LABORATÓRIO DE INSTRUMENTAÇÃO
E FÍSICA EXPERIMENTAL DE PARTÍCULAS
partículas e tecnologia

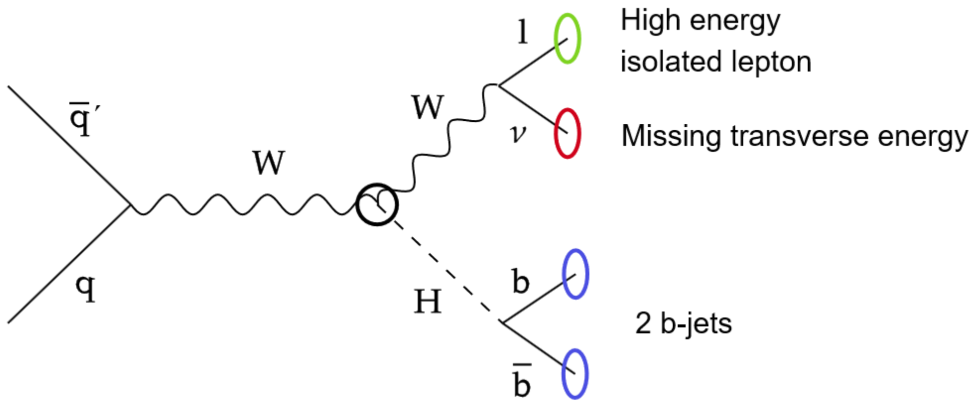
Precision measurements in pp and heavy ion collisions

Ricardo Barrué, on behalf of LIP-ATLAS group

CP violation in HWW in WH

BSM CP violation **required to explain baryonic asymmetry**

- Uncertainty on Higgs couplings can accomodate this
- Focus: HWW interaction in WH production



Ricardo Barrué, Patricia Muíño

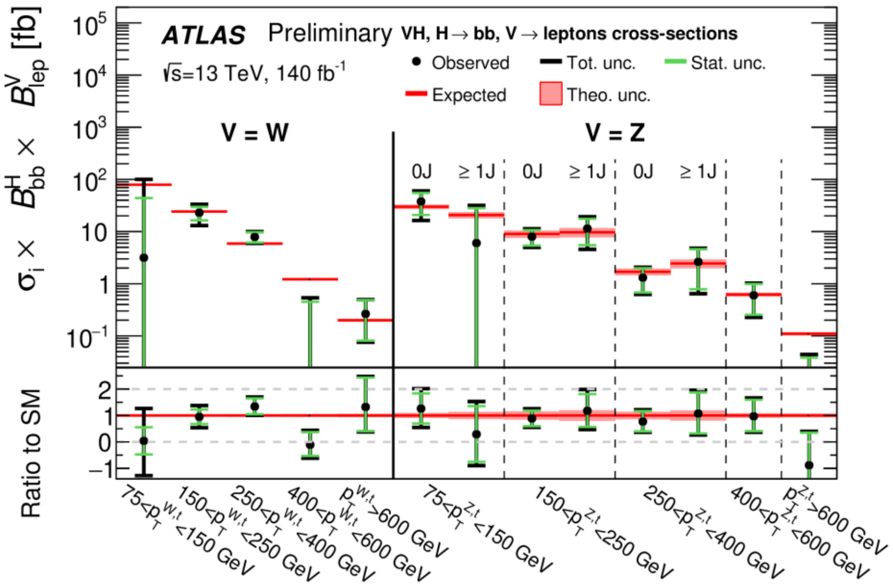
ATLAS VH “Legacy” analysis

Precision measurement of V(W/Z)H(bb) production (CONF/INT).

Goal: combined measurement

Challenge: develop **harmonized** strategy

Most precise measurement of VH(bb).



Ricardo Barrué, Patricia Muíño, Valerio Dao, Rui Santos

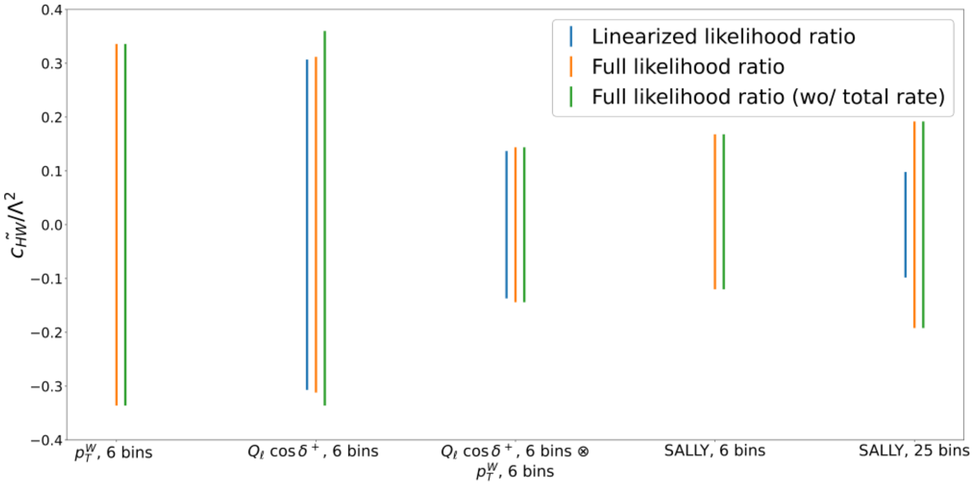
Pheno: observable choice

Compared kinematic observables w/ detector-level optimal observable (SALLY)

$$\cos\delta^+ = \frac{\vec{p}_\ell^{(W)} \cdot \ (\vec{p}_H \times \vec{p}_W)}{\left|\vec{p}_\ell^{(W)}\right| |\vec{p}_H \times \vec{p}_W|}$$

