

SEARCHING FOR THE UNEXPECTED
FROM COLLIDERS TO STARS
WITH MODERN MACHINE LEARNING

CMU STAMPS Colloquium

David Shih
December 6, 2024



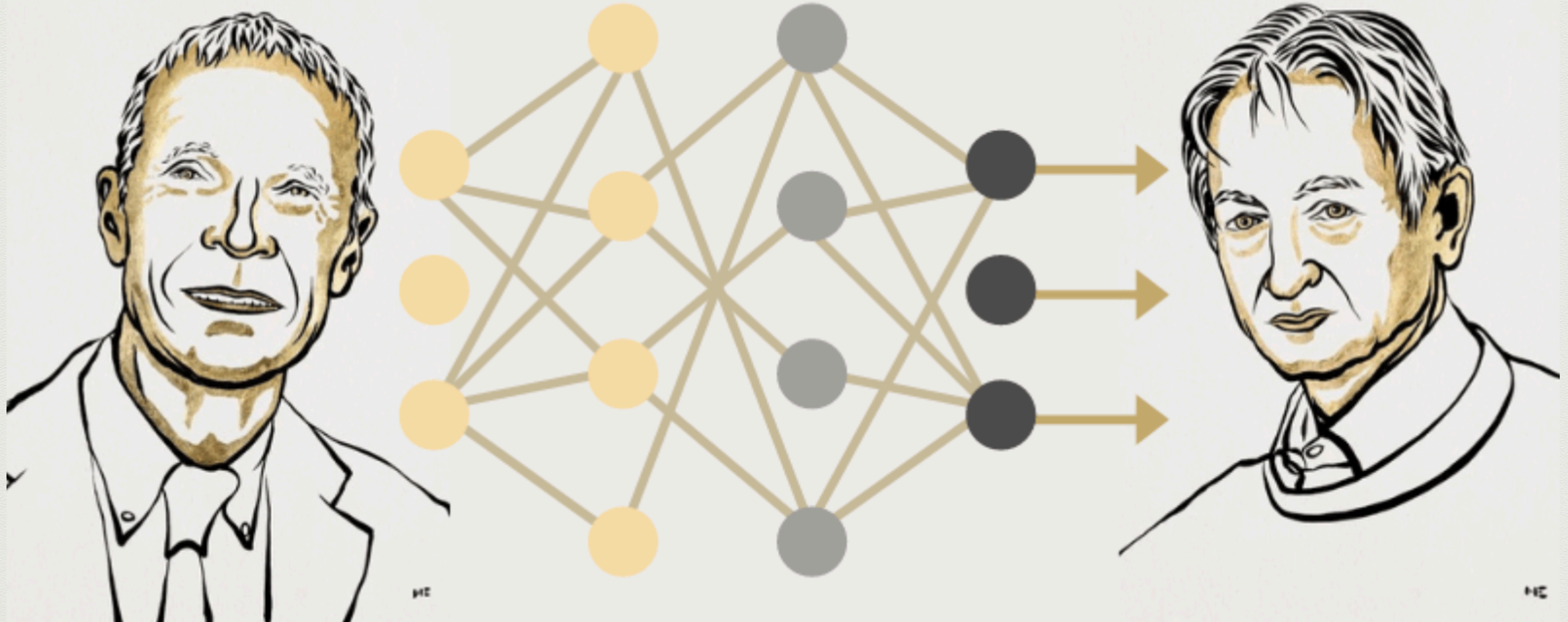
RUTGERS
THE STATE UNIVERSITY
OF NEW JERSEY

A Physics Nobel Prize for AI/ML!



John J. Hopfield

Geoffrey E. Hinton



Generative AI in the news



An A.I.-Generated Picture Won an Art Prize. Artists Aren't Happy.

**Lawyer Used ChatGPT In Court
—And Cited Fake Cases. A
Judge Is Considering Sanctions**

Molly Bohannon Forbes Staff

Future **Technology**

Apple joins generative AI race with iPhone 16 series and promises more to come

ChatGPT's answer goes wrong: Gives away journalist's number to join Signal

**Can We Trust Chatbots?
Artificial Intelligence
Humans' Work?**

***A Conversation With Bing's Chatbot
Left Me Deeply Unsettled***

**ChatGPT creator Sam Altman says the world may not be ready for
away from potentially scary' AI and feels 'regulation will be needed'**

ON TECH: A.I. NEWSLETTER

How Should I Use A.I. Chatbots Like ChatGPT?

Large language models are already good at a wide variety of tasks.

HOME > TECH

Can ChatGPT be a doctor?

Asia Martin Apr 10, 2023, 3:48 AM

TECHNOLOGY EXECUTIVE COUNCIL

How ChatGPT is changing the job hiring process, from the HR department to coders

PUBLISHED SAT, APR 8 2023-10:00 AM EDT | UPDATED SAT, APR 8 2023-11:05 AM UNDEFINED EDT

Kevin Travers, special to CNBC.com

FORBES > INNOVATION

How Generative AI And ChatGPT Are Shaping The Contact Center

Muddu Sudhakar Forbes Councils Member
Forbes Technology Council
COUNCIL POST | Membership (Fee-Based)

ChatGPT: Your AI-Powered Cryptocurrency Resource

Siamak Masnavi
10 Apr 2023 / In #AI, #cryptocurrency

**The Industrial Economy
Generative AI With OpenAI**

Home / Innovation / Artificial Intelligence

How to use ChatGPT to write code

BY PYMNTS
APRIL 7, 2023

Can ChatGPT replace programmers? What programming languages does ChatGPT know? We answer these and your other generative AI coding questions.

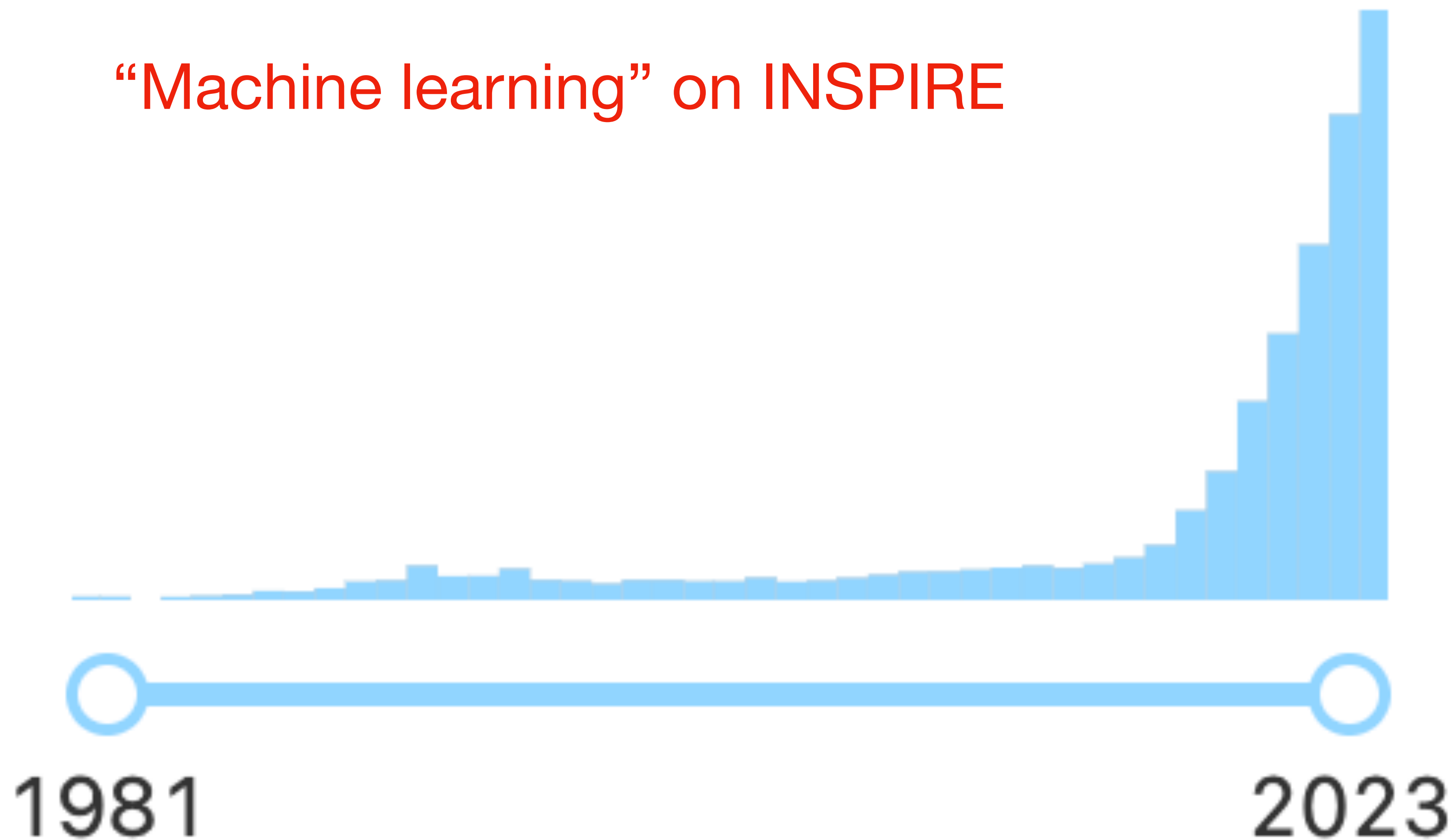
HOME > TECH

A college student got a top grade for an essay written with the help of ChatGPT, report says

Beatrice Nolan Apr 10, 2023, 4:00 AM

ML is also growing rapidly in HEP!

“Machine learning” on INSPIRE



arXiv Category

☐ hep-ex	1,537
☐ hep-ph	1,282
☐ cs.LG	1,203
☐ astro-ph.CO	1,170
☐ astro-ph.IM	1,123
☐ astro-ph.HE	764
☐ physics.data-an	647
☐ physics.ins-det	603
☐ astro-ph.GA	531
☐ stat.ML	468

Will ML take my job?



I am a particle physicist. Will AI take my job?



As an AI language model, I can provide some insights, but please note that predicting the future with certainty is challenging. While AI has the potential to impact various industries, including particle physics, its effect on specific jobs is not always straightforward. Let's consider the role of AI in particle physics:

1. Data analysis: AI can help in analyzing large datasets generated by particle accelerators and detectors. Machine learning algorithms can assist in identifying patterns, anomalies, and new physics signals, which can enhance the efficiency and accuracy of data analysis. Rather than replacing particle physicists, AI can be a valuable tool that complements their expertise.
2. Simulation and modeling: AI techniques, such as generative models, can assist in simulating particle interactions and improving the accuracy of theoretical models. This can help in exploring new theories and predictions, but it still requires the guidance and interpretation of particle physicists.



3. Experimental design: AI can aid in optimizing experimental setups, data collection strategies, and detector designs. Particle physicists can work alongside AI systems to determine the most effective experiments to conduct and interpret the results.
4. Theory development: While AI has shown promise in generating scientific hypotheses and exploring complex data, the creative and abstract thinking required for developing fundamental theories still remains a domain of human scientists.

It's important to note that AI is a tool that can augment the work of particle physicists, helping them handle vast amounts of data and accelerating discoveries. Rather than replacing experts, AI can free up their time to focus on higher-level tasks, interpretation, and advancing the field. It's crucial for particle physicists to adapt and embrace AI as a valuable tool in their research.

Ultimately, the future of any profession, including particle physics, will depend on how it evolves alongside technological advancements. Embracing AI and developing new skills that complement its capabilities can ensure that particle physicists remain at the forefront of scientific discovery.

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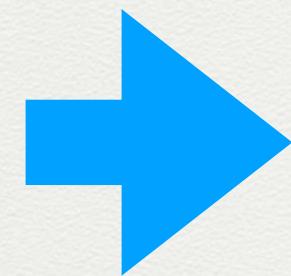


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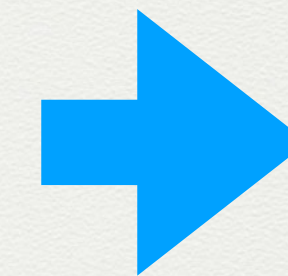
ML — a powerful new tool



Data



Modern
Machine Learning



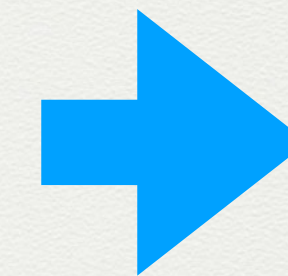
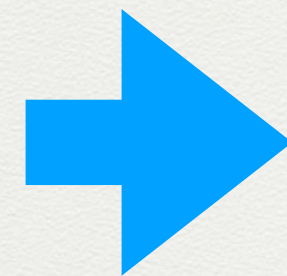
Physics

Modern machine learning allows us to see **farther into the data** than ever before.

ML — a powerful new tool



Data



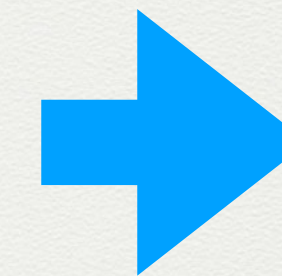
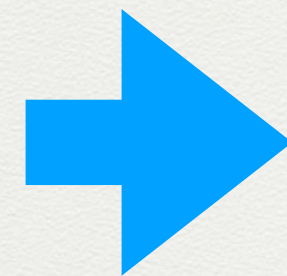
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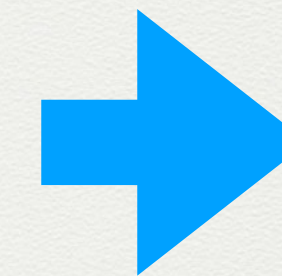
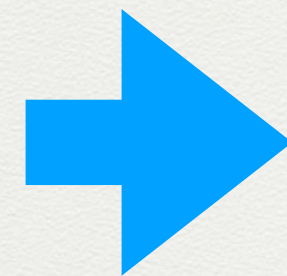
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- ***Amplify*** sensitivity and precision

ML — a powerful new tool



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Physics

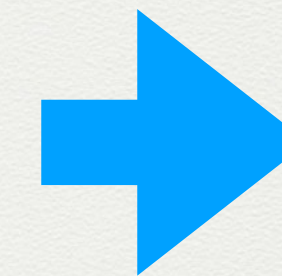
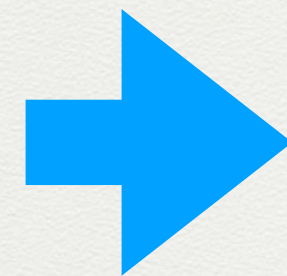
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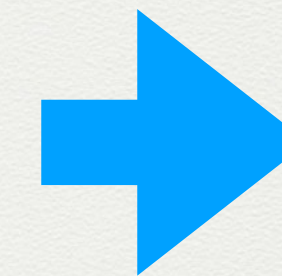
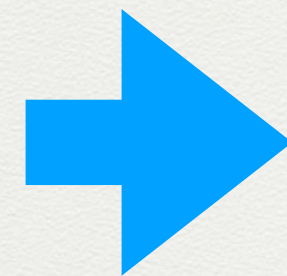
Modern machine learning allows us to see **farther into the data** than ever before.

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- ***Automate*** complex and time-consuming tasks

ML — a powerful new tool



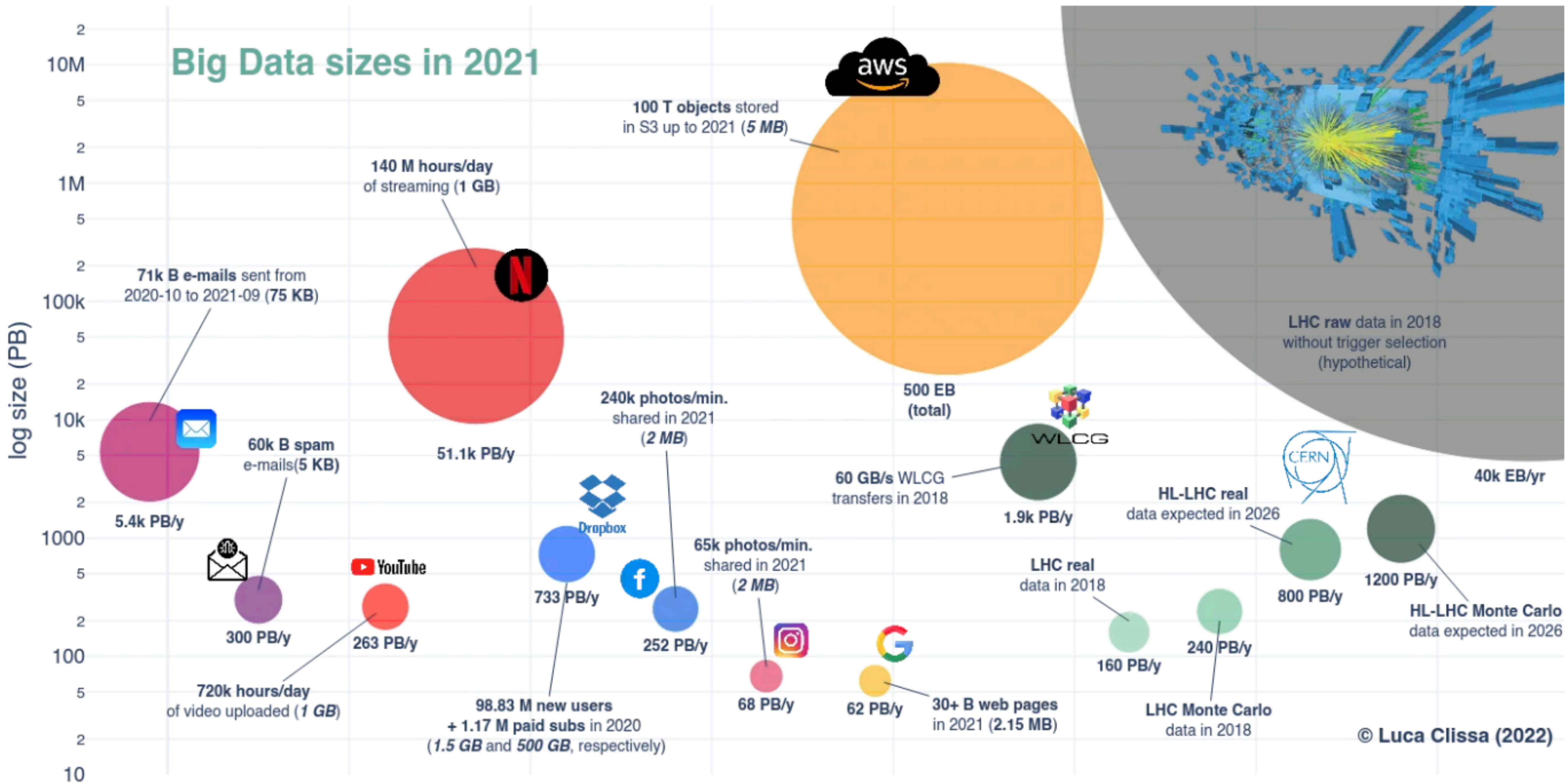
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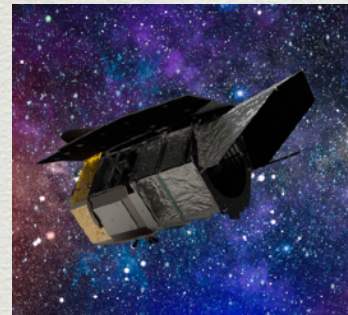
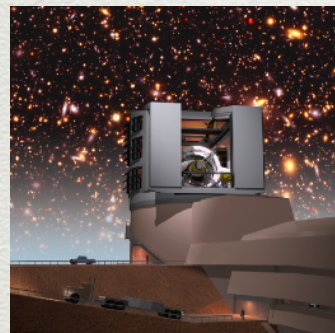
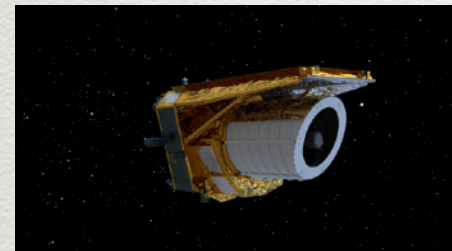
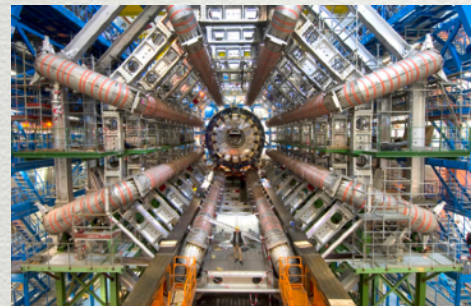
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Era of Big Data in HEP/Astro/Cosmo



Dataset	Year launched (expected)	No. events/ objects	Size
LHC	2010	$10^{15}+$	10^2 PB+
Euclid	2023	10^{10}	10^2 PB
Rubin	2024	10^{10}	10^2 PB
Roman	2027	10^9	10^1 PB
SKA	2030	10^9	1-10 EB

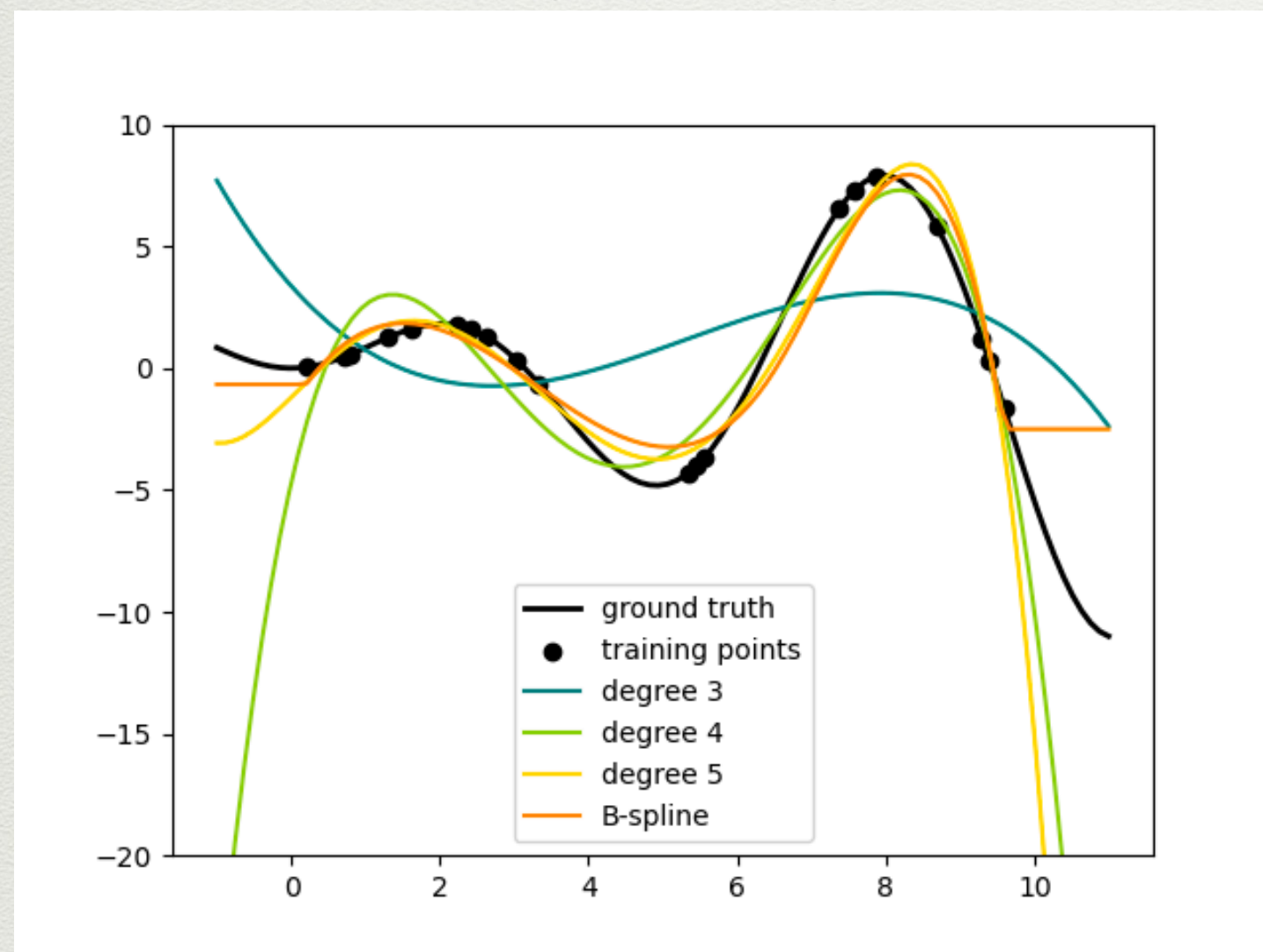
The Big Data era,
already familiar to HEP,
is coming for Astro/Cosmo



Generative AI, briefly

“All the impressive achievements of deep learning amount to just curve fitting” — Judea Pearl

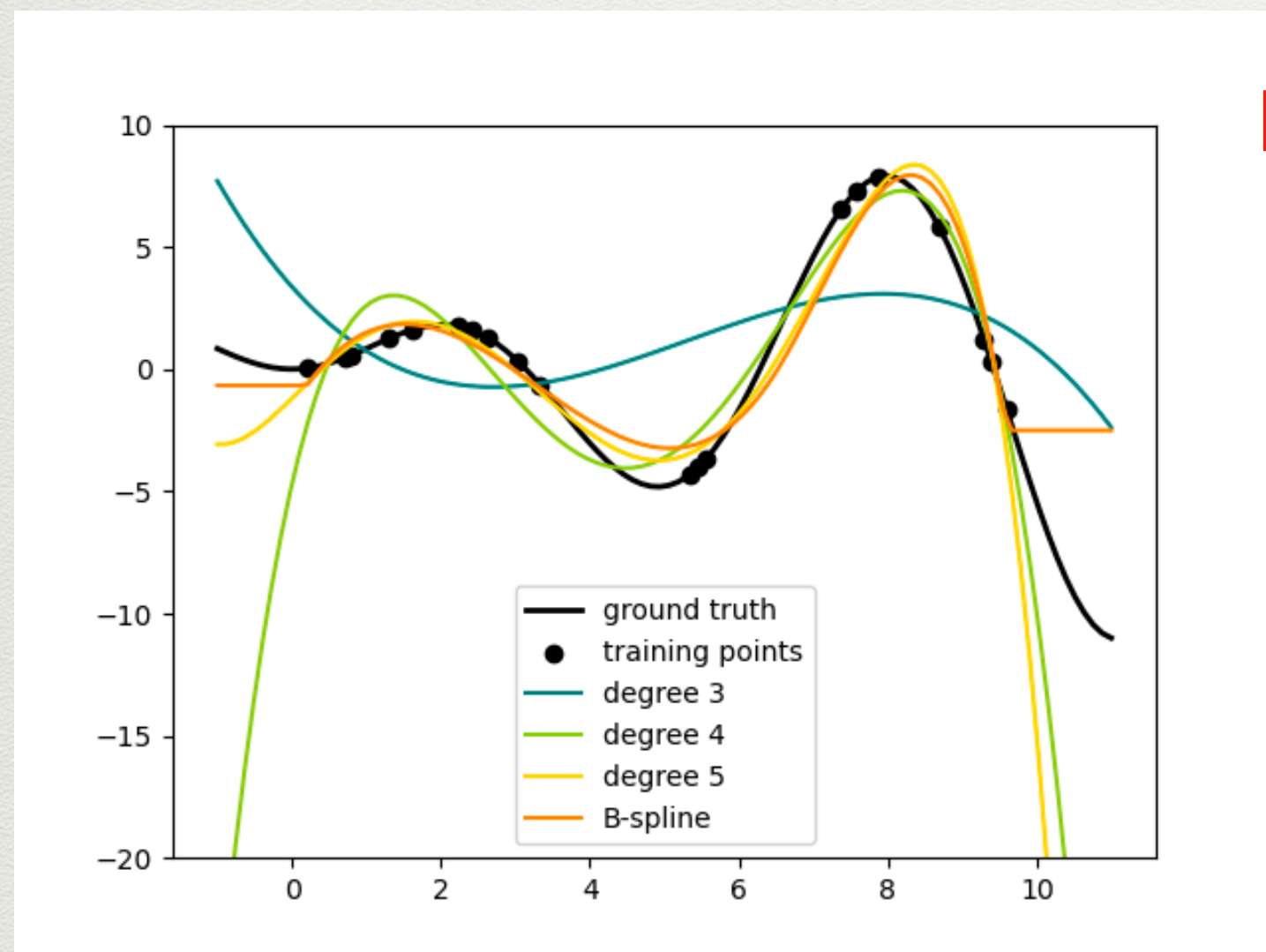
From this



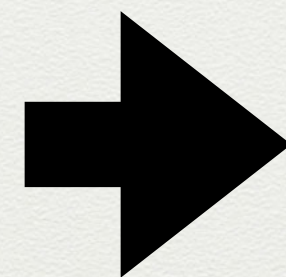
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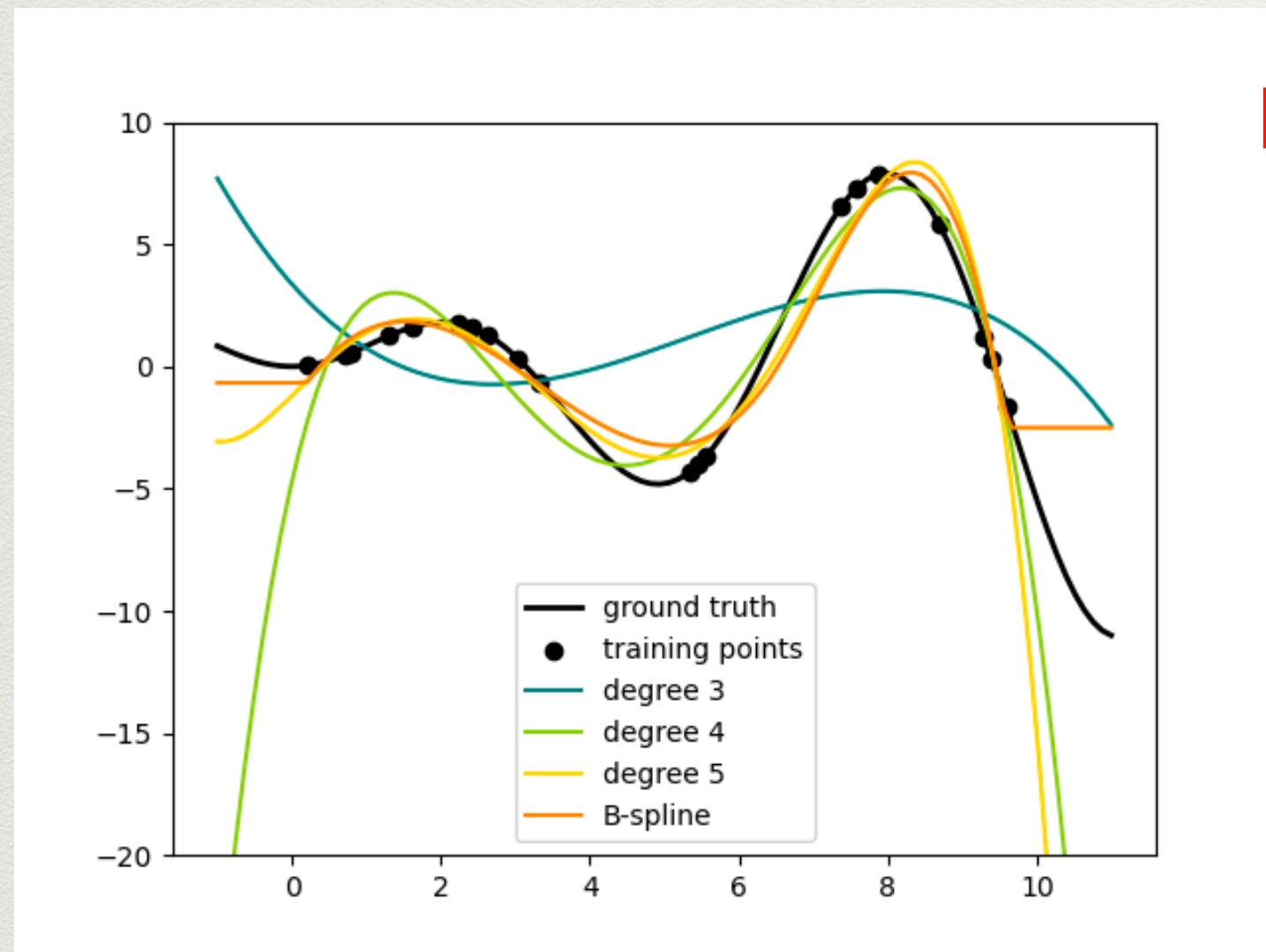
**Deep
neural
networks**



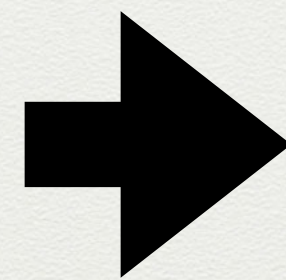
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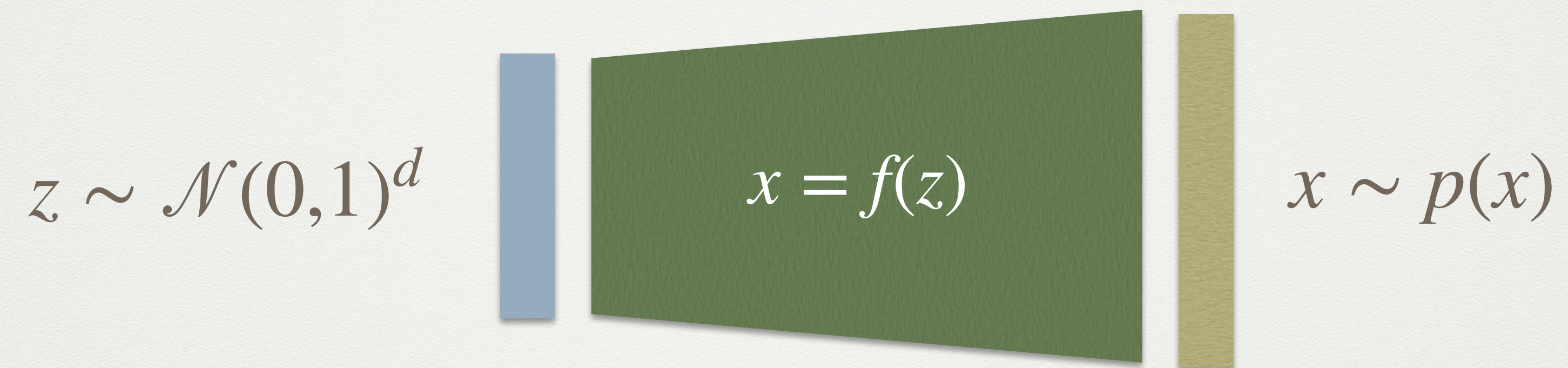
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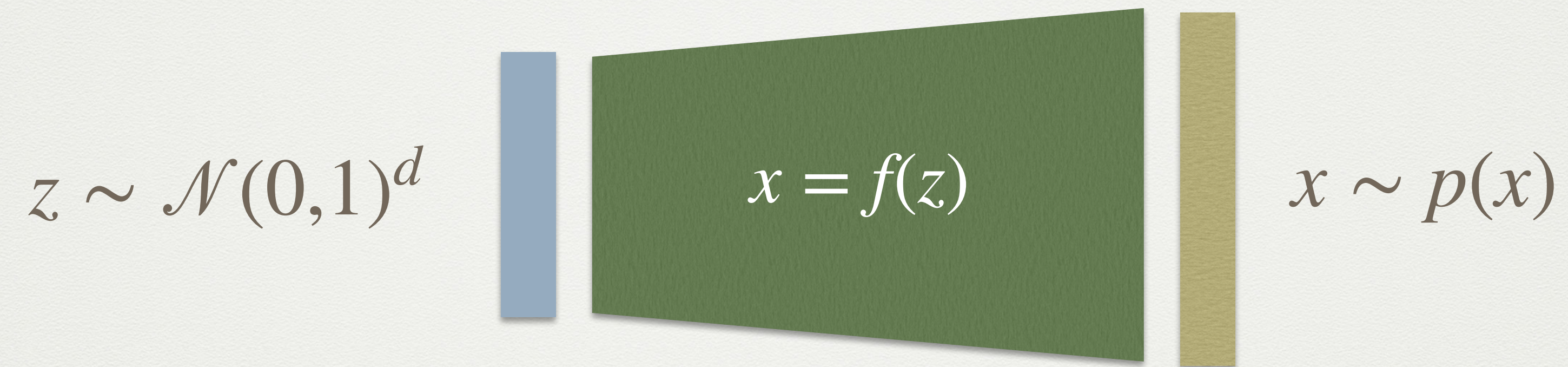
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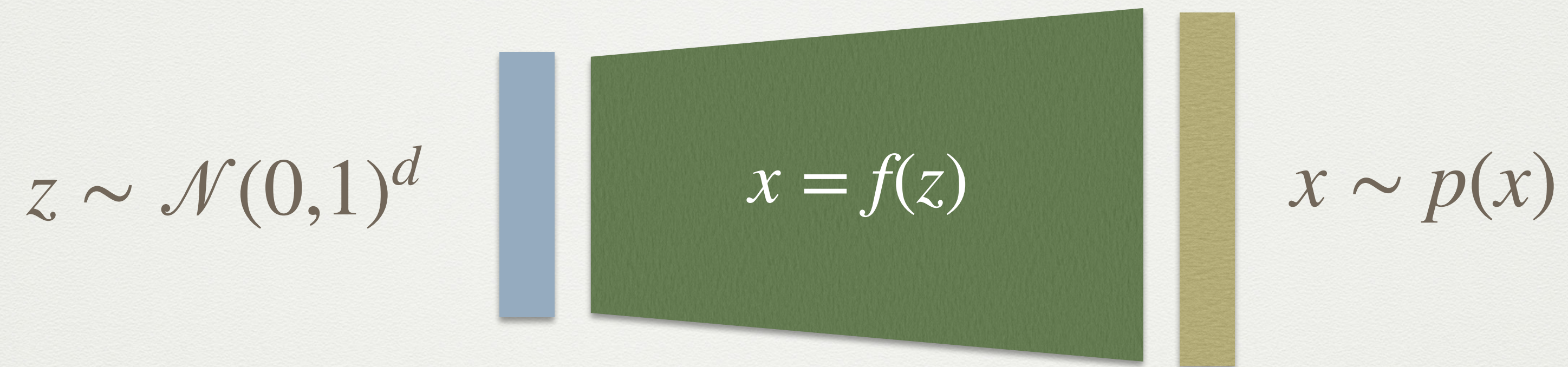


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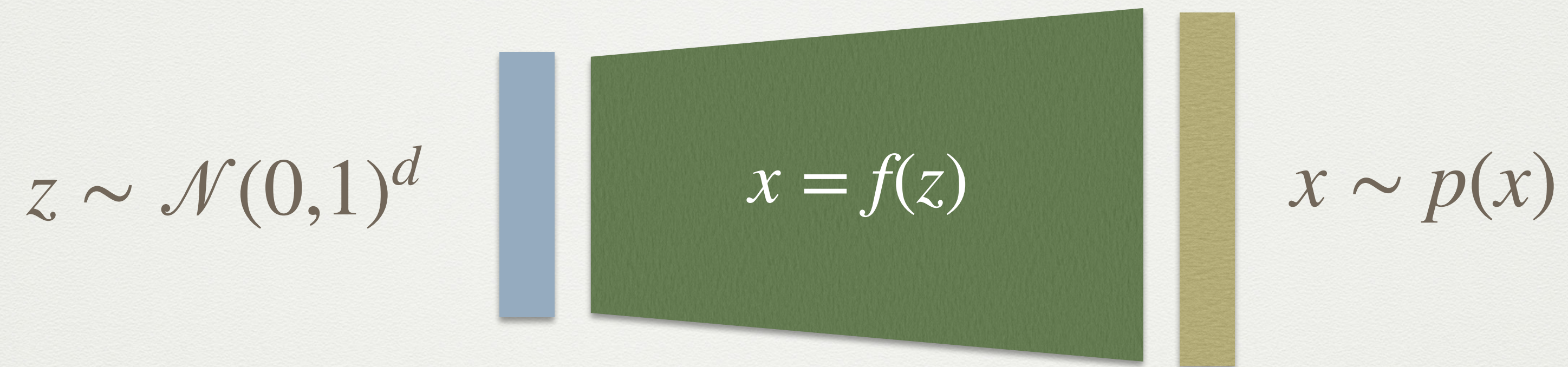
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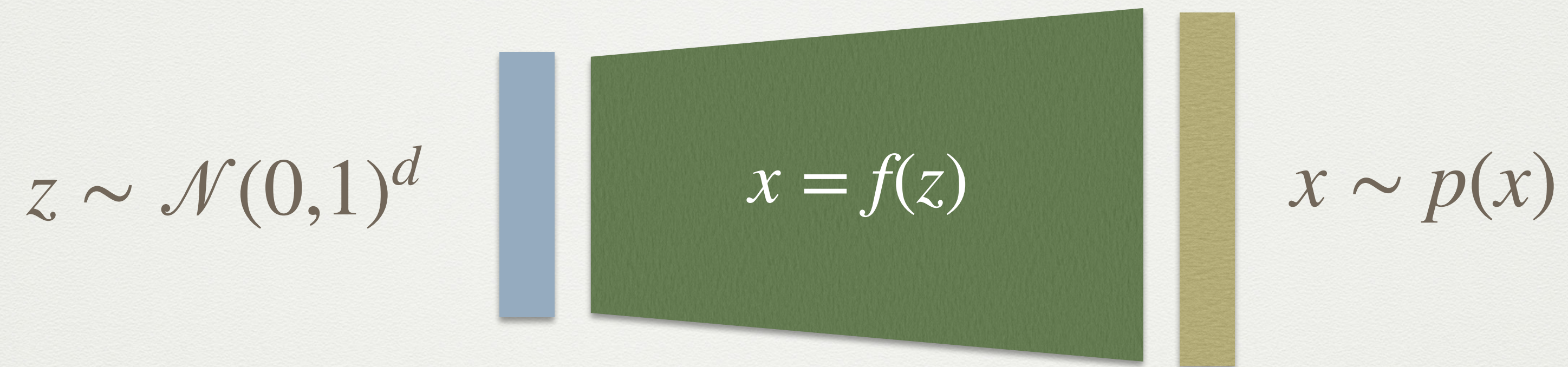
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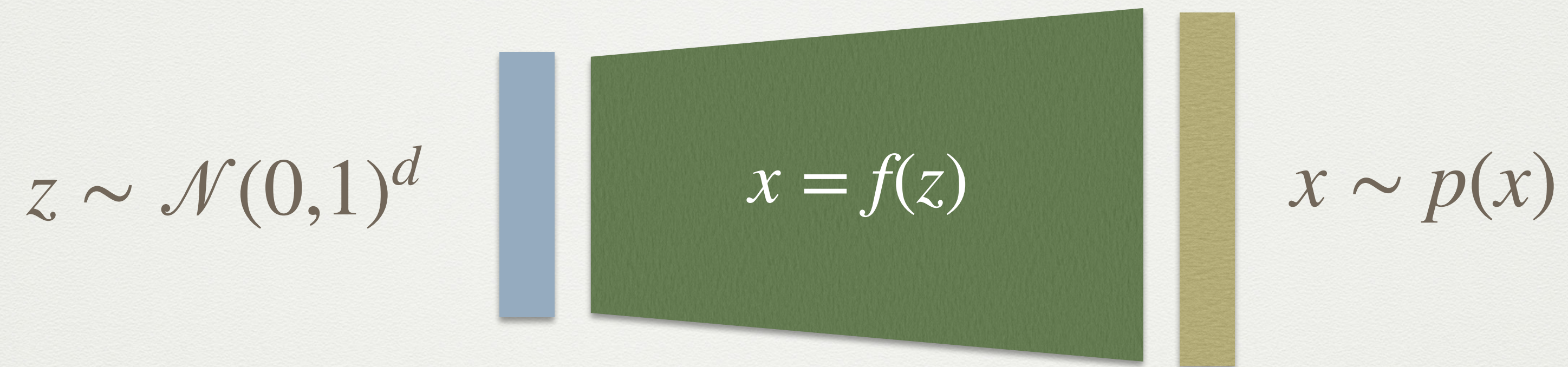
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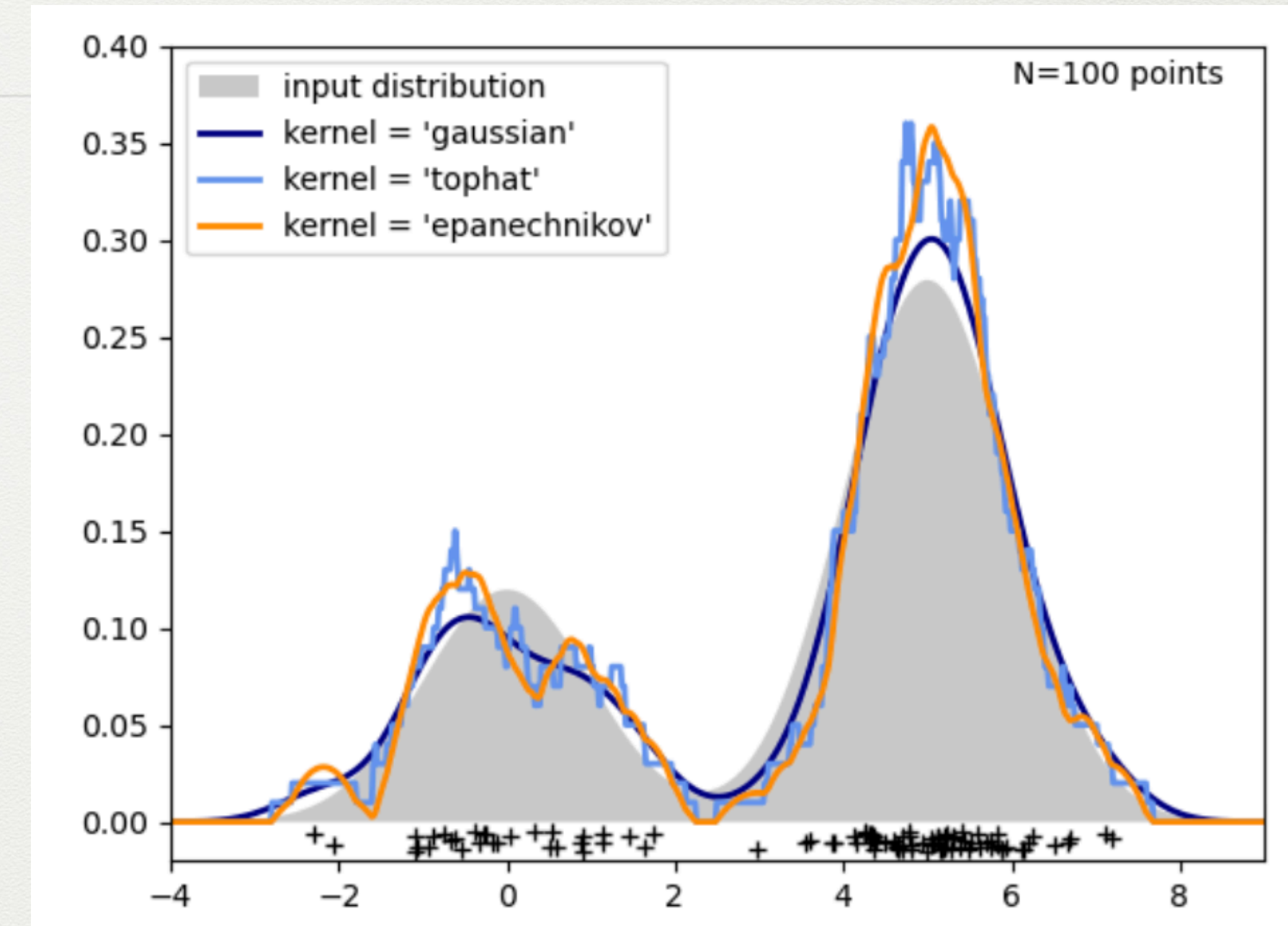
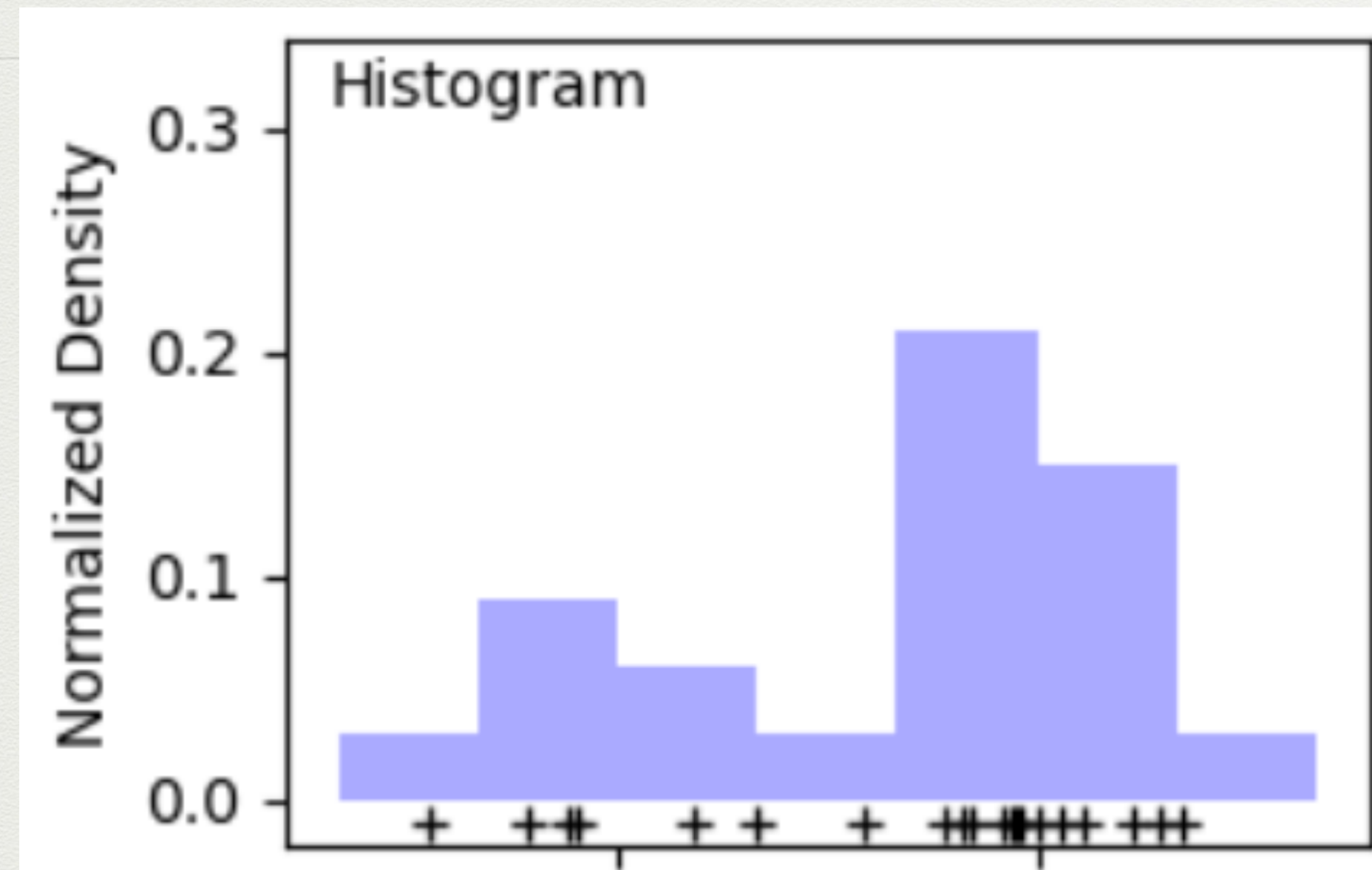
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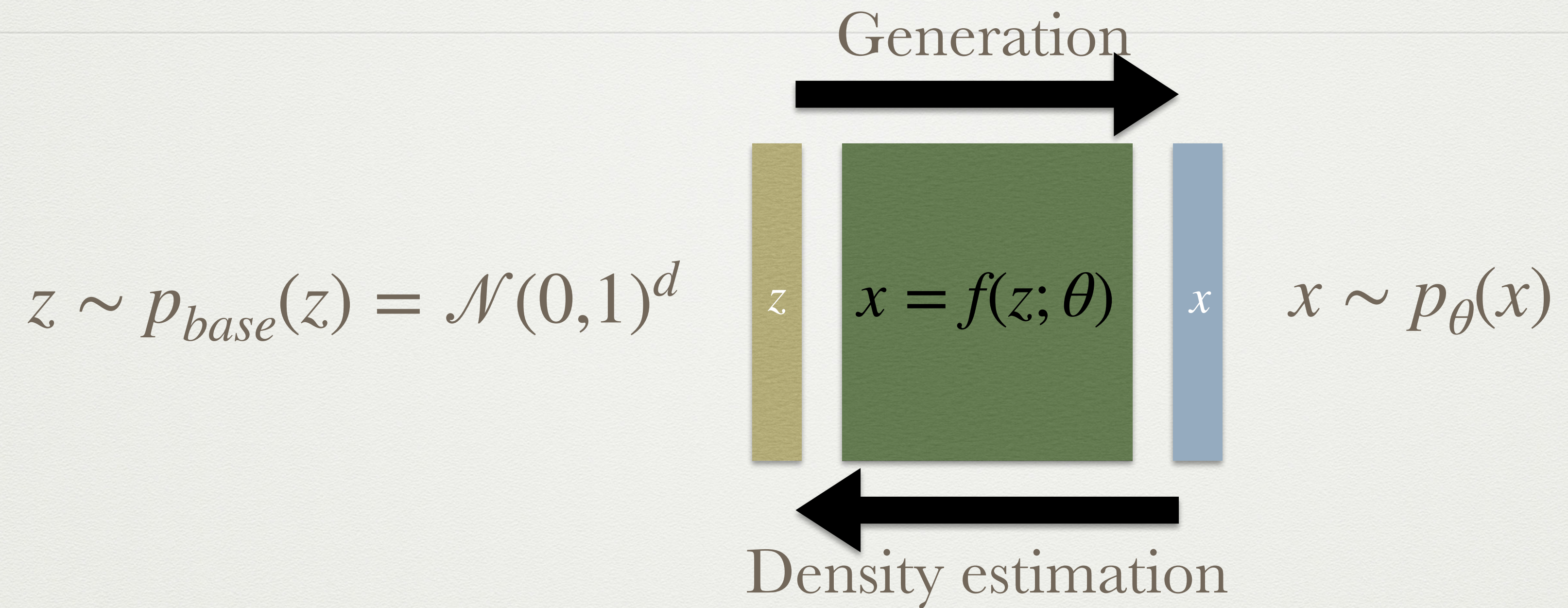
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 - Midjourney: $\text{image} \sim p(\text{image} | \text{caption})$
- (note: both are *conditional* generative models)

