

# Introduction to ESPEI

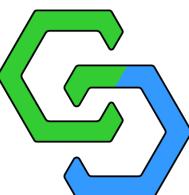
Database development and uncertainty quantification

Brandon Bocklund

Materials Genome Foundation

July 13-14, 2022

“Software Tools from Machine Learning to Phase Diagrams” Virtual Workshop



# CALPHAD modeling

**Derivatives of Gibbs energy  
enthalpy, entropy, heat capacity**

**Phase equilibrium data  
phase boundaries**

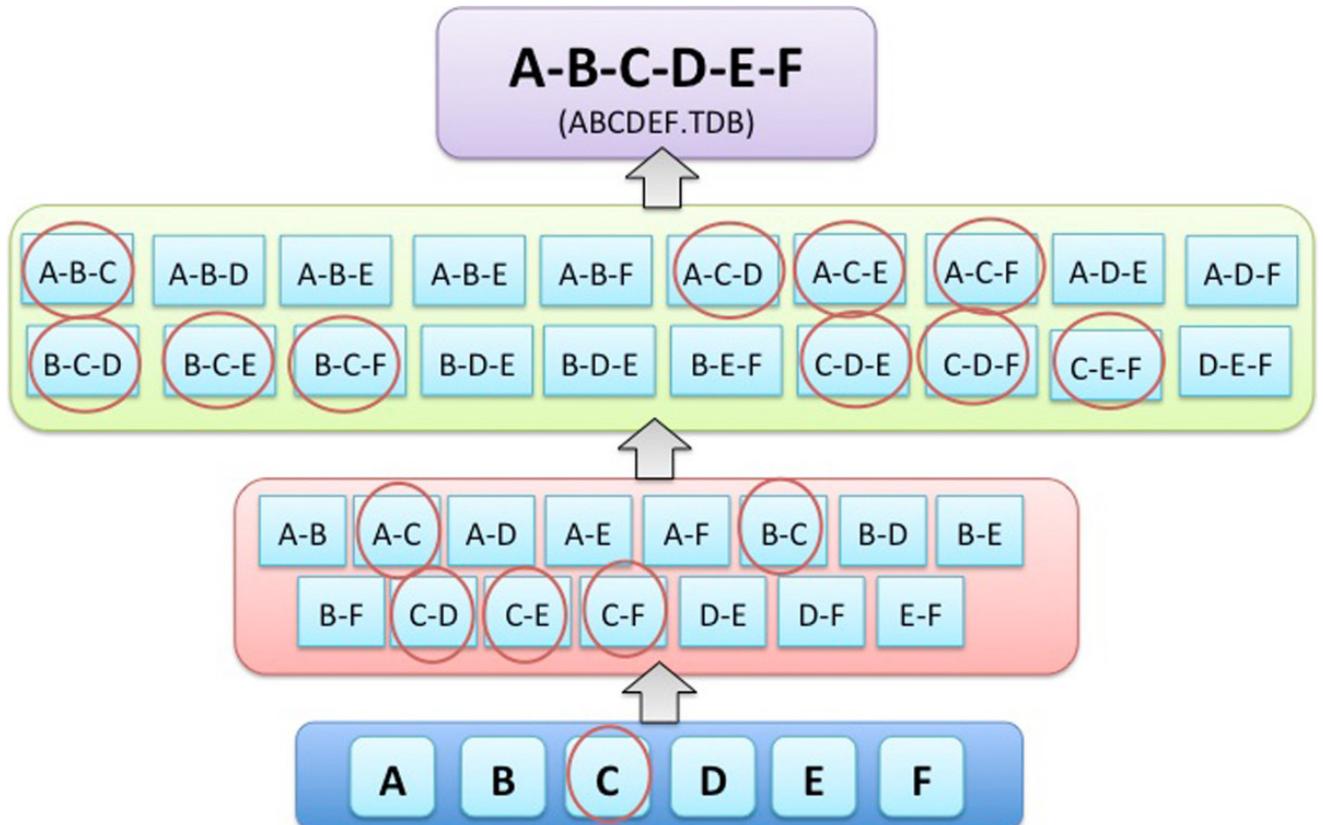
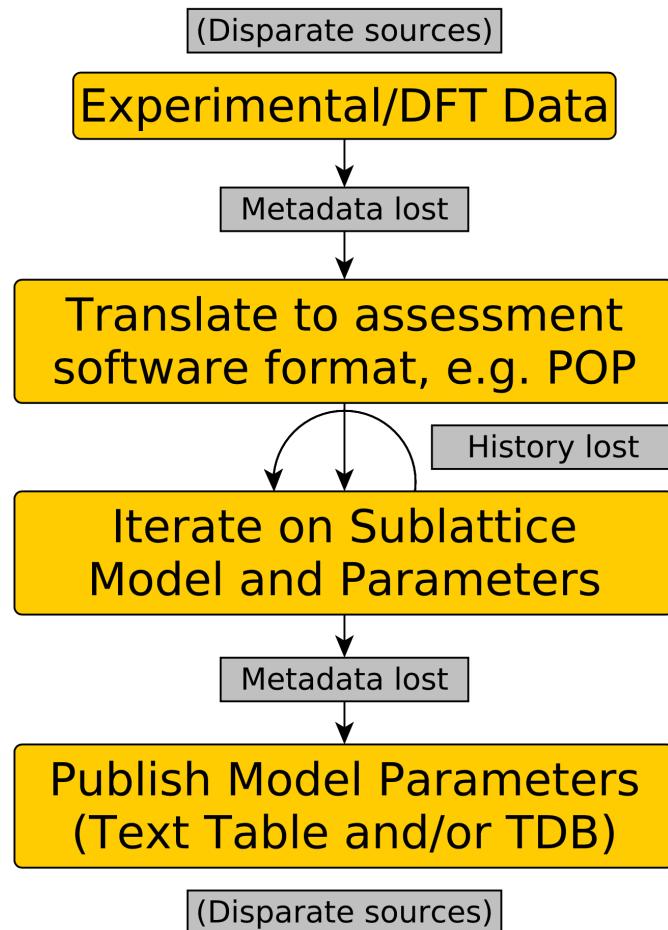
**Gibbs Energy of Individual Phases**

$$G^\phi(T, P, x_i) = G^{\text{sr}} + G^{\text{cn}} + G^{\text{ph}} + G^{\text{xs}}$$

**Equilibrium, phase diagrams,  
driving forces, physical/chemical properties**

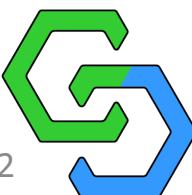
**Pure elements → Binary → Ternary → Multicomponent**

# CALPHAD database development process



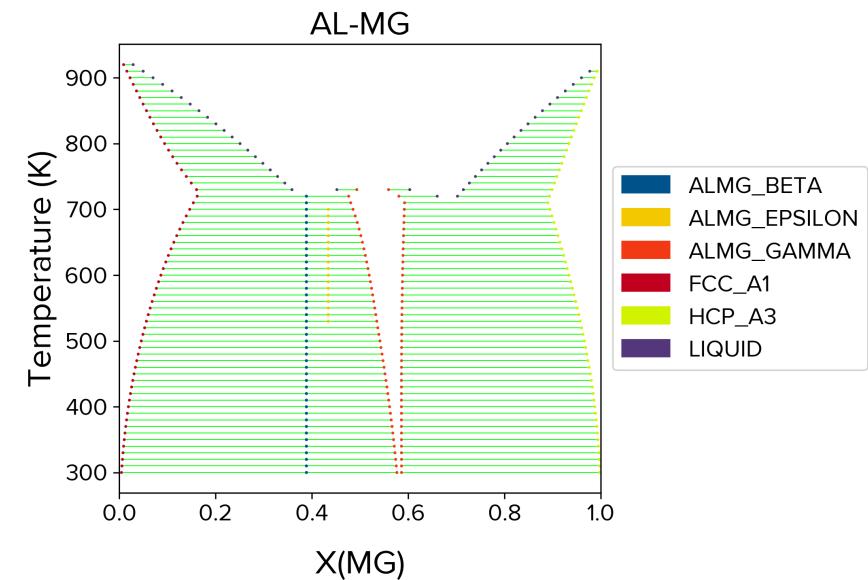
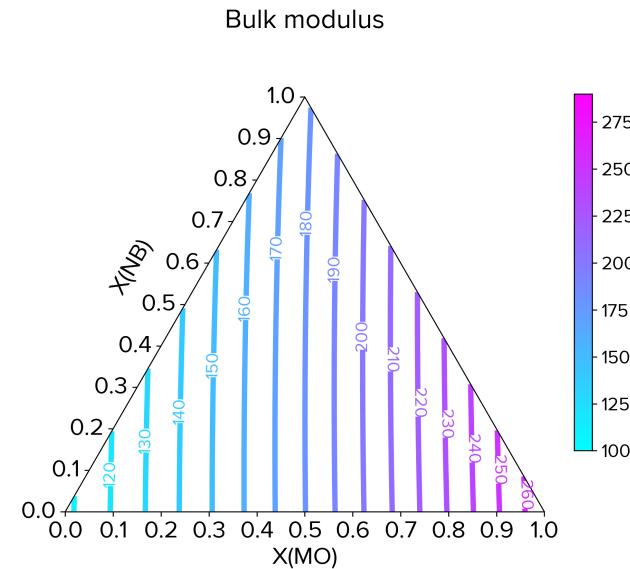
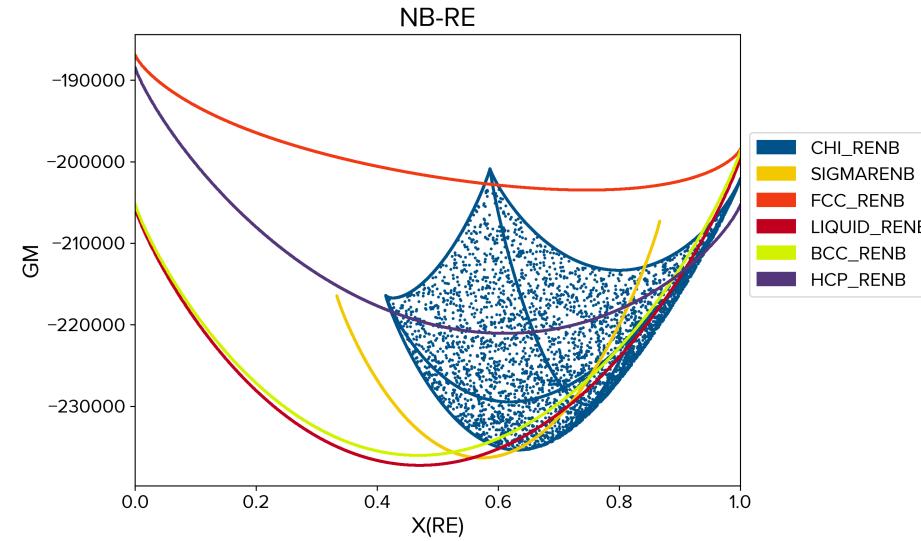
Otis, PhD Thesis (2016)

Campbell, IMMI (2014)



# pycalphad: open-source Calphad library

- Initially released in April 2015
- Built on and integrated with the scientific Python stack
- Defines Calphad models symbolically using SymPy
- Fast numerical core written in Cython

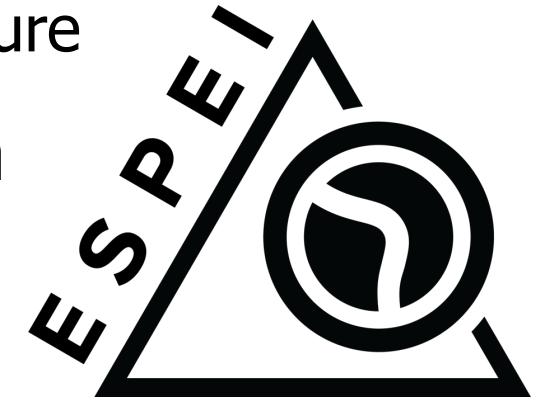


<https://pycalphad.org>

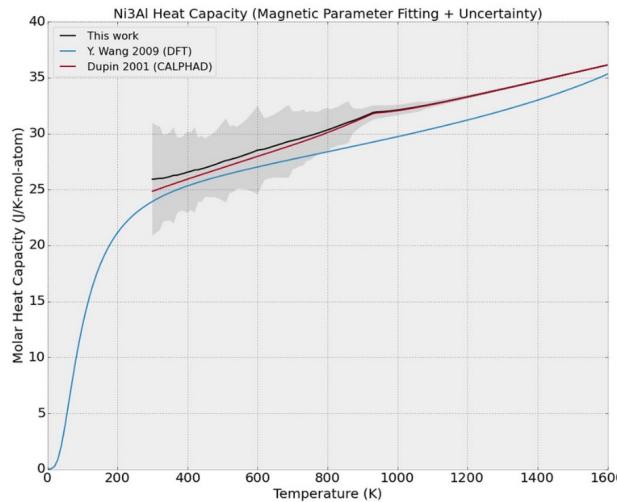
# ESPEI: Database Development and UQ

Extensible Self-optimizing Phase Equilibria Infrastructure

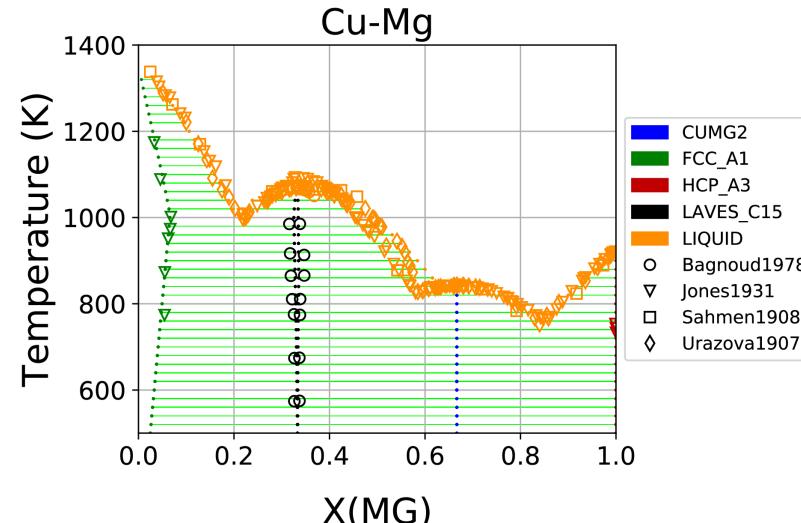
1. Parameterize Calphad models from single phase data
2. MCMC: Optimize and quantify uncertainty
3. Propagate uncertainty to properties



