Modeling Like It Matters

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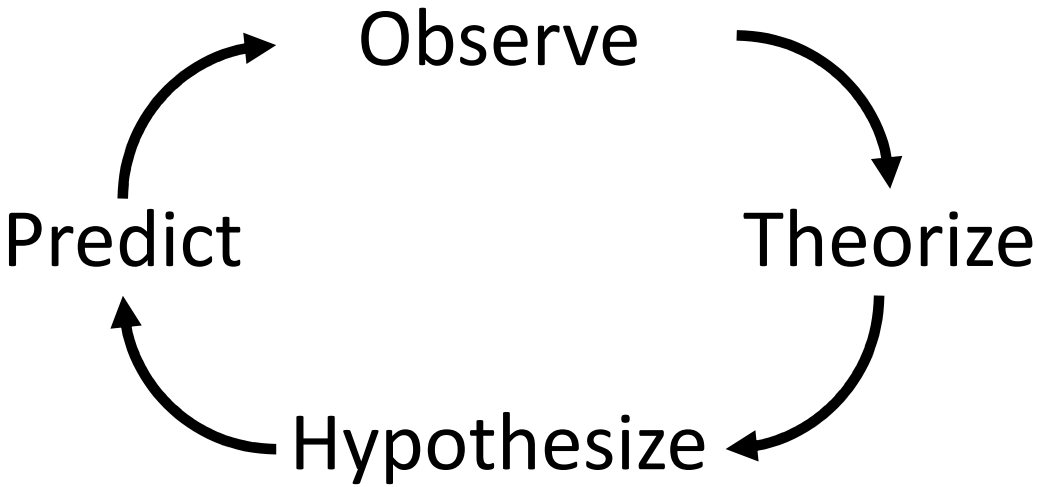
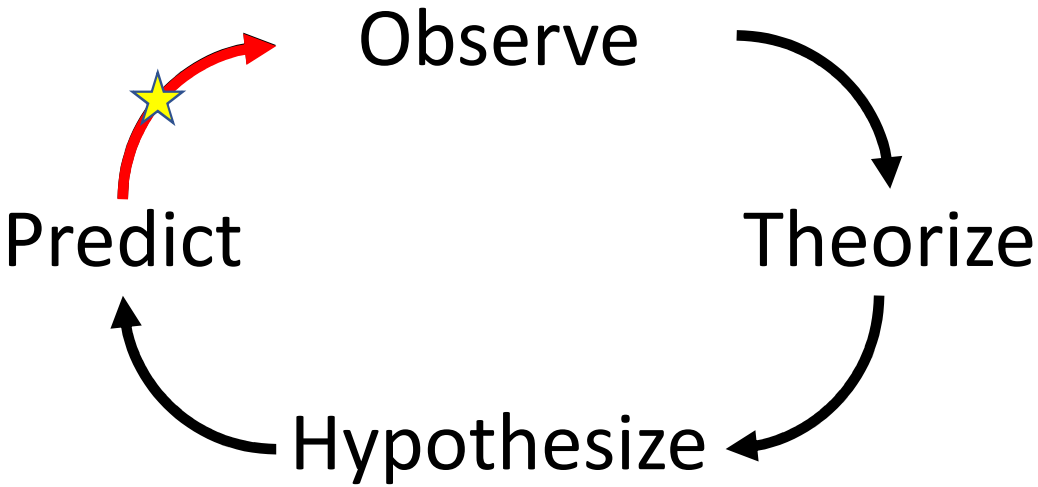
Science
Psychology
The Game

The Scientific Method

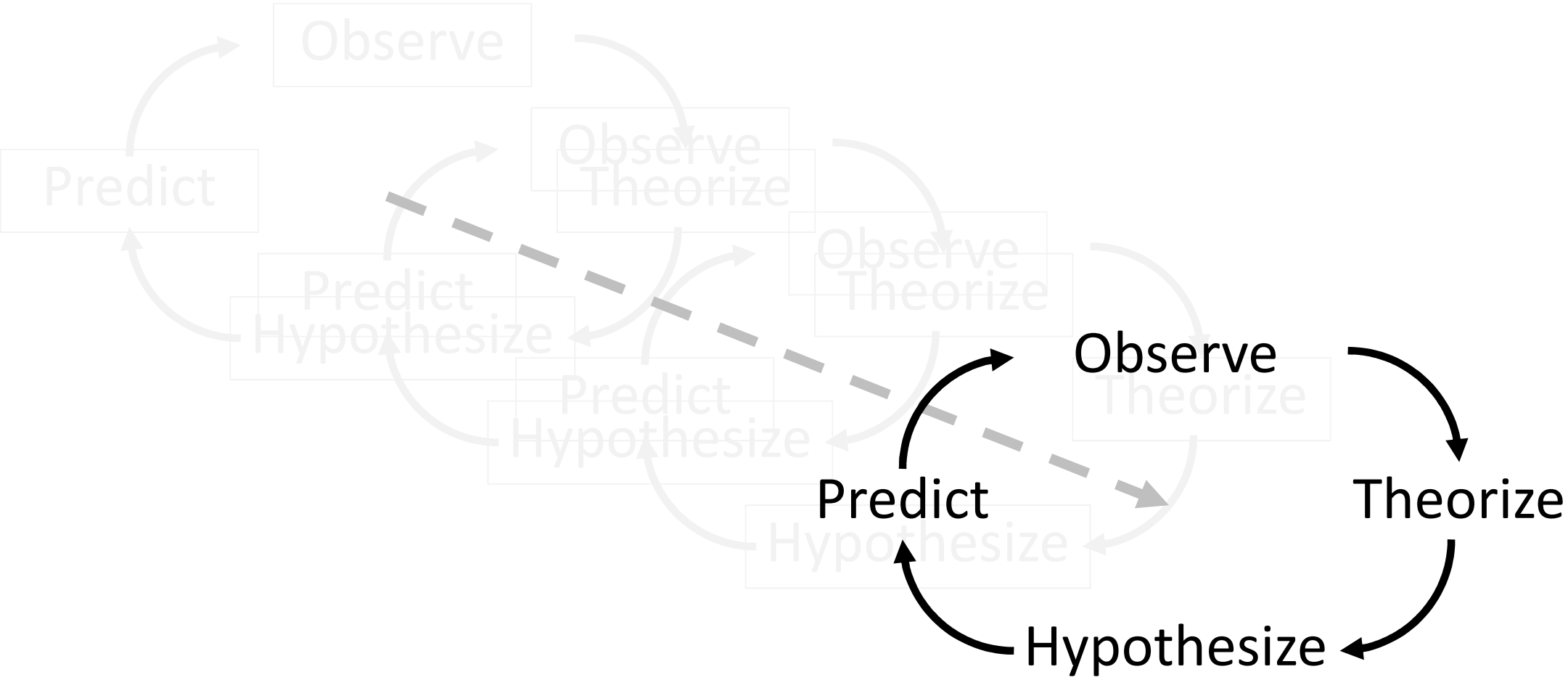


Changing Your Mind

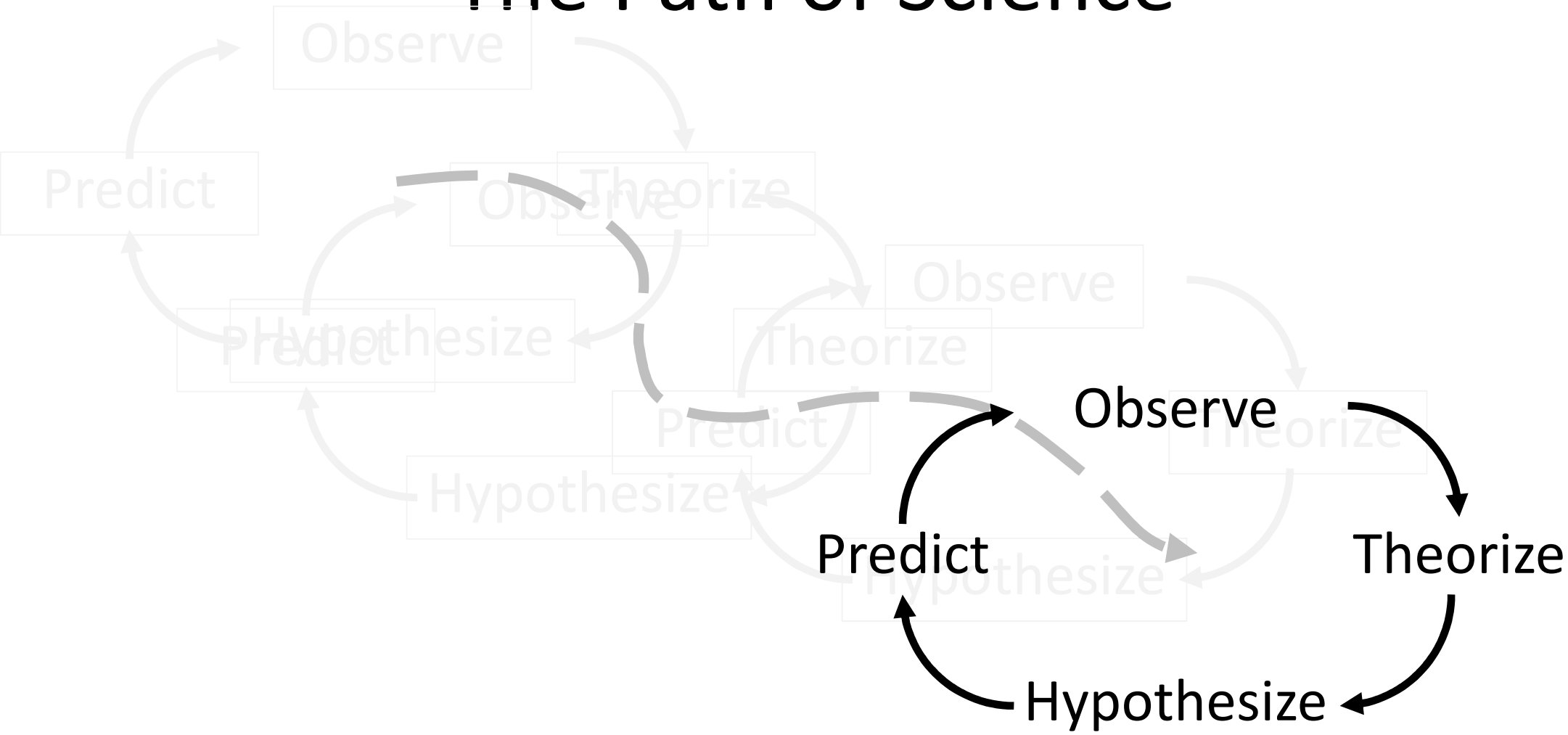


Opportunity for lateral thinking

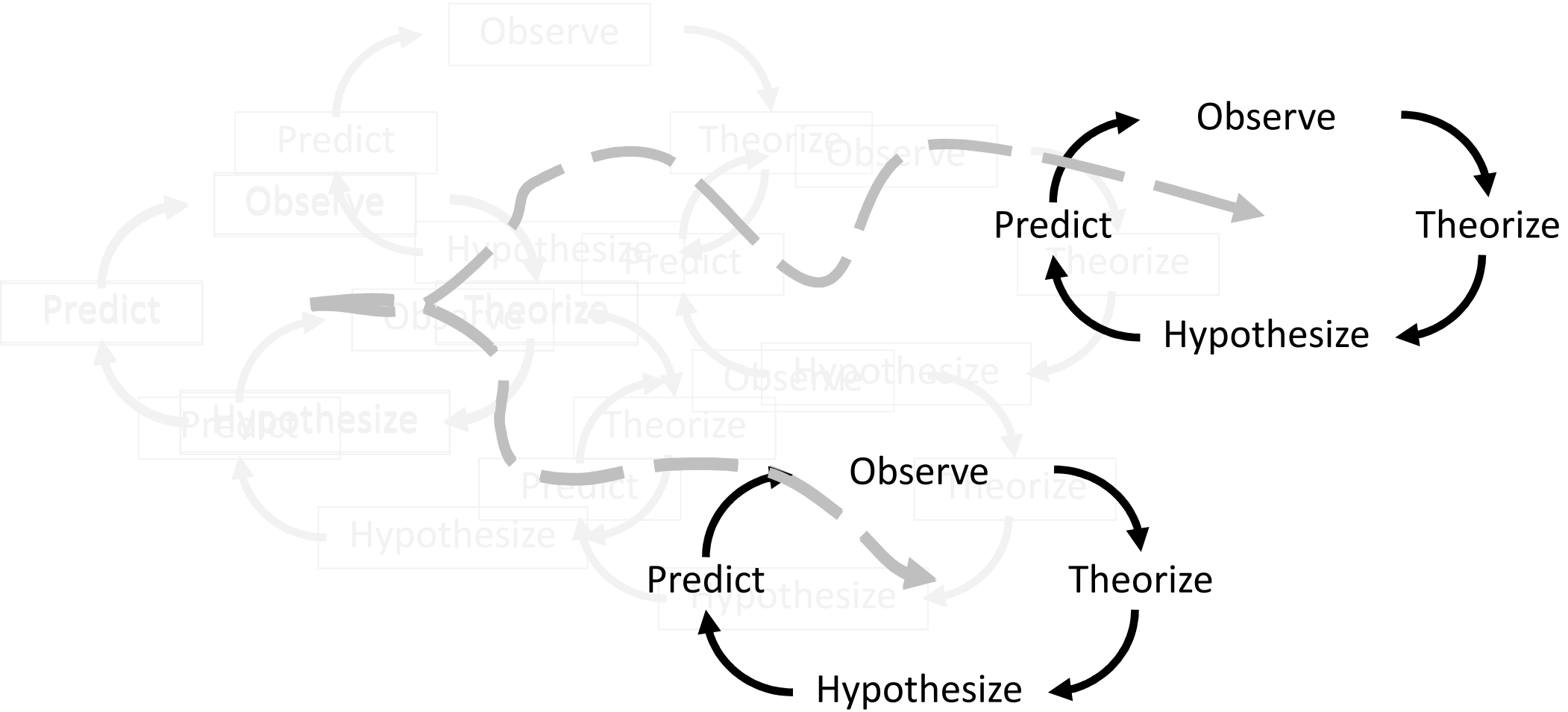
Scientific Progress



The Path of Science



The Paths of Science



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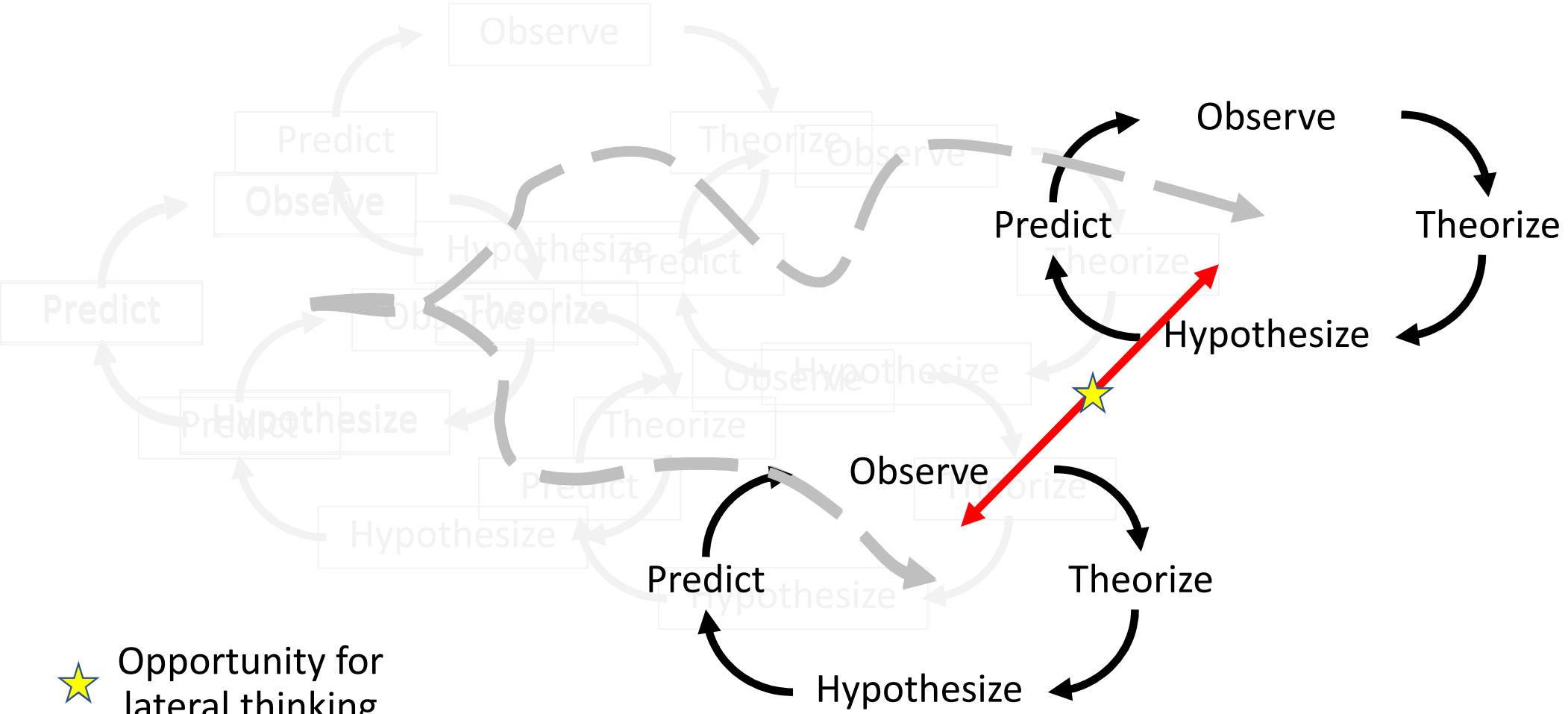

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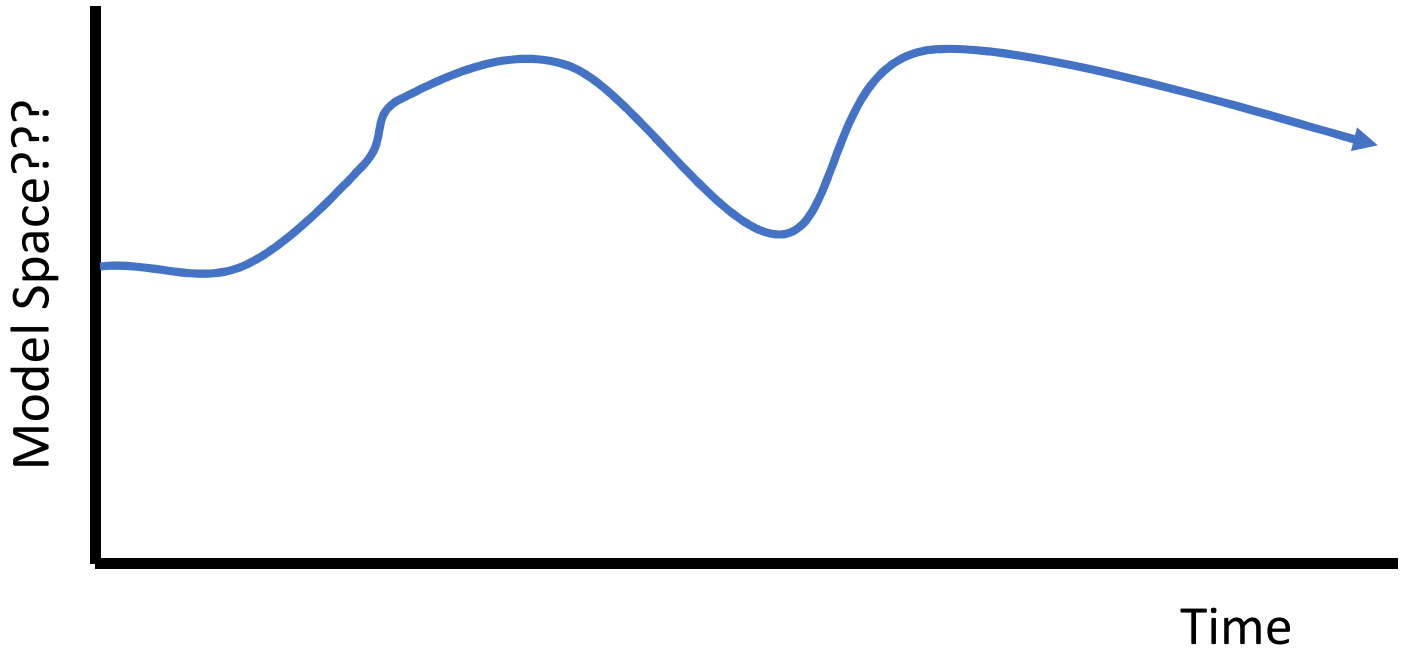
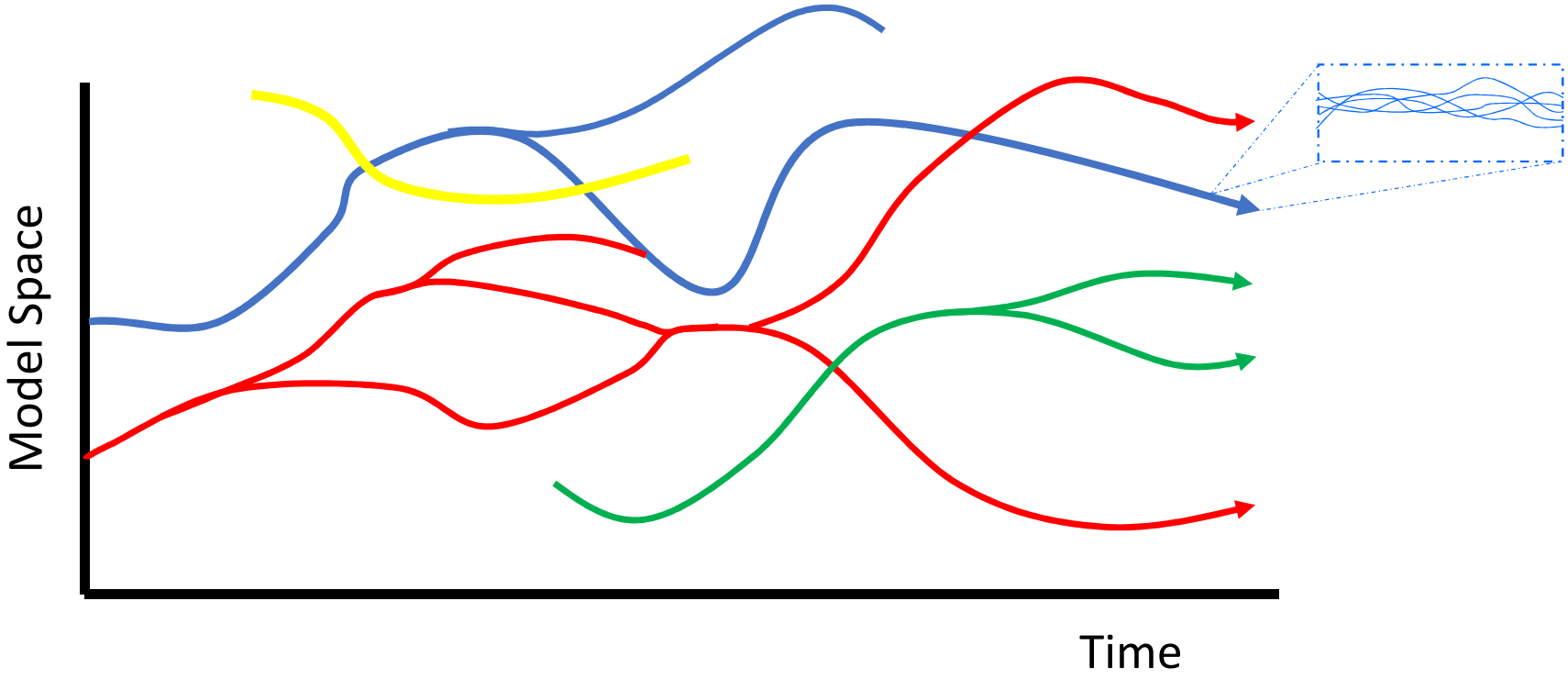
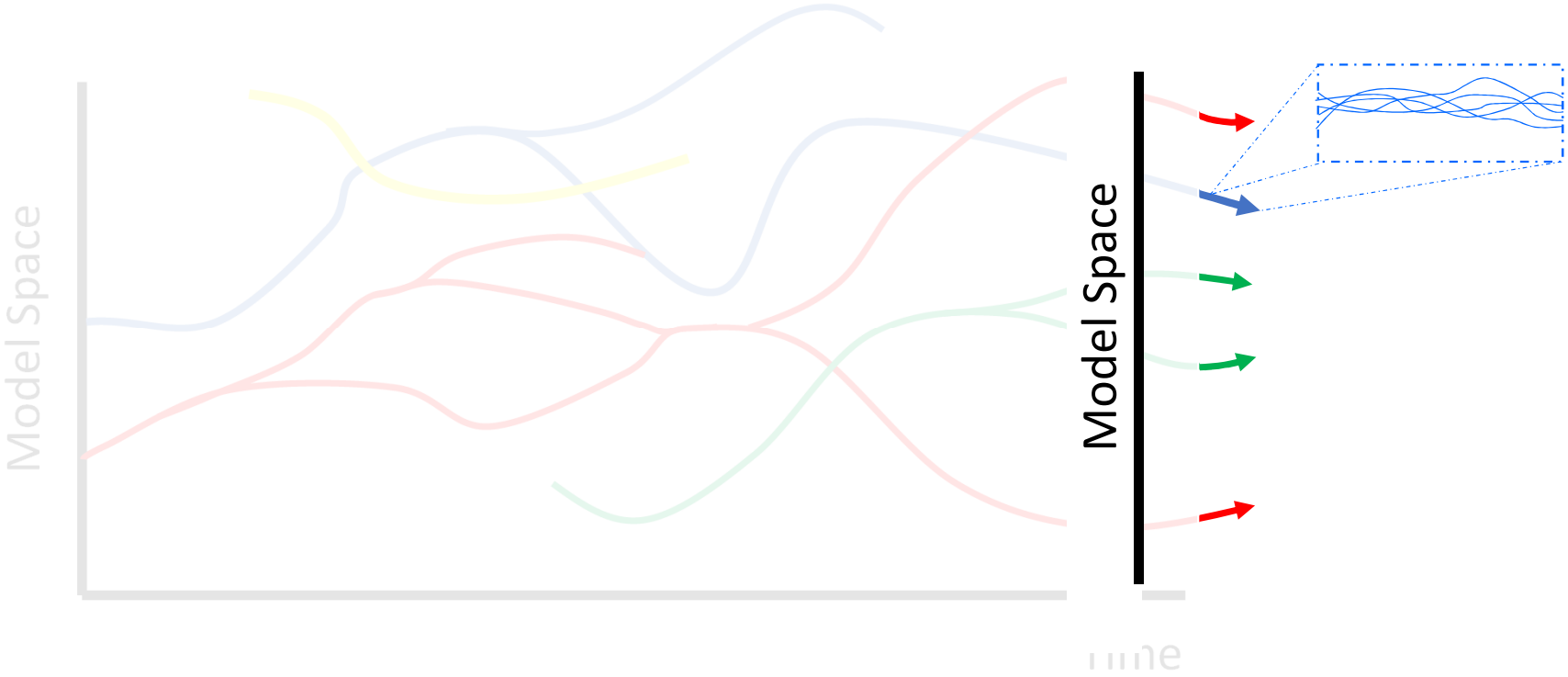


