

# Heuristics In Full-Waveform Inversion

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**SLIM**



# Frequency Domain Full Waveform Inversion Overview

# Full Waveform Inversion - Overview

Define the **misfit function** as

$$\min_{m \in \mathcal{A}} \Phi(m) = \sum_i^{n_s} \left\| d^i - P_r u^i \right\|_W.$$

for some norm  $W$  (usually  $L^2$  with some regularization), and the **gradient** of the reduced formulation

$$\nabla \Phi(m) = \sum_i^{n_s} \mathcal{R} \left\{ (u^i)^T \left[ \frac{\partial A}{\partial m} \right]^T w^i \right\}.$$

- $d^i$  observed data
- $u^i$  (approximated) computed data
- $m$  Earth parameters; what we are trying to invert!

## Forward problem:

$$u^i = A^{-1}(m)q^i$$

(computation of  $\Phi(m)$ )

## Backward problem:

$$w^i = A^{-H}(m)P_r^H(d^i - u^i).$$

(computation of  $\nabla\Phi(m)$ )

Both require a PDE solve, computed with an (sufficiently large) accuracy  $\varepsilon$ .

- $A(m)$  operator governing the physics of Earth
- $d^i, u^i$  observed and computed data
- $P_r$  restricts the computed data to the receivers
- $q^i$  source

# Frugal FWI Overview

# Gradient-Descent with Errors

Let

$$\nabla \tilde{\Phi}(m_k) = \nabla \Phi(m_k) + \mathbf{e}_k$$

for some **error**  $\mathbf{e}_k$ . Then, for **strongly convex** problems:

$$\Phi(m_k) - \Phi(m_*) < a_k (\Phi(m_0) - \Phi(m_*))$$

$$a_k = \max \left\{ c^k, \|\mathbf{e}_k\|_2^2 \right\}, \quad 0 \leq c \leq 1$$

where  $c$  is the condition number of the problem.



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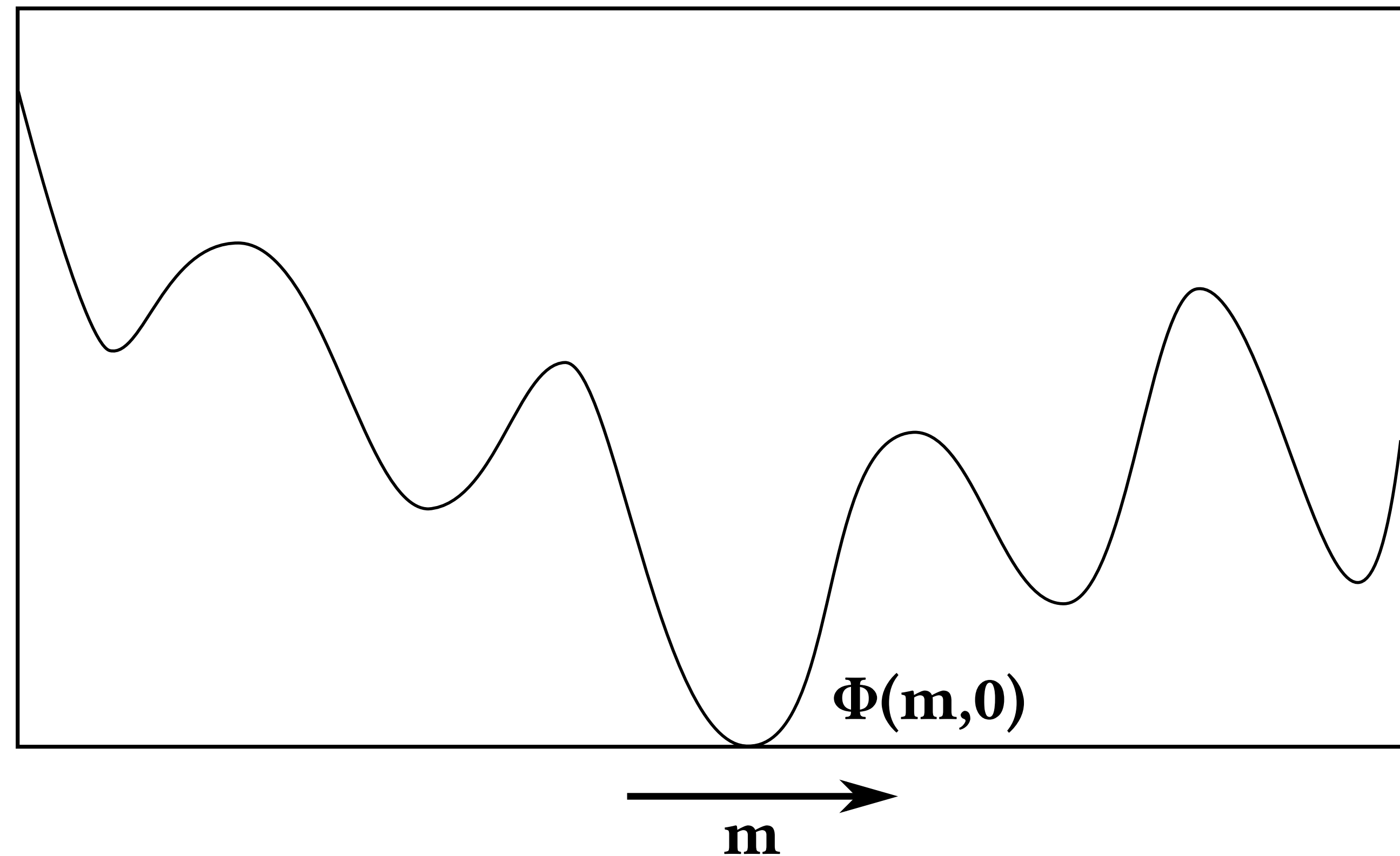
[Friedlander and Schmidt, 2012]

# Relaxing the Physics - Approximating $u^i$ and $w^i$

$$\Phi(m) = \sum_i^{n_s} \left\| d^i - u^i \right\|_W$$

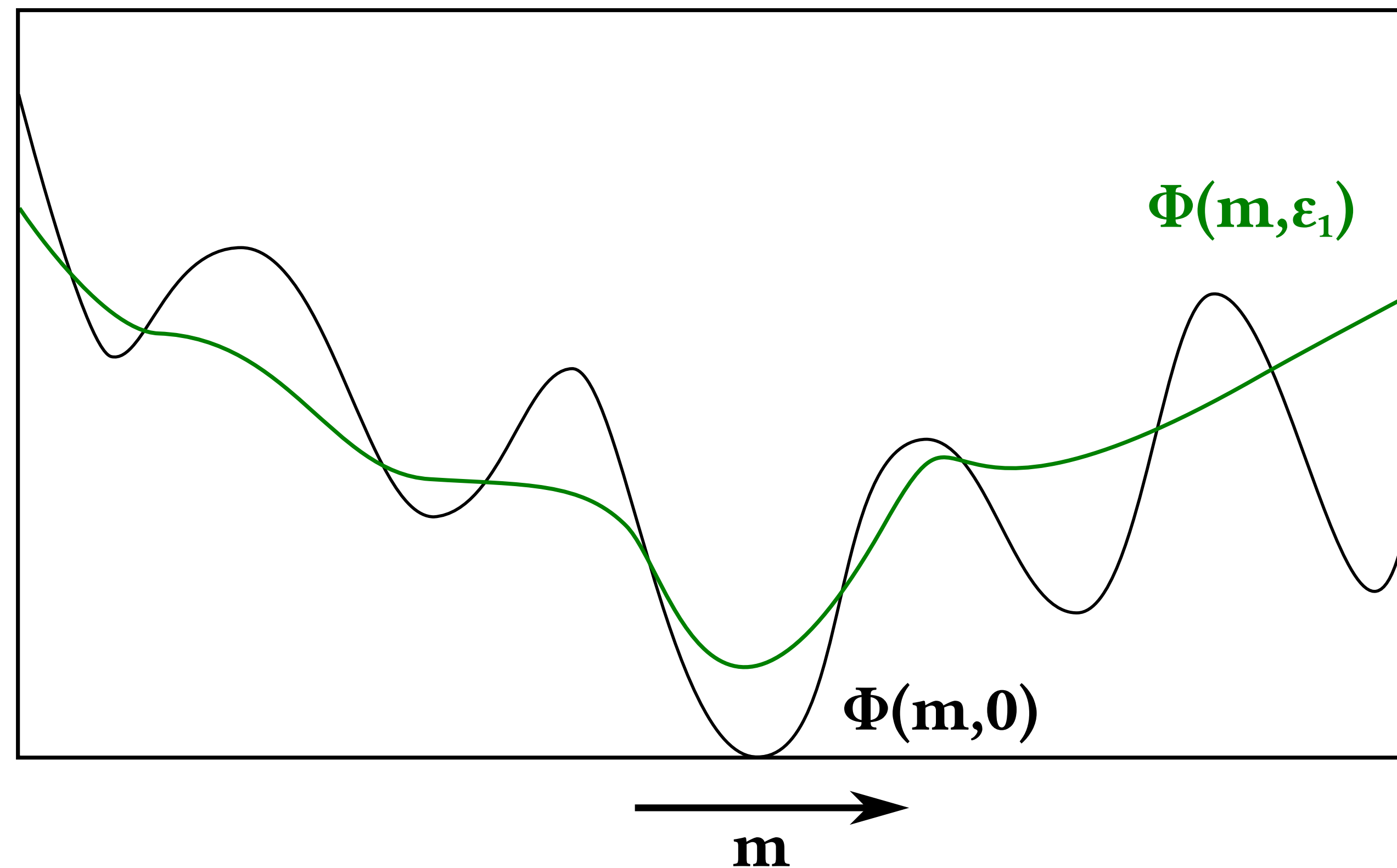
$$u^i \approx A^{-1}(m)q^i$$

$$\frac{\left\| A(m)u^i - q^i \right\|_2}{\left\| q^i \right\|_2} < \epsilon$$



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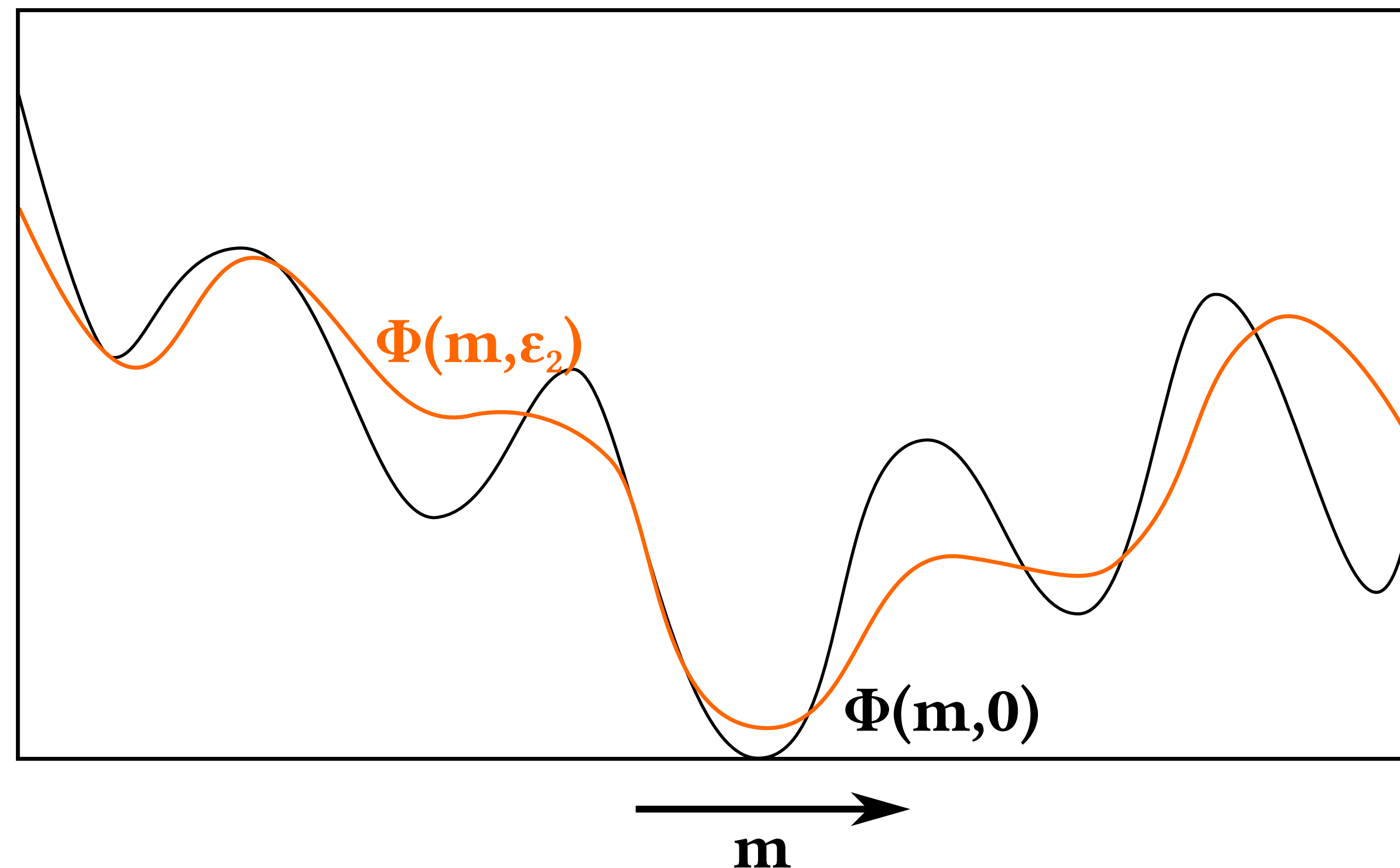


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We hope that “large”  $\epsilon_k$  can “convexify”  $\Phi$  and that  $\Phi(m, \epsilon_k)$  “converges” to  $\Phi(m, 0)$

# Choosing $\epsilon_k$ - Approximating $u^i$ and $w^i$

$$|\Phi(m, \alpha^k \epsilon) - \Phi(m, \alpha^{k+1} \epsilon)| \leq \eta \Phi(m, \alpha^{k+1} \epsilon)$$

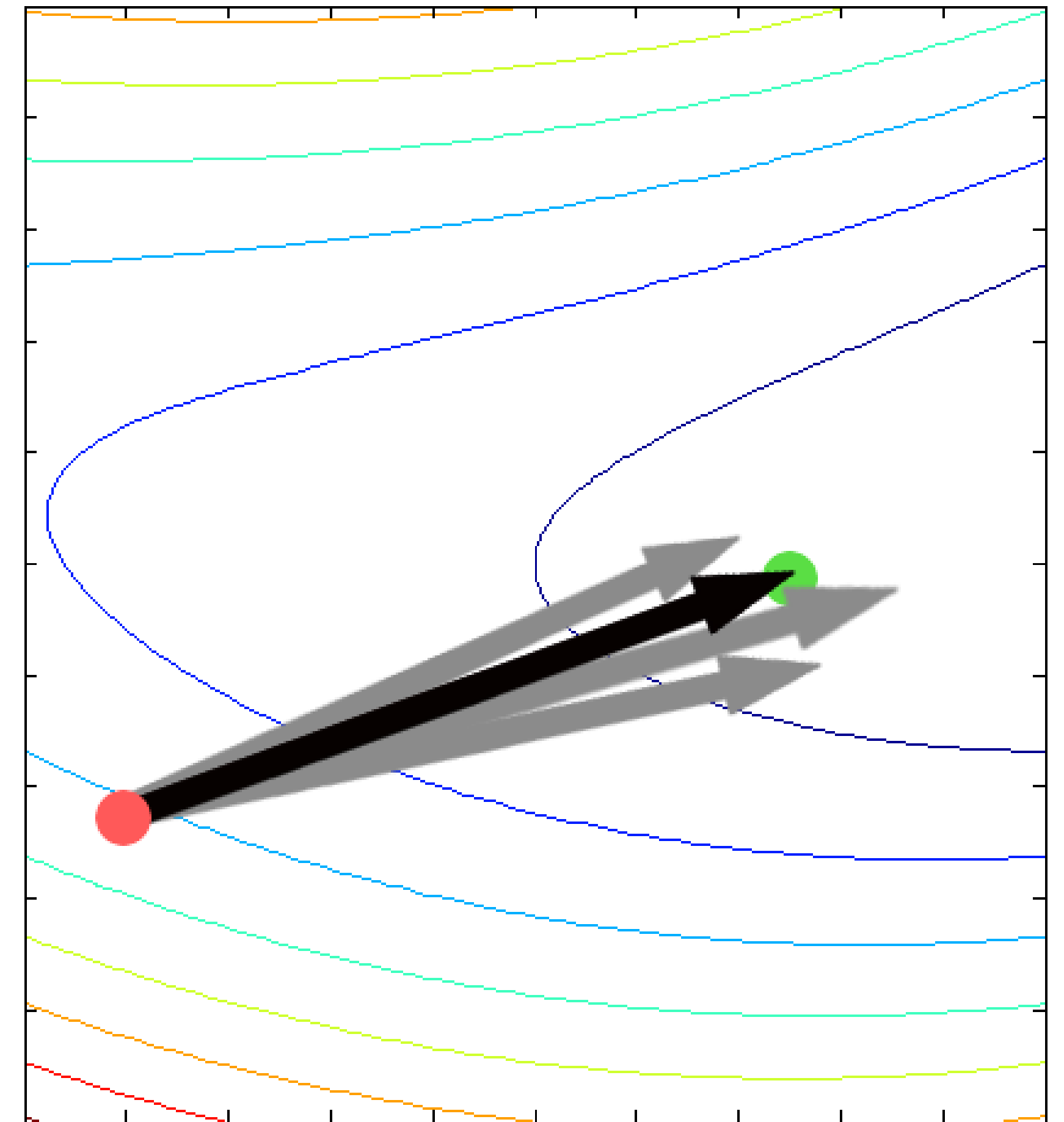
$$u^i \approx A^{-1}(m) q^i$$

$$\frac{\|A(m) u^i - q^i\|_2}{\|q^i\|_2} < \alpha^{k+1} \epsilon$$

(use the final tolerance to compute  $w^i$ )

## Chosen Parameters

- $\alpha = 0.5$
- $\epsilon = 10^{-2}$
- $\eta = 5 \times 10^{-2}$



[Herrmann et al., 2013]

# Frugal FWI - Source Subsampling

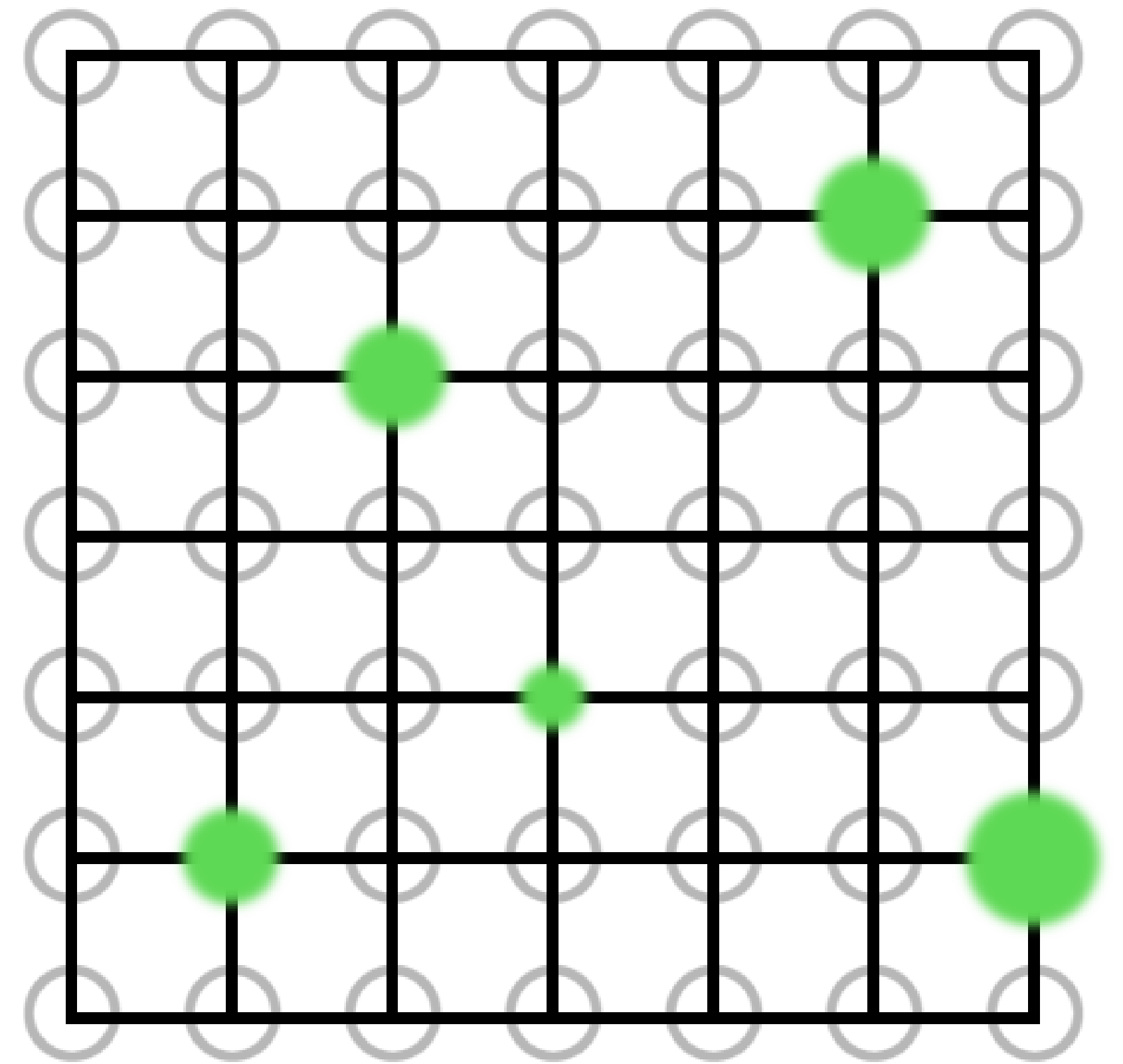
$$\tilde{\Phi}(m) = \sum_{i \in \mathcal{I}_k}^{b_k} \left\| d^i - u^i \right\|_W$$

$$\mathcal{I}_k \subset \{1, 2, \dots, n_s\}, \mathcal{I}_k^\# = b_k$$

$\mathcal{I}_k$  is chosen at random *without replacement*. The expected error is given by

$$\|e_k\|_2 \propto \sqrt{\frac{1}{b_k} - \frac{1}{n_s}}$$

$$b_k \sim \min \left\{ \left( \epsilon^k + \frac{1}{n_s} \right)^{-1}, n_s \right\}.$$



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[Friedlander and Schmidt, 2012] and [Herrmann et al., 2013]

# CGMN, CRMN & Kaczmarz Sweep

# Kaczmarz (Double) Sweep - Overview

$$u_{i+1} = u_i + \frac{\gamma(q_i - a_i^H u_i) a_i}{\|a_i\|_2^2}$$

- $q_i$   $i$ th element of  $q$
- $a_i$   $i$ th row of  $A$  as a column vector
- $\gamma$  relaxation parameter  $\in (0, 2)$

Kaczmarz sweeps **guarantees convergence** in a finite (possibly **large**) number of steps.

# Kaczmarz (Double) Sweep - Overview

$$Q = Q_1 Q_2 \dots Q_N Q_N Q_{N-1} \dots Q_1 \quad Q_i = I - \frac{\gamma}{\|a_i\|_2^2} a_i a_i^H$$

$$u := Qu + Rq \quad \implies \quad (I - Q)u = Rq$$

- $Q$  is **symmetric positive definite**
- We can use **CG** to solve this system
- Neither  $Q$  nor  $R$  need to be computed in practice
- Equivalent to using **CG on the normal equations**, preconditioned by SSOR

## 1 (CGMN).

```
1  $p_0 = r_0 = dkswp(A, u_0, b, \gamma) - u_0;$   
2 while not converged do  
3    $q_k = p_k - dkswp(A, p_k, 0, \gamma);$   
4    $\alpha_k = \langle r_k, r_k \rangle / \langle p_k, q_k \rangle;$   
5    $u_{k+1} = u_k + \alpha_k r_k;$   
6    $r_{k+1} = r_k - \alpha_k q_k;$   
7    $\beta_k = \langle r_{k+1}, r_{k+1} \rangle / \langle r_k, r_k \rangle;$   
8    $p_{k+1} = r_{k+1} + \beta_k p_k;$   
9    $k = k + 1;$   
10 end while
```

- Very **low memory cost**
- Very simple implementation
- Suitable for **any matrix**  $A$  (even nonsquare)

On CG:[Hestenes and Stiefel, 1952], on CGMN: [Björck and Elfving, 1979]

## 2 (CRMN).

```
1 while not converged do
2    $Ar_k := r_k - dkswp(A, r_k, 0, \gamma);$ 
3    $\beta_k = \langle r_k, Ar_k \rangle / \langle r_{k-1}, Ar_{k-1} \rangle;$ 
4    $p_k = r_k + \beta_k p_{k-1};$ 
5    $Ap_k = Ar_k + \beta_k Ap_{k-1};$ 
6    $\alpha_k = \langle r_k, Ar_k \rangle / \langle Ap_k, Ap_k \rangle;$ 
7    $u_{k+1} = u_k + \alpha_k r_k;$ 
8    $r_{k+1} = r_k - \alpha_k q_k;$ 
9    $k = k + 1;$ 
10 end while
```

- Very **low memory cost**
- One **extra** vector storage
- One **extra** inner product
- **Minimal residual** properties

On CR: [Stiefel, 1955], comparisons:[Fong and Saunders, 2012, Eiermann and Ernst, 2001]



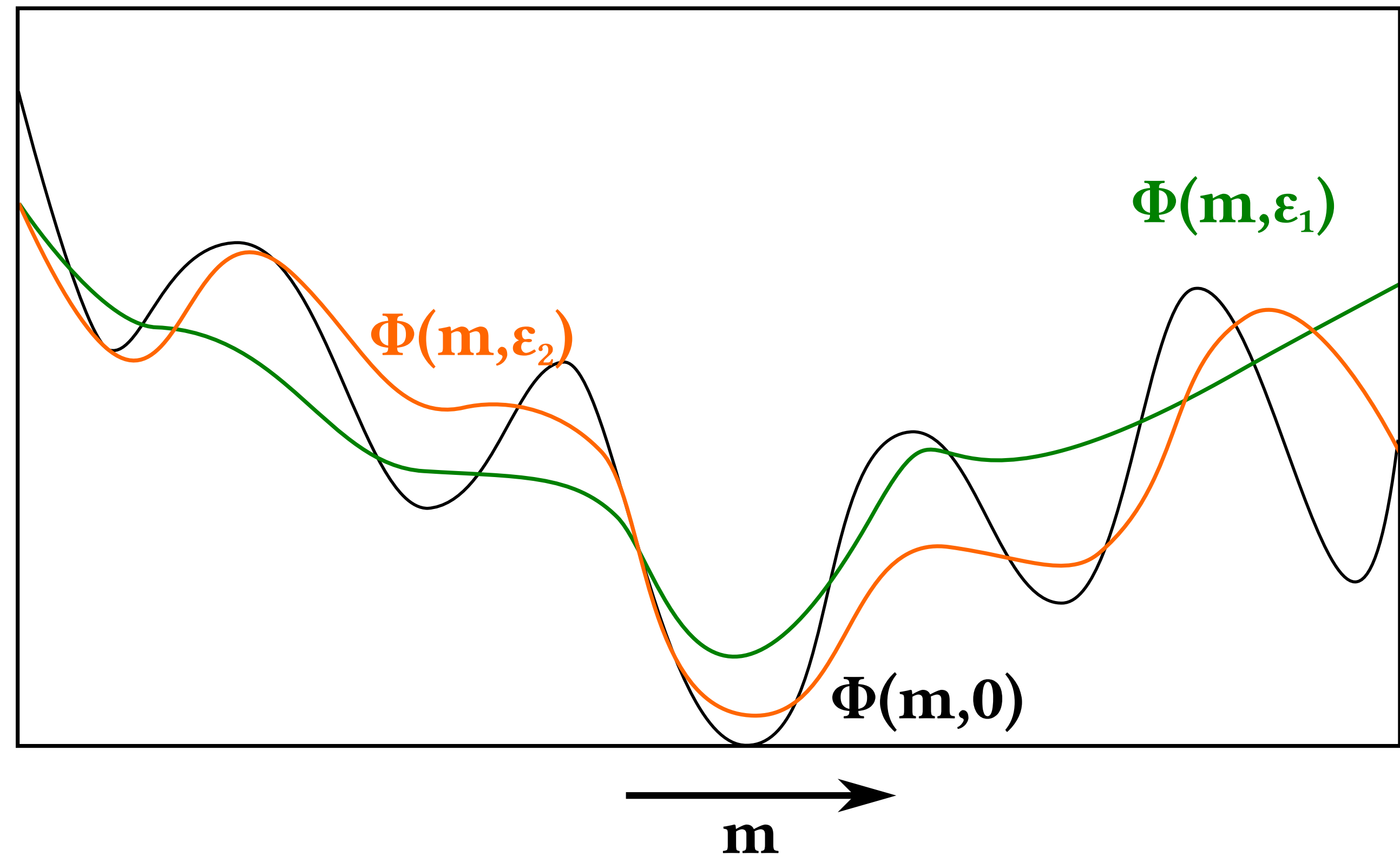
# On Heuristics

# A Matter of Robustness

$$\frac{|\Phi(m, \alpha^k \epsilon) - \Phi(m, \alpha^{k+1} \epsilon)|}{\Phi(m, \alpha^{k+1} \epsilon)} \leq \eta$$

$$\mathbf{u}^i \approx P_r A^{-1}(m) \mathbf{q}^i$$

$$\frac{\|A(m) \mathbf{u}^i - \mathbf{q}^i\|_2}{\|\mathbf{q}^i\|_2} < \alpha^{k+1} \epsilon$$



