

How do I prove this prop?

Condition

If not.

Sequence of bad pts  
 $t \geq 2k/k'$  s.t. each

$x_1, x_2, x_3, \dots, x_t$

$x_i$  is far from

span  $x_1, \dots, x_{i-1}$

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for each  $x_i$  I have  $p_{i1}, p_{i2}, \dots, p_{ik}$  ← sum of singular values of  $A_{x_i}$

$$p_{ij} \cdot (A_{x_i} \underset{\substack{\uparrow \\ w.}}{q}) \leq \eta / \eta_2$$

$$|p_{ij}| = 1$$

$$B_{i,j} = q_i(x) \cdot p_{ij}(y)$$

$$q_i(x) = x \cdot x_i$$

Gram matrix determinant of the  $B_{ij}$ 's  
 $[ \langle B_{ij}, B_{i'j'} \rangle ]$

reasonably big

list  $B_{ij}$ 's in order  $B_{11} \ B_{12} \dots B_{1n} \ B_{21} \dots$

for each  $B_{ij}$  has a reasonably large component orthogonal to previous ones.

$B_{ij}$  vs  $B_{i'j'}$

$$p_{ij} \perp p_{i',j'}$$

$X_i$  had a component of size  $\geq \gamma$  orthogonal to

$$X_1, \dots, X_{i-1}$$

$$\langle p q_i, p' q' \rangle \approx \langle p, p' \rangle \langle q, q' \rangle$$

$B_{ij}$  has a comp of size  $\approx \gamma$  orthogonal to any

$$q_{i'}' (x) p_{i'}$$
 for  $i' < i$

$B_{ij}$  has a  $\gamma$ -sized comp. orthogonal to previous  $B_{ij}$ 's.

$\Rightarrow$  if we apply G-S to  $B_{ij}$ s we get  
comps of size  $\geq \gamma$ .

$$\Rightarrow \det(\text{Gram Matrix}) \geq \gamma \cdot \prod_{i,j} \left( \sum_{k=1}^{\gamma} B_{ij}^2 \right)$$

# Upper Bound

Claim

~~BT~~

If  $P \in W$  then.

$\langle P^{(x,y)}, B_{ij} \rangle$  small.

$$B_{ij} = q_i(x) R_{ij}(y)$$

~~BT~~ Pilt on basis der x.

$$P(x,y) = \underbrace{(x \cdot x)^{q_i}}_{\text{OVthym!}} P_i(y) + \underbrace{(x \cdot x)^{q_m}}_{\text{OVthym!}}$$

$$\langle P(x,y), B_{ij} \rangle \approx \langle P(x_i, y), \underbrace{P_{ij}(y)}_{\text{small}} \rangle$$

$A_{x_i} P.$

small covers  
of  $A_{x_i}$

$$\leq \gamma \cdot |P|$$

~~3~~  $M = [B_{ij}]$  We note  $M$  is  $2k$ -dimensional.

$W$  has  $\dim \leq k$ .

$\Rightarrow \exists k$ -dim'l subspace  $a$ . s.t. Not hard to show that

$$Ma \in W.$$

$M^T M$  has no superfluous evs.

For such  $a$ 's.  $M^T M a = M^T (Ma).$

$$\det(M^T M)$$

$$|M^T M a| \leq 2k\eta |a|.$$

$$= [ \underbrace{\langle B_{ij}, Ma \rangle}_{\leq \eta \cdot |Ma|} ]$$

$$\leq (2k\eta)^k.$$

$\Rightarrow M^T M$  has at least  $k$  eigenvalues  $\leq 2k\eta$

$$\leq \eta \cdot |Ma|$$

$$\uparrow$$

$$2k \cdot |a|$$

$$(\gamma)^{2k} < \det(M^T M) < (2k\eta)^k.$$

as long as  $\eta$  is small enough.



Note: This can be made computationally efficient.

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Learning Mixtures of Spherical Gaussians in TV

- ① reduce <sup>distance.</sup> to  $k$  dimensions.
- ① rough clustering - reduces to case where  
 $|M_i| = \text{Poly}(k)$
- ② Compute 1'st <sup>2d</sup> ~~moments~~ <sup>parameter</sup> moments to error  $(\epsilon/k)^{O(d)}$   
(moments of  $M_i$ ).

④ Define  $Q(p) \stackrel{\text{deg } d \text{ poly.}}{\approx} \sum w_i p^2(\mu_i)$

Let  $U$  be space of small singular vectors of  $Q$ .

for any  $i$  w/  $w_i$  not too small  $\exists$  any  $p \in U$   
 $|p(\mu_i)|$  small.

