Search for heavy resonances decaying into a Z boson and a vector boson in the $\nu\bar{\nu}$ $q\bar{q}$ final state at CMS

Corso di Dottorato di Ricerca in Fisica
XXX ciclo

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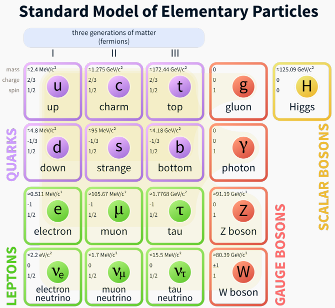
Outline

1. Motivations
2. Signal signatures of the models probed
3. Reconstructed physics objects and selections
4. Background prediction
5. Results and interpretation
6. Future perspectives and conclusion

Motivations

Standard Model of particles

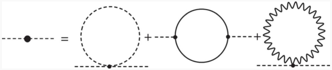
- Standard Model (SM): the best description of elementary particles and their interactions
- Summation of electromagnetic, weak and strong interactions: $SU_C(3) \times SU_L(2) \times U_Y(1)$
- Higgs scalar field gives mass to fermions and weak bosons via spontaneous symmetry breaking



SM open problems

0. phenomenological observations not included (neutrino masses, dark matter candidates, cosmological inflation, matter-antimatter asymmetry)
1. flavour problem (too many free parameters)
2. no complete unification (α_{em}, α_{weak}, α_{strong}, gravitation excluded)
3. **hierarchy problem**:

- ➠ electroweak ($\sim$ 100 GeV) and Planck ($\sim 10^{19}$ GeV) scales are not decoupled
- ➠ Higgs mass is UV-sensitive: divergencies require fine tuning cancellations (1 over 10^{34})



- Solutions: enlarging the SM gauge group
- ➠ Grand Unification Theories, SUper SYmmetry..

Heavy Vector Triplet

HVT in a nutshell

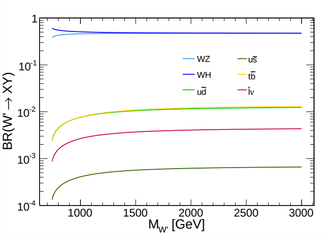
- General framework (including Little Higgs, Composite Higgs, Sequential Standard Model)
- ➡ Introduction a triplet of spin-1 (X^0, X^+, X^-) (Z', W')
- ➡ Simplified model: effective Lagrangian → relevant on-shell physics quantities (cross-section, width, mass of the resonance)
- ➡ Few additional parameters in the SM Lagrangian: g_V (strength), c_H (coupling to bosons), c_F (coupling to fermions)
- HVT triplet protects the Higgs mass if $M_X \sim 1$ TeV:

$$m_{W,Z}/M_X \ll 1$$

  - ➡ SM is reproduced within 1% accuracy (small mixing of X with weak fields)
  - ➡ no need of fine-tuning

Z', W' phenomenology and benchmark scenarios

- HVT production and decays completely determined by g_V, c_H, c_F, M_X
- ➡ X produced mainly via $q\bar{q}$ scattering (Drell-Yan)
- ➡ HVT-A model – weak coupling: $BR(X \to f\bar{f})$ dominates (SSM-like)
- ➡ HVT-B model – strong coupling: $BR(X \to VV) \approx BR(X \to VH)$ dominates (Composite Higgs-like)



- ➡ HVT resonances are narrow (1% of m_X)

Warped extra dimensions

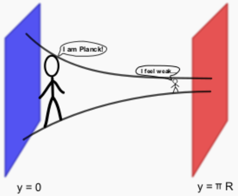
Bulk WED in a nutshell

- Randall-Sundrum model:
  - 5th additional warped extra dimension

$$ds^2 = e^{-2kr_c\varphi}\eta_{\mu\nu}dx^\mu dx^\nu + r_c^2 d\varphi^2$$

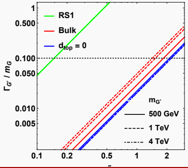
  - spin-2 gravitons: modes $h_{\mu\nu}$ of the quantum fluctuations, expanded in Kaluza-Klein towers
  - TeV-brane and Planck-brane located at $\varphi = (\pi, 0)$
  - small r_c generates large hierarchy between Planck–Higgs scales:

$$m = e^{-kr_c\pi}m_0$$



Bulk gravitons phenomenology

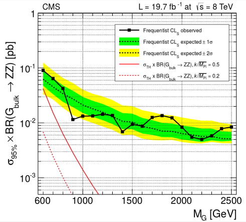
- Bulk extension of the RS model:
  - Higgs sector ↔ TeV brane; light fermions → Planck brane; heavy fermions → TeV brane
  - natural solution of the flavour problem
  - small interaction of massive KK bulk gravitons G with light fermions → G produced via gluon fusion
  - significant branching ratio into bosons
- G production and decays determined by
  - graviton mass m_G
  - curvature parameter $\tilde{k} = k/\bar{M}_{Pl}$; if $\tilde{k} < 1 \rightarrow G$ narrow



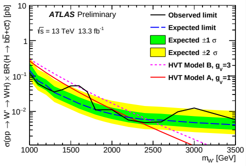
Data-driven motivation: previous results

Diboson excesses

CMS EXO-13-009, 2012 data: local excess @ 1.8 TeV (2. σ)

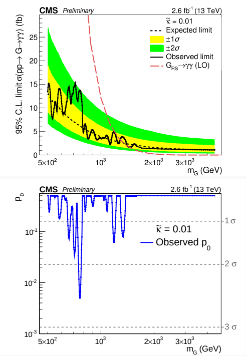


ATLAS-CONF-2016-083, 2016 reduced dataset: local excess @ 1.6 TeV (2.5 σ), @ 3 TeV (3.5 σ)



The infamous $\gamma\gamma$ bump... was a diboson too!

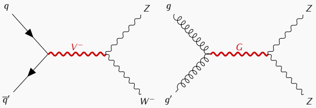
CMS EXO-15-004, 2015 data: local excess @ 760 GeV (2.6 σ)

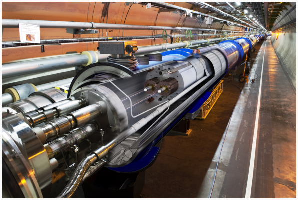


- Rising interest in diboson resonances
- Probing (almost) all the final states..

