

Epistemic and Aleatoric Uncertainty in Joint Mechanics

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Elements

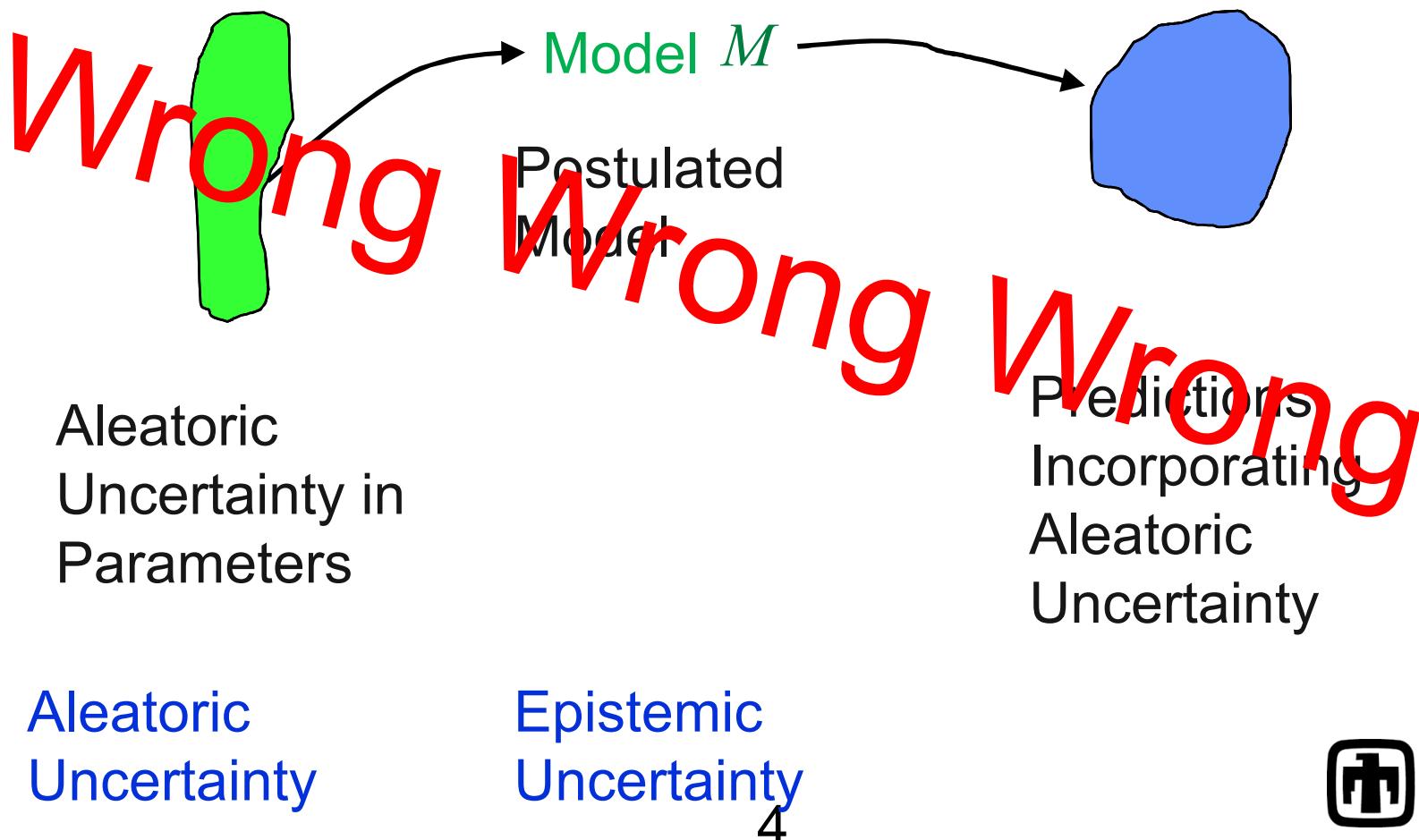
- **Aleatoric and Epistemic Uncertainty**
 - What do they mean?
 - How useful are these concepts?
- **Features of Joint Mechanics and Joint Models**
 - Variability in Measured Properties
 - Model Parameters and Features
- **Uncertainty and Model Quality**

