

Weak Convergence and Empirical Processes

Chapter 2.6: Uniform Entropy Numbers

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What's on the menu today?

- 1 Introduction
- 2 VC-Classes
- 3 VC-Classes of Functions



Goal of this chapter

Uniform Entropy Number

$$\sup_Q N\left(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)\right) \leq K \left(\frac{1}{\epsilon}\right)^V, \quad 0 < \epsilon < 1$$

Recap

$$\sup_Q N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)) \leq K \left(\frac{1}{\epsilon}\right)^V$$

Goal

Empirical process converges weakly to some limiting distribution for some class \mathcal{F} of measurable functions

Recap

$$\sup_Q N\left(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)\right) \leq K \left(\frac{1}{\epsilon}\right)^V$$

Goal

$$\mathbb{G}_n = \sqrt{n}(\mathbb{P}_n - P) \rightsquigarrow \mathbb{G}, \quad \text{in } \ell^\infty(\mathcal{F})$$

Recap

$$\sup_Q N\left(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)\right) \leq K \left(\frac{1}{\epsilon}\right)^V$$

$$\mathbb{G}_n = \sqrt{n}(\mathbb{P}_n - P) \rightsquigarrow \mathbb{G}, \quad \text{in } \ell^\infty(\mathcal{F})$$

\mathcal{F} is called a **P-Donsker class**.

Recap

$$\sup_Q N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)) \leq K \left(\frac{1}{\epsilon}\right)^V$$

Theorem 2.5.2

Let \mathcal{F} be a class of measurable functions that satisfies the uniform entropy bound

$$\int_0^\infty \sup_Q \sqrt{\log N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q))} d\epsilon < \infty,$$

where the supremum is taken over all finitely discrete probability measures with $\|F\|_{Q,2} = \int F^2 dQ > 0$, where F is an envelope function for \mathcal{F} . Let the classes $\mathcal{F}_\delta = \{f - g : f, g \in \mathcal{F}, \|f - g\|_{P,2} < \delta\}$ and \mathcal{F}_∞^2 be P -measurable for every $\delta > 0$. If $P^*F^2 < \infty$, then \mathcal{F} is P -Donsker.

Uniform Entropy Bound

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Covering number

The **covering number** $N(\epsilon, \mathcal{F}, \|\cdot\|)$ is the minimal number of balls $\{g : \|g - f\| < \epsilon\}$ of radius ϵ needed to cover the set \mathcal{F} .

Uniform Entropy Bound

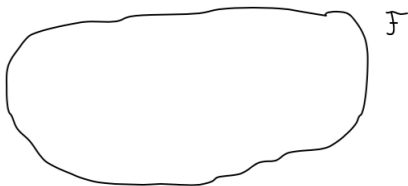
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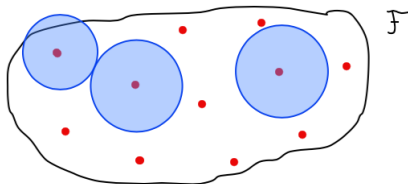
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Uniform Entropy Bound

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Envelope function

An **envelope function** of a class \mathcal{F} is any function $x \mapsto F(x)$ such that $|f(x)| \leq F(x)$, for every $x \in \mathcal{X}$ and $f \in \mathcal{F}$.

Uniform Entropy Bound

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Entropy number for $\epsilon > 1$

- For $\epsilon \geq 2$ we have $N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)) = 1$

Uniform Entropy Bound

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Uniform Entropy Bound

$$\sup_Q N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)) \leq K \left(\frac{1}{\epsilon}\right)^V$$

Uniform Entropy Bound

$$\int_0^1 \sup_Q \sqrt{\log N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q))} d\epsilon < \infty$$

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Goal of this chapter

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Uniform entropy condition

$$\sup_Q \log N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)) \leq K \left(\frac{1}{\epsilon}\right)^{2-\delta}, \quad \delta > 0$$

Goal of this chapter

Uniform Entropy Bound

$$\int_0^1 \sup_Q \sqrt{\log N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q))} d\epsilon < \infty$$

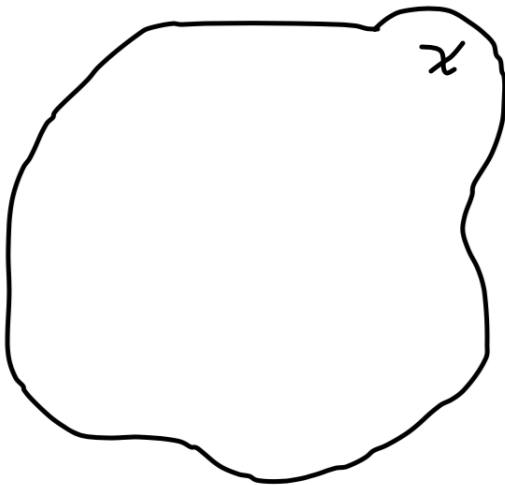
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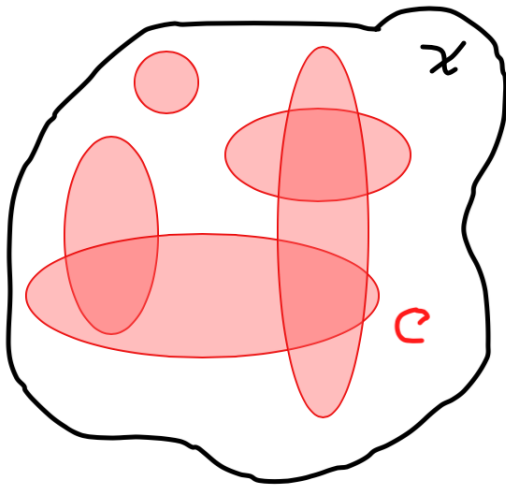
Our goal

$$\sup_Q N(\epsilon \|F\|_{Q,2}, \mathcal{F}, L_2(Q)) \leq K \left(\frac{1}{\epsilon}\right)^V, \quad \text{for some number } V$$

