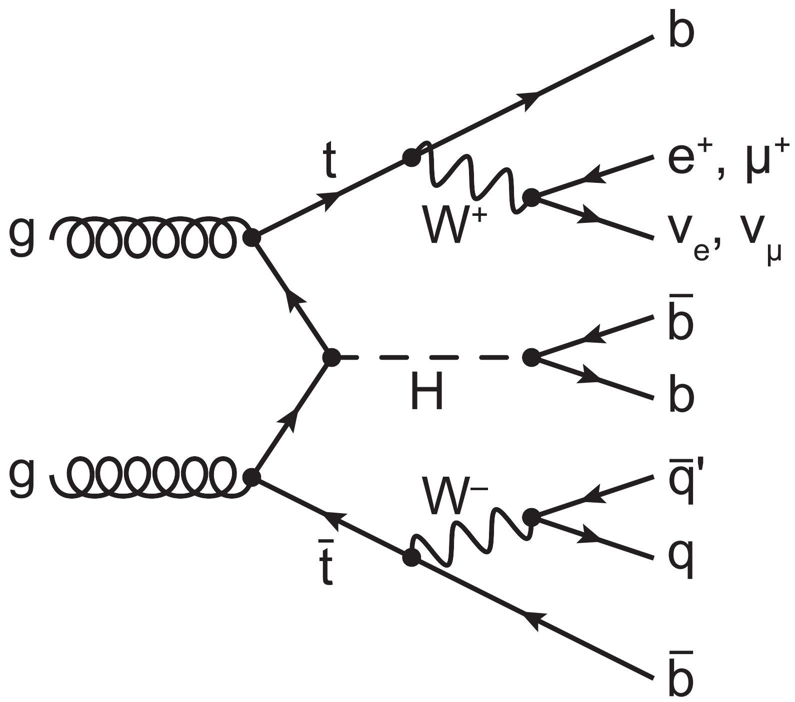


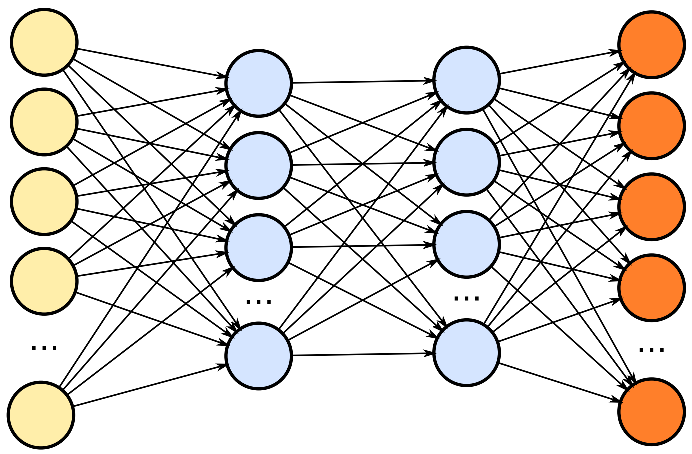

# Event Categorization using Deep Neural Networks for the ttH (H→bb) Analysis at CMS


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IML Workshop 2018

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CMS-HIG-17-035

CERN-EP-2018-064
2018/04/10

# Observation of $t\bar{t}H$ production

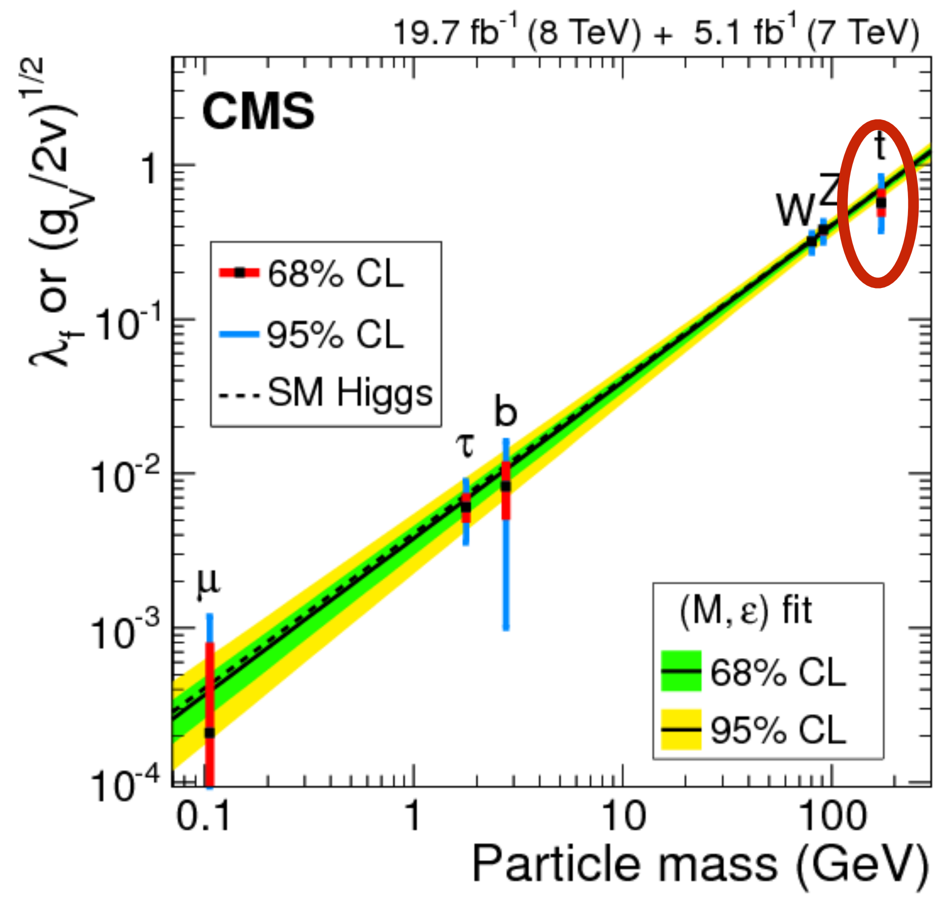
The CMS Collaboration*

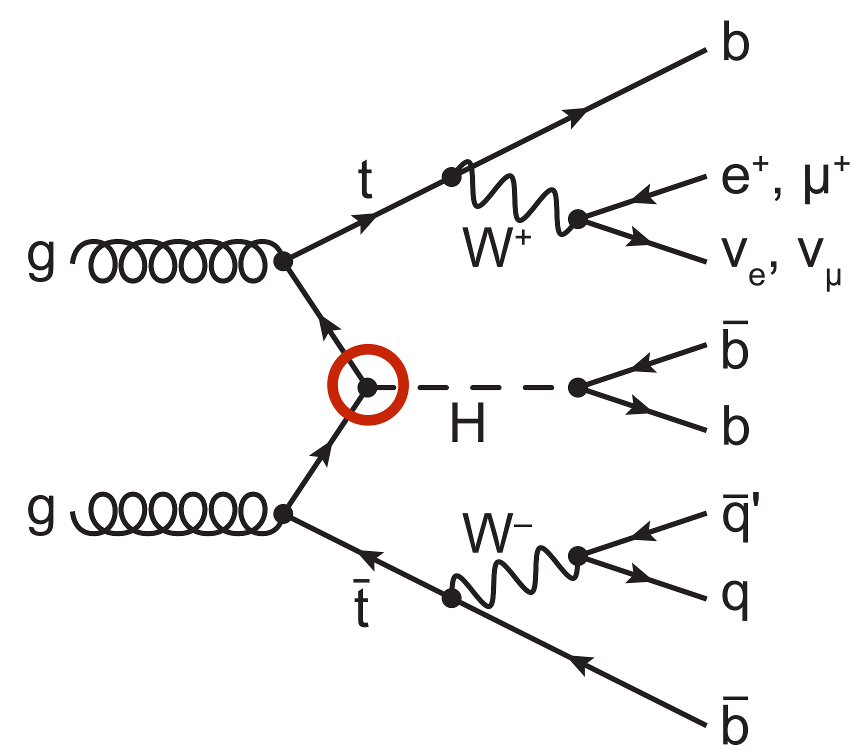
## Abstract

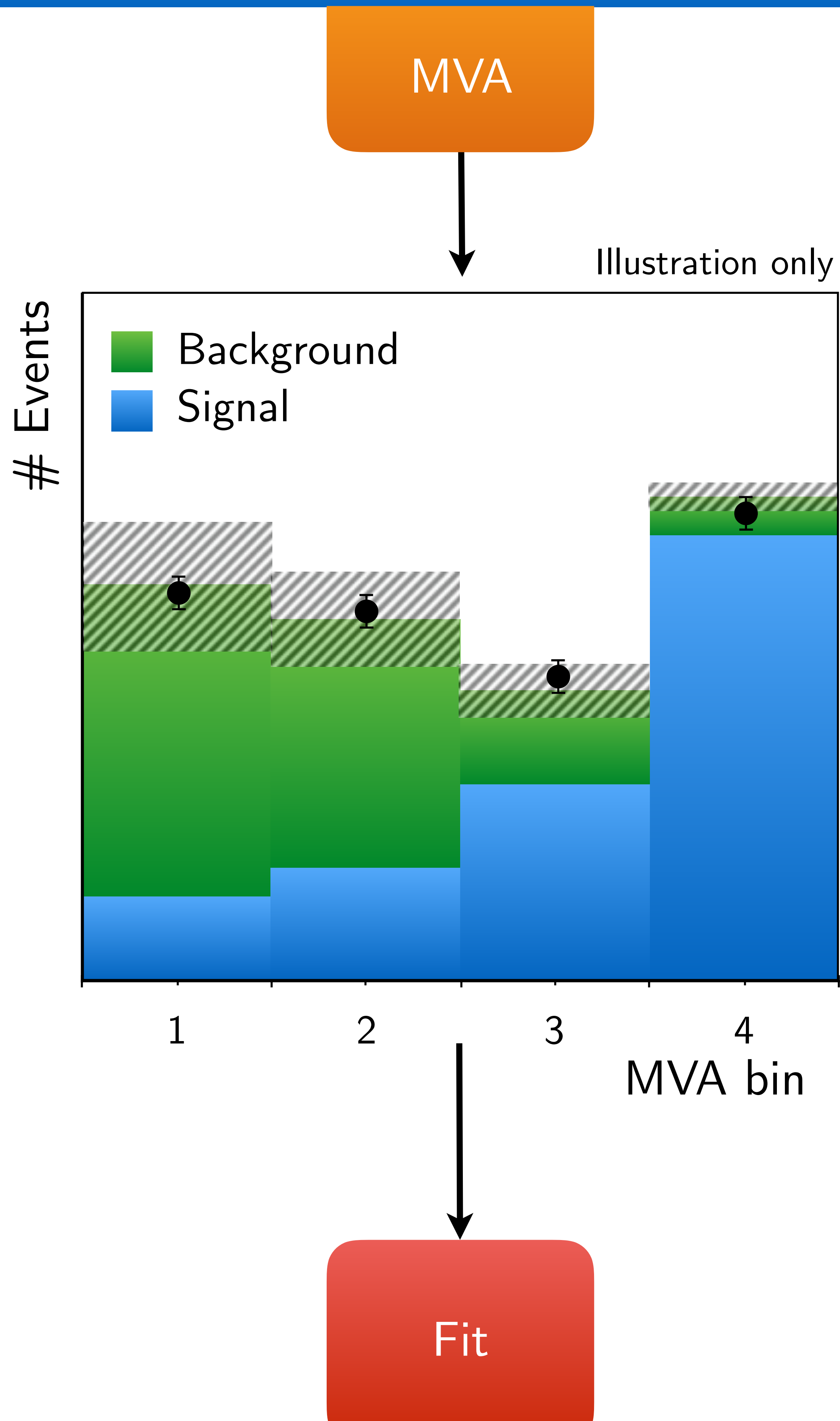
The observation of Higgs boson production in association with a top quark-antiquark pair is reported, based on a combined analysis of proton-proton collision data at center-of-mass energies of $\sqrt{s} = 7$, 8, and 13 TeV, corresponding to integrated luminosities of up to 5.1, 19.7, and 35.9 $\mathrm{fb}^{-1}$, respectively. The data were collected with the CMS detector at the CERN LHC. The results of statistically independent searches for Higgs bosons produced in conjunction with a top quark-antiquark pair and decaying to pairs of W bosons, Z