A Deep Learning Approach for Characterizing Major Galaxy Mergers

Skanda Koppula, Victor Bapst, Marc Huertas-Company, Sam Blackwell, Agnieszka Grabska-Barwinska,
Sander Dieleman, Andrea Huber, Natasha Antropova, Mikolaj Binkowski, Hannah Openshaw, Adria Recasens,
Fernando Caro, Avishai Dekel, Yohan Dubois, Jesus Vega Ferrero, David C. Koo, Joel R. Primack, Trevor Back

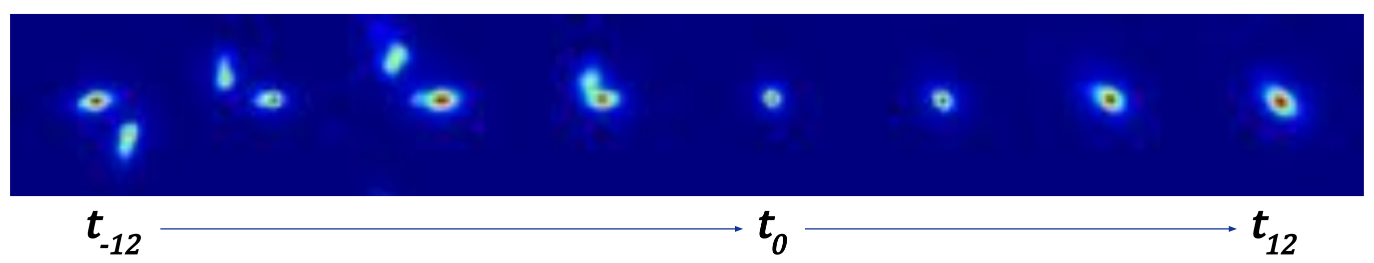
Introduction

Motivation

- Galaxy merging plays a key role in understanding galaxy formation
- The merging process can take millions of years!
- Observational evidence of the effects of mergers remains elusive
- A key challenge in linking observations with galaxy transformations is determining the ***merger stage***
- Observations are a single time-slice snapshot of a galaxy merge at a particular merger stage
- Prior work has shown deep learning able to classify galaxies into interacting and non-interacting systems [1, 2]

Problem

Can we use visual cues to produce a fine-grained merger stage estimate of a galaxy merge observation?

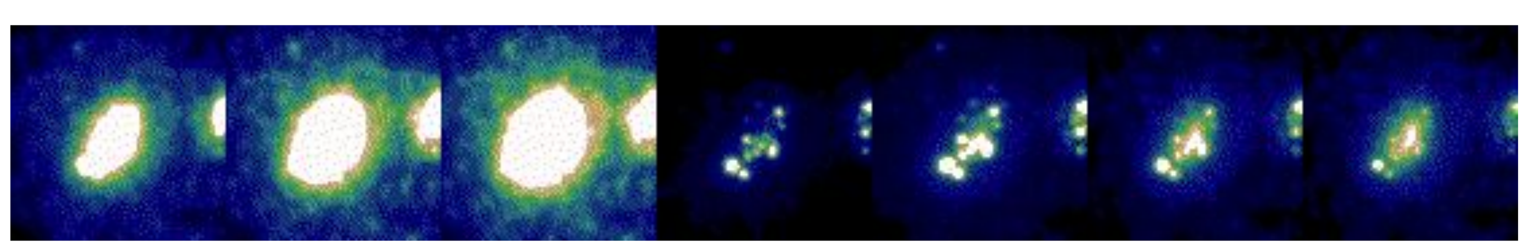


Eight sample observations from the first frequency channel of a galaxy merger sequence with 25 total observations. Given one of these observation snapshots, can we determine the merger stage t_i?

Data

Goal: learn from simulation images, transfer to real observations

1. **Cosmological Simulation**
   - Cosmological hydrodynamical simulation: **Horizon-AGN** [3]
   - Galaxies are identified using AdaptaHOP structure finder [4]
   - More details in our paper!
2. **Galaxy Merger Selection**
   - Use galaxies $>10^{10}$ solar masses in the redshift range z= [0.5,3], matching deep Hubble Space Telescope observations [5]
   - Build ***merger sequences***: complete tracking of the merger process with a time resolution of ~17Myrs
3. **Image Generation**
   - SUNSET for image generation [6], which models emission of all galaxy photons to produce an image in the observed-frame
   - **Seven different filters** going from the near UV to the near IR (F435W-F160W)



The seven frequency channels for a sample galaxy merger sequence

Methods

Image Pre-Processing

1. Views from each filter (F160W-F435W) are stacked into channels
2. Cropped to 80×80, centered around a maximum intensity window
3. Augmentations: flips, rotations, intensity jitter, and rescale

