

Raising the order of multivariate approximation schemes using supplementary derivative data

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Delft University of Technology

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Context

- Functional approximation schemes

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 - Interpolation
 - Quasi-interpolation
 - (Moving) least-squares approximation
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- Minimal requirement: exact to some polynomial degree
- Omnipresent in computational sciences
(and in observational / experimental sciences)

Motivation and preview

- Suppose available: supplementary derivative data

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- How to utilize?
- Full accommodation (fitting) often impossible or cumbersome
- Can we find a way to improve existing approximation schemes?
- **Preview: *Yes we can!***
Using n supplementary orders of derivatives the approximation order can be raised by n .

Approximator

Definition: Approximator

An *approximator of order m at $x \in X$* is a functional:

$$A_x^m : V \rightarrow \mathbb{R}$$

that satisfies

$$A_x^m[p] = p(x) \quad \forall \quad p \in P^m.$$

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- The approximator A_x^m reproduces all polynomials of maximum total degree m at x .
- Summarizes:
 - Sampling
 - Construction of approximant
 - Evaluation of approximant at x

Taylor expansion

Definition: Taylor expansion

n -th order truncated Taylor expansion of $f \in V$ around x :

$$\mathcal{T}_x^n : V \rightarrow P^n$$

$$\mathcal{T}_x^n[f] := \sum_{|\kappa| \leq n} \frac{1}{\kappa!} (\cdot - x)^\kappa f^{(\kappa)}(x)$$

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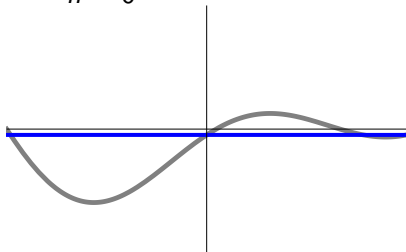
- Compare to: $\mathcal{T}_x^n[f] := \sum_{|\kappa| \leq n} \frac{1}{\kappa!} (\cdot - x)^\kappa f^{(\kappa)}(x)$

Taylor expansion comparison

(Primal) Taylor expansion

$$\mathcal{T}_x^n[f] := \sum_{|\kappa| \leq n} \frac{1}{\kappa!} (\cdot - x)^\kappa f^{(\kappa)}(x)$$

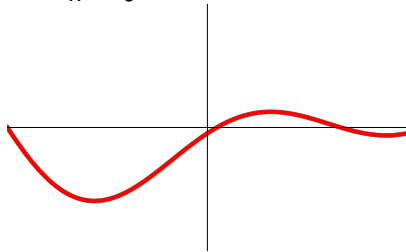
$n = 0$



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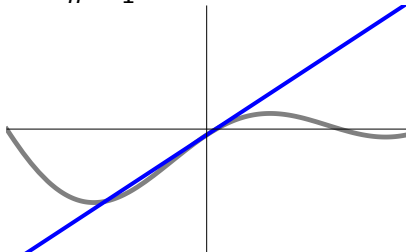


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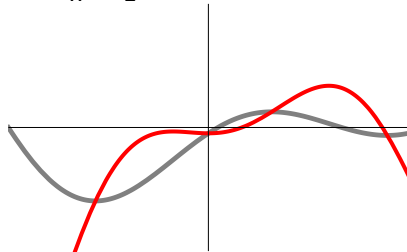
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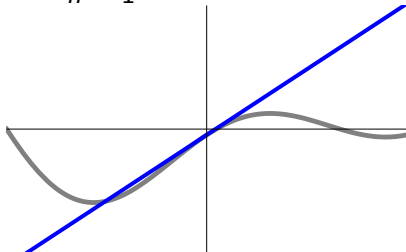


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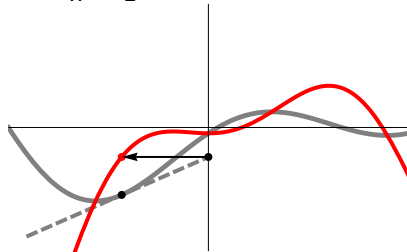
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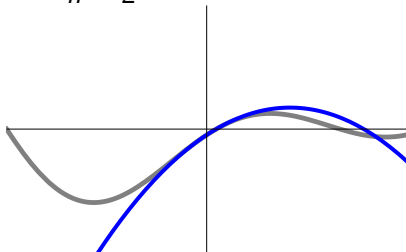


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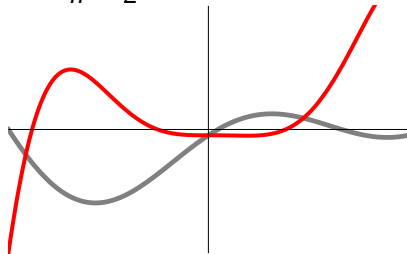
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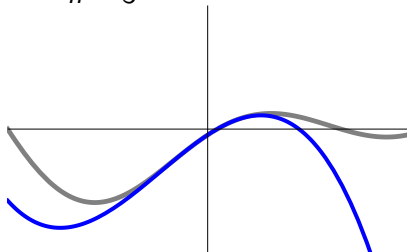


