

# Predictive Modeling for Strongly Correlated *f*-electron Systems:

## *A first-principles and database driven machine learning approach*

Towfiq Ahmed<sup>1</sup>, Adnan Khair<sup>2</sup>, Debbrata Saha<sup>2</sup>, Abdullah Mueen<sup>2</sup>, Heike Harper<sup>3</sup>, Olle Eriksson<sup>3</sup>, John Wills<sup>1</sup>, Jianxin Zhu<sup>1</sup>, Alexander Balatsky<sup>4</sup>

(1) T-Division, LANL, Los Alamos, NM, USA; (2) CSC, UNM, Albuquerque, NM, USA; (3) Uppsala University, Stockholm, Sweden (4) IMS, Los Alamos, NM, USA

**Abstract:** We are developing data driven computational tools for theoretical understanding of electronic properties in *f*-electron based materials, e.g., Ce compounds. Due to a complex interplay among the hybridization of *f*-electrons to non-interacting conduction band, spin-orbit coupling, and strong coulomb repulsion of *f*-electrons, no model or first-principles based theory can fully explain all the structural and functional phases of *f*-electron systems. Motivated by the large need in predictive modeling of actinide compounds, we adopted a data-driven approach. We are developing electronic structure database which will be potentially aided by machine learning (ML) algorithm to extract complex electronic, magnetic and structural properties in *f*-electron system, and thus, will open up new pathways for predictive capabilities and design principles of complex materials.