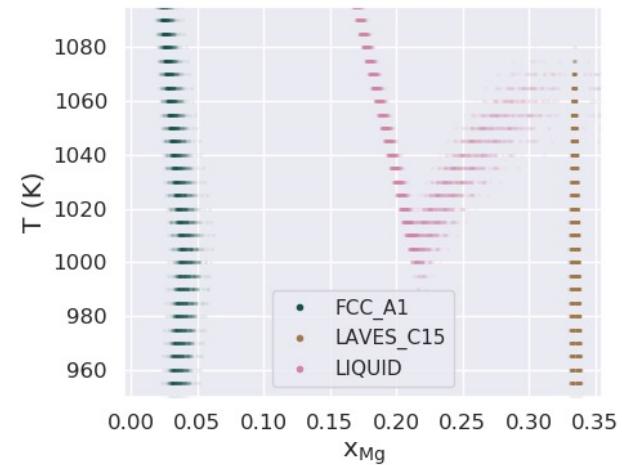
<https://espei.org>



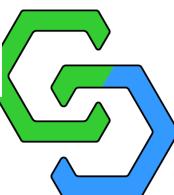
Otis, Liu, JOM (2017)



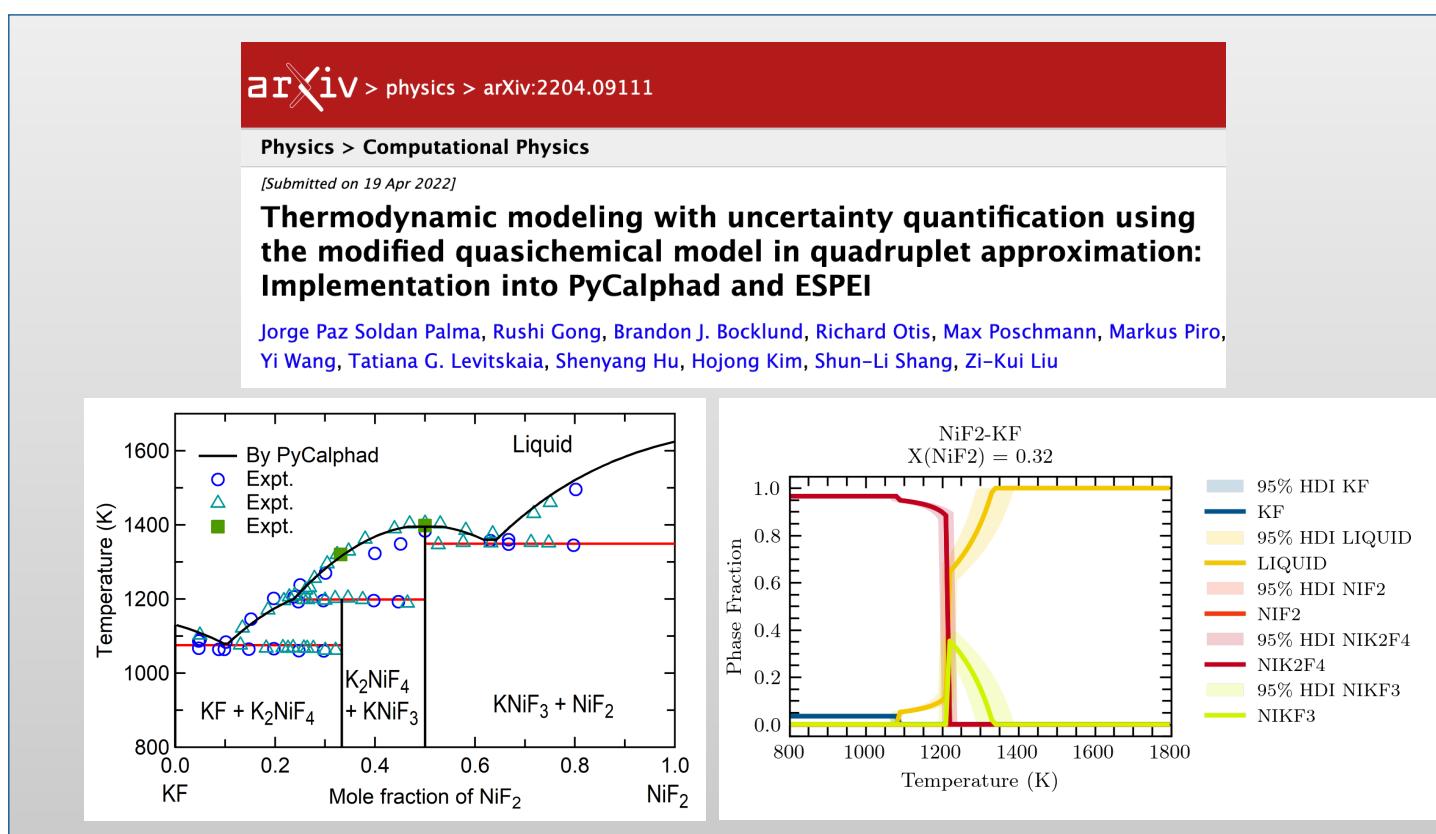
Bocklund, MRS Comm (2019)



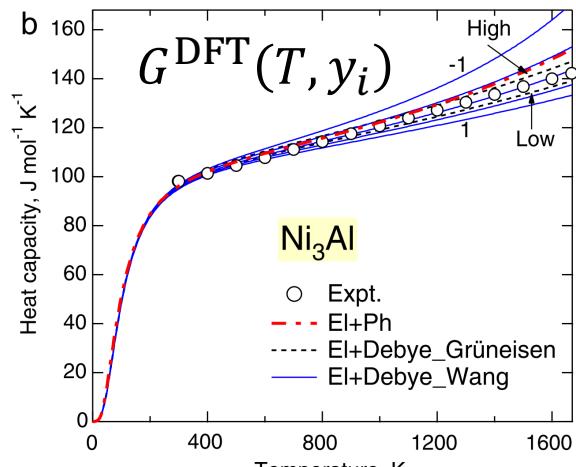
Paulson, Acta Mat. (2019)



# Impact of ESPEI



# Parameter selection in ESPEI

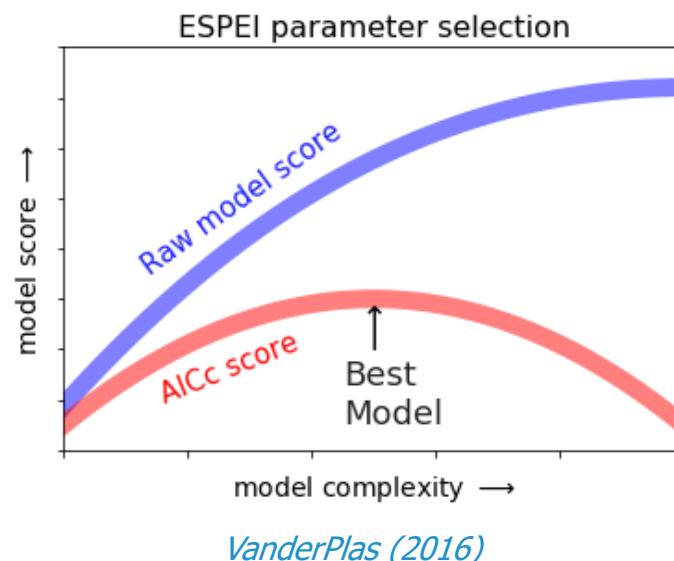


Shang, Comput. Mater. Sci. (2009)

Fit non-equilibrium  
thermochemical data  
to a functional form



Overfitting prevented with  
corrected Akaike  
information criterion



Temperature dependence: power expansion

$$G(T) = a + b T + c T \ln T + d T^2 + e T^{-1}$$

Composition dependence: Redlich-Kister polynomial

$$G^{\text{xs}}(T, y_i) = \sum_{i,j \neq i} y_i y_j (y_i - y_j)^v v L$$

$$v L(T) = a + b T + \dots$$

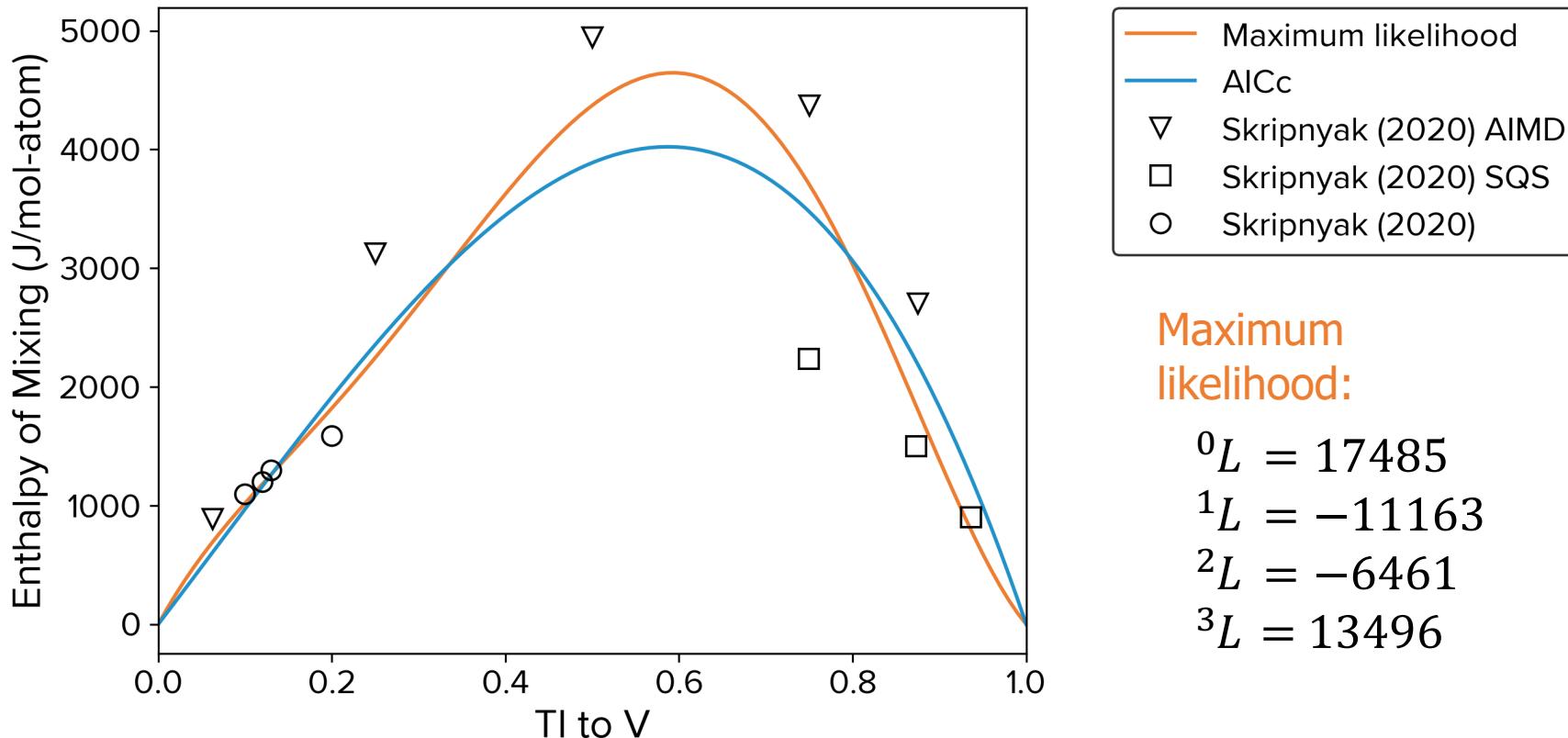
$$\text{AICc} = n \ln \frac{\text{RSS}}{n} + 2k + \frac{2k^2 + 2k}{n - k - 1}$$

