Machine Learning in X-ray Spectral Timing

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The first thing I want you to know about machine learning is ...

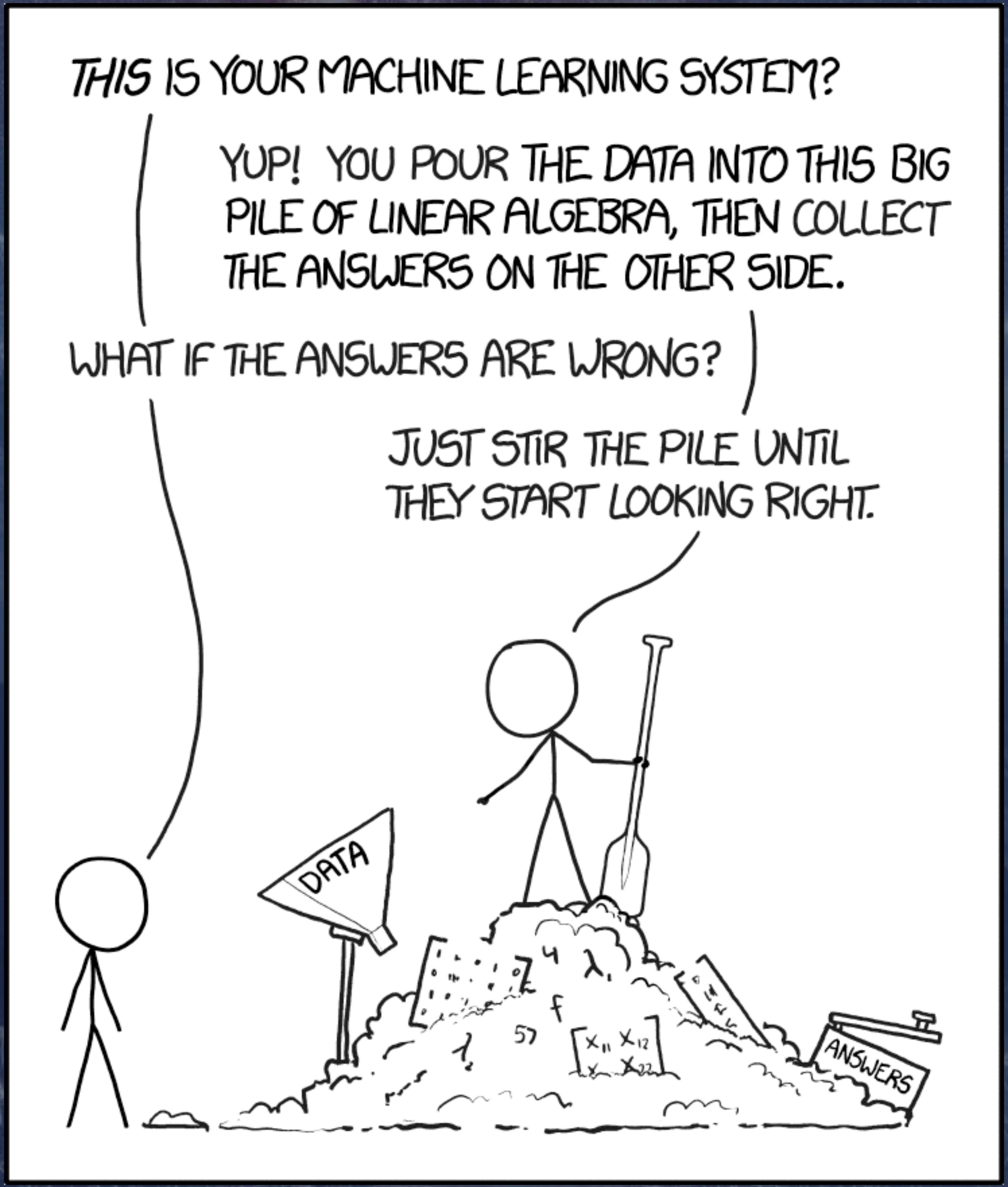
Don’t do machine learning!

Data Science Challenges in Astronomy

adapted from Hernan (2019)

Description	Prediction	Inference
There seem to be bumps in the PSD. Are they QPOs?	Given previous observations of GX 339-4, can I predict what the PSD will look like in the soft state in the next outburst?	Are QPOs caused by relativistic precession?
• Eligibility criteria • Features	• Eligibility criteria • Features • Training examples	• Eligibility criteria • Features • Relativistic precession model
• Exploratory Data Analysis • Representation learning • Dictionary learning • Clustering • …	• (Linear) Regression • Decision trees • Neural networks • …	• (Linear) Regression • Maximum Likelihood • Bayesian inference • …

Machine learning = the ability of computer systems to automatically learn and improve from experience without explicit programming


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

⚠ What is NOT machine learning?

"A ~magical~ universal analysis of complicated data sets"

ML does not provide

- data compilation, and understanding
- scientific interpretation
- critical thinking

Algorithms

- Should never remain a black box
- Will always return "an" answer

Credit: Iva Momcheva and Morgan Fouesneau

Machine learning algorithms learn correlations, not causal relationships!

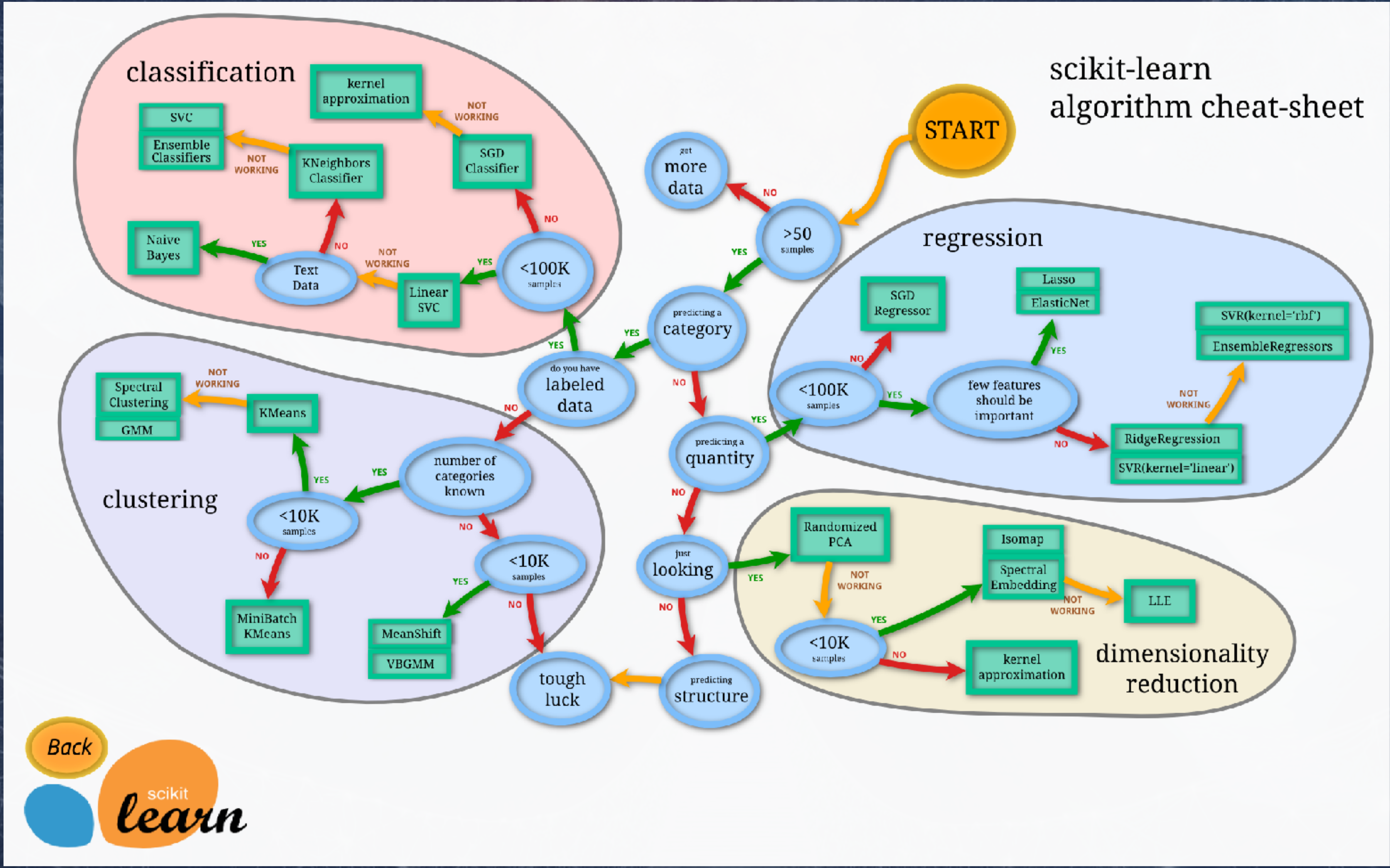
Types of Machine Learning

Supervised learning = learn explicit relationships between input data and known outputs (e.g. image labels, photometric redshifts, ...)

Unsupervised learning = infer labels from data (mainly clustering, some anomaly detection, dimensionality reduction, density estimation, ...)

Semi-supervised learning = uses both labelled and unlabelled data simultaneously

Reinforcement learning = learning method that interacts with the environment by producing actions and discovering errors (trial, error, delay)

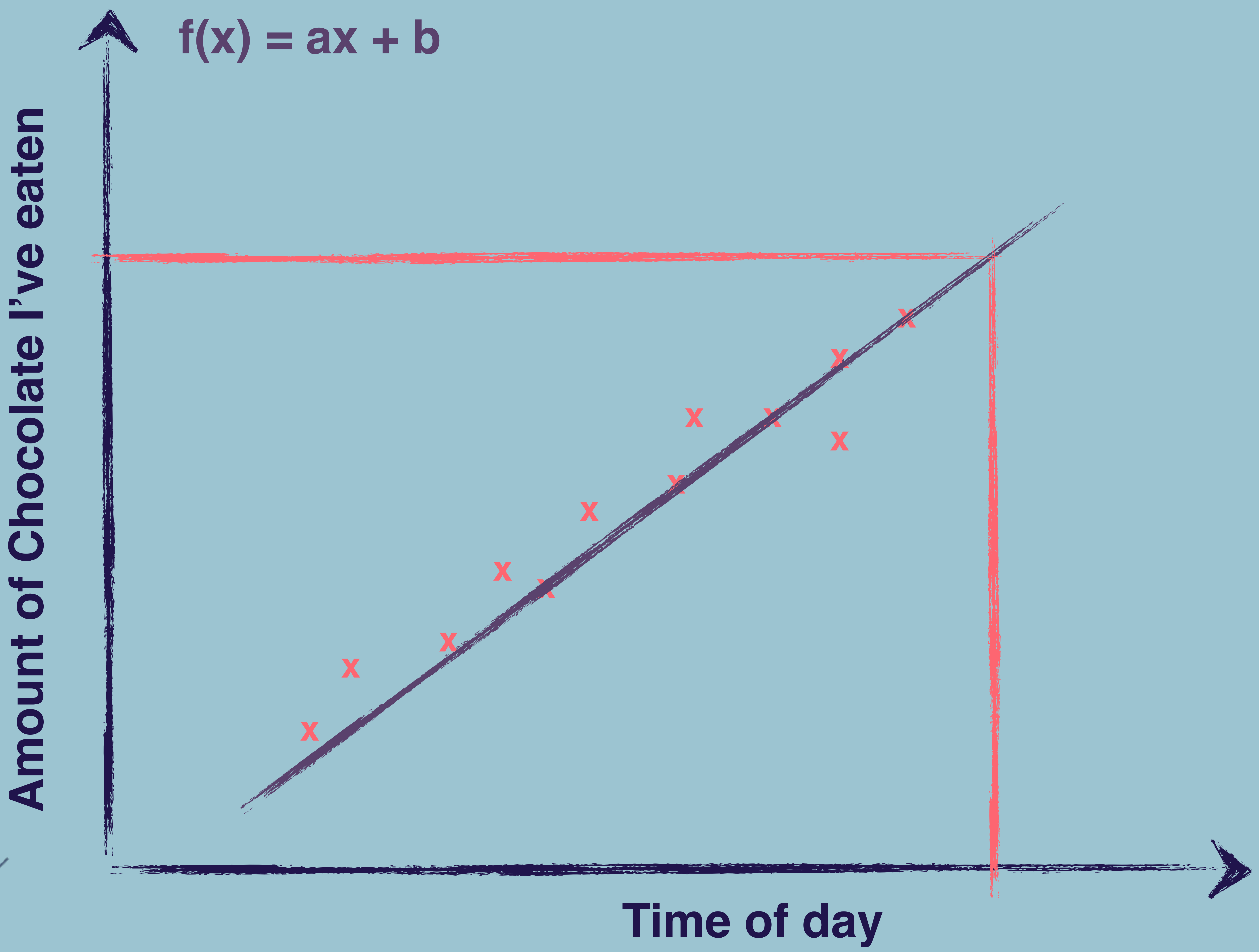


Credit: Andreas Müller

Some terminology ...

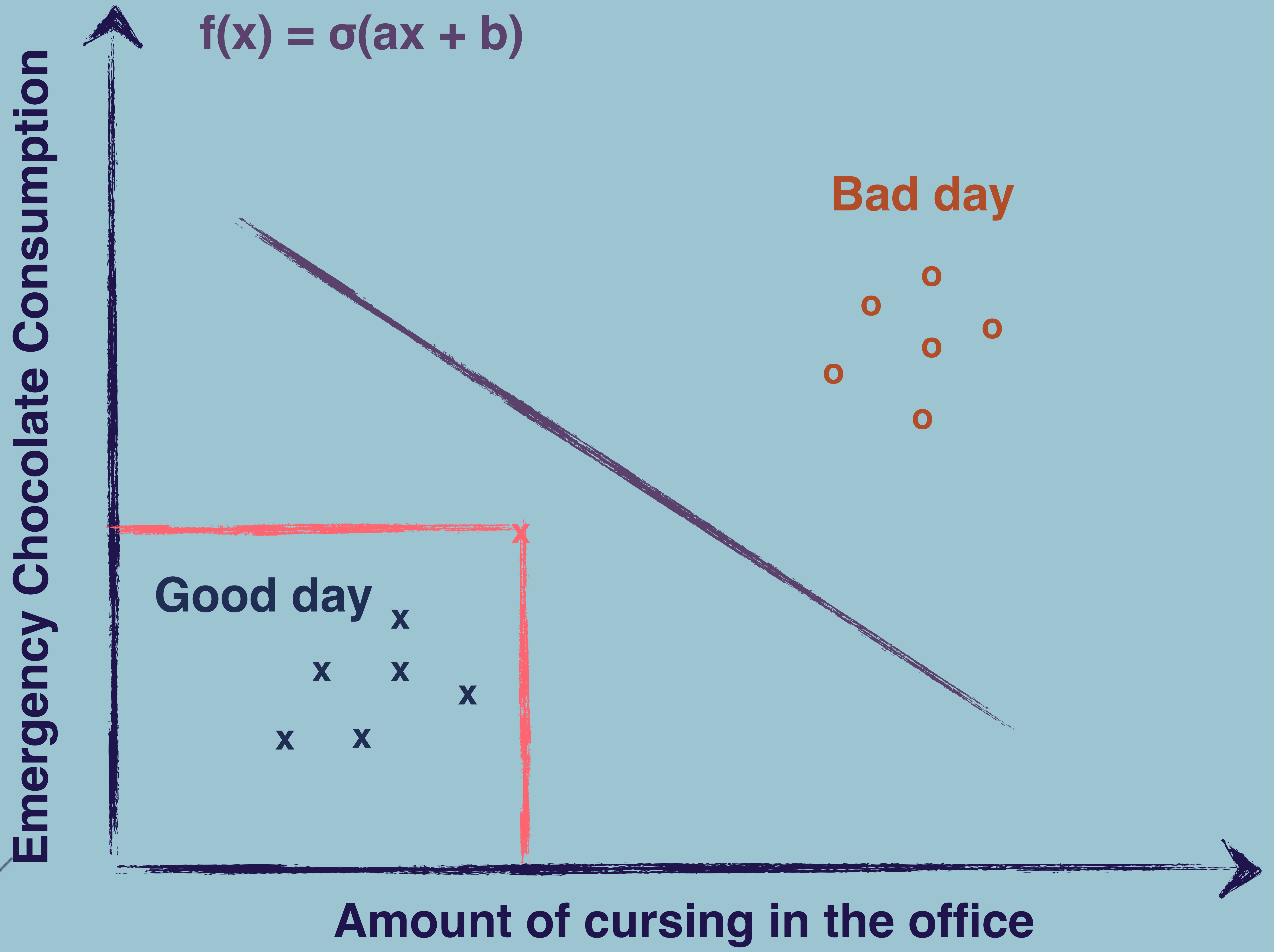
Learning Patterns from Data:

Regression



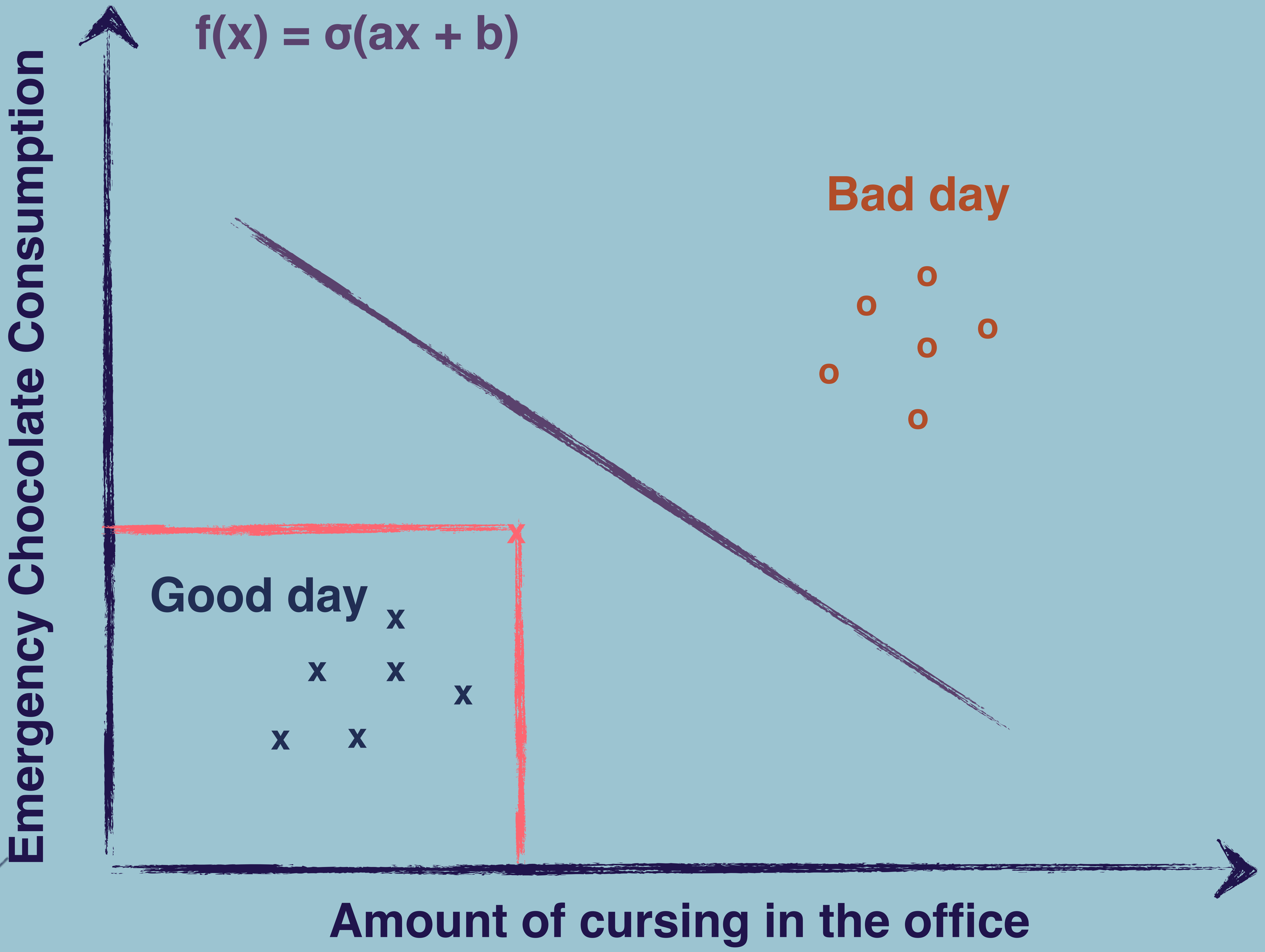
Learning Patterns from Data:

Classification



Linear model:

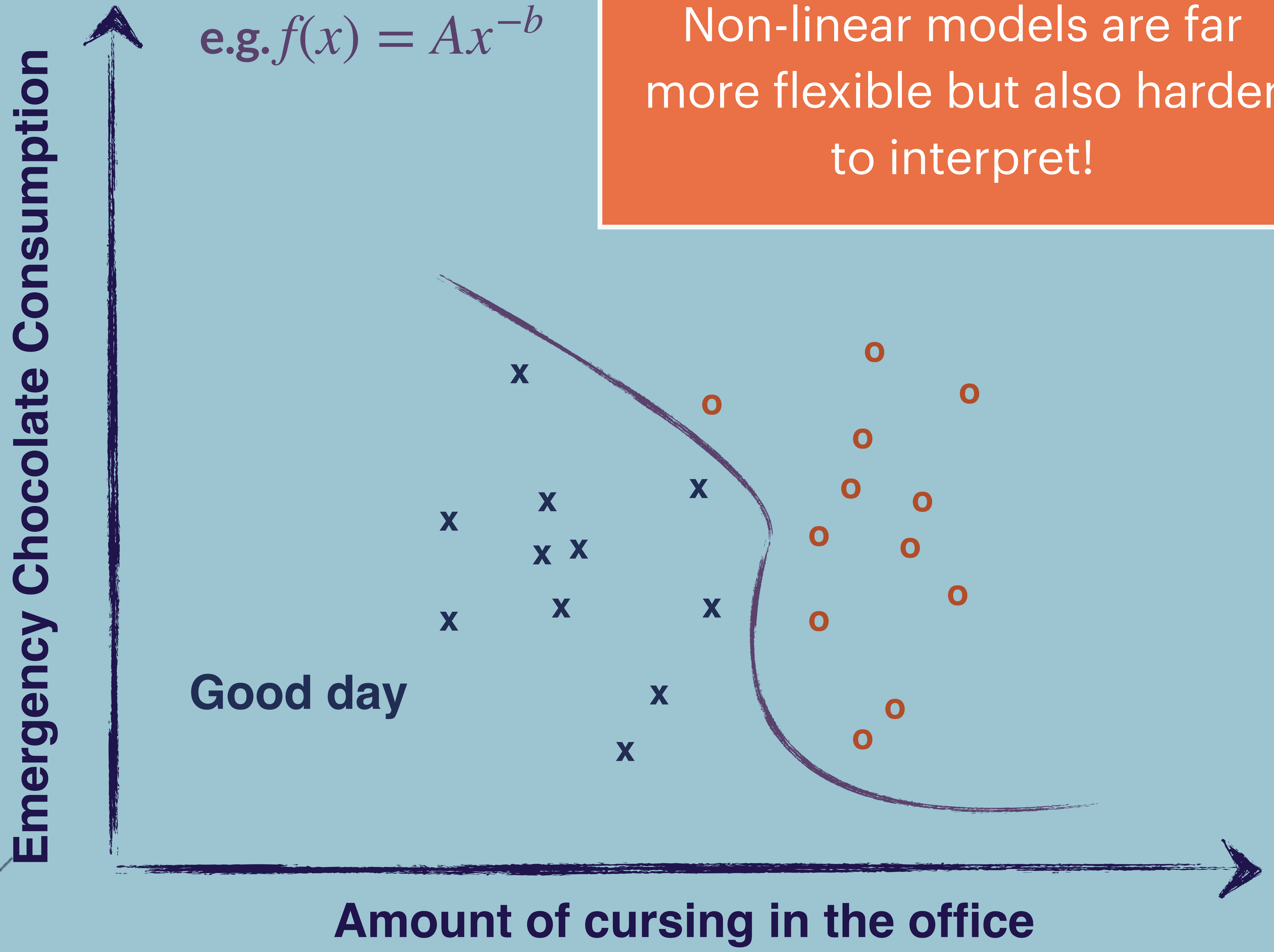
A model that is linear in the parameters



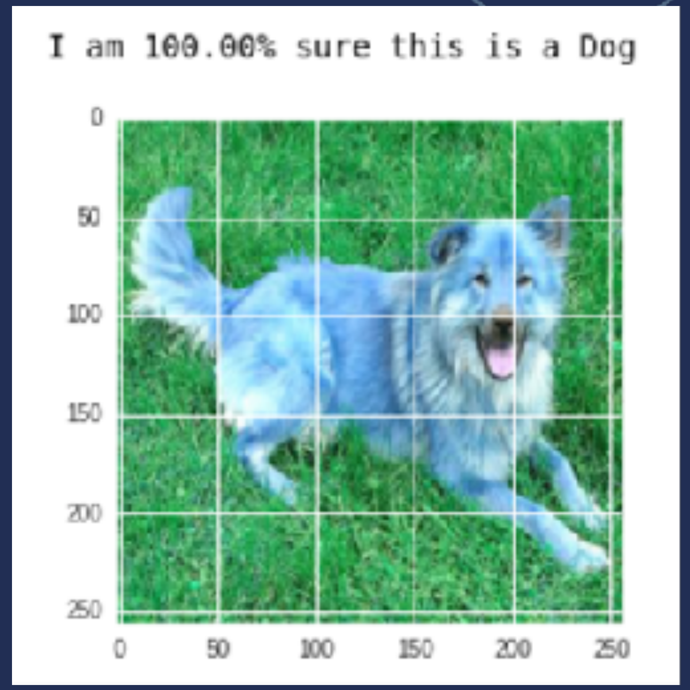
Non-Linear models

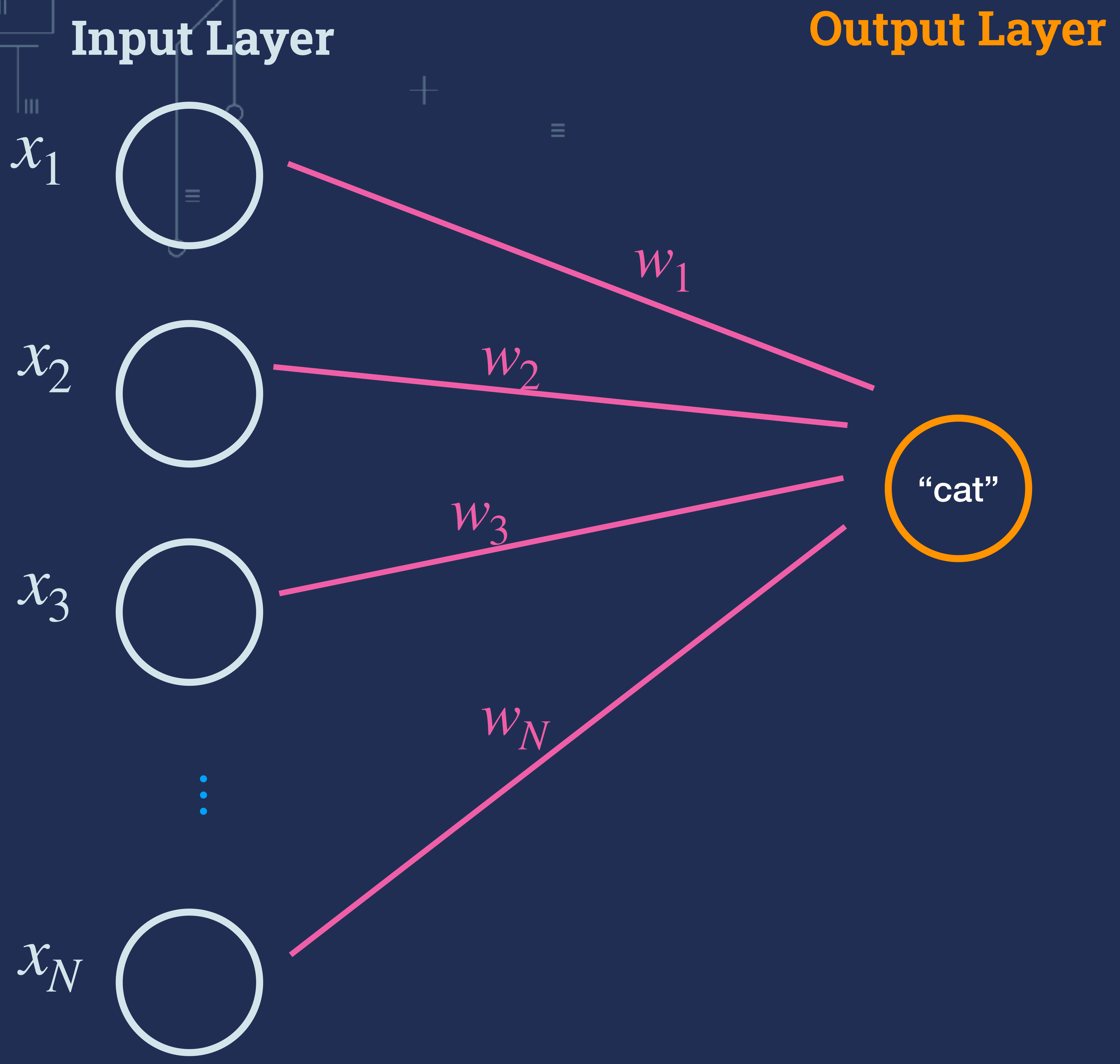
e.g. $f(x) = Ax^{-b}$

Non-linear models are far more flexible but also harder to interpret!



