

# CURTAINS



Weakly Supervised Methods for new physics searches

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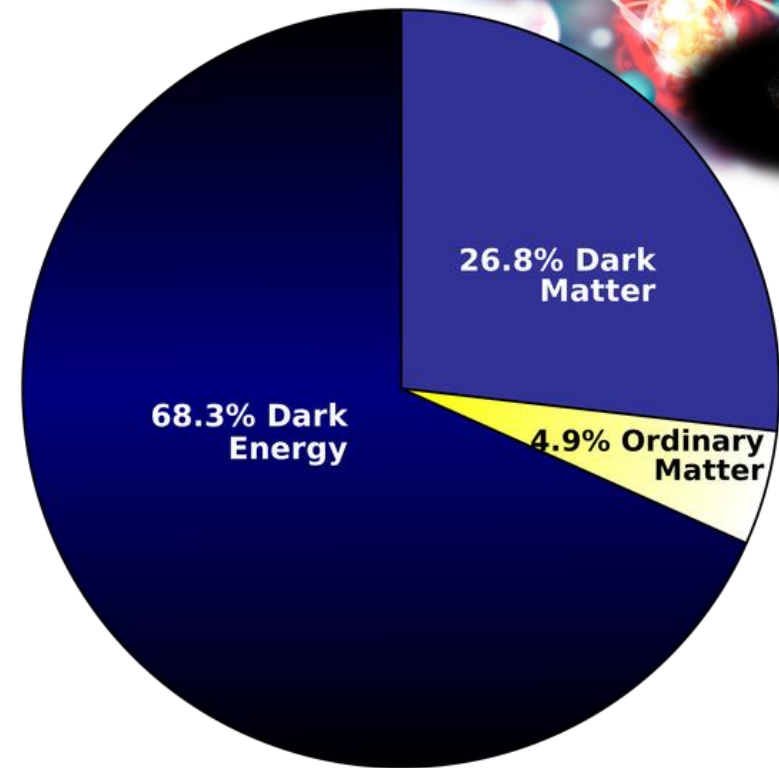
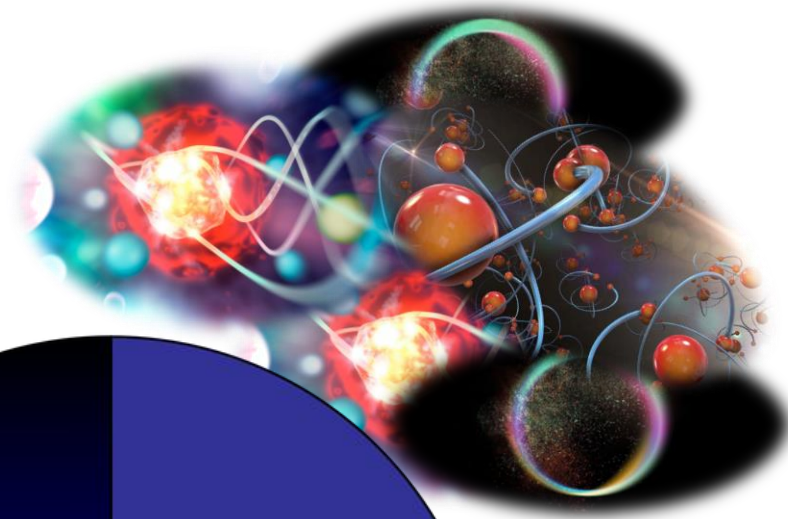
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# Weakly Supervised Methods

~25 % of matter content is unknown ~ Many models

Supervised searches most optimal, **but not feasible**.

No labels in real life ~ but something close.



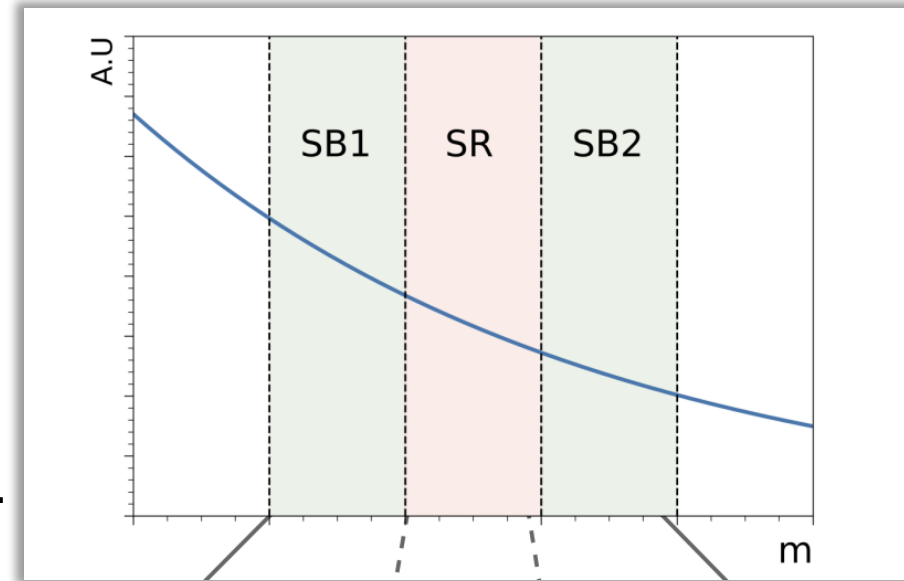
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# Weakly Supervised Methods

- Supervised searches most optimal, **but not feasible**.
- No labels in real life ~ but something close.
- Signal Regions (SR), Sidebands (SB) ~ different fraction of signals.
- CWoLa principle – Optimal classifier for two different admixtures is the optimal classifier between the two classes.