RSS – Sum of square residuals

$k$  – # model parameters (model complexity)

$n$  – # data points

# Parameter selection for bcc Ti-V



Maximum likelihood:

$$\begin{aligned}{}^0L &= 17485 \\ {}^1L &= -11163 \\ {}^2L &= -6461 \\ {}^3L &= 13496\end{aligned}$$

AICc:

$$\begin{aligned}{}^0L &= 15552 \\ {}^1L &= -5977\end{aligned}$$

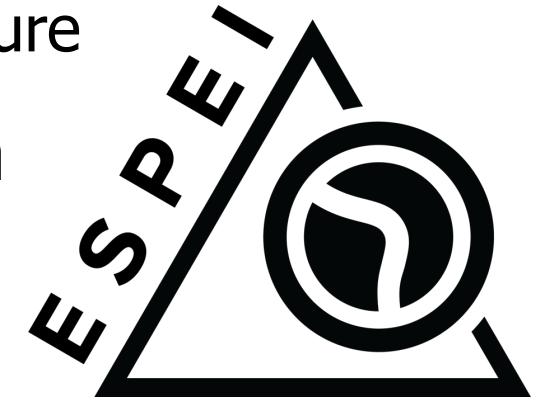
# Interactive Demo

## ESPEI Parameter Generation

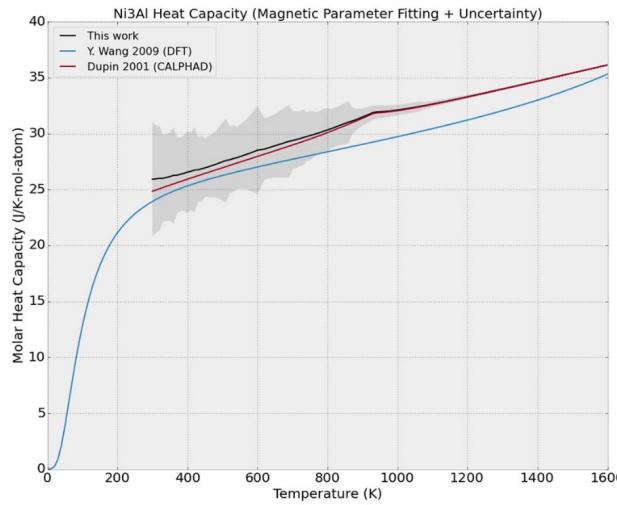
# ESPEI: Database Development and UQ

Extensible Self-optimizing Phase Equilibria Infrastructure

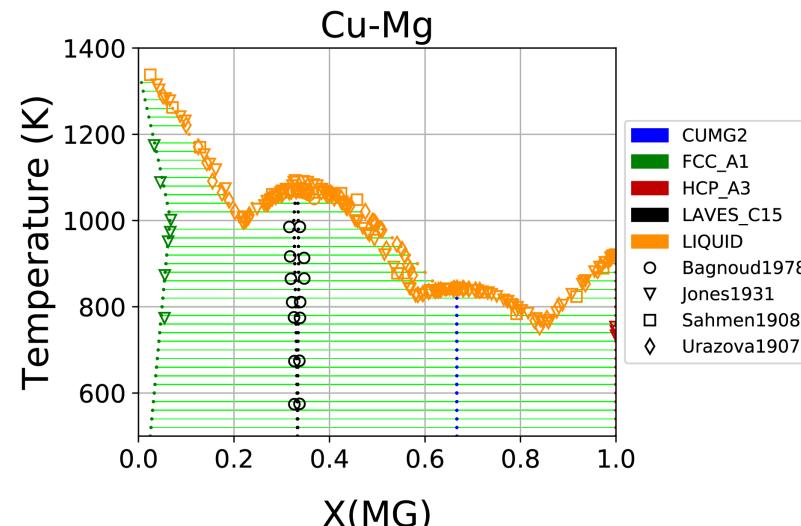
1. Parameterize Calphad models from single phase data
2. **MCMC: Optimize and quantify uncertainty**
3. Propagate uncertainty to properties



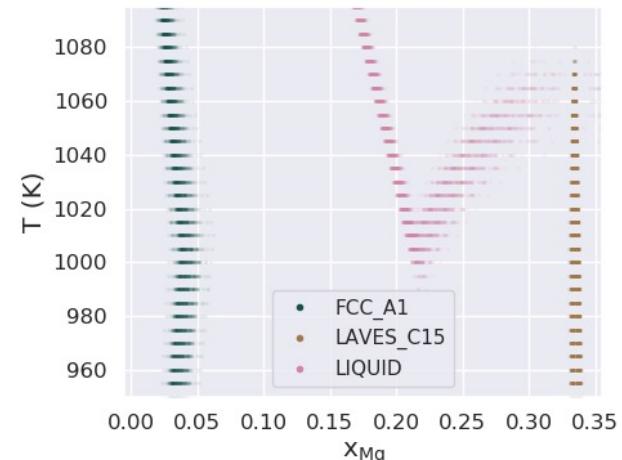
<https://espei.org>



Otis, Liu, JOM (2017)



Bocklund, MRS Comm (2019)



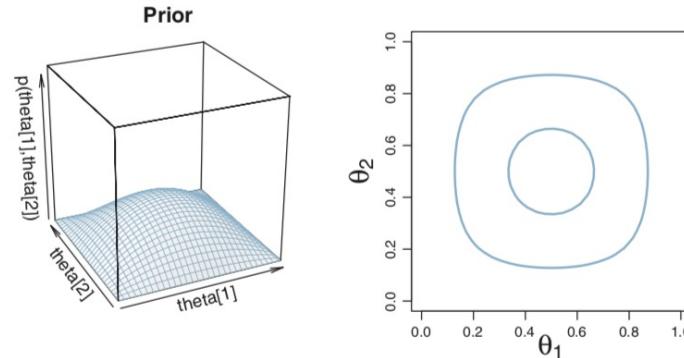
Paulson, Acta Mat. (2019)



# MCMC: Bayesian parameter estimation

$$\text{Posterior} \quad \text{Likelihood} \quad \text{Prior}$$
$$\Pr(\boldsymbol{\theta}|D) = \frac{\Pr(D|\boldsymbol{\theta}) \Pr(\boldsymbol{\theta})}{\Pr(D)}$$

Data

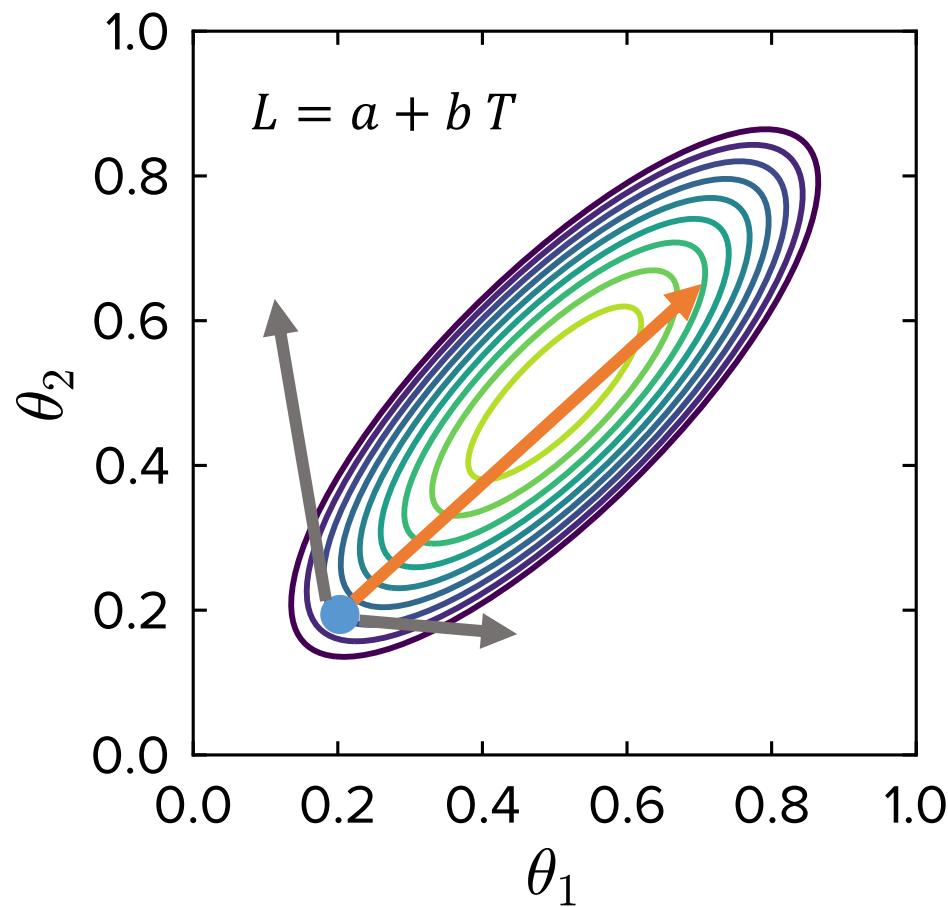


- **Markov chain**
  - Sequence of values that are independent from each other
- **Monte Carlo**
  - Random sampling

**Core principle:** the probability of a parameter value is proportional to the number of times the Markov chains visits that value

# Ensemble MCMC: efficient exploration of correlated parameter space

## Correlated Parameters

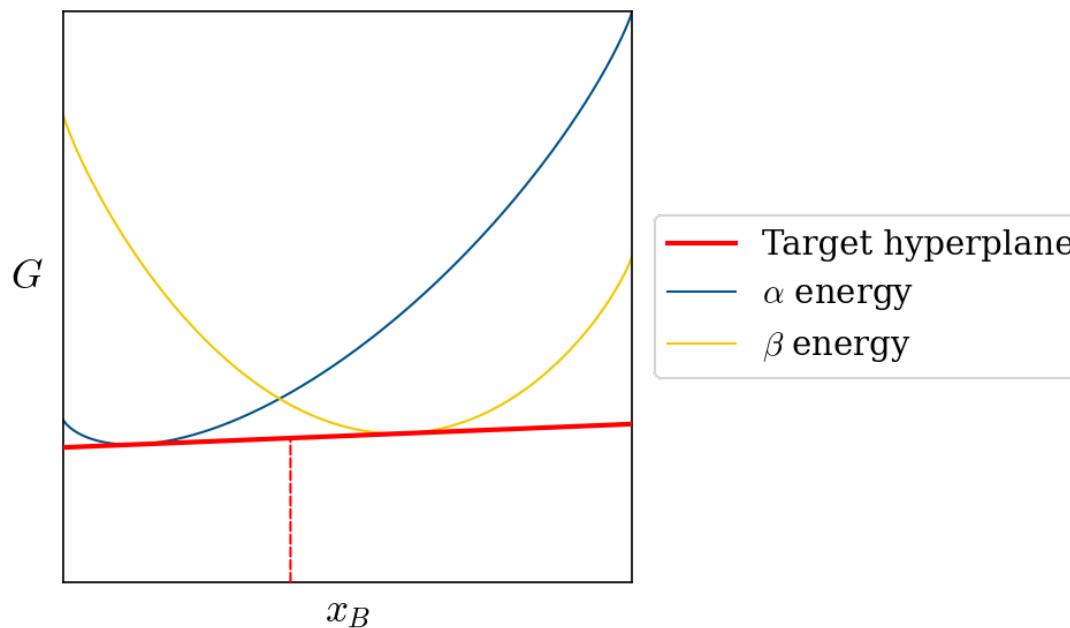


- Use many (an ensemble of) parameter chains simultaneously
  - Proposals are stretched by an affine transformation to a random chain in the ensemble
  - Key property: **affine invariance**
- In ESPEI: the ensemble is generated by multi-variate normal distribution from the initial parameters
  - Mean is at the parameter initial value
  - Standard deviation is a factor of the mean value
  - Wider initial ensemble → better coverage of parameter space, but may be far from the initial local minimum