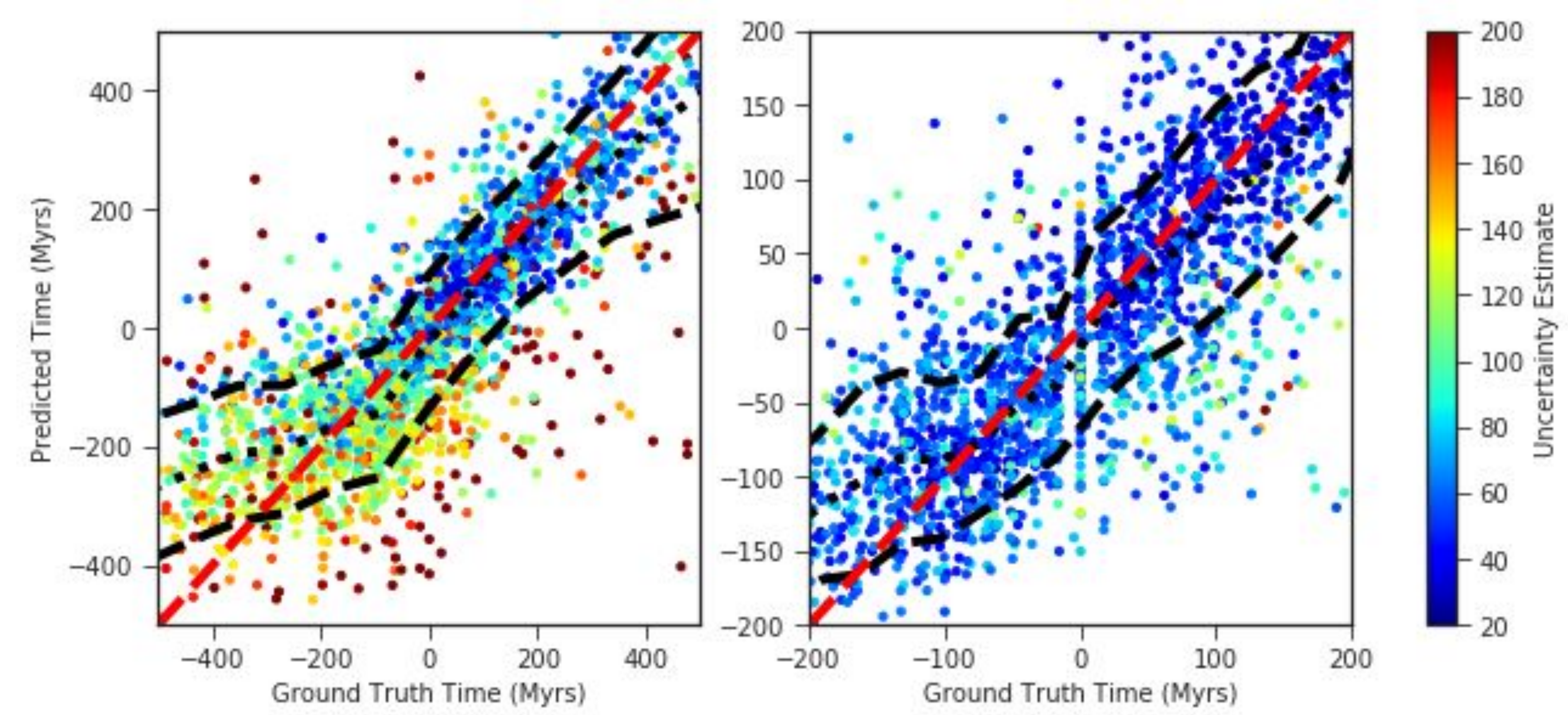
6337 merge sequences, with an **average sequence length of 32 time-steps**. **203667 observations** in total, 3 views / observation

Models and Loss

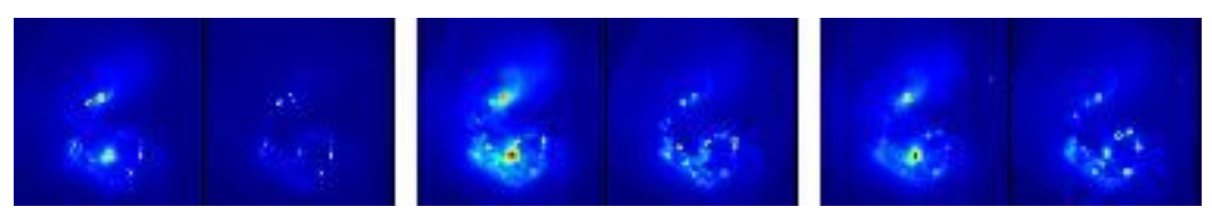
- Standard ResNet-50 to produce two outputs: merger stage estimate t and uncertainty estimate σ
- Fully-connected layer before each ResNet block output to fold in mass and redshift data accompanying each observation
- Minimize sum of scaled MSE and uncertainty loss: $\frac{\log\sigma^2}{2} + \frac{(t-\hat{t})^2}{2\sigma^2}$
- SGD w/ gradient clipping, step-wise LR decay, and L2 regularization
- Full details in paper!