Splitting, Dying, Merging, Emerging



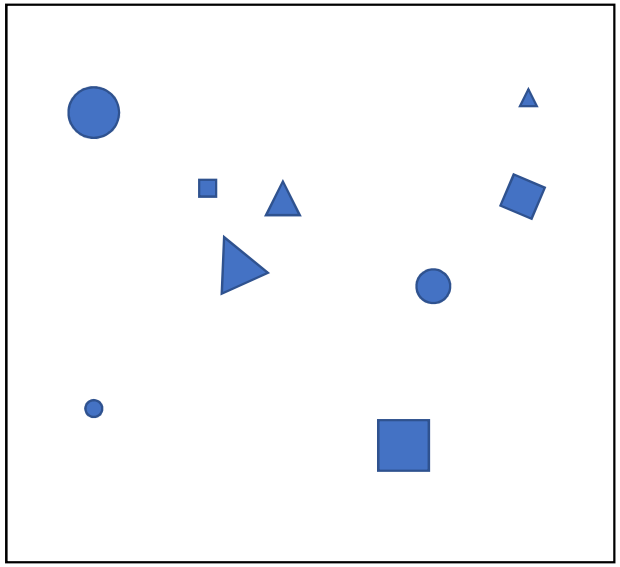
Visualizing Current Model Space



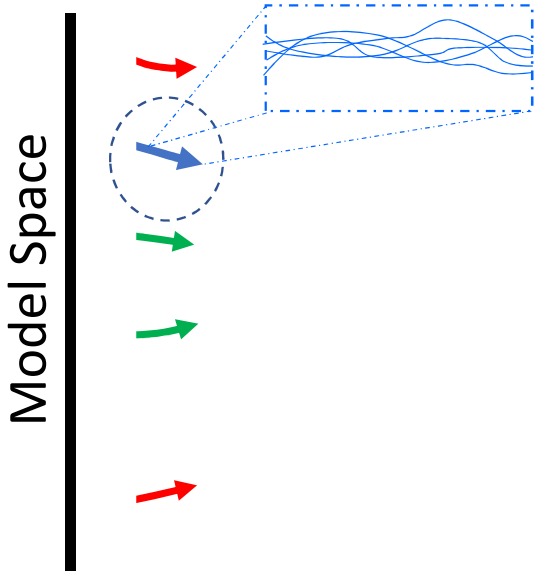
Single Model Space

(Discrete and Continuous Differences)

Concepts
Processes
Structures
Parameterizations
Solution Schemes
Parameter Values
Boundary Conditions
Space/Time Resolutions



Model Space



Multi-Model Space

Concepts
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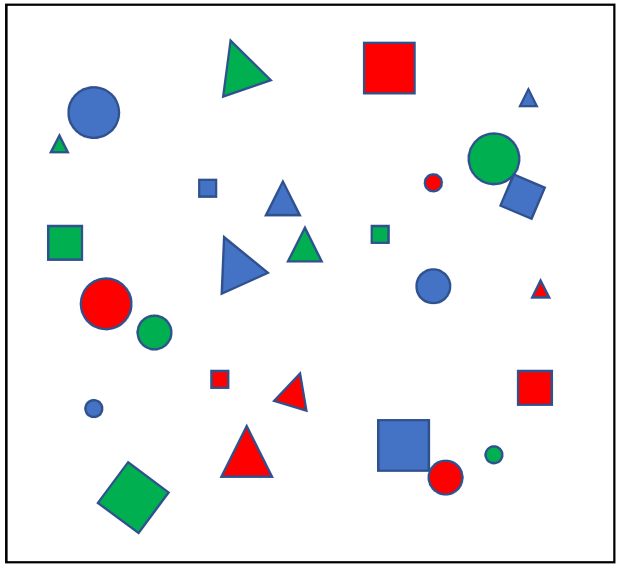
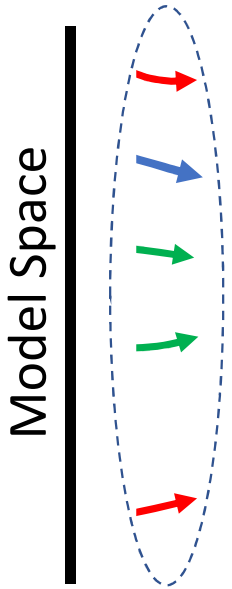
Parameter Values
Boundary Conditions
Space/Time Resolutions

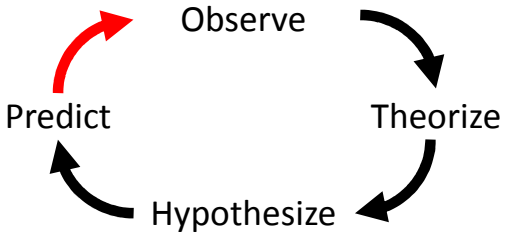


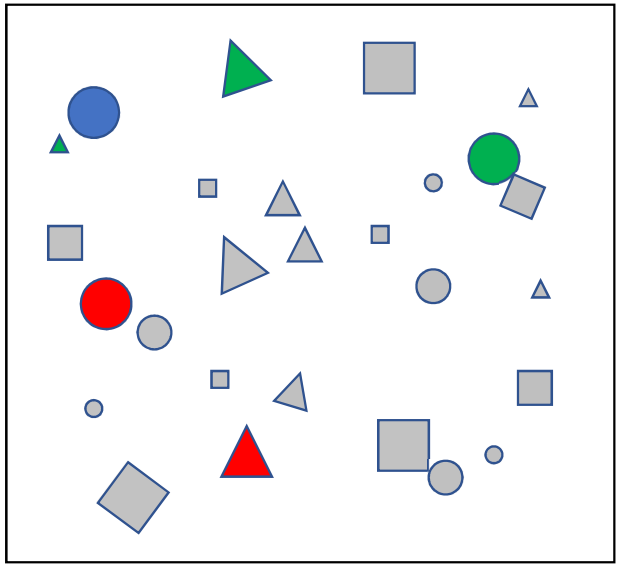
Model Space



Assessing Model Quality

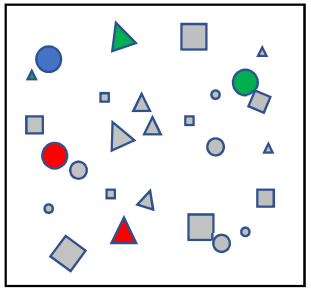
(Focus on A Few Models)

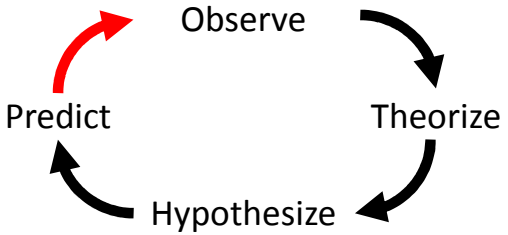


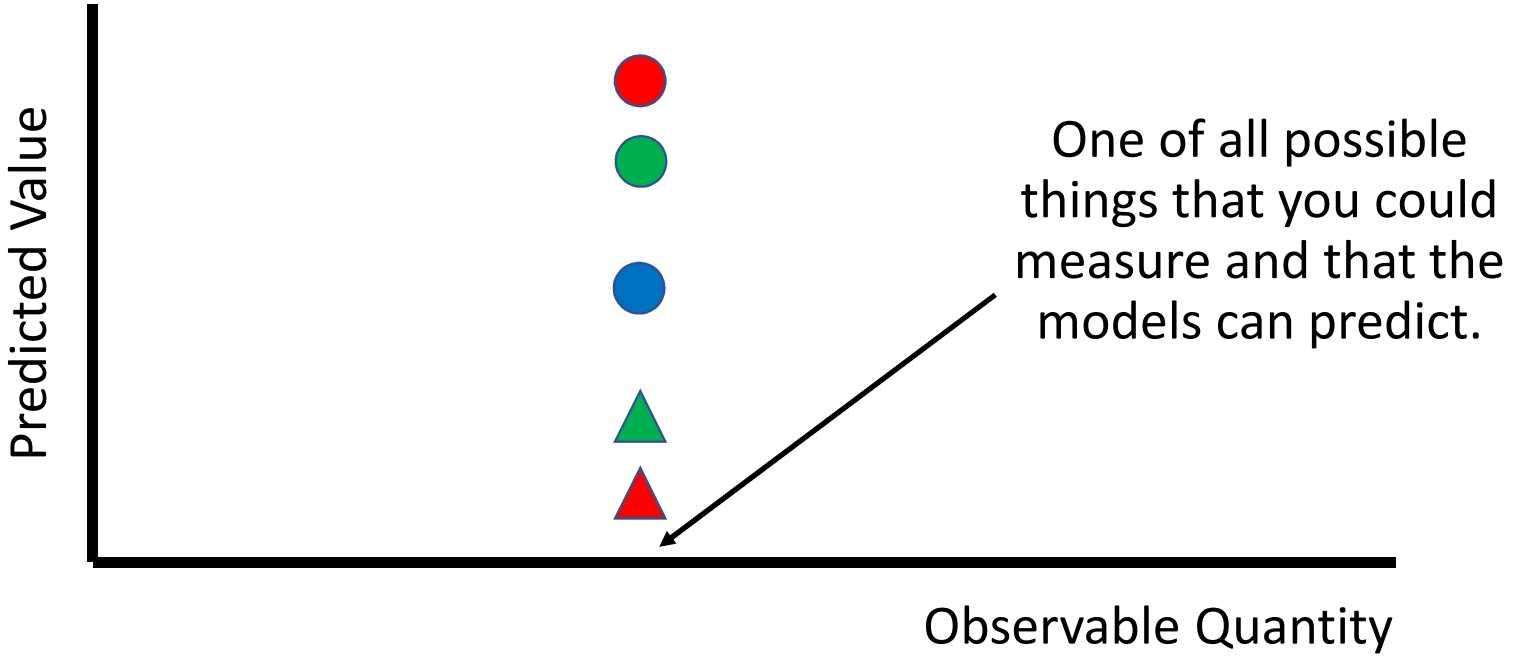


Model Space

Assessing Model Quality







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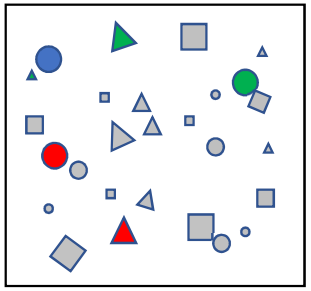
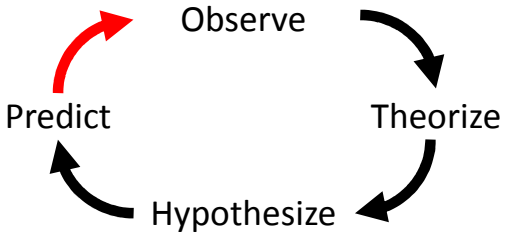
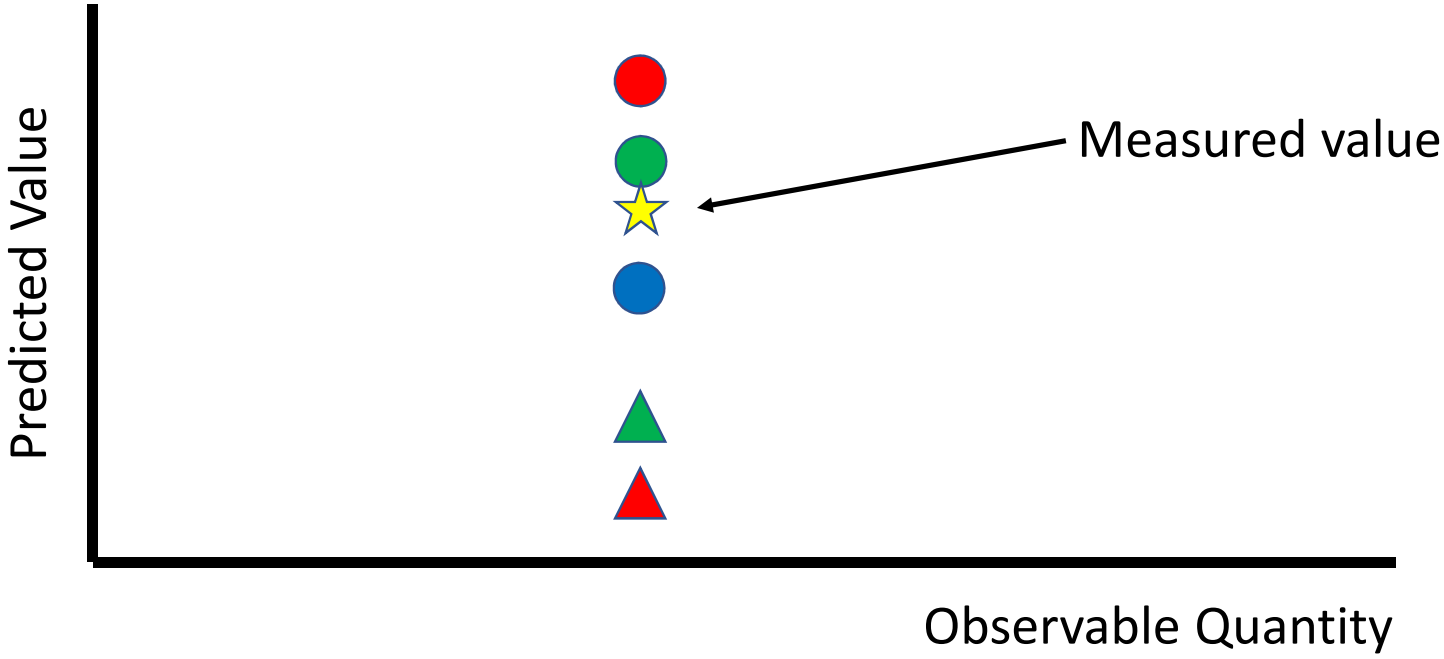
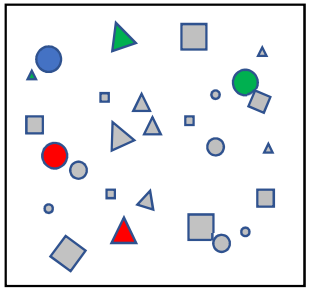




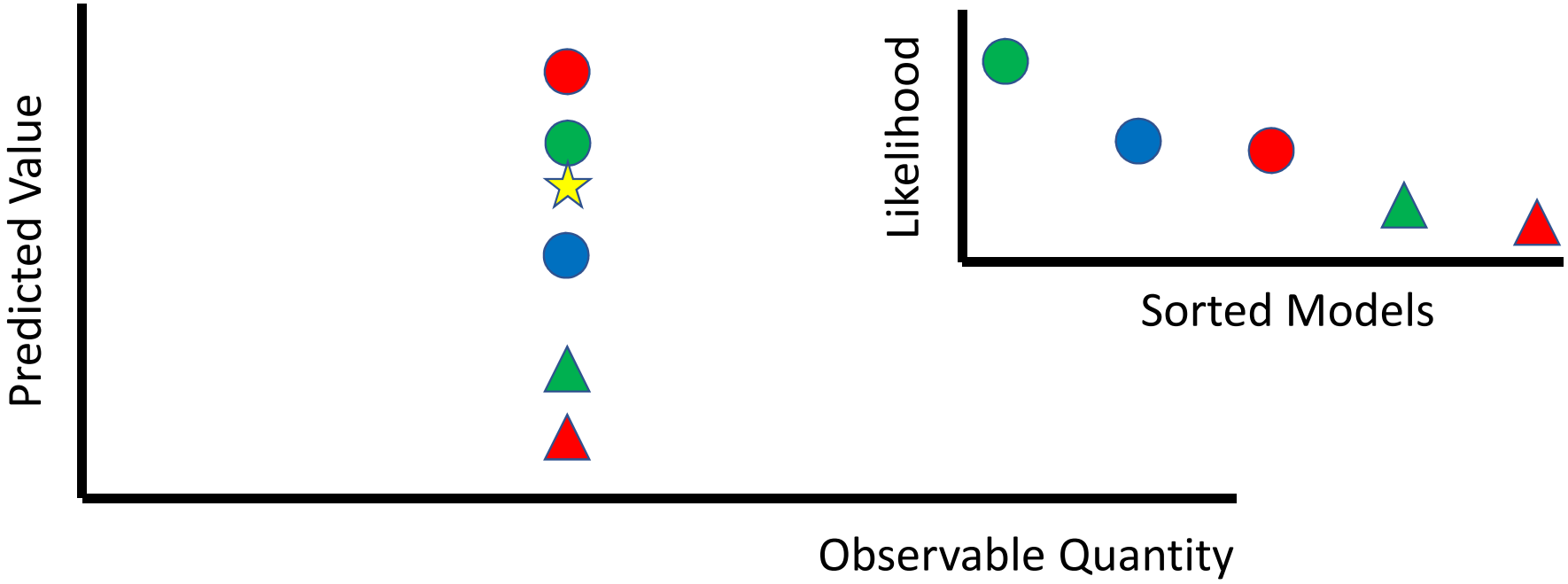


Model Likelihood

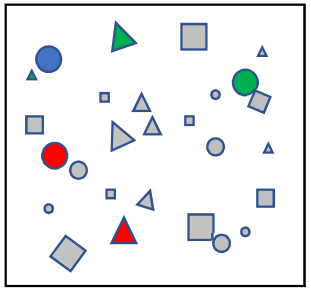


$L = f(1/\text{mismatch})$

$\Sigma L = 1$



Model Likelihood



L = f(1/mismatch)

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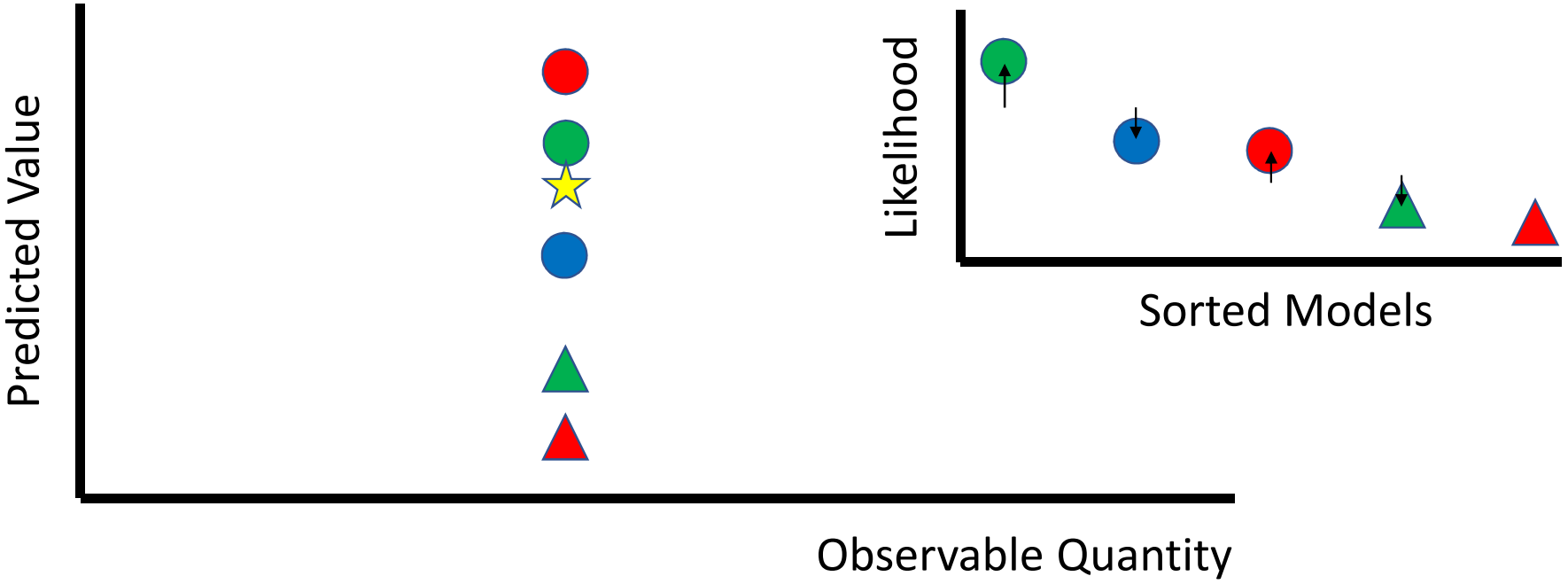
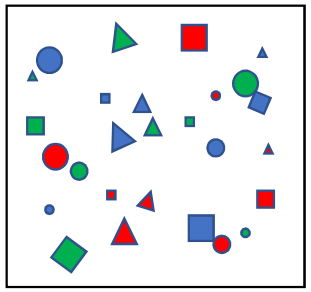
zero sum game