bosons, photons, $\tau$ leptons, or bottom quark jets are combined to maximize sensitivity. An excess of events is observed, with a significance of 5.2 standard deviations over the expectation from the background-only hypothesis. The corresponding expected significance from the standard model for a Higgs boson mass of 125.09 GeV is 4.2 standard deviations. The combined best fit signal strength normalized to the standard model prediction is $1.26^{+0.31}_{-0.26}$.

- *ttH, H → bb*
  - Direct probe of top-Higgs coupling
  - Very rare, $\sigma_{ttH} = 0.51$ pb
  - *H → bb*: largest BR (0.58)
- Backgrounds from *tt*+jets,
  - Esp. *ttbb* irreducible
  - Relatively large cross section uncertainties ($\gtrsim 35\%$)
- Complex final state
  - High combinatorics due to many jets

No "direct" measurement via (e.g.) mass peak
→ Simultaneous fit to MVA distribution(s)

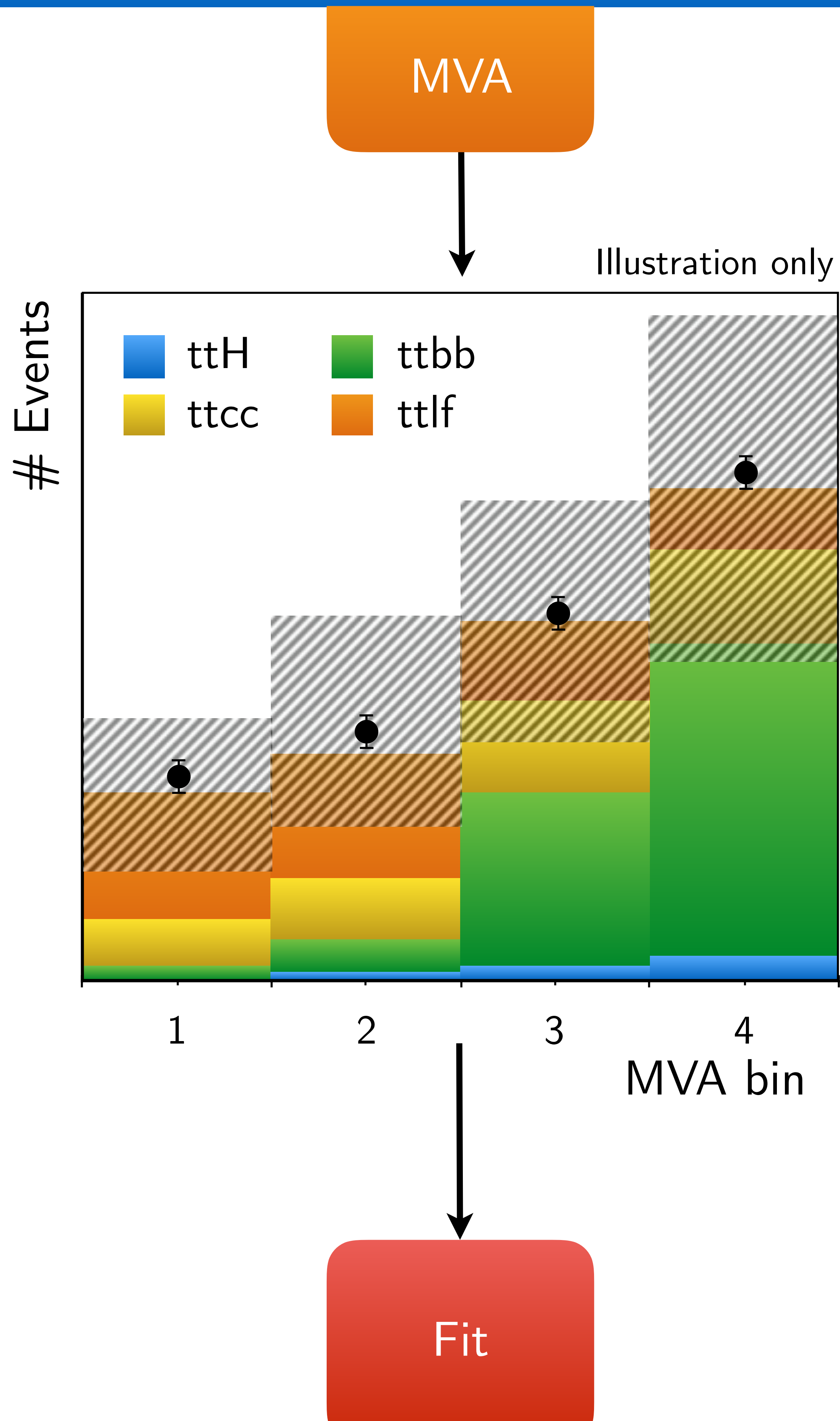





- Fit expected yields (MC) to data simultaneously in all categories / bins
  - **Backgrounds** vary within uncertainties, constrained by prior (e.g. gaussian)
  - No prior on **signal**

