An Algorithm for the Generalized Symmetric Tridiagonal Eigenvalue Problem

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Generalized Eigenvalue Problem

Def

$T, S \in \mathbb{R}^{n\times n}$. We call (T, S) *pencil*.

We consider *only* $\boxed{\begin{array}{l}\text{symmetric}\\ \text{and}\\ \text{tridiagonal}\end{array}}$ pencils.

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Def (Problem)

Find $\lambda \in \mathbb{R}$ such that $Tv = \lambda S v$, with $v \in \mathbb{C}^n$.
T, S symmetric implies $\lambda \in \mathbb{R}$.

Algorithm philosophy

We find zeros of the polynomial equation

$$\mathcal{F}_{(T,S)}(\lambda) = \det(T - \lambda S) = 0$$

using an iterative method, living on real line.

Brainstorming

We want:	Fast and secure iterative method. Starting points for our method. Scalability.
We have:	Laguerre's method. Cuppen's divide and conquer method. Symmetric tridiagonal matrices.
We add:	Unreducible condition. Dynamic programming (Bottom-up). Efficient matrix storing.

Rapid tour

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Def (as in [BG84])

(T, S) is an *unreducible pencil* if $t^2_{i,i+1} + s^2_{i,i+1} \neq 0$ for $i = 1, 2, \ldots, n-1$.

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exempli gratia:

Bad

$$\boxed{\begin{array}{l} T = I, S = 0 \\ T = I, S = I \end{array}}$$

Good

$$\boxed{\begin{array}{l} T = I, S = trid(-1, 2, -1) \\ T = trid(-1, 2, -1), S = trid(-1, 2, -1) \\ T = trid(rnd_{sub}, rnd_{diag}, rnd_{sub}), S = I, \\ \text{with } rnd_{sub} \text{ random number} \neq 0. \end{array}}$$

Matrix storing

$$T = trid(sub, diag, super)$$

But T is symmetric, so $sub = super$. We define and use

```
integer, parameter :: dp = kind(1.d0)
real(dp), dimension(1:n,0:1) :: T, S
```

Listing 1: T, S as couple of array

with $T(:,0) = diag$ and $T(:,1) = super$.

Remark

We don't use T(1,1) and S(1,1).

Fast and secure iterative method

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So we have two sign changes.
Bolzano's Theorem tell us that there are two zeros of g_u between λ_m and λ_{m+1}. We call them X_-, X_+.

Fast and secure iterative method

$$\lambda_m < X_- < x < X_+ < \lambda_{m+1}$$

We have one freedom: the u parameter.
Calling $\hat{X}_- = min_u X_-$ and $\hat{X}_+ = max_u X_+$ we can obtain

$$\lambda_m \approx \hat{X}_- < x < \hat{X}_+ \approx \lambda_{m+1}$$

and with algebraic manipulations:

$$\hat{X}_-, \hat{X}_+ = L_\pm(x) = x + \frac{n}{-\frac{f'}{f} \pm \sqrt{(n-1)[(n-1)(-\frac{f'}{f}) - n\frac{f''}{f}]}}$$

with $\frac{f'}{f} = \frac{(\mathcal{F}_{T,S}(\lambda))'}{\mathcal{F}_{T,S}(\lambda)}$.

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We will see that "only" with the symmetric tridiagonal condition we can have derivatives of determinats.

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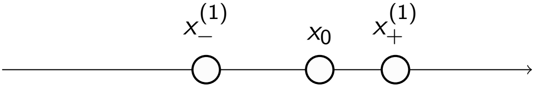

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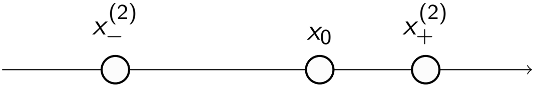

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Fast and secure iterative method

Def (Laguerre's iteration)

If $mlt(\lambda_m) = mlt(\lambda_{m+1}) = 1$ then

$$x_+^{(k)} = L_+^k(x) = L_+(L_+(\dots(x_0)))$$
$$x_-^{(k)} = L_-^k(x) = L_-(L_-(\dots(x_0)))$$

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So Laguerre's method is secure.

Fast and secure iterative method

We also have un important property:

Teo

*If we choose** $\lambda_m < x_0$ *s.t.* $sign\left(\frac{f'(x_0)}{f(x_0)}\right) = sign(\lambda_m - x_0)$ *then* $\{x_-^{(k)}\}_{k=1,\ldots}$ *converges monotonically in asymptotically cubic rate to* λ_m.

*for $x_0 < \lambda_{m+1}$ s.t. $sign\left(\frac{f'(x_0)}{f(x_0)}\right) = sign(\lambda_m - x_0)$ we have $\{x_+^{(k)}\}_{k=1,\ldots}$ conv. mon. cubic to λ_{m+1}

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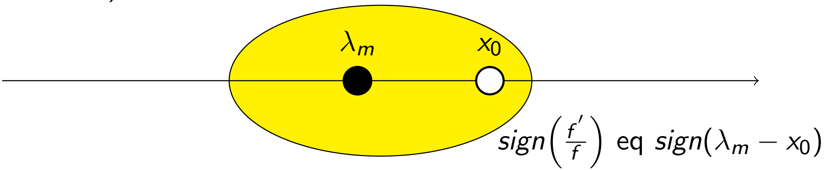

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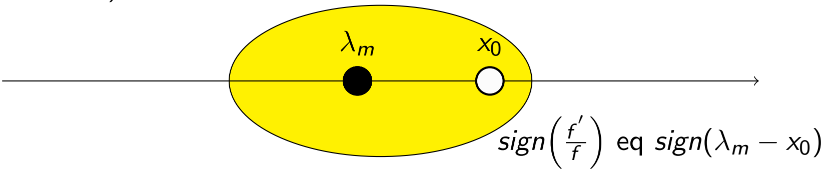

The Laguerre's method is fast.

