



Advancing Cosmology through Artificial Intelligence

Huanyuan Shan

Shanghai Astronomical Observatory

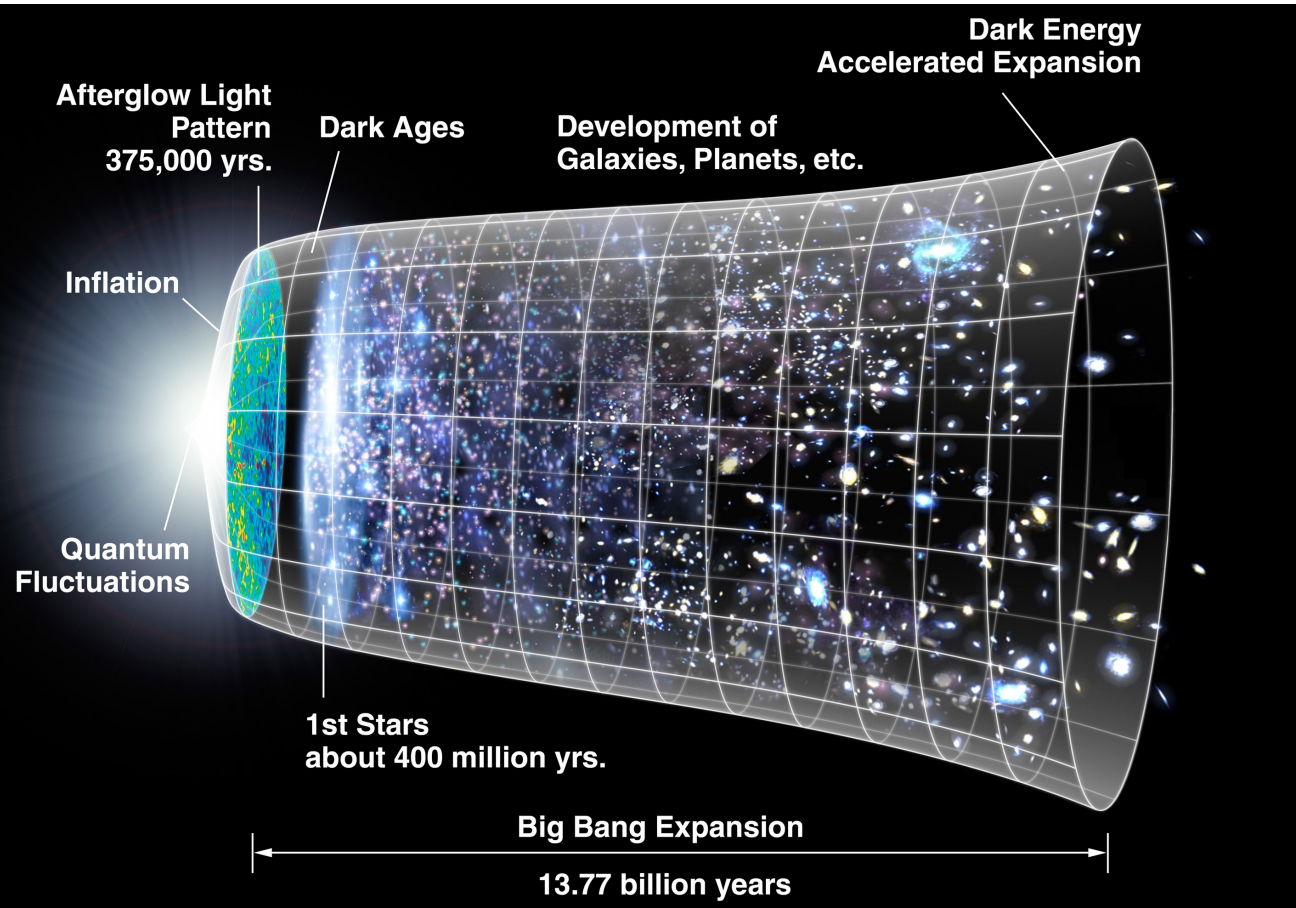
With Chen Su, Jiacheng Ding, Haosong Wang, Zekang Zhang, Shijiao Yin, Qige Ao, Zhenghao Zhu, Ting Tan, Jiajun Zhang, Ji Yao, Christophe Yèche & Jean-Paul Kneib

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Big Data Cosmology: Opportunity & Bottlenecks

- Next-generation surveys (CSST, *Euclid*, LSST, SKA) are entering the PB data era



Three fundamental bottlenecks:

1. Front-end (Data → Observables):

- Limited precision in extracting weak signals
- Human-in-the-loop bottlenecks
- Inefficiency at survey scale

2. Back-end (Observables → Cosmology):

- Information loss (e.g. summary statistics)
- Intractable likelihoods
- Extremely high computational cost

3. Trust Layer (Inference → Reasoning):

- Black-box behavior of AI models
- Manual validation of AI outputs
- Auditable and interpretable reasoning

We need a New Inference Paradigm!