The perceptron



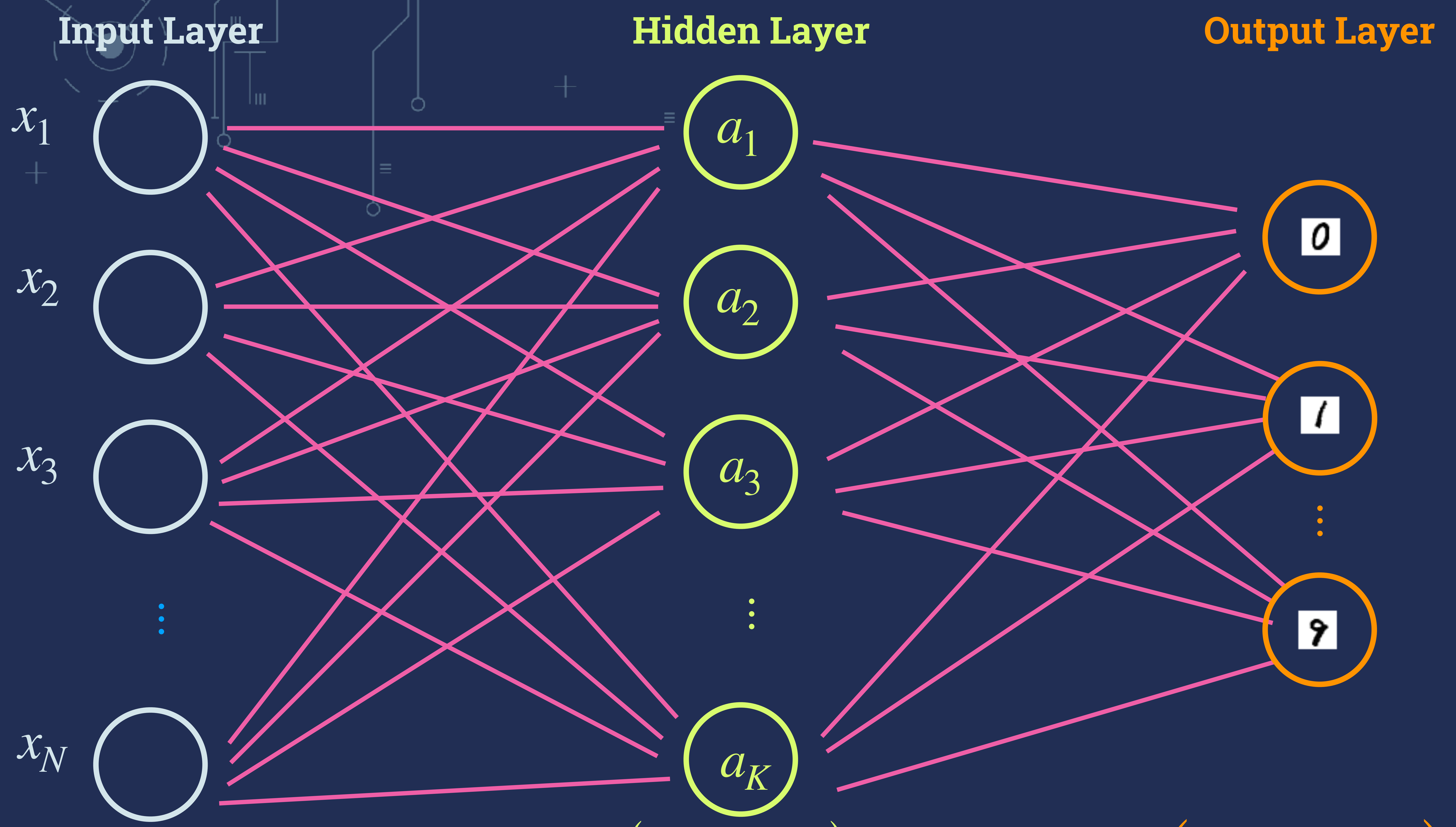


$$y = \sigma\left(\sum_k w_k x_k + b\right)$$

$\sigma(z)$ = Activation function

Example: $\sigma(z) = \dfrac{1}{1+e^{-z}}$

Building a Feed-Forward Neural Network

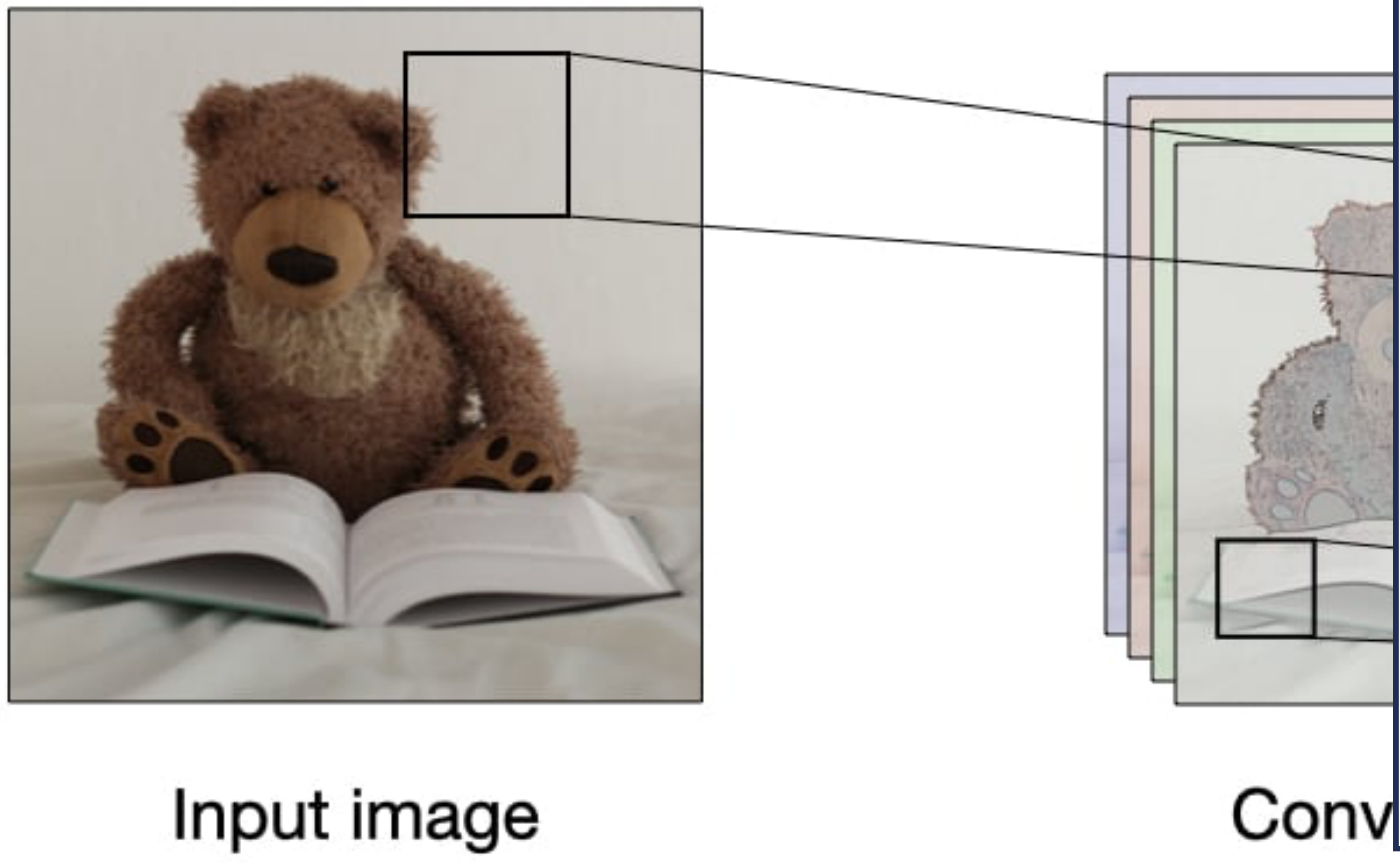


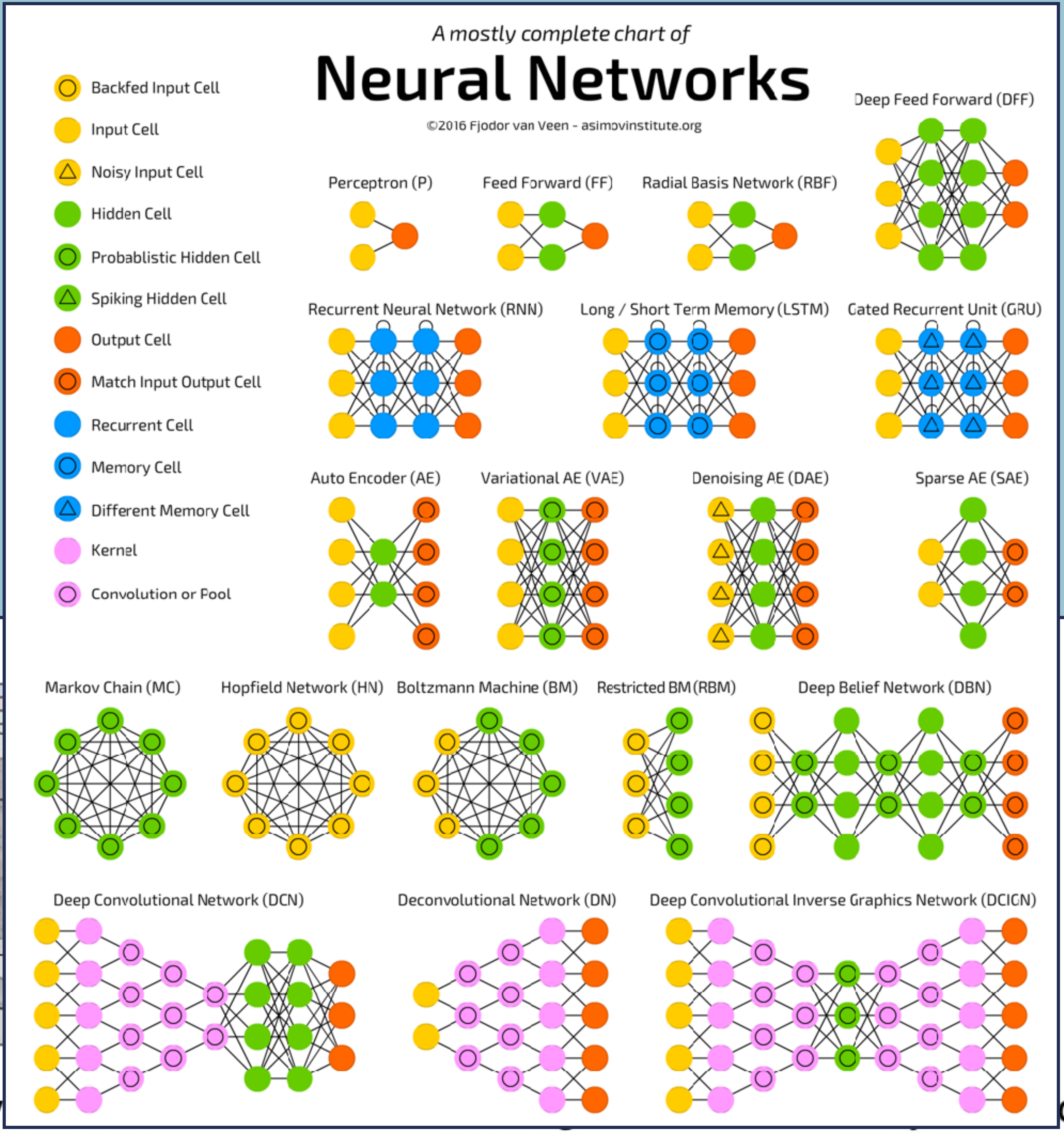
$$a_k = \sigma\left(\sum_j w^1_{kj} x_j + b_k\right)$$

$$y_l = \sigma\left(\sum_k w^2_{lk} x_k + b_l\right)$$

Machine learning algorithms learn correlations, not causal relationships!

Clever Additions Make Neural Networks Work Efficiently





When to be cautious about machine learning

1. Are there ethical implications for using machine learning on your problem?
2. Is your problem really a statistics problem?
3. Do you have enough training data? Does your training data look like your target data?
4. Would (unrecognised) biases in your ML model significantly affect downstream analyses?

ICBINB @ NeurIPS2021

Call for Papers Guidelines Schedule Accepted Talks Panel Breakouts PC CoC Awards Feedback

I (Still) Can't Believe It's Not Better! Workshop

ICBINB@NeurIPS 2021 - A Workshop for "beautiful" ideas that *should* have worked

Side note: the machinery developed for ML can be used outside of machine learning applications!

= “differentiable NumPy that runs on accelerators “

= optimizing compiler for machine learning

Other cool things:

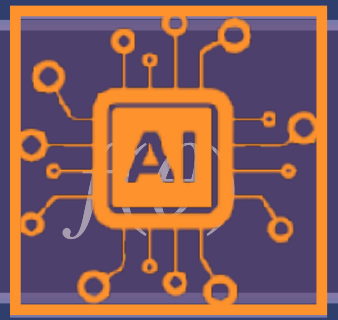
- just-in-time compilation with XLA
- Automatic parallelisation
- Distributed arrays

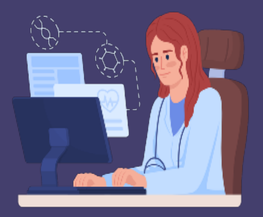
Do I have a good machine learning problem?


$p(\theta \mid D) = \dfrac{p(D \mid \theta)\,p(\theta)}{p(D)}$
SCIENCE

Might be expensive to compute!

$$p(\theta \mid D) = \frac{p(D \mid f(\theta))p(\theta)}{p(D)}$$

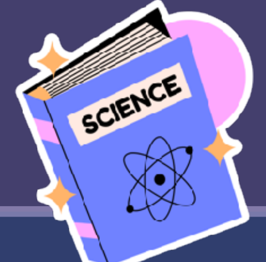
 = a physics model with parameters θ  

D = the data 

$p(D \mid f(\theta))$ = how to generate data from a known set of parameters using physics model $f(\theta)$

$p(\theta)$ = everything we know about the parameters **before** we look at the data

$p(\theta \mid D)$ = the probability of the parameters **after** we've looked at the data

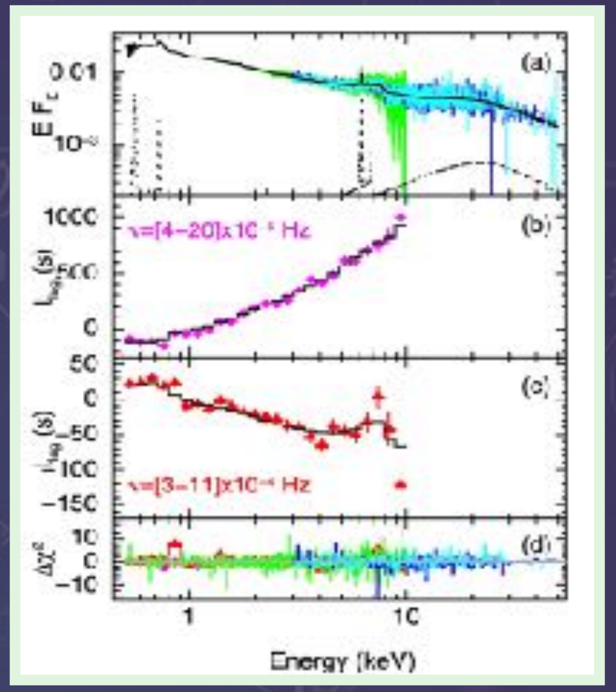


Inference

black hole +

accretion flow

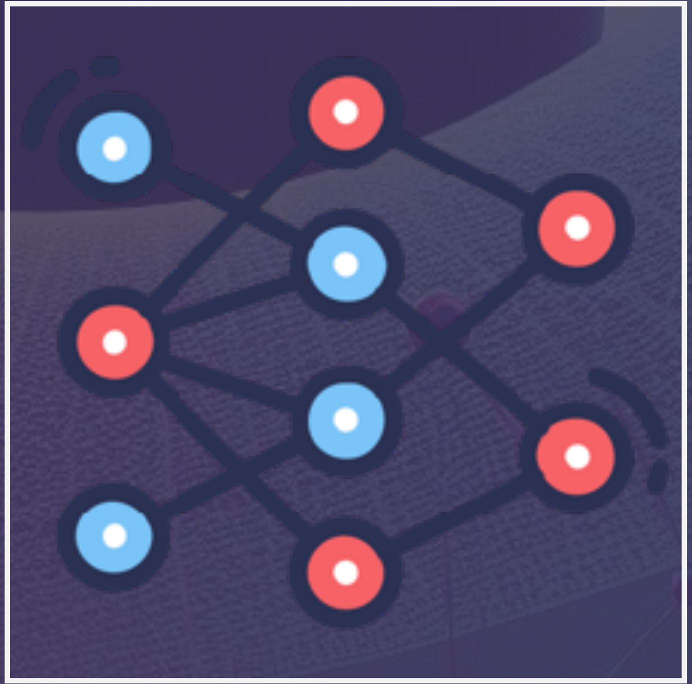
parameters

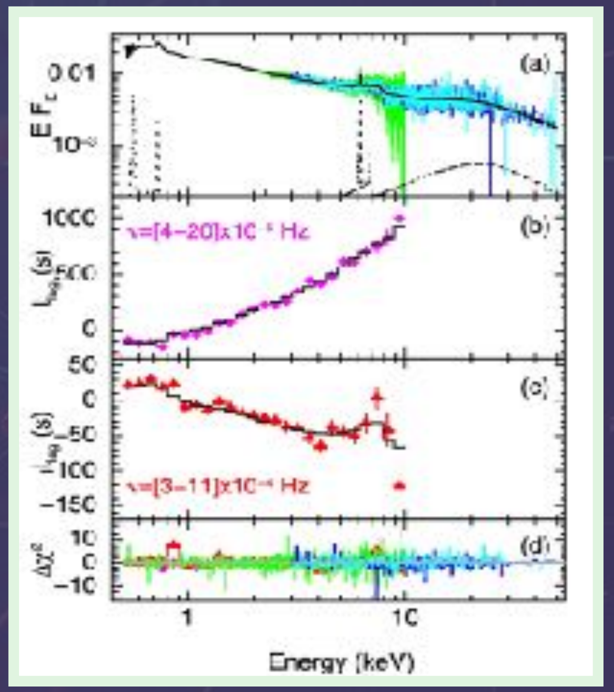


black hole +

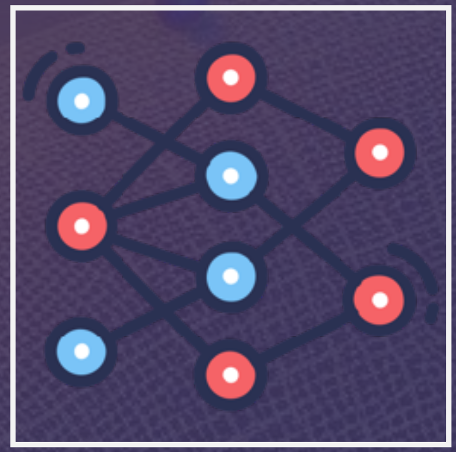
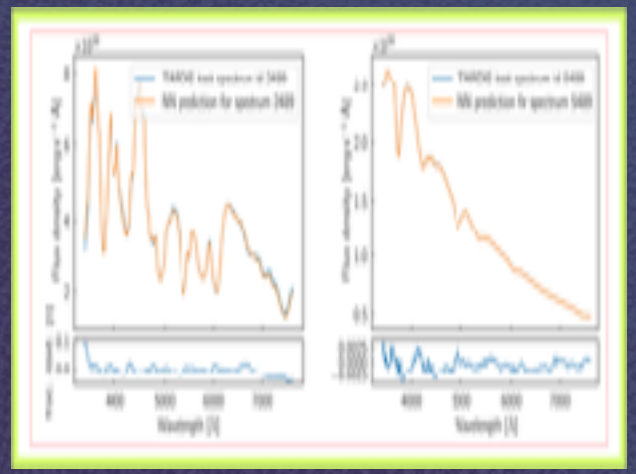
accretion flow

parameters





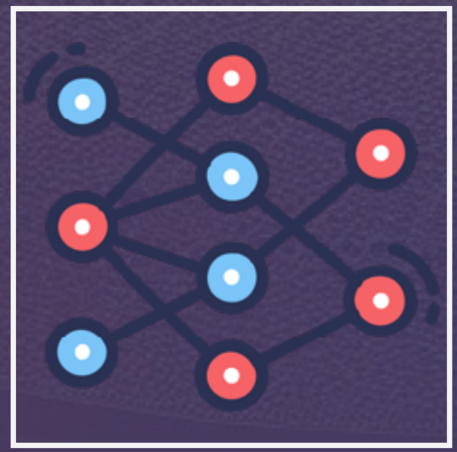
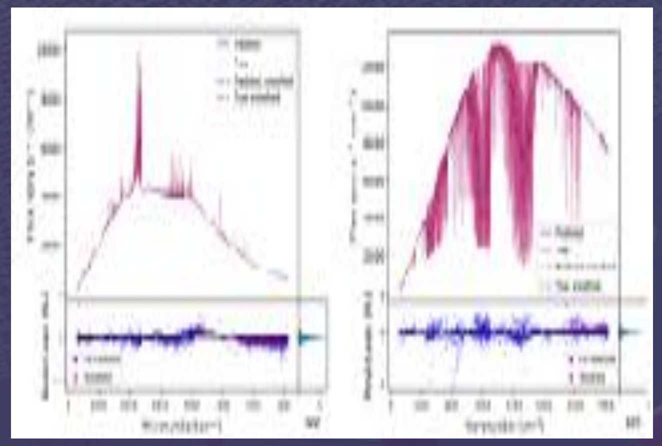
Ricketts et al (2025), Ricketts, Hadzic et al (in prep)

SN 1A parameters →  →  Kerzendorf et al (2021)

blac
m

r Gucht
(2022)

One of the few problems in astronomy where we have reliable training data!

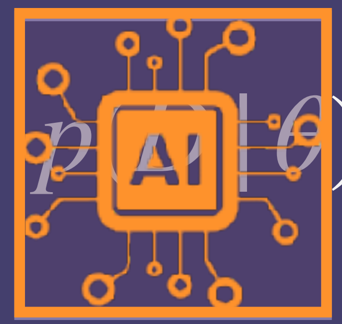
exoplanet atmosphere parameters →  →  Himes et al (2020)

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{p(D)}$$

$f(\theta)$ = a physics model with parameters θ  

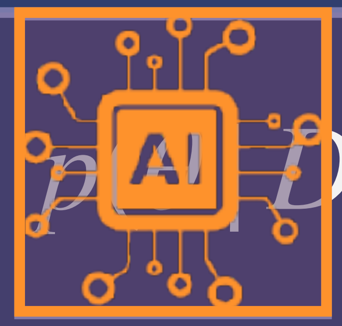
D = the data 

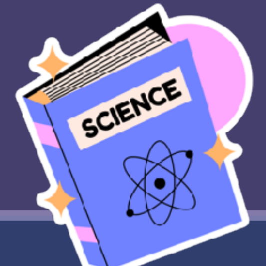
Might not be analytically tractable



= how to generate data from a known set of parameters

$p(\theta)$ = everything we know about the parameters **before** we look at the data



= the probability of the parameters **after** we've looked at the data 

Inference

Why Simulation-Based Inference?