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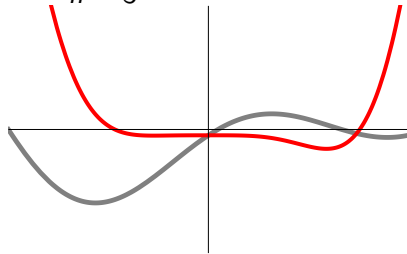
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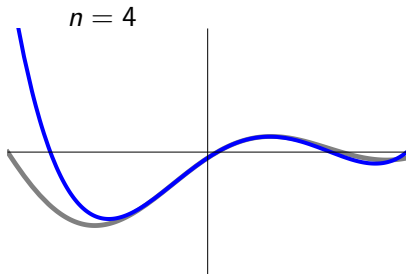
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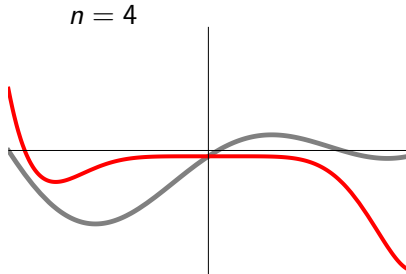
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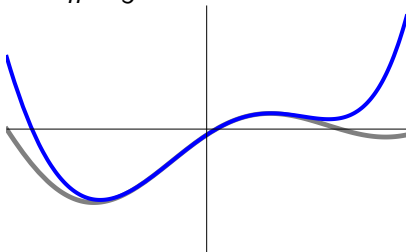


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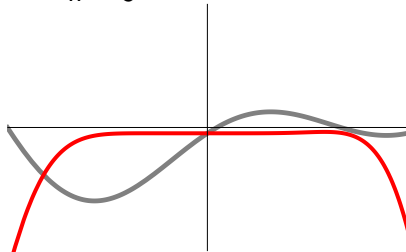
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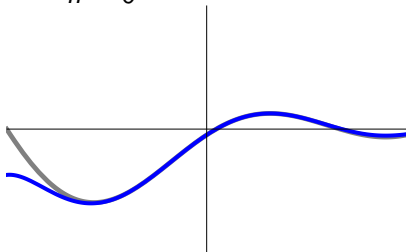


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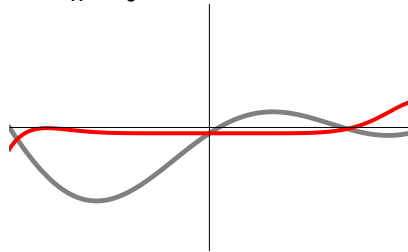
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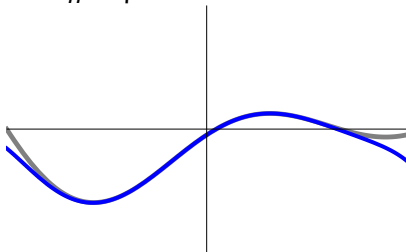


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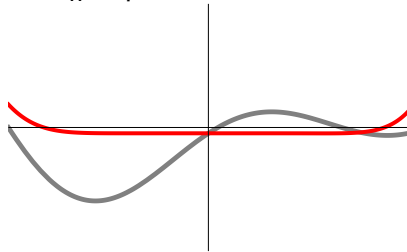
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Suggestion

- Original approximation scheme:

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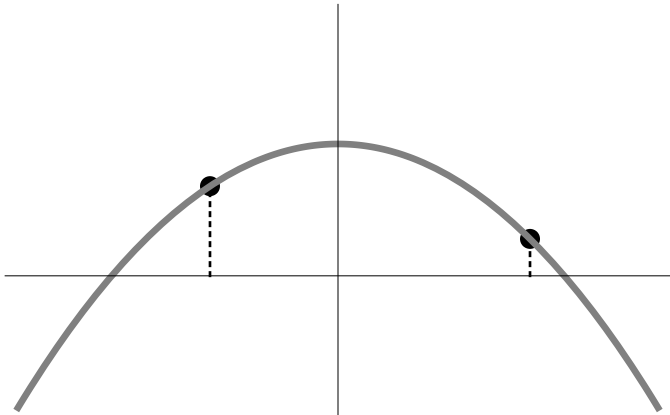
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- Enhanced approximation scheme:

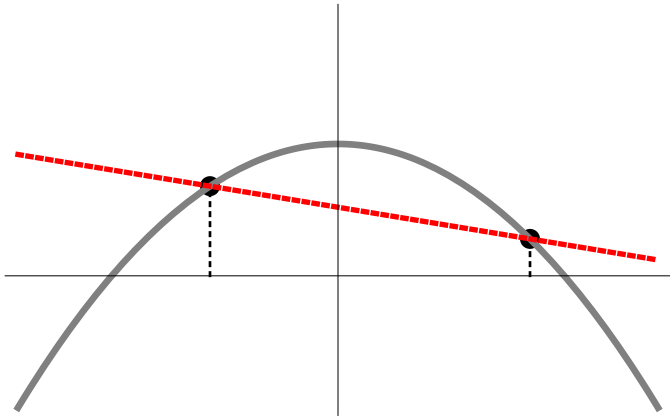
$$\tilde{f}(x) = A_x^m[\tilde{\mathcal{T}}_x^n[f]]$$

- How well does this work?

