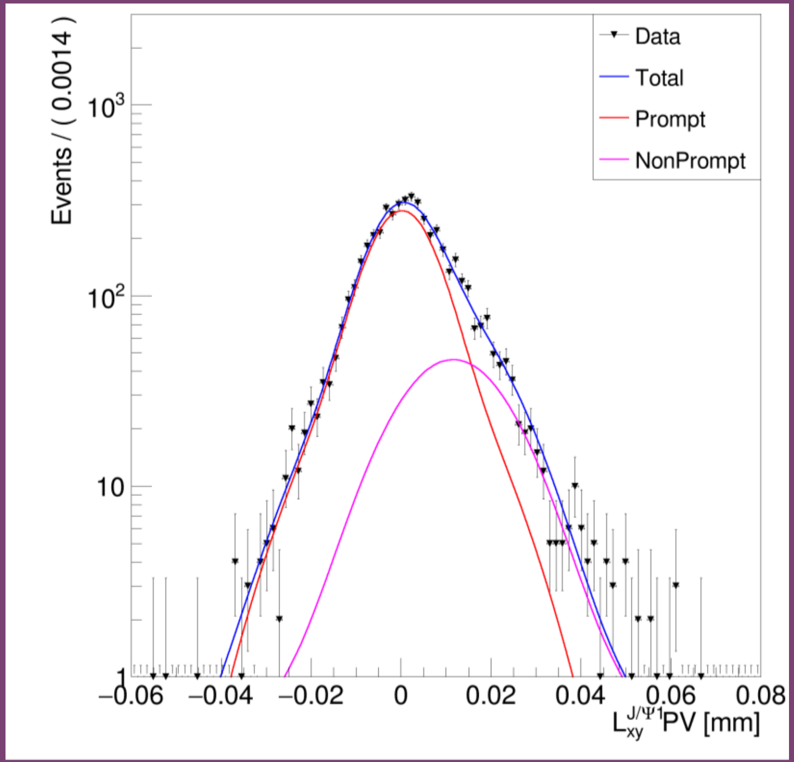
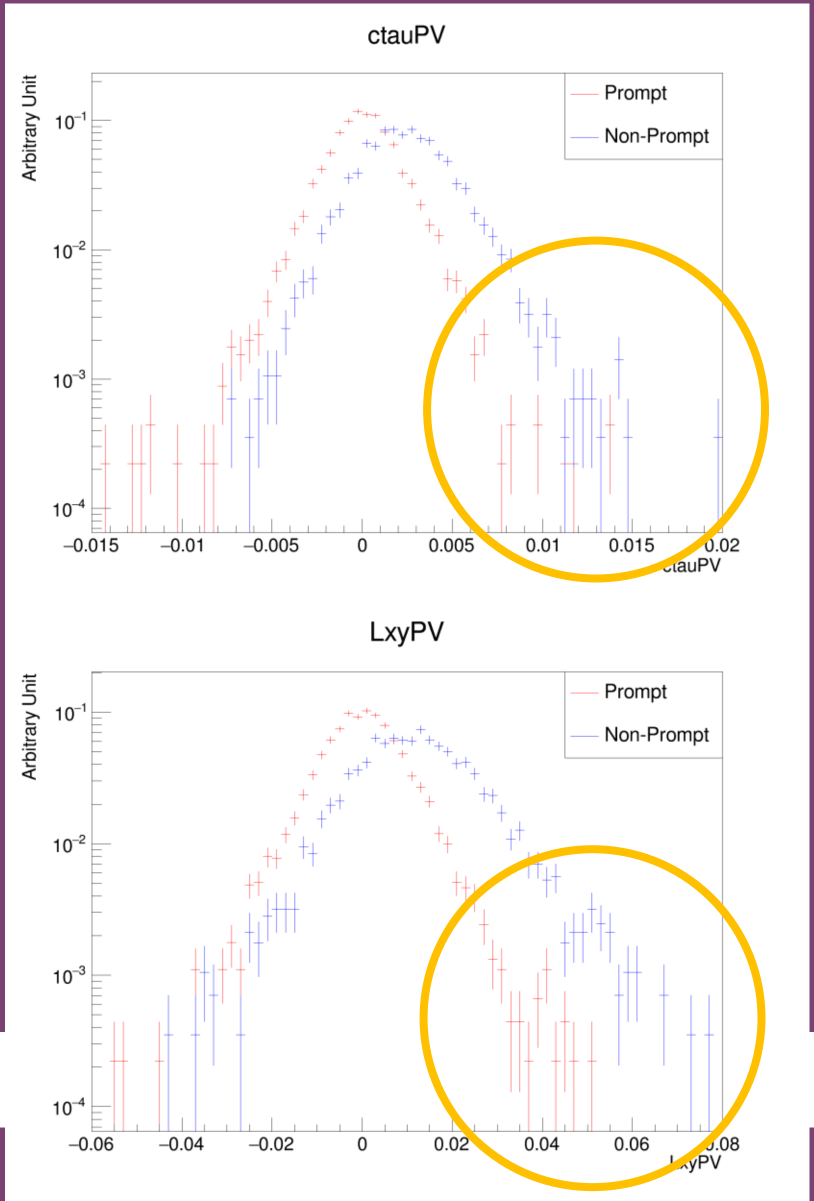
Review of the last week...



$L_{xy}PV$

- **The mean value will be used as the distinguishment**
  - PDF for the prompt component would be double Gaus
  - PDF for the non-prompt component would be double double-side CB (DSCB)
- **Need to decide which variable($c\tau/L_{xy}$) to be used**
- **Need to develop the 3D fitting code**

The variable of the third dimension



- Normalized the histograms to compare the shape
- A more obvious tail can be noticed for $L_{xy}PV$
- Propose to use $L_{xy}PV$ as the variable for the third dimension

Update to the PDF of the third dimension

Prompt: $f_1 \times Gaus_{11}(d_1, \sigma_{11}) + (1 - f_1) \times Gaus_{12}(d_1, \sigma_{12})$

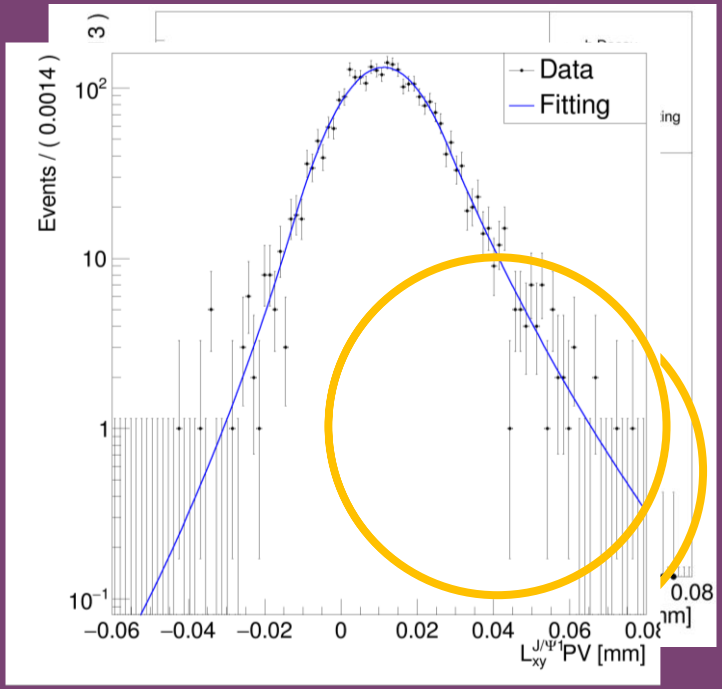
Non-prompt: $f_2 \times Gaus_{21}(d_2, \sigma_{21}) + (1 - f_2) \times Gaus_{22}(d_2, \sigma_{22})$

Non-prompt: $f_2 \times DSCB_1(d_2, \sigma_{21}, \alpha_L, n_L, \alpha_R, n_R) + (1 - f_2) \times DSCB_1(d_2, \sigma_{22}, \alpha_L, n_L, \alpha_R, n_R)$

The tail on the right side can be described better

d_2	σ_{21}	σ_{22}	α_L	n_L	α_R	n_R	f_2
$(1.112 \pm 0.003) \times 10^{-2}$	$(1.15 \pm 0.06) \times 10^{-2}$	$(1.15 \pm 0.12) \times 10^{-2}$	2.024 ± 0.018	10.0 ± 0.3	1.423 ± 0.008	10.00 ± 0.06	0.6 ± 0.5

