"Dark Matters 2022"

ULB

ON MACHINES LEARNING ABOUT SOME DARK MATTERS

Bryan Zaldivar (Valencia)

Outline

- What does machine learning bring to physics?
- Some examples of different uses of ML for Dark Matter
- Good practices when applying ML to physics

MOTIVATION

* Physical knowledge of background is limited
  (common problem in astrophysics)

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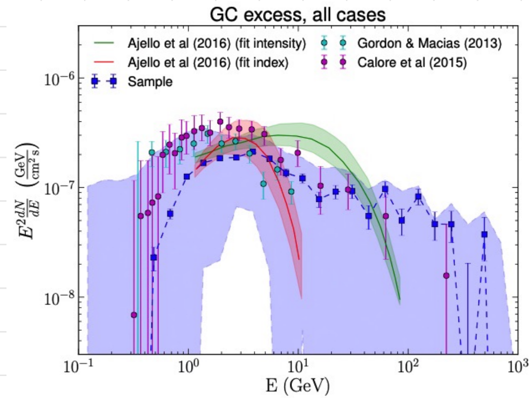
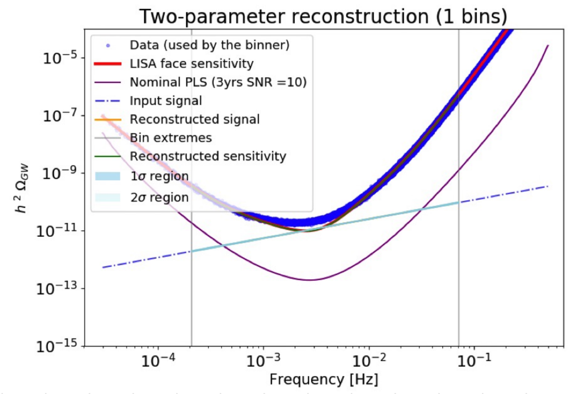
e.g. • γ-rays

• GW's

Fermi-LAT, 1704.03910



Caprini et al, 1906.09244



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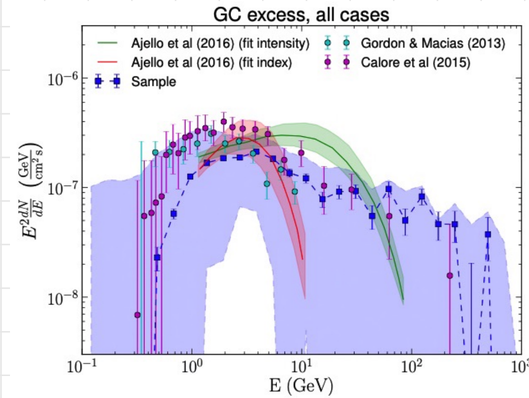

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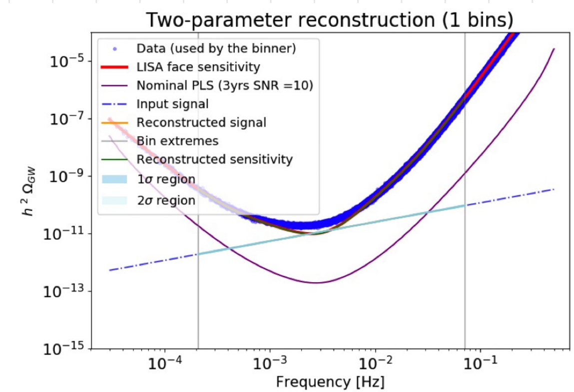

Signal + Background $\Longleftrightarrow$ Data

↳ interest (Physical model)

↳ nuisance (data-driven model)

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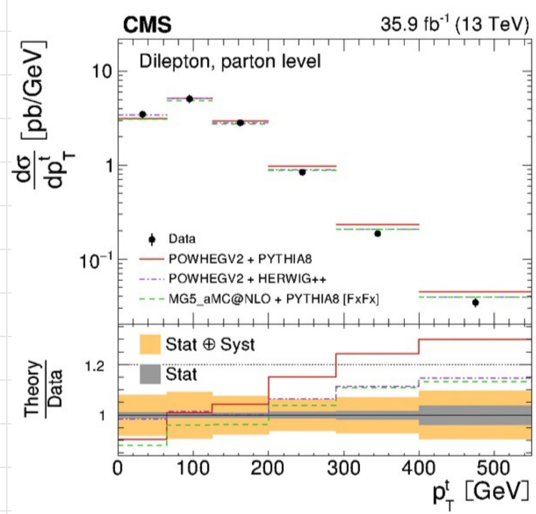
TOP-17-014-PAS



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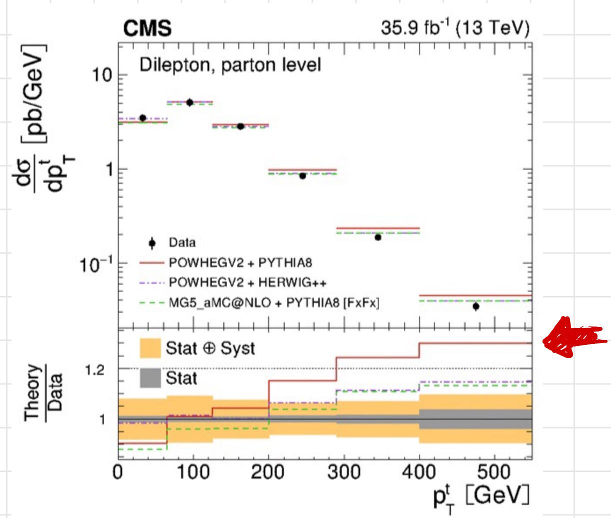
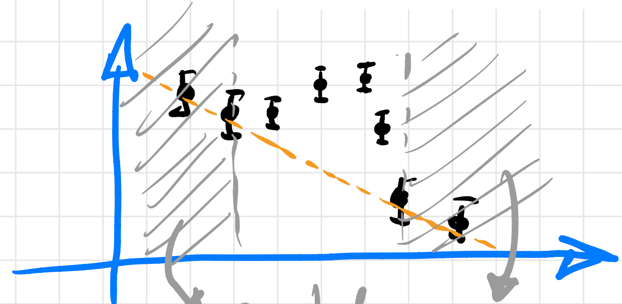