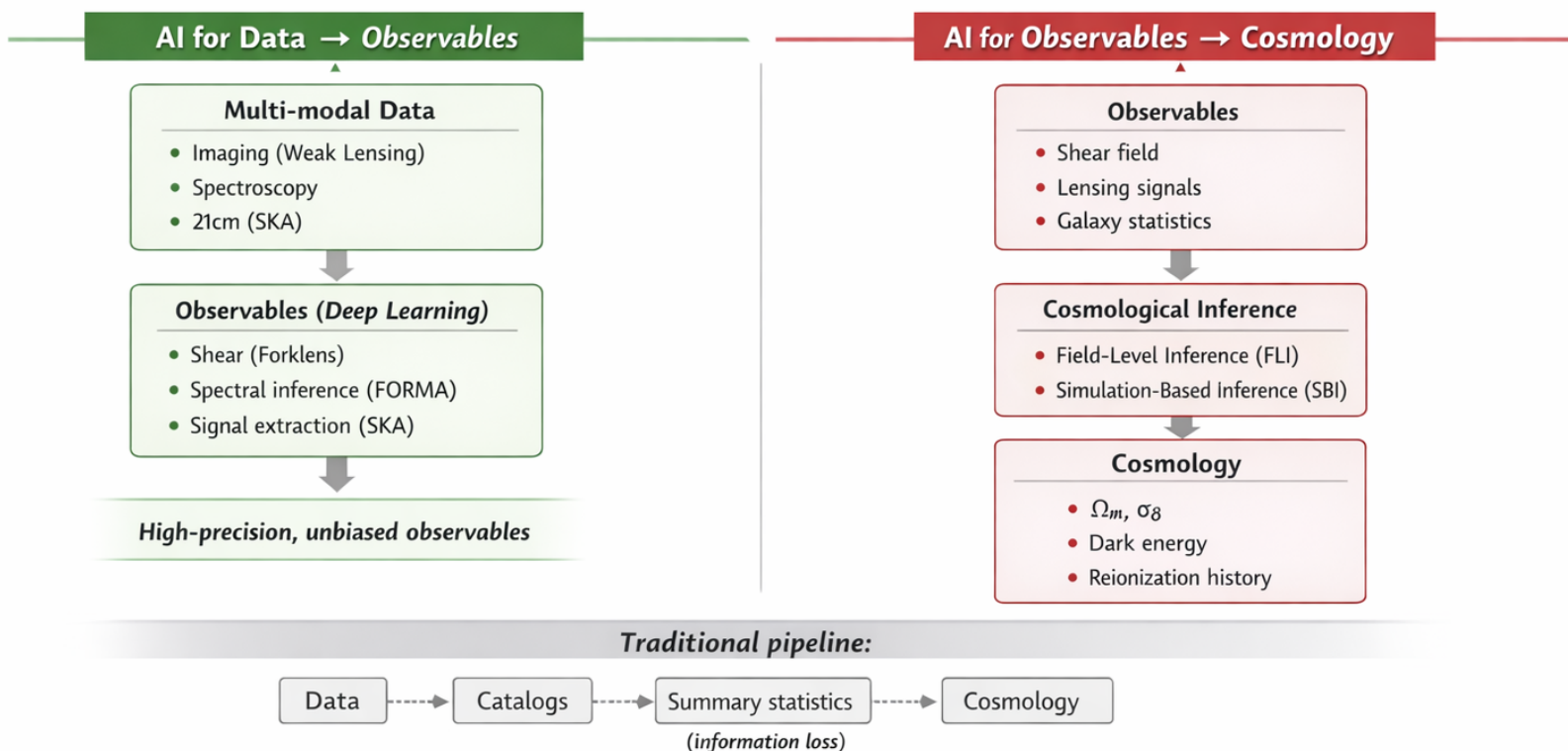


From Pixels to Cosmology: An AI-Driven Framework

FORMA Layer: *From Inference to Reasoning*

- Explicit reasoning chains
- Physically interpretable inference
- Verifiable scientific process

Bridging AI inference and scientific reasoning



- **Front-end** enables high-precision, unbiased measurement from raw data
- **Back-end** enables high-dimensional, likelihood-free cosmological inference
- **Trust layer** formalizes scientific reasoning, transforming AI inference into auditable knowledge

AI transforms cosmology across three layers: perception, inference, and reasoning

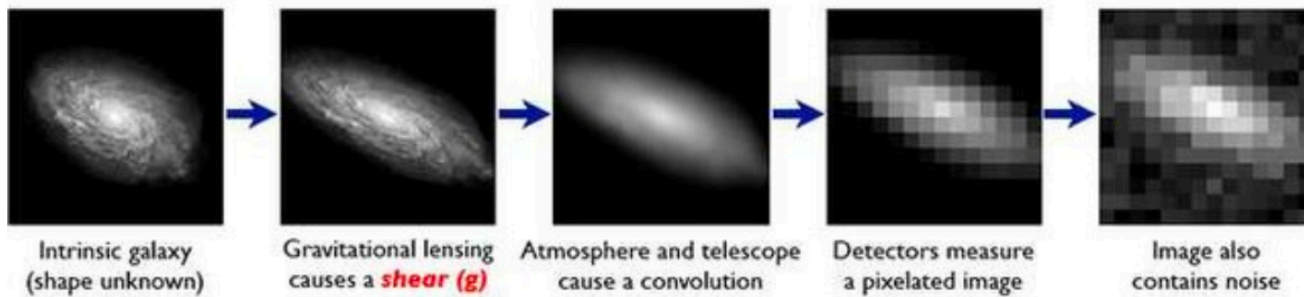


- **AI for Data → Observables (Front-End)**
- AI for Observables → Cosmology (Back-End)
- From Inference to Reasoning (Trust Layer)

Forklens: DL Weak Lensing Shear Measurement

- Weak Lensing: a cornerstone cosmological probe

Galaxies: Intrinsic galaxy shapes to measured image:

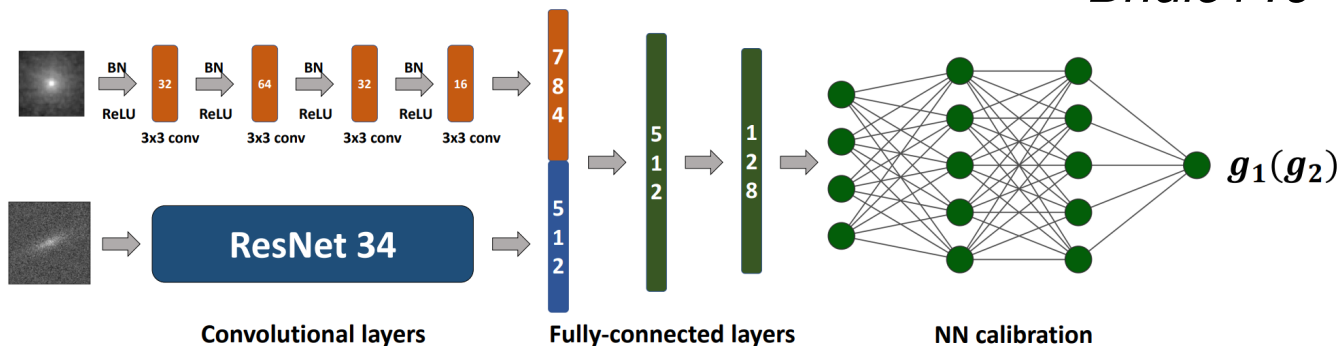


Challenges:

- PSF convolution
- Noise bias
- Morphology–shear degeneracy

Forklens:

- CNN+NN shear estimation & calibration
- Dual-module CNN shape measurement
- No explicit bias calibration



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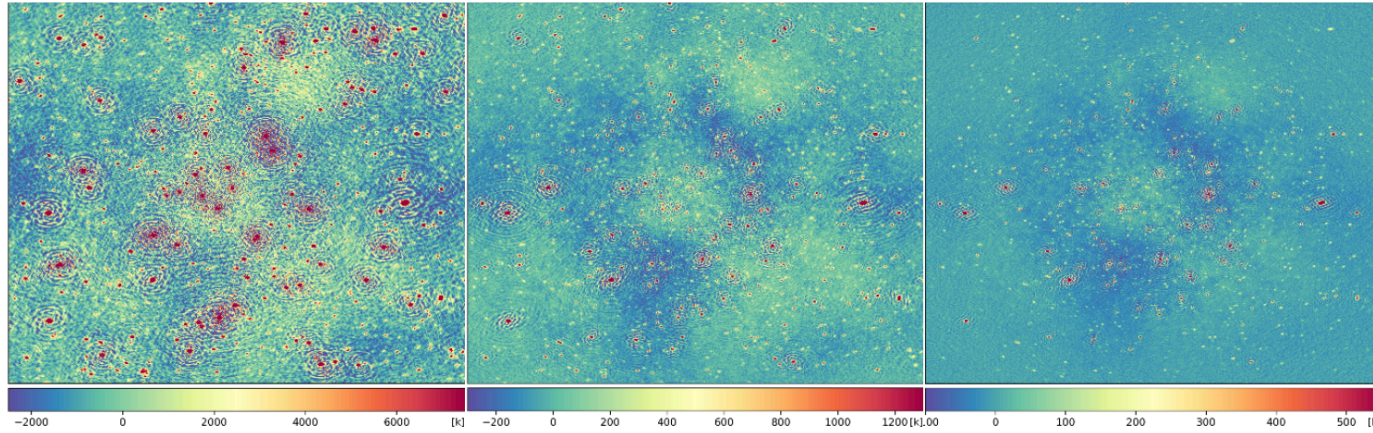
Performance:

- Accuracy: $\sim 2 \times 10^{-3}$
- Speed: ~ 0.7 ms/galaxy

Enabling Stage-IV Precision Weak Lensing

ERWA: SKA Deep Learning Foreground Removal

- 21cm Cosmology: probing the Epoch of Reionization



Challenges:

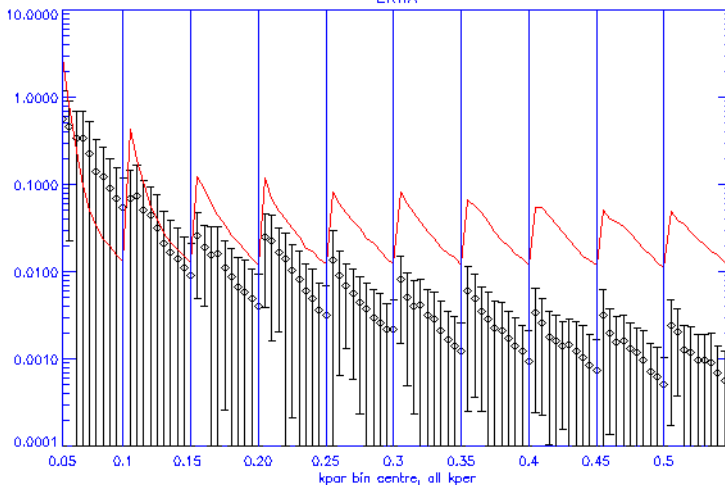
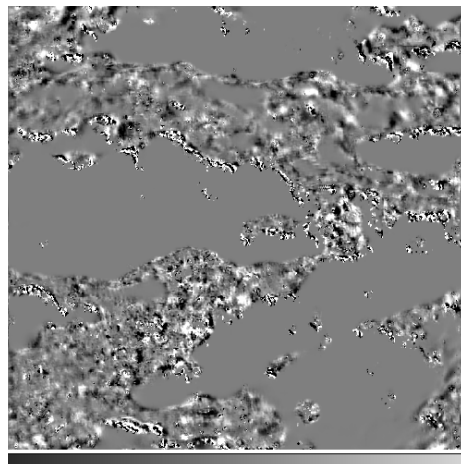
- Foregrounds \gg signal ($\sim 10^5$ stronger)
- Ionosphere+instrumental noise

ERWA Approach:

- DL-based deconvolution + FG removal
- Learn non-linear foreground structures

Performance:

- Accurate signal recovery
- Competitive performance in SKA Data Challenge (4th in total/1st DL category)

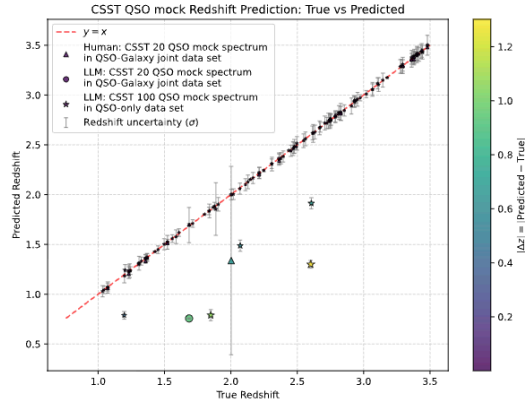
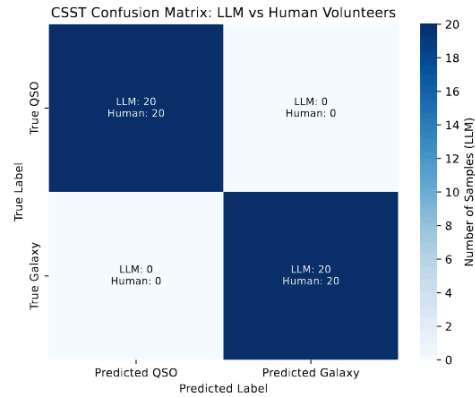


