

# **Addressing a Nobel Challenge to Modeling and Simulation**

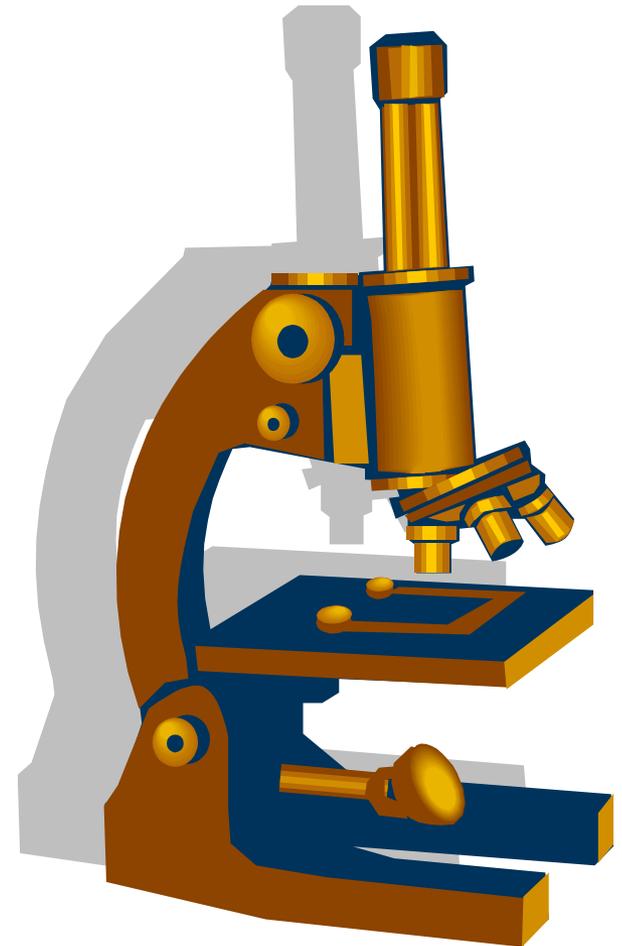
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# Kahneman's Nobel Prize in Economics

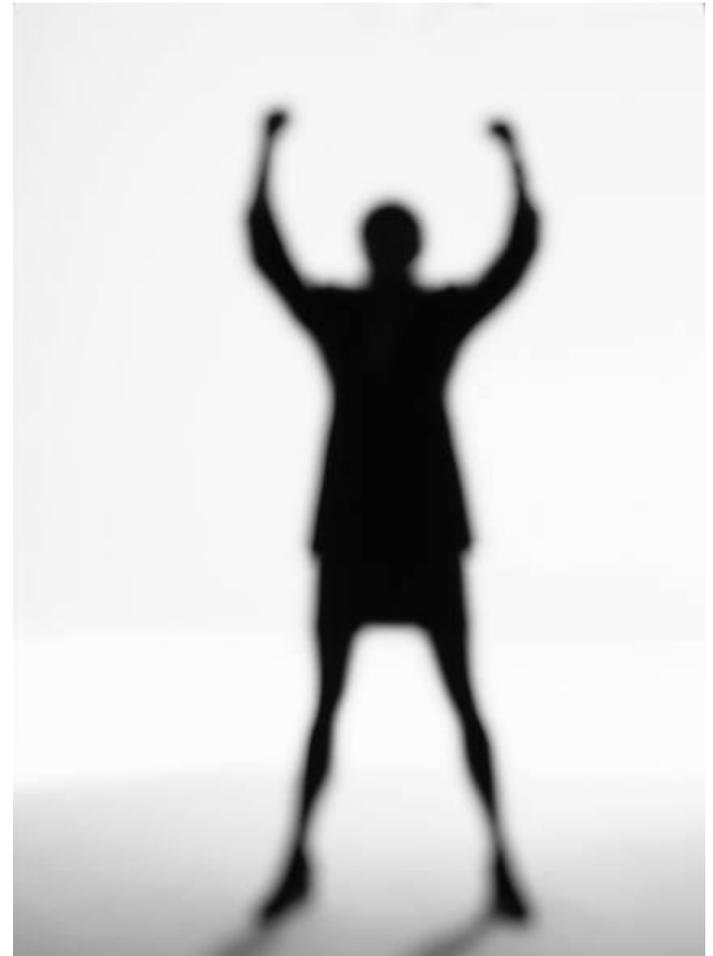
## Extensive Work Documenting Human Biases

