Exoplanet atmospheric retrieval with deep learning

Part 2/2

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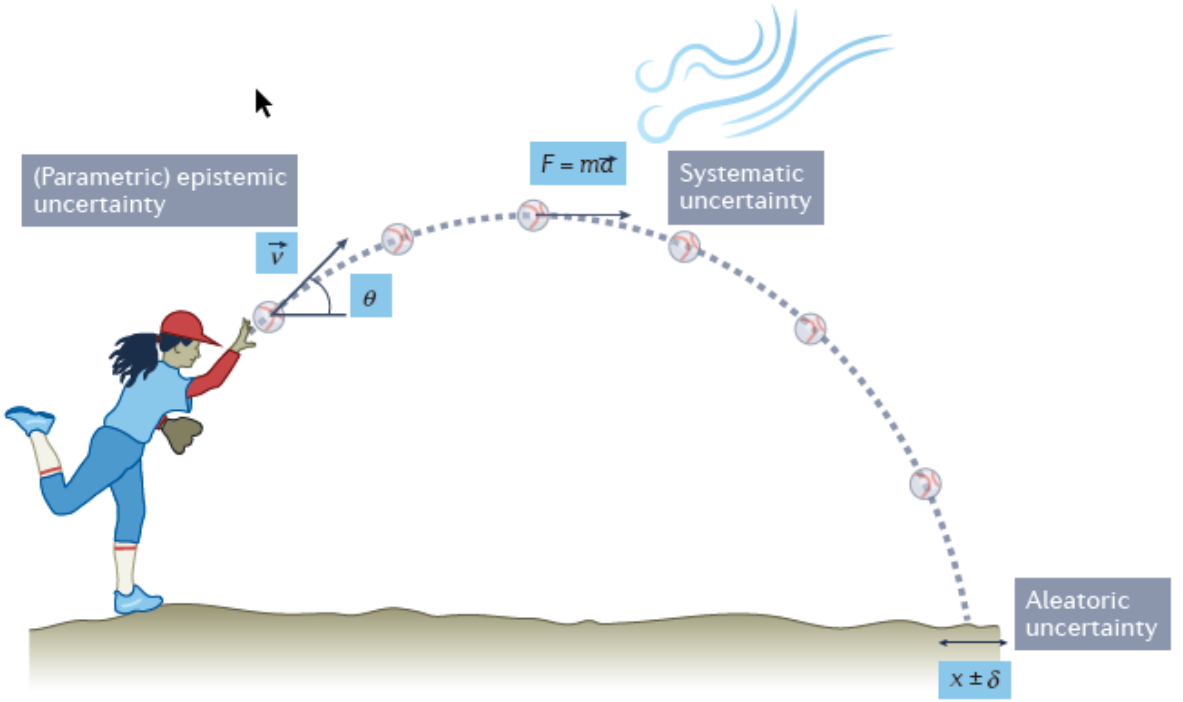
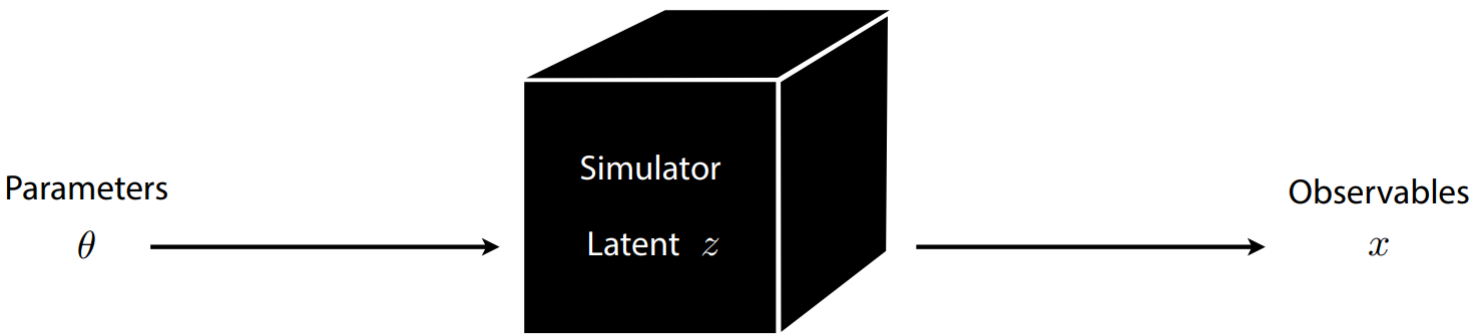
LIÈGE université