Model Likelihood



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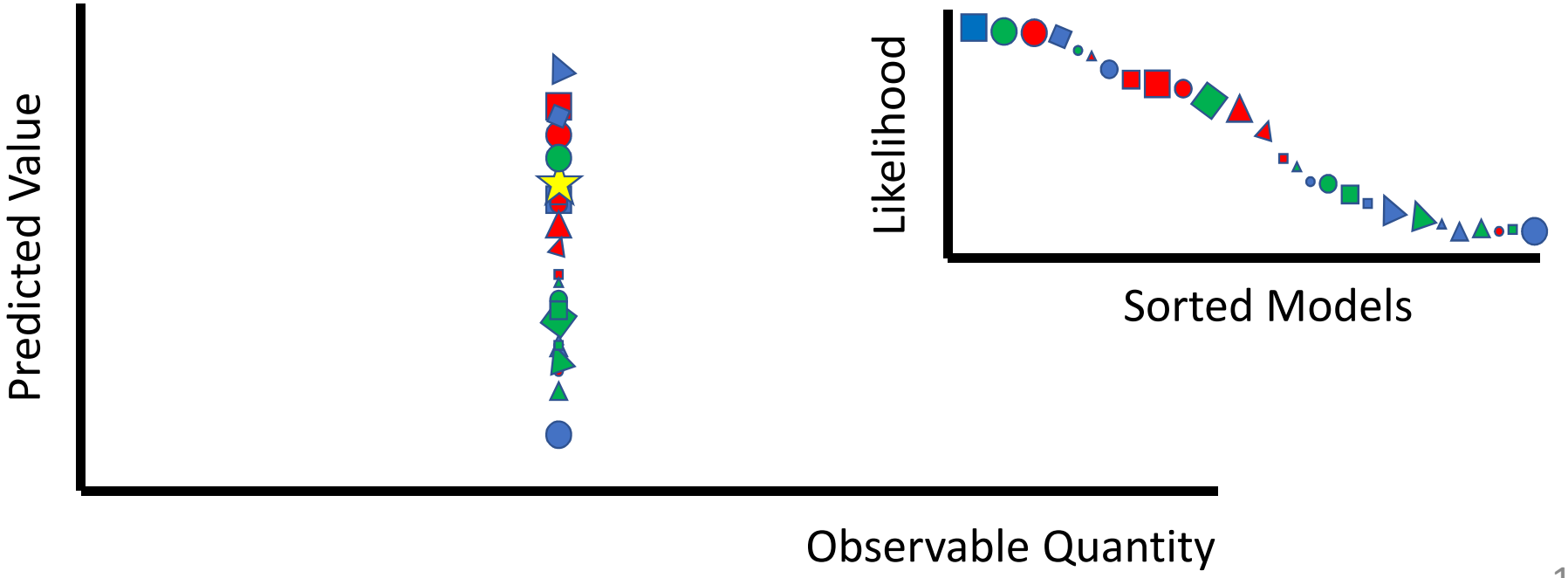
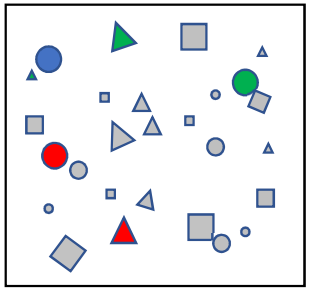
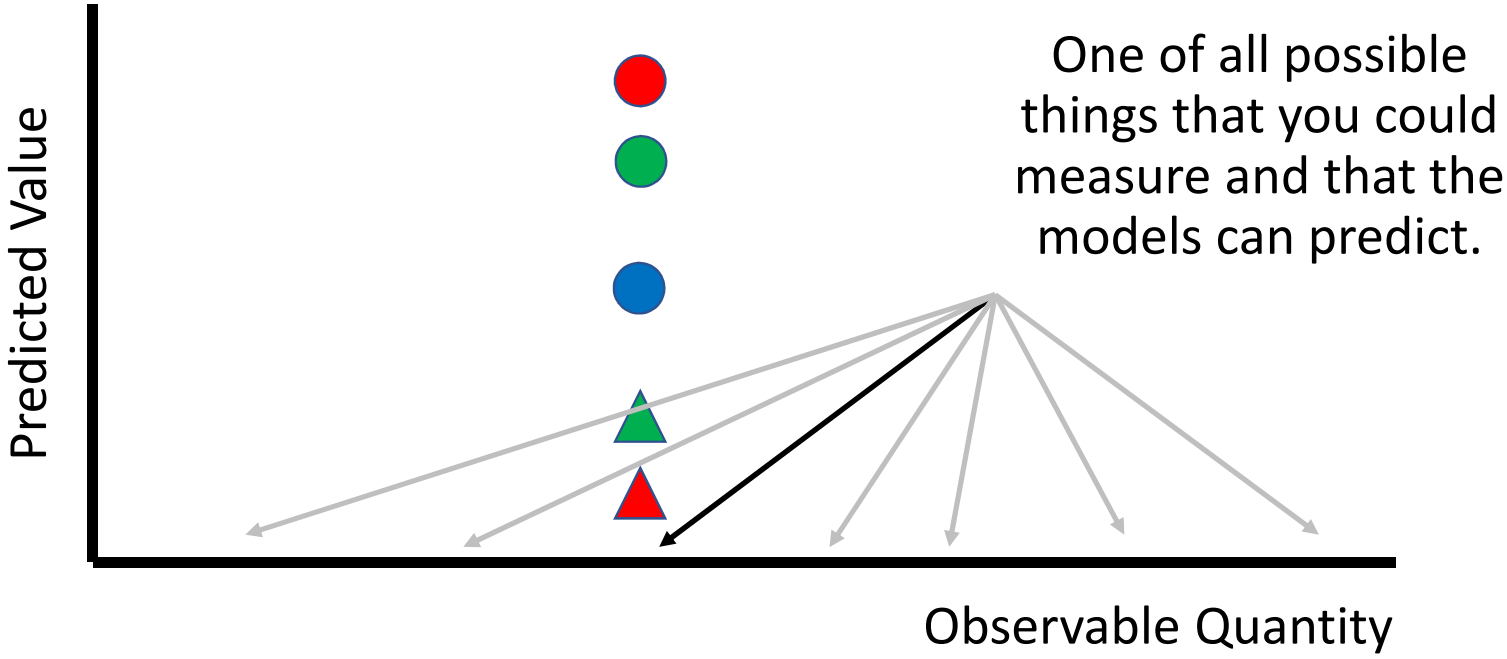


Data Quality





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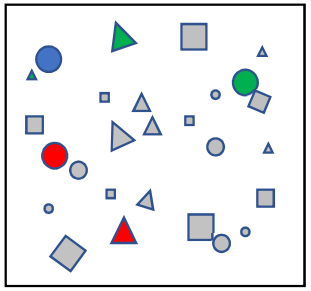

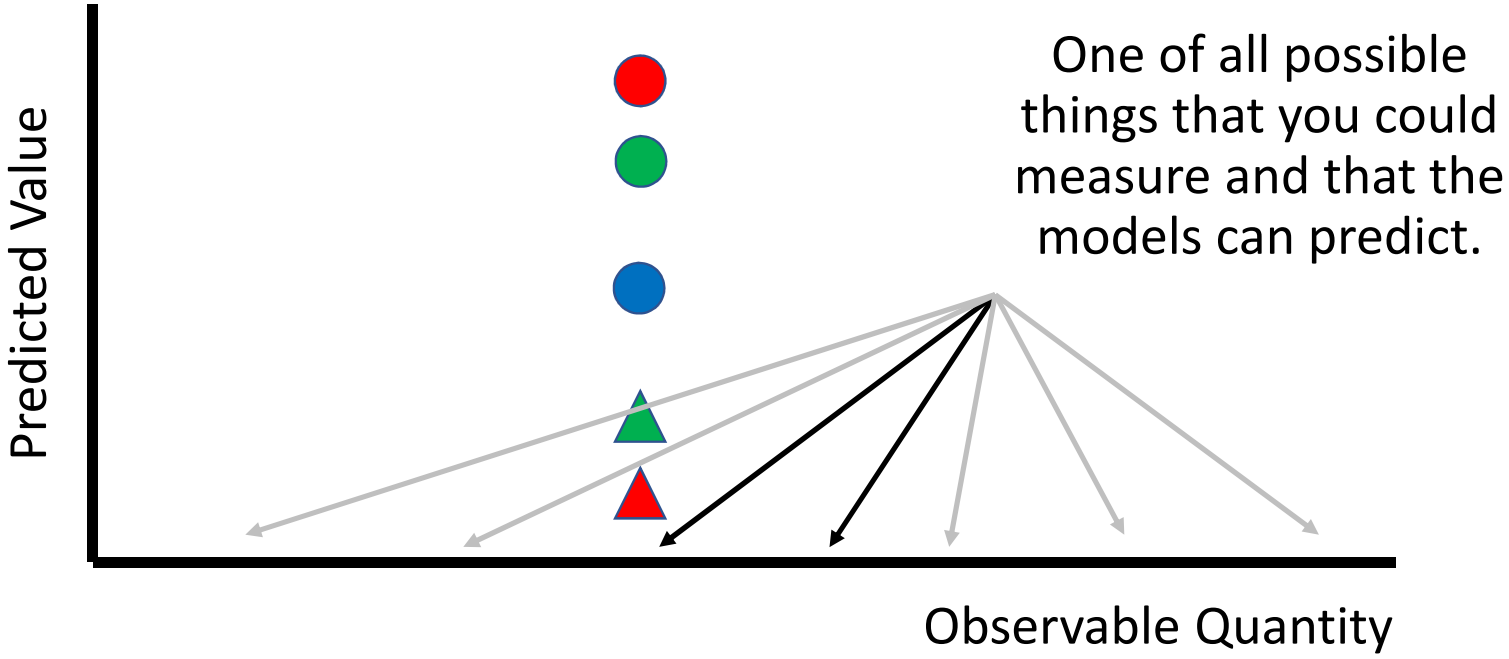

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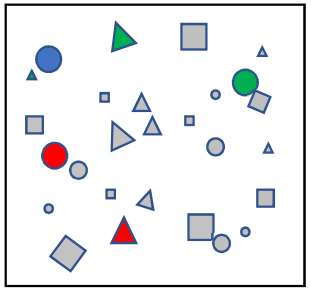
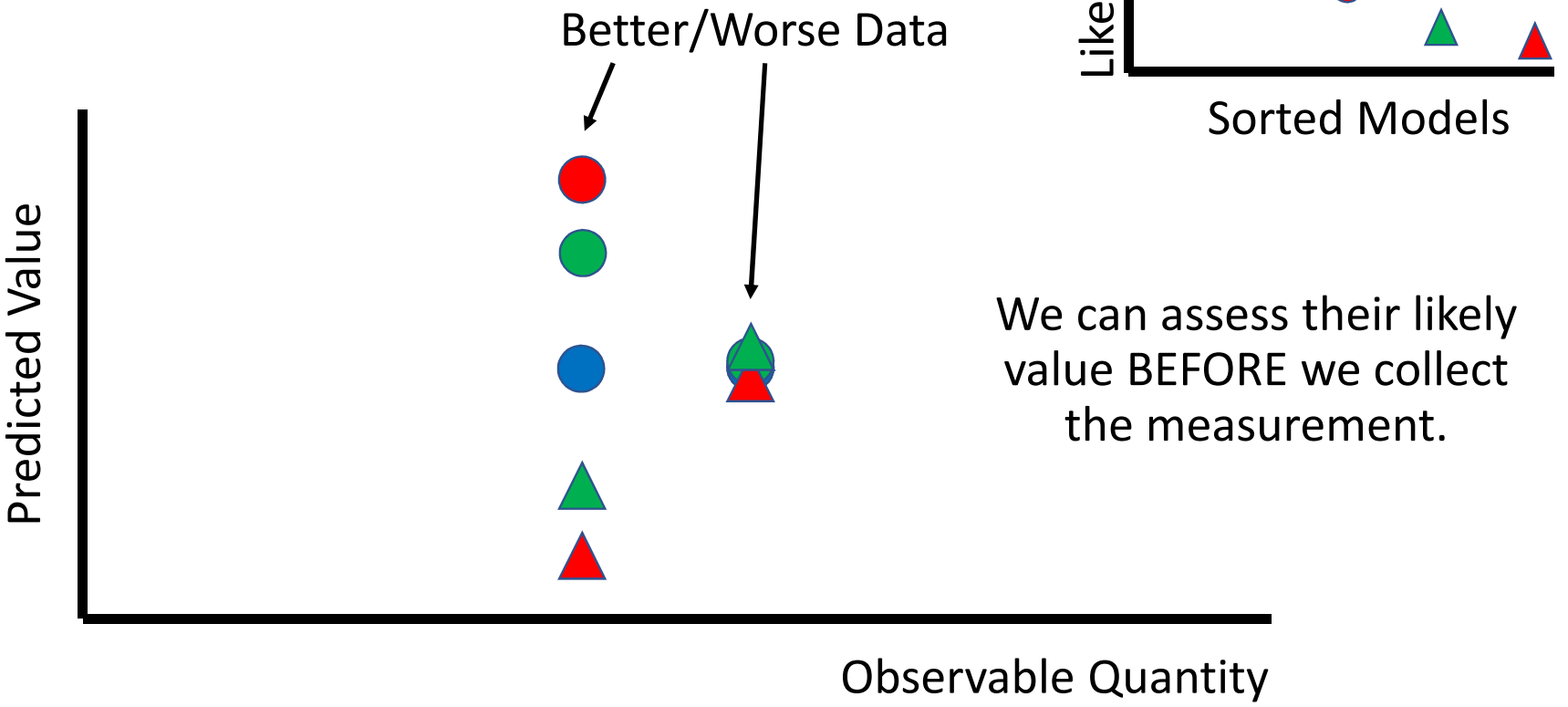
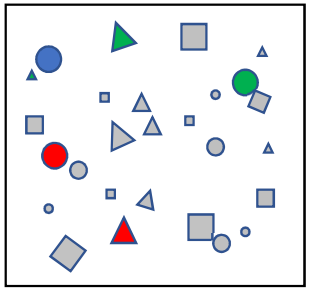
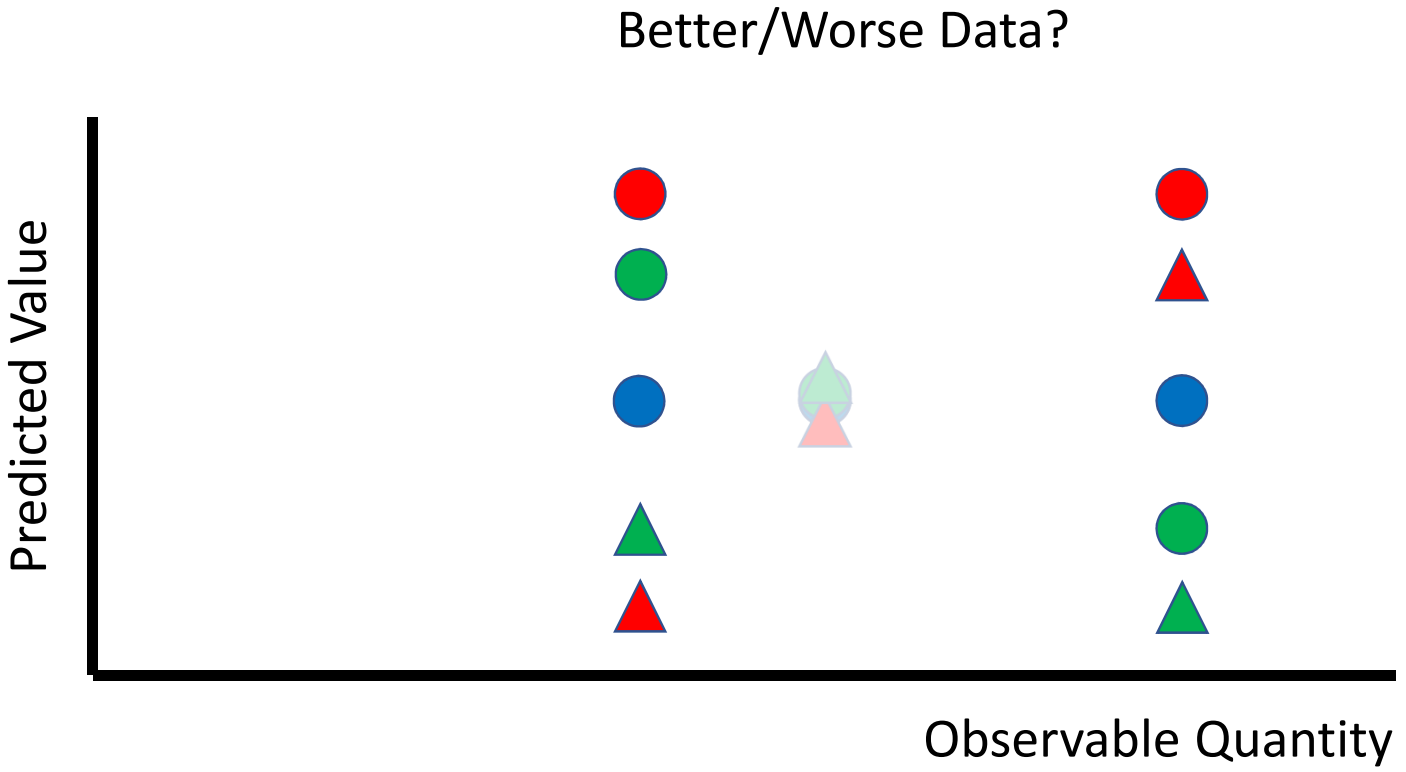




We can assess their likely value BEFORE we collect the measurement.

Discriminatory Data





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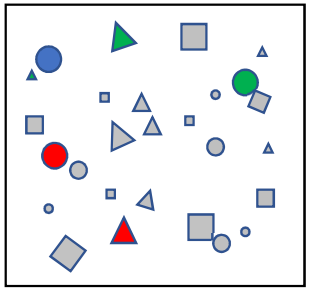
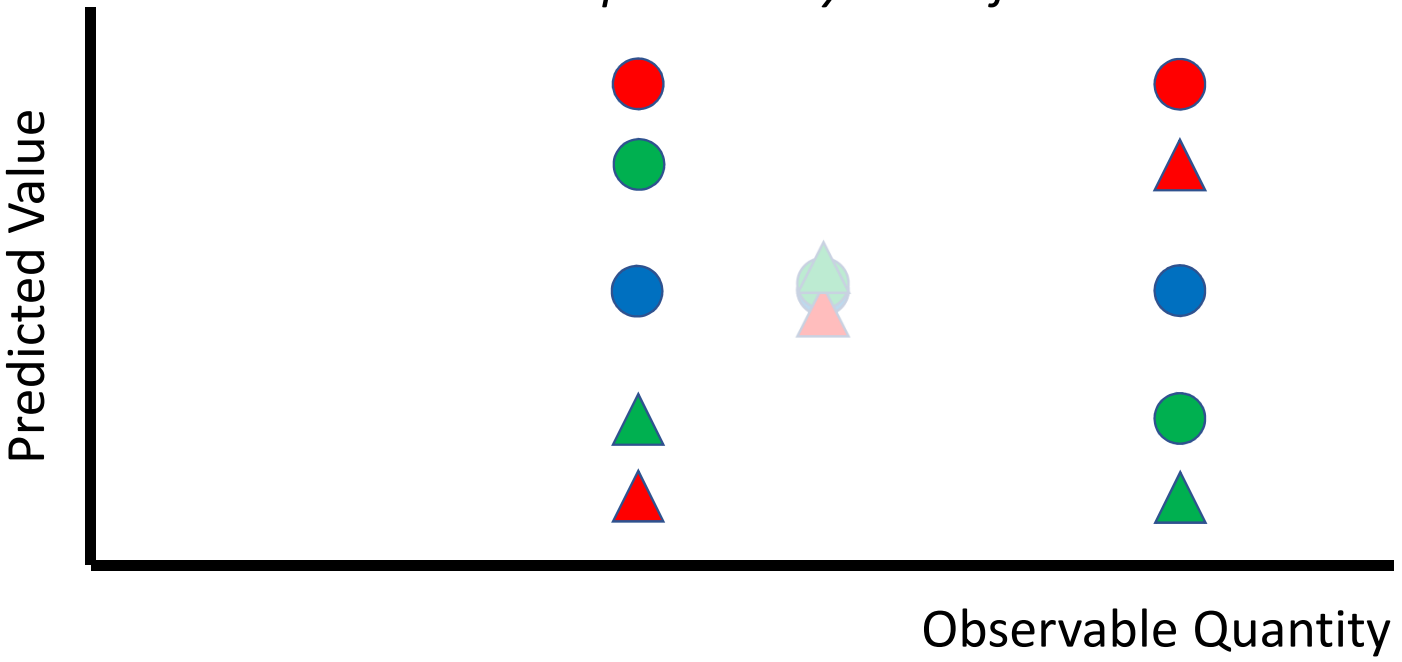
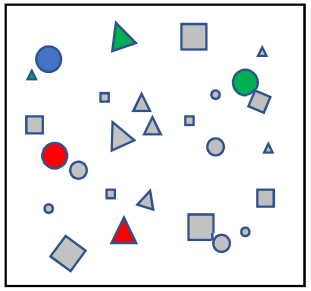