→ Signal extraction crucially depends on ability to measure backgrounds

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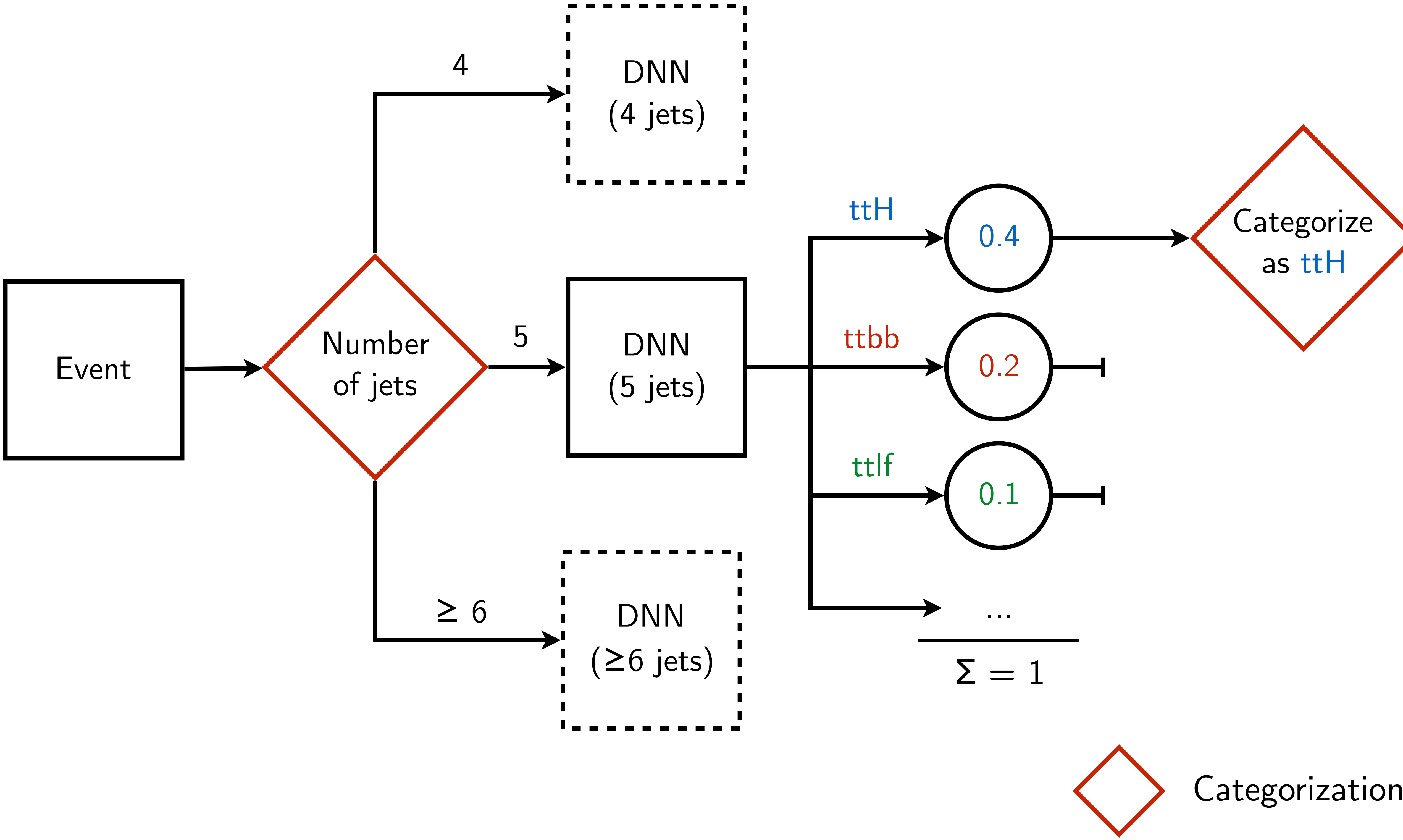
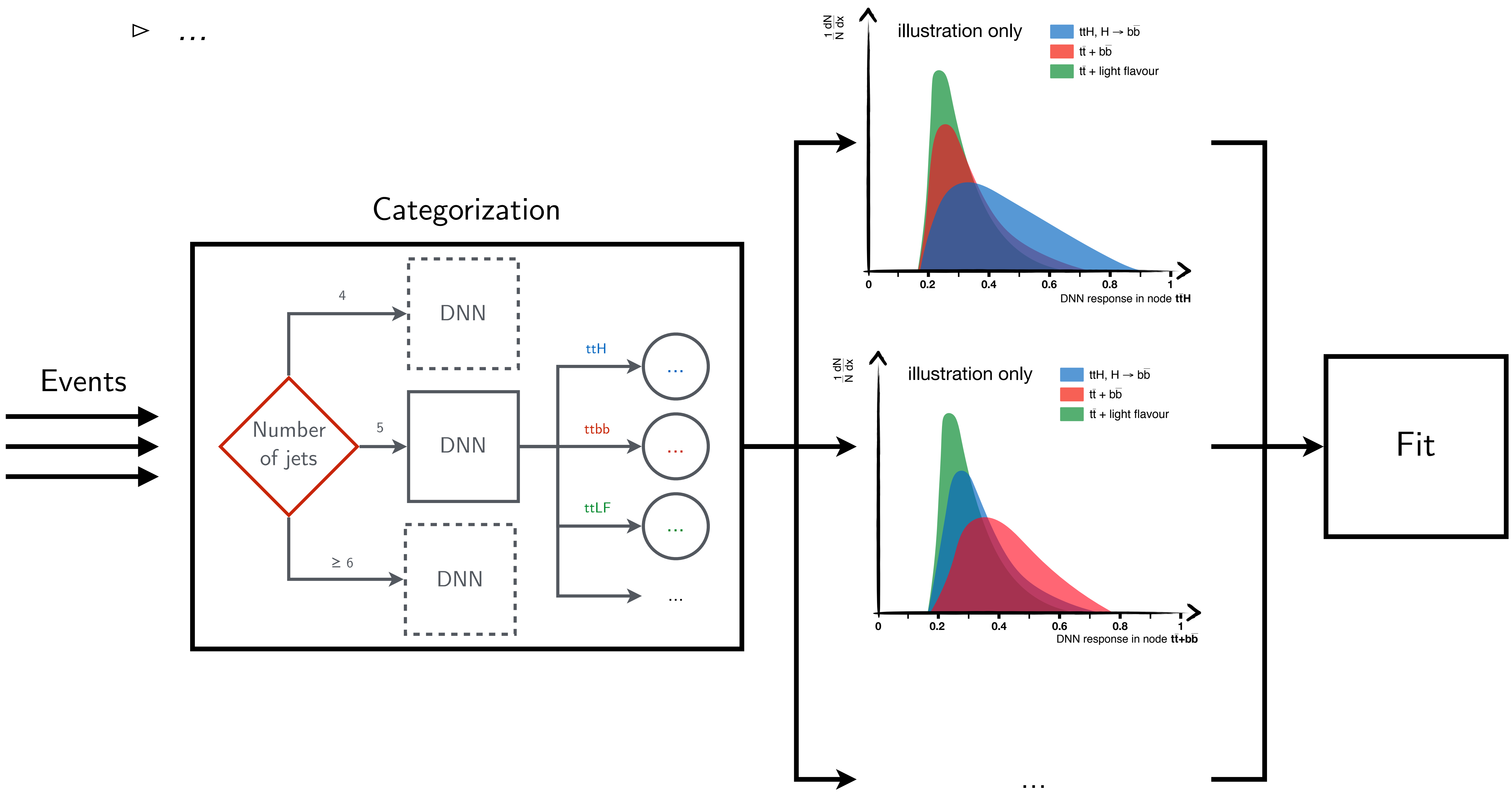
- *ttH* situation:
  - Large backgrounds (e.g. *ttlf*)
  - Irreducible backgrounds (e.g. *ttbb*)
- Idea: Multi-classification DNN
  → Create enriched categories for **signal** and **each background**

## Per event


Event
Number of jets
4
5
≥ 6
DNN (4 jets)
DNN (5 jets)
DNN (≥6 jets)
ttH
ttbb
ttlf
0.4
0.2
0.1
...
Σ = 1
Categorize as ttH
Categorization

- Output nodes of categorization networks yield powerful discriminators
  - → Use output node associated to category for simultaneous fit
    - ▷ *ttH* node for events categorized as *ttH*
    - ▷ *ttbb* node for events categorized as *ttbb*
    - ▷ …



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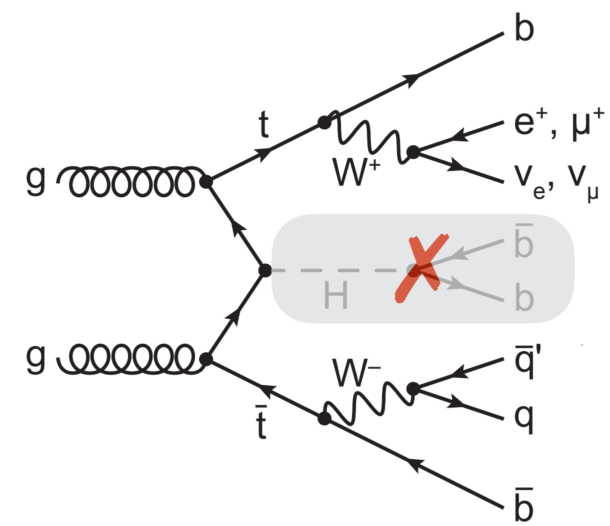
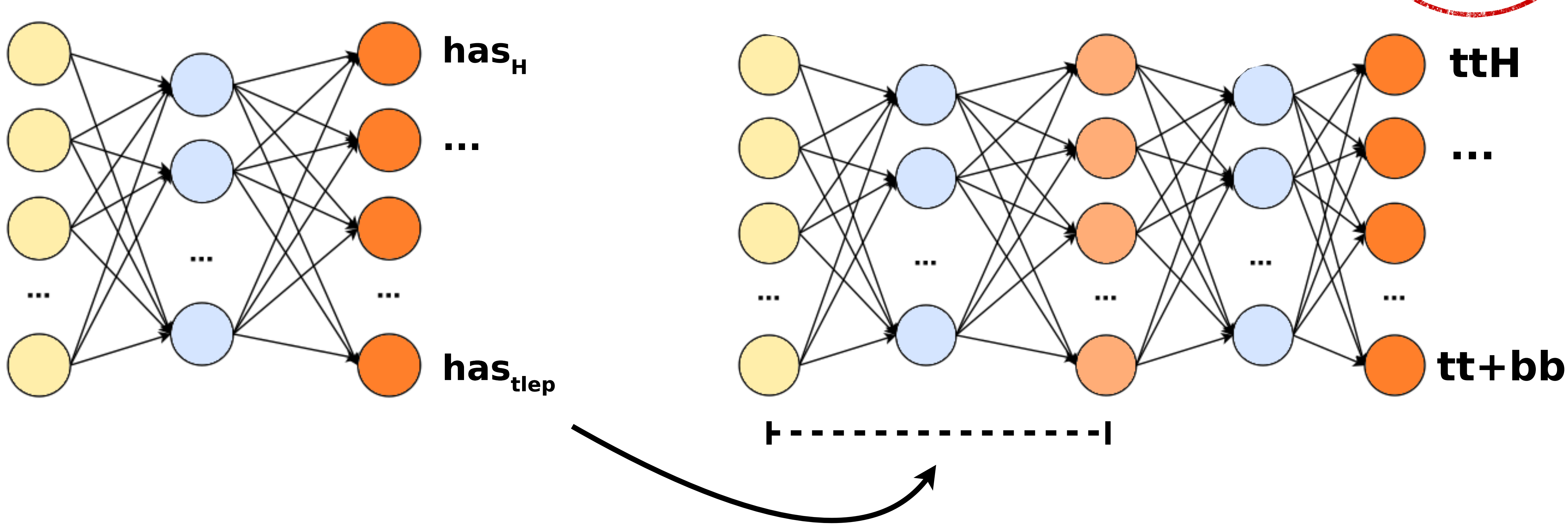
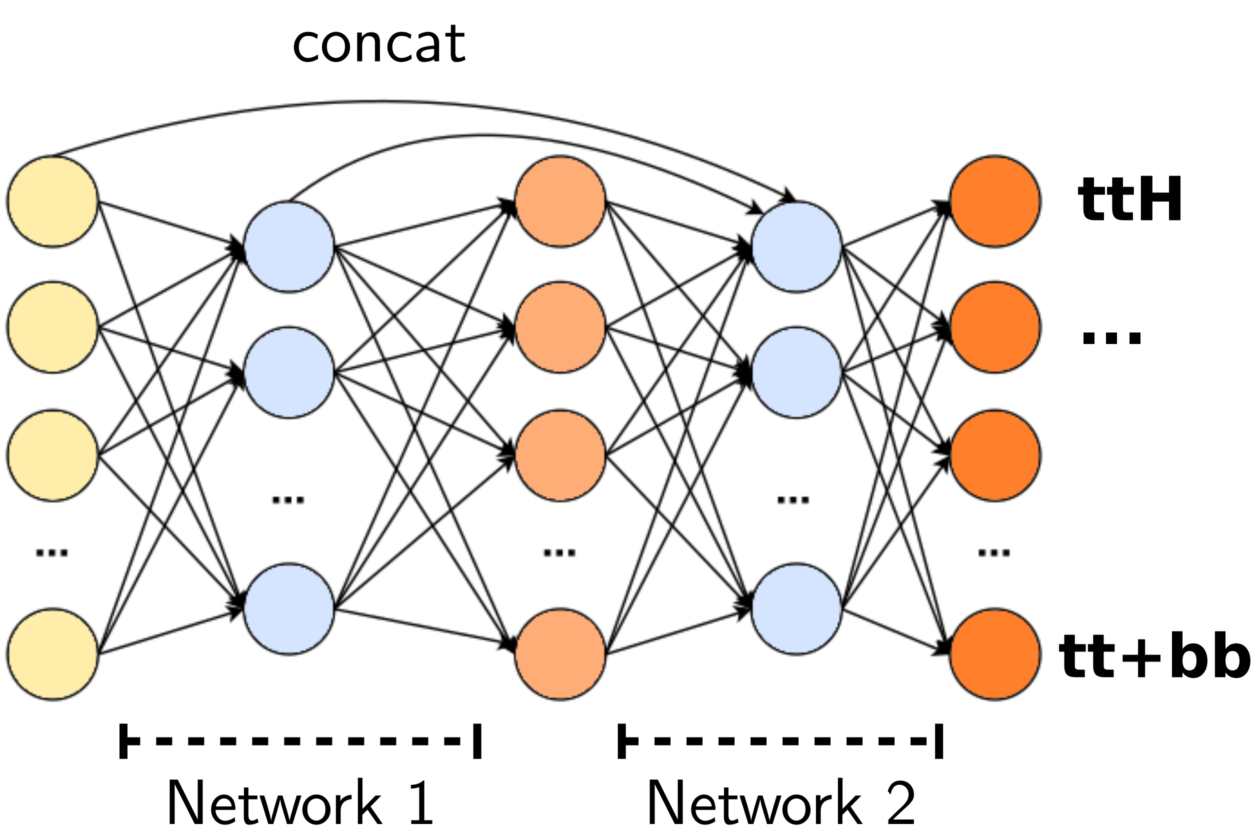
- Events of same class can have different topologies:
  - Jets out of acceptance
  - Merged jets
  - …
  - → Just training on bare event classes will confuse the network