Generative Models and Density Estimation

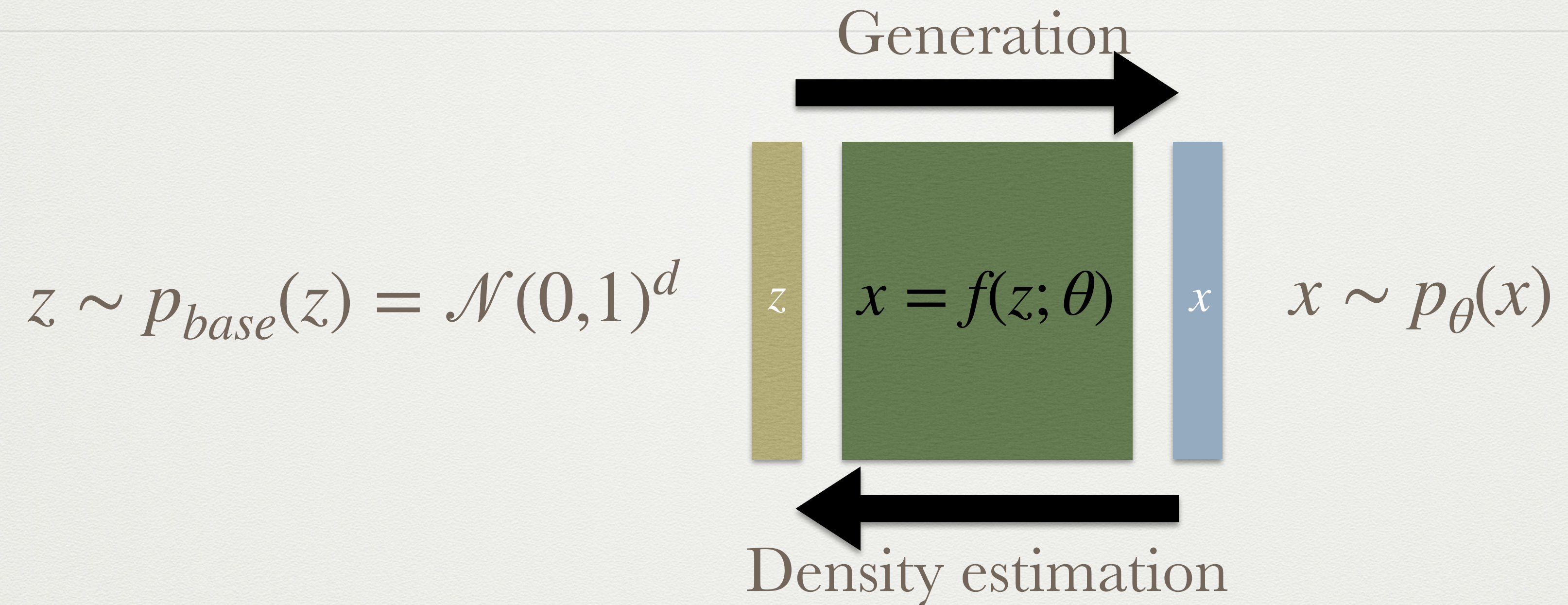


- Generative models closely connected to *density estimation*
 - **Generative model:** sample from $p(x)$
 - **Density estimation:** estimate $p(x)$

Example: Normalizing Flows

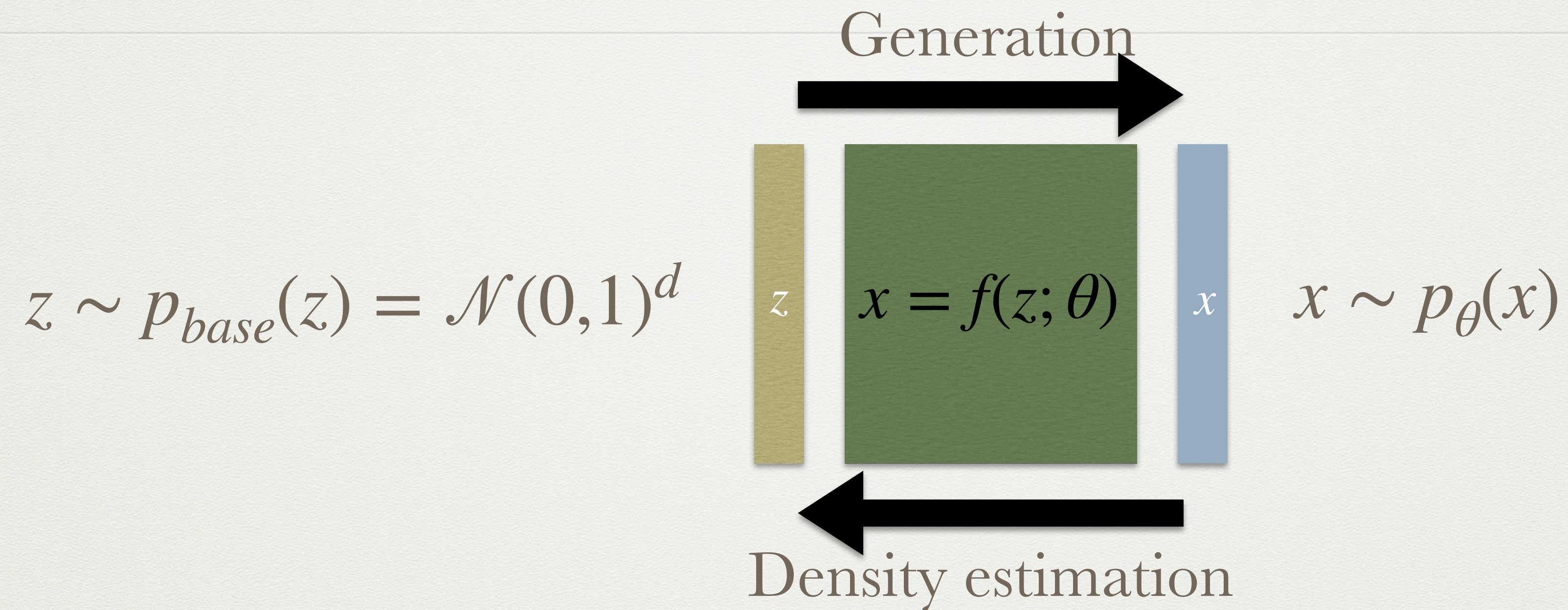


Example: Normalizing Flows



Powerful class of density estimators that are also generative models

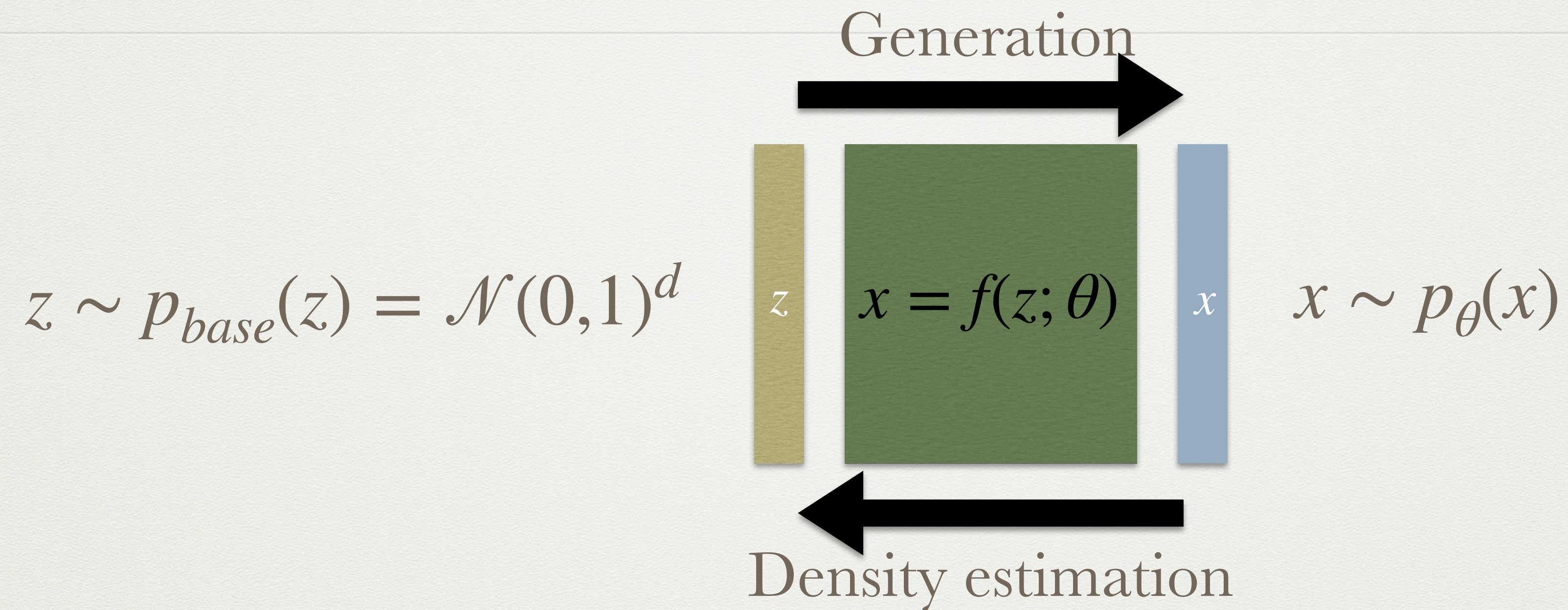
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- Family of invertible maps parametrized by neural networks

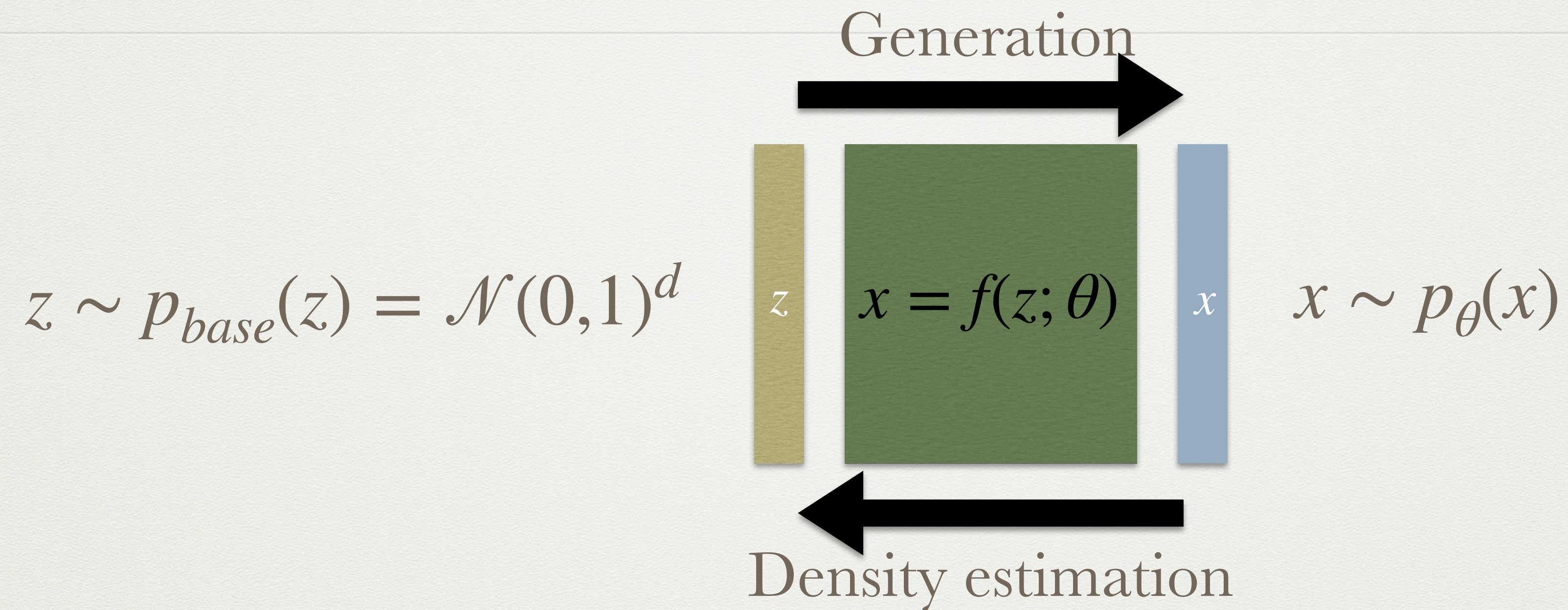
Example: Normalizing Flows



Powerful class of density estimators that are also generative models

- Family of invertible maps parametrized by neural networks
- $$p_{\theta}(x) = p_{base}(z = f_{\theta}(x)) \left| \frac{\partial z}{\partial x} \right|$$
- (need tractable Jacobian!)

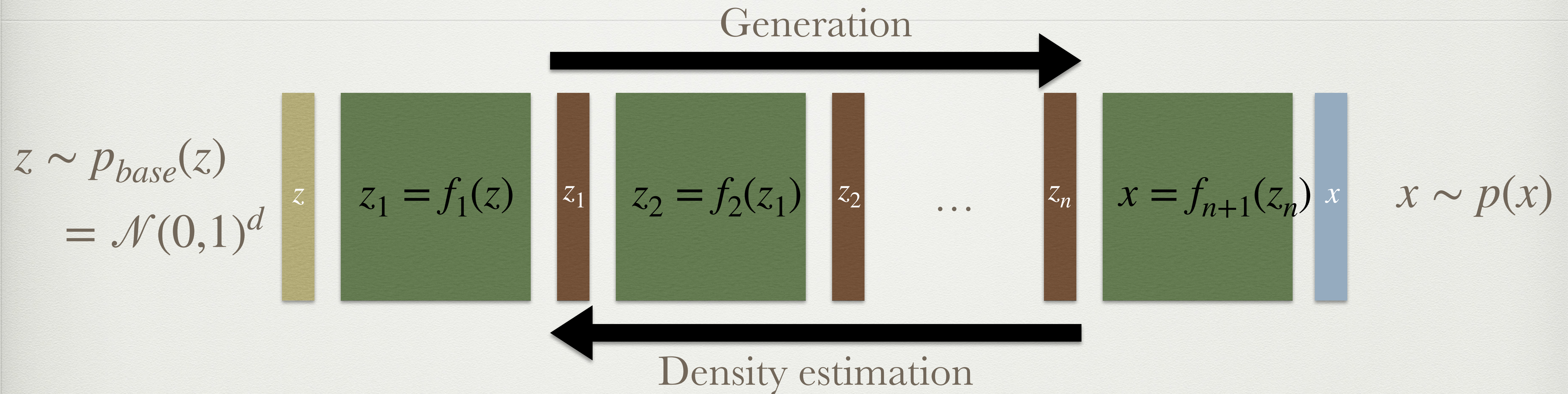
Example: Normalizing Flows



Powerful class of density estimators that are also generative models

- Family of invertible maps parametrized by neural networks
 - Train with maximum likelihood objective
- $$p_{\theta}(x) = p_{base}(z = f_{\theta}(x)) \left| \frac{\partial z}{\partial x} \right|$$
- $$L = - \sum_{x_i \in data} \log p_{\theta}(x_i)$$
- (need tractable Jacobian!)

Example: Normalizing Flows

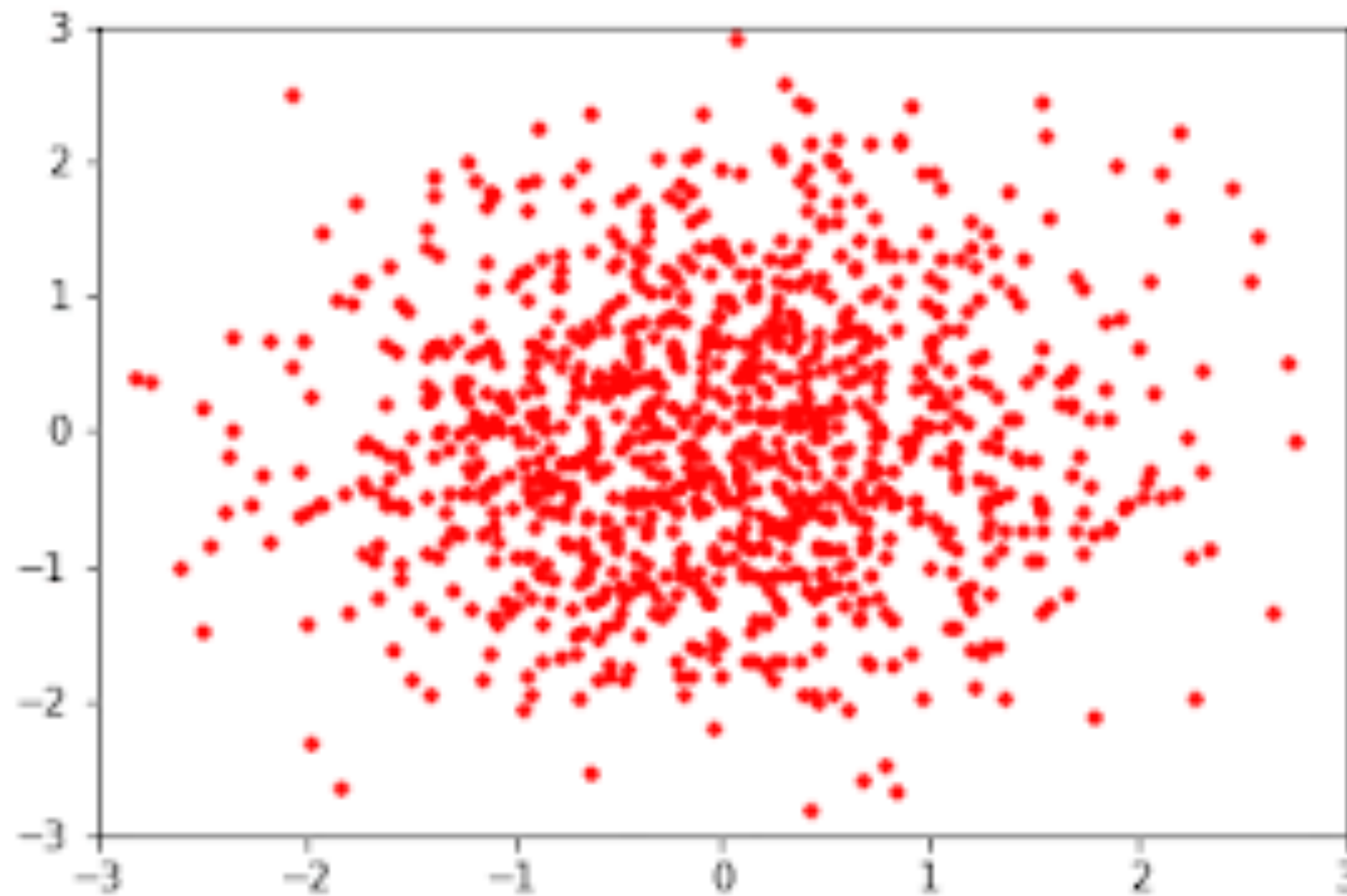


Powerful class of density estimators that are also generative models

- Family of invertible maps parametrized by neural networks
 - Train with maximum likelihood objective
 - **Compose multiple maps for greater expressivity**
- $$p_{\theta}(x) = p_{base}(z = f_{\theta}(x)) \left| \frac{\partial z}{\partial x} \right|$$
- (need tractable Jacobian!)
- $$L = - \sum_{x_i \in data} \log p_{\theta}(x_i)$$

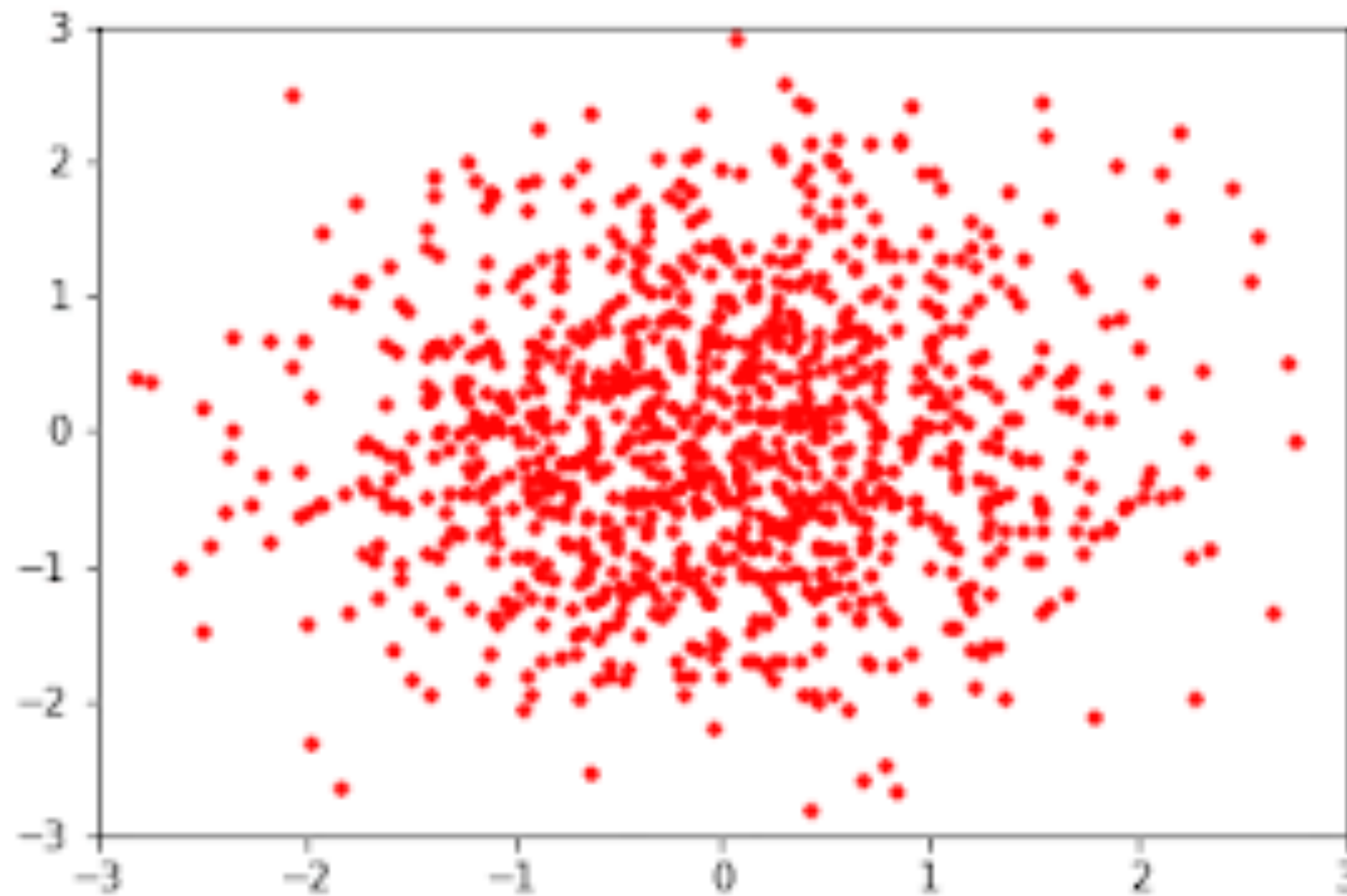
Example: Normalizing Flows

source: [Eric Jang](#)

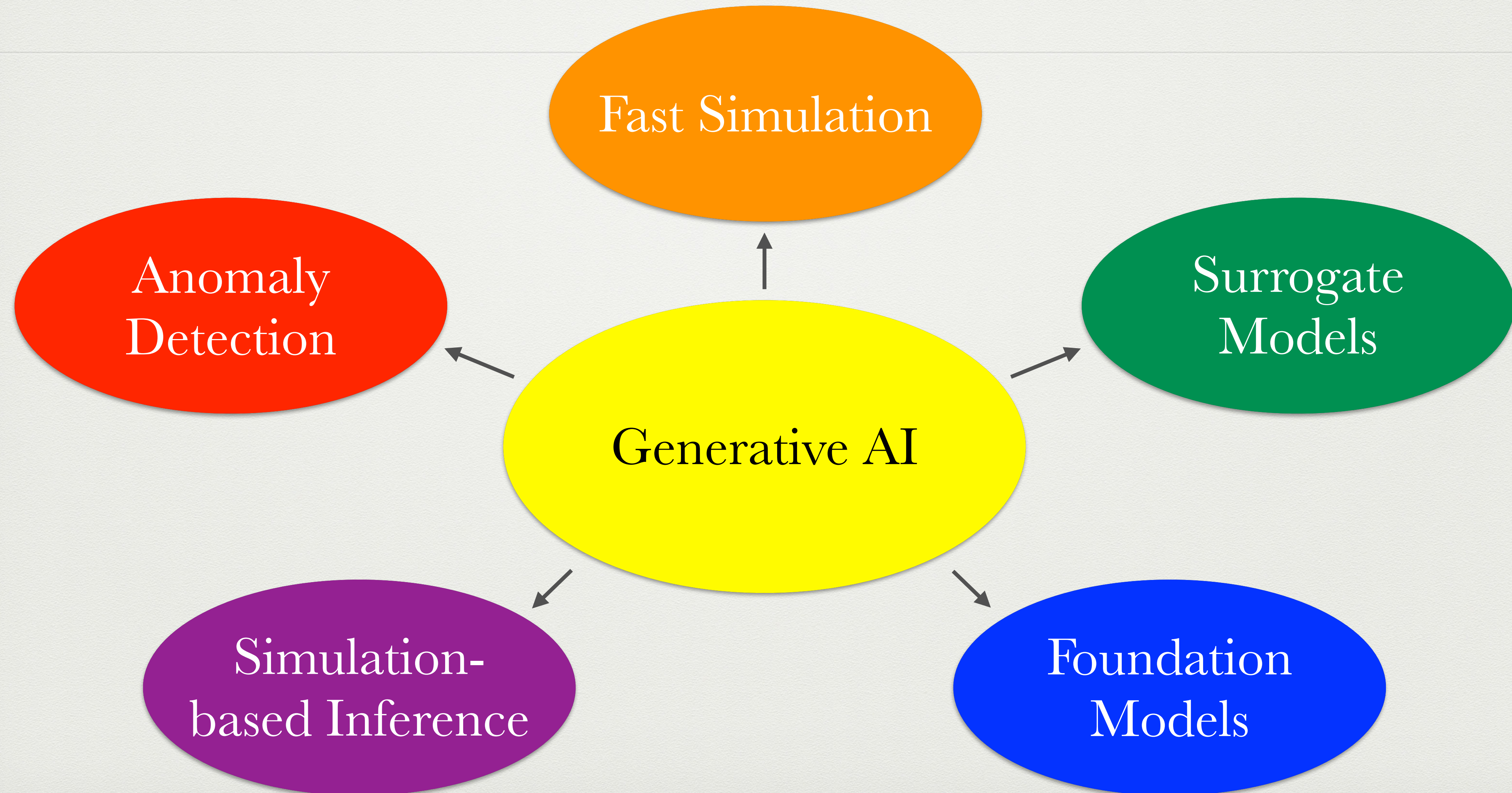


Example: Normalizing Flows

source: [Eric Jang](#)

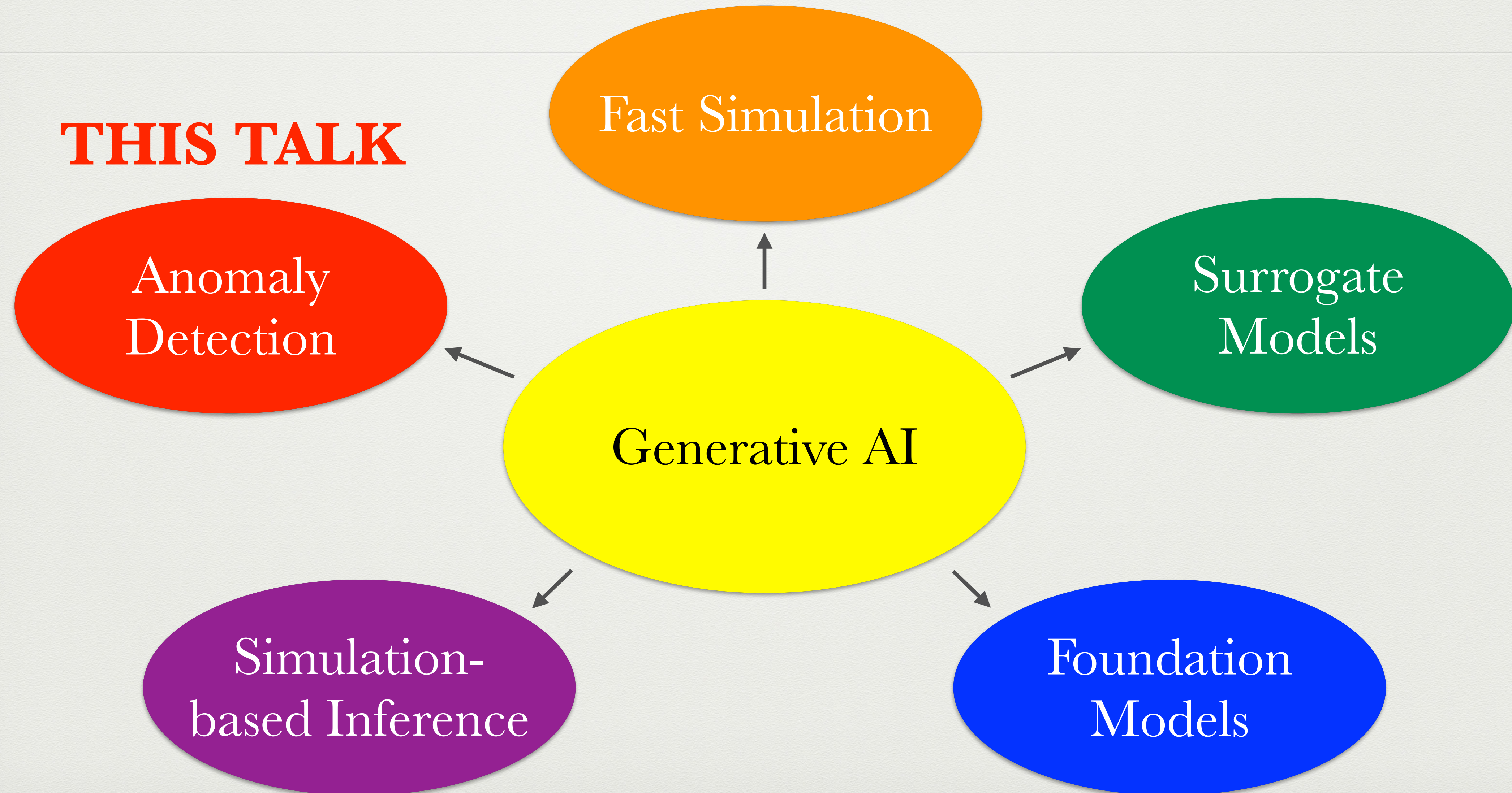


Generative models are also powering recent advances in ML4HEP!

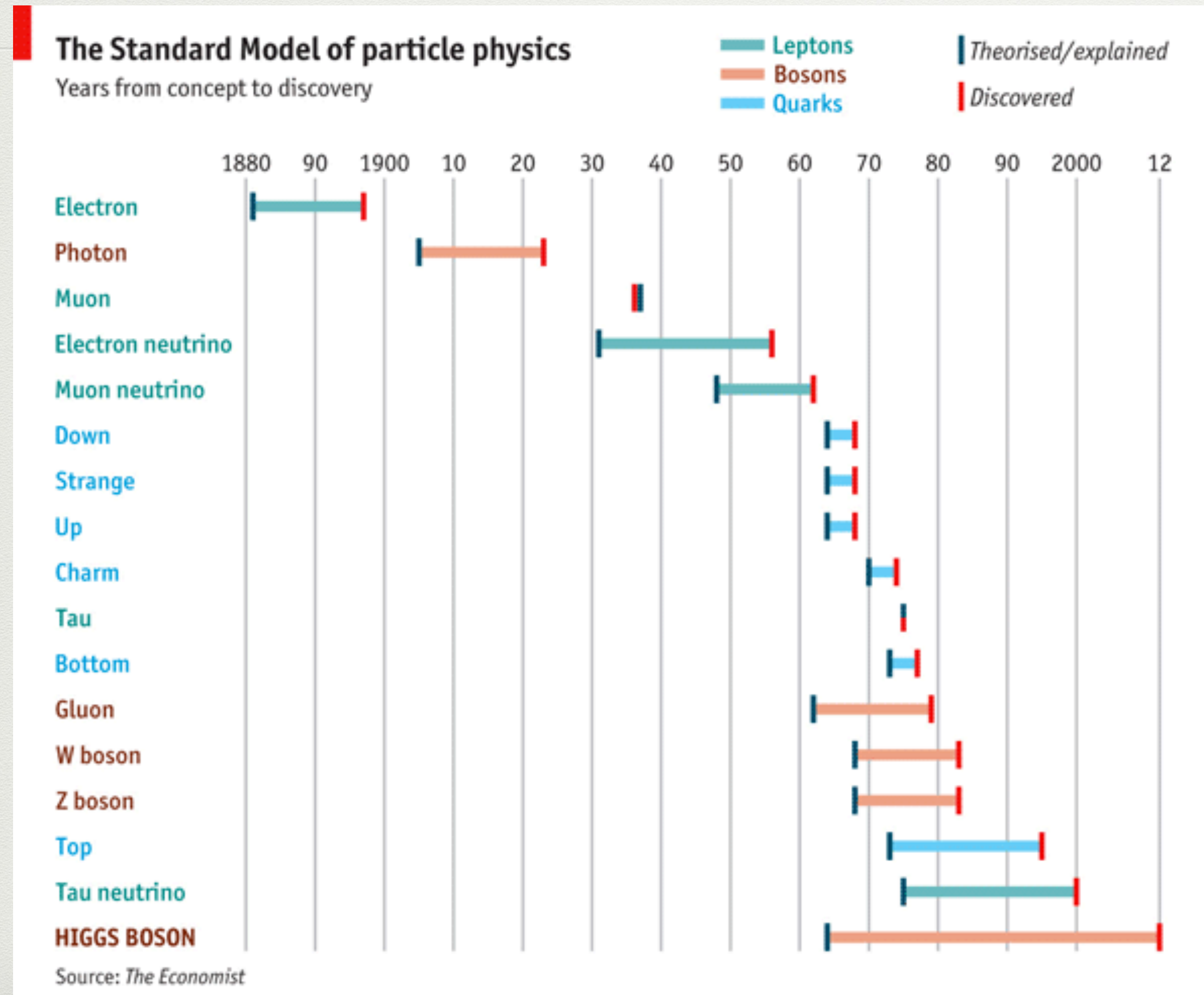
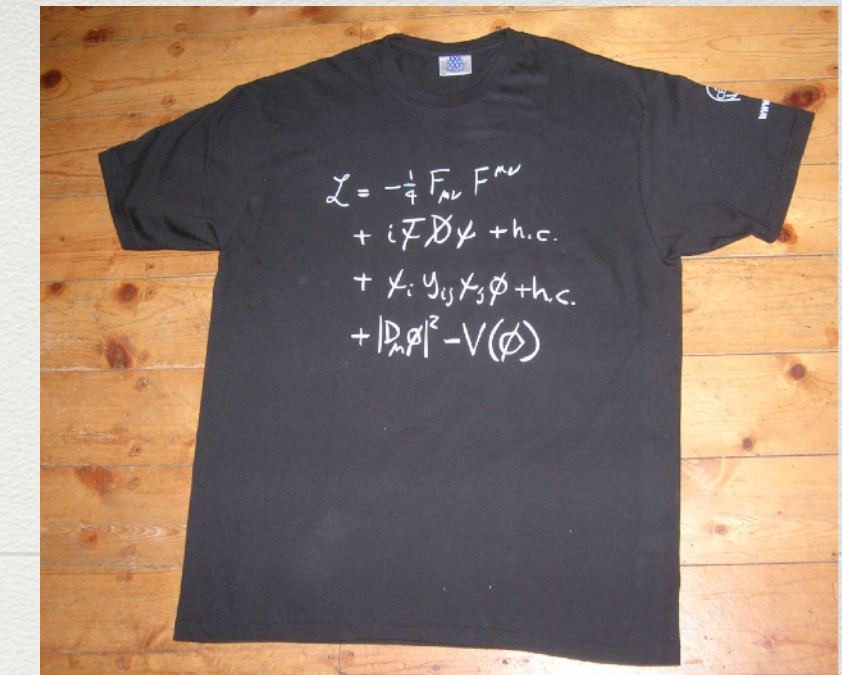


Generative models are also powering recent advances in ML4HEP!

THIS TALK



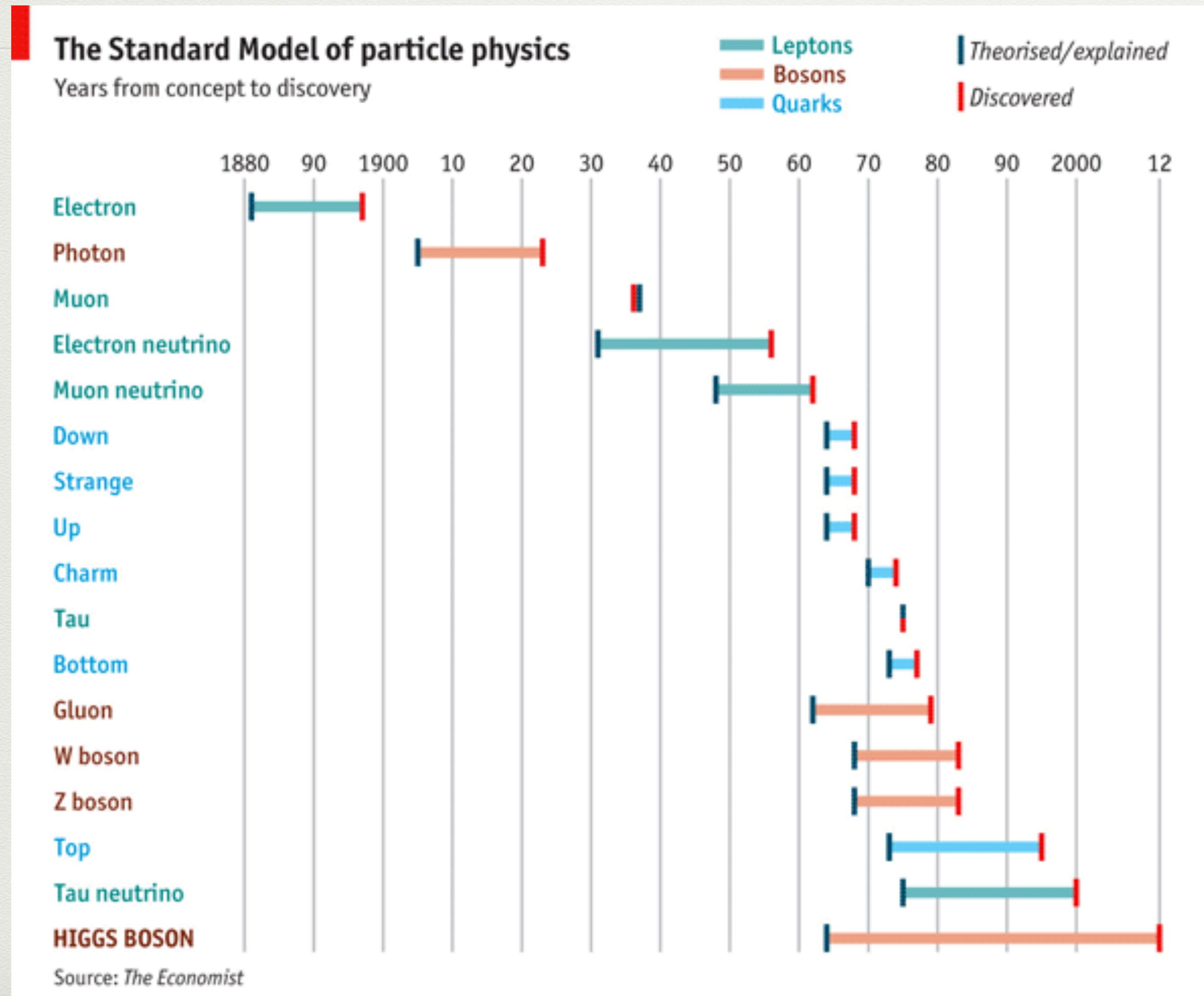
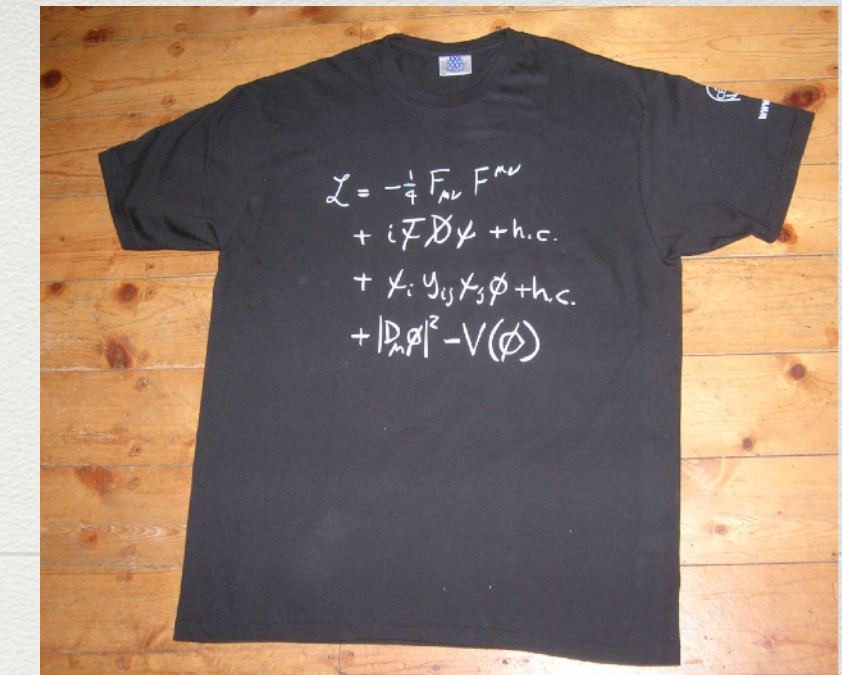
The Search for “New Physics”



The Standard Model was largely established in the '60s, '70s and '80s.

With the discovery of the Higgs boson by the LHC in 2012, it is finally complete.

The Search for “New Physics”



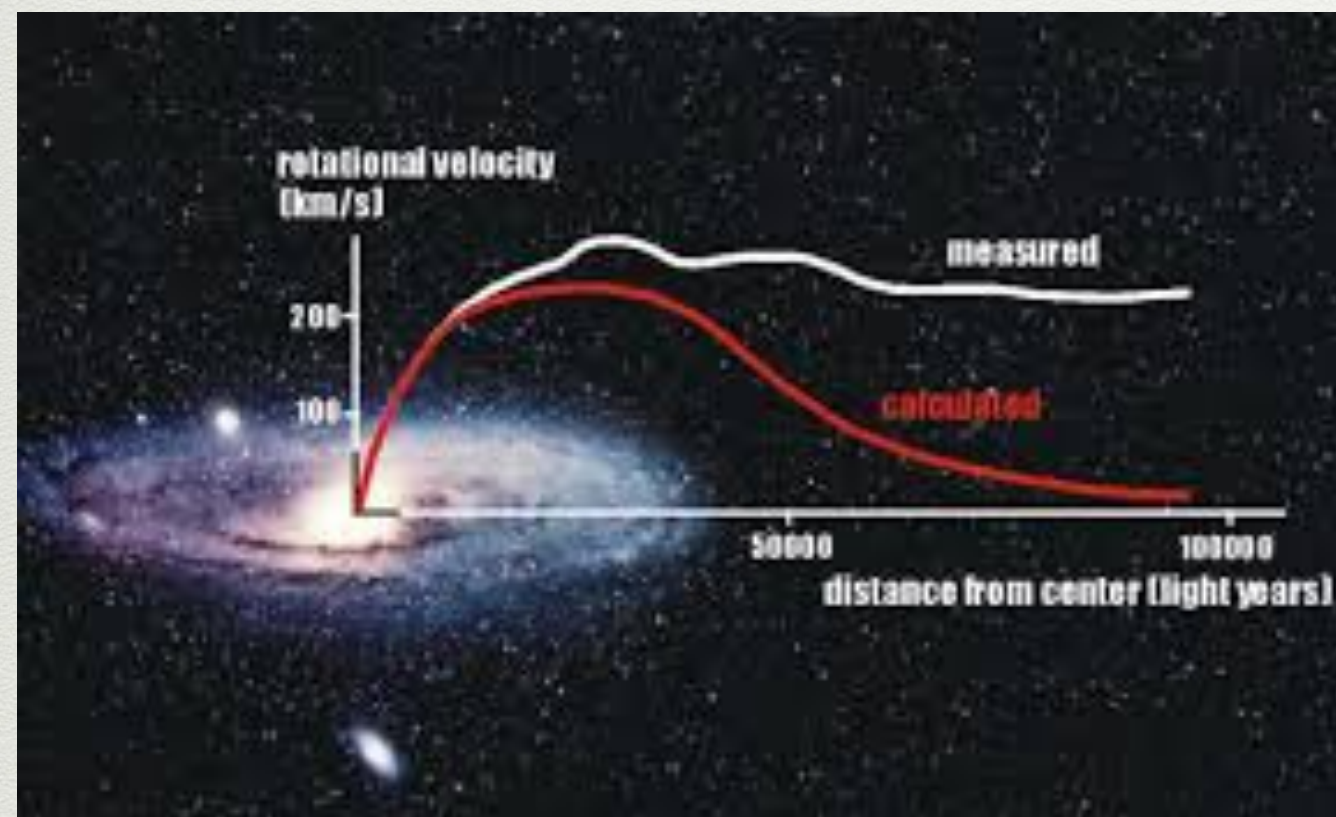
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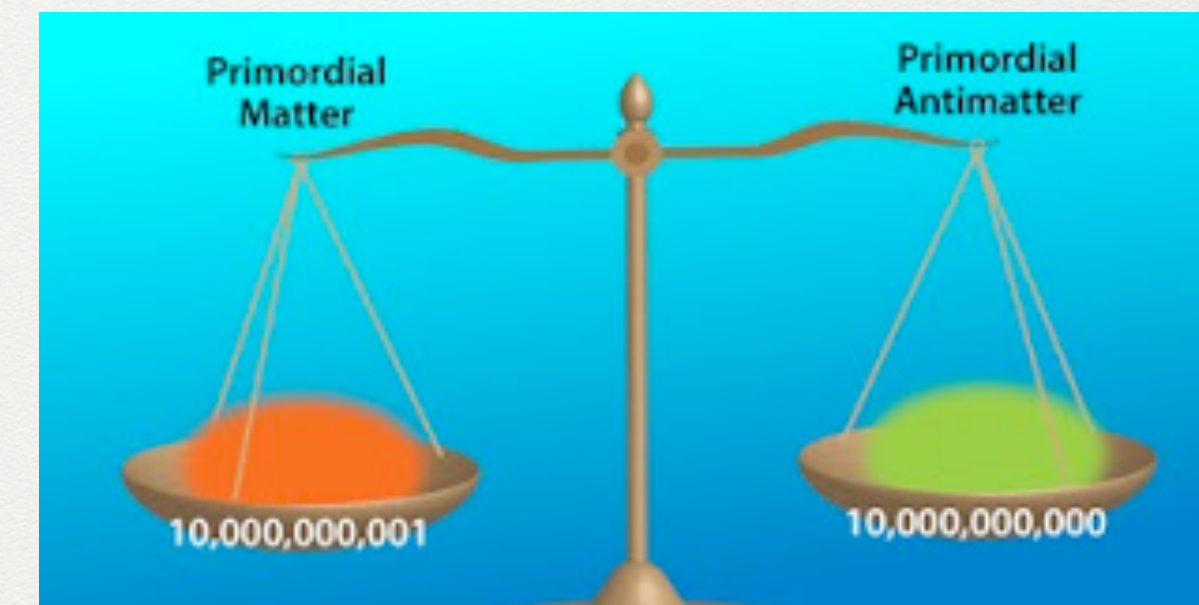
What “new physics” lies beyond the Standard Model?

The Search for “New Physics”

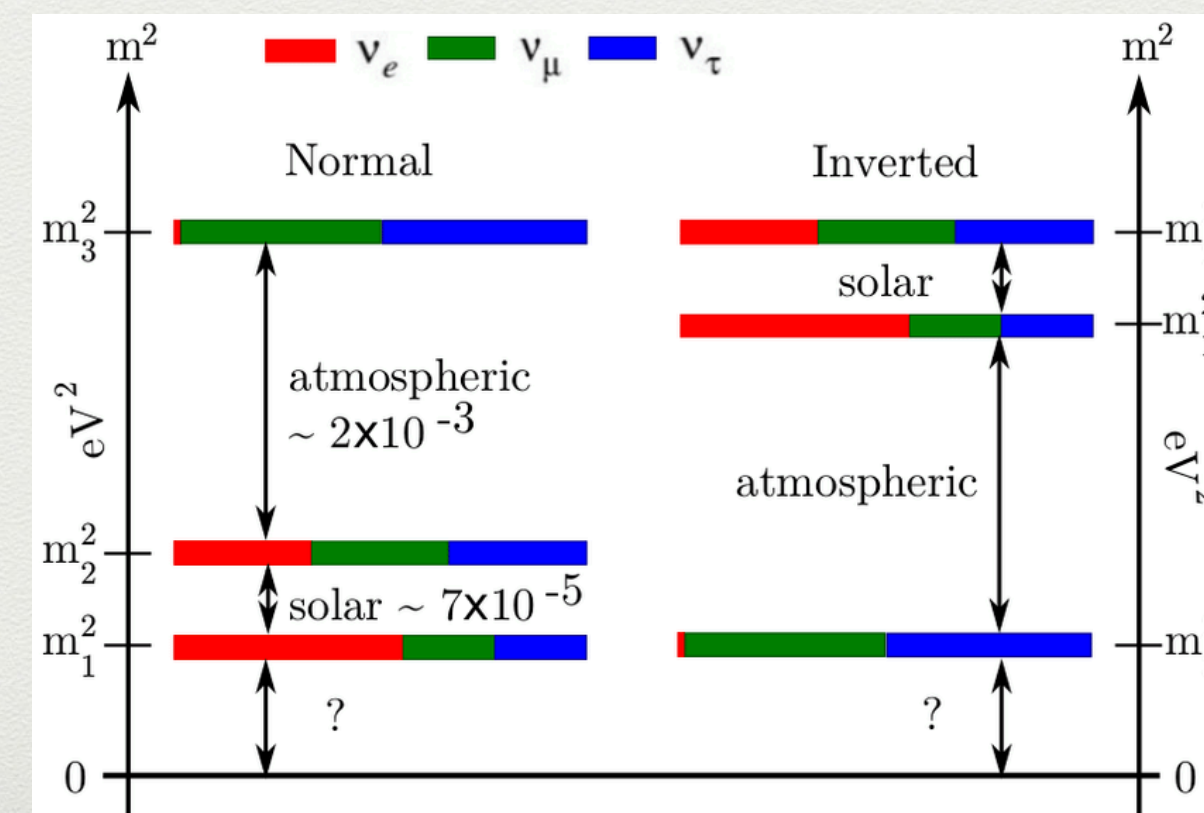
dark matter



matter/anti-matter asymmetry



neutrino masses



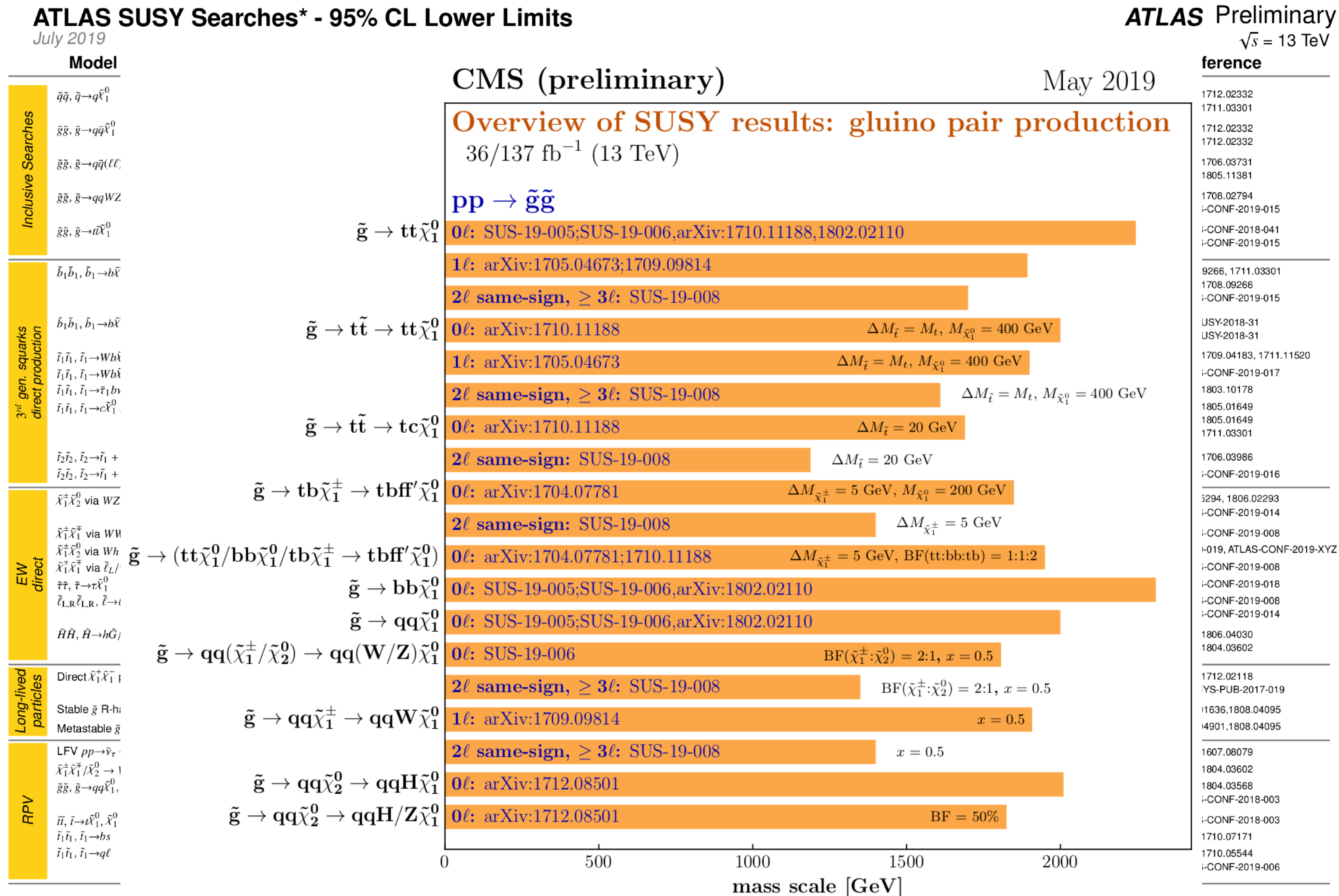
We know the “new physics”
must be out there ...

