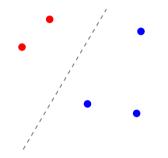
Cover's theorem(s)

Han Xiao

November 30, 2022

separating two sets of points



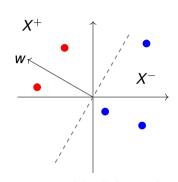
setting

- ▶ given a set of points $\mathcal{X} \in \mathbb{R}^d$
- ▶ a dichotomy (X^+, X^-) of \mathcal{X} is homogeneously linearly separable
- ▶ iff there is a vector $w \in \mathbb{R}^d$ s.t.

$$x \cdot w > 0 \text{ if } x \in X^+$$

 $x \cdot w < 0 \text{ if } x \in X^-$

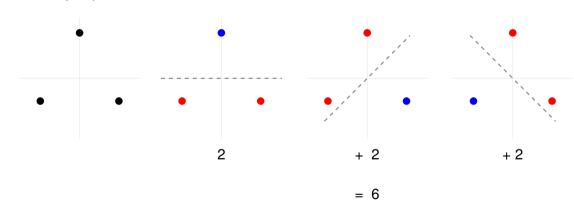
- ▶ the separating hyperplane is the (d-1) orthogonal subspace to w
- the hyperplane must pass through the origin



two separable dichotomies $(\{\bullet\}, \{\bullet\})$ and $(\{\bullet\}, \{\bullet\})$

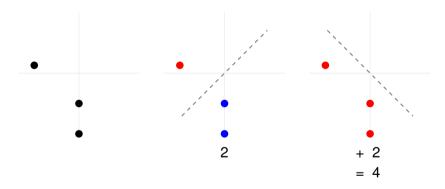
warm-up 1/2

how many separable dichotomies?



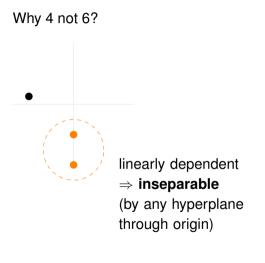
warm-up 2/2

how many separable dichotomies?



Fewer than the previous example.

assumption: points are in general position



\mathcal{X} are in *general position* if

every subset of size d or fewer are linearly independent

Why assuming so?

- we can analyze the upper bound on the number of separable dichotomies
- points are likely to be in general position (e.g., if points are uniformly distributed)

main character – C(N, d)

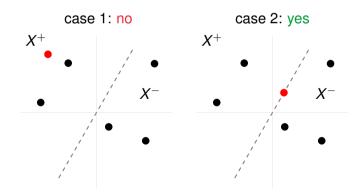
C(N, d) = # of linearly separable dichotomies of N in \mathbb{R}^d

(assuming $\ensuremath{\mathcal{X}}$ in general position)

Question: does C(N, d) have a closed-form formula?

analysis by induction 1/6

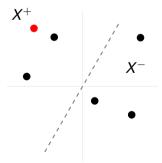
- ightharpoonup assume we have N points \mathcal{X} and add a new point y
- for each separable (X^+, X^-) of \mathcal{X} , there are two possibilities of y, depending on
- ▶ if there is a separating hyperplane w of (X^+, X^-) s.t. $w \cdot y = 0$



analysis by induction 2/6

case 1

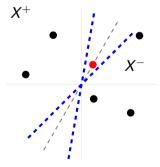
- ▶ i.e., there is **no** such separating hyperplane w s.t. $w \cdot y = 0$
- either $(X^+ \cup \{y\}, X^-)$ or $(X^+, X^- \cup \{y\})$ is separable
- ▶ \Rightarrow 1 separable dichotomy for $\mathcal{X} \cup \{y\}$.



analysis by induction 3/6

case 2

- ▶ i.e., there is such separating hyperplane w s.t. $w \cdot y = 0$
- **both** $(X^+ \cup \{y\}, X^-)$ and $(X^+, X^- \cup \{y\})$ are separable
- ▶ \Rightarrow 2 separable dichotomies for $\mathcal{X} \cup \{y\}$.



analysis 4/6: combining case 1 and case 2

▶ let *D* be the number of "case-2" dichotomies.

$$C(N+1,d) = \underbrace{C(N,d) - D}_{1 \times \# \text{ of case 1 dich.}} + \underbrace{2 D}_{2 \times \# \text{ of case 2 dich.}}$$
 $= C(N,d) + D$

question: what is D?

analysis 5/6: what is *D*?

