University of Science and Technology of China

ALICE

Measurement of non-prompt J/ψ production in Pb-Pb collisions at $\sqrt{s_{NN}}$ = 5.02 TeV

卢鹏忠 唐泽波 白晓智

核探测与核电子学国家重点实验室
中国科学技术大学

中国ALICE实验学术研讨会 2021.07.31-08.01 贵州 贵阳

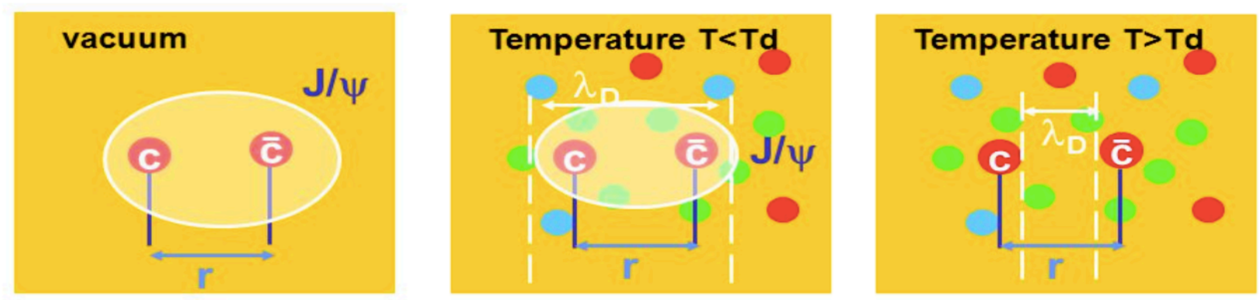
Outline

- **Motivation**
- **Analysis of inclusive J/ψ via machine learning**
- **Analysis of non-prompt J/ψ**
- **Summary**

J/ψ production in heavy ion collisions

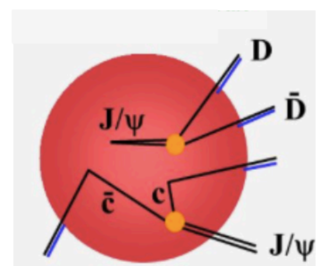
Early creation: J/ψ experience entire evolution of the quark-gluon plasma

Dissociation in QGP: *static* and *dynamic* $r_{q\bar{q}} \sim 1/E_{binding} > r_D \sim 1/T$

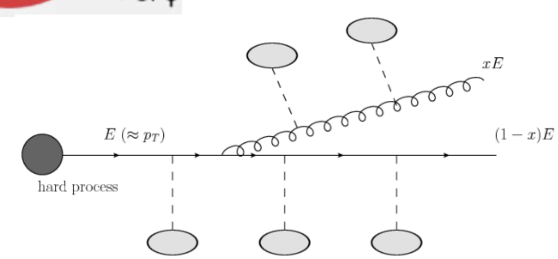


Other effects:

- (Re)generation
- Medium-induced energy loss
- Formation time
- Feed-down contributions
- Cold nuclear matter effects

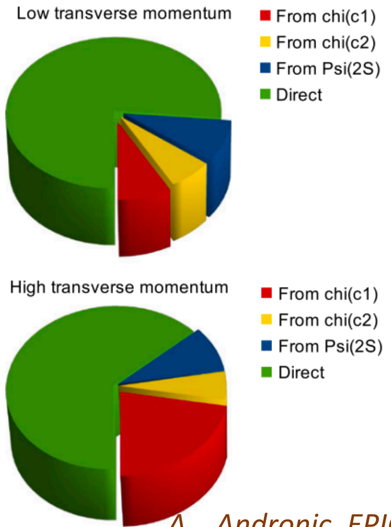


Central AA collisions	SPS 20 GeV	RHIC 200 GeV	LHC 5 TeV
N_{ccbar}/event	~0.2	~10	~115

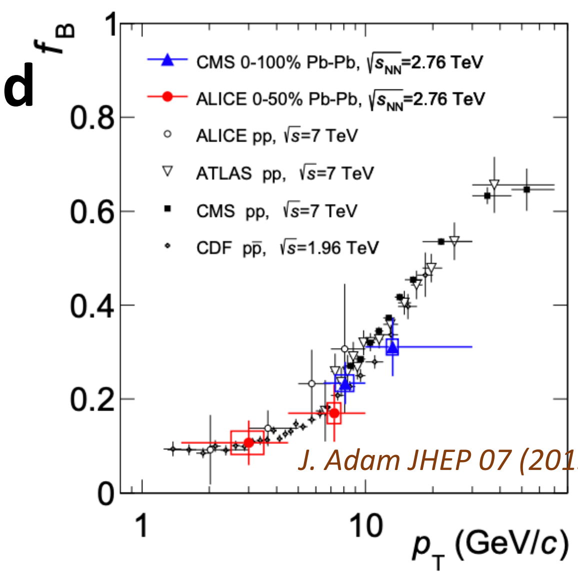


J/ψ production in heavy ion collisions

- J/ψ mesons are produced in 2 ways:
  - Prompt:
    - ✓ Directly from heavy ion collisions
    - ✓ Indirectly from heavier states as χ_c and ψ'
  - Non-prompt from b-hadrons decays
    - ✓ No (re)generation effects
    - ✓ Mass dependent medium effects
- Different mechanisms of non-prompt and prompt J/ψ
- Essential for understanding the charmonium suppression in heavy-ion collisions

