Characterization of exoplanet atmospheres using Machine Learning

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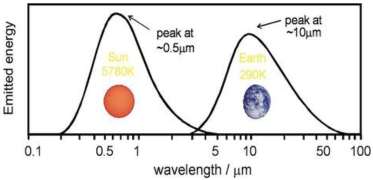
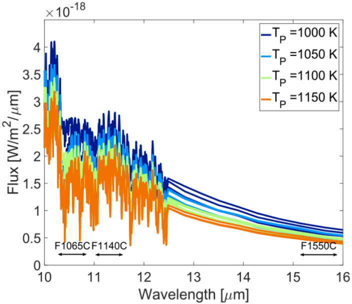
Direct Imaging

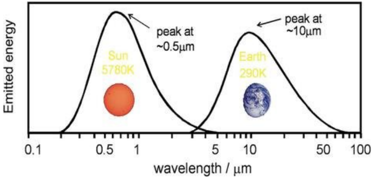


Thermal emission,
(Richard P Tuckett)



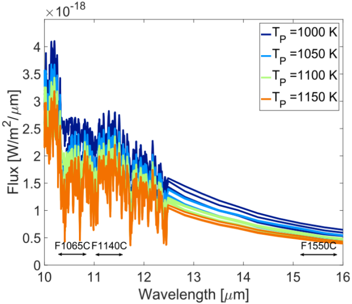
Exoplanet HR8799b
(seen by MIRI JWST via DI)
Danielski et al.

Direct Imaging



Thermal emission,
(Richard P Tuckett)

contains atm signatures



Exoplanet HR8799b
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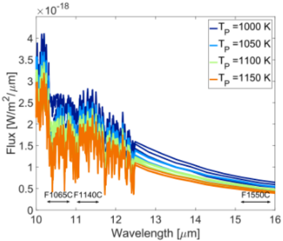
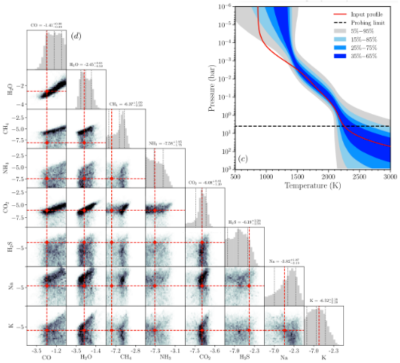
Retrieval



Retrieval tool



Retrieved atm parameters Molliere et.al 2019

JWST Mission

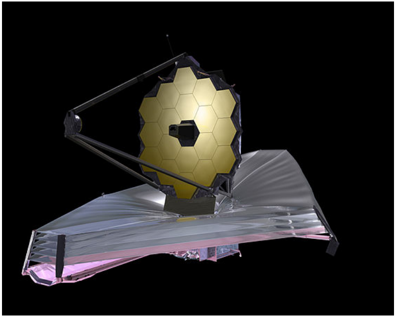


Figure: James Webb Space Telescope (NASA/ ESA/CSA)

- Mid-IR range (5-29um)
- Launch in Oct
- ROSS 458C, 2M2236+4751b, & VHS1256-1257b in MRS mode ERS program.

Retrieval tool

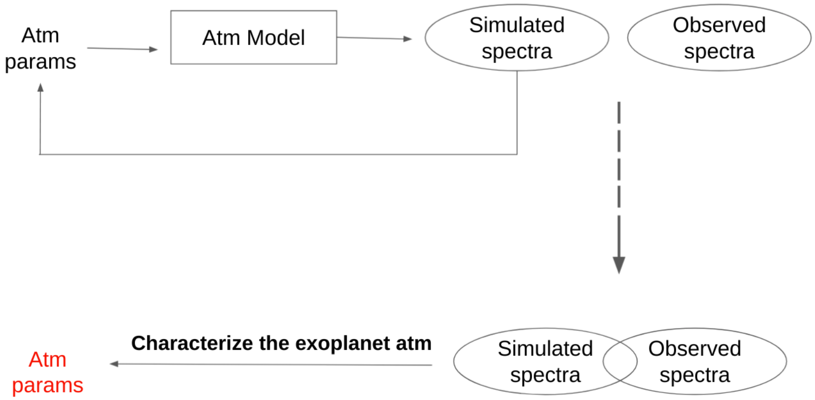


Figure: Principle of Bayesian Inference

Bayesian Inference

Theorem

$$P(param|obs\ spec, M) = \frac{P(obs\ spec|param, M)P(param|M)}{P(obs\ spec|M)}$$