- Idea:
  1. Pre-training on event content from generator ($has_H$, $has_{bH}$, $has_{blep}$, …)
  2. Extend network and train on actual classes




- Network architecture (≥ 6 jets):

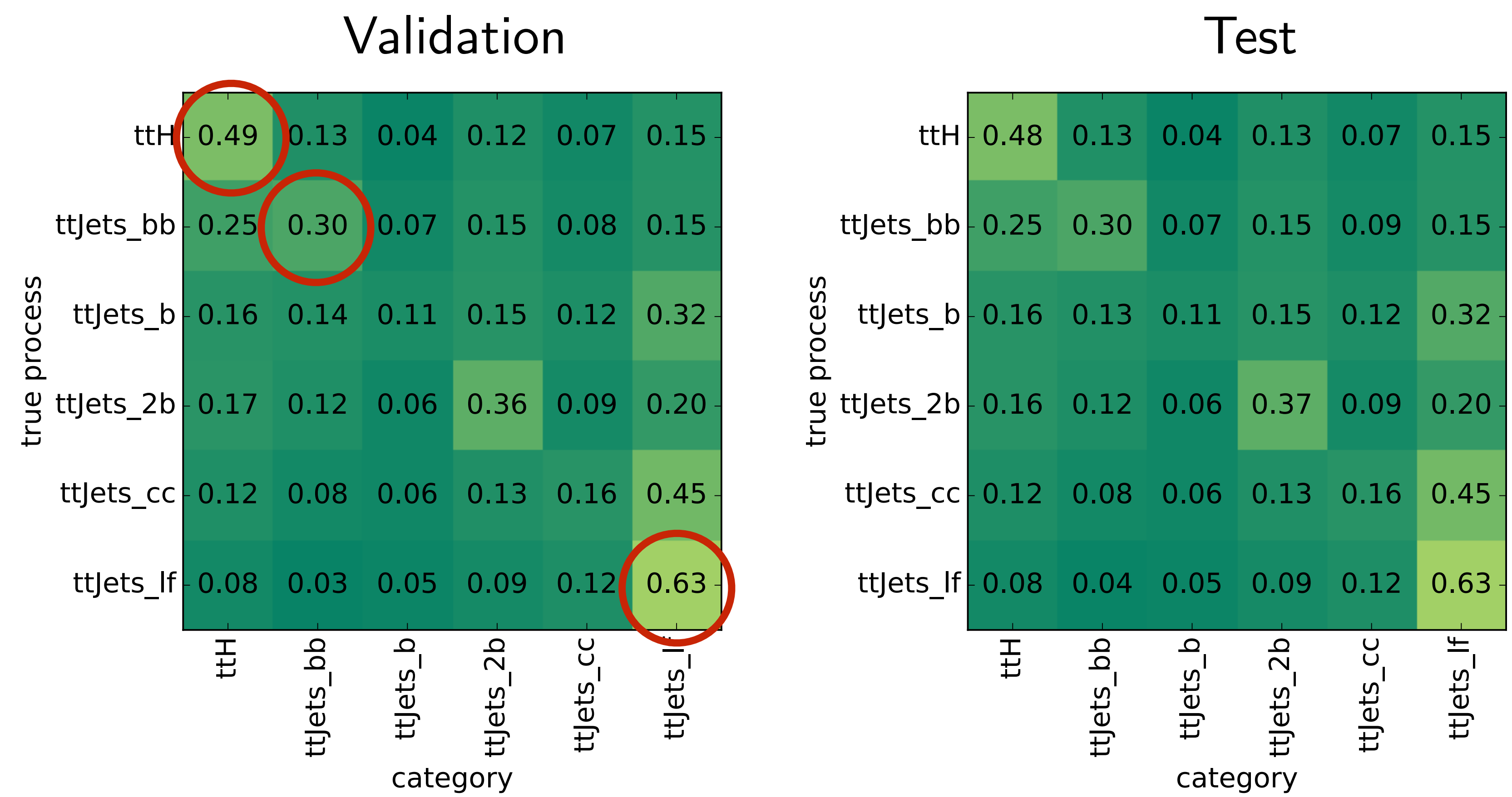
| Network 1 | Network 2 | Activation | L2 | Dropout (keep prob.) | Learning rate (ADAM) |
|---|---|---|---|---|---|
| 100,100 | 100,100 | ELU | $10^{-5}$ | 0.7 | $10^{-4}$ |

