Universitat Autònoma de Barcelona

Treball Final de
Grau en Matemàtiques

Machine learning: mathematical foundations

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Any
2022/23

Convocatòria
Juny

To my colleagues,

$\ldots$

Abstract

Exemple d'abstract no definitiu, x ficar algo.

Abstract – In various studies, researchers have described the activation functions that allow multilayer feedforward networks to act as universal approximators. However, we demonstrate that most of the characterizations presented in the literature are specific instances of the following general finding: A typical multilayer feedforward network that employs a locally bounded piecewise continuous activation function can accurately approximate any continuous function to an arbitrary degree if and only if the activation function is non-polynomial.

Resum

blslalblallb en català

Preface

Inpirat per **?**.

blablalbla amb glosary Universitat Autònoma de Barcelona (UAB) i ara curt UAB.

Contents

Chapter 1

Introduction

> ficar una quote que quedi bé
>
> — John S. Bell, *Against Measurement*

Early computers were used to perform exact computations with high accuracy and efficiency. Back in 1945, one of the first electronic computer was invented for ballistic calculations during World War II. Computers seemed to be limited to these exact computation tasks. However, over time, researchers started pushing the boundaries of what computers can do, eventually leading to the development of what we call now Artificial Intelligence. AI seeks to make computers do the sorts of things that minds can do.

Some of these (e.g. reasoning) are normally described as "intelligent." Others (e.g. vision) aren't. But all involve psychological skills—such as perception, association, prediction, planning, motor control—that enable humans and animals to attain their goals.

3. on les matematiques prenen lloc ? pq son importants . Can we suggest conjectures, relationships , theorems between fields ??? using ml as a tool to see unexpected relationships.

ML might become a bycicle for the mind !!

MATHS USING MCH LEARNING <–> ML USING MATHS

Chapter 2

Artificial Intelligence

2.1 What is Artificial Intelligence

2.2 What is Machine Learning

Machine Learning is the science of programming computers so they can learn from data.

(with the aim to solve a problem without being explicitly programmed.)

For example,
Classification and regression problem.

2.3 Types of Learning

We can think about learning as the way we understand it as a human. We can classify a learning problem based on the degree of feedback. The three main types are:

1. Supervised learning, where we have immidiate feedback.
2. Reinforcement learning, where we have indirect feedback. For example when we are playing the game of chess.
3. Unsupervised learning, where we have non feedback signal. For example, deducing which dog belongs to each owner.

Example 1. Example of a supervised learning task. Recognition of a letter. What we are trying to learn is a probability distribution fuction

$$f : \{0, ..., 255\}^{28\times 28} \longrightarrow \text{probability distribution on } \{0, 1, ..., 9\}$$

2.4 Function Learning

Important principle: Many supervised learning tasks are about function learning.

Example 2. Example of a classification problem. We want to classify if an image is a dog or not a dog. We would like to produce a value which is correlated with the probability of this image being a dog or not a dog. We can approach the problem in the following way. We want to find a function that takes very high values when dog-image and very low val ues when non dog images and takes the value 0 when its uncertain.

$$d : \mathbb{R}^{\#\text{pixels in image}} \to \mathbb{R}$$

such that $\mathbb{P}(d(\text{image})) =$ probability that the image is a dog.

That is what we mean by many problems can be recast as function learning. Note that there is not a god-given reason why this function should exist. We know that certain points in space, and they have certain values associated to them, but we dont know that there is some big function.

Chapter 3

Multilayer Feedforward Networks

3.1 Function Approximation

In this paper we take $C(\mathbb{R}^n)$ to be the family of "real world" functions that one may wish to approximate. If we can show that a given set of functions F is dense in $C(\mathbb{R}^n)$, we can conclude that for every continuous function $g \in C(\mathbb{R}^n)$ and each compact set $K \subset \mathbb{R}^n$, there is a function $f \in F$ such that f is a good approximation to g on K.

Definition 1. A *metric* (or *distance*) on a set X is a function $d : X \times X \to \mathbb{R}$ such that forall $s, t \in X$ the following properties are satisfied:

1. $d(s, t) \geq 0$ and $d(s, t) = 0$ if and only if $s = t$.
2. $d(s, t) = d(t, s)$.
3. $d(s, t) \leq d(s, u) + d(u, t)$ (*triangular inequality*).

A *metric space* is a pair (X, d), where X is a set and d is a distance in X.