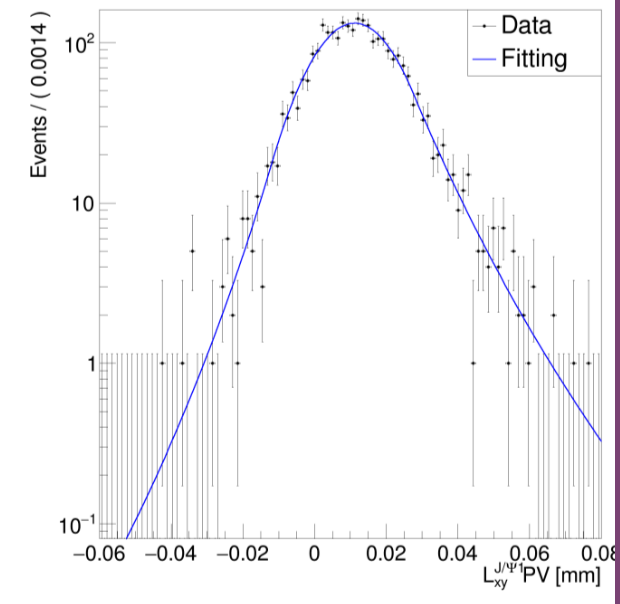
- 'n' would be fixed to 10
- Would use single DSCB

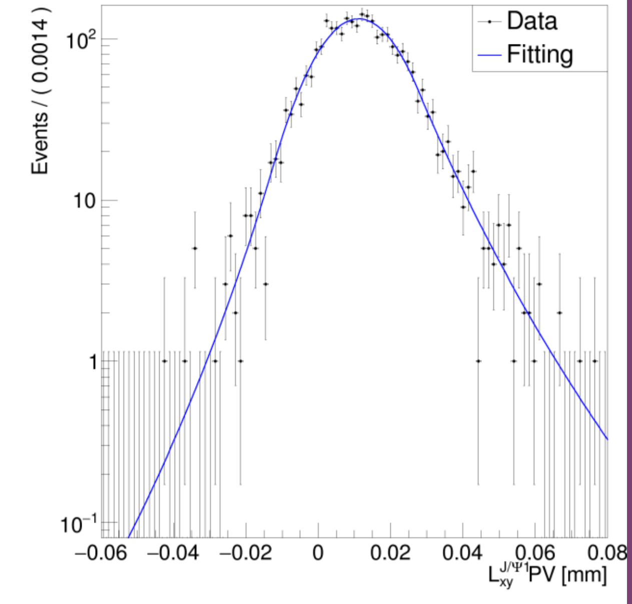


Update to the PDF of the third dimension

Non-prompt: $f_2 \times DSCB_1(d_2, \sigma_{21}, \alpha_L, n_L, \alpha_R, n_R) + (1 - f_2) \times DSCB_1(d_2, \sigma_{22}, \alpha_L, n_L, \alpha_R, n_R)$

Non-prompt: $DSCB(d_2, \sigma_2, \alpha_L, n_L(10), \alpha_R, n_R(10))$





NLL	Double DSCB	Single DSCB
2018	-8289.59	-8289.59
2017	-5166.15	-5166.15
2016	-6776.16	-6775.43
2016APV	-6164.69	-6163.09

- Propose to use single DSCB to describe the non-prompt component

3D fitting code

J/ψ_1 Mass: $f_1 \times CB_{11}(\bar{m}_1, \sigma_{11}, \alpha, n) + (1 - f_1) \times CB_{12}(\bar{m}_1, \sigma_{12}, \alpha, n)$

J/ψ_2 Mass: $f_2 \times CB_{21}(\bar{m}_2, \sigma_{21}, \alpha, n) + (1 - f_2) \times CB_{12}(\bar{m}_2, \sigma_{22}, \alpha, n)$

All parameters float

$L_{xy}PV$: $f_3 \times Gaus_1(d_1, \sigma_{11}) + (1 - f_3) \times Gaus_2(d_1, \sigma_{12}) +$
$DSCB(d_2, \sigma_2, \alpha_L, n_L(10), \alpha_R, n_R(10))$

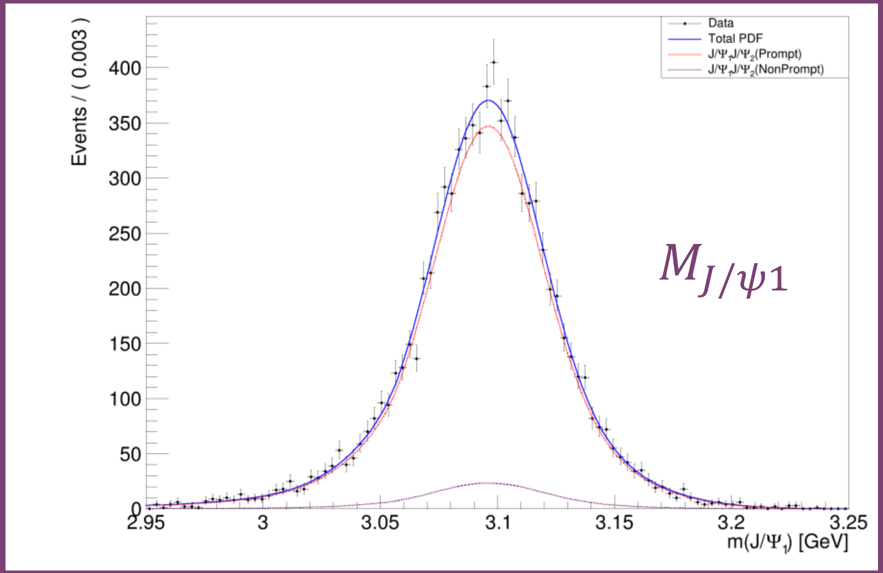
All parameters fixed

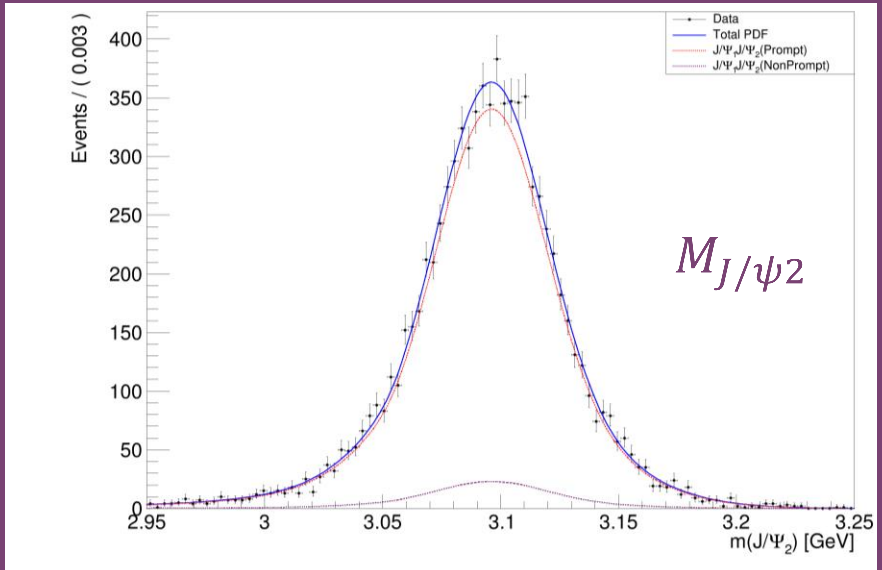
(Parameters for the prompt PDF is the average of SPS and DPS)

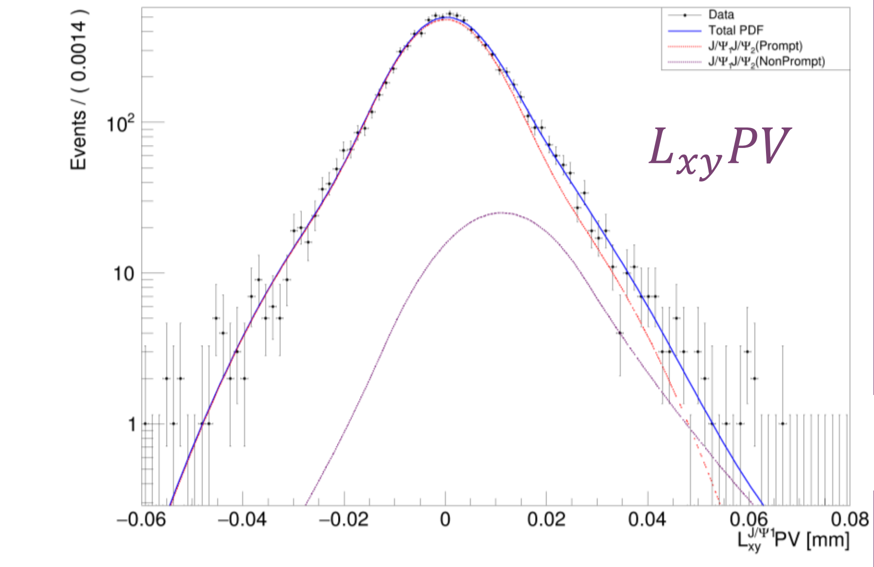
2018	DPS	SPS
σ_{11}	0.0070 ± 0.0003	0.00880 ± 0.00016

- The Chebchev in the mass dimension to describe the combinatorial background was not added for now, which may cause some problems
- Several mixed sample(2018, SPS, DPS ,b decay) was made to test the code

3D fitting code







- The fitting quality is satisfying!