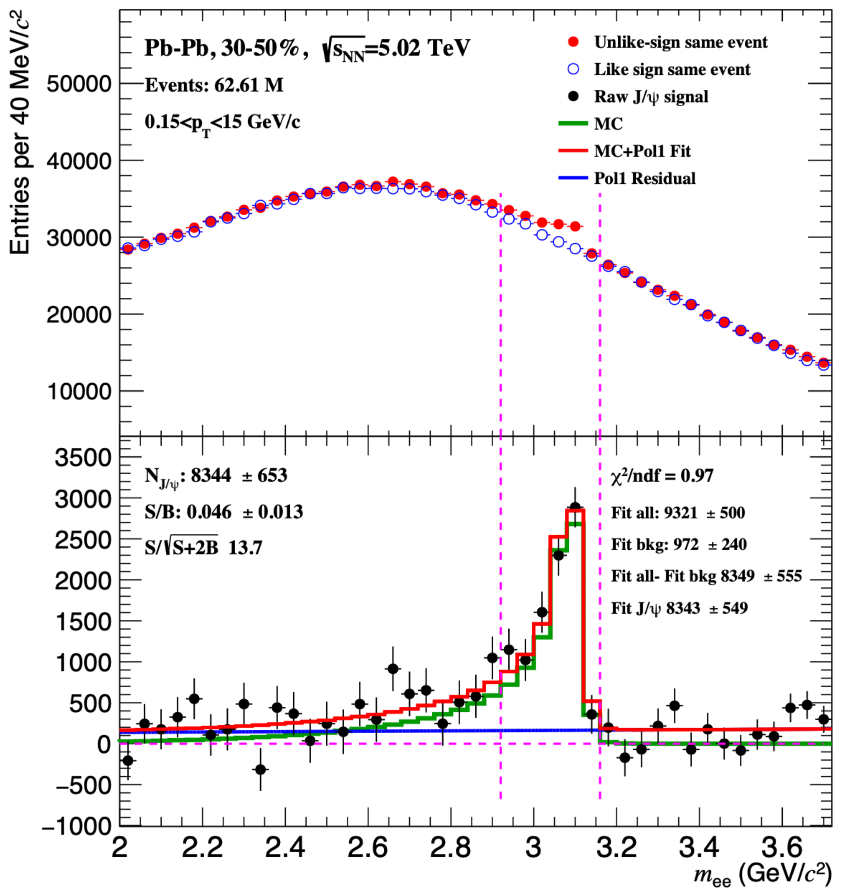


A. Andronic, EPJC 76 (2016) 107



J. Adam JHEP 07 (2015), 051

Inclusive J/ψ via standard method



standard method (Xiaozhi, Alena)

- The S/B is very challenging in the standard J/ψ analysis, particularly in Pb-Pb central collisions.
- Multiple Variables Analysis (MVA) techniques is one of the approach to improve the S/B and suppress the large background.

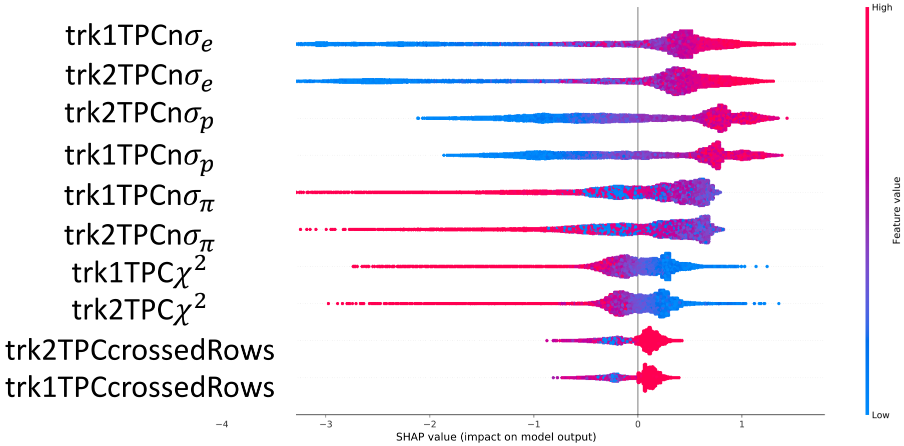
Datasets and pre-selection

- Datasets:
  - ✓ LHC18q and LHC18r
- Event cuts:
  - ✓ $|TPCV_z| < 10\ cm, Vtx\ contributor > 1$
  - ✓ Physics Selection, INT7
  - ✓ Pile-up cuts
- Track quality cuts:
  - ✓ $1\ GeV/c < p_T, |\eta| < 0.9$, Reject kinks
  - ✓ $|DCA_{xy}| < 1\ cm, |DCA_z| < 3\ cm$
  - ✓ $TPC\ Refit, 50(70) < TPC\ Crossed\ Rows < 160$
  - ✓ $TPC\ \chi^2 < 3.0(2.5)$
  - ✓ $0.8 < TPC\ Crossed\ Rows\ Over\ Findable\ Clusters$
  - ✓ $ITS\ Refit, 0 < ITS\ \chi^2 < 36,\ SPD\ any$
- Electron PID cuts:
  - ✓ $|TPC\ n_\sigma^e| < 4.0(3.0)$
  - ✓ $|TPC\ n_\sigma^{proton}| > 2.0(3.5)$
  - ✓ $|TPC\ n_\sigma^\pi| > 2.0(3.5)$
- Pair Prefilter 50 MeV/c^2

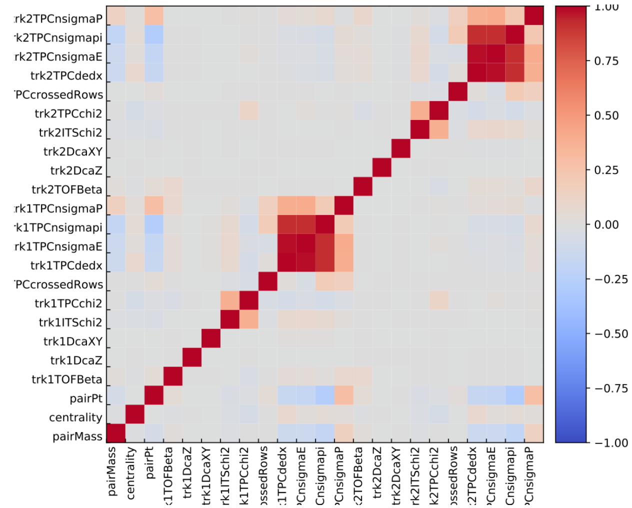
Green color is standard method cut

Input features and hyper-parameters

Features importance:



Features correlation maps:



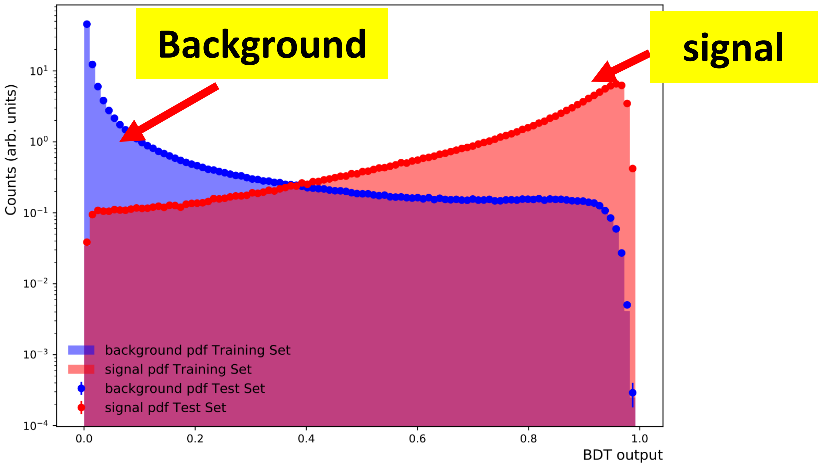
The optimized Hyper-parameters:

nestimators	max_depth	learning_rate	min_child_weight	subsample	colsample_bytree	tree_method
139	4	0.0745	5	0.8567	0.9843	hist

