Studies of beauty hadronization and in-medium energy loss with B^+ and B_s^0 spectra

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for the CMS Collaboration

PLB 829 (2022) 137062

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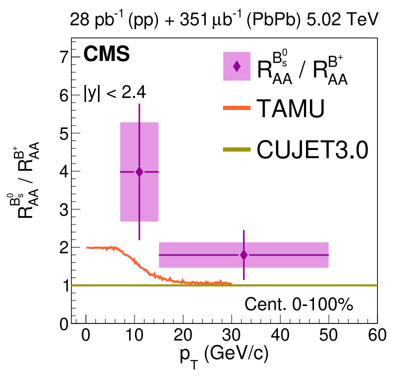
Introduction

B_s^0/B^+ ratio: strangeness enhancement

Double ratio, 2015 data

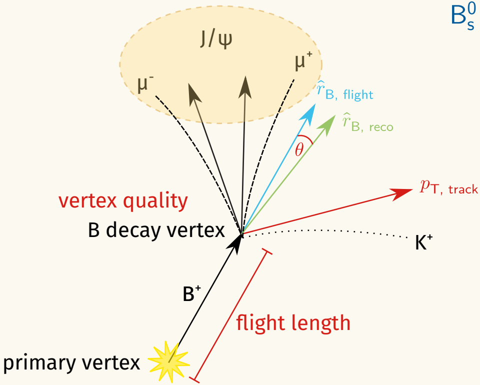


- Enhanced strangeness predicted for $p_T < 15$ GeV in deconfined medium
  [Phys.Lett.B 595 (2004) 202-208, Phys.Lett.B 735 (2014) 445-450]
- Heavy **b**, **c** quarks produced at initial hard scattering, recombining with nearby constituent quarks into hadrons
- This talk: 2018 data, 3 times more statistics compared to 2015 B^+ and B_s^0 samples

B^+: PRL 119, 152301
B_s^0: PLB 796 (2019) 168

B_s^0/B^+ analysis

B_s^0 / B^+ event selection



$B^+ \to J/\psi K^+ \to \mu^- \mu^+ K^+$

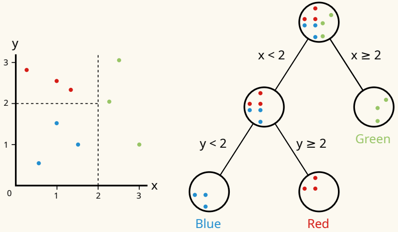
$B_s^0 \to J/\psi \phi(1020) \to \mu^- \mu^+ K^+ K^-$

- Long-lived B mesons $\to$ large flight length
- Angle between B flight direction and PV-SV displacement
  $\cos\theta = \hat{r}_{B,\ flight} \cdot \hat{p}_{T,\ RECO}$
  Expect $\hat{p}_{T,\ RECO} \parallel \hat{r}_{B,\ flight}$
- χ^2 Probability of the decay vertex
- p_T of the daughter tracks

- Additionally for B_s^0:
  $m_{K^+K^-} - m_\phi$

Cut optimization

- Maximize the discriminating power by training a machine learning algorithm in the multi-dimensional parameter space.
- Boosted Decision Tree (BDT):
  - Select on each variable sequentially in a tree structure
  - Train many weak classifiers with subsets of randomly selected samples, emphasizing the misclassified events



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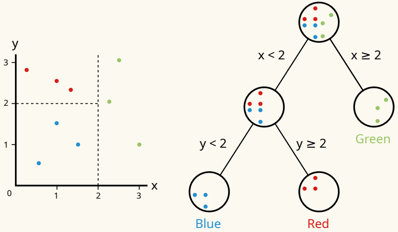
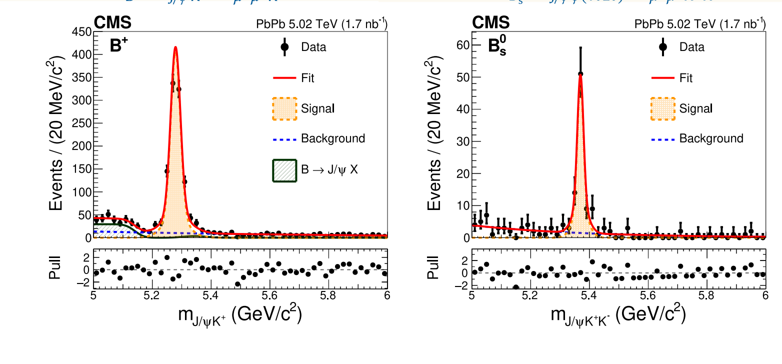


