Los Alamos
NATIONAL LABORATORY

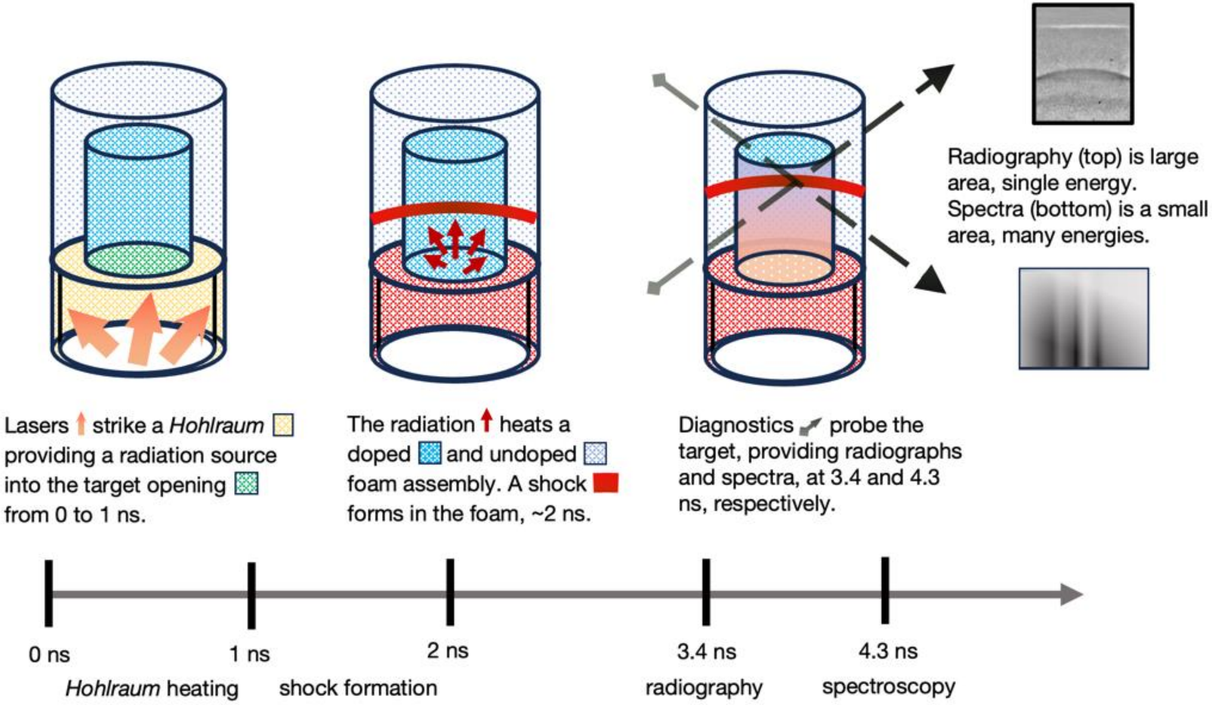
Inferring the complete state-vector evolution underlying HEDP experiments from limited diagnostic views

Ragib Arnab (CAI-3)

Shane Coffing (CAI-2), Garrett Kenyon (CAI-3),
Todd Urbatsch (XTD-IDA)