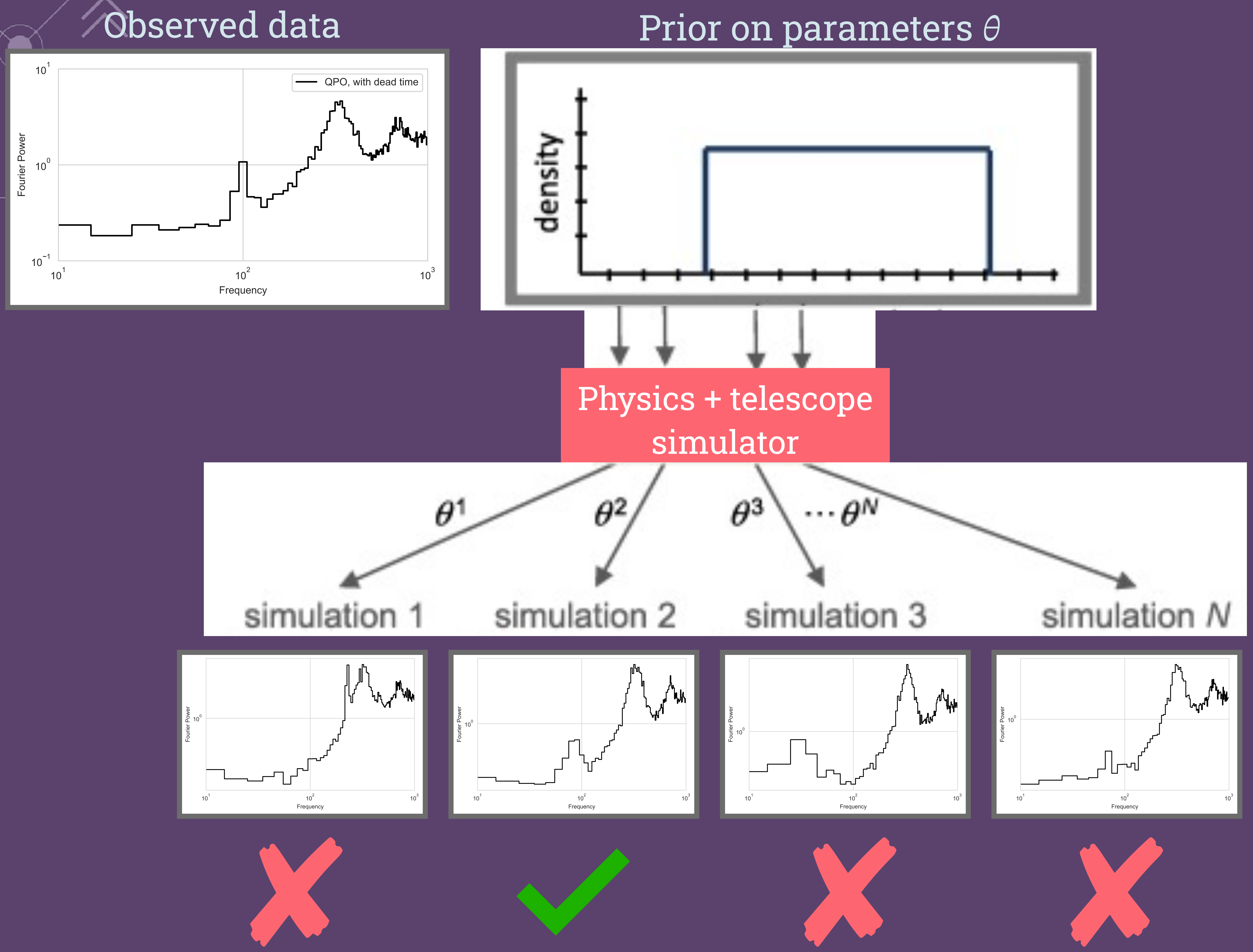
- You have a stochastic numerical model
- You have instrumental biases or selection effects you can simulate but not parametrize
- Fast inference with Normalising Flows

Step 1: draw parameters from prior

Step 2: simulate data sets

Step 3: compare simulated to observed data

Step 4: keep parameters that produce simulations similar to the data



Sadegh + Vrugt, 2014, see also: Brehmer et al (2018a, 2018b), Cranmer et al (2020)

Step 1: draw parameters from prior

Step 2: simulate data sets

Step 3: compare simulated to observed data

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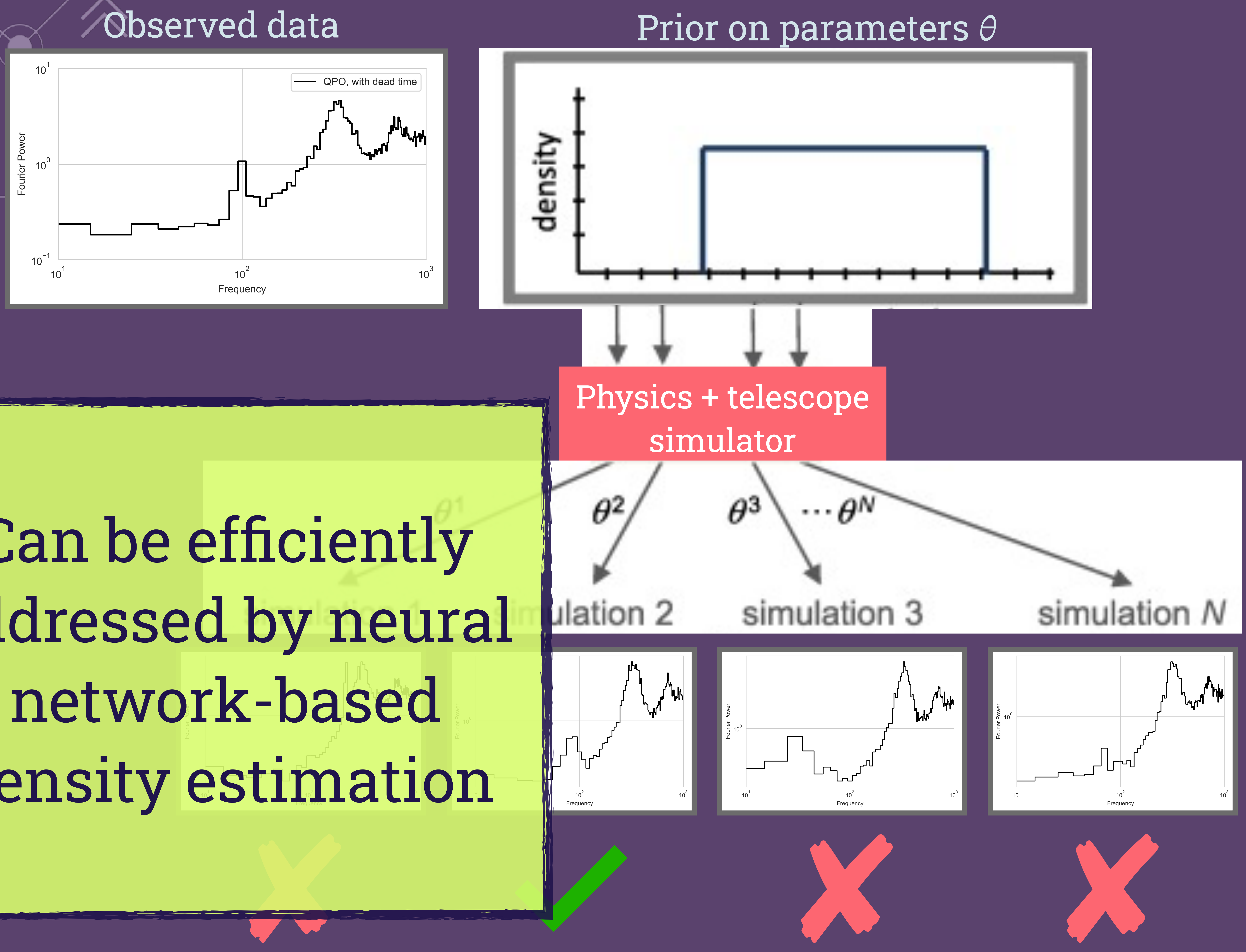
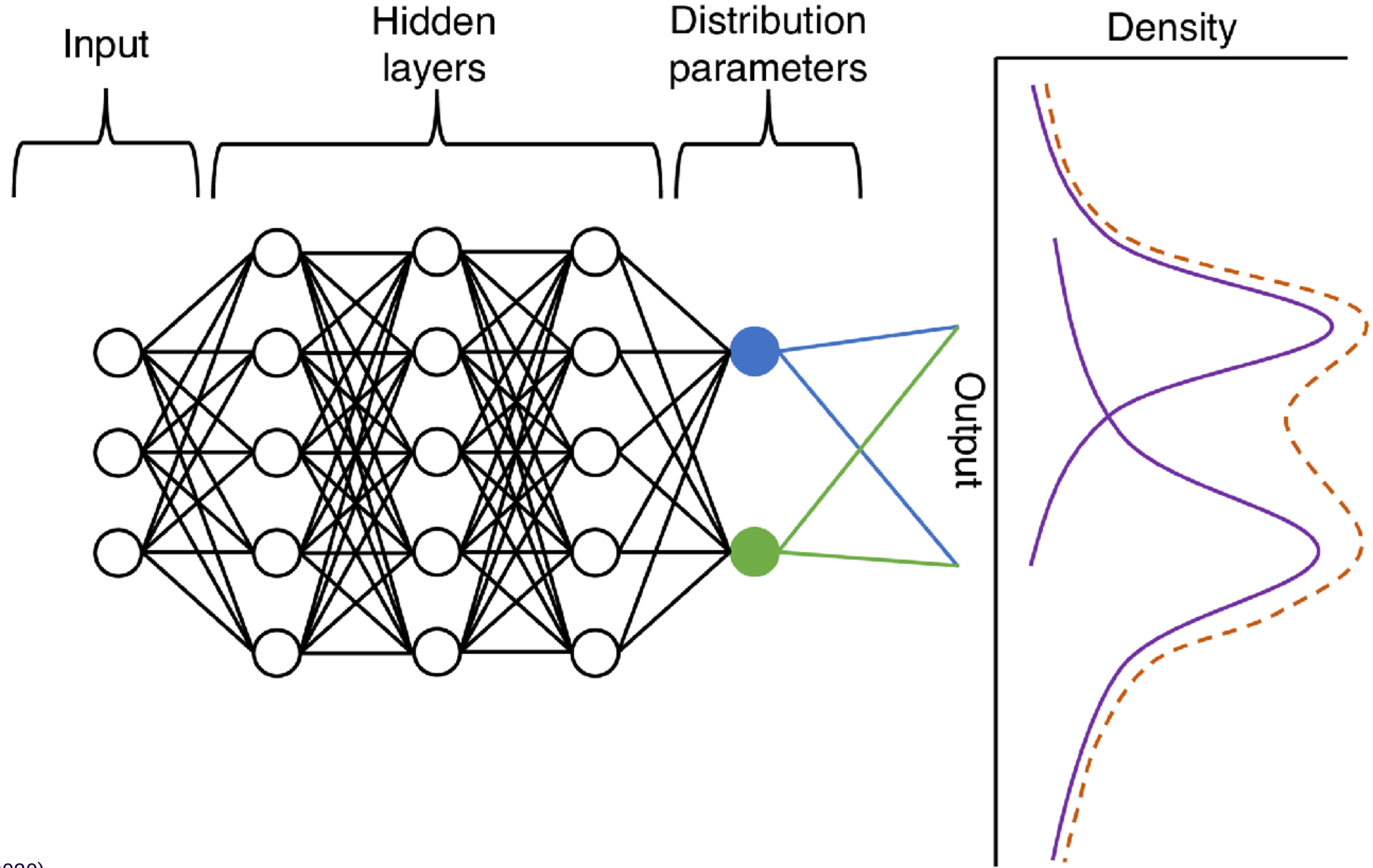
Can be efficiently addressed by neural network-based density estimation



Sadegh + Vrugt, 2014, see also: Brehmer et al (2018a, 2018b), Cranmer et al (2020)

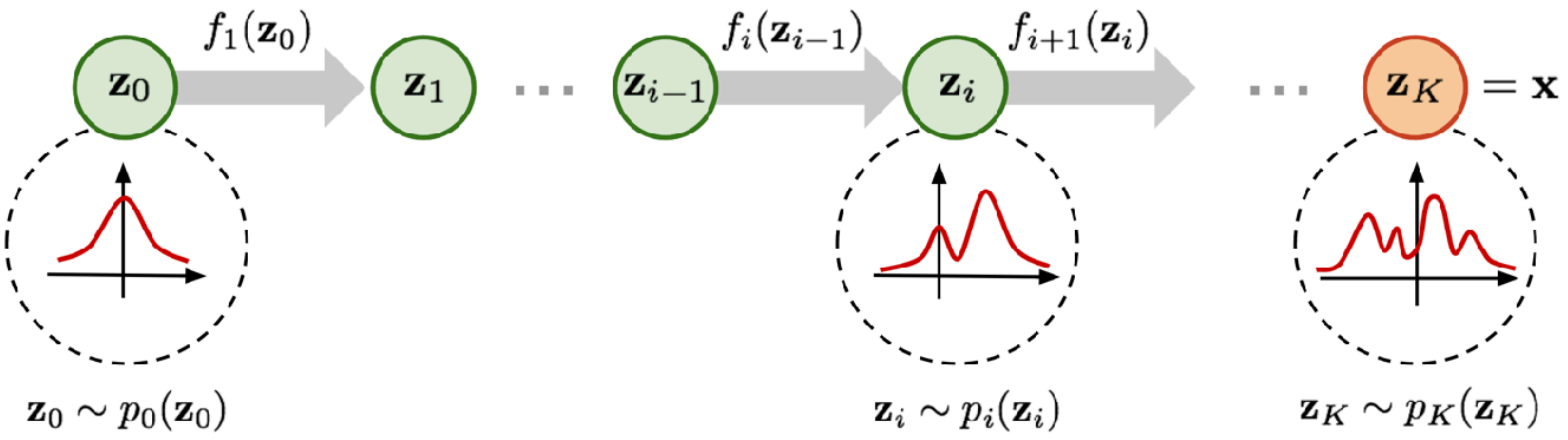
Mixture Density Networks



Bishop (1995)   Davis et al (2020)

Normalizing Flows

- map simple base distribution (e.g. Gaussian) to a much more complex output distribution through a sequence of invertible transformations



good intro and figure reference: https://lilianweng.github.io/lil-log/2018/10/13/flow-based-deep-generative-models.html

Simulation Based Inference

Neural Posterior Estimation

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{p(D)}$$

Neural Likelihood Estimation

$$p(\theta|D) = p(D|\theta)\frac{p(\theta)}{p(D)}$$

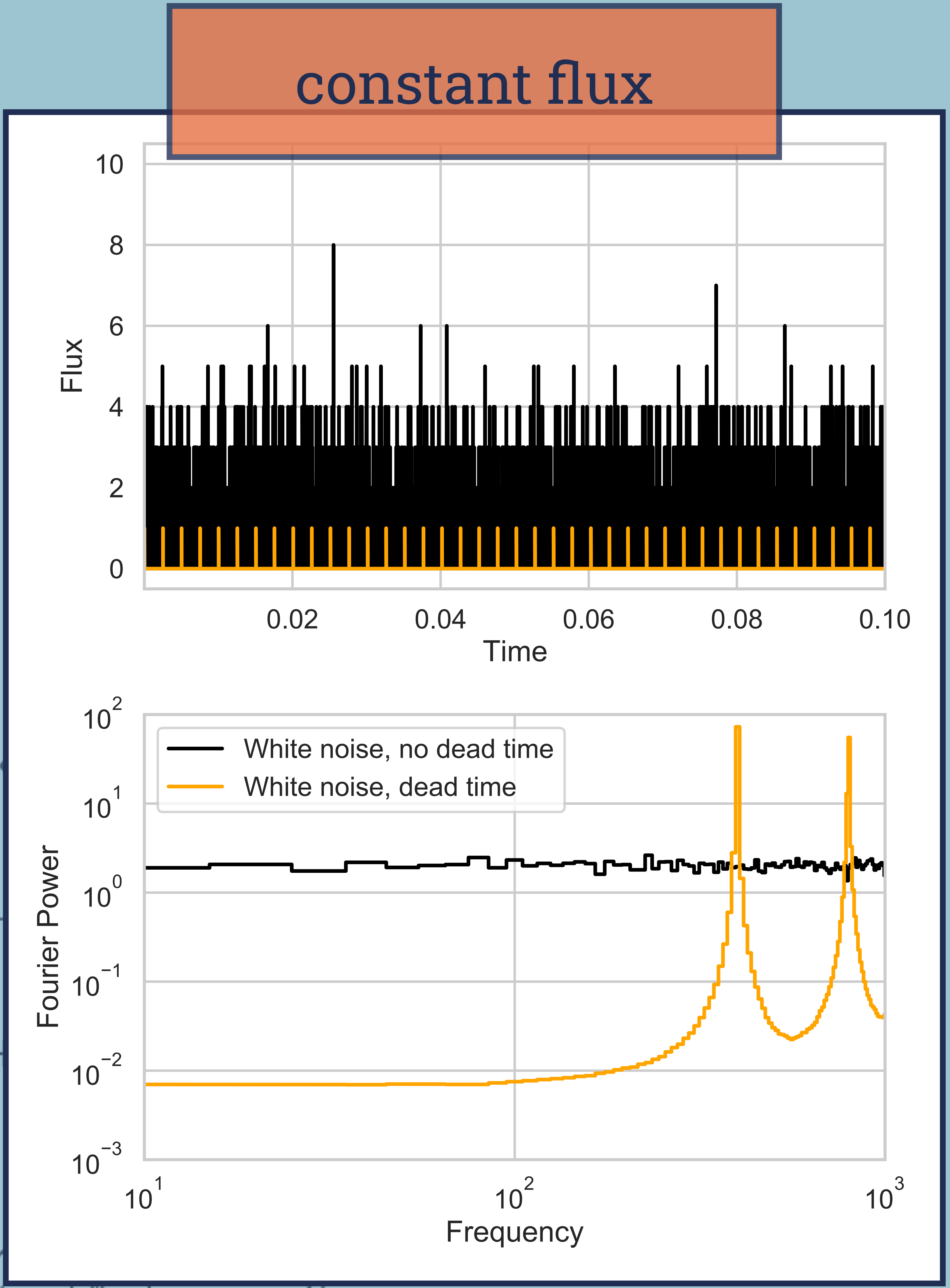
Neural Ratio Estimation

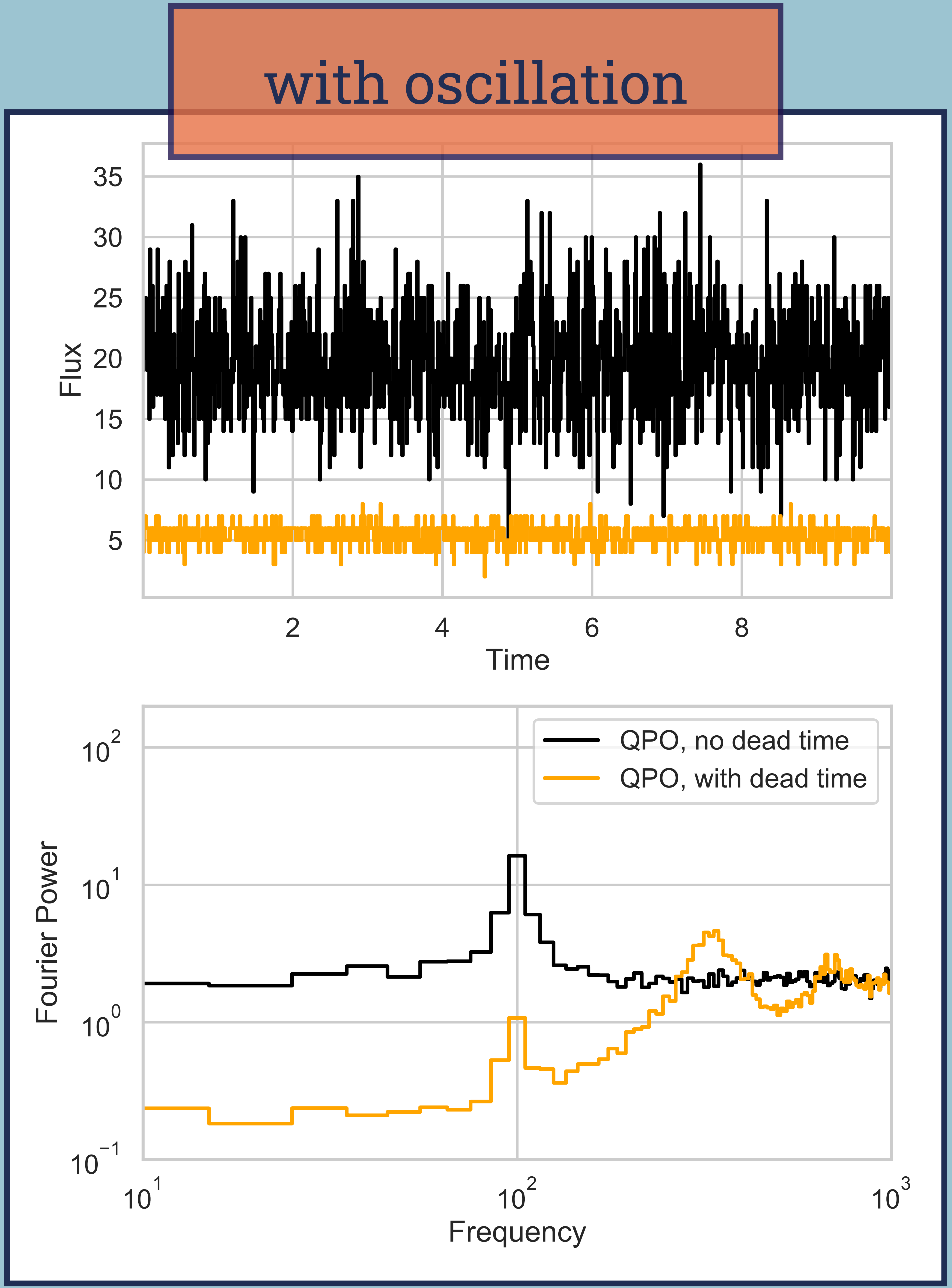
$$p(\theta|D) = \frac{p(D|\theta)}{p(D)}p(\theta)$$

Bachetti et al (2015),
Bachetti + Huppenkothen (2018)

Dead Time in X-ray Detectors

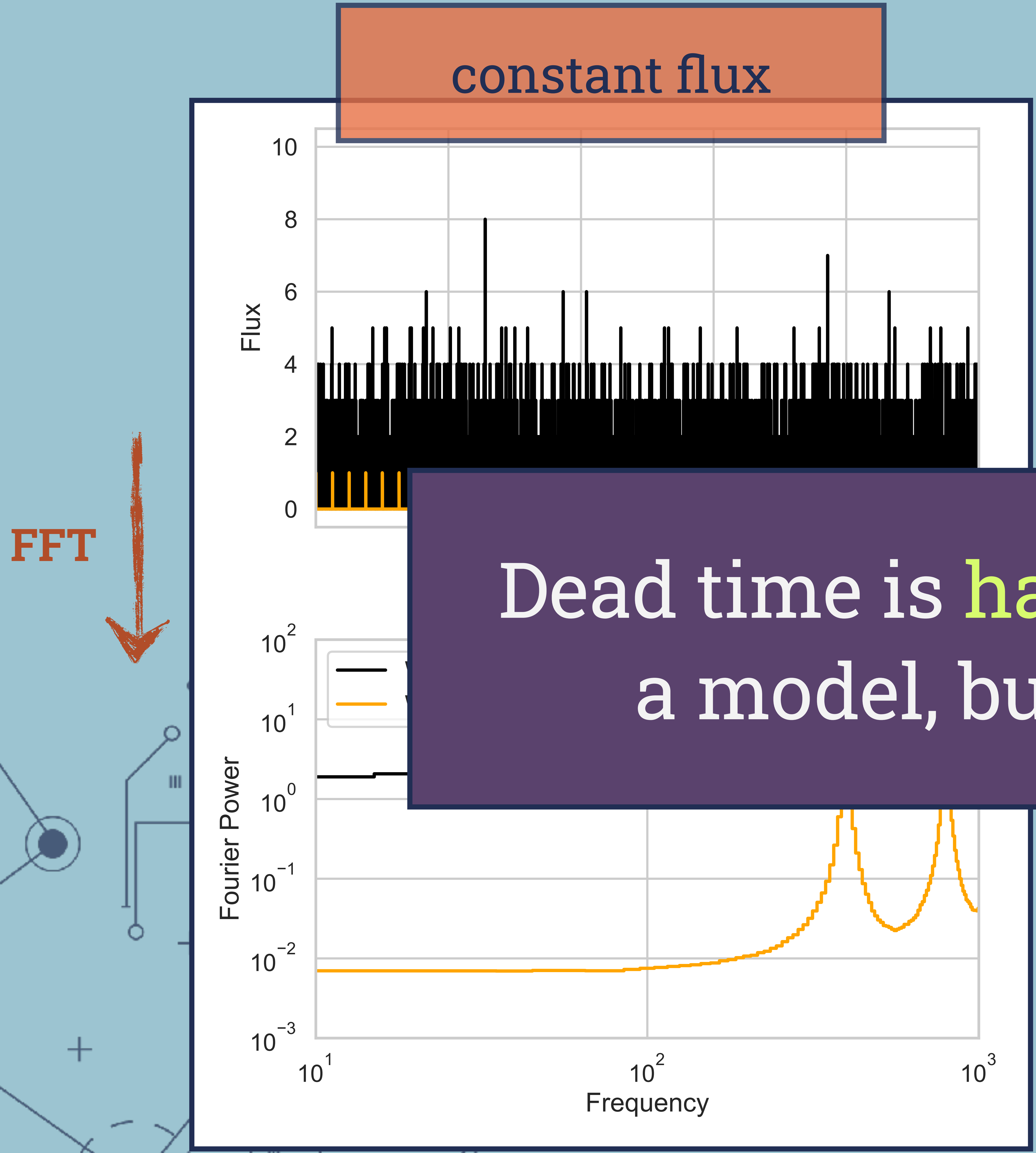
FFT

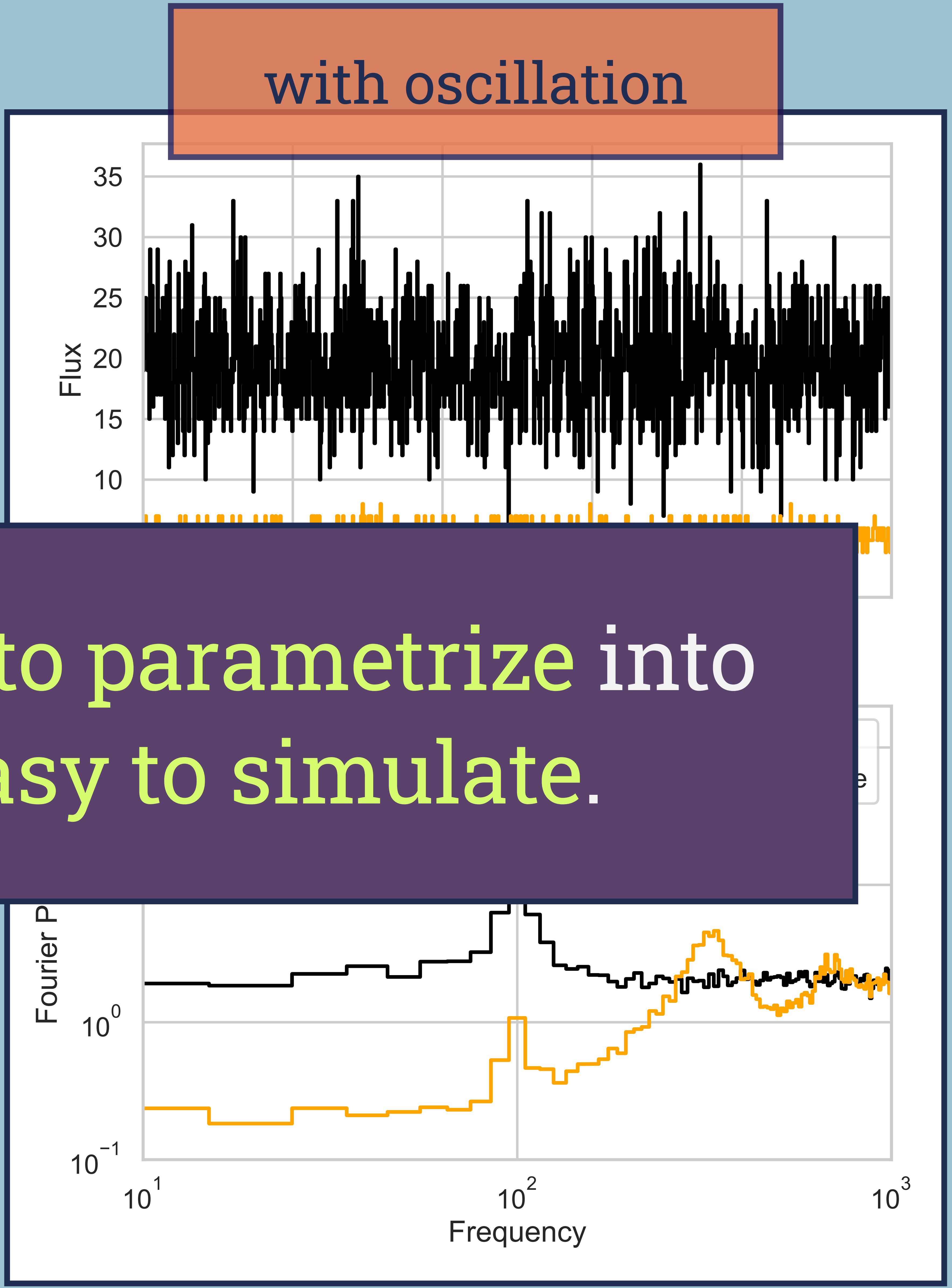




Bachetti et al (2015),
Bachetti + Huppenkothen (2018)

