

TMA 4180 OPTIMERINGSTEORI

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THE CONJUGATE GRADIENT METHOD

- TESTS AND CONVERGENCE

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CONVERGENCE TESTS

Generatating the A matrix

```
% Define matrix
ndim = 100;
R      = randn(ndim); % Random matrix
npot  = .5           % Steers the eigenvalue
A      = (R'*R)^npot; % A matrix, >0.
lamb   = eig(A);     % Eigenvalues
kappa = max(lamb)/min(lamb) % The condition number
xsol   = rand(ndim,1); %The solution
b       = A*xsol;    % The b-vector

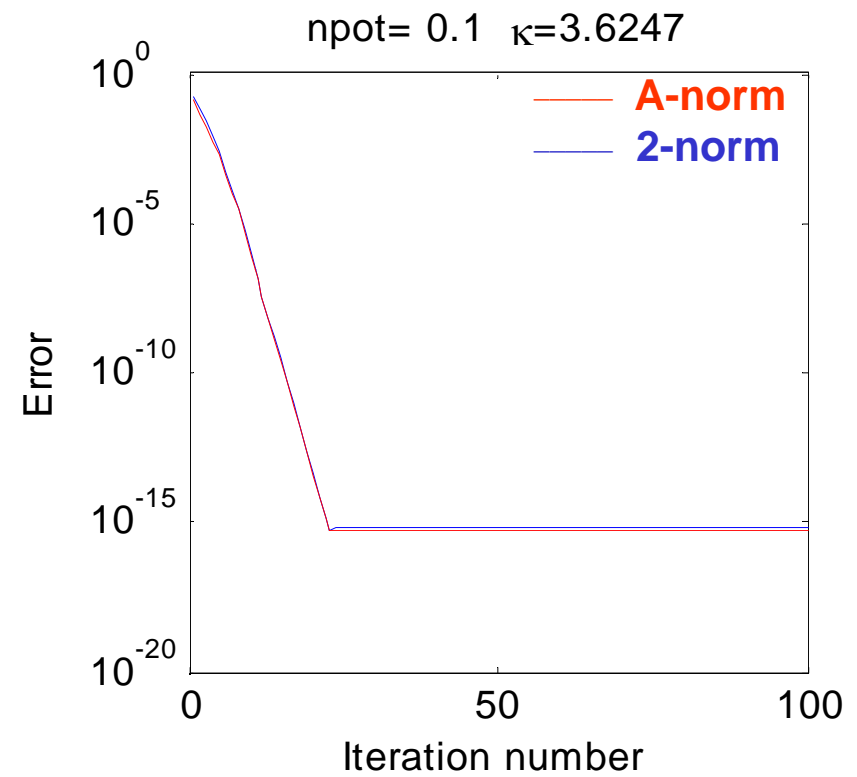
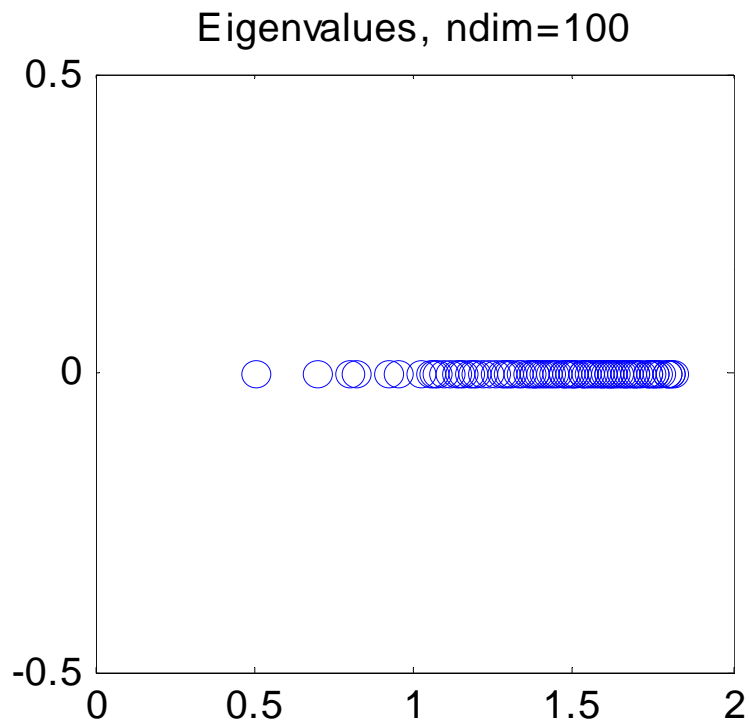
Norm2 = sqrt(xsol'*xsol);
NormA = sqrt(xsol'*A*xsol);
```