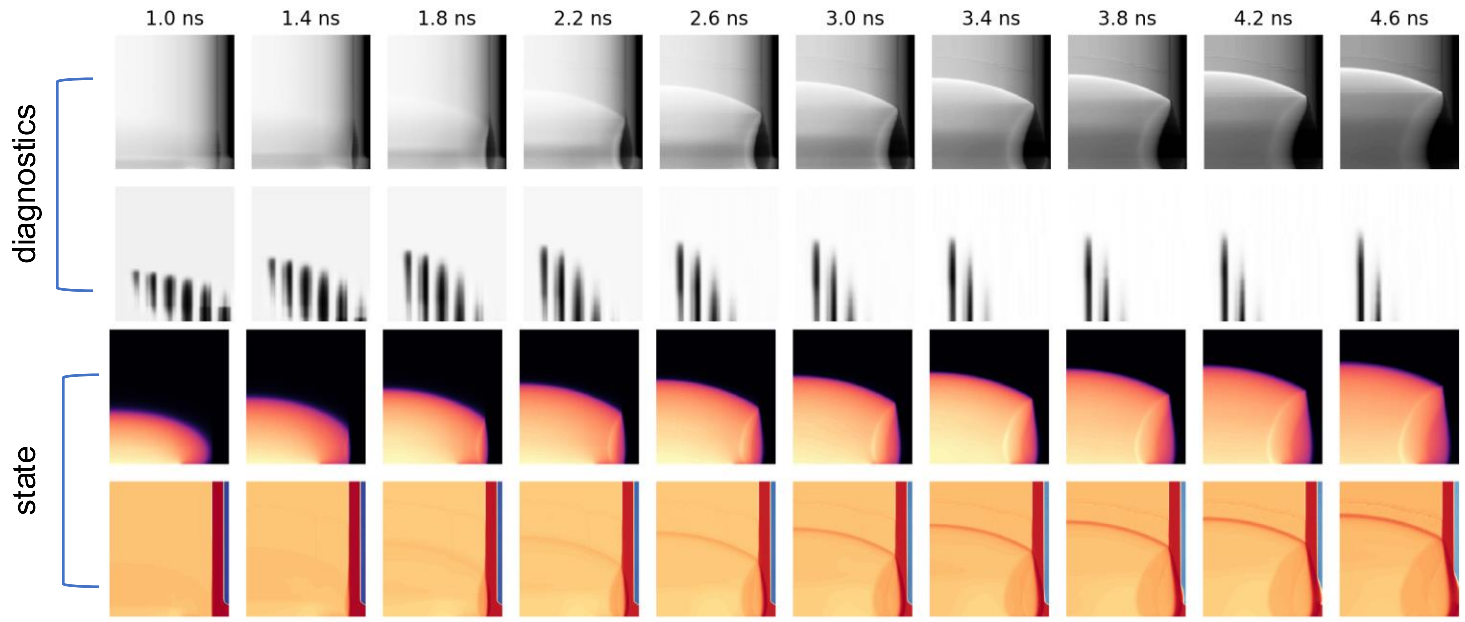
LA-UR-25-31027

We have a radflow experiment called COAX



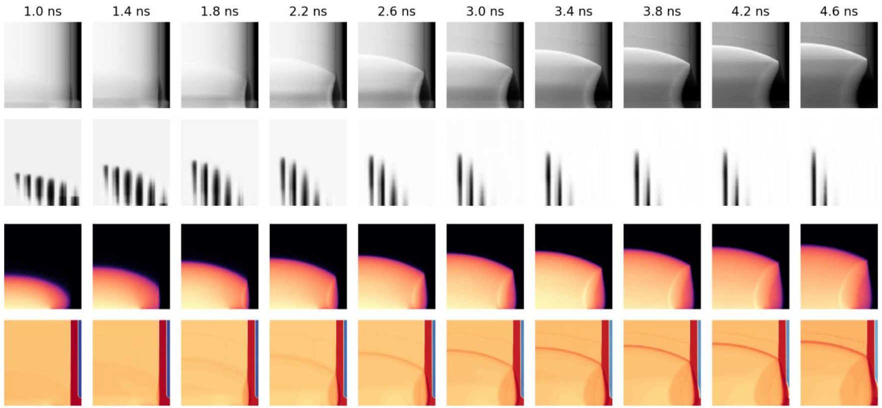
Simulations can model the state evolution

We know the full state and synthetic diagnostic videos in simulation.

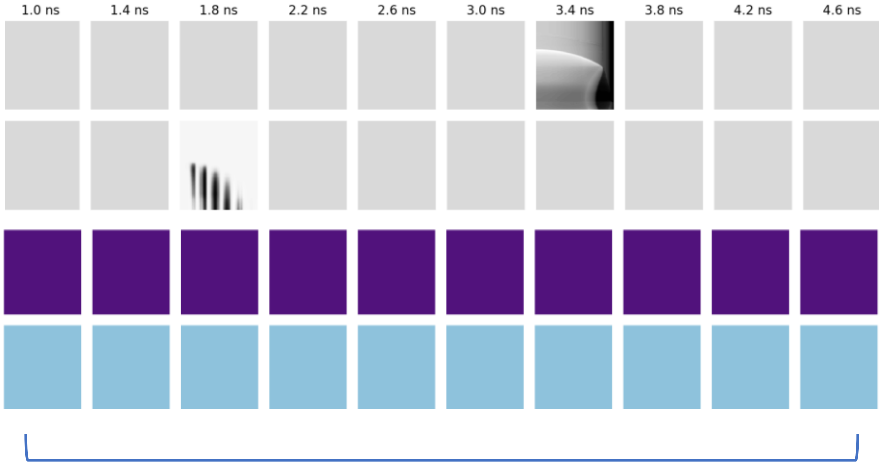


How can we infer the missing state in experiments?

Simulations:
We know everything.