$\vec{p}_\ell^{(W)}$: momentum of lepton in W boson rest frame

JHEP 04 (2015) 103



Kinematic observables give comparable limits to SALLY - JHEP04(2024)014

Ricardo Barrué, Marina Kholodenko, Beatriz Rosalino
Patricia Muíño, Inês Ochoa, Rui Santos

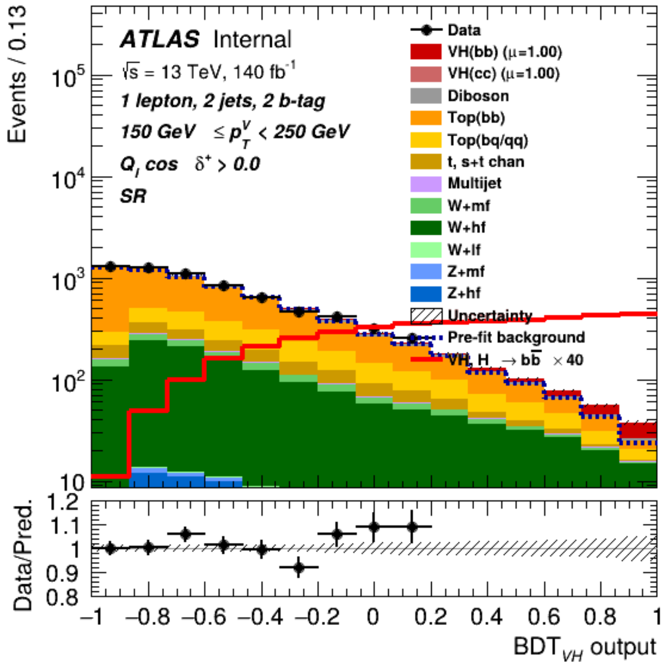
ATLAS CP in WH analysis

Implemented baseline analysis strategy on top of VH Legacy analysis.

Goal:

- Extract μ_{STXS} in categories of $Q_\ell \cos\delta^+$ and $Q_\ell \cos\delta^+ \times p_T^W$
- Interpret μ_{STXS} as a function of $c_{H\widetilde{W}}$

First results competitive with world best !



Marta Silva, Inês Ochoa, Ricardo Barrué

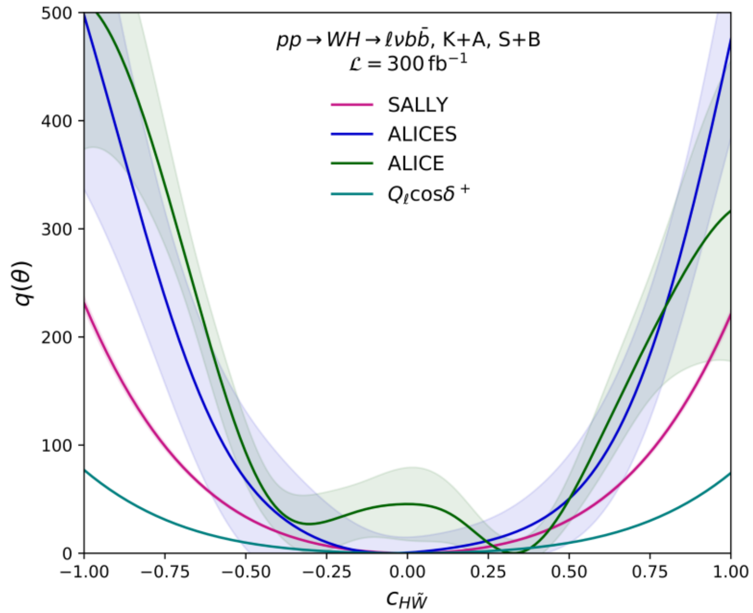
Simulation-based inference for CP violation in WH

Exploring ML-based estimators of the likelihood ratio to search of CP violation in WH

- **unbinned, high-dimensional**

Also exploring simultaneous constraints of CP-even and CP-odd operators

Better results than histograms of kinematic observables and SALLY.