The C-G algorithm

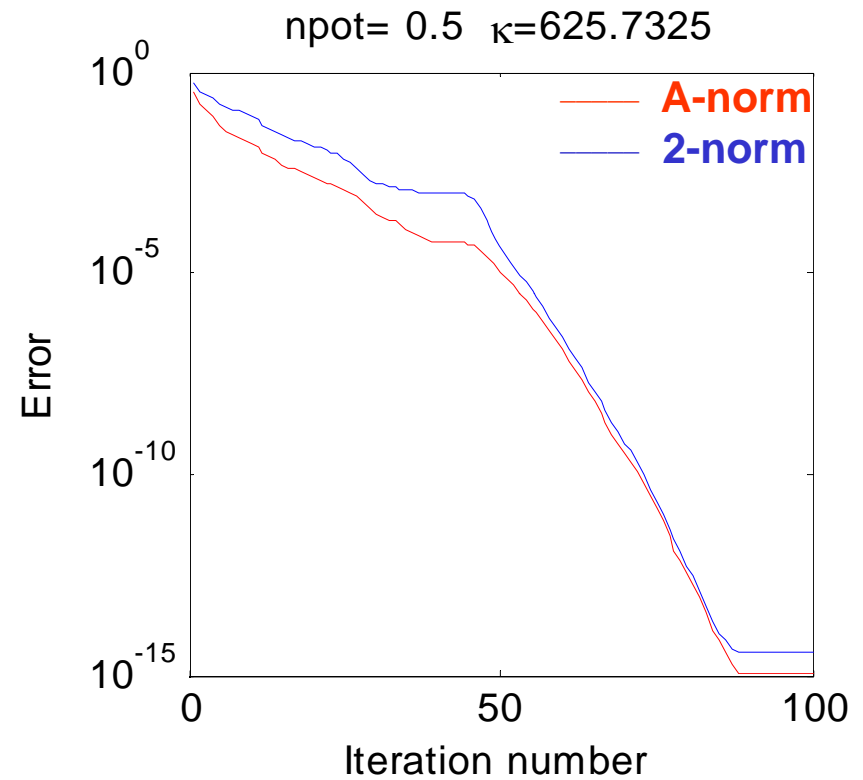
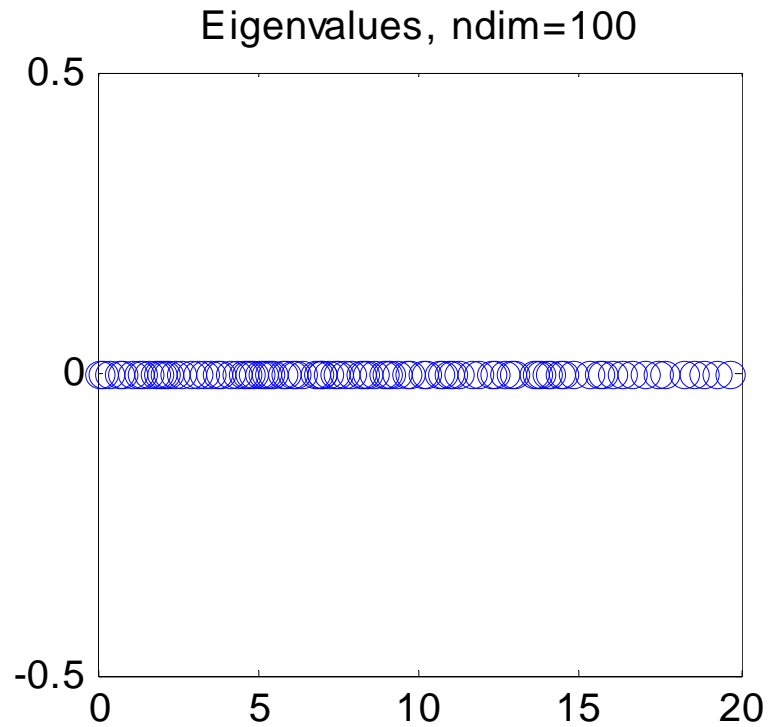
```
x = zeros(size(b));
g = -b; p = -g;
%
for loop = 1:ndim
    Ap = A*p;
    alfa = -(p'*g)./(p'*Ap);
    x = x + alfa*p;
    g = g + alfa*Ap; % g = A*x-b;
    beta = (g'*Ap)./(p'*Ap);
    p = -g + beta*p;
    err2(loop) = sqrt((x-xsol)'*(x-xsol))/Norm2;
    errA(loop) = sqrt((x-xsol)'*A*(x-xsol))/NormA;
end;
```

