List Decoding via Filters

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Outline

- Problem Setup
- Information Theoretic Bounds
- Basic Multifilters
- Higher Degree Tests
- SQ Lower Bounds
- Learning Mixtures
Robust Mean Estimation

- Gaussian $G = N(\mu, I) \subset \mathbb{R}^n$
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- $X = (1 - \epsilon)G + \epsilon E$ for small $\epsilon$
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- $X = (1 - \epsilon)G + \epsilon E$ for small $\epsilon$
- Given $m$ independent samples $x_i$ of $X$
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- Given $m$ independent samples $x_i$ of $X$
- Learn Approximation to $\mu$
Very Robust Mean Estimation

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Very Robust Mean Estimation

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Problem

What if \( X = \sum_i \alpha_i G_i \)? Which is the “real” \( G \)?
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What if $X = \sum_i \alpha_i G_i$? Which is the “real” $G$?

List decoding: return several hypotheses $h_i$ with guarantee that at least one is close.
Before we begin, we should determine what errors are information-theoretically possible.
Lower Bounds

- Suppose $X = N(0, I)$. 
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- Any $\alpha N(\mu, I)$ with $|\mu| \leq \sqrt{\log(1/\alpha)/C}$ nearly hides under $X$ (up to $\alpha^{\Omega(C)}$ error).
Lower Bounds

- Suppose $X = N(0, I)$.
- Any $\alpha N(\mu, I)$ with $|\mu| \leq \sqrt{\log(1/\alpha)/C}$ nearly hides under $X$ (up to $\alpha^{\Omega(C)}$ error).
- Adding a bit to $X$, can hide $\alpha^{-\Omega(C)}$ such Gaussians.
Proposition

There is no algorithm that returns \( \text{poly}(1/\alpha) \) many hypotheses so that with at least \( 2/3 \) probability, at least one is within \( o(\sqrt{\log(1/\alpha)}) \) of the true mean.

- Let \( X \) be the slightly modified Gaussian.
- There are \( \alpha^{-\Omega(C)} \) possibilities, no two within \( \sqrt{\log(1/\alpha)}/C \).
- Algorithm cannot tell which possibility is correct, and must return a hypothesis for each.
Proposition

There is an (inefficient) algorithm that returns $O(1/\alpha)$ hypotheses so that with at least $2/3$ probability, at least one of the hypotheses is within $O(\sqrt{\log(1/\alpha)})$ of the true mean.
Let $H$ be the set of points $x$ for which there is a set $S_x$ of samples so that:

- $S_x$ is large: it contains at least an $\alpha/2$-fraction of the samples.
- $S_x$ is concentrated about $x$: in any direction, at most a $\alpha/10$-fraction of the points $S_x$ are further than $2\sqrt{\log(1/\alpha)}$ from $x$ in that direction.

Note that with high probability $\mu \in H$ with $S_\mu$ the good samples.

Problem: Too many hypotheses.
Hypotheses

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Note that with high probability $\mu \in H$ with $S_\mu = \text{the good samples}$.

**Problem:** Too many hypotheses.
Idea

Cover $H$ with a small number of balls.

Lemma

There is no set of $\frac{5}{\alpha}$ elements of $H$ that are pairwise separated by at least $4\sqrt{\log(1/\alpha)}$. 
Idea

Cover $H$ with a small number of balls.

**Lemma**

*There is no set of $\frac{5}{\alpha}$ elements of $H$ that are pairwise separated by at least $4\sqrt{\log(1/\alpha)}$.*

Take a maximal set of $4\sqrt{\log(1/\alpha)}$-separated hypotheses.

- Size at most $\frac{5}{\alpha}$.
- Every element of $H$ (including $\mu$) within $4\sqrt{\log(1/\alpha)}$ of one.
Overlaps

Idea: If $x$ and $y$ far away, then $S_x$ and $S_y$ have little overlap. If many separated $x$’s, then too many points.

