# Relations between Rayleigh Quotient Iteration and Classical Root Finding Algorithms 

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## Outline

## Classical Root Finding

Newton's Method
The Secant Method
König's Method
The Opitz-Larkin Method
Rayleigh Quotient Iteration
John William Strutt's RQI
Inverse Iteration
Symmetric RQI
Two-Sided RQI
The Hessenberg-Matrix Point Of View

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f: \mathbb{C} \rightarrow \mathbb{C}, \quad f(z):=\frac{p(z)}{q(z)}, \quad p, q \in \mathbb{P}_{m}
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Newton's method costs two function evaluations per step, one evaluation of the function, one evaluation of its derivative.

## The secant method

If the derivative of the function $f: \mathbb{C} \rightarrow \mathbb{C}$ is not at hand, we could use the first divided difference which gives the secant method:

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In general, the secant method locally wins (Raydan, 1993).

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This family is nowadays known as "König's method":

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z_{k+1}=z_{k}+s \frac{(1 / f)^{(s-1)}\left(z_{k}\right)}{(1 / f)^{(s)}\left(z_{k}\right)}, \quad s=1,2, \ldots
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König's method for $s=1$ is Newton's method,

$$
z_{k+1}=z_{k}+\frac{(1 / f)\left(z_{k}\right)}{(1 / f)^{\prime}\left(z_{k}\right)}=z_{k}-\frac{1 / f\left(z_{k}\right)}{f^{\prime}\left(z_{k}\right) /\left(f\left(z_{k}\right)\right)^{2}}=z_{k}-\frac{f\left(z_{k}\right)}{f^{\prime}\left(z_{k}\right)} .
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Die Möglichkeit weitergehender Verallgemeinerungen wird noch untersucht Eine ausführliche Beschreibung des Verfahrens, die Darlegung der Konvergenzverhältnisse und eine Diskussion der angedeuteten Verallgemeinerungen wird an anderer Stelle veröffentlicht.

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We will refer to this method as the Opitz-Larkin method. The Opitz-Larkin method is based on iterations of the form

$$
x_{k+1}=z_{k}+\frac{\left[z_{1}, z_{2}, \ldots, z_{k-1}\right](1 / f)}{\left[z_{1}, z_{2}, \ldots, z_{k-1}, z_{k}\right](1 / f)}
$$

## The Opitz-Larkin method

Mostly, the $z_{i}$ are all distinct and the next iterate is used as new evaluation point $z_{k+1}=x_{k+1}$,

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This variant of the Opitz-Larkin method converges with R-order 2.

Frequently, the Opitz-Larkin method is used with truncation:

$$
z_{k+1}=z_{k}+\frac{\left[z_{k-p}, \ldots, z_{k-1}\right](1 / f)}{\left[z_{k-p}, \ldots, z_{k-1}, z_{k}\right](1 / f)}
$$

see (Opitz, 1958, Seite 277, Gleichung (9)) and (Larkin, 1981, Section 4, pages 98-99).

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When we use only confluent divided differences in the truncated Opitz-Larkin method with truncation parameter $p=s$, we recover König's method:

$$
\begin{aligned}
z_{k+1} & =z_{k}+\frac{[\overbrace{z_{k}, \ldots, z_{k}}^{s}](1 / f)}{[\underbrace{z_{k}, \ldots, z_{k}, z_{k}}_{s+1}](1 / f)} \\
& =z_{k}+\frac{(1 / f)^{(s-1)}\left(z_{k}\right) /(s-1)!}{(1 / f)^{(s)}\left(z_{k}\right) / s!}=z_{k}+s \frac{(1 / f)^{(s-1)}\left(z_{k}\right)}{(1 / f)^{(s)}\left(z_{k}\right)} .
\end{aligned}
$$