Data-driven methods to infer the background from inter/extrapolations



MOTIVATION

Snowmass, 2209.07426

Name	Technology	Target	Active Mass	Experiment Location	Start Ops	End Ops
Currently Running or Under Construction						
LZ	TPC	LXe	7,000 kg	SURF	2021	2026
PandaX-4T	TPC	LXe	4,000 kg	CJPL	2021	2025
XENONnT	TPC	LXe	7,000 kg	LGNS	2021	2025
DEAP-3600	Scintillator	LAr	3,300 kg	SNOLAB	2016	2025
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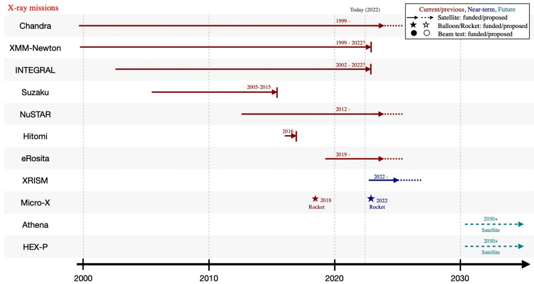

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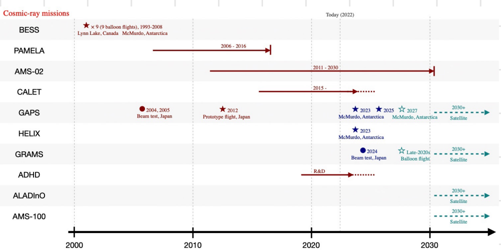
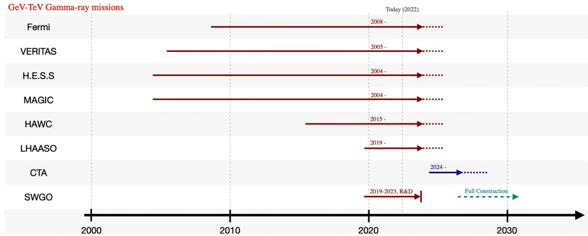
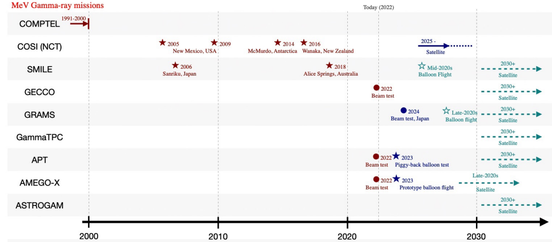
SNOWBALL	Supercooled Liquid H2O					
DarkSide-LowMass	TPC	LAr	1.5 t			
ALETHEIA	TPC	He		China Inst. At. Energy		
TESSERACT	Cryo TES	LHe, SiO_2, Al_2O_3, GaAs		undetermined	2026	
CYGNO	Gas Directional	He + CF_4	0.5 - 1 kg	LNGS	2024	
CYGNUS	Gas Directional	He + SF_6/CF_4		Multiple sites		
Windchime	Accelerometer array			Multiple sites		
MAGNETO-χ	Cryogenic MMC	Diamond, Sapphire, etc.				







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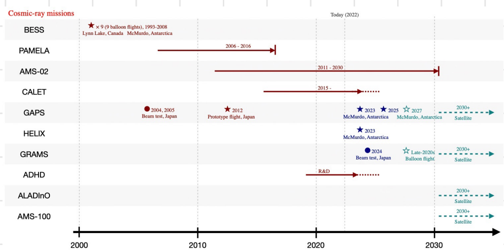
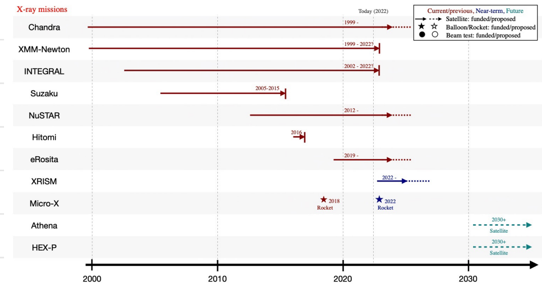
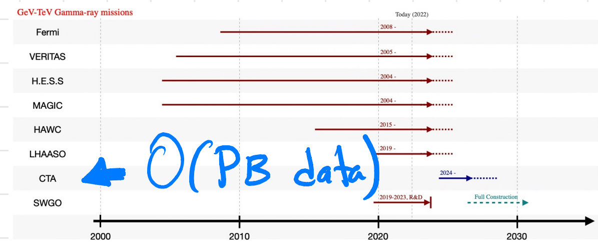
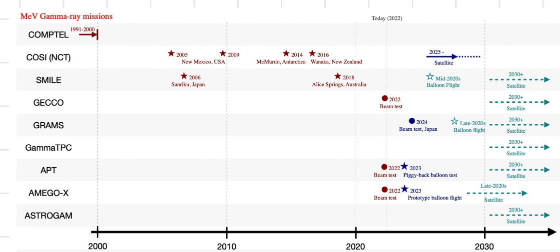


O(40) experiments operative in near future!





O(PB data)



MOTIVATION

* Statistical bottleneck

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- More complex datasets

$\Downarrow$

More complex physical modeling

$\Downarrow$

More complex simulators

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More complex physical modeling

$\Downarrow$

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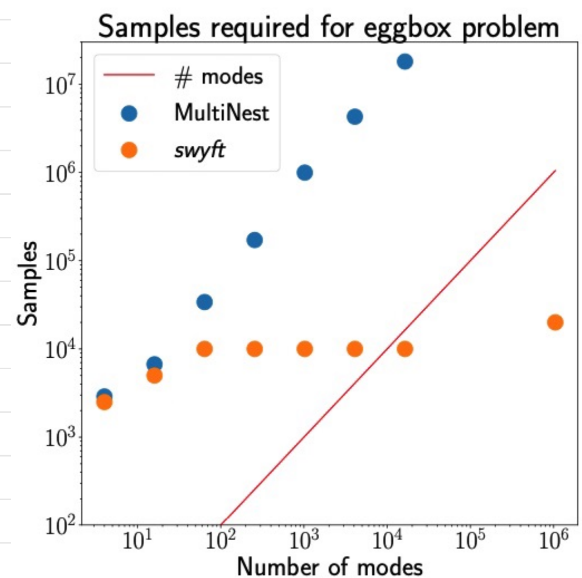
$\Downarrow$

Better statistical treatment !