Lemma

If $x, y \in H$ with $|x - y| \geq 4 \sqrt{\log(1/\epsilon)}$, then $|S_x \cap S_y| \leq \alpha/10(|S_x| + |S_y|)$.

Proof.

Project onto the line between $x$ and $y$.

At most $\alpha |S_x|/10$ items from $S_x$ closer to $y$ than $x$.

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**Proof.**

- Project onto the line between $x$ and $y$.
- At most $\alpha|S_x|/10$ items from $S_x$ closer to $y$ than $x$.
- At most $\alpha|S_y|/10$ items from $S_y$ closer to $x$ than $y$. 
Counting

If $x_1, x_2, \ldots, x_m \in H$ pairwise far, then

$$|S_{x_1} \cup S_{x_2} \cup \ldots \cup S_{x_m}| \geq \sum_{i=1}^{m} |S_{x_i}| - \sum_{1 \leq i < j \leq m} \frac{\alpha}{10}(|S_{x_i}| + |S_{x_j}|)$$

$$= \sum_{i=1}^{m} |S_{x_i}|(1 - \frac{m\alpha}{10})$$

$$\geq \frac{m\alpha}{2|S|(1 - \frac{m\alpha}{10})}.$$
Counting

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$$= \sum_{i=1}^{m} |S_{x_i}|(1 - m\alpha/10)$$

$$\geq m\alpha/2|S|(1 - m\alpha/10).$$

If $m = 5/\alpha$, this is more than the total number of samples.
If the good samples have all but $\alpha/10$-fraction within $t$ of the mean in any direction, can get $O(1/\alpha)$ hypotheses with error $O(t)$. 

Given a set $H$ of hypotheses at least one within $r$ of true mean, can in poly-time reduce to a set of $O(1/\alpha)$ with error $O(r + \sqrt{\log(1/\alpha)})$.

- Use LP to determine if there is a set $S_x$ with concentration about $x$ in the directions $x - y$.
- Cover remaining $x$'s with balls.
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Algorithms

- Filters and Multifilters
- Obstacle at $\alpha^{-1/2}$.
- Higher Degree Idea
- Variance Control
With few errors algorithm looks like:

1. Compute Covariance
2. If large eigenvalue produce filter and repeat
3. Return sample mean
Moderately Robust Algorithm

With few errors algorithm looks like:

1. Compute Covariance
2. If large eigenvalue produce filter and repeat
3. Return sample mean

Would like to do the same thing in the high noise case. It *almost* works.
If $\alpha < 1/2$, might not be able to tell where the real samples are.
Multifilters

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Split into several overlapping sets of samples $S_i$
Multifilters

If $\alpha < 1/2$, might not be able to tell where the real samples are.

Split into several overlapping sets of samples $S_i$ so that:

- At least one $S_i$ has higher fraction of good samples than $S$
- $\sum |S_i|^2 \leq |S|^2$
Split into cases

- **Case 1:** Almost all of the samples are in the same small interval.
- **Case 2:** There are clusters of samples far apart from each other.
Filter Case

Suppose that there is an interval $I$ containing all but an $\alpha/3$-fraction of samples.
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- All but a tiny fraction of good samples within $O(\sqrt{\log(1/\alpha)})$ of $I$. 
Filter Case

Suppose that there is an interval $I$ containing all but an $\alpha/3$-fraction of samples.

- With high probability, true mean in $I$.
- All but a tiny fraction of good samples within $O(\sqrt{\log(1/\alpha)})$ of $I$.
- Unless variance is $O(|I|^2 + \log(1/\alpha))$, so that at most an $\alpha^2$-fraction of removed samples were good.
Suppose that there is an interval $I$ with at least an $\alpha/6$-fraction of samples on either side of it.
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- Find some $x$, let $S_1 = \{\text{samples} \leq x + 10\sqrt{\log(1/\alpha)}\}$, $S_2 = \{\text{samples} \geq x - 10\sqrt{\log(1/\alpha)}\}$. 

