Foundations for Learning in the Age of Big Data

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Brief Overview

This lecture series: theoretical foundations for learning in the age of big data.

Lectures 1 & 2: Foundations of classic ML.

- Generalization guarantees. Sample complexity for supervised classification

Lectures 3: Active Learning.

Lectures 4: Distributed Learning.

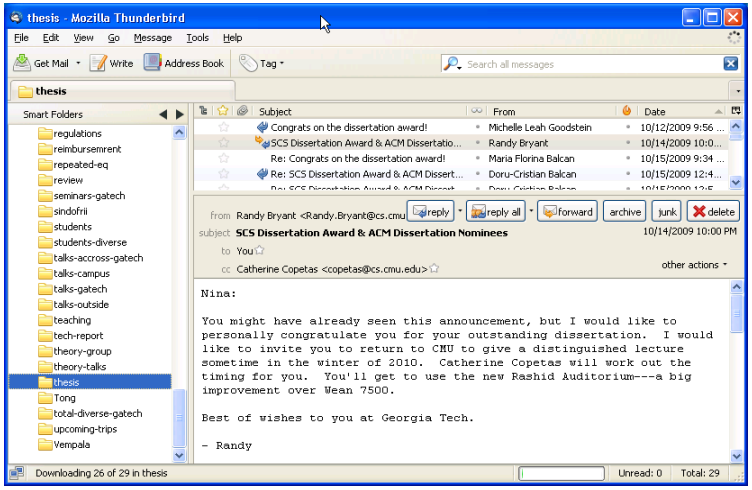
Supervised Classification. Example: Spam Detection

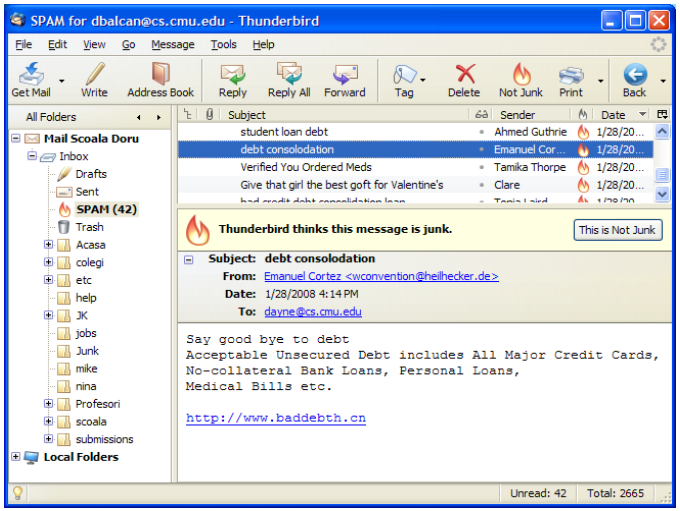
Decide which emails are spam and which are important.

Supervised classification

Not spam

spam





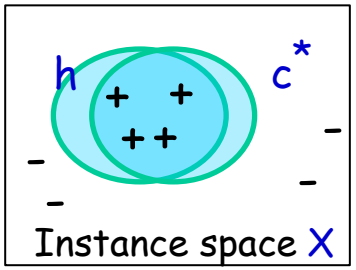
Goal: use emails seen so far to produce good prediction rule for future data.

PAC/SLT models for Supervised Learning

- X – feature/instance space; distribution D over X

  e.g., $X = R^d$ or $X = \{0,1\}^d$

- Algo sees training sample S: $(x_1, c^*(x_1)), \ldots, (x_m, c^*(x_m))$, x_i i.i.d. from D
  - labeled examples - drawn i.i.d. from D and labeled by target c^*
  - labels $\in \{-1,1\}$ - binary classification



- Algo does optimization over S, find hypothesis h.
- Goal: h has small error over D.

$$err_D(h) = \Pr_{x \sim D}(h(x) \neq c^*(x))$$

Bias: fix hypothesis space H [whose complexity is not too large]

- Realizable: $c^* \in H$.
- Agnostic: c^* "close to" H.

PAC/SLT models for Supervised Learning

- Algo sees training sample S: $(x_1, c^*(x_1)), \ldots, (x_m, c^*(x_m))$, x_i i.i.d. from D
- Does optimization over S, find hypothesis $h \in H$.
- Goal: h has small error over D.

