# Chapter 1

### Introduction

- Basic component
- Building the bridge
- Characteristic of a bridge
- Examples

## **Basic Components**

- Two abstract problems:
  - $\diamond$  One is a make-up and is easy.
  - $\diamond$  The other is the real problem and is difficult.
- A bridge:
  - $\diamond$  A continuous path connecting the two problems.
  - $\diamond$  A path that is easy to follow.
- A numerical method:
  - $\diamond$  A method for moving along the bridge.
  - $\diamond$  A method that is readily available.

Introduction

# Building the Bridge

- Specified guidance is available.
  - $\diamond$  The bridge is constructed by monitoring the values of certain specified functions.
  - $\diamond$  The path is guaranteed to work.
  - $\diamond$  e.g. Projected gradient methods.
- Only some general guidance is available.
  - $\diamond$  A bridge is built in a straightforward way.
  - $\diamond$  No guarantee the path will be complete.
  - $\diamond$  e.g. Homotopy methods.
- No guidance at all.
  - $\diamond$  A bridge is built seemingly by accident.
  - $\diamond$  U sually deeper mathematical theory is involved.
  - $\diamond$  e.g. The isospectral flows.

## Characteristics of a Bridge

- A bridge, if exists, usually is characterized by an ordinary differential equation.
- The discretization of a bridge, or a numerical method in traveling along a bridge, usually produces an iterative scheme.

- The eigenvalue problem
- The nonlinear algebraic equation
- The least squares matrix approximation
- List of other applications

#### The Eigenvalue Problem

- The mathematical problem:
  - $\diamond$  A symmetric matrix  $A_0$  is given.
  - $\diamond$  Solve the equation

$$A_0 x = \lambda x$$

for a nonzero vector x and a scalar  $\lambda$ .

- An iterative method :
  - $\diamond$  The QR decomposition:

$$A = QR$$

where Q is orthogonal and R is upper triangular.  $\diamond$  The QR algorithm (Francis '61):

$$A_k = Q_k R_k$$
$$A_{k+1} = R_k Q_k.$$

- $\diamond$  The sequence  $\{A_k\}$  converges to a diagonal matrix.
- $\diamond$  Every matrix  $A_k$  has the same eigenvalues of  $A_0$ .

- A continuous method:
  - ♦ Lie algebra decomposition:

$$X = X^o + X^+ + X^-$$

where  $X^o$  is the diagonal,  $X^+$  the strictly upper triangular, and  $X^-$  the strictly lower triangular part of X.

 $\diamond$  Toda lattice (Symes '82, Deift el al '83):

$$\frac{dX}{dt} = [X, X^{-} - X^{-T}]$$
  
X(0) = X<sub>0</sub>.

- $\diamond$  Sampled at integer times,  $\{X(k)\}$  gives the same sequence as does the QR algorithm applied to the matrix  $A_0 = exp(X_0)$ .
- The bridge between  $X_0$  and the limit point of Toda flow is built on the basis of maintaining isospectrum.
  - $\diamond$  What motivates the construction of Toda lattice?
  - $\diamond$  Why is convergence guaranteed?

#### Nonlinear algebraic equations

- The mathematical problem:
  - $\diamond$  A sufficiently smooth function  $f: R^n \to R^n$  is given.
  - $\diamond$  Solve the equation

$$f(x) = 0.$$

• An iterative method:

 $\diamond$  The Newton method:

$$x_{k+1} = x_k - \alpha_k (f'(x_k))^{-1} f(x_k).$$

 $\diamond$  The sequence  $\{x_k\}$  converges quadratically to a solution, if  $x_0$  is sufficiently close to that solution.

A continuous method (Smale '76, Keller '78, etc.):
The Newton homotopy:

$$H(x,t) = f(x) - tf(x_0).$$

- $\diamond$  The zero set  $\{(x,t)\in R^{n+1}|H(x,t)=0\}$  is a smooth curve.
- $\diamond$  The homotopy curve:

$$f'(x)\frac{dx}{ds} - \frac{1}{t}f(x)\frac{dt}{ds} = 0$$
$$x(0) = x_0$$
$$t(0) = 1$$

where s is the arc length.

 $\diamond$  Suppose f'(x) is nonsingular. Then written as

$$\frac{dx}{ds} = \frac{dt}{ds}\frac{1}{t}(f'(x))^{-1}f(x).$$

 $\diamond$  With appropriate step size chosen, an Euler step is equivalent to a regular Newton method.

- The bridge is built upon the hope that the obvious solution will be deformed mathematically into the solution that we are seeking for.
  - $\diamond$  Will this idea always work?
  - $\diamond$  How to mathematically design an appropriate homotopy?

#### Least Squares Matrix Approximation

- The mathematical problem:
  - $\diamond$  A symmetric matrix N and a set of real values  $\{\lambda_1, \ldots, \lambda_n\}$  are given.
  - $\diamond$  Find a least squares approximation of N that has the prescribed eigenvalues.
- A standard formulation:

Minimize  $F(Q) := \frac{1}{2} ||Q^T \Lambda Q - N||^2$ Subject to  $Q^T Q = I$ 

- $\diamond$  Equality Constrained Optimization:
  - $\triangleright$  Augmented Lagrangian methods.
  - $\triangleright$  Sequential quadratic programming methods.
- $\diamond$  None of these techniques is easy.

- A continuous approach (Brockett '88, Chu & Driessel '90):
  - $\diamond$  The projection of the gradient of F can easily be calculated.
  - $\diamond$  Projected gradient flow:

$$\frac{dX}{dt} = [X, [X, N]]$$
  
$$X(0) = \Lambda$$

- $\triangleright X := Q^T \Lambda Q.$
- $\triangleright \text{Flow } X(t) \text{ moves in a descent direction to} \\ \text{reduce } ||X N||^2.$
- $\diamond$  The optimal solution X can be fully characterized by the spectral decomposition of N and is unique.
- The bridge between a starting point and the optimal point is built on the basis of systematically reducing the difference between the current position and the target position.

- QR flow for normal matrices (Chu '84).
- Generalized Toda flow (Chu '84, Watkins '84).
- QZ flow (Chu '86).
- Continuous Rayleigh quotient flow (Chu '86).
- SVD flow (Chu '86).
- Abstract QR-type flow (Chu '88).
- Scaled Toda-like flow (Chu '95).

# Projected Gradient Flows

- Brockett's double bracket flow (Brockett '88).
- Least squares approximation with spectral constraints (Chu & Driessel '90).
- Simultaneous reduction problem (Chu '91).
- Nearest normal matrix problem (Chu '91).
- Inverse eigenvalue problem for nonnegative matrices (Chu & Driessel '91).
- Inverse singular value problem (Chu '92).

- Matrix differential equations (Chu '92).
- Schur-Horn theorem (Chu '95).
- Least squares inverse eigenvalue problem (Chu & Chen '96).
- Inverse generalized eigenvalue problem (Chu & Guo '98).
- Inverse stochastic eigenvalue problem (Chu & Guo '98).