## The Opitz-Larkin method

Truncated Opitz-Larkin with $p=1$ is the secant method,

$$
\begin{aligned}
z_{k+1} & =z_{k}+\frac{\left[z_{k-1}\right](1 / f)}{\left[z_{k-1}, z_{k}\right](1 / f)} \\
& =z_{k}+\frac{1}{f\left(z_{k-1}\right)} \cdot \frac{z_{k-1}-z_{k}}{1 / f\left(z_{k-1}\right)-1 / f\left(z_{k}\right)} \\
& =z_{k}+\frac{f\left(z_{k}\right) f\left(z_{k-1}\right)}{f\left(z_{k-1}\right)} \cdot \frac{z_{k-1}-z_{k}}{f\left(z_{k}\right)-f\left(z_{k-1}\right)} \\
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Confluent truncated Opitz-Larkin with $p=1$ is Newton's method.

## The Opitz-Larkin method

In general, the Opitz-Larkin method is closely connected to rational interpolation of the inverse function (Larkin, 1981, Theorem 1, page 96):

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## Theorem (Larkin 1981)

If, for any integer $k>1$, there exists a rational function of the form

$$
r_{k}(z)=\frac{q_{d}(z)}{z-\alpha}, \quad \forall z
$$

where $q_{d}$ is a polynomial of degree $d \leqslant k-2$, such that $q_{d}(\alpha) \neq 0$ and

$$
r_{k}\left(z_{j}\right)=f\left(z_{j}\right)^{-1}, \quad j=1,2, \ldots, k
$$

then

$$
z_{k}+\frac{\left[z_{1}, z_{2}, \ldots, z_{k-1}\right](1 / f)}{\left[z_{1}, z_{2}, \ldots, z_{k-1}, z_{k}\right](1 / f)}=\alpha .
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Most important are the articles (Tornheim, 1964) and (Jarratt and Nudds, 1965). We state the main results contained in these articles.

## The Opitz-Larkin method

In the paper (Tornheim, 1964), Tornheim considered the case of direct

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f^{\left(\ell_{j}\right)}\left(x_{i-j}\right)=\left(\frac{p}{q}\right)^{\left(\ell_{j}\right)}\left(x_{i-j}\right)
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and inverse rational interpolation

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where

$$
\ell_{j}=0,1, \ldots m_{j}-1, \quad m=\sum_{j=0}^{k} m_{j}=\operatorname{deg}(p)+\operatorname{deg}(q)+1,
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and $k$ given distinct points $\quad x_{i-j} j=1, \ldots, k$,

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and $k$ given distinct points $\quad x_{i-j} \quad j=1, \ldots, k$, and gave its rate of convergence (Tornheim, 1964, Theorem 2).

## The Opitz-Larkin method

## Theorem (Tornheim 1964; conditions for the theorem)

Suppose an k-point iterative method is defined by the procedure to solve the equation $f(x)=0$ by direct or inverse rational interpolation with $m_{j}$ coincident interpolating points at $x_{i-j}(j=1, \ldots, k)$ for the $i$-th iteration.

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$$
\mathbf{M}=\left|\begin{array}{cccc}
a_{d} & a_{d-1} & \cdots & a_{2 d+2-m} \\
a_{d+1} & a_{d} & \cdots & \\
\vdots & \vdots & & \vdots \\
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Here $d$ is the degree of the numerator and $e$ is the degree of the denominator of the rational function used; $d+e+1=m ; a_{i}$ is 0 if $i<0$, otherwise it is the ith derivative of $f(x)$ (for direct interpolation) or of its inverse function (for inverse interpolation) at $x=x^{\star}$.

## The Opitz-Larkin method

## Theorem (Tornheim 1964; result of the theorem)

Then there is a neighborhood $N^{\star}$ of $x^{\star}$ such that if $x_{1}, \ldots, x_{k}$ are in $N^{\star}$, the sequence $\left\{x_{i}\right\}$ converges to $x^{\star}$.

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In the context of the Opitz-Larkin method, we have to consider the limit of the positive root for $k \rightarrow \infty$.

He also gave a "comparison result" that predicts faster convergence when the (inverse) function is evaluated to higher order at the last iterates.