True error: $\mathrm{err}_D(h) = \Pr_{x \sim D}(h(x) \neq c^*(x))$

How often $h(x) \neq c^*(x)$ over future instances drawn at random from D

- But, can only measure:

Training error: $\mathrm{err}_S(h) = \frac{1}{m}\sum_i I(h(x_i) \neq c^*(x_i))$

How often $h(x) \neq c^*(x)$ over training instances

Sample complexity: bound $err_D(h)$ in terms of $err_S(h)$

Sample Complexity for Supervised Learning

Consistent Learner

- Input: S: $(x_1, c^*(x_1)), \ldots, (x_m, c^*(x_m))$
- Output: Find h in H consistent with the sample (if one exits).

Bound only logarithmic in |H|, linear in $1/\epsilon$

Theorem

$$m \geq \frac{1}{\varepsilon}\left[\ln(|H|) + \ln\left(\frac{1}{\delta}\right)\right]$$

labeled examples are sufficient so that with prob. $1-\delta$, all $h \in H$ with $err_D(h) \geq \varepsilon$ have $err_S(h) > 0$.

Probability over different samples of m training examples

So, if $c^* \in H$ and can find consistent fns, then only need this many examples to get generalization error $\leq \epsilon$ with prob. $\geq 1-\delta$

Supervised Learning: PAC model (Valiant)

- X - instance space, e.g., $X = \{0,1\}^n$ or $X = R^d$
- S_l={(x_i, y_i)} - labeled examples drawn i.i.d. from some distr. D over X and labeled by some target concept c^*
  - labels $\in$ {-1,1} - binary classification

- Algorithm A PAC-learns concept class H if for any target c* in H, any distrib. D over X, any ε, $\delta > 0$:
  - A uses at most poly(d,1/ε,1/δ,size(c*)) examples and running time.
  - With probab. 1-δ, A produces h in H of error at $\cdot\ \varepsilon$.

Sample Complexity: Finite Hypothesis Spaces

Realizable Case

1) PAC: How many examples suffice to guarantee small error whp.

Theorem

$$m \geq \frac{1}{\varepsilon}\left[\ln(|H|) + \ln\left(\frac{1}{\delta}\right)\right]$$

labeled examples are sufficient so that with prob. $1-\delta$, all $h \in H$ with $err_D(h) \geq \varepsilon$ have $err_S(h) > 0$.

2) Statistical Learning Way:

With probability at least $1-\delta$, for all $h \in H$ s.t. $err_S(h) = 0$ we have

$$err_D(h) \leq \frac{1}{m}\left(\ln|H| + \ln\left(\frac{1}{\delta}\right)\right).$$

Sample Complexity: Uniform Convergence

Agnostic Case

Empirical Risk Minimization (ERM)

- Input: S: $(x_1, c^*(x_1)), \ldots, (x_m, c^*(x_m))$
- Output: Find h in H with smallest $\mathrm{err}_S(h)$

Theorem

$$m \geq \frac{1}{2\varepsilon^2}\left[\ln(|H|) + \ln\left(\frac{2}{\delta}\right)\right]$$

labeled examples are sufficient s.t. with probab. $\geq 1-\delta$, all $h \in H$ have $|err_D(h) - err_S(h)| < \varepsilon$.

$1/\epsilon^2$ dependence [as opposed to $1/\epsilon$ for realizable]

Sample Complexity: Finite Hypothesis Spaces Agnostic Case

1) How many examples suffice to get UC whp (so success for ERM).

Theorem

$$m \geq \frac{1}{2\varepsilon^2}\left[\ln(|H|) + \ln\left(\frac{2}{\delta}\right)\right]$$

$1/\epsilon^2$ dependence [as opposed to $1/\epsilon$ for realizable], but get for something stronger.

labeled examples are sufficient s.t. with probab. $\geq 1-\delta$, all $h \in H$ have $|err_D(h) - err_S(h)| < \varepsilon$.

