Data Adjustments

Theory vs. Practice: Lessons Learned,
Cautiously moving forward for Digital Twinning Applications

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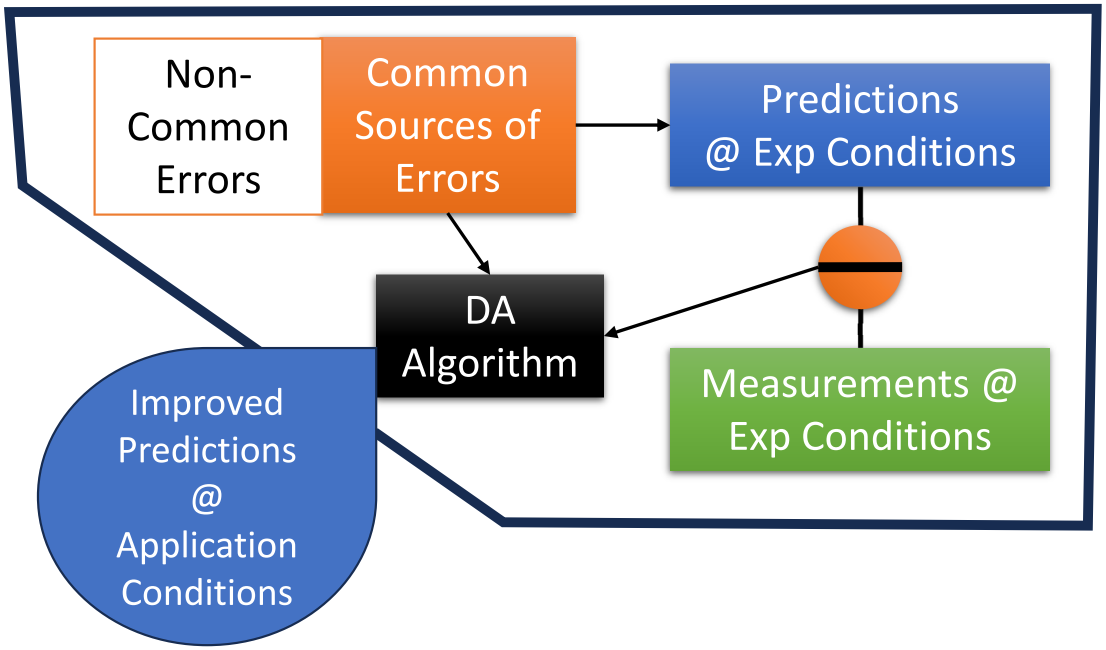
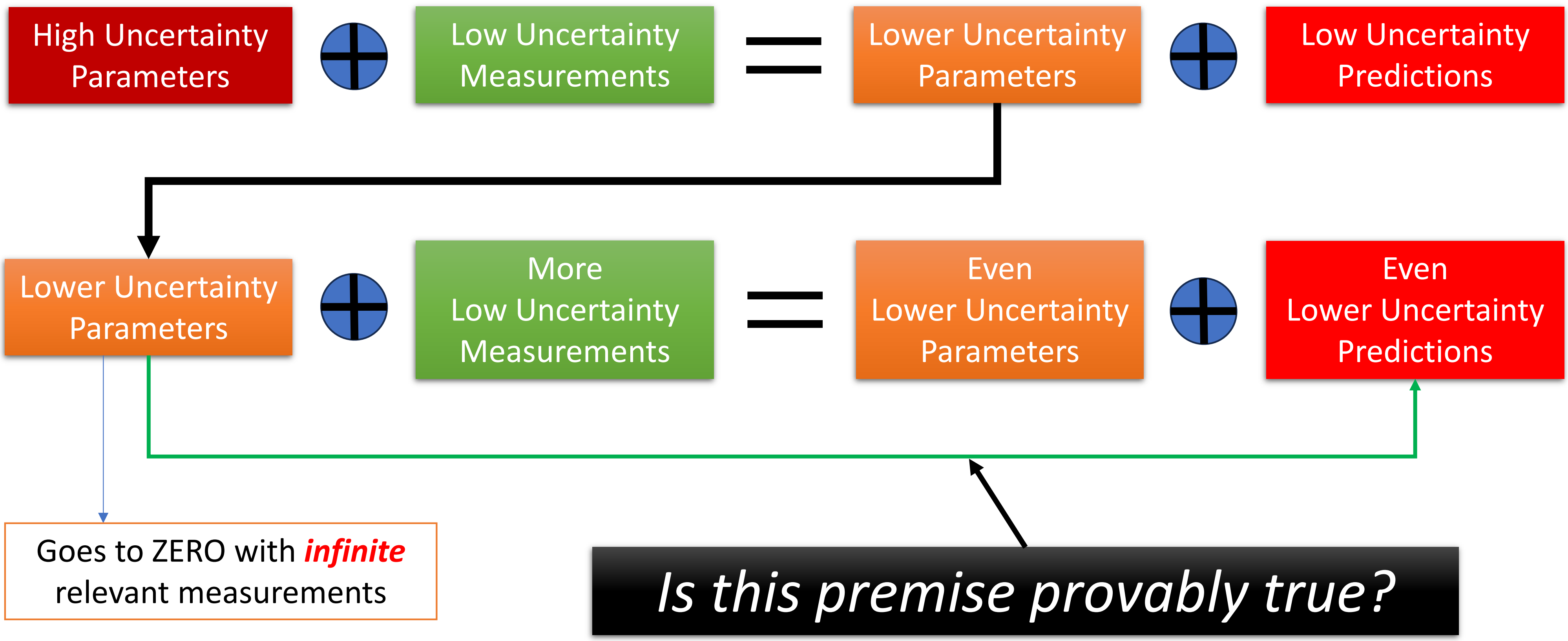
Data Adjustment/Assimilation (DA)