## The Opitz-Larkin method

## Lemma (Tornheim 1964)

Suppose that the coefficients of

$$
a(x):=x^{n}-a_{1} x^{n-1}-\cdots-a_{n}
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$$

By Descartes' rule of signs the polynomial a has a unique positive root $u>1$. If the coefficients $b_{i}$ of

$$
b(x):=x^{n}-b_{1} x^{n-1}-\cdots-b_{n}
$$

are a permutation of the coefficients $a_{i}$, then the positive root $v$ of $b$ is less than u.

## The Opitz-Larkin method

In the paper (Jarratt and Nudds, 1965), Jarratt and Nudds give a detailed treatment of the case of rational interpolation with

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r(z)=\frac{z-\alpha}{q_{k-2}(z)}, \quad q_{k-2} \in \mathbb{P}_{k-2}
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Larkin proves in (Larkin, 1981) that the Opitz-Larkin method is just a stable and cheap way to compute this rational interpolation.

## The Opitz-Larkin method

In the paper (Jarratt and Nudds, 1965), Jarratt and Nudds give a detailed treatment of the case of rational interpolation with

$$
r(z)=\frac{z-\alpha}{q_{k-2}(z)}, \quad q_{k-2} \in \mathbb{P}_{k-2}
$$

Larkin proves in (Larkin, 1981) that the Opitz-Larkin method is just a stable and cheap way to compute this rational interpolation.

As you might already have guessed: We are going to prove that RQI is the Opitz-Larkin method. One instance of RQI actually is the Opitz-Larkin method applied to the characteristic polynomial of the given matrix.

## Outline

## Classical 0 et Figilin Newton's Method

The Secant Method
König's Method
The Opitz-Larkin Method

## Rayleigh Quotient Iteration

John William Strutt's RQI Inverse Iteration

Symmetric RQI
Two-Sided RQI
The Hessenberg-Matrix Point Of Viewo

## Original RQI

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The stationary property of the roots of Lagrange's determinant (3) § 84, suggests a general method of approximating to their values. Beginning with assumed rough approximations to the ratios $A_{1}: A_{2}: A_{3} \ldots \ldots$ we may calculate a first approximation to $p^{2}$ from

$$
\begin{equation*}
p^{2}=\frac{\frac{1}{2} c_{11} A_{1}{ }^{2}+\frac{1}{2} c_{22} A_{2}{ }^{2}+\ldots+c_{12} A_{1} A_{2}+\ldots}{\frac{1}{2} a_{11} A_{1}{ }^{2}+\frac{1}{2} a_{22} A_{2}{ }^{2}+\ldots+a_{19} A_{1} A_{2}+\ldots} \tag{3}
\end{equation*}
$$

With this value of $p^{2}$ we may recalculate the ratios $A_{1}: A_{2} \ldots$ from any ( $m-1$ ) of equations ( 5 ) $\S 84$, then again by application of (3) determine an improved value of $p^{2}$, and so on.]

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In modern notation, stated for the Hermitean algebraic eigenvalue problem

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\mathbf{A v}=\mathbf{v} \lambda, \quad \mathbf{A}=\mathbf{A}^{\mathrm{H}},
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Lord Rayleigh starts with an approximate eigenvector $\mathbf{v}_{k}$, computes its Rayleigh quotient

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and uses the linear system

$$
\left(\mathbf{A}-\rho\left(\mathbf{v}_{k}\right) \mathbf{I}_{n}\right) \mathbf{v}_{k+1}=\mathbf{e}_{j}
$$

for some standard unit vector $\mathbf{e}_{j}$ to compute a new approximate eigenvector $\mathbf{v}_{k+1}$. He was, of course, only interested in its direction.

## Original RQI

This is repeated several times, i.e.,

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\mathbf{v}_{k+1}=\left(\mathbf{A}-\rho\left(\mathbf{v}_{k}\right) \mathbf{I}_{n}\right)^{-1} \mathbf{e}_{j}, \quad k=0,1, \ldots
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Classical RQI can thus be stated in modern notation as

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for some suitably chosen $j \in\{1,2, \ldots, n\}$, which might vary, depending on the computed approximate eigenvector.