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Enabling 21cm Cosmology from Contaminated Data

FORMA: LLM-Driven Spectral Analysis

- Stage IV Spectroscopic surveys face new bottlenecks

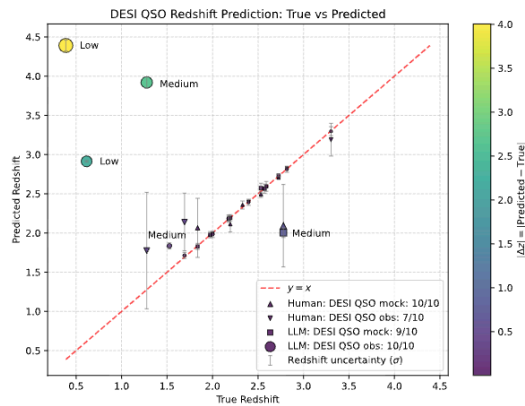
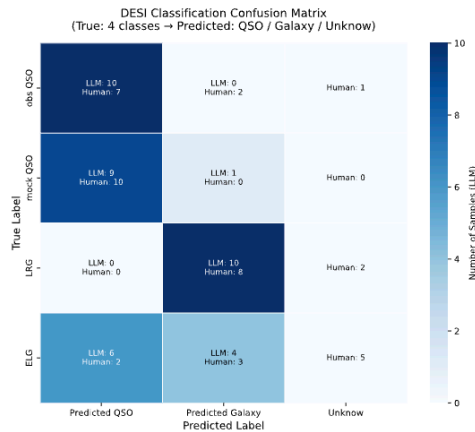


Challenges:

- Massive spectroscopic data
- Human-dependent validation

FORMA: LLM-Driven

- Automated spectral analysis at survey scale
- Removes human-in-the-loop bottleneck
- Consistent and scalable inference



Result:

- CSST: 100% classification accuracy for QSO and LRG; 95% of QSO redshifts meet $|\Delta z| < 0.1$
- DESI: Correctly identified 95% QSOs and all LRGs

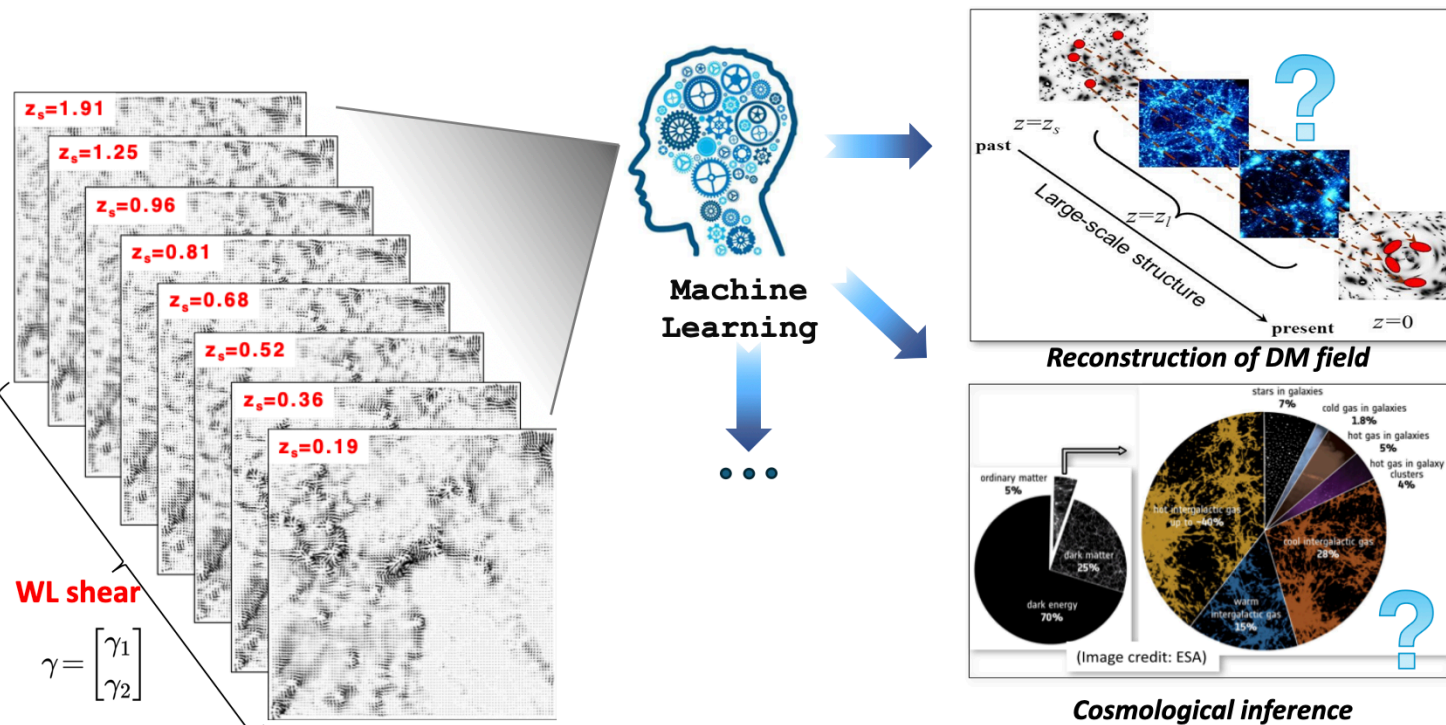
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Enabling Large-Scale Spectroscopic Pipelines