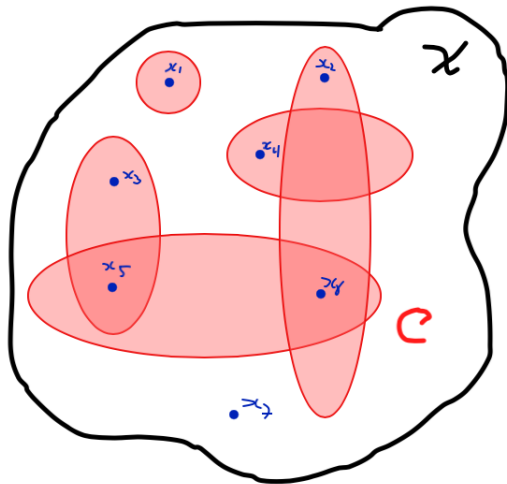
VC-Classes of Sets



VC-Classes of Sets

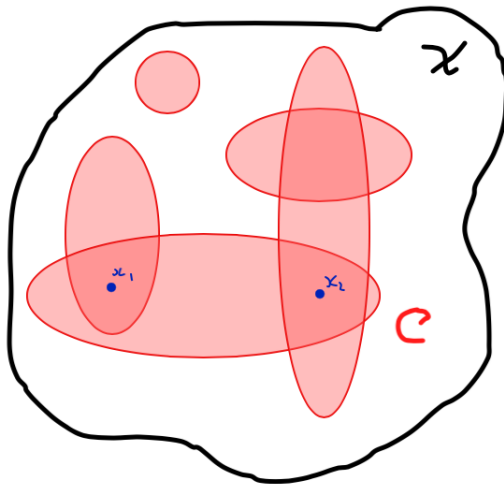


VC-Classes of Sets



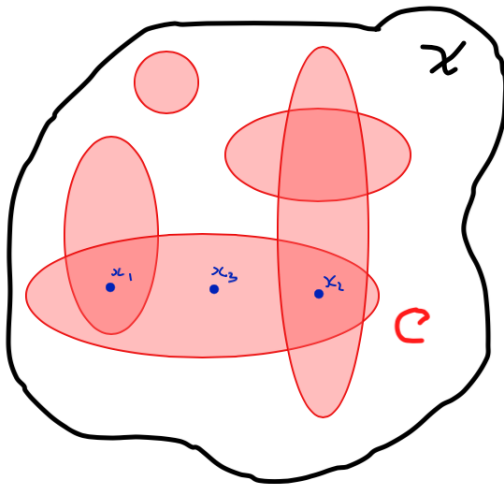
\mathcal{C} picks out a subset $A \subseteq \{x_1, \dots, x_n\}$ if there exists a $C \in \mathcal{C}$ with $C \cap \{x_1, \dots, x_n\} = A$

VC-Classes of Sets



\mathcal{C} **shatters** $\{x_1, \dots, x_n\}$ if each of its 2^n subsets can be picked out

VC-Classes of Sets



The **VC-index** $V(\mathcal{C})$ of the class \mathcal{C} is the smallest n for which no set of size n is shattered by \mathcal{C}

VC-Classes of Sets

VC-index

The **VC-index** of \mathcal{C} is defined as

$$V(\mathcal{C}) = \inf\{n : \max_{x_1, \dots, x_n} \Delta_n(\mathcal{C}, x_1, \dots, x_n) < 2^n\},$$

where

$$\Delta_n(\mathcal{C}, x_1, \dots, x_n) = \#\{\mathbf{C} \cap \{x_1, \dots, x_n\} : \mathbf{C} \in \mathcal{C}\}.$$

A collection of measurable sets \mathcal{C} is called a **VC-class** if its index is finite.

VC-Classes of Sets

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Convention

The infimum over the empty set is taken to be infinity

Example

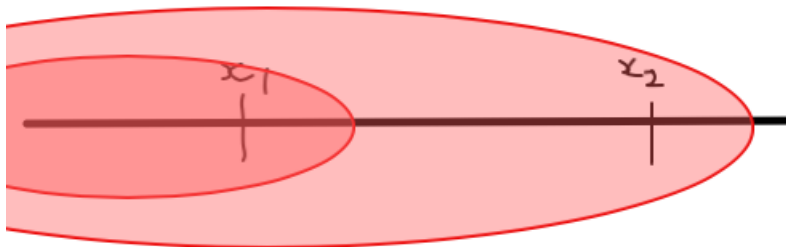
Real line

$$\mathcal{C} = \{(-\infty, c] : c \in \mathbb{R}\}, \quad \{x_1, x_2\} \subset \mathbb{R}$$

Example

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Combinatorial results

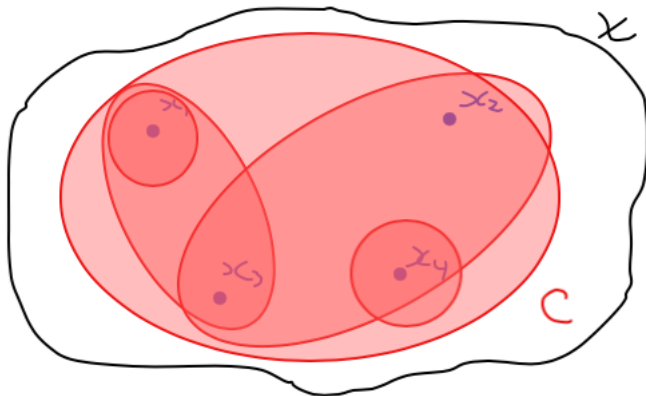
Lemma 2.6.2 (Sauer's lemma)

Let $\{x_1, \dots, x_n\} \subset \mathcal{X}$. Then the total number of subsets $\Delta_n(\mathcal{C}, x_1, \dots, x_n)$ picked out by \mathcal{C} is bounded above by the number of subsets of $\{x_1, \dots, x_n\}$ shattered by \mathcal{C} .

Combinatorial results

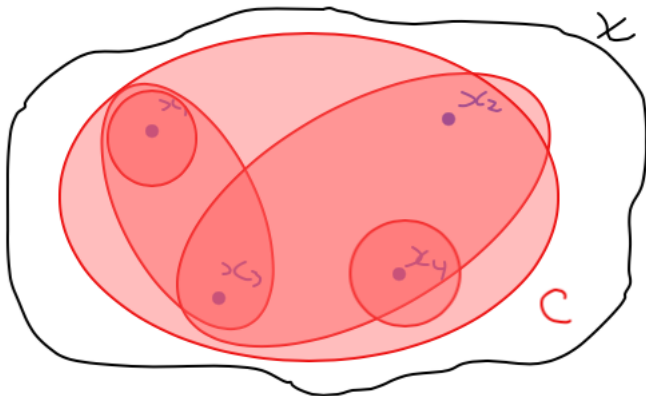
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Proof Idea

$$\Delta_n(\mathcal{C}, x_1, \dots, x_n) = \#\{C \cap \{x_1, \dots, x_n\} : C \in \mathcal{C}\}$$



Without loss of generality:

$$\mathcal{C} = \{\{x_1\}, \{x_4\}, \{x_1, x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

Note that this way $|\mathcal{C}| = \Delta_n(\mathcal{C}, x_1, \dots, x_n)$.

Proof Idea

Lemma 2.6.2 (Sauer's lemma)

Let $\{x_1, \dots, x_n\} \subset \mathcal{X}$. Then $|\mathcal{C}|$ is bounded above by the number of subsets of $\{x_1, \dots, x_n\}$ shattered by \mathcal{C} .

Definition

Call \mathcal{C} **hereditary** if it has the property that $B \in \mathcal{C}$ whenever $B \subset C$, for a set $C \in \mathcal{C}$.

Note

Each of the sets in a hereditary set is shattered.