Strategy:

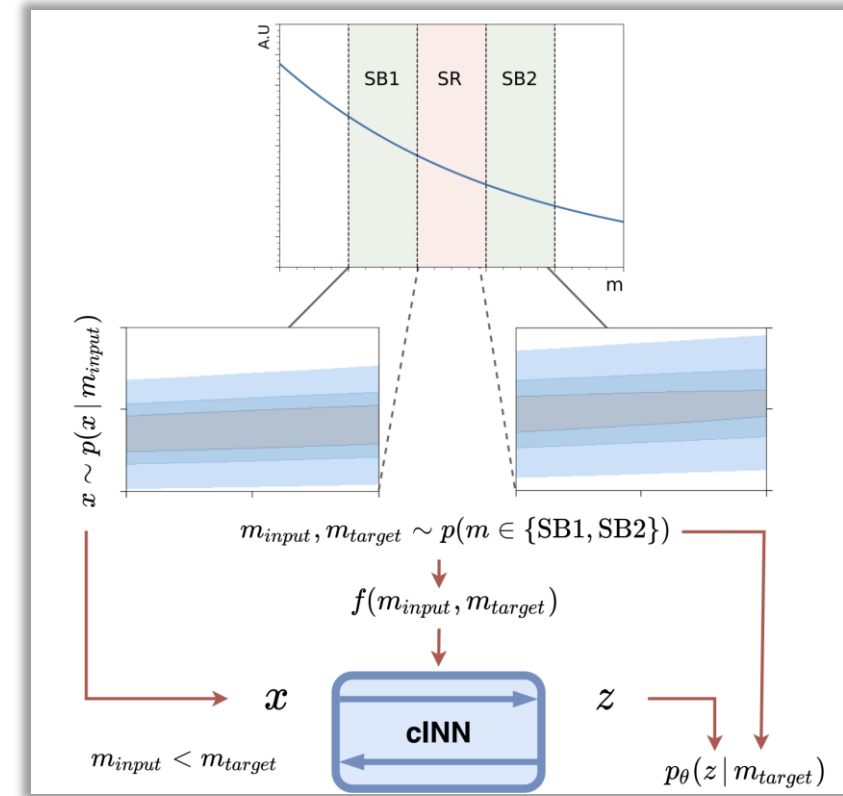
1. Construct background enriched templates in SR
2. CWoLa



Signal region (SR) and Sidebands (SB) around a hypothetical resonance in  $m$ .

# CURTAINS [2203.09470](#) [2305.04646](#)

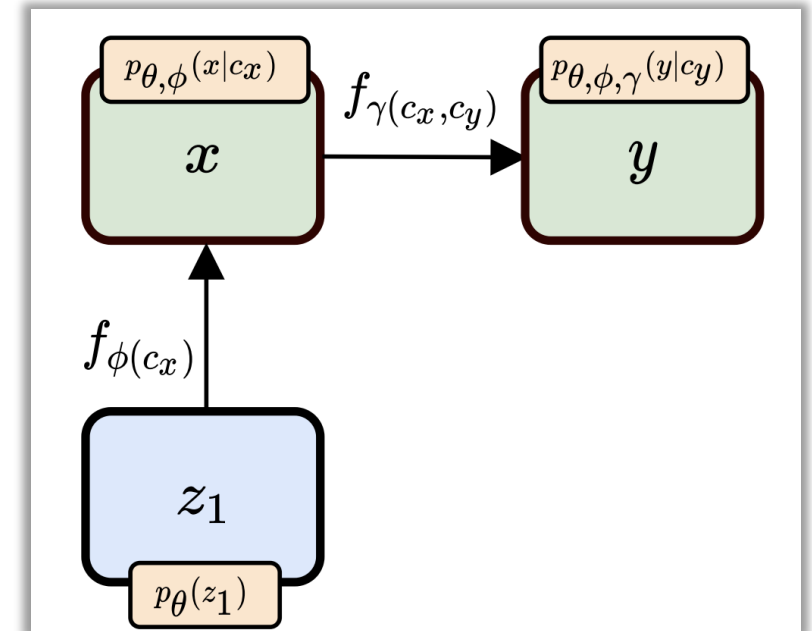
- Transform SB data to SR under exact likelihood
  - Using Flows for Flows
- Background enriched template in the SR



Schema for curtains, data from sidebands are passed through cINN in a forward or inverse pass depending on input and target  $m$

# FLOWS FOR FLOWS

- Transform SB data to SR under exact likelihood
- Train a normalizing flow SB  $\leftrightarrow$  SB
  - $p_{\theta\phi\gamma}(y | c_x, c_y) = p_{\theta\phi}(x | c_x, c_y) \cdot \det |J_{f_\gamma}(x | c_x, c_y)| \rightarrow$  **Top Flow**
  - $p_{\theta\phi}(x | c_x, c_y) = \pi_\theta(z) \cdot \det |J_{f_\phi}(x | c_x)| \rightarrow$  **Base Flow**
- Template  $\rightarrow$  Sample masses from SR and transform SB into SR.



