

On the Effective Dimension of Light Transport

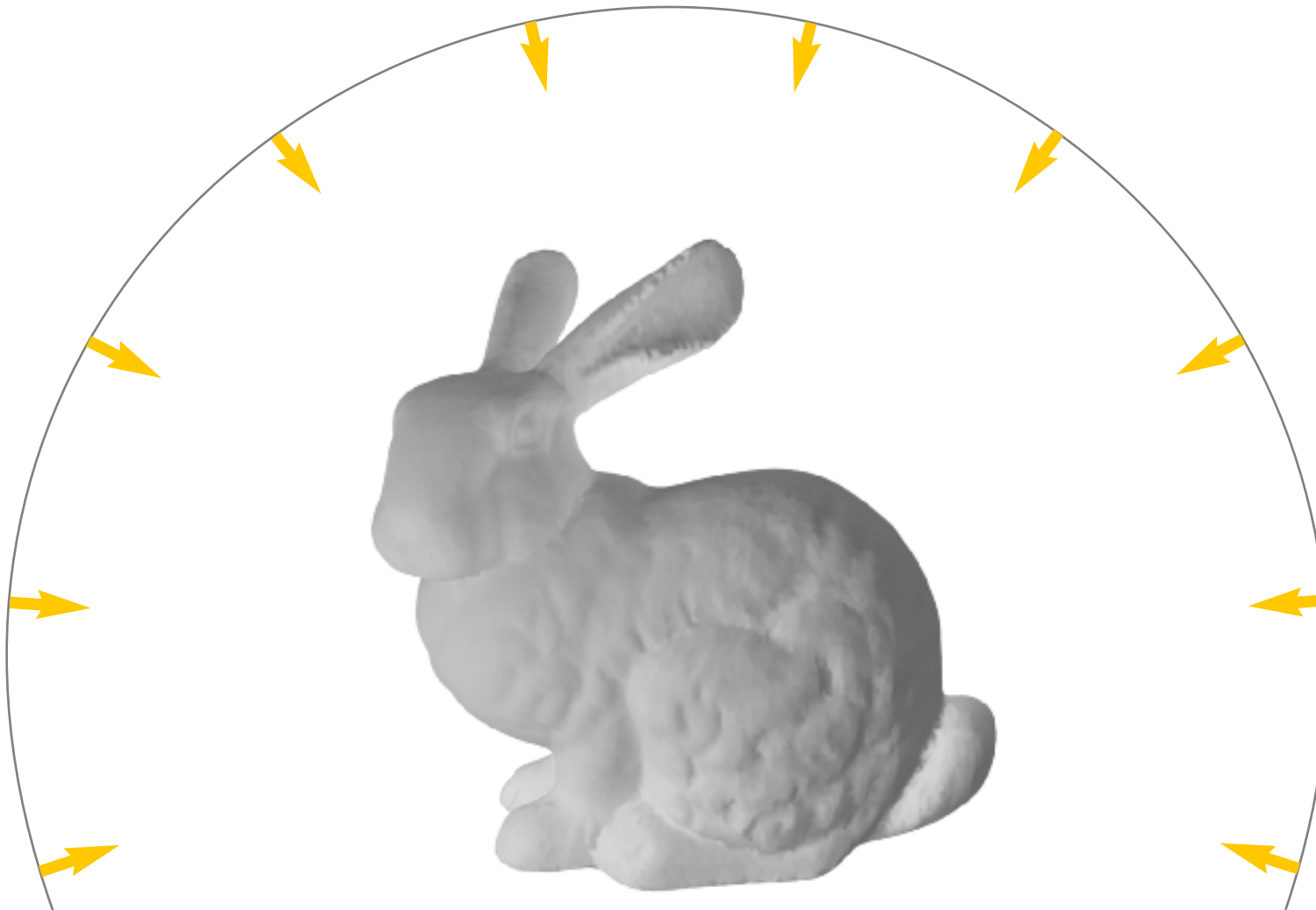
Christian Lessig and Eugene Fiume

Dynamic Graphics Project, Department of Computer Science, University of Toronto

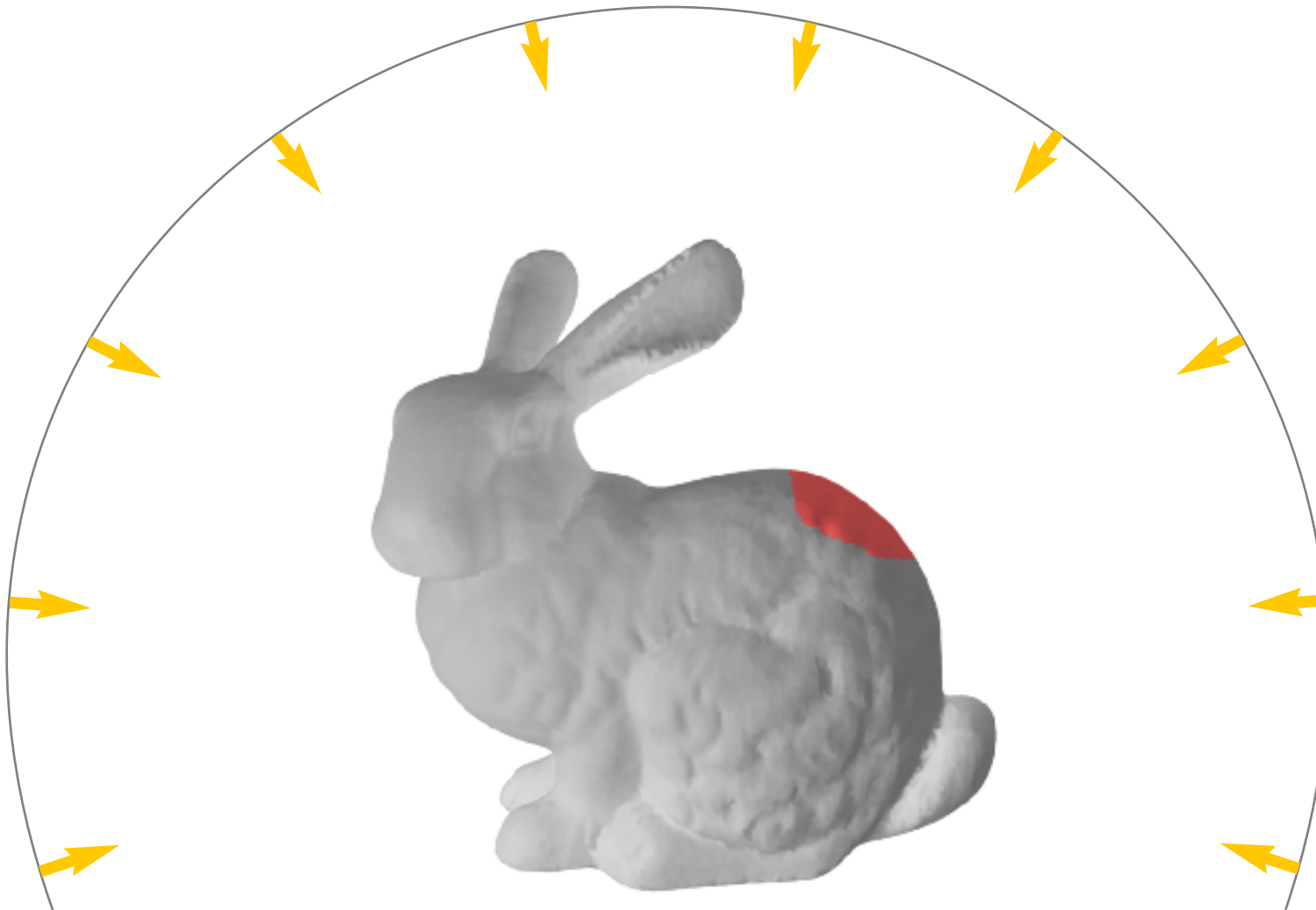
Problem statement



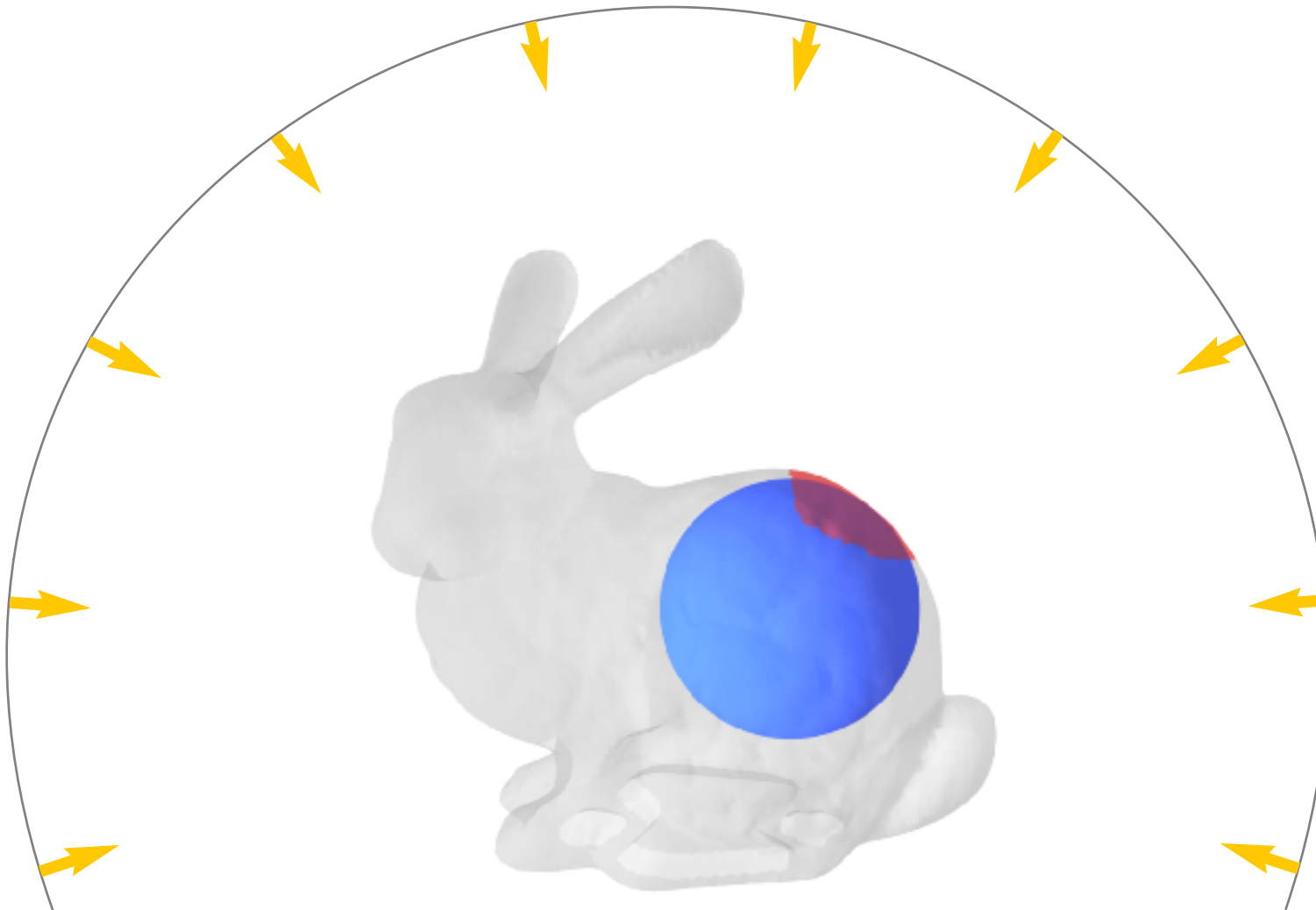
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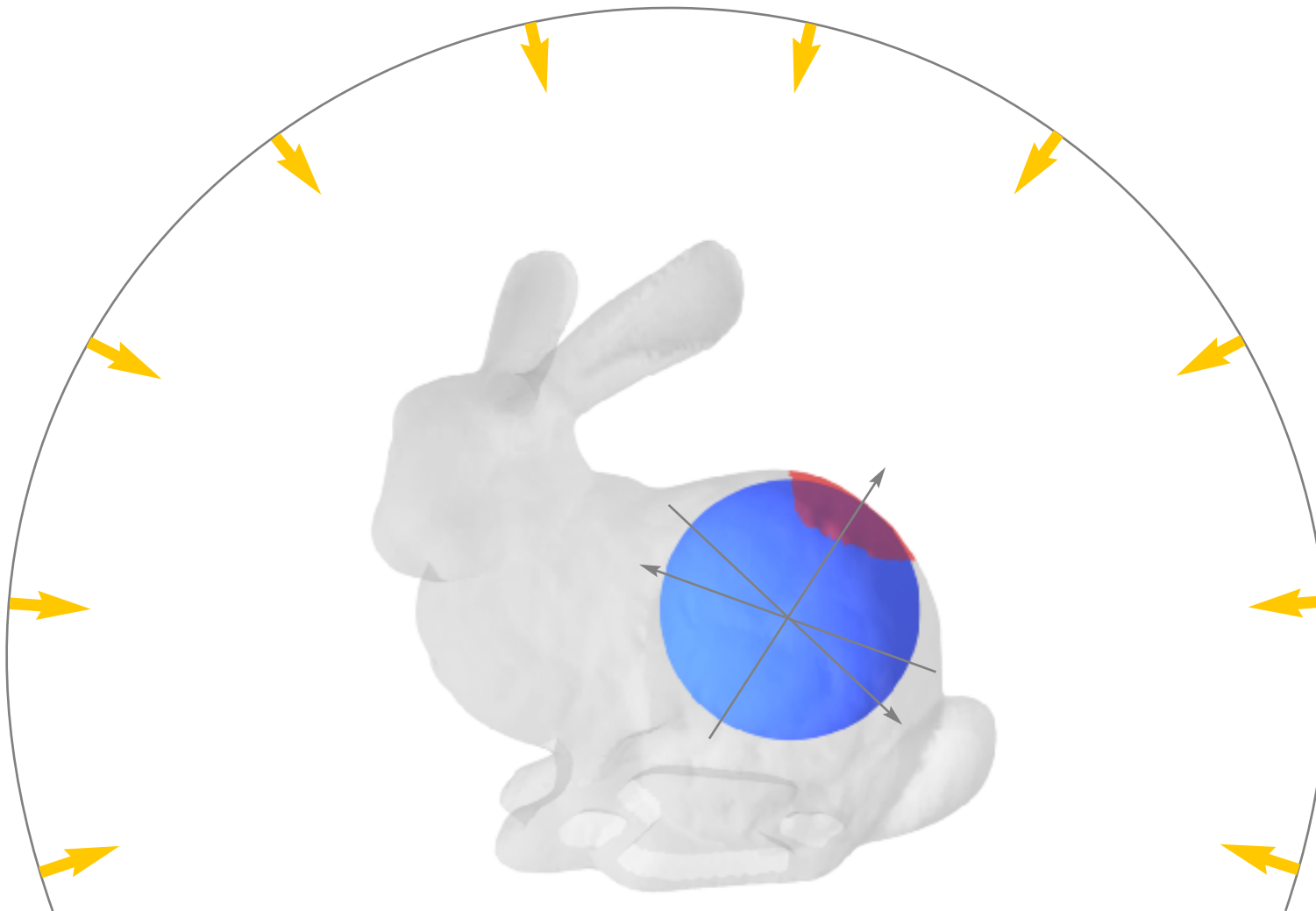
