

Particle identification in SPD: a Bayesian approach

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Outline

- set-up a ‘framework’ to support Bayesian approach within the SPD

Past talks connect to this topic

7 December 2021

- Ruslan Akhunzyanov “*dE/dx studies for particle*”
https://indico.jinr.ru/event/2554/contributions/15153/attachments/11594/19132/Ruslan_dEdx_Dec7_2021.pdf
- Artem Ivanov “*Particle identification with TOF*”
https://indico.jinr.ru/event/2554/contributions/15149/attachments/11593/19130/07.12.2021_Ivanov.A.V.pdf

Current talk based on following articles

- “*Bayesian approach for combined particle identification in ALICE experiment at LHC*”
I. Belikov, P. Hristov, M. Ivanov, T. Kuhr, K. Safarik (2005) Contribution to: CHEP 2004, 423-426
- “*Particle identification in ALICE: a Bayesian approach*”
ALICE Collaboration, Jaroslav Adam (Prague, Tech. U.) et al. (Feb 3, 2016) Published in: Eur.Phys.J.Plus 131 (2016) 5, 168
- “*Идентификация заряженных частиц по ионизационным потерям энергии во время-проекционной камере для экспериментов NICA/MPD*”
С. П. Мерц, С. В. Разин, О. В. Рогачевский, Матем. моделирование, 2012, том 24, номер 12, 102–106

PID formalism

S - a raw signal from a detector

$S(H_i)$ - expected average signal for a given species $H_i(\pi, K, p, \dots)$

The Bayes theorem

probability that the particle is of species H_i , given \vec{S}

$$P(H_i|\vec{S}) = \frac{P(\vec{S}|H_i)C(H_i)}{\sum_{k=\pi, K, p} P(\vec{S}|H_k)C(H_k)}$$

a posterior probability

A priori probability for H_i

$$P(S|H_i) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(S-S(H_i))^2}{2\cdot\sigma^2}} \quad \text{One detector}$$

The conditional probability that a particle of species H_i produces a signal S (in this case expressed with a Gaussian response)

$$P(\vec{S}|H_i) = \prod_{\alpha=TOF, STAW, \dots} P_\alpha(S_\alpha|H_i)$$

Many detectors

The conditional probability that a particle of species H_i produces the set of signals