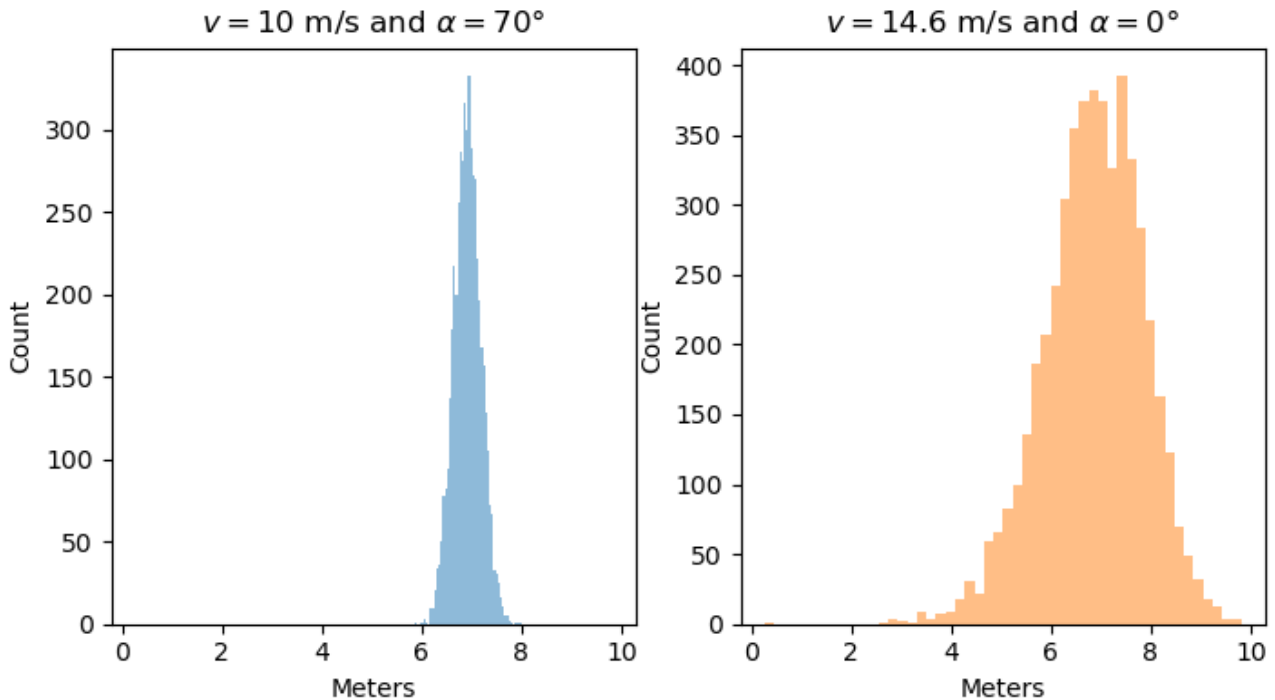

(Parametric) epistemic uncertainty
$\vec{v}$
θ
$F = m\vec{a}$
Systematic uncertainty
Aleatoric uncertainty
$x \pm \delta$

