

Search for Flavor Changing Neutral Currents in Top Quark Decays

$$t \rightarrow q\gamma$$

Jason Barkeloo

July 11, 2019



Overview

Brief Background

- The Top Quark

- FCNC at the LHC

- Transitioning to r21, New Ntuple Production

Searching for Flavor Changing Neutral Current Signatures

- FCNCs with Photons

- Object Preselection Cuts

- Top and Neutrino Reconstruction

Neural Network

- Architecture

- Neural Network Outcomes

Continuing Analysis

- Region Creation

Outlook and Conclusions

Table of Contents

Brief Background

The Top Quark

FCNC at the LHC

Transitioning to r21, New Ntuple Production

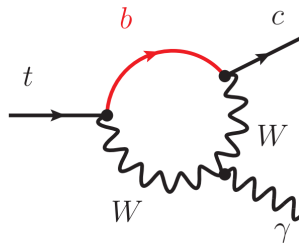
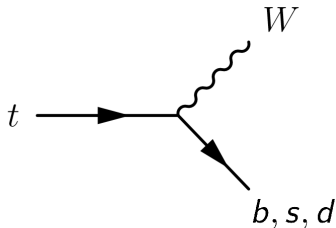
Searching for Flavor Changing Neutral Current Signatures

Neural Network

Continuing Analysis

Outlook and Conclusions

Top Quark Decays in the SM

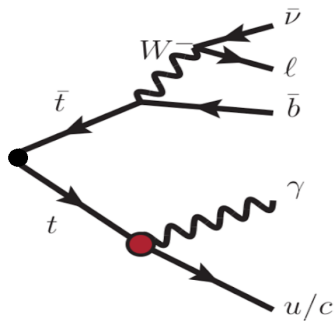


- ▶ $t \rightarrow bW \approx 99.83\%$
- ▶ $t \rightarrow sW \approx 0.16\%$
- ▶ $t \rightarrow dW \approx 0.01\%$

- ▶ $t \rightarrow q_{u,c}X \approx 10^{-17} - 10^{-12}$
- ▶ Limits on $t \rightarrow \gamma q$ processes:
[JHEP 04 (2016) 035]
 - ▶ $t \rightarrow \gamma u < 1.3 \times 10^{-4}$
 - ▶ $t \rightarrow \gamma c < 1.7 \times 10^{-3}$

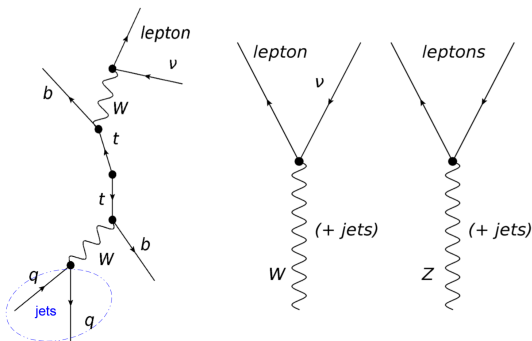
FCNC: What are we looking for? $t\bar{t} \rightarrow W(\rightarrow l\nu)b + q\gamma$

- ▶ Final state topology
 - ▶ One Neutrino, from W
 - ▶ One Lepton, from W
 - ▶ One B-jet, SM Top
 - ▶ One Photon, FCNC Top
 - ▶ One Jet, FCNC Top



Background Processes

- ▶ Due to all of the processes at hadron colliders, it is important to model similar event topologies well
- ▶ Major backgrounds include $t\bar{t}$, W +Jets, Z +Jets, + processes with an associated photon



Migration to Release 21

- ▶ AnalysisTop2.X → AnalysisTop21.X
- ▶ Revalidation of UFO Model, Recreation of signal events
- ▶ Custom basic ntuple maker and post-grid local processing code created
- ▶ Parallelization of post-processing code for use with local tier-3 Condor nodes for quicker code testing and analysis
- ▶ Can now do most work off grid in significantly less time

