# **Numerical Methods for PDEs**

Integral Equation Methods, Lecture 3
Discretization Convergence Theory

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April 30, 2003

### **Outline**

## **Integral Equation Methods**

Reminder about Galerkin and Collocation

## Example of convergence issues in 1D

First and second kind integral equations

Develop some intuition about the difficulties

## Convergence for second kind equations

Consistency and stability issues

## **Nystrom Methods**

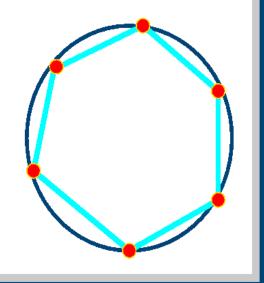
High order convergence

## **Basis Function Approach**

Basic Idea

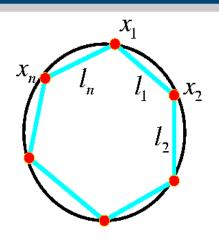
Integral equation: 
$$\Psi(x)=\int G(x,x')\sigma(x')dS'$$
  
Represent  $\sigma_n(x)=\sum_{i=1}^n\sigma_{ni}$   $\varphi_i(x)$   
 $\frac{\varphi_i(x)}{Basis\ functions}$ 

Example Basis
Represent circle with straight lines
Assume  $\sigma$  is constant along each line



# **Basis Function Approach**

Piecewise Constant Straight Sections Example



- 1) Pick a set of n Points on the surface
- 2) Define a new surface by connecting points with n lines.
- 3) Define  $\varphi_i(x) = 1$  if x is on line  $l_i$  otherwise,  $\varphi_i(x) = 0$

$$\Psi(x) = \int_{\substack{approx \\ surface}} G(x, x') \sum_{i=1}^{n} \sigma_{ni} \varphi_{i}(x') dS' = \sum_{i=1}^{n} \sigma_{ni} \int_{\substack{linel_{i} \\ i}} G(x, x') dS'$$

### How do we determine the $\sigma_{ni}$ 's?

# **Basis Function Approach**

**Residual Definition and Minimization** 

$$R(x) \equiv \Psi(x) - \int_{\substack{ ext{approx} \ ext{surface}}} G(x,x') \sum_{i=1}^n \sigma_{ni} arphi_i(x') dS'$$

We will pick the  $\sigma_{ni}$  's to make R(x) small.

General approach: Pick a set of test functions  $\phi_1, \ldots, \phi_n$ , and force R(x) to be orthogonal to the set;

$$\int \phi_i(x) R(x) dS = 0 \;\; for \; all \; i$$

# **Basis Function Approach**

Residual Minimization Using Test Functions

$$\left|\int \phi_i(x) R(x) dS = 0 \right|$$
  $\Rightarrow$ 

$$\int \phi_i(x) \Psi(x) dS - \int \int_{\substack{\text{approx} \\ \text{surface}}} \phi_i(x) G(x, x') \sum_{j=1}^n \sigma_{nj} \varphi_j(x') dS' dS = 0$$

We will generate different methods by choosing the  $\phi_1, \ldots, \phi_n$ 

Collocation:  $\phi_i(x) = \delta(x - x_{t_i})$  (point matching)

Galerkin Method :  $\phi_i(x) = \varphi_i(x)$  (basis = test)

Weighted Residual Method :  $\phi_i(x) = 1$  if  $\varphi_i(x) \neq 0$ 

(averages)

## **Basis Function Approach**

#### Collocation

Collocation:  $\phi_i(x) = \delta(x - x_{t_i})$  (point matching)

$$\int oldsymbol{\delta(x-x_{t_i})R(x)dS} = R(x_{t_i}) = 0$$

$$\sum_{j=1}^{n} \sigma_{nj} \overbrace{\int_{ ext{approx}} G(x_{t_i}, x') arphi_j(x') dS'}^{A_{i,j}} = \Psi(x_{t_i})$$
 surface

$$egin{bmatrix} A_{1,1} & \cdots & \cdots & A_{1,n} \ dash & \ddots & dash \ dash & \ddots & dash \ A_{n,1} & \cdots & \cdots & A_{n,n} \end{bmatrix} egin{bmatrix} \sigma_{n1} \ dash \ dash \ \sigma_{nn} \end{bmatrix} = egin{bmatrix} \Psi(x_{t_1}) \ dash \ dash \ dash \ \Psi(x_{t_n}) \end{bmatrix}$$

