

# Numerical Analysis and Computing

## Lecture Notes #13 — Approximation Theory — Rational Function Approximation

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### Polynomial Approximation: Pros and Cons.

#### Advantages of Polynomial Approximation:

- [1] We can approximate any continuous function on a closed interval to within arbitrary tolerance. (*Weierstrass approximation theorem*)
- [2] Easily evaluated at arbitrary values. (*e.g. Horner's method*)
- [3] Derivatives and integrals are easily determined.

#### Disadvantage of Polynomial Approximation:

- [1] Polynomials tend to be oscillatory, which causes errors. This is sometimes, but not always, fixable: — *E.g.* if we are free to select the node points we can minimize the interpolation error (*Chebyshev polynomials*), or optimize for integration (*Gaussian Quadrature*).



### Outline

- 1 **Approximation Theory**
  - Pros and Cons of Polynomial Approximation
  - New Bag-of-Tricks: Rational Approximation
  - Padé Approximation: Example #1
- 2 **Padé Approximation**
  - Example #2
  - Finding the Optimal Padé Approximation



### Moving Beyond Polynomials: Rational Approximation

We are going to use rational functions,  $r(x)$ , of the form

$$r(x) = \frac{p(x)}{q(x)} = \frac{\sum_{i=0}^n p_i x^i}{1 + \sum_{j=1}^m q_j x^j}$$

and say that the degree of such a function is  $N = n + m$ .

Since this is a richer class of functions than polynomials — rational functions with  $q(x) \equiv 1$  are polynomials, we expect that **rational approximation of degree  $N$  gives results that are at least as good as polynomial approximation of degree  $N$ .**



## Padé Approximation

Extension of **Taylor expansion** to rational functions; selecting the  $p_i$ 's and  $q_i$ 's so that  $r^{(k)}(x_0) = f^{(k)}(x_0) \forall k = 0, 1, \dots, N$ .

$$f(x) - r(x) = f(x) - \frac{p(x)}{q(x)} = \frac{f(x)q(x) - p(x)}{q(x)}$$

Now, use the Taylor expansion  $f(x) \sim \sum_{i=0}^{\infty} a_i(x - x_0)^i$ , for simplicity  $x_0 = 0$ :

$$f(x) - r(x) = \frac{\sum_{i=0}^{\infty} a_i x^i \sum_{i=0}^m q_i x^i - \sum_{i=0}^n p_i x^i}{q(x)}.$$

Next, we choose  $p_0, p_1, \dots, p_n$  and  $q_1, q_2, \dots, q_m$  so that the numerator has no terms of degree  $\leq N$ .



## Padé Approximation: Abstract Example

1 of 2

Find the Padé approximation of  $f(x)$  of degree 5, where  $f(x) \sim a_0 + a_1x + \dots + a_5x^5$  is the Taylor expansion of  $f(x)$  about the point  $x_0 = 0$ .

The corresponding equations are:

$x^0$	$a_0$	$- p_0$	$= 0$
$x^1$	$a_0 q_1 + a_1$	$- p_1$	$= 0$
$x^2$	$a_0 q_2 + a_1 q_1 + a_2$	$- p_2$	$= 0$
$x^3$	$a_0 q_3 + a_1 q_2 + a_2 q_1 + a_3$	$- p_3$	$= 0$
$x^4$	$a_0 q_4 + a_1 q_3 + a_2 q_2 + a_3 q_1 + a_4$	$- p_4$	$= 0$
$x^5$	$a_0 q_5 + a_1 q_4 + a_2 q_3 + a_3 q_2 + a_4 q_1 + a_5$	$- p_5$	$= 0$

