Emission-line diagnostics of HII regions using conditional Invertible Neural Network

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Star-forming region

Massive stars change its natal cloud morphologically, kinematically and energetically

(stellar wind, radiation, and supernova explosion)

→ suppress further star formations

Overall self-regulation process → Stellar Feedback

NASA, ESA and the Hubble Heritage Team (STScI,AURA)

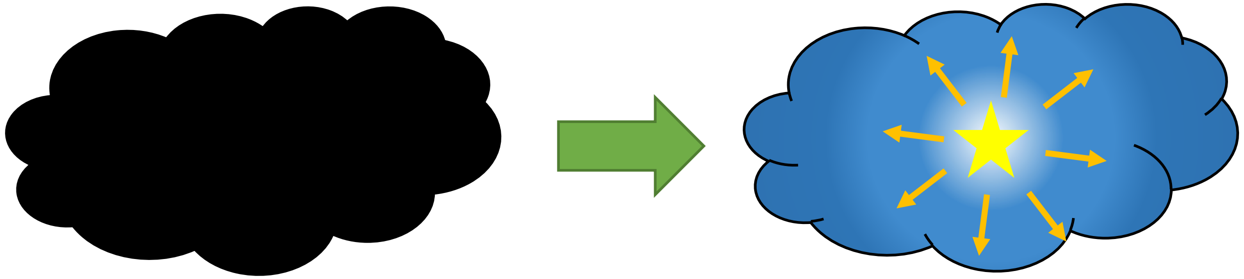

Image from Zwart+2010

Star-forming region

Difficulties in understanding observed SF regions

- Complicated structure and different phases of ISM
- Various emission lines from different regions

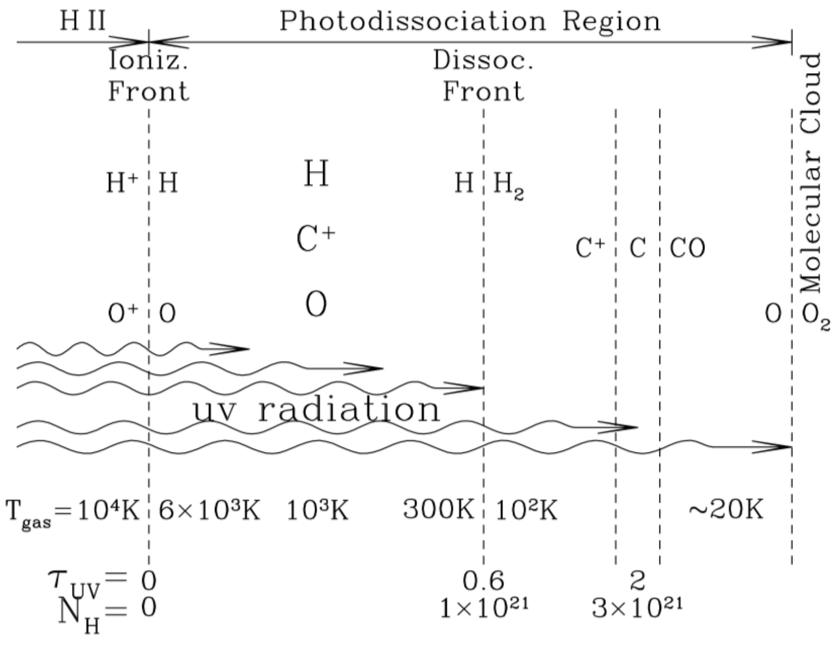

Figure 31.2 Structure of a PDR at the interface between an H II region and a dense molecular cloud.

Draine (2011) “Physics of the Interstellar and Intergalactic Medium”

Image from NAS/APOD

Star-forming region

Difficulties in understanding SF regions with forward modeling

- No model was able to fully describe forward process of stellar feedback

- Impossible to use common fitting methods

  - hard to describe all processes into one function

  - degenerated and highly dimensional so that standard chi-square approaches are not digestible

Star-forming region

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Apply machine learning to breakout the degeneracy in observations and analyze star-forming regions

In this project

Two state of the art techniques used in our project to link emission-line luminosities and characteristics of HII regions

Conditional Invertible Neural Network (cINN)

Lynton et al. 2019

- Deep learning architecture
- Predict backward by learning forward process

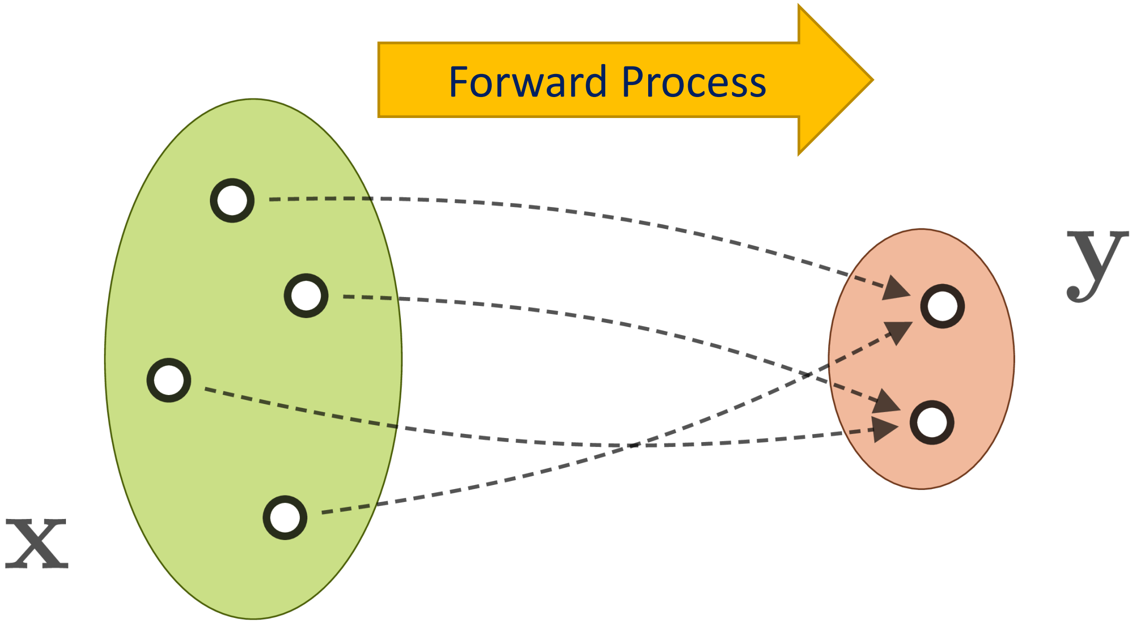
WARPFIELD-EMP

Pellegrini et al. 2020

- Unprecedented emission line predictor of HII region
- Stellar feedback + ISM physics + radiative transfer

conditional Invertible Neural Network

Ambiguous Inverse problems



Internal parameters
of natural world

Observations

- Forward process translates system parameters into observable quantities
- Often, forword process is well understood but incurs a loss of information (e.g., projection effect)