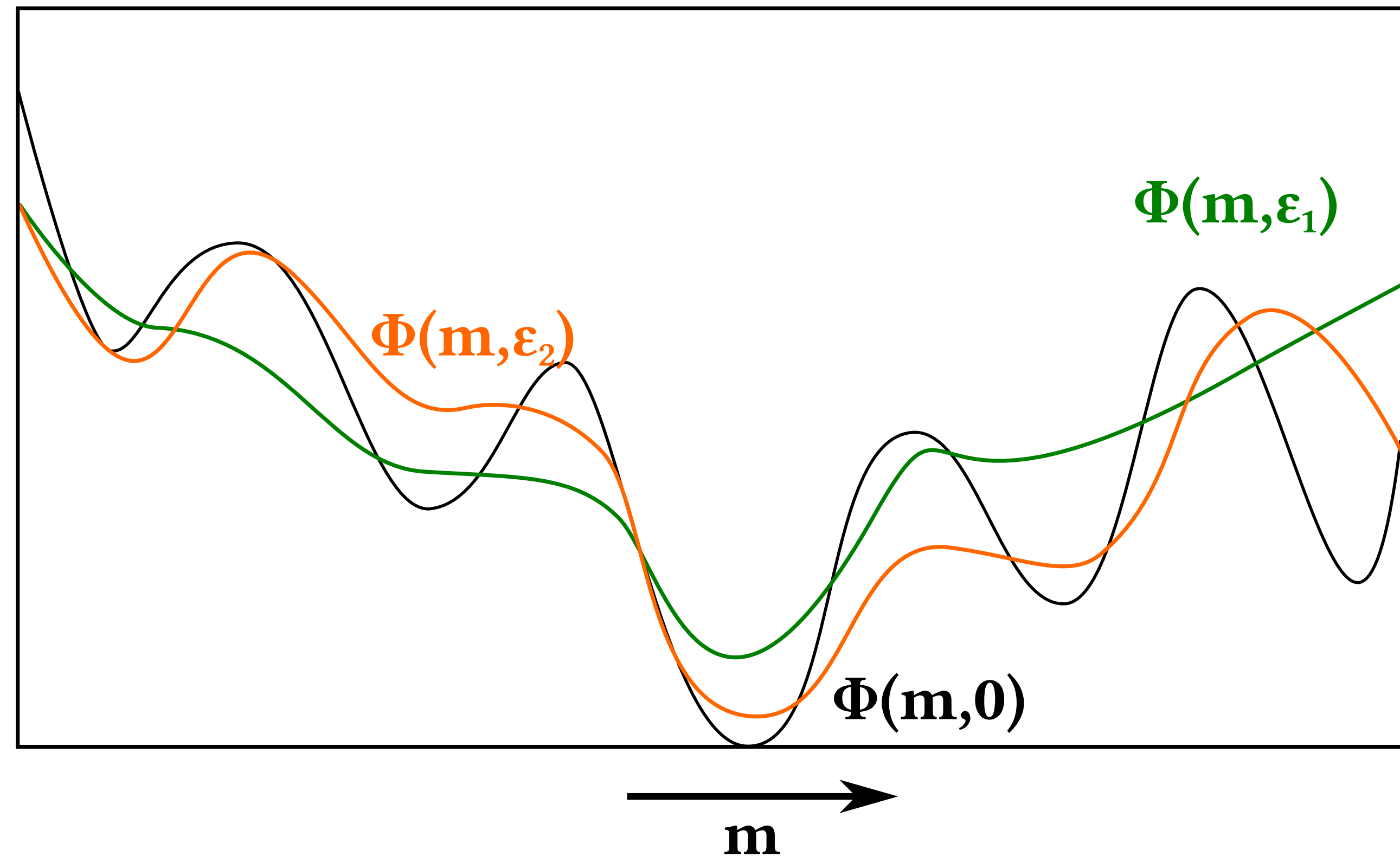
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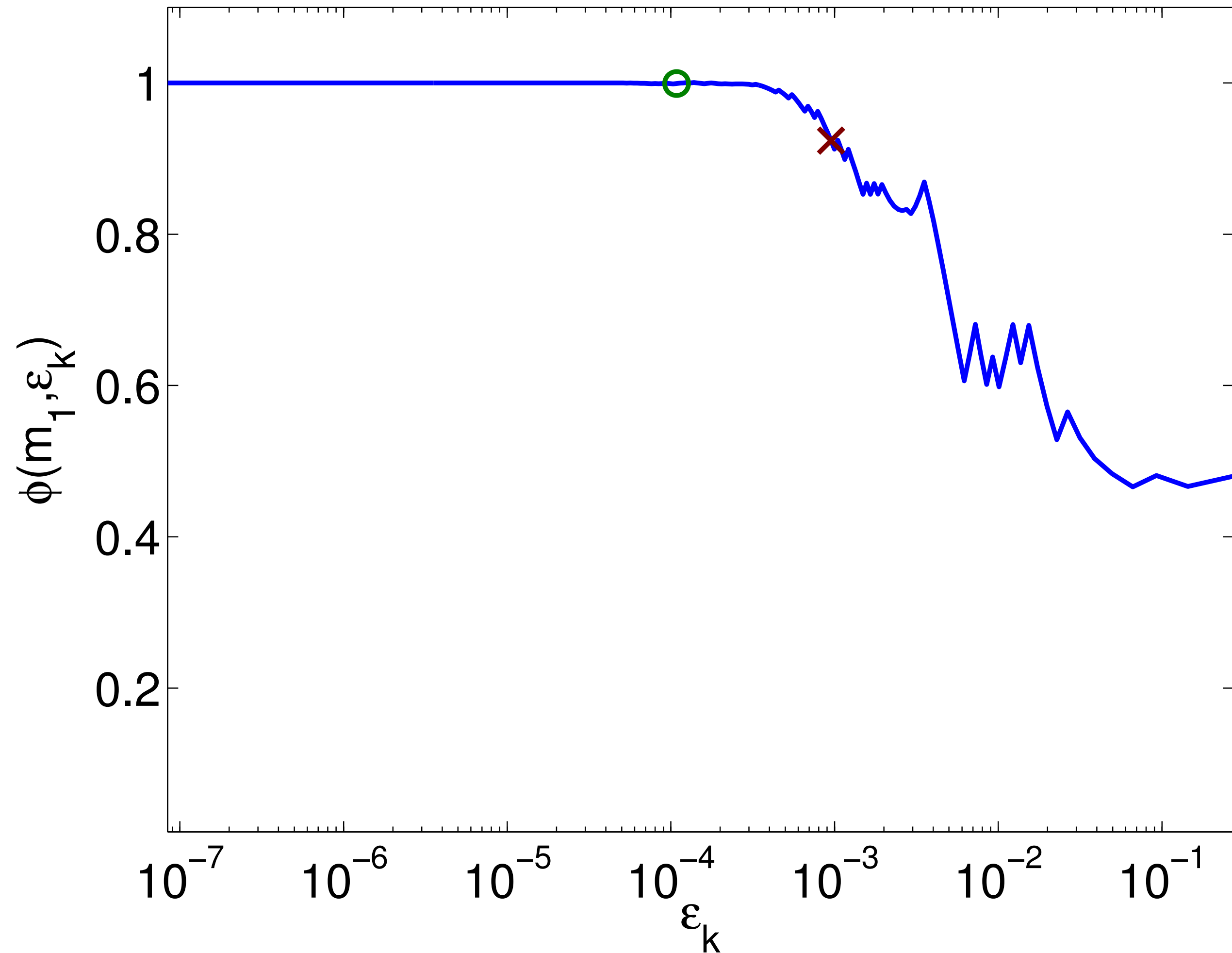
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and that  $\Phi(m, \epsilon_k)$  “converges” to  $\Phi(m, 0)$

But... does this happen? **How quickly? How consistently?**

# A Glance Into The Misfit

- - relative residual at  $10^{-4}$
- ✕ - relative residual at  $10^{-3}$

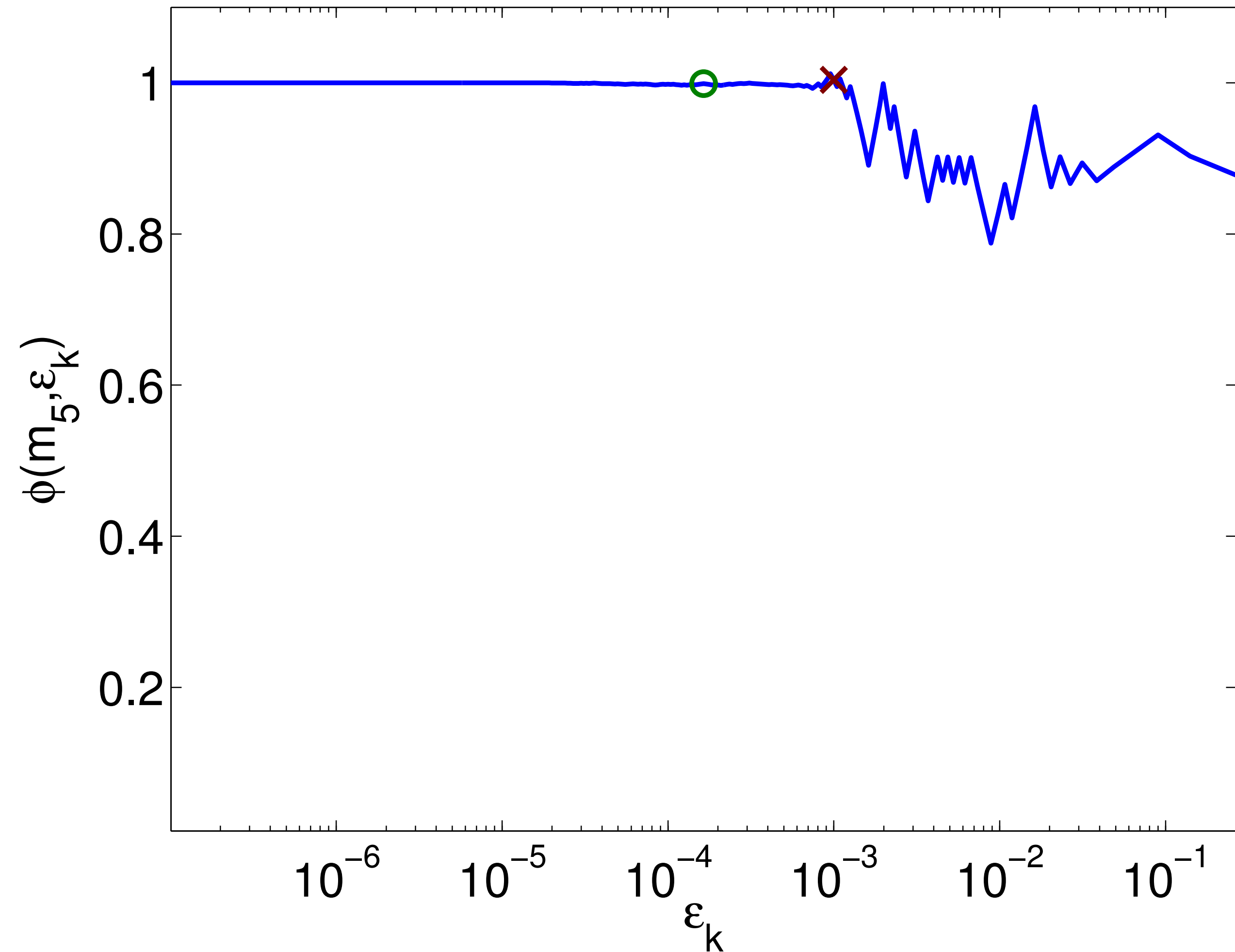
Misfit as a function of  $\varepsilon_k$   
for the **1st** iteration of  
IBFGS



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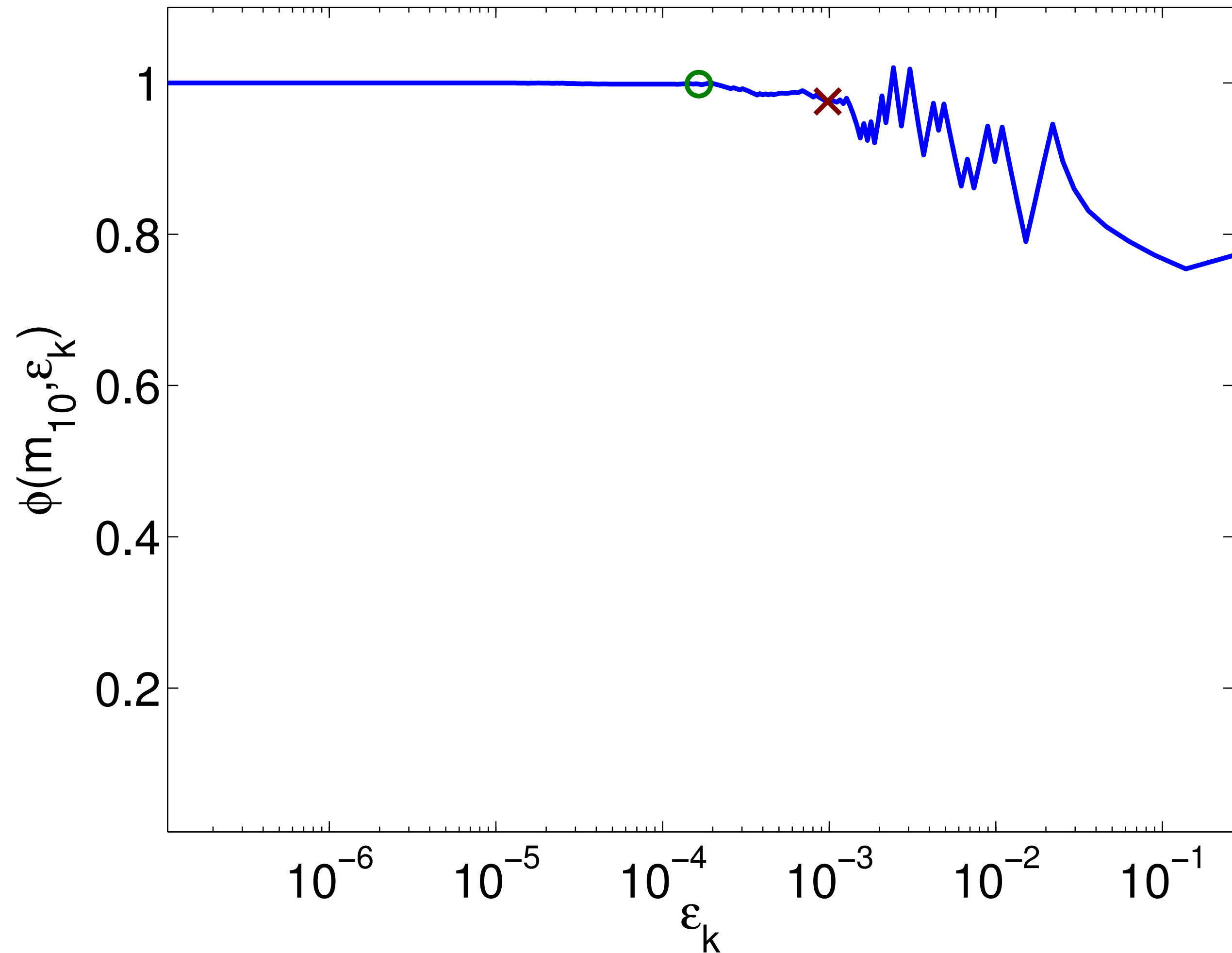
Misfit as a function of  $\varepsilon_k$   
for the **5th** iteration of  
IBFGS



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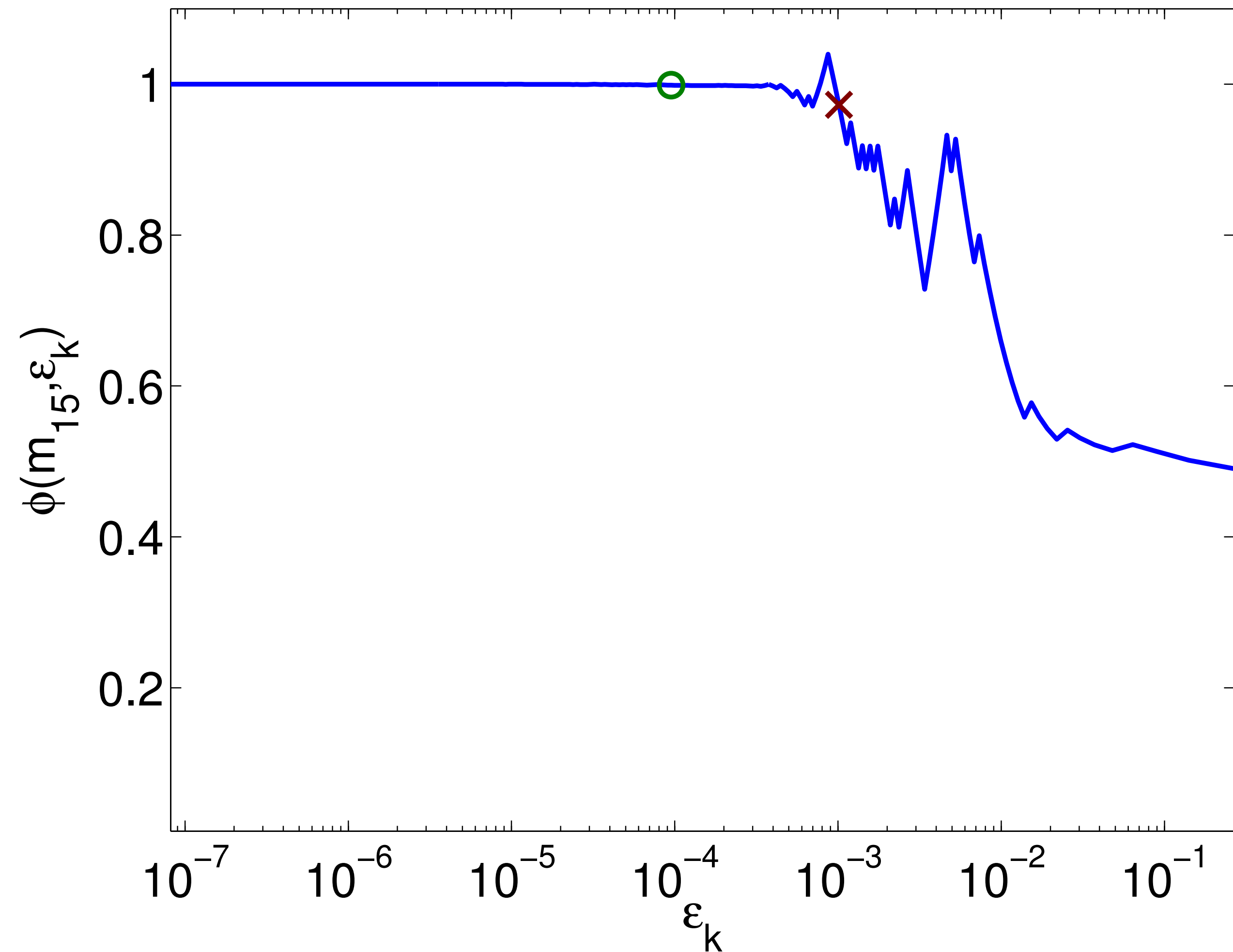
Misfit as a function of  $\varepsilon_k$   
for the **10th** iteration of  
IBFGS



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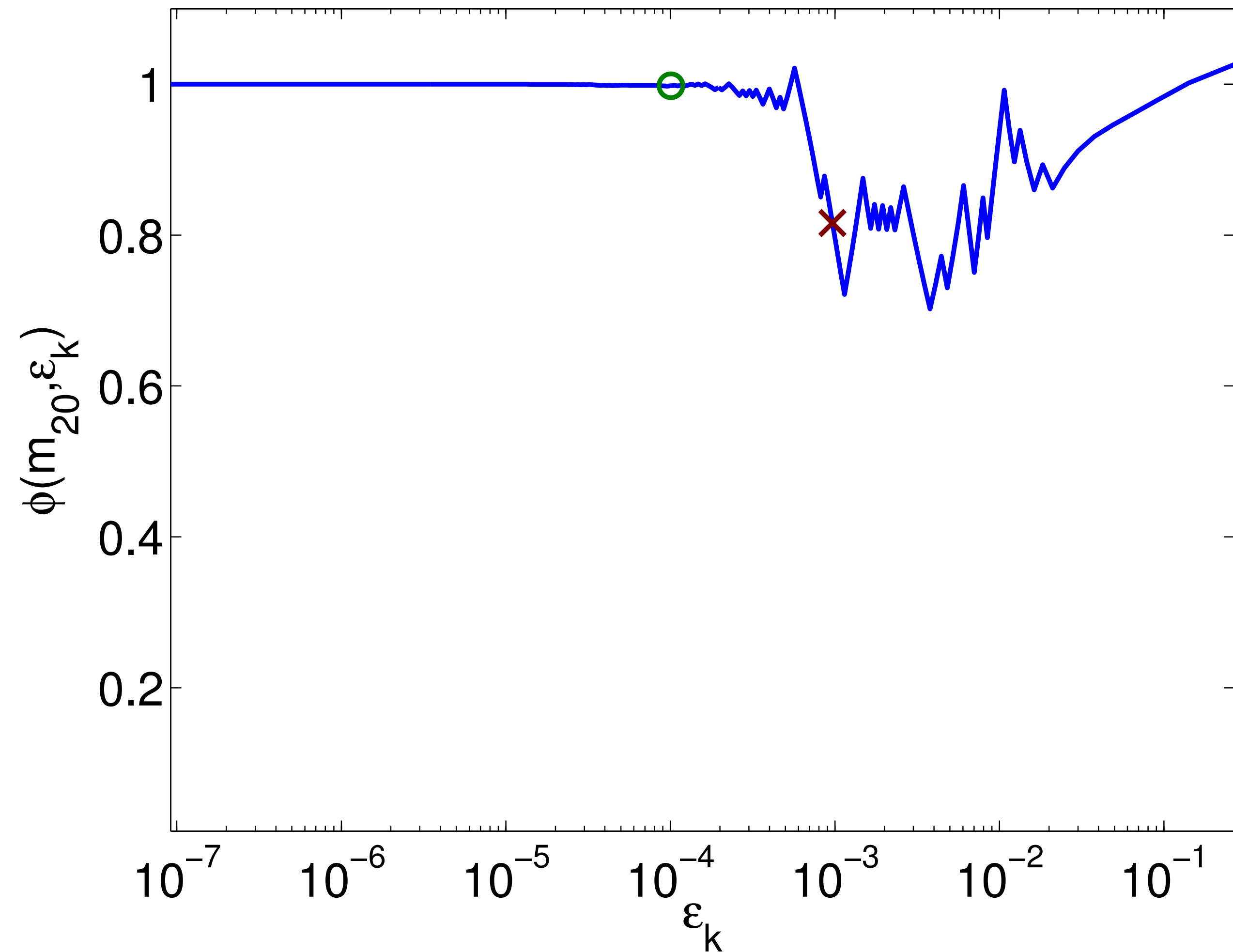
Misfit as a function of  $\varepsilon_k$   
for the **15th** iteration of  
IBFGS



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Misfit as a function of  $\varepsilon_k$   
for the **20th** iteration of  
IBFGS

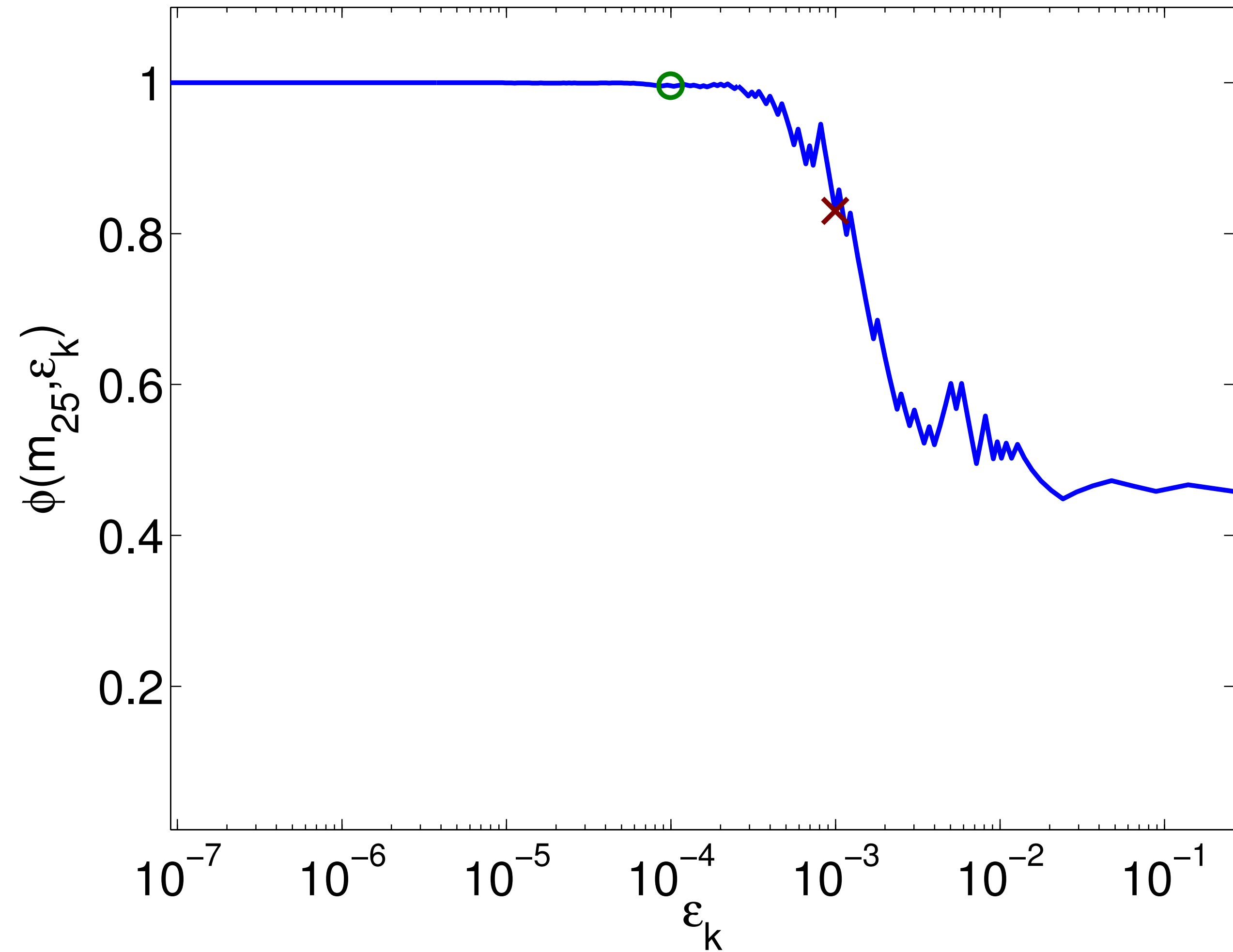




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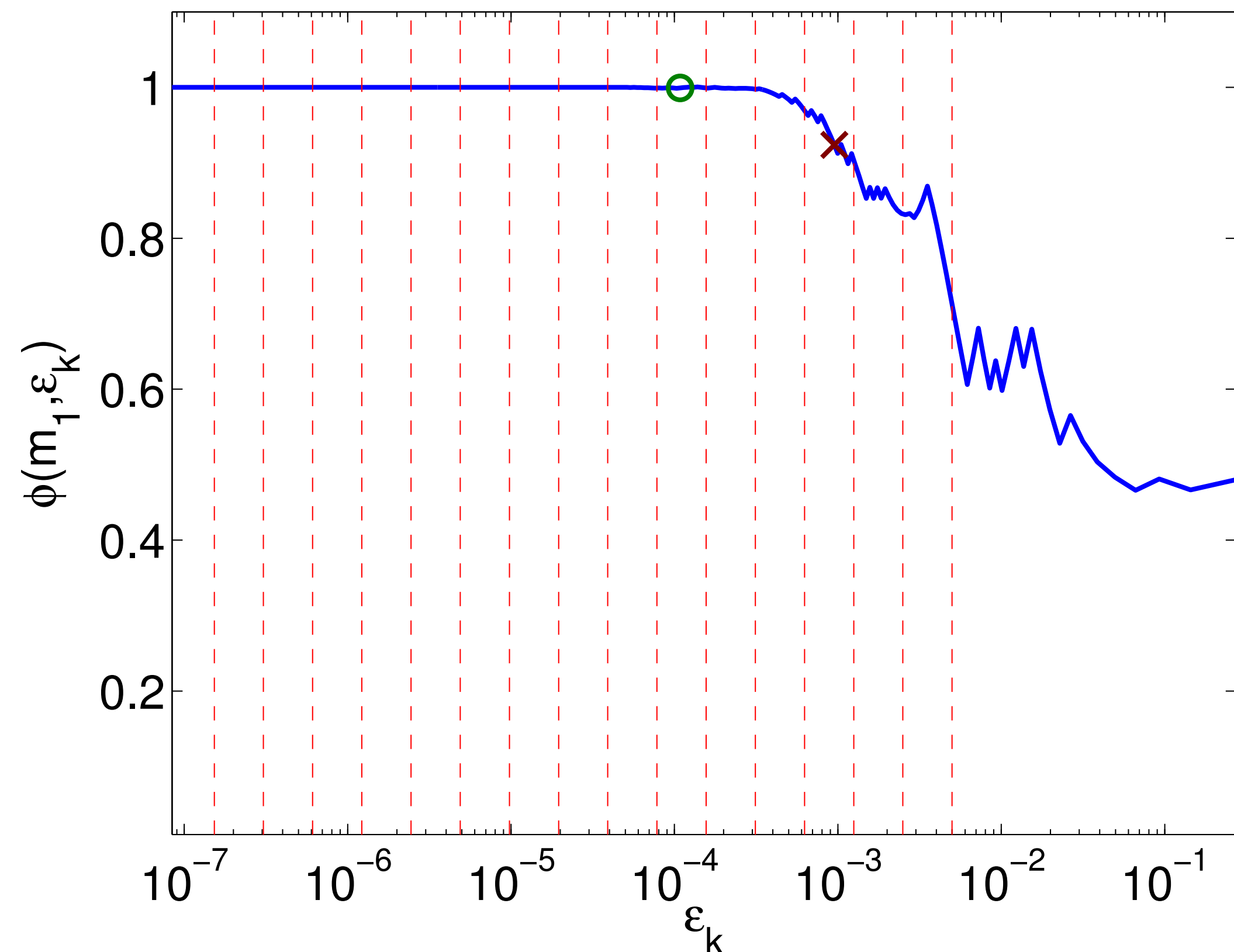
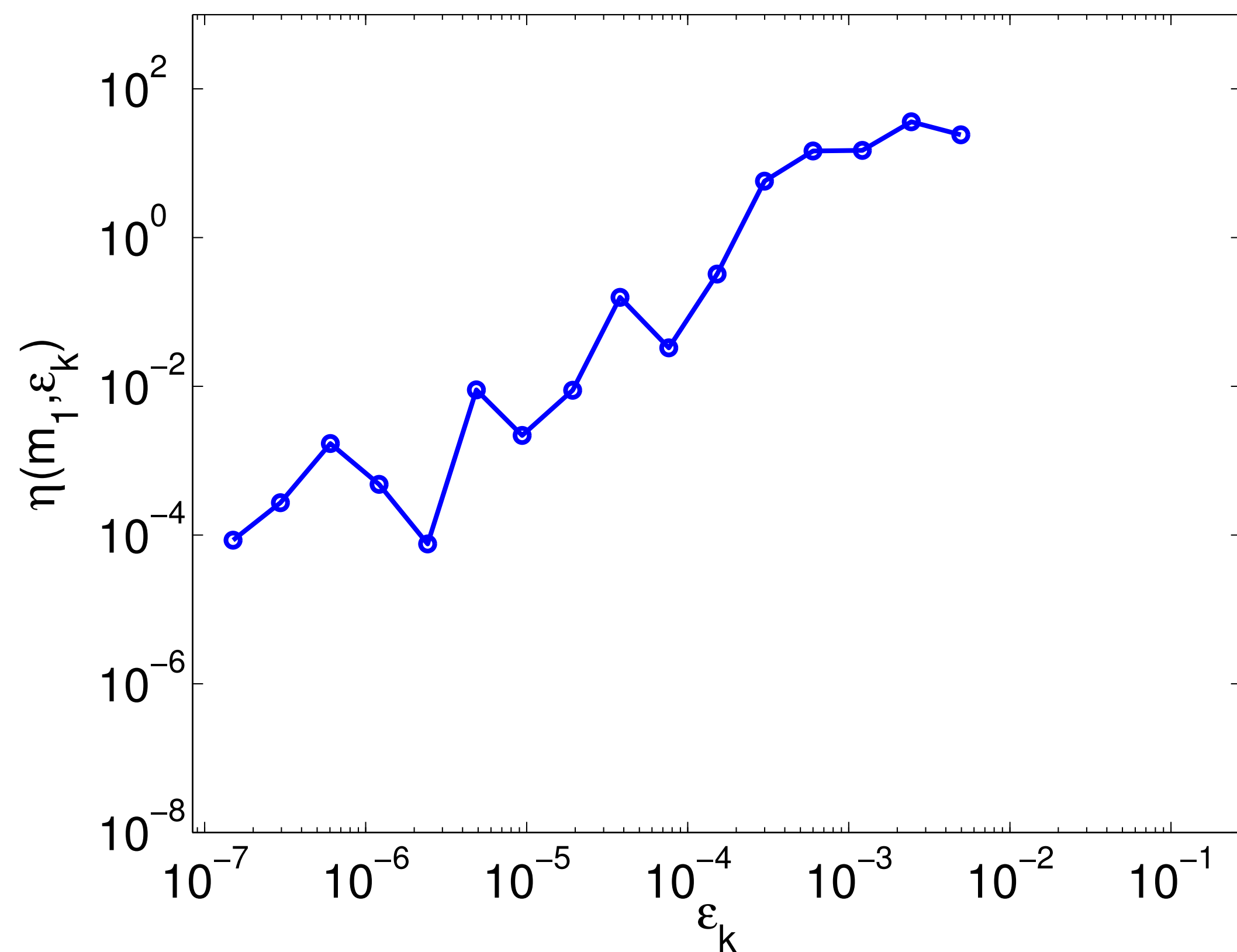
Misfit as a function of  $\varepsilon_k$   
for the **25th** iteration of  
IBFGS



