Top Quark Mass Measurement with a New Profiled Likelihood Nuisance Fit

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GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

Universität Hamburg
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CMS

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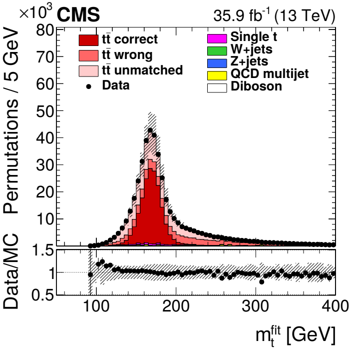
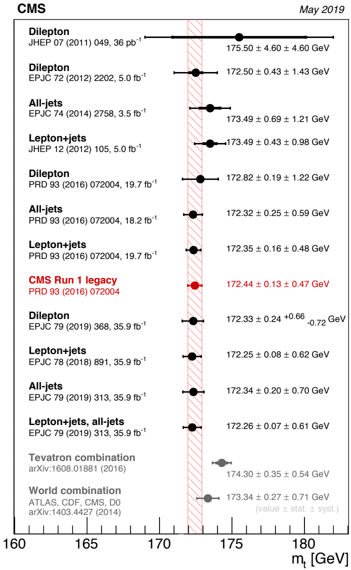
The Top Quark $t\bar{t} \to$ l+jets channel

$t\bar{t} \to$ l+jets useful for precision mass measurement due to

- branching ratio
- easy to trigger
- only one ν

same data epoch as used by EPJC-78-891 (CMS-TOP-17-007)





Samples and Selection

data: 35.9 fb^{-1} Run 2 2016; **signal MC**: `powheg` + `pythia8`

selection: 1 lepton + 4 jets

- HLT: isolated muon (electron) with $p_T > 24(27)$ GeV
- muon (electron) selection: $p_T > 26(29)$ GeV and $|\eta| < 2.4$
- veto on events with additional leptons
- four anti-$k_t^{R=0.4}$ jets with $p_T > 30$ GeV, $|\eta| < 2.4$, ΔR(muon,jet) > 0.3
- b-tagging: *DeepJet* (1% mis-tag, 78% efficiency)
  - at least two b-tags in selected jets

  difference to EPJC-78-891: DeepJet instead of CSVv2 ($\epsilon_{\text{bTag WP medium}}$: 70%→78%)
- fit event kinematics to $t\bar{t}$-hypothesis, cut on $P_{\text{gof}} > 0.2$

	EPJC-78-891 (CMS-TOP-17-007)	**this analysis (CMS-TOP-20-008)**
data	Single[Muon,Electron] Run2016[B-H] 03Feb2017	Single[Muon,Electron] Run2016[B-H] 17Jul2018
lumi-JSON	13TeV Collision 16 23Sep2016ReReco	13TeV Collision 16 07Aug2017
signal MC	TT powheg-pythia8 MiniAODv2 80X CUETP8M2T4 tune	TT powheg-pythia8 MiniAODv3 94X CP5 tune
biggest Unc. src.	JEC, CR, ME gen.	?
#μ events	101 992	140 362
#e events	59 504	87 265

Kinematic Fit

Fit the event kinematics to a $t\bar{t}$ hypothesis

Input: p_T and angles of the jets and lepton and $\not{E}_T$

Constraints:

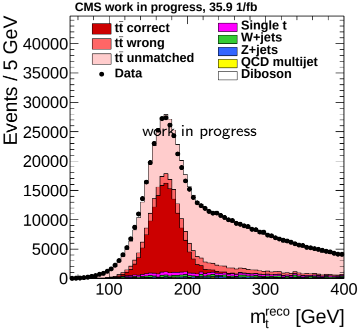
- $m^{fit}_{t_{hadr}} = m^{fit}_{t_{lept}}$
- $m^{fit}_{W} = 80.4\,\text{GeV}$
- p_T balance

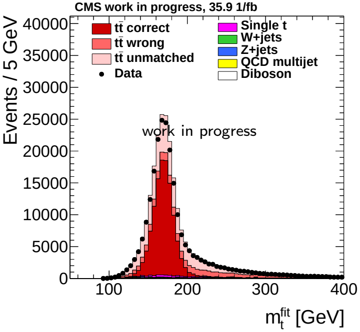
use goodness-of-fit

$P_{gof} = \exp(-\frac{1}{2}\chi^2)$

cut on $P_{gof} > 0.2$

	baseline	final $P_{gof} > 0.2$
$t\bar{t}$ correct	20 %	48 %
$t\bar{t}$ wrong	7 %	15 %
$t\bar{t}$ unmatched	72 %	37 %
signal fraction	90 %	94 %





Observables

m_t is measured by fitting the templates to date

- m_t^{fit} (1D)
- m_t^{fit}, m_W^{reco} (2D)
- m_t^{fit}, m_W^{reco}, $m_{l,b}^{reco}|_{P_{\mathrm{gof}}<0.2}$ (3D)