where,
$P(param|obs, M)$ – *Posterior*
$P(obs|param, M)$ – *Likelihood*
$P(param|M)$ – *Prior*
$P(obs|M)$ – *Evidence*

Evidence - $\int^{all\ params} P(obs\ spec|param)P(param)\,dparam$

Bayesian Inference

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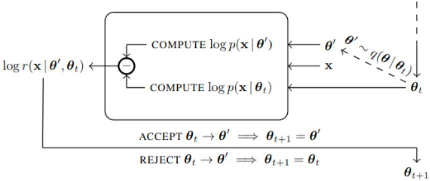
$P(obs|M)$ – *Evidence*

Evidence - $\int^{all\ params} P(obs\ spec|param)P(param)\, dparam$: MCMC

Markov Chain Monte Carlo (MCMC)

MCMC

- Rejection sampling
- Pair(param, obs) $\Rightarrow$ Likelihood
- Posterior $\propto$ Likelihood * Prior



Metropolis Hastings MCMC

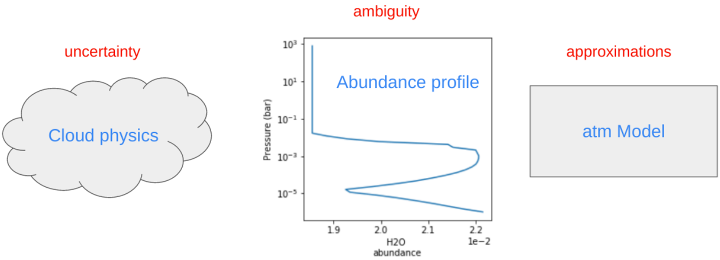
Bayesian Inference

$$\color{red}{P(param|obs, M)} = \frac{\color{blue}{\cancel{\mathrm{P(obs|param,M)}}}\color{orange}{P(param|M)}}{P(obs|M)}$$

Likelihood is intractable.

Atmospheric Model

Atmospheric Model(M) - Radiative-Convective model based on the physics of hydro-dynamics.



Introduces latent parameters contributing to stochasticity in the system.

Bayesian Inference

$$P(param|obs, M) = \frac{P(\text{obs}|\text{param,M}) P(param|M)}{P(obs|M)}$$

Likelihood

$$\int^{all\ latent\ params} P(obs\ spec, latent\ param|param)\, d(latent\ param)$$

Likelihood is implicit.

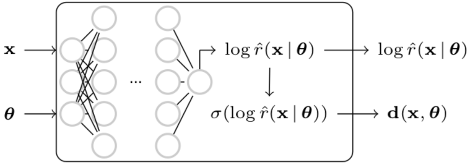
Simulation Based Inference (SBI)

$$P(param|obs\ spec, M) = \frac{P(obs\ spec|param, M)}{P(obs\ spec|M)} P(param|M)$$

Estimate Likelihood to Evidence ratio

Simulation Based Inference (SBI)