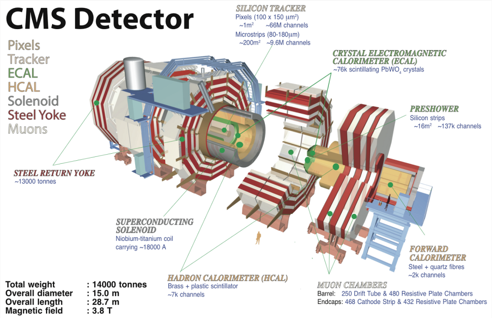
Machines for hunting heavy resonances

LHC: producing heavy particles

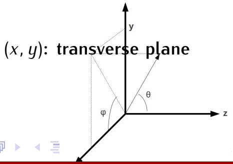




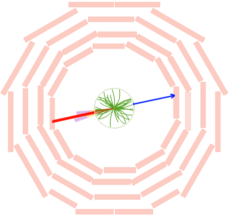
CMS: detecting diboson resonances



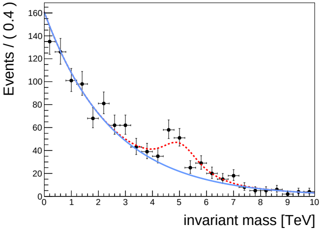
- Data produced by LHC p-p collisions @ $\sqrt{s} = 13$ TeV
- Collected by CMS in 2016, integrated luminosity $\mathcal{L} = 35.9 \pm 0.9$ fb^{-1}



Search for heavy resonances decaying into dibosons



$\Rightarrow$



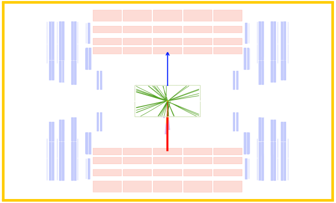
General approach

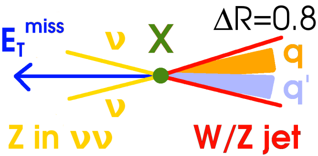
- narrow resonances $\rightarrow$ natural width $<$ resolution
- build the di-boson candidate
- estimate the background (simulations and data driven)
- look for a local excess w.r.t. background in the invariant mass spectrum

Final state probed

- $V = (W, Z) \rightarrow q\bar{q}$: larger branching fraction ($\sim$ 60%) but strong background at hadronic colliders
- $Z \rightarrow \nu\nu$: clear signature, significant branching fraction ($\sim$ 20%)
- $VZ \rightarrow q\bar{q}\nu\nu$: good tradeoff

Search for heavy diboson resonances: $VZ \to q\bar{q}\nu\bar{\nu}$





- Objects identified by CMS Particle-Flow algorithm: informations of all sub-detectors combined

- Heavy ($\sim$1 TeV) $X \to V_{\text{had}} Z_{\text{lep}}$: Lorentz boost

➠ $V_{\text{had}} \to q\bar{q}'$: 1 large-cone boosted jet (2 merged subjets)

➠ $Z_{\text{lep}} \to \nu\nu$: large amount of E_T^{miss} recoiling against the boosted jet (back-to-back)

$$E_T^{\text{miss}} = \left|\vec{p}_T^{\text{miss}}\right| = \left| - \sum_{j \in \text{event}} \vec{p}_T^{\,j} \right|$$

- Expected SM backgrounds:
  - W, Z + jets (85%)
  - $t\bar{t}$, single t (10%)
  - VV diboson (5%)

- Search for local excess: transverse mass of $V_{\text{had}} Z_{\text{lep}} \to q\bar{q}\nu\nu$ candidate

$$m_{VZ}^T = \sqrt{2 E_T^V E_T^{\text{miss}} \cdot (1 - \cos \Delta\varphi(V, \vec{p}_T^{\text{miss}}))}$$

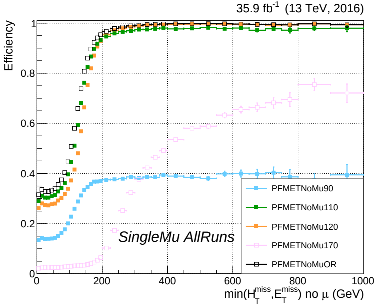
Collecting data: E_T^{miss} trigger

- CMS: hardware Level 1 trigger and software High Level Trigger
- trigger paths: recognize physics objects; if requirements are met → event saved

Trigger: E_T^{miss}

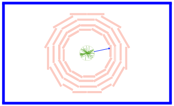
- Given the topology ($Z \to \nu\nu$): E_T^{miss} trigger
- Events collected if $E_T^{miss} >$ certain threshold at trigger level
- Trigger efficiency measured on independent data
- $W \to \mu\nu$ topology (1 good quality μ) and 1 boosted jet

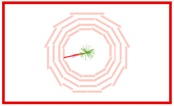
1. W leptonic decay → true E_T^{miss}
2. $W \to \mu\nu \to$ orthogonal dataset w.r.t. the signal region
3. fat jet requirement → kinematics similar to the signal region



- Trigger is efficient @ 200 GeV (96.1%)
- Efficiency data scale factors are applied on simulations
- Independent measurement for $W \to e\nu$

Main ingredients: E_T^{miss} and jet



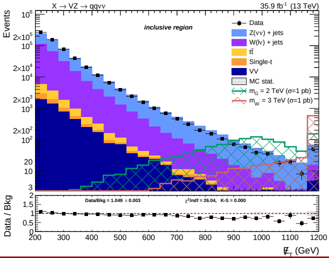


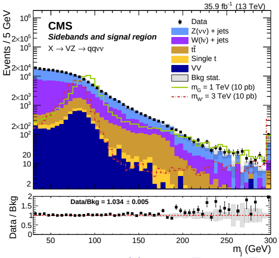
Selections on E_T^{miss}

- $E_T^{miss} > 200$ GeV (plateau of the trigger efficiency)
- Energy corrections (depending on jet)
- Events with detector noise are rejected
- Z candidate $\rightarrow E_T^{\text{miss}}$

Selections on large-cone jet

- Jets clustered in large-cone $\Delta R = 0.8$ with anti-k$_T$ algorithm
- $p_T^j > 200$ GeV, $|\eta| < 2.5$
- Cleaned from ℓ, jet energy corrections applied
- V candidate $\rightarrow$ leading p_T large-cone jet

