Image-to-Image Regression with Distribution-Free Uncertainty Quantification and Applications in Imaging

Anastasios N. Angelopoulos

University of California, Berkeley

Collaborators

Amit Kohli *

Stephen Bates

Michael Jordan

Jitendra Malik

Thayer Alshaabi
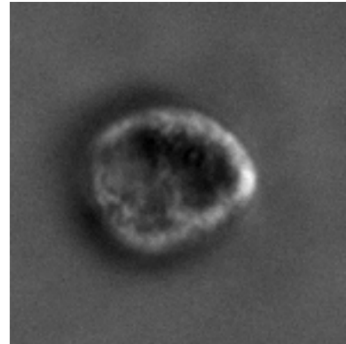
Srigokul
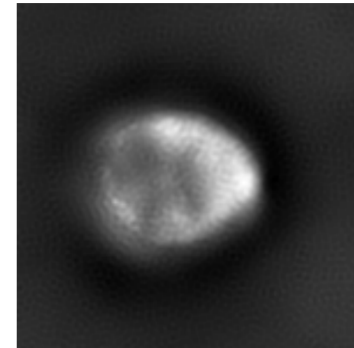Upadhyayula

Yaniv Romano

Image-to-Image Regression

Input: Image

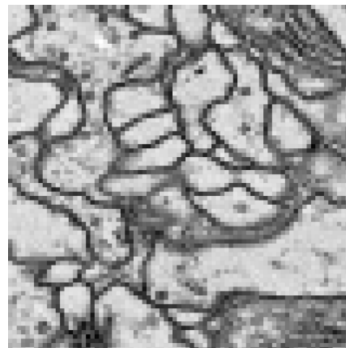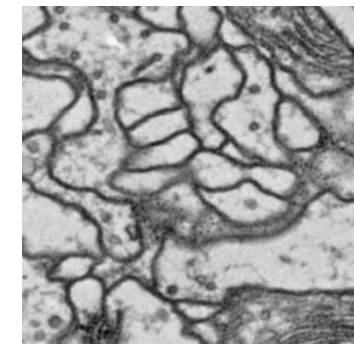**Output:** Another Image