3D fitting code

From sample	SPS	4000	4000	8000	16000	20000	2000	2000
	DPS	4000	4000	4000	4000	4000	4000	8000
	Prompt	8000	8000	12000	20000	24000	6000	10000
	Non-Prompt	2000	500	2000	2000	1000	2000	2000
From Fitting	Prompt	8010 ± 120	7950 ± 110	11770 ± 140	19320 ± 180	23100 ± 190	6090 ± 110	10280 ± 130
	Non-Prompt	1980 ± 100	540 ± 70	2210 ± 110	2650 ± 130	1910 ± 130	1900 ± 90	1700 ± 100

- Great discrepancies can be observed when the SPS/DPS fraction is not 1:1
- May come from the width difference between two samples

Another update to the PDF of the third dimension

Non-prompt: $DSCB(d_2, \sigma_2, \alpha_L, n_L(10), \alpha_R, n_R(10))$

Prompt: $f \times Gaus_1(d_1, \sigma_{11}) + (1-f) \times Gaus_2(d_1, \sigma_{12})$

Prompt: $f \times Gaus_{SPS1}(d_1, \sigma_{SPS1}) + (1-f) \times Gaus_{SPS2}(d_1, \sigma_{SPS2}) + f \times Gaus_{DPS1}(d_1, \sigma_{DPS1}) + (1-f) \times Gaus_{DPS2}(d_1, \sigma_{DPS2})$

(f and d_1 are the average values of SPS and DPS)

J/ψ_1 Mass: $f_1 \times CB_{11}(\bar{m}_1, \sigma_{11}, \alpha, n) + (1-f_1) \times CB_{12}(\bar{m}_1, \sigma_{12}, \alpha, n)$

J/ψ_2 Mass: $f_2 \times CB_{21}(\bar{m}_2, \sigma_{21}, \alpha, n) + (1-f_2) \times CB_{12}(\bar{m}_2, \sigma_{22}, \alpha, n)$

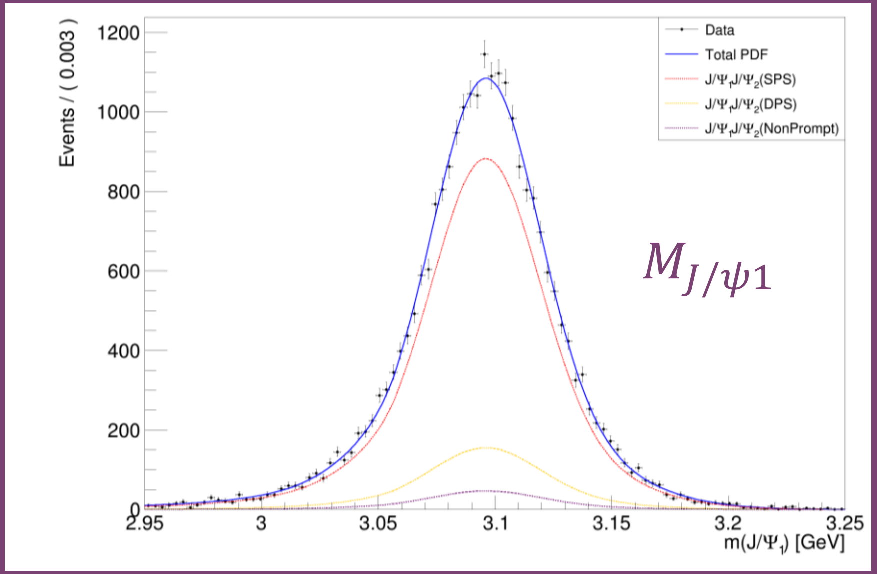
Float parameters

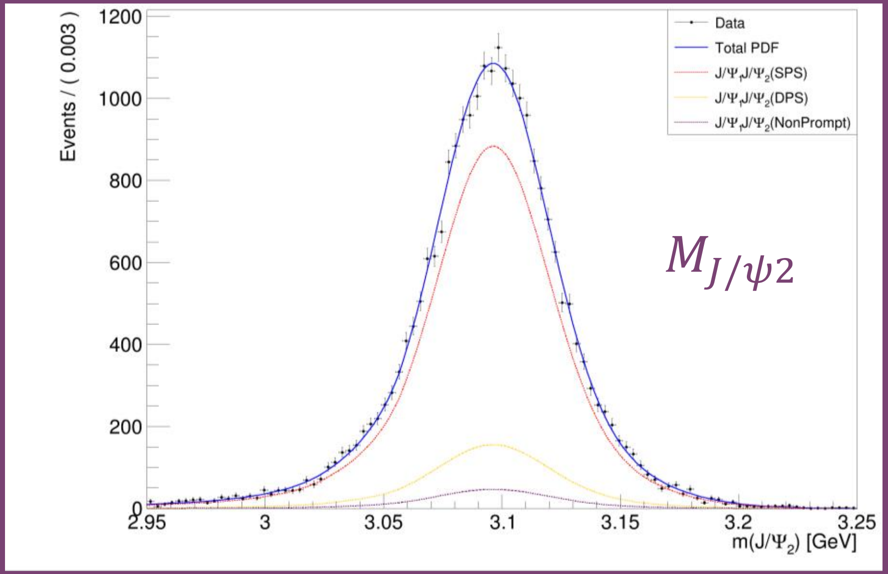
$L_{xy}PV$: $f_3 \times Gaus_{SPS1}(d_1, \sigma_{SPS1}) + (1-f_3) \times Gaus_{SPS2}(d_1, \sigma_{SPS2}) + f_3 \times Gaus_{DPS1}(d_1, \sigma_{DPS1}) + (1-f_3) \times Gaus_{SPS2}(d_1, \sigma_{DPS2})$

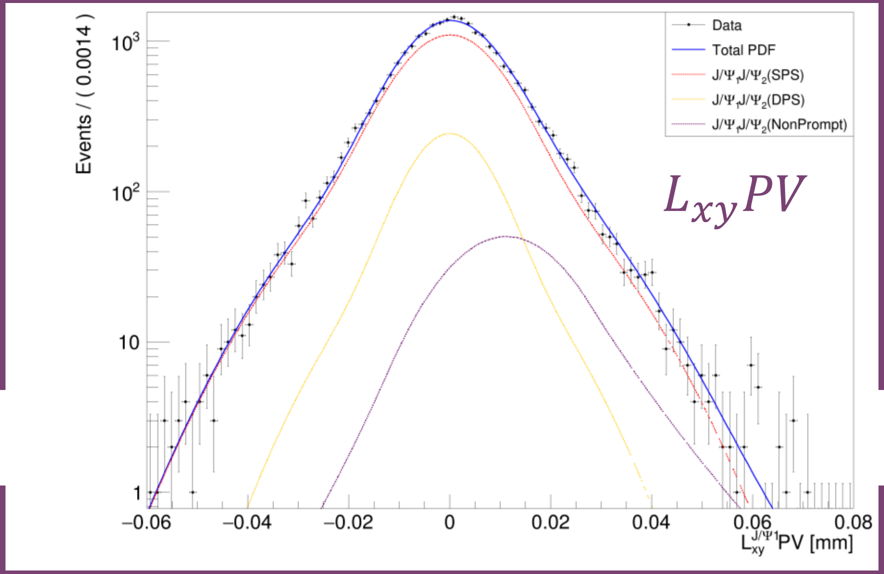
$DSCB(d_2, \sigma_2, \alpha_L, n_L(10), \alpha_R, n_R(10))$

Fixed parameters

3D fitting code







- The fitting quality is satisfying!

3D fitting code

From sample	SPS	4000	4000	8000	16000	20000	2000	2000
	DPS	4000	4000	4000	4000	4000	4000	8000
	Prompt	8000	8000	12000	20000	24000	6000	10000
	Non-Prompt	2000	500	2000	2000	1000	2000	2000
From Fitting	SPS	3900 ± 400	3900 ± 400	8000 ± 600	16100 ± 700	20300 ± 800	1900 ± 400	1500 ± 500
	DPS	4100 ± 400	4100 ± 400	4000 ± 500	3800 ± 700	3600 ± 700	4100 ± 400	8400 ± 400
	Prompt	8000 ± 600	8000 ± 600	12000 ± 800	20000 ± 1000	23900 ± 1100	6000 ± 500	9900 ± 600
	Non-Prompt	2000 ± 100	540 ± 80	2000 ± 120	2000 ± 150	1080 ± 150	2000 ± 100	2040 ± 100

Discrepancies are much smaller, but the statistic uncertainties are much larger

Summary

- **Propose to use $L_{xy}PV$ as the variable for the third dimension**
  - More significant tail can be observed
- **Propose to use single double-side CB for the non-prompt component in the third dimension**
  - Similar NLL but less parameters
- **Propose to use two separate PDF to describe SPS and DPS in the third dimension**
  - Much less discrepancies in the number of events
  - Larger uncertainty although
- **The 3D fit code is ready**

