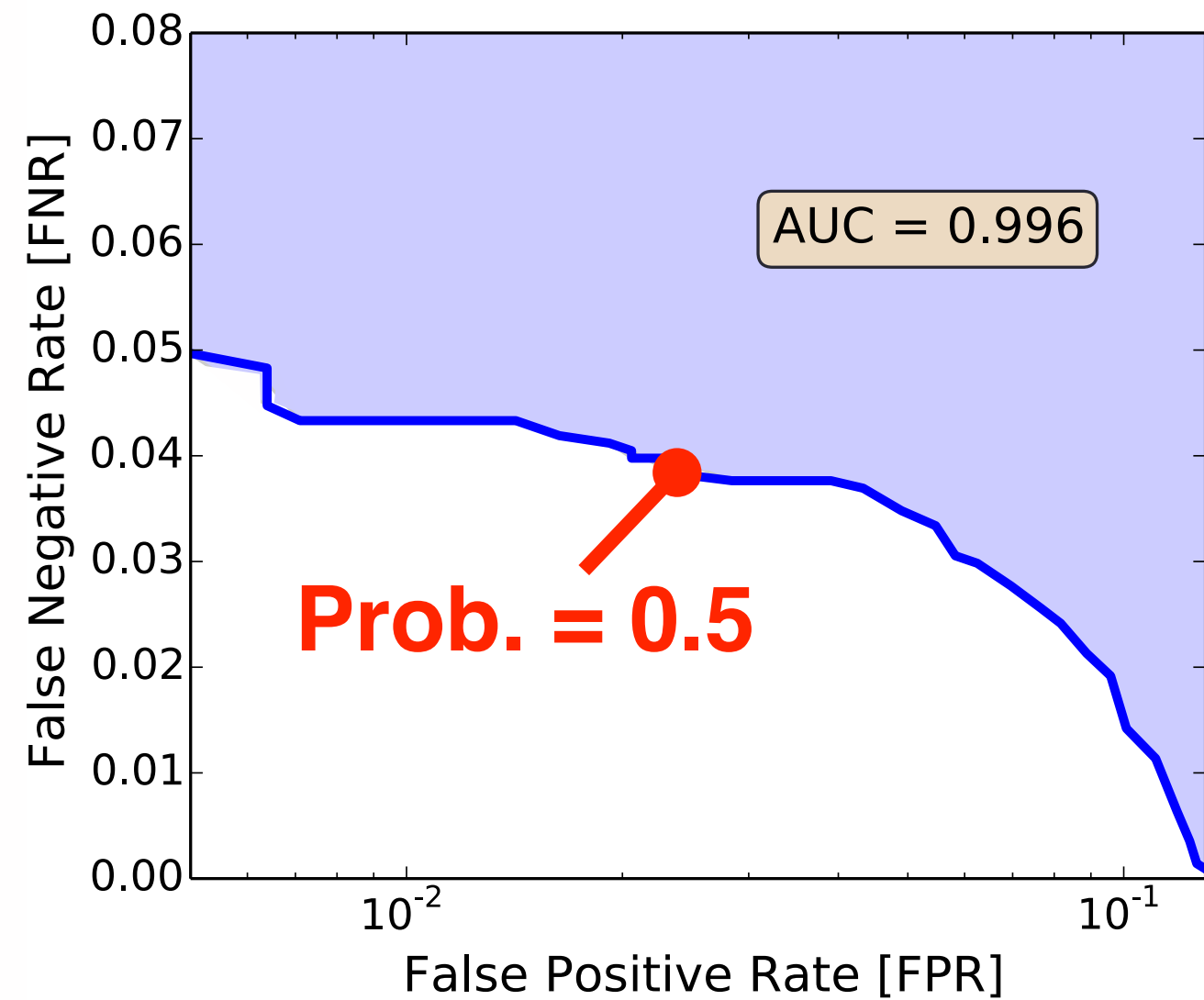
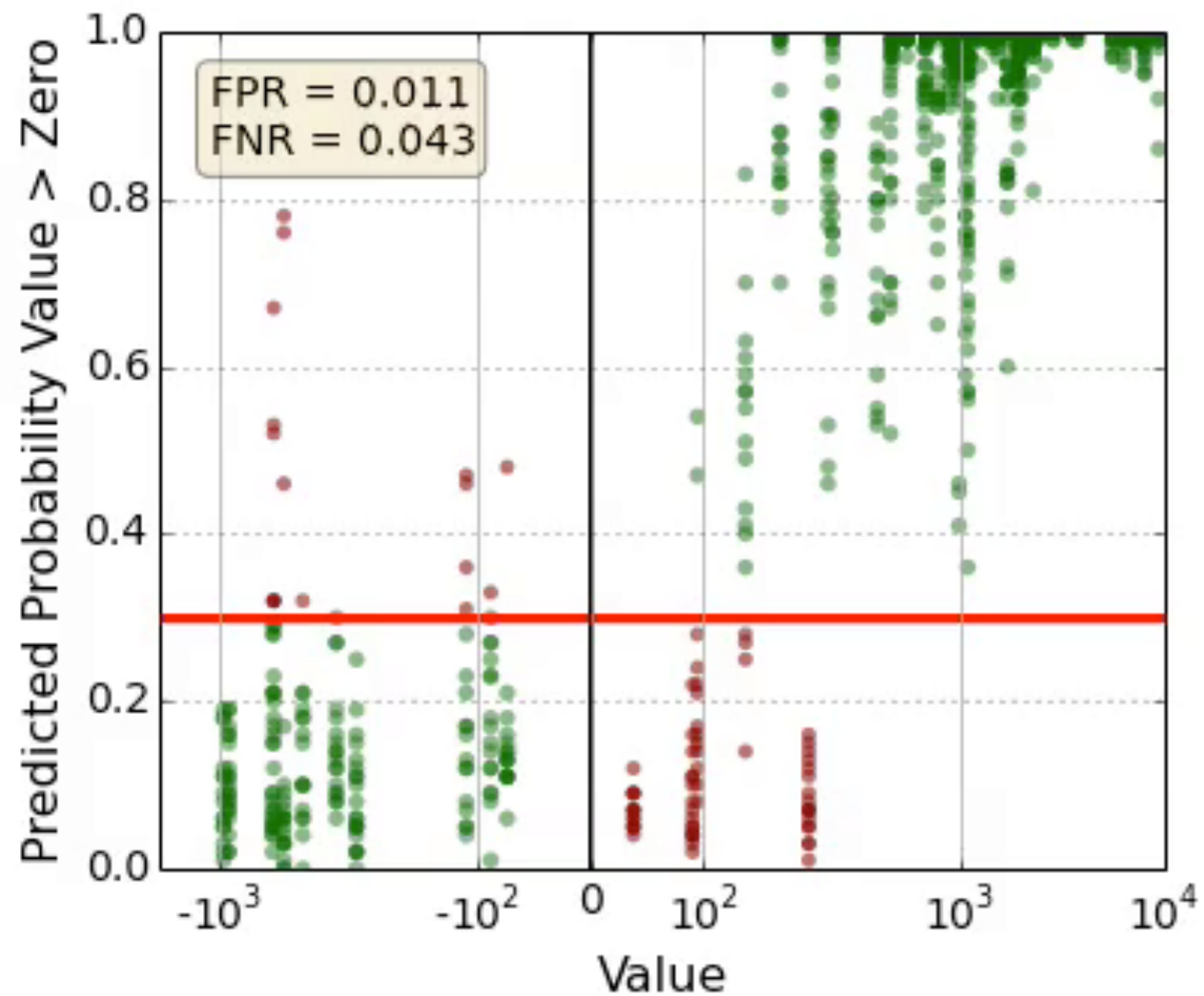
cf. `sklearn.metrics`



