EFT with Machine Learning at ATLAS & CMS

LHC Precision Program (Benasque), 05/10/2023

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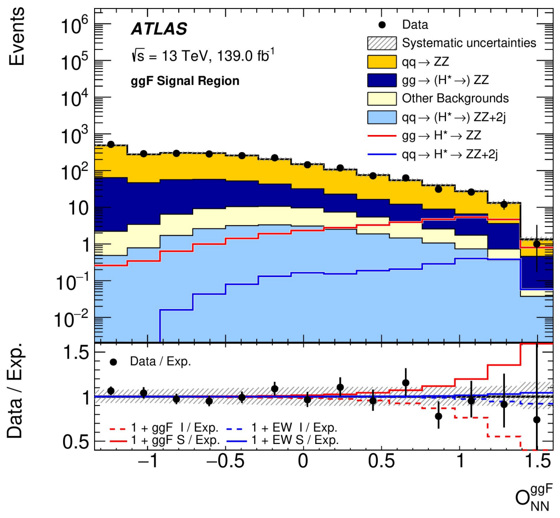
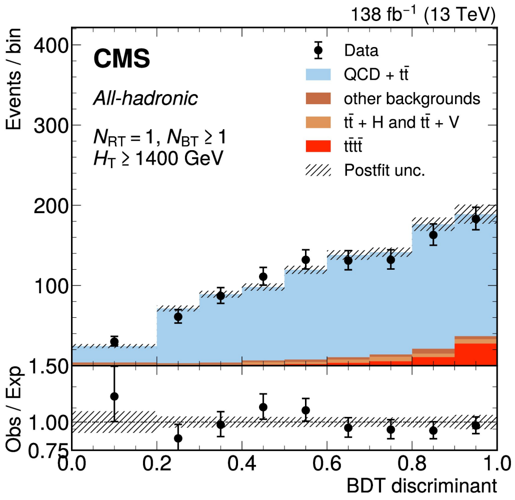
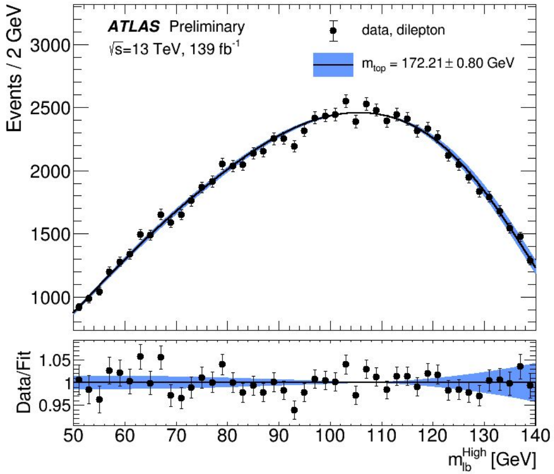
Machine learning in Standard Model measurements

- ML techniques are increasingly ubiquitous in Top / Higgs / SM measurements
  - enables access to rare signals: **off-shell Higgs** HIGG-2018-32
  - better background modelling: **extreme all-hadronic** phase space for 4tops TOP-21-005
  - more accurate reconstruction: **improved b-l pairings** for top mass ATLAS-CONF-2022-058
- Large pheno literature on using ML for EFT at all levels: MC generators, global fits, driving searches, etc. → I will focus on concrete plans