- Implementation using plain TensorFlow
- Training time ~20min on 980 Ti

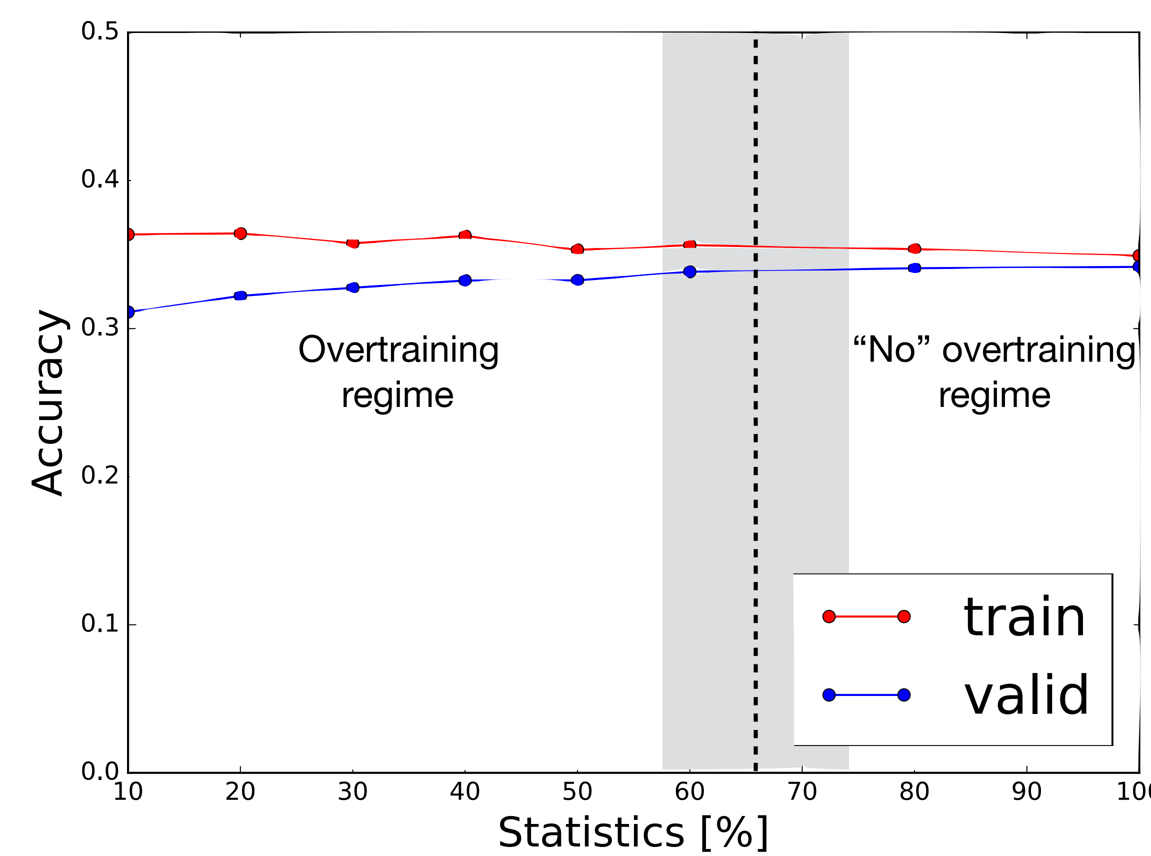
# Network performance



- Classification accuracies



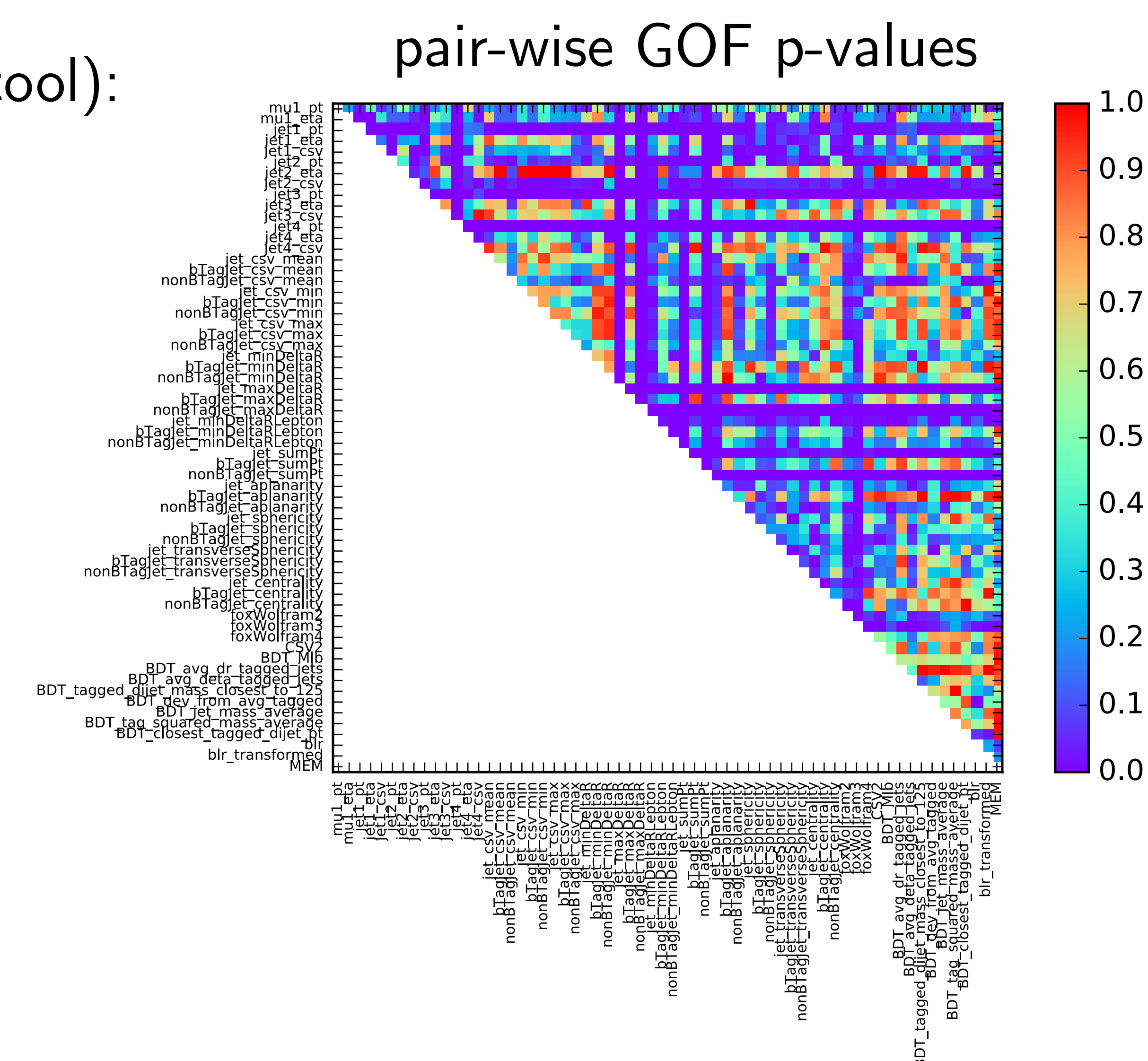

- Common trade-off:
  - → Network size **vs.** amount of data
- Artificially force overtraining by reducing statistics
  - → Results stable down to ~⅔ of events



- Check of agreement between data and MC necessary, but 1D not sufficient
  - → MVA techniques exploit deep correlations
  - → Need to prove agreement of correlations in addition to 1D shapes

- Compare 2D correlation coefficients
  - → Mix low- and high-level variables to cover even deeper correlations

- Recipe using GoodnessOfFit test (CMS `combine` tool):
  1. Create TH2F's for all pairs of input variables
  2. Unroll to 1D histograms
  3. Determine p-value for data MC agreement (using combine and frequentist toys)
  4. Remove variables that yield a bad correlation agreement with other variables, criterion:




p-value $< 0.3$ for $\geq 50\%$ of variables

- Used in CMS ttH(bb) leptonic analysis (CMS-HIG-PAS-17-026)
  - Results shown at Moriond 2018
  - Two methods:
    - ▹ DNN (with MEM as input variable)
    - ▹ Combination of BDT + MEM

From Moriond 2018

| Channel & Analysis | $\mu \pm$ tot ($\pm$stat $\pm$ syst) |
|---|---|
| single lepton 2D BDT+MEM | $0.35^{+0.62}_{-0.62}\ \left({}^{+0.27}_{-0.27}\ {}^{+0.55}_{-0.55}\right)$ |
| single lepton DNN | $0.84^{+0.52}_{-0.50}\ \left({}^{+0.27}_{-0.26}\ {}^{+0.44}_{-0.43}\right)$ |
| primary result | $0.72^{+0.45}_{-0.45}\ \left({}^{+0.24}_{-0.24}\ {}^{+0.38}_{-0.38}\right)$ |

(excerpt)

"primary result": single lepton DNN & dilepton BDT+MEM

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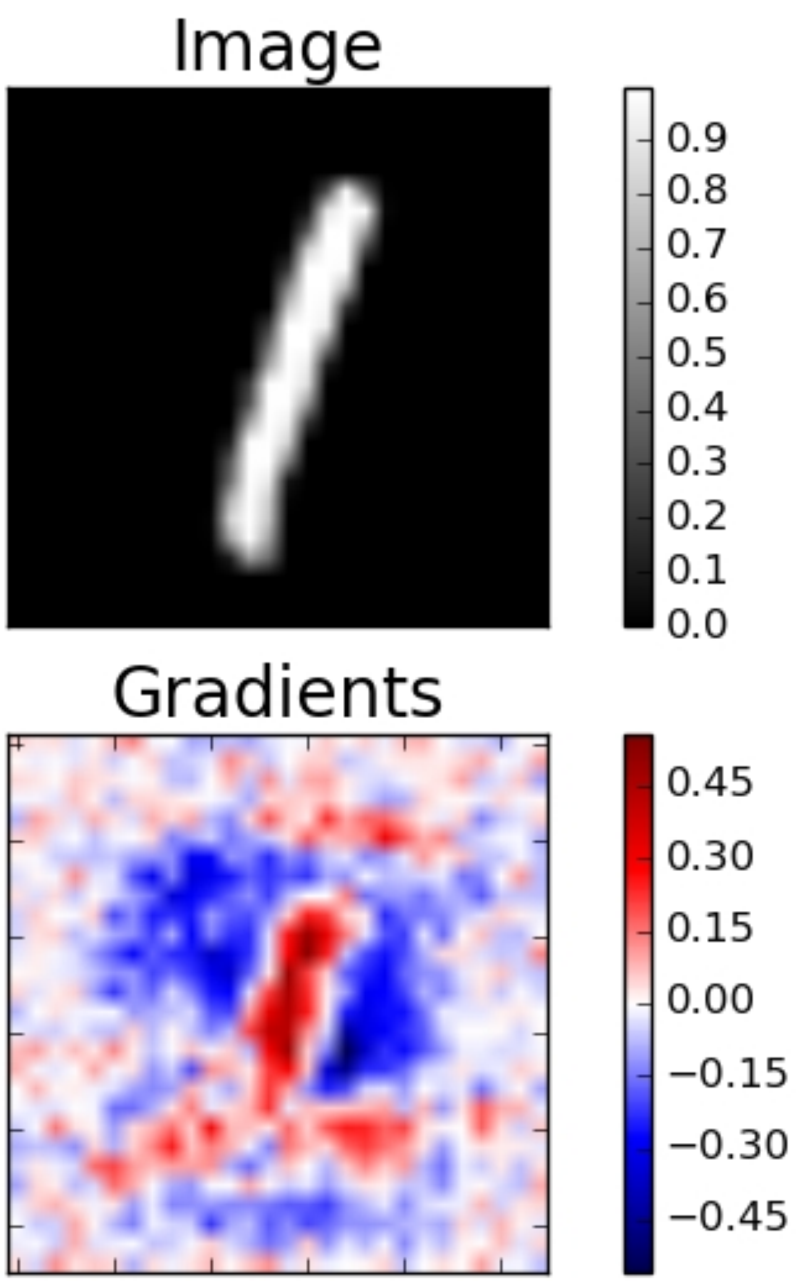
- Methods to interpret NN predictions, inspired by image recognition
- Define sensitivity via gradient of output w.r.t. inputs
  → "If input is varied, how does the output change?"
  - Determine derivative via `tf.gradient()`
- Other approaches possible
  (e.g layer-wise relevance propagation)