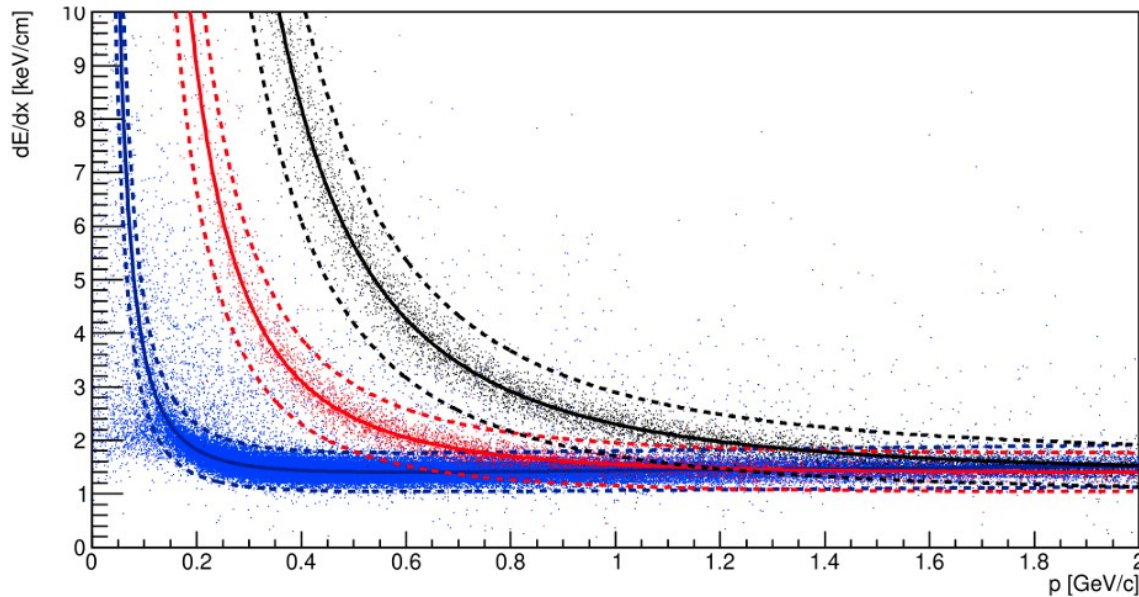
What is S raw signal

Detector	Signal
STRAW	dE/dx
TOF	m^2

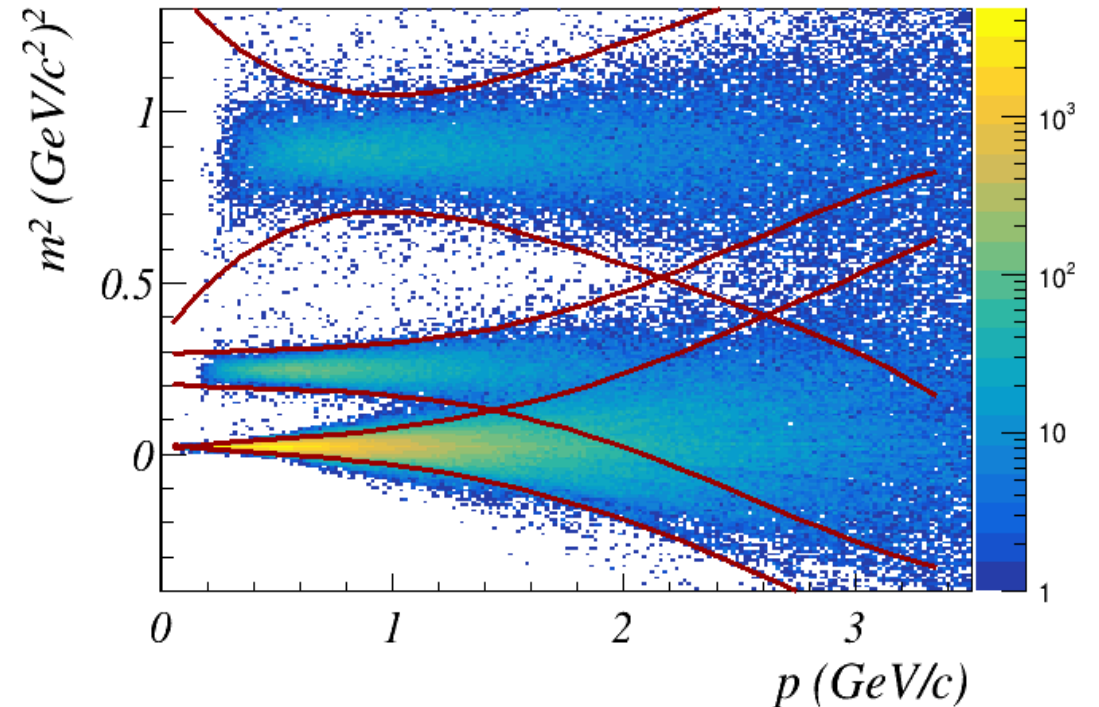
conditional probability

$$P(m^2) = \frac{1}{\sqrt{2\pi}\sigma(p)} e^{-\frac{(m_{TOF}^2 - m_{fit}^2)^2}{2 \cdot \sigma(p)^2}}$$

STRAW



TOF



from talk of Ruslan Akhunzyanov “*dE/dx studies for particle*”

What is priors

Strategy to calculate

Iterative procedure based on a set of unidentified tracks (raw yield $Y(p)$)

1) Start with “flat” priors (i.e 1 for all species)

2) Bayesian posterior $P_n(H_i|S)$ at step n obtained from unidentified raw yield

3) Obtain identified raw yields at step $n+1$ using posteriors as weights

4) Obtain a new set of priors from the relative ratios of identified spectra

$$P(H_i|\vec{S}) = \frac{P(\vec{S}|H_i)C(H_i)}{\sum_{k=\pi,K,p} P(\vec{S}|H_k)C(H_k)}$$

$$P(m^2) = \frac{1}{\sqrt{2\pi}\sigma(p)} e^{-\frac{(m_{TOF}^2 - m_{fit}^2)^2}{2 \cdot \sigma(p)^2}}$$