Dead Time in X-ray Detectors

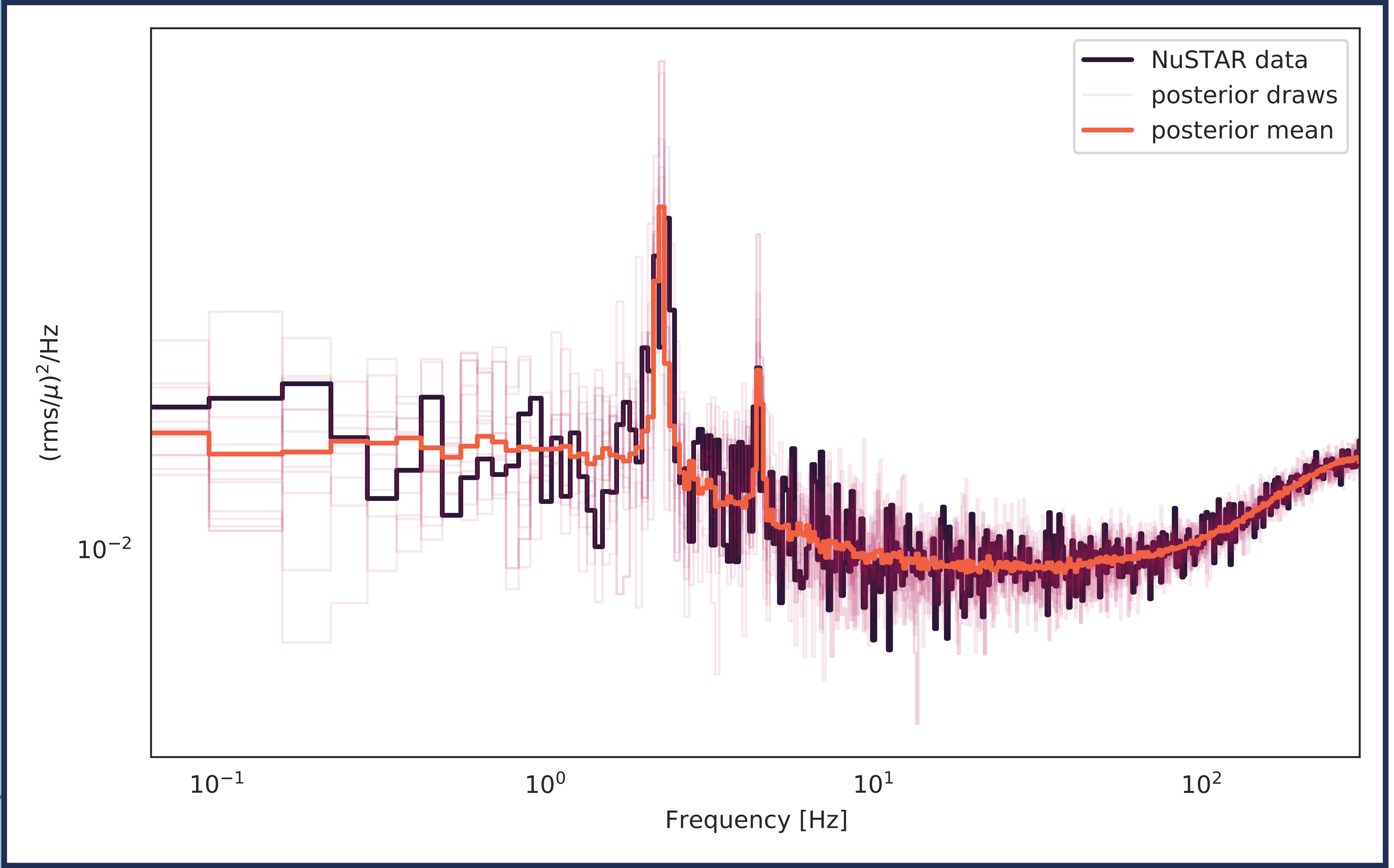


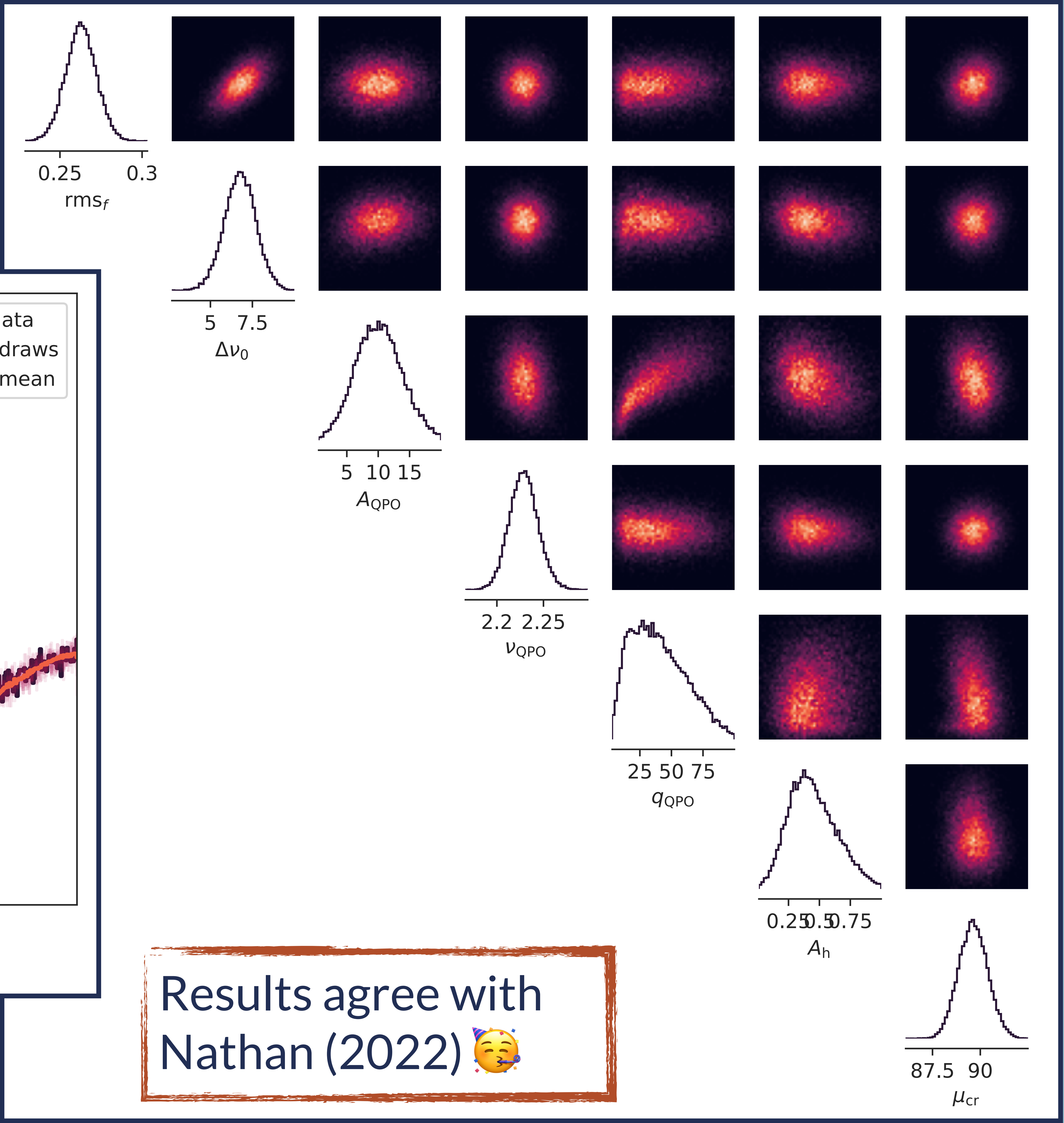


Dead time is hard to parametrize into a model, but easy to simulate.

Huppenkothen & Bachetti (2022)

Simulation-Based Inference for Instrumental Biases

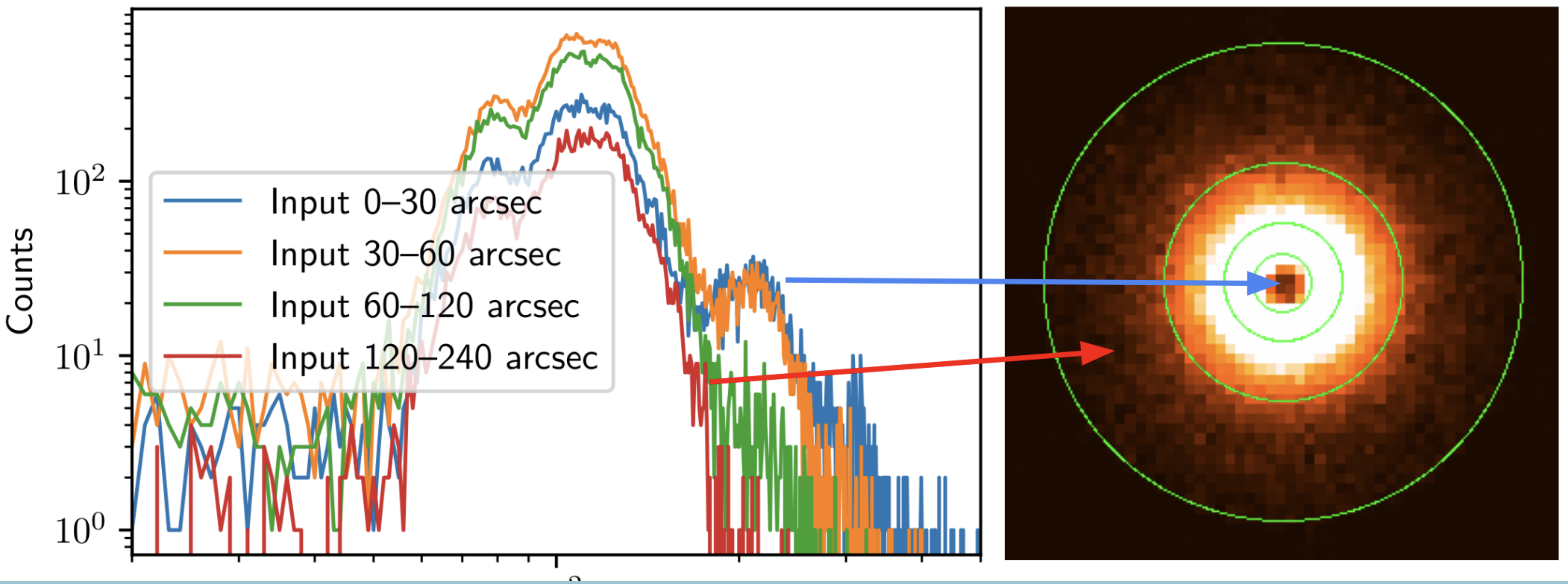


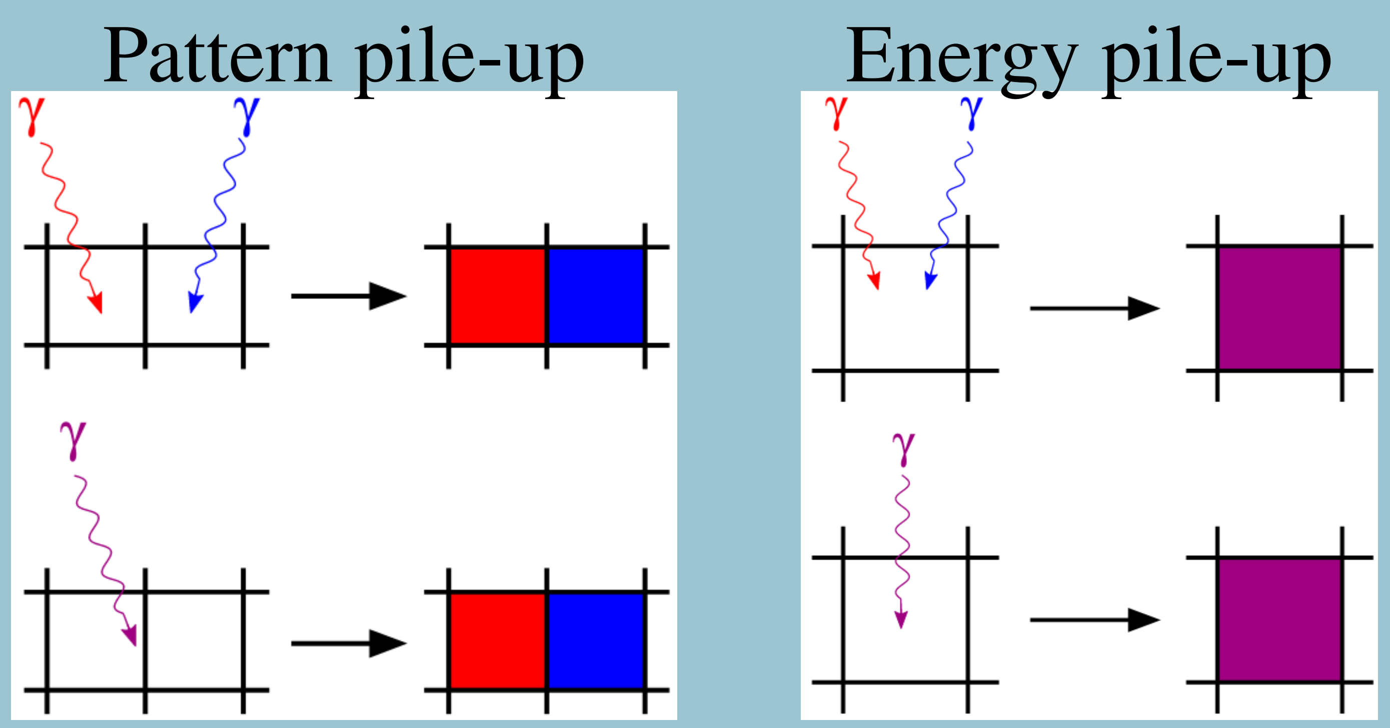


Results agree with Nathan (2022) 🥳

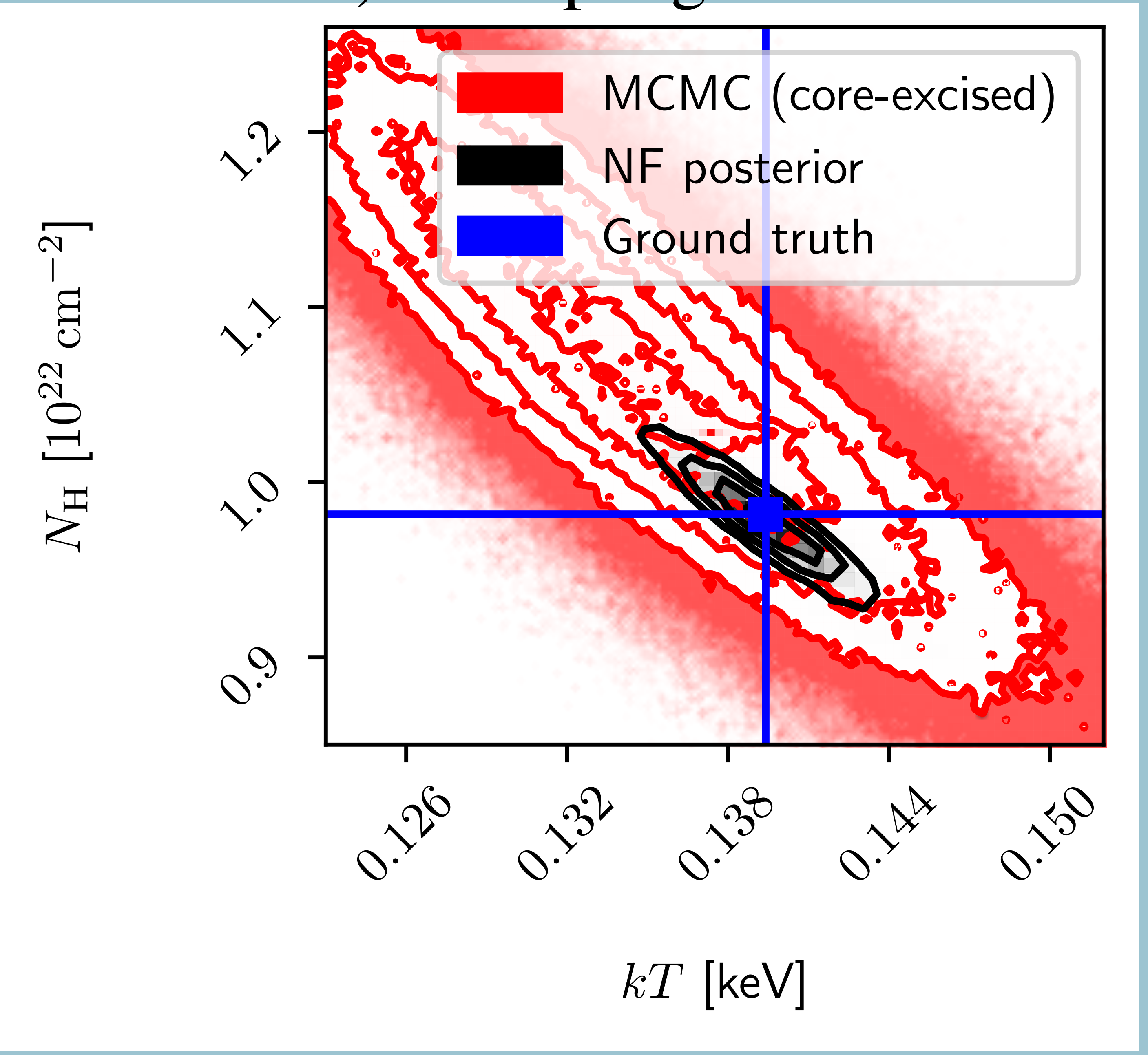
Koenig et al (2025)

Simulation-Based Inference for Instrumental Biases: Pile-up





a) Pile up regime



Should you use machine learning

- If you can do it with regular statistics: no! Statistics gives you mathematical guarantees!
- Machine learning can be used to significantly accelerate numerical models (but at an accuracy trade-off)
- Simulation-based inference is a principled way to infer (less biased) parameter distributions with complex simulators
- Some of the technology that underpins machine learning is useful outside of ML, too!

Use machine learning where (1) you can get away with associations, not causal relationships, (2) you have ground-truth training data you trust

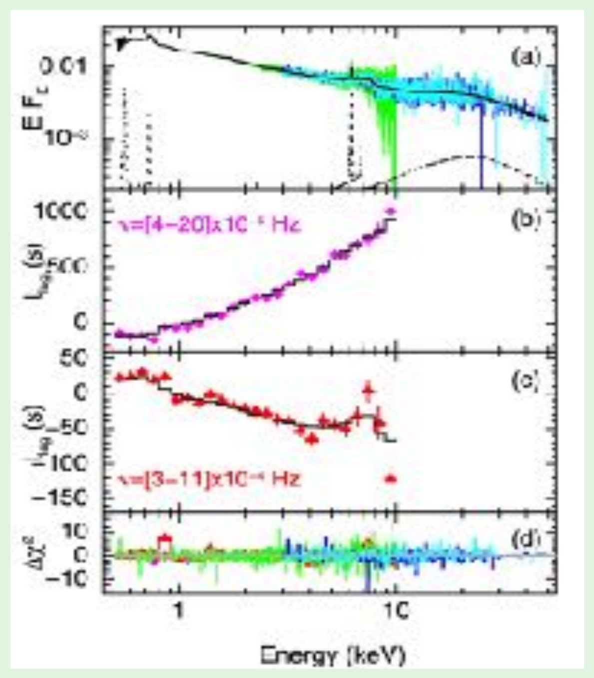
Extra advice:
the newest algorithms aren't always the best suited for scientific applications!

Things I haven't talked about

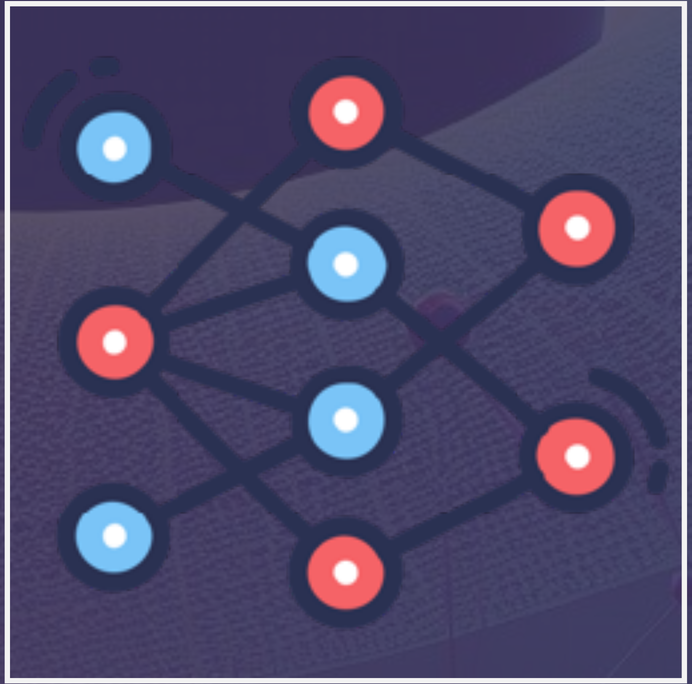
- Classification tasks
- Representation learning/unsupervised learning/clustering
- Foundation models
- Physics-informed machine learning
- The many, many biases and pitfalls you can fall into while doing machine learning!

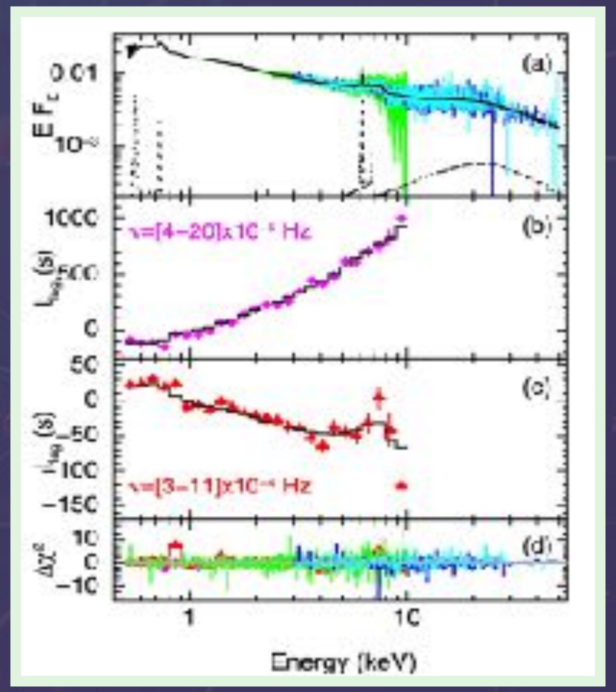
Let’s meet our problem!

Power law parameters



Power law parameters





Important: supervised classification requires ground-truth training data

ML Jargon

Features: informative summaries of the data used in ML tasks

Labels: the true (known) outputs that the ML model is trying to reproduce. For classification, these are discrete class labels, for regression continuous quantities

Sample: a single example in your training data

Time to fire up the notebooks and load the data!

Let’s take a step back …

Machine Learning Overview

1. Figuring out what we want to learn, and why!
2. Exploring the Data, Part I
3. Train-validation-test set splits
4. Exploring the Data, Part II
5. Data Pre-Processing: Dimensionality Reduction, Scaling the Data
6. Choose an evaluation metric
7. Choosing a (simple) algorithm + fit the model
8. Explore results
9. Choose a (more complex?) algorithm, explore results
10. Hyperparameter tuning, explore results
11. Interpret outcomes
12. Science! 🥳

Machine Learning Overview

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90% of your time will be spent on data exploration, data processing, visualising your model, critiquing and interpreting your results, 10% on actually applying a ML algorithm to data

1. Designing and preparing data sets
2. Choosing algorithms
3. Choosing evaluation metrics
4. Exploring and reporting outputs

Use best practices in machine learning to establish trust in results

Machine learning is not just a set of algorithms, but a community of practice with rules, conventions and best practices to guard against challenges (e.g. overfitting, lack of generalisation)

Figuring Out What We Want to Learn

Considerations before starting

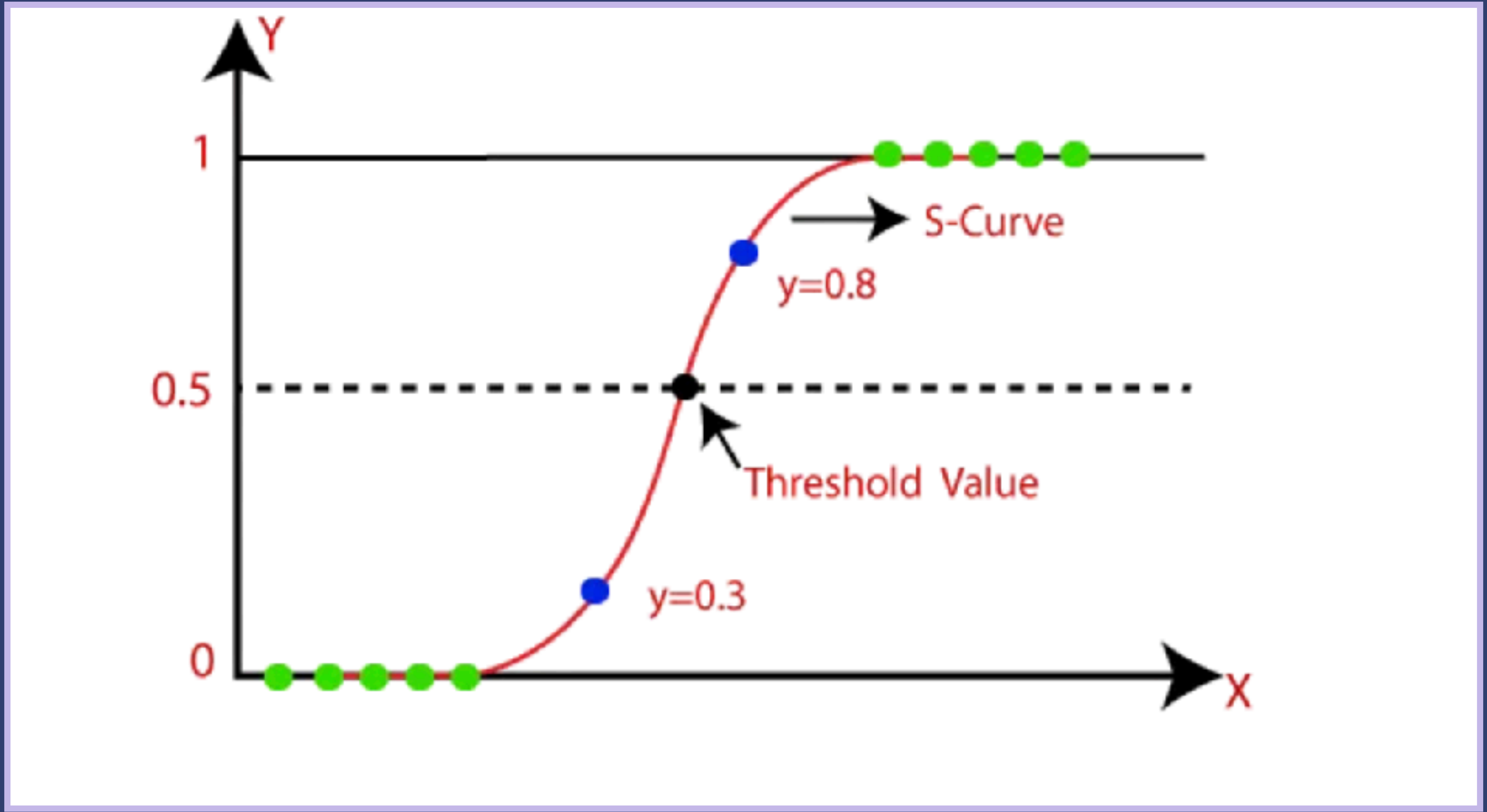
1. Do we only care about predictions, or also the parameters of the model? Do we need the model to be interpretable?
2. How similar is our training data to our target data? Do they come from the same instrument?
3. What biases do you know exist in your training data? Is there a part of feature space that's not covered?
4. What physics knowledge do you have about the data and the problem? Can that knowledge guide you in constructing features and choosing algorithms/evaluation metrics?