# The $\alpha_k$ Criterion

$$\frac{|\Phi(m, \alpha^k \epsilon) - \Phi(m, \alpha^{k+1} \epsilon)|}{\Phi(m, \alpha^{k+1} \epsilon)} \leq \eta \quad u^i \approx P_r A^{-1}(m) q^i$$

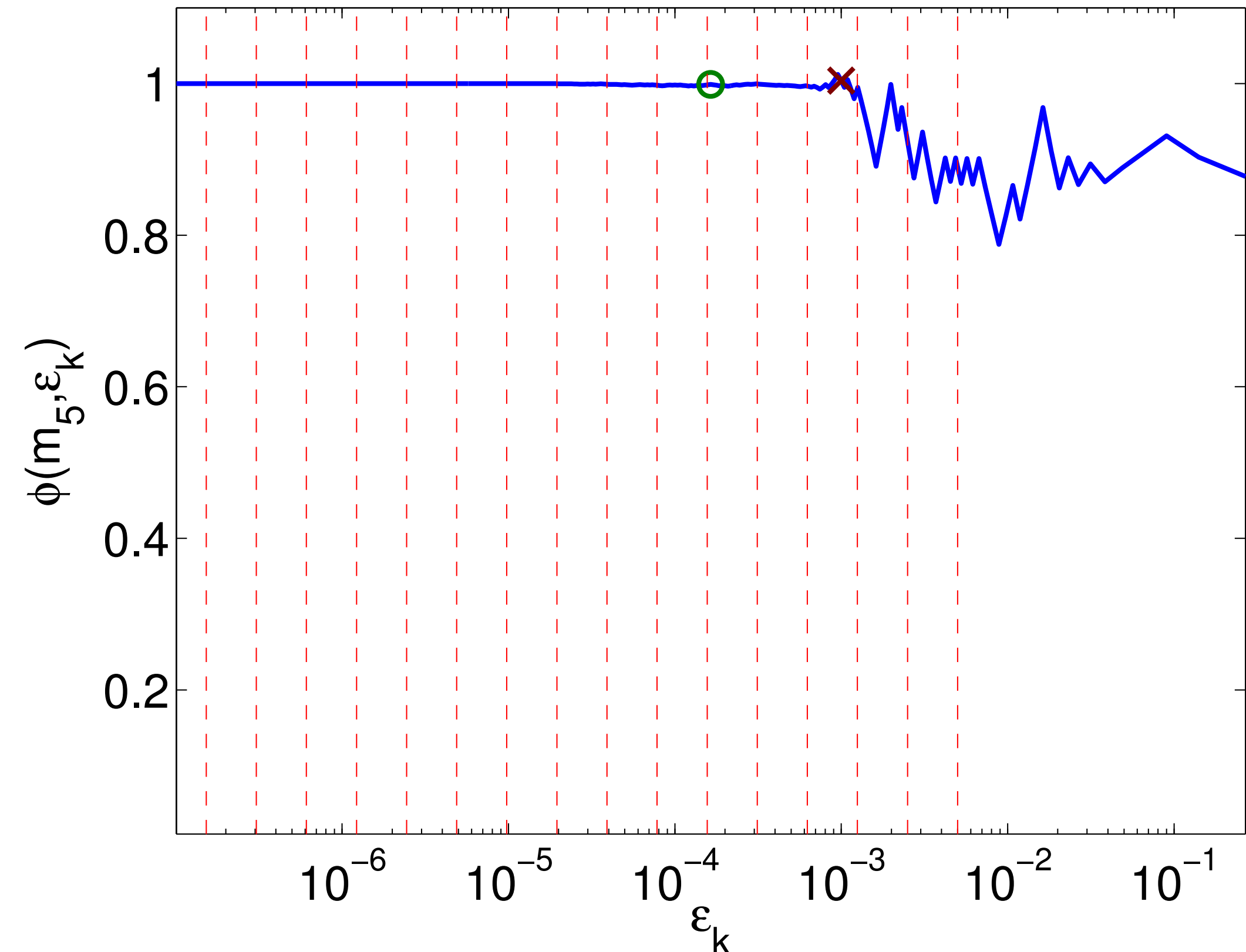
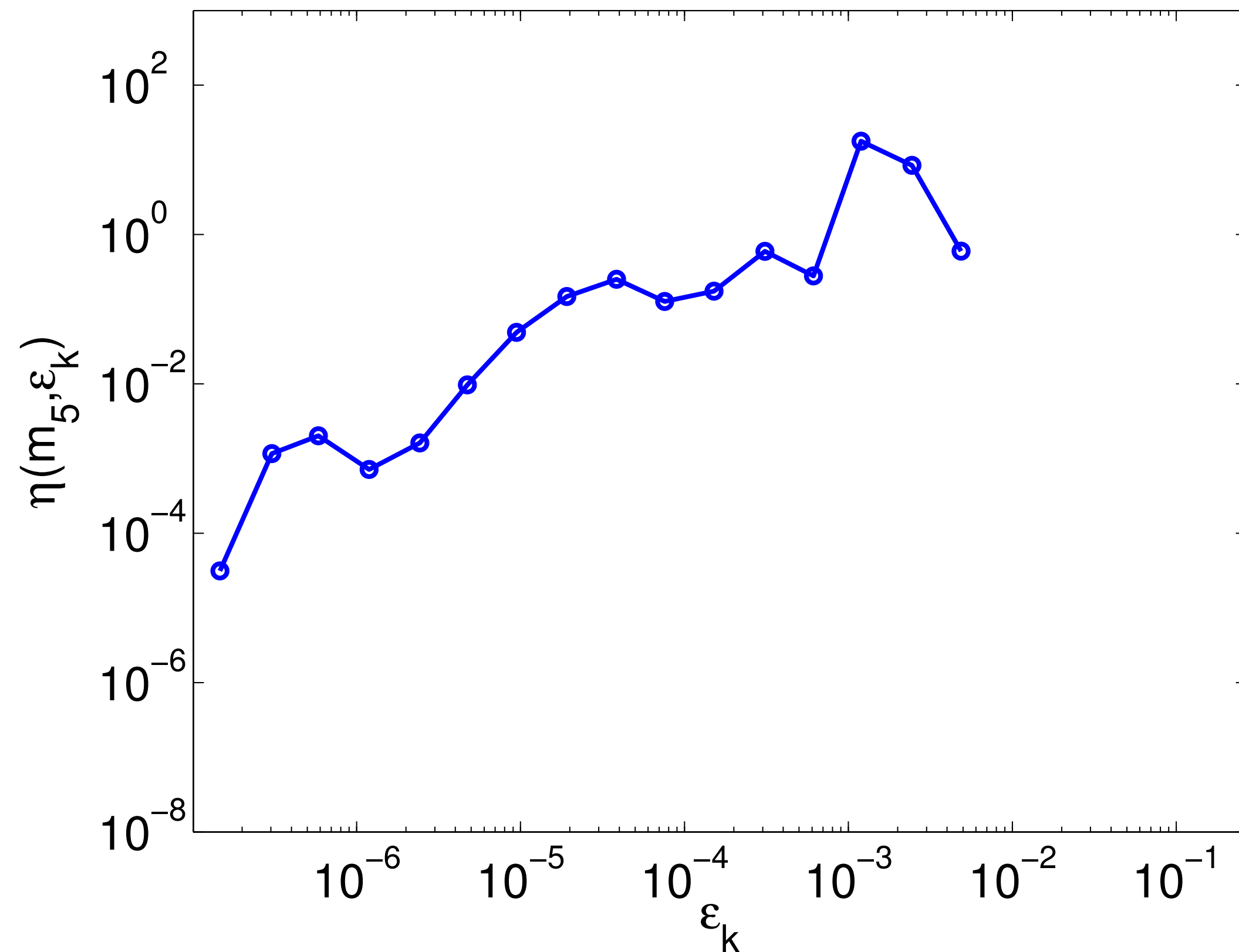
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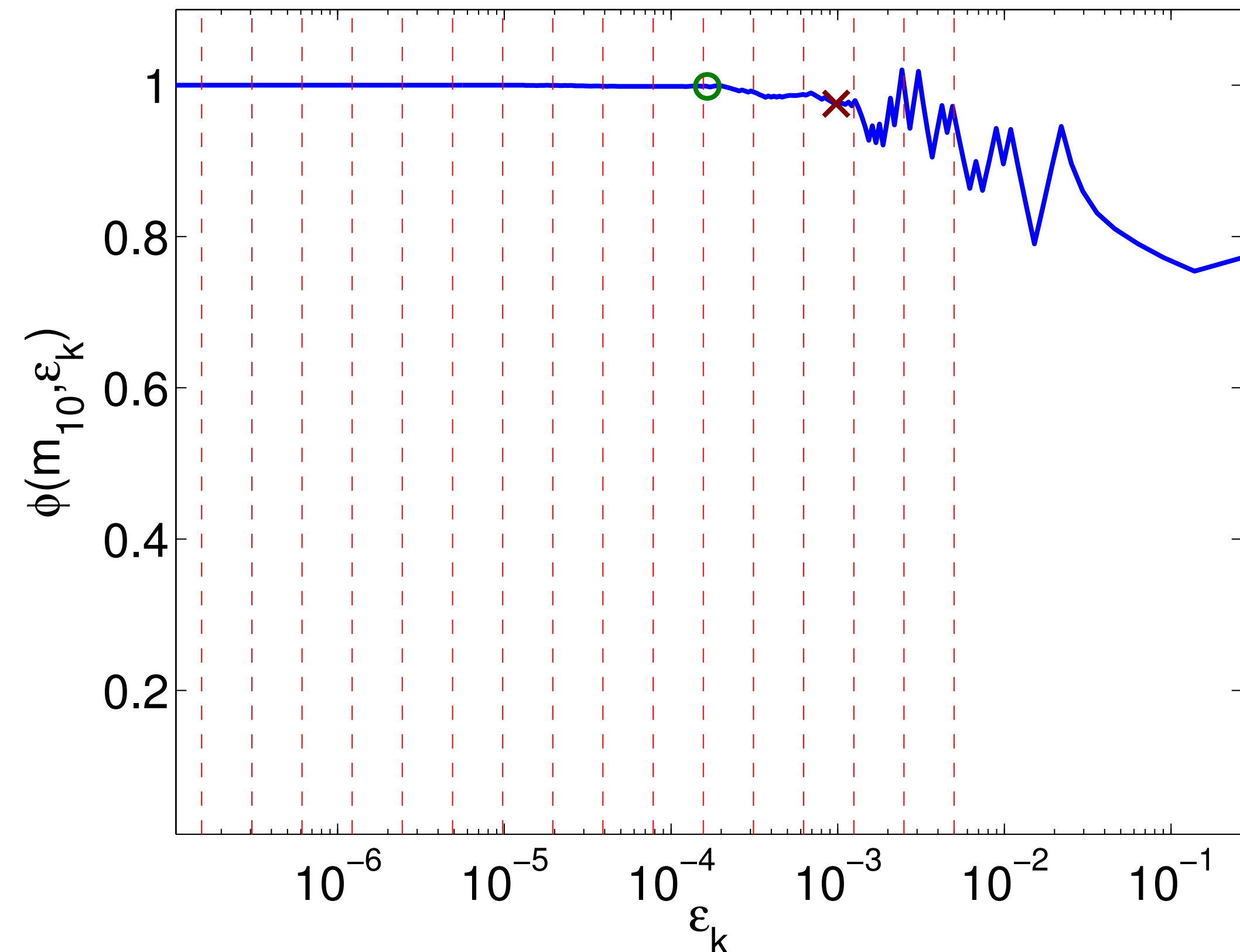
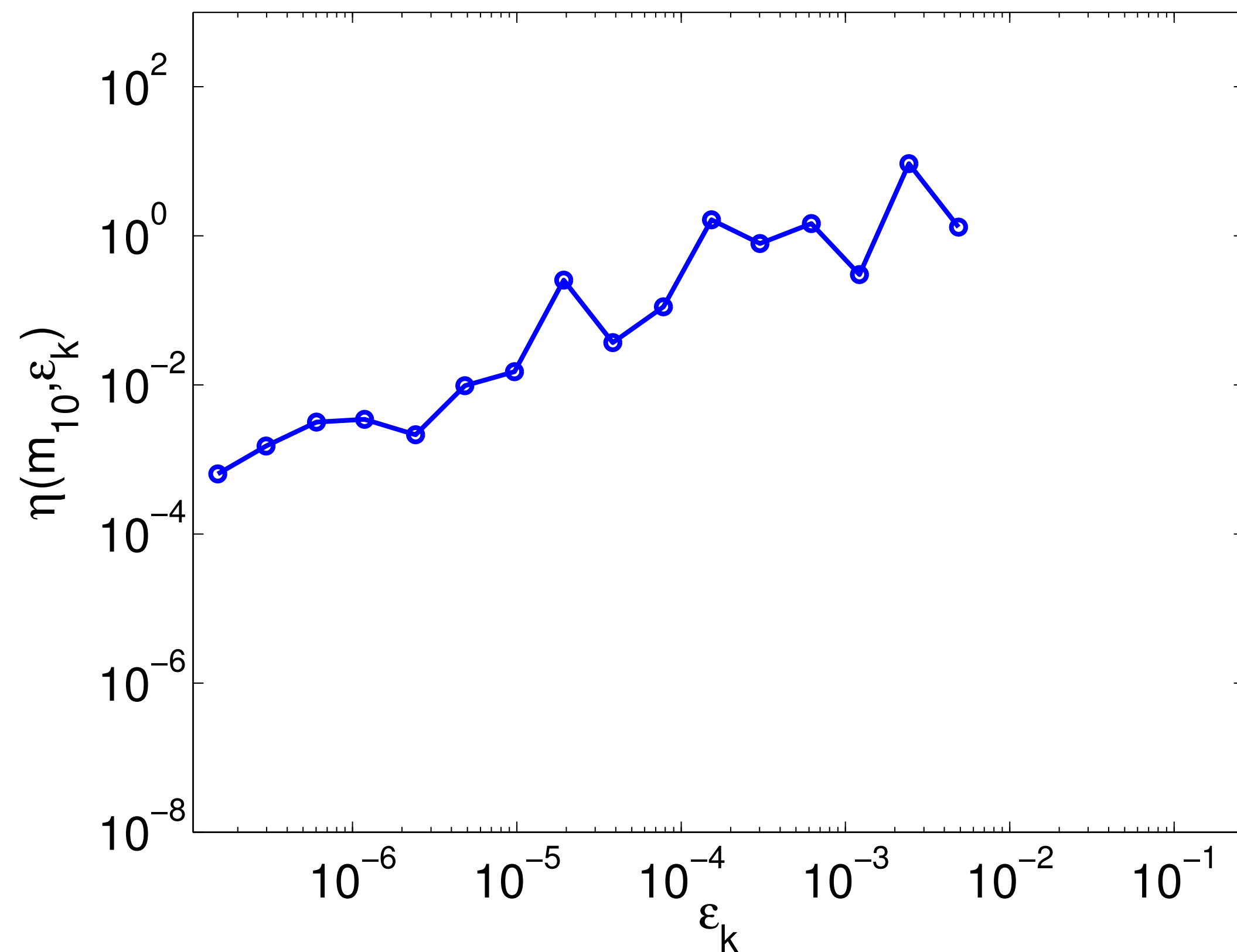
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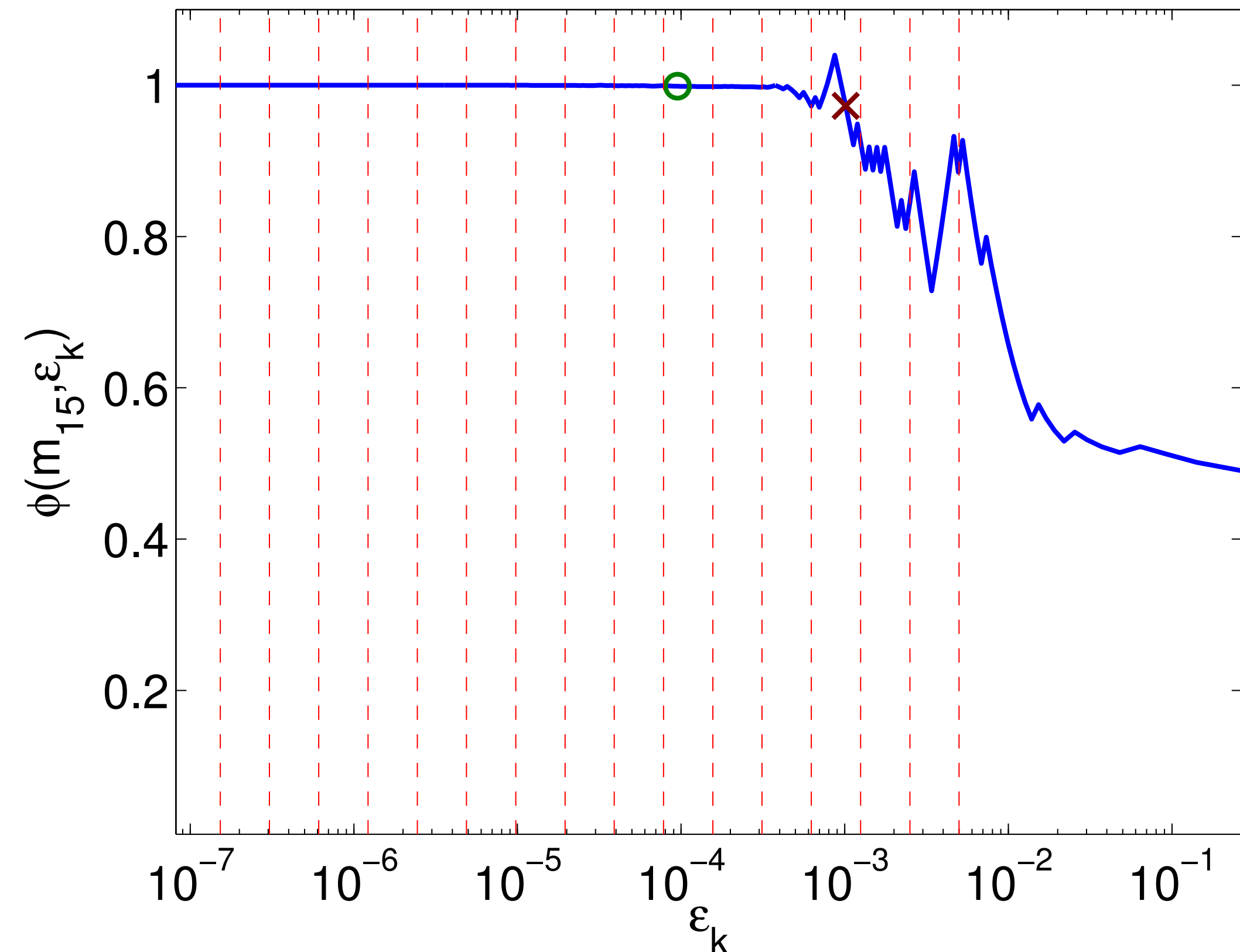
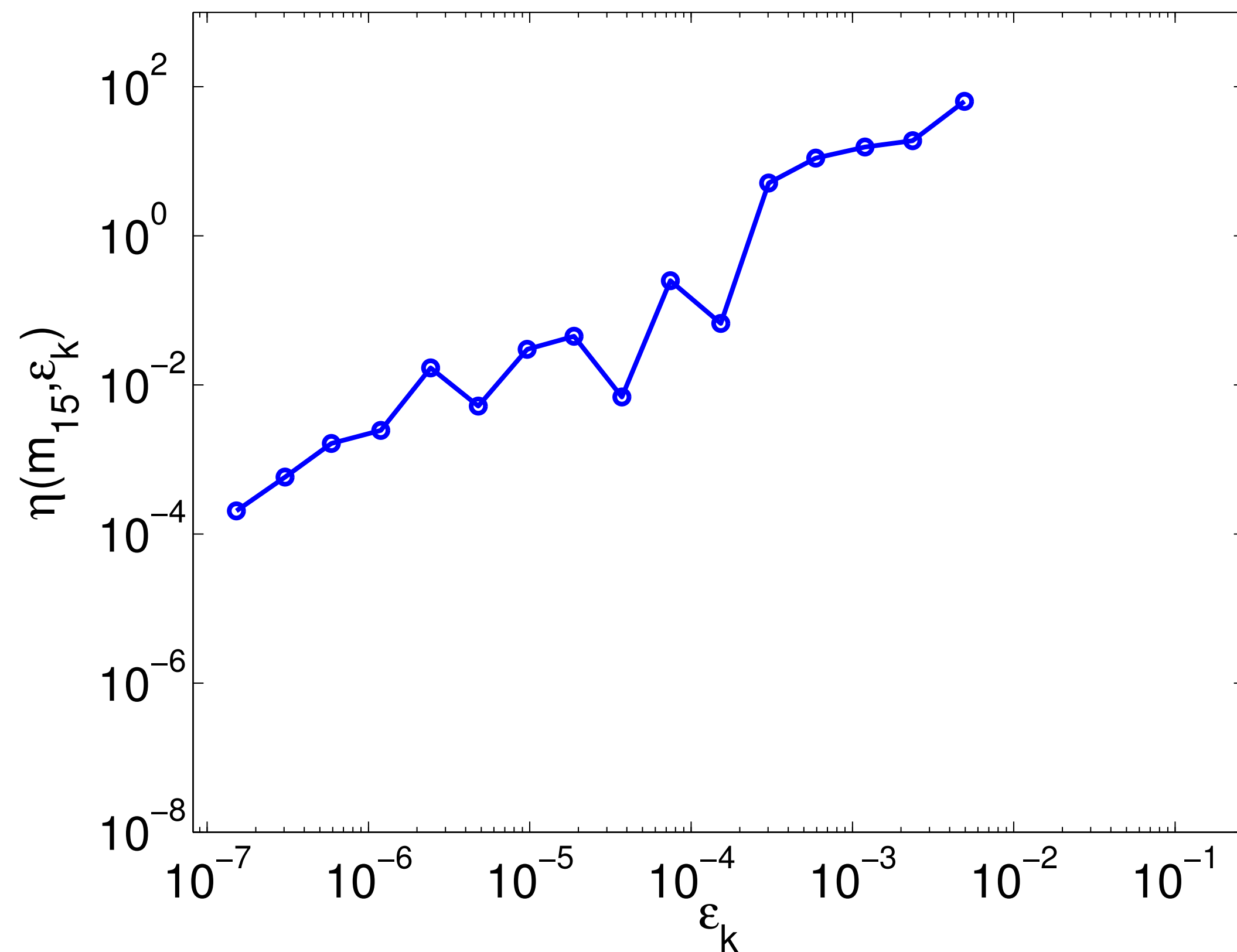
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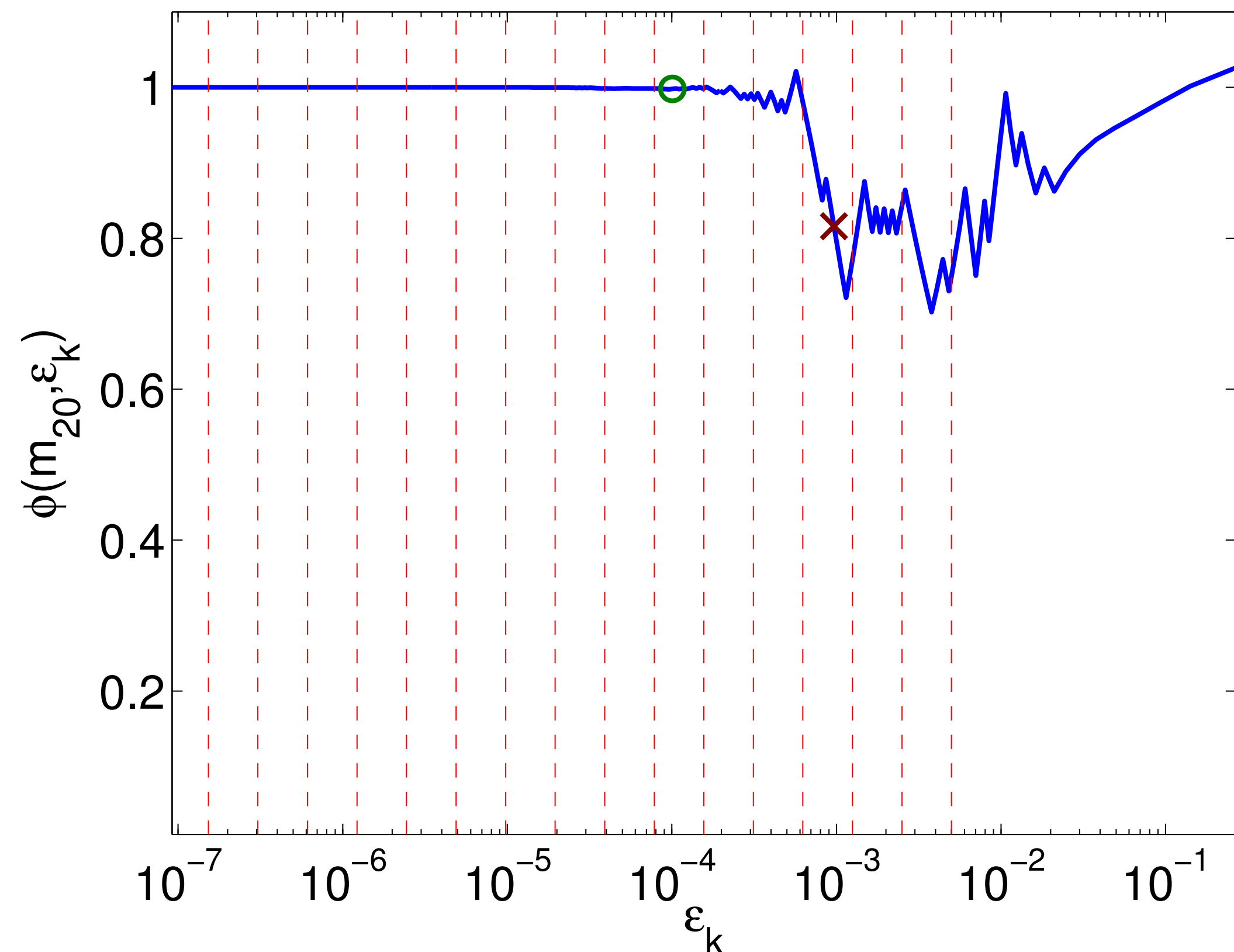
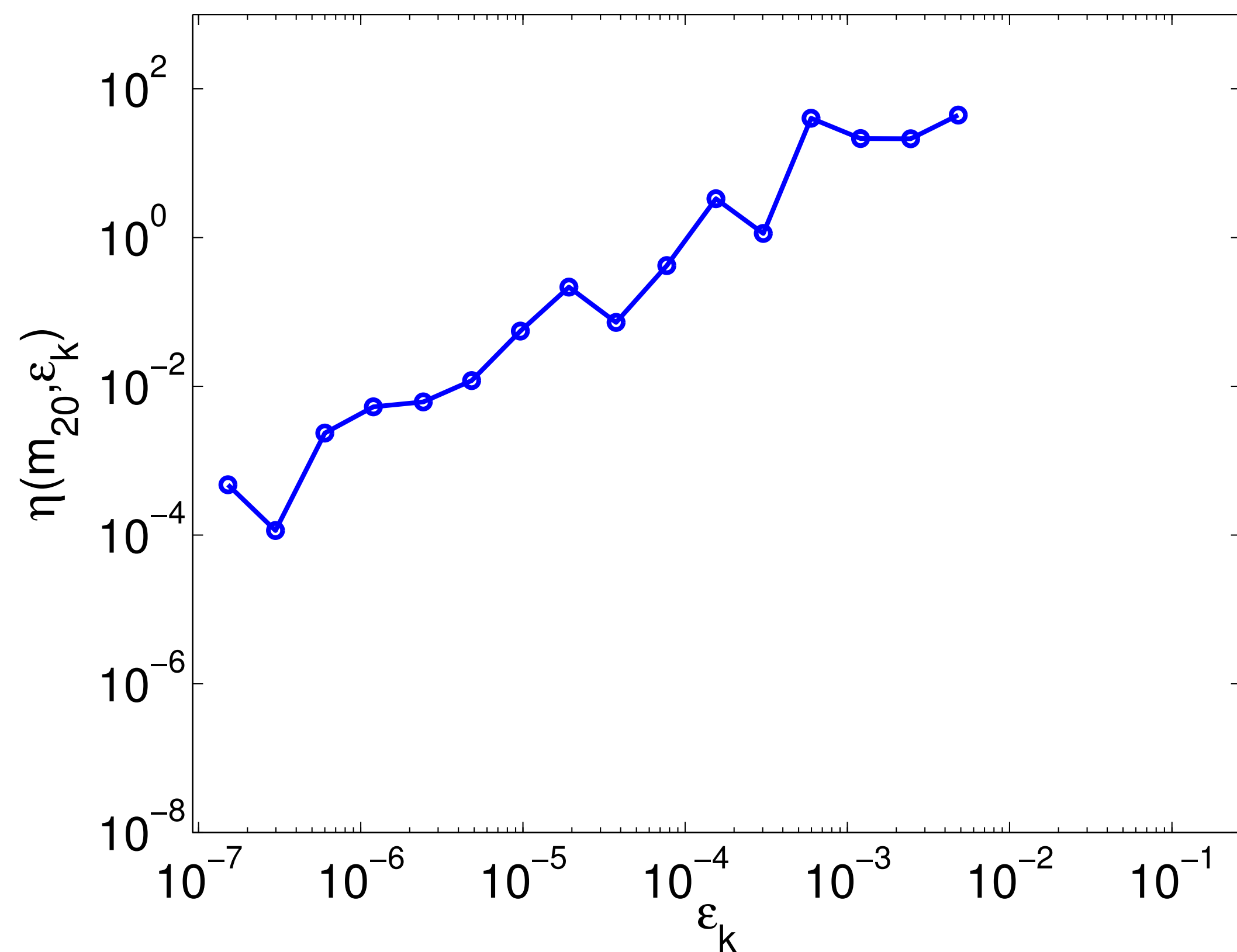
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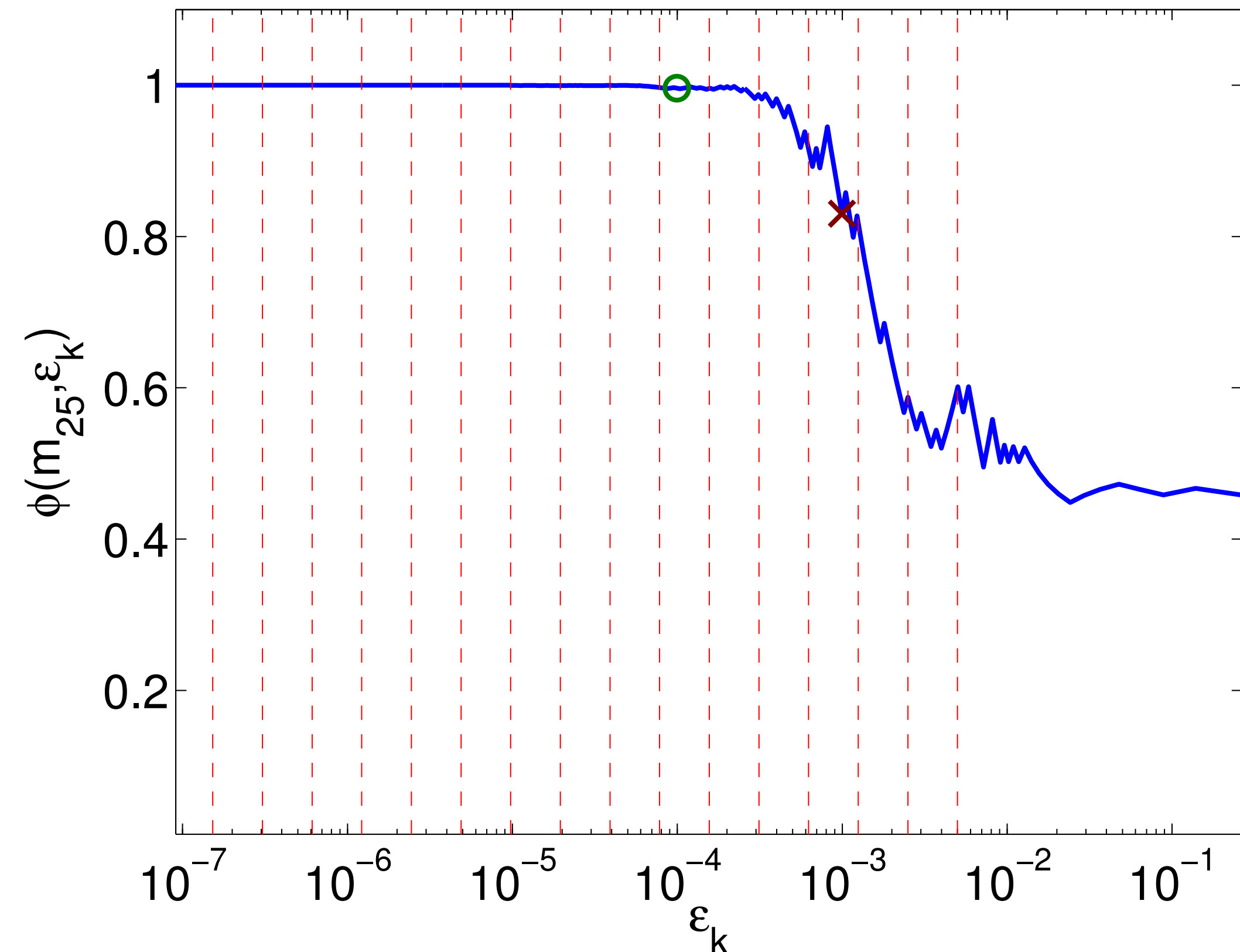
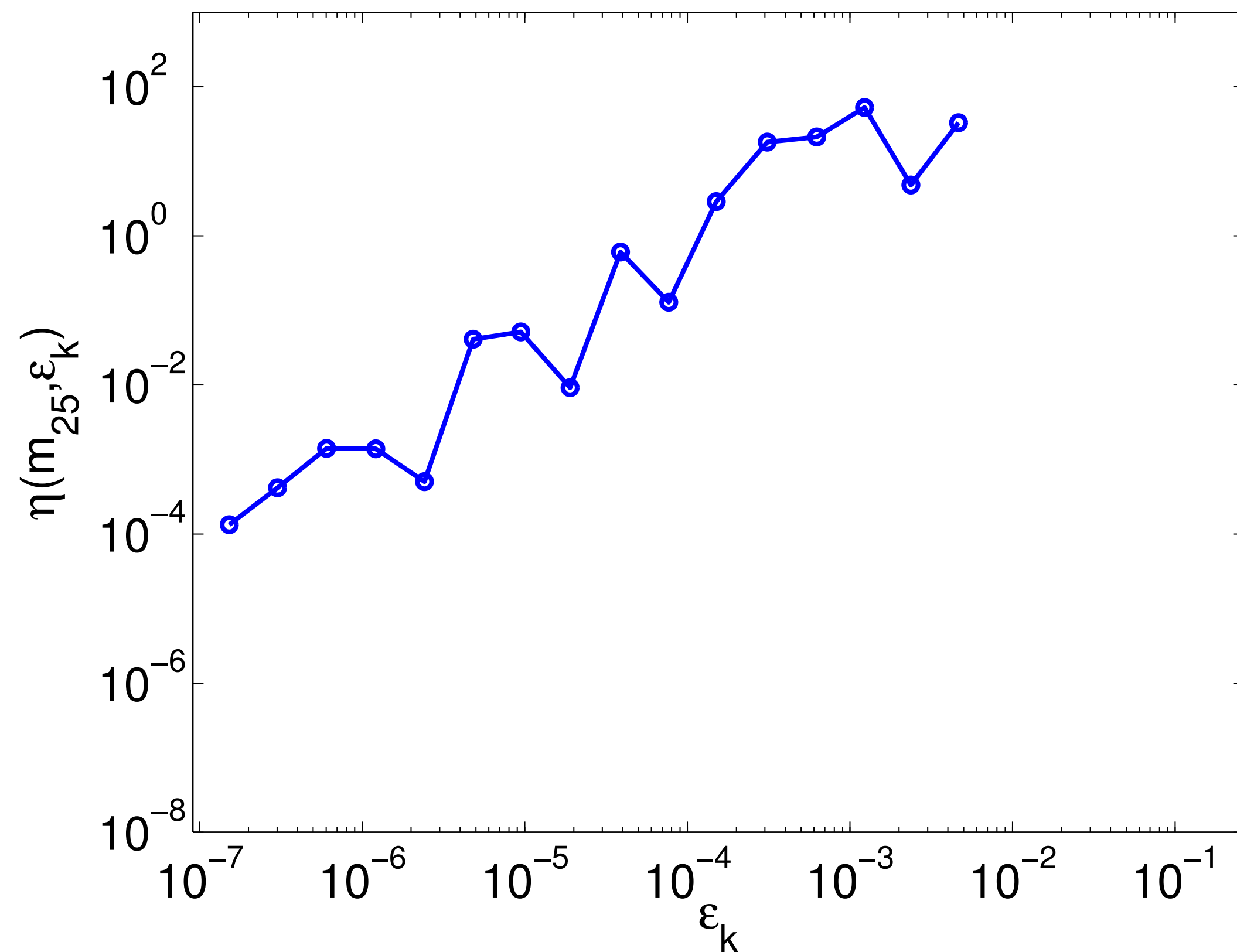
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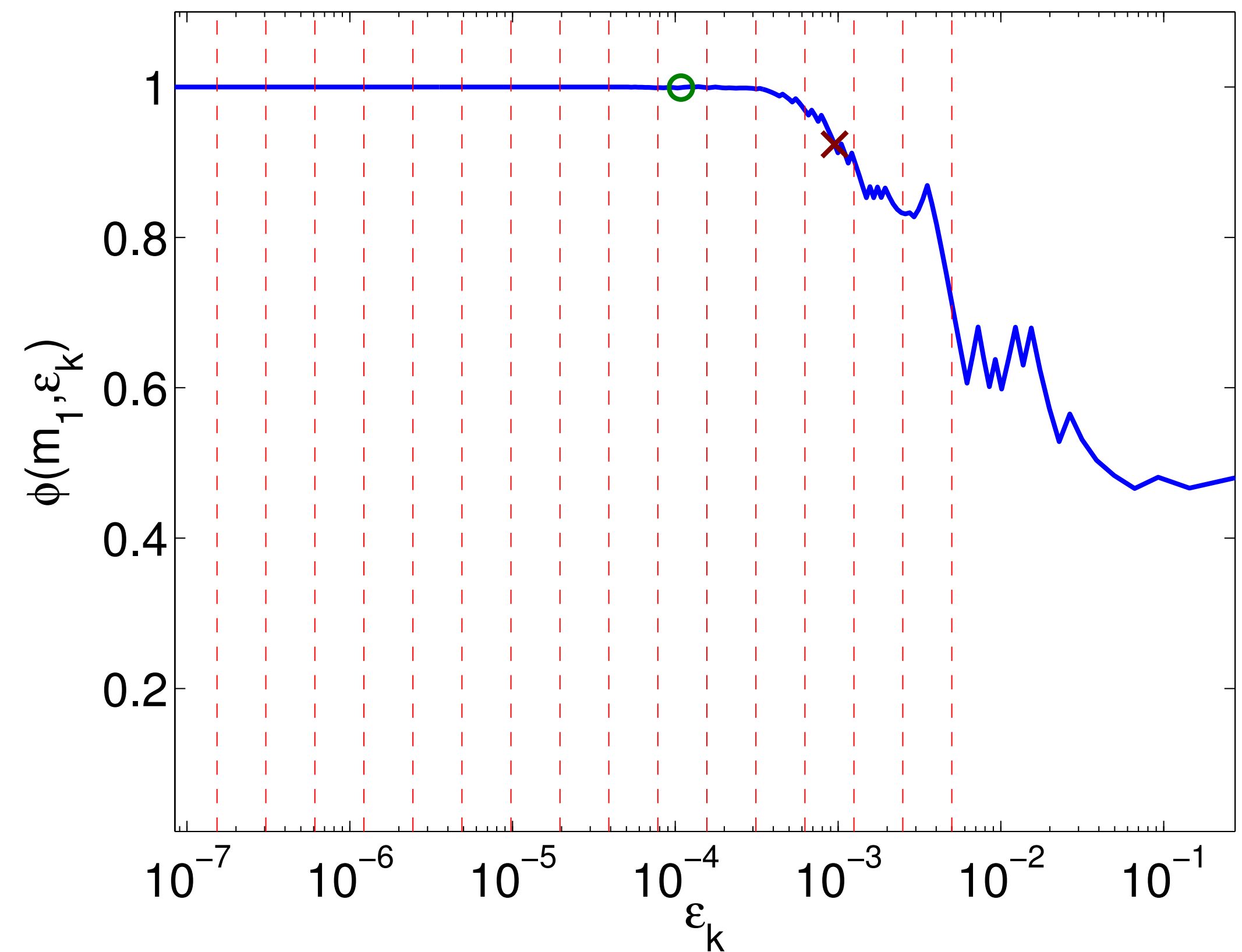
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# Finer Sampling