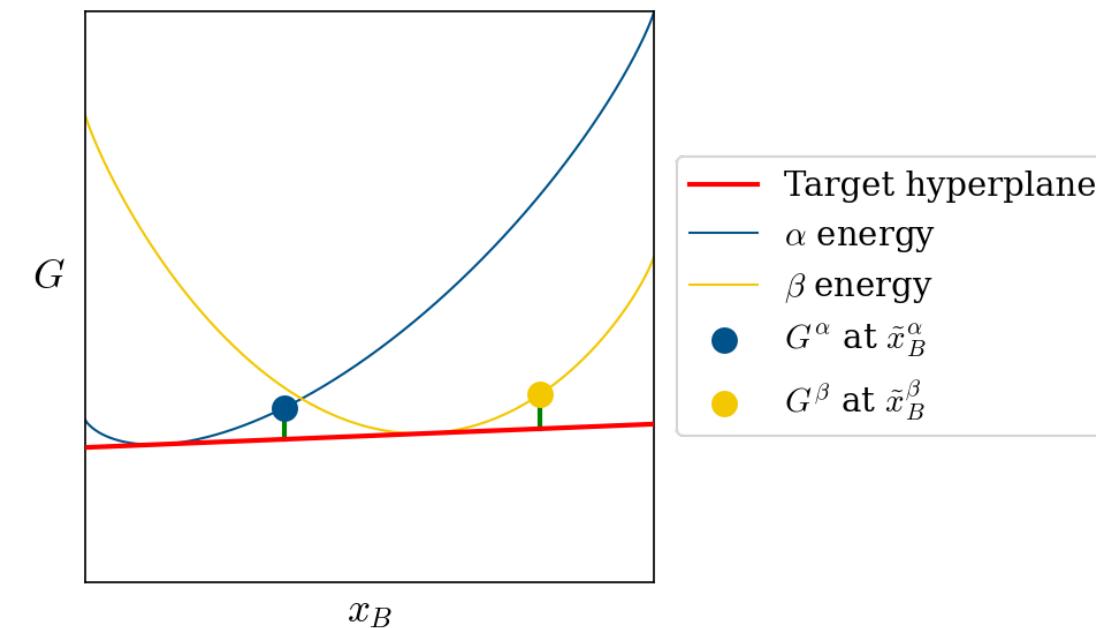
# Calculation of phase equilibria error

Goal: Find the parameters that minimize the driving forces to the target hyperplane defined by the experimental phase compositions

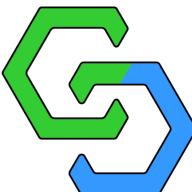
Target hyperplane:  $\tilde{x}$  known



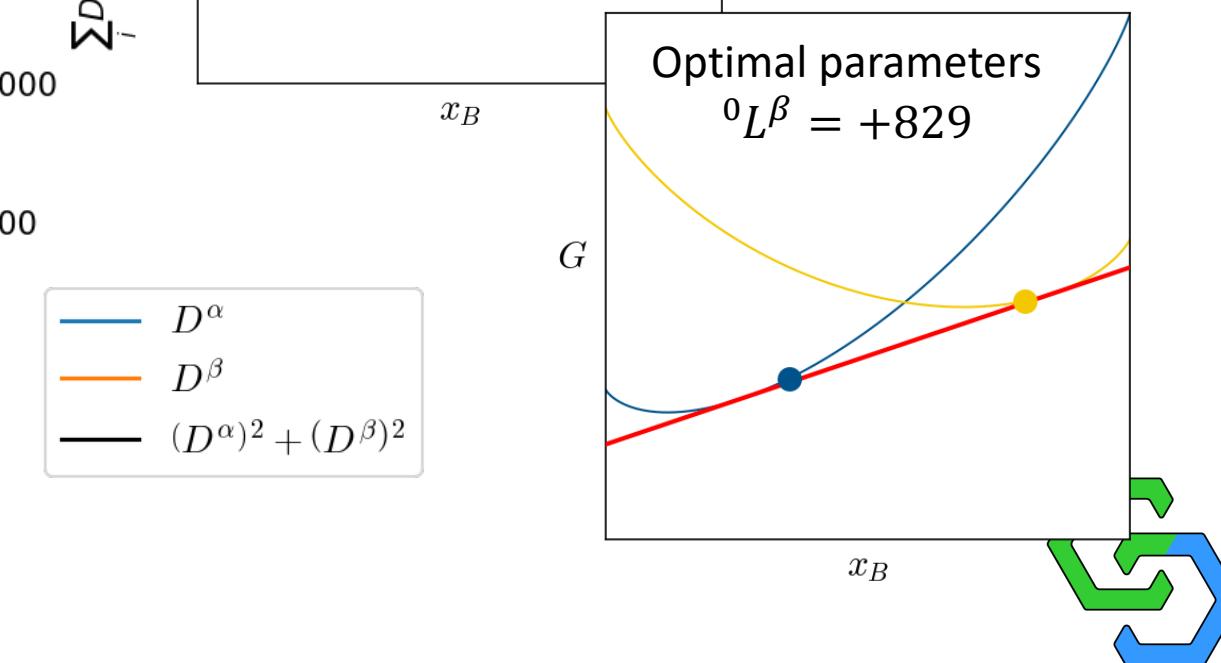
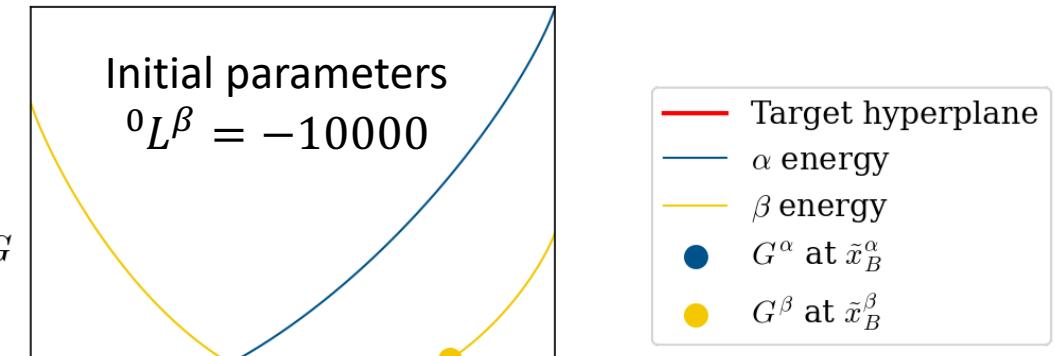
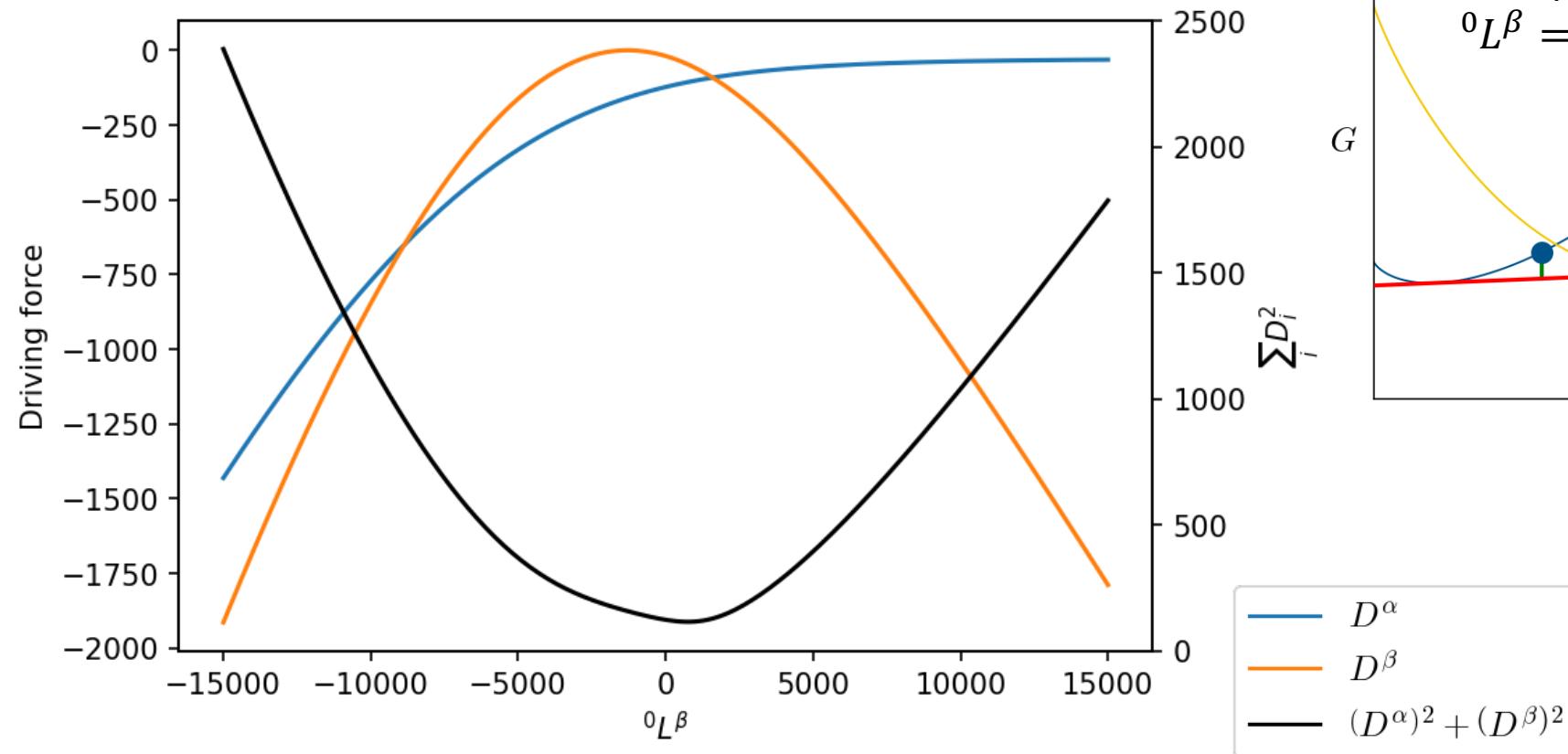
Driving forces:  $\tilde{x}^\phi$  known



Analogous experiment: equilibrated alloy with EPMA-measured phase compositions

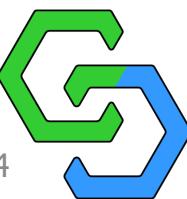
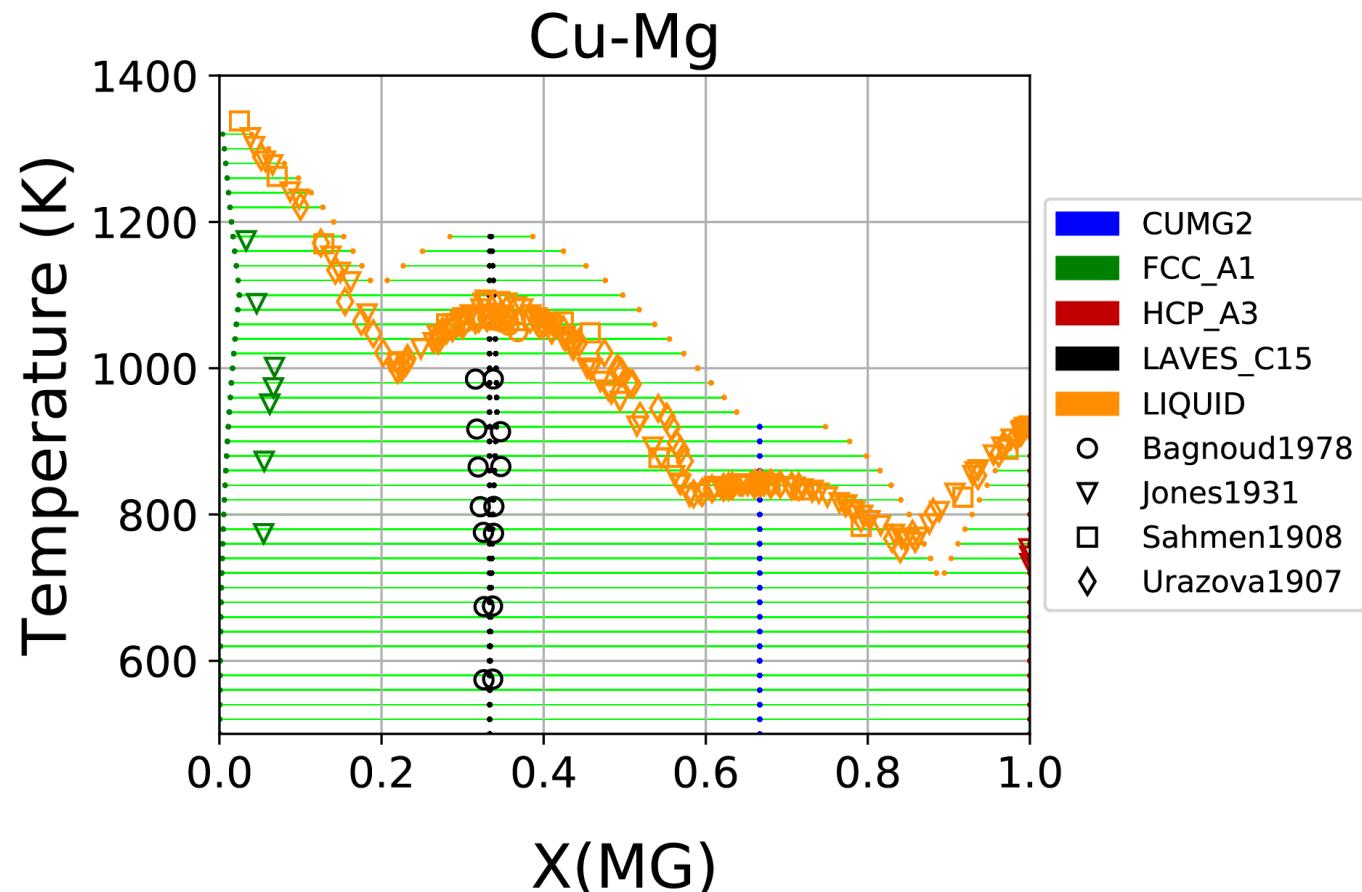