E.g. Modality Transfer

Brightfield

Quantitative phase

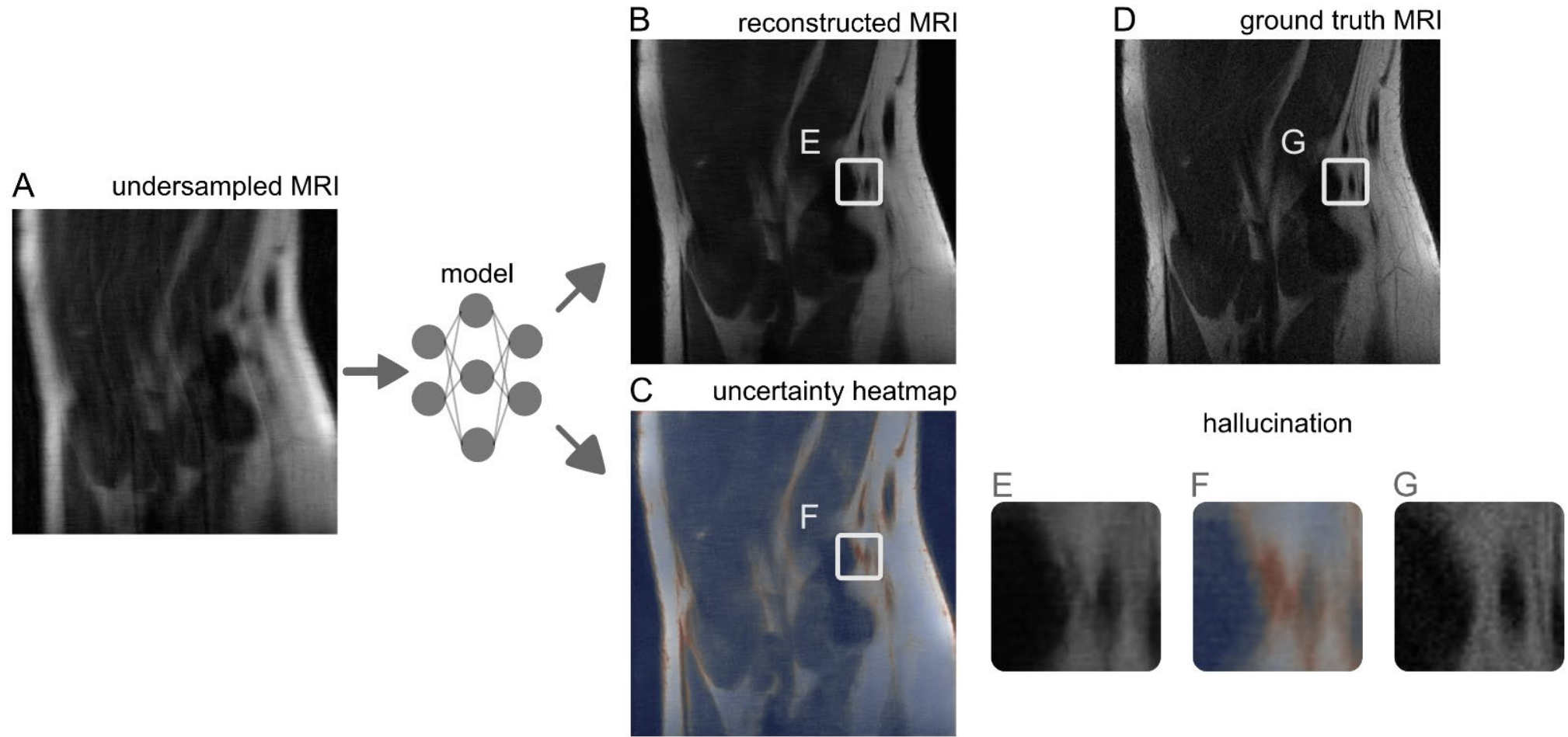**E.g. Super-Resolution**

Low-Res

High-Res

Problem: Hallucinations

The model may introduce spurious new features…

…or "smooth away" important details.