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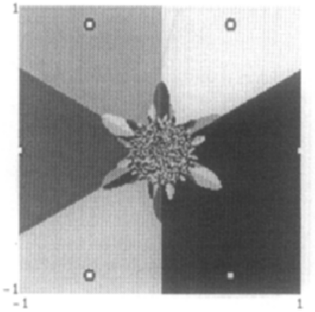
Fast and secure iterative method

It's clear that we need a powerfull method to obtain x_0 and an algorithm to estimate $mlt(\lambda_m)$.
Overstimate $mlt(\lambda_m)$ (as we can read in [LZ94]) causes no trouble, so the most important aspects of our calculation are:

- Good x_0.
- Good evaluation of $L_\pm(x)$.

Complex case (little digression)

According to [Dra03], we observe that with Laguerre's method searching $z \in \mathbb{C}$ such that $z^n - 1 = 0$ for $n > 4$ it's difficult because near the origin there is a Julia fractal set for starting point z_0. (figure: $n = 6$)



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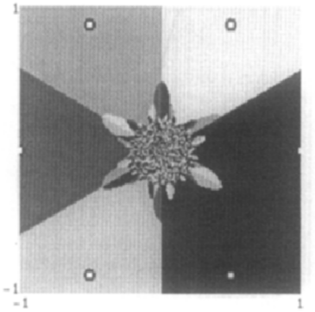

So if we want to solve the Generalized Eigenvalues Problem with $T, S \in \mathbb{C}$ we have great problems to place the starting point if $n > 4$.

Three-term recurrence

For a generic $x \in \mathbb{R}$ we call $\rho_n(x) = \det(T_n - xS_n)$, and $\rho_{n-1}(x) = \det(T_{n-1} - xS_{n-1})$, with T_{n-1} leading principal submatrix.
We have

$$\begin{aligned} \rho_0 &:= 1\,,\ \rho_1 := t_{1,1} - xs_{1,1} \\ \rho_i &:= (t_{i,i} - xs_{i,i})\rho_{i-1} - (t_{i-1,i} - xs_{i-1,i})^2\rho_{i-2}\,,\ i = 2, 3, \ldots, n \end{aligned}$$

Three-term recurrence

We can proove it with the *Laplace expansion* (e.g. $n = 4$)

$$T_4 - xS_4 = \begin{pmatrix} a & b & 0 & 0 \\ b & c & d & 0 \\ 0 & d & e & f \\ 0 & 0 & f & g \end{pmatrix}$$

$$det\left(T_4 - \lambda S_4\right) = g \begin{bmatrix} a & b & 0 \\ b & c & d \\ 0 & d & e \end{bmatrix} - f \begin{bmatrix} a & b & 0 \\ b & c & d \\ 0 & 0 & f \end{bmatrix}$$

$$= g \begin{bmatrix} a & b & 0 \\ b & c & d \\ 0 & d & e \end{bmatrix} - f^2 \begin{bmatrix} a & b \\ b & c \end{bmatrix}$$

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Three-term recurrence

Remark

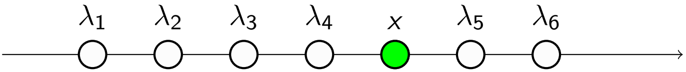
If $x = \lambda$ then $\rho_n(\lambda) = \mathcal{F}_{(T_n, S_n)}(\lambda) = f(\lambda)$

Remark (important results **in Appendix)**

$\rho_0, \rho_1, \dots, \rho_n$ is a *Sturm sequence* of polynomials so, $\forall x \in \mathbb{R}$, we have

$$\kappa(x) := \# \text{ eigenvalues less then } x$$

$$\kappa(x) = \# \text{ consecutive sign changes in } \{\rho_i\}_{i=0,\dots,n}$$



$\kappa(x)$ is 4

Three-term recurrence

Obviusly $f^{'} = \rho_n^{'}, f^{''} = \rho_n^{''}$.

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We have cubic convergence in Laguerre's method with x_0 as starting point.

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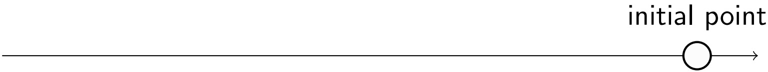
Example



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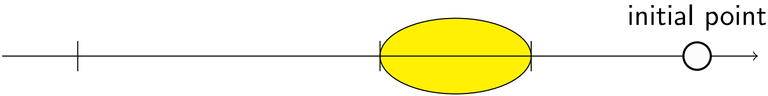
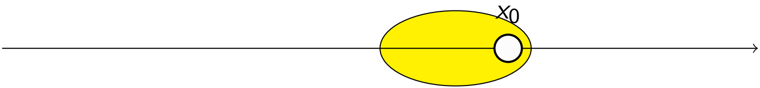


with bisection we can find the neighbourhood of λ_m

Example

we can now use the Laguerre's iteration



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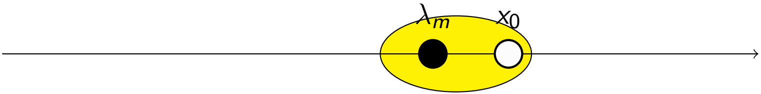

What we really calculate is...