Object Preselection

- ▶ We preselect events with objects that look like similar to our expected topology
- ▶ Require:
 - ▶ Exactly one lepton (e or μ) ≥ 25 GeV
 - ▶ Exactly one good photon ≥ 15 GeV
 - ▶ Missing Transverse Energy ≥ 30 GeV
 - ▶ ≥ 2 Jets (at least 1 b-tag)

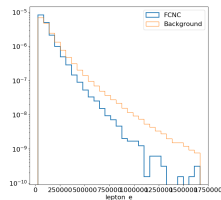
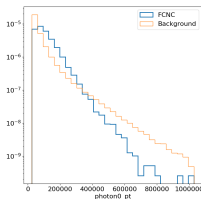
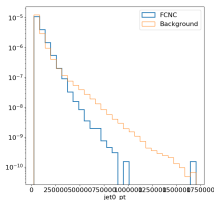
Preselection Objects with $N_{BJet} = 1$

► Leading Jet p_T

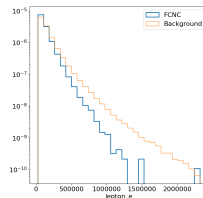
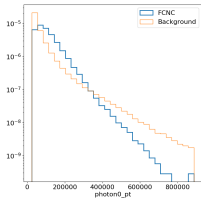
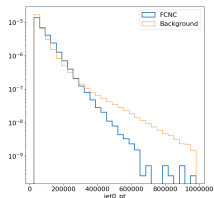
► Lead Photon

► Lepton E

Electron Channel



Muon Channel

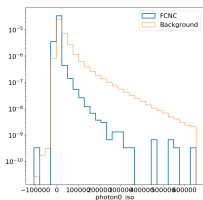


Preselection Objects with $N_{BJet} = 1$

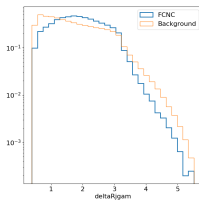
Electron Channel

Muon Channel

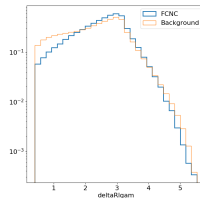
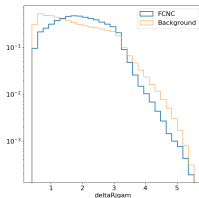
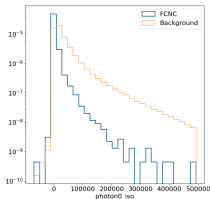
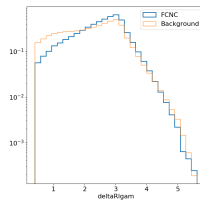
► γ_{iso}



► $\Delta R_{j\gamma}$



► $\Delta R_{l\gamma}$



Individual Top Reconstruction

- ▶ We can reconstruct top candidates from basic physics objects and E_T^{miss}
- ▶ E_T^{miss} is calculated to balance the event energy in the transverse plane of the detector
- ▶ The other particles are combined in the only way the signal topology would allow two top quark candidates
 - ▶ Standard model top candidate: b-jet + lepton + neutrino
 - ▶ FCNC Top: Photon + Light Jet

Neutrinos

- ▶ All missing energy in signal topology is from neutrino
- ▶ We have E_T^{miss} and its direction
 - ▶ Can calculate E_{Tx}^{miss} and E_{Ty}^{miss} easily
 - ▶ Ambiguous direction along the z-axis
- ▶ A minimization of this χ^2 will allow us to determine the z momentum of the neutrino: $\chi^2 = \frac{(m_{b,l,\nu} - m_t)^2}{\sigma_{SMtop}^2} + \frac{(m_{l,\nu} - m_W)^2}{\sigma_W^2}$

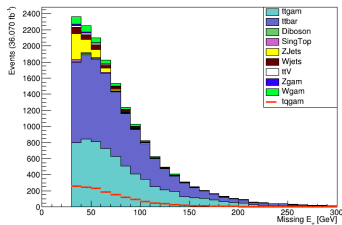


Figure: e-channel E_T^{miss} distribution

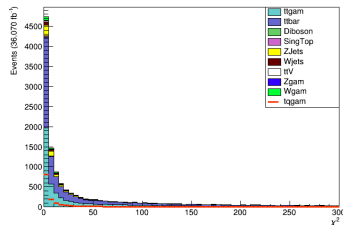
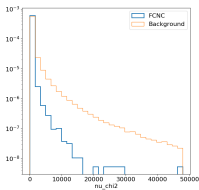
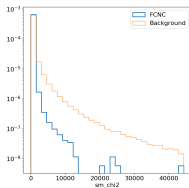
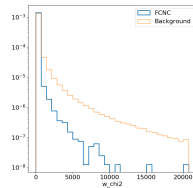