- better scaling
- more descriptive
- Higher statistical power

Miller et al, 2011.13951



MOTIVATION

* Hints about the underlying physics

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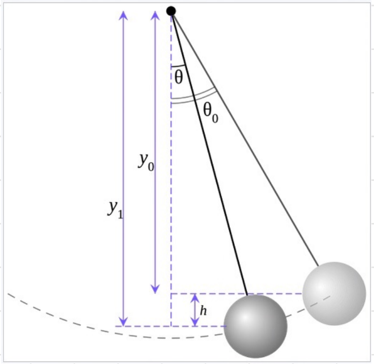
physical variables

- The intrinsic dimension of
  - Single pendulum : 2
  - Lava lamp : ?



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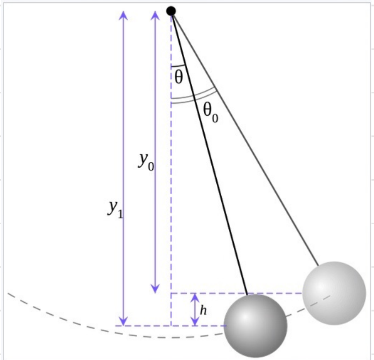
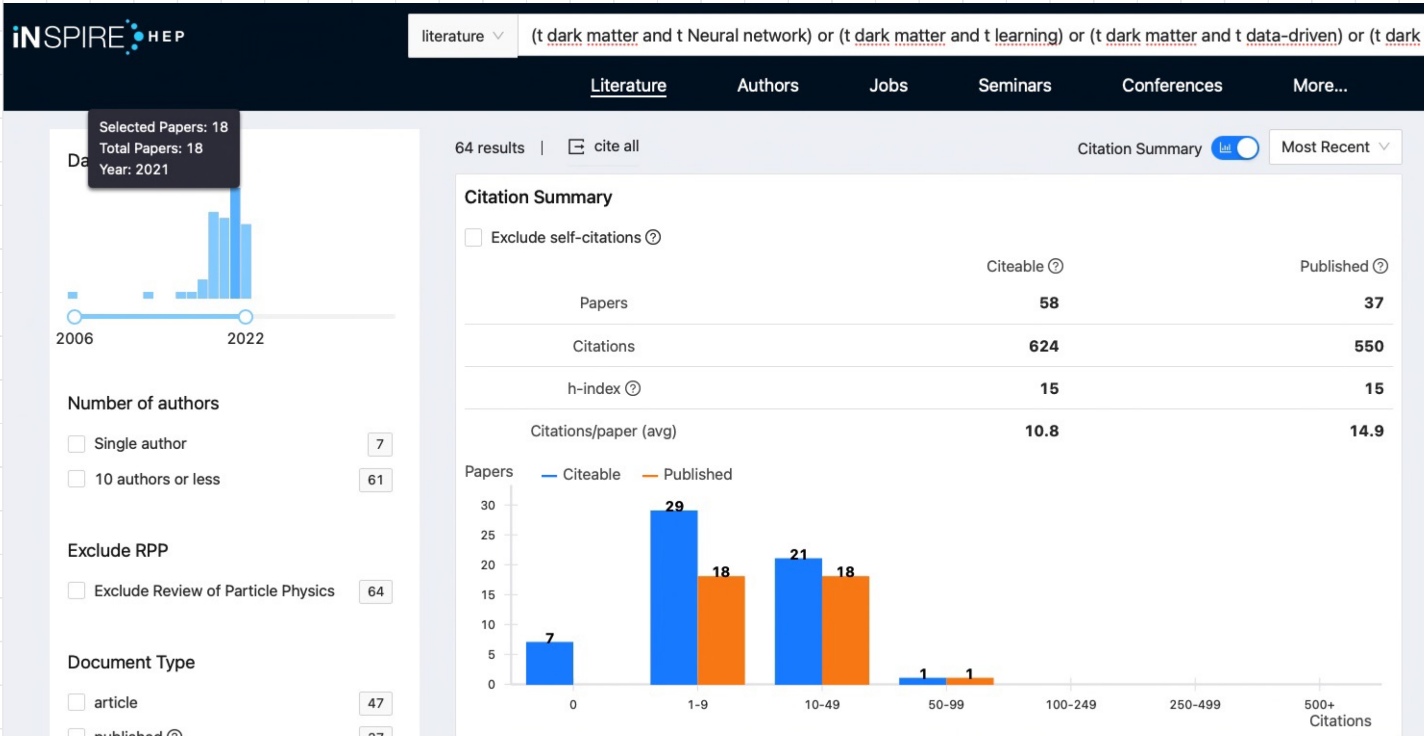


Statistical model (ML)

ID = 7 – 8

(see 2112.10755)

DARK MATTER WITH MACHINE LEARNING



Two main ML paradigms used in physics

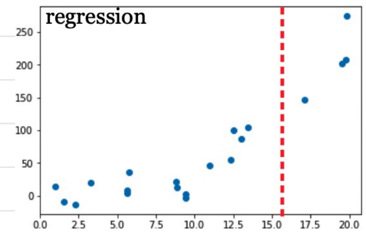
SUPERVISED LEARNING

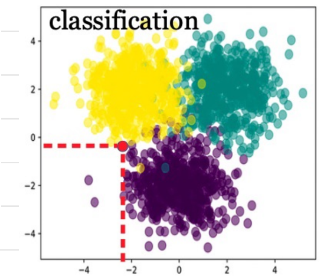
Tasks

1) Estimate underlying distribution

$$y(\vec{x}) \sim p\left(f(\vec{x};\vec{\theta}),\, \sigma\right)$$

$$\text{data} = \{\vec{x}_i,\, y_i\}$$





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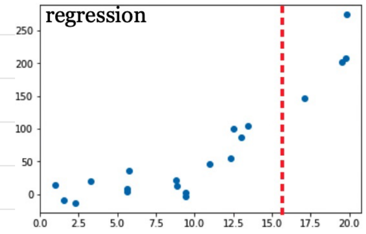

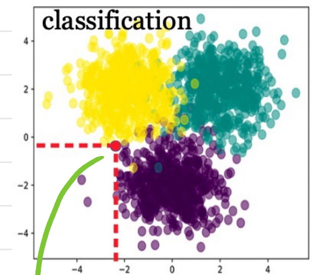

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- Assume shape of p,
  estimate $f(\vec{x},\vec{\theta})$ with a ML model

[useful for estimating nuisance contributions,
(c.f. Motivation #1)]