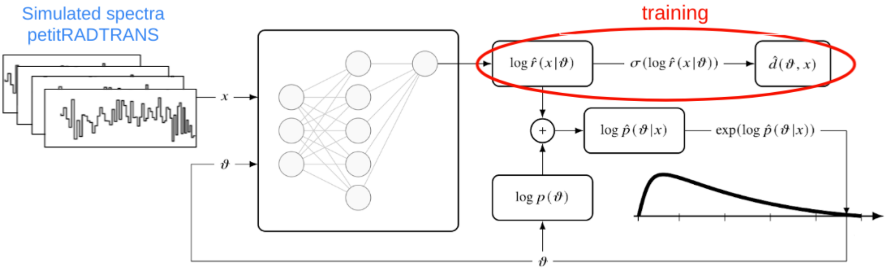
$P(param|obs\ spec, M) =$



$*P(param|M)$

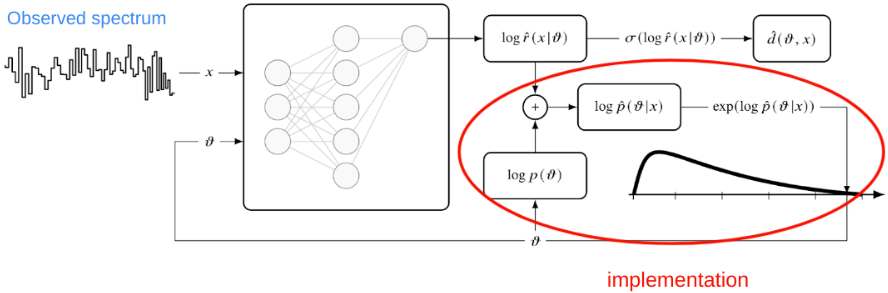
log Likelihood to Evidence ratio

Simulation Based Inference (SBI)



Amortized Approximate Ratio Estimator
(J.Hermans. et al 2020)

Simulation Based Inference (SBI)



Amortized Approximate Ratio Estimator
(J.Hermans. et al 2020)

Results (for a Simulated Observable)

Retrieval of 3 parameters : **Tint, log kappa IR and log gravity**

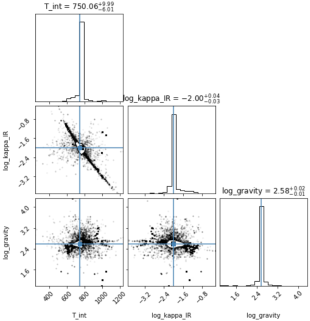


Figure: MCMC

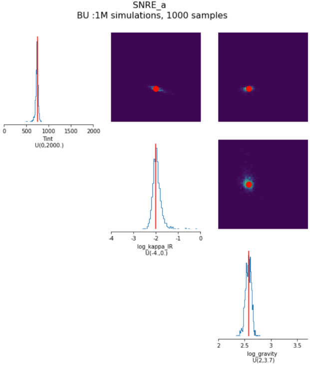


Figure: SBI

Results(for a Simulated Observable)

Retrieval of 4 parameters : **Tint, log kappa IR and log gravity, log ab H2O**. Diagnostic Coverage : 0.983 (C- 0.95)

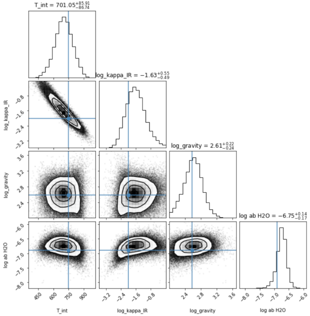


Figure: contour plot

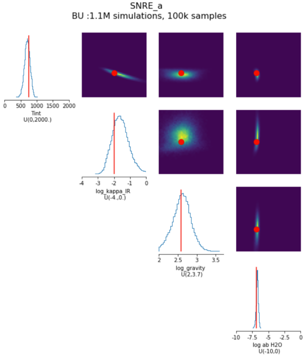


Figure: SBI

Important aspects of SBI

- The training of the ratio estimator is only done once, unlike MCMC where retrieval is started from scratch.
- Retrieval takes less time (observation independent).
- It can be 'updated' in the future with more observations (from future telescopes.)

Future scope

- Hyper parameter tuning of the NN.
- Retrieval with more parameters.
- Incorporating more complexity in the atm Model.
- Verifying the tool with JWST sources in the ERS program.

The End