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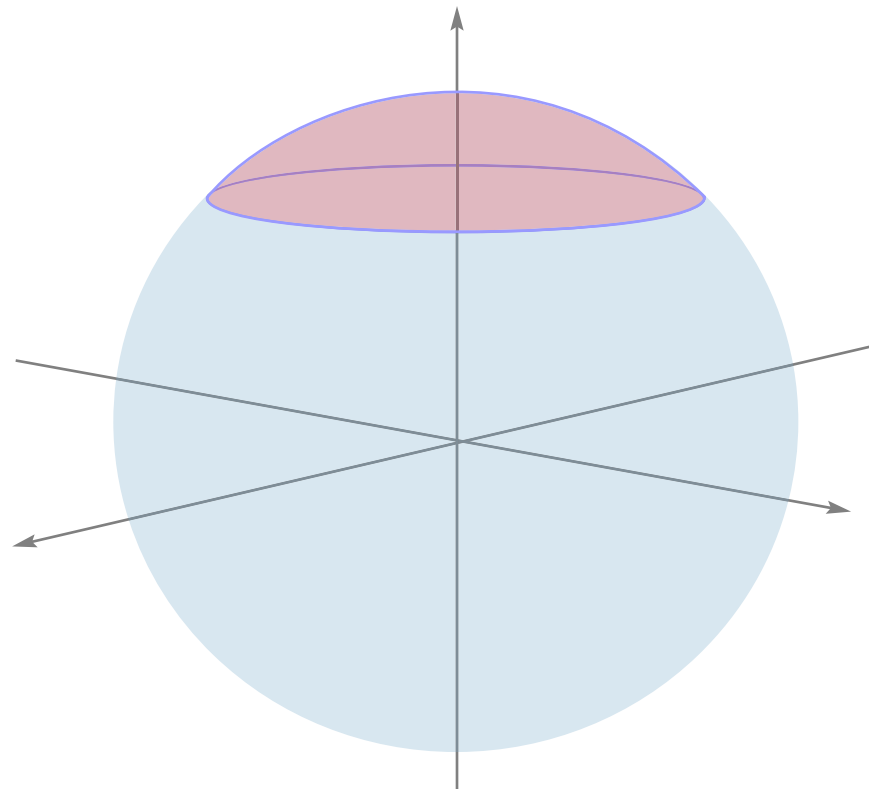
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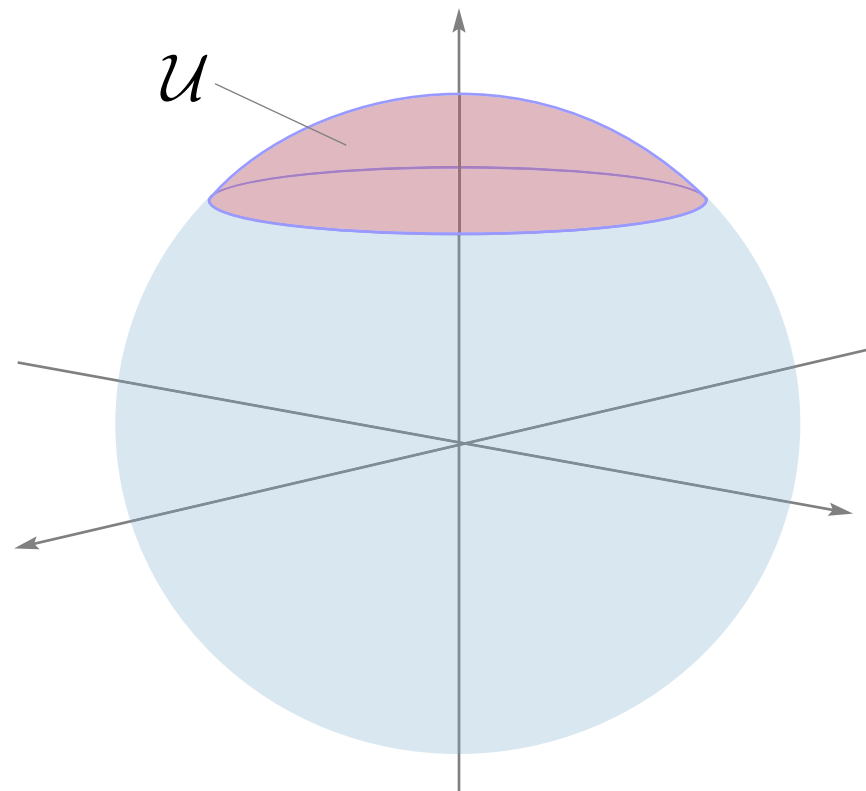
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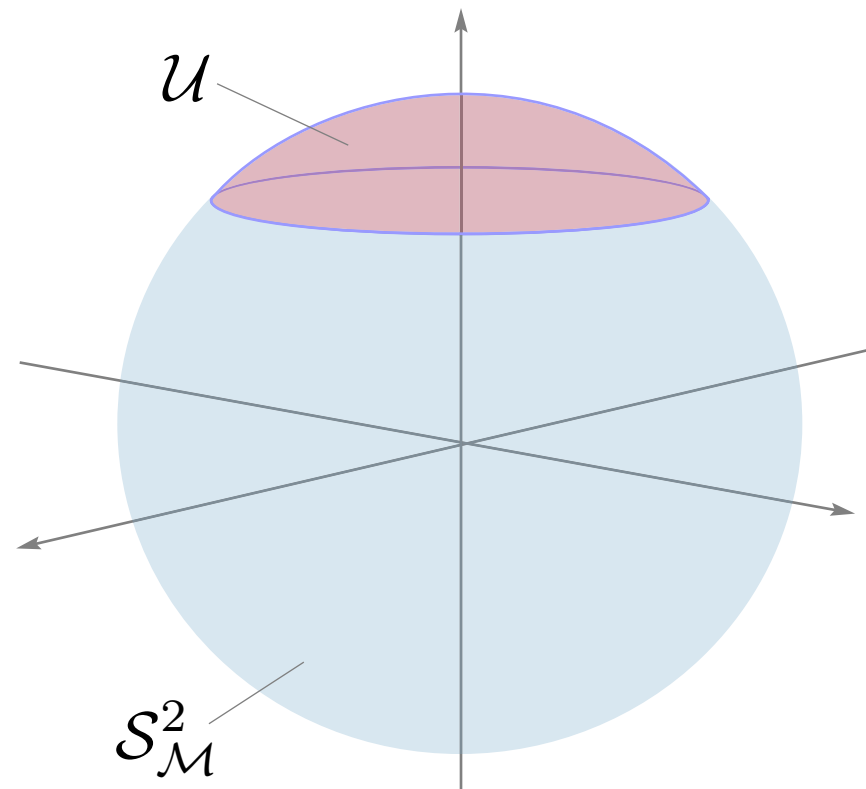
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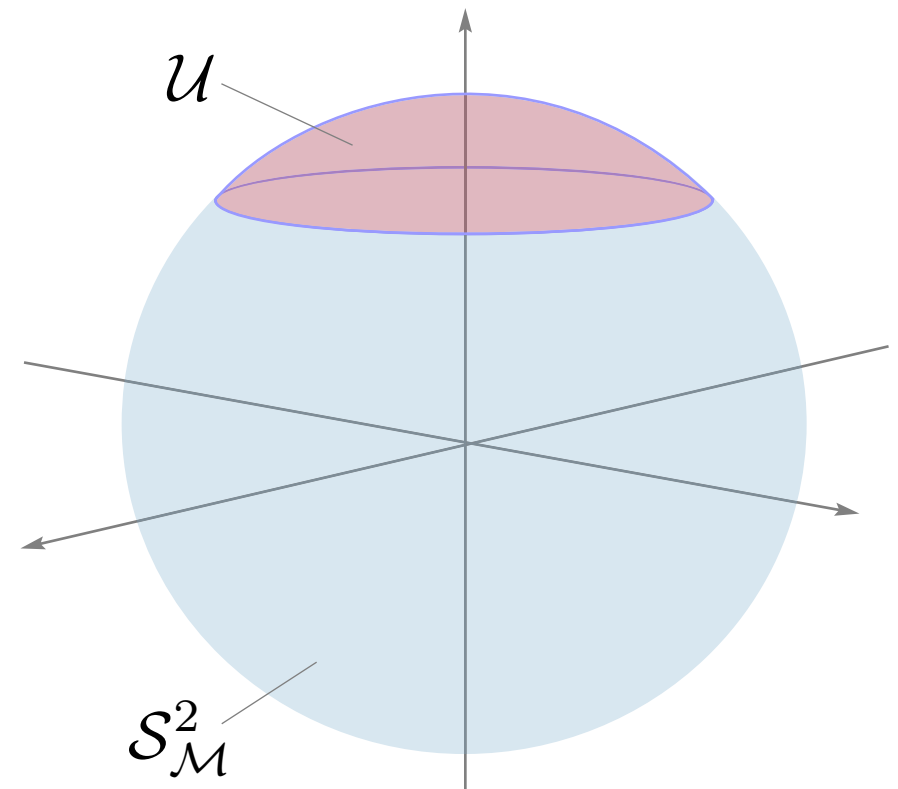
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Shading equation:

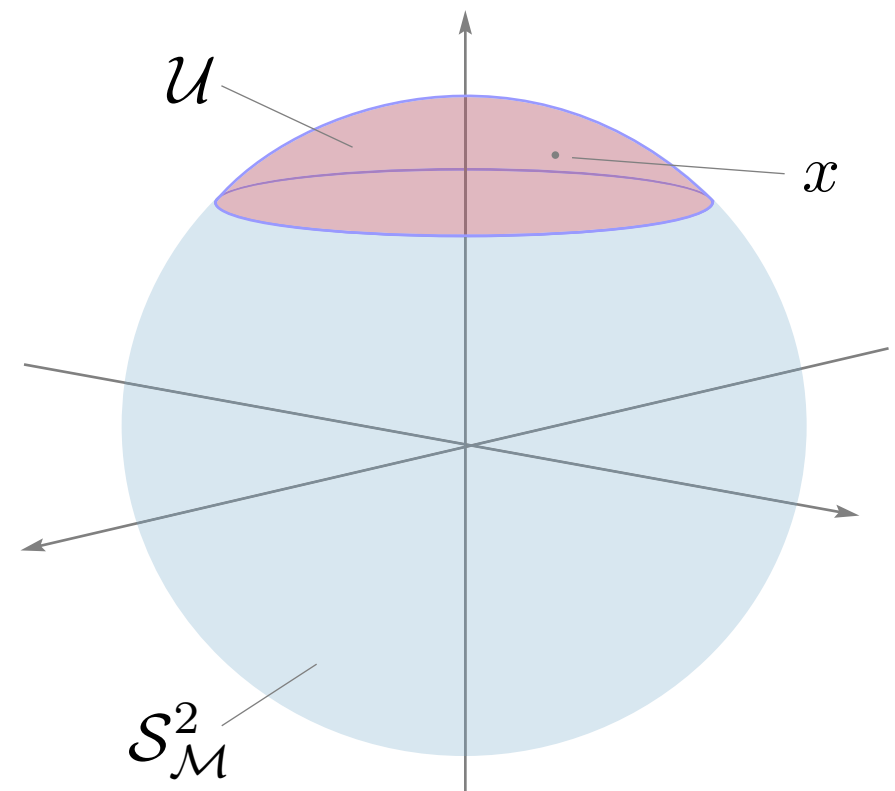
$$B(x) = \int_{\mathcal{H}^2} T(\mathbf{n}(x) \cdot \omega) E(\omega) d\omega$$



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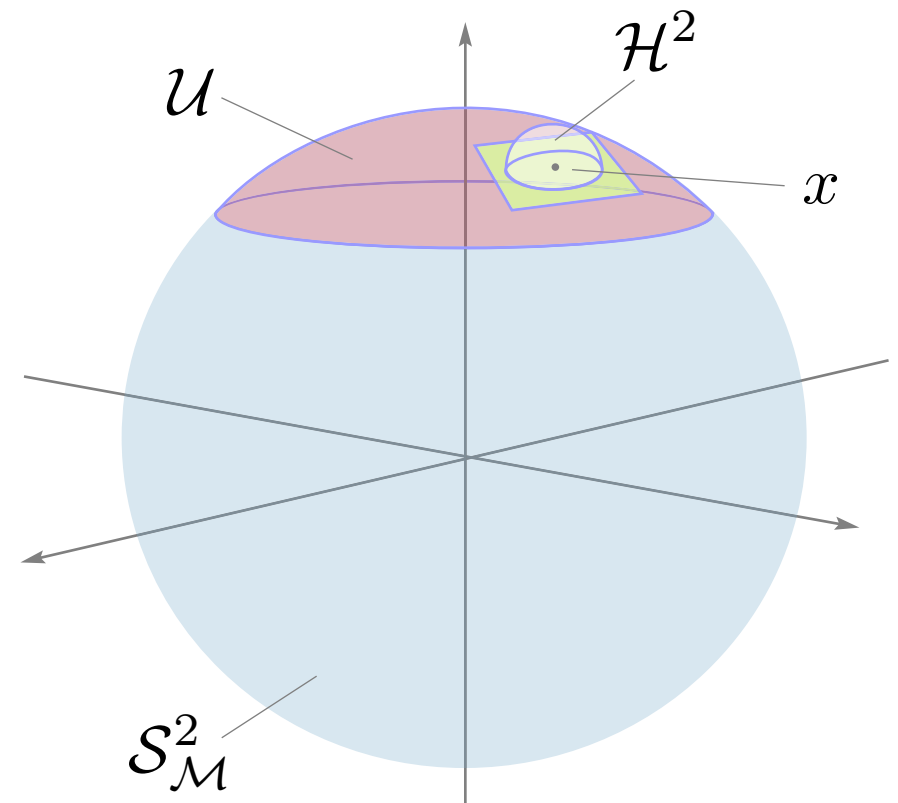
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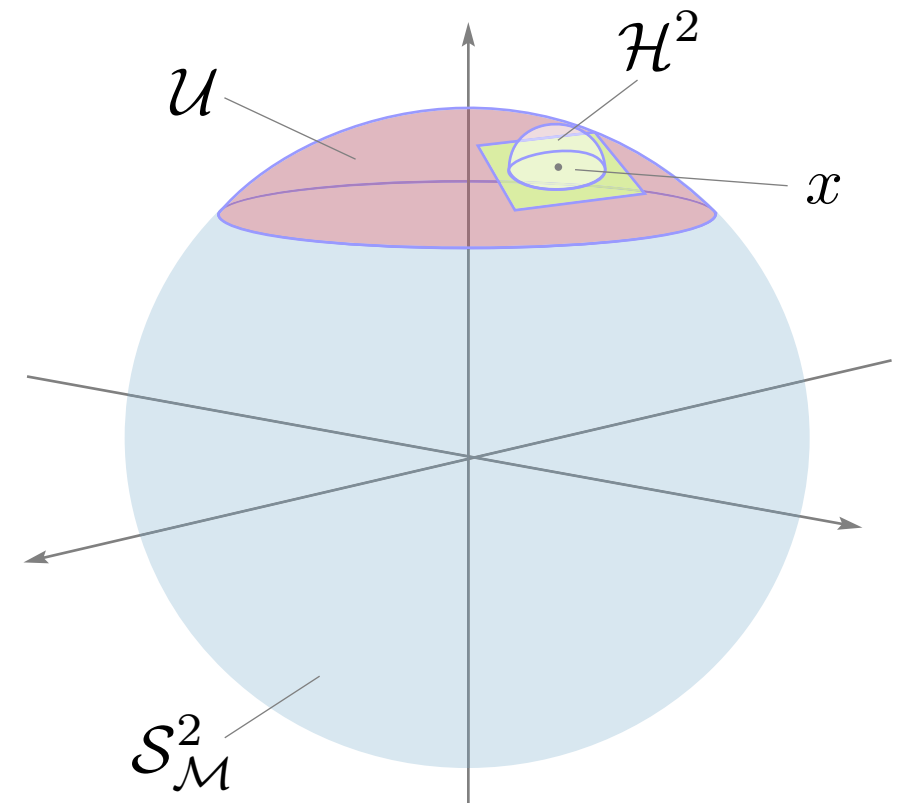
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Objective:

$$\|B - \tilde{B}\|_{\mathcal{U}}^2 = \|TE - \tilde{T}E\|_{\mathcal{U}}^2 \approx \epsilon$$