$$\frac{|\Phi(m, \varepsilon_k) - \Phi(m, \varepsilon_{k+1})|}{\Phi(m, \varepsilon_{k+1})} \leq \eta \frac{\varepsilon_{k+1}}{\varepsilon_k}$$

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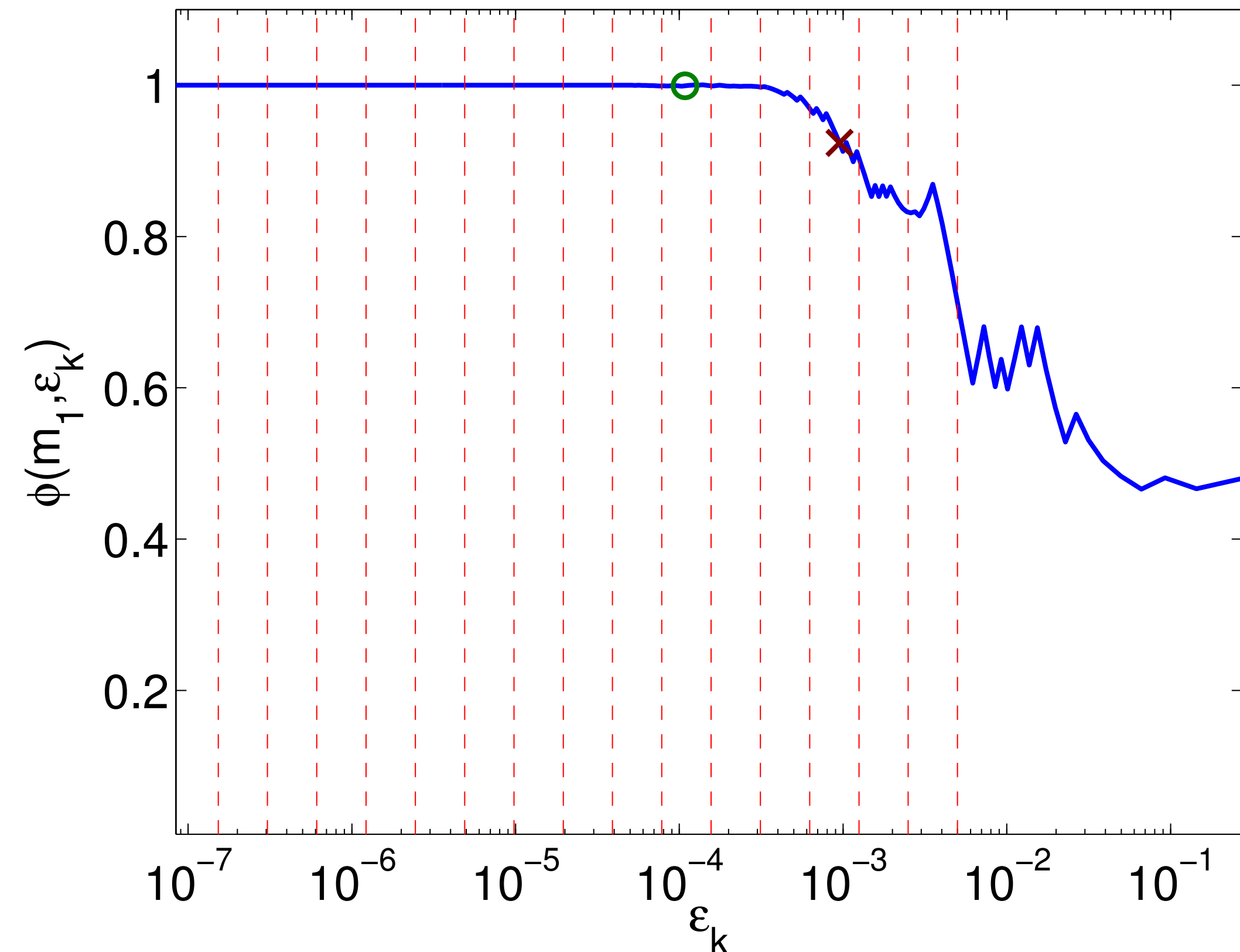
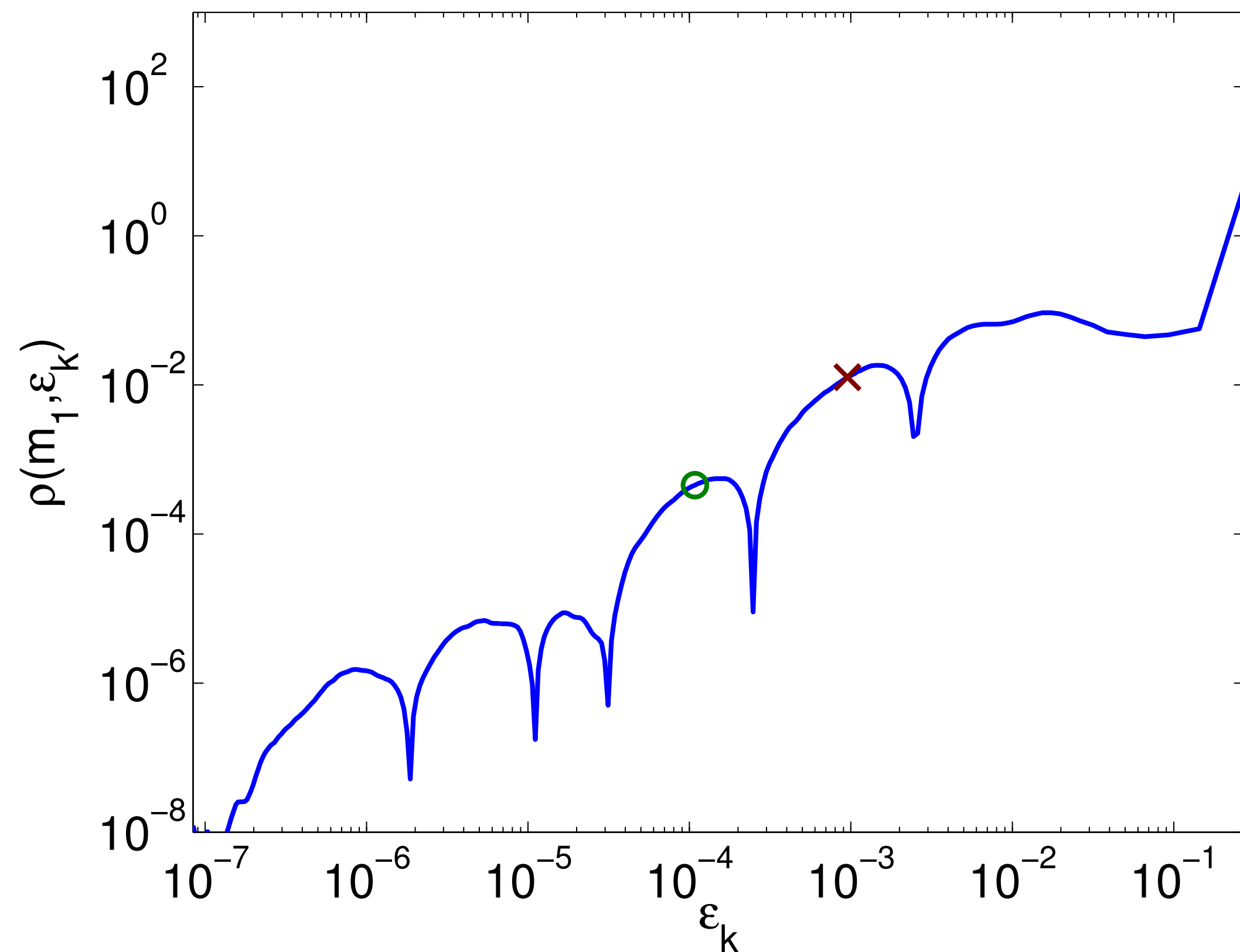




