Searches for the Inert Doublet Model at CMS

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[1]: Imperial College London. [2]: Lomonosov Moscow State University

Theory and Motivation

Inert Doublet Model (IDM)

- Two Higgs Doublet Model with an unbroken discrete Z_2 symmetry

$$\phi_1 \to \phi_1, \quad \phi_2 \to -\phi_2, \quad SM \to SM$$

- ϕ_1 acts as the normal SM Higgs doublet:
  - h_{125}
- ϕ_2 introduces 3 new particles:
  - $\mathbf{H^0}$ - lightest particle
  - $\mathbf{A^0}$
  - $\mathbf{H^\pm}$
- 5 free parameters:

$$M_{H^0}, M_{A^0}, M_{H^\pm}, \lambda_2, \lambda_{345}$$

- Constraint: $M_{H^0} < M_{A^0} < M_{H^\pm}$

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Z_2 symmetry results in:

- IDM particles couple only to gauge bosons → "inert"
- Pair production of inert scalars
- H is stable

H = Dark Matter candidate!

Final States

Electroweak Gauge Bosons + Missing Energy (E_{miss})

➔ This is the first dedicated search for this model

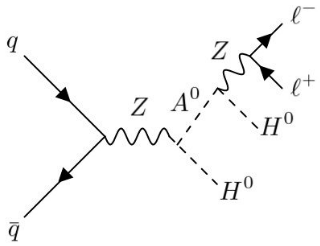
Final State

Dilepton + Missing Energy

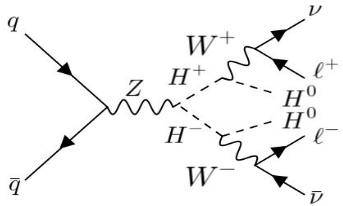
- $e^+e^-/\mu^+\mu^-$ provides clean signature
- H^0 particles produced mainly back to back
  - Cancelling out of missing energy (E_{miss})
  - Reduced missing energy signature < 80 GeV
- Initial studies showed worse sensitivity in on-shell Z region
- Off-shell Z region generally less explored

Dilepton + Reduced E_{miss}, off-shell Z region

$p\,p \rightarrow H^0\,H^0\,l^+\,l^-$



$p\,p \rightarrow H^0\,H^0\,l^+\,l^-\,\nu\nu$



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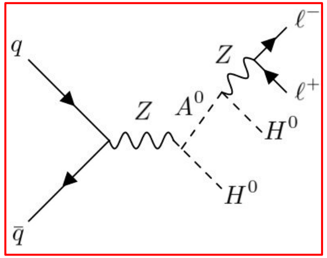

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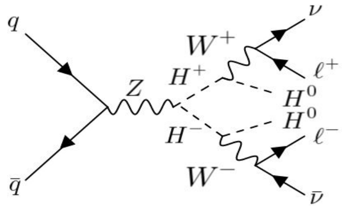


Parameter Scan

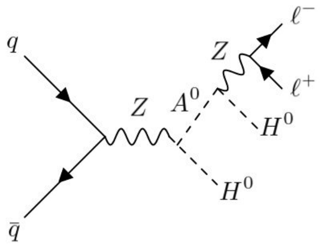
- Dominant process contains only SM couplings
  - $p\,p \to H^0\,H^0\,l^+\,l^-\,\nu\nu$ has little discrimination versus background and much smaller cross-section
- $M_{H\pm}$, λ_2 and λ_{345} have negligible effect on kinematics
- Only dependent on masses M_{H0} and M_{A0}
- Scan over: $M_{H0} \in [70, 130]$ GeV,

  $\Delta(M_{A0}, M_{H0}) = M_{A0} - M_{H0} \in [20, 100]$ GeV
- Whilst maintaining $M_{H0} < M_{A0}$