- Tendency to be overoptimistic
- Tendency to be influenced far too much by recent experience
- Tendency to be influenced by whether a problem is framed in terms of gains or losses
- Tendency for assessments to be biased by self-interest (or pride)



# The Symptom

- Model-Predictions are Overoptimistic regardless of whether the model outputs are
  - *Project Completion Times*
  - *Project Costs*
  - *Product Sales*
  - *Product Performance*



# Lovullo and Kahneman's Diagnosis

- These models infer outputs from input factors
- Who estimates these input factors?
  - *Sometimes Historical Data*
  - *Sometimes human beings*

*Human Bias is the problem*



# Lovallo and Kahneman's Solution

- Identify projects in the past that are 'similar' to the project of interest
- Determine the output value (variable of interest) for those projects
- Weight each project by the degree of similarity
- Use the frequency chart of past project output values to estimate the probability distribution of the current project's output value



# Their Conclusions

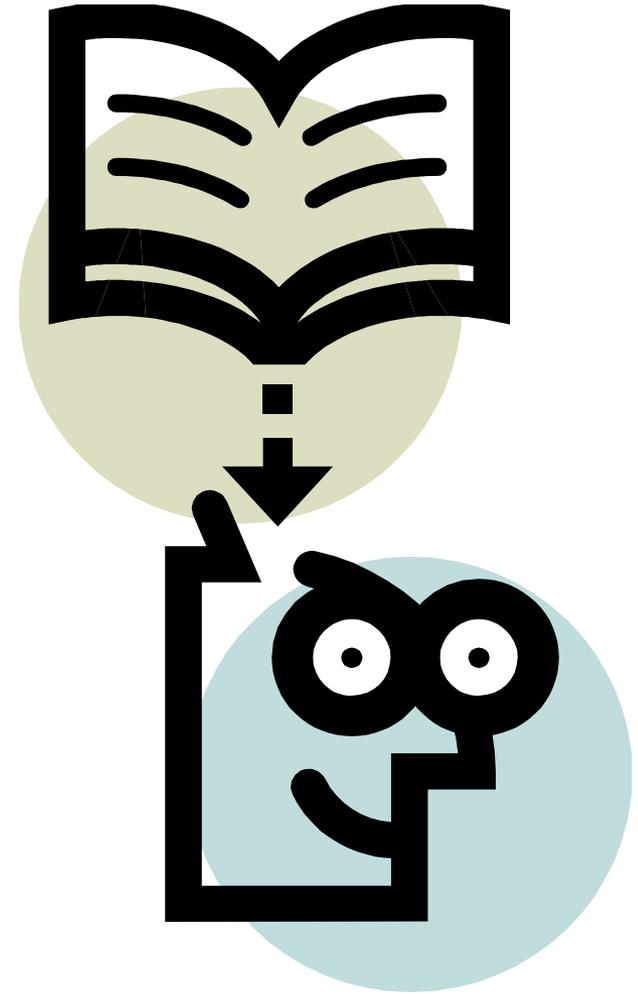
- Modeling is an “Inside-Out Approach”:
  - Predicts OUTPUT from INPUT
- Their approach is an “Outside-In Approach”
  - Predicts OUTPUT from past data on OUTPUT



- They favor Outside-in Approach

# Another Example

- Output of interest: Product Sales
- A model expressed OUTPUT as a function of INPUTS
  - *INPUTS* were 'demand-price elasticities':
    - *Don't worry if you don't know what this is*
  - *Bayesian methods define uncertainty about INPUTS*
  - *Model made inferences about OUTPUTS (sales) from INPUTS*
- The company reaction
  - *Model received serious attention*
  - *But no one felt confident about INPUT values*
  - *Company eventually followed the Garbage-In/Garbage-Out principle and did not use the model*



# The modeler was following the standard recipe

- Create a model defining
  - OUTPUT in terms of INPUTS
  - Classical Physics says: ***Give me the state of the system now and I can predict its future***
- Quantify Uncertainty about INPUTS
  - Use Bayesian ideas if there's extreme uncertainty
- Infer an uncertain forecast of OUTPUTS

Why didn't the standard recipe work?