Results: Simulation

- Evaluated models on our test split of simulation images
- Median absolute error is **69.35 Myrs**; RMSE of **144.1 Myrs**
- Largest errors skew towards the edges of the time interval
- Slightly better models on the half-range estimation task: RMSE of **68.153 Myrs** and median absolute error of **38.391 Myrs**
- **Scatter plot of predicted vs. ground truth estimates**:
  - Oracle (red-dashed); 25%/75% estimate (black-dashed)
  - Model's higher sigma estimates qualitatively increase towards inaccurate early merge stage predictions
  - **Highest uncertainty points are farthest away** from the perfect ground-truth/predicted alignment



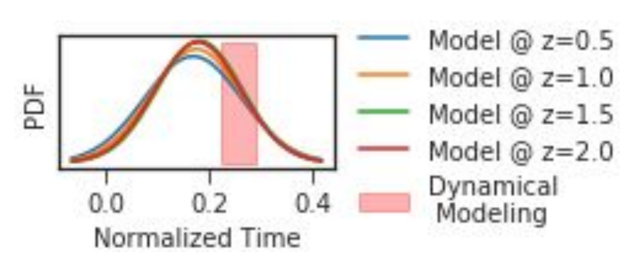
Results: Antennae Galaxies



Observations of the Antennae system at three redshifts using the two available channels (F160W and F850LP)

Our first test whether simulation learned models could be applied directly to real observations

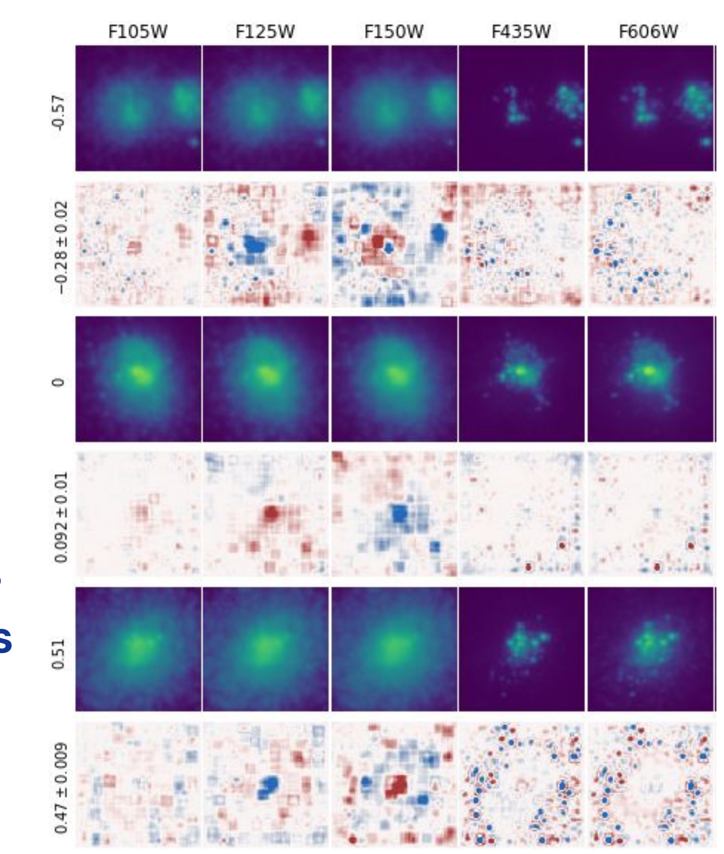
- **Antennae galaxies are a nearby system** that has been extensively studied [7]
- Prior estimates of the current merger stage available through detailed dynamical modeling [8]
- Observations from **Hubble Space Telescope**
- We apply **test-time augmentation** [9] and ensure consistency across augmentations
- Model output is not perfect, but does have correct pre/post merger-stage classification and **approximate alignment** with the ground-truth mean:



Results: Interpretability

What can we qualitatively observe of our models?

- Visualized **input gradients** for three example observations (pre/mid/post-merger samples)
- Patterns of attention depend on frequency and on the merger stage of the observation
- Post-merger example: UV rest-frame bands focuses more of their attention on the outskirts of the system. Potentially capturing **young stars being formed in the outer regions** as a consequence of the interaction



References

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