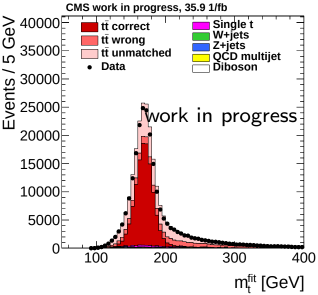
new observable $m_{l,b}^{reco} = \sqrt{\left(P_{lepton}^{reco} + P_b^{reco}\right)^2}$,

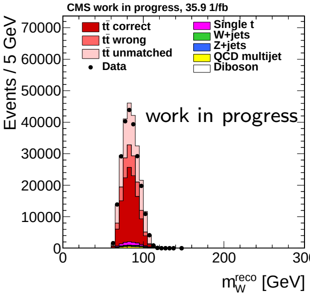
inspired by $t\bar{t} \rightarrow$ di-lepton but different jet-parton assignment

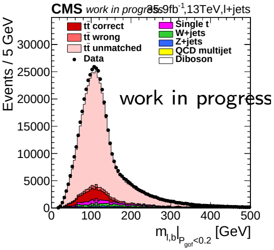
de-correlate $m_{l,b}^{reco}$ from m_t^{fit} as $m_{l,b}^{reco}/m_t^{fit}$

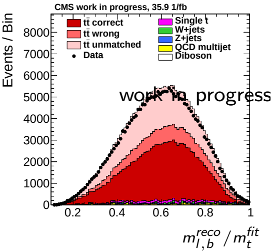
- m_t^{fit}, m_W^{reco}, $m_{l,b}^{reco}|_{P_{\mathrm{gof}}<0.2}$, $m_{l,b}^{reco}/m_t^{fit}$ (4D)
- m_t^{fit}, m_W^{reco}, $m_{l,b}^{reco}|_{P_{\mathrm{gof}}<0.2}$, $m_{l,b}^{reco}/m_t^{fit}$, $R_{b,q}^{reco} = \frac{p_{T_{b1}}^{reco}+p_{T_{b2}}^{reco}}{p_{T_{q1}}^{reco}+p_{T_{q2}}^{reco}}$ (5D)

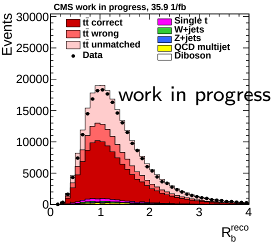
Observables Distribution









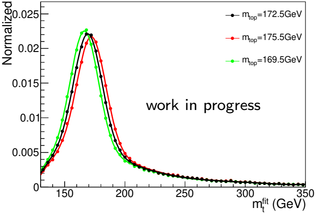


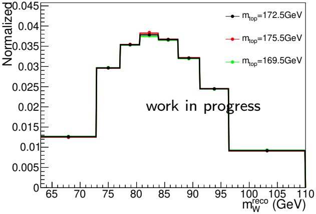
Observables Parameterisation

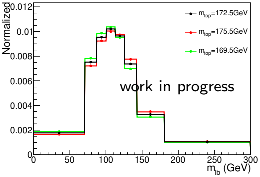
Fit templates

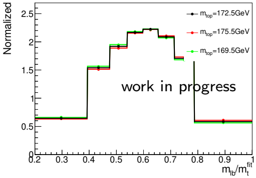
$$P\left(m_t, obs|\alpha_{obs,1}, ..., \alpha_{obs,n}\right), obs \in \left[m_t^{fit}, m_W^{reco}, m_{l,b}^{reco}|_{P_{\text{gof}}<0.2}, m_{l,b}^{reco}/m_t^{fit}, R_{b,q}^{reco}\right]$$

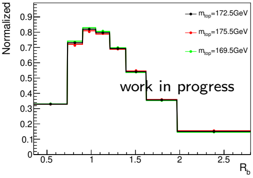
with linear parametrisation $\alpha_k\left(m_t\right) = \left(\alpha_k^0 + s_k^0\left(m_t - 172.5\right)\right)$











Bin edges are set to approx. equal event count per bin to improve the fit stability.

Nuisance Template Fit

Fit templates $P\left(obs|\alpha_{obs,1},...,\alpha_{obs,n}\right)$,
$obs \in \left[m_t^{fit}, m_W^{reco}, m_{l,b}^{reco}|_{P_{\text{gof}}<0.2}, m_{l,b}^{reco}/m_t^{fit}, R_{b,q}^{reco}\right]$
with linear parametrisation
$\alpha_k\left(m_t\right) = \left(\alpha_k^0 + s_k^0\left(mt - 172.5\text{GeV}\right)\right)$.
$\alpha_k^0, \vec{s}_k$ are derived by fitting to simulation.

Add one nuisance θ_i for every systematic uncertainty source
$\alpha_k(m_t,\vec{\theta}\ ) = (\alpha_k^0 + s_k^0\left(m_t - 172.5\text{GeV}\right))\prod_i\left(1 + s_k^i\theta_i\right)$.
θ_i is constrained by Gauss(0,1), corresponding to systematic variation by $\pm 1\sigma$.