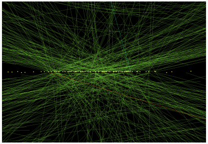




Large-cone jet mass

Grooming of the jet mass

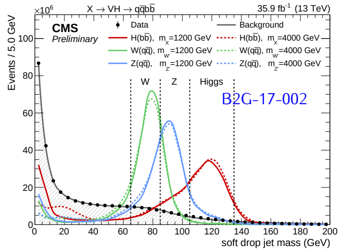
- "soft drop" declustering algorithm:
  - declusters the AK8 jet into 2 subjets
  - removes soft wide-angle radiation components
  - parameters rule the degree of grooming
- PUPPI algorithm:
  - removes pile-up contributions (spectators of X production vertex)
  - builds a local metric, considering charged and neutral particles
  - assigns a weight to each particle (pile-up → 0; non pile-up → 1)



Signal region

Groomed mass of the jets defines the signal region:

- if $V_{\text{had}} = W, Z \rightarrow \text{SR} = [65{,}105]$ GeV
- if $V_{\text{had}} = Higgs \rightarrow \text{SR} = [105{,}135]$ GeV
- SideBands (signal depleted) → SB = [30,65] ; [>135] GeV
- SB are fundamental for the background prediction



V-tagging: exploiting the jet substructure

Jet substructure: n-subjettiness

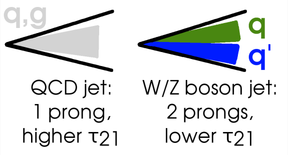
- Re-clustering of jet k constituents with the k_T algorithm, forced to return n subjets

$$\tau_n = \frac{1}{d_0} \sum_k p_{T,k} \min\left(\Delta R_{1,k}, \Delta R_{2,k}, \dots, \Delta R_{n,k}\right)$$

- $d_0 = \sum_k p_{T,k} R_0$
- if $\tau_n \to 0$: larger probability of n subjets
- $\tau_{21} = \tau_2/\tau_1$ subjettiness: "probability" of being a 2-prong jet vs 1-prong jet

➠ 1 prong $\to$ QCD jets $\to$ background!

➠ 2 prongs $\to$ W/Z jets $\to$ signal!

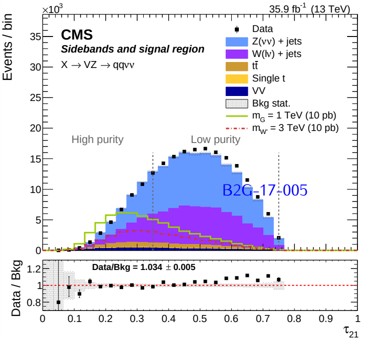


V-tagging

➠ Categorization with softdrop PUPPI τ_{21}:

- Low purity: $0.35 < \tau_{21} < 0.75 \to$ background contamination but high signal efficiency
- High purity: $\tau_{21} < 0.35 \to$ higher signal purity

➠ Combination improves signal sensitivity (40%)

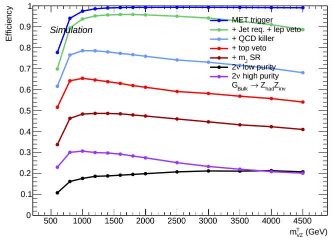


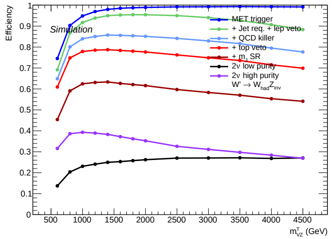
Additional selections

Background rejection

- ✧ rejection of $Z \to \ell\ell$, $W \to \ell\nu$ backgrounds
  - veto of electrons, muons, taus and photons
- ✧ rejection of multijet background (30% → 2%)
  - considering AK4 jets not overlapping the V jet candidate
  - minimum angular separation in the transverse plane $\Delta\varphi(\vec{p}_T^{\,\text{miss}}, \text{AK4 jets}) > 0.5$
- ✧ rejection of t background (20% → 10%)
  - $t \to Wb$: reject events with AK4 jets (not overlapping V jet) generated by b-quarks
  - b-quarks have long lifetimes → secondary vertices
  - b-tagging: MVA approach combining tracker and jet informations
- ✧ rejection of events where V and Z are collinear: $\Delta\varphi(V, \vec{p}_T^{\,\text{miss}}) > 2$

Signal efficiency

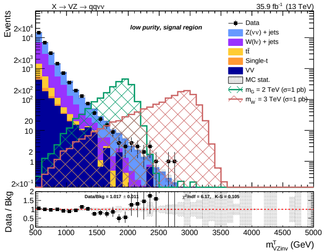




Background estimation: α method introduction

Aim of the method: background prediction

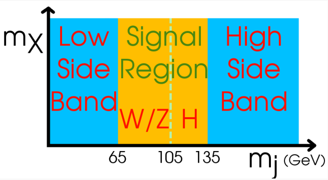
- V+jets (main background) – 85%: $Z \to (\nu\nu)$ + jets and $W \to \ell\nu$ + jets
  - few events in MC simulation (at high p_T)
  - predicted with α method: hybrid data/MC approach
- Secondary backgrounds: predicted with MC simulation
  - Top – 10%: $t\bar{t}$, single top
  - VV – 5%: WW, WZ, ZZ



Main highlights

- The jet mass m_j defines the signal and sideband regions (signal depleted)
- two-steps procedure:

1. fit to m_j spectra → predict the background *normalization* (event yield in SR)
2. fit to m_{VZ}^T spectra → predict the background *shape* (search for a local excess in data SR)



- Data in Side Bands are used to predict the background in the Signal Region through the α SB → SR transfer function
- α-ratio calculated on MC simulations (kinematical differences SB → SR)

Background estimation: α method step 1

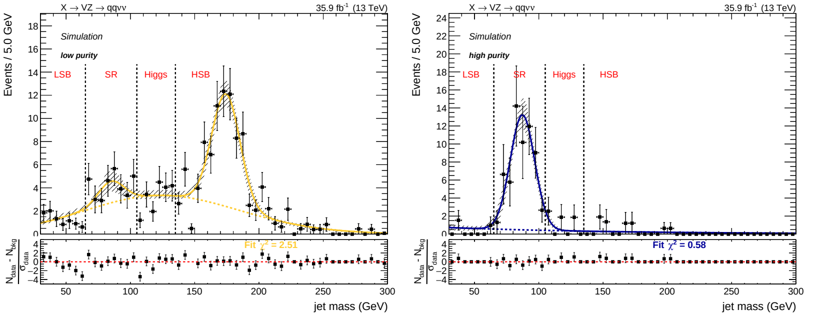
Secondary backgrounds: m_j

Normalization recipe:

- Fit the whole MC spectra of m_j for all the backgrounds with physical motivated functions
- Fix the parameters of the secondary backgrounds

Top and VV

- functional shape depends on purity category
- `ErfExpGaus2, ExpGaus`



Background estimation: α method step 1

Main background: m_j

Normalization recipe:

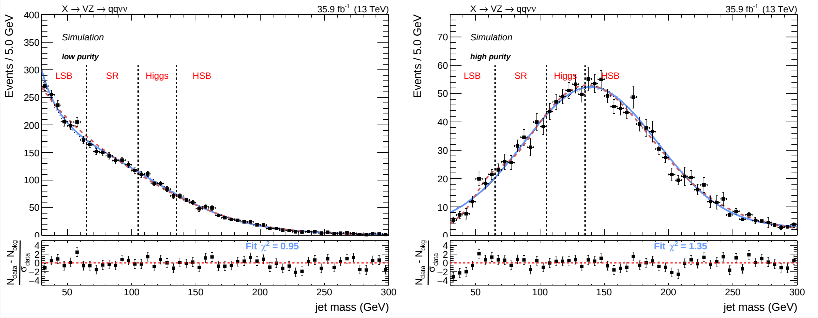
- Fit the whole MC spectra of m_j for all the backgrounds with physical motivated functions
- Fix the parameters of the secondary backgrounds

V+jets

- alternative function considered; discrepancy with main function as systematic uncertainty

LP `ErfPow2` (main), `ExpGaus` (alternative)

HP `ExpGaus` (main), `ErfExpGaus` (alternative)

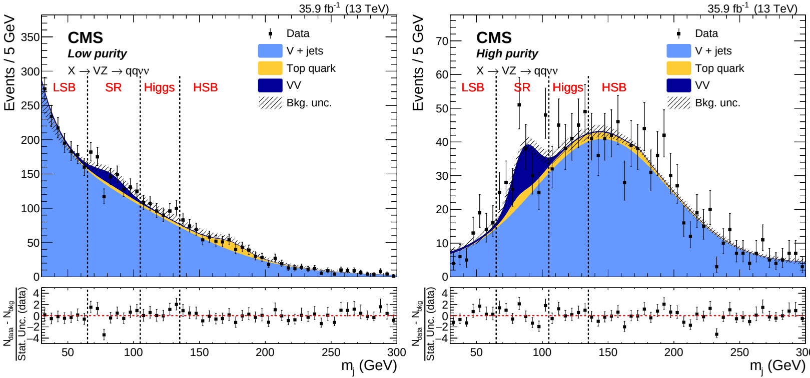


Background estimation: α method step 1

Normalization results

Normalization recipe:

- Fit the m_j spectrum in data SB to extract V+jets parameters
- Calculate the event yield in the SR



region	category	Expected	Stat.	Syst.	Alt. function	Observed
SR	low-purity	1093.2	±48.1	±16.4	±49.1	1153
SR	high-purity	254.4	±15.3	±17.9	±7.8	271

Background estimation: α method step 2

Shape: m^T_{VZ}

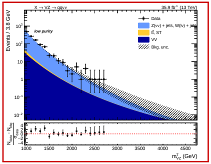
Shape recipe:

- Fit the MC spectra of m^T_{VZ} for the backgrounds with physical motivated functions f (exponential) in SB and SR
- Fix the parameters of the secondary background
- ➠ The α-ratio is calculated in V+jets MC spectra and describes the transfer SB → SR

$$\alpha(m^T_{VZ}) = \frac{f^{Vjet,MC}_{SR}(m^T_{VZ})}{f^{Vjet,MC}_{SB}(m^T_{VZ})}$$

- Fit the m^T_{VZ} in data SB to predict V+jets background
- ➠ The expected shape in SR is

$$f^{data}_{SR}(m^T_{VZ}) = \left[f^{data}_{SB}(m^T_{VZ}) - f^{Top,MC}_{SB}(m^T_{VZ}) - f^{VV,MC}_{SB}(m^T_{VZ})\right] \times \alpha(m^T_{VZ}) + f^{Top,MC}_{SR}(m^T_{VZ}) + f^{VV,MC}_{SR}(m^T_{VZ})$$



Data, SR

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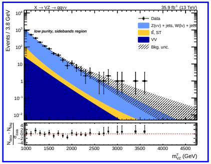

Data, SB

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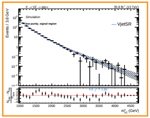
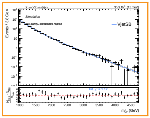
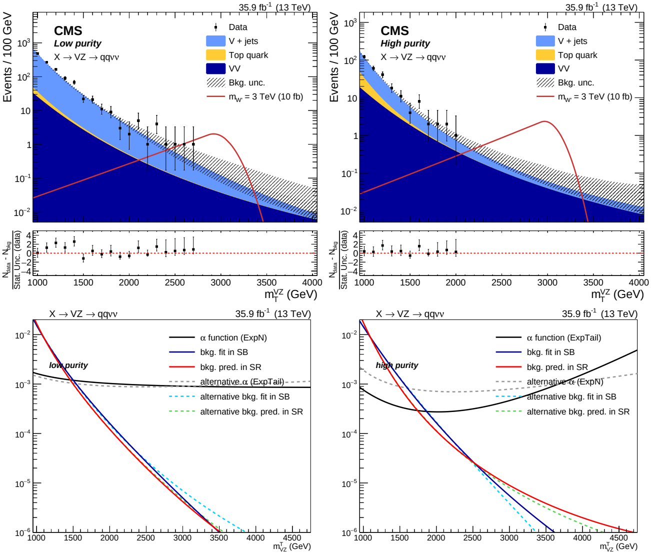




Alpha ratio (MC)