Accuracy



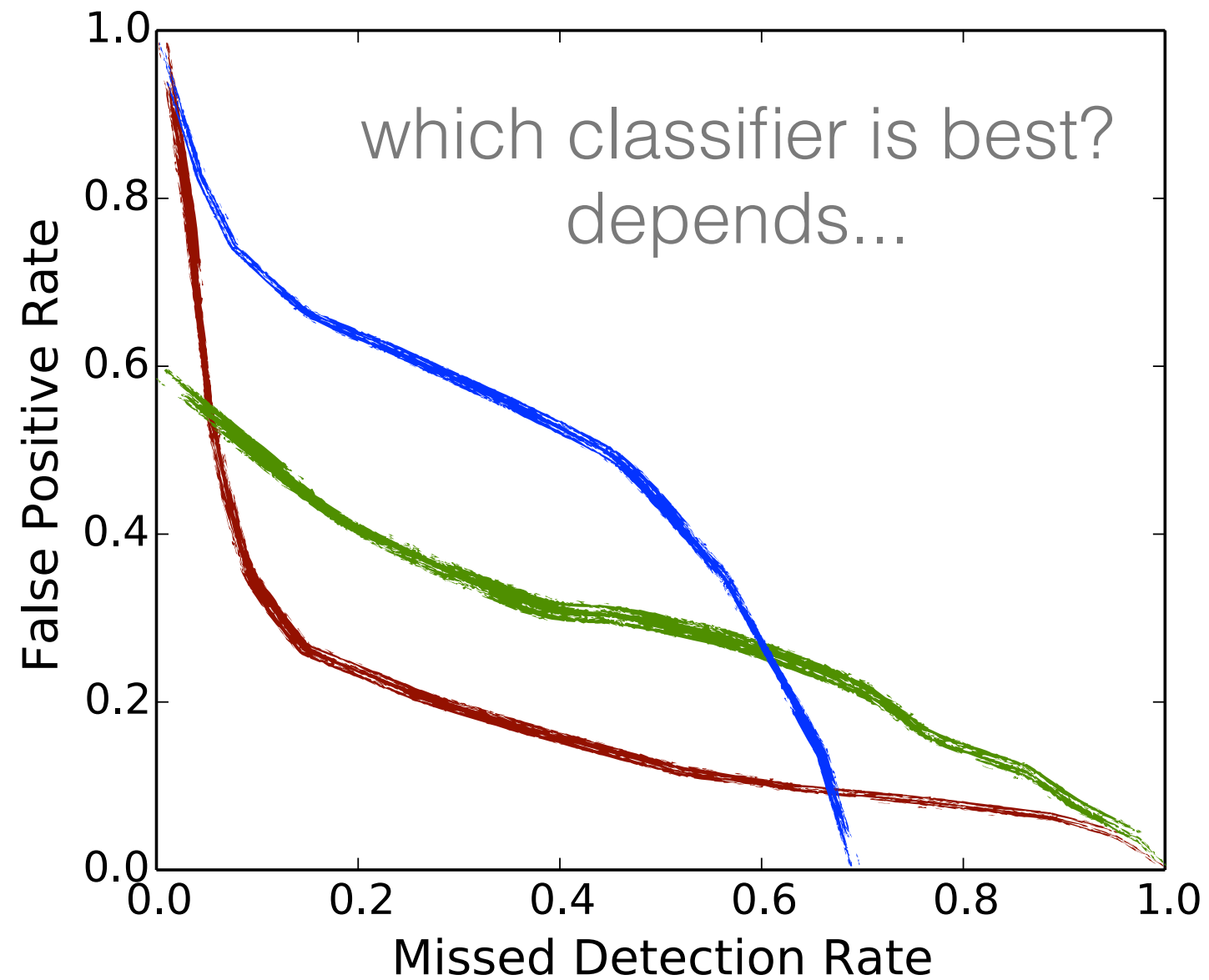
Evaluation Metric: *What's the essence of what I care about?*