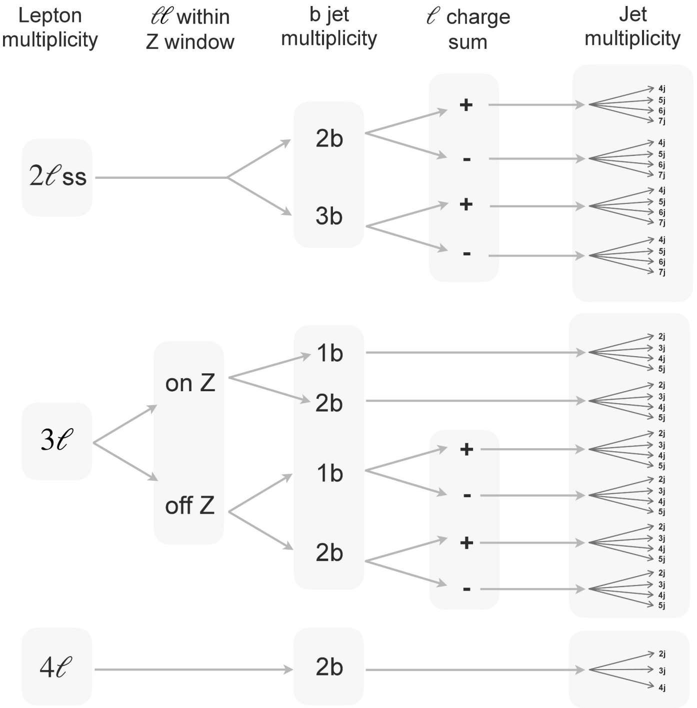


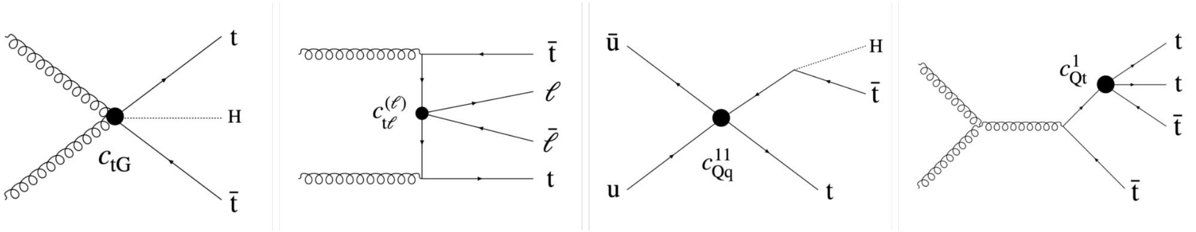


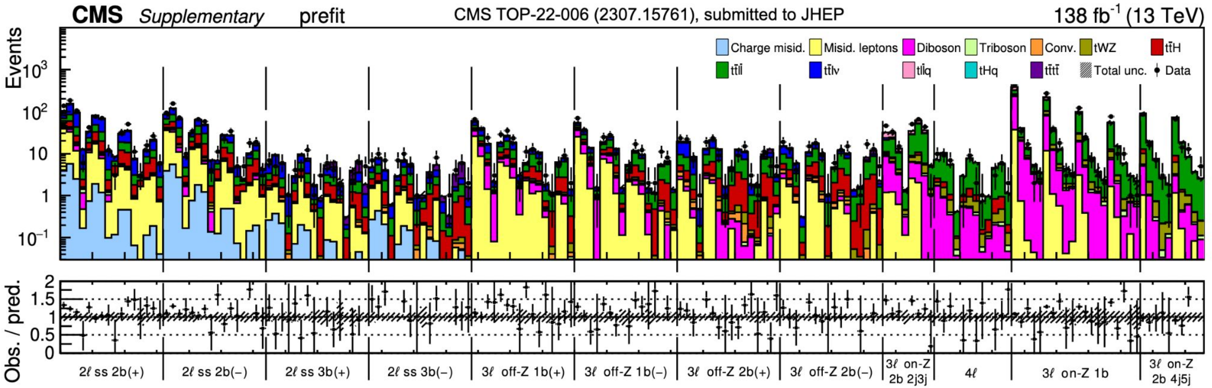


Concrete example from CMS: top-multilepton fit TOP-22-006

- Detector-level search for EFT in the ttbar + leptons final state
- Probe 26 relevant dim-6 operators: top-boson, top-leptons, four-quarks
- Target rare top processes: ttH, ttZ, ttW, tWZ, tZq, tHq, tttt







