

# INFERENCE OVER NETWORKS

## LECTURE #18: Mean Error Network Stability

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# Reference

2

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

## Chapter 9 (Stability of Multi-Agent Networks, pp. 507-551):

A. H. Sayed, ``Adaptation, learning, and optimization over networks," ***Foundations and Trends in Machine Learning***, vol. 7, issue 4-5, pp. 311-801, NOW Publishers, 2014.



# Network Stability

3

Lecture #18: Mean Error Network Stability

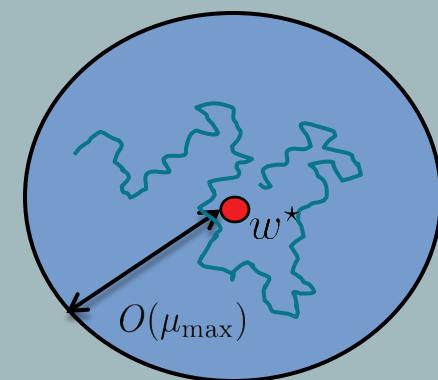
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**Theorems 9.1, 9.2, 9.6:** For sufficiently small step-sizes:

$$\limsup_{i \rightarrow \infty} \|\mathbb{E} \tilde{w}_{k,i}\| = O(\mu_{\max})$$

$$\limsup_{i \rightarrow \infty} \mathbb{E} \|\tilde{w}_{k,i}\|^2 = O(\mu_{\max})$$

$$\limsup_{i \rightarrow \infty} \mathbb{E} \|\tilde{w}_{k,i}\|^4 = O(\mu_{\max}^2)$$



# First-Order Stability

# First-Order Error Moment



Using the fact that  $(\mathbb{E} \mathbf{a})^2 \leq \mathbb{E} \mathbf{a}^2$  for any real-valued random variable  $\mathbf{a}$ , we can readily conclude from (9.11), by using  $\mathbf{a} = \|\tilde{\mathbf{w}}_{k,i}\|$ , that

$$\limsup_{i \rightarrow \infty} \mathbb{E} \|\tilde{\mathbf{w}}_{k,i}\| = O(\mu_{\max}^{1/2}), \quad k = 1, 2, \dots, N \quad (9.158)$$

so that the first-order moment of the error vector tends to a bounded region in the order of  $O(\mu_{\max}^{1/2})$ . However, a smaller upper bound on  $\|\mathbb{E} \tilde{\mathbf{w}}_{k,i}\|$  can be derived with  $O(\mu_{\max}^{1/2})$  replaced by  $O(\mu_{\max})$ , as shown in (9.1) and as we proceed to verify in this section. To do so, we examine the evolution of the mean-error vector more closely.



# First-Order Error Moment

6

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We reconsider the network error recursion (9.12), namely,

$$\tilde{w}_i^e = \mathcal{B}_{i-1} \tilde{w}_{i-1}^e + \mathcal{A}_2^\top \mathcal{M} s_i^e(\mathbf{w}_{i-1}^e) - \mathcal{A}_2^\top \mathcal{M} b^e, \quad i \geq 0 \quad (9.159)$$

where, from the expressions in Lemma 8.1:

$$\mathcal{B}_{i-1} = \mathcal{P}^\top - \mathcal{A}_2^\top \mathcal{M} \mathcal{H}_{i-1} \mathcal{A}_1^\top \quad (9.160)$$

$$\mathcal{P}^\top = \mathcal{A}_2^\top \mathcal{A}_o^\top \mathcal{A}_1^\top \quad (9.161)$$

$$\mathcal{H}_{i-1} \triangleq \text{diag} \{ \mathbf{H}_{1,i-1}, \mathbf{H}_{2,i-1}, \dots, \mathbf{H}_{N,i-1} \} \quad (9.162)$$

$$\mathbf{H}_{k,i-1} \triangleq \int_0^1 \nabla_w^2 J_k(w^* - t\tilde{\phi}_{k,i-1}) dt \quad (9.163)$$

# First-Order Error Moment



7

Lecture #18: Mean Error Network Stability

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Conditioning both sides of (9.159) on  $\mathcal{F}_{i-1}$ , invoking the conditions on the gradient noise process from Assumption 8.1, and computing the conditional expectations we obtain:

$$\mathbb{E} [\tilde{\mathbf{w}}_i^e | \mathcal{F}_{i-1}] = \mathcal{B}_{i-1} \tilde{\mathbf{w}}_{i-1}^e - \mathcal{A}_2^\top \mathcal{M} b^e \quad (9.164)$$

where the term involving  $\mathbf{s}_i^e$  is eliminated since  $\mathbb{E} [\mathbf{s}_i^e | \mathcal{F}_{i-1}] = 0$ . Taking expectations again we arrive at

$$\mathbb{E} \tilde{\mathbf{w}}_i^e = \mathbb{E} [\mathcal{B}_{i-1} \tilde{\mathbf{w}}_{i-1}^e] - \mathcal{A}_2^\top \mathcal{M} b^e \quad (9.165)$$



# First-Order Error Moment

Let

$$\tilde{\mathcal{H}}_{i-1} \triangleq \mathcal{H} - \mathcal{H}_{i-1} \quad (9.166)$$

where, in a manner similar to (9.162), we define the constant matrix

$$\mathcal{H} \triangleq \text{diag}\{H_1, H_2, \dots, H_N\} \quad (9.167)$$

with each  $H_{k,i-1}$  given by the value of the Hessian matrix at the limit point defined by (8.55), namely,

$$H_k \triangleq \nabla_w^2 J_k(w^\star) \quad (9.168)$$

# First-Order Error Moment



9

Lecture #18: Mean Error Network Stability

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Then, using (9.166) in the expression for  $\mathcal{B}_{i-1}$ , we can write

$$\begin{aligned}\mathcal{B}_{i-1} &= \mathcal{P}^T - \mathcal{A}_2^T \mathcal{M} \mathcal{H} \mathcal{A}_1^T + \mathcal{A}_2^T \mathcal{M} \widetilde{\mathcal{H}}_{i-1} \mathcal{A}_1^T \\ &\triangleq \mathcal{B} + \mathcal{A}_2^T \mathcal{M} \widetilde{\mathcal{H}}_{i-1} \mathcal{A}_1^T\end{aligned}\quad (9.169)$$

in terms of the constant coefficient matrix

$$\mathcal{B} \triangleq \mathcal{P}^T - \mathcal{A}_2^T \mathcal{M} \mathcal{H} \mathcal{A}_1^T \quad (9.170)$$

In this way, the mean-error relation (9.165) becomes

$$\mathbb{E} \tilde{\mathbf{w}}_i^e = \mathcal{B} (\mathbb{E} \tilde{\mathbf{w}}_{i-1}^e) - \mathcal{A}_2^T \mathcal{M} b^e + \mathcal{A}_2^T \mathcal{M} c_{i-1} \quad (9.171)$$

# First-Order Error Moment



in terms of a deterministic perturbation sequence defined by

$$c_{i-1} \triangleq \mathbb{E} \left( \tilde{\mathcal{H}}_{i-1} \mathcal{A}_1^\top \tilde{\mathbf{w}}_{i-1}^e \right) \quad (9.172)$$

The constant matrix  $\mathcal{B}$  defined by (9.170), and which drives the mean-error recursion (9.171), will play a critical role in characterizing the performance of multi-agent networks in future chapters. It also plays an important role in characterizing the mean-error stability of the network in this section. We therefore establish several important properties for  $\mathcal{B}$  and subsequently use these properties to establish result (9.1) later in Theorem 9.6.



# Stability of Coefficient Matrix

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**Theorem 9.3** (Stability of  $\mathcal{B}$ ). Consider a network of  $N$  interacting agents running the distributed strategy (8.46) with a primitive matrix  $P = A_1 A_o A_2$ . Assume the aggregate cost (9.10) satisfies condition (6.13) in Assumption 6.1. Then, the constant matrix  $\mathcal{B}$  defined by (9.170) is stable for sufficiently small step-sizes and its spectral radius is given by

$$\rho(\mathcal{B}) = 1 - \lambda_{\min} \left( \sum_{k=1}^N q_k H_k \right) + O\left(\mu_{\max}^{(N+1)/N}\right) \quad (9.173)$$

where  $\lambda_{\min}(\cdot)$  denotes the smallest eigenvalue of its Hermitian matrix argument.

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# Proof

12

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*Proof.* We first establish the result for diffusion and consensus networks and then extend the conclusion to the general distributed structure (8.46) with three combination matrices  $\{A_1, A_o, A_2\}$ . The arguments used in steps (a) and (b) below are justified when all step-sizes in  $\mathcal{M}$  are strictly positive, which is the situation under study. The more general argument under step (c) below is applicable even to situations where some of the step-sizes are zero (a scenario we shall encounter later in Chapter 13).



# Proof

(a) Diffusion strategies. For the case of diffusion strategies, the stability argument follows directly by examining the expression for the matrix  $\mathcal{B}$ . Recall that different choices for  $\{A_o, A_1, A_2\}$  correspond to different strategies, as already shown by (8.7)–(8.10). In particular, for ATC and CTA diffusion, we set  $A_1 = A$  or  $A_2 = A$ , for some left-stochastic matrix  $A$ , and the matrix  $A_o$  disappears from  $\mathcal{B}$  since  $A_o = I_N$  for these strategies. Specifically, the expression for  $\mathcal{B}$  becomes

$$\mathcal{B}_{\text{atc}} = \mathcal{A}^\top (I_{2MN} - \mathcal{M}\mathcal{H}) \quad (9.174)$$

$$\mathcal{B}_{\text{cta}} = (I_{2MN} - \mathcal{M}\mathcal{H}) \mathcal{A}^\top \quad (9.175)$$

# Proof



where  $\mathcal{A} = A \otimes I_{2M}$  is left-stochastic and

$$\mathcal{M} \triangleq \text{diag}\{\mu_1 I_{2M}, \mu_2 I_{2M}, \dots, \mu_N I_{2M}\} \quad (9.176)$$

$$\mathcal{H} \triangleq \text{diag}\{H_1, H_2, \dots, H_N\} \quad (9.177)$$

The important fact to note from (9.174) and (9.175) is that the combination matrix  $\mathcal{A}^\top$  appears *multiplying* (from left or right) the block diagonal matrix  $I_{2MN} - \mathcal{M}\mathcal{H}$ . We can then immediately call upon result (F.24) from the appendix, and employ the block maximum norm with blocks of size  $2M \times 2M$  each, to conclude that



# Proof

15

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\rho(\mathcal{B}_{\text{atc}}) \leq \rho(I_{2MN} - \mathcal{M}\mathcal{H}) \quad (9.178)$$

$$\rho(\mathcal{B}_{\text{cta}}) \leq \rho(I_{2MN} - \mathcal{M}\mathcal{H}) \quad (9.179)$$

Therefore, for both cases of ATC and CTA diffusion, the respective coefficient matrices  $\mathcal{B}$  become stable whenever the block-diagonal matrix  $I_{2MN} - \mathcal{M}\mathcal{H}$  is stable. It is easily seen that this latter condition is guaranteed for step-sizes  $\mu_k$  satisfying

$$\mu_k < \frac{2}{\rho(H_k)}, \quad k = 1, 2, \dots, N \quad (9.180)$$

from which we conclude that sufficiently small step-sizes stabilize  $\mathcal{B}_{\text{atc}}$  or  $\mathcal{B}_{\text{cta}}$ .