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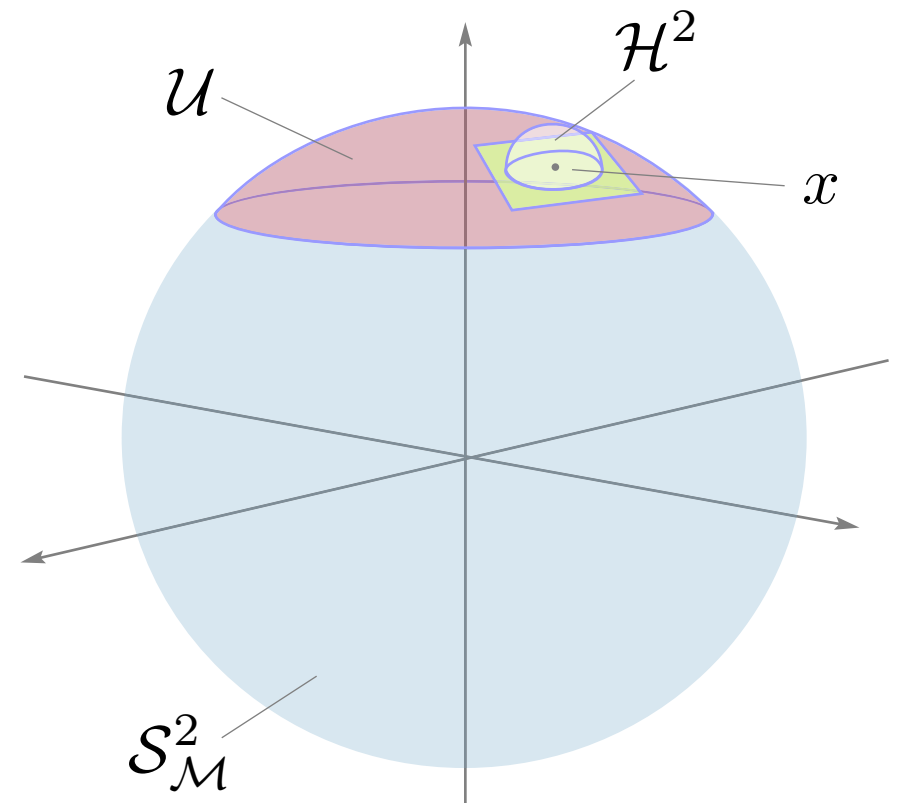
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with

$$\dim(\tilde{T}) \ll \dim(T)$$



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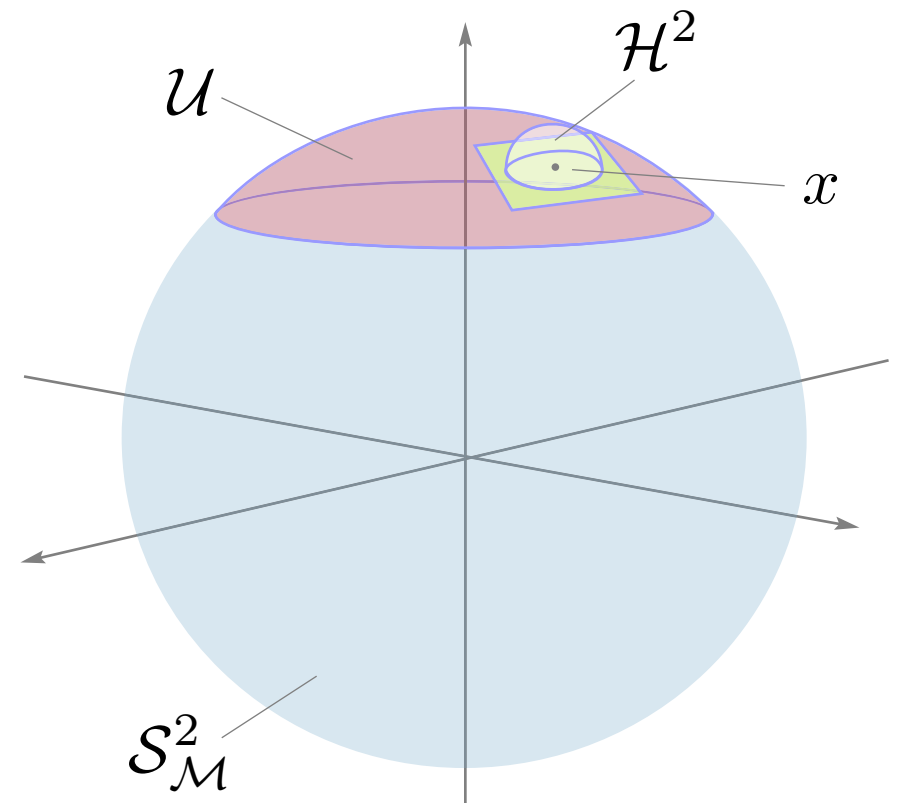
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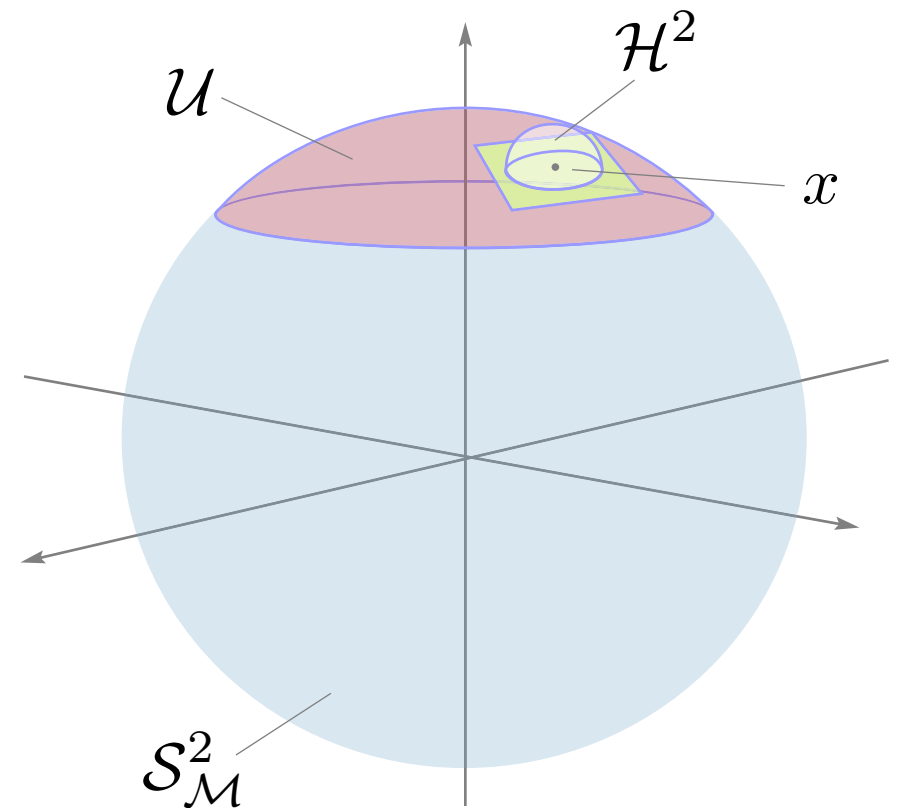
$$\boxed{\dim(\tilde{T})} \ll \dim(T)$$

effective dimension



Simplification

$$B(x) = \int_{\mathcal{H}^2} T(\mathbf{n}(x) \cdot \omega) E(\omega) d\omega$$



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Simplification

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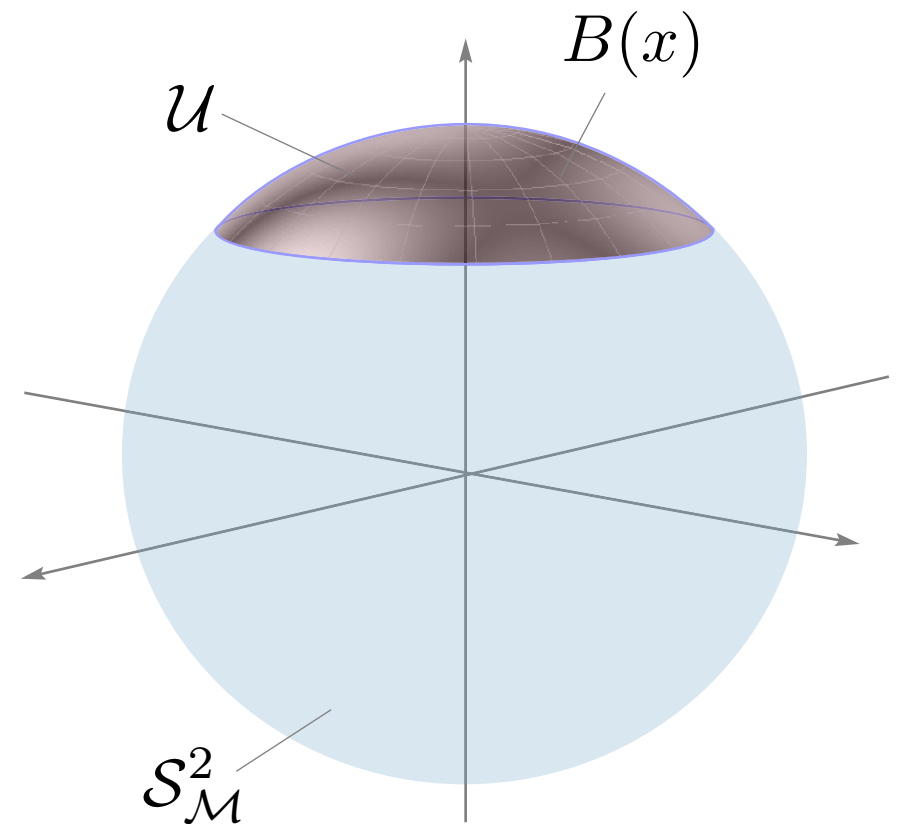
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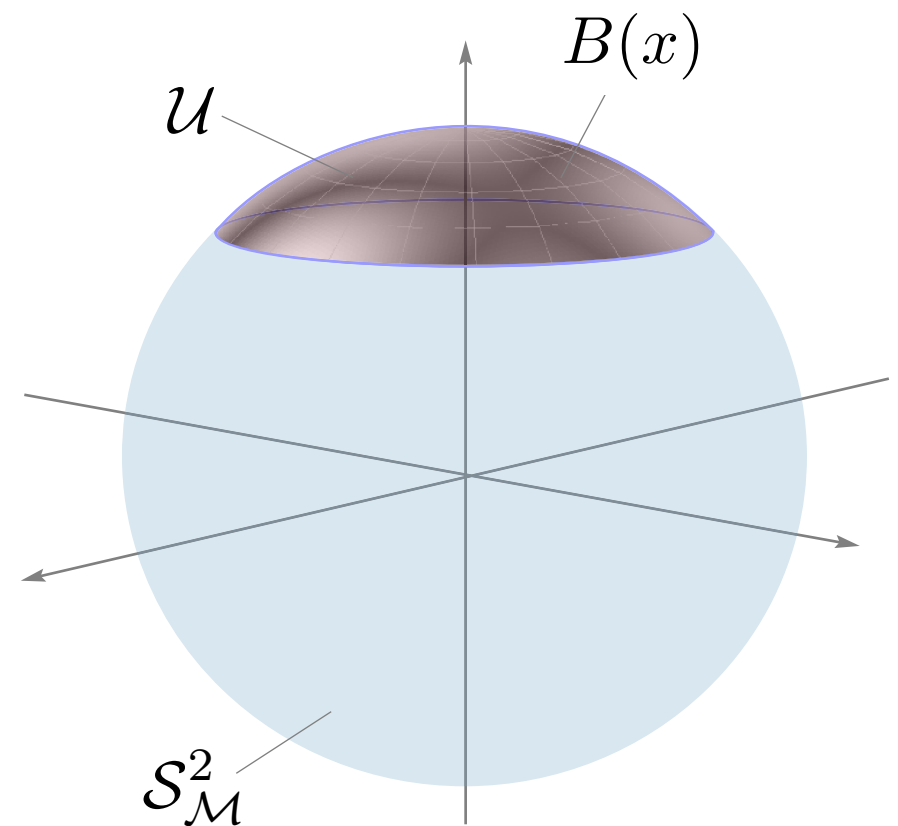
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but $\mathbf{n}(x) \simeq \omega \in \mathcal{S}_{\mathcal{M}}^2$