Status of NP searches at LHC

ATLAS SUSY Searches* - 95% CL Lower Limits										ATLAS Preliminary	
July 2019										$\sqrt{s} = 13 \text{ TeV}$	
Model		Signature		$\int \mathcal{L} dt \text{ [fb}^{-1}\text{]}$	Mass limit					Reference	
Inclusive Searches	$\tilde{q}\tilde{q}, \tilde{q}\rightarrow q\tilde{\chi}_1^0$	0 e, μ	2-6 jets	E_T^{miss}	36.1	$\tilde{q}$ [2x, 8x Degen.]	0.9		1.55	$m(\tilde{\chi}_1^0)<100 \text{ GeV}$	1712.02332
	mono-jet	1-3 jets	E_T^{miss}	36.1	$\tilde{q}$ [1x, 8x Degen.]	0.43	0.71		$m(\tilde{q})\text{-}m(\tilde{\chi}_1^0)=5 \text{ GeV}$	1711.03301	
	$\tilde{g}\tilde{g}, \tilde{g}\rightarrow q\tilde{q}\tilde{\chi}_1^0$	0 e, μ	2-6 jets	E_T^{miss}	36.1	$\tilde{g}$	Forbidden		2.0	$m(\tilde{\chi}_1^0)<200 \text{ GeV}$	1712.02332
									0.95-1.6	$m(\tilde{\chi}_1^0)=900 \text{ GeV}$	1712.02332
	$\tilde{g}\tilde{g}, \tilde{g}\rightarrow q\tilde{q}(\ell\ell)\tilde{\chi}_1^0$	3 e, μ	4 jets	E_T^{miss}	36.1	$\tilde{g}$			1.85	$m(\tilde{\chi}_1^0)<800 \text{ GeV}$	1706.03731
	$ee, \mu\mu$	2 jets	E_T^{miss}	36.1	$\tilde{g}$			1.2	$m(\tilde{g})\text{-}m(\tilde{\chi}_1^0)=50 \text{ GeV}$	1805.11381	
	$\tilde{g}\tilde{g}, \tilde{g}\rightarrow qqWZ\tilde{\chi}_1^0$	0 e, μ	7-11 jets	E_T^{miss}	36.1	$\tilde{g}$			1.8	$m(\tilde{\chi}_1^0)<400 \text{ GeV}$	1708.02794
	SS e, μ	6 jets	E_T^{miss}	139	$\tilde{g}$			1.15	$m(\tilde{g})\text{-}m(\tilde{\chi}_1^0)=200 \text{ GeV}$	ATLAS-CONF-2019-015	
$\tilde{g}\tilde{g}, \tilde{g}\rightarrow t\tilde{\chi}_1^0$	0-1 e, μ	3 b	E_T^{miss}	79.8	$\tilde{g}$			2.25	$m(\tilde{\chi}_1^0)<200 \text{ GeV}$	ATLAS-CONF-2018-041	
	SS e, μ	6 jets	E_T^{miss}	139	$\tilde{g}$			1.25	$m(\tilde{g})\text{-}m(\tilde{\chi}_1^0)=300 \text{ GeV}$	ATLAS-CONF-2019-015	
3 rd gen. squarks direct production	$\tilde{b}_1\tilde{b}_1, \tilde{b}_1\rightarrow b\tilde{\chi}_1^0/\tilde{\nu}_1^\pm$		Multiple		36.1	$\tilde{b}_1$	Forbidden		0.9	$m(\tilde{\chi}_1^0)=300 \text{ GeV}, \text{BR}(b\tilde{\chi}_1^0)=1$	1708.09266, 1711.03301
			Multiple		36.1	$\tilde{b}_1$	Forbidden		0.58-0.82	$m(\tilde{\chi}_1^0)=300 \text{ GeV}, \text{BR}(b\tilde{\chi}_1^0)=\text{BR}(\tilde{\nu}_1^\pm)=0.5$	1708.09266
			Multiple		139	$\tilde{b}_1$	Forbidden		0.74	$m(\tilde{\chi}_1^0)=200 \text{ GeV}, m(\tilde{\chi}_1^\pm)=300 \text{ GeV}, \text{BR}(\tilde{\nu}_1^\pm)=1$	ATLAS-CONF-2019-015
	$\tilde{b}_1\tilde{b}_1, \tilde{b}_1\rightarrow b\tilde{\chi}_2^0\rightarrow bh\tilde{\chi}_1^0$	0 e, μ	6 b	E_T^{miss}	139	$\tilde{b}_1$	Forbidden		0.23-1.35	$\Delta m(\tilde{\chi}_2^0, \tilde{\chi}_1^0)=130 \text{ GeV}, m(\tilde{\chi}_1^0)=100 \text{ GeV}$	SUSY-2018-31
									0.23-0.48	$\Delta m(\tilde{\chi}_2^0, \tilde{\chi}_1^0)=130 \text{ GeV}, m(\tilde{\chi}_1^0)=0 \text{ GeV}$	SUSY-2018-31
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1\rightarrow Wb\tilde{\chi}_1^0$ or $\tilde{\nu}_1^0$	0-2 e, μ	0-2 jets/1-2 b	E_T^{miss}	36.1	$\tilde{t}_1$			1.0	$m(\tilde{\chi}_1^0)=1 \text{ GeV}$	1506.08616, 1709.04183, 1711.11520
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1\rightarrow Wb\tilde{\chi}_1^0$	1 e, μ	3 jets/1 b	E_T^{miss}	139	$\tilde{t}_1$			0.44-0.59	$m(\tilde{\chi}_1^0)=400 \text{ GeV}$	ATLAS-CONF-2019-017
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1\rightarrow \tilde{\tau}_1 b\nu, \tilde{\tau}_1\rightarrow \tau\tilde{G}$	1 $\tau + 1 e, \mu, \tau$	2 jets/1 b	E_T^{miss}	36.1	$\tilde{t}_1$			1.16	$m(\tilde{\tau}_1)=800 \text{ GeV}$	1803.10178
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1\rightarrow c\tilde{\chi}_1^0/\tilde{c}\tilde{c}, \tilde{c}\rightarrow c\tilde{\chi}_1^0$	0 e, μ	2 c	E_T^{miss}	36.1	$\tilde{c}$			0.85	$m(\tilde{\chi}_1^0)=0 \text{ GeV}$	1805.01649
						$\tilde{t}_1$			0.46	$m(\tilde{t}_1, \tilde{c})\text{-}m(\tilde{\chi}_1^0)=50 \text{ GeV}$	1805.01649
	0 e, μ	mono-jet	E_T^{miss}	36.1	$\tilde{t}_1$			0.43	$m(\tilde{t}_1, \tilde{c})\text{-}m(\tilde{\chi}_1^0)=5 \text{ GeV}$	1711.03301	
$\tilde{t}_2\tilde{t}_2, \tilde{t}_2\rightarrow \tilde{t}_1 + h$	1-2 e, μ	4 b	E_T^{miss}	36.1	$\tilde{t}_2$			0.32-0.88	$m(\tilde{\chi}_1^0)=0 \text{ GeV}, m(\tilde{t}_1)\text{-}m(\tilde{\chi}_1^0)=180 \text{ GeV}$	1706.03986	
$\tilde{t}_2\tilde{t}_2, \tilde{t}_2\rightarrow \tilde{t}_1 + Z$	3 e, μ	1 b	E_T^{miss}	139	$\tilde{t}_2$	Forbidden		0.86	$m(\tilde{\chi}_1^0)=360 \text{ GeV}, m(\tilde{t}_1)\text{-}m(\tilde{\chi}_1^0)=40 \text{ GeV}$	ATLAS-CONF-2019-016	
EW direct	$\tilde{\chi}_1^\pm\tilde{\chi}_2^0$ via WZ	2-3 e, μ		E_T^{miss}	36.1	$\tilde{\chi}_1^\pm/\tilde{\chi}_2^0$			0.6	$m(\tilde{\chi}_1^0)=0$	1403.5294, 1806.02293
	$ee, \mu\mu$	≥ 1	E_T^{miss}	139	$\tilde{\chi}_1^\pm/\tilde{\chi}_2^0$	0.205			$m(\tilde{\chi}_1^\pm)\text{-}m(\tilde{\chi}_1^0)=5 \text{ GeV}$	ATLAS-CONF-2019-014	
	$\tilde{\chi}_1^\pm\tilde{\chi}_1^\mp$ via WW	2 e, μ		E_T^{miss}	139	$\tilde{\chi}_1^\pm$			0.42	$m(\tilde{\chi}_1^0)=0$	ATLAS-CONF-2019-008
	$\tilde{\chi}_1^\pm\tilde{\chi}_2^0$ via Wh	0-1 e, μ	2 $b/2 \gamma$	E_T^{miss}	139	$\tilde{\chi}_1^\pm/\tilde{\chi}_2^0$	Forbidden		0.74	$m(\tilde{\chi}_1^0)=70 \text{ GeV}$	ATLAS-CONF-2019-019, ATLAS-CONF-2019-XYZ
	$\tilde{\chi}_1^\pm\tilde{\chi}_1^\mp$ via $\tilde{\ell}_L/\tilde{\nu}$	2 e, μ		E_T^{miss}	139	$\tilde{\chi}_1^\pm$			1.0	$m(\tilde{\ell}, \tilde{\nu})=0.5(m(\tilde{\chi}_1^\pm)+m(\tilde{\chi}_1^0))$	ATLAS-CONF-2019-008
	$\tilde{\tau}\tilde{\tau}, \tilde{\tau}\rightarrow \tau\tilde{\chi}_1^0$	2 τ		E_T^{miss}	139	$\tilde{\tau}$ [$\tilde{\tau}_L, \tilde{\tau}_{R,L}$]	0.16-0.3	0.12-0.39	$m(\tilde{\chi}_1^0)=0$	ATLAS-CONF-2019-018	
	$\tilde{\ell}_{L,R}\tilde{\ell}_{L,R}, \tilde{\ell}\rightarrow \ell\tilde{\chi}_1^0$	2 e, μ	0 jets	E_T^{miss}	139	$\tilde{\ell}$			0.7	$m(\tilde{\chi}_1^0)=0$	ATLAS-CONF-2019-008
		2 e, μ	≥ 1	E_T^{miss}	139	$\tilde{\ell}$	0.256		$m(\tilde{\ell})\text{-}m(\tilde{\chi}_1^0)=10 \text{ GeV}$	ATLAS-CONF-2019-014	
	$\tilde{H}\tilde{H}, \tilde{H}\rightarrow h\tilde{G}/Z\tilde{G}$	0 e, μ	$\geq 3 b$	E_T^{miss}	36.1	$\tilde{H}$	0.13-0.23	0.29-0.88		$\text{BR}(\tilde{\chi}_1^0\rightarrow h\tilde{G})=1$	1806.04030
	4 e, μ	0 jets	E_T^{miss}	36.1	$\tilde{H}$	0.3			$\text{BR}(\tilde{\chi}_1^0\rightarrow Z\tilde{G})=1$	1804.03602	
Long-lived particles	Direct $\tilde{\chi}_1^+\tilde{\chi}_1^-$ prod., long-lived $\tilde{\chi}_1^\pm$	Disapp. trk	1 jet	E_T^{miss}	36.1	$\tilde{\chi}_1^\pm$	0.46			Pure Wino	1712.02118
						$\tilde{\chi}_1^\pm$	0.15			Pure Higgsino	ATL-PHYS-PUB-2017-019
	Stable $\tilde{g}$ R-hadron		Multiple		36.1	$\tilde{g}$			2.0		1902.01636, 1808.04095
	Metastable $\tilde{g}$ R-hadron, $\tilde{g}\rightarrow qq\tilde{\chi}_1^0$		Multiple		36.1	$\tilde{g}$ [$\tau(\tilde{g})=10 \text{ ns}, 0.2 \text{ ns}$]			2.05 2.4	$m(\tilde{\chi}_1^0)=100 \text{ GeV}$	1710.04901, 1808.04095
RPV	LFV $pp\rightarrow \tilde{\nu}_\tau + X, \tilde{\nu}_\tau\rightarrow e\mu/\tau\mu/\tau$	$e\mu, e\tau, \mu\tau$			3.2	$\tilde{\nu}_\tau$			1.9	$\lambda'_{311}=0.11, \lambda_{132/133/233}=0.07$	1607.08079
	$\tilde{\chi}_1^\pm\tilde{\chi}_1^\mp/\tilde{\chi}_2^0\rightarrow WW/Z\ell\ell\ell\nu\nu$	4 e, μ	0 jets	E_T^{miss}	36.1	$\tilde{\chi}_1^\pm/\tilde{\chi}_2^0$ [$\lambda_{333}\neq 0, \lambda_{12k}\neq 0$]	0.82		1.33	$m(\tilde{\chi}_1^0)=100 \text{ GeV}$	1804.03602
	$\tilde{g}\tilde{g}, \tilde{g}\rightarrow qq\tilde{\chi}_1^0, \tilde{\chi}_1^0\rightarrow qq q$		4-5 large- R jets		36.1	$\tilde{g}$ [$m(\tilde{\chi}_1^0)=200 \text{ GeV}, 1100 \text{ GeV}$]			1.3	Large λ'_{112}	1804.03568
			Multiple		36.1	$\tilde{g}$ [$\lambda'_{112}=2\text{e-}4, 2\text{e-}5$]			1.05	$m(\tilde{\chi}_1^0)=200 \text{ GeV}, \text{bino-like}$	ATLAS-CONF-2018-003
									2.0		
	$\tilde{t}\tilde{t}, \tilde{t}\rightarrow t\tilde{\chi}_1^0, \tilde{\chi}_1^0\rightarrow tbs$		Multiple		36.1	$\tilde{g}$ [$\lambda'_{333}=2\text{e-}4, 1\text{e-}2$]	0.55		1.05	$m(\tilde{\chi}_1^0)=200 \text{ GeV}, \text{bino-like}$	ATLAS-CONF-2018-003
	$\tilde{t}_1\tilde{t}_1, \tilde{t}_1\rightarrow bs$		2 jets + 2 b		36.7	$\tilde{t}_1$ [$qq, b\bar{s}$]	0.42	0.61			1710.07171
$\tilde{t}_1\tilde{t}_1, \tilde{t}_1\rightarrow q\ell$	2 e, μ	2 b		36.1	$\tilde{t}_1$			0.4-1.45	$\text{BR}(\tilde{t}_1\rightarrow be/b\mu)>20\%$	1710.05544	
	1 μ	DV		136	$\tilde{t}_1$ [$1\text{e-}10<\lambda'_{23k}<1\text{e-}8, 3\text{e-}10<\lambda'_{23k}<3\text{e-}9$]	1.0		1.6	$\text{BR}(\tilde{t}_1\rightarrow q\mu)=100\%, \cos\theta_t=1$	ATLAS-CONF-2019-006	

*Only a selection of the available mass limits on new states or phenomena is shown. Many of the limits are based on

Status of NP searches at LHC



*Only a selection of phenomena is sketched.

Selection of observed limits at 95% C.L. (theory uncertainties are not included). Probe **up** to the quoted mass limit for light LSPs unless stated otherwise. The quantities ΔM and x represent the absolute mass difference between the primary sparticle and the LSP and the difference between the intermediate

Status of NP searches at LHC

ATLAS SUSY Searches* - 95% CL Lower Limits

July 2019

Model

Searches

$\tilde{q}\tilde{q}, \tilde{q}\rightarrow q\tilde{\chi}_1^0$

$\tilde{g}\tilde{g}, \tilde{g}\rightarrow q\tilde{q}\tilde{\chi}_1^0$

CMS (preliminary)

Overview of SUSY results: gluino pair production

May 2019

ATLAS Preliminary

$\sqrt{s} = 13$ TeV

ference

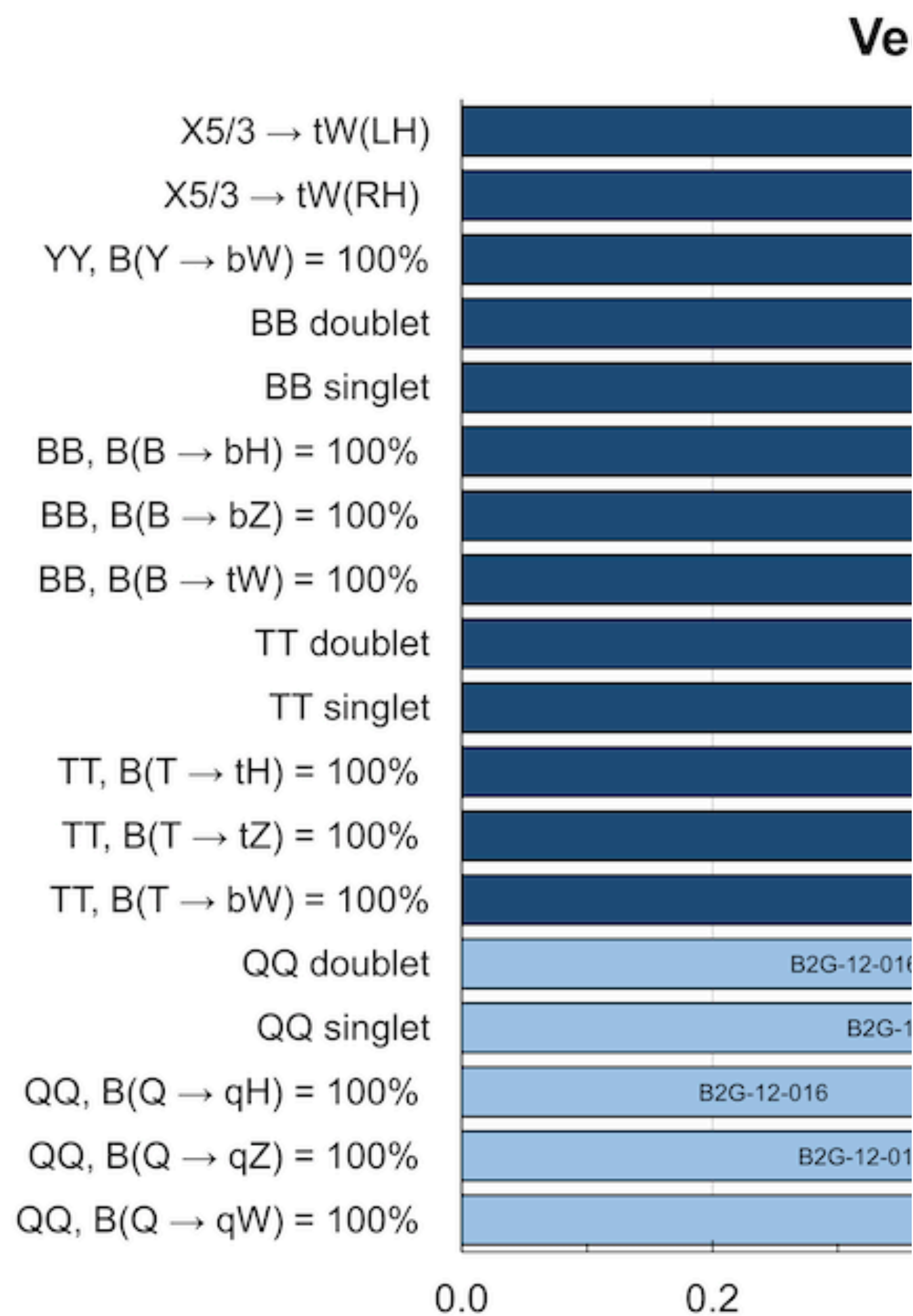
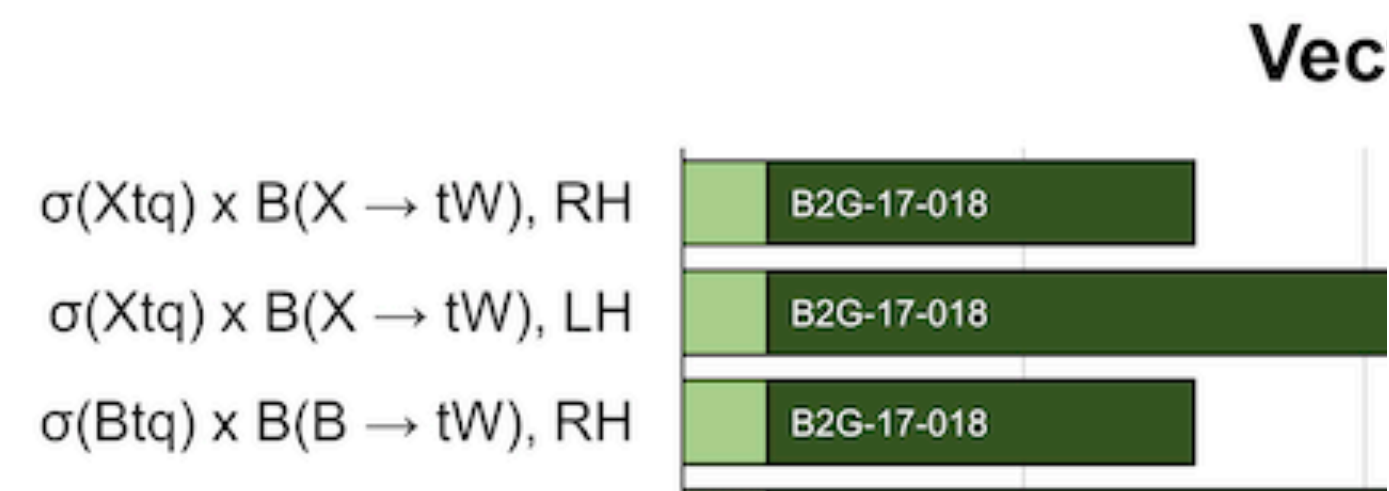
1712.02332

1711.03301

1712.02332

1712.02332

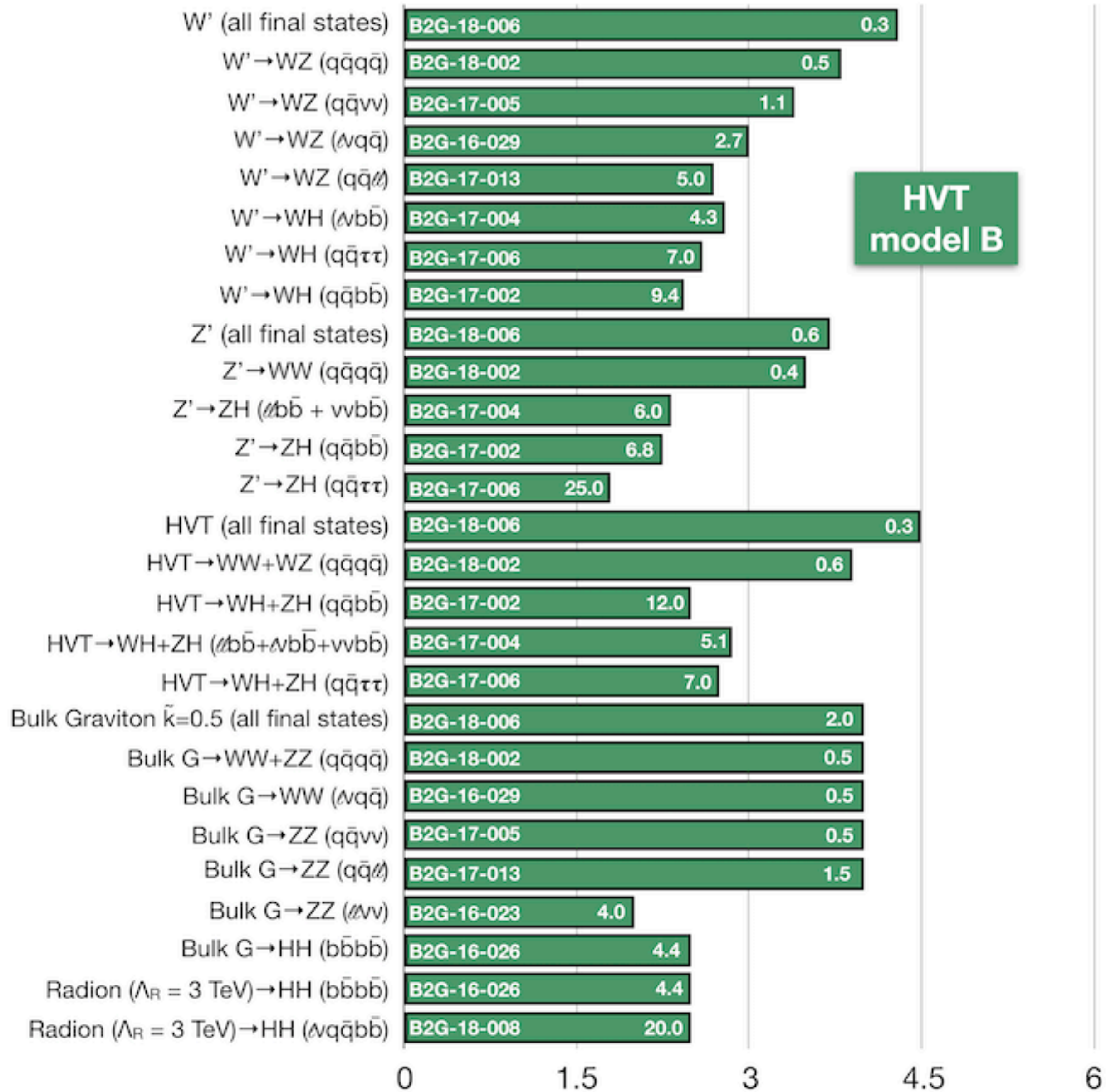
ATLAS Exotics Searches* - 95% CL Upper Exclusion Limits						ATLAS Preliminary					
Status: May 2019						$\sqrt{s} = 8, 13$ TeV					
						$\int \mathcal{L} dt = (3.2 - 139) \text{ fb}^{-1}$					
Model						Reference					
Extra dimensions	ADD $G_{KK} + g/q$	$0\ e, \mu$	$1 - 4\ \text{j}$	Yes	36.1	M_D	7.7 TeV	$n = 2$	1711.03301	9-015	
	ADD non-resonant $\gamma\gamma$	$2\ \gamma$	–	–	36.7	M_S	8.6 TeV	$n = 3$ HLZ NLO	1707.04147	8-041	
	ADD QBH	–	$2\ \text{j}$	–	37.0	M_{th}	8.9 TeV	$n = 6$	1703.09127	9-015	
	ADD BH high $\sum p_T$	$\geq 1\ e, \mu$	$\geq 2\ \text{j}$	–	3.2	M_{th}	8.2 TeV	$n = 6, M_D = 3\ \text{TeV}$, rot BH	1606.02265		
	ADD BH multijet	–	$\geq 3\ \text{j}$	–	3.6	M_{th}	9.55 TeV	$n = 6, M_D = 3\ \text{TeV}$, rot BH	1512.02586	9-015	
	RS1 $G_{KK} \rightarrow \gamma\gamma$	$2\ \gamma$	–	–	36.7	G_{KK} mass	4.1 TeV	$k/\overline{M}_{Pl} = 0.1$	1707.04147		
	Bulk RS $G_{KK} \rightarrow WW/ZZ$	multi-channel			36.1	G_{KK} mass	2.3 TeV	$k/\overline{M}_{Pl} = 1.0$	1808.02380		
	Bulk RS $G_{KK} \rightarrow WW \rightarrow qq\bar{q}\bar{q}$	$0\ e, \mu$	$2\ \text{J}$	–	139	G_{KK} mass	1.6 TeV	$k/\overline{M}_{Pl} = 1.0$	ATLAS-CONF-2019-003		
	Bulk RS $g_{KK} \rightarrow t\bar{t}$	$1\ e, \mu$	$\geq 1\ \text{b}, \geq 1\text{J}/2\text{j}$	Yes	36.1	g_{KK} mass	3.8 TeV	$\Gamma/m = 15\%$	1804.10823		
	2UED / RPP	$1\ e, \mu$	$\geq 2\ \text{b}, \geq 3\ \text{j}$	Yes	36.1	KK mass	1.8 TeV	Tier (1,1), $\mathcal{B}(A^{(1,1)} \rightarrow t\bar{t}) = 1$	1803.09678	9-017	
Gauge bosons	SSM $Z' \rightarrow \ell\ell$	$2\ e, \mu$	–	–	139	Z' mass	5.1 TeV		1903.06248		
	SSM $Z' \rightarrow \tau\tau$	$2\ \tau$	–	–	36.1	Z' mass	2.42 TeV		1709.07242		
	Leptophobic $Z' \rightarrow b\bar{b}$	–	$2\ \text{b}$	–	36.1	Z' mass	2.1 TeV		1805.09299		
	Leptophobic $Z' \rightarrow t\bar{t}$	$1\ e, \mu$	$\geq 1\ \text{b}, \geq 1\text{J}/2\text{j}$	Yes	36.1	Z' mass	3.0 TeV	$\Gamma/m = 1\%$	1804.10823		
	SSM $W' \rightarrow \ell\nu$	$1\ e, \mu$	–	Yes	139	W' mass	6.0 TeV		CERN-EP-2019-100		
	SSM $W' \rightarrow \tau\nu$	$1\ \tau$	–	Yes	36.1	W' mass	3.7 TeV		1801.06992		
	HVT $V' \rightarrow WZ \rightarrow qq\bar{q}\bar{q}$ model B	$0\ e, \mu$	$2\ \text{J}$	–	139	V' mass	3.6 TeV	$g_V = 3$	ATLAS-CONF-2019-003	9-016	
	HVT $V' \rightarrow WH/ZH$ model B	multi-channel			36.1	V' mass	2.93 TeV	$g_V = 3$	1712.06518		
	LRSM $W_R \rightarrow t\bar{b}$	multi-channel			36.1	W_R mass	3.25 TeV		1807.10473		
	LRSM $W_R \rightarrow \mu N_R$	$2\ \mu$	$1\ \text{J}$	–	80	W_R mass	5.0 TeV	$m(N_R) = 0.5\ \text{TeV}, g_L = g_R$	1904.12679		
CI	CI $qq\bar{q}\bar{q}$	–	$2\ \text{j}$	–	37.0	Λ	21.8 TeV	η_{LL}^-	1703.09127	9-008	
	CI $\ell\ell q\bar{q}$	$2\ e, \mu$	–	–	36.1	Λ	40.0 TeV	η_{LL}^-	1707.02424	S-CONF-2019-XYZ	
	CI $t\bar{t}t\bar{t}$	$\geq 1\ e, \mu$	$\geq 1\ \text{b}, \geq 1\ \text{j}$	Yes	36.1	Λ	2.57 TeV	$ C_{4t} = 4\pi$	1811.02305	9-008	
DM	Axial-vector mediator (Dirac DM)	$0\ e, \mu$	$1 - 4\ \text{j}$	Yes	36.1	m_{med}	1.55 TeV	$g_a=0.25, g_v=1.0, m(\chi) = 1\ \text{GeV}$	1711.03301	9-018	
	Colored scalar mediator (Dirac DM)	$0\ e, \mu$	$1 - 4\ \text{j}$	Yes	36.1	m_{med}	1.67 TeV	$g=1.0, m(\chi) = 1\ \text{GeV}$	1711.03301	9-008	
	$VV\chi\chi$ EFT (Dirac DM)	$0\ e, \mu$	$1\ \text{J}, \leq 1\ \text{j}$	Yes	3.2	M_χ	700 GeV	$m(\chi) < 150\ \text{GeV}$	1608.02372	9-014	
	Scalar reson. $\phi \rightarrow t\chi$ (Dirac DM)	$0-1\ e, \mu$	$1\ \text{b}, 0-1\ \text{J}$	Yes	36.1	m_ϕ	3.4 TeV	$y = 0.4, \lambda = 0.2, m(\chi) = 10\ \text{GeV}$	1812.09743		
LQ	Scalar LQ 1 st gen	$1, 2\ e$	$\geq 2\ \text{j}$	Yes	36.1	LQ mass	1.4 TeV	$\beta = 1$	1902.00377		
	Scalar LQ 2 nd gen	$1, 2\ \mu$	$\geq 2\ \text{j}$	Yes	36.1	LQ mass	1.56 TeV	$\beta = 1$	1902.00377		
	Scalar LQ 3 rd gen	$2\ \tau$	$2\ \text{b}$	–	36.1	LQ ₃ mass	1.03 TeV	$\mathcal{B}(\text{LQ}_3^u \rightarrow b\tau) = 1$	1902.08103		
	Scalar LQ 3 rd gen	$0-1\ e, \mu$	$2\ \text{b}$	Yes	36.1	LQ ₃ mass	970 GeV	$\mathcal{B}(\text{LQ}_3^d \rightarrow t\tau) = 0$	1902.08103	17-019	
Heavy quarks	VLQ $T\bar{T} \rightarrow Ht/Zt/Wb + X$	multi-channel			36.1	T mass	1.37 TeV	SU(2) doublet	1808.02343	04095	
	VLQ $B\bar{B} \rightarrow Wt/Zb + X$	multi-channel			36.1	B mass	1.34 TeV	SU(2) doublet	1808.02343	04095	
	VLQ $T_{5/3} \bar{T}_{5/3} / T_{5/3} \rightarrow Wt + X$	$2(\text{SS})/\geq 3\ e, \mu$	$\geq 1\ \text{b}, \geq 1\ \text{j}$	Yes	36.1	$T_{5/3}$ mass	1.64 TeV	$\mathcal{B}(T_{5/3} \rightarrow Wt) = 1, c(T_{5/3} Wt) = 1$	1807.11883		
	VLQ $Y \rightarrow Wb + X$	$1\ e, \mu$	$\geq 1\ \text{b}, \geq 1\ \text{j}$	Yes	36.1	Y mass	1.85 TeV	$\mathcal{B}(Y \rightarrow Wb) = 1, c_R(Wb) = 1$	1812.07343		
	VLQ $B \rightarrow Hb + X$	$0\ e, \mu, 2\ \gamma$	$\geq 1\ \text{b}, \geq 1\ \text{j}$	Yes	79.8	B mass	1.21 TeV	$\kappa_B = 0.5$	ATLAS-CONF-2018-024		
	VLQ $Q\bar{Q} \rightarrow WqVq$	$1\ e, \mu$	$\geq 4\ \text{j}$	Yes	20.3	Q mass	690 GeV		1509.04261		
Excited fermions	Excited quark $q^* \rightarrow qg$	–	$2\ \text{j}$	–	139	q^* mass	6.7 TeV	only u^* and d^* , $\Lambda = m(q^*)$	ATLAS-CONF-2019-007	8-003	
	Excited quark $q^* \rightarrow q\gamma$	$1\ \gamma$	$1\ \text{j}$	–	36.7	q^* mass	5.3 TeV	only u^* and d^* , $\Lambda = m(q^*)$	1709.10440	8-003	
	Excited quark $b^* \rightarrow b\gamma$	–	$1\ \text{b}, 1\ \text{j}$	–	36.1	b^* mass	2.6 TeV		1805.09299		
	Excited lepton ℓ^*	$3\ e, \mu$	–	–	20.3	ℓ^* mass	3.0 TeV	$\Lambda = 3.0\ \text{TeV}$	1411.2921		
	Excited lepton ν^*	$3\ e, \mu, \tau$	–	–	20.3	ν^* mass	1.6 TeV	$\Lambda = 1.6\ \text{TeV}$	1411.2921	9-006	
Other	Type III Seesaw	$1\ e, \mu$	$\geq 2\ \text{j}$	Yes	79.8	N^0 mass	560 GeV		ATLAS-CONF-2018-020		
	LRSM Majorana ν	$2\ \mu$	$2\ \text{j}$	–	36.1	N_R mass	3.2 TeV	$m(W_R) = 4.1\ \text{TeV}, g_L = g_R$	1809.11105		
	Higgs triplet $H^{\pm\pm} \rightarrow \ell\ell$	$2, 3, 4\ e, \mu$ (SS)	–	–	36.1	$H^{\pm\pm}$ mass	870 GeV	DY production	1710.09748		
	Higgs triplet $H^{\pm\pm} \rightarrow \ell\tau$	$3\ e, \mu, \tau$	–	–	20.3	$H^{\pm\pm}$ mass	400 GeV	DY production, $\mathcal{B}(H_L^{\pm\pm} \rightarrow \ell\tau) = 1$	1411.2921		
	Multi-charged particles	–	–	–	36.1	multi-charged particle mass	1.22 TeV	DY production, $ q = 5e$	1812.03673		



CMS, EPS-HEP 2019

Selection of observed limits at 95% C.L.
The quantities ΔM and x represent the
particle and the LSP relative to ΔM , re

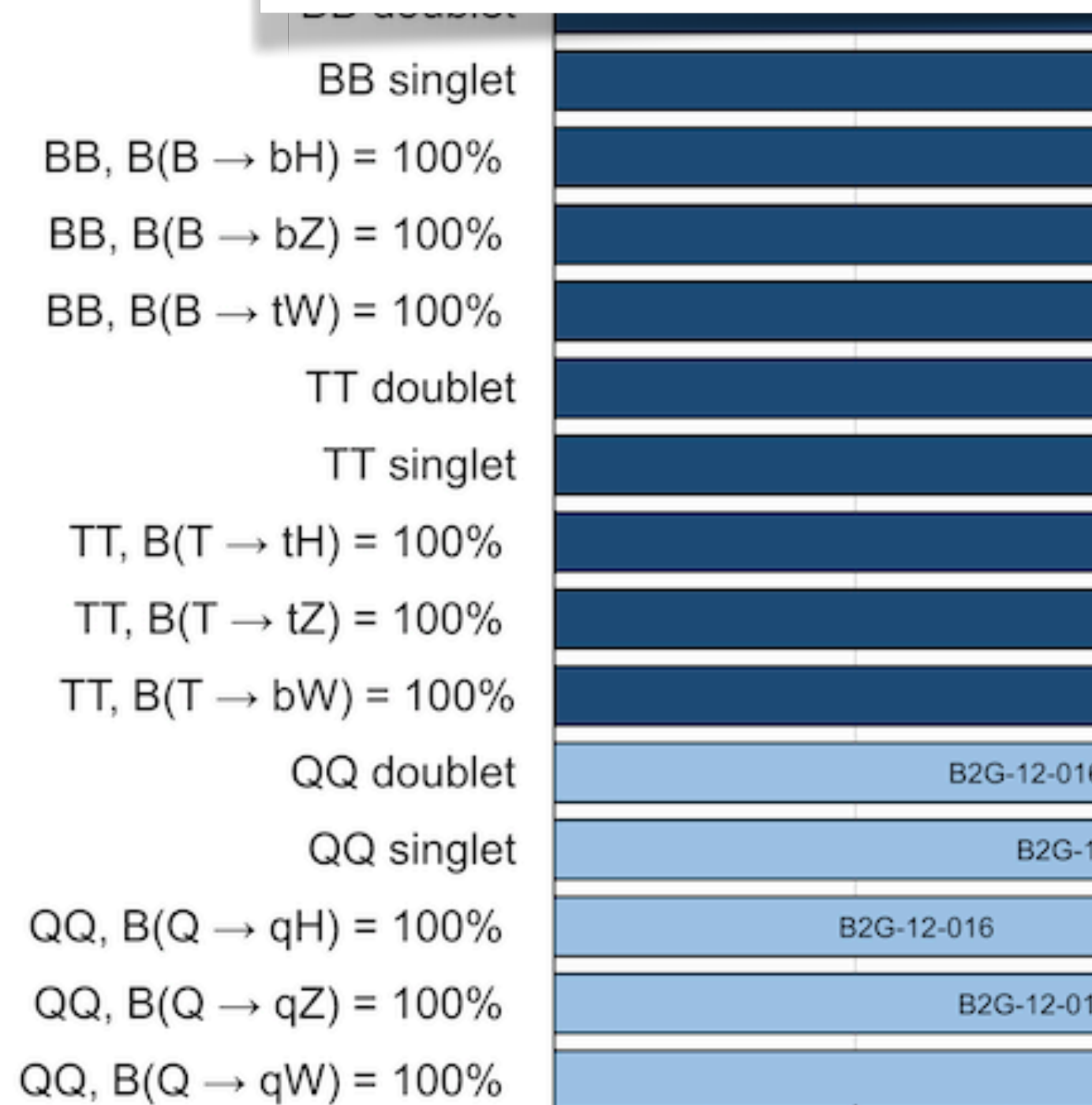
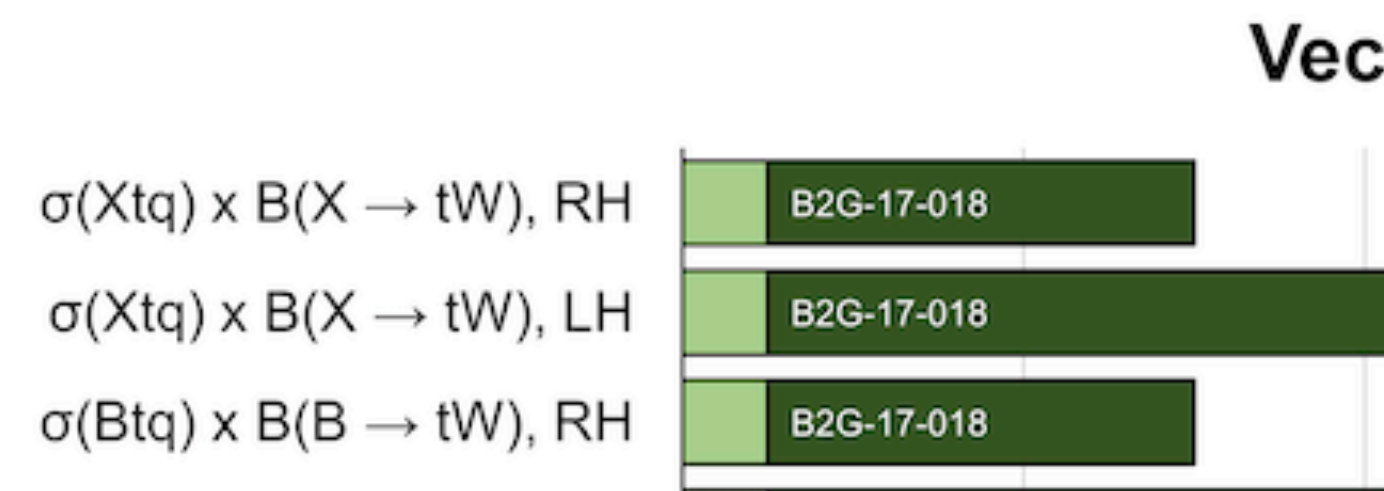
BB $\rightarrow (\ell^\pm, \ell^\pm \ell^\pm)$
BB $\rightarrow (\ell^\pm, \ell^\pm \ell^\pm)$

Resonances to dibosons ($\sqrt{s} = 13$ TeV)

CMS, EPS-HEP 2019

95% CL Lower Mass Limit [TeV]

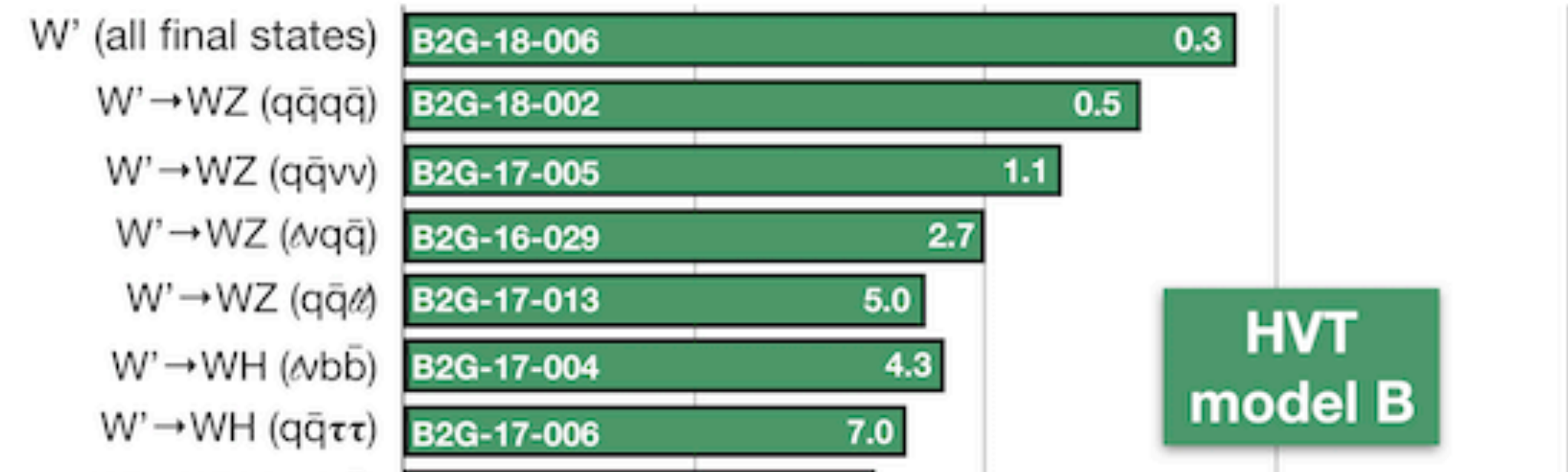
4 Upper Cross Section Limit [fb]



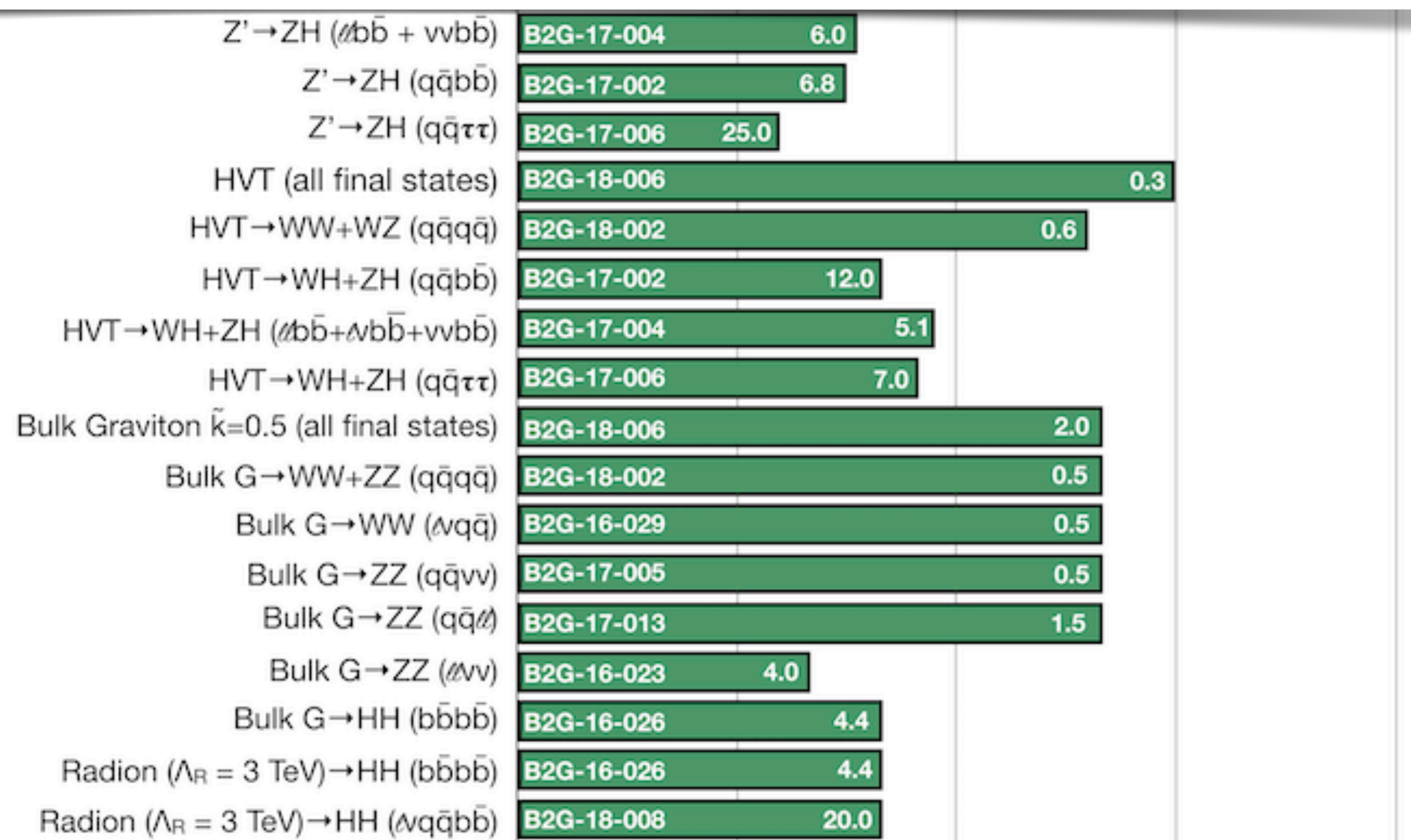
CMS, EPS-HEP 2019

Selection of observed limits at 95% C.L.
The quantities ΔM and x represent the
particle and the LSP relative to ΔM , re

BB $\rightarrow (\ell^\pm, \ell^\pm \ell^\pm)$
BB $\rightarrow (\ell^\pm, \ell^\pm \ell^\pm)$

Resonances to dibosons ($\sqrt{s} = 13$ TeV)HVT
model B

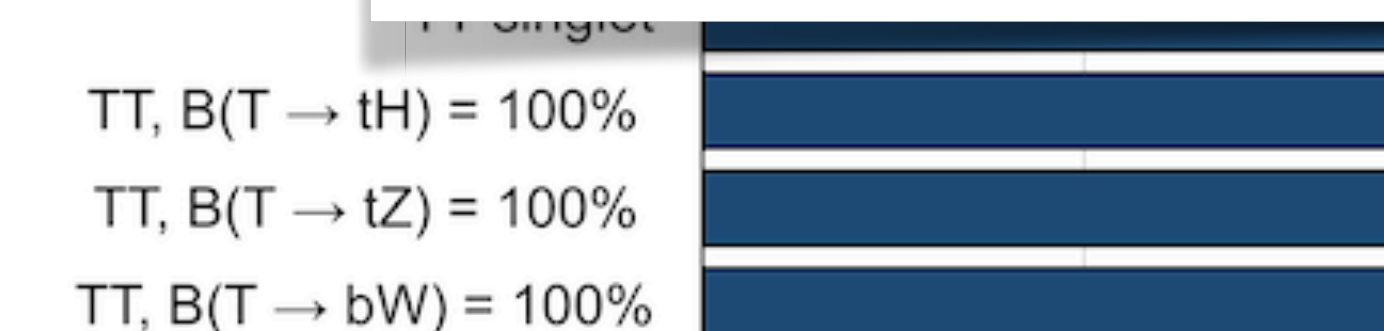
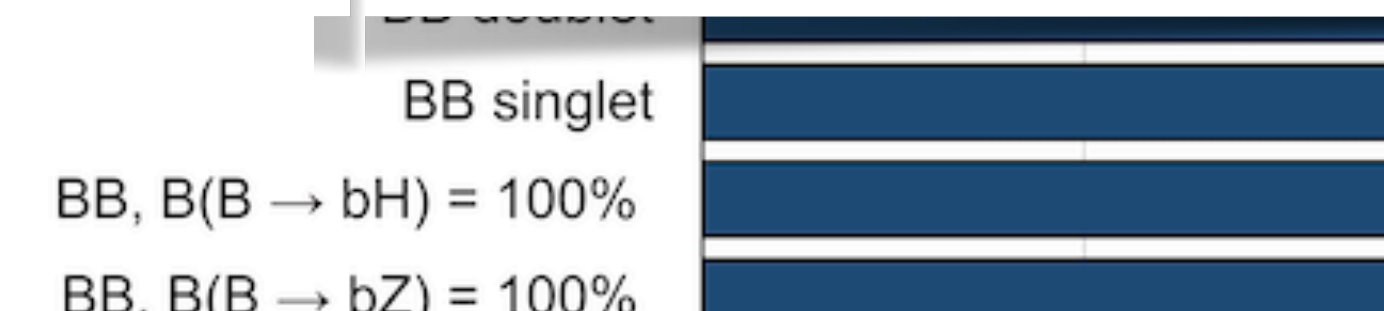
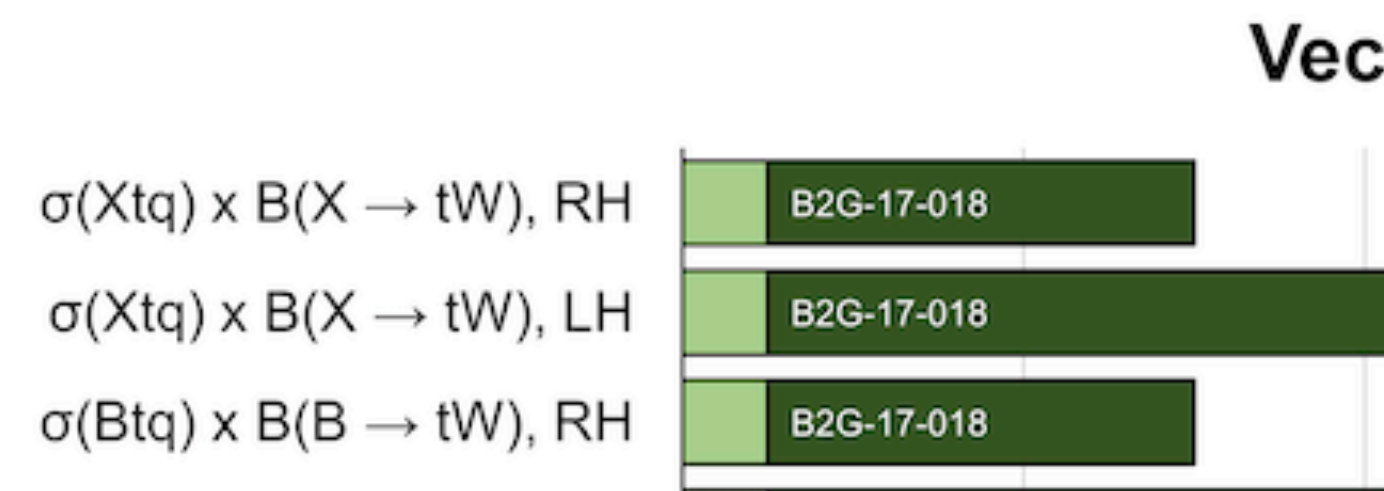
By now, hundreds (thousands?) of searches for new physics at the LHC.



CMS, EPS-HEP 2019

95% CL Lower Mass Limit [TeV]

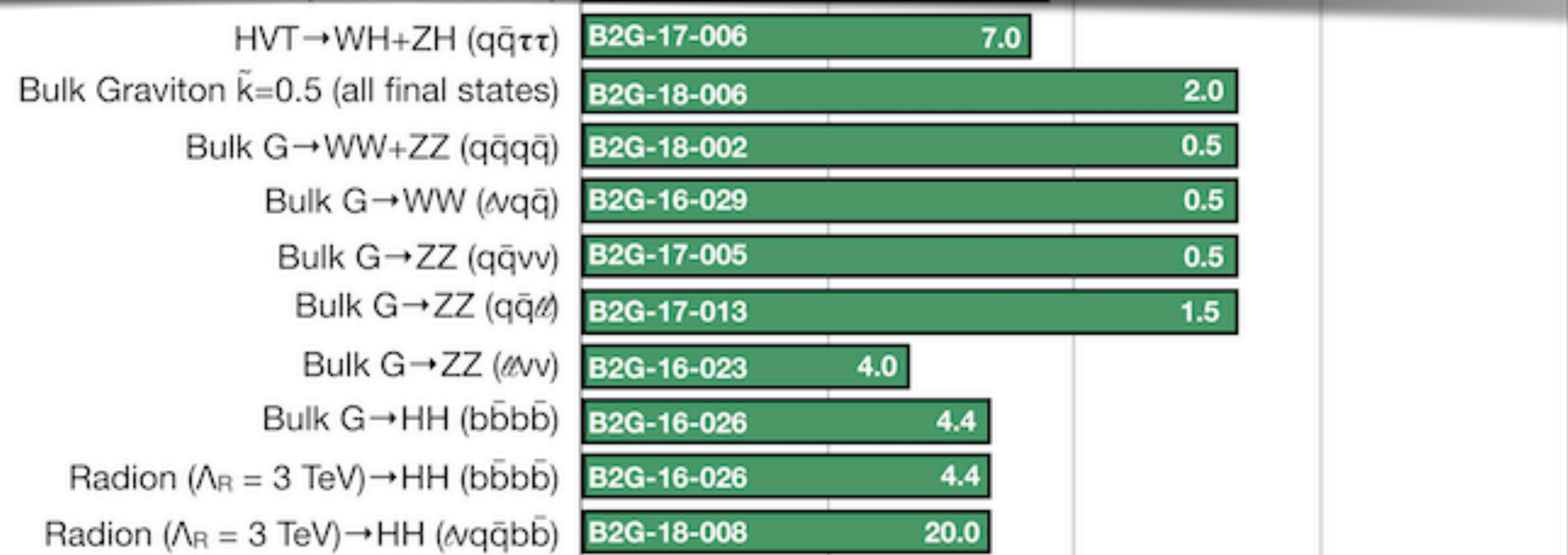
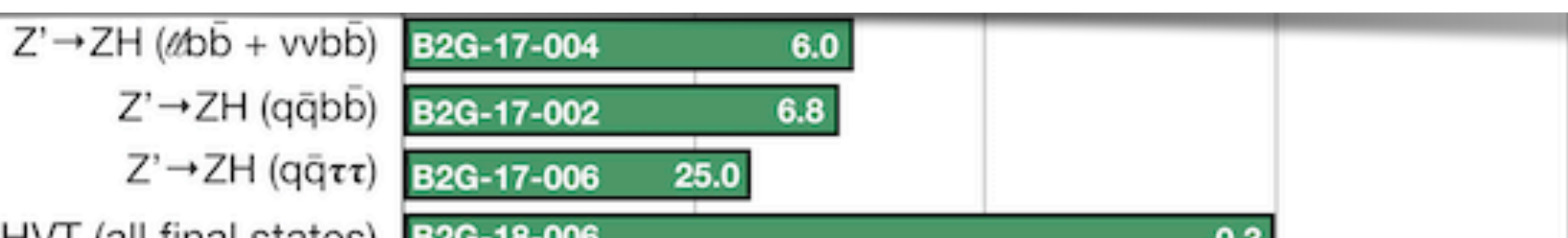
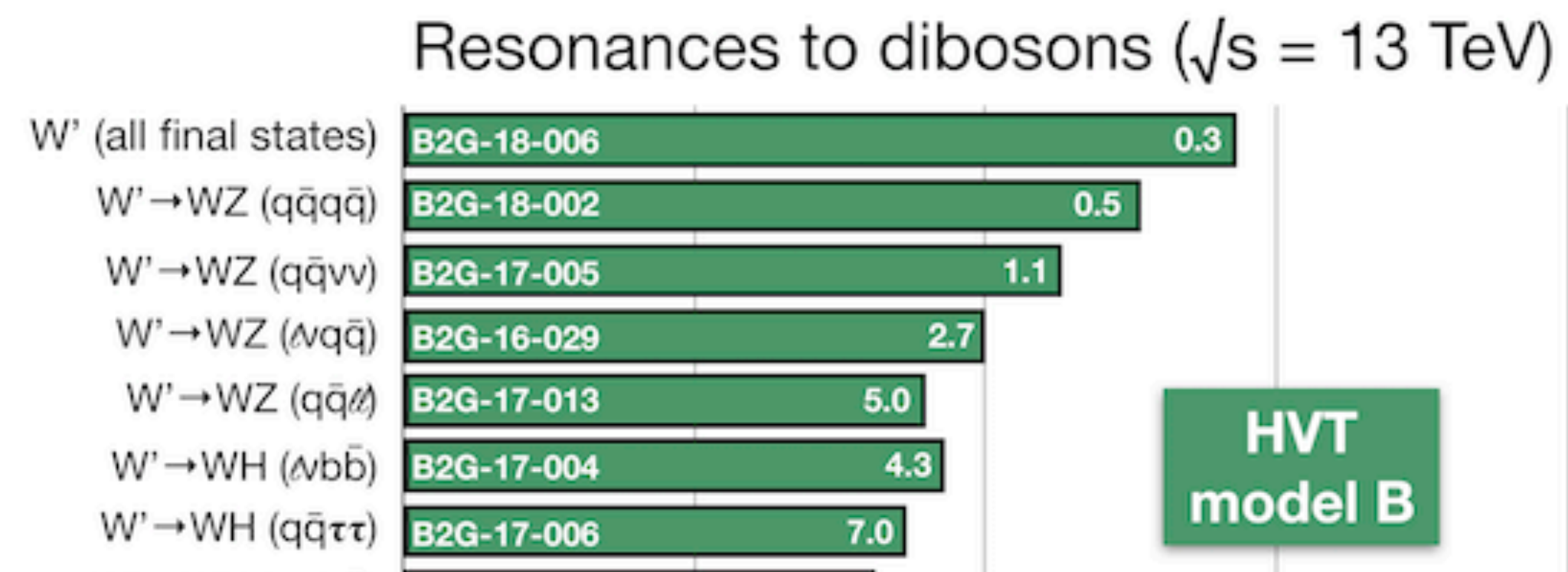
4 Upper Cross Section Limit [fb]



CMS, EPS-HEP 2019

Selection of observed limits at 95% C.L.
The quantities ΔM and x represent the
particle and the LSP relative to ΔM , re

BB→(l±, l±l±)
BB→(l±, l±l±)



CMS, EPS-HEP 2019

95% CL Lower Mass Limit [TeV]

4 Upper Cross Section Limit [fb]

By now, hundreds (thousands?) of searches for new physics at the LHC.