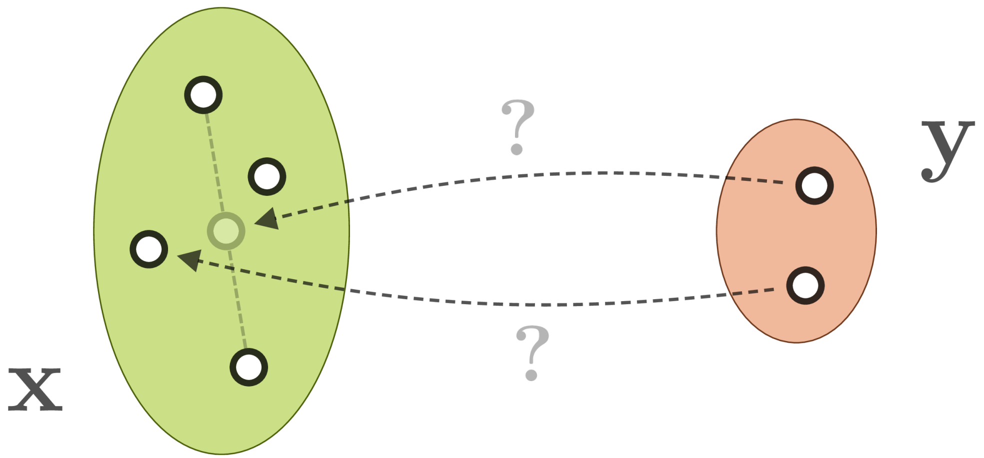
<u>Different states X are mapped onto identical observations Y</u>

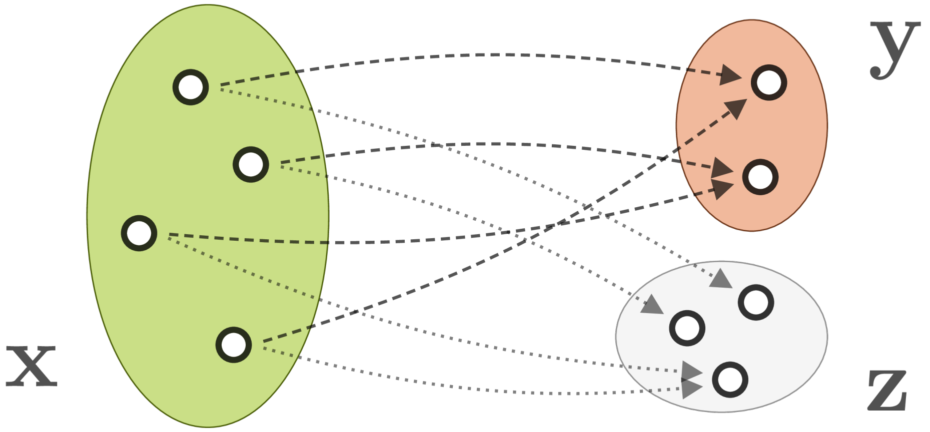
→ Inverse process is ambiguous and ill-posed

Image from Visual Learning Lab
Heidelberg

conditional Invertible Neural Network

Supervised learning of Y → X is problematic for ambiguous inverse problems





Using standrad neural network architecture, the learned mapping will either pick only one of the eligible X, or even worse, will form an average.

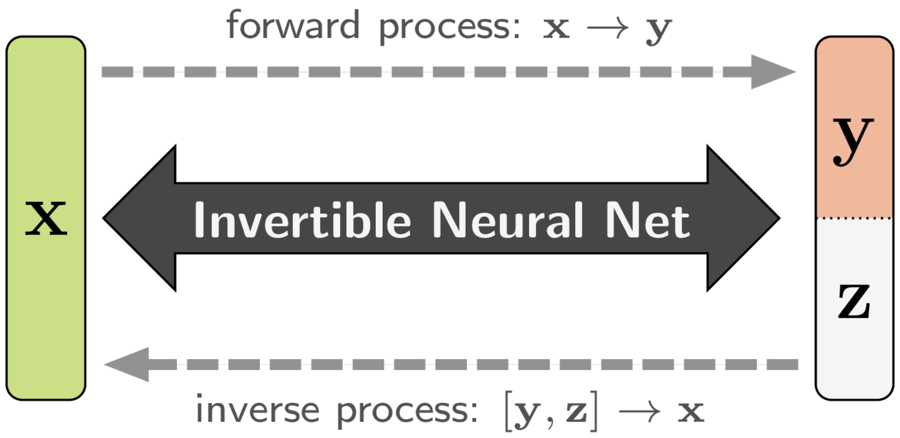
What we want is a full posterior distribution, p(x|y)

Latent variable (Z) captures the lost information during the forward process

Images from Visual Learning Lab Heidelberg

conditional Invertible Neural Network

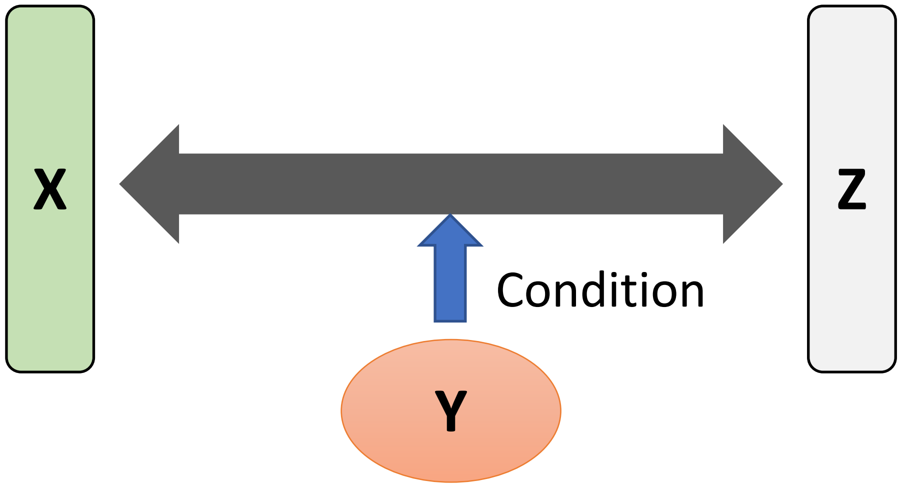
Using invertible neural network



Train the network in forward direction, optimize Z to have a certain probability distribution.