Usually Uncertainty is Categorized into Two Sorts

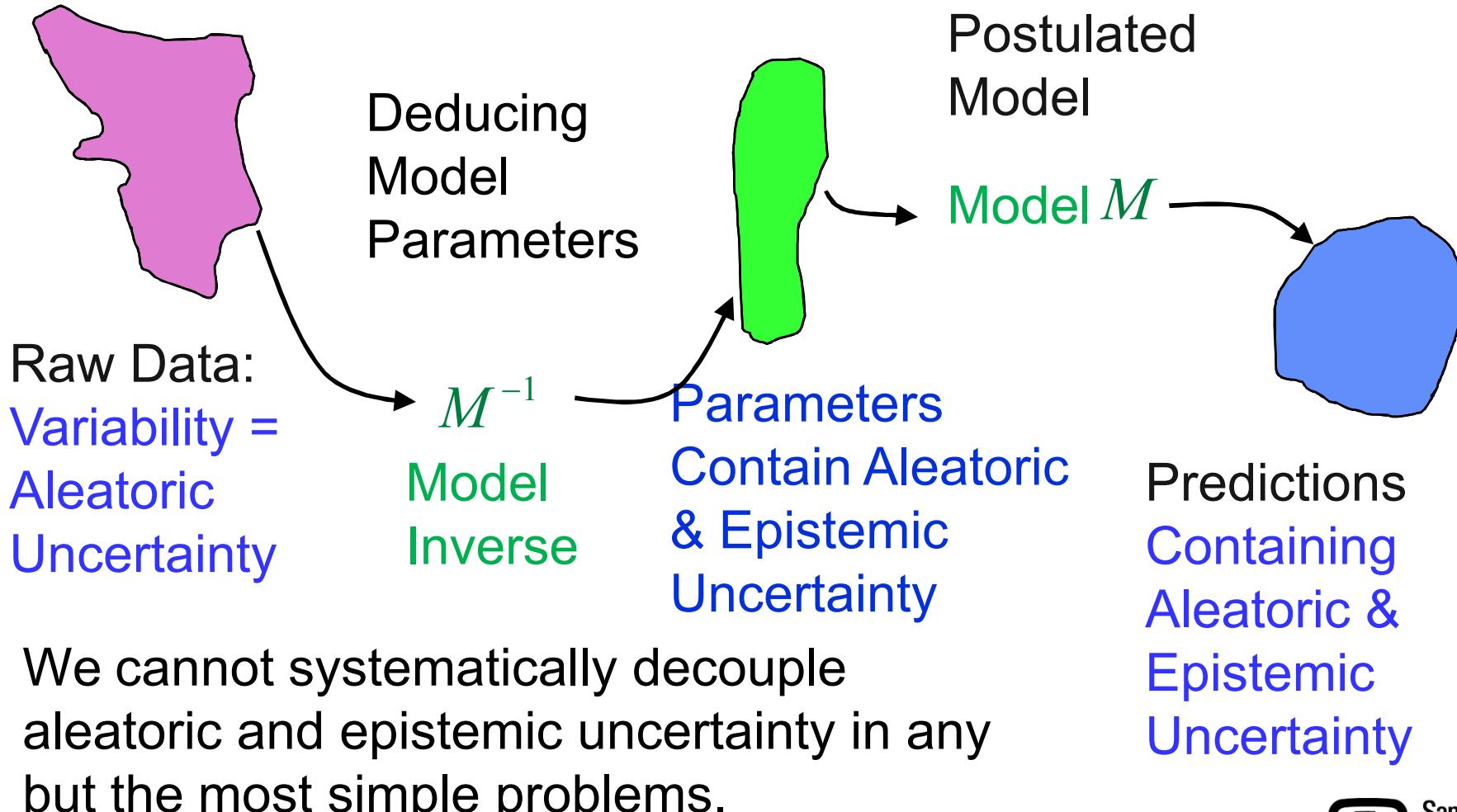
- **Aleatoric Uncertainty: uncertainty due to intrinsic variability.**
- **There is a lot of this in mechanical joints!**

- **Epistemic Uncertainty: uncertainty which is due to things we could know in principle.**
- **This includes things that we are unlikely ever to know in practice.**

A Common View



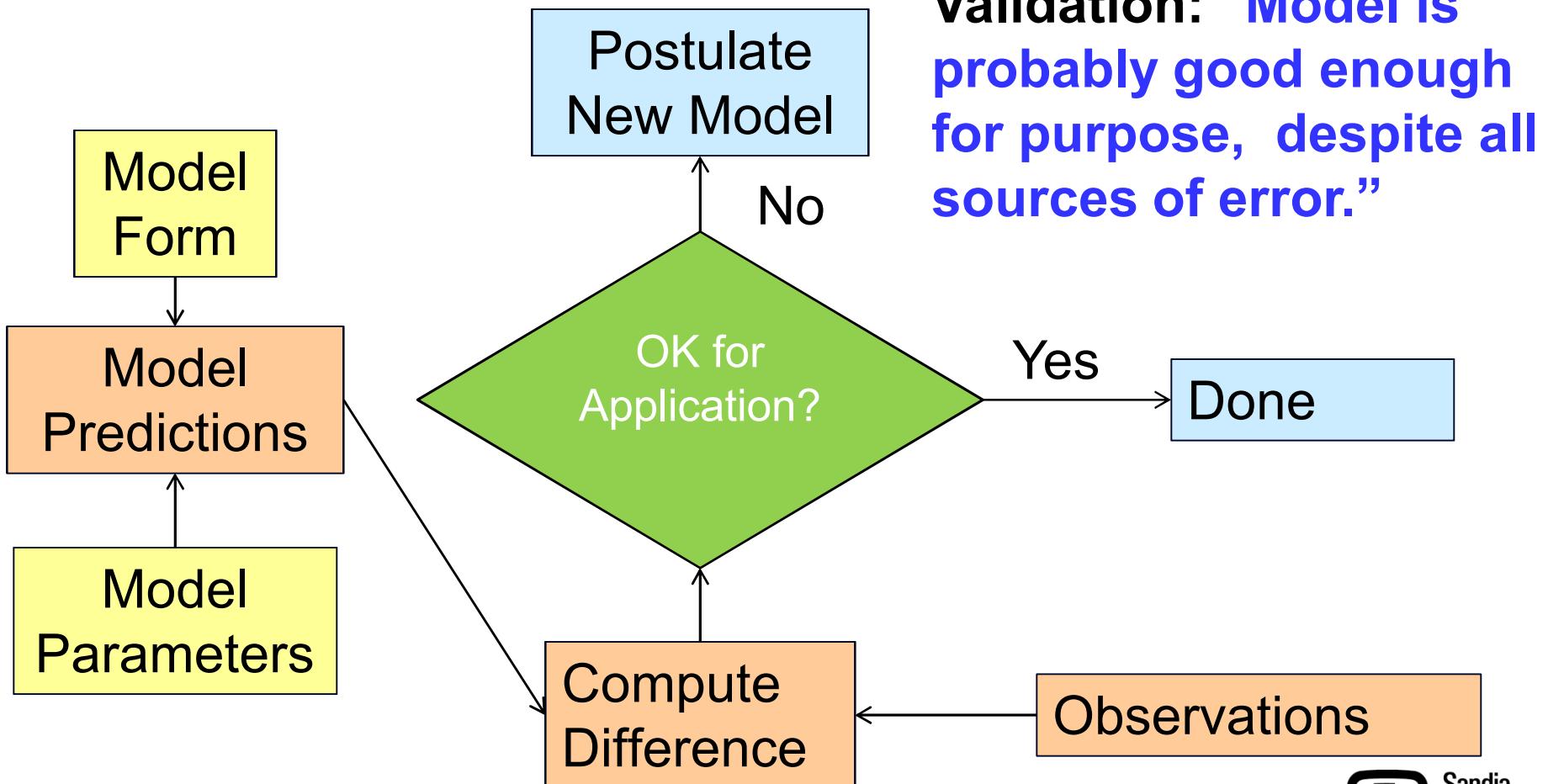
As It ACTUALLY Happens



From Where Does the Confusion Arise?

