Técnicas Bayesianas en física de partículas & +

Maximizar la información extraída de la data

Instituto del Cálculo 2024

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Data & Information

- **Data:** Measure N times the length of the table
- **Information:** An estimation on the length of the table

Data & Information

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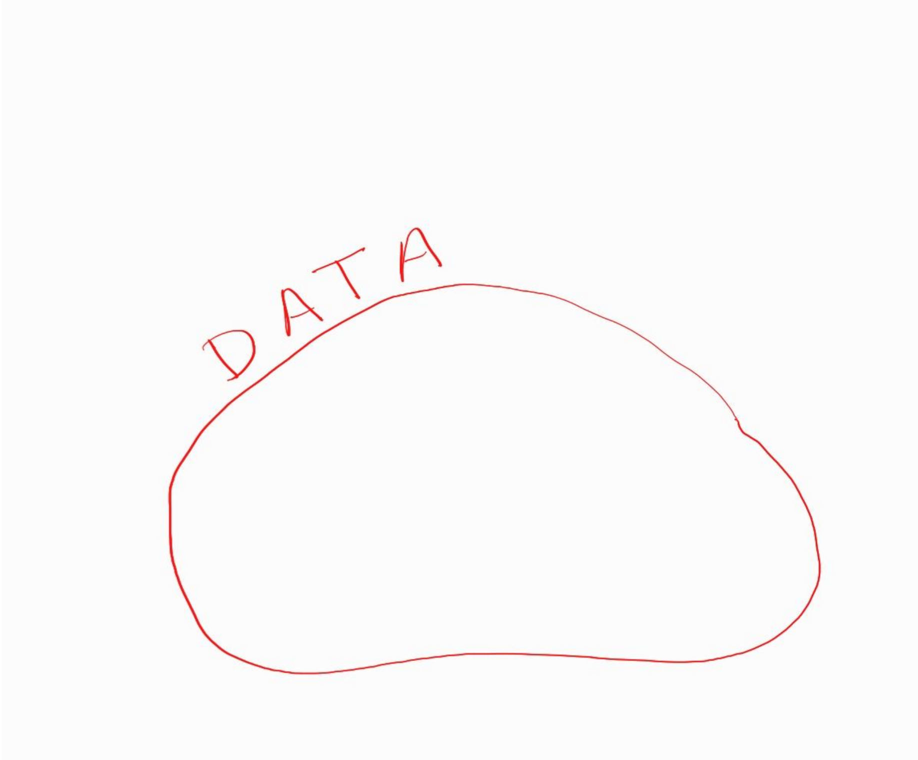
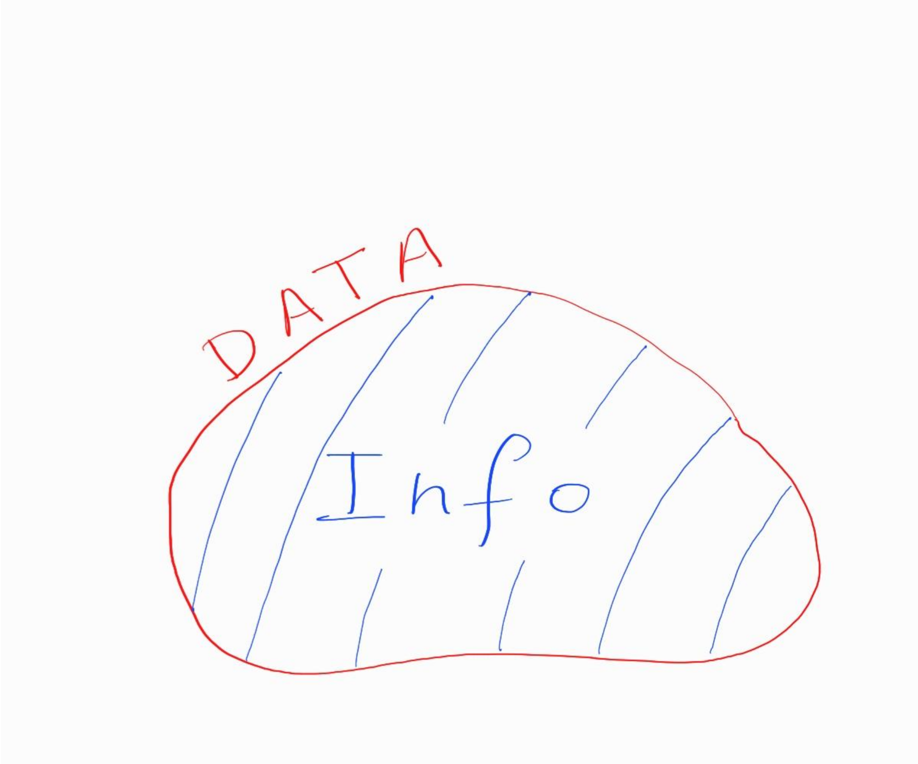
- **Information:** An estimation on the length of the table

There is not such a thing as intrinsic information in the Data

Data & Information



Data & Information



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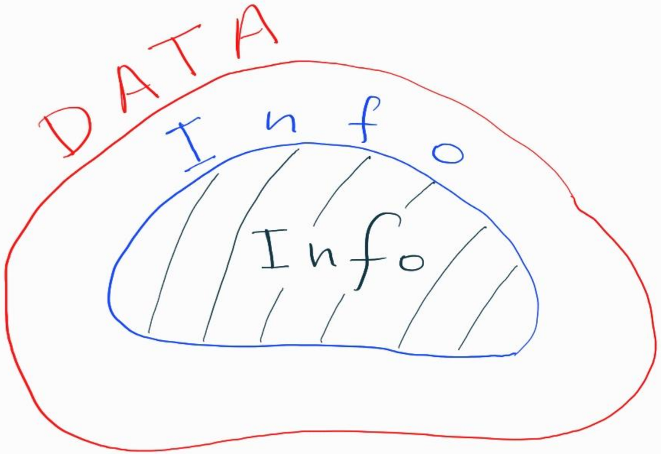
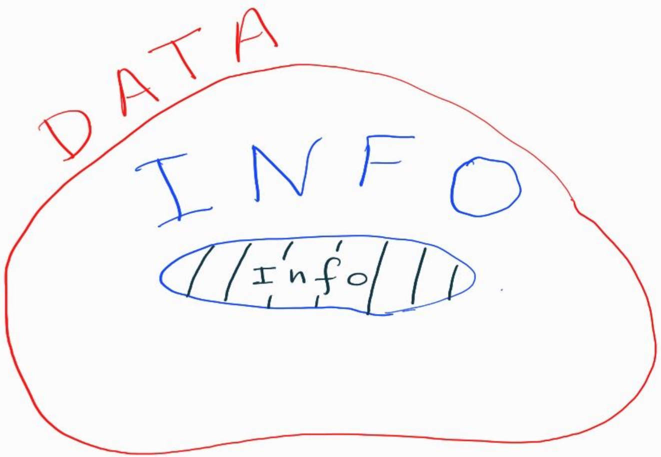
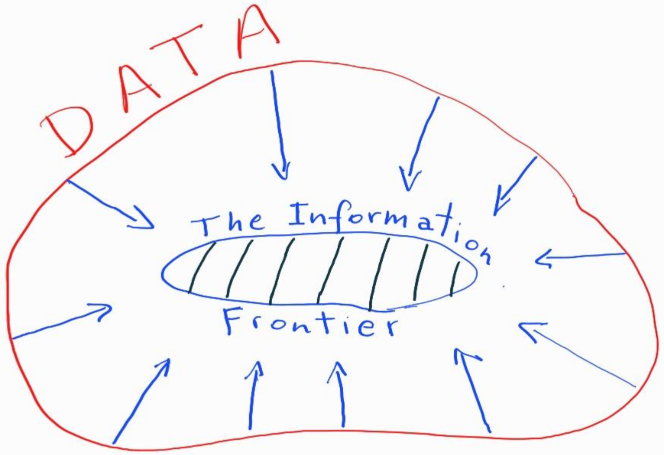


The Information Frontier



The Information Frontier



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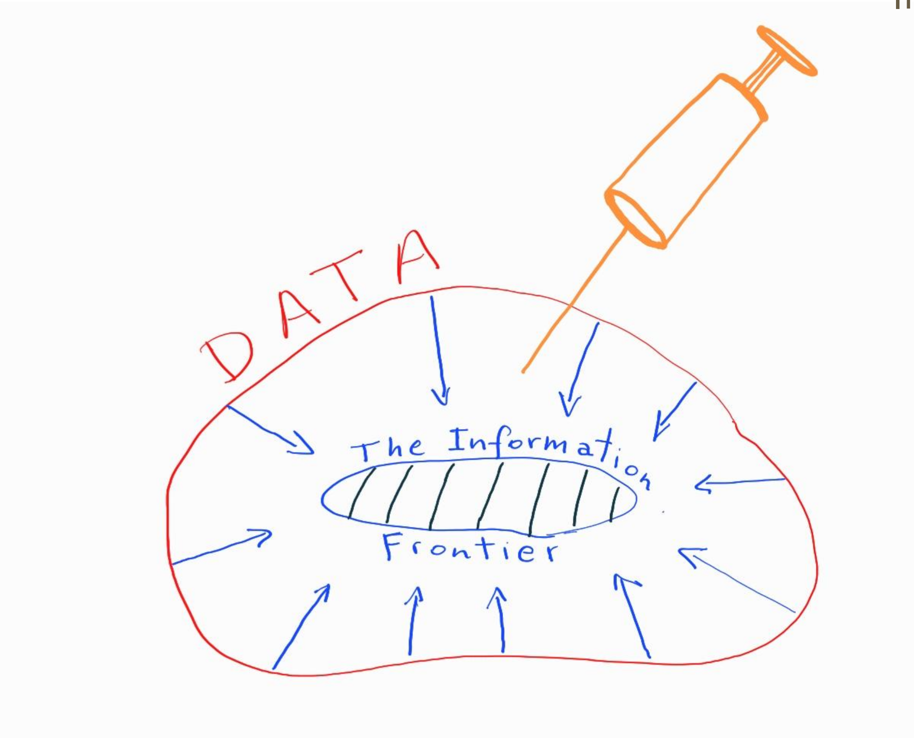
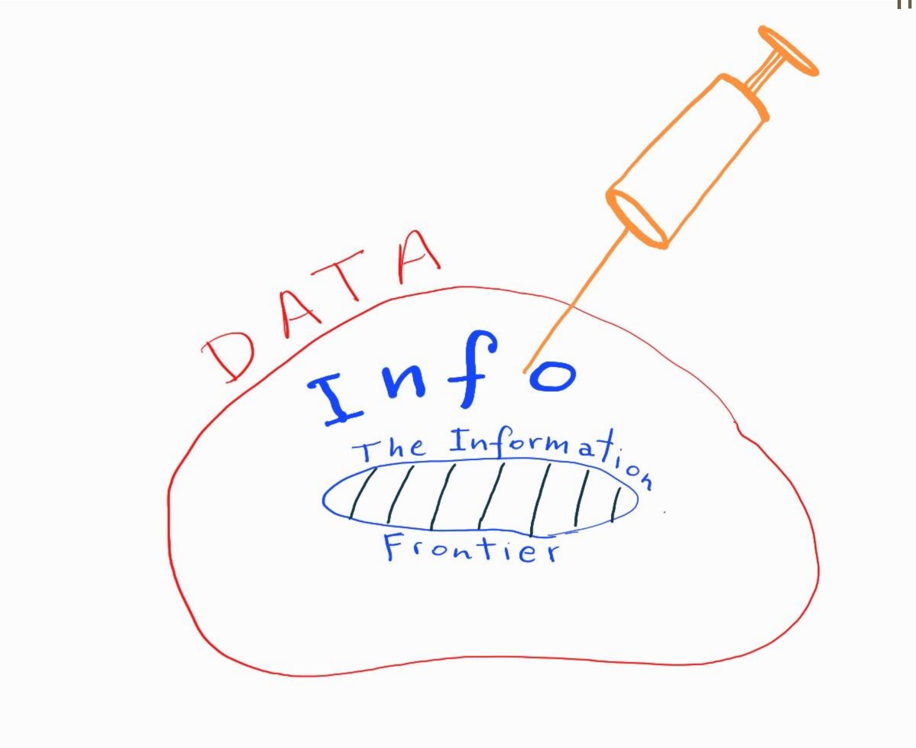


Inject *catalysts*:

- Modeling
- Tools & techniques
- Prior info

The Information Frontier



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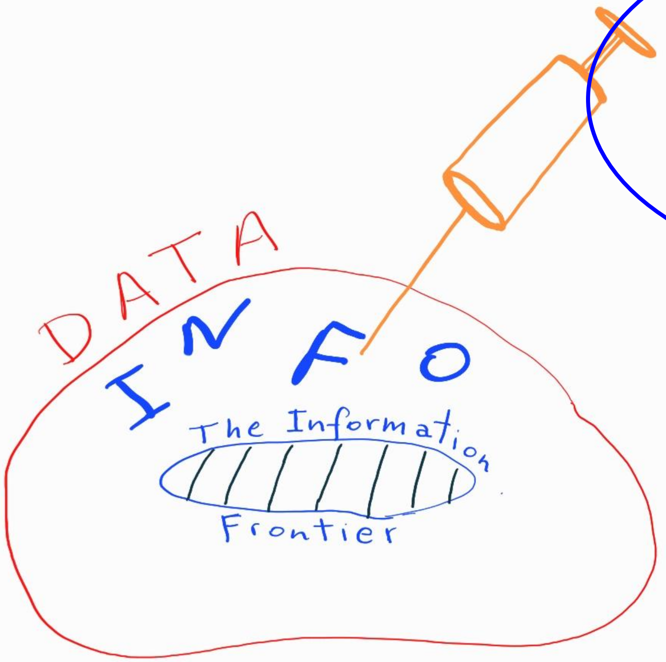

Inject *catalysts*:

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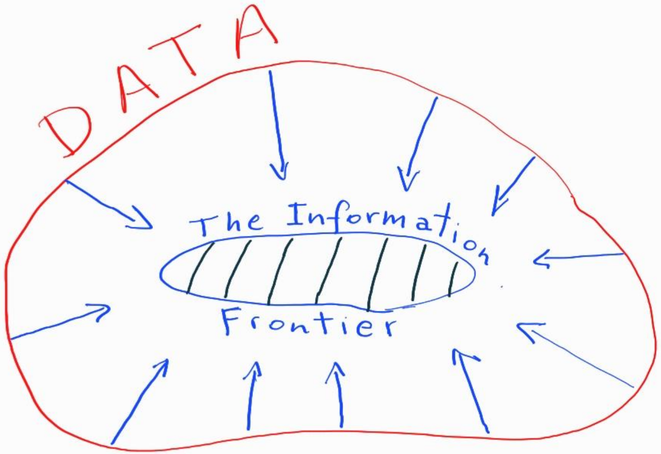
The Information Frontier

Science data is very complex and sophisticated



Different tools can explore differently this frontier

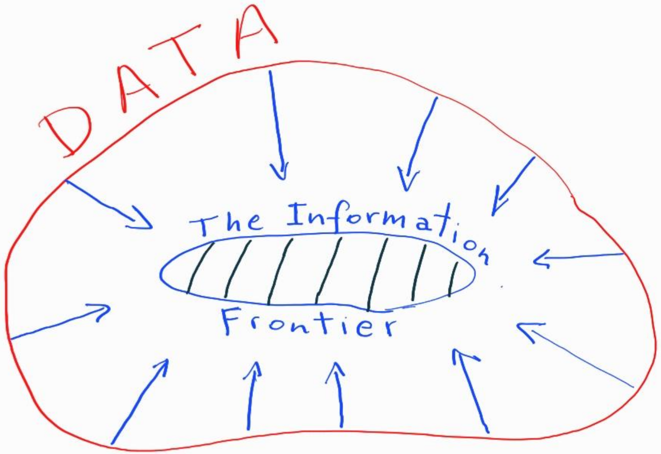
The Information Frontier

Scien
comp
soph

Different tools can
explore differently
this frontier

The Information Frontier

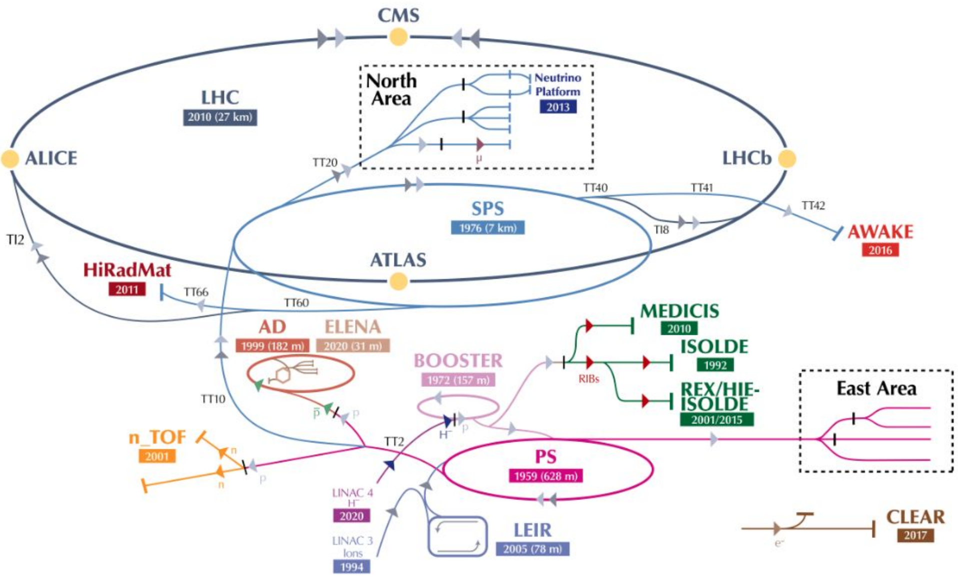
LHC data is very complex and sophisticated



Different tools can explore differently this frontier

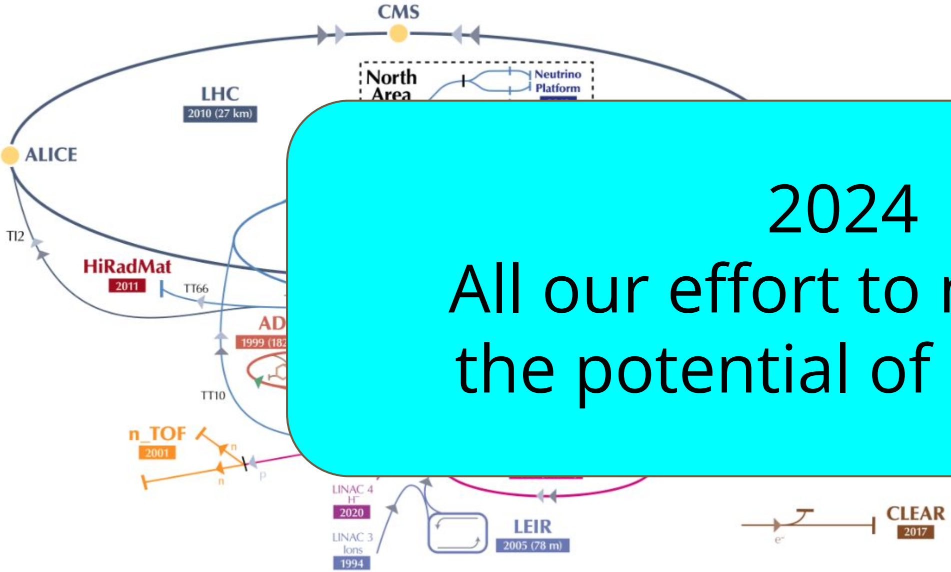
How much effort should we devote to moving the frontier?

LHC History



- 1980's: proposal
- 1995: Approved
- 2008: Started
- Huge effort in coordinating technology achievements
- Outstanding effort in all fields to reach one of the the most outstanding machines ever built by mankind

LHC History



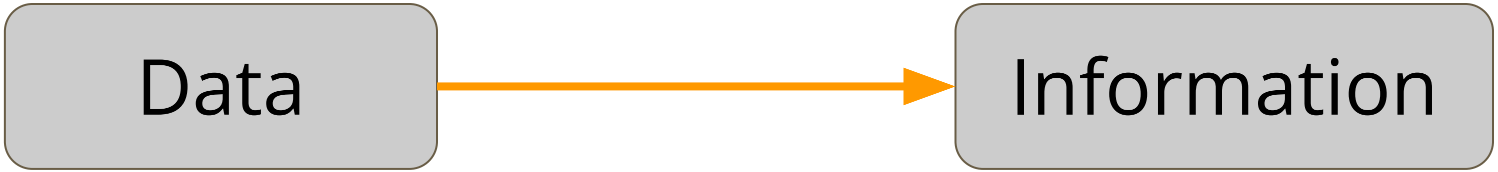
- 1980's: proposal
- 1995: Approved
- 2008: Started
- n coordinating
  chievements
  effort in all fields
  of the the most
  machines ever built

2024
All our effort to maximize the potential of LHC data

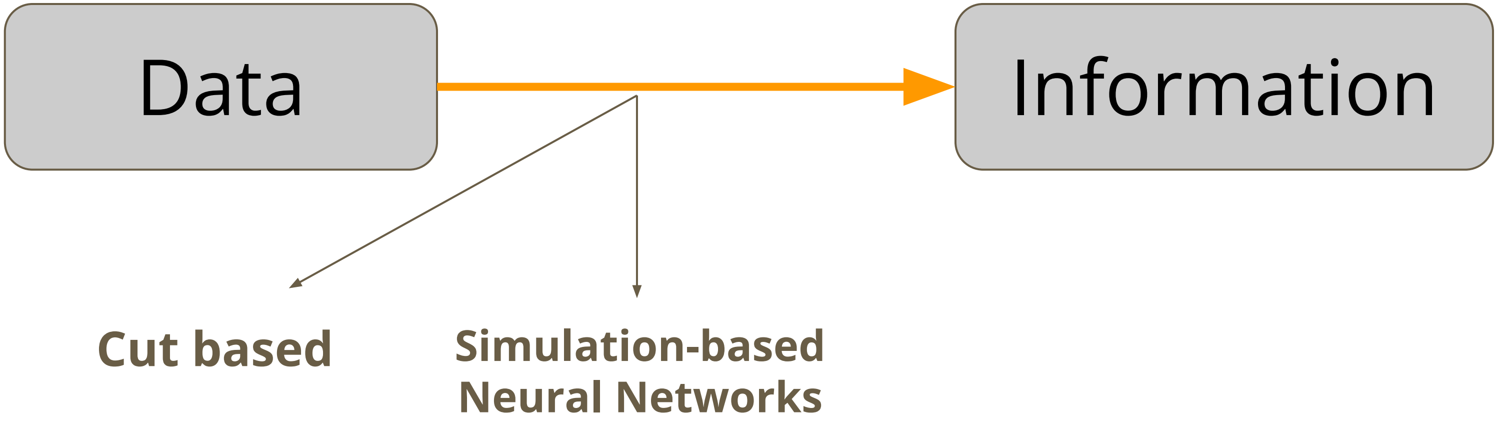
The carrot of a Discovery!

proposal
pproved
arted
n coordinating
chievements
effort in all fields
of the the most
machines ever built

Typical problem in science



Typical problem in science



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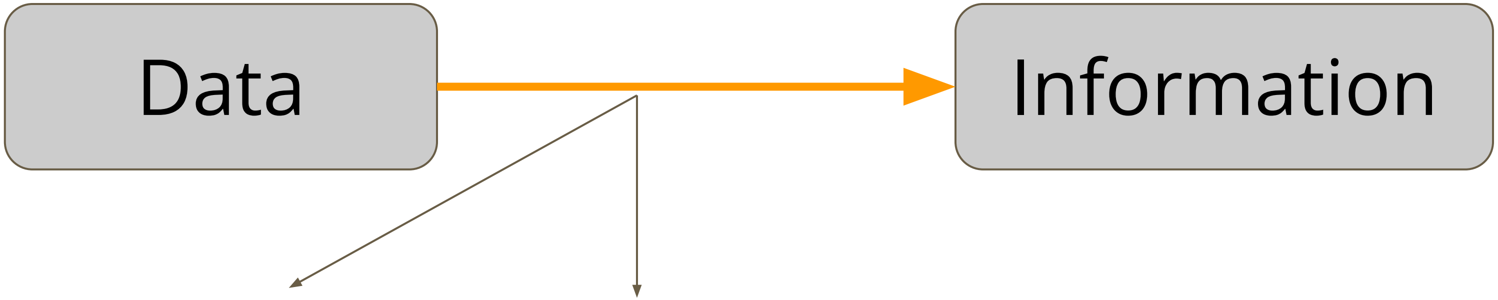
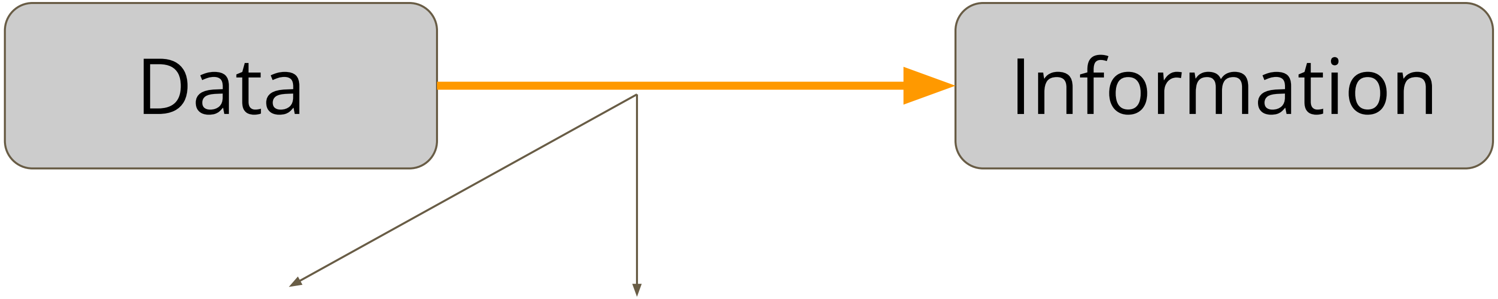


Cut based

Misses to take benefit of correlation at the event-by-event level

Simulation-based Neural Networks

Typical problem in science



Cut based

Misses to take benefit of correlation at the event-by-event level

Simulation-based Neural Networks

Extracts correlations, but learns "too much" from simulations

Typical problem in science

Data → Information

Cut based

Misses to take benefit of correlation at the event-by-event level

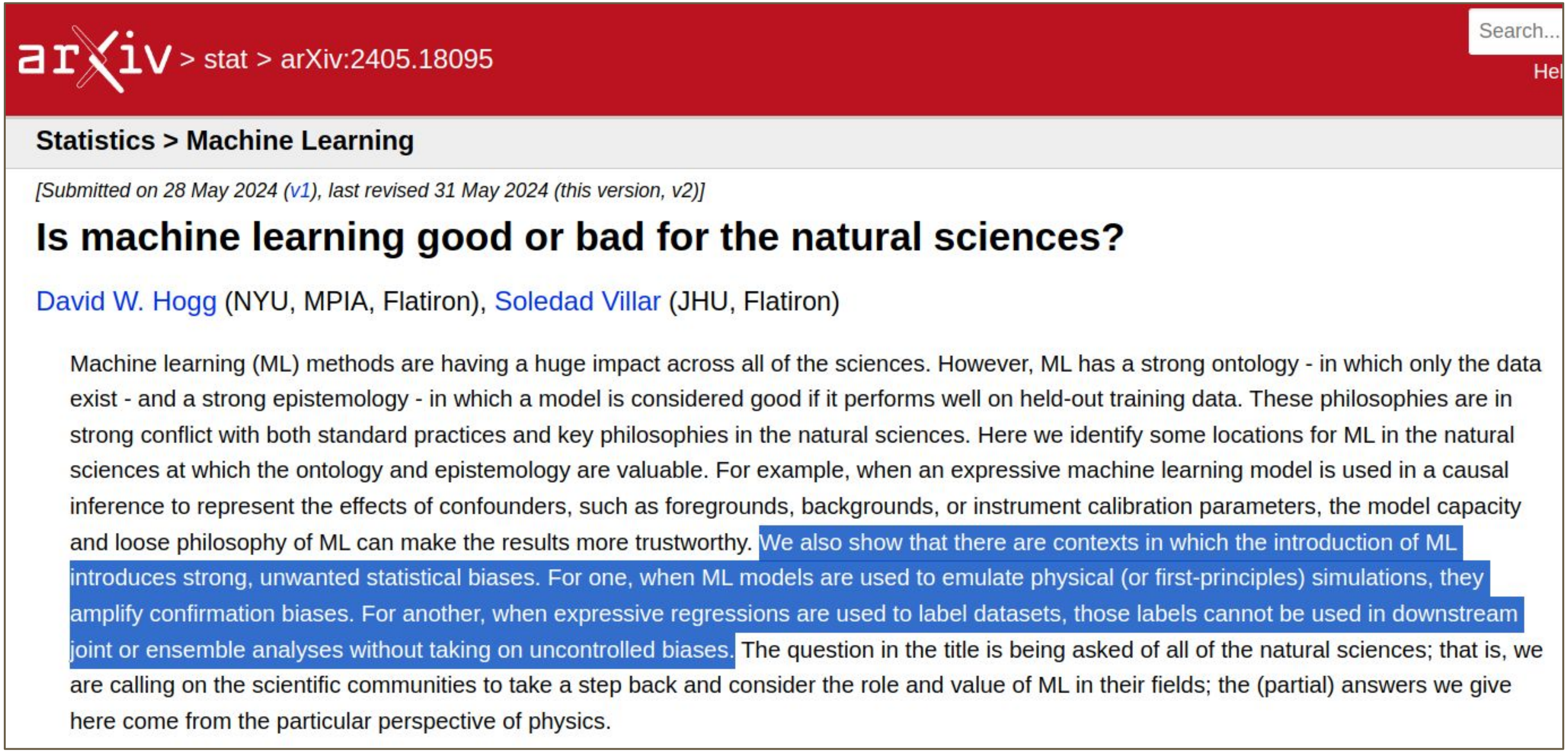
Simulation-based Neural Networks

Extracts correlations, but learns "too much" from simulations

Bayesian tools

This talk!
Reduce simulation's impact at the price of increasing modelling impact

The danger of NN in natural sciences


arXiv > stat > arXiv:2405.18095

Search...

Statistics > Machine Learning

[Submitted on 28 May 2024 (v1), last revised 31 May 2024 (this version, v2)]

Is machine learning good or bad for the natural sciences?

David W. Hogg (NYU, MPIA, Flatiron), Soledad Villar (JHU, Flatiron)

Machine learning (ML) methods are having a huge impact across all of the sciences. However, ML has a strong ontology - in which only the data exist - and a strong epistemology - in which a model is considered good if it performs well on held-out training data. These philosophies are in strong conflict with both standard practices and key philosophies in the natural sciences. Here we identify some locations for ML in the natural sciences at which the ontology and epistemology are valuable. For example, when an expressive machine learning model is used in a causal inference to represent the effects of confounders, such as foregrounds, backgrounds, or instrument calibration parameters, the model capacity and loose philosophy of ML can make the results more trustworthy. We also show that there are contexts in which the introduction of ML introduces strong, unwanted statistical biases. For one, when ML models are used to emulate physical (or first-principles) simulations, they amplify confirmation biases. For another, when expressive regressions are used to label datasets, those labels cannot be used in downstream joint or ensemble analyses without taking on uncontrolled biases. The question in the title is being asked of all of the natural sciences; that is, we are calling on the scientific communities to take a step back and consider the role and value of ML in their fields; the (partial) answers we give here come from the particular perspective of physics.