With given Y, generagte different sets of Z and use inverse process to predict differetn eligible states, X

Conditional Invertible Neural Network



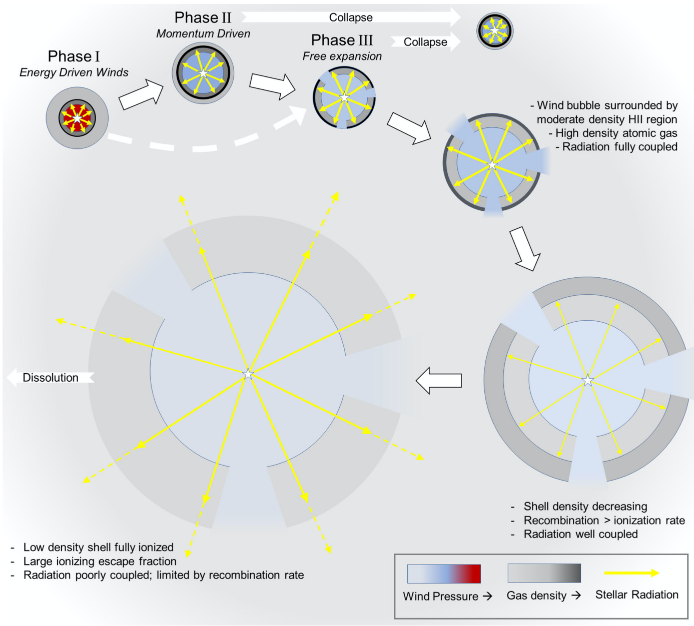
Enhanced version that matches X and Z directly and uses Y as condition in both forward and backward process

Images from Visual Learning Lab Heidelberg

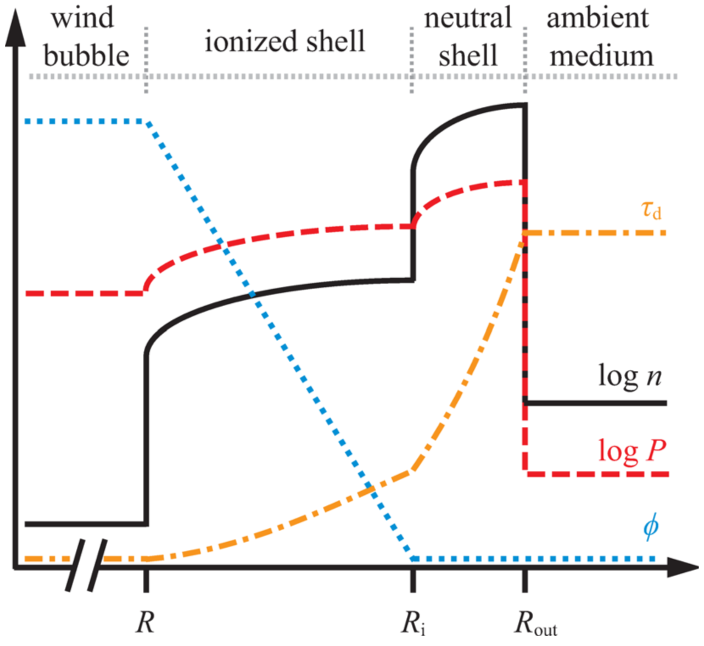
WARPFIELD-EMP

Database generated by WARPFIELD-EMission line Predictor (`WARPFIELD–EMP`, Pellegrini et al. 2020)

Couples 1D feedback model `WARPFIELD` (Rahner+2017) with `CLOUDY` (C17, Ferland+2017) and `POLARIS` (Reissl+2016),



Rahner et al. 2017



`WARPFIELD`

- 1D semi-analytic feedback model
- Stellar winds, SNs, radiation pressure, gravity
- evolve isolated massive star-forming cloud from initial M_{cl}, SFE, and $n_{H,0}$
- calculate cloud properties (E, structure, U, etc) as a function of time and position

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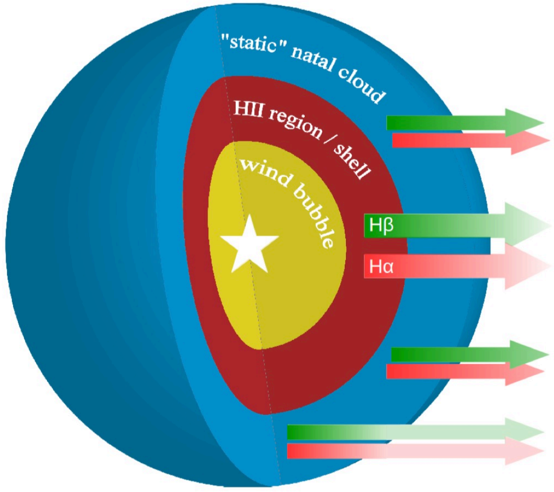
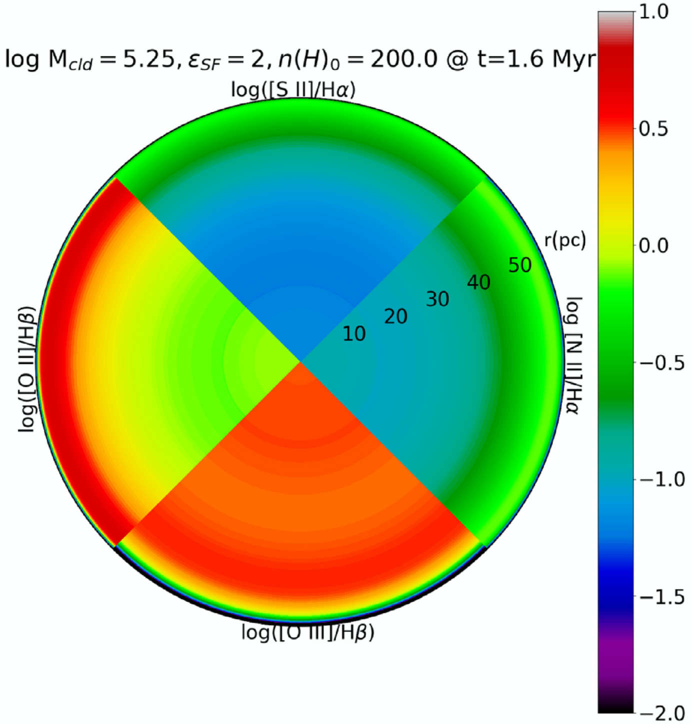




Pellegrini et al. 2020

`CLOUDY`

- non-LTE spectral synthesis and plasma simulation code
- Determine emissivity of emission lines as a function of position

`POLARIS`

- Dust polarization and radiative transfer code
- Calculate luminosity considering internal extinction by dust