$$v_x = v\cos(\alpha),\ \ v_y = v\sin(\alpha),$$

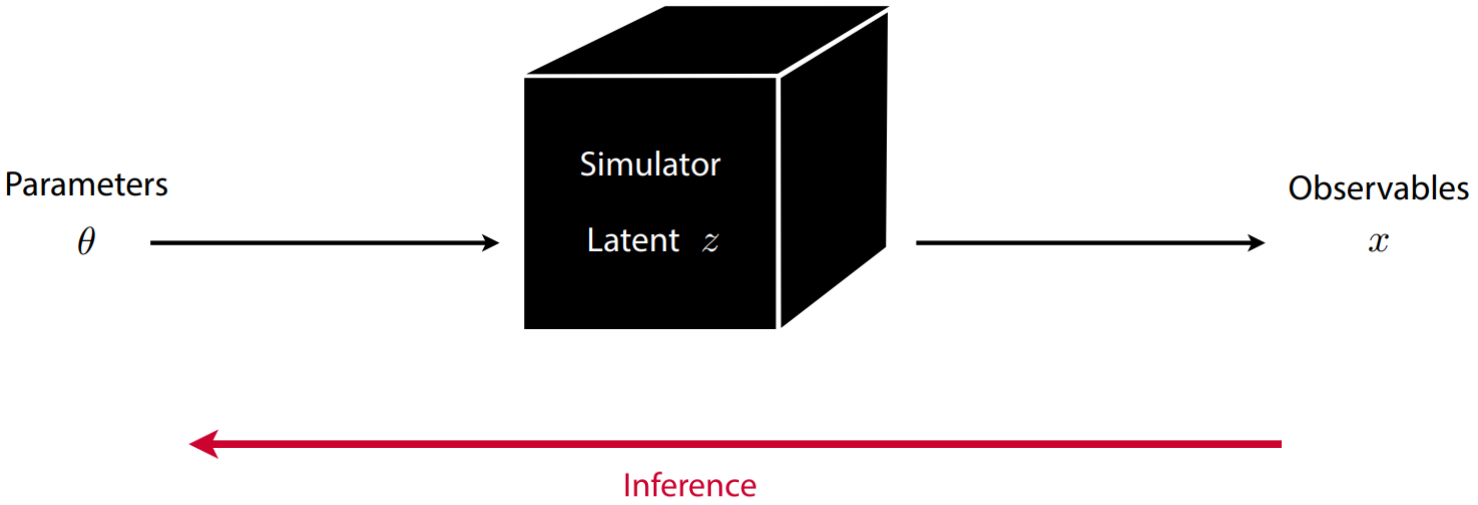
$$\frac{dx}{dt} = v_x,\ \ \frac{dy}{dt} = v_y, \frac{dv_y}{dt} = -G.$$

```
def simulate(v, alpha, dt=0.001):
    v_x = v * np.cos(alpha)  # x velocity m/s
    v_y = v * np.sin(alpha)  # y velocity m/s
    y = 1.1 + 0.3 * random.normal()
    x = 0.0

    while y > 0: # simulate until ball hits floor
        v_y += dt * -G  # acceleration due to gravity
        x += dt * v_x
        y += dt * v_y

    return x + 0.25 * random.normal()
```

