

# Notes on big MRA

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## 1 Setup

We have the following model.  $x$  is a signal of length  $L$ . For large  $n$ , we observe the vector  $Y \in \mathbb{R}^n$ , which is of the form

$$Y = G * x + N \tag{1}$$

where  $G$  is a sum of diracs at locations at least  $2L$  apart, and  $N$  is a vector of  $n$  iid Gaussians. The goal is to recover  $x$ .

We will assume that the first and last copies of  $x$  are at least  $L$  places removed from the boundaries of the interval  $[1, n + L]$  (if not we can just zero-pad the interval). We will also denote by  $I_1, \dots, I_J$  the  $J$  subintervals containing the signal; and take  $I_j = [a_j, b_j]$ . When we take the limit  $n \rightarrow \infty$ , we'll let  $J = J_n$  grow with  $n$ , as is natural. We will see that we require  $J_n = \Omega(n)$  in order for the limits to not vanish (and obviously  $J_n = O(n)$  too).

For the moments computation, I'm not just computing the expected value. I'm actually showing convergence almost surely as  $n \rightarrow \infty$ . I probably made a mistake in the final formulas since I haven't check them carefully yet; the main point I want to record right now is how to get the bookkeeping correct for dealing with the noise terms, namely, we need to break the averages into averages of averages, each with iid terms.

## 2 First moment

We have:

$$M_1 = \frac{1}{n} \sum_{i=1}^n Y_i = \frac{1}{n/L} \sum_{j=1}^{J_n} \frac{1}{L} \sum_{i=1}^L x_i + \frac{1}{n} \sum_{i=1}^n N_i \rightarrow \gamma \cdot \bar{x}, \tag{2}$$

where the limit is almost surely (we've used the strong law of large numbers), where  $\gamma = \lim_{n \rightarrow \infty} J_n L / n$  is the fraction of the observations containing the signal.

### 3 Second moment

We fix a value  $\Delta$  between 0 and  $L - 1$ . We will compute the second moment:

$$M_2(\Delta) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^{n-\Delta} Y_i Y_{i+\Delta}. \quad (3)$$

#### 3.1 Clean signal without noise

First, if there is no noise, and under the wide spacing assumption, we can break the sum into  $J_n$  different sums, one for each copy of  $x$  embedded in the signal:

$$\begin{aligned} M_2(\Delta) &= \frac{1}{n} \sum_{j=1}^{J_n} \sum_{i=a_j}^{b_j-\Delta} Y_i Y_{i+\Delta} = \frac{1}{n} \sum_{j=1}^{J_n} \sum_{i=1}^{L-\Delta} x_i x_{i+\Delta} \\ &= \frac{J_n L}{n} \frac{1}{L} \sum_{i=1}^{L-\Delta} x_i x_{i+\Delta} \rightarrow \gamma \cdot R_2(\Delta), \end{aligned} \quad (4)$$

where here we have defined  $R_2(\Delta)$  as element  $\Delta$  of the autocorrelation of  $x$ .

#### 3.2 Pure noise without signal

Here,  $Y_i = N_i$ . We first fix  $\Delta$  between 1 and  $L - 1$ . Break up the sum into  $\Delta$  terms as follows:

$$\begin{aligned} M_2(\Delta) &= \frac{1}{n} \sum_{i=1}^n N_i N_{i+\Delta} \\ &= \frac{1}{\Delta} \sum_{m=0}^{\Delta-1} \frac{1}{n/\Delta} \sum_{j=1}^{n/\Delta} N_{j+(j-1)\Delta+m} N_{j+j\Delta+m}. \end{aligned} \quad (5)$$

Each term  $\frac{1}{n/\Delta} \sum_{j=1}^{n/\Delta} N_{j+(j-1)\Delta+m} N_{j+j\Delta+m}$  is an average of  $n/\Delta$  iid terms with expectation zero, and so converges to 0 a.s. as  $n \rightarrow \infty$ . (Of course, it's not exactly  $n/\Delta$  terms; there will be finitely many terms unaccounted for this way, but these are negligible).