Accuracy



Evaluation Metric: *What's the essence of what I care about?*

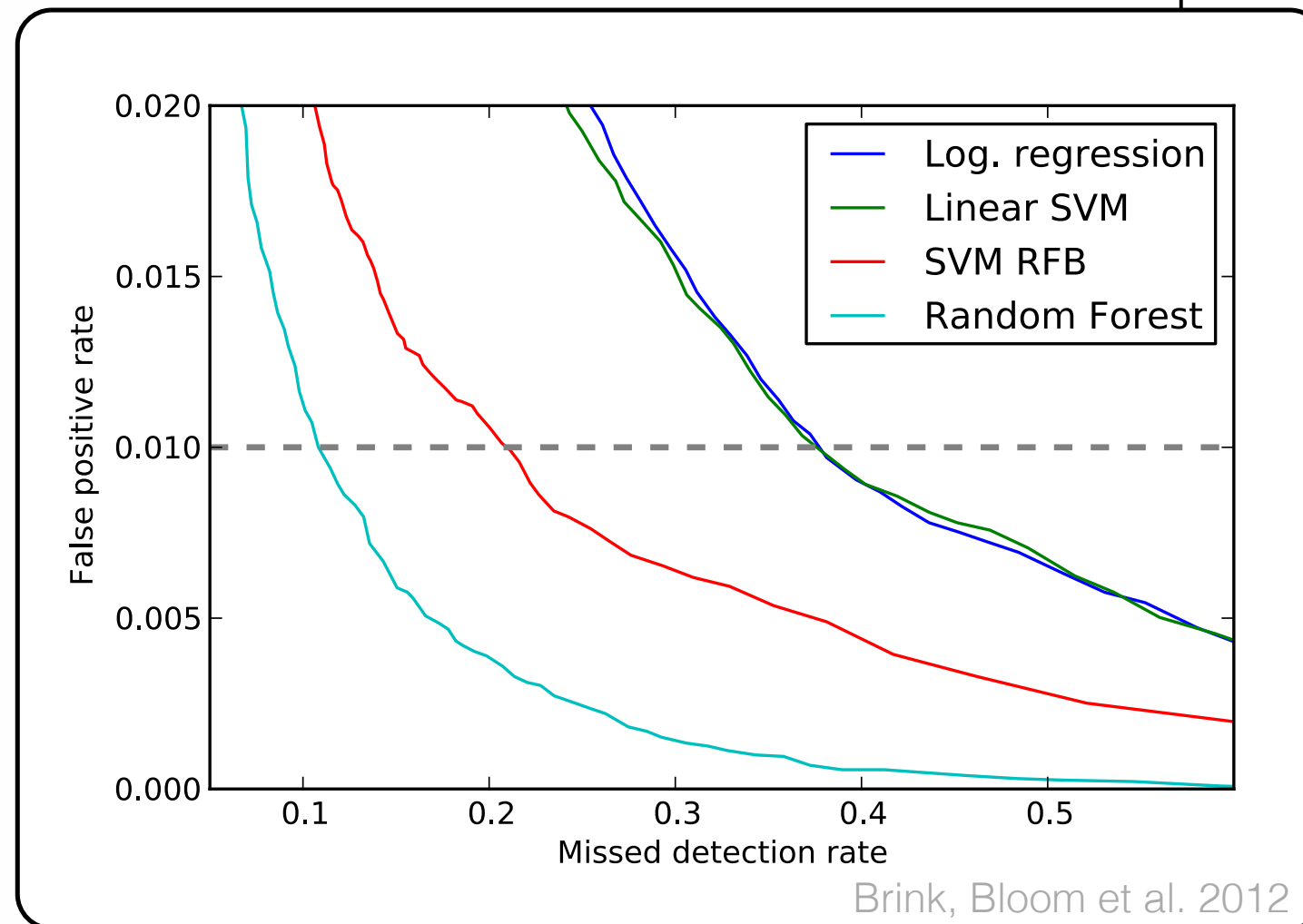


Accuracy



Evaluation Metric: *What's the essence of what I care about?*

42-dimensional feature space

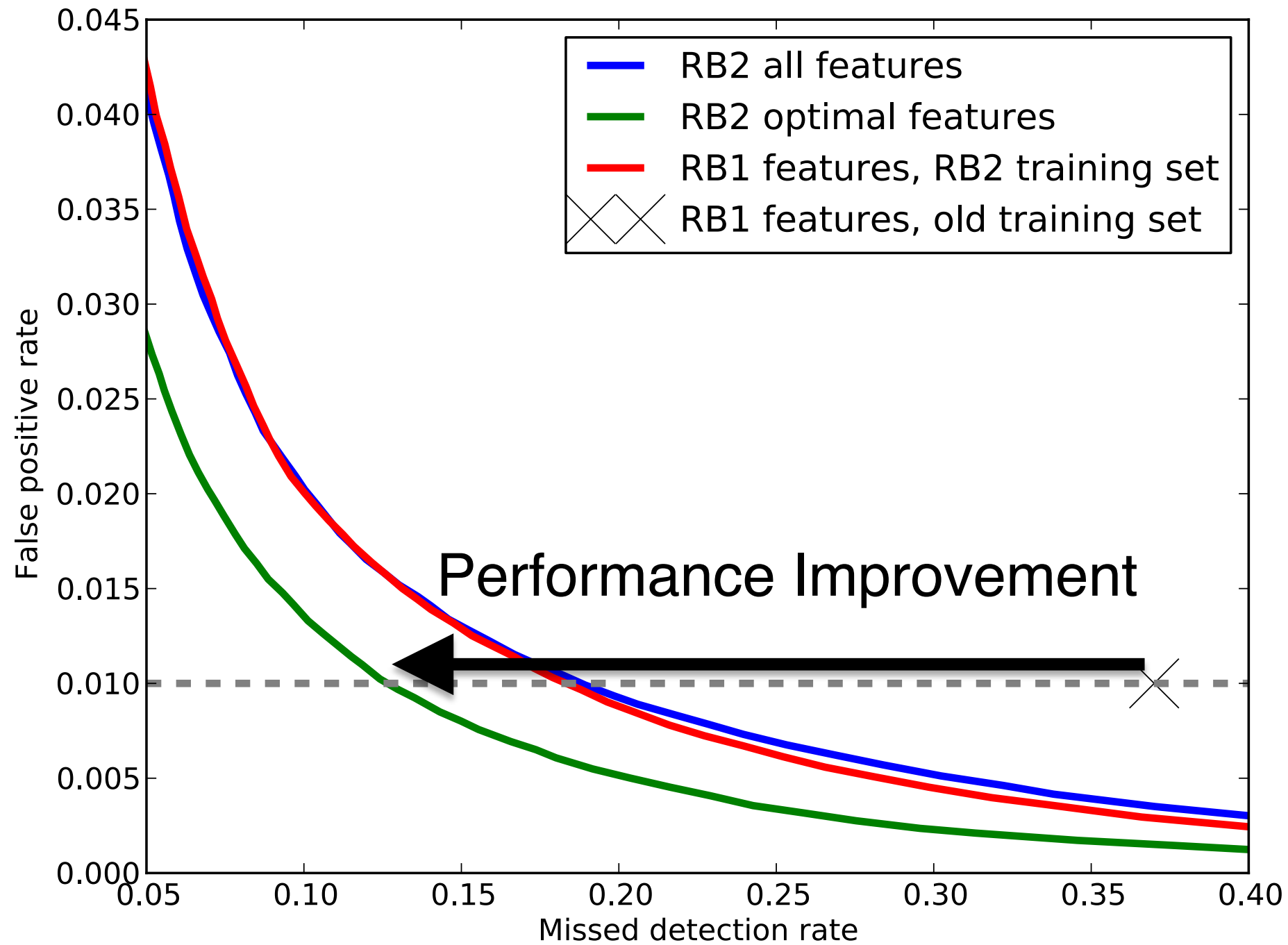


Some ML algorithms just do *better*

Accuracy



More Data (Dimensions) is better, but
Protect Against Curse of Dimensionality