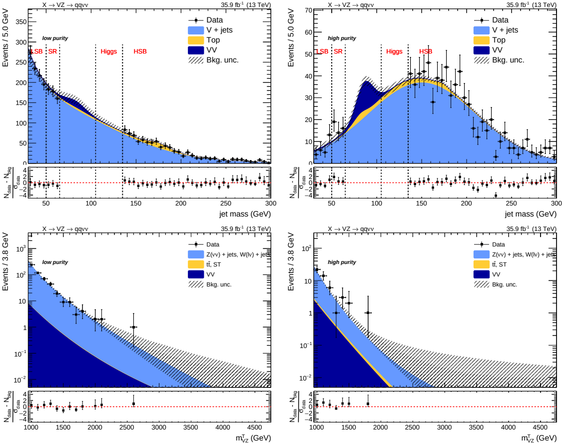
Background estimation: α method

Bacground estimation results



Validation of the α method

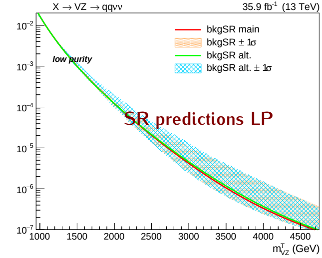
- Split the low sideband into two sub-regions, 30-50 GeV (LSB) and 50-65 GeV (SR)
- Predicted background in the new SR is in agreement wih data

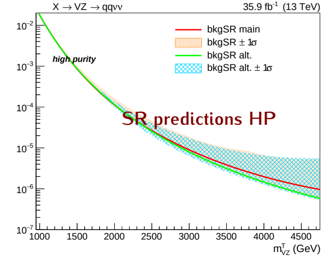


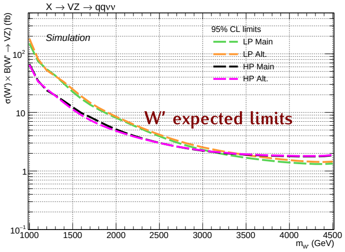
region	category	Expected	Observed
SR	2ν, low-purity	529.9 ± 37.8	521
SR	2ν, high-purity	39.3 ± 5.2	49

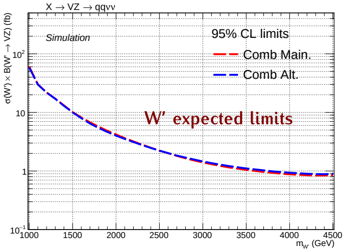
Robustness check

- Shape m^T_{VZ} of main background parametrized with alternative functions (main `ExpTail`; alternative `ExpN`)
- The main-alternative discrepancy in m^T_{VZ} predictions do not impact the final result





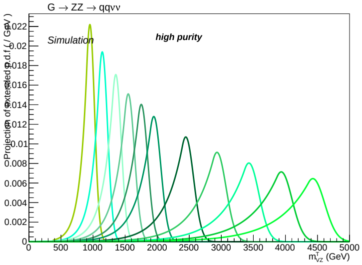


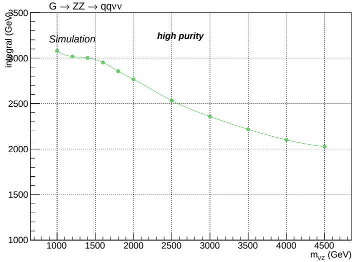


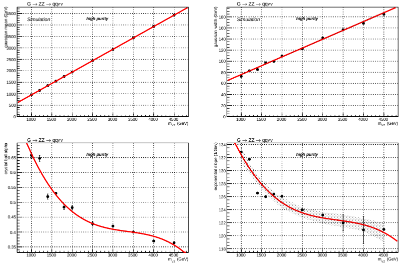
Signal parametrization

Parameters

- m^T_{VZ} distributions modelled as Crystal Ball functions: gaussian (2 D.O.F.) with power-law tails (2 D.O.F.) (shape parameters) and yield (1 D.O.F.) (normalization parameter)
- normalization parameter from a linear interpolation
- shape parameters fitted with a 1st-3rd degree polynomial







Systematic uncertainties

	shape	Main	Top	VV	Signal
α-function	✓	✓	–	–	–
Bkg. normalization		4.8%(LP)	68.2%(LP)	11.4%(LP)	–
(fit)		14.7%(HP)	47.7%(HP)	19.1%(HP)	–
Bkg. normalization		4.9%(LP)	–	–	–
(alternative function)		4.4%(HP)	–	–	–
jet energy scale	–	–	0.2%	0.1%	<0.1%
jet energy resolution	–	–	0.3%	<0.1%	<0.1%
unclustered energy	–	–	<0.1%	<0.1%	<0.1%
jet mass scale	✓	–	0.7%	0.1%	1.8%
jet mass resolution	✓	–	3.1%	2.0%	5.1%
trigger	–	–	1.0%	0.9%	0.7-0.5%
V boson tagging (τ_{21})	–	–	11% (HP), 23% (LP)		
V tagging extrapolation †	–	–	1.4% (LP)	1.7% (LP)	3.2-9.4% (LP)
	–	–	2.8% (HP)	3.3% (HP)	6.9-20.6% (HP)
b-tag veto	–	–	2.2%	0.3%	0.7-1.0%
pile-up	✓	–	0.3%	0.2%	0.4-0.7%
QCD renormalization	✓	–	7.3%	1.3%	<0.1%
QCD factorization ‡	✓	–	3.1%	0.9%	<0.1%
PDF ‡	✓	–	10.3%	2.1%	10.4-18.9% (scale)
luminosity	–	–	2.5%	2.5%	2.5%
cross section	–	–	10%	15%	–
tau veto	–	–	3%	3%	3%

†: extracted as a function of the jet p_T distributions, $X \cdot \log(p_T/200\ \mathrm{GeV})$

‡: PDF-QCD scale uncertainty for signal applied in theory curve

Statistical approach

Modified frequentist approach (CL_s) for upper limits

- Likelihood function: Poissonian p.d.f.
- Likelihood ratio test statistics (signal strength μ)

$$\tilde{q}_\mu = -2\log\frac{\mathfrak{L}(\text{data}\,|\mu,\hat{\theta}_\mu)}{\mathfrak{L}(\text{data}\,|\hat{\mu},\hat{\theta})}$$