2) Statistical Learning Theory style:

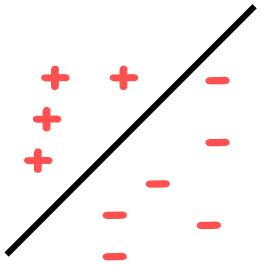
With prob. at least $1-\delta$, for all $h \in H$:

$\sqrt{\frac{1}{m}}$ as opposed to $\frac{1}{m}$ for realizable

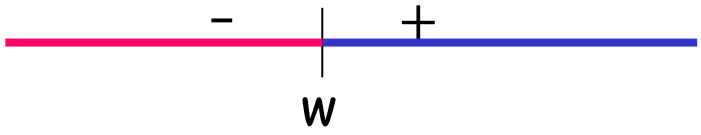
$$\mathrm{err_D(h)} \leq \mathrm{err_S(h)} + \sqrt{\frac{1}{2m}\left(\ln(2|H|) + \ln\left(\frac{1}{\delta}\right)\right)}.$$

What if H is infinite?

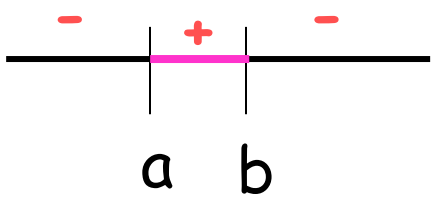
E.g., linear separators in R^d



E.g., thresholds on the real line



E.g., intervals on the real line



Effective number of hypotheses

- H[S] – the set of splittings of dataset S using concepts from H.
- H[m] - max number of ways to split m points using concepts in H

$$H[m] = \max_{|S|=m} |H[S]|$$

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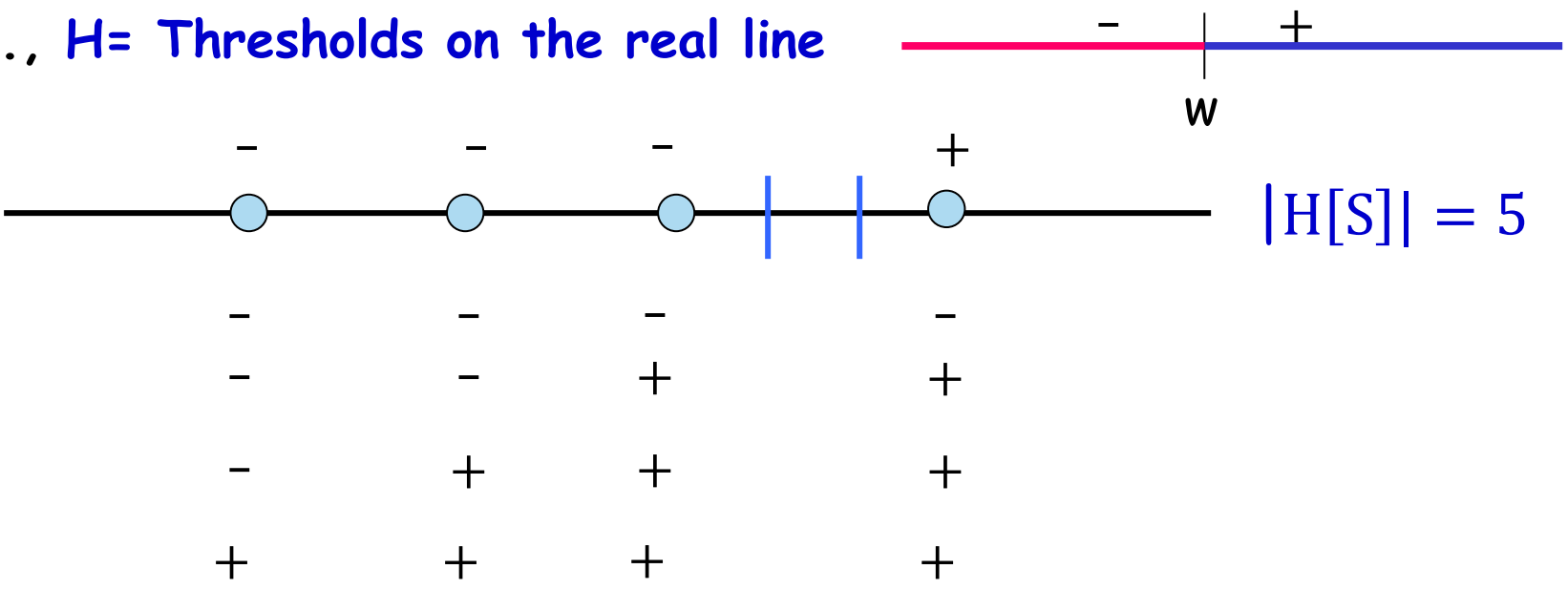
E.g., H= Thresholds on the real line