All but an $\alpha^2$-fraction of removed samples (on the correct side) are bad:

- If $\mu \geq x$, all but $\alpha^3$-fraction of good samples in $S_2$.
- If $\mu \leq x$, all but $\alpha^3$-fraction in $S_1$.
- Always throw away at least $\alpha/6$ samples.

Need: $|S_1|^2 + |S_2|^2 \leq |S|^2$. 

Multifilter Case

Suppose that there is an interval $I$ with at least an $\alpha/6$-fraction of samples on either side of it.

- Find some $x$, let $S_1 = \{\text{samples } \leq x + 10\sqrt{\log(1/\alpha)}\}$, $S_2 = \{\text{samples } \geq x - 10\sqrt{\log(1/\alpha)}\}$.
- All but an $\alpha^2$-fraction of removed samples (on the correct side) are bad:
  - If $\mu \geq x$, all but $\alpha^3$-fraction of good samples in $S_2$.
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  - Always throw away at least $\alpha/6$ samples.

- **Need:** $|S_1|^2 + |S_2|^2 \leq |S|^2$. 
Let \( f(x) \) be the fraction of samples less than \( x \).
Analysis

- Let $f(x)$ be the fraction of samples less than $x$.
- Need $x \in I$ so that $(1 - f(x))^2 + f(x + 20\sqrt{\log(1/\alpha)})^2 \leq 1$. 
Analysis

- Let \( f(x) \) be the fraction of samples less than \( x \).
- Need \( x \in I \) so that \((1 - f(x))^2 + f(x + 20\sqrt{\log(1/\alpha)})^2 \leq 1\).
- Happens unless \( f(x + 20\sqrt{\log(1/\alpha)}) \gg f(x)^{1/2} \).
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Happens unless $f(x + 20 \sqrt{\log(1/\alpha)}) \gg f(x)^{1/2}$.

Good unless $f(x + 20t \sqrt{\log(1/\alpha)}) \gg \alpha^{1/2^t}$, only works for $t \ll \log \log(1/\alpha)$. 

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Good unless $f(x + 20t\sqrt{\log(1/\alpha)}) \gg \alpha^{1/2t}$, only works for $t \ll \log \log(1/\alpha)$.

Can find such sets unless $|I| = O(\sqrt{\log(1/\alpha) \log \log(1/\alpha)})$. 
General Situation

Can create a filter or multifilter if either:

- No interval $I$ of length $O(\sqrt{\log(1/\alpha) \log \log(1/\alpha)})$ contains all but an $\alpha/3$-fraction of samples.
- An interval $I$ of length $O(\sqrt{\log(1/\alpha) \log \log(1/\alpha)})$ contains all but an $\alpha/3$-fraction of samples, and the variance is $\Omega(|I|^2)$. 
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- An interval $I$ of length $O(\sqrt{\log(1/\alpha) \log \log(1/\alpha)})$ contains all but an $\alpha/3$-fraction of samples, and the variance is $\Omega(|I|^2)$.

Proposition

*If the variance in some direction is more than a sufficient multiple of $\log(1/\alpha)$ (with a slight refinement of the argument) then we can find at most two sets of samples $S_i$ so that*

1. For some $i$, at most an $\alpha^2$-fraction of $S \setminus S_i$ is good samples.
2. $\sum_i |S_i|^2 \leq |S|^2$. 
Basic Multifilter Algorithm

1. Maintain several sets $S_i$ of samples
2. For each $i$, compute empirical covariance matrix $\hat{\Sigma}_i$
3. If some $\hat{\Sigma}_i$ has a large eigenvalue
   - Create multifilter
   - Apply to $S_i$
   - Replace $S_i$ by resulting sets in list
   - Go to step 2.
4. Return list of all $\mu_{S_i}$
Analysis

At each step:

- At least one $S_i$ has an $\alpha$-fraction of good samples (in fact at least half of the total good samples)
- $\sum |S_i|^2 \leq |S|^2$
Analysis