Figure: e-channel χ^2 distribution

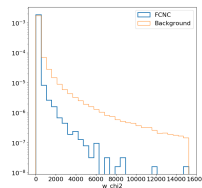
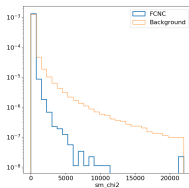
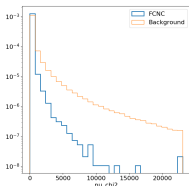
*Plots from previous release, same methodology used, same results

$$\chi^2 = \frac{(m_{b,l,\nu} - m_t)^2}{\sigma_{S\text{Mtop}}^2} + \frac{(m_{l,\nu} - m_W)^2}{\sigma_W^2}$$

Electron Channel

► χ^2 ► $\chi_{S\text{MTop}}^2$ ► χ_W^2 

Muon Channel



Neural Network Architecture

- ▶ Using Keras on top of Tensorflow various input parameters are tested for model behavior
- ▶ A Dense Neural Network with variable number of input variables and hidden layers are explored
- ▶ Cut optimization has been performed with full Run 2 luminosity for potential reach of the search

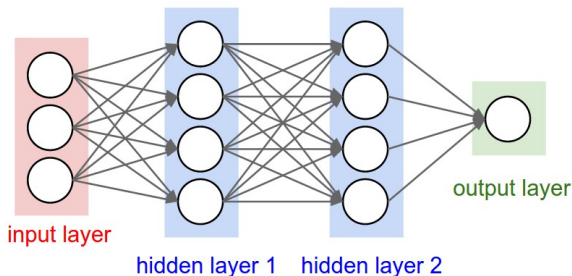


Figure: [Ref: Neural Network]

Neural Network Optimizers

- ▶ Various optimization functions can be used, however we use Adam (Adaptive Moment Estimation)
 - ▶ Adam computes adaptive learning rates for every parameter and stores a history of the parameters used to calculate the next step
 - ▶ Stores first (mean) and second (uncentered variance) moments of the gradients used during training
 - ▶ Converges very fast and is less computationally intensive

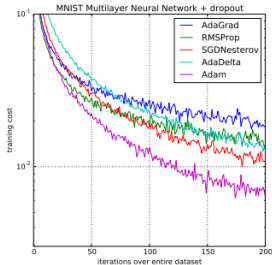


Figure: [Ref:Machine Learning Mastry]

Neural Network Model Inputs

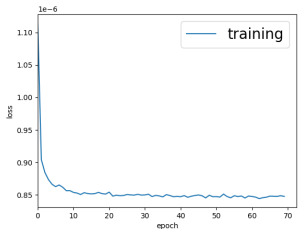
- ▶ Using keras on top of tensorflow various input parameters are tested for model behavior
- ▶ Networks are set up with 1 input layer, either 1 or 2 hidden layers with 10 nodes, and 1 output node
- ▶ Each hidden layer has 20% dropout to prevent overtraining by removing codependency between nodes
- ▶ Batch size of 100 used and each network is allowed 200 epochs (with patience=50), all models converge and end early with reasonable batch sizes
- ▶ Optimizer: Adam
- ▶ Loss Function: Binary Cross Entropy