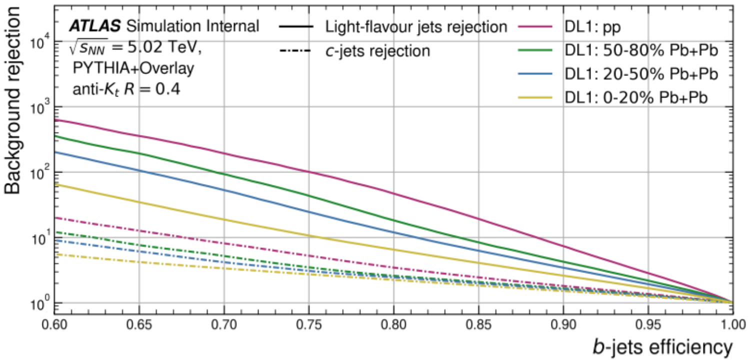


João Pires, Pedro Esperanço, Helena Santos

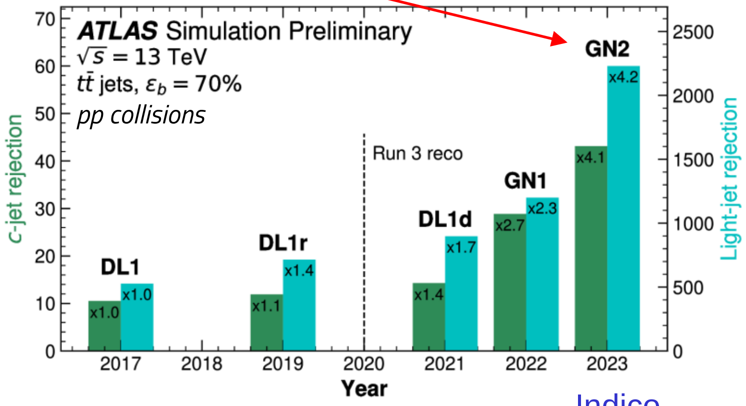
B-tagging in Pb-Pb collisions

B-jets as (hard) probes of QGP – **good b-tagging performance is critical**

- DL1 (baseline) shows reduced performance in Pb-Pb vs. p-p
- How much will we gain with (future) taggers?



[João Pires' thesis - CDS]



[Indico]

Backup

Likelihood ratio trick/CARL

For two POIs, (θ_0, θ_1) and balanced samples $p(\theta_0) = p(\theta_1) = 0.5$, $p(x) = \frac{p(x|\theta_0)+p(x|\theta_1)}{2}$

- For a classifier trained to distinguish between samples from θ_0 and θ_1 the classifier boundary

$$s(x|\theta_0, \theta_1) = p(y = 1|x) = \frac{p(x|\theta_1)}{p(x|\theta_0) + p(x|\theta_1)} = \frac{1}{r\left(x|\theta_{0,}\theta_1\right) + 1}$$

Inverting the relation, one can use classifiers to estimate likelihood ratios – **CARL - arXiv:1506.02169**

$$\hat{r}(x|\theta_0, \theta_1) = \frac{1 - \hat{s}(x|\theta_0, \theta_1)}{\hat{s}(x|\theta_0, \theta_1)}$$

SBI with mining gold

Likelihood cannot be calculated analitically, but can be factorized

- $p(x|\theta) = \int dz_d \int dz_s \int dz_p \, p(x|z_d) \, p(z_d|z_s) \, p(z_s|z_p) \, p(z_p|\theta) \equiv \int dz \, p(x, z|\theta)$

Can extract parton-level likelihood from generators

- $p(z_p|\theta) = d\sigma(z_p|\theta)/\sigma(\theta)$, $d\sigma$: event generator weights

arXiv:1805.00020: quantities based on $p(z_p|\theta)$ can be used to estimate likelihood ratio and score

- Score is a local approximation of the likelihood (statistically optimal observable) around θ_{ref}

SBI with mining gold

Joint score: $t(x,z|\theta) = \nabla_\theta \log p(x,z|\theta) = \frac{\nabla_\theta p(z_p|\theta)}{p(z_p|\theta)} = \frac{\nabla_\theta d\sigma(\theta)}{d\sigma(\theta)} - \frac{\nabla\sigma(\theta)}{\sigma(\theta)}$

- Regressor with $L \propto |\hat{g}(x) \; - t(x,z|\theta)|_{\theta_{ref}}|^2 \rightarrow t(x|\theta)|_{\theta_{ref}}$ - SALLY

Joint likelihood ratio: $\frac{p(x,z|\theta_0)}{p(x,z|\theta_1)} = \frac{p(z_p|\theta_0)}{p(z_p|\theta_1)} = \frac{d\sigma(\theta_0)}{\sigma(\theta_0)} \frac{\sigma(\theta_1)}{d\sigma(\theta_1)}$

- Classifier with $L \propto |\; s(x,z|\theta_0,\theta_1) \log(\hat{s}(x|\theta_0,\theta_1)) + (1 - \; s(x,z|\theta_0,\theta_1) \log(1 - \hat{s}(x|\theta_0,\theta_1)) \;|^2 \rightarrow$ $r(x|\theta_0,\theta_1)|_{\theta_{ref}}$ - ALICE (can be singly or doubly parametrized classifier)
- ALICE + gradient/score loss term, $|t(x,z|\theta_0,\theta_1) - \nabla_\theta \log\left(\frac{1-\hat{s}(x|\theta_0,\theta_1)}{\hat{s}(x|\theta_0,\theta_1)}\right)|_{\theta_0} \;|^2$ - ALICES