In general, if |S|=m (all distinct), $|H[S]| = m + 1 \ll 2^m$

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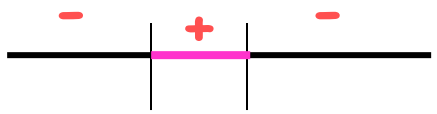

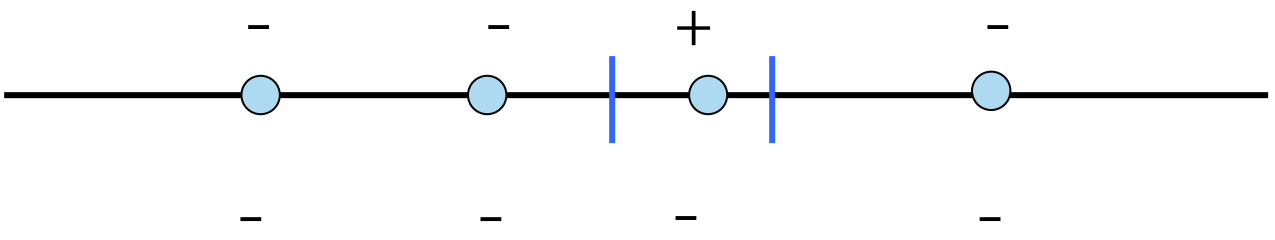

In general, |S|=m (all distinct), $H[m] = \frac{m(m+1)}{2} + 1 = O(m^2) \ll 2^m$

There are m+1 possible options for the first part, m left for the second part, the order does not matter, so ((m+1) choose 2) + 1 (for empty interval).

Effective number of hypotheses

- H[S] – the set of splittings of dataset S using concepts from H.
- H[m] - max number of ways to split m points using concepts in H

$$H[m] = \max_{|S|=m} |H[S]| \qquad H[m] \leq 2^m$$

Definition: H shatters S if $|H[S]| = 2^{|S|}$.

Sample Complexity: Infinite Hypothesis Spaces Realizable Case

H[m] - max number of ways to split m points using concepts in H

Theorem For any class H, distrib. D, if the number of labeled examples seen m satisfies

$$m \geq \frac{2}{\varepsilon}\left[\log_2(2H[2m]) + \log_2\left(\frac{1}{\delta}\right)\right]$$

then with probab. $1-\delta$, all $h \in H$ with $err_D(h) \geq \varepsilon$ have $err_S(h) > 0$.

- Not too easy to interpret sometimes hard to calculate exactly, but can get a good bound using "VC-dimension

  If $H[m] = 2^m$, then $m \geq \frac{m}{\epsilon}(\ldots)$ ☹

- VC-dimension is roughly the point at which H stops looking like it contains all functions, so hope for solving for m.

Sample Complexity: Infinite Hypothesis Spaces

H[m] - max number of ways to split m points using concepts in H

Theorem For any class H, distrib. D, if the number of labeled examples seen m satisfies

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then with probab. $1-\delta$, all $h \in H$ with $err_D(h) \geq \varepsilon$ have $err_S(h) > 0$.

Sauer's Lemma: $H[m] = O(m^{VCdim(H)})$

Theorem

$$m = O\left(\frac{1}{\varepsilon}\left[VCdim(H)\log\left(\frac{1}{\varepsilon}\right) + \log\left(\frac{1}{\delta}\right)\right]\right)$$

labeled examples are sufficient so that with probab. $1-\delta$, all $h \in H$ with $err_D(h) \geq \varepsilon$ have $err_S(h) > 0$.

Shattering, VC-dimension

Definition: H shatters S if $|\mathrm{H}[\mathrm{S}]| = 2^{|S|}$.

A set of points S is shattered by H is there are hypotheses in H that split S in all of the $2^{|S|}$ possible ways, all possible ways of classifying points in S are achievable using concepts in H.