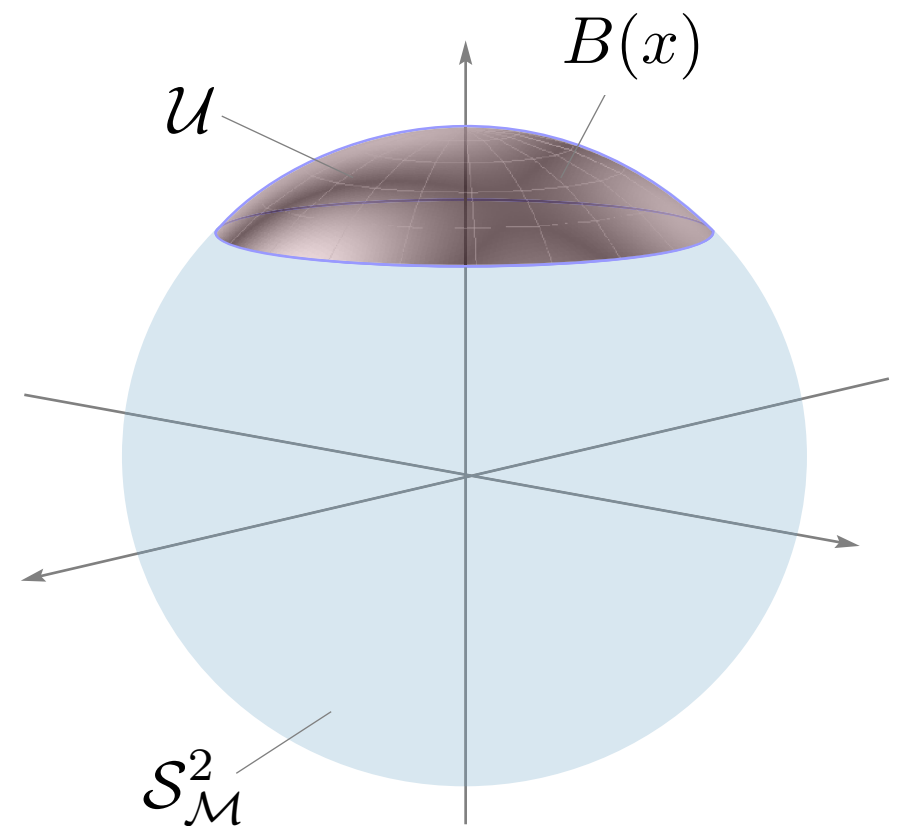


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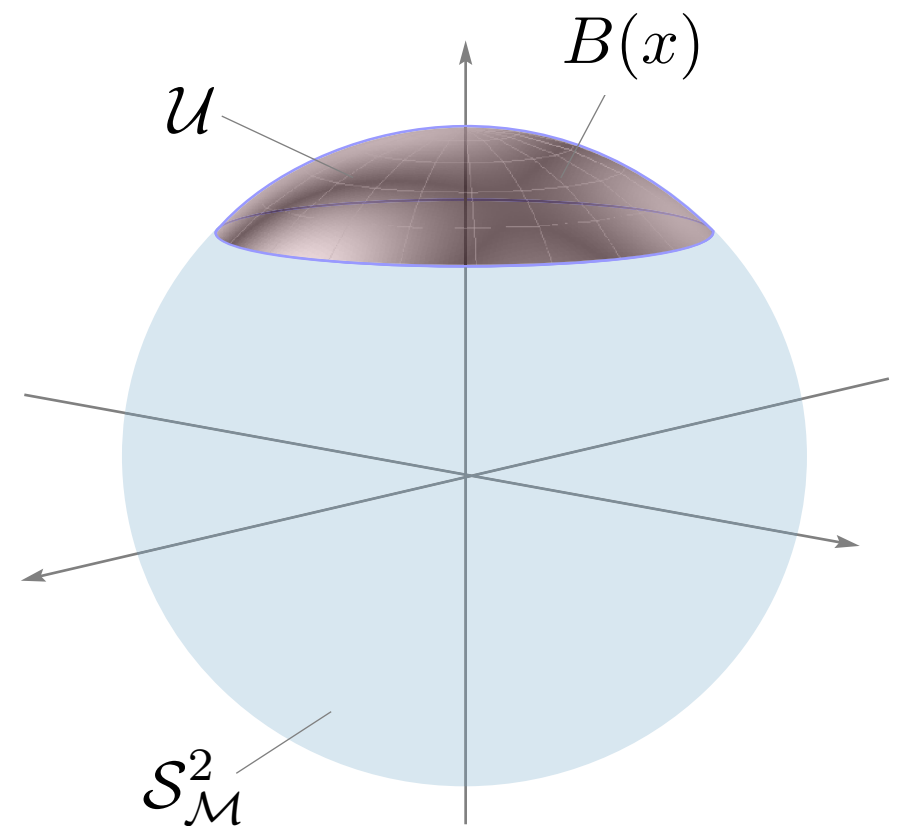


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Approximation

Objective

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We are interested in a basis

$$\left\{ \varphi_i(\omega) \mid i = 1 \dots (L+1)^2, \text{span}_i(\varphi_i) = \mathcal{H}_{\leq L} \right\}$$

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with *effective dimension* $K \ll N$ such that

$$B(\omega) \approx \tilde{B}(\omega) = \sum_{i=1}^K \tilde{b}_i \varphi_i$$

Approximation

Approximation error

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which, for arbitrary input signals, is minimized if

$$\|\varphi_i(\omega)\|_{\mathcal{U}}^2, \quad i = K + 1 \dots N$$

is minimal.

Spatio-Spectral Concentration Theory

Spatio-Spectral Concentration Theory

Objective: Extremize concentration measure¹

$$\lambda = \frac{\|g\|_{\mathcal{U}}^2}{\|g\|_{\mathcal{S}^2}^2} = \frac{\int_{\mathcal{U}} g^2 d\omega}{\int_{\mathcal{S}^2} g^2 d\omega} \quad , \quad g \in \mathcal{H}_{\leq L}$$

¹ Simons FJ, Dahlen FA, Wieczorek MA. *Spatiospectral Concentration on a Sphere*. SIAM Review. 2006;48(3):504-536; Simons FJ. *Slepian Functions and Their Use in Signal Estimation and Spectral Analysis*. In: Freedman W Handbook of Geomathematics.; 2010.

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Solution: Eigenvalue problem

$$D g_i = \lambda_i g_i$$

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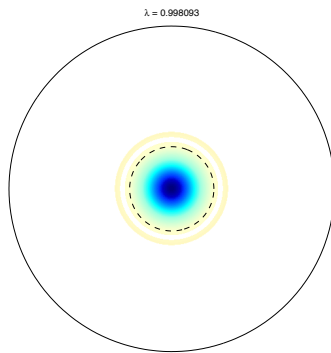
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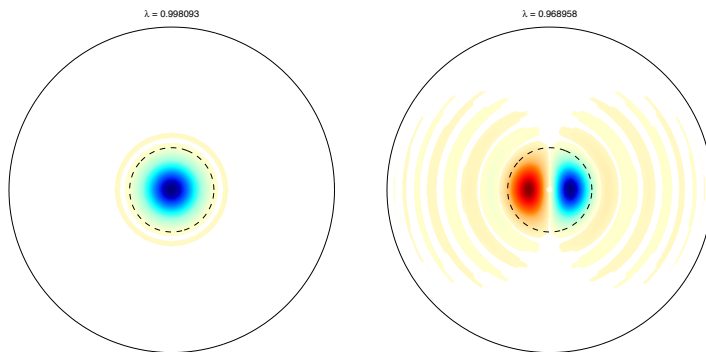
$$d_{lm,l'm'} = \int_U y_{lm}(\omega) y_{l'm'}(\omega) d\omega$$

