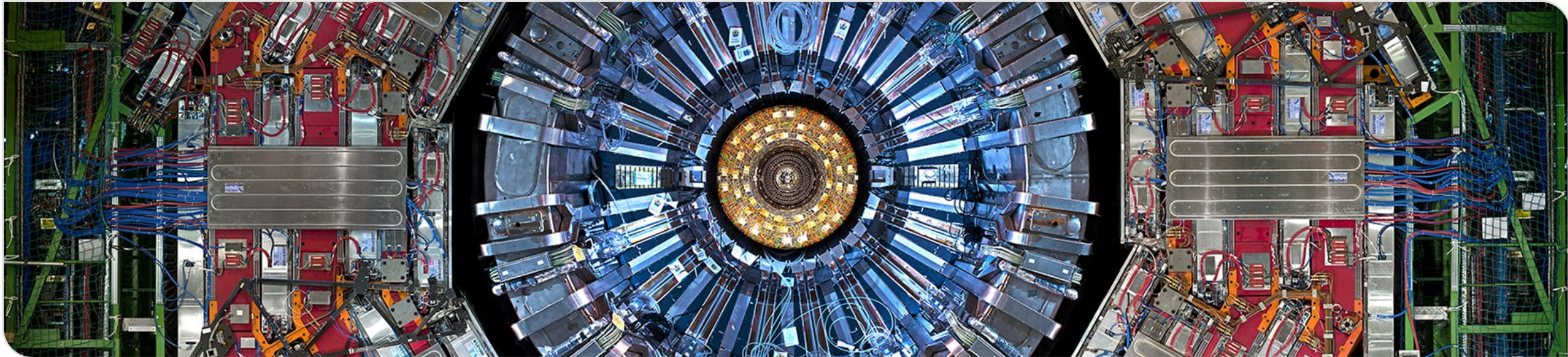


Probing multivariate methods to study $H \rightarrow \mu\mu$ events in the VH and VBF channels

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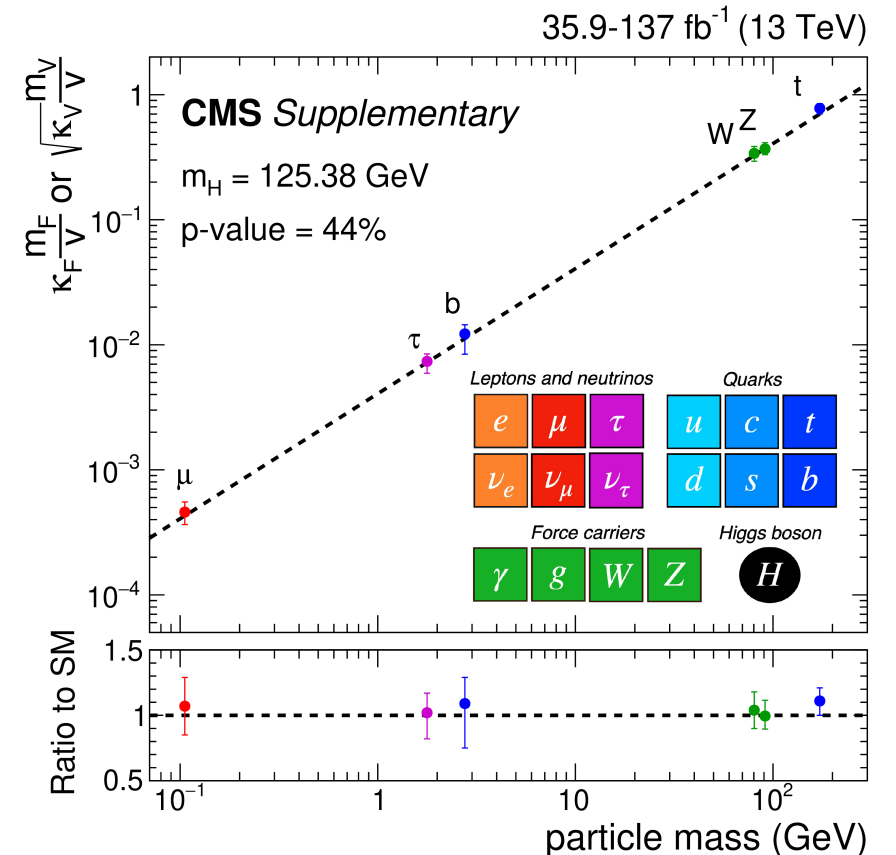


Motivation

„Why does mass appear? We don't know. If we understood that, we'd know a lot more about the whole world.“

R. Feynman

- The Yukawa coupling of the Higgs boson to second generation fermions is of great interest
- Clean final state with high sensitivity due to well understood muons
- Rare decay due to the small muon mass
- High luminosity enables this search



Higgs coupling to fermions

Source: <https://ep-news.web.cern.ch/>

Overview

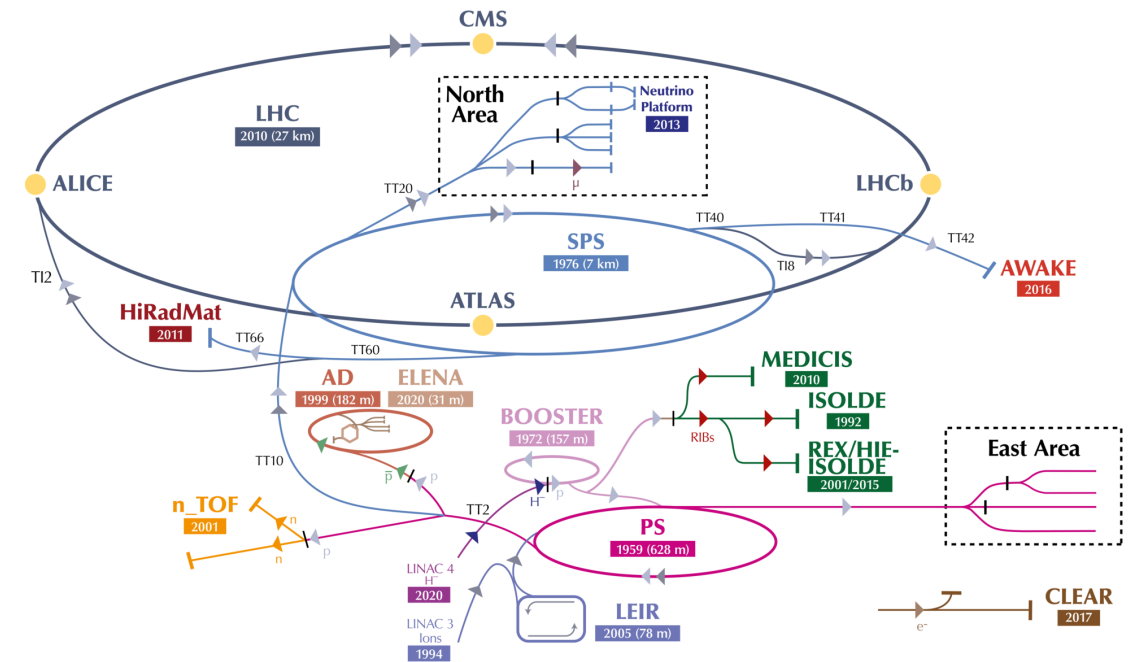
- Introduction
- Run 2 analysis strategy
- Decay signature of $H \rightarrow \mu\mu$ and background processes
- Event Selection
- Invariant dimuon mass spectrum for WH and VBF
- Neural Networks
- $H \rightarrow \mu\mu$ with NN for WH and VBF Higgs boson production
- Summary of expected upper limits on the signal strength parameter
- Conclusion