- There is a common misunderstanding of what is a validated model.
- Definition - Validation: The process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model.

The Validation Process



A Common Misperception

A validated model is accurate and correct, modulo aleatoric – generally parametric – uncertainties.

This is WRONG

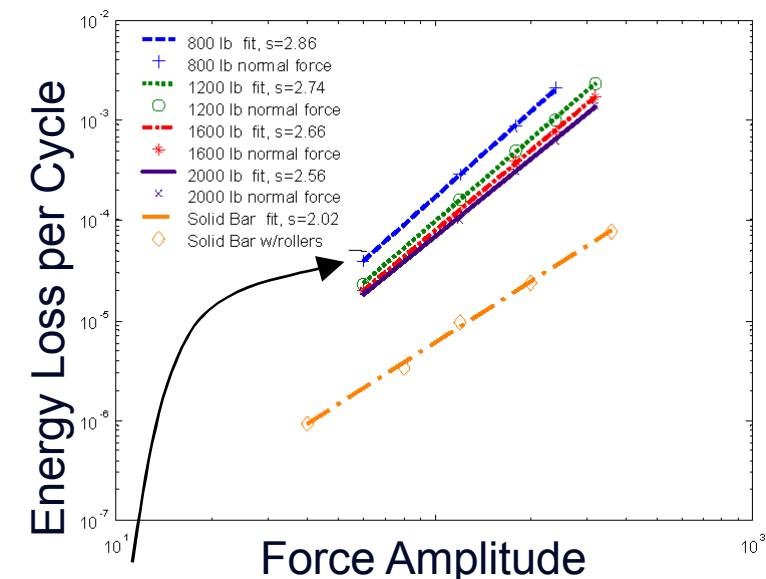
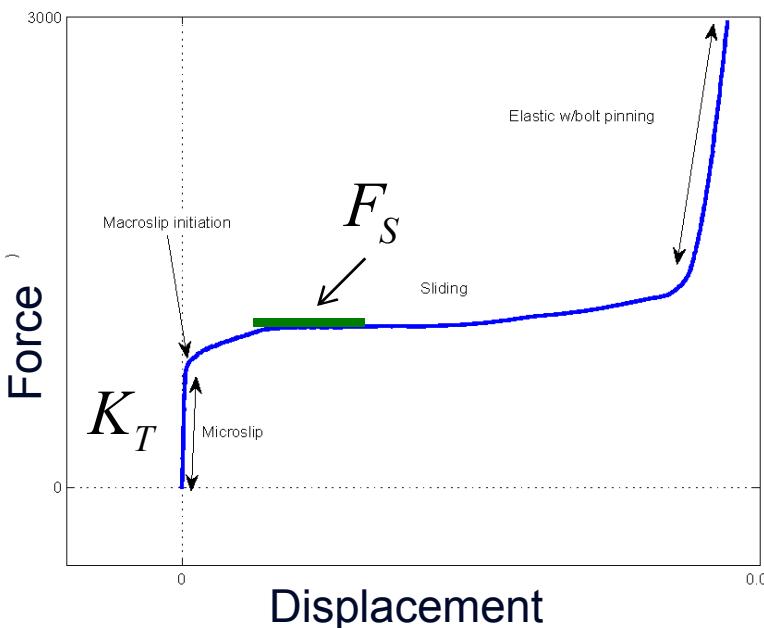
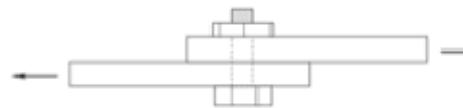
A validated model is sufficiently close to reality that using it for our intended purpose would not be imprudent.

Why Do We Care?

- **In this process, we have not quantified our model form error – we do not even know how.**
- **We cannot in general distinguish error in our predictions due to model form (epistemic uncertainty) from parametric uncertainty.**
- **Our ability to do overall uncertainty quantification (UQ) of our predictions is compromised.**

**Let us talk specifically
about the mechanics of
jointed structures.**

Possibly Measurable Features of Joints

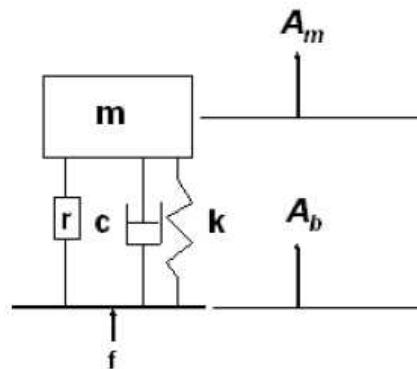


$$D = CF^{3+\chi}$$

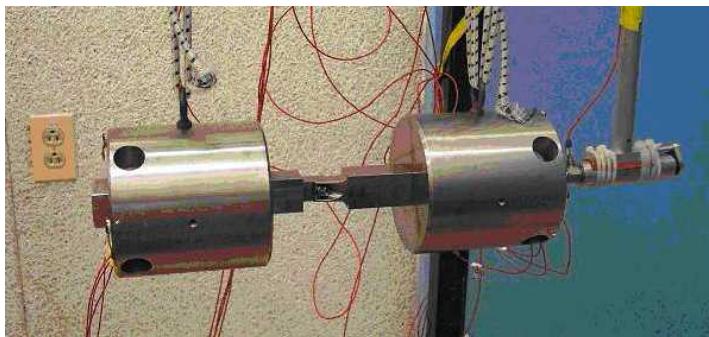
If considering macro-slip, we need at least four parameters