Note: Every iteration requires only one matrix/vector operation!

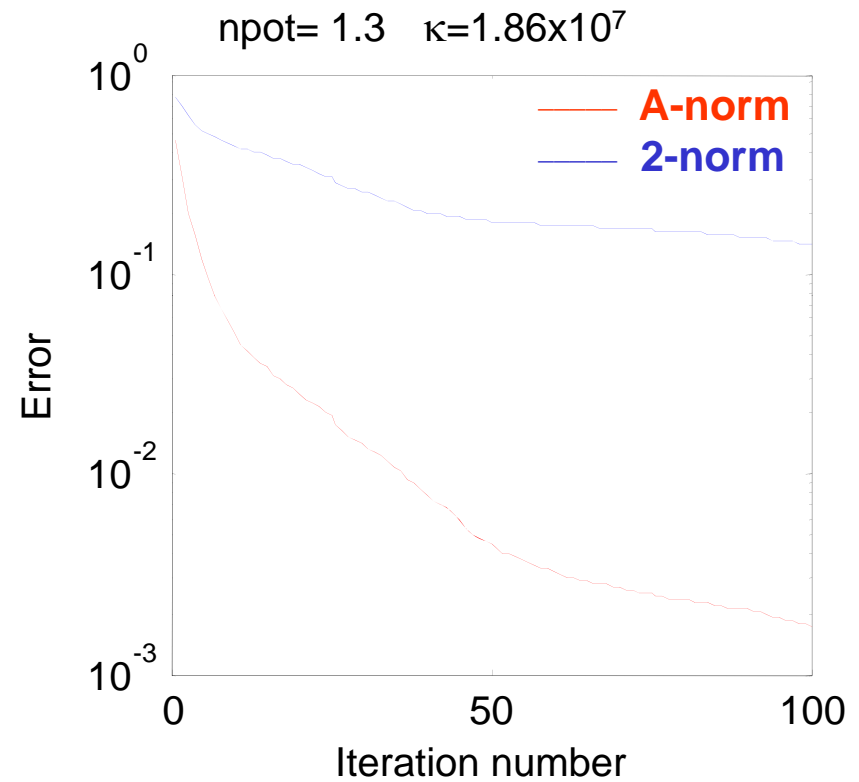
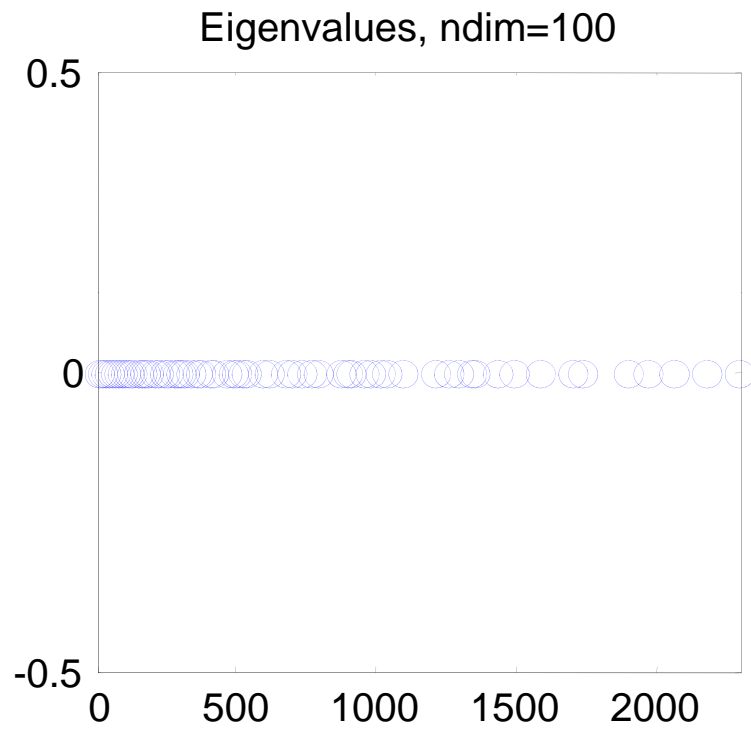
Well-conditioned matrix