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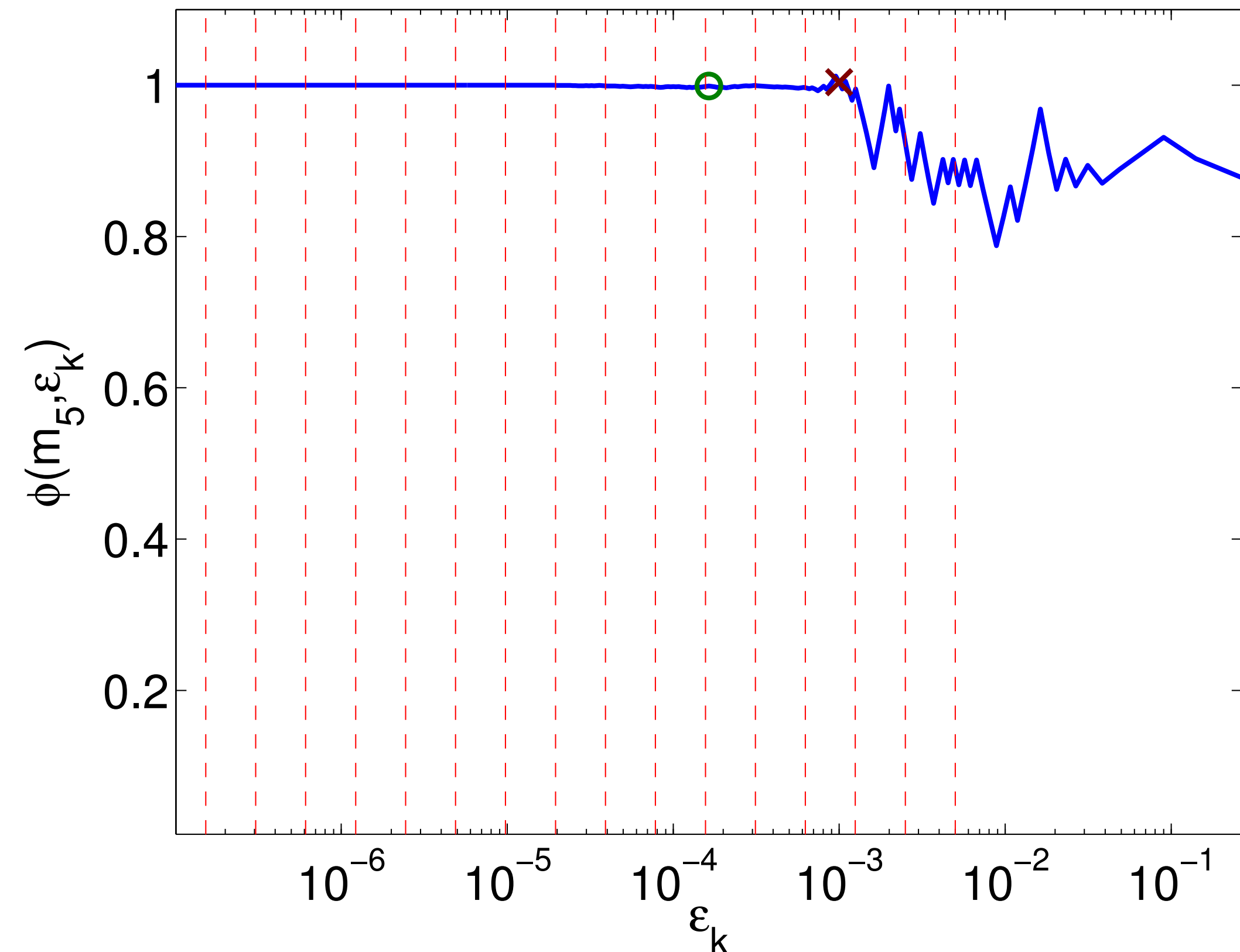
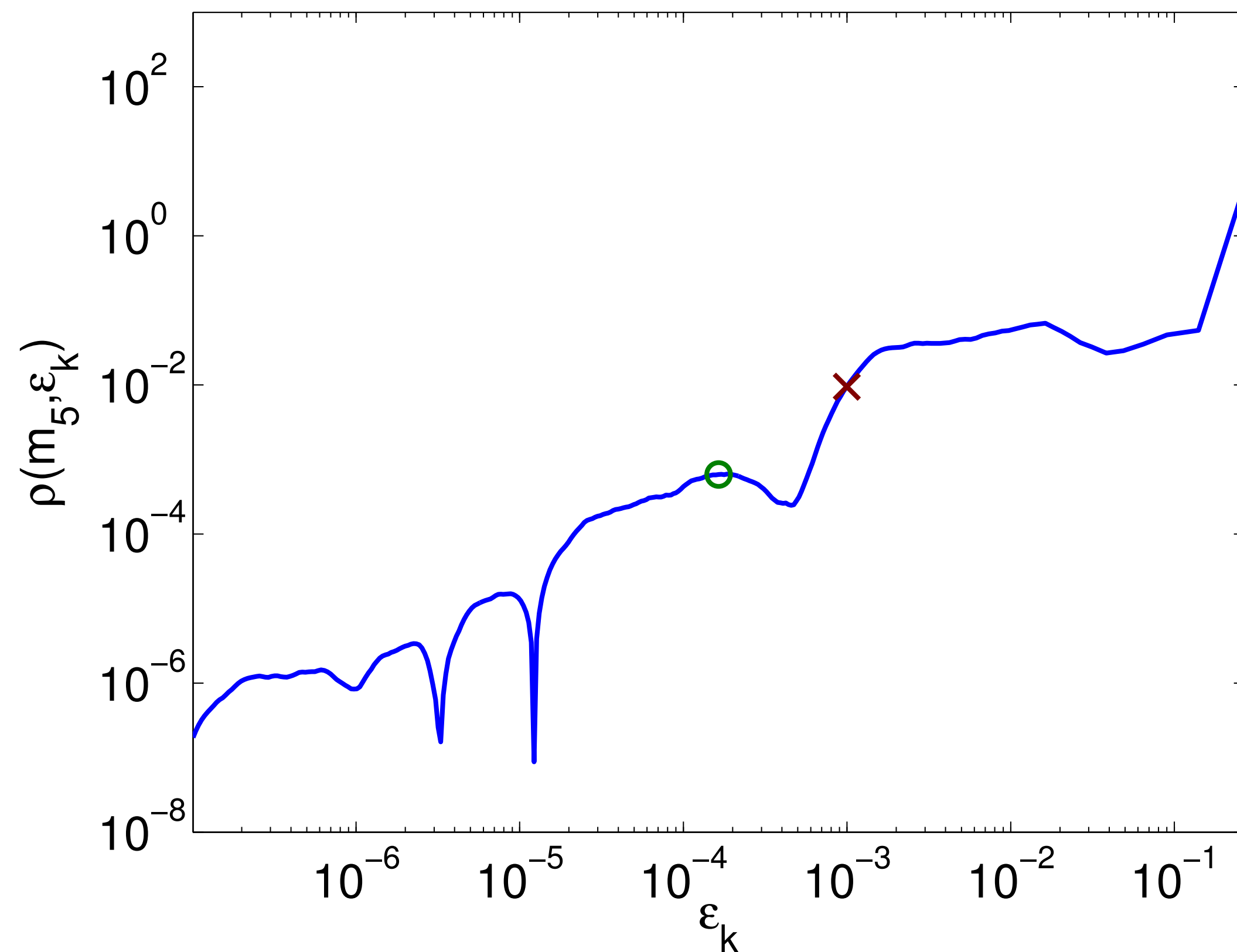
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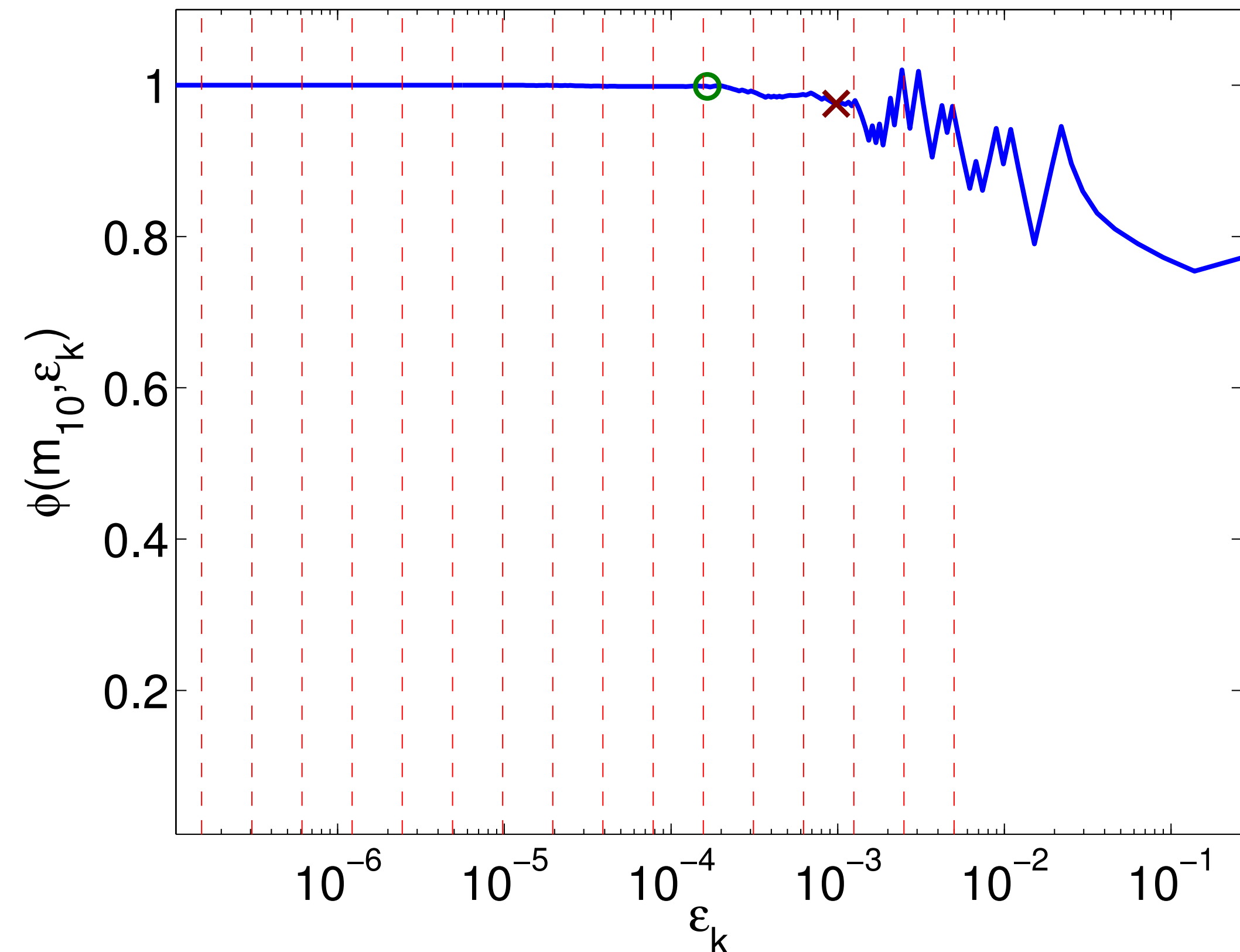
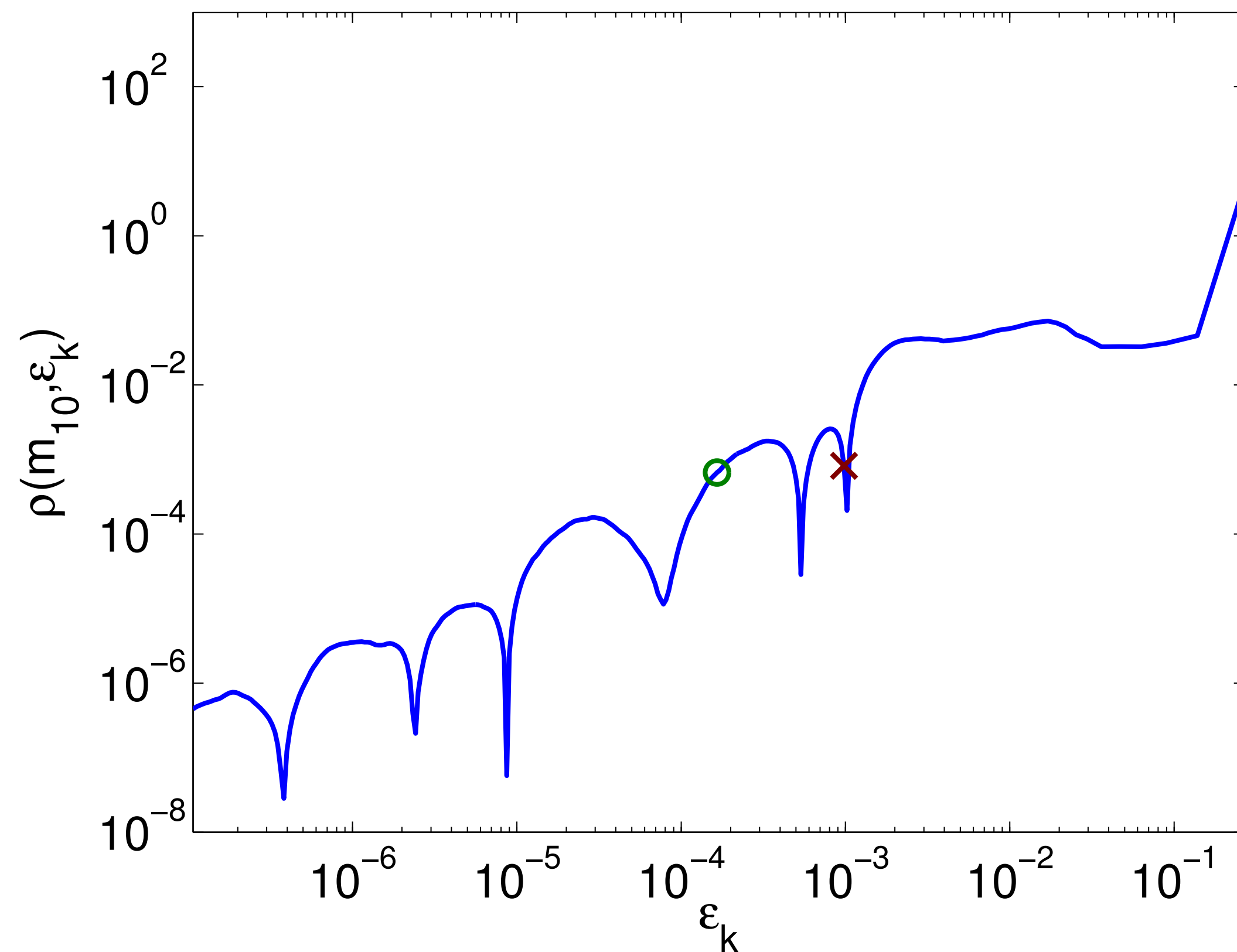
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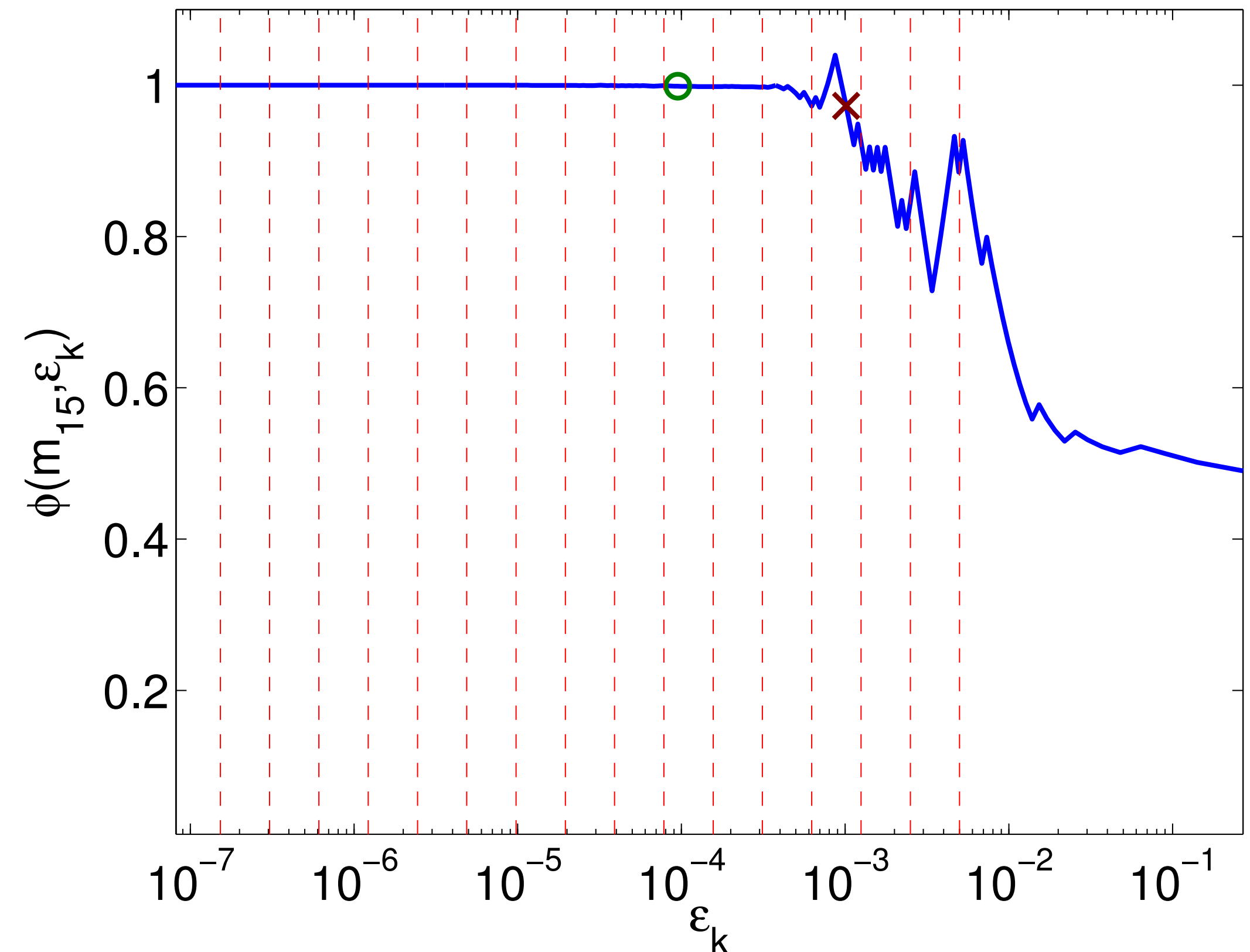
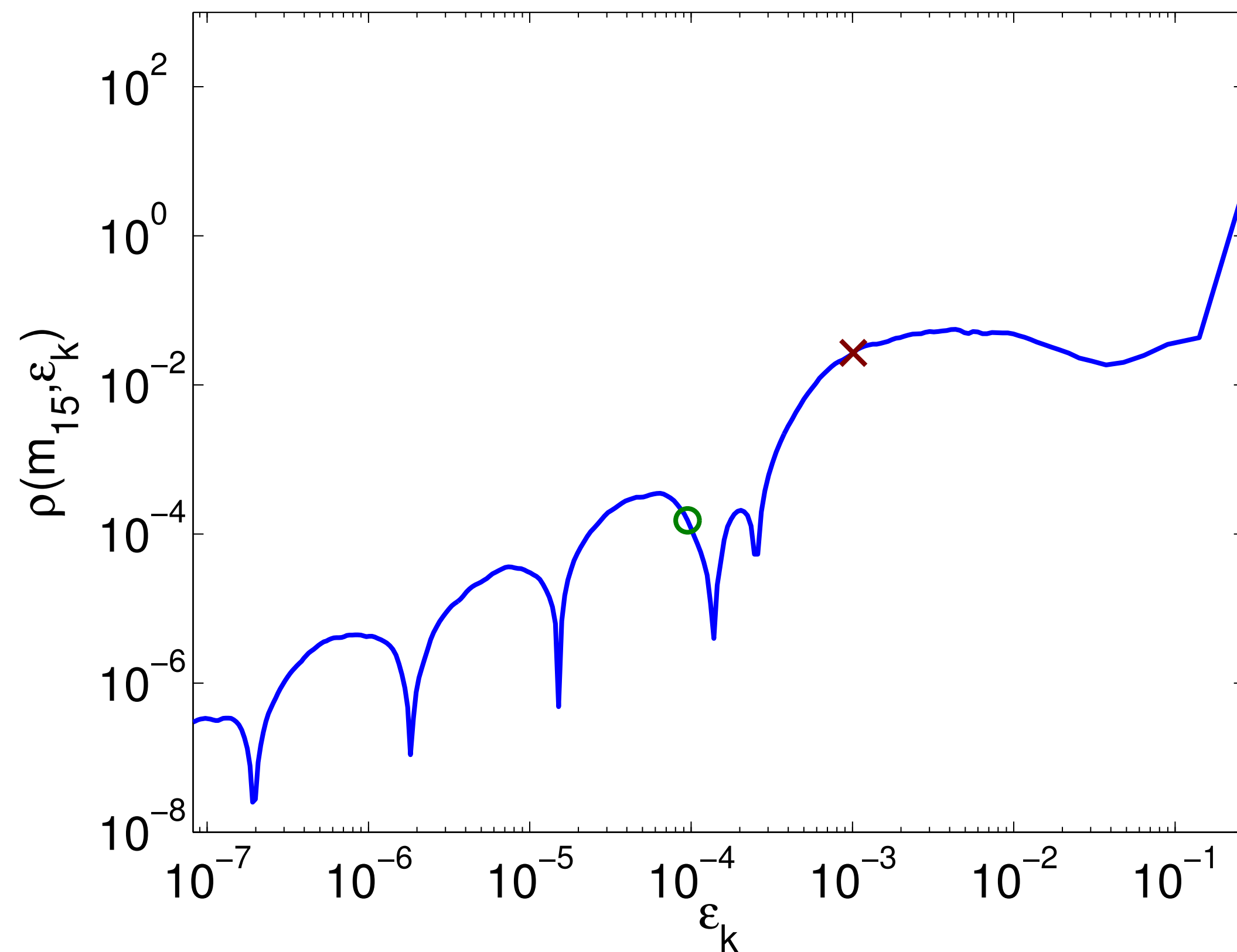
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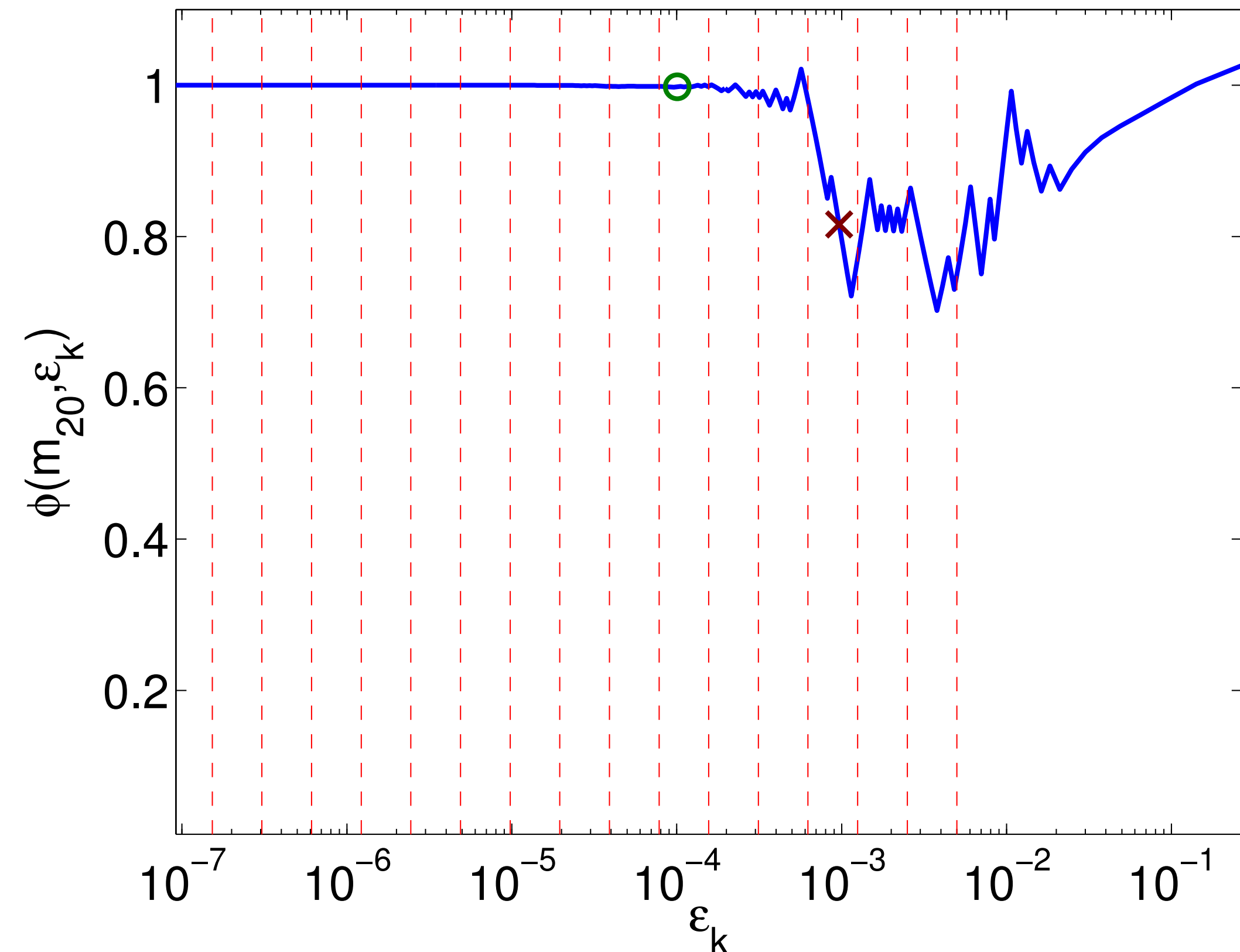
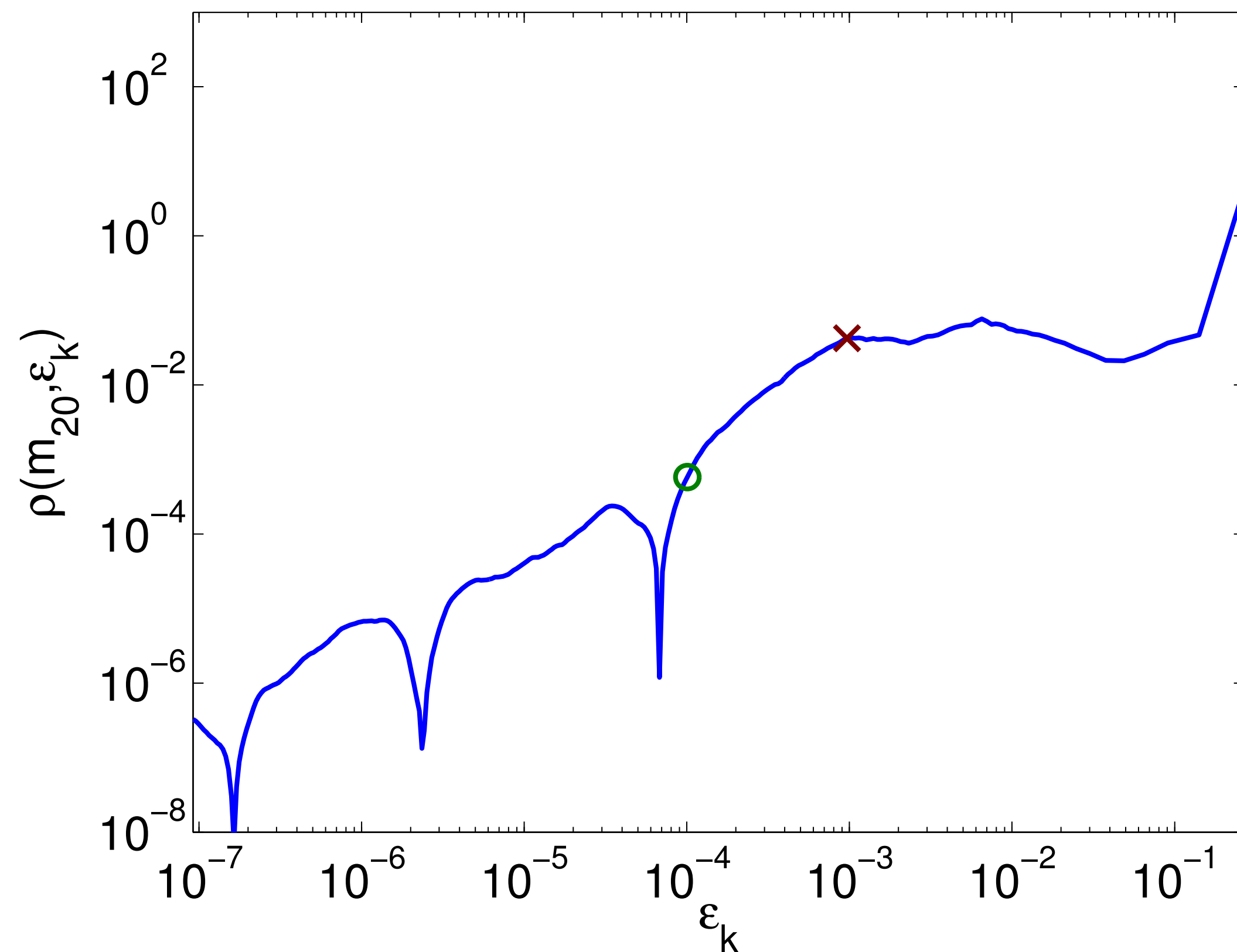
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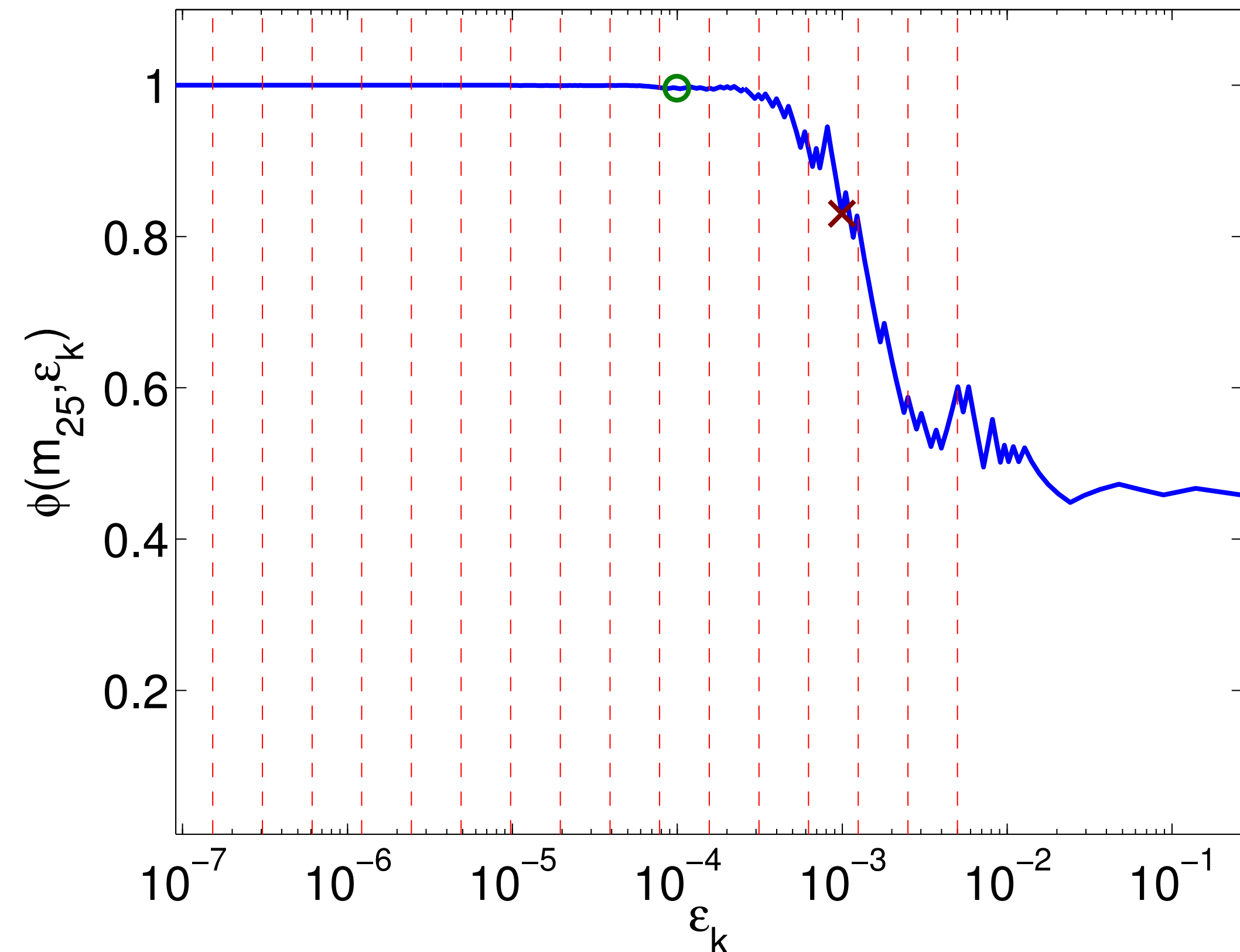
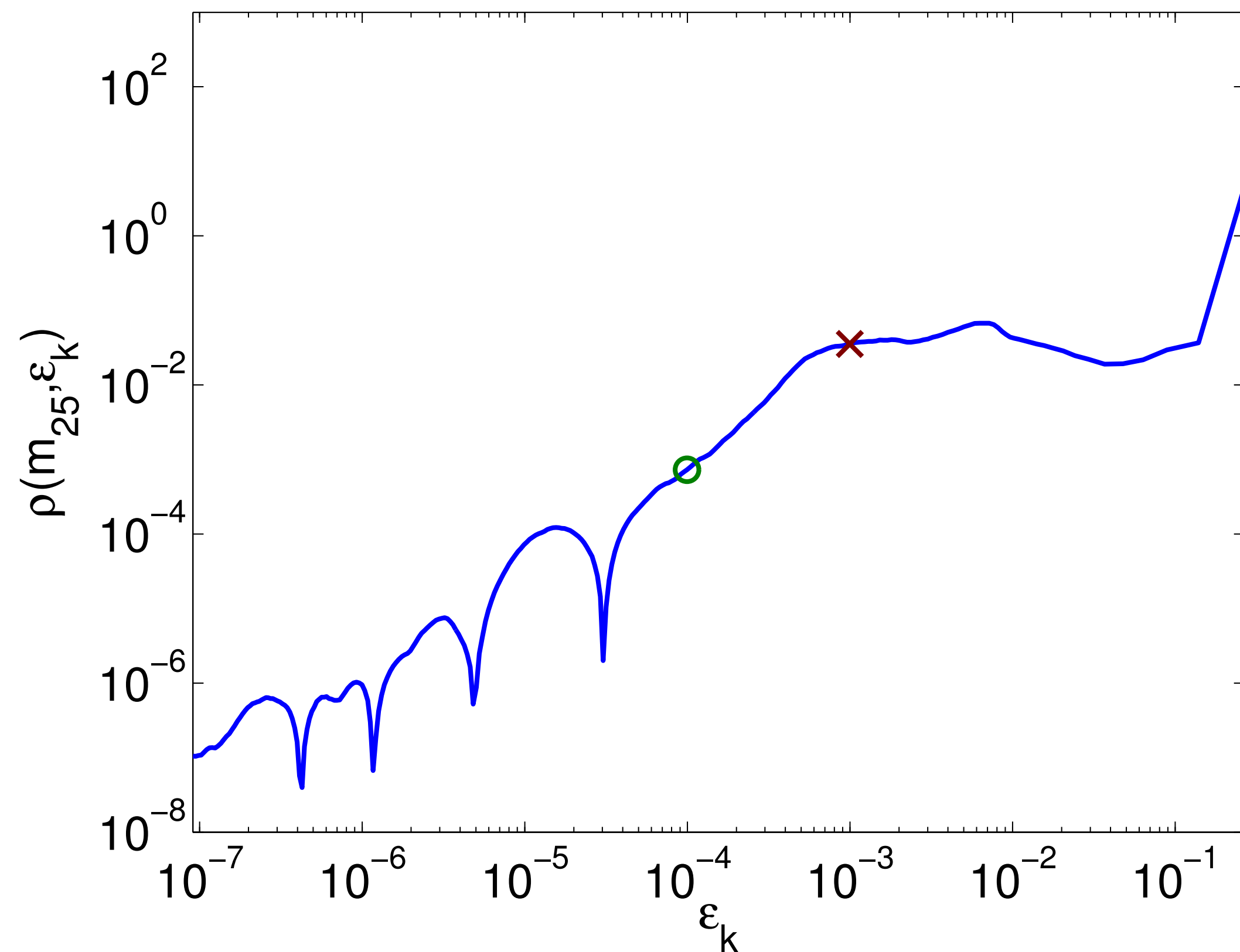
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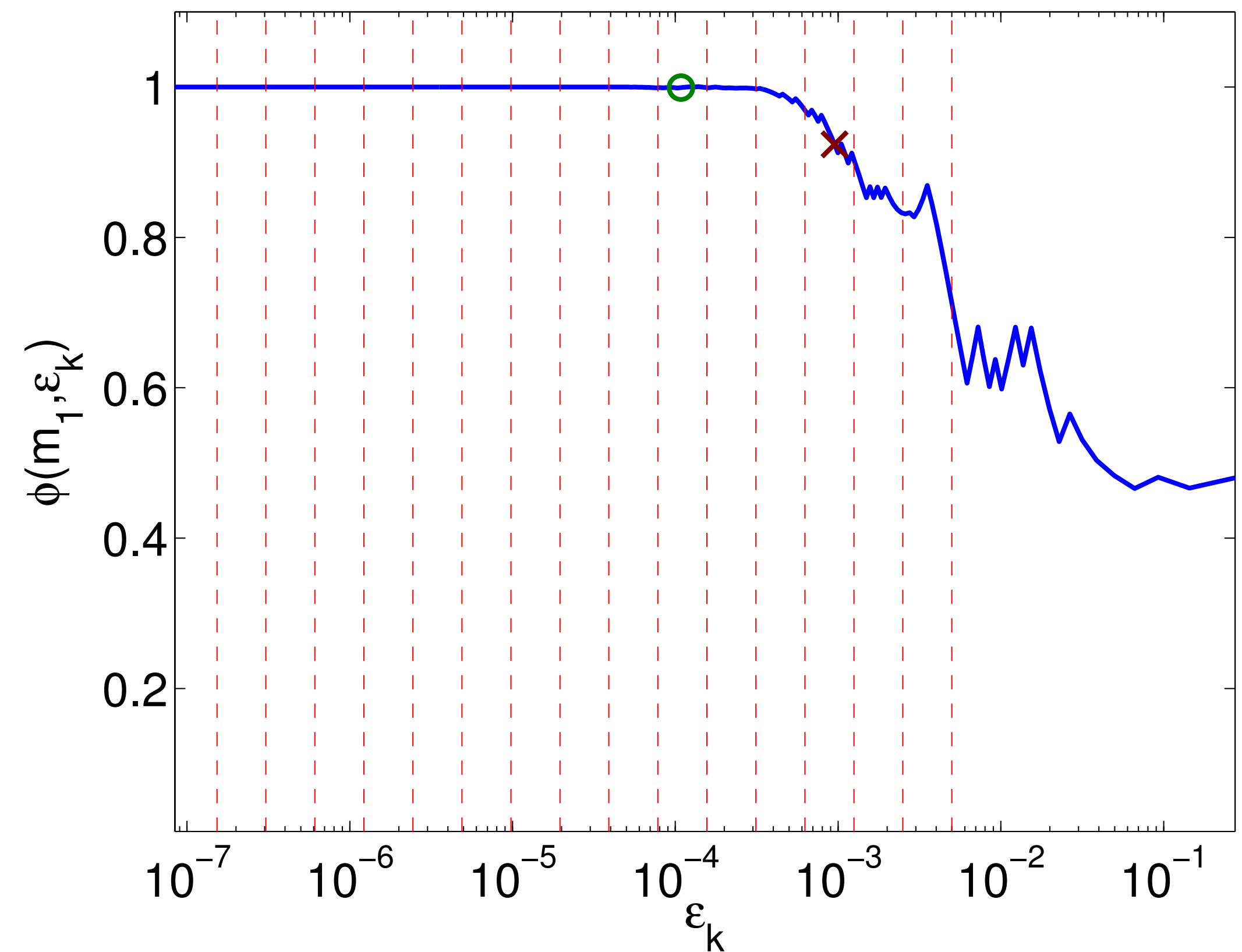
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# First Order - The $\delta\varepsilon_k$ Criterion

