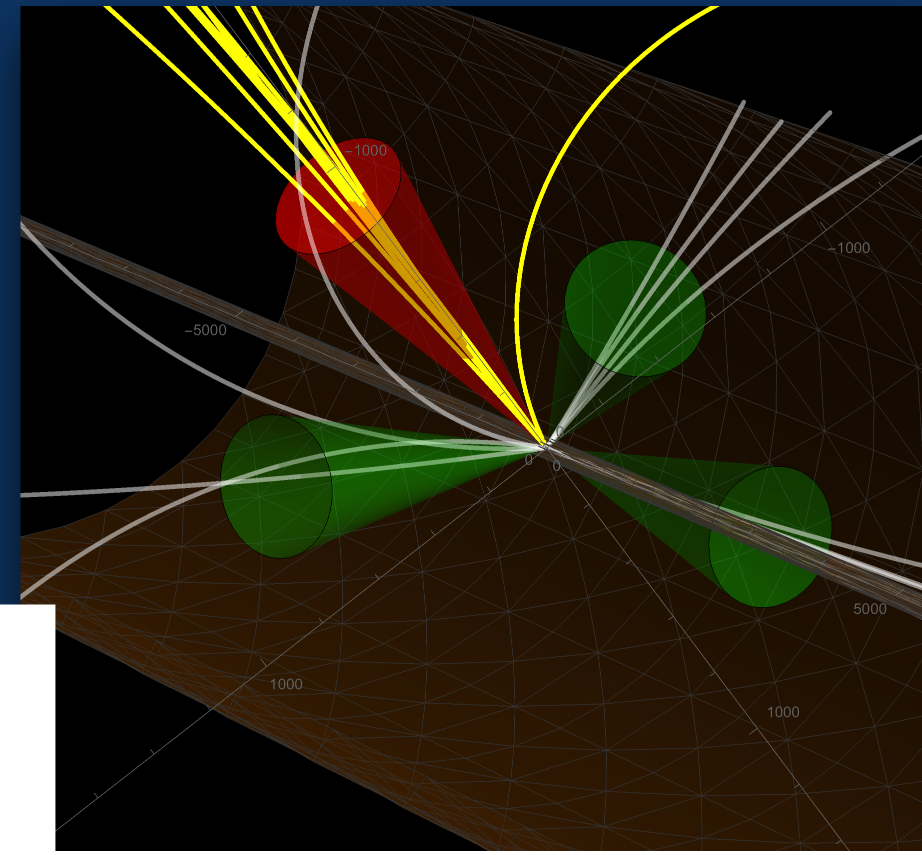
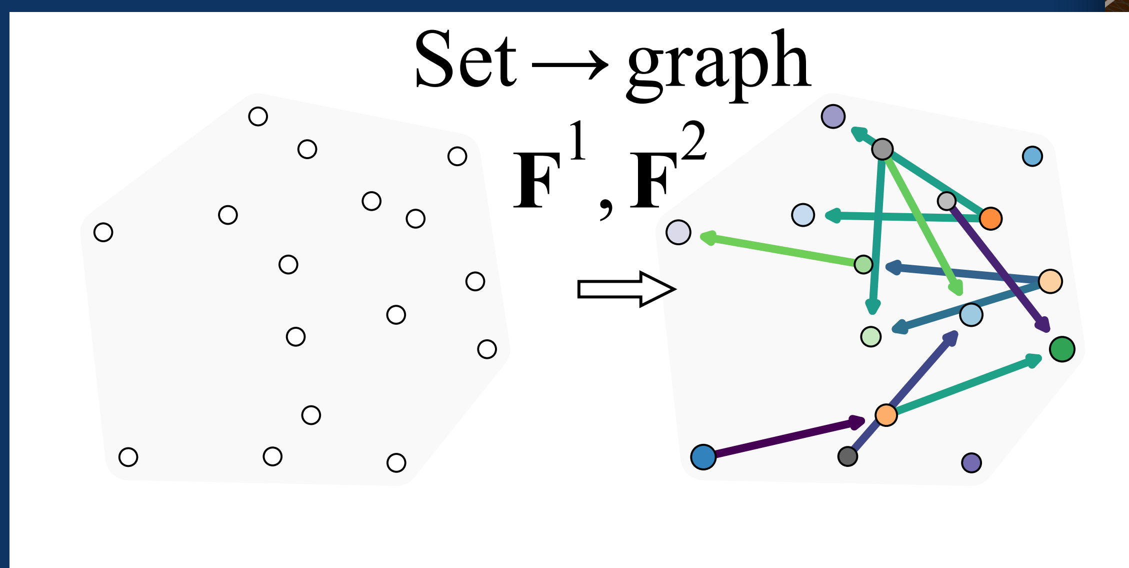
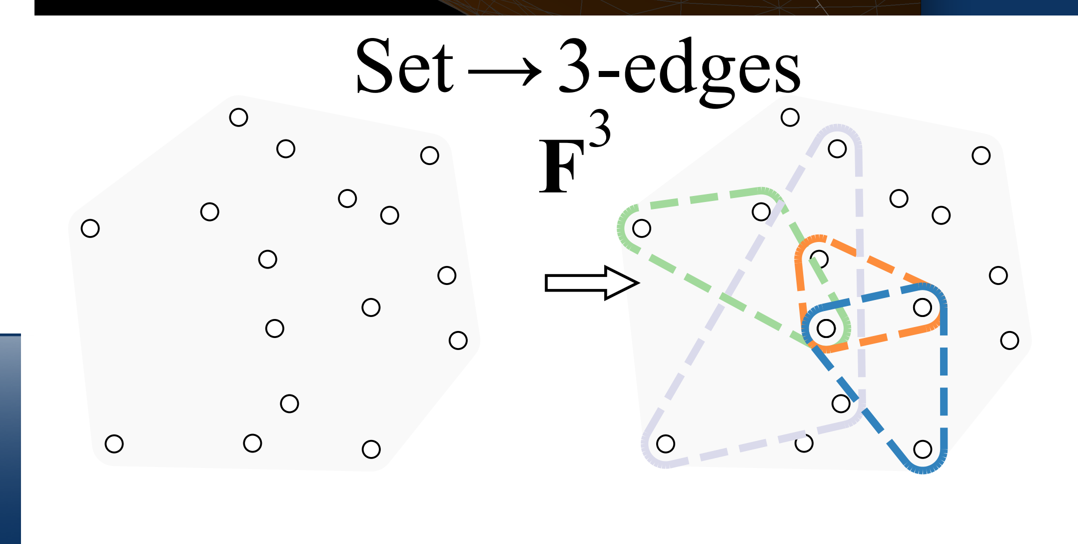
Set2Graph: Secondary vertex finding in jets with neural networks







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מכון ויצמן למדע
WEIZMANN INSTITUTE OF SCIENCE