Is there really no new physics in the LHC data?

ML for New Physics Searches

All but a few of these LHC searches are optimized for *specific models*



ML for New Physics Searches

All but a few of these LHC searches are optimized for *specific models*

There could be vast, untapped discovery potential with *ML-powered model-agnostic searches*

ML for New Physics Searches

The LHC Olympics 2020

A Community Challenge for Anomaly
Detection in High Energy Physics



Gregor Kasieczka (ed),¹ Benjamin Nachman (ed),^{2,3} David Shih (ed),⁴ Oz Amram,⁵ Anders Andreassen,⁶ Kees Benkendorfer,^{2,7} Blaz Bortolato,⁸ Gustaaf Brooijmans,⁹ Florencia Canelli,¹⁰ Jack H. Collins,¹¹ Biwei Dai,¹² Felipe F. De Freitas,¹³ Barry M. Dillon,^{8,14} Ioan-Mihail Dinu,⁵ Zhongtian Dong,¹⁵ Julien Donini,¹⁶ Javier Duarte,¹⁷ D. A. Faroughy,¹⁰ Julia Gonski,⁹ Philip Harris,¹⁸ Alan Kahn,⁹ Jernej F. Kamenik,^{8,19} Charanjit K. Khosa,^{20,30} Patrick Komiske,²¹ Luc Le Pottier,^{2,22} Pablo Martín-Ramiro,^{2,23} Andrej Matevc,^{8,19} Eric Metodiev,²¹ Vinicius Mikuni,¹⁰ Inês Ochoa,²⁴ Sang Eon Park,¹⁸ Maurizio Pierini,²⁵ Dylan Rankin,¹⁸ Veronica Sanz,^{20,26} Nilai Sarda,²⁷ Uroš Seljak,^{2,3,12} Aleks Smolkovic,⁸ George Stein,^{2,12} Cristina Mantilla Suarez,⁵ Manuel Szwec,²⁸ Jesse Thaler,²¹ Steven Tsan,¹⁷ Silviu-Marian Udrescu,¹⁸ Louis Vaslin,¹⁶ Jean-Roch Vlimant,²⁹ Daniel Williams,⁹ Mikael Yunus¹⁸

<https://arxiv.org/abs/2101.08320>

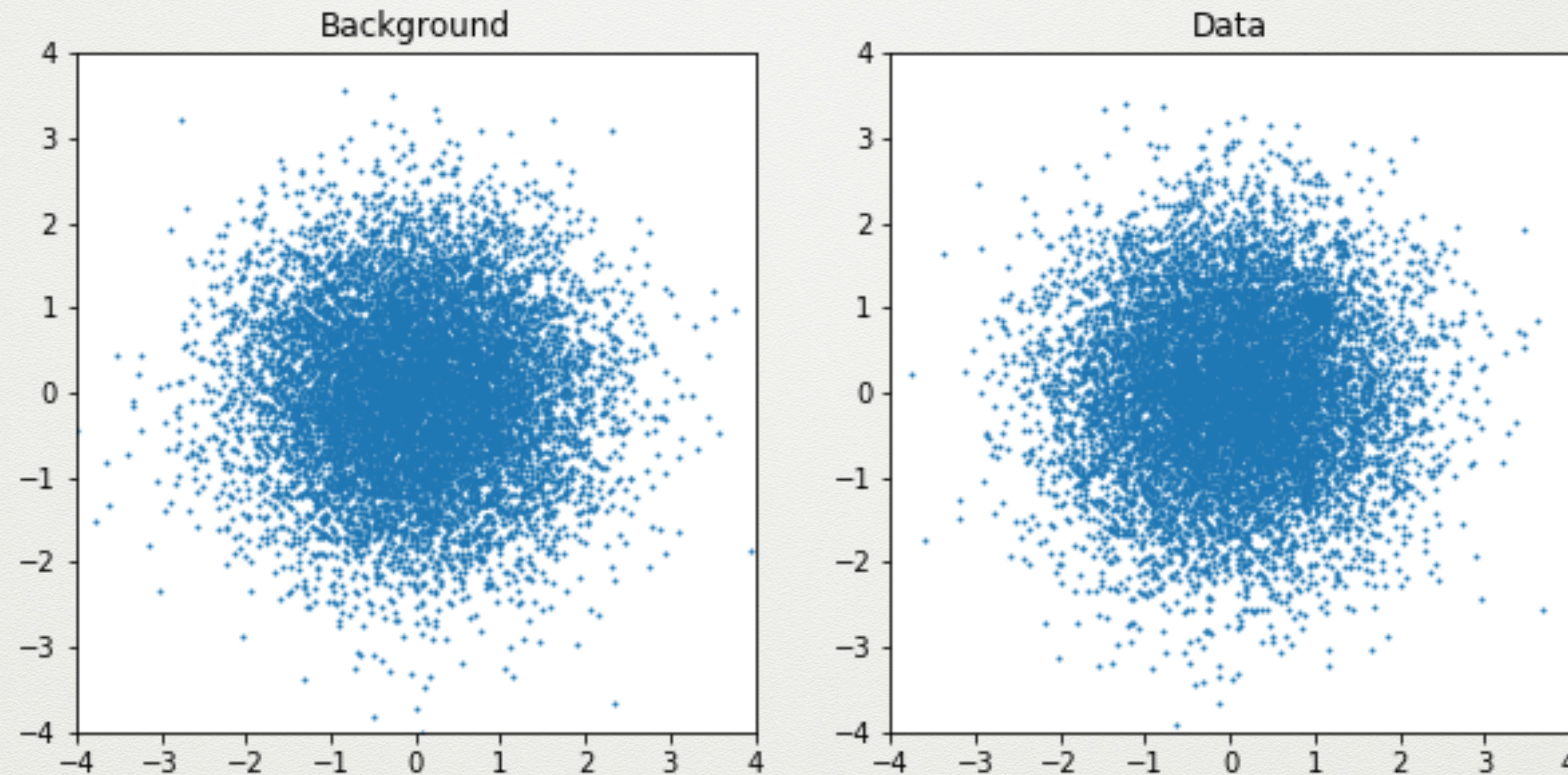
<https://arxiv.org/abs/2105.14027>

The Dark Machines Anomaly Score Challenge: Benchmark Data and Model Independent Event Classification for the Large Hadron Collider

T. Aarrestad^a M. van Beekveld^b M. Bona^c A. Boveia^e S. Caron^d J. Davies^c
A. De Simone^{f,g} C. Doglioni^h J. M. Duarteⁱ A. Farbin^j H. Gupta^k L. Hendriks^d
L. Heinrich^a J. Howarth^l P. Jawahar^{m,a} A. Jueidⁿ J. Lastow^h A. Leinweber^o
J. Mamuzic^p E. Merényi^q A. Morandini^r P. Moskvitina^d C. Nellist^d J. Ngadiuba^{s,t}
B. Ostdiek^{u,v} M. Pierini^a B. Ravina^l R. Ruiz de Austri^p S. Sekmen^w
M. Touranakou^{x,a} M. Vaškevičiūtė^l R. Vilalta^y J.-R. Vlimant^t R. Verheyen^z
M. White^o E. Wulff^h E. Wallin^h K.A. Wozniak^{α,a} Z. Zhang^d

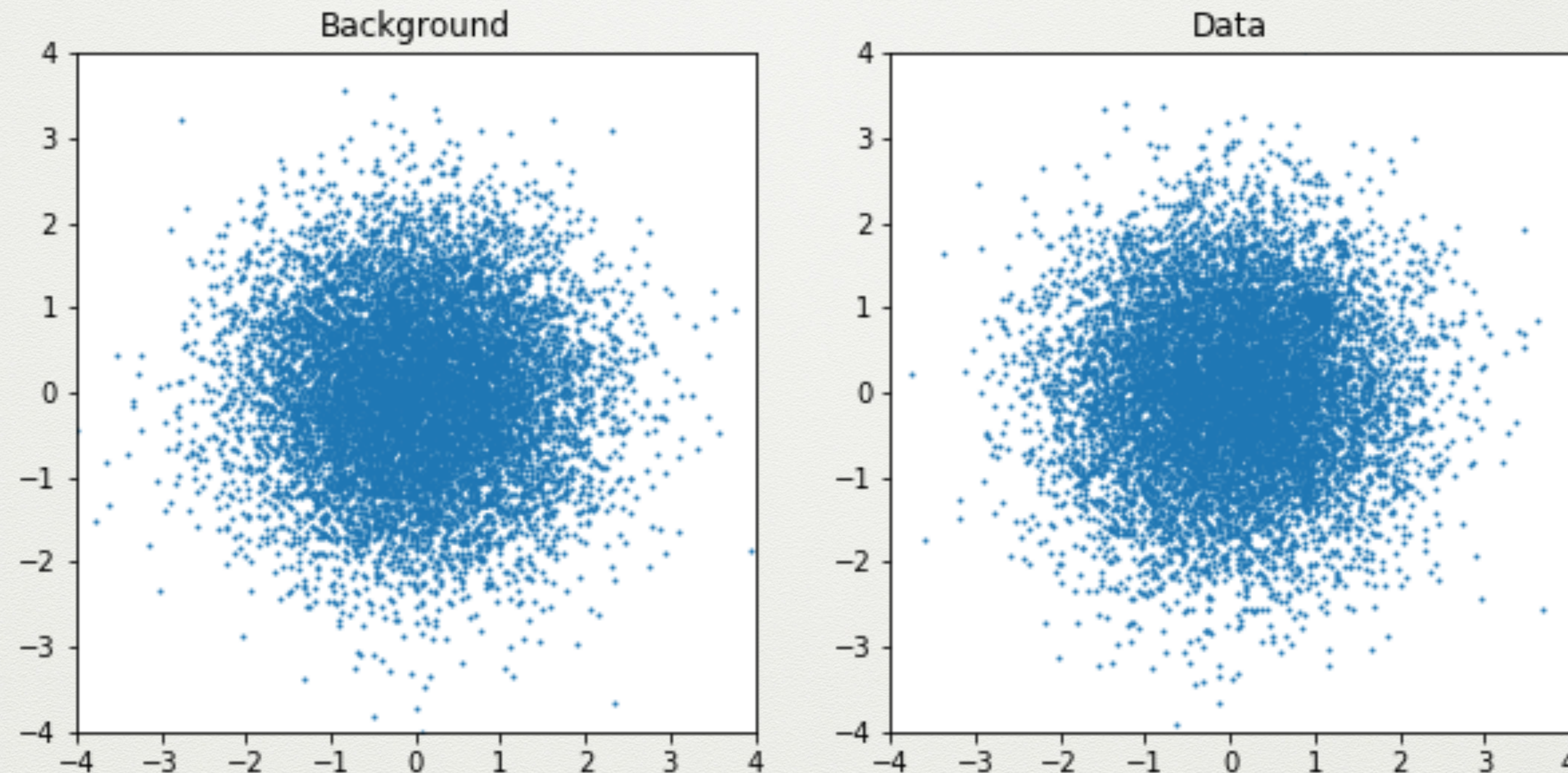
A lot of new ideas for model-agnostic searches!

A simple toy model



There are 200 anomalous events here (out of 10,000), can you spot them?

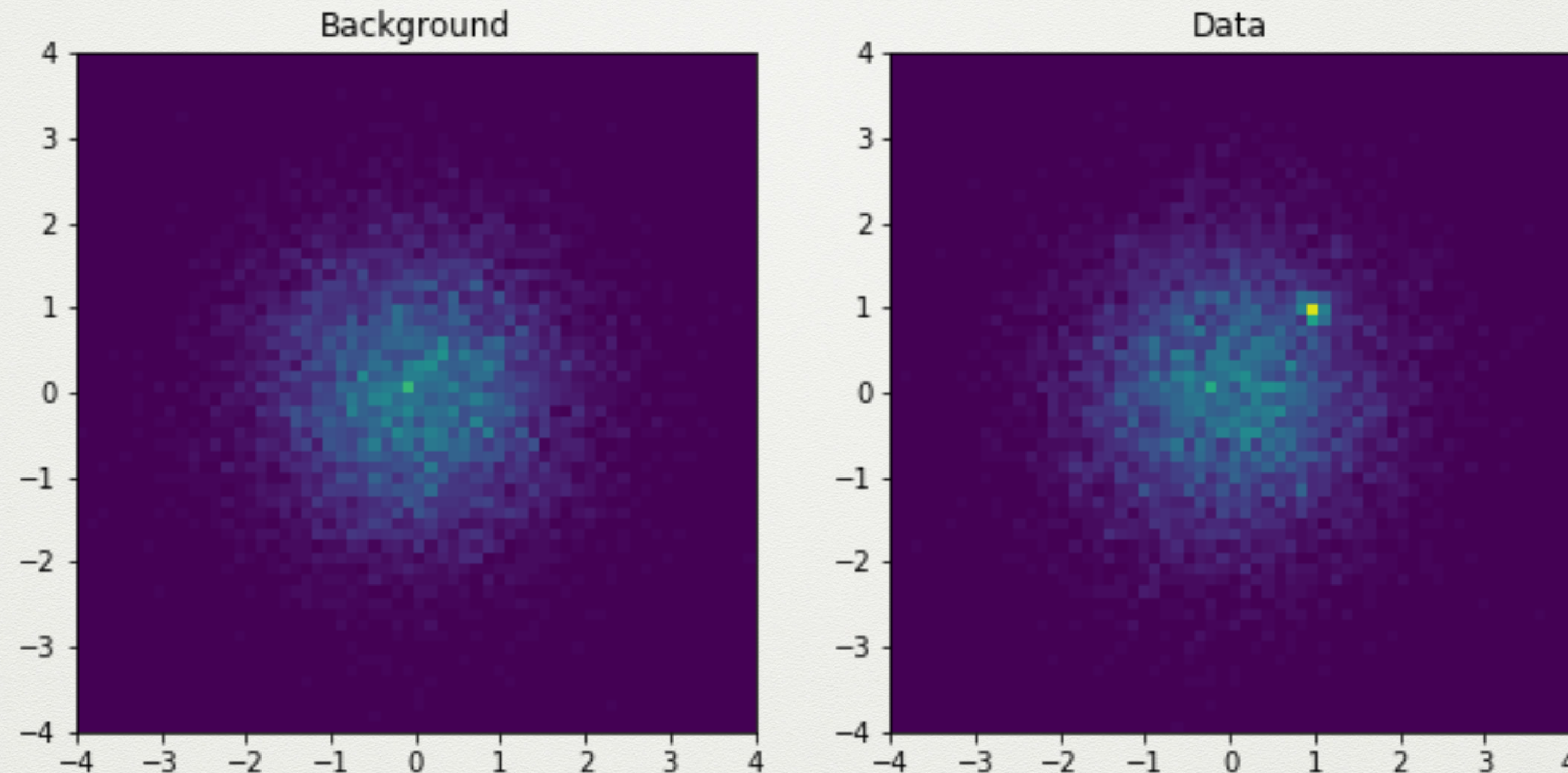
A simple toy model



There are 200 anomalous events here (out of 10,000), can you spot them?

Try: 2d histogram (simple form of density estimation)

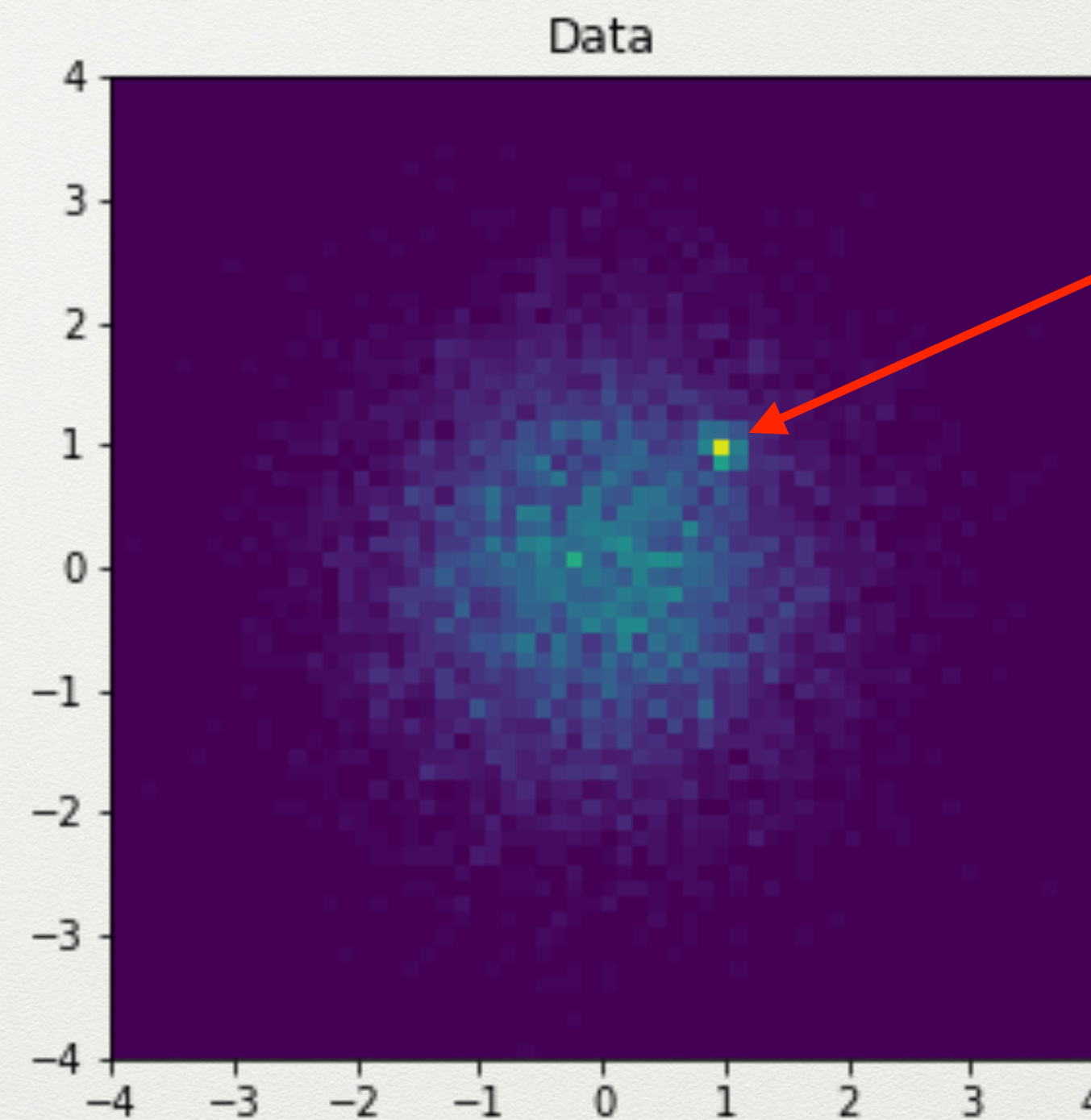
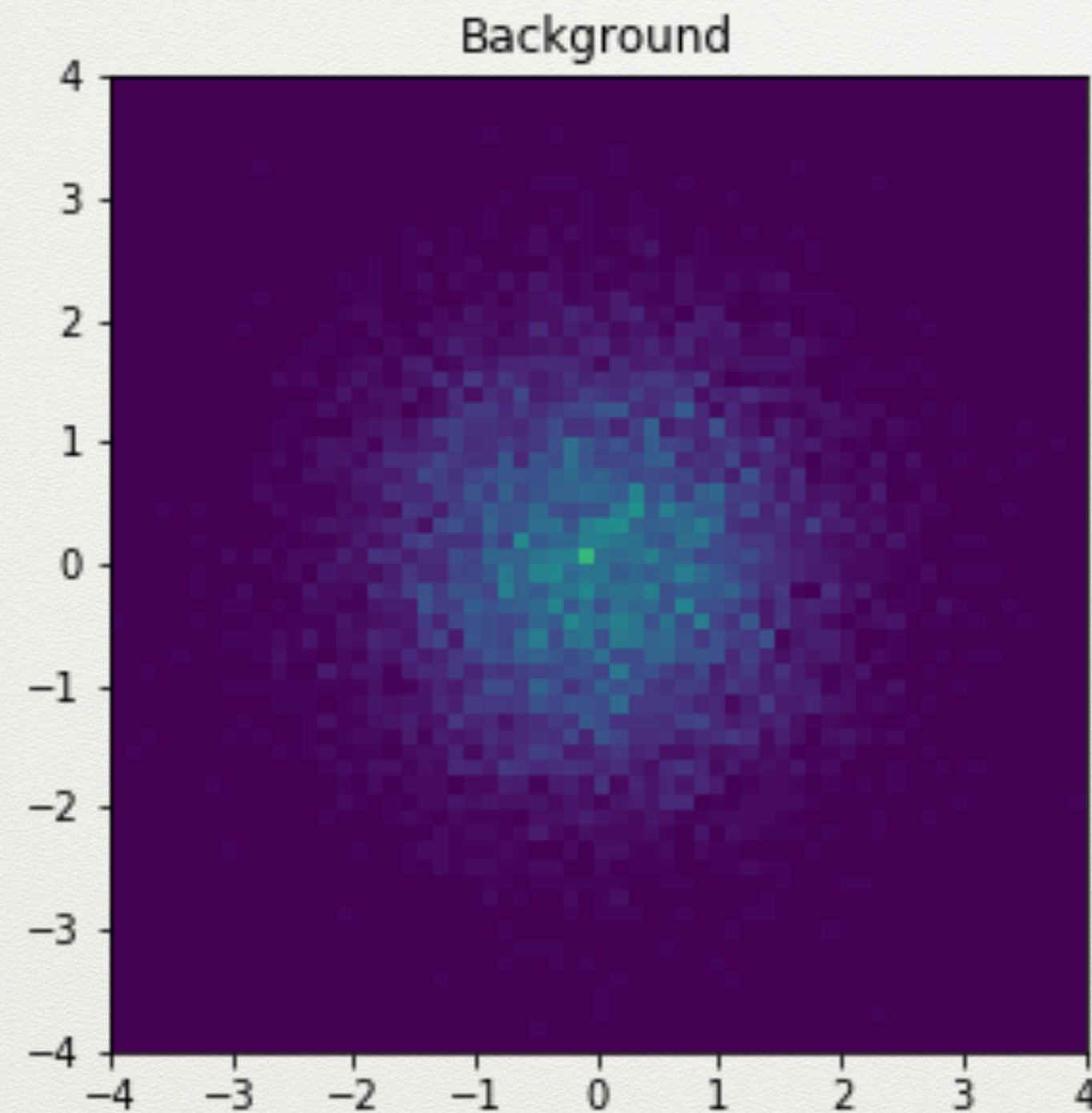
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A simple toy model

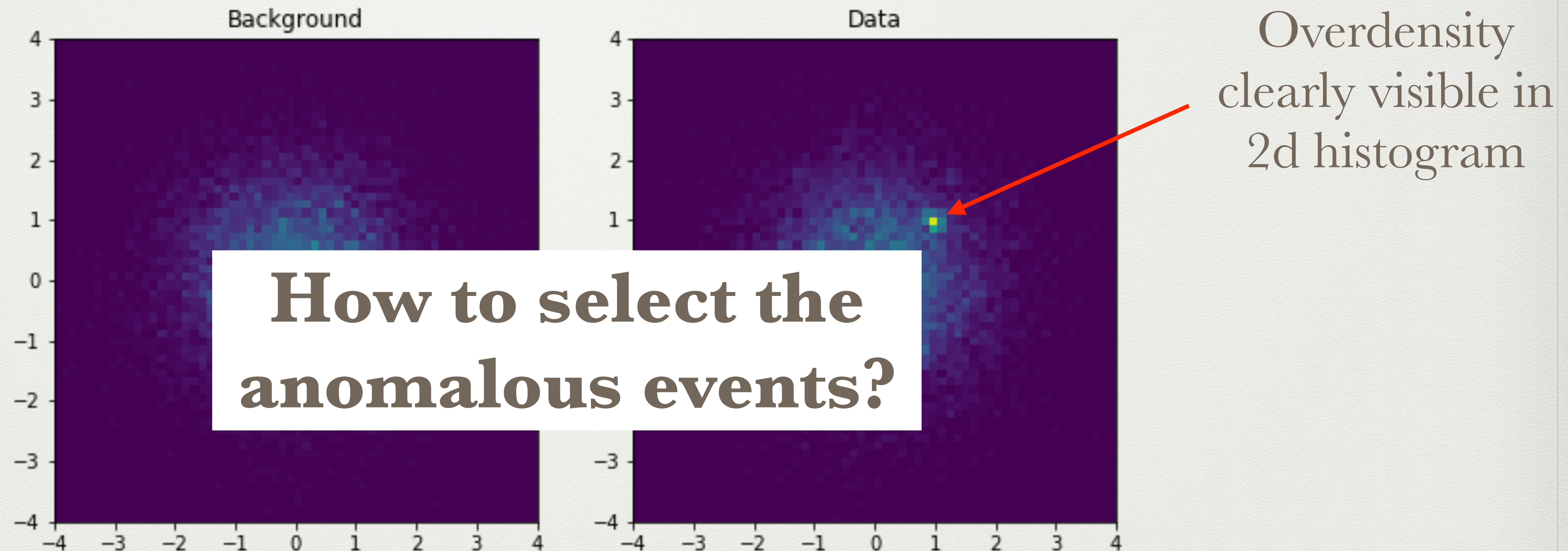


Overdensity
clearly visible in
2d histogram

There are 200 anomalous events here (out of 10,000), can you spot them?

Try: 2d histogram (simple form of density estimation)

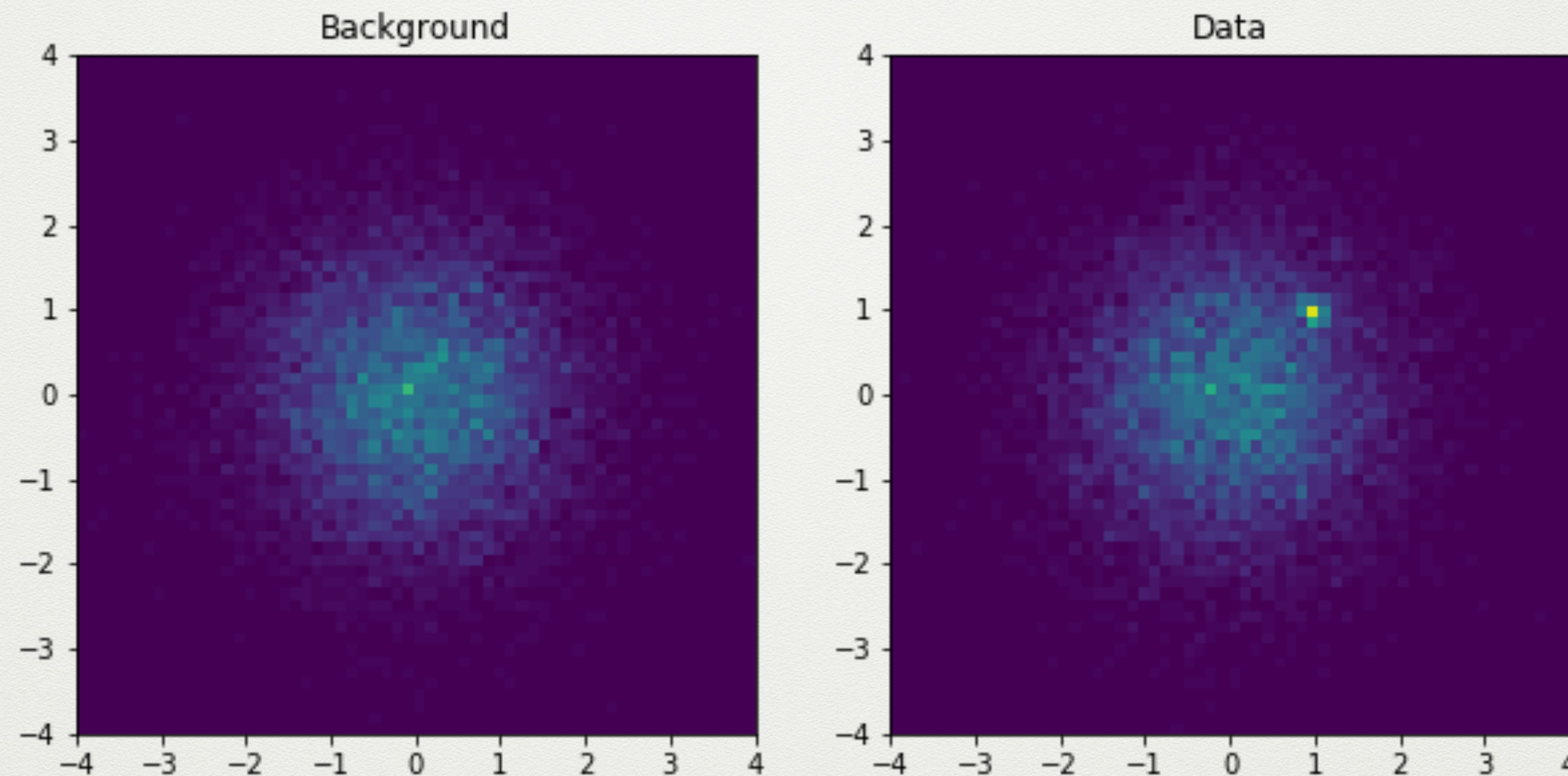
A simple toy model



There are 200 anomalous events here (out of 10,000), can you spot them?

Try: 2d histogram (simple form of density estimation)

The Anomaly Score



Idea: select events using “**anomaly score**” $R(x) = \frac{p_{data}(x)}{p_{bg}(x)}$

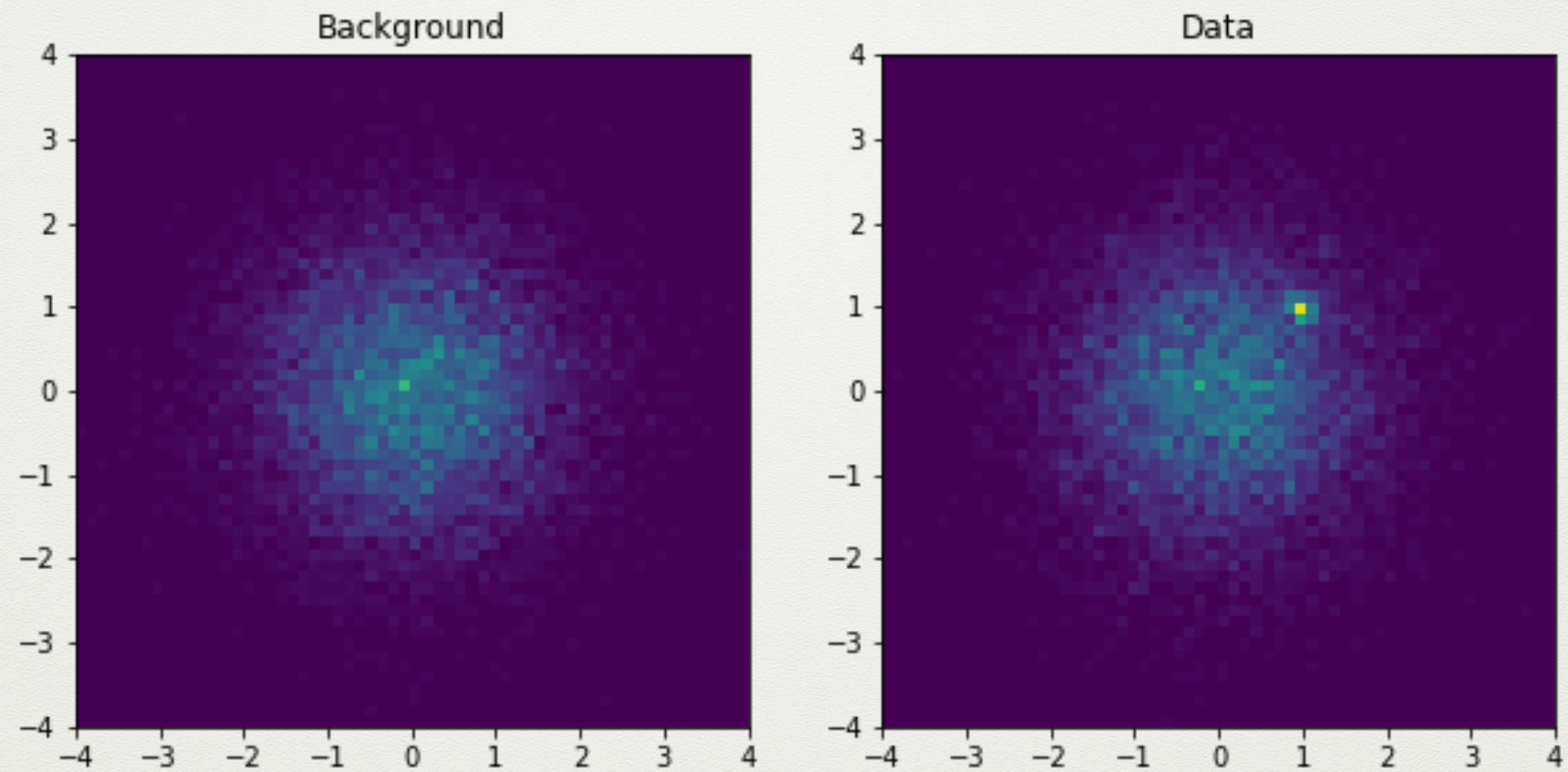
This is actually Neyman-Pearson optimal for any, unknown signal!

$$p_{data}(x) = (1 - \epsilon)p_{bg}(x) + \epsilon p_{sig}(x)$$

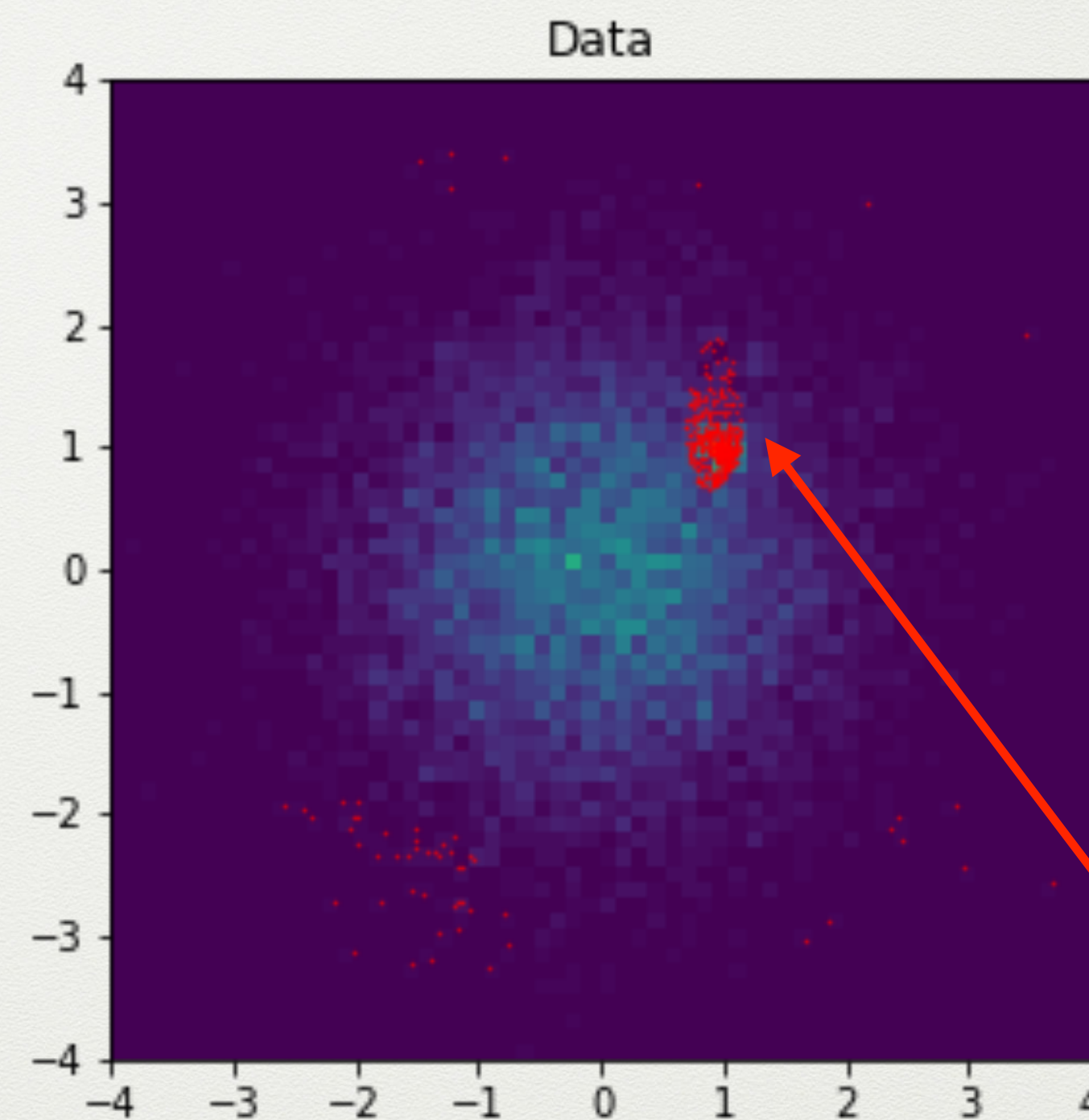
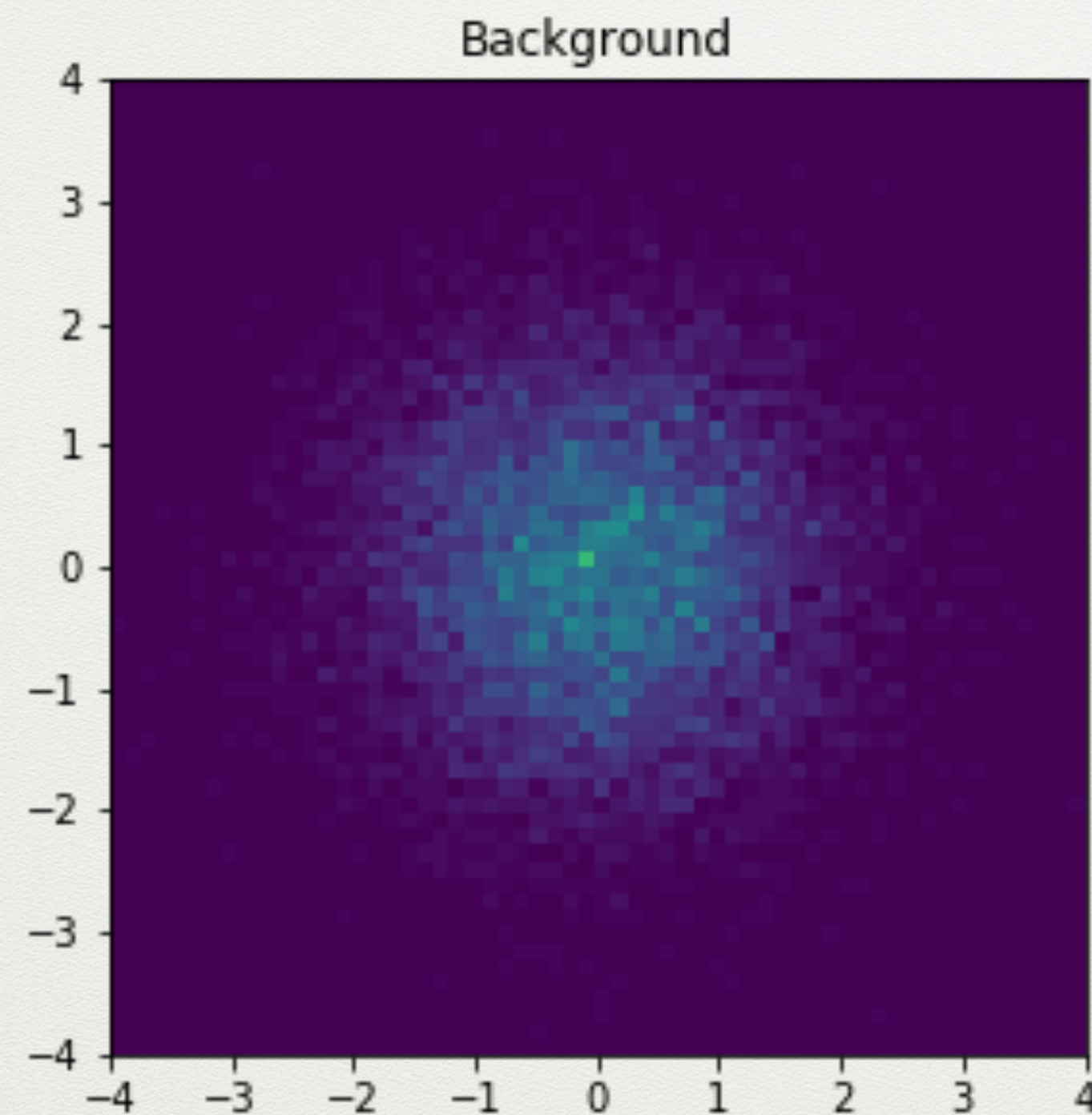
Two approaches to estimating $R(x)$

1. **Direct density estimation**: train density estimators on data and background samples to learn $p_{data}(x)$ and $p_{bg}(x)$
2. **Likelihood ratio trick**: train a binary classifier on data vs. background samples to learn $R(x) = \frac{p_{data}(x)}{p_{bg}(x)}$ **Neyman-Pearson lemma**

Anomaly score in action



Anomaly score in action



events with $R(x) > 1.2$
(density estimation method
with Gaussian mixture models)

How to evaluate performance?

After cut on $R(x)$,

How to evaluate performance?

After cut on $R(x)$,

$$N_{sig} \rightarrow \epsilon_S N_{sig}, \quad N_{bg} \rightarrow \epsilon_B N_{bg}$$

How to evaluate performance?

After cut on $R(x)$,

$$N_{sig} \rightarrow \epsilon_S N_{sig}, \quad N_{bg} \rightarrow \epsilon_B N_{bg}$$

$$S = \frac{N_{sig}}{\sqrt{N_{bg}}}$$

Original significance

How to evaluate performance?

After cut on $R(x)$,

$$N_{sig} \rightarrow \epsilon_S N_{sig}, \quad N_{bg} \rightarrow \epsilon_B N_{bg}$$

$$S = \frac{N_{sig}}{\sqrt{N_{bg}}} \rightarrow \frac{\epsilon_S}{\sqrt{\epsilon_B}} \frac{N_{sig}}{\sqrt{N_{bg}}}$$

Original significance

Enhanced significance

How to evaluate performance?

After cut on $R(x)$,

$$N_{sig} \rightarrow \epsilon_S N_{sig}, \quad N_{bg} \rightarrow \epsilon_B N_{bg}$$

$$S = \frac{N_{sig}}{\sqrt{N_{bg}}} \rightarrow \frac{\epsilon_S}{\sqrt{\epsilon_B}} \frac{N_{sig}}{\sqrt{N_{bg}}}$$

Original significance

Enhanced significance

“Significance improvement factor”

How to evaluate performance?

After cut on $R(x)$,

$$N_{sig} \rightarrow \epsilon_S N_{sig}, \quad N_{bg} \rightarrow \epsilon_B N_{bg}$$

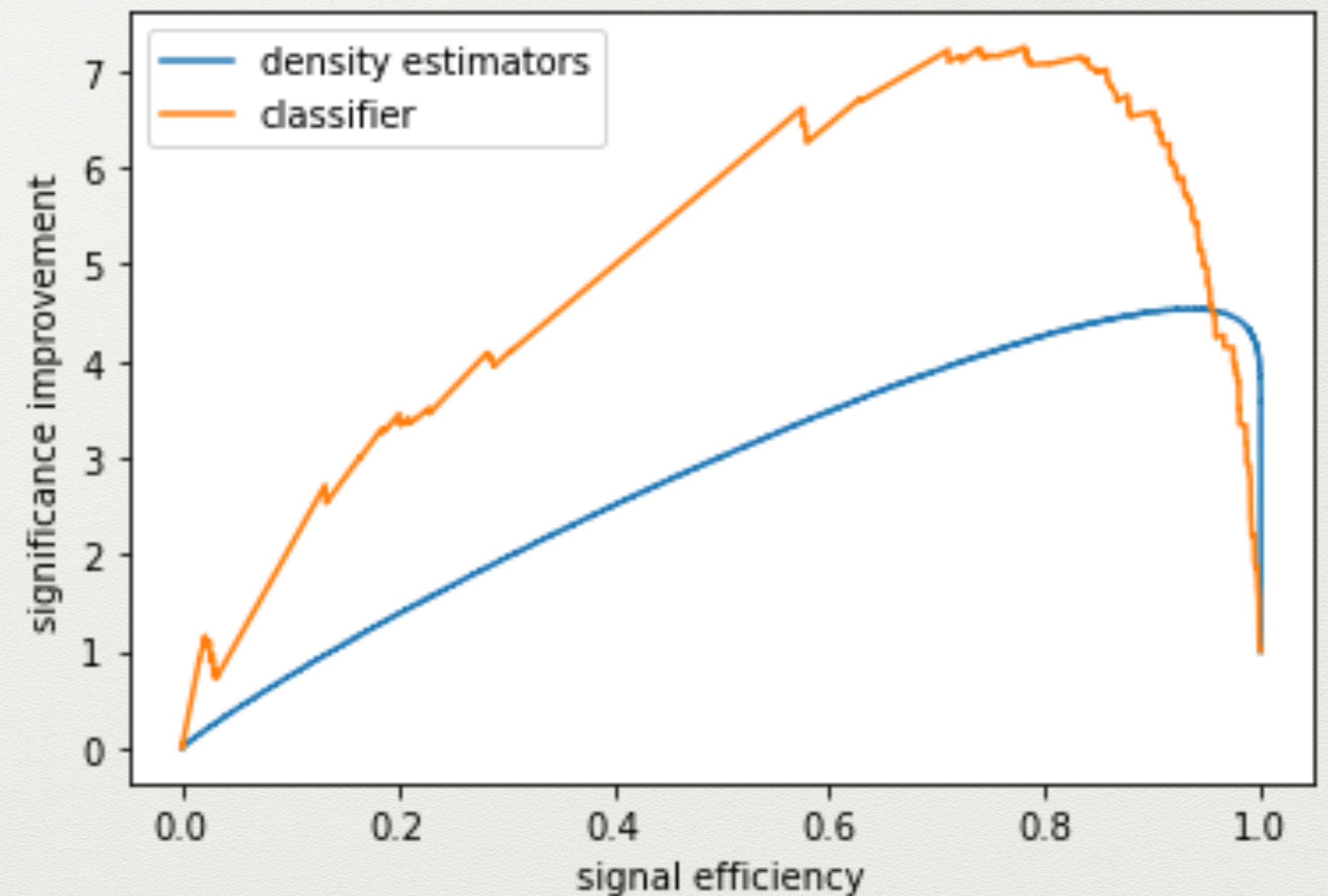
$$S = \frac{N_{sig}}{\sqrt{N_{bg}}} \rightarrow \frac{\epsilon_S}{\sqrt{\epsilon_B}} \frac{N_{sig}}{\sqrt{N_{bg}}}$$

Original significance

Enhanced significance

“Significance improvement factor”

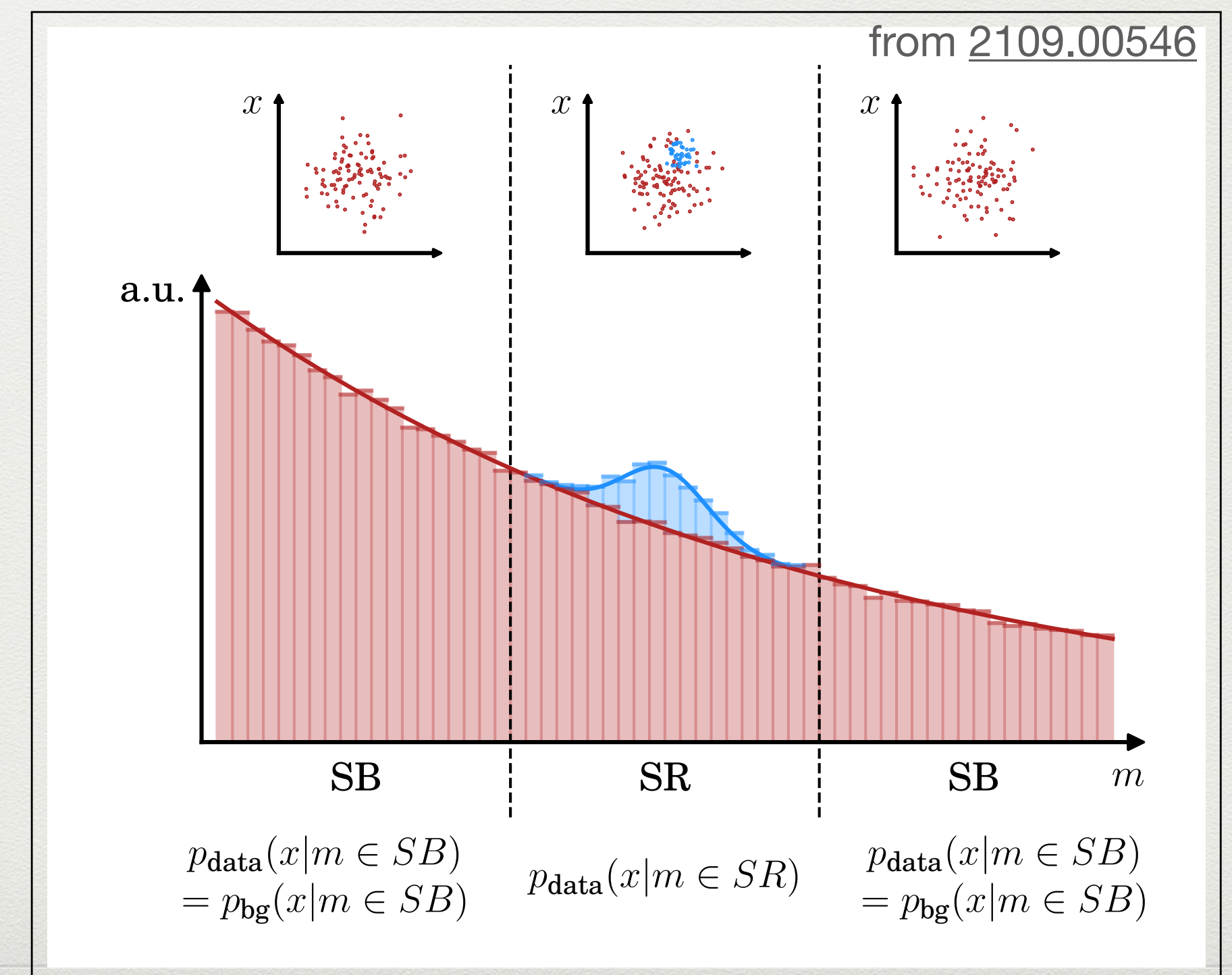
Initial 2σ significance can be enhanced over $\sim 7x$ in the toy example!