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We also define $\eta_i = \frac{\rho_i^{'}}{\rho_i}, \zeta_i = \frac{\rho_i^{''}}{\rho_i}$ for $i = 0, 1, \ldots, n$ and finally we have

$$\kappa(x) = \text{ number of negative terms in } \{\xi_i\}_{i=1}^{n}$$

$$-\frac{f^{'}(x)}{f(x)} = \eta_n$$

$$\frac{f^{''}(x)}{f(x)} = \zeta_n$$

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So we have to calculate three three-term recurrences.
* Total $\leq 2 + 38n$ multiplications.
For every step in Laguerre's iteration we have to do $2 + 7 + 38n$ (at most) multiplications and 1 square root extraction. Because the convergence is cubic we hope in a small number of iteration.

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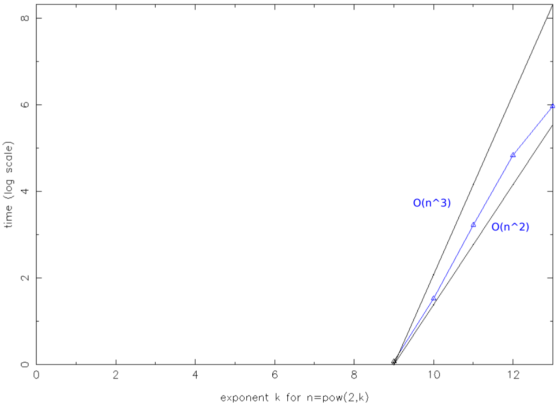
Complexity

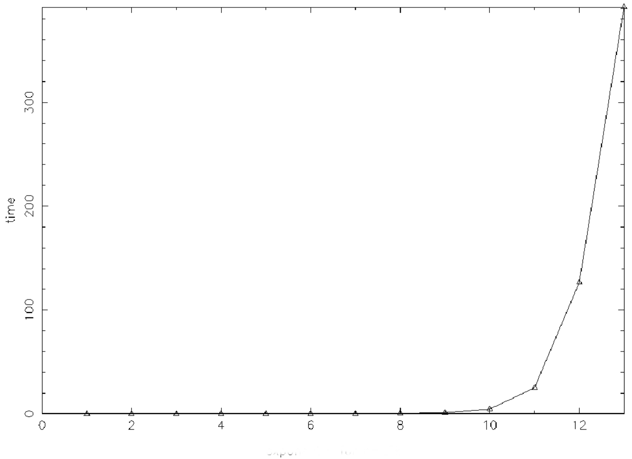
*Author's prevision: $O(n^2)$.
With (I, S) and eigenvalues between 0.5 and 1.5 we have



*They use $n < 100$,
my experiment ends up with $n = 2^{13} = 8192$.

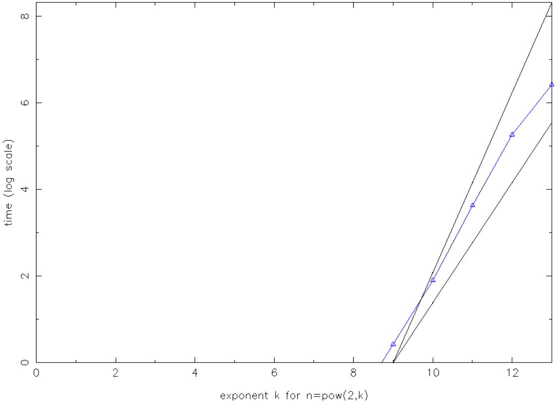
Complexity

And in linear scale:



Complexity

With $T = (a_i, 1, a_i), S = (b_i, c_i, b_i)$ and a_i, b_i random numbers such that $|a_i| \leq 10^{-3}, |b_i| \leq 10^{-1}, c_i = i10^{-1} + |2b_i|$ we have



We can appreciate little differences between $T = (0, 1, 0)$ and $T = (a_i, 1, a_i)$

Error Analysis

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Teo

$$fl[f(x)] = fl[det[T - xS]] = (1+\gamma)det[(T+\delta T) - x(S+\delta S)]$$

where $|\gamma| \leq n\epsilon$, *with* ϵ *machine precision, and both* δT *and* δS *are symmetric tridiagonal matrices satisfying entrywise inequalities* $|\delta T|_\infty \leq 2.51\epsilon|T|_\infty + \sqrt{\epsilon_u}$, $|\delta S|_\infty \leq 3.51\epsilon|S|_\infty$, *where* ϵ_u *is the underflow threshold (in double precision is* 10^{-308}*).*

Error Analysis

We are interested not only in $\mathrm{fl}[f(x)] = \mathrm{fl}\Big[\prod_{i=1}^{n} \mathrm{fl}[\xi_i]\Big]$, but also in $\mathrm{fl}[\eta_n]$ and $\mathrm{fl}[\zeta_n]$, because we use these three value to calculate the Laguerre's iteration.