Back Up

Compare between the two tables

From sample	SPS	4000	4000	8000	16000	20000	2000	2000
	DPS	4000	4000	4000	4000	4000	4000	8000
	Prompt	8000	8000	12000	20000	16000	6000	10000
	Non-Prompt	2000	500	2000	2000	1000	2000	2000
Merged SPS/DPS	Prompt	8010 ± 120	7950 ± 110	11770 ± 140	19320 ± 180	23100 ± 190	6090 ± 110	10280 ± 130
	Non-Prompt	1980 ± 100	540 ± 70	2210 ± 110	2650 ± 130	1910 ± 130	1900 ± 90	1700 ± 100
Separate SPS/DPS	SPS	3900 ± 400	3900 ± 400	8000 ± 600	16100 ± 700	20300 ± 800	1900 ± 400	1500 ± 500
	DPS	4100 ± 400	4100 ± 400	4000 ± 500	3800 ± 700	3600 ± 700	4100 ± 400	8400 ± 400
	Prompt	8000 ± 600	8000 ± 600	12000 ± 800	20000 ± 1000	23900 ± 1100	6000 ± 500	9900 ± 600
	Non-Prompt	2000 ± 100	540 ± 80	2000 ± 120	2000 ± 150	1080 ± 150	2000 ± 100	2040 ± 100

- The SPS and DPS PDF share the same mean value and fraction value (average of SPS/DPS)

Compare between the two tables

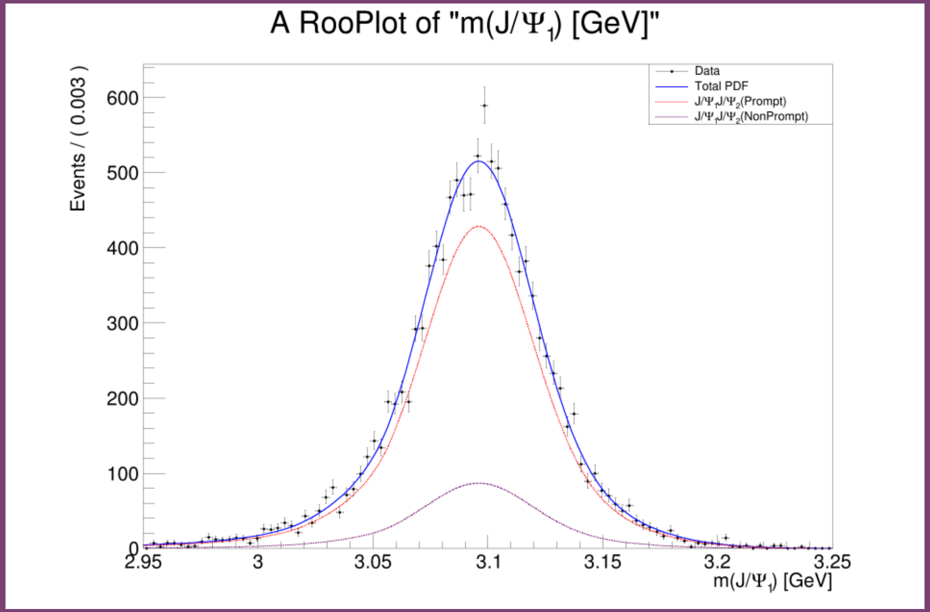
From sample	SPS	4000	4000	8000	16000	20000	2000	2000
	DPS	4000	4000	4000	4000	4000	4000	8000
	Prompt	8000	8000	12000	20000	16000	6000	10000
	Non-Prompt	2000	500	2000	2000	1000	2000	2000
Same mean and fraction (SPS/DPS)	SPS	3900 ± 400	3900 ± 400	8000 ± 600	16100 ± 700	20300 ± 800	1900 ± 400	1500 ± 500
	DPS	4100 ± 400	4100 ± 400	4000 ± 500	3800 ± 700	3600 ± 700	4100 ± 400	8400 ± 400
	Prompt	8000 ± 600	8000 ± 600	12000 ± 800	20000 ± 1000	23900 ± 1100	6000 ± 500	9900 ± 600
	Non-Prompt	2000 ± 100	540 ± 80	2000 ± 120	2000 ± 150	1080 ± 150	2000 ± 100	2040 ± 100
Different mean and fraction (SPS/DPS)	SPS	3900 ± 400	3900 ± 400	7700 ± 500	15200 ± 600	19100 ± 700	2000 ± 300	2000 ± 400
	DPS	4100 ± 400	4100 ± 400	4300 ± 400	4600 ± 600	4800 ± 600	4000 ± 300	8000 ± 400
	Prompt	8000 ± 500	8000 ± 500	12000 ± 700	19900 ± 900	23900 ± 900	6000 ± 400	10000 ± 500
	Non-Prompt	2000 ± 100	530 ± 80	2030 ± 120	2090 ± 140	1150 ± 150	1990 ± 90	2000 ± 100

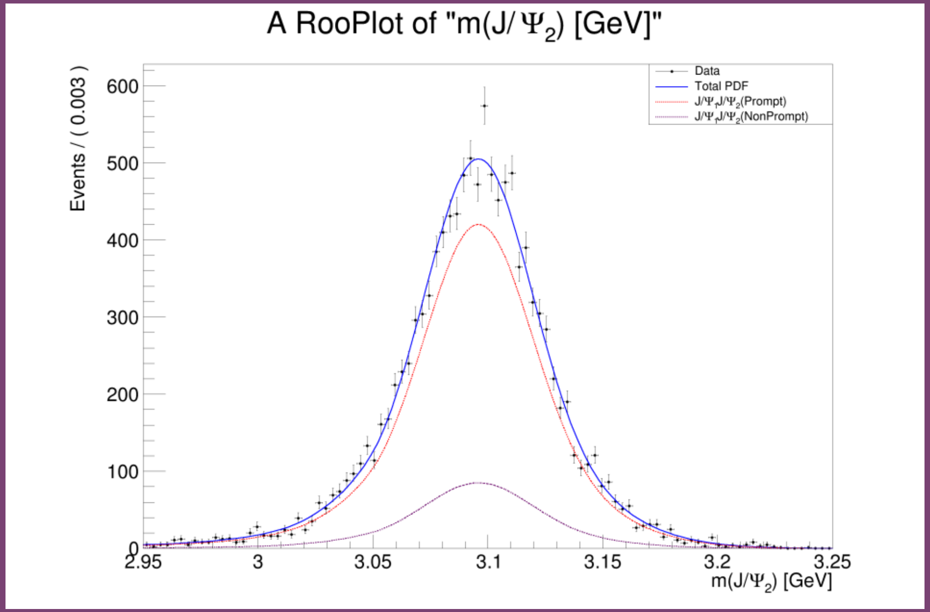
- Smaller uncertainty can be observed if separate mean value and fraction value are applied, although sometimes the discrepancies can be large

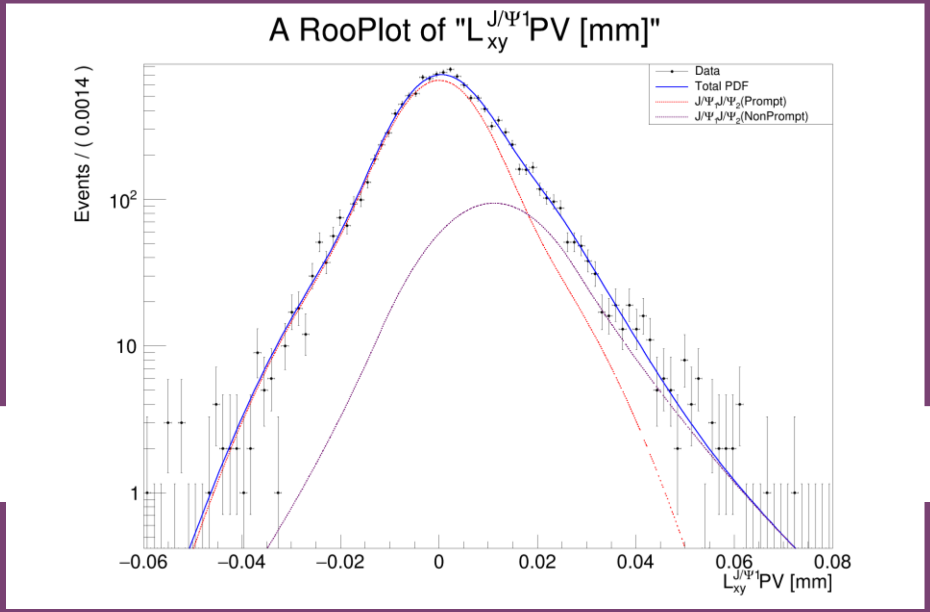
Weighted average for the prompt PDF

- Another method was tried to fix the incorrect prompt component number caused by the different width between SPS and DPS
- There is no difference in PDF form between the two methods, width is the only thing get modified
- In the old method, the width was the average of SPS and DPS. We now tried to use weighted average, the weight came from the fraction of the SPS/DPS in the sample (e.g. there are 20K SPS and 4K DPS in the sample, the weighted average is: $\sigma = (5\sigma_{SPS} + \sigma_{DPS})/6$)
- Two samples were used for the test