Exploring + Pre-Processing Data

Algorithm Spotlight: Logistic Regression

$$p(\overrightarrow{X}_k) = \frac{1}{1 + e^{(-(\beta_0 + \beta_1 \overrightarrow{X}_k))}}$$

- Binary classification, e.g. with GALAXY=0, and STAR=1



Logistic Regression

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- Binary classification, e.g. with GALAXY=0, and STAR=1

$$l = \sum_k l_k$$

Loss function

$$\ell_k = \begin{cases} -\ln p_k & \text{if } y_k = 1, \\ -\ln(1 - p_k) & \text{if } y_k = 0. \end{cases}$$

Logistic Regression

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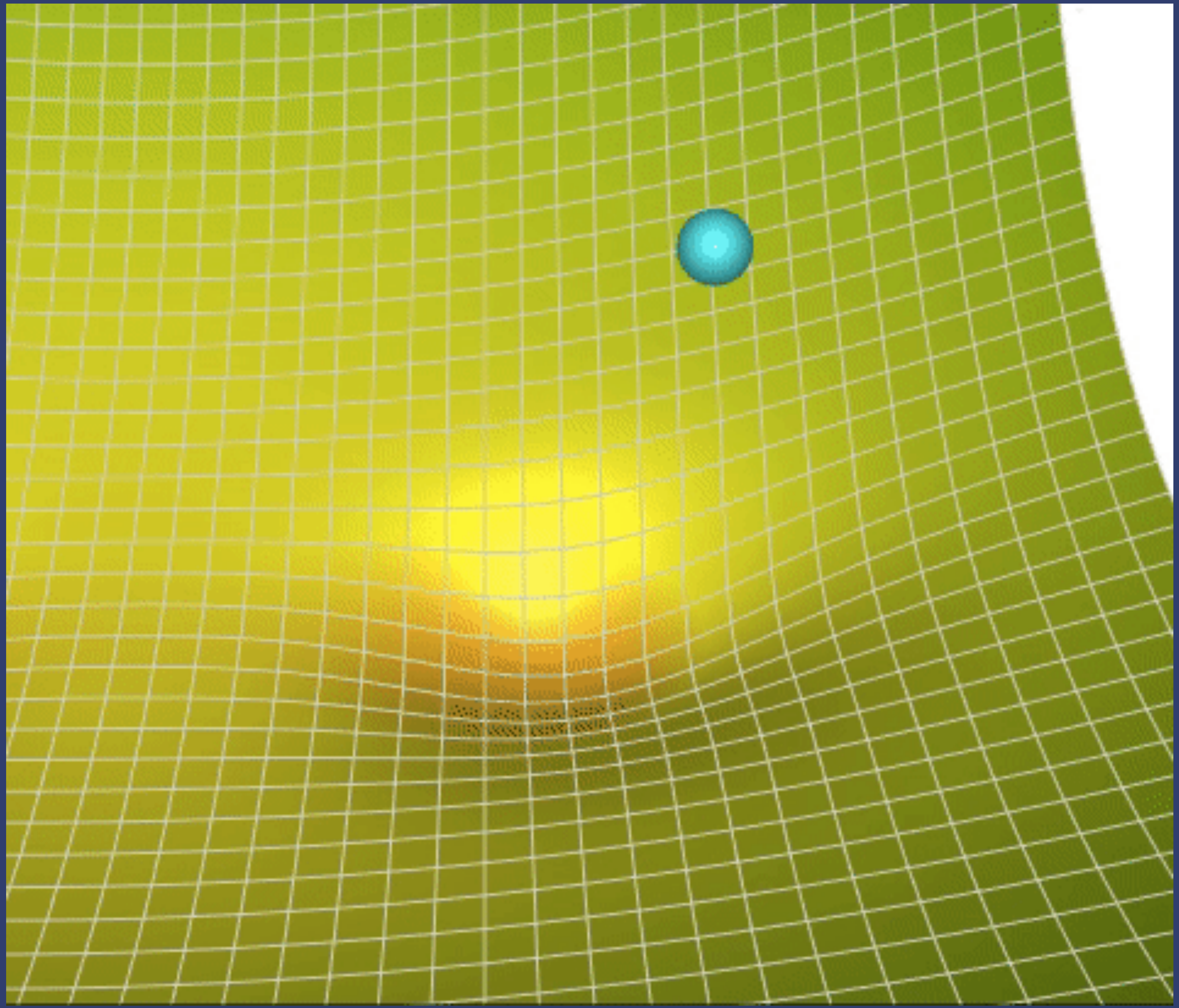
Gradient Descent



https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c/

$$p(\vec{X}_k) = \frac{1}{1 + e^{(-(\beta_0 + \beta_1 \vec{X}_k))}}$$

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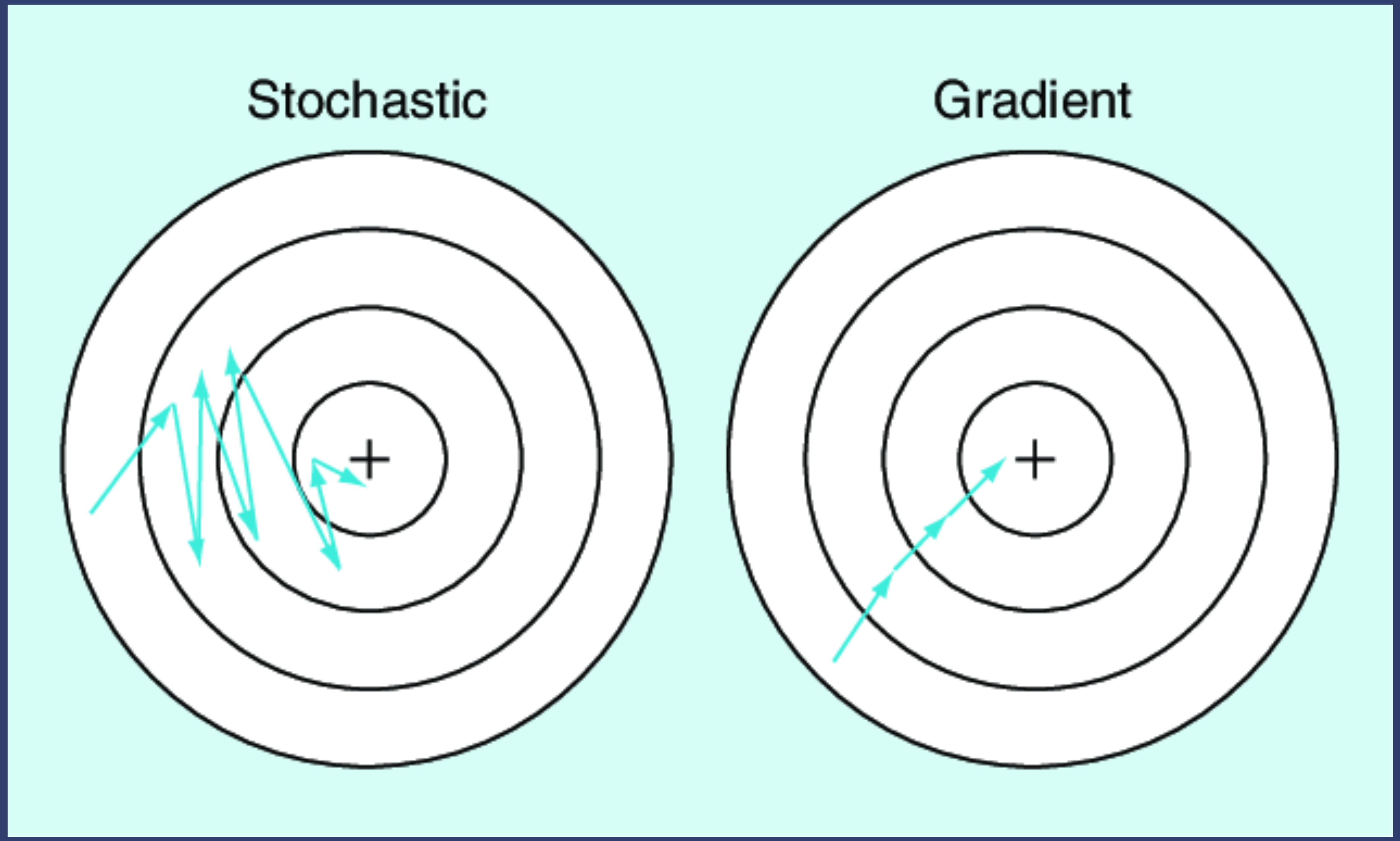
$$\ell_k = \begin{cases} -\ln p_k & \text{if } y_k = 1, \\ -\ln(1 - p_k) & \text{if } y_k = 0. \end{cases}$$

Stochastic + Mini-batch Gradient Descent

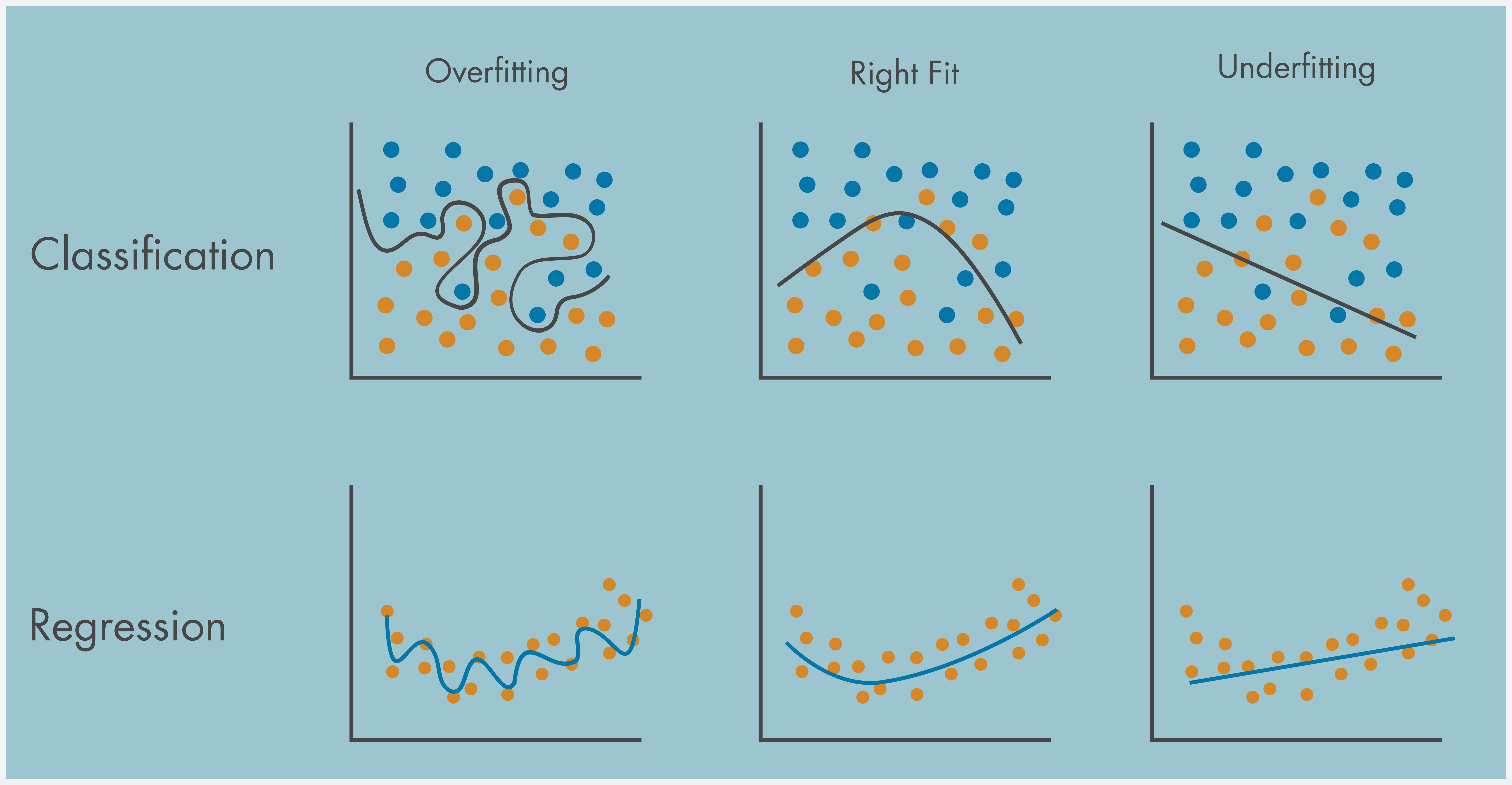
Stochastic Gradient Descent = Update parameters and compute gradients based on a single random training example

Mini-batch SGD = Update parameters based on mean gradient over a mini-batch, i.e. a small subset of the training data



Carpenter et al (2018)

Overfitting versus underfitting



Solution: Regularisation

L1 Norm (LASSO):

$$\boxed{l = \sum_k l_k + C\sum_{j=1}^{n} |\beta_j|}$$

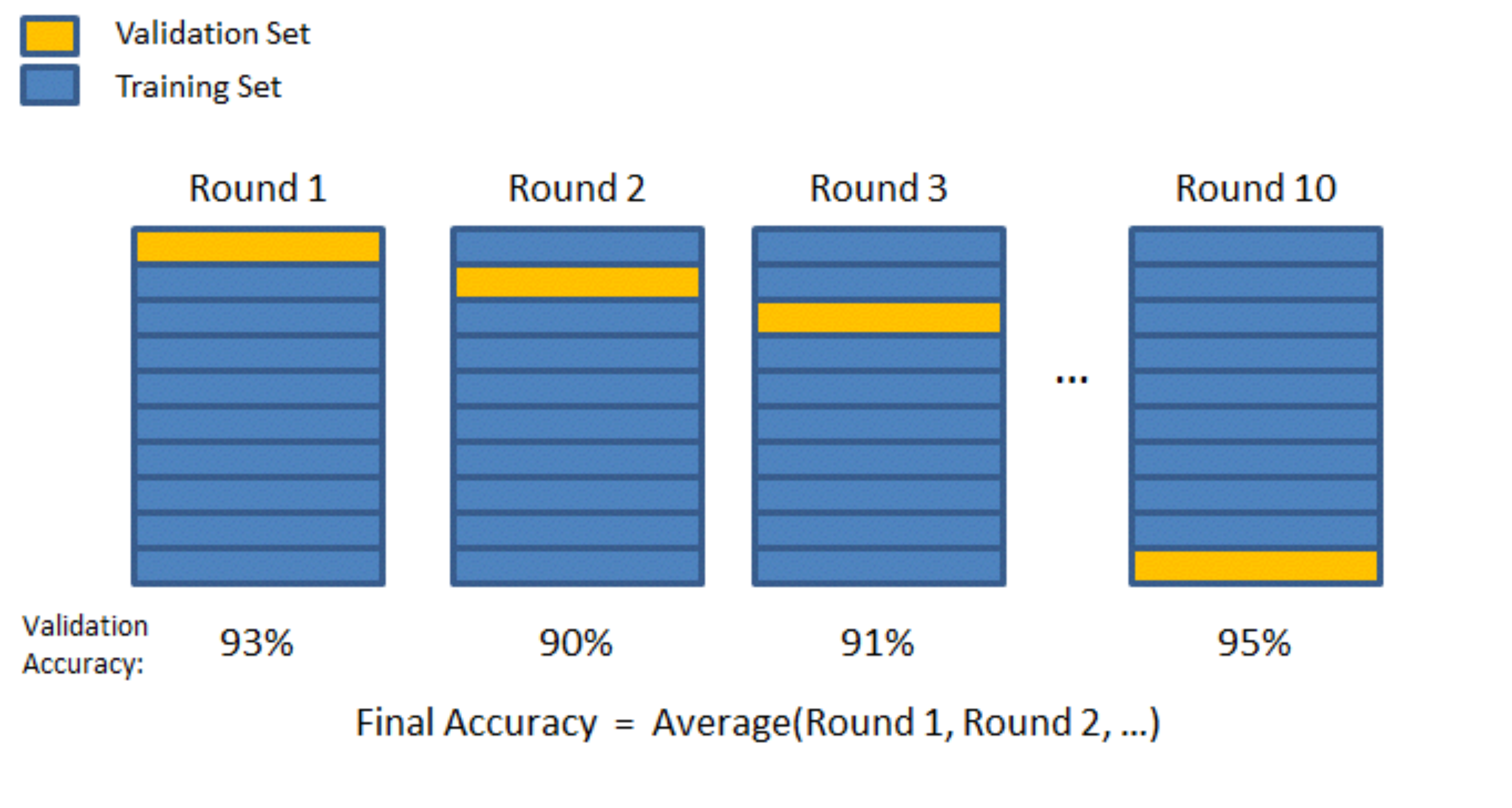
L2 Norm (ridge regression):

$$\boxed{l = \sum_k l_k + C\sqrt{(\sum_{j=1}^{n} |\beta_j|^2)}}$$

p-norm:

$$\boxed{l = \sum_k l_k + C\left(\sum_{j=1}^{n} |\beta_j|^p)\right)^{1/p}}$$

K-Fold Cross Validation



Evaluation Metrics

Evaluation

	Positive Prediction (STAR)	**Negative Prediction (GALAXY)**
Positive class (STAR)	True positive (TP)	False negative (FN)
Negative class (GALAXY)	False positive (FP)	True negative (TN)

Sensitivity = True Positive / (True Positive + False Negative)

Specificity = True Negative / (False Positive + True Negative)

Precision = True Positive / (True Positive + False Positive)

Recall = True Positive / (True Positive + False Negative)

F-score = (2 * Precision * Recall) / (Precision + Recall)

General Advice

Rule 1: Compare against a domain reference and put result into larger context

Rule 2: Adopt best practices from the ML community

Rule 3: Interpret, Diagnose and/or Visualise Models

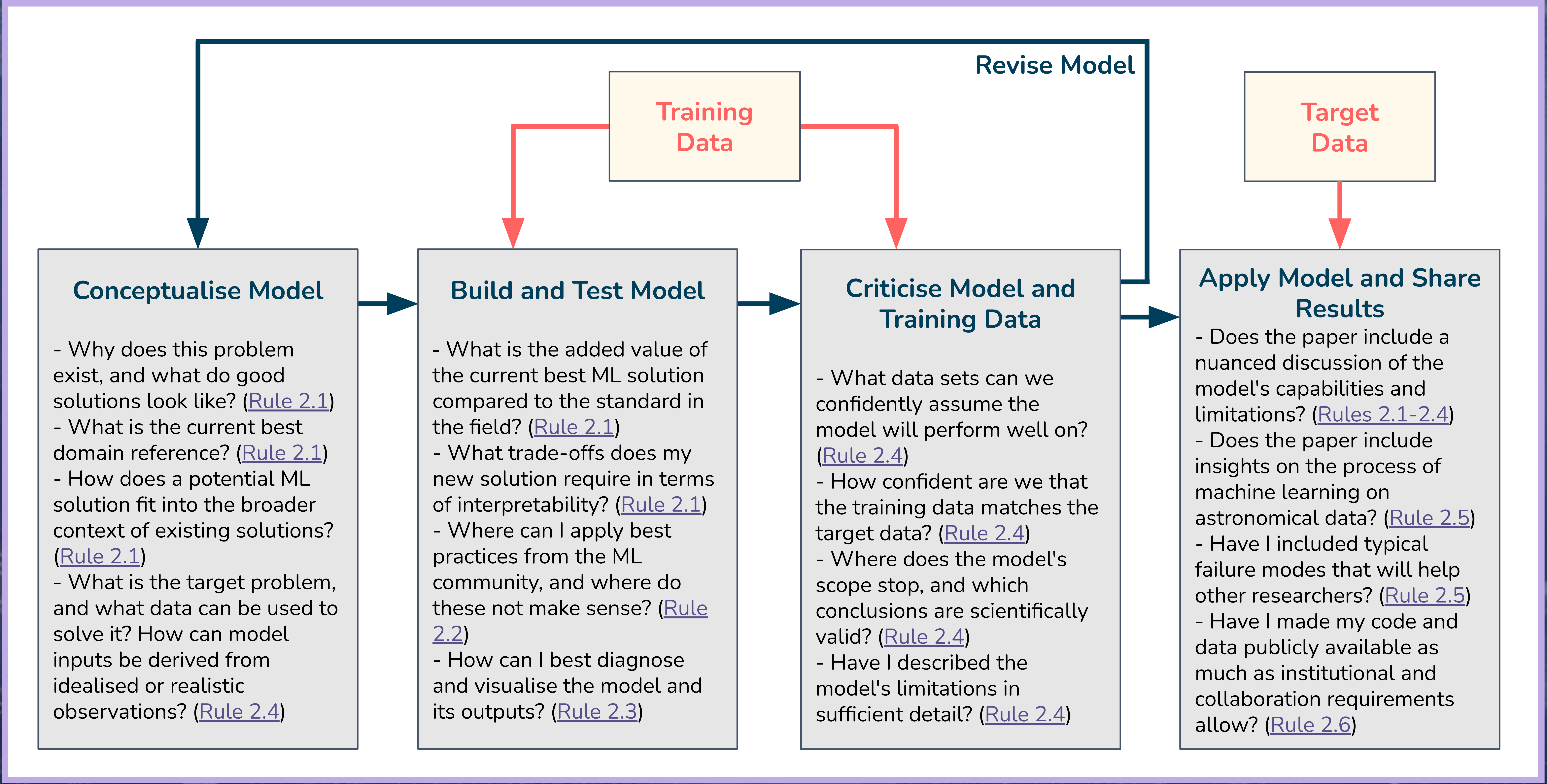
Rule 4: Explore limits and scope of the model

Rule 5: Share and Discuss Lessons Learned

Rule 6: Make Software and Data Publicly Available

Huppenkothen, Ntampaka et al (2024)

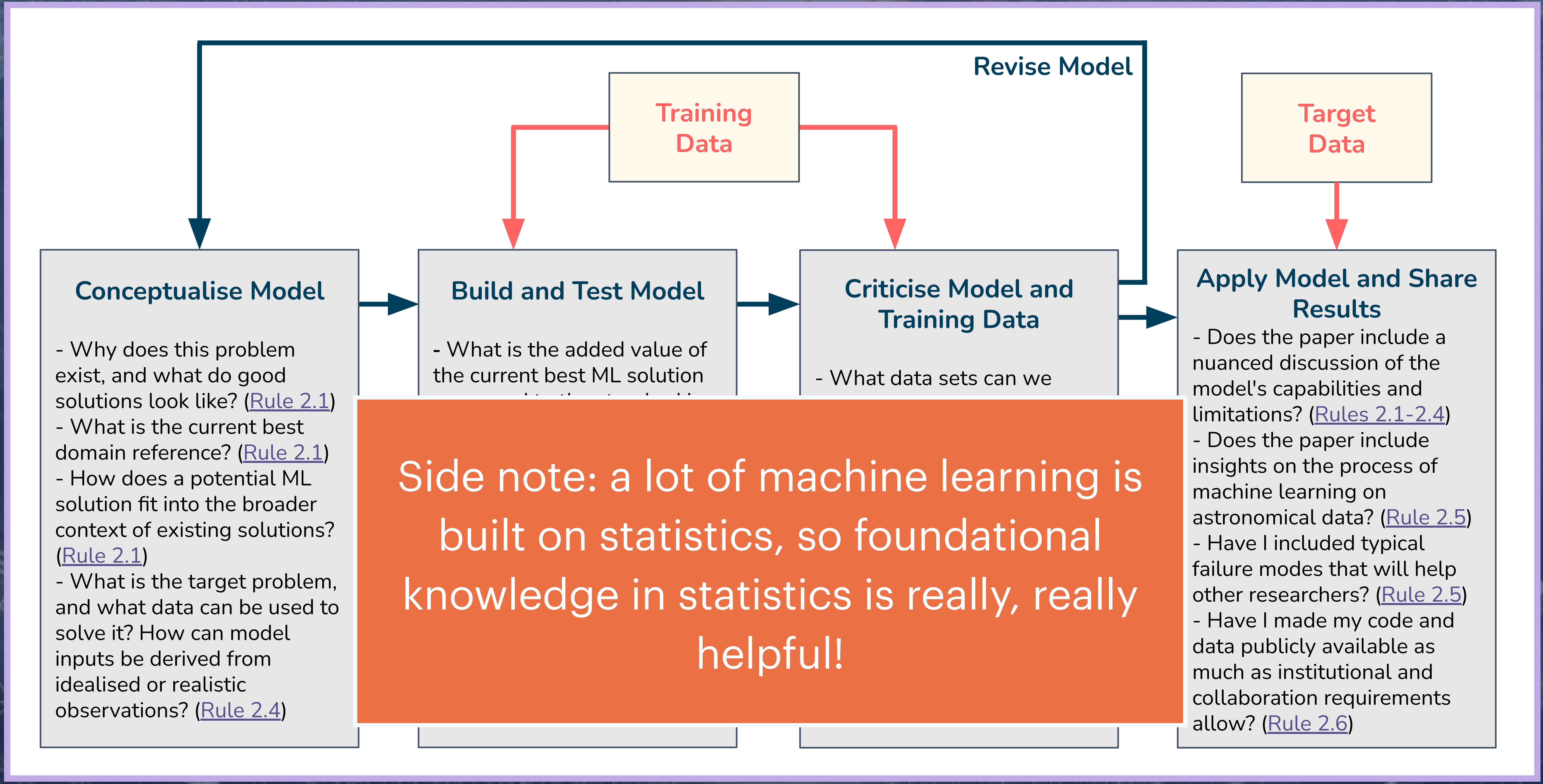
Box Loop for Machine Learning in Astronomy



Adapted from: Blei (2014)

Huppenkothen, Ntampaka et al (2024)

Box Loop for Machine Learning in Astronomy



Side note: a lot of machine learning is built on statistics, so foundational knowledge in statistics is really, really helpful!

Adapted from: Blei (2014)

Huppenkothen, Ntampaka et al (2024)

What to try next

- Viviana Acquaviva, “Machine learning for Physics and Astronomy”, https://press.princeton.edu/books/paperback/9780691206417/machine-learning-for-physics-and-astronomy
- Also chalkboard colloquium: https://www.youtube.com/watch?v=f8NkChOg2oY
- Buchner + Fotopoulou: How to set up your first machine learning project in Astronomy, https://arxiv.org/html/2502.08222v1
- Baron, Machine Learning in Astronomy: A Practical Overview, https://arxiv.org/abs/1904.07248
- Huppenkothen, Ntampaka et al, Constructing Impactful Machine Learning Research in Astronomy, https://arxiv.org/pdf/2310.12528
- Foutopoulou: A review of Unsupervised Learning in Astronomy, https://arxiv.org/pdf/2406.17316
- Scikit-learn tutorials and examples: https://scikit-learn.org/stable/
- Great tutorials by the folks at MPIA: https://mfouesneau.github.io/astro_ds/chapters/datascience/chapter1-introML.html
- NeurIPS and ICML workshops on machine learning for physics and astronomy, e.g. https://ml4physicalsciences.github.io/2024/
- NeurIPS tutorials on specific topics: e.g. at https://neurips.cc/virtual/2024/events/tutorial
- Kaggle competitions on astronomy problems, e.g. https://www.kaggle.com/search?q=astronomy+in:competitions
- Millions of good online resources, e.g. http://www.r2d3.us/visual-intro-to-machine-learning-part-1/
- Great resource: https://distill.pub/
- NASA’s Hello Universe initiative: https://archive.stsci.edu/hello-universe

ML Beyond Astronomy: Ethical Considerations

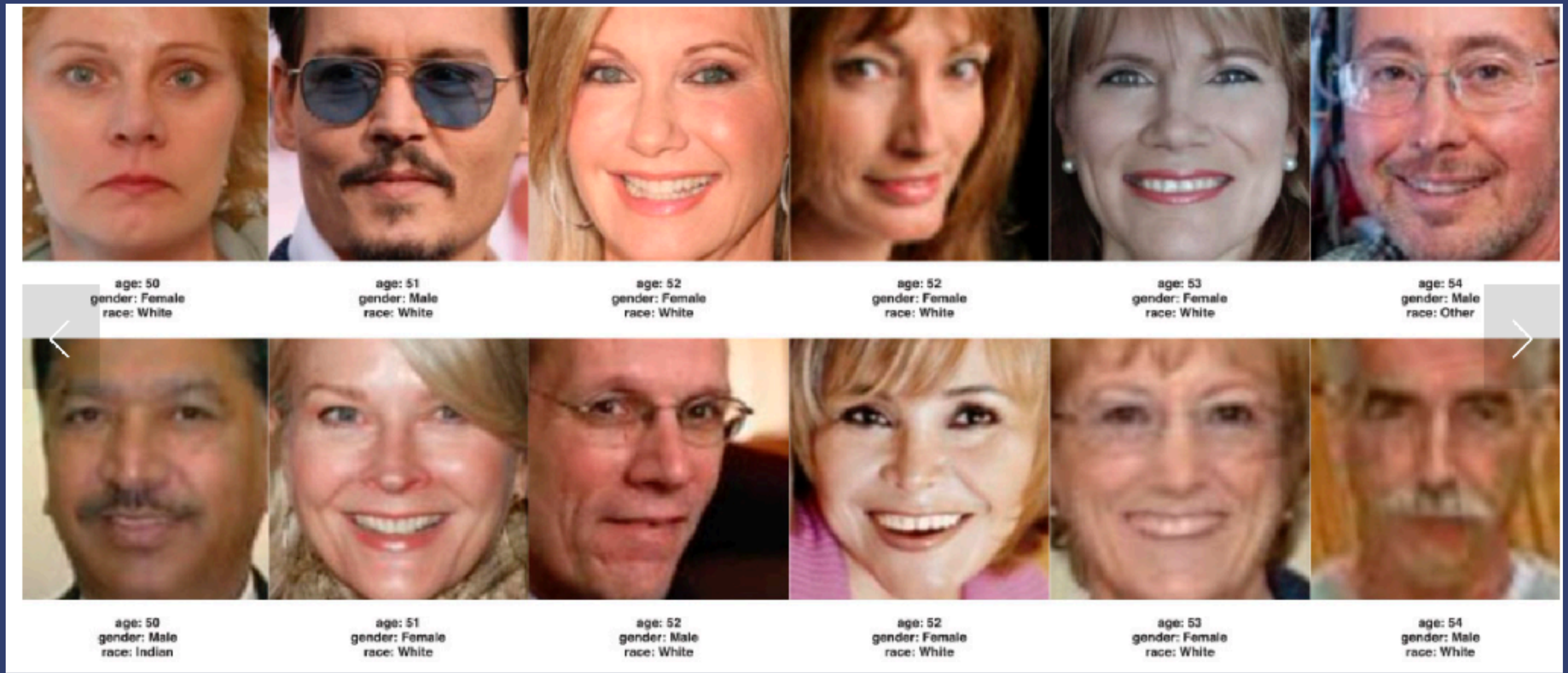
But we are astronomers! Why should we care about ethics when it comes to algorithms and artificial intelligence?