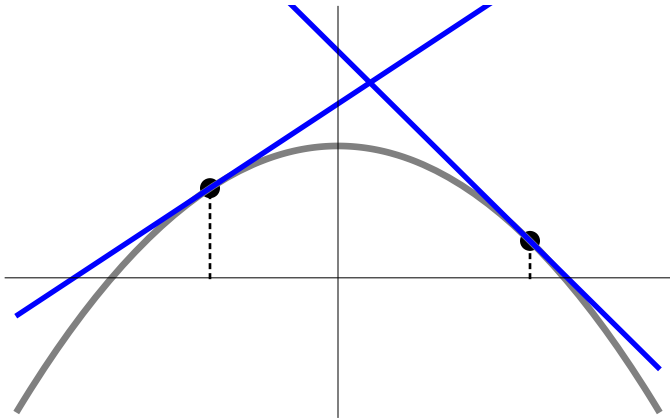
Simple example: 1D, two samples



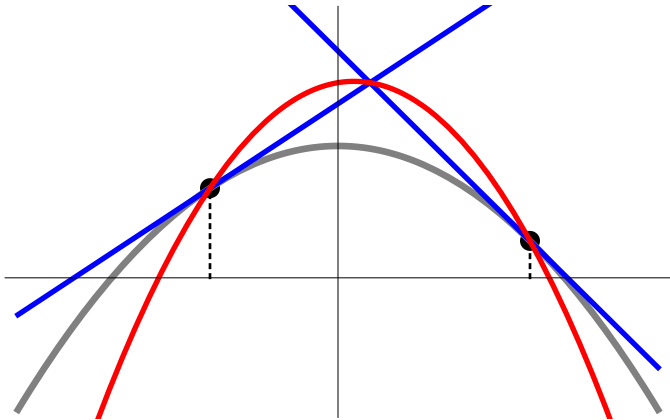
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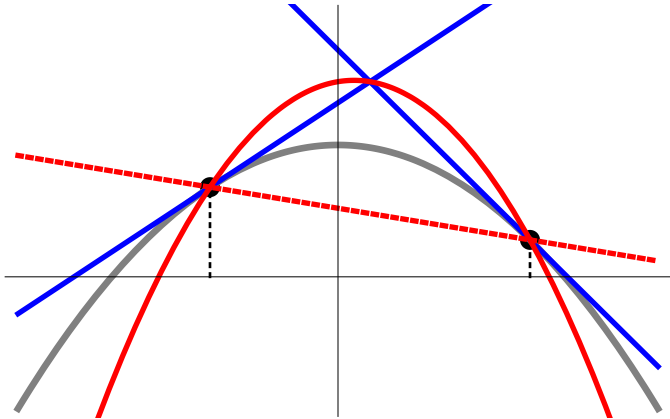
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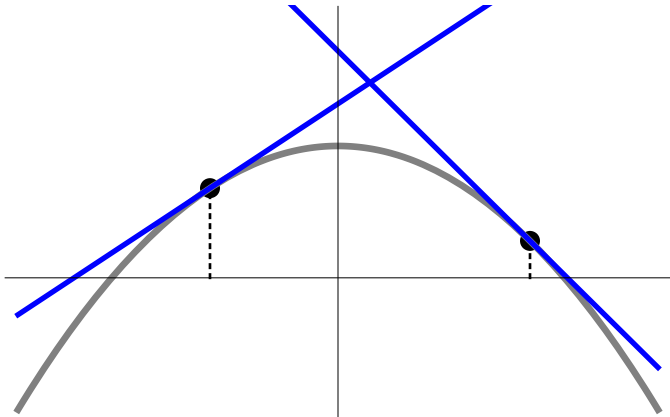
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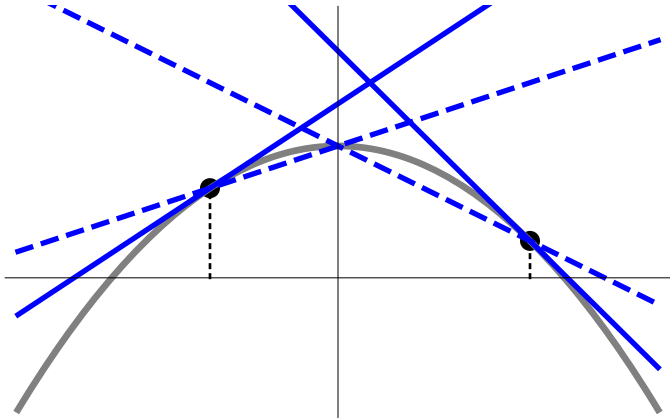
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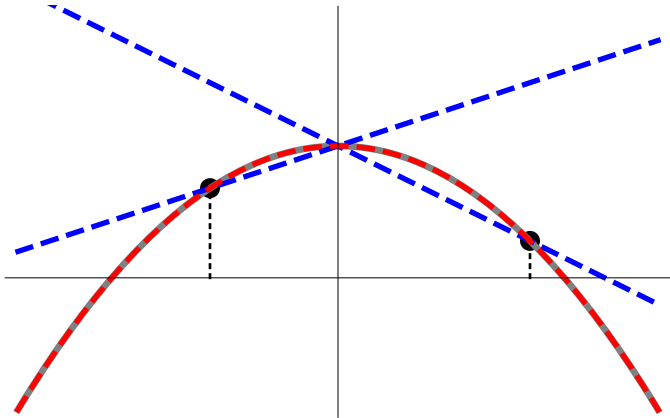
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- Solution: replace