Previous Searches

- Measurements have been performed at CMS for LHC Run 2 data
- Branching Ratio was measured to be within $0.7 \times 10^{-4} < \mathcal{BR}(H \rightarrow \mu\mu) < 4.5 \times 10^{-4}$ at 95% CL
- There is evidence at 3σ for this decay, but no observation can be claimed so far
- Analysis methods in the analysis from 2021 vary between Higgs production channels
- Different methods have been probed in this work to explore possible pathways for a Run 3 analysis
- No systematic uncertainties have been taken into account in this work, so further studies are needed

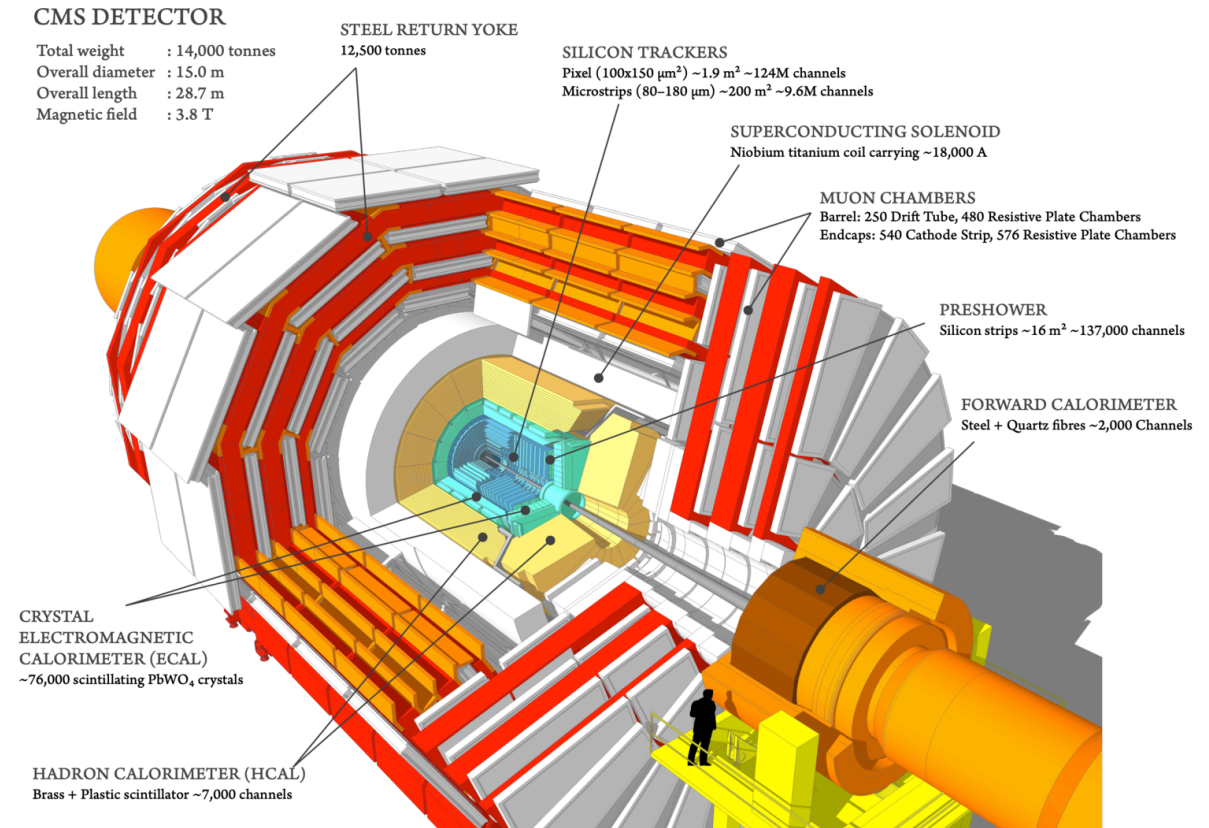
The Large Hadron Collider (LHC)

- High energy particle accelerator that collides protons at 13 TeV
- Four main experiments (ATLAS, CMS, LHCb, ALICE)
- Integrated Luminosity in 2018 (year of subject to this study): $L = 67.86 \text{ fb}^{-1}$
- High energy collisions produce particles of interest like the Higgs boson
- These collisions are studied at the individual experiments



The CMS Experiment

- Hermetic nearly 4π multi purpose particle detector
- Components (inner to outer layers):
 - Silicon Pixel Detector
 - Silicon Strip Detector
 - Electromagnetic Calorimeter
 - Hadron Calorimeter
 - Solenoid Magnet
 - Muon Chambers



Analysis Strategy from 2021

■ ggH, VH, $t\bar{t}$ - Higgs production:

- Phase Space selection
- Training of multiple BDTs on variables
- Selection on classifier output to define samples of different signal purity
- Dimuon mass ML fit on those samples
- Calculation of CLs for each individual sample and combination

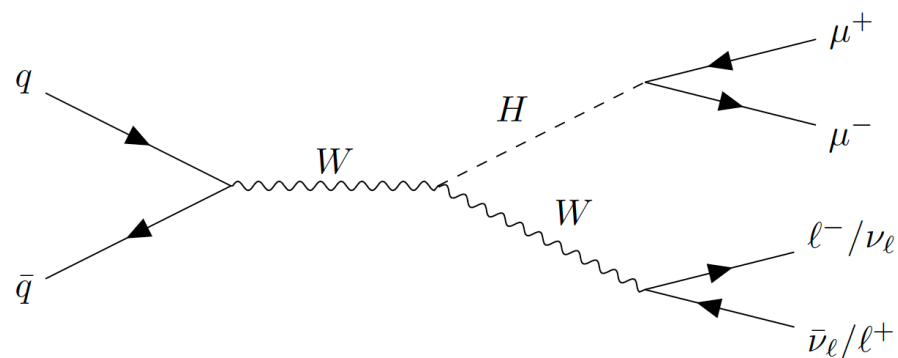
■ VBF Higgs production:

- Phase space selection
- Training of deep neural networks on variables including the dimuon mass
- ML fit of the classifier output
- Calculation of CLs

Decay signature of $H \rightarrow \mu\mu$ and background processes

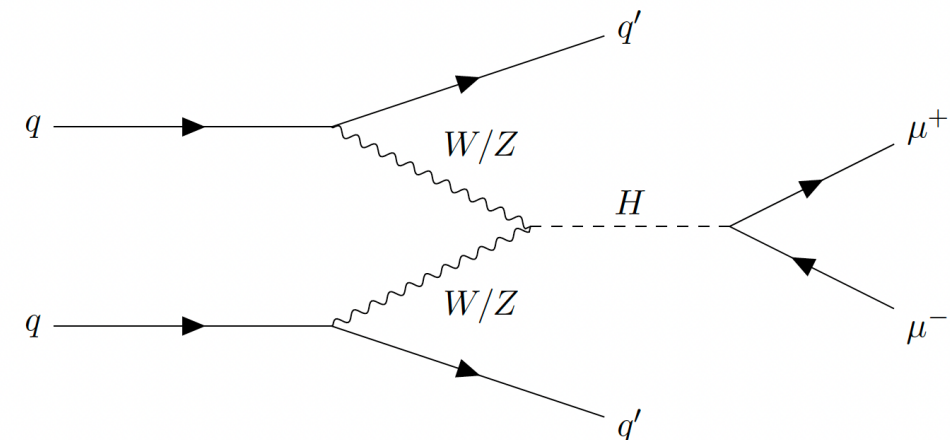
■ WH Higgs production (lept. W decay):

- Two opposite-sign muons
- Invariant muon mass expected close to Higgs mass
- One Additional visible lepton



■ VBF Higgs production:

- Two opposite-sign muons
- Invariant muon mass expected close to Higgs mass
- Two jets from quark interaction



Decay signature of $H \rightarrow \mu\mu$ and background processes

- Any process that produces the same final state is considered a background process
- The primary event selection should reduce these backgrounds as much as possible while preserving the signal
- Cuts on kinematic variables are used to reduce the total phase space

Event Selection Criteria:

- HLT_IsoMu24 trigger
- Loose muon isolation
- $(p_T)_1 > 26 \text{ GeV}$ (offline)
- $(p_T)_{2/3} > 20 \text{ GeV}$

WH leptonic phase space:

- Sum of lepton charges is uneven
- $m_{\mu\mu, \text{cand.Higgs}} \in [110, 150] \text{ GeV}$
- If $m_{\mu\mu} \in [81, 101] \text{ GeV}$ -> discard
- No medium b-tagged jets, max two loose b-tagged jets

VBF phase space:

- Sum of lepton charges is even
- At least two jets (sorted by p_T)
- $(p_T)_{j1} > 35 \text{ GeV}$
- $(p_T)_{j2} > 25 \text{ GeV}$
- $m_{jj} > 400 \text{ GeV}$
- $|\eta_{jj}| > 2.5$
- No medium b-tagged jets, max one loose b-tagged jet

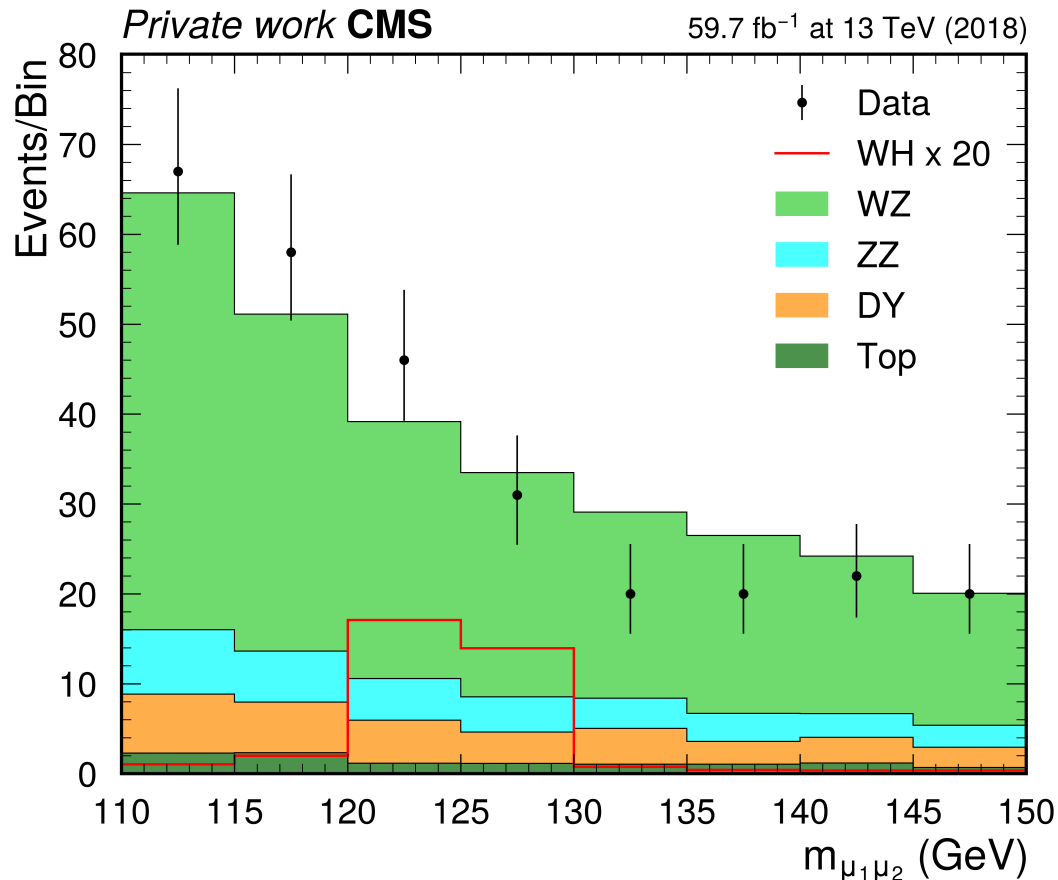
Decay signature of $H \rightarrow \mu\mu$ and background processes

- Any process that produces the same final state is considered a background process
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- Cuts on kinematic variables are used to reduce the total phase space

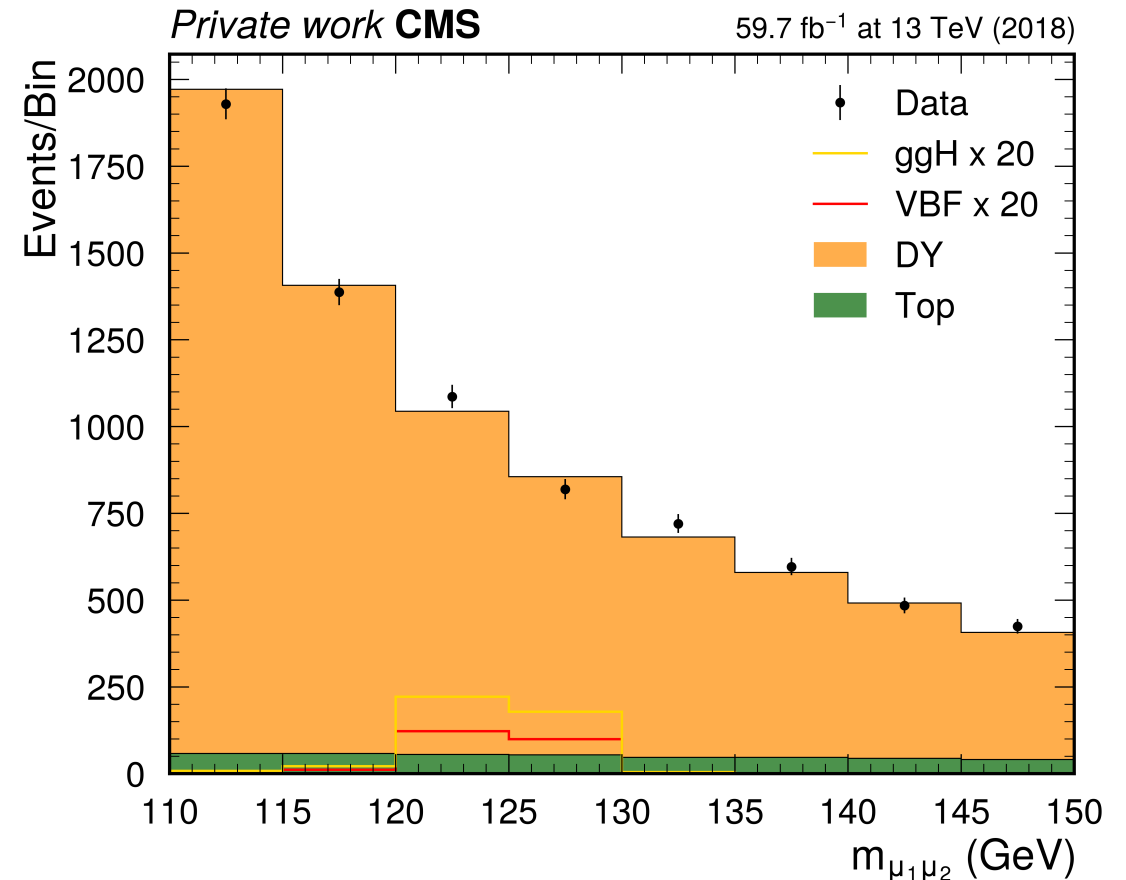
- Backgrounds WH (leptonic):
 - $WZ \rightarrow 3\ell + \nu$
 - $ZZ \rightarrow 4\ell$
 - Drell Yan
 - $t\bar{t}$
- Backgrounds VBF:
 - Drell Yan
 - $t\bar{t}$

Invariant Dimuon Mass Spectrum

WH leptonic phase space:



VBF phase space:



ML Fit of the Dimuon Mass Spectrum

- Goal: Calculate expected upper limits on the signal strength parameter

$$\mu = \frac{\sigma_{\text{observed}}}{\sigma_{\text{SM}}}$$

- It Compares the observed signal to the Standard Model, with $\mu = 1$ matching the prediction, $\mu > 1$ indicating excess, and $\mu < 1$ showing a deficit.