# Recall#1: Weyl's Theorem

16

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Weyl's Theorem [113, 260], shows how the eigenvalues of a Hermitian matrix are disturbed through additive perturbations to the entries of the matrix. Thus, let  $\{A', A, \Delta A\}$  denote arbitrary  $N \times N$  Hermitian matrices with ordered eigenvalues  $\{\lambda_m(A'), \lambda_m(A), \lambda_m(\Delta A)\}$ , i.e.,

$$\lambda_1(A) \geq \lambda_2(A) \geq \dots \geq \lambda_N(A) \quad (\text{F.31})$$



# Recall#1: Weyl's Theorem

17

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

and similarly for the eigenvalues of  $\{A', \Delta A\}$ , with the subscripts 1 and  $N$  representing the largest and smallest eigenvalues, respectively. Weyl's Theorem states that if  $A$  is perturbed to

$$A' = A + \Delta A \quad (\text{F.32})$$

then the eigenvalues of the new matrix are bounded as follows:

$$\lambda_n(A) + \lambda_N(\Delta A) \leq \lambda_n(A') \leq \lambda_n(A) + \lambda_1(\Delta A) \quad (\text{F.33})$$

# Continuing with Proof



(b) Consensus strategy. For the consensus strategy, we set  $A_1 = A_2 = I_N$  and  $A_o = A$ . In this case, the expression for  $\mathcal{B}$  becomes

$$\mathcal{B}_{\text{cons}} = \mathcal{A}^\top - \mathcal{M}\mathcal{H} \quad (9.181)$$

where  $\mathcal{A}$  now appears as an additive term. A condition on the step-sizes to ensure the stability of  $\mathcal{B}_{\text{cons}}$  can be deduced from Weyl's Theorem (F.33) in the appendix if we additionally assume that the left-stochastic matrix  $A$  is *symmetric* [248], in which case it will also be doubly stochastic. Since  $A$  is then both symmetric and left-stochastic, its eigenvalues will be real and lie inside the interval  $[-1, 1]$ . Hence,  $(I_{2MN} - \mathcal{A}^\top) \geq 0$ . Moreover, since the matrices

smallest eigenvalue is zero

# Proof



$\mathcal{M}$  and  $\mathcal{H}$  are block-diagonal Hermitian and commute with each other, i.e.,  $\mathcal{H}\mathcal{M} = \mathcal{M}\mathcal{H}$ , it follows that  $\mathcal{B}_{\text{cons}}$  in (9.181) is Hermitian, as well as the matrix  $\mathcal{B}_{\text{ncop}} = I_{2MN} - \mathcal{M}\mathcal{H}$ . Now note that we can write the following two trivial equalities (by adding and subtracting equal terms):

$$\mathcal{B}_{\text{ncop}} = \mathcal{B}_{\text{cons}} + (I_{2MN} - \mathcal{A}^T) \quad (9.182)$$

$$\mathcal{B}_{\text{cons}} = (\lambda_{\min}(A) \cdot I_{2MN} - \mathcal{M}\mathcal{H}) + (\mathcal{A}^T - \lambda_{\min}(A) \cdot I_{2MN}) \quad (9.183)$$

so that by applying Weyl's Theorem (F.33) to both representations, we obtain the following eigenvalue relations:

smallest eigenvalue is zero

# Proof



$$\lambda_\ell(\mathcal{B}_{\text{cons}}) \leq \lambda_\ell(\mathcal{B}_{\text{ncop}}) \quad (9.184)$$

$$\lambda_\ell(\mathcal{B}_{\text{cons}}) \geq \lambda_\ell \{ \lambda_{\min}(A) \cdot I_{2MN} - \mathcal{M}\mathcal{H} \} \quad (9.185)$$

for  $\ell = 1, 2, \dots, 2MN$  and where we are assuming ordered eigenvalues, namely,  $\lambda_1 \geq \lambda_2 \geq \dots$ , for any of the matrix arguments. It follows that the matrix  $\mathcal{B}_{\text{cons}}$  will be stable, namely,  $-1 < \lambda_\ell(\mathcal{B}_{\text{cons}}) < 1$  for all  $\ell$  if

$$\lambda_\ell(\mathcal{B}_{\text{ncop}}) < 1 \quad (9.186)$$

$$\lambda_\ell \{ \lambda_{\min}(A) \cdot I_{2MN} - \mathcal{M}\mathcal{H} \} > -1 \quad (9.187)$$



# Proof

21

Lecture #18: Mean Error Network Stability

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The first condition is automatically satisfied due to the form of the matrix  $\mathcal{B}_{\text{ncop}}$  and since  $\mathcal{M}\mathcal{H} > 0$ . For the second condition, it will be satisfied by step-sizes  $\{\mu_k\}$  such that

$$\mu_k < \frac{1 + \lambda_{\min}(A)}{\rho(H_k)}, \quad k = 1, 2, \dots, N \quad (9.188)$$

Since we are dealing with strongly-connected networks, the matrix  $A$  is primitive and, therefore, it has a single eigenvalue matching its spectral radius, which is equal to one. That eigenvalue occurs at  $+1$  so that

# Proof



$\lambda_{\min}(A) > -1$  and the upper bound in (9.188) is positive. We therefore conclude that sufficiently small step-sizes stabilize  $\mathcal{B}$  for consensus strategies with a *symmetric* combination policy  $A$ . If  $A$  is not symmetric, then the next argument would apply to this case.

# Proof



(c) General case (eigenvalue perturbation analysis). For the general case, when the matrix  $A_o$  is not necessarily the identity matrix or symmetric, and when all three matrices  $\{A_o, A_1, A_2\}$  or subsets thereof may be present, the argument is more demanding. The argument that follows is based on an eigenvalue perturbation analysis in the small step-size regime similar to [277]. We establish the result for the general case of complex data and, therefore,  $h = 2$  throughout this derivation.



# Proof

We introduce the same Jordan canonical decomposition (9.24) for the matrix  $P$ , namely,

$$P \triangleq V_\epsilon J V_\epsilon^{-1} \quad (9.189)$$

$$J = \left[ \begin{array}{c|c} 1 & 0 \\ \hline 0 & J_\epsilon \end{array} \right] \quad (9.190)$$

where the matrix  $J_\epsilon$  consists of Jordan blocks of forms similar to (9.25) with  $\epsilon > 0$  appearing on the lower diagonal. The value of  $\epsilon$  can be chosen to be arbitrarily small and is independent of  $\mu_{\max}$ . The Jordan decomposition of the extended matrix  $\mathcal{P} = P \otimes I_{2M}$  is given by



# Proof

25

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\mathcal{P} = (V_\epsilon \otimes I_{2M})(J \otimes I_{2M})(V_\epsilon^{-1} \otimes I_{2M}) \quad (9.191)$$

so that substituting into (9.170) we obtain

$$\mathcal{B} = ((V_\epsilon^{-1})^\top \otimes I_{2M}) \left\{ (J^\top \otimes I_{2M}) - \mathcal{D}^\top \right\} (V_\epsilon^\top \otimes I_{2M}) \quad (9.192)$$

where

$$\begin{aligned} \mathcal{D}^\top &\triangleq (V_\epsilon^\top \otimes I_{2M}) \mathcal{A}_2^\top \mathcal{M} \mathcal{H} \mathcal{A}_1^\top ((V_\epsilon^{-1})^\top \otimes I_{2M}) \\ &\equiv \begin{bmatrix} D_{11}^\top & D_{21}^\top \\ D_{12}^\top & D_{22}^\top \end{bmatrix} \end{aligned} \quad (9.193)$$



# Proof

26

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Using the partitioning (9.23)–(9.24) and the fact that

$$\mathcal{A}_1 = A_1 \otimes I_{2M}, \quad \mathcal{A}_2 = A_2 \otimes I_{2M} \quad (9.194)$$

we find that the block entries  $\{D_{mn}\}$  in (9.193) are given by

$$D_{11} = \sum_{k=1}^N q_k H_k^\top \quad (9.195)$$

$$D_{12} = (\mathbf{1}^\top \otimes I_{2M}) \mathcal{H}^\top \mathcal{M}(A_2 V_R \otimes I_{2M}) \quad (9.196)$$

$$D_{21} = (V_L^\top A_1 \otimes I_{2M}) \mathcal{H}^\top (q \otimes I_{2M}) \quad (9.197)$$

$$D_{22} = (V_L^\top A_1 \otimes I_{2M}) \mathcal{H}^\top \mathcal{M}(A_2 V_R \otimes I_{2M}) \quad (9.198)$$



# Proof

27

Lecture #18: Mean Error Network Stability

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In a manner similar to the arguments used in the proof of Theorem 9.1, we can verify that

$$D_{11} = O(\mu_{\max}) \quad (9.199)$$

$$D_{12} = O(\mu_{\max}) \quad (9.200)$$

$$D_{21} = O(\mu_{\max}) \quad (9.201)$$

$$D_{22} = O(\mu_{\max}) \quad (9.202)$$

$$\rho(I_{2M} - D_{11}^T) = 1 - \sigma_{11}\mu_{\max} = 1 - O(\mu_{\max}) \quad (9.203)$$

where  $\sigma_{11}$  is a positive scalar independent of  $\mu_{\max}$ .