⑤ Use Thm compute a core  $S$ .

every  $i$  w/  $w_i \geq \varepsilon/k$  has  $\mu_i$  within  $\varepsilon$  of  
 some elt of  $S$ .

$$|S| = (\varepsilon/k)^{\alpha d^2 k^{1/2}}.$$



$$X = \sum_{i=1}^n w_i N(\mu_i, I).$$

$$\approx \sum w_i N(\mu_i', I)$$

$\uparrow$   
 $S.$

explicit set of distributions,  $X_1, \dots, X_n$ .

$X$  is  $\epsilon$ -close to a mixture of the  $X_i$ 's

Goal learn  $X$  given samples from  $X$  and  $X_i$ 's.

Point is compute MLE.

EP. Convergence program.

$$\frac{X + \varepsilon \left( \frac{x_1 + \dots + x_n}{n} \right)}{n}$$

Runtime

$$N = (k/\varepsilon)^{O(d^2 k^{1/d})}$$

processes required

$$(k/\varepsilon)^{O(d)}$$

Samples.

$$d = \lg(k)$$

runtime

$$(k/\varepsilon)^{O(\lg^2(k))}$$

TV  
distance  
lower  
no  
separation.

Existing algorithms

then

$$\text{If } |\mu_i - \mu_j| \gg \sqrt{\lg(k)}$$

in quasi poly time samples learn ~~the~~ parameters to error  $\varepsilon$ .

If  $|M_i - M_j| > \frac{1}{\sqrt{\lg(k)}}$

and if you have a core for the set  
(of size  $N$ ).

Then in  $\text{poly}(\log(n/k))$  time  $\leq \text{poly}(n/\epsilon)$  samples,  
you can learn the means.

~~is not~~

$$d = \lg k$$

$$(k/\epsilon)^{O(\lg n)}$$

samples

$$(k/\epsilon)^{O(\lg^2 k)}$$

time.

$$|M_i - M_j| > k^{1/d}$$

we have a trade off.  
 $\xleftarrow{\text{precision}}$   $(k/\epsilon)^{O(d)}$  samples

$$(k/\epsilon)^{O(d^2 k^{1/d})}$$

time.

- ① Preprocessing  $R^2$  dim  $|M|$ 's not too big.
- ② Computed parameter moments
- ③ Compute a lower
- ④ use brute force.

# Mixture of linear regressions

$$X \sim N(0, I)$$

$$Y = \beta \cdot X + \text{noise.}$$

$\beta_1, \dots, \beta_k$  weights  $w_1, \dots, w_k$ .

w/ prob  $w_i$

$$Y = \beta_i \cdot X + \text{noise.}$$

~~compute~~

penalize mixtures of  $\beta_i$ 's  $\sum w_i \beta_i^{\otimes d}$ .

# Non-negative linear combinations of ReLU

$$\text{ReLU}(x) = \max(0, x)$$

$$\underline{F(x)} = \sum a_i \text{ReLU}(x \cdot \underline{w_i}) \quad \underline{(a_i \geq 0)}$$

$$(x, F(x))$$

+ noise

approximate  $F$ .

$$\sum a_i \underline{v_i} \otimes d.$$

$$\hookrightarrow \underline{\sum a_i p^2(v_i)}$$

$$\underline{\chi_i^2 = 1.}$$

$$\mathbb{R}^n = \mathbb{R}^{n'} \times \mathbb{R}^{n-n'}$$

$\downarrow$                        $\downarrow$   
 $(x, y)$

$n'$  as smallish

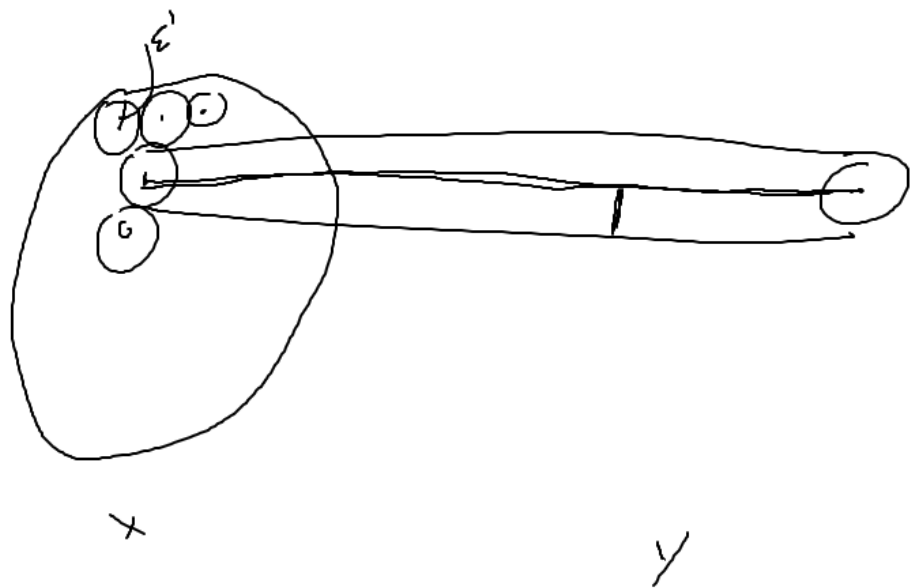
$W = \{ \text{polys in } U \text{ that are degree } \leq d \text{ in } x \text{ \& degree } \leq d-1 \text{ in } y \}$