Weighted average for the prompt PDF







Weighted average for the prompt PDF

From sample	SPS	16000	2000	16000	16000
	DPS	4000	8000	4000	4000
	Prompt	20000	10000	20000	20000
	Non-Prompt	2000	2000	2000	2000
From Fitting	Prompt	19910 ± 190	9970 ± 130	19800 ± 190	19970 ± 190
	Non-Prompt	2060 ± 130	540 ± 70	2170 ± 130	2000 ± 130

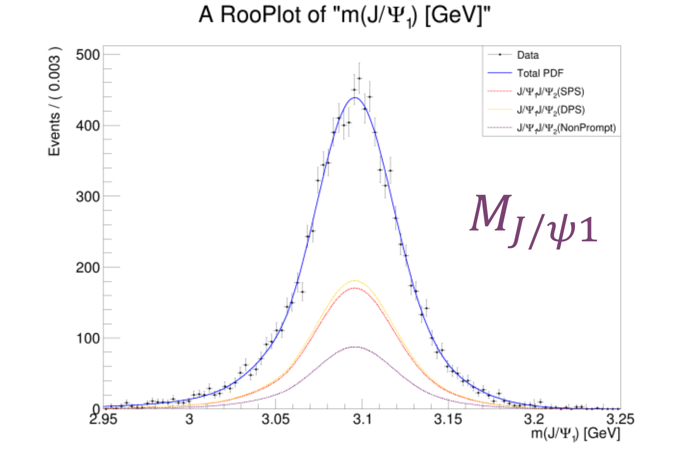
- We tested the robustness by using wrong weight (4:1)

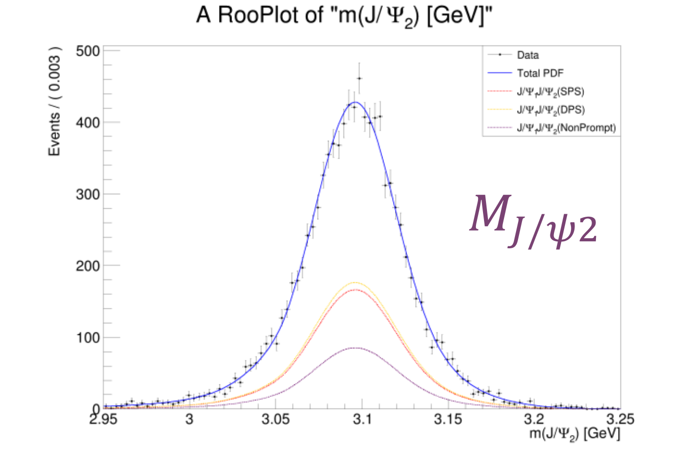
3:1

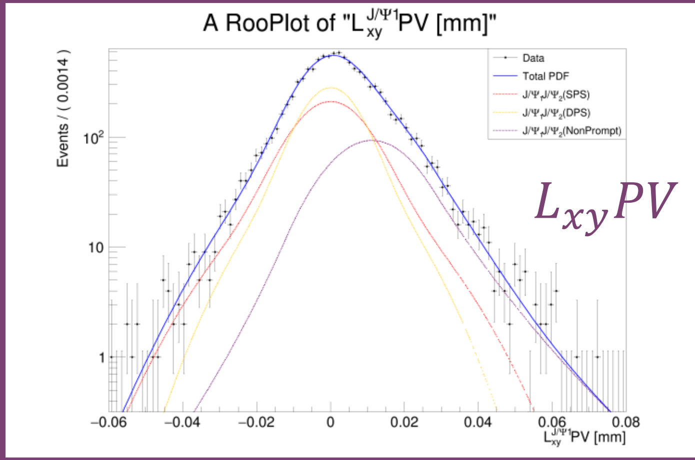
5:1

- Compare to the old method (merged SPS/DPS with average width), this method has much less error in the number
- Compare to the separate SPS/DPS, this method has much less uncertainties
- The most significant drawback of this method is that we need to estimate the fraction of SPS/DPS before the fitting is applies, which may be impossible for the data sample

