

NuGraph2

A graph network for particle reconstruction

V Hewes (she/they)
NuGraph workshop
13th November 2023

NuGraph2

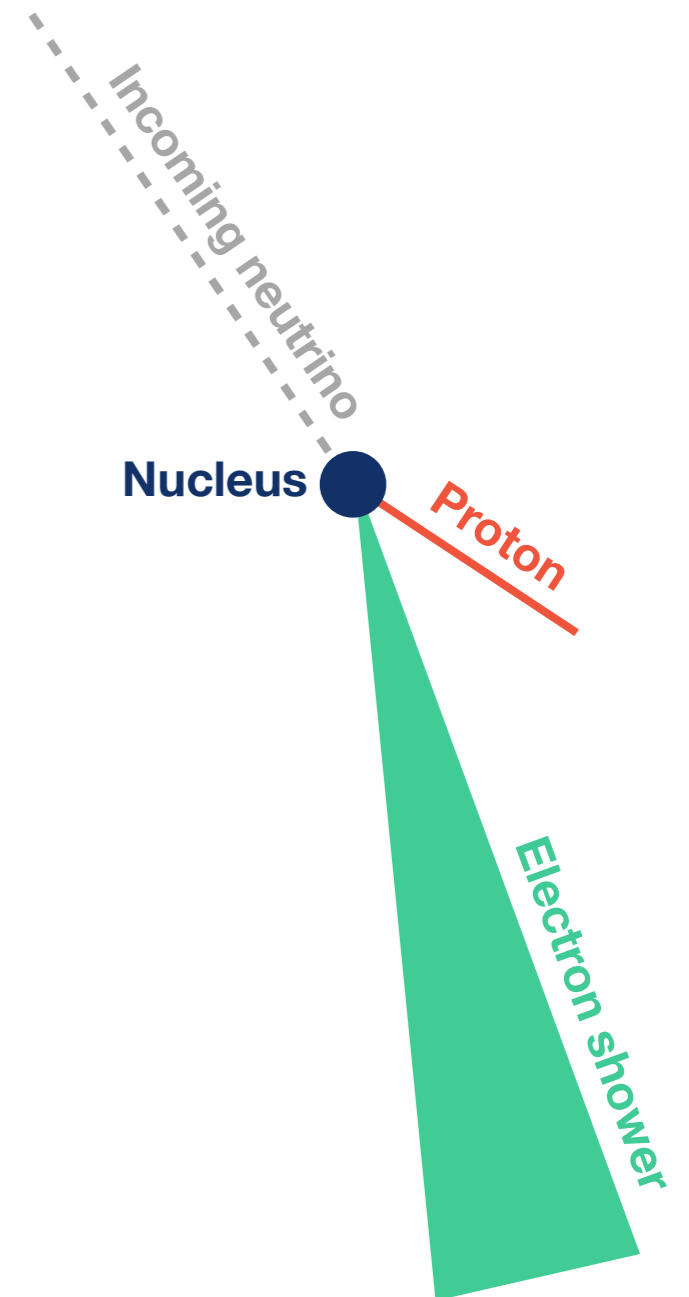
NuGraph2

Neutrino physics

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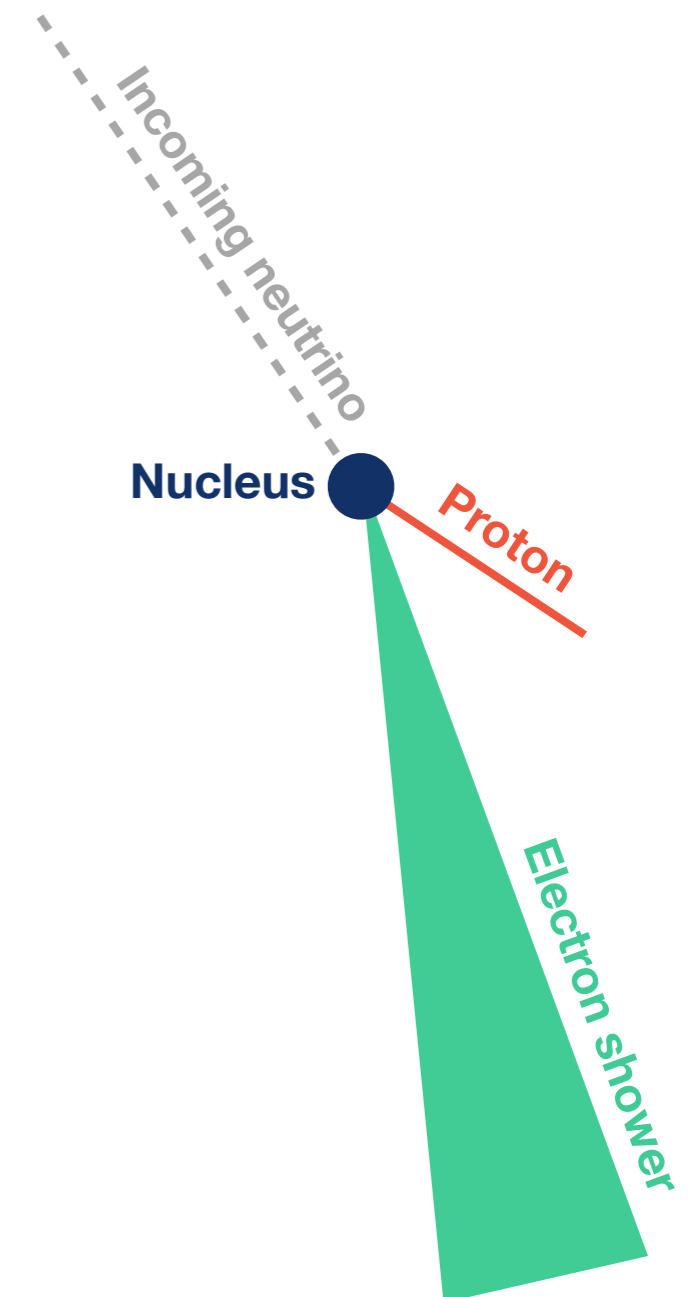
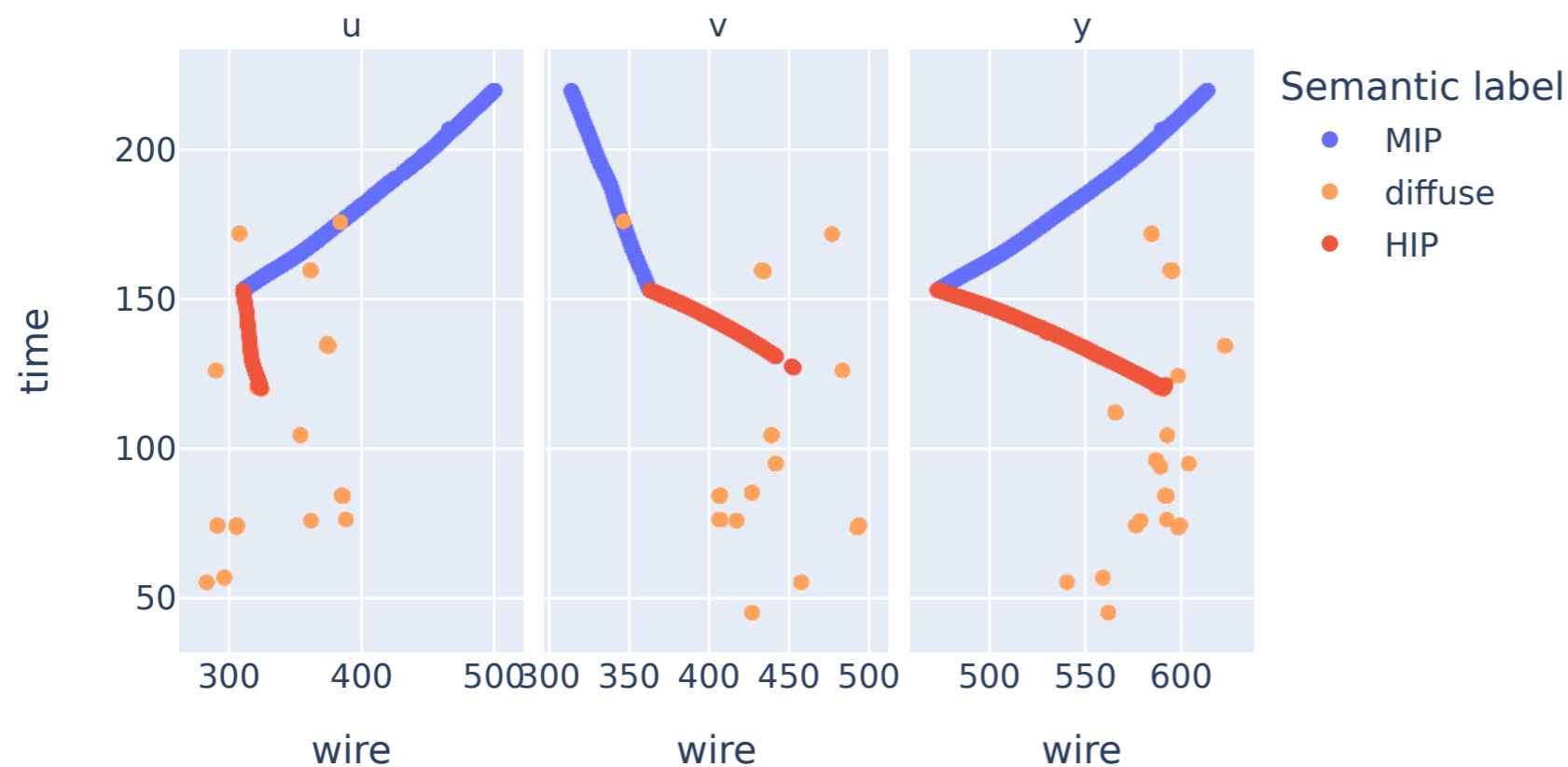
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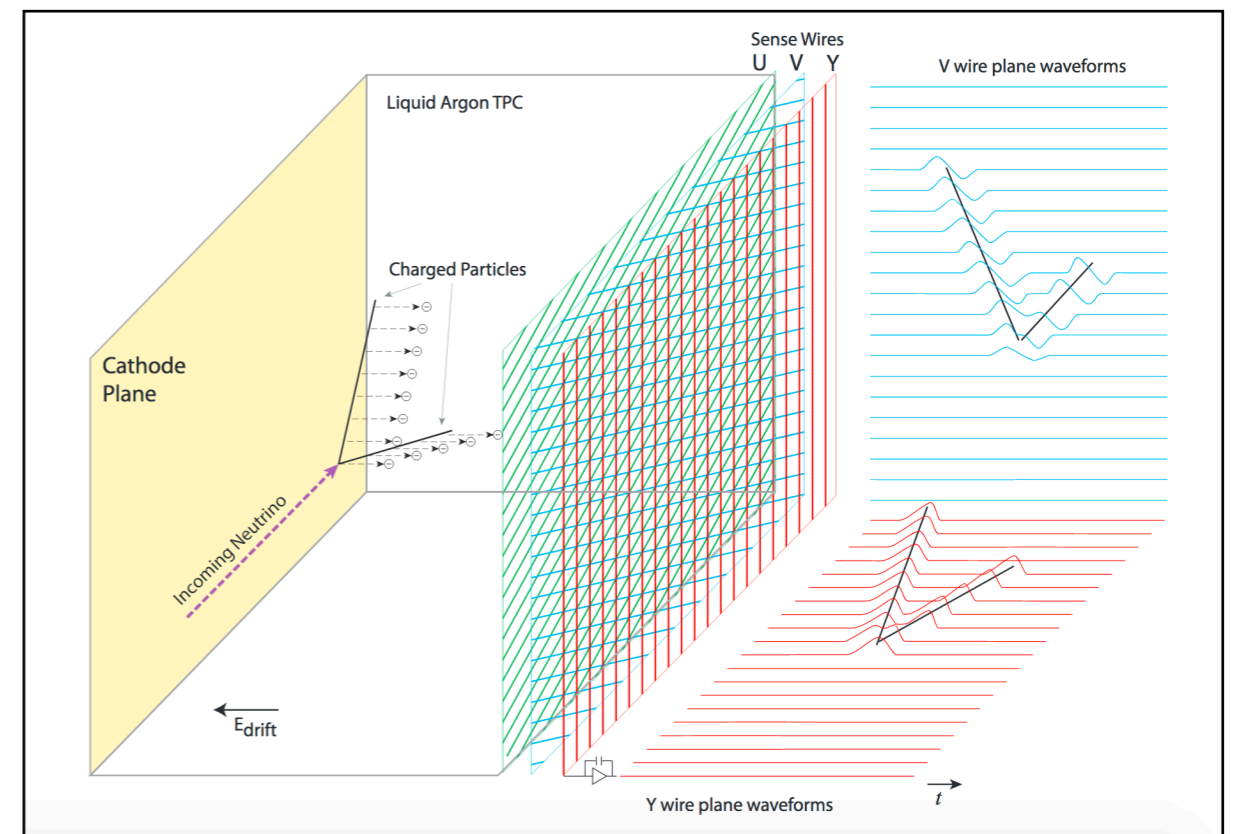
Liquid Argon TPCs

- Liquid Argon Time Projection Chambers (LArTPCs) currently a heavily utilised detector technology in neutrino physics.
 - At FNAL: MicroBooNE, Icarus, SBND.
 - Future: DUNE (70kT LArTPC deep underground, plus near detector).

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- Charged particles ionize liquid argon as they travel.
- Ionisation electrons drift due to HV electrode field, and are collected by anode wires.
- Wire spacing $\sim 3\text{mm}$ – **high-resolution detector.**



MicroBooNE open dataset

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 - Motivation: reconstructing complex and high-multiplicity atmospheric and ν_τ interactions.

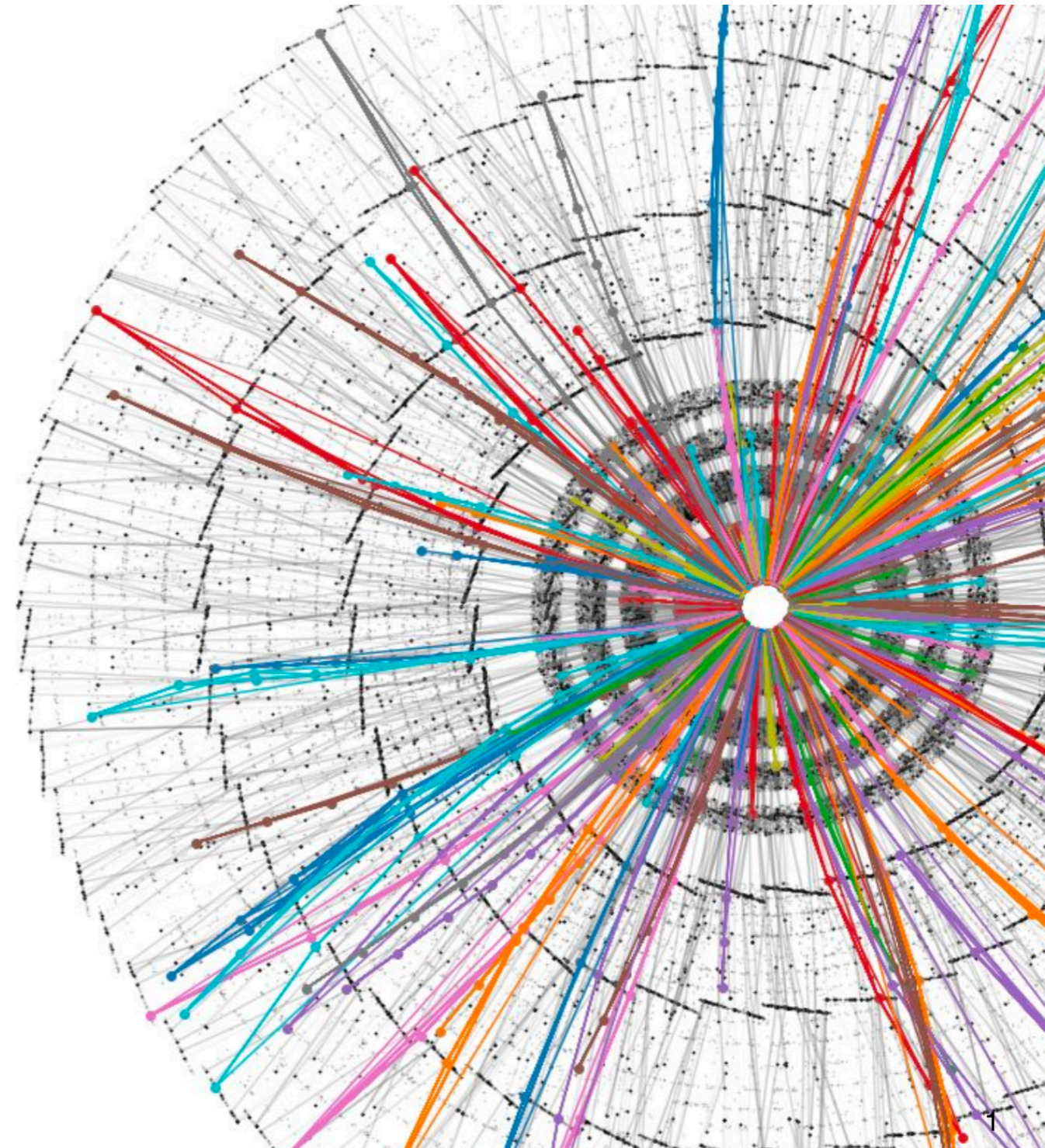
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- This network architecture was originally developed in the context of the **DUNE Far Detector** geometry.
 - Motivation: reconstructing complex and high-multiplicity atmospheric and ν_τ interactions.
- This network architecture is developed to have **broad applicability**, without being tied to any particular detector geometry.
 - NuGraph2 is a **general-purpose particle reconstruction tool**.
 - Developed for use in **neutrino detectors**, but can be deployed for other types of physics interactions!

NuGraph2

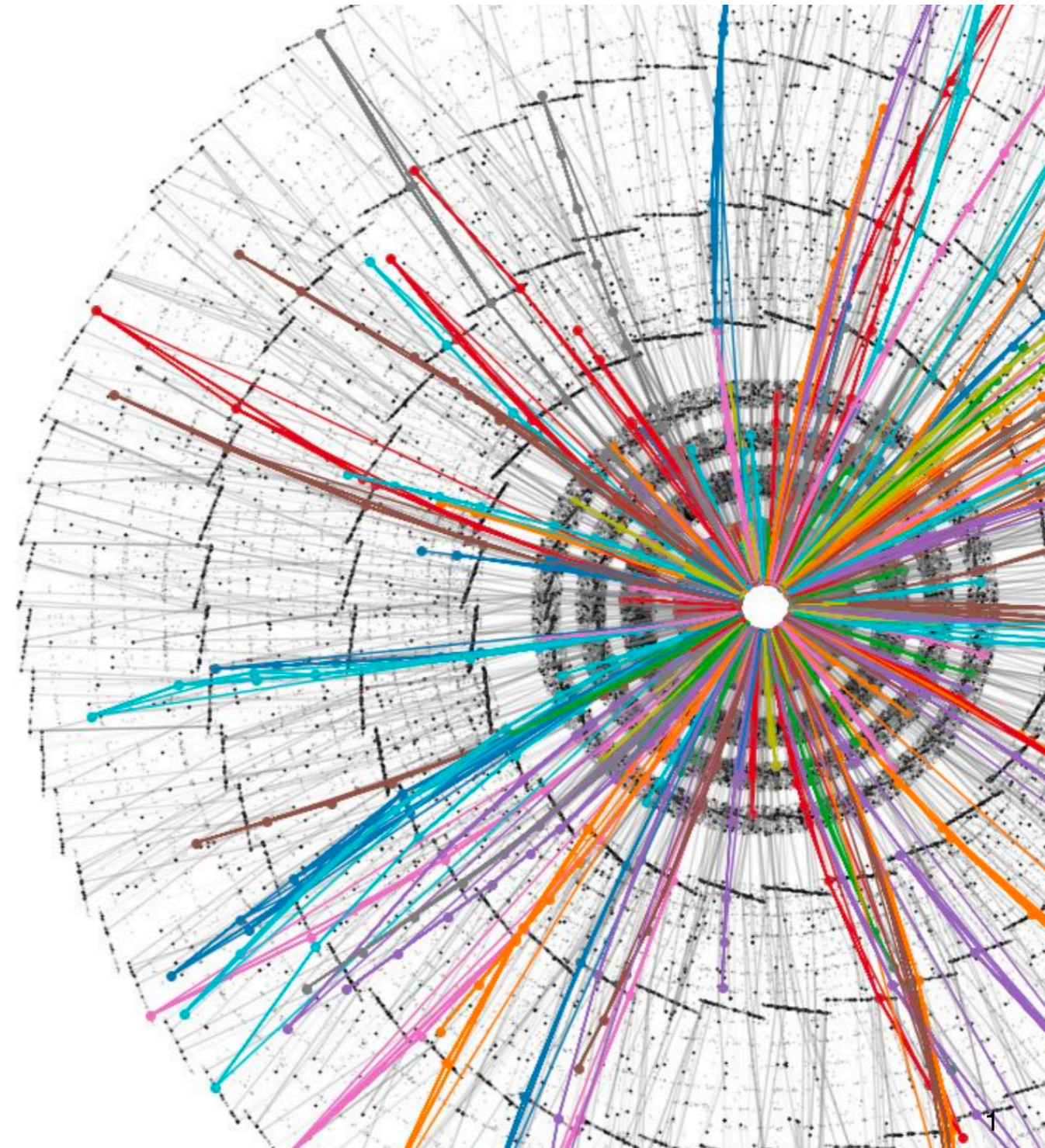
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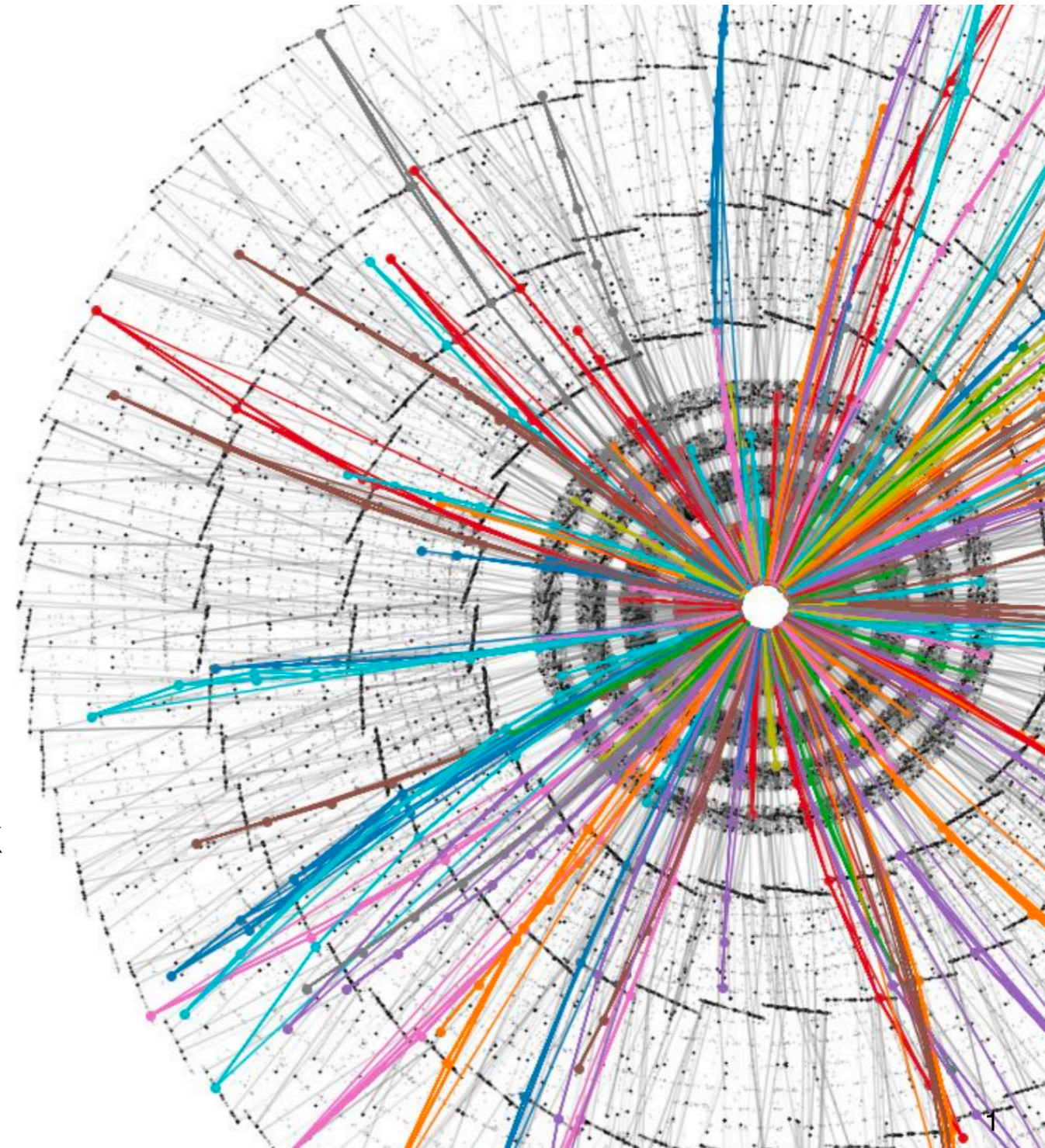
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 - **Energy Frontier**
 - Expand on HEP.TrkX's prototype GNN for HL-LHC.
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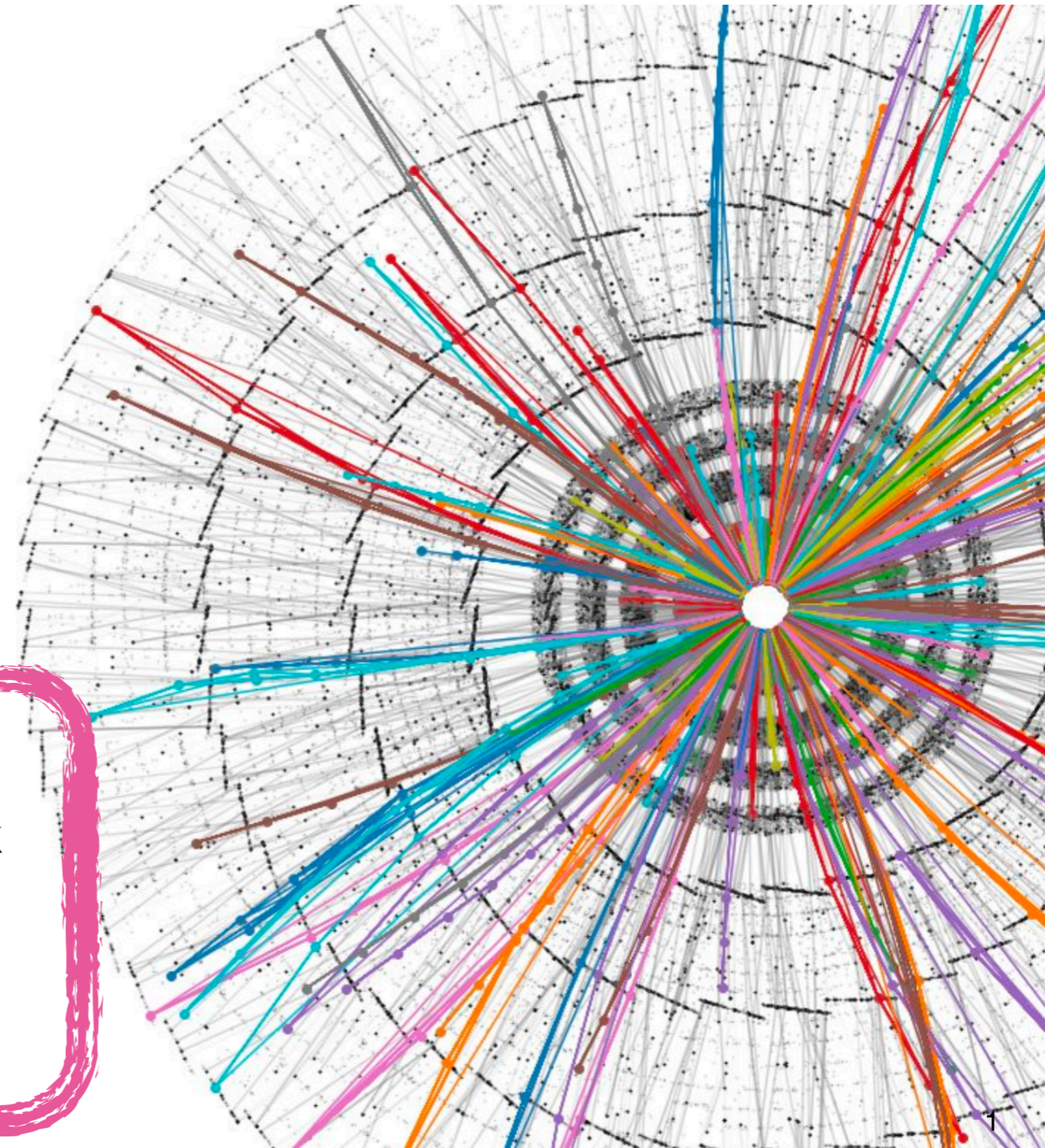
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 - Explore viability of HEP.TrkX network for neutrino physics.
 - Develop GNN-based reconstruction for Liquid Argon TPCs.