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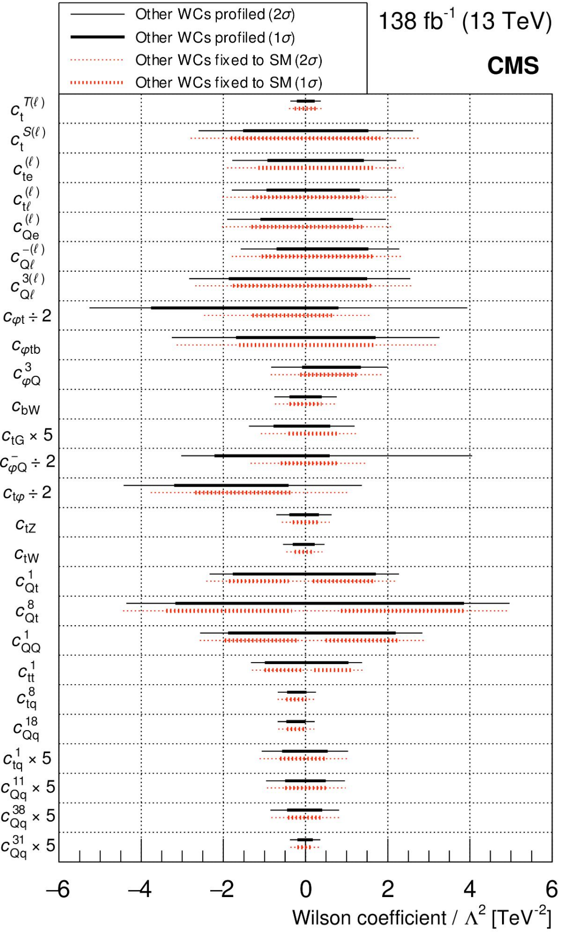
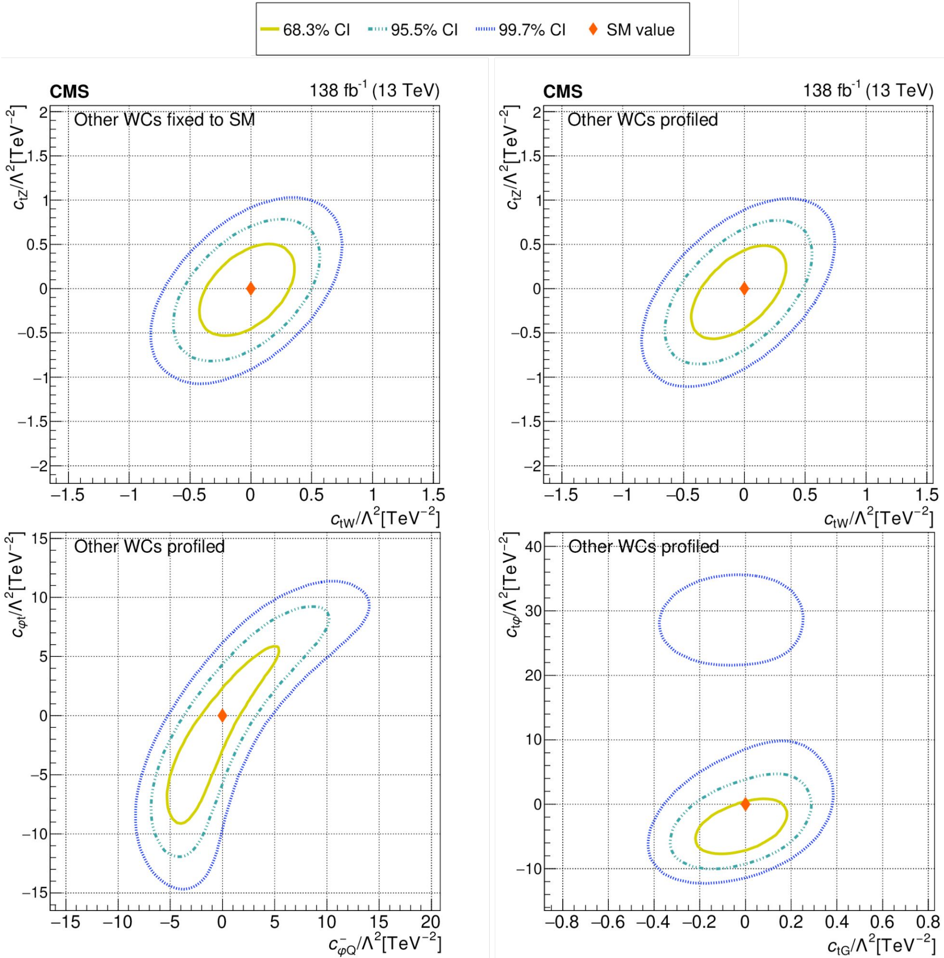