Priors obtained as a function of p

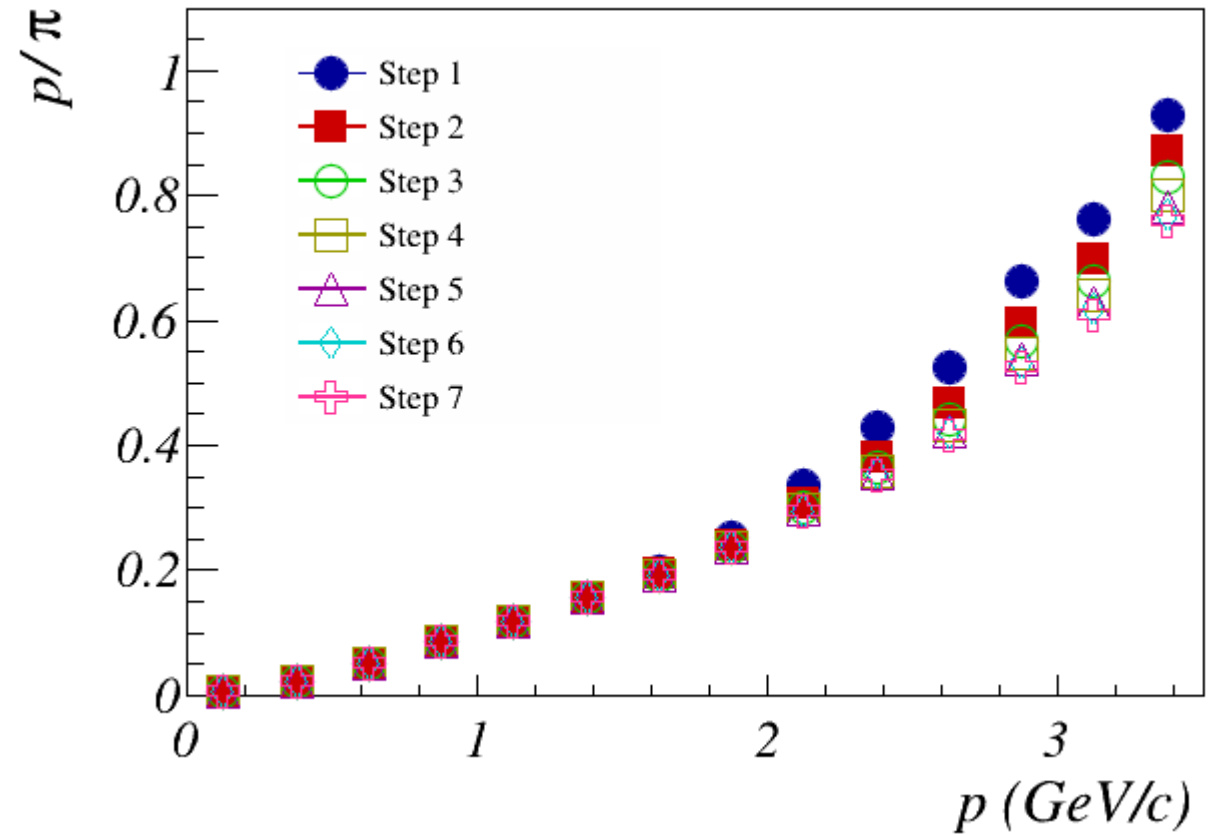
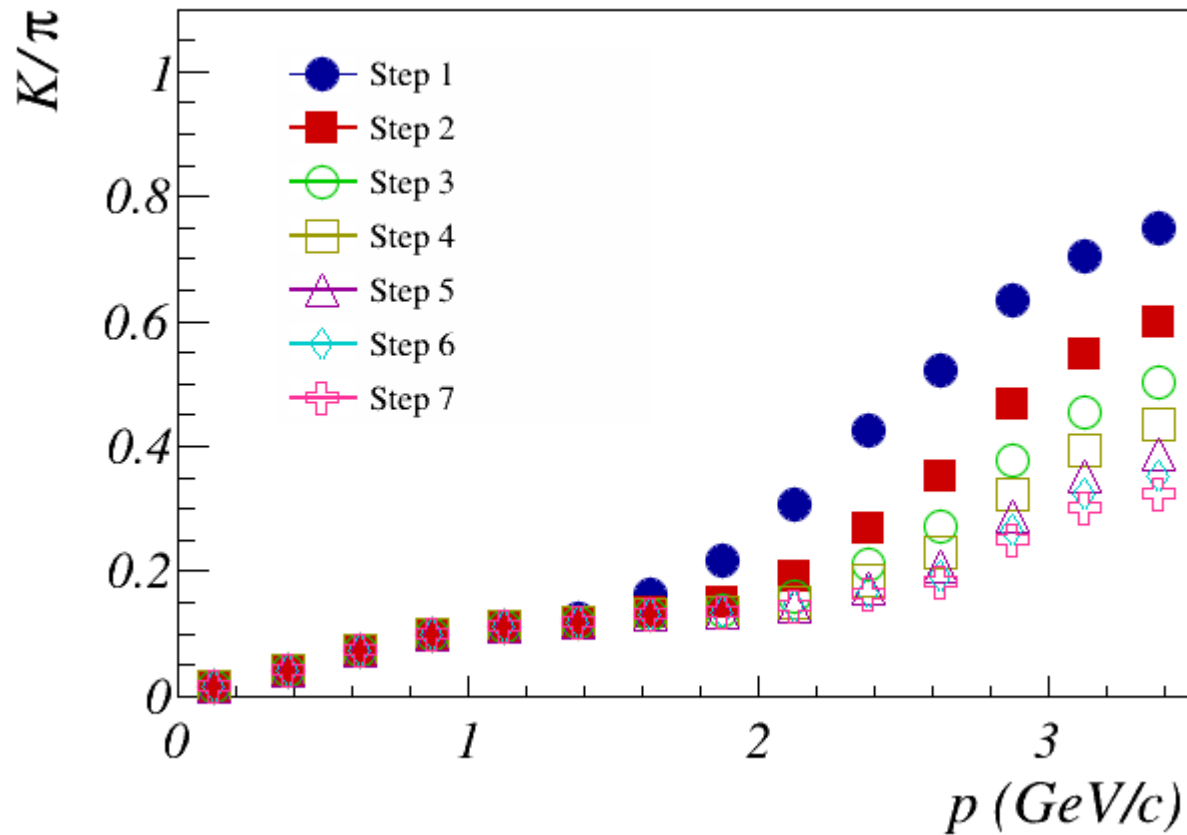
$$Y_{n+1}(H_i, p) = \sum_S P_n(H_i|S)$$