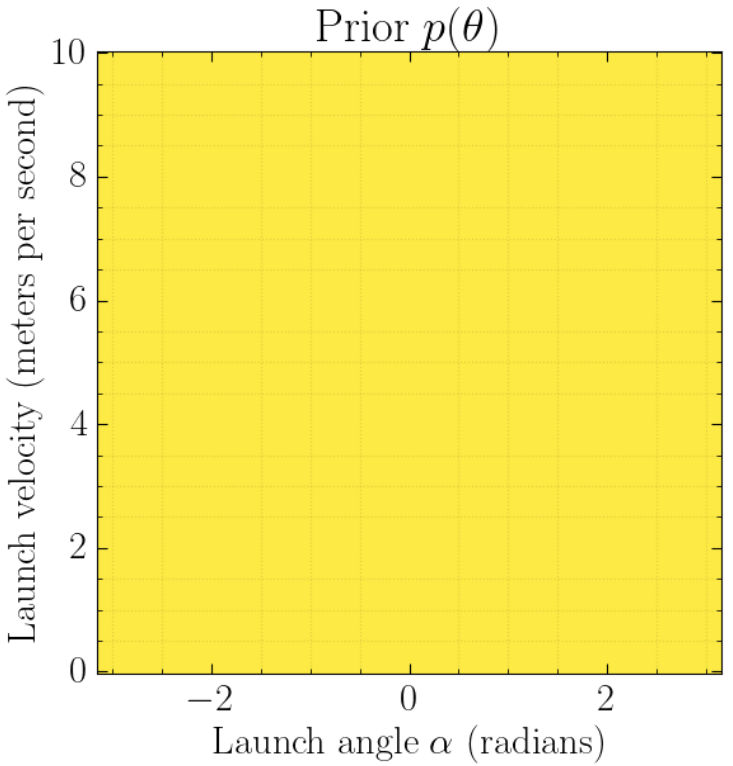

Parameters
θ
Simulator
Latent z
Observables
x

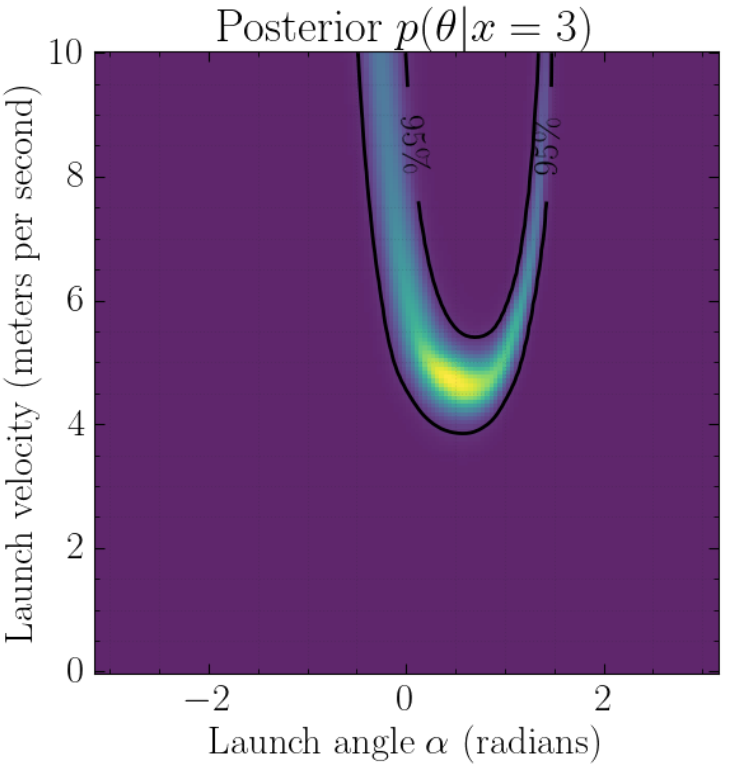

$v = 10$ m/s and $\alpha = 70°$
Count
Meters
0
50
100
150
200
250
300
0
2
