Active Learning for Exclusion Level Set Estimation with the ATLAS experiment

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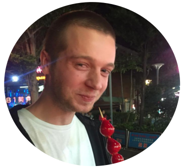

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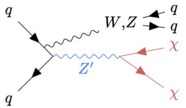
The SCAILFIN Project

Motivation

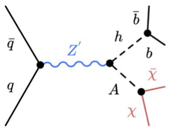
Spin-1 mediator



Mediator:

- Z' boson with couplings g_q, g_χ

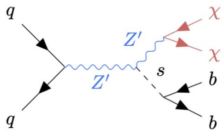
Extended Higgs sector



Two-Higgs-Doublet and

- Z' boson mediator (Z'-2HDM) or
- pseudo-scalar mediator (a-2HDM)

Dark Higgs boson

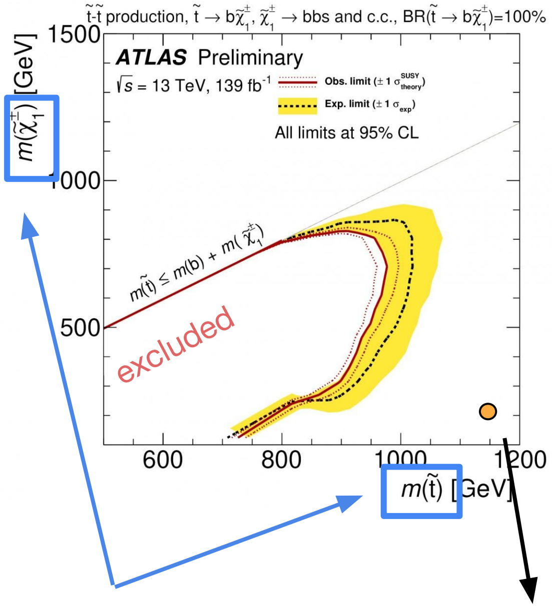


Two mediators in model:

- spin-1 Z' boson and
- spin-0 dark Higgs boson s

searches

constrain

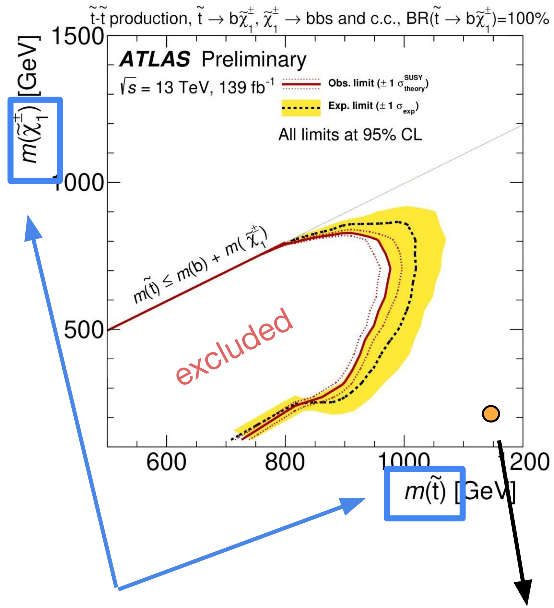


Huge number of New Physics candidates

parameters θ

high latency: computing each point takes days, weeks

Motivation

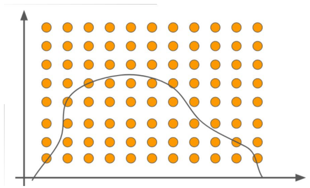


parameters θ

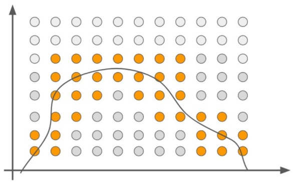
high latency: computing each point takes days, weeks

The naive approach suffers from the curse of dimensionality.
This is a bottleneck for use case theories with 5 or 19 dim.
It is <u>infeasible</u> to make exclusion plots in higher dimensions using ATLAS current approach, *we need a more efficient approach*.

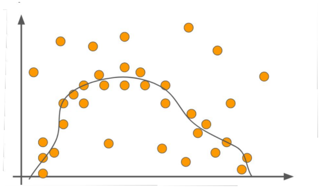
Idea



Current ATLAS approach



Better queries



Excursion method

[From Lukas' Talk at ACAT 2019]

Active Learning

Statement

The black box function is $f(\boldsymbol{\theta}) \rightarrow$ *p-value*.

The goal is to find the excursion set $E_t(f) = \{\boldsymbol{\theta} | f(\boldsymbol{\theta}) = t\}$ for a given a threshold *t* with as few queries as possible.