2) Prediction for new $\vec{x}$

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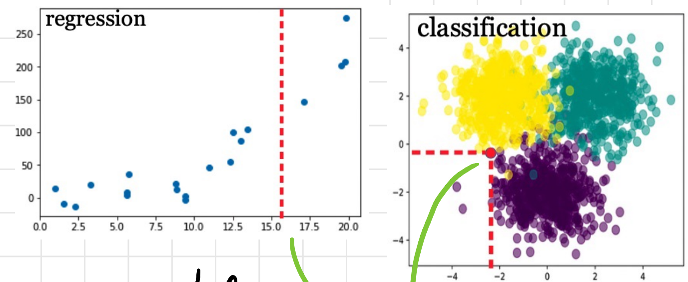

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2) Prediction for new $\vec{x}$

- $f(\vec{x},\vec{\theta})$ given by a physics model (infer physical parameters $\vec{\theta}$)
  Estimate shape of p with a ML procedure

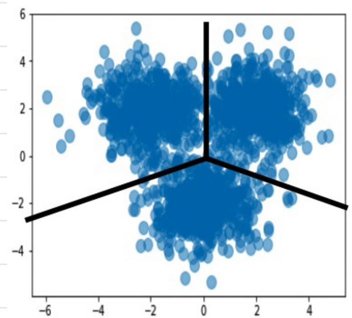
UNSUPERVISED LEARNING

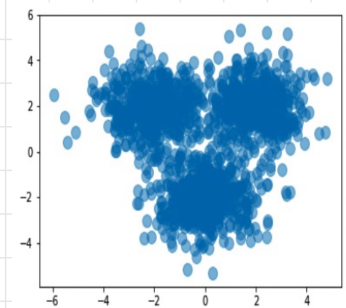
data $= \{ \vec{x}_i \}$

Tasks

1) Clusterize the data

(very useful e.g. in collider physics)





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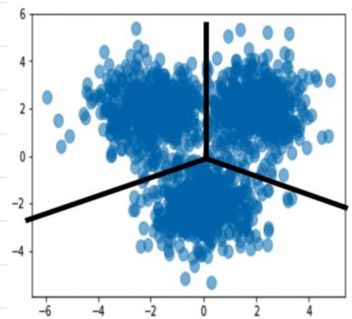
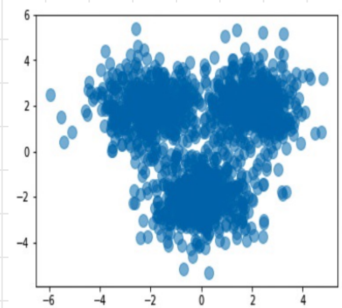
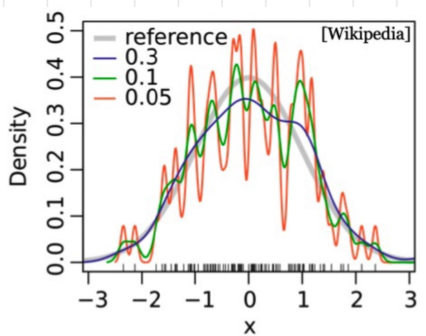




2) Probability density estimation

(astrophysics, cosmology, everywhere...)



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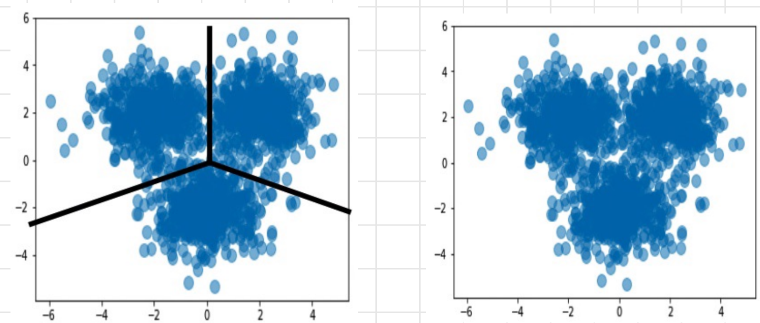

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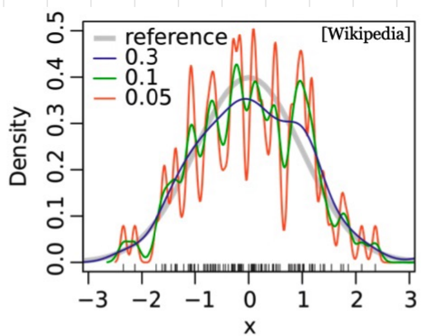
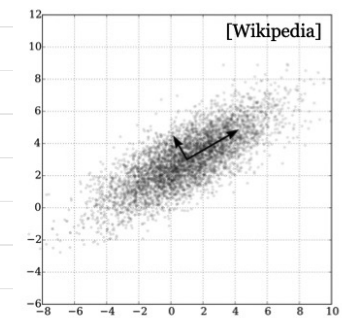


3) Dimensionality reduction

(everywhere)



Some examples of applications

[by no means exhaustive!!]

I DM searches at the LHC (Banerjee et al, 1705.02327)

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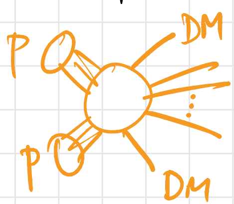
- What is the motivating issue?

Final state topology may be quite complex

$\Rightarrow$ potentially large phase space!



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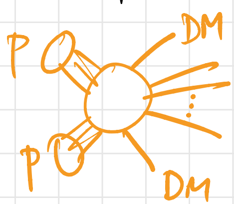


traditional analyses (e.g. cut-based) may give poor performance

- How to address it?

Frame it into a ML classification problem

(optimize signal-to-bckg ratio)

ML classifier is (formally) an approx to the

$$TS = \frac{p(x \mid H_0)}{p(x \mid H_1)}$$

} highest statistical power

$\hookrightarrow$ Neural network, Boosted Decision Trees, ...

I DM searches at the LHC

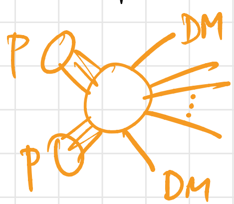
(Banerjee et al, 1705.02327)

simple case study with a monojet signal

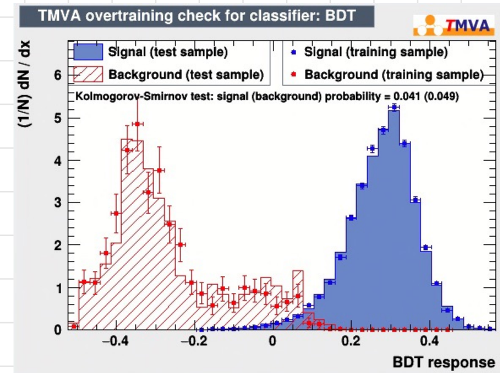
- what is the motivating issue?

