Studying a New Primary Vertex (PV) Identification Algorithm Within ACTS Framework

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Primary Vertices

- A Primary Vertex (PV) is the accurate estimation of the inelastic p-p interaction point
- 50-70 collisions per event in Run3 of LHC, 150-200 expected at HL-LHC
- A fast and efficient algorithm is needed to identify PVs from the reconstructed tracks
Tracks and Track Reconstruction

- Tracks are the paths taken by charged particles while traversing through the detector
- Track Reconstruction: Finding sets of measurement coming from one charged particle and building the associated trajectory

A helical track can be defined by 5 parameters

For our study we are using 2; $d_0$ and $z_0$ and their uncertainties
A Previous Study on a PV Identification Algorithm on ATLAS Data

Promising Results:
The PV-Finder algorithm first developed for LHCb, was adapted for ATLAS simulated data and achieved comparable performance to Adaptive Multi-Vertex Finder (AMVF), and obtained better efficiency and more than two times better resolution with a slight increase in fake rate over all the pile-up range.

https://cds.cern.ch/record/2858348
https://inspirehep.net/literature/1740667
A Deep Learning Based Approach

- **Inputs**: Track parameters and their uncertainties + truth vertices
- **Tracks to KDE**: Analytically calculated 1-D histogram
- **KDE to Hist**: Deep Neural Network (DNN) based-algorithm
- **Output**: Predicted PVs
A Deep Learning Based Approach

By taking reconstructed tracks and their associated uncertainties, we can calculate KDEs which is sufficient to feed it to NN to estimate PVs locations.

- Inputs
- Tracks to KDE
- Analytically calculated 1-D histogram
- KDE to Hist
- Deep Neural Network (DNN) based-algorithm
- Output

Track parameters and their uncertainties + truth vertices
Tracks to KDEs: Analytical Approach to Kernel Density Estimation

- KDE: 1D probability distribution estimation technique that transforms the tracks and their measured resolutions into representations of the track density

- A track’s density in the \((d_0, z_0)\)-plane is given by a transverse and longitudinally correlated Gaussian probability distribution centered around \((d_{0\_i}, z_{0\_i})\)

\[
P(r) = P(d, z) = \frac{1}{2\pi \sqrt{|\Sigma|}} \exp \left( -\frac{1}{2} \left( (d - d_0), (z - z_0) \right)^T \Sigma^{-1} \left( (d - d_0), (z - z_0) \right) \right)
\]

\[
\Sigma_i = \begin{pmatrix}
\sigma^2(d_{0\_i}) & \sigma(d_{0\_i}, z_{0\_i}) \\
\sigma(d_{0\_i}, z_{0\_i}) & \sigma^2(z_{0\_i})
\end{pmatrix}
\]

\[
W(z) = \sum_{i \in \text{Tracks}} P_i(0, z)
\]
ACTS - A Common Tracking Software

- ACTS is an independent, free, open-source software project for track reconstruction in particle physics experiments
- It’s designed to be easily adapting to specific experiment’s needs
- Provides essential components, such as:
  - Track models (e.g. helical, linear)
  - Fitting algorithms
  - Geometry components (surfaces, volumes, detector elements, etc)
  - Propagation components
  - Visualization
  And much more!

Setup in ACTS

1. Detector used: Open Data Detector (ODD)
2. Event generation: Pythia8 with ttbar
3. Reference PVs: AMVF algorithm
4. Pile-up: 50
5. Events Number: 3000
6. Number of tracks/event ~ 300 tracks

Implementing PDFs in ACTS to generate KDE histograms

Gather track parameters and their covariances from tracks generated by CKF algorithm
\[(d_0, z_0, \sigma_{d_0}, \sigma_{z_0}, \sigma_{d_0z_0})\]

KDEgenerator

**Constructor**
{ Initializing I/O ROOT files, TTrees, Branches, vectors, etc. }

**Execute**
{ sorting tracks, defining lambda functions for binning and pdf evaluation, filtering tracks, calculating covariance matrix, grid search, outputs best kernel value for that bin, etc }

**Finalize**
{ write data to output ROOT file, clean-up }

Run KDEgenerator on 3000 events
and generate 1-D binned histogram with 12,000 bins with z-range [-24,24] cm (40μm wide bins)
We encoded the PDFs calculation analytically

```cpp
double GetGaussianPDF(const Eigen::Vector2d& x, const Eigen::Vector2d& mean, const Eigen::MatrixXd& covMat) {
    Eigen::MatrixXd covMat_inverse = covMat.inverse();
    double covMat_det = covMat.determinant();
    Eigen::Vector2d diff = x - mean;
    double chisq = (diff.transpose() * covMat_inverse * diff)(0, 0);
    return std::exp(-0.5 * chisq) / (2 * M_PI * std::sqrt(covMat_det));
}

// Iterate over the filtered tracks
for (size_t k = 0; k < filteredTracks.size(); ++k) {
    int index = filteredTracks[k].second;
    // Construct 2x2 covariance matrix using d_0 and z_0
    Eigen::MatrixXd covMat(2, 2);
    covMat << (*_sigma_d0)[index], (*_sigma_d0_z0)[index],
             (*_sigma_d0_z0)[index], (*_sigma_z0)[index];
    // Calculate the PDF for this track and point p, and accumulate the kernel value
    double pdf_for_this_track = GetGaussianPDF(Eigen::Vector2d(std::sqrt(p.x()) * p.x() + p.y() * p.y()),
                                                 Eigen::Vector2d(*_d0)[index], (*z0)[index]), covMat);
    this_kernel += pdf_for_this_track;
    this_kernel_sq += pdf_for_this_track * pdf_for_this_track;
```

Results from Analytical Approach

**KDE-A** represents the kernel value = pdf of this track
**KDE-B** represents the square of the kernel value = the squared value of pdf of this track

These KDE distributions will be fed into DNN to get PV predictions
A small z-range is shown to better observe the structure
NN Architecture for KDE

- Fully connected neural network trained on 3,000 events
- Track parameters and their uncertainties
- Analytically calculated KDEs
- Converging loss function for training and validation loss
Results from NN Based-Approach

By Ananya Singha, HSF-India Fellow

Analytically calculated KDE-A
NN predicted KDE-A
Conclusion and Future Work

- Completed the first step in the project; to build a DL-based PV Identification algorithm within ACTS
- Compared the results from analytical vs NN approach
- A drawback is our analytical method to produce KDEs takes large run-time

- Next step is to feed KDEs into DNN to get PV predictions
- Use of neural network for KDE generation (Ananya is working on it)
- We are Integrating this algorithm within ACTS to enable adoption by other experiments for broader uses
Thank you!

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Questions?