Summary

- Intro
- Bayesian Machine Learning
- Graphical Models
- Bayesian for the People!
- Bayesian techniques
    - No Signal & Background region
    - No hard assignment
    - Probability, correlation and prior-knowledge
    - Exploiting prior knowledge
        - Continuity
        - Unimodality
- Outlook

Summary

- Intro
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Mutual information

Summary

- Intro
- ABCD method
- Bayesian techniques

  Mutual information
  - No Signal & Background region
  - No hard assignment
  - Probability, ~~correlation~~ and prior-knowledge
- pp $\longrightarrow$ hh $\longrightarrow$ bbbb (inspiration & chimera)
  - Compare ABCD Vs Bayesian: multidimensionality!
  - Exploiting prior knowledge
    - Continuity
    - Unimodality
- Outlook
- Conclusions

Bayesian Inference ML

Bayesian Inference

Bayes Theorem:

$$p(\theta | X) = \frac{p(X | \theta) * p(\theta)}{p(X)}$$

Bayesian Inference

Bayes Theorem:

$$p(\theta | X) = \frac{p(X | \theta) * p(\theta)}{p(X)}$$

Used in very different contexts

Bayesian Inference

Bayes Theorem:

$$p(\theta|X) = \frac{p(X|\theta) * p(\theta)}{p(X)}$$

Our utility: X = data, θ=parameters

Model data as being sampled from a clever PDF with parameters θ

Bayesian Inference

Bayes Theorem:

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→

Infer θ once you see the data X

Bayesian Inference

Bayes Theorem:

$$p(\theta|X) = \frac{p(X|\theta) * p(\theta)}{p(X)}$$

Our utility: X = data, θ=parameters

Model data as being sampled from a clever PDF with parameters θ → Infer θ once you see the data X → Connect θ to physical parameters of interest

Bayesian Inference

Bayes Theorem:

$$p(\theta|X) = \frac{p(X|\theta) * p(\theta)}{p(X)}$$

Data comes from real physical process not from a PDF!

Our utility: X = data, θ=parameters

Model data as being sampled from a clever PDF with parameters θ

→

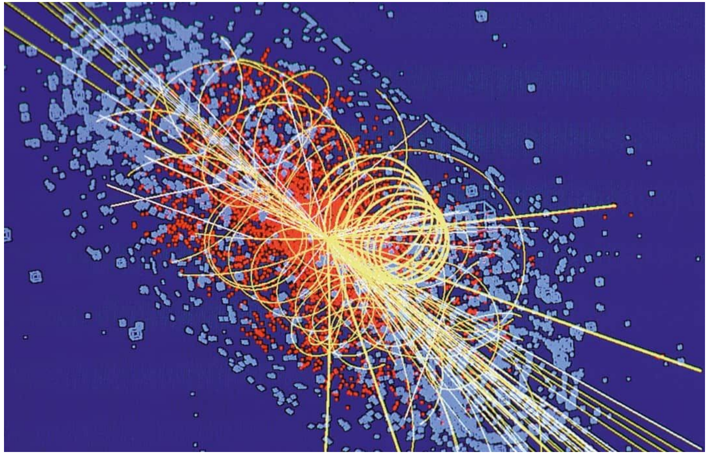
Infer θ once you see the data X

→

Connect θ to physical parameters of interest

Graphical Models

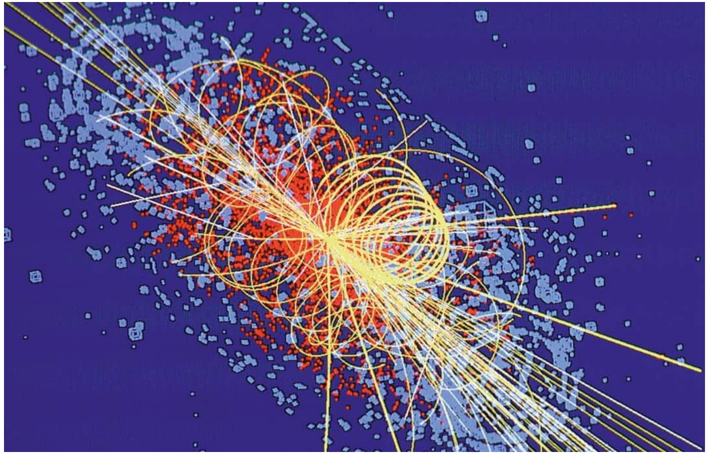
Science: Mixture models



Dataset X:

- Signal
- Few backgrounds

Science: Mixture models



Dataset X:

- Signal
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- Each event is either

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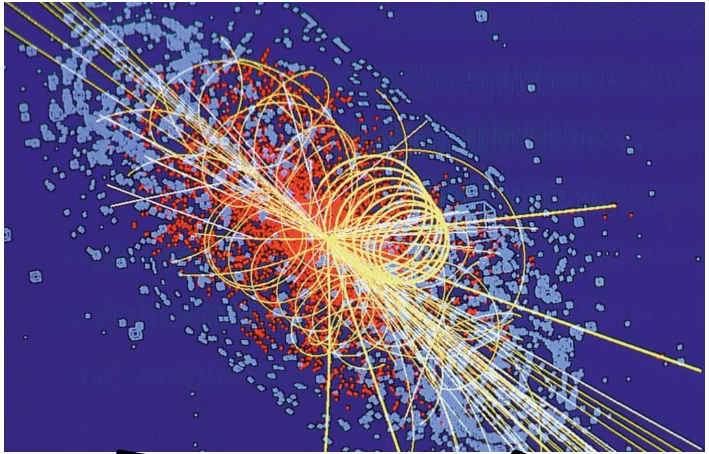


Dataset X:

- Signal
- Few backgrounds
- Each event is either

  signal or one of the backgrounds

How to create such a PDF !?

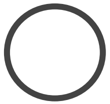
Bayesian Inference: Graphical models

Graphical representation of a PDF to easily visualize the internal structure of the random variables

Bayesian Inference: Graphical models

At each event, sample a multinomial random variable that decides whether is signal or some of the backgrounds

(K classes)



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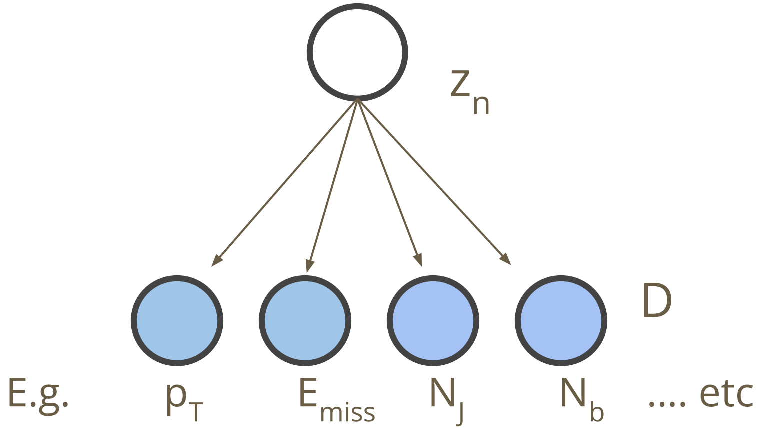
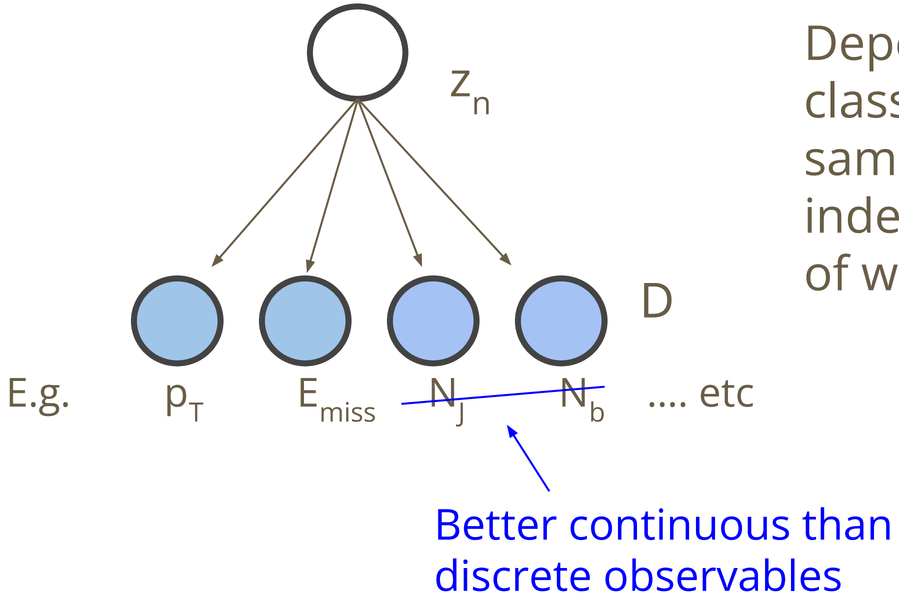
Bayesian Inference: Graphical models



Depending on the class of the event, we sample D random independent variables of what *we measure*

Bayesian Inference: Graphical models



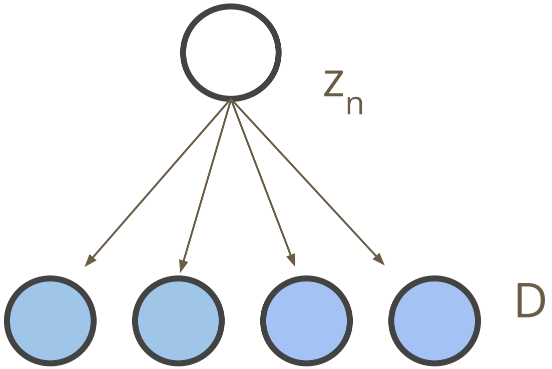
Depending on the class of the event, we sample D random independent variables of what *we measure*

Bayesian Inference: Graphical models

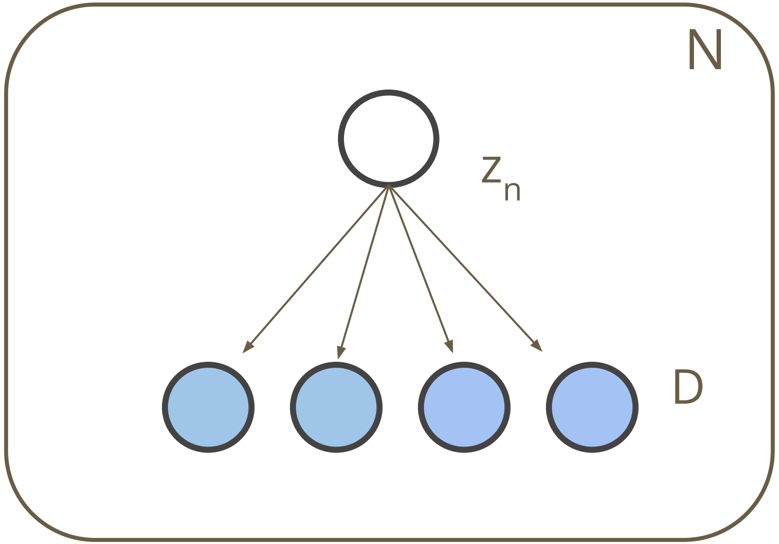
Convention:

Empty circles:
Sampled and unobserved RV

Filled circles:
Sampled and observed RV

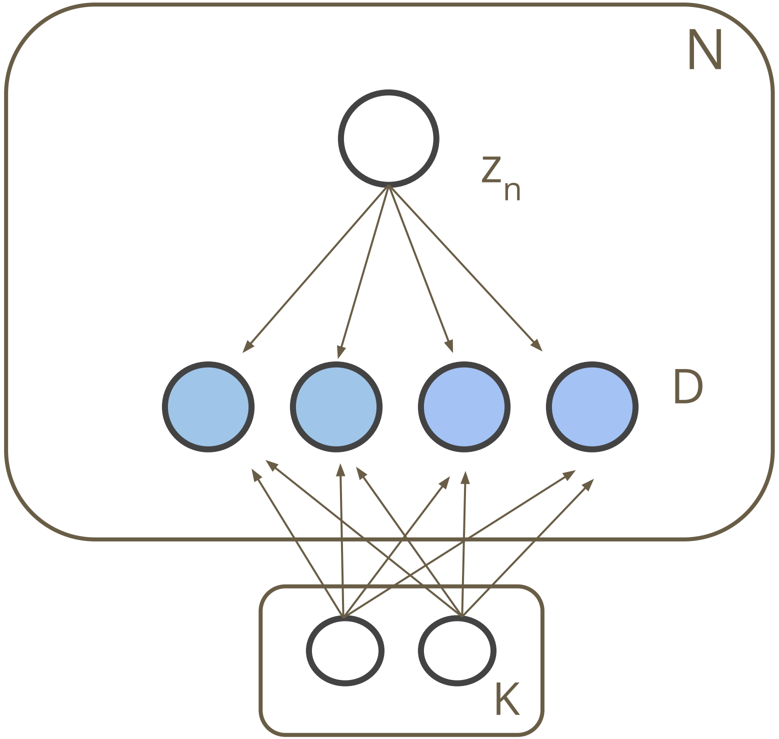


Bayesian Inference: Graphical models



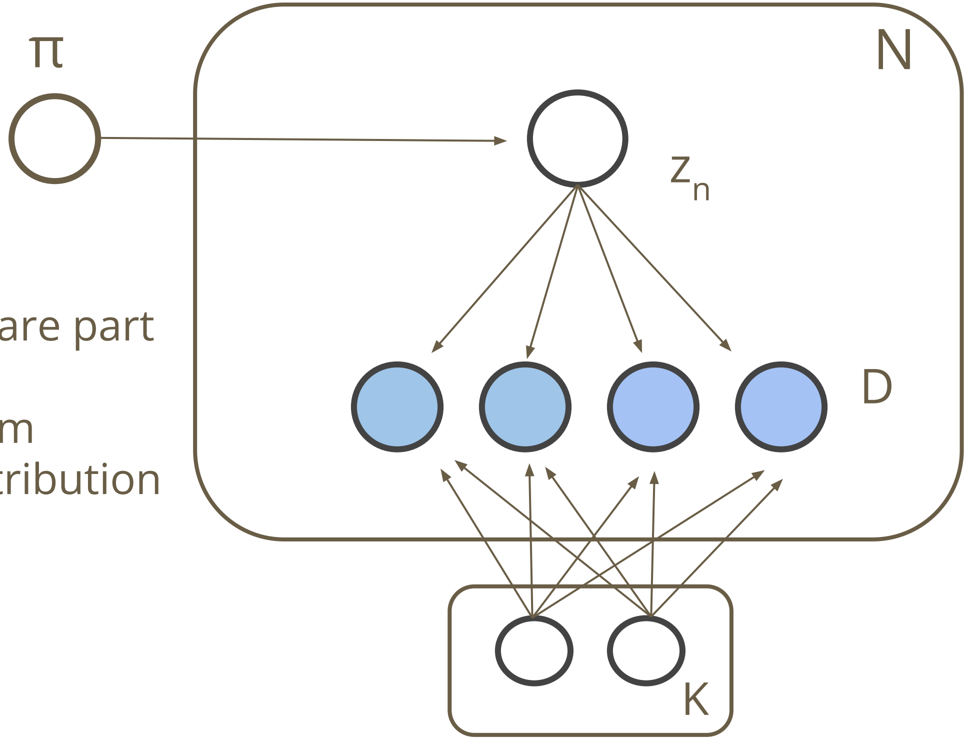
Procedure that is repeated N times

Bayesian Inference: Graphical models



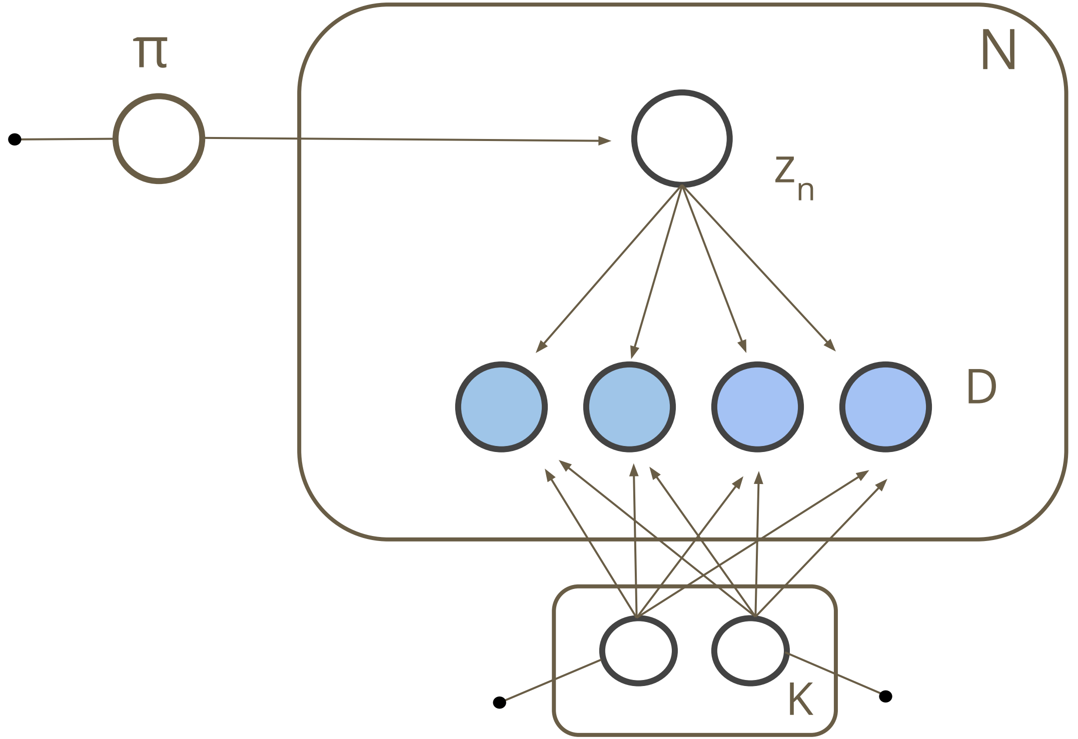
Each one of the K classes has an *expected distribution* over the measured quantities

Bayesian Inference: Graphical models



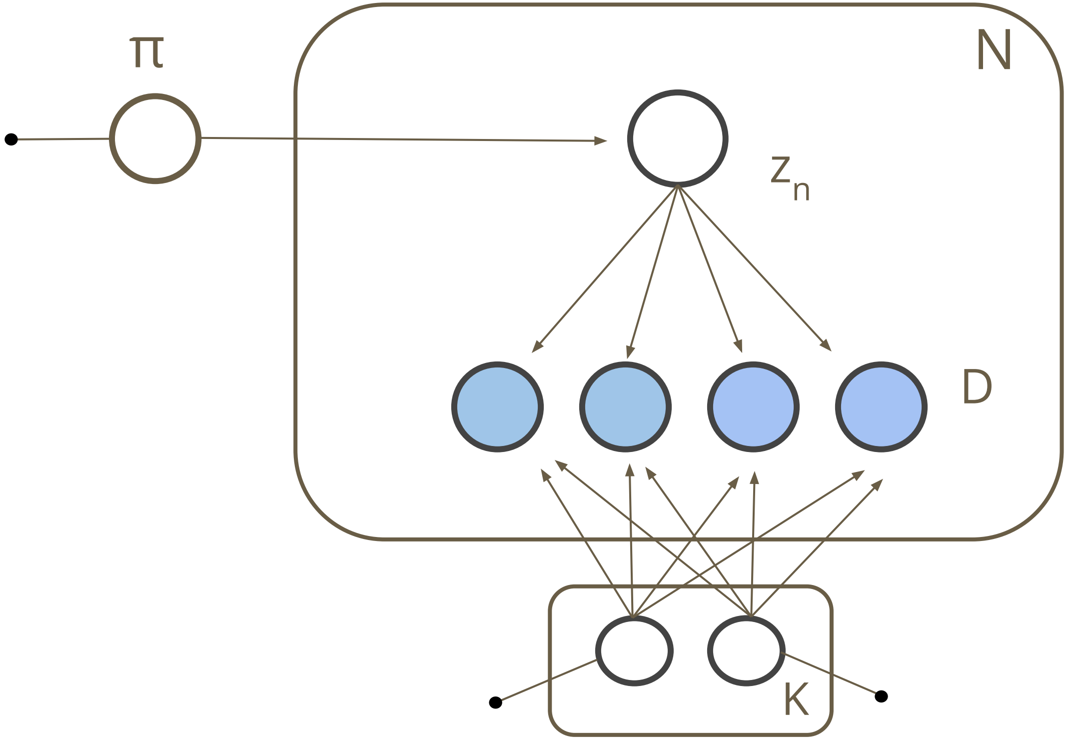
Multinomial parameters are part of the PDF. Sampled from Dirichlet distribution

Bayesian Inference: Graphical models



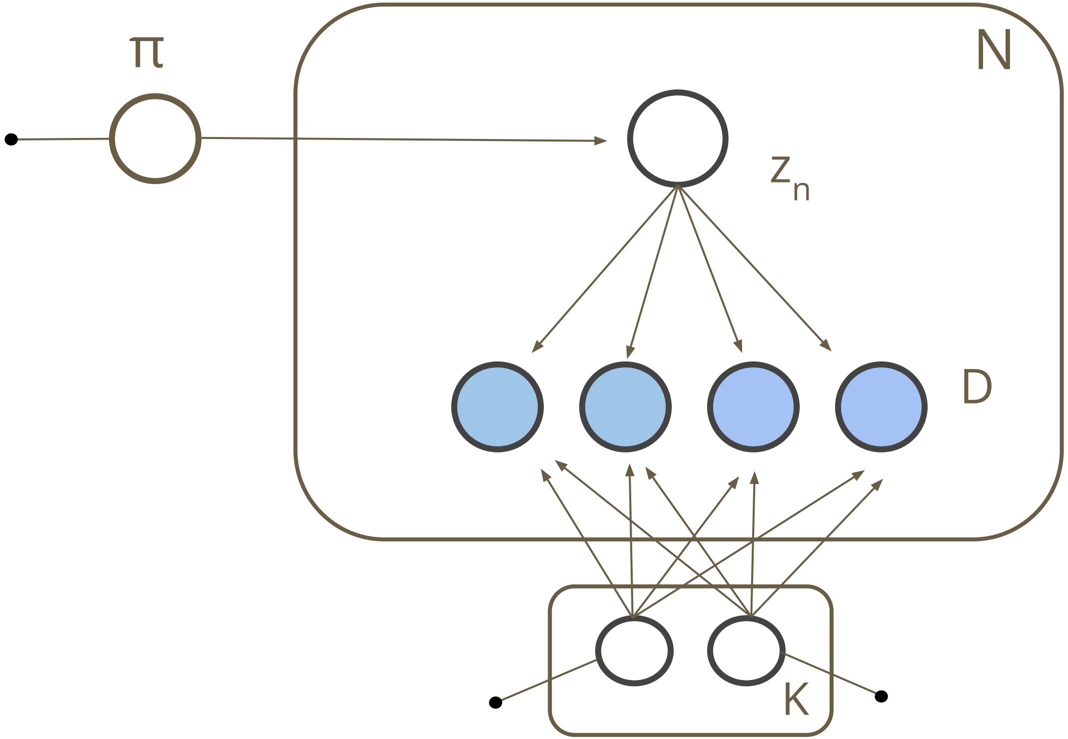
Hyperparameters to define how to sample parameters

Bayesian Inference: Graphical models



Mixture Model

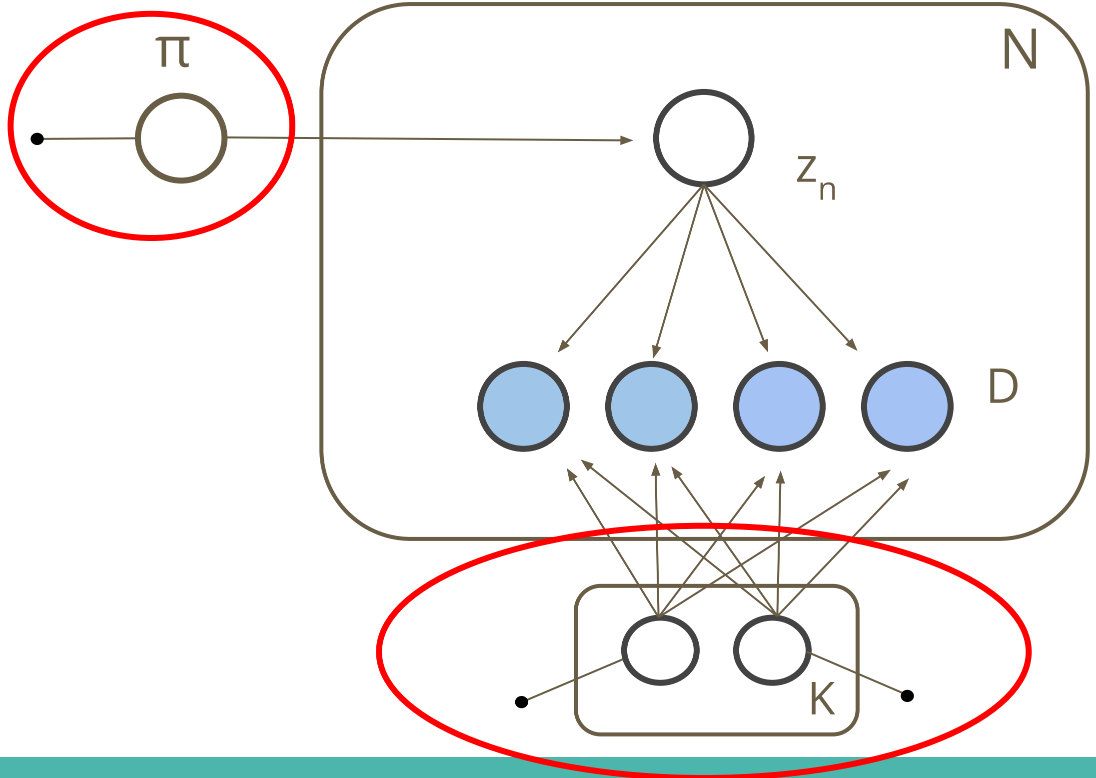
Bayesian Inference: Graphical models



Mixture Model

- Model data as being sampled from a PDF

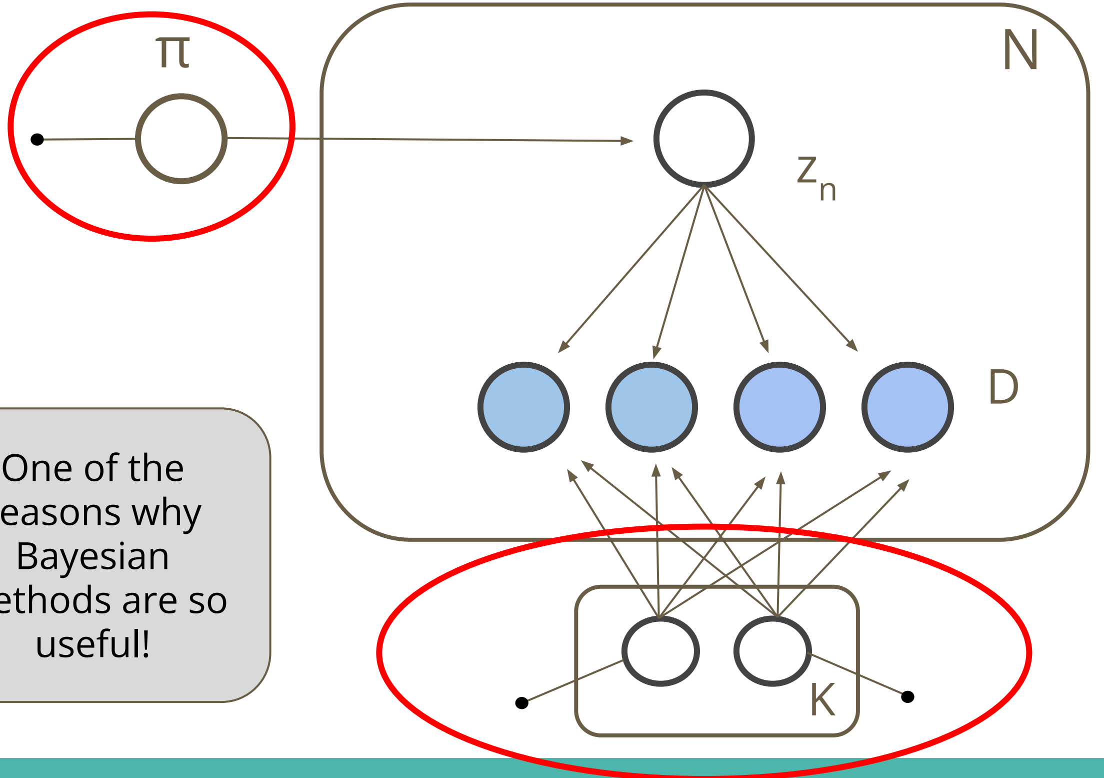
Bayesian Inference: Graphical models



Mixture Model

- Model data as being sampled from a PDF
- Plug our prior knowledge

Bayesian Inference: Graphical models

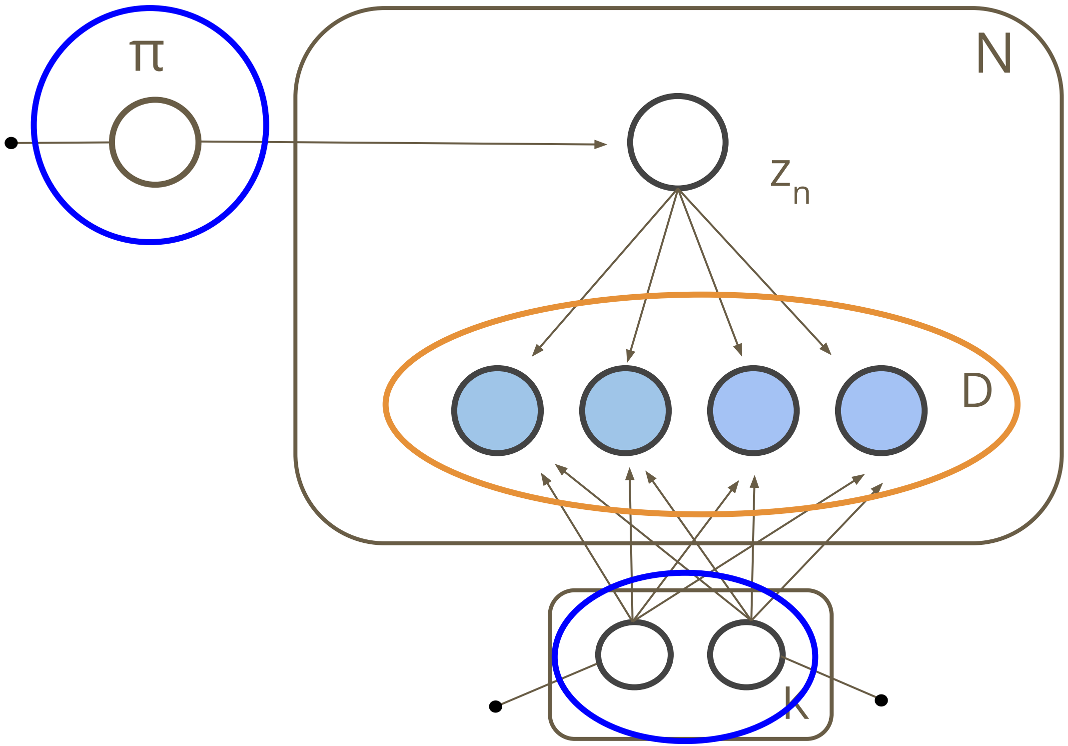


Mixture Model

- Model data as being sampled from a PDF
- Plug our prior knowledge

One of the reasons why Bayesian methods are so useful!