If we take X to be a set of functions, the metric $d(f, g)$ will enable us to measure the distance between functions $f, g \in X$.

Definition 2. Let f, g be real-valued functions with compact support. We define the *convolution* of f with g as

$$(f * g)(x) = \int f(x - t)g(t)\, dt$$

3.2 Lebesgue measure

An essential part of measure theory is the calculation of lengths, areas, volumes, etc. We are already familiar with the Riemann integral, and now we aim to introduce a more general integral, the Lebesgue integral, that comes from the Lebesgue measure.

Definition 3. A box in $\mathbb{R}^d$ is a set of the form

$$Q = [a_1, b_1] \times ... \times [a_d, b_d] = \prod_{i=1}^{d} [a_i, b_i]$$

The volume of the box is

$$vol(Q) = (b_1, a_1)...(b_d - a_d) = \prod_{i=1}^{d} (b_i - a_i)$$

The *exterior measure* (or outer measure) of a set $E \subseteq \mathbb{R}^d$ is

$$|E|^* = \inf\{\sum_k vol(Q_k)\}$$

where the infimum is taken over all finite or countable collection of boxes Q_k such that $E \subseteq \cup_k Q_k$

Definition 4. A set $E \subseteq \mathbb{R}^n$ is *Lebesgue mesurable* (or mesurable) if $\forall \epsilon > 0$, there exist U open set such that $E \subseteq U$ and $|U \setminus E|^* < \epsilon$

Definition 5. A function u defined almost everywhere on a measurable set $\Omega \in \mathbb{R}^n$ is said to be *essentially bounded* on Ω if $|u(x)|$ is bounded almost everywhere on Ω. We denote $u \in L^\infty(\Omega)$ with the norm

$$\|u\|_{L^\infty(\Omega)} = inf(\lambda | \{x : |u(x)| \geq \lambda\} = 0) = ess \sup_{x \in \Omega} |u(x)|$$

We have that $L^\infty(\mathbb{R})$ is the space of essentially bounded functions.

Examples and counterexamples of functions essentially bounded.

- $f : \Omega \to$

Definition 6. A function u defined almost everywhere on a domain Ω (a domain is an open set in $\mathbb{R}^n$) is said to be *locally essentially bounded* on Ω if for every compact set $K \subset \Omega$, $u \in L^\infty(K)$. We denote $u \in L^\infty_{loc}(K)$

Definition 7. We say that a set of functions $F \subset L^\infty_{loc}(\mathbb{R})$ is *dense* in $C(\mathbb{R}^n)$ if for every function $g \in C(\mathbb{R}^n)$ and for every compact $K \subset \mathbb{R}^n$, there exist a sequence of functions $f_j \in F$ such that

$$\lim_{j \to \infty} \|g - f_j\|_{L^\infty(K)} = 0.$$

3.3 Results

Definition 8. Let $\mathcal{M}$ denote the set of functions which are in $L^\infty_{loc}(\mathbb{R})$ and have the following property. The closure of the set of points of discontinuity of any function in $\mathcal{M}$ is of zero Lebesgue measure.

Proposition 9. (This implies that) for any $\sigma \in \mathcal{M}$, interval $[a, b]$. and $\delta > 0$, there exists a finite number of open intervals, the union of which we denote by U, of measure δ, such that σ is uniformly continuous on $[a, b]/U$.

3.4 Neural Networks

intro

The general architecture of a multilayer feedforward network, MFN, consist of: input layer: n-input units, one/more hidden layers : intermediate processing units, output layer: m output-units

Definition 10. (Multilayer feedforward networks) The function that a MFN compute is:

$$f(x) = \sum_{j=1}^{k} \beta_j \cdot \sigma(w_j \cdot x - \theta_j)$$

where $x \in \mathbb{R}^n$ is the input vector, $k \in \mathbb{N}$ is the number of processing units in the hidden layer, $w_j \in \mathbb{R}^n$ is the weight vector that connects the input to processing unit j in the hidden layer, $\sigma : \mathbb{R} \to \mathbb{R}$ is an activation function applied element-wise to the vector $w_j^T x - \theta_j$, where $\theta_j \in \mathbb{R}$ is the threshold (or bias) associated with processing unit j in the hidden layer, and $\beta_j \in \mathbb{R}$ is the weight that connects processing unit j in the hidden layer to the output of the network.

Definition 11. $\mathcal{C}_0^\infty$ functions $\mathcal{C}^\infty$ with compact support.