## **Basis Function Approach**

#### Galerkin

Galerkin:  $\phi_i(x) = \varphi_i(x)$  (test=basis)

$$\int \varphi_{i}(x) R(x) dS = \int \varphi_{i}(x) \Psi(x) dS - \int \int_{\text{approx surface}} \varphi_{i}(x) G(x, x') \sum_{j=1}^{n} \sigma_{nj} \varphi_{j}(x') dS' dS = 0$$

$$\int_{\text{approx surface}} \varphi_{i}(x') \Psi(x) dS' = \sum_{j=1}^{n} \sigma_{nj} \int_{\text{approx approx surface}} G(x, x') \varphi_{i}(x) \varphi_{j}(x') dS' dS$$

$$\int_{i} \varphi_{i}(x') \Psi(x) dS' = \sum_{j=1}^{n} \sigma_{nj} \int_{\text{approx surface}} G(x, x') \varphi_{i}(x) \varphi_{j}(x') dS' dS$$

$$\int_{i} \varphi_{i}(x') \Psi(x) dS' = \sum_{j=1}^{n} \sigma_{nj} \int_{\text{approx surface}} G(x, x') \varphi_{i}(x) \varphi_{j}(x') dS' dS$$

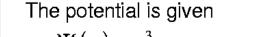
$$egin{bmatrix} A_{1,1} & \cdots & \cdots & A_{1,n} \ dash & \cdots & dash dash \ dash & \cdots & dash dash \ A_{n,1} & \cdots & \cdots & A_{n,n} \end{bmatrix} egin{bmatrix} \sigma_{n1} \ dash dash \ \sigma_{nn} \end{bmatrix} = egin{bmatrix} b_1 \ dash \ dash \ dash \ b_n \end{bmatrix}$$

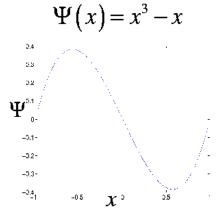
If G(x,x')=G(x',x) then  $A_{i,j}=A_{j,i}\Rightarrow \mathsf{A}$  is symmetric

## **Example Problems**

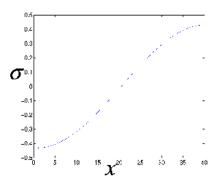
#### 1D First Kind Equation

$$\Psi(x) = \int_{-1}^{1} |x - x'| \sigma(x') dS' \quad x \in [-1, 1]$$





# The density must be computed $\sigma(x)$ is unknown



## **Example Problems**

Collocation Discretization of 1D Equation

$$\Psi(x) = \int_{-1}^{1} |x - x'| \sigma(x') dS' \quad x \in [-1, 1]$$

## **Centroid Collocated Piecewise Constant Scheme**

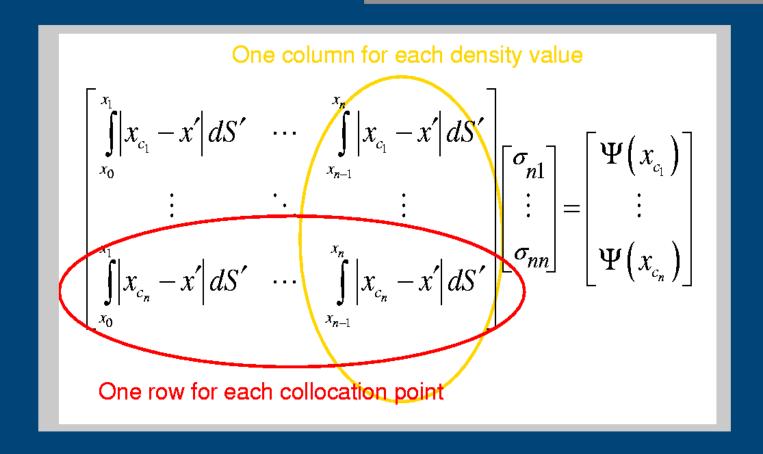
$$x_0 = -1 \qquad x_1 \qquad x_2 \qquad x_{n-1} \qquad x_n = 1$$