- Our lives are affected every day by predictions made by algorithms
- Technology and algorithms can be misused
- There is a growing number of studies about the astronomy community
- You might have a future job or side project that is not in astronomy

Algorithms are designed by people, and people embed (unconscious) biases in algorithms, data collection and interpretation of results.

Meredith Broussard: Artificial Unintelligence

UTK Faces Dataset



Labels

The labels of each face image is embedded in the file name, formated like `[age]_[gender]_[race]_[date&time].jpg`

- `[age]` is an integer from 0 to 116, indicating the age
- `[gender]` is either 0 (male) or 1 (female)
- `[race]` is an integer from 0 to 4, denoting White, Black, Asian, Indian, and Others (like Hispanic, Latino, Middle Eastern).
- `[date&time]` is in the format of yyyymmddHHMMSSFFF, showing the date and time an image was collected to UTKFace

https://www.excavating.ai/

Biases in training data sets

Ethical Concerns in using Algorithms

- purposeful harm or manipulation
- technological solutionism
- ubiquity, trust
- limited perspective of algorithm writer
- errors in algorithm's implementation
- unrepresentative data sets
- insufficient evaluation metrics
- faulty representations (e.g. in langauge)
- fairness
- privacy and data rights
- ...

Deepfake Videos Are Getting Real and That's a Problem

The damaging impact and destabilizing potential of sophisticated video fakery

By Hilke Schellmann
Oct. 15, 2018 11:30 am

Computer-generated videos are getting more realistic and even harder to detect thanks to deep learning and artificial intelligence. As WSJ's Jason Bellini finds in this episode of Moving Upstream, these so-called deepfakes can be playful, but can also have real, damaging consequences for people's lives.

'I was shocked it was so easy': meet the professor who says facial recognition can tell if you're gay

Michal Kosinski: 'I don't believe in free will.' Photograph: Jason Henry/The Guardian

Psychologist Michal Kosinski says artificial intelligence can detect your sexuality and politics just by looking at your face. What if he's right?

How a Self-Driving Uber Killed a Pedestrian in Arizona

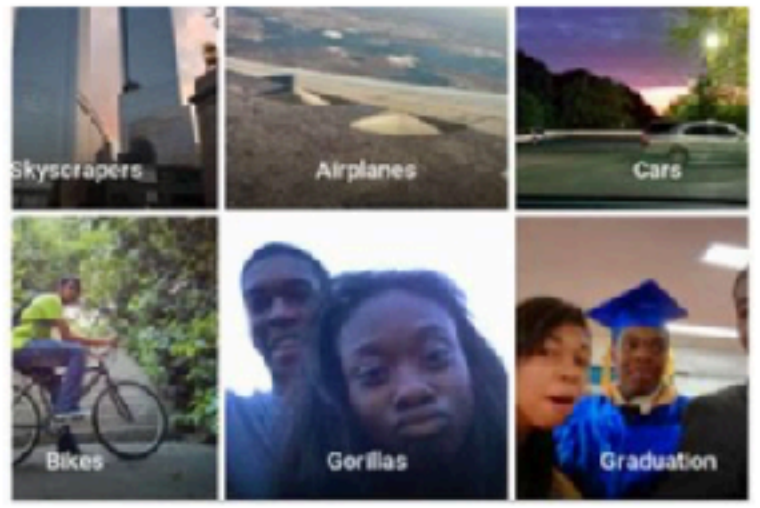
By TROY GRIGGS and DAISUKE WAKABAYASHI UPDATED MARCH 21, 2018

A woman was struck and killed on Sunday night by an autonomous car operated by Uber in Tempe, Ariz. It was believed to be the first pedestrian death associated with self-driving technology.

DIGITS

Google Mistakenly Tags Black People as 'Gorillas,' Showing Limits of Algorithms

By Alistair Barr
Jul 1, 2015 3:40 pm ET



Black programmer Jacky Alciné said on Twitter that the new Google Photos app had tagged photos of him and a friend as gorillas. *JACKY ALCINÉ AND TWITTER*

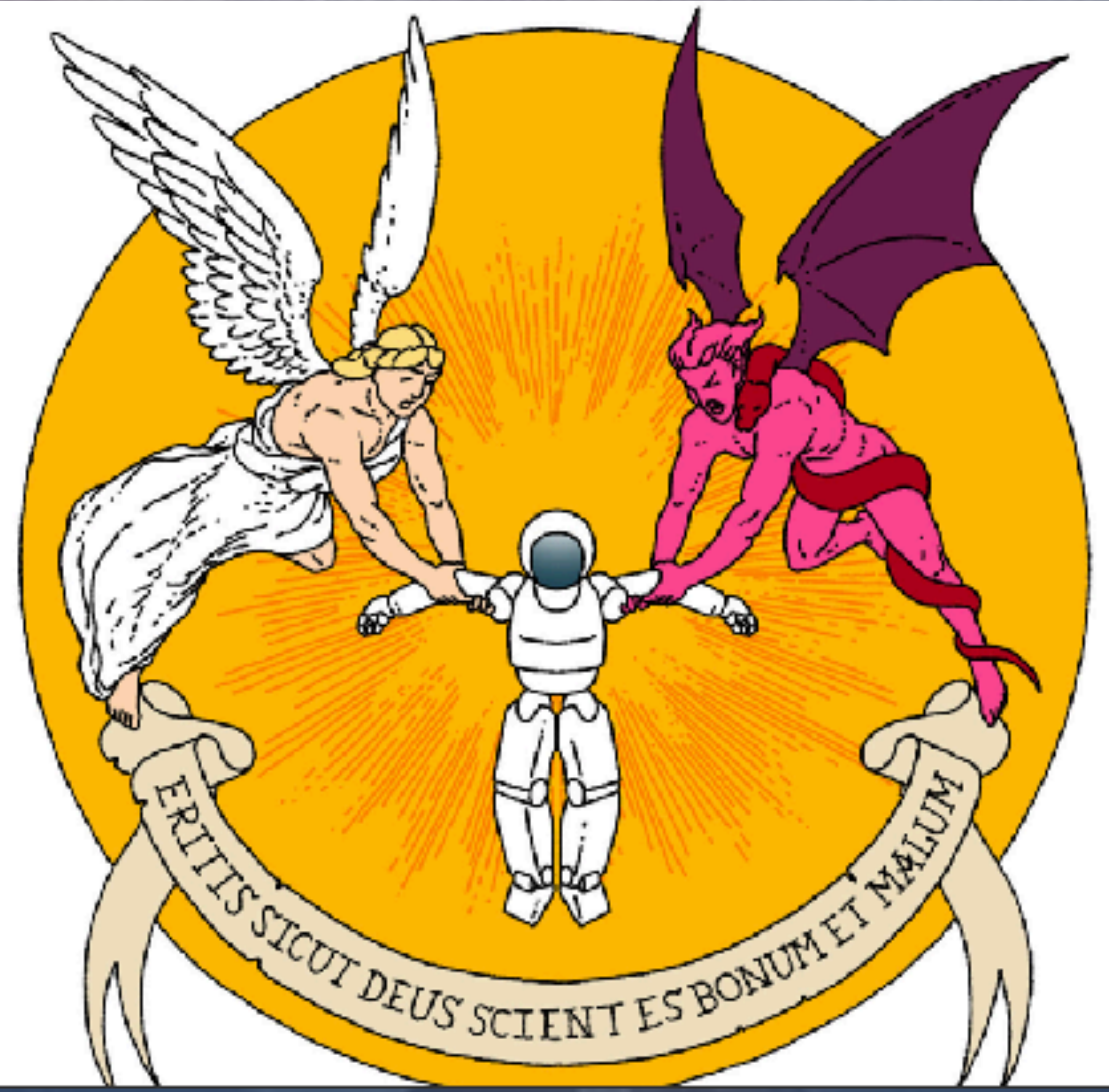
Andrej Karpathy blog　About　Hacker's guide to Neural Networks

What a Deep Neural Network thinks about your #selfie

Oct 25, 2015

Can a Machine Learn Morality?

Researchers at a Seattle A.I. lab say they have built a system that makes ethical judgments. But its judgments can be as confusing as those of humans.



Previously, Delphi said:

"Being a white man"
- ***is more morally acceptable than*** -
"Being a black woman"

Being a black woman vs. Being a white man

Kate MacKay @KLMacKay · Nov 23

I just checked out the **Delphi** Morality AI. I asked **#Delphi** 'should people ask computers for **moral** advice?'
Delphi speculates:
"People shouldn't"
delphi.allenai.org/?a1=should+peo...+

6

Delphi says:

"Bring back dinosaurs using genetic engineering to create theme park jobs."
- ***It's good***

* Input a **situation** for Delphi to ponder:

Procrastinating.

Ponder

Delphi speculates:

Delphi's responses are automatically extrapolated from a survey of US crowd workers and may contain inappropriate or offensive results.

"Procrastinating. "
- ***It's bad***

v1.0.4

The original prototype of Delphi made a number of racist, sexist, homophobic statements

Ethical Concerns in using Algorithms

What makes the application of algorithms ethical?

Why is this important at all?

What can we do to ensure that we are applying algorithms ethically and responsibly?

DATAPRACTICES.ORG

SUBSCRIBE

Data Values & Principles

These values and principles, taken together, describe the most effective, ethical, and modern approach to data teamwork.

READ AND SIGN

Data Practices Courseware

Consume and collaborate on free and open courses designed to help everyone from the novice to the expert data practitioner.

EXPLORE COURSES

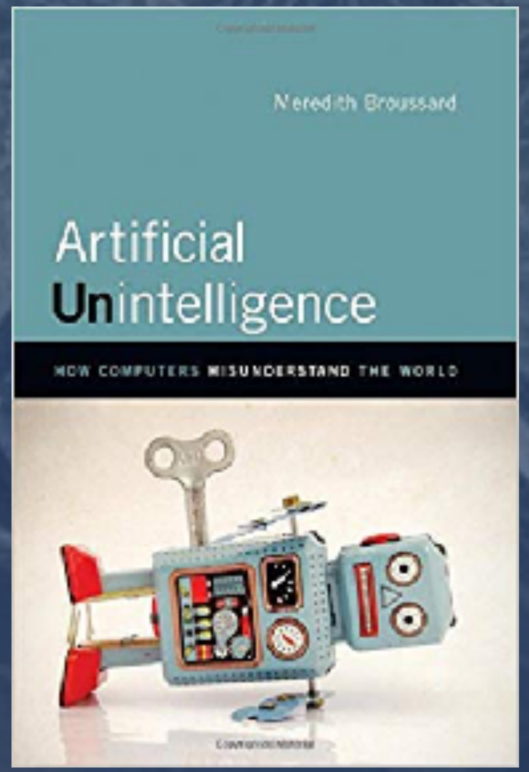
In association with the Global Data Ethics Pledge - Read and sign

Checklists help eliminate basic mistakes

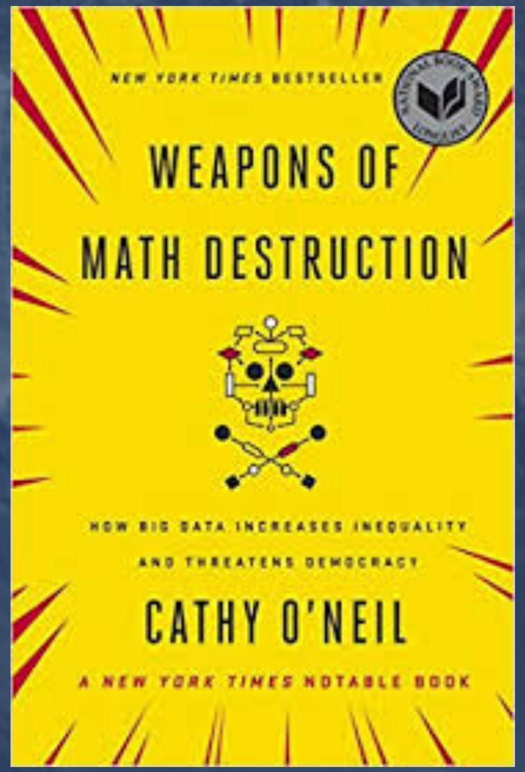
- ❑ Have we listed how this technology can be attacked or abused?
- ❑ Have we tested our training data to ensure it is fair and representative?
- ❑ Have we studied and understood possible sources of bias in our data?
- ❑ Does our team reflect diversity of opinions, backgrounds, and kinds of thought?
- ❑ What kind of user consent do we need to collect to use the data?
- ❑ Do we have a mechanism for gathering consent from users?
- ❑ Have we explained clearly what users are consenting to?
- ❑ Do we have a mechanism for redress if people are harmed by the results?
- ❑ Can we shut down this software in production if it is behaving badly?
- ❑ Have we tested for fairness with respect to different user groups?
- ❑ Have we tested for disparate error rates among different user groups?
- ❑ Do we test and monitor for model drift to ensure our software remains fair over time?
- ❑ Do we have a plan to protect and secure user data?

Mason, Loukides, Patil: Ethics and Data Science (2018)

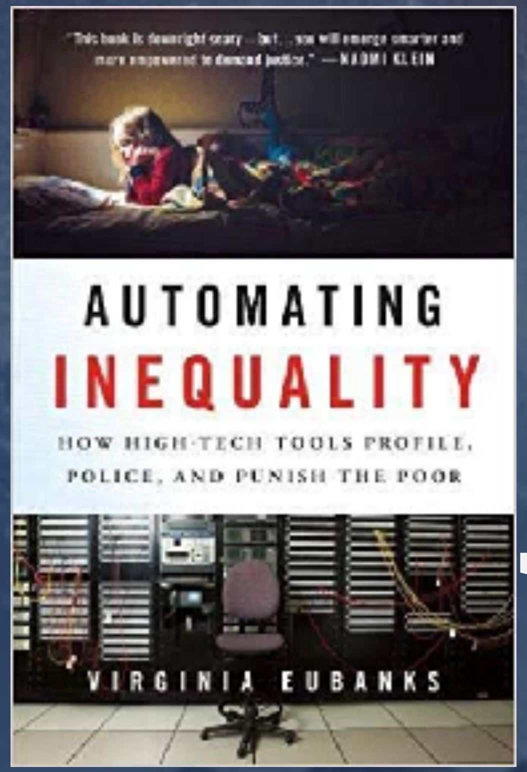
Resources



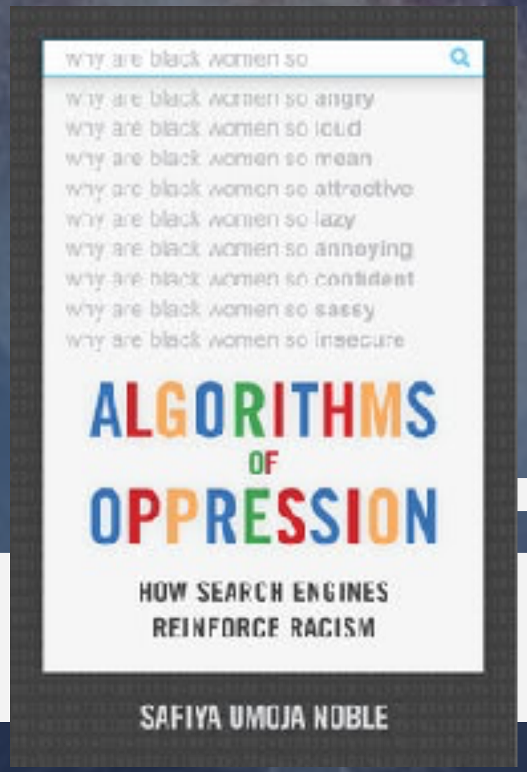
Meredith Broussard
Artificial Unintelligence
HOW COMPUTERS MISUNDERSTAND THE WORLD



NEW YORK TIMES BESTSELLER
WEAPONS OF MATH DESTRUCTION
HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY
CATHY O'NEIL
A NEW YORK TIMES NOTABLE BOOK



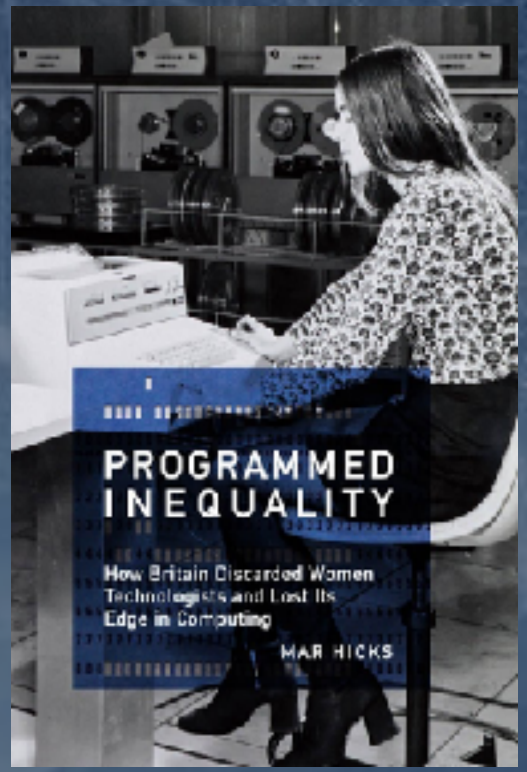
AUTOMATING INEQUALITY
HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR
VIRGINIA EUBANKS



why are black women so
ALGORITHMS OF OPPRESSION
HOW SEARCH ENGINES REINFORCE RACISM
SAFIYA UMOJA NOBLE

O'REILLY
Ethics and Data Science
Mike Loukides, Hilary Mason & DJ Patil

RUHA BENJAMIN
RACE AFTER TECHNOLOGY



PROGRAMMED INEQUALITY
How Britain Discarded Women Technologists and Lost Its Edge in Computing
MAR HICKS





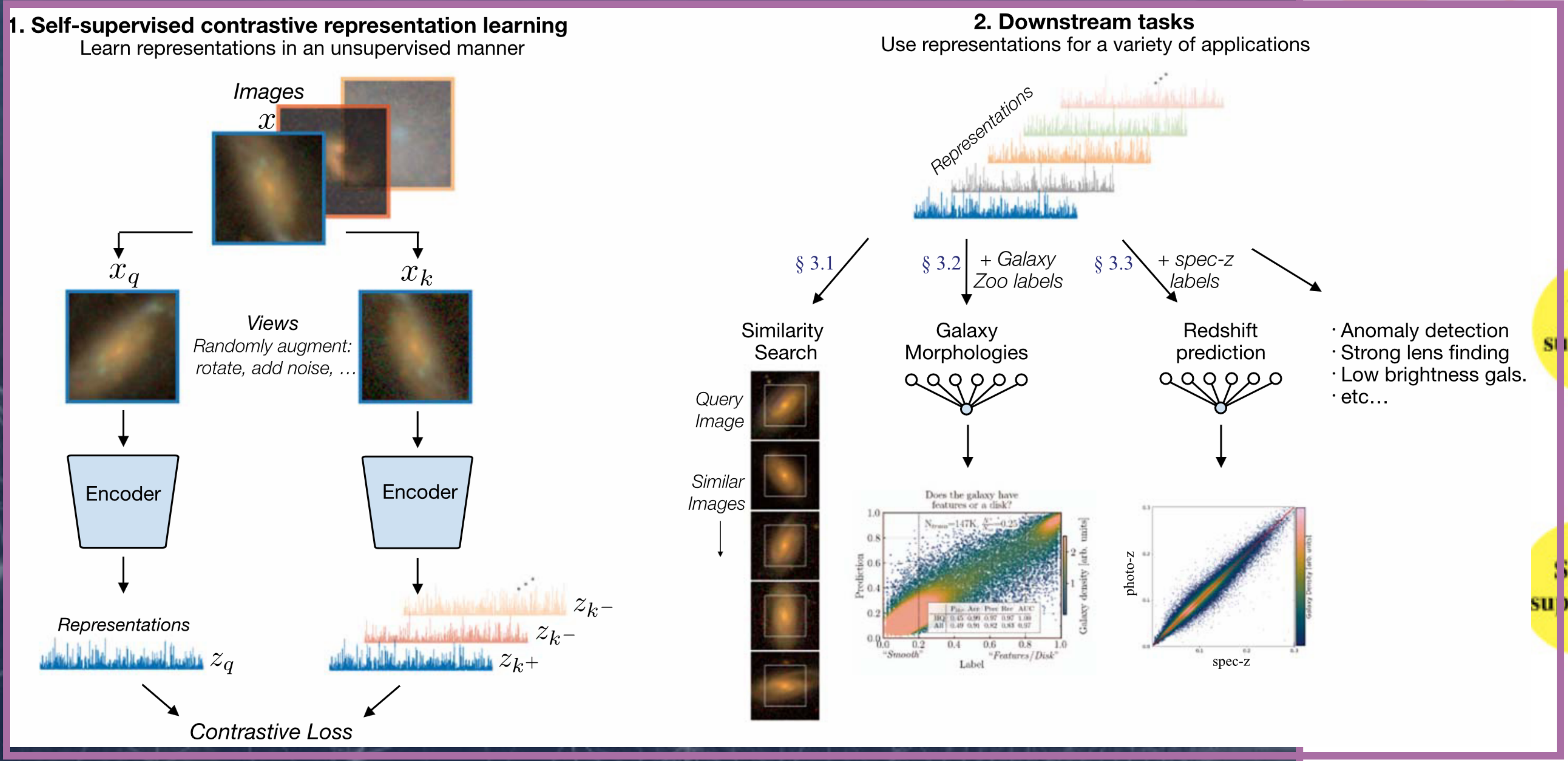




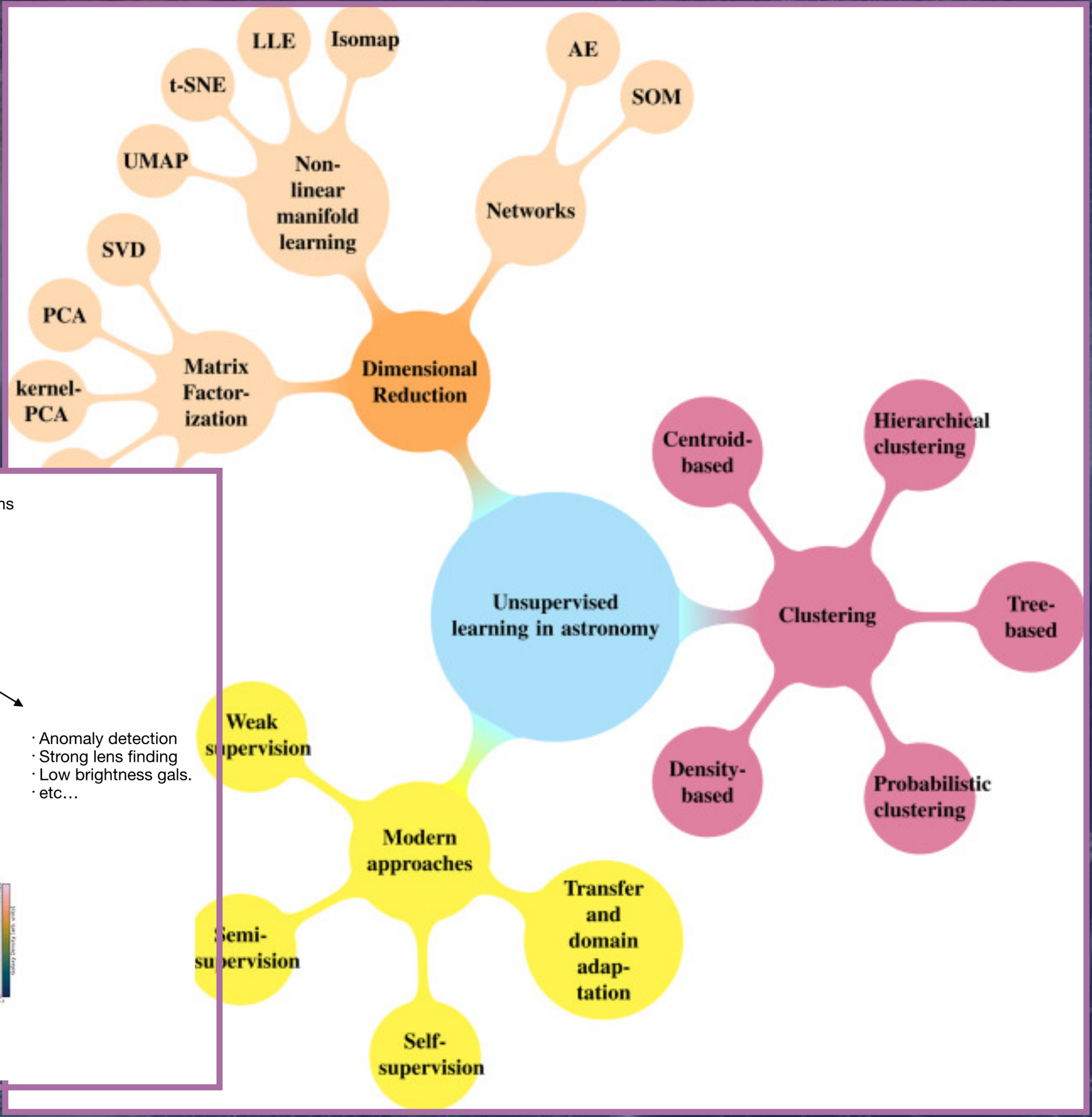


Questions!