$$C_{n+1}(H_i, p) = \frac{Y_{n+1}(H_i, p)}{Y_{n+1}(H_\pi, p)}$$

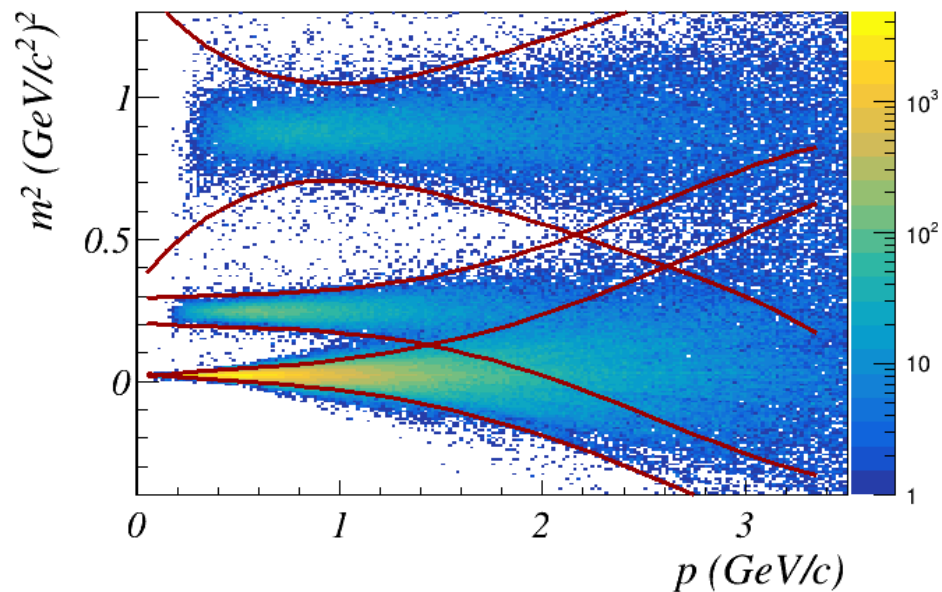
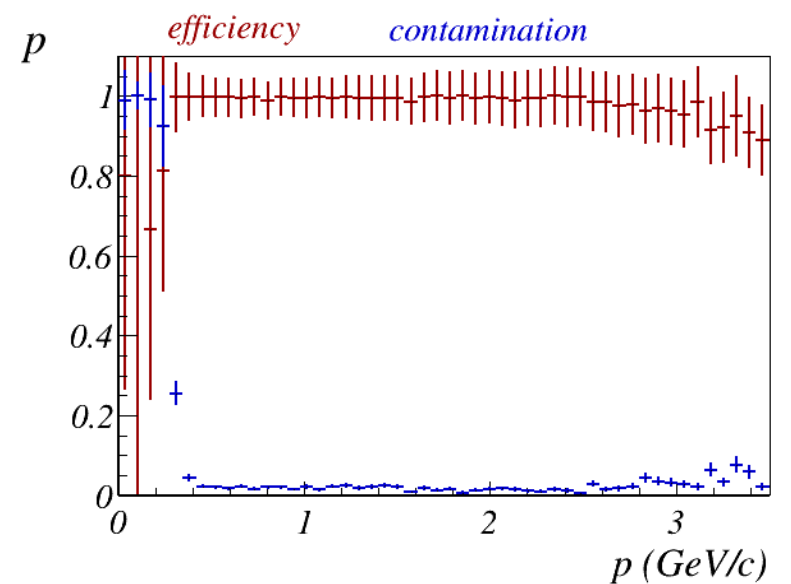
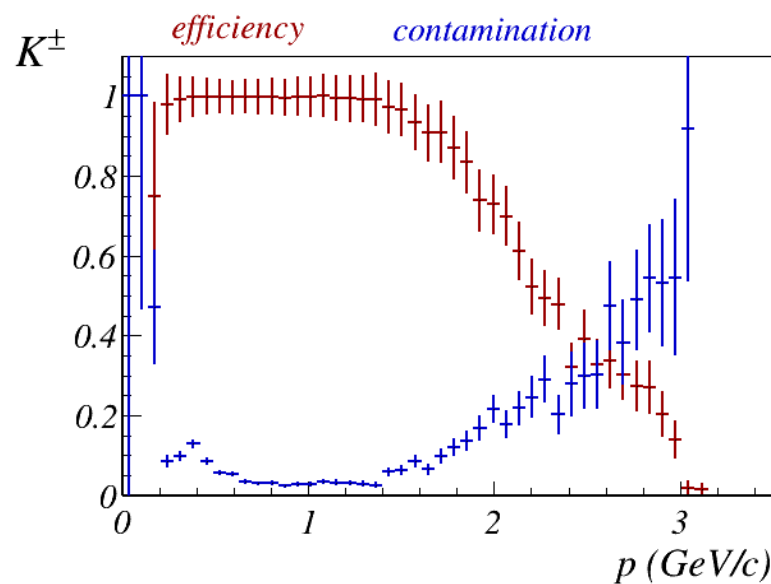
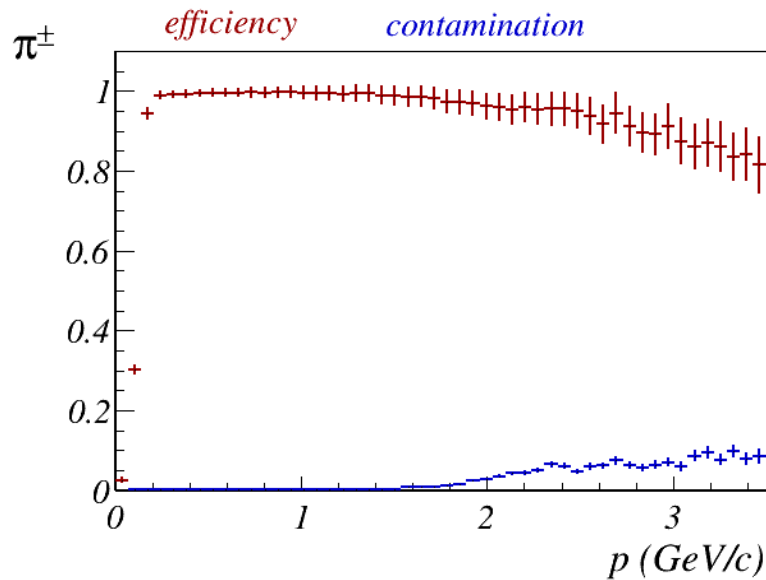
Separate sets of priors have to be evaluated for each collision system p-p, d-d, p-d and energies