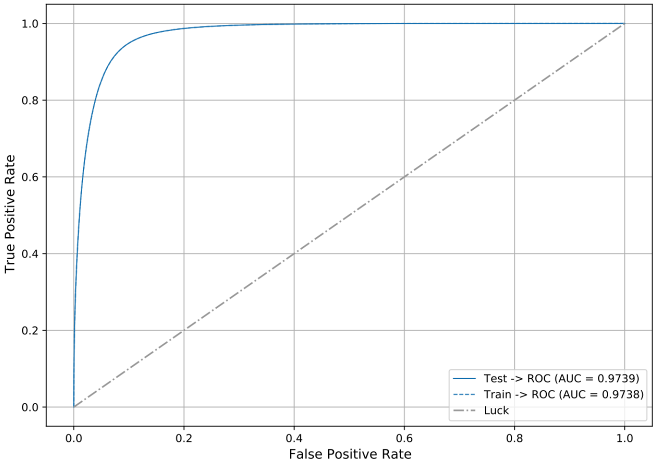
- **The features importance shows the impact on the output model**
- **Variables that carry similar physical information are strongly correlated**
- **Helps to determine the input features**

Model output of inclusive J/ψ via MVA

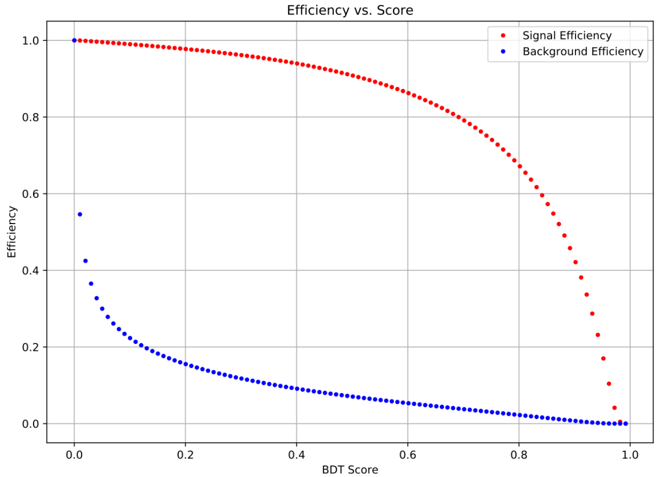
Train and test model:



Receiver operating curve (ROC):



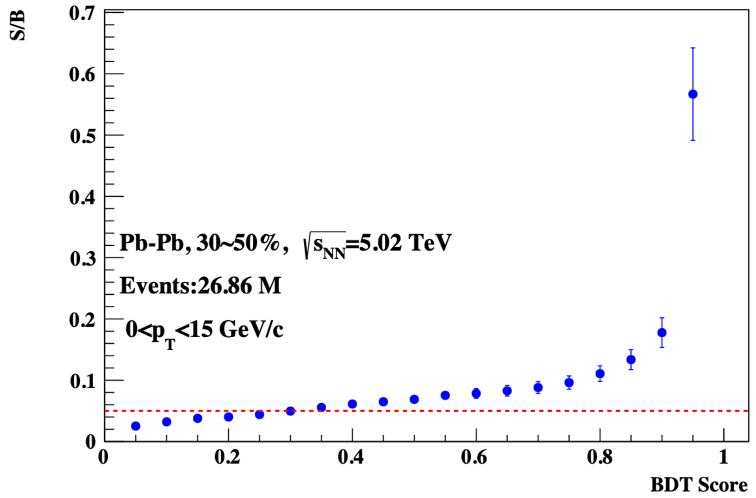
Efficiency vs. BDT cuts:



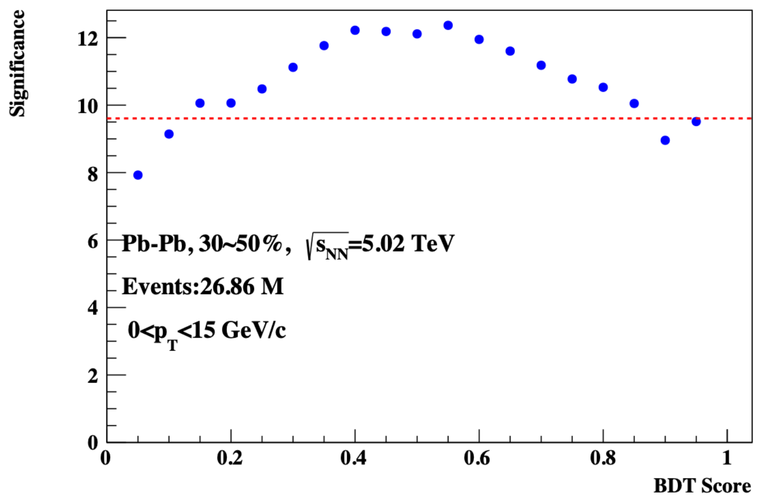
- The signal and background are well discriminated by the ML algorithm
- ROC shows the evaluation of the output model
- Principally, the larger AUC means more efficient to separate signal and background