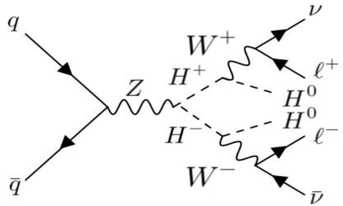
Preselections

Dilepton + Reduced $E_{miss,}$ off-shell Z region

p p → $H^0 H^0 l^+ l^-$



p p → $H^0 H^0 l^+ l^- \nu\nu$



Preselections

- Require opposite sign, same flavour $e^+e^-/\mu^+\mu^-$
- Veto on any third lepton
- Dilepton invariant mass ∈ (20, 80) GeV
- Require 0 hadronic taus
- ≤ 1 jets
- 0 b-tagged jets

Background Modelling

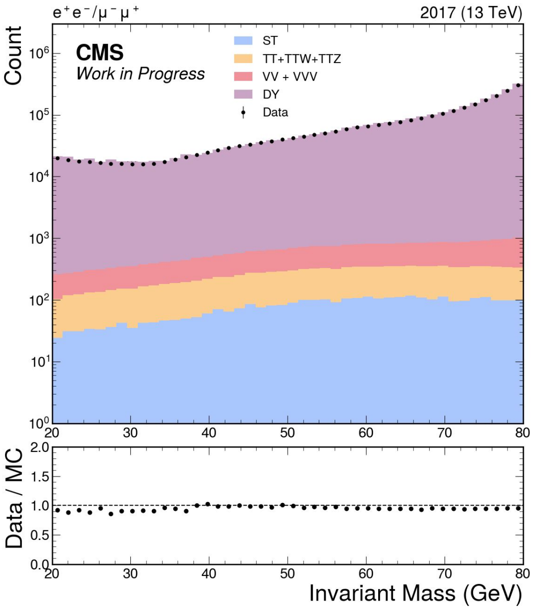
Backgrounds

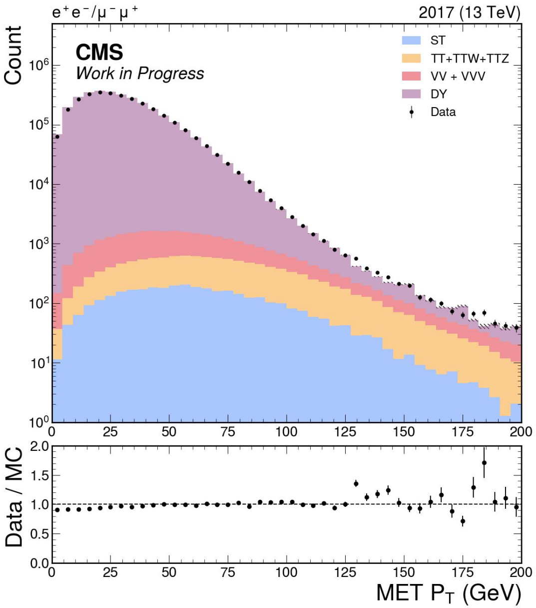
- Currently backgrounds modelled with simulation
- Main backgrounds:
  - $Z/\gamma \rightarrow l\,l$
  - $WW \rightarrow l\,l\,\nu\nu$
  - $TT \rightarrow l\,l\,\nu\nu$
  - $ZZ \rightarrow l\,l\,\nu\nu$

Corrections + Systematics

Included the following systematic uncertainties:

- Electron reconstruction & identification
- Muon reconstruction & Isolation & identification
- Jet identification & energy corrections





Parametric Neural Network

IMPERIAL

pNN Overview

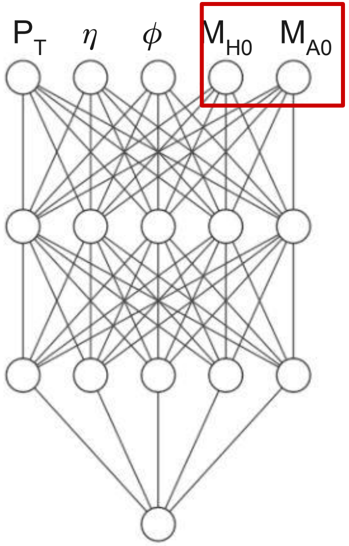
Instead of individual networks trained for each mass point:

- Single network that is optimal at all mass points

Inputs:

- Event features (e.g. lepton P_T, η, ϕ)
- Mass point (M_{H0}, M_{A0})

Example input feature $[P_T, \eta, \phi, M_{H0}, M_{A0}]$



[Parameterized Machine Learning for High-Energy Physics [1601.07913]](https://arxiv.org/abs/1601.07913)

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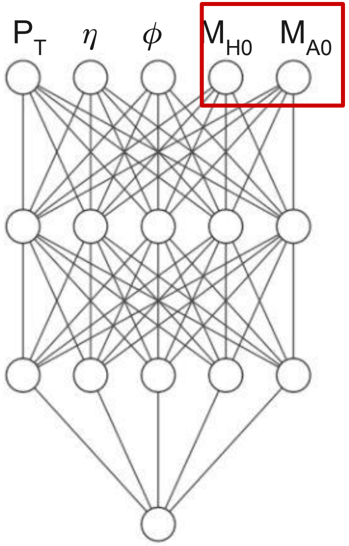
Network learns optimal discrimination between signal and background for a given (M_{H0}, M_{A0})

- For a given (M_{H0}, M_{A0}), network applies optimal set of cuts to separate signal from background



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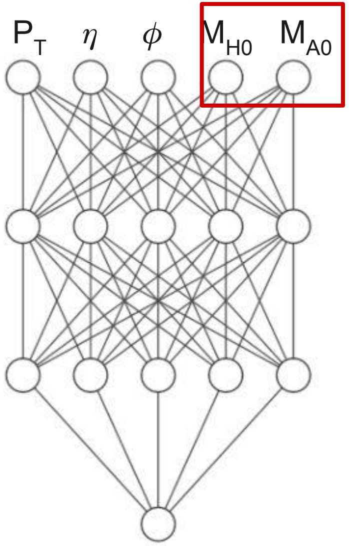
Interpolation:

- Smooth network output allows for interpolation *between* simulated mass points
  - If trained on masses 100 & 110 GeV → Network can also discriminate at 105 GeV



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Parametric Neural Network

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Training

❖ Signal samples:

- Train on all signal samples simultaneously
- Use the masses that signal was simulated with
- $(M_{H0}, M_{A0}) \in S_{MC} = \{(80, 100), (120, 150), (70, 90)...\}$

❖ Background samples:

- These have no inherent IDM masses
- Assign random masses from S_{MC}

Full training details shown in backup

Example batch: Signal = class 1

- Class: [1, 1, 1, 0, 0]
- Masses: [(80, 100), (120, 150), (70, 90), (80, 100), (70, 90)]

Simulated masses

Randomly assigned

Parametric Neural Network

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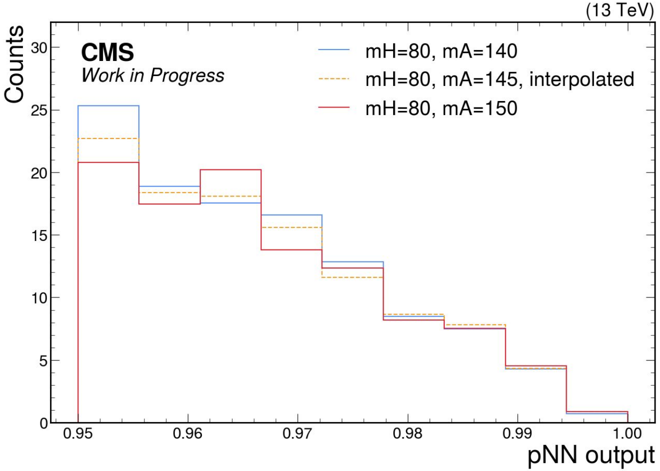
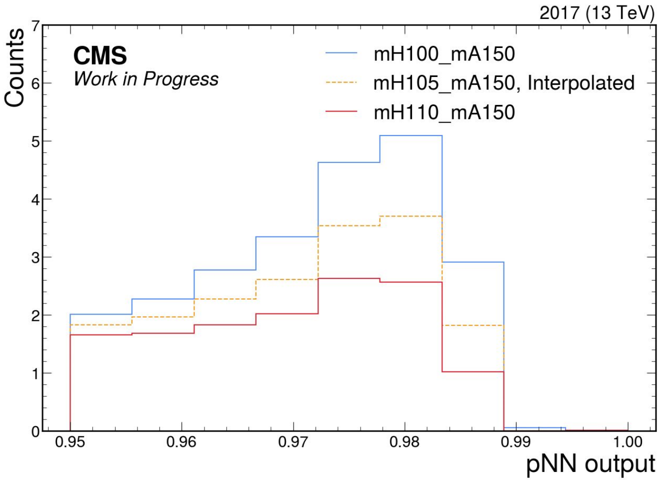
Interpolation Between Simulated Points