- Based on “limited” measurements, and prior knowledge about common error sources, DA to improve predictions @ application conditions
- Non-common errors ignored, considered to have minor impact on predictions



Data Adjustment/Assimilation Process

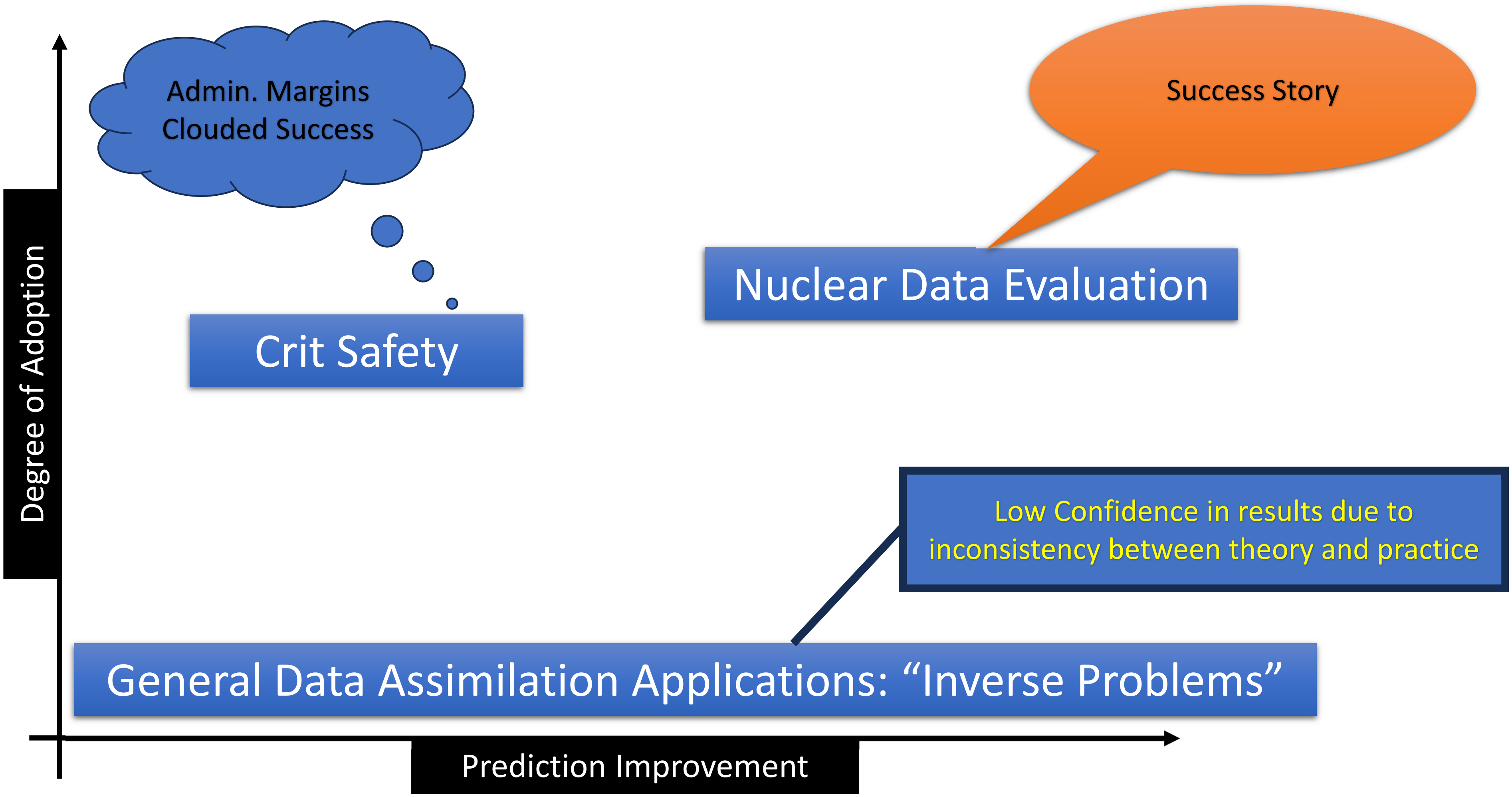


Thoughts on DA Process

- Problem setup looks like an "***inverse***" problem
  - Inverse problems are typically ill-posed, i.e., under-determined
  - Using prior information, Bayes theorem makes it well-posed

- DA calculational process ***not function*** of application conditions
  - All parameters must be common to both experiments & applications
  - Analyst should be smart enough to pick experiments that are close to application conditions, calling for "relevance/similarity" metrics