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- $\sum |S_i|^2 \leq |S|^2$

When return if:
- $S_i$ has $\alpha$-fraction of good samples AND
- $\hat{\Sigma}_i$ has no large eigenvalues

$$\log(1/\alpha) \gg \text{Var}(v \cdot S_i) \geq \alpha \left[ v \cdot (\mu_{S_i} - \mu) \right]^2,$$

so $|\mu_{S_i} - \mu| = O\left(\alpha^{-1/2} \sqrt{\log(1/\alpha)}\right)$. 
Analysis

At each step:

- At least one $S_i$ has an $\alpha$-fraction of good samples (in fact at least half of the total good samples)
- $\sum |S_i|^2 \leq |S|^2$

When return if:

- $S_i$ has $\alpha$-fraction of good samples AND
- $\hat{\Sigma}_i$ has no large eigenvalues

Then for all $|v| = 1$,

$$\log(1/\alpha) \gg \text{Var}(v \cdot S_i) \geq \alpha [v \cdot (\mu_{S_i} - \mu)]^2,$$

so

$$|\mu_{S_i} - \mu| = O(\alpha^{-1/2} \sqrt{\log(1/\alpha)}).$$
Obstacle at $\alpha^{-1/2}$

Unfortunately, the error can be as much as $\alpha^{-1/2}$. 
Idea

Bounds on the second moments are not enough to ensure concentration.
Bounds on the second moments are not enough to ensure concentration. **Fix:** use higher moments.
Analysis

If for all unit vectors $\nu$,

$$\mathbb{E}[|\nu \cdot (X - \mu_X)|^{2d}] = O(1),$$

then

$$1 \gg \alpha |\nu \cdot (\mu - \mu_X)|^{2d},$$

so

$$|\mu - \mu_X| = O(\alpha^{-1/2d}).$$
Computational Difficulty

It is computationally intractable to determine whether or not there is a unit vector $v$ for which $\mathbb{E}[(v \cdot X)^{2d}]$ is large when $d > 1$. 
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**Idea:** Look at a relaxation of this problem.

- Last talk: Look for SoS proof that $\mathbb{E}[(v \cdot X)^{2d}] \ll |v|^{2d}$ for all $v$. 
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**Idea:** Look at a relaxation of this problem.

- Last talk: Look for SoS proof that $\mathbb{E}[(v \cdot X)^{2d}] \ll |v|^{2d}$ for all $v$.
- This talk: See if there is any degree-$d$ polynomial $p$ with $\mathbb{E}[p(X)^2]$ too big.
Basic Idea

Determine whether or not there is a degree-$d$ polynomial $p$ with $\mathbb{E}[p(S)^2]$ substantially larger than $\mathbb{E}[p(G_{\mu S})^2]$. 
Basic Idea

Determine whether or not there is a degree-$d$ polynomial $p$ with $\mathbb{E}[p(S)^2]$ substantially larger than $\mathbb{E}[p(G_{\mu_S})^2]$.

- Eigenvalue computation.
- If not, implies $|\mu - \mu_S| = \tilde{O}(\alpha^{-1/2d})$.
- If yes, create a (multi-)filter.
A Failed Attempt

If $\text{Var}(p(X))$ is too large, create a (multi-)filter based on the values of $p$. 
A Failed Attempt

If $\text{Var}(p(X))$ is too large, create a (multi-)filter based on the values of $p$.

- Compute values of $p(x)$ for $x \in S$.
- Fairly spread out.
- Values of $p(G)$ are clustered.
- Use same multifilter ideas as before.
A Failed Attempt

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**Problem:** $\text{Var}(p(G))$ might also be large!
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- Fairly spread out.
- Values of $p(G)$ are clustered.
- Use same multifilter ideas as before.