For small Displacement
possibly K_T, C, χ, F_S

Resonance Tools for Measuring Stiffness and Dissipation



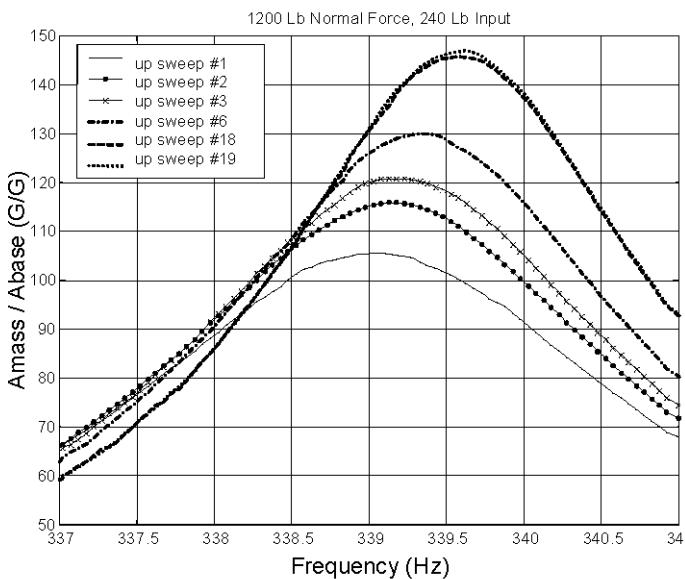
Big Mass Device:
Forced oscillation
around resonance



Dumbbell Configuration:
Ring-down experiments

Credit Dan Gregory & Brian Resor,
Facilities in SNL Albuquerque

Meaningful Experimentation is Very Difficult



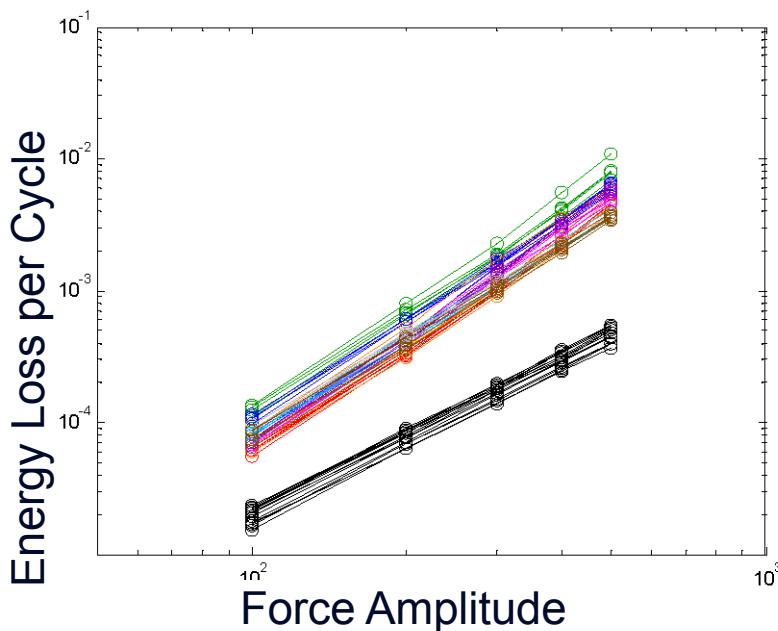
- **Wearing in phenomena in steel and titanium**
- **Galling in aluminum**
- **Alignment issues**

Static Test Fixture



Quasi-static testing is intrinsically difficult: The displacements across the joint are difficult to define and very hard to measure before macro-slip.

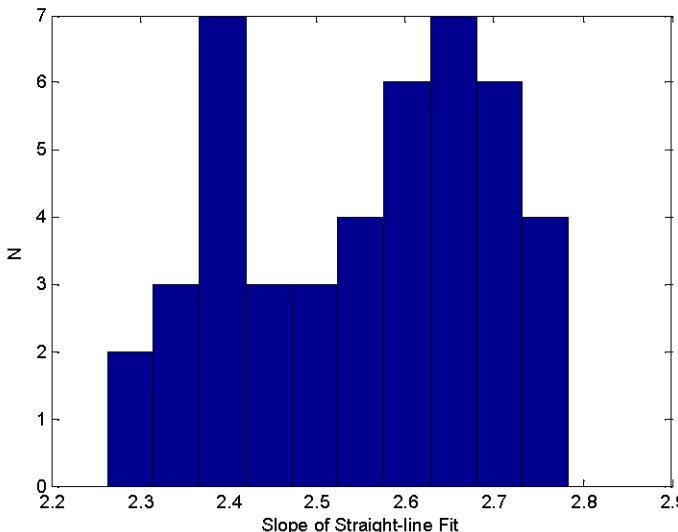
Intrinsic Part-to-Part Variability with respect to Stiffness & Dissipation