Add $\beta_k, \vec{\omega}_k$ to account for simulation statistics.
$\alpha_k(m_t, \vec{\theta},\ \beta_k, \vec{\omega}_k\ )$
$= (\alpha_k^0 + \beta_k + s_k^0\left(m_t - 172.5\text{GeV}\right) + \omega_k^0 \cdot 1\text{GeV}\right)\prod_i(1 + s_k^i\theta_i + \ \omega_k^i)$
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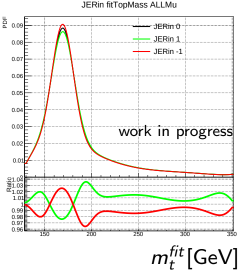
$\beta_k, \vec{\omega}_k$ are constrained by multi-dim Gaussian around 0 from the covariance of the $\alpha_k^0, \vec{s}_k$ fits.

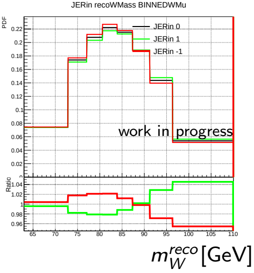
Nuisance Fit Example Variations

Example variation effects on the templates

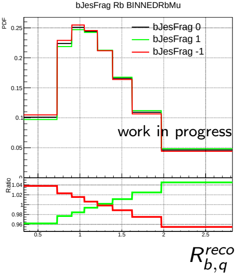
JER



JER



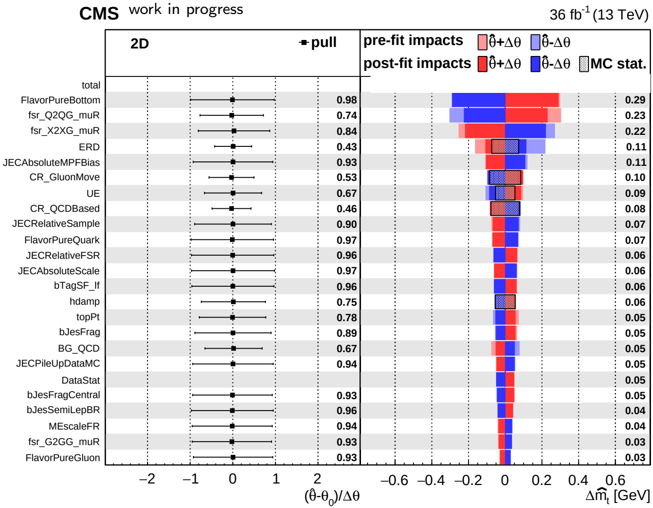
B JES Frag.



i.e. m_W^{reco} depends on JER much more than m_t^{fit}, giving a way to reduce its impacts, $R_{b,q}^{reco}$ could do the same for the b-fragmentation modelling uncertainty

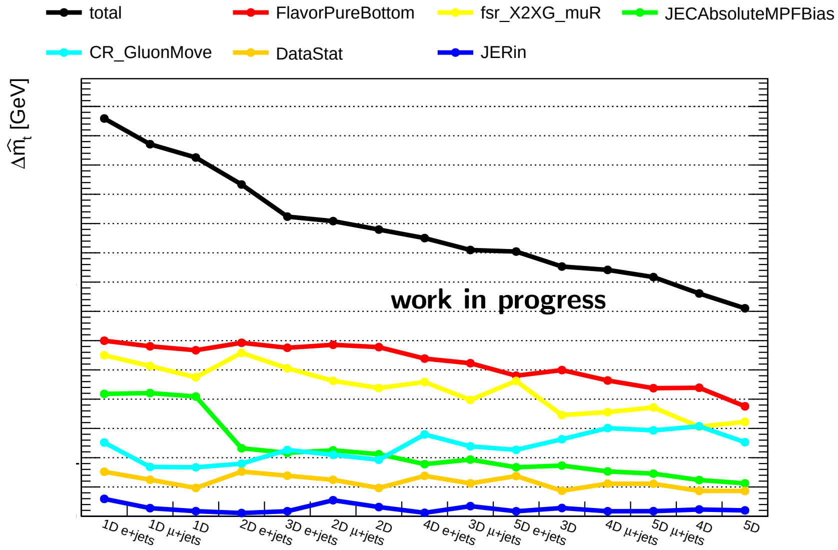
Nuisances Impact Example

Systematic uncertainties predicted from pseudo-experiments when using the two observables m_t^{fit} and m_W^{reco} as the former CMS analyses in $t\bar{t} \rightarrow$l+jets



only biggest uncertainties shown

Nuisance Impact Comparison



Summary and Outlook

- Used new reference simulation, including updated UE tune
- Improved event selection with *DeepJet* b-tagger and different electron HLT
- Included systematic uncertainties as nuisances in the fit
- New observables $R^{reco}_{b,q}$, $m^{reco}_{l,b}/m^{fit}_{t}$, $m^{reco}_{l,b}|_{P_{gof}<0.2}$
- Improve of syst. unc. in $t\bar{t} \rightarrow$ l+jets
  0.62 GeV $\rightarrow <$ 0.5 GeV expected