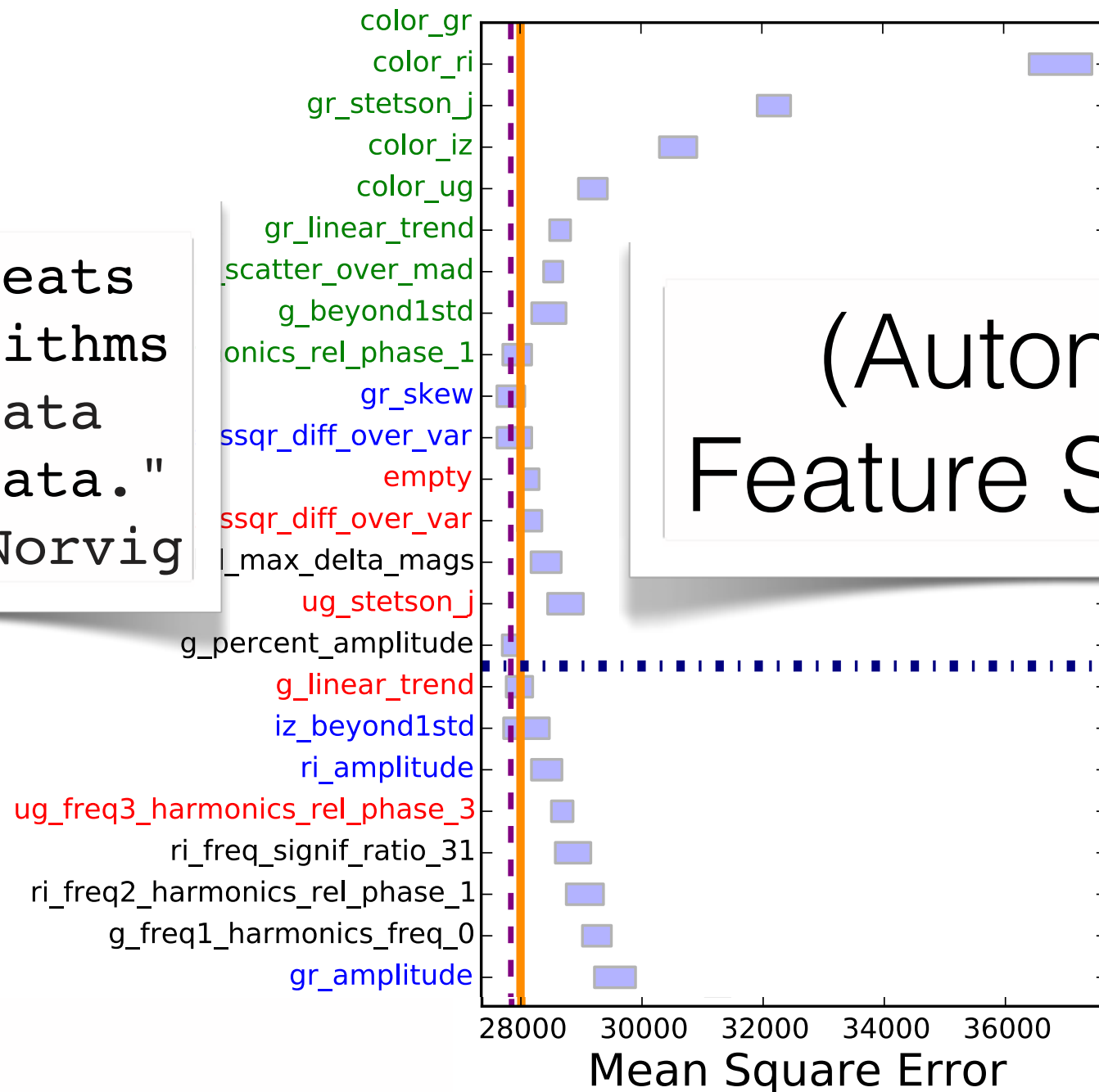


Accuracy



More Data (Dimensions) is better, but
Protect Against Curse of Dimensionality

"More data beats
clever algorithms
but better data
beats more data."
- Peter Norvig



(Automatic)
Feature Selection

Accuracy



Testing Set & Continuous (Streaming) Testing & Model Updates

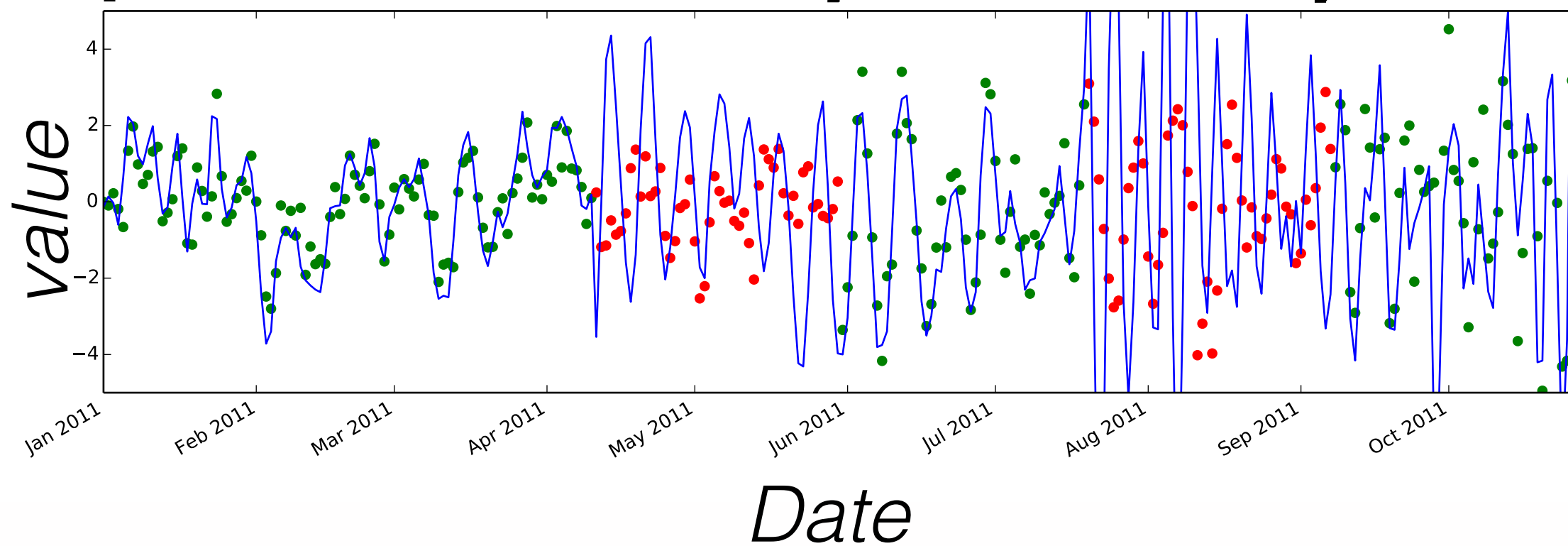
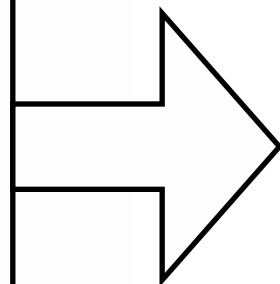
Model # in production