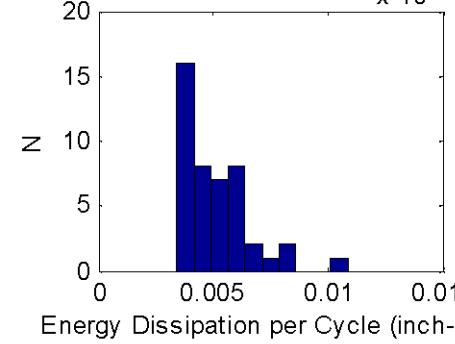
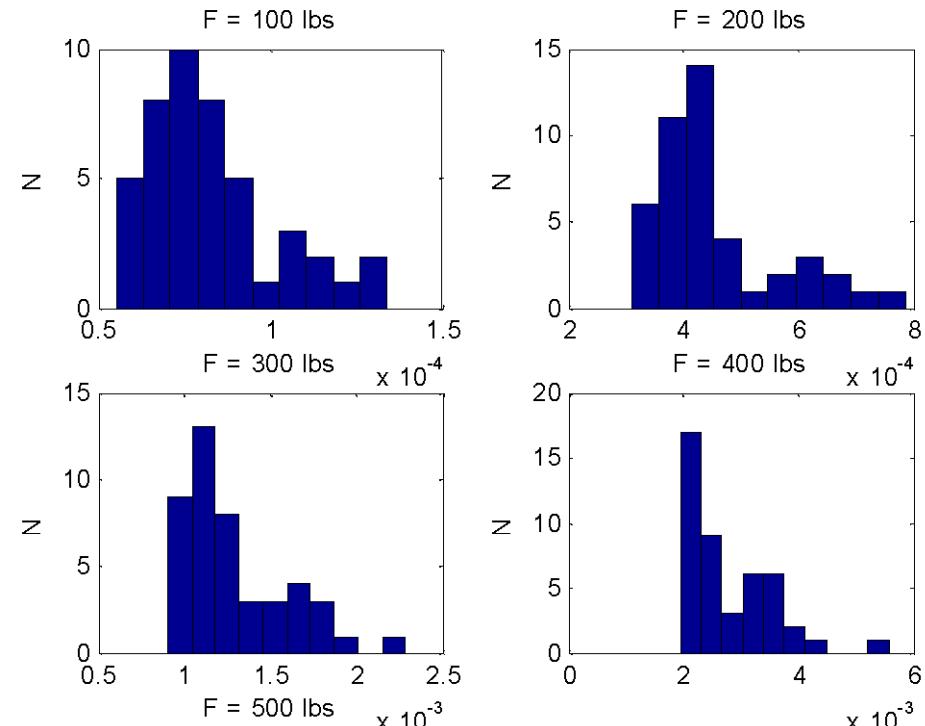
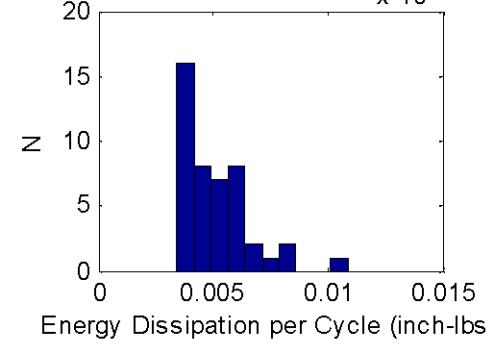
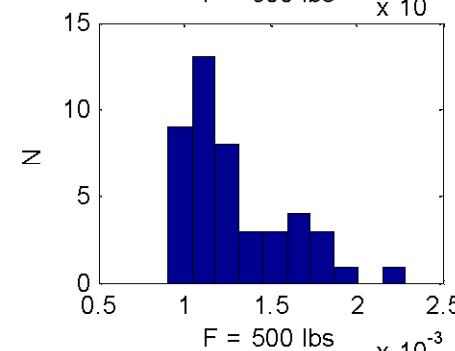
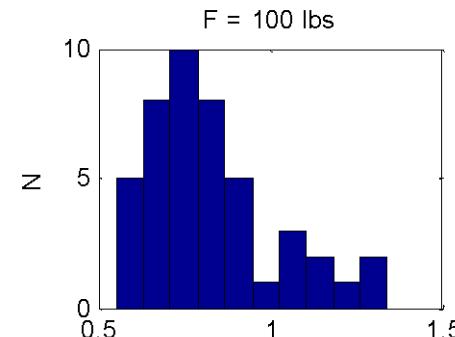
It is common for **stiffness measurements** of nominally identical bolted joint hardware to vary by as much as 25%.

It is common for **energy dissipation measurements** on nominally identical bolted joint hardware to vary by as much as 300%.

Histograms of Slope and of Dissipation

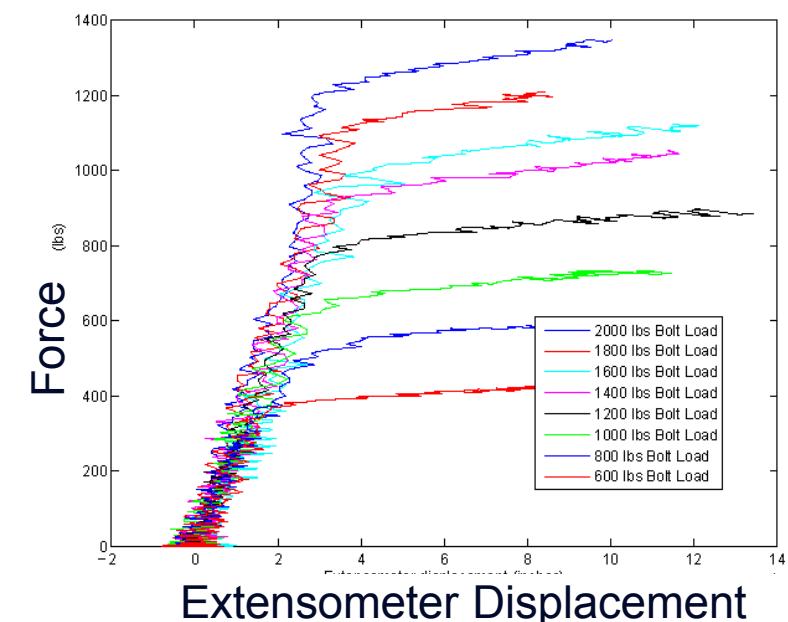
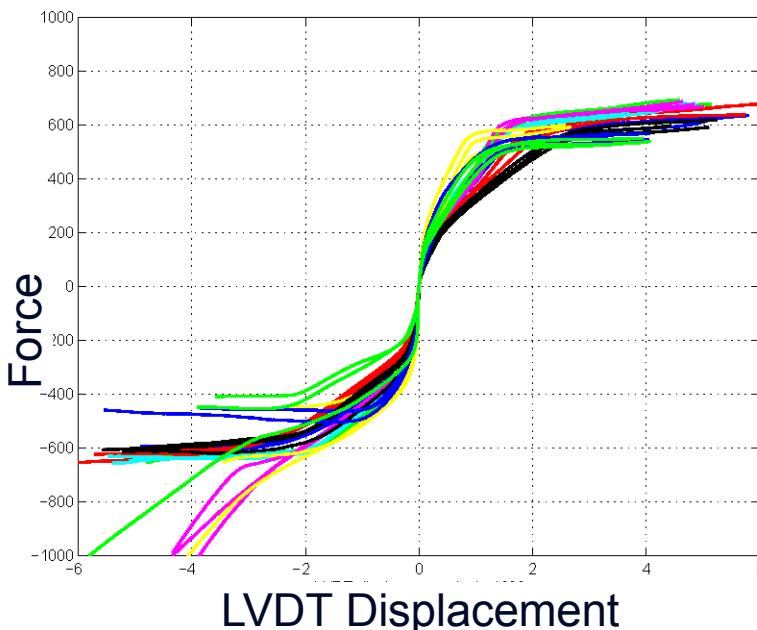