Solution: Uncertainty Quantification

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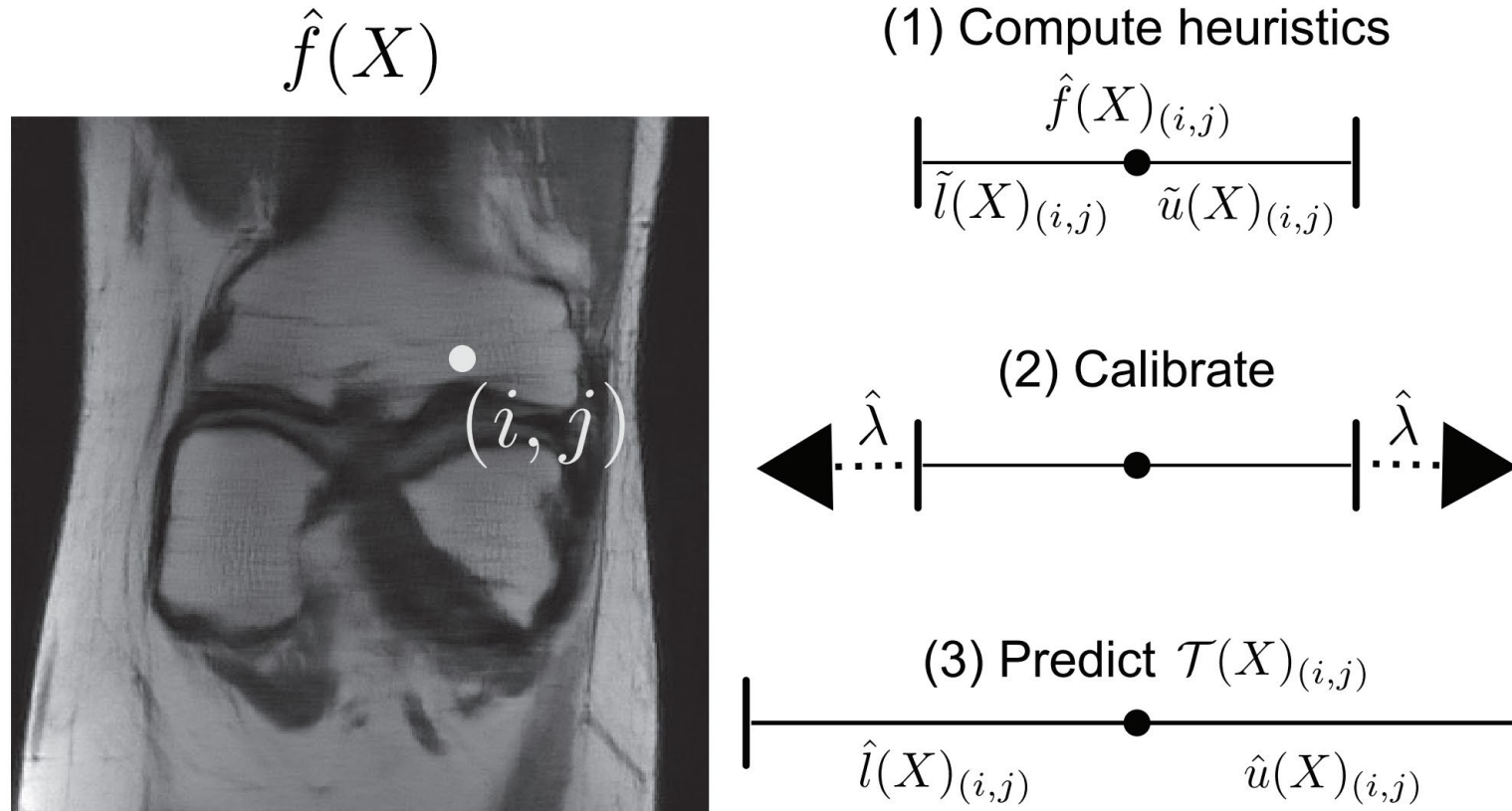
$$\mathbb{P}\left(\mathbb{E}\left[L(\mathcal{T}(X), Y)\right] > \alpha\right) \le \delta$$
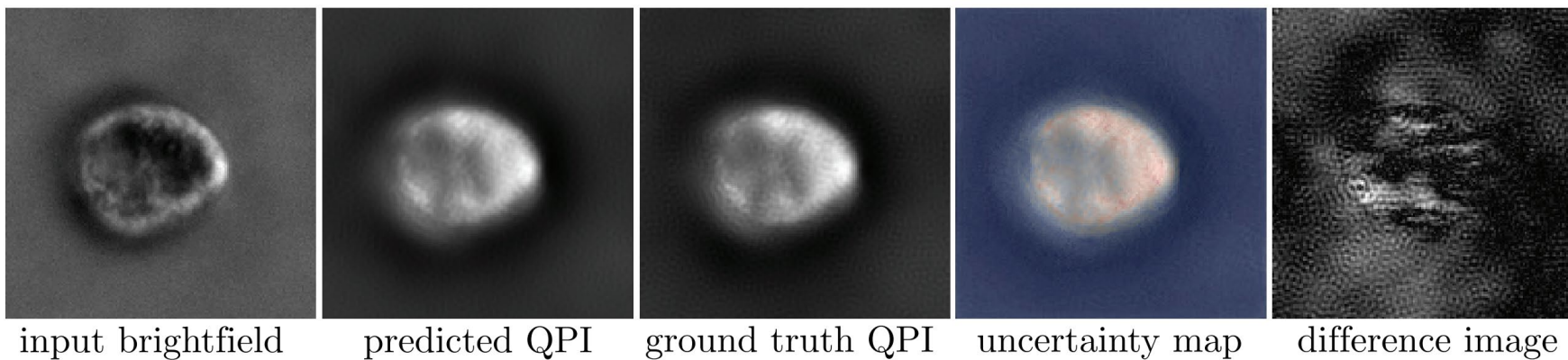
What's New: DFUQ