1

2

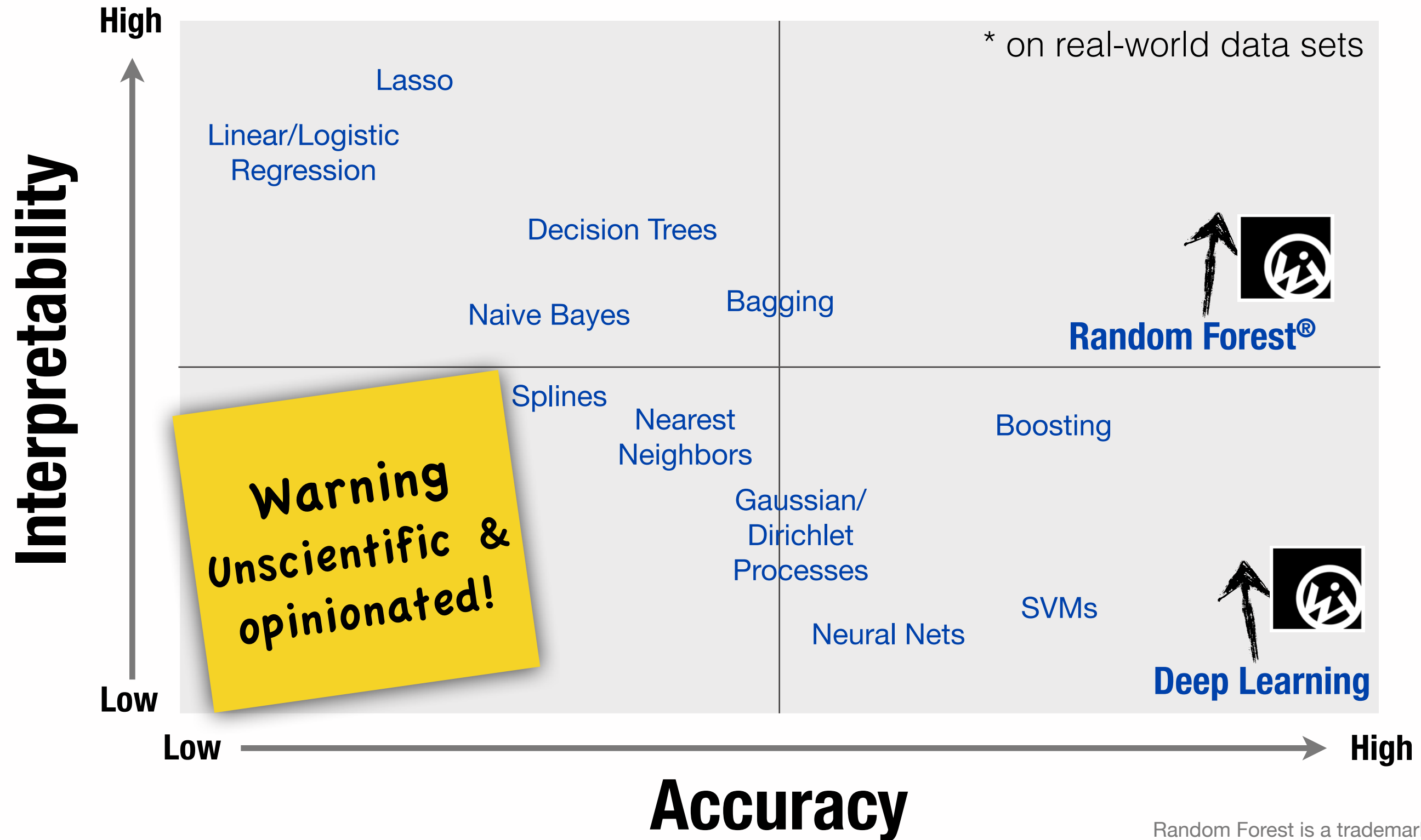
3

model 1
building +
validation
on
historical
data



— actual value ● good prediction ● “bad” prediction

ML Algorithmic Trade-Off





Interpretability



Interpretability

How does the model work?

