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## Lecture 22: Approximate Message Passing

(See slides for derivation of AMP, state evolution)

If we set  $f_t(y) = \mathbb{E}[X | \mu_t X + \sigma_t \zeta = y]$ ,

$$\begin{aligned} \text{then } \mathbb{E}_{X, \zeta} [X f_t(\mu_t X + \sigma_t \zeta)] &= \mathbb{E}_{X, \zeta} [f_t(\mu_t X + \sigma_t \zeta)^2] \\ &= \mathbb{E} [\mathbb{E}[X | \mu_t X + \sigma_t \zeta]^2] \quad (\star) \end{aligned}$$

Dist. recursion thus simplifies to

$$\mu_{t+1} = \sqrt{\lambda} \sigma_t^2 \quad (1)$$

Note,  $\mathbb{E} \left[ \left( X - \mathbb{E}[X | \mu_t X + \sigma_t \zeta] \right)^2 \right]$

$$= \mathbb{E} \left[ X^2 \right] - \mathbb{E} \left[ \mathbb{E}[X | \mu_t X + \sigma_t \zeta]^2 \right]$$

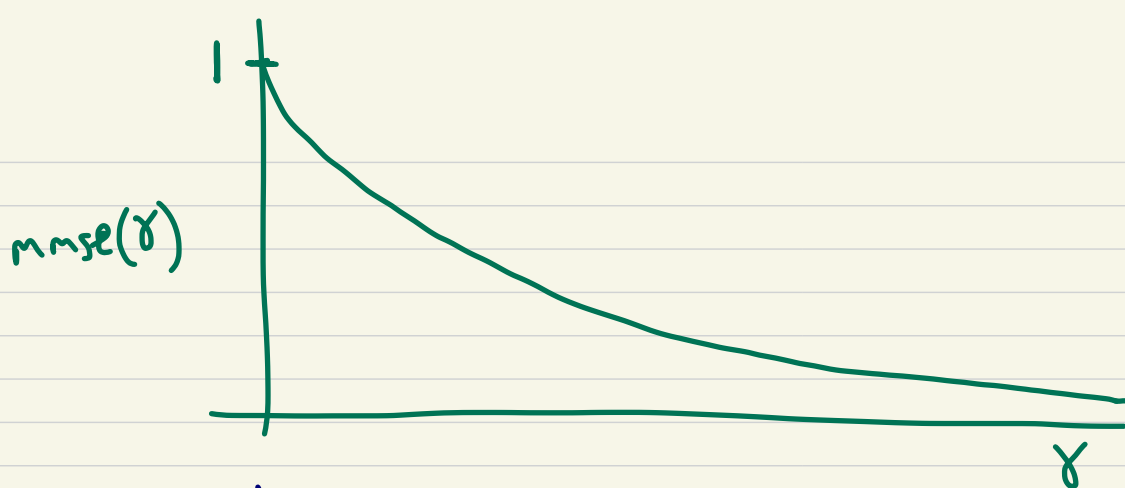
$$= 1 - (\star),$$

→ this is MMSE for estimating  $X$  given  $\mu_t X + \sigma_t \zeta$ ,

Define  $\text{mmse}(\gamma)$  to be MMSE for estimating  $X$  given

$\sqrt{\gamma} X + \zeta$ . Then quantity  $1 - (\star)$  above is

$$\text{mmse} \left( \frac{\mu_t^2}{\sigma_t^2} \right) = \text{mmse}(\lambda \sigma_t^2)$$



Other part of dist. recursion thus simplifies to

$$\sigma_{t+1}^2 = 1 - \text{mmse}(\lambda \sigma_t^2) \quad (2)$$

Can combine (1) and (2) into 1D recursion by defining  $\gamma_t = \lambda \sigma_t^2$ . Then we get

$$\gamma_0 = 0, \quad \boxed{\gamma_{t+1} = \lambda (1 - \text{mmse}(\gamma_t))} \quad (\text{REC})$$

$$\text{and } \mu_t = \frac{\gamma_t}{\sqrt{\lambda}}, \quad \sigma_t^2 = \frac{\gamma_t}{\lambda}.$$

Can show that iterating (REC) will converge to fixed pt.  $\gamma_{\Delta}^{(\lambda)}$  solving

$$\gamma_{\Delta}^{(\lambda)} = \lambda (1 - \text{mmse}(\gamma_{\Delta}^{(\lambda)}))$$