

# Rational functions with positive normalised denominator

(no poles)

James Chok w/ Geoff Vasil

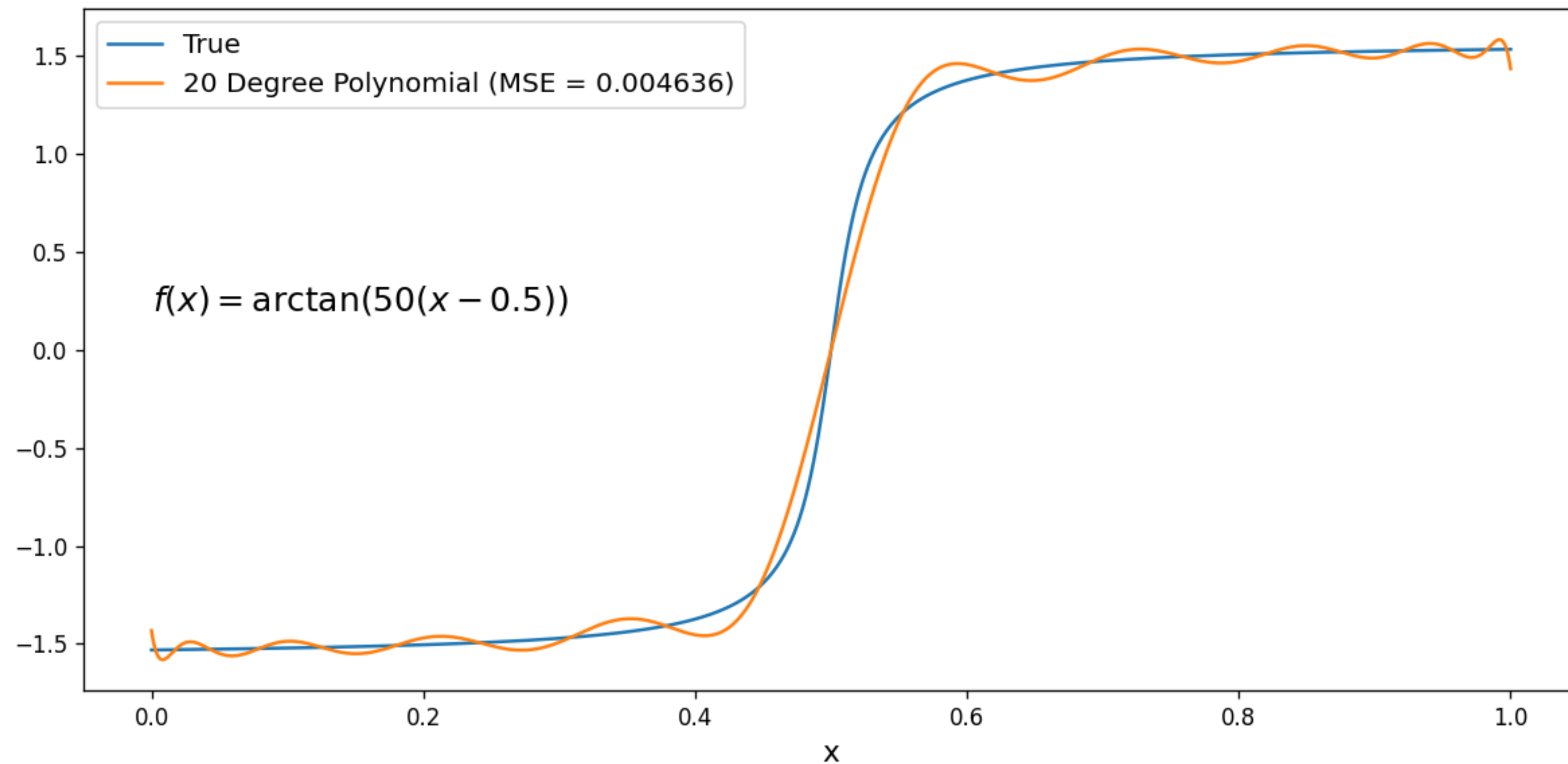
(U Edinburgh)

\*Thanks to the organisers / LNT

# Polynomial Approximation

$$f(x) \approx \sum_{n=0}^N a_n P_n(x) = \sum_{n=0}^N c_n x^n$$

(e.g. Legendre or Chebyshev)



# Rational Approximation

$$f(x) \approx R_{N,M}(x) = \frac{\sum_{n=0}^N a_n P_n(x)}{\sum_{m=0}^M b_m Q_m(x)}$$

- Reduces Runge's Phenomena
- Faster convergence than ordinary polynomials

# AAA Algorithm

Nakatsukasa, Sète, and Trefethen (2018)

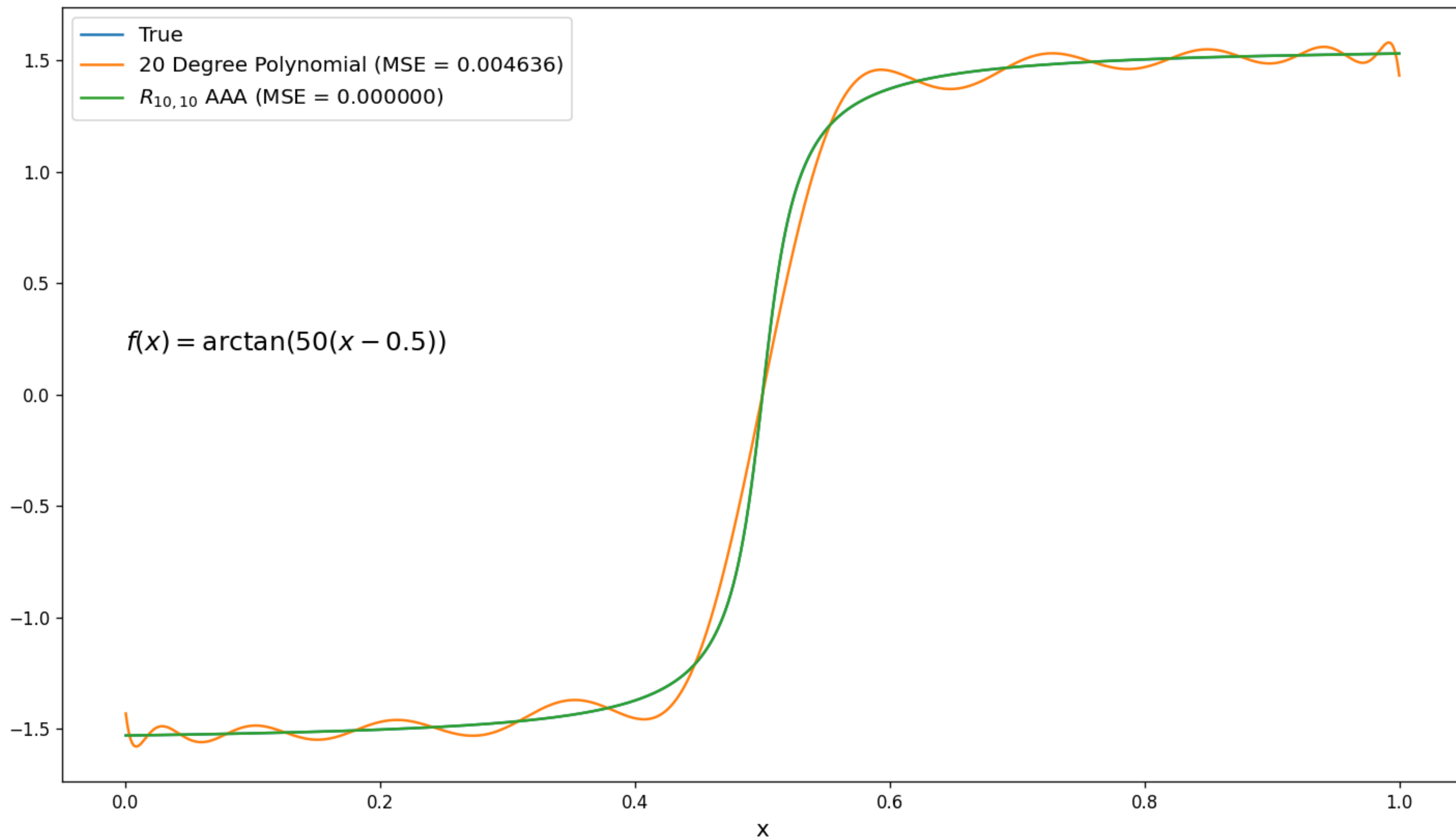
$$f(x) \approx R_{N,N}(x) = \sum_{n=0}^N \frac{w_n f_n}{x - x_n} \bigg/ \sum_{n=0}^N \frac{w_n}{x - x_n}$$

$$f_n = f(x_n), \quad w_n \neq 0$$

$0 < x_0 < x_1 < \dots < x_N \leq 1$  partitions  $[0,1]$ . Non-zero denominator at  $x_i$

$$\min_w \sum_i \left[ f_i \left( \sum_{n=0}^N \frac{w_n}{x_i - x_n} \right) - \left( \sum_{n=0}^N \frac{w_n f_n}{x_i - x_n} \right) \right]^2$$

Normalizing Condition:  $\|w\| = 1$



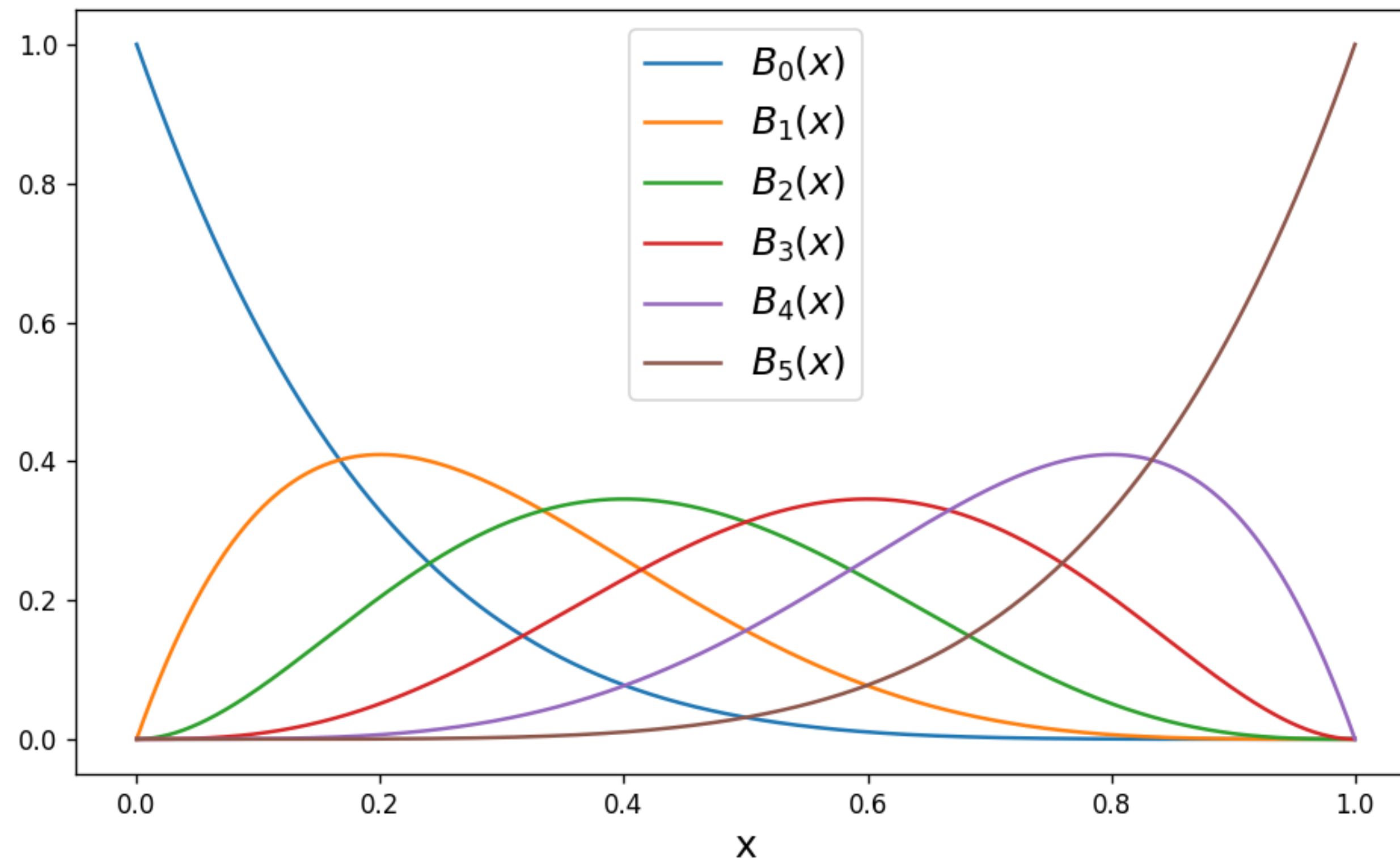
# New Problem

$$f(x) \approx R_{N,M}(x) = \frac{P(x)}{Q(x)} \quad \text{with} \quad \underline{Q(x) > 0} \quad \text{for} \quad x \in [0,1]$$