4
6
8
10
$v = 14.6$ m/s and $\alpha = 0°$
Count
Meters
0
50
100
150
200
250
300
350
400
0
2
4
6
8
10

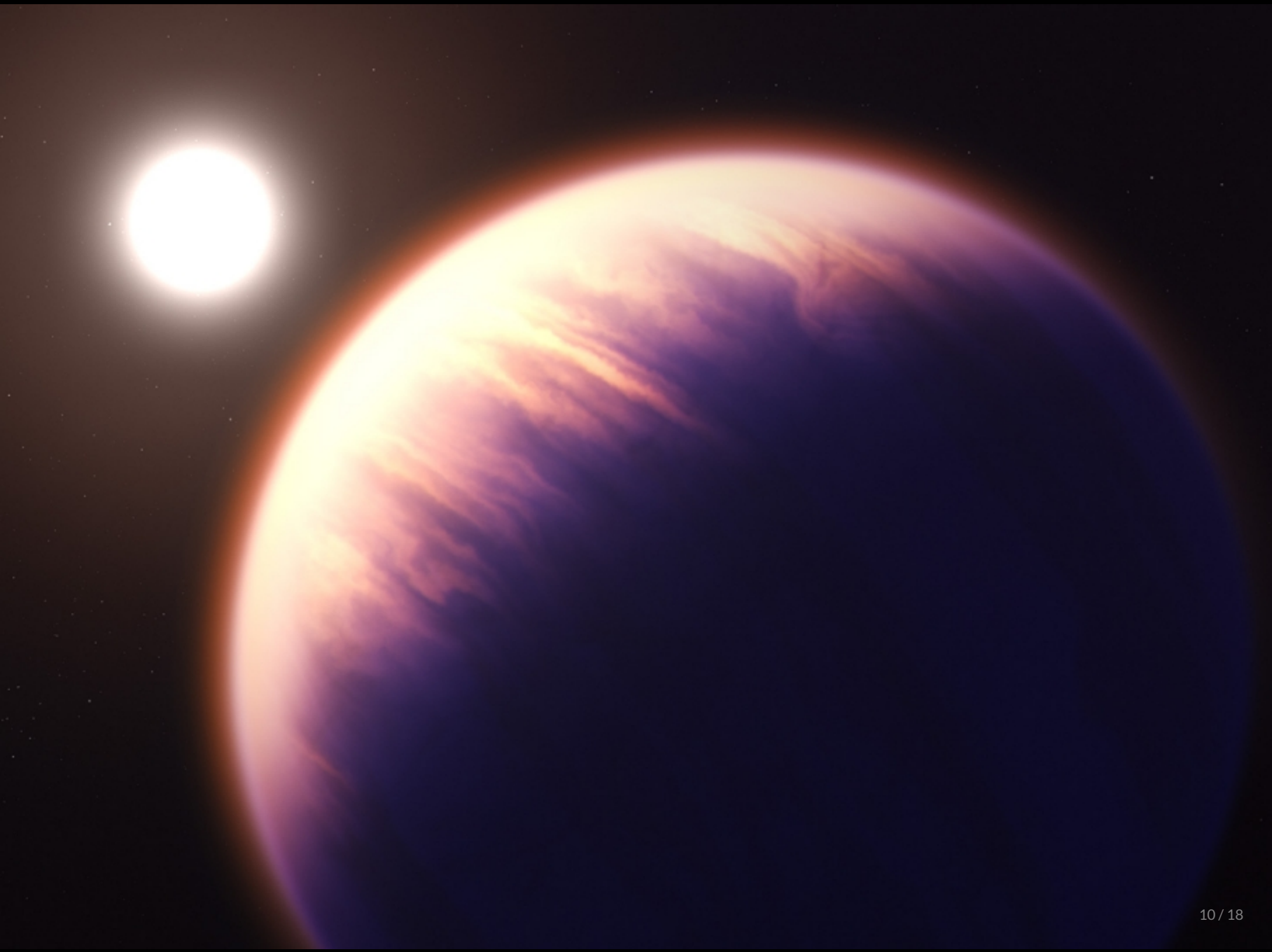
What parameter values θ are the most plausible given x_{obs}?


