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.

Retrieval with direct imaging
Bayesian Inference
SBI
Results
Conclusion
Future scope
Direct Imaging

Thermal emission, (Richard P Tuckett)

contains atm signatures

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

Retrieved atm parameters Molliere et.al 2019
JWST Mission

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

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

![Diagram showing the principle of Bayesian Inference]

**Figure**: Principle of Bayesian Inference
Bayesian Inference

Theorem

\[ P(\text{param}|\text{obs spec}, M) = \frac{P(\text{obs spec}|\text{param}, M)P(\text{param}|M)}{P(\text{obs spec}|M)} \]

where,
\[ P(\text{param}|\text{obs}, M) \] – Posterior
\[ P(\text{obs}|\text{param}, M) \] – Likelihood
\[ P(\text{param}|M) \] – Prior
\[ P(\text{obs}|M) \] – Evidence

Evidence - \( \int \text{all params} P(\text{obs spec}|\text{param})P(\text{param}) \, d\text{param} \)
Bayesian Inference

Theorem

\[ P(\text{param}|\text{obs spec}, M) = \frac{P(\text{obs spec}|\text{param}, M)P(\text{param}|M)}{P(\text{obs spec}|M)} \]

where,
\begin{align*}
P(\text{param}|\text{obs}, M) & \quad \text{Posterior} \\
P(\text{obs}|\text{param}, M) & \quad \text{Likelihood} \\
P(\text{param}|M) & \quad \text{Prior} \\
P(\text{obs}|M) & \quad \text{Evidence} \\
\end{align*}

Evidence - \( \int_{\text{all params}} P(\text{obs spec}|\text{param})P(\text{param}) \, d\text{param} \): MCMC
Markov Chain Monte Carlo (MCMC)

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

Metropolis Hastings MCMC
Bayesian Inference

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

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

\[ P(param|obs, M) = \frac{P(obs|param, M)P(param|M)}{P(obs|M)} \]

Likelihood
\[ \int_{all \ latent \ params} P(obs \ spec, latent \ param|param) \, d(latent \ param) \]

Likelihood is implicit.
Simulation Based Inference (SBI)

\[
P(\text{param} | \text{obs spec}, M) = \frac{P(\text{obs spec} | \text{param}, M)}{P(\text{obs spec} | M)} P(\text{param} | M)
\]

Estimate Likelihood to Evidence ratio
Simulation Based Inference (SBI)

\[ P(\text{param}|\text{obs spec}, M) = \frac{P(\text{obs spec}|\text{param}, M)}{P(\text{obs spec}|M)} \times P(\text{param}|M) \]

\( \theta \rightarrow \log \hat{r}(x | \theta) \rightarrow \log \hat{r}(x | \theta) \)

\[ \sigma(\log \hat{r}(x | \theta)) \rightarrow d(x, \theta) \]

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