MVA and standard method comparison

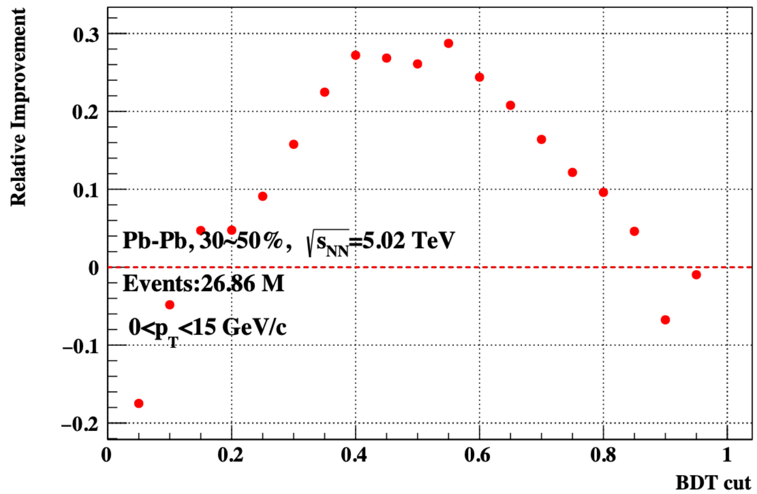
S/B vs. BDT cuts



Significance vs. BDT cuts



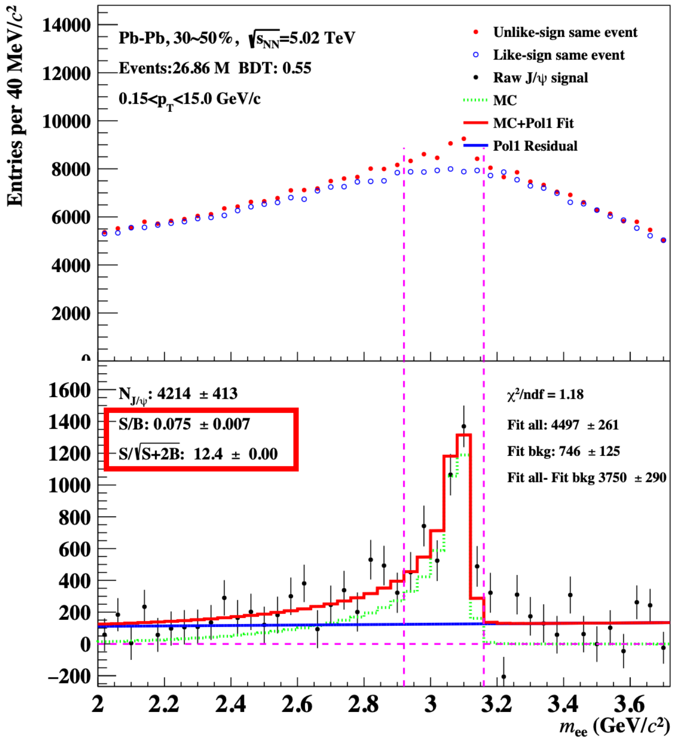
Significance relative improvement



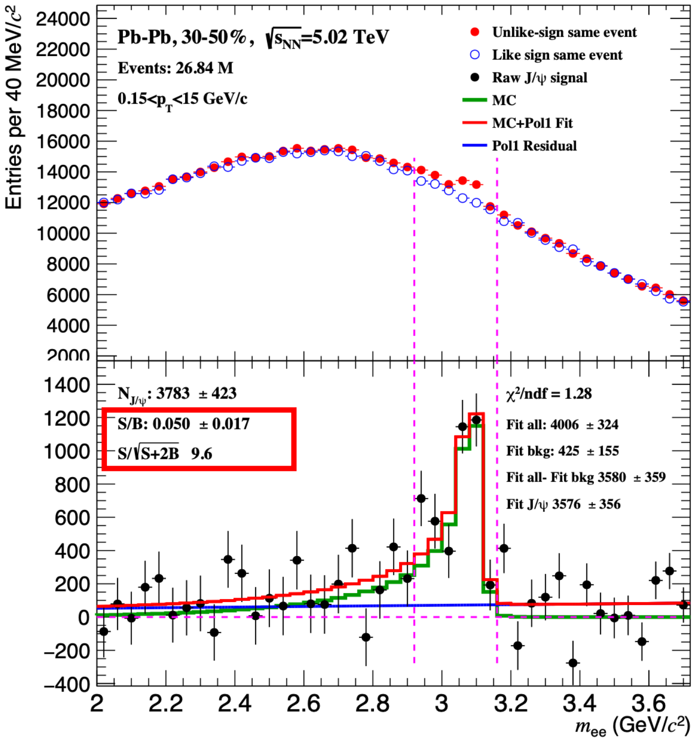
- Both S/B and Significance are improved obviously w.r.t. the standard method
- Expect more improvement from the central collisions

J/ψ signal extraction after ML

Machine learning

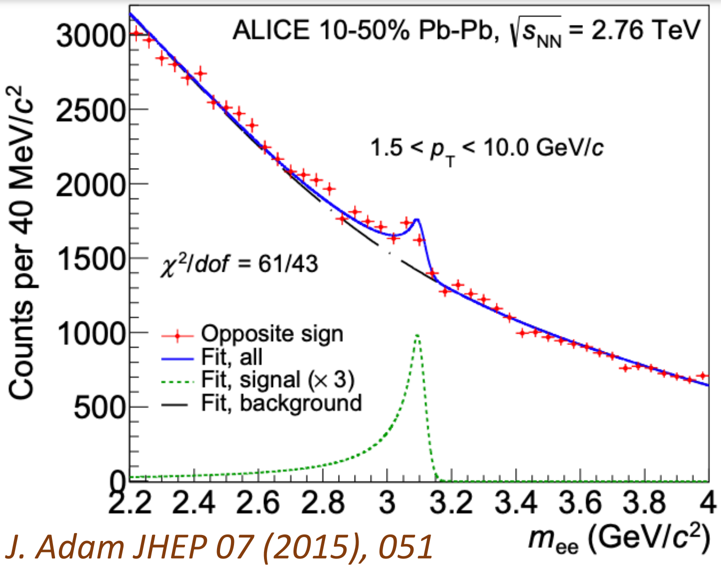


Standard method (Xiaozhi, Alena)