# Bernstein Polynomials

$$B_k^{(N)}(x) = \binom{N}{k} x^k (1-x)^{N-k}$$

$$B_k^{(N)}(x) > 0 \quad \text{for } x \in (0,1)$$



**Sergei Natanovich Bernstein**



# Our Proposal

$$f(x) \approx R_{N,M}(x) = \frac{P(x)}{Q(x)} \quad \text{with} \quad Q(x) > 0 \quad \text{for} \quad x \in [0,1]$$

$$Q(x) = \sum_{m=0}^M w_m B_m(x) \quad \text{where} \quad B_m(x) = \binom{M}{m} x^m (1-x)^{M-m}$$



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**Positivity**

$$w_m \geq 0$$

**Normalization**

$$\sum_m w_m = 1$$

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$$w_m \geq 0$$

**Normalization**

$$\sum_m w_m = 1$$

$$f(x) \approx R_{N,M}(x) = \sum_{n=0}^N a_n P_n(x) \bigg/ \sum_{m=0}^M w_m B_m(x)$$

For some  $\{P_n(x)\}_n$

# How to Solve

$$f(x) \approx R_{N,M}(x) = \sum_{n=0}^N a_n P_n(x) \bigg/ \sum_{m=0}^M w_m B_m(x)$$

$$w \in \Delta^{M+1} = \left\{ w \in \mathbb{R}^{M+1} \mid w_m \geq 0 \text{ and } \sum_m w_m = 1 \right\}$$

## Linearized Problem

$$\min_{\substack{a \in \mathbb{R}^{N+1} \\ w \in \Delta^{M+1}}} \left\| f(x) \sum_m w_m B_m(x) - \sum_n a_n P_n(x) \right\|$$



Very much like Lanczos (1938)

# How to Solve

$$f(x) \approx R_{N,M}(x) = \sum_{n=0}^N a_n P_n(x) \bigg/ \sum_{m=0}^M w_m B_m(x)$$

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**Linearized**

$$\min_{\substack{a \in \mathbb{R}^{N+1} \\ w \in \Delta^{M+1}}} \left\| f(x) \sum_m w_m B_m(x) - \sum_n a_n P_n(x) \right\|$$

**Non-linearized**

$$\min_{\substack{a \in \mathbb{R}^{N+1} \\ w \in \Delta^{M+1}}} \left\| f(x) - \sum_n a_n P_n(x) \bigg/ \sum_m w_m B_m(x) \right\|$$

# Linearized Residuals

$$\min_{\substack{a \in \mathbb{R}^{N+1} \\ w \in \Delta^{M+1}}} \int \left( f(x) \sum_m w_m B_m(x) - \sum_n a_n P_n(x) \right)^2 d\mu$$

$$\approx \min_{a, w} \sum_i \mu_i \left( f(x_i) \sum_m w_m B_m(x_i) - \sum_n a_n P_n(x_i) \right)^2 \quad \text{for } \mu_i \geq 0$$

$$\text{with } w_m \geq 0, \quad \sum_m w_m = 1$$

# Non-linearized Residuals

$$\min_{\substack{a \in \mathbb{R}^{N+1} \\ w \in \Delta^{M+1}}} \left\| f(x) - \frac{\sum_n a_n P_n(x)}{\sum_m w_m B_m(x)} \right\|$$

$$\min_{\substack{a \in \mathbb{R}^{N+1} \\ w \in \Delta^{M+1}}} \int \left( f(x) \sum_m w_m B_m(x) - \sum_n a_n P_n(x) \right)^2 \frac{d\mu}{\left( \sum_m w_m B_m(x) \right)^2}$$

**Like the linearized part**

**Like an adjusted measure**

(Like Sanathanan and Koerner. - 1963)

# Optimizing Over a Simplex

Chok, and Vasil (2023)

$$\min_{w \in \Delta^M} F(w)$$

Enforces positivity

$$\frac{dw_i}{dt} = w_i (\nabla_{w_i} F - w \cdot \nabla_w F)$$

Enforces unit sum constraint

$$\sum_i \frac{dw_i}{dt} = (w \cdot \nabla_w F) - (w \cdot \nabla_w F) \sum_i w_i$$

$$F(w) = \left\| f(x) - \sum_n a_n P_n(x) \middle/ \sum_m w_m B_m(x) \right\|$$

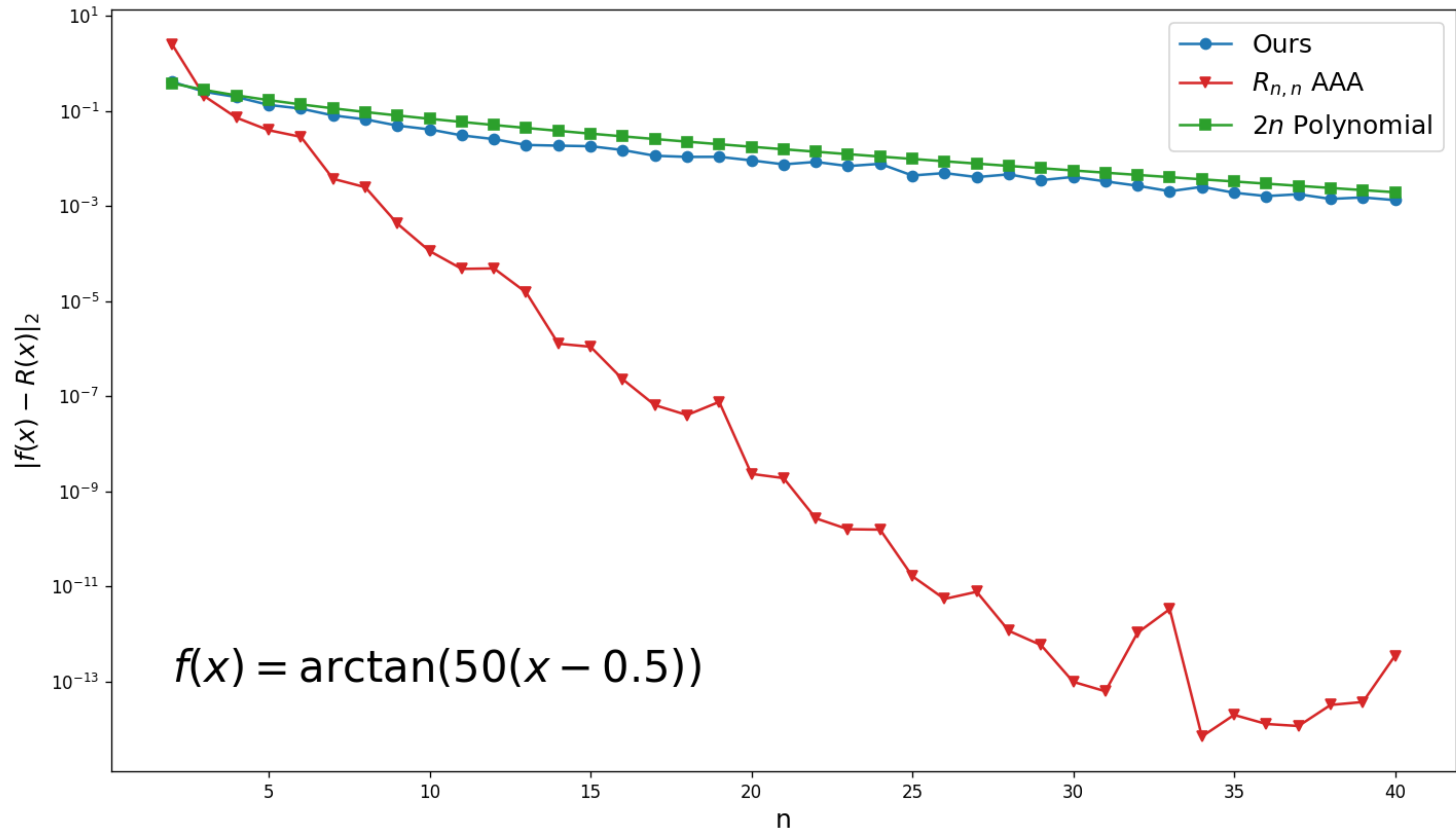
# How to Solve

$$F(a, w) = \left\| f(x) - \sum_n a_n P_n(x) \middle/ \sum_m w_m B_m(x) \right\|$$

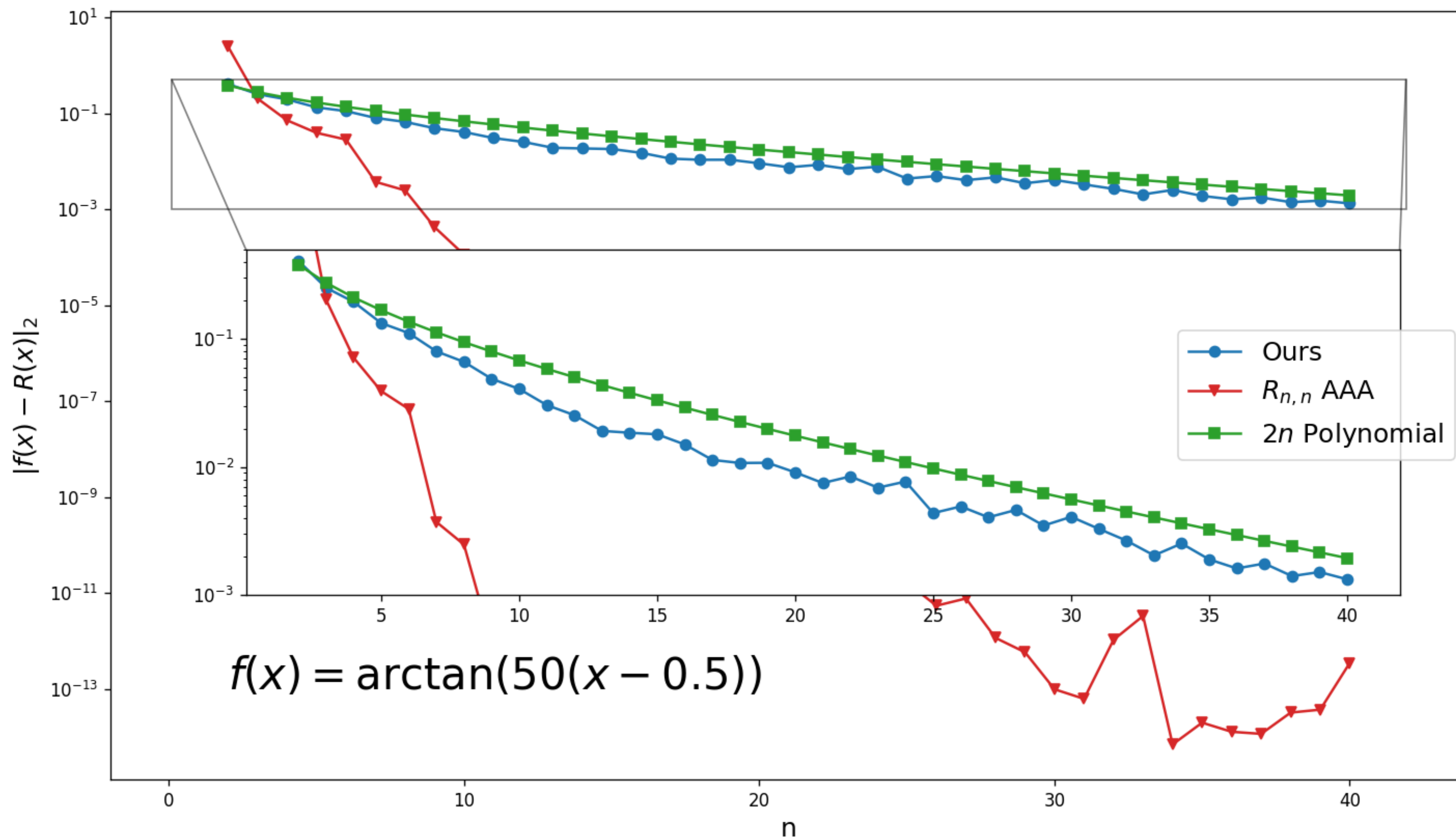
1. Fix  $a \in \mathbb{R}^{N+1}$  and take step(s) in  $w \in \Delta^{M+1}$
2. Fix  $w \in \Delta^{M+1}$  and solve for  $a \in \mathbb{R}^{N+1}$  exactly
3. Repeat