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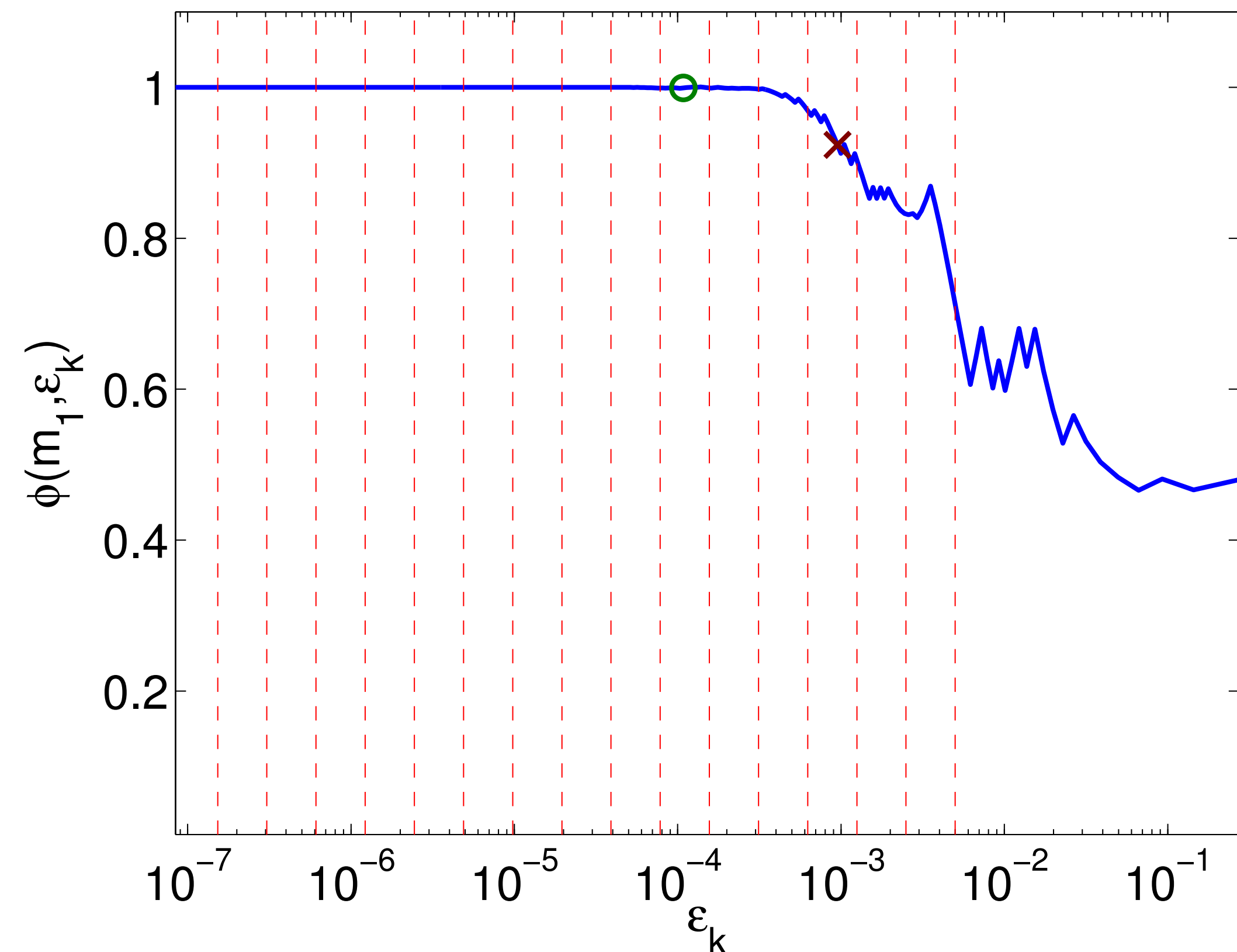
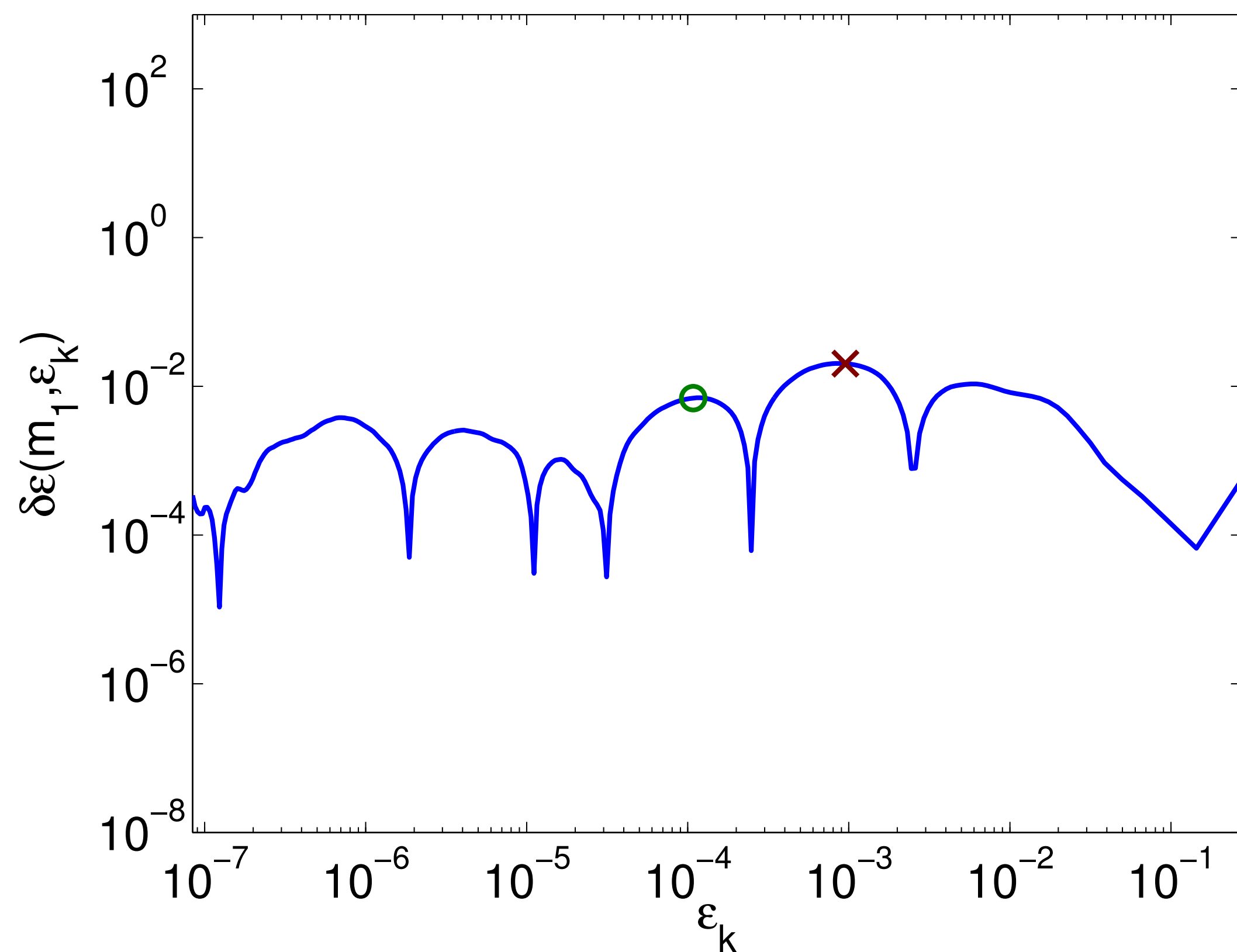
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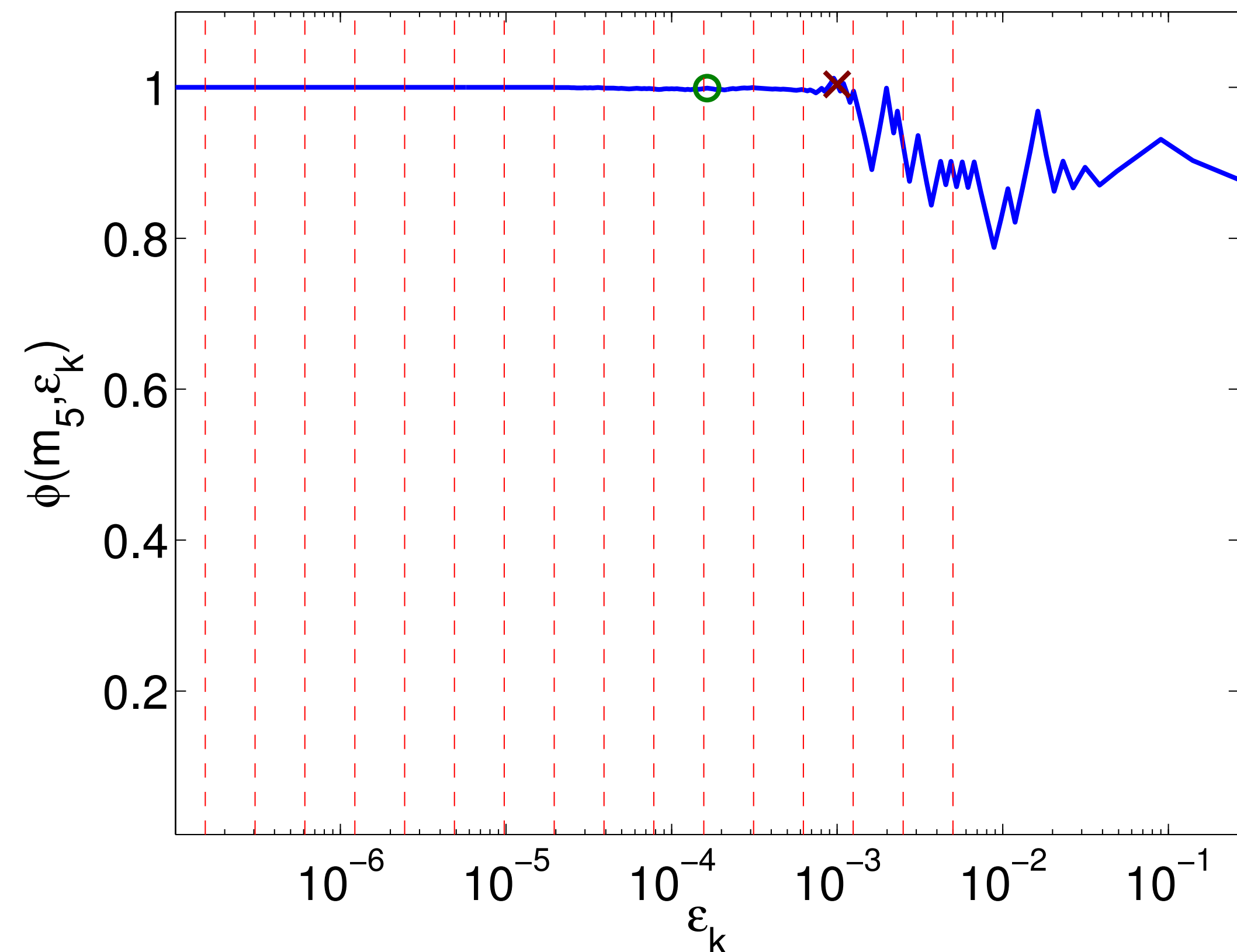
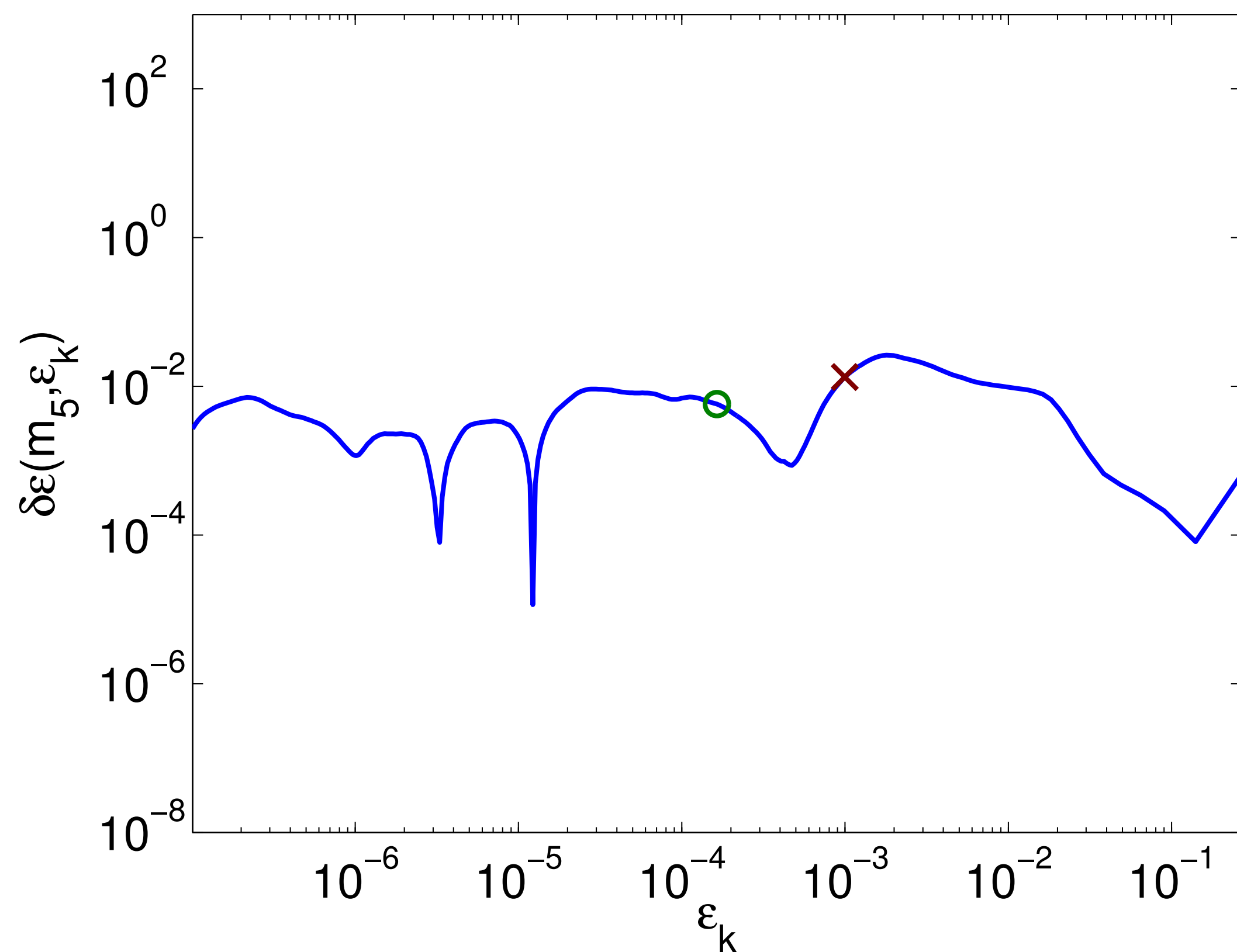




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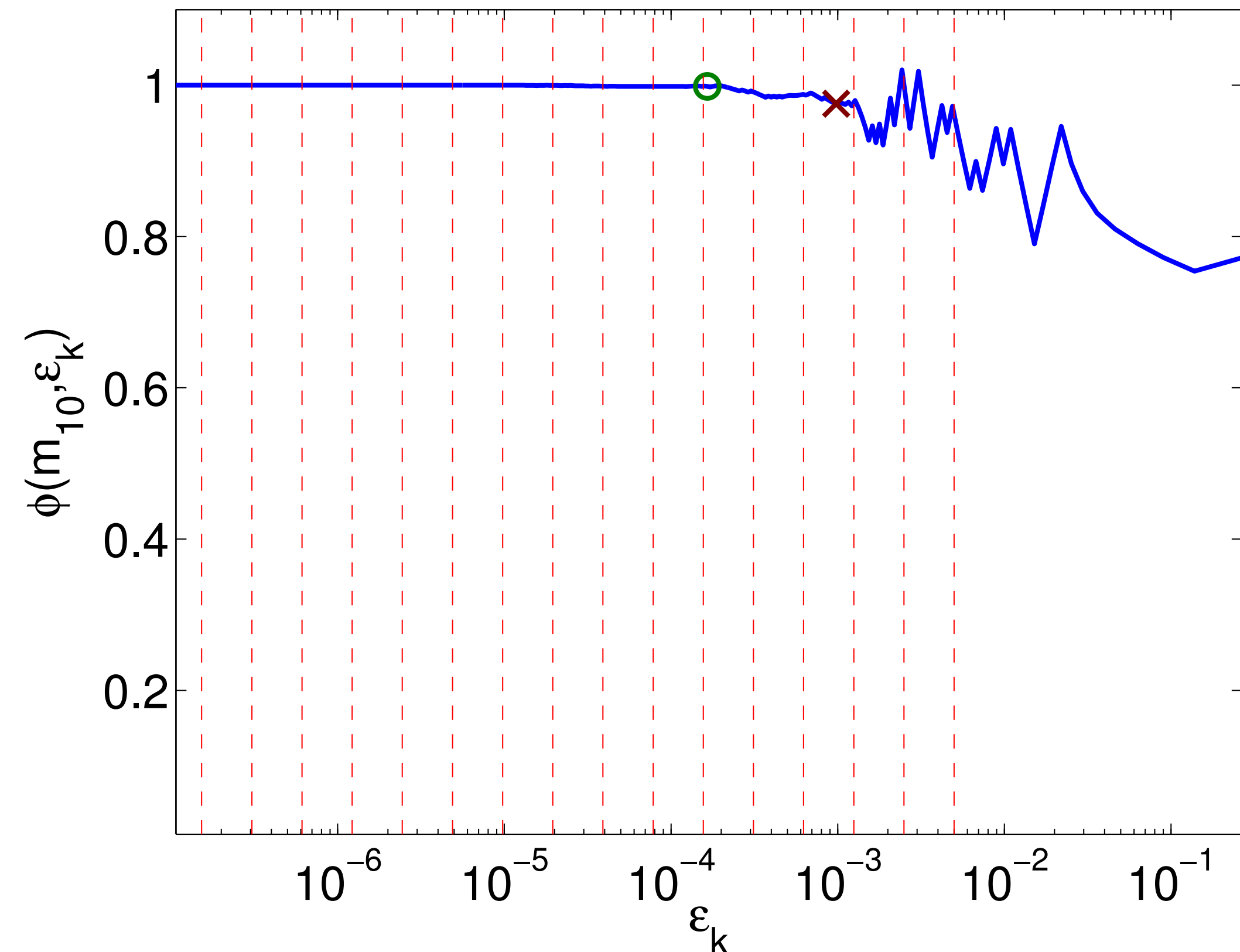
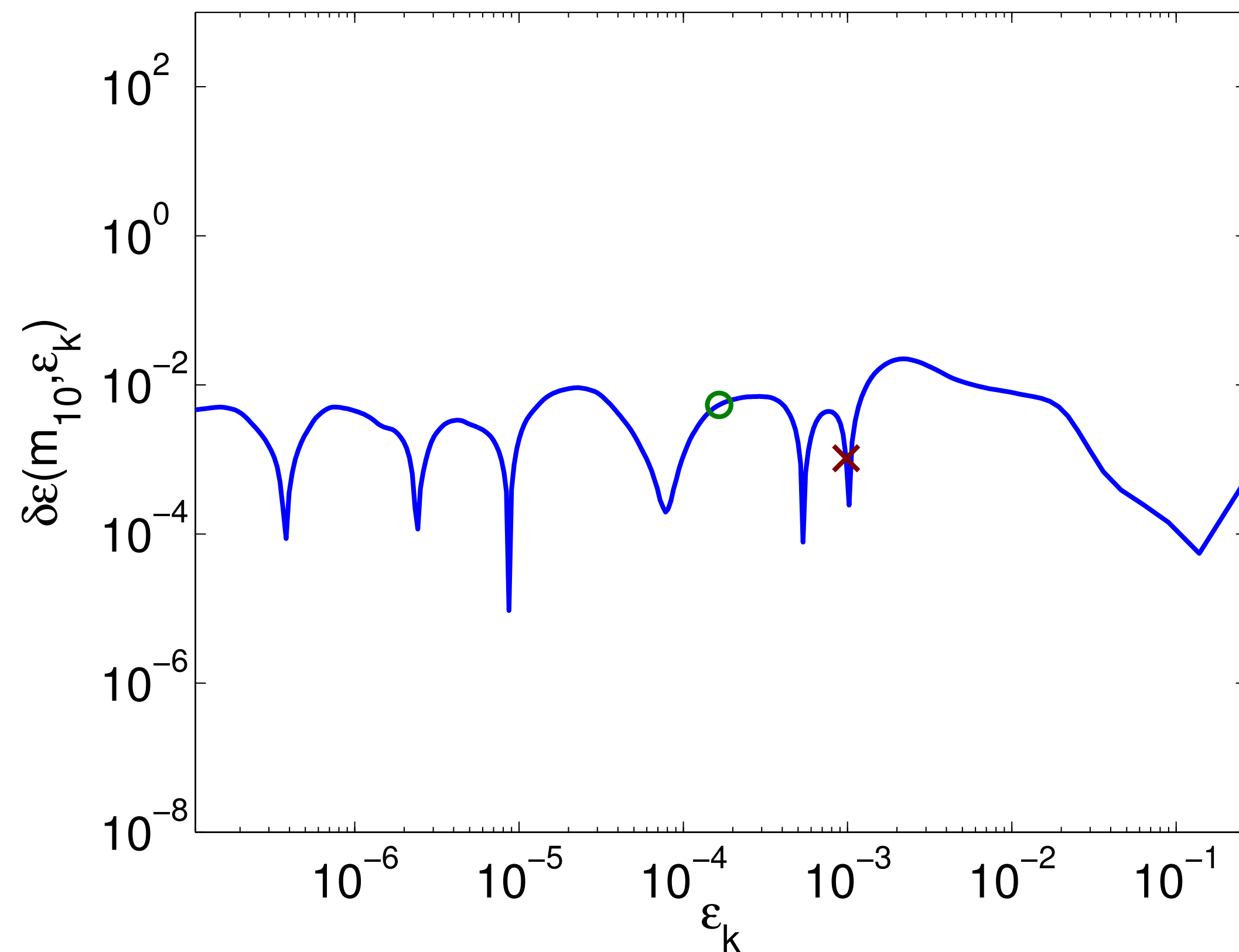
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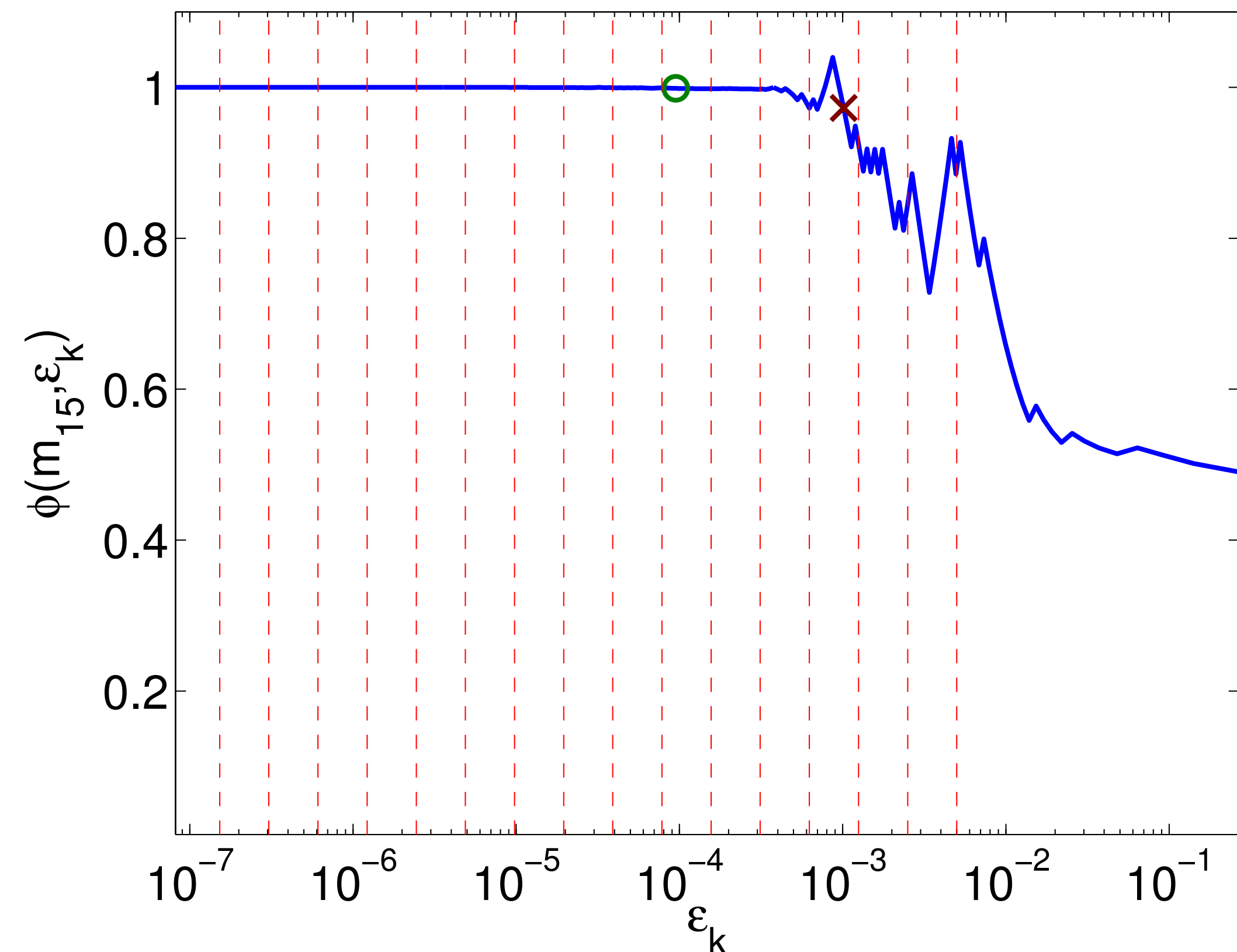
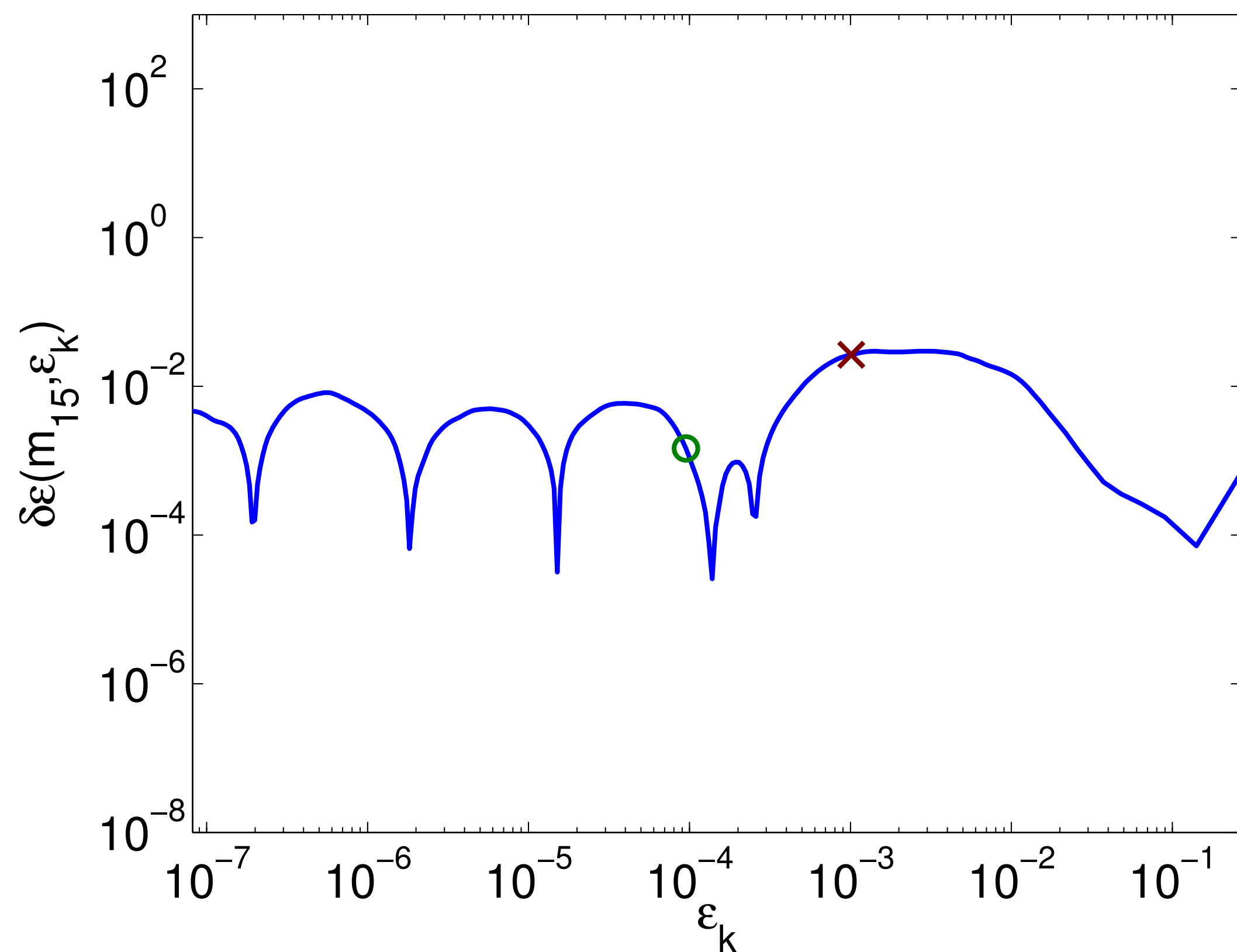
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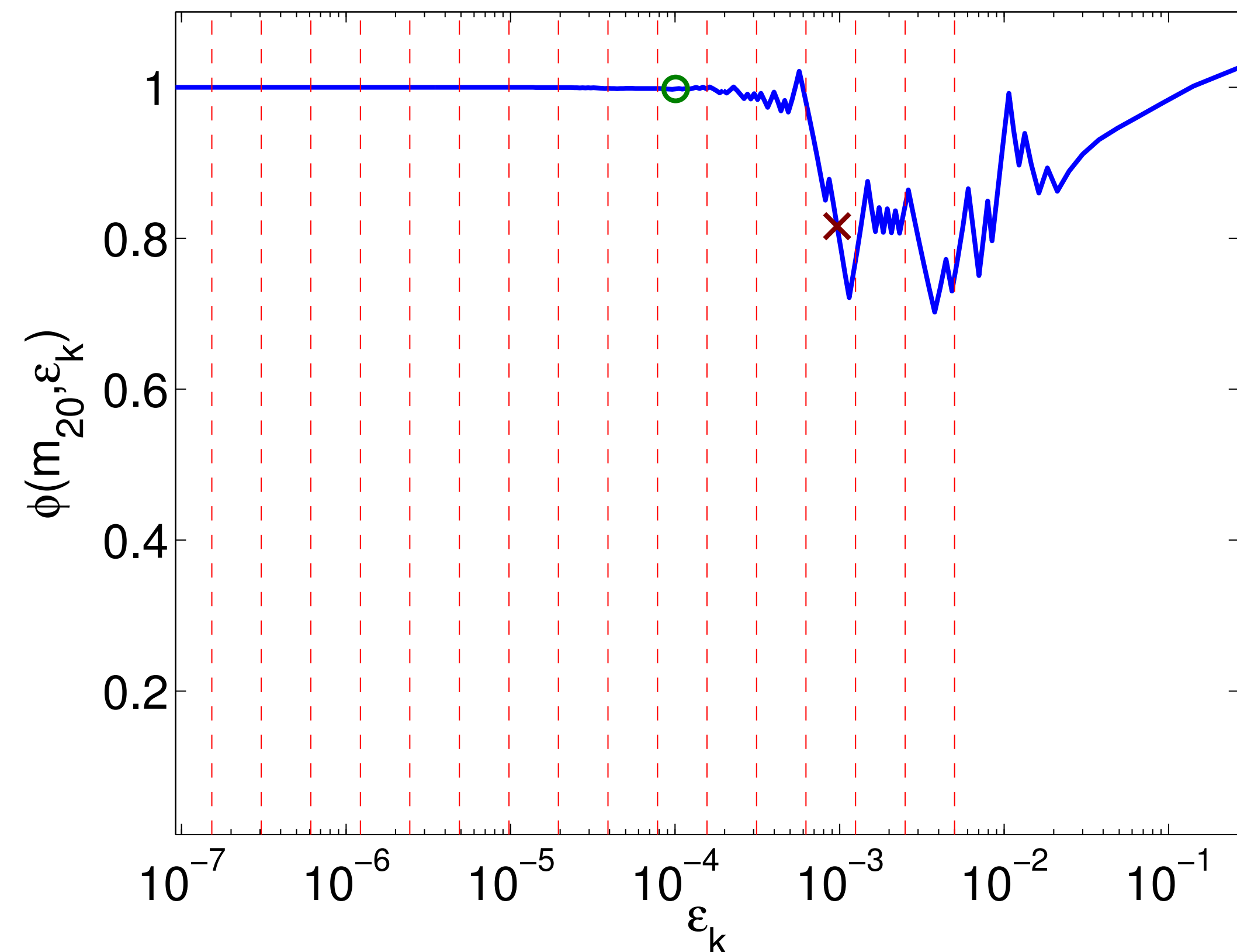
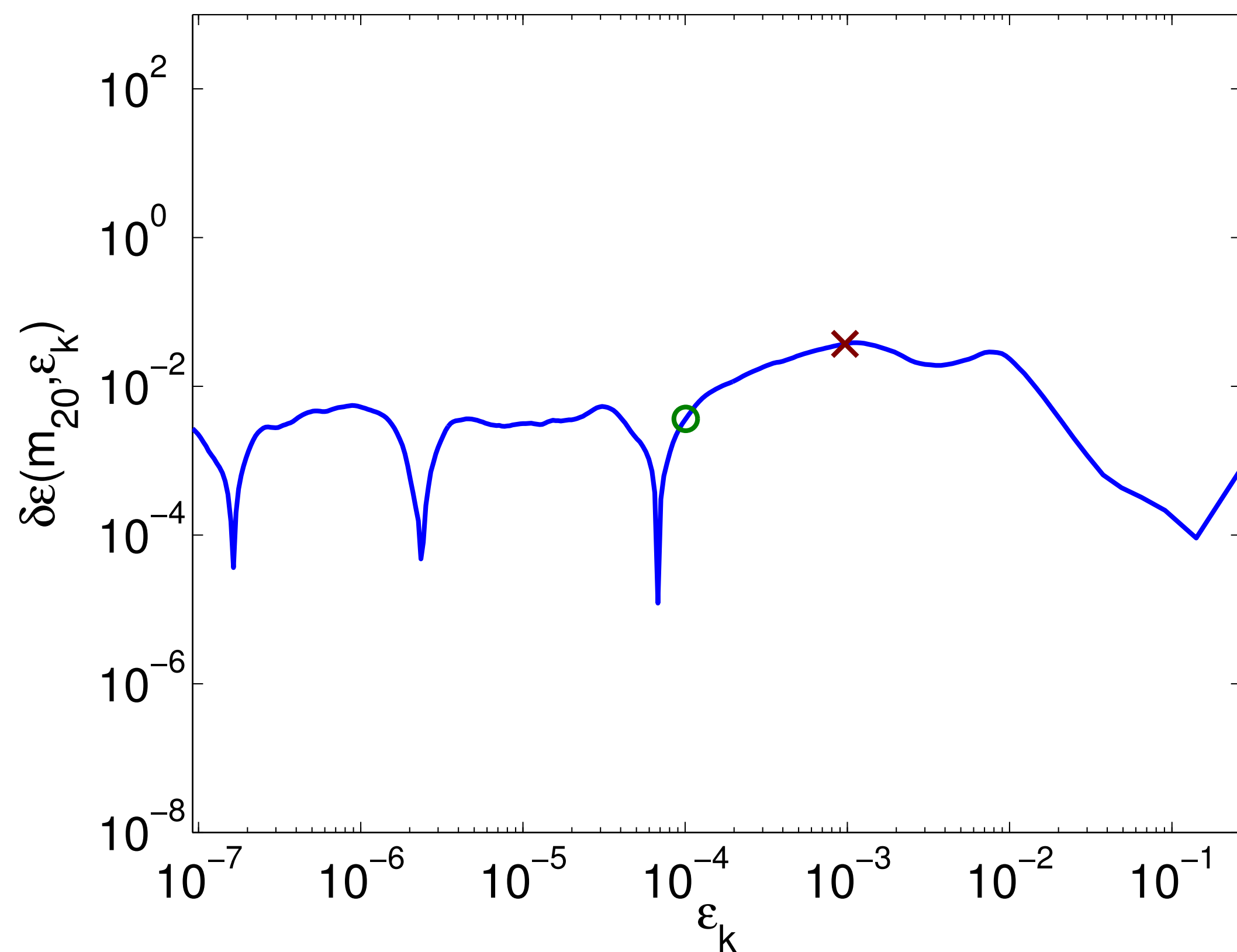
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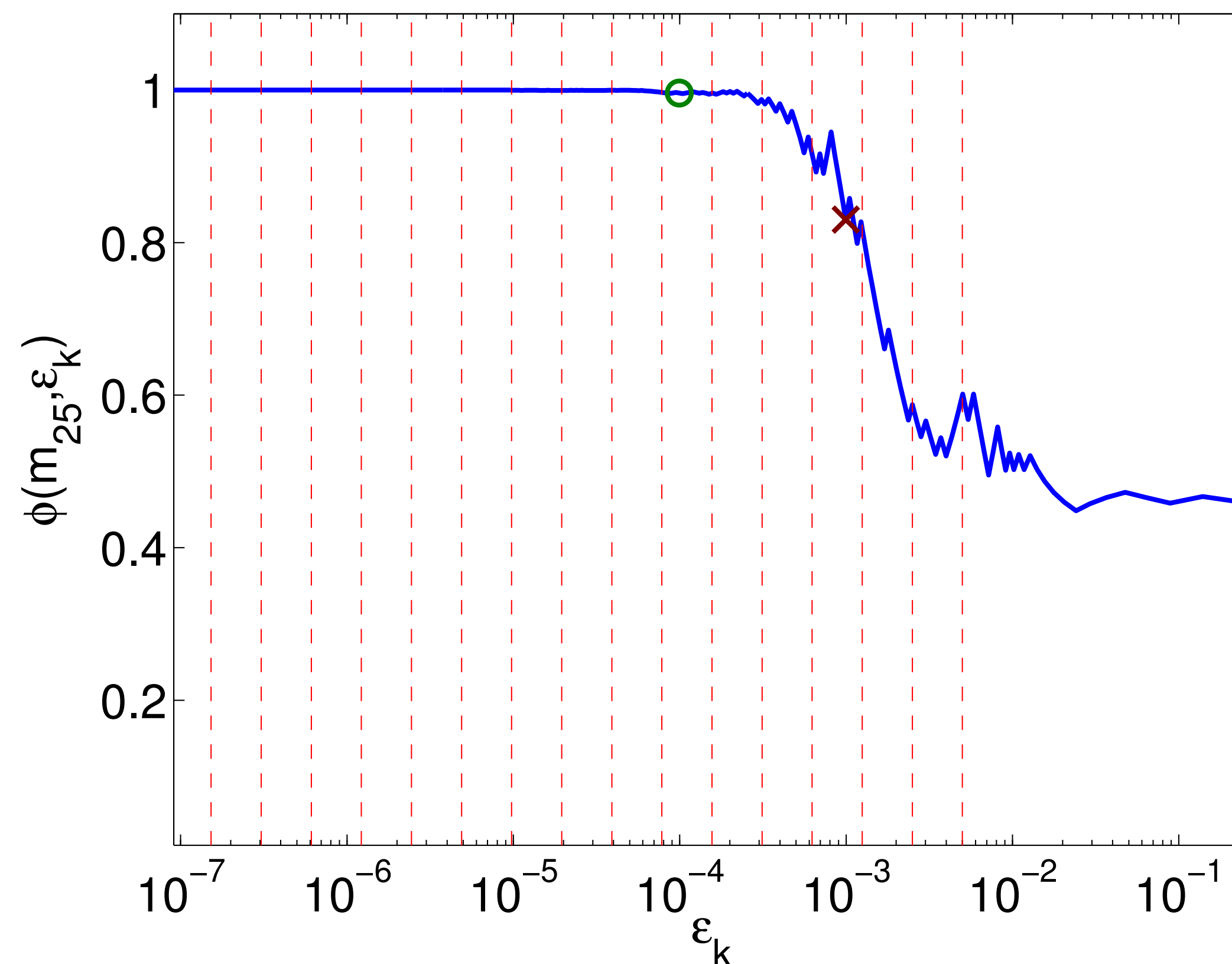
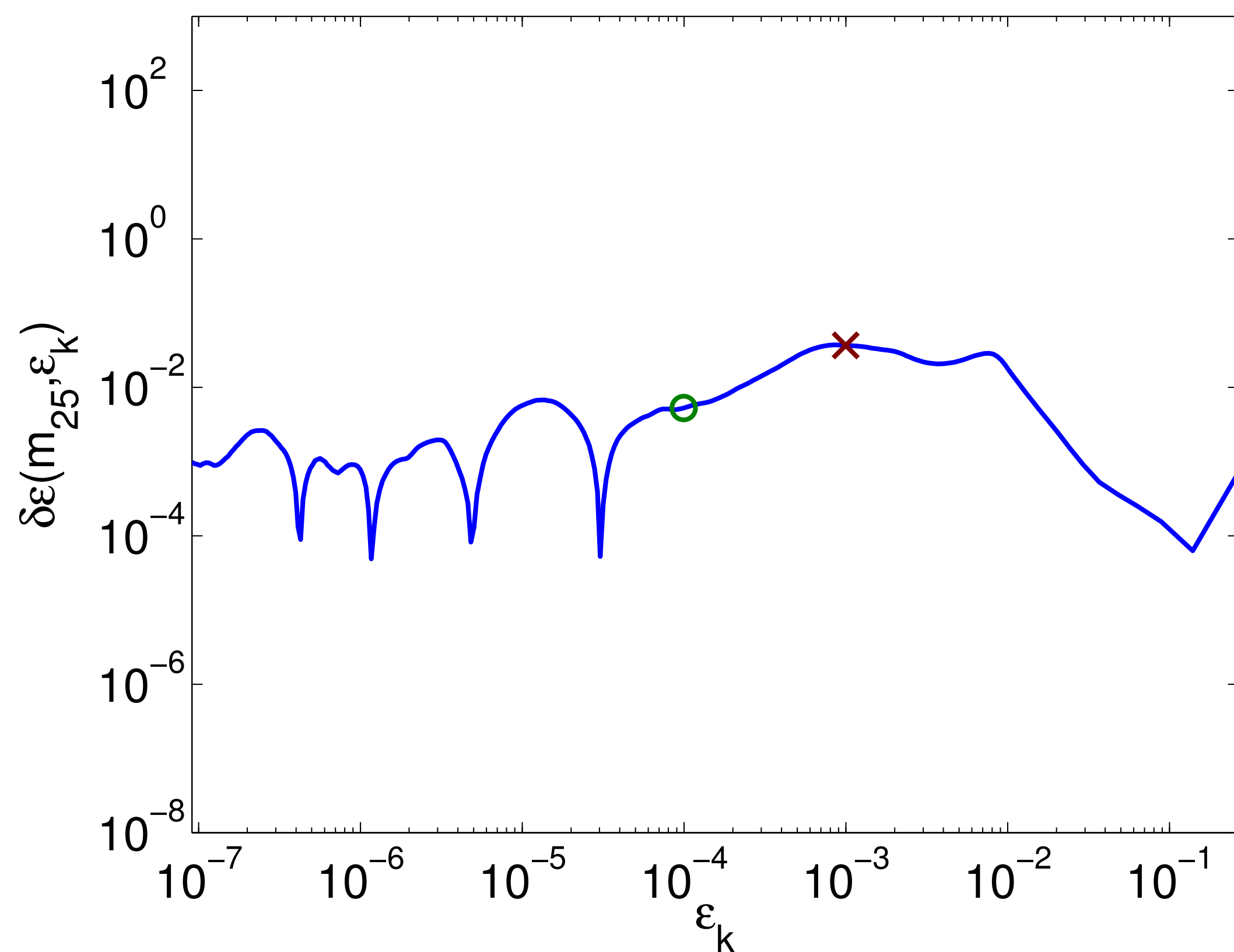
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# Blaming the Model $m$ - The $\delta s_k$ Criterion