# Clairvoyant Test

- An individual who is uncertain about the answer to question should at least understand the question
- There should be some way, possibly hypothetical, of determining what the answer to the question is
- This is the clairvoyant test: a clairvoyant robot who sees the future and the past can determine what the answer to the question is
- Does 'price impact' pass the clairvoyant test?
  - It is technically defined as an elasticity which is a derivative of a function
  - That is a mathematical abstraction which is not directly observable

# Established Rules of Assessment

- Do not
  - Ask people to provide estimates of abstract quantities
  - Ask people to estimate non-abstract quantities about which they have no experience or intuition
- Do
  - Ask people about concrete quantities about which they may have some intuition
  - It is OK to infer estimates of abstract quantities from intuitions about concrete quantities
- So individuals could not use their intuition to estimate the INPUTS to the model

# Summarizing these Two Examples

- Model specifies OUTPUTS as a function of INPUTS
- Garbage-In/Garbage-Out Example
  - Model INPUTS aren't intuitive
  - Reject Model:
    - Rely on experienced intuitions about OUTPUTS
- Lovallo and Tversky
  - Model INPUTS are biased
  - Reject Model:
    - Reply on `reference class' historical data on OUTPUTS



# The problem is there are two recipes

## The two recipes

- *Model recipe: specifies OUTPUT from uncertain beliefs about INPUTS*
- *Experience recipe: specifies OUTPUT from direct information (experience) about that OUTPUT*

## How about an Integrated recipe?

which balances  
INPUT and  
OUTPUT  
information

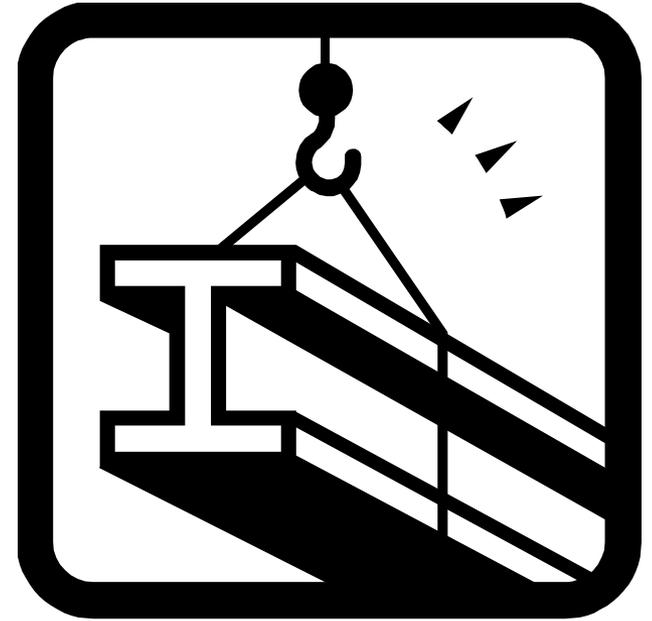


# My challenge: Rigorously building an integrated recipe



# Key Steps in Recipe

- Assume
  - Uncertainty in measurement of INPUTS
  - Uncertainty in measurement of OUTPUTS
  - Model relates true values of INPUTS to true values of OUTPUTS
- CROMWELL'S RULE: BE OPEN TO BEING WRONG ABOUT ANYTHING!



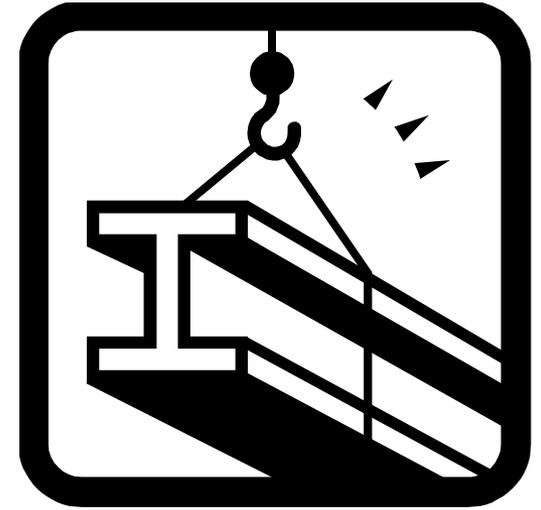
# Motivation for next assumption

- There are three kinds of information
  - Information about outputs
    - Often based on manager intuition or experience
  - Information about inputs
    - Often based on measurements by manager's subordinates
  - Information about how inputs and outputs are related
    - This is the information in the model
    - Often reflects scientific or logical principles