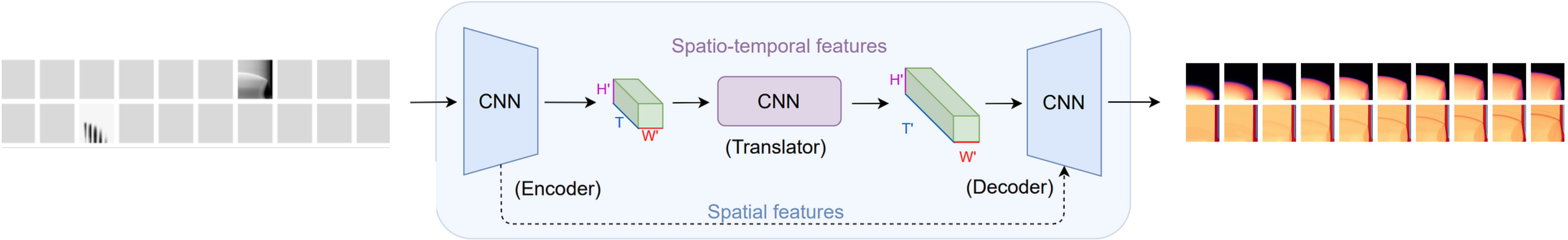
Experiment:
We know *very little*.



Can we infer ***any*** of this?

We use a video prediction network to infer state

We select SimVP* as our neural network.

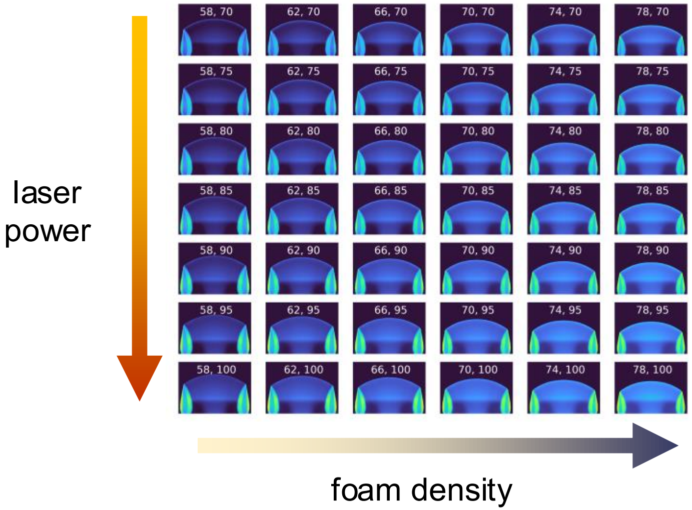


*Z. Gao, C. Tan, L. Wu and S. Z. Li, “SimVP: Simpler Yet Better Video Prediction,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2022, pp. 3170-3180.

We train on COAX simulations

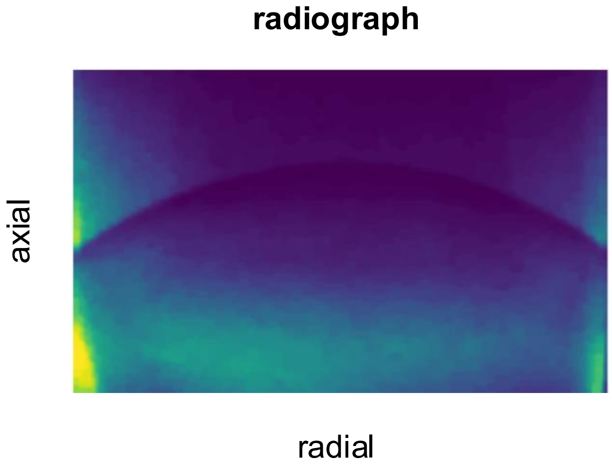
- 42 simulations
- 40 frames per simulation
- 6 state variables per frame
- Spectra and radiograph per frame
- We train on 1 ns sequences of 10 frames, for a total of 1,302 sequences

