

Lecture 9

We now show that Moser's argument on p90 et seq  
on the long-time behavior of solutions of the Toda

flow applies in the full symmetric matrix case. In

place of (10.1),  $\frac{dx}{dt} = [x, B(x)]$ ,  $x(0) \in \Sigma_N$ , we

will consider more generally its complexification

$$(135.1) \quad \frac{dx}{dt} = [x, \tilde{B}(x)], \quad x(0) = x_0 = x_0^* \in \Gamma_N$$

where  $\Gamma_N$  denotes the  $N \times N$  Hermitian matrices and

$$(135.2) \quad \tilde{B}(x) = x_- - x_-^* = -(\tilde{B}(x))^*$$

Using suitable analogs of the calculations on p10 et seq

it is easy to show that (135.1) has a

unique global solution  $x(t) = x(t)^*$  with

$\text{spec}(x(t)) = \text{spec } x_0$ . Clearly if  $x_0 = \bar{x}_0 = x_0^T$ ,

then (135.1) reduces to (10.1).

Theorem (135.3)

Let  $x(t)$ ,  $t \geq 0$ , solve (135.1.) with  $x(0) = x_0 = x_0^*$ .

Then as  $t \rightarrow \infty$ ,

$$X(t) \rightarrow \text{diag}(\lambda_{\pi(1)}, \dots, \lambda_{\pi(N)})$$

where  $\lambda_{\pi(1)}, \dots, \lambda_{\pi(N)}$ , is some permutation of the eigenvalues of  $X_0$ .

Proof: We have  $\frac{dX}{dt} = X \tilde{B} + (X \tilde{B})^T$ , and

using the complex inner product for  $\mathbb{C}^N$ , we obtain

$$\frac{dX_{11}}{dt} = \underbrace{\left( (e_1, X \tilde{B} e_1) \right)}_{2\operatorname{Re}}$$

$$= 2\operatorname{Re}(x_{e_1}, (X - X_{11})e_1)$$

$$= 2 \sum_{i=1}^N |x_{i1}|^2 - 2 |x_{11}|^2$$

$$= -2 \sum_{i=2}^N |x_{i1}|^2$$

Following Moser's argument we now conclude that

$$(136.1) \quad x_{11}(t) \uparrow x_{11}(\infty) \quad \text{and} \quad \sum_{i=2}^N (x_{i1}(t))^2 \rightarrow 0.$$

Now

$$\frac{d(x_{11} + x_{22})}{dt} = 2\operatorname{Re}((e_1, X \tilde{B} e_1) + (e_2, X \tilde{B} e_2))$$

$$= 2\operatorname{Re}\left(\sum_{i=1}^N |x_{i1}|^2 + \sum_{i=1}^N |x_{i2}|^2 - (x_{22})^2 - 2|x_{12}|^2\right)$$

$$= 2 \sum_{i=1}^2 \sum_{2 < j \leq N} |x_{ji}(t)|^2$$

and we conclude that as  $t \rightarrow \infty$

$$x_{i2}(t) \rightarrow x_{i2}(\infty) \quad \text{and} \quad \sum_{i=3}^N |x_{i2}(t)|^2 \rightarrow 0$$

Continuing we find for  $1 \leq k \leq N$

$$\frac{d(x_{1k} + \dots + x_{nk})}{dt} = 2 \sum_{i=1}^k \sum_{k < j \leq N} |x_{ij}(t)|^2$$

which leads to the desired result.  $\square$ .

Remark 137.1 Unlike the Jacobi case,

Note that  $X(t)$  is not always ordering i.e.

$\lambda_{1(t)}, \dots, \lambda_{\pi(N)}(t)$  is not always ordered. Indeed if

$X_0$  is diagonal, then  $X(t) \in X_0$  for all  $t \geq 0$ , and

no no <sup>re-</sup>ordering can take place. Below we will

discuss a sufficient condition that  $X(t) \in \mathbb{E}_{\Sigma_N}$  is ordering.

Remark 137.2

The extended generalized flow,  $p \geq 3$ ,

$$(137.3) \quad \frac{dX}{dt} = [X, \tilde{B}(X^{p-1})], \quad X(0) = X_0 = x_0^*$$

is not always diagonalizing. For example, in the case

(137+)

$p=3$  with  $X_0 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} = X_0^* = X_0^T$ . Then  $\prod X(t) = Q(t)^T X_0 Q(t)$  and

$$X(t)^{p-1} = X(t)^2 = Q(t)^T X_0^2 Q(t) = I \text{ as } X_0^2 = I.$$

In particular  $\tilde{B}(X^{p-1}) = 0$  and so  $X(t) = \text{const} = X_0 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$

However, it follows as in Lecture 1, that if  $X(t)$

solves (137.3) for any  $p \geq 2$ , then  $\frac{dX^{p-1}}{dt} = [X^{p-1}, \tilde{B}(X^{p-1})]$ ,

which is the Toda flow. Hence  $X^{p-1}(t)$  converges to the

diagonal matrix  $\text{diag}(\lambda_{1(1)}^{p-1}, \dots, \lambda_{N(N)}^{p-1})$  as  $t \rightarrow \infty$ .