Definition: VC-dimension (Vapnik-Chervonenkis dimension)

The VC-dimension of a hypothesis space H is the cardinality of the largest set S that can be shattered by H.

If arbitrarily large finite sets can be shattered by H, then $\mathrm{VCdim}(\mathrm{H}) = \infty$

Shattering, VC-dimension

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The VC-dimension of a hypothesis space H is the cardinality of the largest set S that can be shattered by H.

If arbitrarily large finite sets can be shattered by H, then $\mathrm{VCdim}(H) = \infty$

To show that VC-dimension is d:

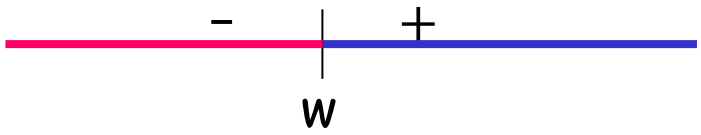
- there exists a set of d points that can be shattered
- there is no set of d+1 points that can be shattered.

Fact: If H is finite, then $\mathrm{VCdim}(H) \leq \log(|H|)$.

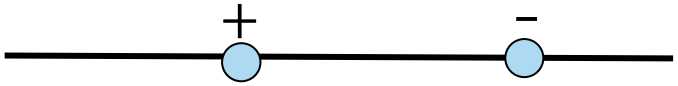
Shattering, VC-dimension

If the VC-dimension is d, that means there exists a set of d points that can be shattered, but there is no set of d+1 points that can be shattered.

E.g., H= Thresholds on the real line



$\mathrm{VCdim(H)} = 1$



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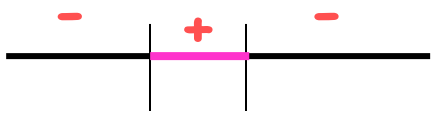
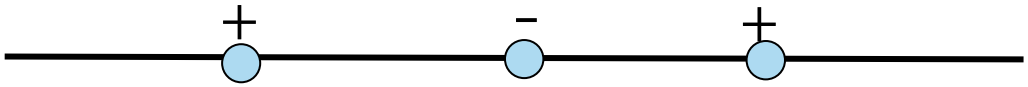


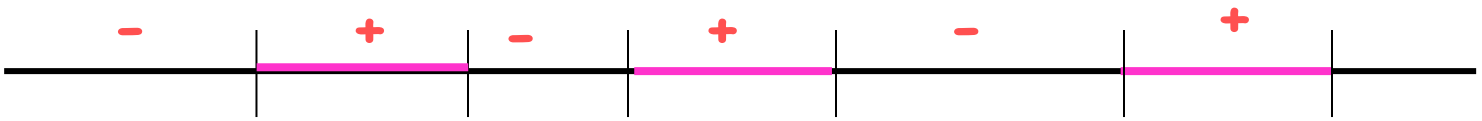
$\mathrm{VCdim(H)} = 2$



Shattering, VC-dimension

If the VC-dimension is d, that means there exists a set of d points that can be shattered, but there is no set of d+1 points that can be shattered.

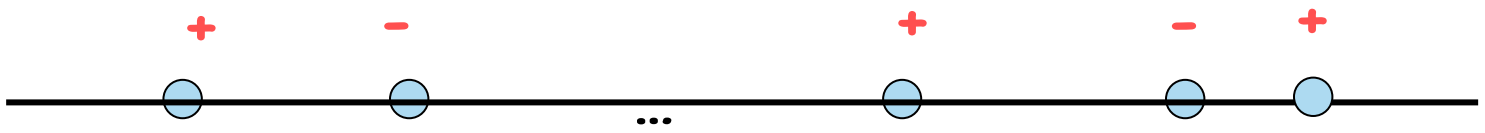
E.g., H= Union of k intervals on the real line $\mathrm{VCdim(H)} = 2k$



$\mathrm{VCdim(H)} \geq 2k$

A sample of size 2k shatters
(treat each pair of points as a separate case of intervals)