Final state topology may be quite complex

$\Rightarrow$ potentially large phase space!



traditional analyses (e.g. cut-based) may give poor performance



- How to address it?

Frame it into a ML classification problem

(optimize signal-to-bckg ratio)

ML classifier is (formally) an approx to the

$$TS = \frac{p(x \mid H_0)}{p(x \mid H_1)}$$

highest statistical power

Neural network, Boosted Decision Trees, ...

II Direct Detection searches (Herrero-Garcia et al 2110.12248)

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Solution: "Anomaly awareness" (unsupervised) [2007.14462]

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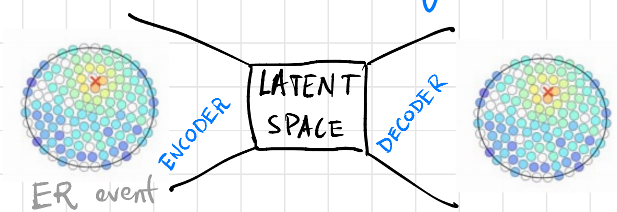
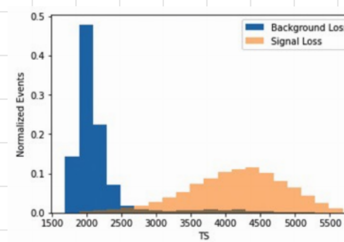


2) Feed it with signal events

The resulting distribution should be distinguishable from the bckg one



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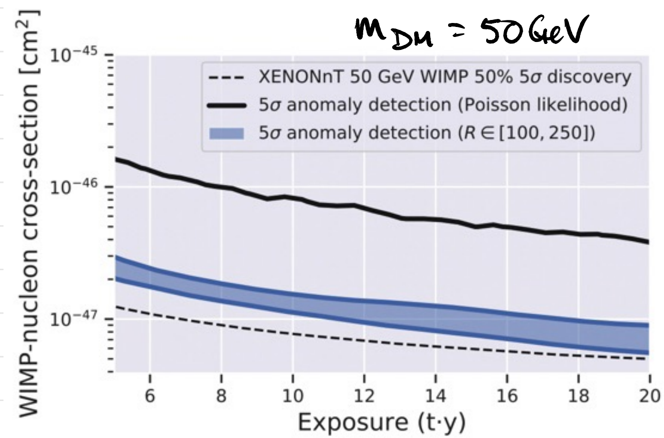

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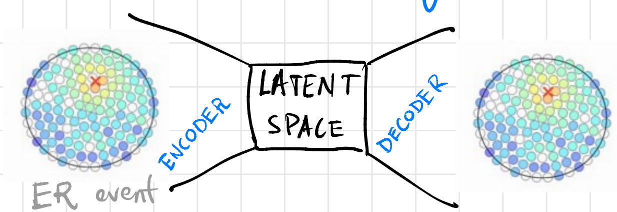

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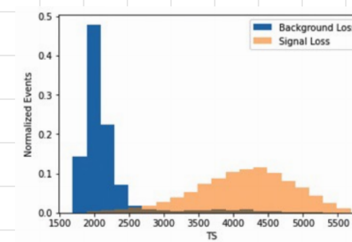

III Indirect Detection Searches

(modeling the background)

(Calore, Serpico, Zaldivar, 1803.05508)

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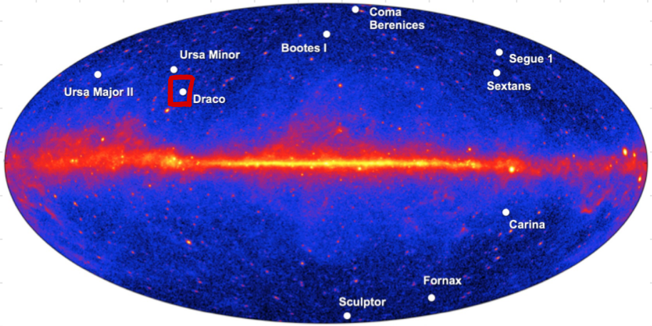
Fermi γ-rays at dSphs



Motivation

1) Typical bckg estimation has limitations
   * Templates are biased (limited knowledge of physics)
   * Local fitting of templates (no global consistency)
   * No clear way of accounting for prediction uncertainties

(Calore, Serpico, Zaldivar, 1803.05508) cont...

Aiming for a global, unbiased estimation of the background probability distribution

(Calore, Serpico, Zaldivar, 1803.05508) cont...

Aiming for a global, unbiased estimation of the background probability distribution

$$\text{Data} = \{ \vec{x}_i , y_i \}_{i=1}^{N}$$

N → all pixels of the sky

$\vec{x}_i$: spatial coordinates

y_i: counts

⇒ Prediction : $\mathbb{E}[y|\vec{x}] \equiv \hat{y}$

⇒ Variance : $\mathbb{E}[(y-\hat{y})^2]$

$$p(\vec{x}, y) = \frac{1}{N} \sum_i k_\alpha(\vec{x}-\vec{x}_i) \cdot g_\beta(y-y_i)$$

⇒ unbiased estimator of the true PDF

$k_\alpha(\cdot)$, $g_\beta(\cdot)$: kernel functions

(Calore, Serpico, Zaldivar, 1803.05508) cont...