Unsupervised Learning



Hayat et al (2021)



Fotopoulou (2024, arXiv:2406.17316

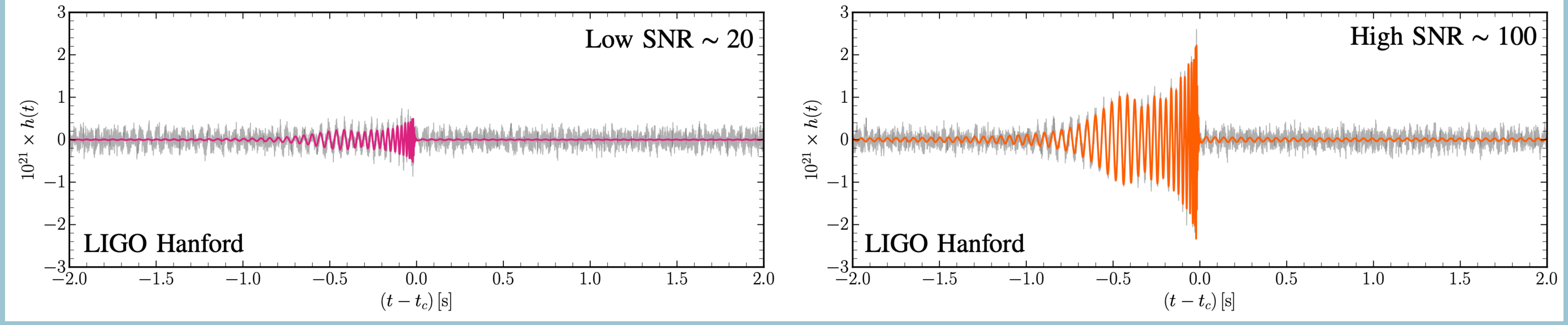
Data Science Challenges in Astronomy

adapted from Hernan (2019)

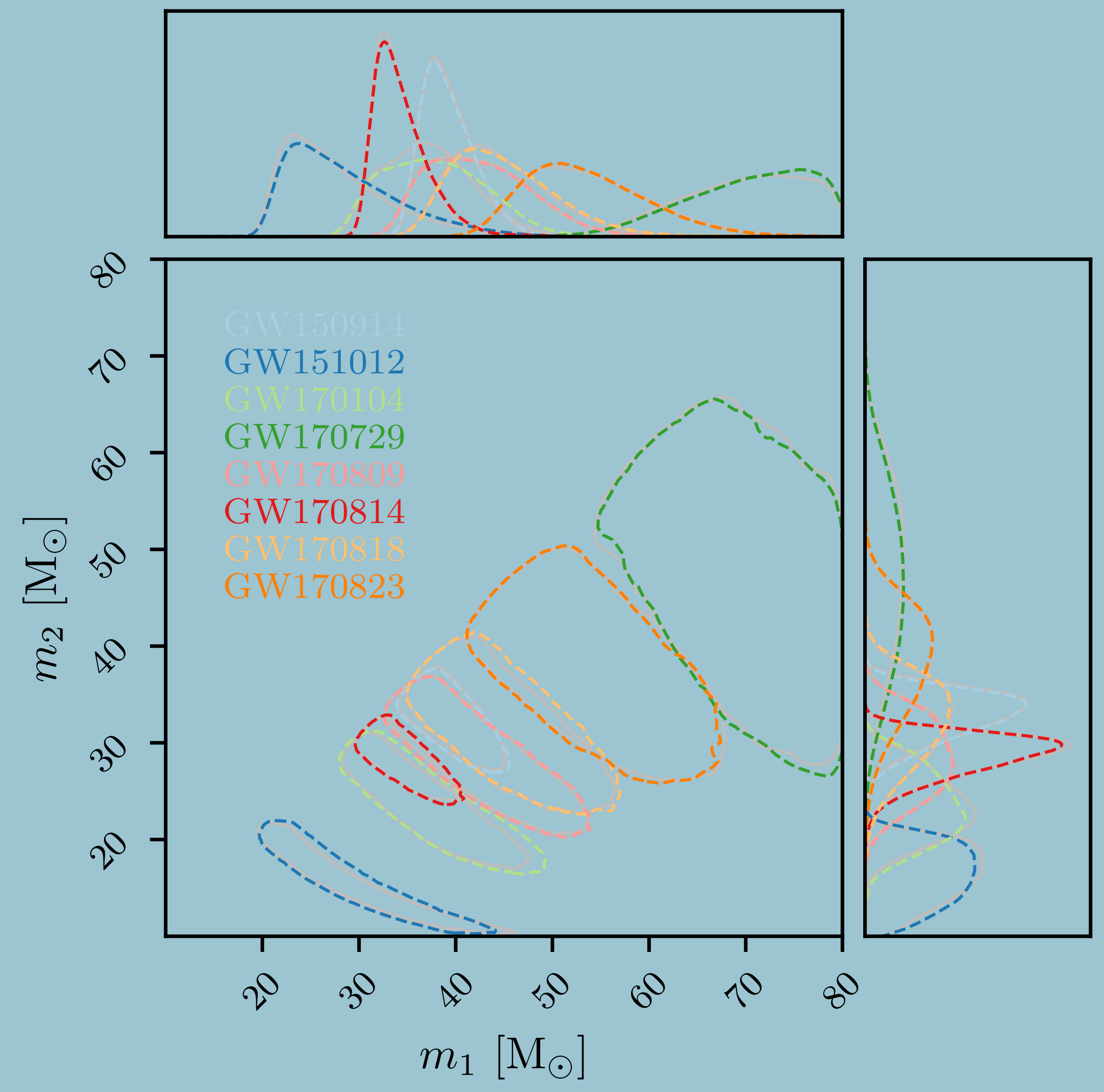
Description	Prediction	Inference
How can we split supernovae into different classes?	What is the probability of an observed supernova to be Type Ia?	Are Type Ia supernovae caused by the explosion of white dwarfs?
• Eligibility criteria • Features	• Eligibility criteria • Features • Training examples	• Eligibility criteria • Features • White dwarf explosion model
• Representation learning • Dictionary learning • Clustering • …	• (Linear) Regression • Decision trees • Neural networks • …	• (Linear) Regression • Maximum Likelihood • Bayesian inference • Simulation-based inference • Physics-informed ML

Gravitational Wave Inference

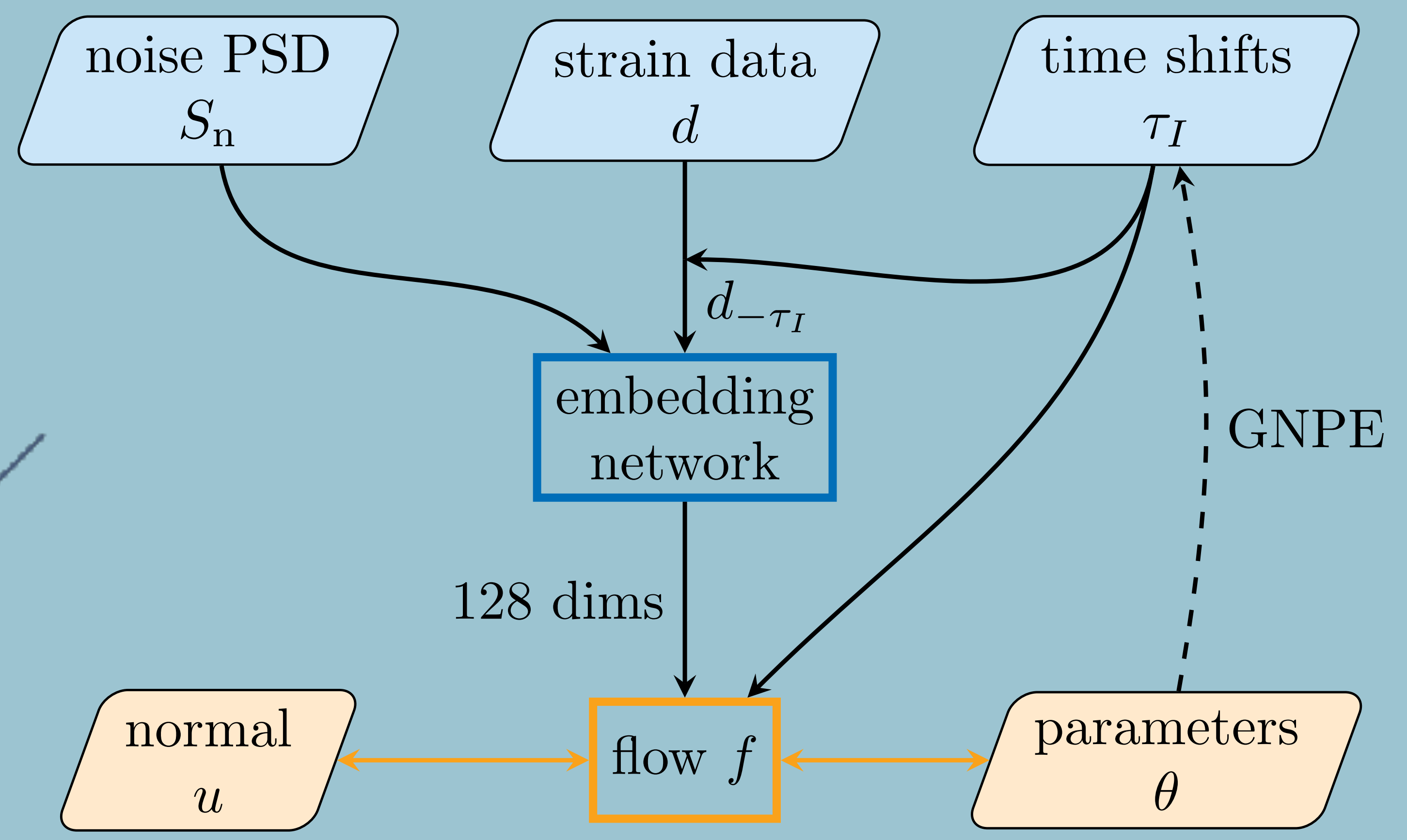
Bhardwaj et al (2023)

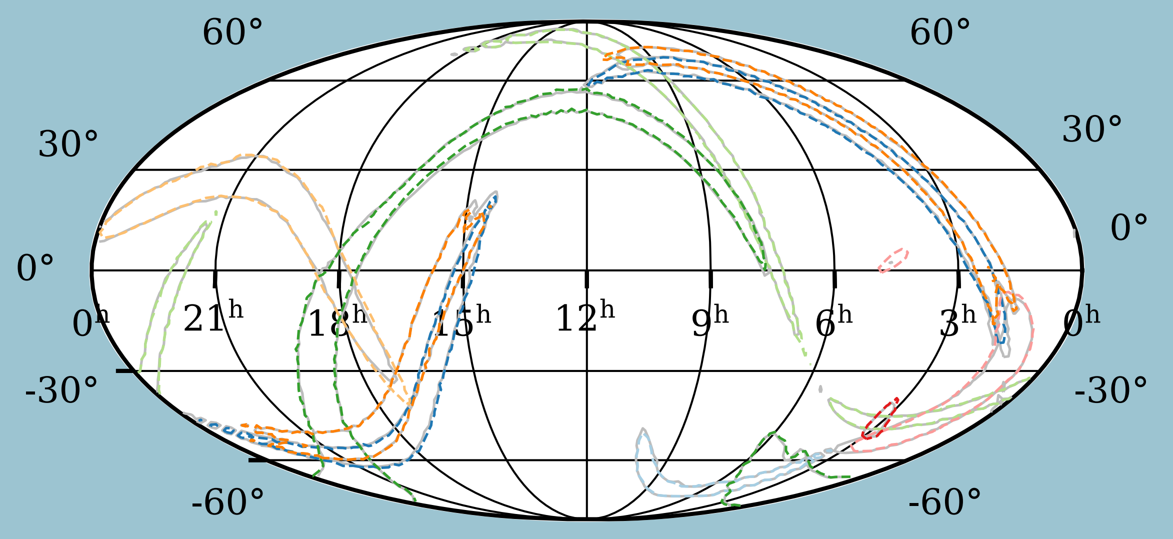


- signals that arrive coincidentally in detectors
- longer signals that are in the presence of non-stationary noise or other shorter transients
- noisy, potentially correlated, coherent stochastic backgrounds



(a)



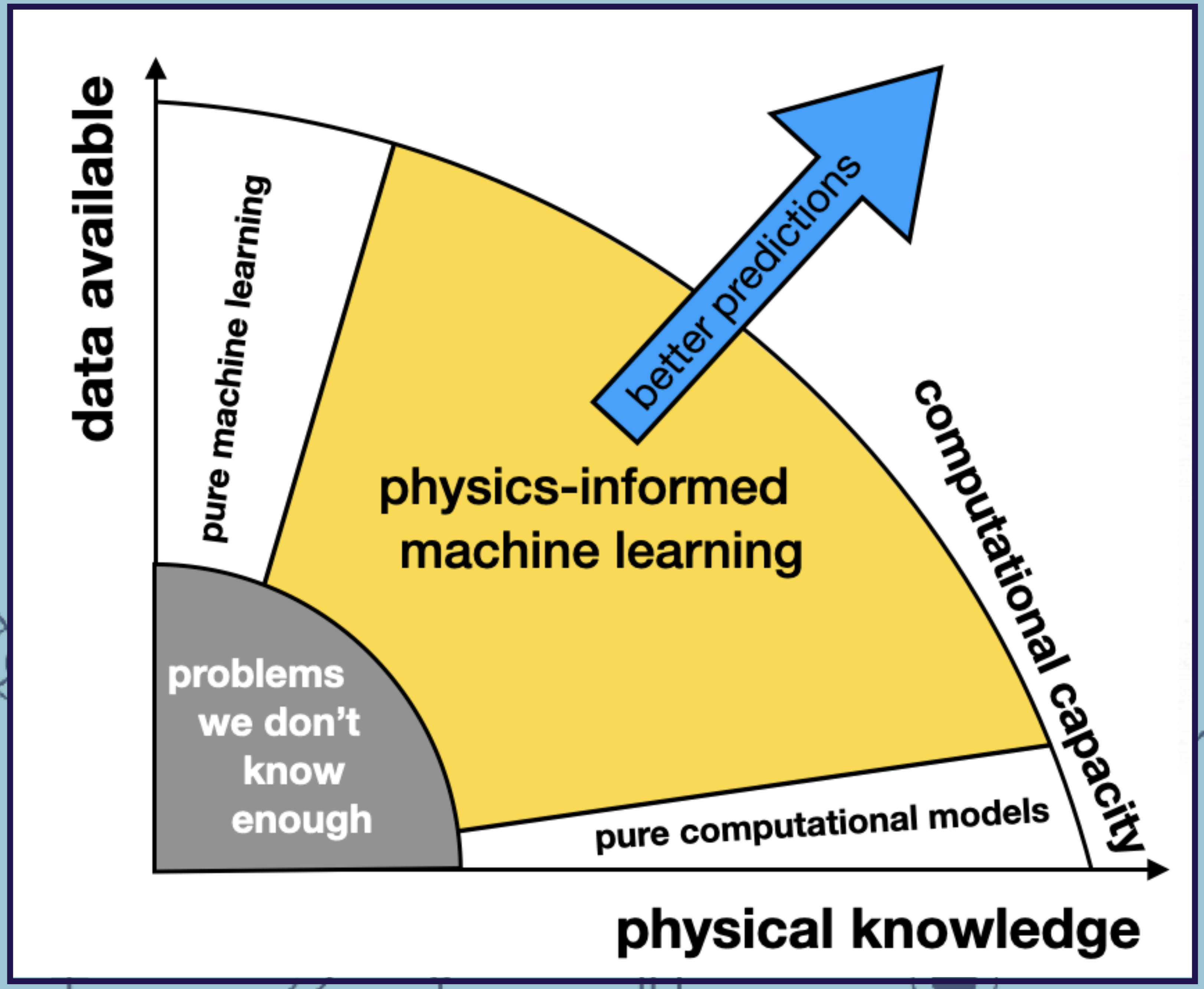


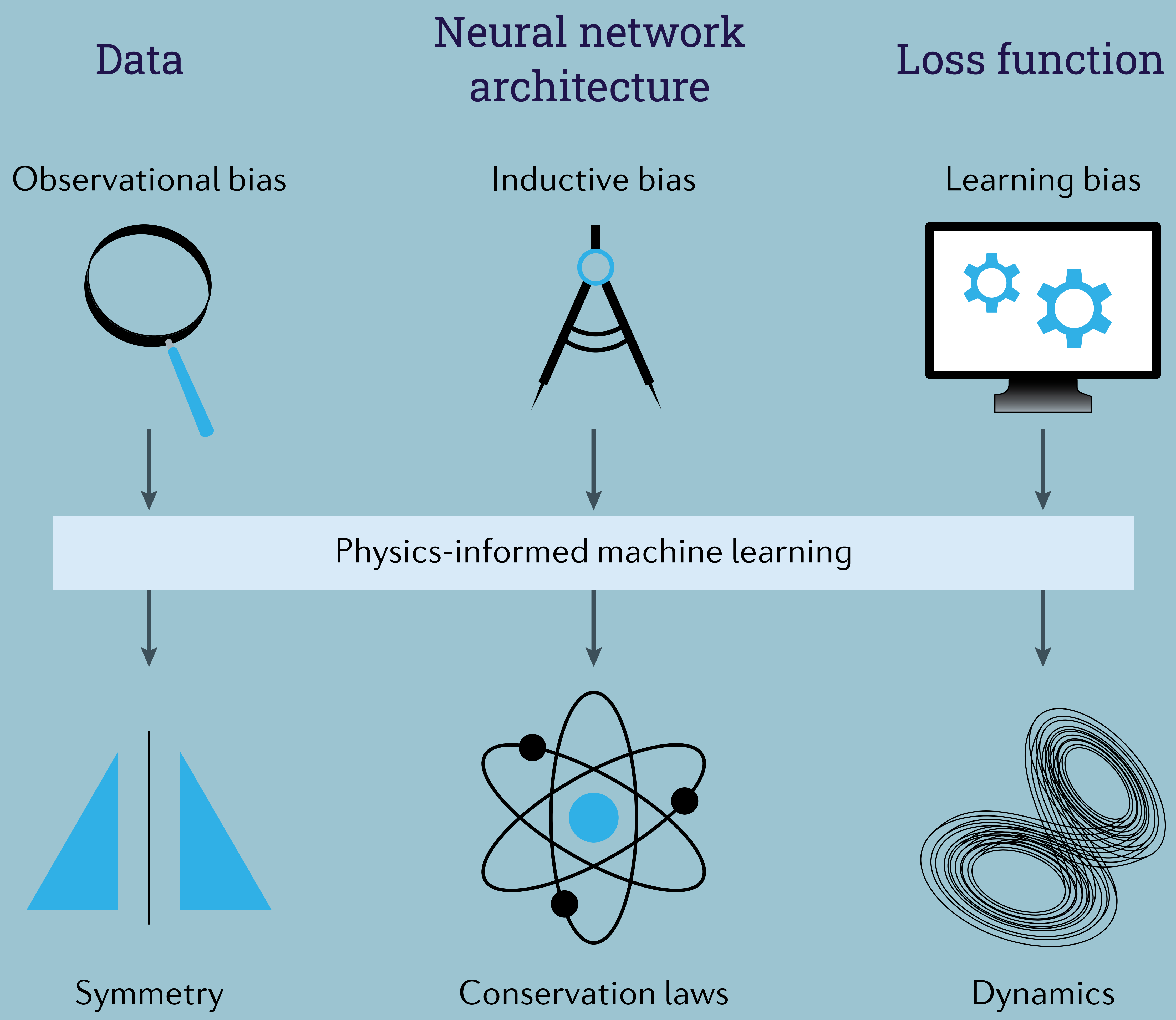
(b)

Dax et al (2021)

Physics-Informed Machine Learning

- seamlessly integrate data and mathematical physics models, even in partially understood, uncertain and high-dimensional contexts.
- Learn solutions from severely limited data by constraining neural network architecture and loss functions



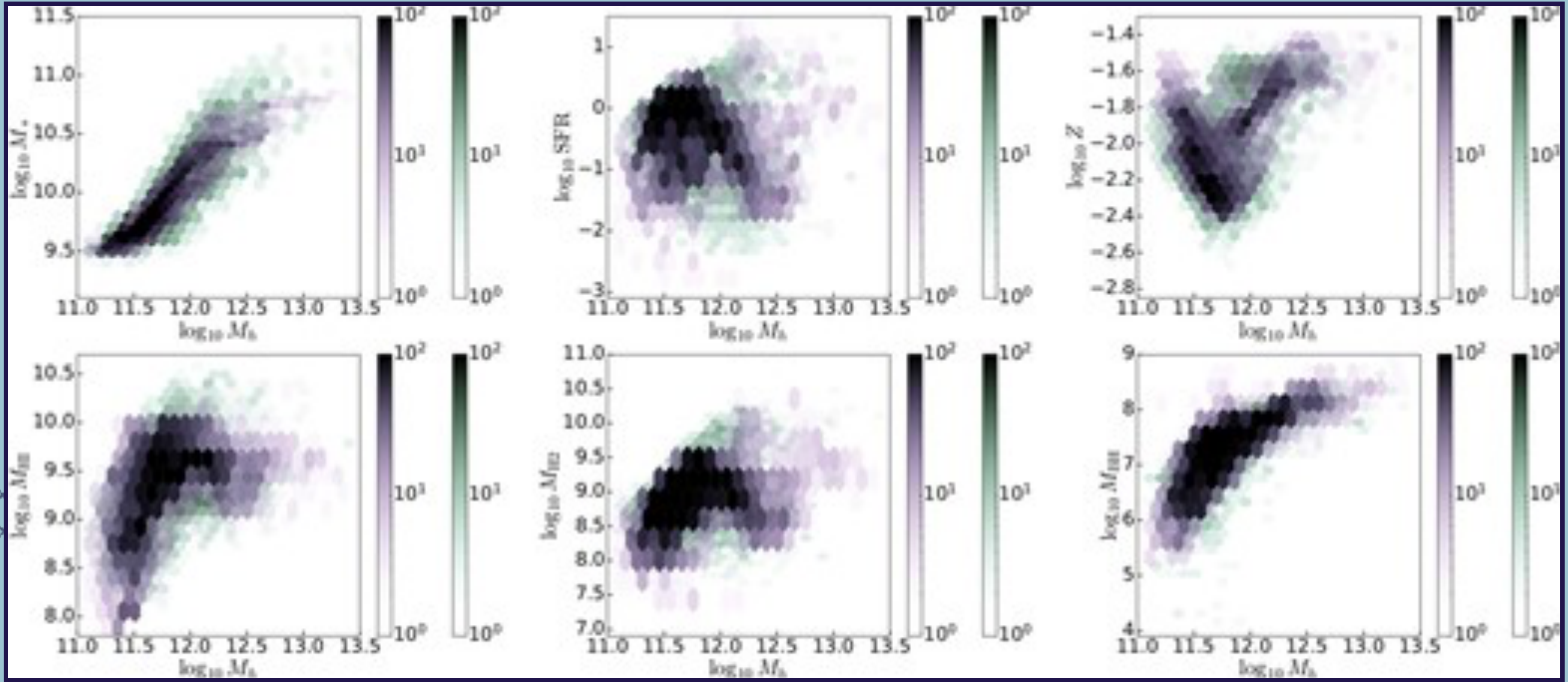


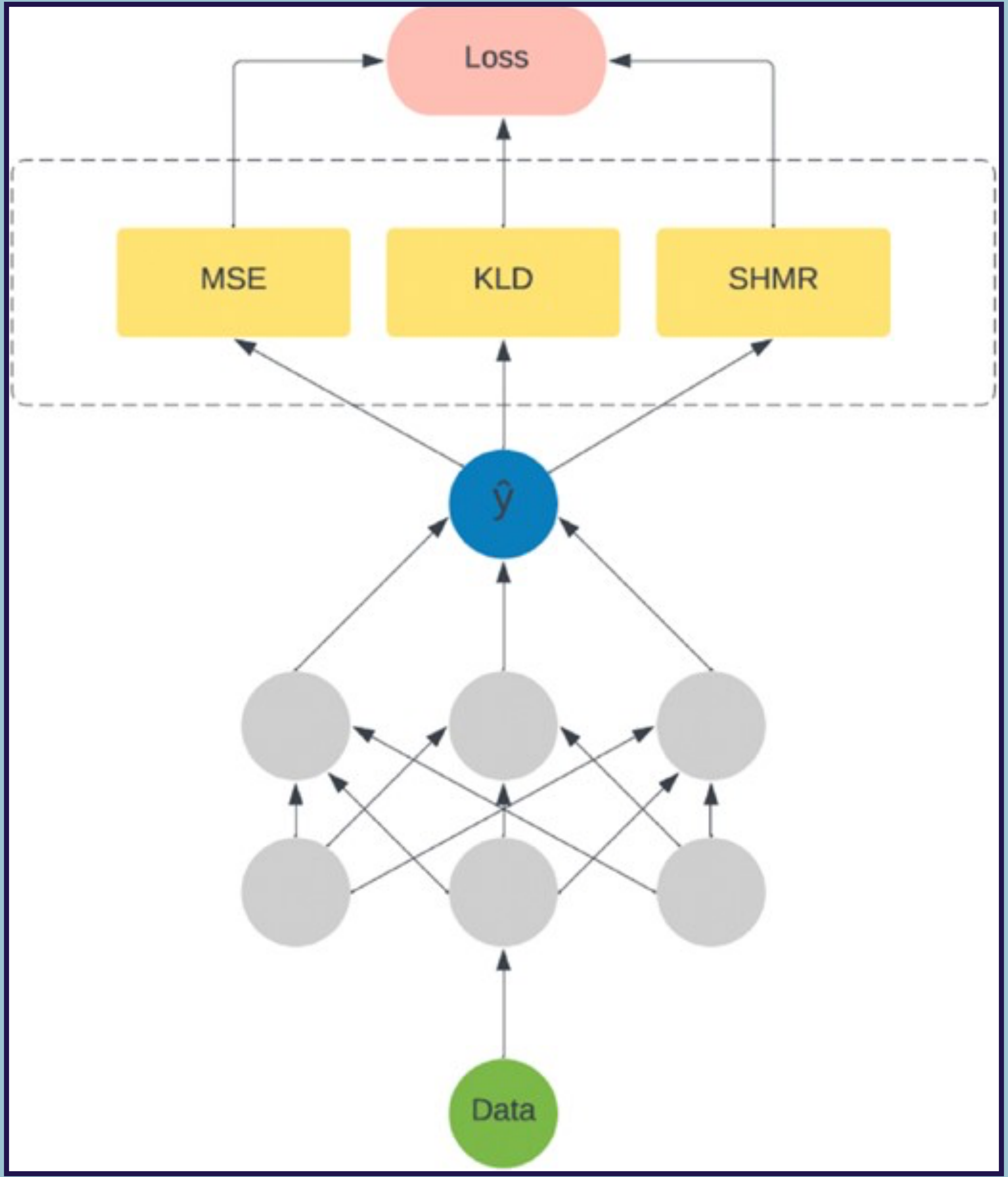
Karniadakis et al (2021): "Physics-Informed Machine Learning" (Nature Reviews Physics)

Baryon Inpainting in Dark Matter Simulations

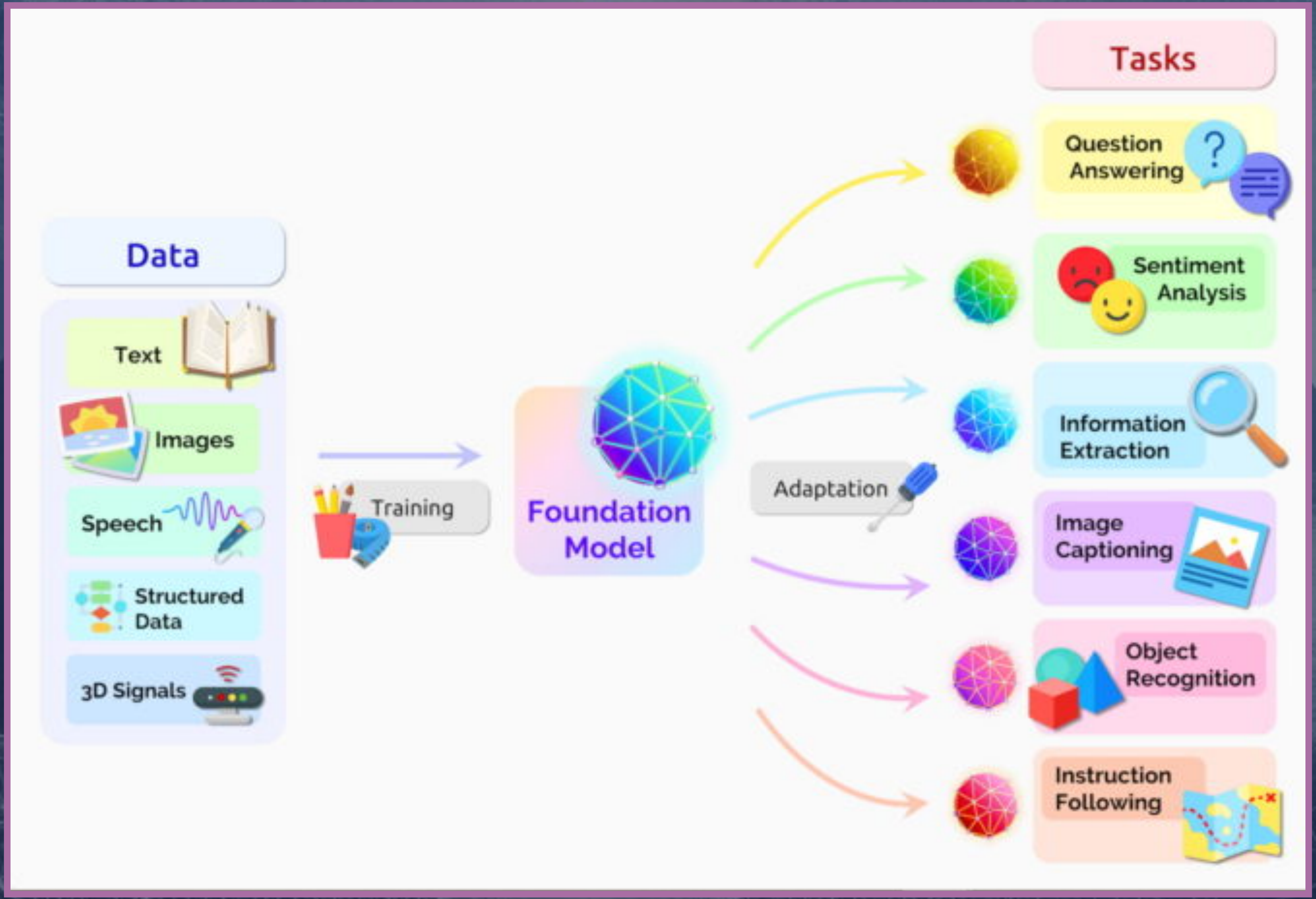
- Dark matter simulations are relatively fast and cheap, but hydrodynamic simulations of baryons are expensive
- Predict limited set of baryon properties from analytical models, then combine with halo properties to predict the complete set of baryons using machine learning
- Incorporate stellar-to-halo mass relation (SHMR) and baryon conversion efficiency into training process

Dai et al (2024)