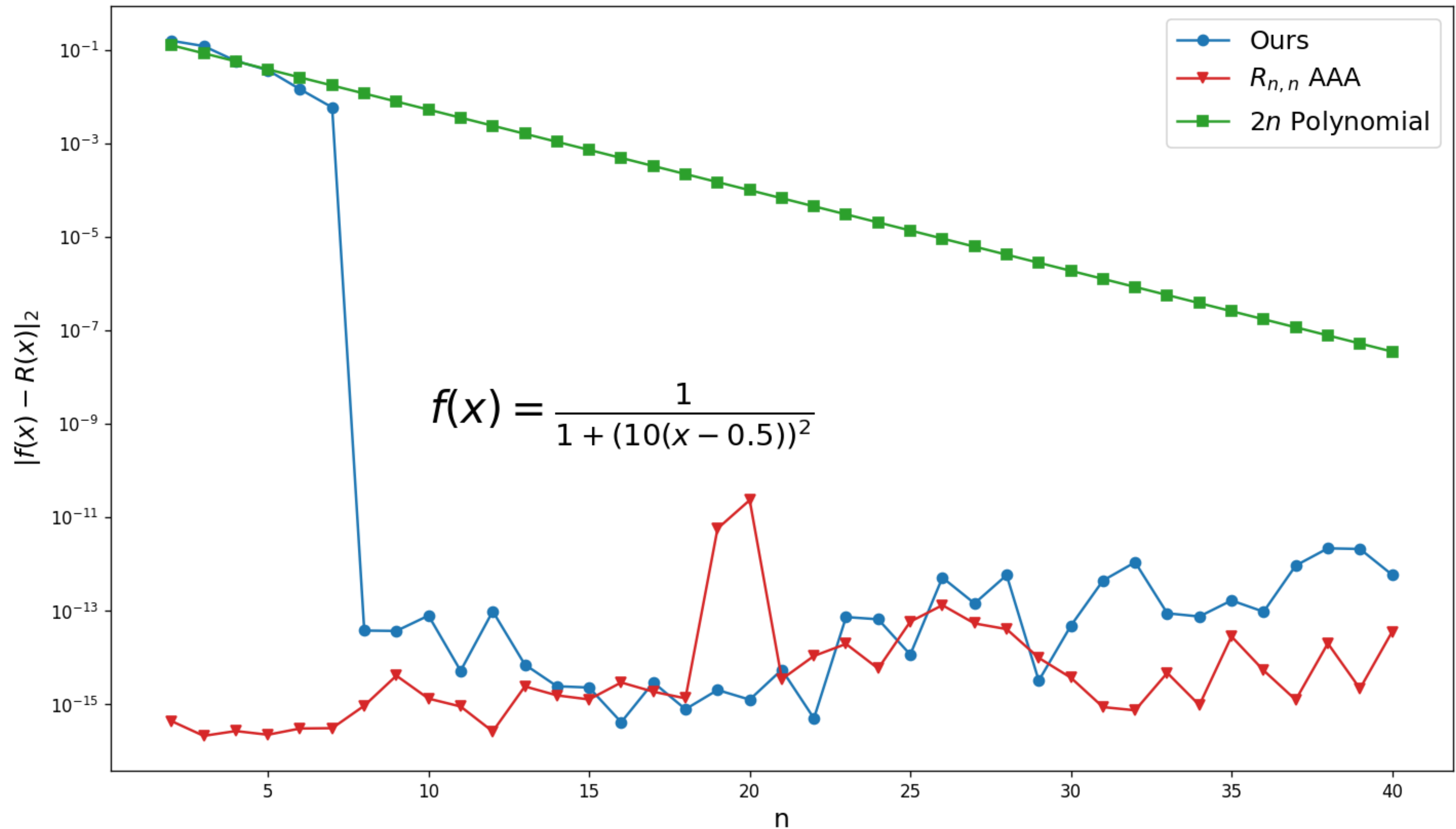
# Numerical Convergence



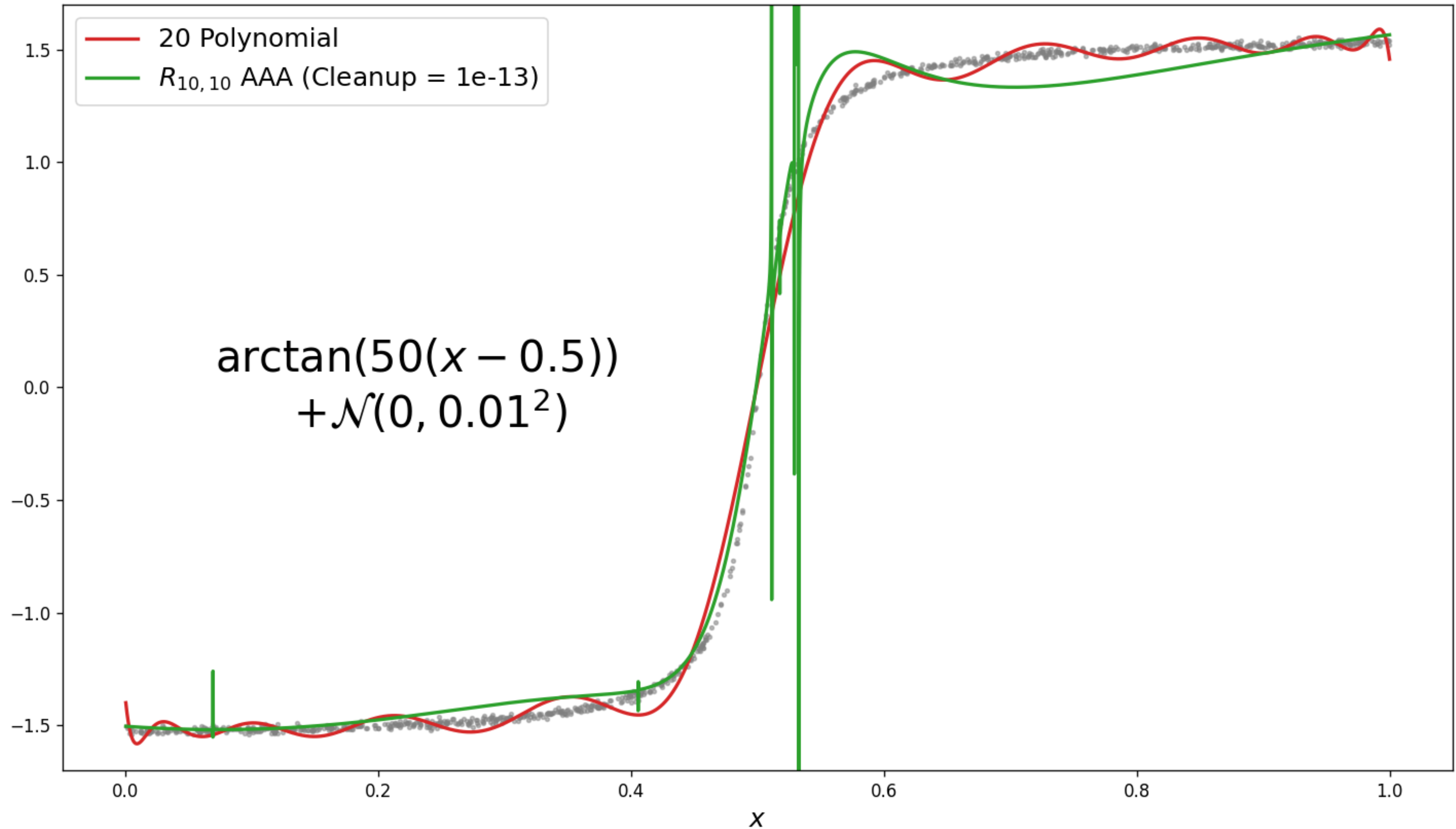
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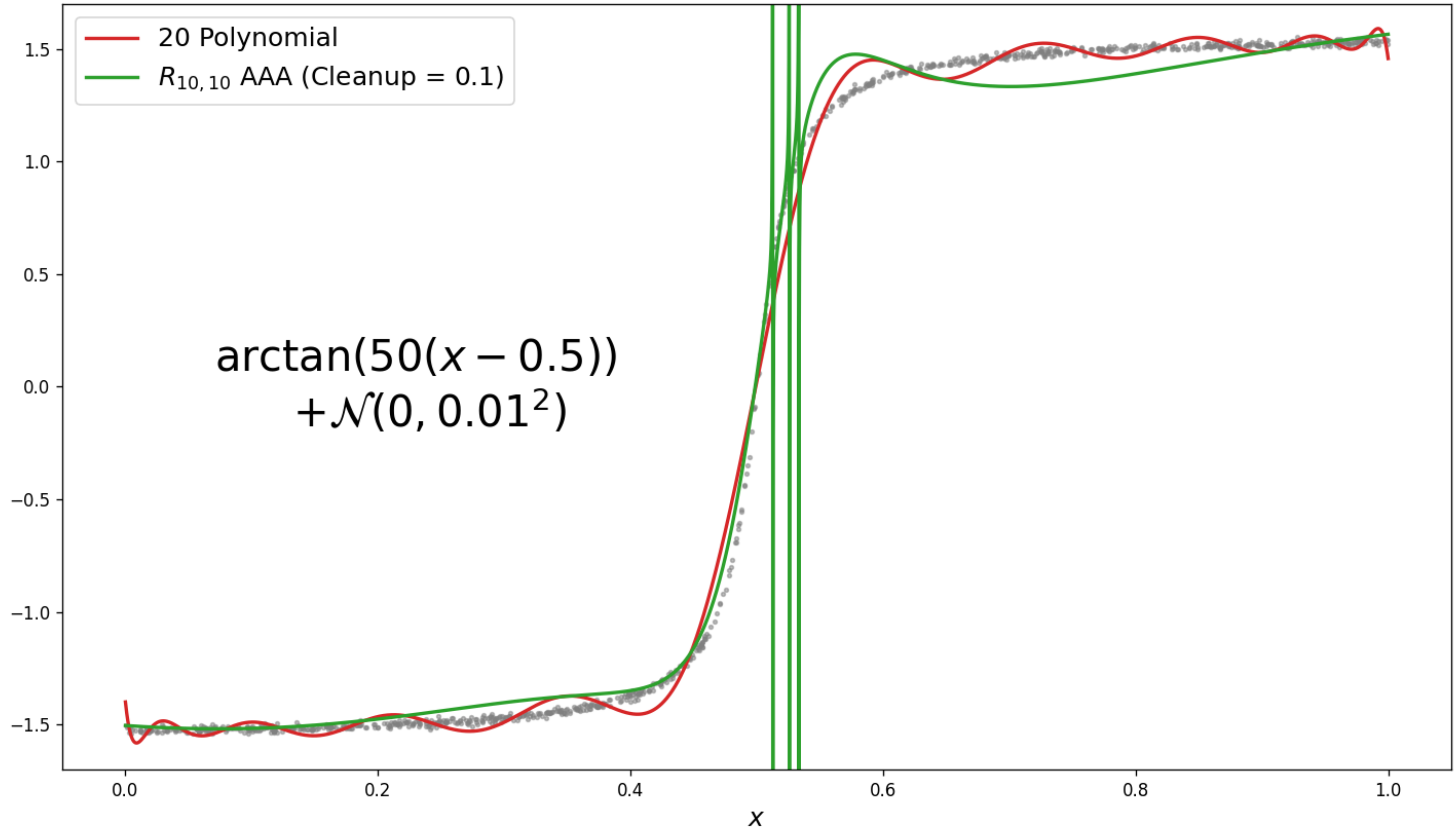
# Numerical Convergence (Runge's Example)