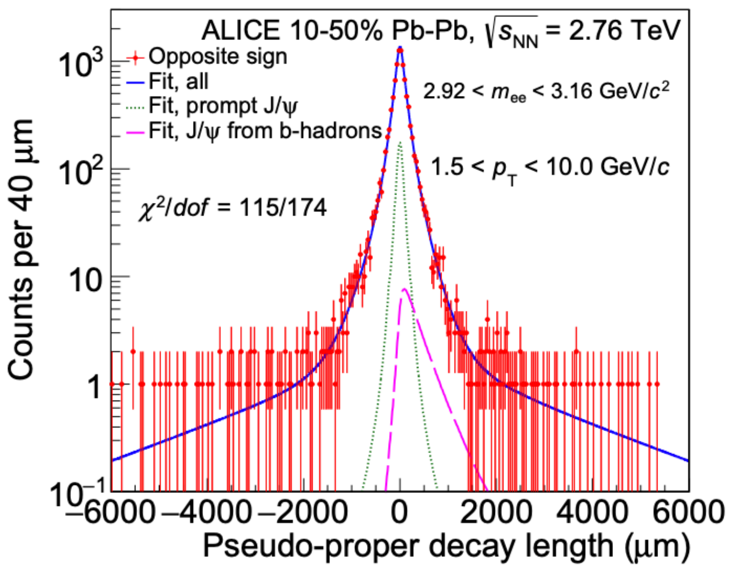


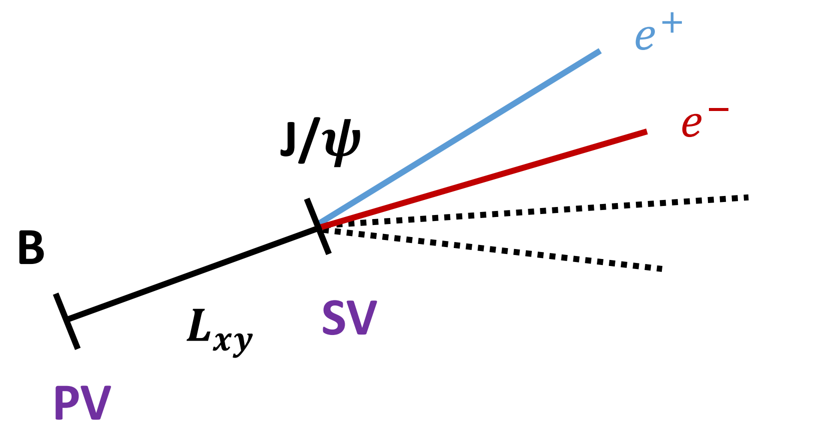
- **An example of the performance after BDT cuts (left) and classical cuts (right).**
- **Both S/B and Significance Improved obviously w.r.t. the standard method.**

Analysis of non-prompt J/ψ



J. Adam JHEP 07 (2015), 051





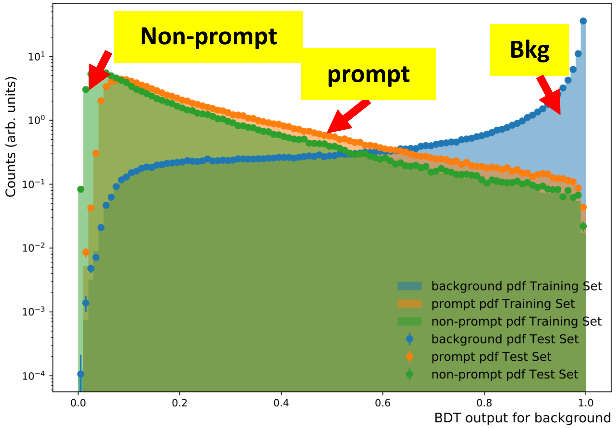
Lifetime of b hadrons ($\mathcal{O}$(500) $\mu m/c$)

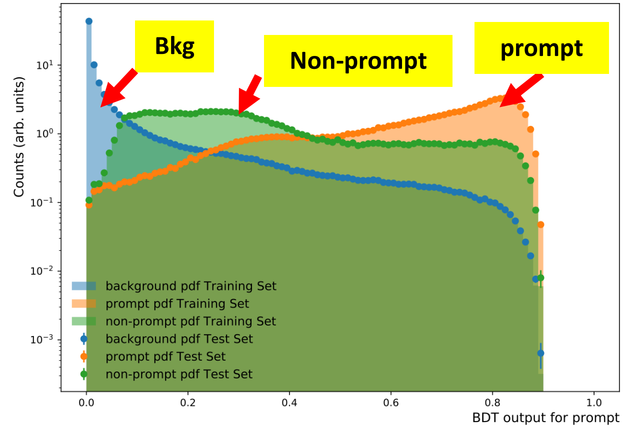
- **Non-prompt J/ψ with a larger decay length: $\ell_{J/\psi} = L_{xy}\frac{m_{J/\psi}}{p_T}$**
- **Measurements of non-prompt/prompt components with a 2D ML fit: invariant mass and pseudo-proper decay length**

Multi-classification in ML

Inclusive input features + pseudo-proper decay length

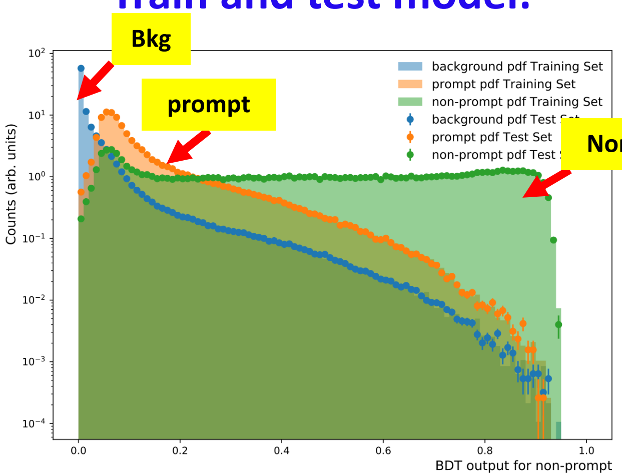
Train and test model:



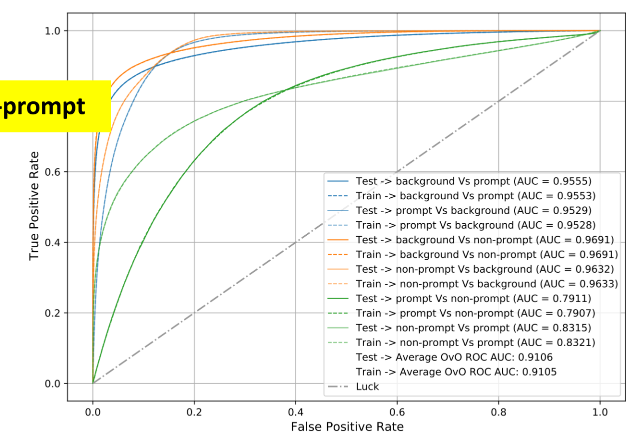


- **More efficient to separate combinatorial background and signal**

Train and test model:



Receiver operating curve (ROC):



- **A larger ROCAUC between combinatorial background and signal**

Data-driven method to calculate f_B

$$\varepsilon_i^{\mathrm{p}} \cdot N_{\mathrm{p}} + \varepsilon_i^{\mathrm{np}} \cdot N_{\mathrm{np}} = Y_i,$$

- ε is the acceptance times efficiency factor
- N is the corrected yield of prompt and non-prompt mesons
- Y is the extracted raw yield after the BDT cuts