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for some suitably chosen $j \in\{1,2, \ldots, n\}$, which might vary, depending on the computed approximate eigenvector.
Classical Rayleigh quotient iteration mostly converges locally with quadratic order of convergence.

## Inverse Iteration

Closely connected to RQI is inverse iteration. Inverse iteration was developed by Helmut Wielandt in 1944, (Wielandt, 1944).

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In the most basic variant of inverse iteration the shift $\tau$ is never updated, but the right-hand side is replaced by the latest approximate eigenvector:

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There exist variants which use other scalings, mostly using as left vector some standard unit vector $\ell=\mathbf{e}_{j}$ :

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\mathbf{v}_{k+1}=\frac{\left(\mathbf{A}-\tau \mathbf{I}_{n}\right)^{-1} \mathbf{v}_{k}}{\mathbf{e}_{j}^{\top}\left(\mathbf{A}-\tau \mathbf{I}_{n}\right)^{-1} \mathbf{v}_{k}}, \quad k=0,1, \ldots
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In the latter context, $\mathbf{e}_{j}^{\top}\left(\mathbf{A}-\tau \mathbf{I}_{n}\right)^{-1} \mathbf{v}_{k} \approx(\lambda-\tau)^{-1}$ gives an eigenvalue approximation.

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In both variants also the Rayleigh quotient can be used, the Rayleigh quotient uniquely solves the least squares problem

$$
\rho\left(\mathbf{v}_{k}\right)=\operatorname{argmin}_{\rho \in \mathbb{C}}\left\|\mathbf{A v}_{k}-\mathbf{v}_{k} \rho\right\|
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Both these methods typically exhibit a quadratic convergence behavior.

## Symmetric RQI

When automatic computers became available, the combination of inverse iteration with Rayleigh's original RQI resulted in the locally Q-cubically convergent (symmetric) RQI

$$
\mathbf{v}_{k+1}=\frac{\left(\mathbf{A}-\rho\left(\mathbf{v}_{k}\right) \mathbf{I}_{n}\right)^{-1} \mathbf{v}_{k}}{\left\|\left(\mathbf{A}-\rho\left(\mathbf{v}_{k}\right) \mathbf{I}_{n}\right)^{-1} \mathbf{v}_{k}\right\|}, \quad k=0,1, \ldots
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Crandall was the first who investigated the three variants (the original Rayleigh quotient iteration; inverse iteration with fixed shift; symmetric RQI) and proved their convergence rates to be quadratic, linear, and cubic, respectively, see (Crandall, 1951).

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Crandall was the first who investigated the three variants (the original Rayleigh quotient iteration; inverse iteration with fixed shift; symmetric RQI) and proved their convergence rates to be quadratic, linear, and cubic, respectively, see (Crandall, 1951).
Ostrowski proved that unsymmetric RQI still has a quadratic convergence rate, (Ostrowski, 1959e). In (Ostrowski, 1959c), he also gave a variant that recovers the cubic convergence rate at the expense of the necessity to solve two linear systems every step instead of only one.

## Two-Sided RQI

When $\mathbf{A} \in \mathbb{C}^{n \times n}$ is no longer Hermitean, the cubic convergence is lost and Ostrowski suggested in (Ostrowski, 1959c) the use of a two-sided RQI.

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$$

The iteration involves two sequences of vectors,

$$
\begin{aligned}
\mathbf{v}_{k+1} & =\left(\mathbf{A}-\rho\left(\mathbf{w}_{k}, \mathbf{v}_{k}\right) \mathbf{I}_{n}\right)^{-1} \mathbf{v}_{k}, \\
\mathbf{w}_{k+1} & =\left(\mathbf{A}-\rho\left(\mathbf{w}_{k}, \mathbf{v}_{k}\right) \mathbf{I}_{n}\right)^{-H} \mathbf{w}_{k},
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\end{aligned}
$$

This trick recovers the cubic convergence of RQI at the price of the solution of an additional system.