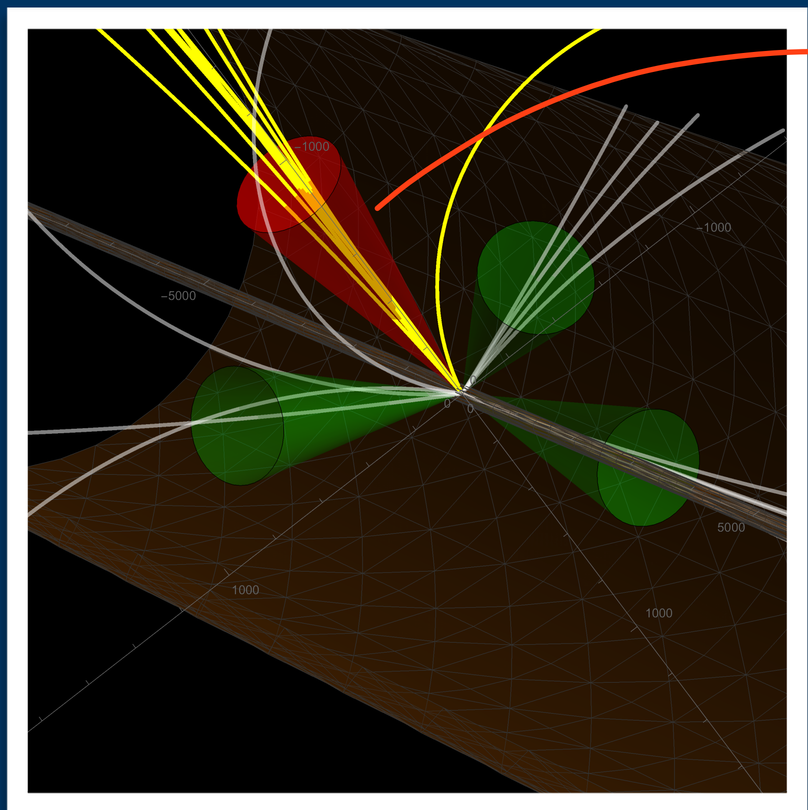
NVIDIA

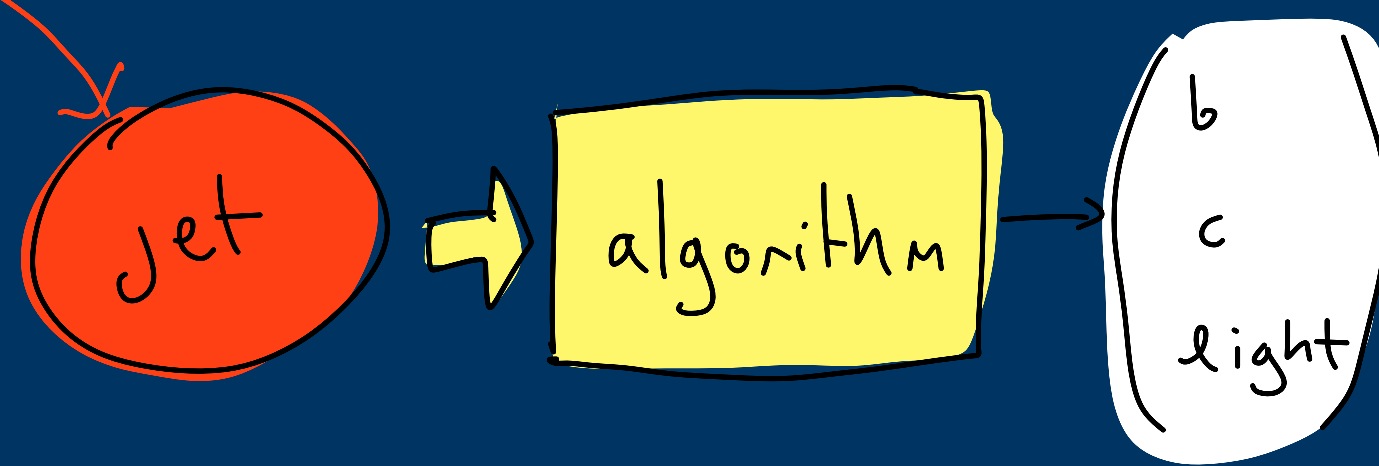
ATLAS EXPERIMENT

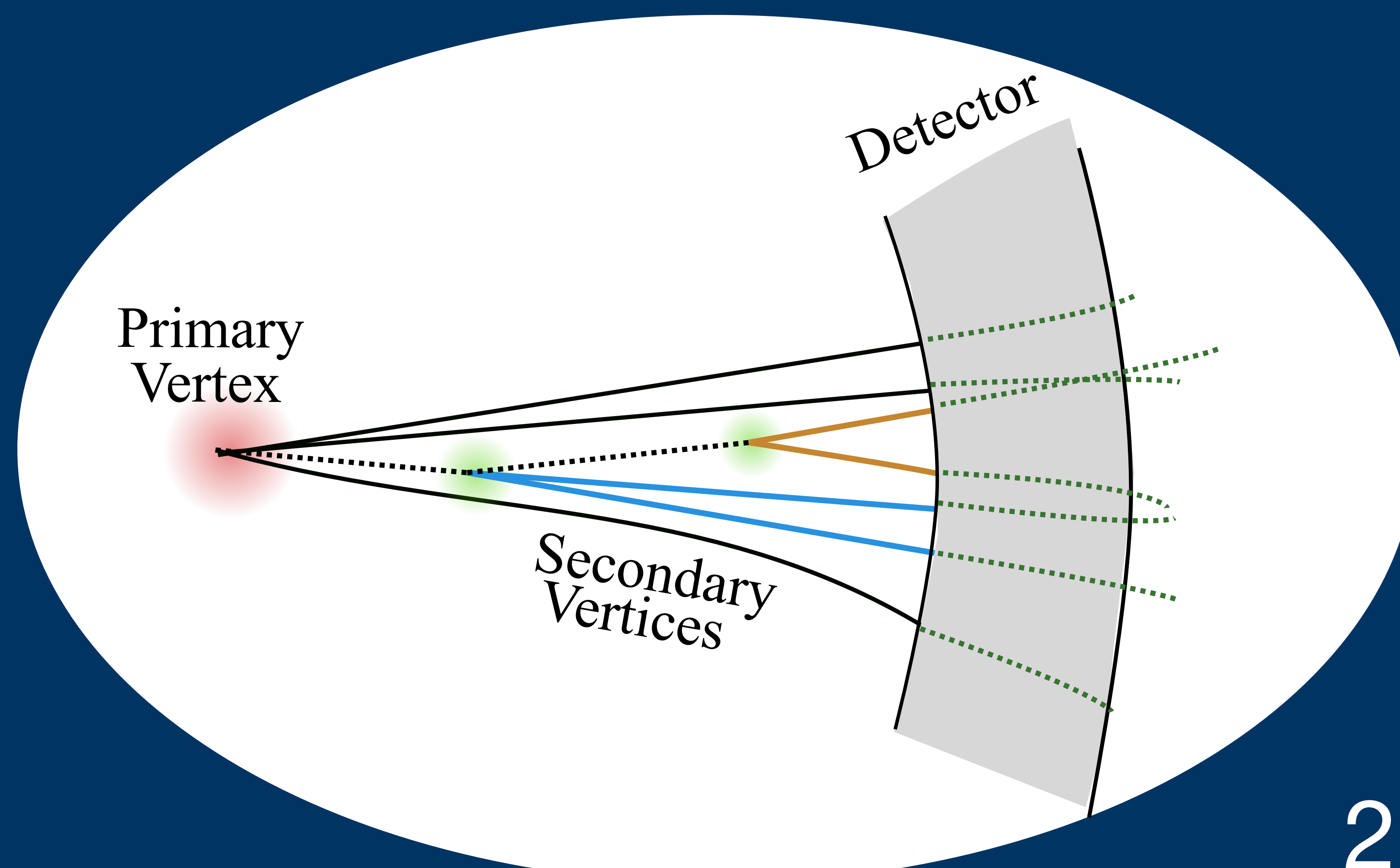
NYUAD-WISKickoff meeting
Tuesday, 22 December 2020

Jonathan Shlomi, Sanmay Ganguly, Eilam Gross, Kyle Cranmer, Yaron Lipman, Hadar Serviansky, Haggai Maron, Nimrod Segol

