

# Fast Computation of Multilinear Operators

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# Outline

- Multilinear operator in harmonic analysis
- Direct computation of multilinear operator
- Fast algorithm for multilinear operator
  - Fast Fourier transform and non uniform fast Fourier transform
  - Matrix decomposition
  - Matrix approximation

# Multilinear Operators

- Definition: For  $k$  fixed, we consider the  $k$ -linear operator

$$(f_1, \dots, f_k) \mapsto M(f_1, \dots, f_k)$$

initially defined for  $f_k \in S$  as follows. We write

$$\bar{\xi} = (\xi^{(1)}, \dots, \xi^{(k)}) \in R^{nk}, \quad \xi^{(j)} \in R^n,$$

and set  $\sigma(\bar{\xi}) = \xi^{(1)} + \dots + \xi^{(k)}$ . If  $\bar{\xi} \mapsto m(\bar{\xi})$  is a bounded function on  $R^{nk}$ , we define multilinear operator  $M$  by

$$M(f_1, \dots, f_k)(x) = \int_{R^{nk}} e^{2\pi i x \cdot \sigma(\bar{\xi})} m(\bar{\xi}) \hat{f}_1(\xi^{(1)}) \dots \hat{f}_k(\xi^{(k)}) d\bar{\xi}.$$

- Here we just talk about the cases when  $n=1$  and  $k=2$ . So the multilinear operator is

$$M(f_1, f_2)(x) = \int_{R^2} e^{2\pi i x \cdot (\eta + \lambda)} m(\eta, \lambda) \hat{f}_1(\eta) \hat{f}_2(\lambda) d\eta d\lambda.$$

We can get the results for higher  $n$  and  $k$  similarly.

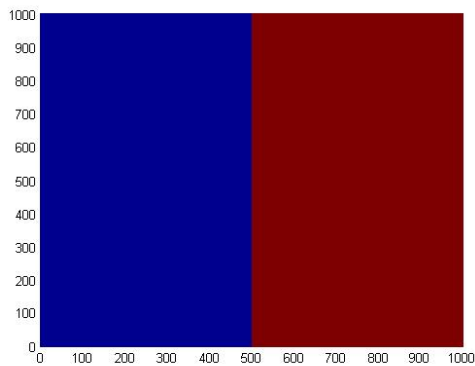
# Multilinear Operators

- Some examples of  $M$ :

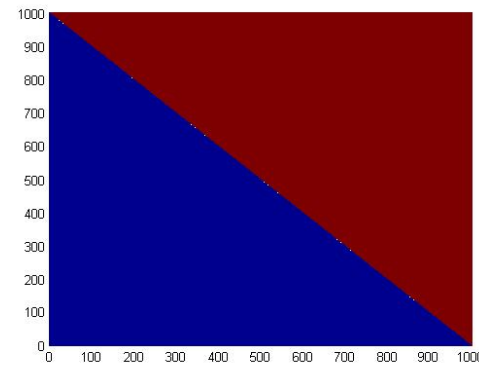
(1)  $M(f_1, f_2)(x) = f_1(x)f_2(x)$ , when  $m(\eta, \lambda) \equiv 1$ .

(2)  $M(f_1, f_2) = f_1 H(f_2) - H(f_1 f_2)$ , where  $H$  is the Hilbert transform, and

$$m(\eta, \lambda) = \frac{1}{i} [\text{sign}(\lambda) - \text{sign}(\eta + \lambda)].$$



Matrix m corresponding to  $\text{sign}(\lambda)$



Matrix m corresponding to  $\text{sign}(\eta + \lambda)$

# Direct Computation

- Upon discretization of the multilinear operator, we get

$$M(f_1, f_2)(x) = \sum_{\eta} \sum_{\lambda} e^{2\pi i x \cdot (\eta + \lambda)} m(\eta, \lambda) \hat{f}_1(\eta) \hat{f}_2(\lambda),$$

where  $\eta_s = s - 1 - \frac{N}{2}$ ,  $\lambda_t = t - 1 - \frac{N}{2}$ ,  $s, t = 1, \dots, N$ ,

and  $x_j = \frac{j-1}{2N-1}$ ,  $j = 1, \dots, 2N-1$ .