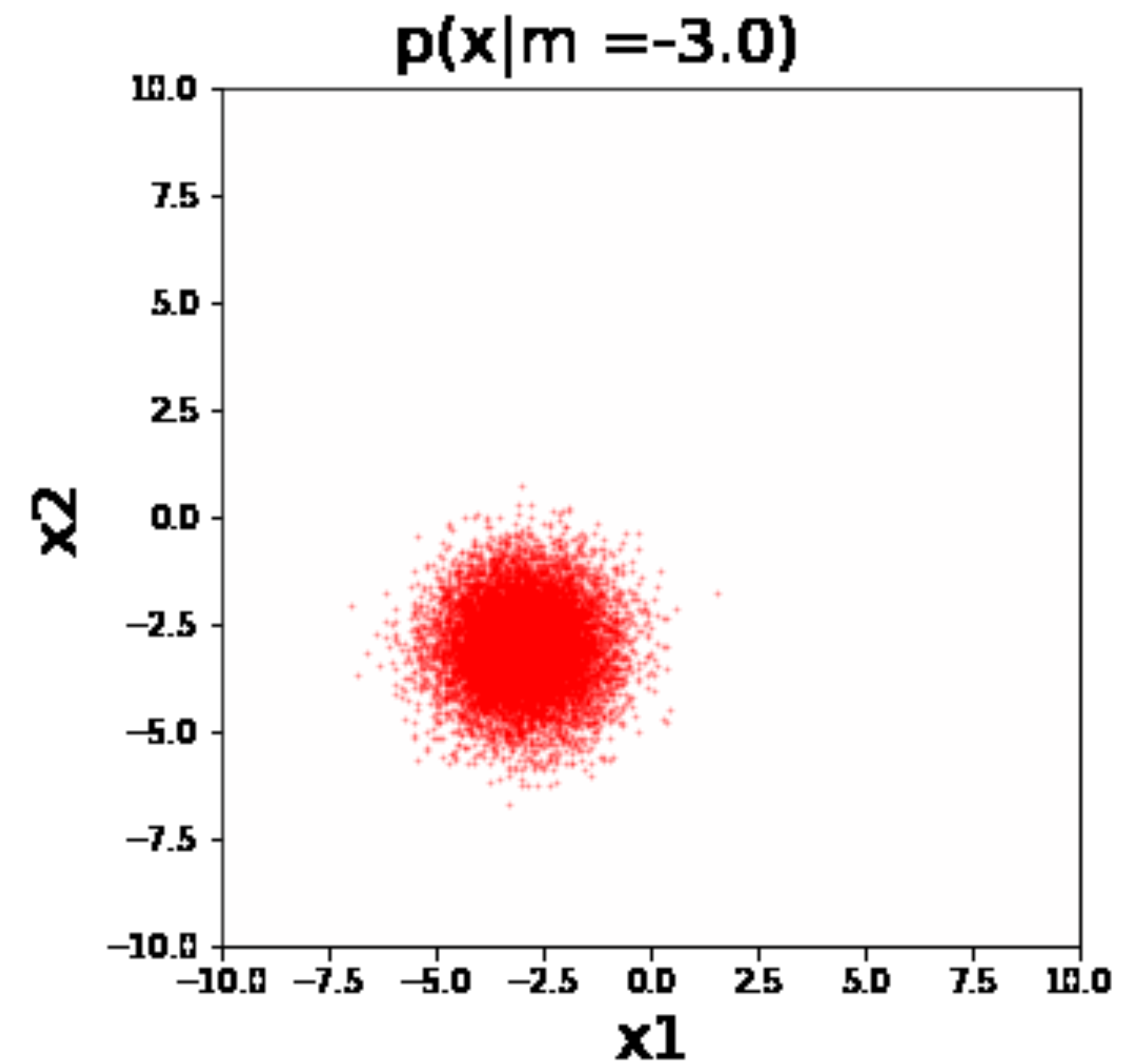
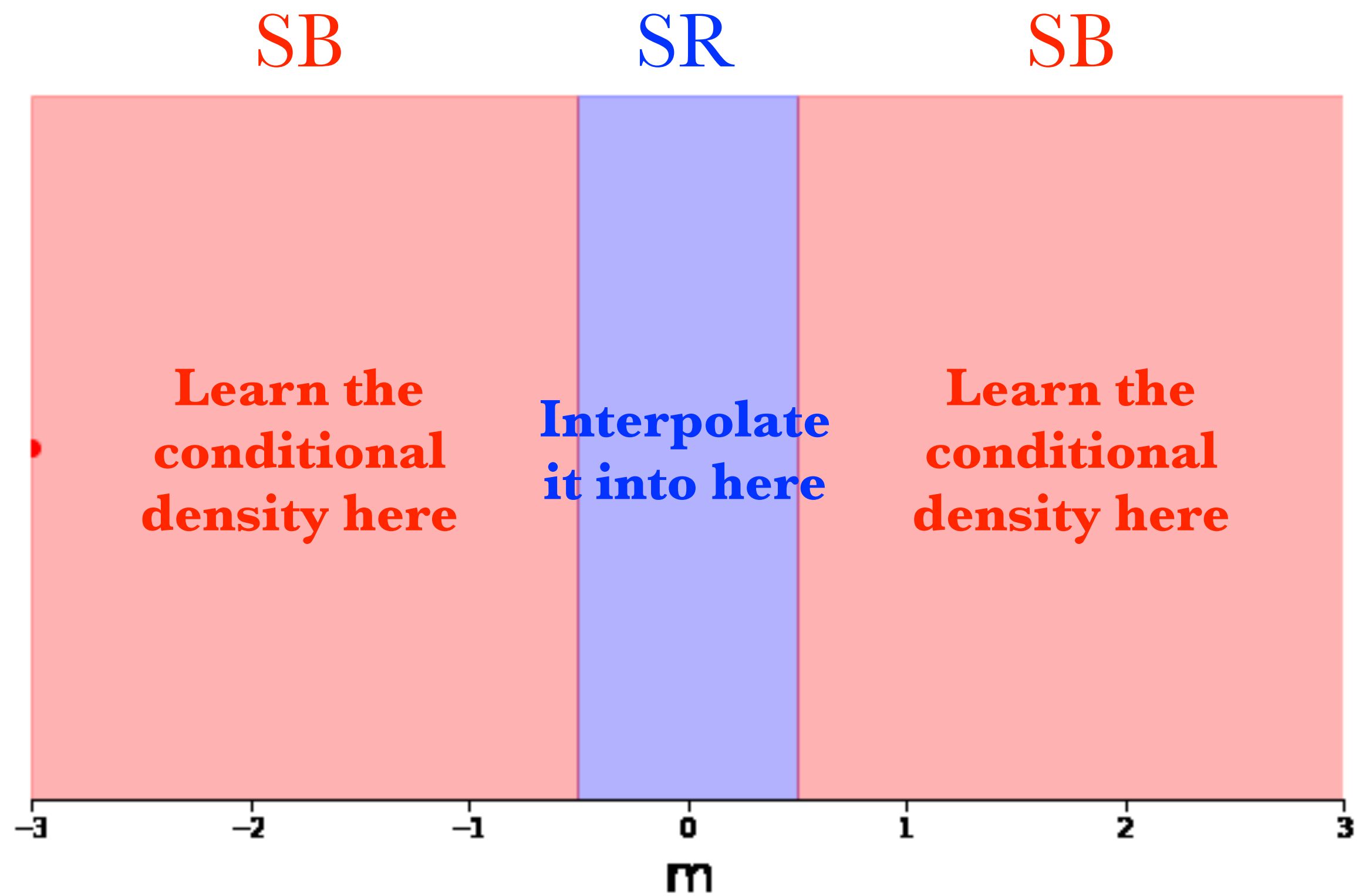
Resonant Anomaly Detection

- In practice, don't have access to perfect background samples. Need **simulation** or **data-driven control regions**
- **One successful strategy:** build on the classic “bump hunt”
 - assume signal is localized in some feature m
 - learn background in **sidebands**
 - **interpolate** this to approximate background in signal region

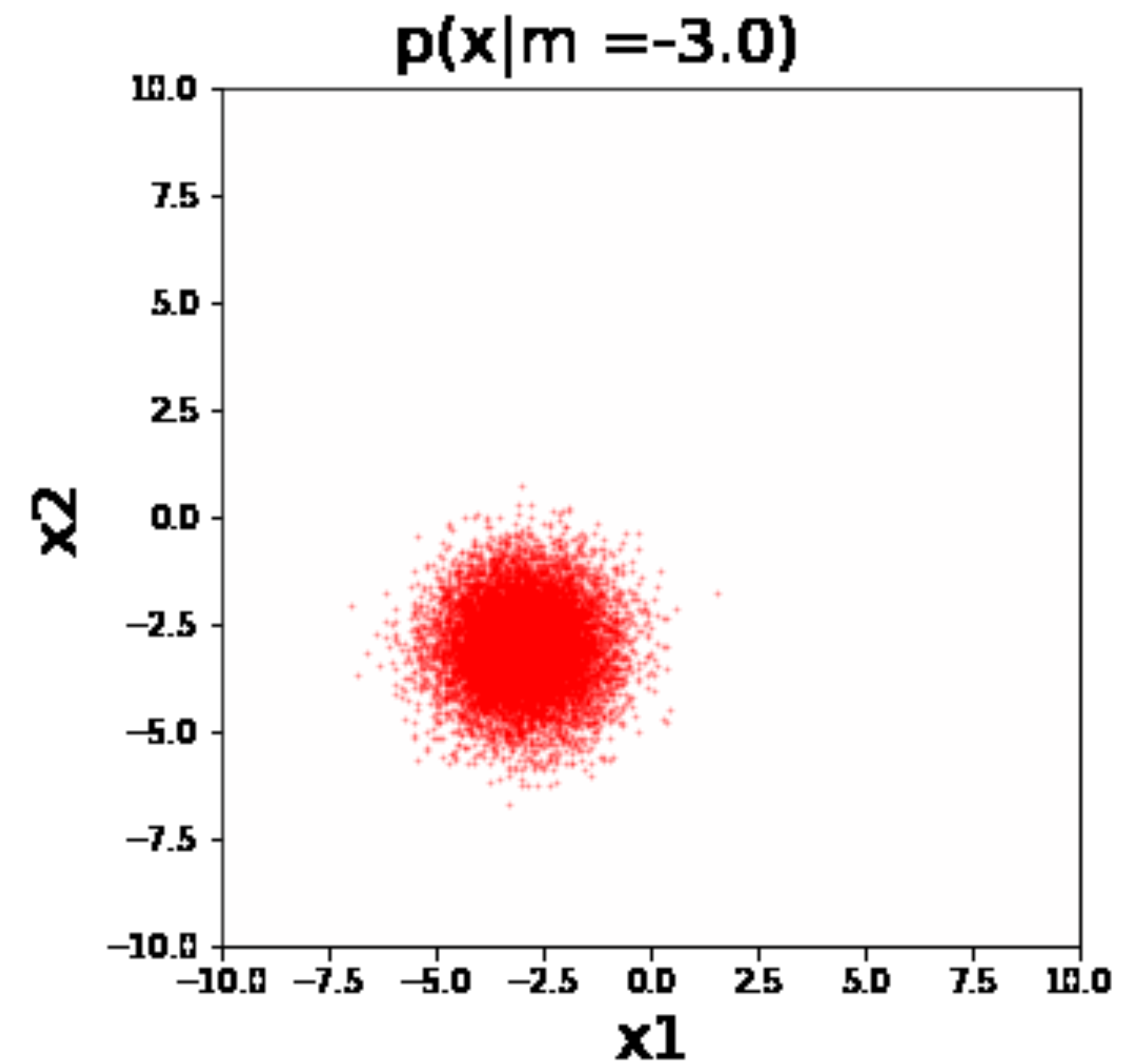
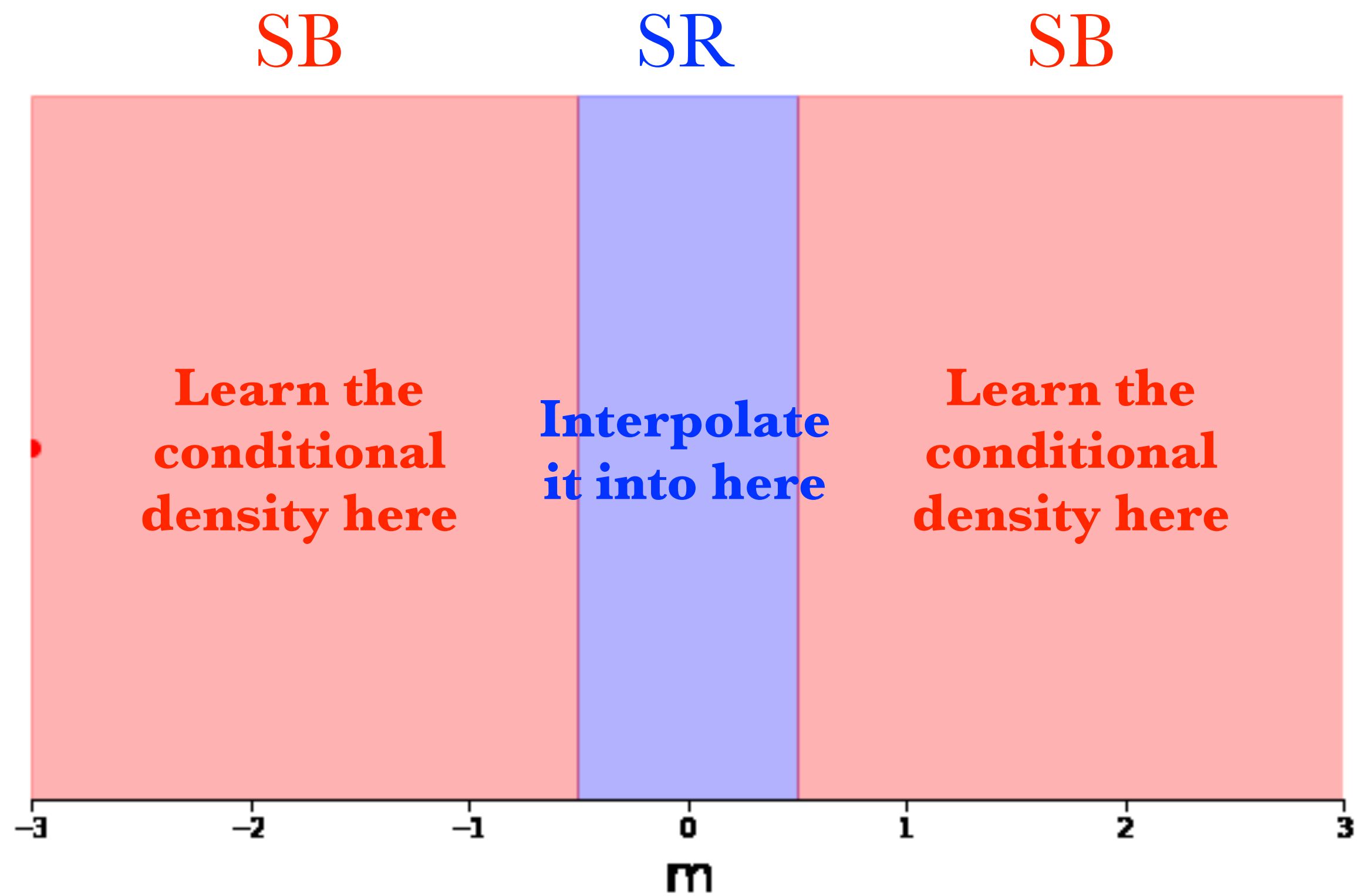
$$p_{bg}(x | m \in SB) \rightarrow p_{bg}(x | m \in SR)$$



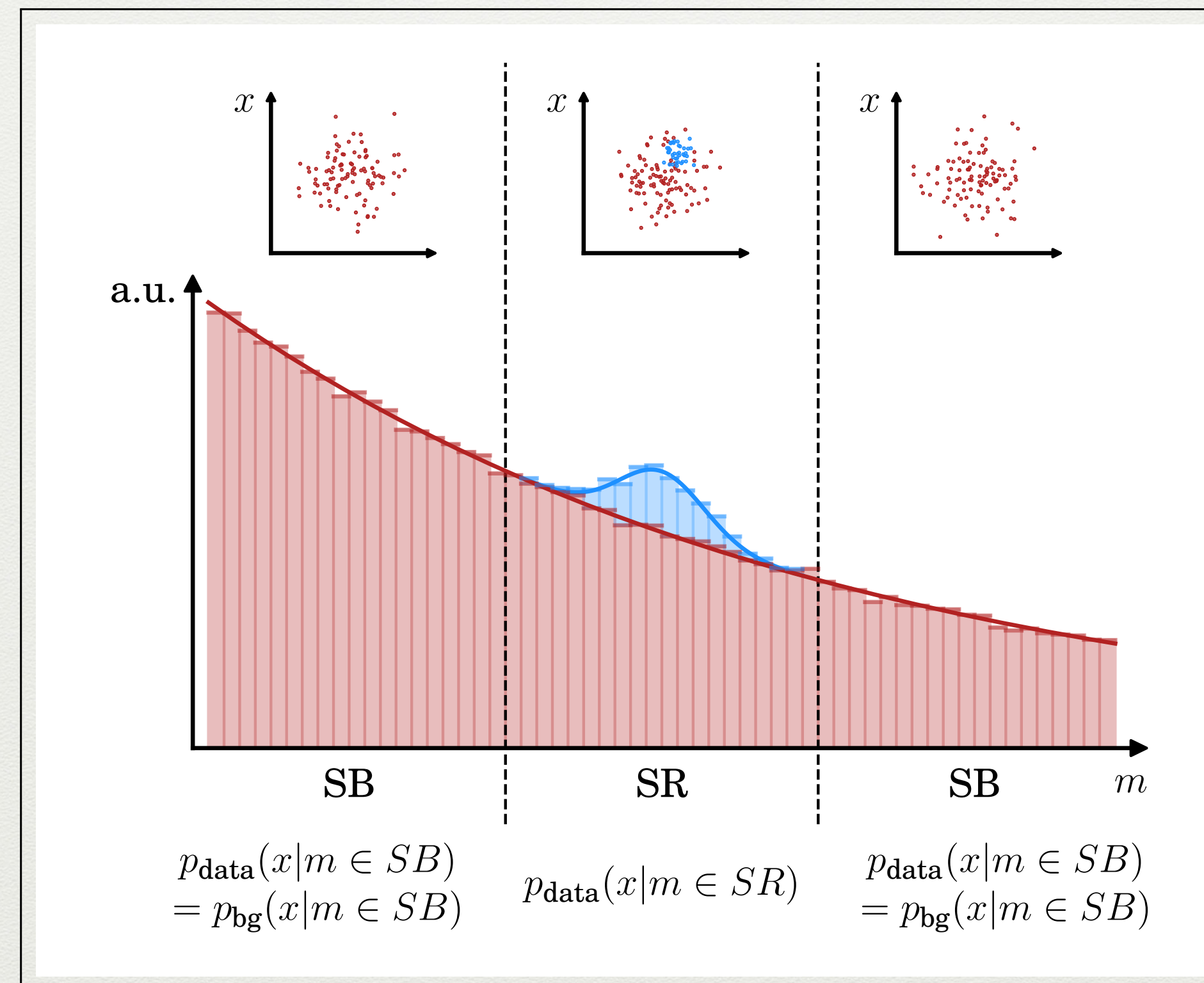
Interpolating the toy model



Interpolating the toy model



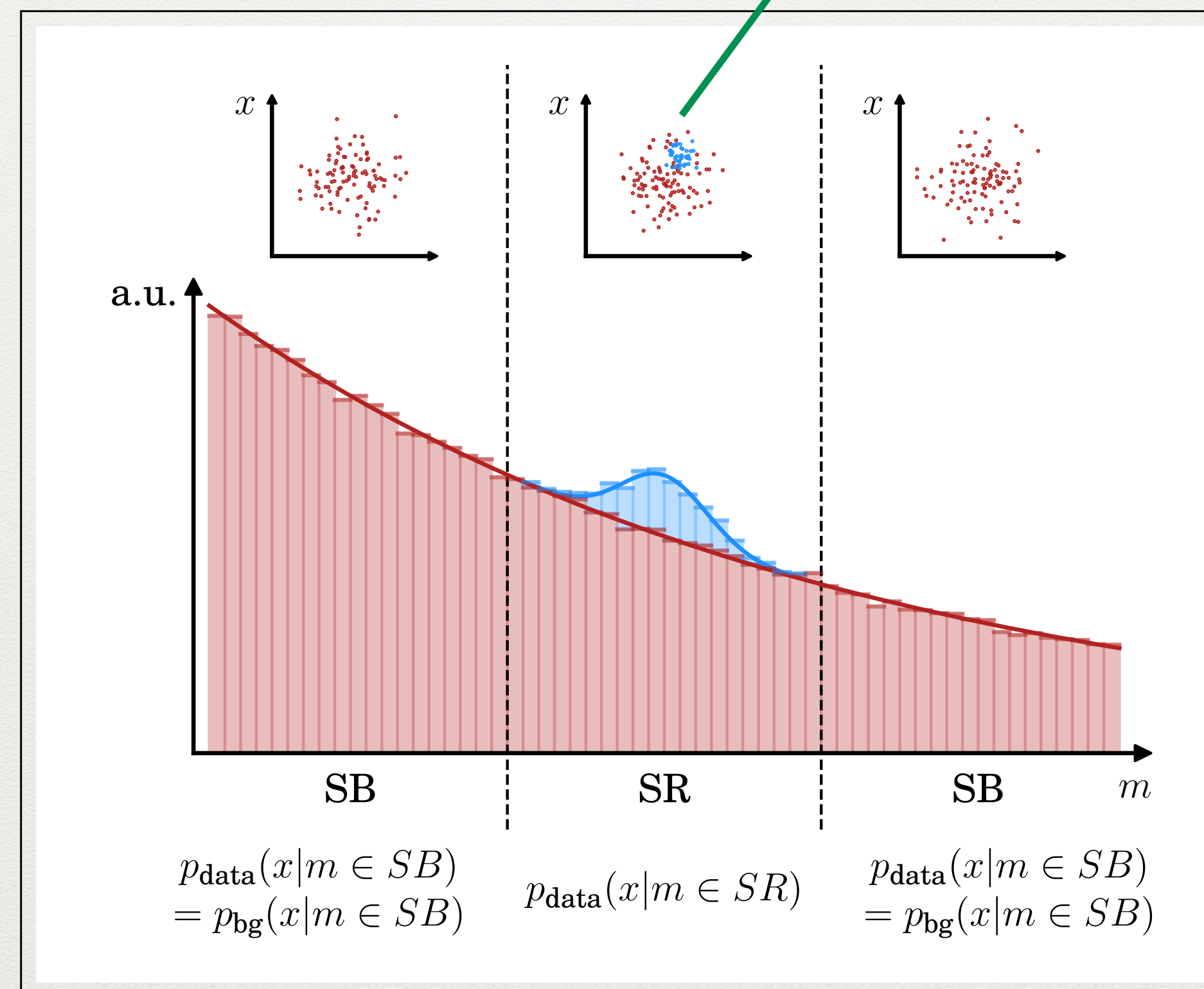
Resonant Anomaly Detection Methods



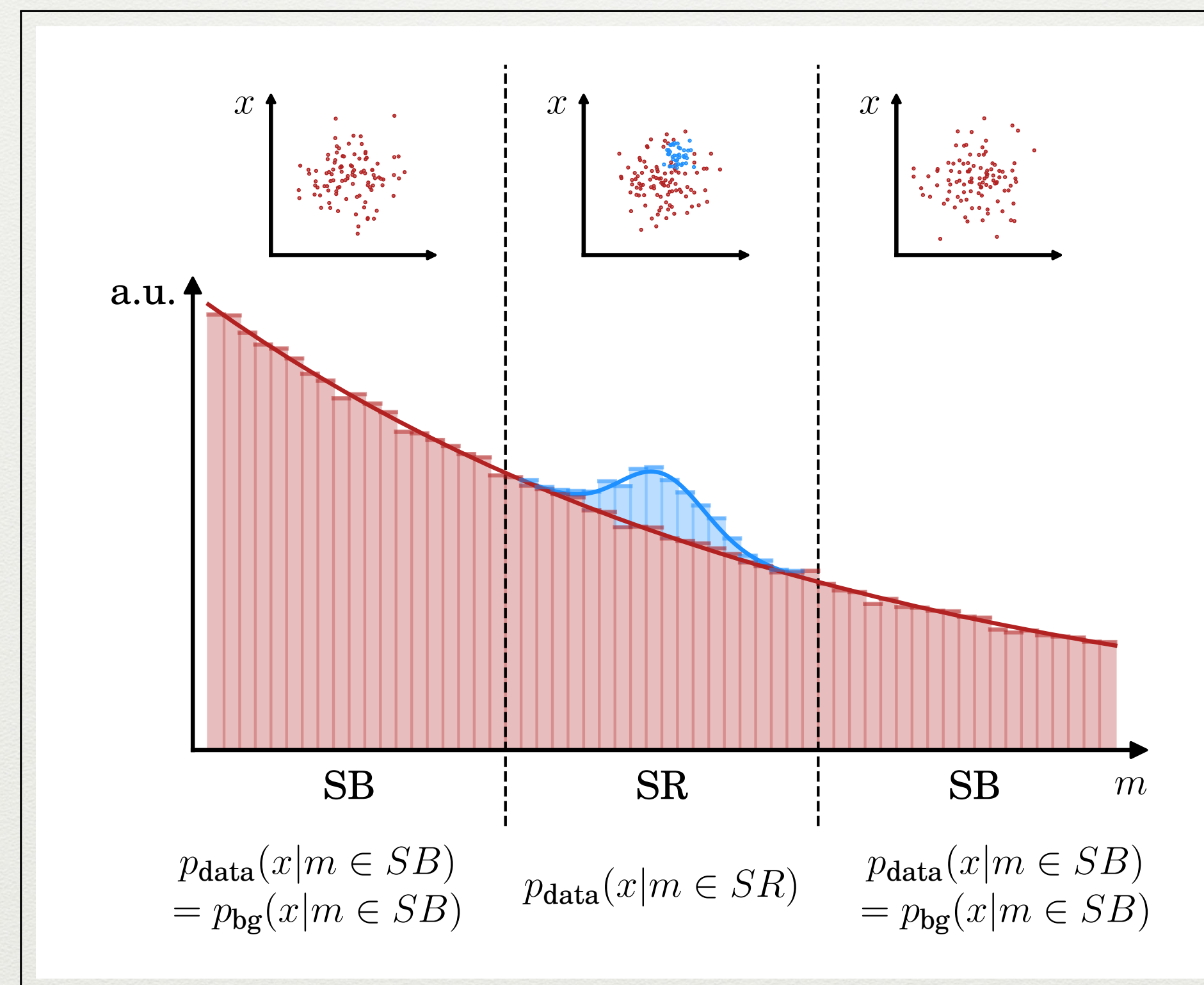
Resonant Anomaly Detection Methods

Idealized Anomaly Detector

perfect background samples from $p_{bg}(x | m \in SR)$



Resonant Anomaly Detection Methods

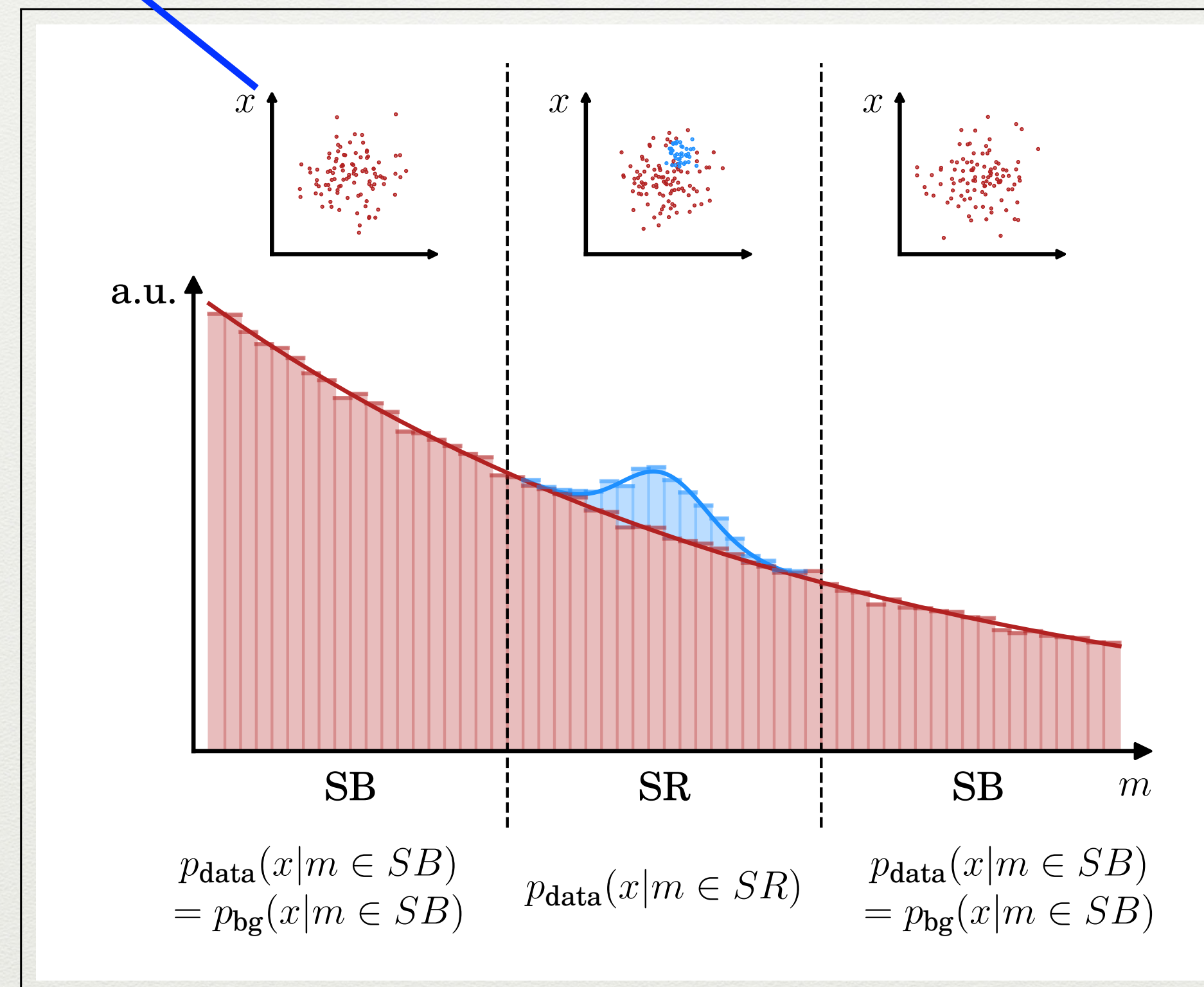


Resonant Anomaly Detection Methods

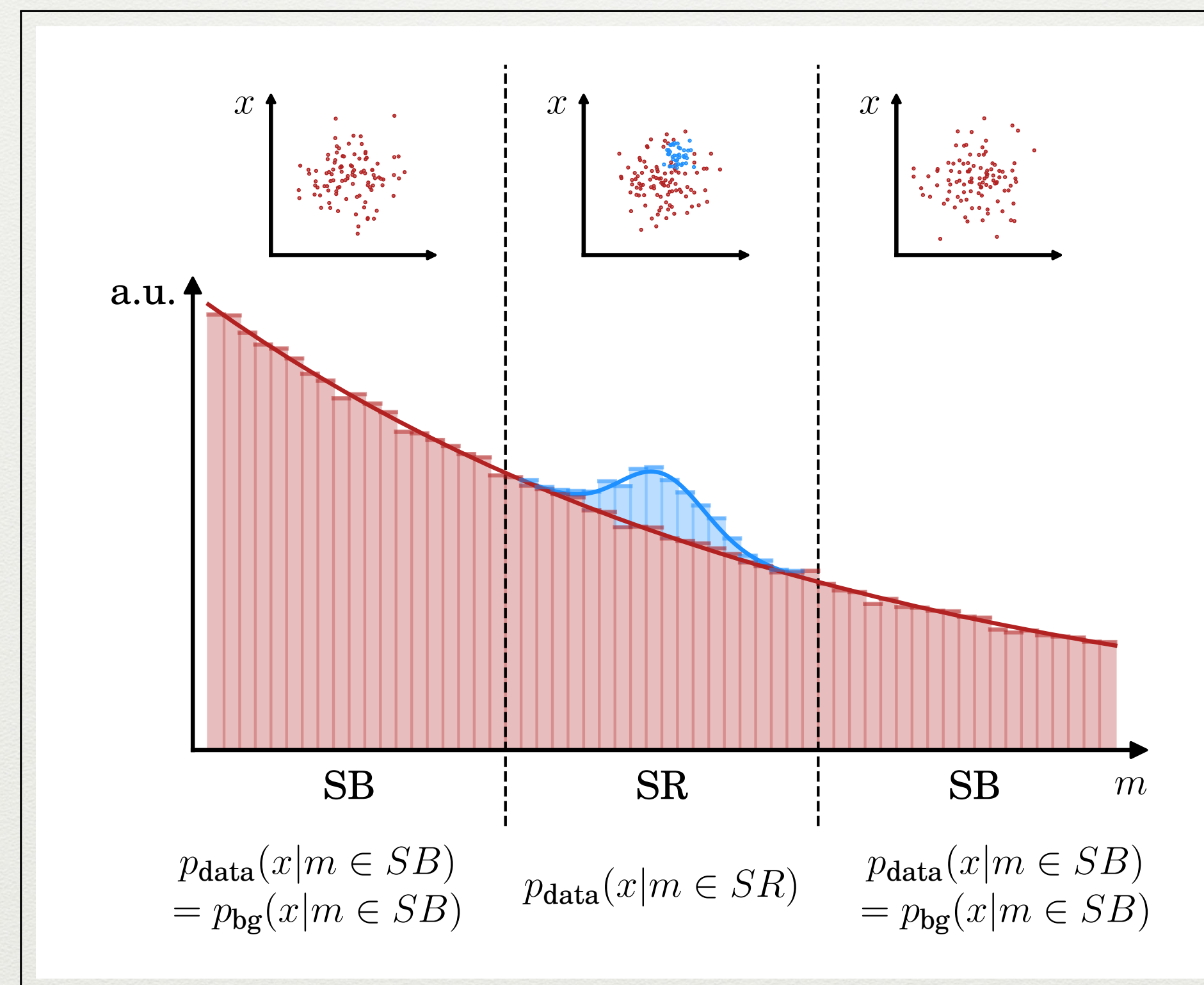
CWoLa Hunting

[Collins et al \(2018\)](#), [\(2019\)](#)

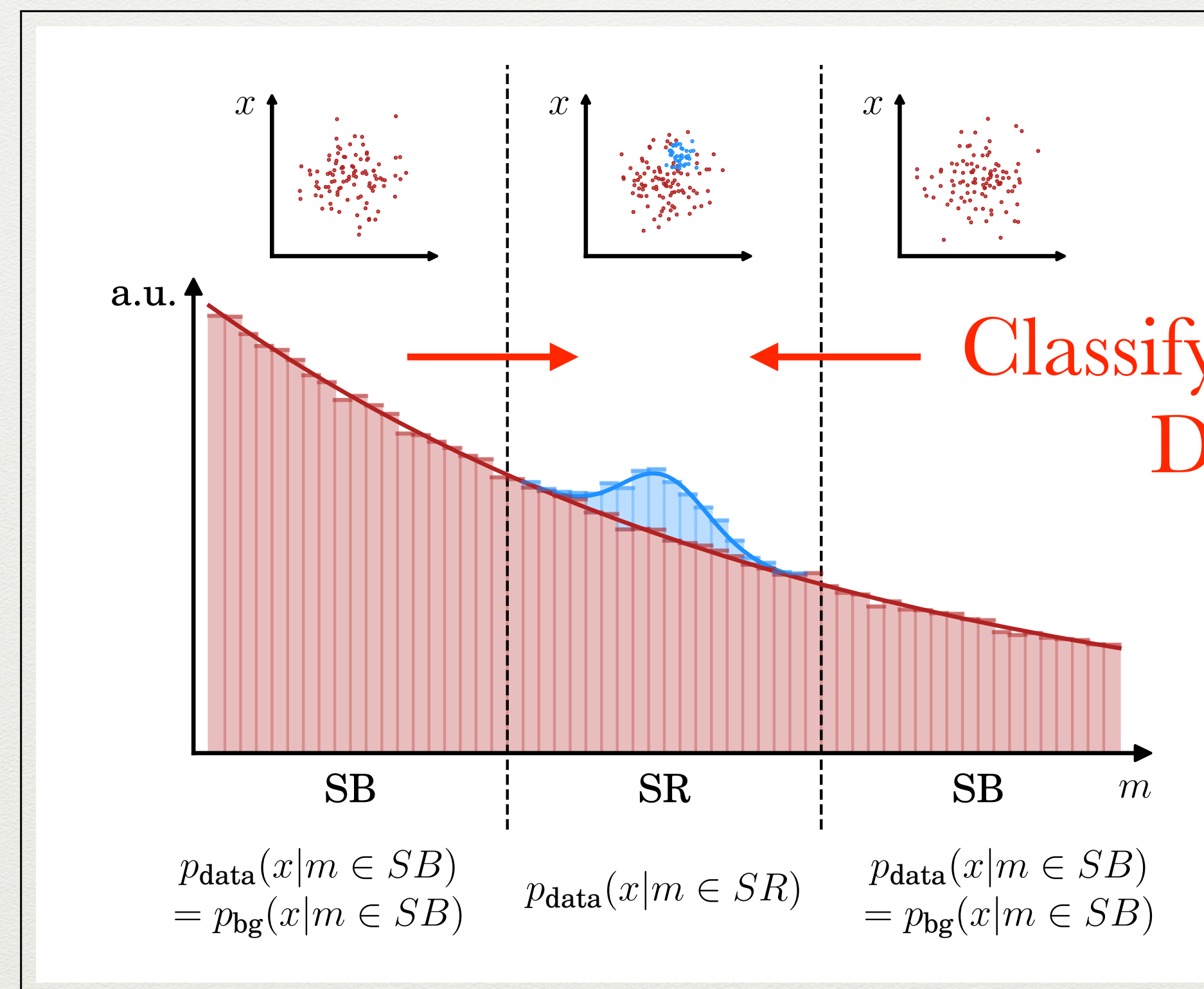
background samples directly
from SB, valid if
 $p_{bg}(x | m \in SB) = p_{bg}(x | m \in SR)$



Resonant Anomaly Detection Methods



Resonant Anomaly Detection Methods



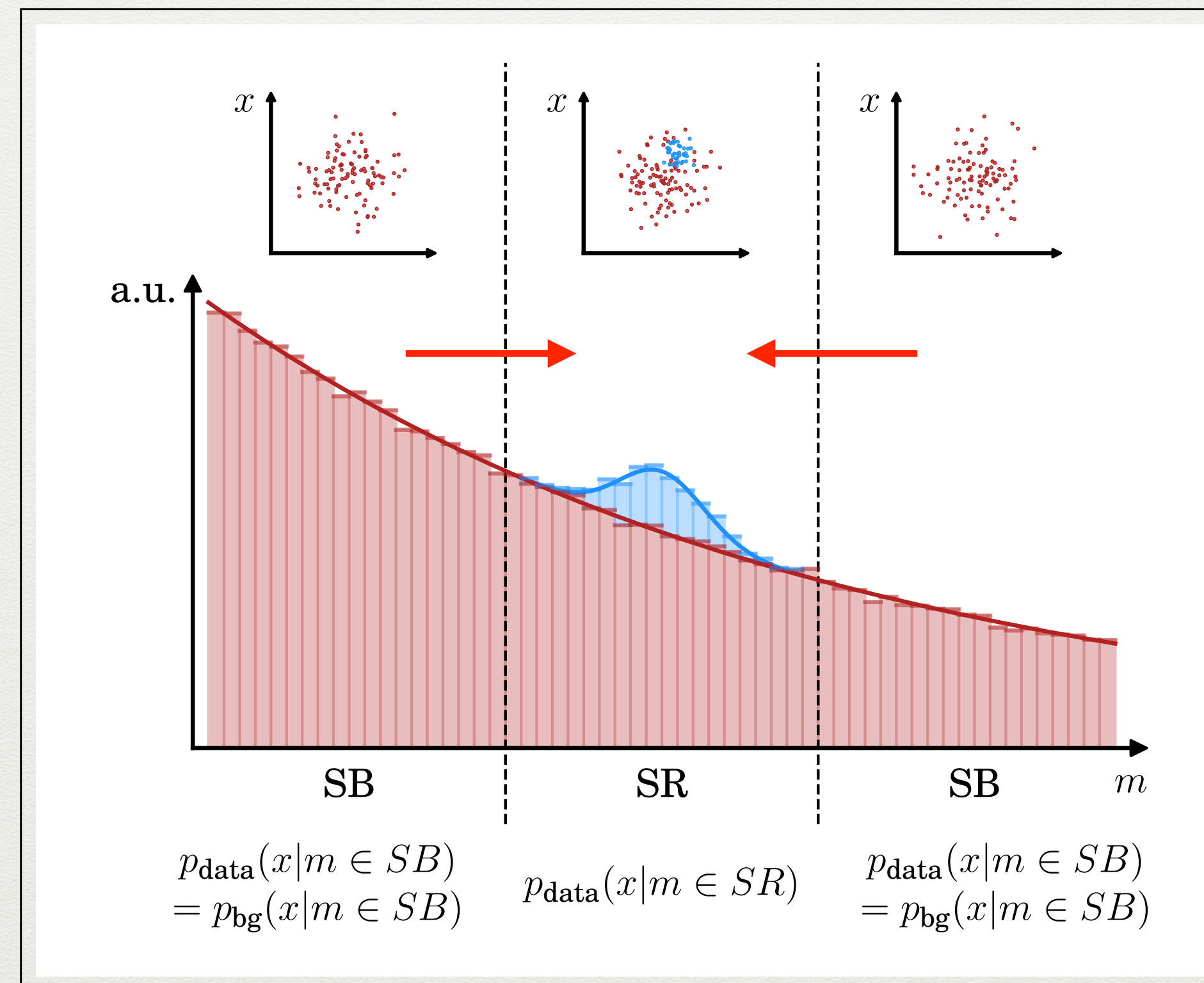
Classifying Anomalies THrough Outer
Density Estimation (CATHODE)

DS+ Hallin et al (2022)

background samples from
normalizing flow fit to sidebands

$$p_{bg}(x|m \in SB) \rightarrow p_{bg}(x|m \in SR)$$

Resonant Anomaly Detection Methods



Resonant Anomaly Detection Methods

ANOmaly detection through Density Estimation (ANODE)

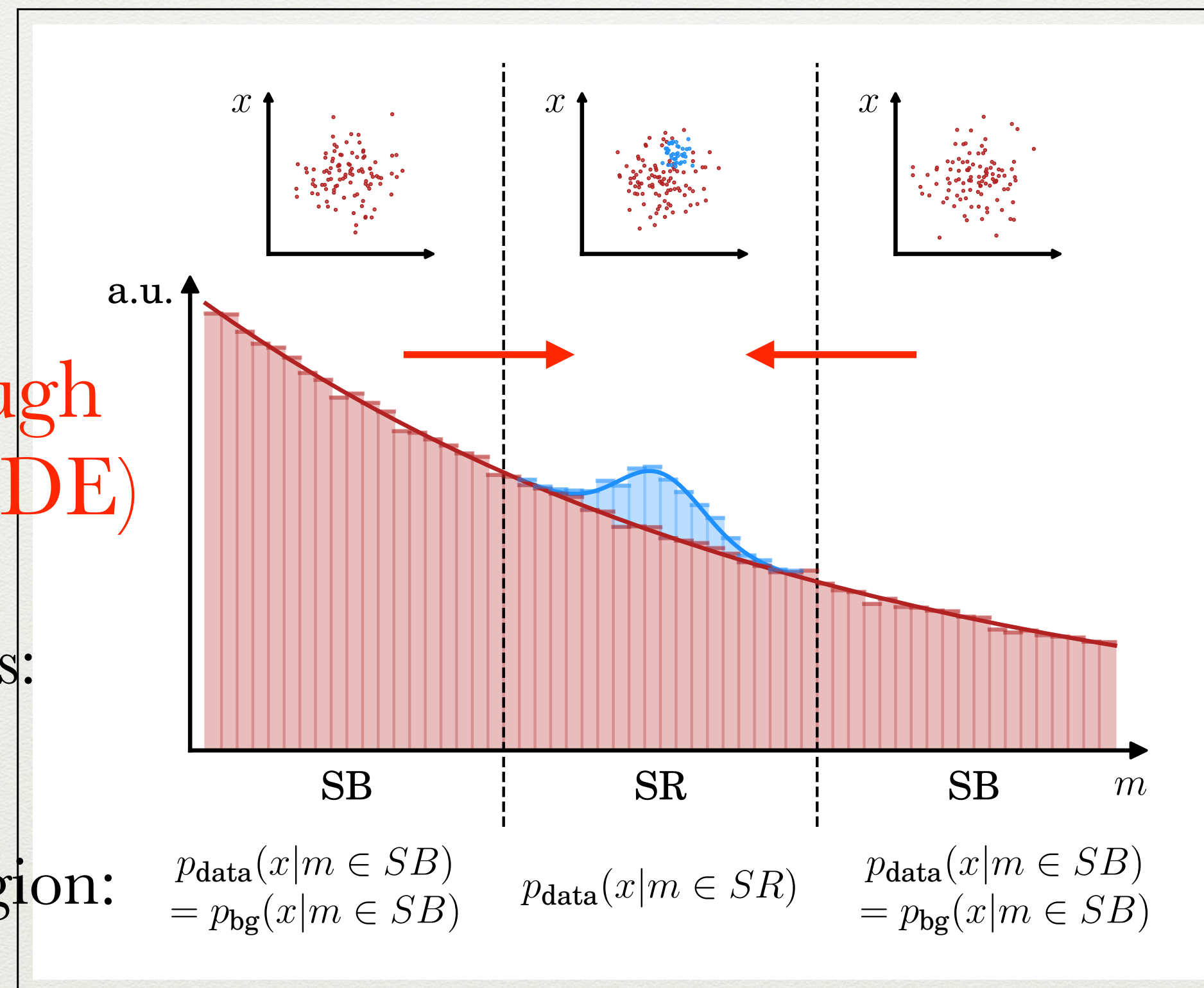
Nachman & DS (2020)

Normalizing flow fit to sidebands:

$$p_{bg}(x | m \in SB) \rightarrow p_{bg}(x | m \in SR)$$

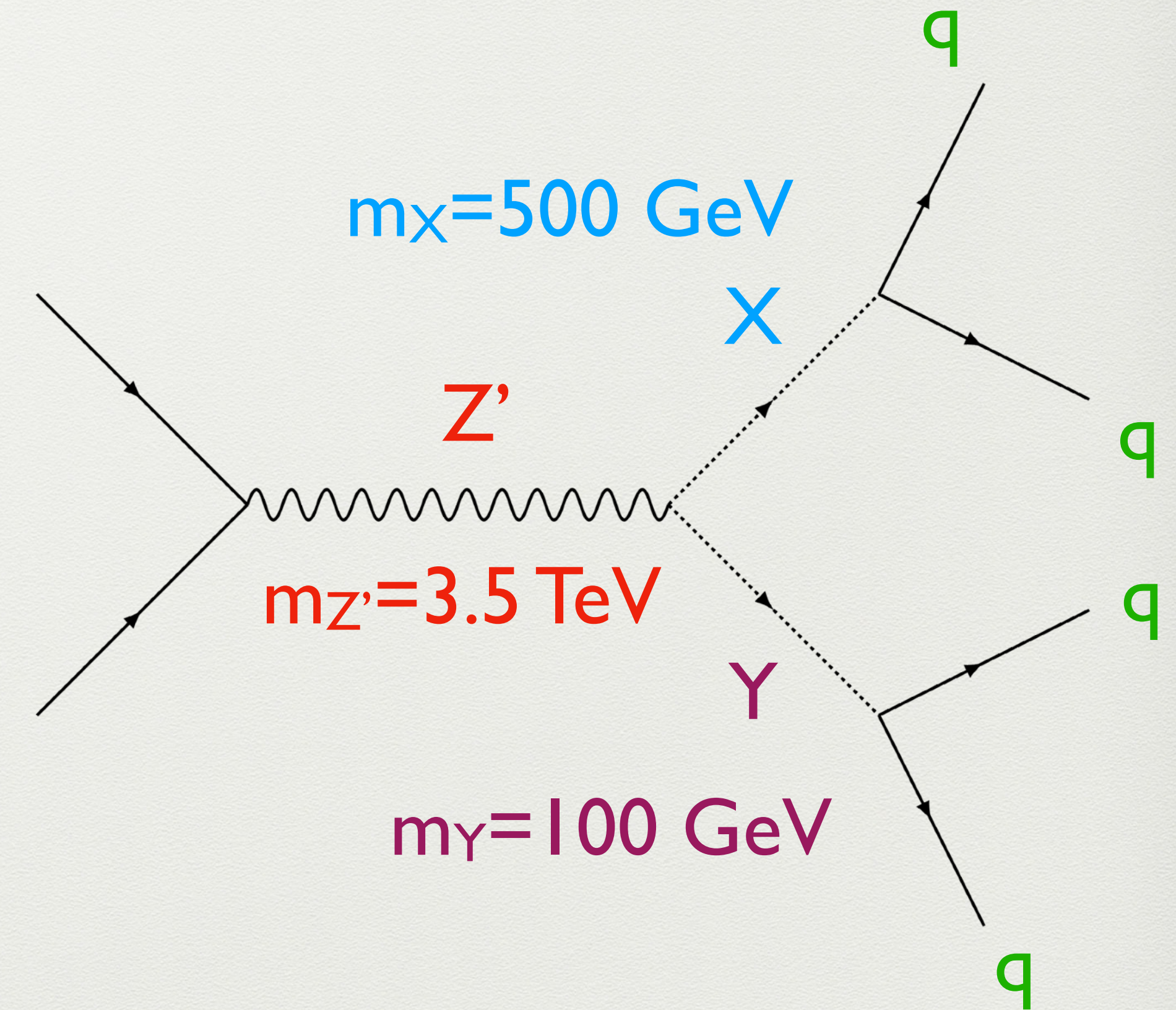
Normalizing flow fit to signal region:

$$p_{data}(x | m \in SR)$$



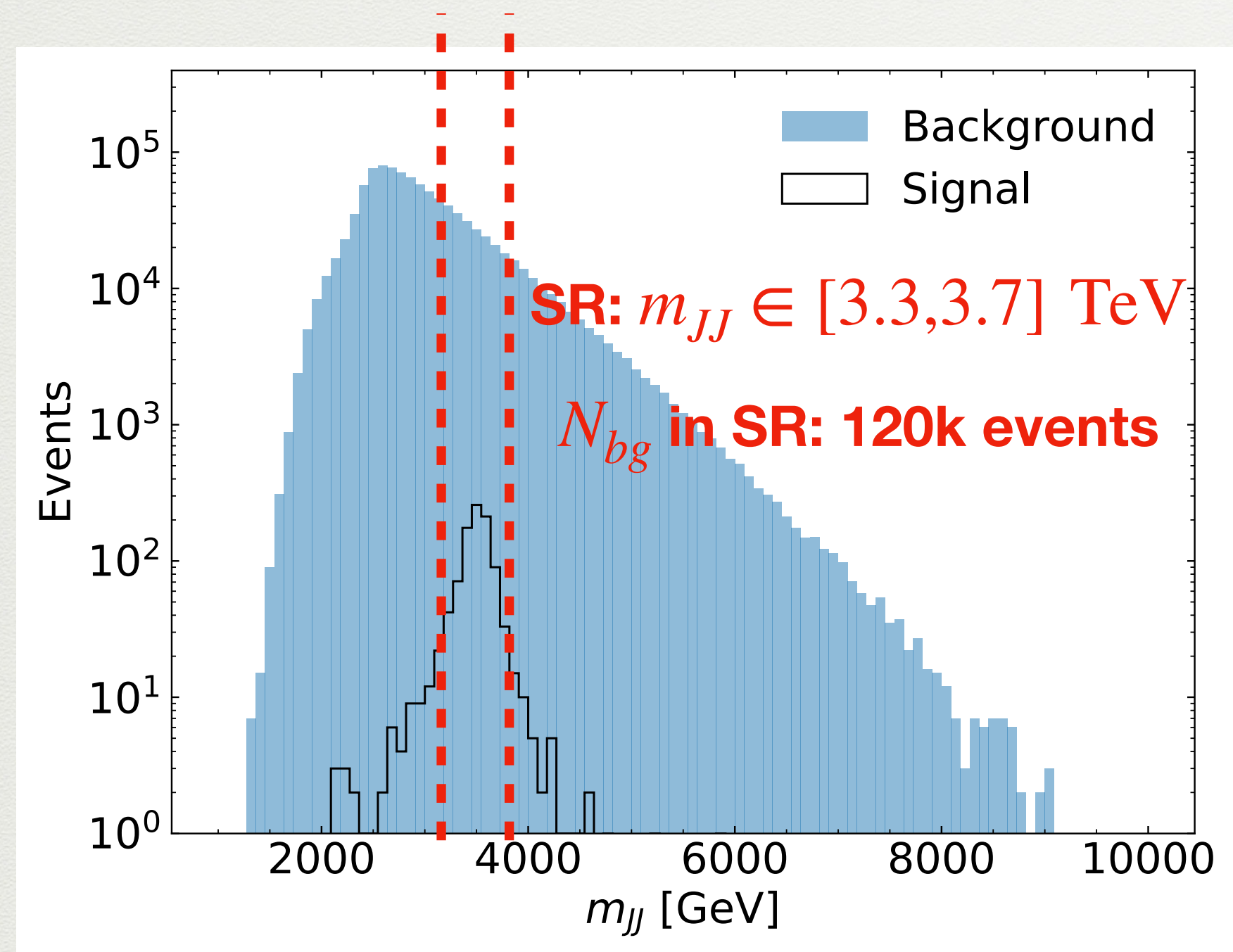
Proof of concept: LHC Olympics 2020 R&D Dataset

- **SM background:**
1M QCD dijet events
(Pythia8+Delphes, $(p_T)_{J_1} > 1.2 \text{ TeV}$)
- **BSM signal:**
 $Z'(3.5 \text{ TeV}) \rightarrow X(500 \text{ GeV})Y(100 \text{ GeV})$,
 $X \rightarrow q\bar{q}$, $Y \rightarrow q\bar{q}$
- A good set of features:
 $m = m_{JJ}$, $x = (m_{J_1}, m_{J_2}, (\tau_{21})_{J_1}, (\tau_{21})_{J_2})$



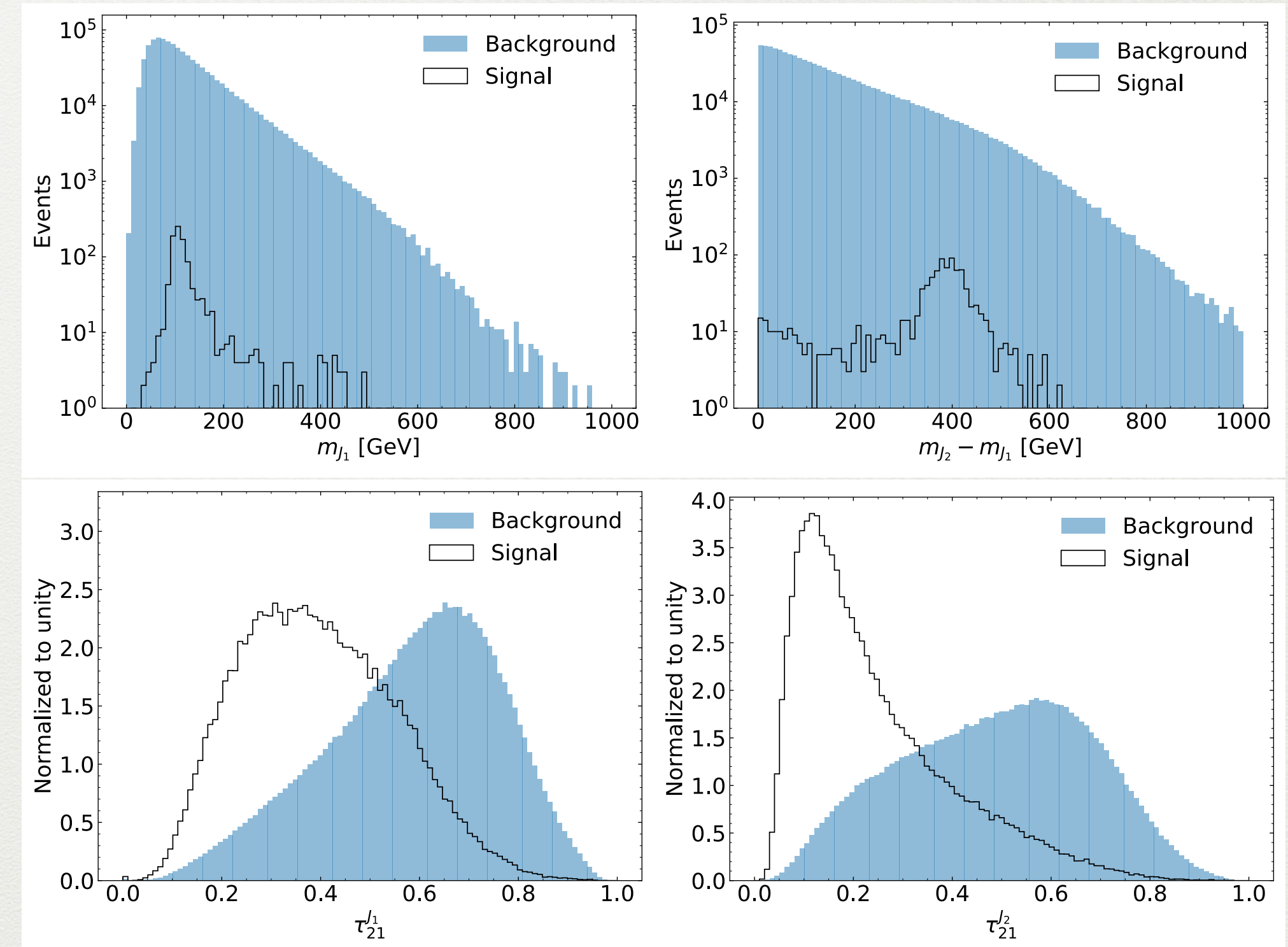
Proof of concept: LHC Olympics 2020 R&D Dataset