Method

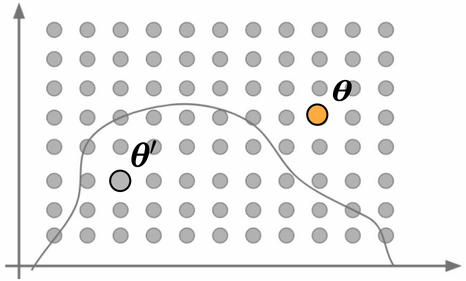
1. Start with dataset $\mathcal{D} = \{\boldsymbol{\theta}_i, f(\boldsymbol{\theta}_i)\}$
2. Train a Gaussian process $Y|\boldsymbol{\theta}, \mathcal{D}$ with predictive mean $\mu_{Y|\mathcal{D}}(\boldsymbol{\theta})$ and covariance $\Sigma^2_{Y|\mathcal{D}}(\boldsymbol{\theta}, \boldsymbol{\theta}')$
3. Evaluate the acquisition function $U_t(\boldsymbol{\theta})$ for all $\boldsymbol{\theta}$ (cheap) using $Y|\boldsymbol{\theta}, \mathcal{D}$
4. Select new point $\boldsymbol{\theta}^* = \text{argmax} \quad U_t(\boldsymbol{\theta})$
5. Query the simulator at $f(\boldsymbol{\theta}^*)$ and update dataset $\mathcal{D} \leftarrow \mathcal{D} \cup (\boldsymbol{\theta}^*, f(\boldsymbol{\theta}^*))$

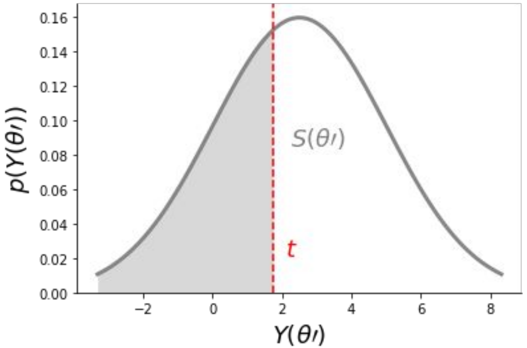
Acquisition function (for reference)

Consider the level set estimation problem as a classification problem for the parameter points over a subjacent grid

$Z|\boldsymbol{\theta} \sim Bernoulli(S(\boldsymbol{\theta}))$ with $S(\boldsymbol{\theta}) = \int_{-\infty}^{t} p(Y = y|\boldsymbol{\theta}, \mathcal{D})dy$ and consider the entropy

$$H[Z|\boldsymbol{\theta}] = -S(\boldsymbol{\theta}) \log S(\boldsymbol{\theta}) + (S(\boldsymbol{\theta}) - 1) \log(1 - S(\boldsymbol{\theta}))$$