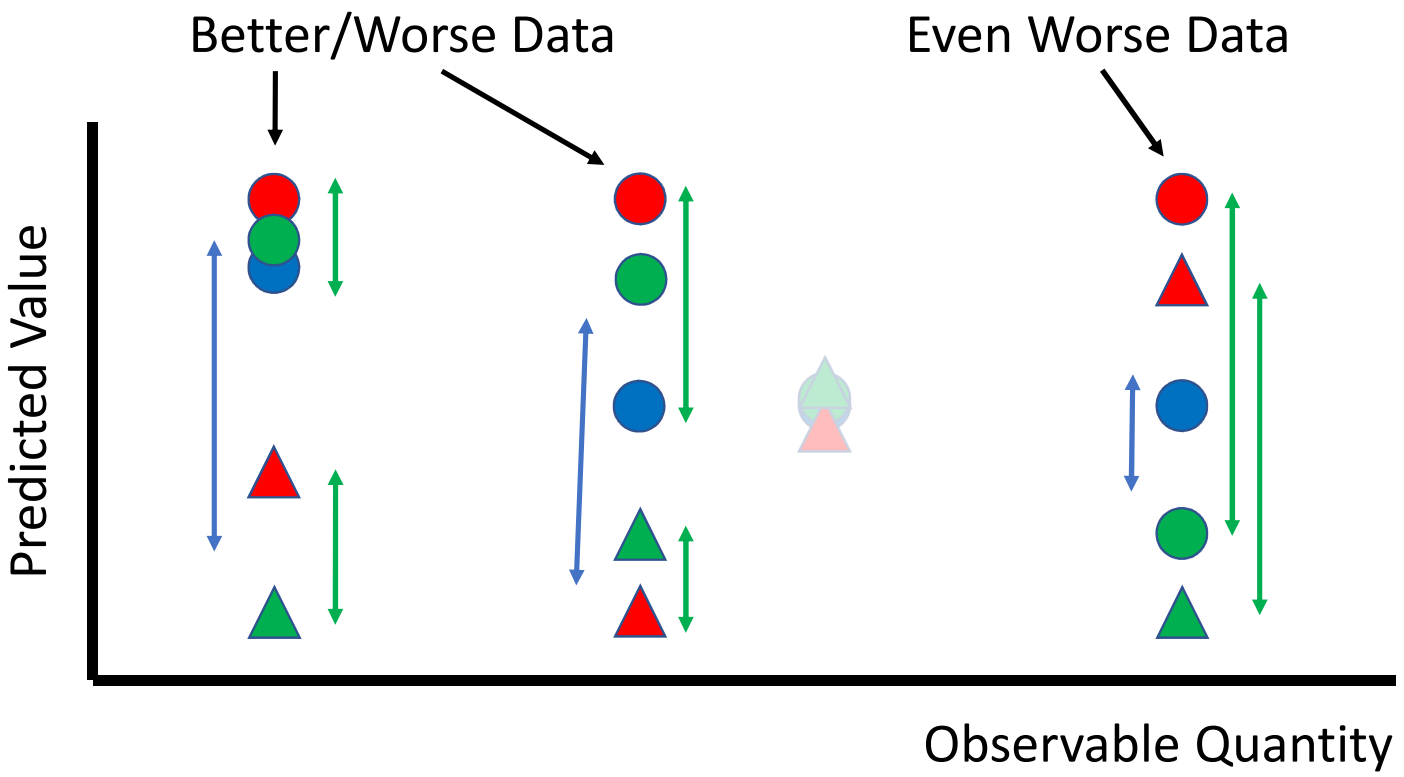
Better/Worse Data?
Depends on your objective



Discriminatory Index



DI = f(intergroup difference / intragroup spreads)



Discriminatory Ind

DI = f(intergroup difference / int

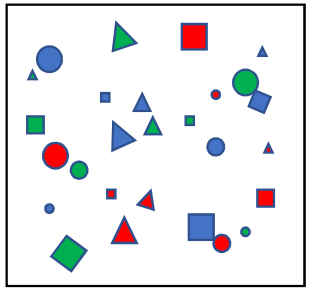
Better/Worse D

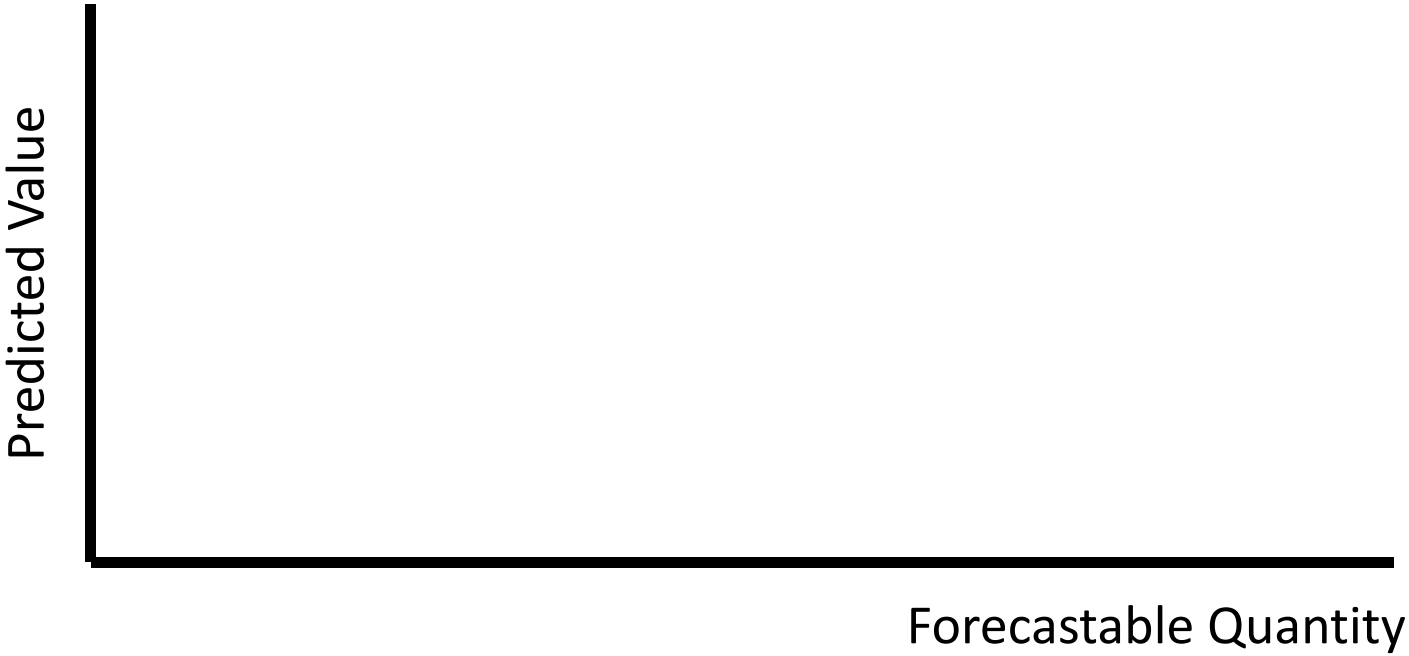
alue

Observable Quantity

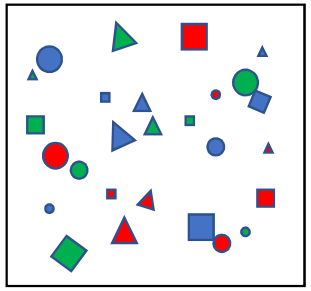
The choice of model ‘groups’ is subjective and will likely vary among stakeholders