- Training samples: signal MC vs side-band data

B_s^0/B^+ Yield extraction

$B^+ \to J/\psi K^+ \to \mu^-\mu^+K^+$ $\qquad$ $B_s^0 \to J/\psi\phi(1020) \to \mu^-\mu^+K^+K^-$



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- First 5σ+ observation of B_s^0 in PbPb collision
- B^+ peaking background:
  - Partially reconstructed B decay (e.g. $B^0 \to J/\psi(K^* \to K^+\pi^-)$)
  - misidentified π in $B^+ \to J/\psi\pi^+$

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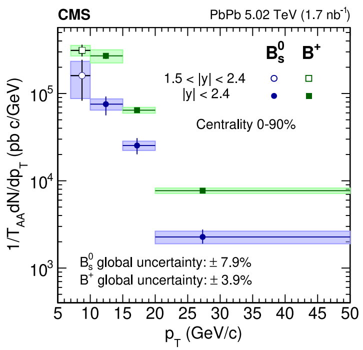
  - But $\varepsilon_{i,j}(p_{\mathrm{T}}, y)$ is too different from normal distribution
- Use inverse efficiency

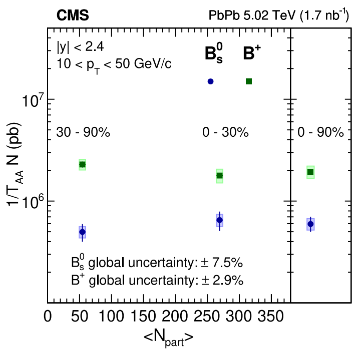
$$\frac{1}{\varepsilon} = \sum_{i,j}^{N_i,N_j} \frac{\frac{1}{\varepsilon_{i,j}(p_{\mathrm{T}}, y)} n_i(p_{\mathrm{T}}) n_j(y)}{n_i(p_{\mathrm{T}}) n_j(y)}$$

B_s^0 and B^+ yields

yield vs p_T



yield vs centrality



$T_{AA} = \frac{N_{coll}}{\sigma_{NN}^{inel}}$ effective nucleon luminosity

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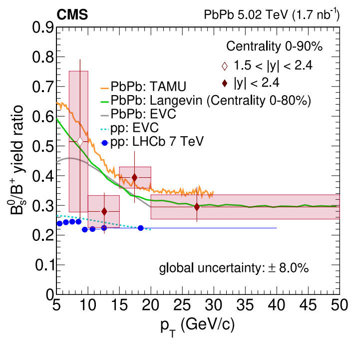
- Enhanced yields in PbPb at low p_T and high centrality
- Dominant uncertainty:
  - Data/MC disagreement on selection variables (BDT score)
  - Tracking efficiency