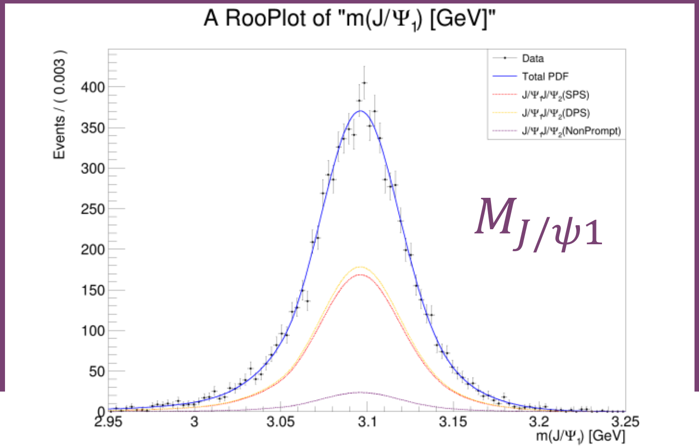
Fitting plot of all the mixed samples

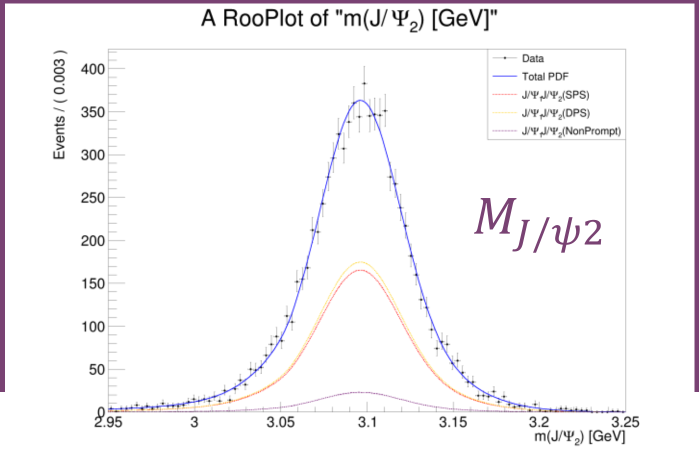


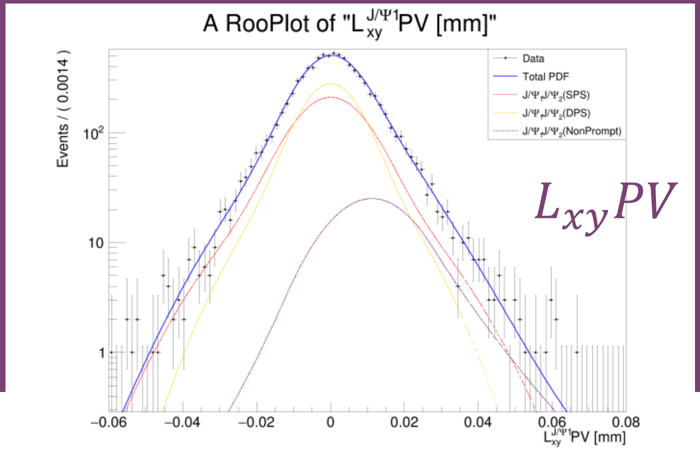




SPS : DPS : b = 4K : 4K : 2K

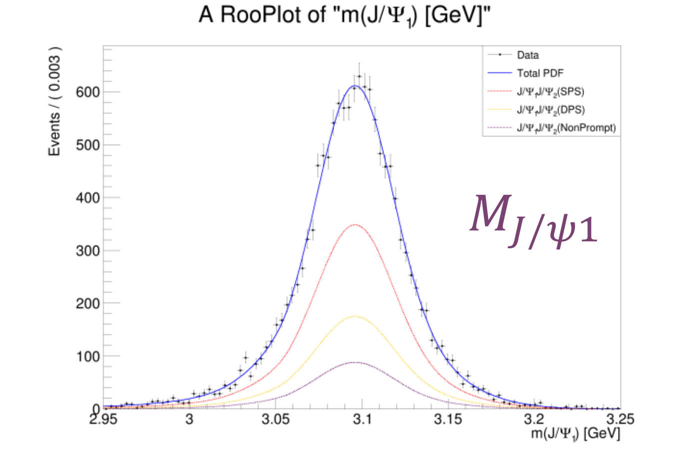


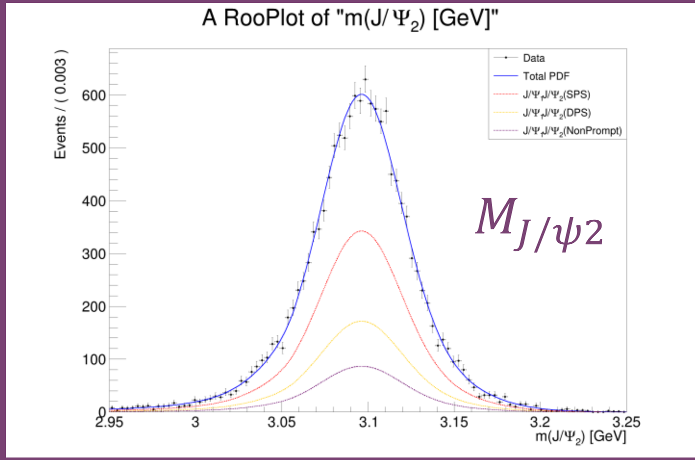


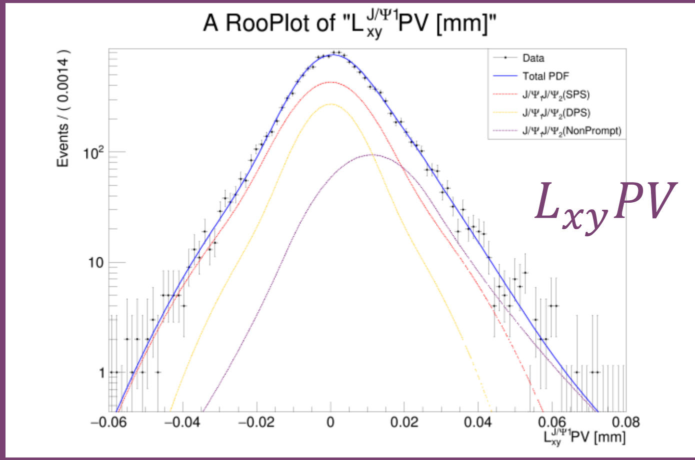


SPS : DPS : b = 4K : 4K : 500

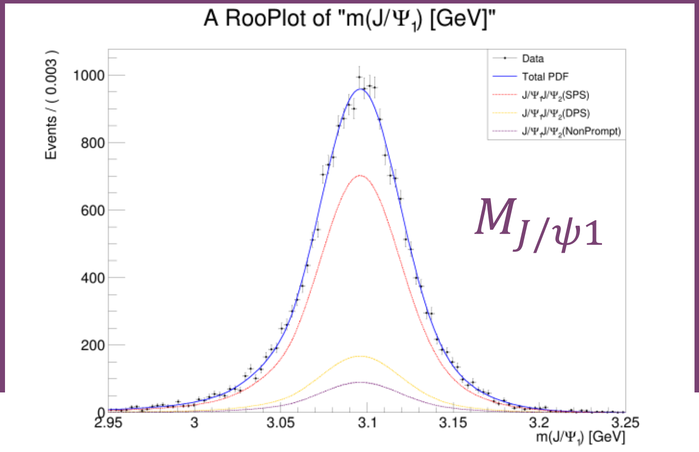
Fitting plot of all the mixed samples

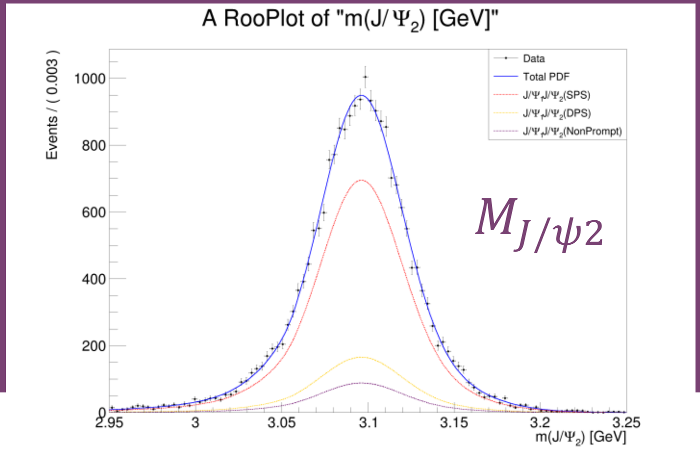


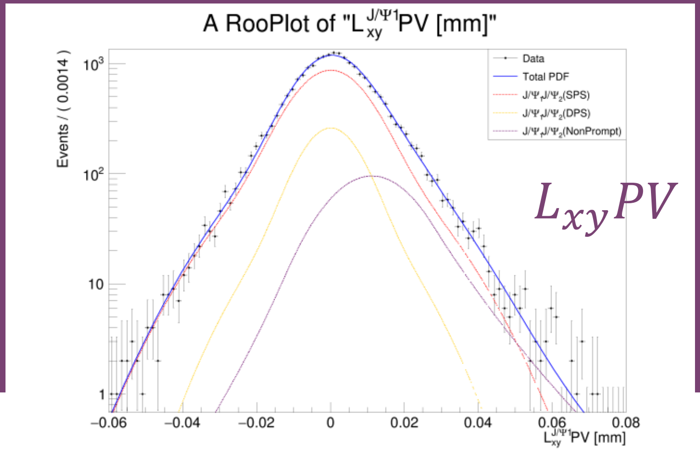




$SPS : DPS : b = 8K : 4K : 2K$

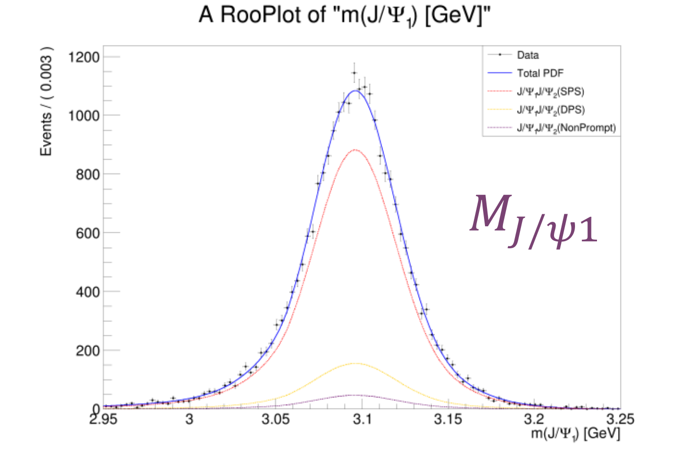


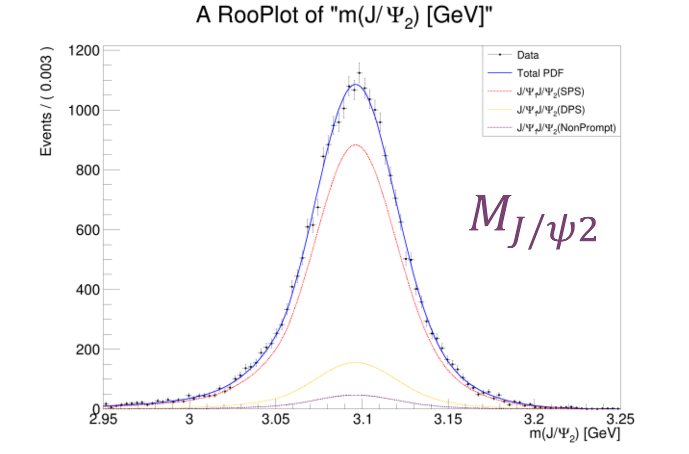


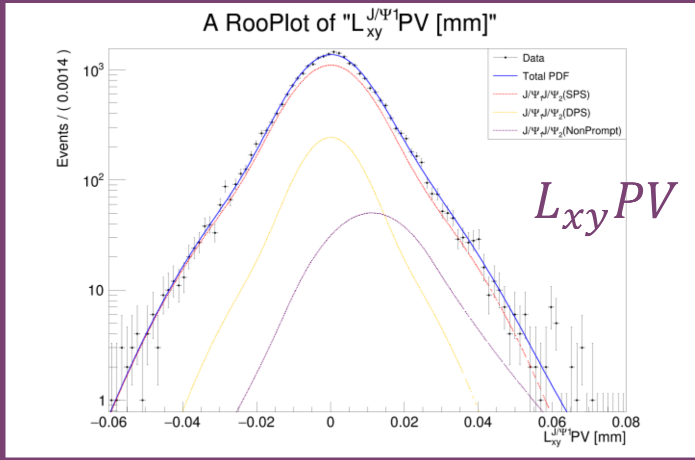


$SPS : DPS : b = 16K : 4K : 2K$