"Distribution-Free" --- No assumptions on the prediction system, only i.i.d. or exchangeability assumed of the data.
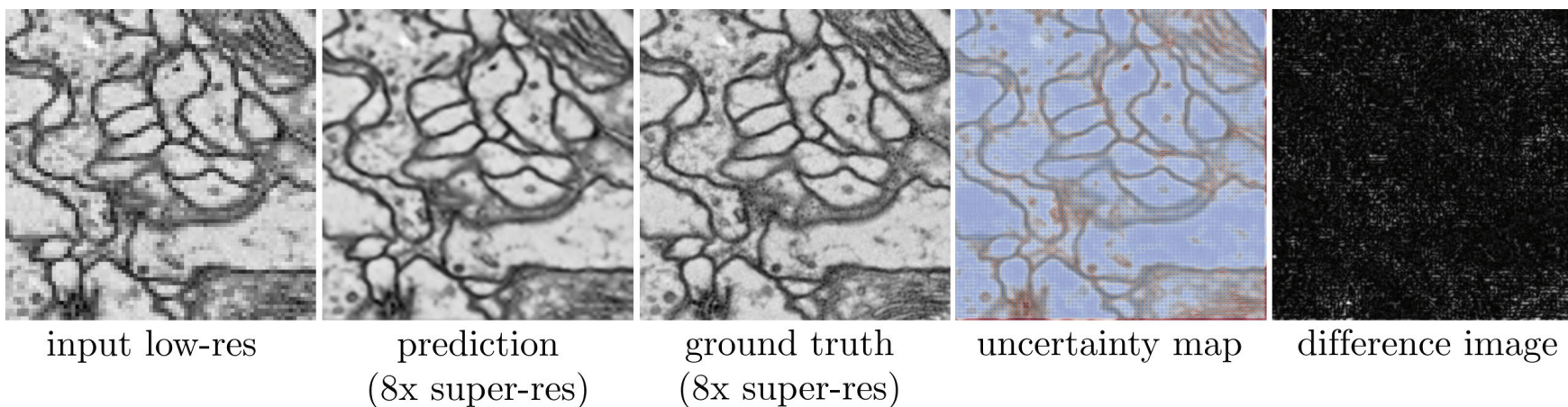
| Classical Statistics	Distribution-Free UQ
Parametric distribution or nonparametric complexity class	No assumed distribution
Modify prediction system to get guarantees	Works for any prediction system without retraining
Asymptotics	Finite-sample guarantees
Central limit theorem	Concentration inequalities, exchangeability

Examples

Phase imaging of leukocytes

input brightfield   predicted QPI   ground truth QPI   uncertainty map   difference image

Supperresolution electron microscopy of fly brain

input low-res   prediction (8x super-res)   ground truth (8x super-res)   uncertainty map   difference image
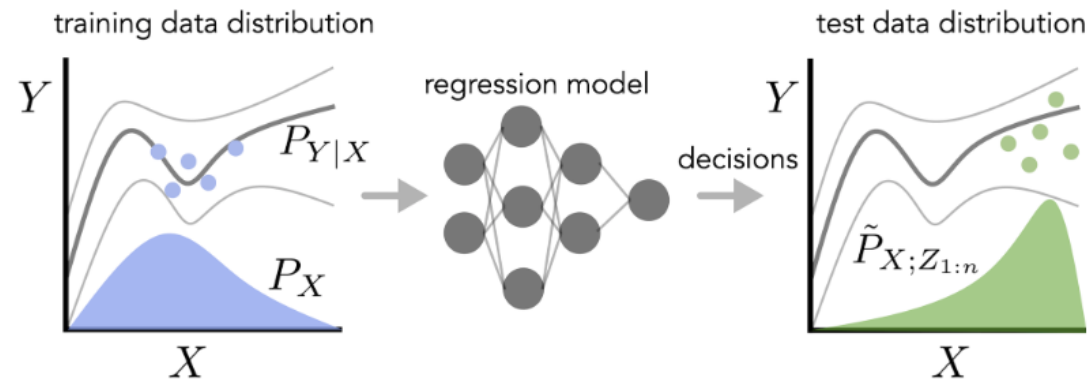
Conclusion: Not your Grandma's Intervals

In real life, problems have complex structure and real-world consequences.

- Massachussets General Hospital:
  - Providing guarantees on automated diagnostics of spinal stenosis. [LAS'22]
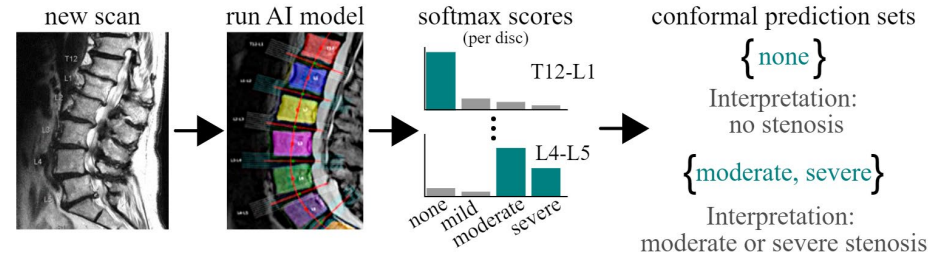
- Protein design
  - Calibration and test data are dependent --- "Feedback Covariate Shift" [FBALJ'22]

Moving towards modular, black-box uncertainty in imaging.

Come find us:

Poster Session: Hall E #629

Saturday Workshop on DFUQ: [link]

Twitter: @ml_angelopoulos