



NEURAL NETWORK LEARNING AND QUANTUM GRAVITY

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BASED ON:
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• WHY WE NEED MACHINE LEARNING IN QUANTUM GRAVITY

The number of consistent string theory vacua ranges from $\sim 10^{500}$ to $\sim 10^{272,000}$.

⇒ The string landscape is **too vast** for a systematic exploration!

With Machine Learning we can study **big data sets** of consistent theories and extract relevant information

This could be beneficial for the **Swampland Program**:

Test existent conjectures with **supervised techniques**

Uncover new patterns with **unsupervised techniques**

• WHAT CAN WE 'LEARN' IN QUANTUM GRAVITY?

But what can we **'learn'** in
Quantum Gravity effective field theories?

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We address this question with **three key tools**:

• A mathematical definition of **Learning**

• The shattering dimensions

• o-minimal structures, defining Quantum Gravity interactions

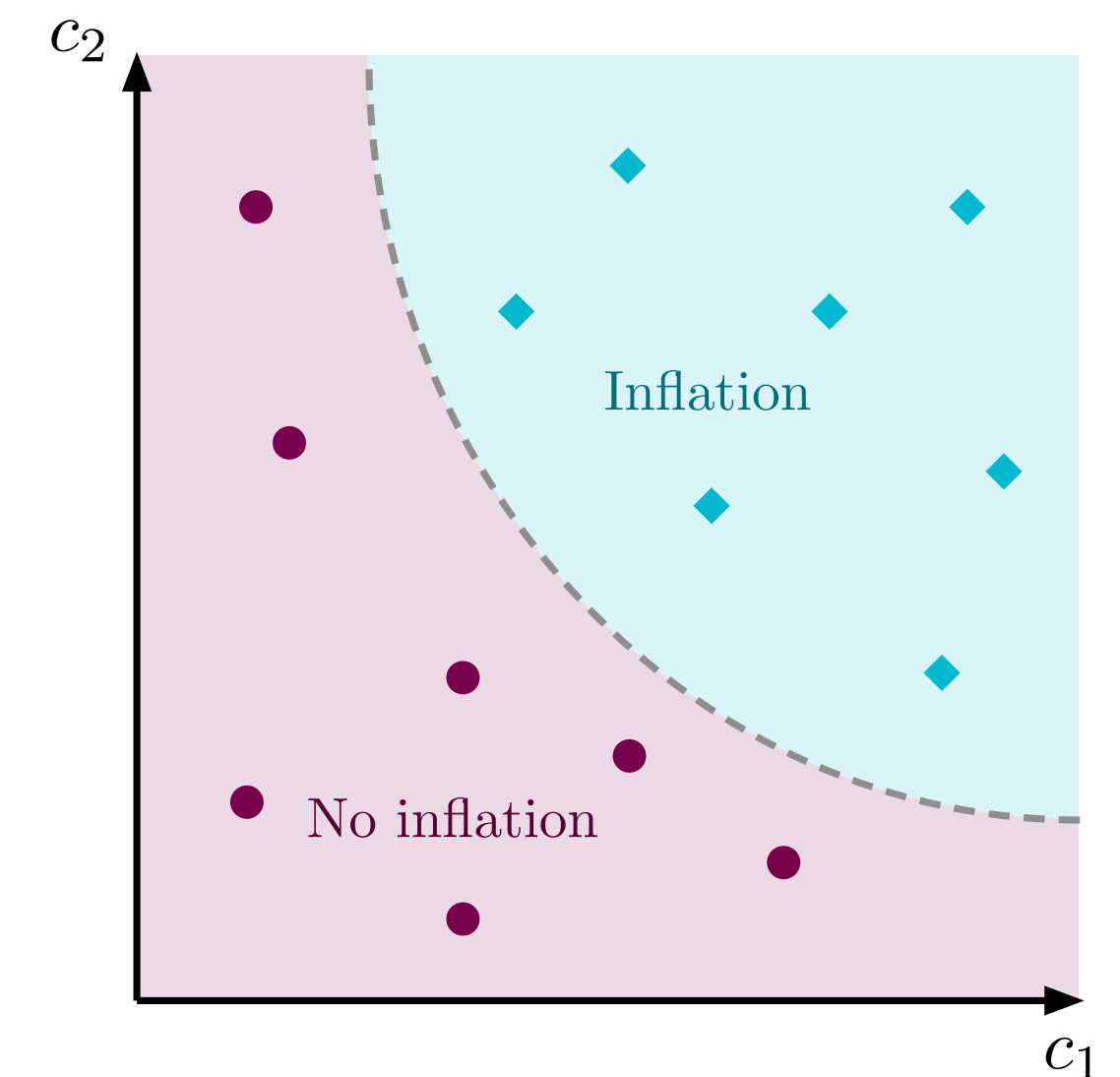
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But what can we 'learn' in
Quantum Gravity effective field theories?

Here, we will focus only on **binary supervised problems**, namely problems that can be answered with a 'yes' or a 'no'.

Example:

Consider an effective theory with a scalar potential $V(\varphi, c)$. Does it accommodate slow-roll inflation for some parameters c^a ?

