

The Numerical Stability of Barycentric Lagrange Interpolation

Abhigyan Roy
Hrishav Das
Agni Ravi Deepa
Reva Dhillon

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Why the need for alternate forms?

The main reasons:

- ▶ **To reduce time complexity**, as the original formulation using the lagrange basis polynomials needs the computation of products of differences. This becomes an issue in bigger datasets as the complexity is $O(n^2)$



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- ▶ **To reduce time complexity**, as the original formulation using the lagrange basis polynomials needs the computation of products of differences. This becomes an issue in bigger datasets as the complexity is $O(n^2)$
- ▶ Adding a new data point is costly as well since the lagrange polynomials need to be computed again.
- ▶ Lagrange interpolation is numerically unstable especially if the node points are not chosen appropriately.



The solution?

- ▶ To come up with alternate formulations of the lagrange interpolation methods that reduce the time complexity and are numerically stable.



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- ▶ To come up with alternate formulations of the lagrange interpolation methods that reduce the time complexity and are numerically stable.
- ▶ Two modified forms have been formulated, both being the **Barycentric forms** of Lagrange interpolation.



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The error analysis has been done for both these forms and compared with the Newton divided difference form for two different functions.



Error Analysis and Stability

Let's define some preliminaries

- ▶ Condition Number
- ▶ Notions of Stability
- ▶ Lebesgue Constant
- ▶ Floating Point Arithmetic Model



Condition Number

The condition number of p_n at x with respect to f is defined for $p_n(x) \neq 0$:

$$\text{cond}(x, n, f) = \lim_{\Delta f \rightarrow 0} \sup \frac{|p_f(x) - p_{f+\Delta f}(x)|}{|\epsilon p_f(x)|}, \text{ where } |\Delta f| \leq \epsilon |f|. \quad (1)$$

In the notation, $\text{cond}(x, n, f)$, the term ' n ' indicates the dependence on the points x_j .



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$$\text{cond}(x, n, f) = \sum_{j=0}^n \left| \frac{\ell_j(x) f_j}{p_n(x)} \right| \geq 1, \quad (2)$$

and for any Δf with $|\Delta f| \leq \epsilon |f|$ we have

$$\frac{|p_f(x) - p_{f+\Delta f}(x)|}{|p_f(x)|} \leq \text{cond}(x, n, f) \cdot \epsilon \quad (3)$$



Notions of Stability: Forward Stable

A numerical method is **forward stable** if the error between **computed solution** and actual solution is small:

$$\text{Forward Error} = \frac{|\hat{f}(x) - f(x)|}{|f(x)|}$$



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Forward Error Bound:

The forward error can be bounded as:

$$\frac{|\hat{f}(x) - f(x)|}{|f(x)|} \leq \text{cond}(x, n, f) \cdot u$$

where u is the **unit roundoff** (machine precision) and $\text{cond}(x, n, f)$ is the **condition number**.



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Backward Stability Condition:

A method is backward stable if:

$$|\delta x| \leq u \cdot |x|$$

meaning the computed result corresponds to a nearby problem.



Lebesgue Constant

We assume that the nodes, x_j lie in $[-1, 1]$ and express the bound in terms of Λ_n , the Lebesgue constant associated with the points x_j :

$$\Lambda_n = \sup_{f \in C([-1,1])} \frac{\|P_n f\|_\infty}{\|f\|_\infty} \quad (4)$$

where P_n is the operator mapping f to its interpolating polynomial at the points x_j ,

$$\|f\| = \max_{x \in [-1,1]} |f(x)|$$

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It can be shown that:

$$\Lambda_n = \sup_{x \in [-1,1]} \sum_{j=0}^n |\ell_j(x)| \quad (5)$$



Floating-Point Arithmetic Model

Standard Model of Floating-Point Arithmetic (Higham, 2002):

$$\text{fl}(x \text{ op } y) = (x \text{ op } y)(1 + \delta)^{\pm 1}, \quad |\delta| \leq u$$

where:

- ▶ $\text{fl}(x \text{ op } y)$: result in floating-point arithmetic
- ▶ u : unit roundoff
- ▶ δ : rounding error, $|\delta| \leq u$

This formula models how floating-point arithmetic introduces errors in operations like $+$, $-$, $*$, $/$.