# How does the model contribute to the understanding of outputs?

- In the beginning
  - Beliefs about both inputs and outputs
  - People may have felt they were unrelated
- Then comes the model
  - The model provides new information on how inputs and outputs are related
- This leads to beliefs about BOTH inputs and outputs being updated
  - The model might convince the manager that his beliefs about outputs are wrong or
  - The model might convince the manager that his beliefs about inputs are wrong
  - Or both

# Focus on Joint Information about both Inputs & Output



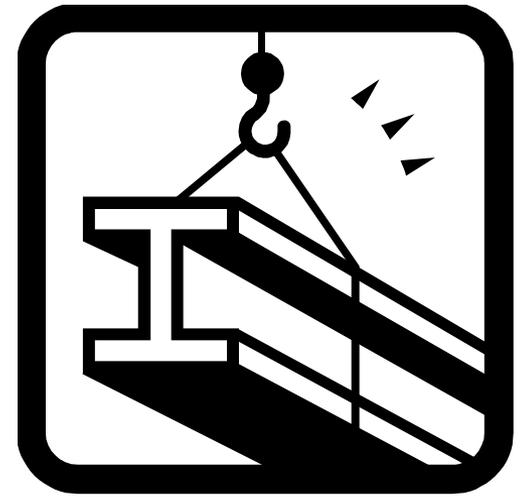
- Prior to knowing how the model relates inputs and outputs
  - We express our joint information with a probability distribution
- Once we learn about the model
  - We update this probability distribution

# What is the information provided by a model?

- It is common to suppose you have several models
  - One of them is right
  - The others are wrong

You have different beliefs about which one is right
- In reality
  - All models are wrong
  - So you can't make it about which model is right
- So how do we think about model?

# Summarize model as list of of simulation outcomes



- $(X_1, Y_1)$ : If you INPUT values  $X_1$  into model, you get  $Y_1$
- $(X_2, Y_2)$ : If you INPUT values  $X_2$  into model, you get  $Y_2$
- $(X_3, Y_3)$ : If you INPUT values  $X_3$  into model, you get  $Y_3$
- $(X_4, Y_4)$ : If you INPUT values  $X_4$  into model, you get  $Y_4$
  
- $(X_K, Y_K)$ : If you INPUT values  $X_K$  into model, you get  $Y_K$

# What does Bayes Rule tell you?

- Your probability distribution over **OUTPUTS** and **INPUTS** (given the model) is the product of
  - Your initial probability distribution over **OUTPUTS** and **INPUTS**
  - The **LIKELIHOOD** of getting these simulation results given the model, if the **INPUT AND OUTPUT** values were known



# Problem!

We know how to estimate the likelihood of an INPUT/OUTPUT combination occurring in reality randomly

- But the INPUT was made up based on our prior beliefs
- So how do we estimate the likelihood?