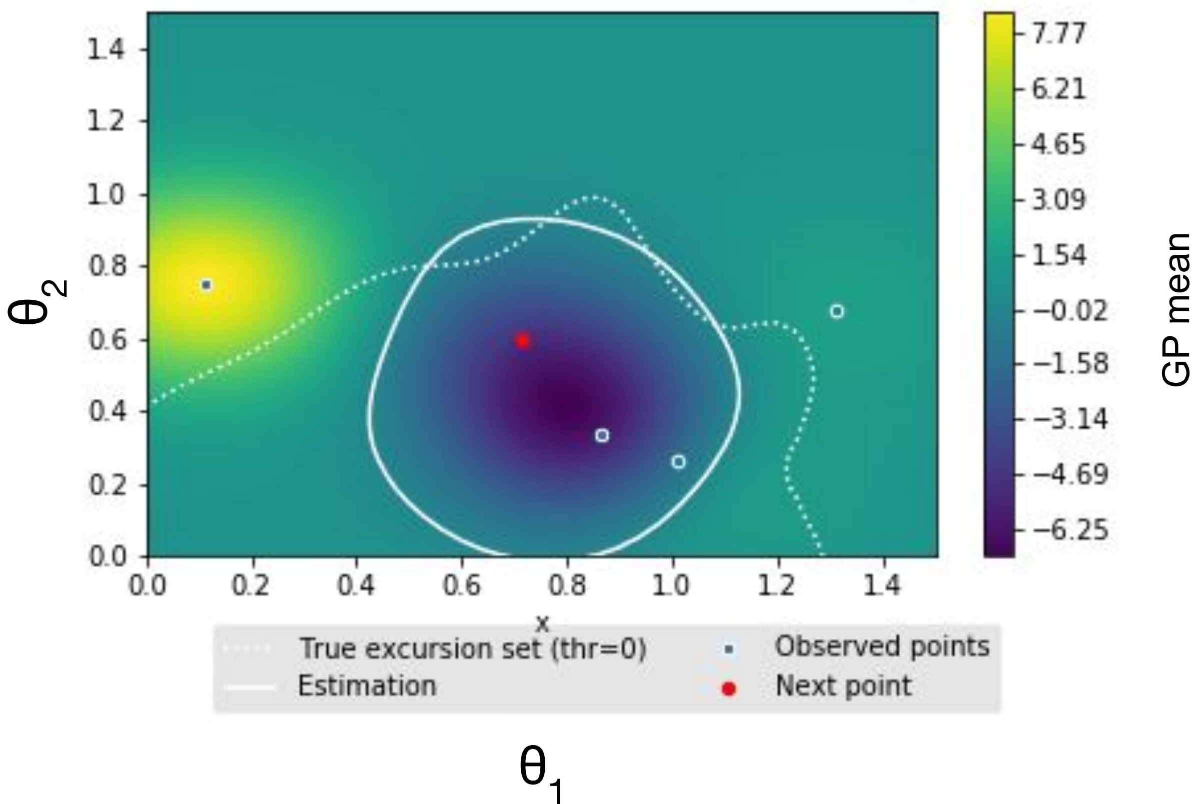




- ***Maximum Entropy Search (MES)***

$$\boxed{U_{MES}(\boldsymbol{\theta}) = H[Z|\boldsymbol{\theta}]}$$

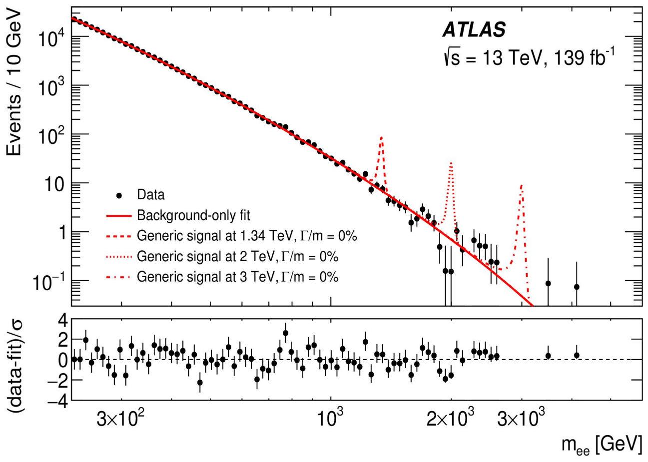
Excursion toy example in 2D



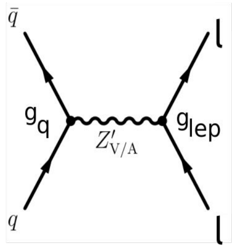
Actively Learning Exotic Physics

Prototype example: dilepton resonance search

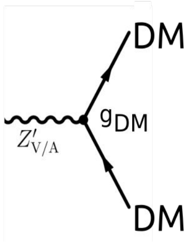
- Straightforward to reinterpret the *2ℓ resonance search* using truth level MC events
  - Not strictly in need of active learning, but useful as a *test case*
- Signal Model: Spin-1 Dark Matter mediator Z'
  - *5 parameters to investigate:*
    $\{\mathbf{x}\} = \{ (m_{Z'}, m_{DM}, g_q, g_\ell, g_{DM}) \}$