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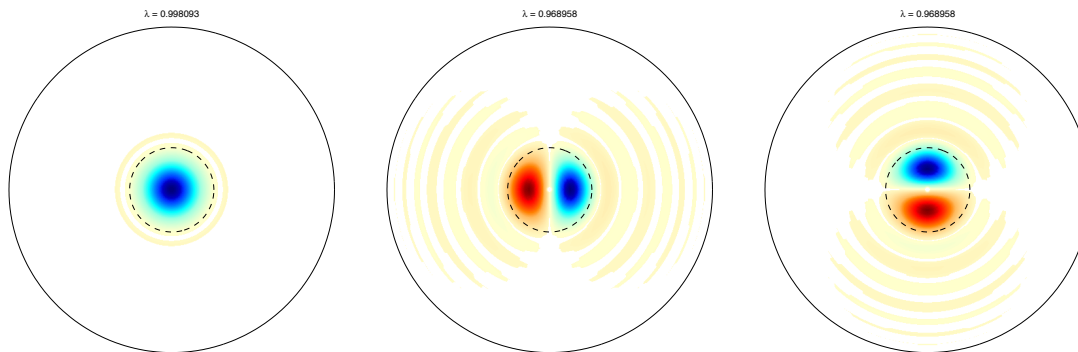
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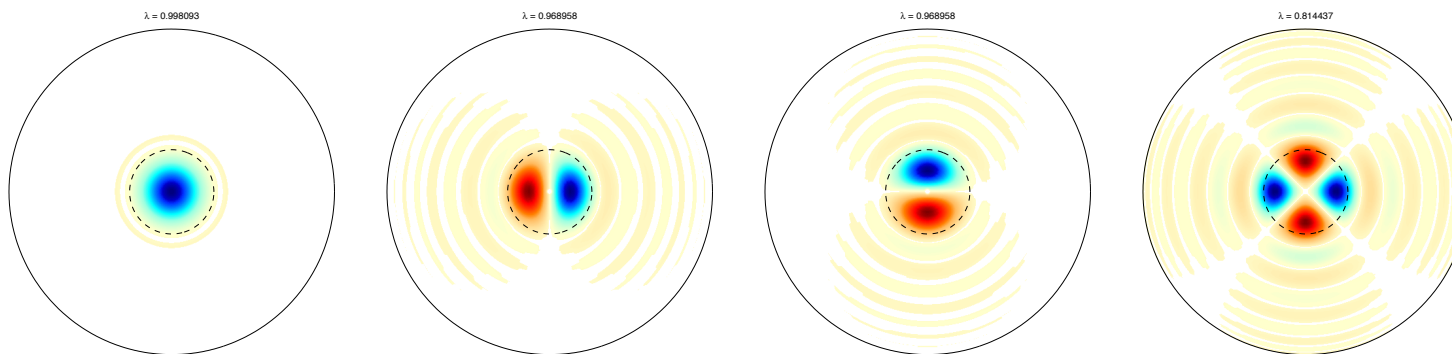
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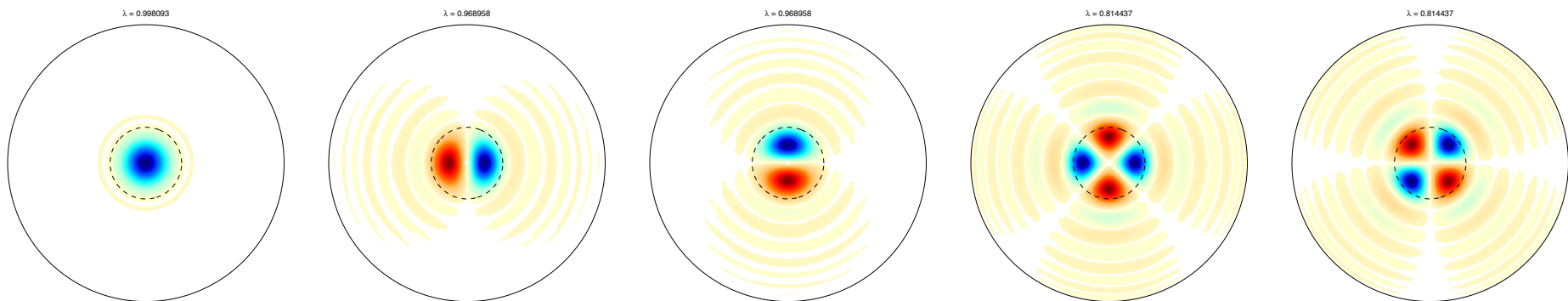
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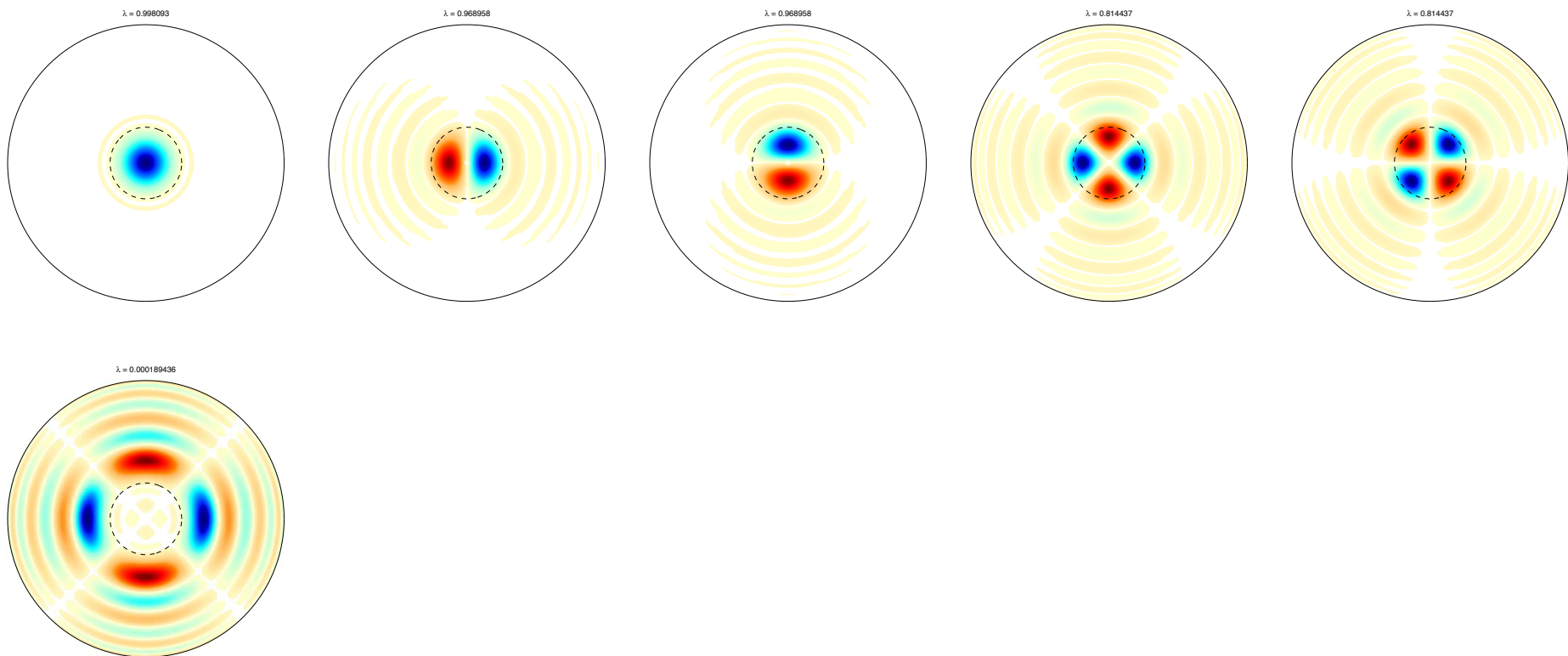