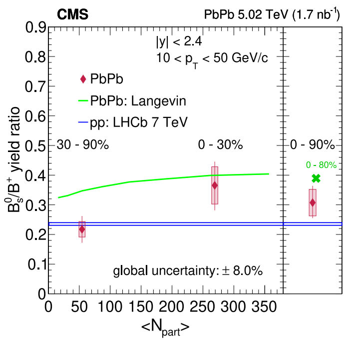
B_s^0/B^+ yield ratio

B_s^0/B^+ vs p_T



- Compatible with PbPb recombination models
- Compatible with pp data

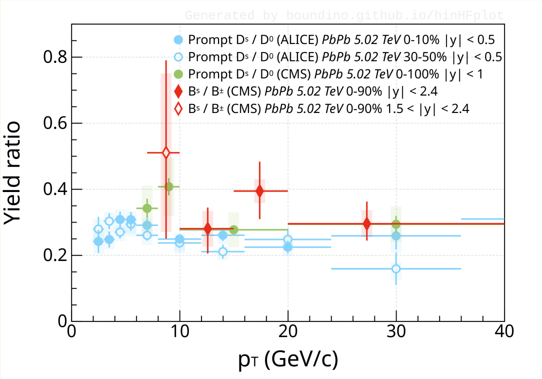
B_s^0/B^+ vs centrality



both plots: PLB 829 (2022) 137062

- Indicate higher B_s^0/B^+ ratio in central events but not significant

B_s^0/B^+ yield ratio compared with charm



arXiv:2109.01908

CMS-PAS-HIN-18-017

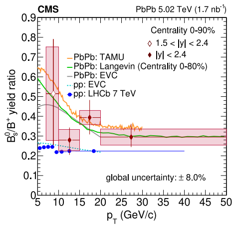
PLB 827 (2022) 13698

- Similar magnitudes of D_s/D^0 and B_s^0/B^+

Summary

Updated B_s^0/B^+ ratio with the 2018 CMS data

- First observation of $B_s^0 > 5\sigma$ in PbPb collision
- Enhancement at low p_T but not significant with the current precision



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Outlook

- Update with 2017 pp data at the LHC coming soon $\rightarrow R_{AA}$ measurement
- New PbPb run at the end of this year

The MIT group's work was supported by US DOE-NP

Backup

Muon selection for B^+ / B_s^0

- $p_T^\mu > 3.5$ for $|\eta^\mu| < 1.2$
- $p_T^\mu > 1.5$ for $2.1 < |\eta^\mu| < 2.4$
- $p_T^\mu > (5.47 - 1.89|\eta^\mu|)$ for $1.2 < |\eta^\mu| < 2.1$
- $m_{\mu^-\mu^+}$ in J/ψ or ϕ range
- Probability of 2μ fitted to a common vertex

Systematic uncertainty for B^+/B_s^0

- Due to fit modeling
  - Signal variation: 3-Gaussian, 10% variation of its width, fixing common mean to MC
  - Background variation: low-order polynomial for combinatorial background
  - Estimated with squared sum of maximum variations
- Due to limited MC sample size
  - 1000 generated $\alpha \times \varepsilon$ 2D maps
  - Estimated with the width of the $1/\langle \alpha \times \varepsilon \rangle$
- Due to data/MC discrepancy
  - Data/MC ratio from sPlot method are used to re-weight the MC distribution

B_s^0/B^+ systematic uncertainty

	B^+			B_s^0		
Centrality class	0–30%	30–90%	0–90%	0–30%	30–90%	0–90%
Muon efficiency	$^{+4.2}_{-3.8}$	$^{+4.1}_{-3.8}$	$^{+4.2}_{-3.8}$	$^{+5.5}_{-4.9}$	$^{+4.6}_{-4.2}$	$^{+5.3}_{-4.7}$
Data/MC agreement	13	8.0	12	3.1	3.7	3.2
MC sample size	3.2	2.2	2.4	6.6	2.3	4.4
Fit modeling	2.5	2.8	2.6	2.5	3.2	2.3
Tracking efficiency	5.0	5.0	5.0	10	10	10
T_{AA}	2.0	3.6	2.2	2.0	3.6	2.2
N_{MB}	1.3	1.3	1.3	1.3	1.3	1.3
Branching fraction		2.9			7.5	

- Data/MC disagreement from reweighted $\alpha \times \varepsilon$ using the sPlot method

B_s^0/B^+ production yield calculation

$$\frac{1}{T_{AA}}\frac{\mathrm{d}N}{\mathrm{d}p_{\mathrm{T}}} = \frac{1}{2\mathcal{B}N_{\mathrm{MB}}T_{AA}}\frac{N_{\mathrm{obs}}(p_{\mathrm{T}})}{\Delta p_{\mathrm{T}}} \times \left\langle \frac{1}{\alpha(p_{\mathrm{T}},y)\times\varepsilon(p_{\mathrm{T}},y)} \right\rangle$$

- 1/2: raw yield measured with particles and antiparticles
- $T_{AA} = (5.6 \pm 0.2)\,\mathrm{mb}^{-1}$
- Acceptance and efficiency corrected using a fine (p_{T}, y) 2D map
- Efficiency map corrected by data/MC scale factors with *tag-and-probe* (with J/ψ)