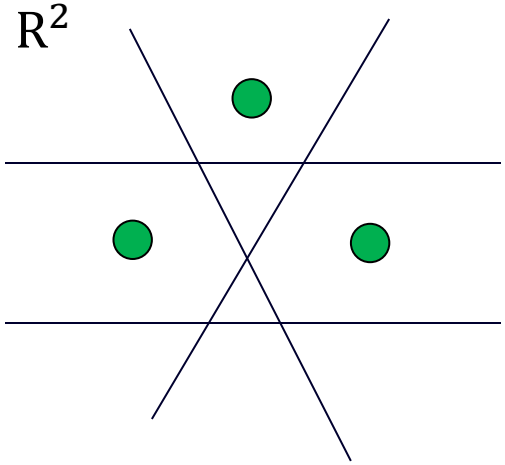
$\mathrm{VCdim(H)} < 2k + 1$



Shattering, VC-dimension

E.g., **H**= linear separators in R^2

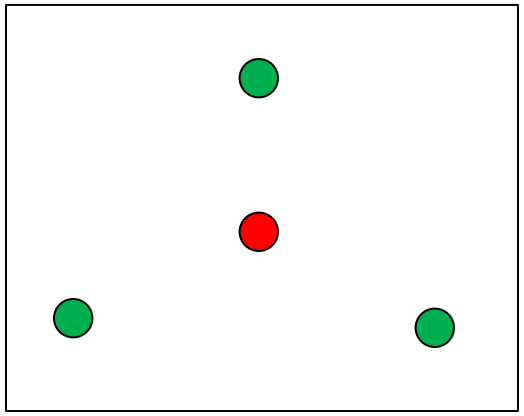
$\mathrm{VCdim}(H) \geq 3$



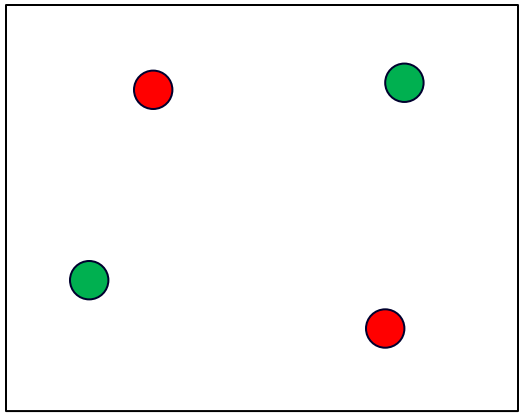
Shattering, VC-dimension

E.g., **H=** linear separators in R^2

$\mathrm{VCdim(H)} < 4$



Case 1: one point inside the triangle formed by the others. Cannot label inside point as positive and outside points as negative.



Case 2: all points on the boundary (convex hull). Cannot label two diagonally as positive and other two as negative.

Fact: VCdim of linear separators in R^d is d+1

Sauer's Lemma

Sauer's Lemma:

Let d = VCdim(H)

- $m \leq d$, then $H[m] = 2^m$
- m>d, then $H[m] = O(m^d)$

Sample Complexity: Infinite Hypothesis Spaces

Realizable Case

Theorem For any class H, distrib. D, if the number of labeled examples seen m satisfies

$$m \geq \frac{2}{\varepsilon}\left[\log_2(2H[2m]) + \log_2\left(\frac{1}{\delta}\right)\right]$$

then with probab. $1-\delta$, all $h \in H$ with $err_D(h) \geq \varepsilon$ have $err_S(h) > 0$.

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E.g., H= linear separators in R^d $\quad m = O\left(\frac{1}{\varepsilon}\left[d\log\left(\frac{1}{\varepsilon}\right) + \log\left(\frac{1}{\delta}\right)\right]\right)$

Sample complexity linear in d

So, if double the number of features, then I only need roughly twice the number of samples to do well.

Data Dependent Generalization Bounds

- Distribution/data dependent. Tighter for nice distributions.
- Apply to general classes of real valued functions & can be used to recover the VC-bounds for supervised classification.
- Prominent technique for generalization bounds since 2000.

Covering Numbers Generalization Bounds

See Anthony-Bartlett, "Neural Network Learning: Theoretical Foundations", 1999.

Rademacher Complexity Generalization Bounds

See Bousquet-Boucheron-Lugosi, "Introduction to Statistical Learning Theory", 2014.

Summary

- PAC/SLT models for supervised learning.
- Notion of sample complexity.
- Shattering, VC dimension as measure of complexity, Sauer's lemma, form of the VC bounds .