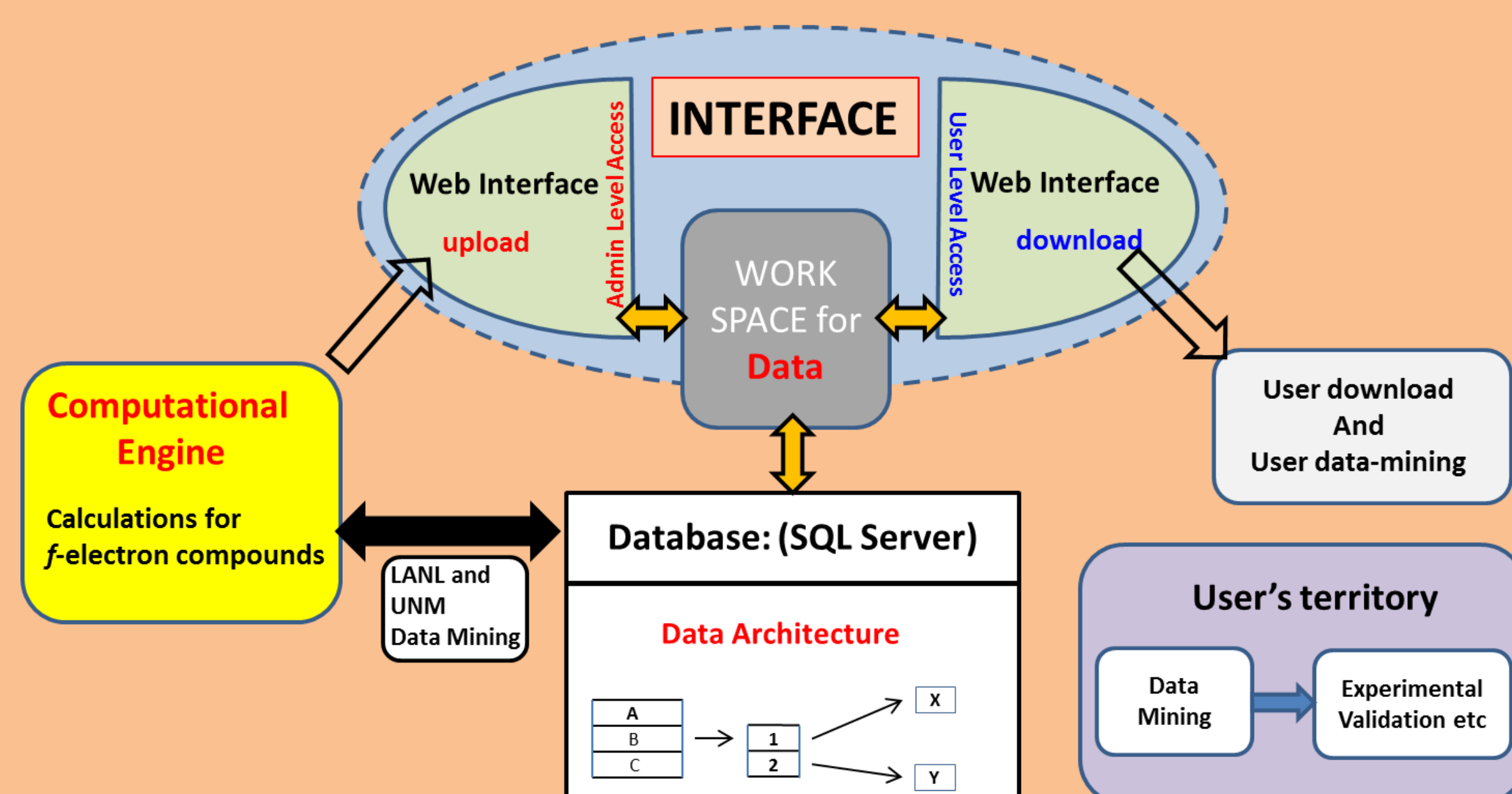
### Overview

**Goal:** Explore the rich and complex electronic and structural properties of *f*-electron systems aided by theory, large simulated data and machine learning (ML) methods in order to achieve deeper physical understanding and better predictability to engineer next generation correlated materials.

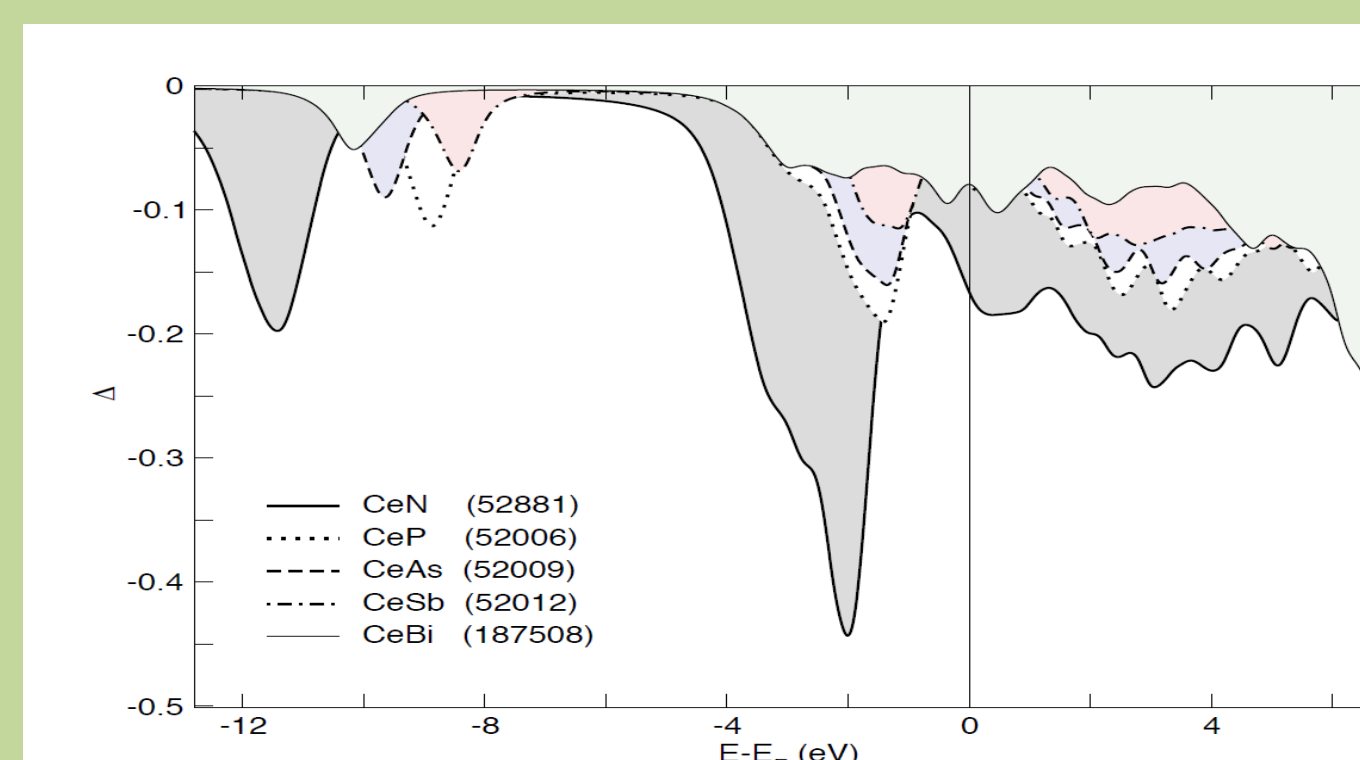
### Why “Theory + ML” ?