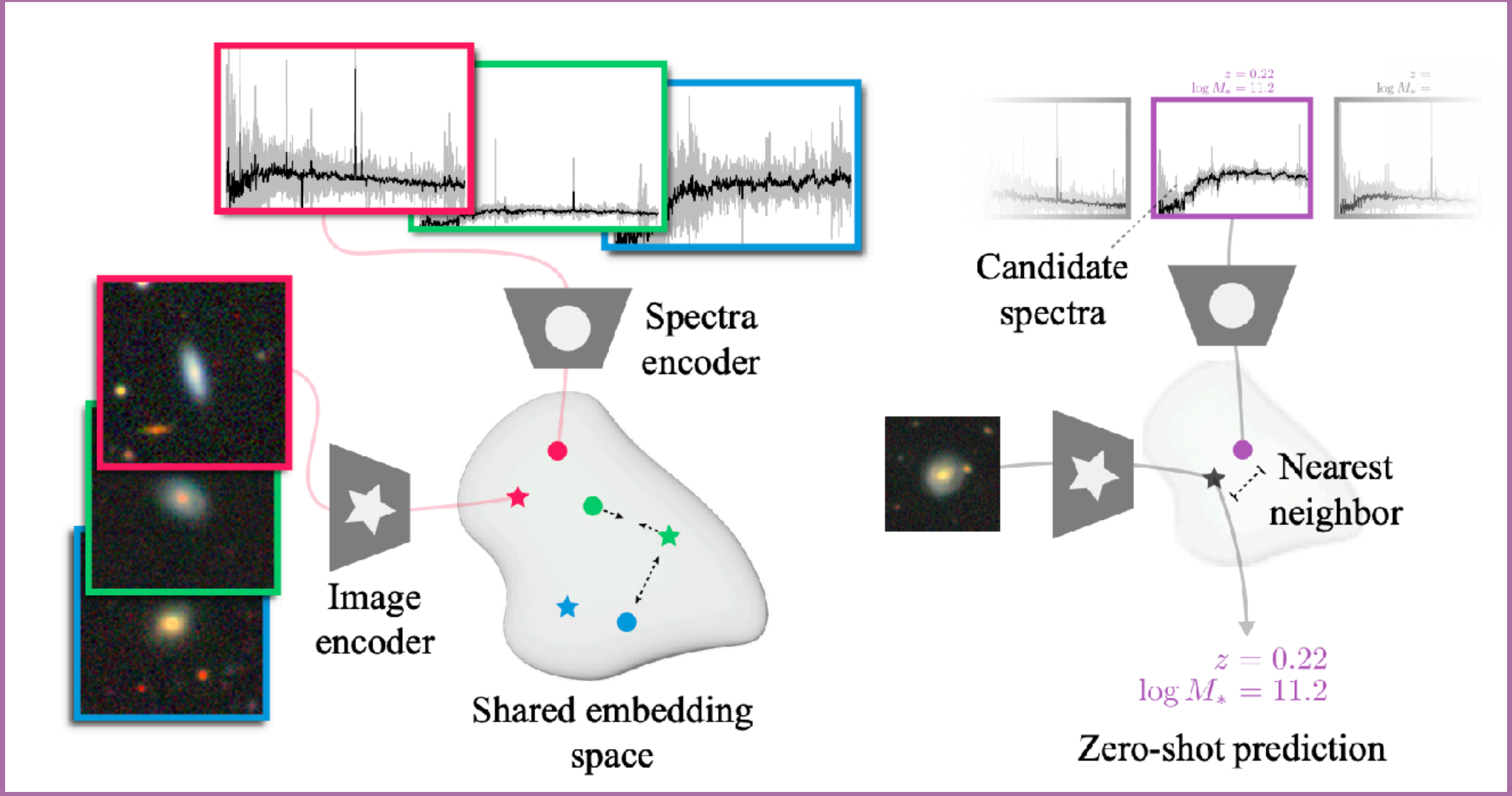


Foundation Models



https://blogs.nvidia.com/blog/what-are-foundation-models/

AstroCLIP



Parker et al (2024)

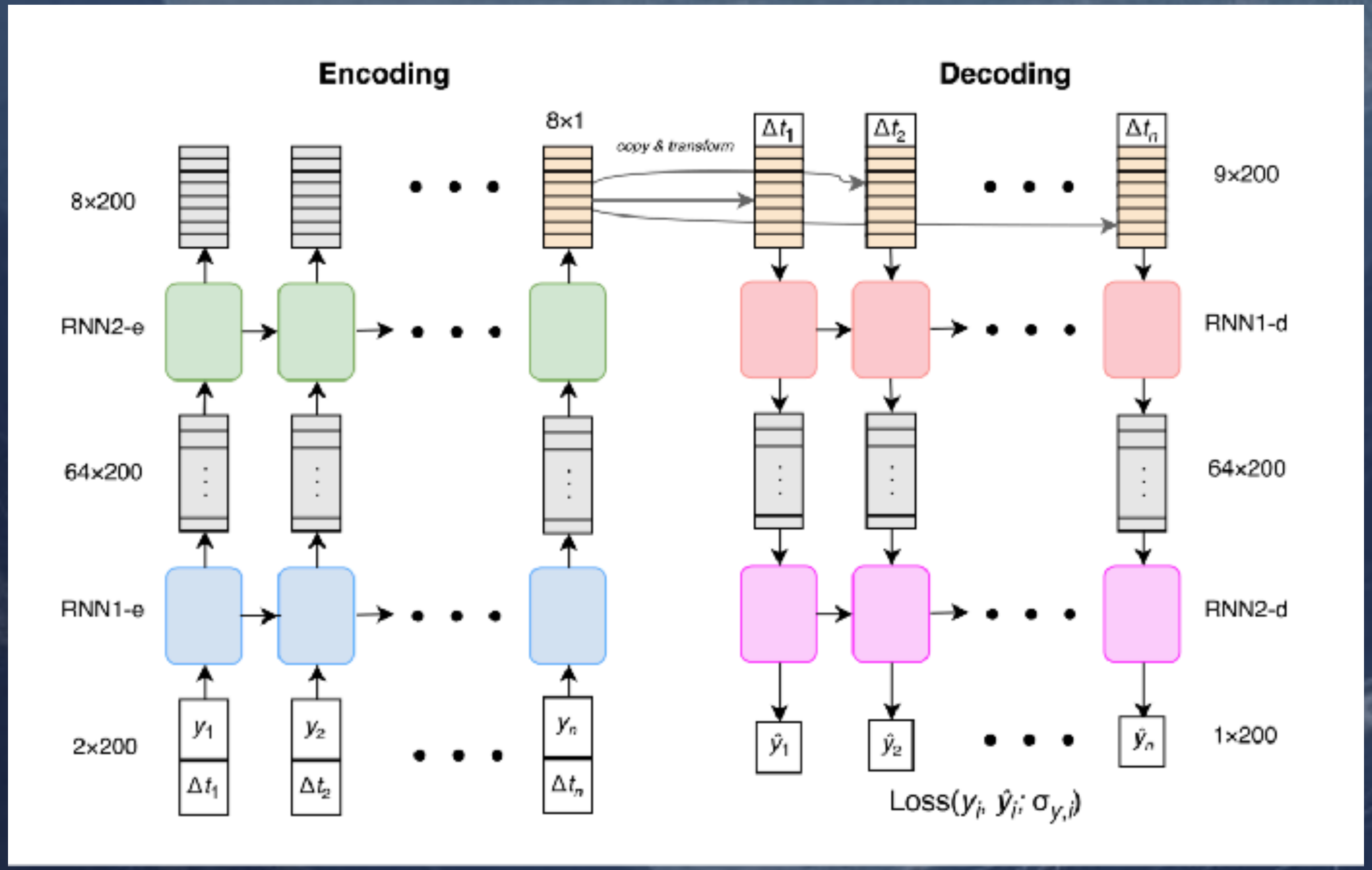
Challenges

Features or no features, that's the question!

Feature	Description
amplitude	Half the difference between the maximum and the minimum magnitude
beyond1std	Percentage of points beyond one st. dev. from the weighted mean
flux_percentile_ratio_mid20	Ratio of flux percentiles (60th - 40th) over (95th - 5th)
flux_percentile_ratio_mid35	Ratio of flux percentiles (67.5th - 32.5th) over (95th - 5th)
flux_percentile_ratio_mid50	Ratio of flux percentiles (75th - 25th) over (95th - 5th)
flux_percentile_ratio_mid65	Ratio of flux percentiles (82.5th - 17.5th) over (95th - 5th)
flux_percentile_ratio_mid80	Ratio of flux percentiles (90th - 10th) over (95th - 5th)
linear_trend	Slope of a linear fit to the light curve fluxes
max_slope	Maximum absolute flux slope between two consecutive observations
median_absolute_deviation	Median discrepancy of the fluxes from the median flux
median_buffer_range_percentage	Percentage of fluxes within 20% of the amplitude from the median
pair_slope_trend	Percentage of all pairs of consecutive flux measurements that have positive slope
percent_amplitude	Largest percentage difference between either the max or min magnitude and the median
percent_difference_flux_percentile	Diff. between the 2nd & 98th flux percentiles, converted to magnitude[a]
QSO	Quasar variability metric in Butler & Bloom (2010)
non_QSO	Non-quasar variability metric in Butler & Bloom (2010)
skew	Skew of the fluxes
small_kurtosis	Kurtosis of the fluxes, reliable down to a small number of epochs
std	Standard deviation of the fluxes
stetson_j	Welch-Stetson variability index J[b]
stetson_k	Welch-Stetson variability index K[b]

[a] Eyer (2005)

Richards et al (2011)



Naul et al (2017)

Biased Training Data

This stop sign has been covered by a full-size replica that includes subtle camo marks. This was 100 percent effective at fooling their machine into thinking it was also a 45mph speed limit sign.

Biased Training Data

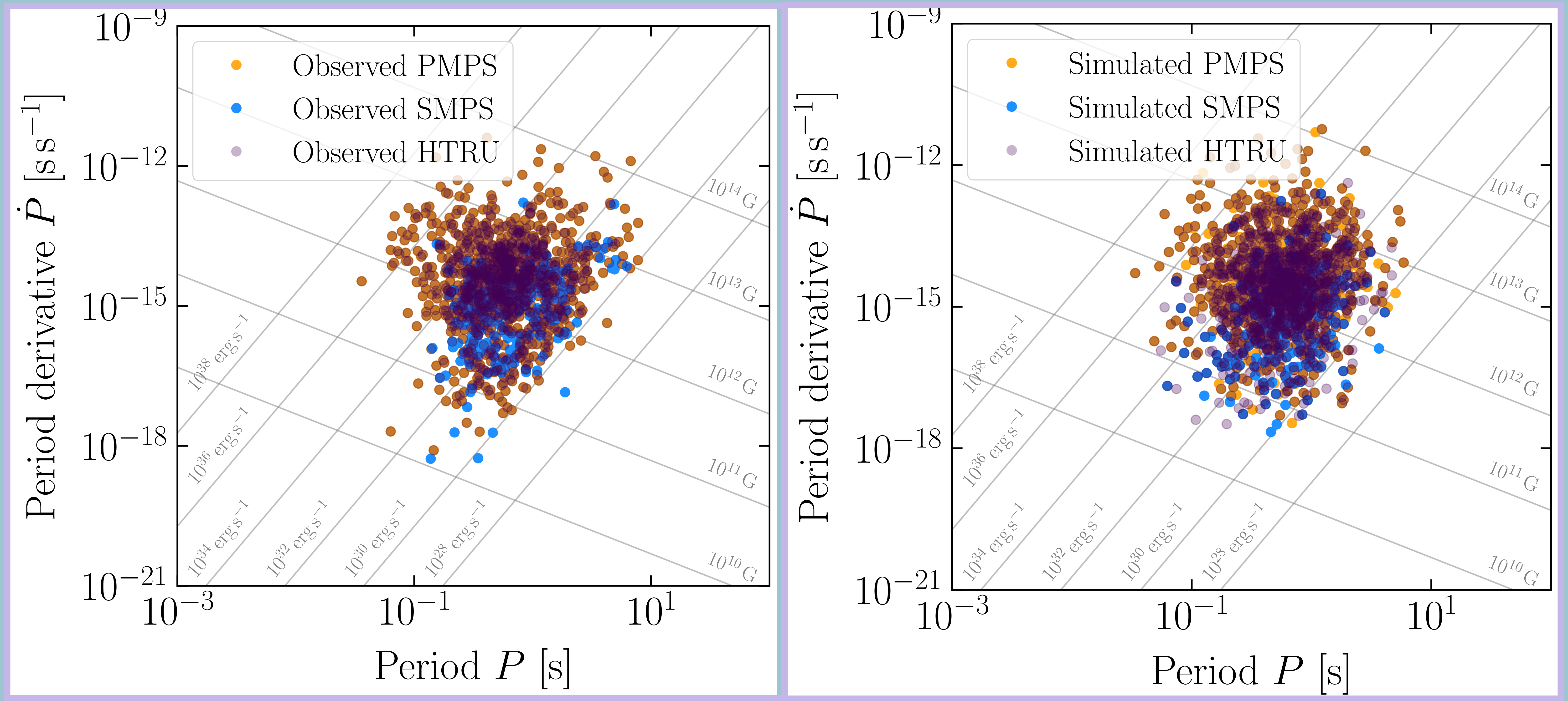
GALAXY ZOO: MORPHOLOGICAL CLASSIFICATION AND CITIZEN SCIENCE

L. FORTSON[1], K. MASTERS[2], R. NICHOL[2], K. BORNE[3], E. EDMONDSON[2], C. LINTOTT[4,5], J. RADDICK[6], K. SCHAWINSKI[7], J. WALLIN[8]

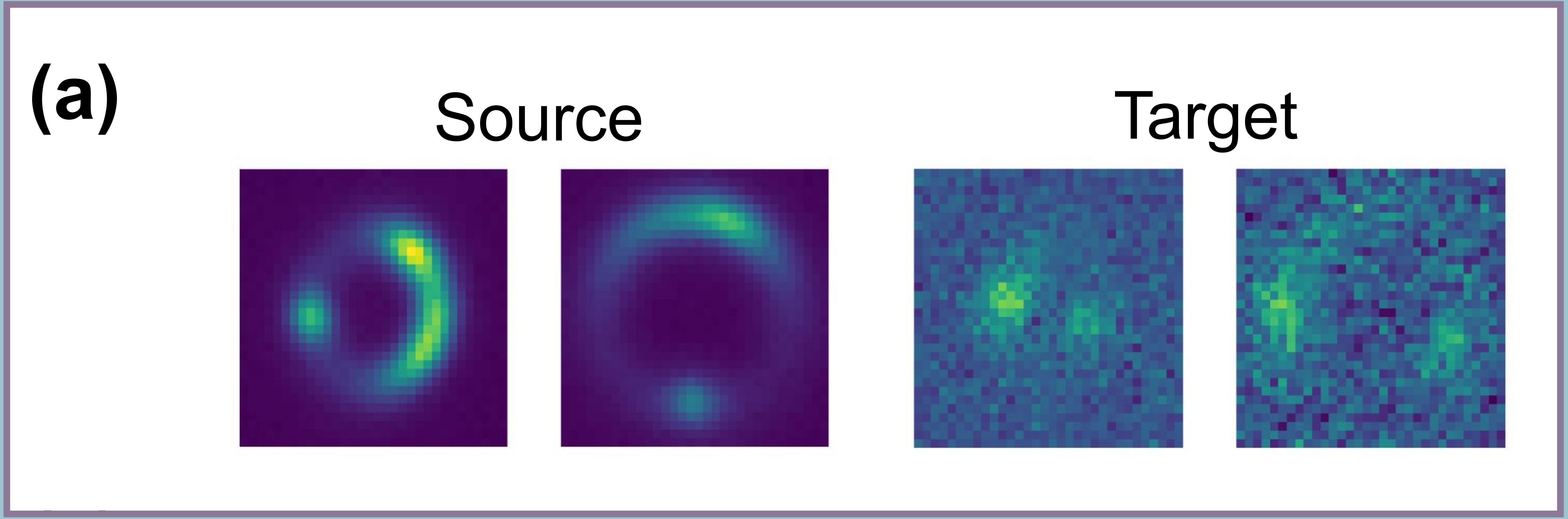
to be published in Advances in Machine Learning and Data Mining for Astronomy

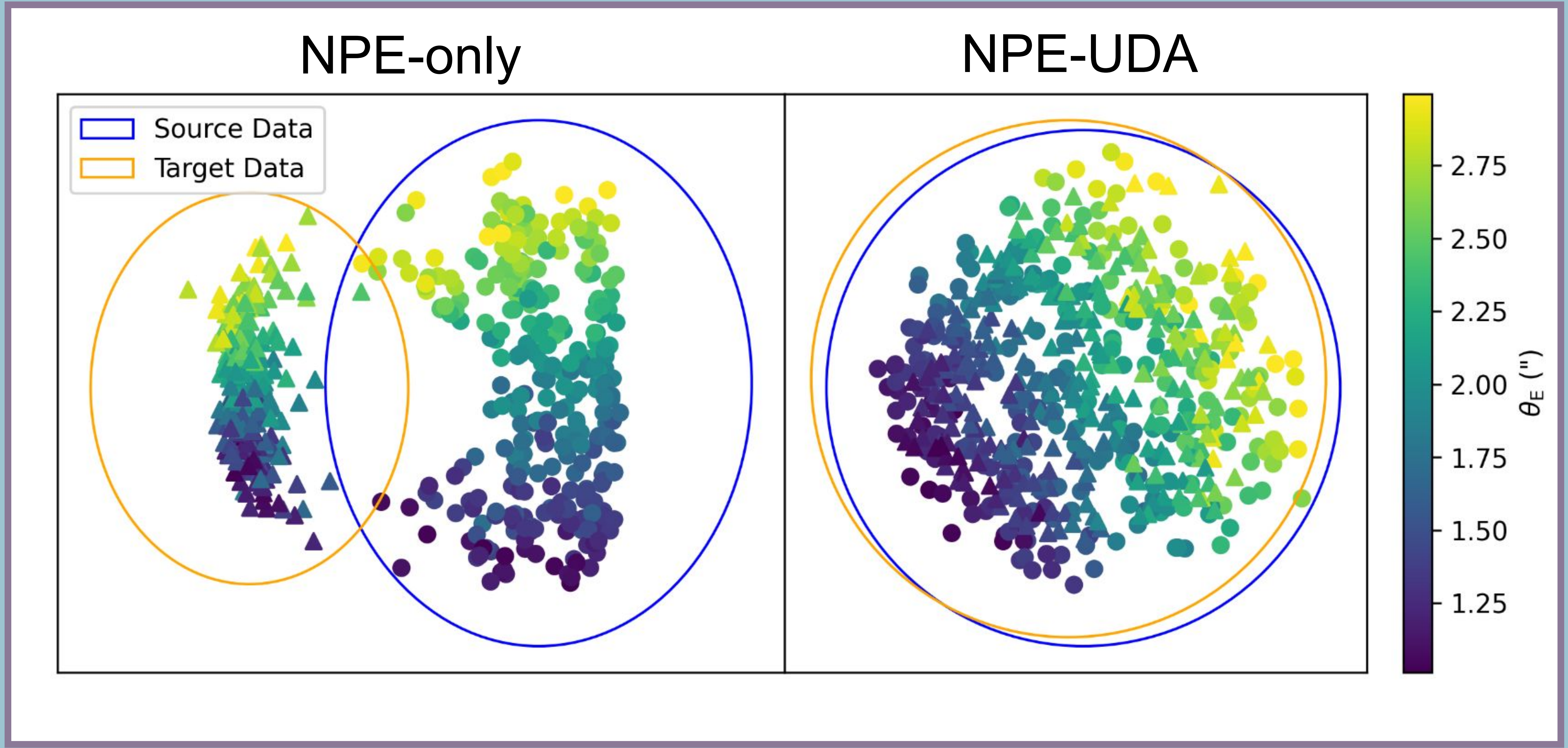
The results of the mirror image bias testing are discussed extensively in Land et al. (2008). They showed a significant bias in favour of anti-clockwise direction arms (in both the original and mirrored images). The interpretation of this bias could be due to psychological effects (possibly related to the preference for right handedness amongst the population), or possibly site design (it being easier to click the anti-clockwise button for example). However, once this bias was corrected for, the data could still be used (see below).

Challenge: Out-of-domain target data



Solution: Unsupervised Domain Adaptation

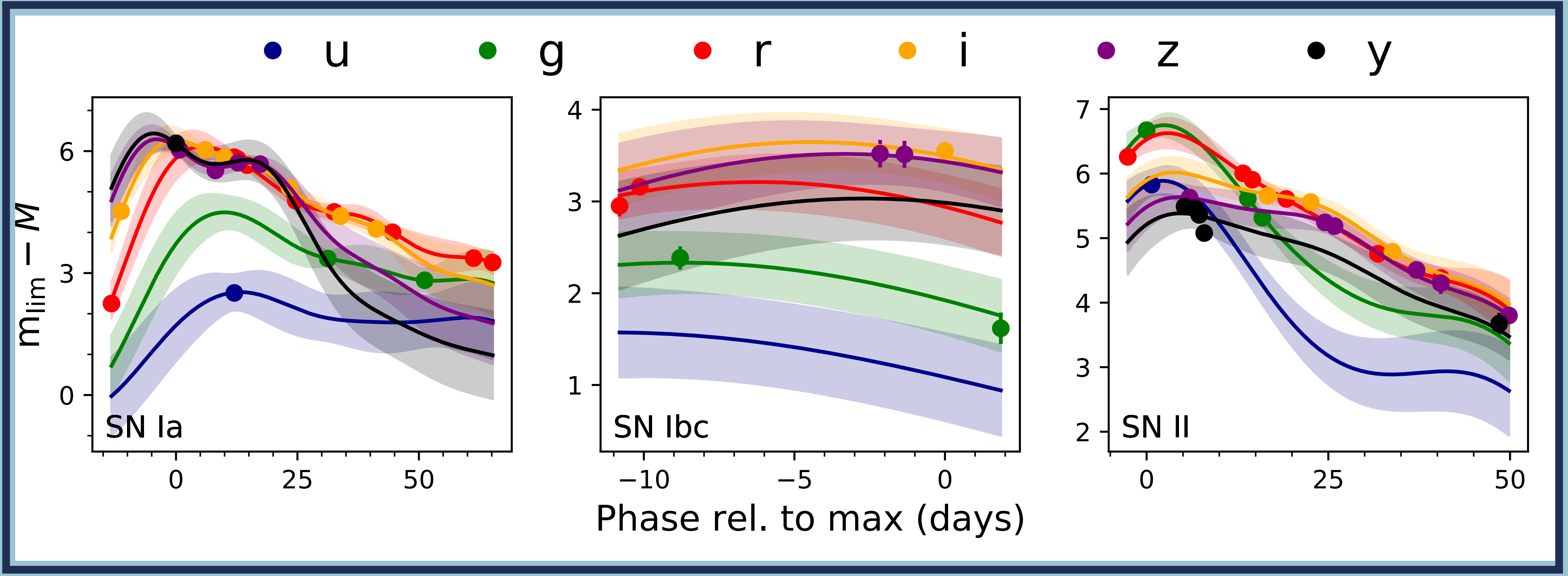




Swirl et al (2024)

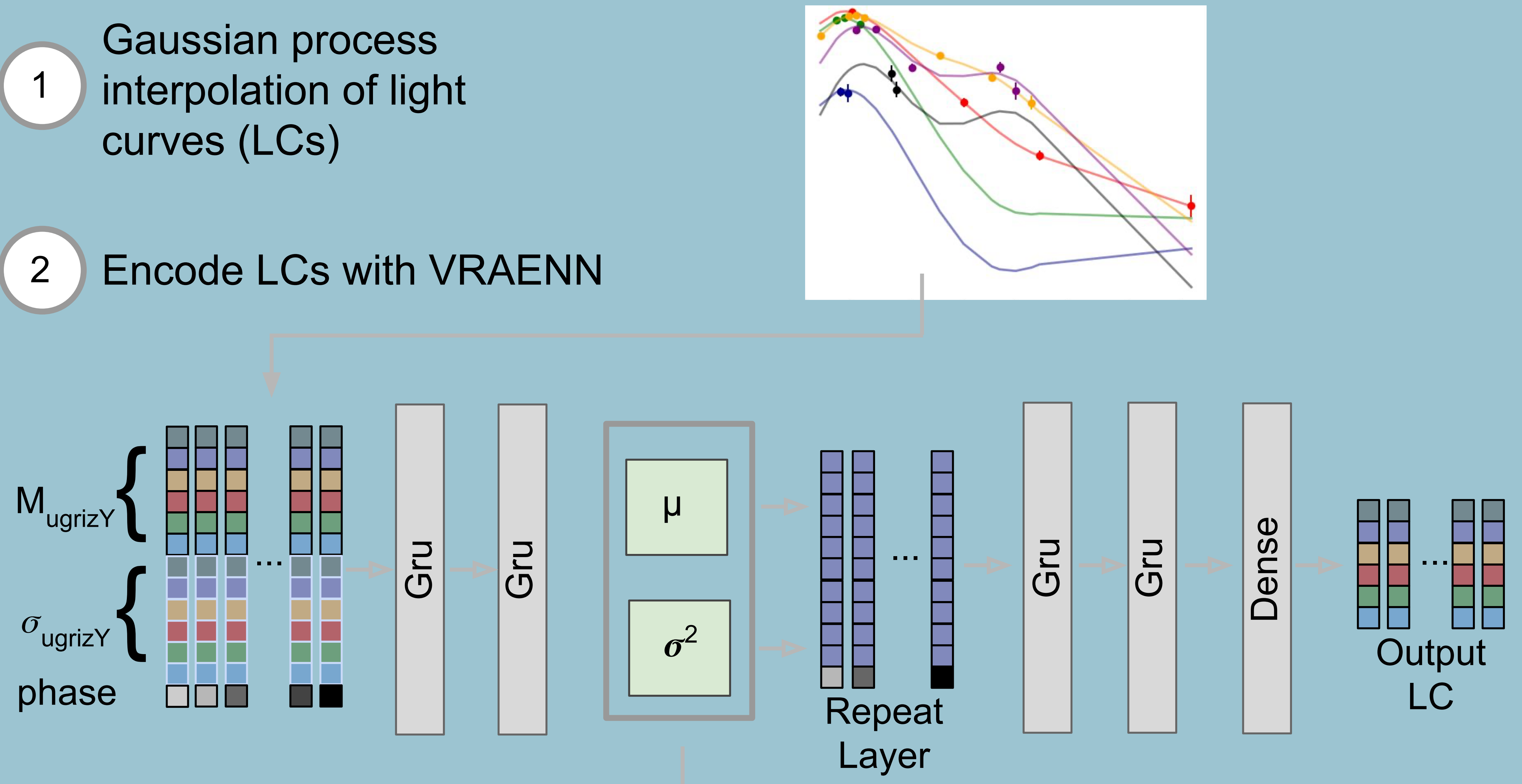
Out-of-distribution data: Anomaly detection in transients

Villar et al (2020)

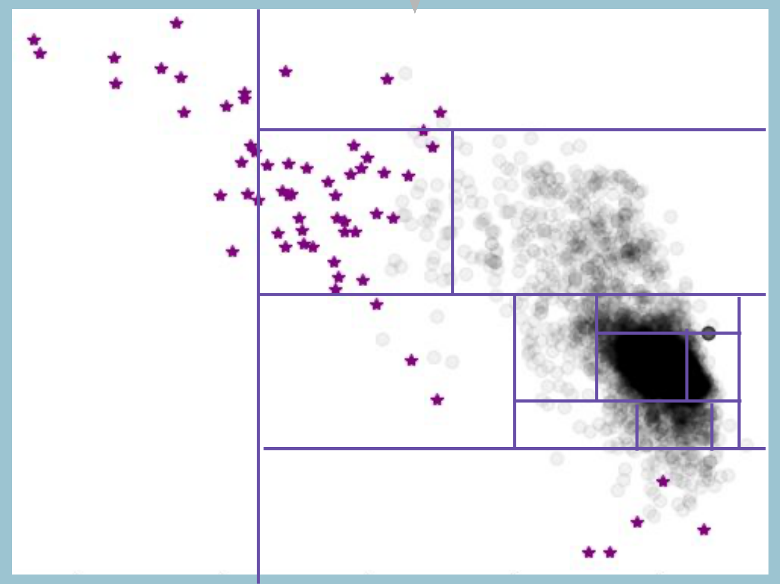


1 Gaussian process interpolation of light curves (LCs)

2 Encode LCs with VRAENN



3 Assign each LC an anomaly score via isolation forest



Confirmation bias

If simulations are prohibitively expensive, we might only check a neural network emulator's results if they are surprising.

(See also: David Hogg "Is Machine learning Useful for Astrophysics?")

Villaescusa-Navarro et al (2022)