Jet flavour tagging:
identifying the quark flavour at the origin of the jet

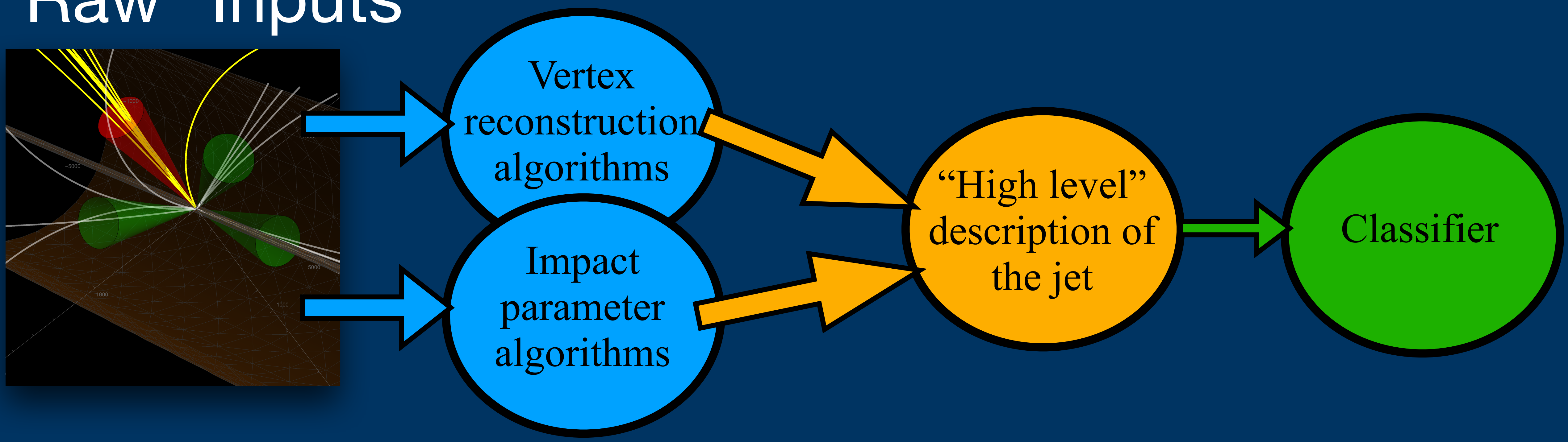






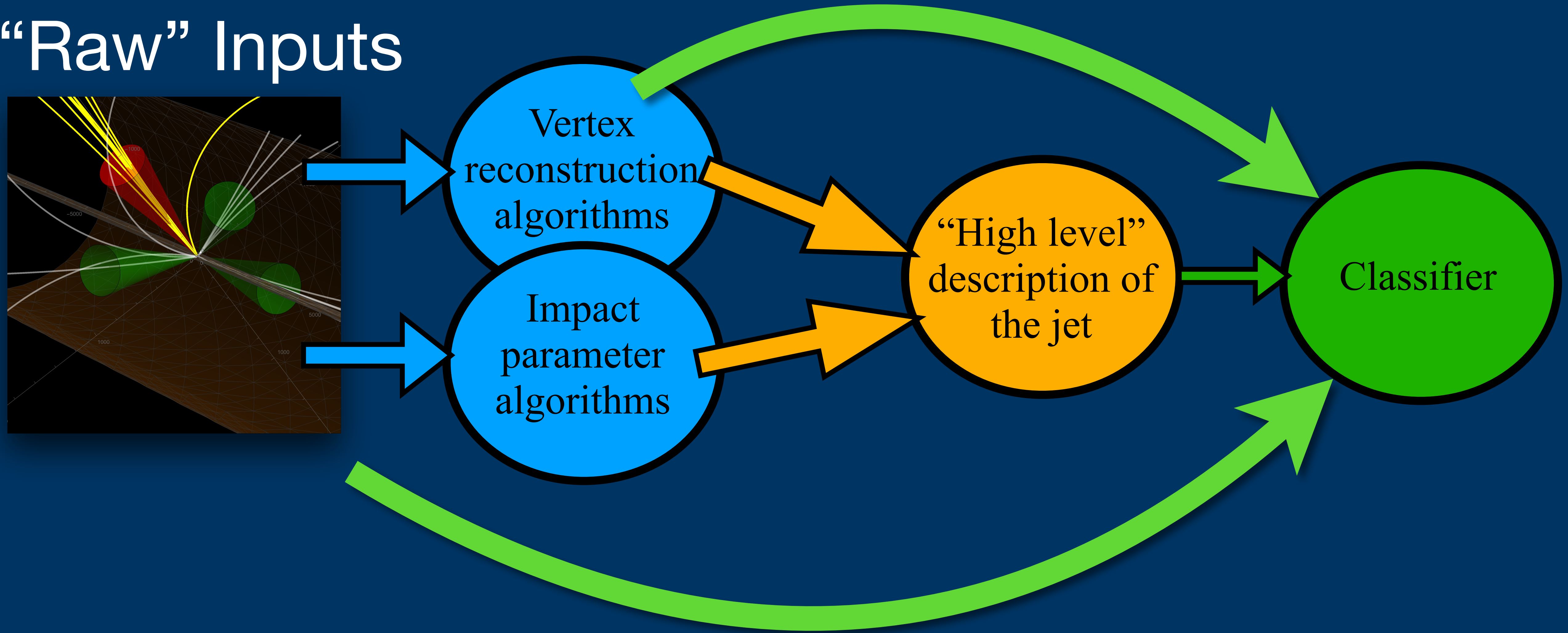
- Classifiers were built on human-designed discriminating "high level" features.

"Raw" Inputs

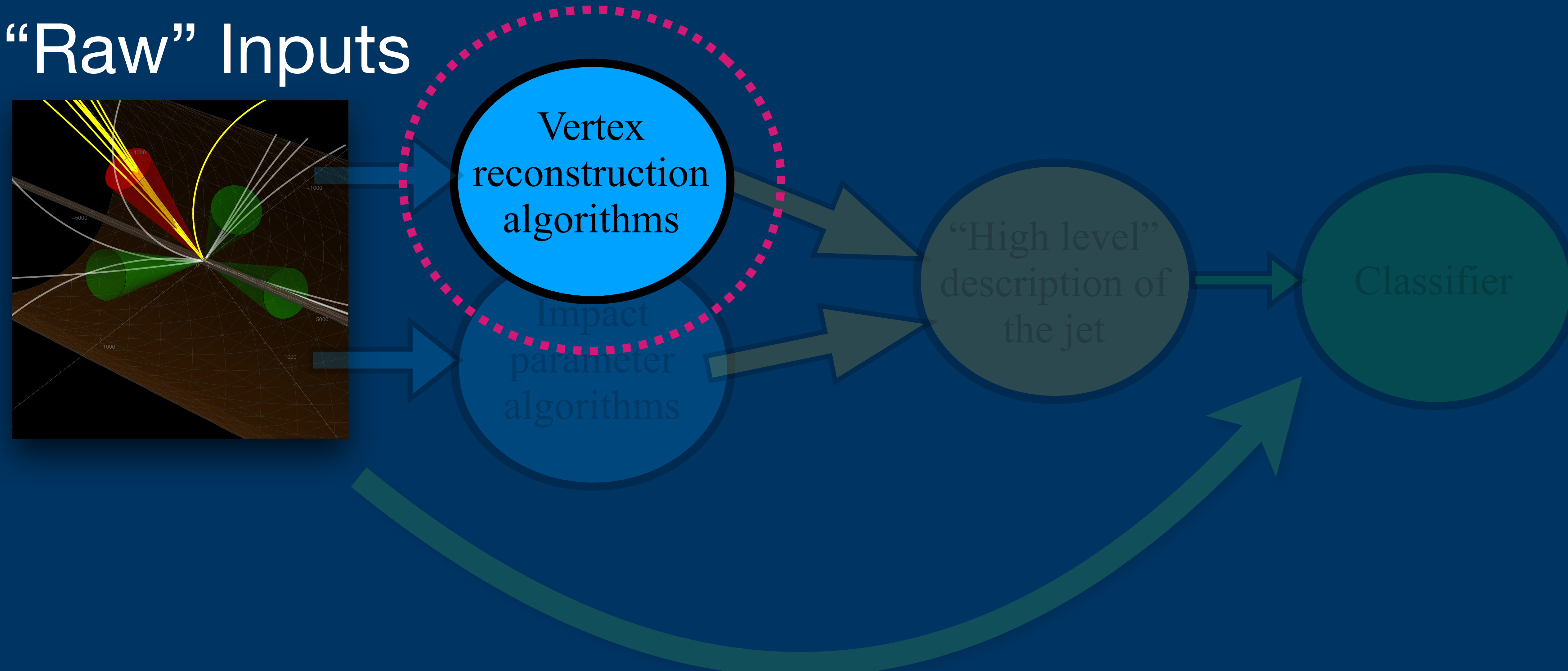


- In recent years, classifiers are using the raw reconstructed tracks/ vertices in the jet - in addition to the high level features.