Medium Conditioned Matrix



Ill-conditioned Matrix



ERROR ANALYSIS

Krylov sequence

$$x_k - x_0 \in \text{span}\{g_0, Ag_0, A^2g_0, \dots, A^{k-1}g_0\}$$

\Rightarrow

Matrix polynomial

$$x_k - x_0 = \sum_{j=0}^{k-1} \gamma_j A^j g_0 = P_k(A) g_0 = P_k(A)(Ax_0 - b)$$

&

$$x_k - x^* = (x_k - x_0) + (x_0 - x^*)$$

\Rightarrow

$$x_k - x^* = [P_k(A)A + I](x_0 - x^*) = Q_k(A)(x_0 - x^*)$$

\Rightarrow

$\{\lambda_1, \dots, \lambda_n\}$ *eigenvalues*

$$\|x_k - x^*\|_A^2 = \sum_{i=1}^n Q_k^2(\lambda_i) \lambda_i \xi_i^2, \quad \|x_0 - x^*\|_A^2 = \sum_{i=1}^n \lambda_i \xi_i^2$$

THE EXACT ERROR BOUND

$$\|x_k - x^*\|_A^2 = \sum_{j=1}^n Q^2(\lambda_j) \xi_j^2,$$

$$x_0 - x^* = \sum_{j=1}^n \xi_j e_j,$$

where, because we know that this A-norm is as small as possible:

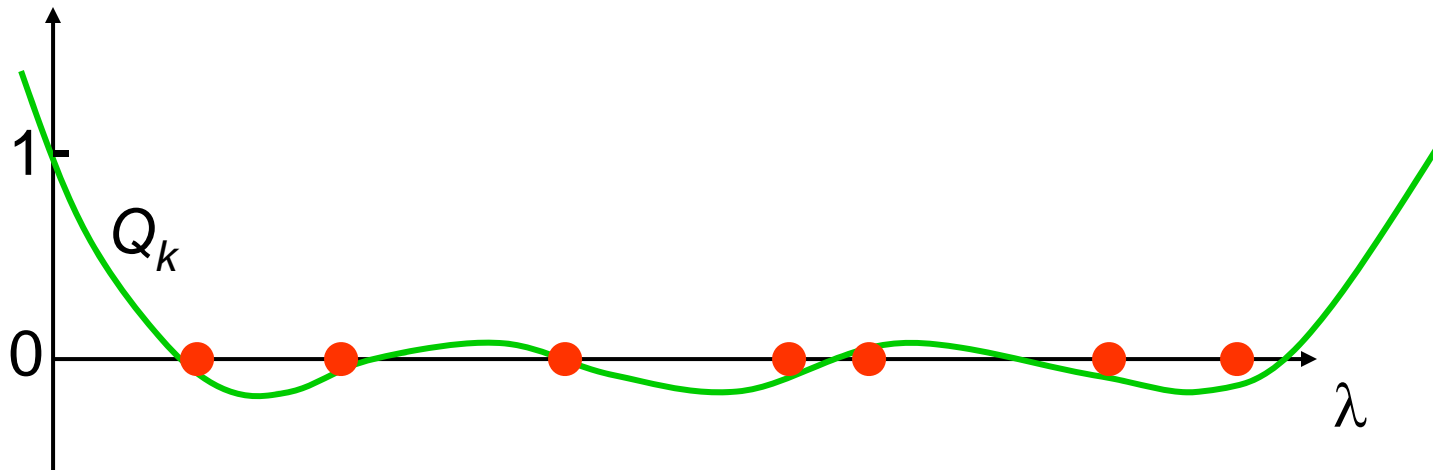
$$Q = \arg \min_{\substack{Q \text{ k-th order,} \\ Q(0)=1}} \left(\sum_{j=1}^n Q^2(\lambda_j) \xi_j^2 \right)$$

A more convenient form:

$$\frac{\|x_k - x^*\|_A}{\|x_0 - x^*\|_A} \leq \max_i |Q_k(\lambda_i)|$$

Q_k of order k

$$Q_k(0) = 1$$



● n eigenvalues (some may be equal)

For the *best universal bound* on the convergence of the CG-method (if we only know the extreme eigenvalues), we need to solve

$$Q(\lambda) = \arg \min_{\substack{Q \text{ k-th order,} \\ Q(0)=1}} \left(\max_{\lambda_1 \leq \lambda \leq \lambda_n} |Q(\lambda)| \right)$$

Solution:

$$Q(\lambda) = \frac{T_k \left(\frac{2\lambda - \lambda_1 - \lambda_n}{\lambda_n - \lambda_1} \right)}{T_k \left(\frac{\lambda_1 + \lambda_n}{\lambda_1 - \lambda_n} \right)}$$

The Chebyshev Polynomials – the flattest polynomials in the universe!