Resonant feature



$$m = m_{JJ}$$

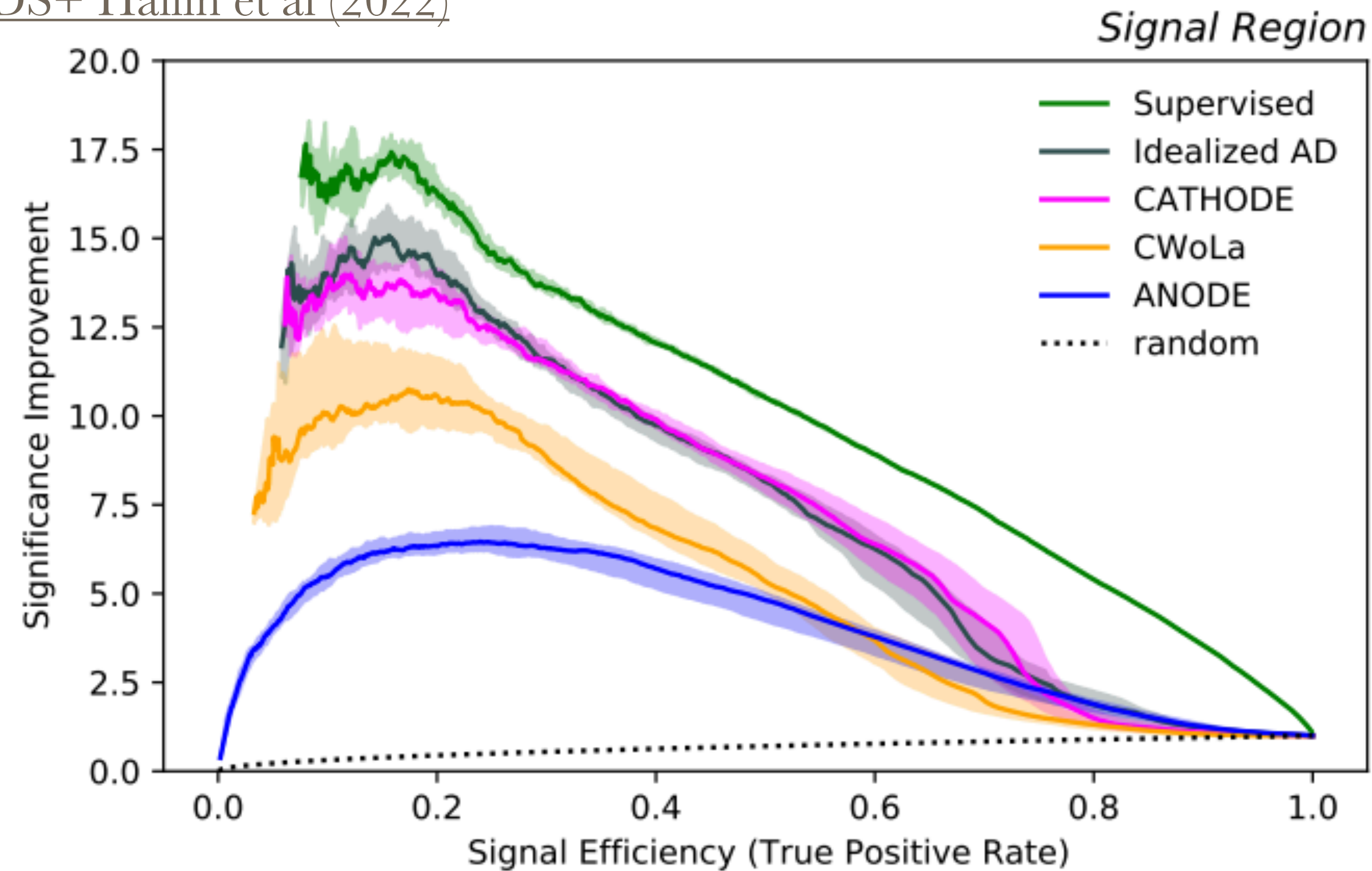
Additional features



$$x = (m_{J_1}, m_{J_2}, \tau_{21}^{J_1}, \tau_{21}^{J_2})$$

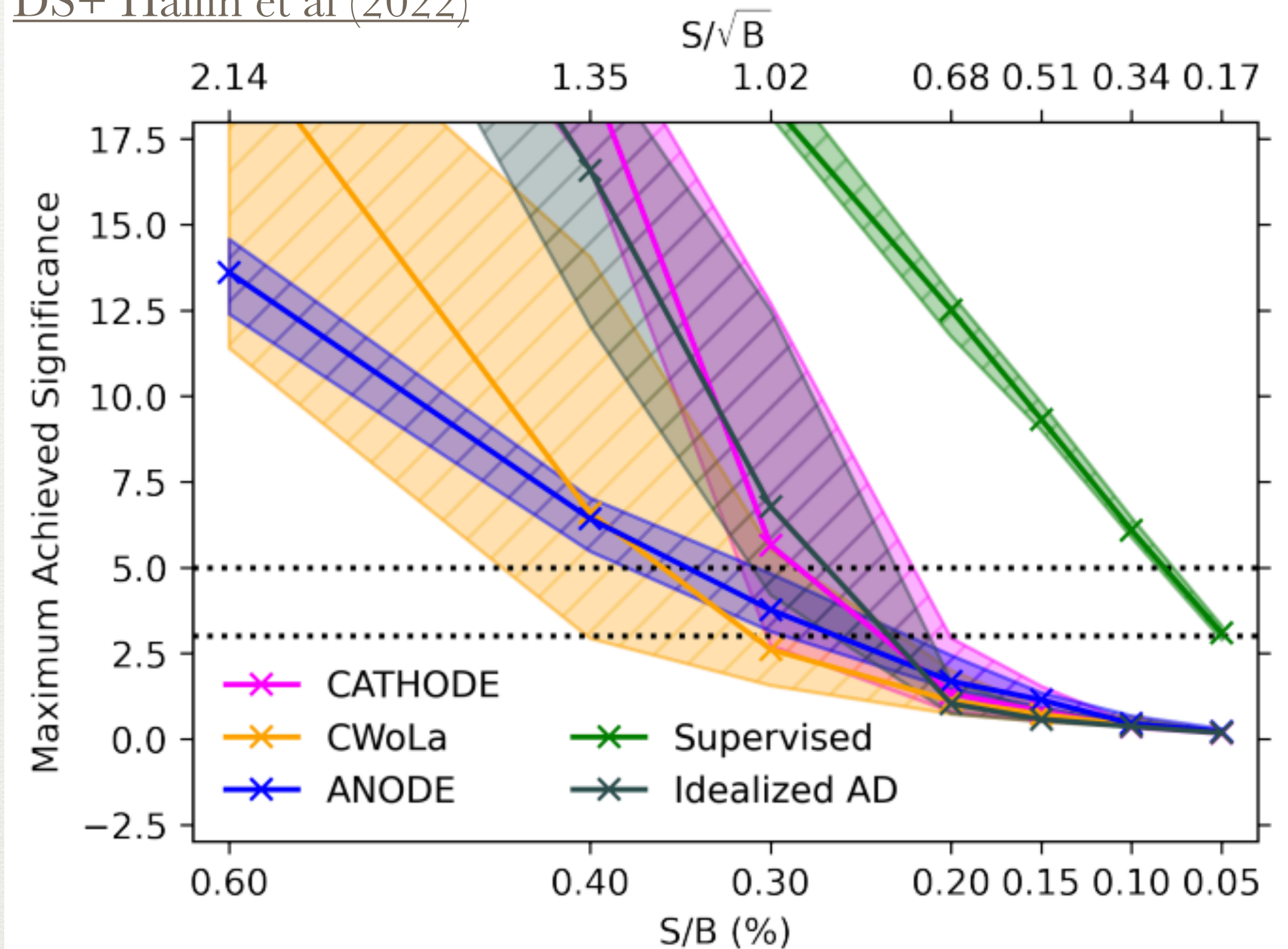
Performance on LHCO

DS+ Hallin et al (2022)



for N_{sig} in SR: 800 events
 initial $S/\sqrt{B} \approx 2$
 enhanced up to 15x by CATHODE

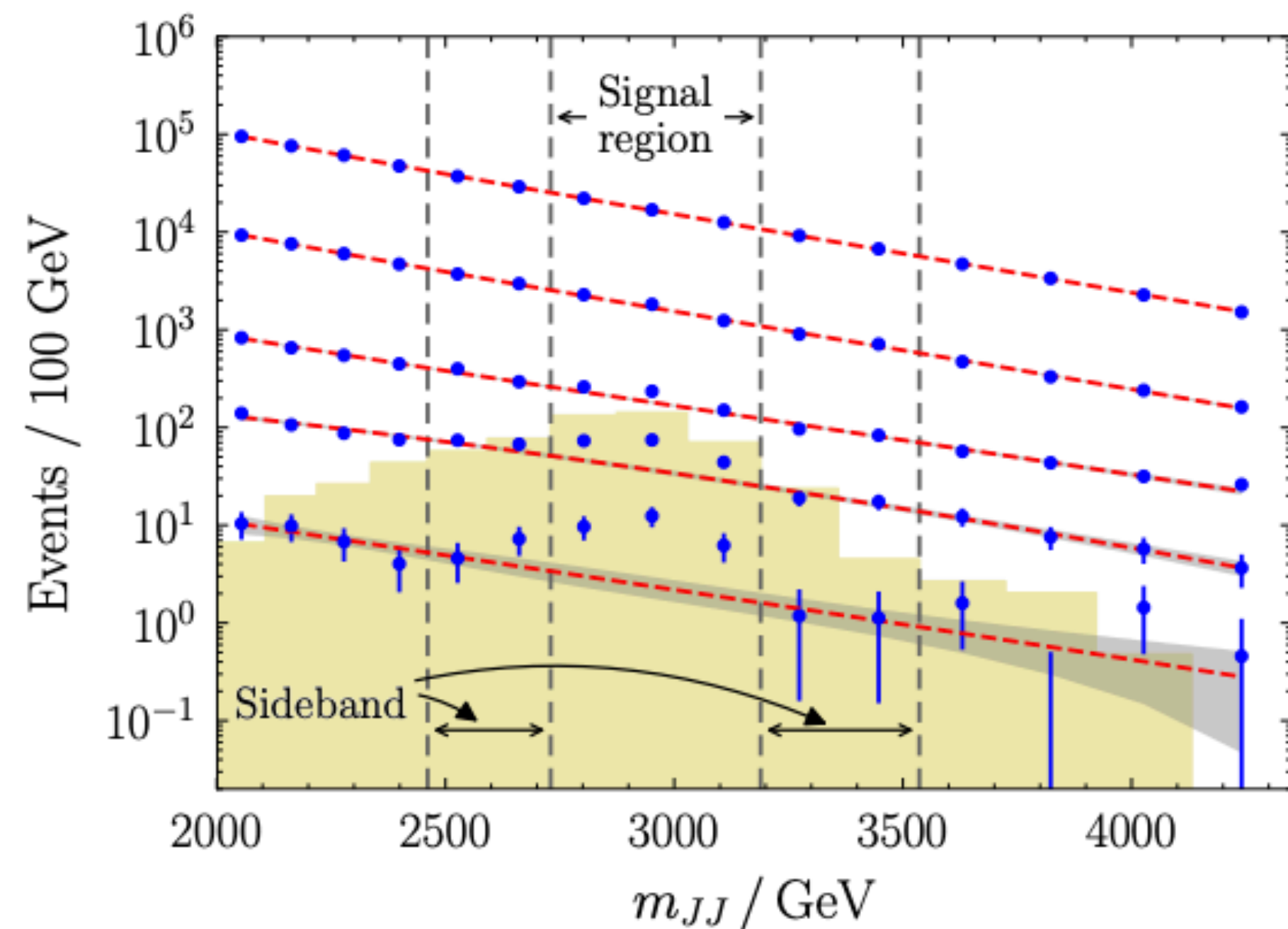
DS+ Hallin et al (2022)



Can improve discovery potential 5x
 in signal cross section

Full statistical procedure

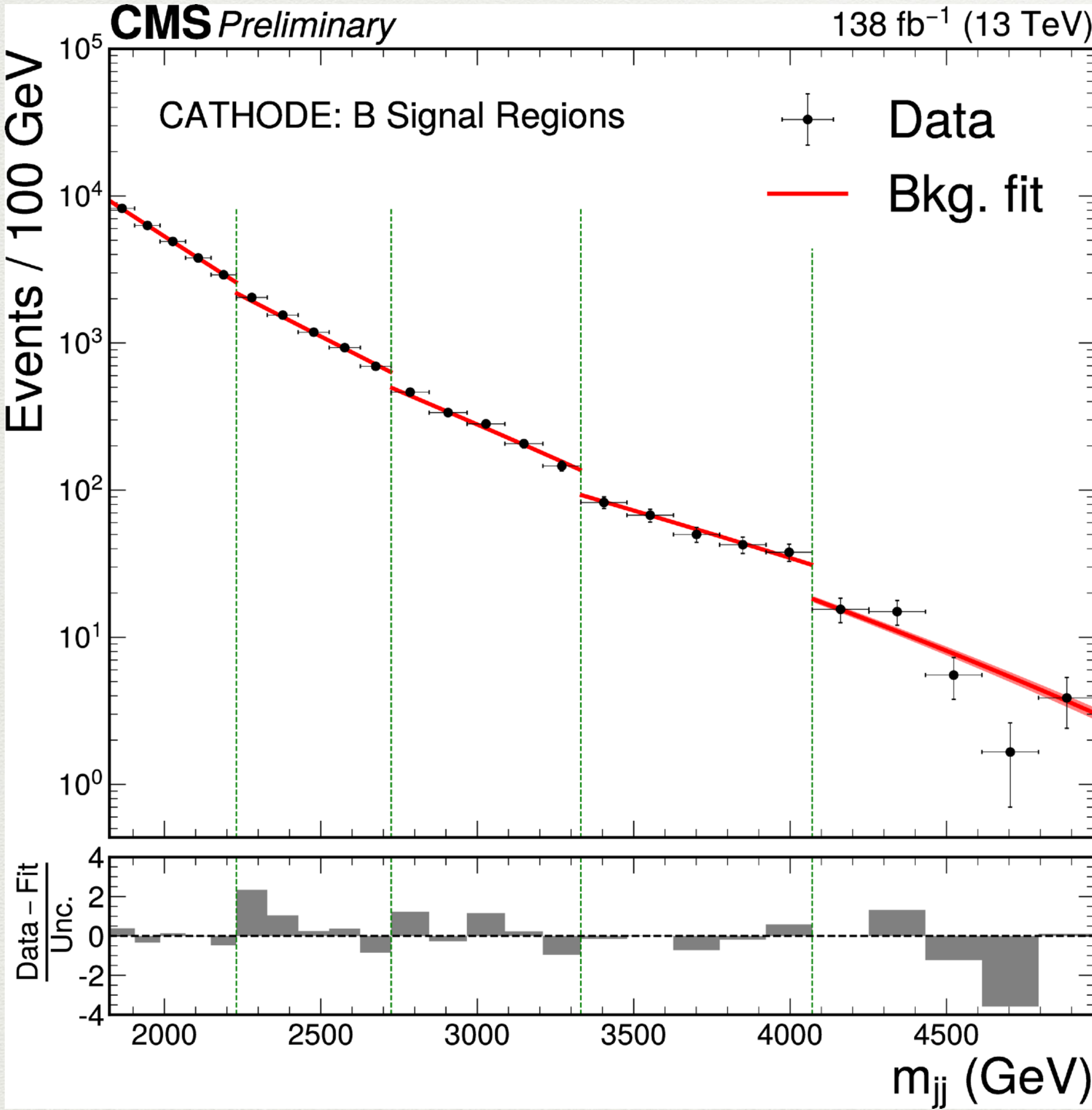
From 1902.02634



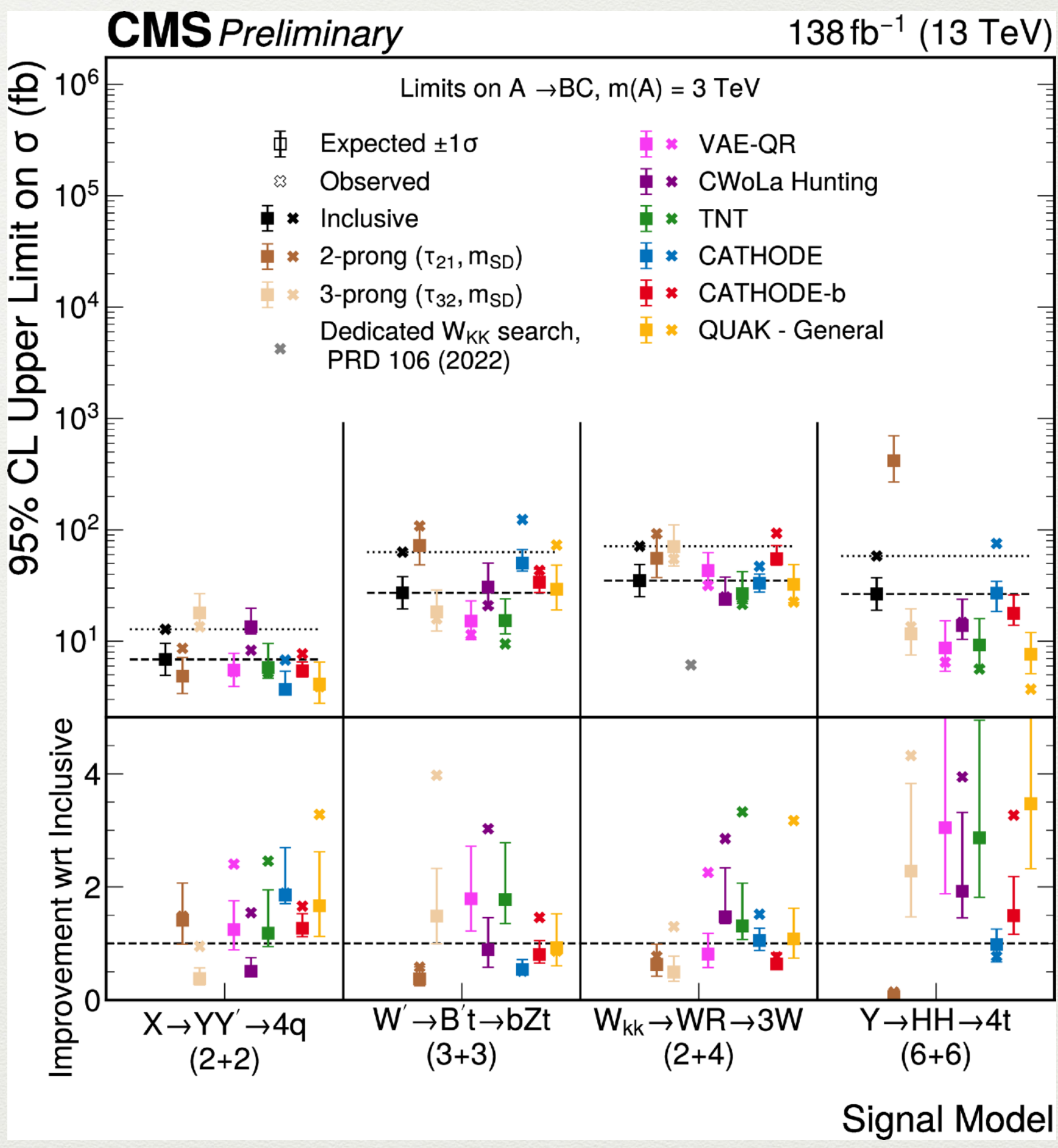
- How to discover anything with resonant anomaly detection?
- Signal sensitivity not enough, need an accurate background estimate
- Cut on $R(x)$, traditional 1d bump hunt after that
- Background estimation from sidebands, assuming no sculpting
- Robustness: can be suboptimal but not wrong

From proof-of-concept to actual search

CMS-PAS-EXO-22-026



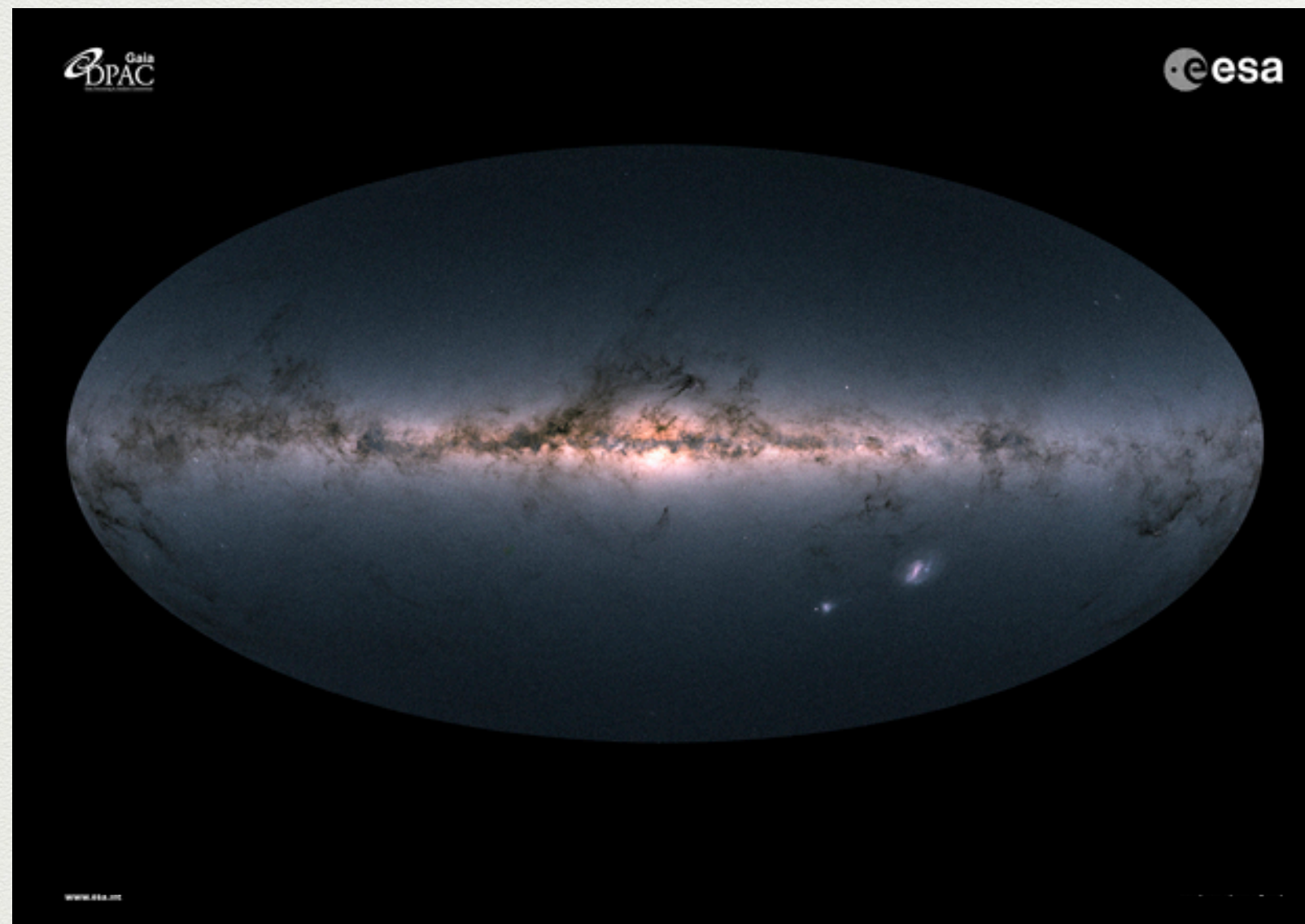
CMS-PAS-EXO-22-026



CATHODE is a CMS search now!

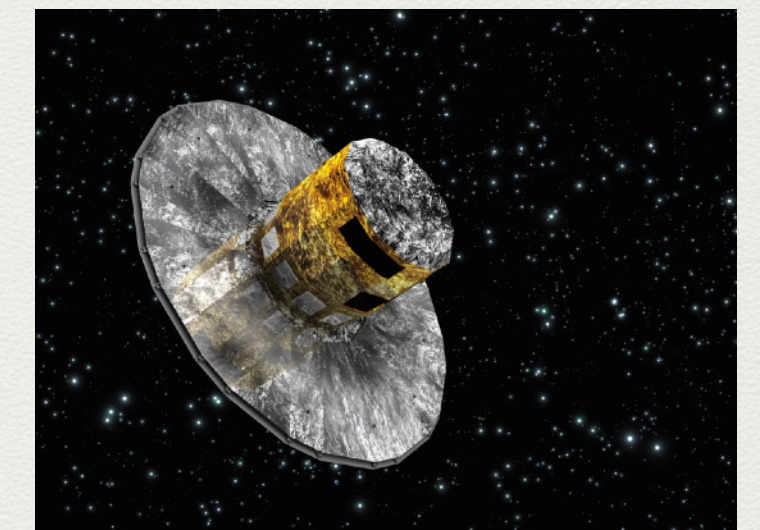
From LHC to Astro: Search for Stellar Streams

- We realized that the same resonant anomaly detection techniques could be used to search for **stellar streams** in **Gaia data**



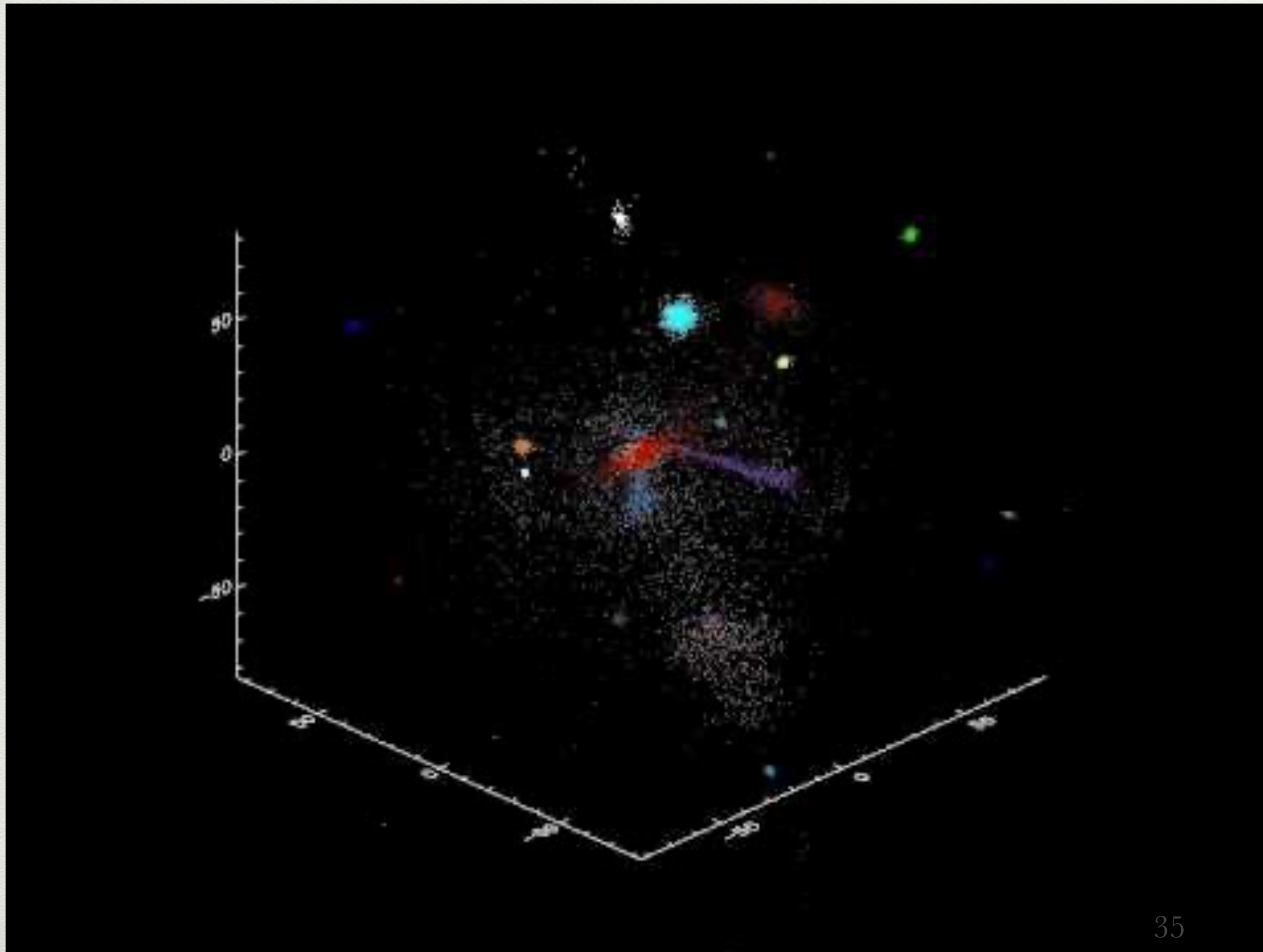
Gaia satellite:

- Launched in 2013; ongoing
- Angular positions, proper motions, color and magnitude of over **1 billion stars** in our Galaxy
- Distances and radial velocities for a smaller subset of nearby stars



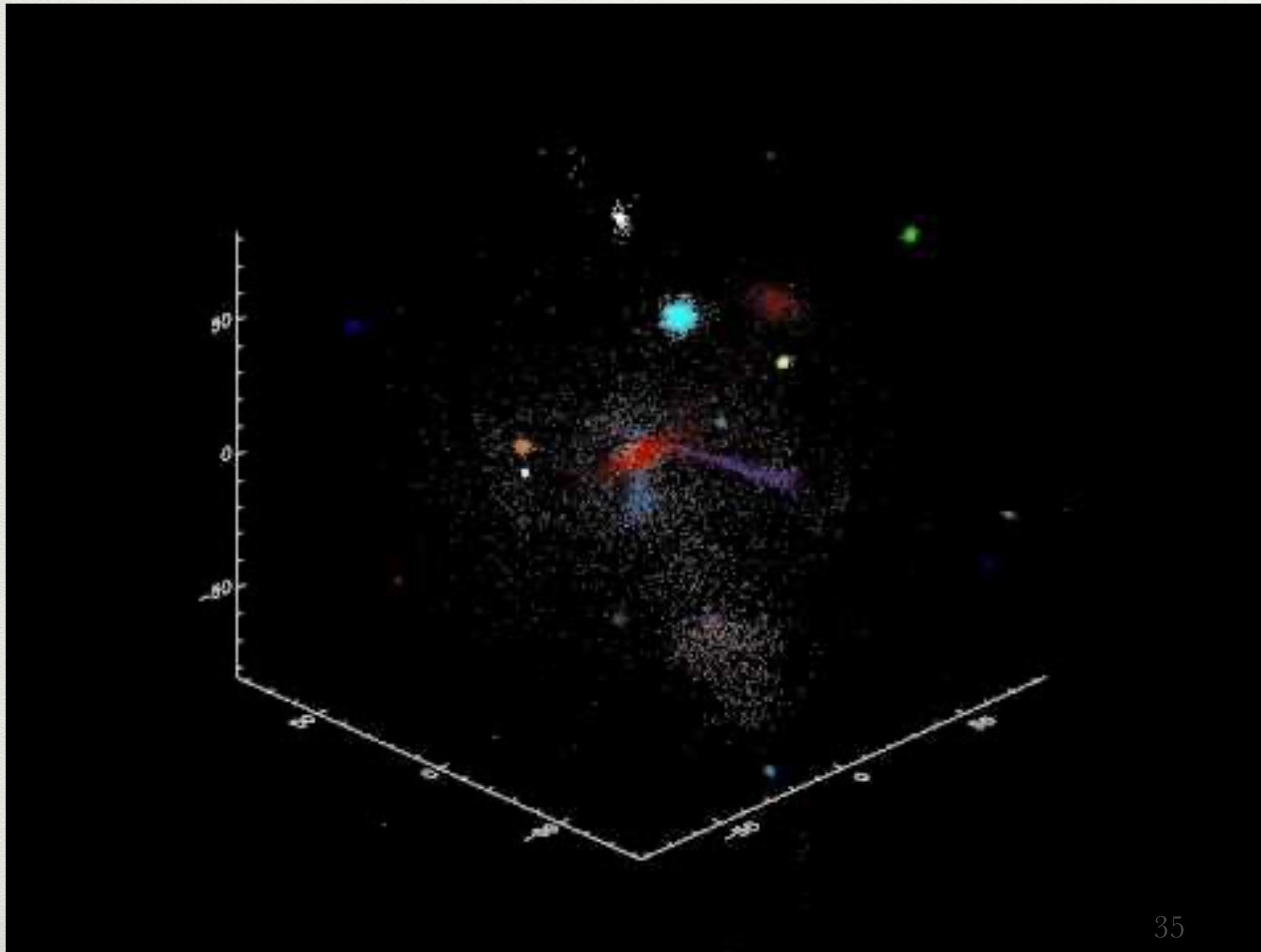
Stellar streams

Stellar streams are tidally disrupted dwarf galaxies and globular clusters



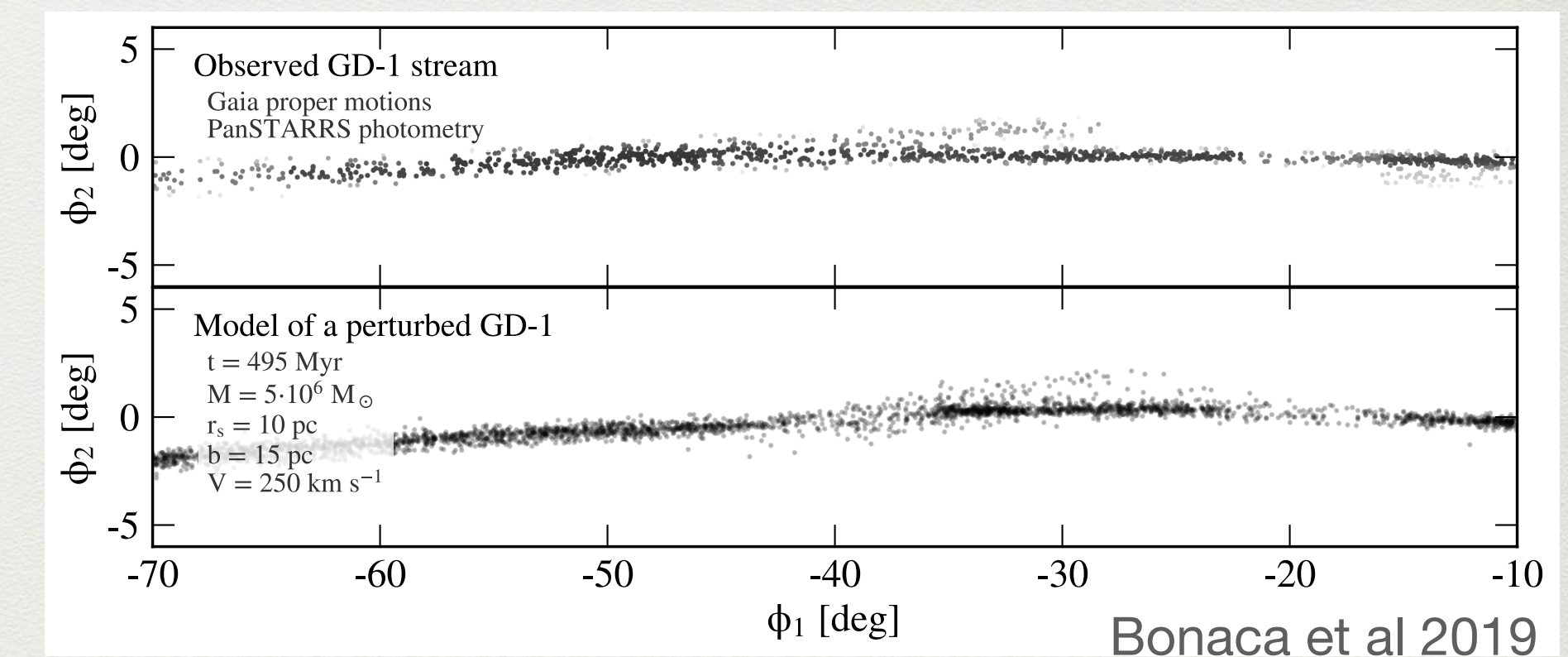
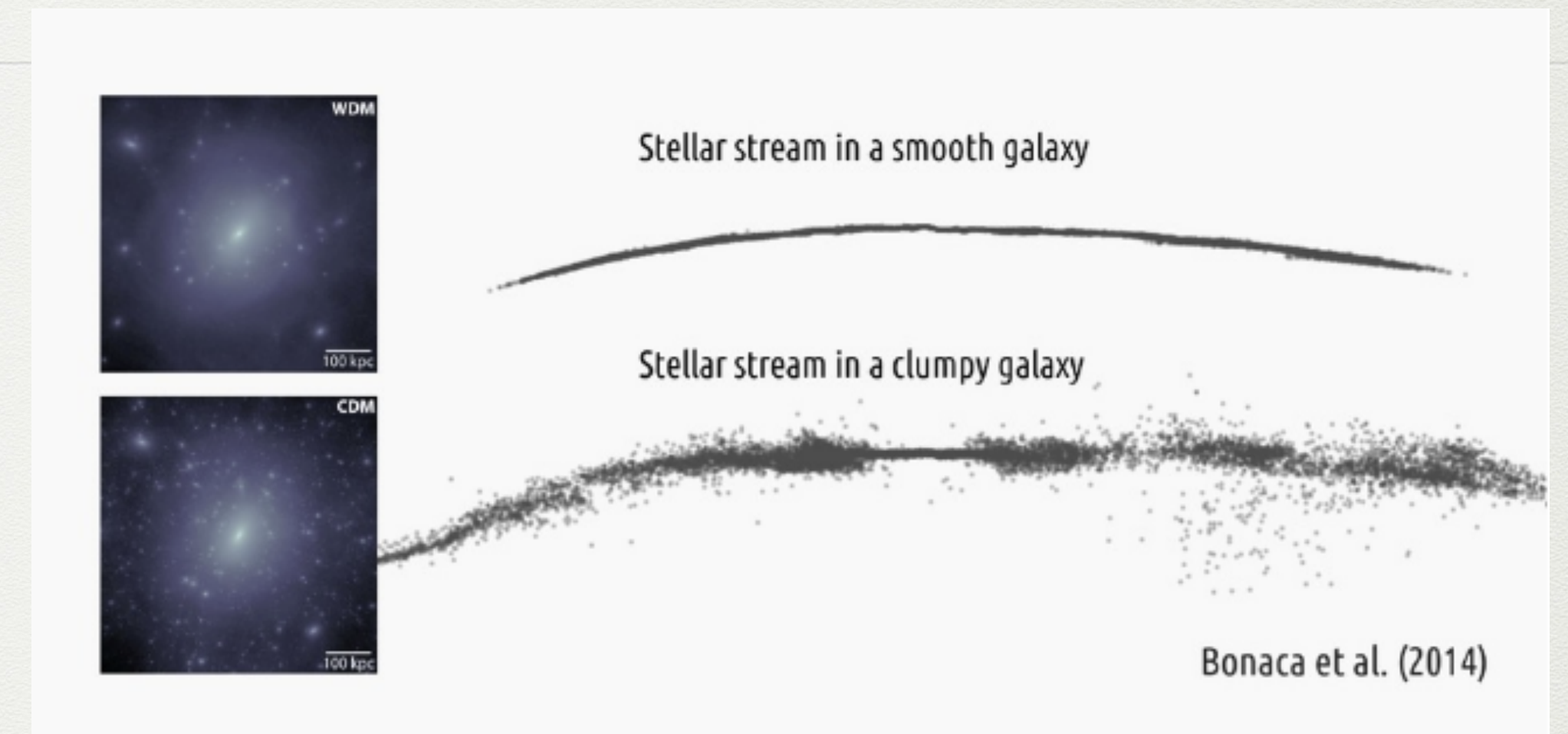
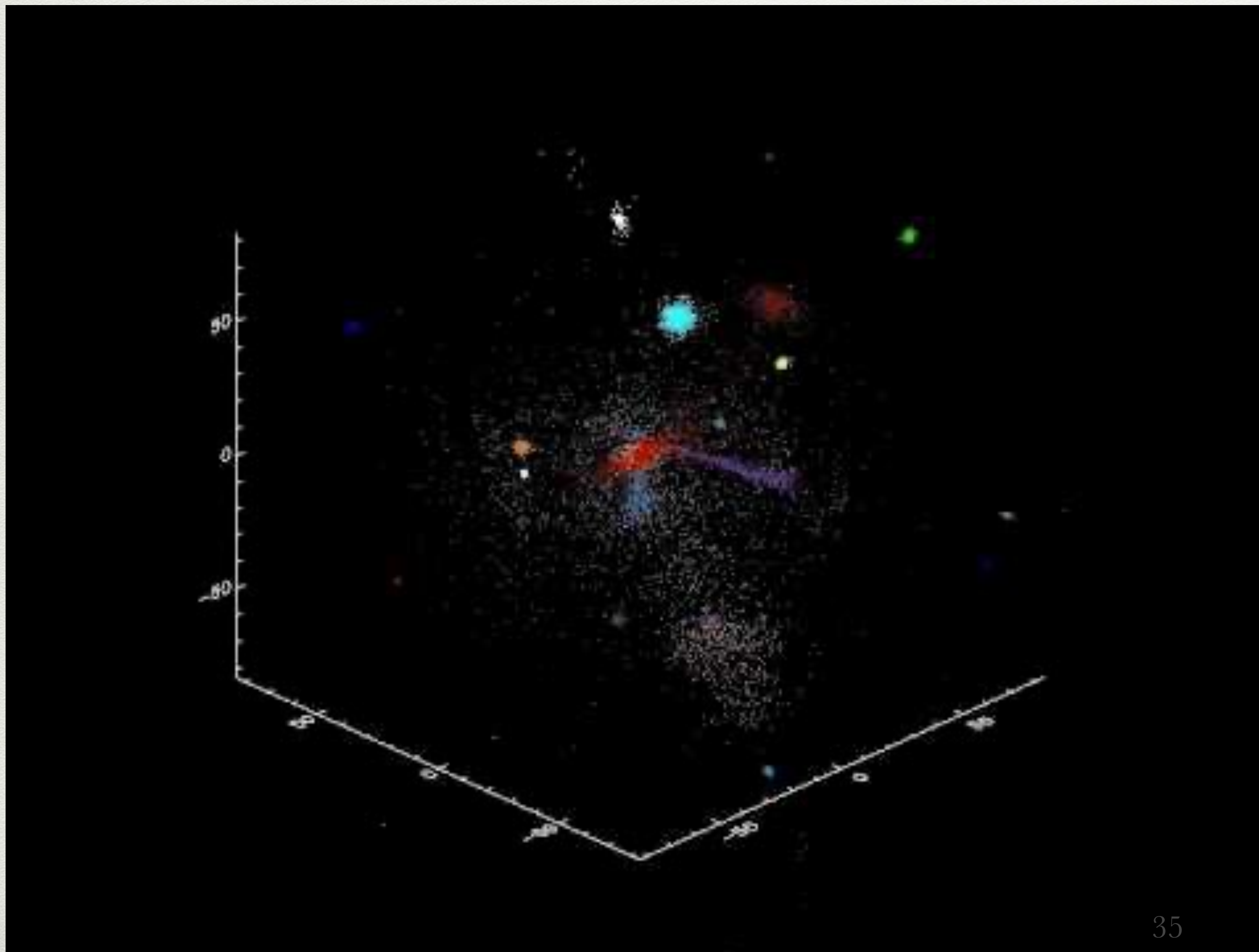
Stellar streams

Stellar streams are tidally disrupted dwarf galaxies and globular clusters



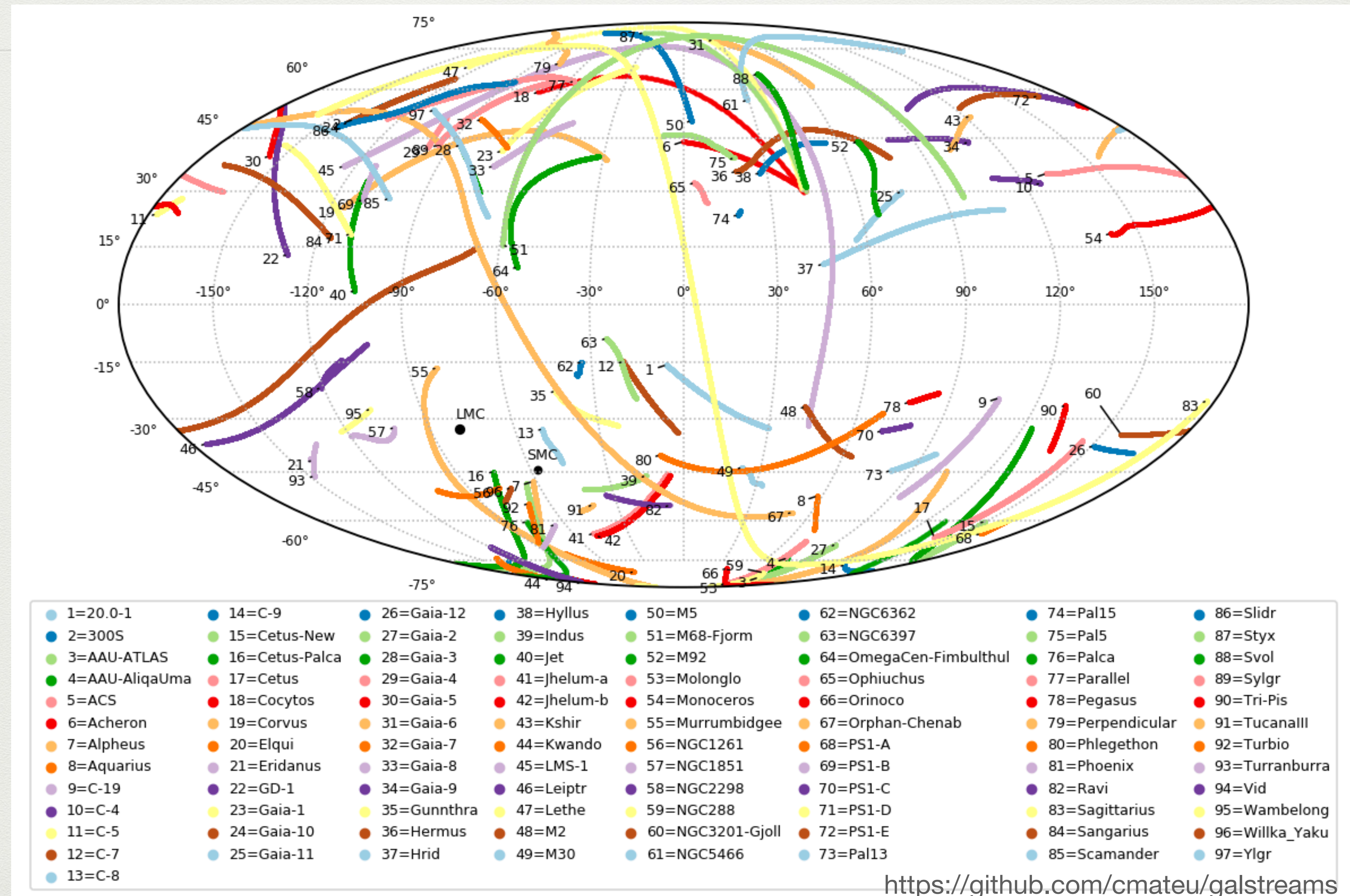
Stellar streams

Stellar streams are tidally disrupted dwarf galaxies and globular clusters



Streams are unique astrophysical probes
of **dark matter**

Known stellar streams of the Milky Way



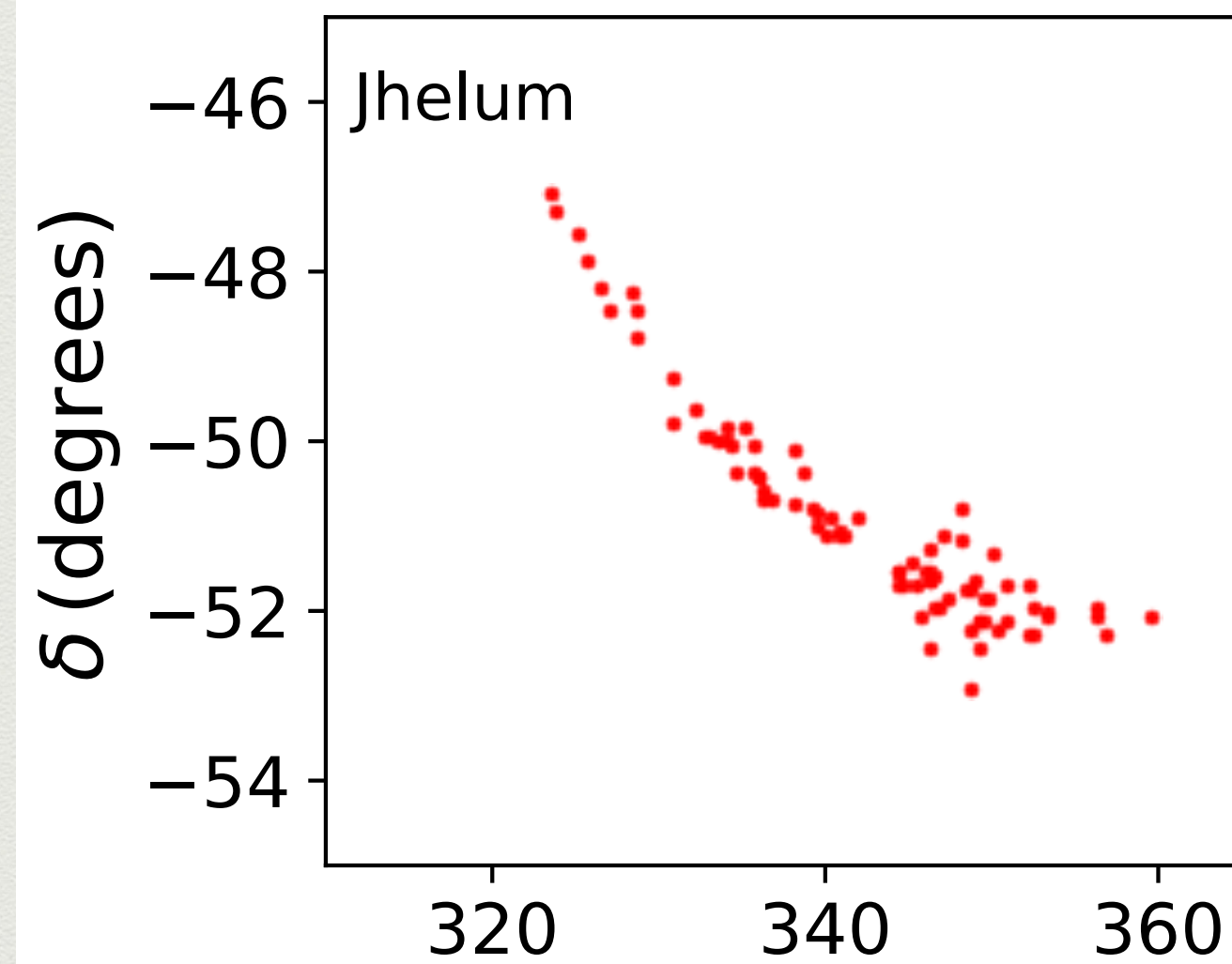
<https://github.com/cmateu/galstreams>

Via Machinae

[DS, Buckley, Necib '23] [DS, Buckley, Necib, Tamanas '21]

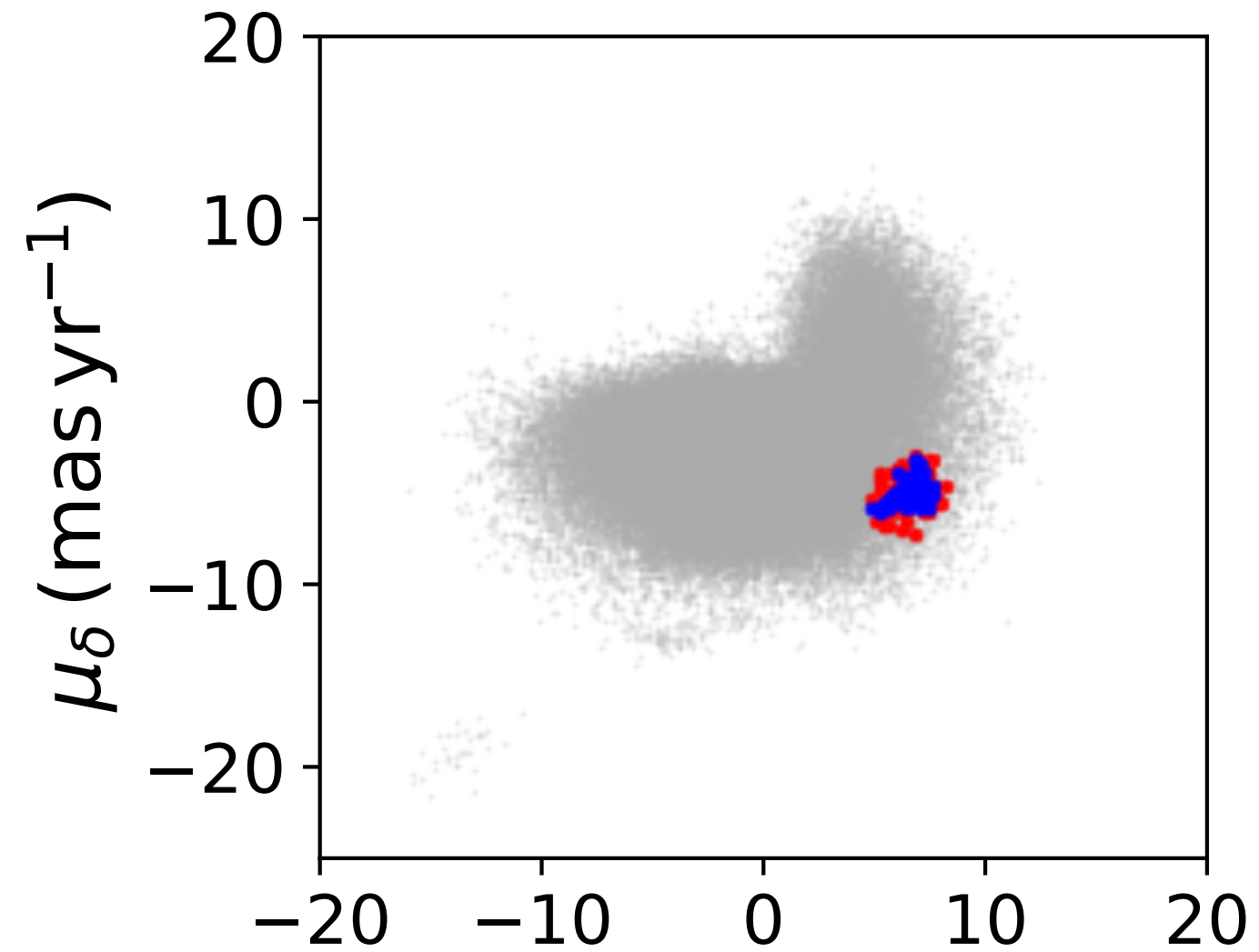
Malhan et al (2018)