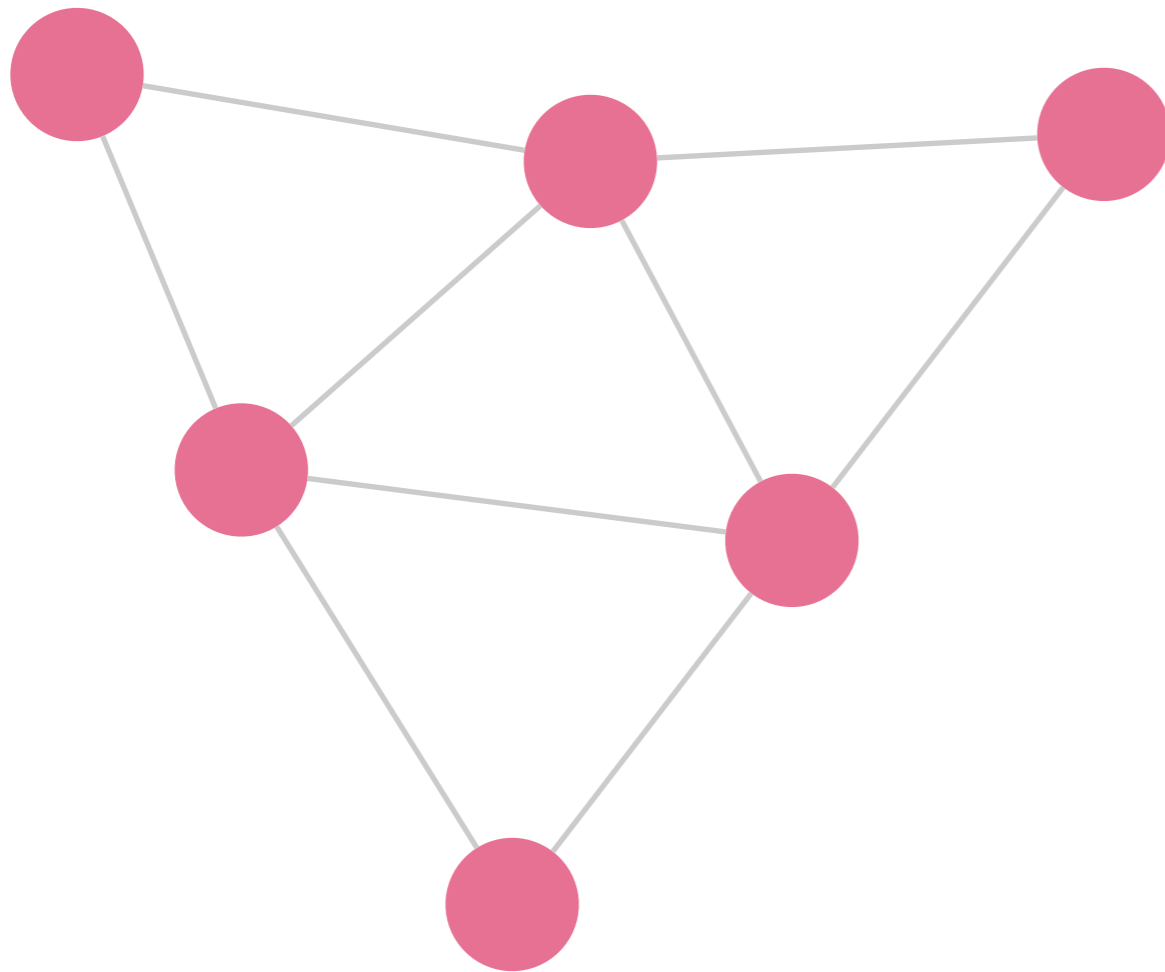
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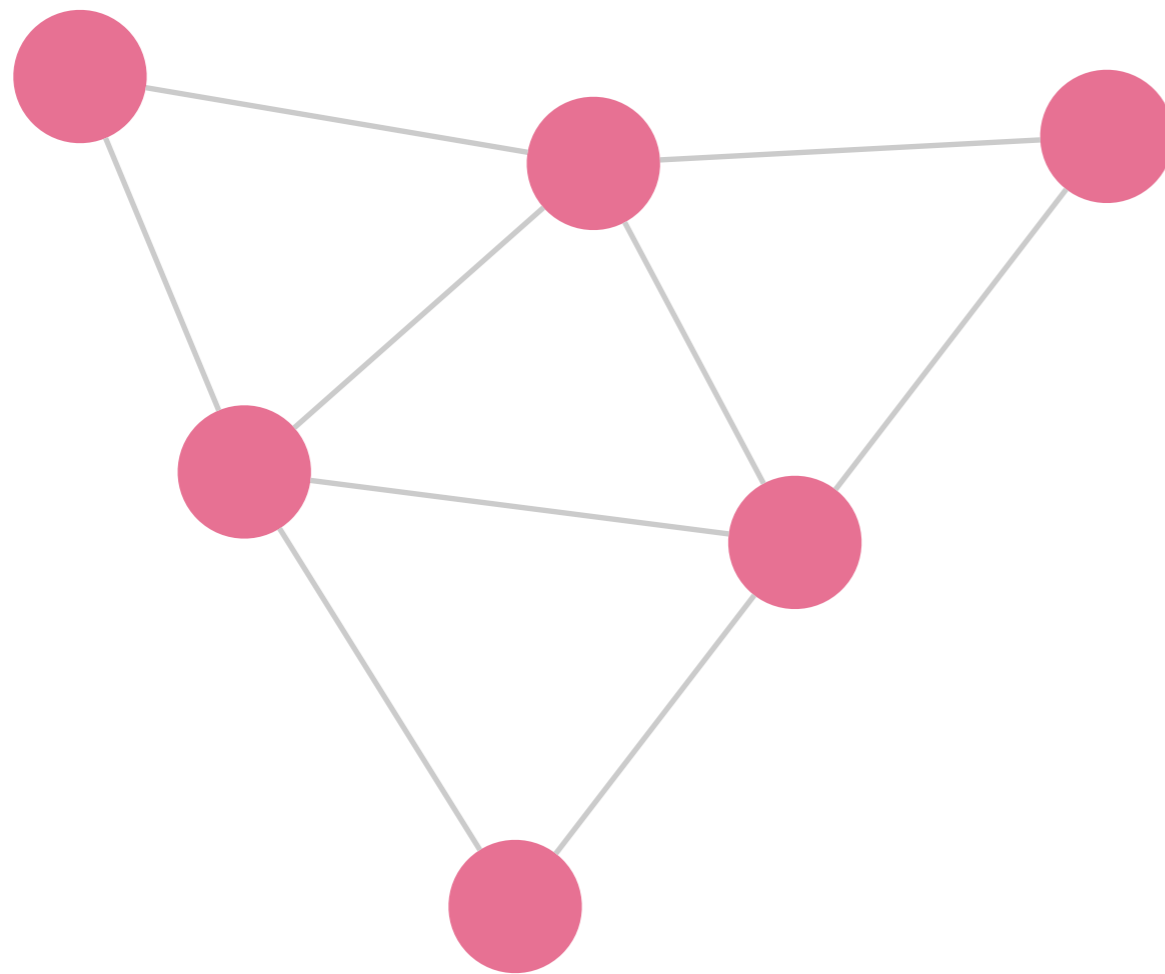


Graph Neural Networks

Construct **graph** where each **node** is a **detector hit**

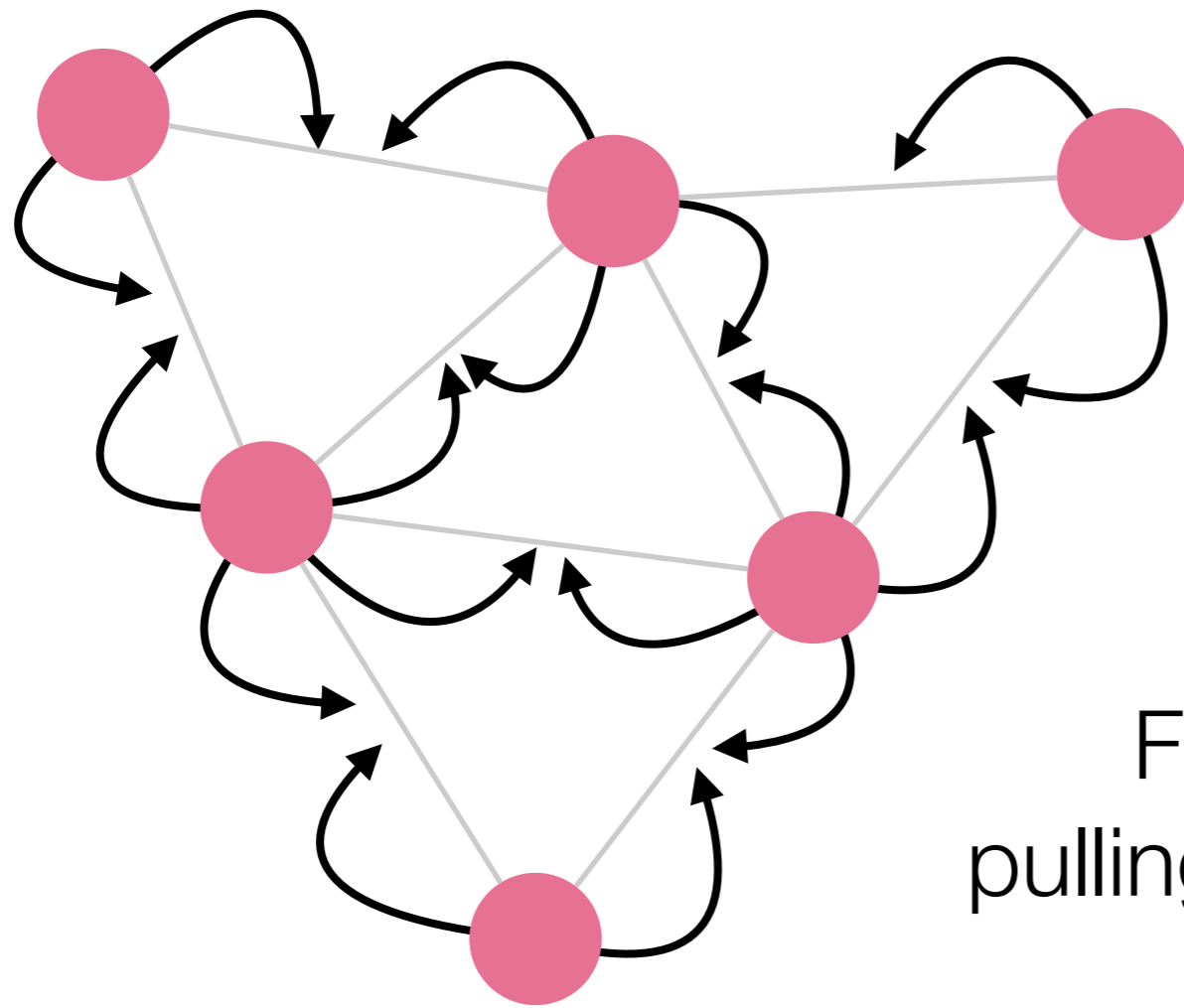


Graph Neural Networks



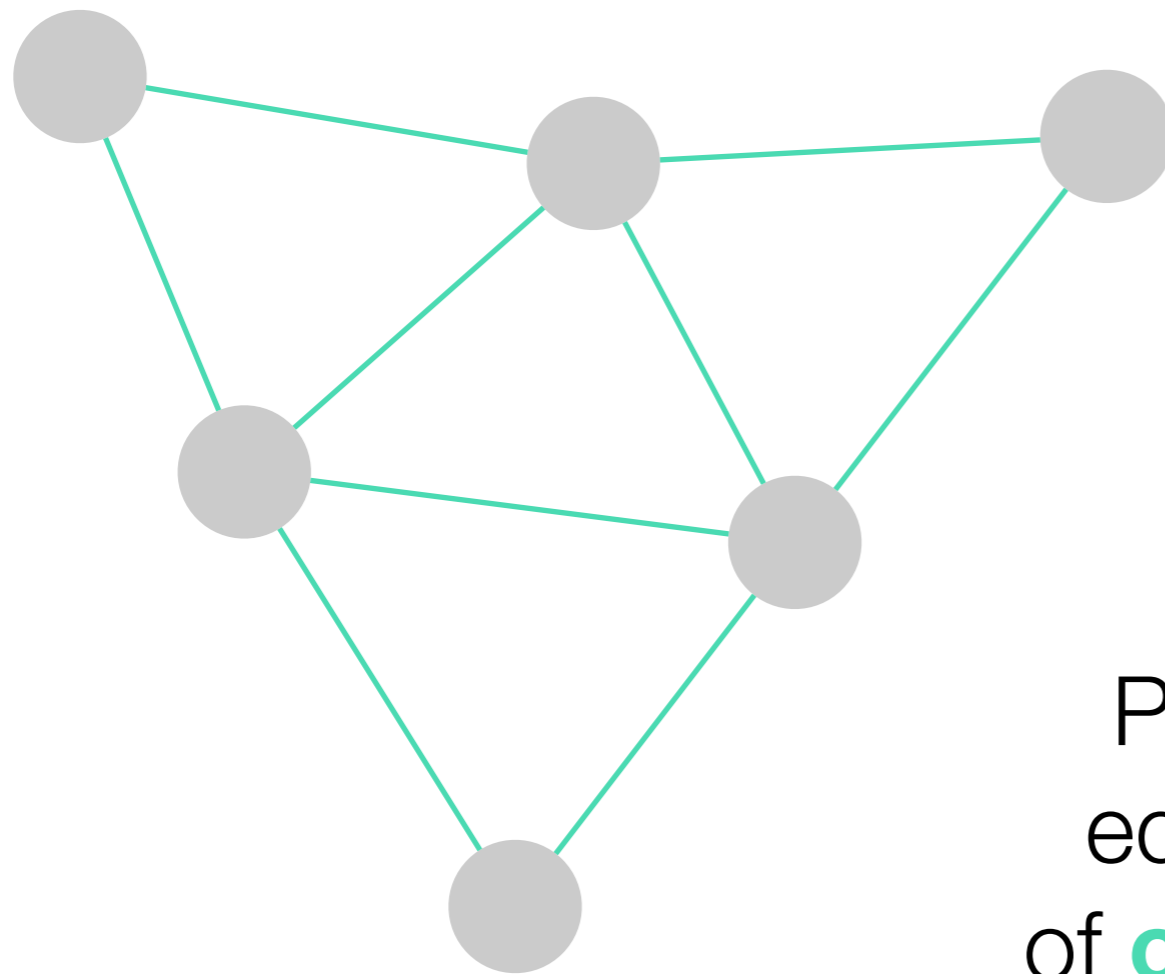
Node features:
wire index, time tick,
charge integral & RMS

Graph Neural Networks



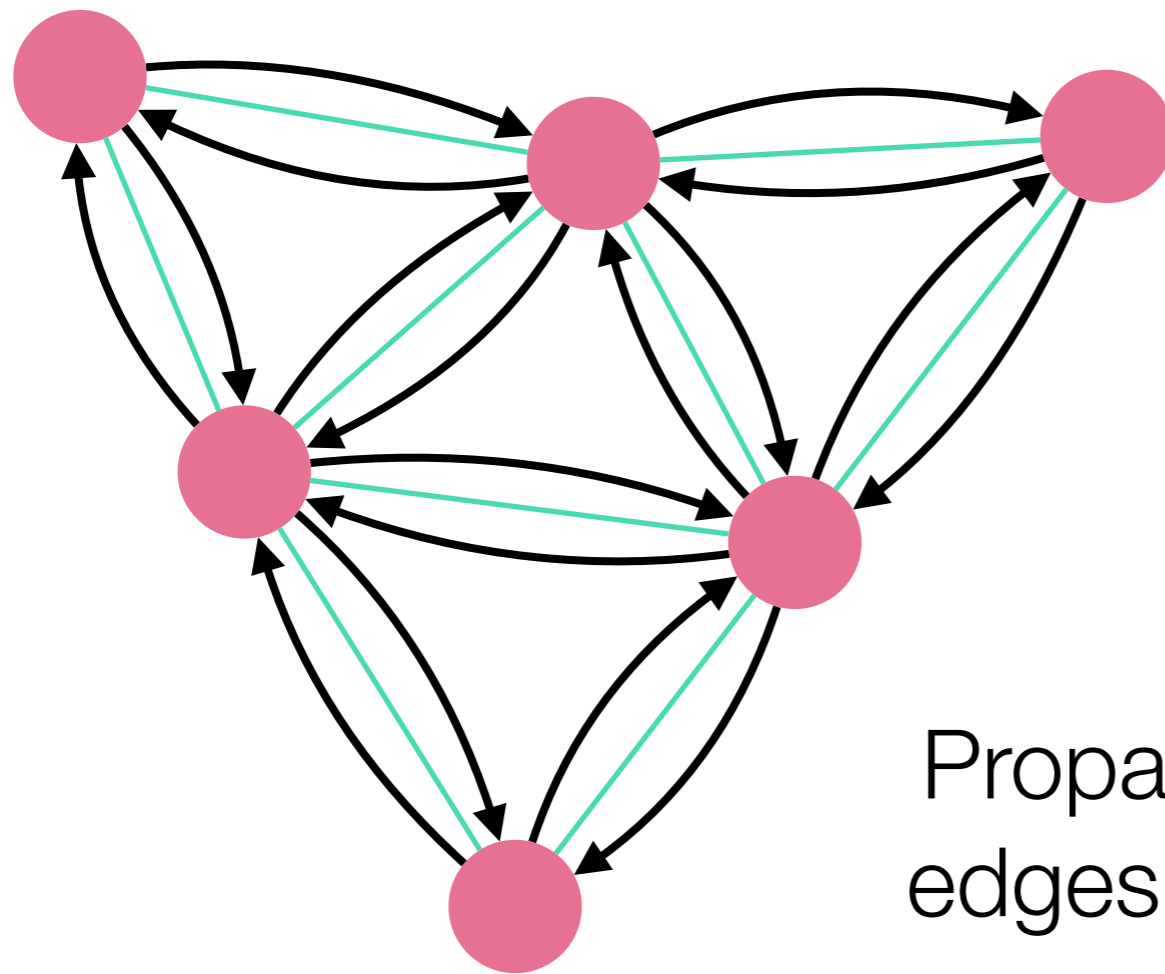
Form **edge features** by pulling in features from incoming and outgoing nodes

Graph Neural Networks



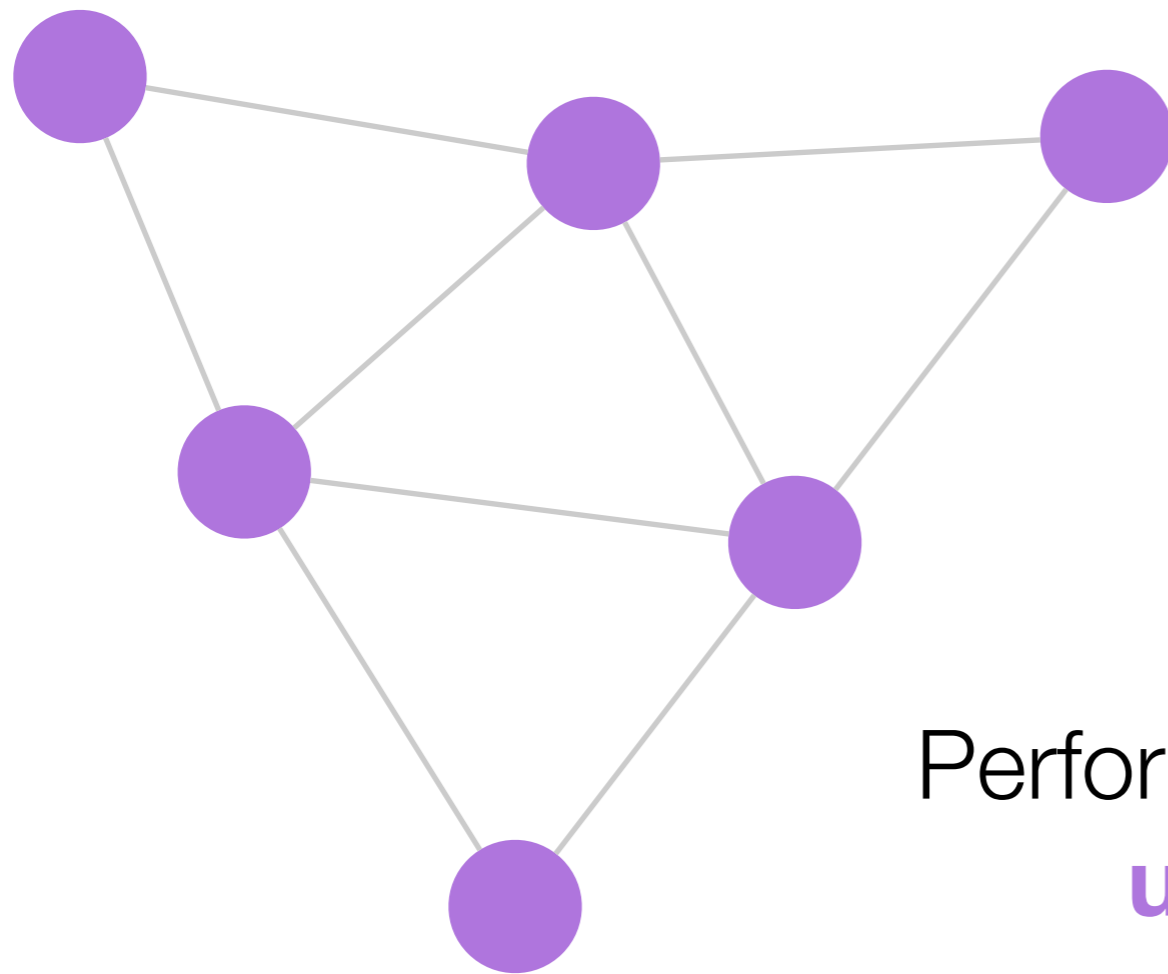
Perform convolutions on edge scores to form a set of **class-wise probabilities**