- Backgrounds:
  - Network output is smooth
  - To find background distribution at (M_{H0}, M_{A0}):
    - Evaluate simulation with mass inputs set to (M_{H0}, M_{A0})
- Signal:
  - To find signal distribution at (M_{H0}, M_{A0}) use cubic spline interpolation
- Previous studies shown interpolation performance comparable to single network performance

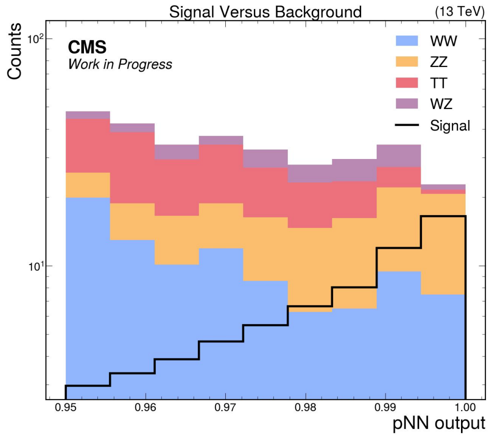


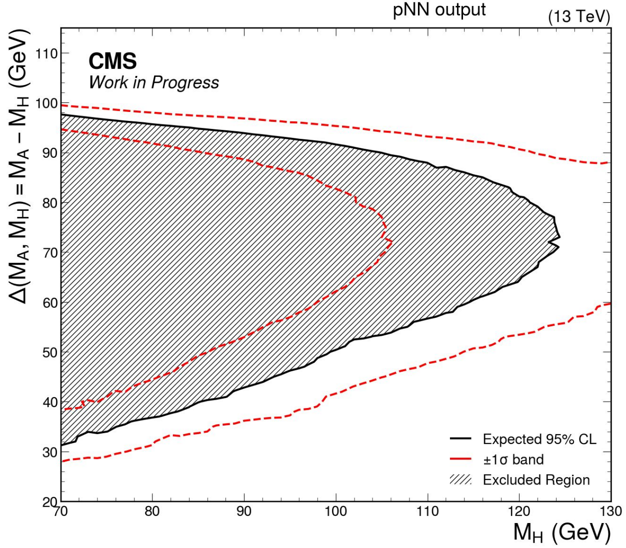


Limit Setting

Expected Limits on M_{H0} and M_{A0}

- Limits found by fitting to pNN output
  - SR: pNN output > 0.95
  - Here, interpolated at every 1 GeV split
  - Previous uncertainties included in fit
- Set 95% CL upper limits on IDM masses M_{H0} and M_{A0}
- Need to simulate higher M_{H0} signal
- Most sensitivity for mass splitting ~70 GeV
  - M_{H0} excluded up to ~120 GeV
- Limits get worse for smaller mass splittings
  - Leptons fall out of acceptance