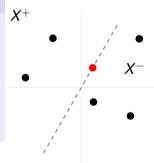
recall D is the number of (X^+, X^-) for which there is a separating w s.t. $w \cdot y = 0$.

Lemma

 $(X^{+} \cup \{y\}, X^{-})$ and $(X^{+}, X^{-} \cup \{y\})$ are both separable in \mathbb{R}^{d}

 \Leftrightarrow

 (X^+, X^-) is separable by a (d-1)-dimensional space containing v

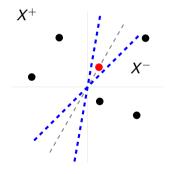


$$\Rightarrow D = C(N, d-1) \leftarrow \text{the key!}$$

proof of lemma 1/2

 $(X^+ \cup \{y\}, X^-)$ and $(X^+, X^- \cup \{y\})$ are separable $\Leftarrow (X^+, X^-)$ is separable by a (d-1)-dimensional space containing y

Simple, recall that the hyperplane can be shifted either way



proof of lemma 2/2

 $(X^+ \cup \{y\}, X^-)$ and $(X^+, X^- \cup \{y\})$ are separable $\Rightarrow (X^+, X^-)$ is separable by a (d-1)-dimensional space containing y

- ▶ let w_1 by a hyperplane that separates $(X^+ \cup \{y\}, X^-)$
 - $\triangleright w_1 \cdot y > 0$
- ▶ let w_2 by a hyperplane that separates $(X^+, X^- \cup \{y\})$
 - $\sim w_2 \cdot y < 0$
- ► let $w^* = (-w_2 \cdot y)w_1 + (w_1 \cdot y)w_2$
- $fact 1: w^* \cdot v = 0$
- $\rightarrow v$ is contained by the hyperplane w^*
 - \rightarrow what is this hyperplane? the subspace orthogonal to y!
- ▶ fact 2: $w^* \cdot x > 0$ for $x \in X^+$ and $w^* \cdot x < 0$ for $x \in X^ \rightarrow (X^+, X^-)$ is separated by w^*

analysis 6/6

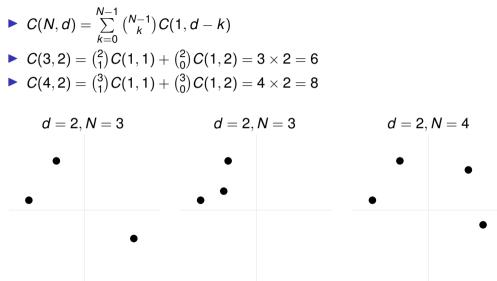
$$C(N,d) = C(N-1,d) + C(N-1,d-1)$$
..... expand recursively
$$= \sum_{k=0}^{N-1} {N-1 \choose k} C(1,d-k)$$

note that:

$$C(1,m) = \begin{cases} 2, & m \ge 1 \\ 0, & m < 1 \end{cases}$$

$$\Rightarrow$$
 $C(N, d) = 2 \sum_{k=1}^{d-1} {N-1 \choose k} \leftarrow \text{Cover's theorem}$

verify it!



generalization of Cover's theorem

Theorem

if the hyperplane is constrained to contain k linearly independent points $\{y_1, \ldots, y_k\}$, then there are C(N, d - k) separable dichotomies of \mathcal{X} .