$$T_k(x) = \cos(k \arccos x)$$

$$T_0(x) = 1$$

$$T_1(x) = x$$

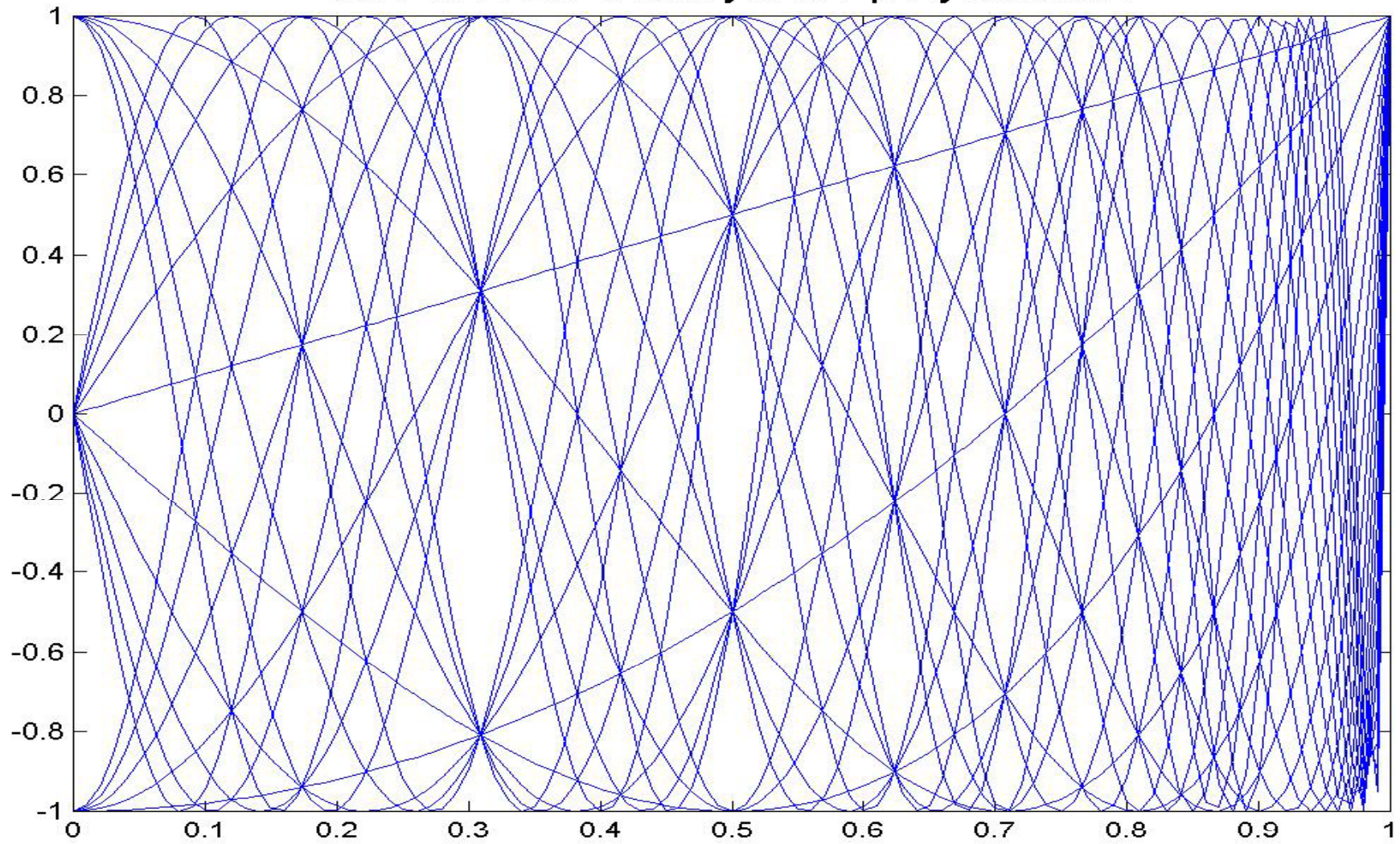
$$T_2(x) = -x + x^2$$

$$T_3(x) = -3x + 4x^3$$

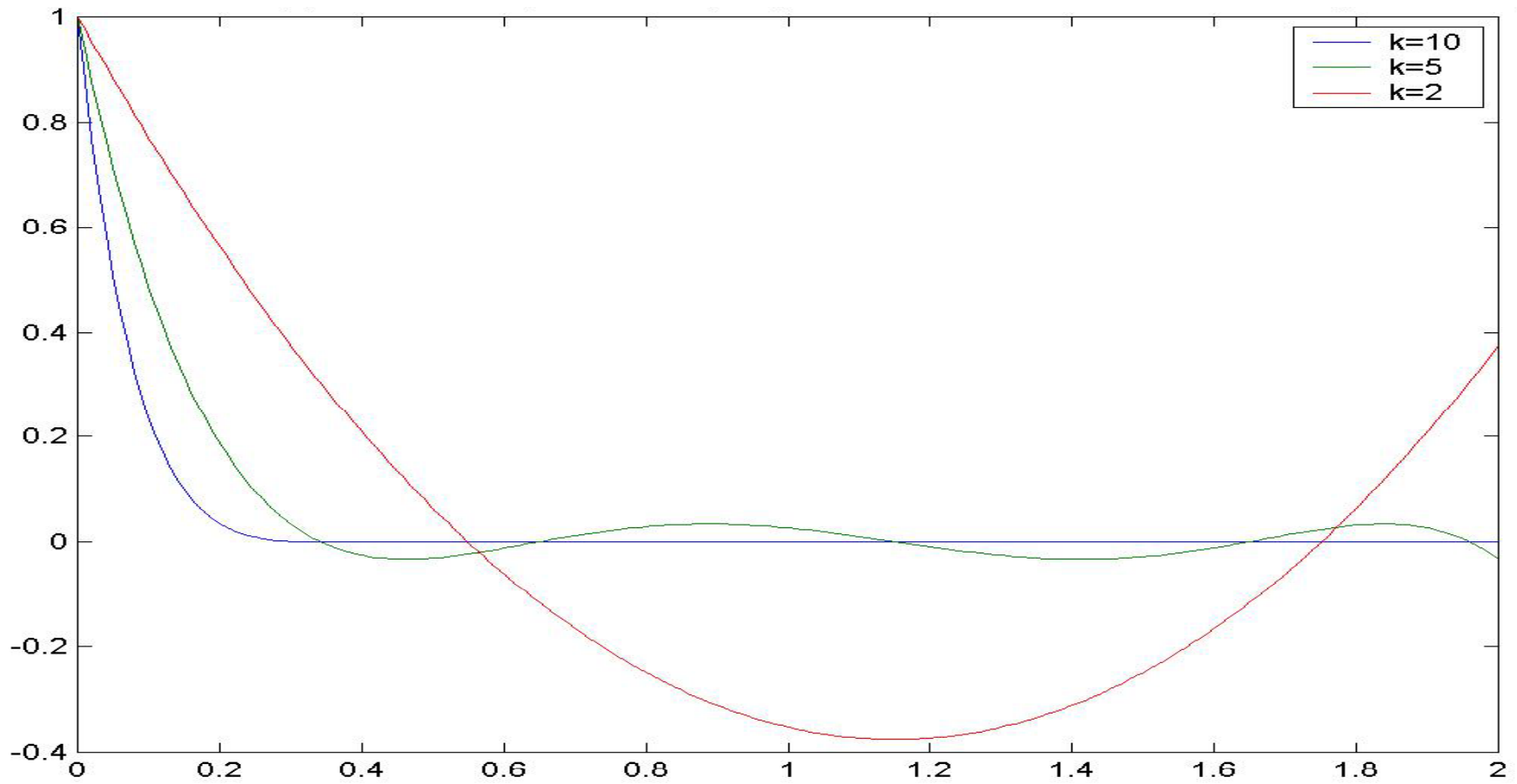
$$T_4(x) = 1 - 8x^2 + 8x^4$$

(interval [-1,1])

The first 20 Chebyshev polynomials



The optimal Ch. polynomials on the interval [0.3, 2.0]



Interval

$$\max_{\lambda_1 \leq \lambda \leq \lambda_n} |Q(\lambda)| = \left| \frac{T_k \left(\frac{2\lambda - \lambda_1 - \lambda_n}{\lambda_n - \lambda_1} \right)}{T_k \left(\frac{\lambda_1 + \lambda_n}{\lambda_1 - \lambda_n} \right)} \right| = \frac{1}{T_k \left(\frac{\kappa + 1}{\kappa - 1} \right)} \leq 2 \left(\frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^k$$

$$\|x_k - x^*\|_A \leq 2 \left(\frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^k \|x_0 - x^*\|_A$$

(more info in the note on the web)