- Given μ hypothesis ($\mu = 0$ background-only), $\tilde{q}_\mu^{\text{obs.}}$ measured on data

$$CL_s = \frac{\mathcal{P}\left(\tilde{q}_\mu \geq \tilde{q}_\mu^{\text{obs.}} \mid \text{signal + background}\right)}{\mathcal{P}\left(\tilde{q}_\mu \geq \tilde{q}_\mu^{\text{obs.}} \mid \text{background-only}\right)} = \frac{\int_{\tilde{q}_\mu^{\text{obs.}}}^{\infty} f(\tilde{q}_\mu|\mu,\hat{\theta}_\mu^{\text{obs.}})\,d\tilde{q}_\mu}{\int_{\tilde{q}_\mu^{\text{obs.}}}^{\infty} f(\tilde{q}_\mu|0,\hat{\theta}_0^{\text{obs.}})\,d\tilde{q}_\mu}$$

- Given α, a model with μ excluded at $(1-\alpha)$ C.L. if $\text{CL}_s \leq \alpha$

Local p-value scan

- Discovery test statistics:

$$q_0 = -2\log\frac{\mathfrak{L}(\text{data}\,|0,\hat{\theta}_0)}{\mathfrak{L}(\text{data}\,|\hat{\mu},\hat{\theta})}$$

$$p_0 = \mathcal{P}\left(q_0 \geq q_0^{\text{obs.}} \mid \text{background-only}\right) = \int_{q_0^{\text{obs.}}}^{\infty} f(q_0|0,\hat{\theta}_0^{obs})\,dq_0$$

Asymptotic formulae

- Wilk's and Wald's theorems: distributions inferred out of one pseudo-dataset (no statistical fluctuation)
- upper limit at 95% CL

$$CL_s = \frac{1-\Phi\left(\sqrt{\tilde{q}_\mu}\right)}{\Phi\left(\sqrt{\tilde{q}_{\mu,A}}-\sqrt{\tilde{q}_\mu}\right)}$$

$$\mu_{up} = \sigma\cdot\Phi^{-1}(1-0.5\alpha)$$

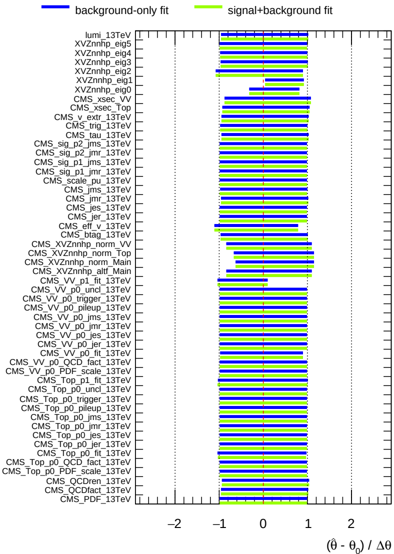
$$p_0 = \int_Z^{\infty}\frac{1}{\sqrt{2\pi}}e^{-x^2/2}dx$$

Likelihood fit diagnostics

- Likelihood fits performed per purity category and combining the categories

Nuisance pulls

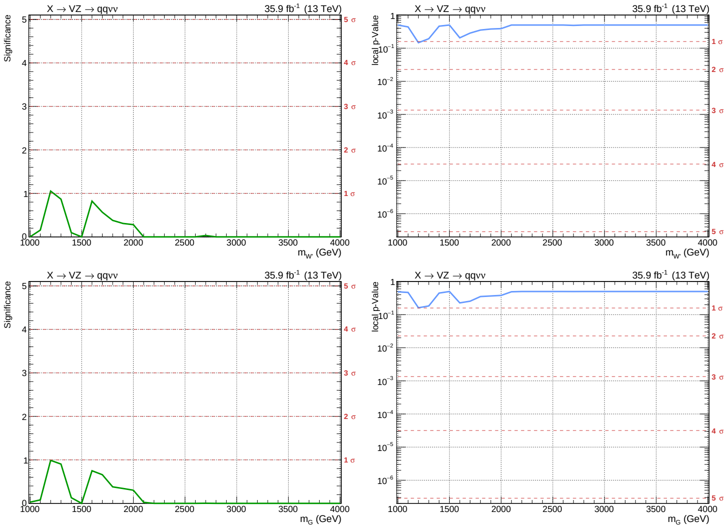
- Nuisance parameters: log-normal priors (positively defined nuisances), profiled during the minimization
- Pre/post-fit values compared: nuisance pulls $(\hat{\theta} - \theta_0)/\Delta\theta$
- Computed in background-only ($\mu = 0$) and signal+background ($\mu = 1$) hypotheses
- No pathological behaviour observed



Results

Local p-value scan

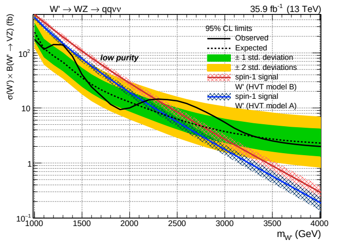
- No excesses w.r.t. background-only hypothesis

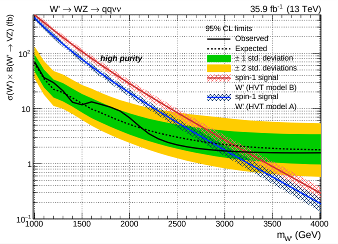


Results

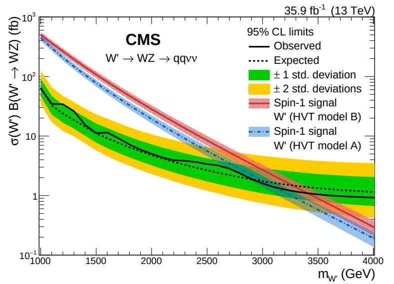
Exclusion limits for HVT W'

Low-high purity



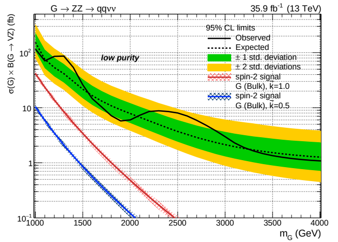


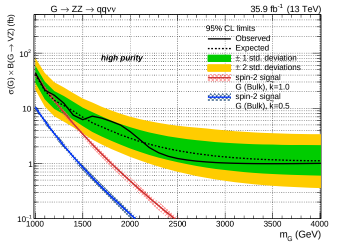
Combination



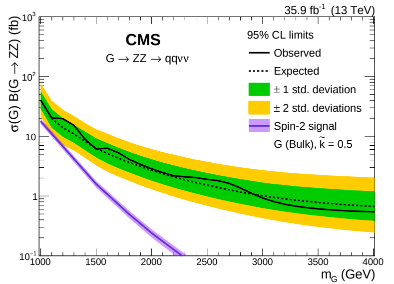
- 95% CL limits set for HVT W' production cross-section times branching fraction
- $\sigma\mathcal{B}(W' \to W_{\text{had}} Z_{\text{inv}})$: 0.9 fb (63 fb) for W' with mass 4.0 TeV (1.0 TeV)
- W' rejected for $m_{W'} < 3.1$ TeV in HVT model A ($f\bar{f}$ dominant) (1.4 fb)
- W' rejected for $m_{W'} < 3.4$ TeV in HVT model B (VV, VH dominant) (1.1 fb)