“Raw” Inputs

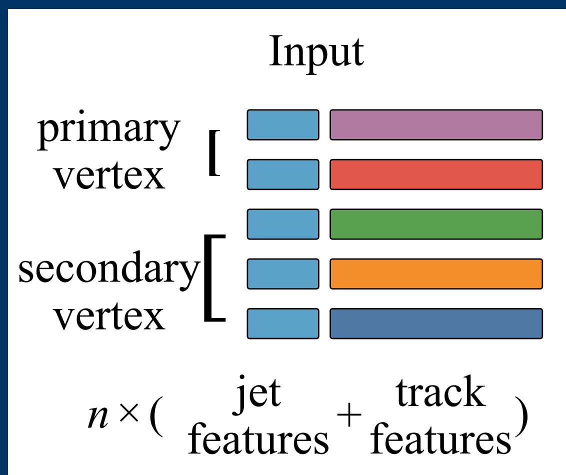


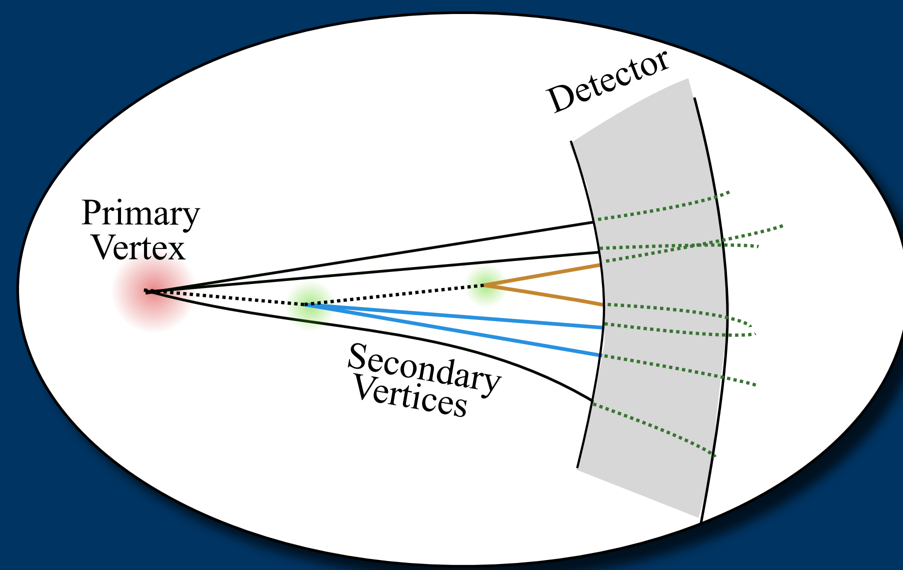
- We look at techniques for using ML in the actual reconstruction, using the more of the "truth information" we have in the simulation

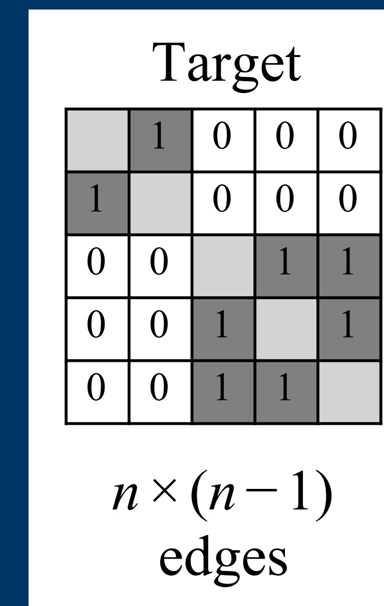


The Task - secondary vertex finding

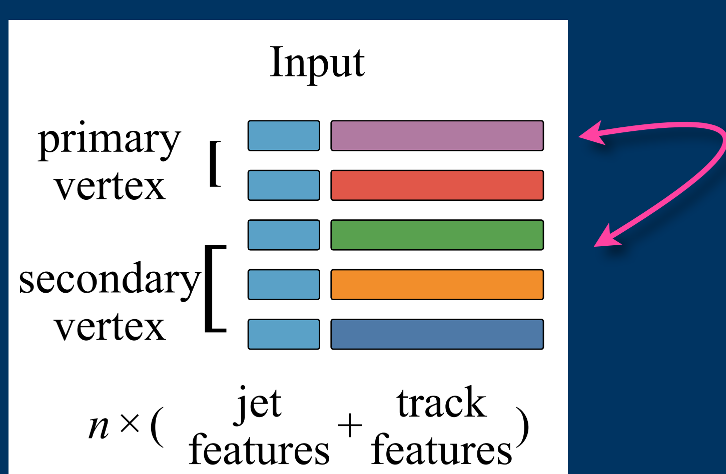
- We want to learn a function from $\mathbb{R}^{n \times d_{in}} \rightarrow \mathbb{R}^{n \times n \times 1}$

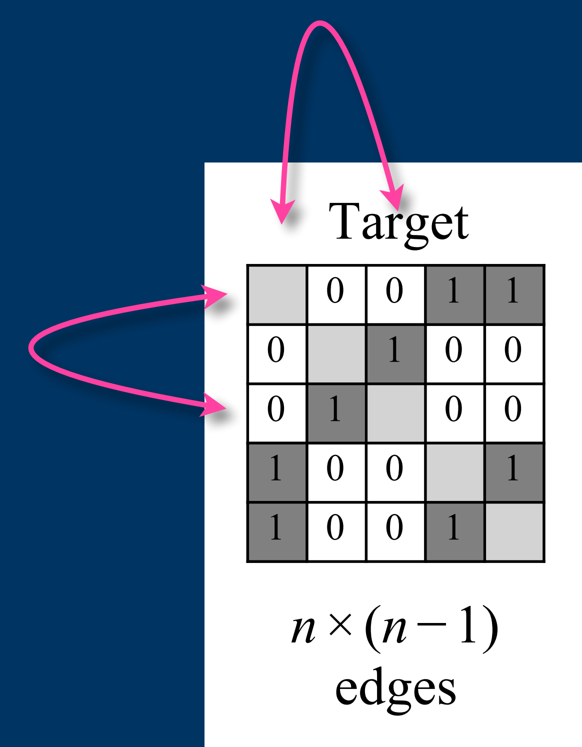




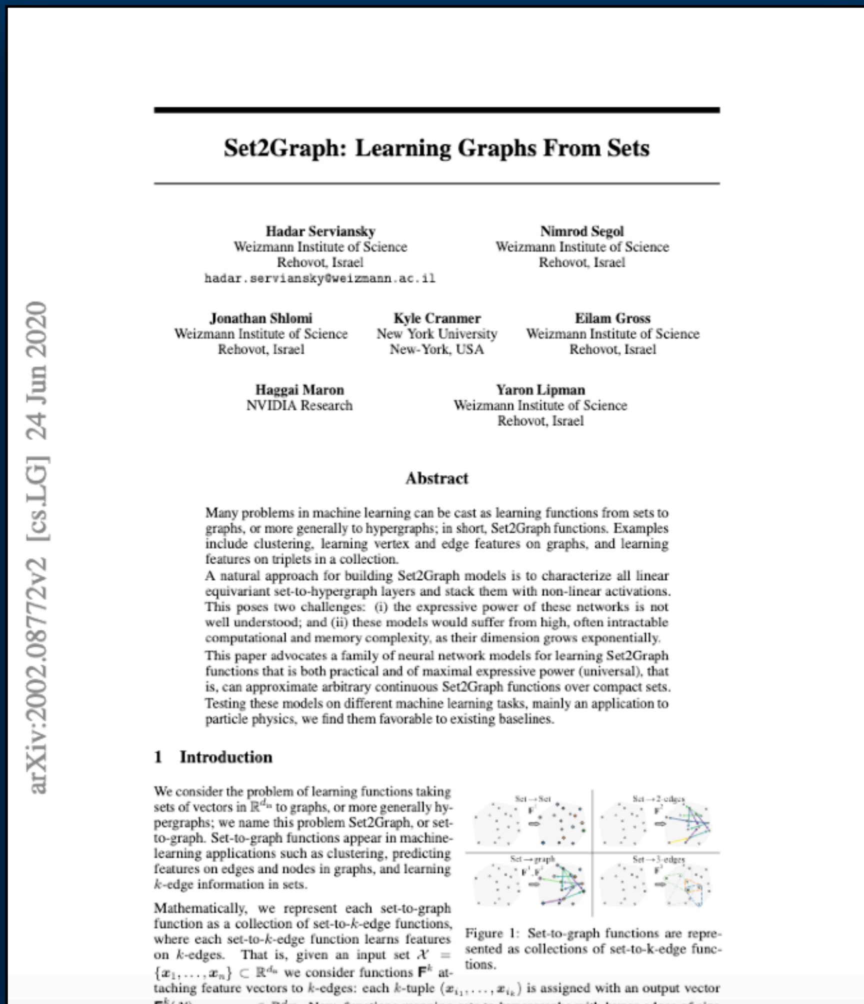


- The function from $\mathbb{R}^{n \times d_{in}} \rightarrow \mathbb{R}^{n \times n \times 1}$ is equivariant - If we permeate the inputs the output undergoes a similar permutation





https://arxiv.org/abs/2002.08772



arXiv:2002.08772v2 [cs.LG] 24 Jun 2020

Set2Graph: Learning Graphs From Sets

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Abstract

Many problems in machine learning can be cast as learning functions from sets to graphs, or more generally to hypergraphs; in short, Set2Graph functions. Examples include clustering, learning vertex and edge features on graphs, and learning features on triplets in a collection.
A natural approach for building Set2Graph models is to characterize all linear equivariant set-to-hypergraph layers and stack them with non-linear activations. This poses two challenges: (i) the expressive power of these networks is not well understood; and (ii) these models would suffer from high, often intractable computational and memory complexity, as their dimension grows exponentially.
This paper advocates a family of neural network models for learning Set2Graph functions that is both practical and of maximal expressive power (universal), that is, can approximate arbitrary continuous Set2Graph functions over compact sets. Testing these models on different machine learning tasks, mainly an application to particle physics, we find them favorable to existing baselines.