**Problem:** $\text{Var}(p(G))$ might also be large!

- Unlike degree-1 polynomials, for degree-$d$, $\text{Var}(p(G))$ depends on $\mu$.
- Want a way to verify that $\text{Var}(p(G))$ is small.
The Strategy

Given a $p$ with $\mathbb{E}[p(S)^2] \gg \mathbb{E}[p(G_{\mu S})^2]$ try to either:

- Verify that $\mathbb{E}[p(G)^2] \approx \mathbb{E}[p(G_{\mu S})^2]$
  - Can then filter out points with $p(x)^2$ too large.
The Strategy

Given a $p$ with $\mathbb{E}[p(S)^2] \gg \mathbb{E}[p(G_{\mu_S})^2]$ try to either:

- Verify that $\mathbb{E}[p(G)^2] \approx \mathbb{E}[p(G_{\mu_S})^2]$
  - Can then filter out points with $p(x)^2$ too large.
- OR produce a (multi-)filter in failing to verify this.
Bounding $\mathbb{E}[p(G)^2]$ 

- For any degree-$d$ polynomial $p$, $\mathbb{E}[p(G)^2] = q(\mu)$ for some degree-$2d$ polynomial $q$. 

Point: If $\mathbb{E}[p(G)^2]$ is too big, then $r(x_1, x_2, ... , x_{2d})$ (where $x_i \in S$), has an $\alpha^2$ chance of being large.
For any degree-$d$ polynomial $p$, $\mathbb{E}[p(G)^2] = q(\mu)$ for some degree-$2d$ polynomial $q$.

This in turn equals $\mathbb{E}[r(G_1, G_2, \ldots, G_{2d})]$ for some multilinear $r$ with $|r| \approx |p|$ and $G_i$ i.i.d. copies of $G$. 
Bounding $\mathbb{E}[p(G)^2]$ 

- For any degree-$d$ polynomial $p$, $\mathbb{E}[p(G)^2] = q(\mu)$ for some degree-$2d$ polynomial $q$.
- This in turn equals $\mathbb{E}[r(G_1, G_2, \ldots, G_{2d})]$ for some multilinear $r$ with $|r| \approx |p|$ and $G_i$ i.i.d. copies of $G$.

**Point:** If $\mathbb{E}[p(G)^2]$ is too big, then $r(x_1, x_2, \ldots, x_{2d})$ ($x_i \in S$), has an $\alpha^{2d}$ chance of being large.
Large Values

Suppose that $r(x_1, x_2, \ldots, x_{2d})$ is much larger than expected.
Large Values

Suppose that \( r(x_1, x_2, \ldots, x_{2d}) \) is much larger than expected.

- Assign \( x_i \)'s one at a time.
- At some stage the size of the polynomial must jump.
- In particular,

\[
\mathbb{E}[|r(x_1, x_2, \ldots, x_{i+1}, G'_{i+2}, \ldots, G'_{2d})|^2] \\
\gg \mathbb{E}[|r(x_1, x_2, \ldots, x_i, G'_{i+1}, \ldots, G'_{2d})|^2]
\]

where \( G'_j \) are i.i.d. copies of \( G_{\mu_S} \).
Quadratic

Note that

\[ s(y) = \mathbb{E}[|r(x_1, x_2, \ldots, x_i, y, G'_{i+2}, \ldots, G'_{2d})|^2] \]

is a quadratic polynomial in \( y \) with \( s(x_{i+1}) \gg \mathbb{E}[s(G_{\mu_S})] \).
Quadratic

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Can diagonalize \( s \) as

\[ s(y) = \sum L_j(y)^2 \]

for linear polynomials \( L_j \).
Quadratic

- Note that

  \[ s(y) = \mathbb{E}[|r(x_1, x_2, \ldots, x_i, y, G'_{i+2}, \ldots, G'_{2d})|^2] \]

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- Can diagonalize \( s \) as

  \[ s(y) = \sum L_j(y)^2 \]

  for linear polynomials \( L_j \).