**Note:**  $p_0 = a_0!!!$  (This reduces the number of unknowns and equations by one (1).)



## Padé Approximation: The Mechanics.

For simplicity we (sometimes) define the “indexing-out-of-bounds” coefficients:

$$\begin{cases} p_{n+1} = p_{n+2} = \dots = p_N = 0 \\ q_{m+1} = q_{m+2} = \dots = q_N = 0, \end{cases}$$

so we can express the **coefficients of  $x^k$**  in

$$\sum_{i=0}^{\infty} a_i x^i \sum_{i=0}^m q_i x^i - \sum_{i=0}^n p_i x^i = 0, \quad k = 0, 1, \dots, N$$

as

$$\sum_{i=0}^k a_i q_{k-i} = p_k, \quad k = 0, 1, \dots, N.$$



## Padé Approximation: Abstract Example

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We get a linear system for  $p_1, p_2, \dots, p_N$  and  $q_1, q_2, \dots, q_N$ :

$$\begin{bmatrix} a_0 & & & & \\ a_1 & a_0 & & & \\ a_2 & a_1 & a_0 & & \\ a_3 & a_2 & a_1 & a_0 & \\ a_4 & a_3 & a_2 & a_1 & a_0 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ q_3 \\ q_4 \\ q_5 \end{bmatrix} - \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \end{bmatrix} = - \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix}.$$

If we want  $n = 3, m = 2$ :

$$\begin{bmatrix} a_0 & 0 & -1 & & \\ a_1 & a_0 & 0 & -1 & \\ a_2 & a_1 & 0 & 0 & -1 \\ a_3 & a_2 & 0 & 0 & 0 \\ a_4 & a_3 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ p_1 \\ p_2 \\ p_3 \end{bmatrix} = - \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix}.$$



Padé Approximation: Concrete Example,  $e^{-x}$ 

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The Taylor series expansion for  $e^{-x}$  about  $x_0 = 0$  is  $\sum_{k=0}^{\infty} \frac{(-1)^k}{k!} x^k$ , hence  $\{a_0, a_1, a_2, a_3, a_4, a_5\} = \{1, -1, \frac{1}{2}, -\frac{1}{6}, \frac{1}{24}, -\frac{1}{120}\}$ .

$$\begin{bmatrix} 1 & 0 & -1 \\ -1 & 1 & 0 & -1 \\ 1/2 & -1 & 0 & 0 & -1 \\ -1/6 & 1/2 & 0 & 0 & 0 \\ 1/24 & -1/6 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ p_1 \\ p_2 \\ p_3 \end{bmatrix} = - \begin{bmatrix} -1 \\ 1/2 \\ -1/6 \\ 1/24 \\ -1/120 \end{bmatrix},$$

which gives  $\{q_1, q_2, p_1, p_2, p_3\} = \{2/5, 1/20, -3/5, 3/20, -1/60\}$ , i.e.

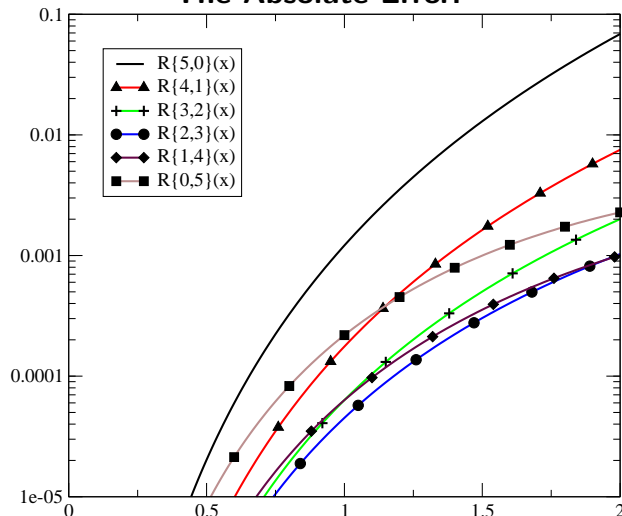
$$r_{3,2}(x) = \frac{1 - \frac{3}{5}x + \frac{3}{20}x^2 - \frac{1}{60}x^3}{1 + \frac{2}{5}x + \frac{1}{20}x^2}.$$

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Padé Approximation: Concrete Example,  $e^{-x}$ 

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The Absolute Error.



