Non-Parametric Data-Driven Background Modelling using Conditional Probabilities

Konstantinos Nikolopoulos
University of Birmingham
Discoveries of new signals

…are all about controlling the backgrounds
Discoveries of new signals

...are all about controlling the backgrounds

Construct the profile likelihood ratio test statistic: \[ \lambda(\mu) = \frac{L(\mu, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})} \]
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and test the background-only hypothesis ($\mu = 0$): $\lambda(0) = \frac{L(0, \hat{\theta})}{L(\hat{\mu}, \hat{\theta})}$
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Observing the Higgs boson


- Data
- Background ZZ
- Background Z+jets, $t\bar{t}$
- Signal ($m_H = 125$ GeV)
- Syst.Unc.

$\sqrt{s} = 7$ TeV: $\int Ldt = 4.8$ fb$^{-1}$

$\sqrt{s} = 8$ TeV: $\int Ldt = 5.8$ fb$^{-1}$

$H \rightarrow ZZ^{(*)} \rightarrow 4l$


- Data
- Sig+Bkg Fit ($m_H = 126.5$ GeV)
- Bkg (4th order polynomial)

$\sqrt{s} = 7$ TeV, $\int Ldt=4.8fb^{-1}$

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$H \rightarrow \gamma\gamma$

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Observing the Higgs boson

ATLAS

Events/5 GeV

Data
Background ZZ
Background Z+jets, f̅f
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s = 7 TeV: \int L dt = 4.8 fb^{-1}

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m_{4l} [GeV]

100 150 200 250

H→ZZ

H→γγ

Events / 2 GeV

Data
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s=7 TeV, \int L dt=4.8fb^{-1}

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m_{γγ} [GeV]

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**ATLAS**

H → ZZ(*) → 4l

\[ \text{Events/5 GeV} \]

- **Data**
- **Background ZZ(*)**
- **Background Z+jets, \( \bar{t} \bar{t} \)**
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\[ \text{m}_4l \text{ [GeV]} \]

\[ 100 \quad 150 \quad 200 \quad 250 \]

\[ 0 \quad 5 \quad 10 \quad 15 \quad 20 \quad 25 \]

**ATLAS**

H → γγ

\[ \text{Events / 2 GeV} \]

\( \sqrt{s} = 7 \text{ TeV}, \int L dt = 4.8 \text{ fb}^{-1} \)

\( \sqrt{s} = 8 \text{ TeV}, \int L dt = 5.9 \text{ fb}^{-1} \)

\[ \text{m}_{\gamma\gamma} \text{ [GeV]} \]

\[ 100 \quad 110 \quad 120 \quad 130 \quad 140 \quad 150 \quad 160 \]

di-photon, photon+jet, jet+jet

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Observing the Higgs boson

**Data**

- Red: Background ZZ$^{(*)}$
- Purple: Background Z+jets, $tar{t}$
- Blue: Signal ($m_H = 125$ GeV)
- Grey: Syst. Unc.

**ATLAS**

- $\sqrt{s} = 7$ TeV: $\int L dt = 4.8$ fb$^{-1}$
- $\sqrt{s} = 8$ TeV: $\int L dt = 5.8$ fb$^{-1}$

**Events / 5 GeV**

- 25
- 20
- 15
- 10
- 5
- 0

**$m_{4l}$ [GeV]**

- 100
- 150
- 200
- 250

**Events / 2 GeV**

- 3500
- 3000
- 2500
- 2000
- 1500
- 1000
- 500
- 0

**$m_{\gamma\gamma}$ [GeV]**

- 100
- 110
- 120
- 130
- 140
- 150
- 160

**Trying to maximise data-driven input, e.g. signal side-bands**

- Di-photon, photon+jet, jet+jet
Parametric methods

Both ATLAS and CMS $H \rightarrow \gamma\gamma$ use parametric methods

Also $H \rightarrow \mu\mu$, $H \rightarrow Z\gamma$, $H \rightarrow b\bar{b}\gamma\gamma$, etc
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Choose a function with $N_{\text{par}}$ free parameters

- Too many parameters: Reduced statistical power
- Too few parameters: Not enough flexibility to model the background
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**Question:** Does the true, but unknown, background shape belong to the family of curves parametrised by the chosen function?
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Question: Does the true, but unknown, background shape belong to the family of curves parametrised by the chosen function?
Spurious signal

ATLAS uses the concept of “spurious signal”

Possible systematic mismodelling due to function choice leading to apparent signal
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Choices:

- What function to use?
- What systematic uncertainty to assign?
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Use MC sample of background to perform S+B fits.