3.5 Theorem

Theorem 12. *Let $\sigma \in M$. Set*

$$\Sigma_n = span\{\sigma(w \cdot x + \theta) : w \in \mathbb{R}^n, \theta \in \mathbb{R}\}$$

Then Σ_n is dense in $\mathcal{C}(\mathbb{R}^n)$ if and only if σ is not an algebraic polynomial.

3.5.1 Why does not contradict the Weierstrass approximation theorem?

Theorem 13. *(Weierstrass approximation theorem). Let $f : [a, b] \to \mathbb{R}$ be a continuous function. Then, there exists polynomials $p_n \in \mathcal{R}[x]$ such that the sequence (p_n) converge uniformly to f on $[a, b]$.*

Corollary 14. The set of polynomial functions $\mathcal{R}^n[x]$ is dense in the space of continuous functions on a closed and bounded interval $\mathcal{C}([a, b]^n)$.

Com que σ té grau fix "k", aleshores $\sigma(wx + \theta)$ grau com a molt k. Per tant el conjunt σ_n és un espai vectorial finit i no pot ser dens.

Chapter 4

Lemmas and proof

This chapter presents the lemmas that are necessary to prove the main theorem.

4.1 Part 1

Lemma 15. If we have that $\sigma * \varphi$ is a polynomial for all $\varphi \in \mathcal{C}_0^\infty$. Then the degree of the polynomial $\sigma * \varphi$ is finite, i.e. there exists an m $\in \mathbb{N}$ such that $deg(\sigma * \varphi) \leq m$ for all $\varphi \in \mathcal{C}_0^\infty$.

Proof. We first prove the claim in the case of $\varphi \in \mathcal{C}_0^\infty[a, b]$, where $\mathcal{C}_0^\infty[a, b]$ is the set of functions $\mathcal{C}_0^\infty$ with support in $[a, b]$ for any $a < b$.

Let ρ be a metric on $\mathcal{C}_0^\infty[a, b]$ defined by

$$\rho(\varphi_1, \varphi_2) = \sum_{n=0}^{\infty} 2^{-n} \frac{\|\varphi_1 - \varphi_2\|_n}{1 + \|\varphi_1 - \varphi_2\|_n}$$

where $\|\varphi\|_n = \sum_{j=0}^{n} \sup_{x \in [a,b]} |\varphi^{(j)}(x)|$. We can show that $(\mathcal{C}_0^\infty[a, b], \rho)$ is a complete metric space. By assumption, we have that $\sigma * \varphi$ is a polynomial (for any $\varphi \in \mathcal{C}_0^\infty[a, b]$).

Consider the following set, which has the property that we want to show.

$$V_k = \{\varphi \in \mathcal{C}_0^\infty[a, b] \,|\, deg(\sigma * \varphi) \leq k\}$$

Clearly, if $\varphi \in V_k$, then $deg(\sigma * \varphi) \leq k$. We want to show that $\mathcal{C}_0^\infty[a, b] \subseteq V_k$. This set fulfills the following properties, $V_k \subset V_{k+1}$, V_k is a closed subspace and $\cup_{k=0}^{\infty} V_k = \mathcal{C}_0^\infty[a, b]$. As $\mathcal{C}_0^\infty[a, b]$ is a complete metric space, for Blaire's Category Theorem (appendix) then there exists an integer m such that $V_m = \mathcal{C}_0^\infty[a, b]$.

For the general case where $\varphi \in \mathcal{C}_0^\infty$, we note that the number m does not deppend on the interval $[a, b]$.

□

Lemma 16. If $\sigma * \varphi$ is a polynomial such that $deg(\sigma * \varphi) \leq m$ for all $\varphi \in \mathcal{C}_0^\infty$, then σ is a polynomial of degree at most m.

Proof. If $\sigma * \varphi$ is a polynomial of degree m. For all $\varphi \in \mathcal{C}_0^\infty$, we have that

$$(\sigma * \varphi)^{(m+1)}(x) = \int \sigma(x-y)\varphi^{(m+1)}(y)\, dy = 0$$

From standard results in Distribution Theory, σ is itself a polynomial of degree at most m (a.e.). NO SE PQ ☐

Conclusion: If we have that $\sigma * \varphi$ is a polynomial then σ is a polynomial. This contradicts the hypothesis. Therefore, $\sigma * \varphi$ will not be a polynomial.