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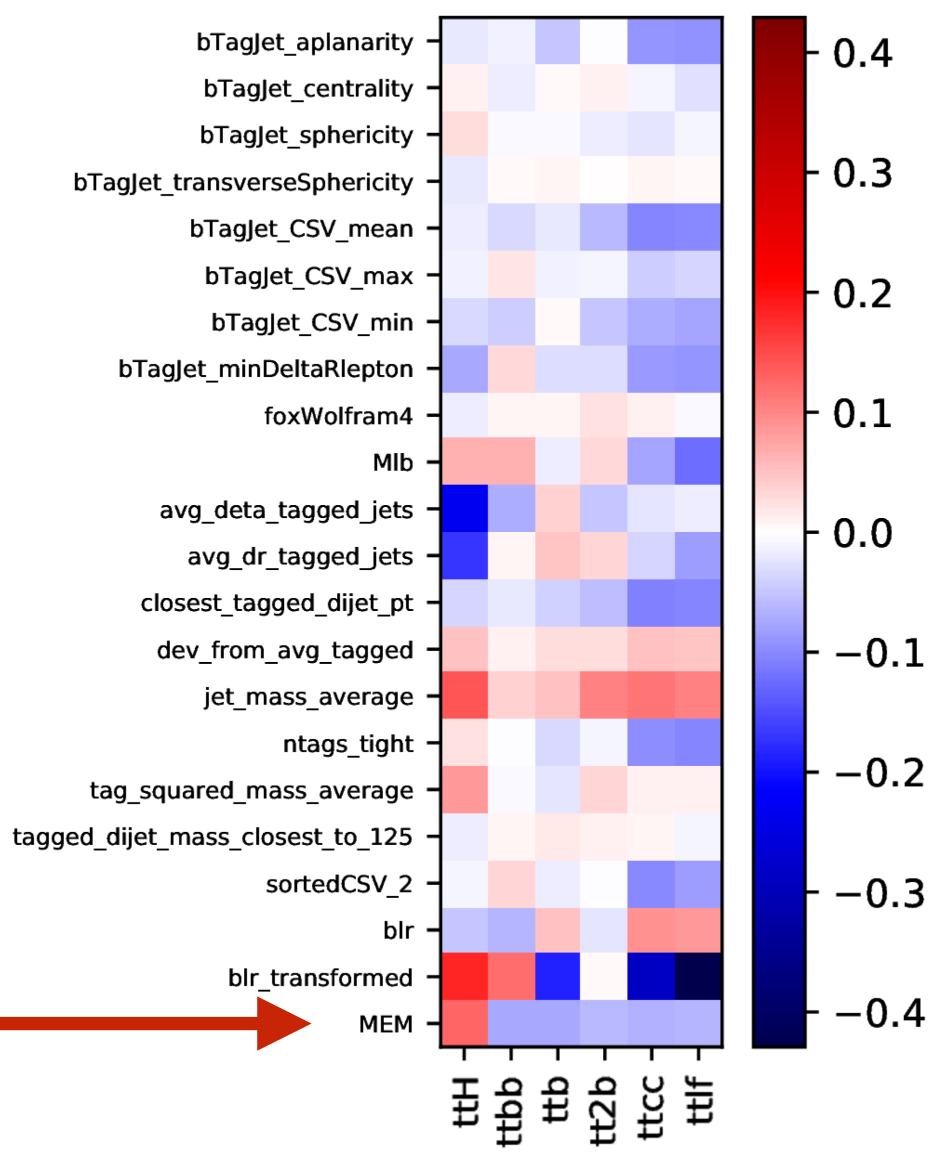
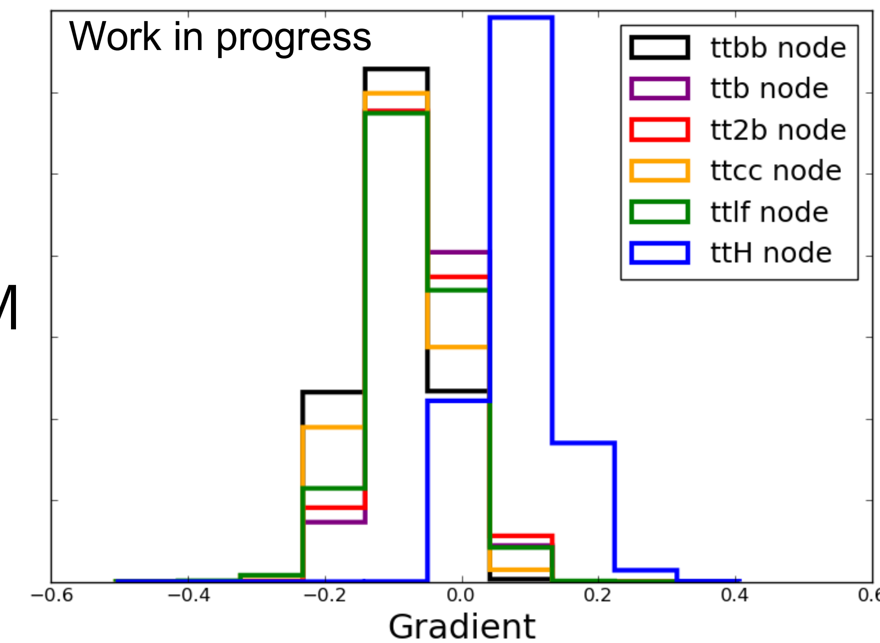
## Apply per event *(here: ttH)*

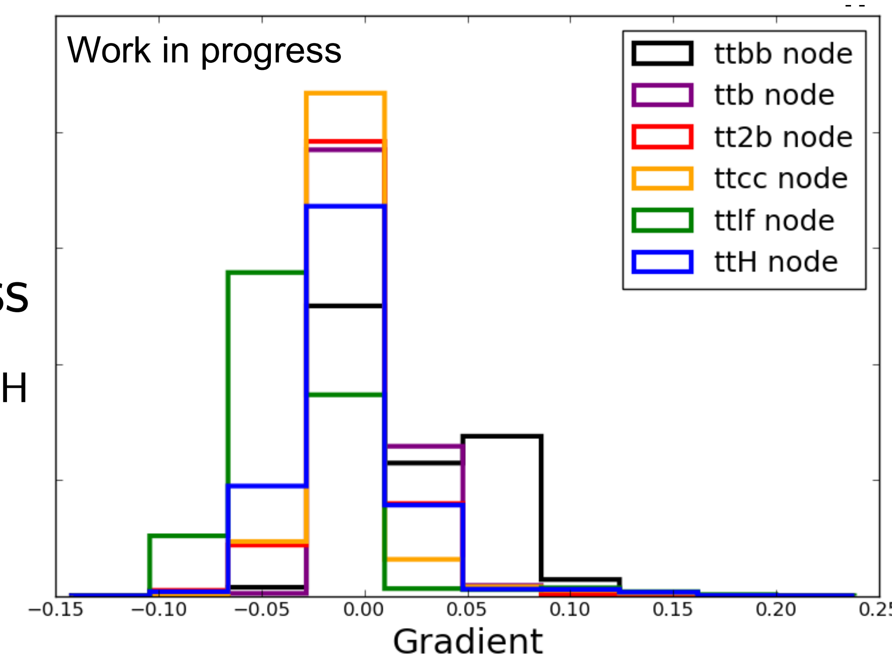



## Apply to all events

MEM

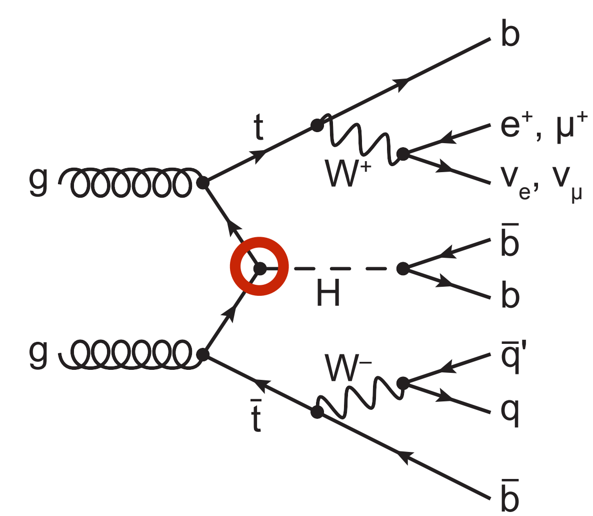



Jet pair mass closest to $m_H$

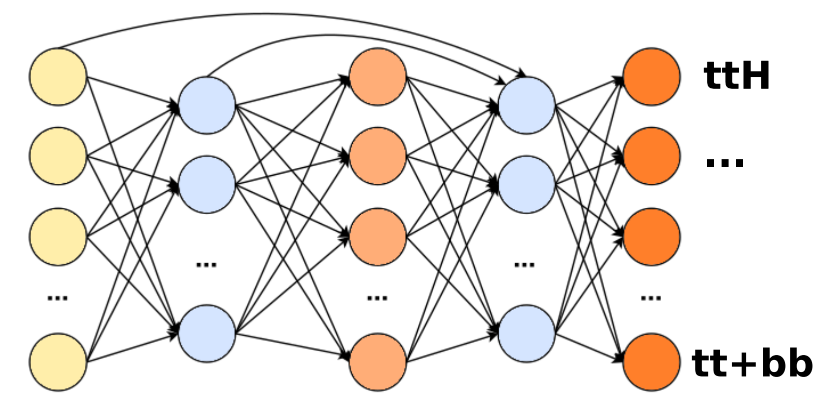



- Method to open the network “black box”
- Possible to check impact of 2D correlations with 2$^{nd}$ derivatives
- Sensitivity can be used for variable ranking (e.g. “rank = `mean(abs(sensitivity))`”)

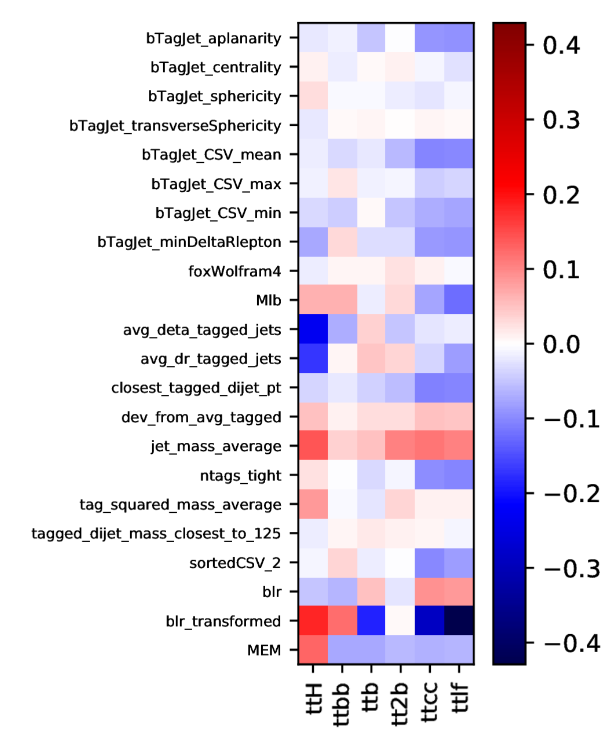
- Measurement of top-Higgs coupling provides a direct probe of the SM and BSM models




- Categorization of events into underlying physics processes using multi-classification DNNs
  - → Dedicated categories per background
  - → Improved sensitivity by ~20%