Bayesian Inference: Graphical models

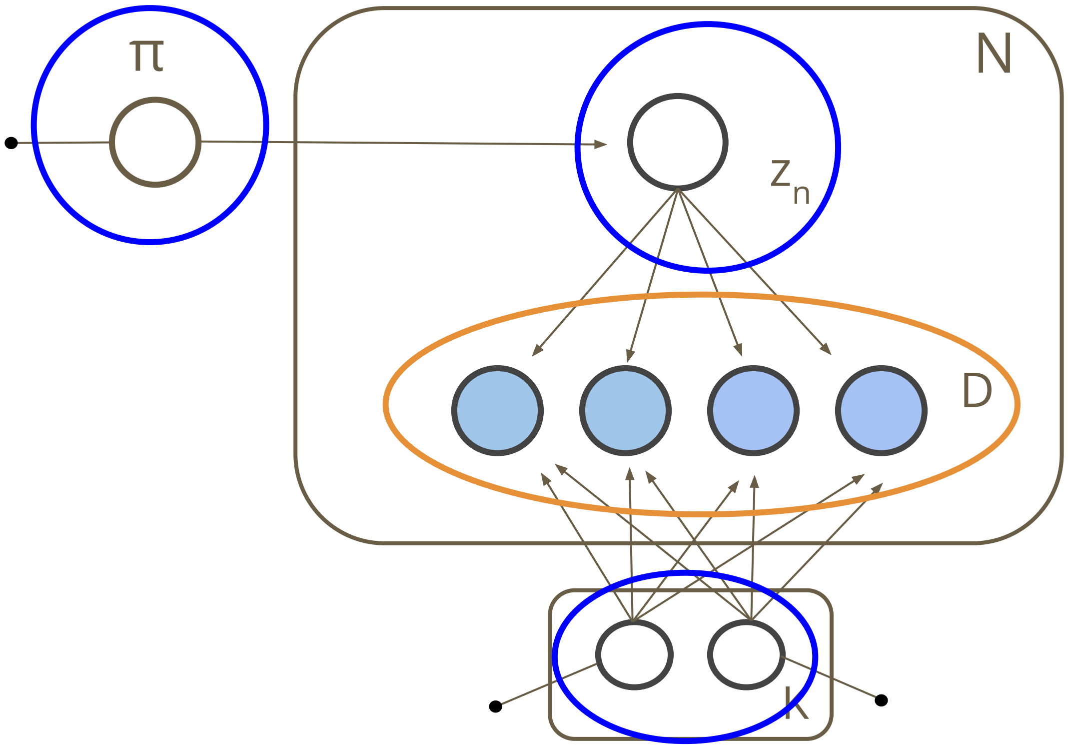


Mixture Model

- Model data as being sampled from a PDF
- Plug our prior knowledge
- Infer the parameters conditioned in the observed data

$p(\theta|X) = p(X|\theta)\, p(\theta) / p(x)$

Bayesian Inference: Graphical models



Mixture Model

- Model data as being sampled from a PDF
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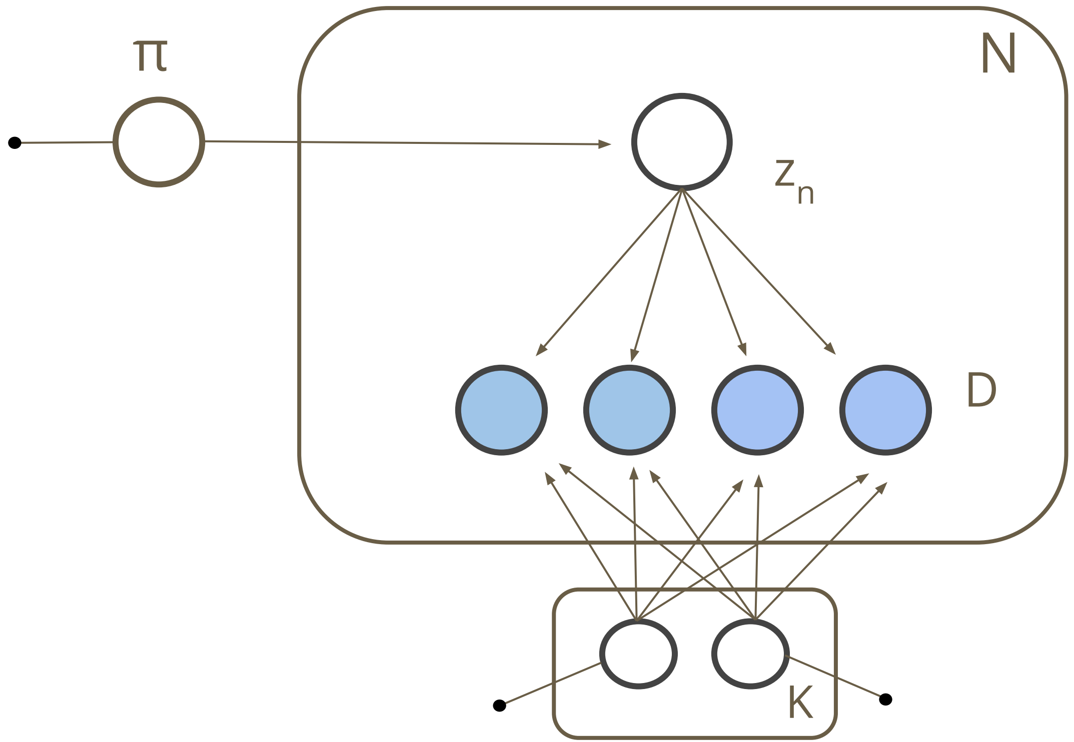
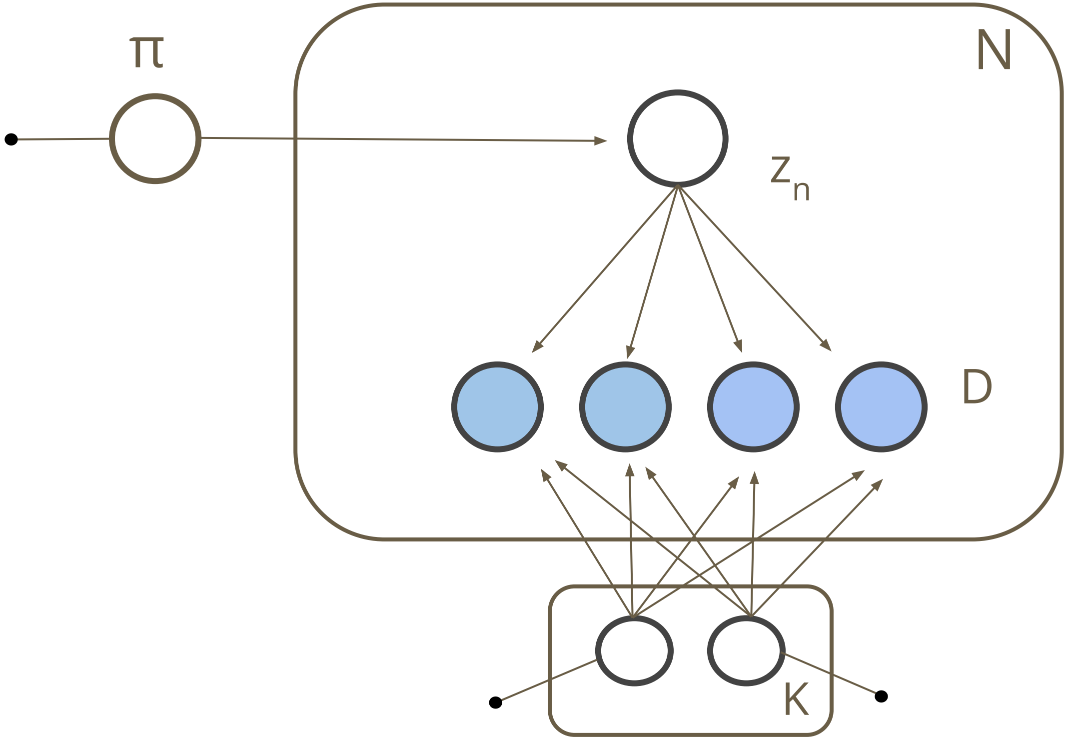
$p(\theta|X) = p(X|\theta)\, p(\theta) / p(x)$

- Infer the latent variables

Bayesian Inference

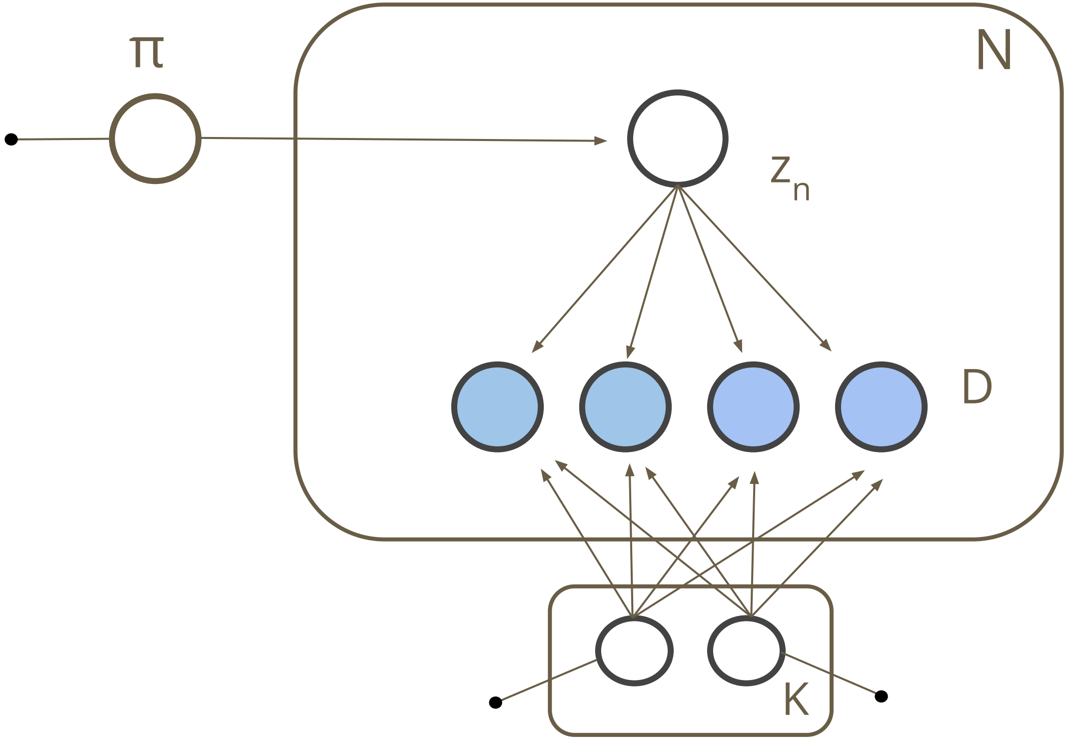


Bayesian Inference



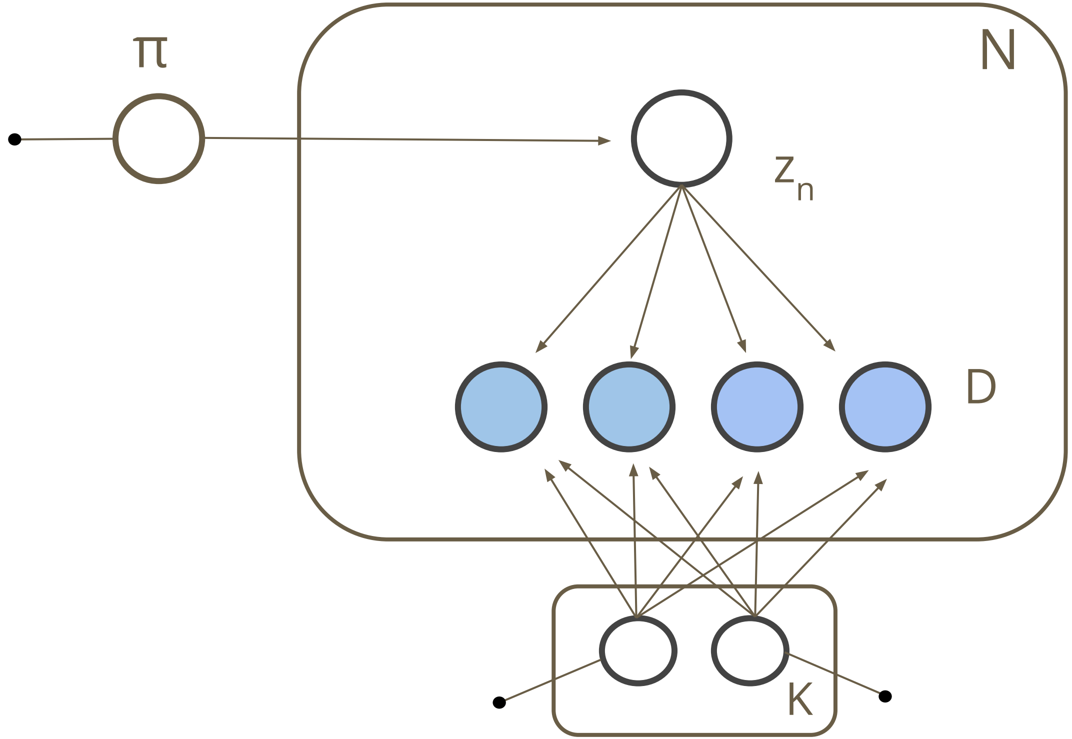
- No hard cuts

Bayesian Inference



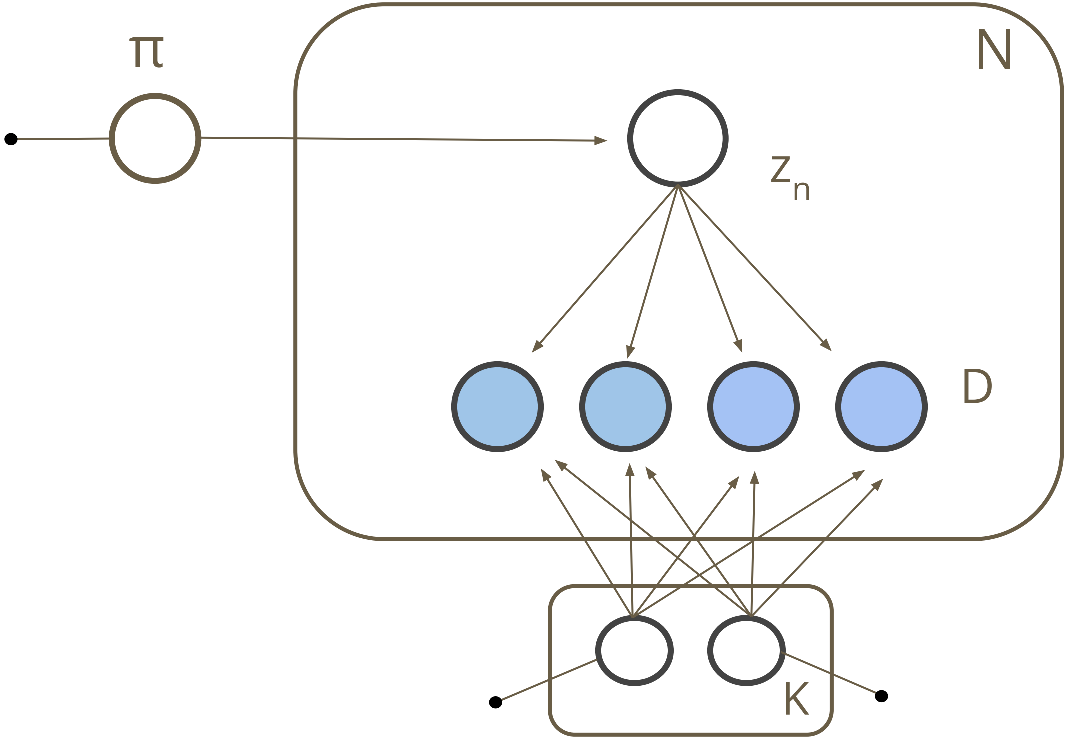
- No hard cuts
- Soft assignments

Bayesian Inference



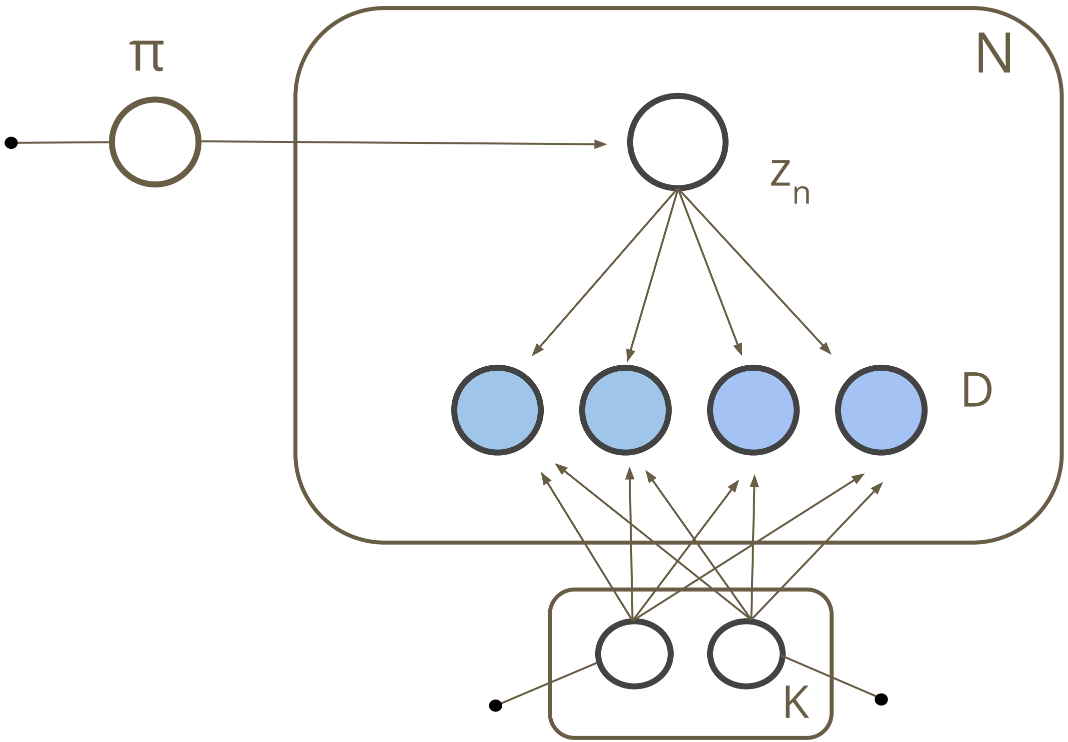
- No hard cuts
- Soft assignments
- No signal/control regions

Bayesian Inference



- No hard cuts
- Soft assignments
- No signal/control regions
- K classes & D observables

Bayesian Inference



- No hard cuts
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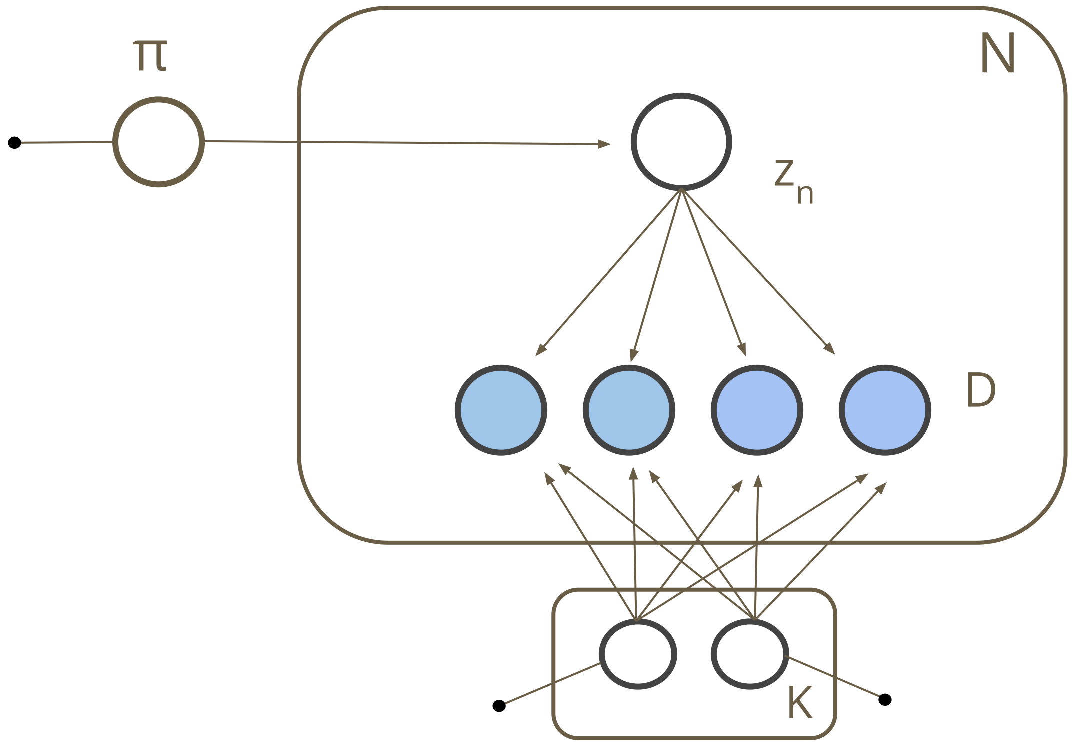
- K classes &
  D observables
- Deployment of data internal structure

Bayesian Inference



- No hard cuts
- Soft assignments
- No signal/control regions
- K classes & D observables
- Deployment of data internal structure
- Controlled injection of prior knowledge

ABCD Vs Bayesian

Improvement & Generalization

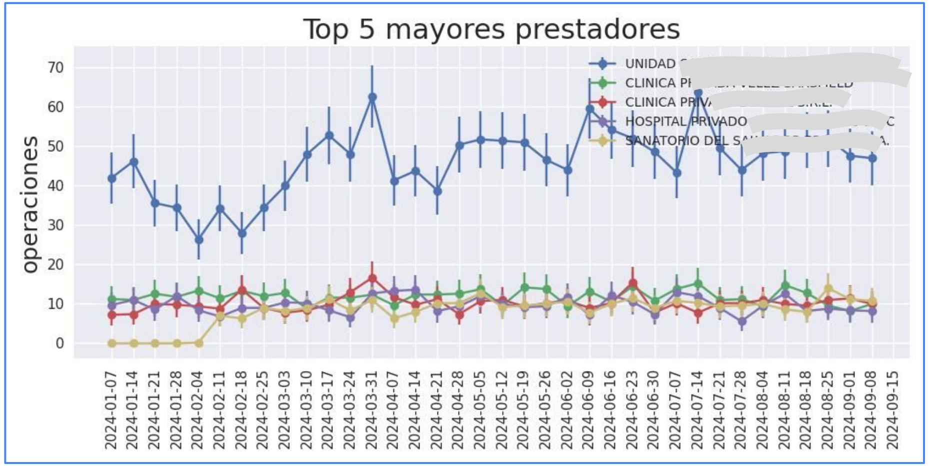
ABCD	Bayesian framework
2 observables	D observables
Signal & Background	Signal & K-1 backgrounds
Prior knowledge to define A, B, C & D, and get signal events in A	Visualize, understand and exploit *internal structure of the data*. Plug prior knowledge to *simultaneously* infer classes fractions and posterior distributions
Separated: signal & control regions	Signal & backgrounds can be mixed in all phase space.

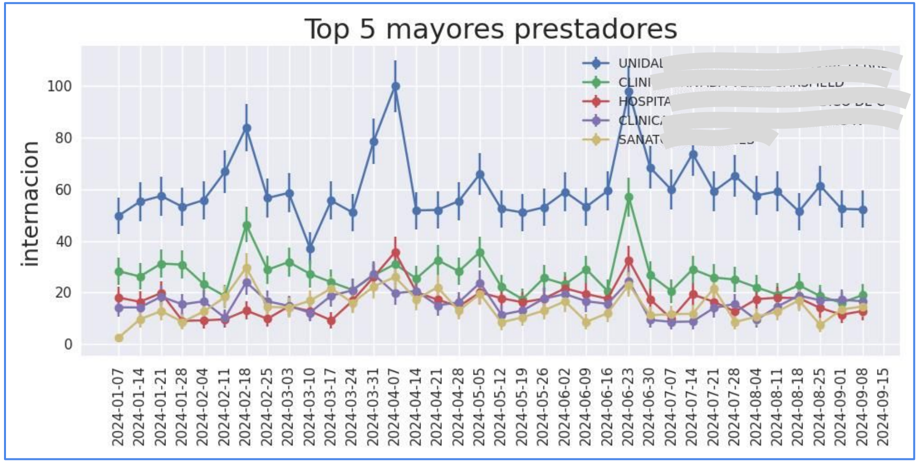
(Aplicaciones para la Sociedad)

Bayesian for the People!

Disclaimer:
Licencia porque estoy en el IC!

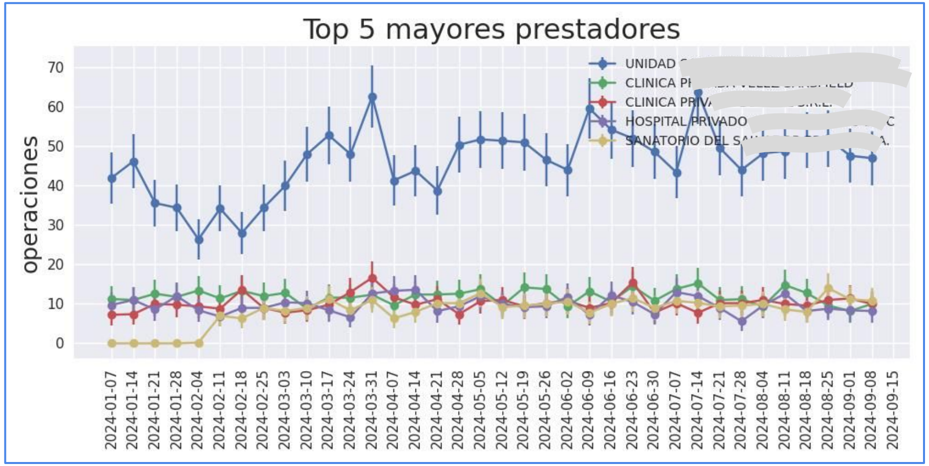
Bayesian @ Clínicas médicas

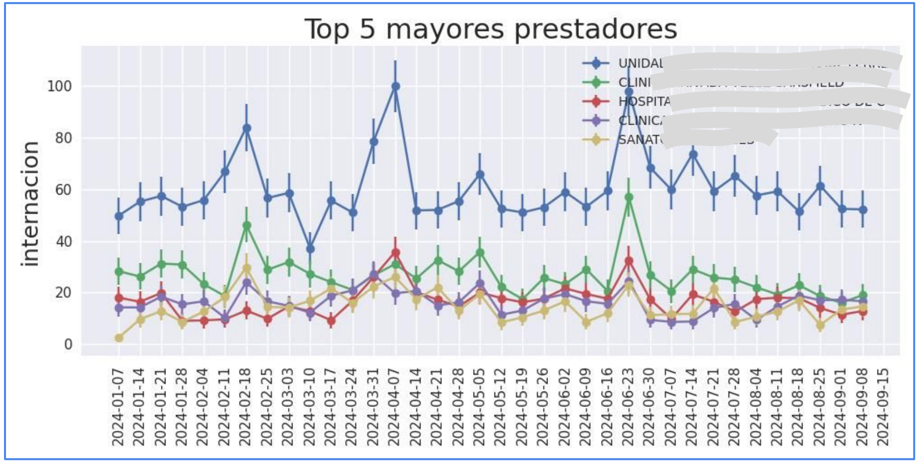




Bayesian @ Clínicas médicas

Cómo darse cuenta si alguna está fuera de lo normal ?