Dilepton Production

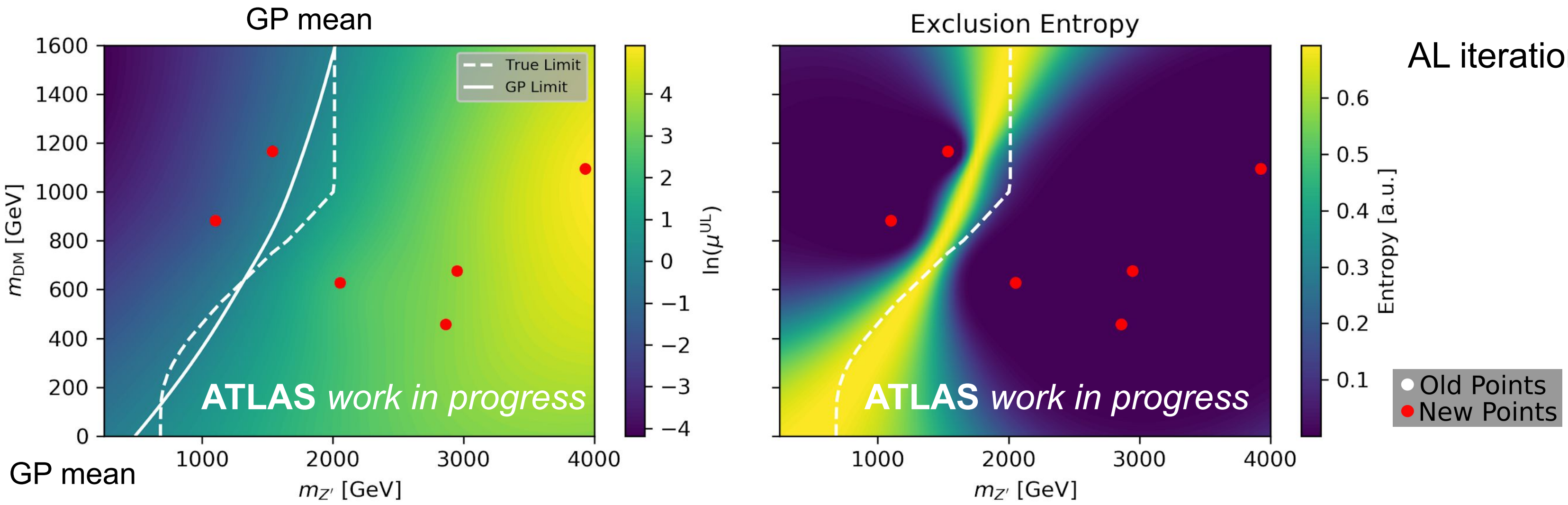


Dark Matter Coupling affecting Z' width



Slide from Phillip Gadow

Exclusion limits from dilepton resonance search

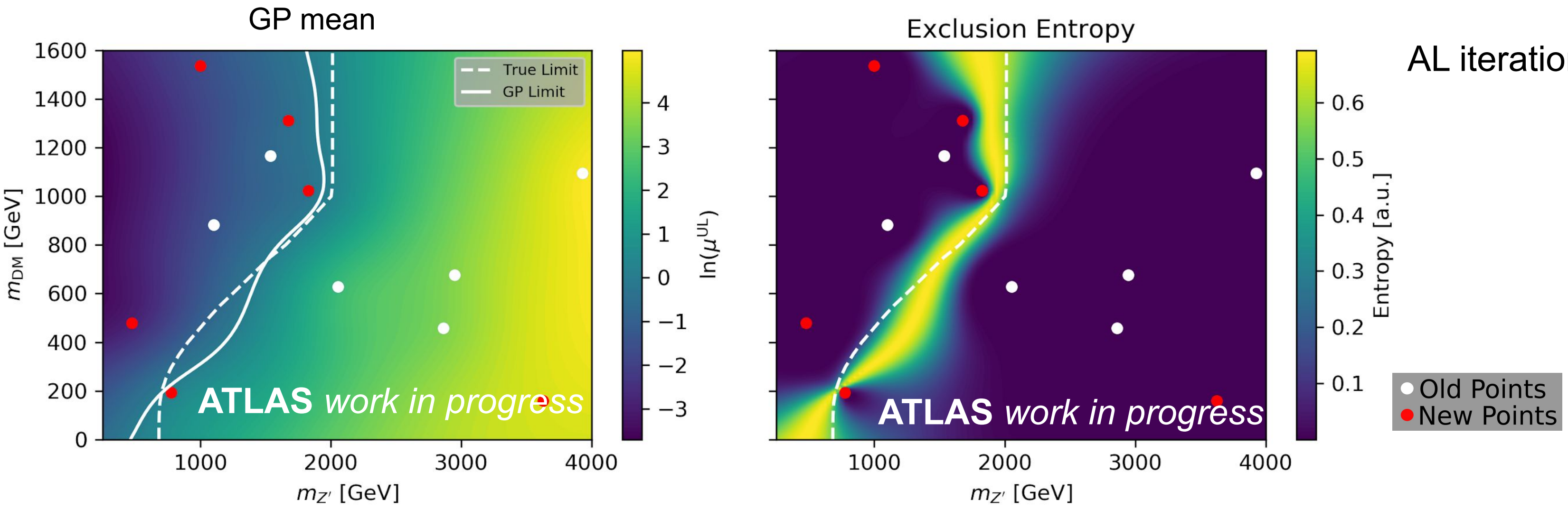


GP mean

- Vector mediator benchmark model, $g_q = 0.1$, $g_l = 0.01$, $g_{DM} = 1.0$
  scanning $(m_{Z'}, m_{DM})$ – 2-dim parameter space

Pictures from Patrick Rieck

Exclusion limits from dilepton resonance search



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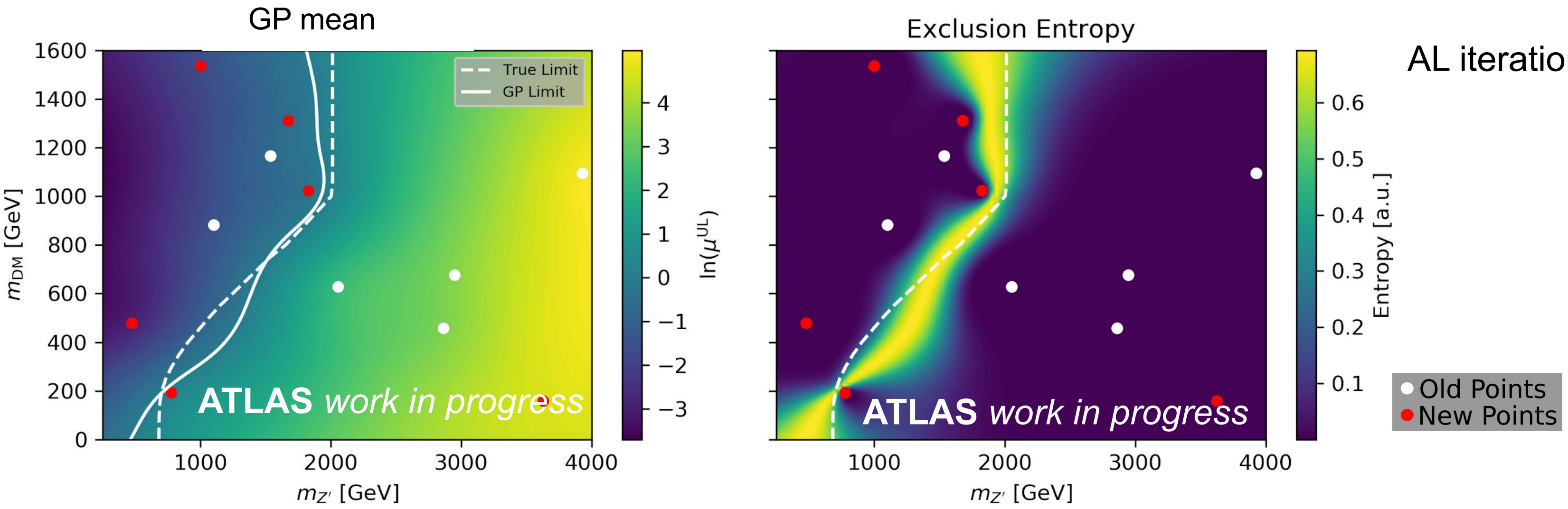