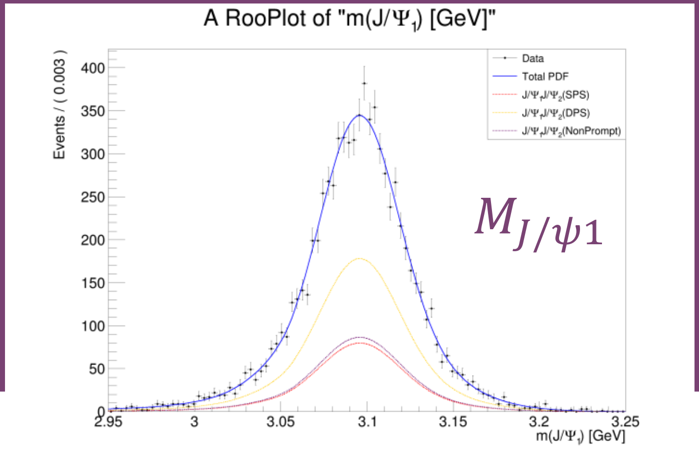
Fitting plot of all the samples

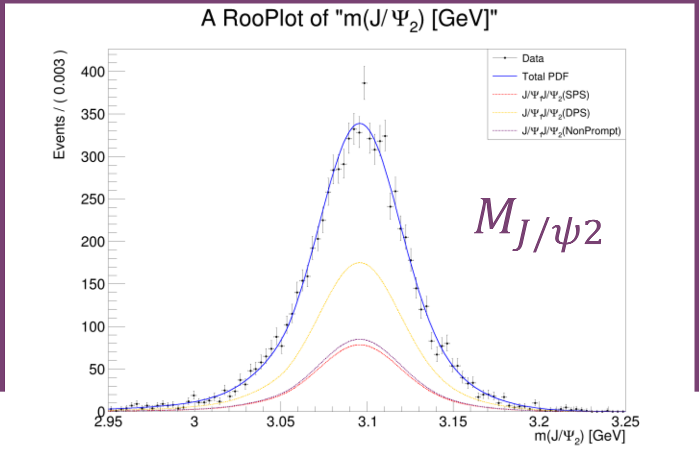


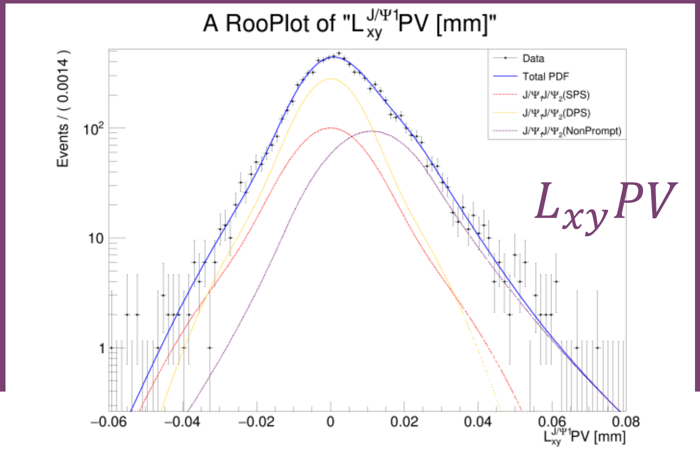




SPS : DPS : b = 20K : 4K : 1K

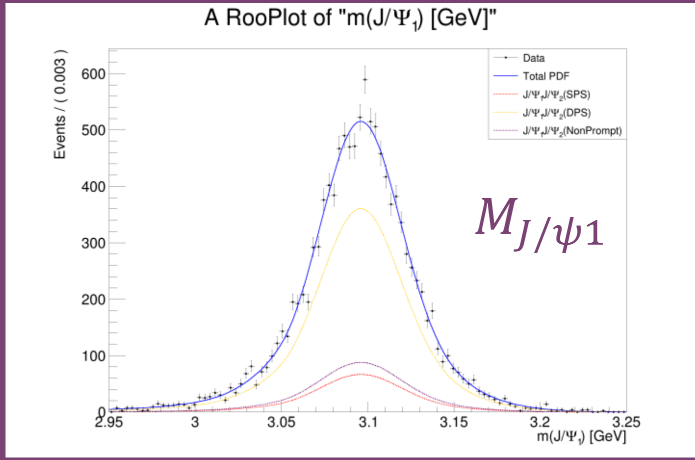


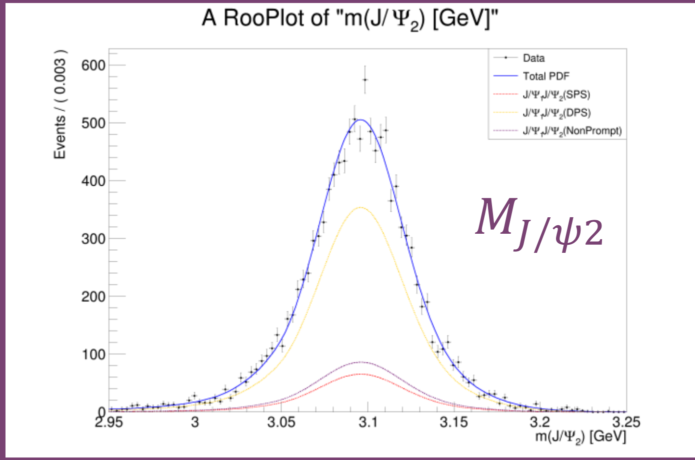


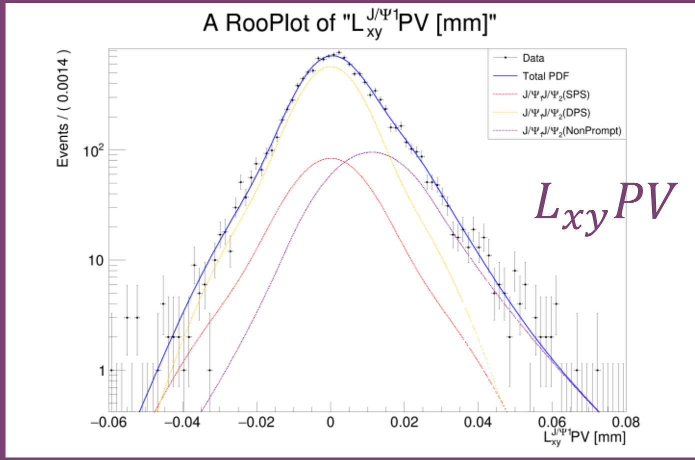


SPS : DPS : b = 2K : 4K : 2K

Fitting plot of all the mixed samples

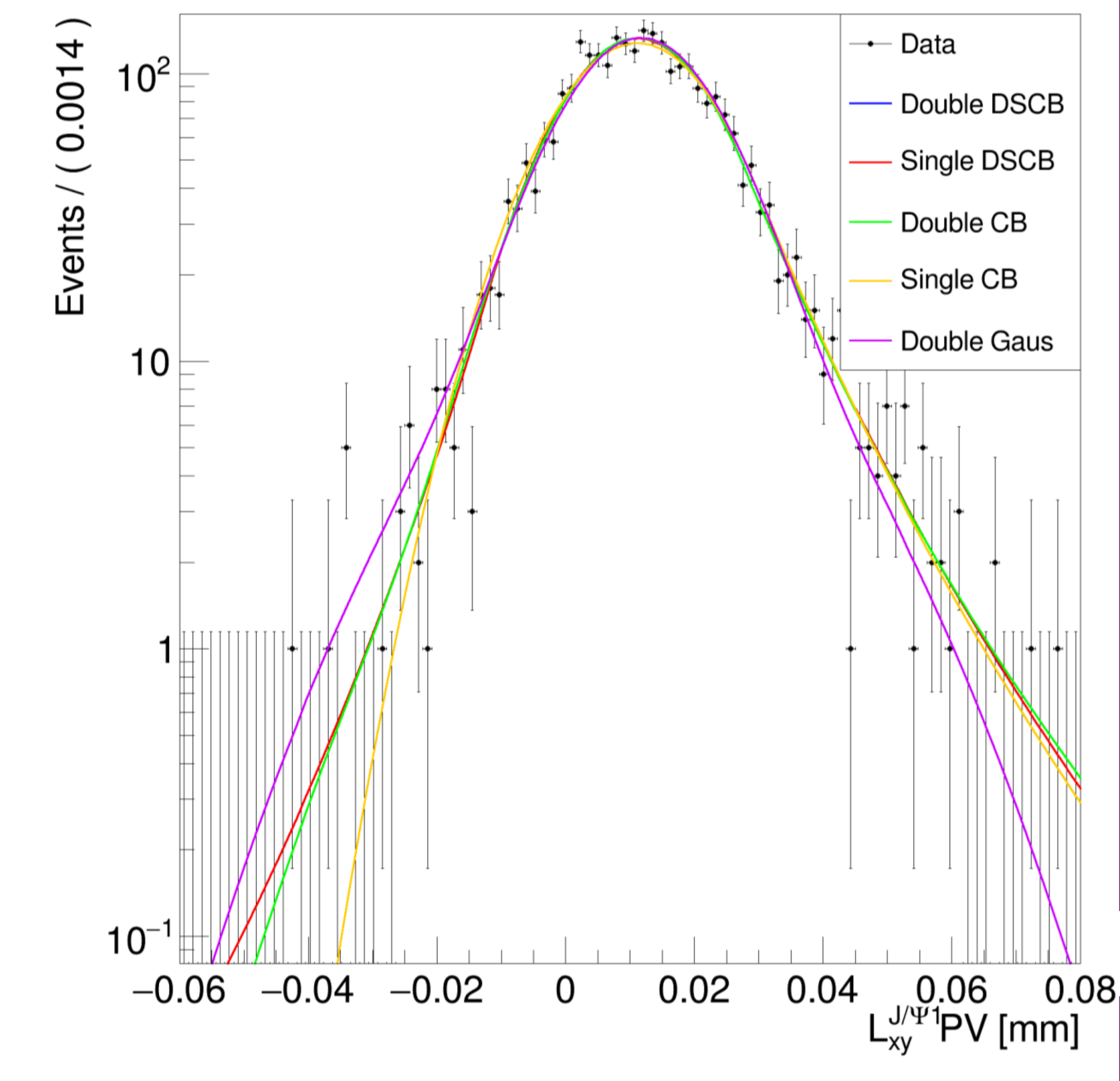






SPS : DPS : b = 2K : 8K : 2K

Different PDF for the non-prompt component



2018 sample, the double DSCB and the single DSCB overlap with each other totally

	NLL	Number of parameters
Double DSCB	-8289.59	6
Single DSCB	-8289.59	4
Double CB	-8289.09	5
Single CB	-8277.3	3
Double Gaus	-8279.13	3