- The signal confidence level is defined as:

$$\text{CL}_s = \frac{\text{CL}_{s+b}}{\text{CL}_b} \quad \text{with } \text{CL}_{s+b} = 1 - p_{s+b} \text{ and } \text{CL}_b = 1 - p_b$$

- Avoids overly conservative results by including the possibility of background fluctuations

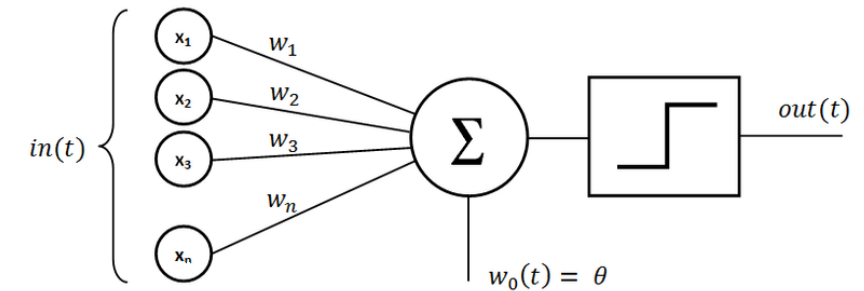
Fit Results Dimuon Mass Fit

- The resulting distributions have been fit using COMBINE under a background only hypothesis
- An expected 95% CLs upper limit is calculated on the signal strength parameter μ

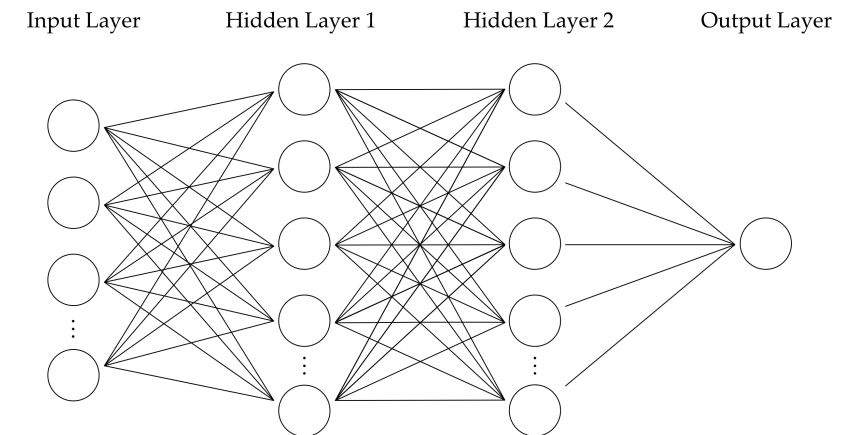
	WH leptonic	VBF
Expected upper Limit	$\mu = 10.19^{+4.47}_{-3.01}$	$\mu = 3.64^{+1.45}_{-1.04}$
Expected Significance	0.21 σ	0.55 σ

Interlude: Neural Networks

- **Perceptron:** A basic unit in neural networks that computes a weighted sum of inputs.
- **Activation:** An activation function determines the output.
- **Linear Limit:** A single perceptron solves linearly separable problems.
- **MLP:** A multi-layer perceptron connects neurons to solve non-linear problems.
- **Hidden Layers:** Layers between input and output that learn abstract features.
- **Weights & Biases:** Values that adjust how inputs influence the output during training.



Source: https://upload.wikimedia.org/.../Perceptron_moj.png



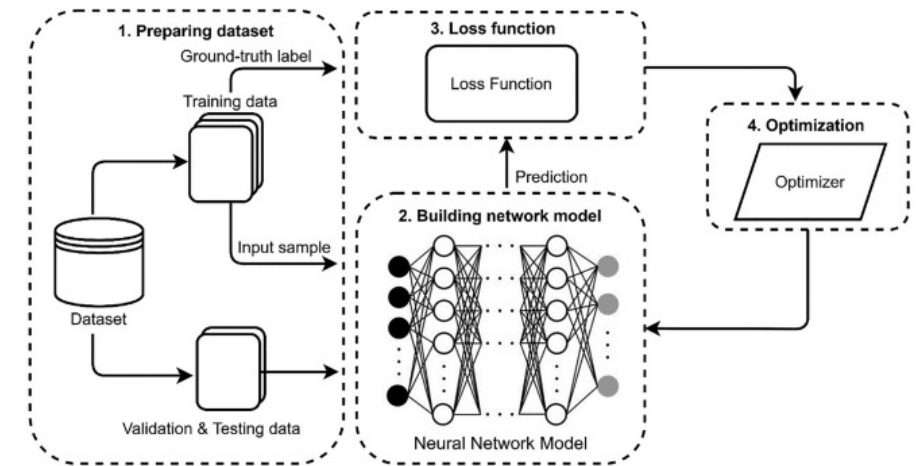
Interlude: Neural Networks

■ Training:

- Feed data through the network (feedforward).
- Calculate the error using a loss function.
- Use back-propagation to update weights and biases.
- Repeat until the model converges or reaches a stopping criterion.

■ Inference:

- Feed new data into the trained network.
- Generate predictions using the learned weights.



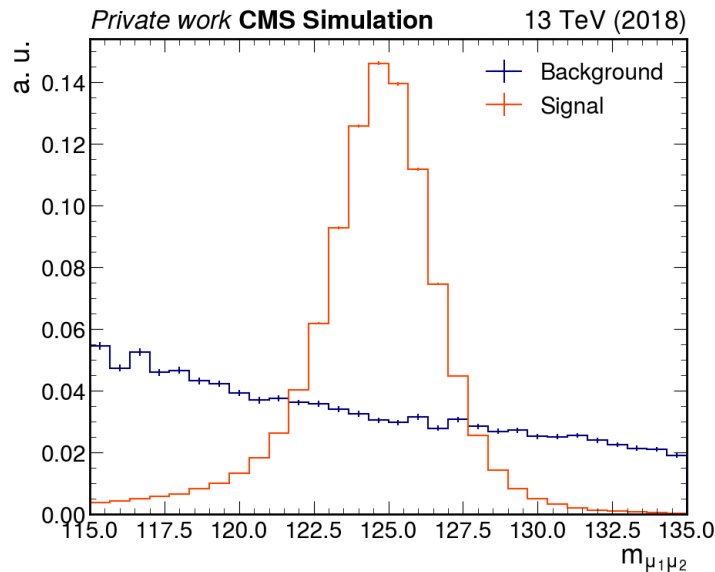
Source: <https://www.sciencedirect.com/.../neural-network-training>