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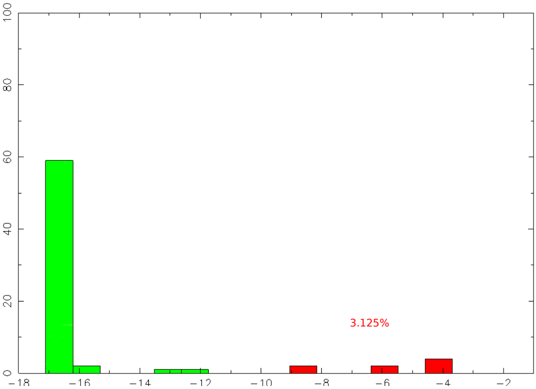
The authors don't report this important aspect of analysis.
($\mathrm{fl}[\eta_n], \mathrm{fl}[\zeta_n]$ suffer from similar problems and have similar backward analysis, but they are -in partucular ζ_n- enourmous in magnitude; sometimes this can cause troubles)

Exponent of absolute error ($n = 256$)

With (I, S) and eigenvalue between 0.5 and 1.5 we have



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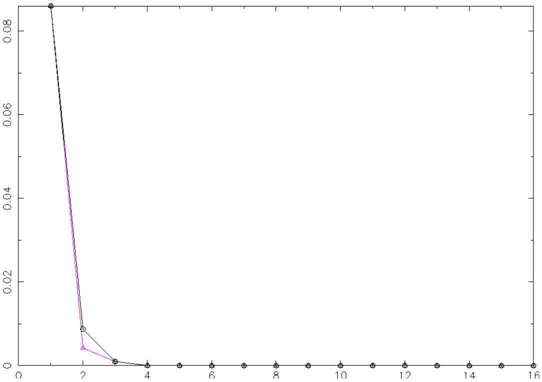
Sometimes, when $|\lambda_j - x_0| \leq 10^{-4}$ and (T, S) have small elements, we can have troubles.
If we compare $\kappa(x_i)$ and the same number obtained with *inertia* for $|\lambda_j - x_i| \leq 10^{-i}$ and $i = 1, \ldots, 16$ we have

Where is the problem?

$n = 256$, $\dim = 64$ and pencil$=(T(193 : 4\dim), S(193 : 4\dim))$



For $i = 1, \ldots, 16$, absolute errors between λ_{32} and x_i with κ, absolute errors between λ_{32} and x_i with *inertia*.

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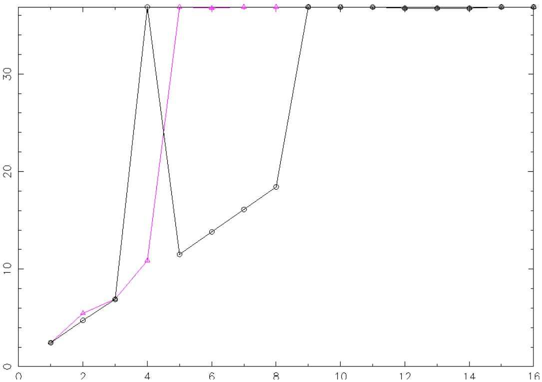
$n = 256$, dim $= 64$ and pencil$=(T(193 : 4\text{dim}), S(193 : 4\text{dim}))$



For $i = 1, \ldots, 16$, absolute errors between λ_{32} and x_i with κ,
absolute errors between λ_{32} and x_i with *inertia*.
I use a different scale: $log(\frac{1}{|error|})$

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When x_0 for Laguerre's iteration is into our good neighbourhood but $10^{-9} \leq |x_0 - \lambda_m| \leq 10^{-1}$, we can have troubles...

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When x_0 for Laguerre's iteration is into our good neighbourhood but $10^{-9} \leq |x_0 - \lambda_m| \leq 10^{-1}$, we can have troubles...
Starting points are the most important aspect of our calculation.

Searching initial points

We want:	Fast and secure iterative method. Starting points for our method. Scalability.
We have:	Laguerre's method. Cuppen's divide and conquer method. Symmetric tridiagonal matrices.
We add:	Unreducible condition. Dynamic programming (Bottom-up). Efficient matrix storing.

Ideas:

If $n = 1$ we have $t \cdot v = \lambda \cdot s \cdot v$ with $s \neq 0$, so $\lambda = \frac{t}{s}$.

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calling*

$$S^{-1}T = \delta^{-1} \cdot \begin{pmatrix} \alpha & \gamma \\ \gamma & \beta \end{pmatrix}$$

we resolve $det[S^{-1}T - \lambda I] = 0$ with

$$\lambda_{1,2} = \frac{1}{2\delta}\left(\alpha + \beta \pm \sqrt{\alpha^2 + \beta^2 + \gamma^2 - \alpha\beta}\right)$$

$^*\alpha = s_{2,2}t_{1,1} - s_{1,2}t_{1,2}, \beta = -s_{1,2}t_{1,2} + s_{1,1}t_{2,2}$
$\gamma = -s_{1,2}t_{1,2} + s_{1,1}t_{1,2}, \delta = s_{1,1}s_{2,2} - s_{1,2}^2$.

Ideas:

And if $n = 4$?

$$\begin{pmatrix} t_{1,1} & t_{1,2} & 0 & 0 \\ t_{2,1} & t_{2,2} & t_{2,3} & 0 \\ 0 & t_{3,2} & t_{3,3} & t_{3,4} \\ 0 & 0 & t_{4,3} & t_{4,4} \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{pmatrix} = \lambda \begin{pmatrix} s_{1,1} & s_{1,2} & 0 & 0 \\ s_{2,1} & s_{2,2} & s_{2,3} & 0 \\ 0 & s_{3,2} & s_{3,3} & s_{3,4} \\ 0 & 0 & s_{4,3} & s_{4,4} \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{pmatrix}$$

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We can solve the blue part and obtain μ_1, μ_2, the cyan part and obtain μ_3, μ_4.