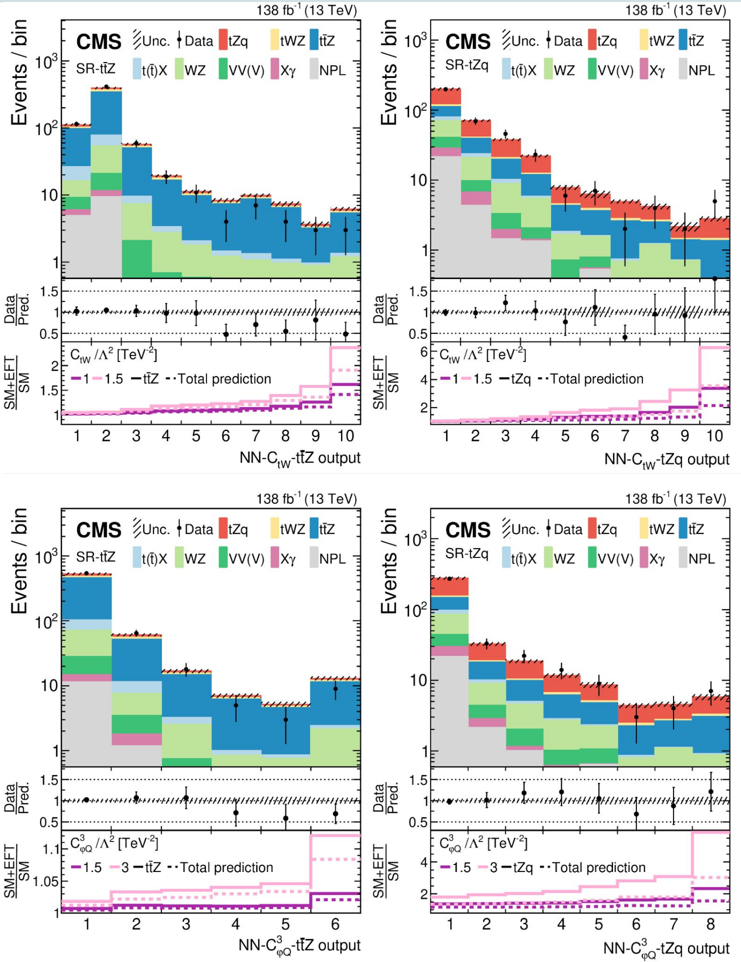
Now with machine learning: CMS top-Z fit TOP-21-001

- Also at detector-level, similar phase-space
  - but now focusing only on ttZ and tZq
  - only 5 operators (affecting t-Z coupling) → non-zero SM/EFT interference term
- **Train DNN classifiers**
  - multi-class SM: ttZ vs tZq vs Backgrounds
  - binary EFT: SM events vs specific operator
  - multi-class EFT: SM events vs mixture of operators
- This is a version of the "likelihood ratio trick"

$$L[\hat{s}] = -\frac{1}{N}\sum_{e}\left(y_e \log \hat{s}(x_e) + (1-y_e)\log(1-\hat{s}(x_e))\right)$$