# Proof

28

Let

$$\mathcal{V}_\epsilon \triangleq V_\epsilon \otimes I_{2M}, \quad \mathcal{J}_\epsilon \triangleq J_\epsilon \otimes I_{2M} \quad (9.204)$$

Then, using (9.192), we can write

$$\mathcal{B} = (\mathcal{V}_\epsilon^{-1})^\top \begin{bmatrix} I_{2M} - D_{11}^\top & -D_{21}^\top \\ -D_{12}^\top & \mathcal{J}_\epsilon^\top - D_{22}^\top \end{bmatrix} \mathcal{V}_\epsilon^\top \quad (9.205)$$

so that

$$\mathcal{V}_\epsilon^\top \mathcal{B} (\mathcal{V}_\epsilon^{-1})^\top = \begin{bmatrix} I_{2M} - D_{11}^\top & -D_{21}^\top \\ -D_{12}^\top & \mathcal{J}_\epsilon^\top - D_{22}^\top \end{bmatrix} \quad (9.206)$$

which shows that the matrix  $\mathcal{B}$  is similar to, and therefore has the same eigenvalues as, the block matrix on the right-hand side, written as

# Proof



$$\mathcal{B} \sim \begin{bmatrix} I_{2M} - O(\mu_{\max}) & O(\mu_{\max}) \\ O(\mu_{\max}) & \mathcal{J}_\epsilon^\top + O(\mu_{\max}) \end{bmatrix} \quad (9.207)$$

Now recall that  $J_\epsilon$  is  $(N - 1) \times (N - 1)$  and has a Jordan structure. For ease of presentation, and without any loss of generality, let us assume that  $J_\epsilon$  consists of two Jordan blocks, say, as

$$J_\epsilon = \left[ \begin{array}{cc|cc} \lambda_a & & & \\ \epsilon & \lambda_a & & \\ \hline & & \lambda_b & \\ & & \epsilon & \lambda_b \\ & & & \epsilon & \lambda_b \end{array} \right] \quad (9.208)$$



# Proof

30

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Then, the matrix  $\mathcal{J}_\epsilon = J_\epsilon \otimes I_{2M}$  has dimensions  $2M(N-1) \times 2M(N-1)$  and is given by

$$\mathcal{J}_\epsilon = J_\epsilon \otimes I_{2M} \left[ \begin{array}{cc|cc} \lambda_a I_{2M} & & & \\ \epsilon I_{2M} & \lambda_a I_{2M} & & \\ \hline & & \lambda_b I_{2M} & \\ & & \epsilon I_{2M} & \lambda_b I_{2M} \\ & & \epsilon I_{2M} & \lambda_b I_{2M} \end{array} \right] \quad (9.209)$$

More generically, for multiple Jordan blocks, it is clear that we can express  $\mathcal{J}_\epsilon$  in the following lower-triangular form:



# Proof

31

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$$\mathcal{J}_\epsilon = \begin{bmatrix} \lambda_{a,2} I_{2M} & & & \\ & \lambda_{a,3} I_{2M} & & \\ & & \ddots & \\ \mathcal{K} & & & \lambda_{a,L} I_{2M} \end{bmatrix} \quad (9.210)$$

with scalars  $\{\lambda_{a,\ell}\}$  on the diagonal, all of which have norms strictly less than one, and where the entries of the strictly lower-triangular matrix  $\mathcal{K}$  are either  $\epsilon$  or zero. In the above representation, we are assuming that  $J_\epsilon$  consists of several Jordan blocks. It follows that



# Proof

32

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\mathcal{J}_\epsilon^\top + O(\mu_{\max}) = \begin{bmatrix} \lambda_{a,2} I_{2M} + O(\mu_{\max}) & \mathcal{K}^\top + O(\mu_{\max}) \\ & \ddots \\ O(\mu_{\max}) & \lambda_{a,L} I_{2M} + O(\mu_{\max}) \end{bmatrix} \quad (9.211)$$

We introduce the eigen-decomposition of the Hermitian positive-definite matrix  $D_{11}^\top$  and denote it by:

$$D_{11}^\top \triangleq U \Lambda U^* \quad (9.212)$$

where  $U$  is unitary and  $\Lambda$  has positive-diagonal entries  $\{\lambda_k\}$ ; the matrices  $U$  and  $\Lambda$  are  $2M \times 2M$ . Using  $U$ , we further introduce the following block-diagonal similarity transformation:



# Proof

33

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\mathcal{T} \triangleq \text{diag} \left\{ \mu_{\max}^{1/N} U, \mu_{\max}^{2/N} I_{2M}, \dots, \mu_{\max}^{(N-1)/N} I_{2M}, \mu_{\max} I_{2M} \right\} \quad (9.213)$$

where all block entries are defined in terms of  $I_{2M}$ , except for the first entry defined in terms of  $U$ . We now use (9.205) to get

$$\mathcal{T}^{-1} \left( \mathcal{V}_\epsilon^\top \mathcal{B} (\mathcal{V}_\epsilon^{-1})^\top \right) \mathcal{T} = \quad (9.214)$$

# Proof



$$\begin{bmatrix} B & O\left(\mu_{\max}^{(N+1)/N}\right) \\ \hline \lambda_{a,2}I_{2M} + O(\mu_{\max}) & O\left(\mu_{\max}^{1/N}\right) \\ O(\mu_{\max}^{1/N}) & \ddots \\ & O\left(\mu_{\max}^{1/N}\right) & \lambda_{a,L}I_{2M} + O(\mu_{\max}) \end{bmatrix}$$

where we introduced the  $2M \times 2M$  diagonal matrix

$$B \stackrel{\Delta}{=} I_{2M} - \Lambda \quad (9.215)$$



# Recall#2: Gershgorin's Theorem

Gershgorin's Theorem [48, 94, 101, 104, 113, 254, 264], specifies circular regions within which the eigenvalues of a matrix are located. Thus, consider an  $N \times N$  matrix  $A$  with scalar entries  $\{a_{\ell k}\}$ . With each diagonal entry  $a_{\ell\ell}$  we associate a disc in the complex plane centered at  $a_{\ell\ell}$  and with

$$r_\ell \triangleq \sum_{k \neq \ell, k=1}^N |a_{\ell k}| \quad (\text{F.35})$$



# Recall#2: Gershgorin's Theorem

That is,  $r_\ell$  is equal to the sum of the magnitudes of the non-diagonal entries on the same row as  $a_{\ell\ell}$ . We denote the disc by  $D_\ell$ ; it consists of all points that satisfy

$$D_\ell = \{z \in \mathbb{C}^N \text{ such that } |z - a_{\ell\ell}| \leq r_\ell\} \quad (\text{F.36})$$

The theorem states that the spectrum of  $A$  (i.e., the set of all its eigenvalues, denoted by  $\lambda(A)$ ) is contained in the union of all  $N$  Gershgorin discs:

$$\lambda(A) \subset \bigcup_{\ell=1}^N D_\ell \quad (\text{F.37})$$



# Recall#2: Gershgorin's Theorem

A stronger statement of the Gershgorin theorem covers the situation in which some of the Gershgorin discs happen to be disjoint. Specifically, if the union of  $L$  of the discs is disjoint from the union of the remaining  $N - L$  discs, then the theorem further asserts that  $L$  eigenvalues of  $A$  will lie in the first union of  $L$  discs and the remaining  $N - L$  eigenvalues of  $A$  will lie in the second union of  $N - L$  discs.



# Continuing with Proof

38

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It follows from (9.214) that all off-diagonal entries of the above transformed matrix are at least  $O(\mu_{\max}^{1/N})$ . Although the factor  $\mu_{\max}^{1/N}$  decays slower than  $\mu_{\max}$ , it nevertheless becomes small for sufficiently small  $\mu_{\max}$ . Then, calling upon Gershgorin's Theorem (F.37) from the appendix, we conclude from (9.214) that the eigenvalues of  $\mathcal{B}$  are either located in the Gershgorin circles that are centered at the eigenvalues of  $B$  with radii  $O(\mu_{\max}^{(N+1)/N})$  or in the Gershgorin circles that are centered at the  $\{\lambda_{a,\ell}\}$  with radii  $O(\mu_{\max}^{1/N})$ , namely,

# Proof



$$|\lambda(\mathcal{B}) - \lambda(B)| \leq O\left(\mu_{\max}^{(N+1)/N}\right) \quad \text{or} \quad |\lambda(\mathcal{B}) - \lambda_{a,\ell}| \leq O\left(\mu_{\max}^{1/N}\right) \quad (9.216)$$

where  $\lambda(\mathcal{B})$  and  $\lambda(B)$  denote any of the eigenvalues of  $\mathcal{B}$  and  $B$ , and  $\ell = 2, \dots, L$ . It follows that

$$\rho(\mathcal{B}) \leq \rho(B) + O\left(\mu_{\max}^{(N+1)/N}\right) \quad \text{or} \quad \rho(\mathcal{B}) \leq \rho(J_\epsilon) + O(\mu_{\max}^{1/N}) \quad (9.217)$$

Now since  $J_\epsilon$  is a stable matrix, we know that  $\rho(J_\epsilon) < 1$ . We express this spectral radius as

$$\rho(J_\epsilon) = 1 - \delta_J \quad (9.218)$$



# Proof

40

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

where  $\delta_J$  is positive and independent of  $\mu_{\max}$ . We also know from (9.203) that

$$\rho(B) = 1 - \sigma_{11}\mu_{\max} < 1 \quad (9.219)$$

since  $B = U^*(I_{2M} - D_{11}^\top)U$ . We conclude from (9.217) that

$$\rho(\mathcal{B}) \leq 1 - \sigma_{11}\mu_{\max} + O\left(\mu_{\max}^{(N+1)/N}\right) \quad \text{or} \quad \rho(\mathcal{B}) \leq 1 - \delta_J + O(\mu_{\max}^{1/N}) \quad (9.220)$$

If we now select  $\mu_{\max} \ll 1$  small enough such that

$$O\left(\mu_{\max}^{(N+1)/N}\right) < \sigma_{11}\mu_{\max} \quad \text{and} \quad O\left(\mu_{\max}^{1/N}\right) + O(\mu_{\max}) < \delta_J \quad (9.221)$$