Calculation priors: only TOF

The extracted K/π and p/π ratio of the priors is shown as a function of p at each step of the iteration.



Efficiency and Contamination: only TOF



$$\text{efficiency} = \frac{N_{\text{corr}}}{N_{\text{true}}}$$

$$\text{contamination} = \frac{N_{\text{incorr}}}{(N_{\text{incorr}} + N_{\text{corr}})}$$

N_{corr} – the number of correctly identified particles of a certain type

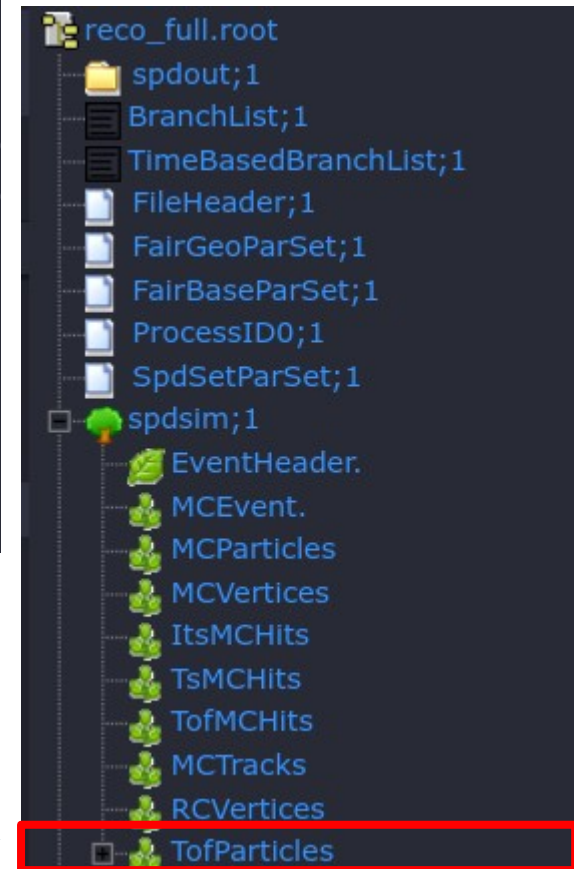
N_{incorr} – number of misidentified particles a certain type

N_{true} – the true number of particles of a certain type.