But, as above,  $X(t)$  may not converge to a diagonal matrix

Exercise Does  $X(t)$  always converge under (137.3)?

To some matrix

We now prove the analog of (84.1) (84.2) generalized for the extended flow (137.3). This requires some interpretation as the eigenvalues of a general Hermitian matrix  $X$  may not be simple and, in particular, the eigenvalues and eigenvectors may not be smooth (see D+Troydon, Univ. for... function of  $X$ ). We proceed as follows. For  $X|_0 = x_0$

There exists a (not necessarily unique) unitary matrix  $U_0$  such that  $x_0 = U_0 \Lambda U_0^*$  where  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ .

Let  $Q(t)$  solve (cf (13.11))

$$(138.1) \quad \frac{dQ}{dt} = Q \tilde{B}(X^{(t)}) \quad , \quad Q(0) = I \quad ,$$

where  $X(t)$  solves (137.3). Then

$$\frac{d}{dt} Q Q^* = \dot{Q} Q^* + Q \dot{Q}^* = Q \tilde{B} Q^* + Q \tilde{B}^* Q^* = 0$$

as  $\tilde{B} = -\tilde{B}^*$ . Thus  $Q(t)$  is unitary,  $Q(t) Q(t)^* = \text{const.} = I$

Following (14.1) we find

$$(139.1) \quad X(t) = Q(t)^* X_0 Q(t)$$

and

$$(139.2) \quad X(t) = U(t) \Lambda U(t)^*$$

where  $U(t)$  is the unitary matrix

$$(139.3) \quad U(t) = Q(t)^* U_0,$$

(as  $Q(t)$  is smooth,

then the  $j$ th column  $u_j(t)$  of  $U(t)$  is a smooth

eigenvector of  $X(t)$  corresponding to the (constant) eigenvalue

$\lambda_i$ . From the eigenvalue equation  $(X(t) - \lambda_i) u_i(t) = 0$

we obtain

$$\dot{X}(t) u_i(t) + (X(t) - \lambda_i) u_i(t) = 0$$

which yields using (137.3)

$$(X(t) - \lambda_i) \dot{u}_i(t) + \tilde{B}(\overset{p-1}{X(t)}) u_i(t) = 0$$

This last equation implies that  $\dot{u}_i(t) + \tilde{B}(\overset{p-1}{X(t)}) u_i(t)$

must be a (possibly time dependent) linear combination

of the eigenvectors corresponding to  $\lambda_i$ . Let

$$U_i(t) = [u_{i1}(t), \dots, u_{im}(t)]$$

be the eigenvectors corresponding to a repeated eigenvalue

$\lambda_i$  so that for  $i=1, \dots, m$

$$(140.1) \quad \dot{u}_{i,i}(t) + \tilde{B}(x^{p-1}(t)) u_{i,i}(t) = \sum_{k=1}^m d_{ki}(t) u_{i,k}(t)$$

and so

$$(140.2) \quad \left( \frac{d}{dt} + \tilde{B}(x^{p-1}(t)) \right) u_i(t) = u_i(t) D(t)$$

where

$$D(t) = (d_{ki}(t))_{k,i=1}^m$$

Clearly  $D(t)$  is smooth.

Note that  $U_i^*(t) U_i(t) = I_m$ , the  $m \times m$  identity matrix.

Then multiplying (140.1) on the left by  $U_i^*(t)$  and

then multiplying the conjugate transpose of (140.2) on the

right by  $U_i(t)$ , we obtain

$$(140.3) \quad U_i^*(t) \dot{U}_i(t) + U_i^*(t) \tilde{B}(x(t)) U_i(t) = D(t)$$

and

$$(140.4) \quad \dot{U}_i^*(t) U_i(t) + U_i^*(t) \tilde{B}(x(t))^* U_i(t) = D^*(t).$$