Need at least two equations

$$\begin{cases} \varepsilon_1^{\mathrm{p}} \cdot N_{\mathrm{p}} + \varepsilon_1^{\mathrm{p}} \cdot N_{\mathrm{np}} = Y_1 \\ .. \\ .. \\ \varepsilon_n^{\mathrm{p}} \cdot N_{\mathrm{p}} + \varepsilon_n^{\mathrm{p}} \cdot N_{\mathrm{np}} = Y_n \end{cases}$$

- n different sets of cuts to obtain a system of n equations
- Ideally, the system can be exactly solved in the case of two equations
- Y and ε are affected by statistical and systematic uncertainties, a number of sets of cuts lead to a better estimation of the N

$$\boldsymbol{\varepsilon N = Y} \longrightarrow \boldsymbol{\varepsilon N - Y = \delta}$$

Data-driven method to calculate f_B

✓ **The definition of the χ^2**

$$\chi^2 = \delta^T C^{-1} \delta$$

$$\sigma_i^2 = \sigma_{Y_i}^2 + N_p \cdot \sigma_{\varepsilon_i^p}^2 + N_{np} \cdot \sigma_{\varepsilon_i^{np}}^2$$

Related to N

$$\rho_{i,j} = \frac{\sigma_i}{\sigma_j}, \text{ with } i \subset j$$

$$C = \begin{pmatrix} \sigma_1^2 & \sigma_{1,2} & \cdots & & \\ \sigma_{2,1} & \sigma_2^2 & & & \\ \vdots & & \ddots & & \vdots \\ & & & \sigma_{n-1}^2 & \sigma_{n-1,n} \\ & & \cdots & \sigma_{n,n-1} & \sigma_n^2 \end{pmatrix}$$

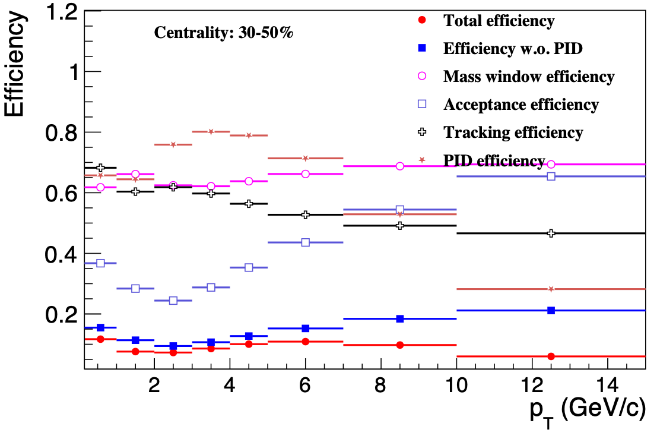
✓ **Leading by the minimum χ^2 method**

$$N = Cov(N)\varepsilon^T C^{-1} Y \qquad Cov(N) = (\varepsilon^T C^{-1} \varepsilon)^{-1}$$

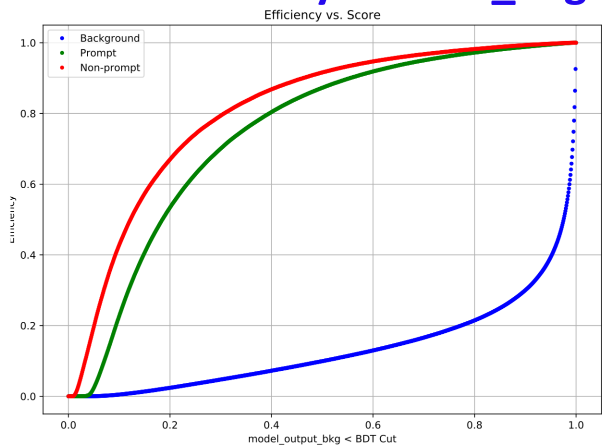
- **Principally, calculate efficiency and raw yields matrix**
- **Then we can calculate the corrected yields of prompt and non-prompt J/ψ**

Efficiency matrix

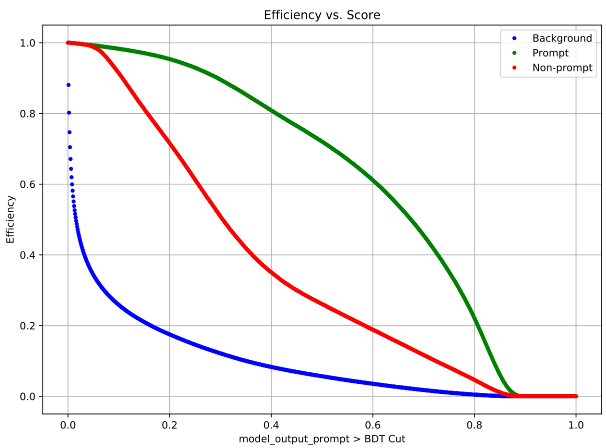
Pre-selection efficiency:



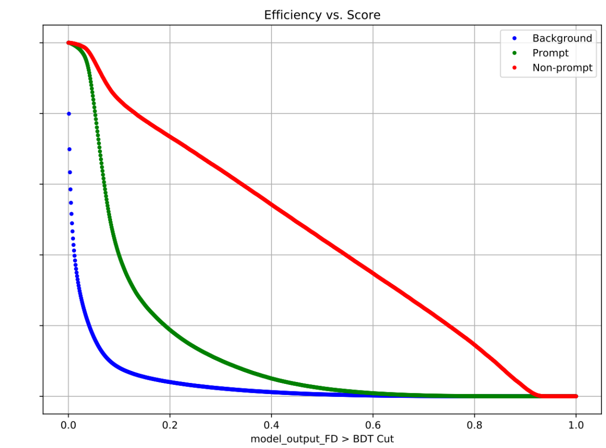
ML efficiency vs. BDT_bkg:



ML efficiency vs. BDT_prompt:



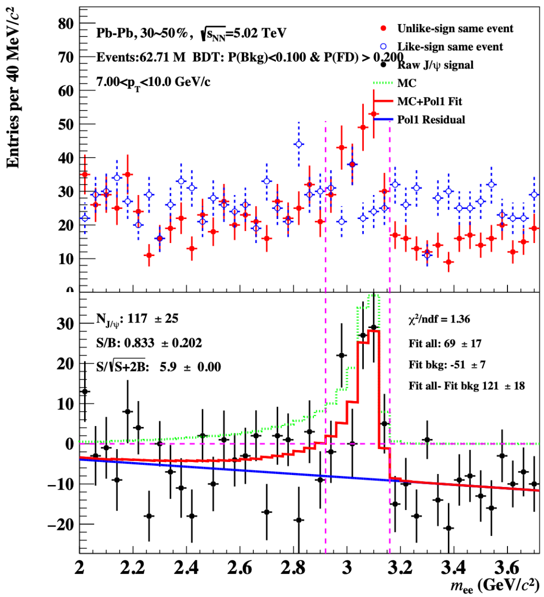
ML efficiency vs. BDT_FD:



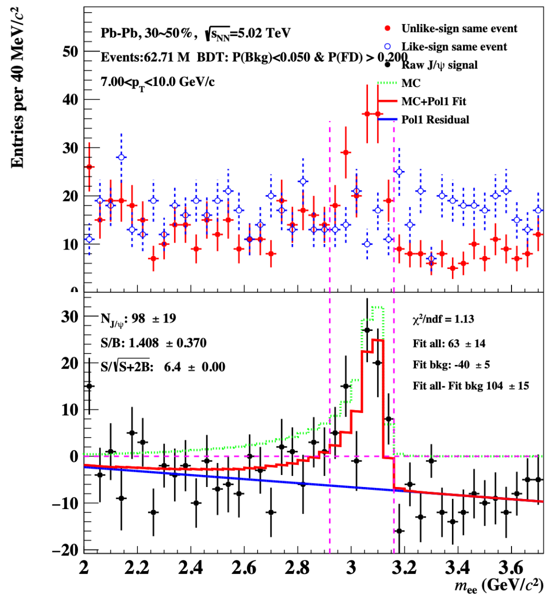
- **The Pre-selection efficiency part has checked with Xiaozhi`s inclusive analysis**
- **ML efficiency vs. the three model_outputs cut show as has been expected**

Raw yields matrix

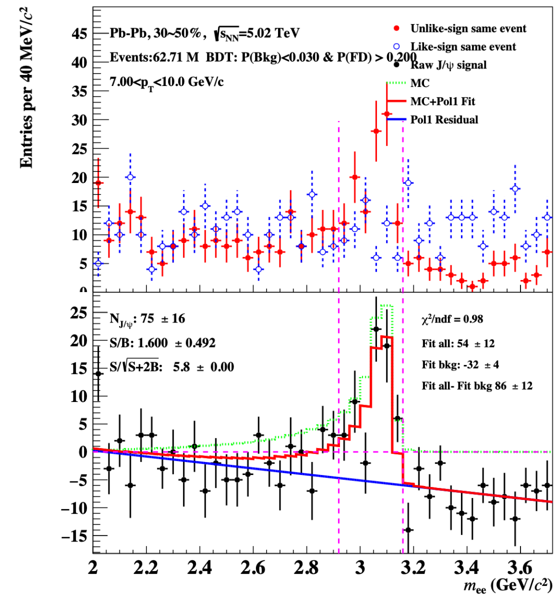
Raw yields vs. BDT cut sets:



BDT_bkg<0.10 & BDT_FD>0.20



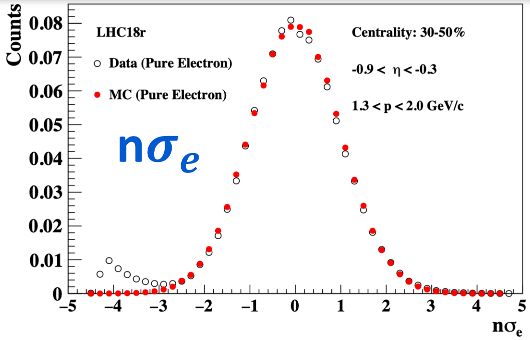
BDT_bkg<0.05 & BDT_FD>0.20

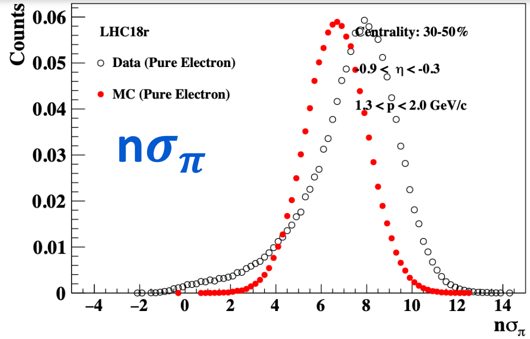


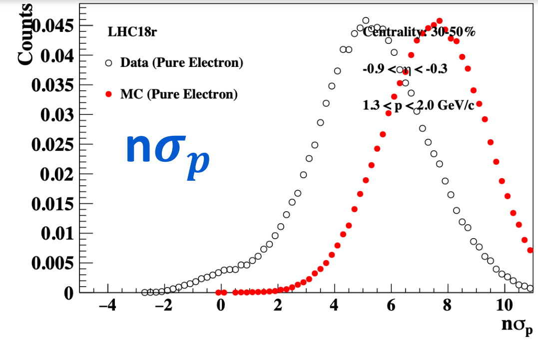
BDT_bkg<0.03 & BDT_FD>0.20

- Raw yields vs. BDT cut sets in the same p_T and centrality bin
- Each cut is the subsample of the previous one