Neural Network Model Inputs

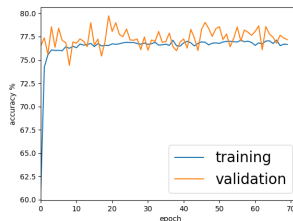
- ▶ Minimal set of variables including kinematic and geometric variables chosen based on their separation power
- ▶ Minimal variable set tested: $\gamma_{iso}, \gamma_{p_T}, \Delta R_{j\gamma}, \Delta R_{bl}, M_T^W, S_T, n_{jets}, \chi_W^2, jet_{0p_T}, \Delta R_{l\gamma}, lepton_E, MET, bjet_{0p_T}$
- ▶ Add in extra variables to help training and see if improvement: High level variables/combinations that we know would be helpful in a cut based approach such as $m_{q\gamma}, m_{l\gamma}$, more χ^2 fit information, etc.
- ▶ A complex enough network should be able to figure out most of these straight forward combinations by itself
- ▶ Every MC sample is split into train/test/validation Sets (64%,20%,16%) combined and shuffled for network analysis

Neural Network, Electron Channel

► Loss



► Accuracy

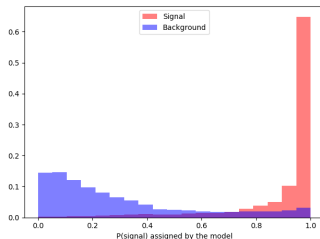
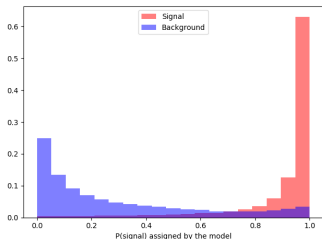


Neural Network Separation, Electron Channel

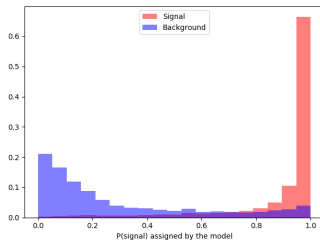
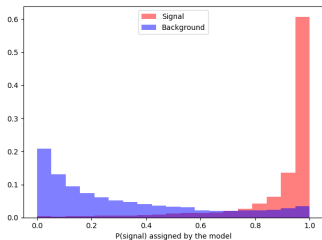
► 1 Hidden Layer

► 2 Hidden Layers

Extended Inputs



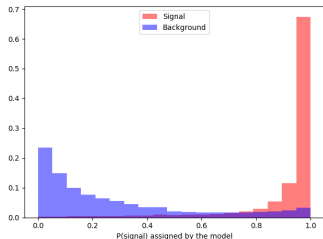
Minimal Inputs



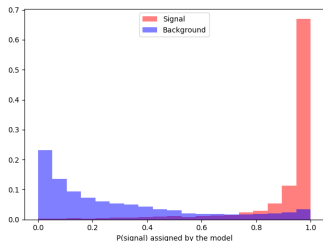
Neural Network Separation, Muon Channel

► 1 Hidden Layer

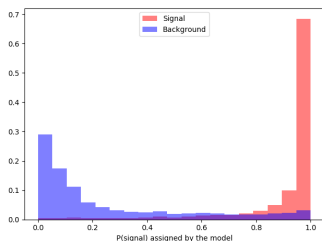
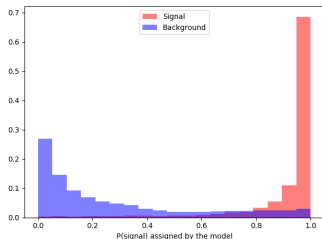
Extended Inputs



Minimal Inputs

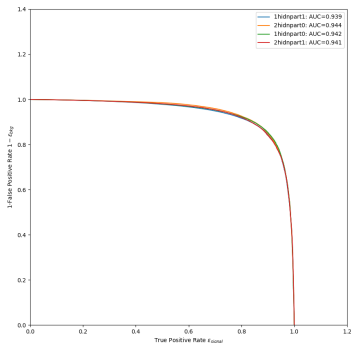


► 2 Hidden Layers

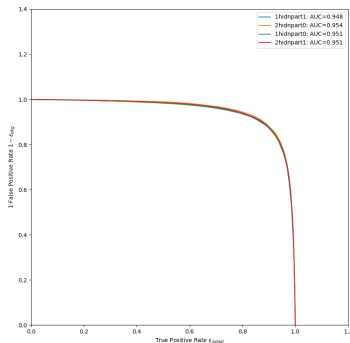


ROC Curves for Multiple Models

► Electron Channel



► Muon Channel

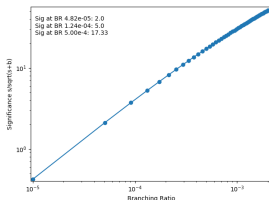
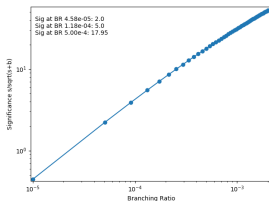