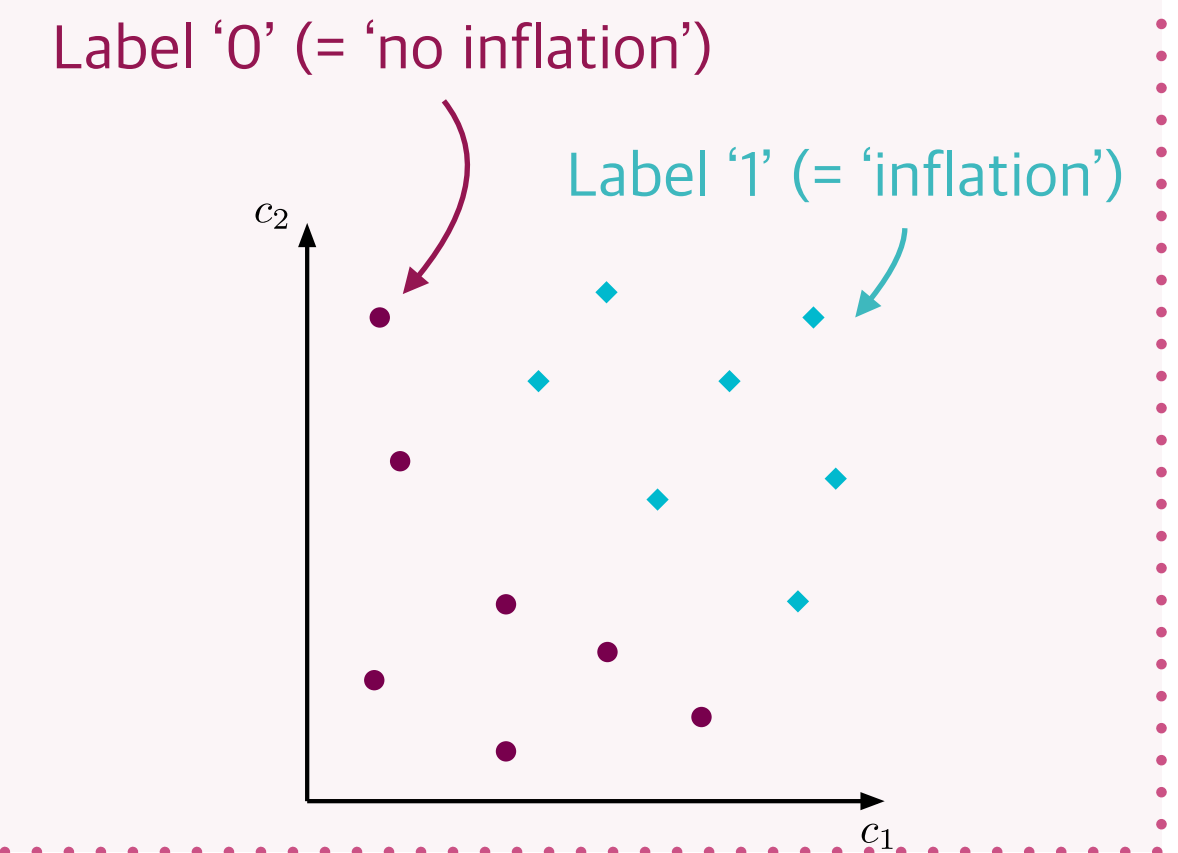


• 1. A DEFINITION FROM STATISTICAL LEARNING THEORY



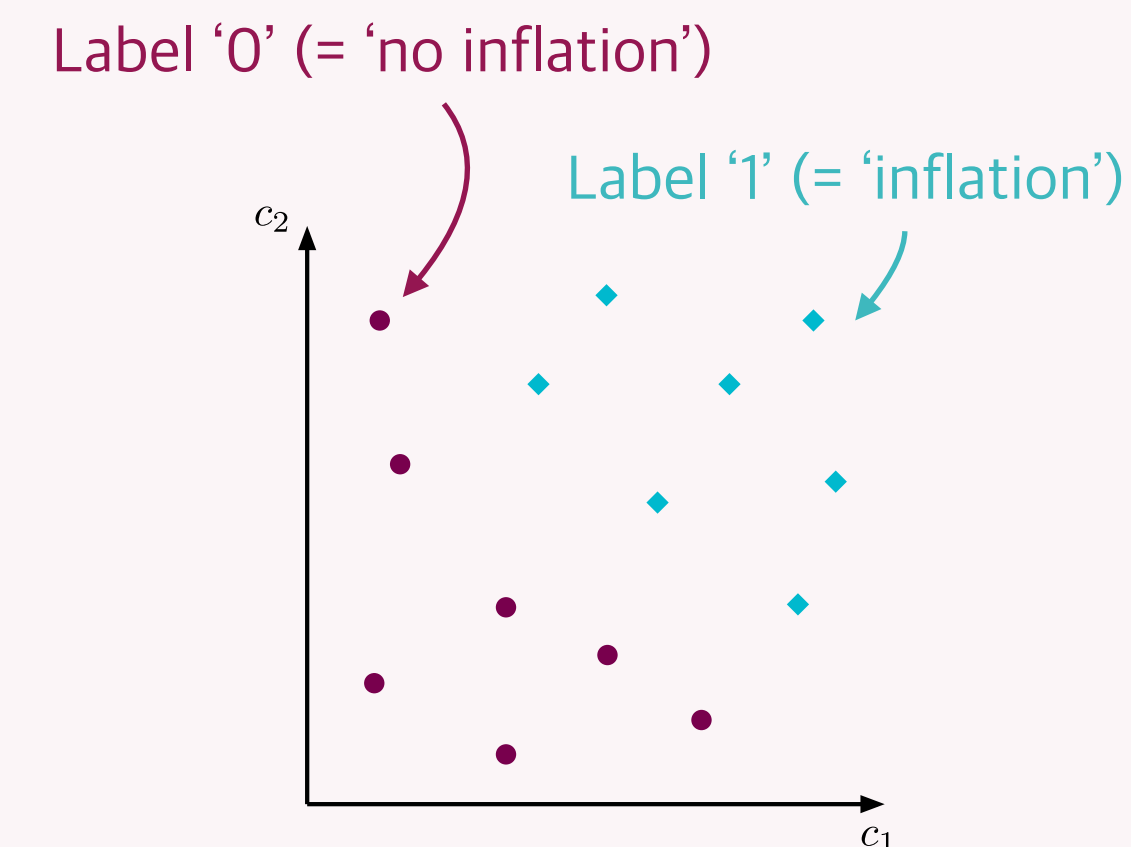
1. A DEFINITION FROM STATISTICAL LEARNING THEORY

- The **Data space** is $Z = X \times Y$ with
 $X =$ input (coordinate) space $\subset \mathbb{R}^n$, $Y =$ output (label) space $= \{0,1\}$
- The **Data set** fed to the algorithm is a discrete subset of the Data space:
Data set $= \{(x_i, y_i)\} \subset X \times Y \subset \mathbb{R}^n \times \{0,1\}$, $i = 1, \dots, N_{\text{data}}$



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- Introduce a set of functions \mathcal{F} among which we search for a function

$$f(x) : X \rightarrow Y$$

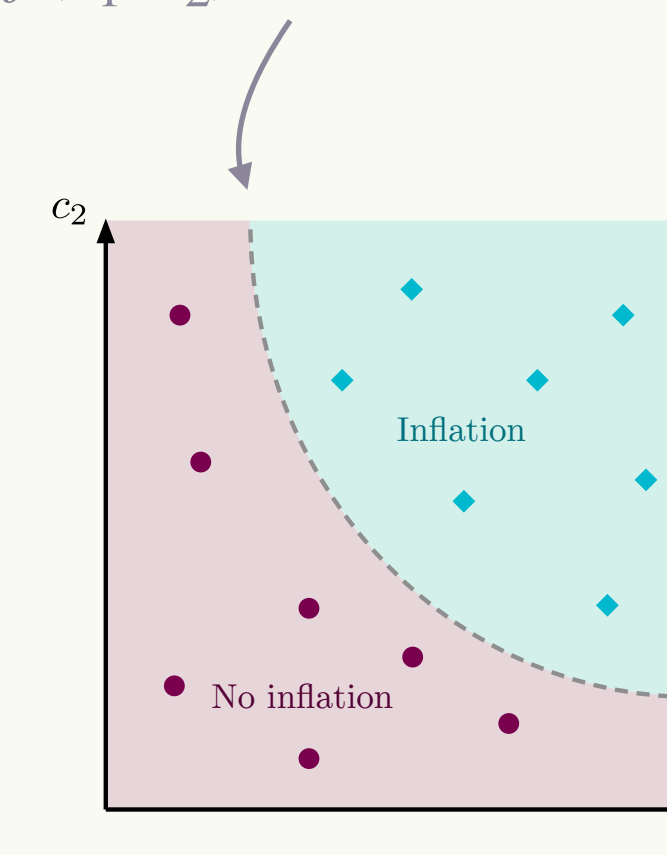
that best models the data, with the smallest possible error.

- A **learning algorithm** ℓ is a map

$$\ell : \text{Data set}_m \rightarrow \mathcal{F}$$

that selects a function f , within \mathcal{F} , with the property that, if m is sufficiently large, then the error of $f(x)$ is small enough, $\text{error}_P(\ell) < \text{opt}_P(\mathcal{F}) + \epsilon$, with high enough probability.

Function $f(c_1, c_2)$ specifying the boundary



• 2. THE VAPNIK–CHERVONENKIS DIMENSION

Consider a family of sets \mathcal{C} and a set S . We say that the set S is ‘**shattered**’ by the sets of the family \mathcal{C} if all the subsets of S are contained in \mathcal{C} , namely:

$$\mathcal{C} \cap S := \{C \cap S \mid C \in \mathcal{C}\} \text{ contains all the subsets of } S$$

The **Vapnik-Chervonenkis dimension** of \mathcal{C} is the cardinality of the largest set that \mathcal{C} can shatter.