Parameters
θ
Simulator
Latent z
Observables
x
Inference

$$p(\theta|x_{\text{obs}}) = \frac{p(x_{\text{obs}}|\theta)p(\theta)}{p(x_{\text{obs}})}$$


Prior $p(\theta)$
Launch velocity (meters per second)
Launch angle α (radians)
0
2
4
6
8
10
−2
0
2

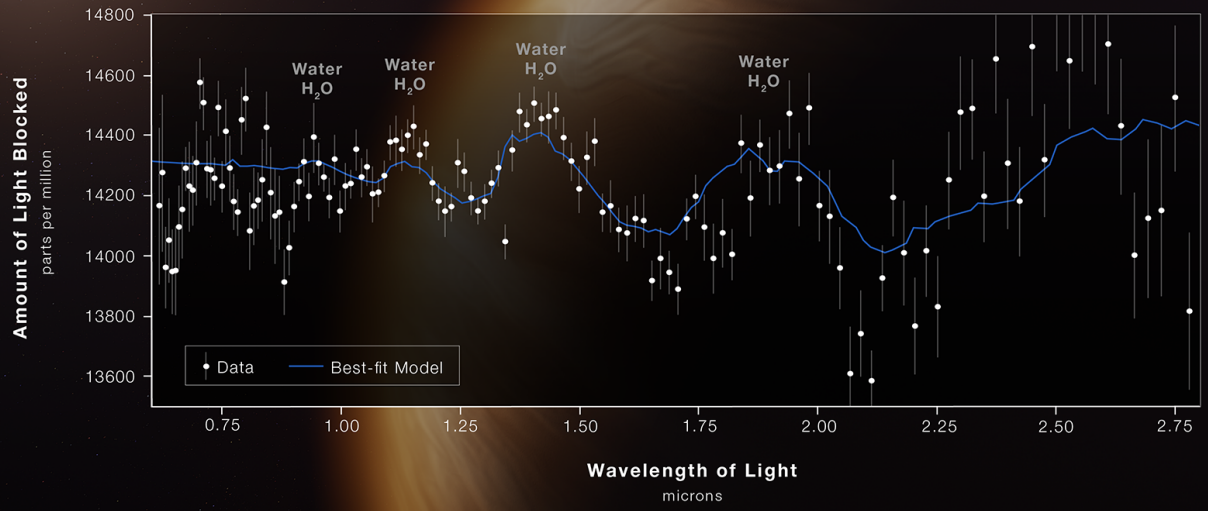

Posterior $p(\theta|x = 3)$
95%
95%
Launch velocity (meters per second)
Launch angle α (radians)
0
2
4
6
8
10
−2
0
2



