# Algorithmic Aspects of Machine Learning: Problem Set \# 2 

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Due: April 6th
You can work with other students, but you must write-up your solutions by yourself and indicate at the top who you worked with!

## Problem 1

In the multi-reference alignment problem we observe many noisy copies of the same unknown signal $x \in \mathbb{R}^{d}$, but each copy has been circularly shifted by a random offset (as pictured).


Figure: Three shifted copies of the true signal $x$ are shown in gray. Noisy samples $y_{i}$ are shown in red.

Formally, for $i=1,2, \ldots, n$ we observe

$$
y_{i}=R_{\ell_{i}} x+\xi_{i}
$$

where: the $\ell_{i}$ are drawn uniformly and independently from $\{0,1, \ldots, d-1\} ; R_{\ell}$ is the operator that circularly shifts a vector by $\ell$ indices; $\xi_{i} \sim \mathcal{N}\left(0, \sigma^{2} I_{d \times d}\right)$ with $\left\{\xi_{i}\right\}_{i}$ independent; and $\sigma>0$ is a known constant. Think of $d, x$ and $\sigma$ as fixed while $n \rightarrow \infty$. The goal is to recover $x$ (or a circular shift of $x$ ).
(a) Consider the tensor $T(x)=\frac{1}{d} \sum_{\ell=0}^{d-1}\left(R_{\ell} x\right) \otimes\left(R_{\ell} x\right) \otimes\left(R_{\ell} x\right)$. Show how to use the samples $y_{i}$ to estimate $T$ (with error tending to zero as $n \rightarrow \infty$ ). Take extra care with the entries that have repeated indices (e.g. $T_{a a b}, T_{a a a}$ ).
(b) Given $T(x)$, prove that Jennrich's algorithm can be used to recover $x$ (up to circular shift). Assume that $x$ is generic in the following sense: let $x^{\prime} \in \mathbb{R}^{d}$ be arbitrary and let $x$ be obtained from $x^{\prime}$ by adding a small perturbation $\delta \sim \mathcal{N}(0, \epsilon)$ to the first entry. Hint: form a matrix with rows $\left\{R_{\ell} x\right\}_{0 \leq \ell<d}$, arranged so that the diagonal entries are all $x_{1}$.

## Problem 2

In this problem we will study the task of learning the high-dimensional parameters of a mixture model from its one-dimensional projections. Suppose we have a $d$ dimensional mixture model

$$
\mathcal{F}=\frac{1}{2} F_{1}+\frac{1}{2} F_{2}
$$

where $F_{1}$ and $F_{2}$ have means $\mu_{1}$ and $\mu_{2}$ respectively. Suppose are given access to an oracle, that when we query a direction $r$, outputs the set

$$
\left\{r^{T} \mu_{1} \pm \gamma, r^{T} \mu_{2} \pm \gamma\right\}
$$

That is, we learn the means of the projected distributions up to accuracy $\gamma$ but we do not know which estimates correspond to which components.
(a) Explain how to interpret the oracle as giving noisy estimates of quadratic forms on the matrix

$$
M=\left(\mu_{1}-\mu_{2}\right)\left(\mu_{1}-\mu_{2}\right)^{\top}
$$

Why doesn't it matter that we don't know which estimates corresponds to which components?
(b) Give an algorithm that makes $O\left(d^{2}\right)$ queries and recovers the entries of $M$ up to accuracy $O(\gamma)$.
(c) Explain how to use your estimate of $M$ to estimate $\mu_{1}$ and $\mu_{2}$ up to permutation. A sketch of the algorithm and how you would go about analyzing it is enough, since the details can get messy.

## Problem 3

In this problem we will show that a monotone adversary can break even very powerful approaches for community detection. Consider the planted bisection model on $n$ nodes with inter- and intra-connection probabilities $p$ and $q$ respectively. Suppose we look for a bisection $(A, V \backslash A)$ with the property that every node $u$ has more neighbors on its side of the bisection than on the other side. We will call such a bisection admissible. Show how a monotone adversary can construct an admissable bisection that is far from the planted one.