1 Introduction

We consider the problem of learning functions taking sets of vectors in $\mathbb{R}^{d_{in}}$ to graphs, or more generally hypergraphs; we name this problem Set2Graph, or set-to-graph. Set-to-graph functions appear in machine-learning applications such as clustering, predicting features on edges and nodes in graphs, and learning k-edge information in sets.

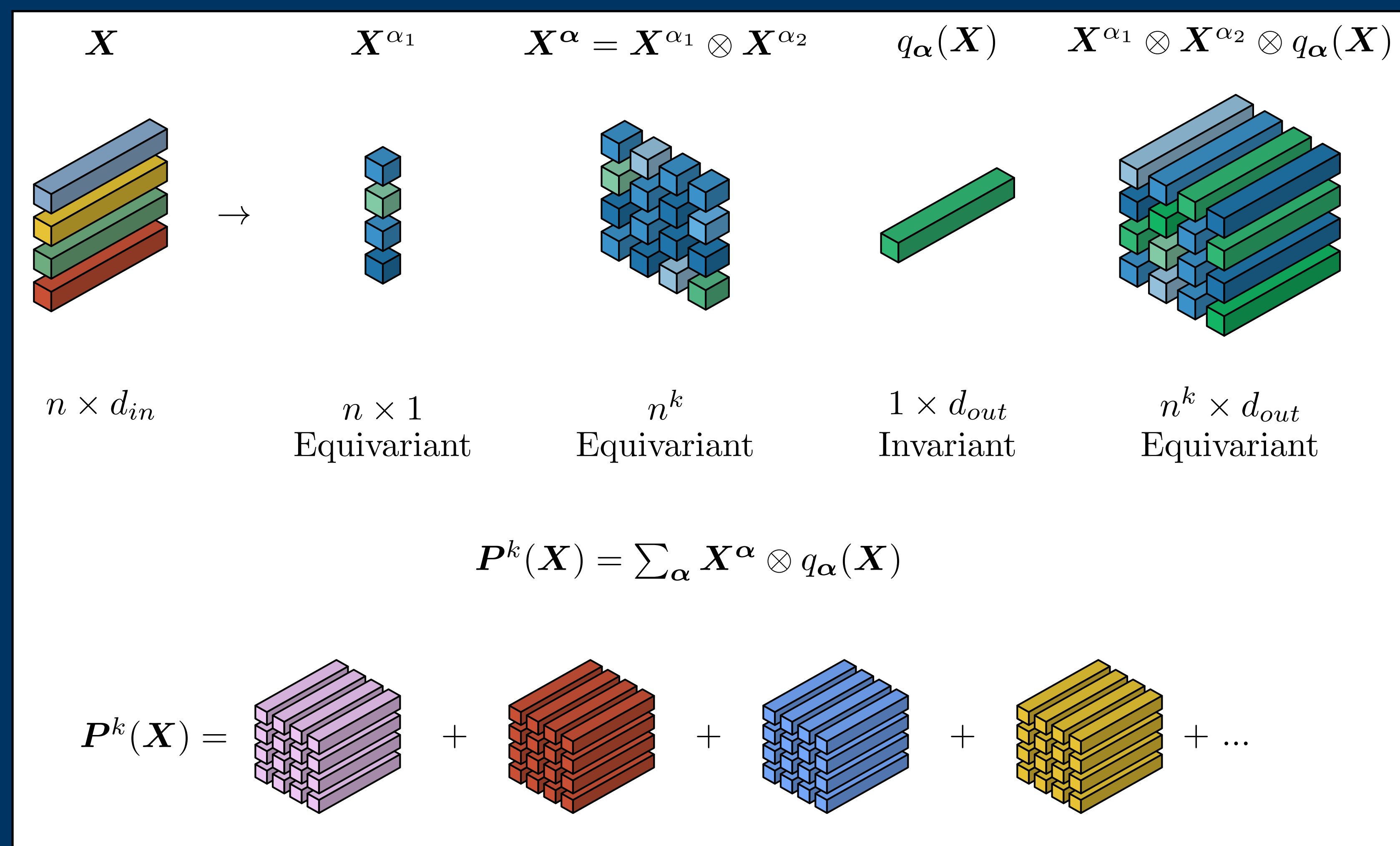
Mathematically, we represent each set-to-graph function as a collection of set-to-k-edge functions, where each set-to-k-edge function learns features on k-edges. That is, given an input set $\mathcal{X} = \{x_1, \dots, x_n\} \subset \mathbb{R}^{d_{in}}$ we consider functions $\mathbf{F}^k$ attaching feature vectors to k-edges: each k-tuple $(x_{i_1}, \dots, x_{i_k})$ is assigned with an output vector $\mathbf{F}^k(\mathcal{X})_{i_1, i_2, \dots, i_k} \in \mathbb{R}^{d_{out}}$. Now, functions mapping sets to hypergraphs with hyper-edges of size

Set → Set
Set → 2-edges
Set → graph
Set → 3-edges

Figure 1: Set-to-graph functions are represented as collections of set-to-k-edge functions.

The idea of the proof of universality of the model:

- Any continuous equivariant function G from set to k-edges can be approximated by an equivariant polynomial $P^k(X)$
- This polynomial has a very specific structure because it is equivariant
- We can build our neural network model to match this structure of $P^k(X)$