Flows for Flows schematic

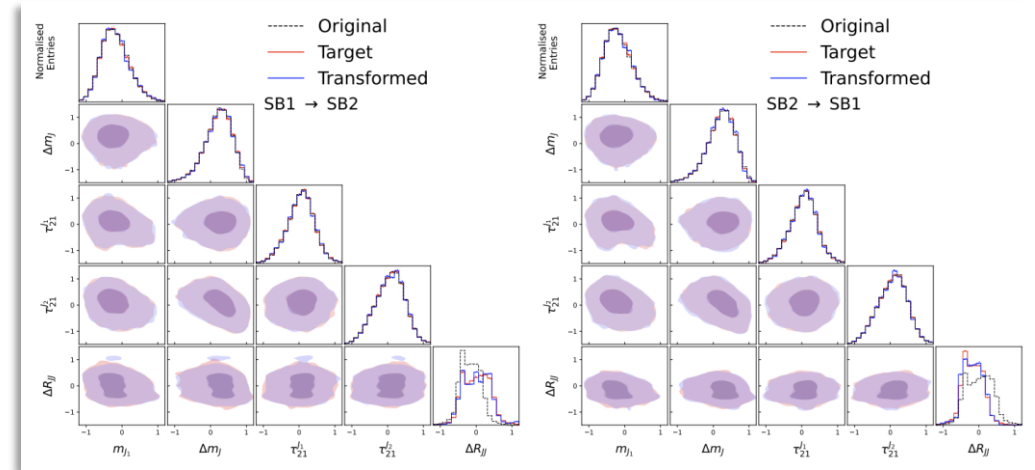
# CURTAINS FOR DIJETS

- Public benchmark dataset: LHCO dijet ([Zenodo](#))
- Background: QCD dijets  $\sim 1\text{M}$
- Signal:  $W'$  (3.5TeV)  $\rightarrow$  X (.5TeV) (qq) Y (.1TeV) (qq)  $\sim 100\text{k}$
- $R=1.0$  Jets,  $p_T > 1.2 \text{ TeV}$
- Features used:
  - $M_{j1}$ ,  $M_{j1-Mj2}$ ,  $\tau_{21}$ ,  $\tau_{32}$ ,  $dR$

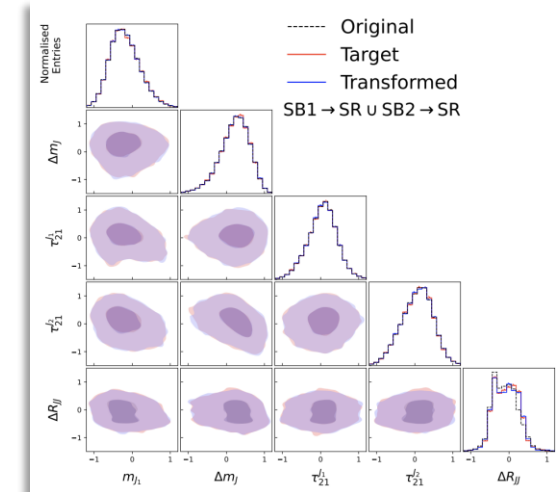
# TEMPLATE FIDELITY

- Train a classifier between generated template and Data.
- If template is good  $\rightarrow$  Classifier should have a nearly random selection  $\rightarrow$  AUC 0.5
  - SB1, SB2 templates look nearly perfect with AUC 0.51
    - SR template AUC of 0.50
- A good template is crucial for downstream anomaly detection!
  - Bad template might kill sensitivity to weak signals.

AUC: 0.51

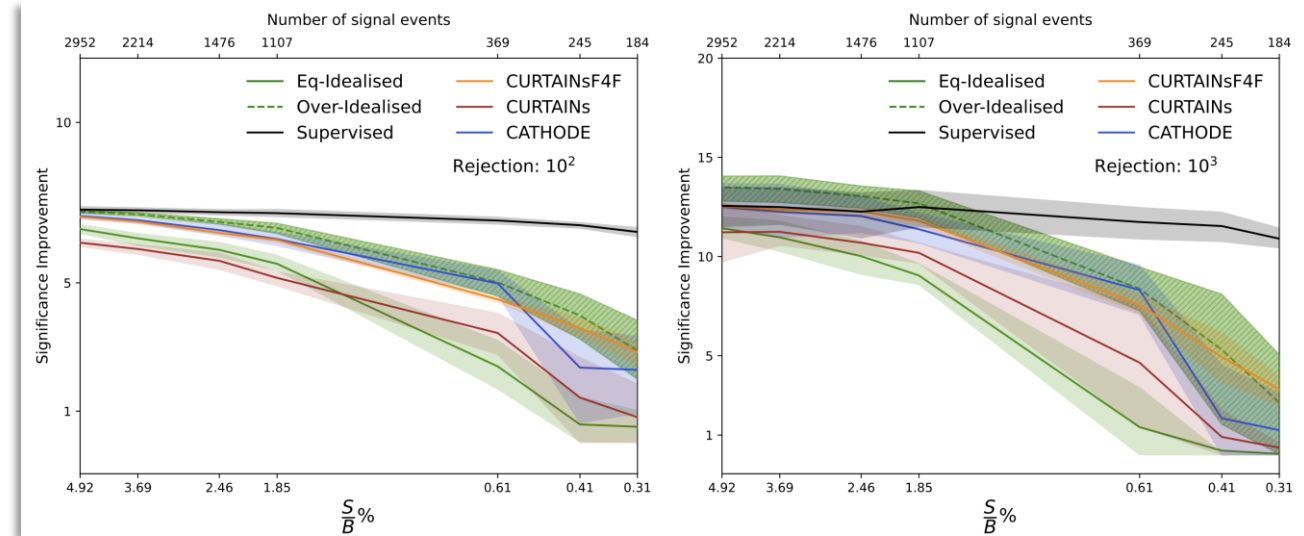


AUC: 0.501



# SIGNAL SENSITIVITY

- Dope the data with n signal events
  - $SIC = \frac{\epsilon_S}{\sqrt{(\epsilon_B)}}$
  - CURTAINsF4F (orange) sensitive to signal even at quite low signal presence.
  - Can find evidence of a signal when initial  $\frac{s}{\sqrt{b}} = 0.7$
  - Idealised and Supervised lines for comparison.