- We want to compute  $M(f_1, f_2)(x_j)$  for all  $j$ . The time complexity of direct computation is  $O(N^3)$ .
- Note that we suppose  $f_1$  and  $f_2$  have support in  $[0, 1]$  and discretize  $[0, 1]$  with  $N$  points  $\{0, \frac{1}{N}, \dots, \frac{N-1}{N}\}$ . So  $\hat{f}_1$  and  $\hat{f}_2$  take value at the points  $\{-\frac{N}{2}, \dots, \frac{N}{2}-1\}$ .

# Fast Fourier transform

- Uniform  $x \in X = \{0, 1, \dots, N-1\}$
- Uniform  $k \in K = \{-N/2, -N/2+1, \dots, N/2-1\}$
- Fourier coeff  $\{f(k), k \in K\}$

- Fourier kernel  $G(x, k) = e^{-2\pi i \frac{xk}{N}}$

- Compute  $u(x)$  for each  $x$  in  $X$

$$u(x) = \sum_{k \in K} e^{-2\pi i \frac{xk}{N}} f(k)$$

- Order of FFT is  $O(N \log N)$

# Non-uniform fast Fourier transform

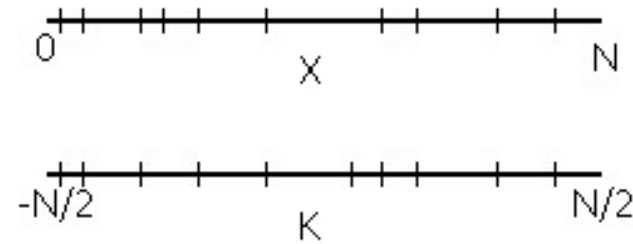
- Non-uniform  $X \subset [0, N]$ , and  $|X| = O(N)$
- Non-uniform  $K \subset [-N/2, N/2]$   
and  $|K| = O(N)$ .
- Fourier coeff  $\{f(k), k \in K\}$
- Fourier kernel

$$G(x, k) = e^{-2\pi i \frac{xk}{N}}$$

- Compute  $u(x)$  for each  $x$  in  $X$

$$u(x) = \sum_{k \in K} e^{-2\pi i \frac{xk}{N}} f(k)$$

- The idea of Non-uniform FFT: use equispaced data to approximate the non-uniform data.
- Order  $O(N \log N + pN)$



$$u(x) = e^{-2\pi i \frac{xk}{N}} f(k)$$

We use nearest  $p$  equispaced data of  $x$  and  $k$  to get the approximation, where  $p$  is depending on error  $\varepsilon$

# Fast Algorithm for Multilinear Operator

(a) Special case for constant multiplication function

When the multiplier function  $m(\eta, \lambda)$  is a constant, then

$$\begin{aligned} M(f_1, f_2)(x) &= \sum_{\eta} \sum_{\lambda} e^{2\pi i x \cdot (\eta + \lambda)} \hat{f}_1(\eta) \hat{f}_2(\lambda) \\ &= \sum_{\xi} \sum_{\eta} e^{2\pi i x \xi} \hat{f}_1(\eta) \hat{f}_2(\xi - \eta) \\ &= \sum_{\xi} e^{2\pi i x \xi} \sum_{\eta} \hat{f}_1(\eta) \hat{f}_2(\xi - \eta) \\ &= \sum_{\xi} e^{2\pi i x \xi} T(\xi) \end{aligned}$$

where we let  $\xi = \eta + \lambda$ , and  $T(\xi) = \sum_{\eta} \hat{f}_1(\eta) \hat{f}_2(\xi - \eta)$

# Fast Algorithm for Multilinear Operator

- Observation:

(1)  $T(\xi)$  is the convolution of  $\hat{f}_1(\eta)$  and  $\hat{f}_2(\lambda)$  .

$$\text{So } T = \hat{f}_1 * \hat{f}_2 = ((2\pi)^{d/2} \hat{\hat{f}}_1 \hat{\hat{f}}_2)^\vee.$$

(2)  $M(f_1, f_2)(x)$  is the inverse Fourier transform of  $T(\xi)$ .