If any set can be shattered by the family of sets \mathcal{C} , we say that the Vapnik-Chervonenkis dimension of \mathcal{C} is **infinite**.

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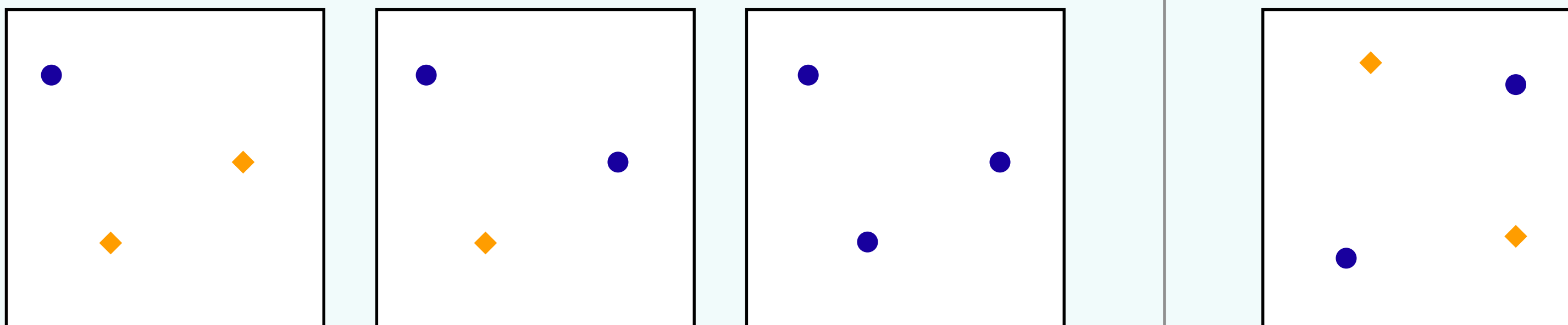
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Example: $S =$ set of points, with subsets represented as **blue circles** and **orange squares**; we want to ‘shatter’ its subsets via $\mathcal{C} =$ sets separated by a single line



Our models are lines, such that they ‘shatter’ the points as

Above: **blue circles**

Below: **orange squares**

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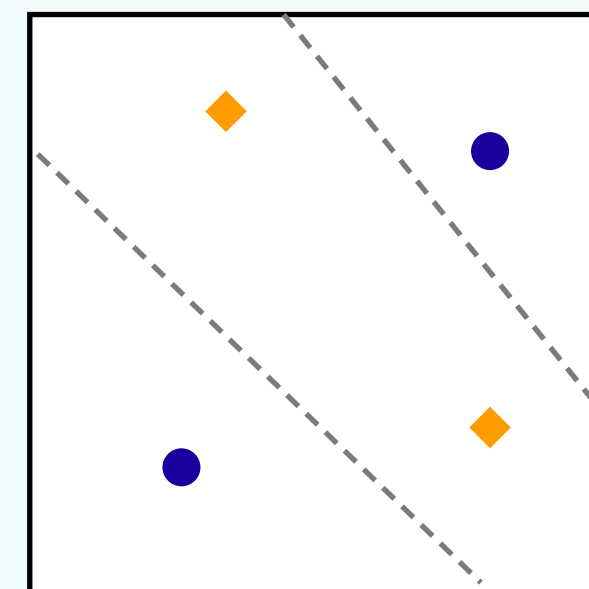
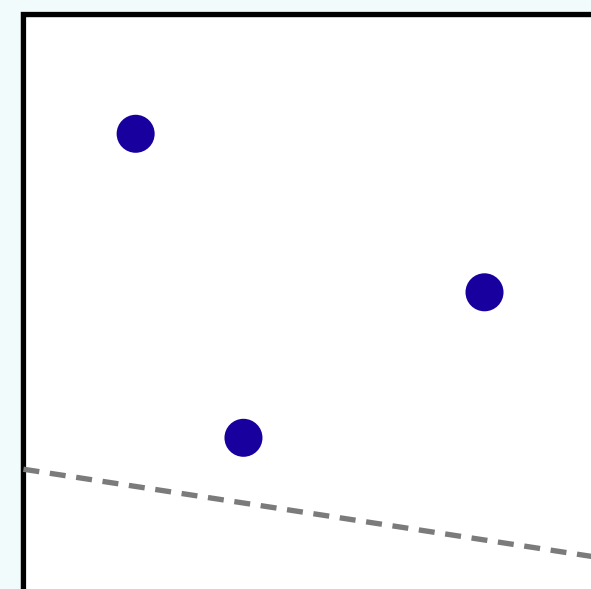
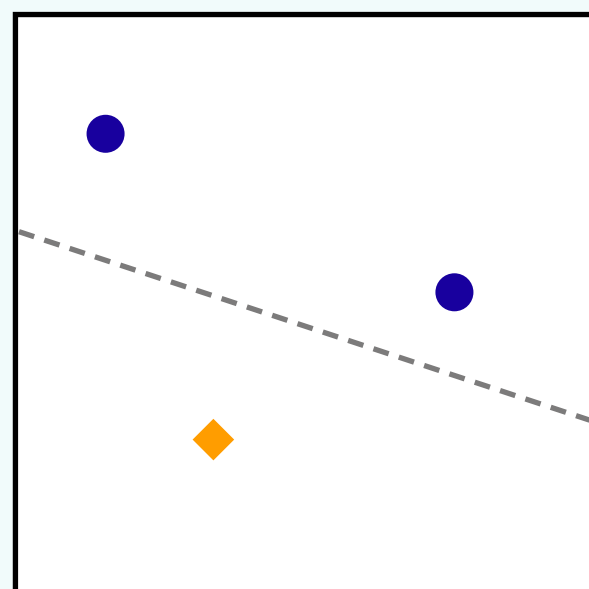
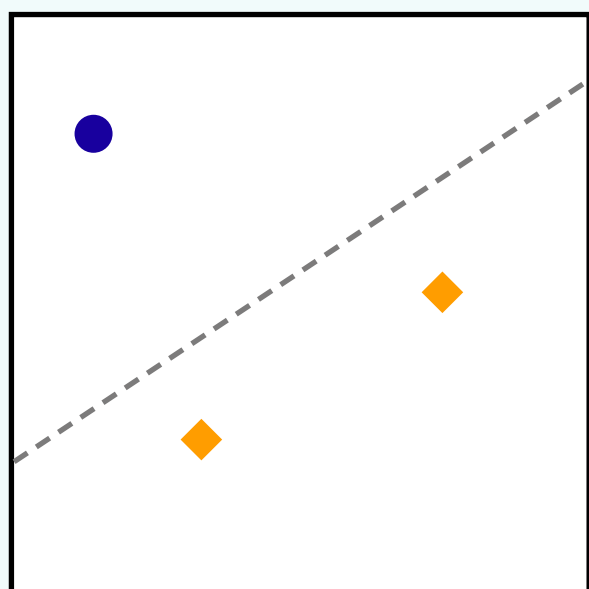
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Example: the set of lines can ‘shatter’ (separate) set of three (non-collinear) points with any label assignment, but not set of four points \Rightarrow **The Vapnik-Chervonenkis dimension of the set of lines is three.**