Proof Idea

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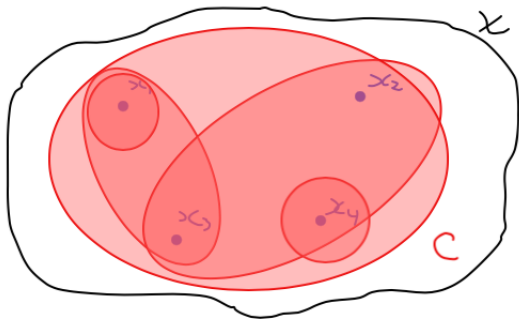
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Idea

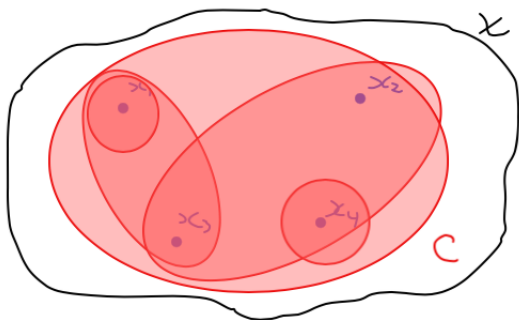
Transform each \mathcal{C} to a hereditary collection, without changing the cardinality and without increasing the number of shattered sets.

Proof Idea



$$C = \{\{x_1\}, \{x_4\}, \{x_1, x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

Proof Idea



$$\mathcal{C} = \{\{x_1\}, \{x_4\}, \{x_1, x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

Definition

For $1 \leq i \leq n$ and $C \in \mathcal{C}$

$$T_i(C) = \begin{cases} C - \{x_i\}, & C - \{x_i\} \notin \mathcal{C} \\ C, & \text{else.} \end{cases}$$

Proof Idea

Definition

For $1 \leq i \leq n$ and $C \in \mathcal{C}$

$$T_i(C) = \begin{cases} C - \{x_i\}, & C - \{x_i\} \notin \mathcal{C} \\ C, & \text{else.} \end{cases}$$

Note

- T_i is one-to-one, so $|\mathcal{C}| = |T_i(\mathcal{C})|$

Example

$$\mathcal{C} = \{\{x_1\}, \{x_4\}, \{x_1, x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

$$T_1(\mathcal{C}) = \{\{x_1\}, \{x_4\}, \{x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

Proof Idea

Definition

For $1 \leq i \leq n$ and $C \in \mathcal{C}$

$$T_i(C) = \begin{cases} C - \{x_i\}, & C - \{x_i\} \notin \mathcal{C} \\ C, & \text{else.} \end{cases}$$

Note

- T_i is one-to-one, so $|\mathcal{C}| = |T_i(\mathcal{C})|$
- Every subset $A \subset \{x_1, \dots, x_n\}$ that is shattered by $T_i(\mathcal{C})$ is shattered by \mathcal{C}

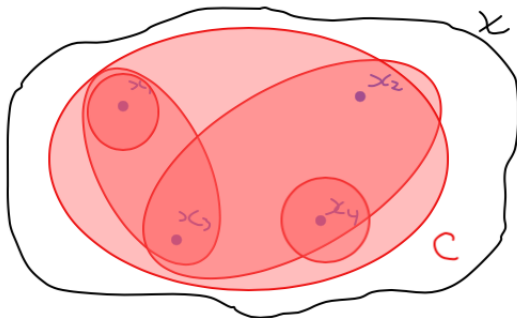
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$$T_1(\mathcal{C}) = \{\{x_1\}, \{x_4\}, \{x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

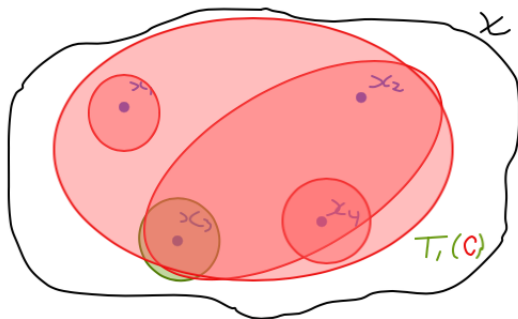
$T_1(\mathcal{C})$ shatters $\{x_1\}, \{x_2\}, \{x_3\}, \{x_4\}, \{x_1, x_2\}, \{x_1, x_3\}, \{x_1, x_4\}, \{x_3, x_4\}$

Proof Idea



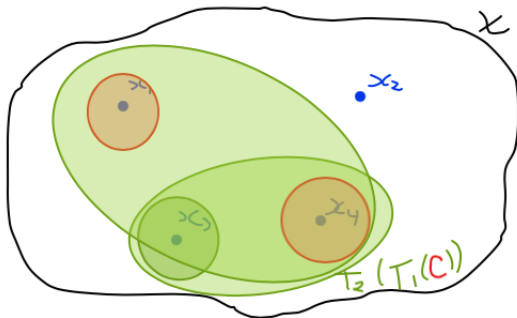
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Proof Idea



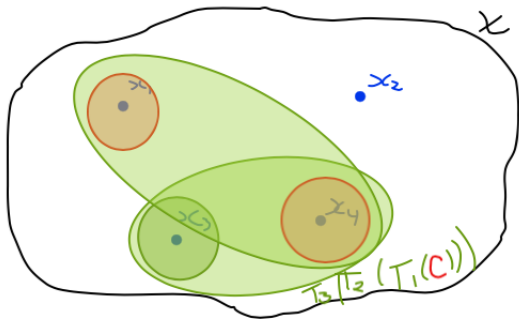
$$T_1(C) = \{\{x_1\}, \{x_4\}, \{x_3\}, \{x_2, x_3, x_4\}, \{x_1, x_2, x_3, x_4\}\}$$

Proof Idea



$$(T_2 \circ T_1)(C) = \{\{x_1\}, \{x_4\}, \{x_3\}, \{x_3, x_4\}, \{x_1, x_3, x_4\}\}$$

Proof Idea



$$(T_3 \circ T_2 \circ T_1)(C) = \{\{x_1\}, \{x_4\}, \{x_3\}, \{x_3, x_4\}, \{x_1, x_4\}\}$$

Corollary

Corollary 2.6.3

For a VC-class of sets of index $V(\mathcal{C})$, one has

$$\max_{x_1, \dots, x_n} \Delta_n(\mathcal{C}, x_1, \dots, x_n) \leq \sum_{j=0}^{V(\mathcal{C})-1} \binom{n}{j}.$$

Consequently, the numbers on the left side grow polynomially of order at most $O(n^{V(\mathcal{C})-1})$ as $n \rightarrow \infty$.