4.2 Σ_1 dense in $\mathcal{C}(\mathbb{R})$

Lemma 17. For each $\varphi \in \mathcal{C}_0^\infty$, $\sigma * \varphi \in \overline{\Sigma_1}$.

Proof. Consider

$$h_m = \sum_{i=1}^{m} \varphi(y_i)\Delta y_i \sigma(x - y_i)$$

The sequence (h_m) satisfies $h_j \in \Sigma_1$ for $j = 1, ..., m$. $(w_i = 1, \theta_i = -y_i, \beta_i = \varphi(y_i)\Delta y_i)$.

Where $y_i = -\alpha + \frac{2i\alpha}{m}$, $\Delta y_i = \frac{2\alpha}{m}$ for $i = 1, ..., m$. Partition of the interval $[-\alpha, \alpha]$

We want to show that $h_m \rightrightarrows \sigma * \varphi$ in $[-\alpha, \alpha]$.

Given $\epsilon > 0$, we choose $\delta > 0$ such that $10\delta\|\sigma\|_{L^\infty\{-2\alpha,2\alpha\}}\|\varphi\|_{L^\infty} \leq \frac{\epsilon}{3}$. Note that ...

We know that $\sigma \in M$. Hence, for this given $\delta > 0$ and $[-\alpha, \alpha]$ interval, there exists $r(\delta)$ finite number of intervals the measure of whose union $\mathfrak{U}$ is δ such that σ is uniformly continuous on $[-2\alpha, 2\alpha]$. We now choose m_i sufficiently large so that

1. $m_1\delta > \alpha r(\delta)$. We can do this by Archimedes' principle.
2. From the uniform continuity of φ.
3. From the previous, σ is uniformly continuous on $[-2\alpha, 2\alpha]$.

We choose m such that $m = max\{m_1, m_2, m_3\}$.

Now, fix $x \in [-\alpha, \alpha]$. Set $\Delta_i = [y_{i-1},]$ where .. dibuix.

First, recall that,

$$\int \sigma(x-y)\varphi(y)dy = \sum_{i=1}^{m} \int_{\Delta_i} \sigma(x-y)\varphi(y)dy$$

Consider the following difference

$$\left| \int \sigma(x-y)\varphi(y)dy - \sum_{i=1}^{m} \int_{\Delta_i} \sigma(x-y_i)\varphi(y)dy \right| =$$
$$= \left| \sum_{i=1}^{m} \int_{\Delta_i} \sigma(x-y)\varphi(y)dy - \sum_{i=1}^{m} \int_{\Delta_i} \sigma(x-y_i)\varphi(y)dy \right|$$
$$= \left| \sum_{i=1}^{m} \int_{\Delta_i} \varphi(y)\Big(\sigma(x-y) - \sigma(x-y_i)\Big)dy \right|$$
$$\leq \sum_{i=1}^{m} \int_{\Delta_i} |\varphi(y)|\, |\sigma(x-y) - \sigma(x-y_i)|\, dy$$

If $x - \Delta_i \cap U = \varnothing$. Since $x - y \notin U$, $x - y_i \notin U$ and $x - y_i \in [-2\alpha, 2\alpha]$, bc (2) we have

$$\sum_{i=1}^{m} \int_{\Delta_i} |\varphi(y)|\, |\sigma(x-y) - \sigma(x-y_i)|\, dy \leq \frac{\epsilon}{\|\varphi\|_{L_1}} \sum_{i=1}^{m} \int_{\Delta_i} |\varphi(y)| =$$
$$= \frac{\epsilon}{3\|\varphi\|_{L_1}} \int |\varphi(y)|\, dy$$
$$= \frac{\epsilon}{3\|\varphi\|_{L_1}} |\varphi(y)|_{L_1} = \frac{\epsilon}{3}$$

If $x - \Delta_i \cap U \neq \varnothing$

$\sum_i |\widetilde{\Delta_i}| = \sum_i |(x - \Delta_i \cap U)| \leq |U| + 2|\Delta_i| r(\delta) \leq \delta + 2 \cdot \frac{2\alpha}{m} r(\delta) \leq \delta + 4\delta = 5\delta$