- Ideas: Use FFT to compute the Fourier transform above to reduce the time complexity, supposing that the data is uniformly distributed.

- Time complexity for T:  $O(N \log N) + O(N \log N) + O(N) + O(N \log N) = O(N \log N)$

Time complexity for  $M(f_1, f_2)(x) = \sum_{\xi} e^{2\pi i x \xi} T(\xi)$  is  $O(N \log N)$  .

Total time complexity to compute  $M$  is  $O(N \log N)$  .

- If the data is non-uniform, then the time complexity is  $O(N \log N + pN)$  using NFFT.

# Fast Algorithm for Multilinear Operator

(b) Smooth multiplicative function

- Suppose that  $m(\eta, \lambda)$  is smooth enough, it has a  $h$ -term  $\varepsilon$ -expansion about  $\eta$  and  $\lambda$ , which means there exists functions  $\{\alpha_p(\eta)\}_{1 \leq p \leq h}$  and  $\{\beta_p(\lambda)\}_{1 \leq p \leq h}$  such that

$$|m(\eta, \lambda) - \sum_{p=1}^h \alpha_p(\eta) \beta_p(\lambda)| \leq \varepsilon.$$

- We can use the random method provided by V. Rokhlin, B. Engquist and L.Ying to get the  $h$ -term  $\varepsilon$ -expansion of it with time complexity  $O(hN)$  for a  $N \times N$  matrix.

A diagram illustrating the expansion of the multilinear operator  $m(\eta, \lambda)$ . It consists of three rectangular boxes arranged horizontally, separated by an approximation symbol  $\approx$ . The first box on the left is a square and contains the expression  $m(\eta, \lambda)$ . The second box is a vertical rectangle and contains the expression  $\alpha_p(\eta)$ . The third box is a horizontal rectangle and contains the expression  $\beta_p(\lambda)$ . This visualizes the equation  $m(\eta, \lambda) \approx \alpha_p(\eta) \beta_p(\lambda)$ .

# Fast Algorithm for Multilinear Operator

■ Then

$$\begin{aligned} M(f_1, f_2)(x) &= \sum_{\eta} \sum_{\lambda} e^{2\pi i x \cdot (\eta + \lambda)} m(\eta, \lambda) \hat{f}_1(\eta) \hat{f}_2(\lambda) \\ &= \sum_{\eta} \sum_{\lambda} e^{2\pi i x \cdot (\eta + \lambda)} \sum_{p=1}^h \alpha_p(\eta) \beta_p(\lambda) \hat{f}_1(\eta) \hat{f}_2(\lambda) \\ &= \sum_{\eta} \sum_{\lambda} e^{2\pi i x \cdot (\eta + \lambda)} \sum_{p=1}^h [\alpha_p(\eta) \hat{f}_1(\eta)] [\beta_p(\lambda) \hat{f}_2(\lambda)] \\ &= \sum_{\xi} e^{2\pi i x \xi} \sum_{p=1}^h \sum_{\eta} [\alpha_p(\eta) \hat{f}_1(\eta)] [\beta_p(\lambda) \hat{f}_2(\lambda)] \\ &= \sum_{\xi} e^{2\pi i x \xi} \sum_{p=1}^h T_p(\xi) \end{aligned}$$

- Time complexity is  $O(hN \log N)$  for uniform data and  $O(hN \log N + hpN)$  for non-uniform data for a single matrix of size  $N$ .