SIC at two different working points as a function of doping



# CURTAINS IN EXPERIMENTAL HEP

- Data driven method ~ few assumptions about potential signal.
  - Resonant in some feature ~invariant mass
- Deployed in ATLAS for a model agnostic search – ongoing.

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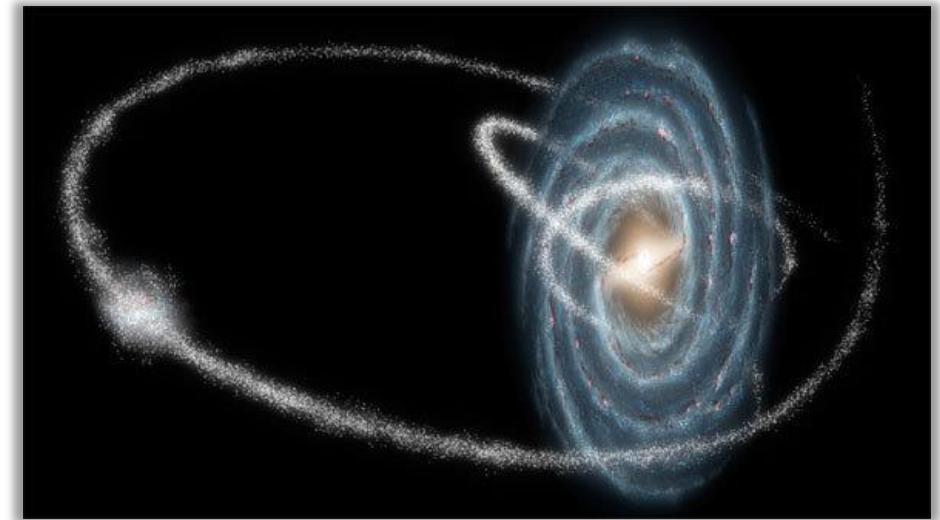
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# CURTAINS IN THE SKY

# STELLAR STREAMS

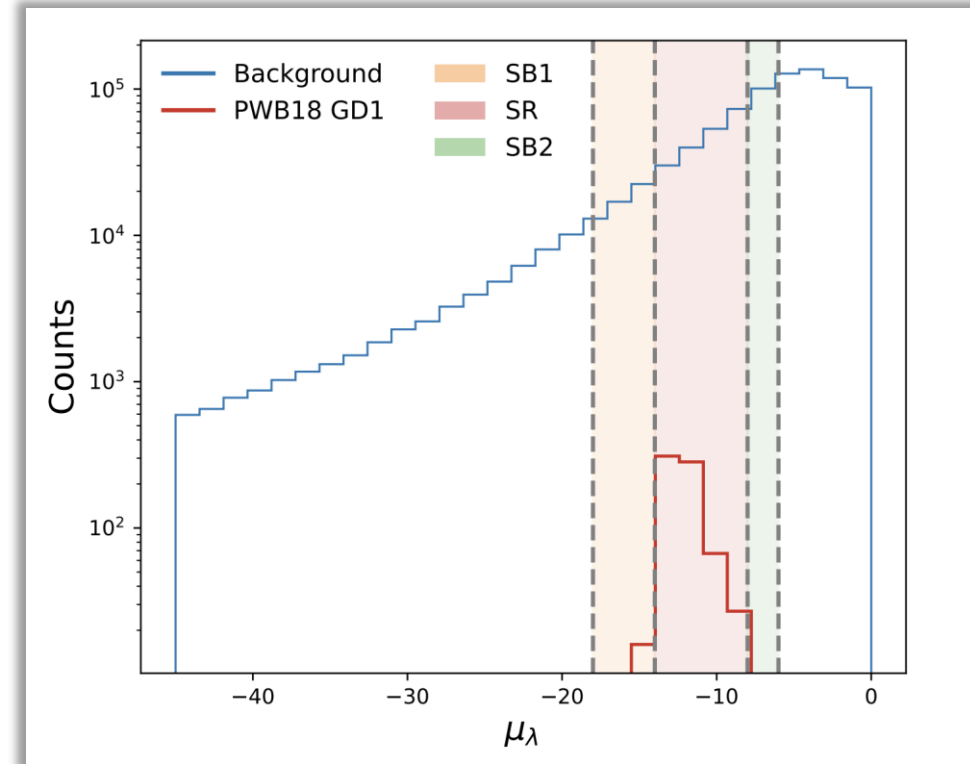
- Tidally stripped remnants of a dwarf galaxy
- Excellent probe for:
  - Galaxy merger history, formation
  - Galaxy mass, potential
  - **Dark Matter Subhalos Mass Function**
    - Density perturbations along the stream indicate subhalo flyby
    - Nature of DM ~compact, self interacting?
- Typically  $O(100)$ - $O(1000)$  stars in a stream
- Know about  $40^*$  streams in the Milky Way
  - Expensive searches
  - Mostly model dependent ~ Assume MW potential, Chemical composition
  - Can we do this in a model agnostic way?