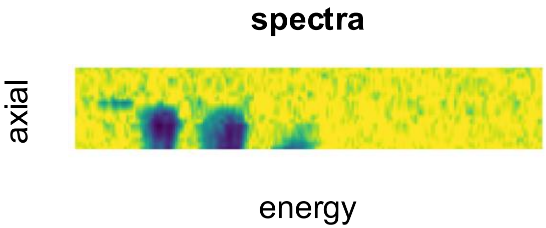
energy density at 3 ns



example model input

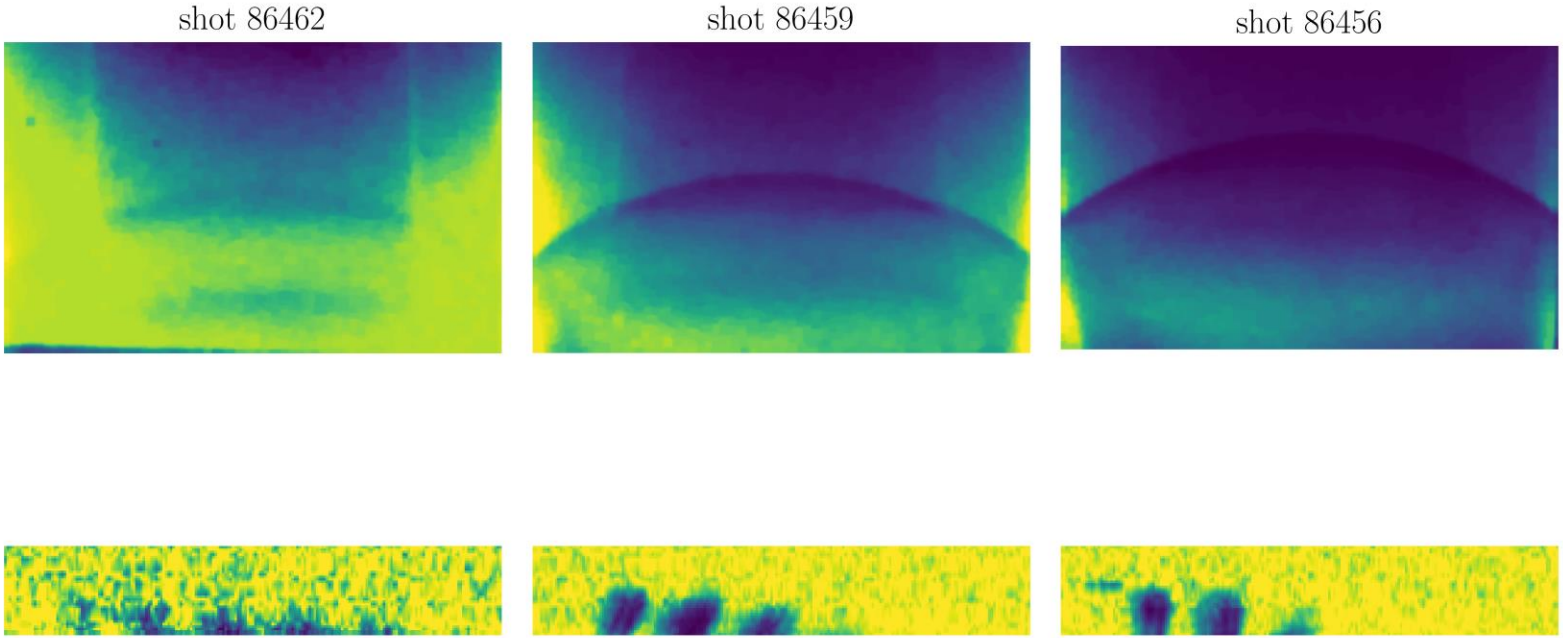
COAX 17C experimental data: radiography and spectra



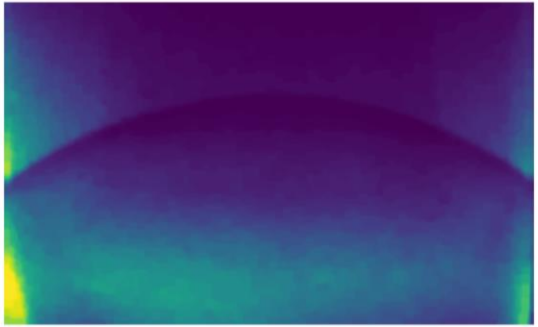


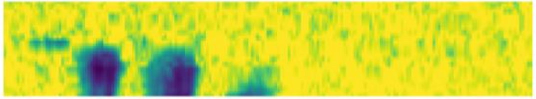
- Simulations are high quality, experiments… not so much
- We down-select and interpolate simulated data to match experimental data

Raw COAX data is *noisy*

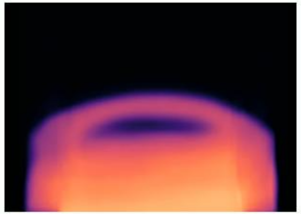


Shot 86456



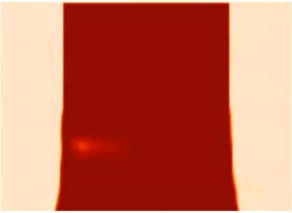


Temperature

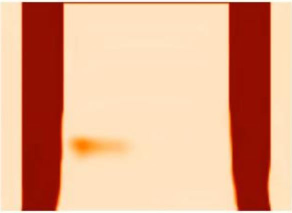


Density

Ti mass frac.