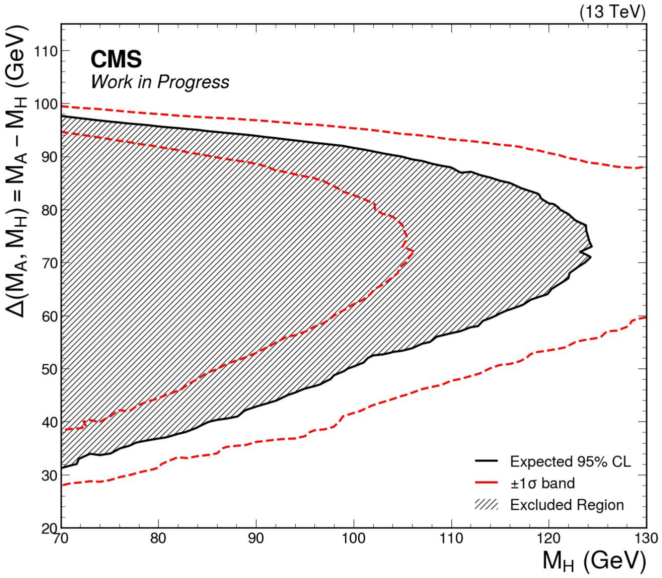




Summary

IMPERIAL

- This is the first dedicated search for the IDM
- Searching in the Dilepton + E_{miss} final state, off-shell Z region
    - $M_{H0} \in [70, 130]$ GeV, $\Delta(M_{A0}, M_{H0}) = M_{A0} - M_{H0} \in [20, 100]$ GeV
- Parametric Neural Network to discriminate signal versus background
    - Single network for whole parameter space
- Fitting to pNN output



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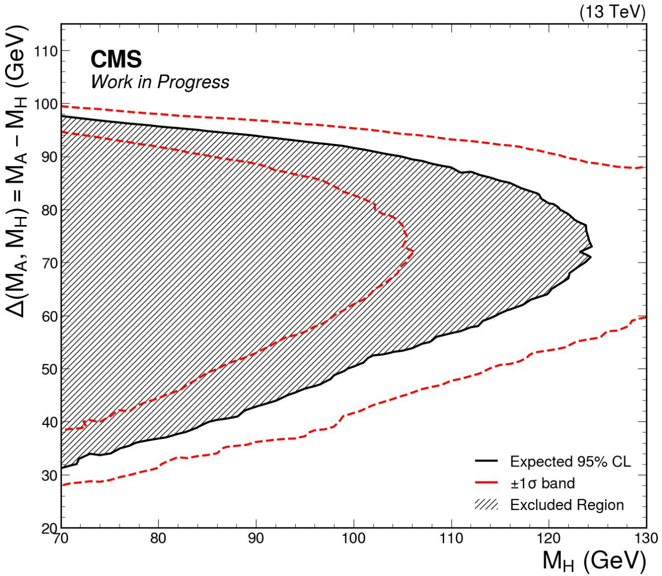

Backups

Theory and Motivation

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- λ_{345} is the coupling constant for IDM to the higg
- λ_2 is the quartic self coupling of the IDM particl

$$V = -\frac{1}{2}\left[m_{11}^2(\phi_S^\dagger\phi_S)+m_{22}^2(\phi_D^\dagger\phi_D)\right] + \frac{\lambda_1}{2}(\phi_S^\dagger\phi_S)^2+\frac{\lambda_2}{2}(\phi_D^\dagger\phi_D)^2$$
$$+\lambda_3(\phi_S^\dagger\phi_S)(\phi_D^\dagger\phi_D)+\lambda_4(\phi_S^\dagger\phi_D)(\phi_D^\dagger\phi_S) + \frac{\lambda_5}{2}\left[(\phi_S^\dagger\phi_D)^2+(\phi_D^\dagger\phi_S)^2\right],$$