Angular position on the sky



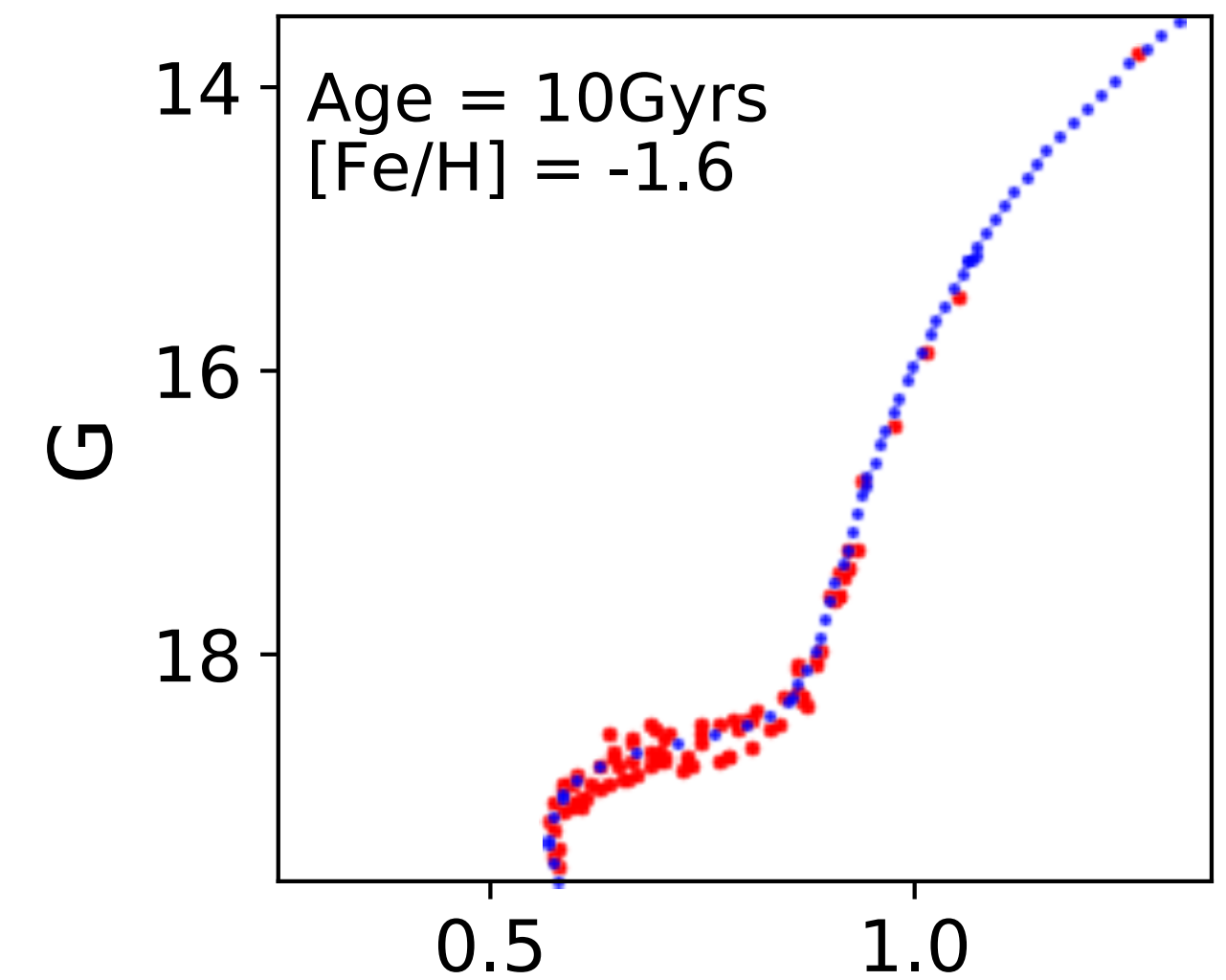
α (degrees)

Velocity on the sky (proper motion)



μ_α^* (mas yr⁻¹)

Photometry

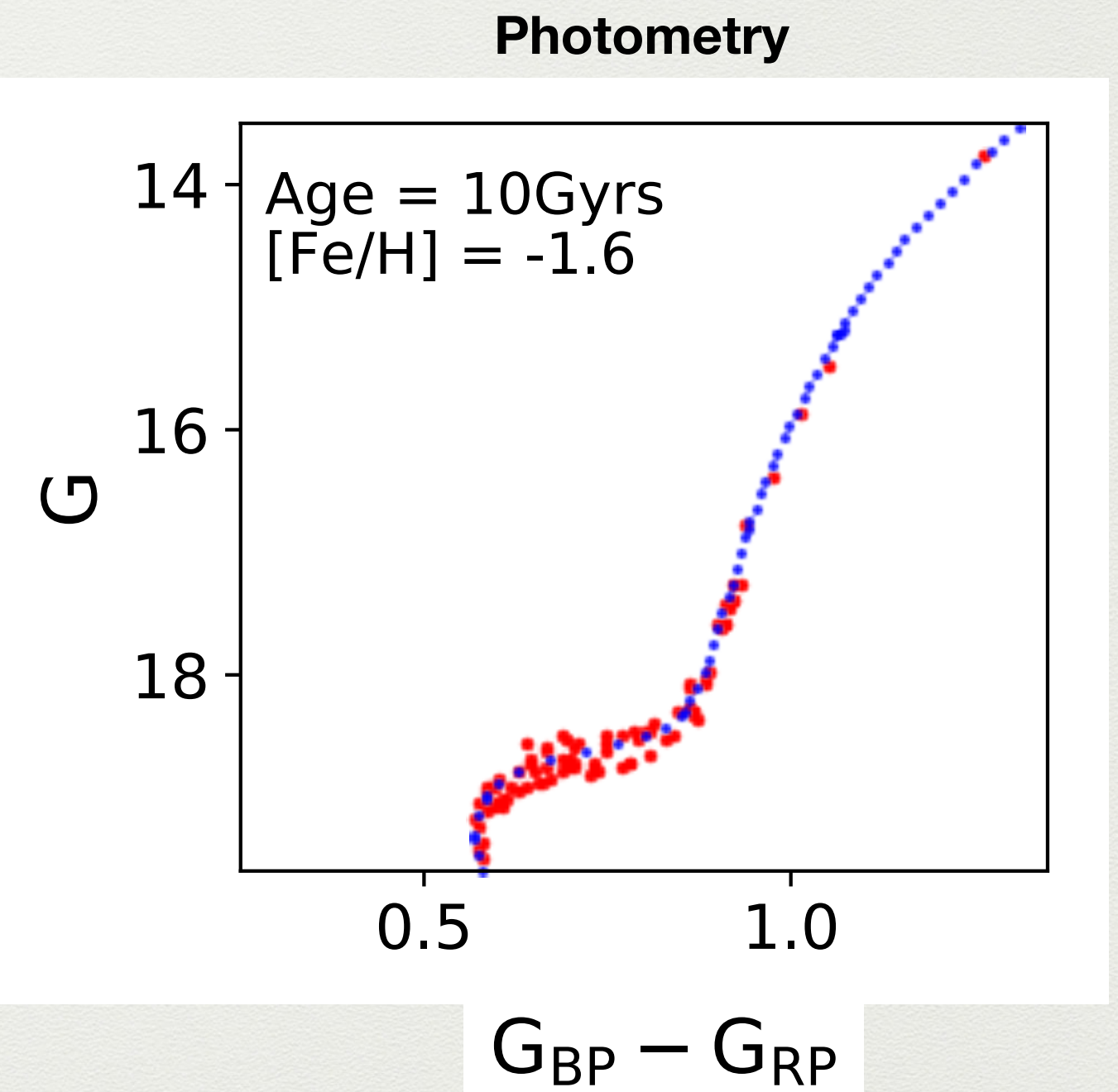
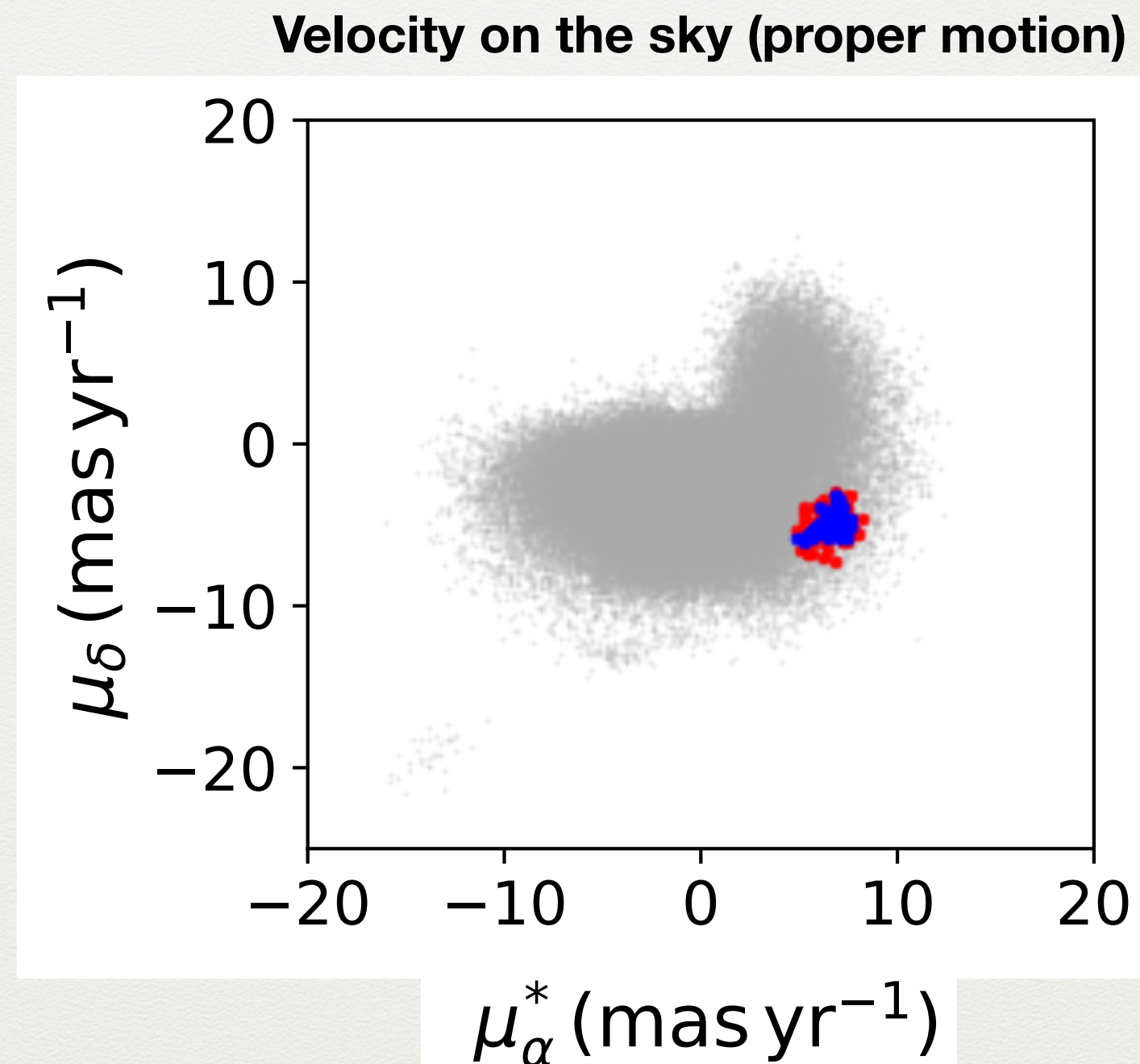
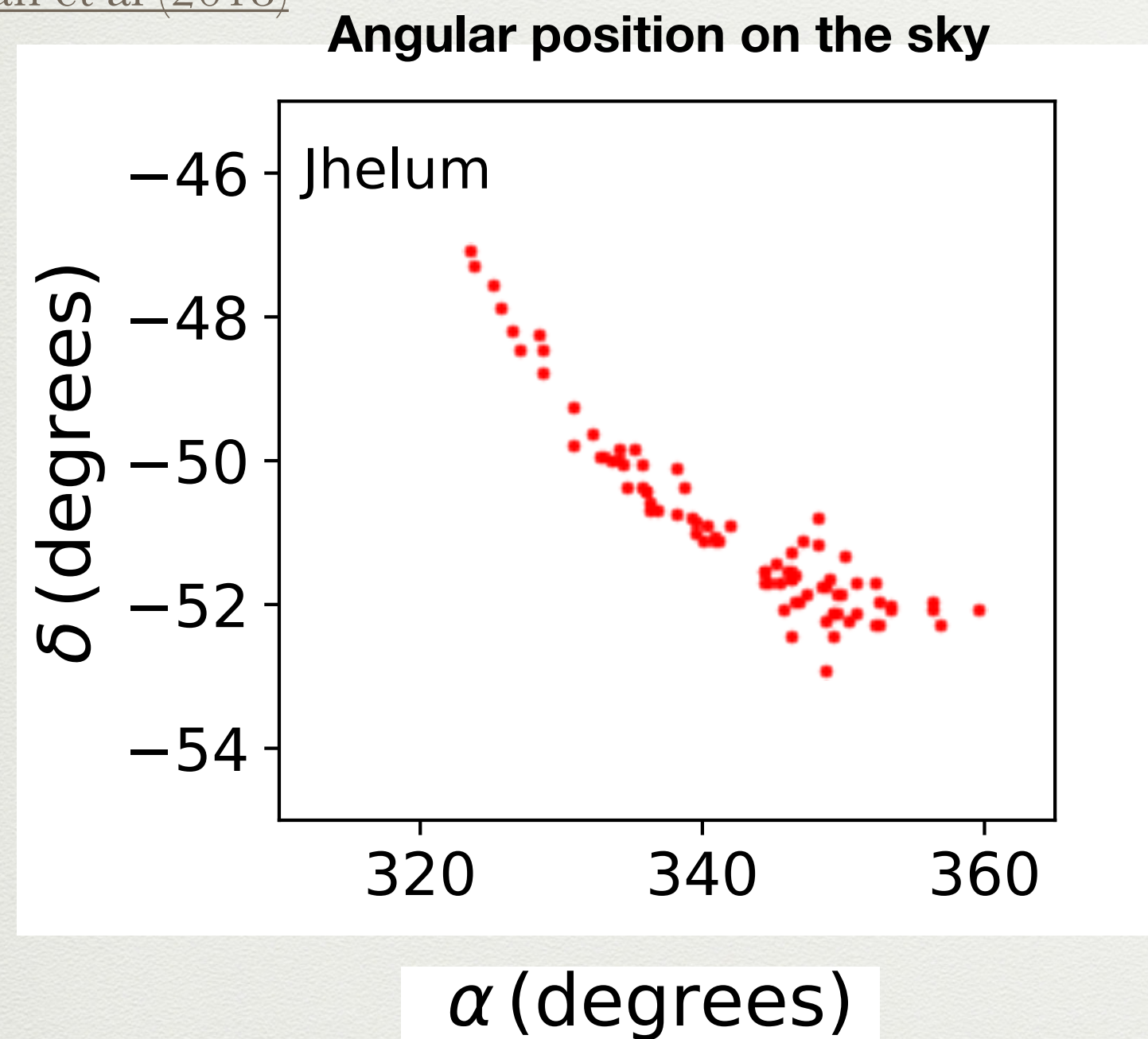


$G_{BP} - G_{RP}$

Via Machinae

[DS, Buckley, Necib '23] [DS, Buckley, Necib, Tamanas '21]

Malhan et al (2018)

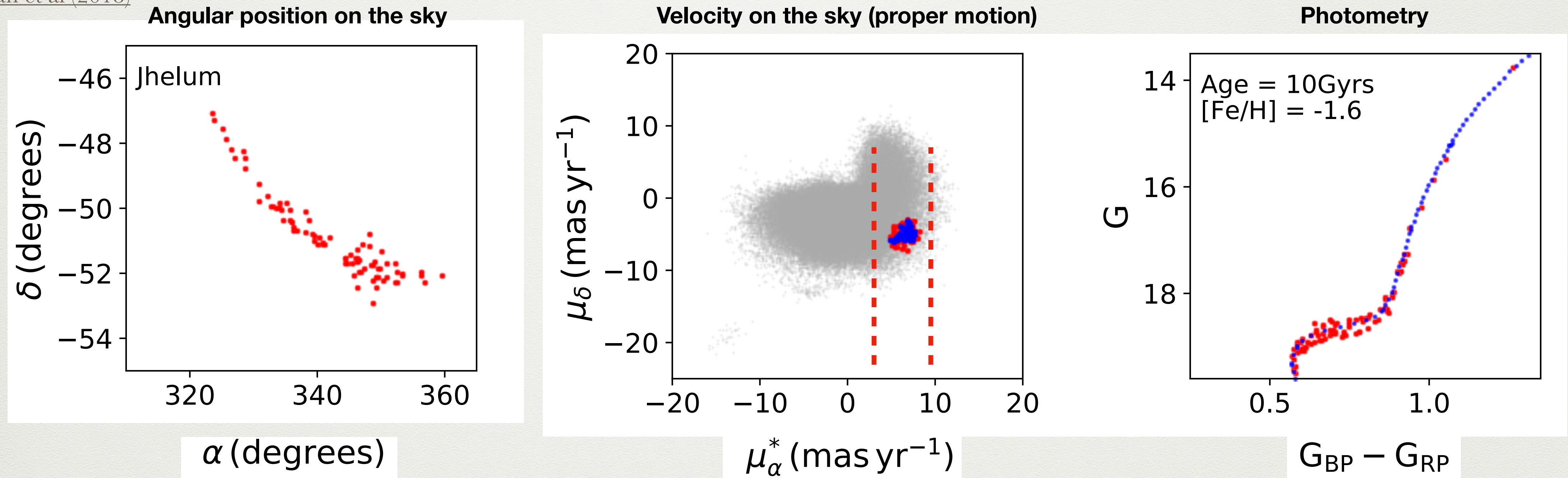


- Streams are local overdensities in multiple features — ideal for **enhanced bump hunt methods!**

Via Machinae

[DS, Buckley, Necib '23] [DS, Buckley, Necib, Tamanas '21]

Malhan et al (2018)

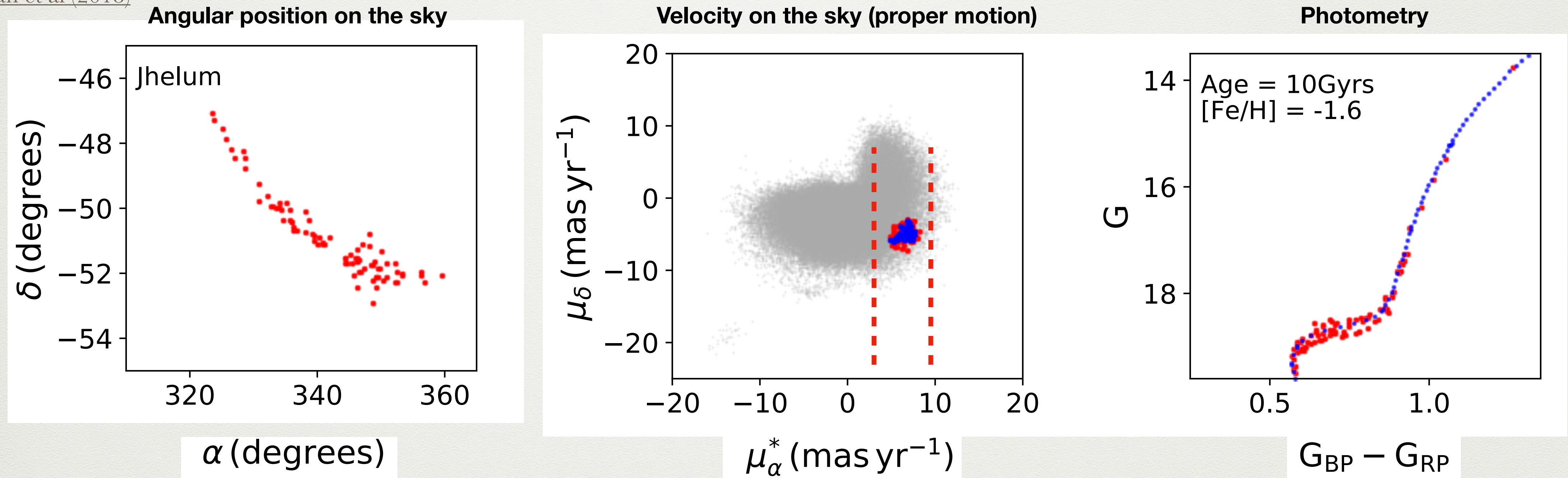


- Streams are local overdensities in multiple features — ideal for **enhanced bump hunt methods!**
- Choose either proper motion coordinate as resonant feature

Via Machinae

[DS, Buckley, Necib '23] [DS, Buckley, Necib, Tamanas '21]

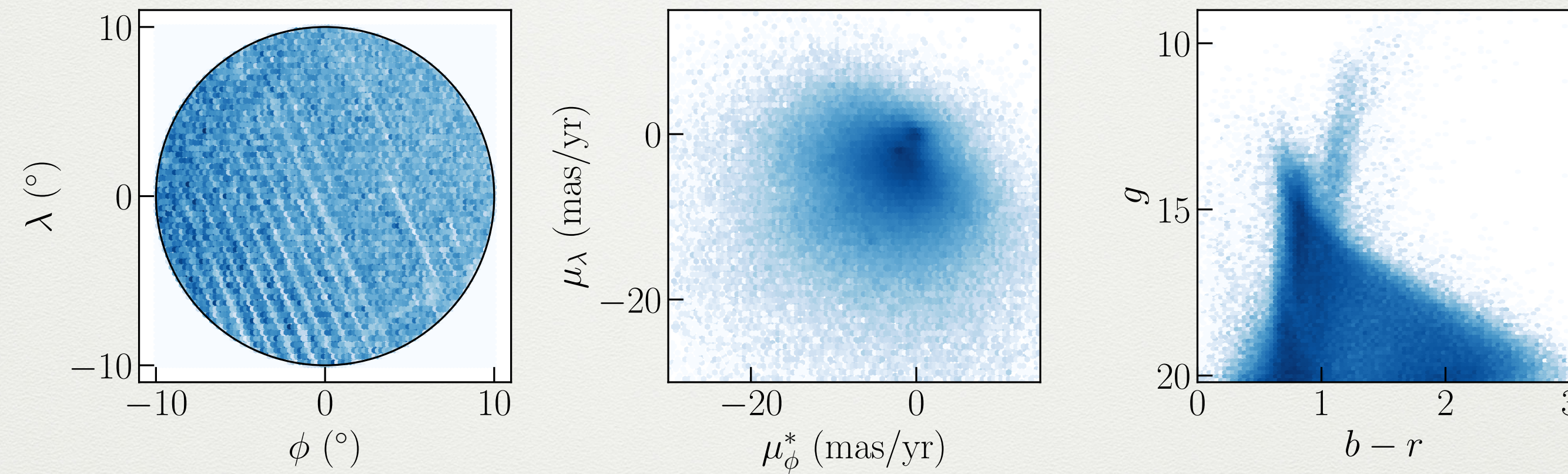
Malhan et al (2018)



- Streams are local overdensities in multiple features — ideal for **enhanced bump hunt methods!**
- Choose either proper motion coordinate as resonant feature
- Learn anomaly score (using normalizing flows) with remaining five features

Core method — illustrated with GD-1 stream

[DS, Buckley, Necib, Tamasas '21]

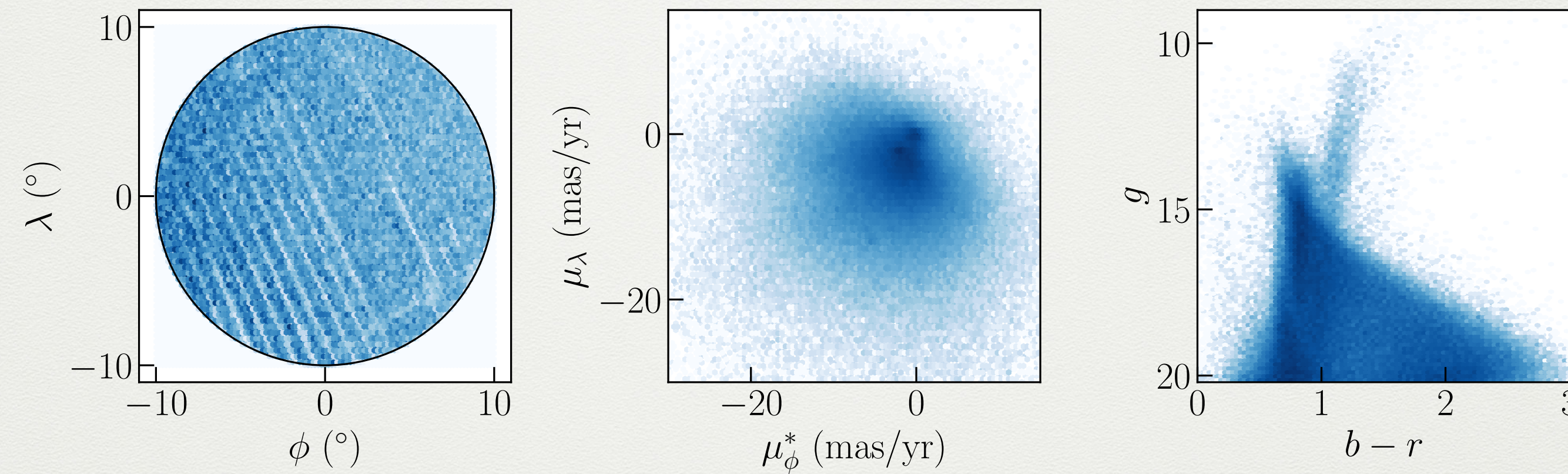


All stars in a patch of the sky
containing (part of) GD-1
(ra,dec)=(148.6,24.2)

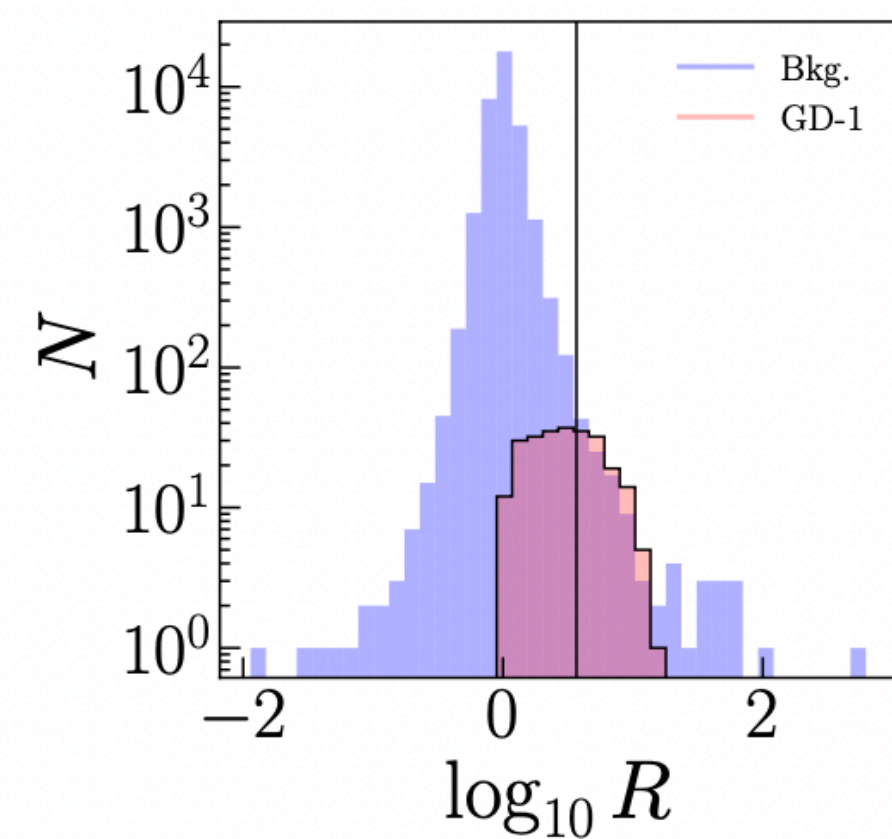
Core method — illustrated with GD-1 stream

[DS, Buckley, Necib, Tamasas '21]

Train ANODE on a
proper motion window
containing GD-1



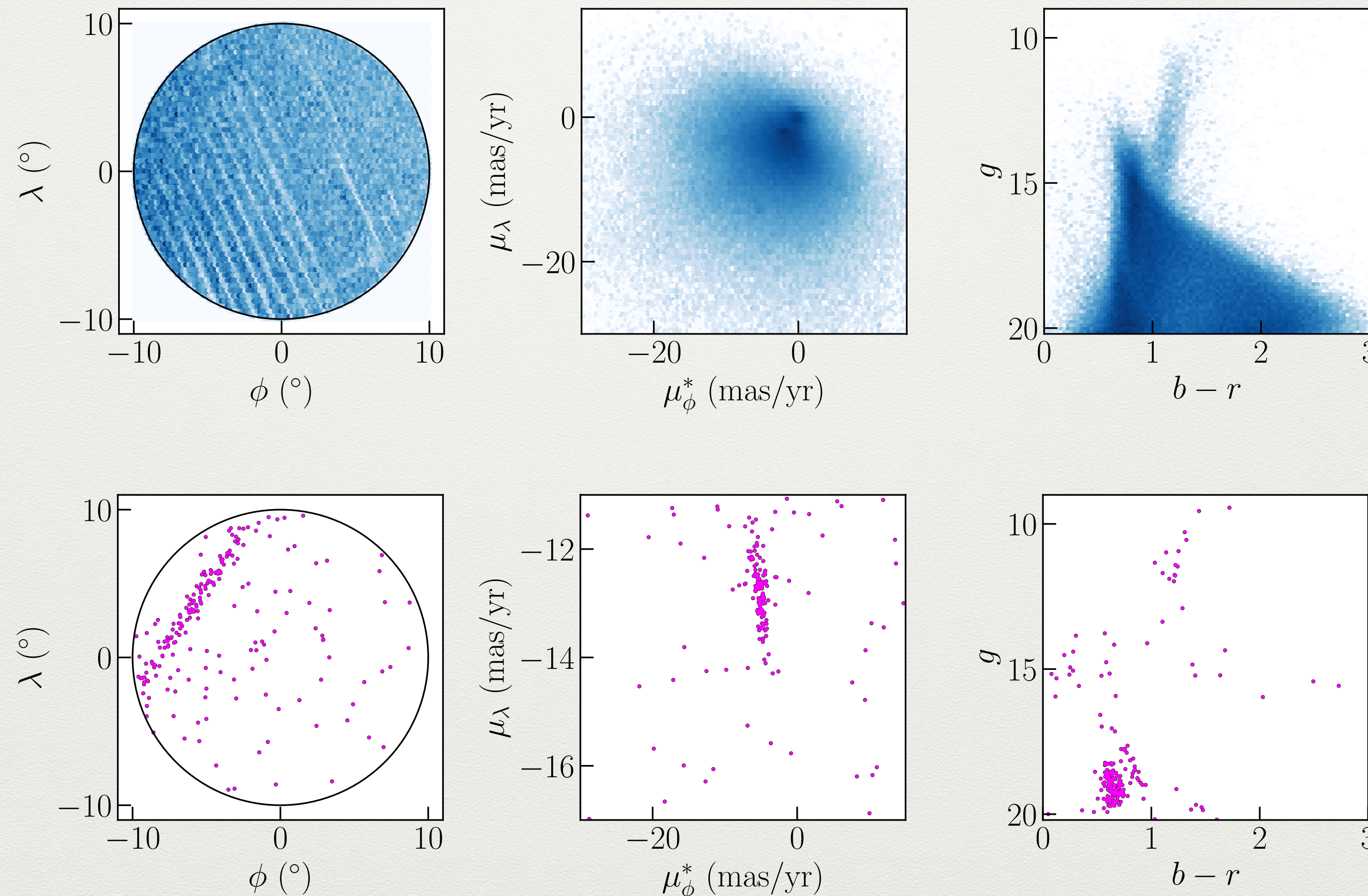
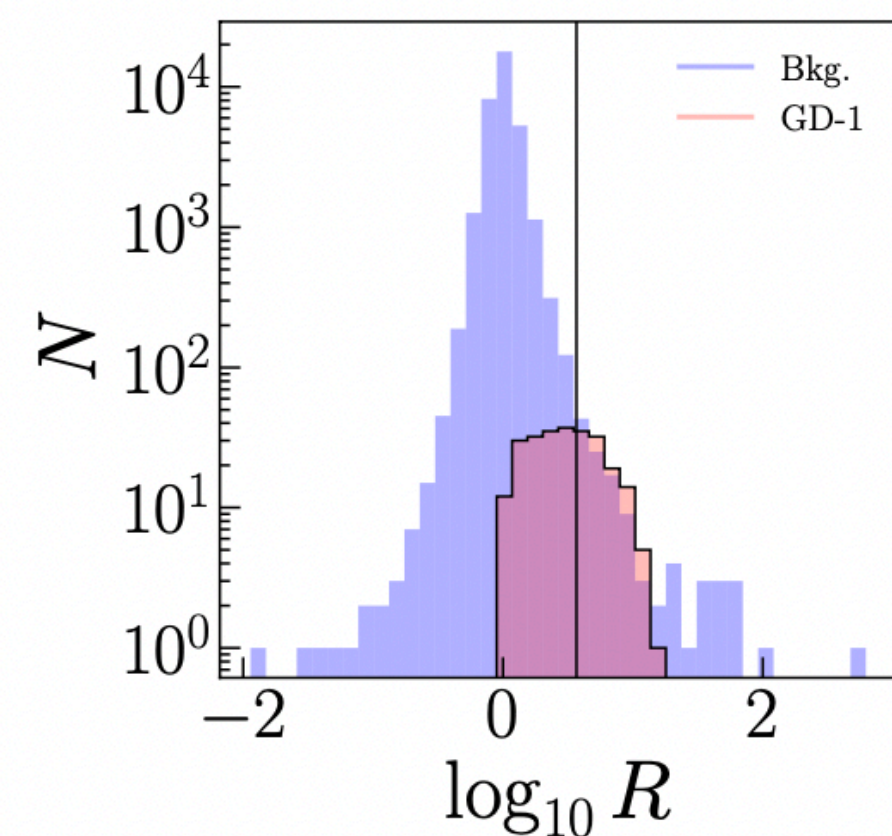
All stars in a patch of the sky
containing (part of) GD-1
(ra,dec)=(148.6,24.2)



Core method — illustrated with GD-1 stream

[DS, Buckley, Necib, Tamasas '21]

Train ANODE on a proper motion window containing GD-1



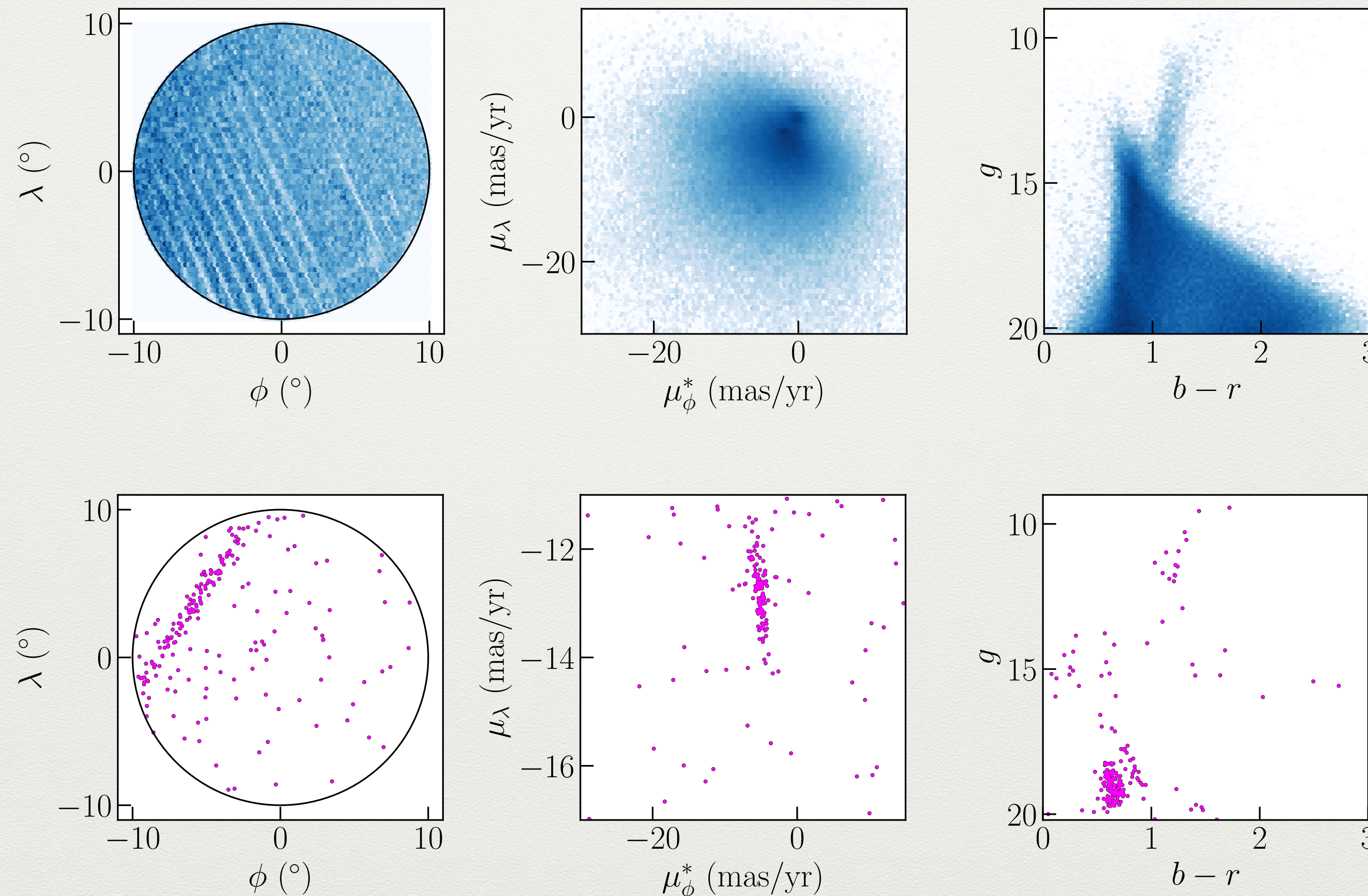
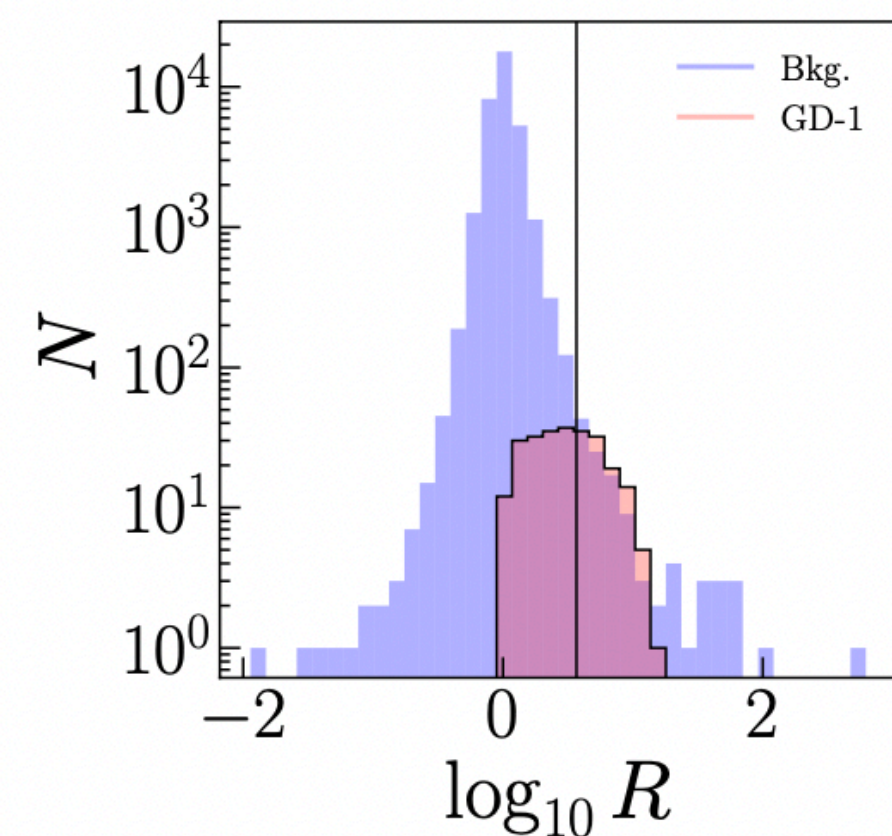
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Stars in SR after cut on $R(x)$ obtained from ANODE

Core method — illustrated with GD-1 stream

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Train ANODE on a proper motion window containing GD-1



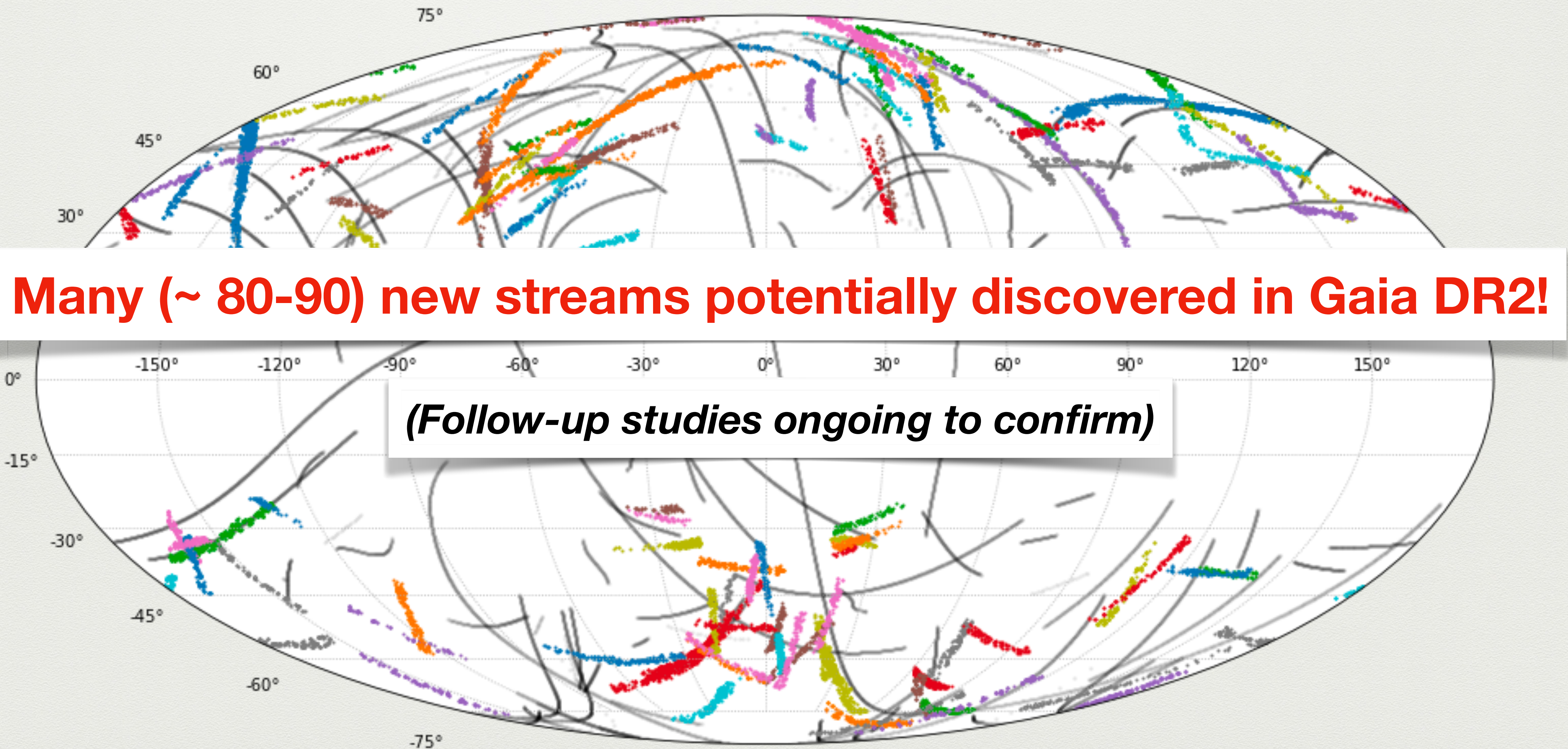
All stars in a patch of the sky containing (part of) GD-1 (ra,dec)=(148.6,24.2)

Stars in SR after cut on $R(x)$ obtained from ANODE

It works! Fully data-driven, simulation-independent

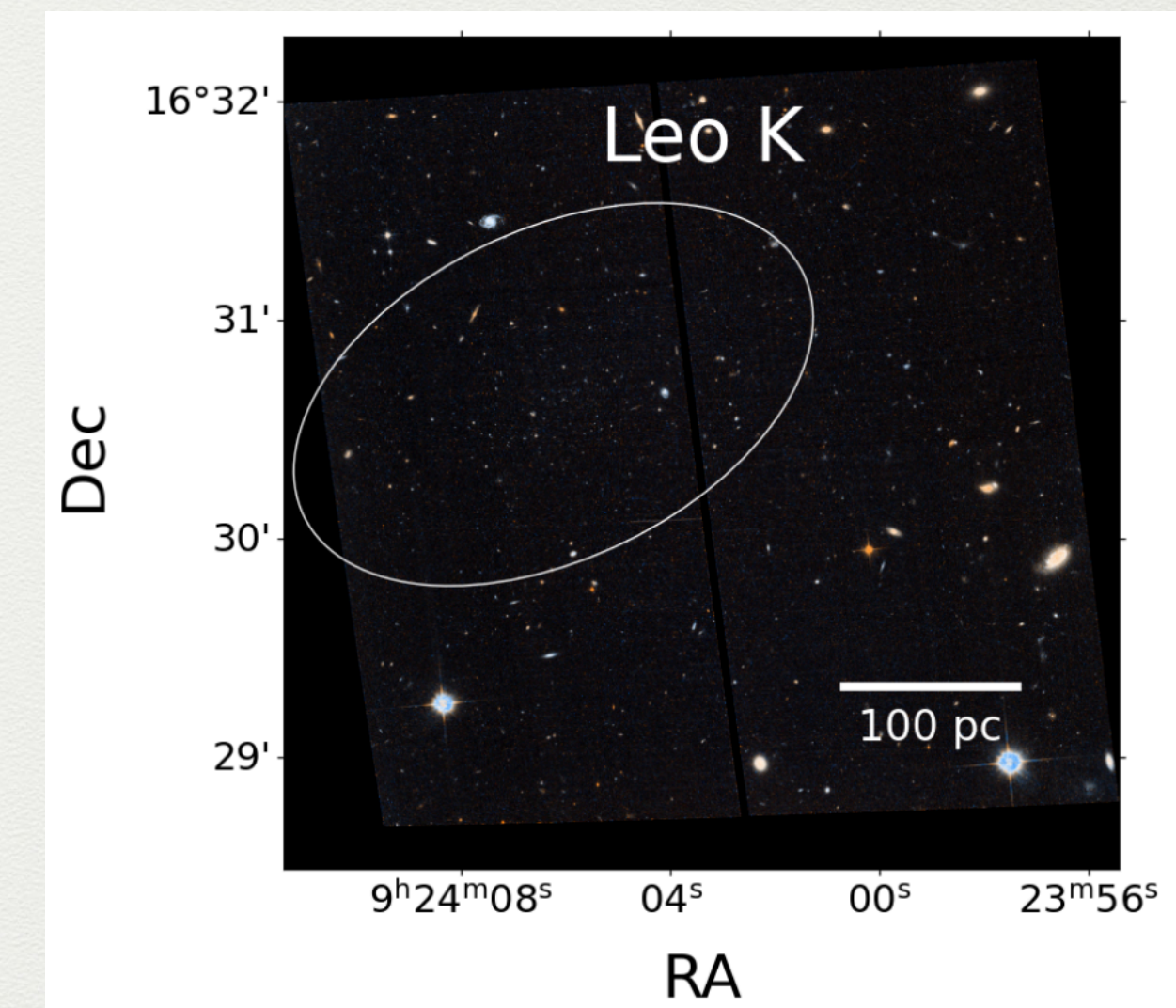
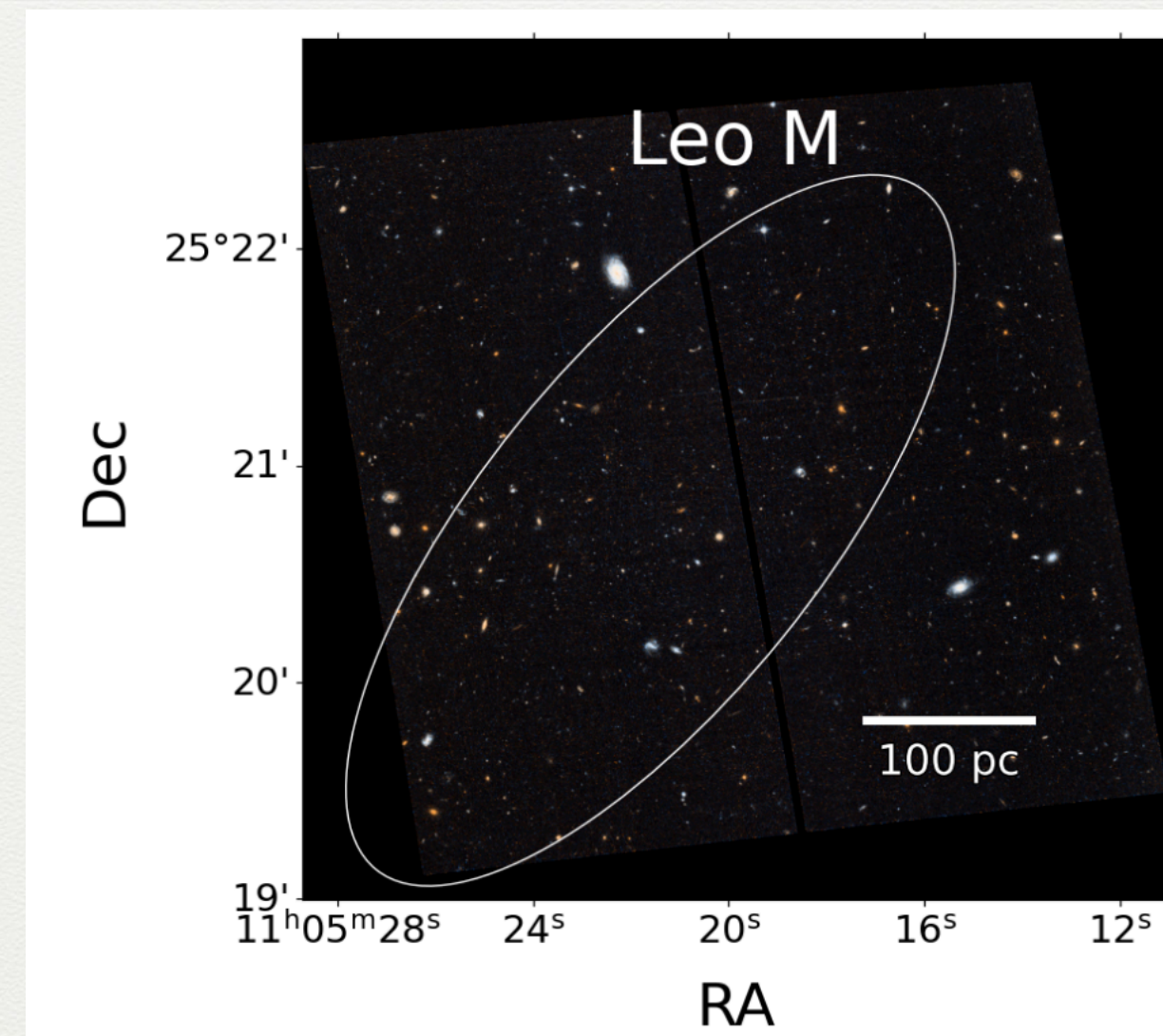
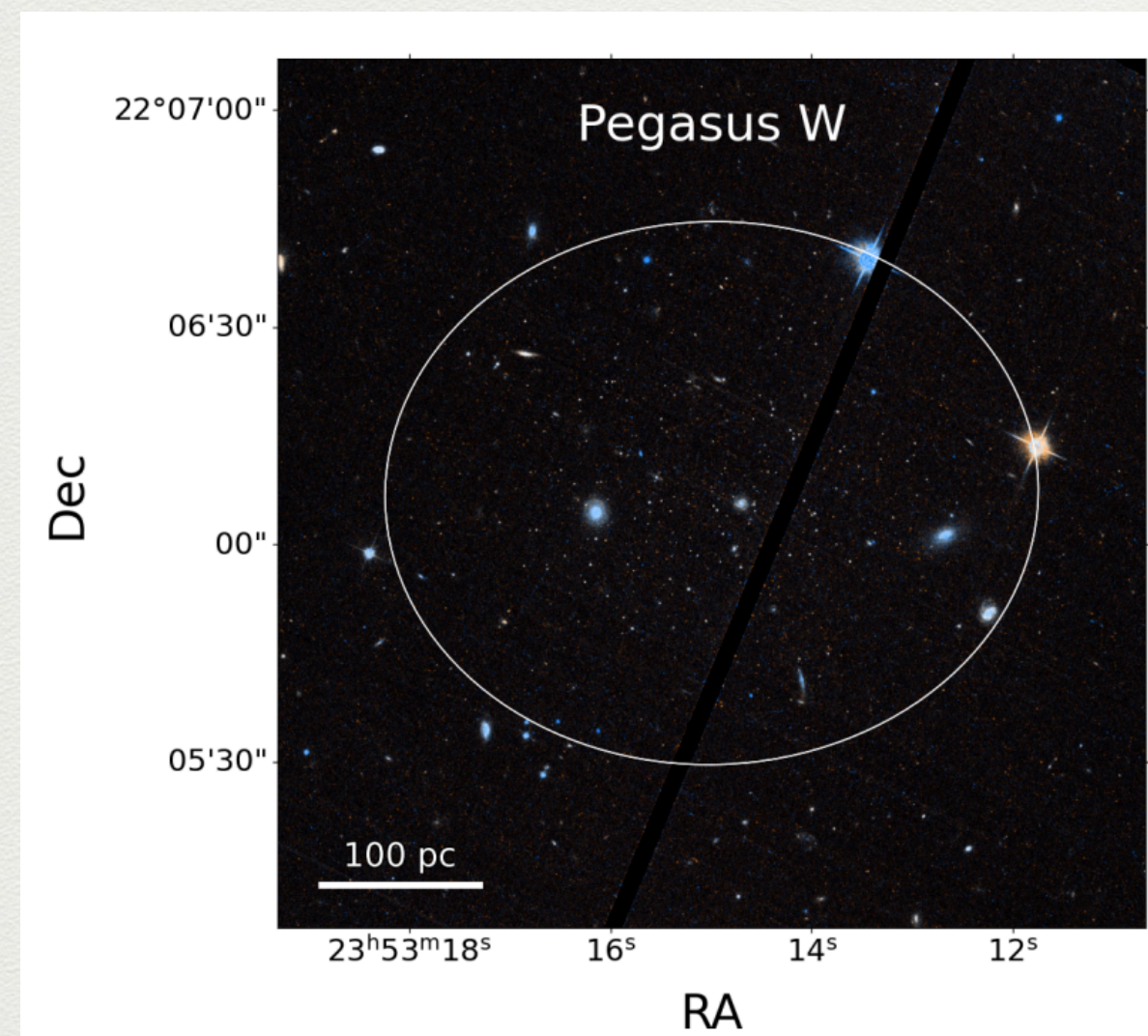
New Stream Candidates from Gaia DR2