# Proof



41

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

then we would be able to conclude that  $\rho(\mathcal{B}) < 1$  so that  $\mathcal{B}$  is stable for sufficiently small step-sizes. Both conditions in (9.221) can be satisfied simultaneously and they will ensure

$$\rho(\mathcal{B}) = 1 - O(\mu_{\max}) \quad (9.222)$$



# Proof

42

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

With regards to expression (9.173) for the spectral radius of  $\mathcal{B}$ , we call upon the stronger statement of Gershgorin's theorem mentioned after (F.37) in the appendix and which relates to how the eigenvalues of a matrix are distributed over disjoint Gershgorin sets. To begin with, note from (9.203) that for  $\mu_{\max} \ll 1$ , all eigenvalues of  $B = I_{2M} - \Lambda$  are real-valued and positive. We then conclude from (9.222) that all eigenvalues of  $B$  lie inside the open interval

$$\lambda(B) \in (1 - O(\mu_{\max}), 1) \quad (9.223)$$

It further follows from this result that the eigenvalues of  $B$  are at most  $O(\mu_{\max})$  apart from each other.



$$B \sim I_{2M} - D_{11}^T, \quad c_1 \mu_{\max} \leq \lambda_\ell(D_{11}^T) \leq c_2 \mu_{\max}$$

# Proof



43

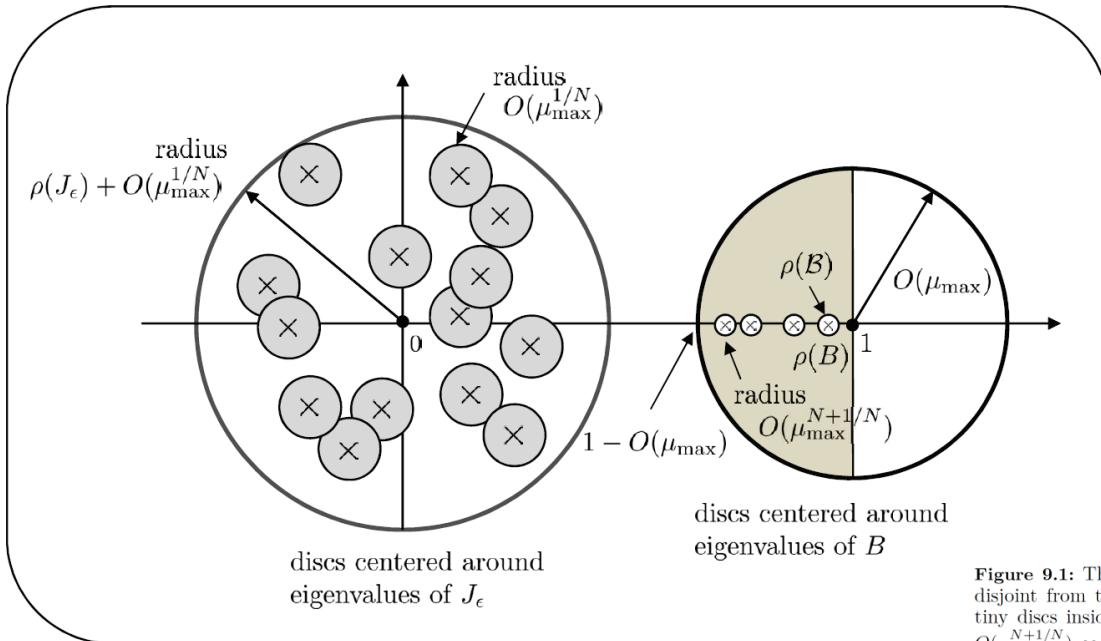
Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

Now, referring to (9.216), the condition on the left describes a region in space that consists of the union of  $2M$  Gershgorin discs: each disc is centered at one of the eigenvalues of  $B$  with radius  $O(\mu_{\max}^{(N+1)/N})$ . We can then choose

$\mu_{\max}$  small enough such that the discs that are centered at distinct eigenvalues of  $B$  remain disjoint from each other. The union of these discs will be contained within the circle that is centered at one and with radius  $O(\mu_{\max})$  — see the region described by the smaller circle on the right in Figure 9.1.

# Proof



**Figure 9.1:** The larger circle on the left has radius  $\rho(J_\epsilon) + O(\mu_{\max}^{1/N})$  and is disjoint from the smaller circle on the right whose radius is  $O(\mu_{\max})$ . The tiny discs inside the smaller circle on the right are disjoint and have radii  $O(\mu_{\max}^{N+1/N})$  each. The eigenvalue corresponding to the spectral radius of  $B$  lies inside the rightmost smaller disc centered around  $\rho(B)$ .



# Proof

Let us now examine the rightmost condition in (9.216). This condition describes a region in space that consists of the union of  $2M(N-1)$  Gershgorin discs: each disc is now centered at an eigenvalue of  $\mathcal{J}_\epsilon$  with radius  $O(\mu_{\max}^{1/N})$ . Therefore, again for  $\mu_{\max} \ll 1$ , the union of these discs is contained within a circle centered at the origin and with radius  $\rho(J_\epsilon) + O(\mu_{\max}^{1/N})$ ; this radius is smaller than  $1 - O(\mu_{\max})$  by virtue of the second condition in (9.221) — see the region described by the larger circle on the left in Figure 9.1. It follows that the two circular regions that we identified are disjoint from each other:

# Proof



one region is determined by the circle on the left that is centered at the origin with radius smaller than  $1 - O(\mu_{\max})$ , while the other region is determined by the circle on the right that is centered at one and has radius  $O(\mu_{\max})$ . The  $2M$  discs that appear within this smaller circle are disjoint from the discs that appear inside the larger circle on the left. We conclude that  $2M$  of the eigenvalues of  $\mathcal{B}$  are located inside the discs in the rightmost circle. The eigenvalue that attains the spectral radius of  $\mathcal{B}$  occurs inside this region so that

$$\rho(\mathcal{B}) = \rho(B) + O\left(\mu_{\max}^{(N+1)/N}\right) \quad (9.224)$$



# Proof

47

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

Since it is assumed that  $\mu_{\max} \ll 1$ , and by referring back to expression (9.195) for  $D_{11}$ , we have

$$\rho(B) = \rho(I_{2M} - D_{11}^T) = 1 - \lambda_{\min} \left( \sum_{k=1}^N q_k H_k \right) \quad (9.225)$$

Combining this relation with (9.224), we arrive at (9.173).

□



# Size of Entries of $\mathcal{B}$

48

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

We can further exploit the structure revealed by expression (9.205) for  $\mathcal{B}$  to examine the size of the entries of  $(I - \mathcal{B})^{-1}$ . In our derivations, the matrix  $\mathcal{B}$  also appears transformed under the similarity transformation:

$$\bar{\mathcal{B}} \triangleq \mathcal{V}_\epsilon^\top \mathcal{B} (\mathcal{V}_\epsilon^{-1})^\top \stackrel{(9.206)}{=} \begin{bmatrix} I_{2M} - D_{11}^\top & -D_{21}^\top \\ -D_{12}^\top & \mathcal{J}_\epsilon^\top - D_{22}^\top \end{bmatrix} \quad (9.226)$$

where, according to (9.204),

$$\mathcal{V}_\epsilon \triangleq V_\epsilon \otimes I_{hM} \quad (9.227)$$

We therefore examine both matrices. The following result clarifies the size of the entries of  $(I - \mathcal{B})^{-1}$  and  $(I - \bar{\mathcal{B}})^{-1}$ .



# Size of Entries of $\mathcal{B}$

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**Lemma 9.4** (Similarity transformation). Assume the matrix  $P$  is primitive. It holds that for sufficiently small step-sizes:

$$(I - \mathcal{B})^{-1} = O(1/\mu_{\max}) \quad (9.228)$$

$$(I - \bar{\mathcal{B}})^{-1} = \left[ \begin{array}{c|c} O(1/\mu_{\max}) & O(1) \\ \hline O(1) & O(1) \end{array} \right] \quad (9.229)$$

where the leading  $(1, 1)$  block in  $(I - \bar{\mathcal{B}})^{-1}$  has dimensions  $hM \times hM$ .

---



# Proof

50

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

*Proof.* We carry out the derivation for the complex case  $h = 2$  without loss of generality following arguments similar to [69, 278]. We first remark that, by similarity, the matrix  $\bar{\mathcal{B}}$  is stable by Theorem 9.3. Let

$$\begin{aligned} \mathcal{X} = I - \bar{\mathcal{B}} &= \begin{bmatrix} D_{11}^T & D_{21}^T \\ D_{12}^T & I - \mathcal{J}_\epsilon^T + D_{22}^T \end{bmatrix} \\ &\triangleq \begin{bmatrix} \mathcal{X}_{11} & \mathcal{X}_{12} \\ \mathcal{X}_{21} & \mathcal{X}_{22} \end{bmatrix} \end{aligned} \tag{9.230}$$

where, from (9.199)–(9.202),



# Proof

51

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\mathcal{X}_{11} = O(\mu_{\max}) \quad (9.231)$$

$$\mathcal{X}_{12} = O(\mu_{\max}) \quad (9.232)$$

$$\mathcal{X}_{21} = O(\mu_{\max}) \quad (9.233)$$

$$\mathcal{X}_{22} = O(1) \quad (9.234)$$

The matrix  $\mathcal{X}$  is invertible since  $I - \bar{\mathcal{B}}$  is invertible. Moreover,  $\mathcal{X}_{11}$  is invertible since  $D_{11} > 0$ . We now appeal to the useful block matrix inversion formula [113, 206]:



# Proof

52

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} A^{-1} & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} A^{-1}B\Delta^{-1}CA^{-1} & -A^{-1}B\Delta^{-1} \\ -\Delta^{-1}CA^{-1} & \Delta^{-1} \end{bmatrix} \quad (9.235)$$

for matrices  $\{A, B, C, D\}$  of compatible dimensions with invertible  $A$  and invertible Schur complement  $\Delta$  defined by

$$\Delta = D - CA^{-1}B \quad (9.236)$$

Using this formula we can write

$$\mathcal{X}^{-1} = \begin{bmatrix} \mathcal{X}_{11}^{-1} + \mathcal{X}_{11}^{-1}\mathcal{X}_{12}\Delta^{-1}\mathcal{X}_{21}\mathcal{X}_{11}^{-1} & -\mathcal{X}_{11}^{-1}\mathcal{X}_{12}\Delta^{-1} \\ -\Delta^{-1}\mathcal{X}_{21}\mathcal{X}_{11}^{-1} & \Delta^{-1} \end{bmatrix} \quad (9.237)$$



# Proof

53

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

where  $\Delta$  denotes the Schur complement of  $\mathcal{X}$  relative to  $\mathcal{X}_{11}$ :

$$\Delta \triangleq \mathcal{X}_{22} - \mathcal{X}_{21}\mathcal{X}_{11}^{-1}\mathcal{X}_{12} = O(1) \quad (9.238)$$

We then use (9.231)–(9.234) and (9.238) to deduce that

$$\mathcal{X}^{-1} = \begin{bmatrix} O(1/\mu_{\max}) & O(1) \\ O(1) & O(1) \end{bmatrix} \quad (9.239)$$

as claimed.