$$\text{Codim}(W) \leq k.$$

if  $U$  is Codim  $k$  in  $V$ .

then  $U \cap W$  is Codim  $\leq k$  in  $V \cap W$ .





$\epsilon'$  very small

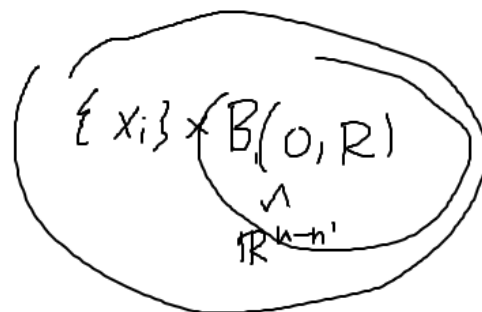
Small enough

If I change  $\delta$  by a bit...

It is enough to cover

this center line.  $\{x_0\} \times \mathbb{R}^{n-1}$

$\{x_i\}$



$$A_{x_i} : W \longrightarrow \{ \text{new deg } d-1 \text{ polys, in } y \}$$

$$P(x, y) \longrightarrow P(x_i, y)$$

$d$   
deg 1, deg d-1  
polys, in  $U$ .

$$S_{x_i} = \{ \text{new vanishing pts w/ } x = x_i \}$$

$\eta$  not too small!

$$n' \times (n-1).$$

$$\text{If } q = A_{x_i} P.$$

$$\cancel{1/q} \quad |q| > \eta |p|.$$

then  $S_{x_i}$  must nearly vanish on  $q$ .

$(x_i, y)$   
nearly vanishes

$U_{x_i} = \text{Span of the singular vectors of } A_{x_i} \text{ w/}$   
singular value  $\geq \eta$

$$\delta |p| = (\delta/\eta) |q|.$$

$$S_{x_i} \subset \{ \text{pts that nearly vanish on } U_{x_i} \}$$

recursive version of Drigan's problem.

Say  $x_i$  is good if  $\text{codim}(U_{x_i}) \leq R'$

If  $x_i$  is good then the cylinder can be covered by a set of size.

$$f(d-1, R', n-n', R, \tilde{\epsilon}, \tilde{\delta}/\eta)$$

What about the not good pts

Then I can cover all of the cylinders using all of the good

$$\delta \leq d \dots$$

$$\eta \approx \text{poly}(\epsilon)$$

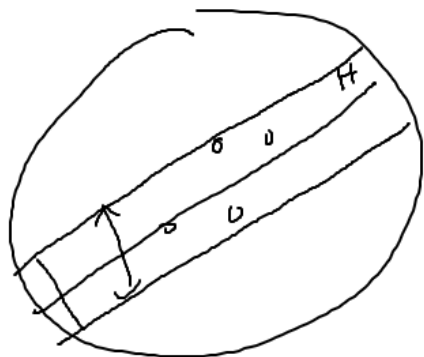
$$f(\dots) \leq (\dots)^{d^2 R^{d-1}}$$

$$R' \approx R^{\frac{d-1}{d}}$$

points w/ an appropriate # of covers.

Prop There exists a subspace  $H \subset \mathbb{R}^{n'}$   
 of dimension  $\leq 2k/k!$

s.t. all of the bad pts are  
close to  $H$



Cover  $H \times \mathbb{R}^{h-n'}$  as close as  
 $n' \gg k/k! \approx k^{1/d}$ .  
 Subspace of dim  $\mathbb{R}^{h-n' + 2k/k!}$  Then I  
 should be fine.

$\rightarrow f(d, k, R, \tilde{\epsilon}, \delta, \underline{n-n'+2k/k!})$