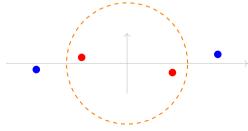
an assumption: projection of \mathcal{X} onto the orthogonal subspace of $S(\{y_1, \ldots, y_k\})$ are in general position, where $S(\{\cdot\})$ is the space spanned by $\{\cdot\}$.

generalization to arbitrary surfaces

- ▶ say \mathcal{X} are in \mathbb{R}^m , for now, we only considered *linear separability* in \mathbb{R}^m .
- \blacktriangleright what if \mathcal{X} are not linearly separable in \mathbb{R}^m ?



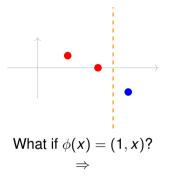
- ightharpoonup can we transform them into a higher-dimensional space \mathbb{R}^d so that they are linearly separable?
- ▶ the separating surface in \mathbb{R}^m is possibly *non-linear*.



generalization to arbitrary surfaces

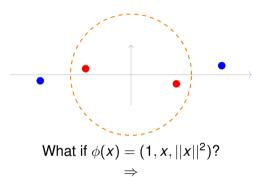
- ▶ assume each point $x \in \mathbb{R}^m$ is transformed into \mathbb{R}^d where d > m
- **b** by some function $\phi: \mathbb{R}^m \to \mathbb{R}^d$

arbitrary surface examples 1/2



separating surfaces = hyperplanes not necessarily passing through origin

degree of freedom: d + 1



separating surfaces = hyperspheres

degree of freedom: d + 2

arbitrary surface examples 2/2

- let ϕ be all r-wise products of x_i
- i.e., $\phi(x) = (1, x_1, x_2, \dots, x_m, (x_1)^2, x_1x_2, \dots, x_ix_j, \dots, x_m^r)$
- the surface is called a rational rth-order variety
- ightharpoonup degree of freedom: $\binom{m+r}{r}$

generalization to arbitrary surfaces: a summary

def. of $\phi(x)$	separating surface	degree of freedom	number of sepa- rable dichotomies	separating capacity
(x)	hyperplane through origin	т	C(N, m)	2 <i>m</i>
(1,x)	hyperplane	m+1	C(N, m + 1)	2(m+1)
$(1, x, x _2)$	hypersphere	m+2	C(N, m + 2)	2(m+2)
$(x, x _2)$	hypercone	m+1	C(N, m + 1)	2(m+1)
all r -wise products of x_i	rational <i>r</i> -order variety	$\binom{m+r}{r}$	$C(N, \binom{m+r}{r})$	$2\left(\binom{m+r}{r}\right)$

let's go back to \mathbb{R}^d and consider linear separability again.

probability of being separable

- \blacktriangleright let P(N, d) be the probability of a random dichotomy being linearly separable
- ▶ further assume each dichotomy has equal chance of being drawn $\rightarrow 1/2^N$

$$P(N,d) = \sum_{(X^+,X^-)} \left(\frac{1}{2}\right)^N \mathbb{1}\left[\left(X^+,X^-\right) \text{ is separable}\right]$$

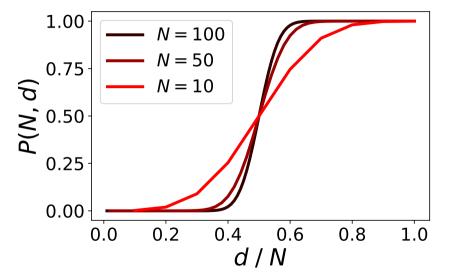
$$= \left(\frac{1}{2}\right)^N C(N,d)$$

$$= \left(\frac{1}{2}\right)^{N-1} \sum_{k=0}^{d-1} {N-1 \choose k}$$

- \blacktriangleright What is P(N, d)?
- ➤ ⇒ cumulative binomial distribution

i.e., N-1 flips of a fair coin resulting in d-1 or fewer heads.

What does P(N, d) look like?

