A statistics "question arising" from ATLAS' arXiv:1307.1432

Hypothesis testing versus goodness-of-fit: A statistics "meetion atsits" from ATLAS, arXiv:1907.1432

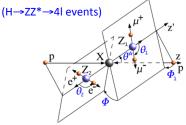
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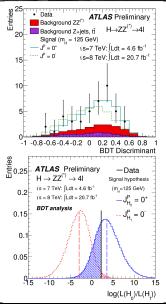
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- Sensitive variables:
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 - Four decay angles Φ_1 , Φ , θ_1 , θ_2

• Perform multivariate analysis (BDT)

Exclude $J^P=0^-$ (vs. 0⁺) with 97.8% CL

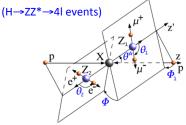


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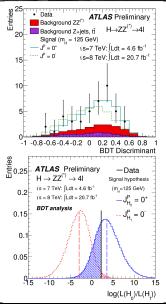
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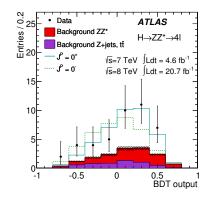
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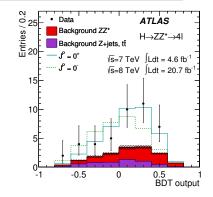
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 - hypothesis testing, which the ATLAS analysis is doing

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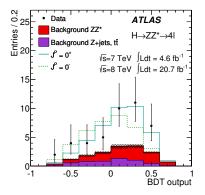
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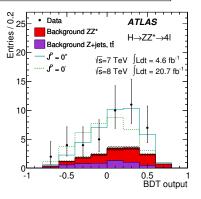
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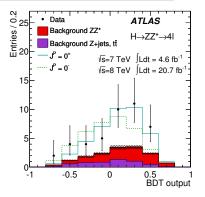


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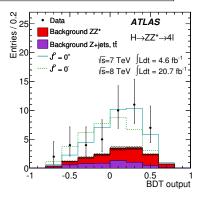
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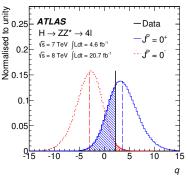
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> Vormalised to unity 0.25 0.2

> > 0.1

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ATLAS

 $H \rightarrow ZZ^* \rightarrow 4I$

√s = 7 TeV [Ldt = 4.6 fb⁻¹

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 Neyman-Pearson theorem: this gives the most powerful possible test,
 i.e. the best direction in 6D (after some nonlinear transformⁿ)

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—Data

 $-J^{P} = 0^{+}$

----J^P = 0

Hypothesis testing versus goodness-of-fit (2) A statistics investor arising from ATLAS arXiv:1507.1412

The example is simple enough that one can check the plot by eye, and calculate the result by hand (ignoring systematics)

bin	0-	0+	data	$\ln(\mathcal{L}(0^+)/\mathcal{L}(0^-))$
-0.7	1.0	0.6	2	
-0.5	3.8	2.25	4	
-0.3	6.2	4.5	4	
-0.1	7.8	7.0	5	
+0.1	8.9	10.2	10	
+0.3	6.6	10.4	11	
+0.5	3.1	5.9	7	

bin	0-	0+	data	$\ln(\mathcal{L}(0^+)/\mathcal{L}(0^-))$
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 note luck in the actual dataset obtained is a factor. are fluctuations along the privileged axis? in the right direction?

Bruce Yabsley (Sydney)

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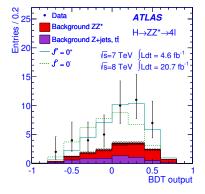
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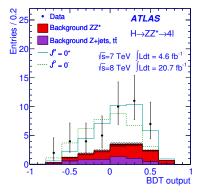
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Hypothesis testing versus goodness-of-fit (3) A statistics investion arising from ATLAS arXiv:1207.1132

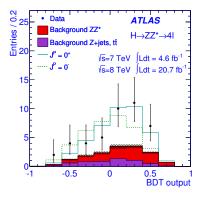
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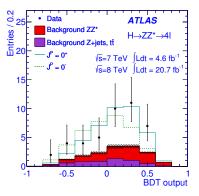
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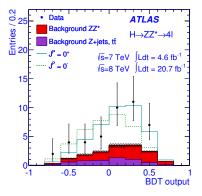
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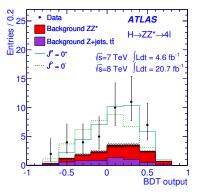
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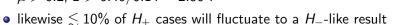


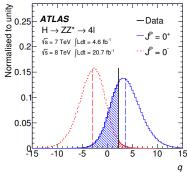
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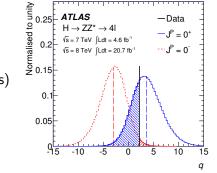


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 $H \rightarrow ZZ^* \rightarrow 4I$

-Data

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- likewise $\lesssim 10\%$ of H_+ cases will fluctuate to a H_- -like result
- *i.e.* it may be essential to be correct, but it's also important to be lucky Exercise: Show that the \mathcal{L}/\mathcal{L} technique gives an equivalent answer.

Bruce Yabsley (Sydney)

Stats: Hyp. testing vs g.o.f