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by

$$\tilde{\mathcal{D}}_x^{11}[f] = f(\cdot) + \frac{1}{2}(x - \cdot)f^{(1)}(\cdot)$$

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- Modifying coefficient raises approximation order
- Is this possible more generally?

Reduced dual Taylor expansion

Definition: Reduced dual Taylor expansion

n-th order reduced dual Taylor expansion of the *m*-th kind:

$$\tilde{\mathcal{D}}_x^{mn} : V \rightarrow V$$

$$\tilde{\mathcal{D}}_x^{mn}[f] := \sum_{|\kappa| \leq n} \frac{1}{\kappa!} C_{|\kappa|}^{mn}(x - \cdot)^{\kappa} f^{(\kappa)}(\cdot)$$

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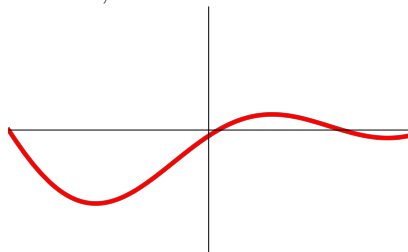
$$C_{|\kappa|}^{mn} := \binom{m+n}{m}^{-1} \binom{m+n-|\kappa|}{m}$$

Coefficients "reduced": $C_{|\kappa|}^{mn} \leq 1$

- $C_k^{11} = \{1, \frac{1}{2}\}$
- $C_k^{12} = \{1, \frac{2}{3}, \frac{1}{3}\}$
- $C_k^{13} = \{1, \frac{3}{4}, \frac{2}{4}, \frac{1}{4}\}$
- $C_k^{22} = \{1, \frac{3}{6}, \frac{1}{6}\}$

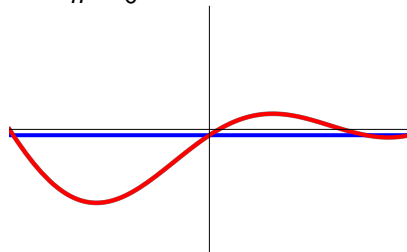
Reduced dual Taylor expansions

$$m = 1, n = 0$$



Reduced dual
Taylor
expansion

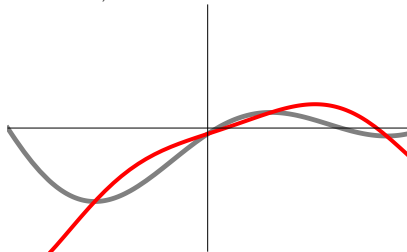
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(Dual) Taylor
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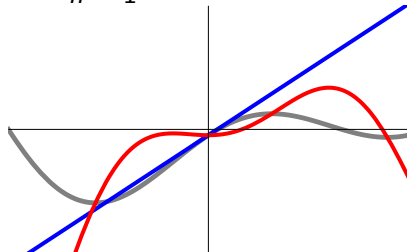
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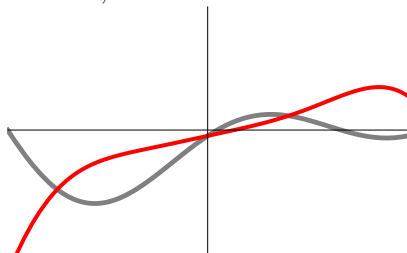
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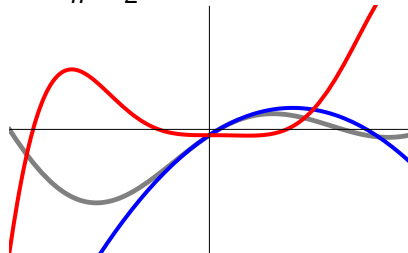
Reduced dual Taylor expansions