- AI for Data → Observables (Front-End)
- **AI for Observables → Cosmology (Back-End)**
- From Inference to Reasoning (Trust Layer)

Field-Level Inference: Beyond Summary Statistics



Traditional approach:

- 2PCF \rightarrow Gaussian approximation

Limitation:

- Discards non-Gaussian information
- Introduces reconstruction biases

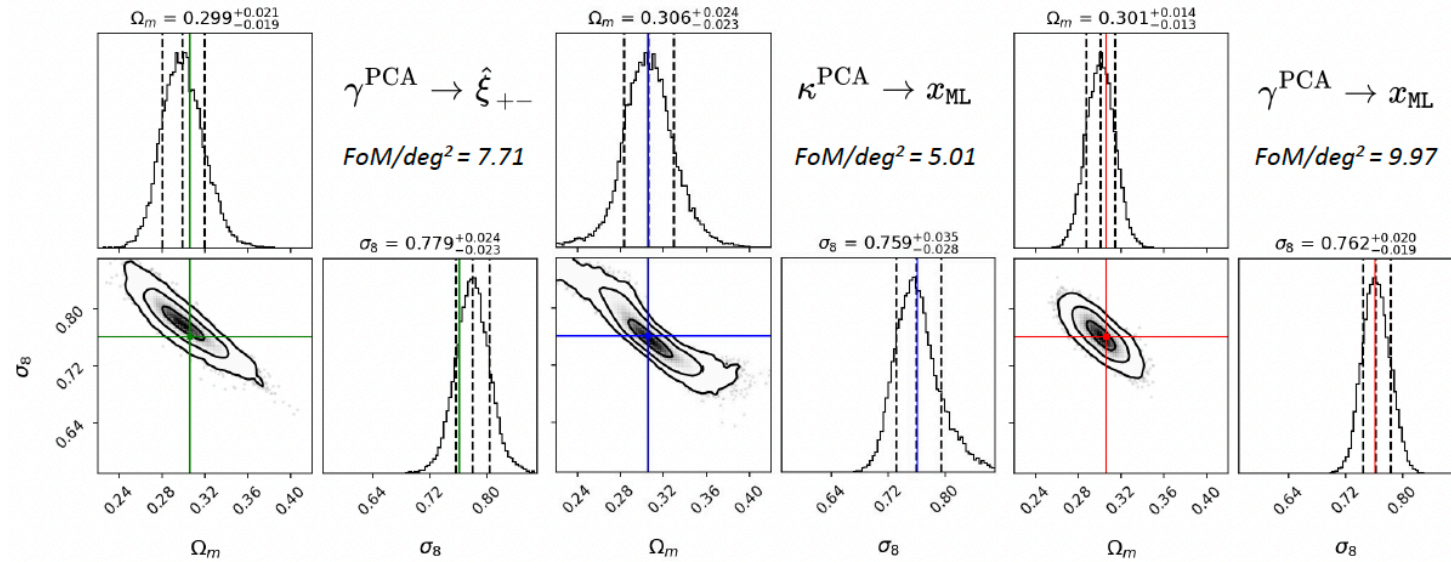
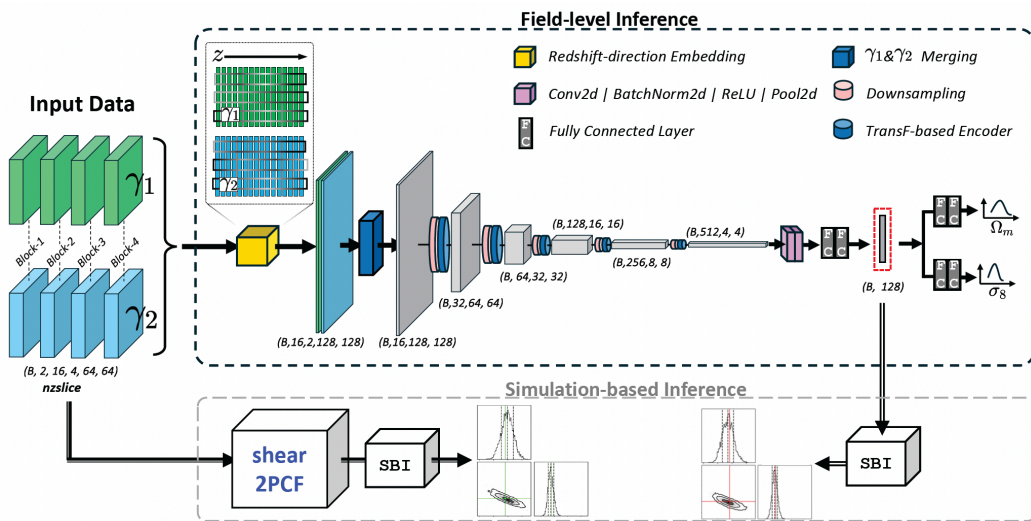
Field-Level Inference (FLI):

- Directly map shear field \rightarrow cosmology

Cosmology without Summary Statistics

Shear-to-Cosmology: Lossless Inference

- Framework: FLI for feature extraction+SBI for posterior distribution



Key advantages:

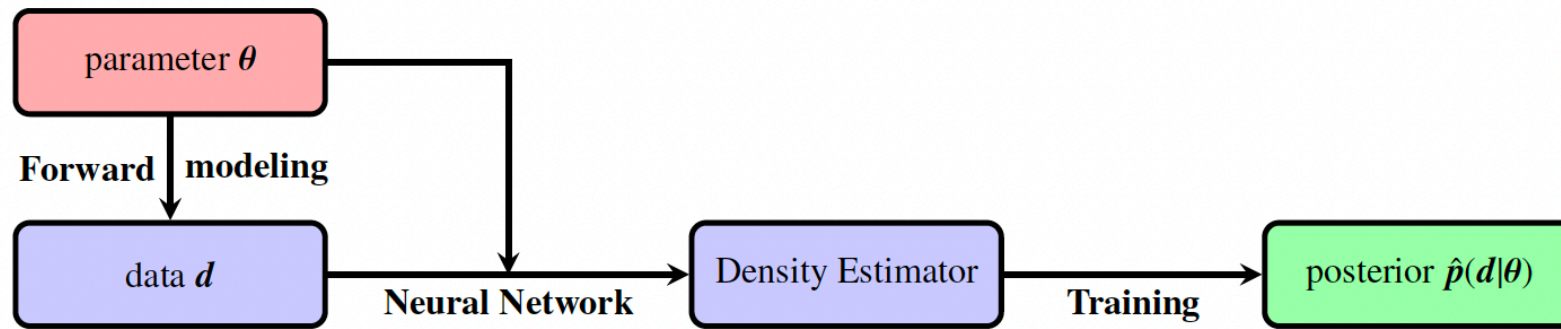
- No mass reconstruction (avoid noise & E/B mixing)
- Full spatial information retained
- +36.4% information vs 2pt statistics
- ~2x improvement vs KS-based methods

Direct Inference from Fields, not Compressed Observables

Simulation-Based Inference (SBI)

Challenges: Likelihoods are intractable for complex observables

Solution: Learn posterior directly from simulations



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Workflow:

- Simulate across parameter space
- Train neural density estimator
- Perform fast inference

Advantages:

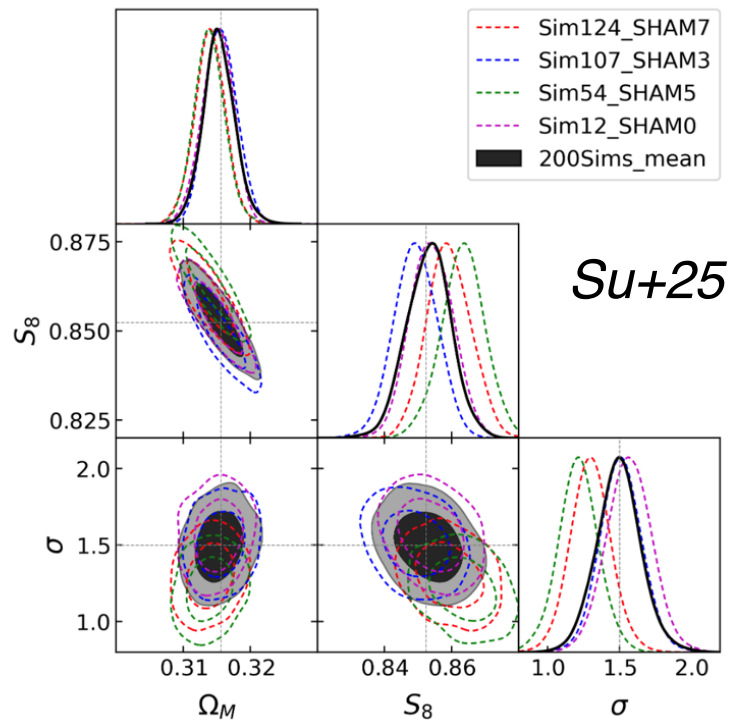
- Likelihood-free
- Captures non-Gaussianity
- Scalable to complex probes

A Universal Cosmological Inference Engine

SBI: Across Cosmological Probes

Void lensing:

- Sensitive to gravity & DE

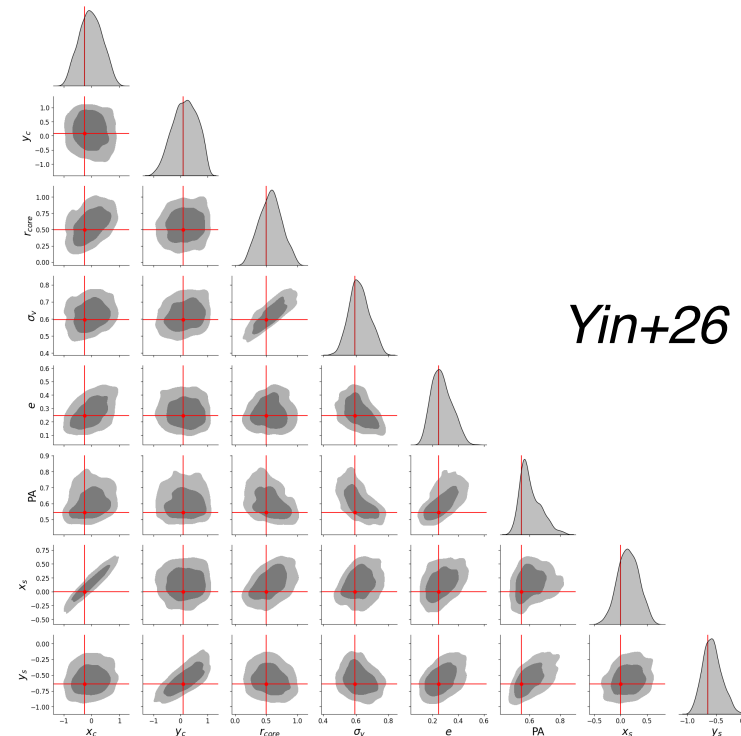


Result:

- Unbiased inference
- Orders-of-magnitude speedup

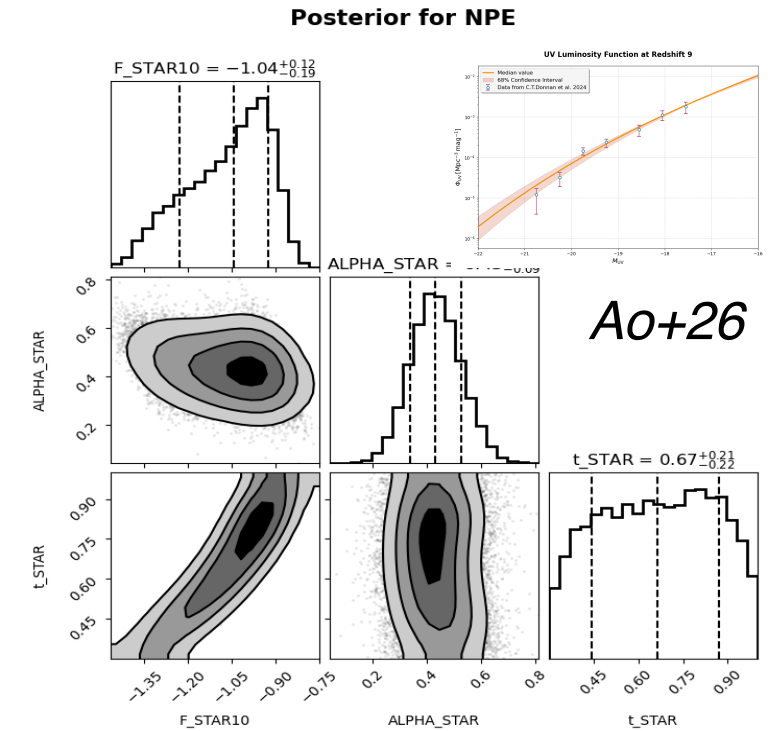
Cluster strong lensing:

- Precise mass reconstruction



High-z UVLF:

- Constrains EoR history



One Framework, Multiple Probes



- AI for Data → Observables (Front-End)
- AI for Observables → Cosmology (Back-End)
- **From Inference to Reasoning (Trust Layer)**

Can We Trust AI Cosmology?

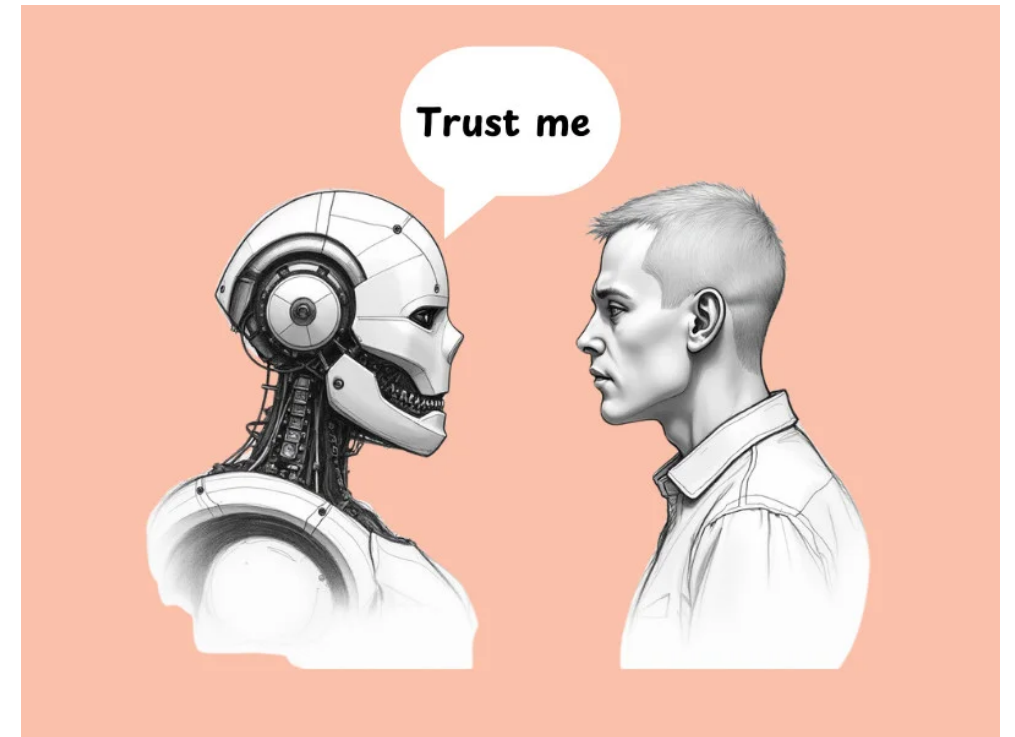
AI enables:

- End-to-end inference
- Likelihood-free modeling

But introduce:

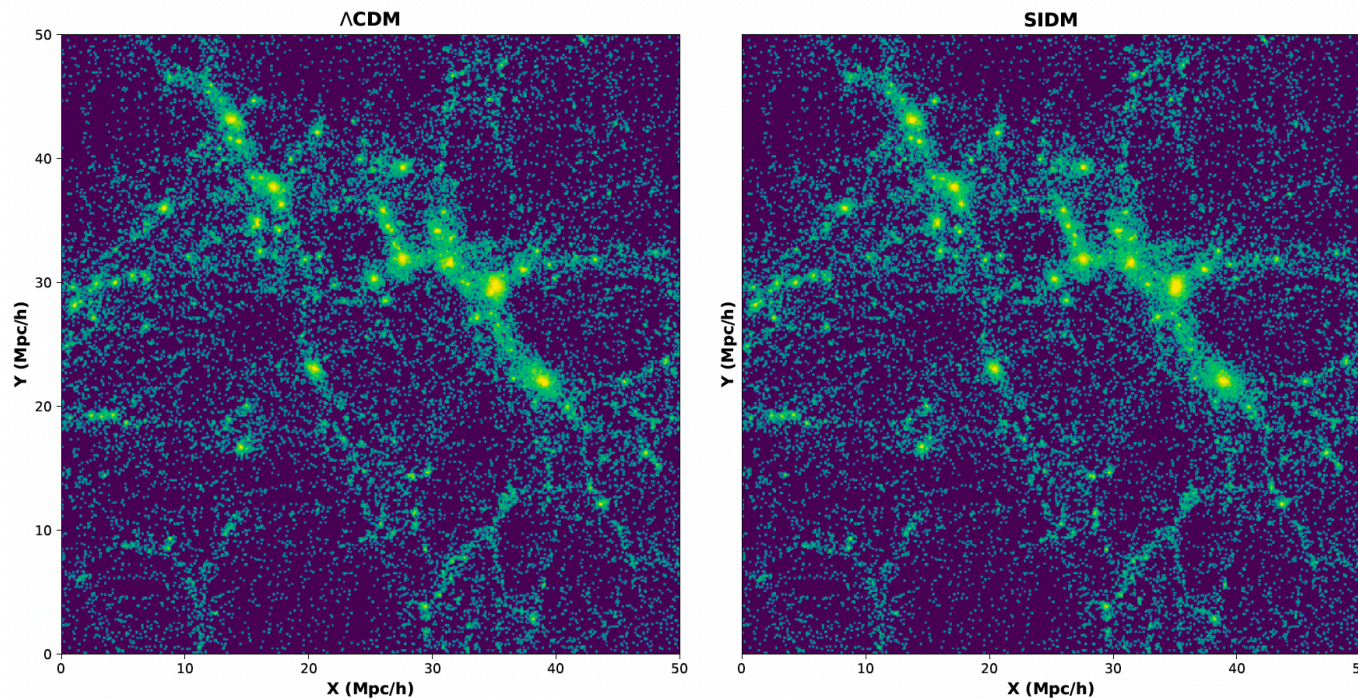
- Black-box behavior
- Lack of interpretability
- Limited physical transparency