# Parameters optimized by minimizing driving forces



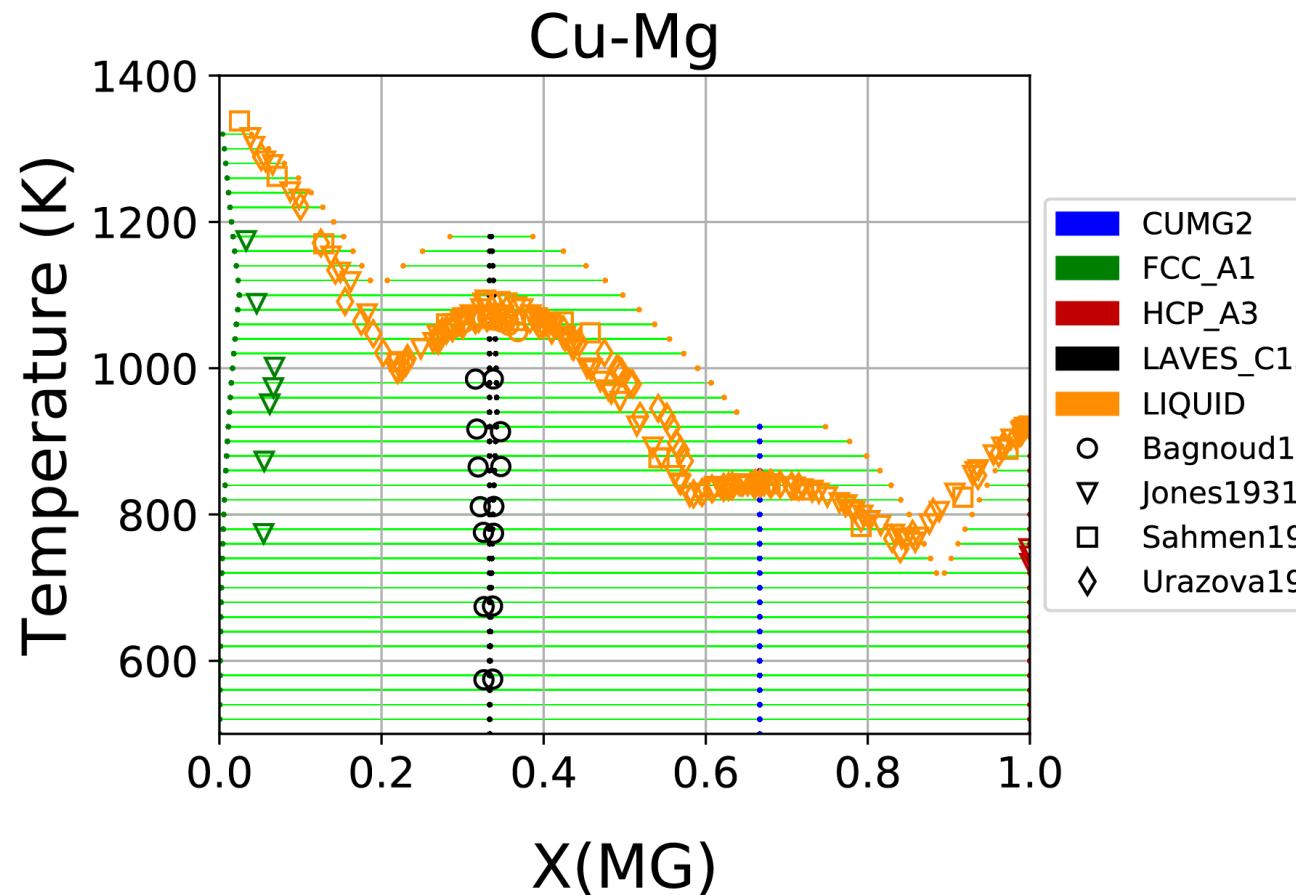
# Applying parameter selection to Cu-Mg

Single phase data start point

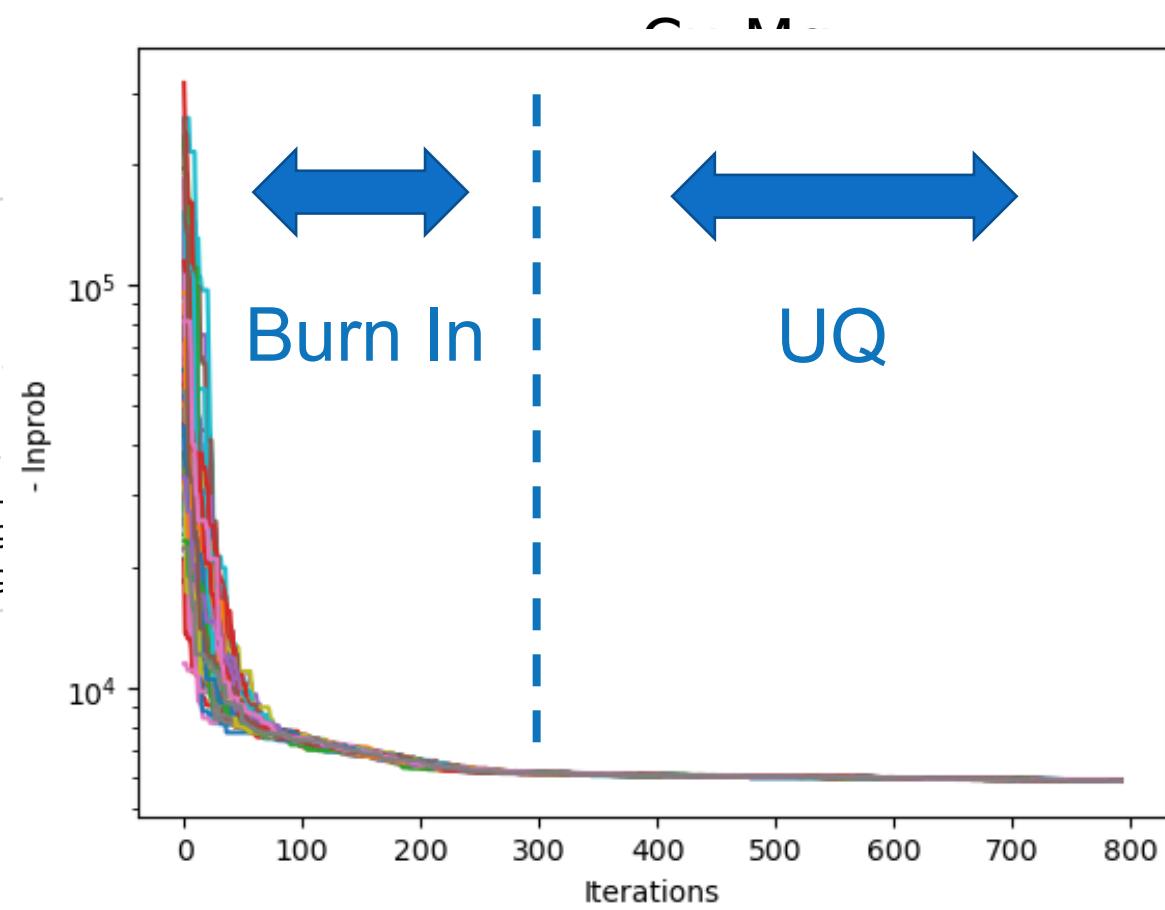


# Updating selected parameters with MCMC

Single phase data start point



MCMC to fit to thermochemical and phase equilibrium data



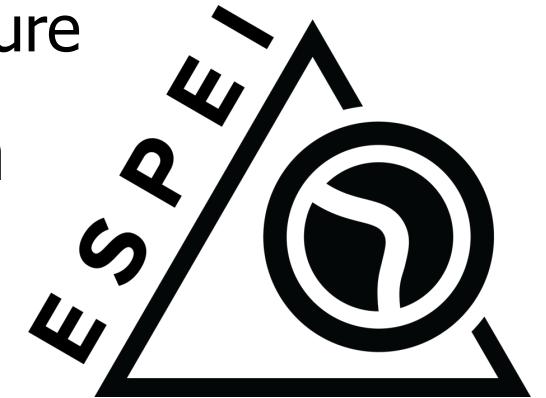
# Interactive Demo

# Optimization and Uncertainty Quantification

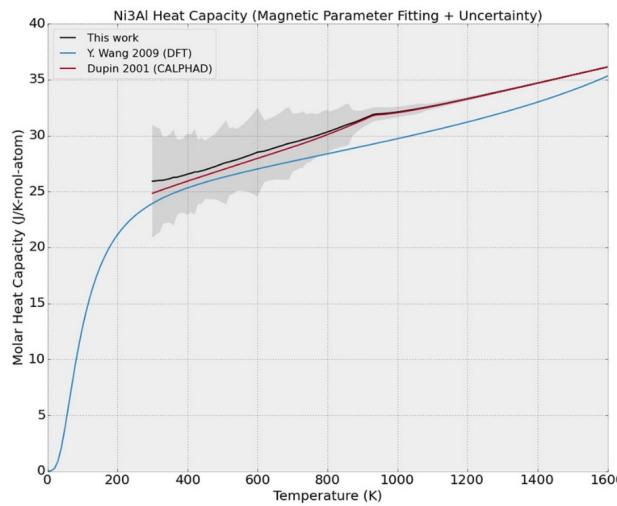
# ESPEI: Database Development and UQ

Extensible Self-optimizing Phase Equilibria Infrastructure

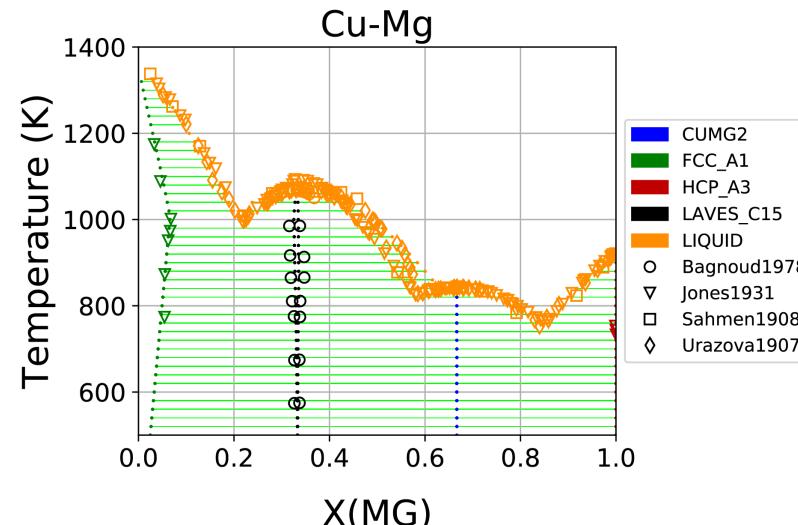
1. Parameterize Calphad models from single phase data
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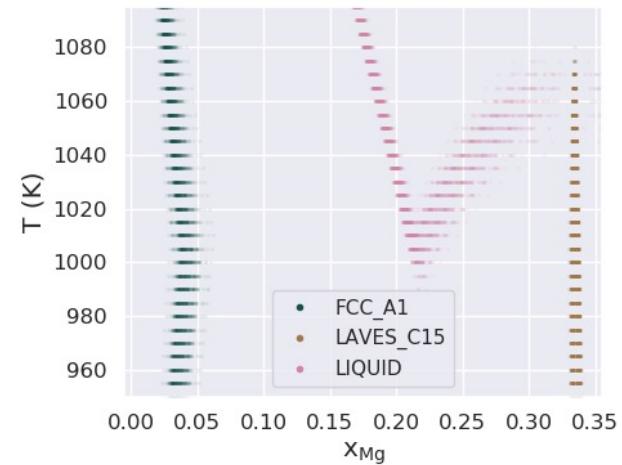
<https://espei.org>



Otis, Liu, JOM (2017)