## Two-Sided RQI

Ostrowski worked out a more detailed analysis than Crandall. He published a series of six papers on RQI, (Ostrowski, 1959b; Ostrowski, 1959c; Ostrowski, 1959d; Ostrowski, 1959e; Ostrowski, 1959a). He measured the rate of convergence with respect to the number of solutions of linear systems, which he called one "Horner". He was a little unfair to the two-sided variant, as these two Horners are related to each other (one decomposition, two forward and backward substitutions with the same two triangular matrices).

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The proofs by Crandall and Ostrowski are beautiful and worth reading.

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The proofs by Crandall and Ostrowski are beautiful and worth reading.

But we feel that a more direct proof of convergence for the different variants of RQI and related algorithms would be very helpful, especially when we want to investigate the overall behavior: the basins of attraction; global convergence; effects of perturbation and inexact methods, ...

## Outline

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## Simplification

Hessenberg matrices are in some sense the closest computable normal form of square matrices under unitary similarity transformations.

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We use the implicit Q-Theorem to unitarily transform the pair $(\mathbf{A}, \mathbf{q})$ with $\|\mathbf{q}\|_{2}=1$ to the pair $\left(\mathbf{H}_{n}, \mathbf{e}_{1}\right)$, where $\mathbf{H}_{n}$ is upper Hessenberg and $\mathbf{e}_{1}$ denotes the first standard unit vector.

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The following Matlab-code gives the transformed pair:

```
[Q,R] = qr(q);
[P,H] = hess(Q'*A*Q);
signs = sign(diag(H,-1));
S = diag(cumprod([1;signs]));
P = P*S;
H = S'* * * S;
```


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When $\mathbf{A}$ is non-derogatory, the Hessenberg matrix $\mathbf{H}_{n}$ is unreduced and uniquely determined. In other cases, only the leading part of $\mathbf{H}_{n}$ up to the first zero in the lower diagonal is uniquely determined.

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The first resolvent identity (Chatelin, 1993, Lemma 2.2.1, p. 63), valid for $z_{1} \neq z_{2}$ from the resolvent set, gives

$$
\begin{align*}
\left({ }^{\left(z_{1}\right.} \mathbf{H}_{n}\right)^{-1}\left({ }_{2} \mathbf{H}_{n}\right)^{-1} & =\left(z_{1} \mathbf{I}_{n}-\mathbf{H}_{n}\right)^{-1}\left(z_{2} \mathbf{I}_{n}-\mathbf{H}_{n}\right)^{-1}  \tag{1a}\\
& =\frac{\left({ }_{z} \mathbf{H}_{n}\right)^{-1}-\left({ }_{2} \mathbf{H}_{n}\right)^{-1}}{z_{2}-z_{1}}=-\left[z_{1}, z_{2}\right]\left({ }^{2} \mathbf{H}_{n}\right)^{-1} . \tag{1b}
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The first resolvent identity is based on the trivial observation that

$$
\left(z_{2} \mathbf{I}_{n}-\mathbf{H}_{n}\right)-\left(z_{1} \mathbf{I}_{n}-\mathbf{H}_{n}\right)=\left(z_{2}-z_{1}\right) \mathbf{I}_{n}
$$

## Simplification

This identity can be generalized to $k$ distinct points of evaluation:

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\begin{equation*}
\prod^{k}\left({ }^{z} \mathbf{H}_{n}\right)^{-1}=(-1)^{k-1}\left[z_{1}, \ldots, z_{k}\right]\left({ }^{z} \mathbf{H}_{n}\right)^{-1} \tag{2}
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The inverse of the characteristic matrix ${ }^{z} \mathbf{H}_{n}$ is the rational function

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\begin{equation*}
\left({ }^{z} \mathbf{H}_{n}\right)^{-1}=\frac{\operatorname{adj}\left({ }^{z} \mathbf{H}_{n}\right)}{\chi(z)}=: \frac{\mathbf{P}_{n}(z)}{\chi(z)}, \quad \chi(z):=\operatorname{det}\left({ }^{z} \mathbf{H}_{n}\right), \tag{3}
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The inverse of the characteristic matrix ${ }^{2} \mathbf{H}_{n}$ is the rational function