Bayesian @ Clínicas médicas

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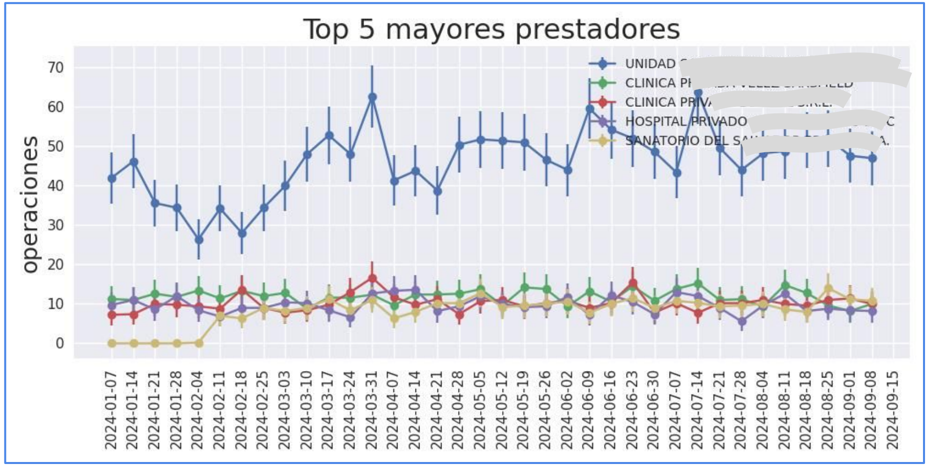
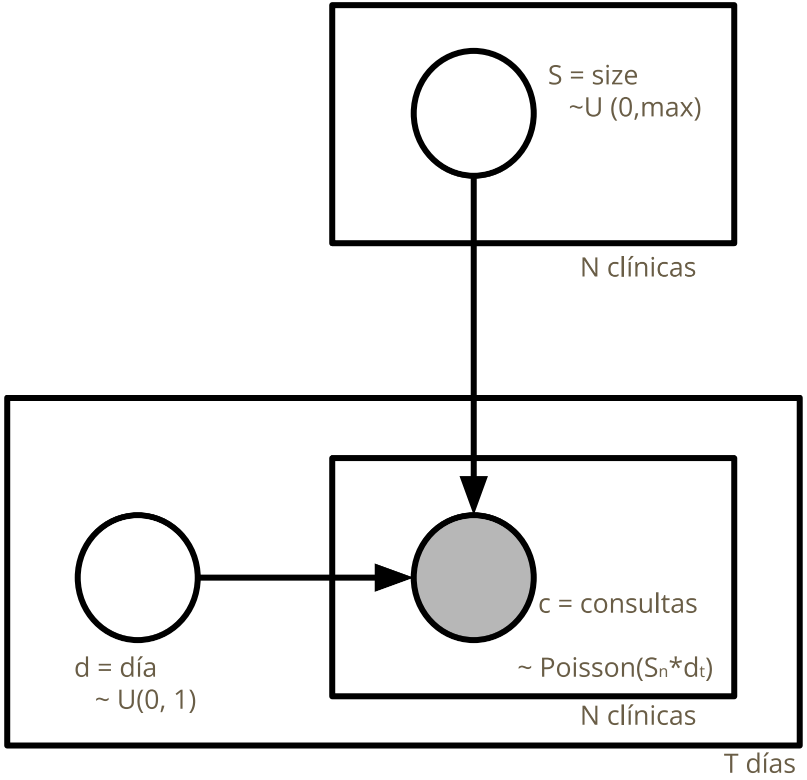
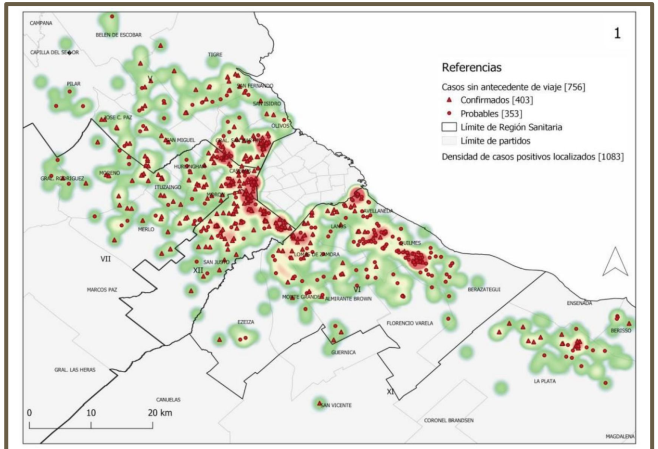
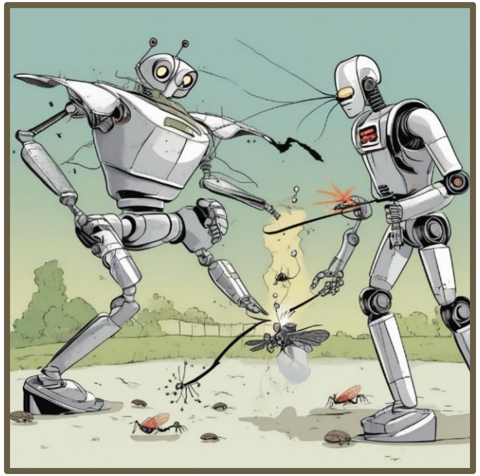




Bayesian ML @ Dengue @ PBA



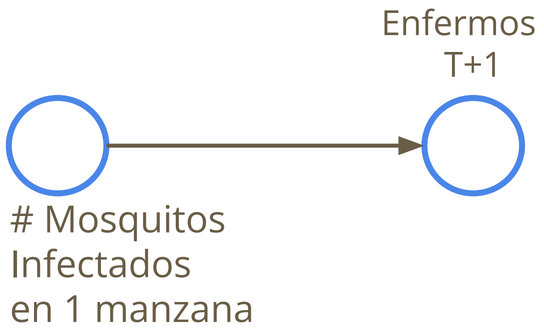
Fuente: Dirección Epidemiología. Provincia de Buenos Aires. SNVS 2.0



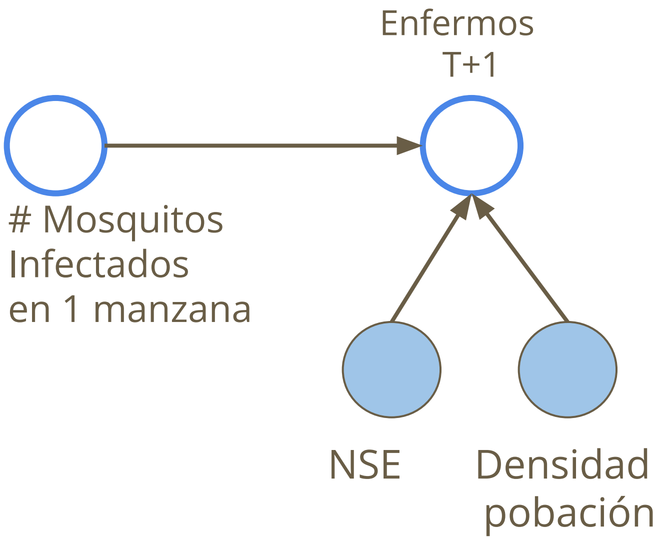
Bayesian Intelligent Dengue Alarm (BIDA)

Mosquitos
Infectados
en 1 manzana

Bayesian Intelligent Dengue Alarm (BIDA)



Bayesian Intelligent Dengue Alarm (BIDA)



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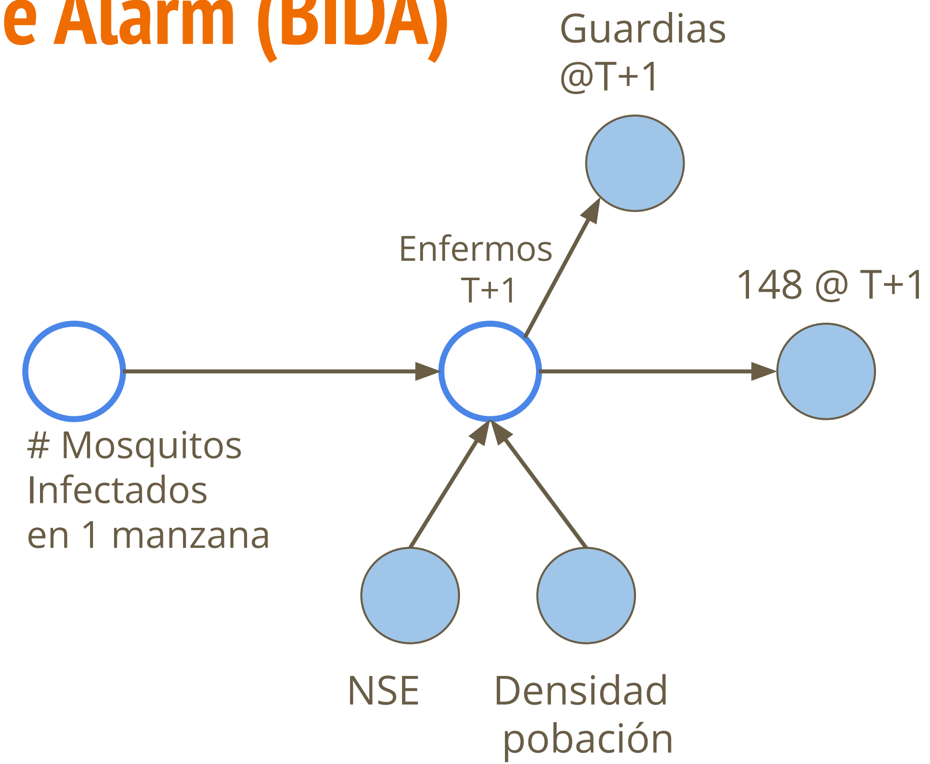

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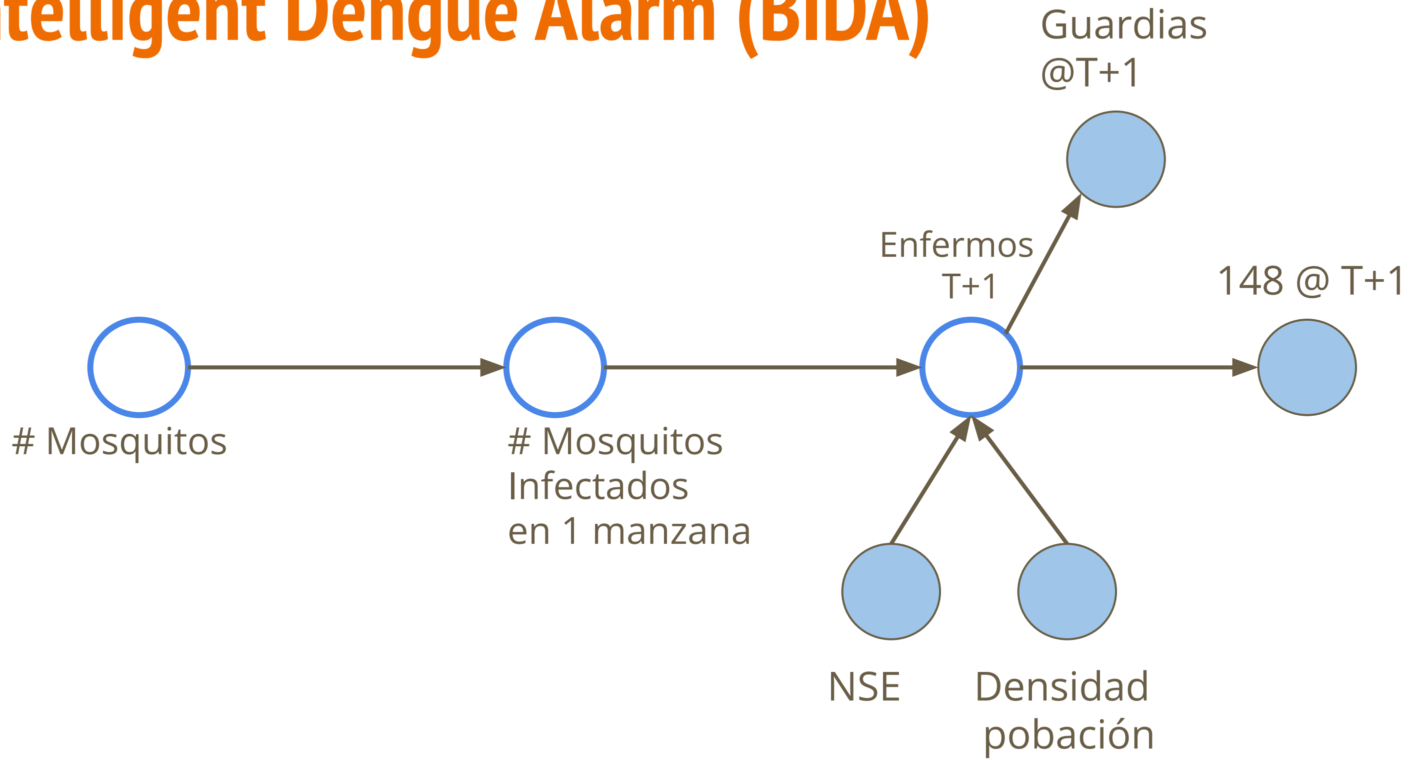

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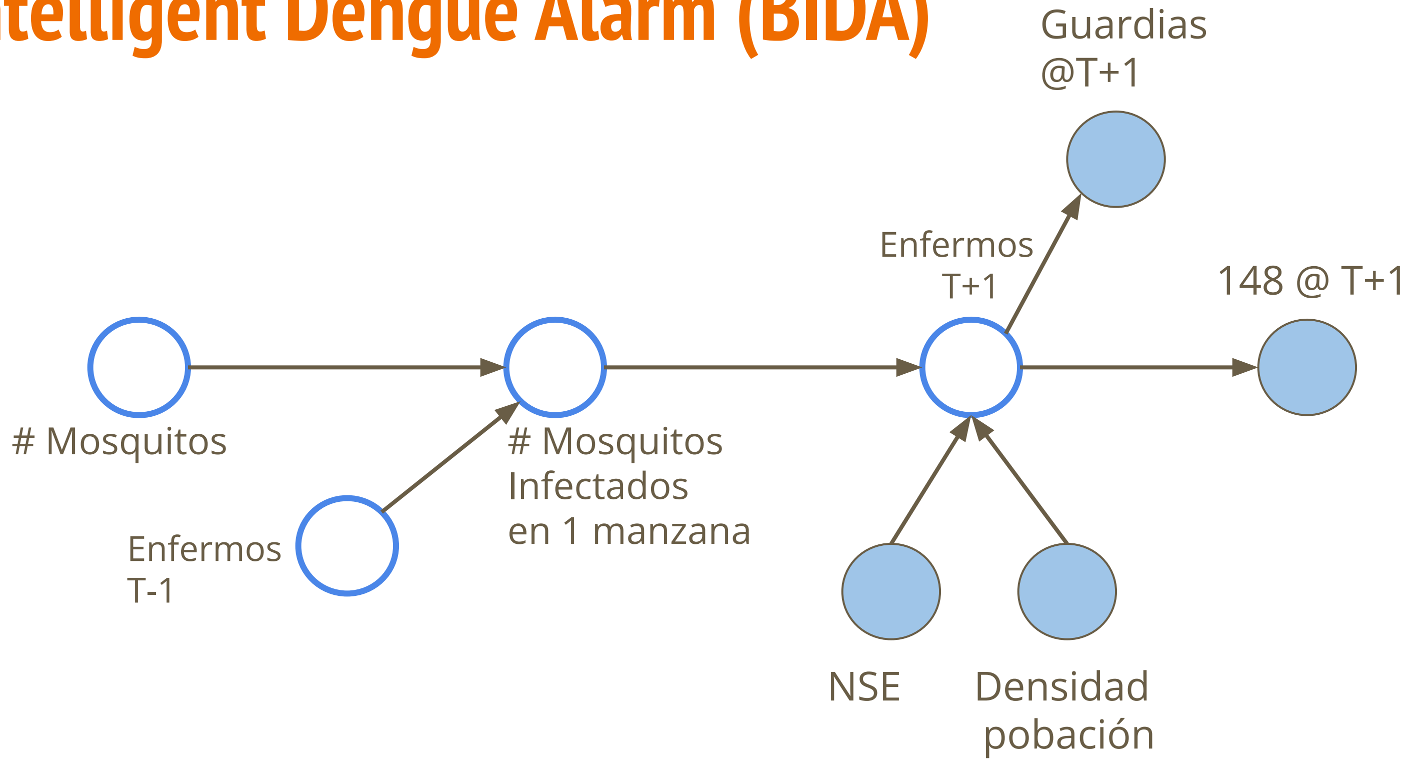

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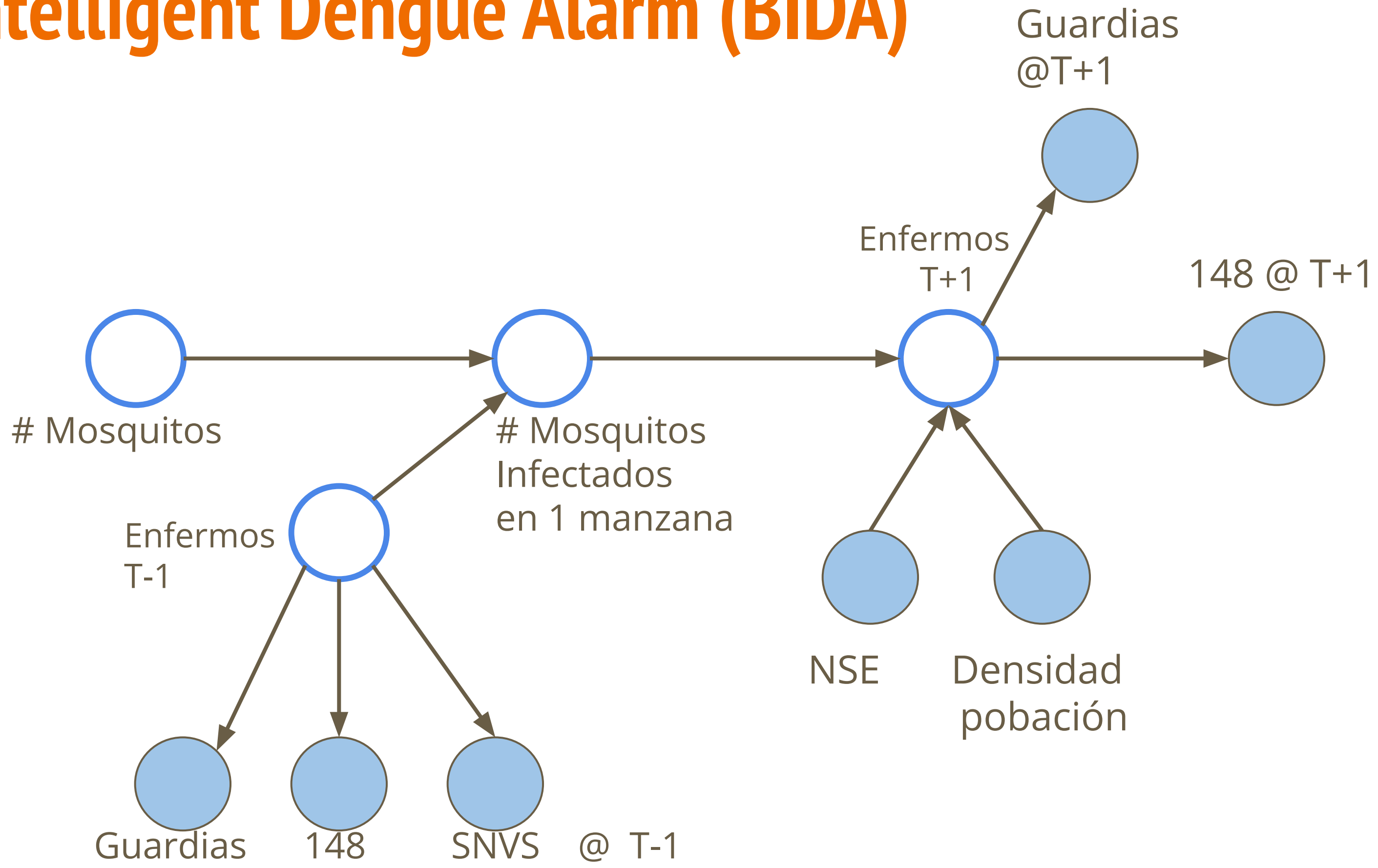

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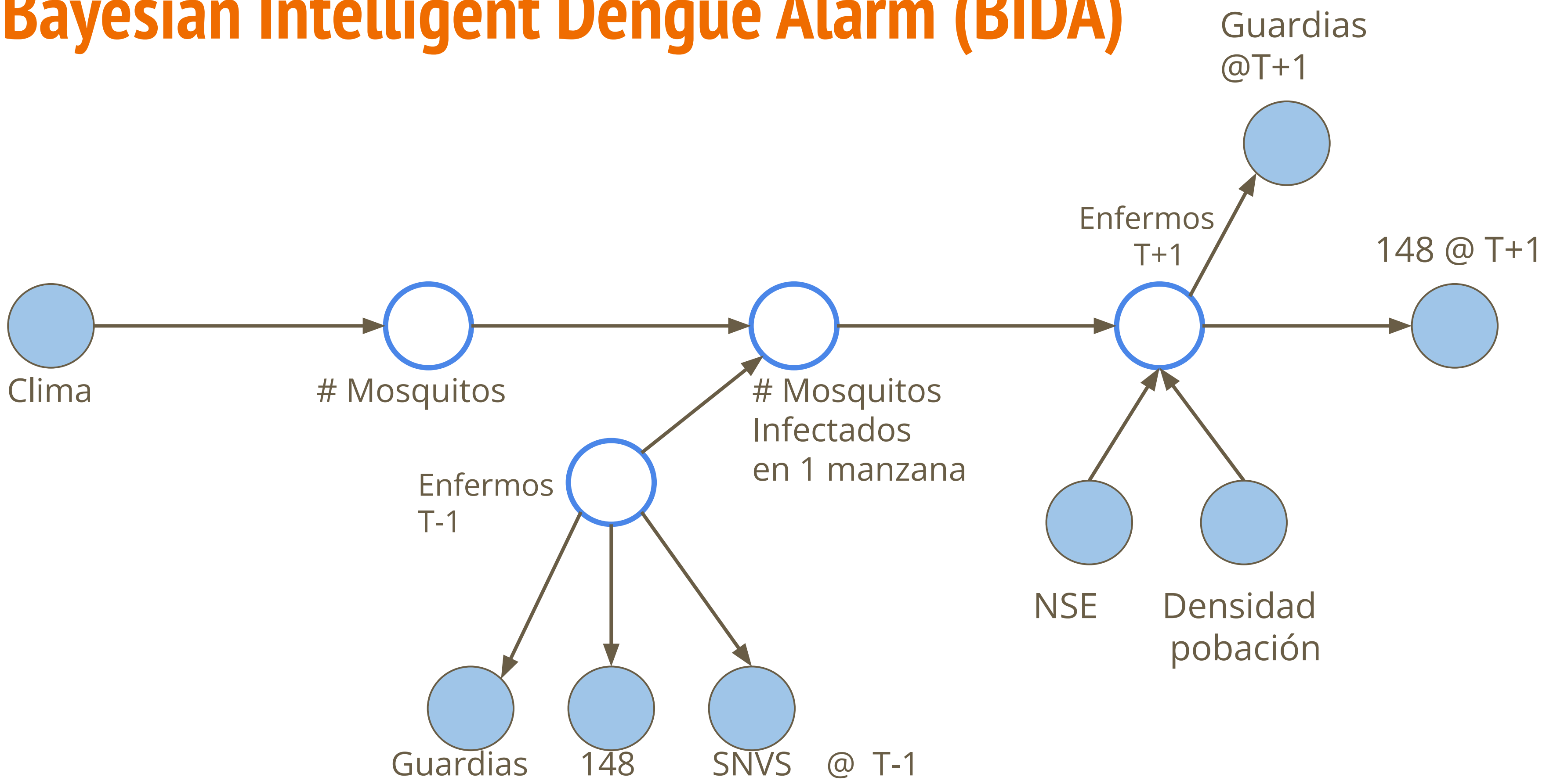

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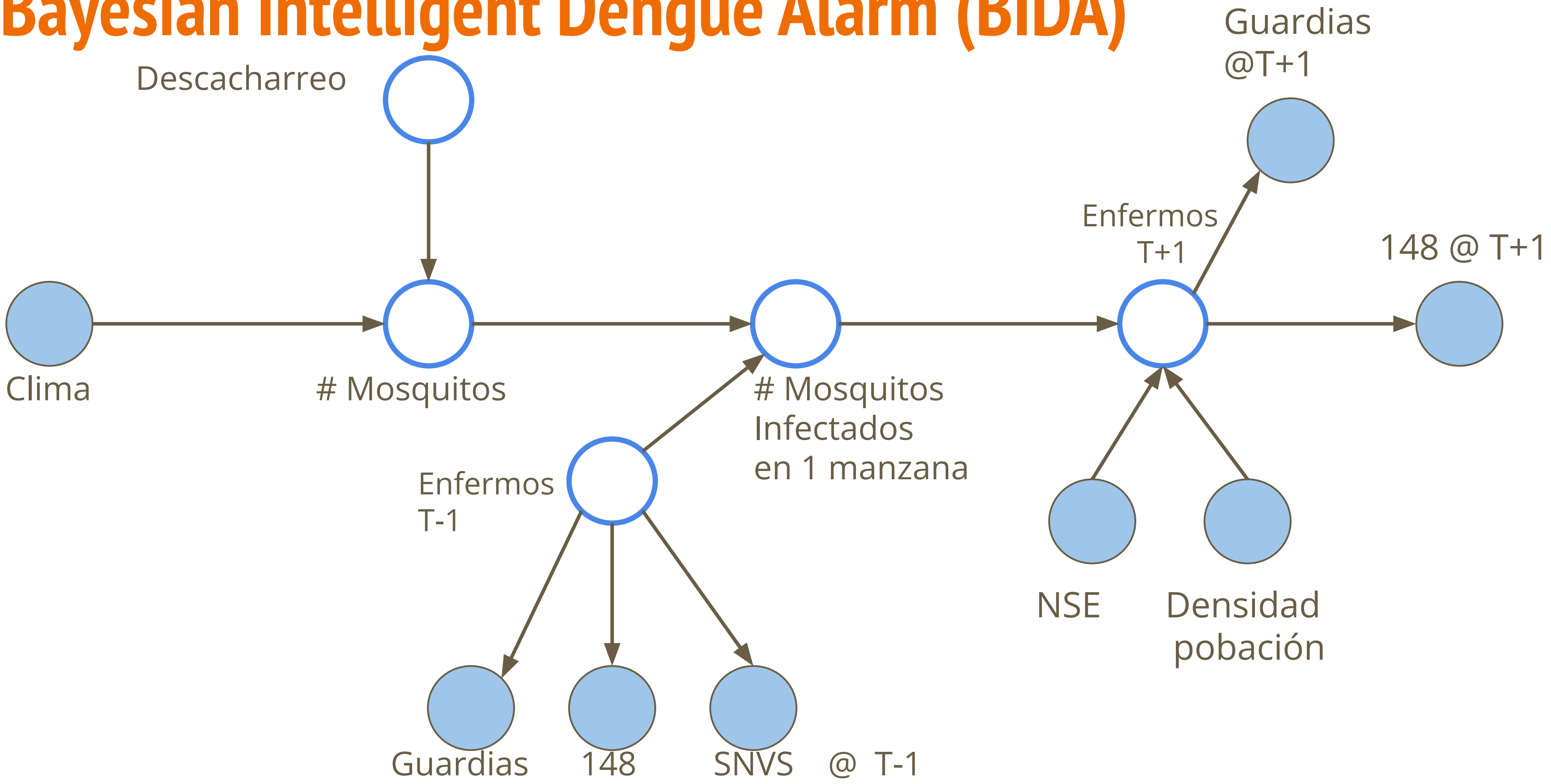

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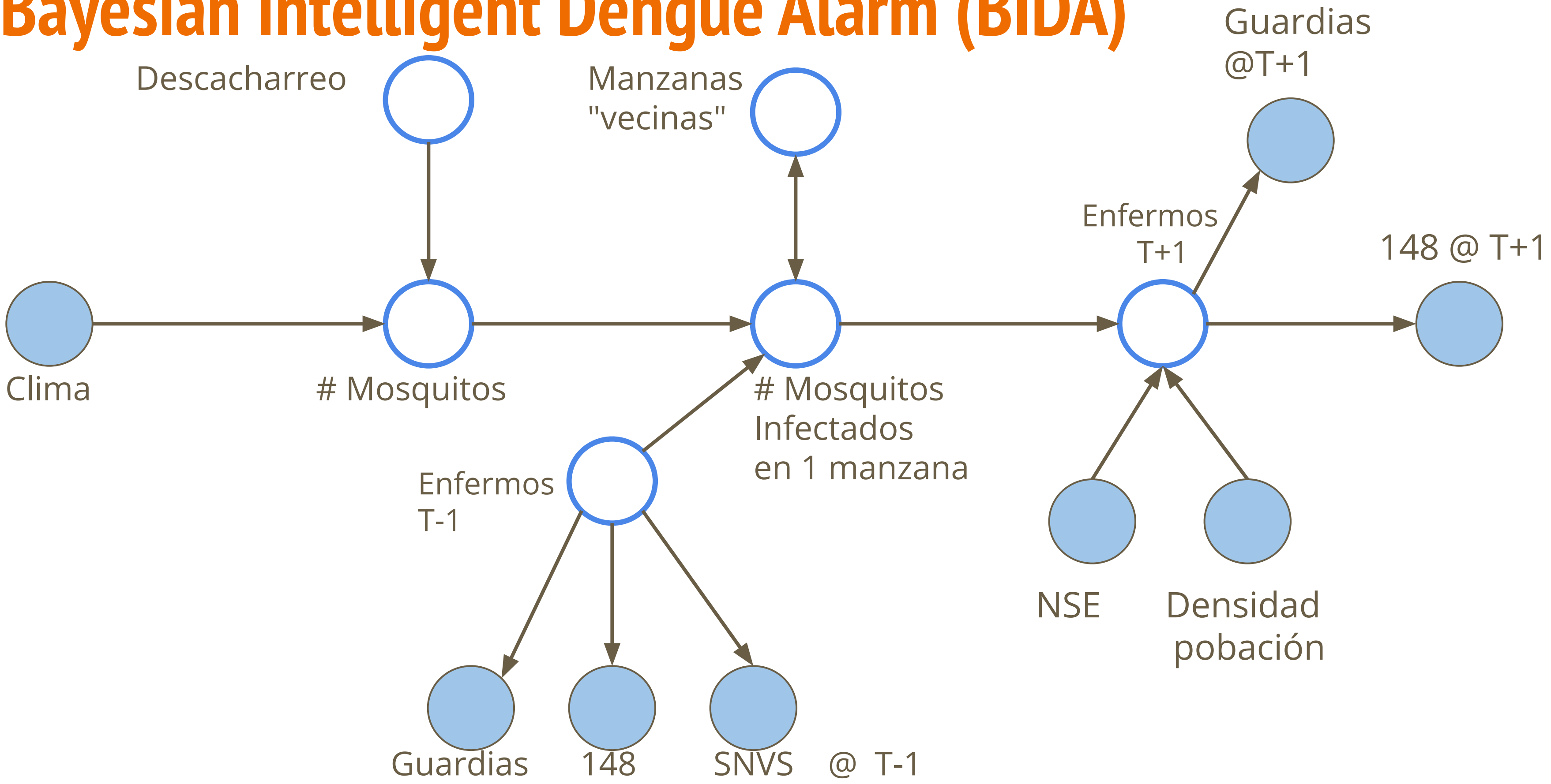