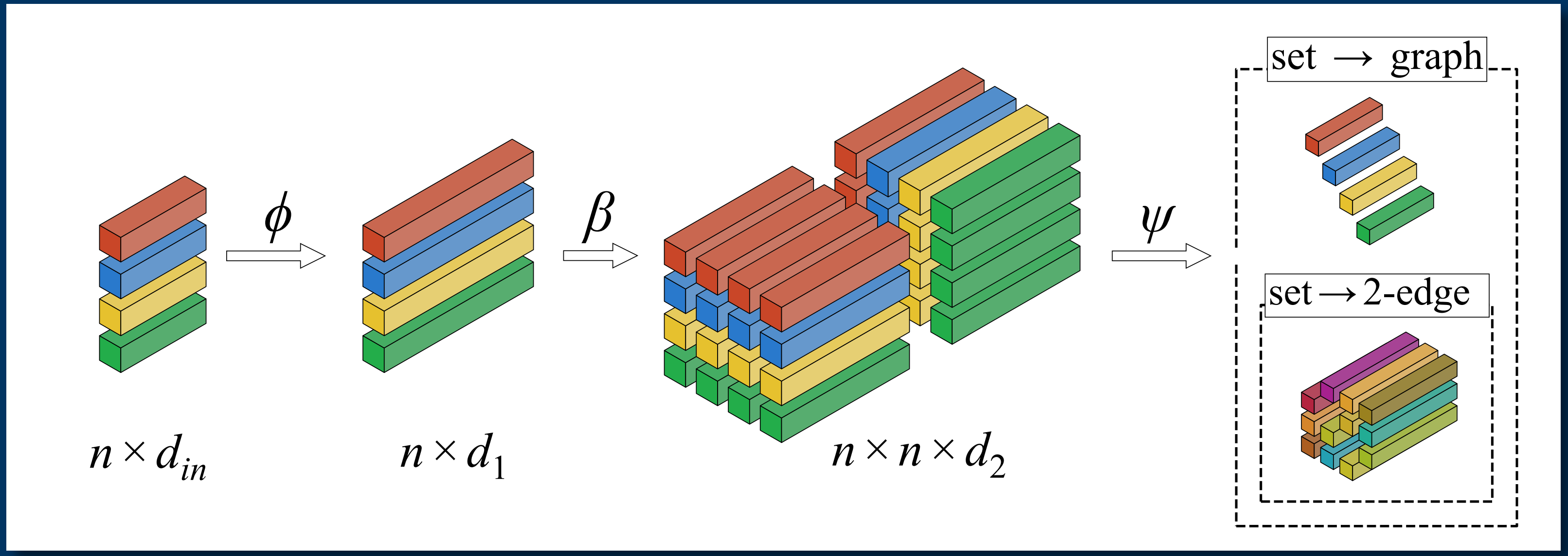


The model has the form $\psi(\beta(\phi(X)))$

ϕ is an equivariant set to set function

β is a broadcasting layer, it forms all the possible k-tuples of nodes

ψ is an MLP that operates on each edge/hyperedge to produce the final output



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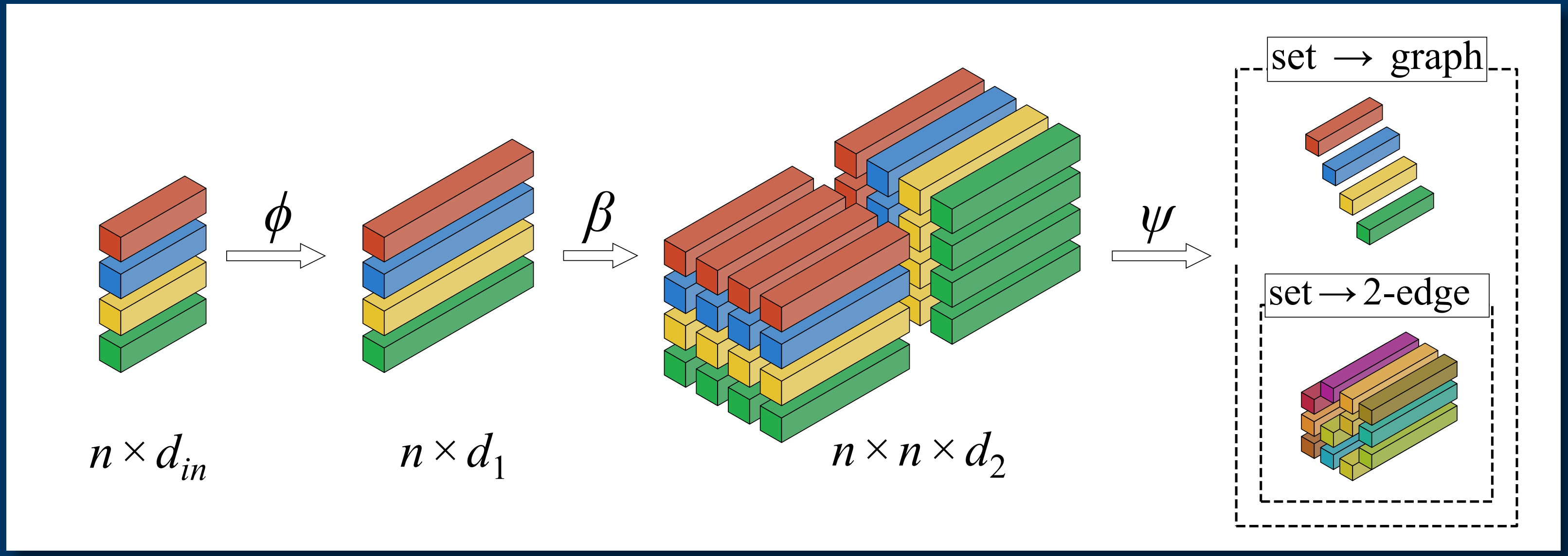

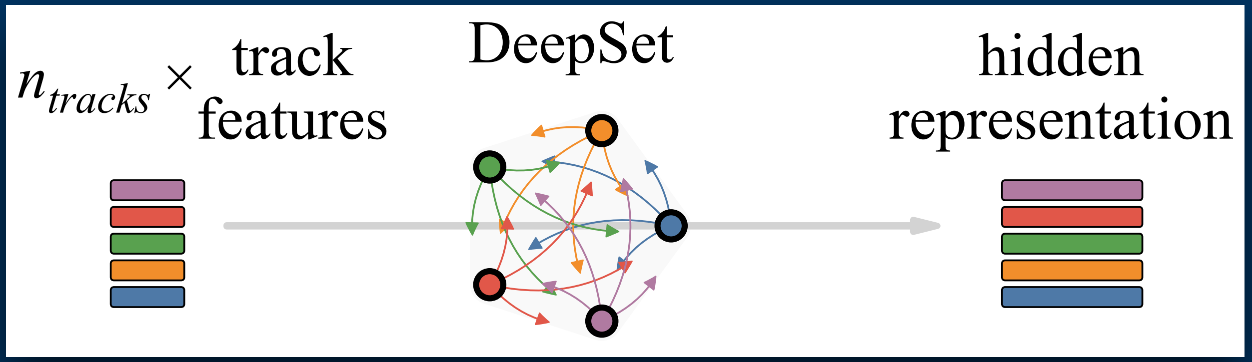

https://arxiv.org/abs/2008.02831

Secondary Vertex Finding in Jets with Neural Networks

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Received: date / Accepted: date

Abstract Jet classification is an important ingredient in measurements and searches for new physics at particle coliders, and secondary vertex reconstruction is a key intermediate step in building powerful jet classifiers. We use a neural network to perform vertex finding inside jets in order to improve the classification performance, with a focus on separation of bottom vs. charm flavor tagging. We implement a novel, universal set-to-graph model, which takes into account information from all tracks in a jet to determine if pairs of tracks originated from a common vertex. We explore different performance metrics and find our method to outperform traditional approaches in accurate secondary vertex reconstruction.

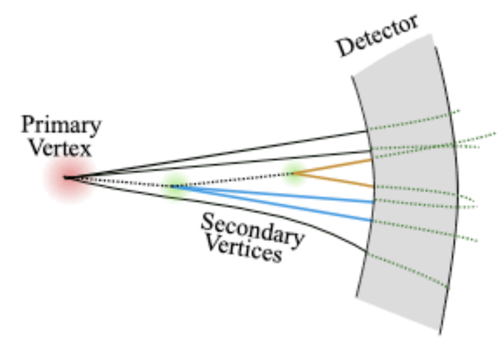


Fig. 1: Illustration of a jet with secondary decay vertices. In order to identify the flavor of the jet, vertex reconstruction aims to group together the tracks measured in the detector based on their point of origin.

1 Introduction

Identifying jets containing bottom and charm hadrons and separating them from jets that originate from lighter quarks, is a critical task in the LHC physics program, referred to as "flavour tagging". Bottom and charm jets are characterized by the presence of secondary decays "inside" the jet - the bottom and charm hadrons will decay several millimeters past the primary interaction point (primary vertex), and only stable outgoing particles will be measured by the detector. Figure 1 illustrates a typical bottom jet decay, with two consecutive displaced vertices from a bottom decay (blue lines) and charm decay (yellow lines).

Existing flavor tagging algorithms use a combination of low-level variables (the charged particle tracks, reconstructed secondary vertices), and high-level features engineered by experts as input to neural networks of various architectures in order to perform jet flavor classification [1].

Vertex reconstruction can be separated to two tasks, *vertex finding*, and *vertex fitting* [2]. Vertex finding refers to the task of partitioning the set of tracks, and vertex fitting refers to estimating the vertex positions given each sub-set of tracks. Existing algorithms typically use an iterative procedure of finding and fitting to perform both tasks together. We focus on using a neural network for vertex finding only. Vertex finding is a challenging task due to two factors:

- Secondary vertices can be in close proximity to the primary vertex, and to each other, within the measurement resolution of the track trajectories.
- The charged particle multiplicity in each individual vertex is low, typically between 1 and 5 tracks.

Vertex reconstruction is in essence an inverse problem of a complicated noisy (forward) function:

$$\text{Particle Decay} \rightarrow \text{Particle Measurement in Detector} \qquad (1)$$

Neural networks can find a model for this inverse problem without expert intervention by using supervised learn-