# Noisy Data

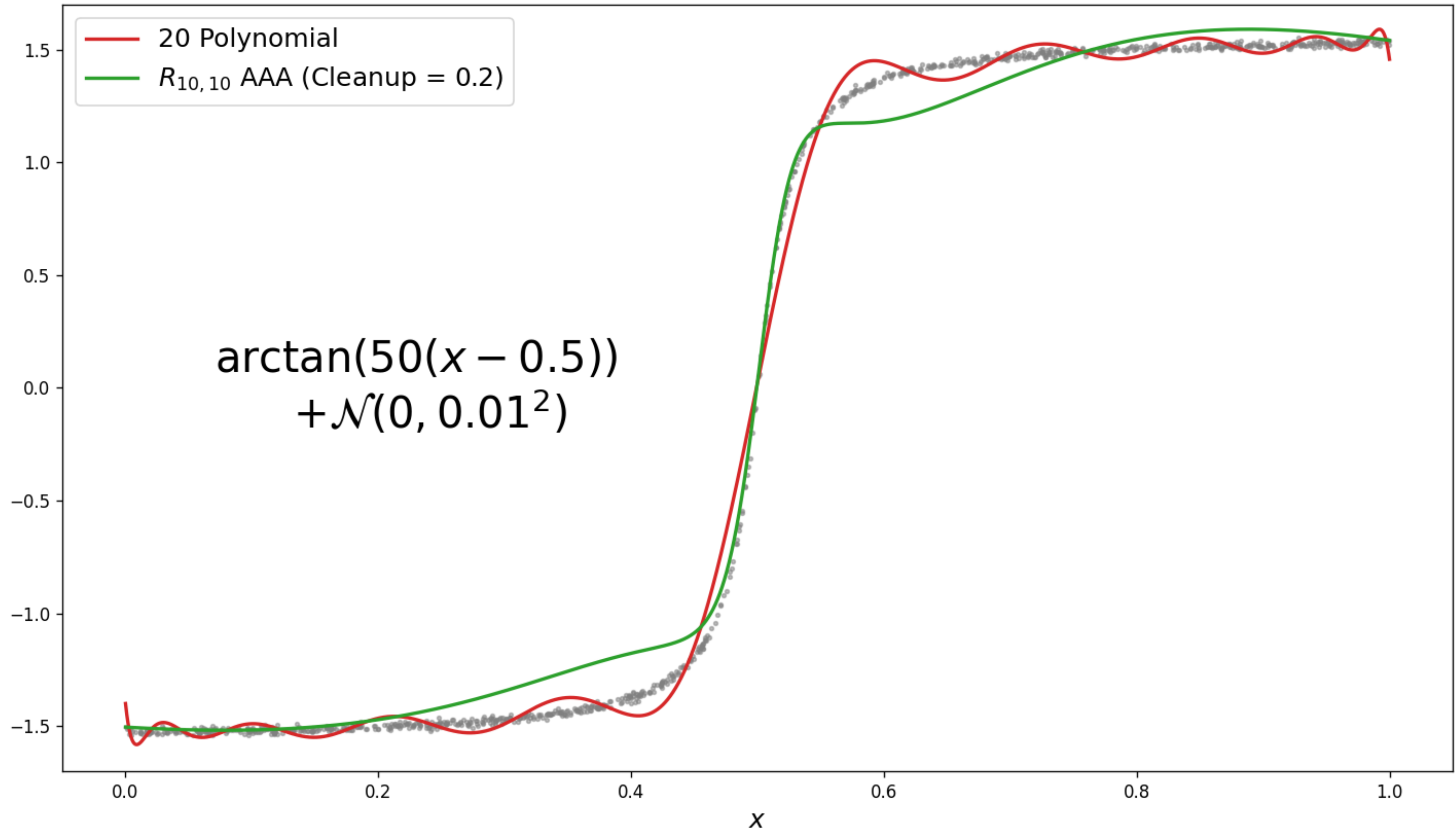


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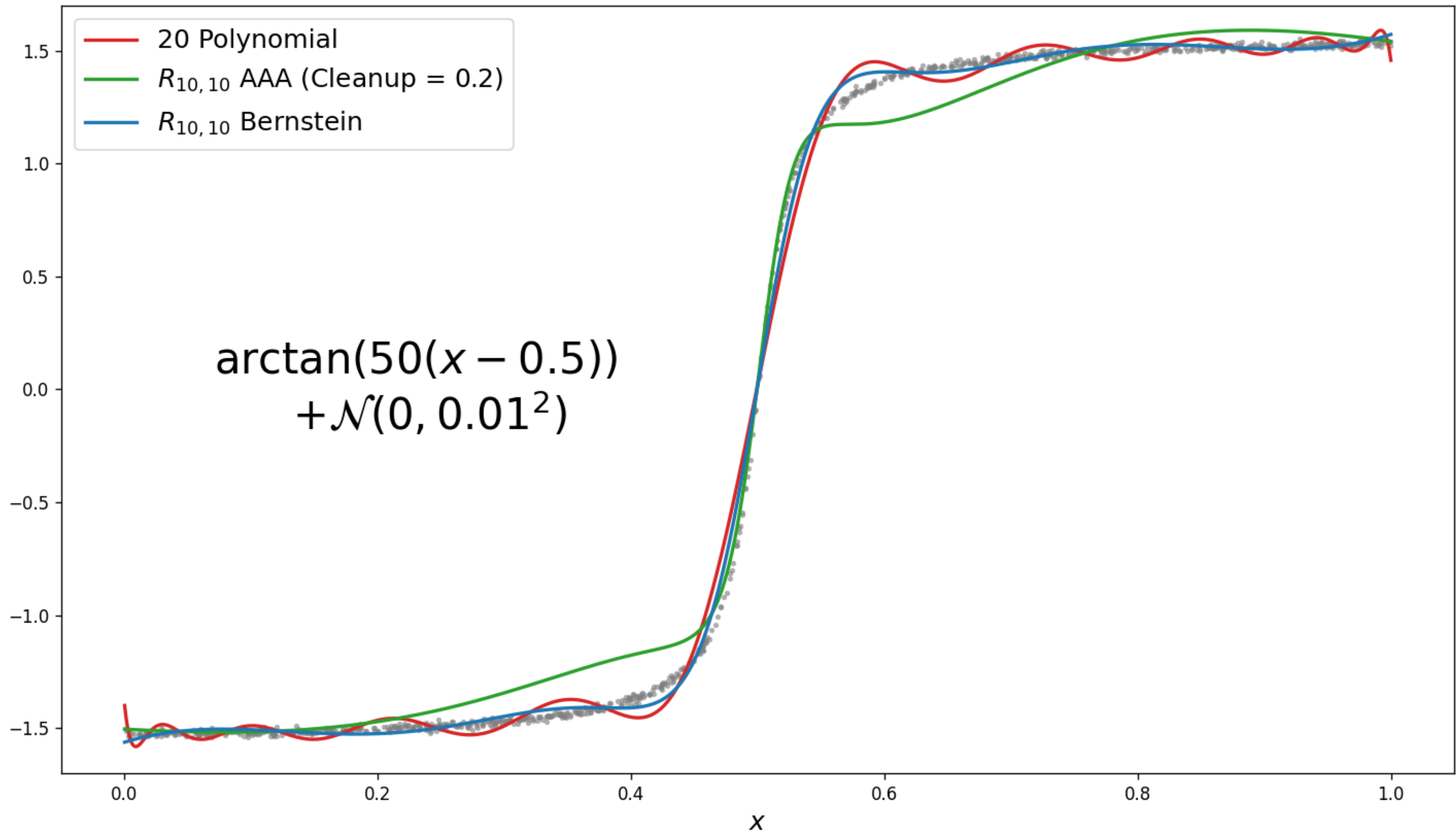




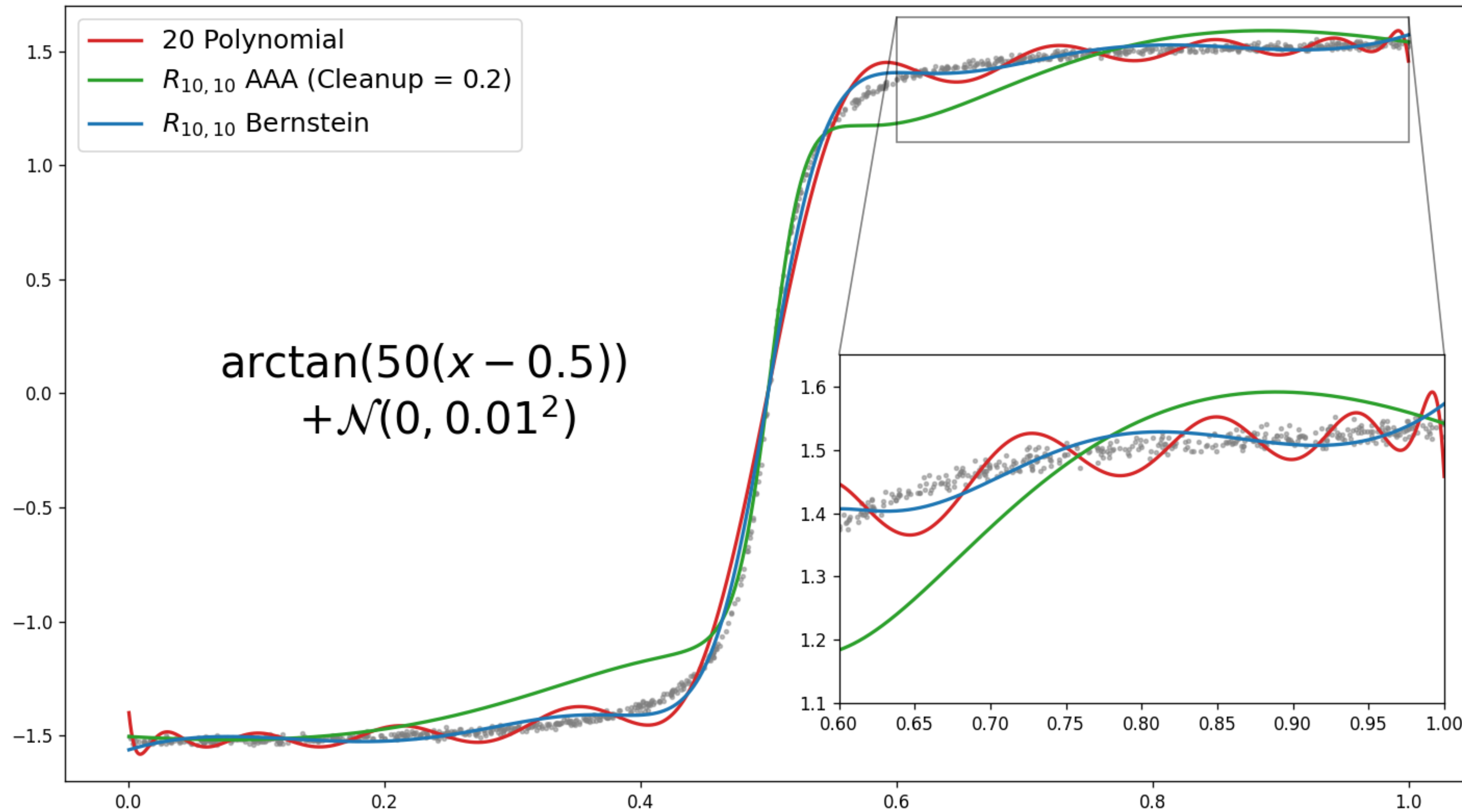
# Noisy Data



# Noisy Data



# Noisy Data





# Penalization & smoothing

$f(x) \approx R_{N,M}(x)$  and  $R_{N,M}$  is smooth

$\approx R_{N,M}(x)$  and Numerator is smooth

$$\rightarrow \min_g \left\| f(x) - g(x) \right\| + \sum_{k \geq 0} \lambda_k \int (g^{(k)}(x))^2 d\mu_k \quad \text{for } \lambda_k \geq 0$$

## Legendre

$$\sum_{k \geq 0} \lambda_k \int_0^1 \left( \sum_{n=0}^N a_n P_n^{(k)}(x) \right)^2 d\mu_k = \sum_{n=0}^N a_n^2 (\lambda_n n^{2n})$$