Let

$$A(m)u \approx q \quad \text{s.t.} \quad \frac{\|A(m)u - q\|_2}{\|q\|_2} < \varepsilon$$

however, provided that no entry in  $u$  is zero, there is always a matrix  $E$  such that

$$(A(m) + E)u = q$$

for instance, defining  $r = A(m)u - q$ ,

$$E = \text{diag} \left( \frac{r_i}{u_i} \right).$$

# Blaming the Model $m$ - The $\delta s_k$ Criterion

If there is a perturbation  $\delta s$  such that

$$A(m + \delta s) = A(m) + E$$

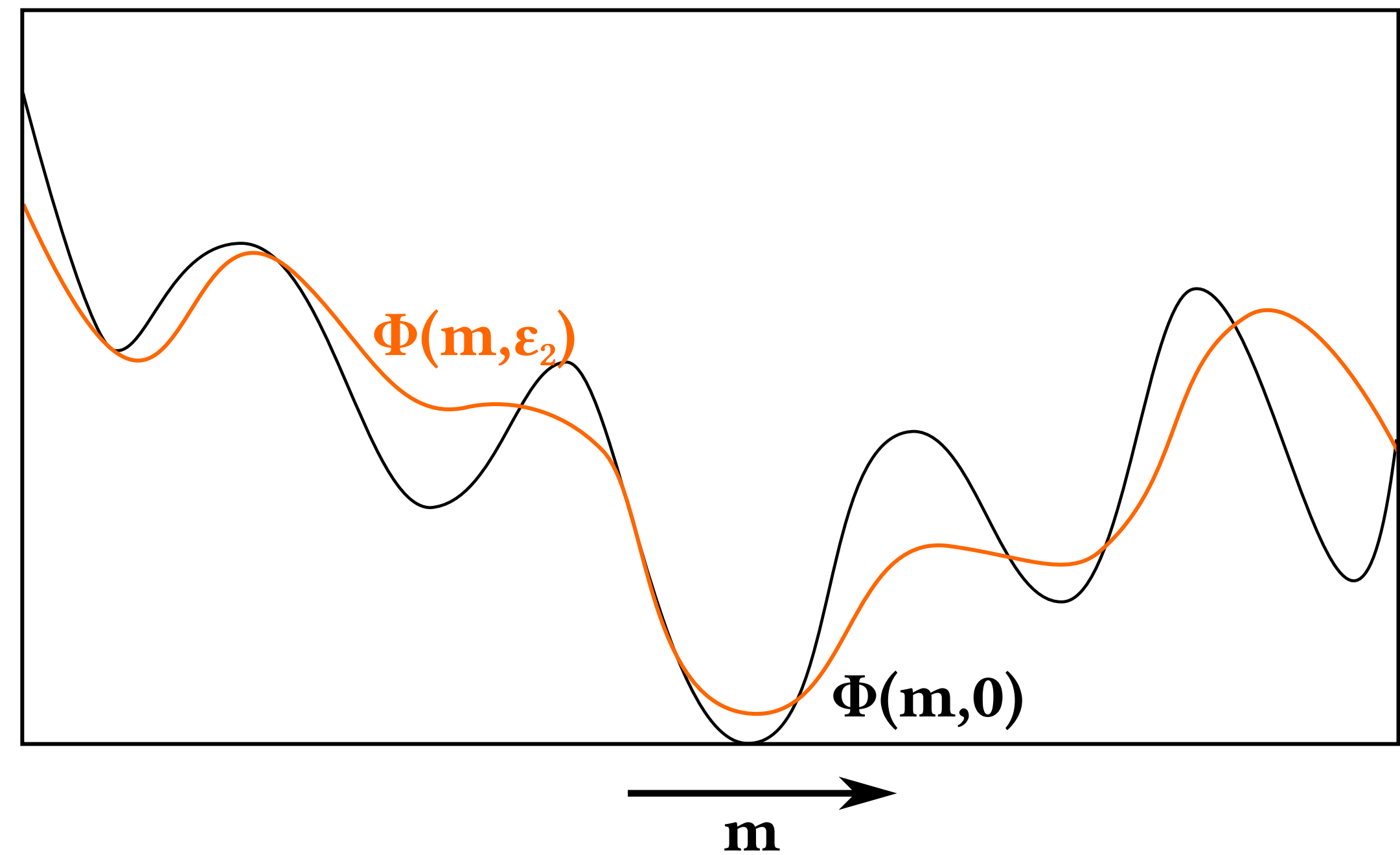
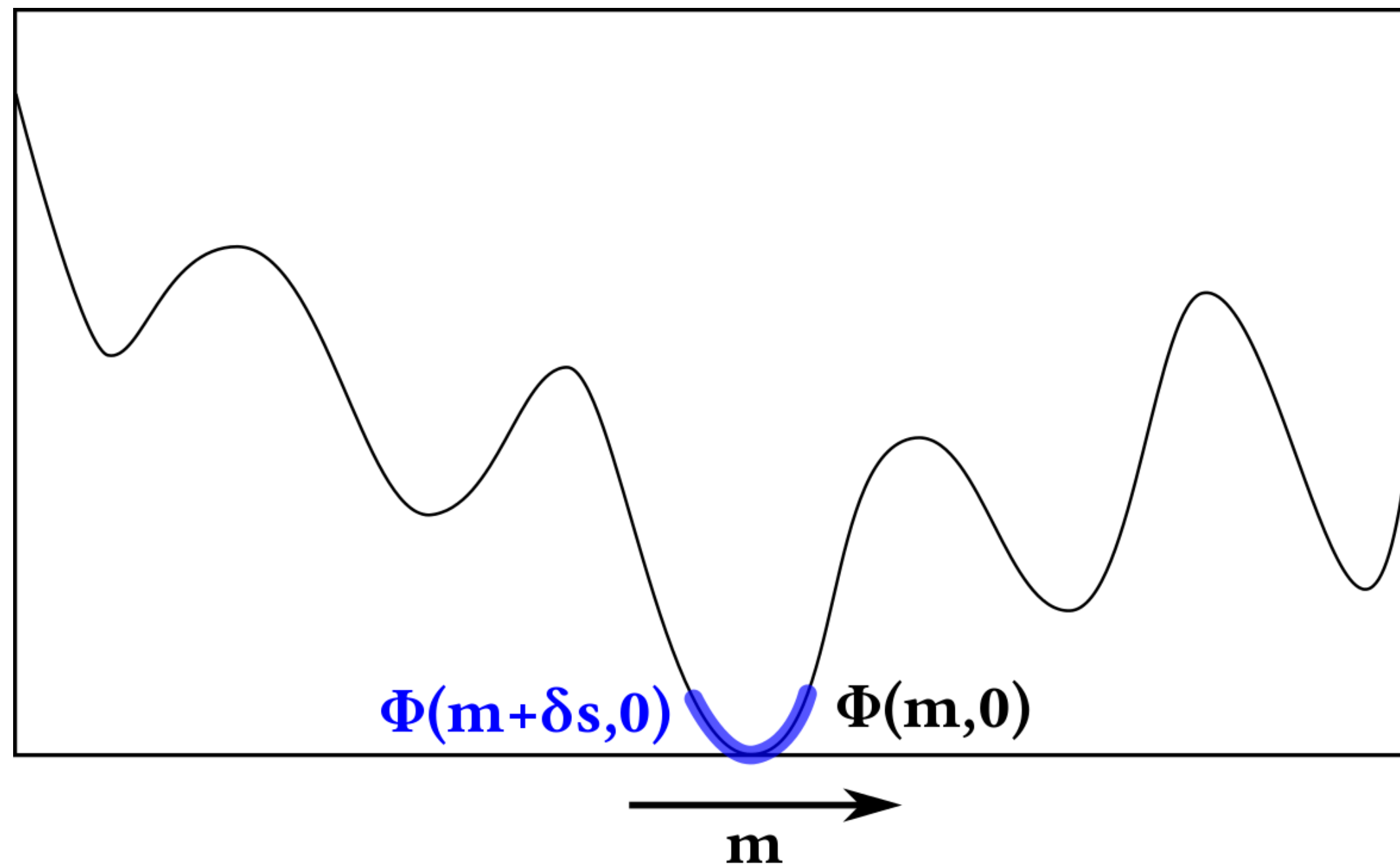
then  $u$  is the **exact solution** the model  $m + \delta s$ , that is

$$\Phi(m + \delta s, 0) = \Phi(m, \varepsilon)$$

We thus want to choose  $\varepsilon$  such that  **$\delta s$  is small**.

Finding  **$\delta s$**  (or an approximation) may be possible depending on the discretization scheme.

# Blaming the Model $m$ - The $\delta s_k$ Criterion



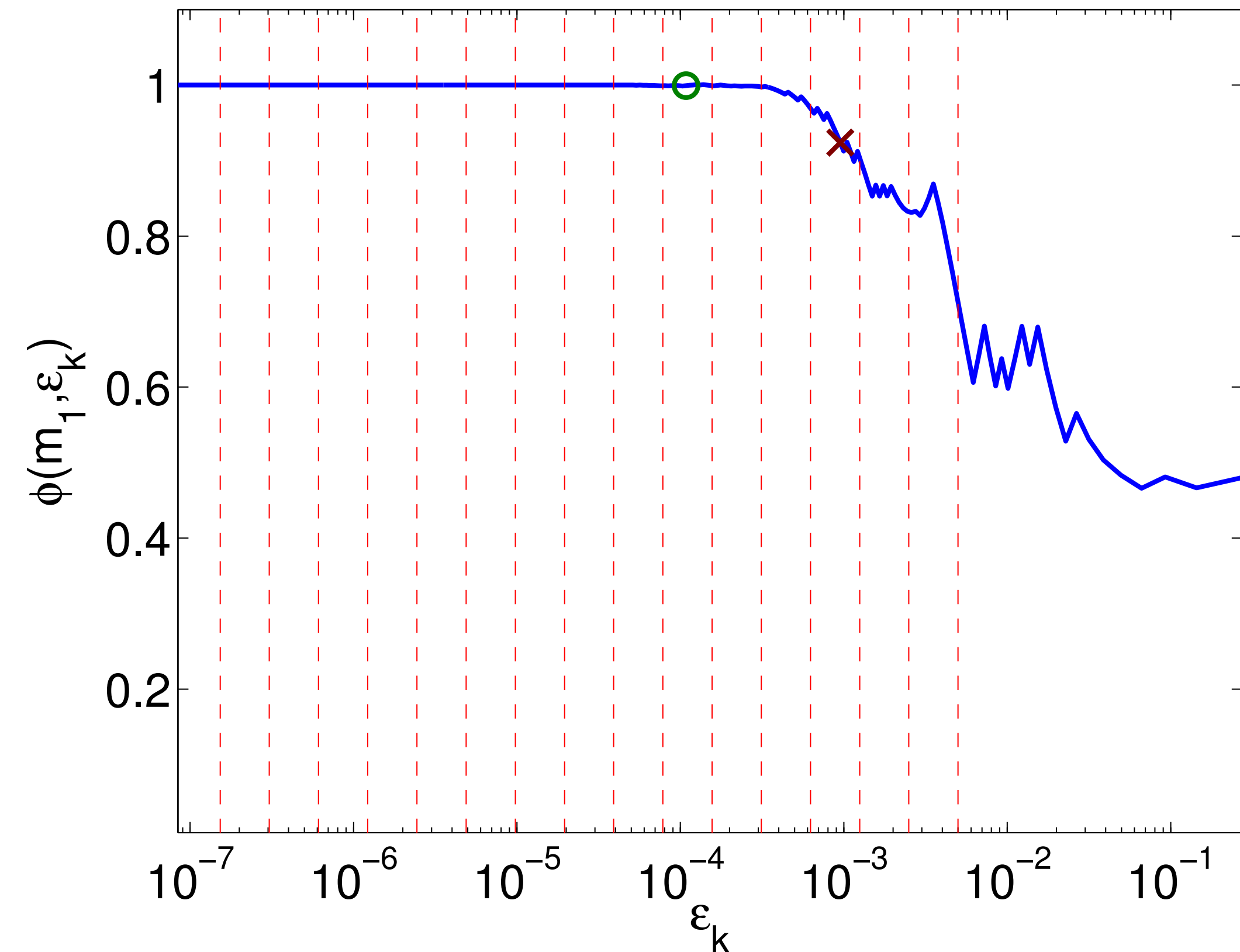
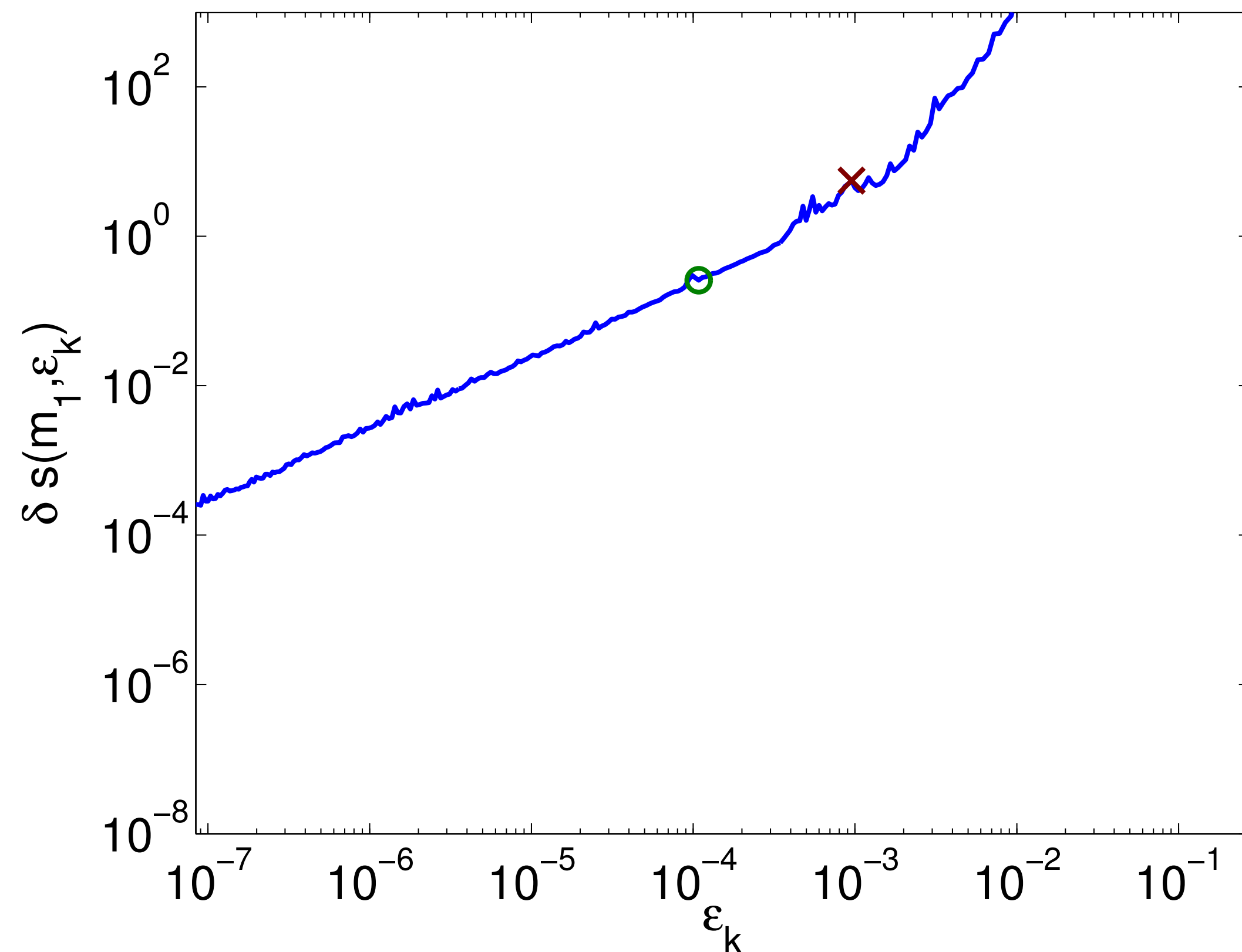


# Blaming the Model $m$ - The $\delta s_k$ Criterion

$$\left| \frac{\delta s_k}{m} \right| \leq \eta$$

$$\delta s_k := \frac{1}{C\omega^2} \frac{A(m)u^i - q^i}{u^i}$$

(pointwise division)

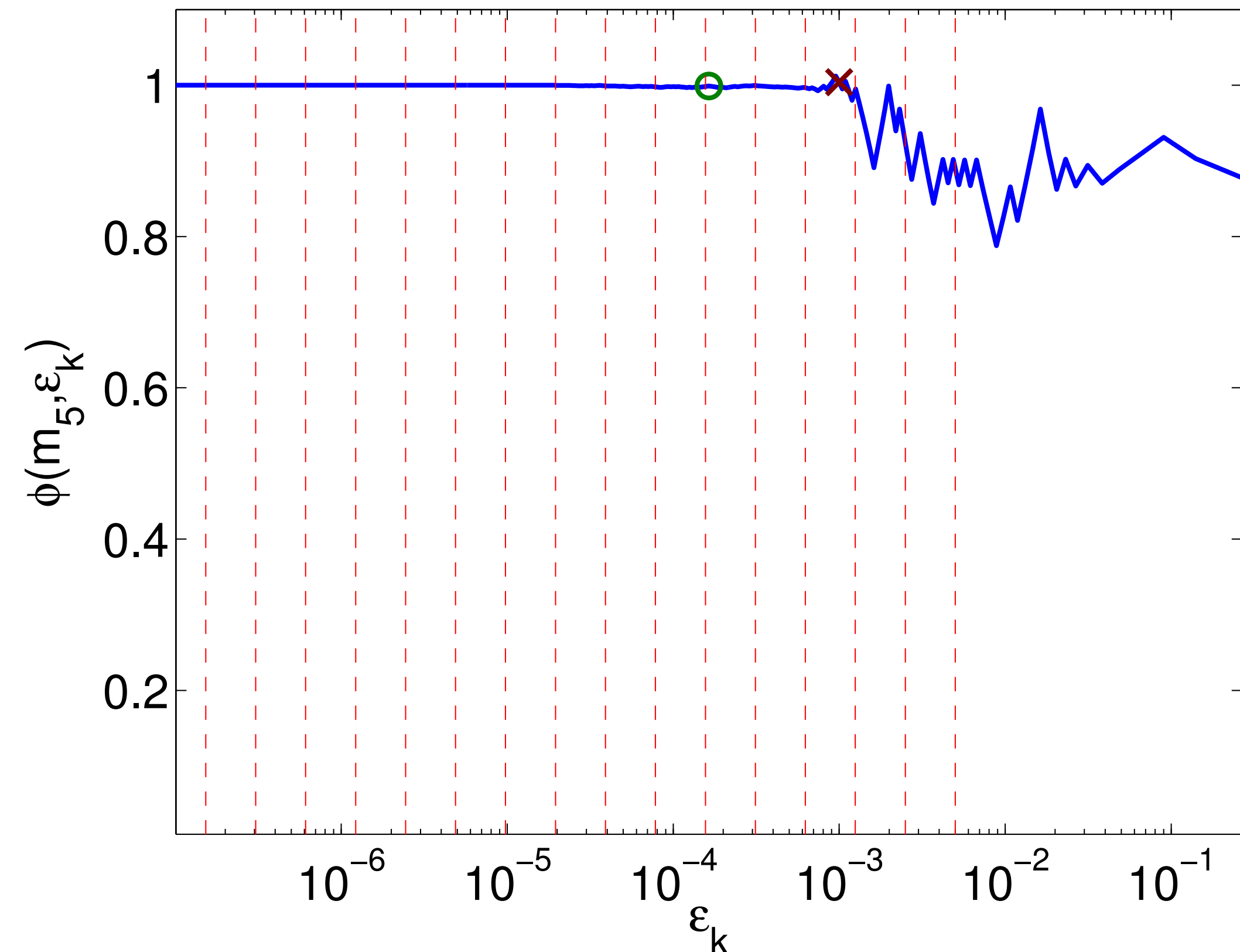
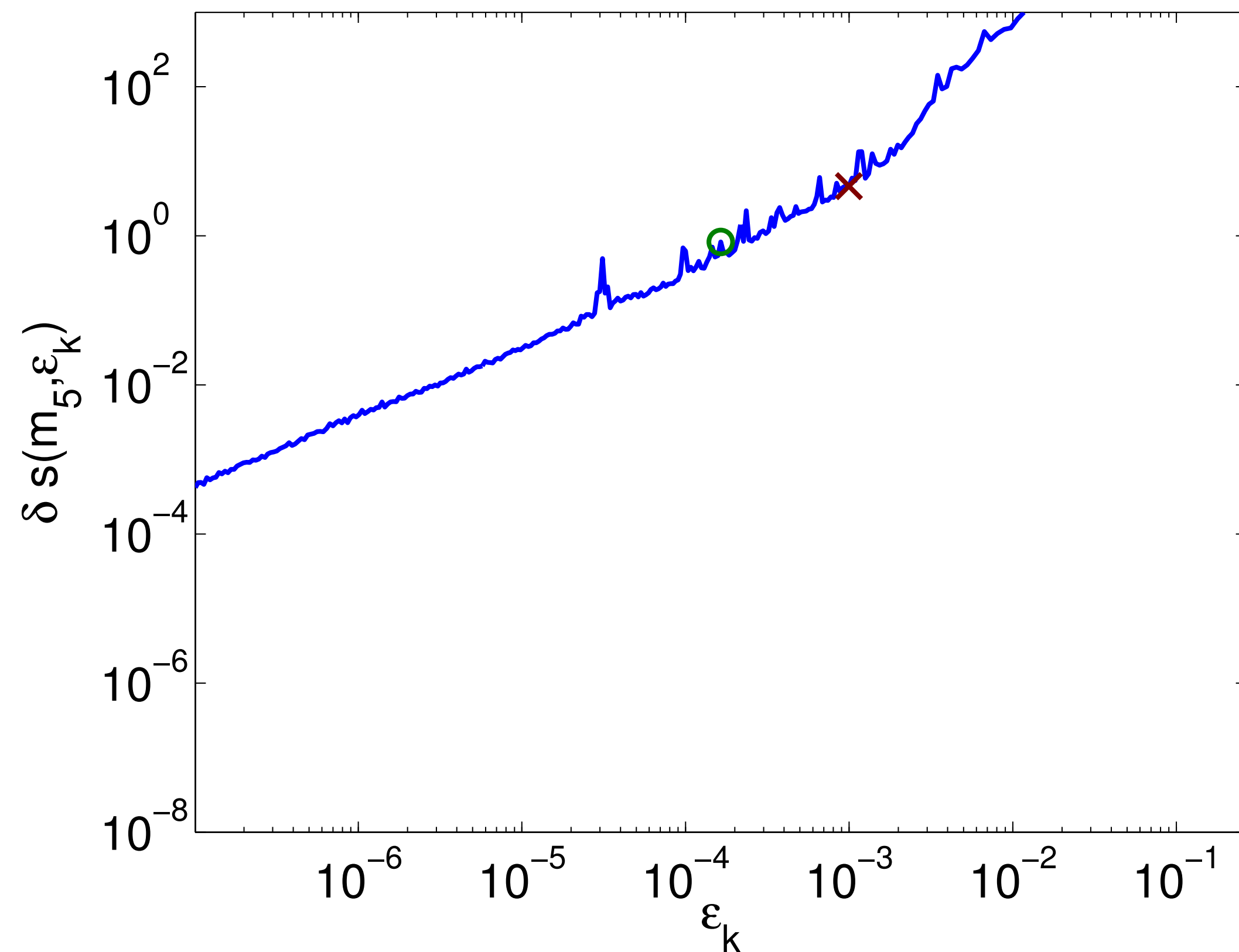