Event Categorization using Neural Networks

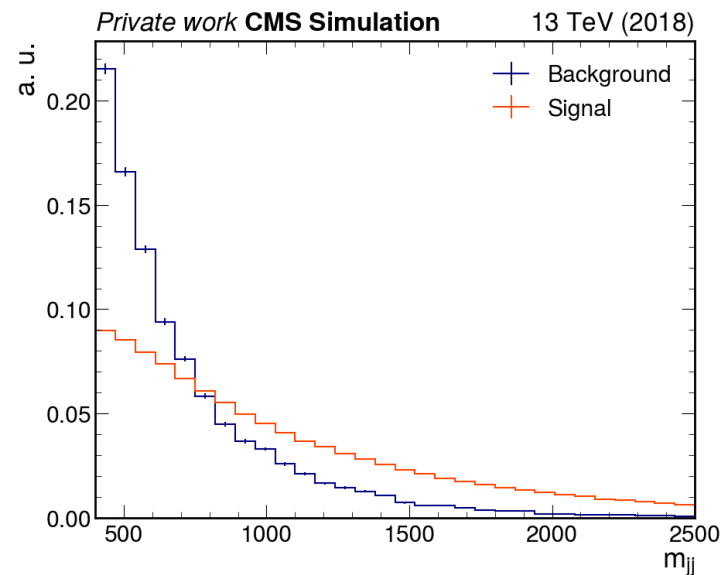
- The main discriminating variable in this problem is the invariant dimuon mass
- Other variables do also possess discriminating power
- Utilizing more variables may lead to better signal sensitivity

Event Categorization using Neural Networks

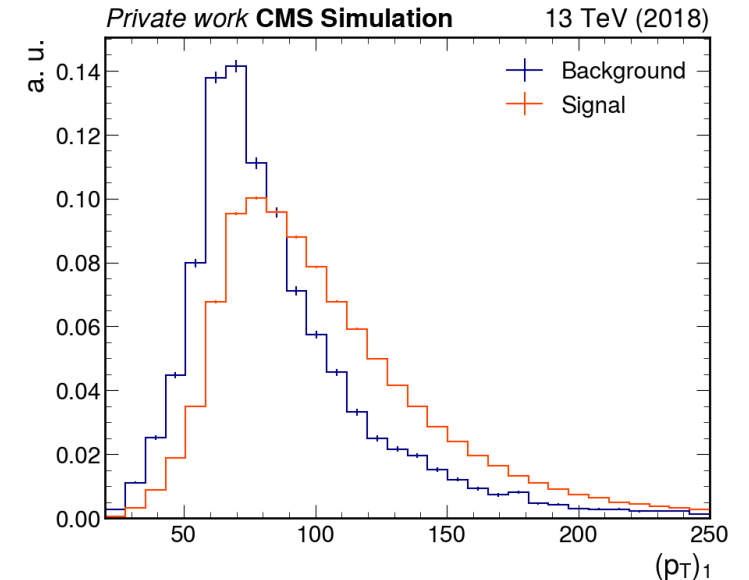
- The main discriminating variable in this problem is the invariant dimuon mass
- Other variables do also possess discriminating power
- Utilizing more variables may lead to better signal sensitivity



VBF: dimuon mass



dijet mass



leading muon transverse momentum

Event Categorization using Neural Networks

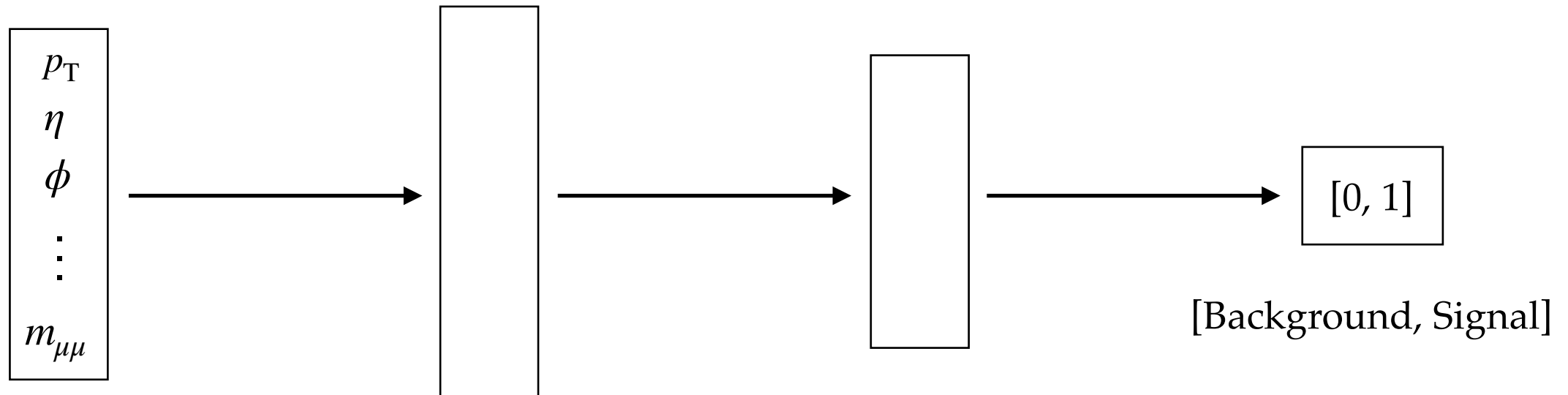
- The main discriminating variable in this problem is the invariant dimuon mass
- Other variables do also possess discriminating power
- Utilizing more variables may lead to better signal sensitivity

Input $\mathcal{O}(20)$ Features

1. Hidden Layer [256]

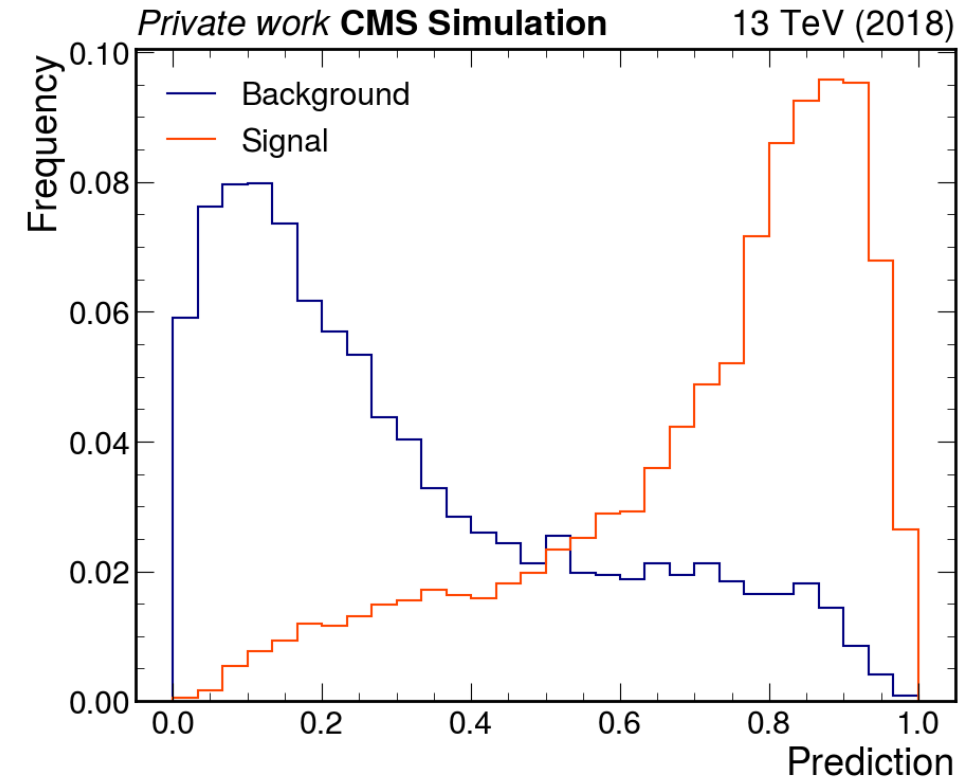
2. Hidden Layer [128]