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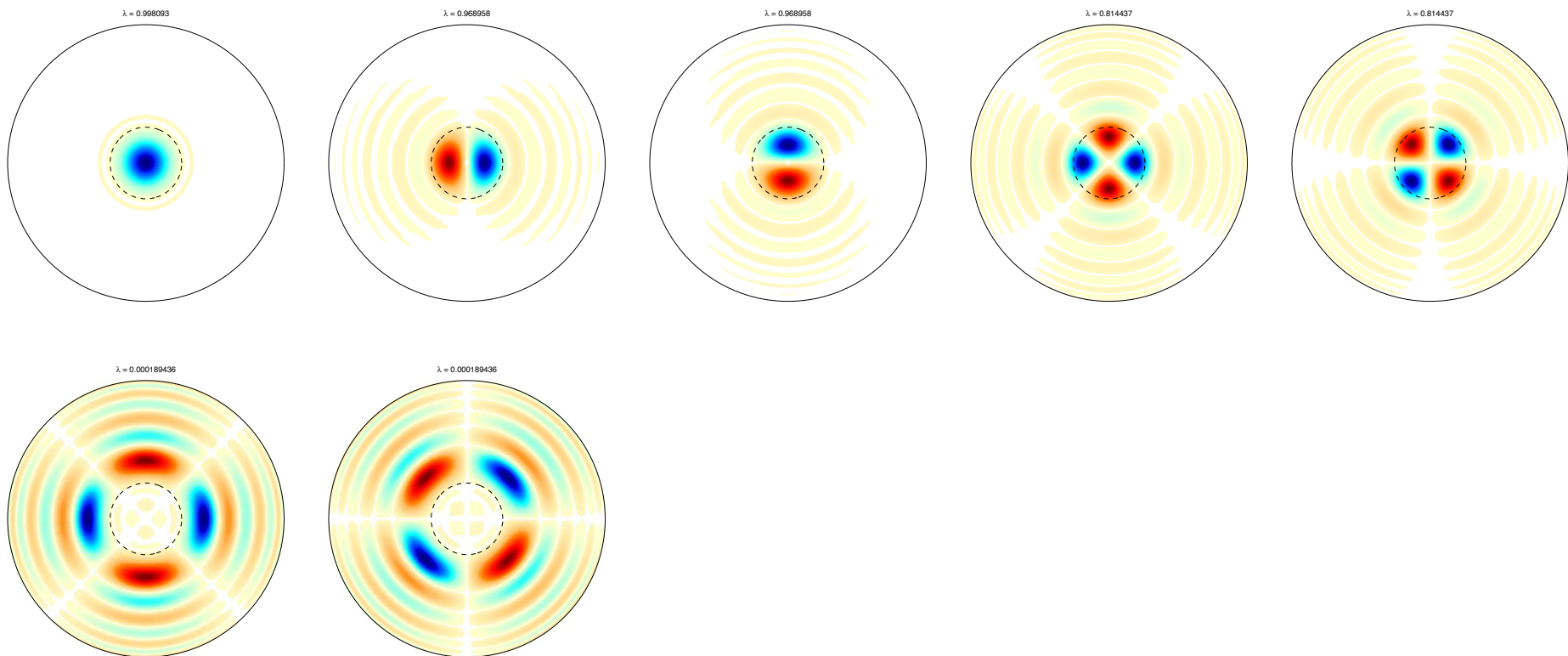
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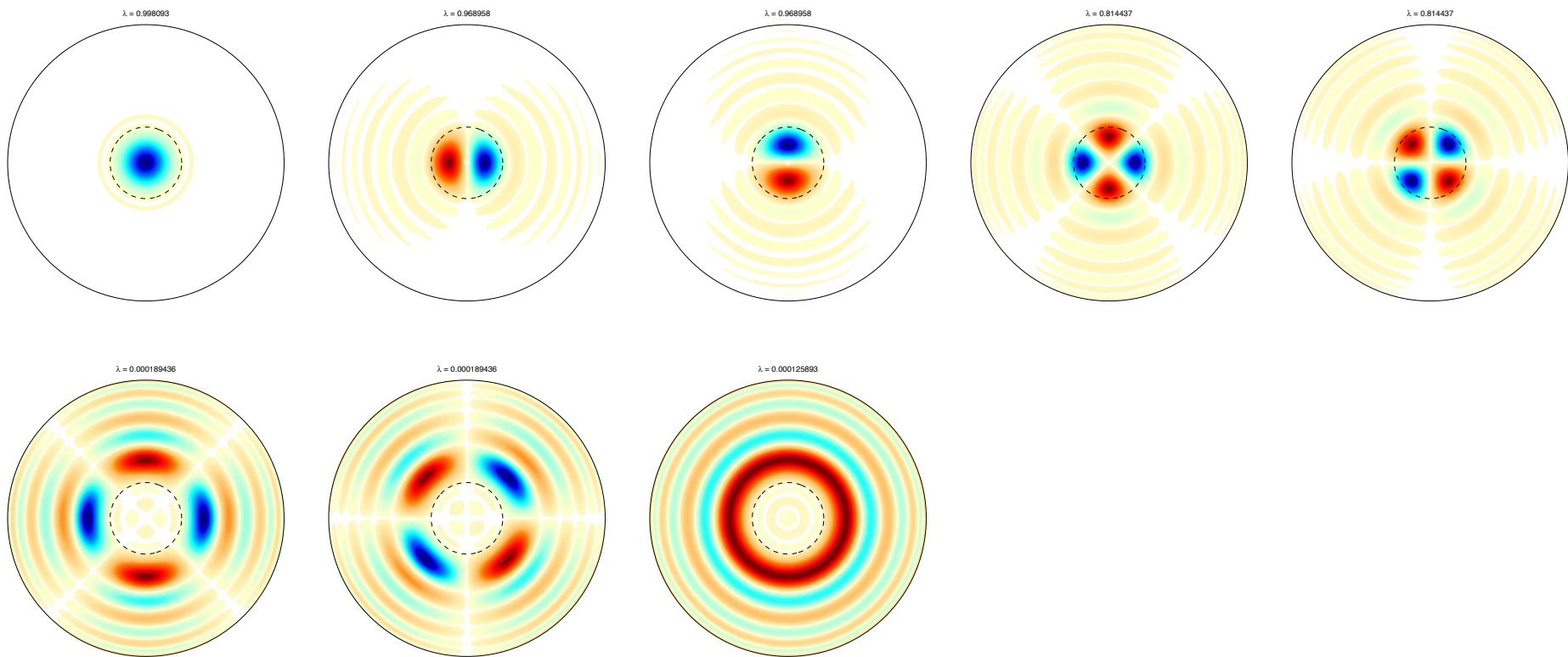
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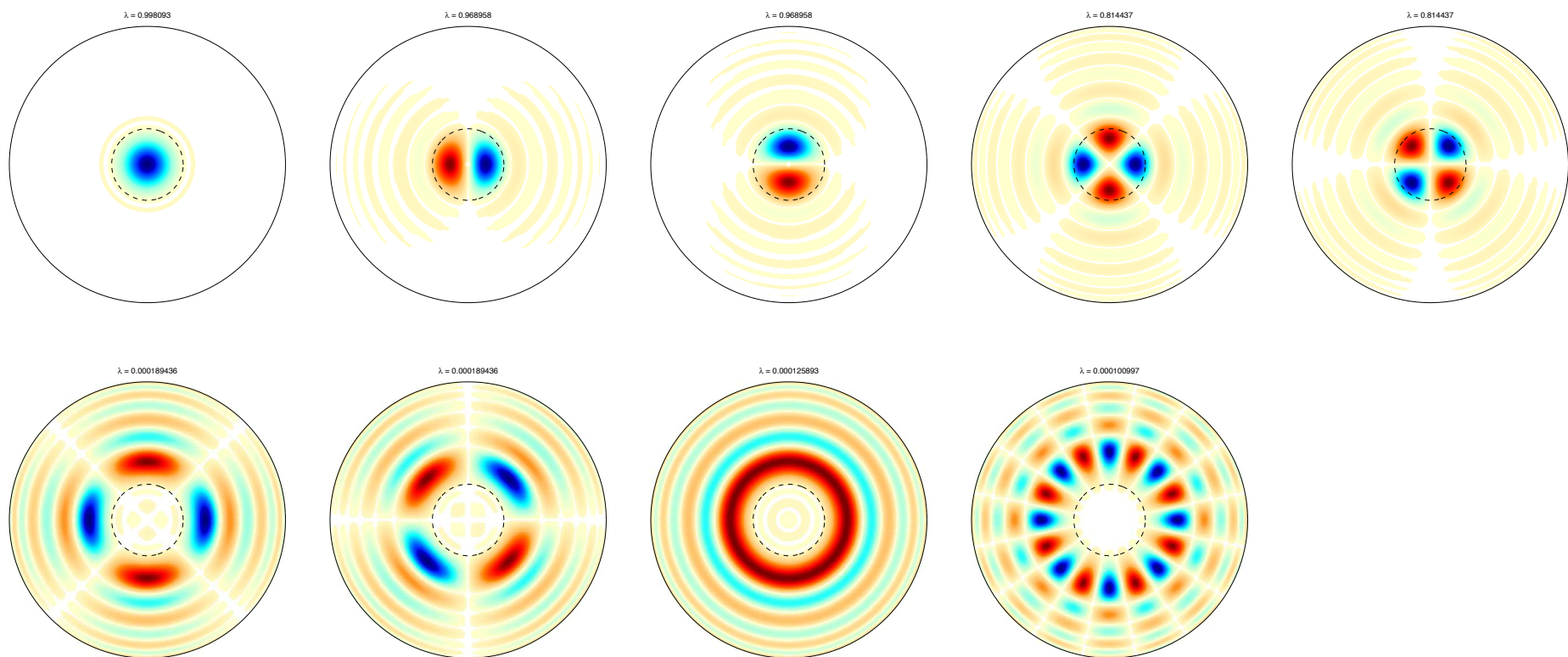
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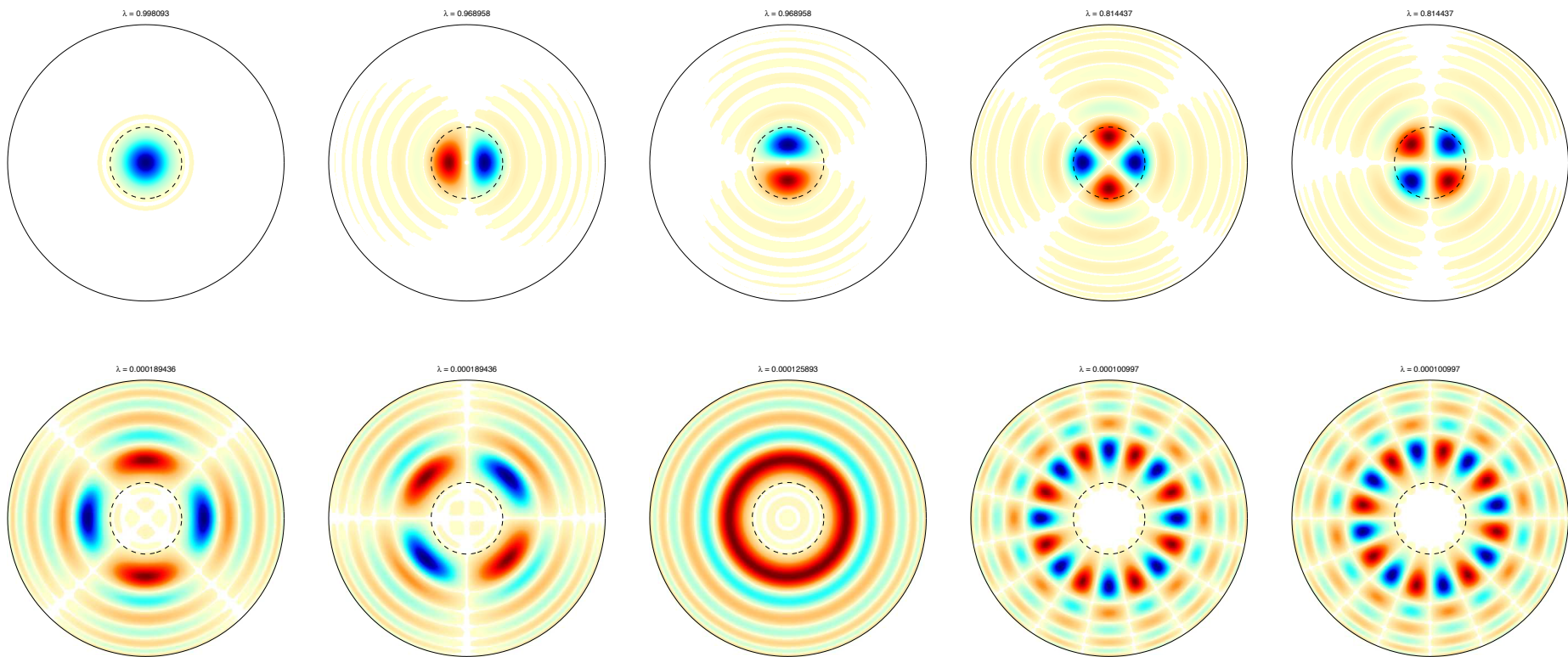