Most important theorem

Theorem 2.6.4

There exists a universal constant K such that for any VC-class \mathcal{C} of sets, any probability measure Q , any $r \geq 1$, and $0 < \epsilon < 1$,

$$N(\epsilon, \mathcal{C}, L_r(Q)) \leq KV(\mathcal{C})(4e)^{V(\mathcal{C})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{C})-1)}$$

Proof idea

- 1 Prove it for $r = 1$ and use a simple argument to show for $r > 1$
- 2 Use problem 2.6.3 to show it is enough to check if it holds for empirical type measures
- 3 Use some difficult arguments on the n -dimensional hypercube to obtain a bound on the packing number

Proof (idea)

Proof parts

- 1 Simple argument for the covering number for general $r > 1$ if the inequality holds for $r = 1$

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Suppose

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- 1 Simple argument for the covering number for general $r > 1$ if the inequality holds for $r = 1$

Suppose

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq f(\epsilon).$$

Note that for any $C, D \in \mathcal{C}$ we have

$$\begin{aligned}\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,r} &= \left(\int |\mathbb{1}_C - \mathbb{1}_D|^r dQ \right)^{1/r} \\ &= \left(\int |\mathbb{1}_C - \mathbb{1}_D| dQ \right)^{1/r} \\ &= \left(\int \mathbb{1}_{(C \cup D) \setminus (C \cap D)} dQ \right)^{1/r} \\ &= Q^{1/r}(C \triangle D)\end{aligned}$$

Proof (idea)

Proof parts

- 1 Simple argument for the covering number for general $r > 1$ if the inequality holds for $r = 1$

Suppose

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq f(\epsilon).$$

Then

$$N(\epsilon, \mathcal{C}, L_r(Q)) = N(\epsilon^r, \mathcal{C}, L_1(Q)) \leq f(\epsilon^r)$$

Prrof (idea)

Proof parts

- 2 Use problem 2.6.3 to show that it is enough to check if it holds for empirical type measures

Prrof (idea)

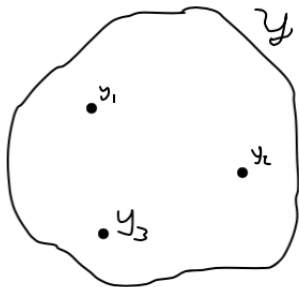
Suppose Q is a measure on a finite set of points y_1, \dots, y_k such that $Q(\{y_i\}) = l_i/n$ for integers l_1, \dots, l_k that add up to n . We assume again that each set in \mathcal{C} is a subset of these points.

Prrof (idea)

$$Q(\{y_1\}) = \frac{1}{5}$$

$$Q(\{y_2\}) = \frac{2}{5}$$

$$Q(\{y_3\}) = \frac{2}{5}$$

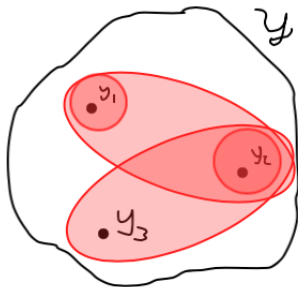


Prrof (idea)

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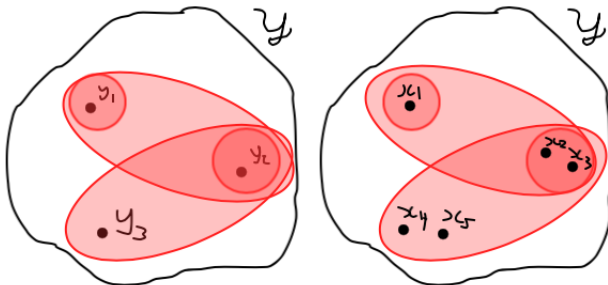
$$Q(\{y_2\}) = \frac{2}{5}$$

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$$\mathcal{C} = \{\{y_1\}, \{y_2\}, \{y_1, y_2\}, \{y_2, y_3\}\}$$

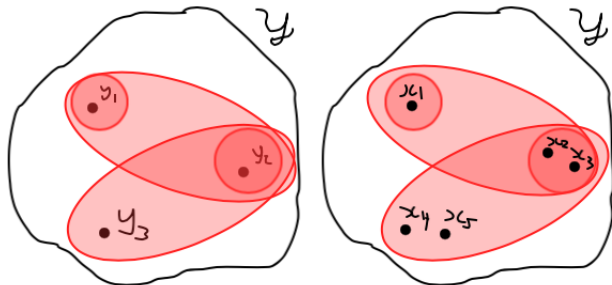
Prrof (idea)



$$\mathcal{C} = \{\{y_1\}, \{y_2\}, \{y_1, y_2\}, \{y_2, y_3\}\}$$

$$\tilde{\mathcal{C}} = \{\{x_1\}, \{x_2, x_3\}, \{x_1, x_2, x_3\}, \{x_2, x_3, x_4, x_5\}\}$$

Prrof (idea)



$$\mathcal{C} = \{\{y_1\}, \{y_2\}, \{y_1, y_2\}, \{y_2, y_3\}\}$$

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Note

The VC-index of $\tilde{\mathcal{C}}$ is the same as \mathcal{C}

Prrof (idea)

Covering number for the new collection $\tilde{\mathcal{C}}$

Let $C, D \in \mathcal{C}$, then we have $\tilde{C}, \tilde{D} \in \tilde{\mathcal{C}}$. Take $\tilde{Q}(\{x_i\}) = \frac{1}{n}$ for all $1 \leq i \leq n$. Then

$$Q(C \triangle D) = \tilde{Q}(\tilde{C} \triangle \tilde{D})$$

Prrof (idea)

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$$Q(C \triangle D) = \tilde{Q}(\tilde{C} \triangle \tilde{D})$$

Remember

$$\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,1} = Q(C \triangle D)$$

Prrof (idea)

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$$Q(C \triangle D) = \tilde{Q}(\tilde{C} \triangle \tilde{D})$$

Remember

$$\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,1} = Q(C \triangle D)$$

Conclusion

$$N\left(\epsilon, \tilde{\mathcal{C}}, L_1(\tilde{Q})\right) = N(\epsilon, \mathcal{C}, L_1(Q))$$

Proof (idea)

Proof parts

- 3 Use arguments on the n -dimensional hypercube to obtain a bound on the packing number

Proof (idea)

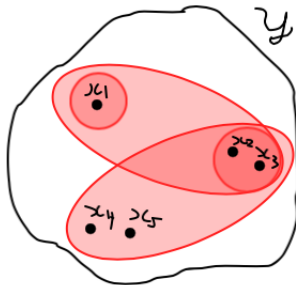
Proof parts

- 3 Use arguments on the n -dimensional hypercube to obtain a bound on the packing number

Note

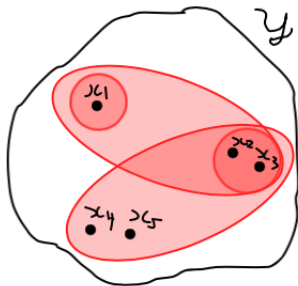
$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq D(\epsilon, \mathcal{C}, L_1(Q))$$

Proof (idea)



$$\mathcal{C} = \{\{x_1\}, \{x_2, x_3\}, \{x_1, x_2, x_3\}, \{x_2, x_3, x_4, x_5\}, \emptyset\}$$