Graph Neural Networks



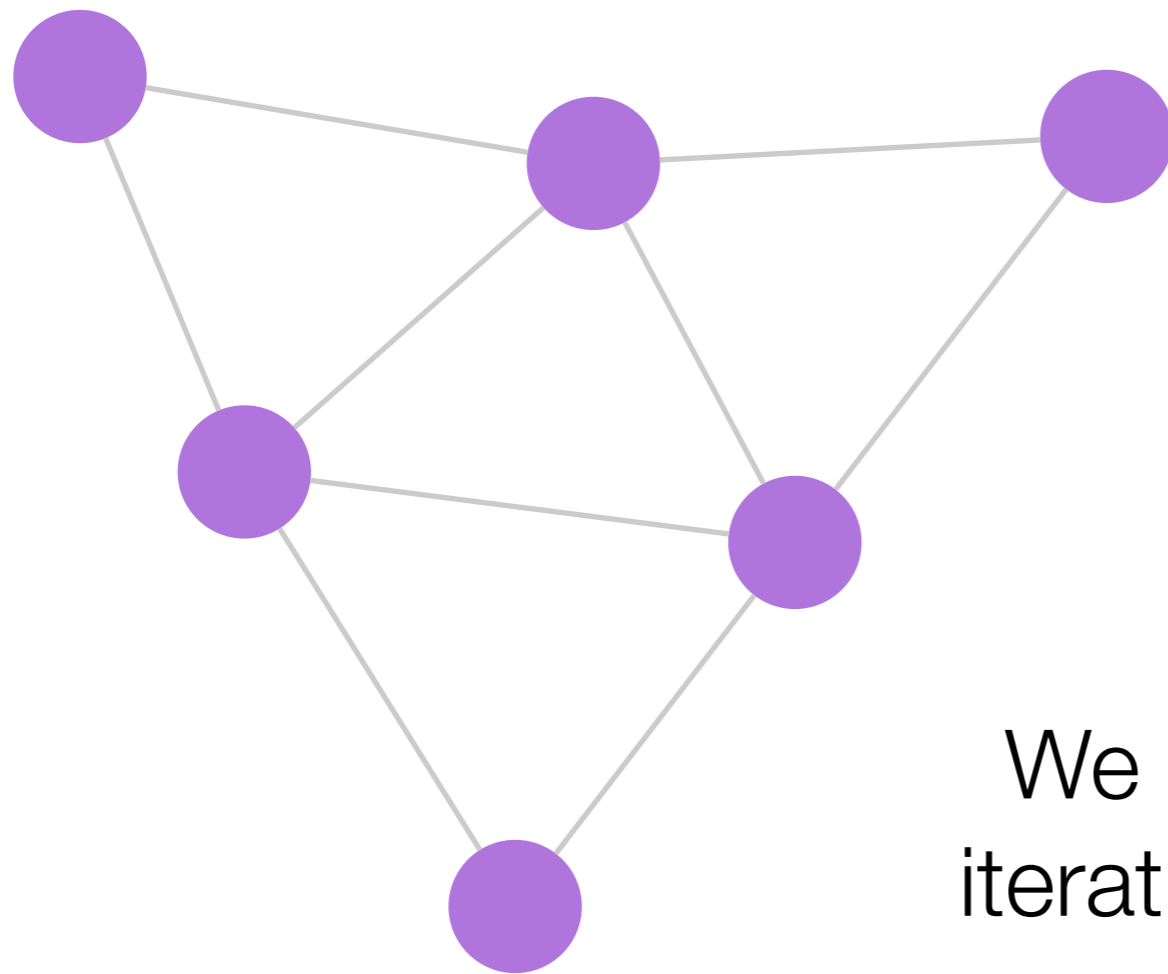
Propagate **node features** across edges, weighting by **edge scores**

Graph Neural Networks



Perform convolutions on nodes to
update node features

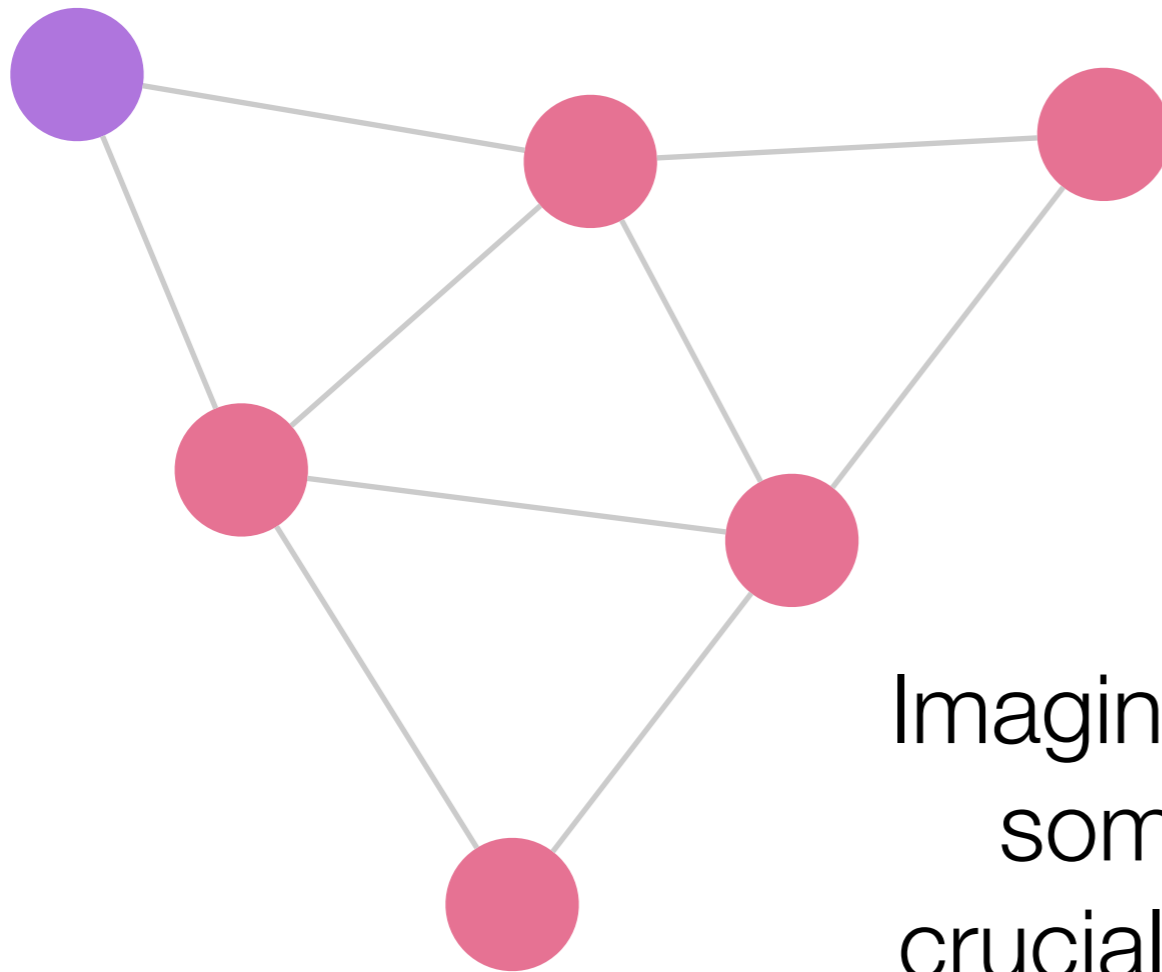
Graph Neural Networks



We can repeat this procedure iteratively to "**pass messages**"

Graph Neural Networks

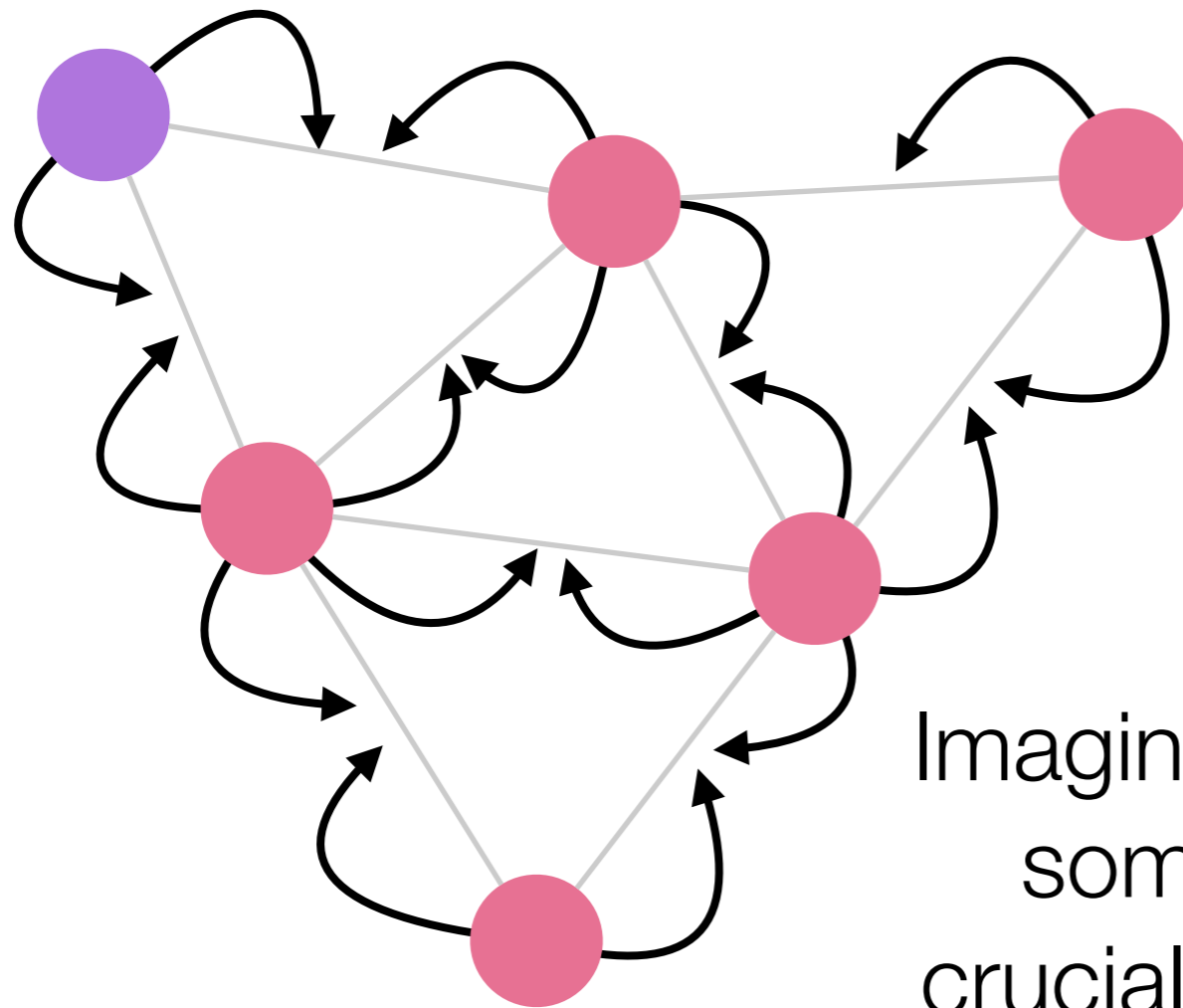
0 iterations



Imagine that one graph node holds some **key information** that's crucial for understanding the event

Graph Neural Networks

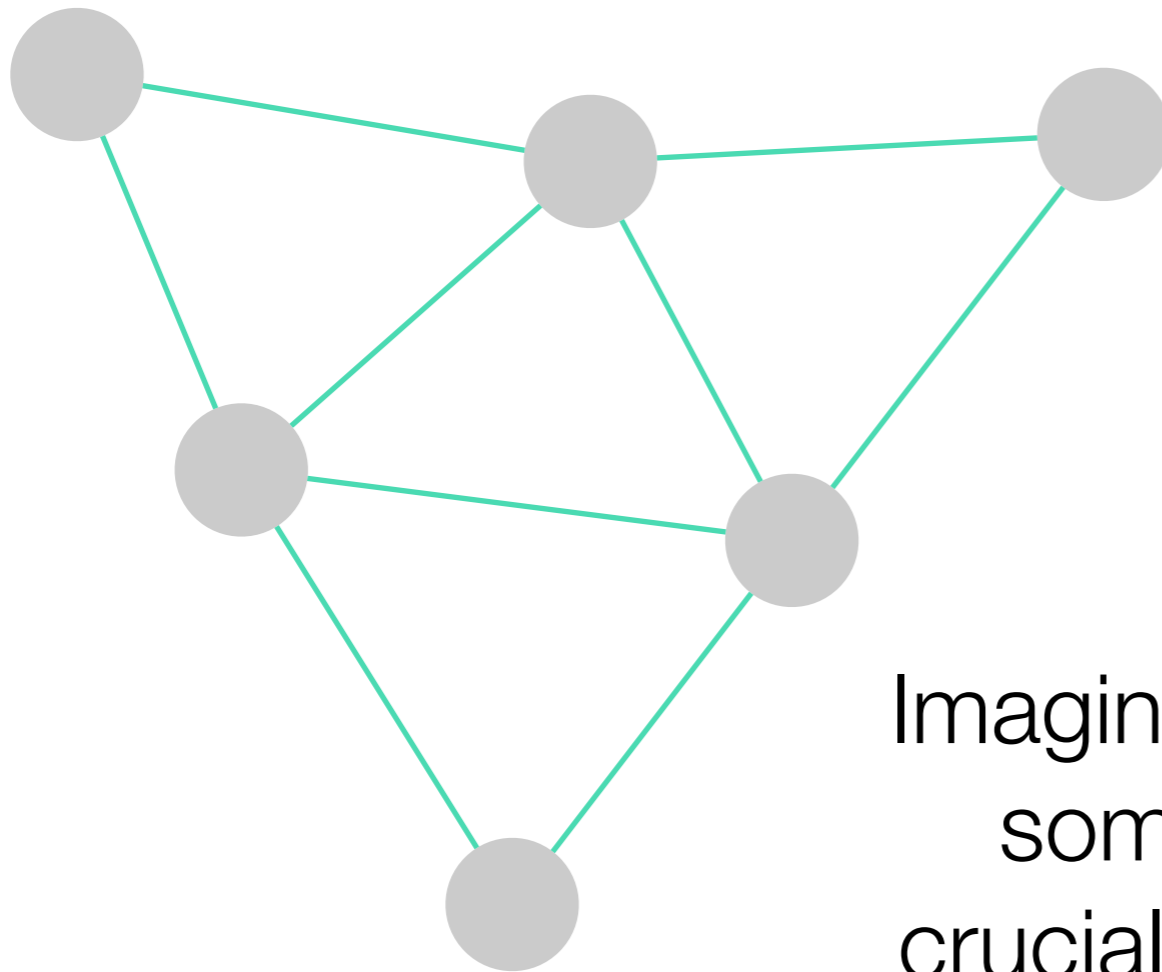
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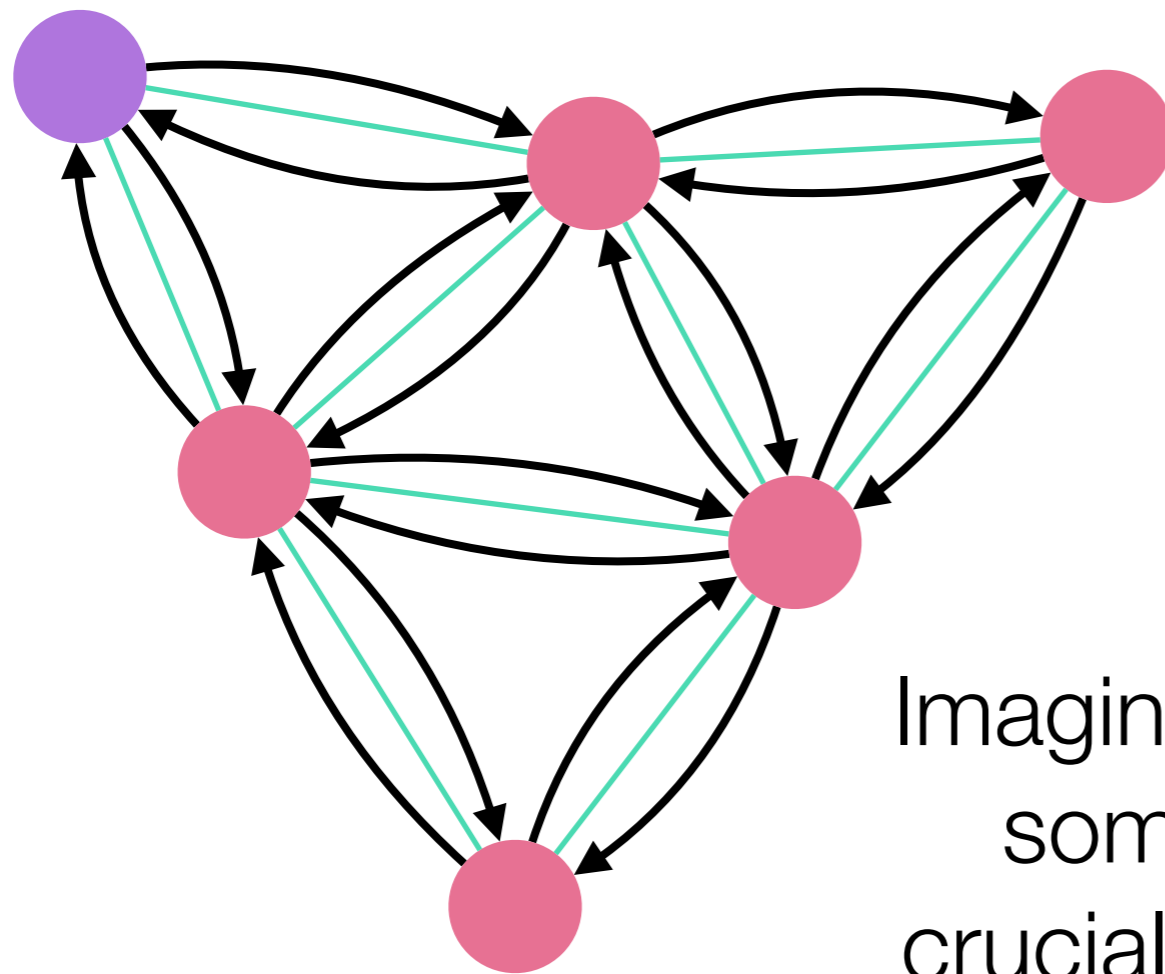
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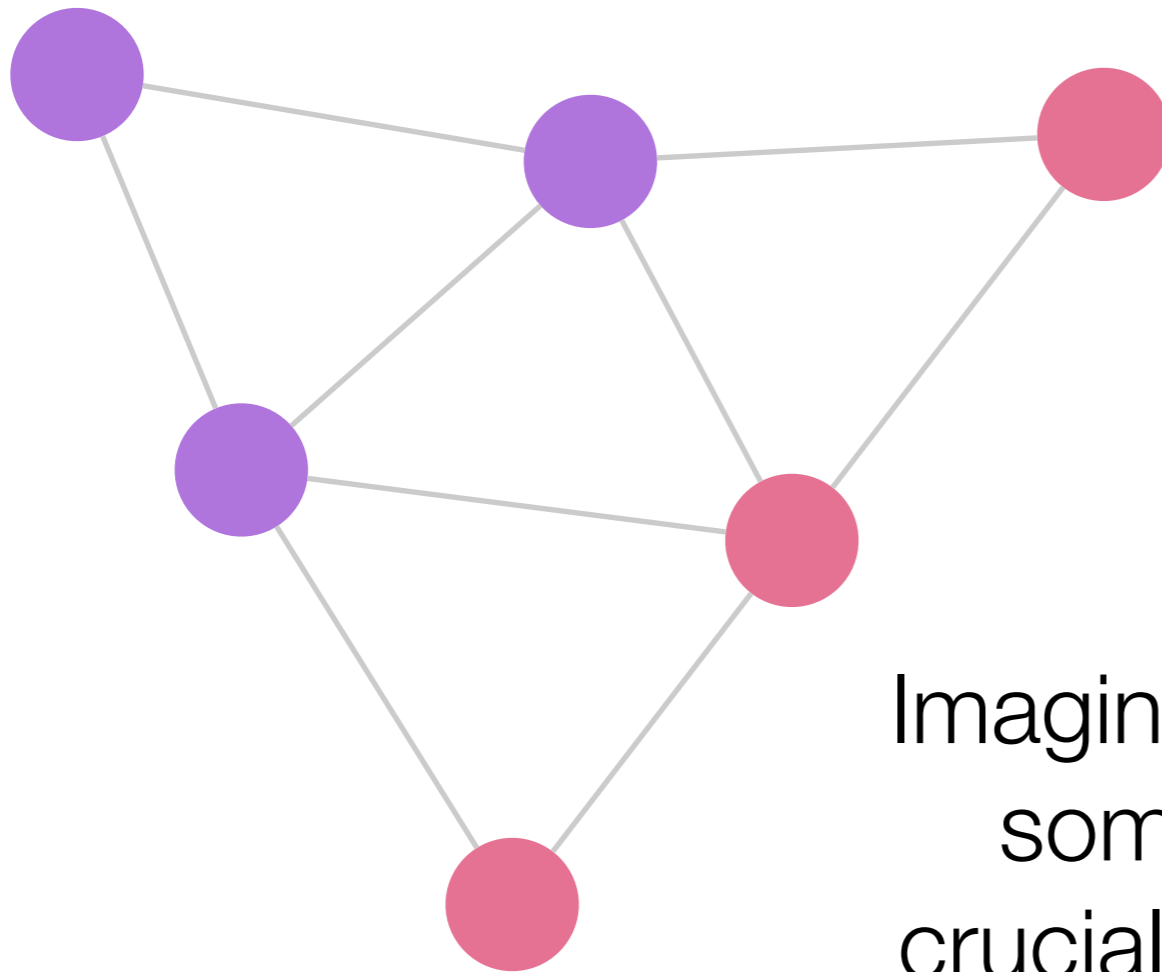
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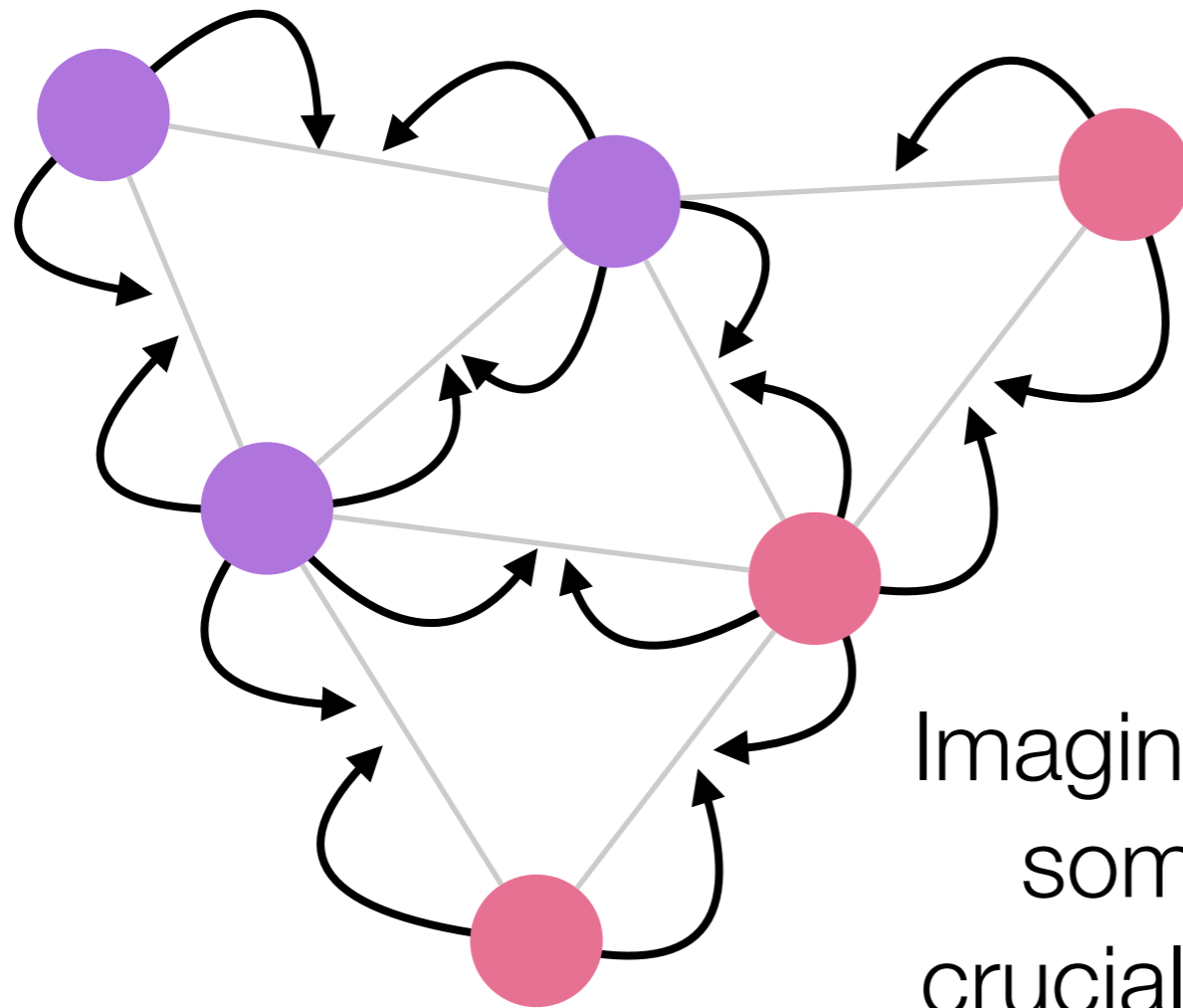
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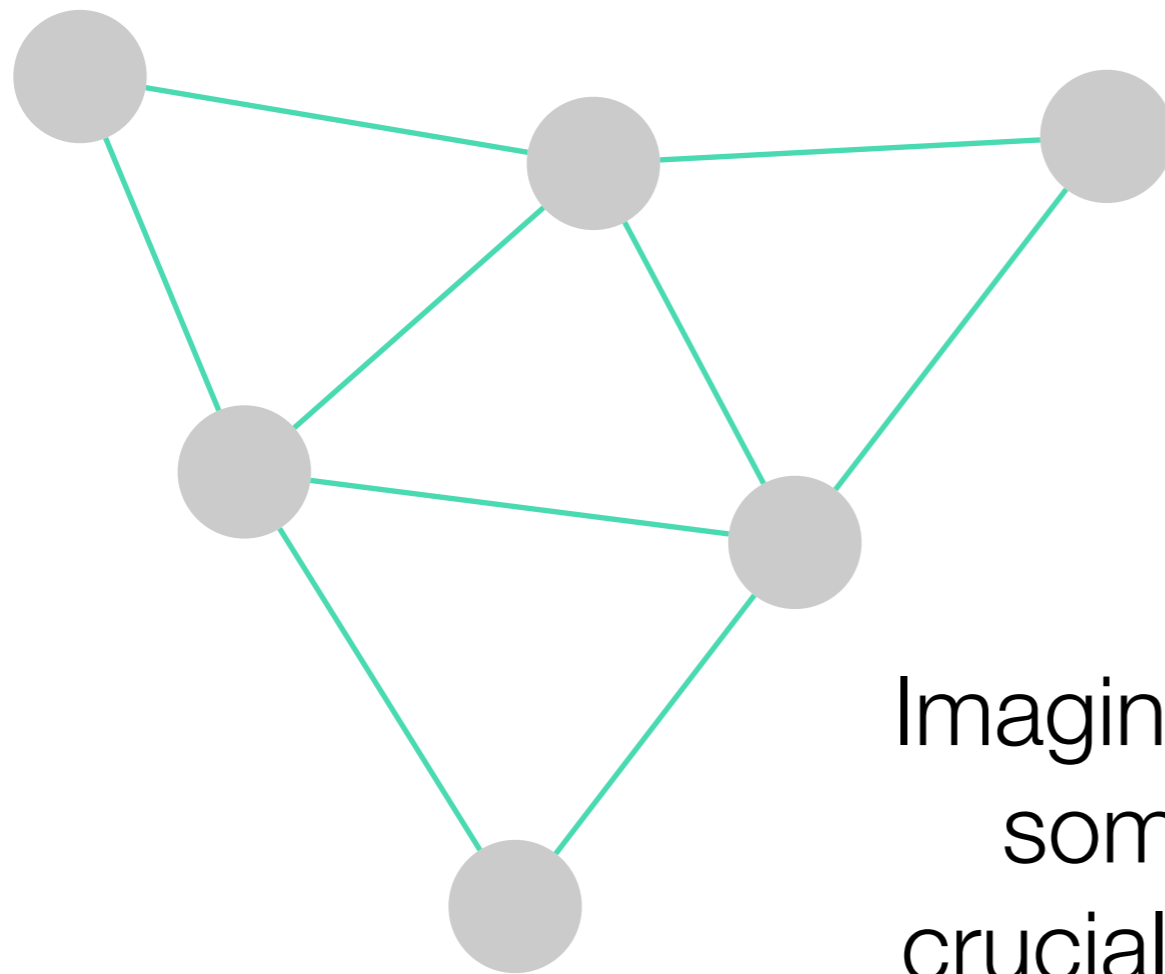
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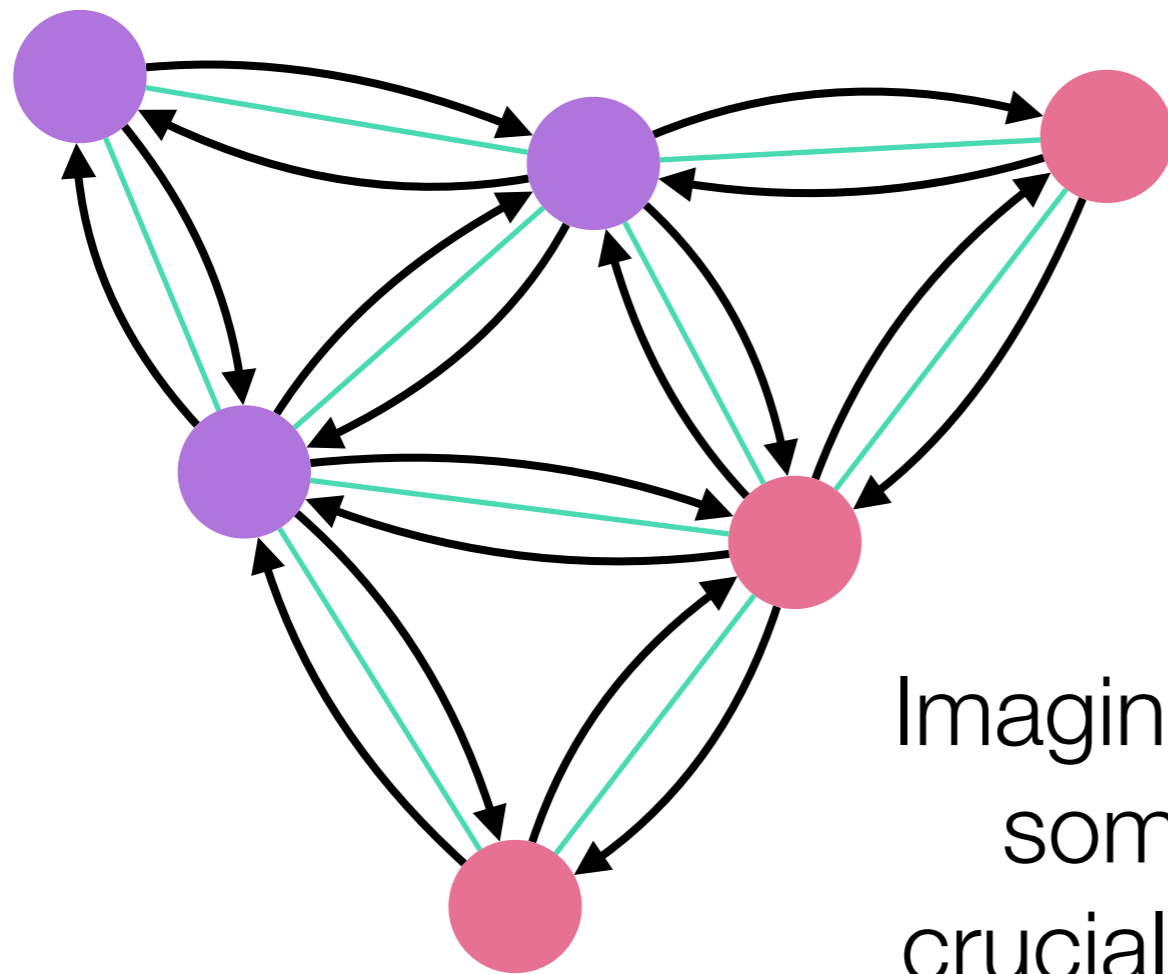
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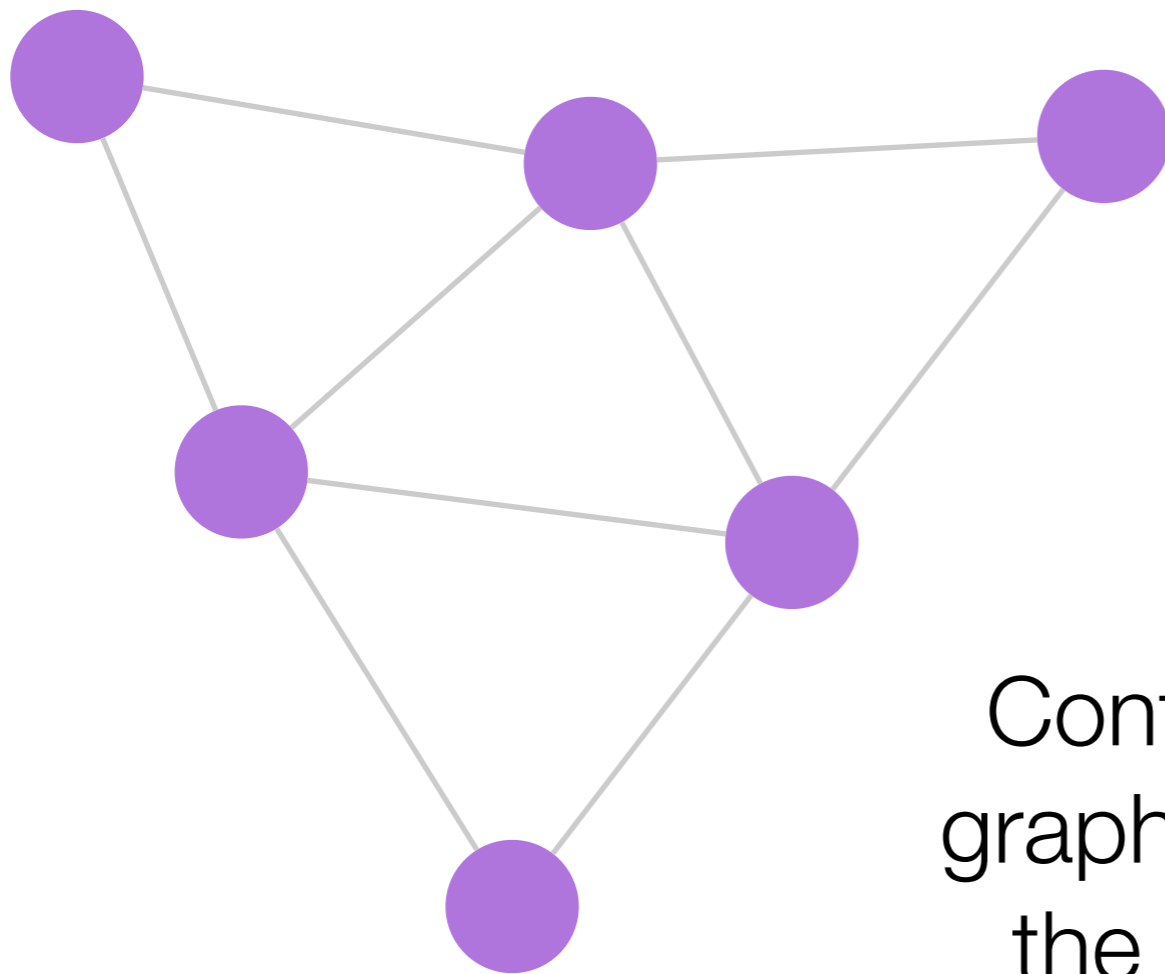
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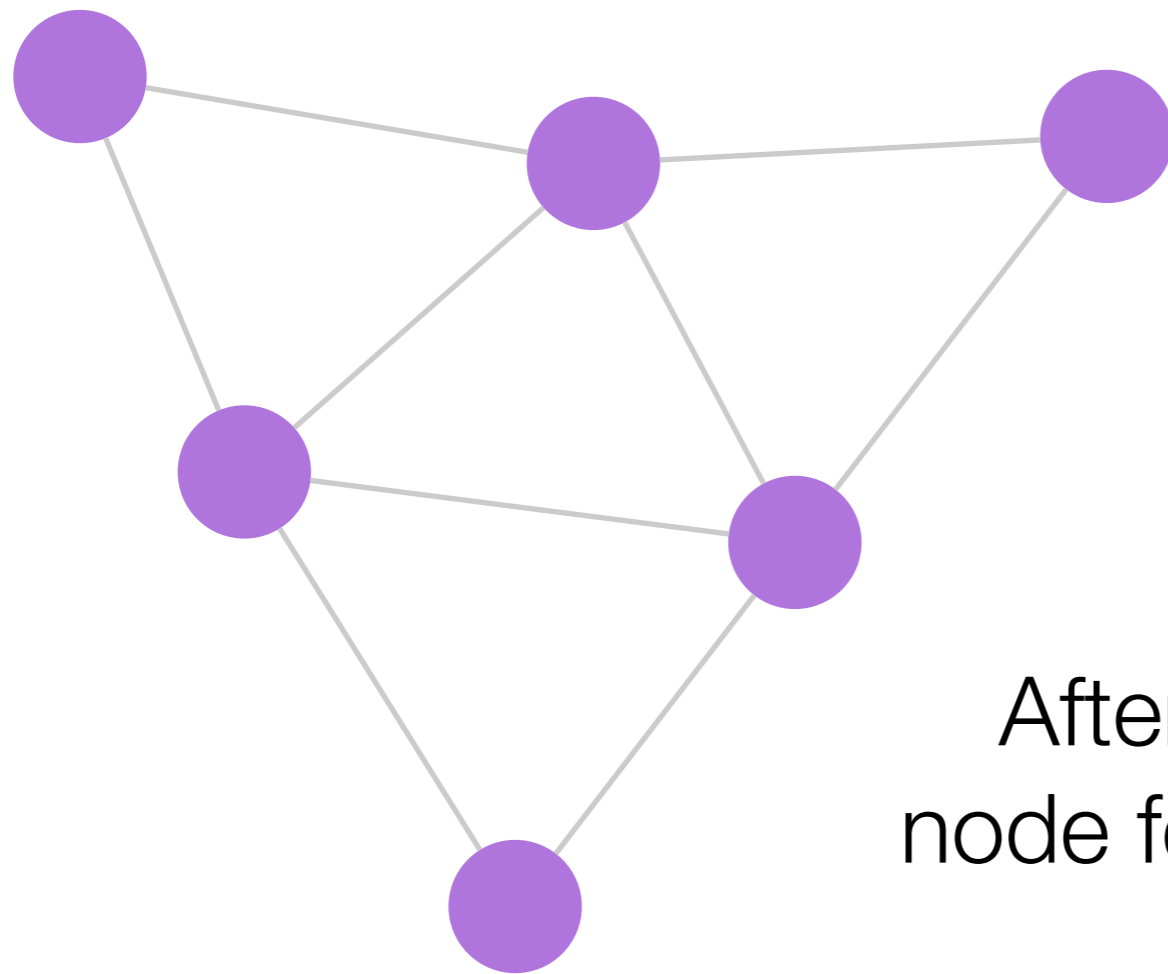
Graph Neural Networks