Calculation TOF $P(H_i | S)$ probability in SpdRoot

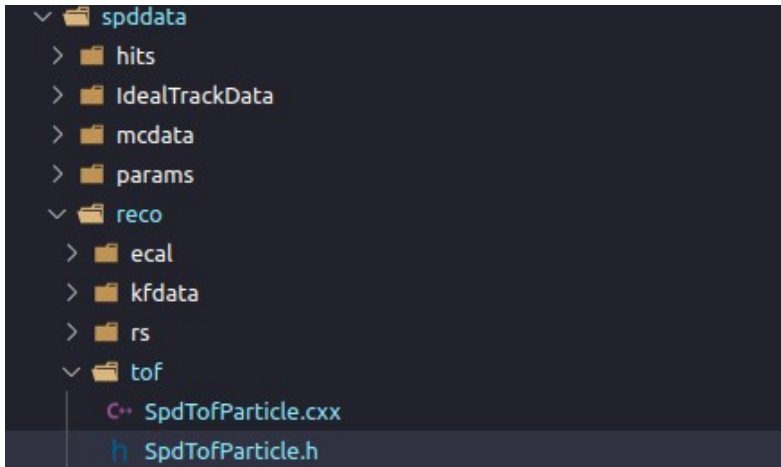
RecoEventFull.C

```
//      ///-----//  
//      // [MC-PRODUCER FOR TOF-PARTICLES]  
//      // Input: mc-event, mc-particles, mc-tracks(+ fit pars.), mc-tof-hits  
//      // Output: tof-particles  
//  
SpdMCTofParticleProducer* mctof_part = new SpdMCTofParticleProducer();  
//  
//mctof_part->SaveParticles(false);  
//  
mctof_part->SetVerboseLevel(1);  
//  
Run->AddTask(mctof_part);
```



This code will create branch with name "TofParticles" which contains an information about probabilities of track to be pion, kaon, proton

Calculation TOF $P(H_i | S)$ probability in SpdRoot



Function from Class *SpdTofParticle*

```
std::vector<Double_t> GetProb() const { return fprob; }
Double_t GetProbPion() const { return fprob[0]; }
Double_t GetProbKaon() const { return fprob[1]; }
Double_t GetProbProton() const { return fprob[2]; }
Double_t GetProbMax() const { return *std::max_element(fprob.begin(), fprob.end());};
```

YourScriptForAnalysis.C

```
Int_t IdhitTof = fparticle->GetTofParticleId();
if (IdhitTof < 0) continue;

SpdTofParticle *ftofparticle = (SpdTofParticle *)tofparticles->At(IdhitTof);
if (!ftofparticle)
    continue;

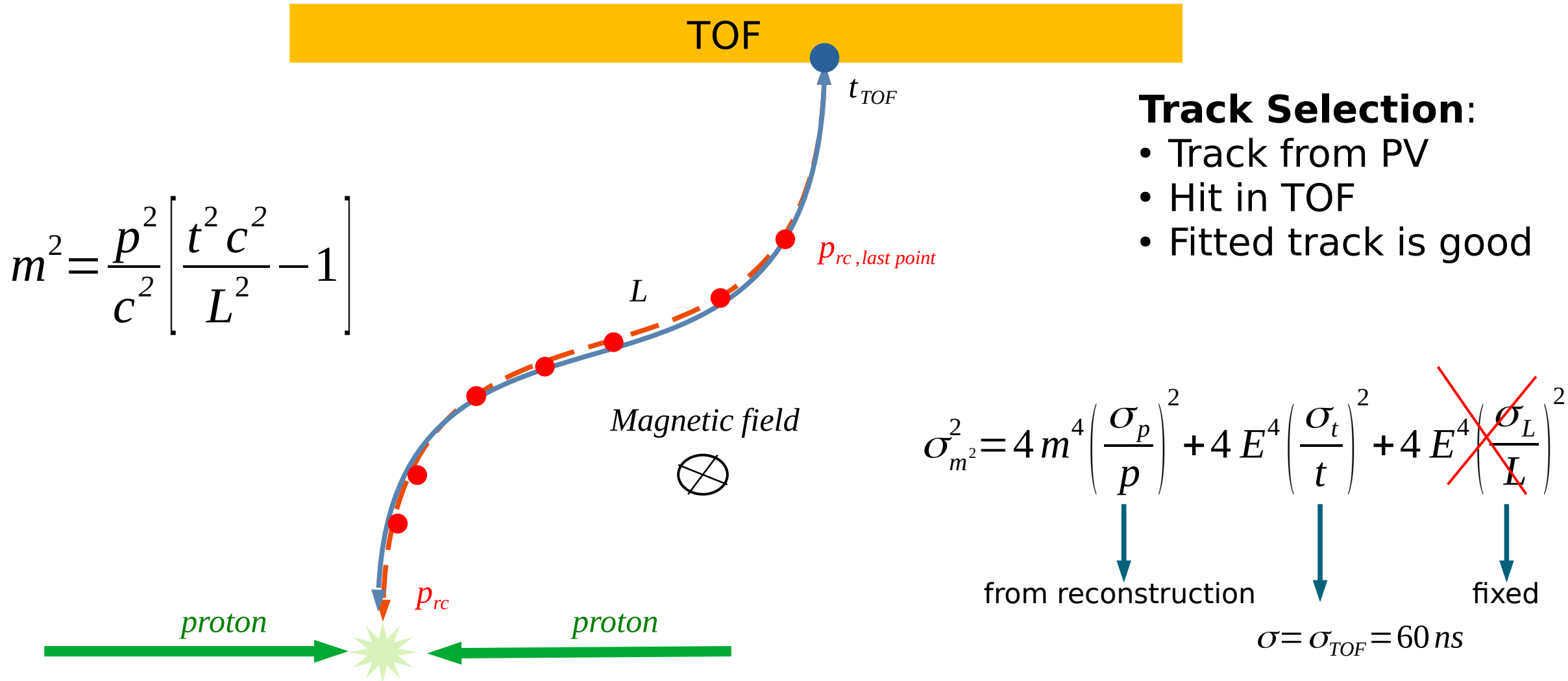
std::vector<Double_t> vprob = ftofparticle->GetProb();
```