**Theory** → Accurate physical theories for strongly correlated system involve quantum many-body effect. Thus, computationally extremely expensive and impractical for simulating larger systems.

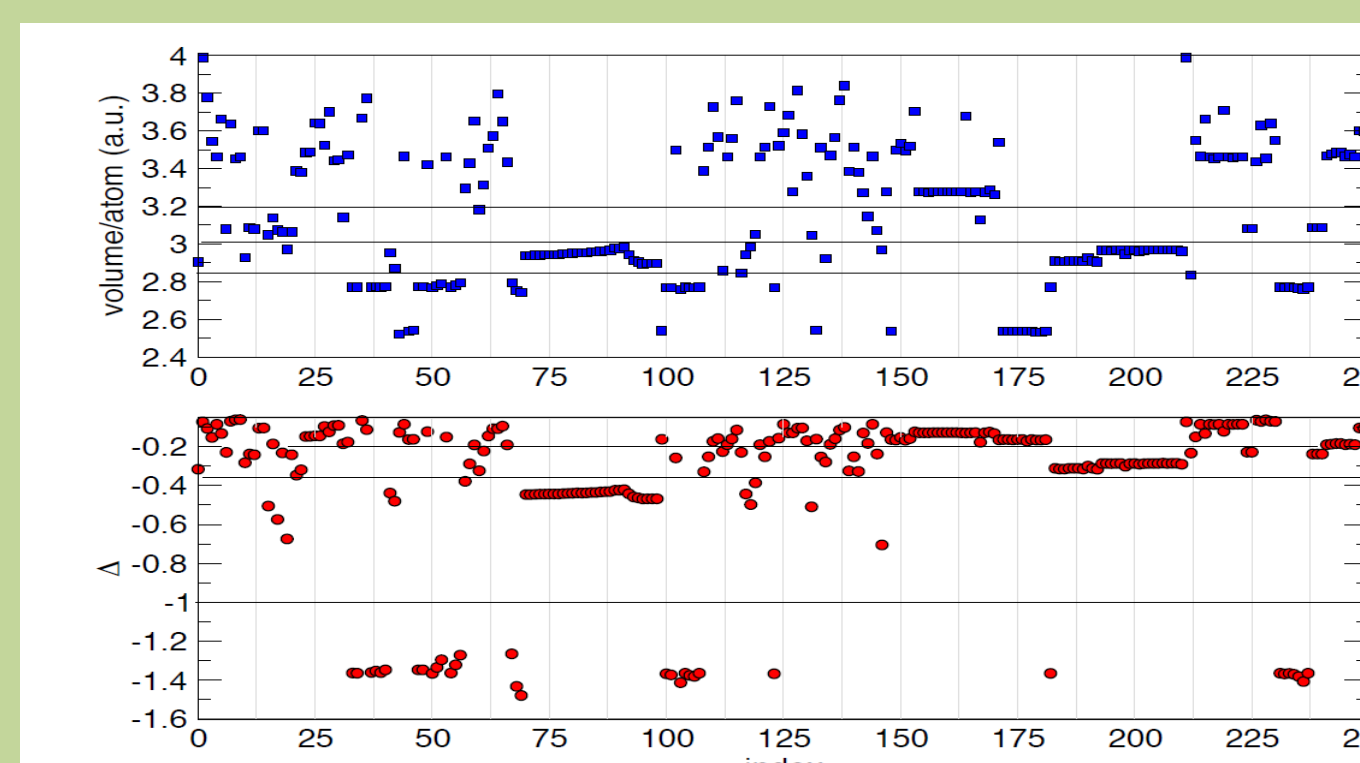
**Theory + ML** → Density functional theory with LDA gives approximate results and computationally faster. Therefore, aided by large number of simulation data and ML, qualitative trend can help build new physical insight.