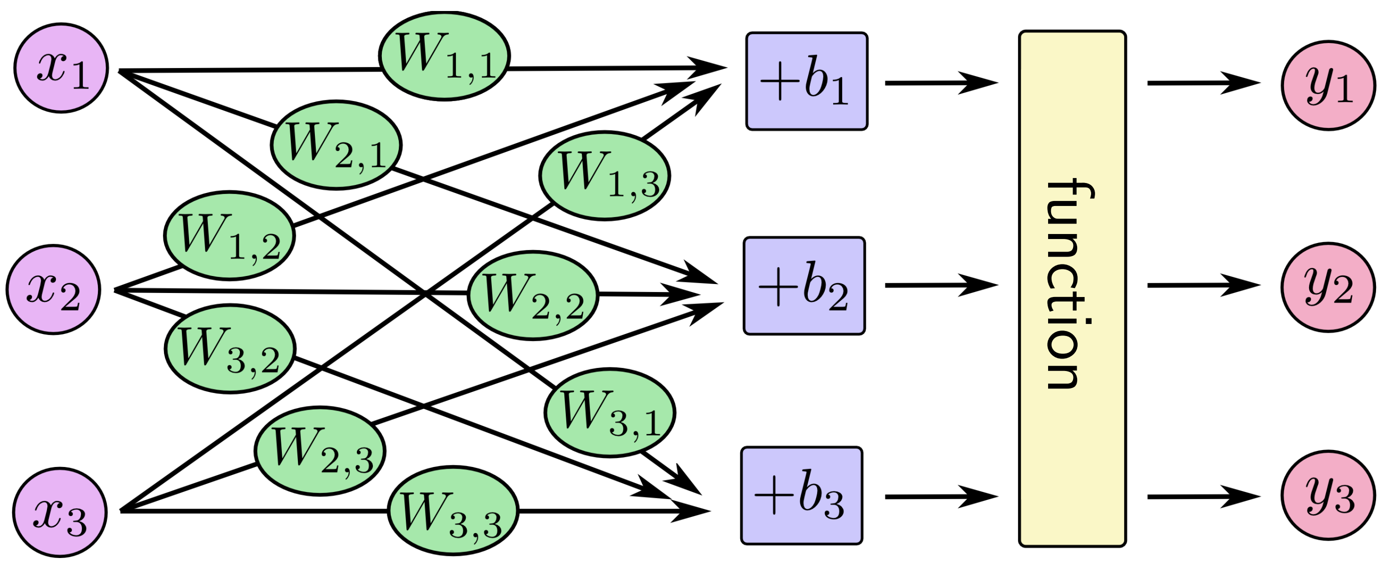

- Interpretation of network results using sensitivity analysis
  - Impact of variables consistent with physics expectation
  - Allows ranking of input variables



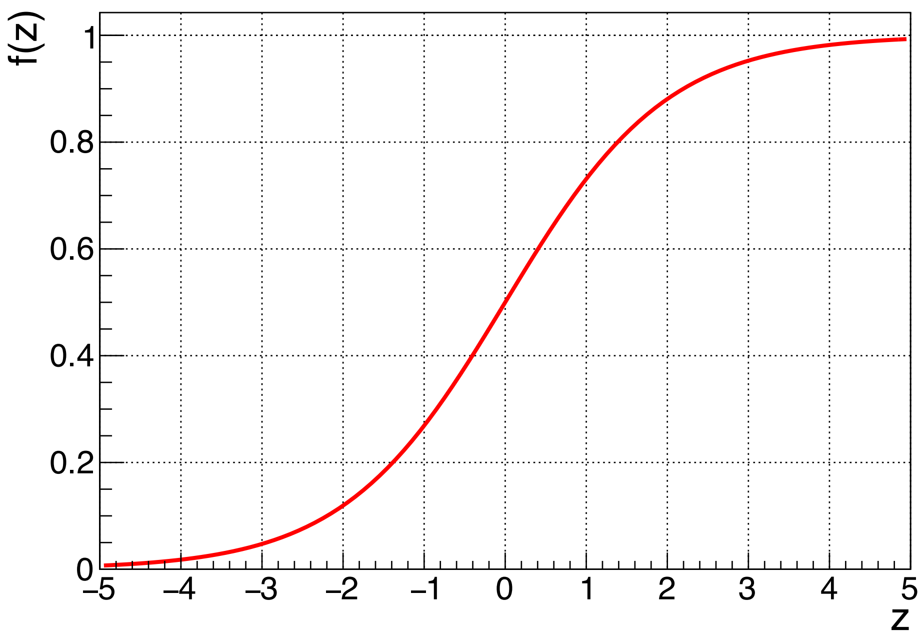
# Backup

- Map input variables x to outputs y: $\vec{x} \rightarrow \vec{y} = \vec{D}(\vec{x}; \boldsymbol{W}, \vec{b}) \in \mathbb{R}^n$
  - D is the model which has to be defined
  - W and b are parameters, or weights, to be learned
  - n is the output dimension, BDT: 1, DNN: ≥ 1
- One layer network with logistic function f:

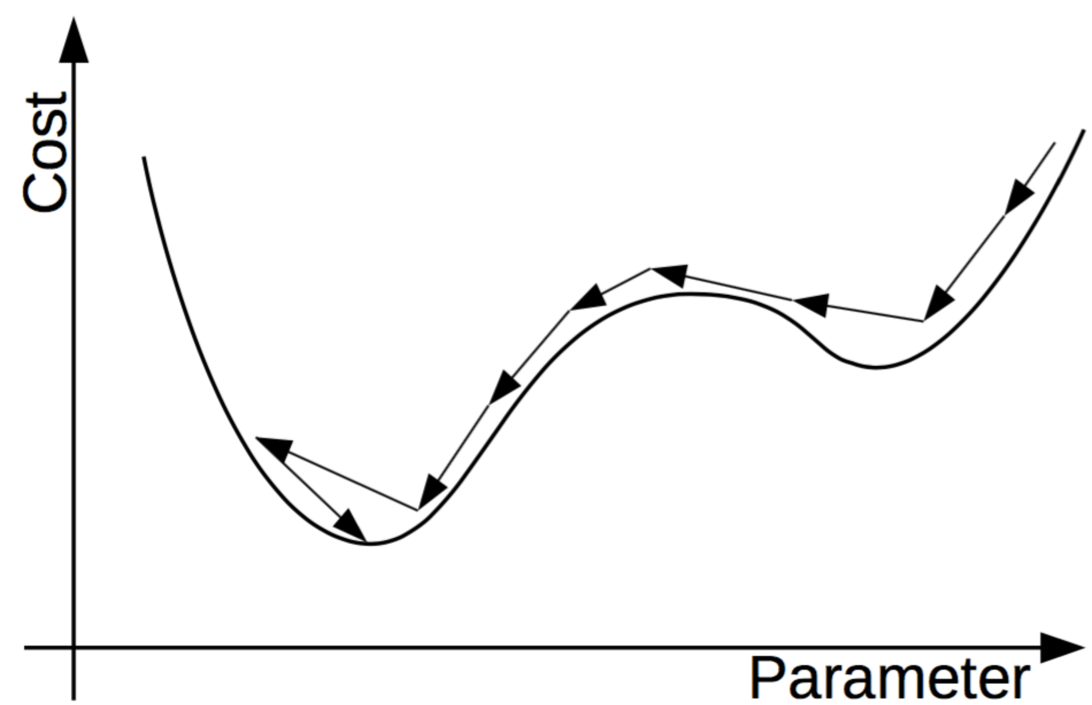
$$\vec{y} = f(\boldsymbol{W} \cdot \vec{x} + \vec{b}) \quad \text{with} \quad f(z) = \frac{1}{1 + e^{-z}}$$




tensorflow.org



- Plug *y* into *cost function*, compares to expected outputs $y_{exp}$ (e.g. $\chi^2$)
- Minimize costs using *gradient descent* algorithms
  - Direction of minimization ≙ current slope
  - Give feedback to weights
  - → But: computational too expensive to evaluate all derivations of cost function w.r.t. all weights ($\mathcal{O}(10^5)$)
  - → Back-propagation: change of weights ∝ costs
- Combine layers to build deep networks:
  - 2 layers: $\vec{y} = f(\boldsymbol{W_2} \cdot \vec{y_1} + \vec{b_2})$
  - n layers: $\vec{y} = (f_1 \circ f_2 \circ ... \circ f_n)(\boldsymbol{W} \cdot \vec{x} + \vec{b})$
- Many matrix and vector operations
  - → GPUs are mandatory!

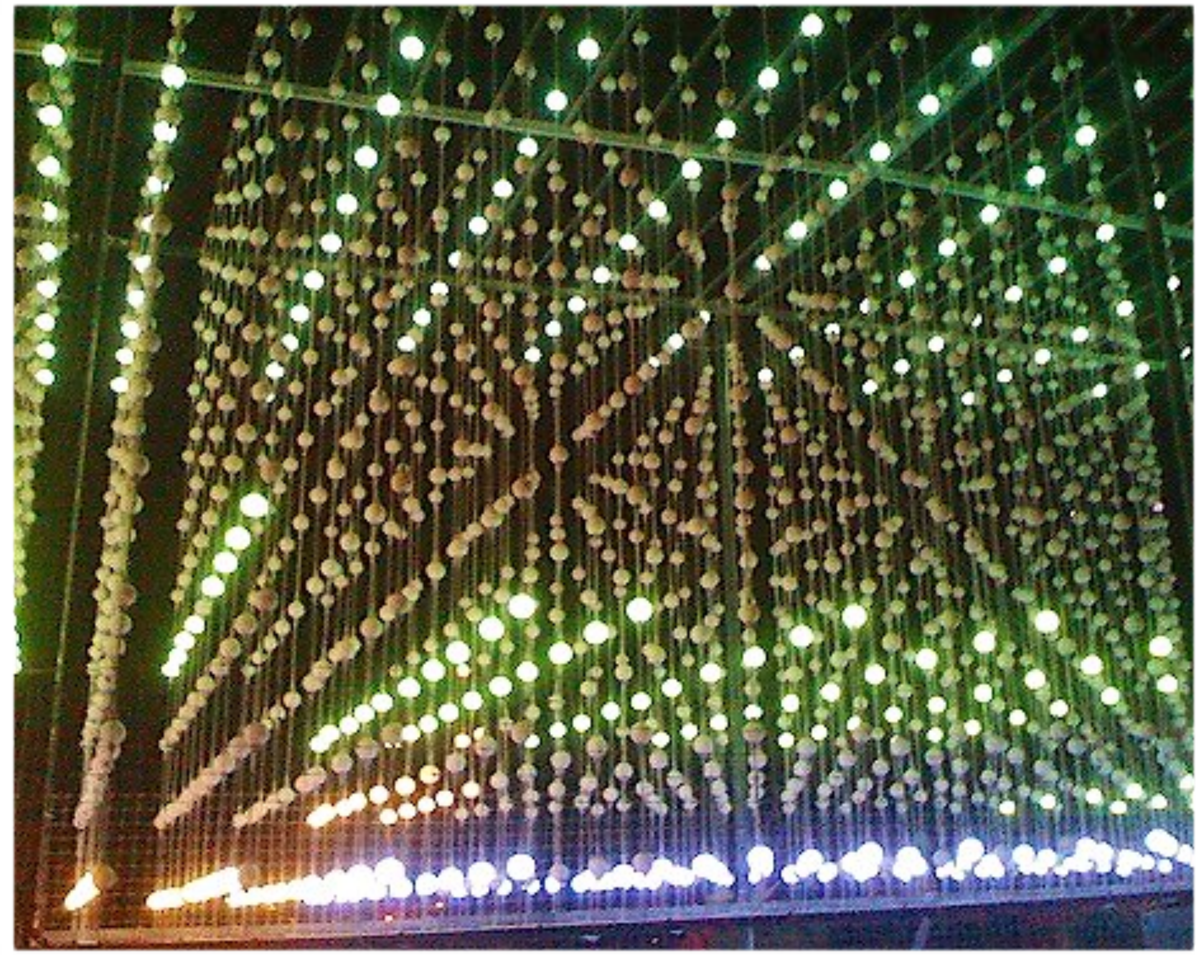


# Deep Neural Networks (3)



- Network architecture
- Layer activations
- Optimization algorithm
- Overtraining suppression:
  - L2 normalization
  - Random unit dropout
- Event weights
- Feature scaling
- ...