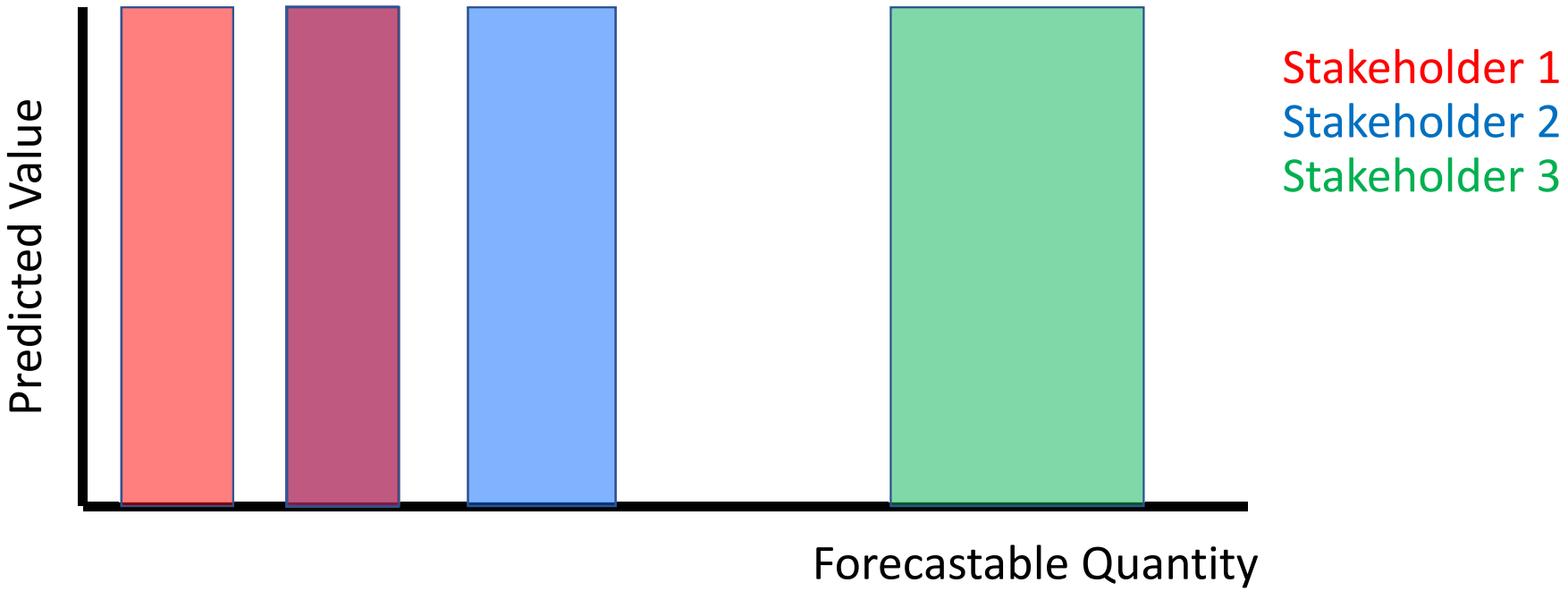
Model Importance



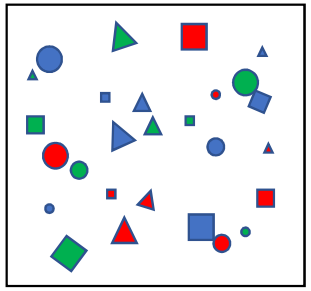


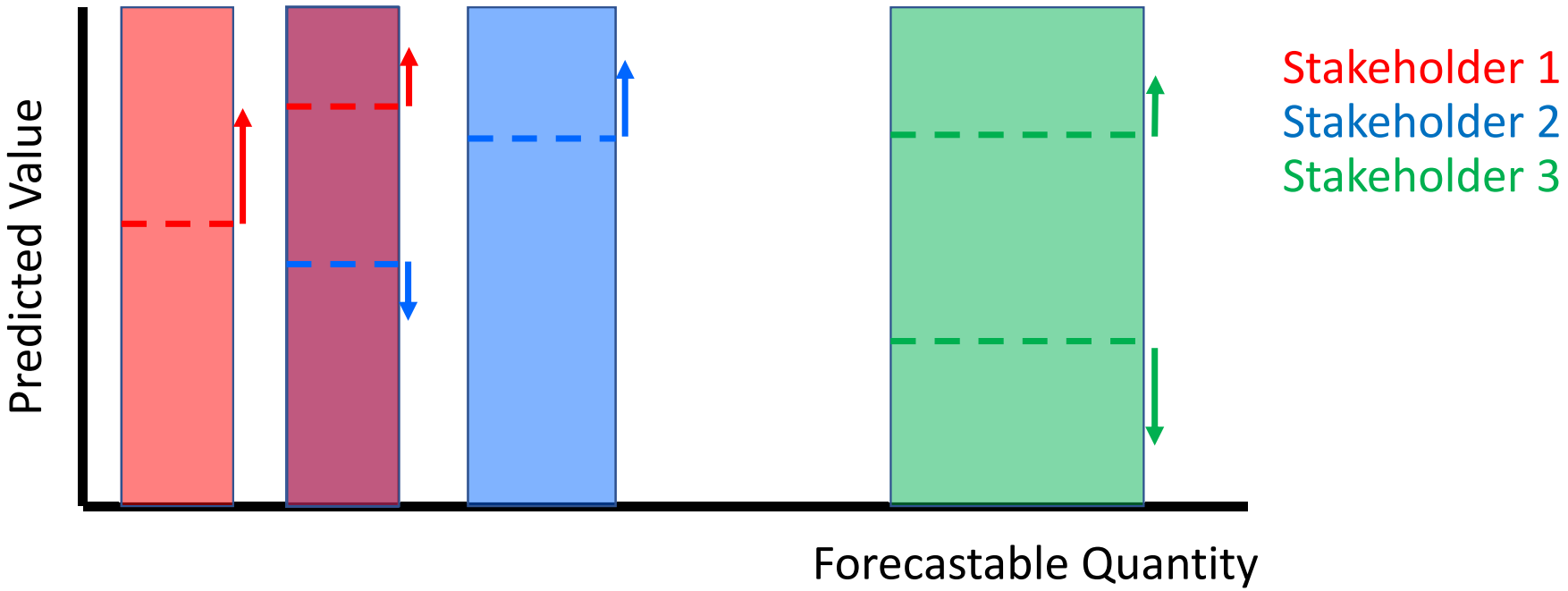
Predictions of Interest



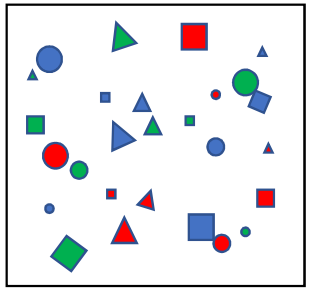


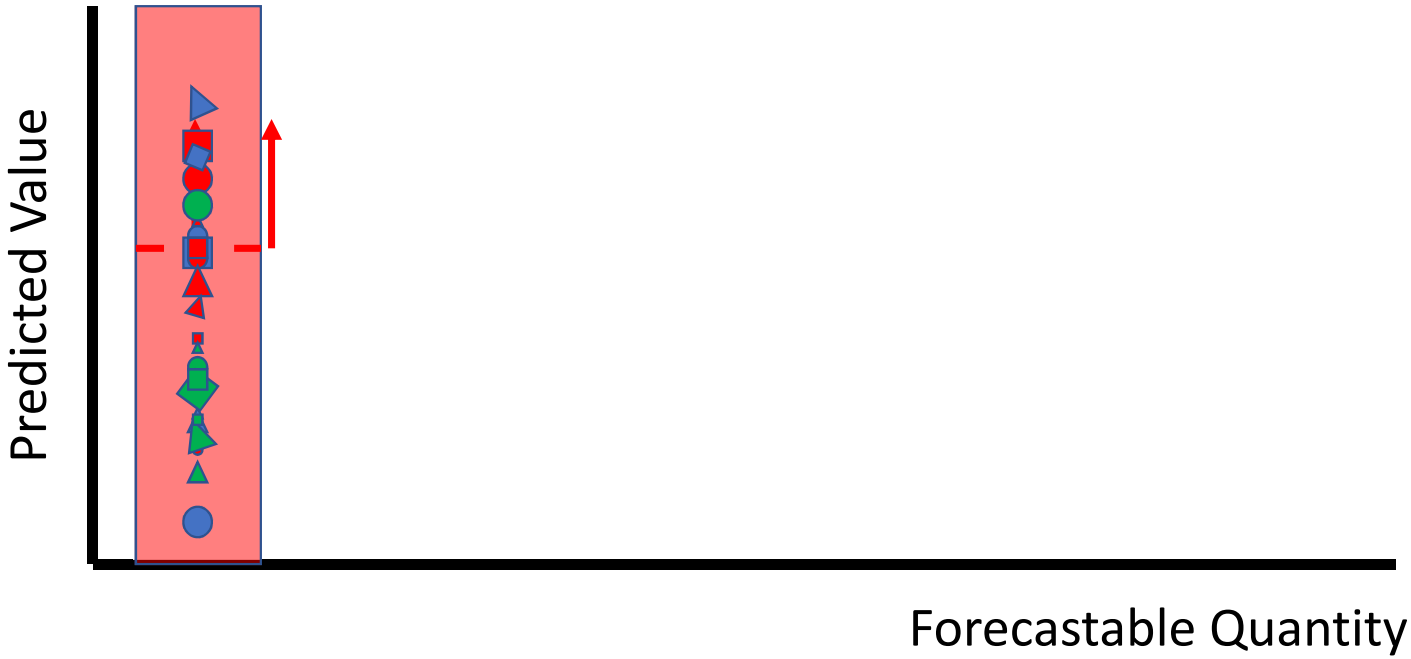
Outcomes of Concern





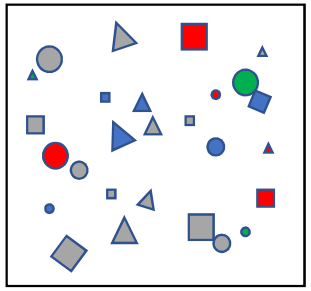
Models vs Outcomes of Concern

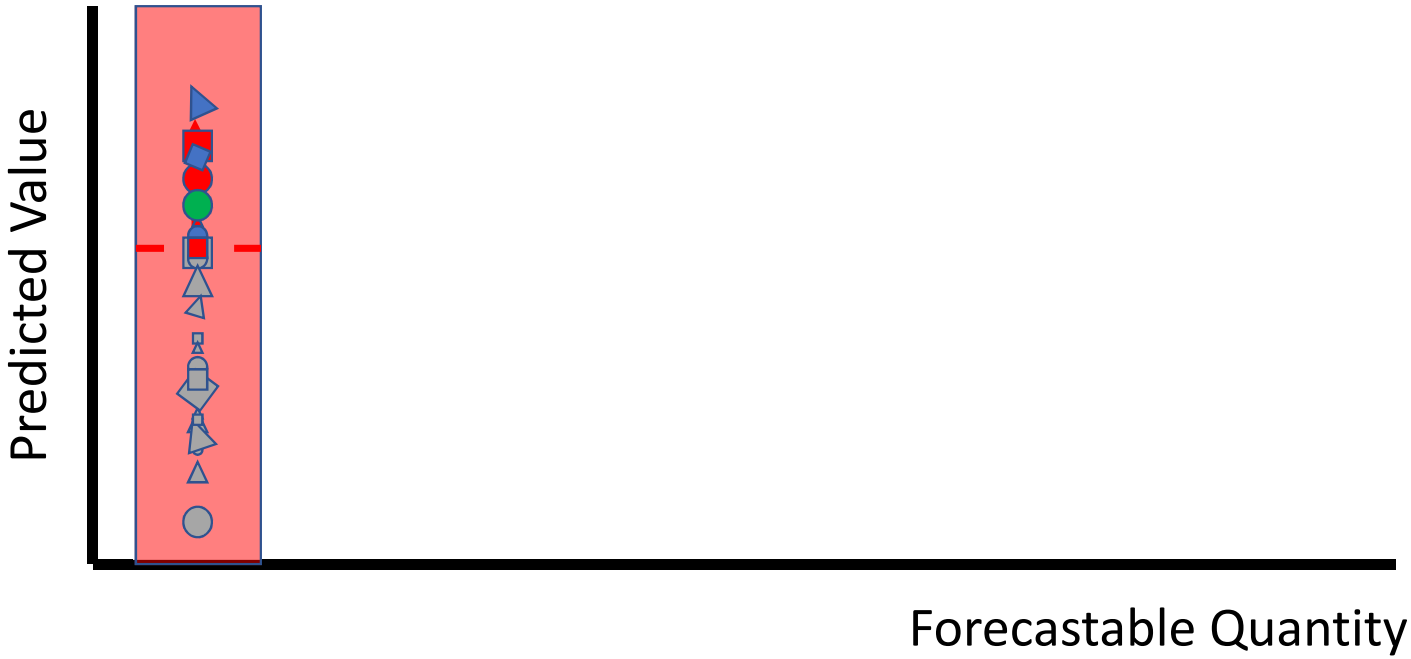




Stakeholder 1

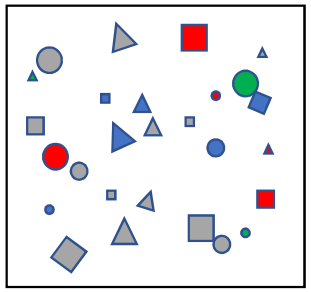
Models of Concern / Other Models

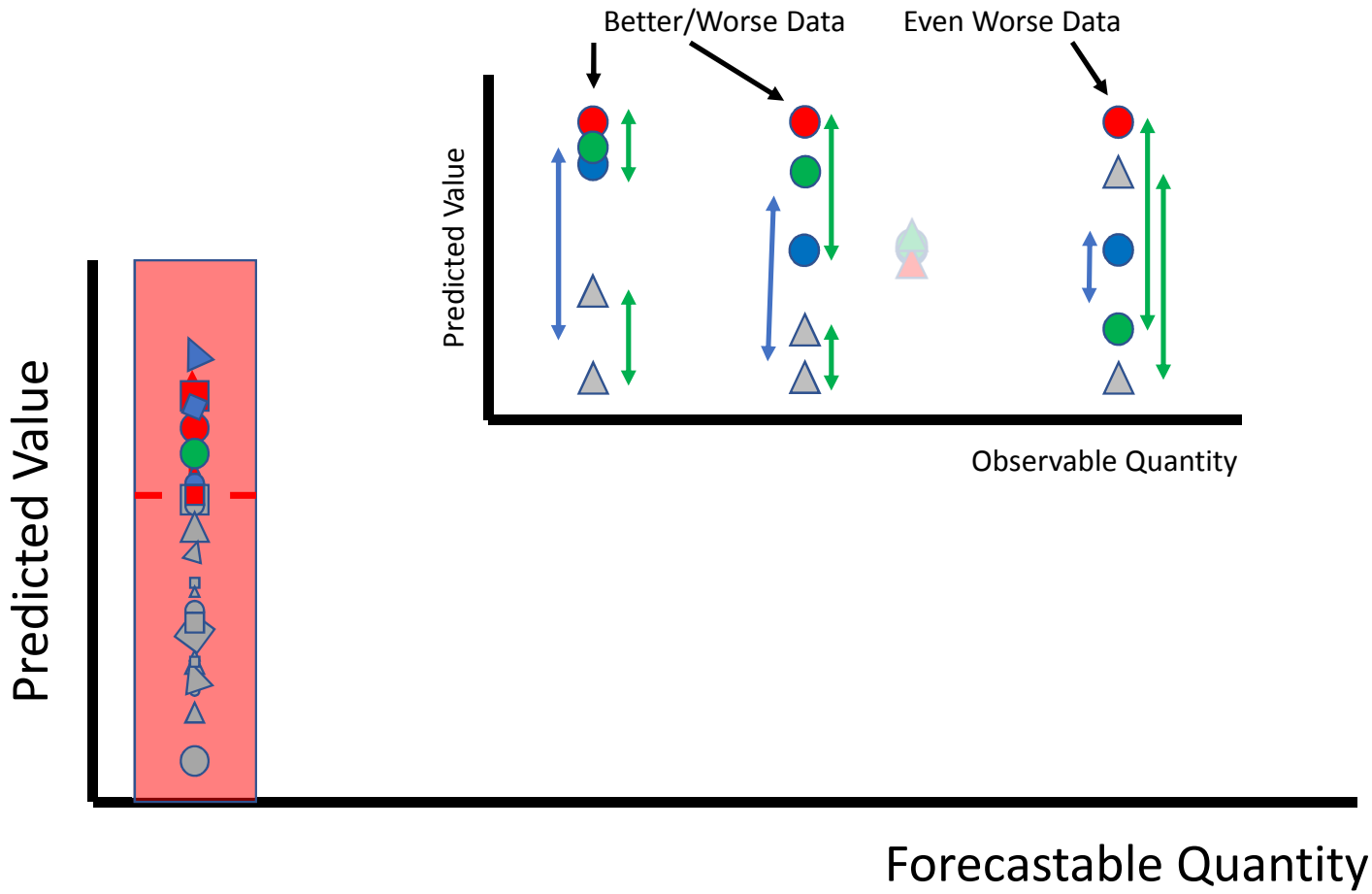




Stakeholder 1

Discriminatory Data for a Stakeholder's Models of Concern

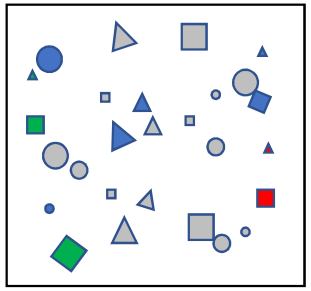


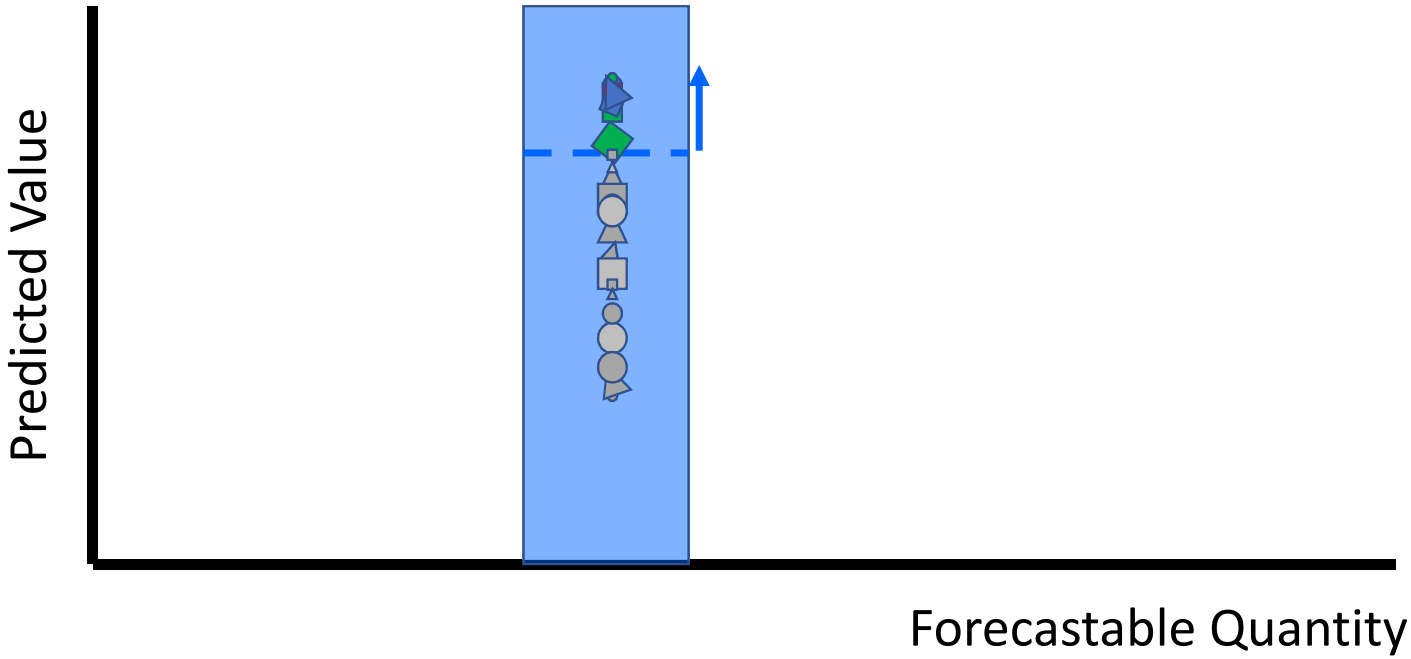


Stakeholder 1

32

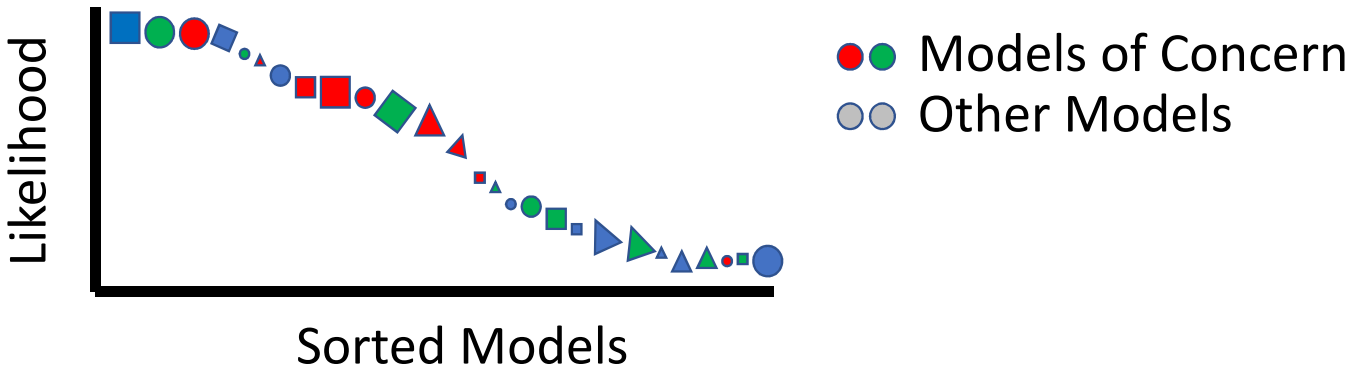
Models of Concern / Other Models





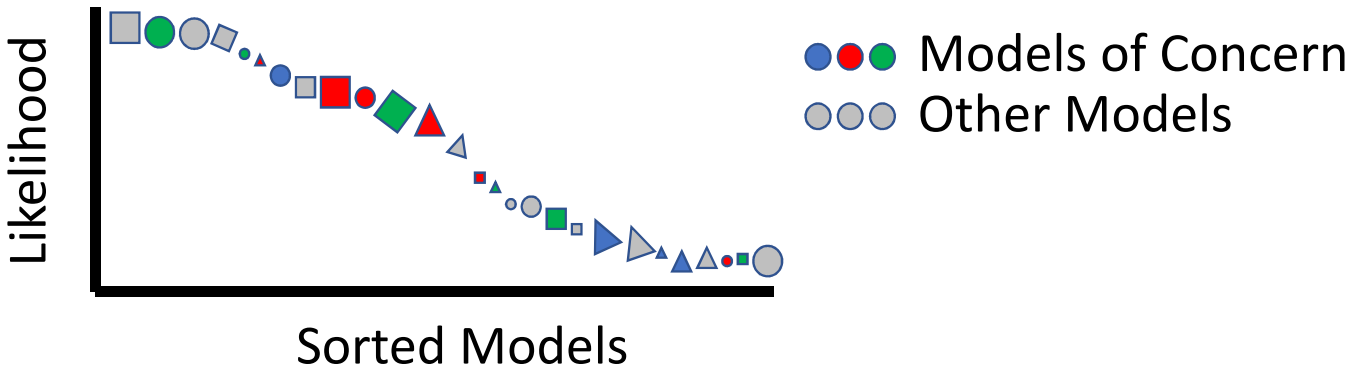
Stakeholder 2

Decision Confidence Index



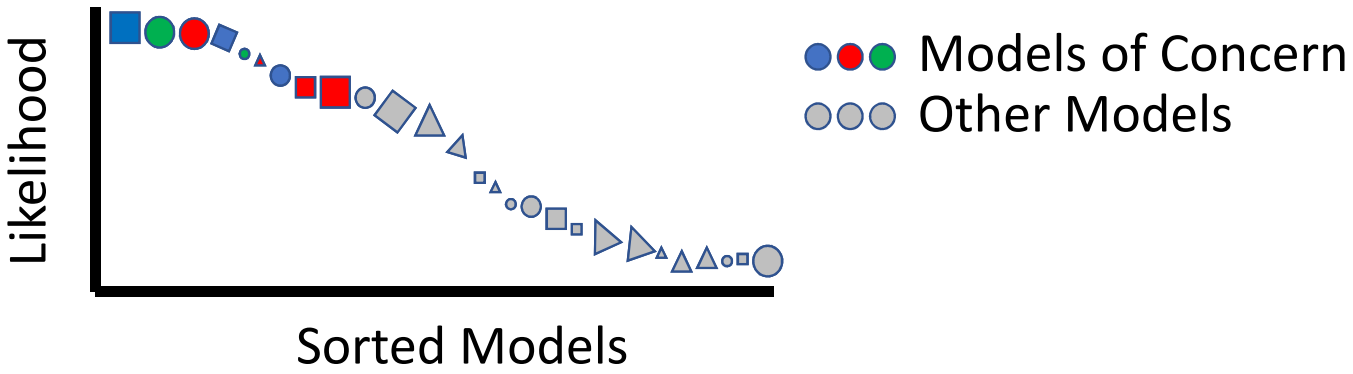
Decision Confidence Index

LOW CONFIDENCE



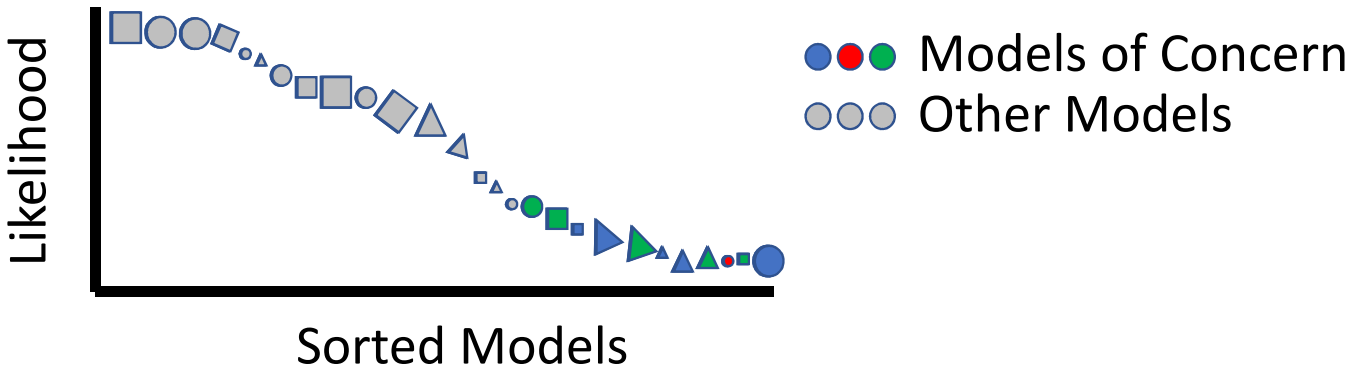
Decision Confidence Index

HIGH CONFIDENCE – but unhappy



Decision Confidence Index

HIGH CONFIDENCE – and happy



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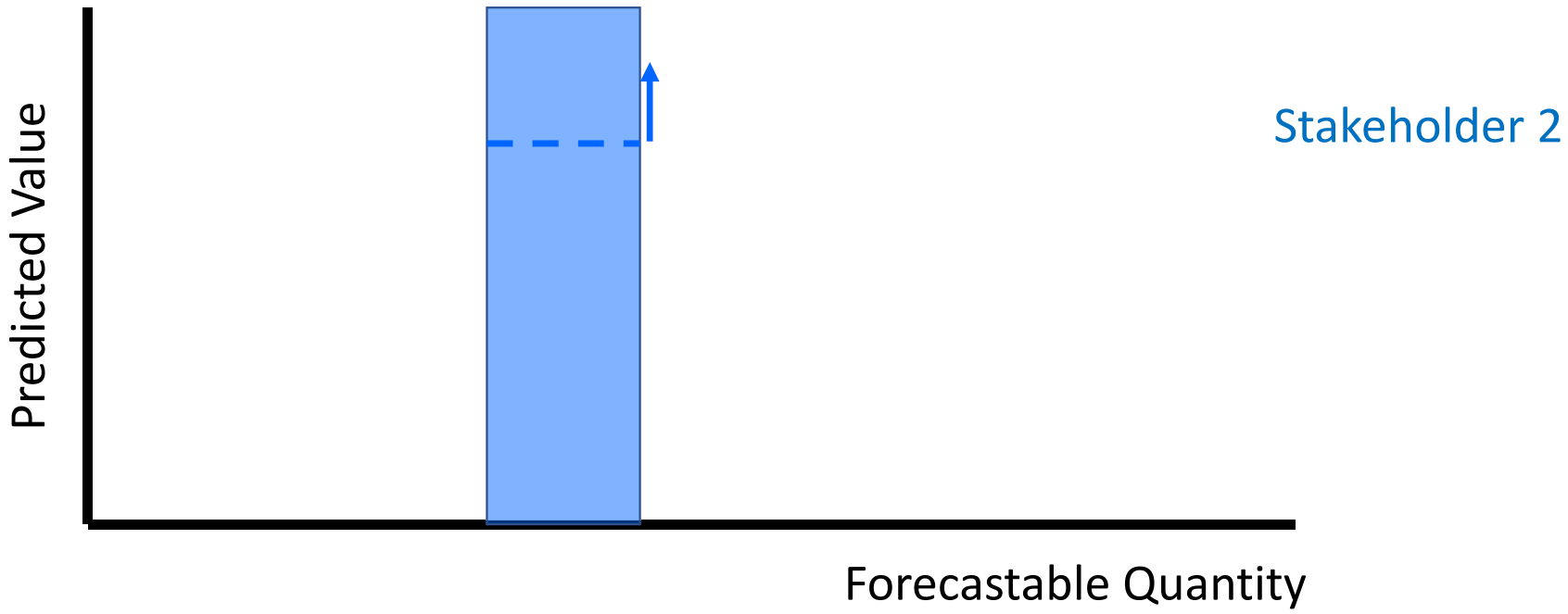
Summary of Talk One

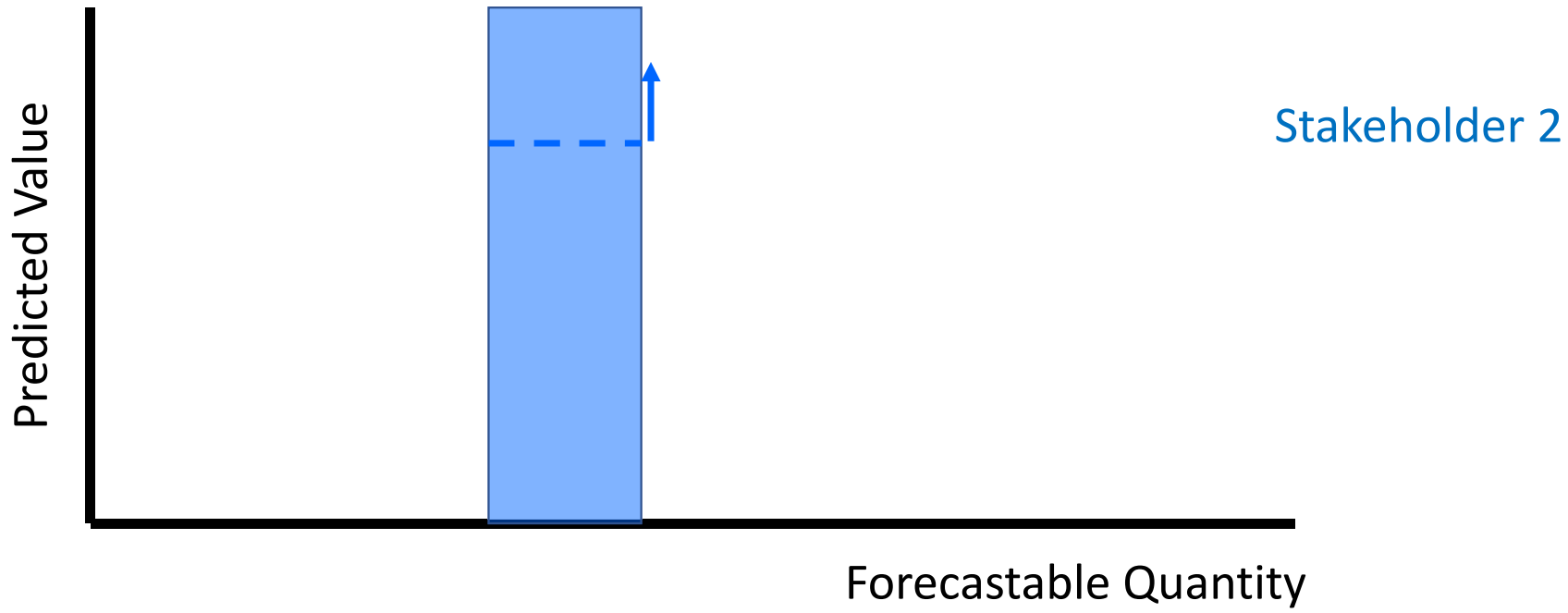
- Multiple plausible models can be built for any system;
- Model likelihoods can be defined based on fit to data;
- The expected value of data for any prediction(s) of interest can be assessed ***before*** the data are collected;
- Stakeholders must define the prediction(s) of interest, which will identify the models of concern;
- Decision support relies on segregating ***either*** models of concern or other models as high likelihood.

Talk Two: Time for Some Psychology



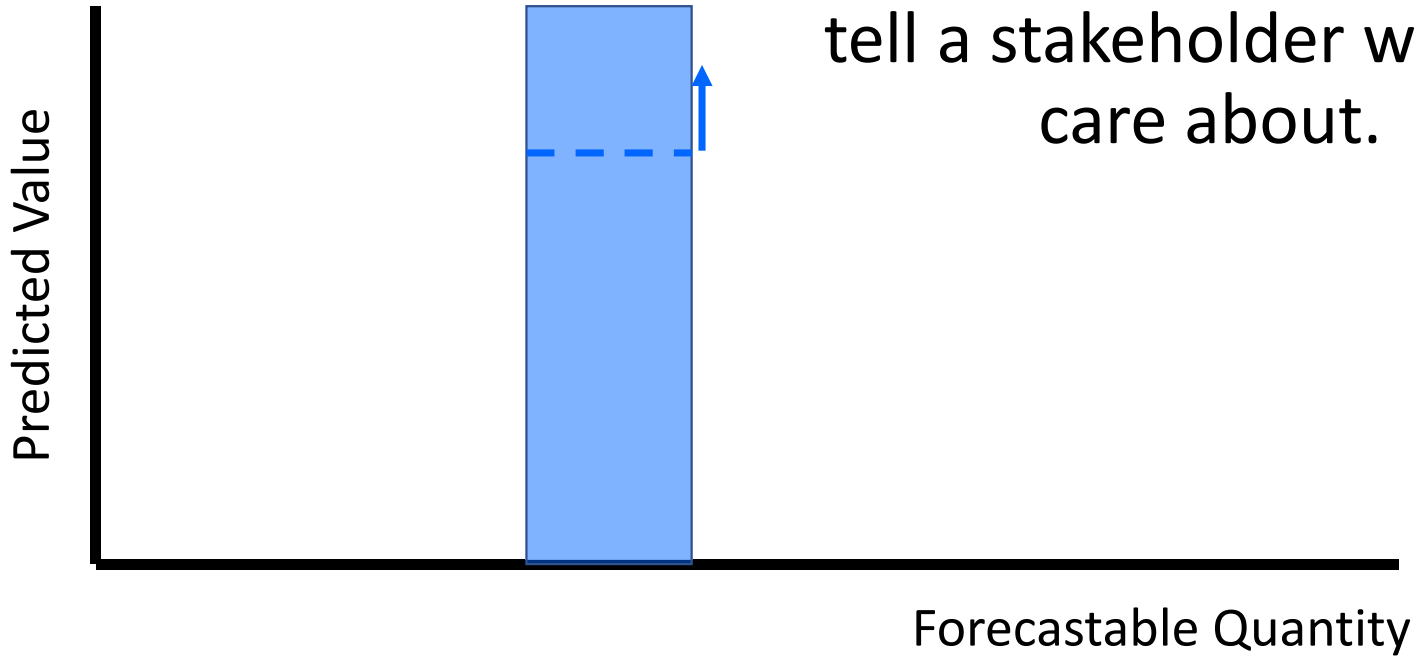
Stakeholders Must Drive the Process

Each stakeholder must define their outcomes of concern.



Stakeholders Must Drive the Process

(Stakeholders are Human)

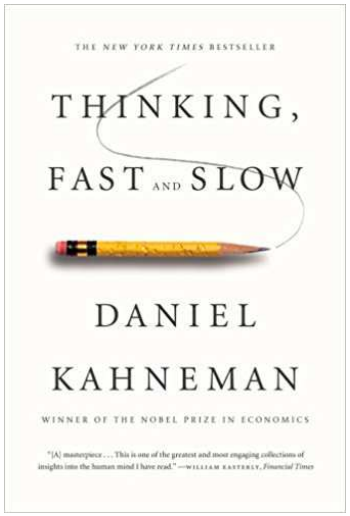


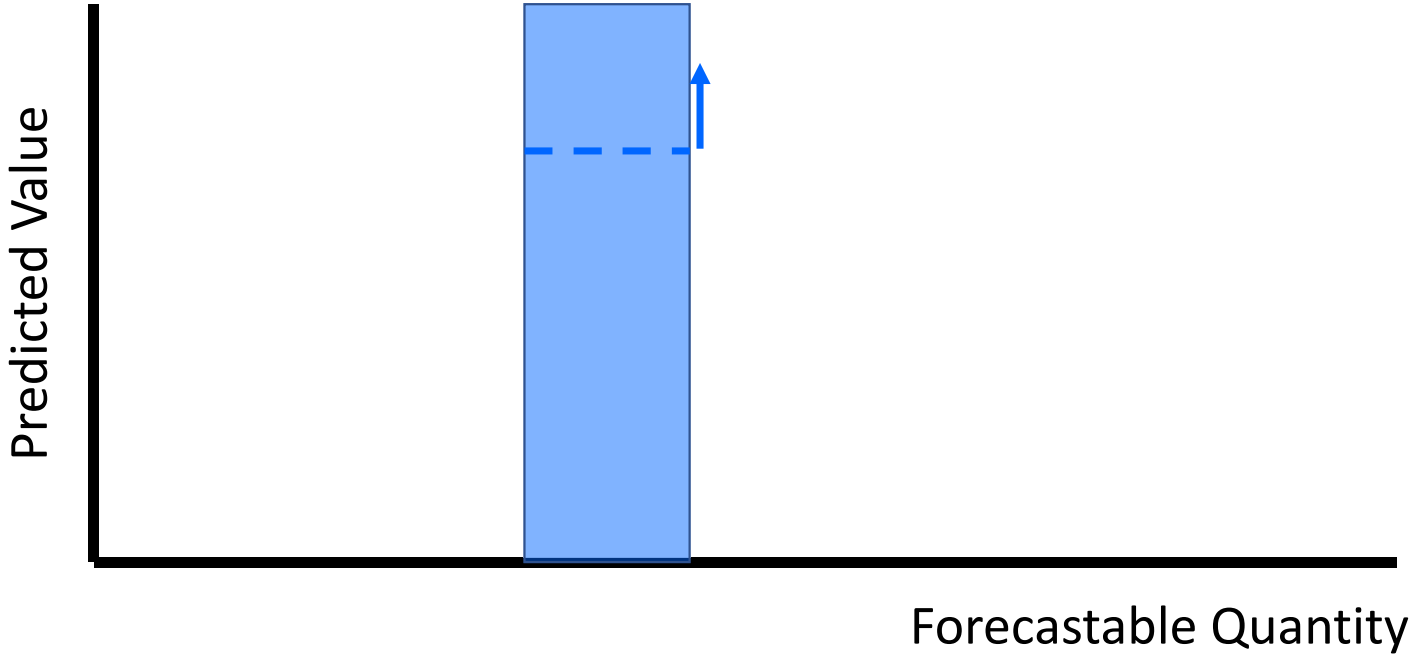
It is not a scientist's job to tell a stakeholder what to care about.