□



# Recall#3: Block Kronecker Products

$$\mathcal{K} \triangleq \mathcal{A} \otimes_b \mathcal{B} = \begin{bmatrix} K_{11} & K_{12} & \dots & K_{1n} \\ K_{21} & K_{22} & \dots & K_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ K_{n1} & K_{n2} & \dots & K_{nn} \end{bmatrix} \quad (\text{F.2})$$

where each block  $K_{ij}$  is  $mp^2 \times mp^2$  and is constructed as follows:



# Recall#3: Block Kronecker Products

$$K_{ij} = \begin{bmatrix} A_{ij} \otimes B_{11} & A_{ij} \otimes B_{12} & \dots & A_{ij} \otimes B_{1m} \\ A_{ij} \otimes B_{21} & A_{ij} \otimes B_{22} & \dots & A_{ij} \otimes B_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A_{ij} \otimes B_{m1} & A_{ij} \otimes B_{m2} & \dots & A_{ij} \otimes B_{mm} \end{bmatrix} \quad (\text{F.3})$$



# Recall#3: Block Kronecker Products

**Table F.2:** Properties of the block Kronecker product definition (F.2).

- 
- 1.  $(\mathcal{A} + \mathcal{B}) \otimes_b \mathcal{C} = (\mathcal{A} \otimes_b \mathcal{C}) + (\mathcal{B} \otimes_b \mathcal{C})$
- 2.  $(\mathcal{A} \otimes_b \mathcal{B})(\mathcal{C} \otimes_b \mathcal{D}) = (\mathcal{A}\mathcal{C} \otimes_b \mathcal{B}\mathcal{D})$
- 3.  $(A \otimes B) \otimes_b (C \otimes D) = (A \otimes C) \otimes (B \otimes D)$
4.  $(\mathcal{A} \otimes_b \mathcal{B})^\top = \mathcal{A}^\top \otimes_b \mathcal{B}^\top$
5.  $(\mathcal{A} \otimes_b \mathcal{B})^* = \mathcal{A}^* \otimes_b \mathcal{B}^*$
6.  $\{\lambda(\mathcal{A} \otimes_b \mathcal{B})\} = \{\lambda_i(\mathcal{A})\lambda_j(\mathcal{B})\}_{i=1,j=1}^{np,mp}$
7.  $\text{Tr}(\mathcal{A}\mathcal{B}) = [\text{bvec}(\mathcal{B}^\top)]^\top \text{bvec}(\mathcal{A}) = [\text{bvec}(\mathcal{B}^*)]^* \text{bvec}(\mathcal{A})$
8.  $\text{bvec}(\mathcal{A}\mathcal{C}\mathcal{B}) = (\mathcal{B}^\top \otimes_b \mathcal{A})\text{bvec}(\mathcal{C})$
9.  $\text{bvec}(xy^\top) = y \otimes_b x$
-



# Low-Rank Approximation

We can establish similar results for the matrix

$$\mathcal{F} \triangleq \mathcal{B}^T \otimes_b \mathcal{B}^* \quad (9.240)$$

which is defined in terms of the block Kronecker product operation using blocks of size  $hM \times hM$ , where  $h = 1$  for real data and  $h = 2$  for complex data. The matrix  $\mathcal{F}$  will play a critical role in characterizing the performance and convergence rate of distributed algorithms, as will be revealed by future [Theorem 11.2](#). In our derivations, the matrix  $\mathcal{F}$  will also sometimes appear transformed under the similarity transformation:

$$\bar{\mathcal{F}} \triangleq (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon)^{-1} \mathcal{F} (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon) \quad (9.241)$$

# Low-Rank Approximation



**Lemma 9.5** (Low-rank approximation). Assume the matrix  $P$  is primitive. For sufficiently small step-sizes, it holds that

$$(I - \mathcal{F})^{-1} = O(1/\mu_{\max}) \quad (9.242)$$

$$(I - \bar{\mathcal{F}})^{-1} = \left[ \begin{array}{c|c} O(1/\mu_{\max}) & O(1) \\ \hline O(1) & O(1) \end{array} \right] \quad (9.243)$$

where the leading  $(hM)^2 \times (hM)^2$  block in  $(I - \bar{\mathcal{F}})^{-1}$  is  $O(1/\mu_{\max})$ . Moreover, we can also write

$$(I - \mathcal{F})^{-1} = [(p \otimes p)(\mathbb{1} \otimes \mathbb{1})^T] \otimes Z^{-1} + O(1) \quad (9.244)$$



# Second-Order Error Moment

in terms of the regular Kronecker product operation, where the matrix  $Z$  has dimensions  $(hM)^2 \times (hM)^2$  and consists of blocks of size  $hM \times hM$  each:

$$Z \triangleq \sum_{k=1}^N q_k \left[ (I_{hM} \otimes H_k) + (H_k^\top \otimes I_{hM}) \right] \quad (9.245)$$

where the vectors  $\{p, q\}$  were defined earlier by (9.7)–(9.9). In addition,  $Z = O(\mu_{\max})$ .

---



# Proof

60

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

*Proof.* We again carry out the derivation for the complex case  $h = 2$  without loss of generality by extending an argument from [278] to the current context. We recall from (9.170) the expression for  $\mathcal{B}$ :

$$\mathcal{B} = \mathcal{P}^T - \mathcal{A}_2^T \mathcal{M} \mathcal{R} \mathcal{A}_1^T = \mathcal{A}_2^T (\mathcal{A}_o^T - \mathcal{M} \mathcal{H}) \mathcal{A}_1^T \quad (9.246)$$

where  $\mathcal{P} = P \otimes I_{2M}$  and  $P = A_1 A_o A_2$ . Since the matrices  $\{\mathcal{A}_o, \mathcal{A}_1, \mathcal{A}_2, \mathcal{M}\}$  are real-valued, and  $\mathcal{H}$  is Hermitian, we have

$$\mathcal{B}^T = \mathcal{A}_1 (\mathcal{A}_o - \mathcal{H}^T \mathcal{M}) \mathcal{A}_2 \quad (9.247)$$

$$\mathcal{B}^* = \mathcal{A}_1 (\mathcal{A}_o - \mathcal{H} \mathcal{M}) \mathcal{A}_2 \quad (9.248)$$



# Proof

61

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

We introduce the same Jordan canonical decomposition (9.21)–(9.24) and verify, in a manner similar to (9.53), that

$$\mathcal{B}^* = (V_\epsilon \otimes I_{2M}) \begin{bmatrix} I_{2M} - E_{11} & -E_{12} \\ -E_{21} & (J_\epsilon \otimes I_{2M}) - E_{22} \end{bmatrix} (V_\epsilon^{-1} \otimes I_{2M}) \quad (9.249)$$

where the block matrices  $\{E_{mn}\}$  are given by



# Proof

62

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$E_{11} = \sum_{k=1}^N q_k H_k = O(\mu_{\max}) \quad (9.250)$$

$$E_{12} = (\mathbf{1}^\top \otimes I_{2M}) \mathcal{HM}(A_2 V_R \otimes I_{2M}) = O(\mu_{\max}) \quad (9.251)$$

$$E_{21} = (V_L^\top A_1 \otimes I_{2M}) \mathcal{H}(q \otimes I_{2M}) = O(\mu_{\max}) \quad (9.252)$$

$$E_{22} = (V_L^\top A_1 \otimes I_{2M}) \mathcal{HM}(A_2 V_R \otimes I_{2M}) = O(\mu_{\max}) \quad (9.253)$$



# Proof

63

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

and their entries are in the order of  $\mu_{\max}$ ; this fact can be verified in the same manner that we assessed the size of the block matrices  $\{\mathbf{D}_{11,i-1}, \mathbf{D}_{12,i-1}, \mathbf{D}_{21,i-1}, \mathbf{D}_{22,i-1}\}$  in the proof of the earlier [Theorem 9.1](#). Moreover, the dimensions of  $E_{11}$  are  $2M \times 2M$ .