Ideas:

From μ_j we can enter in our neighbourhood of λ_j using simple bisection:

---

*This is an important part of our method.
Authors of [BG84, LZ94] doesn't explain this point. ▸ code

Ideas:

From μ_j we can enter in our neighbourhood of λ_j using simple bisection:

Pseudocode:

set $a_j = 0$ and $b_j = \mu_j$
set $x = \mu_j$
IF $\kappa(x) < j$
THEN set $a_j = x$
ELSE set $b_j = x$
*IF $-\frac{f^{'}(x)}{f(x)} = sign(\lambda_j - x)$
THEN stop
ELSE set $x = \frac{b_j - a_j}{2}$ and go to #
set $x_0 = x$

---

*This is an important part of our method.
Authors of [BG84, LZ94] doesn't explain this point.

code

Ideas:

Hopefully we have

$$\begin{aligned}
&x_0^1, L(x_0^1), L(L(x_0^1)), \cdots \rightsquigarrow \lambda_1 \\
&x_0^2, L(x_0^2), L(L(x_0^2)), \cdots \rightsquigarrow \lambda_2 \\
&x_0^3, L(x_0^3), L(L(x_0^3)), \cdots \rightsquigarrow \lambda_3 \\
&x_0^4, L(x_0^4), L(L(x_0^4)), \cdots \rightsquigarrow \lambda_4
\end{aligned}$$

Split

Consider $(\hat{T}, \hat{S})$ with

$$\hat{T} = \begin{pmatrix} T_0 & 0 \\ 0 & T_1 \end{pmatrix}$$

$$\hat{S} = \begin{pmatrix} S_0 & 0 \\ 0 & S_1 \end{pmatrix}$$

with T_0, T_1, S_0, S_1 symmetric tridiagonal, and let be

$$\hat{\lambda}_1 \leq \hat{\lambda}_2 \leq \cdots \leq \hat{\lambda}_n$$

eigenvalues of $(\hat{T}, \hat{S})$, they are what we call $\mu_1, \ldots, \mu_n$.

Split

Teo (A sort of “interlacing” with proof)

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-\infty <& \lambda_1 \leq \hat{\lambda}_1 \\
\hat{\lambda}_{i-1} \leq& \lambda_i \leq \hat{\lambda}_{i+1} \\
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\end{aligned}
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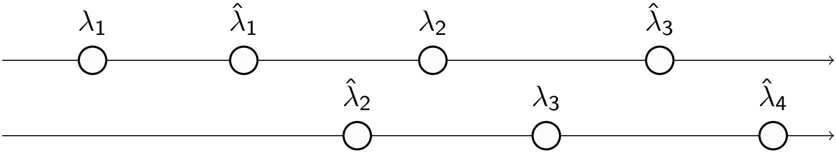
with $i = 2, 3, \dots, n-1$.

Remark

It's possible that



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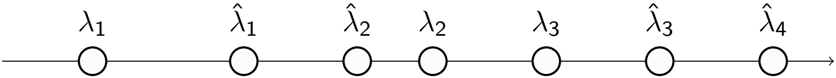

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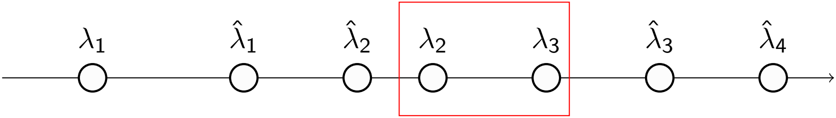

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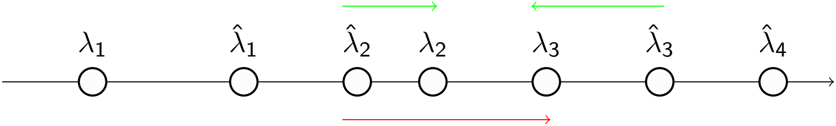
Remark

Our method is monotonic



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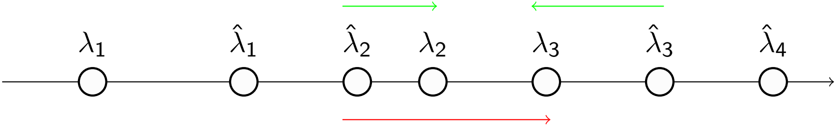

We can reach λ_2 only from $\hat{\lambda}_2$, moving from left to right (and similar λ_3 only from $\hat{\lambda}_3$, moving from right to left).