$$x_{n-1} \qquad x_n = 1$$

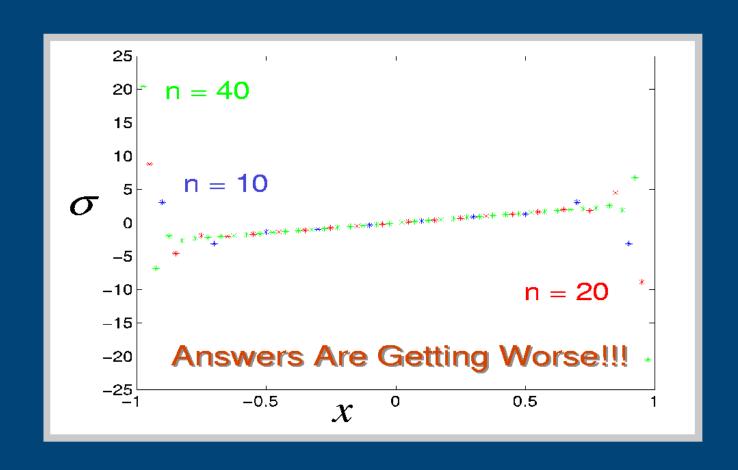
$$\Psi(x_{c_i}) = \sum_{j=1}^n \sigma_{nj} \int_{x_{j-1}}^{x_j} |x_{c_i} - x'| dS'$$

## **Example Problems**

Collocation Discretization of 1D Equation-The Matrix



## Numerical Results with Increasing n



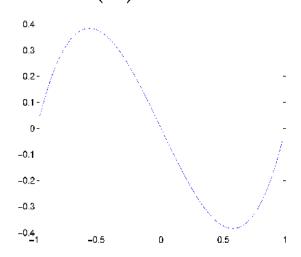
## **Example Problems**

1D Second Kind Equation

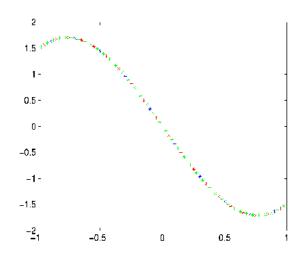
$$\Psi(x) = \sigma(x) + \int_{-1}^{1} |x - x'| \sigma(x') dS' \quad x \in [-1, 1]$$

The potential is given

$$\Psi(x) = x^3 - x$$



The density must be computed  $\sigma(x)$  is unknown



## **Example Problems**

Collocation Discretization of 1D Equation

$$\Psi(x) = \sigma(x) + \int_{-1}^{1} |x - x'| \sigma(x') dS' \quad x \in [-1, 1]$$

## **Centroid Collocated Piecewise Constant Scheme**

$$x_0 = -1 \qquad x_1 \qquad x_2 \qquad x_{n-1} \qquad x_n = 1$$

$$x_{n-1} \qquad x_n = 1$$

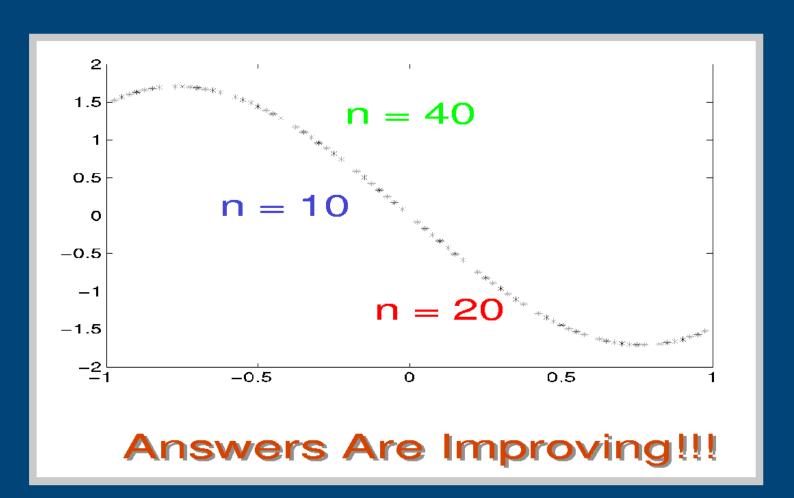
$$\Psi(x_{c_i}) = \sigma_{ni} + \sum_{j=1}^n \sigma_{nj} \int_{x_{j-1}}^{x_j} |x_{c_i} - x'| dS'$$