- Use function with lowest obtained $S_{\text{spurious}}$, and said $S_{\text{spurious}}$ as systematic
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Use MC sample of background to perform S+B fits.

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Challenges:
- **Conceptual:** use MC sample not deemed reliable for modelling the background
- **Practical:** required MC sample orders of magnitude larger than dataset of interest
Spurious signal

**H\rightarrow\gamma\gamma** inclusive fiducial cross section measurement uncertainties

<table>
<thead>
<tr>
<th>Source</th>
<th>Uncertainty (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fit (stat.)</td>
<td>10</td>
</tr>
<tr>
<td>Fit (syst.)</td>
<td>8.3</td>
</tr>
<tr>
<td>Photon energy scale &amp; resolution</td>
<td>4.0</td>
</tr>
<tr>
<td>Background modeling (spurious signal)</td>
<td>7.3</td>
</tr>
</tbody>
</table>

**Correction factor** | 5.2  
**Photon isolation efficiency** | 4.6  
**Pileup** | 1.9  
**Photon ID efficiency** | 1.3  
**Trigger efficiency** | 0.7  
**Dalitz Decays** | 0.4  
**Theoretical modeling** | +0.3 \(-0.4\)  
**Diphoton vertex selection** | 0.1  
**Photon energy scale \& resolution** | 0.1  

<table>
<thead>
<tr>
<th>Source</th>
<th>Systematic uncertainty in $m_H$ [MeV]</th>
</tr>
</thead>
<tbody>
<tr>
<td>EM calorimeter response linearity</td>
<td>60</td>
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<tr>
<td>Non-ID material</td>
<td>55</td>
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<tr>
<td>EM calorimeter layer intercalibration</td>
<td>55</td>
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<tr>
<td>$Z \rightarrow ee$ calibration</td>
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<td>ID material</td>
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<tr>
<td>Lateral shower shape</td>
<td>40</td>
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<tr>
<td>Muon momentum scale</td>
<td>20</td>
</tr>
<tr>
<td>Conversion reconstruction</td>
<td>20</td>
</tr>
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<tr>
<td>$e/\gamma$ energy resolution</td>
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</tr>
<tr>
<td>All other systematic uncertainties</td>
<td>10</td>
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Discrete Profiling Method

CMS uses the **discrete profiling method**

- Combine different parametric models at the likelihood level
- Treat shape options as discrete nuisance parameter
  - Use envelope of individual likelihood scans to obtain result
Discrete Profiling Method

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![Graph showing discrete profiling](JINST 10 (2015) 04, P04015)
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The Discrete Profiling Method

Practical and conceptual complications when models have different $N_{par}$
The Discrete Profiling Method

Practical and conceptual complications when models have different $N_{\text{par}}$

**Correction:** penalise functions with more parameters

- Inspired by p-value and Akaike information criterion
- Parametrised as $\Lambda_{\text{corr}} = \Lambda + cN_{\text{par}}$
- Bias vs coverage trade-off versus $c$ studied case-by-case
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\[ c = 0 \quad \text{No Correction} \quad c = 1 \quad \text{Approx. p-value} \quad c = 2 \quad \text{Akaike} \]
The Discrete Profiling Method

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Common systematic effects across categories: All combinations of functions and nuisance parameters need to be scanned

→ Naive implementation impractical and usually approximations used.
Higgs-fermion interactions

- **Higgs interactions to vector bosons:** defined by symmetry breaking
- **Higgs interactions to fermions:** ad-hoc hierarchical Yukawa couplings $\propto m_f$

\[ g_{HV} = \frac{2m^2_V}{\nu} \]

\[ g_{hf} = \frac{m_f}{\nu} \]
Higgs-fermion interactions

- **Higgs interactions to vector bosons:** defined by symmetry breaking
- **Higgs interactions to fermions:** ad-hoc hierarchical Yukawa couplings $\propto m_f$

Yukawa couplings **not** imposed by fundamental principle

Modified Higgs-fermion couplings in BSM scenarios

Probing fermion mass generation scale $\rightarrow$ independent task

Standard Model successful

but matter particle mass hierarchy unexplained!