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• 3. 0-MINIMALITY AND QUANTUM GRAVITY

Consider a generic effective field theory of string theory:

$$S^{(D)} = \int \left(\frac{1}{2} R \star 1 - \frac{1}{2} G_{ab}(\varphi, \lambda) d\varphi^a \wedge \star d\varphi^b - \frac{1}{2} f_{IJ}(\varphi, \lambda) F_{p_I+1}^I \wedge \star F_{p_J+1}^J - V(\varphi, \lambda) \star 1 + \dots \right)$$

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Namely, any coupling $g(\varphi, \lambda)$ can be written as unions, intersections or complements of a **finite** number of loci:

$$\exists x_1, \dots, x_l : \quad P_i(\varphi, \lambda, x, g, f_1, \dots, f_m) = 0, \quad Q_j(\varphi, \lambda, x, g, f_1, \dots, f_m) > 0,$$

with x_k auxiliary variables, and f_a restricted analytic functions.

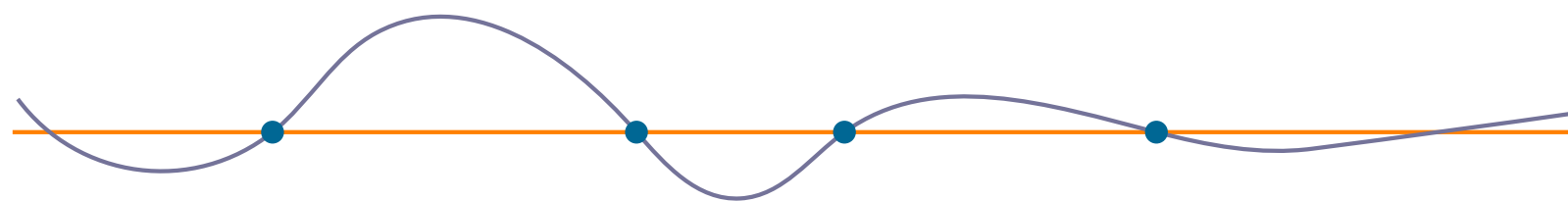
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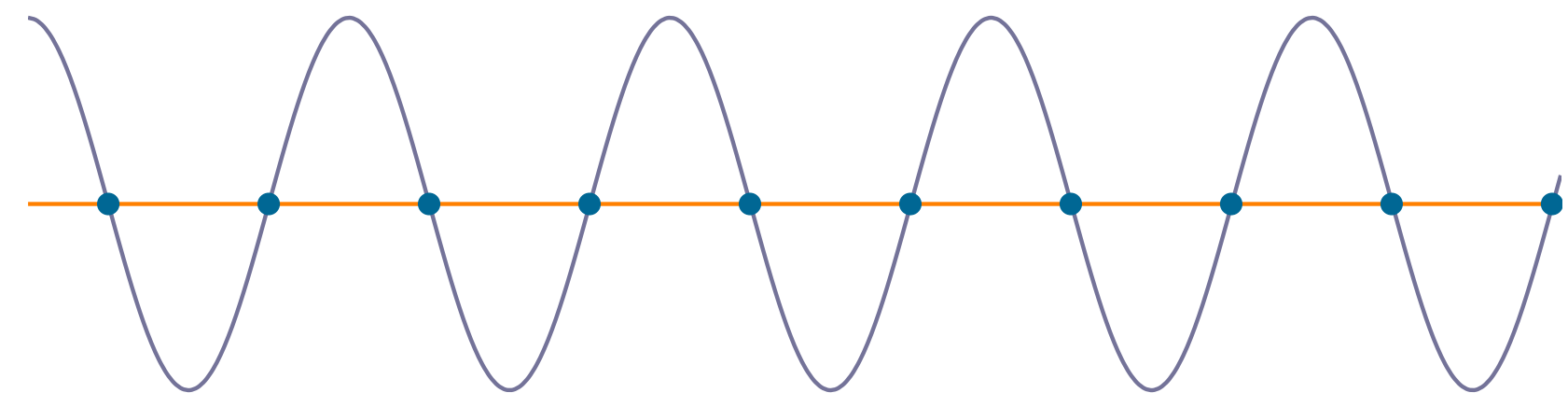
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⇒ Couplings and interactions have **regular, monotonic** tails and **finite** critical loci:



Tame ✓



Non tame ✗

● COMBINING ALL THE INGREDIENTS



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The tameness of Quantum Gravity effective field theories implies that **the set of functions \mathcal{F}** among which the ‘true’ model resides have to be definable in a given o-minimal structure:

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Every o-minimal structure is characterized by **finite Vapnik-Chervonenkis dimension** [Laskowski 1990].

Notice that an infinite shattering dimension would imply an infinite amount of information to learn the function!

• THE LEARNABILITY OF QUANTUM GRAVITY

Fundamental Theorem of Statistical Learning

Consider a set of functions \mathcal{F} with binary output, then:

- \mathcal{F} is **learnable** if and only if \mathcal{F} has **finite Vapnik-Chervonenkis dimension**;
- there exist two constants c_1, c_2 such that the **complexity** of the data set is **bounded** as

$$\frac{c_1}{\epsilon^2} \log \frac{1}{\delta} < \min_{\ell} m < \frac{c_2}{\epsilon^2} \log \frac{1}{\delta}$$

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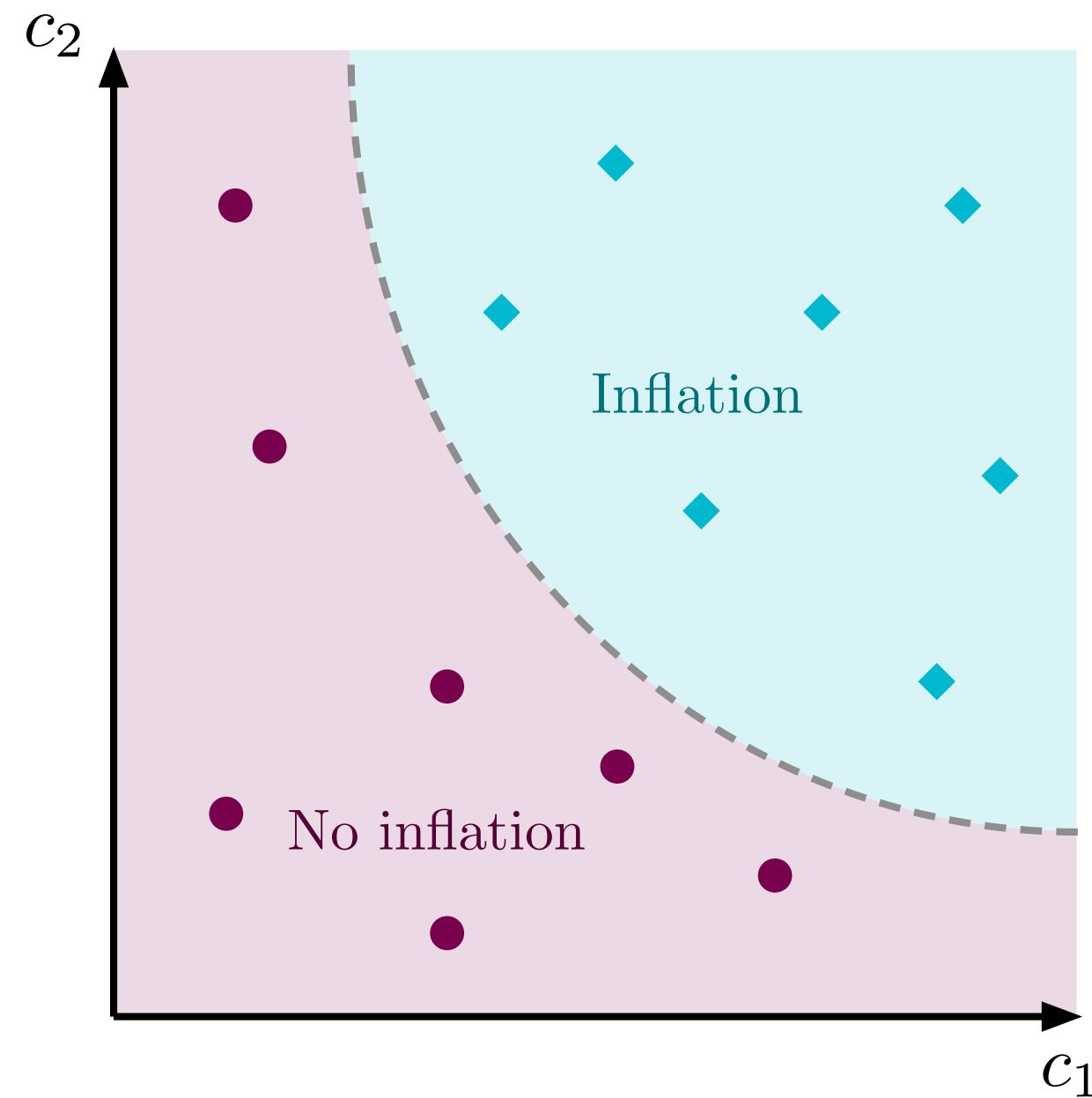
$$\frac{c_1}{\epsilon^2} \log \frac{1}{\delta} < \min_{\ell} m < \frac{c_2}{\epsilon^2} \log \frac{1}{\delta}$$