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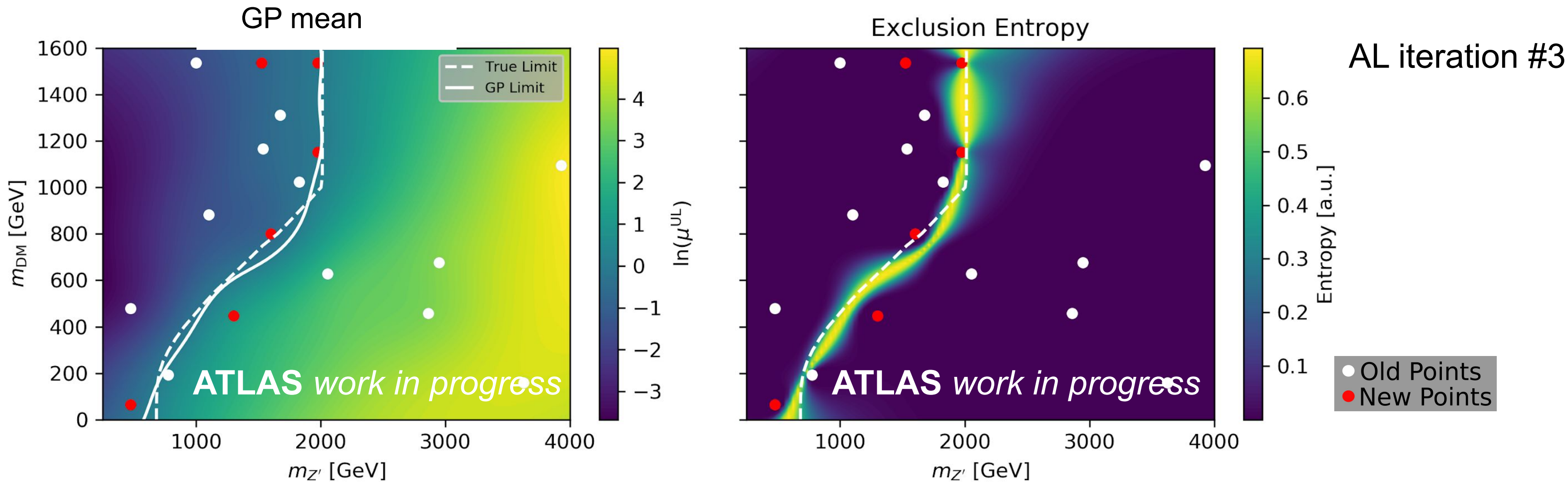
Exclusion limits from dilepton resonance search



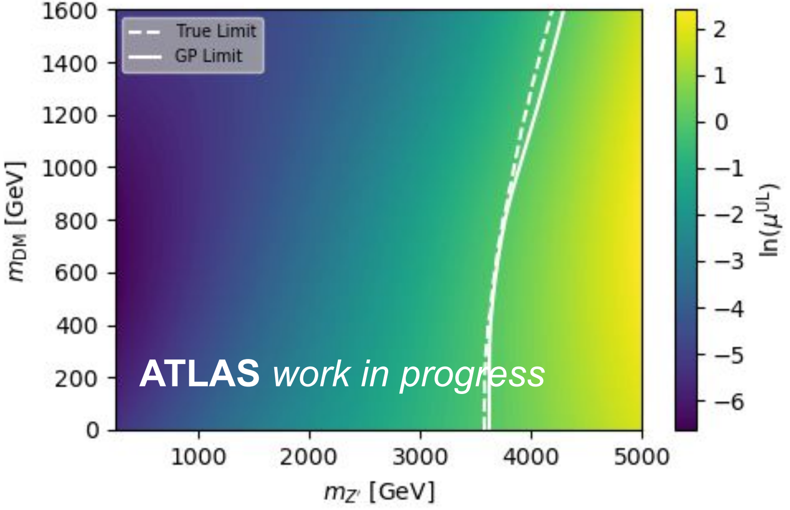
- Vector mediator benchmark model, $g_q = 0.1$, $g_l = 0.01$, $g_{DM} = 1.0$ scanning ($m_{Z'}$, m_{DM}) – 2-dim parameter space
- Efficient convergence to the exclusion limit surface with 18 points from 3 iterations