Proof (idea)



$$\mathcal{C} = \{\{x_1\}, \{x_2, x_3\}, \{x_1, x_2, x_3\}, \{x_2, x_3, x_4, x_5\}, \emptyset\}$$

$$C_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

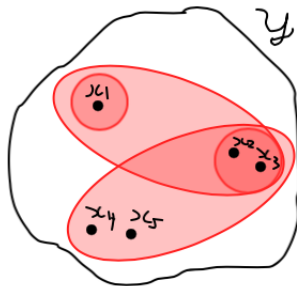
$$C_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

$$C_3 = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

$$C_4 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

$$C_5 = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

Proof (idea)



$$\mathcal{C} = \{\{x_1\}, \{x_2, x_3\}, \{x_1, x_2, x_3\}, \{x_2, x_3, x_4, x_5\}, \emptyset\}$$

Note

The collection \mathcal{C} can be identified with a subset \mathcal{Z} of the vertices of the n -dimensional hypercube $[0, 1]^n$

Proof (idea)

$$\mathcal{C} \longrightarrow \mathcal{Z} \longrightarrow \begin{pmatrix} 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

Proof (idea)

$$\mathcal{C} \longrightarrow \mathcal{Z} \longrightarrow \begin{pmatrix} 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

$$I = \{1, 2\} \qquad \mathcal{Z}_I := \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Proof (idea)

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$$I = \{1, 2\} \qquad \mathcal{Z}_I := \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Note

- \mathcal{Z}_I corresponds to the collection of $\mathcal{C} \cap \{x_i : i \in I\}$
- $\{x_i : i \in I\}$ is shattered if \mathcal{Z}_I consist of all $2^{|I|}$ possible columns
- This is only possible for $|I| < V(\mathcal{C})$, so define $V = V(\mathcal{C}) - 1$

Proof (idea)

Note

We transformed our problem from \mathcal{C} to \mathcal{Z} . However, we also need to transform our metric!

$$\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,1} = Q(C \triangle D)$$

Proof (idea)

Note

We transformed our problem from \mathcal{C} to \mathcal{Z} . However, we also need to transform our metric!

$$\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,1} = Q(C \triangle D)$$

Hamming metric

Let the vertices $w, z \in \mathcal{Z}$ correspond to the sets $C, D \in \mathcal{C}$ respectively. The *Hamming metric* on \mathcal{Z} is defined by

$$d(w, z) = \frac{1}{n} \sum_{j=1}^n |w_j - z_j| = \frac{1}{n} \sum_{j=1}^n (w_j - z_j)^2, \quad z, w \in \mathcal{Z}.$$

With this metric we have $Q(C \triangle D) = d(w, z)$.

Proof (idea)

Note

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq D(\epsilon, \mathcal{C}, L_1(Q))$$

Proof (idea)

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$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq D(\epsilon, \mathcal{C}, L_1(Q))$$

ϵ -seperation

Fix a maximal ϵ -seperated collection of sets $C \in \mathcal{C}$. For simplicity of notation we assume that \mathcal{C} is ϵ -seperated, so for $C, D \in \mathcal{C}$

$$\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,1} > \epsilon$$

Proof (idea)

Note

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq D(\epsilon, \mathcal{C}, L_1(Q))$$

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$$\|\mathbb{1}_C - \mathbb{1}_D\|_{Q,1} > \epsilon$$

Note

In this way, \mathcal{Z} is also ϵ -seperated using the Hamming distance. For $w, z \in \mathcal{Z}$ corresponding to $C, D \in \mathcal{C}$ we have

$$d(w, z) > \epsilon.$$

Proof (idea)

Note

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq D(\epsilon, \mathcal{C}, L_1(Q)) \leq |\mathcal{Z}|$$

ϵ -seperation

Fix a maximal ϵ -seperated collection of sets $C \in \mathcal{C}$. For simplicity of notation we assume that \mathcal{C} is ϵ -seperated, so for $C, D \in \mathcal{C}$

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In this way, \mathcal{Z} is also ϵ -seperated using the Hamming distance. For $w, z \in \mathcal{Z}$ corresponding to $C, D \in \mathcal{C}$ we have

$$d(w, z) > \epsilon.$$

Proof

Introducing random variables

Let Z be a random variable with a discrete uniform distribution on the set \mathcal{Z} in $[0, 1]^n$, so

$$P(Z = z) = \frac{1}{|\mathcal{Z}|}, \quad z \in \mathcal{Z}.$$

Proof

Introducing random variables

Let Z be a random variable with a discrete uniform distribution on the set \mathcal{Z} in $[0, 1]^n$, so

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Fix integer

Fix integer $V \leq m < n$. Let $I \subseteq \{1, 2, \dots, n\}$ such that $|I| = m + 1$.

Proof

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Lemma 2.6.6

Let Z be an arbitrary random vector taking values in $\mathcal{Z} \subset \{0, 1\}^n$ that corresponds to a VC-class \mathcal{C} of subsets of a set of points $\{x_1, \dots, x_n\}$. Then

$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$

Proof

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Let Z be a random variable with a discrete uniform distribution on the set \mathcal{Z} in $[0, 1]^n$, so

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Fix integer $V \leq m < n$. Let $I \subseteq \{1, 2, \dots, n\}$ such that $|I| = m + 1$.

Our case

Apply the lemma to Z_I :

$$\sum_{i \in I} \mathbb{E} [\text{Var} (Z_i | Z_{I - \{i\}})] \leq V$$

Proof

$$\sum_{i \in I} \mathbb{E} [\text{Var} (Z_i | Z_{I - \{i\}})] \leq V$$

Proof

$$\sum_{\substack{I \subseteq \{1, \dots, n\} \\ |I| = m+1}} \sum_{i \in I} \mathbb{E} [\text{Var} (Z_i | Z_{I - \{i\}})] \leq \sum_{\substack{I \subseteq \{1, \dots, n\} \\ |I| = m+1}} v$$

Proof

$$\sum_{\substack{J \subseteq \{1, \dots, n\} \\ |J|=m}} \sum_{i \notin J} \mathbb{E} [\text{Var}(Z_i | Z_J)] \leq \binom{n}{m+1} v$$

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$$\sum_{\substack{J \subseteq \{1, \dots, n\} \\ |J|=m}} \mathbb{E} \left[\sum_{i \notin J} \text{Var}(Z_i | Z_J) \right] \leq \binom{n}{m+1} v$$

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Proof

Remember

Z is uniformly distributed on the set \mathcal{Z}

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Consequence

$Z|Z_J = s$ is uniformly distributed over the set of columns $z \in \mathcal{Z}$ with $z_J = s$. Call N_s the number of these columns.

Proof

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Z is uniformly distributed on the set \mathcal{Z}

Consequence

$Z|Z_J = s$ is uniformly distributed over the set of columns $z \in \mathcal{Z}$ with $z_J = s$. Call N_s the number of these columns.

Define

Let W and \tilde{W} be independent random vectors defined on a common probability space distributed uniformly over these columns.