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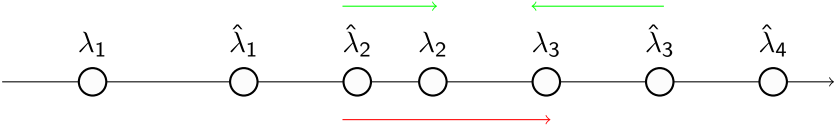

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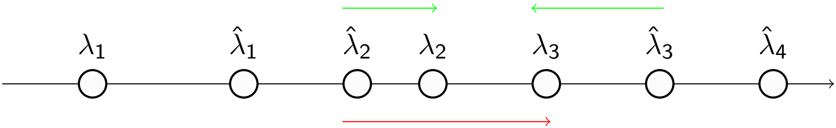

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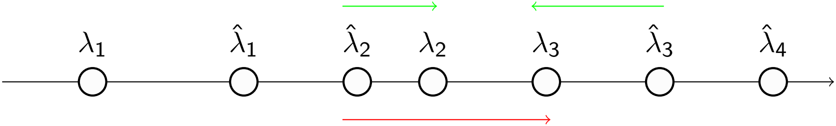

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If $mlt = 2$ then we consider $\lambda_2 = \lambda_3$, i.e. we said that λ_2 has multiplicity 2.

EstMlt

We have $j, x,$ $\operatorname{sgn}\Big(-\frac{f^{'}(x)}{f(x)}\Big)$ and $\hat{\lambda}_1, \ldots, \hat{\lambda}_n$ as *INPUT*.

Pseudocode:

```
mlt = 1
do k = 1, ...
m = j + k sgn( - f'(x)/f(x) )
if m ≤ 0 then
something goes wrong
set mlt = 1
go to #
end if
if |λ̂_j − λ̂_m| ≤ 0.01|λ̂_j − x| then
mlt = mlt + 1
else go to #
end if
end do
# stop
```

Dynamic programming

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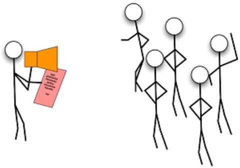
We add:	Unreducible condition. Dynamic programming (Bottom-up). Efficient matrix storing.

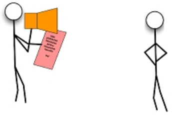
Dynamic programming

The author's point of view is parallel computating.



Dynamic programming

My point of view is sequential computating.



Dynamic programming

Instead of recurtion I chose dynamic programming, *i.e.* "solving complex problems by breaking them down into simpler subproblems. [...] In general, to solve a given problem, we need to solve different parts of the problem (subproblems), then combine the solutions of the subproblems to reach an overall solution." (cit. Wikipedia)

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If $n = 2^k$, to compute eigenvalues of (T, S) we use $(\hat{T}, \hat{S})$, that use $(\hat{\hat{T}}, \hat{\hat{S}})$, that use $(\hat{\hat{\hat{T}}}, \hat{\hat{\hat{S}}})$, $\ldots$

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There is a natural binary tree structure.

Dynamic programming

We can

- compute eigenvalues for all the pencils 2×2 (they are 2^{k-1})
- compute eigenvalues for all the pencils 4×4 (they are 2^{k-2})
- $\vdots$
- compute eigenvalues for all the pencils $\frac{n}{2} \times \frac{n}{2}$ (they are 2)
- compute eigenvalues of (T, S)

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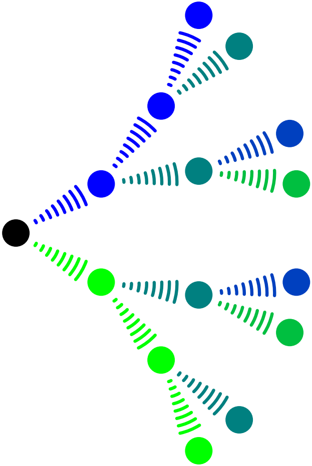
- compute eigenvalues for all the pencils $\frac{n}{2} \times \frac{n}{2}$ (they are 2)
- compute eigenvalues of (T, S)

This is a "Bottom-up approach" because we start with dimension 2 and finish with dimension n.

Dynamic programming

e.g. $n = 16$



We start from leaves (dim=2) and finish with the root (dim=16)

Dynamic programming

Code:

WHILE dim $\leq n$
DO $k = 0, \frac{n}{\text{dim}} - 1$
set $Tstart = 1 + k\text{dim}$ and $Tend = (1 + k)\text{dim}$
set $Sstart = 1 + k\text{dim}$ and $Send = (1 + k)\text{dim}$
IF dim $= 2$
THEN
explicit calculation
ELSE
search eigenvalues of
$(T(Tstart \ldots Tend, 0 \ldots 1), S(Sstart \ldots Send, 0 \ldots 1))$
knowing eigenvalues of
$(T(Tstart \ldots \frac{Tend}{2}, 0 \ldots 1), S(Sstart \ldots \frac{Send}{2}, 0 \ldots 1))$
and
$(T(\frac{Tend}{2} + 1 \ldots Tend, 0 \ldots 1), S(\frac{Send}{2} + 1, 0 \ldots 1))$
END DO

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e.g. we are interested in $[0, 10^{-16}]$ or $[10^3, 10^8]$ or we want to use *Gershgorin theorems* to isolate particolar eigenvalues.
...If also T is *definite* we can search eigenvalues in $[1, \infty]$ using our method with (S,T) and $\lambda_j = \frac{1}{\mu_j}$.