In a similar manner, we find that

$$\mathcal{B}^T = (V_\epsilon \otimes I_{2M}) \begin{bmatrix} I_{2M} - D_{11} & -D_{12} \\ -D_{21} & (J_\epsilon \otimes I_{2M}) - D_{22} \end{bmatrix} (V_\epsilon^{-1} \otimes I_{2M}) \quad (9.254)$$



# Proof

64

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

where the block matrices  $\{D_{mn}\}$  are given by

$$D_{11} = \sum_{k=1}^N q_k H_k^\top = O(\mu_{\max}) \quad (9.255)$$

$$D_{12} = (\mathbb{1}^\top \otimes I_{2M}) \mathcal{H}^\top \mathcal{M} (A_2 V_R \otimes I_{2M}) = O(\mu_{\max}) \quad (9.256)$$

$$D_{21} = (V_L^\top A_1 \otimes I_{2M}) \mathcal{H}^\top (q \otimes I_{2M}) = O(\mu_{\max}) \quad (9.257)$$

$$D_{22} = (V_L^\top A_1 \otimes I_{2M}) \mathcal{H}^\top \mathcal{M} (A_2 V_R \otimes I_{2M}) = O(\mu_{\max}) \quad (9.258)$$



# Proof

and  $D_{11}$  has dimensions  $2M \times 2M$ . Substituting expressions (9.249) and (9.254) into (9.240), and using the second property for block Kronecker products from Table F.2 in the appendix, we obtain

$$\mathcal{F} = (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon) \mathcal{X} (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon)^{-1} \quad (9.259)$$

where the block Kronecker product operation is relative to blocks of size  $2M \times 2M$ , and where we introduced

$$\mathcal{X} \triangleq \begin{bmatrix} I_{2M} - D_{11} & -D_{12} \\ -D_{21} & (J_\epsilon \otimes I_{2M}) - D_{22} \end{bmatrix} \otimes_b \begin{bmatrix} I_{2M} - E_{11} & -E_{12} \\ -E_{21} & (J_\epsilon \otimes I_{2M}) - E_{22} \end{bmatrix} \quad (9.260)$$



# Proof

66

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

We conclude that

$$(I - \mathcal{F})^{-1} = (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon) (I - \mathcal{X})^{-1} (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon)^{-1} \quad (9.261)$$

We partition  $\mathcal{X}$  into the following block structure:

$$\mathcal{X} = \begin{bmatrix} \mathcal{X}_{11} & \mathcal{X}_{12} \\ \mathcal{X}_{21} & \mathcal{X}_{22} \end{bmatrix} \quad (9.262)$$

where, for example,  $\mathcal{X}_{11}$  is  $(2M)^2 \times (2M)^2$  and is given by

$$\mathcal{X}_{11} = (I_{2M} - D_{11}) \otimes (I_{2M} - E_{11}) \quad (9.263)$$



# Proof

67

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

It follows that

$$I - \mathcal{X} = \begin{bmatrix} I_{(2M)^2} - \mathcal{X}_{11} & -\mathcal{X}_{12} \\ -\mathcal{X}_{21} & I - \mathcal{X}_{22} \end{bmatrix} \quad (9.264)$$

and, in a manner similar to the way we assessed the size of the block matrices  $\{\mathbf{D}_{11,i-1}, \mathbf{D}_{12,i-1}, \mathbf{D}_{21,i-1}, \mathbf{D}_{22,i-1}\}$  in the proof of Theorem 9.1, we can likewise verify that

$$I_{(2M)^2} - \mathcal{X}_{11} = O(\mu_{\max}) \quad (9.265)$$

$$\mathcal{X}_{12} = O(\mu_{\max}) \quad (9.266)$$

$$\mathcal{X}_{21} = O(\mu_{\max}) \quad (9.267)$$

$$I - \mathcal{X}_{22} = O(1) \quad (9.268)$$



# Proof

68

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

In particular, note that

$$\begin{aligned} I_{(2M)^2} - \mathcal{X}_{11} &= I_{(2M)^2} - (I_{2M} - D_{11}) \otimes (I_{2M} - E_{11}) \\ &= (I_{2M} \otimes E_{11}) + (D_{11} \otimes I_{2M}) - (D_{11} \otimes E_{11}) \\ &= O(\mu_{\max}) \end{aligned} \tag{9.269}$$

and

$$\begin{aligned} I - \mathcal{X}_{22} &= I - ((J_\epsilon \otimes I_{2M}) - D_{22}) \otimes_b ((J_\epsilon \otimes I_{2M}) - E_{22}) \\ &= I - (J_\epsilon \otimes I_{2M}) \otimes_b (J_\epsilon \otimes I_{2M}) + O(\mu_{\max}) \\ &= O(1) \end{aligned} \tag{9.270}$$

# Proof



To proceed, we call again upon the useful block matrix inversion formula (9.235). The matrix  $I - \mathcal{X}$  is invertible since  $I - \mathcal{F}$  is invertible; this is because  $\rho(\mathcal{F}) = [\rho(\mathcal{B})]^2 < 1$ . Therefore, applying (9.235) to  $I - \mathcal{X}$  we get

$$(I - \mathcal{X})^{-1} = \begin{bmatrix} (I_{(2M)^2} - \mathcal{X}_{11})^{-1} & 0 \\ 0 & 0 \end{bmatrix} + \quad (9.271)$$

$$\begin{bmatrix} (I - \mathcal{X}_{11})^{-1} \mathcal{X}_{12} \Delta^{-1} \mathcal{X}_{21} (I - \mathcal{X}_{11})^{-1} & (I - \mathcal{X}_{11})^{-1} \mathcal{X}_{12} \Delta^{-1} \\ \Delta^{-1} \mathcal{X}_{21} (I - \mathcal{X}_{11})^{-1} & \Delta^{-1} \end{bmatrix}$$

# Proof



It is seen from (9.269) that the entries of  $(I - \mathcal{X}_{11})^{-1}$  are  $O(1/\mu_{\max})$ , while the entries in the second matrix on the right-hand side of equality (9.271) are  $O(1)$  when the step-sizes are small. That is, we can write

$$(I - \mathcal{X})^{-1} = \left[ \begin{array}{c|c} O(1/\mu_{\max}) & O(1) \\ \hline O(1) & O(1) \end{array} \right] \quad (9.272)$$

where the leading  $(2M)^2 \times (2M)^2$  block is  $O(1/\mu_{\max})$ . Moreover, since  $O(1/\mu_{\max})$  dominates  $O(1)$  for sufficiently small  $\mu_{\max}$ , we can also write



# Proof

71

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\begin{aligned}(I - \mathcal{X})^{-1} &= \begin{bmatrix} (I_{(2M)^2} - \mathcal{X}_{11})^{-1} & 0 \\ 0 & 0 \end{bmatrix} + O(1) \quad (9.273) \\ &= \begin{bmatrix} \{(I_{2M} \otimes E_{11}) + (D_{11} \otimes I_{2M})\}^{-1} & 0 \\ 0 & 0 \end{bmatrix} + O(1) \\ &= \begin{bmatrix} I_{(2M)^2} \\ 0 \end{bmatrix} Z^{-1} \begin{bmatrix} I_{(2M)^2} & 0 \end{bmatrix} + O(1)\end{aligned}$$

where we used the fact from (9.245) that, for  $h = 2$ ,

$$Z = (I_{2M} \otimes E_{11}) + (D_{11} \otimes I_{2M}) \quad (9.274)$$



# Proof

72

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

Substituting (9.273) into (9.261) and using expressions (9.250) and (9.255) for  $D_{11}$  and  $E_{11}$  we arrive at the following low-rank approximation:

$$\begin{aligned} & (I - \mathcal{F})^{-1} \\ = & (p \otimes I_{2M}) \otimes_b (p \otimes I_{2M}) Z^{-1} (\mathbb{1}^\top \otimes I_{2M}) \otimes_b (\mathbb{1}^\top \otimes I_{2M}) + O(1) \\ \stackrel{(a)}{=} & [(p \otimes p) \otimes (I_{2M} \otimes I_{2M})] (1 \otimes Z^{-1}) [(\mathbb{1} \otimes \mathbb{1})^\top \otimes (I_{2M} \otimes I_{2M})] + O(1) \\ = & [(p \otimes p) \otimes I_{4M^2}] (1 \otimes Z^{-1}) [(\mathbb{1} \otimes \mathbb{1})^\top \otimes I_{4M^2}] + O(1) \\ = & [(p \otimes p) \otimes Z^{-1}] [(\mathbb{1} \otimes \mathbb{1})^\top \otimes I_{4M^2}] + O(1) \\ = & [(p \otimes p)(\mathbb{1} \otimes \mathbb{1})^\top] \otimes Z^{-1} + O(1) \end{aligned} \tag{9.275}$$

# Proof



where step (a) uses the third property from Table F.2 in the appendix. Observe that the matrix  $(p \otimes p)(\mathbf{1} \otimes \mathbf{1})^\top$  has rank one and, therefore, the above representation for  $(I - \mathcal{F})^{-1}$  amounts to a low-rank approximation. Moreover, since  $Z = O(\mu_{\max})$ , we conclude from (9.275) that (9.243) holds. We also conclude that (9.242) holds since

$$(I - \bar{\mathcal{F}})^{-1} = (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon)^{-1} (I - \mathcal{F})^{-1} (\mathcal{V}_\epsilon \otimes_b \mathcal{V}_\epsilon) = (I - \mathcal{X})^{-1} \quad (9.276)$$

□



# Mean-Error Stability

We now return to examine the mean-error stability of recursion (9.171). For this purpose, we need to introduce a smoothness condition on the Hessian matrices of the individual costs. This condition was not needed while establishing the stability of the second and fourth-order moments,  $\mathbb{E} \|\tilde{\mathbf{w}}_{k,i}\|^2$  and  $\mathbb{E} \|\tilde{\mathbf{w}}_{k,i}\|^4$ , in the earlier sections. This same smoothness condition will be adopted in the next two chapters when we study the long-term behavior of the network and its performance.

# Mean-Error Stability



**Theorem 9.6** (Network mean-error stability). Consider a network of  $N$  interacting agents running the distributed strategy (8.46) with a primitive matrix  $P = A_1 A_o A_2$ . Assume the aggregate cost (9.10) and the individual costs,  $J_k(w)$ , satisfy the conditions in Assumption 6.1. Assume additionally that each  $J_k(w)$  satisfies a smoothness condition relative to the limit point  $w^*$ , defined by (8.55), of the following form:

$$\|\nabla_w^2 J_k(w^* + \Delta w) - \nabla_w^2 J_k(w^*)\| \leq \kappa_d \|\Delta w\| \quad (9.277)$$

for small perturbations  $\|\Delta w\| \leq \epsilon$  and for some  $\kappa_d \geq 0$ . Assume further that the first and second-order moments of the gradient noise process satisfy the conditions of Assumption 8.1. Then, the first-order moment of the network errors satisfy

$$\limsup_{i \rightarrow \infty} \|\mathbb{E} \tilde{w}_{k,i}\| = O(\mu_{\max}), \quad k = 1, 2, \dots, N \quad (9.278)$$



# Proof

76

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

*Proof.* We multiply both sides of the error recursion (9.171) from the left by  $\mathcal{V}_\epsilon^\top$  and use (9.57) and (9.206) to get

$$\underbrace{\begin{bmatrix} \mathbb{E} \bar{w}_i^e \\ \mathbb{E} \check{w}_i^e \end{bmatrix}}_{\triangleq z_i} = \underbrace{\begin{bmatrix} I_{2M} - D_{11}^\top & -D_{21}^\top \\ -D_{12}^\top & \mathcal{J}_\epsilon^\top - D_{22}^\top \end{bmatrix}}_{\triangleq \bar{\mathcal{B}}} \underbrace{\begin{bmatrix} \mathbb{E} \bar{w}_{i-1}^e \\ \mathbb{E} \check{w}_{i-1}^e \end{bmatrix}}_{\triangleq z_{i-1}} - \begin{bmatrix} 0 \\ \check{b}^e \end{bmatrix} + \mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1} \quad (9.279)$$

where the matrix  $\bar{\mathcal{B}}$  from (9.226) is stable. We already know from (9.59) that  $\|\check{b}^e\| = O(\mu_{\max})$ . We now verify that the limit superior of  $\|\mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1}\|$  is  $O(\mu_{\max}^2)$ .