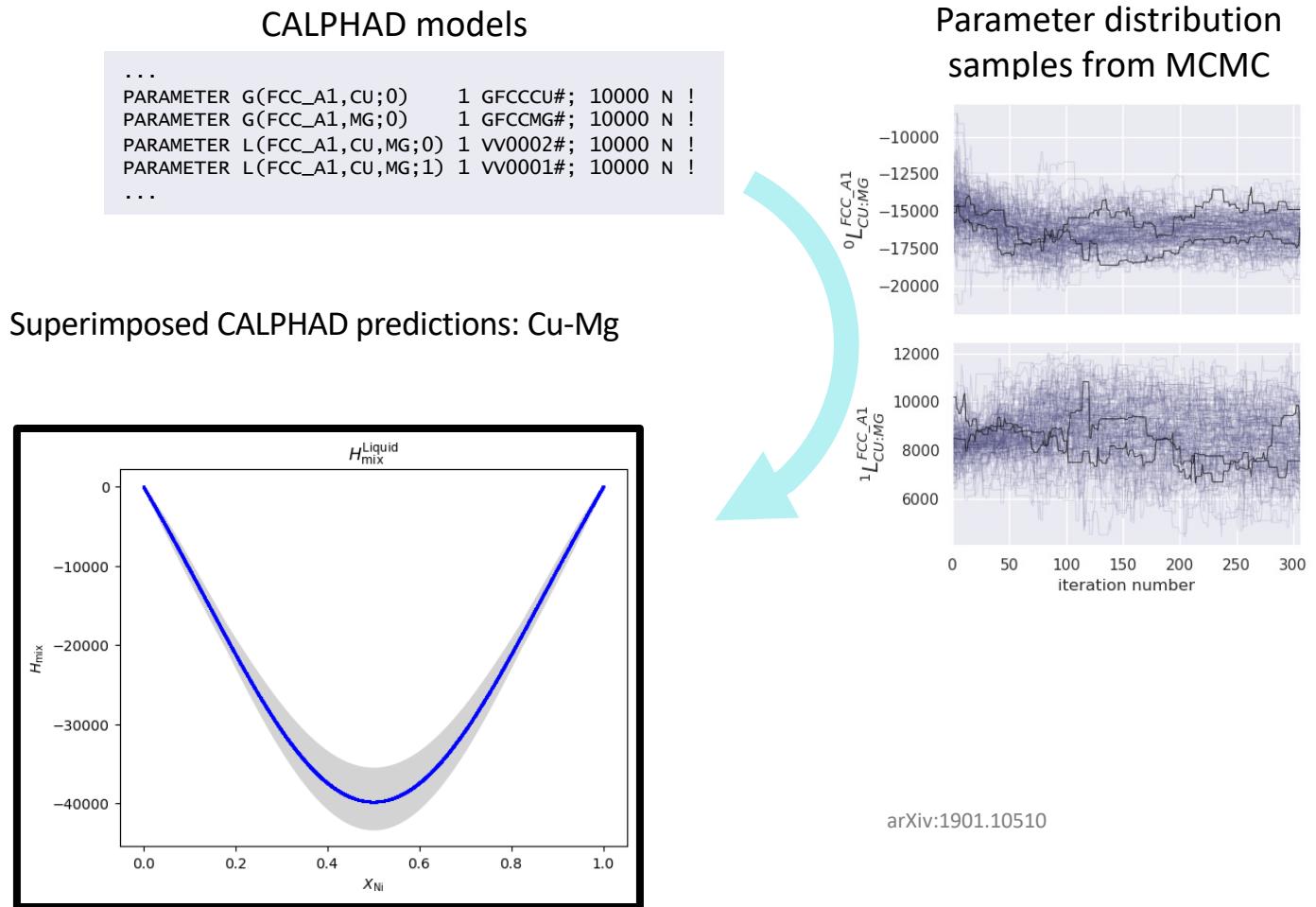
Bocklund, MRS Comm (2019)



Paulson, Acta Mat. (2019)



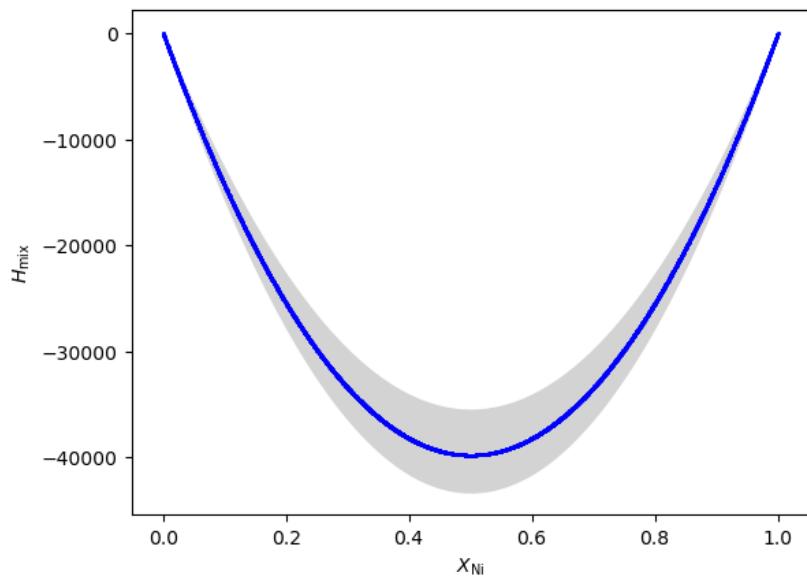
# Propagate uncertainty to thermodynamic properties



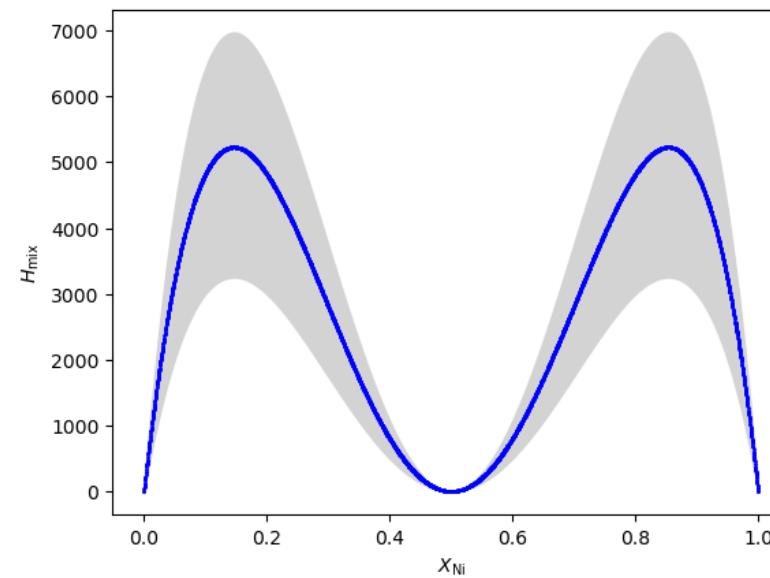
Paulson, Acta Mat. (2019)

# Uncertainty quantification in liquid interaction parameters

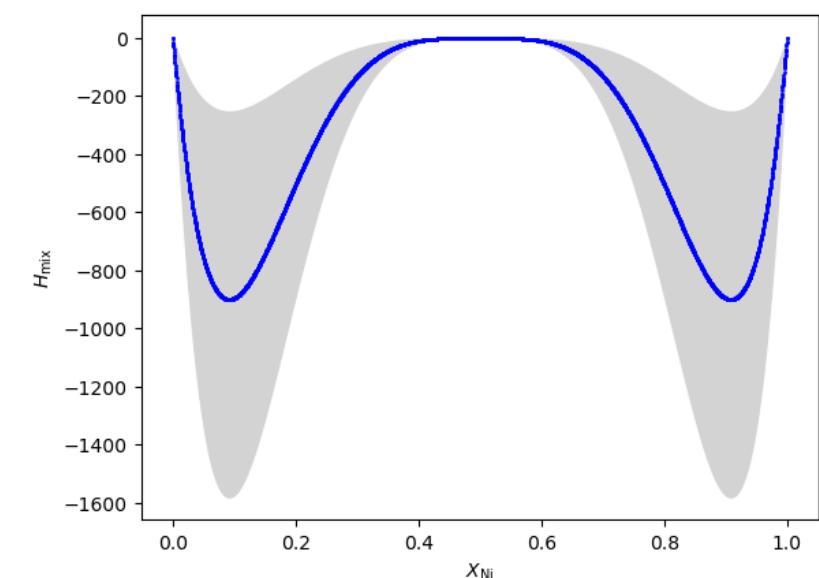
${}^0L^{\text{liquid}}$



${}^1L^{\text{liquid}}$



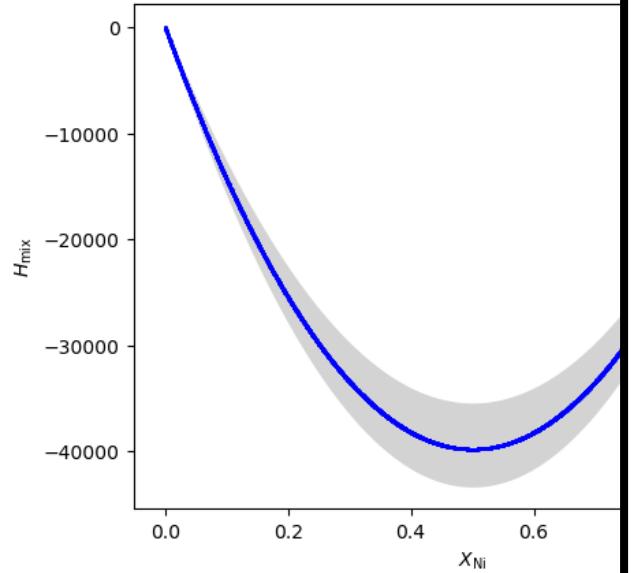
${}^2L^{\text{liquid}}$



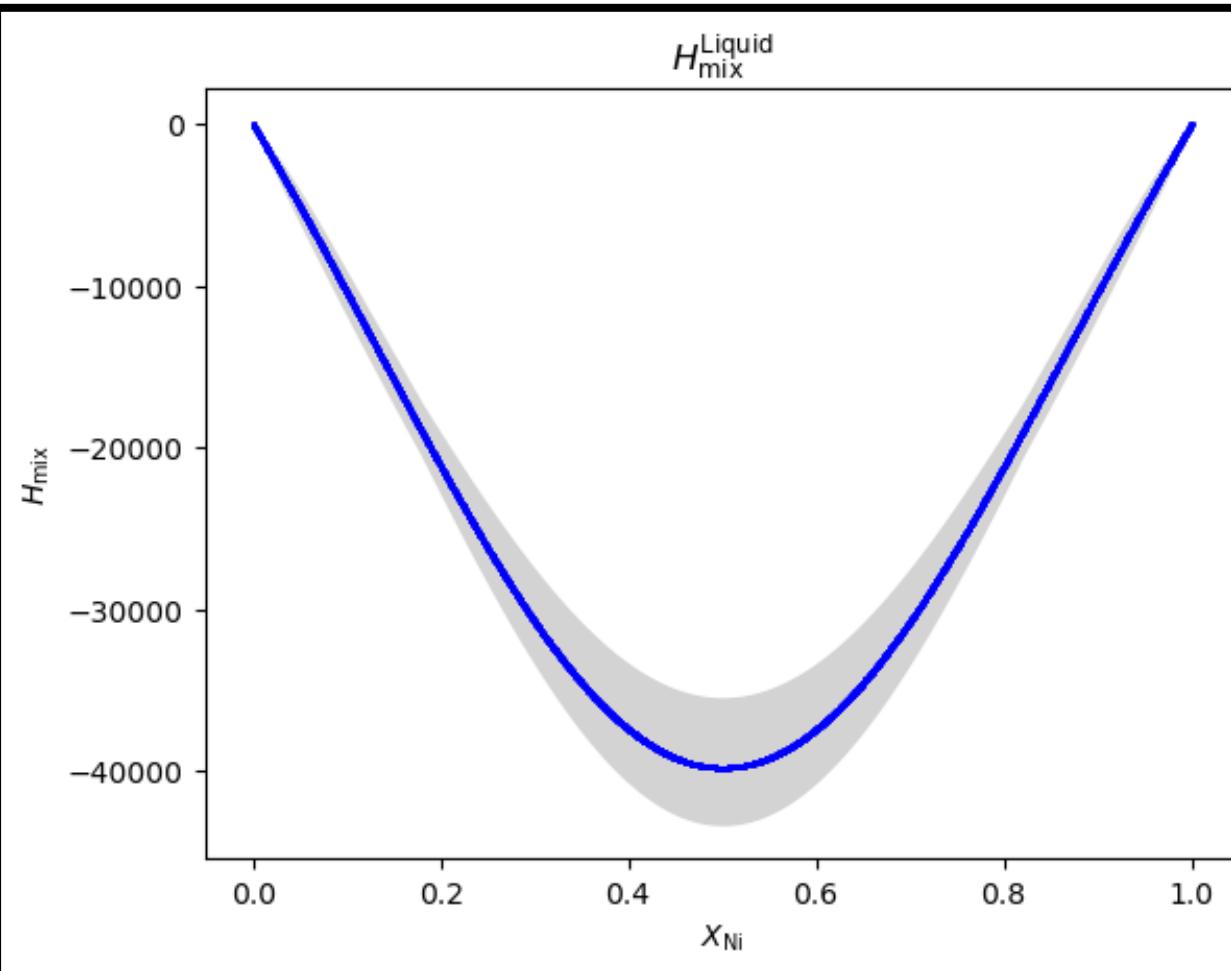
$$\sum_{i,j \neq i} x_i x_j (x_i - x_j)^\nu {}^{\nu}L$$