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where the elements $p_{i j}(z)$ of $\mathbf{P}_{n}(z)$ are polynomials. The matrix-valued function $\left.{ }^{2} \mathbf{H}_{n}\right)^{-1}$ is meromorphic and analytic in the resolvent set.
Thus, confluent divided differences are well-defined and we do not need to restrict the points $\left\{z_{i}\right\}_{i=1}^{k}$ from the resolvent set.

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We only need here a well-known result on a recurrence for the determinants of unreduced Hessenberg matrices, see, e.g., (Franklin, 1968, Section 7.11, p. 252, Eqn. (8)), or, the probably earliest reference (Schweins, 1825, Erste Abtheilung, IV. Abschnitt, § 154, Seite 361, Gleichung 560)).

## Simplification

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There exist short proofs based on Laplace expansion and Cramer's rule.

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The polynomials $\chi_{i: j}$ are the characteristic polynomials of submatrices of $\mathbf{H}_{n}$,

$$
\chi_{i: j}(z):=\operatorname{det}\left({ }^{z} \mathbf{H}_{i \cdot j}\right)=\operatorname{det}\left(z \mathbf{I}_{j-i+1}-\mathbf{H}_{i \cdot j}\right) .
$$

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By (Z, 2006, Lemma 3.1, Eqn. (3.5)) for $z$ in the resolvent set

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\begin{align*}
\left({ }^{z} \mathbf{H}_{n}\right) \nu(z) & =\frac{\chi(z)}{h_{1: n-1}} \mathbf{e}_{1} \quad \Leftrightarrow \quad \frac{\nu(z) h_{1: n-1}}{\chi(z)}=\left({ }^{z} \mathbf{H}_{n}\right)^{-1} \mathbf{e}_{1},  \tag{5a}\\
\check{\nu}(z)^{\top}\left({ }^{z} \mathbf{H}_{n}\right) & =\mathbf{e}_{n}^{\top} \frac{\chi(z)}{h_{1: n-1}} \quad \Leftrightarrow \quad \frac{h_{1: n-1} \check{\nu}(z)}{\chi(z)}=\mathbf{e}_{n}^{\top}\left({ }^{z} \mathbf{H}_{n}\right)^{-1} . \tag{5b}
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The repeated application of resolvents to $\mathbf{e}_{1}$ results in

$$
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$$

and thus the approximate eigenvalues are given by the Opitz-Larkin method:

$$
\begin{align*}
x_{k+1} & =\frac{\mathbf{e}_{n}^{\top} \mathbf{H}_{n}\left(\prod_{i=1}^{k}\left({ }_{i}^{z_{i}} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}{\mathbf{e}_{n}^{\top}\left(\prod_{i=1}^{k}\left({ }^{z_{i}} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}=\frac{\left.\mathbf{e}_{n}^{\top}\left(z_{k} \mathbf{I}_{n}-\left({ }_{k} \mathbf{H}_{n}\right)\right)\left(\prod_{i=1}^{k}{ }^{\left(z_{i}\right.} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}{\mathbf{e}_{n}^{\top}\left(\prod_{i=1}^{k}\left({ }_{i} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}  \tag{8a}\\
& =z_{k}-\frac{\left.\mathbf{e}_{n}^{\top} z_{k} \mathbf{H}_{n}\left(\prod_{i=1}^{k}{ }^{z_{i}} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}{\mathbf{e}_{n}^{\top}\left(\prod_{i=1}^{k}\left(z_{i} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}=z_{k}-\frac{\mathbf{e}_{n}^{\top}\left(\prod_{i=1}^{k-1}\left({ }_{i} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}{\mathbf{e}_{n}^{\top}\left(\prod_{i=1}^{k}\left(z_{i} \mathbf{H}_{n}\right)^{-1}\right) \mathbf{e}_{1}}  \tag{8b}\\
& =z_{k}+\frac{\left[z_{1}, \ldots, z_{k-1}\right](1 / \chi)}{\left[z_{1}, \ldots, z_{k-1}, z_{k}\right](1 / \chi)} . \tag{8c}
\end{align*}
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When we update the shifts by choosing $z_{k+1}=x_{k+1}$ we obtain the standard variant of the Opitz-Larkin method. This method has asymptotically second order convergence against the roots of the characteristic polynomial $\chi$.