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

arXiv:1805.00020



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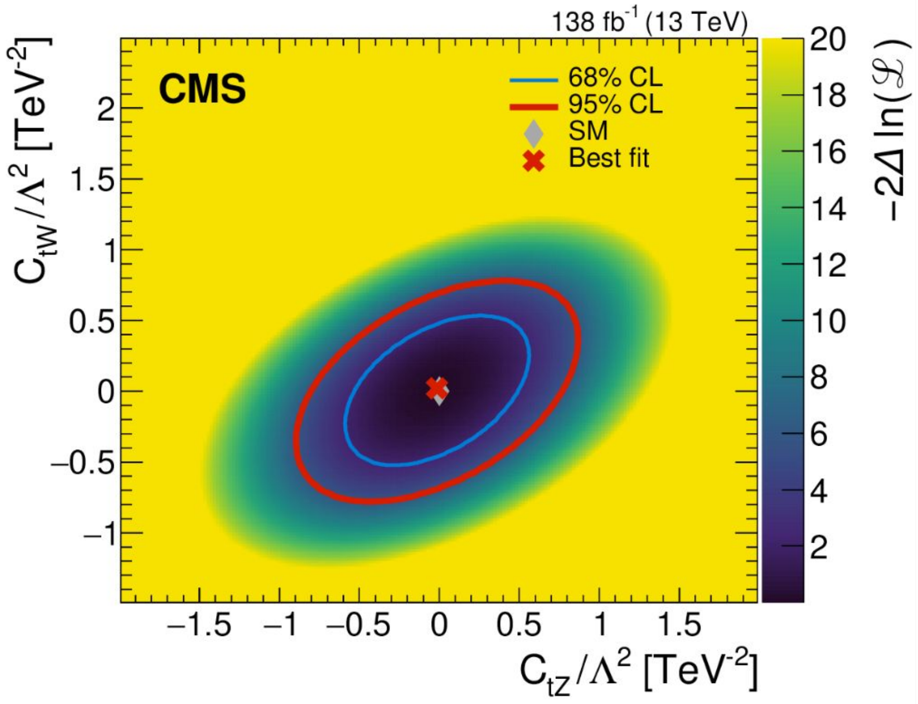
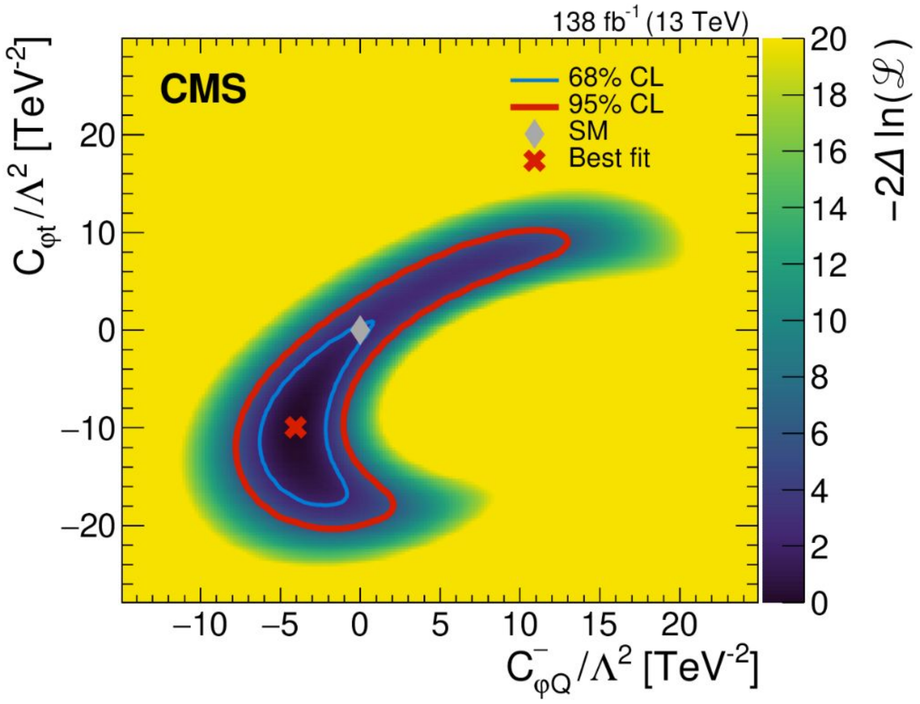
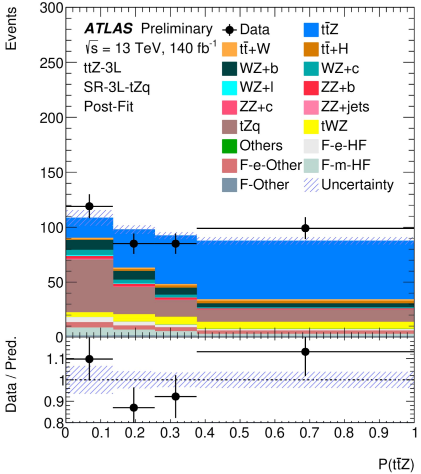
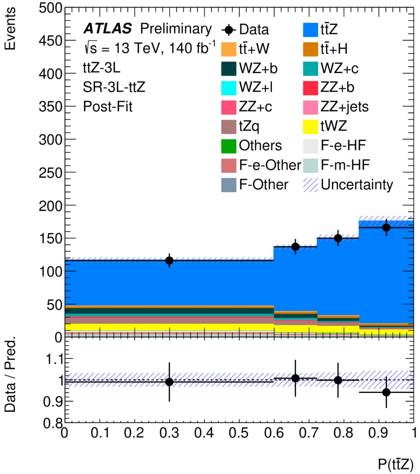