- So there must be some \( j \) for which \( L_j(x_{i+1}) \) is much larger than expected. This will let us create a (multi-)filter.
Algorithm

1. Try to find polynomial $p$ with $\mathbb{E}[p(S)^2] \gg \log^{4d}(1/\alpha)\mathbb{E}[p(G_{\mu_S})^2]$.
   - If none exist, return $\mu_S$.
2. Compute corresponding multilinear $r$. See if $|r(x_1, \ldots, x_{2d})|^2 \gg \log^{2d}(1/\alpha)\mathbb{E}[p(G_{\mu_S})^2]$ with probability at least $\alpha^{2d}$.
   - If not, $\mathbb{E}[p(G)^2]$ is small, filter out $x$ with $p(x)^2$ more than average, and return to step 1.
3. Find $x_1, x_2, \ldots, x_i$ so that with $\alpha$ probability over $y \in S$, $|r(x_1, \ldots, x_i, y)|^2 \gg \log(1/\alpha)|r(x_1, \ldots, x_i)|^2$.
4. Compute the corresponding quadratic $s(y) = \sum L_j(y)^2$.
5. Find an $j$ so that $L_j(y)$ is likely larger than expected. Use to create a (multi-)filter. Apply and return to step 1.
Requirements

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**Runtime:**
- Need to check for events with probability $\alpha^{2d}$.
- Runtime is $\text{poly}(|S|/\alpha^d)$. 
Final Results

Theorem

There exists an algorithm that given $O(d^{2d})n^{O(d)}/\text{poly}(\alpha)$ i.i.d. samples from $X$, there is an $(nd/\alpha)^{O(d)}$ time algorithm which with high probability returns a list of $O(1/\alpha)$ hypotheses so that at least one hypothesis is within $\tilde{O}_d(\alpha^{-1/2d})$ of $\mu$. 

Note: in quasi-polynomial time/samples can achieve polylog error. We think we can improve to $O(\sqrt{\log(1/\alpha)})$. 

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Note: in quasi-polynomial time/samples can achieve polylog error. We think we can improve to $O(\sqrt{\log(1/\alpha)})$. 
In fact, this list decoding result is qualitatively tight for SQ algorithms (though note that our algorithm is not quite SQ).

**Theorem**

Any SQ list decoding algorithm that with 2/3 probability returns a list of hypotheses at least one of which is closer than $\alpha^{-1/d}$ from the mean must do one of the following:

- Return exponentially many hypotheses.
- Perform exponentially many queries.
- Perform queries with accuracy $n^{-\Omega(d)}$. 
Proof

Using our lower bounds framework, we want a one-dimensional distribution that matches $d$ moments. We have one of the form

$$A(x) = (1 - \alpha)N(0, 1) + \alpha N(\alpha^{-1/d} / C_d, 1) + E$$

where the $E(x)$ is what it needs to be to make the moments work.
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We now have exponentially many distributions $P_v$ that cannot be distinguished by an SQ algorithm unless it uses exponentially many queries or queries of accuracy $n^{-\Omega(d)}$, each would could have $\mu = v\alpha^{-1/d}/C_d$. Finding a better approximation to $\mu$ requires determining which $P_v$ we have.
Learning Mixtures of Spherical Gaussians

Application: Let $X = 1/k \sum_{i=1}^{k} G_i$ with each $G_i \sim N(\mu_i, I)$. 
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**Question:** How much separation is actually needed?
List Decoding

Run list decoding algorithm. Since $X$ is a noisy version of each $G_i$, our list contains approximations to all means with error $D$. 
Clustering

Round samples to nearest hypothesis. With high probability samples round to one of hypotheses within $O(D)$ of the mean.

Cluster used hypotheses.

Recover original Gaussians to estimate means.
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Theorem

If the means have separation $\Omega(k^{1/2d})$, there is an algorithm that takes $\text{poly}(n, (dk)^d)$ samples, runs in sample polynomial time and returns accurate approximations to the $\mu_i$. Can be improved to polylogarithmic separation in quasi-polynomial time/samples. We think we can improve this to $O(\sqrt{\log(k)})$ separation. Can be generalized to unequal mixtures or to Gaussians with different radii (though still spherical).
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Conclusion

Have a robust list decoding algorithm with much better error. Can use to learn mixtures of spherical Gaussians with $k^\delta$ separation.
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Open problems:

1. How much can the Gaussian assumption be relaxed?
2. Can you do better for learning mixtures than for list decoding?
3. Are there better algorithms for density estimation?