# Proof



Indeed, in view of result (E.61) from the appendix, we know that condition (9.277) also holds globally for any  $\Delta w$  with  $\kappa_d$  replaced by some constant  $\kappa'_d$ . Then, for each agent  $k$ :

$$\begin{aligned}\|\widetilde{\mathbf{H}}_{k,i-1}\| &\stackrel{\Delta}{=} \|H - \mathbf{H}_{k,i-1}\| \\ &\leq \int_0^1 \left\| \nabla_w^2 J_k(w^\star) - \nabla_w^2 J_k(w^\star - t\widetilde{\phi}_{k,i-1}) \right\| dt \\ &\stackrel{(9.277)}{\leq} \int_0^1 \kappa'_d \|t\widetilde{\phi}_{k,i-1}\| dt \\ &= \frac{1}{2} \kappa'_d \|\widetilde{\phi}_{k,i-1}\|\end{aligned}$$

# Proof



$$\begin{aligned}
 &\leq \frac{1}{2} \kappa'_d \left\| \sum_{\ell \in \mathcal{N}_k} a_{1,\ell k} \tilde{\mathbf{w}}_{\ell,i-1} \right\| \\
 &\stackrel{(F.26)}{\leq} \frac{1}{2} \kappa'_d \sum_{\ell \in \mathcal{N}_k} a_{1,\ell k} \|\tilde{\mathbf{w}}_{\ell,i-1}\| \\
 &\leq \frac{1}{2} \kappa'_d \sum_{\ell \in \mathcal{N}_k} \|\tilde{\mathbf{w}}_{\ell,i-1}\| \\
 &\leq \frac{1}{2} \kappa'_d \sum_{\ell \in \mathcal{N}_k} \|\tilde{\mathbf{w}}_{\ell,i-1}^e\| \\
 &\leq \frac{1}{2} \kappa'_d N \|\tilde{\mathbf{w}}_{i-1}^e\|
 \end{aligned} \tag{9.280}$$

# Proof



so that

$$\|\tilde{\mathcal{H}}_{i-1}\| = \max_{1 \leq k \leq N} \|\tilde{\mathbf{H}}_{k,i-1}\| \leq \frac{1}{2} \kappa'_d N \|\tilde{\mathbf{w}}_{i-1}^e\| \quad (9.281)$$

and, consequently,

$$\begin{aligned}
 \|\mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1}\| &\stackrel{(9.172)}{\leq} \|\mathcal{V}_\epsilon\| \|\mathcal{A}_2\| \|\mathcal{M}\| \|\mathbb{E} \tilde{\mathcal{H}}_{i-1} \mathcal{A}_1^\top \tilde{\mathbf{w}}_{i-1}^e\| \\
 &\leq \|\mathcal{V}_\epsilon\| \|\mathcal{A}_2\| \|\mathcal{M}\| \|\mathcal{A}_1\| \mathbb{E} [\|\tilde{\mathcal{H}}_{i-1}\| \|\tilde{\mathbf{w}}_{i-1}^e\|] \\
 &\leq \frac{1}{2} \kappa'_d N \|\mathcal{V}_\epsilon\| \|\mathcal{A}_2\| \|\mathcal{M}\| \|\mathcal{A}_1\| \mathbb{E} \|\tilde{\mathbf{w}}_{i-1}^e\|^2 \\
 &\triangleq r \mu_{\max} \mathbb{E} \|\tilde{\mathbf{w}}_{i-1}^e\|^2
 \end{aligned} \quad (9.282)$$



# Proof

80

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

for some constant  $r$  that is independent of  $\mu_{\max}$ . It then follows from (9.11) that

$$\limsup_{i \rightarrow \infty} \|\mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1}\| = O(\mu_{\max}^2) \quad (9.283)$$

as claimed, where one  $\mu_{\max}$  arises from  $\mathcal{M}$  and the other  $\mu_{\max}$  arises from (9.11).

Returning to (9.279), we partition the vectors  $z_i$  and  $\mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1}$  into

$$z_i \triangleq \begin{bmatrix} \bar{z}_i \\ \check{z}_i \end{bmatrix}, \quad \mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1} \triangleq \begin{bmatrix} \bar{c}_{i-1} \\ \check{c}_{i-1} \end{bmatrix} \quad (9.284)$$



# Proof

81

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

with the leading vectors,  $\{\bar{z}_i, \bar{c}_{i-1}\}$ , having dimensions  $hM \times 1$  each. It follows that

$$\begin{bmatrix} \bar{z}_i \\ \dot{\bar{z}}_i \end{bmatrix} = \begin{bmatrix} I_{2M} - D_{11}^T & -D_{21}^T \\ -D_{12}^T & \mathcal{J}_\epsilon^T - D_{22}^T \end{bmatrix} \begin{bmatrix} \bar{z}_{i-1} \\ \dot{\bar{z}}_{i-1} \end{bmatrix} + \begin{bmatrix} \bar{c}_{i-1} \\ \dot{\bar{c}}_{i-1} \end{bmatrix} + \begin{bmatrix} 0 \\ O(\mu_{\max}) \end{bmatrix} \quad (9.285)$$

This recursion has a form similar to the earlier recursion we encountered in (9.60) while studying the mean-square stability of the original error dynamics (10.2), with two differences. First, the matrices  $\{D_{11}, D_{12}, D_{21}, D_{22}\}$  in (9.285) are constant matrices; nevertheless, they satisfy the same bounds as the matrices  $\{D_{11,i-1}, D_{12,i-1}, D_{21,i-1}, D_{22,i-1}\}$  in (9.60). In particular, it continues to hold that



# Proof

$$\|I_{2M} - D_{11}^T\| \stackrel{(9.47)}{\leq} 1 - \sigma_{11}\mu_{\max} \quad (9.286)$$

$$\|D_{12}\| \stackrel{(9.51)}{\leq} \sigma_{12}\mu_{\max} \quad (9.287)$$

$$\|D_{21}\| \stackrel{(9.50)}{\leq} \sigma_{21}\mu_{\max} \quad (9.288)$$

$$\|D_{22}\| \stackrel{(9.51)}{\leq} \sigma_{22}\mu_{\max} \quad (9.289)$$

for some positive constants  $\{\sigma_{11}, \sigma_{12}, \sigma_{21}, \sigma_{22}\}$  that are independent of  $\mu_{\max}$ . Second, the gradient noise terms that appeared in (9.60) are now replaced by



# Sketch of Argument

83

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

$$\begin{bmatrix} \|\bar{z}_i\|^2 \\ \|\check{z}_i\|^2 \end{bmatrix} \preceq \underbrace{\begin{bmatrix} a & b \\ c & d \end{bmatrix}}_{\Gamma} \begin{bmatrix} \|\bar{z}_{i-1}\|^2 \\ \|\check{z}_{i-1}\|^2 \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix} \mathbb{E} \|\tilde{w}_{i-1}^e\|^4 + \begin{bmatrix} 0 \\ O(\mu_{\max}^2) \end{bmatrix}$$

(9.301)

$$(I - \Gamma)^{-1} = \begin{bmatrix} O(1/\mu_{\max}) & O(1) \\ O(\mu_{\max}) & O(1) \end{bmatrix}$$

# Sketch of Argument



We conclude that, as  $i \rightarrow \infty$ ,

$$\limsup_{i \rightarrow \infty} \|\bar{z}_i\|^2 = O(\mu_{\max}^2), \quad \limsup_{i \rightarrow \infty} \mathbb{E} \|\check{z}_i\|^2 = O(\mu_{\max}^2) \quad (9.303)$$

and, hence,

$$\limsup_{i \rightarrow \infty} \|z_i\|^2 = O(\mu_{\max}^2) \quad (9.304)$$

It follows that

$$\limsup_{i \rightarrow \infty} \|z_i\| = O(\mu_{\max}) \quad (9.305)$$

Consequently,

$$\limsup_{i \rightarrow \infty} \left\| \begin{bmatrix} \mathbb{E} \bar{w}_i^e \\ \mathbb{E} \check{w}_i^e \end{bmatrix} \right\| = O(\mu_{\max}) \quad (9.306)$$

# Sketch of Argument



and, hence,

$$\begin{aligned}
 \limsup_{i \rightarrow \infty} \|\mathbb{E} \tilde{\mathbf{w}}_{k,i}\| &\leq \limsup_{i \rightarrow \infty} \|\mathbb{E} \tilde{\mathbf{w}}_i^e\| \\
 &\leq \limsup_{i \rightarrow \infty} \left\| (\mathcal{V}_\epsilon^{-1})^\top \begin{bmatrix} \mathbb{E} \bar{\mathbf{w}}_i^e \\ \mathbb{E} \check{\mathbf{w}}_i^e \end{bmatrix} \right\| \\
 &\leq \left\| (\mathcal{V}_\epsilon^{-1})^\top \right\| \left( \limsup_{i \rightarrow \infty} \left\| \begin{bmatrix} \mathbb{E} \bar{\mathbf{w}}_i^e \\ \mathbb{E} \check{\mathbf{w}}_i^e \end{bmatrix} \right\| \right) \\
 &= O(\mu_{\max})
 \end{aligned} \tag{9.307}$$

as claimed.