### Example DFT Calculation: Ce compounds

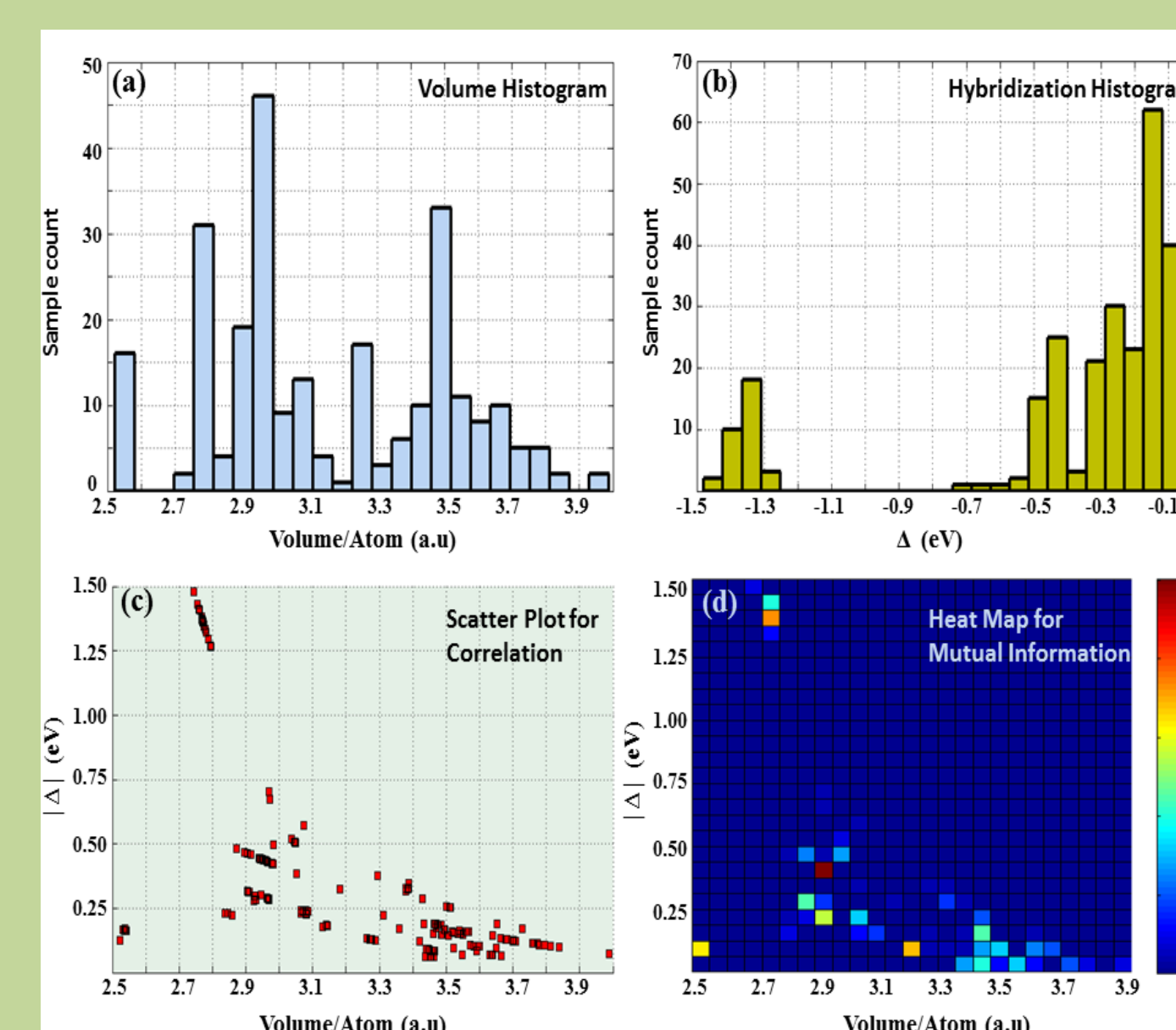


Calculated hybridization function  $\Delta$  depends on the energy relative to the Fermi level  $E_F$  for binary Ce compounds. The numbers in the brackets denote the ICSD references number.



Maximum values of the hybridization function for binary cubic Ce compounds (bottom) and the experimental volume/atom for the same set of compounds (top).

### Correlation between ‘Volume’ and ‘Hybridization’



Reference: Manuscript under preparation

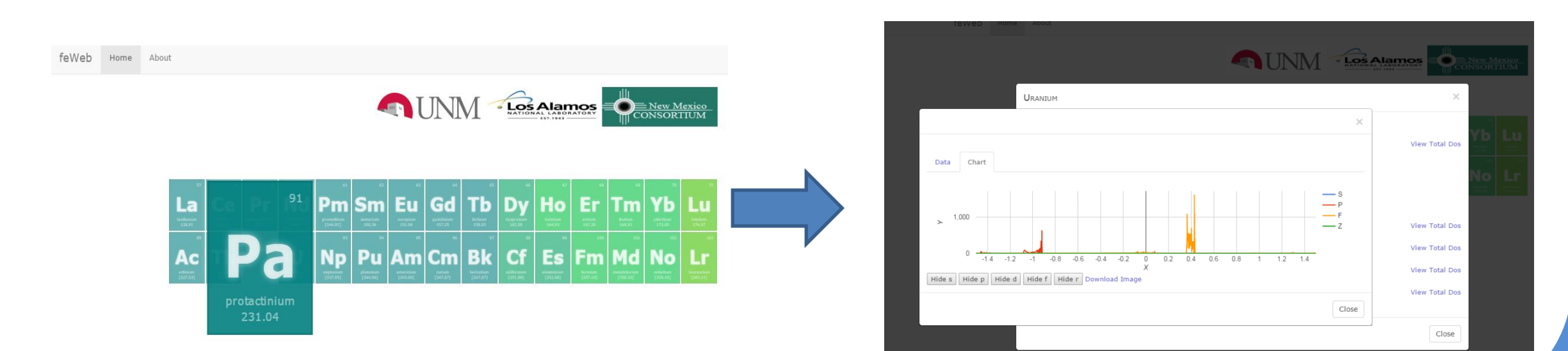
(a) and (b) are the distribution of 257 Ce compound data on volume/atom (V) and hybridization energy ( $\Delta$ ) correspondingly. In (c)  $\Delta$  vs. V provides correlation between the two data sets (see text for details). 2D heat-map is (d). Colors represents the number count of Ce compounds in each cell. Heat-map provides joint probability distribution and measures mutual information  $I(V, \Delta)$ .