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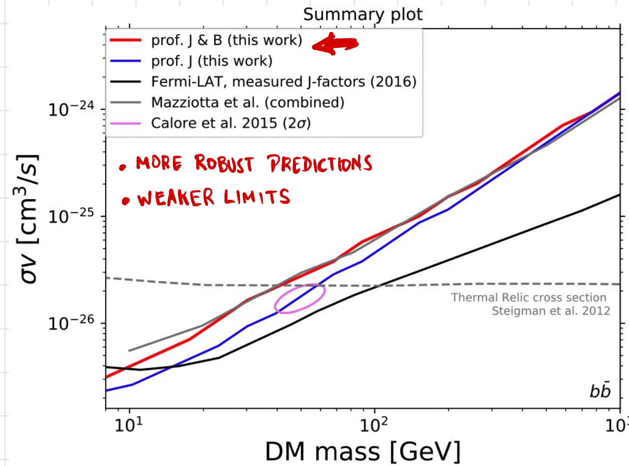

IV DM searches from Fermi's unidentified PLS's

(Gammaldi et al, 2207.09307)

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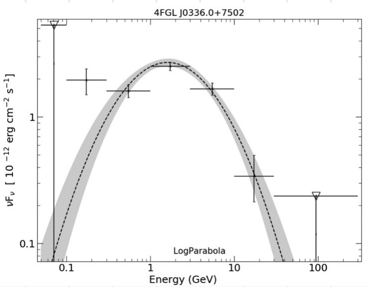
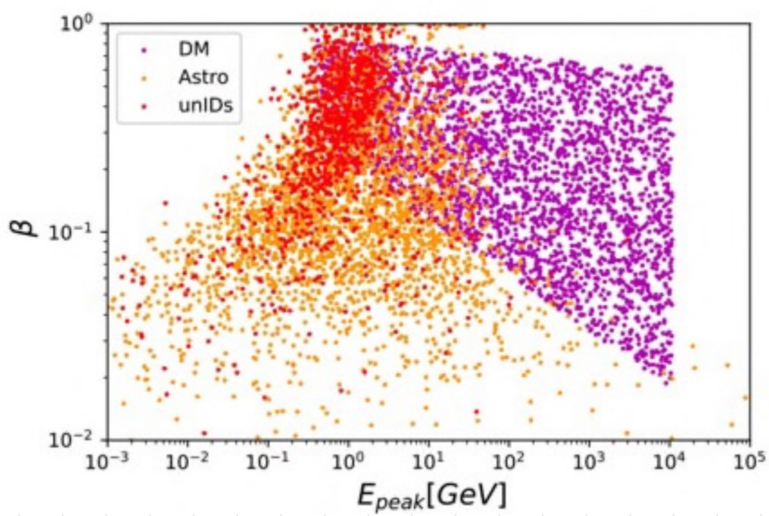
Astrophysical sources vs. Dark Matter sources



✓ ✓ Energy spectrum

✓ X Exp. uncertainties

✓ X Detection significance



Idea: DM inherits statistical properties of the unID's

(Gammaldi et al, 2207.09307) cont...

A standard classification problem?

Not so: input data have uncertainties

(Gammaldi et al, 2207.09307) cont...

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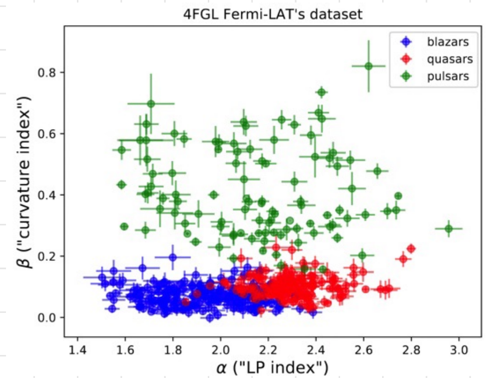
surprisingly not addressed before in the ML literature!

[Villacampa et al, 2001.10523]



Gaussian Process model

$\vec{x} \sim N(\vec{\mu}, \vec{\sigma})$

latent variables to be inferred

(Gammaldi et al, 2207.09307) cont...

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- Another way $\Rightarrow$ uncertainties as separate input variables

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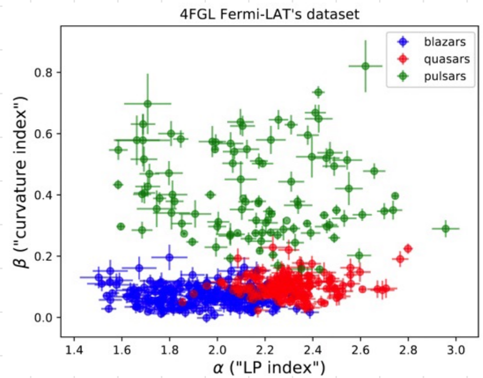

* Train a NN on Astro-vs-DM

* NN output is probability for DM class

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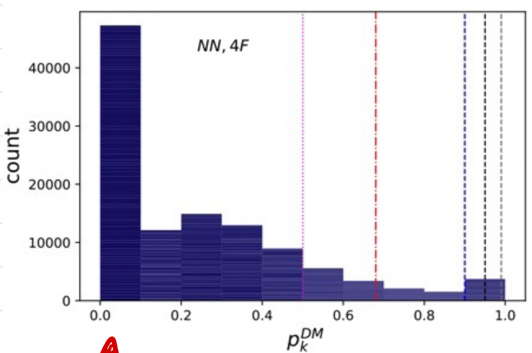
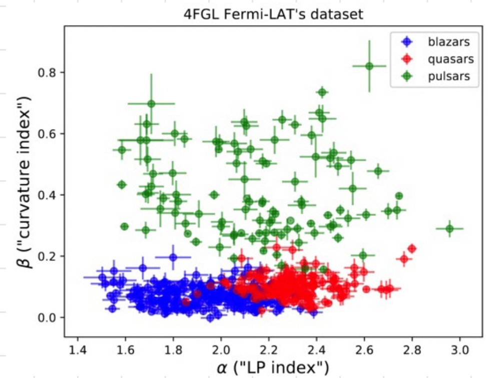


No statistically significant evidence for DM



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V Estimating the DM density profile

(de los Rios et al, 2111.08725)

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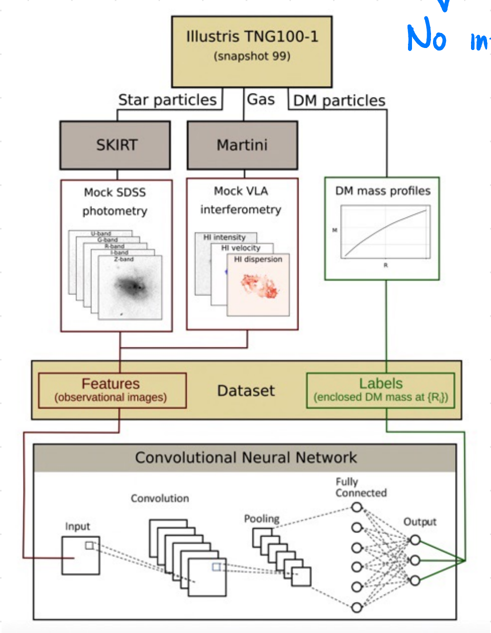
No info-loss