Outcomes of Concern Are Biased

(Stakeholders are Human)

esp. loss aversion

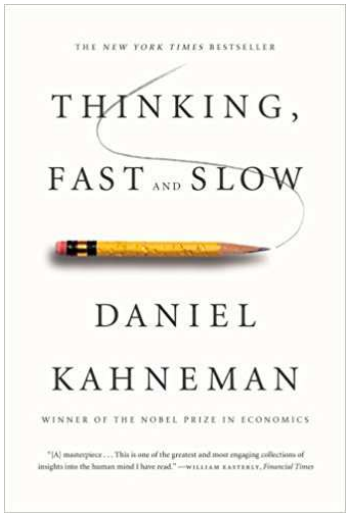


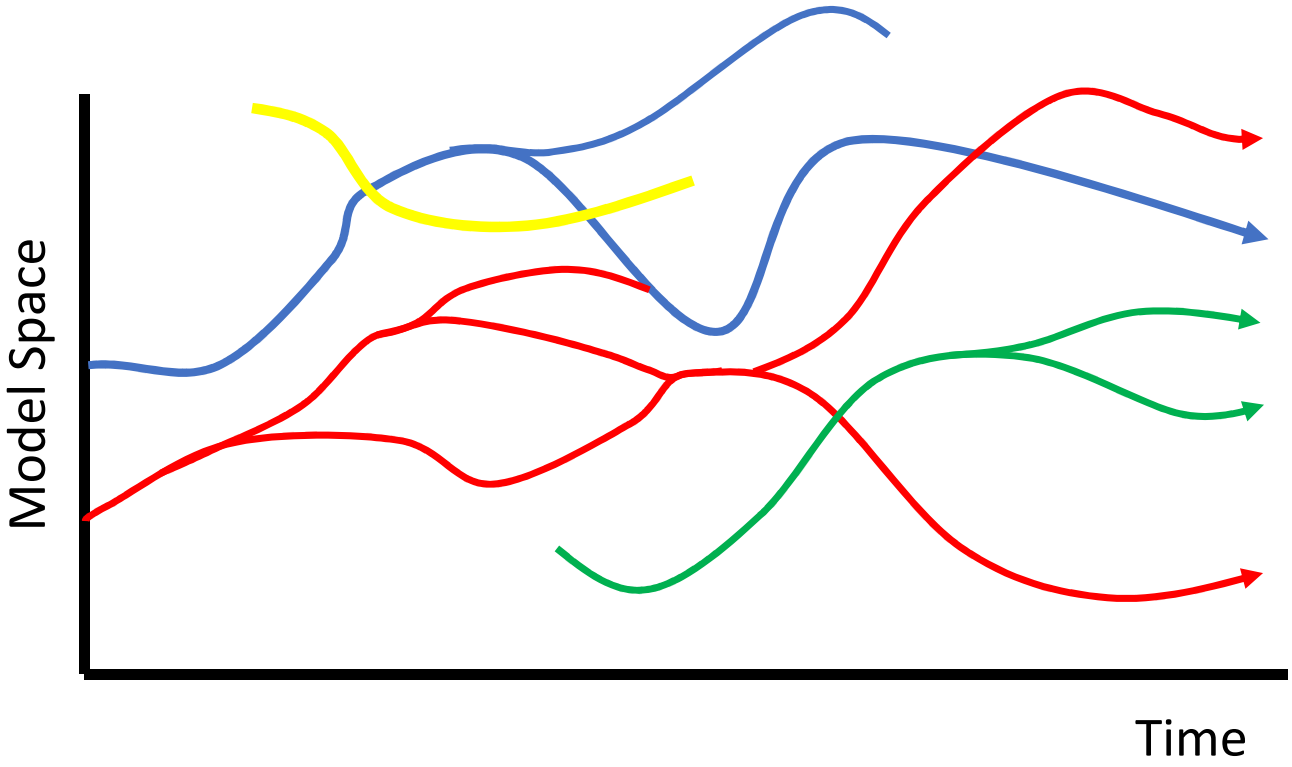


Modeling Is Biased

(Modelers are Human)

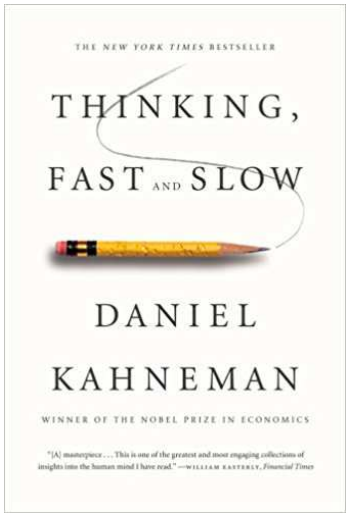
esp. confirmation bias

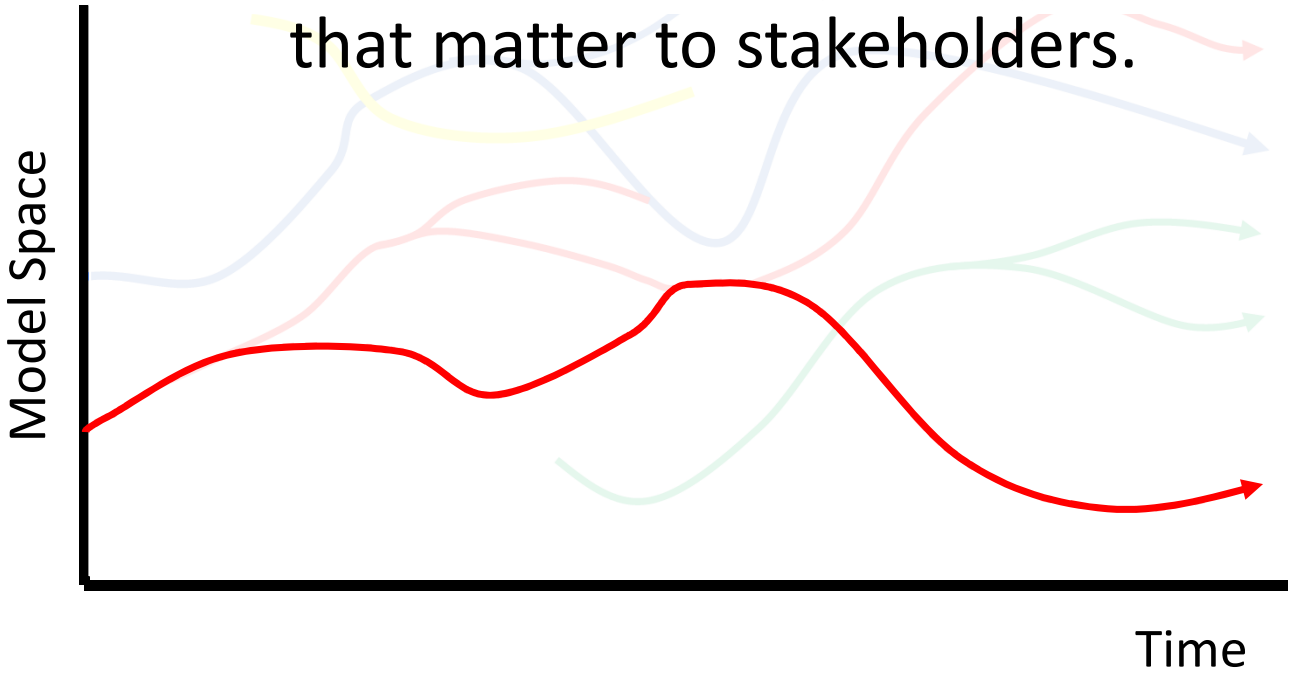




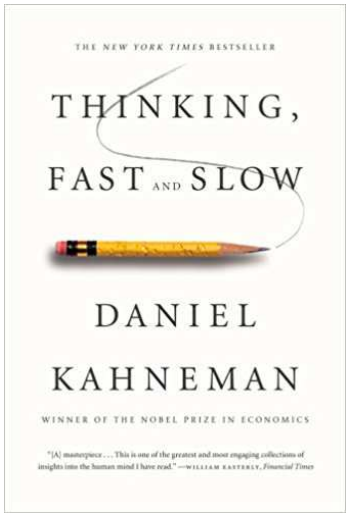
Embrace the Bias

It is not a scientist's job to inject false objectivity – but, rather, to test hypotheses – especially those that matter to stakeholders.

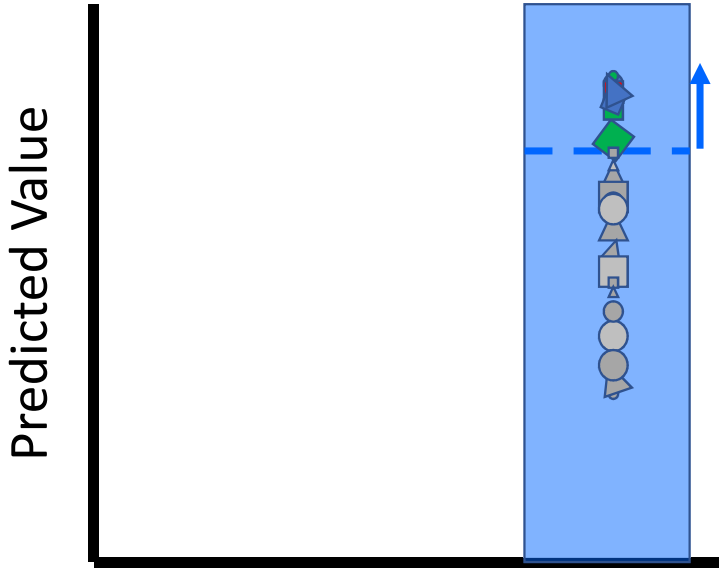


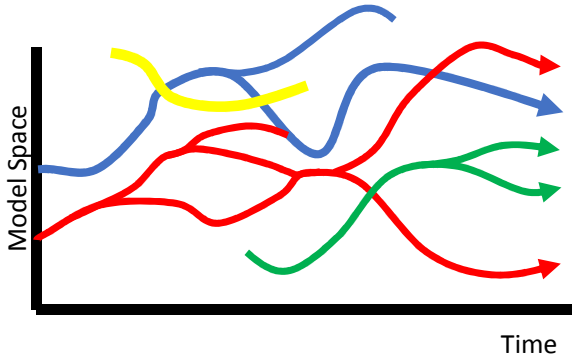


Develop Plausible Models of Concern

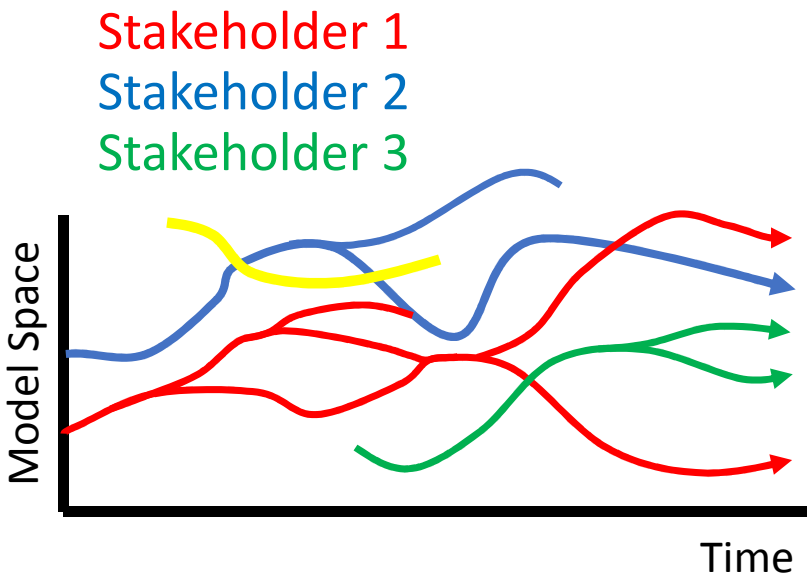


Stakeholders, with their experts (modelers), are best able to identify ***their*** outcomes of concern and find discriminatory data.



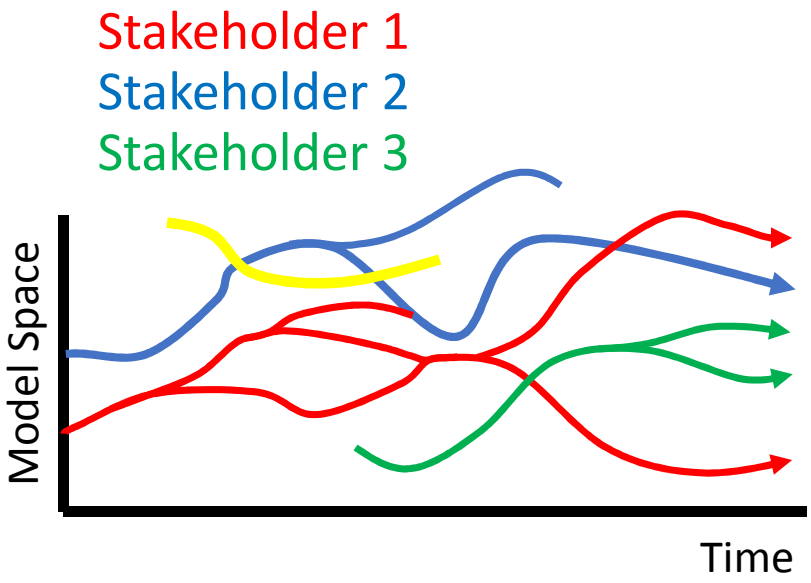


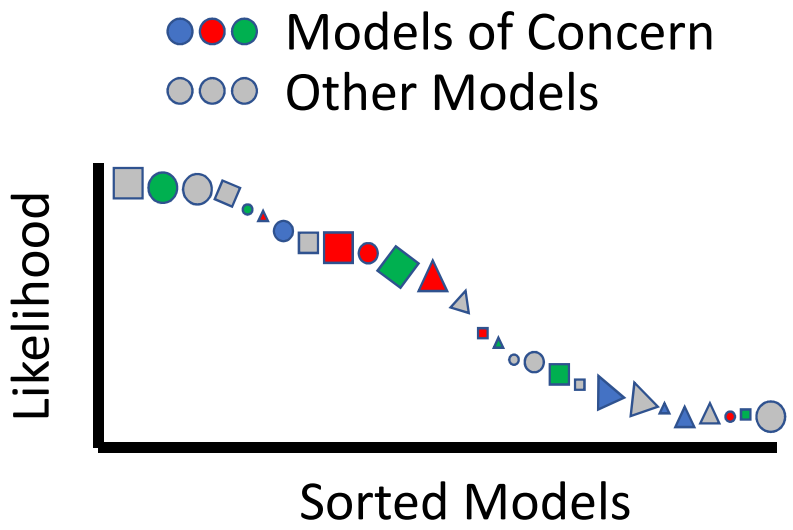
An Ensemble of Diverse Biased Models Is Not Biased



- Each stakeholder's modelers should be ***encouraged*** to form plausible models of concern to address their interests.

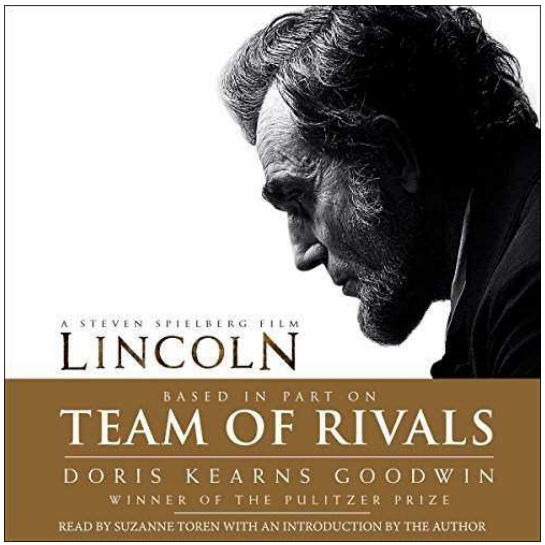
An Ensemble of Diverse Biased Models Is Not Biased

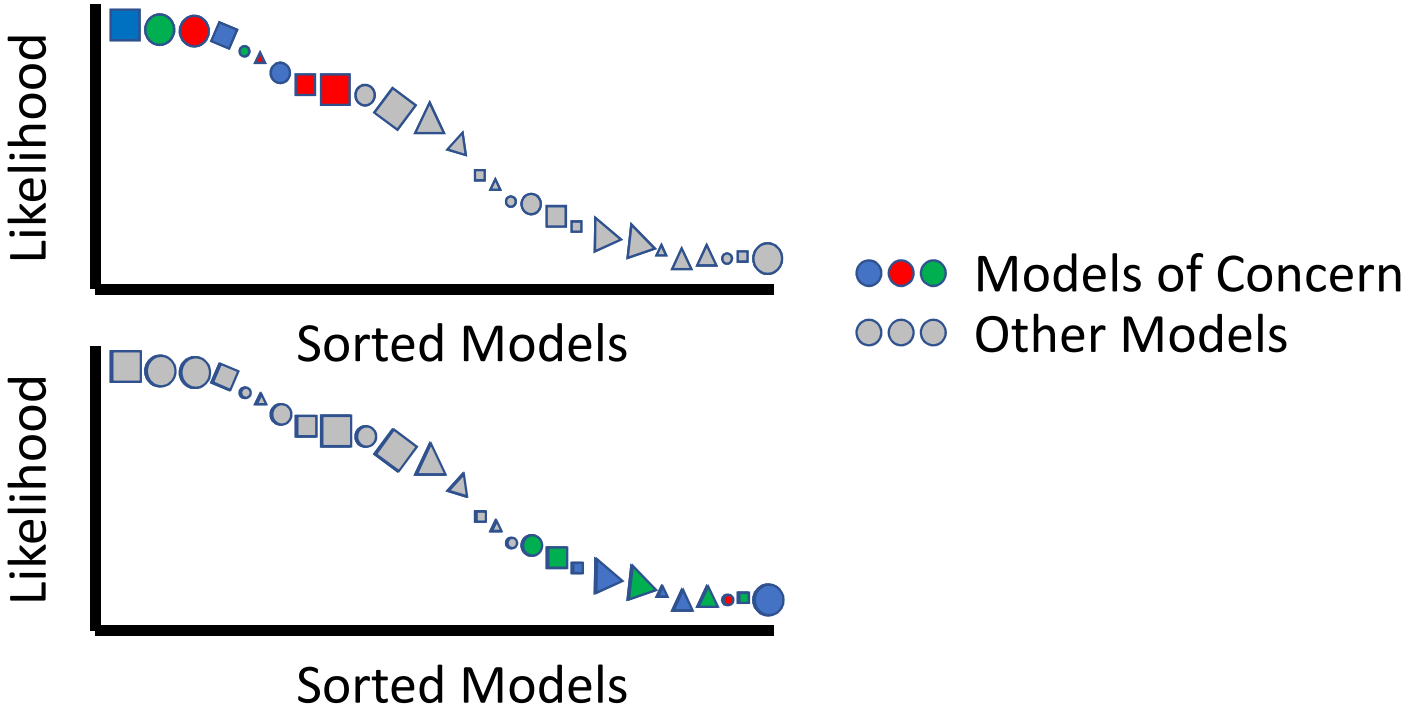




- Each stakeholder's modelers should be ***encouraged*** to form plausible models of concern to address their interests.
- Decisions should be made using a combined model ensemble.

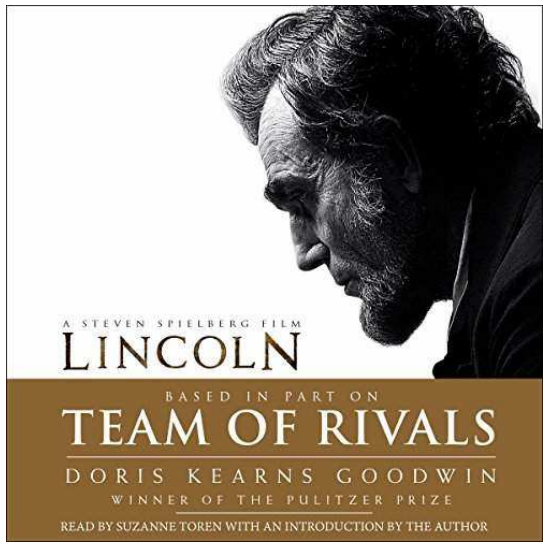
View the Model Ensemble As a Team of Rivals

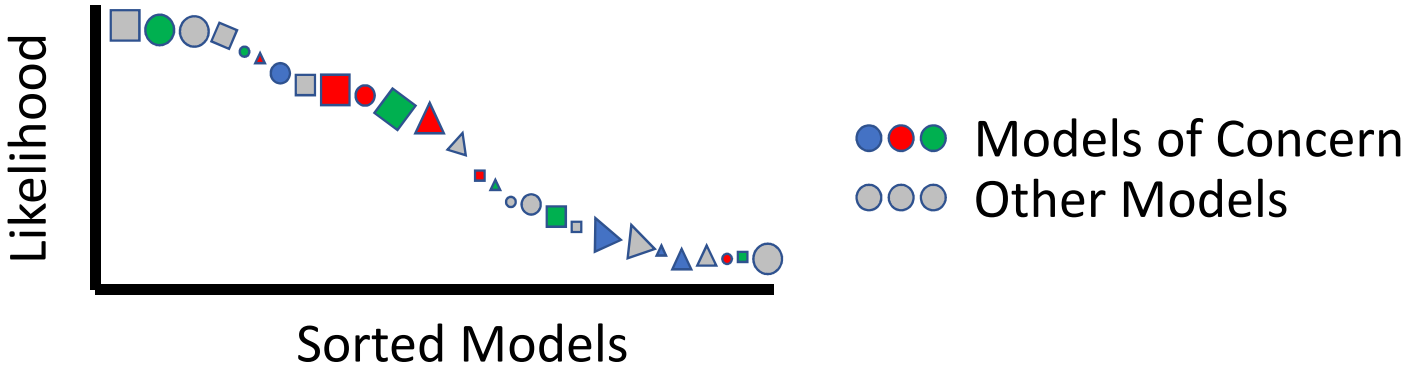




Where advisors (models) agree, a clear decision can be made.

View the Model Ensemble As a Team of Rivals





Where advisors (models) agree, a clear decision can be made.

Where models disagree, more information (data) is needed.

Summary of Talk Two

- Decision-making is inherently biased;

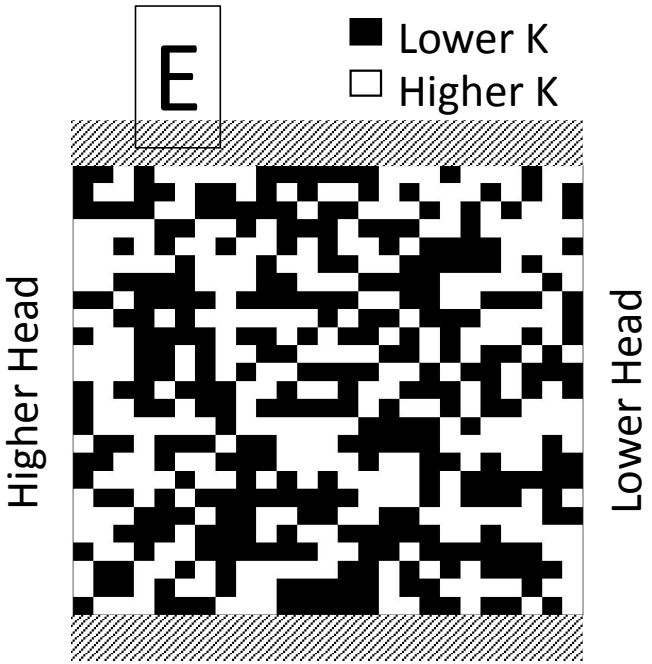
Summary of Talk Two

- Decision-making is inherently biased;
- Model construction is inherently biased;
- We should embrace bias to form a diverse ensemble of biased models to consider all stakeholders' concerns;

Summary of Talk Two

- Decision-making is inherently biased;
- Model construction is inherently biased;
- We should embrace bias to form a diverse ensemble of biased models to consider all stakeholders' concerns;
- Discriminatory data should be chosen collectively.