# Fast Algorithm for Multilinear Operator

(c) P.W. smooth multiplicative function

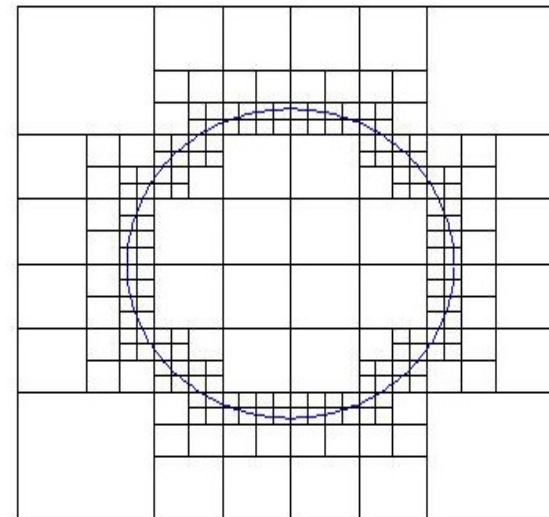
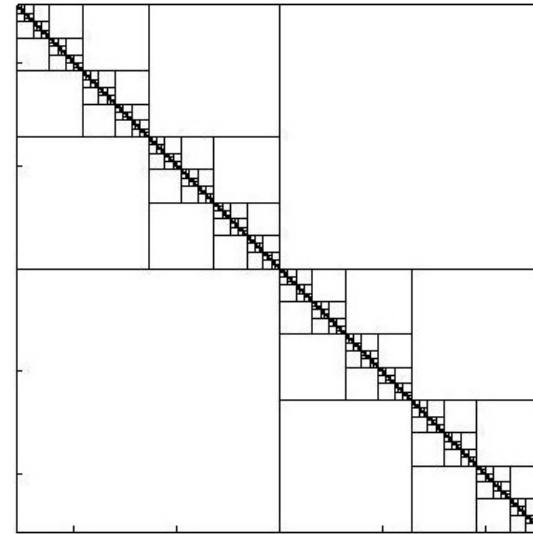
■ If  $m(\eta, \lambda)$  is discontinuous along a curve, we can use matrix division to get the small square domains in which the function is smooth.

■ Number of squares:

- $O(N)$  squares of size 1 by 1
- $O(N/2)$  squares of size 2 by 2
- ...
- $O(1)$  squares of size  $N$  by  $N$
- Total number of squares is  $O(N)$ .

■ Time complexity of low rank approximation:

$$\begin{aligned} &O(h \cdot 1 \cdot N) + O(h \cdot 2 \cdot \frac{N}{2}) + \dots + O(h \cdot N \cdot 1) \\ &= O(hN \log N) \end{aligned}$$



# Fast Algorithm for Multilinear Operator

■ *Time complexity for uniform data:*

$$\begin{aligned} &O(Nh \cdot 1 \log 1 + Nh) + O\left(\frac{N}{2}h \cdot 2 \log 2 + \frac{N}{2}h \cdot 2\right) + \dots \\ &+ O(1 \cdot h \cdot N \log N + 1 \cdot h \cdot N) \leq O(hN(\log N)^2) \end{aligned}$$