slope



Dissipation at
different axial
loads

Quasi-Static Data Has Some Clear Trends



Displacement includes elastic displacement of everything else. Only the force information can be interpreted directly.

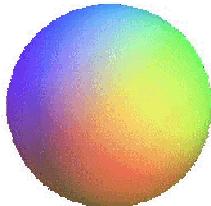
Observation

- **There is a lot of intrinsic variability (aleatoric uncertainty) associated with nominally identical joints.**
- **Even how we define the parameters we use to characterize the experiments is imprecise – epistemic uncertainty.**
- **Of course how we map from parameters of the experiment to parameter of the model is model dependent.**

On to Model Form and Model Form Error

A Thought Experiment

- **Problem – Given a bowl of small objects, estimate the statistical distribution of their volumes**
- **Procedure**
 1. **Data: taking one specimen at a time, and without looking, measure a dimension**
 2. **Model Form: assume the specimens are spherical**
 3. **Calculations: using that model, estimate the statistical distributions of specimen volume**

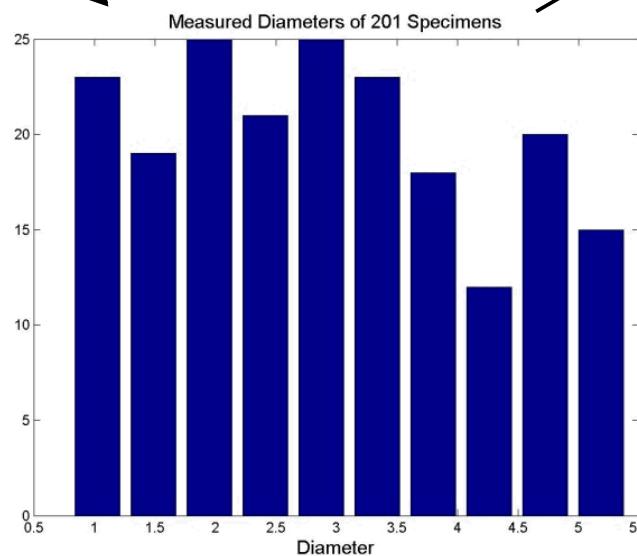


$$V = \frac{4\pi}{3} \left(\frac{D}{2}\right)^3$$

As We See the Process

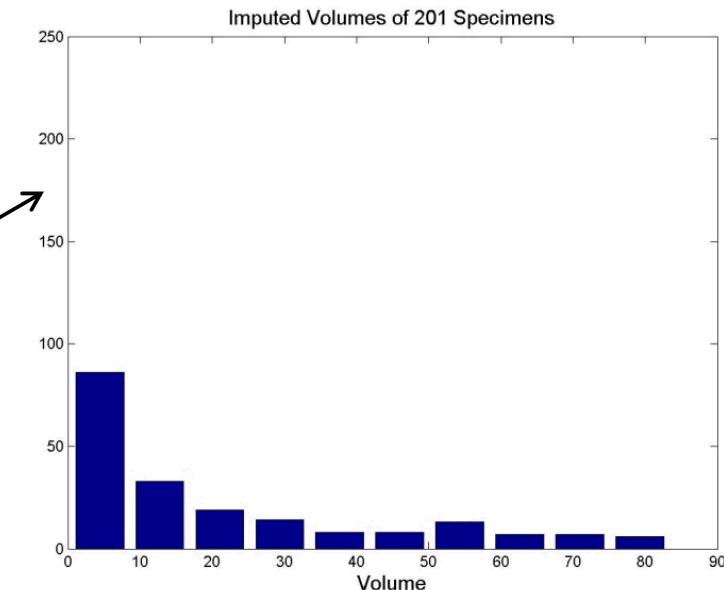


Sampling



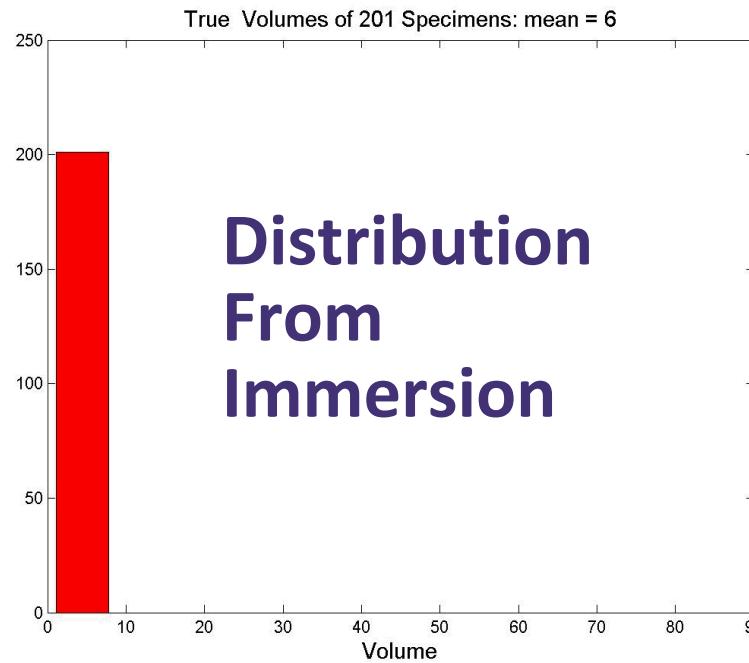
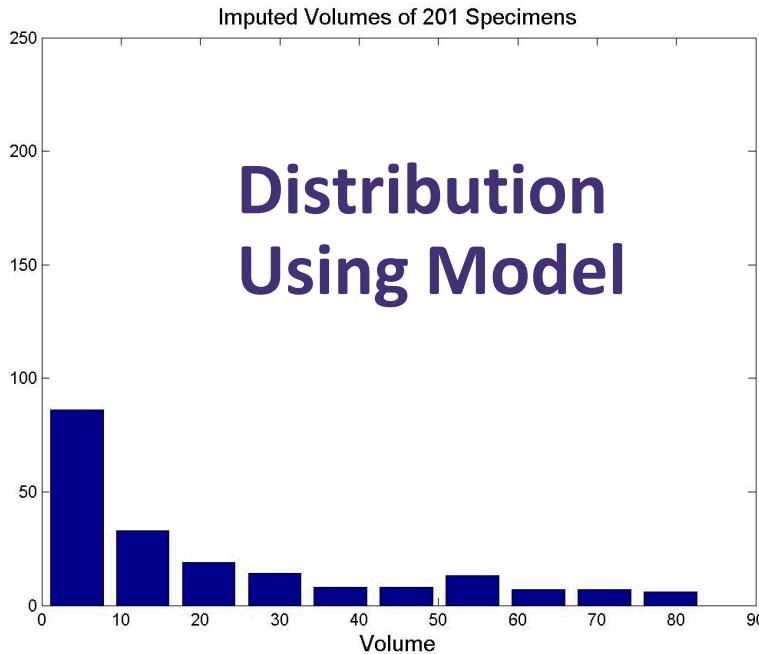