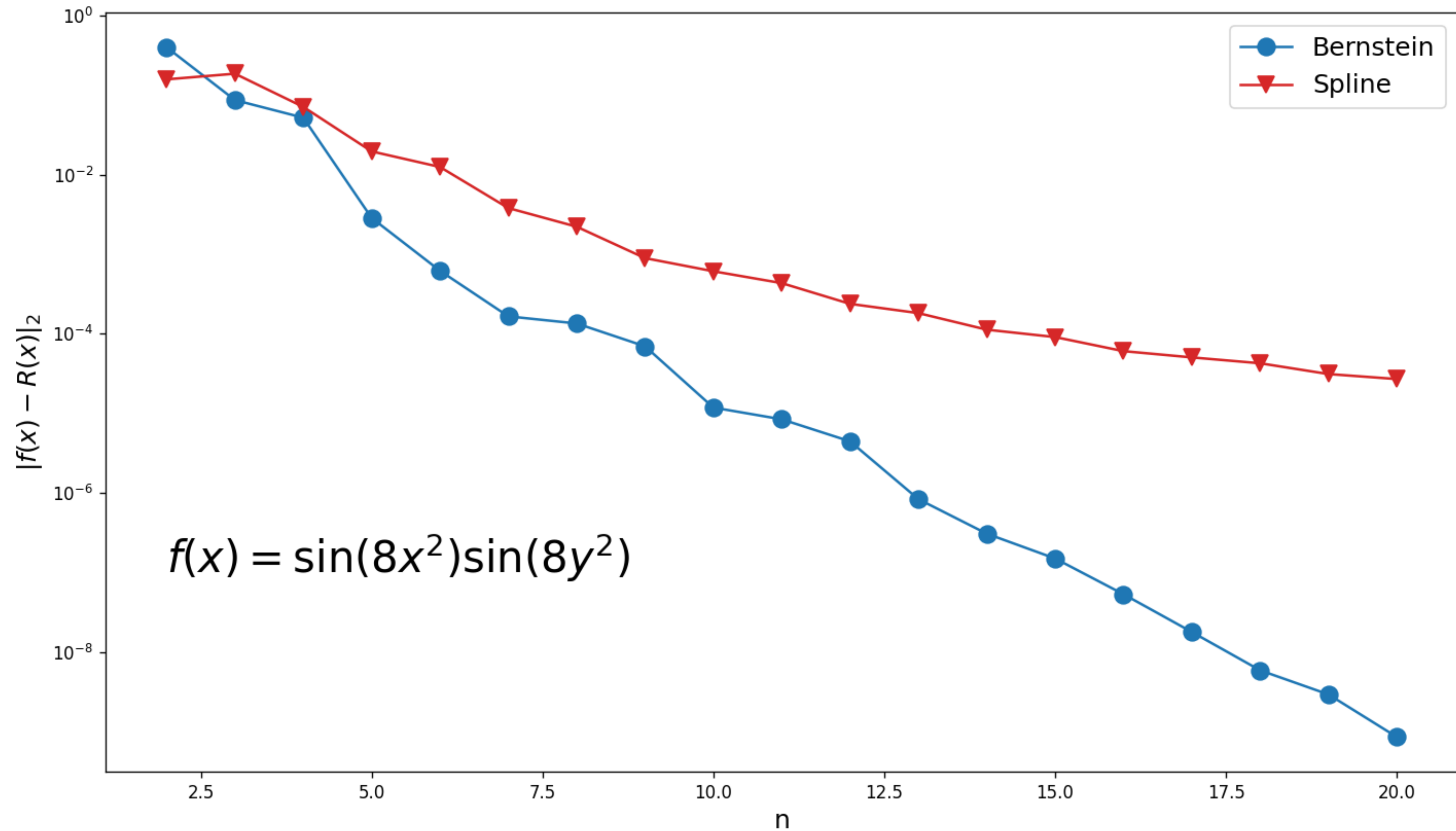


# Bivariate

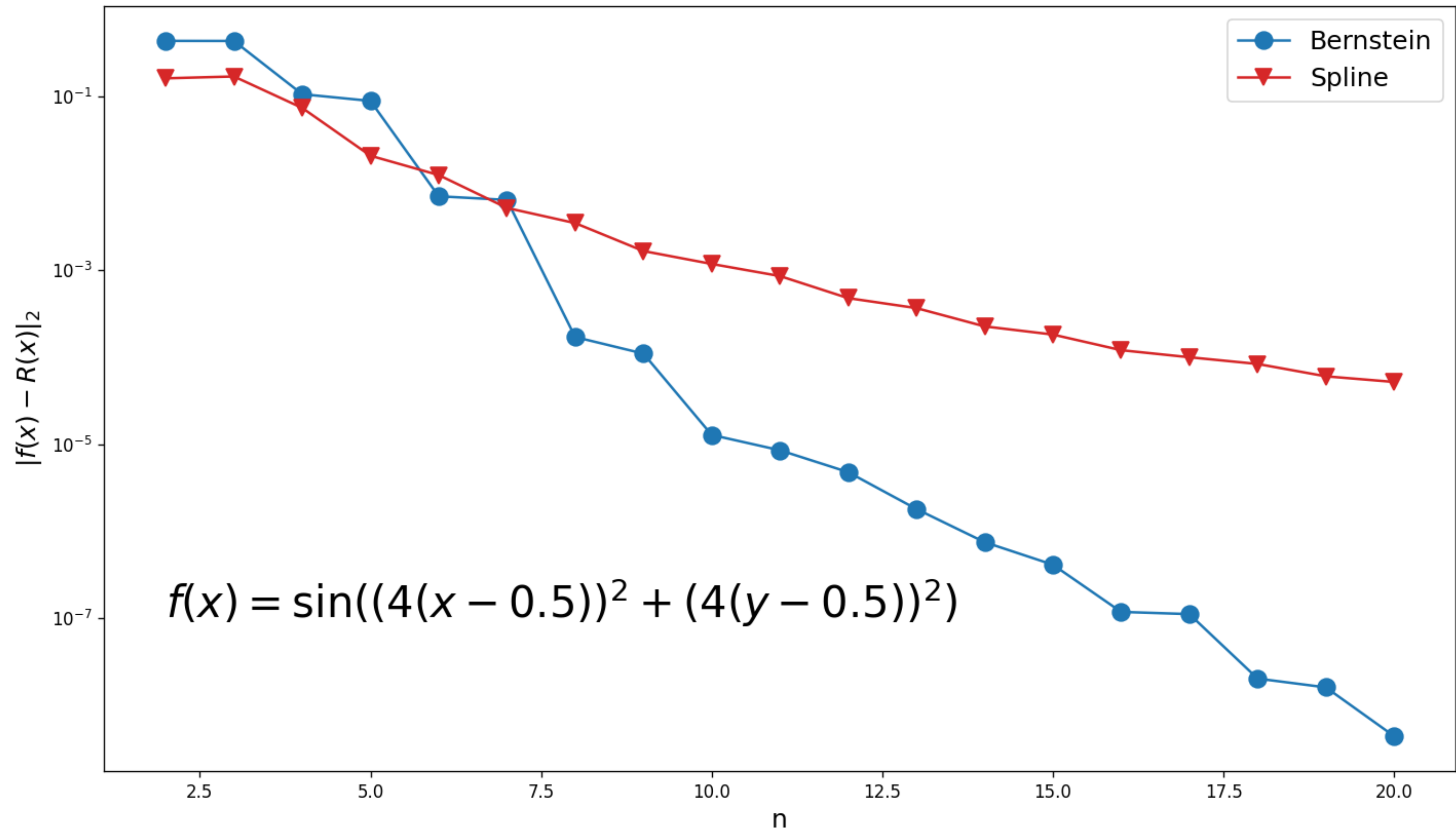
$$R(x, y) = \sum_{n, m} a_{n, m} P_n(x) P_m(y) \bigg/ \sum_{j, k} w_{j, k} B_j(x) B_k(y)$$