■ *For non-uniform data, it's*

$$O(hN(\log N)^2 + hpN \log N)$$

# Summary of ideas

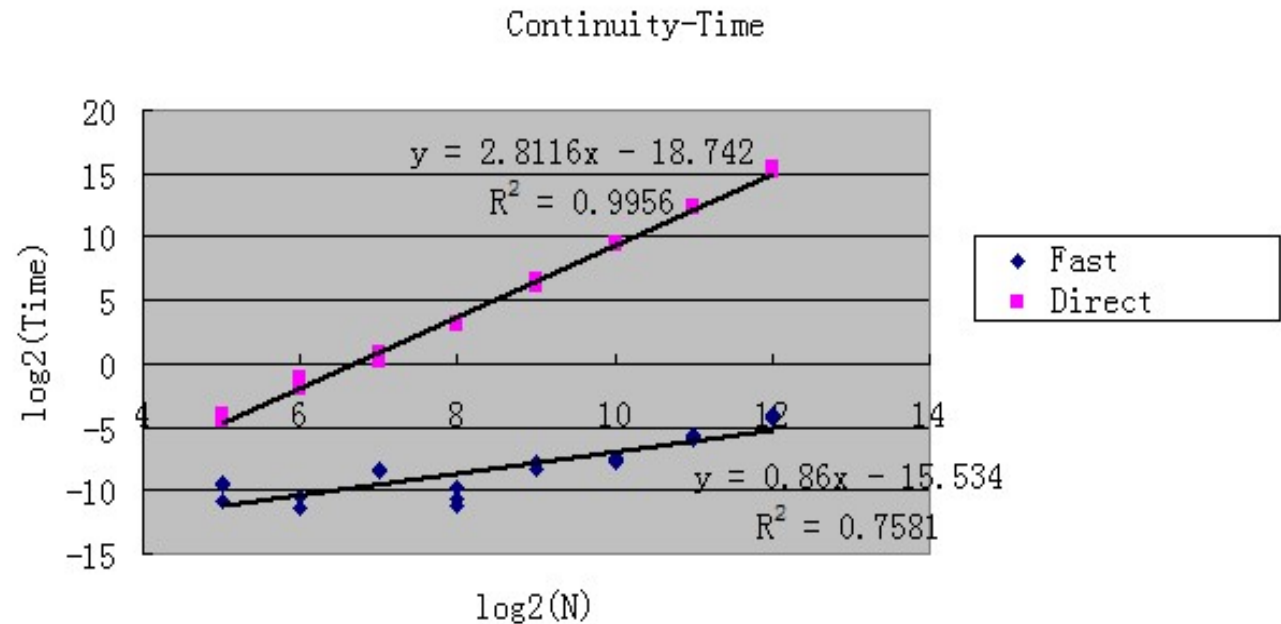
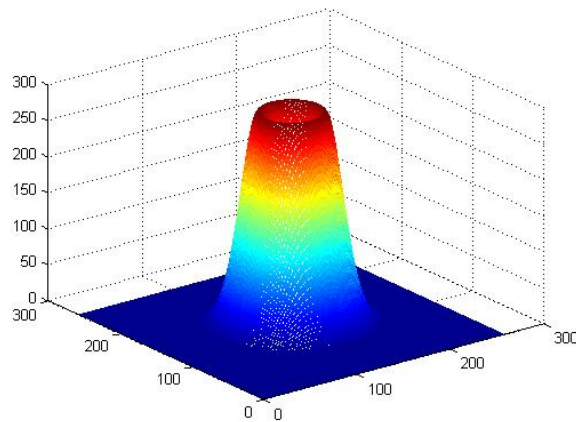
- Division of matrices according to the discontinuous curve, so that the function  $m(\eta, \lambda)$  is smooth enough.
- Use the random method to get the low rank approximation of  $m(\eta, \lambda)$ .
- Use the low rank approximation to get the form of separated variables

$$m(\eta, \lambda) \approx \sum_{p=1}^h \alpha_p(\eta) \beta_p(\lambda),$$

such that we can reduce the general cases to the simplest case in which  $m(\eta, \lambda)$  is constant.

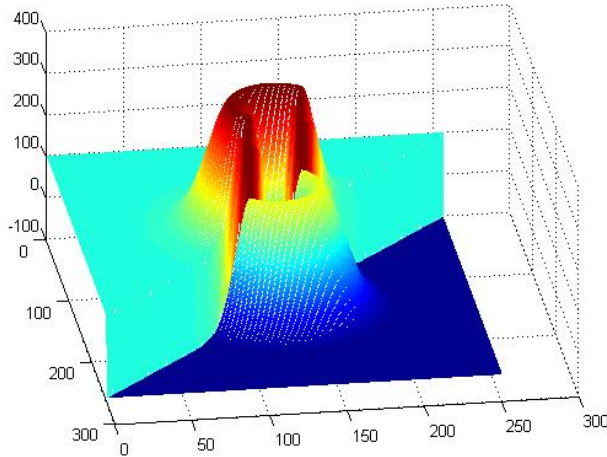
- Use FFT or DFFT to compute the multilinear operator in the simplest case.