Conclusion

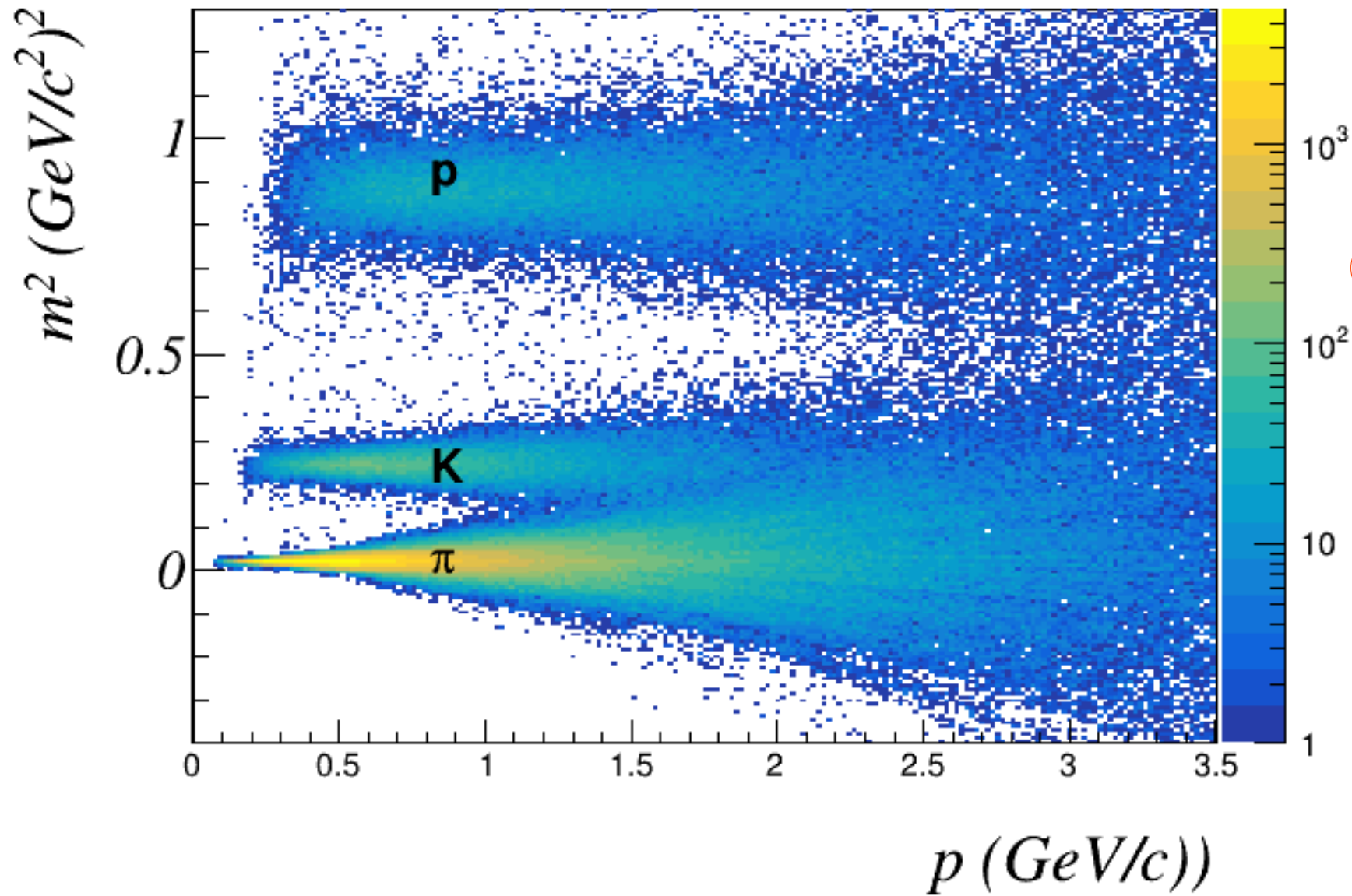
- The ‘framework’ for Bayesian approach was added in my folk SpdRoot (<https://git.jinr.ru/aivanov/spdroot>)
- To add in the official repository
- To combine results with STRAW