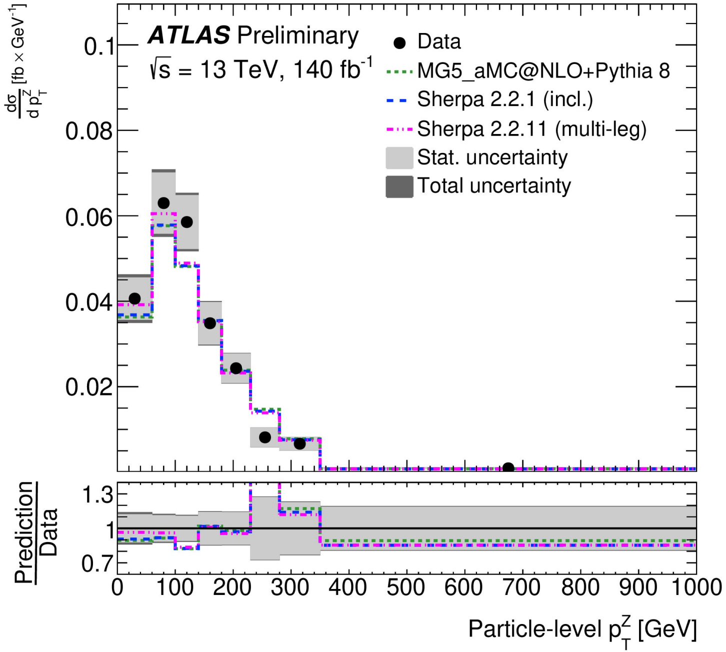


The ATLAS case: ttZ EFT at particle-level ATLAS-CONF-2023-065

- Re-analysis of the Run 2 dataset: uses ML to increase acceptance and reject/model backgrounds better → **40% improvement** on inclusive cross section precision
- Multiple observables unfolded to particle-level
  - **full likelihood is available!**
  - can leverage correlations between observables
- Constraints on 23 dim-6 operators







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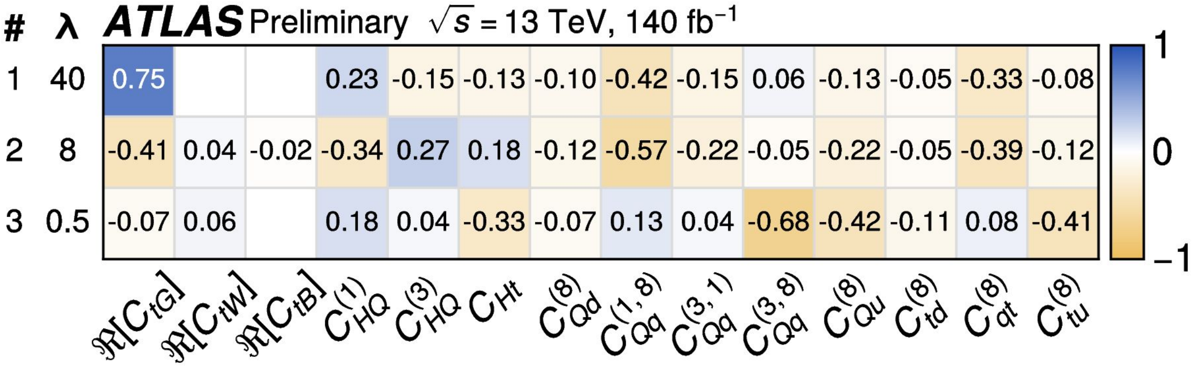
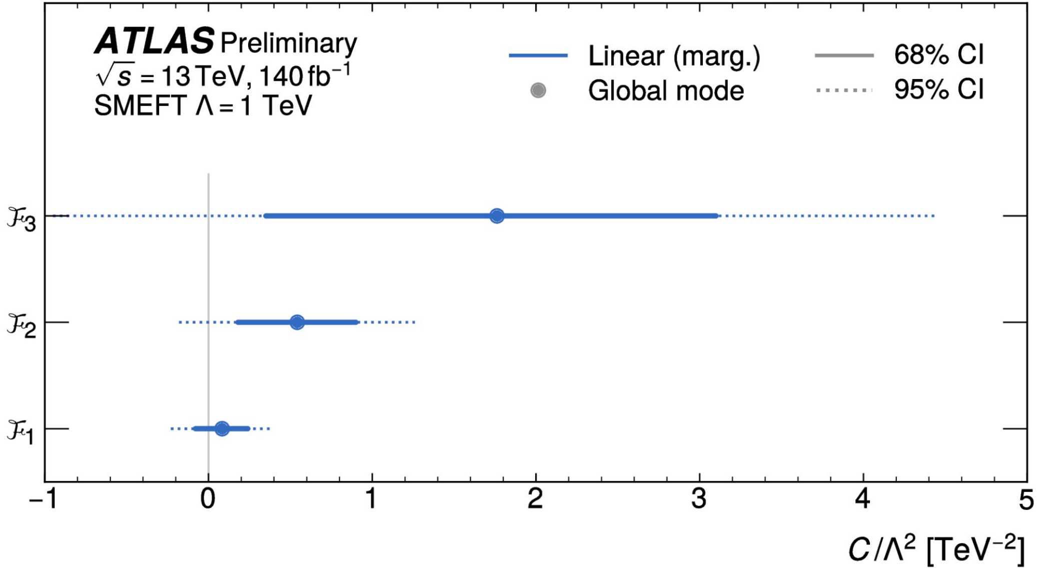