Distribution
of Diameters

Calculations
using model



Distribution
of Volume

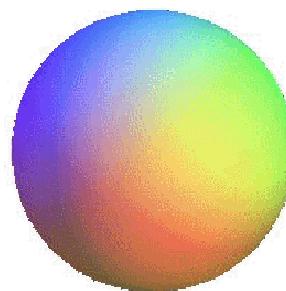
Now We Set Aside the Model and Measure Volume by Immersion



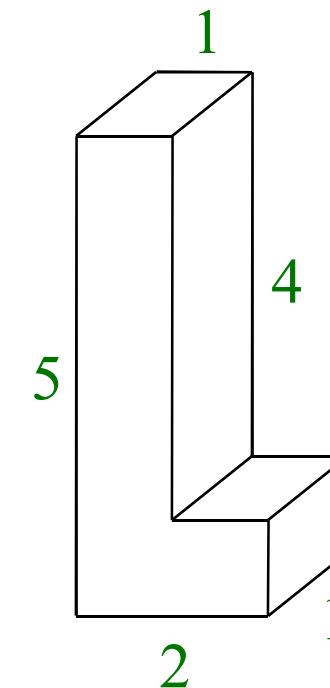
What is Going On?

Model Form Error

- Model assumed shape as spherical



- True shape is quite different



Observation

- Model form error can manifest itself as fallacious variability
(In this case, the model was insensitive to a dependence on orientation.)
- Perhaps we can use some feature of apparent variability of the predictions or of the parameters to assess the model overall.

Look to Analogous Problem

- Consider some sample of random data.
- Pose the problem: Which form of probability distribution is an appropriate fit to this data?
- Reasonable considerations
 - The better the fitted distribution matches the histograms of sampled data the better
 - The more parameters needed to fit the data, the less natural the fit.

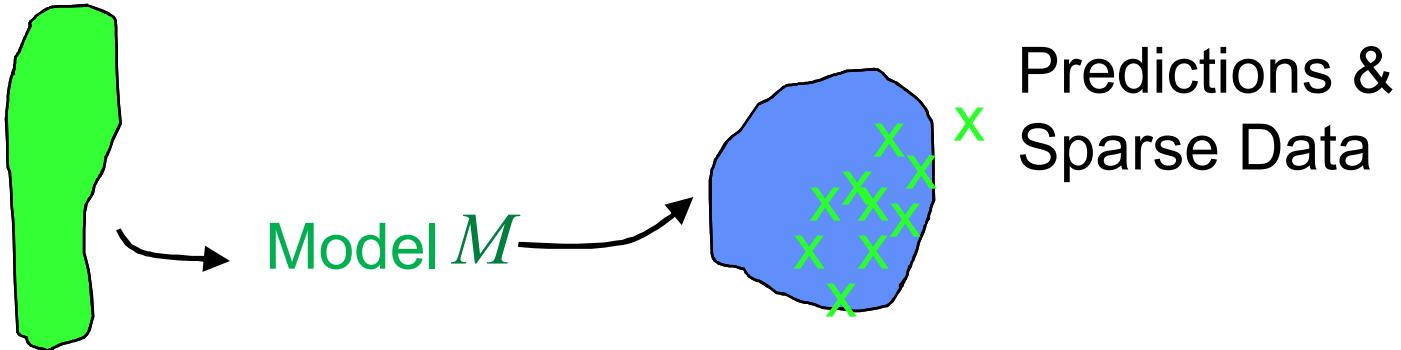
Akaike Information Criterion (AIC)

$$AIC = 2k - \ln(L(\{X_j\}))$$

- **k is the number of parameters in the statistical model.**
- **L is the maximized value of the likelihood function for the estimated model given observations $\{X_j\}$.**
- **Based on information theory**