Relative Error Counter:

$$\langle k \rangle = \prod_{i=1}^k (1 + \delta_i)^{\rho_i}, \quad \rho_i = \pm 1, \quad |\delta_i| \leq u$$

This captures how errors accumulate over multiple operations.



Relative Error Accumulation

Relative Error Counter:

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This captures how errors accumulate over multiple operations.

Bound on Relative Error:

$$|\langle k \rangle - 1| \leq \gamma_k = \frac{ku}{1 - ku}$$

where k is the number of operations and u is the unit roundoff. The error grows as a function of ku , controlling the relative error in the worst case.



1st Form: Definition

Recall traditional Lagrange representation of an interpolating polynomial is written as:

$$p_n(x) = \sum_{j=0}^n \mathcal{L}_j(x) f_j \quad (6)$$

where $\mathcal{L}_j(x) = \prod_{k=0, k \neq j}^n \frac{x - x_k}{x_j - x_k}$



1st Form: Definition

We can rewrite this expression as follows:

$$p_n(x) = \underbrace{\left(\prod_{k=0}^n (x - x_k) \right)}_{\ell(x)} \sum_{j=0}^n \left(\frac{1}{x - x_j} \right) \underbrace{\left(\prod_{k=0, k \neq j}^n \frac{1}{x_j - x_k} \right)}_{w_j} f_j \quad (7)$$

$$\boxed{p_n(x) = \ell(x) \sum_{j=0}^n \left(\frac{w_j}{x - x_j} \right) f_j} \quad (8)$$

The form presented in Eq.8 is called the **First Form of the Barycentric Interpolation Formula**.



Error Analysis on First Form:

- ▶ The computed weights w_j satisfy:

$$\hat{w}_j = w_j \langle 2n \rangle_j, \quad j = 0 : n \quad (9)$$

- ▶ The computed $\hat{l}(x)$ satisfies:

$$\hat{l}(x) = l(x) \langle 2n + 1 \rangle_j \quad (10)$$

- ▶ The computed interpolating polynomial $\hat{p}_n(x)$ satisfies:

$$\hat{p}_n(x) = l(x) \sum_{j=0}^n \frac{w_j}{x - x_j} f_j \langle 5n + 5 \rangle_j \quad (11)$$



Error Analysis on the First Form:

- ▶ Eq.11 can be interpreted as the value of $\hat{p}_n(x)$ computed in presence of perturbations in f_i . Therefore, it is backward stable.
- ▶ We can also bound a forward error as follows:

$$\frac{\|p_n(x) - \hat{p}_n(x)\|}{\|p_n(x)\|} \leq (\gamma_{5N+5})\text{cond}(x, n, f) \quad (12)$$

- ▶ The First Form representation is shown to be **Backward Stable and Forward Stable**.



2nd Form: Definition

If the function values f_j are 1, they will be interpolated by $p_n(x) = 1$. From eq. 8, this gives,

$$\ell(x) = \frac{1}{\sum_{j=0}^n \left(\frac{w_j}{x-x_j} \right)} \quad (13)$$

Substituting the expression for $\ell(x)$ in eq. 8, we obtain:

$$p_n(x) = \frac{\sum_{j=0}^n \left(\frac{w_j}{x-x_j} \right) f_j}{\sum_{j=0}^n \left(\frac{w_j}{x-x_j} \right)} \quad (14)$$

The form presented in Eq.14 is called the **Second (proper) form of the barycentric formula**.