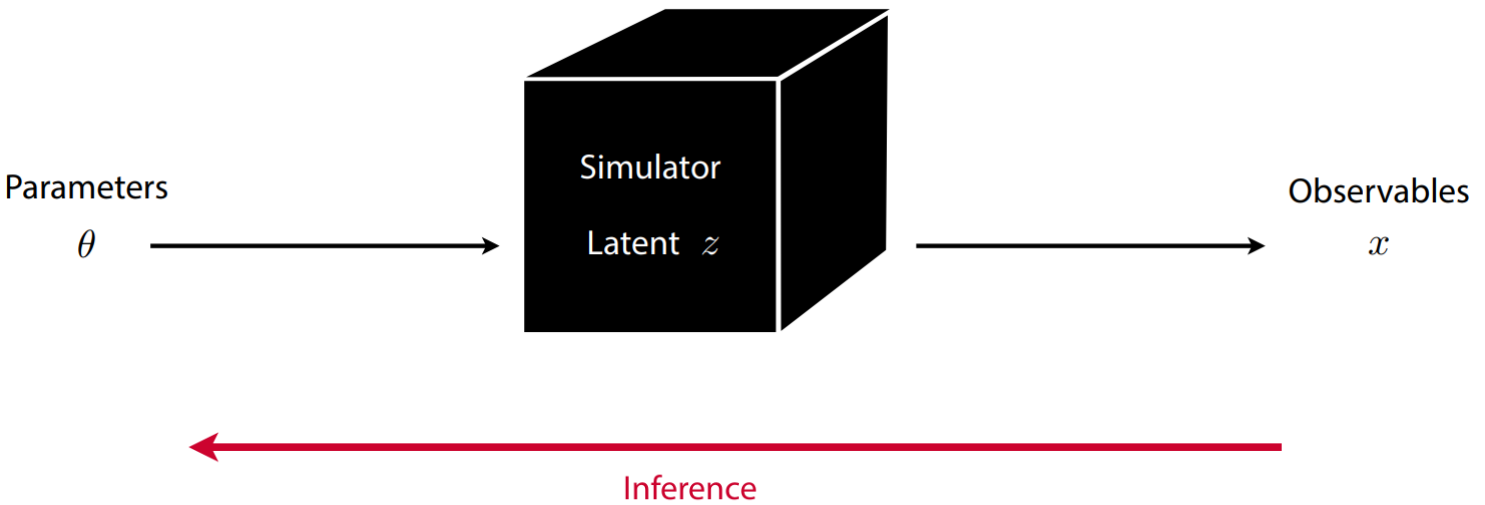
HOT GAS GIANT EXOPLANET WASP-96 b

ATMOSPHERE COMPOSITION

NIRISS | Single-Object Slitless Spectroscopy



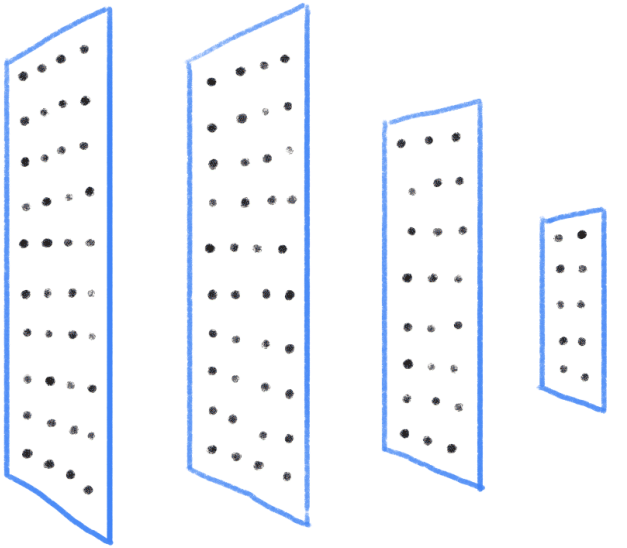
WEBB
SPACE TELESCOPE


Parameters
θ
Simulator
Latent z
Observables
x
Inference

CAT

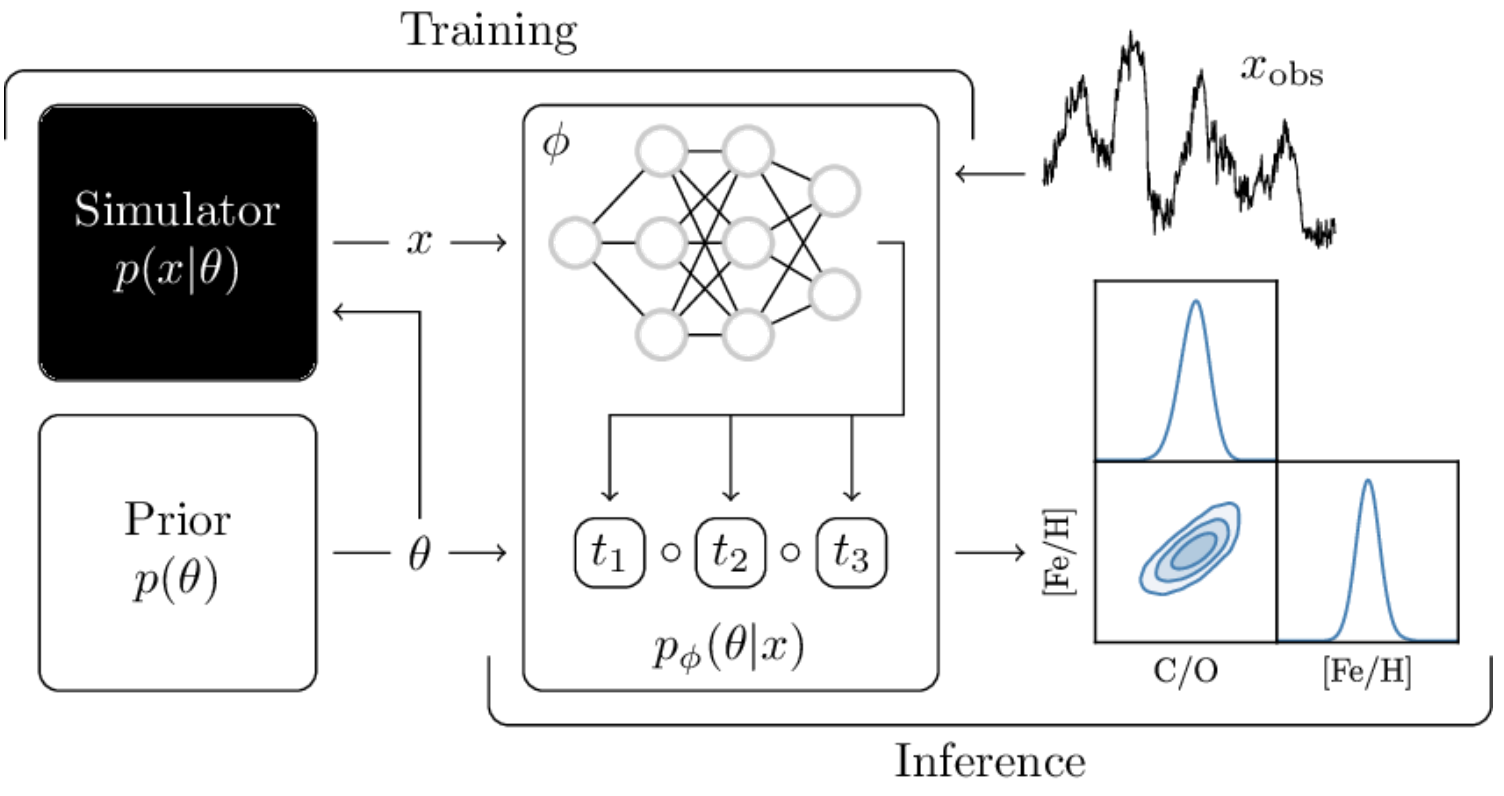
(LABELED PHOTOS)