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Padé Approximation: Concrete Example,  $e^{-x}$ 

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All the possible Padé approximations of degree 5 are:

$$r_{5,0}(x) = 1 - x + \frac{1}{2}x^2 - \frac{1}{6}x^3 + \frac{1}{24}x^4 - \frac{1}{120}x^5$$

$$r_{4,1}(x) = \frac{1 - \frac{4}{5}x + \frac{3}{10}x^2 - \frac{1}{15}x^3 + \frac{1}{120}x^4}{1 + \frac{1}{5}x}$$

$$r_{3,2}(x) = \frac{1 - \frac{3}{5}x + \frac{3}{20}x^2 - \frac{1}{60}x^3}{1 + \frac{2}{5}x + \frac{1}{20}x^2}$$

$$r_{2,3}(x) = \frac{1 - \frac{2}{5}x + \frac{1}{20}x^2}{1 + \frac{3}{5}x + \frac{3}{20}x^2 + \frac{1}{60}x^3}$$

$$r_{1,4}(x) = \frac{1 - \frac{1}{5}x}{1 + \frac{4}{5}x + \frac{3}{10}x^2 + \frac{1}{15}x^3 + \frac{1}{120}x^4}$$

$$r_{0,5}(x) = \frac{1}{1 + x + \frac{1}{2}x^2 + \frac{1}{6}x^3 + \frac{1}{24}x^4 + \frac{1}{120}x^5}$$

**Note:**  $r_{5,0}(x)$  is the Taylor polynomial of degree 5.

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## Padé Approximation: Matlab Code.

The algorithm in the book looks frightening! If we think in term of the matrix problem defined earlier, it is easier to figure out what is going on:

```
% The Taylor Coefficients, a_0, a_1, a_2, a_3, a_4, a_5
a = [1 -1 1/2 -1/6 1/24 -1/120]';
N = length(a); A = zeros(N-1,N-1);
% m is the degree of q(x), and n the degree of p(x)
m = 3; n = N-1-m;
% Set up the columns which multiply q_1 through q_m
for i=1:m
    A(i:(N-1),i) = a(1:(N-i));
end
% Set up the columns that multiply p_1 through p_n
A(1:n,m+(1:n)) = -eye(n)
% Set up the right-hand-side
b = -a(2:N);
% Solve
c = A\b;
Q = [1; c(1:m)]; % Select q_0 through q_m
P = [a_0; c((m+1):(m+n))]; % Select p_0 through p_n
```

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## Optimal Padé Approximation?

	One Point	Optimal Points
Polynomials	Taylor	Chebyshev
Rational Functions	Padé	???

From the example  $e^{-x}$  we can see that Padé approximations suffer from the **same problem** as Taylor polynomials – they are very accurate near **one point**, but away from that point the approximation degrades.

“Chebyshev-placement” of interpolating points for polynomials gave us an optimal (uniform) error bound over the interval.

Can we do something similar for rational approximations???

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## The Resulting Equations

Again, the coefficients  $p_0, p_1, \dots, p_n$  and  $q_1, q_2, \dots, q_m$  are chosen so that the numerator has zero coefficients for  $T_k(x)$ ,  $k = 0, 1, \dots, N$ , i.e.

$$\sum_{k=0}^{\infty} a_k T_k(x) \sum_{k=0}^m q_k T_k(x) - \sum_{k=0}^n p_k T_k(x) = \sum_{k=N+1}^{\infty} \gamma_k T_k(x).$$

We will need the following relationship:

$$T_i(x) T_j(x) = \frac{1}{2} [T_{i+j}(x) + T_{|i-j|}(x)].$$

Also, we must compute (maybe numerically)

$$a_0 = \frac{1}{\pi} \int_{-1}^1 \frac{f(x)}{\sqrt{1-x^2}} dx \quad \text{and} \quad a_k = \frac{2}{\pi} \int_{-1}^1 \frac{f(x) T_k(x)}{\sqrt{1-x^2}} dx, \quad k \geq 1.$$

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## Chebyshev Basis for the Padé Approximation!

We use the **same** idea — instead of expanding in terms of the basis functions  $x^k$ , we will use the **Chebyshev polynomials**,  $T_k(x)$ , as our basis, i.e.

$$r_{n,m}(x) = \frac{\sum_{k=0}^n p_k T_k(x)}{\sum_{k=0}^m q_k T_k(x)}$$

where  $N = n + m$ , and  $q_0 = 1$ .