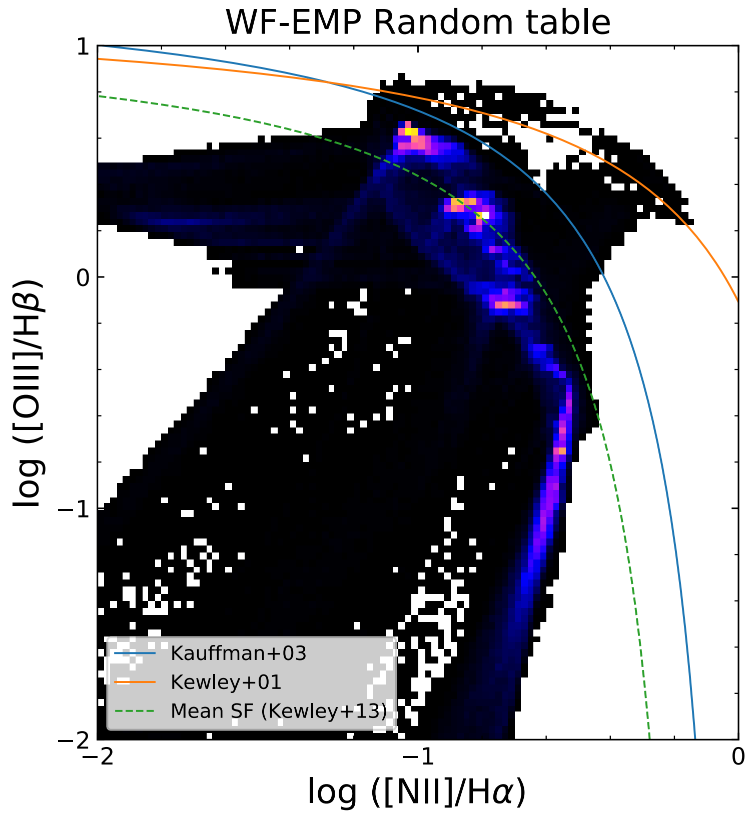
Training data

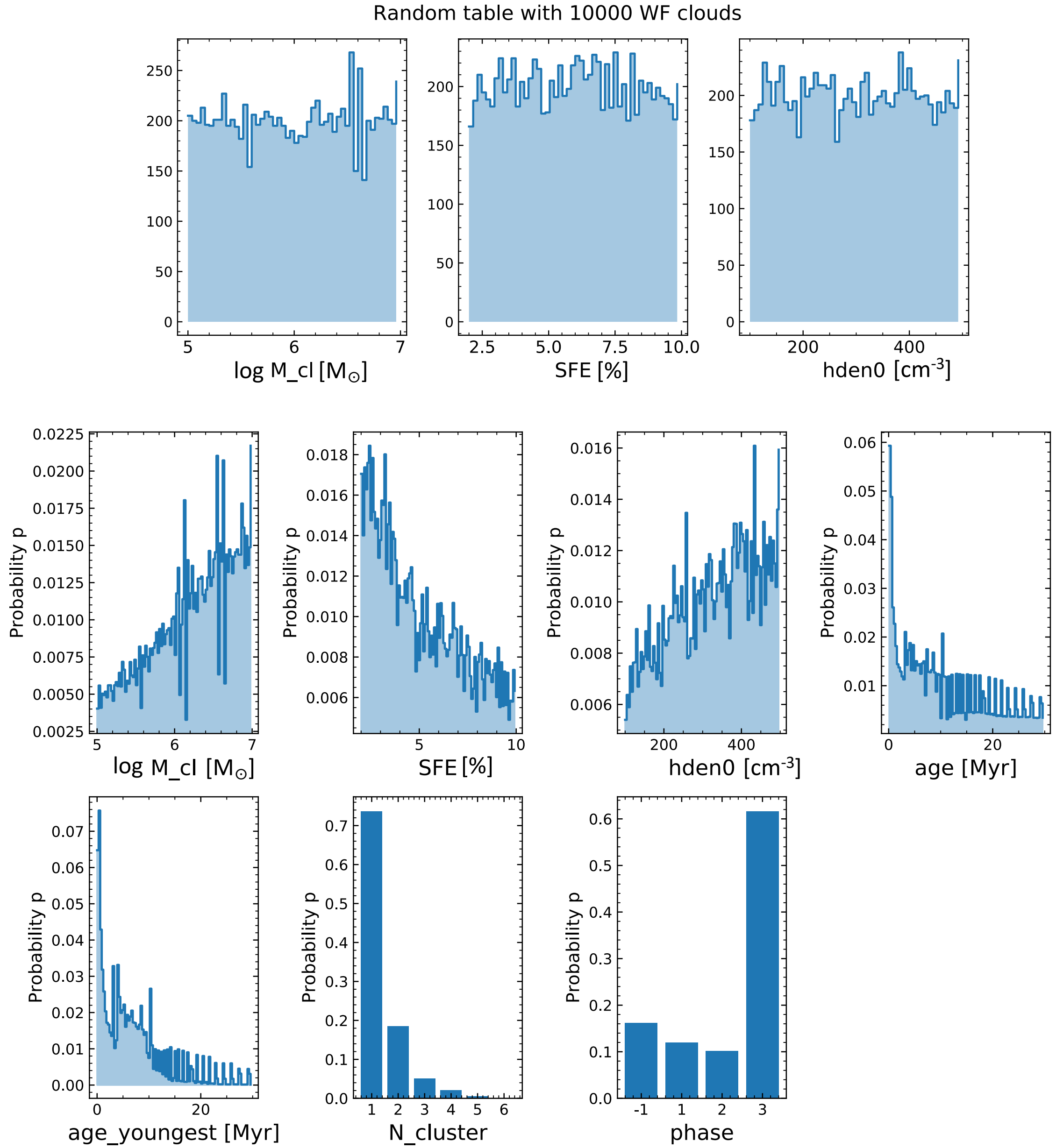
Current database (WARPFIELD-EMP dr 2)

We are now using randomized database which consists of

10,000 WF clouds (1 WF cloud = [M_{cl}, SFE, $n_{H,0}$])

505,748 model (1 model = [M_{cl}, SFE, $n_{H,0}$, t])

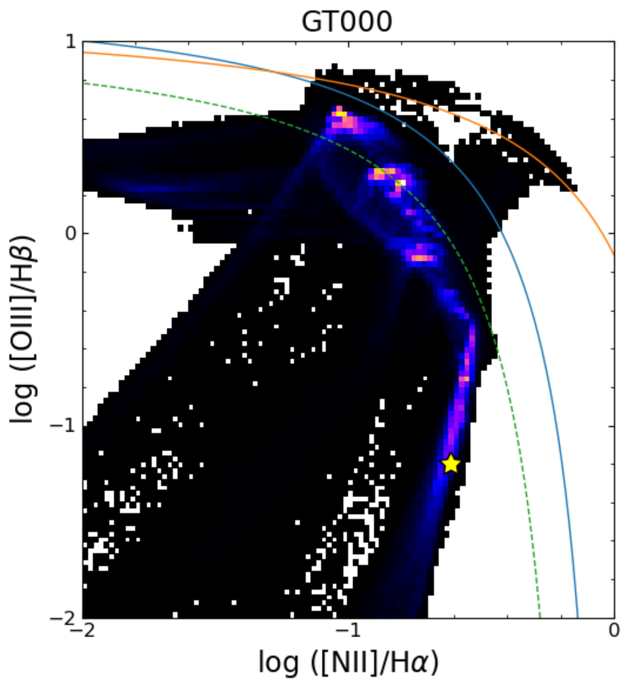




cINN with WARPFIELD-EMP

Configuration of the network

- 7 HII region properties (X): M_{cl}, SFE, $n_{H,0}$, t, $t_{youngest\_cluster}$, $N_{cluster}$, phase
- 12 optical emission line luminosities (Y): Ha, Hb, [OIII], [NII], [SII], [SIII], [OI], [OII], etc
- We use 80% of the data for training-set and remain 20% for test-set
- Choose example test models from test-set which was not used for the training (i.e., unlearned model)