## **Example Problems**

Collocation Discretization of 1D Equation-The Matrix

$$\begin{bmatrix}
1+\int_{x_0}^{x_1} |x_{c_1}-x'| dS' & \cdots & \int_{x_{n-1}}^{x_n} |x_{c_1}-x'| dS' \\
\vdots & \ddots & \vdots & \vdots \\
\int_{x_0}^{x_1} |x_{c_n}-x'| dS' & \cdots & 1+\int_{x_{n-1}}^{x_n} |x_{c_n}-x'| dS'
\end{bmatrix}
\begin{bmatrix}
\sigma_{n1} \\
\vdots \\
\sigma_{nn}
\end{bmatrix} = \begin{bmatrix}
\Psi(x_{c_1}) \\
\vdots \\
\Psi(x_{c_n})
\end{bmatrix}$$

## Numerical Results with Increasing n



## **Example Problems**

1D First Kind Equation Difficulty

Denote the integral operator as K

$$K\sigma \equiv \int_{-1}^{1} |x-x'| \sigma(x') dS' \Rightarrow K\sigma = \Psi$$

The integral operator is singular : K has a null space

$$\sigma_0(x) = 0, x \neq 0, \sigma_0(0) = 1$$

$$K\sigma_0=\int_{-1}^1|x-x'|\sigma_0(x')dS'=0$$
  
If  $K\sigma^a=\Psi$   $then$   $K(\sigma^a+\sigma_0)=\Psi$ 

## **Example Problems**

1D First Kind Equation Difficulty from the Matrix

## Collocation generates a discrete form of K

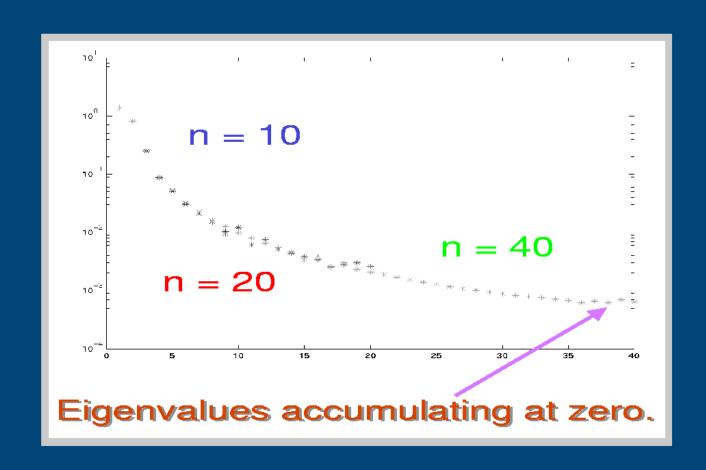
$$K\sigma = \Psi \ \ o K_n\sigma_n = \Psi_n$$

$$\begin{bmatrix}
\int_{x_{0}}^{x_{1}} |x_{c_{1}} - x'| dS' & \cdots & \int_{x_{n-1}}^{x_{n}} |x_{c_{1}} - x'| dS' \\
\vdots & \ddots & \vdots \\
\int_{x_{1}}^{x_{1}} |x_{c_{n}} - x'| dS' & \cdots & \int_{x_{n-1}}^{x_{n}} |x_{c_{n}} - x'| dS'
\end{bmatrix} \begin{bmatrix} \sigma_{n1} \\ \vdots \\ \sigma_{nn} \end{bmatrix} = \begin{bmatrix} \Psi(x_{c_{1}}) \\ \vdots \\ \Psi(x_{c_{n}}) \end{bmatrix}$$

$$\underline{K}n$$

The matrix  $\underline{K}_n$  is the not the operator  $K_n$ !

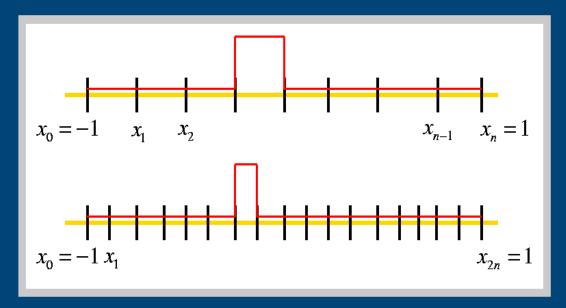
## Numerical Results with Increasing n



## **Example Problems**

**Intuition About the Eigenvalues** 

As the discretization is refined,  $\sigma_0(x)$  becomes better approximated



As the discretization is refined, K's null space can be more accurately represented.