Output [1]



Training Process

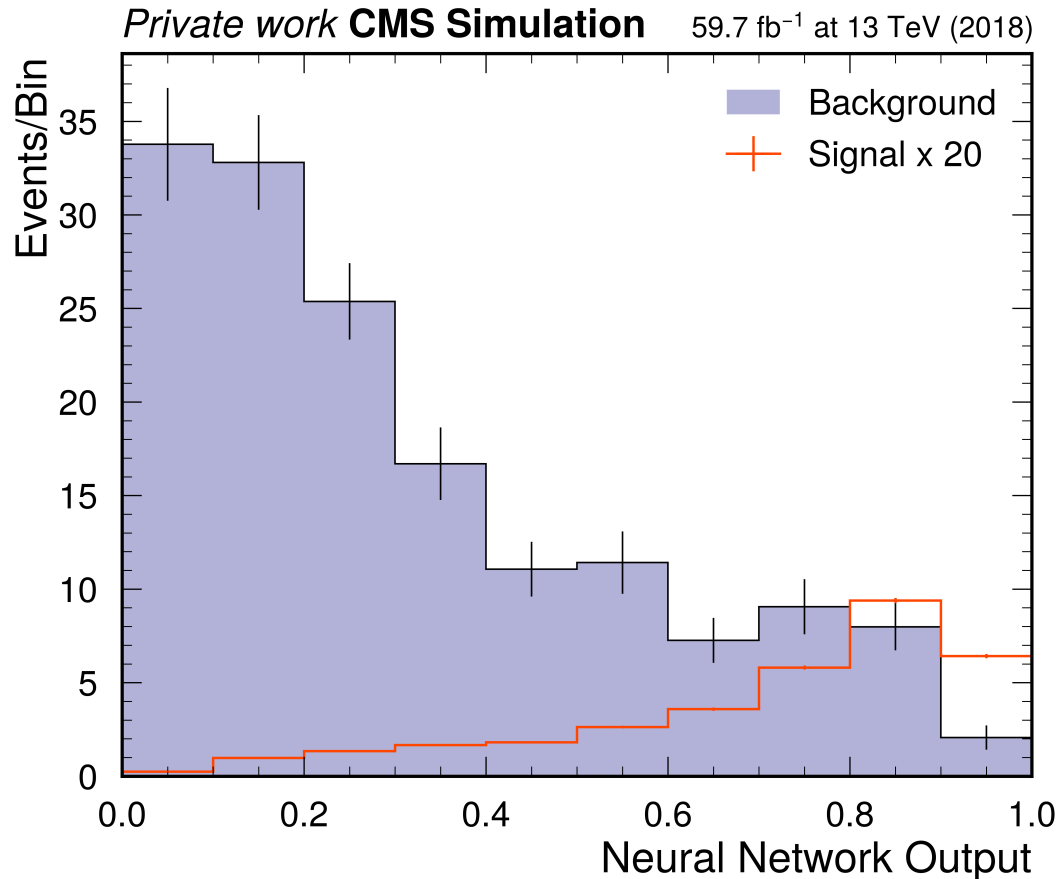
- Neural Network is trained on Monte Carlo (MC) simulated events
- Training / Validation dataset split of 4 / 1
- Uses batch normalisation as well as Dropout of 0.5 to avoid over-fitting
- ReLU activation between layers + sigmoid activation for output layer
- Bayesian optimisation used to find optimal hyperparameters



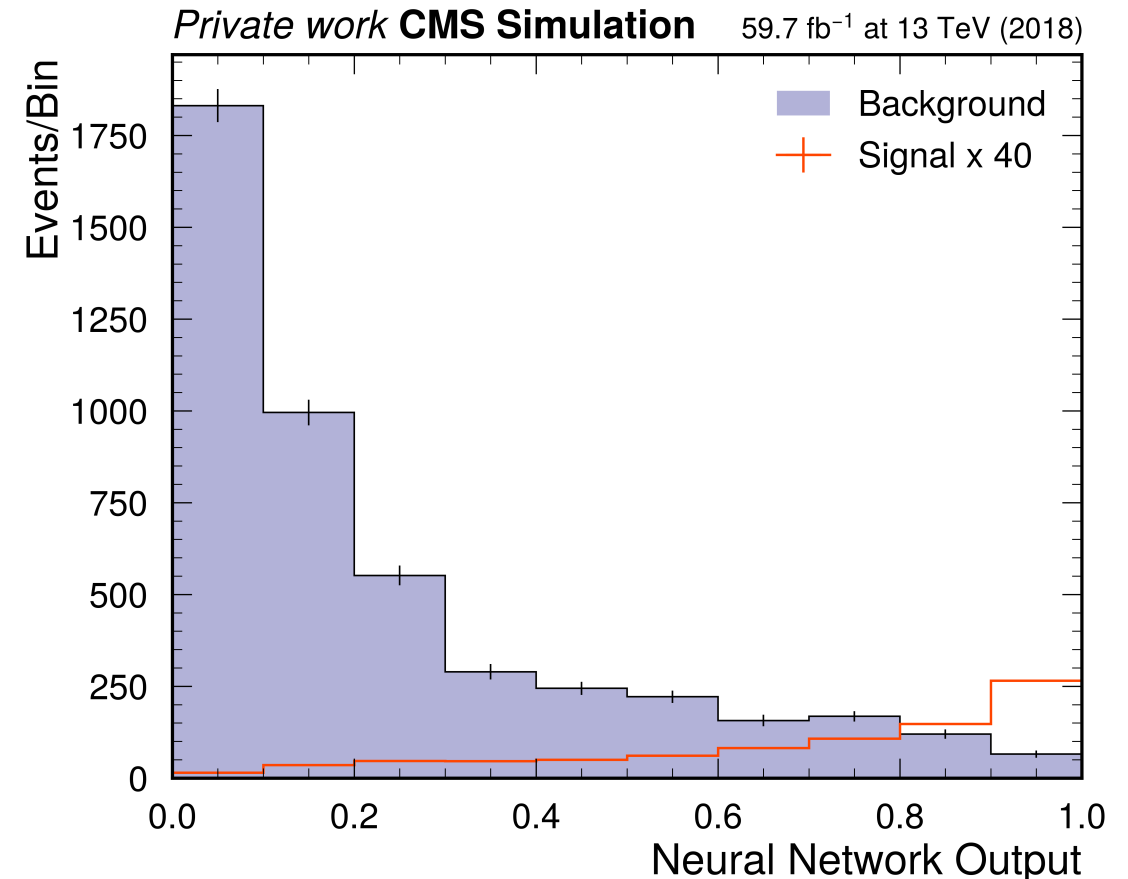
WH leptonic NN output inclusive $m_{\mu\mu}$

Neural Network Output

WH leptonic phase space:



VBF phase space:



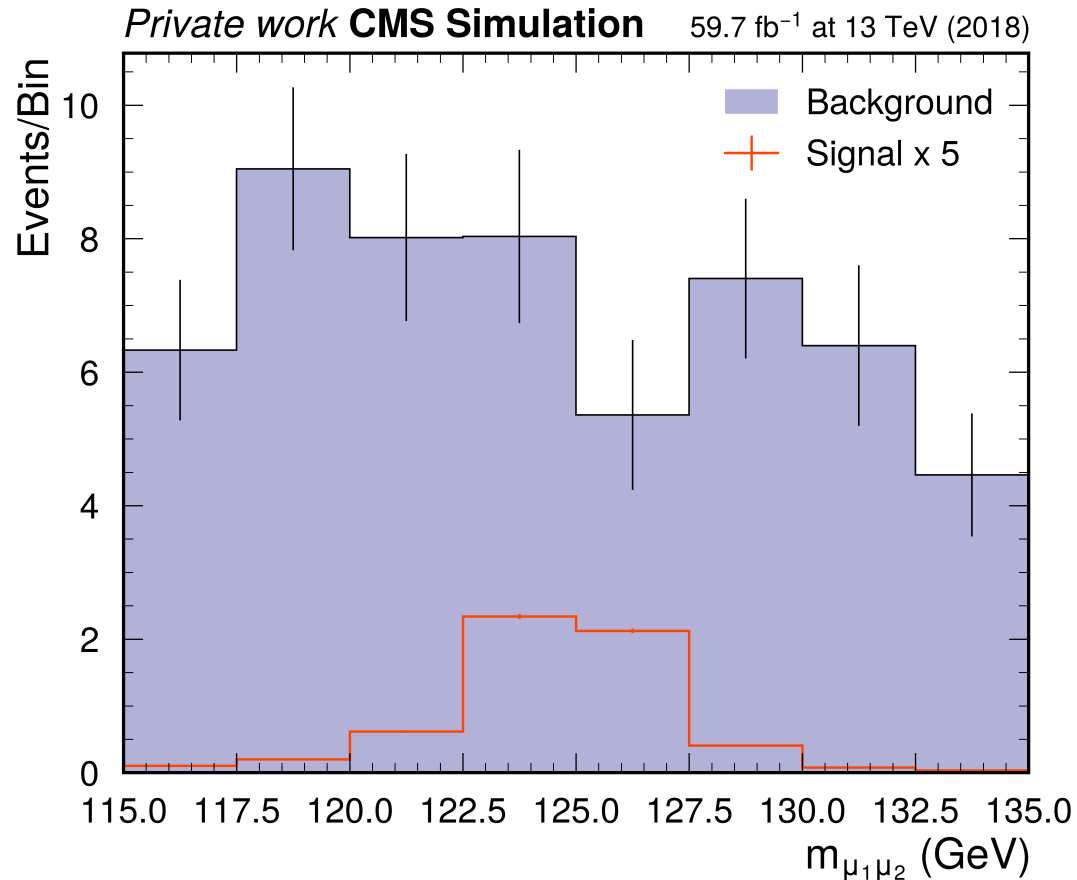
Fit results NN Output

- The resulting distributions have been fit using COMBINE under a background only hypothesis
- An expected 95% CLs upper limit is calculated on the signal strength parameter μ

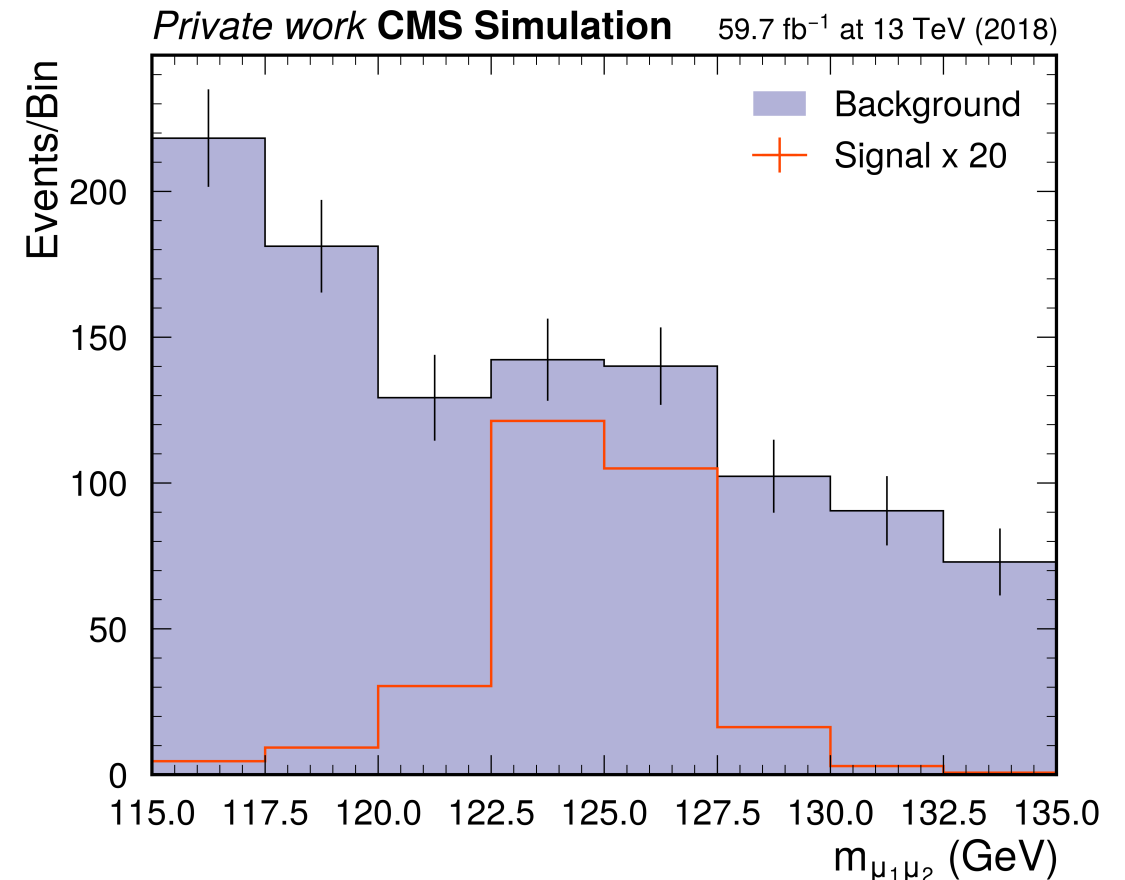
	WH leptonic	VBF
Expected upper Limit	$\mu = 7.72^{+3.66}_{-2.42}$	$\mu = 2.21^{+0.92}_{-0.64}$
Expected Significance	0.3σ	0.93σ

Neural Network Output Cut + Dimuon Mass Fit

WH leptonic phase space:



VBF phase space:

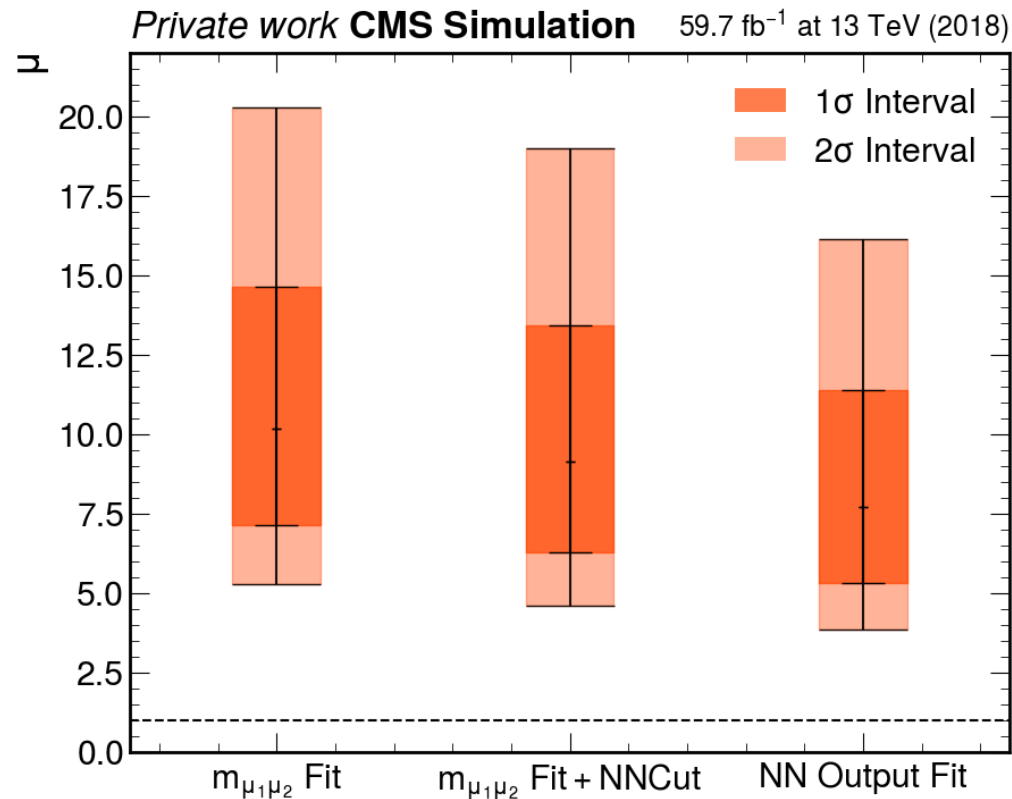


Results NN Output Cut + Dimuon Mass Fit

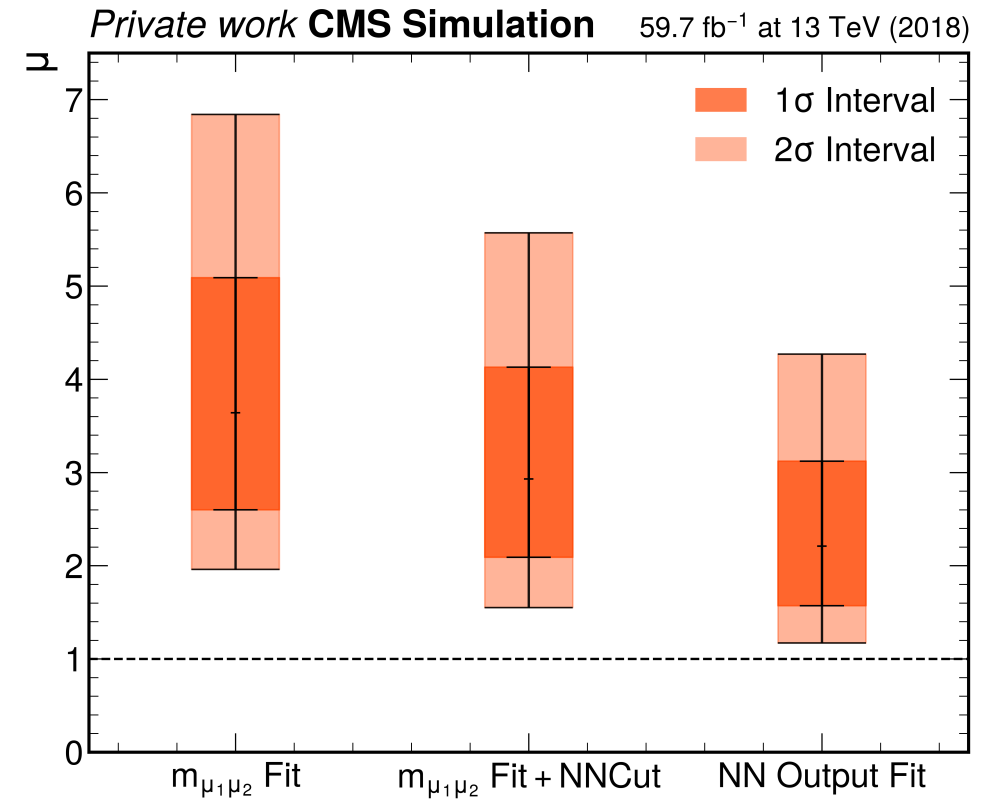
- The resulting distributions have been fit using COMBINE under a background only hypothesis
- An expected 95% CLs upper limit is calculated on the signal strength parameter μ

	WH leptonic	VBF
Expected upper Limit	$\mu = 9.13^{+4.29}_{-2.83}$	$\mu = 2.93^{+1.20}_{-0.84}$
Expected Significance	0.25σ	0.69σ

Summary of Expected upper limits through different methods



WH leptonic



VBF

Conclusion

- Expected upper limits on the signal strength parameter where set in two Higgs production channels using three different methods:
 - Fitting the invariant dimuon mass spectrum
 - Fitting the classifier output of a deep neural network
 - Fitting the dimuon mass spectrum after cutting on the classifier
- The best result is obtained when fitting the classifier output directly for both channels
- Care must be taken when using this approach to model all contributions correctly!
- The neural network works as a de facto black box which carries an inherent risk
- Both multivariate methods carry this risk but one seems to perform better

Training Variables

WH leptonic phase space

Variable Name	Description
$p_T(\mu_1)$	transverse momentum of the leading muon
$p_T(\mu_2)$	transverse momentum of the sub-leading muon
$p_T(\ell_3)$	transverse momentum of the remaining lepton
$m_{\mu_1\mu_2}$	dimuon mass of Higgs boson candidate
$p_T(\mu_1\mu_2)$	transverse momentum of Higgs candidate
$\eta(\mu_1\mu_2)$	pseudorapidity of Higgs candidate
$\phi(\mu_1\mu_2)$	azimuth angle of Higgs candidate
$\Delta\eta_{13}$	difference in pseudorapidity between μ_1 and ℓ_3
$\Delta\eta_{23}$	difference in pseudorapidity between μ_2 and ℓ_3
$\Delta\eta_{12;3}$	difference in pseudorapidity between Higgs cand. and ℓ_3
$\Delta\phi_{13}$	difference in azimuth angle between μ_1 and ℓ_3
$\Delta\phi_{23}$	difference in azimuth angle between μ_2 and ℓ_3
$\Delta\phi_{12;3}$	difference in azimuth angle between Higgs cand. and ℓ_3
ΔR_{12}	measure of separation between μ_1 and μ_2
ΔR_{13}	measure of separation between μ_1 and ℓ_3
ΔR_{23}	measure of separation between μ_2 and ℓ_3
$\cos\theta_{12}^*$	opening angle between μ_1 and μ_2 in the μ_1 rest frame
$\cos\theta_{13}^*$	opening angle between μ_1 and ℓ_3 in the μ_1 rest frame
$\cos\theta_{23}^*$	opening angle between μ_2 and ℓ_3 in the μ_2 rest frame
η_1	pseudorapidity of μ_1
η_2	pseudorapidity of μ_2
q_n	charge of the lepton n

VBF phase space

Variable Name	Description
$p_T(\mu_1)$	transverse momentum of the leading muon
$p_T(\mu_2)$	transverse momentum of the sub-leading muon
ϕ_1	azimuth angle of μ_1
ϕ_2	azimuth angle of μ_2
η_1	pseudorapidity of μ_1
η_2	pseudorapidity of μ_2
$(p_T)_{j1}$	transverse momentum of the leading jet
$(p_T)_{j2}$	transverse momentum of the sub-leading jet
ϕ_{j1}	azimuth angle of leading jet
ϕ_{j2}	azimuth angle of sub-leading jet
η_{j1}	pseudorapidity of leading jet
η_{j2}	pseudorapidity of sub-leading jet
$(p_T)_{jj}$	di-jet transverse momentum
$(p_T)_{\mu\mu}$	dimuon transverse momentum
m_{jj}	di-jet mass
$m_{\mu\mu}$	dimuon mass
n_{jets}	number of jets
n_μ	number of muons