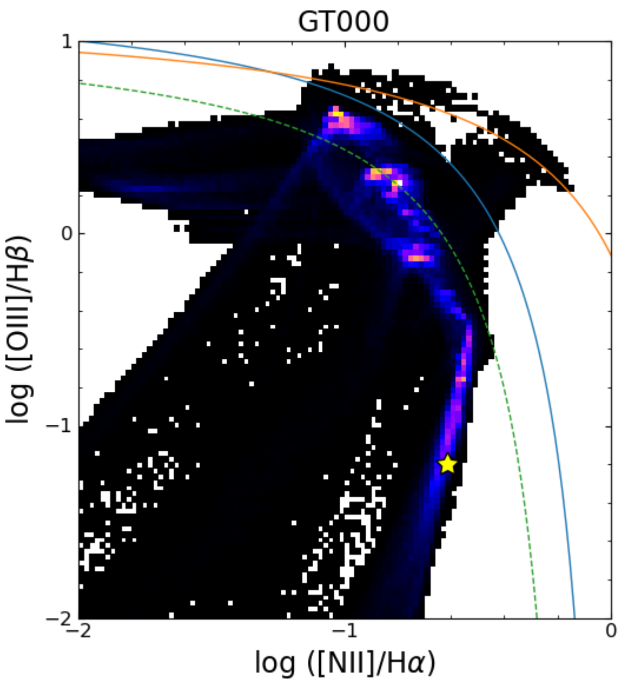
Feed luminosity of 12 emission lines

Generate thousands of candidate models expected to have the same luminosities

cINN with WARPFIELD-EMP

Posterior distribution of test model (GT000)

- Precise and accurate
- Width of each distribution: M < 0.05dex, SFE < 1%, n_H<100cm^{-3}, age < 0.1Myr



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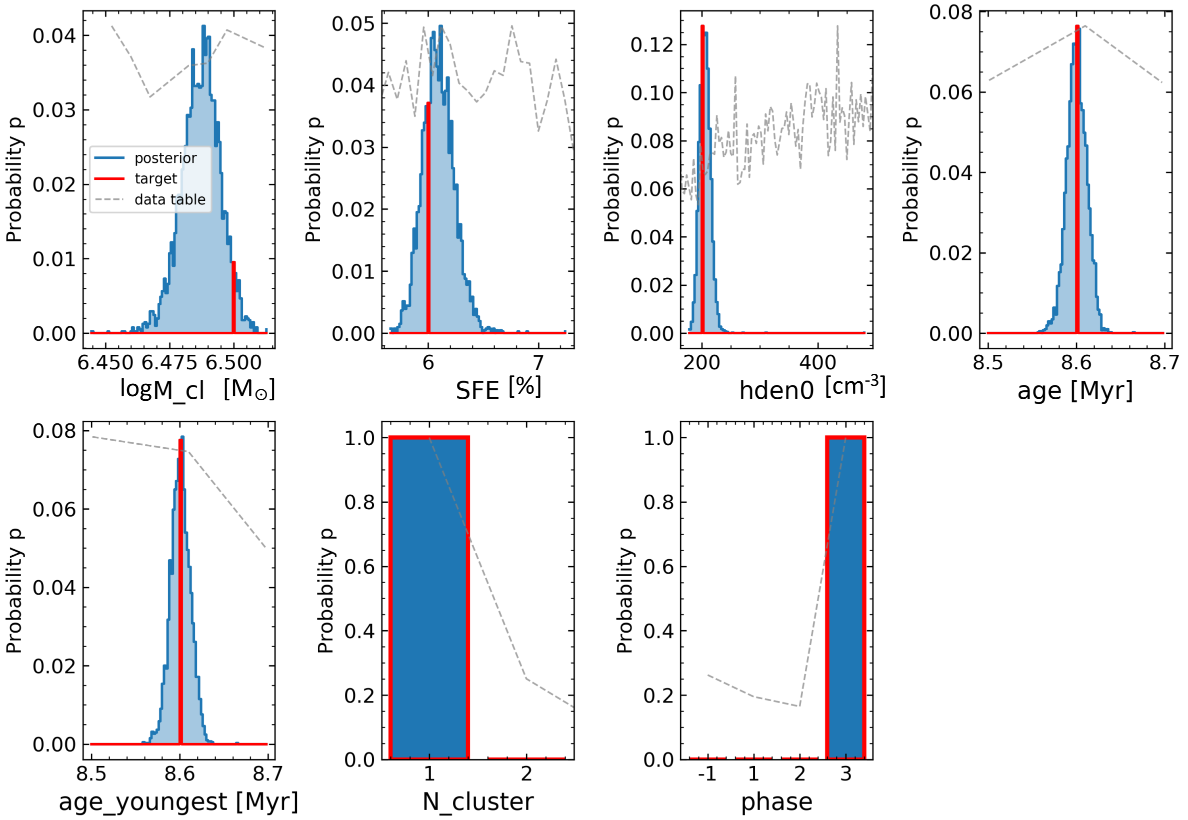
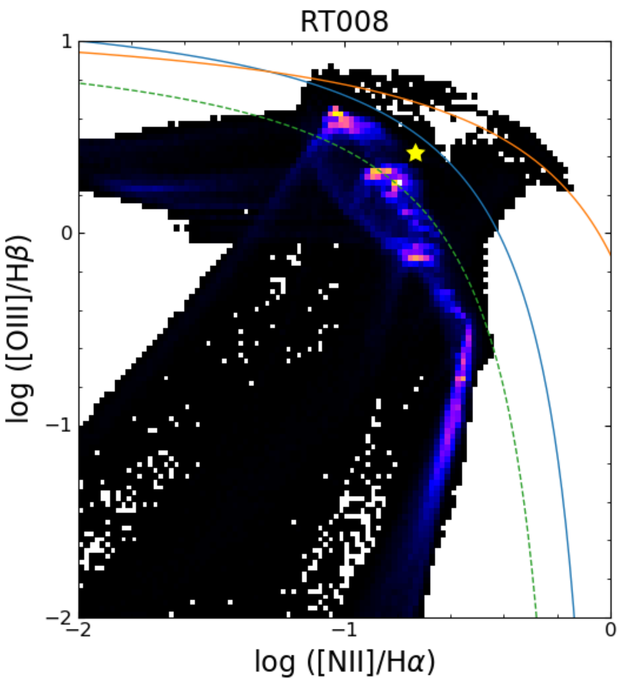


cINN with WARPFIELD-EMP

Posterior distribution of test model (RT008)

- Precise and accurate
- Width of each distribution: M < 0.05dex, SFE < 0.5%, n_H<20cm^{-3}, age < 0.05Myr