vertex	coupling
hHH	$\lambda_{345}\, v$
hAA	$\bar{\lambda}_{345}\, v$
hhh	$3\,\lambda_1\, v$
$h\,H^+\,H^-$	$\lambda_3\, v$
$hhhh$	$3\,\lambda_1$
$H^+\,H^+\,H^-\,H^-$	$2\,\lambda_2$
$HHAA$	λ_2
$HHHH$	$3\,\lambda_2$
$AAAA$	$3\,\lambda_2$
$H^+H^-\,AA$	λ_2
$H^+H^-\,HH$	λ_2
hhH^+H^-	λ_3
$hhHH$	λ_{345}
$hhAA$	$\bar{\lambda}_{345}$

vertex	coupling
$H^-\,H^+\,\gamma$	$i\,e$
$H^-\,H^+\,Z$	$i\,\frac{g}{2}\,\frac{\cos(2\theta_W)}{\cos\theta_W}$
$H\,H^\pm\,W^\mp$	$\mp i\,\frac{g}{2}$
$A\,H^\mp\,W^\pm$	$-\frac{g}{2}$
$H\,A\,Z$	$-\frac{g}{2\cos\theta_W}$

Preselection

- Showing base object selections
- All leptons used in this analysis need to pass these

Object Preselections:

Electrons	
Quantity	Value
P_T	≥ 10 GeV
$\|\eta\|$	≤ 2.5
d_{xy}	≤ 0.3 cm
d_z	≤ 20 cm
Id	$mvaFall17V2Iso\_WPL$
Veto Transition	True

Muons	
Quantity	Value
P_T	≥ 10 GeV
$\|\eta\|$	≤ 2.4
d_{xy}	≤ 0.3 cm
d_z	≤ 20 cm
Id	Loose ID
Isolation	$pfIsoId \geq 2$ (Loose)

Taus	
Quantity	Value
P_T	≥ 20 GeV
$\|\eta\|$	≤ 2.3
d_z	≤ 20 cm
ΔR Electrons	≥ 0.4
ΔR Muons	≥ 0.4
deepTauVsElectron	VVLoose
deepTauVsMuon	VLoose
deepTauVsJets	VVLoose

Jets	
Quantity	Value
P_T	≥ 20 GeV
$\|\eta\|$	≤ 2.4
Pile-up Id	Tight
ΔR Electrons	≥ 0.4
ΔR Muons	≥ 0.4
ΔR Taus	≥ 0.4
b-Jets	
P_T	≥ 20 GeV
$\|\eta\|$	≤ 2.4
btagDeepFlavB ID	Loose WP

Triggers
HLT_Ele35_WPTight_Gsf
HLT_IsoMu27

Flags
goodVertices
globalSuperTightHalo2016Filter
HBHENoiseFilter
HBHENoiseIsoFilter
EcalDeadCellTriggerPrimitiveFilter
BadPFMuonFilter
BadPFMuonDzFilter
eeBadScFilter
ecalBadCalibFilter

Preselection

- Lead lepton PT is 2 GeV above the trigger threshold

Dilepton Selection		Target Background
Opposite Sign Same Flavour		WZ, VVV
Lead/Sublead P_T	29/10 (Muon), 37/10 (Electron) GeV	
Lead/Sublead ID	$TightId$	
Lead/Sublead Isolation	$Tight$ ($pfIsoId \geq 4$)	
Dimuon Invariant Mass	$20 \leq M \leq 80$ GeV	DY, ZZ
Veto Lepton (e, μ) PT	≥ 10 GeV	WZ, VVV
Veto Lepton (e, μ) ID	$LooseId$ (Muons), Iso_WPL (Electron)	
Veto Lepton (e, μ) Iso	$Loose$	
No. Taus	$= 0$, $P_T \geq 20$ GeV	WZ
No. Jets	≤ 1, $P_T \geq 30$ GeV, $\lvert\eta\rvert \leq 2.4$	DY, Top, VVV, ZZ
No. b Jets	$= 0$, $P_T \geq 20$ GeV, $\lvert\eta\rvert \leq 2.4$	Top