2 iterations



Context information from each graph node is dispersed through the graph with each iteration.

Graph Neural Networks



After multiple iterations, graph node features can be convolved to
label graph nodes

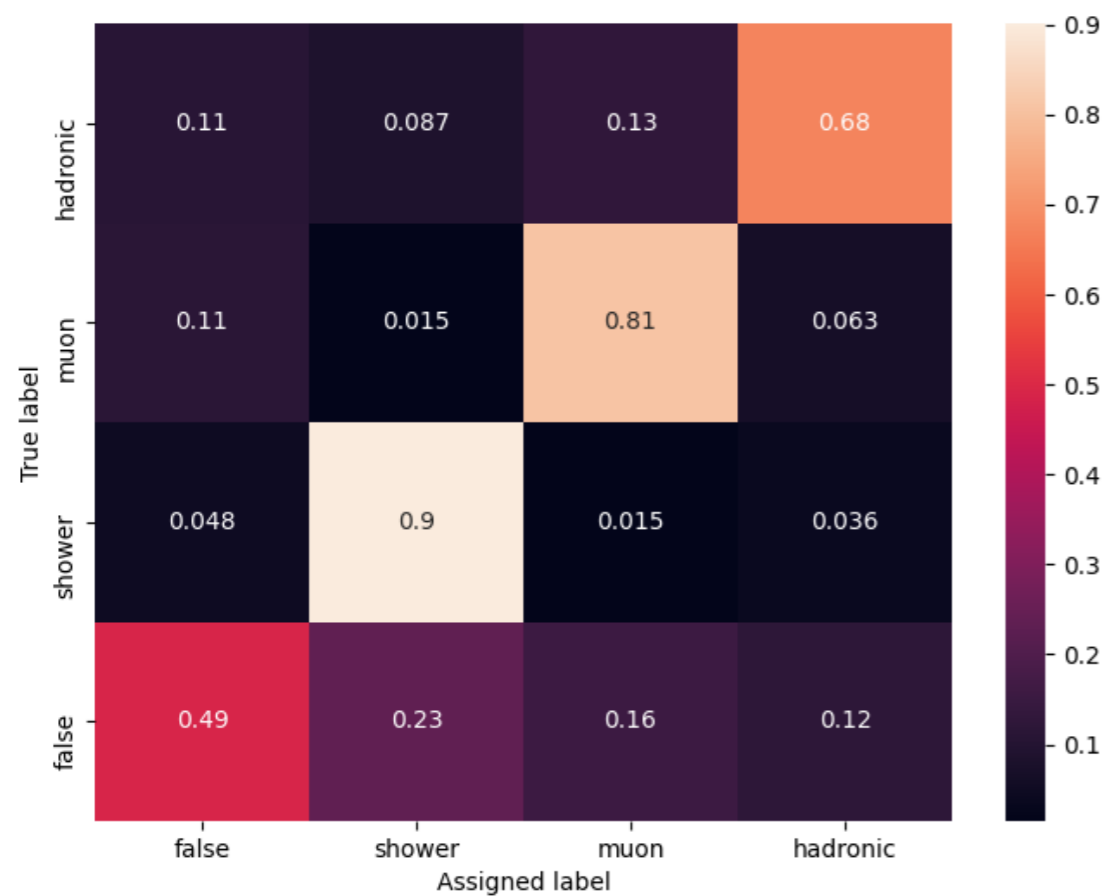
NuGraph2

NuGraph1

- First proof-of-concept model achieved 84% accuracy in **classifying graph edges**.
 - Reasonable performance on showers, struggled to correctly identify type of track.
 - See [arxiv:2103.06233](https://arxiv.org/abs/2103.06233).

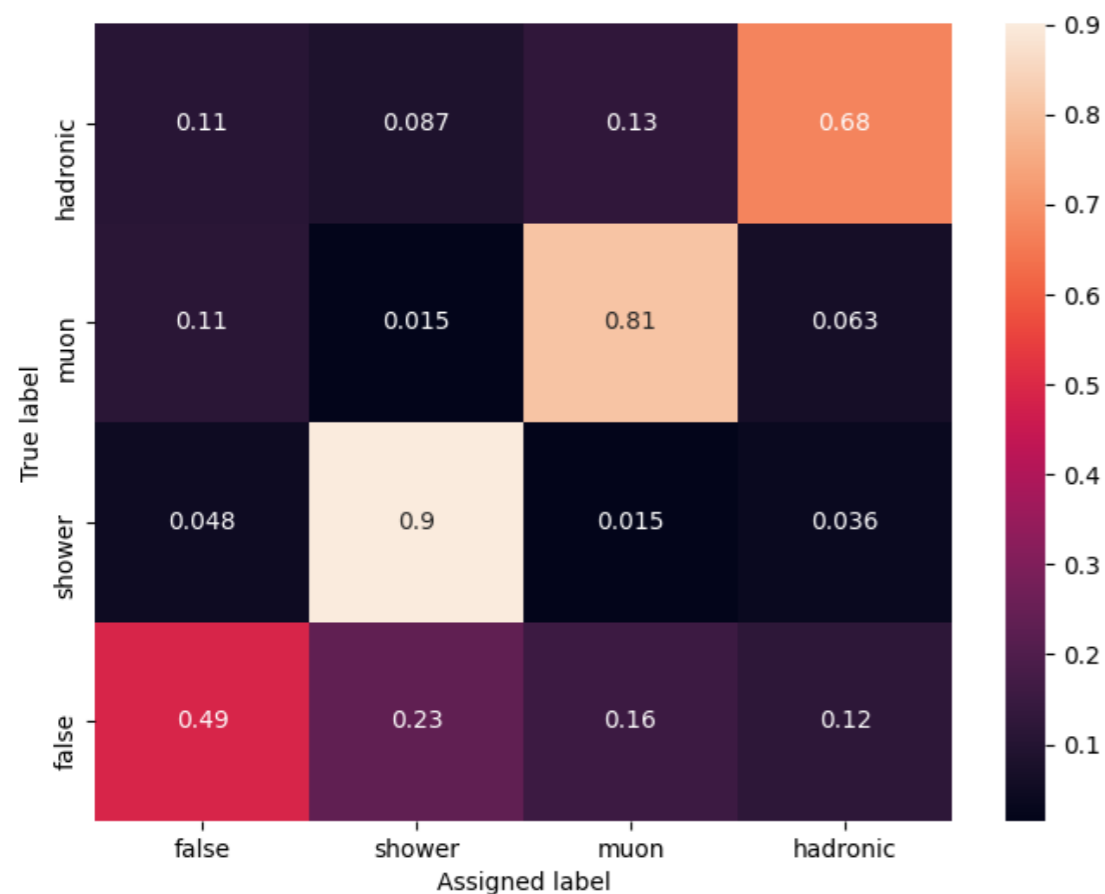
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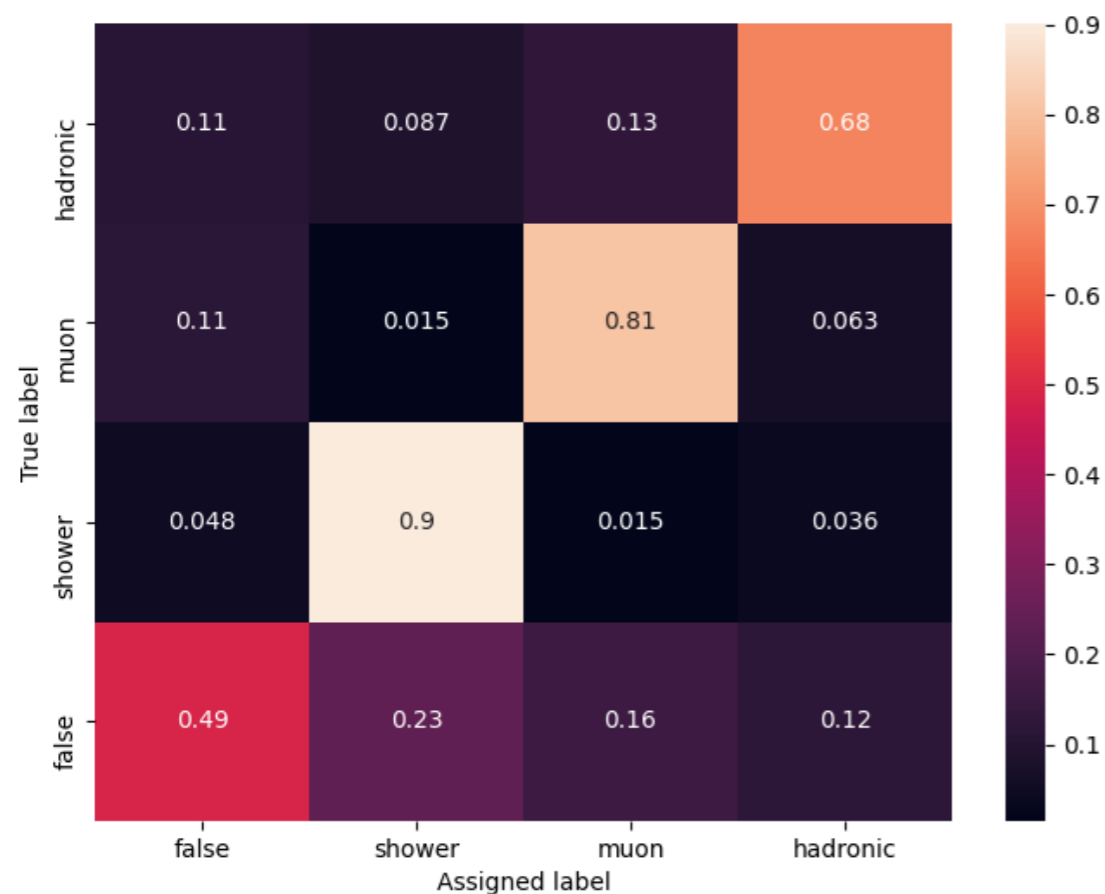
Ground truth

Model output

hadronic, muon, shower, false

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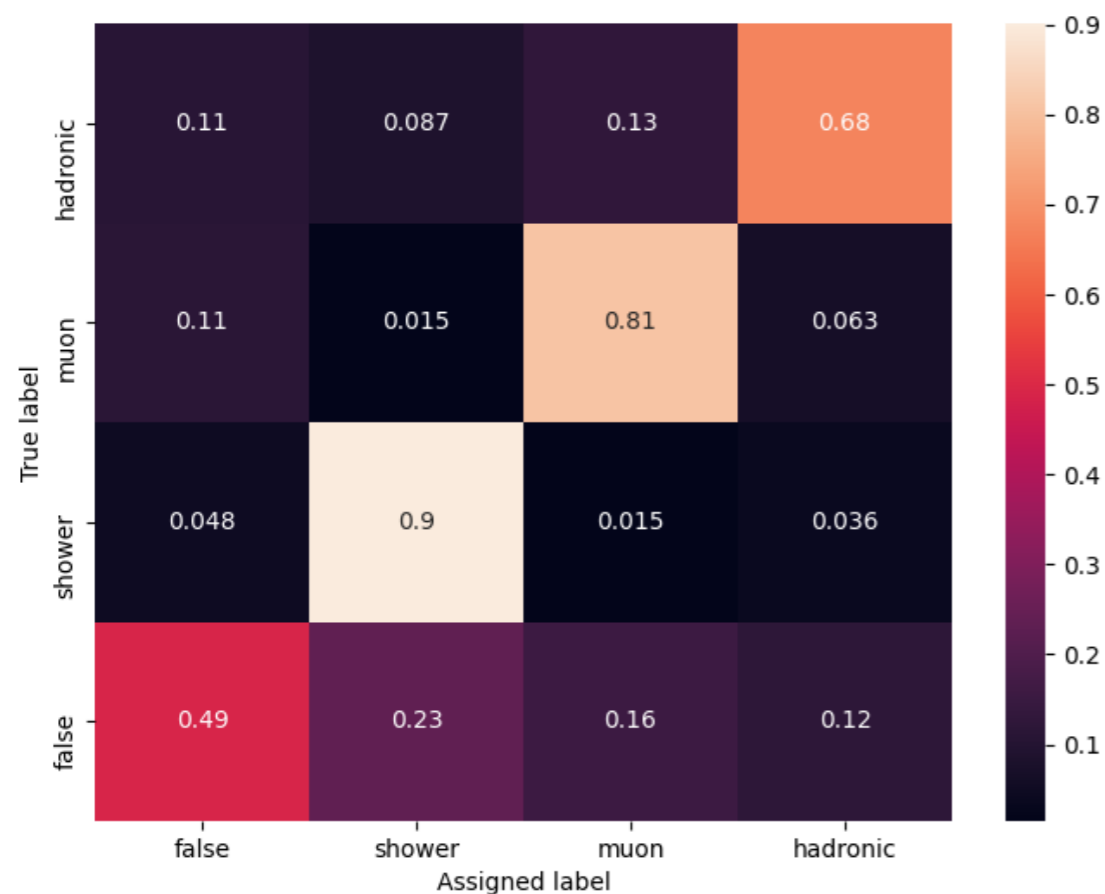
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- Move from **edge classification** to **node (ie. hit) classification**.
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- Introduce **more sophisticated semantic labelling** which considers a wider variety of particle types, ie. EM showers, Michel electrons, diffuse EM activity.
- Build a model which **classifies all views simultaneously**, instead of classifying each detector views as an independent event.
 - Furthermore, allow **information exchange between 2D views** to break degeneracies.