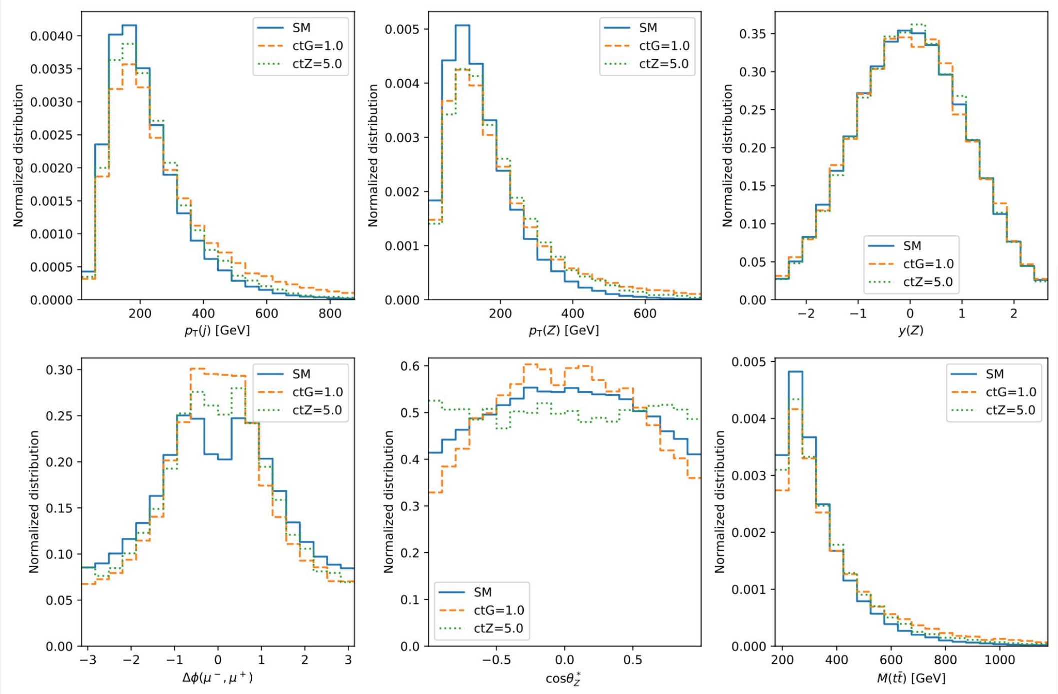
#	λ	$\Re[C_{tG}]$	$\Re[C_{tW}]$	$\Re[C_{tB}]$	$C_{HQ}^{(1)}$	$C_{HQ}^{(3)}$	C_{Ht}	$C_{Qd}^{(8)}$	$C_{Qq}^{(1,8)}$	$C_{Qq}^{(3,1)}$	$C_{Qq}^{(3,8)}$	$C_{Qu}^{(8)}$	$C_{td}^{(8)}$	$C_{qt}^{(8)}$	$C_{tu}^{(8)}$
1	40	0.75			0.23	-0.15	-0.13	-0.10	-0.42	-0.15	0.06	-0.13	-0.05	-0.33	-0.08
2	8	-0.41	0.04	-0.02	-0.34	0.27	0.18	-0.12	-0.57	-0.22	-0.05	-0.22	-0.05	-0.39	-0.12
3	0.5	-0.07	0.06		0.18	0.04	-0.33	-0.07	0.13	0.04	-0.68	-0.42	-0.11	0.08	-0.41