  - Will adding experiments always improve predictions?
  - What if added experiments are of low relevance?

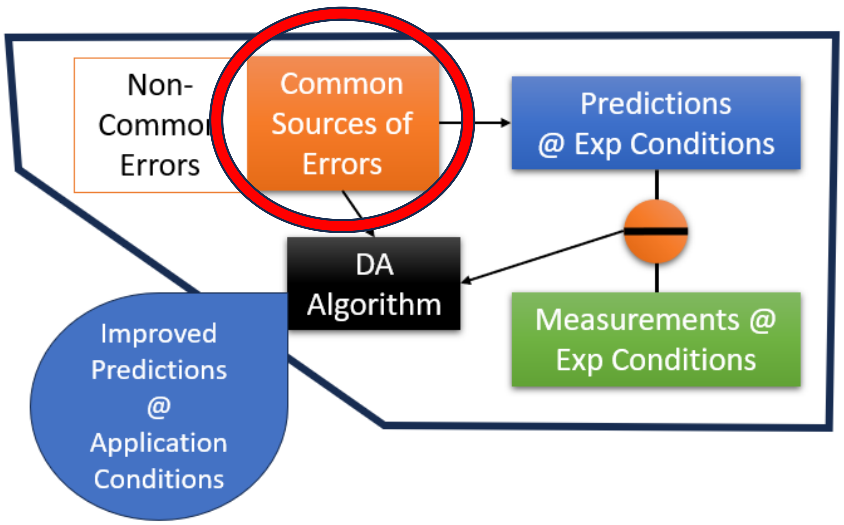
DA Application Areas to Date



Lesson #1 – Can we isolate Errors?

Theory

Adjustments can correct for common parameters errors



Practice

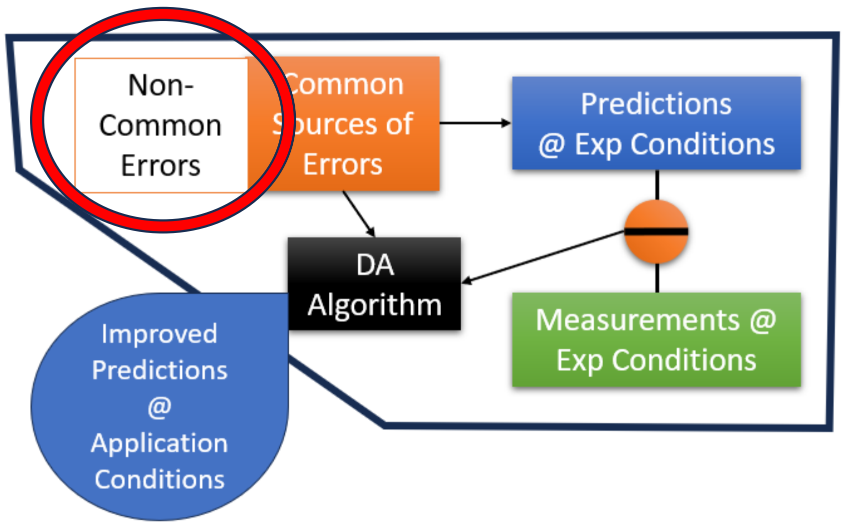
This is true only when number of measurements equal/exceed number of parameters, not possible for practical applications

Verification exercises lacking, starting with known embedded errors to be compared to adjustments

Lesson #2 – Are Non-common Errors important?

Theory

Parameters are dominant source of errors, no non-common sources.