⇒ In every low-energy effective theory of Quantum Gravity, **any binary classification problem** (involving the tame interactions of the theory) **is learnable**.

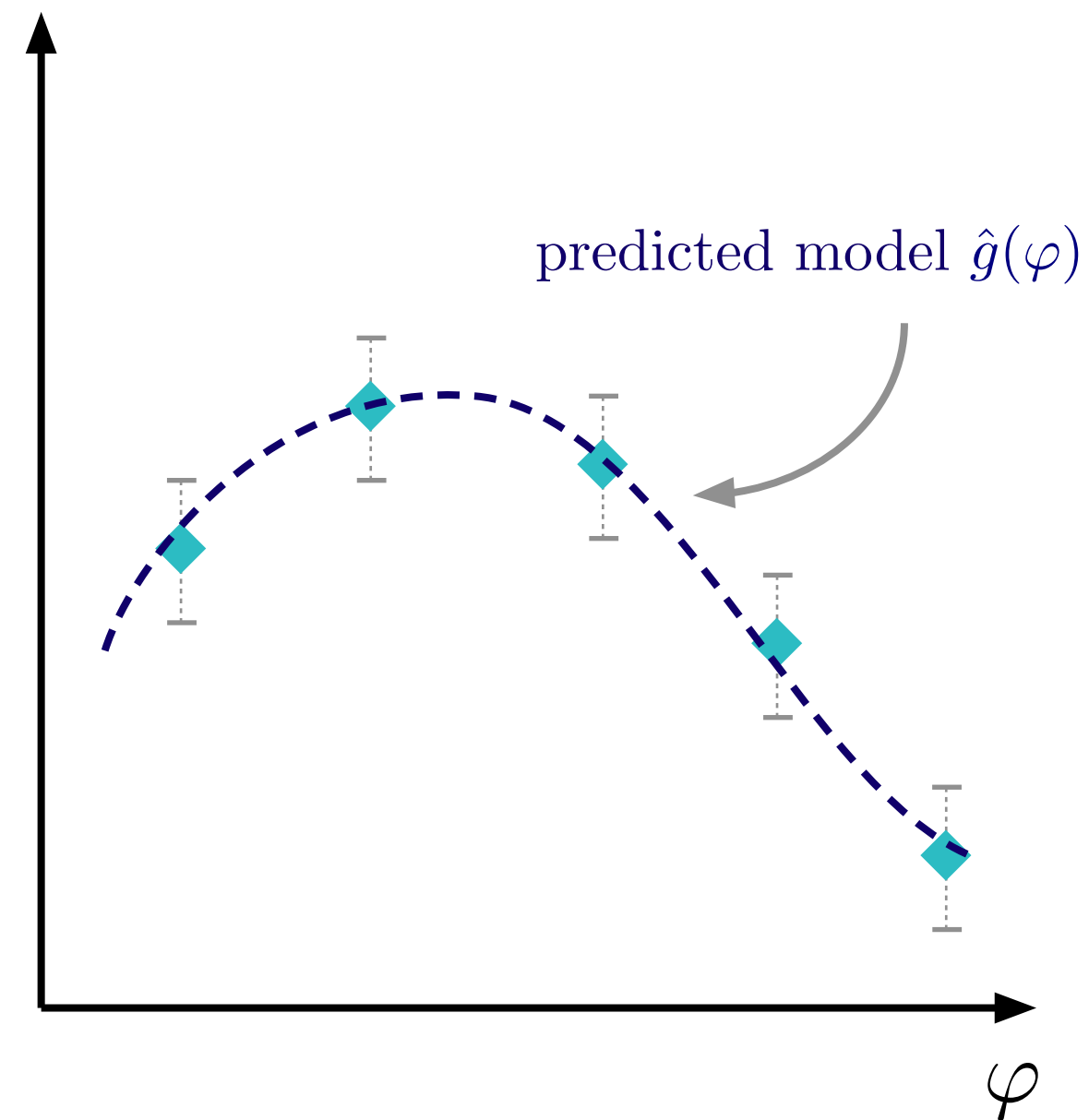
Similarly, also more general Quantum Gravity **regression problems** can be shown to be learnable.