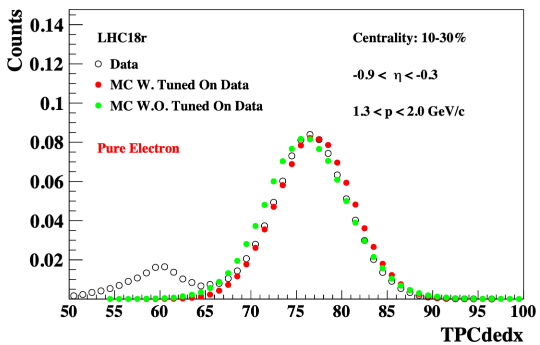
PID checks between data and MC

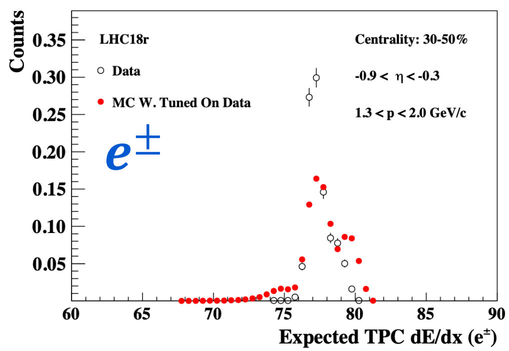


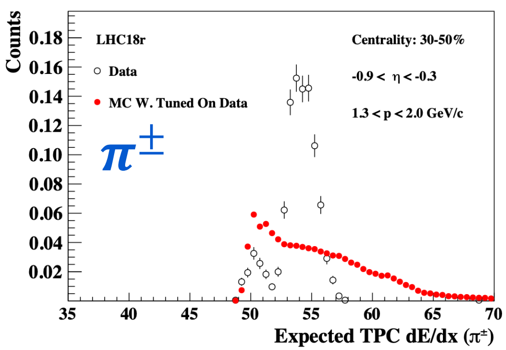


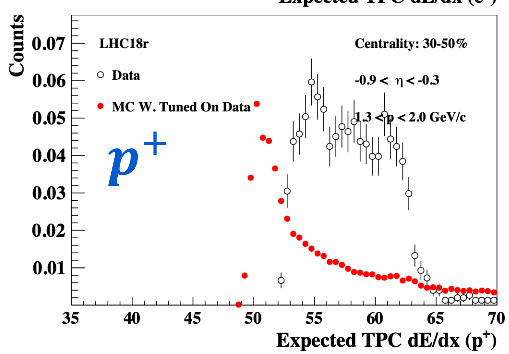


Significant difference in $n\sigma_{hadron}$ between data and MC









- The TPC dE/dx of MC is similar with data after tuning on data.
- Observe some difference in the TPC dE/dx splines of p^{+} and $\pi^{\pm}$ between data and MC
- Need more works on it

Summary and outlook

Summary:

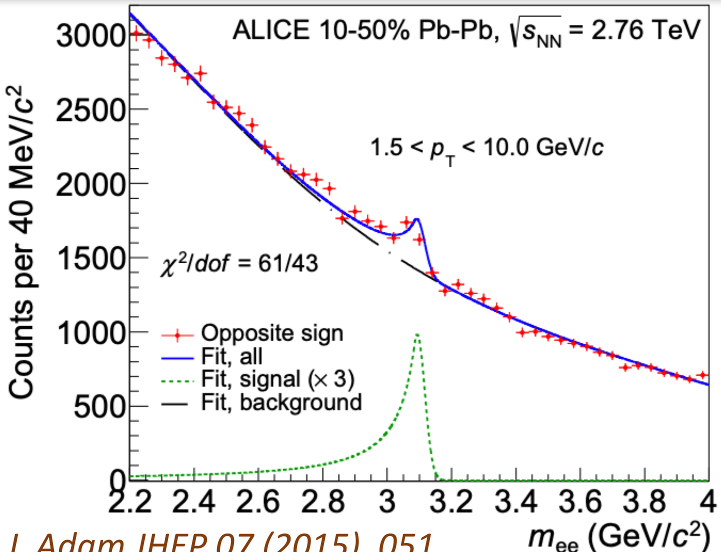
- ✓ Improved the S/B and significance of inclusive J/ψ via the MVA method
- ✓ Implement ML on non-prompt J/ψ analysis
- ✓ Set up the data-driven method to calculate the f_B
- ✓ Pre-selection efficiency has been calculated
- ✓ Methods to calculate the ML efficiency and raw yields matrix has been established

Outlook:

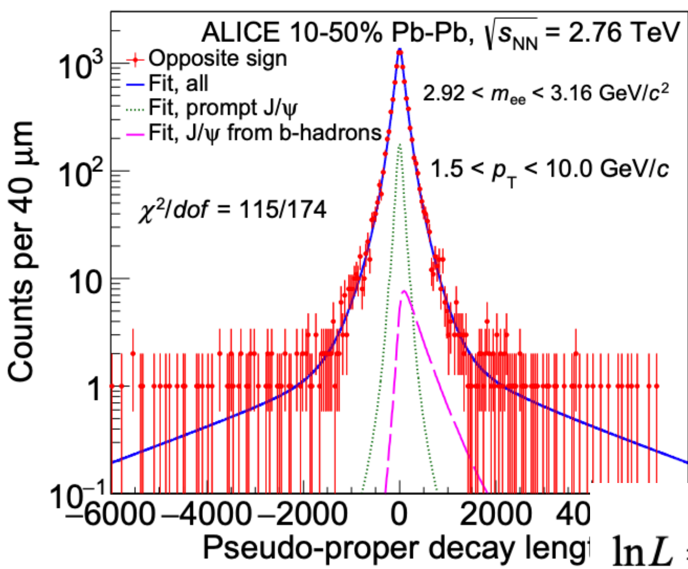
- ☐ Verify the efficiency and raw yields matrix
- ☐ Calculate the f_B vs. p_T and vs. centrality

Backup

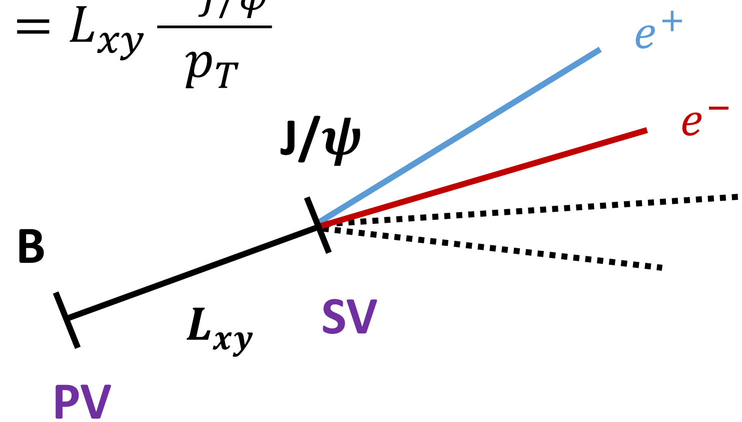
Analysis of non-prompt J/ψ



J. Adam JHEP 07 (2015), 051



$$\ell_{J/\psi} = L_{xy}\frac{m_{J/\psi}}{p_T}$$



Lifetime of b hadrons ($\mathcal{O}$(500) μm/c)

- **Non-prompt J/ψ with a larger decay length: $\ell_{J/\psi} = L_{xy}\frac{m_{J/\psi}}{p_T}$**
- **Measurements of non-prompt/prompt components with a 2D ML fit: invariant mass and pseudo-proper decay length**

$$\ln L = \sum^{N} \ln\left[f_{\text{Sig}} \cdot F_{\text{Sig}}(x) \cdot M_{\text{Sig}}(m_{\text{ee}}) + (1 - f_{\text{Sig}}) \cdot F_{\text{Bkg}}(x) \cdot M_{\text{Bkg}}(m_{\text{ee}})\right]$$