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Inverse iteration with fixed shift $\tau=z_{1}=z_{2}=\ldots=z_{k}$ results in the recurrence

$$
\begin{equation*}
x_{k+1}=\tau+\frac{[\tau, \ldots, \tau](1 / \chi)}{[\tau, \ldots, \tau, \tau](1 / \chi)}=\tau+k \frac{(1 / \chi)^{(k-1)}(\tau)}{(1 / \chi)^{(k)}(\tau)} \tag{9}
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This knowledge together with an estimate for the cost of preprocessing (computing the LU decomposition; initializing a Krylov method using a seed system) and the cost of the (approximate) solutions of the systems enables to decide when to compute an update of the shift.

## Simplification

The original Rayleigh quotient iteration (Strutt, 1894) with the symmetric Rayleigh quotient and, because of the symmetry, a tridiagonal Hermitean Hessenberg matrix $\mathbf{H}_{n}$, gives the update

$$
\begin{align*}
z_{k+1} & =\frac{\mathbf{e}_{1}^{\top}\left(z_{k} \mathbf{H}_{n}\right)^{-H} \mathbf{H}_{n}\left(z_{k} \mathbf{H}_{n}\right)^{-1} \mathbf{e}_{1}}{\mathbf{e}_{1}^{\top}\left(z_{k} \mathbf{H}_{n}\right)^{-\mathrm{H}}\left({ }_{k} \mathbf{H}_{n}\right)^{-1} \mathbf{e}_{1}}=\frac{\mathbf{e}_{1}^{\top} \mathbf{H}_{n}\left(z_{k} \mathbf{H}_{n}\right)^{-2} \mathbf{e}_{1}}{\mathbf{e}_{1}^{\top}\left({ }_{k} \mathbf{H}_{n}\right)^{-2} \mathbf{e}_{1}}  \tag{10a}\\
& =\frac{\left.\left.\mathbf{e}_{1}^{\top}\left(z_{k} \mathbf{I}_{n}-{ }^{2} \mathbf{H}_{n}\right)\right)^{z_{k}} \mathbf{H}_{n}\right)^{-2} \mathbf{e}_{1}}{\mathbf{e}_{1}^{\top}\left(z_{k} \mathbf{H}_{n}\right)^{-2} \mathbf{e}_{1}}  \tag{10b}\\
& =z_{k}-\frac{\mathbf{e}_{1}^{\top}\left(z_{k} \mathbf{H}_{n}\right)^{-1} \mathbf{e}_{1}}{\mathbf{e}_{1}^{\top}\left(z_{k} \mathbf{H}_{n}\right)^{-2} \mathbf{e}_{1}}=z_{k}+\frac{\left[z_{k}\right]\left(\chi_{2: n} / \chi\right)}{\left[z_{k}, z_{k}\right]\left(\chi_{2: n} / \chi\right)}  \tag{10c}\\
& =z_{k}-\frac{r\left(z_{k}\right)}{r^{\prime}\left(z_{k}\right)}, \quad r(z):=\frac{\chi(z)}{\chi_{2: n}(z)} . \tag{10d}
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$$

This is Newton's method on the meromorphic function $r$. As the poles of this meromorphic function are the eigenvalues of a submatrix, they interlace by Cauchy's interlace theorem the roots, which are the eigenvalues.