Artist rendition of stellar streams overserved from the Milky Way Galaxy

# PROBLEM PARALLELS

- Stellar Stream search is essentially an overdensity search in a feature space
- Group of stars moving congruently ~ produce overdensities in proper motion
- Features:
  - Proper motion in the sky
  - Position in the sky
  - Color of the star
  - Luminosity of the star
- Gaia Survey: > 1.8 billion sources catalogued in the Milky Way Galaxy
- Benchmark CURTAINS!

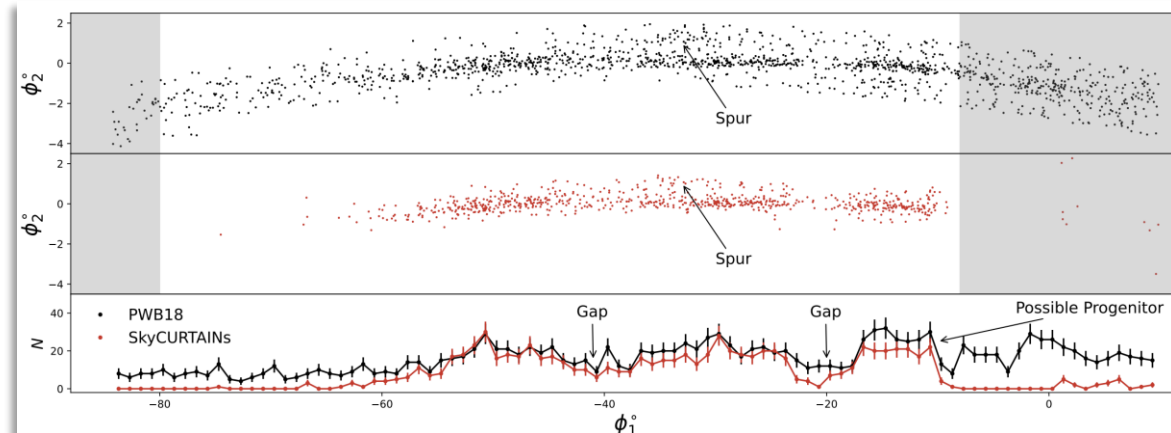


Distribution of proper motion of bg sources and members of a known stream GD-1

# THE GD-1 STREAM

- Well known, narrow, large stream in the galaxy.
- CURTAINS finds GD1 in different patches of the sky with a very high purity.
- Recovers the density perturbations within the stream.
  - Without any prior model dependence!

SkyC Recovered GD1 stream in stream aligned coordinates

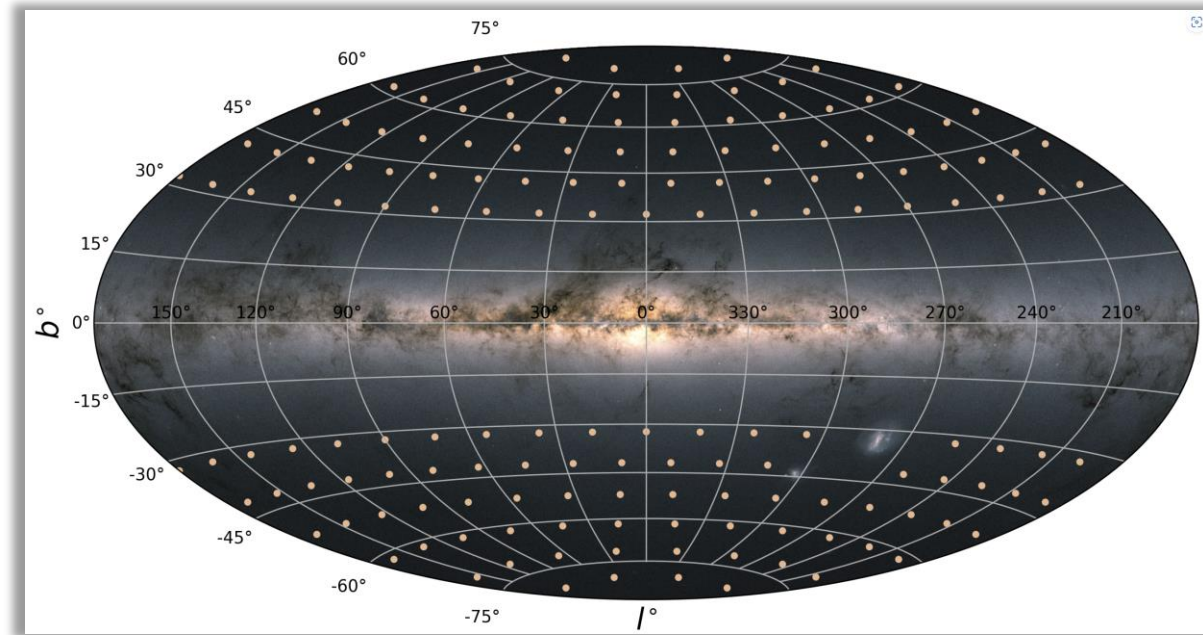


| Patch ( $\alpha, \delta$ ) | $P$<br>SkyCURTAINS |
|----------------------------|--------------------|
| (128.4°, 28.8°)            | 82.99              |
| (132.6°, 16.9°)            | 78.05              |
| (136.5°, 36.1°)            | 90.56              |
| (138.8°, 25.1°)            | 90.79              |
| (142.7°, 14.5°)            | 86.79              |
| (146.9°, 35.6°)            | 91.79              |
| (148.6°, 24.2°)            | 94.9               |
| (148.6°, 47.0°)            | 93.15              |
| (156.2°, 57.5°)            | 70.14              |
| (156.9°, 34.1°)            | 88.17              |
| (160.5°, 45.5°)            | 87.43              |
| (171.4°, 43.0°)            | 89.52              |
| (171.8°, 54.7°)            | 89.66              |
| (174.3°, 65.1°)            | 64.94              |
| (185.4°, 50.0°)            | 84.0               |
| (192.0°, 58.7°)            | 83.87              |
| (138.1°, 5.7°)             | 0.0                |
| (203.7°, 49.1°)            | 0.13               |
| (212.7°, 55.2°)            | 0.0                |
| (224.7°, 60.6°)            | 2.58               |
| (202.4°, 66.5°)            | 0.0                |