$\frac{m_e}{m_t} \approx 3 \times 10^{-6}$
Extended Higgs sectors

- The Standard Model Higgs sector is an SU(2)_L doublet of complex scalar fields: this is the most economic way to obtain spontaneous symmetry breaking
- Extended Higgs sectors are possible, and can potentially provide answers to a number of open questions
- The $\rho$ parameter puts tight constraints on model viability
  - For SM $\rho=1$ (with small corrections)
  - Constraints naturally fulfilled for appropriate configurations of scalar singlets and doublets

\[
\rho = \frac{M_W^2}{M_Z^2 \cos^2 \theta_W} = 1.00039 \pm 0.00019
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    \[
    \rho = \frac{M_W^2}{M_Z^2 \cos^2 \theta_W} = 1.00039 \pm 0.00019
    \]
- A number of possibilities with rich phenomenology:
  - Higgs double with one or more scalar singlets,
  - Two Higgs Doublets (2HDM),
  - 2HDM with additional scalar singlet (2HDM+S)
- Particularly interesting: additional scalar lighter than observed Higgs boson.
  - \( h \rightarrow aa \)
  - \( h \rightarrow Za \)
Searches for new physics

Exclusive Higgs decays

Higgs decays to light hadronically decaying scalars

\[ BR(h \rightarrow \phi \gamma) = (2.31 \pm 0.03_{f\phi} \pm 0.11_{h\rightarrow\gamma\gamma}) \cdot 10^{-6} \]

These analyses share the challenge that the respective backgrounds are not straightforward to model with simulations.
Beyond Parametric Methods

**Parametric methods** have several advantages but also important issues
In the following: aim to develop **fully data-driven non-parametric background models**
Beyond Parametric Methods

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Non-Parametric Data-Driven Background Modelling using Conditional Probabilities

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arXiv:2112.00650
Beyond Parametric Methods

Parametric methods have several advantages but also important issues. In the following, aim to develop fully data-driven non-parametric background models.

Non-Parametric Data-Driven Background Modelling using Conditional Probabilities


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Methods motivated by specific analyses, but with wide applicability.
The strategy

Complete Phase-space
The strategy

Complete Phase-space

Signal Region
The strategy

Complete Phase-space

Generation Region

Signal Region
The strategy

Complete Phase-space

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Signal Region

Analysis Selection
The strategy

Complete Phase-space

Generation Region

Signal Region

Validation Region

Analysis Selection

N
1
2
3
4
5
\ldots
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The strategy

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⊗
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Exclusive Higgs decays

\[ BR(h \rightarrow \phi \gamma) = (2.31 \pm 0.03_{f_{\phi}} \pm 0.11_{h \rightarrow \gamma\gamma}) \cdot 10^{-6} \]
\( h/Z \rightarrow \phi \gamma / \rho \gamma \)

**Exclusive decays → distinct experimental signature**
- Pair of collimated high-\( p_T \) isolated tracks recoils against high-\( p_T \) isolated photon

**Meson decays:**
- \( \phi \rightarrow K^+K^- \), BR=49%
- \( \rho \rightarrow \pi^+\pi^- \), BR≈100%

**Small opening angles between decay products**
- Particularly for \( \phi \rightarrow K^+K^- \)
- Tracking in dense environments

- **Small angular separation of decay products**
- **Tracking in dense environments**
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- $\phi \rightarrow K^+K^-$, BR=49%
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Small opening angles between decay products

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Event Selection

meson decay products

Higgs

photon

ATLAS Simulation

H → φγ

Before selection
After selection

p_T^1

p_T^2

Events / 2 GeV

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Event Selection

“Tight” identification criteria
Isolated (calorimeter- and track-based)