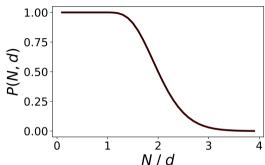


how many points can a d-dimensional space naturally have

s.t. P(N, d) is high?

⇒ separating capacity

separating capacity 1/2



▶ given some integer *n*, consider

$$P(n,d)-P(n+1,d)=\left(\frac{1}{2}\right)^n\binom{n-1}{d-1}$$

- ▶ interpretation: speed of change w.r.t. *n* at *n* ("derivative")
- ▶ → negative binomial distribution!

Separating capacity 2/2

> asymptotic behaviour, for $\epsilon > 0$

$$\lim_{d \to \infty} P(2d(1+\epsilon), d) = 0$$

$$\lim_{d \to \infty} P(2d, d) = \frac{1}{2}$$

$$\lim_{d \to \infty} P(2d(1+\epsilon), d) = 1$$

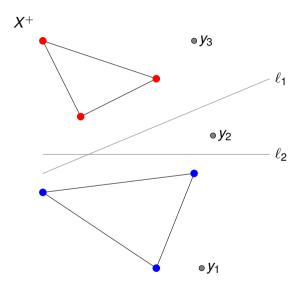
2d is the separating capacity of a surface family having d degrees of freedom. Implications on classification – generalization and learning

generalization and learning: setting

- assume we have a binary classification problem
- \blacktriangleright with training set (X^+, X^-)
- ▶ a new point y is said to be ambiguous w.r.t. a family of surfaces
- ▶ if there exists one surface inducing the dichotomy $(X^+ \cup \{y\}, X^-)$
- ▶ and there exists another surface inducing the dichotomy $(X^+, X^- \cup \{y\})$

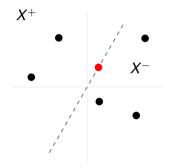
two classifiers trained on (X^+, X^-) give different predictions on y.

an example of being ambiguous



condition of ambiguity

- ▶ when is *y* ambiguous?
- ▶ when there exists a separating surface containing *y*!



probability of ambiguity

- what is the probability that y is ambiguous, given a training set of N points in \mathbb{R}^d ?
- ightharpoonup let A(N, d) denote this probability

$$A(N, d) = \frac{\text{# of separable dich. containing } y}{\text{# of separable dich.}}$$

$$= \frac{C(N, d - 1)}{C(N, d)}$$

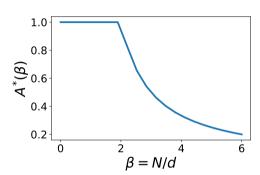
asymptotic behaviour of A(N, d))

▶ let
$$\beta = \frac{N}{d}$$

$$\blacktriangleright \mathsf{let} \, A^*(\beta) = \lim_{\mathsf{N} = \beta \mathsf{d}, \mathsf{d} \to \infty} \mathsf{A}(\mathsf{N}, \mathsf{d})$$

► (after some analysis)

$$A^*(eta) = egin{cases} 1, & 0 \leq eta \leq 2 \ rac{1}{eta - 1} & eta \geq 2 \end{cases}$$



Implications

- ▶ more data ⇒ less ambiguity
- ▶ one manifestation of "curse of dimensionality" as $d \uparrow$, more data is need to *generalize unambiguously*

Big Data To Good Data: Andrew Ng Urges ML Community To Be More Data-Centric And Less Model-Centric

5/04/2021

summary

Cover's theorem (proved by induction):

$$C(N,d) = 2 \sum_{k=0}^{d-1} {N-1 \choose k}$$

- ightharpoonup separating capacity of a family of surfaces having d degree of freedom \Rightarrow 2d
- implications
 - ► transforming data into a higher-dimensional space → linear separability (kernel SVM, neural networks, etc)
 - the need for more data for classifiers to generalize unambiguously
 - more?

reference

Cover, Thomas M. "Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition." *IEEE transactions on electronic computers* (1965)