Proof

Remember

\mathcal{Z} is ϵ -seperated

Proof

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\mathcal{Z} is ϵ -separated

Consequence

If $W \neq \tilde{W}$, we have $d(W, \tilde{W}) > \epsilon$. This event happens with probability $1 - 1/N_s$. Else, $d(W, \tilde{W}) = 0$.

Proof

Distance

$d(W, \tilde{W}) > \epsilon$ with probability $1 - 1/N_s$

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$$\begin{aligned}\sum_{i \notin J} \text{Var}(Z_i | Z_J = s) &= \frac{1}{2} \sum_{i=1}^n \left(2\mathbb{E}[W_i^2] - 2\mathbb{E}[W_i]^2 \right) \\ &= \frac{1}{2} \sum_{i=1}^n \left(\mathbb{E}[W_i^2] + \mathbb{E}[\tilde{W}_i^2] - 2\mathbb{E}[W_i]\mathbb{E}[\tilde{W}_i] \right) \\ &= \frac{1}{2} \sum_{i=1}^n \mathbb{E}[(W_i - \tilde{W}_i)^2]\end{aligned}$$

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Remember

$$d(w, z) = \frac{1}{n} \sum_{j=1}^n |w_j - z_j| = \frac{1}{n} \sum_{j=1}^n (w_j - z_j)^2, \quad z, w \in \mathcal{Z}.$$

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Inequality

$$\sum_{\substack{J \subseteq \{1, \dots, n\} \\ |J|=m}} \mathbb{E} \left[\sum_{i \notin J} \text{Var}(Z_i | Z_J) \right] \leq \binom{n}{m+1} v$$

$$\sum_{i \notin J} \text{Var}(Z_i | Z_J = s) \geq \frac{1}{2} n \epsilon \left(1 - \frac{1}{N_s} \right)$$

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Note

Z is uniformly distributed over \mathcal{Z} and there are N_s columns with $z_J = s$:

$$P(Z_J = s) = \frac{N_s}{|\mathcal{Z}|}$$

Inequality

$$\sum_{\substack{J \subseteq \{1, \dots, n\} \\ |J|=m}} \mathbb{E} \left[\sum_{i \notin J} \text{Var}(Z_i | Z_J) \right] \leq \binom{n}{m+1} V$$

$$\mathbb{E} \left[\sum_{i \notin J} \text{Var}(Z_i | Z_J) \right] \geq \sum_{s \in \mathcal{Z}_j} \frac{N_s}{|\mathcal{Z}|} \frac{1}{2} n \epsilon \left(1 - \frac{1}{N_s} \right)$$

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Inequality

$$\sum_{\substack{J \subseteq \{1, \dots, n\} \\ |J|=m}} \mathbb{E} \left[\sum_{i \notin J} \text{Var}(Z_i | Z_J) \right] \leq \binom{n}{m+1} V$$

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$$\binom{n}{m} \frac{1}{2} n^{\epsilon} \left(1 - \frac{|\overline{\mathcal{Z}_J}|}{|\mathcal{Z}|} \right) \leq \binom{n}{m+1} \nu$$

$$\binom{n}{m} \frac{1}{2} n^\epsilon \left(1 - \frac{|\overline{\mathcal{Z}_J}|}{|\mathcal{Z}|} \right) \leq \binom{n}{m+1} V$$

Remember

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq D(\epsilon, \mathcal{C}, L_1(Q)) \leq |\mathcal{Z}|$$

$$|\mathcal{Z}| \leq \frac{|\overline{\mathcal{Z}_J}|n\epsilon(m+1)}{n\epsilon(m+1) - 2nV + 2mV} \leq \frac{|\overline{\mathcal{Z}_J}|\epsilon(m+1)}{\epsilon(m+1) - 2V}$$

$$|\mathcal{Z}| \leq \frac{|\overline{\mathcal{Z}_J}|n\epsilon(m+1)}{n\epsilon(m+1) - 2nV + 2mV} \leq \frac{|\overline{\mathcal{Z}_J}|\epsilon m}{\epsilon m - 2V}$$

Proof

Corollary 2.6.3

For a VC-class of sets of index $V(\mathcal{C})$, one has

$$\max_{x_1, \dots, x_n} \Delta_n(\mathcal{C}, x_1, \dots, x_n) \leq \sum_{j=0}^{V(\mathcal{C})-1} \binom{n}{j} \leq \left(\frac{n \cdot e}{V(\mathcal{C}) - 1} \right)^{V(\mathcal{C})-1}.$$

Proof

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Note

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Proof

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Note

\mathcal{Z}_I corresponds to the collection of $\mathcal{C} \cap \{x_i : i \in I\}$

Consequence

$$|\mathcal{Z}| \leq \frac{|\overline{\mathcal{Z}_J}| \epsilon m}{\epsilon m - 2V} \leq \frac{\sum_{j=0}^V \binom{m}{j} \epsilon m}{\epsilon m - 2V} \leq \left(\frac{e}{V} \right)^V \frac{m^{V+1} \epsilon}{m \epsilon - 2V}$$

Proof

Optimization

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq |\mathcal{Z}| \leq \left(\frac{e}{V}\right)^V \frac{m^{V+1}\epsilon}{m\epsilon - 2V}$$

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$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq |\mathcal{Z}| \leq \left(\frac{e}{V}\right)^V \frac{m^{V+1}\epsilon}{m\epsilon - 2V}$$

Optimal m

Differentiating gives $m = 2(V + 1)/\epsilon$ as the optimal solution.

Proof

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$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq |\mathcal{Z}| \leq \left(\frac{e}{V}\right)^V \frac{m^{V+1}\epsilon}{m\epsilon - 2V}$$

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Note

- Discretizing m changes the upper bound only by a constant factor
- $V \leq m < n$
- n depends on Q , but we can make this arbitrarily large

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- $V \leq m < n$
- n depends on Q , but we can make this arbitrarily large

Bound

$$N(\epsilon, \mathcal{C}, L_1(Q)) \leq K(V + 1)(4e)^V \left(\frac{1}{\epsilon}\right)^V$$

Lemma 2.6.6

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Let Z be an arbitrary random vector taking values in $\mathcal{Z} \subset \{0, 1\}^n$ that corresponds to a VC-class \mathcal{C} of subsets of a set of points $\{x_1, \dots, x_n\}$. Then

$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$

Proof idea

$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$

Probabilities

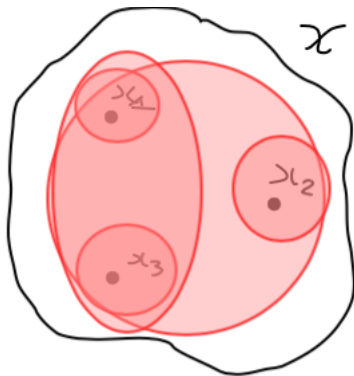
$Z_i | Z_j, j \neq i$ means that Z can only have two values. Call these v and w , where $v_i = 0$ and $w_i = 1$. Write $p(z) := P(Z = z)$, then $Z_i = 1$ or 0 with probabilities

$$p := \frac{p(w)}{p(w) + p(v)}$$

$$1 - p = \frac{p(v)}{p(w) + p(v)}$$

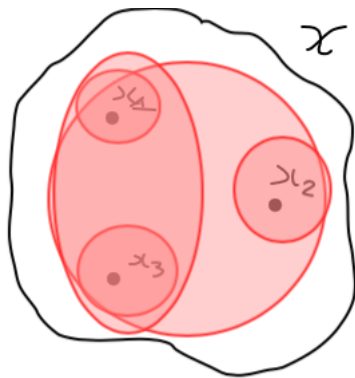
Proof idea

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$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