# Detailed Proof

$$\begin{bmatrix} \bar{z}_i \\ \check{z}_i \end{bmatrix} = \begin{bmatrix} I_{2M} - D_{11}^\top & -D_{21}^\top \\ -D_{12}^\top & \mathcal{J}_\epsilon^\top - D_{22}^\top \end{bmatrix} \begin{bmatrix} \bar{z}_{i-1} \\ \check{z}_{i-1} \end{bmatrix} + \begin{bmatrix} \bar{c}_{i-1} \\ \check{c}_{i-1} \end{bmatrix} + \begin{bmatrix} 0 \\ O(\mu_{\max}) \end{bmatrix} \quad (9.285)$$

This recursion has a form similar to the earlier recursion we encountered in (9.60) while studying the mean-square stability of the original error dynamics (10.2), with two differences. First, the matrices  $\{D_{11}, D_{12}, D_{21}, D_{22}\}$  in (9.285) are constant matrices; nevertheless, they satisfy the same bounds as the matrices  $\{D_{11,i-1}, D_{12,i-1}, D_{21,i-1}, D_{22,i-1}\}$  in (9.60).



# Proof

87

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

From (9.282) and using the fact that  $(\mathbb{E} \mathbf{a})^2 \leq \mathbb{E} \mathbf{a}^2$  for any real random variable  $\mathbf{a}$ , we have that

$$\|\mathcal{V}_\epsilon^\top \mathcal{A}_2^\top \mathcal{M} c_{i-1}\|^2 \leq r^2 \mu_{\max}^2 \mathbb{E} \|\tilde{\mathbf{w}}_{i-1}^e\|^4 \quad (9.290)$$

and, hence,

$$\|\bar{c}_{i-1}\|^2 \leq r^2 \mu_{\max}^2 \mathbb{E} \|\tilde{\mathbf{w}}_{i-1}^e\|^4, \quad \|\check{c}_{i-1}\|^2 \leq r^2 \mu_{\max}^2 \mathbb{E} \|\tilde{\mathbf{w}}_{i-1}^e\|^4 \quad (9.291)$$

Now, if we repeat the argument that led to (9.106), with proper adjustments, we can show that relations similar to (9.69) and (9.81) continue to hold for  $\{\|\bar{z}_i\|^2, \|\check{z}_i\|^2\}$ . The argument is as follows.



# Proof

88

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

We first appeal to Jensen's inequality (F.26) from the appendix and apply it to the function  $f(x) = \|x\|^2$  to obtain the bound:

$$\begin{aligned}\|\bar{z}_i\|^2 &= \left\| (1-t) \frac{1}{1-t} (I_{2M} - D_{11}^T) \bar{z}_{i-1} + t \frac{1}{t} (-D_{21}^T \check{z}_{i-1} + \bar{c}_{i-1}) \right\|^2 \\ &\leq \frac{1}{1-t} (1 - \sigma_{11} \mu_{\max})^2 \|\bar{z}_{i-1}\|^2 + \frac{2}{t} (\sigma_{21}^2 \mu_{\max}^2 \|\check{z}_{i-1}\|^2 + \|\bar{c}_{i-1}\|^2) \\ &\leq (1 - \sigma_{11} \mu_{\max}) \|\bar{z}_{i-1}\|^2 + \frac{2}{\sigma_{11} \mu_{\max}} (\sigma_{21}^2 \mu_{\max}^2 \|\check{z}_{i-1}\|^2 + \|\bar{c}_{i-1}\|^2) \\ &\leq (1 - \sigma_{11} \mu_{\max}) \|\bar{z}_{i-1}\|^2 + \frac{2\sigma_{21}^2 \mu_{\max}}{\sigma_{11}} \|\check{z}_{i-1}\|^2 + \frac{2r^2 \mu_{\max}}{\sigma_{11}} \mathbb{E} \|\tilde{w}_{i-1}^e\|^4\end{aligned}\tag{9.292}$$



# Proof

89

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

for any arbitrary positive number  $t \in (0, 1)$ . We selected  $t = \sigma_{11}\mu_{\max}$  in the above derivation. We repeat a similar argument for  $\|\check{z}_i\|^2$ . Thus, using Jensen's inequality again we have

$$\begin{aligned} \|\check{z}_i\|^2 &= \left\| t \frac{1}{t} \mathcal{J}_\epsilon^\top \check{z}_{i-1} - (1-t) \frac{1}{1-t} \left[ -D_{22}^\top \check{z}_{i-1} - D_{12}^\top \bar{z}_{i-1} + \check{c}_{i-1} + O(\mu_{\max}) \right] \right\|^2 \\ &\stackrel{(9.76)}{\leq} \frac{1}{t} (\rho(J_\epsilon) + \epsilon)^2 \|\check{z}_{i-1}\|^2 + \\ &\quad \frac{4}{1-t} \left[ \sigma_{22}^2 \mu_{\max}^2 \|\check{z}_{i-1}\|^2 + \sigma_{12}^2 \mu_{\max}^2 \|\bar{z}_{i-1}\|^2 + \|\check{c}_{i-1}\|^2 + O(\mu_{\max}^2) \right] \end{aligned} \tag{9.293}$$



# Proof

90

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

for any arbitrary positive number  $t \in (0, 1)$ . Since we know that  $\rho(J_\epsilon) \in (0, 1)$ , then we can select  $\epsilon$  small enough to ensure  $t = \rho(J_\epsilon) + \epsilon \in (0, 1)$  and rewrite (9.293) as

$$\begin{aligned} \|\check{z}_i\|^2 &\leq \left( \rho(J_\epsilon) + \epsilon + \frac{4\sigma_{22}^2 \mu_{\max}^2}{1 - \rho(J_\epsilon) - \epsilon} \right) \|\check{z}_{i-1}\|^2 + \\ &\quad \left( \frac{4\sigma_{12}^2 \mu_{\max}^2}{1 - \rho(J_\epsilon) - \epsilon} \right) \|\bar{z}_{i-1}\|^2 + \\ &\quad \left( \frac{4r^2 \mu_{\max}^2}{1 - \rho(J_\epsilon) - \epsilon} \right) \mathbb{E} \|\tilde{w}_{i-1}^e\|^4 + O(\mu_{\max}^2) \end{aligned} \tag{9.294}$$

# Proof



If we now introduce the scalar coefficients

$$a = 1 - \sigma_{11}\mu_{\max} = 1 - O(\mu_{\max}) \quad (9.295)$$

$$b = \frac{2\sigma_{21}^2\mu_{\max}}{\sigma_{11}} = O(\mu_{\max}) \quad (9.296)$$

$$c = \frac{4\sigma_{12}^2\mu_{\max}^2}{1 - \rho(J_\epsilon) - \epsilon} = O(\mu_{\max}^2) \quad (9.297)$$

$$d = \rho(J_\epsilon) + \epsilon + \frac{4\sigma_{22}^2\mu_{\max}^2}{1 - \rho(J_\epsilon) - \epsilon} = \rho(J_\epsilon) + \epsilon + O(\mu_{\max}^2) \quad (9.298)$$

$$e = \frac{2r^2\mu_{\max}}{\sigma_{11}} = O(\mu_{\max}) \quad (9.299)$$

$$f = \frac{4r^2\mu_{\max}^2}{1 - \rho(J_\epsilon) - \epsilon} = O(\mu_{\max}^2) \quad (9.300)$$

# Proof



we can combine (9.292) and (9.294) into a single compact inequality recursion as follows:

$$\begin{bmatrix} \|\bar{z}_i\|^2 \\ \|\check{z}_i\|^2 \end{bmatrix} \preceq \underbrace{\begin{bmatrix} a & b \\ c & d \end{bmatrix}}_{\Gamma} \begin{bmatrix} \|\bar{z}_{i-1}\|^2 \\ \|\check{z}_{i-1}\|^2 \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix} \mathbb{E} \|\tilde{w}_{i-1}^e\|^4 + \begin{bmatrix} 0 \\ O(\mu_{\max}^2) \end{bmatrix} \quad (9.301)$$

$\begin{bmatrix} O(\mu_{\max}) \\ O(\mu_{\max}^2) \end{bmatrix}$

in terms of the  $2 \times 2$  coefficient matrix  $\Gamma$  indicated above. We know from the argument (9.102) that  $\Gamma$  is stable for sufficiently small step-sizes. If we now recall the result

$$\limsup_{i \rightarrow \infty} \mathbb{E} \|\tilde{w}_i^e\|^4 \stackrel{(9.107)}{=} O(\mu_{\max}^2) \quad (9.302)$$



# Proof

93

We conclude that, as  $i \rightarrow \infty$ ,

$$\limsup_{i \rightarrow \infty} \|\bar{z}_i\|^2 = O(\mu_{\max}^2), \quad \limsup_{i \rightarrow \infty} \mathbb{E} \|\check{z}_i\|^2 = O(\mu_{\max}^2) \quad (9.303)$$

and, hence,

$$\limsup_{i \rightarrow \infty} \|z_i\|^2 = O(\mu_{\max}^2) \quad (9.304)$$

It follows that

$$\limsup_{i \rightarrow \infty} \|z_i\| = O(\mu_{\max}) \quad (9.305)$$

Consequently,

$$\limsup_{i \rightarrow \infty} \left\| \begin{bmatrix} \mathbb{E} \bar{w}_i^e \\ \mathbb{E} \check{w}_i^e \end{bmatrix} \right\| = O(\mu_{\max}) \quad (9.306)$$



# Proof

94

Lecture #18: Mean Error Network Stability

EE210B: Inference over Networks (A. H. Sayed)

and, hence,

$$\begin{aligned} \limsup_{i \rightarrow \infty} \|\mathbb{E} \tilde{\mathbf{w}}_{k,i}\| &\leq \limsup_{i \rightarrow \infty} \|\mathbb{E} \tilde{\mathbf{w}}_i^e\| \\ &\leq \limsup_{i \rightarrow \infty} \left\| (\mathcal{V}_\epsilon^{-1})^\top \begin{bmatrix} \mathbb{E} \bar{\mathbf{w}}_i^e \\ \mathbb{E} \check{\mathbf{w}}_i^e \end{bmatrix} \right\| \\ &\leq \left\| (\mathcal{V}_\epsilon^{-1})^\top \right\| \left( \limsup_{i \rightarrow \infty} \left\| \begin{bmatrix} \mathbb{E} \bar{\mathbf{w}}_i^e \\ \mathbb{E} \check{\mathbf{w}}_i^e \end{bmatrix} \right\| \right) \\ &= O(\mu_{\max}) \end{aligned} \tag{9.307}$$

as claimed.

□

# End of Lecture

Course EE210B  
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