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- Also perform **hit filtering** to remove hits that are not part of the primary physics interaction.

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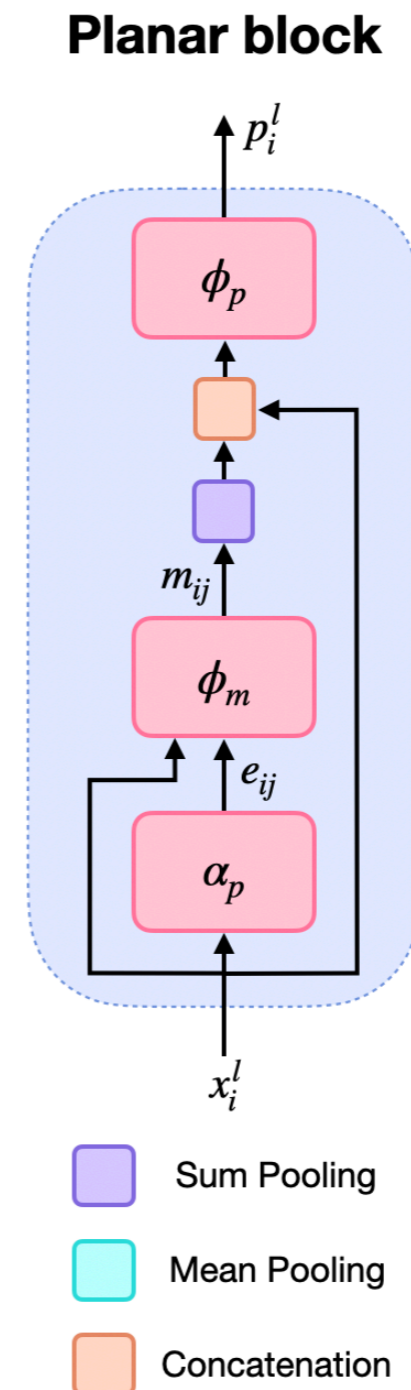
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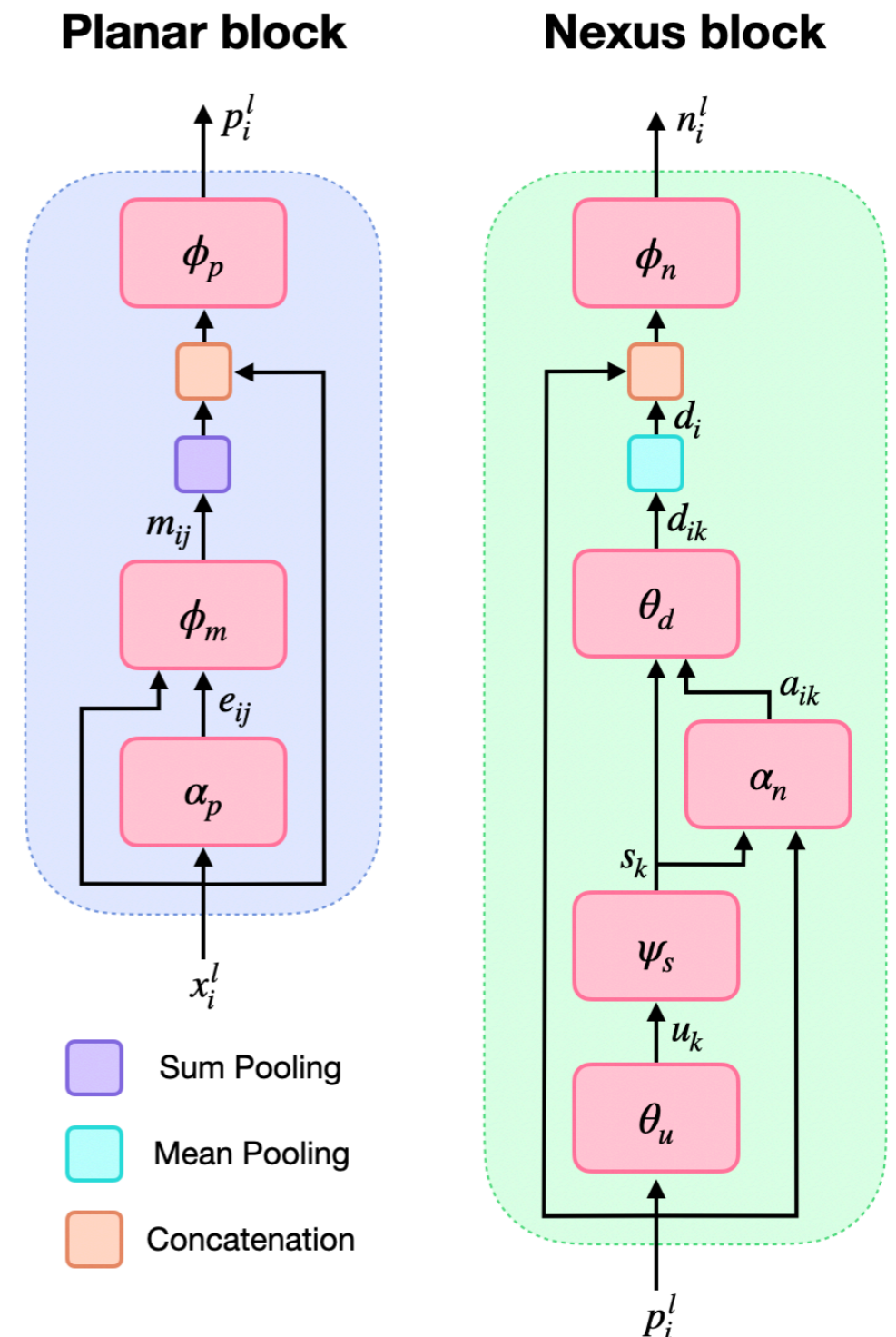
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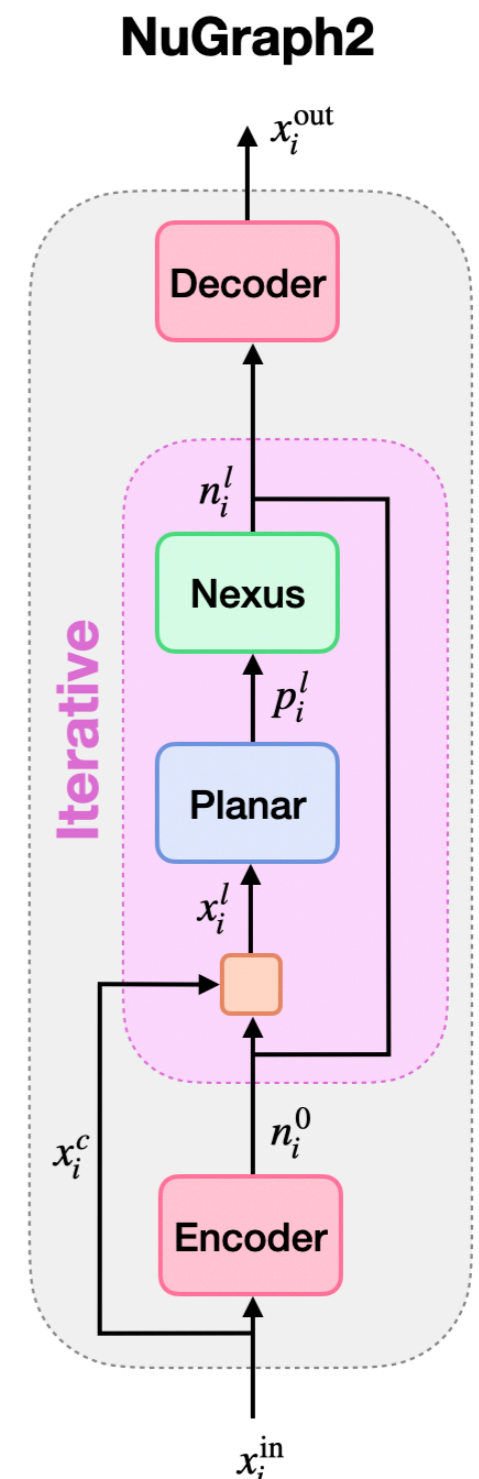
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 - Pass messages up to 3D nexus nodes to share context information.



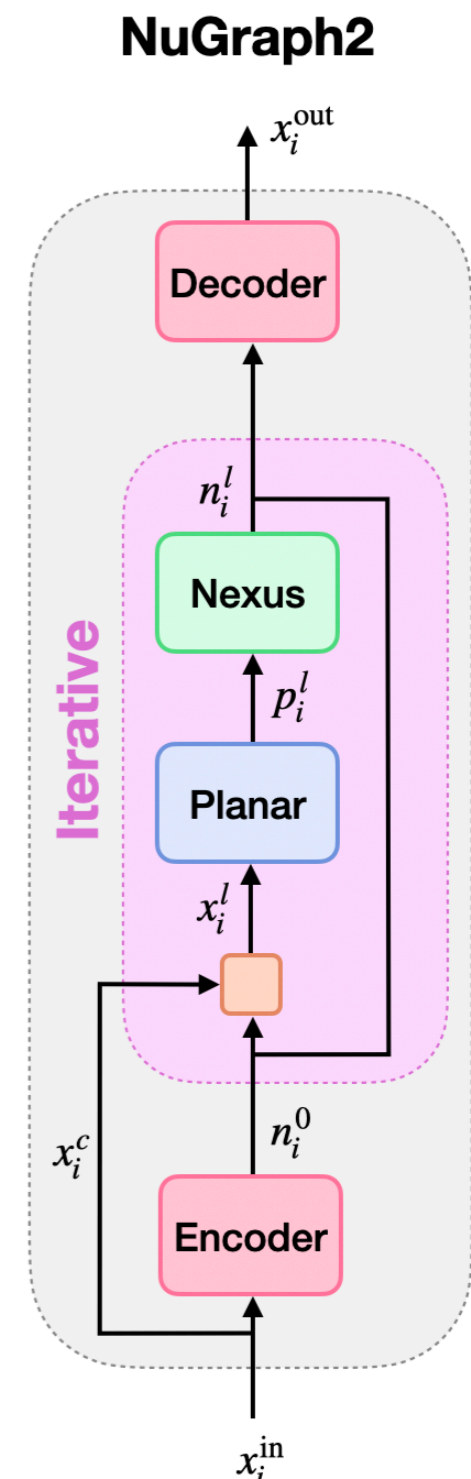
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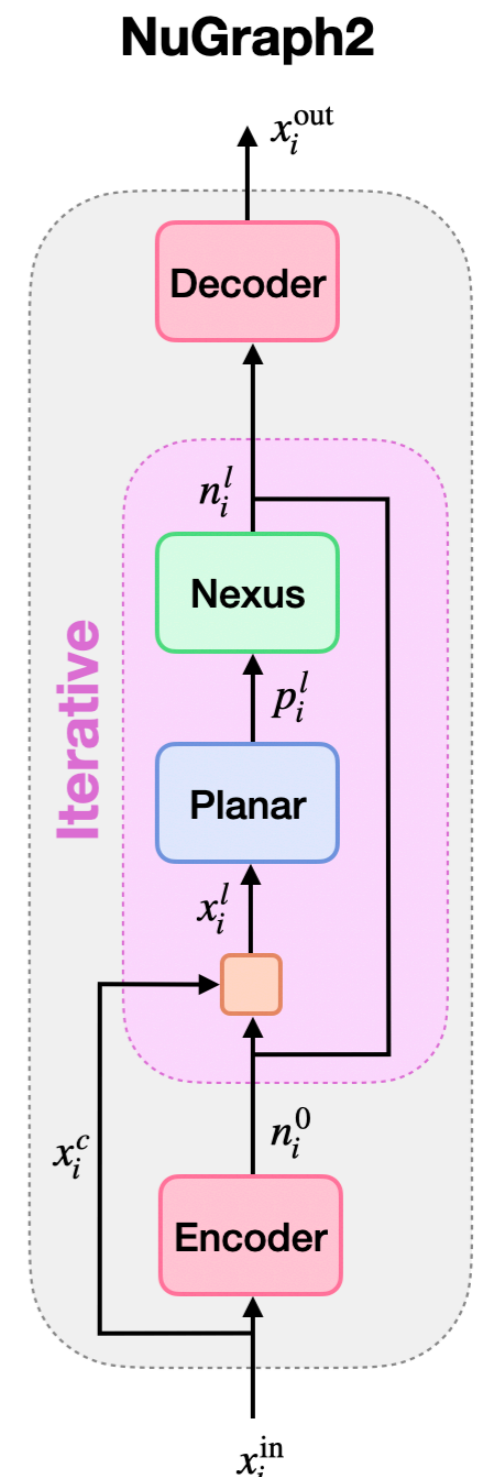
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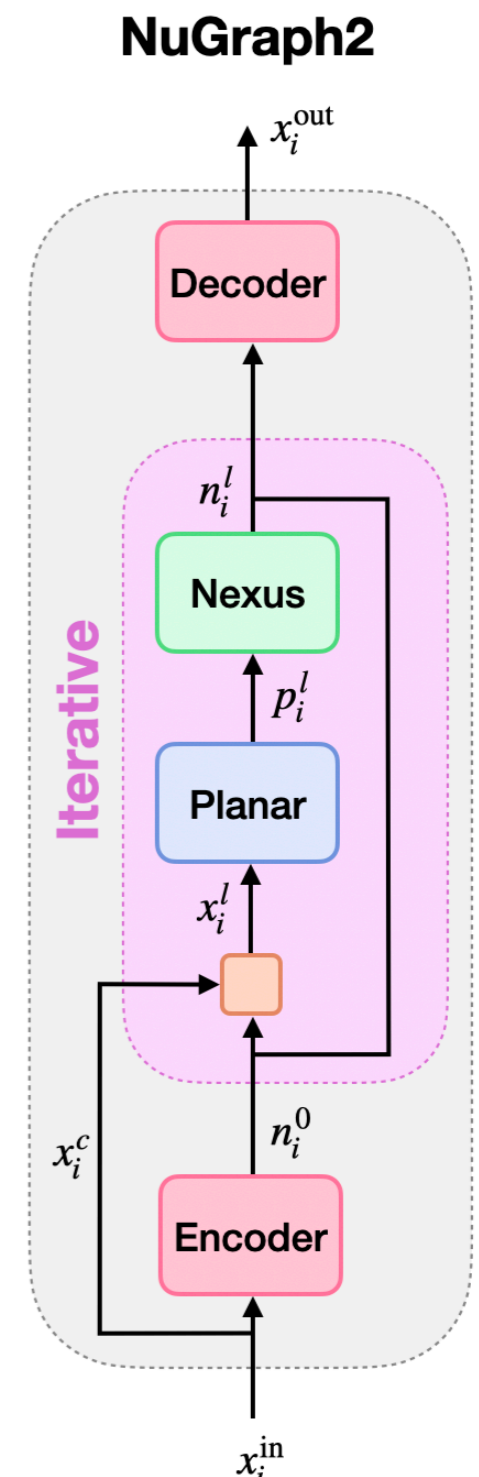
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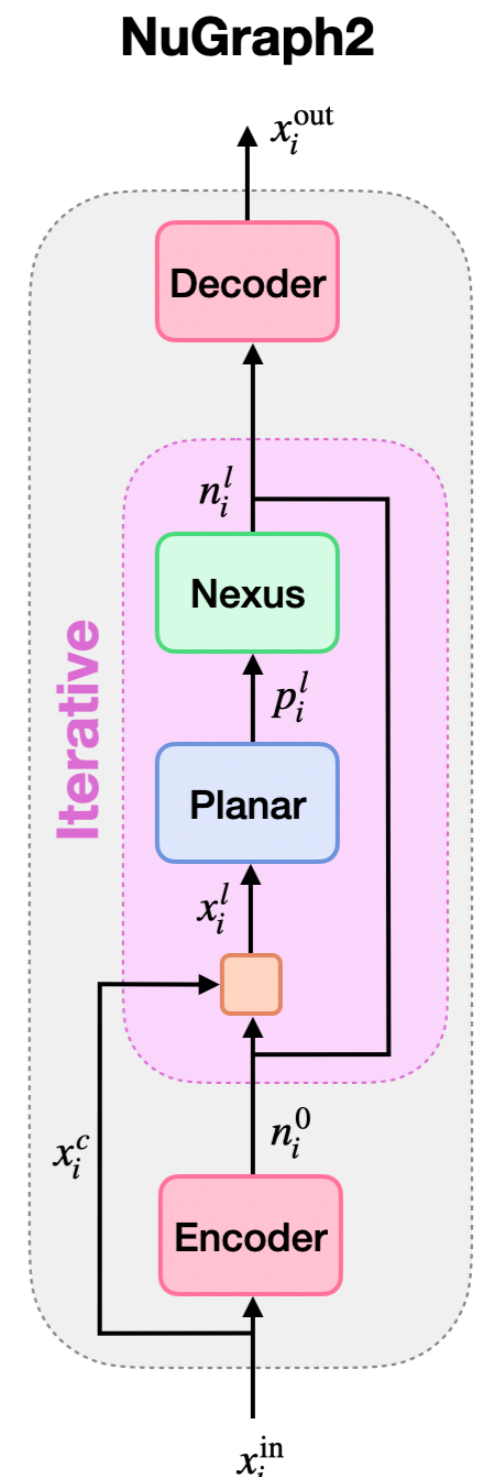
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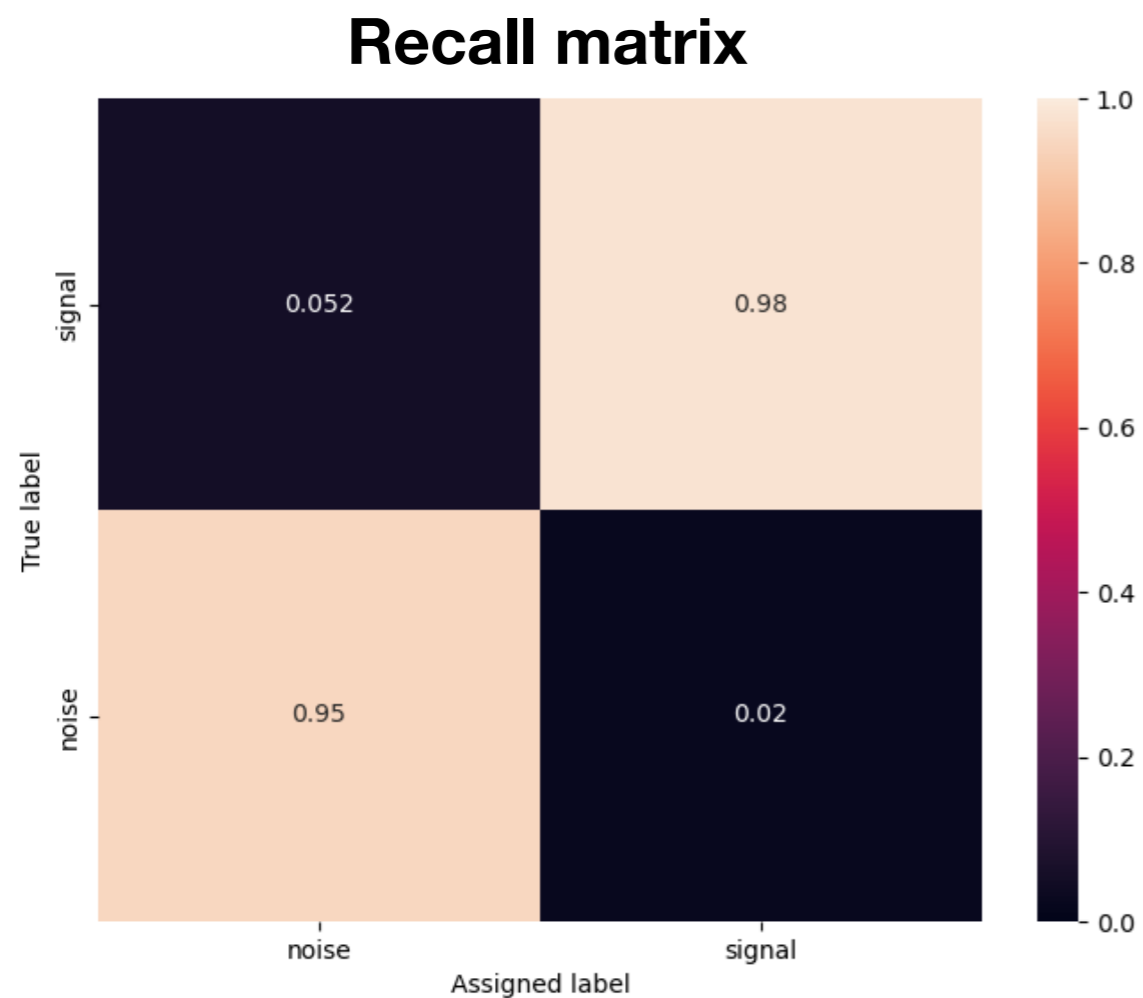
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- The output of the message-passing engine can be forwarded into **any number of decoders** for a variety of tasks.
 - In this talk, we present two tasks: **semantic hit segmentation** and **background filtering**.
 - This engine can be leveraged for much more than just these two tasks. See the **NuGraph3** talk later for more details ;)



NuGraph2

Background filtering

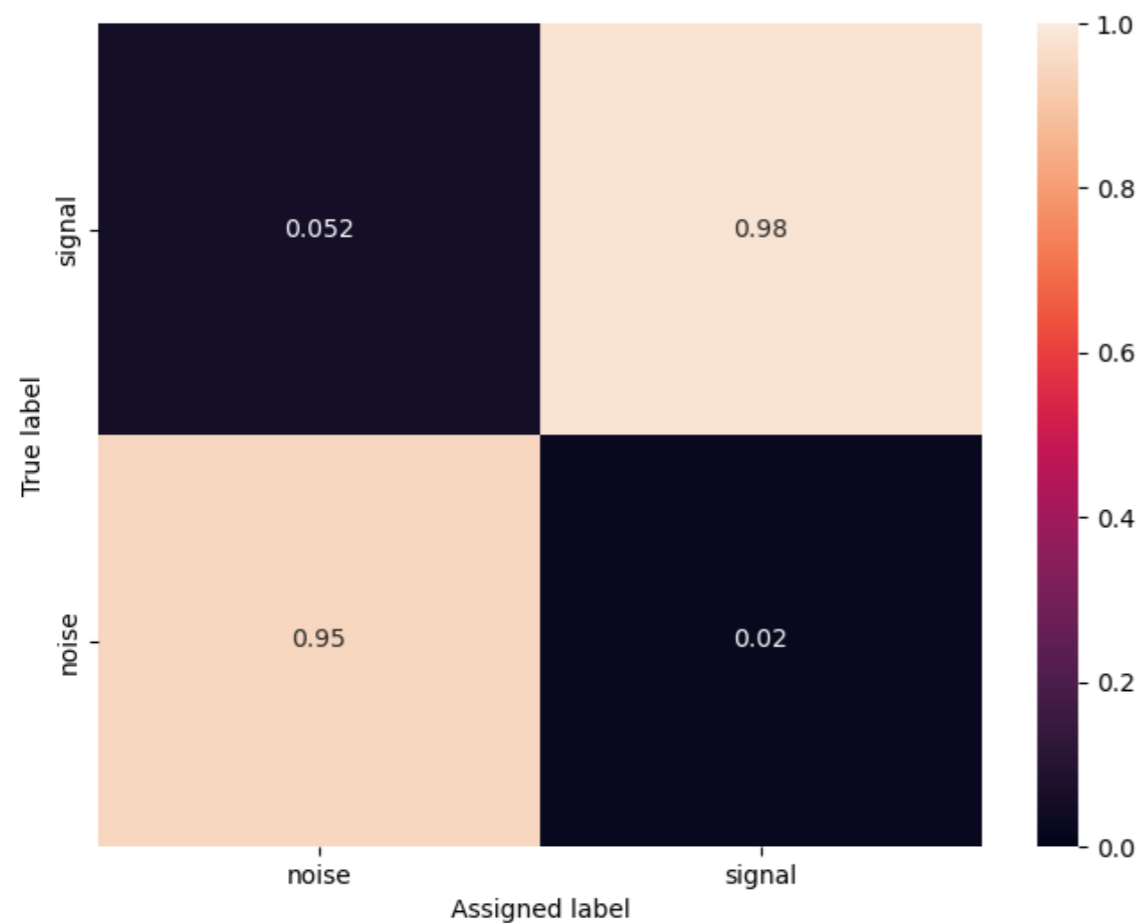
- Performance metrics: **recall 0.978**, **precision 0.977**.