Practice

DA suffers from error compensation phenomena, i.e., parameters adjusted to correct for non-common errors, leading to biased results

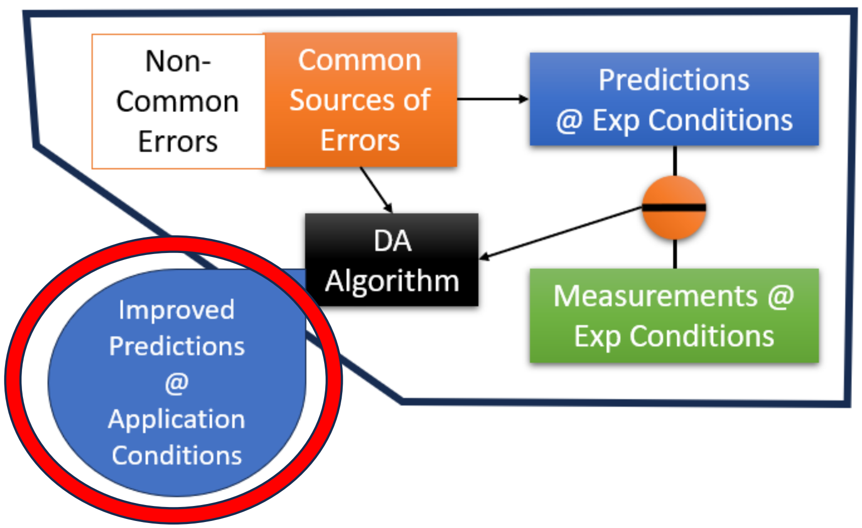
Impact can be reduced by artificial increase in measurement uncertainty

For multi-physics models with nonlinear behavior, impact on predictions is unquantifiable

Lesson #3 – Are better predictions guaranteed?

Theory

Adjustments improve predictions for application of interest



Practice

Adjustments reduce discrepancies between predictions and measurements at experimental (training) conditions

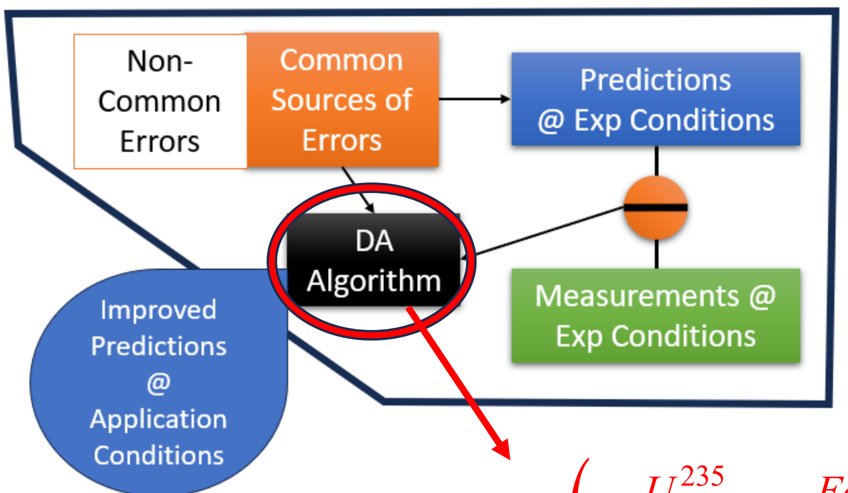
Adjustments are blind to application conditions, cannot guarantee improved predictions with few updates

Strong reliance on cleverness of analyst to pick relevant experiments

Lesson #4 – What is going on under the hood?

Theory

Priors are not important, post uncertainties to converge to zero in limit of infinite measurements



$$\rho_{post}\left(\sigma_f^{U^{235}}, \sigma_s^{Fe^{56}}\right) \neq 0$$

Practice

Priors are **very** important and Post uncertainties have **new correlations**, which change based on order of experiments, and vanish in limit of infinite measurements

These (artificial?!) correlations hard to justify/understand by practitioners, only accepted by DA theorists.

Path Forward *(incl. activities ongoing/planned at ORNL)*

- Developing reliable DA process is more important than ever
  - First principles models of limited value without assimilating measurements
  - Reliable DA methods require rigorous verification, debiasing, extension to multi-physics non-Gaussian uncertainties
  - Need benchmarks to compare performance of various DA methods
  - Value of experiment(s) should be quantified
  - Reliable metrics to assess (non)-coverage of uncertainty space

- Digital Twin must be as intuitive as its Human Twin
  - Not a black box: graphical aids to demonstrate value
  - Intuitive behavior: more experiments to improve not worsen predictions, redundant or low relevant experiments not to impact predictions

OECD/NEA – WPNCS Activity

A new SG14 formed on Feb 14th, 2024:

"Performance Benchmark for
Error Recovery and Experimental Coverage"

Please join us