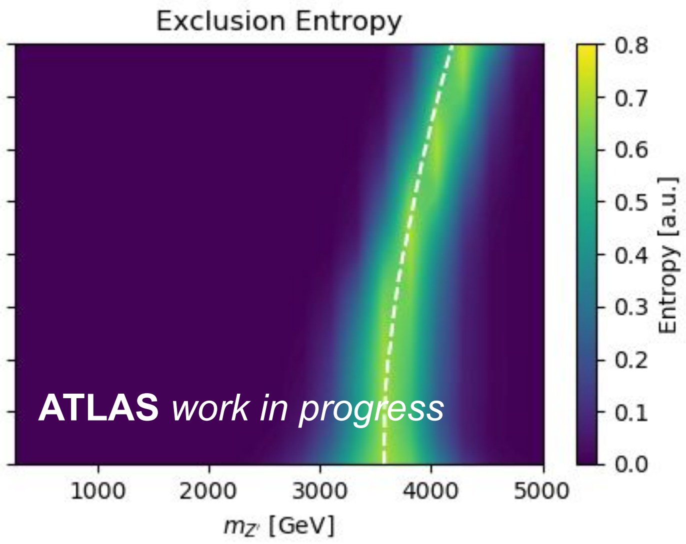
Pictures from Patrick Rieck

4-D exclusion limits from dilepton resonance search

GP mean

Axial-vector benchmark subset $g_q = g_\ell = 0.1$

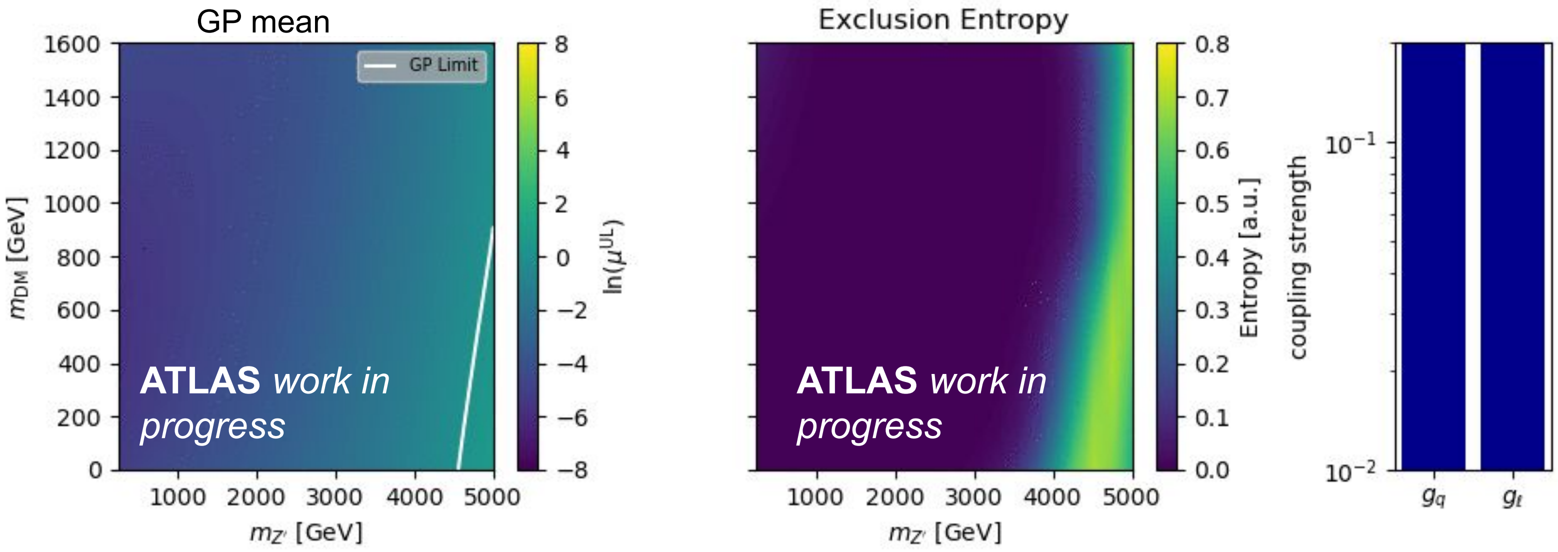




- 4-dim. parameter space $\{\boldsymbol{x}\} = \{ (m_{Z'}, m_{DM}, g_q, g_\ell) \}$, $g_{DM} = 1$
- Axial-vector benchmark subset $g_q = g_\ell = 0.1$: reproducing true limit