[2405.12131](https://doi.org/10.1093/mnras/stz2405)

# A FULL SKY SCAN

- Currently being deployed on GDR3 data of more than 1.8 billion sources.
  - Each dot represents the center of a 15-degree circular patch ~ 154 patches
- Expect to recover known streams
- Discover and catalogue new streams



Mollweide projection of the Milky Way Galaxy and the patch centers for the search

# OUTLOOK

- Data driven methods powerful, versatile ~ Applicable across different domains
- Abstracting problems ~ Your problem may have been solved two doors down the office!



**BACKUP**



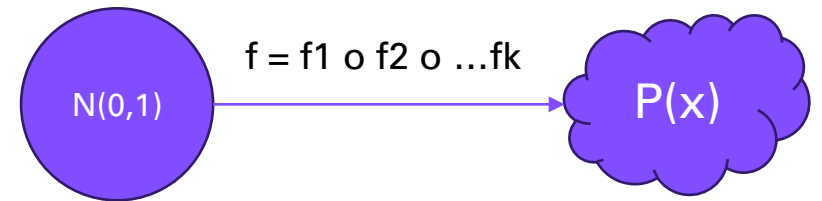


# FLAWS FOR FLOWS

# NORMALISING FLOWS

- Map a known distribution to an arbitrary distribution through change of variables

- $p_{\theta\phi}(x|c_x, c_y) = \pi_{\theta}(z) \cdot \det |J_{f\phi}(x|c_x)|$



# FLOWS FOR FLOWS

- To map between two arbitrary distributions under exact likelihood – employ the change of variables formula.
  - $p_{\theta\phi\gamma}(y | c_x, c_y) = p_{\theta\phi}(x | c_x, c_y) \cdot \det | J_{f_\gamma}(x | c_x, c_y) |$
- But we do not know  $p(x)$  → learn it with another flow!



# CURTAINS DIJET

# TRAINING

- Mix SB1,SB2 – conditionally learn to transform random pairs of data.
  - Condition on some function of  $m_{jj1}$ ,  $m_{jj2}$ .
- First train BaseFlow for ~100 epochs.
- Freeze BaseFlow, train TopFlow~10 epochs.
- *EfficientMode* : When scanning multiple SR – train one BaseFlow, use it everywhere.

<sup>†</sup> Timing is for the nominal side-bands, this would vary as the signal region changes due to total number of training events.

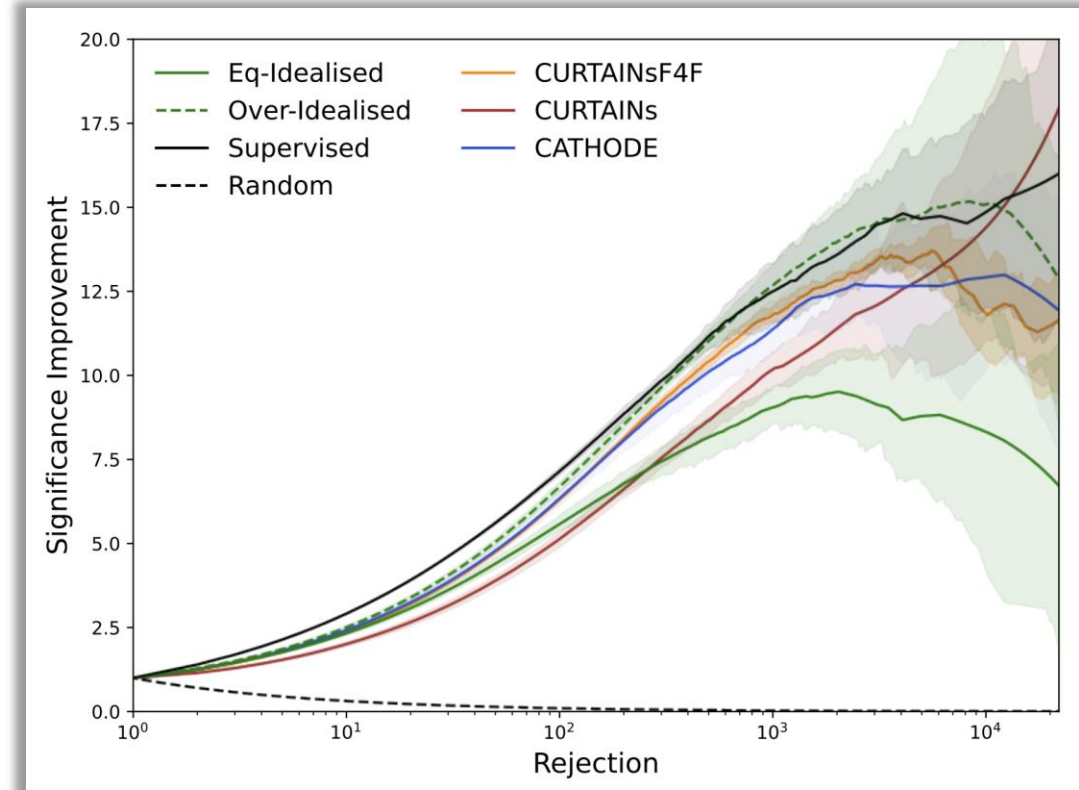
|   | Time / epoch [s]  | $N$ epochs | Total time [min]   |
|---|-------------------|------------|--------------------|
| Default   |                   |            |                    |
| Base  | 32.4 <sup>†</sup> | 100        | 54                 |
| Top flow  | 31.5 <sup>†</sup> | 100        | 53                 |
| One Signal Region<br>(Extrapolated <sup>†</sup> ) Ten Signal Region   |                   |            | 107<br>1070        |
| Efficient   |                   |            |                    |
| Base  | 104.2             | 100        | 174                |
| Top flow  | 21.3 <sup>†</sup> | 20         | 7                  |
| One Signal Region<br>(Extrapolated <sup>†</sup> ) Ten Signal Region<br>(Extrapolated <sup>†</sup> ) 125 Signal Region |                   |            | 181<br>244<br>1049 |