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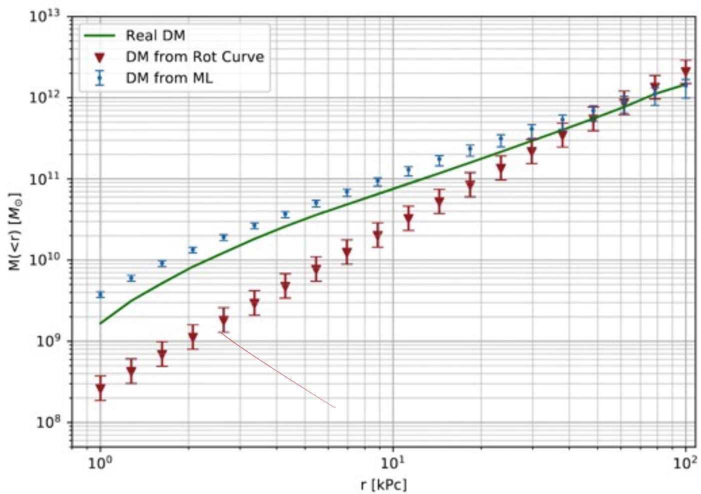
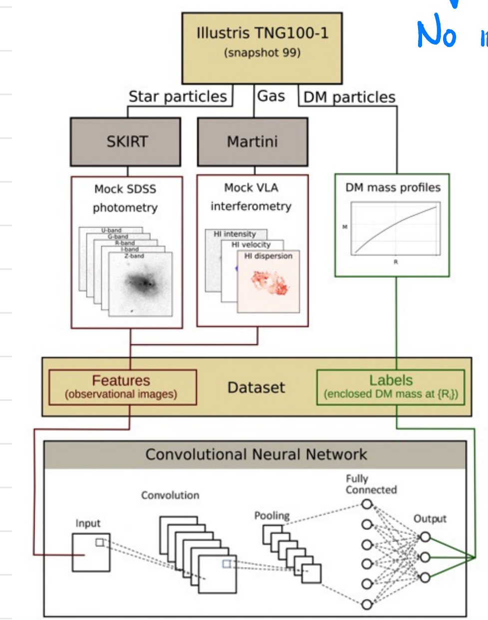


better performance than Rotation Curves method



VI Warm dark matter mass from strong lensing

(Anau Montel et al, 2205.09126)

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Characterizing collective subhalo properties from gravitational lensing is very difficult!

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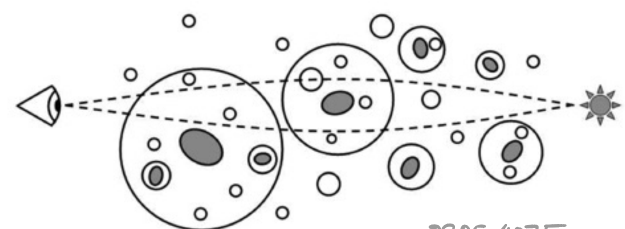

0905.4075

nuisance
- Size and position of the main lens
- Brightness distribution and position of the source
- Position, mass, distance, etc of all the subhalos

→ Warm dark matter mass ← parameter of interest

Typical MCMC algorithms don't scale well with dimensionality of the param. space

(Anau Montel et al, 2205.09126) cont...

- getting samples from $p(\vec{\theta}, \vec{\alpha} \mid \text{data})$ is typically intractable

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Alternative

- $p(\vec{\theta} \,|\, \text{data}) = p(\text{data} \,|\, \vec{\theta})\, p(\vec{\theta}) / p(\text{data})$

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(Anau Montel et al, 2205.09126) cont...

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Solution

Estimate $p(\vec{\theta} \,|\, \text{data})$ directly with a neural network

$\Downarrow$

no need to evaluate the likelihood (see next talk by Androniki)

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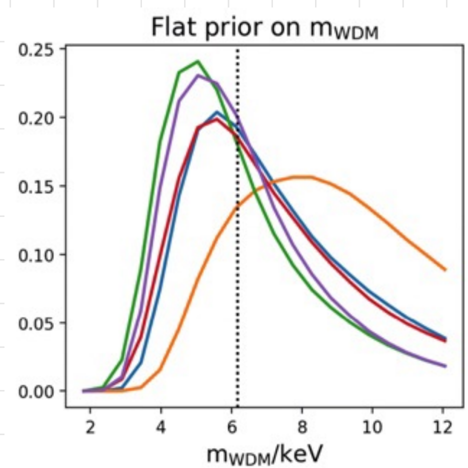
Inferring the warm DM mass $\Rightarrow$



Important warnings to beware of

i) Occam's razor

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Facts:
- Very large models (DNNs) have built-in overfitting control
- Data scientists typically adopt a "one-hammer-for-all" strategy
  (motivated by industry problems)
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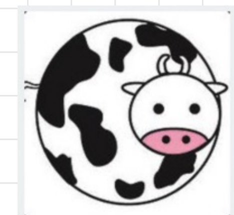