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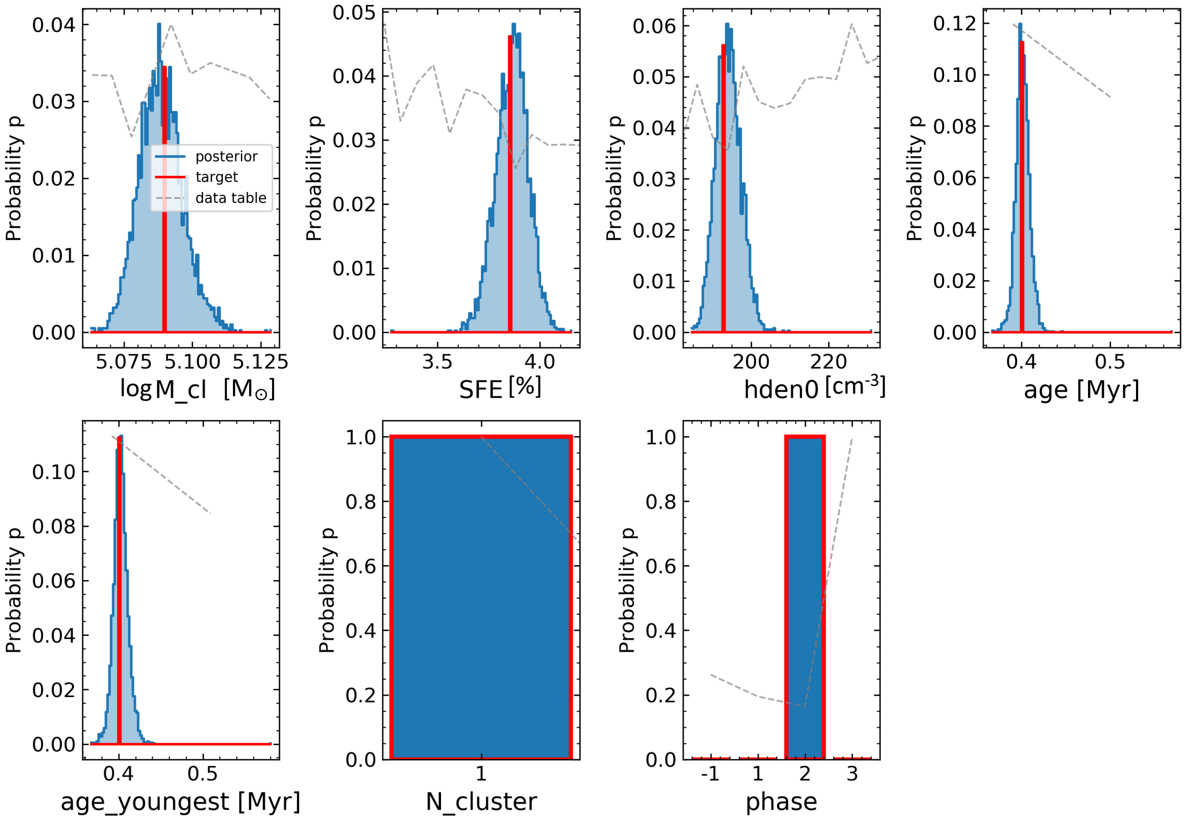
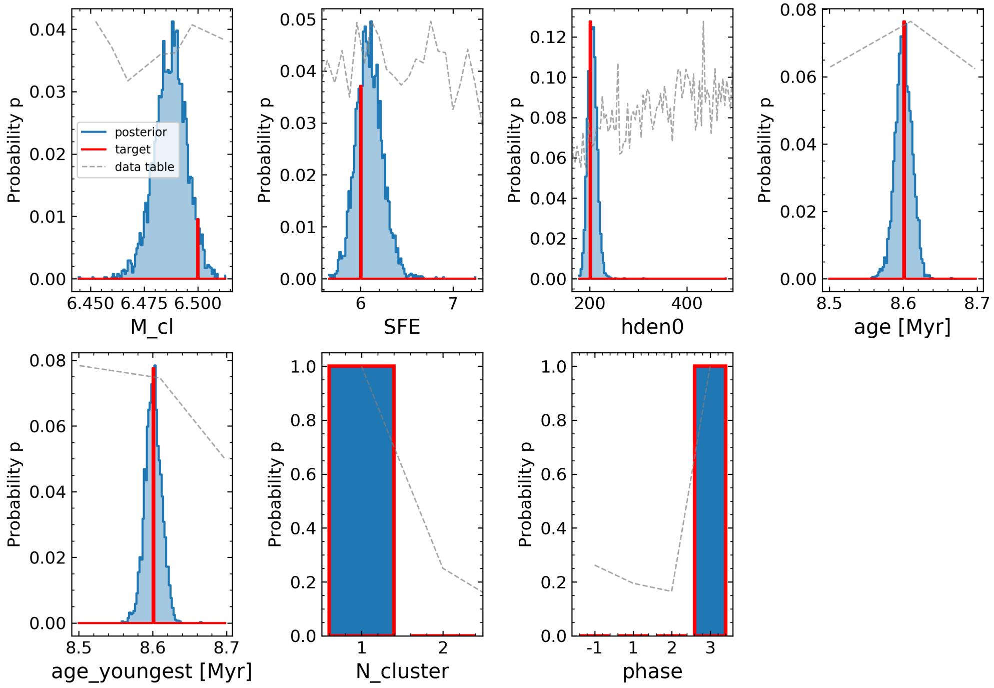
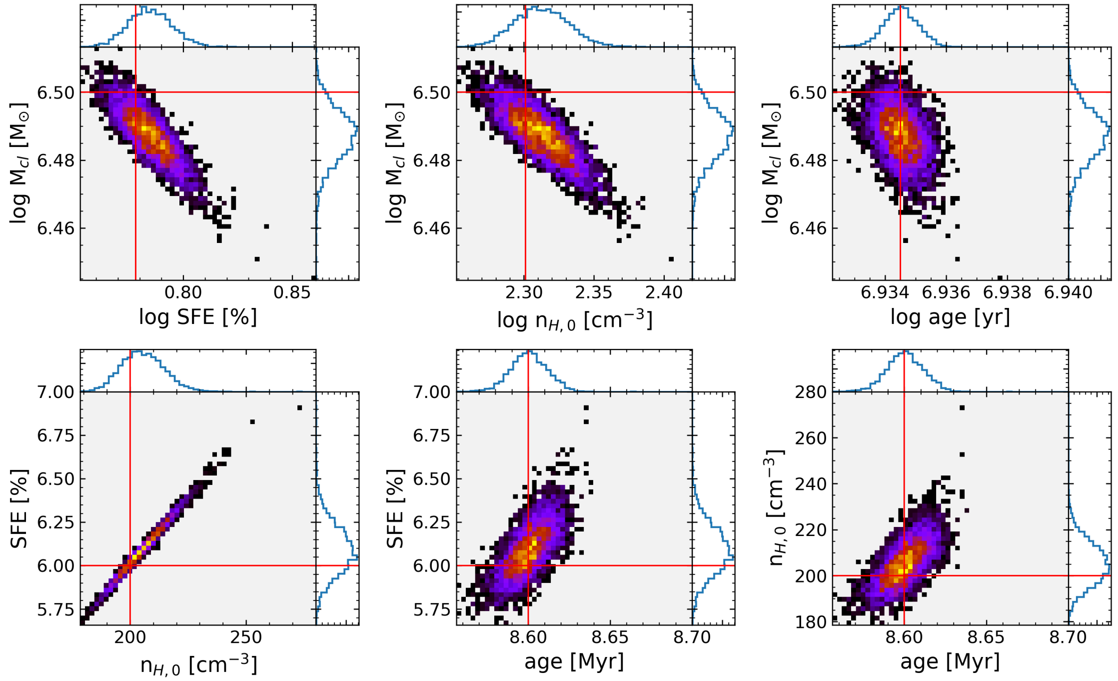


Degeneracy between different properties

- All candidates models are expected to have the same luminosity (different models can have the same luminosity)
- 1D posterior disstribution does not means error range of prediction
- Multi-dimensional posterior distribution shows a relation between different properties to satisfy the luminosity



1D posterior of GT000



2D posterior of GT000

Validation of the network

Does network give correct predictions?