Because  $\frac{d}{dt} U_i^*(t) U_i(t) = 0$  and  $\tilde{B}(x(t))$  is skew

Hermitian, the addition of these two equations yields

$D(t) = -D^*(t)$ . Let  $S(t)$  solve  $\dot{S}(t) = -D(t) S(t)$ ,

$S(0) = I_m$ . Then one finds as above that  $S^*(t) S(t)$

$= \text{const.} = I_m$ . In particular

$$\tilde{U}_i(t) = U_i(t) S(t)$$

has orthonormal columns and we find

$$(141.1) \quad \left( \frac{d}{dt} + \tilde{B}(X^{p-1}(t)) \right) \tilde{U}_i(t) = U_i(t) D(t) S(t) - U_i(t) A(t) S(t) \\ = 0$$

We conclude that a smooth normalization for the eigenvalues of  $X(t)$  can always be chosen so that

$A(t) = 0$  in (140.2). So without loss of generality

we can assume that  $U(t)$  solves (140.2) with  $D(t) = 0$ .

Then for  $U(t) = (U_{ij}(t))_{i,j=1}^n$ ,

$$\dot{U}_{ij}(t) = -(\epsilon_1, \tilde{B}(X^{p-1}(t)) u_j(t))$$

$$= (\tilde{B}(X^{p-1}(t)) \epsilon_1, u_j(t))$$

$$= ((X^{p-1}(t) - (X^{p-1}(t))_{ii}) \epsilon_1, u_j(t))$$

$$(141.2) \quad \dot{u}_{ij}(t) = (\lambda_j^{p-1} - (X^{p-1}(t))_{ii}) u_{ij}(t)$$

Using  $(X(t))_{ii} = \sum_{j=1}^N \lambda_j^p |U_{ij}(t)|^c$ , a direct calculation

shows the following

generalized

Theorem 142.0 Let  $X(t)$  solve the extended Toda flow (137.3),

$$(142.1) \quad U_{ij}(t) = \frac{U_{ij}(0) e^{\lambda_i^{p-1} t}}{\left( \sum_{j=1}^N U_{ij}(0) |e^{\lambda_j^{p-1} t}|^c \right)^{\frac{1}{c}}}$$

$$\left( \sum_{j=1}^N U_{ij}(0) |e^{\lambda_j^{p-1} t}|^c \right)^{\frac{1}{c}}$$

Then there exists a smooth orthonormal eigenbasis  $U(t)$

for  $X(t)$  such that

Moreover for  $p=2$ , in particular, we have

$$(142.2) \quad X_{ii}(t) = \sum_{j=1}^N \lambda_j^2 |U_{ij}(t)|^c$$

and

$$(142.3) \quad E(t) = \sum_{k=2}^N |X_{kk}(t)|^c = \sum_{j=1}^N (\lambda_j - X_{ii}(t))^2 |U_{ij}(t)|^c$$

Proof: We must prove (142.3). From the spectral

representation  $X(t) = U(t) \Lambda U(t)^*$ , we have

$$X_{kk}(t) = \sum_{j=1}^N \lambda_j^2 |U_{kj}(t)|^c$$

and hence

$$E(t) = \sum_{k=2}^N |X_{kk}(t)|^c = \sum_{k=2}^N X_{kk}(t) X_{k-1,k}(t) = (X^2(t))_{ii} - X_{ii}^2(t)$$

(143)

$$\begin{aligned}
 &= \sum_{h=1}^N \lambda_h^2 |U_{1,h}(t)|^c - \left( \sum_{h=1}^N \lambda_h |U_{1,h}(t)|^c \right)^c \\
 &= \sum_{k=1}^N (\lambda_k - \chi_{11}(t))^c |U_{1,k}(t)|^c,
 \end{aligned}$$

which proves (142.3).  $\square$

As we will see  $E(t)$  controls the computation of  $\lambda_1$ , the top eigenvalue of  $X_0$ .

Note that

$$(143.0) \quad \lambda_1 - \chi_{11}(t) = \sum_{j=1}^n (\lambda_1 - \lambda_j) |U_{1,j}(t)|^c.$$

Suppose the eigenvalues of  $X_0$  are arranged in non-increasing order

$$(143.1) \quad \lambda_1 = \lambda_2 = \dots = \lambda_m > \lambda_{m+1} > \lambda_{m+2} \geq \dots \geq \lambda_N$$

Suppose  $|U_{1,j}(0)| \neq 0$  for some  $1 \leq j \leq m$ . Then without

loss of generality, after permutation, we can assume that

$U_{1,1}(t), \dots, U_{1,e}(t)$  are non-zero for some  $1 \leq e \leq m$ , and

$U_{1,e+1}(t), \dots, U_{1,m}(t) \equiv 0$ . It follows from (142.1) that

$$(143.2) \quad U_{1,j}(t) \rightarrow 0 \quad \text{for } e+1 \leq j \leq N$$

and

$$(143.3) \quad U_{1,i}(t) \rightarrow \frac{|U_{1,i}(0)|}{\left(\sum_{j=1}^e |U_{1,j}(0)|^c\right)^{\frac{1}{c}}} \quad \text{for } 1 \leq i \leq e.$$