Consider a nonlinear system of equations:

$$\begin{cases} 3x_1 - \cos(x_2x_3) - \frac{3}{2} = 0 \\ 4x_1^2 - 625x_2^2 + 2x_2 - 1 = 0 \\ \exp(-x_1x_2) + 20x_3 + \frac{10\pi-3}{3} = 0 \end{cases}$$

suppose we have the function

$$G(\mathbf{x}) = \begin{bmatrix} 3x_1 - \cos(x_2x_3) - \frac{3}{2} \\ 4x_1^2 - 625x_2^2 + 2x_2 - 1 \\ \exp(-x_1x_2) + 20x_3 + \frac{10\pi-3}{3} \end{bmatrix}$$

where

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

and the objective function

$$\begin{aligned} F(\mathbf{x}) &= \frac{1}{2}G^T(\mathbf{x})G(\mathbf{x}) \\ &= \frac{1}{2}\left(\left(3x_1 - \cos(x_2x_3) - \frac{3}{2}\right)^2 + \left(4x_1^2 - 625x_2^2 + 2x_2 - 1\right)^2 + \left(\exp(-x_1x_2) + 20x_3 + \frac{10\pi-3}{3}\right)^2\right) \end{aligned}$$

With initial guess

$$\mathbf{x}^{(0)} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

We know that

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} - \gamma_0 \nabla F(\mathbf{x}^{(0)})$$

where

$$\nabla F(\mathbf{x}^{(0)}) = J_G(\mathbf{x}^{(0)})^T G(\mathbf{x}^{(0)})$$

The Jacobian matrix $J_G(\mathbf{x}^{(0)})$

$$J_G = \begin{bmatrix} 3 & \sin(x_2x_3)x_3 & \sin(x_2x_3)x_2 \\ 8x_1 & -1250x_2 + 2 & 0 \\ -x_2 \exp(-x_1x_2) & -x_1 \exp(-x_1x_2) & 20 \end{bmatrix}$$

Then evaluating these terms at $\mathbf{x}^{(0)}$

$$J_G(\mathbf{x}^{(0)}) = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 20 \end{bmatrix}$$

and

$$G(\mathbf{x}^{(0)}) = \begin{bmatrix} -2.5 \\ -1 \\ 10.472 \end{bmatrix}$$

So that

$$\mathbf{x}^{(1)} = 0 - \gamma_0 \begin{bmatrix} -7.5 \\ -2 \\ 209.44 \end{bmatrix}$$

and

$$F(\mathbf{x}^{(0)}) = 0.5((-2.5)^2 + (-1)^2 + (10.472)^2) = 58.456$$

Now a suitable γ_0 must be found such that $F(\mathbf{x}^{(1)}) \leq F(\mathbf{x}^{(0)})$. This can be done with algorithms. One might also simply guess $\gamma_0 = 0.001$ which gives

$$\mathbf{x}^{(1)} = \begin{bmatrix} 0.0075 \\ 0.002 \\ -0.20944 \end{bmatrix}$$

evaluating at this value,

$$F(\mathbf{x}^{(1)}) = 0.5((-2.48)^2 + (-1.00)^2 + (6.28)^2) = 23.306$$



Interpretability

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Interpretability

Why do I
get these
answers?

e.g., Credit score








Sample FICO® Scoring Model

Category	Characteristic	Attributes	Points
Payment History	Number of months since the most recent derogatory public record	No public record	75
		0 – 5	10
		6 – 11	15
		12 – 23	25
		24+	55
Outstanding Debt	Average balance on revolving trades	No revolving trades	30
		0	55
		1 – 99	65
		100 – 499	50
		500 – 749	40
		750 – 999	25
		1000 or more	15
Credit History Length	Number of months in file	Below 12	12
		12 – 23	35
		24 – 47	60
		48 or more	75
		Pursuit of New Credit	Number of inquiries in last 6 mos.
1	60		
2	45		
3	25		
4+	20		
Credit Mix	Number of bankcard trade lines		
		1	25
		2	50
		3	60
		4+	50



Interpretability

Peering Inside the Black Box

Feature	Importance
over_draft : 'no checking'	
over_draft : '<0'	
credit_usage	
current_balance	
cc_age	
Average_Credit_Balance : '<100'	
credit_history : 'critical/other existing credit'	

Random Forest®
model-level
feature importance



Interpretability

Peering Inside the Black Box

Individual-level
prediction
feature importance

Probability of Default in 1 year:
76% [deny loan]