# Numerical Examples

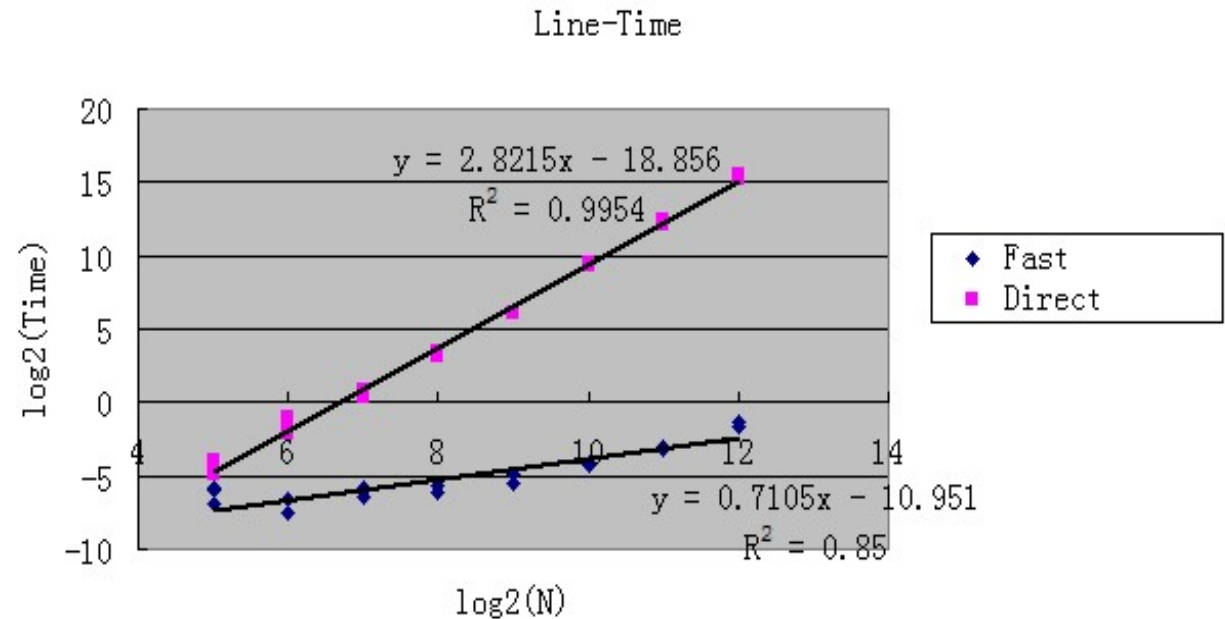


Let  $m(\eta, \lambda) = (\eta^2 + \lambda^2)e^{-(\eta^2 + \lambda^2)/C}$  and increase the number  $N$  of data to compare the time complexity. Direct computation is approximately  $O(N^3)$  and the fast algorithm has almost linear order.

# Numerical Examples

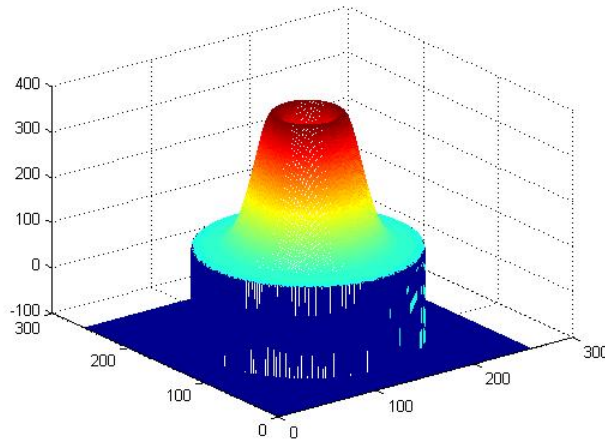


Increasing the number  $N$  of data to compare the time complexity. Direct computation is approximately  $O(N^3)$  and the fast algorithm has almost linear order.