$$(c) \text{ Correlation Coefficient: } r(V, \Delta) = \frac{\sum_{i=1}^{257} (V(i) - \bar{V})(\Delta(i) - \bar{\Delta})}{\sqrt{(\sum_{i=1}^{257} (V(i) - \bar{V})^2)(\sum_{i=1}^{257} (\Delta(i) - \bar{\Delta})^2)}} = -0.5565$$

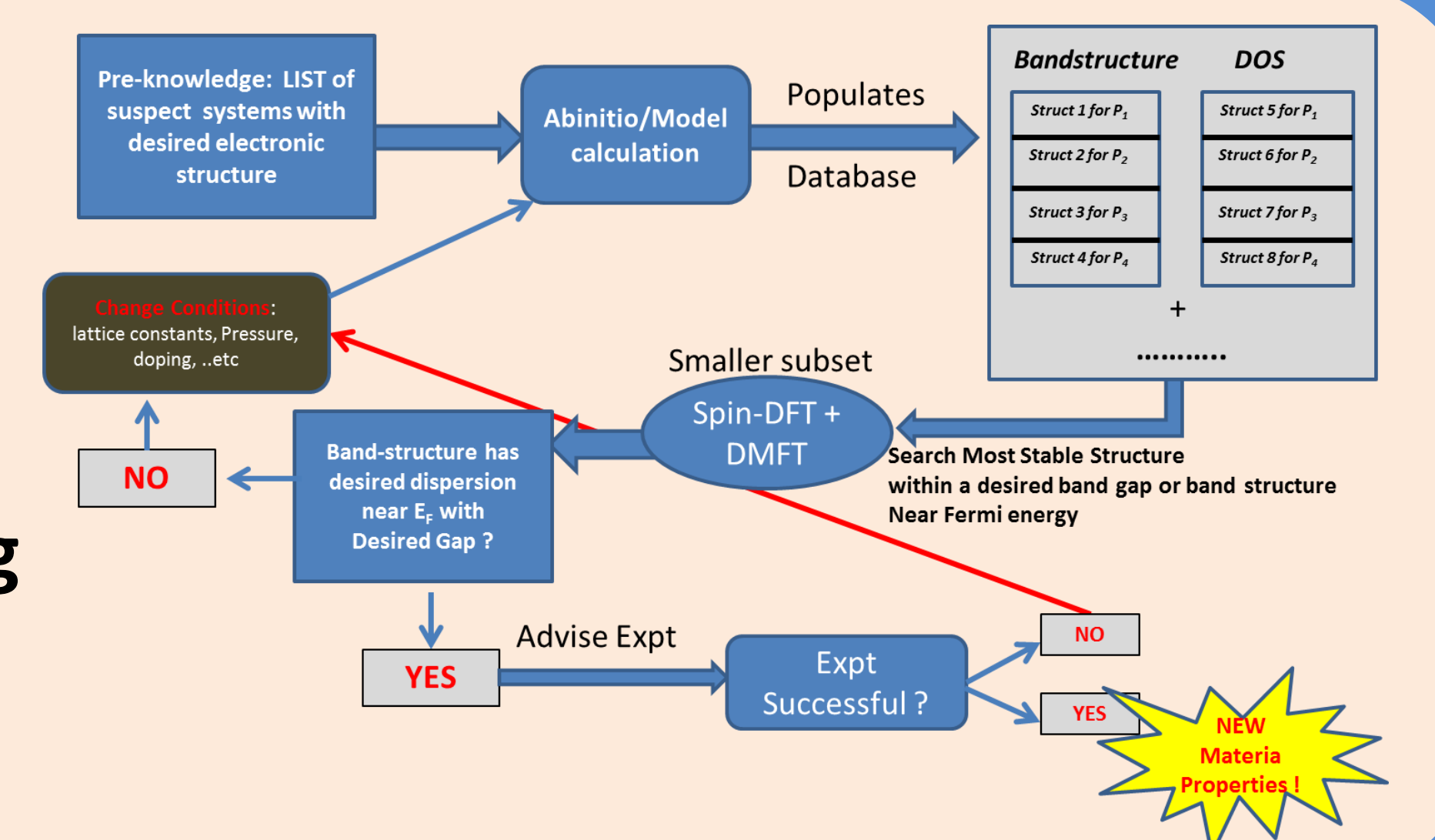
$$(c) \text{ Mutual Information: } I(V, \Delta) = \sum_{i \in V, j \in \Delta} P(i, j) \log \left( \frac{P(i, j)}{P(i)P(j)} \right) = 0.5757.$$