We also need to expand  $f(x)$  in a series of Chebyshev polynomials:

$$f(x) = \sum_{k=0}^{\infty} a_k T_k(x),$$

so that

$$f(x) - r_{n,m}(x) = \frac{\sum_{k=0}^{\infty} a_k T_k(x) \sum_{k=0}^m q_k T_k(x) - \sum_{k=0}^n p_k T_k(x)}{\sum_{k=0}^m q_k T_k(x)}.$$

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Example: Revisiting  $e^{-x}$  with Chebyshev-Padé Approximation

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The 8<sup>th</sup> order Chebyshev-expansion (ALL PRAISE MAPLE) for  $e^{-x}$  is

$$\begin{aligned} P_8^{\text{CT}}(x) = & 1.266065878 T_0(x) - 1.130318208 T_1(x) + 0.2714953396 T_2(x) \\ & - 0.04433684985 T_3(x) + 0.005474240442 T_4(x) \\ & - 0.0005429263119 T_5(x) + 0.00004497732296 T_6(x) \\ & - 0.000003198436462 T_7(x) + 0.0000001992124807 T_8(x) \end{aligned}$$

and using the same strategy — building a matrix and right-hand-side utilizing the coefficients in this expansion, we can solve for the Chebyshev-Padé polynomials of degree  $(n + 2m) \leq 8$ :

Next slide shows the matrix set-up for the  $r_{3,2}^{\text{CP}}(x)$  approximation.

**Note:** Due to the “folding”,  $T_i(x) T_j(x) = \frac{1}{2} [T_{i+j}(x) + T_{|i-j|}(x)]$ , we need  $n + 2m$  Chebyshev-expansion coefficients. (Burden-Faires do not mention this, but it is “obvious” from algorithm 8.2; Example 2 (p. 519) is broken, – it needs  $\tilde{P}_7(x)$ .)

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Example: Revisiting  $e^{-x}$  with Chebyshev-Padé Approximation

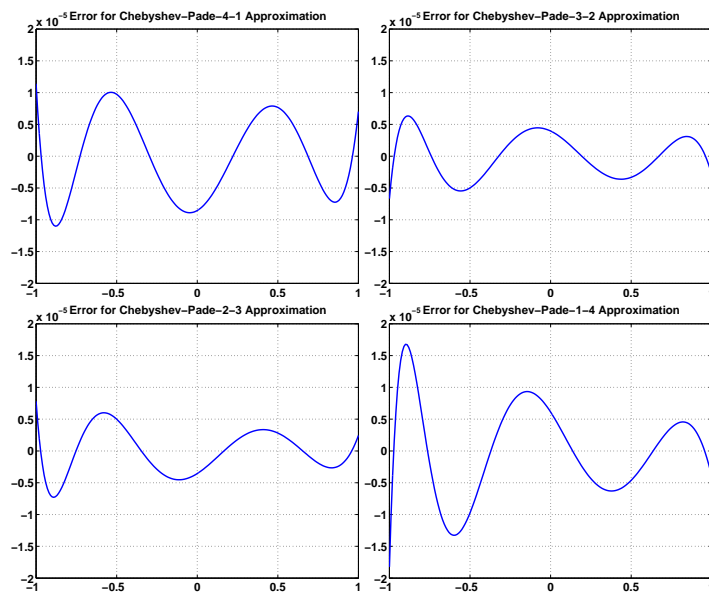
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$$\begin{aligned}
 T_0(x) : \frac{1}{2} \begin{bmatrix} a_1 q_1 & + & a_2 q_2 & - & 2p_0 & = & 2a_0 \end{bmatrix} \\
 T_1(x) : \frac{1}{2} \begin{bmatrix} (2a_0 + a_2)q_1 & + & (a_1 + a_3)q_2 & - & 2p_1 & = & 2a_1 \end{bmatrix} \\
 T_2(x) : \frac{1}{2} \begin{bmatrix} (a_1 + a_3)q_1 & + & (2a_0 + a_4)q_2 & - & 2p_2 & = & 2a_2 \end{bmatrix} \\
 T_3(x) : \frac{1}{2} \begin{bmatrix} (a_2 + a_4)q_1 & + & (a_1 + a_5)q_2 & - & 2p_3 & = & 2a_3 \end{bmatrix} \\
 T_4(x) : \frac{1}{2} \begin{bmatrix} (a_3 + a_5)q_1 & + & (a_2 + a_6)q_2 & - & 0 & = & 2a_4 \end{bmatrix} \\
 T_5(x) : \frac{1}{2} \begin{bmatrix} (a_4 + a_6)q_1 & + & (a_3 + a_7)q_2 & - & 0 & = & 2a_5 \end{bmatrix}
 \end{aligned}$$