## Simplification

## Symmetric RQI for Hermitean matrices gives the update

$$
\begin{equation*}
z_{k+1}=z_{k}+\frac{\left[z_{1}, z_{1}, \ldots, z_{k-1}, z_{k-1}, z_{k}\right]\left(\chi_{2: n} / \chi\right)}{\left[z_{1}, z_{1}, \ldots, z_{k-1}, z_{k-1}, z_{k}, z_{k}\right]\left(\chi_{2: n} / \chi\right)} \tag{11}
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This update has by the result of Tornheim asymptotically a cubic convergence rate, as we have to compute the limit of the real roots of the equations

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x^{k}-2 x^{k-1}-2 x^{k-2}-\cdots-2=0
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i.e., the maximal eigenvalue of a Hessenberg matrix with ones in the lower diagonal and twos in the last column. The approximate eigenvector of all ones to the approximate eigenvalue 3 gives the backward error $1 / \sqrt{k}$ and the only real positive eigenvalue of the matrix is well separated, the other eigenvalues lie close to a circle of radius one around zero.

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If we take another standard unit vector $\mathbf{e}_{\ell}$ as left vector, we obtain the Opitz-Larkin method applied to the meromorphic function

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\begin{equation*}
m_{\ell}(z)=\frac{\chi(z)}{h_{1: \ell-1} \chi_{1+\ell: n}(z)} \tag{12}
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\end{equation*}
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The polynomials $\chi_{1+i: n}$ have degree $\operatorname{deg}\left(\chi_{1+i: n}\right)=n-i$ and leading coefficient one, thus they form a basis of the space of polynomials of degree less $n$.

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By luck or accident, we can construct a polynomial that is zero (of any order up to order $n-1$ ) at one eigenvalue. This is of interest in case of (algebraically) multiple eigenvalues. In theory, there is always a left starting vector which ensures that the root is simple, as the multiple zero is reduced to a simple one.

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The best choice is the starting vector $\mathbf{y}$ that represents the derivative of $\chi$, i.e., the vector $\overline{\mathbf{y}}$ such that

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In this special case the rational function is the Newton's update

$$
\begin{equation*}
r(z ; \overline{\mathbf{y}})=\frac{\chi(z)}{\chi^{\prime}(z)} \tag{15}
\end{equation*}
$$

which has only simple zeros and poles between the eigenvalues.

## Simplification

The Academic Example: The matrix $\mathbf{H}_{4}=\operatorname{triu}(\operatorname{ones}(4),-1)$ has the eigenvalues 0 (double), 1 , and 3 , and the vector

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\mathbf{y}=\left(\begin{array}{l}
4  \tag{16}\\
0 \\
2 \\
2
\end{array}\right)
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The two-sided RQI with left-hand vector $\mathbf{e}_{1}$ and right-hand vector $\mathbf{y}$ performs confluent Opitz-Larkin with double nodes on the Newton's update $\chi / \chi^{\prime}$.

A variant of original RQI with starting vector $\mathbf{e}_{1}$ and test vector $\mathbf{y}$ and updated shifts performs Newton's method on the Newton's update $\chi / \chi^{\prime}$.

## Simplification

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The two-sided RQI method corresponds to a confluent Opitz-Larkin method with double nodes. In this method the left vector determines a polynomial, which is formed as a linear combination of characteristic polynomials of trailing submatrices.
Measured in Horners, single-sided RQI applied to non-Hermitean matrices performs better. In the QR algorithm we implicitly perform a single-sided RQI in every step.

## Simplification

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Measured in Horners, single-sided RQI applied to non-Hermitean matrices performs better. In the QR algorithm we implicitly perform a single-sided RQI in every step.
In single-sided RQI for non-Hermitean matrices, we change the vector $\mathbf{y}$ that determines the denominator polynomial of the rational function

$$
r(z ; \mathbf{y})=\frac{\chi(z)}{p(z ; \mathbf{y})}
$$

in every step and apply one step of the Opitz-Larkin method without confluent nodes. This gives second order convergence.

## Conclusions and Outlook

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- Much remains to be done ...


## Thank you very much for your attention!

## Hartelijk dank!

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