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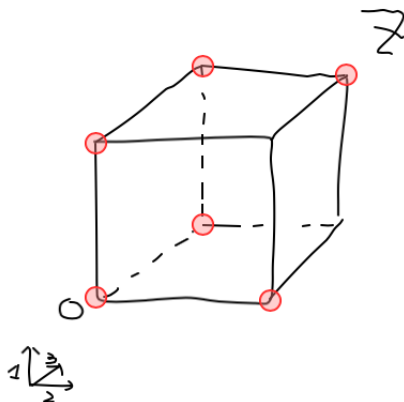
$$\begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$$

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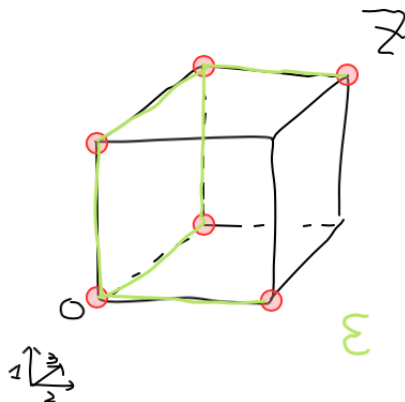
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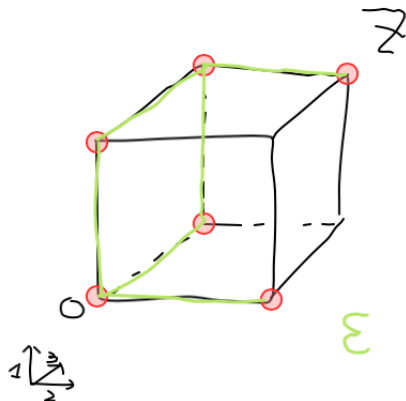


Notation

Let \mathcal{E} be all edges in the graph and \mathcal{E}_i be the set of edges that cross the i th dimension.

Proof idea

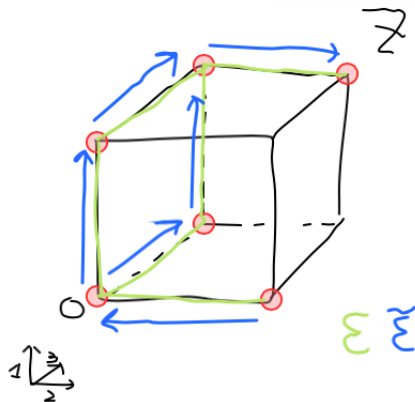
$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$



$$\begin{aligned} \sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] &= \sum_{i=1}^n \sum_{\{v,w\} \in \mathcal{E}_i} (p(v) + p(w)) \cdot p(1-p) \\ &= \sum_{\{v,w\} \in \mathcal{E}} p(v) \cdot p(w) \end{aligned}$$

Proof idea

$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$



$$\begin{aligned} \sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] &= \sum_{\{v, w\} \in \mathcal{E}} p(v) \cdot p(w) \\ &= \sum_{v \in \mathcal{Z}} \sum_{(v, w) \in \tilde{\mathcal{E}}} p(v) \cdot p(w) \end{aligned}$$

Proof idea

$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$

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Note

Problem 2.6.5 shows that $\tilde{\mathcal{E}}$ can be formed such that

$$\sum_{(v,w) \in \tilde{\mathcal{E}}} 1 \leq V(\mathcal{C}) - 1, \quad v \in \mathcal{Z}$$

Proof idea

$$\sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] \leq V(\mathcal{C}) - 1$$

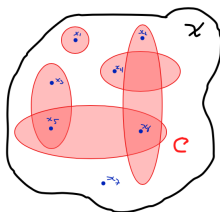
$$\begin{aligned} \sum_{i=1}^n \mathbb{E} [\text{Var} (Z_i | Z_j, j \neq i)] &= \sum_{\{v,w\} \in \mathcal{E}} p(v) \cdot p(w) \\ &= \sum_{v \in \mathcal{Z}} \sum_{(v,w) \in \tilde{\mathcal{E}}} p(v) \cdot p(w) \\ &\leq \sum_{v \in \mathcal{Z}} p(v) \cdot (V(\mathcal{C}) - 1) \\ &= V(\mathcal{C}) - 1 \end{aligned}$$

VC-Classes of Functions

Theorem 2.6.4

There exists a universal constant K such that for any VC-class \mathcal{C} of sets, any probability measure Q , any $r \geq 1$, and $0 < \epsilon < 1$,

$$N(\epsilon, \mathcal{C}, L_r(Q)) \leq KV(\mathcal{C})(4e)^{V(\mathcal{C})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{C})-1)}.$$

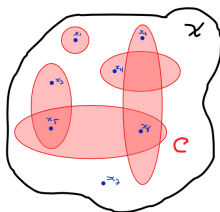


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Question

Can we also find such a result for function classes?

Subgraphs

Subgraph

The *subgraph* of a function $f : \mathcal{X} \rightarrow \mathbb{R}$ is the subset of $\mathcal{X} \times \mathbb{R}$ given by

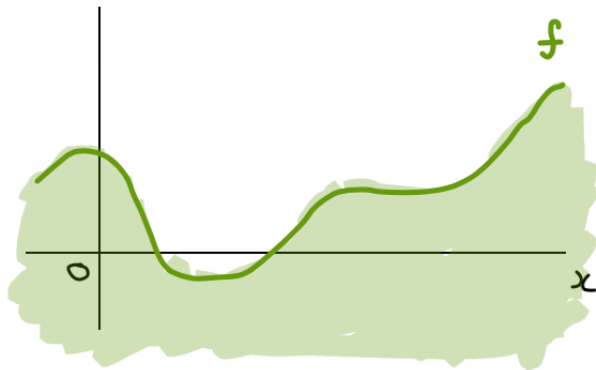
$$\{(x, t) : t < f(x)\}$$

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VC-Class

A collection \mathcal{F} of measurable functions is called a *VC-class*, if the collection of all subgraphs of the functions in \mathcal{F} forms a VC-class of sets in $\mathcal{X} \times \mathbb{R}$.

Main Theorem

Theorem 2.6.7

For a VC-class of functions with measurable envelope function F and $r \geq 1$, one has for any probability measure Q with $\|F\|_{Q,r} > 0$,

$$N\left(\epsilon\|F\|_{Q,r}, \mathcal{F}, L_r(Q)\right) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)},$$

for a universal constant K and $0 < \epsilon < 1$.