# TEMPLATE GENERATION

- Context generation in SR is done with fitting a PDF in SB and then sampling in SR.
  - ATLAS 3 parameter function  $f(x) = p_1(1-x)^{p_2}(x)^{p_3}$
- Can generate a template in any Window, provided context can be provided.

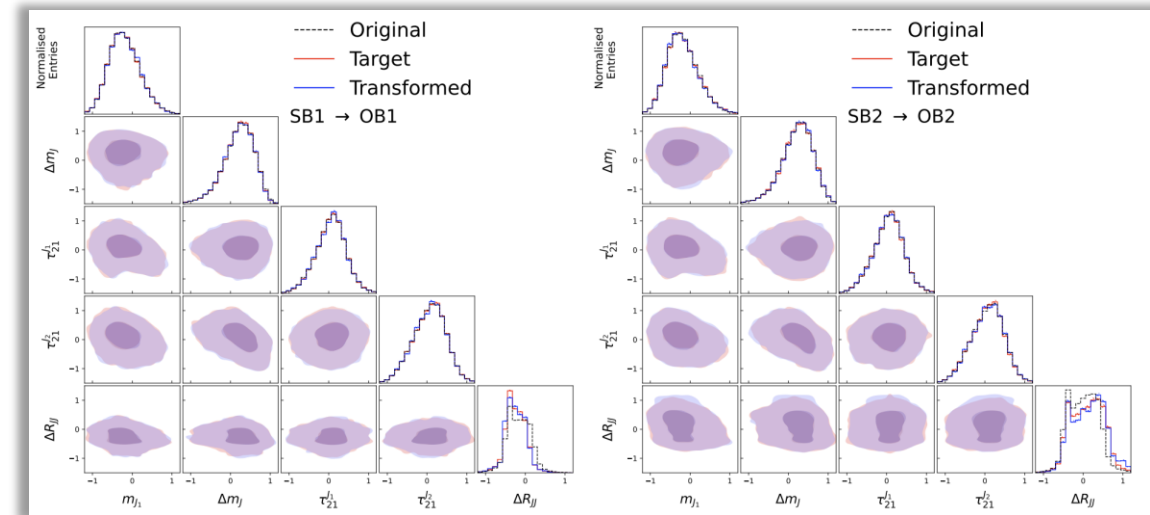
# CWOLA

- Template vs SR Data in 5-Fold setup.
- MLP 32x3 for 20 epochs (overfits otherwise).
  - Tuned to get 0.5 AUC in zero doping case, good separability in 3000 doping case.



# VALIDATION

- SR blinded, check performance in other control regions.
- AUC for OB1, OB2  $\leq 0.52$







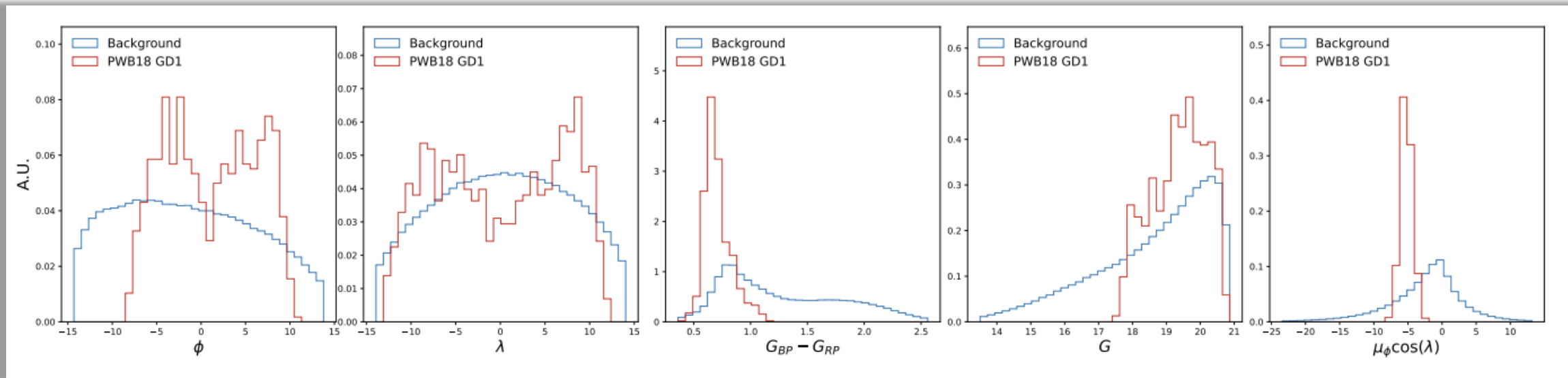
# SKYCURTAINS

# GAIA SURVEY

- Most precise 3D map of the Milky Way Galaxy from the L2 point.
- Astro and photometric observations of nearly 2 billion sources.
- Positions of objects as faint as magnitude 20, and those  $< 15$ , accuracy upto 24 microarcsec.
- Expected to function until 2025