$m = 1, n = 2$



Reduced dual
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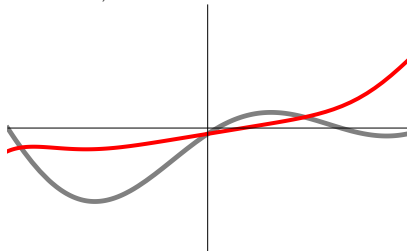
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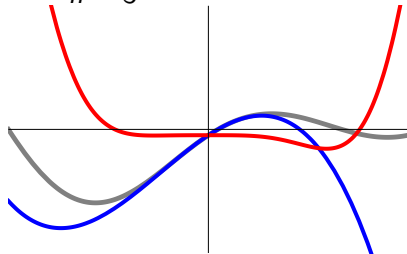
Reduced dual Taylor expansions

$m = 1, n = 3$



Reduced dual
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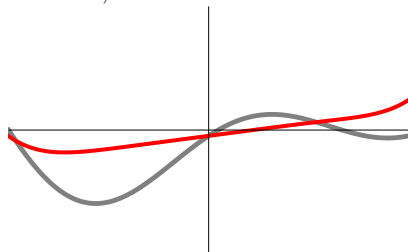
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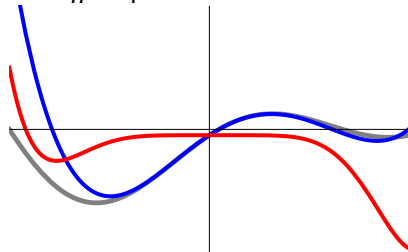
Reduced dual Taylor expansions

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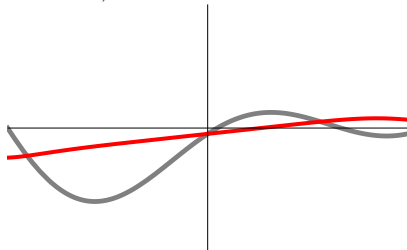
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(Dual) Taylor
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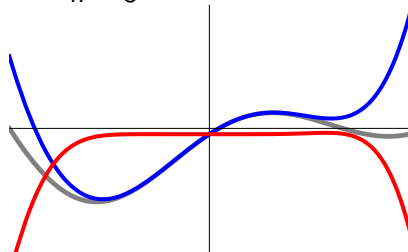
Reduced dual Taylor expansions

$m = 1, n = 5$



Reduced dual
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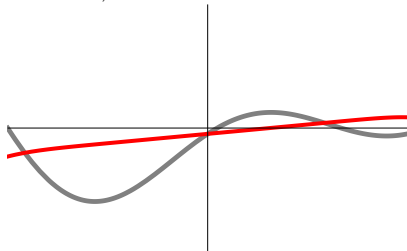
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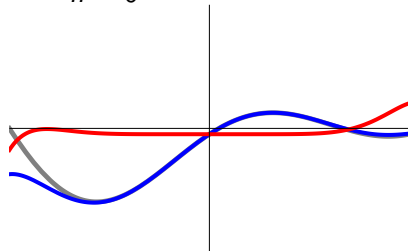
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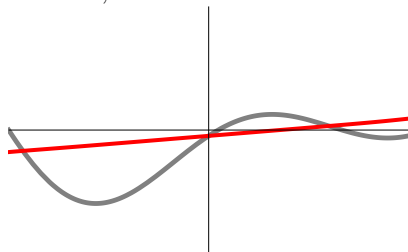
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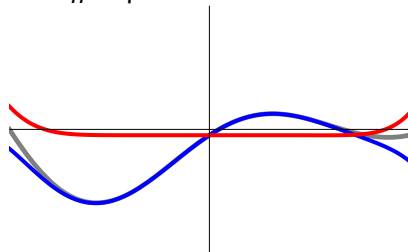
Reduced dual Taylor expansions

$$m = 1, n = 7$$



Reduced dual
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(Dual) Taylor
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Main theorem

Theorem

The combination of reduced dual Taylor expansion $\tilde{\mathcal{D}}_x^{mn}$ and approximator A_x^m yields an effective approximation order of $m + n$:

$$A_x^m[\tilde{\mathcal{D}}_x^{mn}[p]] = p(x) \quad \forall \quad p \in P^{m+n}.$$

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- Proof: several binomial identities
- General procedure for arbitrary A_x^m !