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Example: Revisiting  $e^{-x}$  with Chebyshev-Padé Approximation

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Example: Revisiting  $e^{-x}$  with Chebyshev-Padé Approximation

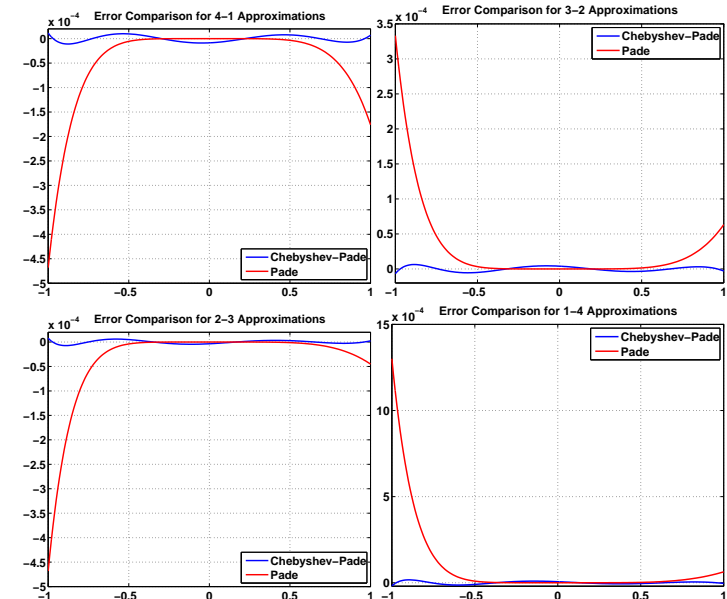
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$$\begin{aligned}
 R_{4,1}^{\text{CP}}(x) &= \frac{1.155054 T_0(x) - 0.8549674 T_1(x) + 0.1561297 T_2(x) - 0.01713502 T_3(x) + 0.001066492 T_4(x)}{T_0(x) + 0.1964246628 T_1(x)} \\
 R_{3,2}^{\text{CP}}(x) &= \frac{1.050531166 T_0(x) - 0.6016362122 T_1(x) + 0.07417897149 T_2(x) - 0.004109558353 T_3(x)}{T_0(x) + 0.3870509565 T_1(x) + 0.02365167312 T_2(x)} \\
 R_{2,3}^{\text{CP}}(x) &= \frac{0.9541897238 T_0(x) - 0.3737556255 T_1(x) + 0.02331049609 T_2(x)}{T_0(x) + 0.5682932066 T_1(x) + 0.06911746318 T_2(x) + 0.003726440404 T_3(x)} \\
 R_{1,4}^{\text{CP}}(x) &= \frac{0.8671327116 T_0(x) - 0.1731320271 T_1(x)}{T_0(x) + 0.73743710 T_1(x) + 0.13373746 T_2(x) + 0.014470654 T_3(x) + 0.00086486509 T_4(x)}
 \end{aligned}$$

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Example: Revisiting  $e^{-x}$  with Chebyshev-Padé Approximation

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## The Bad News — It's Not Optimal!

The Chebyshev basis does not give an optimal (in the min-max sense) rational approximation. However, the result can be used as a starting point for **the second Remez algorithm**. It is an iterative scheme which converges to the best approximation.

A discussion of how and why (and why not) you may want to use the second Remez' algorithm can be found in **Numerical Recipes in C: The Art of Scientific Computing** (Section 5.13). [You can read it for free on the web<sup>(\*)</sup> — just Google for it!]

(\*) The old 2nd Edition is Free, the new 3rd edition is for sale...