- All of these are very close (visually and by area), want to explore deeper to pick best model

Significance Plots, Electron Channel

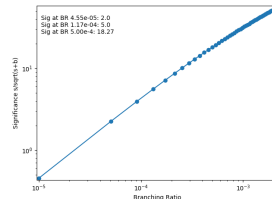
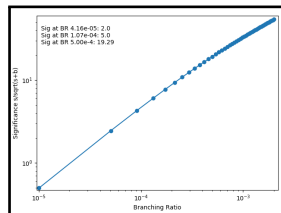
Extended Inputs

► 1 Hidden Layer



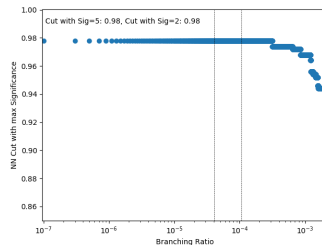
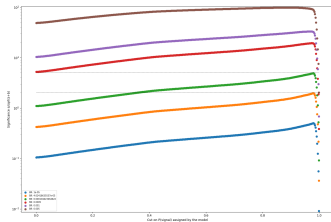
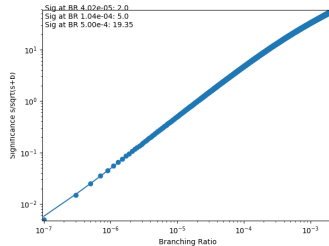
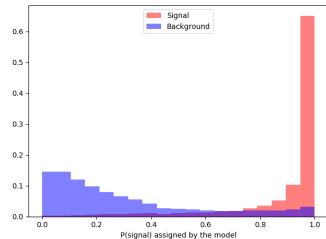
Minimal Inputs

► 2 Hidden Layers

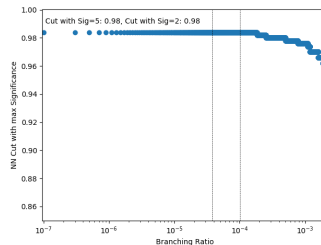
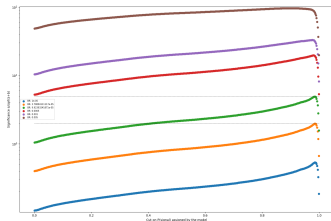
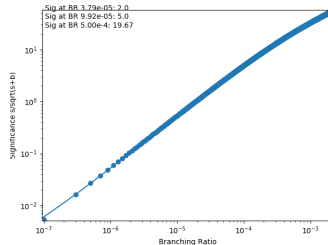
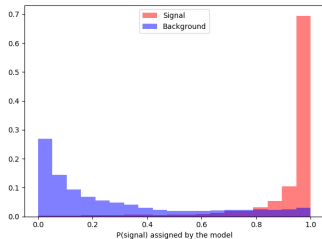


► Significance:
$$S = \frac{n_S}{\sqrt{n_S + n_B}}$$

Significance Plots, Electron Channel



Significance Plots, Muon Channel



Cut Optimization

- ▶ Cut optimization gives a pretty consistent value for a wide range of Branching Ratios
- ▶ Close depending on the model but can differ slightly if optimizing for discovery vs. optimal limit setting
- ▶ To reasonable precision the suggested cuts from the previous plots are identical $NN_{\text{cut}} = 0.98$ for both channels
- ▶ Can implement this cut going forward with the rest of the analysis and make sure it behaves in various orthogonal control and validation regions