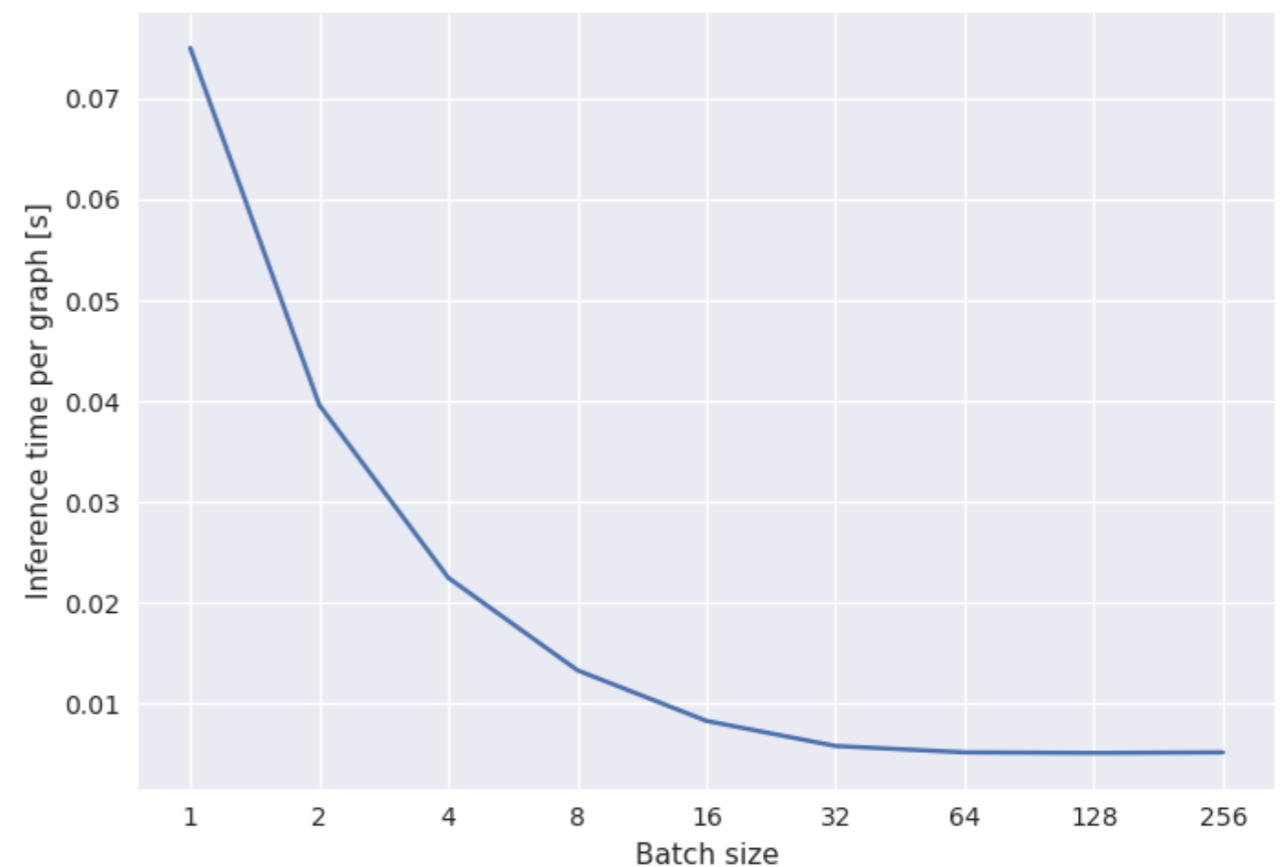
Background filtering

- Performance metrics: **recall 0.978, precision 0.977.**
- Inference time: **0.12 s/evt on CPU, 0.005s/evt batched on GPU**

Recall matrix



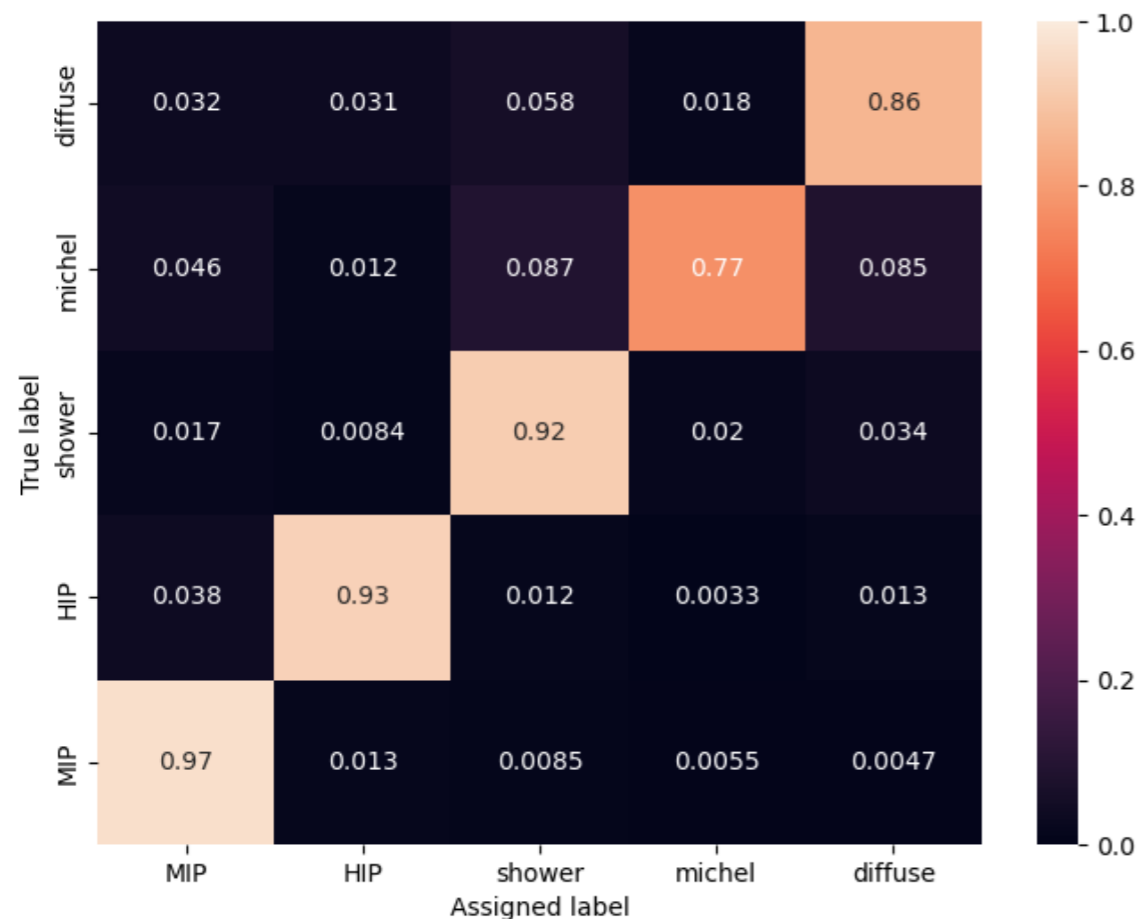
GPU inference time vs batch size



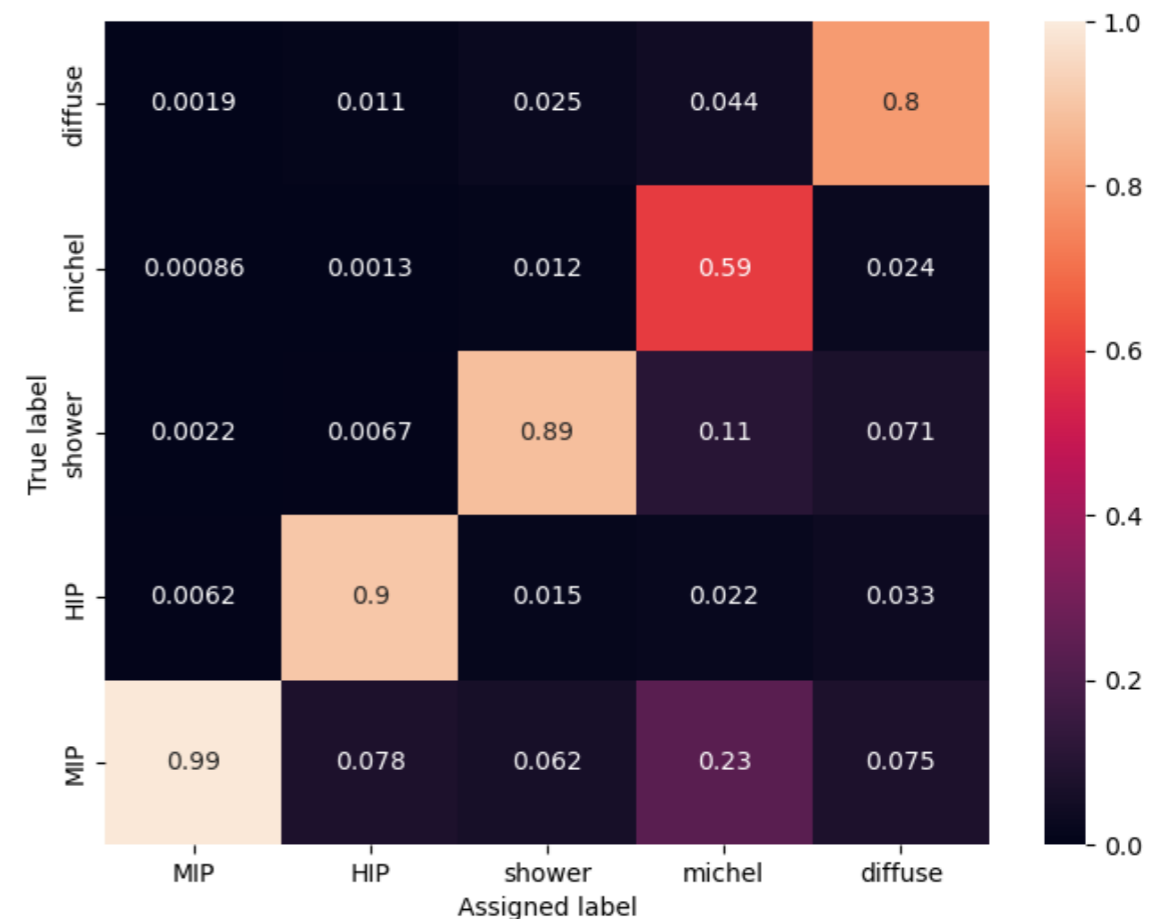
Hit classification

- Performance metrics: **recall 0.948, precision 0.948.**
- Recently improved performance by enhancing ν_μ component of dataset, and using **recall loss** to counteract class imbalance.

Recall matrix

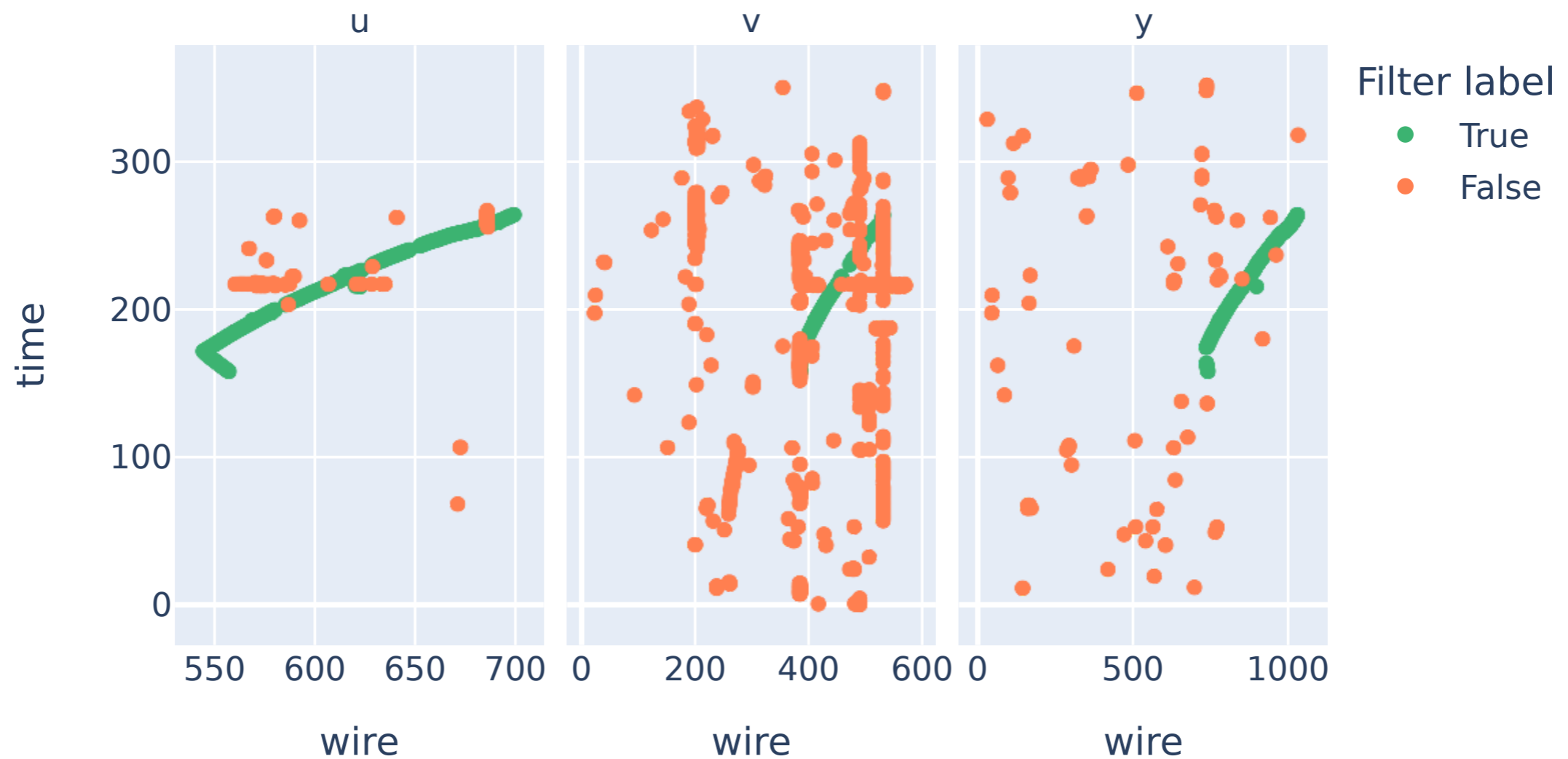


Precision matrix



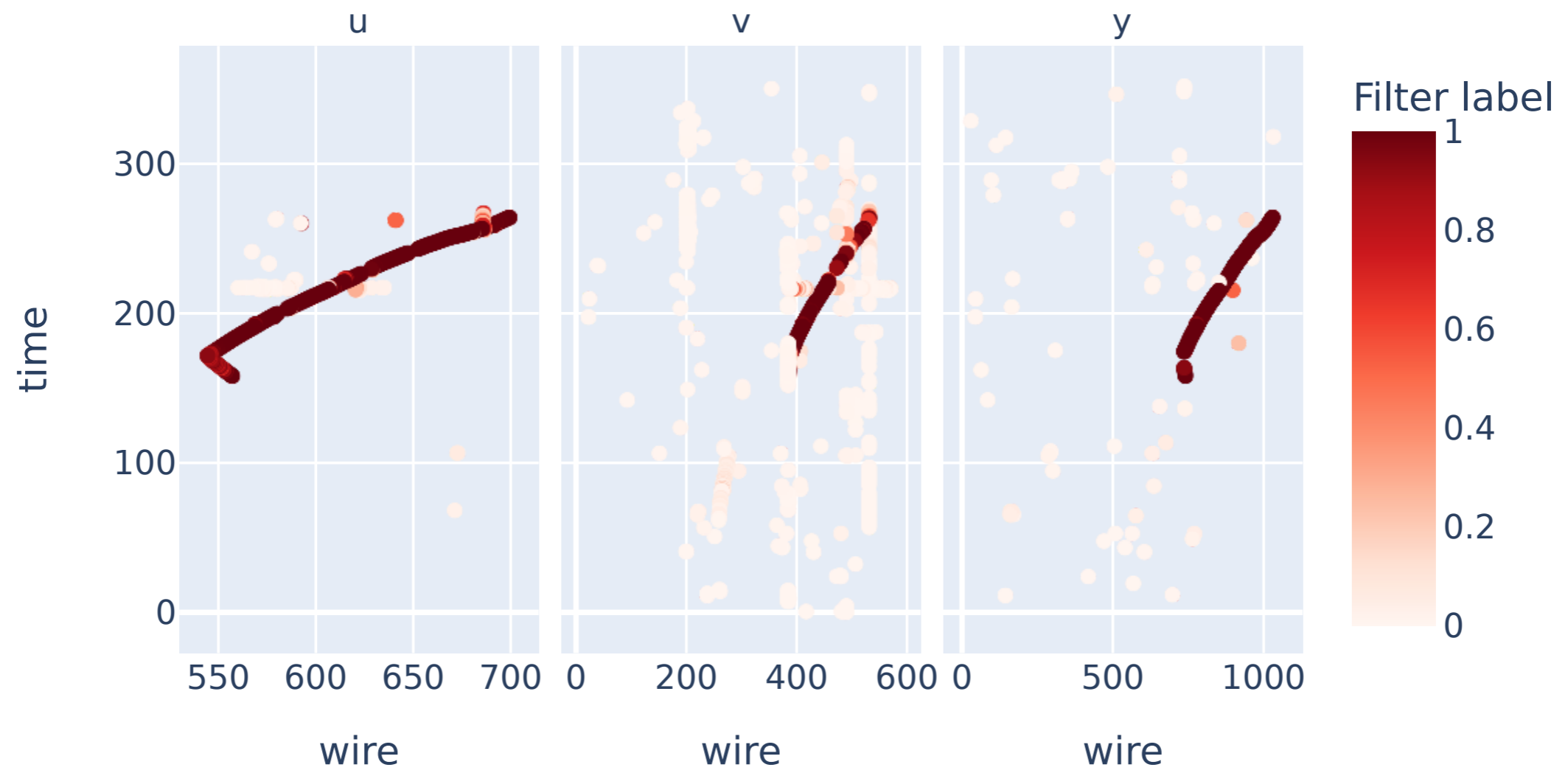
Example event #1

True filter labels



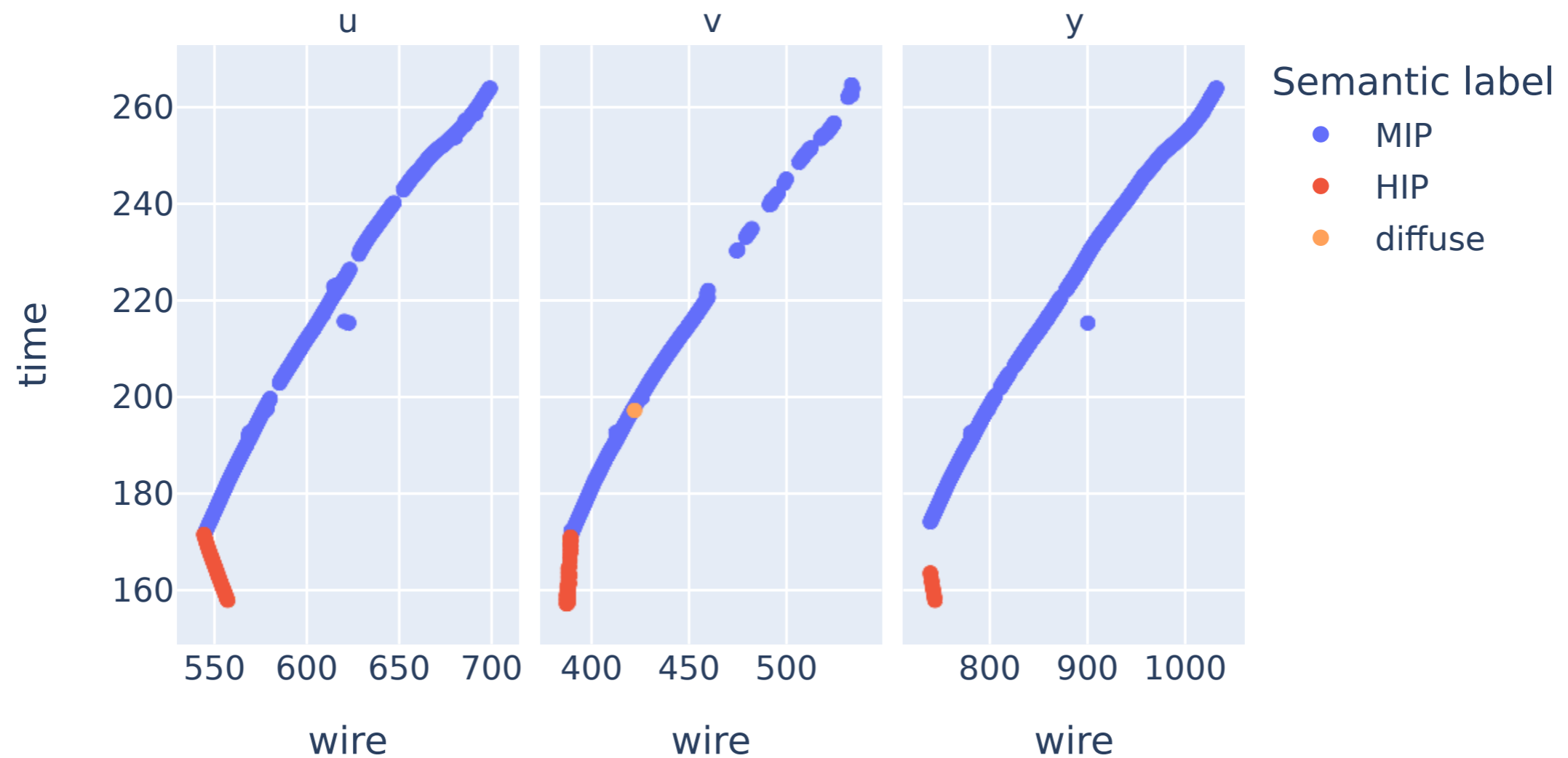
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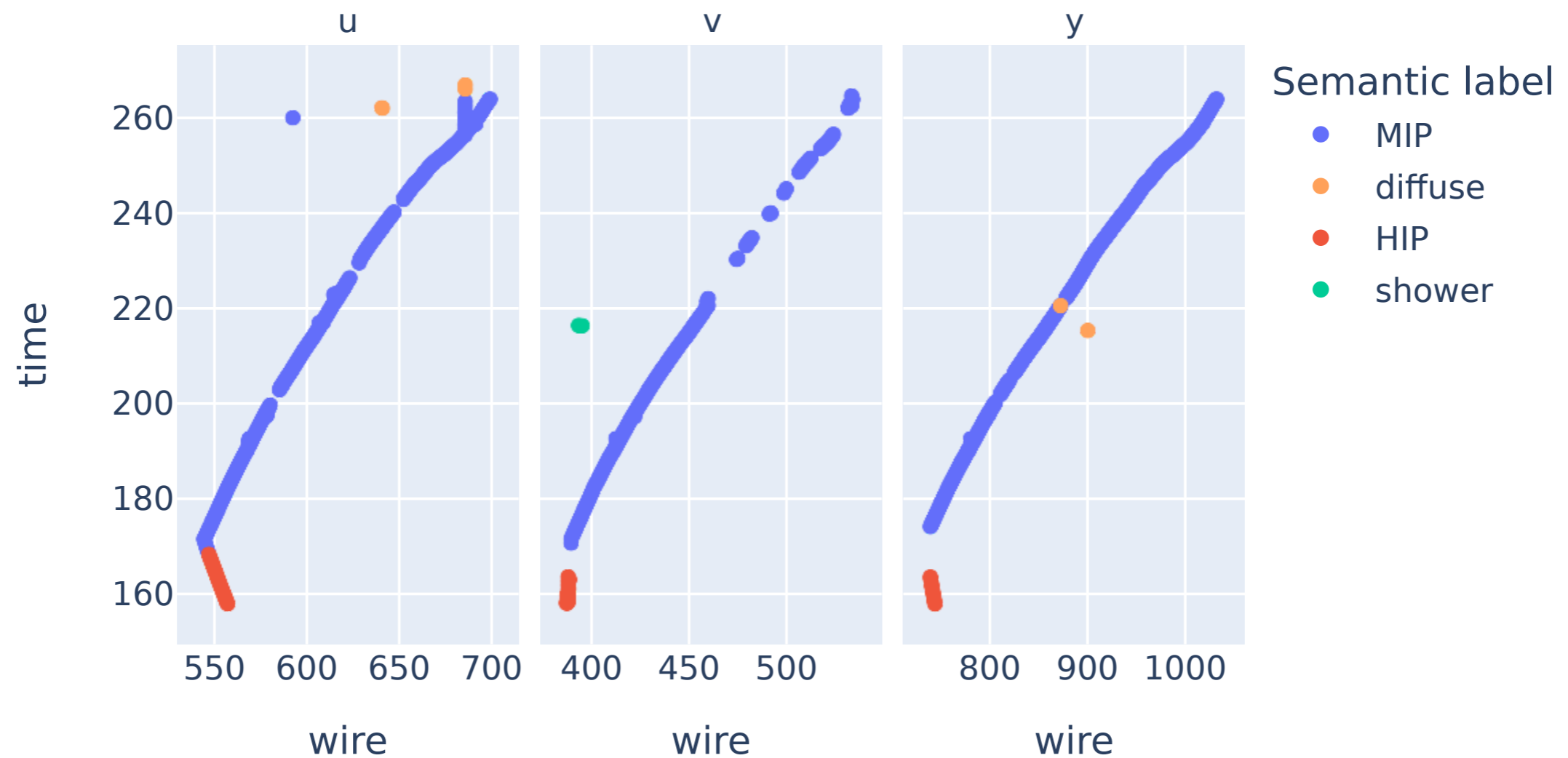
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True semantic labels (filtered by truth)