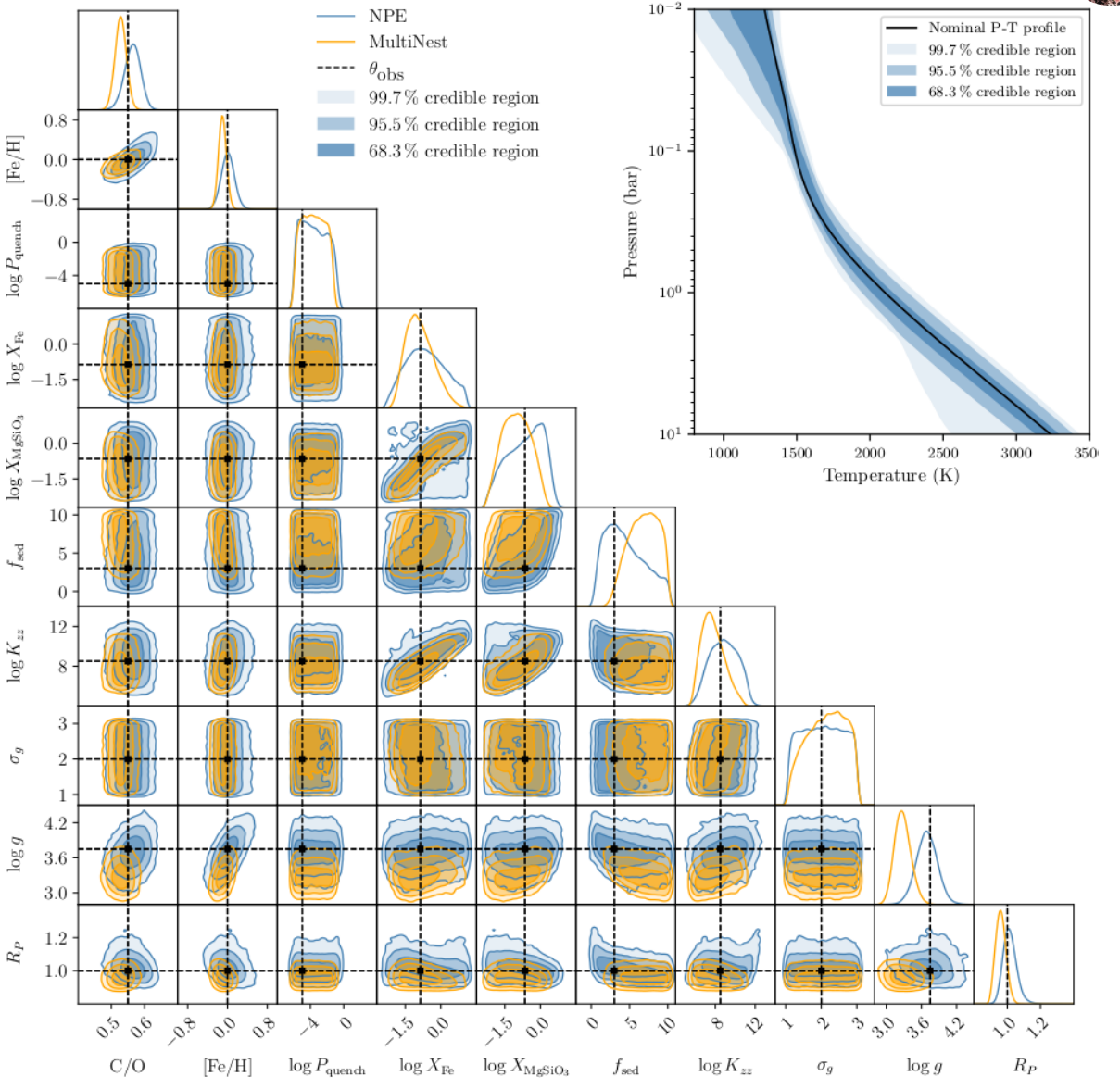
DOG



OUTPUT

> Input: "An astronaut riding a horse on a distant planet"
Ouput:


Training
Simulator
$p(x|\theta)$
Prior
$p(\theta)$
x
θ
ϕ
$t_1 \circ t_2 \circ t_3$
$p_\phi(\theta|x)$
x_{obs}
[Fe/H]
C/O
[Fe/H]
Inference


NPE
MultiNest
$\theta_{\rm obs}$
99.7 % credible region
95.5 % credible region
68.3 % credible region
Nominal P-T profile
99.7 % credible region
95.5 % credible region
68.3 % credible region
Pressure (bar)
Temperature (K)
C/O
[Fe/H]
$\log P_{\rm quench}$
$\log X_{\rm Fe}$
$\log X_{\rm MgSiO_3}$
$f_{\rm sed}$
$\log K_{zz}$
σ_g
$\log g$
R_P

So what?

- Deep learning can be used to inverse models of exoplanet atmospheres.
- Inference time reduces from days/weeks to minutes, enabling large-scale surveys.
- Sophisticated models can be tested, without making compromises.