$P_T > 20 \text{ GeV}$

$P_T > 15 \text{ GeV}$

$P_T > 20 \text{ GeV}$

$P_T > 15 \text{ GeV}$

$P_T > 35 \text{ GeV}$

photons

meson decay products

Higgs

ATLAS Simulation

Before selection

After selection

$H \rightarrow \phi \gamma$

$P_T^K$

$p_T^\gamma$

$p_T^{K1}$

$p_T^{K2}$
Event Selection

“Tight” identification criteria
Isolated (calorimeter- and track-based)

\[ p_T^\gamma > 35 \text{ GeV} \]

\[ p_T > 20 \text{ GeV} \]

\[ p_T > 15 \text{ GeV} \]

\[ m_\phi \pm 8 \text{ MeV} \]

\[ m_\rho \pm 140 \text{ MeV} \]
Event Selection

Photon Selection:
- "Tight" identification criteria
  - Isolated (calorimeter- and track-based)
  - $P_T^\gamma > 35$ GeV
  - $P_T > 20$ GeV
  - track-based isolation
  - $P_T > 15$ GeV
- $m_{\phi} \pm 8$ MeV or $m_{\rho} \pm 140$ MeV

Meson decay products

$\Delta \phi (M, \gamma) > \pi/2$

$P_T^T > 35$ GeV

"Tight" identification criteria
Isolated (calorimeter- and track-based)
Event Selection

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  - $p_T > 20$ GeV
  - $p_T > 15$ GeV
  - $p_T > 35$ GeV
  - Track-based isolation

$\Delta \phi (M, \gamma) > \pi/2$

$m_\phi \pm 8$ MeV or $m_\rho \pm 140$ MeV

"Inclusive" backgrounds
- $\gamma + \text{jet}, \text{di-jet with jet "seen" as } \gamma$

"FixedCutTight" photon isolation

Tracking CP "Loose" working point

Leading/sub-leading track $p_T > 20, 15$ GeV

$m_{KK} \neq m_{\phi}$

Track isolation (ptcone20) relative to $p_{KK} T < 0.10$

Di-track system transverse momentum requirement:
- $p_M T > 40$ GeV
- $40 + 5/34 \times (m_{M\gamma} - 91)$ GeV
- For $m_{M\gamma} \leq 91$ GeV
- $47.2$ GeV
- For $91$ GeV $< m_{M\gamma} < 140$ GeV
- For $m_{M\gamma} \geq 140$ GeV

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Non-parametric data-driven background model based on Ancestral Sampling

- Obtain loose sample of candidates
- Model kinematic and isolation distributions
  - Conditional PDFs modelled using histograms
- Generate “pseudo”-background events and apply event selection

Used in several analyses already!

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Example application on γ+jet MC sample
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γ+jet MC  

Model  
arXiv:2112.00650
Background Model

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Example application on $\gamma$+jet MC sample

K. Nikolopoulos / 26 January 2022 / Non-Parametric Data-Driven Background Modelling
Background Model

Example application on γ+jet MC sample

Shape variations
- Modifying sampling distributions
- Overall transformations of signal shape

Observed after unblinding
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Observed after unblinding

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Background Validation

ATLAS
\( \sqrt{s} = 13 \text{ TeV}, 35.6 \text{ fb}^{-1} \)

ATLAS
\( \sqrt{s} = 13 \text{ TeV}, 32.3 \text{ fb}^{-1} \)
Background Validation

**ATLAS**

- Data $\bar{s}s = 13$ TeV, 35.6 fb$^{-1}$
- Fit Result
- $\phi \rightarrow K^+K^-$
- Total Background

**JHEP 1807 (2018) 127**

**ATLAS**

- Data $\bar{s}s = 13$ TeV, 32.3 fb$^{-1}$
- Fit Result
- $\rho \rightarrow \pi^+\pi^-$
- Total Background

**ATLAS**

- $\phi$ Sideband Region
- Background Model
- Model Shape Uncertainty

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- $\rho$ Sideband Region
- Background Model
- Model Shape Uncertainty
h/Z→φγ/ργ: Results

Final discriminant: $m_{KKγ}$ and $m_{ππγ}$

No significant signal observed

<table>
<thead>
<tr>
<th>Branching Fraction Limit (95% CL)</th>
<th>Expected</th>
<th>Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B(H \rightarrow φγ)$ [$10^{-4}$]</td>
<td>$4.2_{-1.2}^{+1.8}$</td>
<td>4.8</td>
</tr>
<tr>
<td>$B(Z \rightarrow φγ)$ [$10^{-6}$]</td>
<td>$1.3_{-0.4}^{+0.6}$</td>
<td>0.9</td>
</tr>
<tr>
<td>$B(H \rightarrow ργ)$ [$10^{-4}$]</td>
<td>$8.4_{-2.4}^{+4.1}$</td>
<td>8.8</td>
</tr>
<tr>
<td>$B(Z \rightarrow ργ)$ [$10^{-6}$]</td>
<td>$33_{-9}^{+13}$</td>
<td>25</td>
</tr>
</tbody>
</table>
Model Robustness