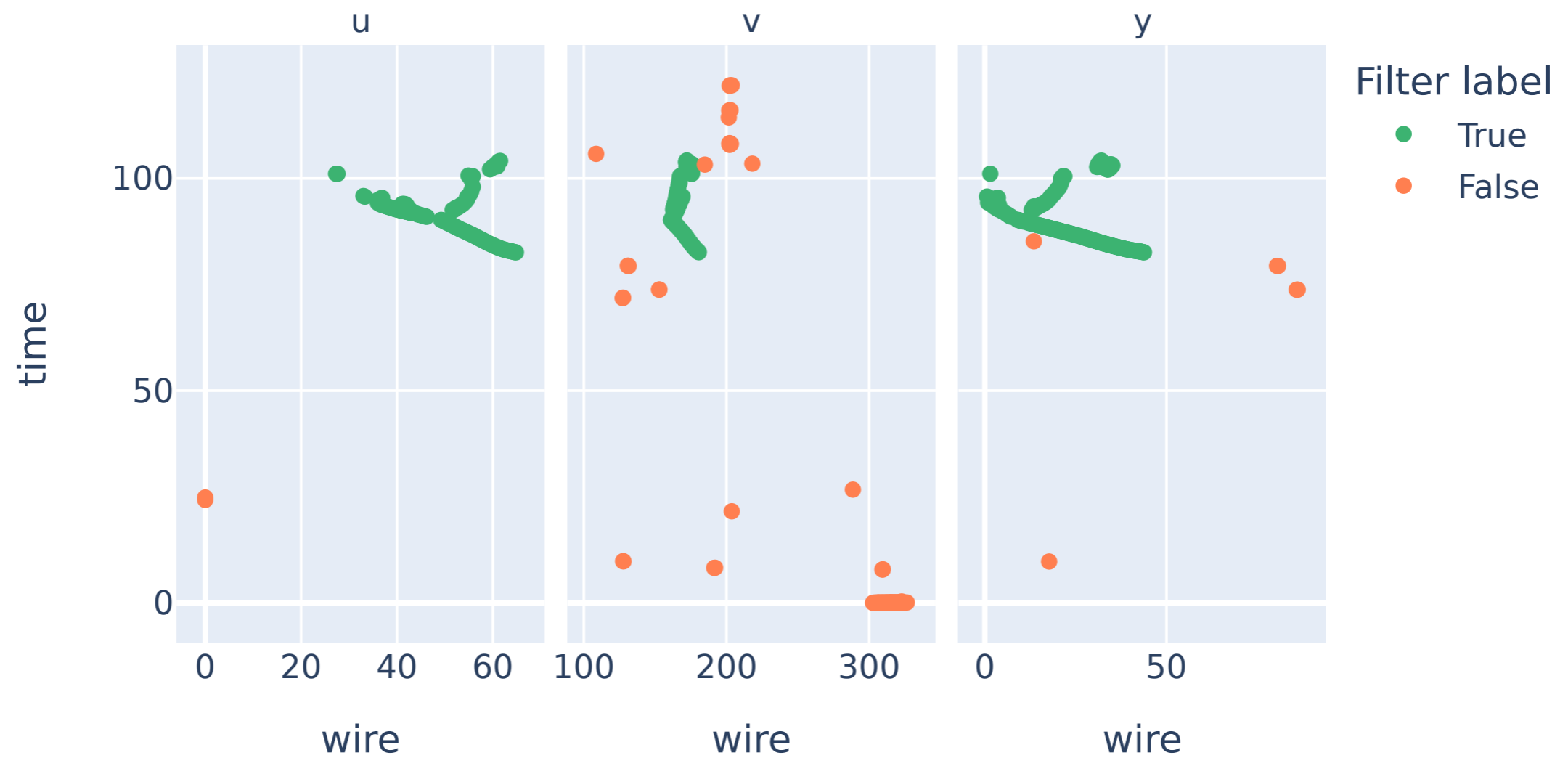
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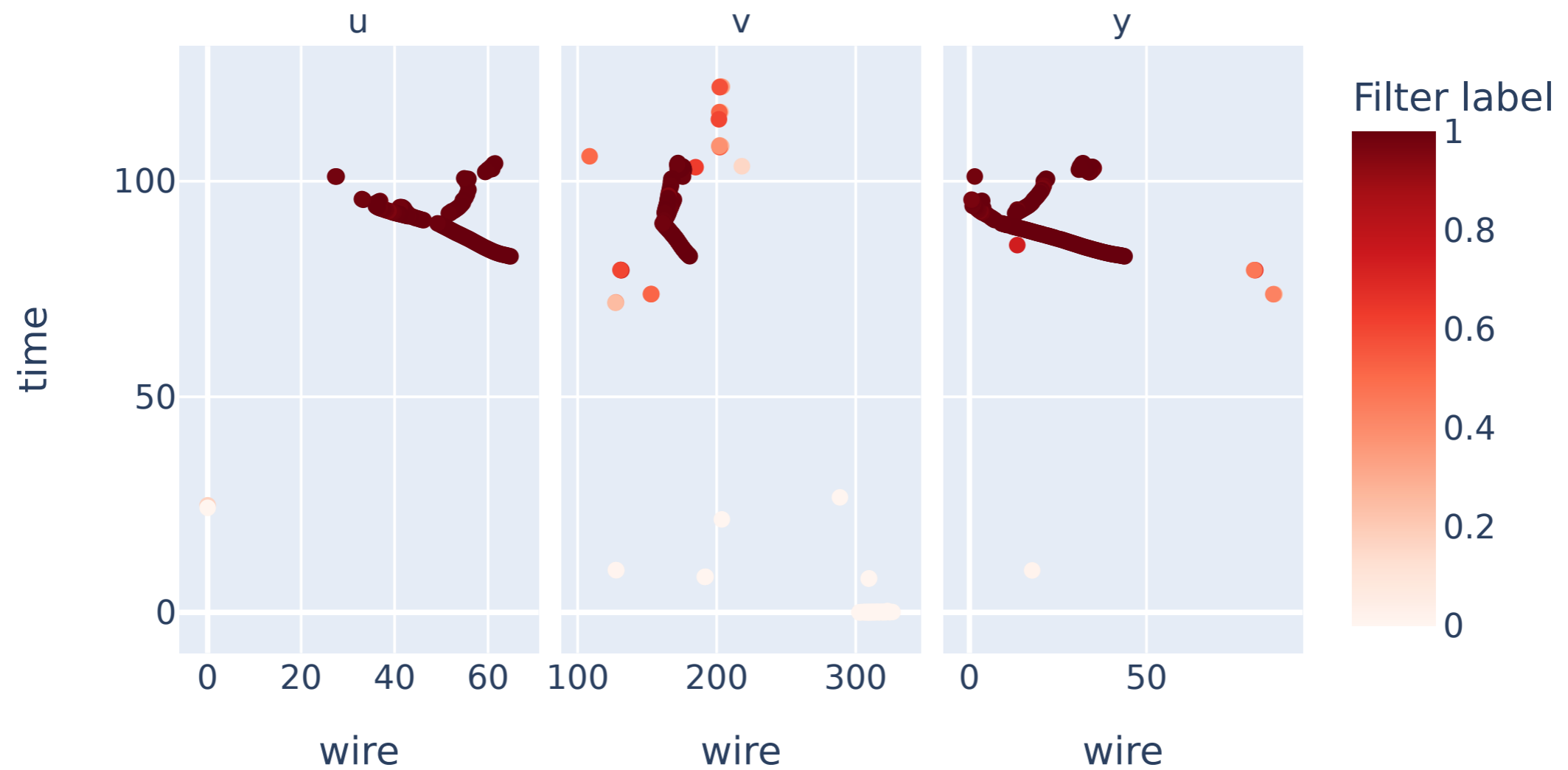
Example event #2

True filter labels



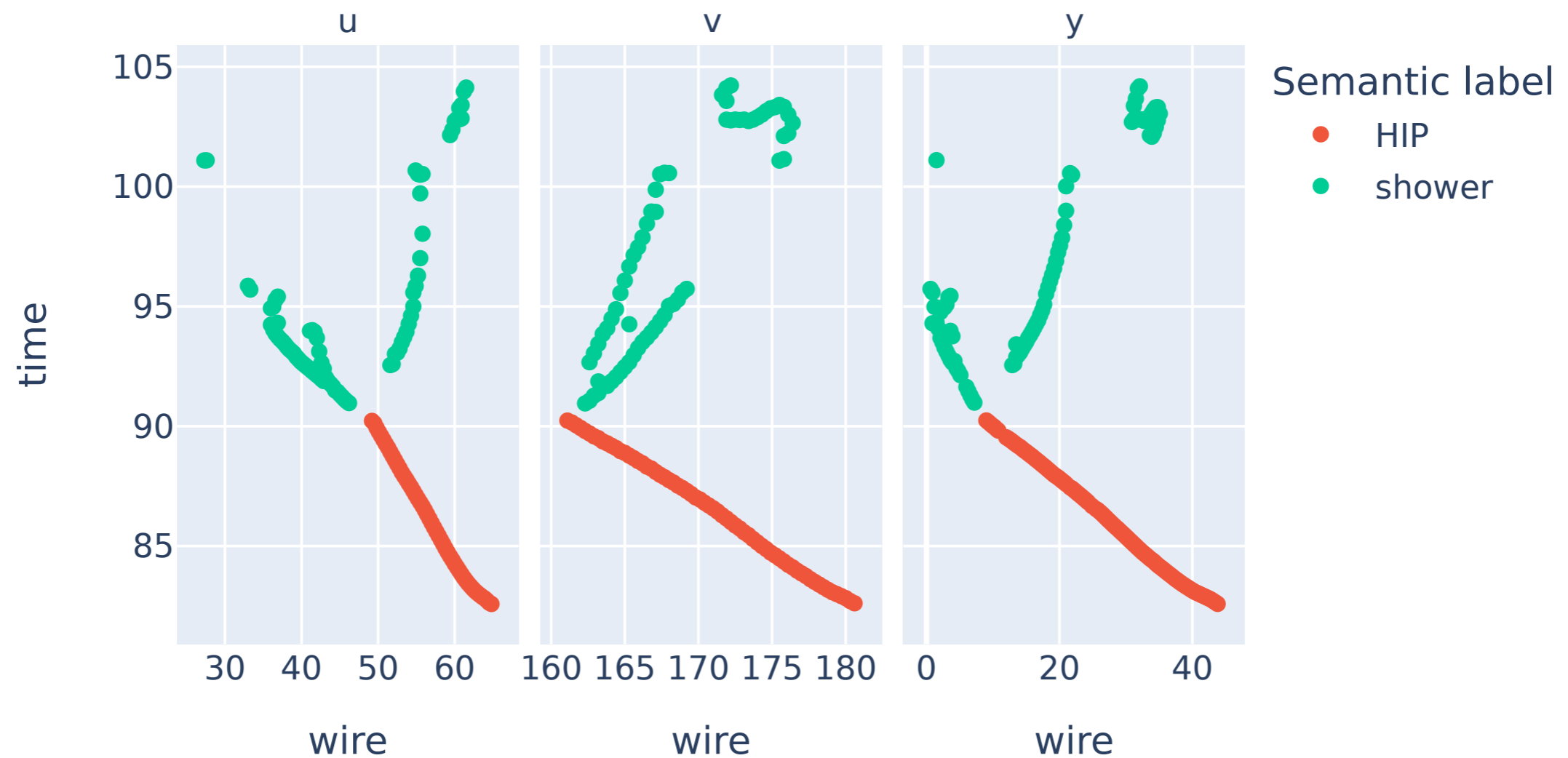
Example event #2

Predicted filter labels



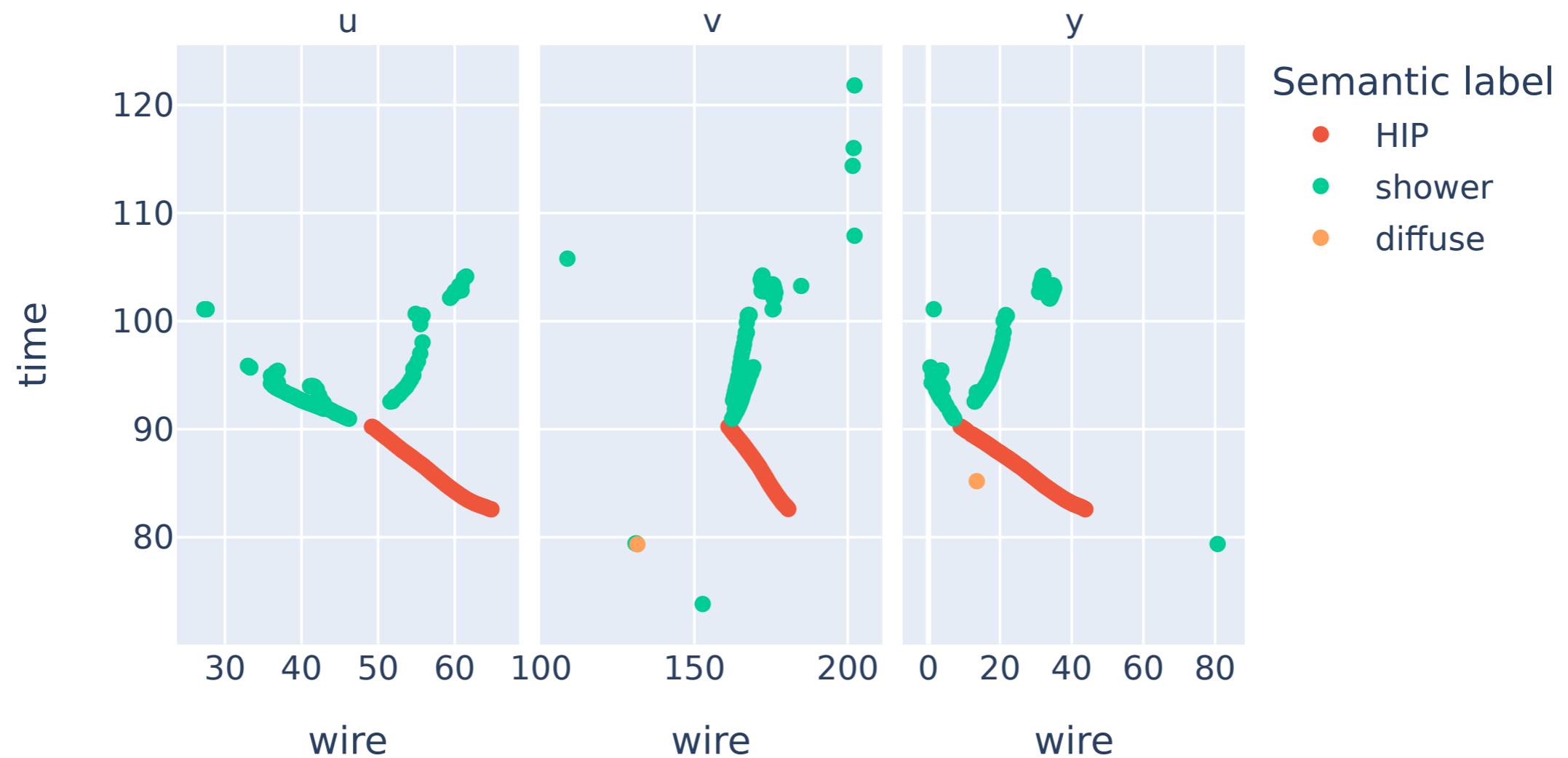
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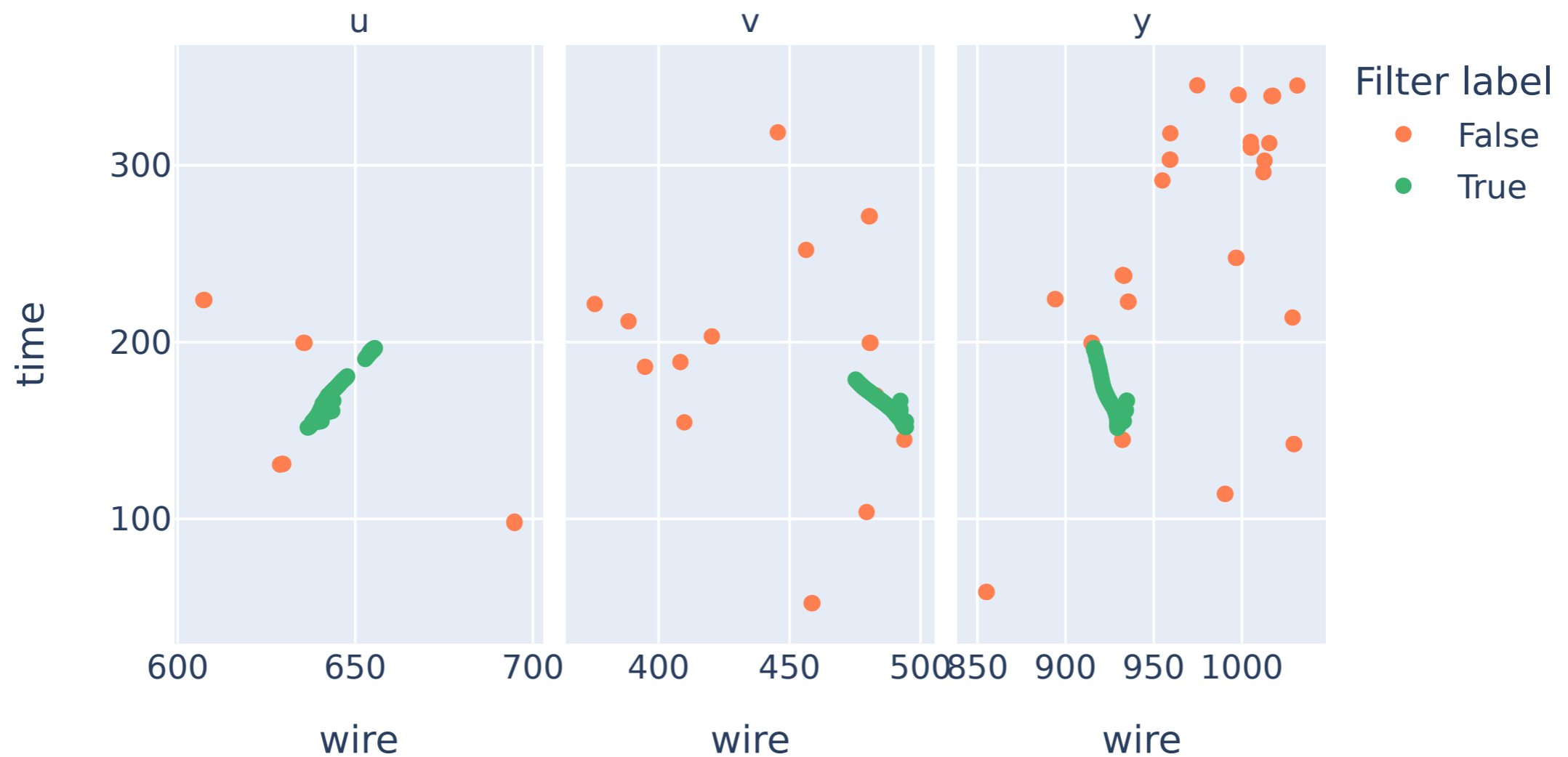
Example event #2

Predicted semantic labels (filtered by prediction)



