Generalization and Overfitting

Sample Complexity Results for Supervised Classification

Maria-Florina (Nina) Balcan
March 18th, 2019
Admin

Midterm graded.

Median 87.5; mean 86.26

HWK 4 released on March 22\textsuperscript{nd}.

No office hours today.
PAC/SLT models for Supervised Learning

Data Source

Distribution $D$ on $X$

Learning Algorithm

Labeled Examples

$h : X \rightarrow Y$

(\(x_1, c^*(x_1)\), ..., \((x_m, c^*(x_m))\))

Alg.outputs

Expert / Oracle

\(c^* : X \rightarrow Y\)
PAC/SLT models for Supervised Learning

- **X** - feature/instance space; distribution **D** over **X**
  
  e.g., \( X = \mathbb{R}^d \) 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 \( D \).

\[
\text{err}_D(h) = \Pr_{x \sim D} (h(x) \neq c^*(x))
\]

**Bias**: fix hypothesis space \( H \) [whose complexity is not too large]

- **Realizable**: \( c^* \in H \).
- **Agnostic**: \( c^* \) “close to” \( H \).
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).

**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 $\text{err}_D(h) \geq \varepsilon$ have $\text{err}_S(h) > 0$.

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 $\leq \varepsilon$ with prob. $\geq 1 - \delta$
**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 $err_S(h)$

**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/\varepsilon^2 dependence [as opposed to 1/\varepsilon for realizable]
What if $H$ is infinite?

E.g., linear separators in $\mathbb{R}^d$

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 $H$

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

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

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

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

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

E.g., $H =$ Intervals on the real line

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 $(m \text{ choose } 2) + 1$ (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 $H$

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

**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 \( m \geq \frac{m}{\varepsilon} \) (...)

- 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

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

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

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

**Theorem**

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

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

**Definition:** \( H \) shatters \( S \) if \( |H[S]| = 2^{|S|} \).

A set of points \( S \) is shattered by \( H \) if 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 \( \text{VCdim}(H) = \infty \).
**Shattering, VC-dimension**

**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 $\text{VCdim}(H) = \infty$.

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 $\text{VCdim}(H) \leq \log(|H|)$. 
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., $H= \text{Thresholds on the real line}$

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

E.g., $H= \text{Intervals on the real line}$

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

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

[A sample of size $2k$ shatters (treat each pair of points as a separate case of intervals)]
Shattering, VC-dimension

E.g., $H = \text{linear separators in } \mathbb{R}^2$

$\text{VCdim}(H) \geq 3$
Shattering, VC-dimension

E.g., $H =$ linear separators in $\mathbb{R}^2$

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

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 $\mathbb{R}^d$ is $d+1$
Sauer's Lemma:

Let $d = \text{VCdim}(H)$

- $m \leq d$, 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 $err_S(h) > 0$.

**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 $err_S(h) > 0$. 
Sample Complexity: Infinite Hypothesis Spaces

Realizable Case

**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 \( err_S(h) > 0 \).

E.g., \( H = \) linear separators in \( \mathbb{R}^d \)

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

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.
Sample Complexity: Infinite Hypothesis Spaces

Realizable Case

Theorem

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

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

Statistical Learning Theory Style

\[ err_D(h) \leq err_S(h) + \sqrt{\frac{1}{2m} \left( VCdim(H) + \ln \left( \frac{1}{\delta} \right) \right)}. \]
What you should know

• Notion of sample complexity.

• Shattering, VC dimension as measure of complexity, Sauer’s lemma, form of the VC bounds.