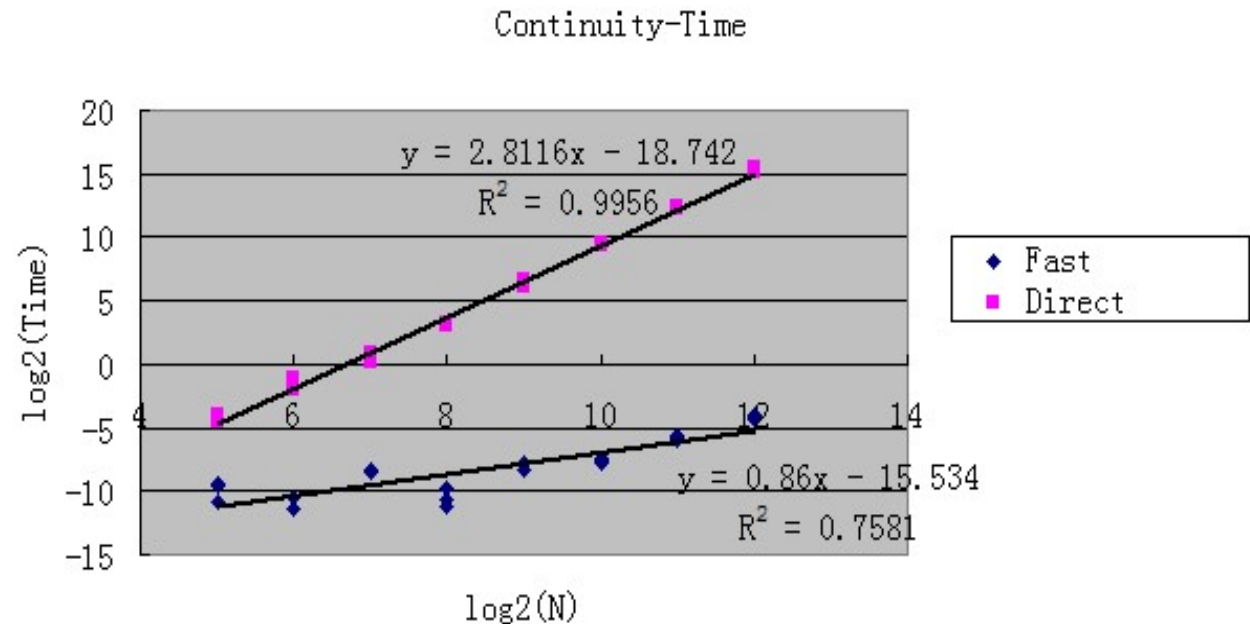


$$m(\eta, \lambda) = \begin{cases} (\eta^2 + \lambda^2)e^{-(\eta^2 + \lambda^2)/C} + 100 & \text{if } \eta + \lambda \leq 0, \\ (\eta^2 + \lambda^2)e^{-(\eta^2 + \lambda^2)/C} - 100 & \text{if } \text{otherwise.} \end{cases}$$