# FEATURE SPACE



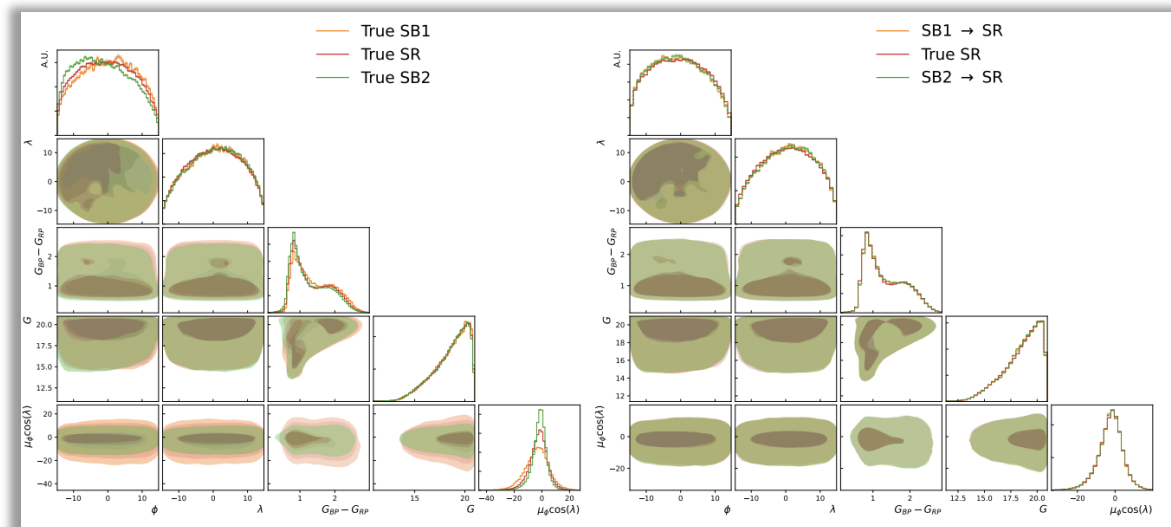
- Longitude, latitude local to patch
- Color =  $G_{BP} - G_{RP}$
- Magnitude =  $G$
- Proper motion across the sky

# FIDUCIAL CUTS

- Proper motion  $> 2$  mas/yr – reject too distant stars
- Magnitude  $< 20.2$  – Gaia has a non-completeness fainter than this
- Color in (0.5, 1.2) – select out stars with similar metallicity.

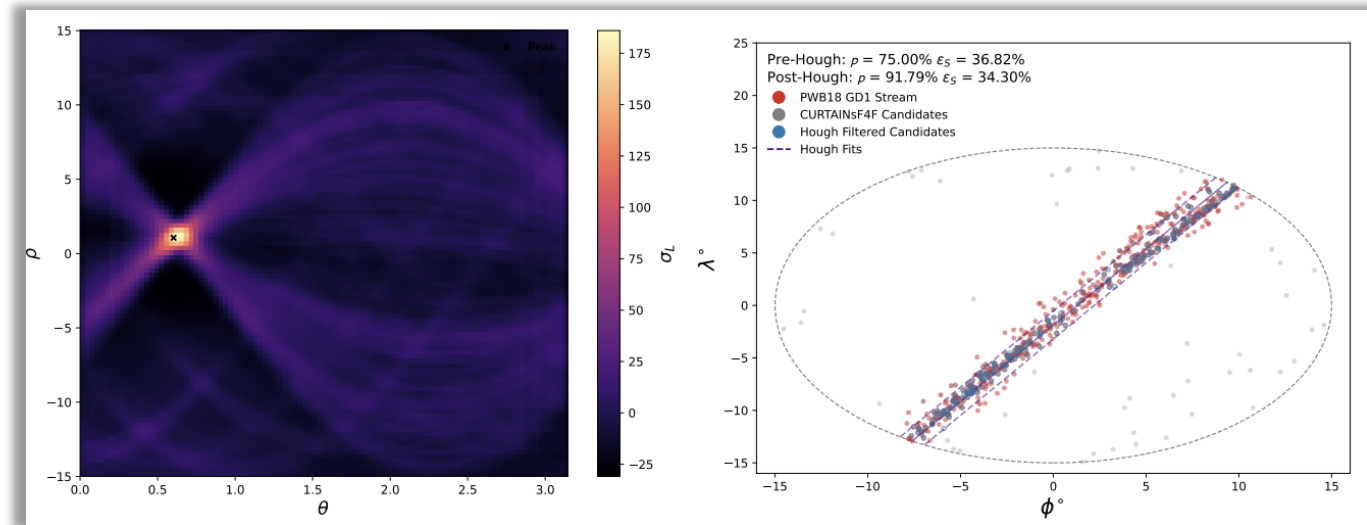
# TEMPLATE FIDELITY

- AUC  $\sim 0.51$
- Decent for downstream CWoLa



# HOUGH FILTERS

- $\rho = \phi' \cos \theta - \lambda' \sin \theta$
- Line candidates in image space  $\sim$  points in parameter space.
- Finding line = finding overdensity in parameter space.



Hough space for curtains candidates (left), hough filtered candidates in blue (right)