Driving factors

☀ Credit history: 10 months **14%**

☀ Outstanding debt: \$1200 **5%**

☀ Inquiries in 6 months: 2 **1%**

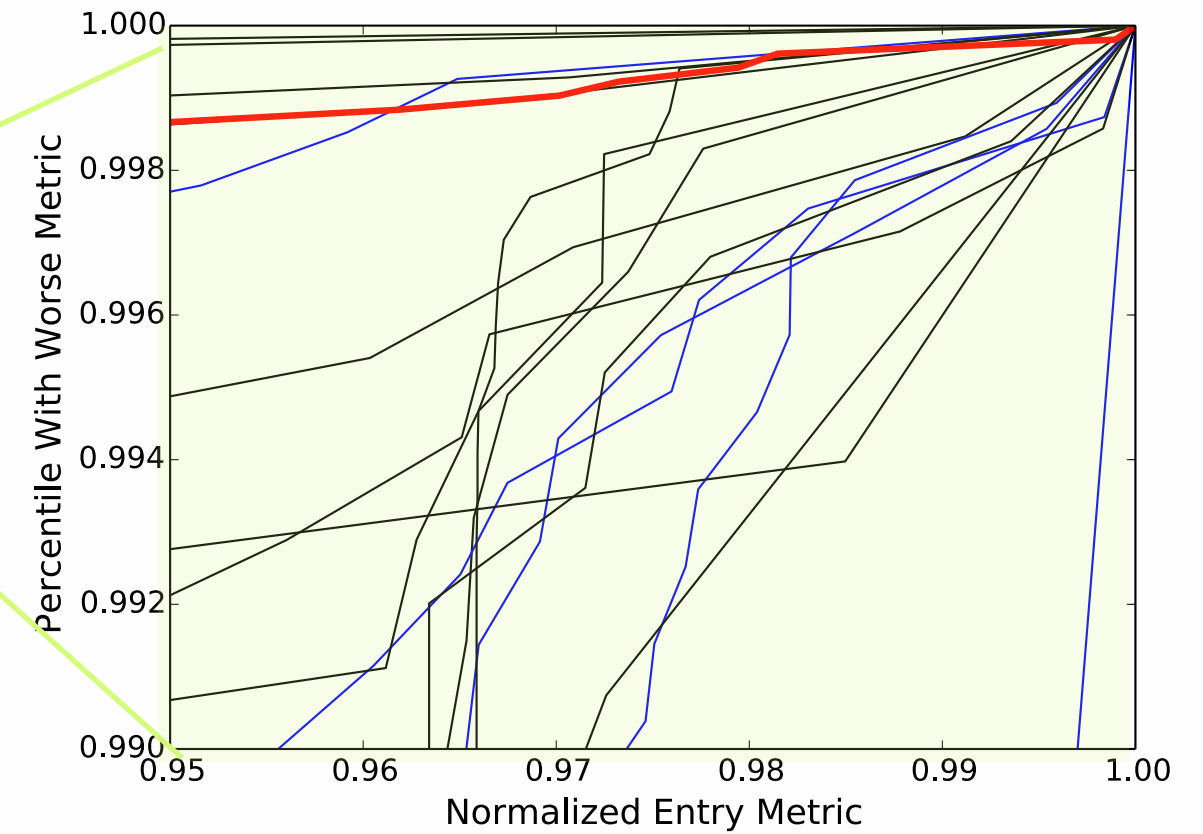
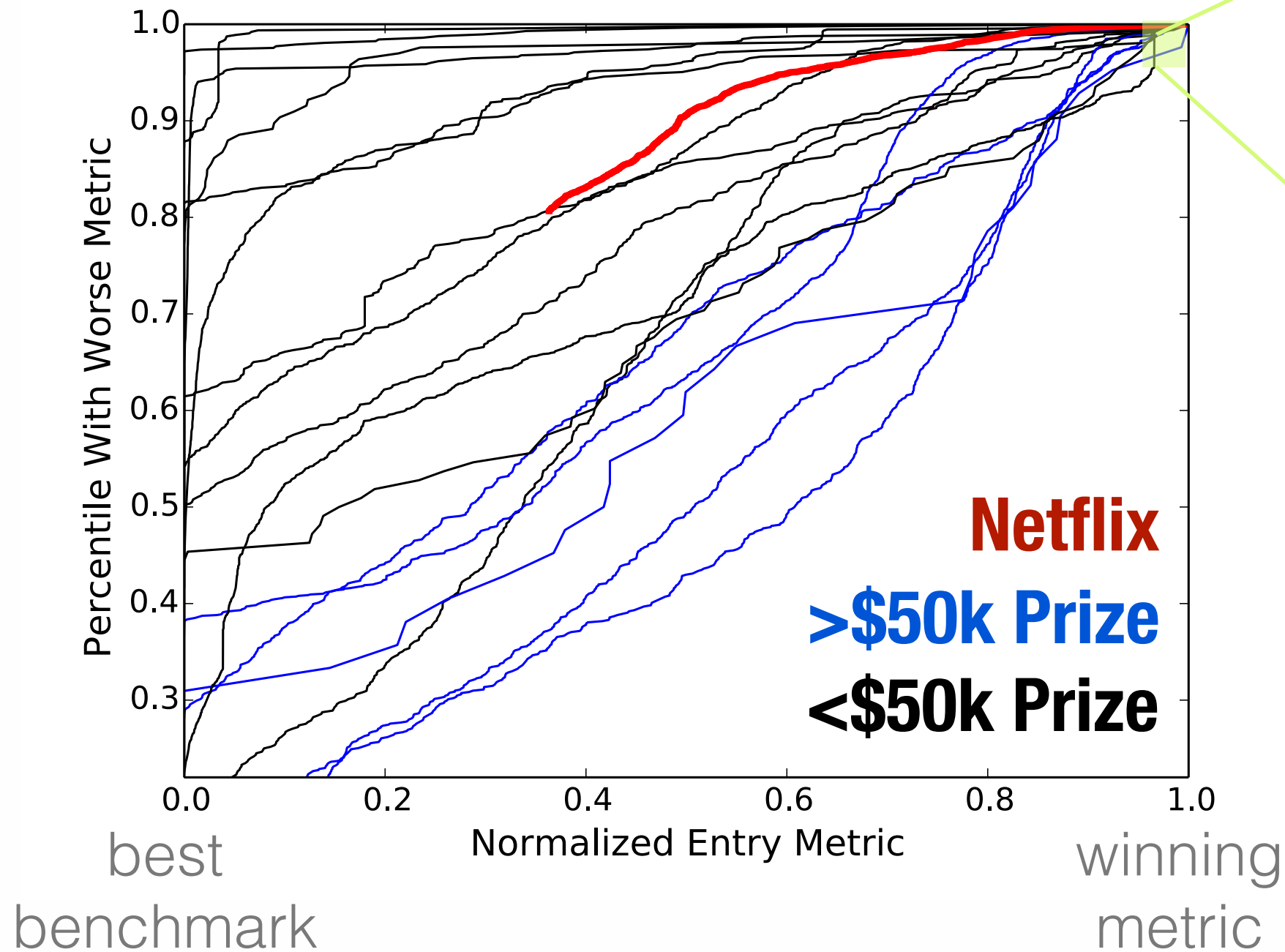
e.g. microcredit application scorecard



Implementability

How long does it take to put
the model into production?
At what cost?

Implementability



many teams get within
~few % of optimum
**so which is easier to
put into production?**

Leaderboard data from Kaggle & Netflix



Implementability

On the **NETFLIX** Prize

“We evaluated some of the new methods offline but the **additional accuracy gains** that we measured **did not seem to justify the engineering effort** needed to bring them into a **production environment.**”

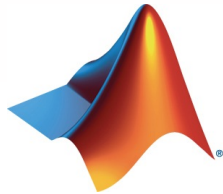
Xavier Amatriain and Justin Basilico (April 2012)



Implementability



python



Microsoft
.net



Java

The divide
between
data science
& **production**



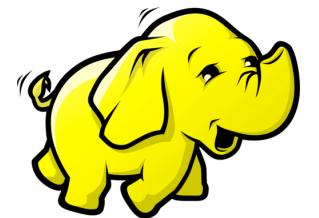
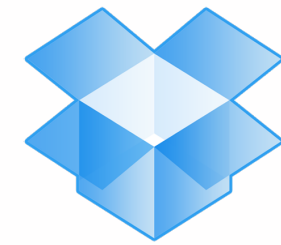
Implementability

Treat Machine
Learning
Deployment as
you would
Software

- ▶ Continuous Deployment
- ▶ RESTful API
- ▶ Language bindings
- ▶ Security
- ▶ SLA