True by our choice of m, satisfies $m\delta > \alpha r(\delta) \iff \delta > \frac{\alpha \cdot r(\delta)}{m}$

$$\sum_{i=1}^{m} \int_{\widetilde{\Delta_i}} |\varphi(y)|\, |\sigma(x-y) - \sigma(x-y_i)|\, dy \leq$$
$$\leq \sum_{i=1}^{m} \int_{\widetilde{\Delta_i}} \|\varphi\|_{L^\infty}\, 2\|\sigma\|_{L^\infty[-2\alpha,2\alpha]}$$
$$= \|\varphi\|_{L^\infty}\, 2\|\sigma\|_{L^\infty[-2\alpha,2\alpha]} \sum_i |\widetilde{\Delta_i}|$$
$$\leq \|\varphi\|_{L^\infty}\, 2\|\sigma\|_{L^\infty[-2\alpha,2\alpha]}\, 5\delta \leq \epsilon/3$$

□

Lemma 18. If $\sigma \in \mathcal{C}^\infty$, then Σ_1 is dense in $\mathcal{C}(\mathbb{R})$.

Proof. We recall that set $\Sigma_1 = span\{\sigma(w \cdot x + \theta) : w \in \mathbb{R}, \theta \in \mathbb{R}\}$. We can write any function $h \in \Sigma_1$ as $h = \sum_i \beta_i \sigma_i(w_i x + \theta_i) = \beta_1 \sigma_1(w_1 x + \theta_1) + ...$

$\frac{\sigma([w+h]x+\theta)-\sigma(wx+\theta)}{h} \in \Sigma_1$ because is a linear combination, where $\beta_1 = \frac{1}{h}, \beta_2 = \frac{-1}{h}$....
By hypothesis, we have $\sigma \in \mathcal{C}^\infty$. By definition of derivative we have

$$\frac{d}{dw}\sigma(wx+\theta) = \lim_{h\to 0}\frac{\sigma([w+h]x+\theta)-\sigma(wx+\theta)}{h} \in \overline{\Sigma_1}^{*}$$

Because the limit of a set belongs to the closure of the set.
By the same argument, $\frac{d^k}{dw^k}\sigma(wx+\theta) \in \overline{\Sigma_1}$ for all $k \in \mathbb{N}, w, \theta \in \mathbb{R}$.
We observe that $\frac{d}{dw}\sigma(wx+\theta) = \sigma'(wx+\theta)\cdot x$. If we differentiate this expression k times, we obtain

$$\frac{d^k}{dw^k}\sigma(wx+\theta) = \sigma^{(k)}(wx+\theta)\cdot x^k$$

Since σ is not a polynomial (theorem hypothesis) then there exists a $\theta_k \in \mathbb{R}$ such that $\sigma^{(k)}(\theta_k) \neq 0$
Lets see.**** If σ is not a polynomial and $\sigma \in \mathcal{C}^\infty$, lets assume that $\nexists \theta_k \in \mathbb{R}$ such that $\sigma^{(k)}(\theta_k) \neq 0$. This means that the k-th derivative at every point is 0, i.e, $\sigma^{(k)}(\theta) = 0\ \forall\theta \in \mathbb{R}$. If we integrate k times, $\int \sigma^{(k)} = \int 0 \iff \sigma^{(k-1)} = C$, $\int \sigma^{(k-1)} = \int C \iff \sigma^{(k-2)} = Cw$, then we end up σ is a polynomial. Contradiction.
Therefore, there always exists a point where the derivative does not vanish.
Thus, we evaluate at this point θ_k where the derivative does not vanish.

$$\sigma^{(k)}(\theta_k)\cdot x^k = \frac{d^k}{dw^k}\sigma(wx+\theta)\Big|_{w=0,\theta=\theta_k} \in \overline{\Sigma_1}$$

That implies that $\overline{\Sigma_1}$ contains all polynomials, because the expression $\sigma^{(k)}(\theta_k)x^k$ generates all polynomials. By the Weierstrass theorem, it follows that Σ_1 contains... falta mirar. □

Lemma 19. If for some $\varphi \in \mathcal{C}_0^\infty$ we have that $\sigma * \varphi$ is not a polynomial, then Σ_1 is dense in $\mathcal{C}(\mathbb{R})$

Proof. From Lemma 3, $\sigma * \varphi \in$ □

4.3 Σ_n dense in $\mathcal{C}(\mathbb{R}^n)$

Lemma 20. If Σ_1 is dense in $\mathcal{C}(\mathbb{R})$, then Σ_n is dense in $\mathcal{C}(\mathbb{R}^n)$.