- Model describes main features of background
  - Robust under signal contamination
  - Resonant backgrounds need to be considered separately
### Model Robustness

- **Model describes main features of background**
- Robust under signal contamination
- Resonant backgrounds need to be considered separately

![Graph showing signal injection at ~10.4% of the background](image)

**Signal injection at ~10.4% of the background**

---

**arXiv:2112.00650**
Model Robustness

- Model describes main features of background
  - Robust under signal contamination
  - Resonant backgrounds need to be considered separately

Signal injection at ~10.4% of the background

Background prediction increased by ~2%

arXiv:2112.00650
**h/Z→Qγ: Resonant Backgrounds**

- **Model describes main features of background**
  - Robust under signal contamination
  - Resonant backgrounds need to be considered separately

---

**ATLAS**

\[ \bar{s} = 13 \text{ TeV}, 36.1 \text{ fb}^{-1} \]

Region: VR1 \( \psi(nS)_\gamma \)

Data

<table>
<thead>
<tr>
<th>Events / 2.50 GeV</th>
</tr>
</thead>
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<tr>
<td>Z FSR</td>
</tr>
<tr>
<td>Model uncertainty</td>
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</table>

\[ m_{\mu^+\mu^-} \text{ [GeV]} \]

50 100 150 200 250 300

**ATLAS**

\[ \bar{s} = 13 \text{ TeV}, 36.1 \text{ fb}^{-1} \]

Region: VR2 \( \psi(nS)_\gamma \)

Data

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<th>Events / 2.50 GeV</th>
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\[ m_{\mu^+\mu^-} \text{ [GeV]} \]

50 100 150 200 250 300

**ATLAS**

\[ \bar{s} = 13 \text{ TeV}, 36.1 \text{ fb}^{-1} \]

Region: VR3 \( \psi(nS)_\gamma \)

Data

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50 100 150 200 250 300

---

K. Nikolopoulos / 26 January 2022 / Non-Parametric Data-Driven Background Modelling
$h \rightarrow Z a \rightarrow \ell \ell + \text{jet}$

Higgs decays to light hadronically decaying scalars
**Aims and Motivation**

**Aims**

- Use full ATLAS Run II dataset (139 fb⁻¹) to perform first search for $h_{125} \to Z(a/\phi/Q_{had})$, $\phi = e\nu or \mu\tau$.

**Charmonium Motivation**

- Higgs boson decay to $Z + light$ resonances unconstrained.

**BSM Motivation**

- Potential constraints on charm Yukawa coupling.

**Elliot Reynolds**

- Higgs Decays To Light Scalars

---

**New search: $h\to Za$ with $a\to hadrons$**

- Experimental focus mostly on:
  - $h\to aa$
  - $a\to down$-type fermions

- Overwhelming $Z + jets$ background

- $a\to hadrons$ reconstruction using sub-structure techniques

---

**PRL 125 (2020) 22, 221802**

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**Diagram: $h\to Za\to ll + jet$**

- $h_{125}$
- $Z$
- $\ell^+$
- $\ell^-$

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**Aims and Motivation**

**Aims**
- Use full ATLAS Run II dataset ($139 \text{ fb}^{-1}$) to perform first search for $h_{125} \to Z \ell^+ \ell^-$.
- Interpret resonance as $J/\psi$ or $\Upsilon$, or a (BSM) with $m_a < 4 \text{ GeV}$.

**Charmonium Motivation**
- $h_{125}$ Higgs boson decay to $Z$ + light resonances unconstrained.
- Potential constraints on charm Yukawa coupling.