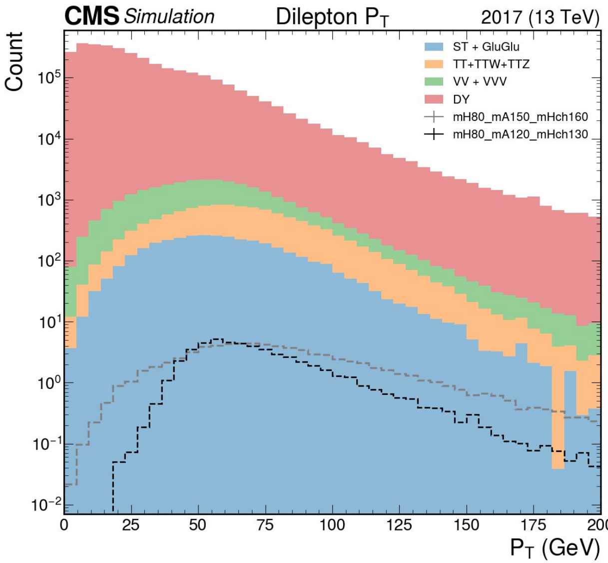
Background Modelling

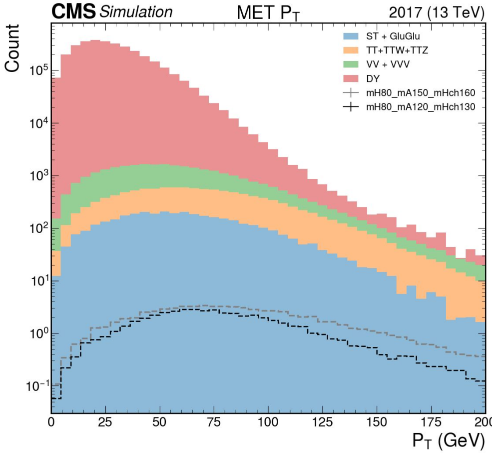
- Currently only modelled with MC
- Run II UL nanoAODv9 samples
- Cross-sections taken from latest, highest-order, theory predictions[7]
- Correction factors:
  - All corrections taken from either nanoAOD or the jsonPOG-integration[8]
  - L1 Pre-firing
  - Electron Reconstruction, ID, Trigger
  - Muon ID, Isolation and Trigger
  - PU weight SF

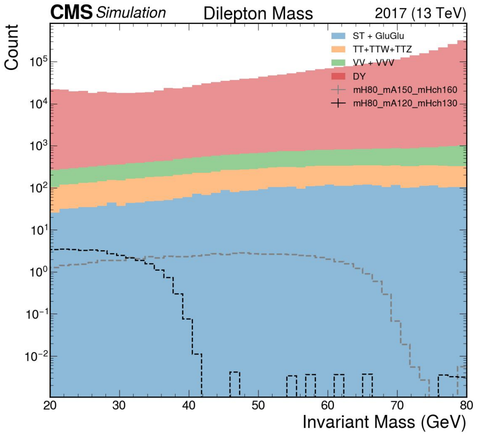
Background MC	
Process	Samples
Drell-Yan	DYJetsToLL_{0-4}J_M10-50 (LO) DYJetsToLL_{0-4}J_M50 (LO)
ZZ	ZZTo2L2Nu ZZTo2Q2L_mllmin4p0 ZZTo4L_5f ZZZ
WZ	WZTo3LNu WZTo2Q2L_mllmin4p0 WZTo1L3Nu_4f WZZ
WW	WWTo1L1Nu2Q_4f WWTo2L2Nu WWZ_4F WWW_4F
TT	TTTo2L2Nu TTZToLLNuNu_M-10 TTWJetsToLNu
tW	ST_tW_(anti)top_5f ST_t-channel_(anti)top_5f
GluGlu	GluGluToContinToZZTo2L2L

Initial Distributions

- Plots shown after initial object + dilepton selections
- Includes two IDM benchmark points:
  - mH = 80, mA = 120, mHch = 130
  - mH = 80, mA = 150, mHch = 160
- For 127fb^{-1} of data, expect ~ 100-300 IDM events
- Clear that cut-based analysis is not possible
- After initial selection, DY is overwhelming background