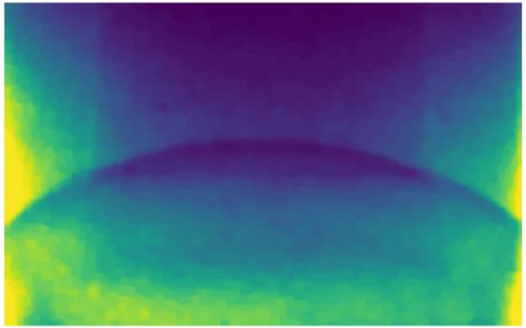
Si mass frac.

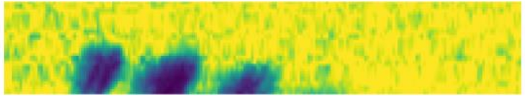


Be mass frac.

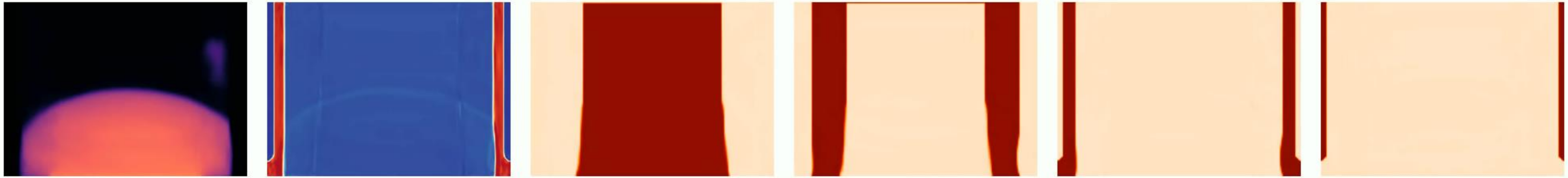
Air mass frac.

Shot 86459

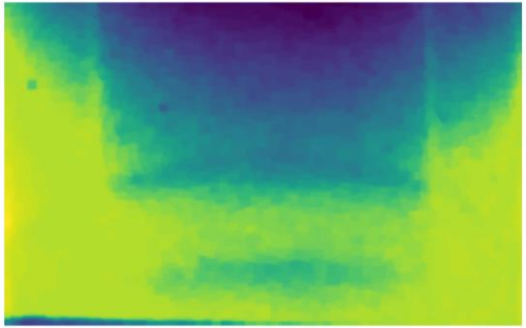


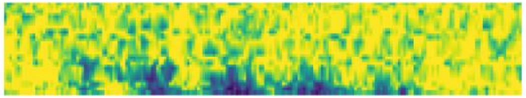


Temperature | Density | Ti mass frac. | Si mass frac. | Be mass frac. | Air mass frac.

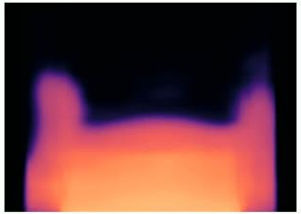


Shot 86462





Temperature



Density

Ti mass frac.

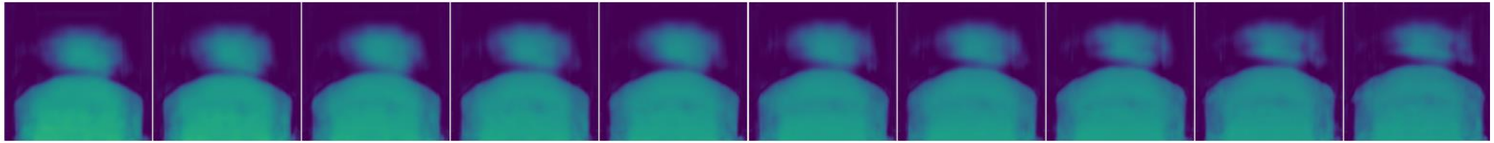
Si mass frac.

Be mass frac.