Validation Region - With Real Photons

- ▶ Validation and Control Regions are created orthogonal to Signal Region for large backgrounds
- ▶ VR for $(t\bar{t} + \gamma)$
 - ▶ Same preselection cuts as SR
 - ▶ > 4 jets
 - ▶ Reverse FCNC top mass cut $|m_{q\gamma} - m_{top}| > 50\text{GeV}$: Guarantees orthogonality
- ▶ VR for $W + \gamma$
 - ▶ Similar preselection cuts to SR
 - ▶ $= 0$ BJets (orthogonal cut)
- ▶ Similar regions have been created for regions without real photons - included in recent grid run
 - ▶ These regions include $t\bar{t}$ and W rich samples with 0 good photons and different amounts of jets
 - ▶ Including these regions greatly increases processing time necessary because of glut of $0b/0\gamma$ events - Requires reoptimization of current analysis code

Outlook

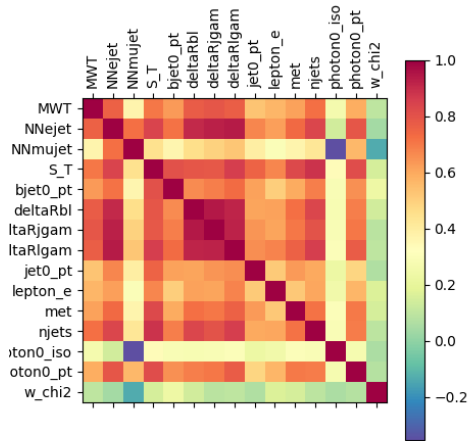
- ▶ Still lots to be done
- ▶ Fake Rates $e \rightarrow \gamma$ and $j \rightarrow \gamma$ will be investigated next
- ▶ Full MC grid run of MC16a/d/e samples is complete, using for current investigations
- ▶ Full Analysis transitioned to be able to run on condor nodes
 - ▶ Capable of handling much larger samples by directly using grid output files
 - ▶ Necessary to look at MC16a/d/e samples and full 2018 data set in a reasonable amount of time (especially with VRs/CRs)
- ▶ Initial neural network studies are completing, can push forward with another step of the analysis

Conclusion

- ▶ Any excess signal would be indicative of some physics beyond the Standard Model that couples strongly to the top sector
- ▶ With the inclusion of the neural network significant gains can be made in the search for FCNCs with top quark decays
- ▶ FCNCs with enhanced rates are important pieces for testing many new theories
- ▶ Analysis is going after a long lull due to MC Production delays
- ▶ Thank you!

Backup

NN Input Variable Correlations



Neural Network Model Inputs

$$\text{Separation} = \sum_i^{\text{bins}} \frac{n_{si} - n_{bi}}{n_{si} + n_{bi}}$$

mu+jets channel

Variable	Separation
photon0iso	41.18
mqgam	28.27
photon0pt	24.07
mtSM	11.60
mlgam	7.56
deltaRjgam	5.64
deltaRbl	4.42
MWT	3.34
ST	3.30
nuchi2	3.12
jet0pt	2.81
njets	2.07
smchi2	1.89
wchi2	1.87
jet0e	1.52
deltaRlgam	1.17
leptone	0.87
deltaRjb	0.86
met	0.68
bjet0pt	0.52
leptoniso	0.27

e+jets channel

Variable	Separation
photon0pt	23.14
mqgam	22.73
photon0iso	18.70
mtSM	11.02
mlgam	9.53
deltaRbl	5.00
deltaRjgam	4.60
ST	3.83
MWT	3.16
jet0pt	2.47
njets	1.70
nuchi2	1.59
deltaRlgam	1.40
wchi2	1.33
smchi2	1.09
deltaRjb	0.88
leptone	0.85
leptoniso	0.56
bjet0pt	0.50
met	0.47