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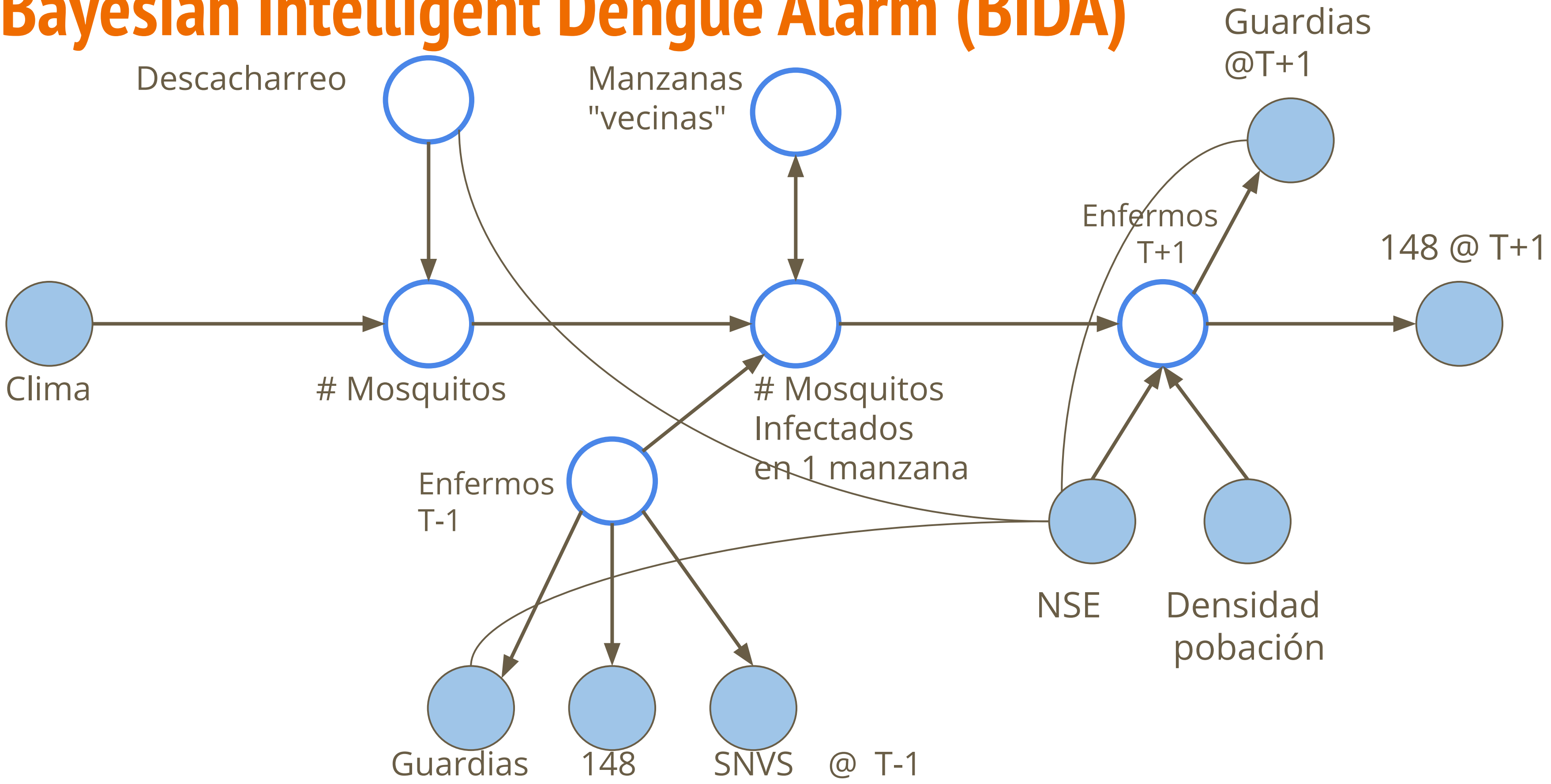


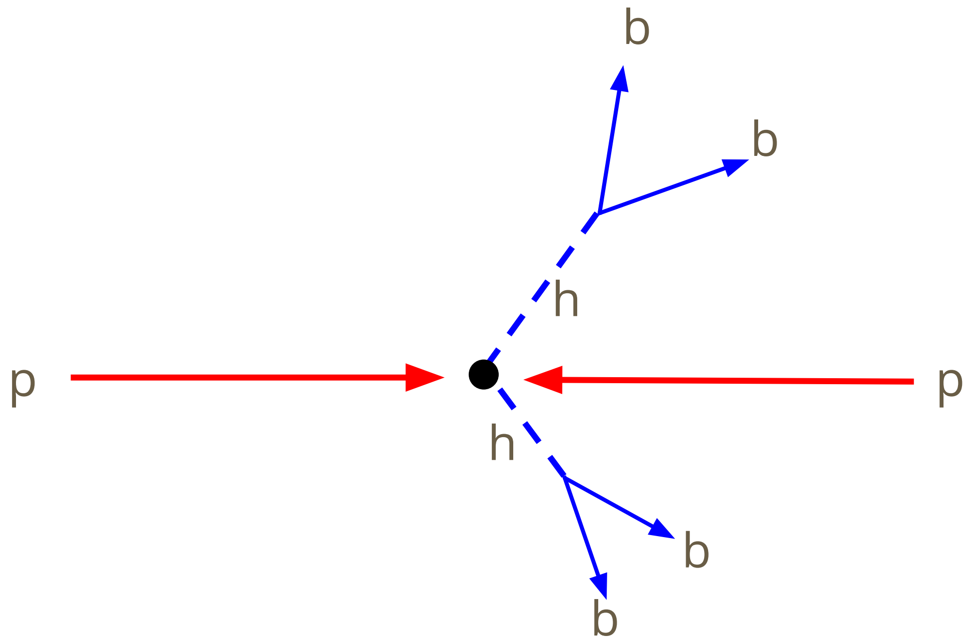
Application in *particle physics*

$pp \longrightarrow hh \longrightarrow bbbb$

2402.08001

E.A., L.Da Rold, S. Tanco, M, Szewc, A. Szynkman, S. Tanco, T. Tarutina

Physics: $pp \longrightarrow hh \longrightarrow bbbb$



Physics: pp ⟶ hh ⟶ bbbb

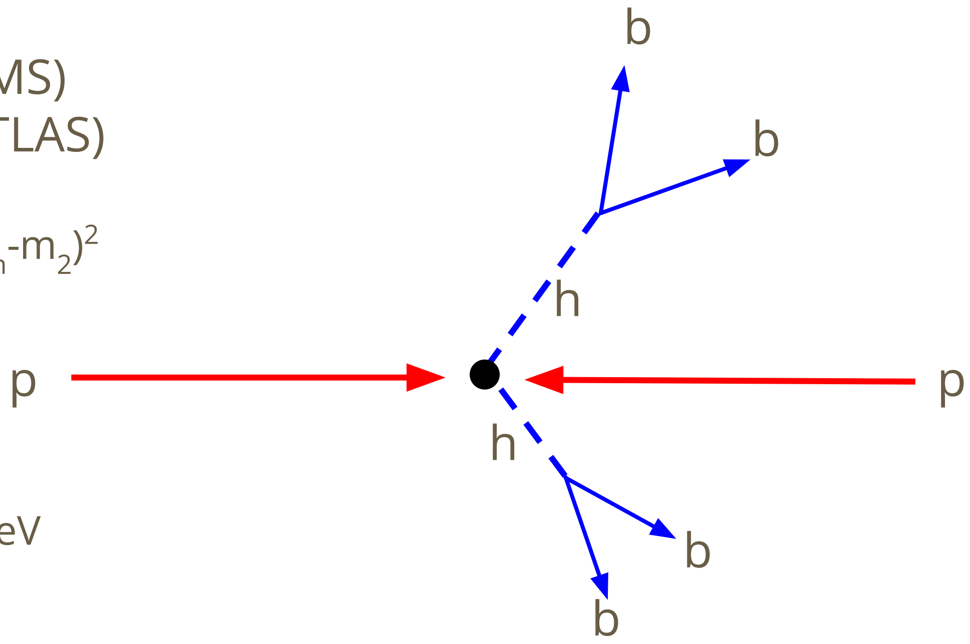
2202.09617 (CMS)
2301.03212 (ATLAS)

$\chi^2 = (m_h - m_1)^2 + (m_h - m_2)^2$

O_1: χ > or < 25 GeV

O_2: 3b or 4b

Plus *improvements*



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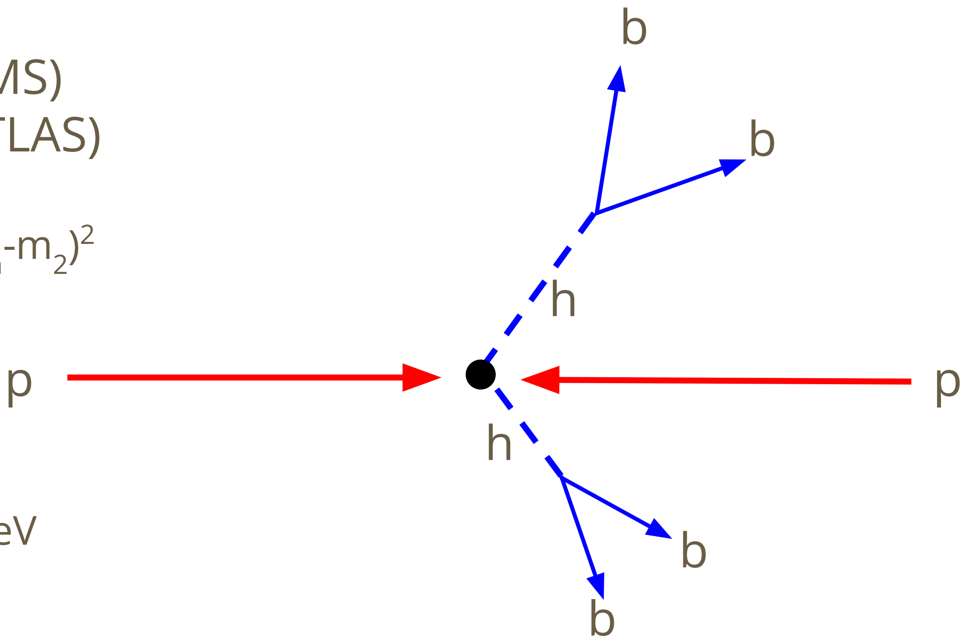

Bayesian framework

O_1: b-tagging score jet 1

O_2: b-tagging score jet 2

O_3: b-tagging score jet 3

O_4: b-tagging score jet 4

O_5: m_1

O_6: m_2

Physics: pp ⟶ hh ⟶ bbbb

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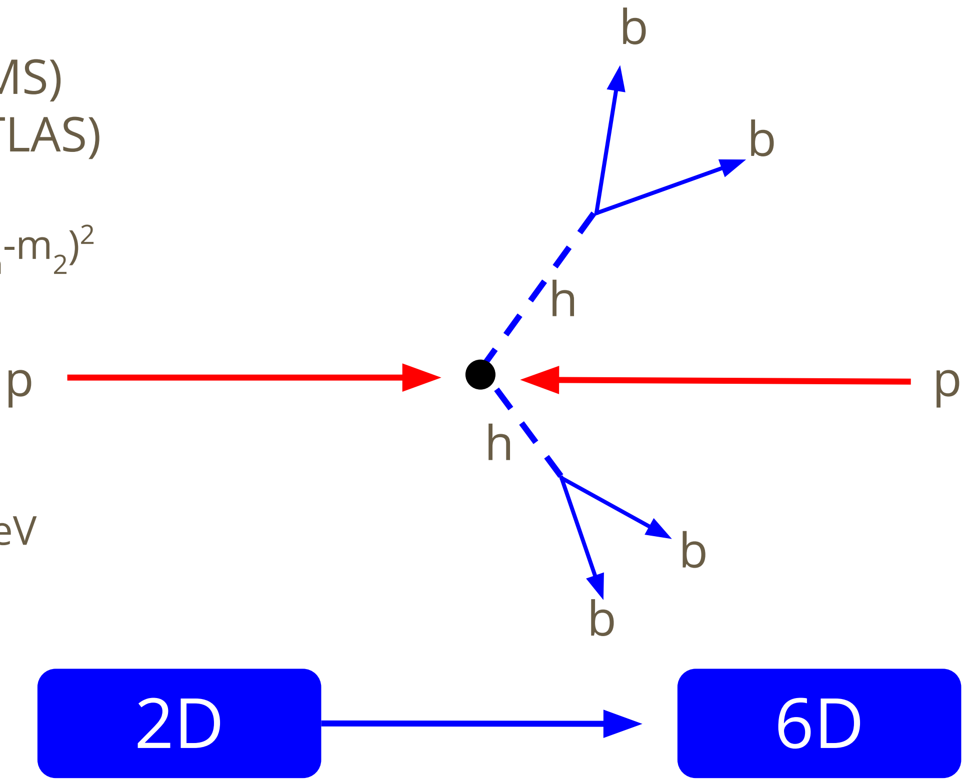

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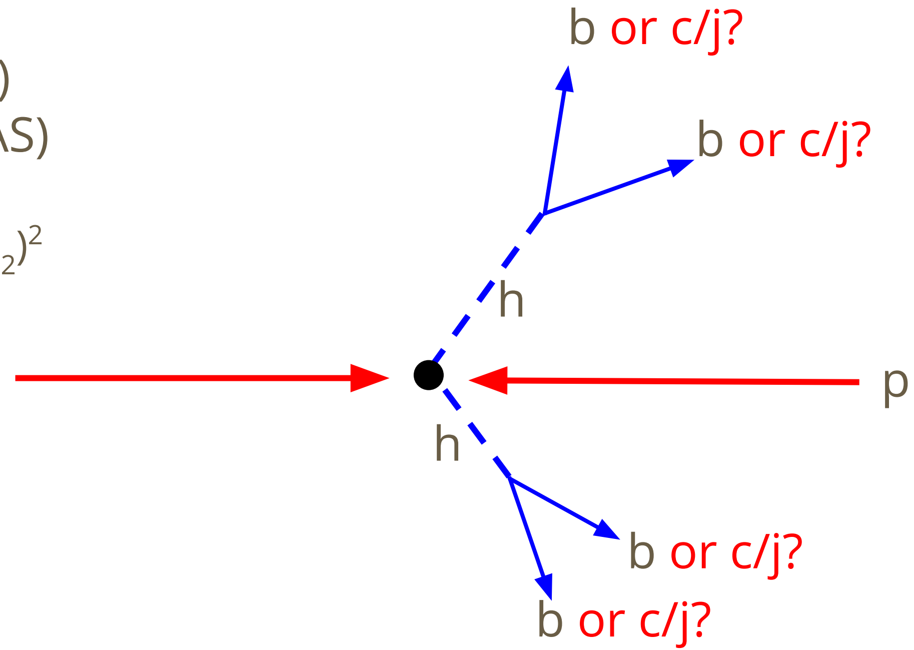

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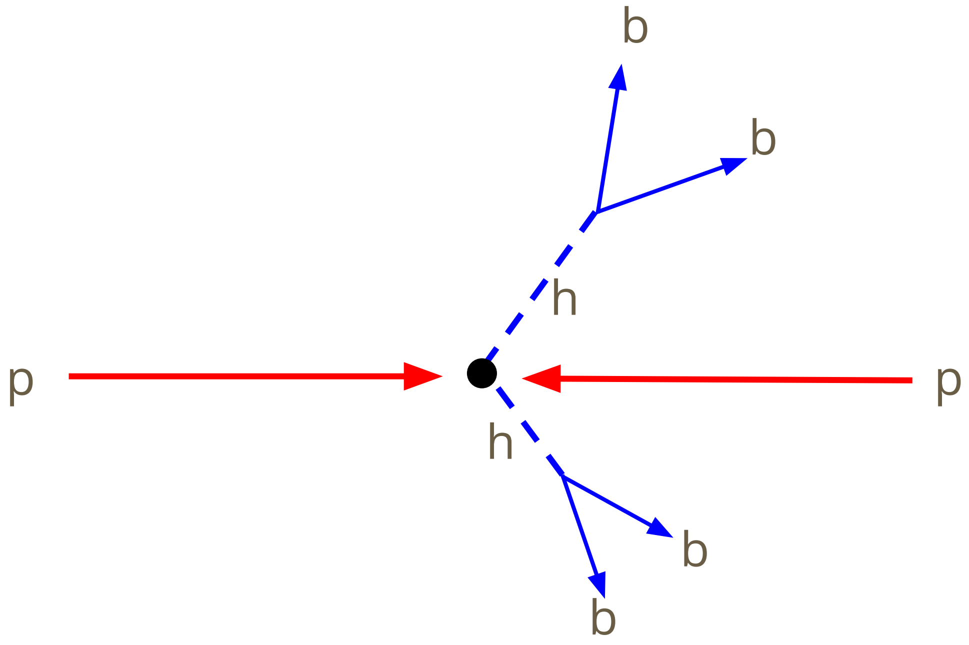
Plus *improvements*

2D → 6D

Math: bbbb



Repeat N times:

- D = 6 numbers sampled
- K = 3 classes
- Depending on the class the D numbers are sampled from given (unknown) PDFs

Toy-model and Toy-problem

Setup:

Synthetic signal (bbbb) and backgrounds (bbcc, cccc)

Toy-model and Toy-problem

Setup:

Synthetic signal (bbbb) and backgrounds (bbcc, cccc)

Data:

20k events, signal is 1%, 0.5% or 0%

Toy-model and Toy-problem

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Toy problem:

m_{bb} ~ N(125,10) or ~ Exp(0.003)

B-tag: 4 x b-scores ~ beta(), sampled from either *bbbb*, *bbcc*, *cccc*

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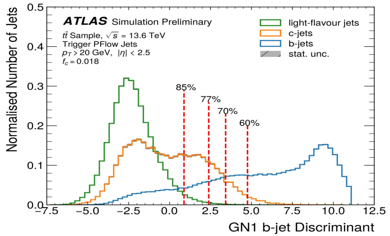

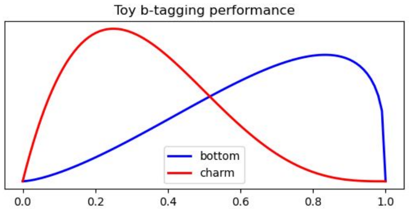

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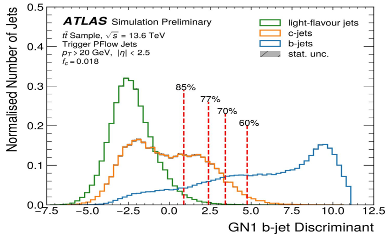

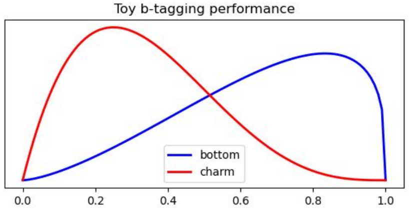

We'll start from biased priors

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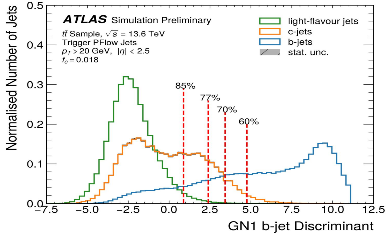

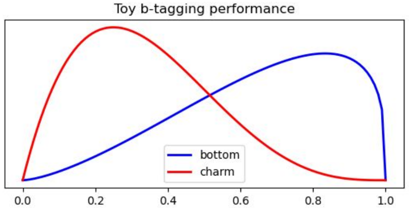

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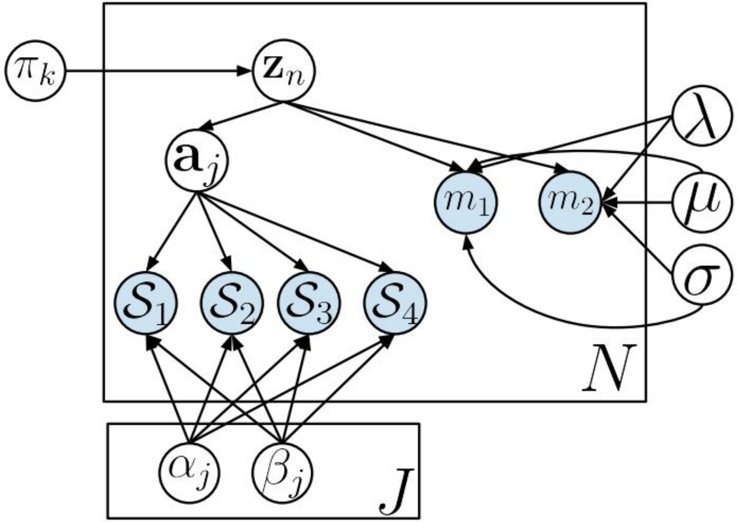
Important
prior-knowledge

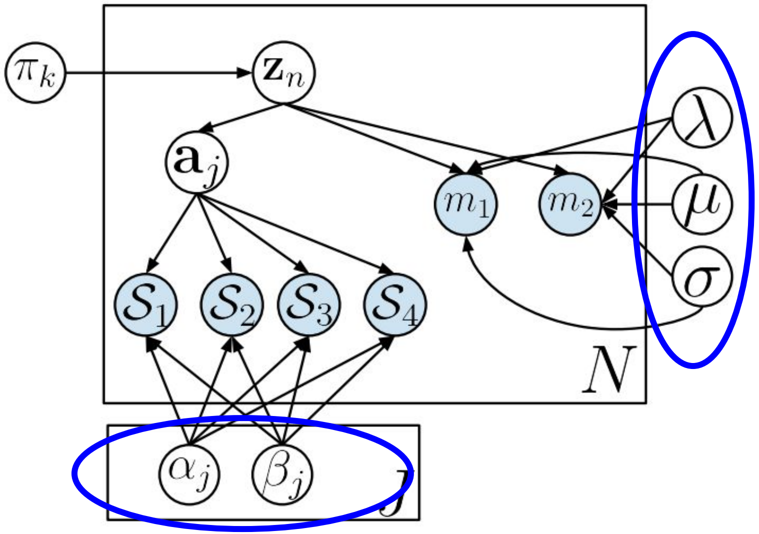
Bayes @ Toy-problem

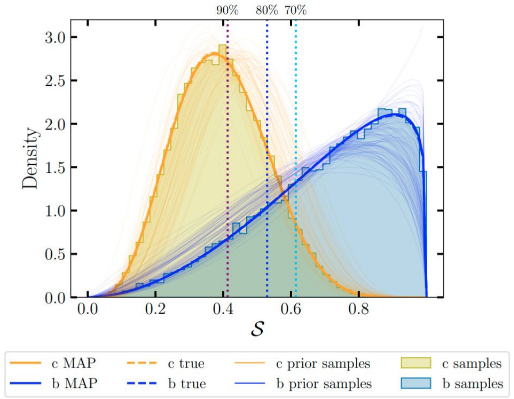
6 Observables

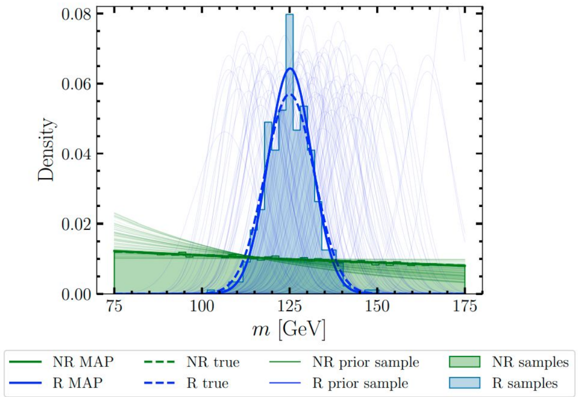


Bayes @ Toy-problem

6 Observables



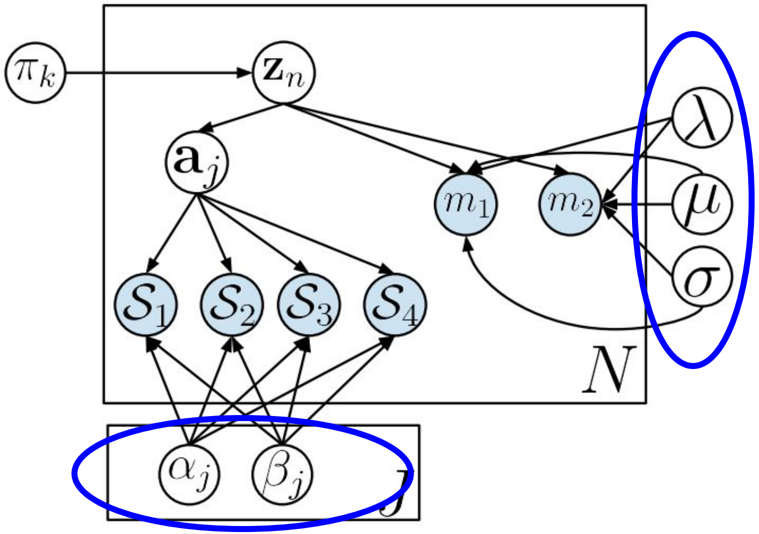




Inference results

Bayes @ Toy-problem

6 Observables



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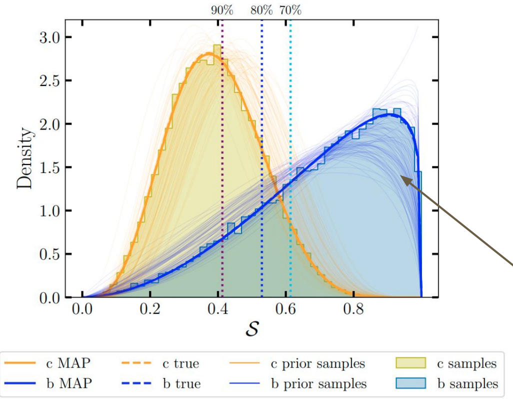
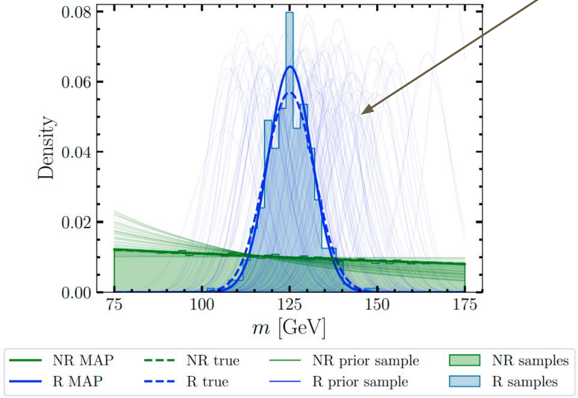
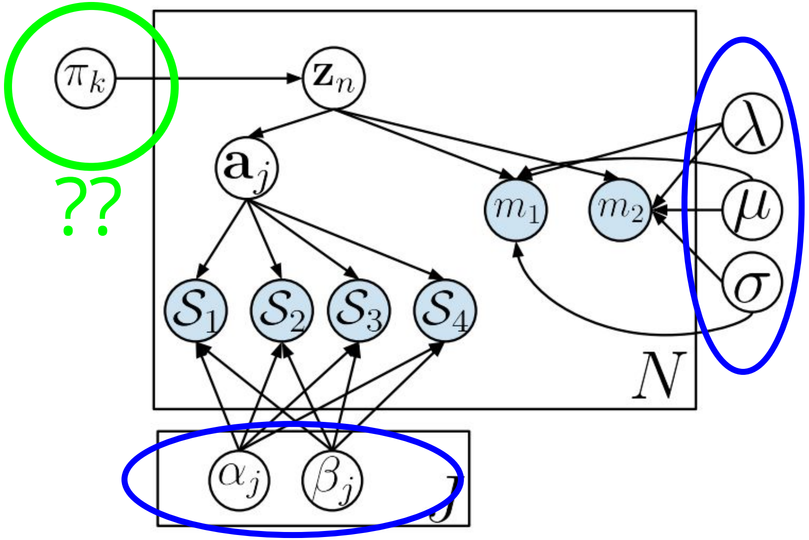


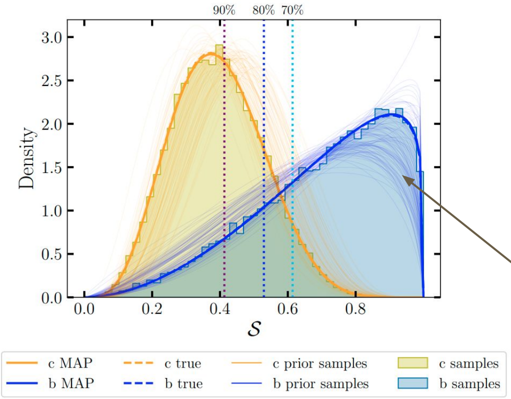


Biased priors, but inference gets correct curves!