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Collection of sets

Let \mathcal{C} be the collection of subgraphs C_f of functions $f \in \mathcal{F}$.

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Collection of sets

Let \mathcal{C} be the collection of subgraphs C_f of functions $f \in \mathcal{F}$.

Goal

$$N(\epsilon 2QF, \mathcal{F}, L_1(Q)) \rightarrow N(\epsilon, \mathcal{C}, L_1(P))$$

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Transform distances

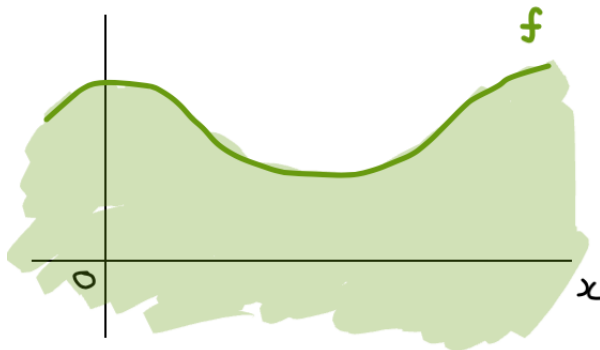
We want to show $Q \times \lambda(C_f \Delta C_g) = Q(|f - g|)$.

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

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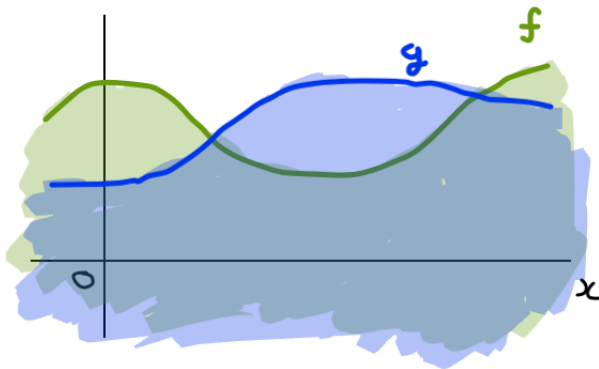


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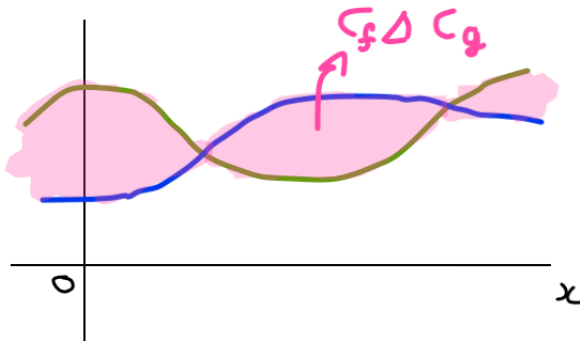


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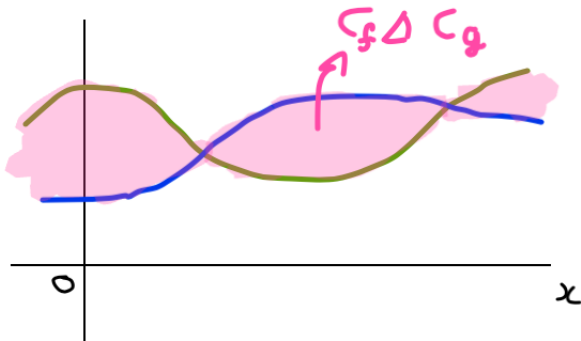


Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Transform distances

We want to show $Q \times \lambda(C_f \Delta C_g) = Q(|f - g|)$.



$$f(x) \wedge g(x) \leq t \leq f(x) \wedge g(x) + |f(x) - g(x)|, \quad x \in \mathcal{X}$$

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Transform distances

We want to show $Q \times \lambda(C_f \Delta C_g) = Q(|f - g|)$.

$$Q \times \lambda(C_f \Delta C_g) = \int_{\mathcal{X}} \int_{\mathbb{R}} \mathbb{1}_{\{t: f(x) \wedge g(x) \leq t \leq f(x) \wedge g(x) + |f(x) - g(x)|\}} d\lambda(t) dQ(x)$$

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Transform distances

We want to show $Q \times \lambda(C_f \Delta C_g) = Q(|f - g|)$.

$$\begin{aligned} Q \times \lambda(C_f \Delta C_g) &= \int_{\mathcal{X}} \int_{\mathbb{R}} \mathbb{1}_{\{t: f(x) \wedge g(x) \leq t \leq f(x) \vee g(x) + |f(x) - g(x)|\}} d\lambda(t) dQ(x) \\ &= \int_{\mathcal{X}} |f(x) - g(x)| dQ(x) \\ &= Q(|f - g|) \end{aligned}$$

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Note

F is an envelope function so $|f(x)| \leq F(x)$ for all $x \in \mathcal{X}$.

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

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Measure

Renormalize $Q \times \lambda$ to a probability measure on the set
 $\{(x, t) : |t| \leq F(x)\}$

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

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Measure

Renormalize $Q \times \lambda$ to a probability measure on the set
 $\{(x, t) : |t| \leq F(x)\}$

Total mass

$$Q \times \lambda(\{(x, t) : |t| \leq F(x)\}) = 2Q(F)$$

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

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F is an envelope function so $|f(x)| \leq F(x)$ for all $x \in \mathcal{X}$.

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Renormalize $Q \times \lambda$ to a probability measure on the set
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Total mass

$$Q \times \lambda(\{(x, t) : |t| \leq F(x)\}) = 2Q(F)$$

So $P := \frac{Q \times \lambda}{2Q(F)}$ is a probability measure on $\{(x, t) : |t| \leq F(x)\}$.

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

Covering numbers

$$Q(\|f - g\|) = Q \times \lambda(C_f \Delta C_g) = 2Q(F) \cdot P(C_f \Delta C_g)$$

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$$Q(\|f - g\|) = Q \times \lambda(C_f \Delta C_g) = 2Q(F) \cdot P(C_f \Delta C_g)$$

Conclusion

$$N(\epsilon QF, \mathcal{F}, L_1(Q)) = N(\epsilon/2, \mathcal{C}, L_1(P)) \leq KV(\mathcal{F}) \left(\frac{8e}{\epsilon}\right)^{V(\mathcal{F})-1}$$

Proof

$$N(\epsilon \|F\|_{Q,r}, \mathcal{F}, L_r(Q)) \leq KV(\mathcal{F})(16e)^{V(\mathcal{F})} \left(\frac{1}{\epsilon}\right)^{r(V(\mathcal{F})-1)}$$

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$$\epsilon \|F\|_{Q,1} = \epsilon Q(|F|) \geq \epsilon Q(F)$$

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Rest of the proof

For $r > 1$, us a measure R with density $\frac{F^{r-1}}{QF^{r-1}}$ such that

$$Q|f - g|^r \leq 2^{r-1} R|f - g| QF^{r-1}$$