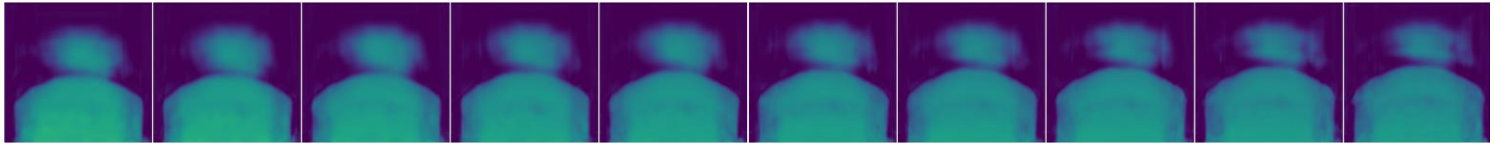
Air mass frac.

Data augmentation: evolution of success…

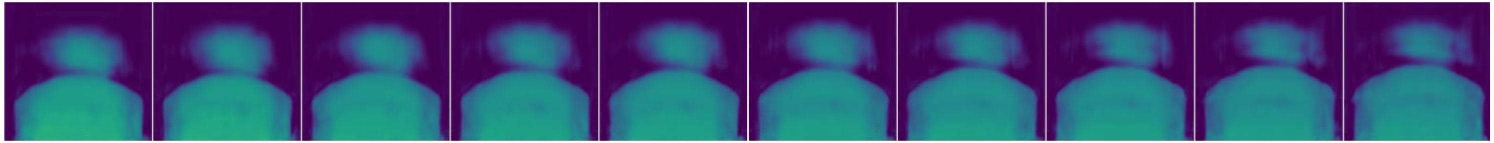
No modification



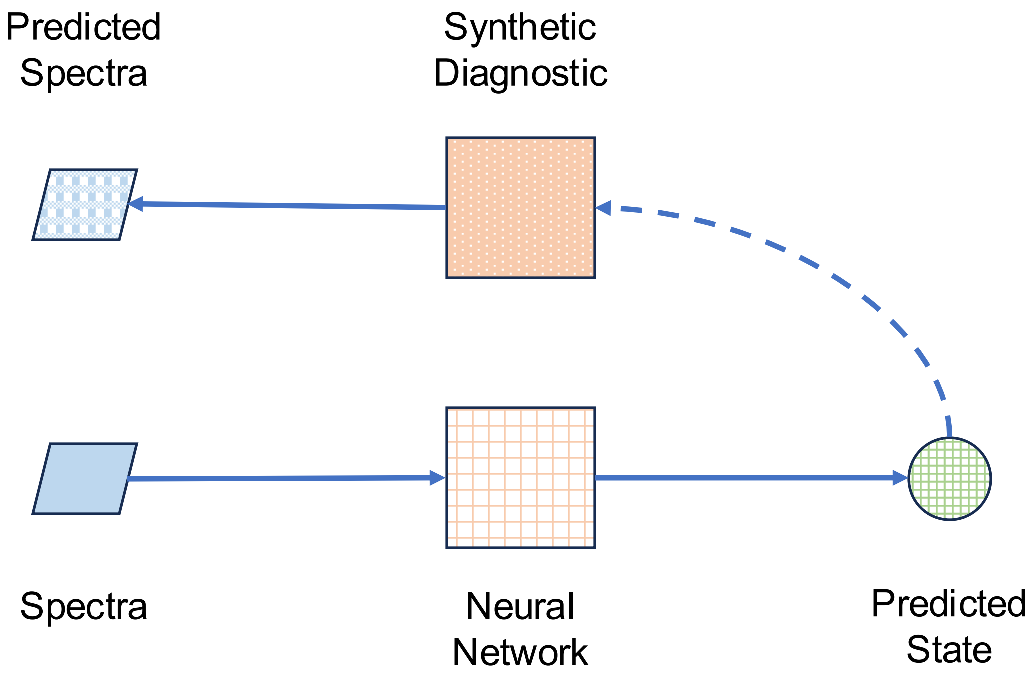
Add affine transforms

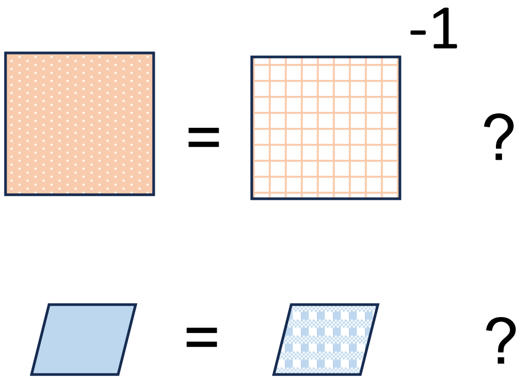


Add noise, blur

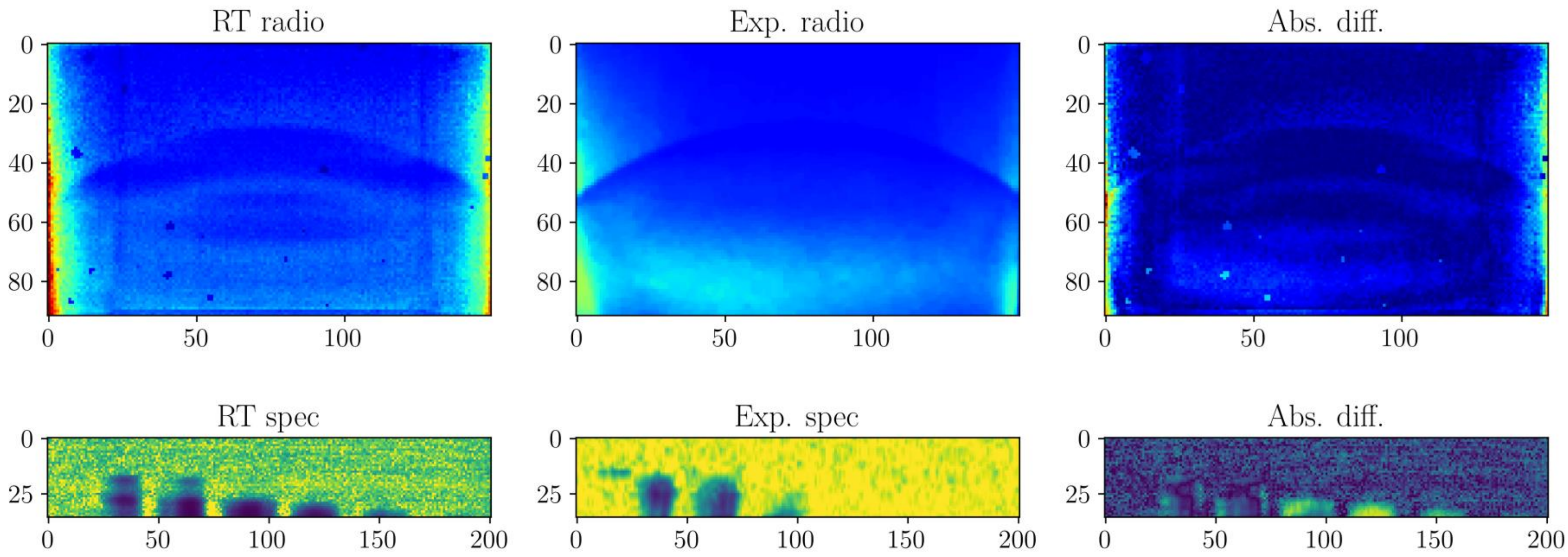


Round trip consistency



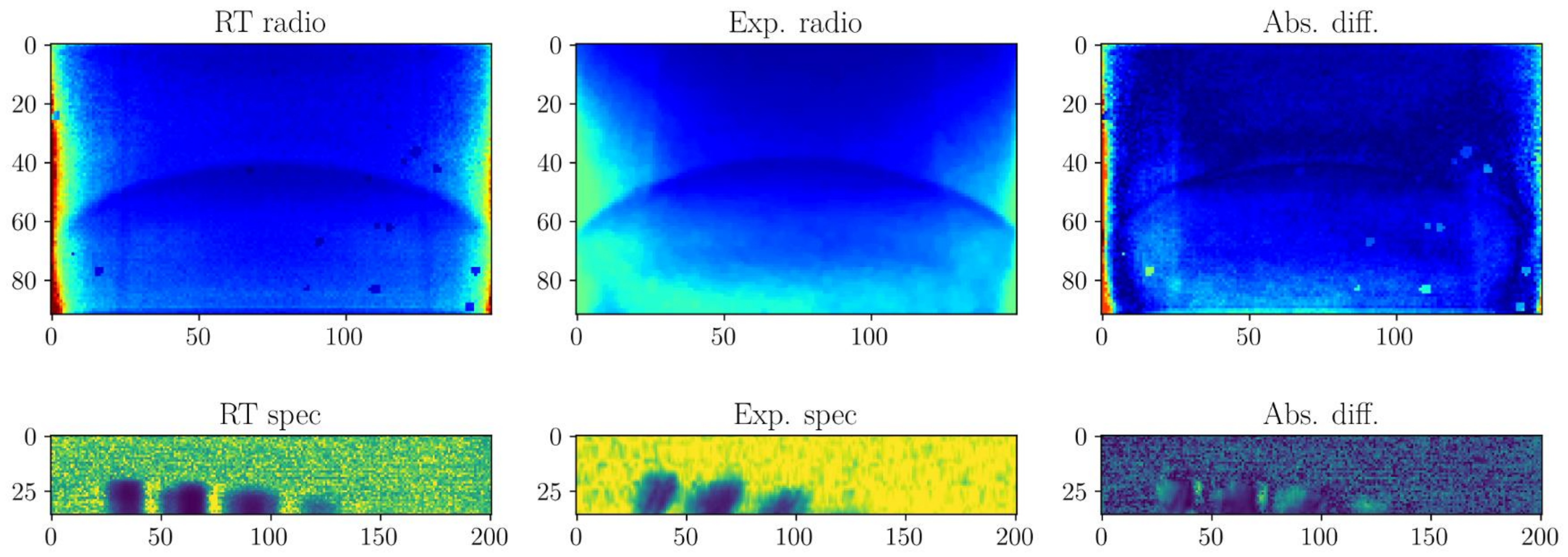