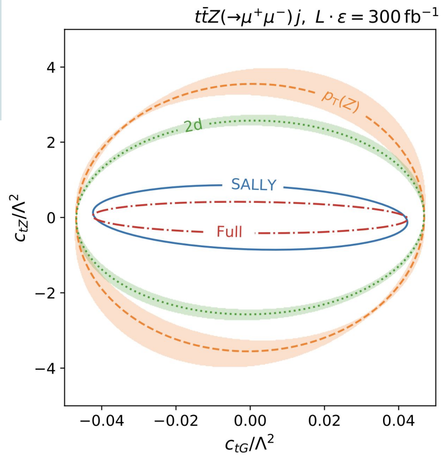


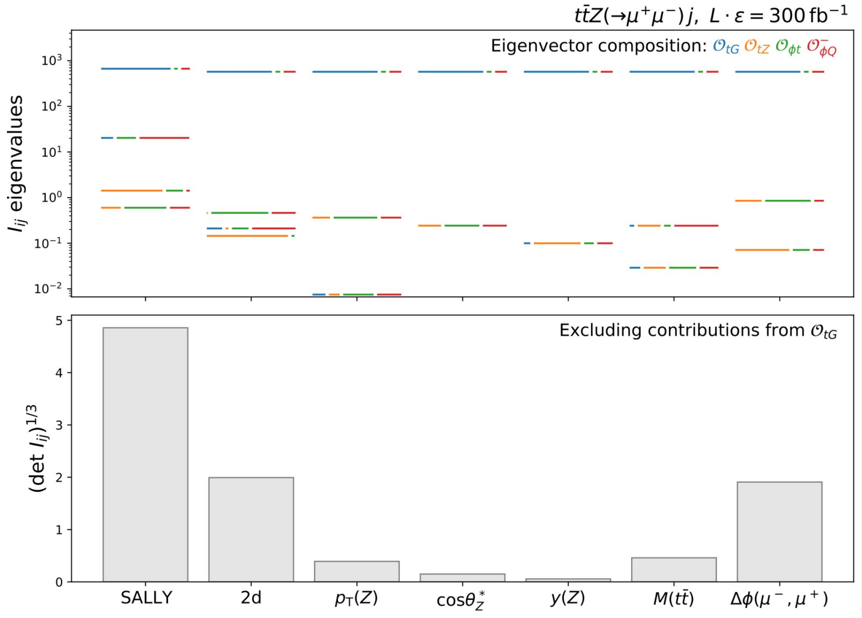
Some comments on these approaches

- ML is a powerful tool for detector-level EFT searches
  - possibly close to Optimal Observables, **use more information about each event**
  - can “clean up” the final state / target specific processes
  - but results are (in general) impossible to reproduce
  - model dependence is built in: EFT predictions + simulations
- Unfolding seems like a more robust approach
  - can improve both the SM and EFT predictions
  - model dependence is largely reduced (can check effects of EFT on unfolding)
  - so far **no proper treatment of backgrounds** (how realistic is it to unfold the full final state?)
- Computational limits are real
  - most often **using LO samples**, for NLO have to simplify processes (e.g. assume on-shell)
  - detailed studies being conducted within LHC EFT WG on the **validity of reweighting**
  - multi-leg samples as a proxy for higher-order corrections? what about running of EFT scales?
  - **ML for Optimal Observables / likelihood-free inference** à la MadMiner is also very challenging to put in practice within official software framework
    - under study in both collaborations…

MadMiner to go beyond 2D fits







The ATLAS roadmap for EFT in the top+X sector

- Recently outlined in ATL-PHYS-PUB-2023-030
- Recognises **top-multilepton final states** as a valuable addition to global EFT fits
- Most processes already measured (to varying degrees of precision), some discrepancies
- **How do we move forward?**
  - "object-based" detector-level fits: split in lepton/jet/tag multiplicities → identify tensions?
  - "process-based" detector-level fits: rely on ML to suppress non-top backgrounds, split top processes → easier BSM interpretations?
  - "EFT-optimised" detector-level fits: rely heavily on EFT MC to look for OOs, try to take into account interference effects → quite challenging, may not be easily re-interpretable?
  - multi-process unfolding: identified as the final goal, but many experimental challenges to overcome
- These options all represent significant amounts of work, so please take a look at the document and let us know your thoughts 😇 (e.g. at the next LHC EFT WG meeting)

Conclusions

- **ML for EFT** is very nice on paper, but raises many questions in practice
  - can it be fed into global EFT fits? or does it make for one-off measurements?
  - is it tied to detector-level measurements? is it worth investigating ML models running on unfolded data?
  - should we use it to determine approximate/fully OOs and focus on those instead?
- So far, only very limited set of experimental results
  - likely many more to come in the not-so-distant future
  - but would rather get input from theorists early on, as these are highly involved analyses to run

BA

Come up with a very short closing statement after a presentation that didn't bring anything new to the table

"To wrap up, let's reaffirm the fundamentals and keep building on our solid foundation. Thank you for your attention."