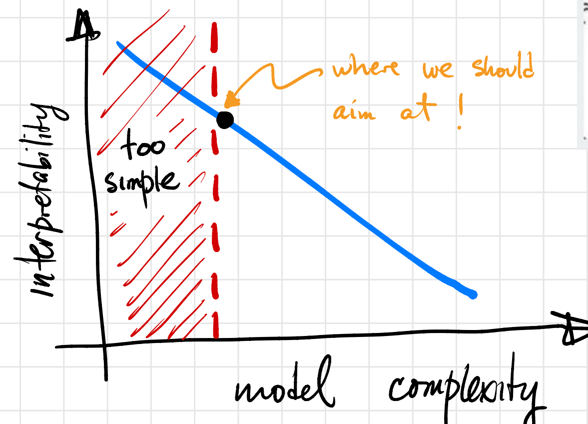

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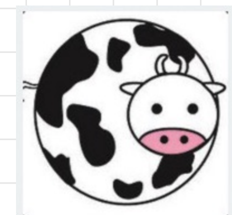
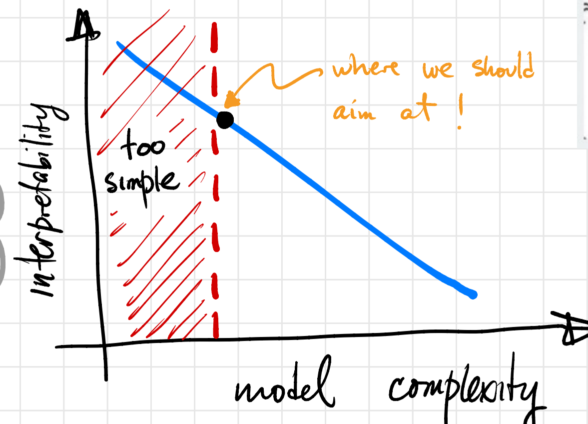
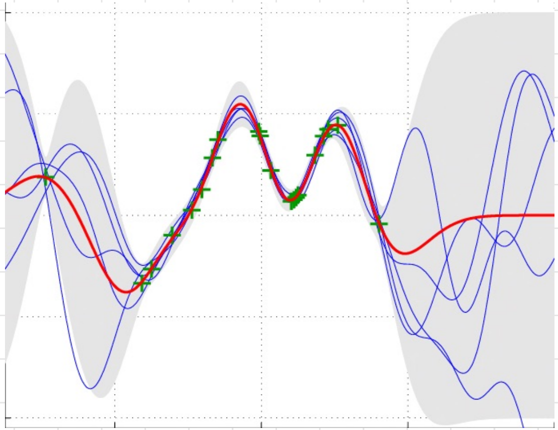




Remember that polymials are also -as neural nets- Universal approximators !!

ii) Uncertainties related to the modeling itself

(a.k.a. "epistemic" uncertainties)



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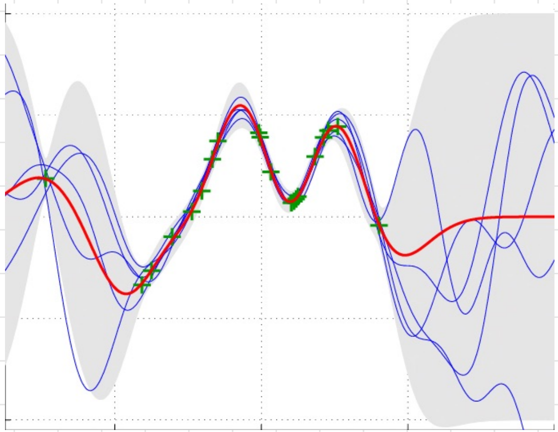

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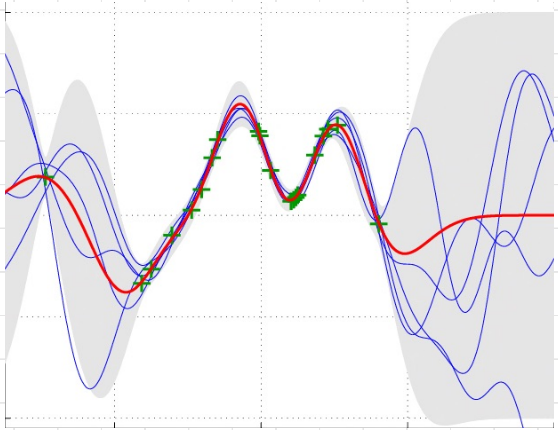

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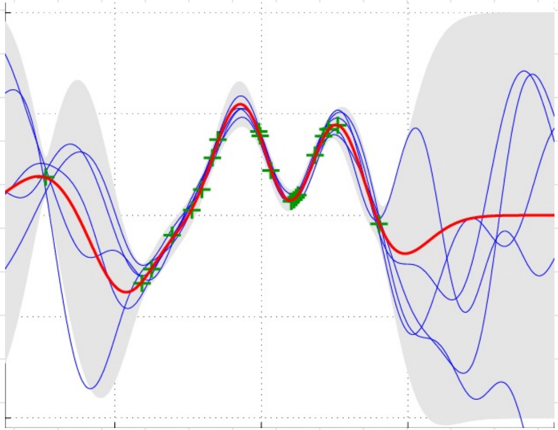

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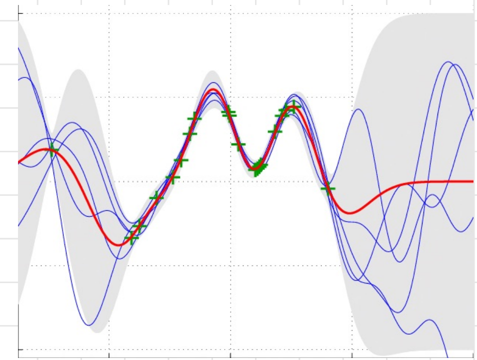
- The larger the model, the more challenging is the uncertainty estimate (large body of dedicated literature)
- Cats don't have error bars (maybe) but in science, uncertainty estimation is mandatory!

iii) ML predictions vs. physical plausibility

How many of these possible solutions are physically meaningful?

[a priori no physics knowledge]



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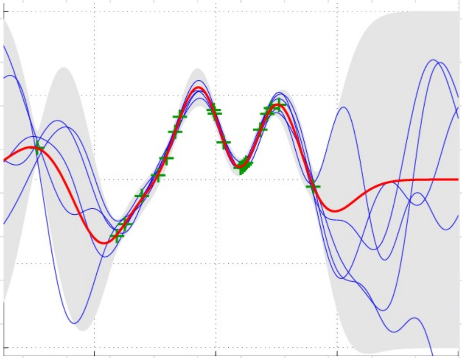

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↳ Enforce solutions to satisfy physical laws

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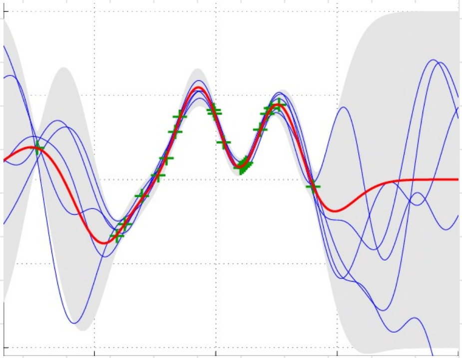

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Data

$\{\vec{x}_i, y_i\}$

Loss function Partial diff. eq.

$$-\ln p(y|f_{ML}) + \mathcal{F}(f_{ML}, \partial_{\vec{x}} f_{ML})$$

Statistical (ML) model

$$P(y|f_{ML}(\vec{x}, \vec{\theta}))$$

Take-home messages

* ML is proving to be an essential tool in modern physics (unfortunately embedded in a gigantic hype)
* As physicists, we have the responsability to make use of such tools in a scientific meaningful way
* ML for science still in its infancy
  ⇒ A lot to do in Physics–ML symbiosis