Modeling Like It Matters

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Science
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The Game
The Scientific Method

Observe ➔ Theorize
Predict ➔ Hypothesize
Changing Your Mind

Observe

Theorize

Predict

Hypothesize

Opportunity for lateral thinking
Scientific Progress

Observe → Theorize → Hypothesize → Predict → Observe

Predict → Hypothesize → Observe → Theorize

Theorize → Hypothesize → Predict → Observe
The Path of Science
The Paths of Science
Changing Your Mind

Opportunity for lateral thinking
The Paths of Science
Splitting, Dying, Merging, Emerging

Model Space

Time
Visualizing Current Model Space
Single Model Space

*(Discrete and Continuous Differences)*

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

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

(Focus on A Few Models)

Model Space
Assessing Model Quality

One of all possible things that you could measure and that the models can predict.
Assessing Model Quality

Observable Quantity

Predicted Value

Measured value

Predict

Hypothesize

Observe

Theorize

Predicted Value

Observable Quantity
Model Likelihood

\[ L = f\left(\frac{1}{\text{mismatch}}\right) \]

\[ \sum L = 1 \]
Model Likelihood

L = f(1/mismatch)

ΣL = 1

zero sum game
Model Likelihood

\[ L = f\left(\frac{1}{\text{mismatch}}\right) \]

\[ \Sigma L = 1 \]
One of all possible things that you could measure and that the models can predict.
One of all possible things that you could measure and that the models can predict.
We can assess their likely value BEFORE we collect the measurement.
Discriminatory Data

Better/Worse Data?

Observable Quantity

Predicted Value
Discriminatory Data

Better/Worse Data?
Depends on your objective
Discriminatory Index

DI = f\left(\frac{\text{intergroup difference}}{\text{intragroup spreads}}\right)
The choice of model groups is subjective and will likely vary among stakeholders.
Model Importance

Forecastable Quantity

Predicted Value
Predictions of Interest

<table>
<thead>
<tr>
<th>Stakeholder</th>
<th>Predicted Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stakeholder 1</td>
<td>Red bar</td>
</tr>
<tr>
<td>Stakeholder 2</td>
<td>Magenta bar</td>
</tr>
<tr>
<td>Stakeholder 3</td>
<td>Blue bar</td>
</tr>
</tbody>
</table>

Forecastable Quantity
Outcomes of Concern
Models vs Outcomes of Concern

Stakeholder 1
Discriminatory Data for a Stakeholder’s Models of Concern

Stakeholder 1

Better/Worse Data
Even Worse Data

Predicted Value
Observable Quantity
Forecastable Quantity
Predicted Value

32
Models of Concern / Other Models

Predicted Value vs. Forecastable Quantity

Stakeholder 2
Decision Confidence Index

- Models of Concern
- Other Models
Decision Confidence Index

LOW CONFIDENCE

- Models of Concern
- Other Models

Sorted Models vs. Likelihood
Decision Confidence Index

HIGH CONFIDENCE – but unhappy

![Graph showing decision confidence index with models of concern and other models sorted by likelihood.](image)
Decision Confidence Index

HIGH CONFIDENCE – and happy

- □ Models of Concern
- ⬤ Other Models

Likelihood

Sorted Models
Summary of Talk One

• Multiple plausible models can be built for any system;
Summary of Talk One

- Multiple plausible models can be built for any system;
- Model likelihoods can be defined based on fit to data;
Summary of Talk One

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• The expected value of data for any prediction(s) of interest can be assessed before the data are collected;
Summary of Talk One

• Multiple plausible models can be built for any system;
• Model likelihoods can be defined based on fit to data;
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• Stakeholders must define the prediction(s) of interest, which will identify the models of concern;
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 \textit{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 \textit{either} models of concern or other models as high likelihood.
Talk Two: Time for Some Psychology

![Diagram: Predicted Value vs. Forecastable Quantity]
Stakeholders Must Drive the Process

Each stakeholder must define their outcomes of concern.

Stakeholder 2

Predicted Value

Forecastable Quantity
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

Predicted Value

Forecastable Quantity
Modeling Is Biased
(Modelers are Human)

esp. confirmation bias

Model Space

Time

Modeler 1
Modeler 2
Modeler 3
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

Higher Head

Lower K

Higher K

Lower Head

E

40%

Higher Head

Lower K

Higher K

Lower Head

B

60%

Higher Head

Lower K

Higher K

Lower Head

S

70%

Lower Head
The Game

- **E**
  - Lower K
  - Higher K
  - 40%
  - $K_{\text{eff}} = 0.04$

- **B**
  - Lower K
  - Higher K
  - 60%
  - $K_{\text{eff}} = 0.17$

- **S**
  - Lower K
  - Higher K
  - 70%
  - $K_{\text{eff}} = 0.46$
Normalized $K_{eff}$

Percent High $K$

-- arithmetic mean

-- harmonic mean
Percolating

90%

10%
Harmonicish
Harmonicish
$R^2 = 0.7895$
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.