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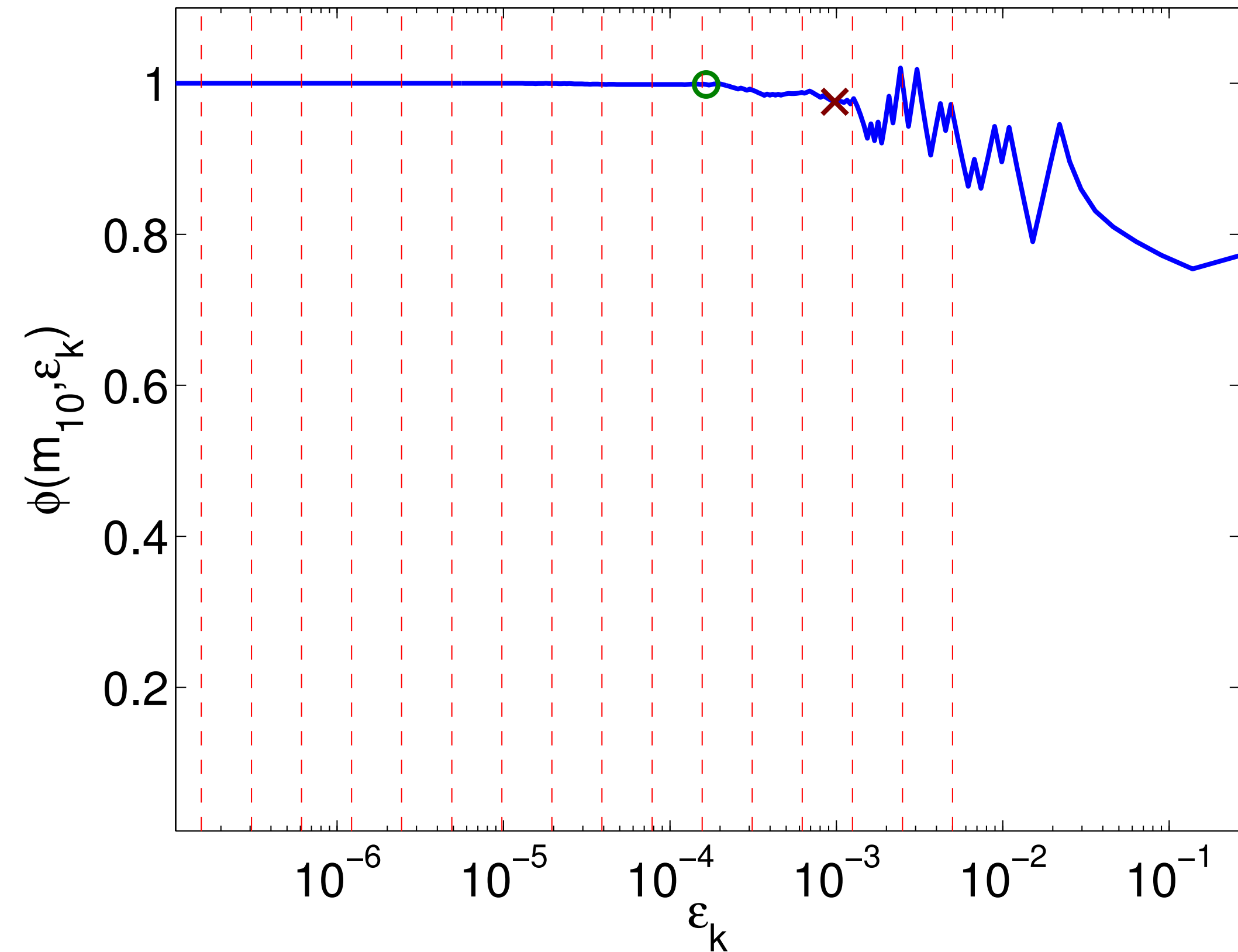
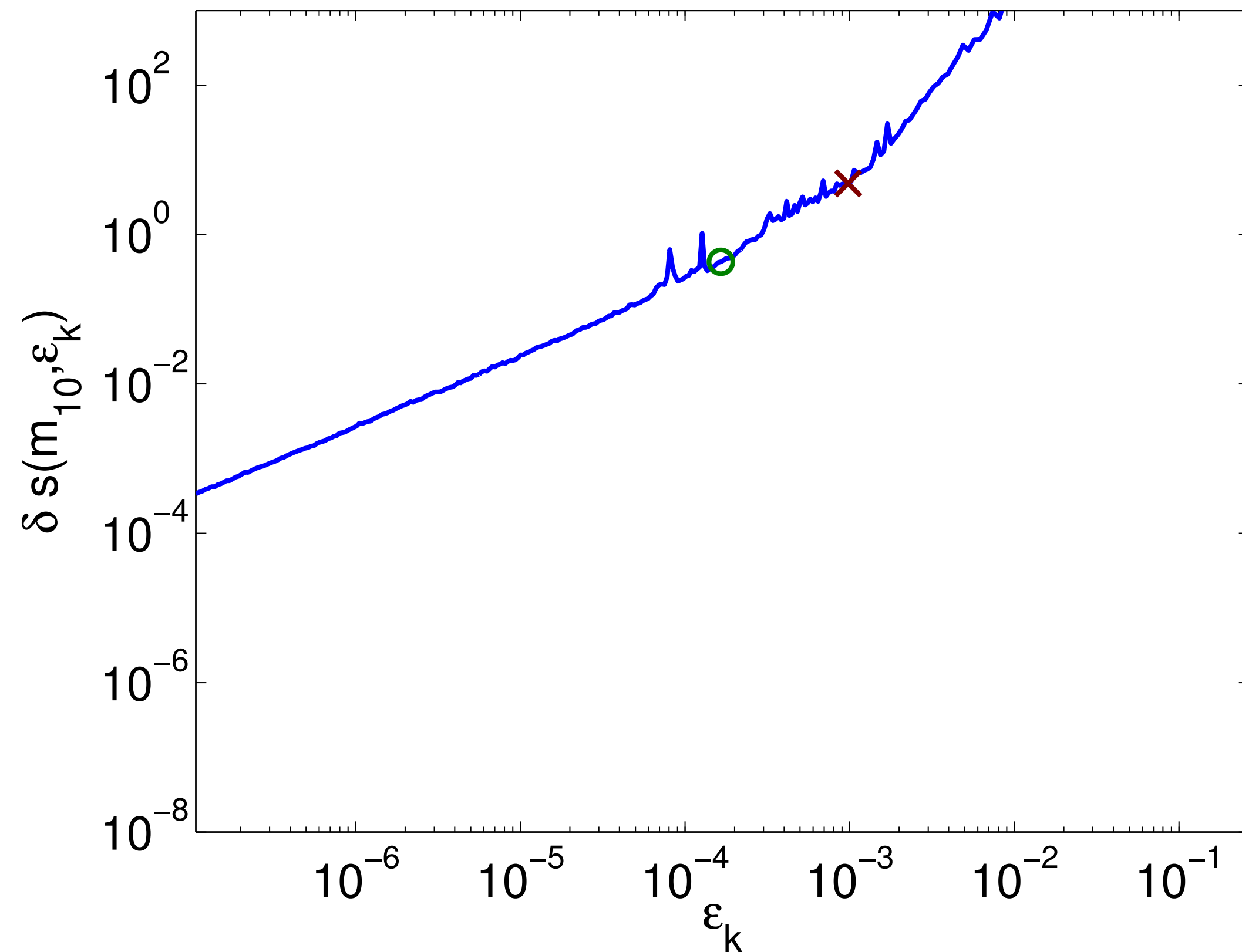


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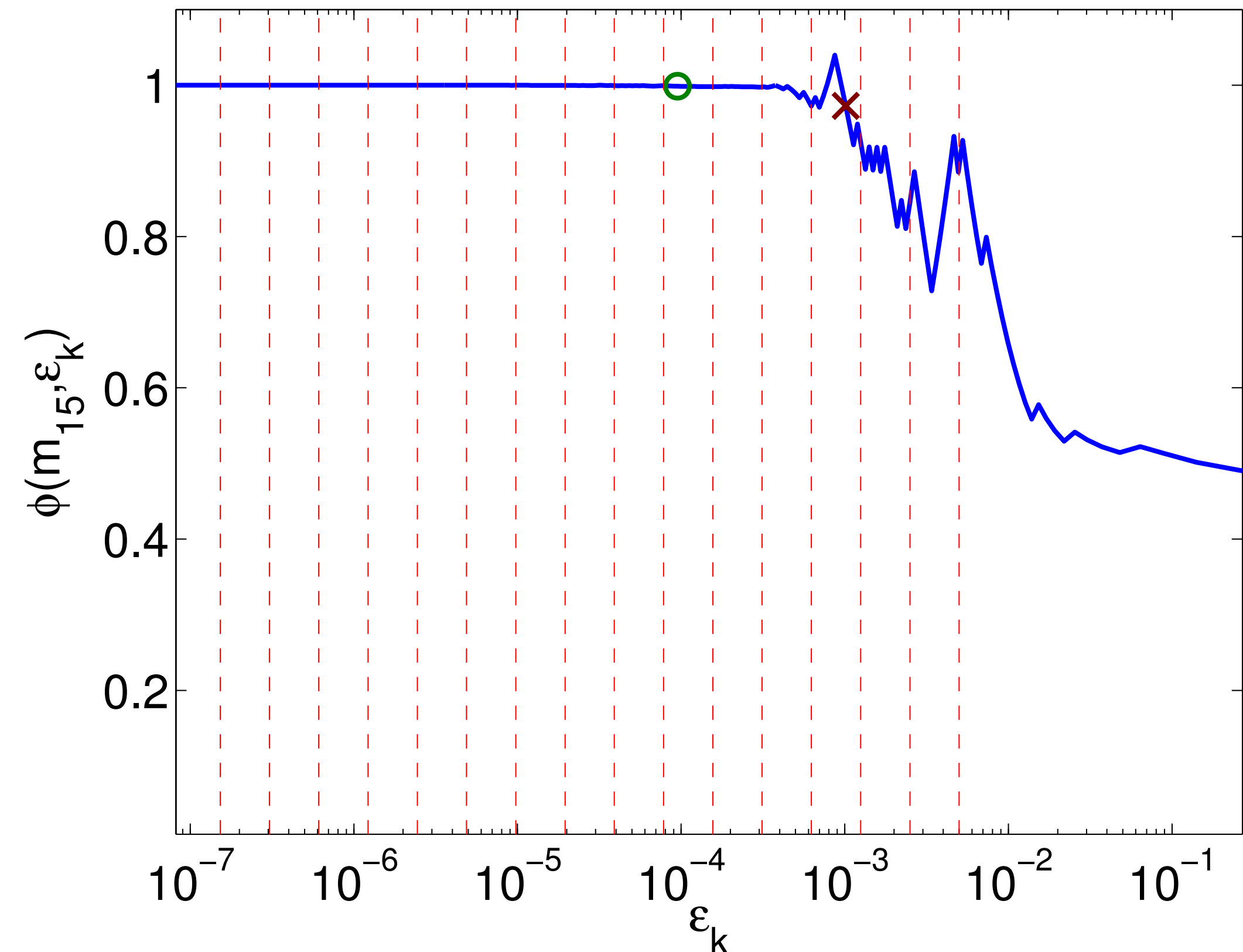
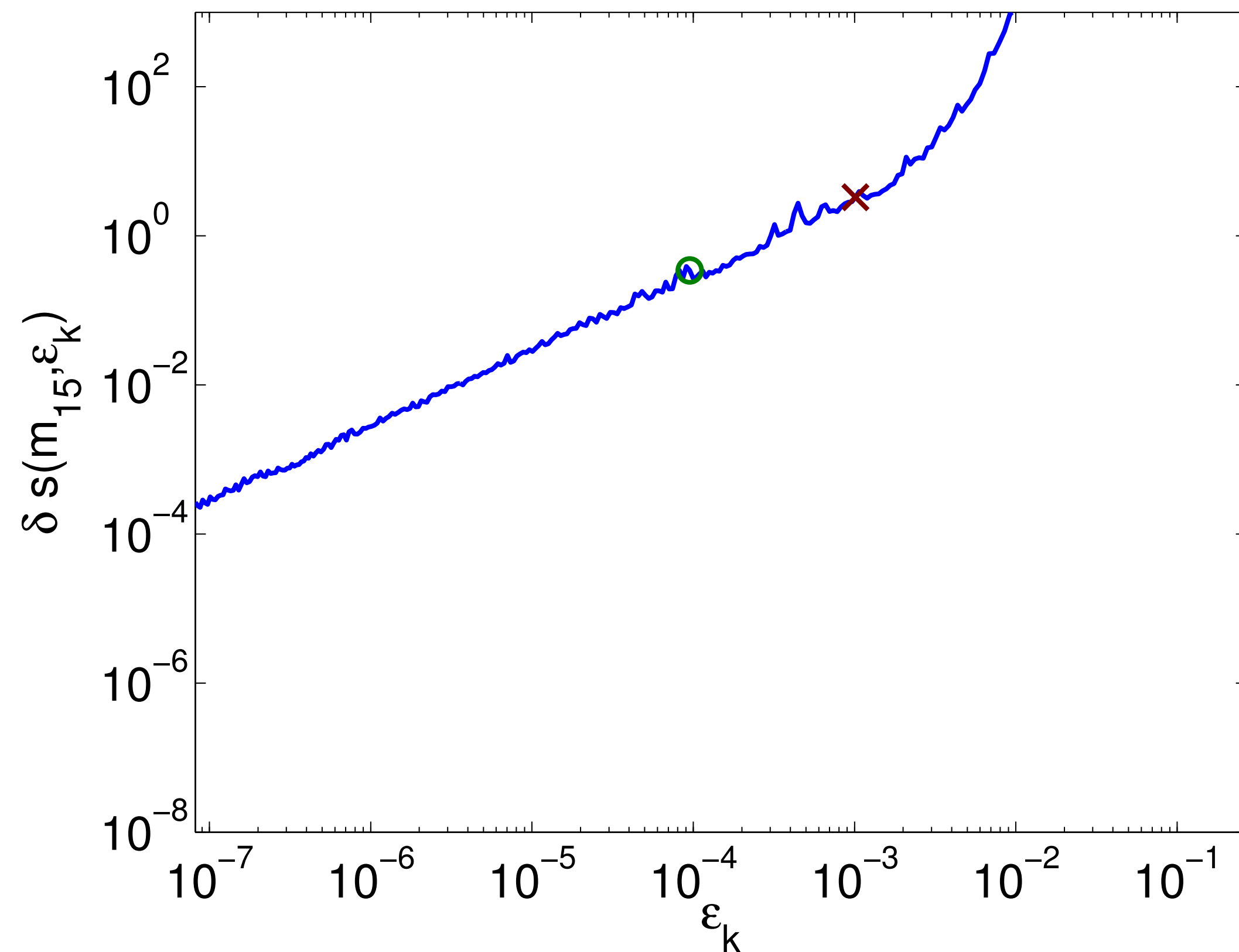


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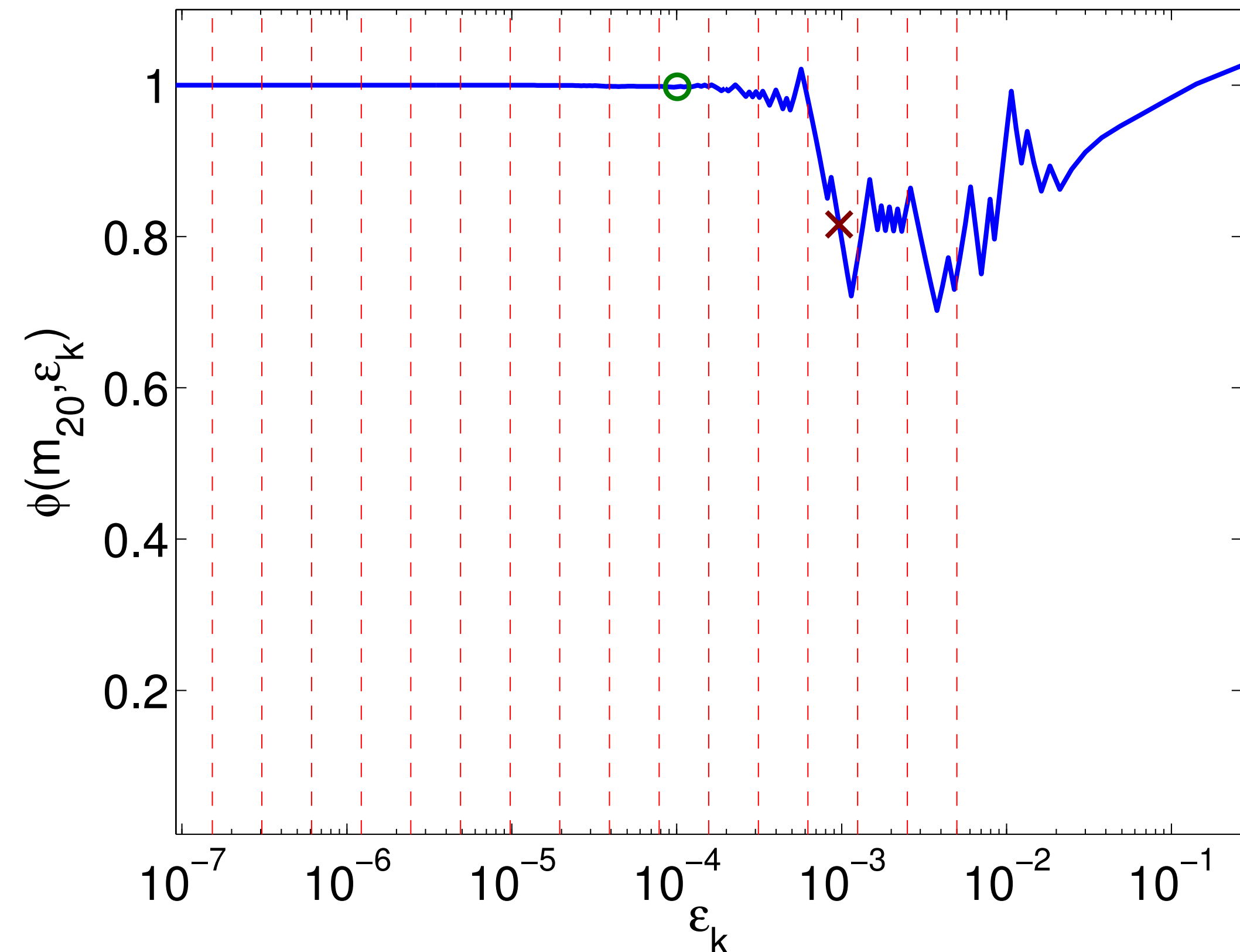
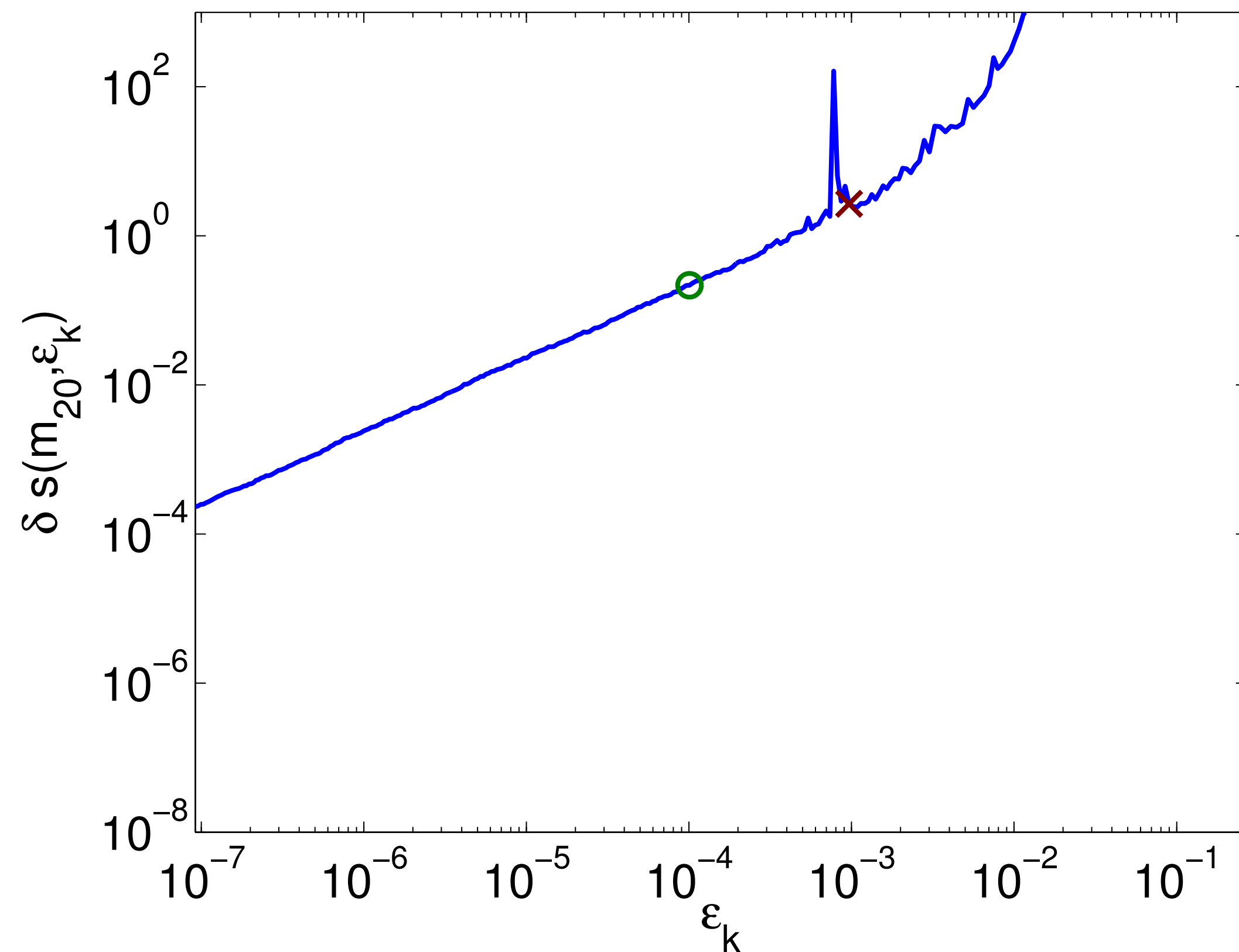


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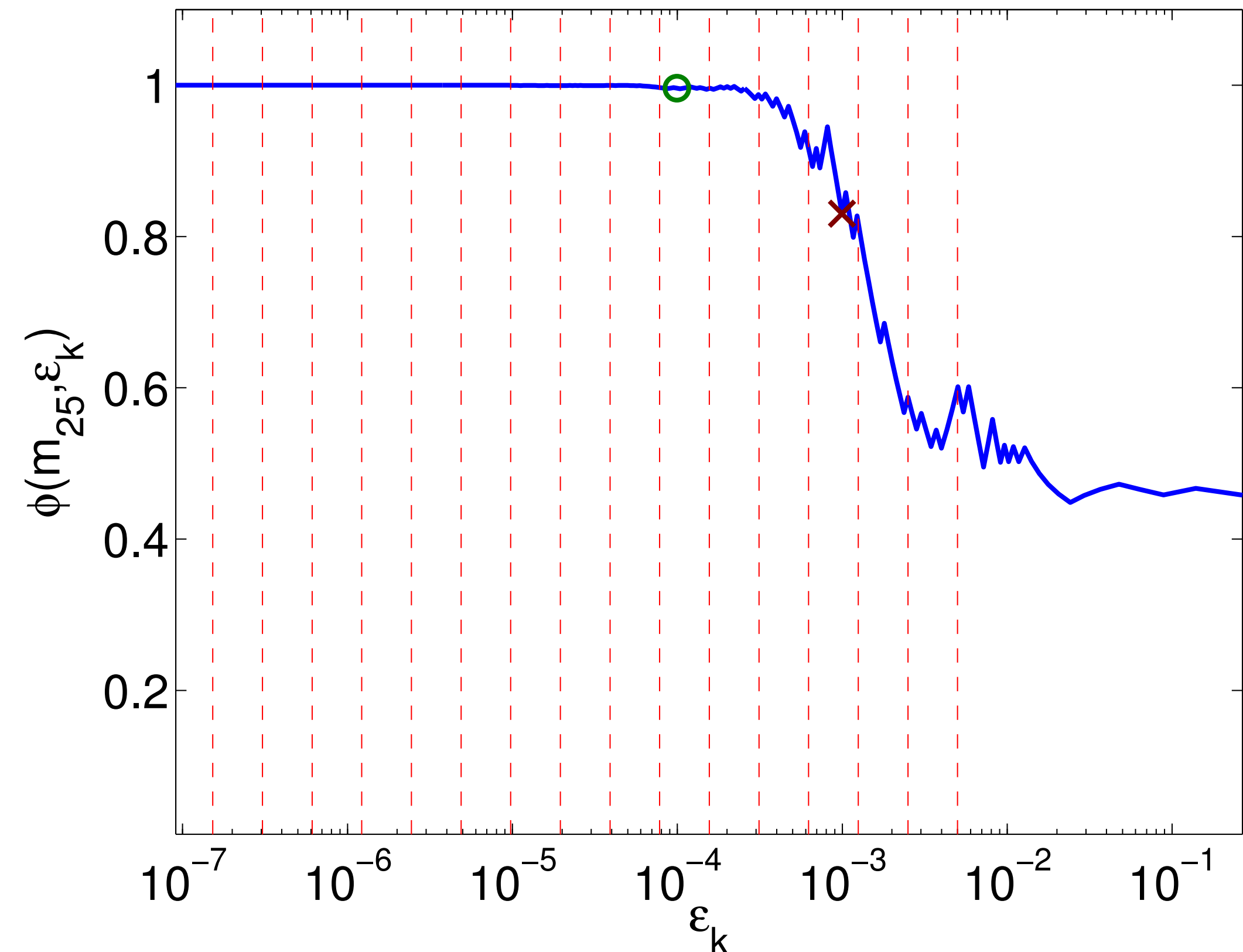
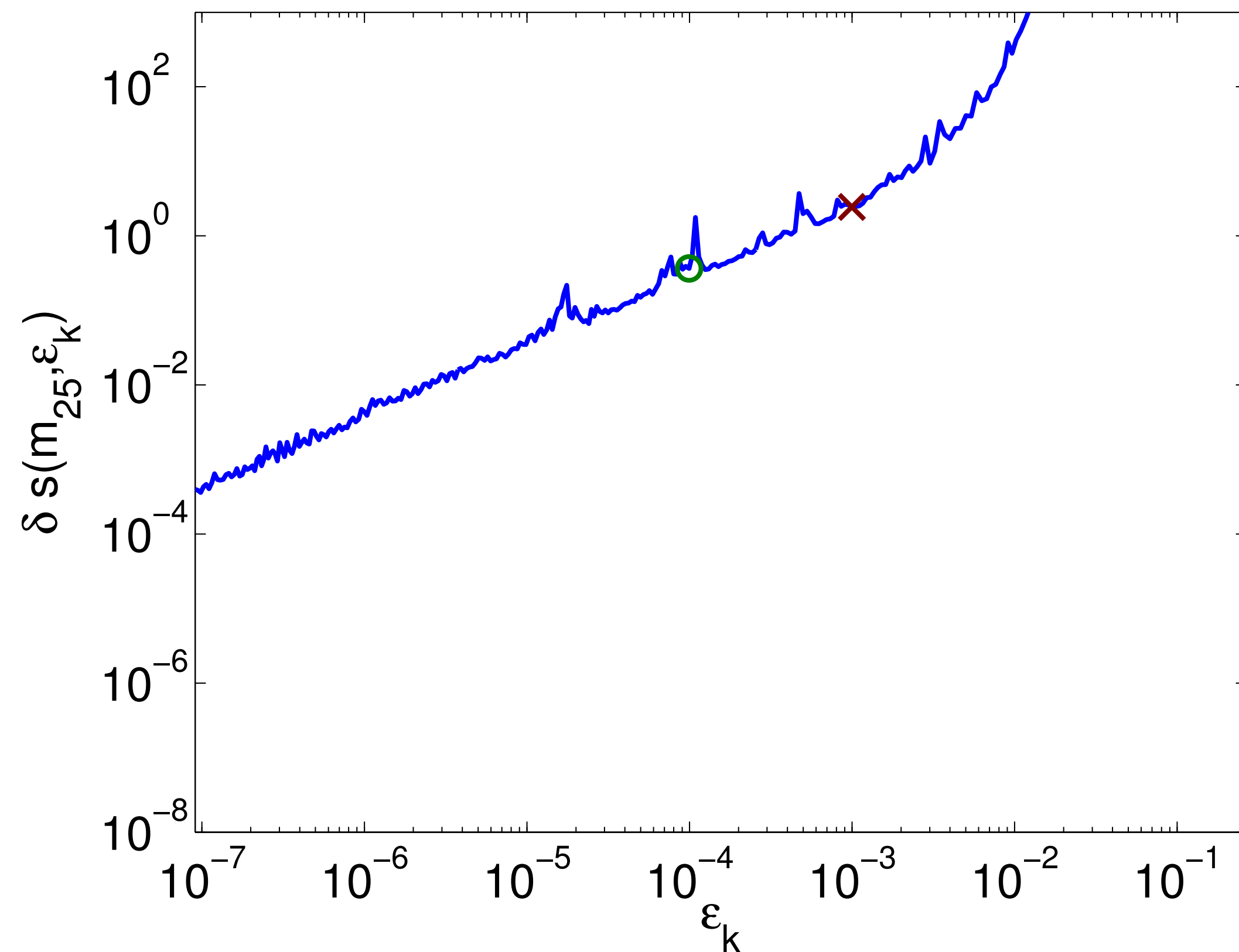


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# Conclusions

# Questions?

This work was in part financially supported by the Natural Sciences and Engineering Research Council of Canada Discovery Grant (22R81254) and the Collaborative Research and Development Grant DNOISE II (375142-08). This research was carried out as part of the SINBAD II project with support from the following organizations: BG Group, BGP, BP, CGG, Chevron, ConocoPhillips, ION, Petrobras, PGS, Total SA, WesternGeco, and Woodside.