### Database Web Interface for *f*-electron System

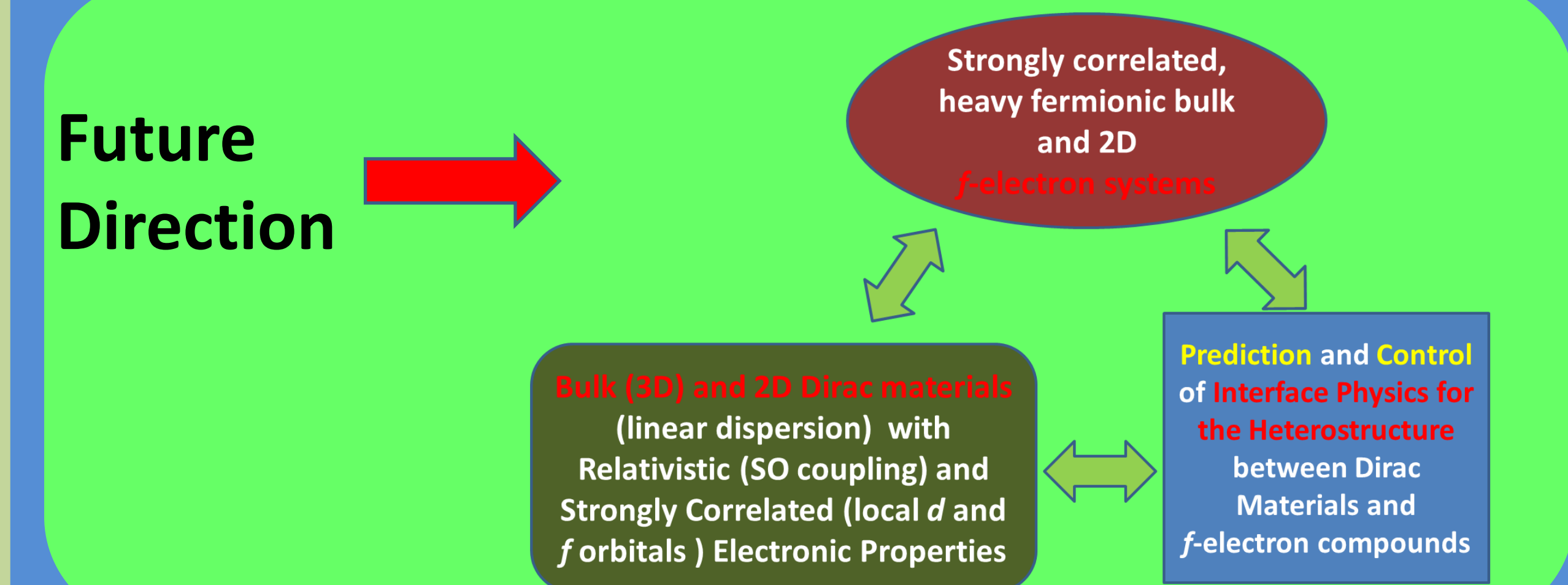
Website Hosted at NMC Server by Institute for Materials Sciences, LANL **Snapshot**



### Prediction using ML and Datamining



### Future Direction



### Acknowledgement

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