# Uncertainty quantification in liquid interaction parameters

${}^0L^{\text{liquid}}$

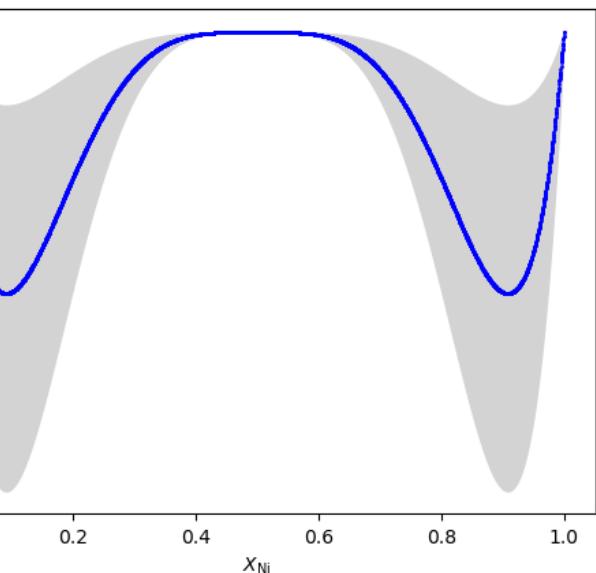


$H_{\text{mix}}^{\text{Liquid}}$

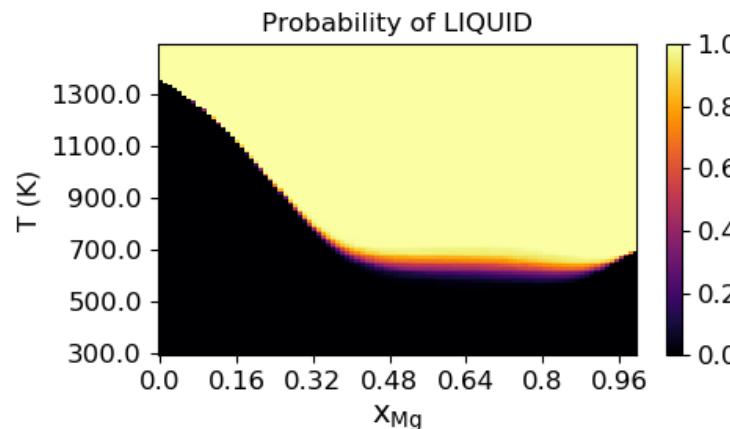
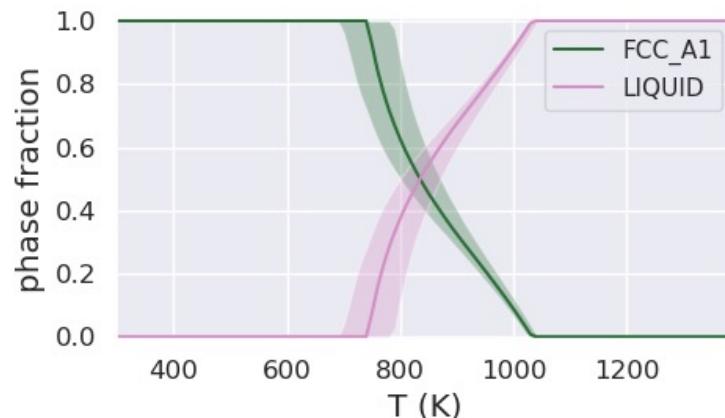
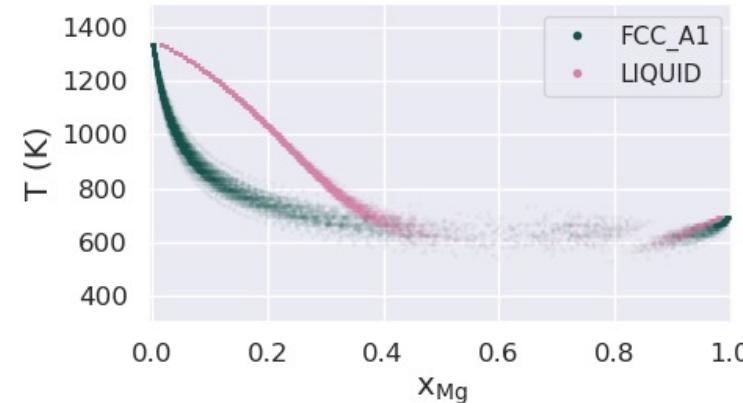
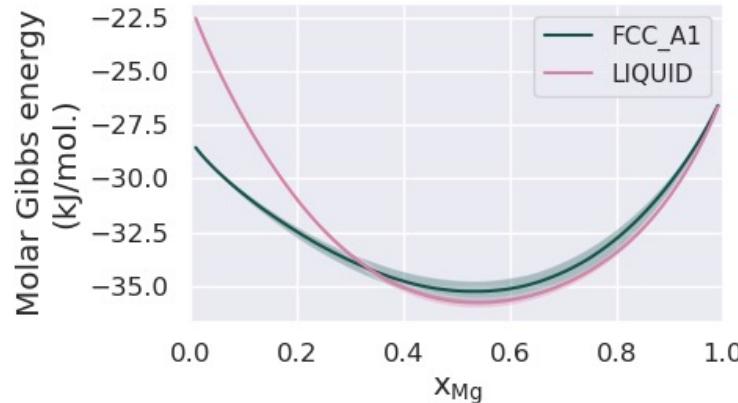


$i, j \neq i$

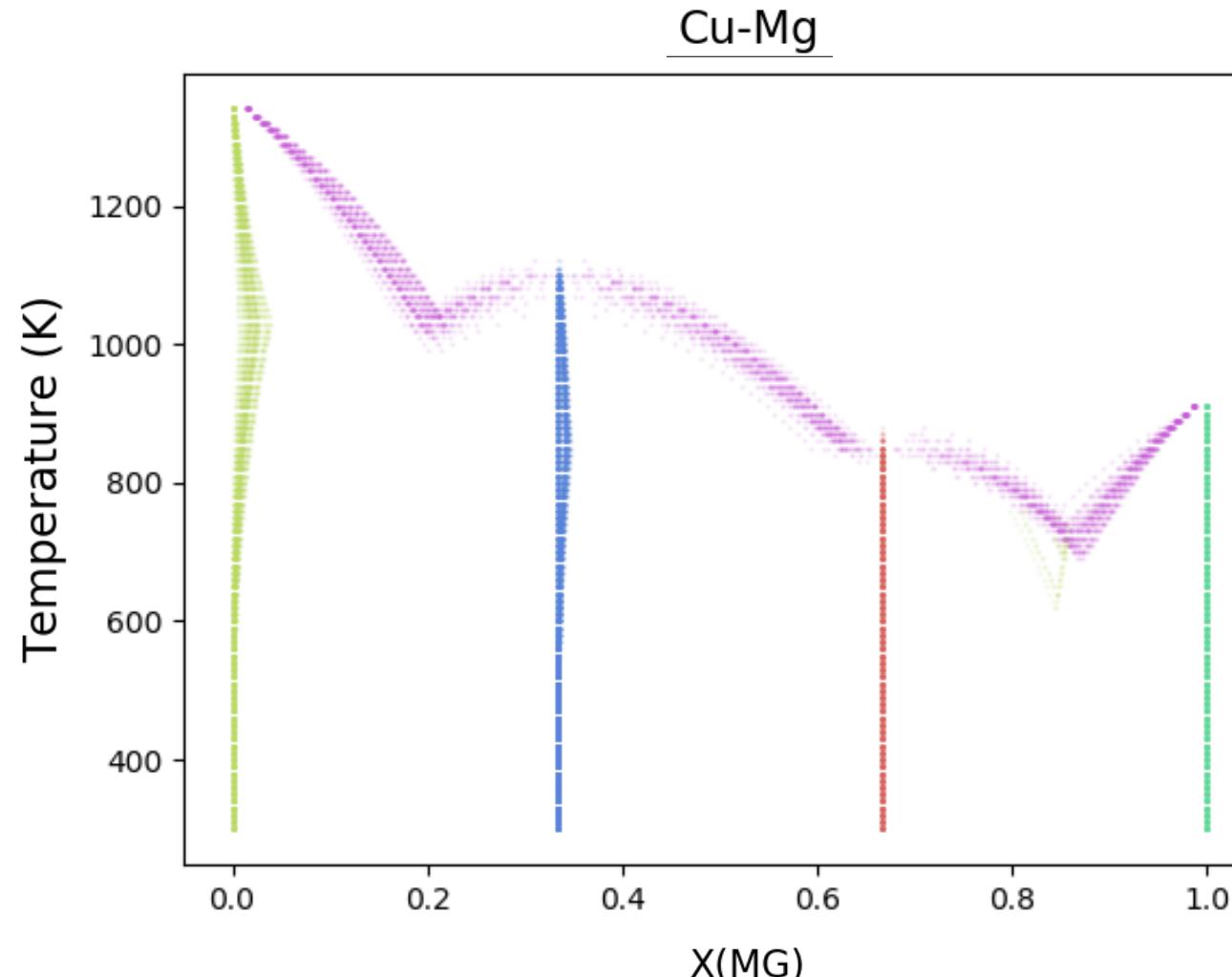
${}^2L^{\text{liquid}}$



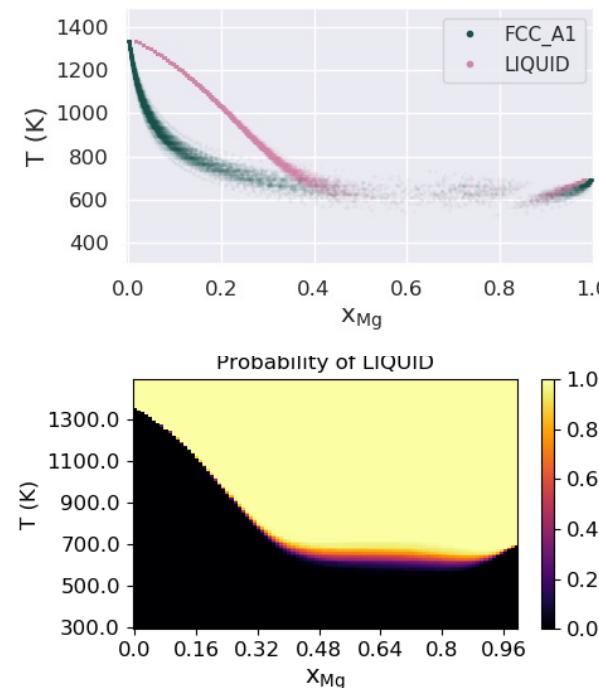
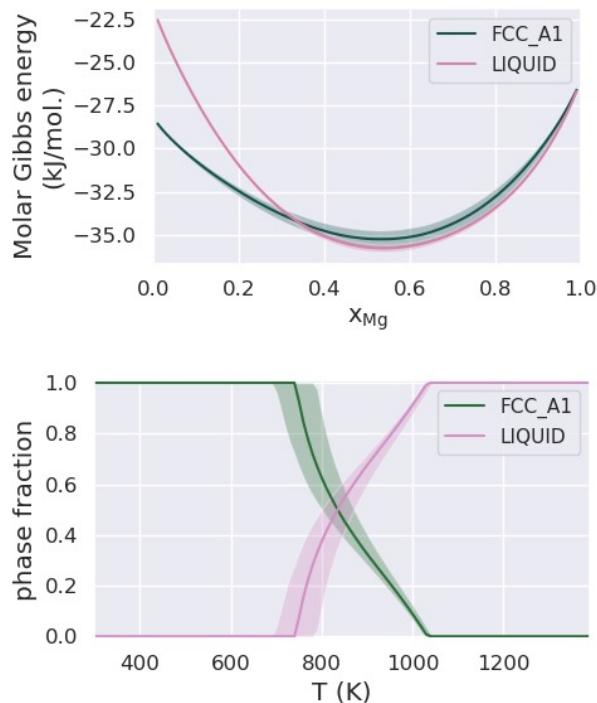
# Propagation of uncertainty to calculated properties and phase diagrams