Proof. Let $V := span\{f(ax) : a \in \mathbb{R}^n, f \in \mathcal{C}(\mathbb{R})\}$. V is dense in $\mathcal{C}(\mathbb{R}^n)$.
Let $g \in \mathcal{C}(\mathbb{R})$, for any compact subset $K \subset \mathbb{R}^n$, V dense in $\mathcal{C}(K)$. That is, given $\epsilon > 0$, there exist $f_i \in \mathcal{C}(\mathbb{R})$ and $a_i \in \mathbb{R}^n$ $_{i=1,\dots,k}$ such that □

4.4 Proof of the theorem

Proof.

*$\overline{\Sigma_1}$ denotes the clausure of the set Σ_1

$\Rightarrow$ To prove the implication, we will use proof by contrapositive. We will see the following. If σ is a polynomial then Σ_n is not dense in $\mathcal{C}(\mathbb{R}^n)$. Let σ be a polynomial of degree k, then $\sigma(wx+\theta)$ is a polynomial of degree k for every w, θ. We have $\Sigma_n = span\{\sigma(w \cdot x + \theta) : w \in \mathbb{R}^n, \theta \in \mathbb{R}\}$ that is the set of algebraic polynomials of degree at most k.

Σ_n is not dens in $\mathcal{C}(\mathbb{R}^n)$ if for a function $f(x) \in \mathcal{C}(\mathbb{R}^n)$ we can find $\epsilon > 0$ and K such that $\|p - f\| > \epsilon$ for all p polynomial of degree k. For example, let $f(x) = cos(x)$, and $p(x) = \sigma(wx + \theta)$ that has degree k. This implies has maximum k roots. We can find a interval where there are k+1 roots.

$\Leftarrow$ Recapitulem el que hem vist als lemes ..

$\square$

Leshno et al. [1993]

Chapter 5

Results

$$t = x + y \tag{5.1}$$

Chapter 6

Conclusions

It is a mistake to confound strangeness with mystery.
— Sherlock Holmes, *A Study in Scarlet*

6.1 Summary

6.2 Outlook and Future Work

Hem trobat:

- Aaaaa
- Bbbbbb

Chapter 7

References

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Appendix A

Theory used

Definition 21. Riemann integral reminder. The Riemann integral is a method for calculating the volume under a curve of a continuous function on a closed, bounded domain in R^n. The method involves dividing the domain into smaller subregions and approximating the volume of each subregion with a rectangular solid whose height is the function value at a specific point in the subregion. The Riemann sum is the sum of the volumes of all the rectangular solids, and as the size of the subregions approaches zero, the Riemann sum converges to the Riemann integral.

Definition 22. Let Σ be a σ-algebra over a set Ω. A *measure* over Ω is any function

$$\mu : \Sigma \longrightarrow [0, \infty]$$

satisfying the following properties:

1. $\mu(\varnothing) = 0$.
2. σ*-additivity*: If $(A_n) \in \Sigma$ are pairwise disjoint, then:

$$\mu\left(\bigsqcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} \mu(A_n)$$

Definition 23. A metric space (X, d) is said to be *complete* if every Cauchy sequence in X converges to a point in X.

Definition 24. We say that a property holds almost everywhere (a.e.) if the set of points that doesn't hold it is null.

Definition 25. $\varphi : I \to \mathbb{R}$ is uniformly continuous on I if $\forall \epsilon > 0 \exists\ \delta > 0$ such that $|\varphi(x) - \varphi(y)| < \epsilon$ whenever $|x - y| < \delta$

A.1 Blaire's category theorem

Definition 26. Let A be a subset of the metric space (X, d). A is said to be *nowhere dense* if for every (nonempty) open subset $U \subseteq X$, the intersection $U \cap \overline{A}$ is not dense in U, meaning that U contains a point that is not in the closure of A.

Definition 27. A set it is said to be category I if it can be written as a countable union of nowhere-dense sets. Otherwise it is said to be of *category II*

Theorem 28. *(Blaire's Category Theorem) Any complete metric space is of category II.*

Therefore, if we have $\mathcal{C}_0^\infty[a,b]$ complete metric space, we know that is of category II, i.e. $\mathcal{C}_0^\infty[a,b]$ cannot be written as a countable union of nowhere-dense sets. We have $\cup_{k=0}^{\infty} V_k = \mathcal{C}_0^\infty[a,b]$. Therefore, some V_m contains a nonempty open set. V_m is a vector space thus $V_m = \mathcal{C}_0^\infty[a,b]$. no entenc el final