If  $\Delta = 0$ , then the computation is even easier:

$$M_2(\Delta) = \frac{1}{n} \sum_{i=1}^n N_i^2 \xrightarrow{a.s.} \sigma^2. \quad (6)$$

So  $M_2(\Delta) = \sigma^2$  if  $\Delta = 0$ , and 0 otherwise.

### 3.3 Signal plus noise

We will denote by  $\mathcal{X} = x * G$ , so  $Y = \mathcal{X} + N$ . Then the second moment of the signal plus noise is:

$$M_2(\Delta, Y) = M_2(\Delta, \mathcal{X}) + M_2(\Delta, N) + \frac{1}{n} \sum_{i=1}^{n-\Delta} \mathcal{X}_i N_{i+\Delta} + \frac{1}{n} \sum_{i=1}^{n-\Delta} \mathcal{X}_{i+\Delta} N_i. \quad (7)$$

The law of large numbers says the cross terms vanish as  $n \rightarrow \infty$ . So the limit is simply:

$$M_2(\Delta, Y) = \begin{cases} \gamma \cdot R_2(\Delta), & \text{if } \Delta > 0; \\ \gamma \cdot R_2(\Delta) + \sigma^2, & \text{if } \Delta = 0. \end{cases} \quad (8)$$

## 4 Third moments

The same idea lets us compute the third moments. We fix two indices  $\Delta_1 < \Delta_2$ , and define:

$$M_3(\Delta_1, \Delta_2) = \sum_{i=1}^{n-\Delta_2} Y_i Y_{i+\Delta_1} Y_{i+\Delta_2}. \quad (9)$$

### 4.1 Pure noise, no signal

Again, the idea is to break up the big average over  $n$  terms into a sum of  $\Delta_2$  averages, each of  $\approx n/\Delta_2$  independent terms. We write:

$$\begin{aligned} M_3(\Delta_1, \Delta_2) &= \frac{1}{\Delta_2} \sum_{m=0}^{\Delta_2-1} \frac{1}{(n/\Delta_2)} \sum_{j=1}^{n/\Delta_2} N_{j+(j-1)\Delta_2+m} N_{j+\Delta_1+(j-1)\Delta_2+m} N_{j+j\Delta_2+m}. \end{aligned} \quad (10)$$

Each of the  $\Delta_2$  terms indexed by  $m$  converges is an average of  $n/\Delta_2$  independent terms with mean zero, and so converges a.s. to zero as  $n \rightarrow \infty$ .

### 4.2 Clean signal, no noise

Again, this is just like the second moment case. Write:

$$\begin{aligned} M_3(\Delta_1, \Delta_2) &= \frac{1}{n} \sum_{j=1}^{J_n} \sum_{i=a_j}^{b_j-\Delta_2} Y_i Y_{i+\Delta_1} Y_{i+\Delta_2} = \frac{1}{n} \sum_{j=1}^{J_n} \sum_{i=1}^{L-\Delta_2} x_i x_{i+\Delta_1} x_{i+\Delta_2} \\ &= \frac{J_n L}{n} \frac{1}{L} \sum_{i=1}^{L-\Delta} x_i x_{i+\Delta_1} x_{i+\Delta_2} \rightarrow \gamma \cdot R_3(\Delta_1, \Delta_2), \end{aligned} \quad (11)$$

where here we have defined  $R_3(\Delta_1, \Delta_2)$  as element  $(\Delta_1, \Delta_2)$  of the third moment of  $x$ .

### 4.3 Signal plus noise

We have:

$$M_3(\Delta_1, \Delta_2, Y) = M_3(\Delta_1, \Delta_2, \mathcal{X}) + M_3(\Delta_1, \Delta_2, N) + \text{cross terms.} \quad (12)$$

If  $0 < \Delta_1 < \Delta_2$ , then all of the cross terms can be shown to go to zero by the same kind of argument we've used several times before.