$$w_{j, k} \geq 0 \quad \text{and} \quad \sum_{j, k} w_{j, k} = 1$$

# Numerical Convergence



# Numerical Convergence

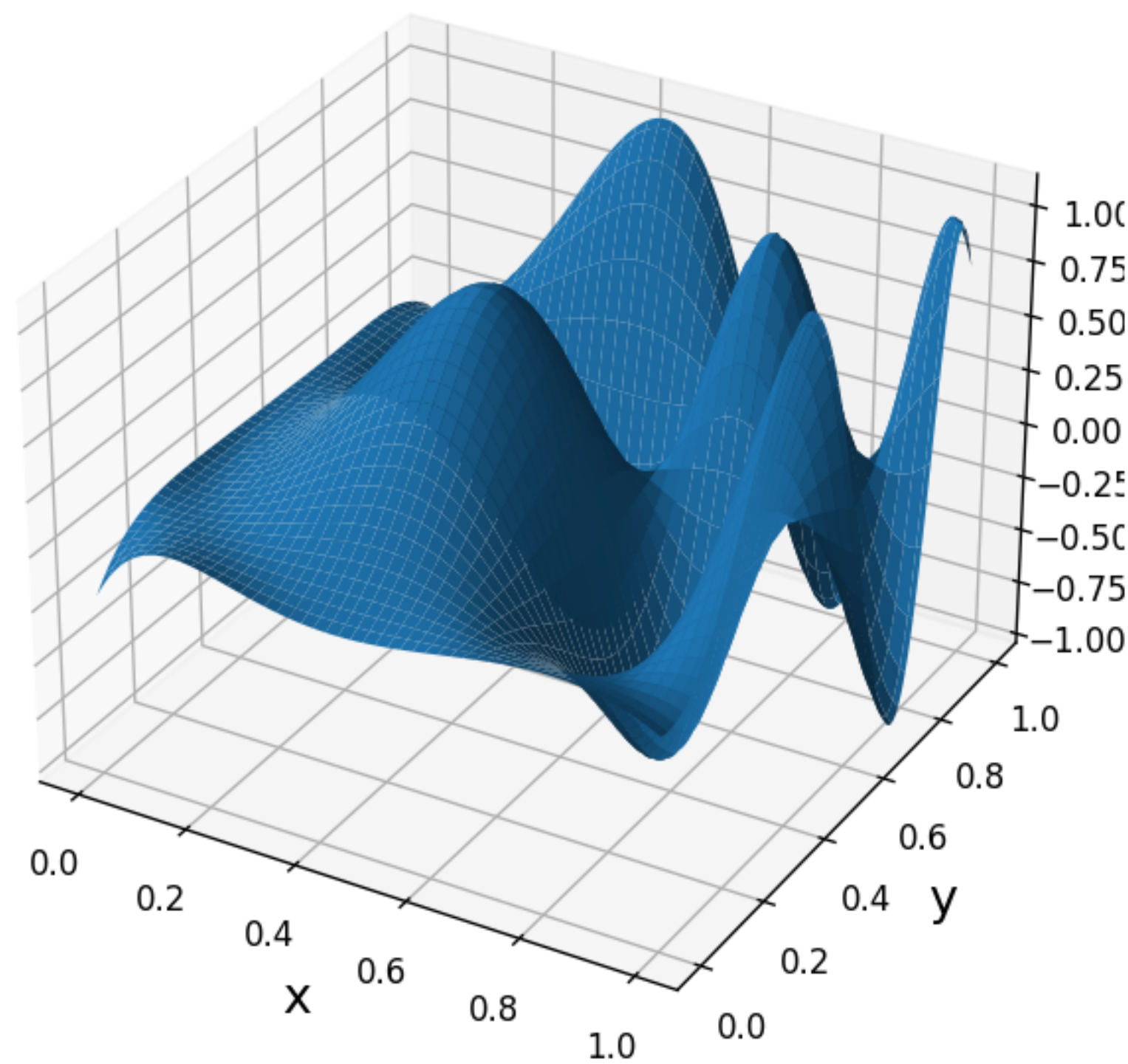




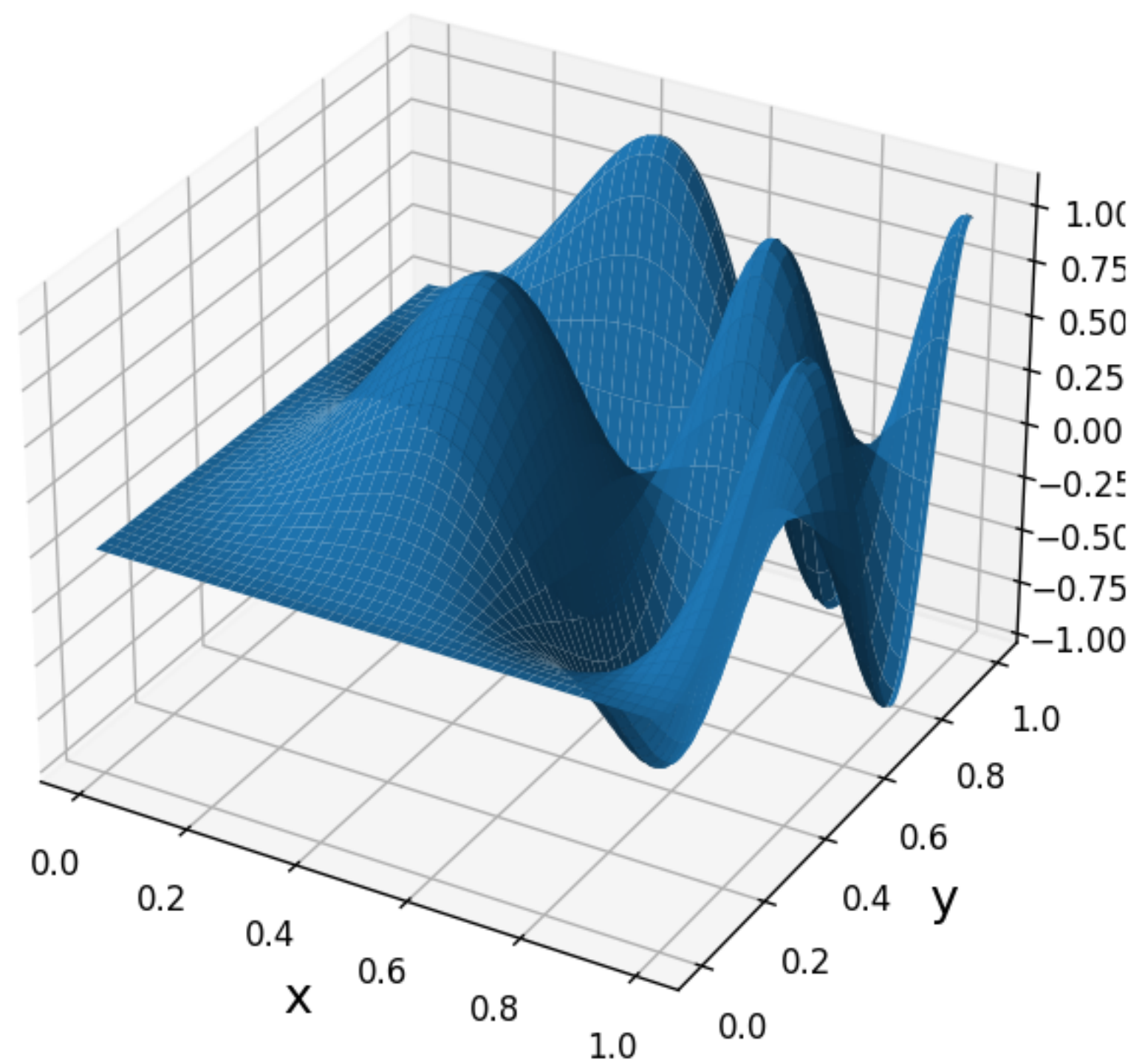
# Bernstein vs Spline

$$\sin(8x^2 + 8y^2) + \mathcal{N}(0, 0.1^2)$$

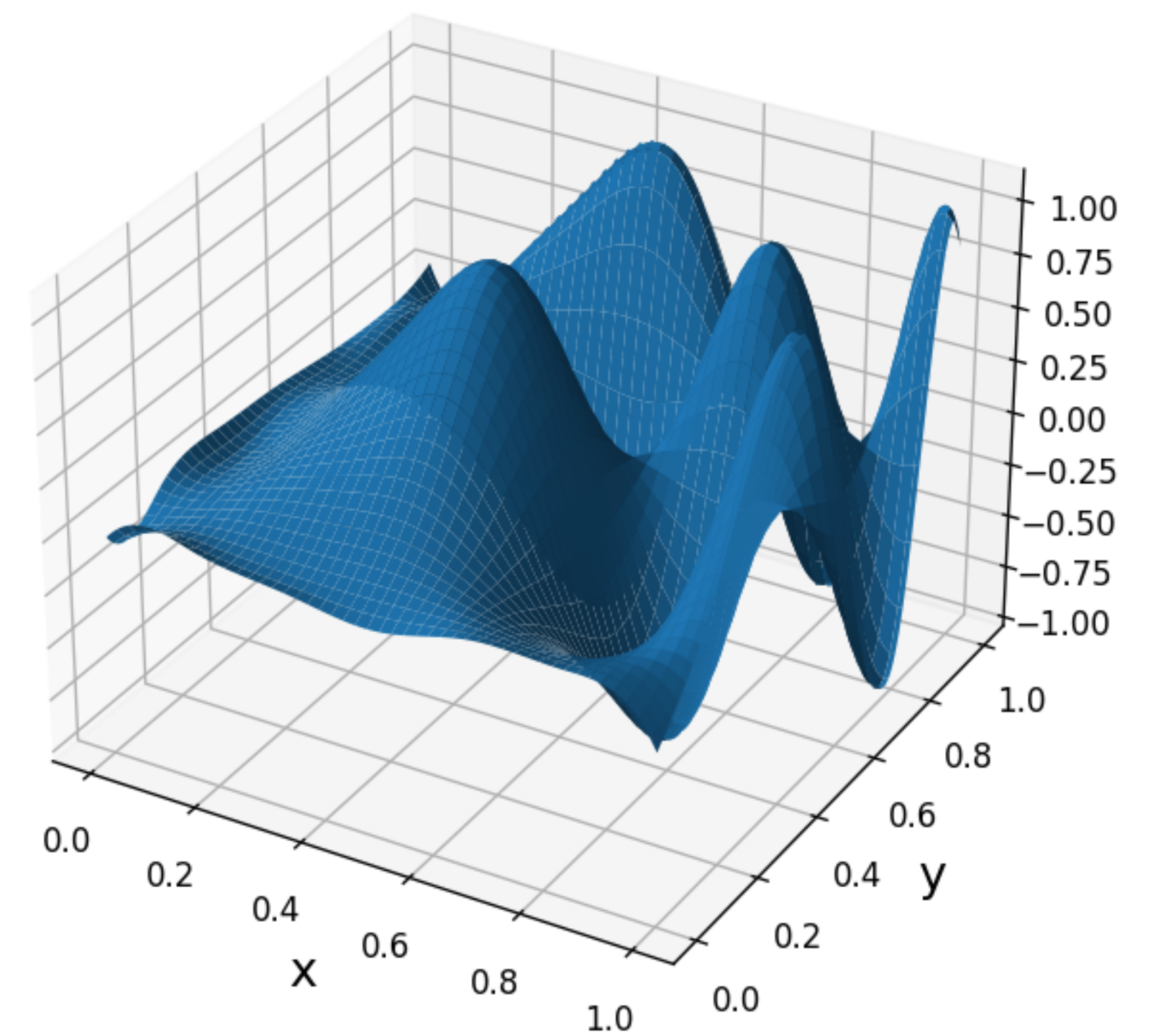
Bernstein



True



Spline

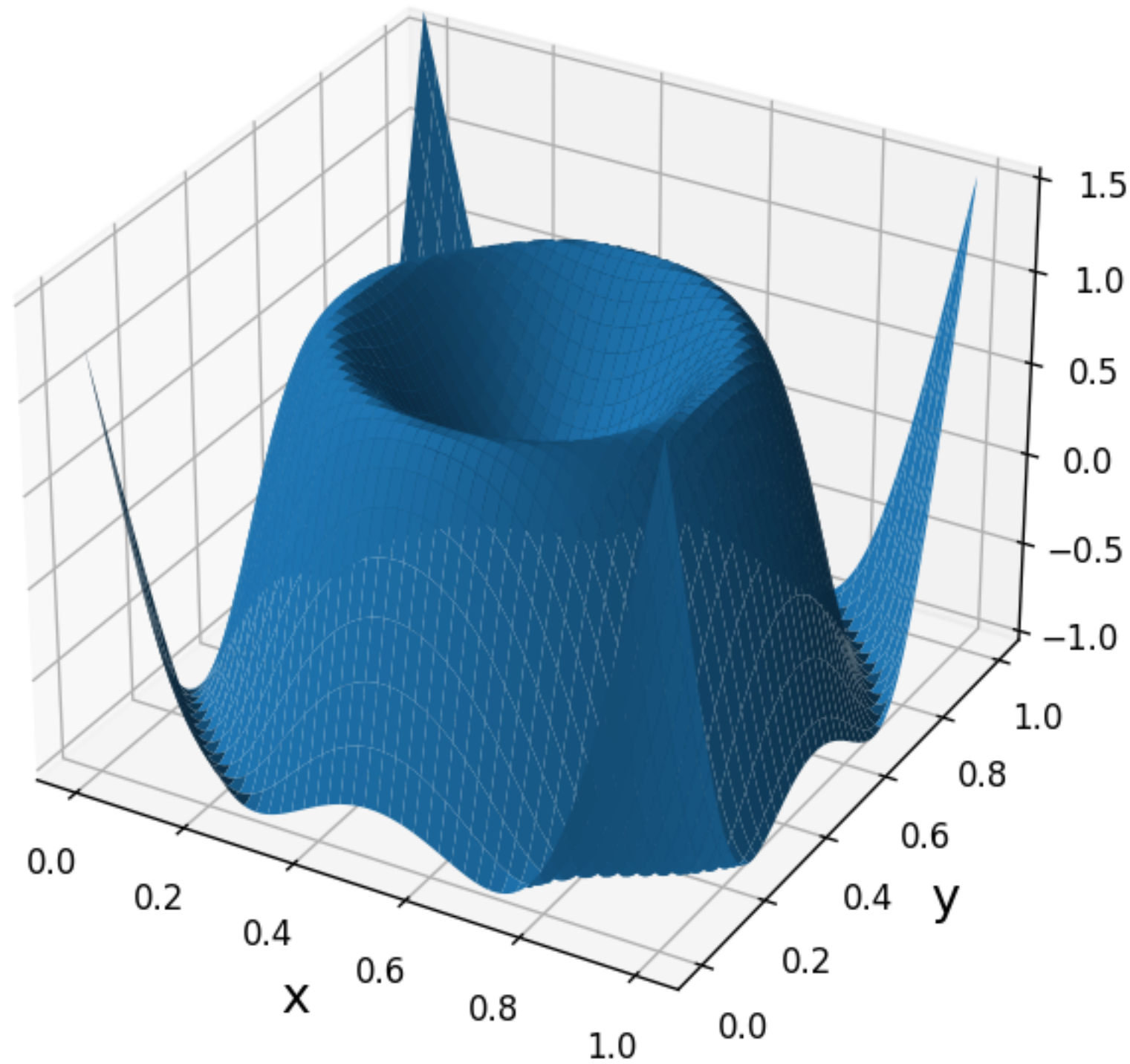




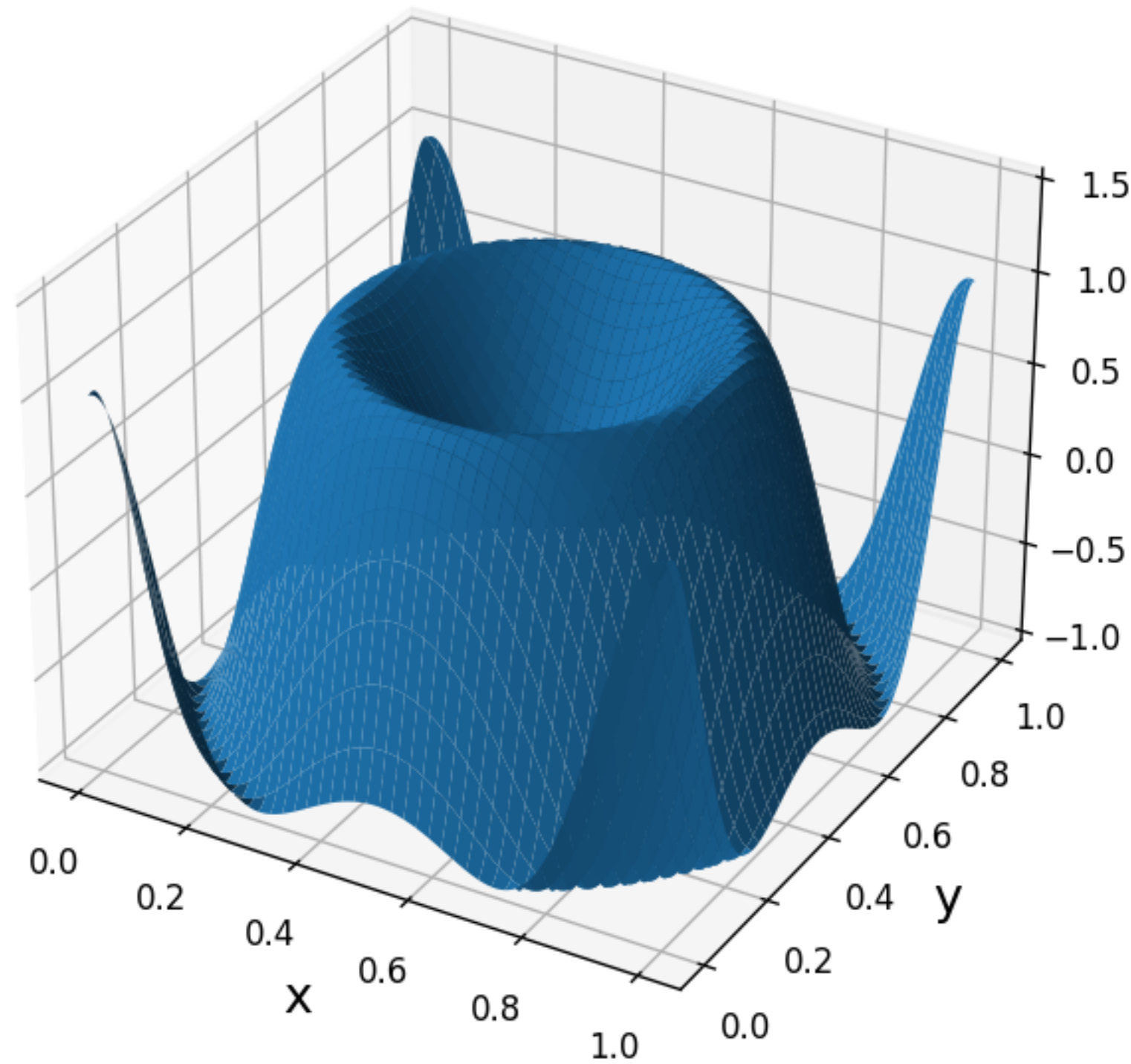