Backup

PID analysis with TOF in SpdRoot



Momentum dependence of m^2 distribution



$$m^2 = \frac{p^2}{c^2} \left[\frac{t^2 c^2}{L^2} - 1 \right]$$

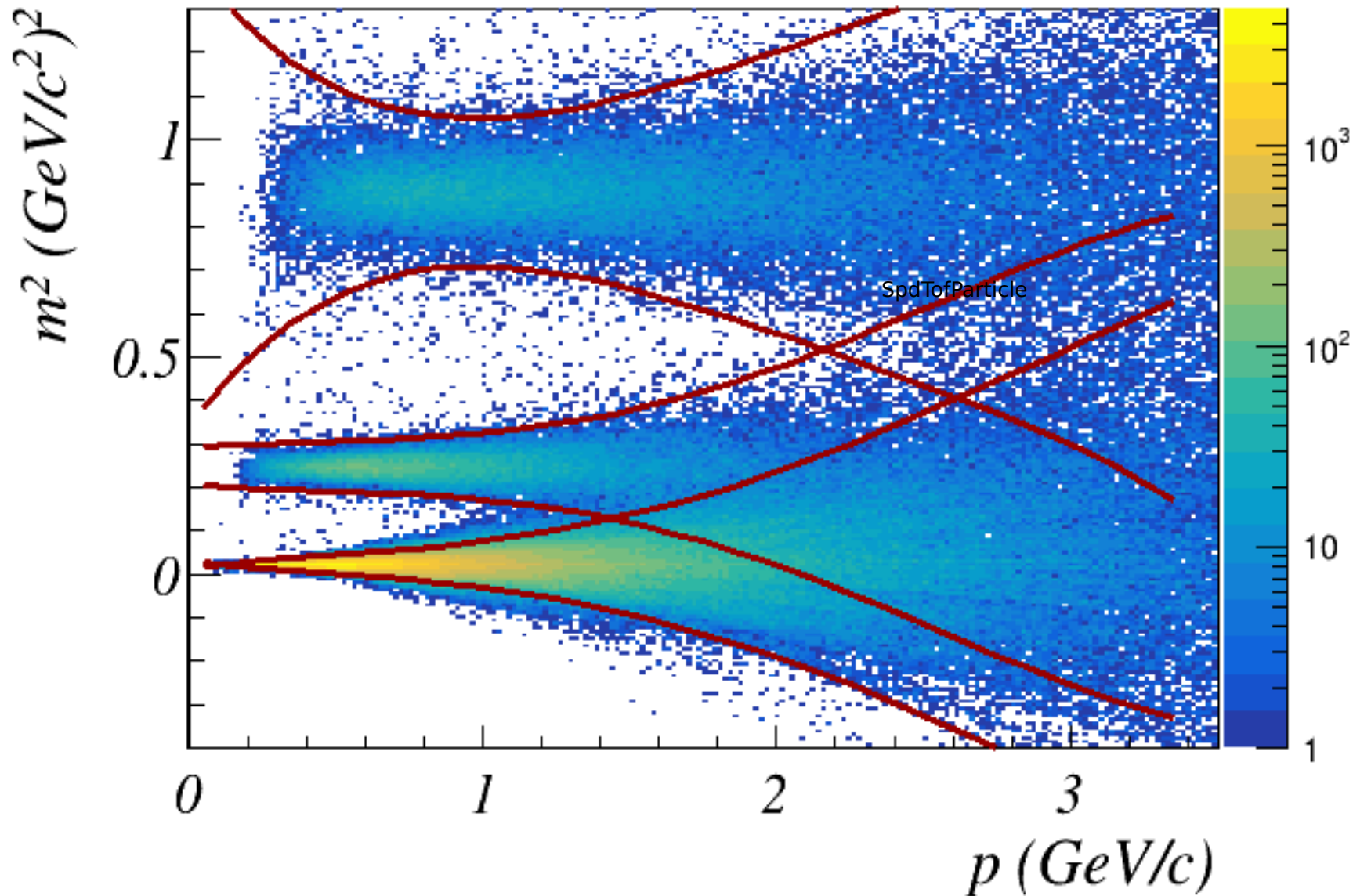
$\frac{p_{rc} + p_{rc, \text{last point}}}{2}$

$t = \text{gaus}(t_{\text{TOF}}, 60)$

Momentum dependence of m^2 distribution

Red lines depict 3σ bands

$$P(m^2) = \frac{1}{\sqrt{2\pi}\sigma(p)} e^{-\frac{(m_{TOF}^2 - m_{fit}^2)^2}{2\cdot\sigma(p)^2}}$$



Momentum dependence of m^2 distribution