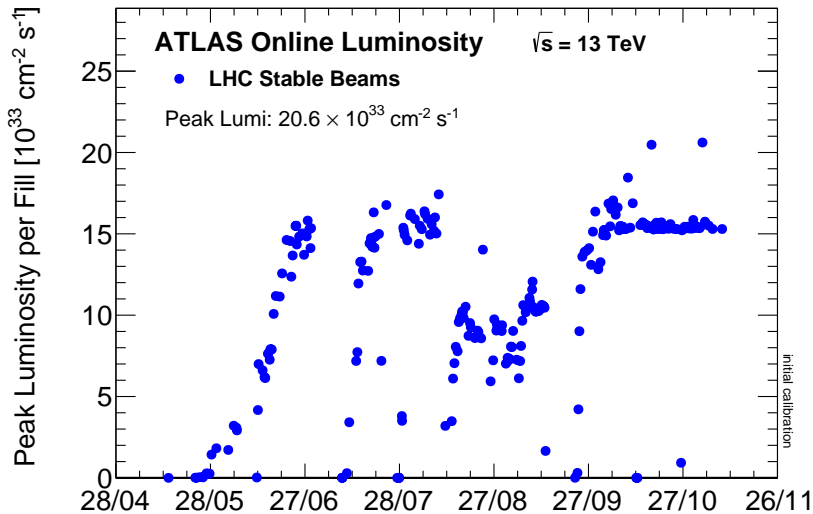
Input Variables

Extended Inputs: ['photon0iso', 'photon0pt', 'mqgam', 'mlgam', 'mtSM',
'deltaRjgam', 'deltaRbl', 'MWT', 'ST', 'njets', 'nbjets', 'wchi2', 'jet0pt',
'deltaRlgam', 'leptone', 'met', 'bjet0pt']

Minimal Inputs:

['photon0iso', 'photon0pt', 'deltaRjgam', 'deltaRbl', 'MWT',
'ST', 'njets', 'wchi2', 'jet0pt', 'deltaRlgam', 'leptone', 'met', 'bjet0pt']

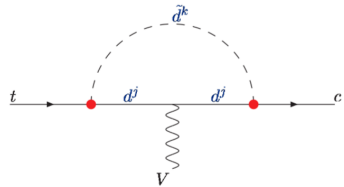
Integrated Luminosity



A Couple BSM Diagrams

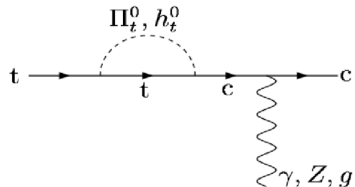
- R-parity-violating supersymmetric models

[arXiv:hep-ph/9705341]



- Top-color-assisted technicolor models

[arXiv:hep-ph/0303122]



Jets/AntiKT

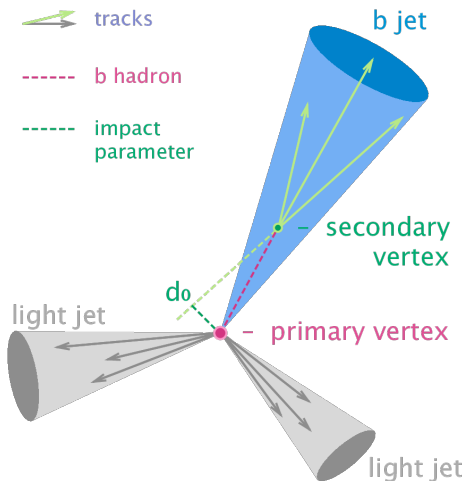
$$d_{ij} = \min\left(\frac{1}{p_{ti}^2}, \frac{1}{p_{tj}^2}\right) \frac{\Delta_{ij}^2}{R^2}$$

$$d_{iB} = \frac{1}{p_{ti}^2}$$

$$\Delta_{ij}^2 = (\eta_i - \eta_j)^2 + (\phi_i - \phi_j)^2$$

- ▶ Find minimum of entire set of $\{d_{ij}, d_{iB}\}$
- ▶ If d_{ij} is the minimum particles i, j are combined into one particle and removed from the list of particles
- ▶ If d_{iB} is the minimum i is labelled as a final jet and removed from the list of particles
- ▶ Repeat until all particles are part of a jet with distance between jet axes Δ_{ij} is greater than R

B-tagging



$$\mathcal{L}_{tq\gamma}^{\text{eff}} = -e\bar{c}\frac{i\sigma^{\mu\nu}q_\nu}{m_t}(\lambda_{ct}^L P_L + \lambda_{ct}^R P_R)tA_\mu + H.c.$$