EXAMPLE OF LEARNING PROBLEMS

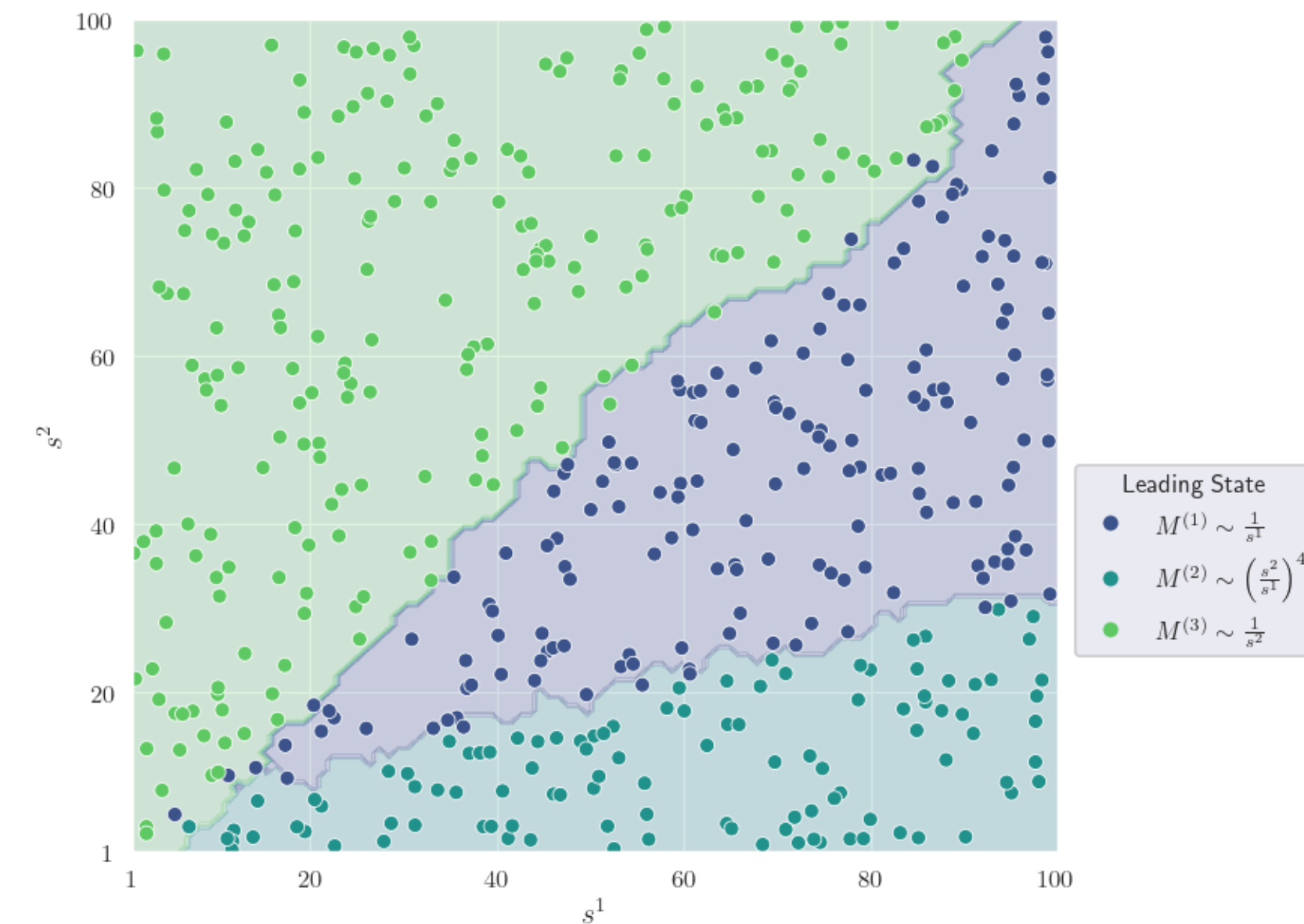
Can an EFT support inflation for some choice of parameters?



What is the predicted value of a gauge coupling?



Which kinds of states first break down an EFT?



• CONCLUSIONS AND OUTLOOK

- We have seen that **binary classification problems** formulated within Quantum Gravity effective field theories are **learnable**;
- Similarly, more **general regression or interpolation problems** can be shown to be **learnable**.

⇒ **The usage of neural network to machine-learn critical properties of Quantum Gravity is justified by the geometrical structures of Quantum Gravity.**

It would be interesting to further investigate:

- the learnability via **unsupervised techniques** and the **Swampland Conjectures**;
- relations with **decidability** and the **halting problem**.

Thank you!