From (143.0) we see that

$$(144.1) \quad \lambda_i - x_{ii}(t) = \sum_{j=m+1}^N (\lambda_j - \gamma_j) |u_{ij}(t)|^2.$$

and

$$(144.2) \quad E(t) = \sum_{i=1}^m (\lambda_i - x_{ii}(t))^2 |u_{ii}(t)|^2 + \sum_{i=m+1}^N (\lambda_i - x_{ii}(t)) |u_{ii}(t)|^2$$

go to zero as  $t \rightarrow \infty$

While  $\lambda_i - x_{ii}(t)$  is of course the true error in computing  $\lambda_i$ , we will use  $E(t)$  to determine a convergence criterion as it is easily observable; Indeed, it follows from the min-max principle, that if

$E(t) < \varepsilon$  then  $|x_{ii}(t) - \gamma_i| < \varepsilon$  for some  $i$ . With high

probability (see ? below),  $\gamma_i = \gamma_1$ .

Now it turns out that there is a remarkable way to solve (10.1) or (135.1), the Hamiltonians  $H_p(x) = \frac{1}{p} \text{tr } x^p$ , explicitly. For more information see, e.g., [Symes] [DLNT] and the references therein.

Exercise 145.0 (QR factorization). Let  $Y$  be an invertible, complex matrix. Then  $Y$  has a unique factorization  $Y = QR$  where  $Q$  is unitary, and  $R$  is upper triangular with  $R_{ii} > 0$ ,  $i=1, \dots, N$ . 145

Theorem 145.1

Let  $X(t)$  solve the generalized and extended flow

$$(145.2) \quad \frac{dX}{dt} = [X, \tilde{B}(X^{P^{-1}})] , \quad X(0) = X_0 = X_0^*$$

Let

$$(145.3) \quad e^{tX_0^{P^{-1}}} = Q(t) R(t)$$

be the QR factorization for  $e^{tX_0^{P^{-1}}}$ . Then

$$(145.4) \quad X(t) = Q(t) X_0 Q(t)^*$$

Proof: The QR factorization of a matrix  $Y$  is

just the result of applying Gram-Schmidt to

the columns of  $Y$ , starting from the left. It

follows that as  $e^{tX_0^{P^{-1}}}$  is differentiable and

non-singular for all  $t$ , that  $Q(t)$ , and  $R(t)$

are differentiable functions of  $t$ . From (145.3)

we have

$$X_0^{P^{-1}} QR = \dot{Q}R + Q\dot{r}$$

or

$$(146.1) \quad \hat{X}(t) \stackrel{P}{=} Q^* X_0^{P^{-1}} Q = Q^* \dot{Q} + \dot{r} R^{-1}, \text{ where}$$

$$(146.2) \quad \hat{X}(t) = Q^* X_0 Q$$

As  $\dot{r} R^{-1}$  is upper triangular, it follows that

$$(Q^* \dot{Q})_- = \hat{x}_-$$

But  $Q^* Q = I$  implies that  $\dot{Q}^* Q + Q^* \dot{Q} = 0$

and hence  $Q^* \dot{Q}$  is skew-adjoint with a purely imaginary diagonal i.e.

$$Q^* \dot{Q} = (Q^* \dot{Q})_- - (Q^* \dot{Q})_+^* + D$$

where  $D + D^*$  is diagonal. But from (146.1), as  $\hat{X}$

is Hermitian,

$$D = \text{diag } \hat{X}^{P^{-1}} + \text{diag } \dot{r} R^{-1}$$

is real. Thus we must have  $D = 0$  and hence

$$Q^* \dot{Q} = \tilde{B}(\hat{X}^{P^{-1}})$$

or

$$(146.3) \quad \frac{dQ}{dt} = Q \tilde{B}(\hat{X}^{P^{-1}}), \quad Q|_{t=0} = I$$

Thus

(147)

$$\begin{aligned}\frac{d\hat{x}}{dt} &= \tilde{Q}^* x_0 Q + Q^* x_0 Q \\ &= -\tilde{B}(\hat{x}^{p-1}) \hat{x} + \hat{x} \tilde{B}(\hat{x}^{p-1}) \\ &= (\hat{x}, \tilde{B}(\hat{x}^{p-1}))\end{aligned}$$

where  $\hat{x}(0) = x_0$ . As the solution to (145.2)

is unique. This completes the proof of (145.4).  $\square$ .