The Game



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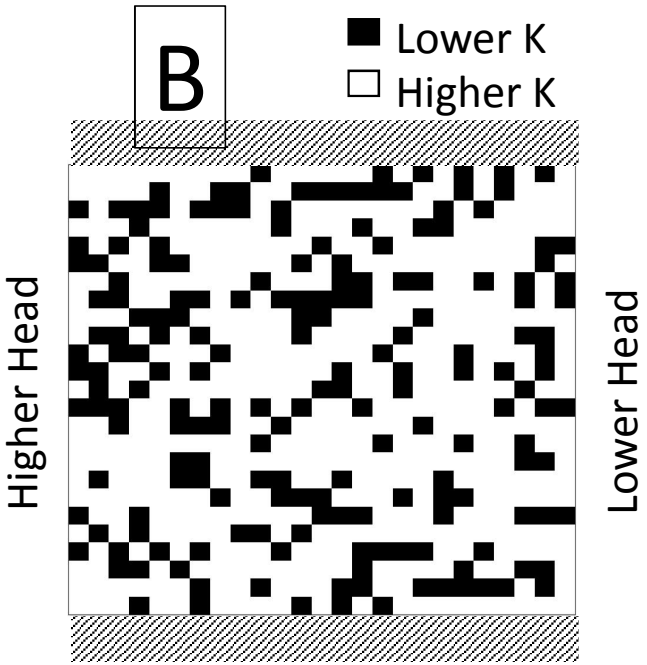

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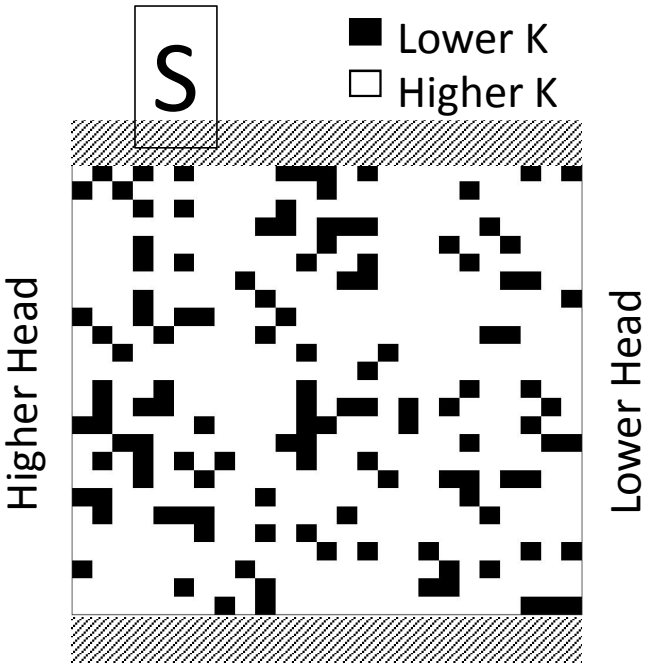
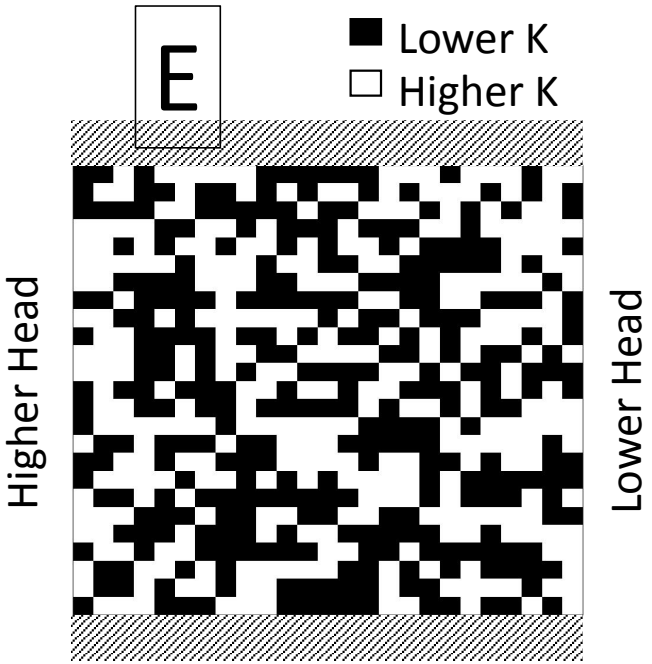


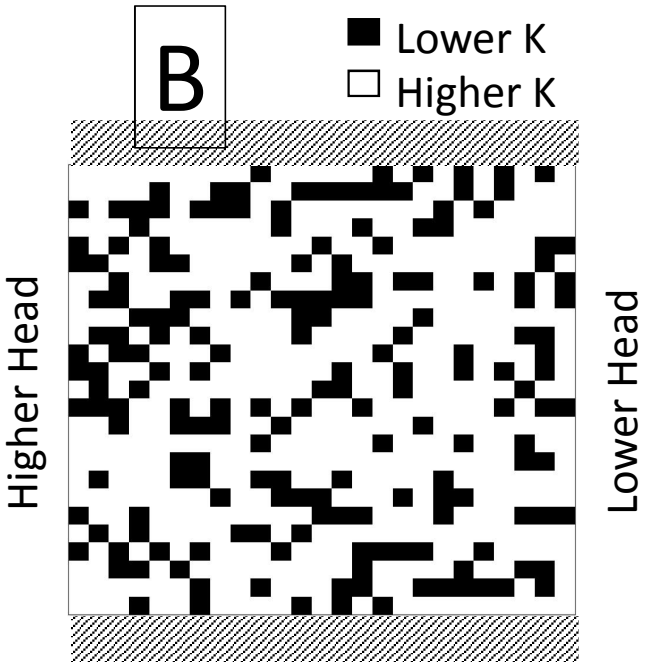
70%

The Game



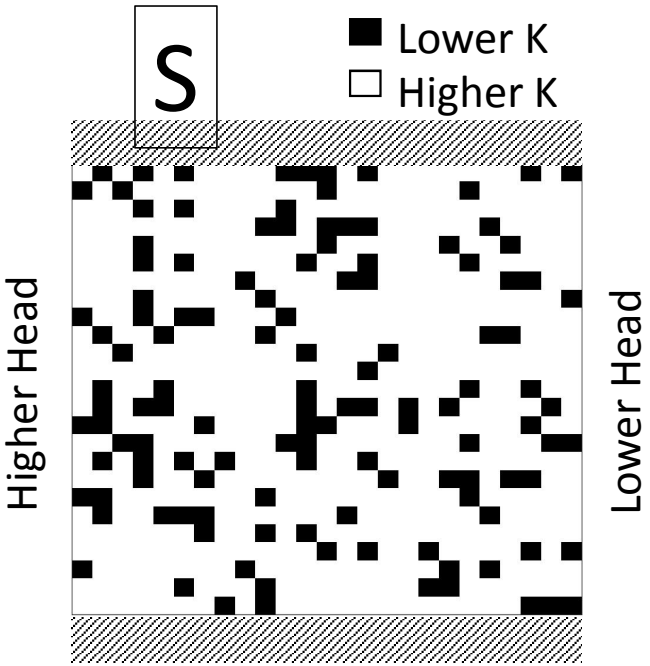
40%

$K_{eff} = 0.04$



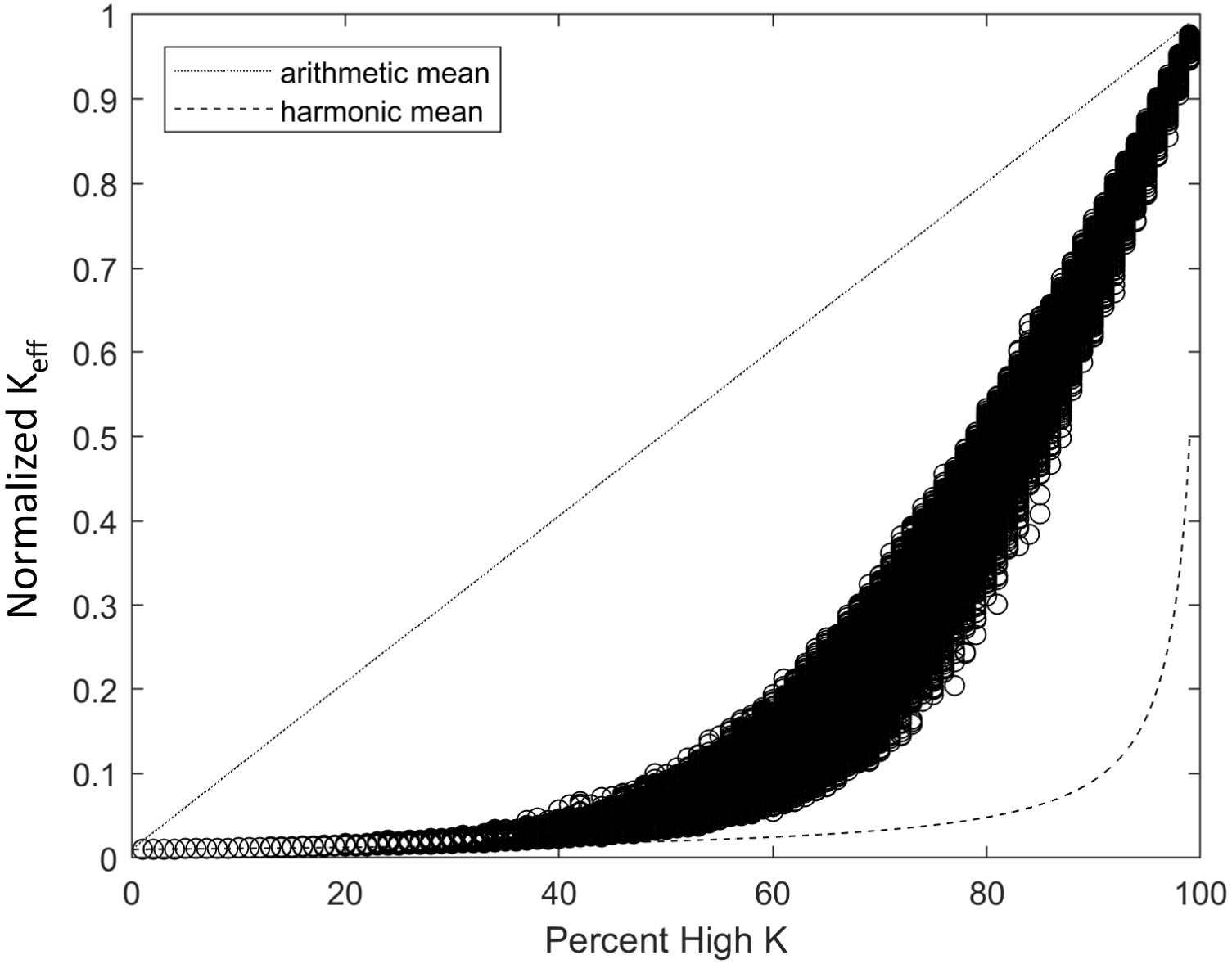
60%

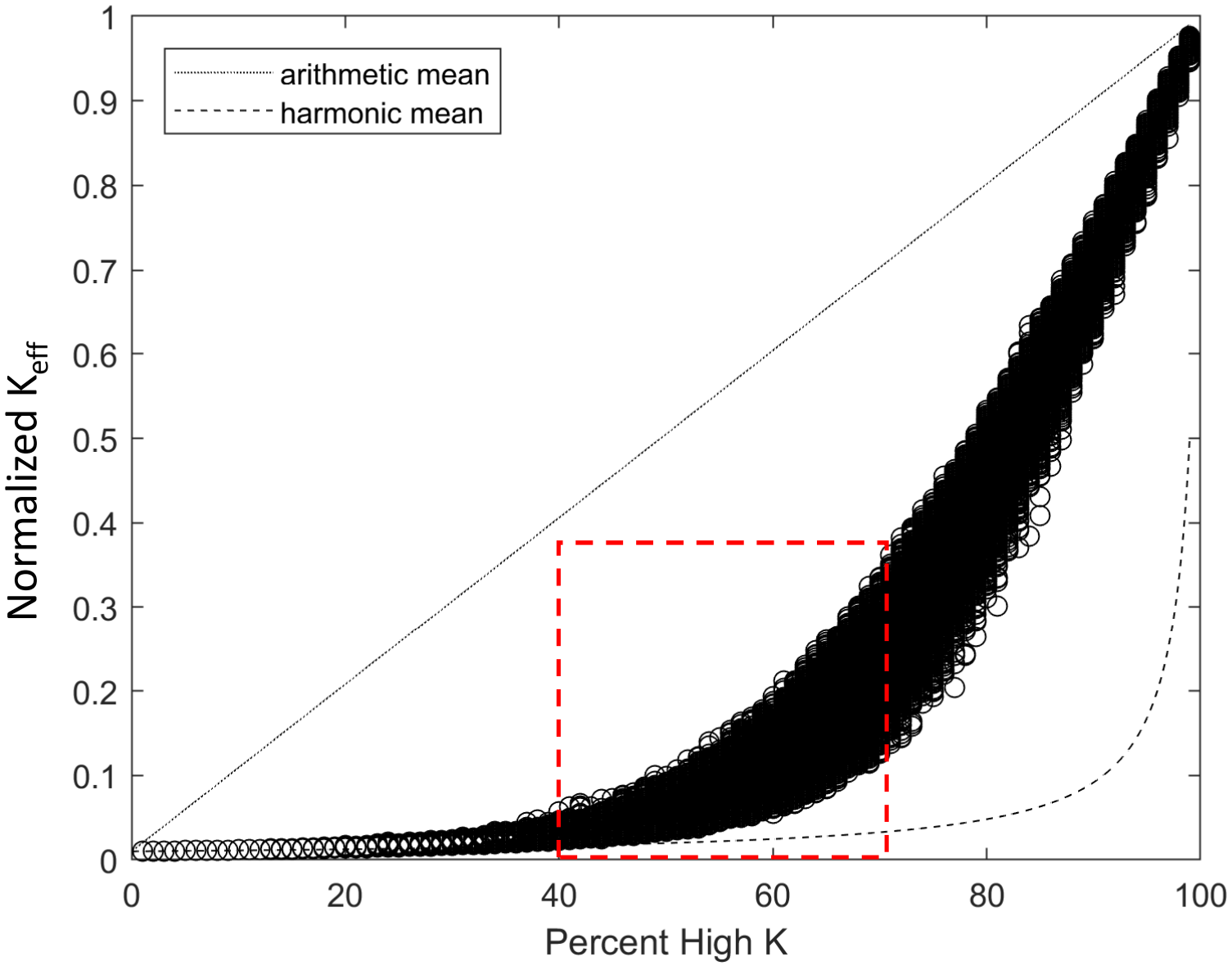
$K_{eff} = 0.17$



70%

$K_{eff} = 0.46$


arithmetic mean
harmonic mean
Normalized K_{eff}
Percent High K
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
20
40
60
80
100