**BSM Motivation**
- Fills both of the aforementioned gaps in the search programme.

**Experimental focus mostly on:**
- $h \to aa$
- $a \to$ down-type fermions

**New search:** $h \to Z a$ with $a \to$ hadrons
- Overwhelming $Z$ + jets background
- $a \to$ hadrons reconstruction using sub-structure techniques.
$h \rightarrow Za \rightarrow ll + \text{jet}$
$h \rightarrow Za \rightarrow ll + \text{jet}$

Expected Bkg: $82400 \pm 3700$
Observed: $82908$

\textbf{ATLAS} 
$\bar{v}s=13$ TeV, 139 fb$^{-1}$
$\sigma(H)=\sigma_{SM}(H)$
$B(H \rightarrow Za)=100\%$

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Expressed in $B(H \rightarrow Za) \times B(a \rightarrow \text{hadrons})$ limits start from $\text{BR}<31\%$

K. Nikolopoulos / 26 January 2022 / Non-Parametric Data-Driven Background Modelling
**h → Za → ll+jet**

**Expected Bkg:** 82400 ± 3700

**Observed:** 82908

Expressed in \( B(H \rightarrow Za) \times B(a \rightarrow \text{hadrons}) \) limits start from BR<31%

K. Nikolopoulos / 26 January 2022 / Non-Parametric Data-Driven Background Modelling
Background estimation: MC-corrected ABCD method using $m_{\ell\ell j}$ and MLP discriminant

Accounts for 13% correlation between $m_{\ell\ell j}$ and MLP discriminant

$$A_{\text{SR}}^{\text{ABCD Est.}} = \frac{B_{\text{data}} C_{\text{data}}}{D_{\text{data}}} \times \frac{A_{\text{MC}}}{B_{\text{MC}} C_{\text{MC}}/D_{\text{MC}}}$$

Data-driven ABCD Estimate

MC-based ABCD Correction Factor
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- Data-driven ABCD Estimate
- MC-based ABCD Correction Factor

MLP Discriminant vs. $m_{\ell\ell j}$ plot:

- SR
- A
- C
- B
- D
h→Za→ll+jet

**Background estimation:** MC-corrected ABCD method using $m_{\ell\ell j}$ and MLP discriminant

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\[
A_{SR}^{ABCD \text{ Est.}} = \frac{B_{\text{data}} C_{\text{data}}}{D_{\text{data}}} \\
\text{Data-driven ABCD Estimate}
\]

![Diagram showing SR, A, B, C, and D regions with $m_{\ell\ell j}$ as the horizontal axis and MLP Discriminant as the vertical axis.]
**Background estimation**: MC-corrected ABCD method using $m_{\ell\ell j}$ and MLP discriminant

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**Diagram**: MLP Discriminant vs. $m_{\ell\ell j}$

- SR
- A
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<tr>
<th>$a$ mass</th>
<th>0.5 GeV</th>
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<th>2.5 GeV</th>
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<tbody>
<tr>
<td>Total Uncertainty</td>
<td>8.3</td>
<td>10.7</td>
<td>20.3</td>
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<tr>
<td>Total Statistical Uncertainty</td>
<td>0.6</td>
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**Signal Systematic Uncertainties**
- Jet Energy Scale: 1.3, 1.5, 1.5
- Parton Shower: 1.4, 1.4, 1.4
- Luminosity, Pileup, Trigger, Leptons, & JVT: 0.2, 0.3, 0.5
- MC Statistics: 0.2, 0.2, 0.6
- Renormalization Scale: 0.1, < 0.1, 0.2
- Acceptance: 0.1, < 0.1, 0.2

**Background Systematic Uncertainties**
- MC Statistics: 6.4, 8.4, 15.8
- Parton Shower and ME: 3.9, 5.1, 9.6
- Renormalization Scale: 3.4, 4.4, 8.3
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**ATLAS**

13 TeV, 139 fb$^{-1}$
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Suppressing MC statistical/modelling uncertainties would improve limit from 31% to 7.5%!
Generative Adversarial Network

To improve analysis sensitivity → improve background model

- Increase sample size
- Improve Generator-level modelling uncertainties
Generative Adversarial Network

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**Ancestral sampling** procedure presented earlier is impractical
- Culprit: background discrimination uses multivariate techniques on variables
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Ancestral sampling procedure presented earlier is impractical

- Culprit: background discrimination uses multivariate techniques on variables

Solution to sample size: Use a Generative Adversarial Network to generate the background sample

Novelty: directly use data in superset of signal region for model generation

- Resolves concerns about modelling uncertainties
conditioned-GAN

**Complication:** dataset used for model generation may be contaminated by signal

- Blind the Signal Region while training the GAN
conditioned-GAN

**Complication:** dataset used for model generation may be contaminated by signal
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**conditioned-GAN** (cGAN): generator depends on *conditioning variable* → model can be interpolated
**conditioned-GAN**