[DS, Buckley, Necib (2023)]



Spinoff: discovering new ultra-faint dwarf galaxies

[DS+ McQuinn et al (2023a), (2023b)]



- Helped astronomers to discover 3 new ultra-faint “field” dwarf galaxies
 - First as overdensities of star counts in DESI Legacy Survey data
 - Then confirmed with dedicated Hubble time

Mapping Dark Matter in the Milky Way

[Lim, Putney, Buckley & DS (2022), (2023)]

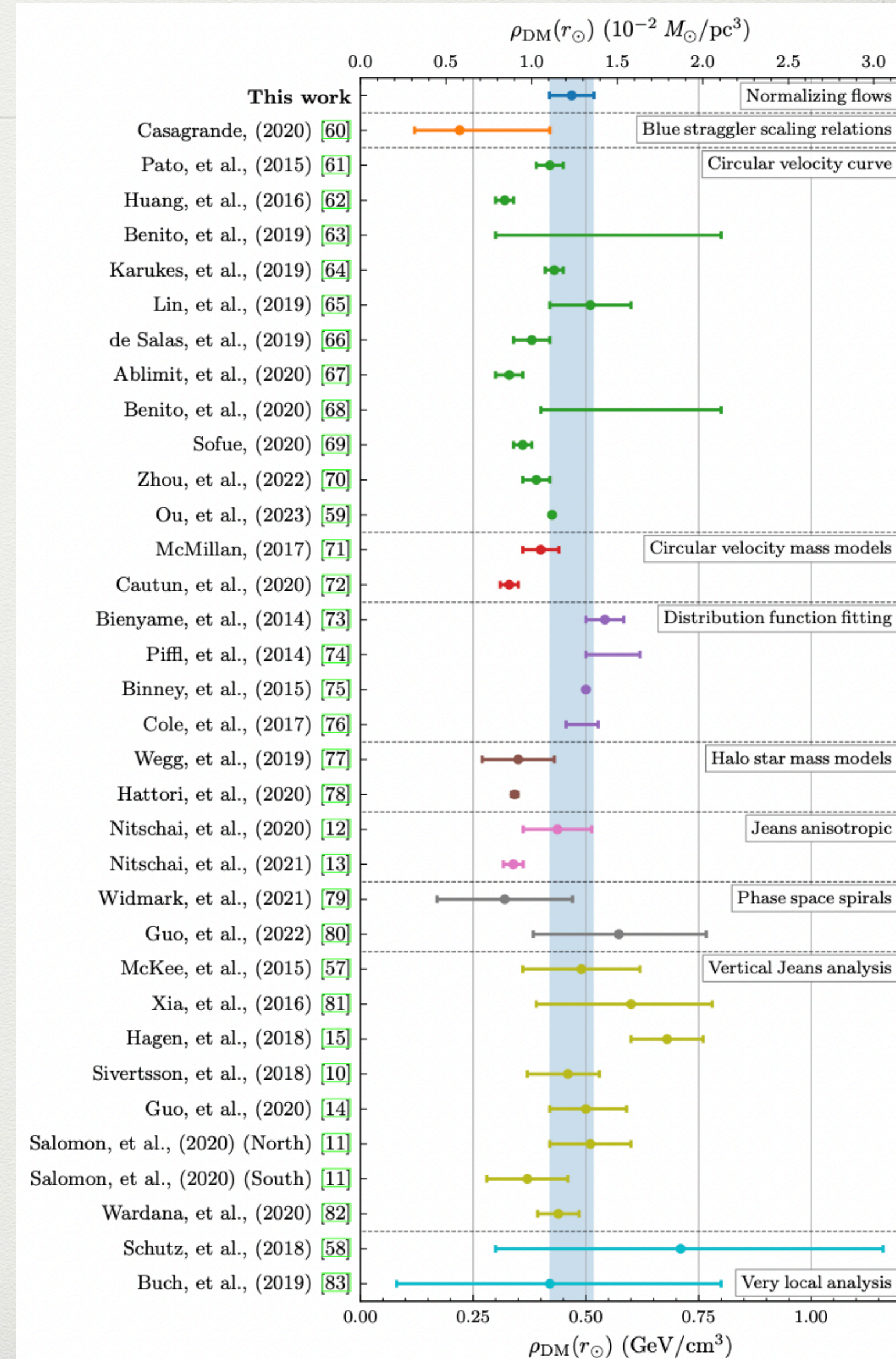
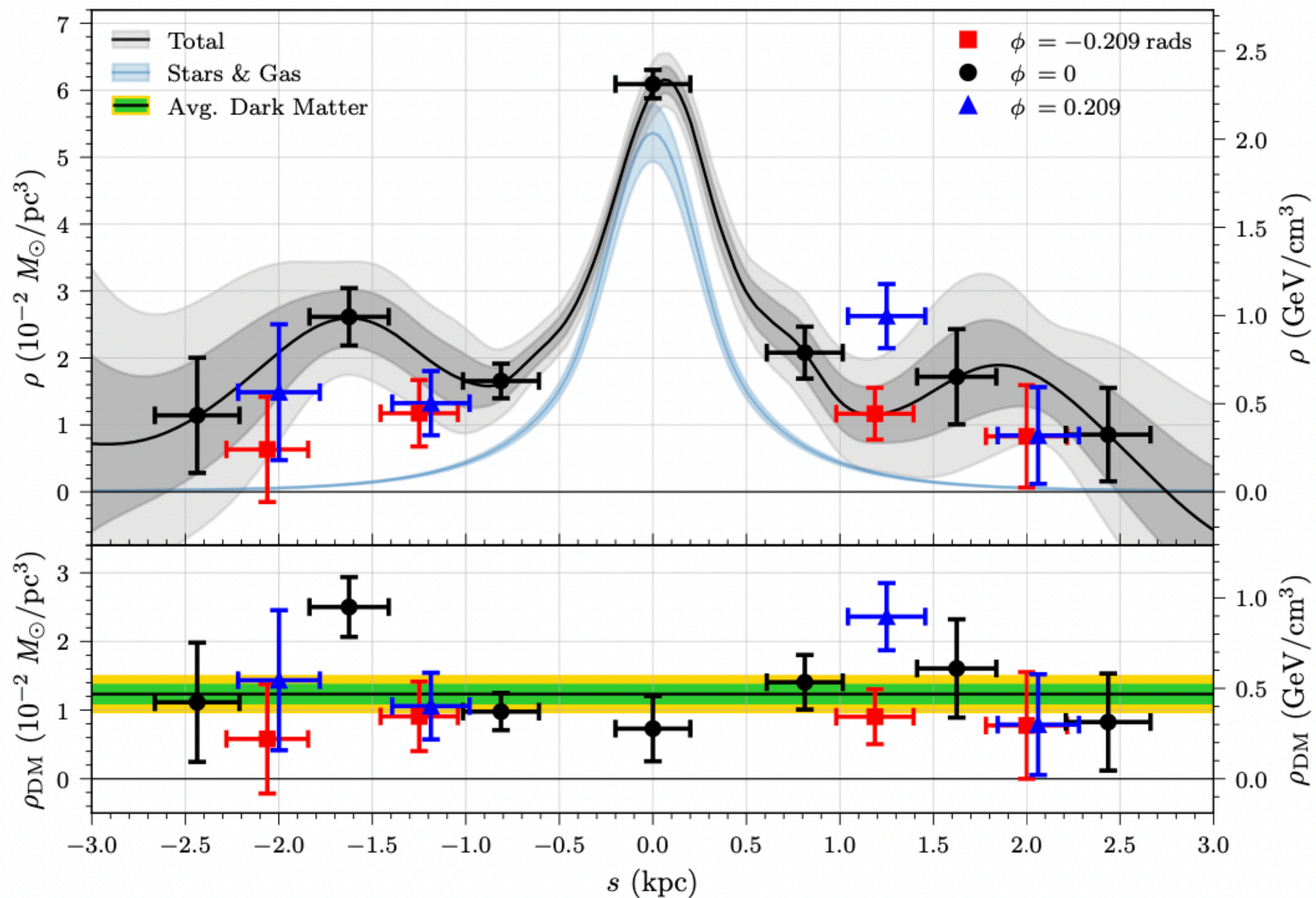
- **Idea:** can measure **3d map of dark matter density** $\rho_{DM}(\vec{x})$ near the Sun using Gaia data!
 1. Fit **normalizing flows** to stellar positions and velocities => phase space density $f(\vec{x}, \vec{v})$
 2. Use the **Boltzmann equation** to extract **acceleration** and **mass density**


$$\frac{\partial f}{\partial t} + v_i \frac{\partial f}{\partial x_i} = \frac{\partial \Phi}{\partial x_i} \frac{\partial f}{\partial v_i}$$


$$4\pi G\rho = \nabla^2 \Phi$$

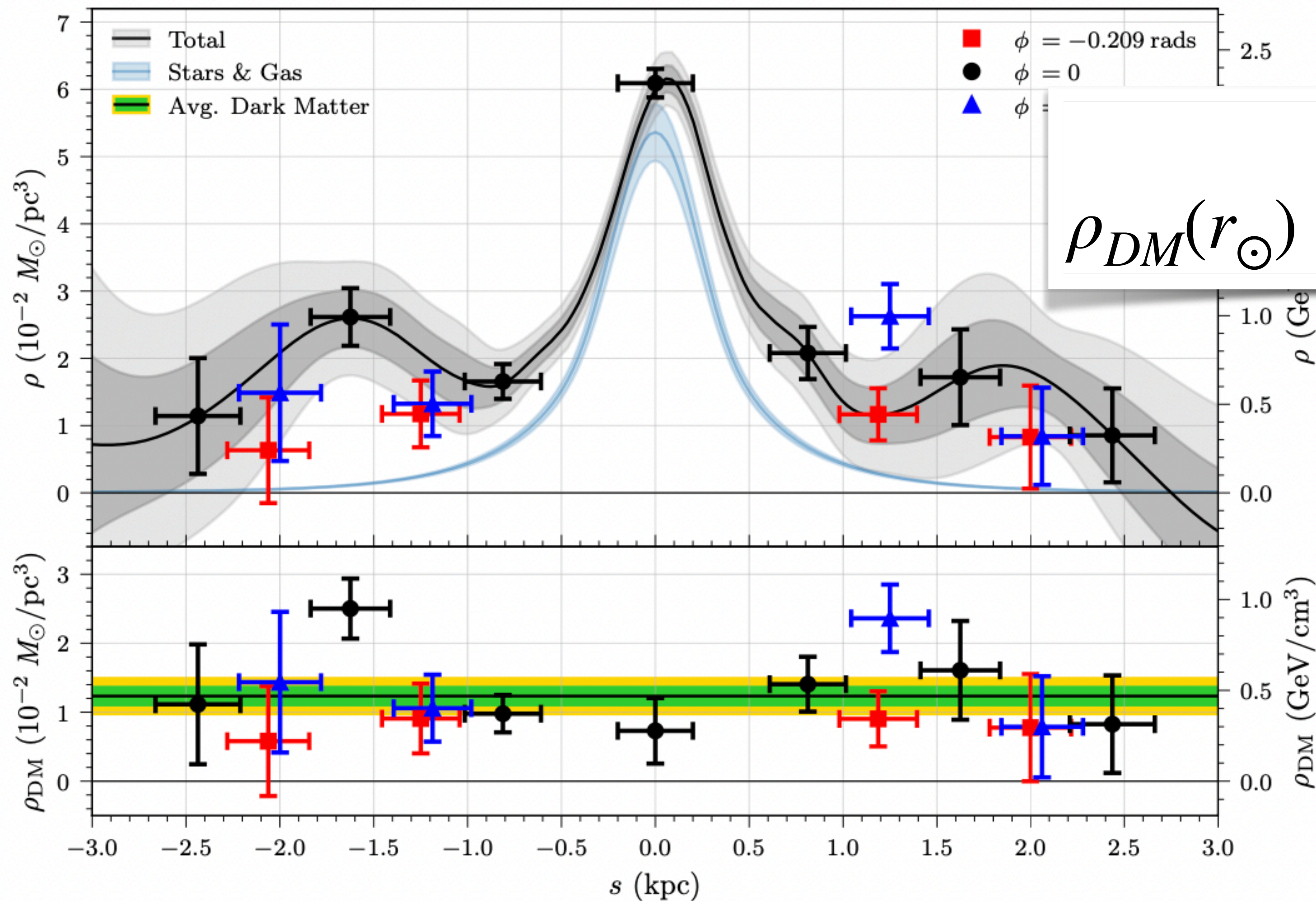
Mapping Dark Matter in the Milky Way

[Lim, Putney, Buckley & DS (2022), (2023)]



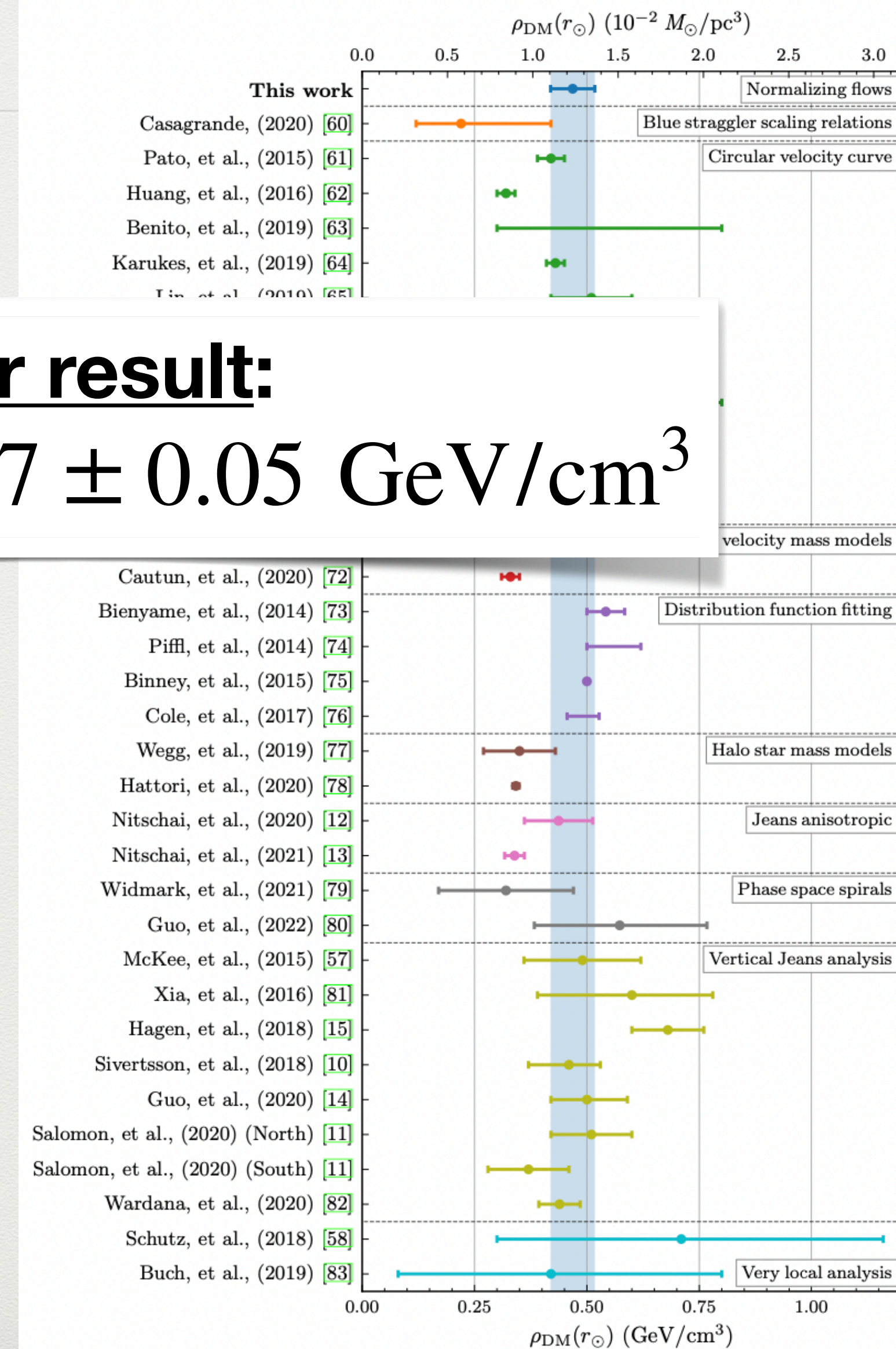
Mapping Dark Matter in the Milky Way

[Lim, Putney, Buckley & DS (2022), (2023)]



Our result:

$$\rho_{\text{DM}}(r_{\odot}) = 0.47 \pm 0.05 \text{ GeV}/\text{cm}^3$$



Summary/Outlook

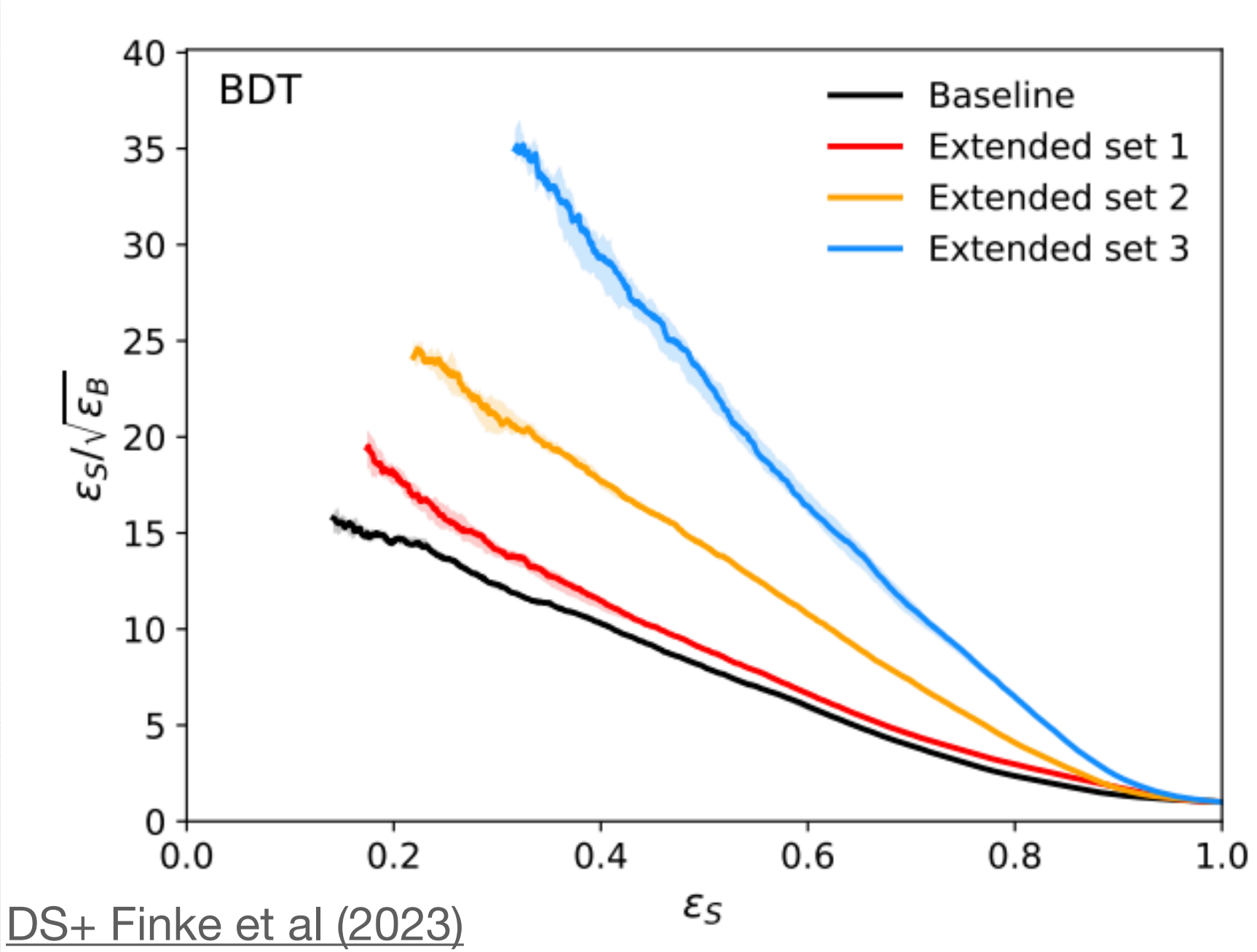
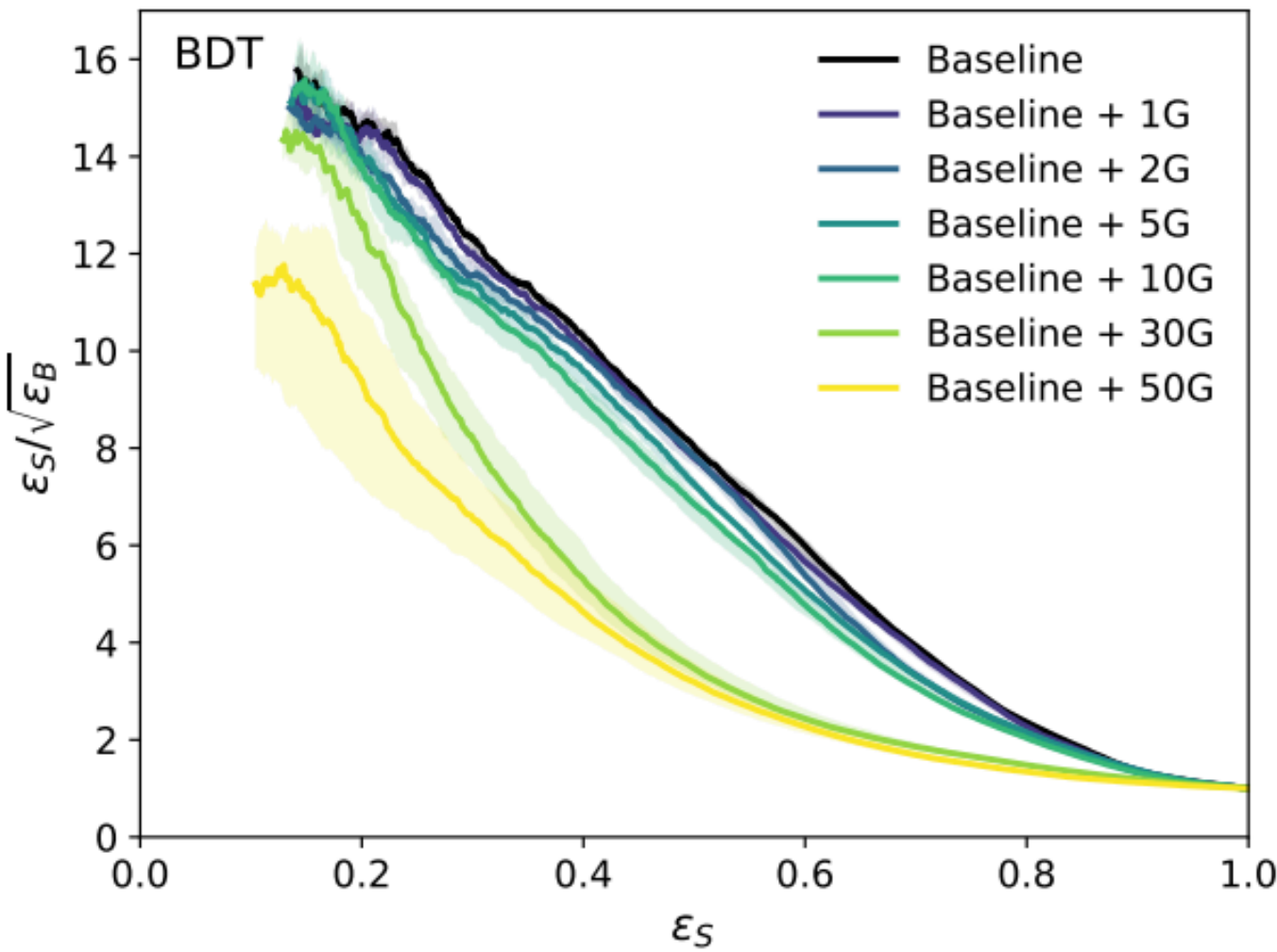
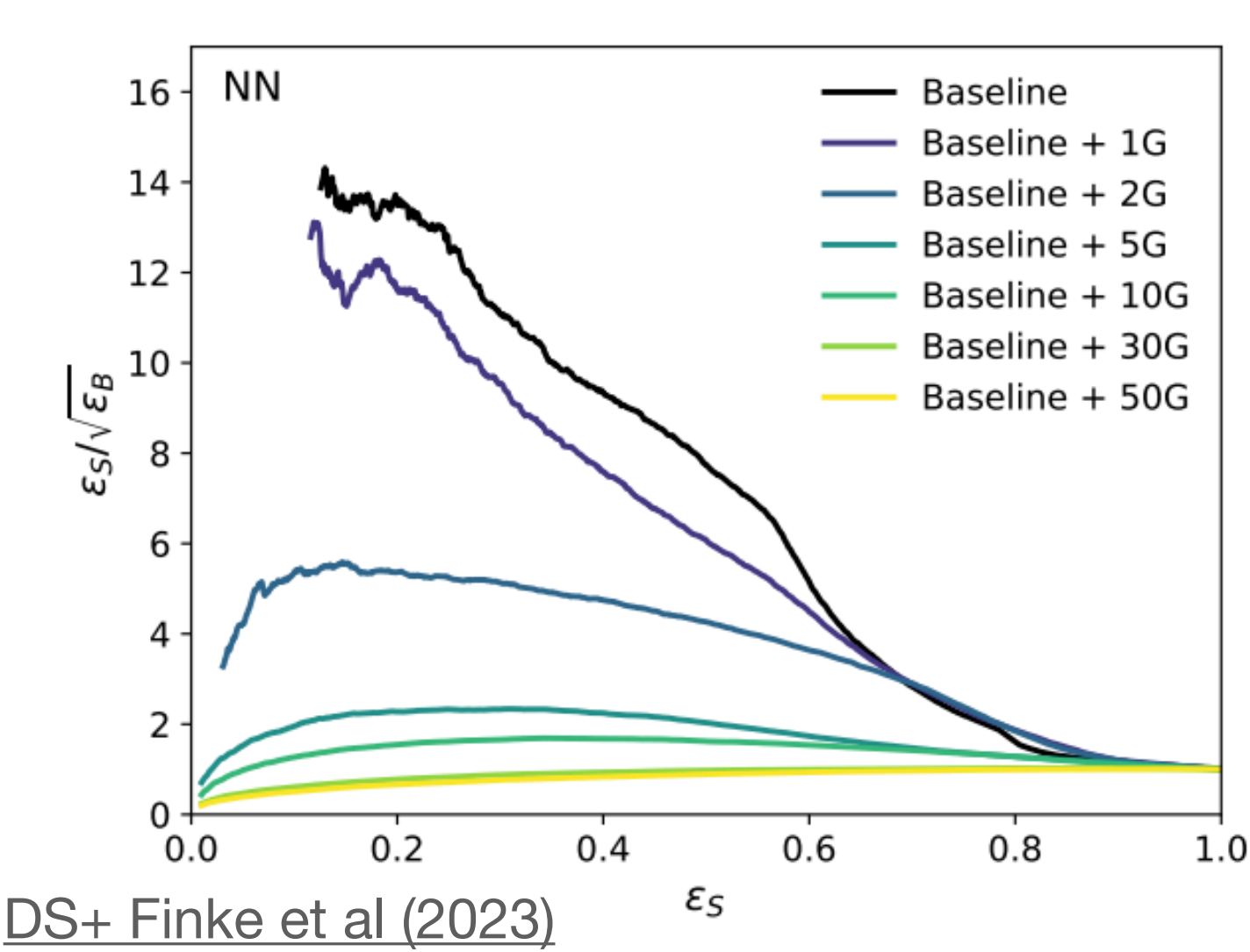
- Breakthroughs in AI/ML are enabling a **new paradigm** for new physics searches
- The new techniques we are developing for new physics searches have broader applicability, e.g. to search for stellar streams in Gaia data.
- There is a lot more data coming, including HL-LHC, Gaia DR4, Euclid, LSST, Roman, SKA, ...
- Modern ML gives us new ways to look deeper into the data. Exciting discoveries await!

Thanks!

Further improvements

BDTs are more robust than NNs...

Name	# features	Features
Baseline	4	$\{m_{J_1}, \Delta m_J, \tau_{21}^{\beta=1,J_1}, \tau_{21}^{\beta=1,J_2}\}$
Extended 1	10	$\{m_{J_1}, \Delta m_J, \tau_{N,N-1}^{\beta=1,J_1}, \tau_{N,N-1}^{\beta=1,J_2}\}$ for $2 \leq N \leq 5$
Extended 2	12	$\{m_{J_1}, \Delta m_J, \tau_N^{\beta=1,J_1}, \tau_N^{\beta=1,J_2}\}$ for $N \leq 5$
Extended 3	56	$\{m_{J_1}, \Delta m_J, \tau_N^{\beta,J_1}, \tau_N^{\beta,J_2}\}$ for $N \leq 9$ and $\beta \in \{0.5, 1, 2\}$



...leading to much higher performance using more features!

Further improvements

Relying on high-level physics features is not fully model-agnostic...

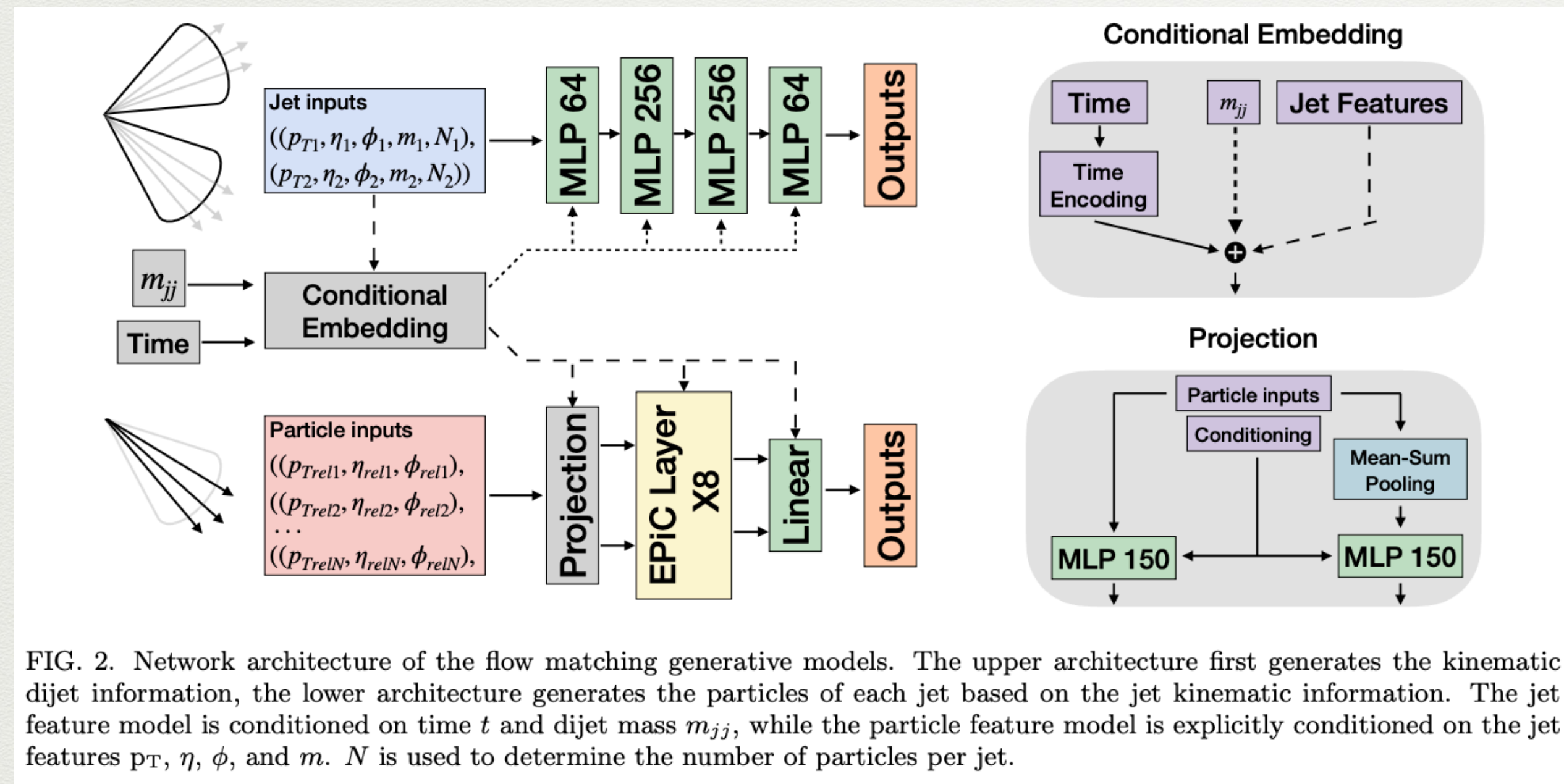
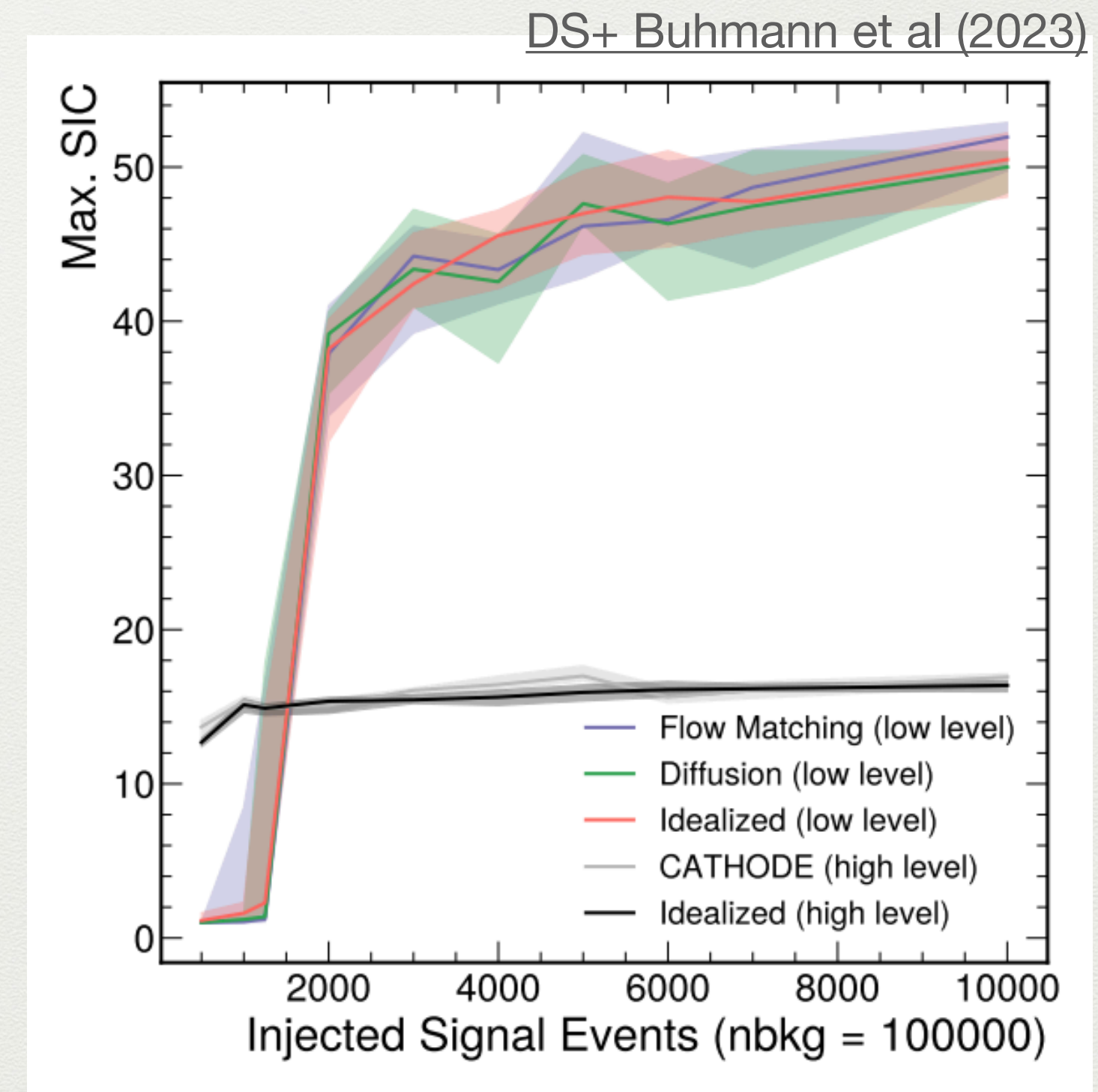


FIG. 2. Network architecture of the flow matching generative models. The upper architecture first generates the kinematic dijet information, the lower architecture generates the particles of each jet based on the jet kinematic information. The jet feature model is conditioned on time t and dijet mass m_{jj} , while the particle feature model is explicitly conditioned on the jet features p_T , η , ϕ , and m . N is used to determine the number of particles per jet.



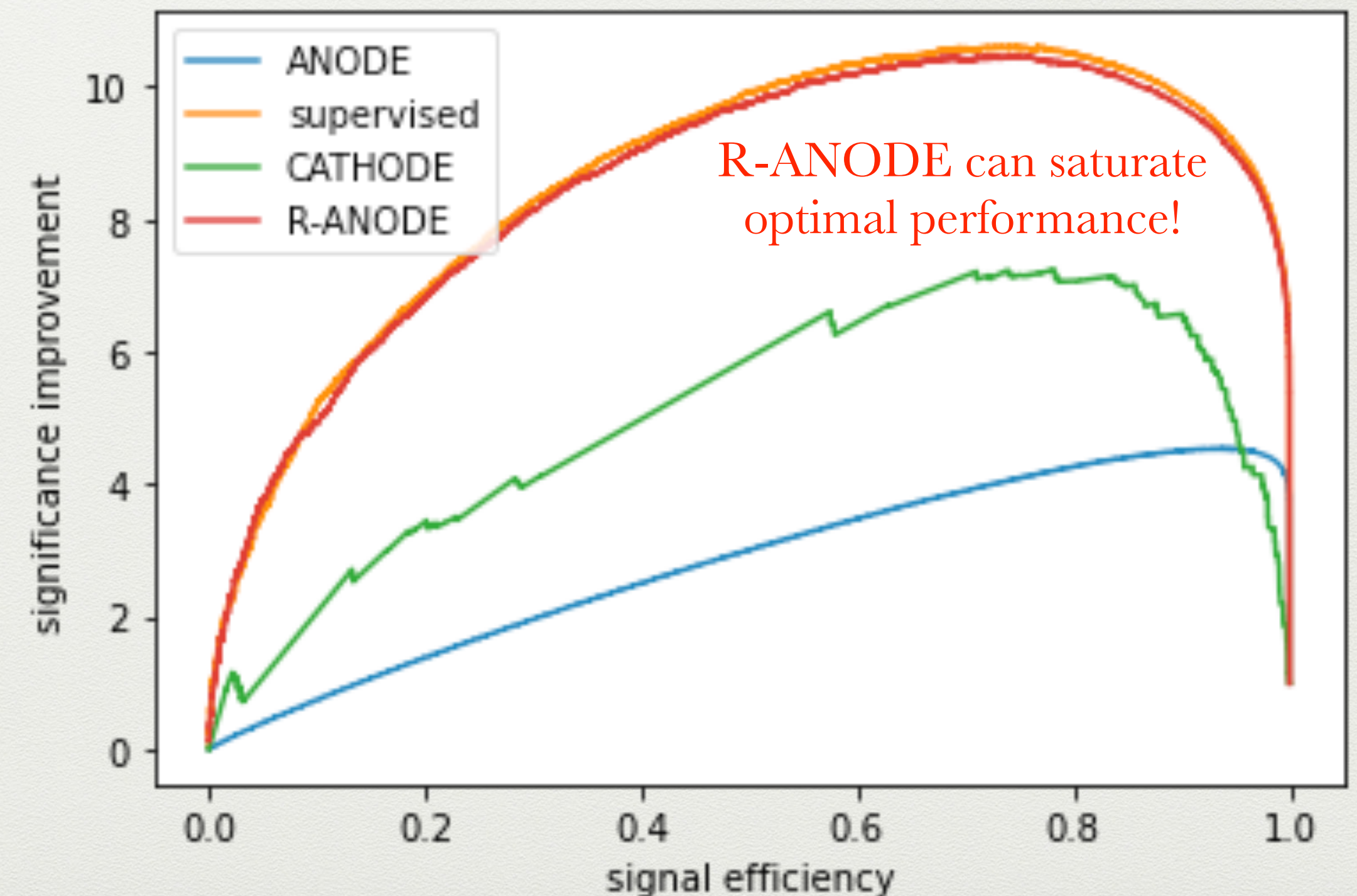
With recent breakthroughs in generative modeling (diffusion, flow-matching), using all the low-level information (jet constituents) is becoming possible!

Residual ANODE

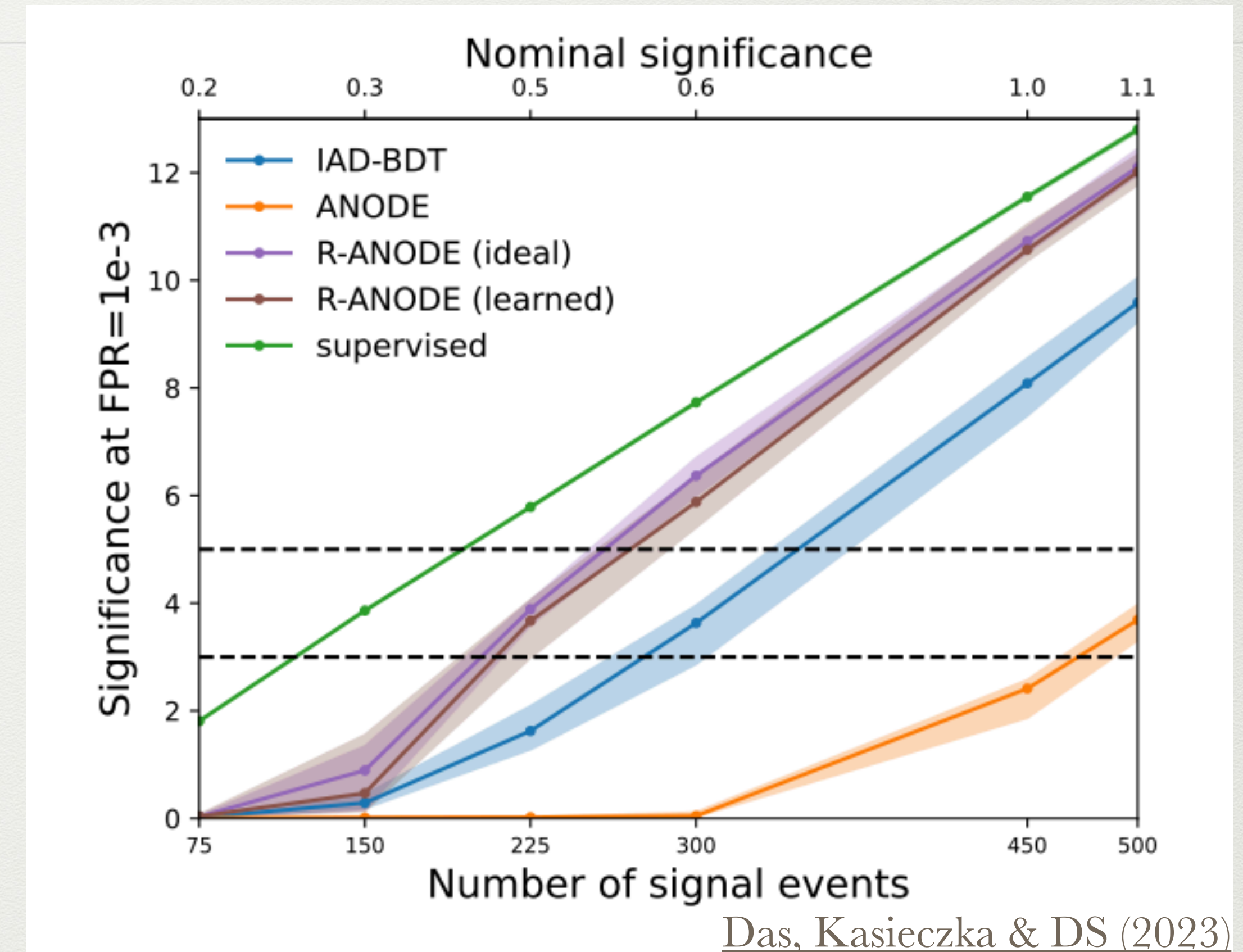
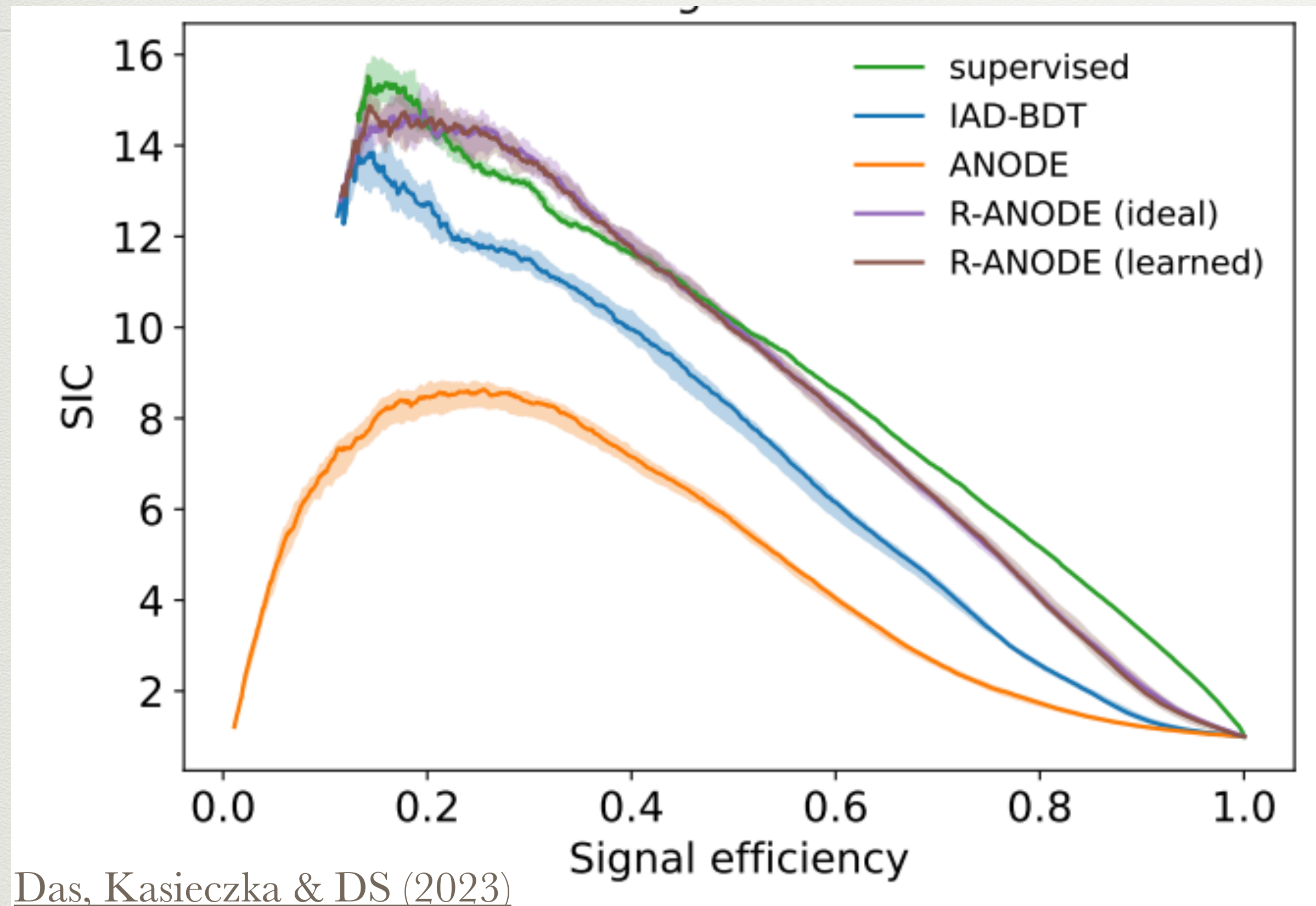
[Das, Kasieczka & DS (2023)]

Can do even better by freezing background density and only fitting a small “residual” density estimator to learn the signal in data

1. Fit $p_{bg}(x)$ to background
2. Freeze $p_{bg}(x)$ and fit $(1-w)p_{bg}(x) + wp_{sig}(x)$ to data

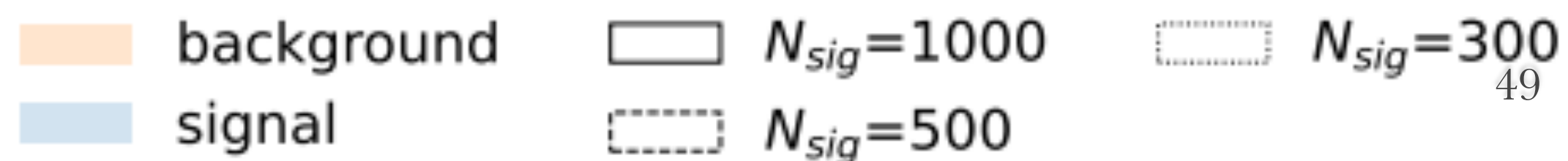
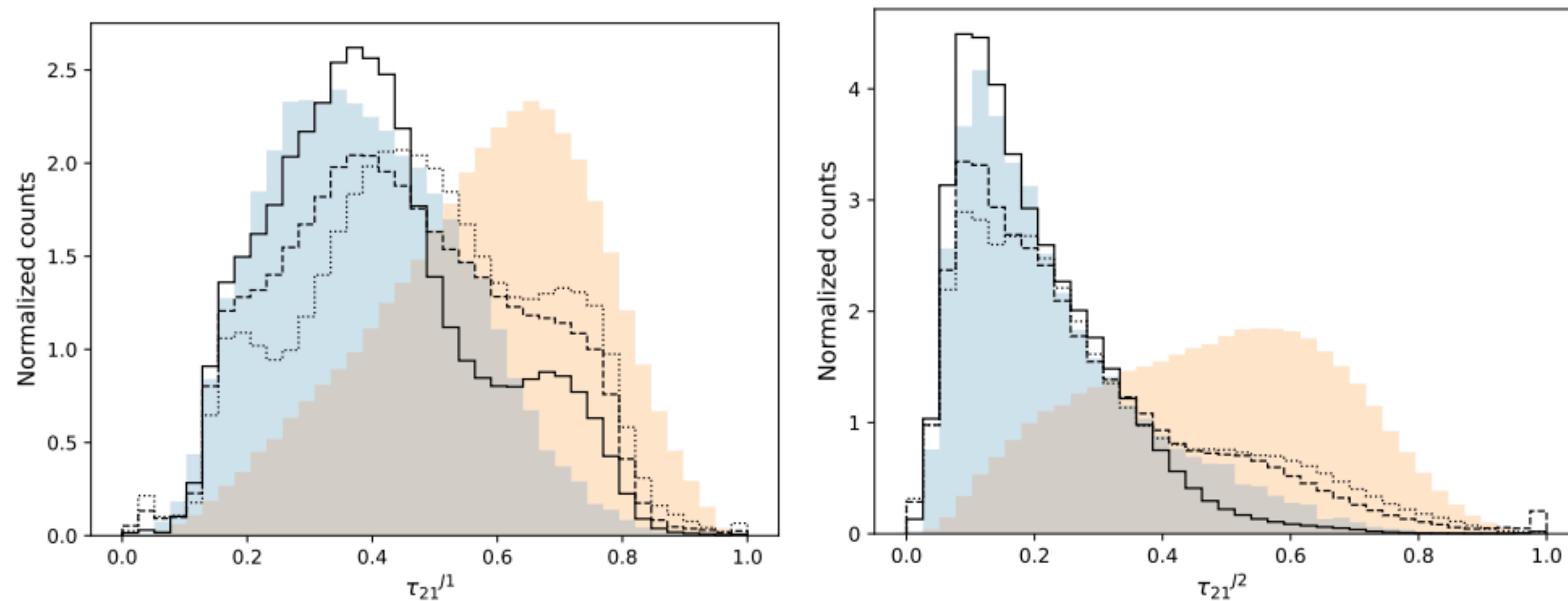
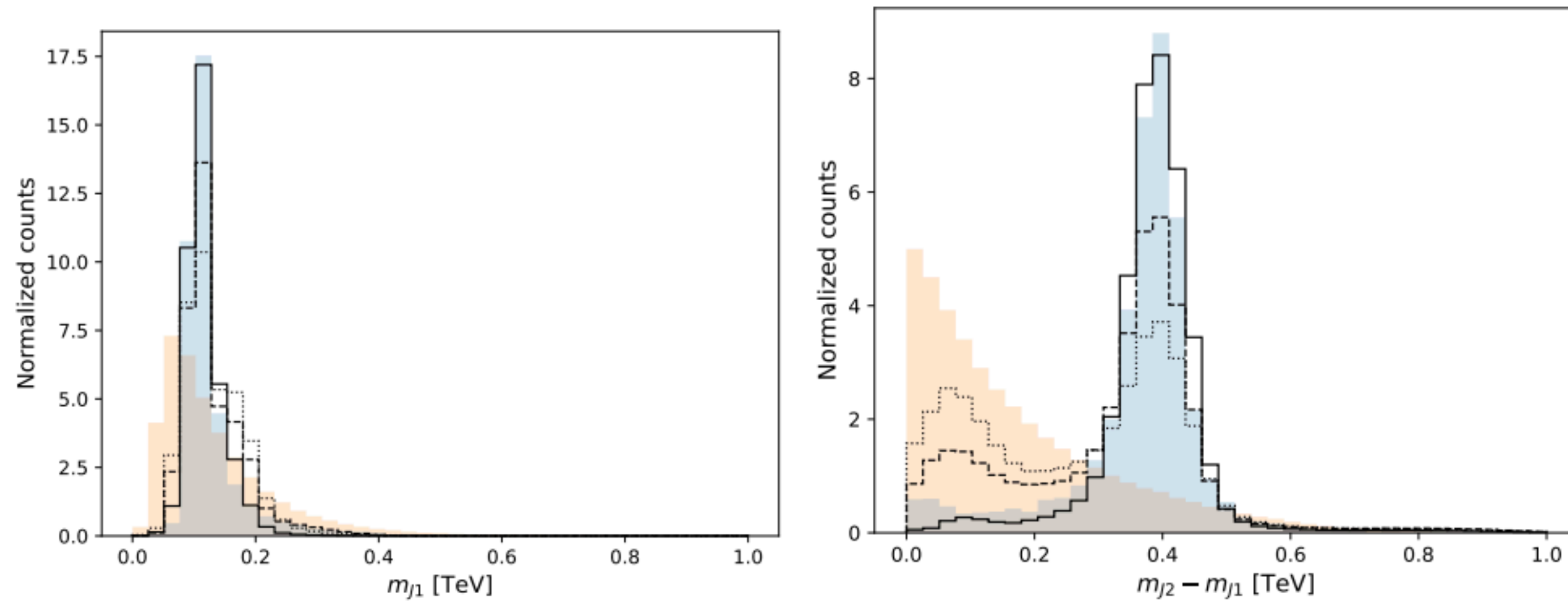


Performance on LHCO



R-ANODE exceeds classifier-based approaches
Closes/narrows the gap with fully supervised

Interpretability with R-ANODE



$$p_{data}(x) = (1 - w)p_{bg}(x) + wp_{sig}(x)$$

In R-ANODE, fitting $p_{sig}(x)$ to the data in the signal region directly gives an empirical model for the signal. Can visualize this!

Can also directly infer the signal strength!