Code and Dataset:

https://github.com/hadarser/SetToGraphPaper/

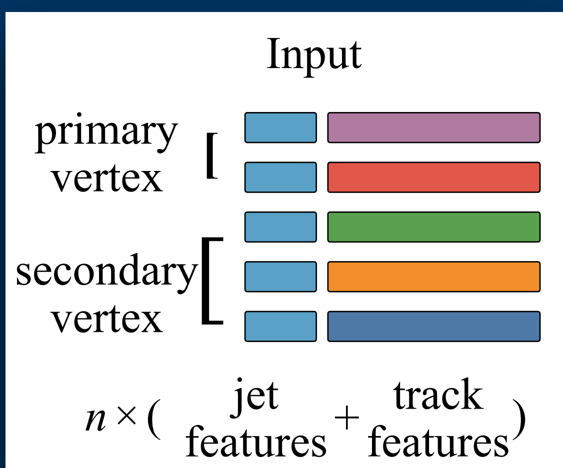
https://zenodo.org/record/4044628

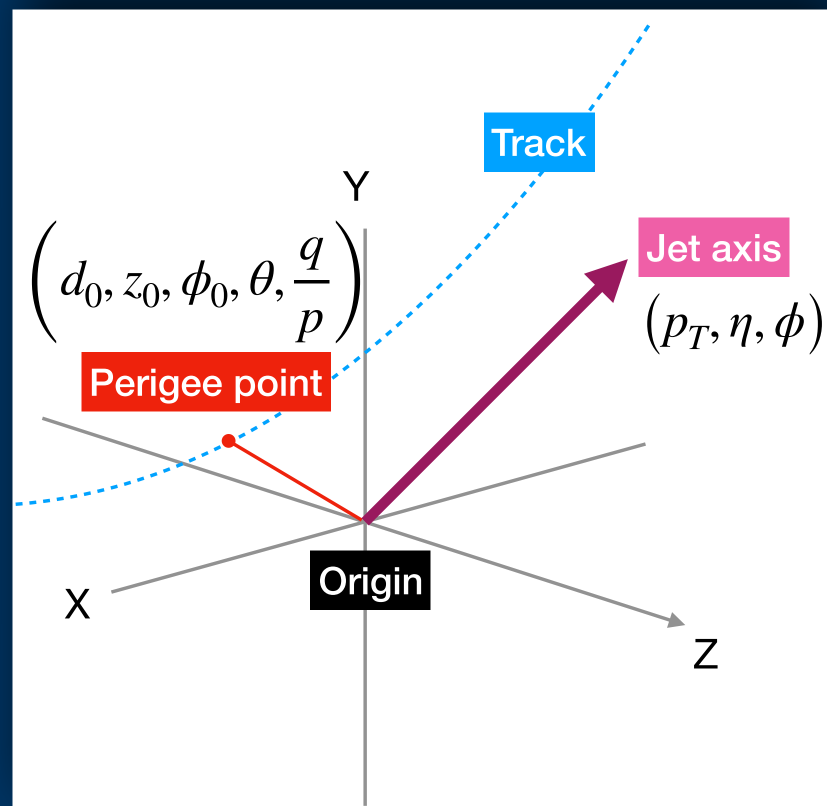
DOI 10.5281/zenodo.4044628

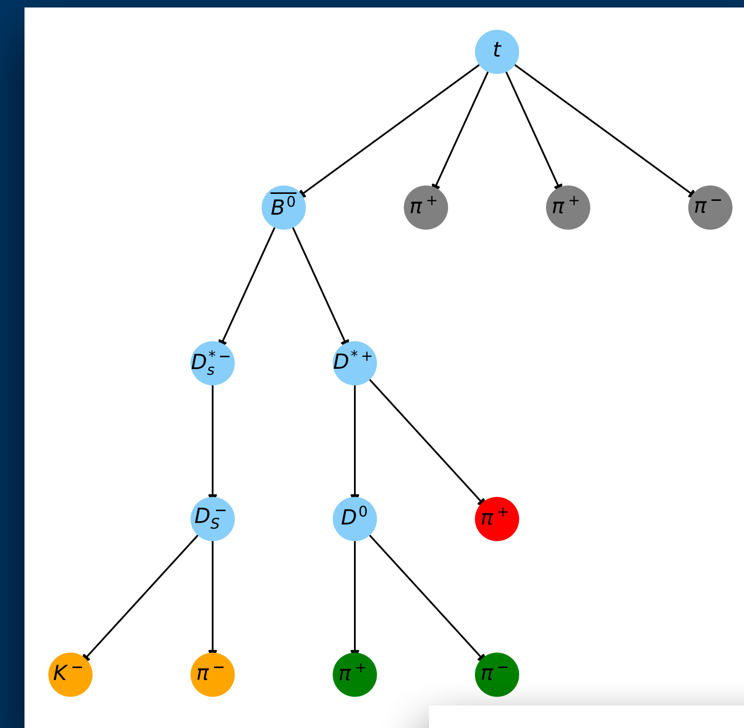
The Dataset

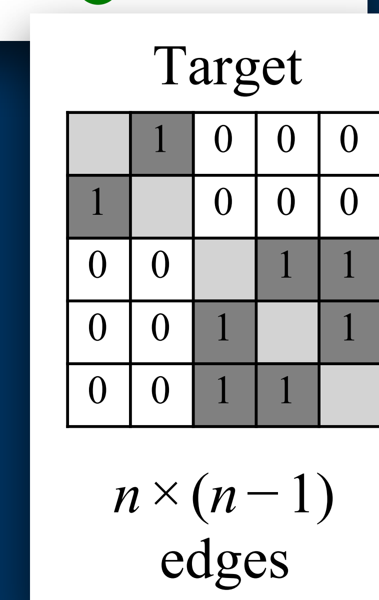
https://zenodo.org/record/4044628

DOI 10.5281/zenodo.4044628









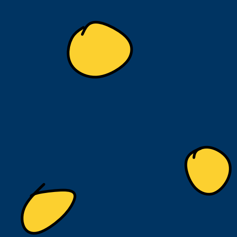
http://home.thep.lu.se/Pythia/ https://github.com/delphes/delphes

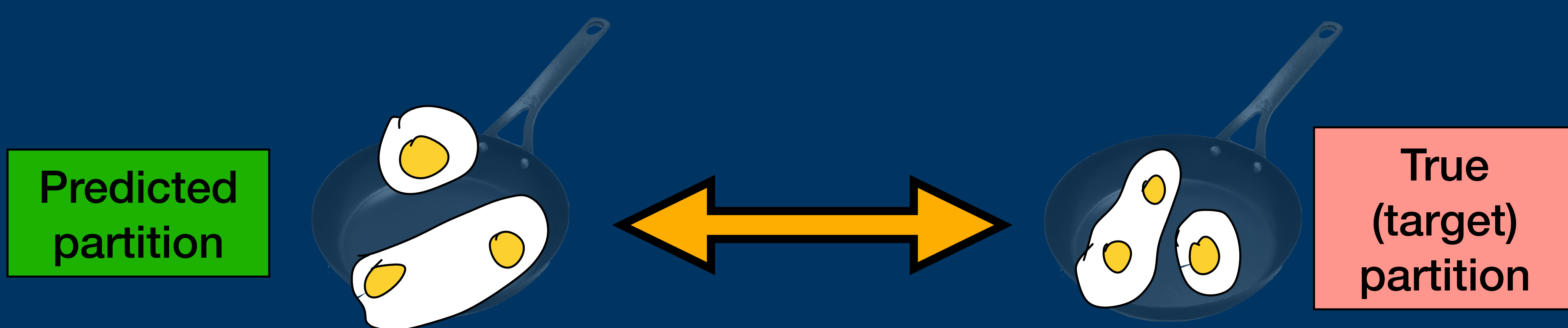
Evaluating the performance

At the jet level:

$$\text{Rand Index} = \frac{\text{True positives} + \text{true negatives}}{n \cdot (n-1)/2}$$

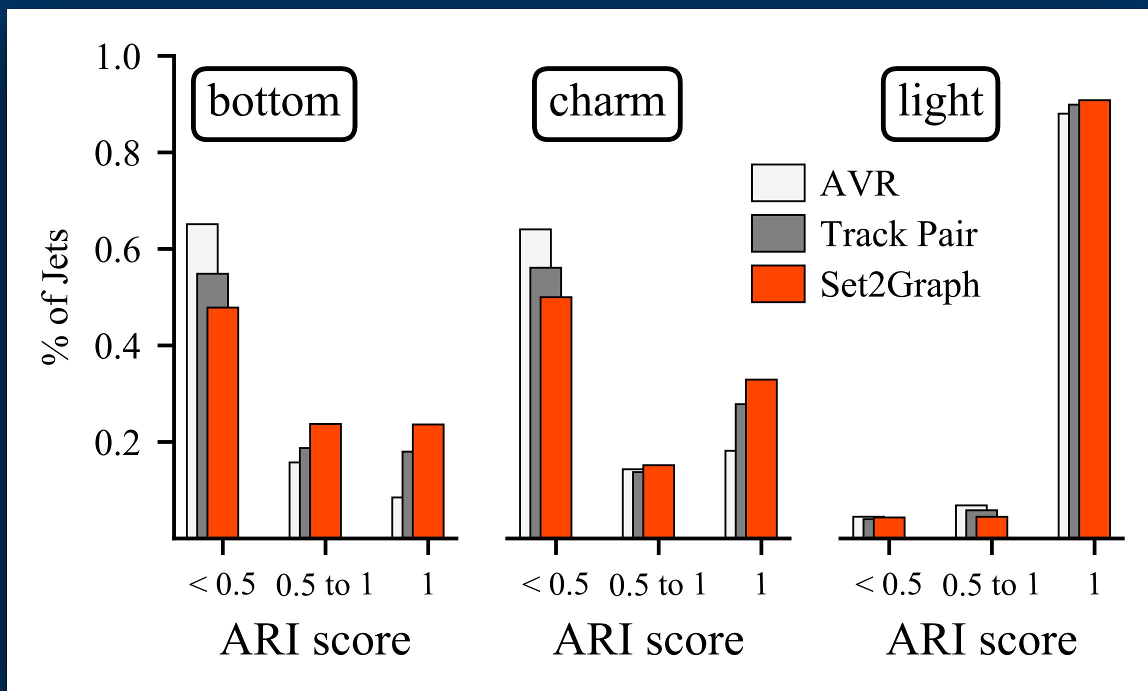
Input set:

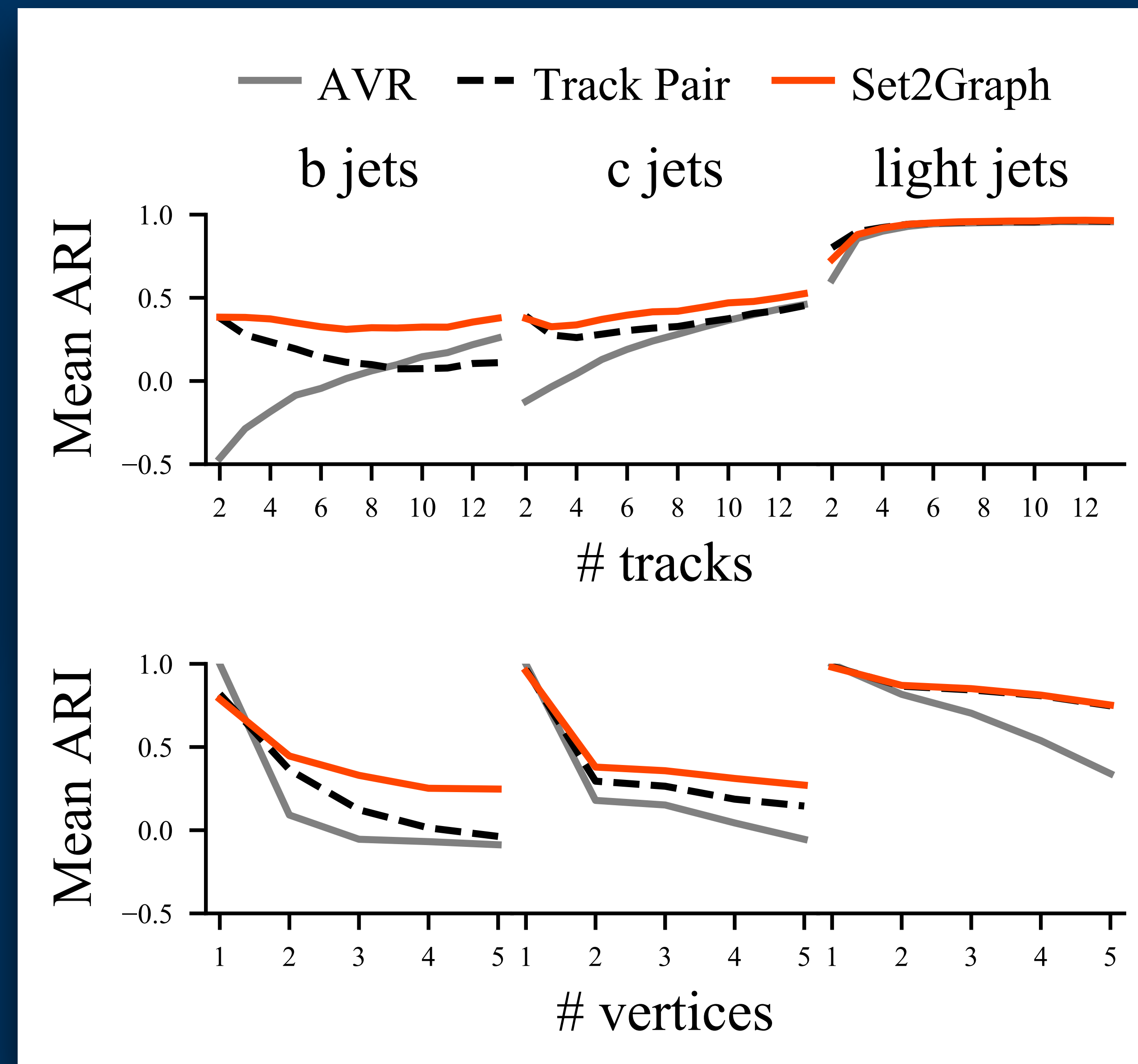




$$\text{ARI} = \frac{\text{RI} - \mathbb{E}[\text{RI}]}{1 - \mathbb{E}[\text{RI}]}$$

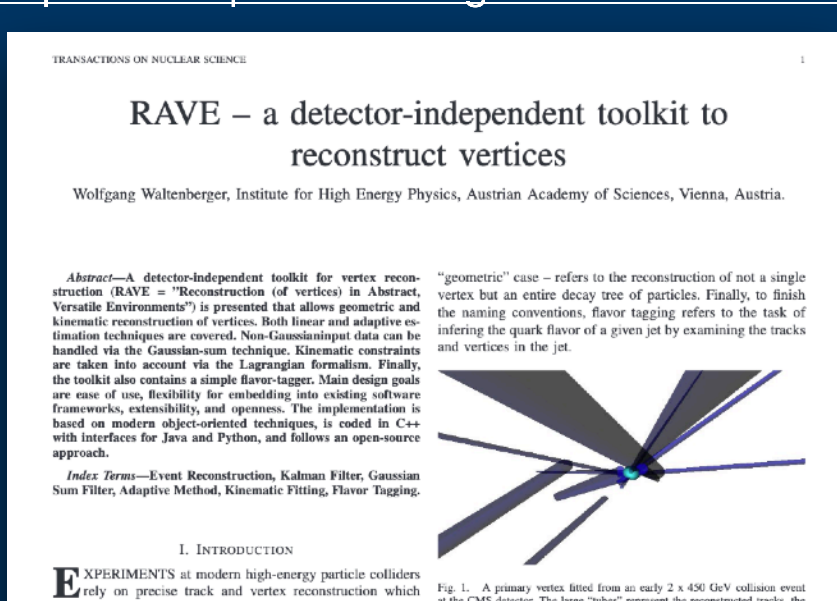
Evaluating the performance





The baseline:

https://ieeexplore.ieee.org/document/5734880



TRANSACTIONS ON NUCLEAR SCIENCE

RAVE – a detector-independent toolkit to reconstruct vertices

Wolfgang Waltenberger, Institute for High Energy Physics, Austrian Academy of Sciences, Vienna, Austria.

Abstract—A detector-independent toolkit for vertex reconstruction (RAVE = "Reconstruction (of vertices) in Abstract, Versatile Environments") is presented that allows geometric and kinematic reconstruction of vertices. Both linear and adaptive estimation techniques are covered. Non-Gaussianinput data can be handled via the Gaussian-sum technique. Kinematic constraints are taken into account via the Lagrangian formalism. Finally, the toolkit also contains a simple flavor-tagger. Main design goals are ease of use, flexibility for embedding into existing software frameworks, extensibility, and openness. The implementation is based on modern object-oriented techniques, is coded in C++ with interfaces for Java and Python, and follows an open-source approach.

Index Terms—Event Reconstruction, Kalman Filter, Gaussian Sum Filter, Adaptive Method, Kinematic Fitting, Flavor Tagging.

I. Introduction

EXPERIMENTS at modern high-energy particle colliders rely on precise track and vertex reconstruction which must fully exploit the high spatial resolution achieved by state-

"geometric" case – refers to the reconstruction of not a single vertex but an entire decay tree of particles. Finally, to finish the naming conventions, flavor tagging refers to the task of infering the quark flavor of a given jet by examining the tracks and vertices in the jet.

Fig. 1. A primary vertex fitted from an early 2 x 450 GeV collision event at the CMS detector. The large "tubes" represent the reconstructed tracks, the widths representing the positional 2x2 subpart of the covariance matrix. The

Summary

- Neural networks are useful for secondary vertex finding
- Set2Graph model is universal
- S2G model outperforms traditional approach in a variety of performance metrics

What next?

- How well does it work in real data from the LHC?
- How does better reconstruction impact downstream tasks?

Thank you for your attention!