Low-high purity



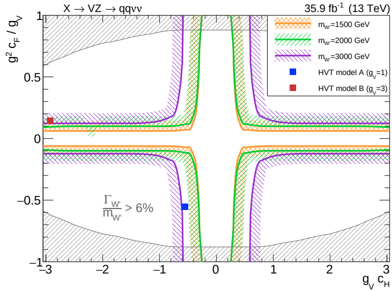


Combination



- 95% CL limits set for bulk graviton production cross-section times branching fraction
- $\sigma\mathcal{B}(G \to Z_{\text{had}} Z_{\text{inv}})$: 0.5 fb (40 fb) for G with mass 4.0 TeV (1.0 TeV)
- theoretical predictions for curvature parameter $\tilde{k} = 0.5$ shown for comparison

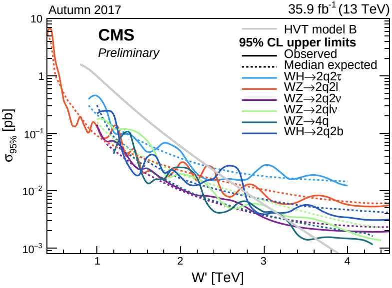
Interpretation of the results

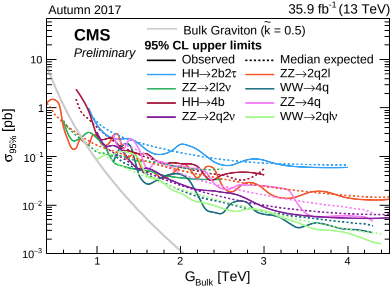


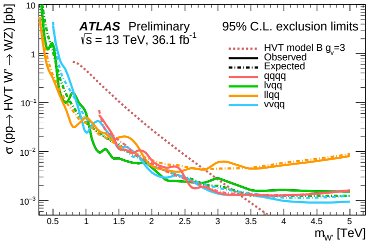
Parameter space exclusion

- Upper limits on $\sigma\mathcal{B}(W')$ interpreted in parameter space $\left(g_V c_H, g^2 c_F / g_V\right)$
- Benchmark model A ($g_V = 1, c_H = -0.556, c_F = -1.316$) (blue dot)
- Benchmark model B ($g_V = 3, c_H = 0.976, c_F = 1.024$) (red dot)
- coloured curves: contours of parameter space excluded by data
- shaded gray area: parameter space where the narrow width approximation fails (width comparable to resolution, 6%)

Comparison with diboson searches







- This search (violet curve) has the best sensitivity to HVT W' in the range 1–3 TeV at CMS
- Comparable to limits obtained by ATLAS (combining the $q\bar{q}\ell\bar{\ell}$)
- The HVT W' limits presented in this thesis are the best single limits obtained in $q\bar{q}\nu\bar{\nu}$ final state

Future perspectives

- LHC delivered $\mathcal{L} \sim 40\text{fb}^{-1}$ in 2017
- Combination 2016 + 2017 data (double statistics) $\rightarrow$ marginal improvement
- Improve sensitivity by reducing systematic uncertainties: novel techniques

New tools

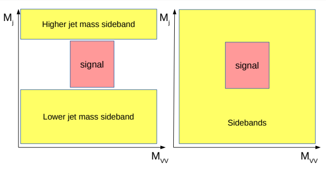
- Improving the jet mass resolution: recursive softdrop
- Improving the pile-up removal Soft PUPPI
  - Soft killer: particles clustered with a per-event p_T cut
- Machine learning:
  - to remove pile-up
  - to improve b-tagging (boosted topology)
  - jet substructure

New ideas for the background estimation: 2D fit

α: SB-SR fitted separately

2D fit: simultaneous fit to m_j and m_{VZ}

- better treatment of correlations
- no categorization in SB $\rightarrow$ more statistics (less uncertainty) & simultaneous extraction of different signals (VV, VH)



- Signal and background: non-parametric estimation $\rightarrow$ Gaussian Kernel method: 2D templates populated from simulations (function of generated p_T^J)
- Method applied in $VW \rightarrow q\bar{q}\ell\nu$ (2016 data)
- Extension to 3D fit $VV \rightarrow J_1 J_2$ (+2017 data)

Conclusions

- This is the first search for diboson resonances in the $q\bar{q}\nu\bar{\nu}$ performed by CMS, using p-p collisions data produced by LHC at $\sqrt{s} = 13$ TeV in 2016
- Probed final state: $Z \to \nu\nu$ decays (missing transverse momentum); $W/Z \to q\bar{q}$ decays (large-cone jet)
- Categorization of the events depending on the jet substructure
- No significant excesses with regards to SM predictions
- Results interpreted in beyond standard model scenarios as upper limits on production cross-section
    - Heavy Vector Triplet spin-1 W': $\sigma\mathcal{B}(W' \to W_{\text{had}} Z_{\text{inv}})$: 0.9 fb (63 fb) for W' with mass 4.0 TeV (1.0 TeV)
    - lower limit $m_{W'} < 3.1$ TeV in HVT model A ($f\bar{f}$ dominant)
    - lower limit $m_{W'} < 3.4$ TeV in HVT model B (VV, VH dominant)
    - Bulk graviton spin-2 G: $\sigma\mathcal{B}(G \to Z_{\text{had}} Z_{\text{inv}})$: 0.5 fb (40 fb) for G with mass 4.0 TeV (1.0 TeV)
- Ultimate goal of the search: grand combination of all the diboson searches at CMS
- This final state provides the best sensitivity to HVT model in the range 1–3 TeV
- Improvements are foreseen combining the results with 2017 data and exploiting novel techniques

Backup slides

Validation: W+jet and Z+jet

Softdrop algorithm

arXiv 1402.2657

Softdrop procedure:

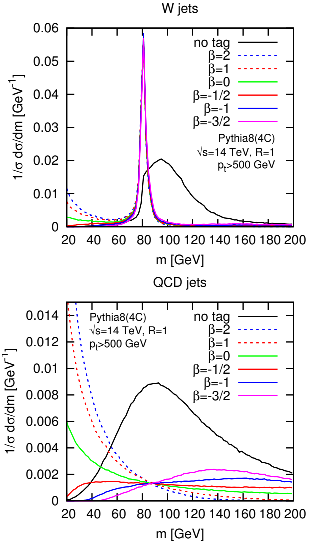
- jet declustered into two subjets, j_1 and j_2, by reverting the final step of Cambridge-Aachen algorithm;
- if j_1 and j_2 respect the softdrop condition (eq. 1), j is defined as the groomed jet;
- if they don't pass the condition, the leading subjet in p_T is redefined as the new j;
- if j can't be declustered anymore, it is defined as the groomed jet.