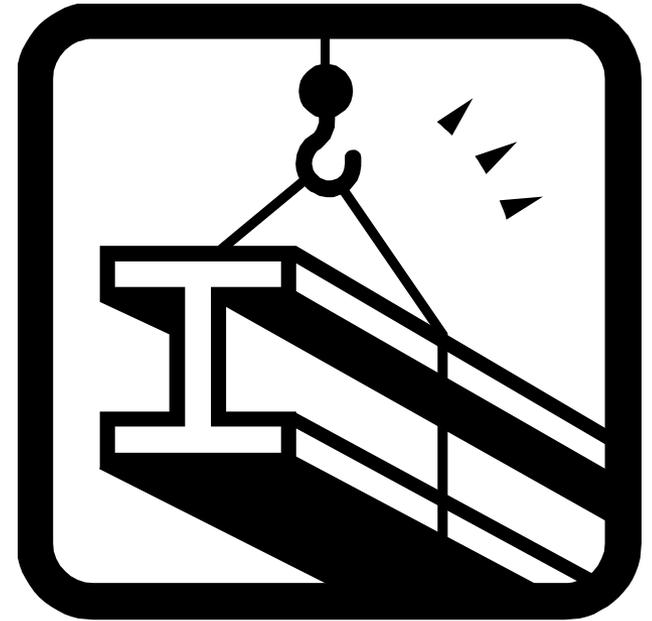
# One Approach

- We could assume model tells you nothing about the values of the inputs
- But that's not right
  - If your input values consistently gave rise to bizarre output values
  - You could begin to question your input values
- So model does provide you information about the input values
  - If you also know the output values associated with those inputs

# ASSUMPTION

Assume that the Simulation Inputs are randomly drawn from decision maker's prior beliefs about what values of INPUTS are reasonable

- Assume that knowing only the INPUT Values --- without knowing anything about OUTPUT values --- gives you no new information



# These assumptions imply

THE LIKELIHOOD OF THE  
INPUT/OUTPUT COMBINATIONS  
IMPLIED BY THE MODEL

EQUALS

THE LIKELIHOOD OF THESE  
INPUT/OUTPUT COMBINATIONS  
*occurring in reality*

THE LIKELIHOOD OF THE  
INPUTS  
*occurring in reality*



# Model Probability over OUTPUT

MODEL PROBABILITY FORECAST OVER OUTPUT

Equals

Average of Model Likelihood over all INPUT  
Values

**Overall  
Probability**

**=**

**Reference  
Class  
Probability** **X** **Model  
Probability**

# CONCLUSION

- When you have no intuition about outputs,
  - Reference class probability is constant
  - Overall probability is model probability
- When you have no intuition about inputs,
  - Model probability is constant
  - Overall probability is reference class probability
- When you have some intuition about both, multiply the two probabilities

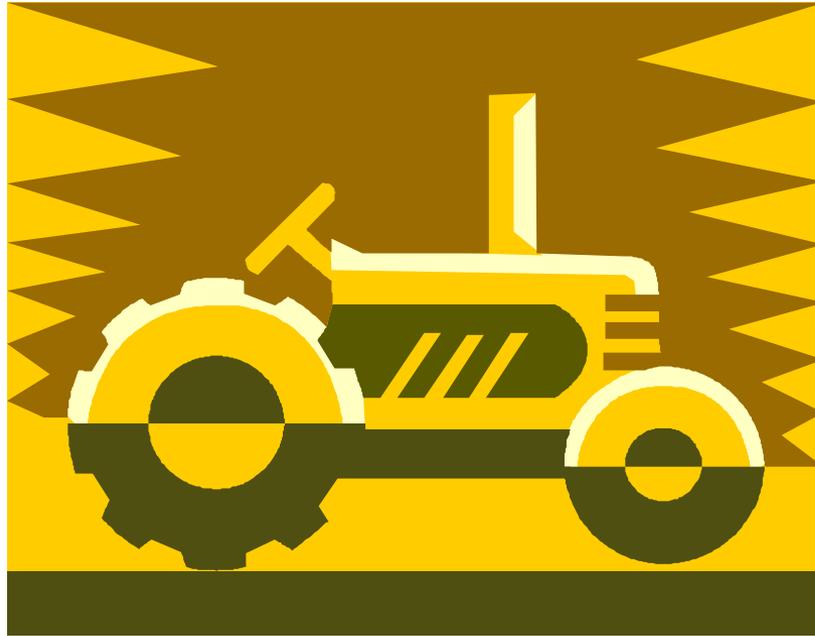
# Special Cases



- Everything is Gaussian
- Then
  - Treat reference class information on OUTPUT as a forecast
  - Treat model information using INPUTS as a second FORECAST
- Final Forecast is weighted average of both forecasts

But reference class information on  $Y$   
will typically not be Gaussian

- You need to calculate formula numerically



# Conclusion

- Battle between
  - Experienced intuition  
*Outside-In*
  - Models  
*Inside-Out*
- Existing recipes force you to choose one or the other
- New recipe allows you to combine both.