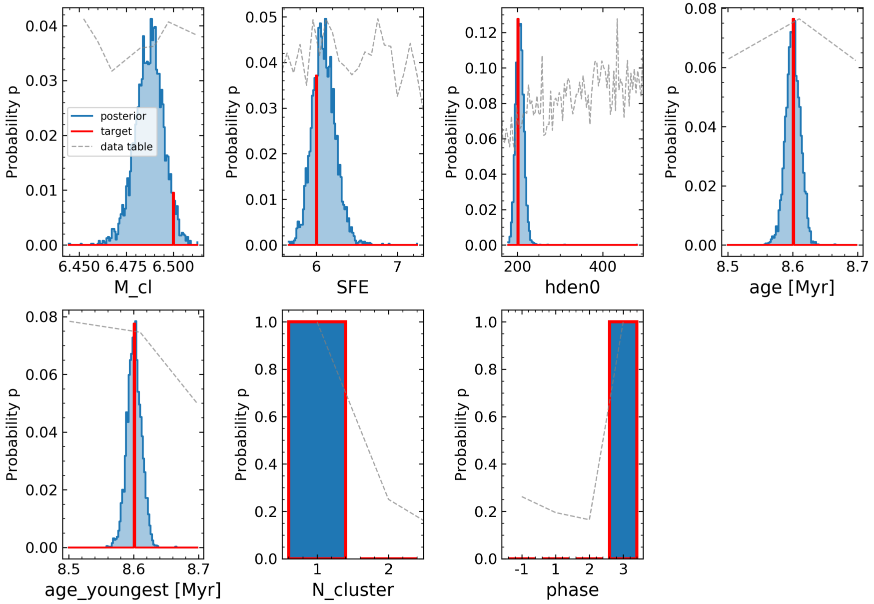
- Check the luminosity (Y') of all candidate models (X') and compare them with that of original test model (Y*)
- cINN cannot predict observation (Y) from cloud model (X) because Y is used in both forward and backward process as a condition
- Calculate emission-line luminosity using WARPFIELD-EMP as we did to generate the training data

Known information of the test model

X*, Y*

Feed Y* to cINN

Candidate models (X')



Run WF-EMP

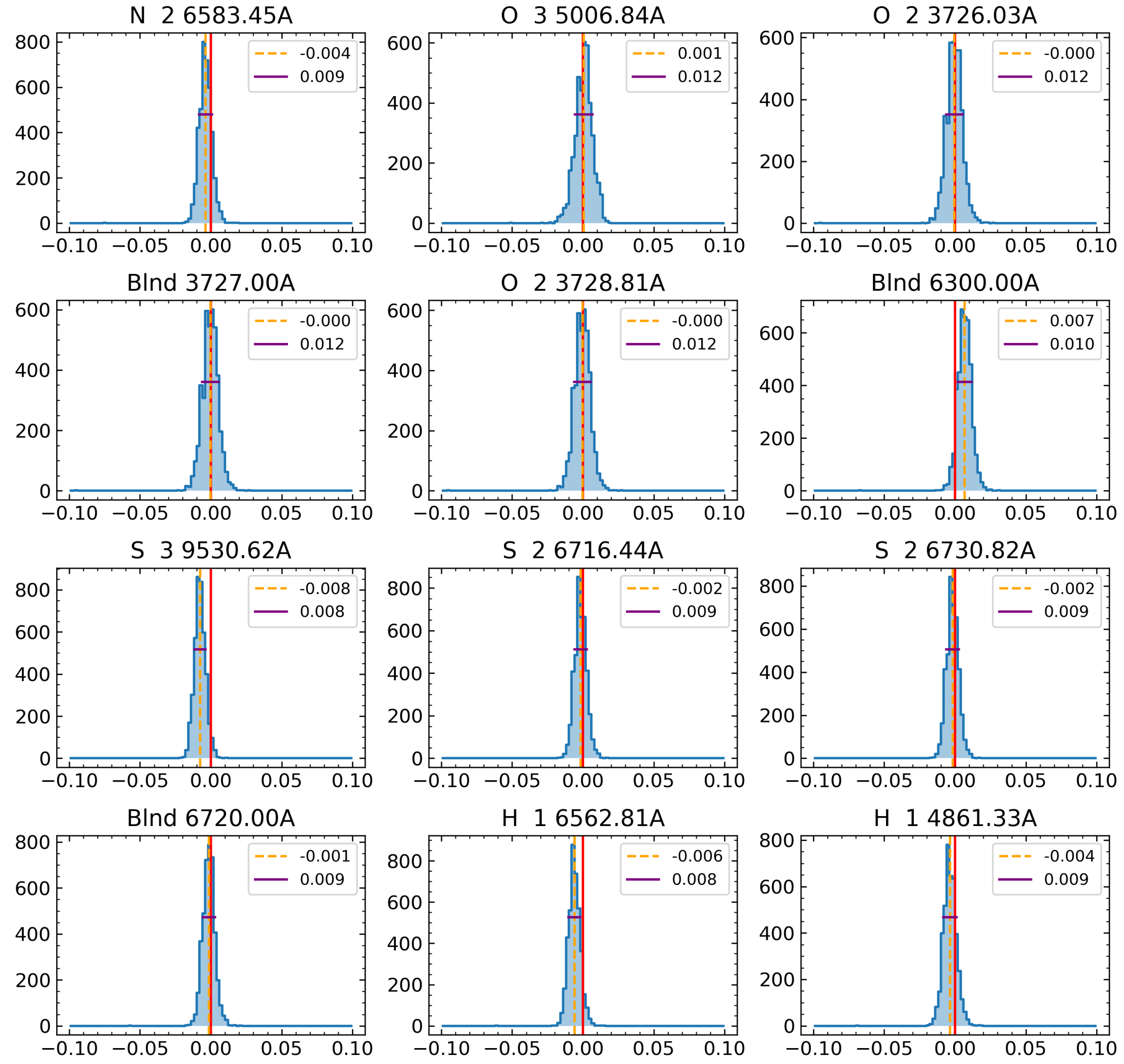
Luminosity of candidate models

Y'

Validation Test

GT000

Simulated models

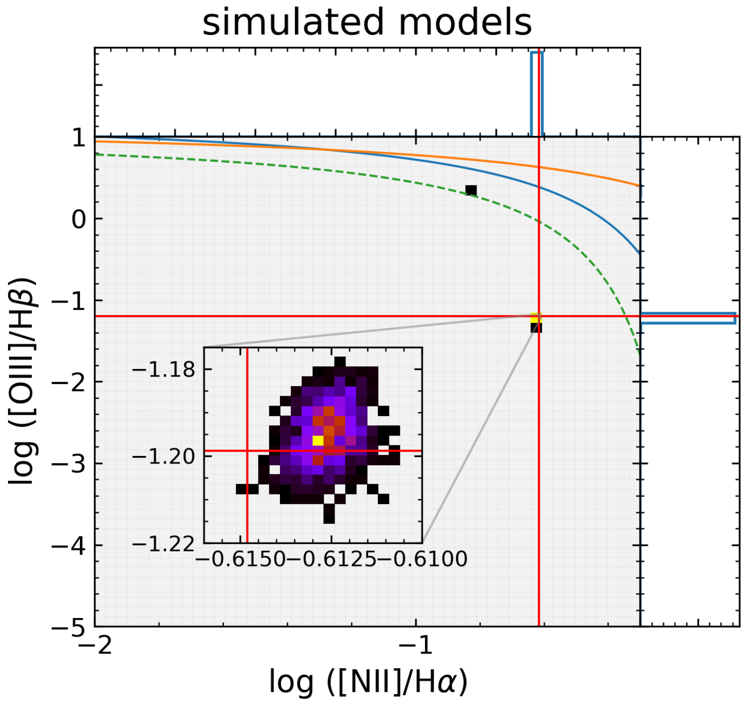


log L/L_0

Luminosity distribution is shifted with respect to the original value (L_0)