Full version of the 3D fit code

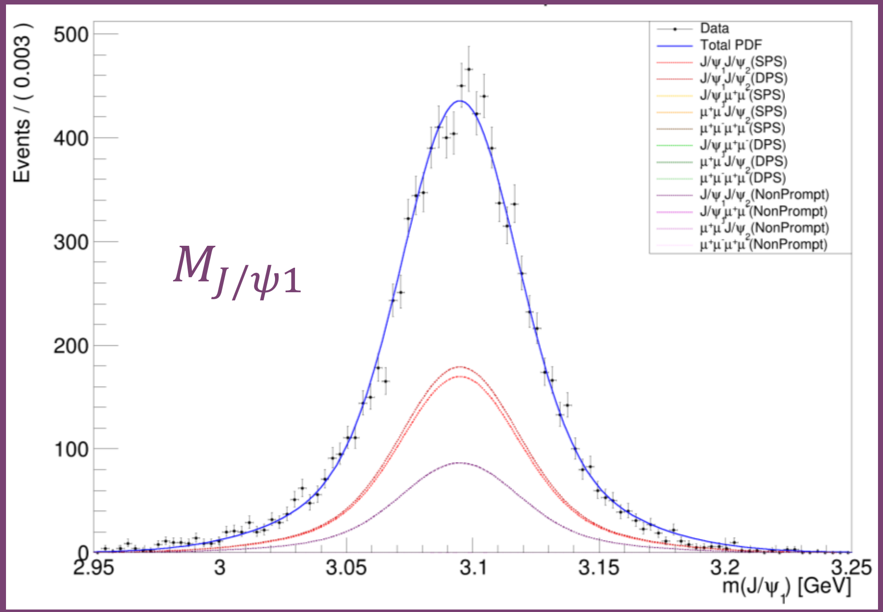
$$J/\psi_1 \text{ Mass: } f_1 \times CB_{11}(\bar{m}_1, \sigma_{11}, \alpha, n) + (1 - f_1) \times CB_{12}(\bar{m}_1, \sigma_{12}, \alpha, n) + Cheb_1(Co_{11}, Co_{12})$$

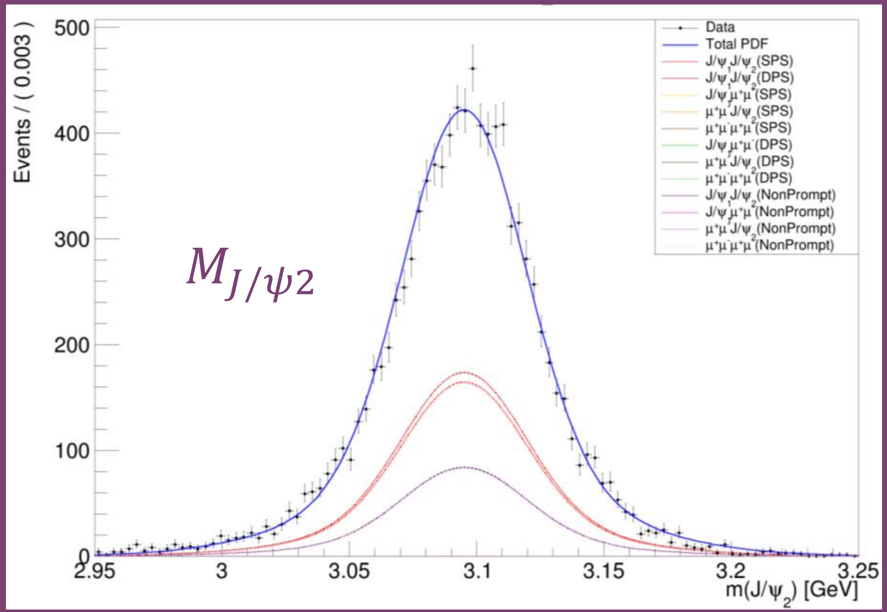
$$J/\psi_2 \text{ Mass: } f_2 \times CB_{21}(\bar{m}_2, \sigma_{21}, \alpha, n) + (1 - f_2) \times CB_{12}(\bar{m}_2, \sigma_{22}, \alpha, n) + Cheb_2(Co_{21}, Co_{22})$$

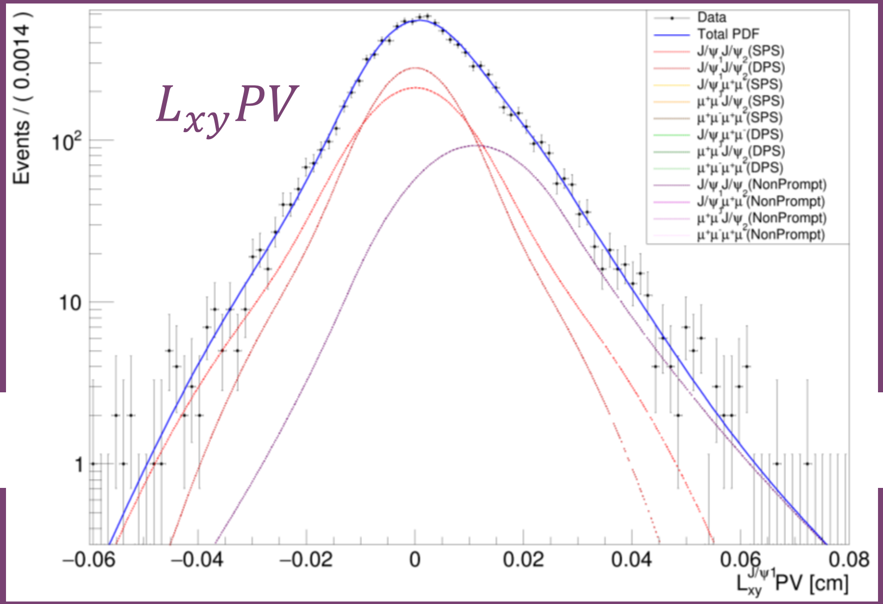
$$L_{xy}PV{:}f_3 \times Gaus_{SPS1}(d_1, \sigma_{SPS1}) + (1 - f_3) \times Gaus_{SPS2}(d_1, \sigma_{SPS2}) +$$
$$f_3 \times Gaus_{DPS1}(d_1, \sigma_{DPS1}) + (1 - f_3) \times Gaus_{SPS2}(d_1, \sigma_{DPS2}) +$$
$$DSCB(d_2, \sigma_2, \alpha_L, n_L(10), \alpha_R, n_R(10))$$

- A double CB and a second order Chebchev for each mass dimension($M_{J/\psi 1}, M_{J/\psi 2}$)
  - All parameters float (14 free parameters in total)
  - Two CB in the same dimension share the same mean value
  - Four CB in total share the same α, n
- Two double Gaussian and a double-side CB for the distance dimension($L_{xy}PV$)
  - All parameters fixed (n for the DSCB are fixed to 10)
  - All the gaussian share the same mean, and two double gaussian share the same fraction (average of SPS/DPS)
- 12 components in total
- The fitting can be extremely time consuming sometimes

Full version of the 3D fit code







Full version of the 3D fit code

From sample	SPS	4000	4000	8000	16000	20000	2000	2000
	DPS	4000	4000	4000	4000	4000	4000	8000
	Prompt	8000	8000	12000	20000	24000	6000	10000
	Non-Prompt	2000	500	2000	2000	1000	2000	2000
From Fitting (combi excluded)	SPS	3900 ± 400	3800 ± 400	8200 ± 400	16000 ± 800	20200 ± 800	4300 ± 300	9300 ± 30
	DPS	4100 ± 400	4100 ± 400	3700 ± 400	3800 ± 700	3600 ± 700	3920 ± 180	9400 ± 20
	Prompt	8000 ± 600	7900 ± 600	11900 ± 600	19900 ± 1100	23900 ± 1100	8300 ± 300	18700 ± 40
	Non-Prompt	1990 ± 100	500 ± 80	1990 ± 120	2000 ± 200	1080 ± 170	$0 \pm 7 \times 10^5$	0.62 ± 0.14

- The result can be a disaster sometimes
- In other cases, results (including the number of the combinatorial background) are reasonable