# Propagation of uncertainty to calculated properties and phase diagrams



# PDUQ: Phase Diagram Uncertainty Quantification package



Noah Paulson

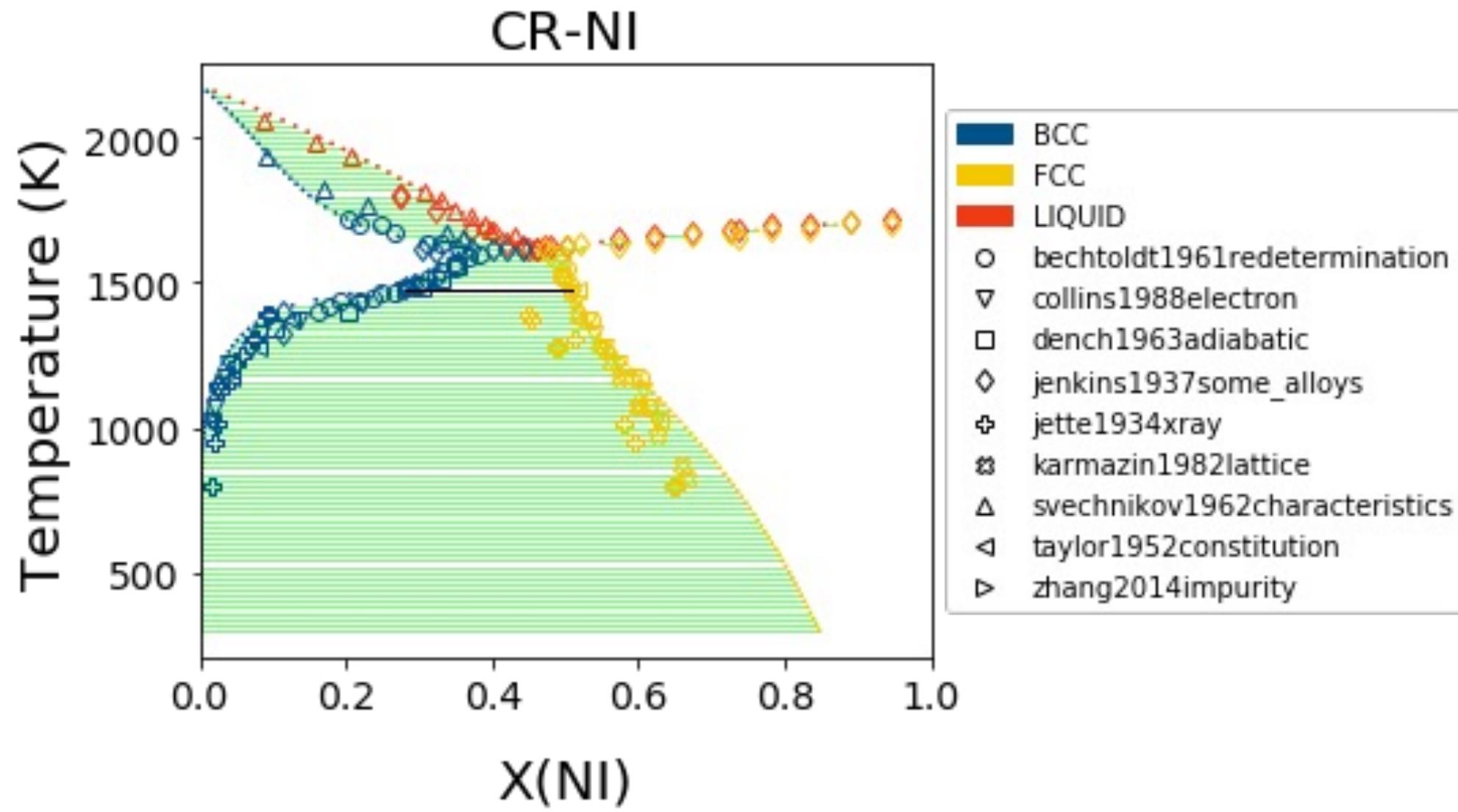


Marius Stan

Argonne National Lab

<https://pduq.readthedocs.io>

# Cr-Ni Phase Diagram (2000 MCMC iterations)



<https://doi.org/10.1557/jmr.2020.269>

## Sensitivity estimation for calculated phase equilibria

Richard Otis<sup>1,a)</sup> , Brandon Bocklund<sup>2</sup> , Zi-Kui Liu<sup>2</sup>

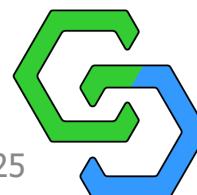
<sup>1</sup>*Engineering and Science Directorate, Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California 91109, USA*

<sup>2</sup>*Department of Materials Science and Engineering, Pennsylvania State University, University Park, Pennsylvania 16802, USA*

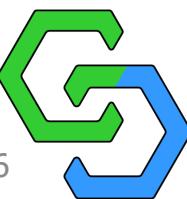
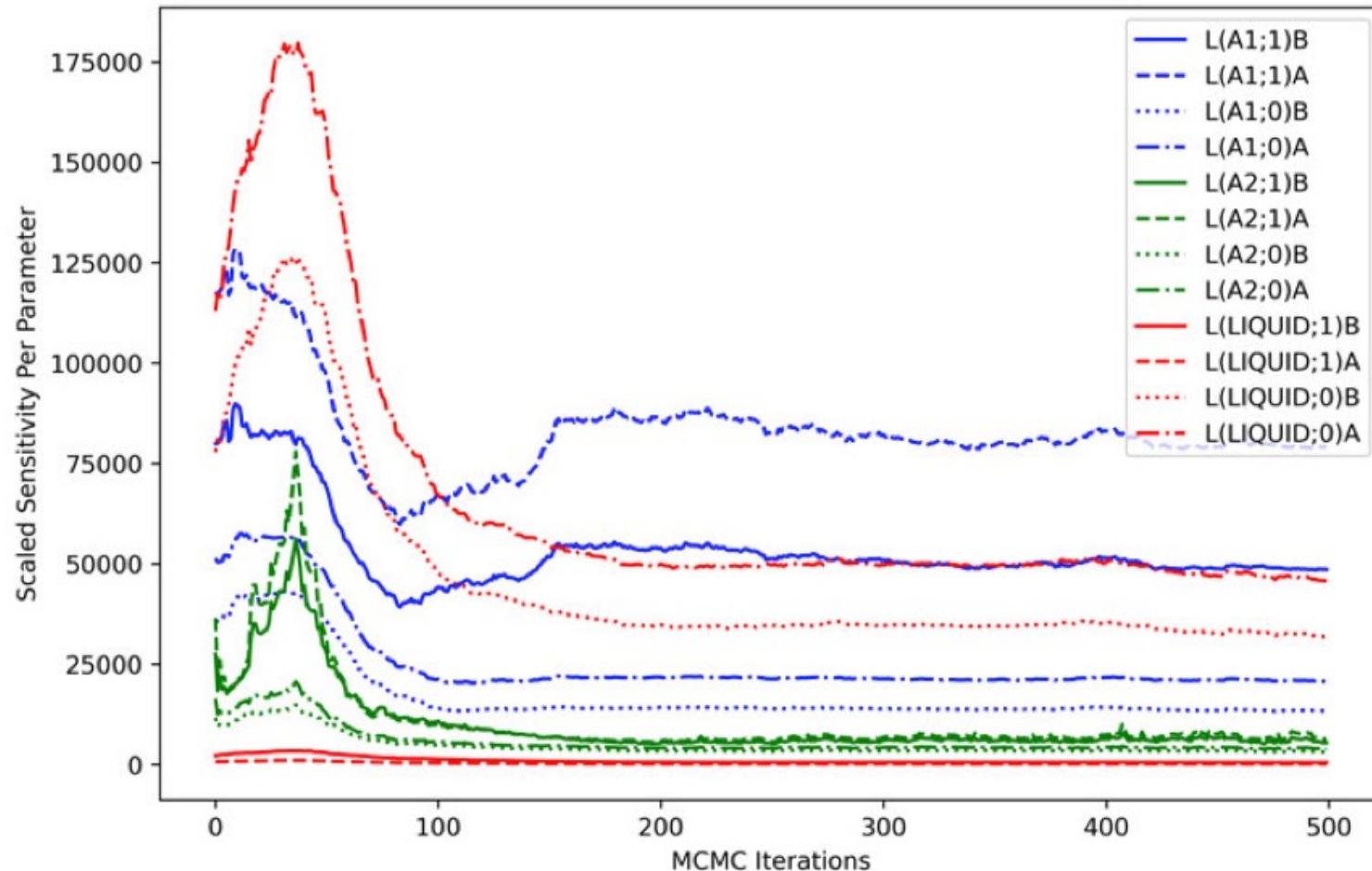
<sup>a)</sup>Address all correspondence to this author. e-mail: richard.otis@jpl.nasa.gov

Received: 29 June 2020; accepted: 4 September 2020

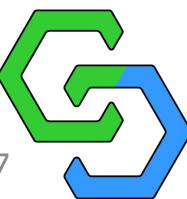
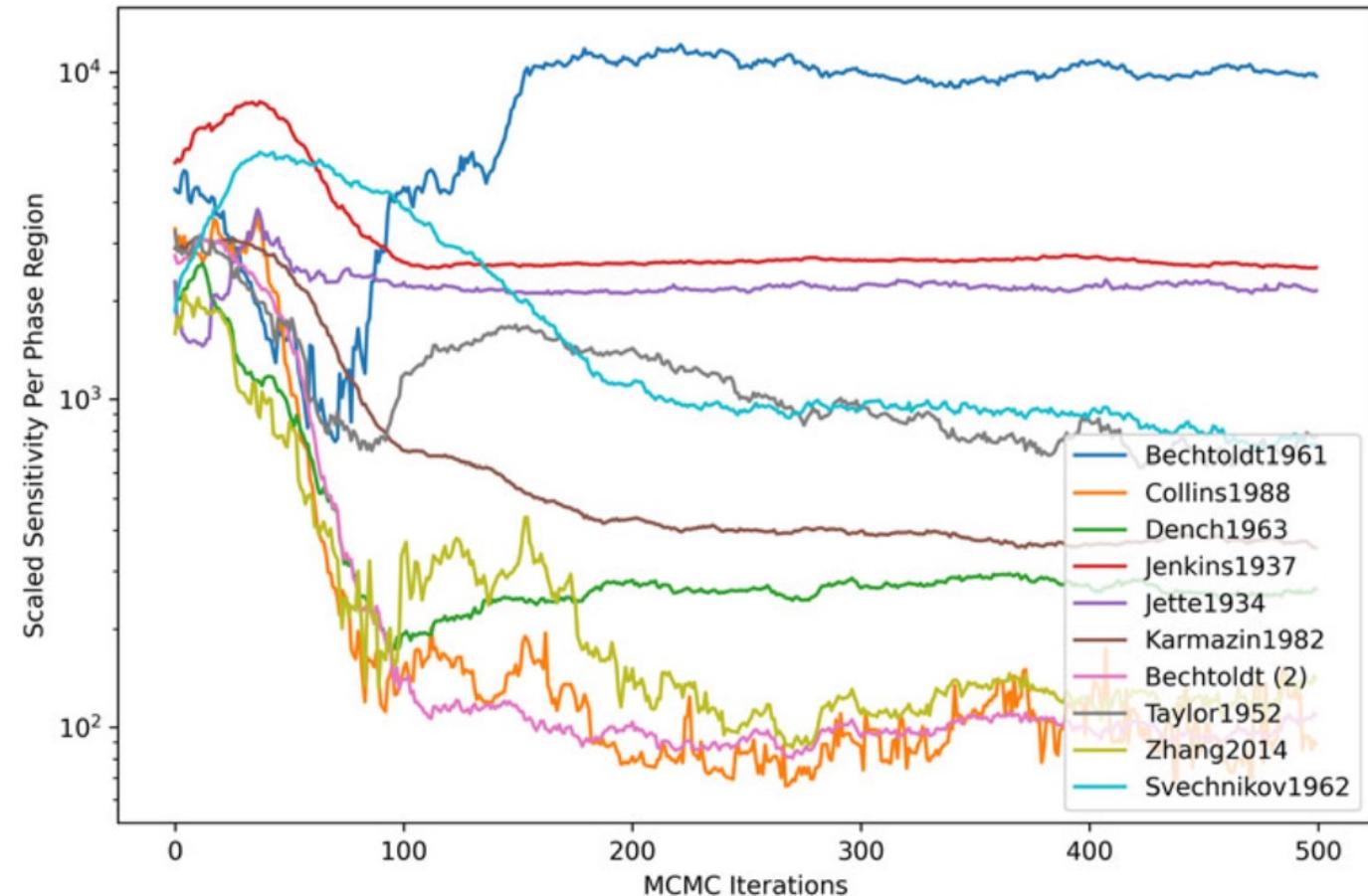
The development of a consistent framework for Calphad model sensitivity is necessary for the rational reduction of uncertainty via new models and experiments. In the present work, a sensitivity theory for Calphad was developed, and a closed-form expression for the log-likelihood gradient and Hessian of a multi-phase equilibrium measurement was presented. The inherent locality of the defined sensitivity metric was mitigated through the use of Monte Carlo averaging. A case study of the Cr–Ni system was used to demonstrate visualizations and analyses enabled by the developed theory. Criteria based on the classical Cramér–Rao bound were shown to be a useful diagnostic in assessing the accuracy of parameter covariance estimates from Markov Chain Monte Carlo. The developed sensitivity framework was applied to estimate the statistical value of phase equilibria measurements in comparison with thermochemical measurements, with implications for Calphad model uncertainty reduction.



# Cr-Ni Parameter Sensitivity



# Cr-Ni Dataset Sensitivity



# Interactive Demo

## Uncertainty Propagation

# Summary of Notable Features

- Parameter generation
  - Generate multicomponent CEF models with Redlich-Kister polynomials from thermochemical data
  - Select optimal model forms based on statistical information criteria
- MCMC optimization, UQ, and UP
  - Optimize and quantify uncertainty for any PyCalphad model
  - Software infrastructure designed to be extendable to new types of data and different optimization and UQ backends
  - HPC capable
- Command line interface and interactive Python API are supported

# Getting help

- PyCalphad
  - <https://pycalphad.org>
  - Gitter channel (chat)
    - <https://gitter.im/pycalphad/pycalphad>
  - GitHub Discussions (forums)
    - <https://github.com/pycalphad/pycalphad/discussions>
- ESPEI
  - <https://espei.org>
  - Gitter channel (chat)
    - <https://gitter.im/PhasesResearchLab/ESPEI>
  - GitHub Discussions (forums)
    - <https://github.com/phasesresearchlab/espei/discussions>



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