“Real world” matrices

Consider *piecewise linear finite element discretization of* the Sturm-Liouville problem

$$-\frac{d}{dx}\left(p(x)\frac{du}{dx}\right) + q(x)u = \lambda u$$

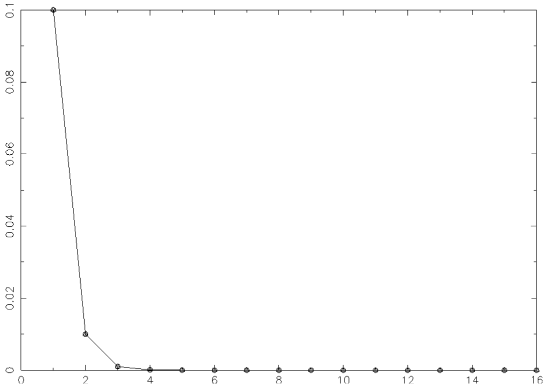
where $u = u(x), 0 < x < \pi$ and $u(0) = u^{'}(\pi) = 0$ and $p(x) = x + 1, q(x) = 1$ ($h = \frac{1}{n+1}$).
We obtain*

$$t_{k,k} = 2(n+1+i) + \frac{2}{3}\frac{1}{n+1}$$
$$t_{k,k+1} = -n - \frac{3}{2} - i + \frac{1}{6}\frac{1}{n+1}$$
$$s_{k,k} = \frac{4h}{6}$$
$$s_{k,k+1} = \frac{h}{6}$$

*authors doesn't report (T, S)

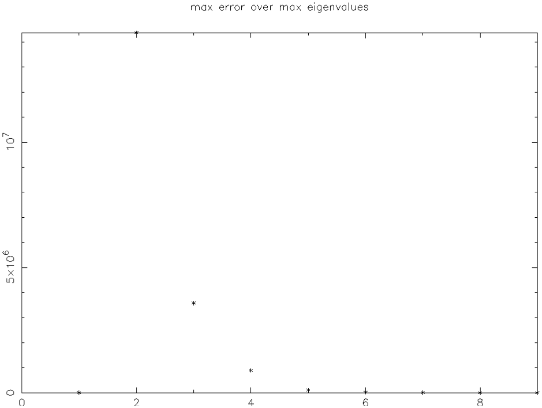
"Real world" matrices

Error analysis with $\{x_i\}_{i=1,\ldots,9}$ and $n = 256$. We consider $|\lambda_4 - x_i| \leq 10^{-i}$



“Real world” matrices

In this case we plot* the absolute module of $\frac{\text{larger error}}{\text{larger eigenvalues}}$



In this case we observe a great error: η_n, ζ_n are too small to produce a good Laguerre's iteration.

*for $n = 2^k$ with $k = 1, \ldots, 9$

Thank you.

Appendix A: proof of Laguerre's convergence

According to [Wil65, p.444] we can write

$$x_{\pm}^{(k+1)} = x_{\pm}^{(k)} - \frac{nf}{f' \pm H^{\frac{1}{2}}}$$
$$H = (n-1)^2 (f')^2 - n(n-1) f f''$$

If we choose the sign so that the $|f' \pm H^{\frac{1}{2}}|$ has the larger absolute value then we can approx $x_{\pm}^{(k+1)} - \lambda_m$ as

$$x_{\pm}^{(k+1)} - \lambda_m \approx \frac{1}{2}(x_{\pm}^{(k)} - \lambda_m)^3 \frac{(n-1)\Sigma_2' - (\Sigma_1')^2}{n-1}$$
$$\Sigma_2' = \sum_{i \neq n} \frac{1}{(\lambda_m - \lambda_i)^2}$$
$$\Sigma_1' = \sum_{i \neq n} \frac{1}{\lambda_m - \lambda_i}$$

Appendix A: proof of Laguerre's convergence

So we have convergence and $x_{\pm}^{(k+1)} - \lambda_m \approx$ number $(x_{\pm}^{(k)} - \lambda_m)^3$ tell us that the convergence is cubic.

back

Appendix B: interlacing

Def

For $\alpha \in [0,1]$ we define the pencil
$\big(T(\alpha), S(\alpha)\big) := \big((1-\alpha)\hat{T} + \alpha T, (1-\alpha)\hat{S} + \alpha S\big)$.

Lemm

$\big(T(\alpha), S(\alpha)\big)$ is a symmetric definite pencil for each $\alpha \in [0,1]$.

Calling $\lambda_1(\alpha) \leq \lambda_2(\alpha) \leq \cdots \leq \lambda_n(\alpha)$ the n real eigenvalues of the pencil $\big(T(\alpha), S(\alpha)\big)$ we have

Lemm

Each $\lambda_i(\alpha)$ is a continuous function of $\alpha \in [0,1]$.

Appendix B: interlacing

Teo (A sort of "interlacing")

$$
\begin{aligned}
-\infty < &\lambda_1 \leq \hat{\lambda}_1 \\
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Classic interlacing still works for $-\infty < \lambda_1 \leq \hat{\lambda}_1$ and for $\hat{\lambda}_n \leq \lambda_n < \infty$.

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Classic interlacing still works for $-\infty < \lambda_1 \leq \hat{\lambda}_1$ and for $\hat{\lambda}_n \leq \lambda_n < \infty$.

We have to proove that $\lambda_i \geq \hat{\lambda}_{i-1}$ (and similar $\lambda_i \leq \hat{\lambda}_{i+1}$).