Pictures from Patrick Rieck

4-D exclusion limits from dilepton resonance search



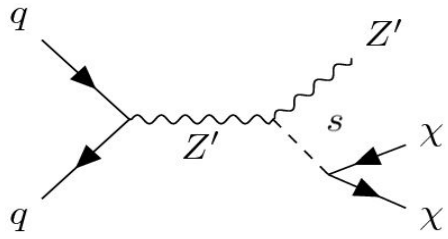
- 4-dim. parameter space $\{\boldsymbol{x}\} = \{ (m_{Z'}, m_{DM}, g_q, g_{l'}) \}, g_{DM} = 1$
- Axial-vector benchmark subset $g_q = g_{l'} = 0.1$: reproducing true limit
- Sufficient to evaluate 200 (5x40) points $\{\boldsymbol{x}\}$ (out of the box run, no optimisation), compared to about 10 000 points when scanning a grid

Two mediator dark matter model: E_T^{miss} + Higgs(bb) search

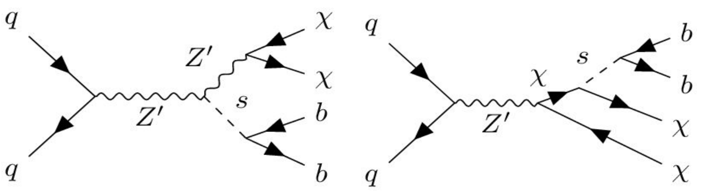
[ATLAS-CONF-2021-006]

JHEP 09 (2016) 042

New signatures emerge, depending on the parameter choices:



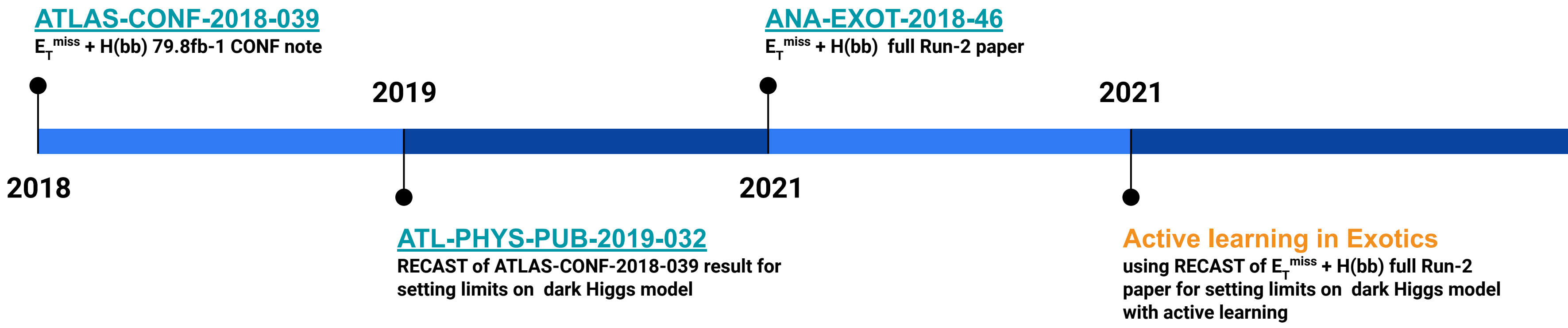
E_T^{miss} + Z'



E_T^{miss} + dark Higgs

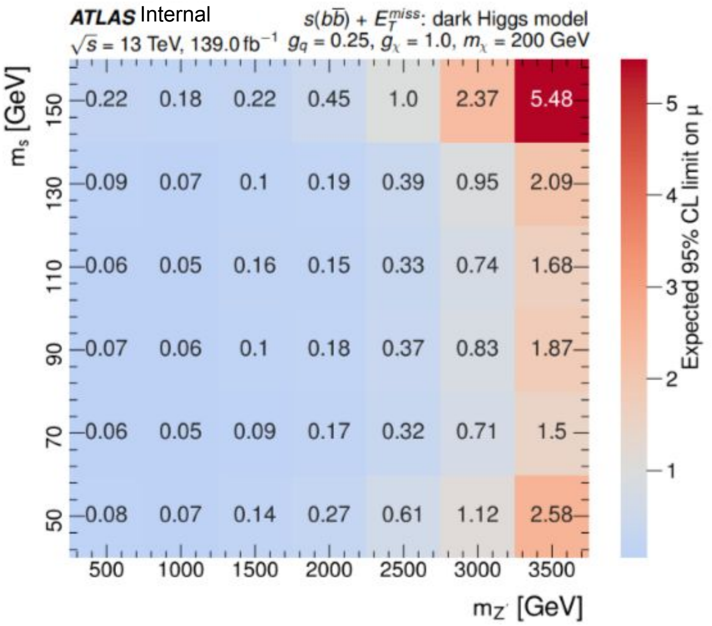
particle masses		coupling constants	
DM mass	m_χ	dark-sector coupling	g_χ or y_χ
Z' mass	$m_{Z'}$	quark–Z' coupling	g_q
dark Higgs mass	m_s	Higgs mixing angle	θ