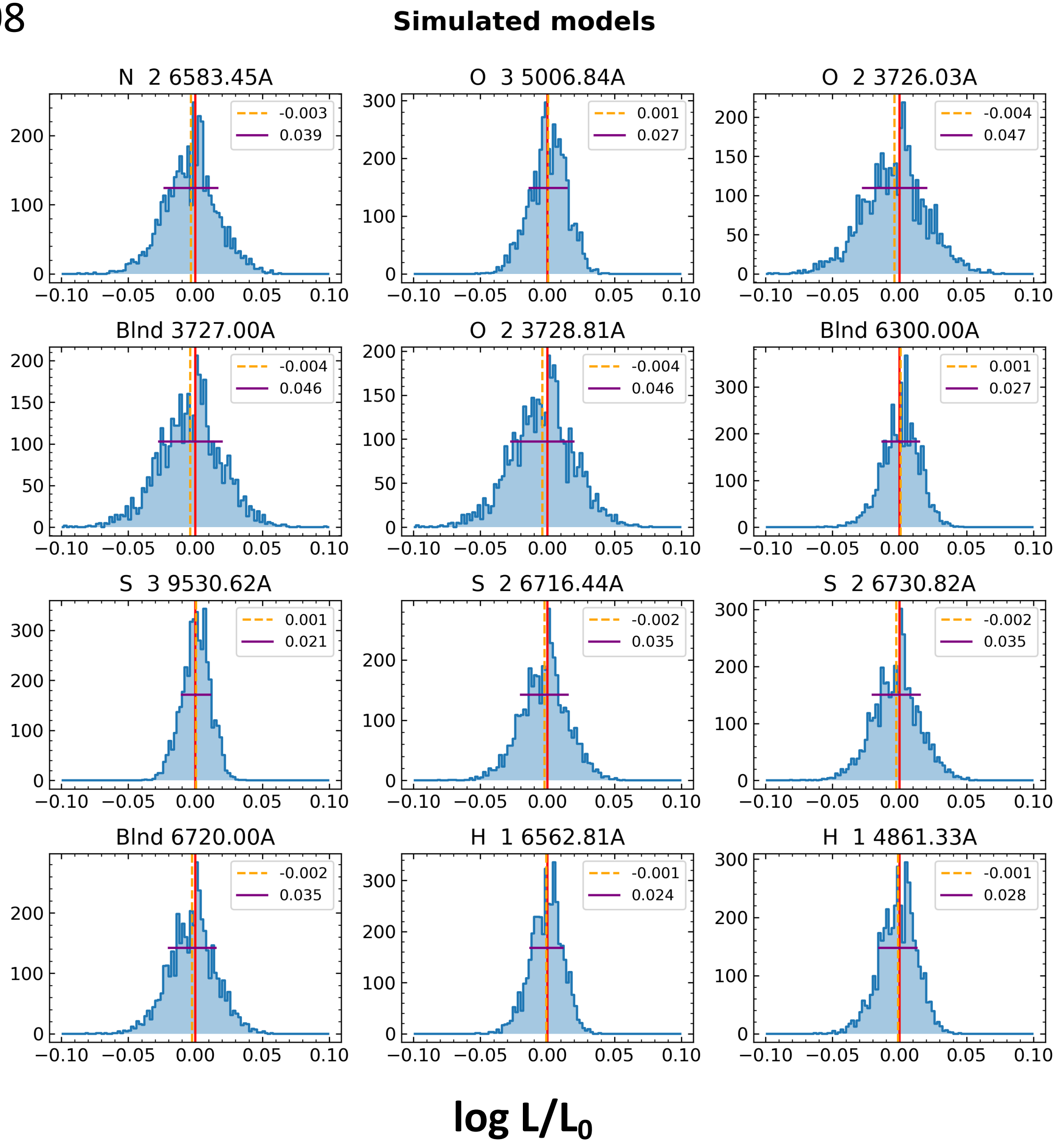
Orange dashed line: 1st moment of the distribution (i.e., offset)

Purple bar: 2 x (2nd moment of the distribution) (i.e., width)



Validation Test

RT008



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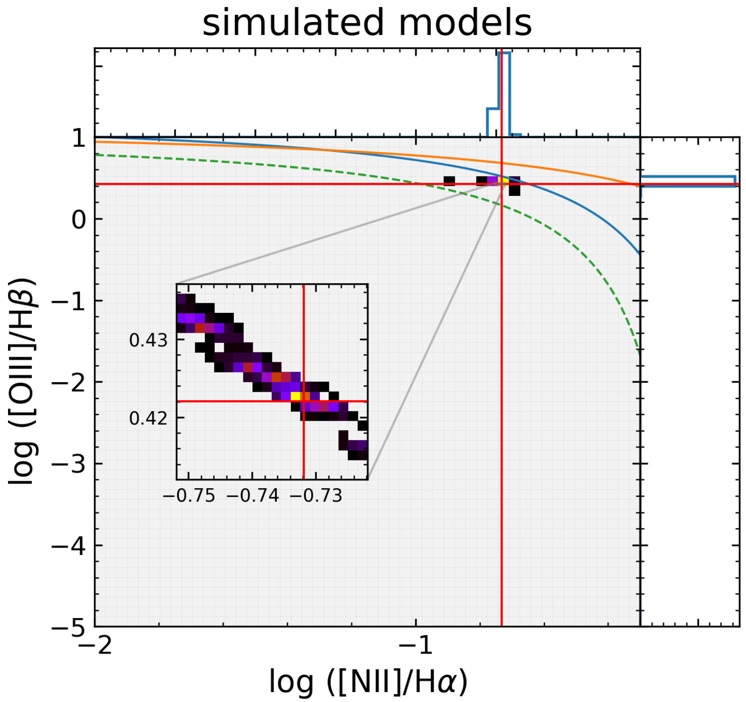

Summary

We developed a machine learning tool that can characterize HII regions from observations

- We use conditional invertible neural network (cINN)
- ~500,000 cloud-observation pairs were generated by WARPFIELD-EMP and used for training

Our network provides candidiate models (7 HII region properties) expected to have the same luminosities

- Precise and accurate prediction of HII region properties (1D posterior distribution)
- Degeneracy between different HII region properties (2D posterior distribution)
- We validate the network performace by reproducing luminosity of all candidate models
- Luminosity difference between candidate models and test model is very small (e.g., for RT008 test model, 0.001±0.024 dex for Ha and 0.004±0.047 dex for [OII])