Challenge: trustworthy scientific inference



SIMAgent: AI Assistant for Simulation

Challenges: Adapting Beyond- Λ CDM simulation is highly non-trivial and time-consuming



SIMAgent: co-pilots simulation workflow

- **Literature-to-Code:** Automatically mapping models to specific code structures
- **Autonomous Code Navigation:** Pinpointing modifications within full codebase
- **Intelligent Synthesis:** Generating technical reports and modification suggestions for human verification

Result:

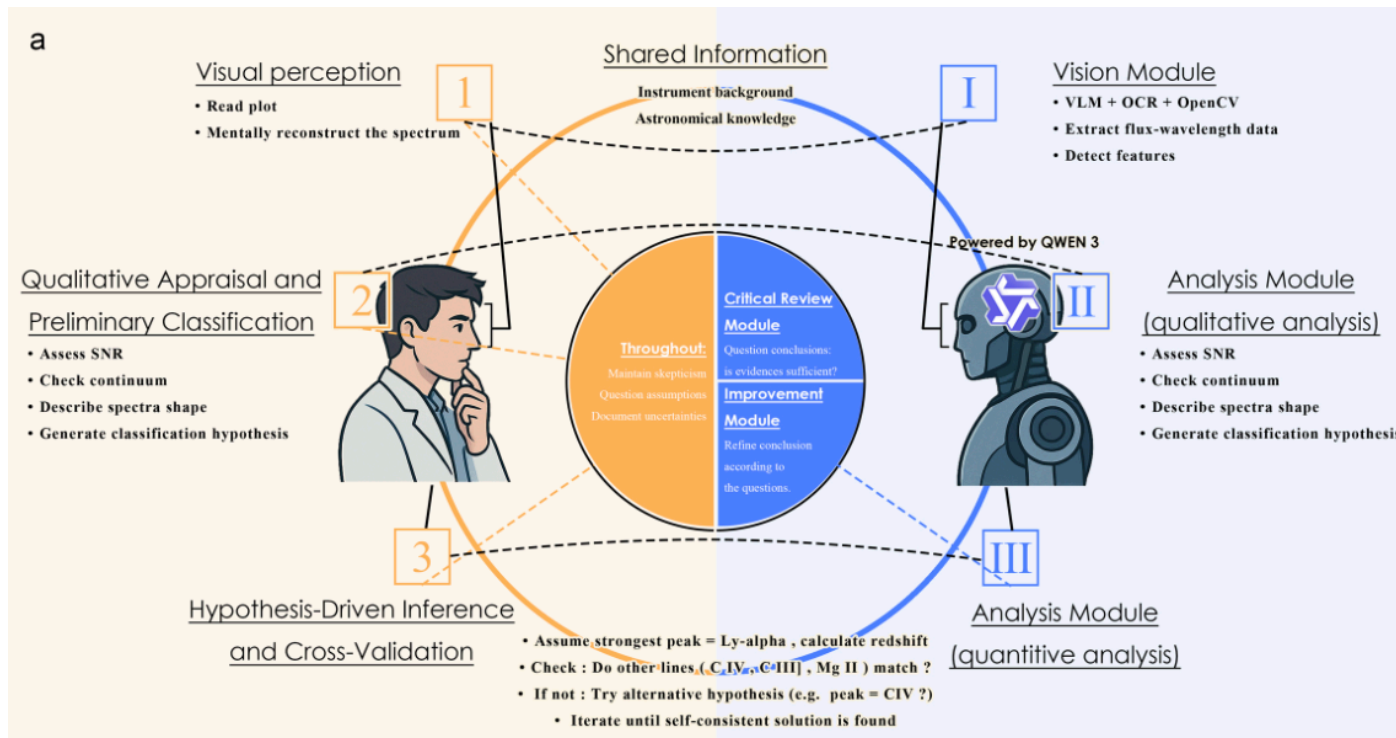
- Validated for multiple DM simulations (CDM, WDM, FDM, SIDM..)
- Compilable, fully runnable code with results matching theoretical expectations

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From Black-Box Prediction → Auditable Scientific Reasoning

FORMA: LLM-based Scientific Reasoning

Motivation: Scientific inference requires explicit reasoning, but traditional AI models lack interpretability



FORMA (LLM-based framework):

- Visual: Extracts features from spectral images
- Qualitative Analysis: generates redshift and classification hypotheses
- Hypothesis Inference: Validates hypotheses

Capabilities:

- Interpretability
- Verifiable reasoning steps
- Human-aligned scientific logic

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From AI Inference → LLM-driven Scientific Reasoning



Summary

- **A New Paradigm** for AI-Driven Cosmology
- AI transforms cosmology at three fundamental levels:
 - Perception** → DL enables high-precision, unbiased measurement
 - Inference** → FLI+SBI enables high-dimensional, likelihood-free inference
 - Reasoning** → LLM-driven framework formalizes scientific reasoning

**A Lossless, Trustworthy, and Reasoning-Driven Paradigm
for the PB-data Era**