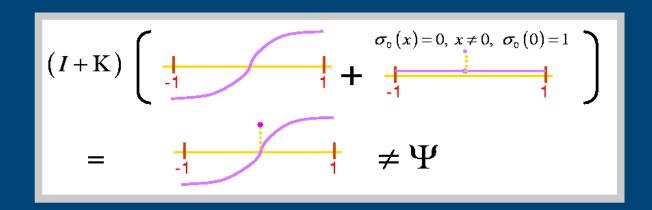
## **Example Problems**

Second kind Equation has Fewer Problems

### Second Kind equation

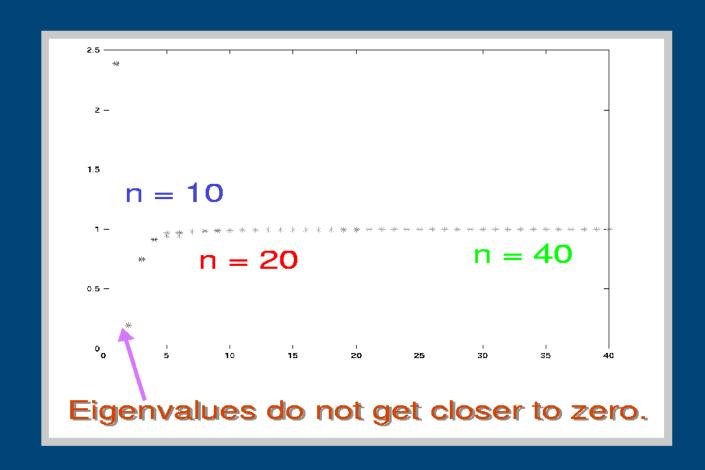
$$(I+K)\sigma \equiv \sigma(x) + \int_{-1}^{1} |x-x'|\sigma(x')dS' \Rightarrow (I+K)\sigma = \Psi$$

$$(I+K)(\sigma_0+\sigma) 
eq (I+K)\sigma$$



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## Numerical Results with Increasing n



## **Second Kind Theory**

#### **General Framework**

General Second kind integral equation

$$\Psi(x) = \sigma(x) + \int G(x, x') \sigma(x') dx' \Rightarrow \Psi = (I+K) \sigma$$

Discrete equivalent

$$\Psi_n = (I + K_n) \, \sigma_n$$

where  $\Psi_n$  and  $\sigma_n$  are functions of x.

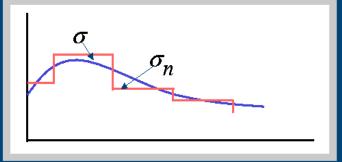
What is  $\Psi_n$  ?  $K_n$ ?

# **Second Kind Theory**

**Discrete Equivalent for Galerkin** 

Representation 
$$\sigma_n(x) = \sum_{i=1}^n \sigma_{ni} \varphi_i(x)$$
  
Projection  $\sigma_n = P\sigma$ 

$$P\sigma \equiv \sum_{i=1}^n \left( \int \sigma(x) arphi_i(x) dx 
ight) arphi_i(x)$$



Note 
$$K\sigma_n(x) = KP\sigma(x) = \sum_{i=1}^n \sigma_{ni} \int G(x,x') \varphi_i(x') dx'$$

# **Second Kind Theory**

Discrete Equivalent for Galerkin, contd..

$$egin{aligned} P(KP\sigma) &= \sum_{j=1}^n \left(\int arphi_j(x) KP\sigma(x) dx 
ight) arphi_j(x) \ &= \sum_{j=1}^n \left(\sum_{i=1}^n \sigma_{ni} \int \int arphi_j(x) G(x,x') arphi_i(x') dx dx' 
ight) arphi_j(x) \end{aligned}$$

$$(I+PKP)\sigma_n=P\Psi \ (I+K_n)\sigma_n=\Psi_n$$

## **Second Kind Theory**

#### **Main Theorem**

Given 
$$(I+K)\sigma=\Psi$$
 and  $||(I+K)^{-1}||< C$  (Equation uniquely solvable) 
$$(I+K_n)\sigma_n=\Psi_n$$
 (Discrete Equivalent )