Error expression

$$f(x) - A_x^m[\tilde{\mathcal{D}}_x^{mn}[f]] = A_x^m \left[\int_0^1 \frac{(-t)^m (1-t)^n}{(m+n)!} \frac{d^{m+n+1}}{dt^{m+n+1}} f(\cdot + t(x - \cdot)) dt \right].$$

Linear interpolation

- $f(x, y) = \cos(2\pi x) + x \sin(2\pi y) + y^2 - x$

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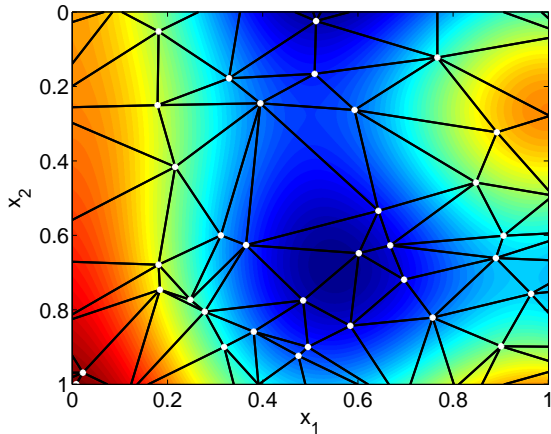
$$\tilde{f}(x, y) = \sum_{k=0}^{N-1} w_k(x, y) f_k$$
- Procedure: $f_k \rightarrow \tilde{\mathcal{D}}^{1,n}[f](x_k, y_k)$

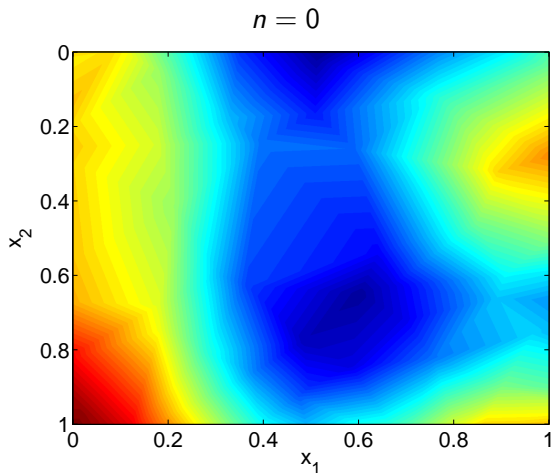
Linear interpolation

- $f(x, y) = \cos(2\pi x) + x \sin(2\pi y) + y^2 - x$
- sampled on N random locations
- Linear interpolation on Delaunay triangulation:

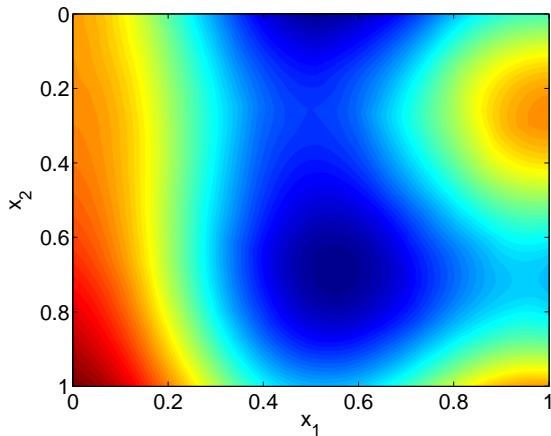
$$\tilde{f}(x, y) = \sum_{k=0}^{N-1} w_k(x, y) f_k$$
- Procedure: $f_k \rightarrow \tilde{\mathcal{D}}^{1,n}[f](x_k, y_k)$
- Expected convergence rate $\mathcal{O}(N^{-(n+2)/2})$