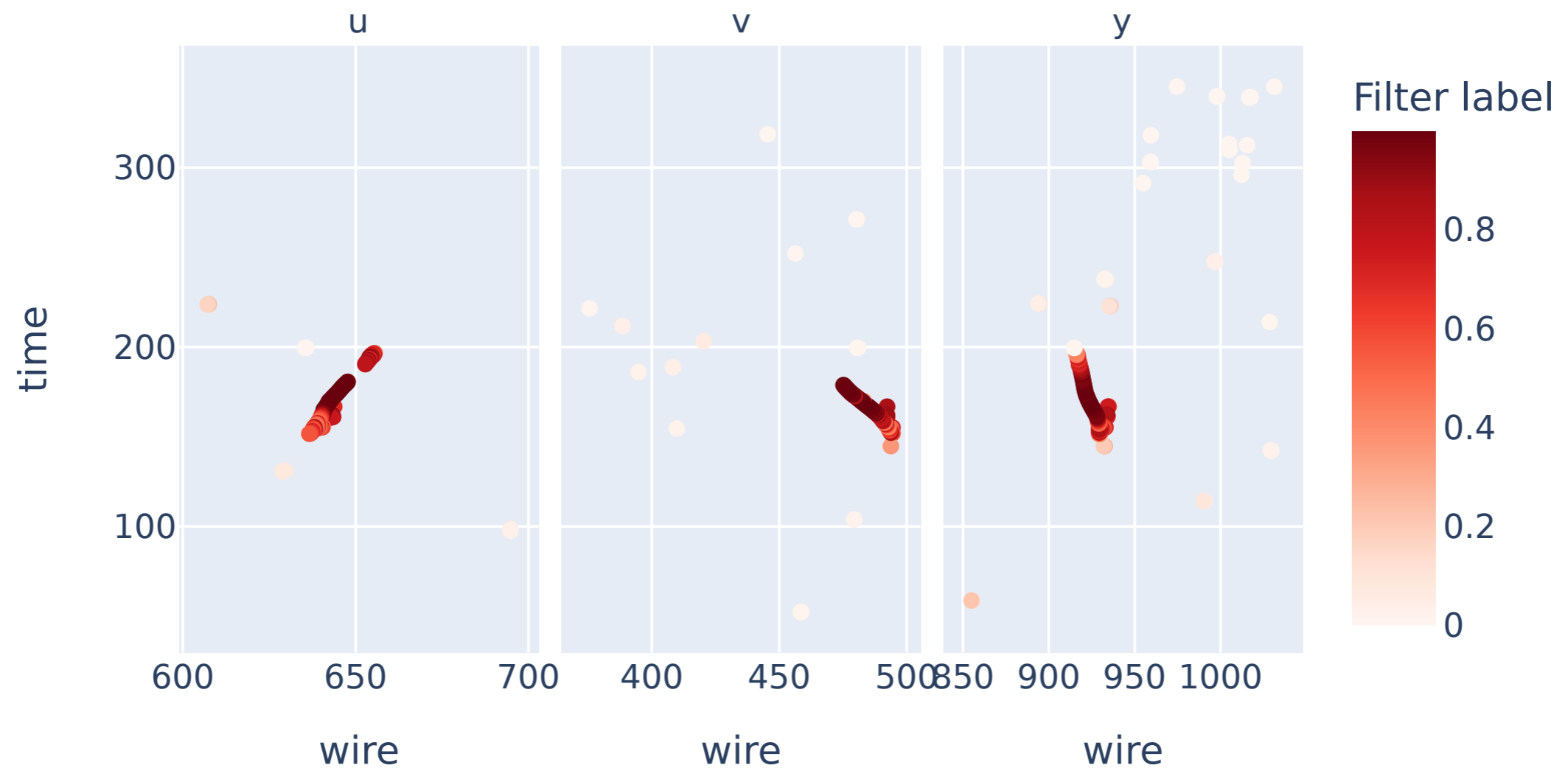
Example event #3

True filter labels



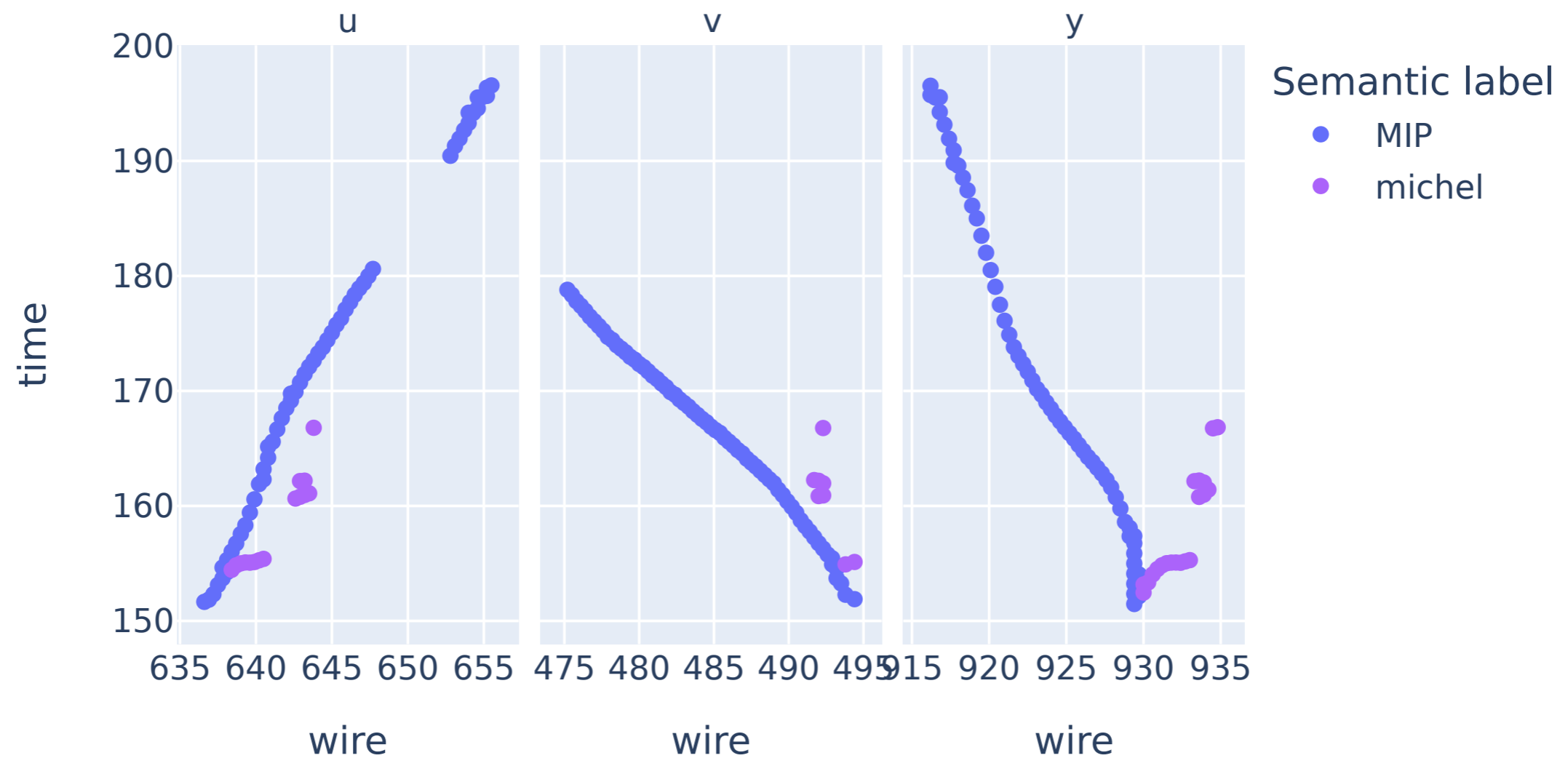
Example event #3

Predicted filter labels



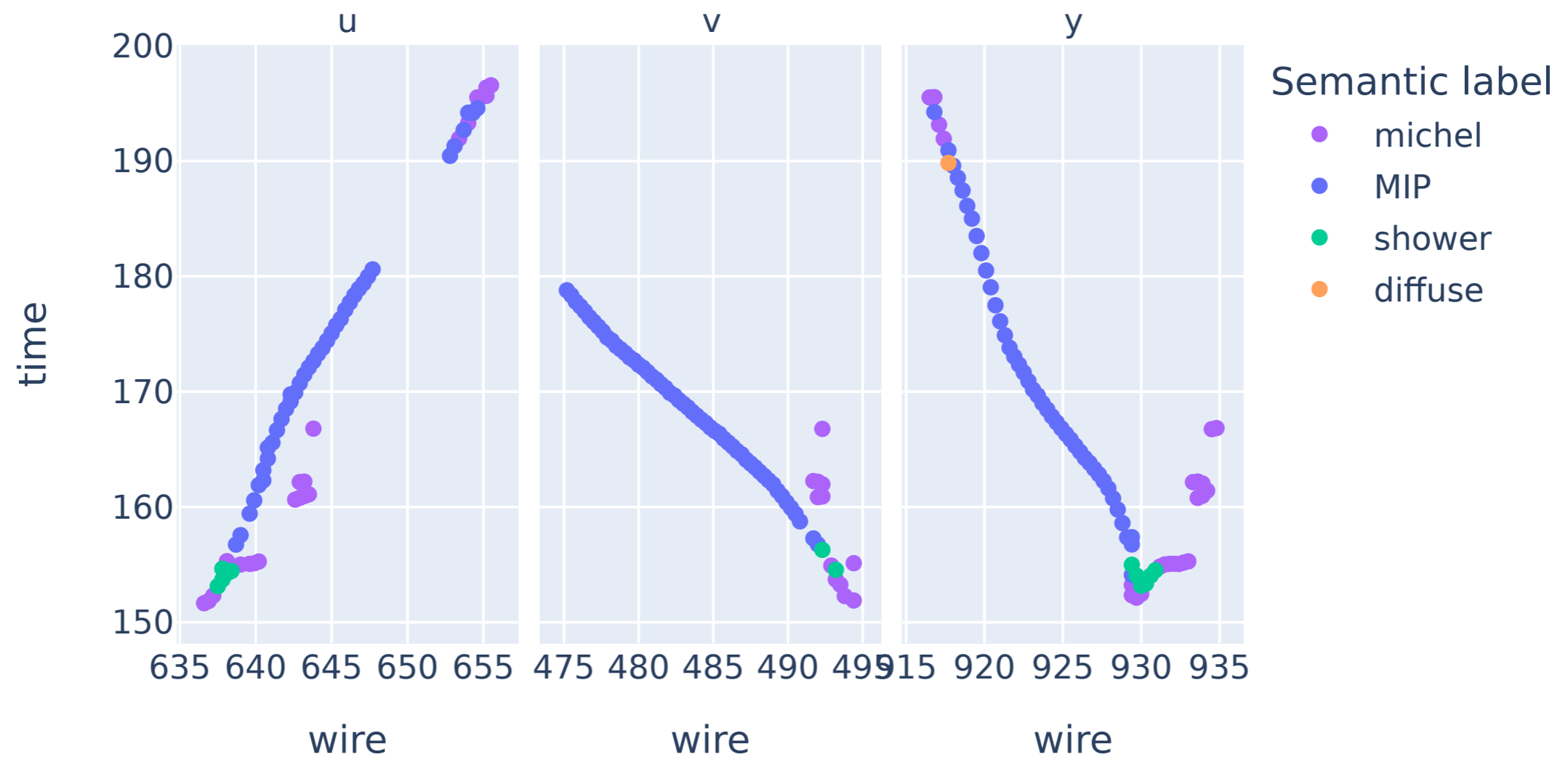
Example event #3

True semantic labels (filtered by truth)



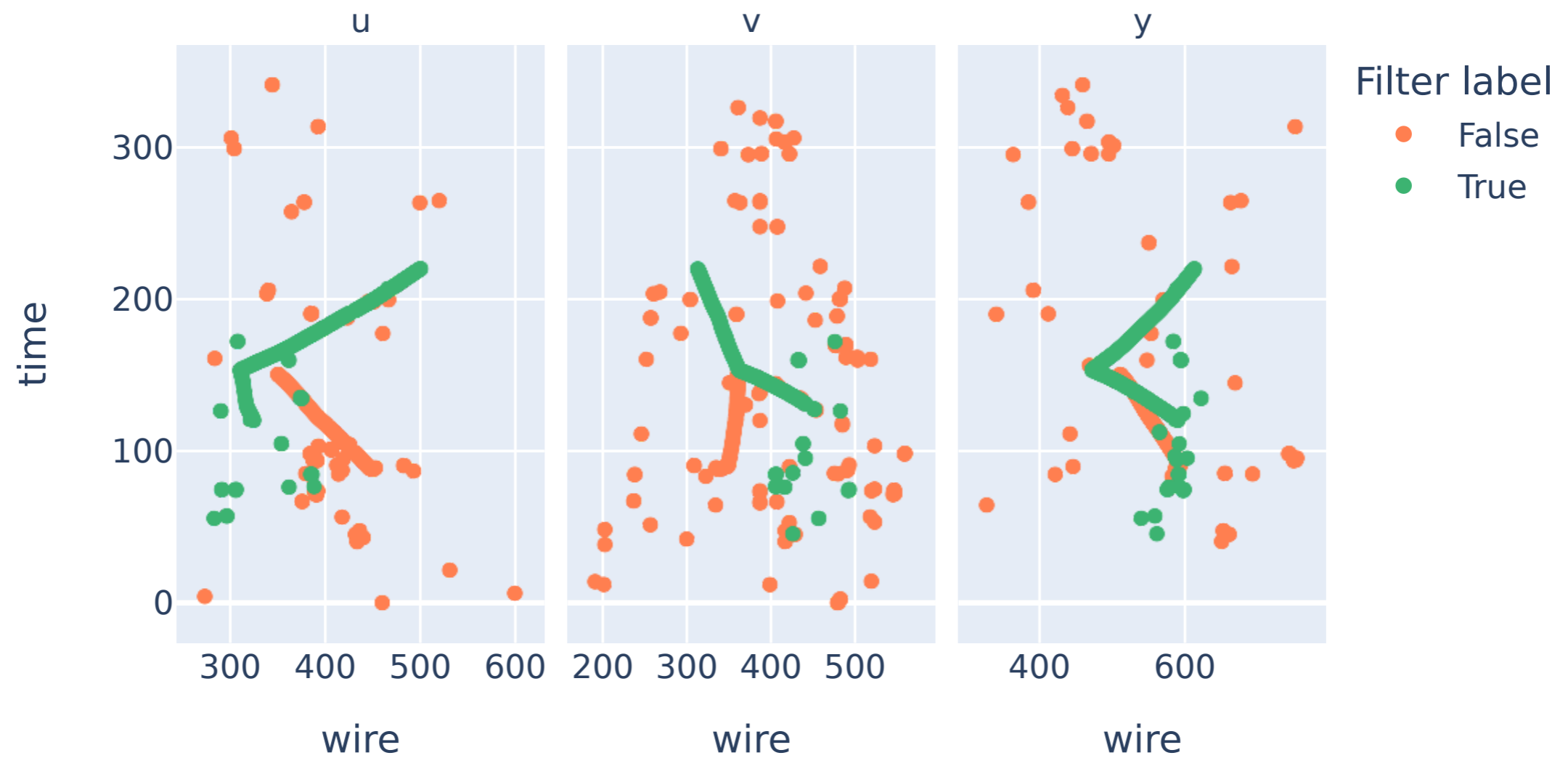
Example event #3

Predicted semantic labels (filtered by prediction)



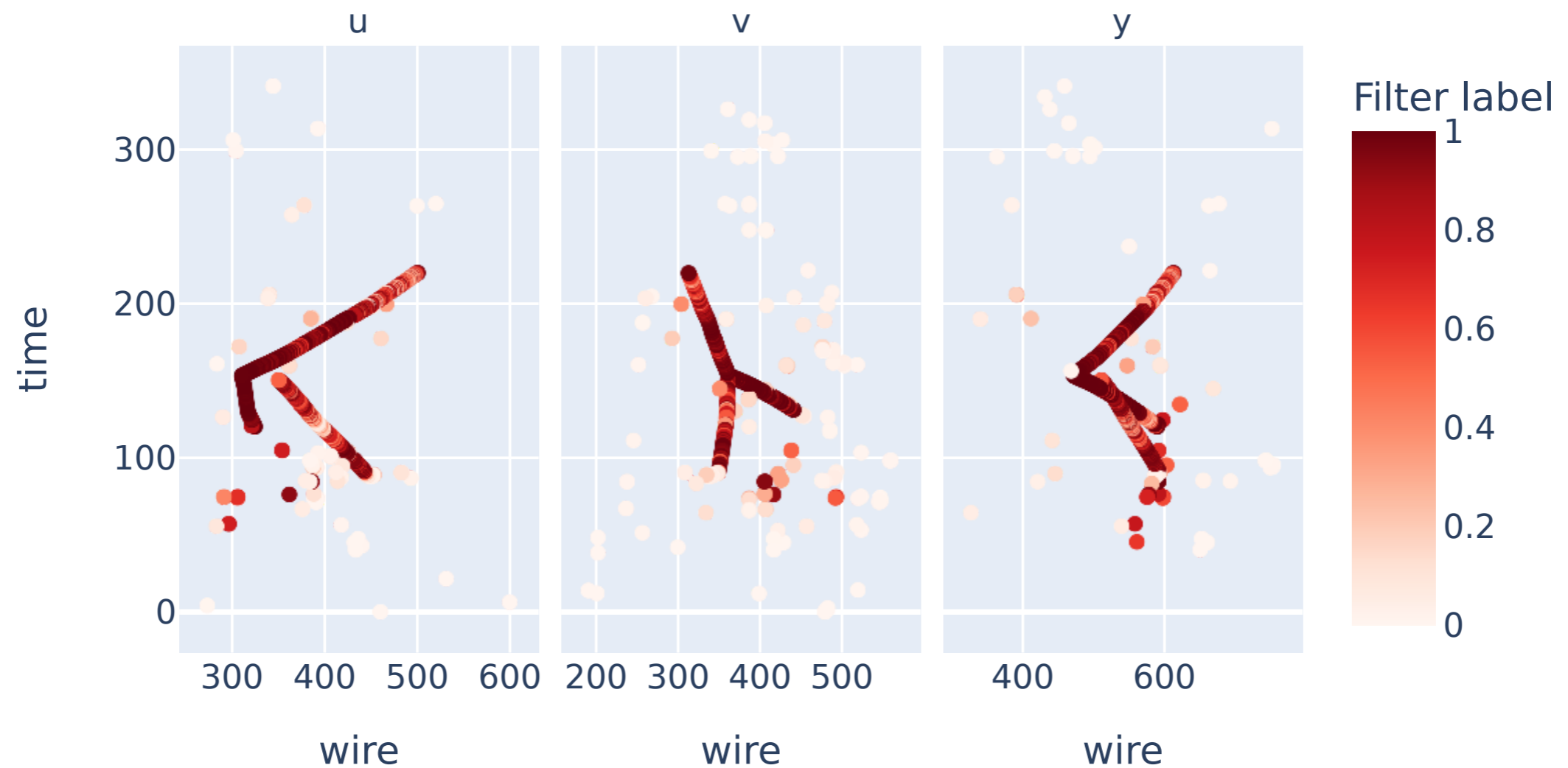
Example event #4

True filter labels



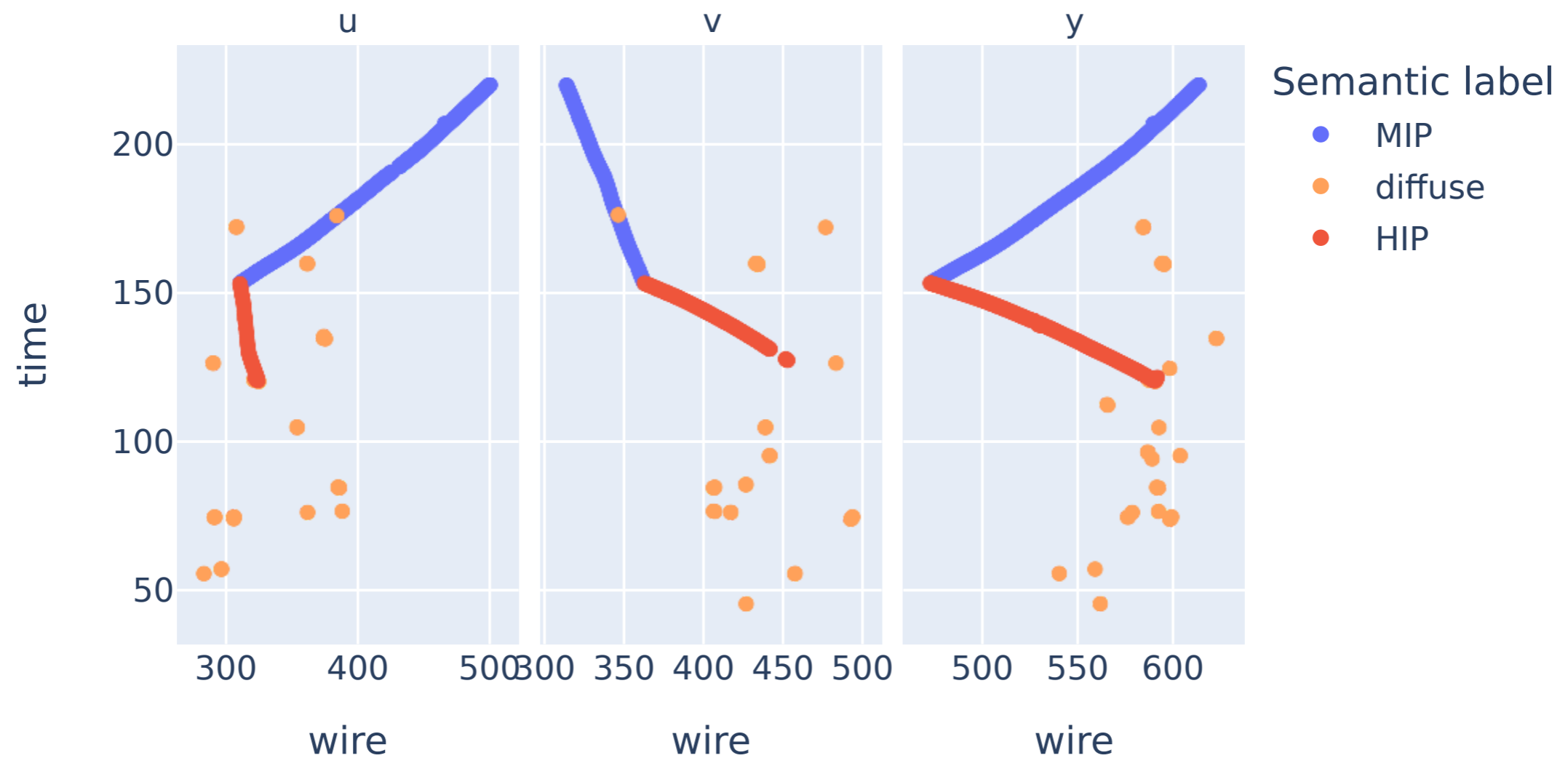
Example event #4

Predicted filter labels



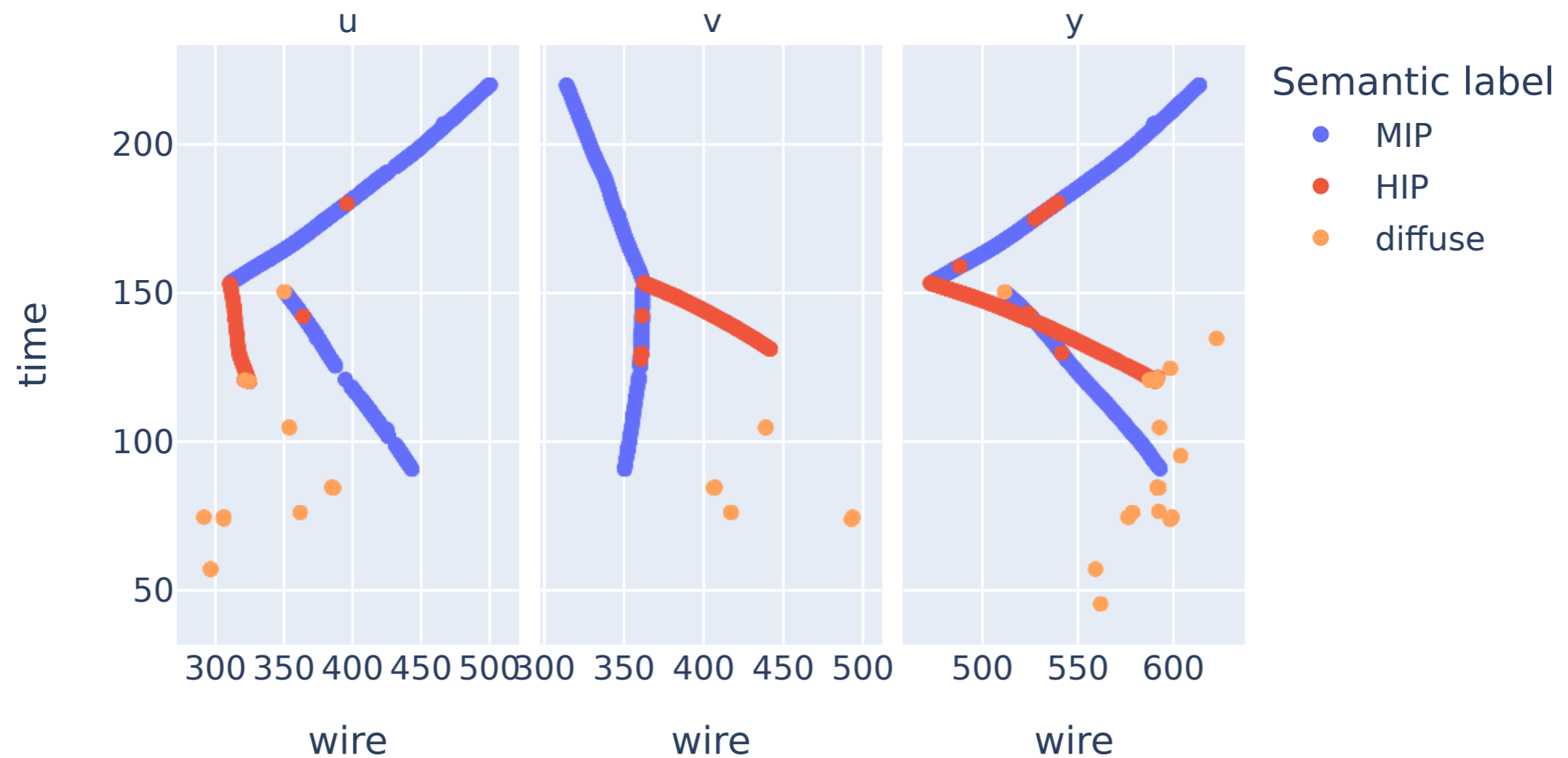
Example event #4

True semantic labels (filtered by truth)



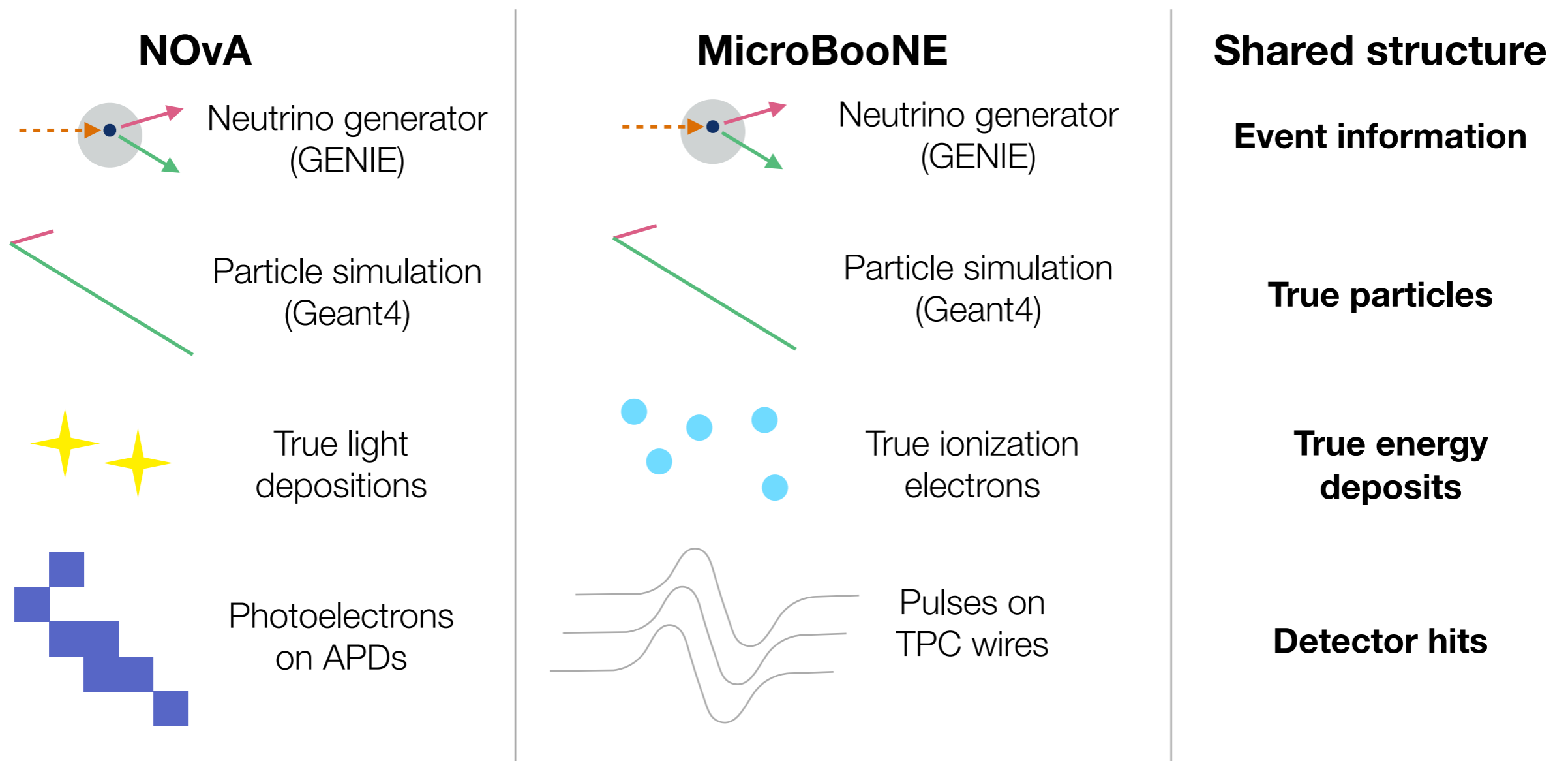
Example event #4

Predicted semantic labels (filtered by prediction)



Common abstraction for neutrino experiments

- Although the details of many neutrino physics experiments vary, the majority of them share a common paradigm at a high level.



The NuML ecosystem

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- A **conda environment** to easily install these packages and all their dependencies is available [here](#).

Summary

- **NuGraph2** is a multi-purpose GNN architecture for reconstructing neutrino interactions in MicroBooNE, DUNE and elsewhere.
 - **Efficiently reject background detector hits.**
 - **Classify detector hits according to particle type.**
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- **NuGraph2** is a multi-purpose GNN architecture for reconstructing neutrino interactions in MicroBooNE, DUNE and elsewhere.
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 - Future: **vertexing, clustering, hierarchical graphs!**
- **NuML** toolkit for standardising the process of producing ML inputs from HEP data for general use.
 - Utilised for MicroBooNE's public data release.
 - Open-source, easy-to-install code packages.