# Bernstein vs Spline

$$\sin\left((4(x-0.5))^2 + (4(y-0.5))^2\right) + \mathcal{N}(0,0.1^2)$$

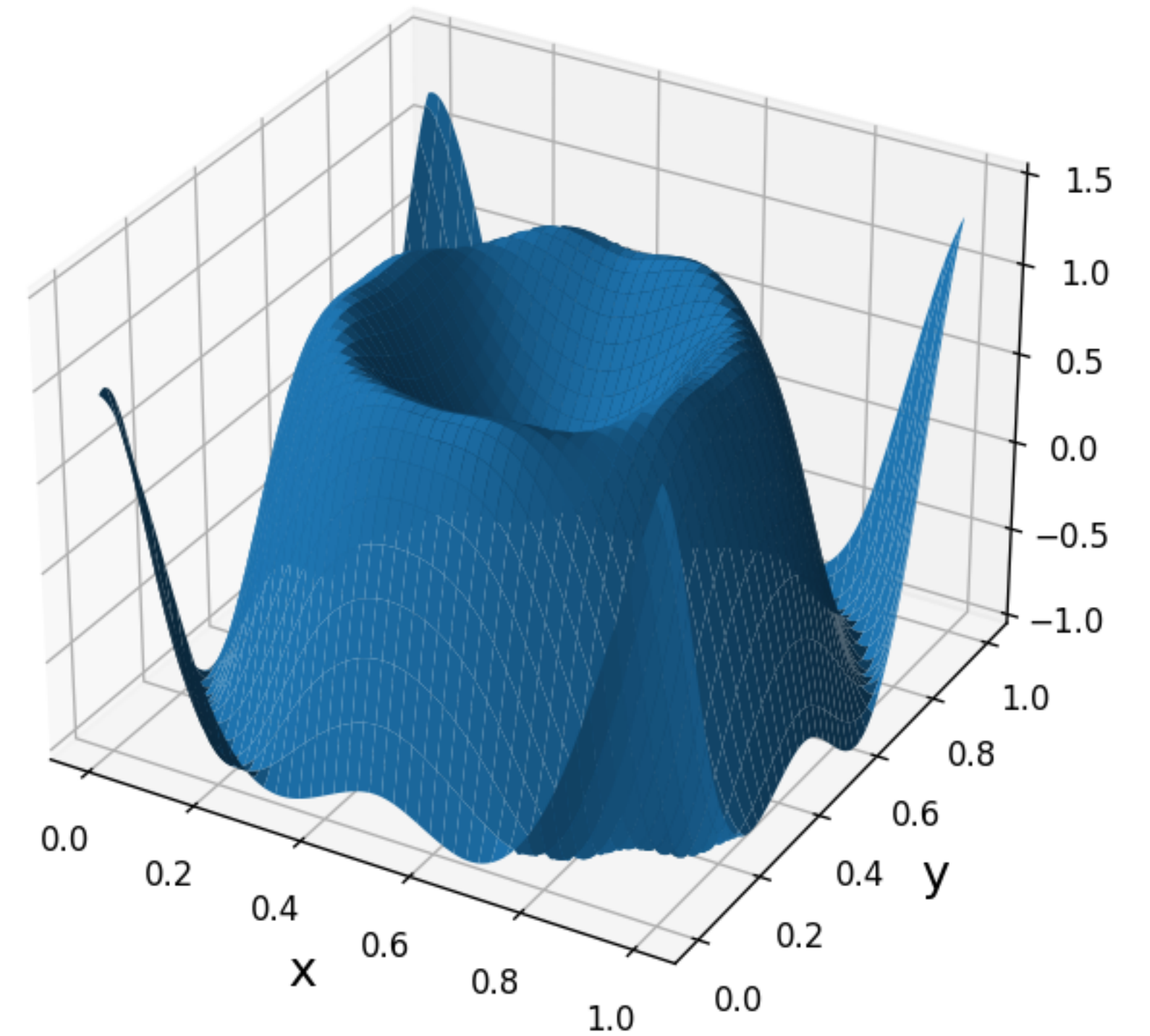
Bernstein



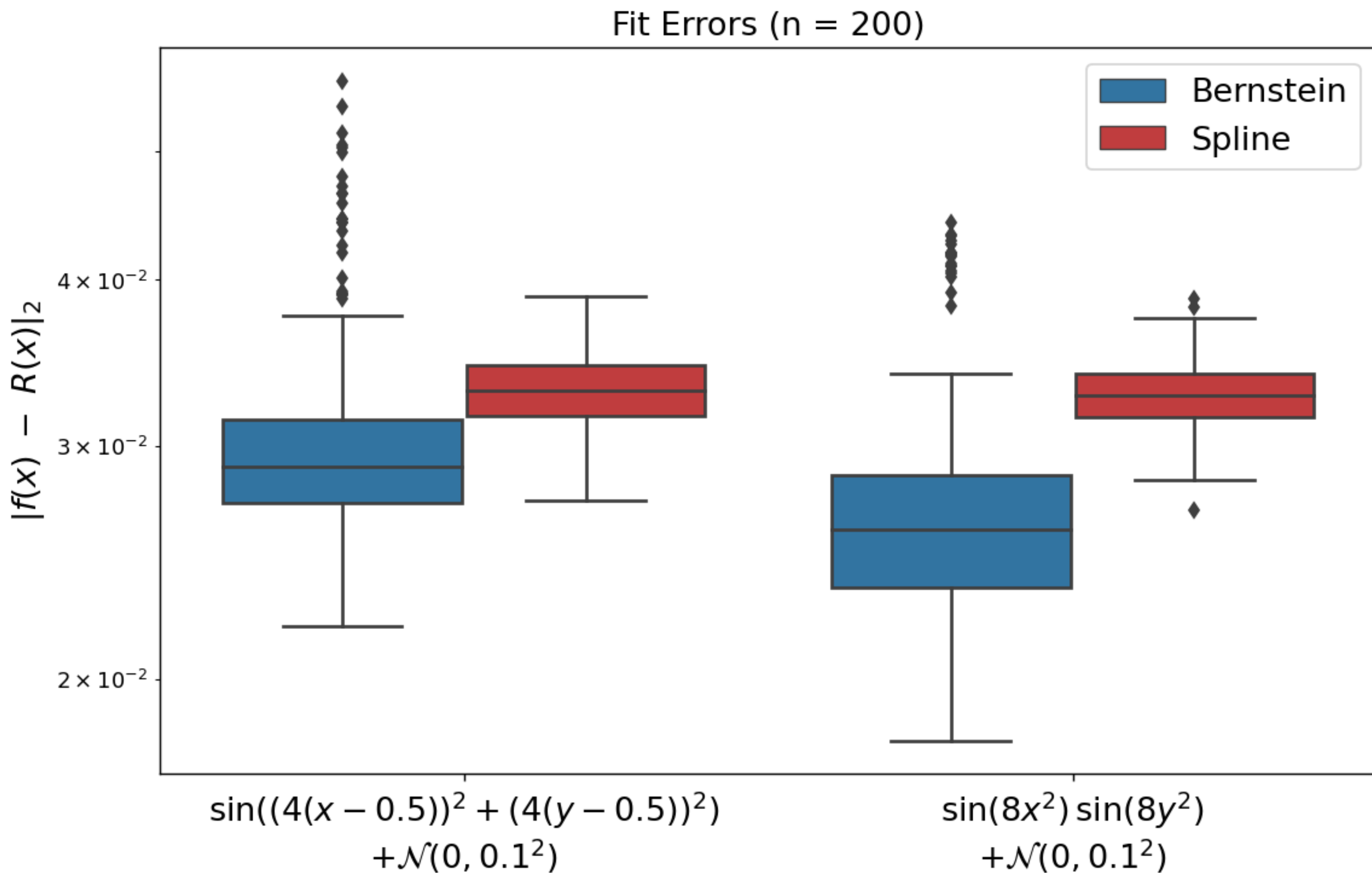
True



Spline



# Bernstein vs Spline



**“Which approximation would be more useful in an application?**

**I think the only reasonable answer is, it depends.**

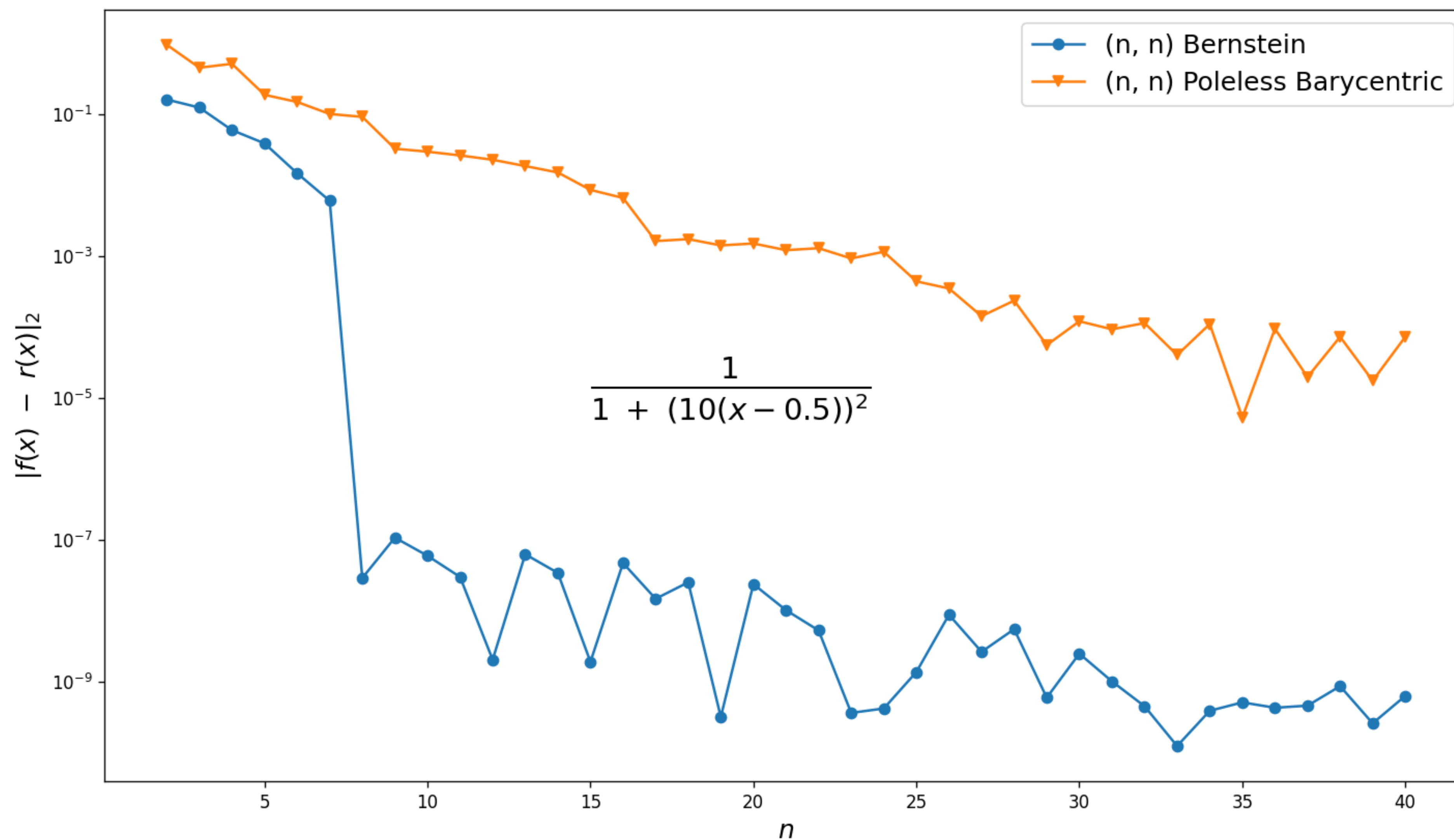
**Sometimes one really does need a guarantee about worst-case behavior.”**