**Complication:** dataset used for model generation may be contaminated by signal
- Blind the Signal Region while training the GAN

*conditioned-GAN* (cGAN): generator depends on **conditioning variable** → model can be interpolated

Generator and discriminator:
- 5 layers × 256 hidden nodes with leaky ReLU activation function
- Binary cross entropy loss function and L2 regularisation
cGAN: Modelling of variables

Trained 100 cGANs with random hyper-parameters

- Ensemble of top 5 cGANs, based on $\chi^2$, retained
cGAN: Modelling of variables

$123 \text{ GeV} < m_{\ell\ell j} < 135 \text{ GeV}$
cGAN: Modelling of variables

\begin{align*}
\text{Background} & \quad \text{GAN} \\
110 \text{ GeV} < m_{\ell\ell j} < 123 \text{ GeV} \\
123 \text{ GeV} < m_{\ell\ell j} < 135 \text{ GeV} \\
135 \text{ GeV} < m_{\ell\ell j} < 145 \text{ GeV} \\
145 \text{ GeV} < m_{\ell\ell j} < 155 \text{ GeV}
\end{align*}
cGAN: Ensemble and Shape Variations

Shape variations:

- Perform Principal Component Analysis on differences of individual cGANs to ensemble
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Shape variations:

- Perform Principal Component Analysis on differences of individual cGANs to ensemble

PCA components account for: 89%, 9.6%, 0.55%, and 0.40% of variance.
cGAN: Fitting the “data”

Validation Region
Background strength = 1.000±0.006
Shape Variation 1 = -1.83±0.24
Shape Variation 2 = -1.50±0.50
cGAN: Fitting the “data”

Validation Region
Background strength = 1.000±0.006
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Background strength = 1.000±0.006
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- Background strength = 1.000±0.006
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**Signal+Background fit**
- Obtained signal compatible with 0

**Signal+Background fit** behaves as expected
CATHODE: Classifying Anomalies Through Outer Density Estimation

- Training a conditional density estimator (Masked Autoregressive Flow) on the discriminant variables in the side-band
- Interpolating it into the signal region and sampling from it
- Train classifier: separate SR data from produced “background” sample
- Anomaly detection: Apply the trained classifier to data in SR

In real life: the CATHODE method would need to be combined with a background estimation procedure

\[
p_{\text{data}}(x|m \in \text{SB}) = p_{\text{bg}}(x|m \in \text{SB})
\]

\[
p_{\text{data}}(x|m \in \text{SR})
\]
### CATHODE

- **CATHODE: Classifying Anomalies Through Outer Density Estimation**
  - Training a conditional density estimator (Masked Autoregressive Flow) on the discriminant variables in the side-band
  - Interpolating it into the signal region and sampling from it
  - Train classifier: separate SR data from produced “background” sample
  - Anomaly detection: Apply the trained classifier to data in SR
- **In real life:** the CATHODE method would need to be combined with a background estimation procedure

---

#### Signal Region

<table>
<thead>
<tr>
<th>Superseded</th>
<th>Idealized AD</th>
<th>CATHODE</th>
<th>CWoLa</th>
<th>ANODE</th>
<th>random</th>
</tr>
</thead>
</table>

---

#### Signal Region

- **Rejection** (1/False Positive Rate)
- **Significance Improvement**

---

\[ p_{\text{data}}(x|m \in SB) = p_{\text{bg}}(x|m \in SB) \]
\[ p_{\text{data}}(x|m \in SR) = p_{\text{bg}}(x|m \in SR) \]
CATHODE: Classifying Anomalies Through Outer Density Estimation

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CATHODE: Classifying Anomalies Through Outer Density Estimation
arXiv:2109.00546
Summary

Background modelling crucial in searches for new physics and precision measurements
- Variety of methods has been developed
- Many rely on availability of large, reliable, simulated data samples
- Parametric methods suffer “spurious signal” type of effects

Developed non-parametric, conditional probability-based, methods for data-driven modelling:
- Histogram-based ancestral sampling method
- Machine learning technique using conditioned-Generative Adversarial Network

Presented methods applicable to any analysis!

This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme under grant agreement 714893 (ExclusiveHiggs) and under Marie Skłodowska-Curie agreement 844062 (LightBosons)