## **Consistency:**

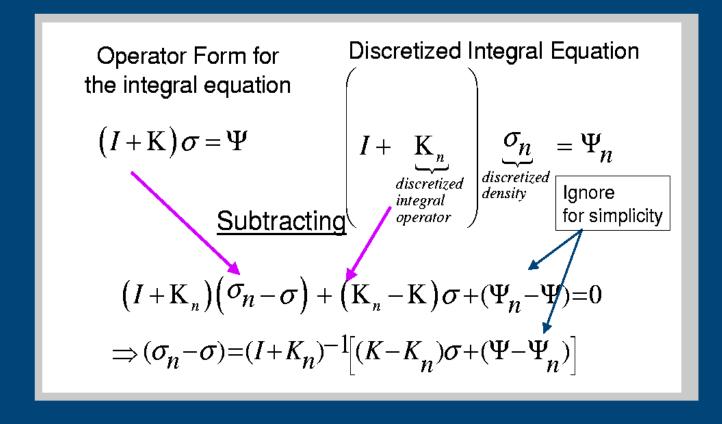
If 
$$lim_{n o\infty} max_{||\sigma_{smooth}||=1}||(K-K_n)\sigma|| o 0$$
 and  $lim_{n o\infty}||\Psi-\Psi_n|| o 0$ 

#### Then

$$lim_{n
ightarrow\infty}\left\Vert \sigma-\sigma_{n}
ight\Vert 
ightarrow0$$

## **Second Kind Theory**

#### **Rough Proof**



# **Second Kind Theory**

**Rough Proof Continued** 

The equation for the solution error (previous slide)

$$\underbrace{(\sigma_n - \sigma)}_{solution\ error} = (I + K_n)^{-1}(K - K_n)\sigma$$

Taking norms

$$\lfloor |\sigma_n - \sigma| \rfloor \le \lfloor |(I + K_n)^{-1}| \rfloor \lfloor |(K - K_n)\sigma| \rfloor$$

Error which Needs a Goes to

should go to bound, that is zero

zero as n stability by consistency

increases

# **Second Kind Theory**

**Stability Bound** 

Norm of solution error

$$||(\sigma_n-\sigma)||\leq ||(I+K_n)^{-1}||||(K-K_n)\sigma||$$

Deriving the stability bound

$$(I+K_n)^{-1} = (I+K-(K-K_n))^{-1} = (I+K)^{-1} (I-(I+K)^{-1}(K-K_n))^{-1}$$

Taking norms

$$||(I+K_n)^{-1}|| \le ||(I+K)^{-1}|| ||(I-(I+K)^{-1}(K-K_n))^{-1}||$$
  
Bounded by C  
by Assumption

# **Second Kind Theory**

**Stability Bound Contd...** 

Repeating from last slide

$$||(I + K_n)^{-1}|| \le ||(I + K)^{-1}|| ||(I - (I + K)^{-1}(K - K_n))^{-1}||$$
Bounded by C
by Assumption

Bounding terms

$$||(I+K_n)^{-1}|| \leq \frac{C}{1-||(I+K)^{-1}(K-K_n)||} \leq \frac{C}{1-\epsilon} < C \text{ for } n \geq n_0$$
Less than  $\epsilon$  for n larger
than  $n_0$  by consistency

# **Second Kind Theory**

**Rough Proof Completed** 

Final result

$$|lim_{n o \infty}||(\sigma_n - \sigma)|| \leq C |lim_{n o \infty}||(K - K_n)\sigma|| = 0$$

What does this mean?

The discretization convergence of a second kind integral equation solver depends on how well the integral is approximated.

# **Nystrom Method**

Collocation Discretization of 1D Equation

Integral Equation

$$\Psi(x) = \sigma(x) + \int_{-1}^{1} G(x, x') \sigma(x') dS' \qquad x \in [-1, 1]$$

Apply quadrature to Collocation equation

$$\Psi(x_i) = \sigma(x_i) + \int_{-1}^1 G(x_i, x') \sigma(x') dS'$$
  
 $\Rightarrow \Psi(x_i) = \sigma(x_i) + \sum_{j=1}^n w_j G(x_i, x_j) \sigma(x_j)$   
 $x_i$  is a collocation point  
 $x_j$ 's are quadrature points

Now set quadrature points = collocation points

# **Nystrom Method**

Collocation Discretization of 1D Equation, Contd...