Soft drop condition:

$$\frac{\min(p_T^1, p_T^2)}{p_T^1 + p_T^2} > z_{\text{cut}} \left(\frac{\Delta R_{12}}{R_0} \right)^\beta , \quad (1)$$

z_{cut} (soft threshold) and β parameters affect the degree of jet grooming: if $\beta \to \infty$ – jet ungroomed, if $\beta \to 0$ – more soft collinear radiation removed.

Fig: Distributions of the jet mass in W + jet signal simulations (top) and multi-jet QCD background (bottom), before (in black) and after applying softdrop algorithm. Each curve corresponds to a different value of the parameter β. arXiv 1402.2657



N-subjettiness

arXiv 1011.2268

Re-clustering of jet constituents with the k_T algorithm, forced to return n subjets. The n-subjettiness, τ_n, is:

$$\tau_n = \frac{1}{d_0} \sum_k p_{T,k} \min\left(\Delta R_{1,k}, \Delta R_{2,k}, \ldots, \Delta R_{n,k}\right), \qquad (2)$$

k labels the particles in the jet, $p_{T,k}$ is the transverse momentum of k, $\Delta R_{i,k}$ is the angle between k and i subjet candidate. The parameter d_0 is a normalization factor:

$$d_0 = \sum_k p_{T,k} R_0, \qquad (3)$$

R_0 is the clustering parameter of the jet. The τ_n variable describes to what degree a jet can be considered as composed by n substructures; smaller values of τ_n correspond to higher compatibility with the n-prong hypotesis. The most powerful discriminating variable is the ratio $\tau_{21} = \tau_2/\tau_1$:

$$\tau_{21} = \frac{\frac{1}{d_0} \sum_k p_{T,k} \min(\Delta R_{1,k}, \Delta R_{2,k})}{\frac{1}{d_0} \sum_k p_{T,k} \Delta R_{1,k}}. \qquad (4)$$

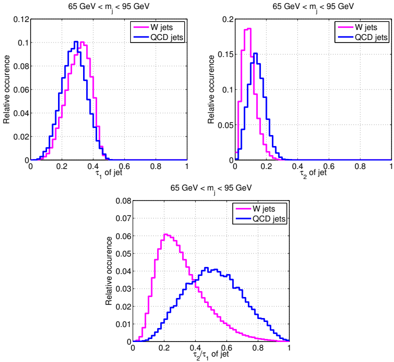
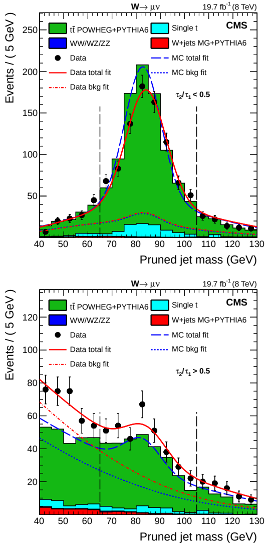


Figure: Distribution of τ_1 (top left), τ_2 (top center), and τ_{21} (bottom) variables, in simulations of a W plus jets process (in pink) and for a multi-jet QCD originated process (in blue). Selections applied: $65 < m_j < 95$ GeV; jets clustered with parameter $R_0 = 0.6$, $p_T > 300$ GeV, $|\eta| < 1.3$ (arXiv 1011.2268).

W tagging scale factors

arXiv 1410.4227

- a selection on the jet τ_{21} scuplts the jet mass spectrum is sculpted
- distributions of the groomed jet mass and τ_{21} compared in data and simulations, by selecting samples of di-jet, $t\bar{t}$ and W + jets events: discrepancy observed (10%)
- scale factors extracted by selecting a $t\bar{t}$ sample in data (high p_T W boson is produced by the top quark decay)
- jet mass distributions of events passing (top plot) and failing (bottom plot) the selection on the τ_{21} variable are fitted simultaneously, both in data and in simulations
- V-tagging scale factors are the ratio of the τ_{21} categorization efficiencies in data and MC



2D templates building in $VW \to q\bar{q}\ell\nu$

B2G-16-029

✧ Signal events in (m_{WV}, m_J) plane modelled as:

$$P_{sig}(m_{WV}, m_J\theta(M_X)) = P_{WV}(m_{WV}|\theta_1(M_X)) \times P_j(m_J|\theta_2(M_X))$$

- P_{WV} and P_j are double crystal-ball functions; parameters described by polynomial interpolations, θ_1 and θ_2

✧ W+jets background is a conditional probability of m_{WV}, function of m_J:

$$P_{W+\text{jets}}(m_{WV}, m_J) = P_{WV}(m_{WV}|m_J, \theta_1) \times P_j(m_J|\theta_2)$$

- conditional probability accounts for the correlations between m_J and m_{WV}; due to dependence of m_J with jet p_T during hadronization process
- 2D templates populated with a kernel method starting from generated events
- a resolution model is derived for m_J and m_{WV} as a function of true jet p_T $\to$ sums of 2D Gaussian distributions fill the 2D template (mean of the Gaussians is the true value of m_J and m_{WV}; the 2D covariance matrix given by the resolution model
- Gaussians weighted by the cross section
- final step: smooth the tails for high values of m_{WV} (no empty bins)
- nuisances: accounts for differences between data and simulation

✧ $W+t$ and WV backgrounds modelled as:

$$P_{W+V}(m_{WV}, m_J|\theta) = P_{WV}(m_{WV}|\theta_1) \times P_j(m_J|\theta_2(m_{WV}))$$