Error and Stability Analysis of the Second Form

- ▶ **Different stability properties expected:** This formula is obtained by using a mathematical identity that does not necessarily hold in floating point arithmetic.
- ▶ The computed interpolating polynomial is:

$$\hat{p}_n(x) = \frac{\sum_{j=0}^n \left(\frac{w_j}{x-x_j} \right) f_j \langle 3n+4 \rangle_j}{\sum_{j=0}^n \left(\frac{w_j}{x-x_j} \right) \langle 3n+2 \rangle_j} \quad (15)$$

- ▶ Now, from eq. 2,

$$\text{cond}(x, n, f) = \frac{\sum_{j=0}^n \left| \frac{w_j f_j}{x-x_j} \right|}{\left| \sum_{j=0}^n \frac{w_j f_j}{x-x_j} \right|} \quad (16)$$



Error and Stability Analysis of the Second Form

► Similarly,

$$\text{cond}(x, n, 1) = \frac{\sum_{j=0}^n \left| \frac{w_j}{x-x_j} \right|}{\left| \sum_{j=0}^n \frac{w_j}{x-x_j} \right|} \quad (17)$$

► Theorem: The computed $\hat{p}_n(x)$ satisfies,

$$\begin{aligned} \frac{|p_n(x) - \hat{p}_n(x)|}{|p_n(x)|} &\leq (3n+4)u \frac{\sum_{j=0}^n \left| \frac{w_j f_j}{x-x_j} \right|}{\left| \sum_{j=0}^n \frac{w_j f_j}{x-x_j} \right|} + (3n+2)u \frac{\sum_{j=0}^n \left| \frac{w_j}{x-x_j} \right|}{\left| \sum_{j=0}^n \frac{w_j}{x-x_j} \right|} + O(u^2) \\ &= (3n+4)u \text{cond}(x, n, f) + (3n+2)u \text{cond}(x, n, 1) + O(u^2) \quad (18) \end{aligned}$$



Error and Stability Analysis of the Second Form

- ▶ It can be observed that for suitable choice of the x_j the second term in eq. 18 can be made arbitrarily large.
- ▶ For further analysis, we see that the Lebesgue constant may be written as:

$$\Lambda_n = \sup_{x \in [-1,1]} \sum_{j=0}^n |\ell_j(x)| \quad (19)$$

- ▶ Therefore, the forward error bound is given by:

$$\frac{|p_n(x) - \hat{p}_n(x)|}{|p_n(x)|} \leq -(3n+4)u \text{cond}(x, n, f) + (3n+2)u\Lambda_n + O(u^2) \quad (20)$$



Stability Variation with Node Distributions

Chebyshev Points

For the Chebyshev points of the first kind (the zeros of the degree $(n + 1)$ Chebyshev polynomial) and the Chebyshev points of the second kind (the extreme points of the degree n Chebyshev polynomial):

$$\Lambda_n \leq \frac{2}{\pi} \log(n + 1) + 1.$$

For other 'good' sets of points, Λ_n is also slowly growing.

Comparison with Equally Spaced Points

For equally spaced points, Λ_n grows exponentially at a rate proportional to:

$$\frac{2^n}{n \log n}.$$



Stability Variation with Node Distributions

- ▶ We conclude that while the barycentric formula is not forward stable in general, it can be significantly less accurate than the modified Lagrange formula only for a poor choice of interpolating points and special functions f .
- ▶ More specifically, for both sets of Chebyshev points, the barycentric formula is guaranteed to be forward stable - that is, it produces relative errors bounded by:

$$g(n)u \cdot \text{cond}(x, n, f), \quad \text{with } g \text{ a slowly growing function of } n.$$

- ▶ The computational advantage of the barycentric formula over the modified Lagrange formula: Since the w_j appear linearly in both the numerator and the denominator, they can be rescaled ($w_j \leftarrow \alpha w_j$) to avoid overflow and underflow.



Numerical Experiments

- ▶ Computations performed in MATLAB with $u \approx 10^{-16}$.
- ▶ 30 equally spaced points x_j on $[-1, 1]$ (thus $n = 29$).
- ▶ Evaluated interpolant at 100 points on $[-1 + 10^3\epsilon, 1 - 10^3\epsilon]$.
- ▶ 'Exact' values obtained using 50-digit arithmetic with MATLAB's Symbolic Math Toolbox.