Inverse diagnostics: shot 86456



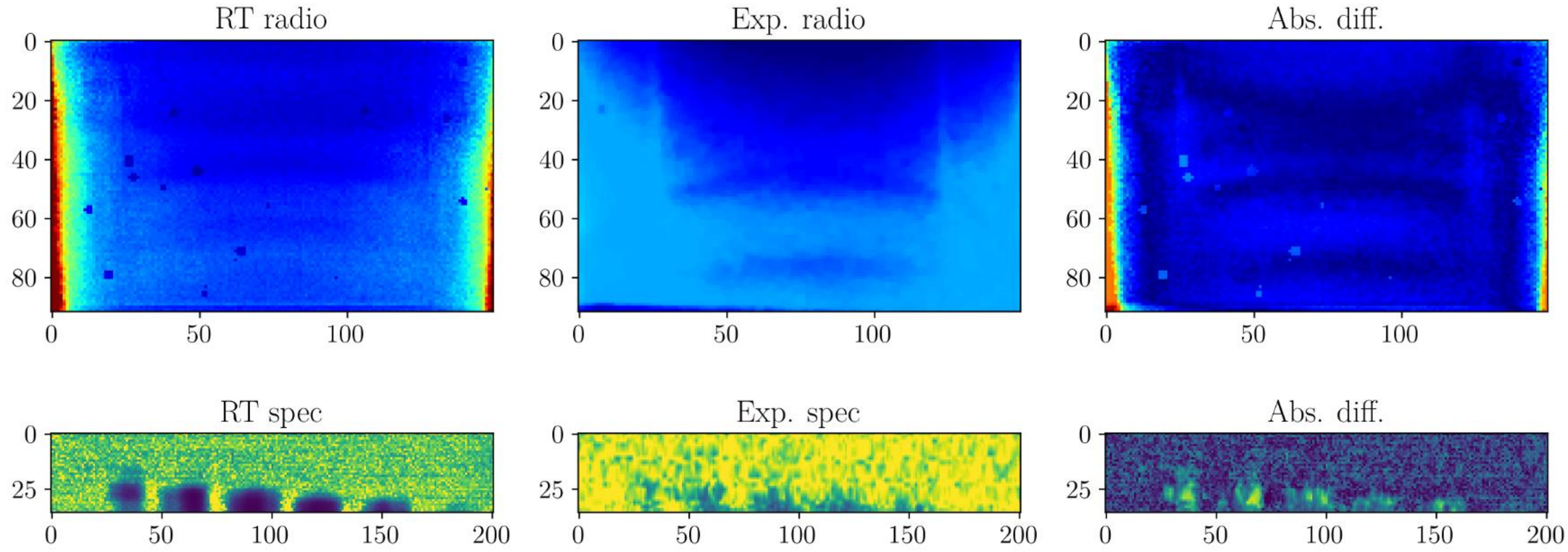
Radiography is outstanding, thinks spectra should be hotter?

Inverse diagnostics: shot 86459



Corrections to both radiography and spectra appear strong.

Inverse diagnostics: shot 86462



Remarkable **interpretation of spectra. Did its best with radiography.**

Conclusion

In this study:

We showed that we can infer state vector evolution underlying the COAX experiment from limited diagnostics, by leveraging machine learning.

We also demonstrated self-consistency by performing a round-trip process.

What's next?

Design theory study:

How can we learning to design better experiments?

Advancing predictions:

Differentiable diagnostics.

More models:

New data and experiments.

Add more physics!