Appendix B: interlacing

(Proof by contradiction) if we consider $\lambda_i < \hat{\lambda}_{i-1}$ for some $i \in \{2, 3, \ldots, n-1\}$ (that, in our new writing, is $\lambda_i(1) < \lambda_{i-1}(0)$ because all $\lambda_j(1)$ are eigenvalues of (T, S) and all $\lambda_j(0)$ are eigenvalues of $(\hat{T}, \hat{S})$) then

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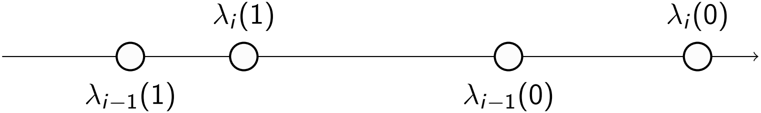

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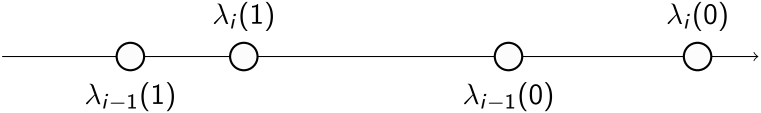

in symbols: $\lambda_{i-1}(1) \leq \lambda_i(1) < \lambda_{i-1}(0) \leq \lambda_i(0)$.

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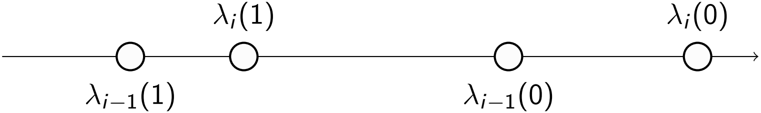
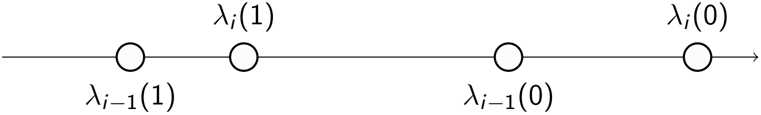
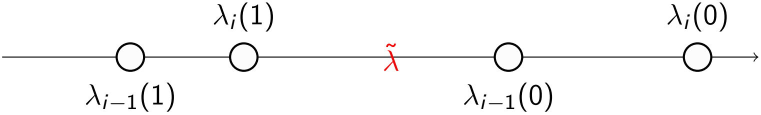


in symbols: $\lambda_{i-1}(1) \leq \lambda_i(1) < \lambda_{i-1}(0) \leq \lambda_i(0)$.
For all $\tilde{\lambda} \in [\lambda_i(1), \lambda_{i-1}(0)]$ we can find α_i, α_{i-1} such as $\tilde{\lambda} = \lambda_i(\alpha_i) = \lambda_{i-1}(\alpha_{i-1})$.

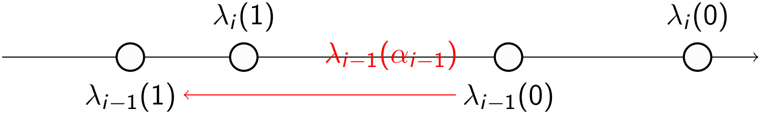
Appendix B: interlacing



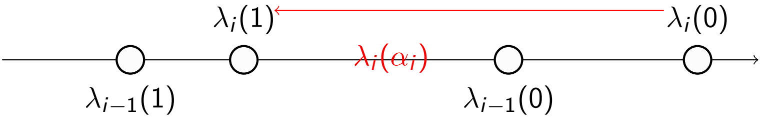
Appendix B: interlacing



Appendix B: interlacing



Appendix B: interlacing



Appendix B: interlacing

$$H(\alpha,\lambda) := det[T(\alpha) - \lambda S(\alpha)] =$$

$$\begin{bmatrix} \ddots & \ddots & & \\ \ddots & t_{k,k} - \lambda s_{k,k} & \alpha(t_{k,k+1} - s_{k,k+1}) & \\ & \alpha(t_{k,k+1} - s_{k,k+1}) & t_{k+1,k+1} - \lambda s_{k+1,k+1} & \ddots \\ & & \ddots & \ddots \end{bmatrix}$$

Appendix B: interlacing

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So

$$H(\alpha, \lambda) = p(\lambda) + \alpha^2 q(\lambda)$$

with p, q polynomials.

Appendix B: interlacing

If $q(\tilde{\lambda}) \neq 0$ then $\tilde{\alpha} = +\sqrt{H(\tilde{\alpha}, \tilde{\lambda}) - \frac{p(\tilde{\lambda})}{q(\tilde{\lambda})}} \in [0, 1]$.

only one solution in α.

Appendix B: interlacing

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But we have, for all $\tilde{\lambda}$, two solution in α, named α_i and α_{i-1}.

Appendix B: interlacing

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We have $\tilde{\lambda}$ eigenvalue of $(\hat{T}, \hat{S})$, for all $\tilde{\lambda}$ and $(\hat{T}, \hat{S})$ have exactly n eigenvalues.

Appendix B: interlacing

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Appendix C: property about Sturm sequence

According to [Wil65, p.300] we can proove by induction the following

Teo

Let the quantities $\rho_0(x), \ldots, \rho_n(x)$ be evalueted for some value of x. Then $s(x)$, the number of agreements in sign of consecutive members of yhis sequence, is the number of eigenvalues of the problems which are strictly greater than x.

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There is an equivalent way to mesure $\#$ eigenvalues befor (after) x

Teo (Sylvester's law of inertia)

T, S symmetric real matrices. For all Q such that $Q(T - xS)Q^T = D$, where D is diagonal with only entries $0, +1, -1$, the number of $0, +1, -1$ is invariant.

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Appendix D: code

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