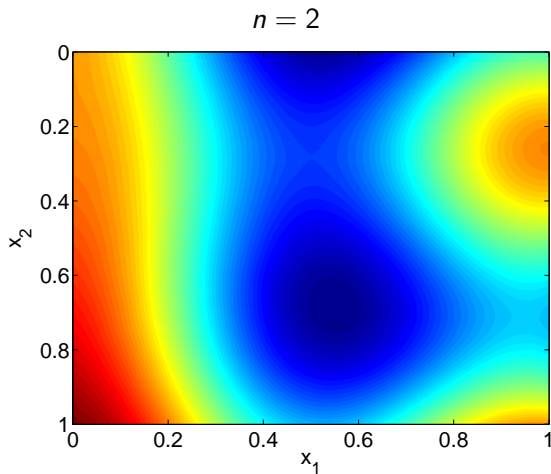
triangulation, $N = 75$



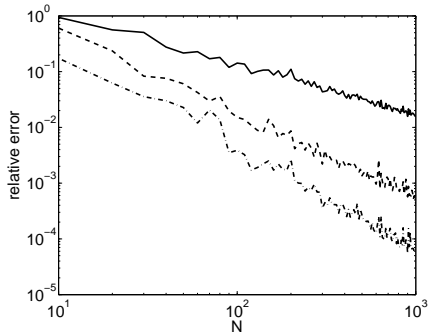


$n = 1$





convergence



$-n = 0, -n = 1, -n = 2$

Moving least-squares approximation

- $f(x, y) = \cos(2\pi x) + x \sin(2\pi y) + y^2 - x$

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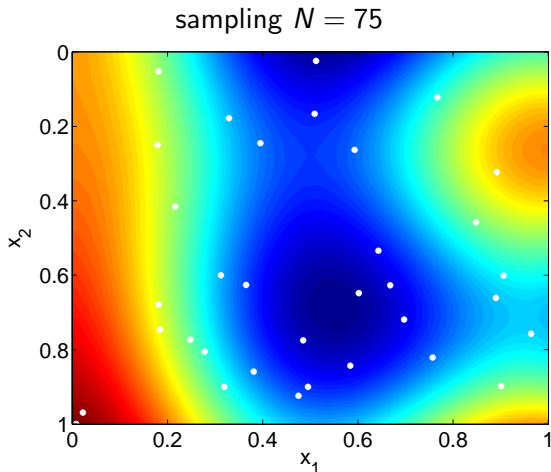
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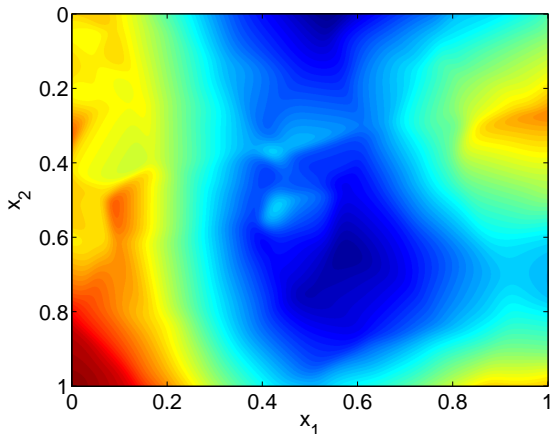
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Moving least-squares approximation