Map onto our problem

N
Dimensional
Parameter
Space

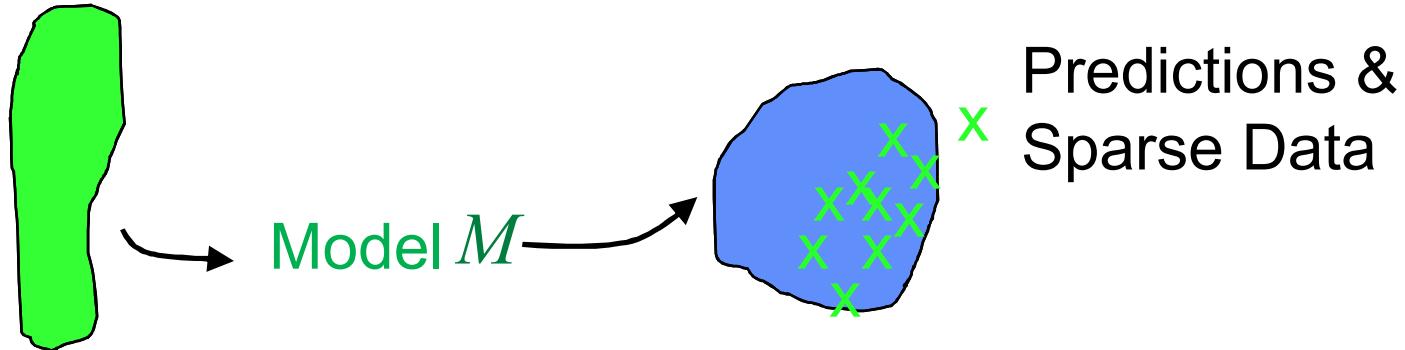


$$P = 2k - \ln(L(\{X_j\}))$$

- In this case
 - k is the number of parameters of our model
 - L is a “likelihood” computed using random input loads and a finite number of observed outputs
- We still do not capture the artificial variability in our parameters

Map onto our problem

N
Dimensional
Parameter
Space

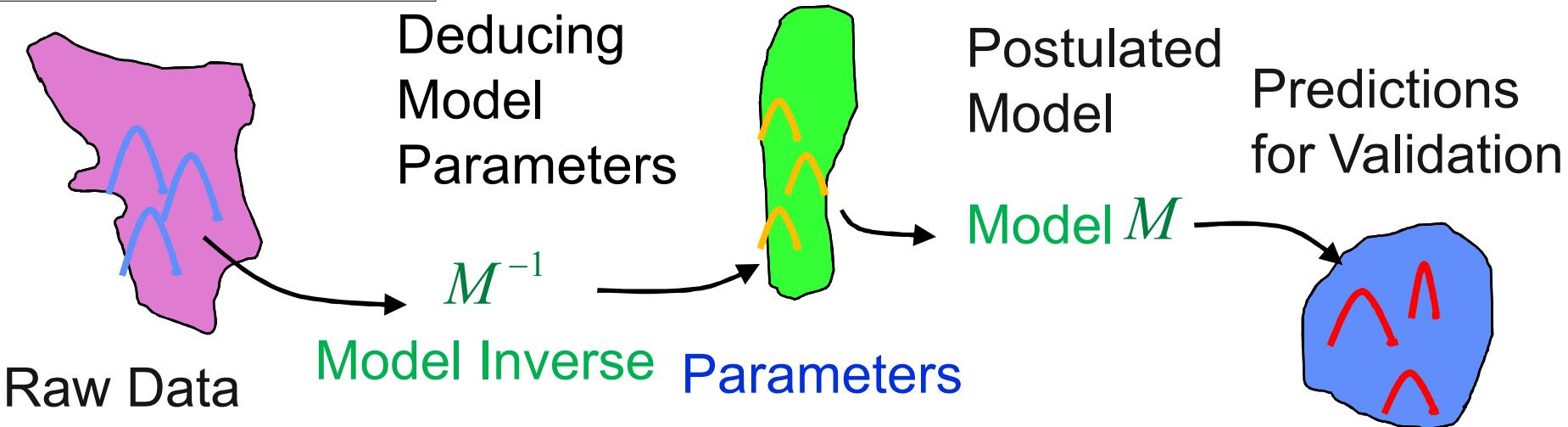


$$P = 2k - \ln(L(\{X_j\})) + E_P$$

x

- **In this case**
 - **k is the number of parameters of our model**
 - **L is a “likelihood” computed using random input loads and a finite number of observed outputs**
 - **E_P is the entropy of the parameter space**

A Similar Approach Using Fuzzy Sets (Hagg, González, Hanss)



- Experimental calibration is represented by fuzzy sets.
- These map via M^{-1} to other fuzzy sets in parameter space.
- Fuzzy sets representation in parameter space maps to other fuzzy sets in test space.
- A measure is devised employing the features of these fuzzy sets to capture the information entropy and accuracy of the model.

Conclusion

- There is much aleatoric uncertainty (intrinsic variability) among nominally identical joints.
- There is at least as much uncertainty in our predictive capability due to incomplete understanding of joint mechanics (epistemic).
- Separating out how each source of uncertainty affects various aspects of prediction is not straightforward.
- Assessment of model forms requires consideration both conformance to test and the uncertainties involved.

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