Exotics pilot project: Active learning with the E_T^{miss} + H(bb) search

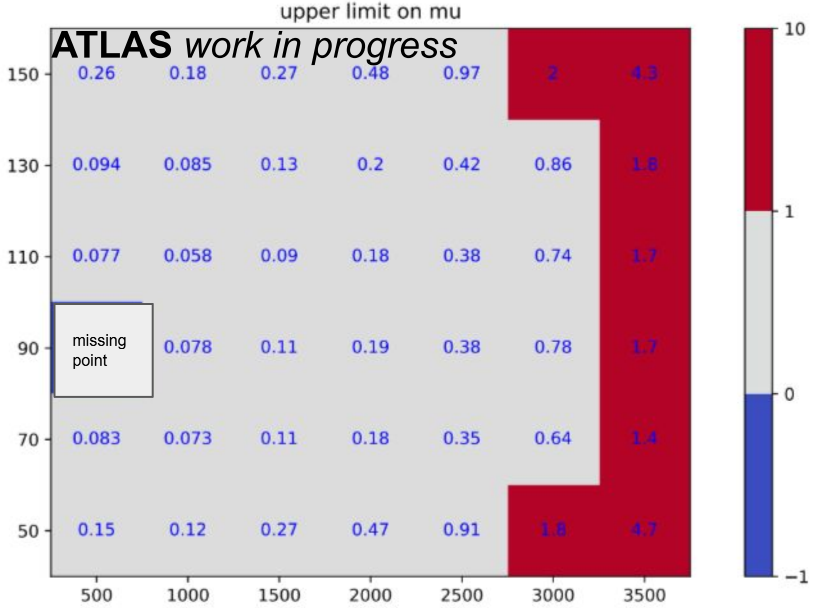


- RECAST-based reinterpretation of E_T^{miss} + H(bb) search for *dark Higgs boson model*
  - *5 parameters to investigate:* $\{\boldsymbol{x}\} = \{ (m_{Z'}, m_{DM}, m_s, g_q, g_{DM}) \}$
  - Pilot project similar to *ATL-PHYS-PUB-2019-032* demonstrating RECAST use in Exotics
  - Complementary effort to dedicated E_T^{miss} + dark Higgs(bb) search in JDM
- Active learning effort ongoing in SUSY WG - Run 2 pMSSM scan
  - Demanding 19 parameters to constrain in this case

Validation of truth-level analysis: limits E_T^{miss} + Higgs(bb) search



reco-level (RECAST)



truth-level (SimpleAnalysis)

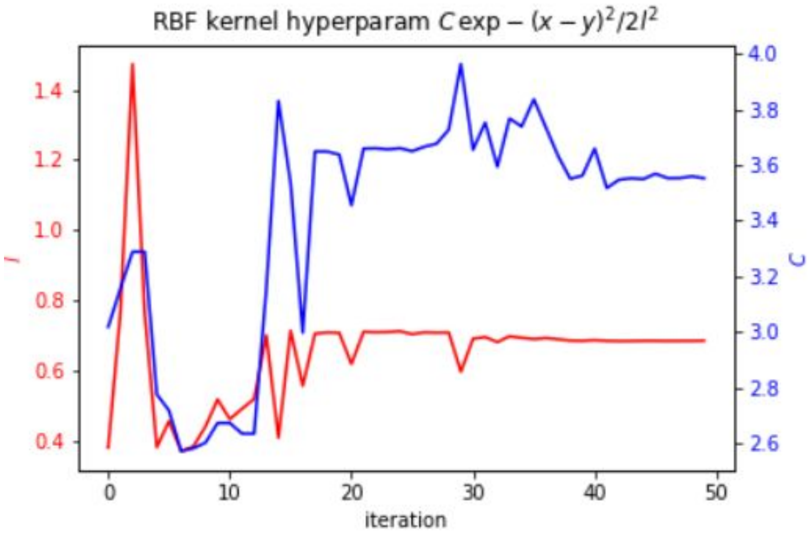
Good agreement between limits from RECAST with reco-level signals (left) and truth-level estimate with private TRUTH1 signals processed with SimpleAnalysis (right).

Summary

- Active learning can raise efficiency in BSM limit setting
- Demonstrated applicability using our Run 2 dilepton resonance search
- Mono-H(bb) reinterpretation as an Exotics active learning pilot project
    - setting stringent limits on dark Higgs boson dark matter model
    - first application of active learning, including use of GPUs

Back up

Will I converge?



Yes, if the target function can be sampled from a Gaussian Process with your selected kernel(x, x')

(see Bayesian model selection theory)

Back up