Bayes @ Toy-problem

6 Observables





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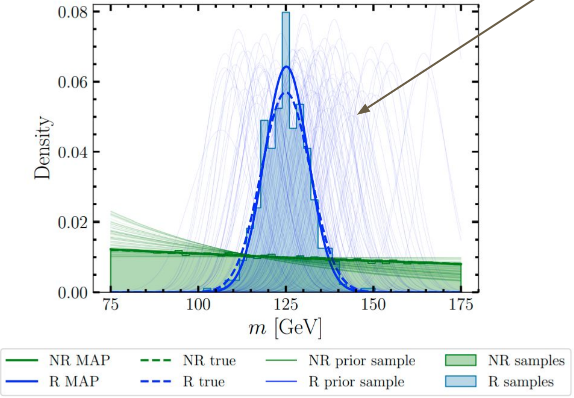
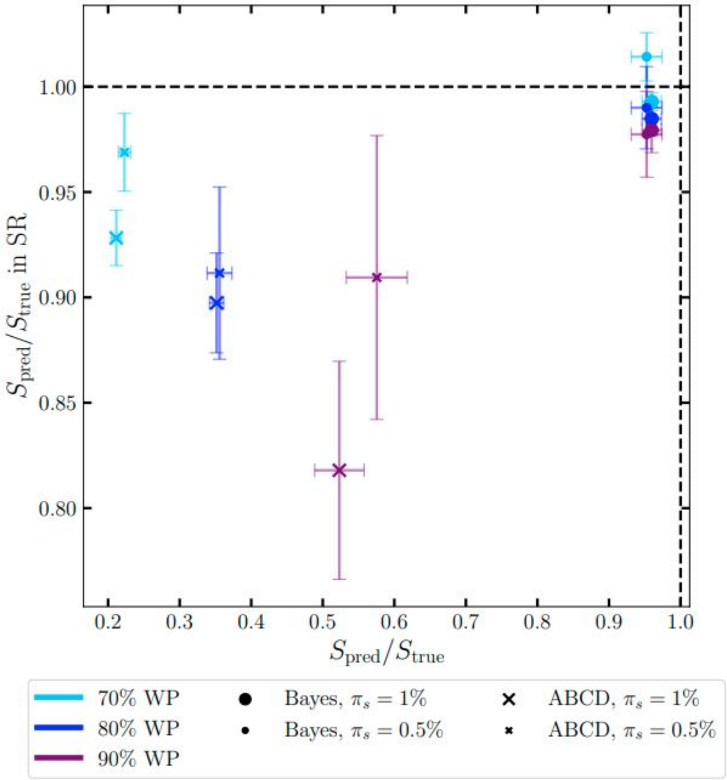


Improvements at Bayesian framework

1% &
0.5%
signal



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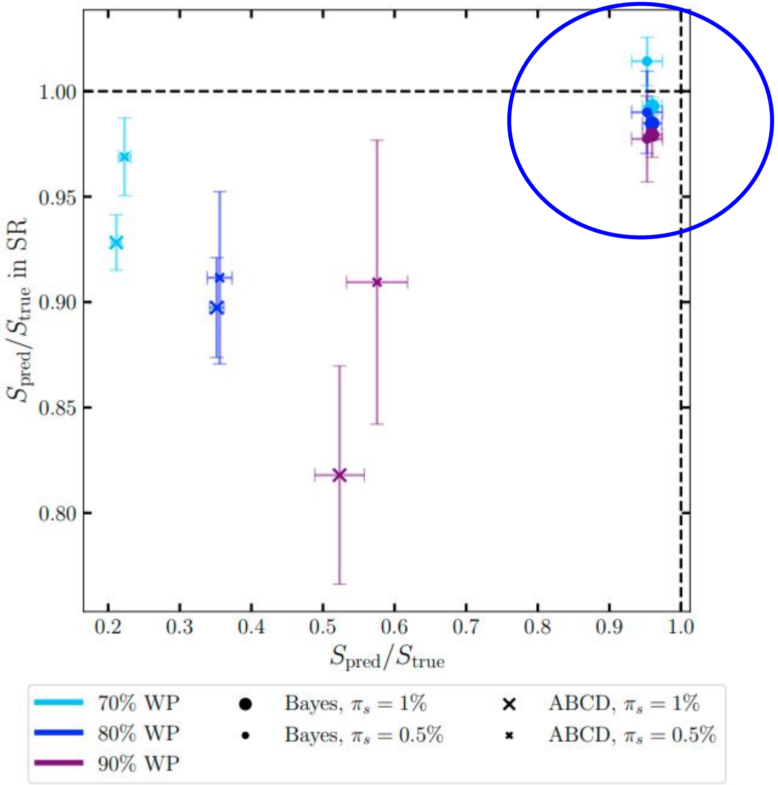
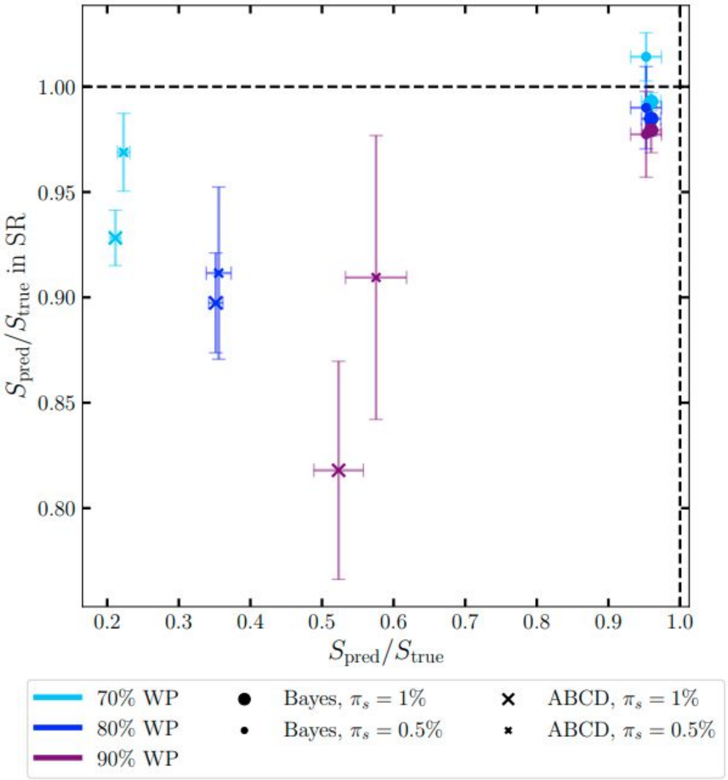


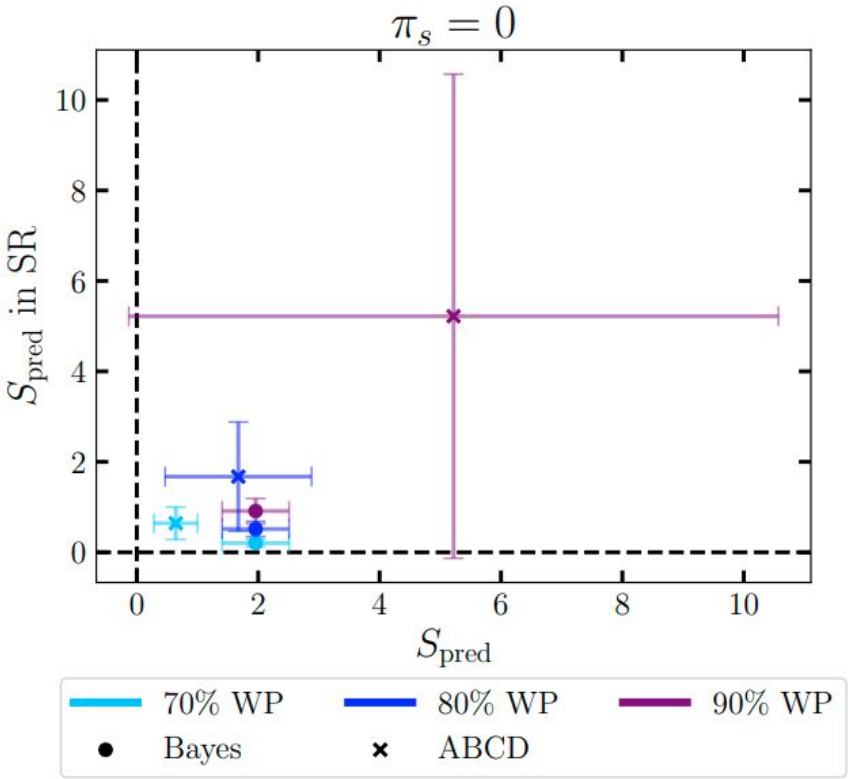
Bayesian framework improves usual methods exploiting correlations

ABCD Vs Bayesian framework

0% signal

1% & 0.5% signal

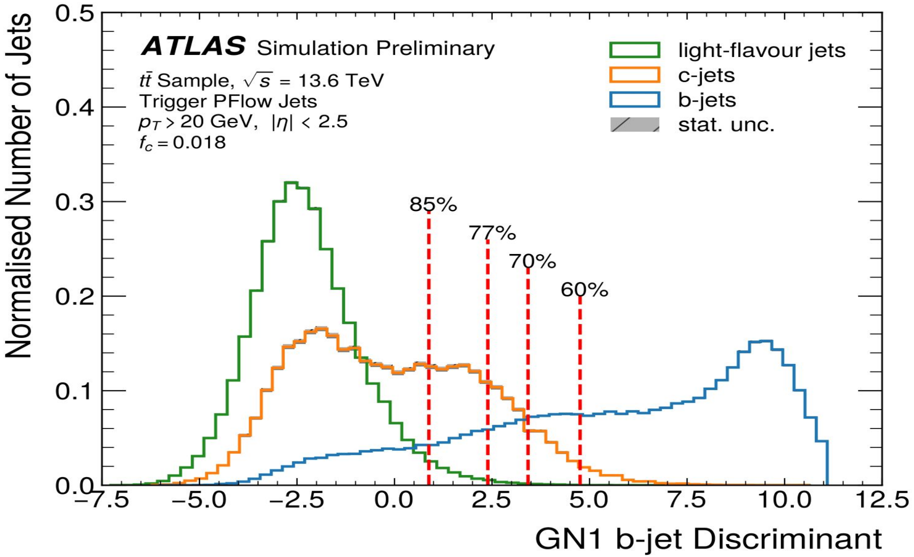




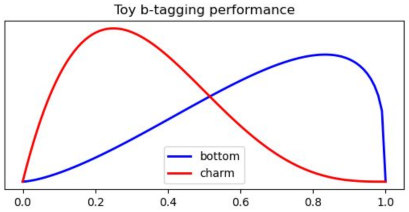
Bayesian exploitation of continuity and unimodality

Yuling Yao + EA
2404.01387

Exploit Continuity and Unimodality

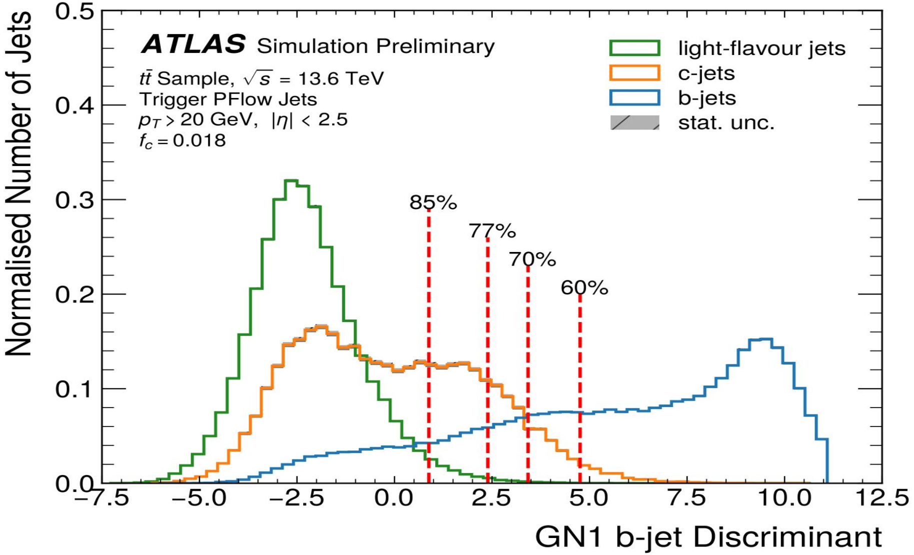


≈



Previously

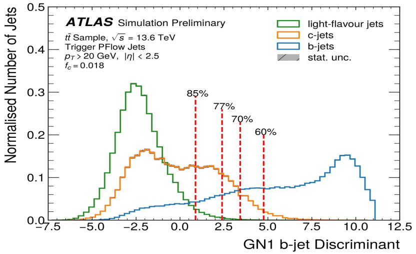
Exploit Continuity and Unimodality



We'll infer these continuous arbitrary distributions!

The leverage: continuity, unimodality & multidimensionality!

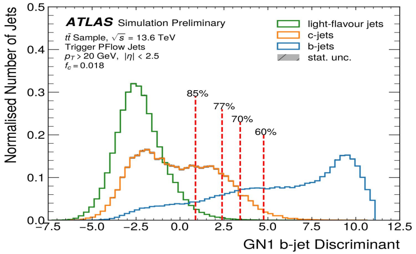
Gaussian Processes



$$f(\boldsymbol{x};\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{\sqrt{(2\pi)^k * det(\boldsymbol{\Sigma})}} * e^{-\frac{1}{2}*((\boldsymbol{x}-\boldsymbol{\mu})^T \cdot inv(\boldsymbol{\Sigma}) \cdot (\boldsymbol{x}-\boldsymbol{\mu}))}$$

We bin the score and ***x*** contains the distribution values in each bin

Gaussian Processes



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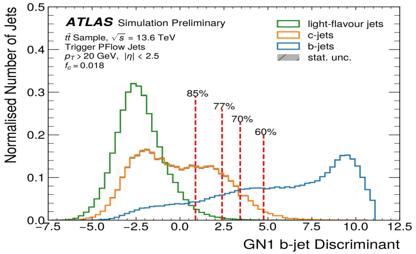
We bin the score and ***x*** contains the distribution values in each bin

Each bin is sampled around some expected μ

Define uncertainty and how related are neighbouring bins: Continuity!

$$\Sigma^{-1} = \begin{pmatrix} 2 & 1 & 0.5 & 0 & \ldots. & & & & \\ 1 & 2 & 1 & 0.5 & 0 & \ldots & & & \\ 0.5 & 1 & 2 & 1 & 0.5 & 0 & \ldots & & \\ 0 & 0.5 & 1 & 2 & 1 & 0.5 & 0 & \ldots. & \\ \ldots. & \ldots\ldots. & & \ldots.. & \ldots.. & & & & \end{pmatrix}$$

Gaussian Processes



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Define uncertainty and how related are neighbouring bins: Continuity!

We can sample continuous curves around a central curve with very few hyperparameters

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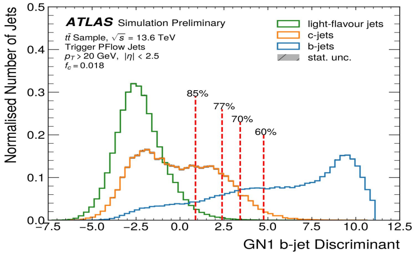
Gaussian Processes



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Define uncertainty and how related are neighbouring bins: Continuity!

Prior information

We can sample continuous curves around a central curve with very few hyperparameters

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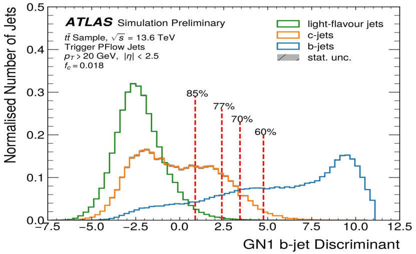
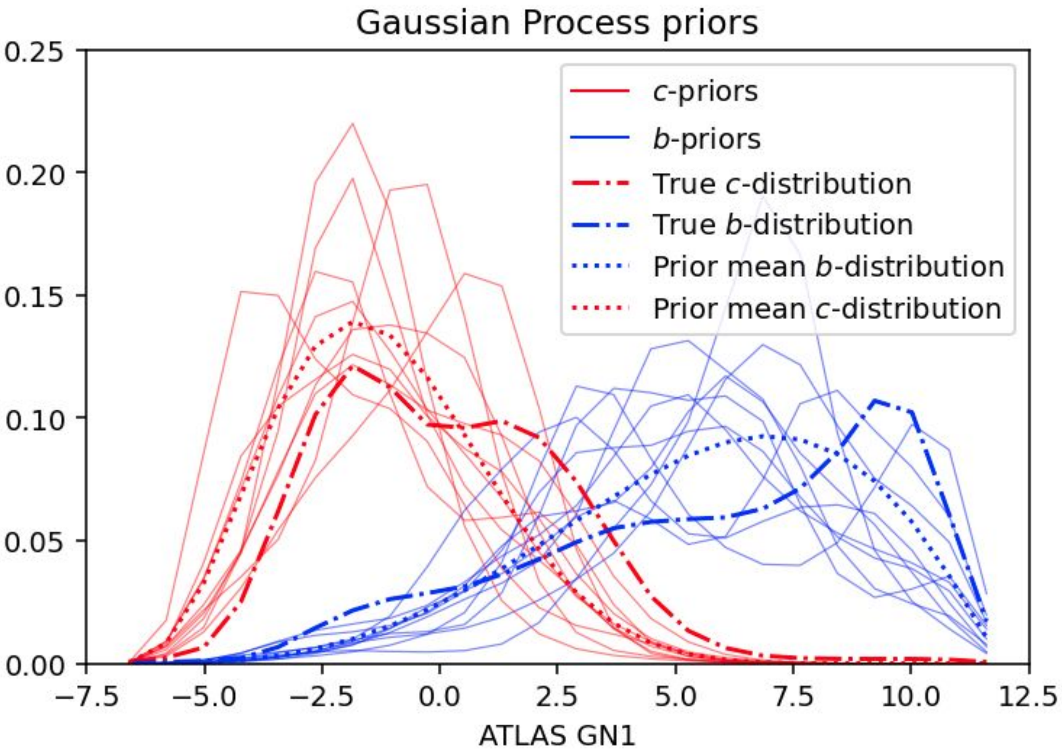
Gaussian Processes

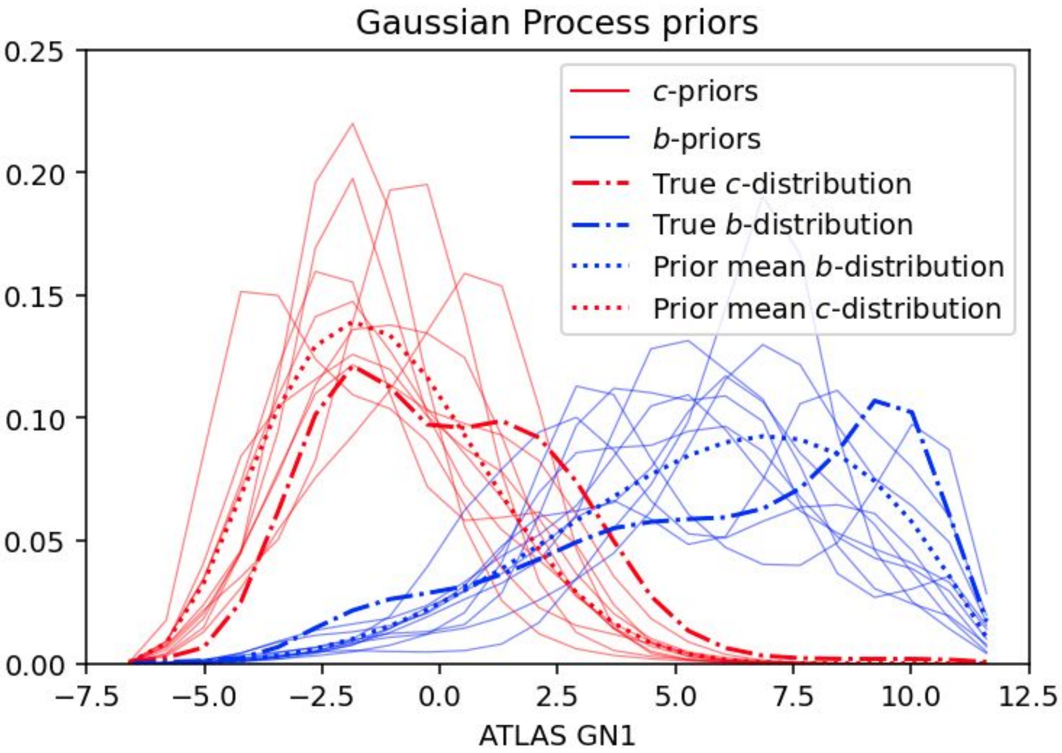




Gaussian Processes

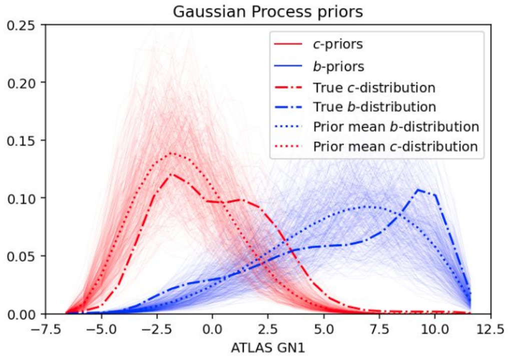
The game:

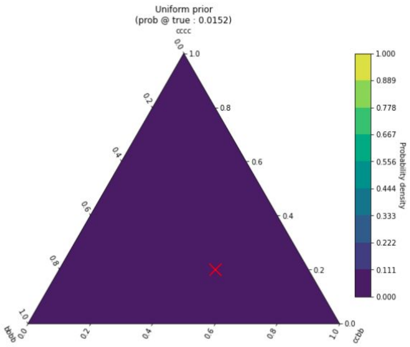
- Starts with biased prior
- The data will shift the posterior to the most likely distribution, which should be the true
- Leverage:
  - Multidimensionality
  - Continuity
  - bbbb, ccbb, cccc



Gaussian Processes: Results

This is how we start





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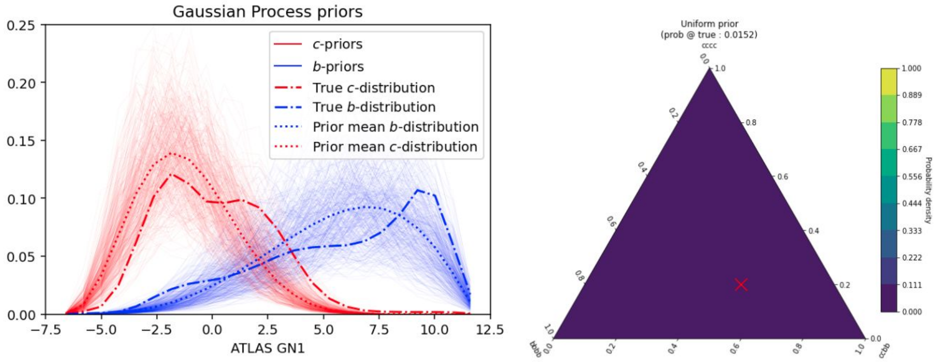
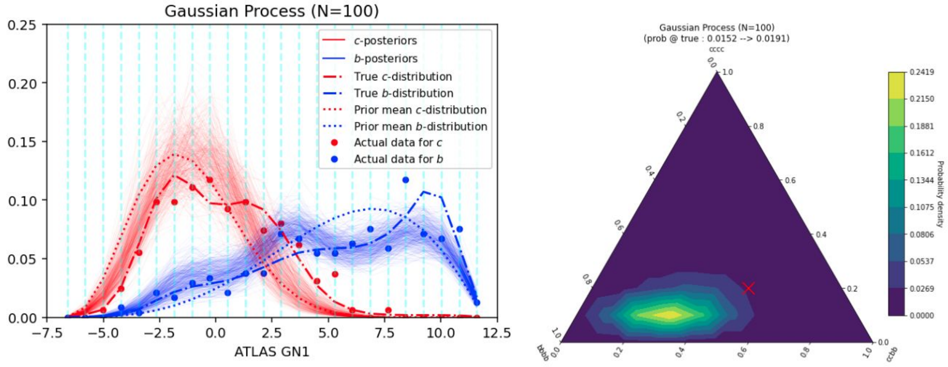


After seeing 100 events



Gaussian Processes: Results

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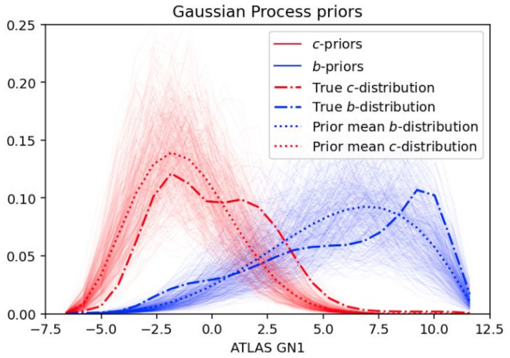
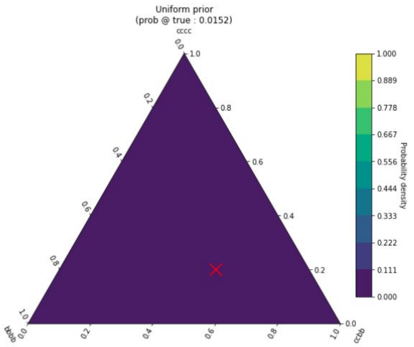
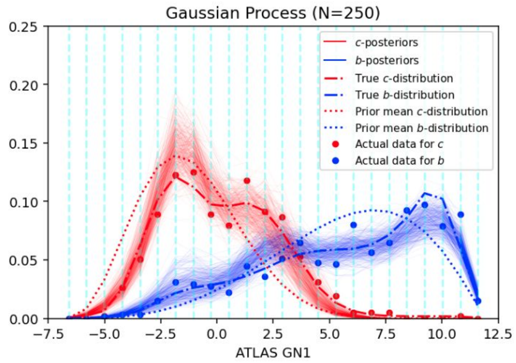
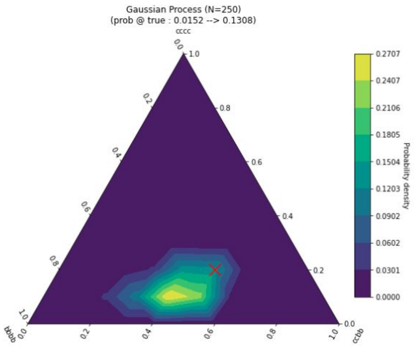




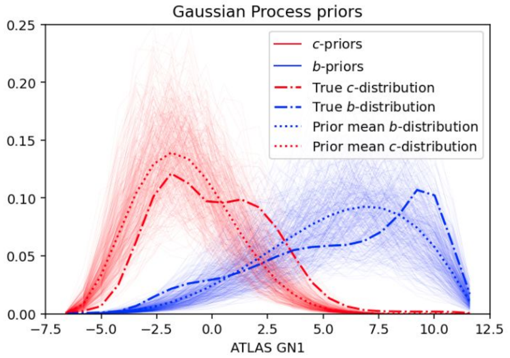
After seeing 250 events

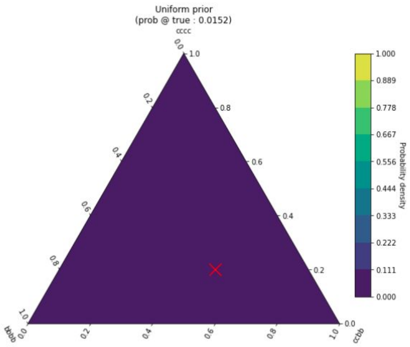




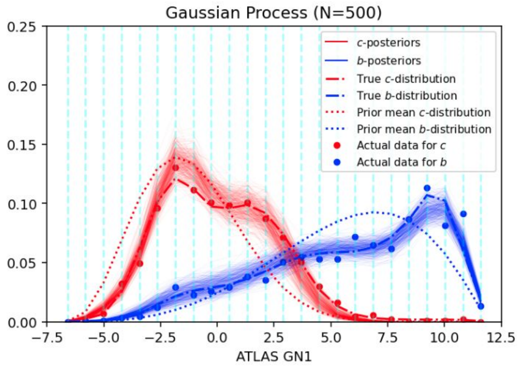
Gaussian Processes: Results

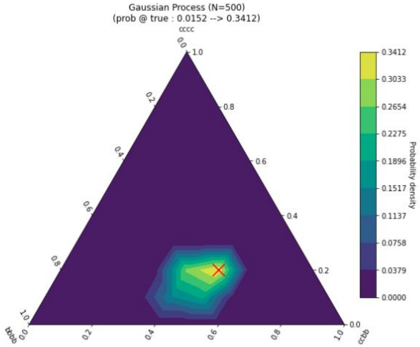
This is how we start





After seeing 500 events

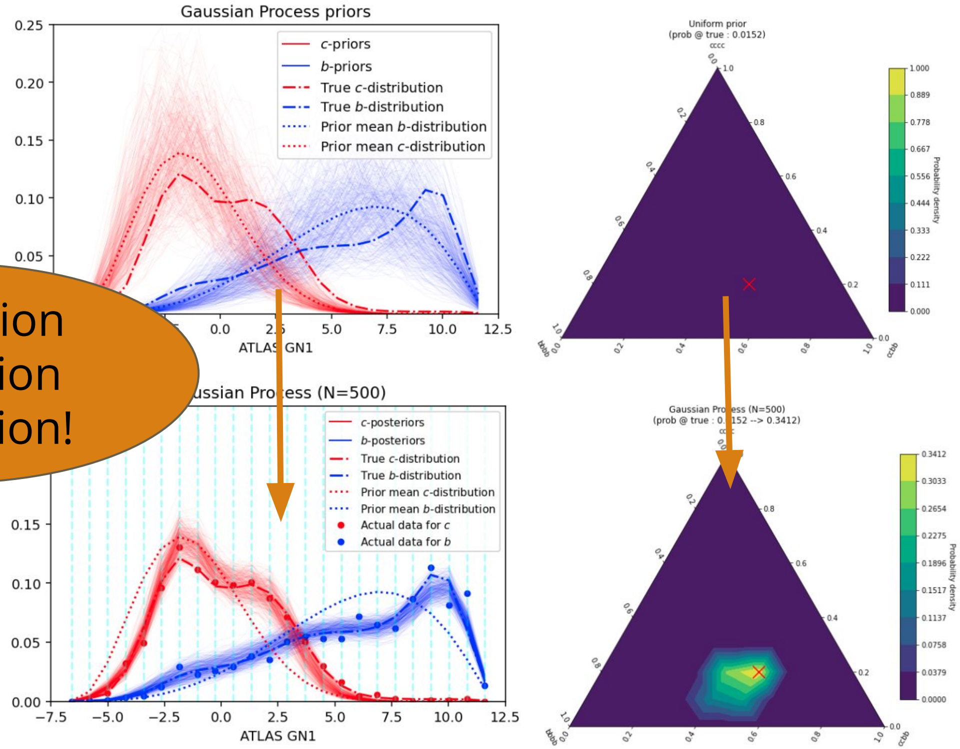




Gaussian Processes: Results

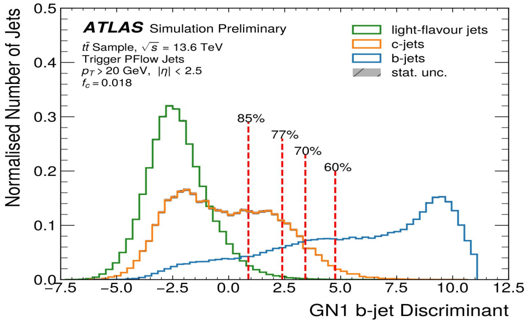
This is how we start

After seeing 500 events



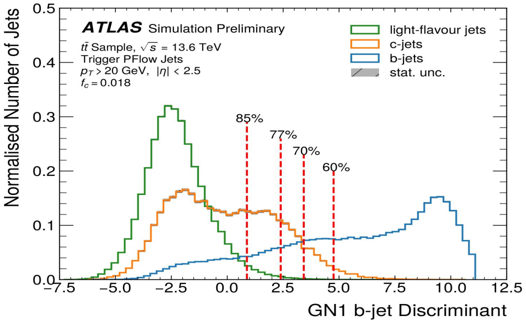
Correlation correlation correlation!

Unimodal model



How to sample unimodal arbitrary continuous curves ?

Unimodal model

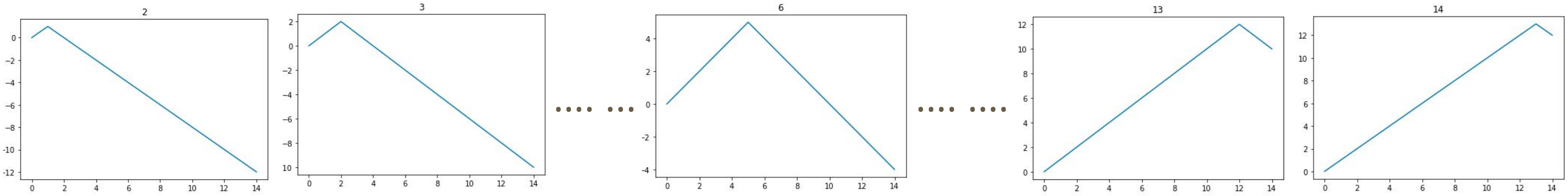


Prior information!

How to sample unimodal arbitrary continuous curves ?