Integration

Connect data



Consume predictions

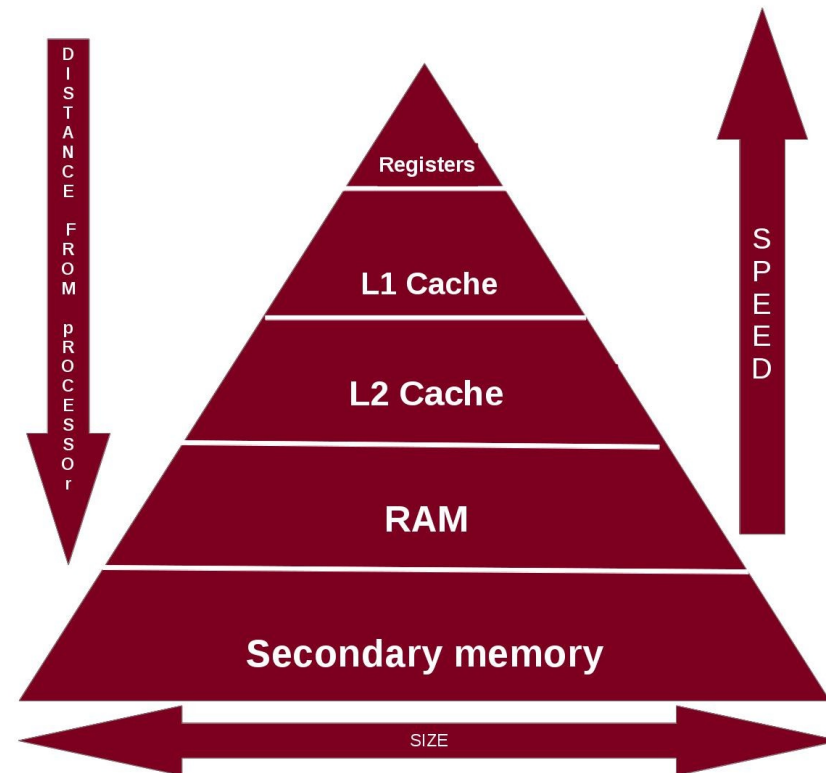



Implementability

Scalability & Speed

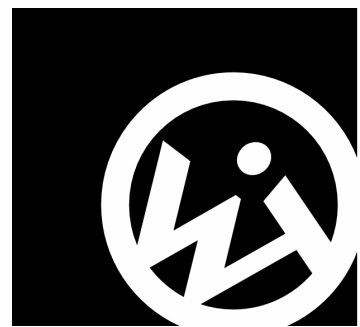
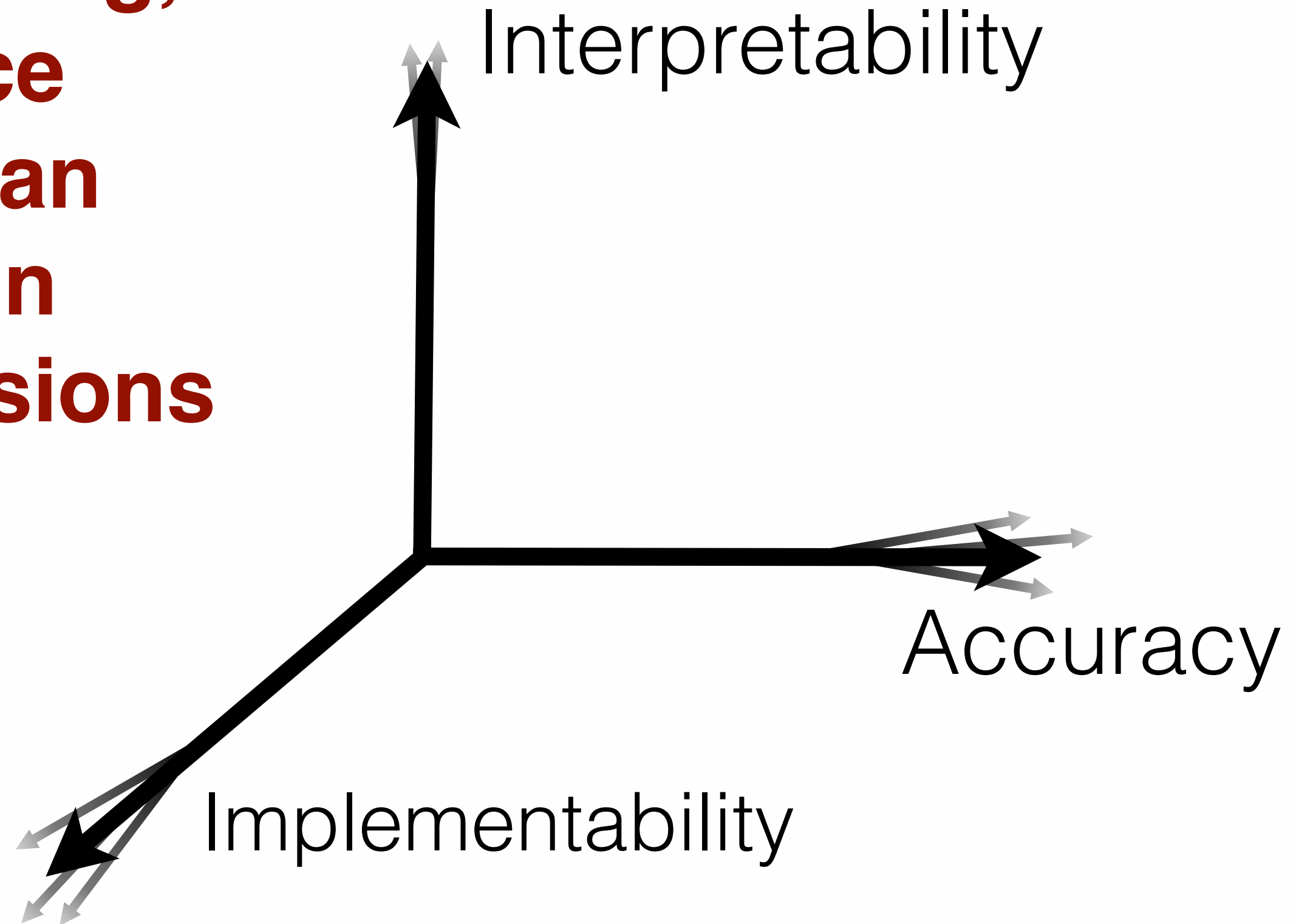
Micro-scaling

Fast, efficient
use of memory
hierarchy



**Horizontally
scalable
data
processing**

**Machine-Learning,
Data Science
Workflow is an
Optimization
in *many* dimensions**



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We are Hiring!

- ▶ **Full-stack developers**
 - ▶ Javascript, Python, Spark/Shark
- ▶ **Front end developers**
- ▶ **DevOps engineers**
- ▶ **C++ engineers**
 - ▶ C++ template metaprogramming
- ▶ **Data scientists**
 - ▶ Python, Deep NN, ML expertise



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