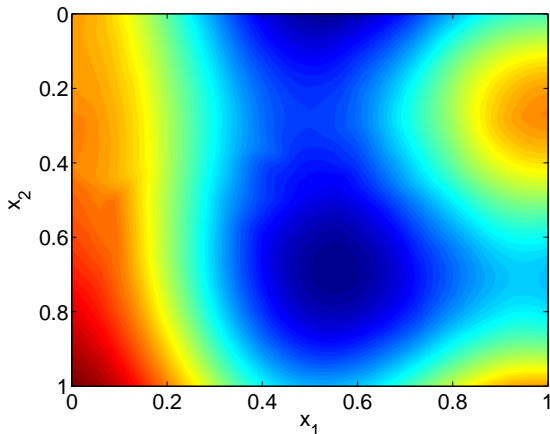
Moving least-squares approximation

$$m = 1, n = 0$$



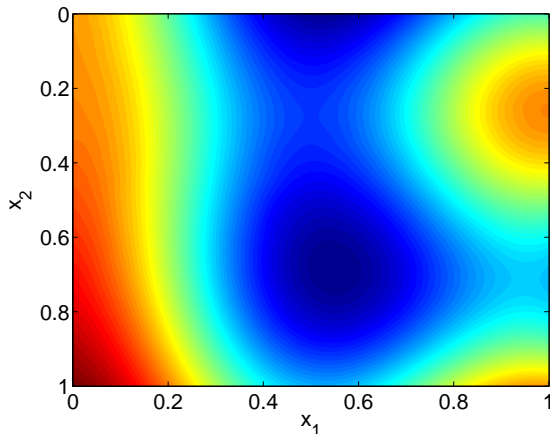
Moving least-squares approximation

$$m = 1, n = 1$$



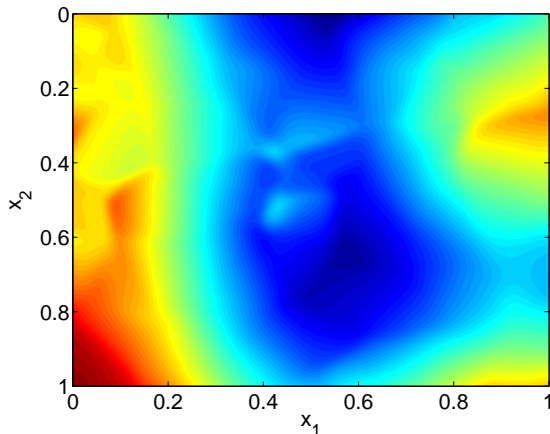
Moving least-squares approximation

$$m = 1, n = 2$$



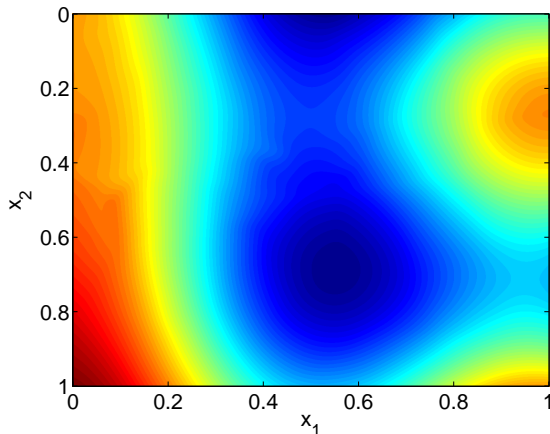
Moving least-squares approximation

$$m = 2, n = 0$$



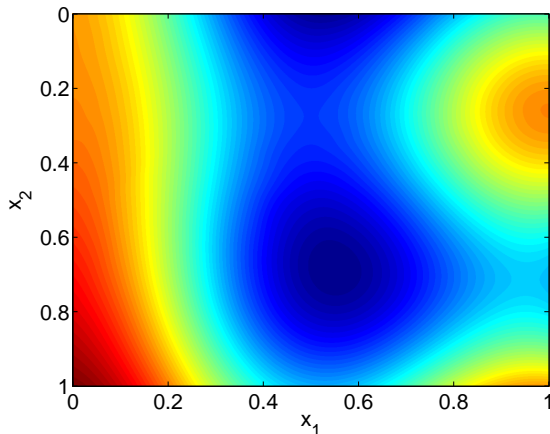
Moving least-squares approximation

$$m = 2, n = 1$$

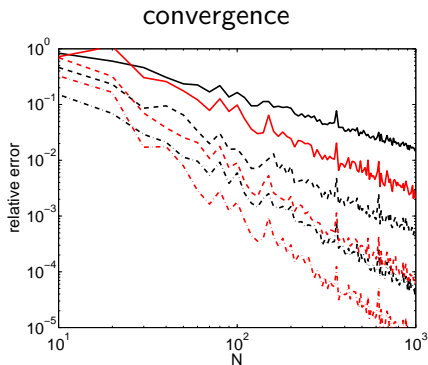


Moving least-squares approximation

$$m = 2, n = 2$$



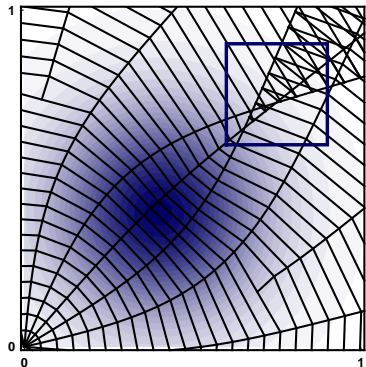
Moving least-squares approximation



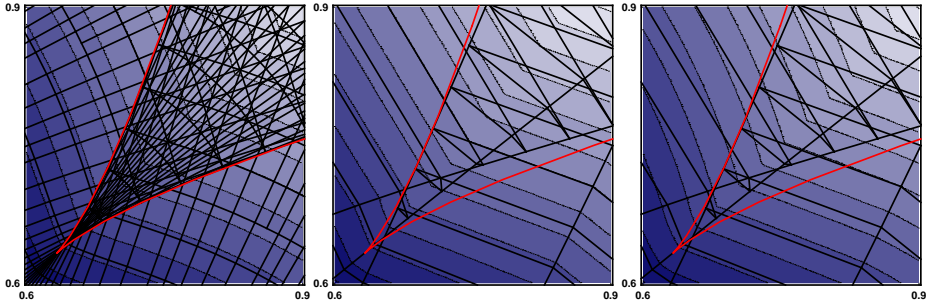
$m \backslash n$	0	1	2
1	—	- -	- .
2	-	- -	- .

Ray tracing

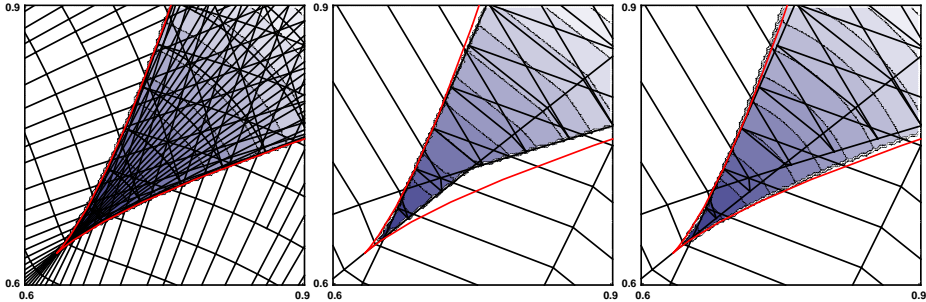
- Gaussian low velocity anomaly
- Triplication
- Sparse ray field



Ray tracing



Ray tracing



Conclusion

- Introduced *Reduced dual Taylor expansion*

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- Expected to be useful in a wide range of applications

Acknowledgements

- Netherlands Research Centre for Integrated Solid Earth Science (ISES)
- Foundation for Fundamental Research on Matter (FOM)

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- You. Thanks for listening!