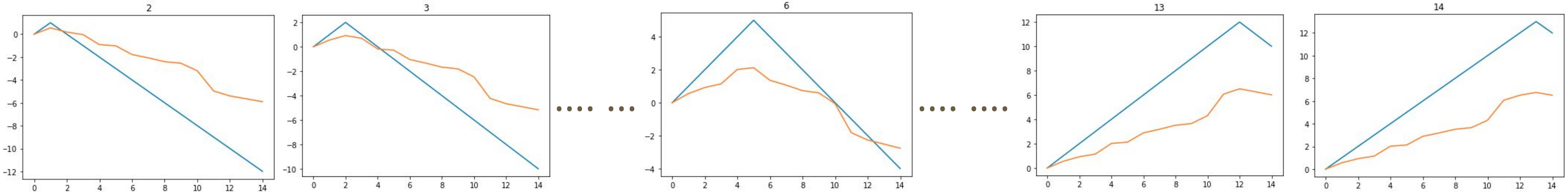
Unimodal model

Construct strict linear unimodal, one for each bin



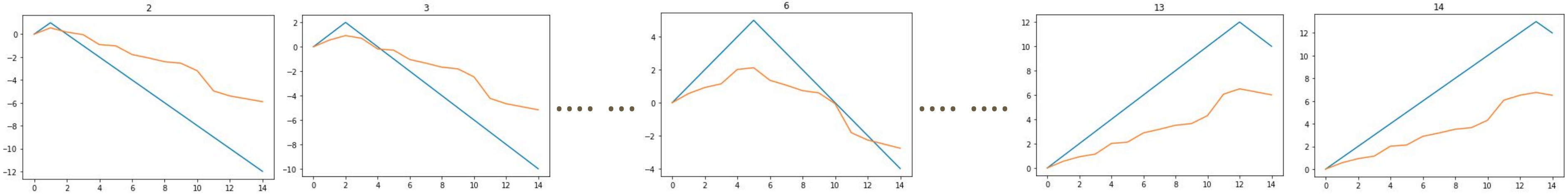
Unimodal model

Allow for randomness with a half normal $|N(0,0.5)|$ at each step

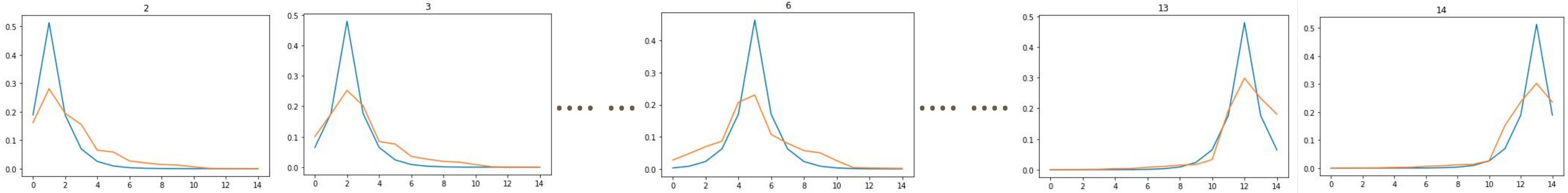


Unimodal model

Allow for randomness with a half normal |*N*(0,0.5)| at each step



Apply *softmax()* to make them integrate to unity



Unimodal model

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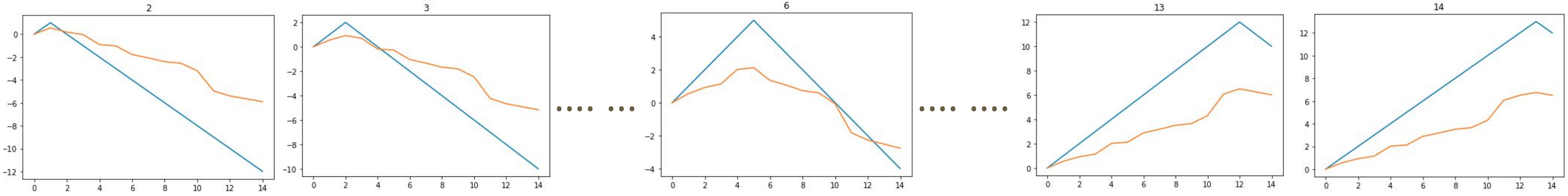

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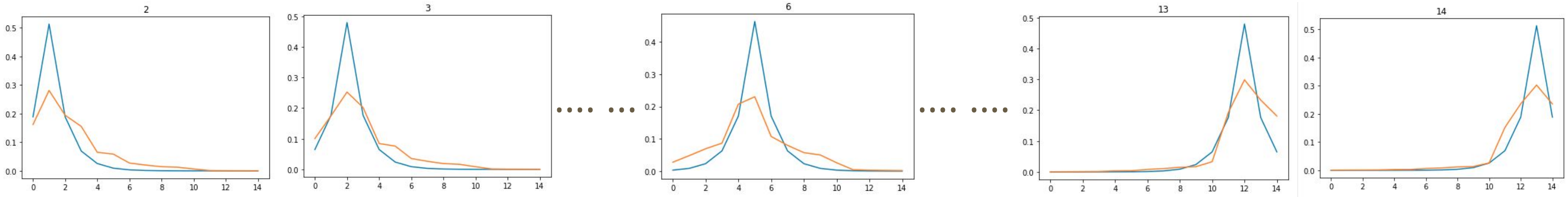
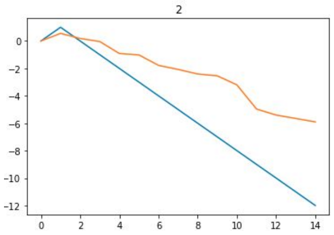
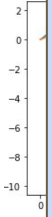


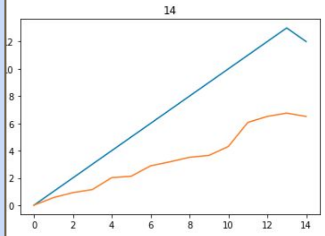
How to have unimodal at any bin and with some freedom of shape in other bins?

Unimodal model

Allow for random



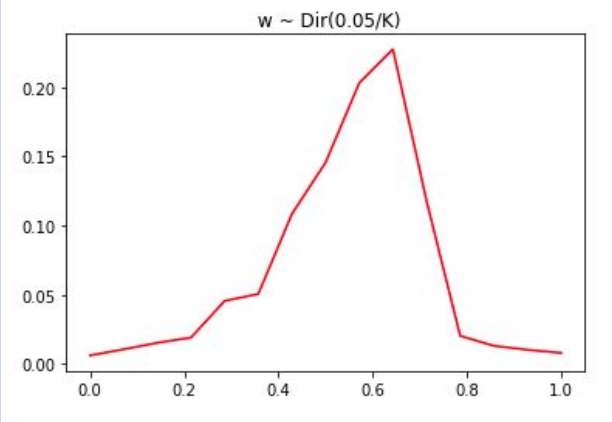




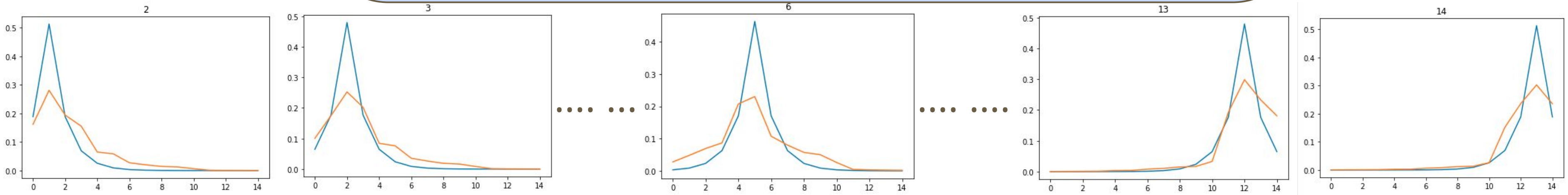
Sum orange curves weighted by

w ~Dirichlet(α)

With α small



Apply *softmax()* to



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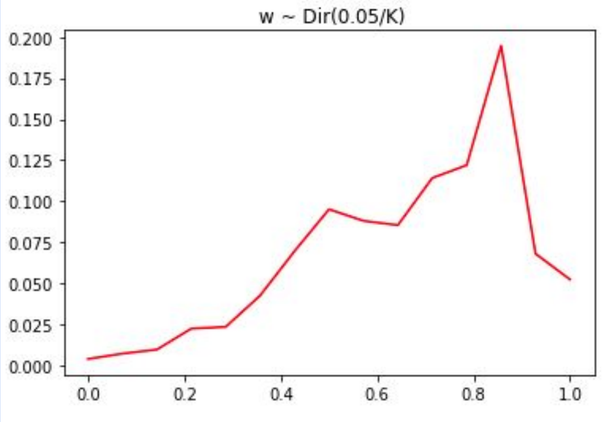

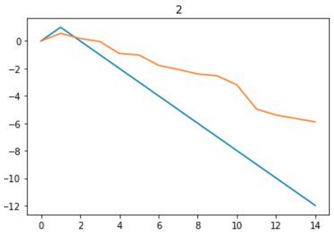

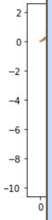

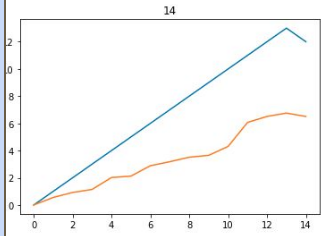

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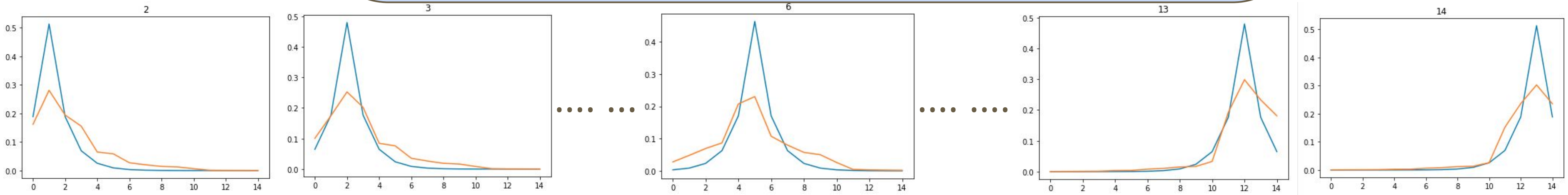
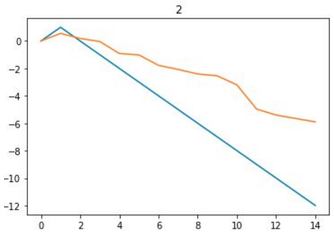
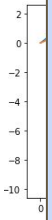


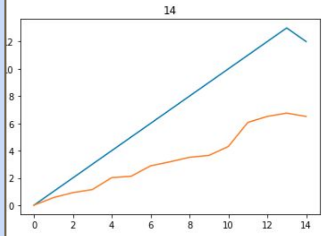
How to have unimodal at any bin and with some freedom of shape in other bins?

Unimodal model

Allow for random







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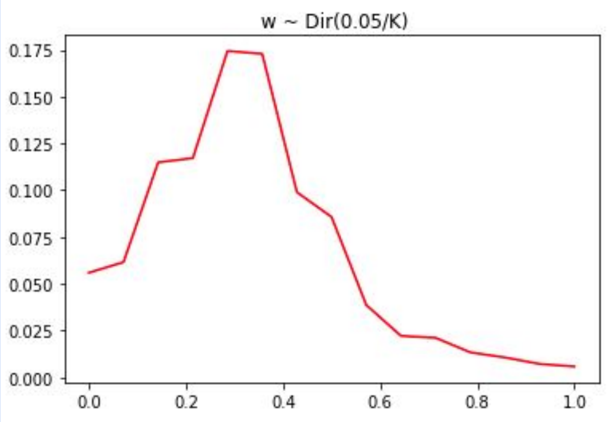

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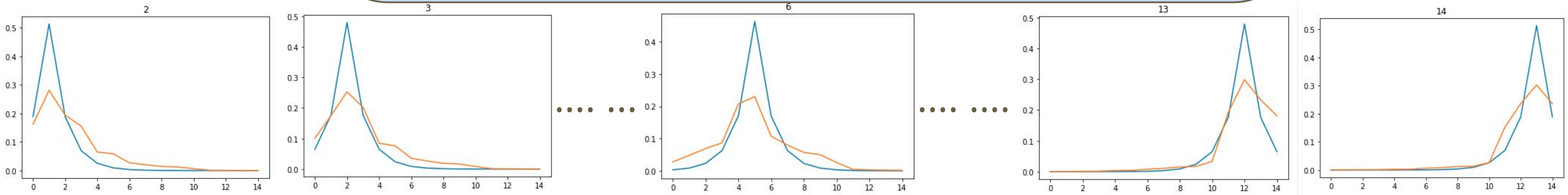

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Unimodal model

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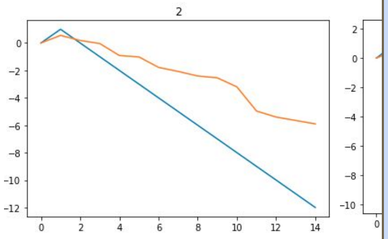

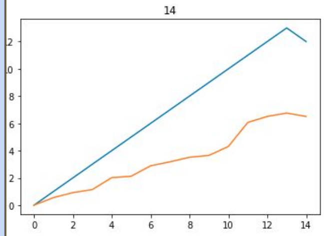

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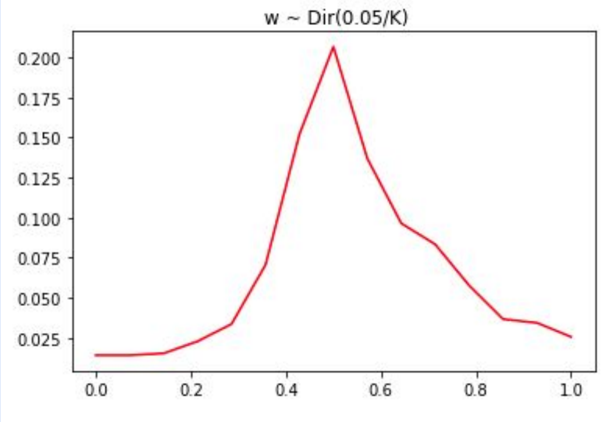

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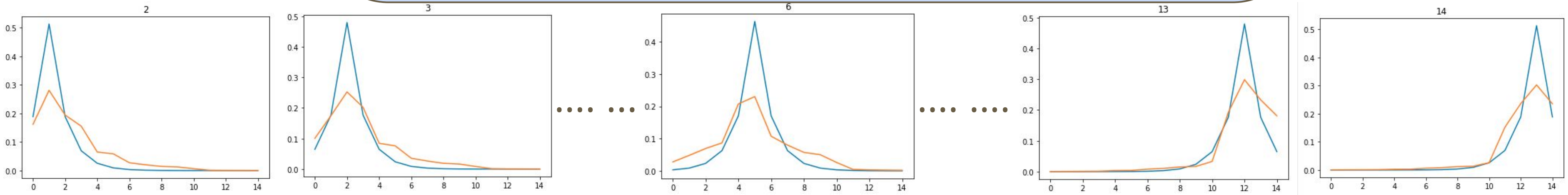

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Unimodal model

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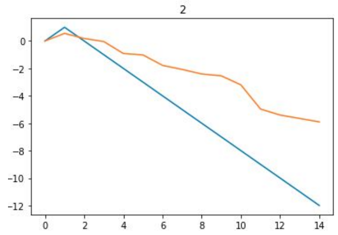

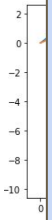

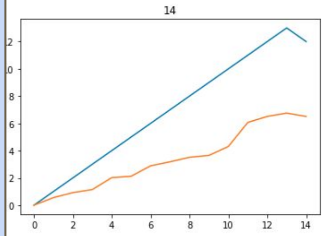

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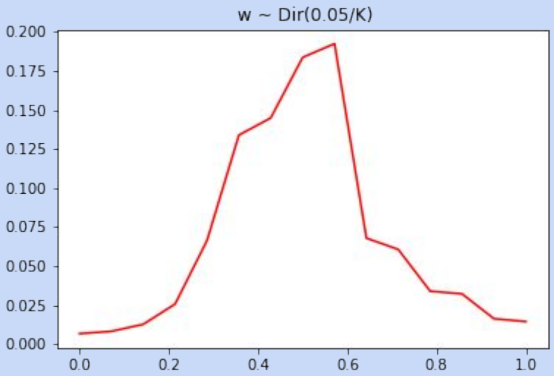

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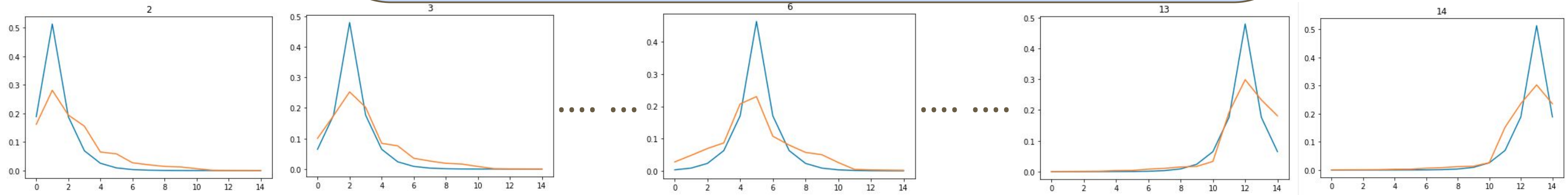

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Unimodal model

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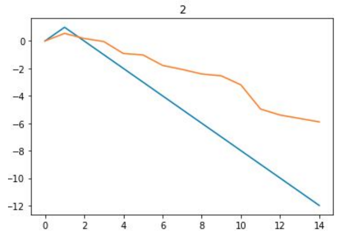

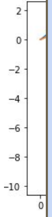

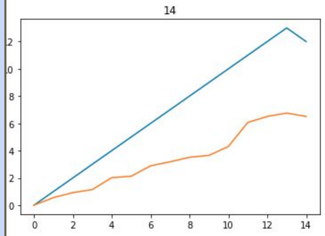

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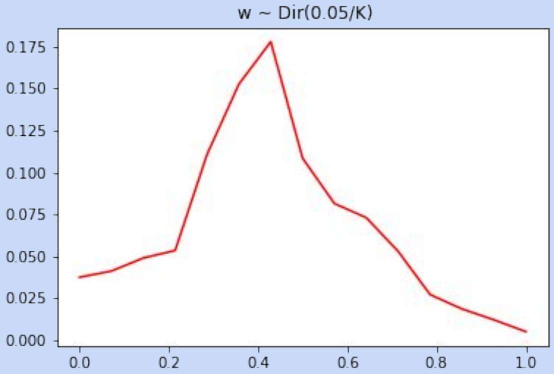

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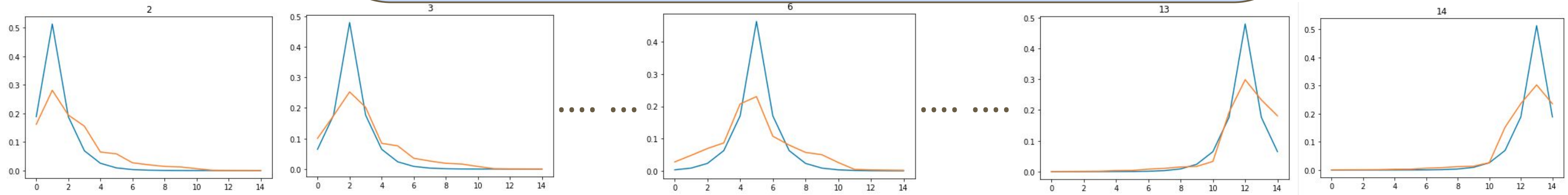
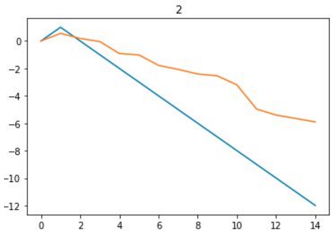


How to have unimodal at any bin and with some freedom of shape in other bins?

Unimodal model

Allow for random



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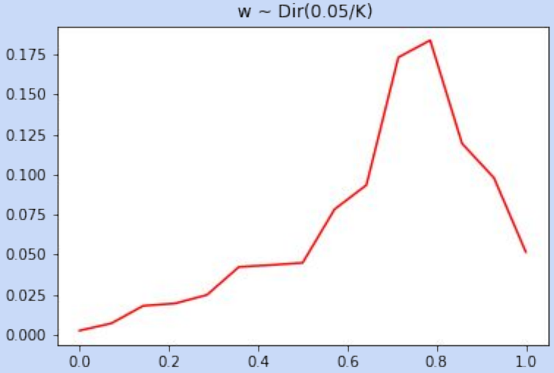

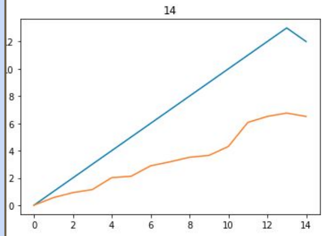

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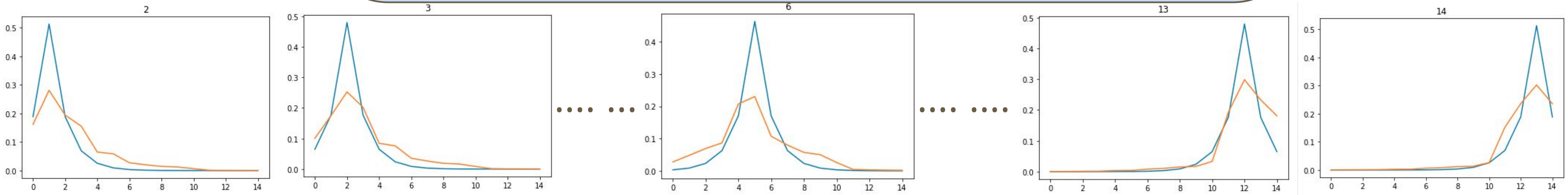
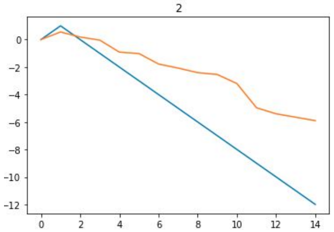
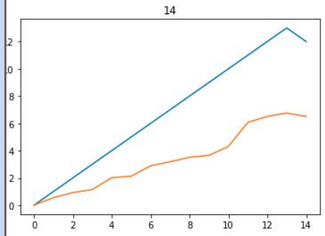


How to have unimodal at any bin and with some freedom of shape in other bins?

Unimodal model

Allow for random





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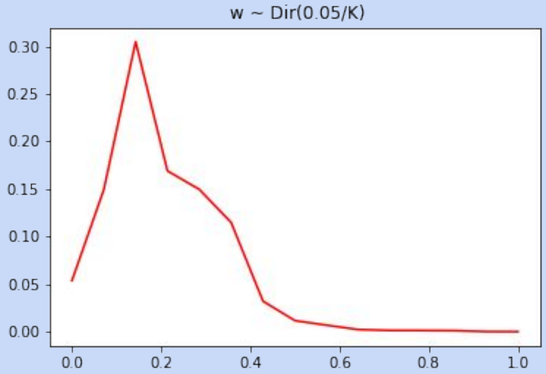

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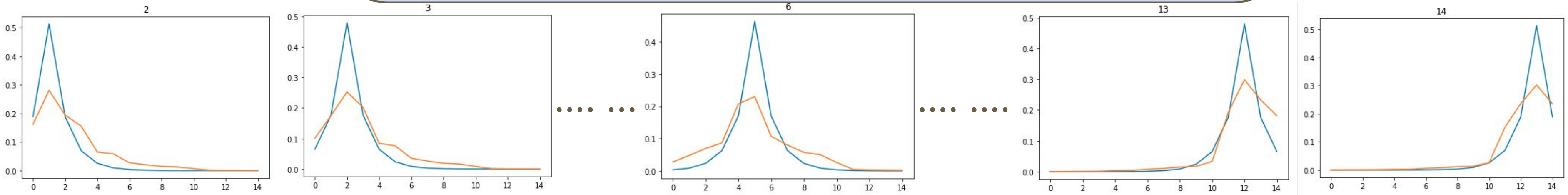
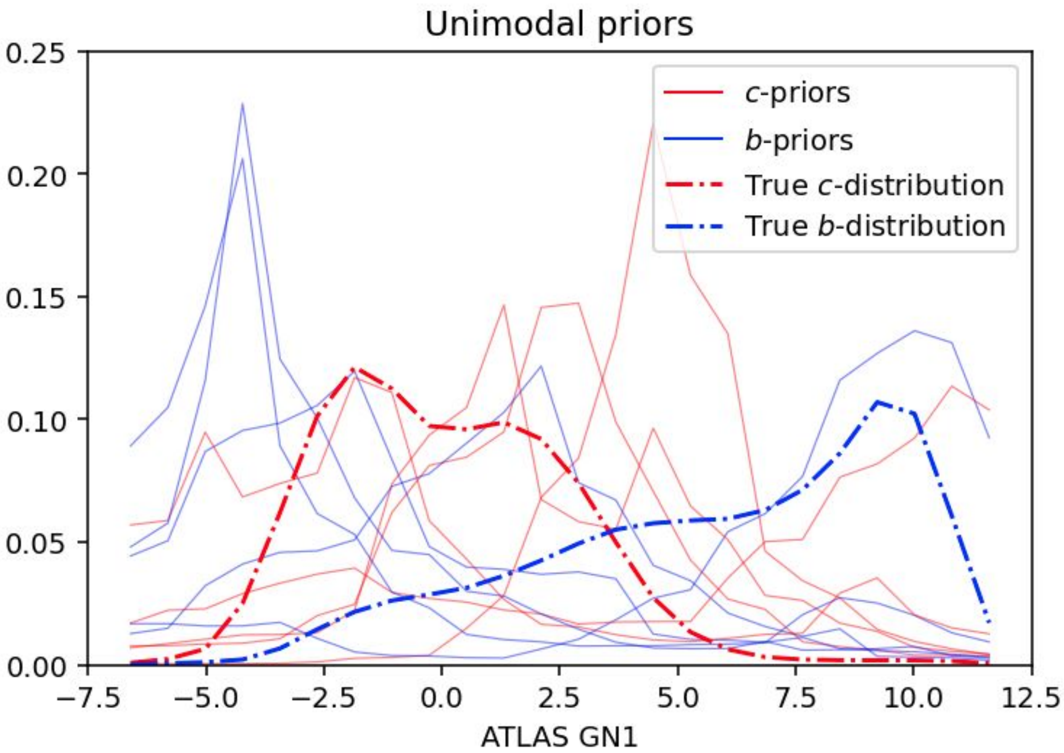


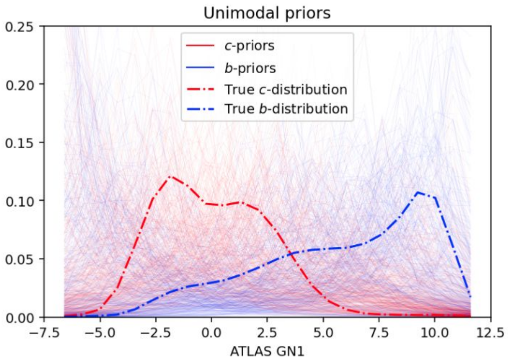
How to have unimodal at any bin and with some freedom of shape in other bins?

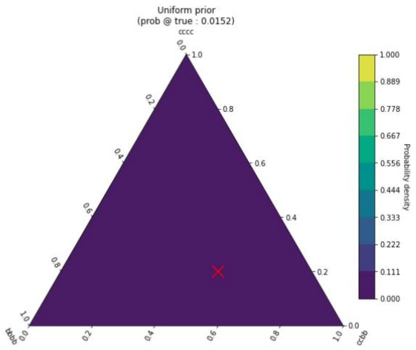
Unimodal model



Unimodal model: Results

This is how we start





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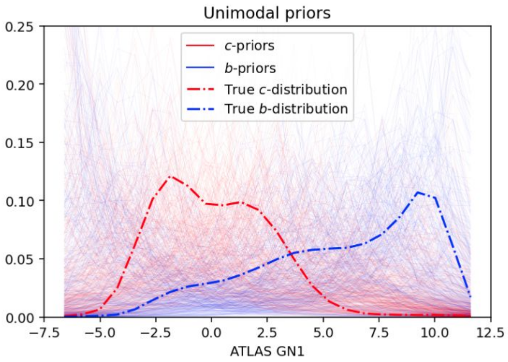
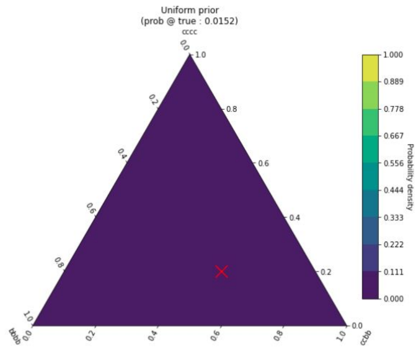
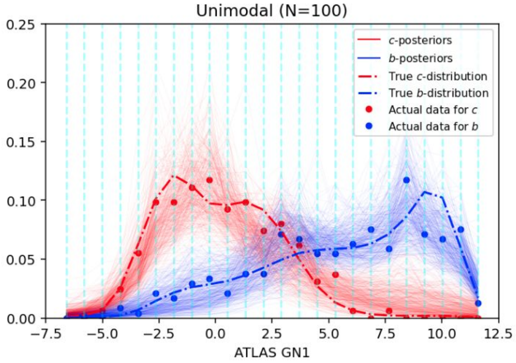
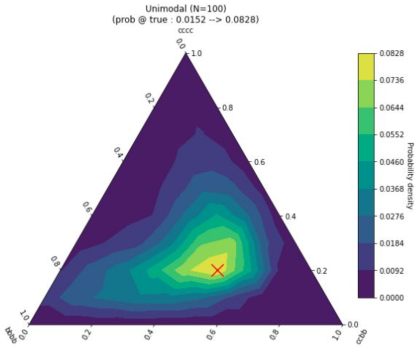




After seeing 100 events





Unimodal model: Results

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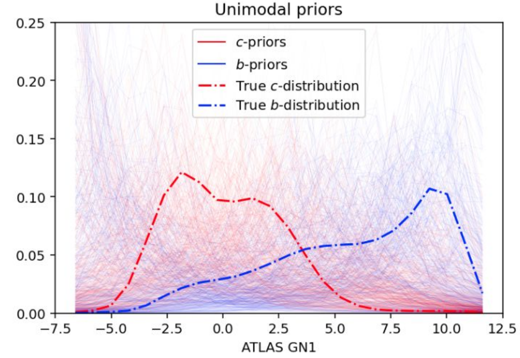
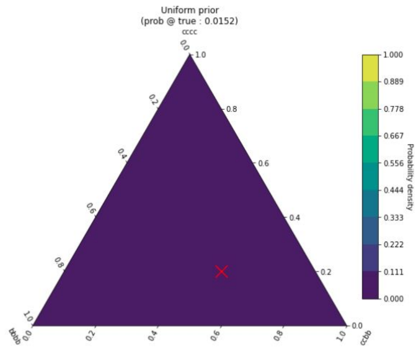
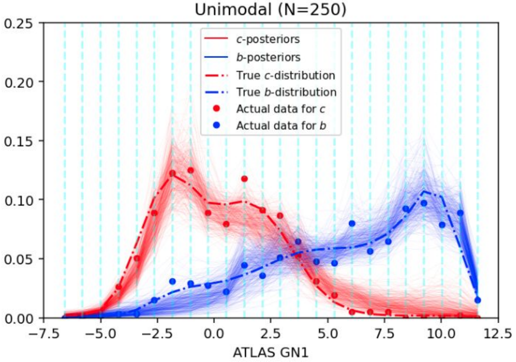
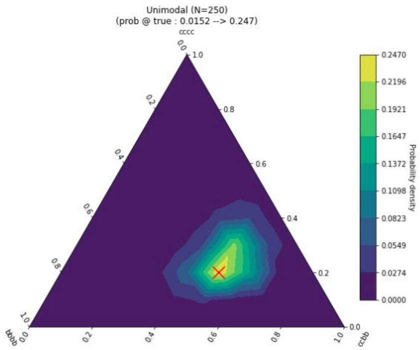