arithmetic mean
harmonic mean
Normalized K_{eff}
Percent High K
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0.1
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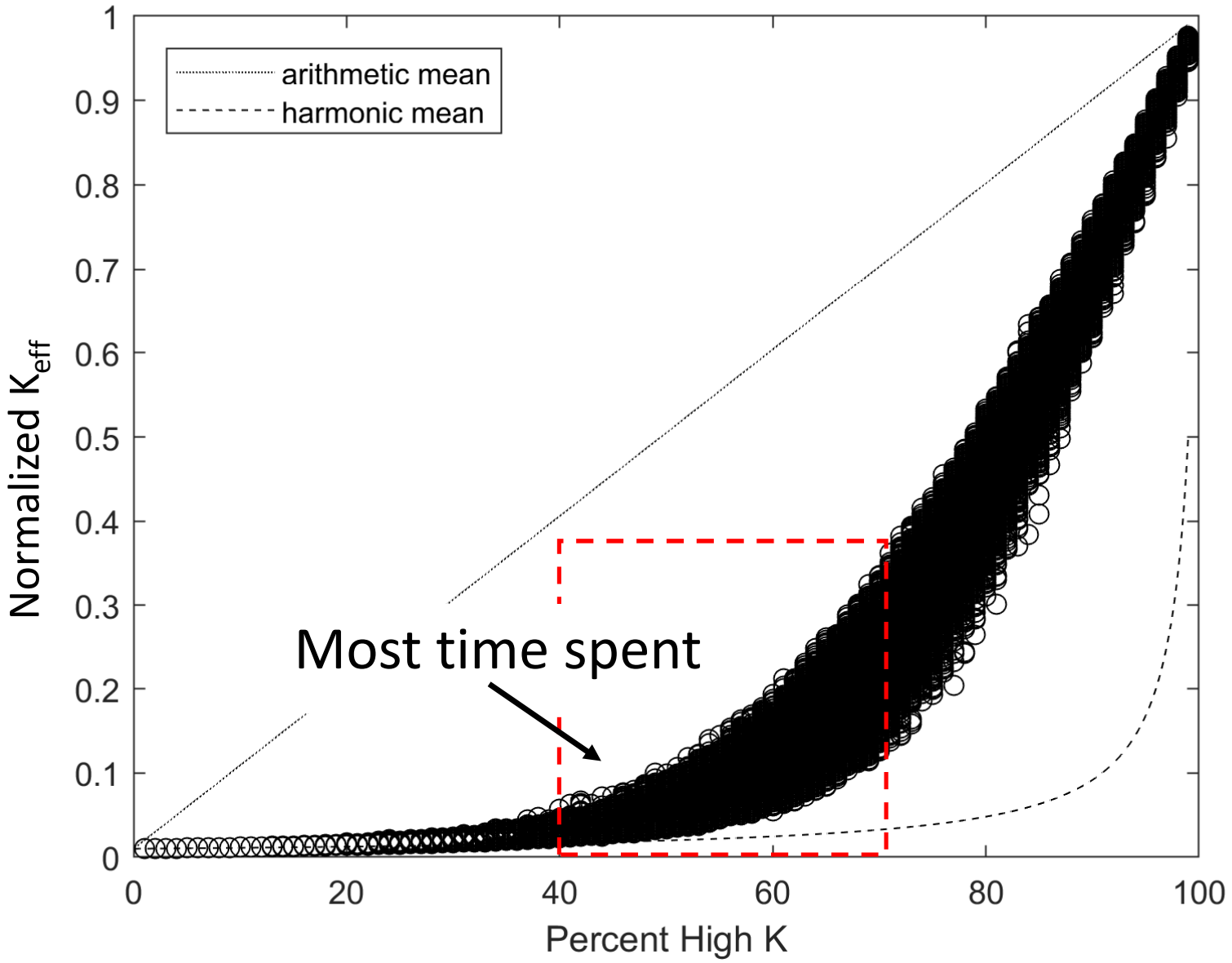
arithmetic mean
harmonic mean
Most time spent
Normalized K_{eff}
Percent High K
0
0.1
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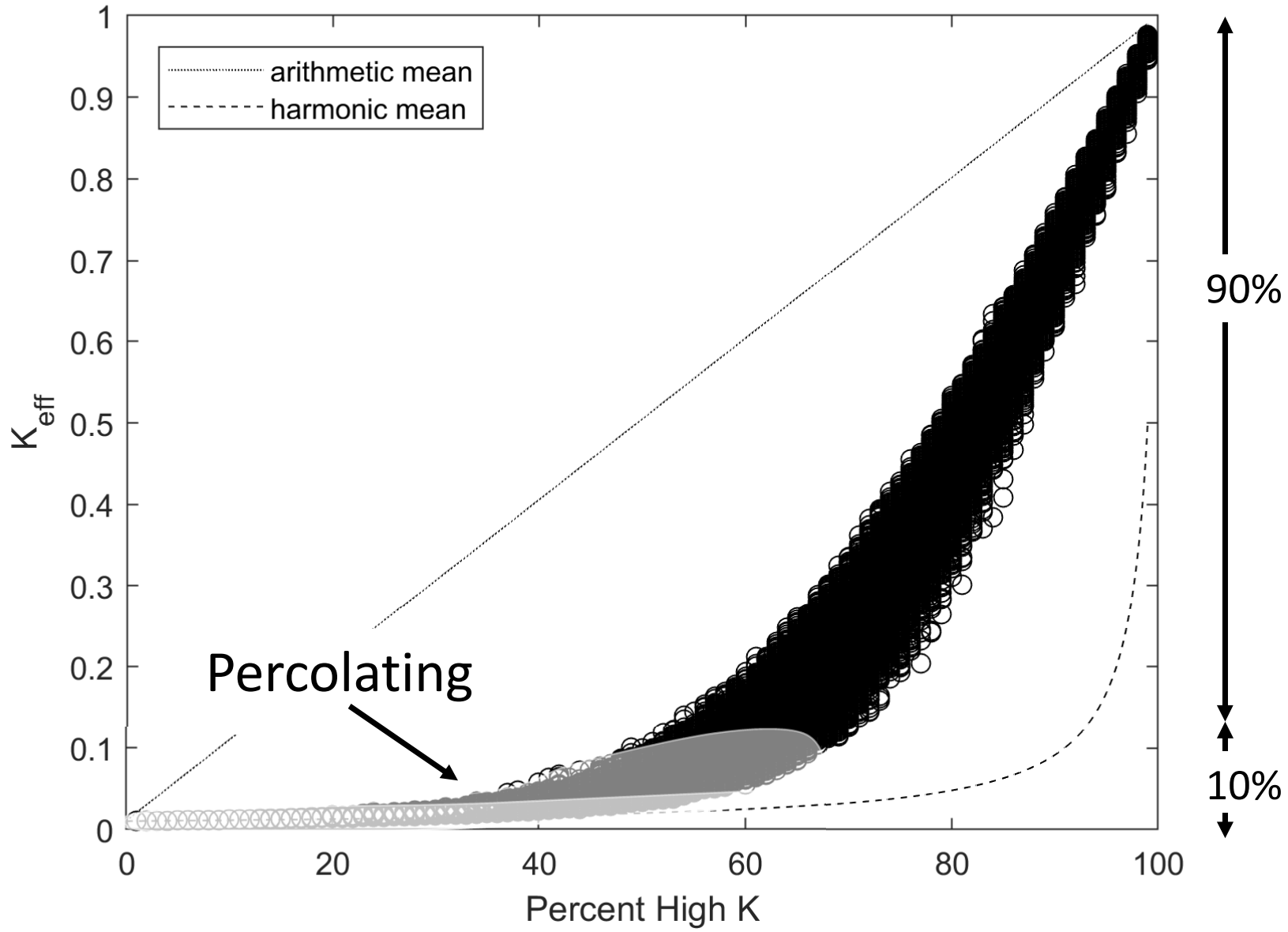
arithmetic mean
harmonic mean
Percolating
90%
10%
K_{eff}
Percent High K
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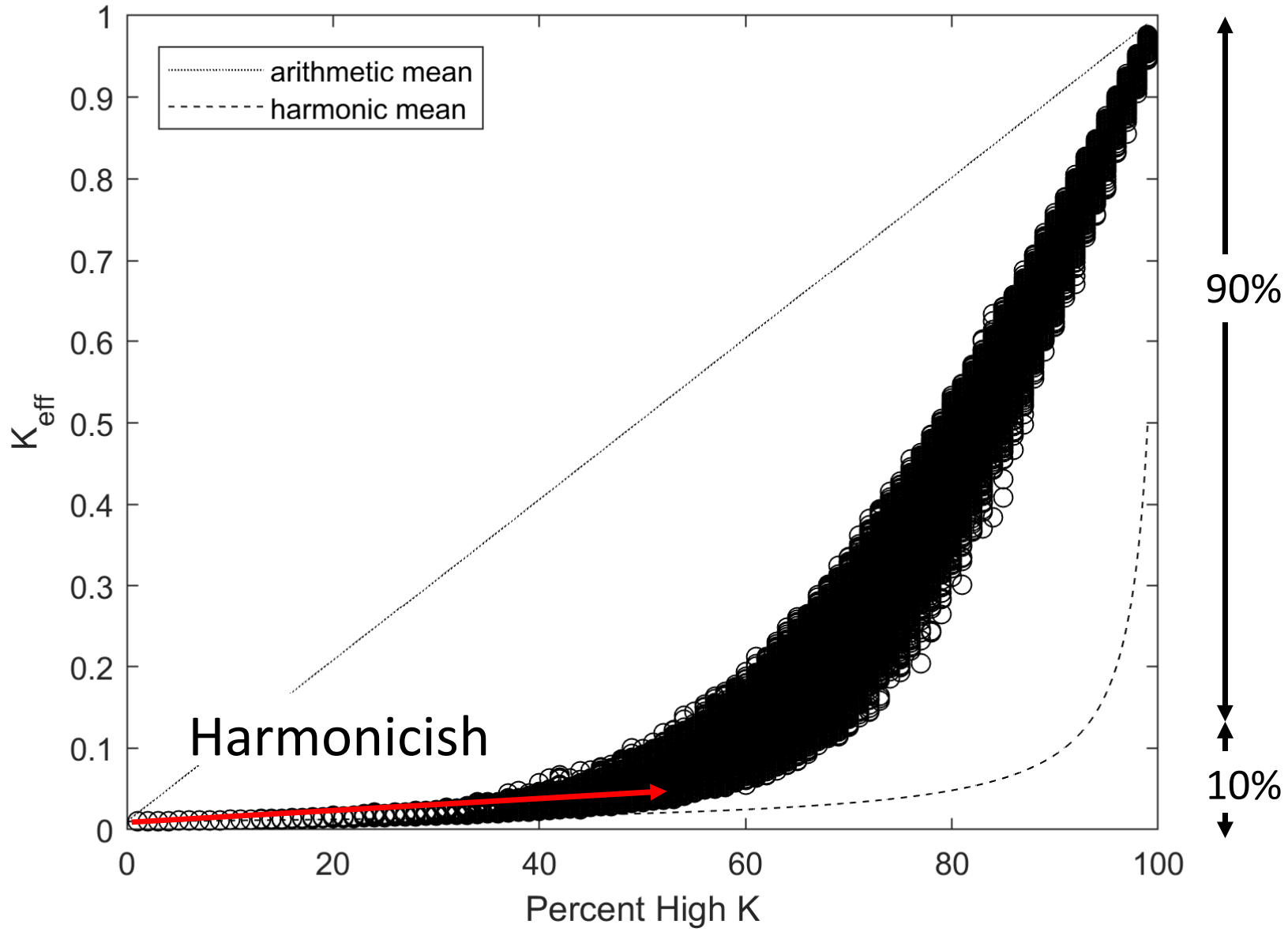
arithmetic mean
harmonic mean
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90%
10%
K_{eff}
Percent High K
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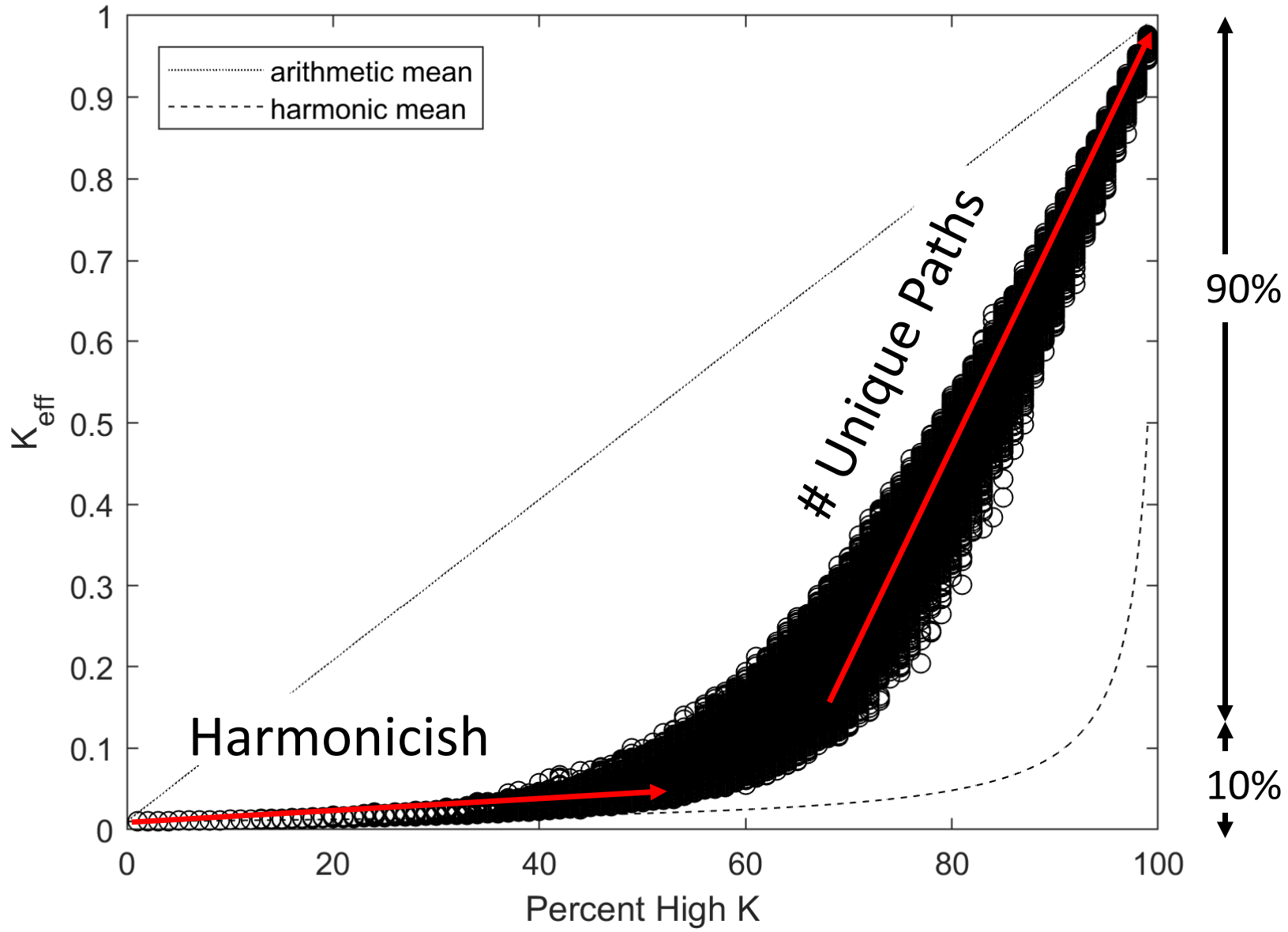
arithmetic mean
harmonic mean
Unique Paths
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90%
10%
K_{eff}
Percent High K
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40
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80
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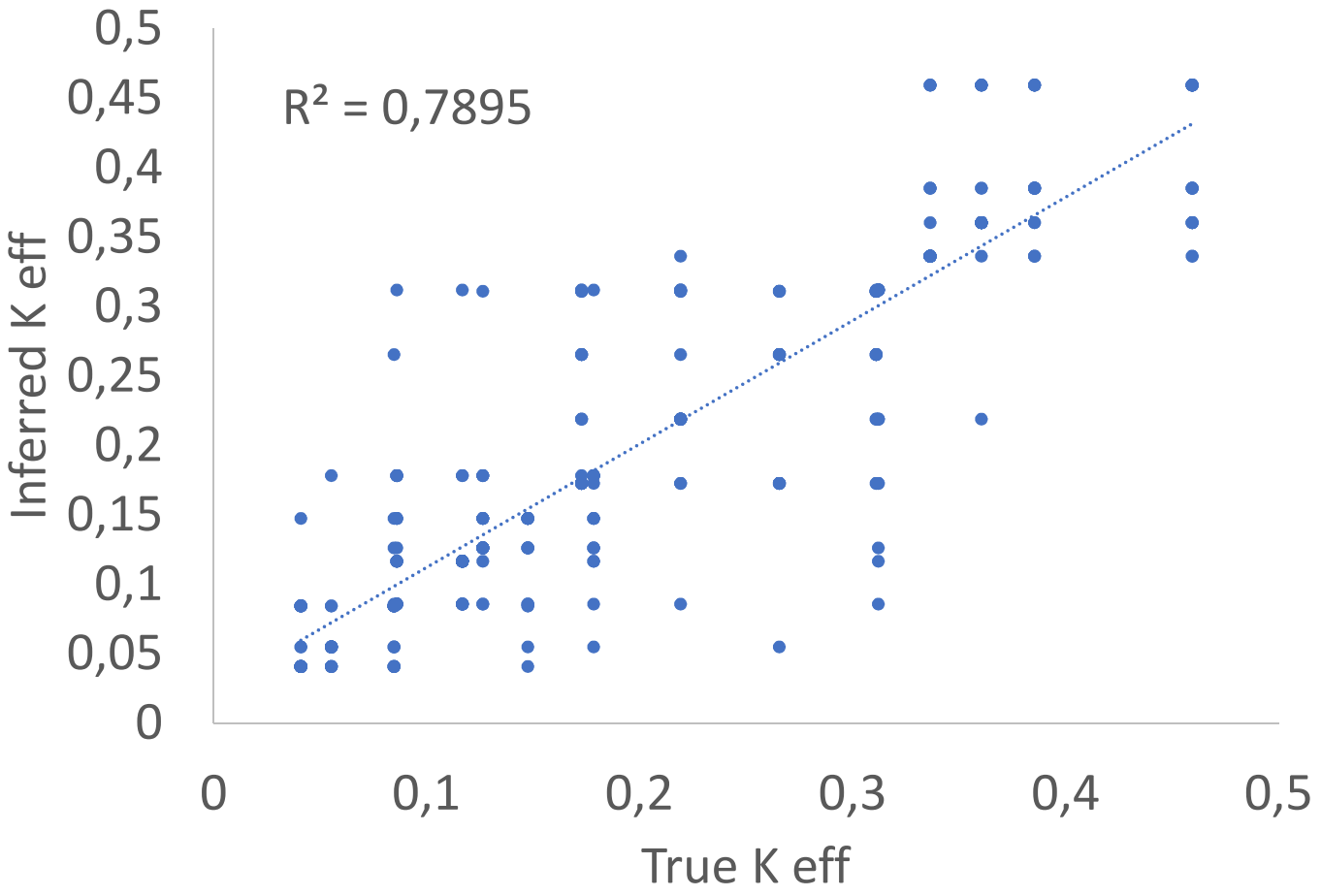
R² = 0,7895
Inferred K eff
True K eff
0,5
0,45
0,4
0,35
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0
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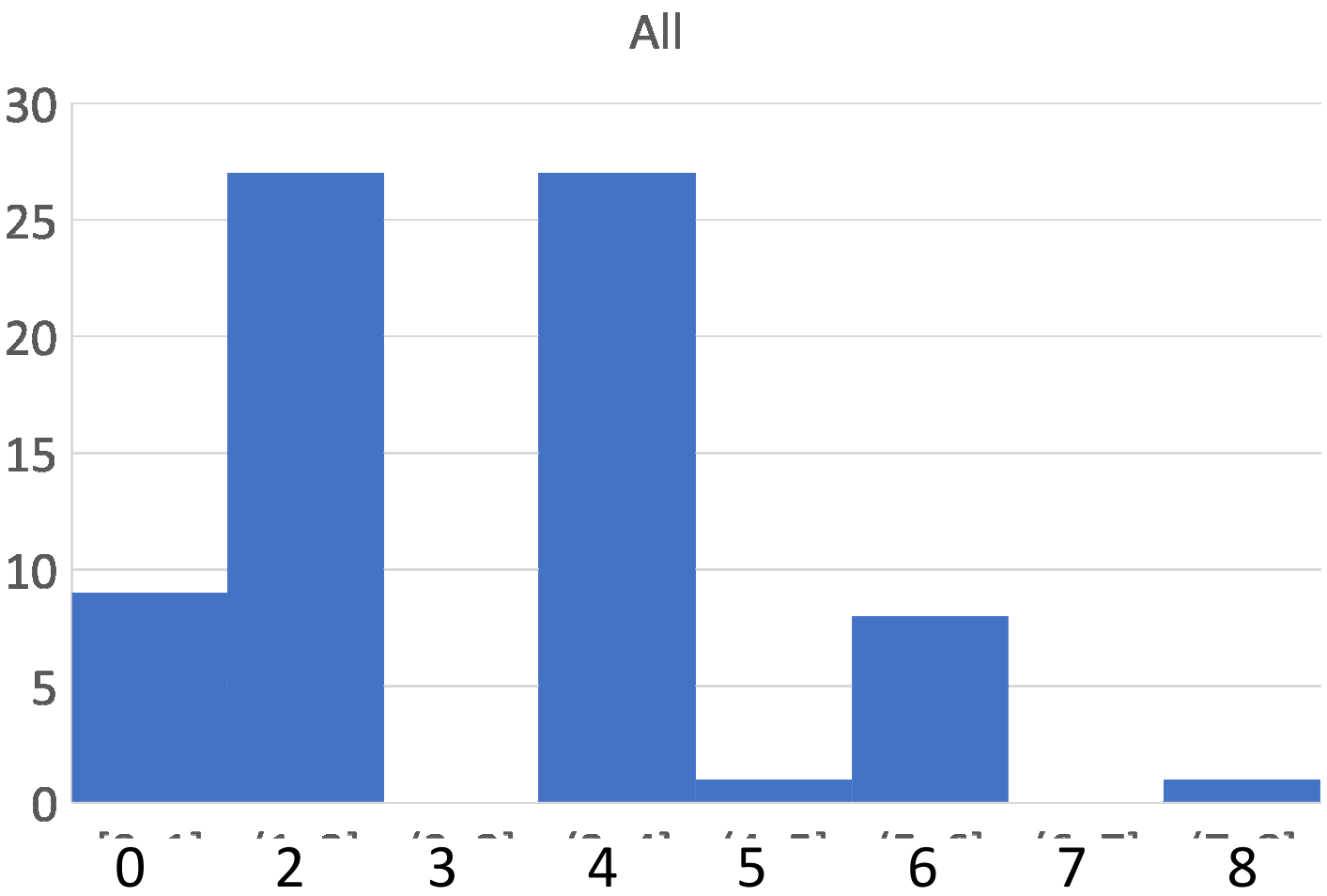
All
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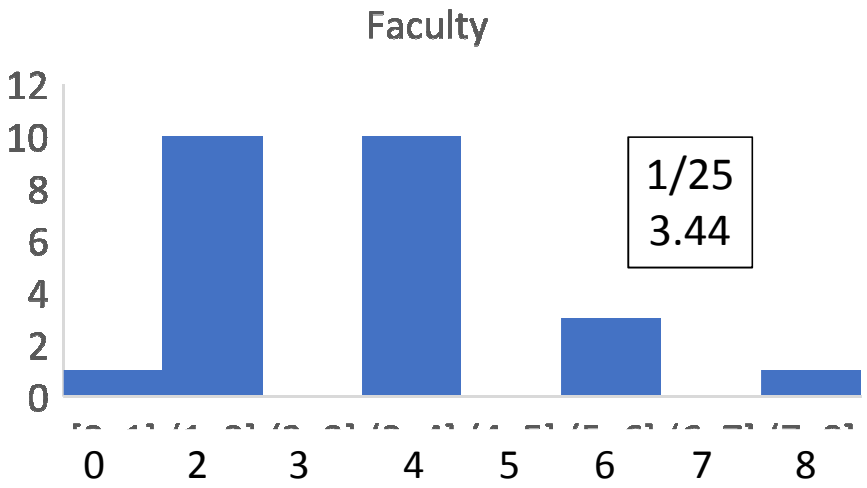
Faculty
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10
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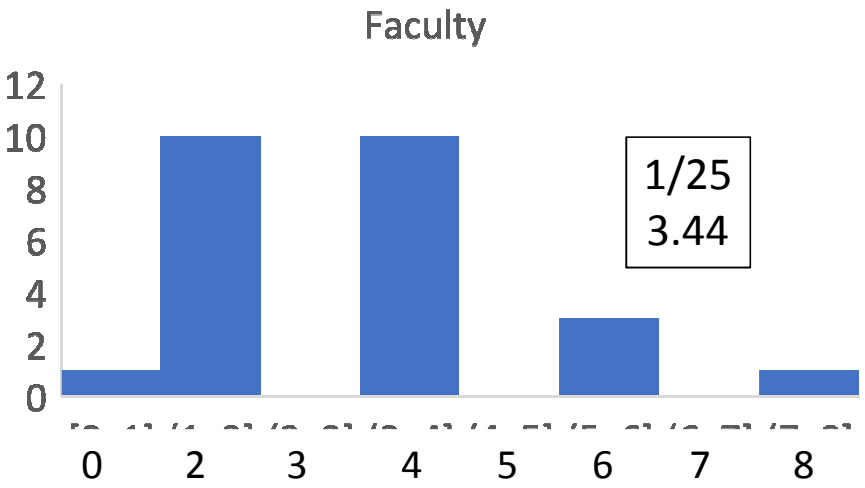
Faculty
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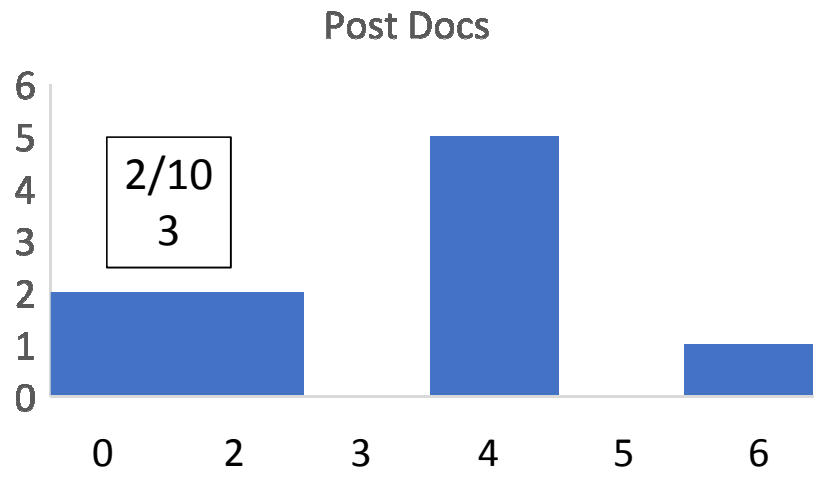
Post Docs
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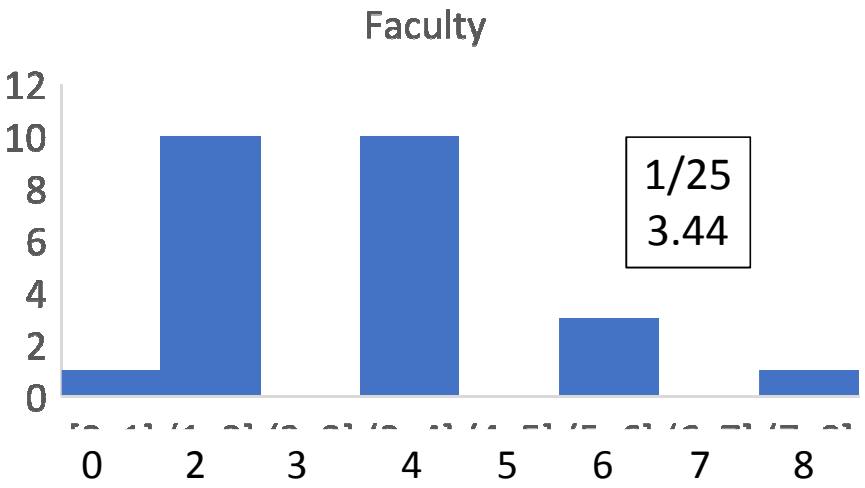
Faculty
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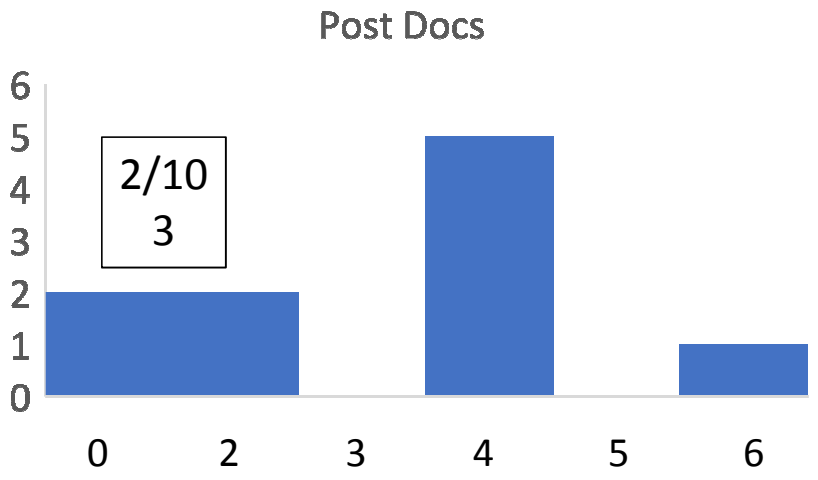
Post Docs
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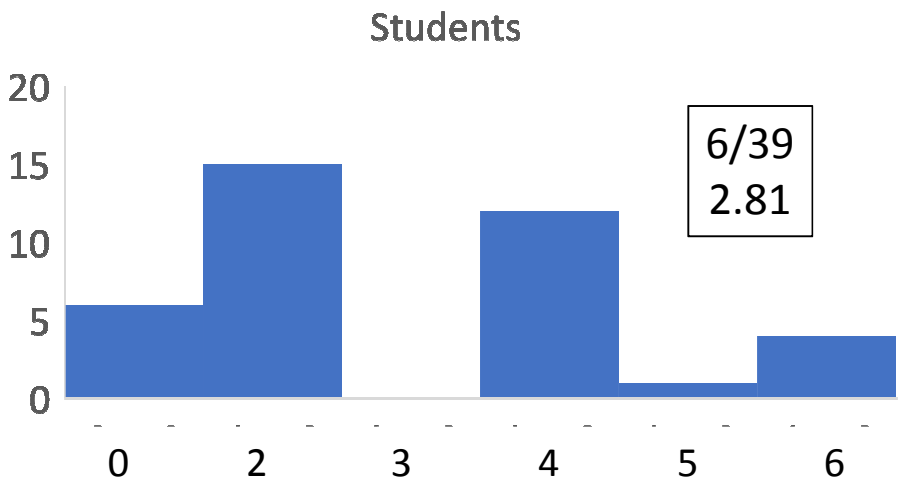
Students
20
15
10
5
0
6/39
2.81
0
2
3
4
5
6

Summary of Talk Three

- Use models to train your intuition;

Summary of Talk Three

- Use models to train your intuition;
- Students rock.

Summary of the Three Talks

- A scientist's job is to propose different plausible models;
- Then to find discriminatory data;
- This can be guided by stakeholder's interests;
- This requires trained intuition.