Function values for first case: $f_j = 0$ for $j = 0 : n - 1$ and $f_n = 1$,
 $\text{cond}(x, n, f) = 1$ and that $\Lambda_n = 3 \times 10^6$

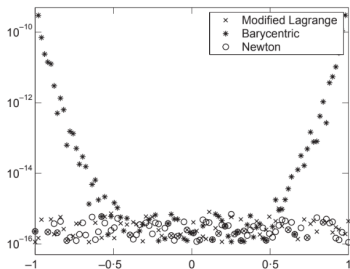
Runge function for second case and $\text{cond}(x, n, f) = 7.5$



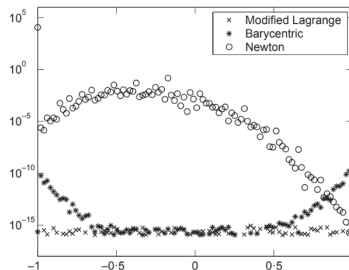
Observations from Numerical Experiments

- ▶ Modified Lagrange formula performs stably; barycentric formula performs unstably.
- ▶ Newton divided difference formula performs stably in increasing order but unstably in decreasing order.

N. J. HIGHAM



(a) x_i in increasing order.



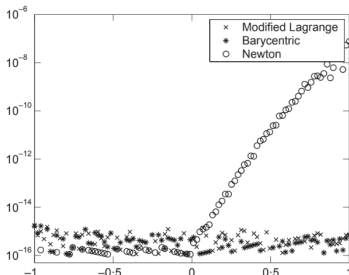
(b) x_i in decreasing order.

Figure 1: Comparison of Relative errors in computed $p_n(x)$ for 30 equally spaced points x_i

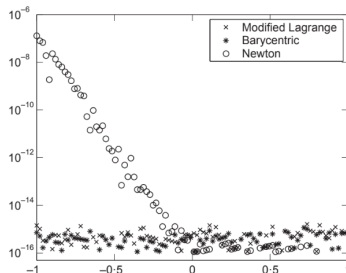


Further Experiments and Conclusions

- ▶ A second typical example with the Runge function $f(x) = \frac{1}{1+25x^2}$ and Chebyshev points.
- ▶ Modified Lagrange and barycentric formulas behave stably; Newton divided difference becomes unstable.



(a) Increasing order of Chebyshev points.



(b) Decreasing order of Chebyshev points.

Figure 2: Relative errors in computed $p_n(x)$ for 30 Chebyshev points of the first kind.



Conclusions

- ▶ It is evident that in all cases the the modified lagrange formula (first form of barycentric lagrange) is stable which implies unconditional stability.

¹Higham, Nicholas J. / The numerical stability of barycentric Lagrange interpolation. In: IMA Journal of Numerical Analysis. 2004 ; Vol. 24, No. 4. pp. 547-556.



Conclusions

- ▶ It is evident that in all cases the the modified lagrange formula (first form of barycentric lagrange) is stable which implies unconditional stability.
- ▶ For the second form we can see see unstability for the dataset having a high Lebesgue constant. The requirement of a low Lebesgue constant for stability implies conditional stability.

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Conclusions

- ▶ It is evident that in all cases the the modified lagrange formula (first form of barycentric lagrange) is stable which implies unconditional stability.
- ▶ For the second form we can see see unstability for the dataset having a high Lebesgue constant. The requirement of a low Lebesgue constant for stability implies conditional stability.
- ▶ Both barycentric forms perform significantly better than the Newton divided difference form.

Reference ¹

¹Higham, Nicholas J. / The numerical stability of barycentric Lagrange interpolation. In: IMA Journal of Numerical Analysis. 2004 ; Vol. 24, No. 4. pp. 547-556.



All team members contributed equally to the completion of this assignment and making of presentation, with active participation in research, analysis, and execution of tasks.