Parametric Neural Network

IMPERIAL CMS

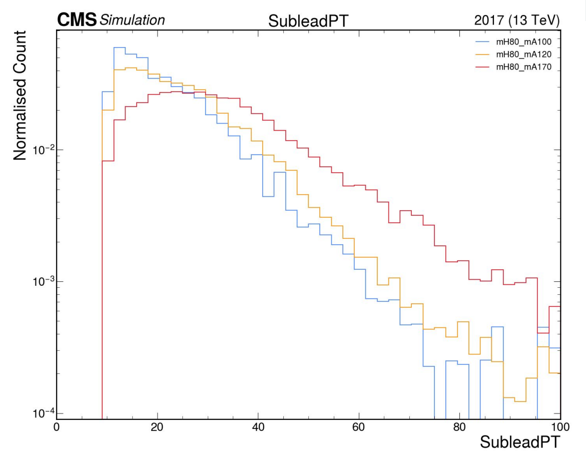
- Model is 4 linear layers with leaky ReLU and dropout=0.1
  - Parameterisation is done by concatenating input event features with the ma
  - E.g. [phi, mH, mA]
- Weighted Cross-Entropy
- Adam optimiser
- Trained for 10 epochs
- Learning rate = 1e-08
- Batch size = 500

```
MLPRelu(
  (fc_process): ModuleList(
    (0): Sequential(
      (0): Dropout(p=0.1, inplace=False)
      (1): Linear(in_features=54, out_features=200, bias=True)
      (2): LeakyReLU(negative_slope=0.01)
    )
    (1): Sequential(
      (0): Dropout(p=0.1, inplace=False)
      (1): Linear(in_features=200, out_features=200, bias=True)
      (2): LeakyReLU(negative_slope=0.01)
    )
    (2): Sequential(
      (0): Dropout(p=0.1, inplace=False)
      (1): Linear(in_features=200, out_features=200, bias=True)
      (2): LeakyReLU(negative_slope=0.01)
    )
    (3): Sequential(
      (0): Dropout(p=0.1, inplace=False)
      (1): Linear(in_features=200, out_features=50, bias=True)
      (2): LeakyReLU(negative_slope=0.01)
    )
  )
  (output_mlp_linear): Linear(in_features=50, out_features=1, bias=True)
)
Number of parameters in model = 101501
```

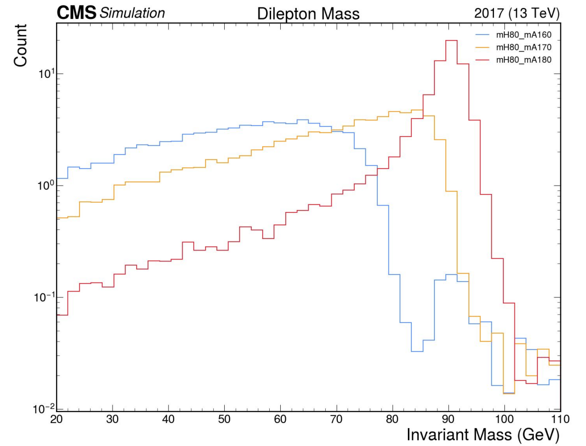
Precuts
$P_T^{ll} > 15$ GeV
$\Delta\phi_{ll,E_T^{miss}} > 1$
$M_T > 30$
$cos(\Delta\phi_{ll}) > -0.75$

Limit Setting

- Smaller mass splittings (M_A - M_H) leads to softer leptons
  - These fall out of acceptance
  - Showing normalised count



- Mass splitting of 90 GeV still has good acceptance with the dilepton invariant mass cut
  - This point still has off-shell Z



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IMPERIAL

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  - $M_H \in [70, 130]$ GeV, $\Delta(M_A, M_H) = M_A - M_H \in [20, 100]$ GeV
- Single Parametric Neural Network (pNN) optimises search at each mass point
- Limits found by fitting to pNN output

Thanks!