# Numerical Examples



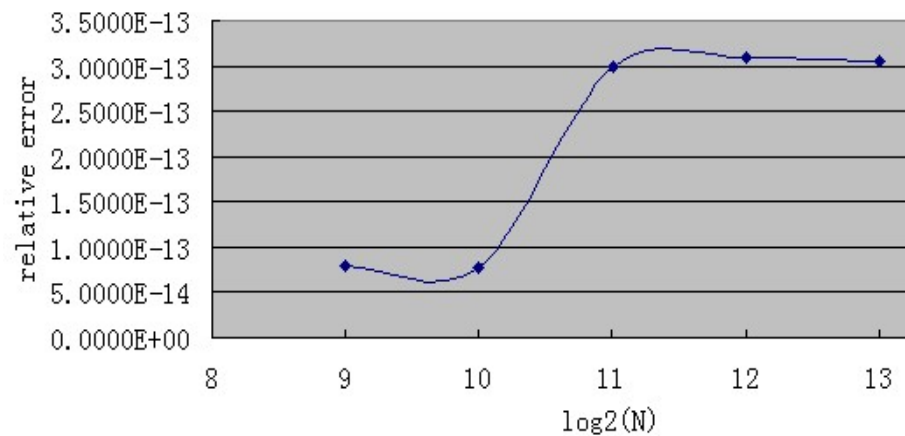
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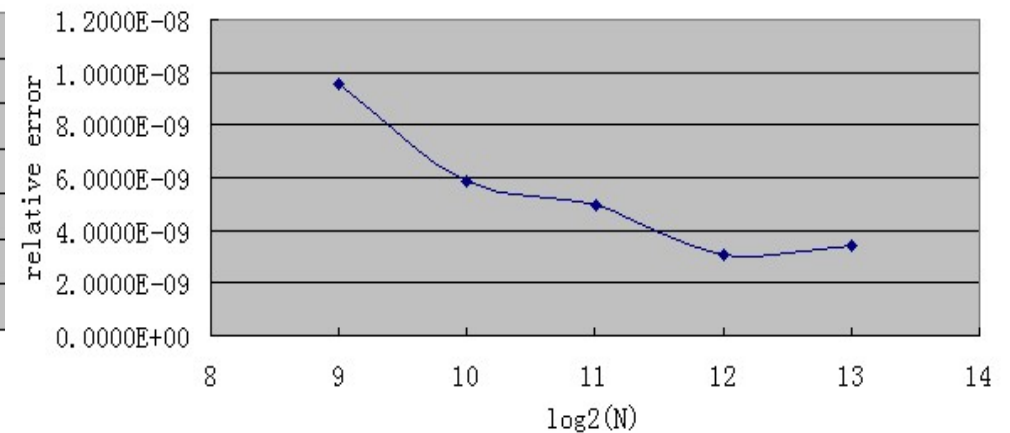
$$m(\eta, \lambda) = \begin{cases} (\eta^2 + \lambda^2)e^{-(\eta^2 + \lambda^2)/C} + 100 & \text{if } (\eta)^2 + (\lambda)^2 \leq R^2, \\ (\eta^2 + \lambda^2)e^{-(\eta^2 + \lambda^2)/C} - 100 & \text{if } \text{otherwise.} \end{cases}$$

# Numerical Examples

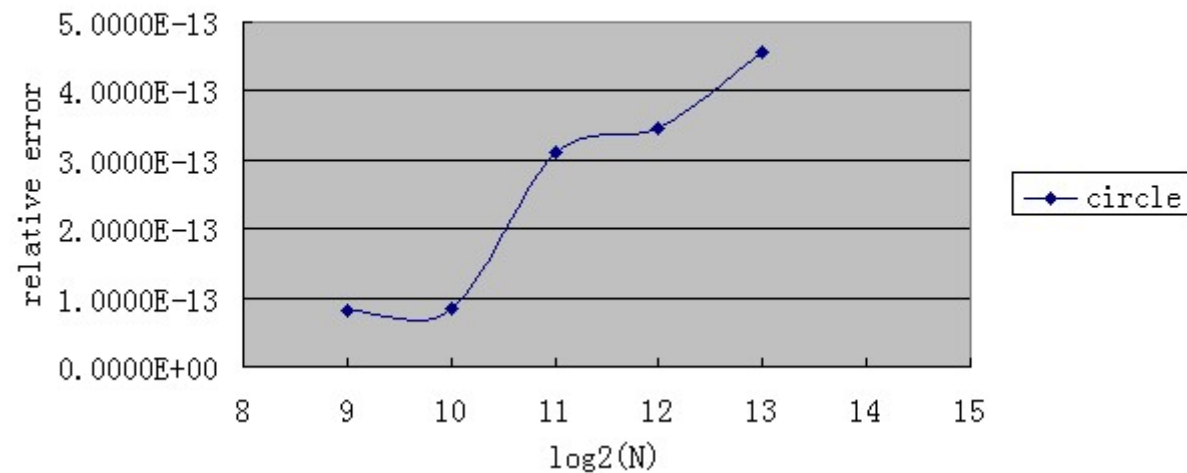
continuity error analysis



line error analysis



error analysis



**Thank you!**