If  $\Delta_1 = \Delta_2 = \Delta$ , there is a surviving cross-term, namely:

$$\frac{1}{n} \sum_{i=1}^{n-\Delta} \mathcal{X}_i N_{i+\Delta}^2 = \frac{1}{(n/L)} \sum_{j=1}^{J_n} \frac{1}{L} \sum_{i=a_j}^{b_j} \mathcal{X}_i N_{i+\Delta}^2. \quad (13)$$

Each of  $S_j \equiv \frac{1}{L} \sum_{i=a_j}^{b_j} \mathcal{X}_i N_{i+\Delta}^2 \sim \frac{1}{L} \sum_{i=1}^L x_i \varepsilon_i^2$ , where  $\varepsilon_i \sim N(0, \sigma^2)$ ; and they are independent random variables with mean  $\mathbb{E}[S_j] = \sigma^2 \cdot \bar{x}$ . So by the law of large numbers,

$$\frac{1}{(n/L)} \sum_{j=1}^{J_n} \frac{1}{L} \sum_{i=a_j}^{b_j} \mathcal{X}_i N_{i+\Delta}^2 \rightarrow \gamma \cdot \sigma^2 \cdot \bar{x}. \quad (14)$$

Similarly, if  $\Delta_1 = 0$ , then there is a surviving cross-term which converges to  $\gamma \cdot \sigma^2 \cdot \bar{x}$  as well. So in summary,

$$M_3(\Delta_1, \Delta_2, Y) = \begin{cases} \gamma \cdot R_3(\Delta_1, \Delta_2), & \text{if } 0 < \Delta_1 < \Delta_2; \\ \gamma \cdot R_3(\Delta_1, \Delta_2) + \gamma \cdot \sigma^2 \cdot \bar{x}, & \text{if } \Delta_1 = 0 \text{ or } \Delta_1 = \Delta_2. \end{cases} \quad (15)$$



## 5 Attempt at EM

Let's derive the EM algorithm, where we treat the locations  $a_j$  as random latent variables. A simple model is that the  $a_j$  are chosen independently and uniformly at random (though take note that this permits overlaps of the signal copies).



We will denote by  $G = \sum_{j=1}^J \delta_{a_j}$  the random vector of signal locations. We'll assume the number of signals  $J$  is known. The generative model is:

$$p(Y, G|x) = \frac{\exp\{-\|Y - G * x\|^2 / (2\sigma^2)\}}{(2\pi\sigma^2)^{n/2}} \cdot \frac{1}{n^J}. \quad (16)$$

The log-likelihood is then (up to an additive constant):

$$\mathcal{L}(x; Y, G) \propto -\|Y - G * x\|^2. \quad (17)$$

The probability distribution of  $G$ , given  $Y$  and  $x$ , is:

$$p(G|Y, x) = \frac{p(Y, G|x)}{p(Y|x)} \propto \exp\{-\|Y - G * x\|^2 / (2\sigma^2)\}. \quad (18)$$

If  $x^{(t)}$  is a guess for  $x$  on the  $t^{th}$  iterate of EM, then we define the weights:

$$w_t(G) = p(G|Y, x^{(t)}) = \exp\{-\|Y - G * x^{(t)}\|^2 / (2\sigma^2)\}, \quad (19)$$

and the  $Q$ -function:

$$\begin{aligned} Q(x|x^{(t)}) &= \mathbb{E}_{G|Y, x^{(t)}} [\mathcal{L}(x^{(t)}; Y, G)] \\ &\propto - \sum_G \|Y - G * x\|^2 \cdot w_t(G). \end{aligned} \quad (20)$$

The EM algorithm defines the next guess of  $x$  to be:

$$x^{(t+1)} = \arg \max_x Q(x|x^{(t)}) = \arg \min_x \sum_G \|Y - G * x\|^2 \cdot w_t(G). \quad (21)$$

But finding this minimum is hard, since the sum is over all  $\binom{n}{J}$  possible values of  $G$ ; if  $J \sim n$ , as we expect is necessary to have any chance of recovery (this was suggested by the moments method), the number of terms will grow exponentially with  $n$ .