**L. N. Trefethen (2012)**



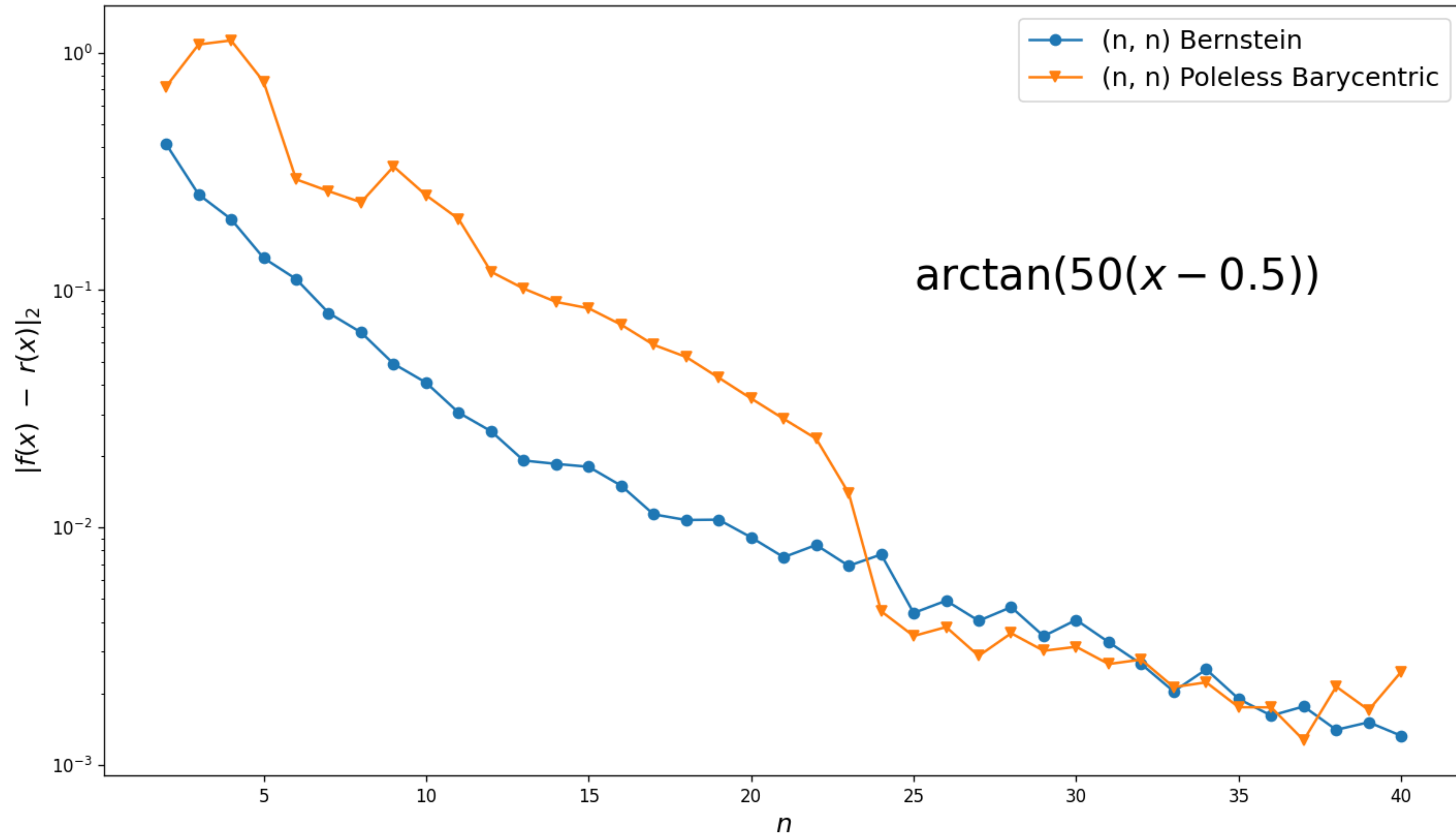
# Poleless Barycentric

J. P. Berrut (1988) and M. S. Floater and K. Hormann (2007)



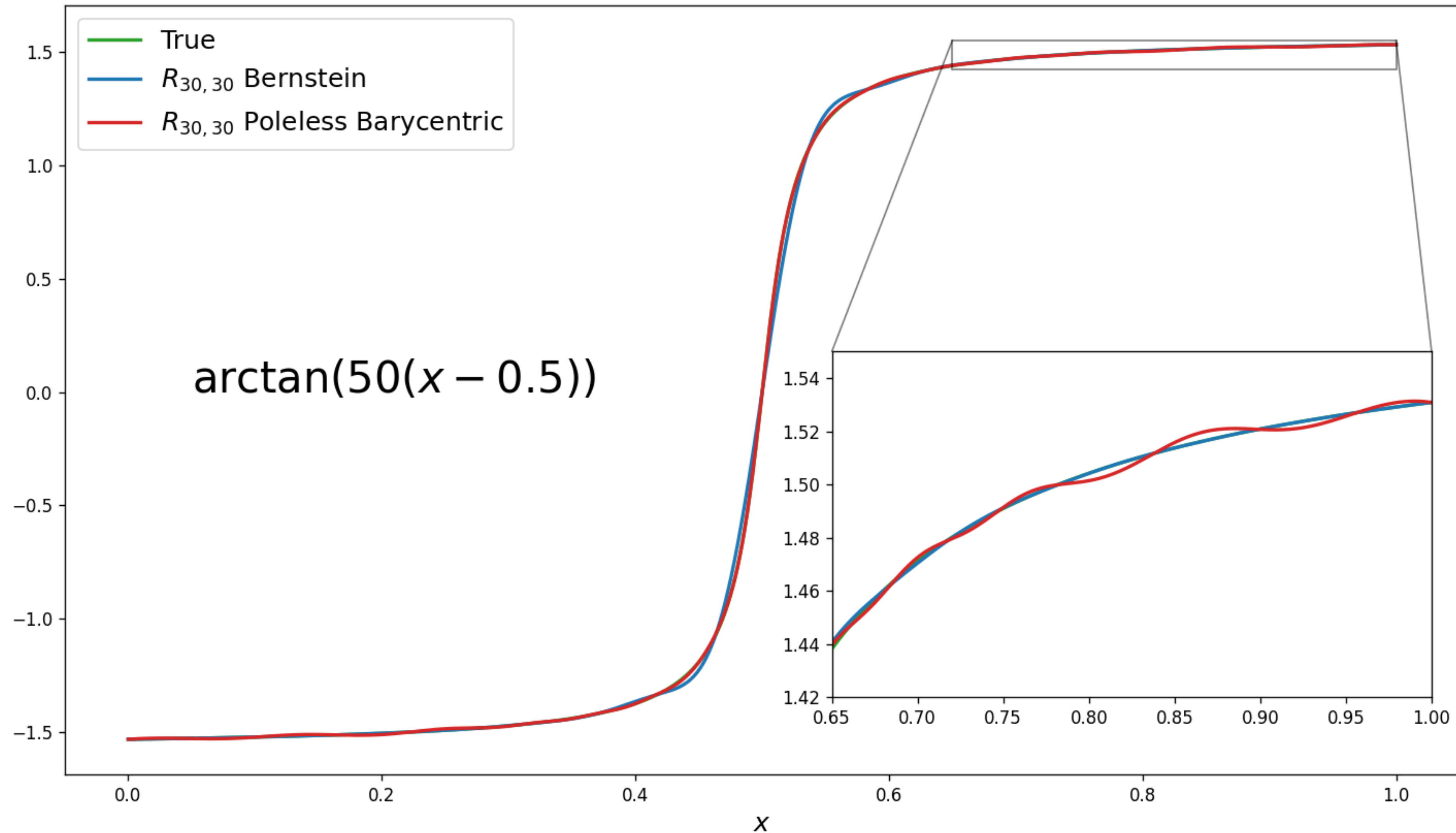
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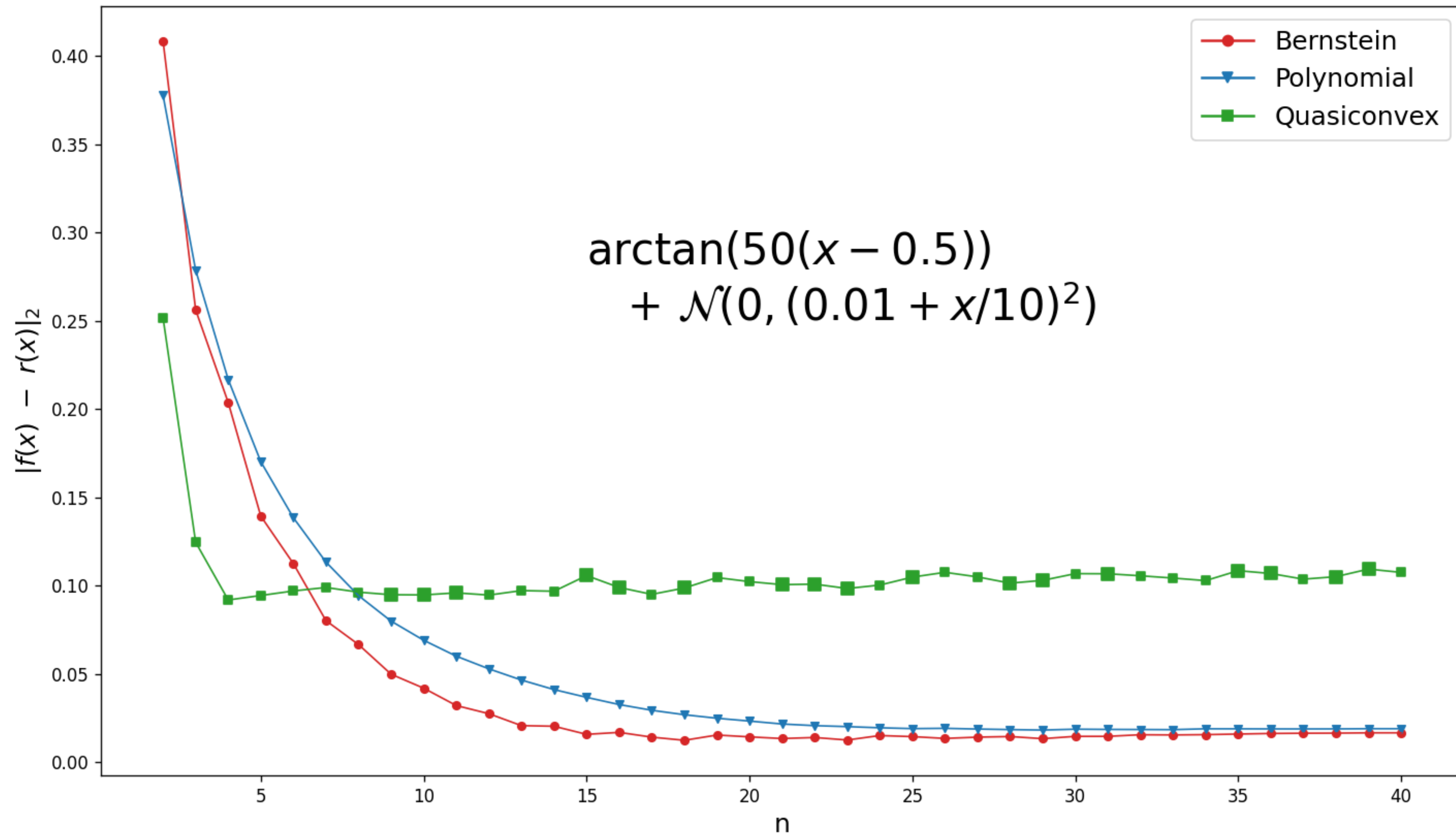
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# Quasiconvex

V. Peiris, N. Sharon, N. Sukhorukova, and J. Ugon (2021)



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