## Set quadrature points = collocation points

$$\Psi(x_1) = \sigma_{n1} + \sum_{j=1}^n w_j G(x_1,x_j) \sigma_{nj}$$

$$\Psi(x_n) = \sigma_{n1} + \sum_{j=1}^n w_j G(x_n, x_j) \sigma_{nj}$$

System of *n* equations in *n* unknowns

Collocation equation per quad/colloc point

Unknown density per quad/colloc point

# **Nystrom Method**

1D Discretization-Matrix Comparison

## **Nystrom Matrix**

$$\begin{bmatrix} 1 + w_1 G(x_1, x_1) & \cdots & w_n G(x_1, x_n) \\ \vdots & \ddots & \vdots \\ w_1 G(x_n, x_1) & \cdots & 1 + w_n G(x_n, x_n) \end{bmatrix} \begin{bmatrix} \sigma_{n1} \\ \vdots \\ \sigma_{nn} \end{bmatrix} = \begin{bmatrix} \Psi(x_1) \\ \vdots \\ \Psi(x_n) \end{bmatrix}$$

### **Piecewise Constant Collocation Matrix**

$$\begin{bmatrix} 1 + \int_{x_0}^{x_1} G(x_{c_1}, x') dS' & \cdots & \int_{x_{n-1}}^{x_n} G(x_{c_1}, x') dS' \\ \vdots & \ddots & \vdots \\ \int_{x_0}^{x_1} G(x_{c_n}, x') dS' & \cdots & 1 + \int_{x_{n-1}}^{x_n} G(x_{c_n}, x') dS' \end{bmatrix} \begin{bmatrix} \sigma_{n1} \\ \vdots \\ \sigma_{nn} \end{bmatrix} = \begin{bmatrix} \Psi(x_{c_1}) \\ \vdots \\ \Psi(x_{c_n}) \end{bmatrix}$$

# **Nystrom Method**

1D Discretization-Matrix Comparison, Contd..

## **Nystrom Matrix**

Just Green's function evals - No integrals Entries each have a quadrature weight Collocation points are quadrature points High order quadrature=faster convergence?

#### **Piecewise Constant Collocation Matrix**

Integrals of Green's function over line sections Distant terms equal Green's function Collocation points are basis function centroids Low order method always

# **Nystrom Method**

 $K_n$  and  $\Psi_n$  for Nystrom Method

$$K_n \sigma = \sum_{i=1}^n \left( \sum_{j=1}^n w_j G(x_i, x_j) \sigma(x_j) \right) arphi_i(x)$$

$$\Psi_n = \sum_{i=1}^n \Psi(x_i) arphi_i(x)$$

# Nystrom Method

# 1D Second Kind Example

**Convergence Theorem** 

In the limit as  $n \to \infty$  (number of quad points  $\to \infty$ )
The discretization error =

$$max_{||\sigma||=1}||(K-K_n)\sigma|| o 0$$

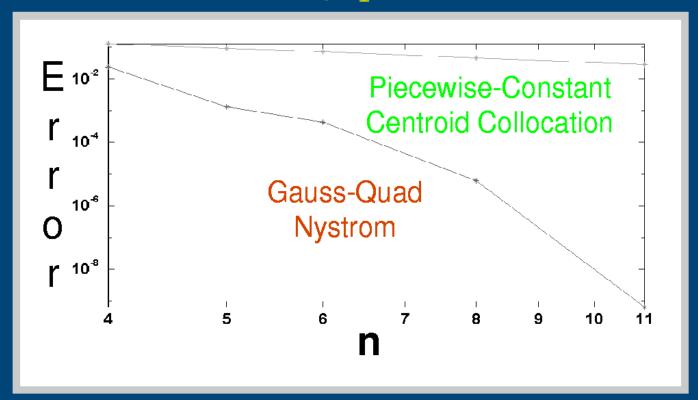
AT THE SAME RATE as the underlying quadrature!!

Gauss Quadrature → Exponential Convergence!

# **Nystrom Method**

**Convergence Comparison** 

$$cos2\pi x = \sigma(x) + \int_{-1}^{1} (x - x')^2 \sigma(x') dS'$$



# **Nystrom Method**

**Convergence Caveat** 

If Nystrom method can have exponential convergence, why use anything else?

Gaussian quadrature has exponential convergence for nonsingular kernels

Most physical problems of interest have singular kernels  $(1/r, \exp ikr/r, \text{ etc})$ 

# Summary

## **Integral Equation Methods**

Reviewed Galerkin and Collocation

## Example of Convergence Issues in 1D

1st and 2nd kind integral equations, null spaces

## Convergence for second kind equations

Show consistency and stability issues

## **Nystrom methods**

High order convergence

Did not address singular integrands