After seeing 250 events





Unimodal model: Results

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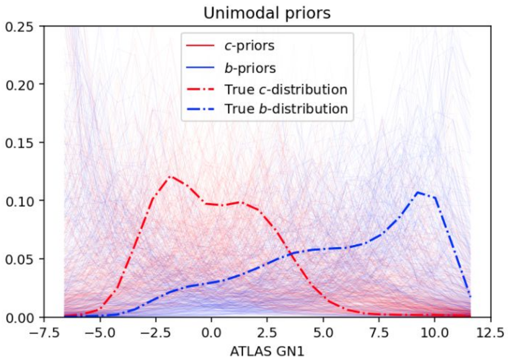
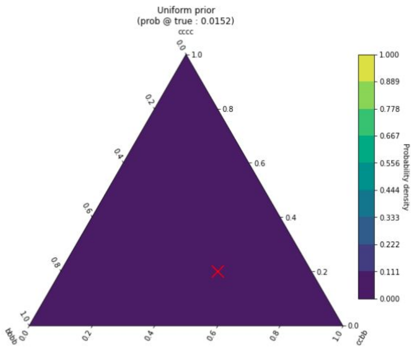
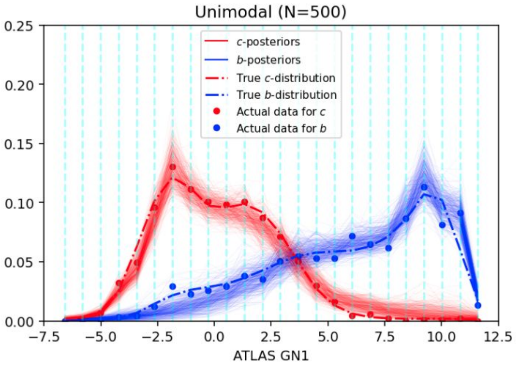
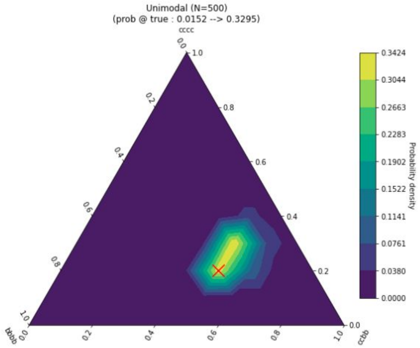




After seeing 500 events



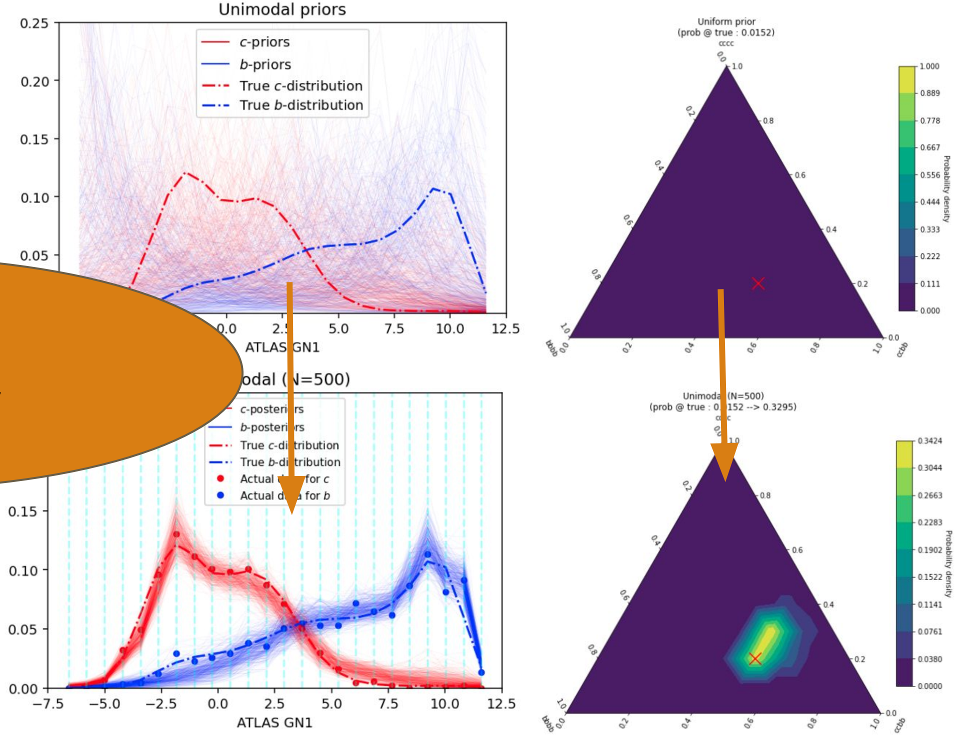


Unimodal model: Results

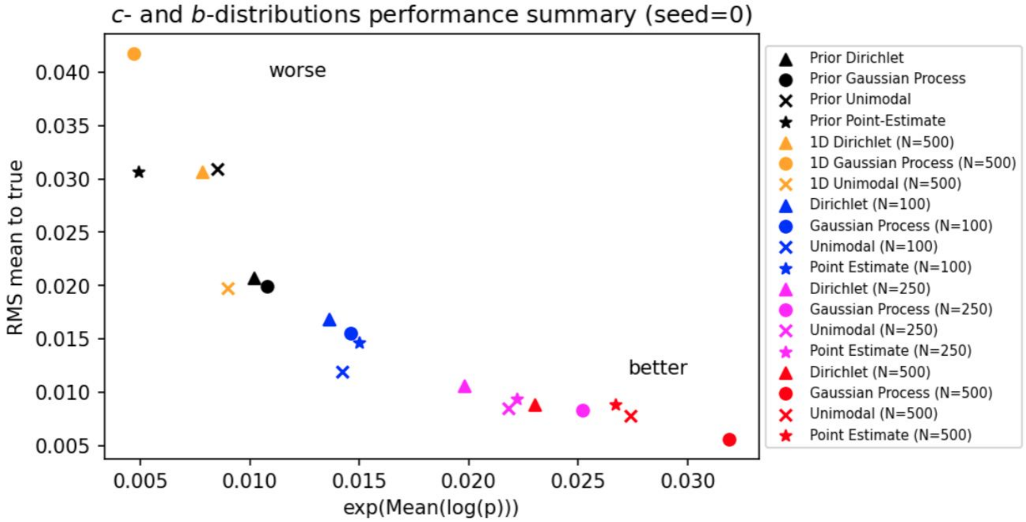
This is how we start

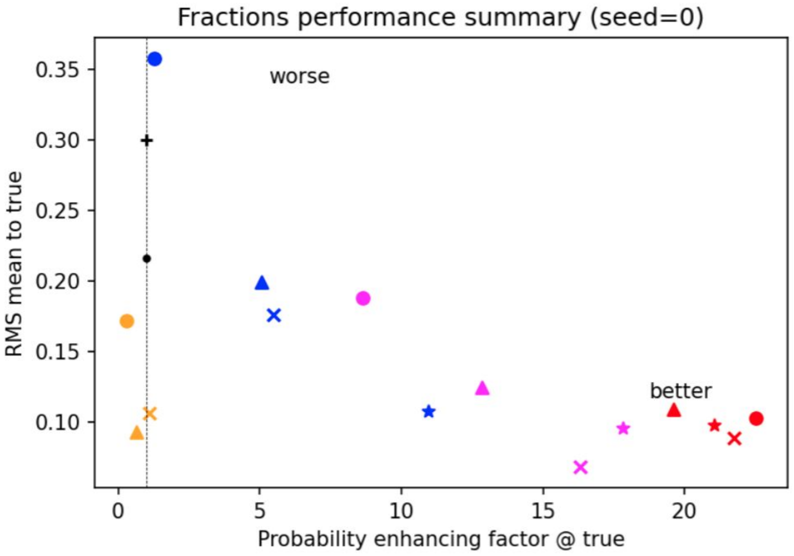
After seeing 500 events

Correlation
+
unimodality
knowledge



Exploiting prior info: summary results





Outlook & Conclusions

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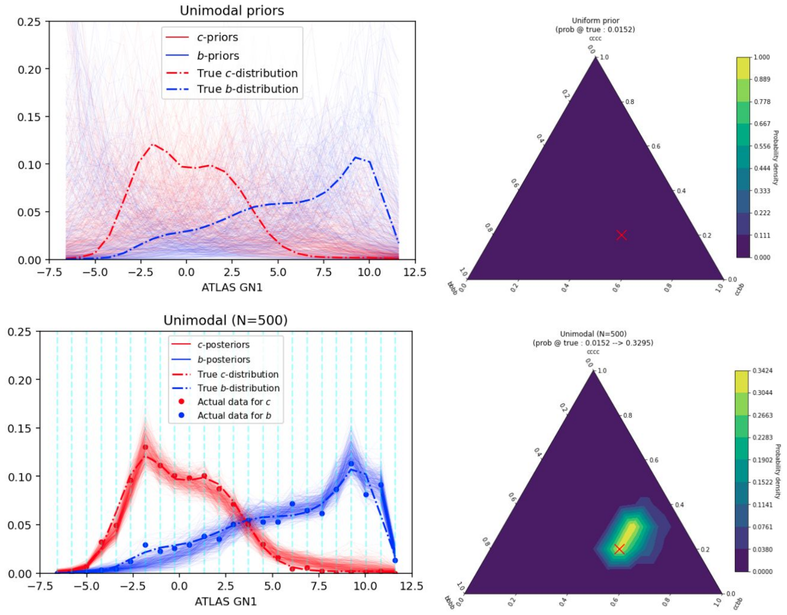
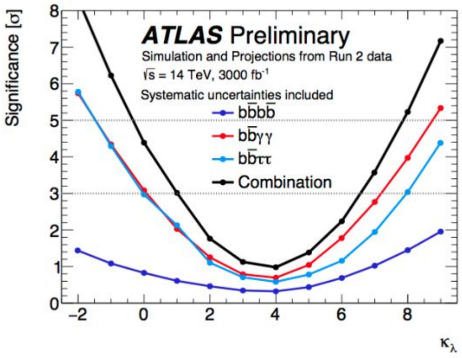


- Bayesian tools seem very suitable for hard sciences
- Trade-off:
  Neural Networks ⟵⟶ Bayesian
  Simulations ⟵⟶ the Art of Modelling
- Still not fully exploited in many fields
- Big opportunities for Statisticians

Outlook & Conclusions

Expected significance for SM HH production

	Statistical-only		Statistical + Systematic	
	ATLAS	CMS	ATLAS	CMS
$HH \to b\bar{b}b\bar{b}$	1.4	1.2	0.61	0.95
$HH \to b\bar{b}\tau\tau$	2.5 → 4.0	1.6	2.1 → 2.8	1.4
$HH \to b\bar{b}\gamma\gamma$	2.1 → 2.3	1.8	2.0 → 2.2	1.8 → 2.2
$HH \to b\bar{b}VV(ll\nu\nu)$	-	0.59	-	0.56
$HH \to b\bar{b}ZZ(4l)$	-	0.37	-	0.37
combined	3.5	2.8	3.0 → 3.2	2.6
	Combined		Combined	
mmm..	$\boxed{4.5}$		$\boxed{4.0}$	



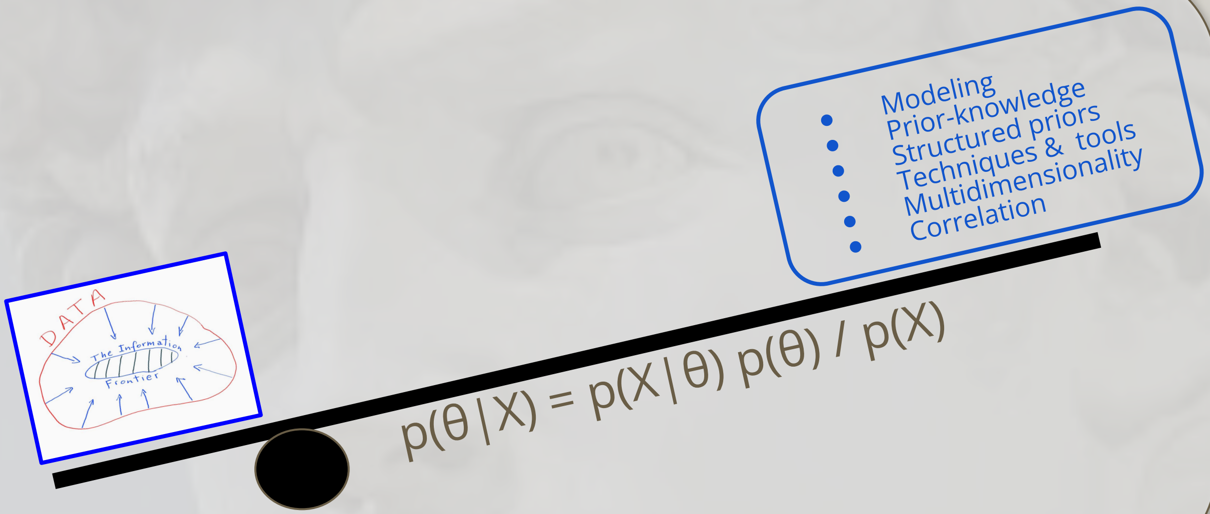
pp > hh > bbbb

Bayesian tools could provide discovery for the last parameter of the Standard Model

Outlook & Conclusions

- Bayesian tools look promising
- No hard cuts. No signal & background regions. No hard-assignments
- Go *analytic* and *probabilistic!*
- Multidimensionality: correlation, correlation, correlation!
- There is more info in the data that what is currently being used ?

The Information Frontier



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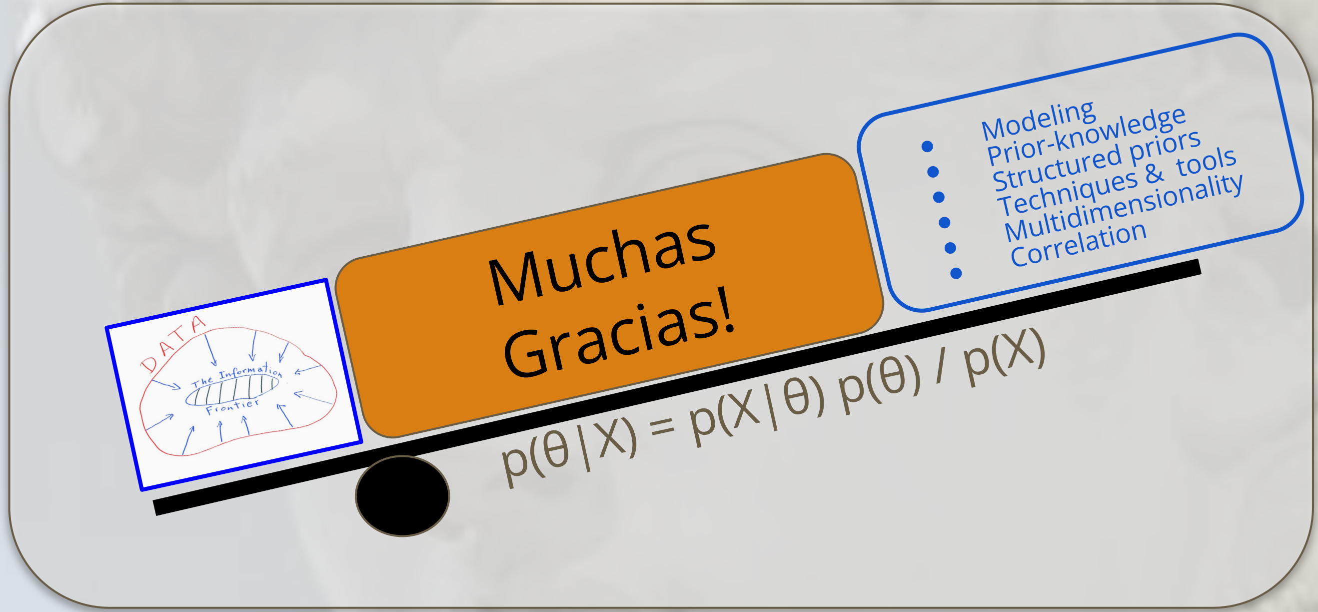

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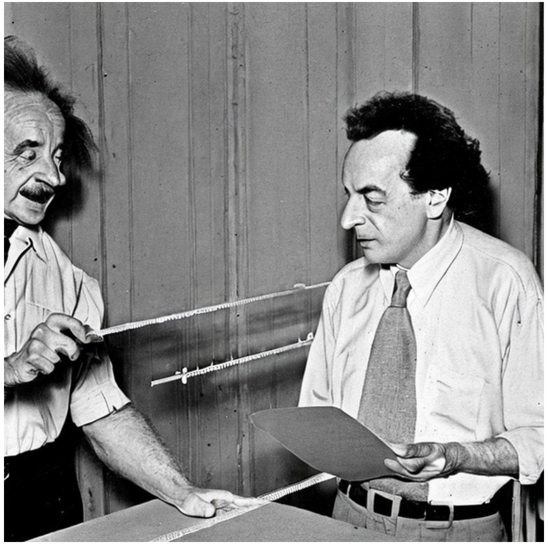
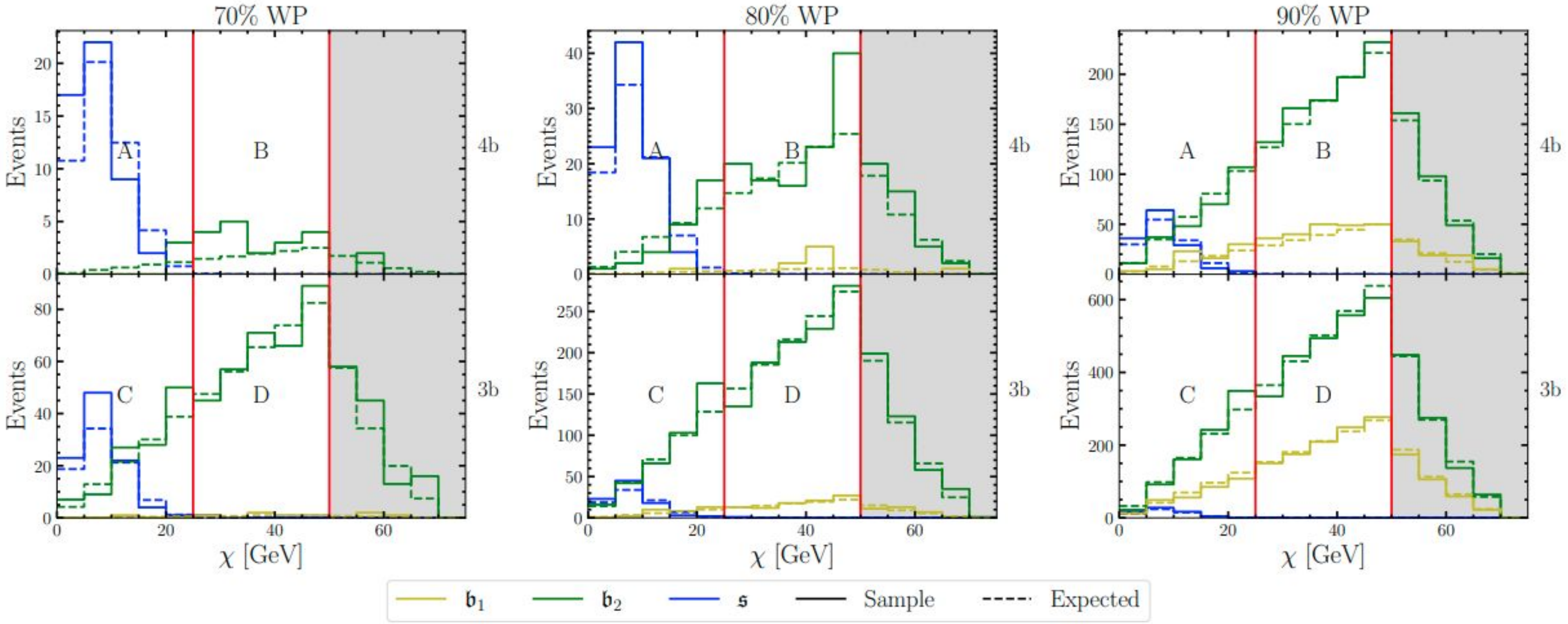
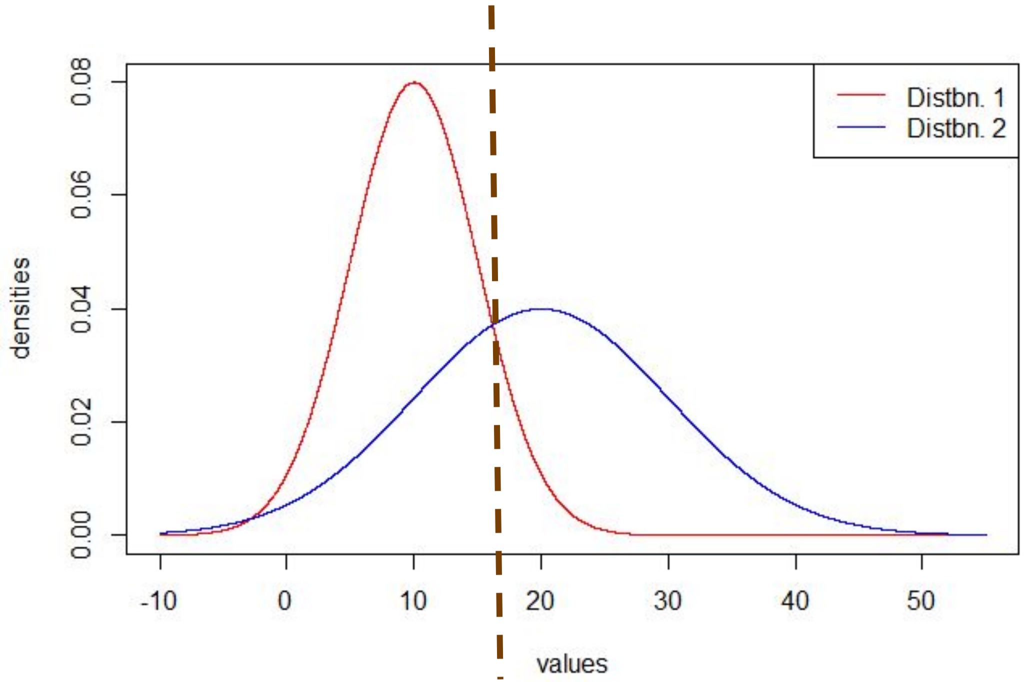


Backup slides

ABCD for WP = 70%, 80% and 90%



Hard- Vs Soft-assignment

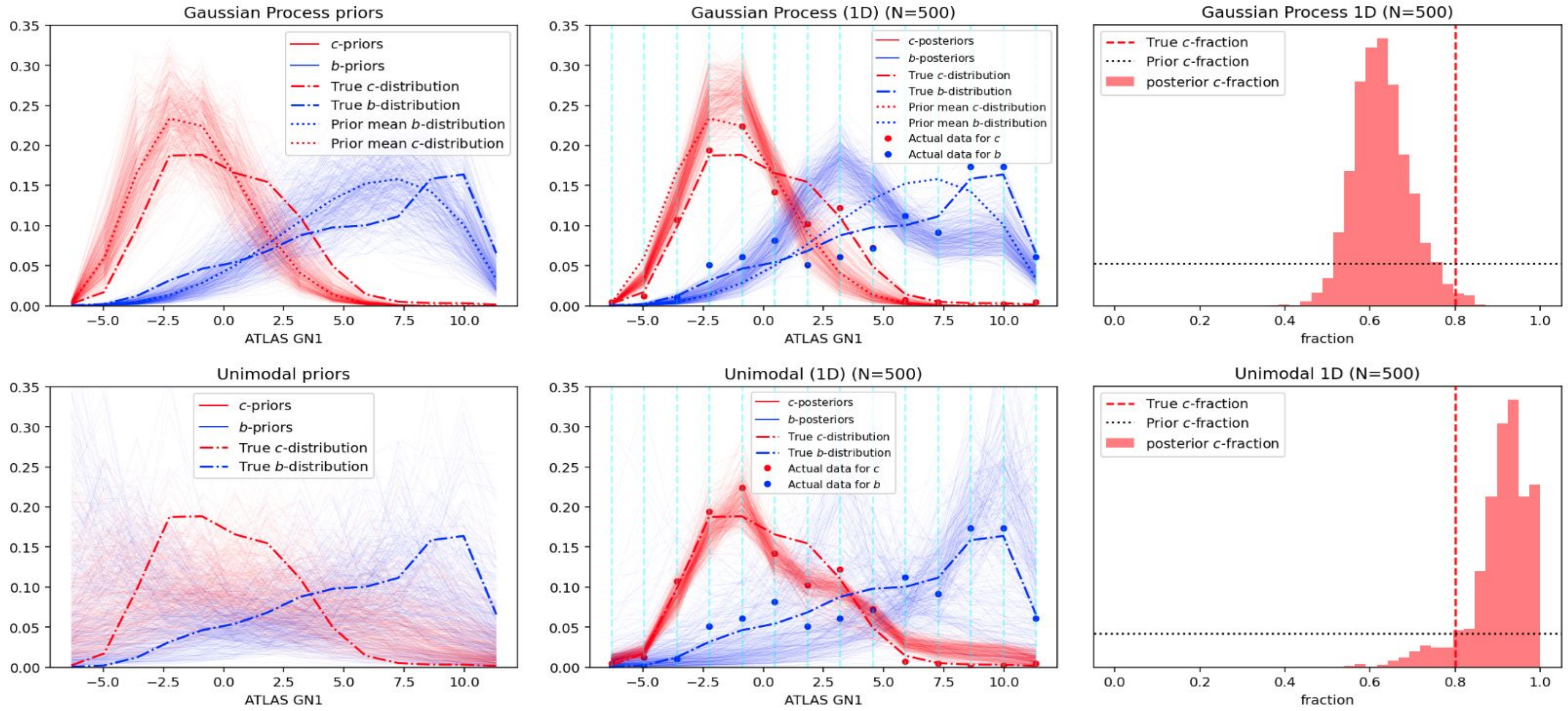


The only way of having same number of events is if blue area on the left equals red area on the right. Very unlikely.

And even in that case the behaviors are different

1D inference problem

The problem has non-identification



Joke

Scotland Yard, FBI and Argentine Federal police are in the world's final Police-detective Contest, in which a rabbit is set free and it has to be found.

First day, FBI takes 2hs and finds the rabbit. How did you do it? Well.. we computed the wind, the trees distribution and the genetic pattern, and we knew where it was going to be. Clap clap clap....👏👏👏

Second day, Scotland Yard takes 30m! How did you do it?! Well, quite easy, we knew its shape, its skills, the forest distribution, we plugged everything to our AI, and we knew exactly where to find it. Wooow...👏👏👏👏👏👏!!!!

And then the third day came the Argentine Federal Police... 30m.. Nothing... 2hs..nothing....10hs... nothing....1 day...nothing... 2days... nothing!!! And after a week they arrived.... [page down]

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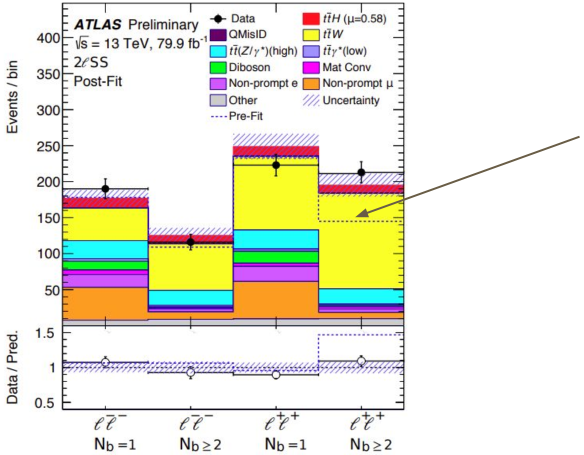
Typical problem at LHC

- **Theory**: SM or BSM
- **Data**: events with p_T, E_{miss}, N_b, N_j, etc.
- **Simulations**: a guide of what to expect of Signal and few Backgrounds



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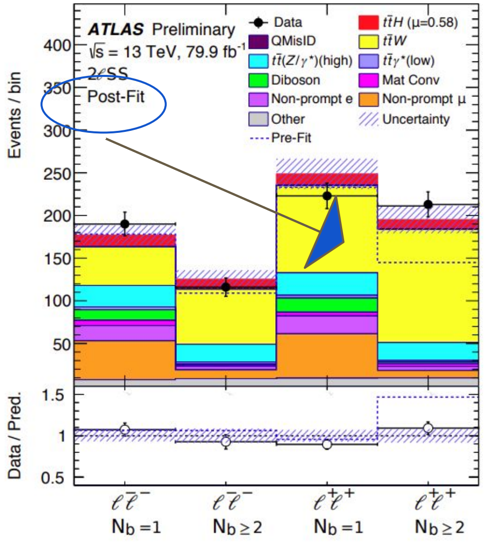

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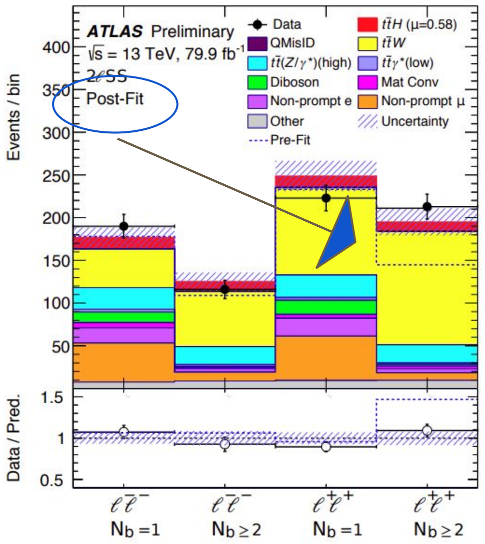

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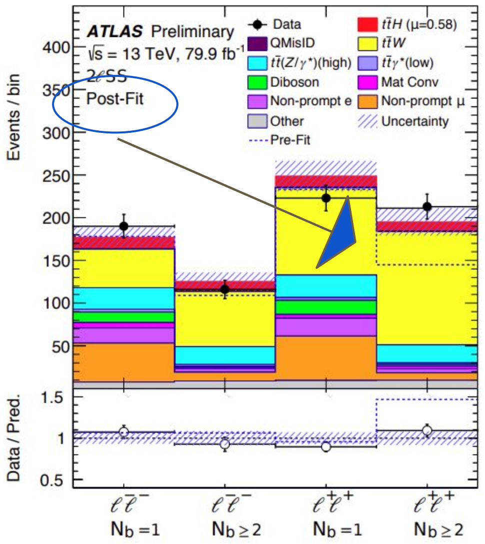

[Submitted on 28 May 2024]

Is machine learning good or bad for the natural sciences?

David W. Hogg (NYU, MPIA, Flatiron), Soledad Villar (JHU, Flatiron)

Machine learning (ML) methods are having a huge impact across all of the sciences. However, ML has a strong ontology - in which only the data exist - and a strong epistemology - in which a model is considered good if it performs well on held-out training data. These philosophies are in strong conflict with both standard practices and key philosophies in the natural sciences. Here, we identify some locations for ML in the natural sciences at which the ontology and epistemology are valuable. For example, when an expressive machine learning model is used in a causal inference to represent the effects of confounders, such as foregrounds, backgrounds, or instrument calibration parameters, the model capacity and loose philosophy of ML can make the results more trustworthy. We also show that there are contexts in which the introduction of ML introduces strong, unwanted statistical biases. For one, when ML models are used to emulate physical (or first-principles) simulations, they introduce strong confirmation biases. For another, when expressive regressions are used to label datasets, those labels cannot be used in downstream joint or ensemble analyses without taking on uncontrolled biases. The question in the title is being asked of all of the natural sciences; that is, we are calling on the scientific communities to take a step back and consider the role and value of ML in their fields; the (partial) answers we give here come from the particular perspective of physics.