Challenging hyper-parameter space





→ Many hyper-parameter combinations but only a few appear to work

- Challenge: "No separation in output distribution. Reason?"
  - BDT: Unfortunate variable selection
  - DNN: Unfortunate variable selection or network architecture not optimal (more likely)

# DNN-based discriminants for fitting

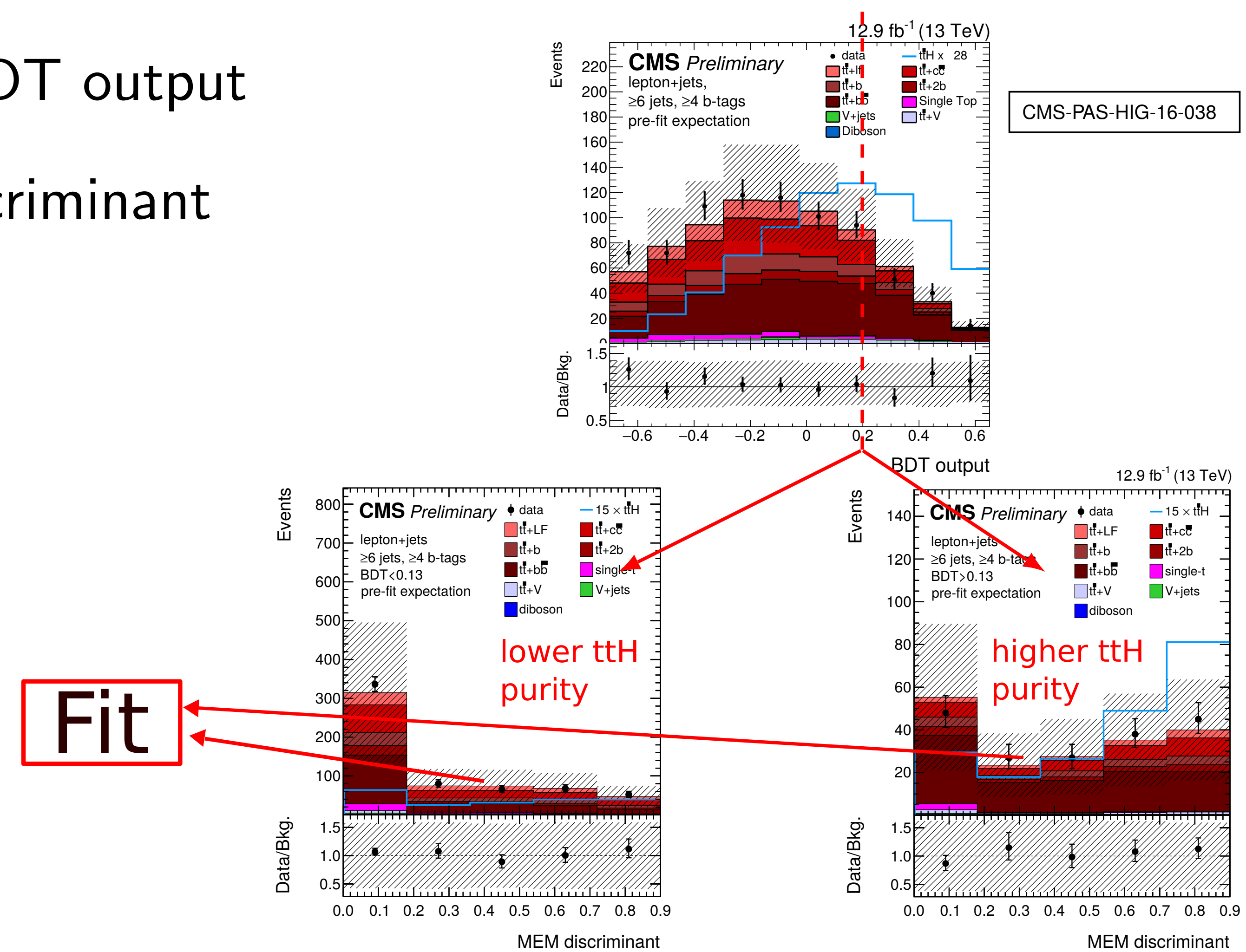


Category →

Output node ↓

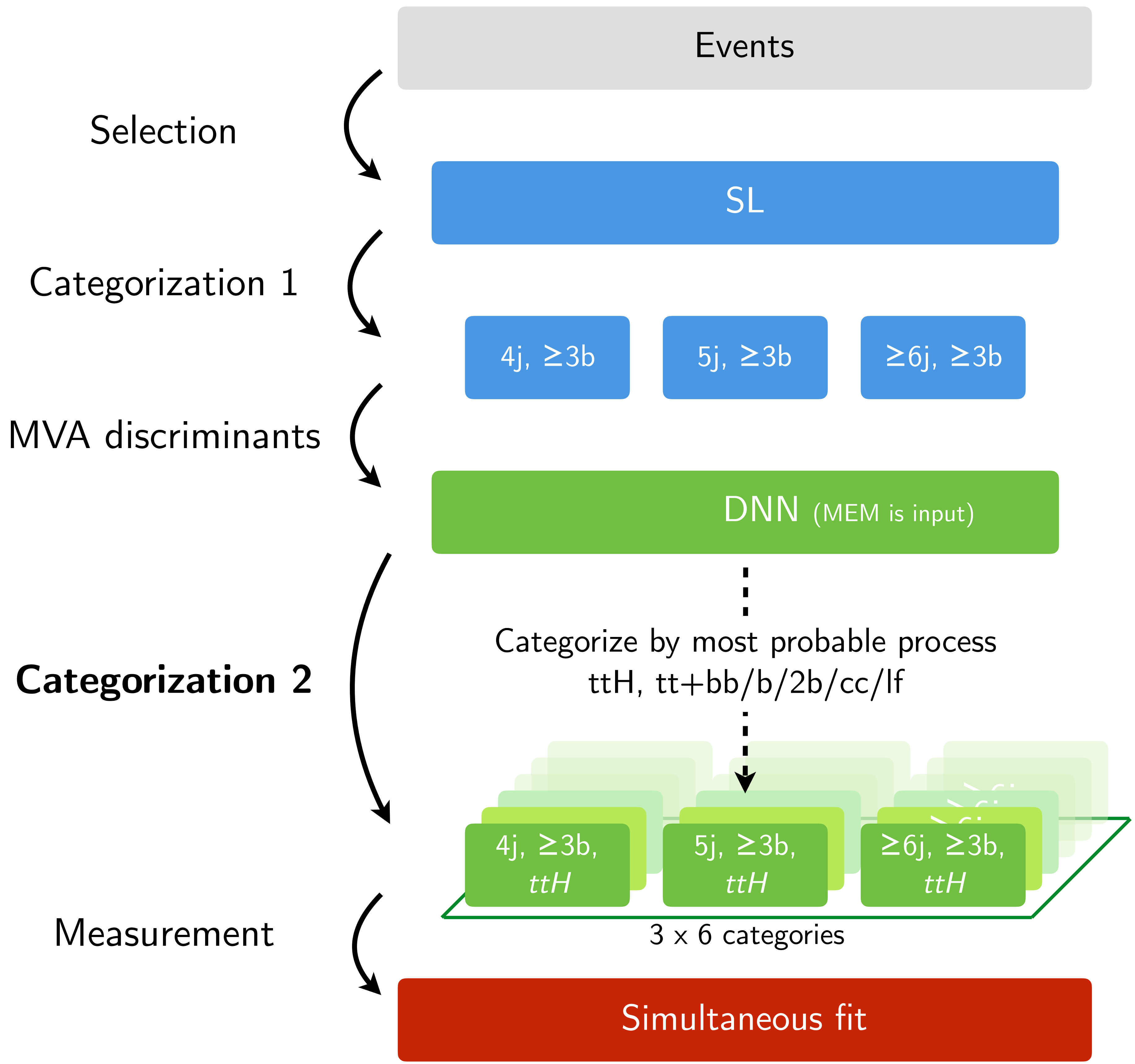
| | ttH | ttbb | ttb | tt2b | ttcc | ttlf |
|---|---|---|---|---|---|---|
| ttH | ✔ | | | | | |
| ttbb | | ✔ | | | | |
| ttb | | | ✔ | | | |
| tt2b | | | | ✔ | | |
| ttcc | | | | | ✔ | |
| ttlf | | | | | | ✔ |

- Well established method in previous Run II analyses (HIG-16-038, HIG-16-004)
- Jet - b-tag categorization: (≥4j,3t), (≥4j,≥4t)
  - (≥4j,3t): use BDT output as discriminant
  - (≥4j,≥4t): combine strengths of BDT and MEM
    - ▹ BDTs trained to discriminate ttH(bb) vs. inclusive tt+jets
    - ▹ Matrix element discriminants constructed to separate ttH(bb) and tt+bb
    - → Split events at median of signal BDT output
    - → In each *category*, use MEM as discriminant
- 3 categories in total



# Overall analysis strategy





# Overall analysis strategy