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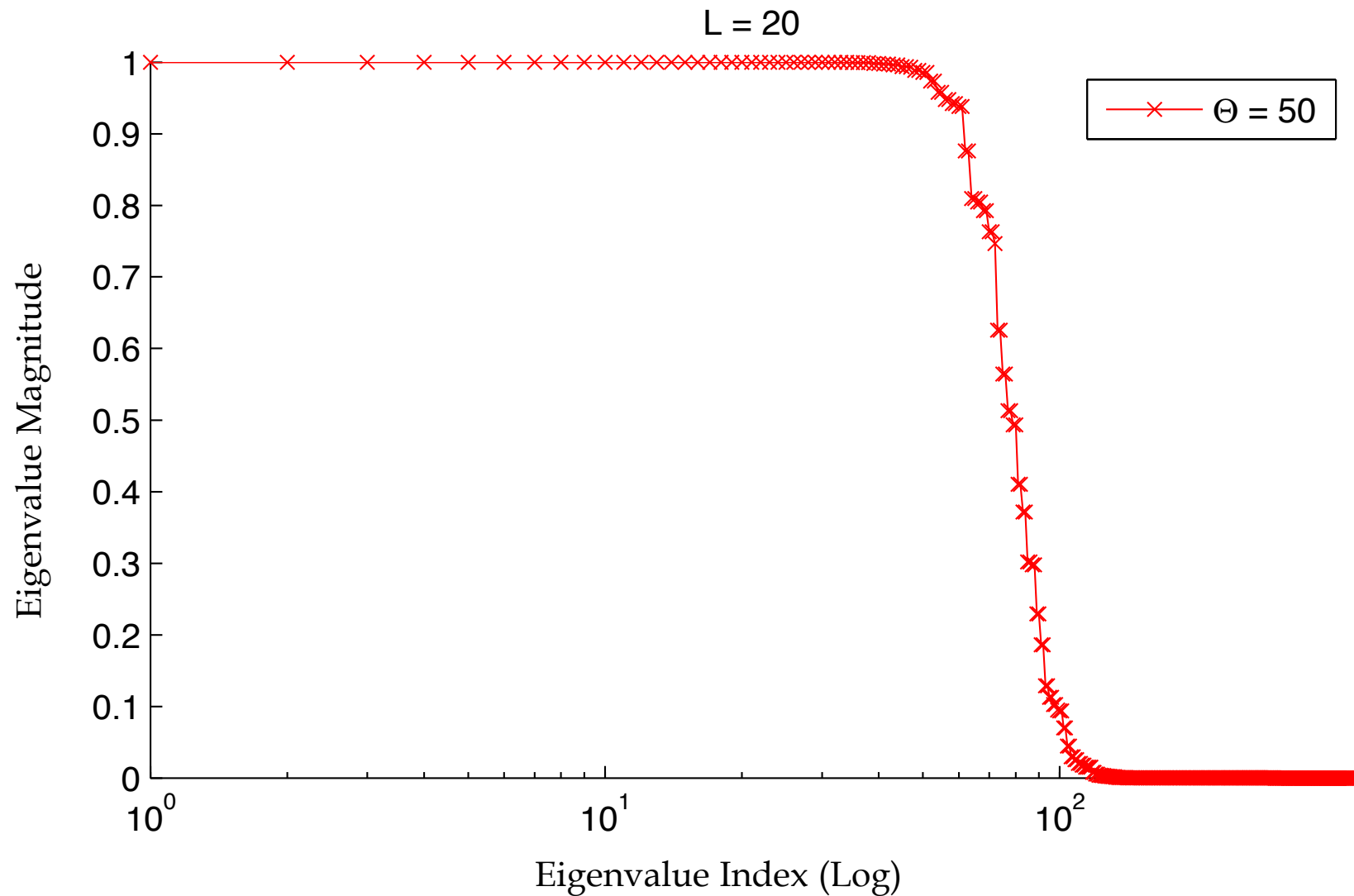
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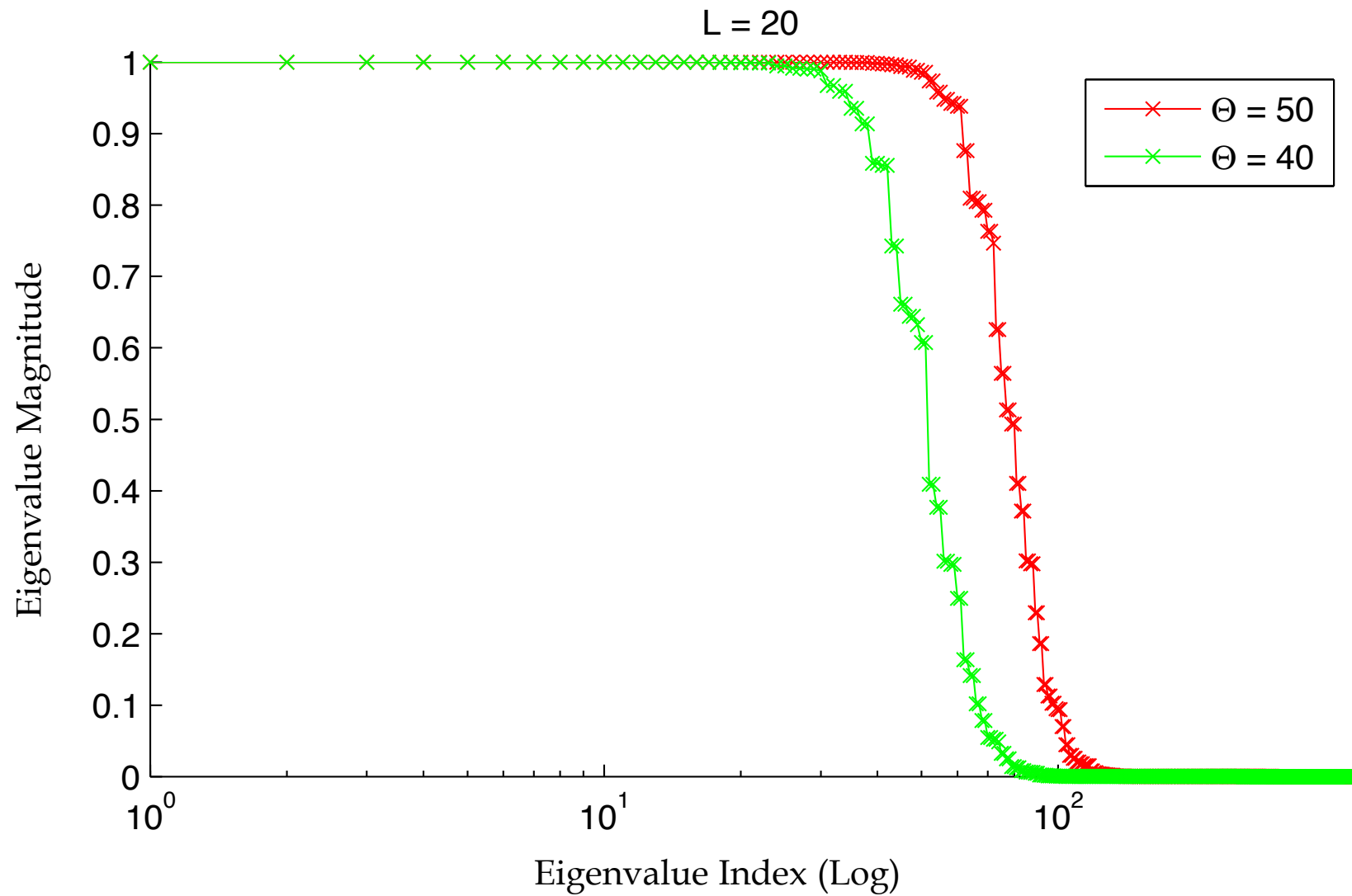
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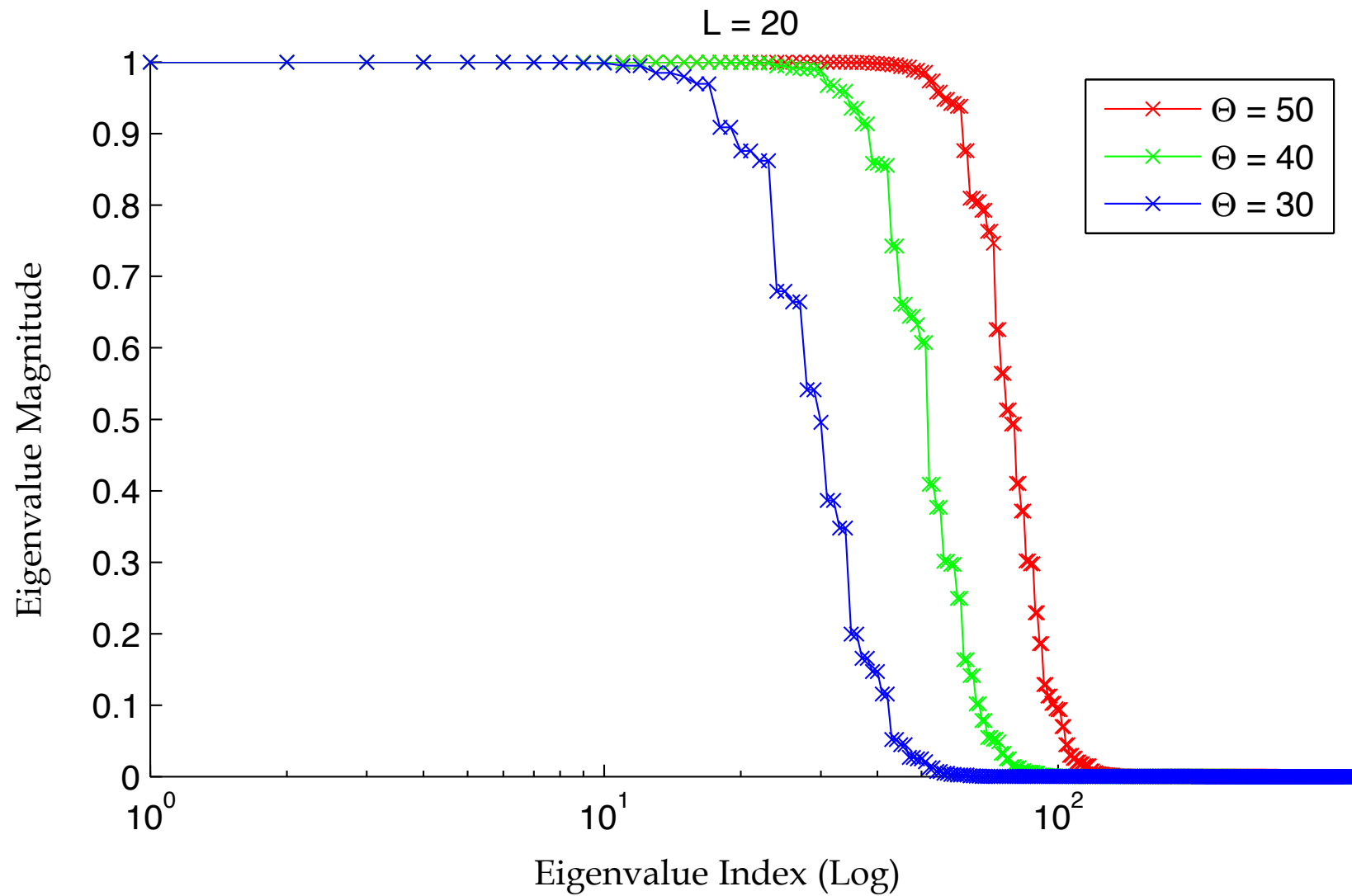
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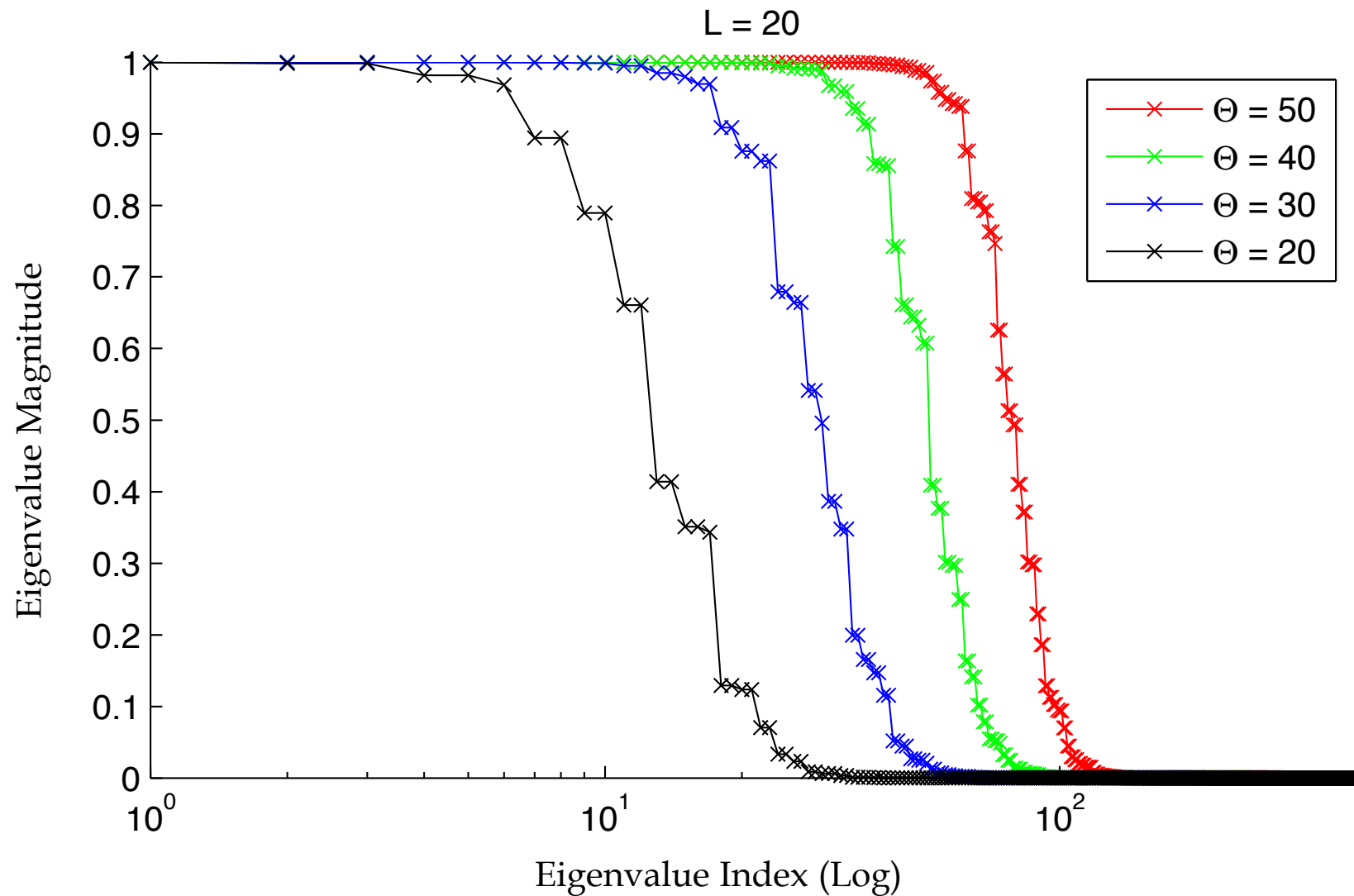
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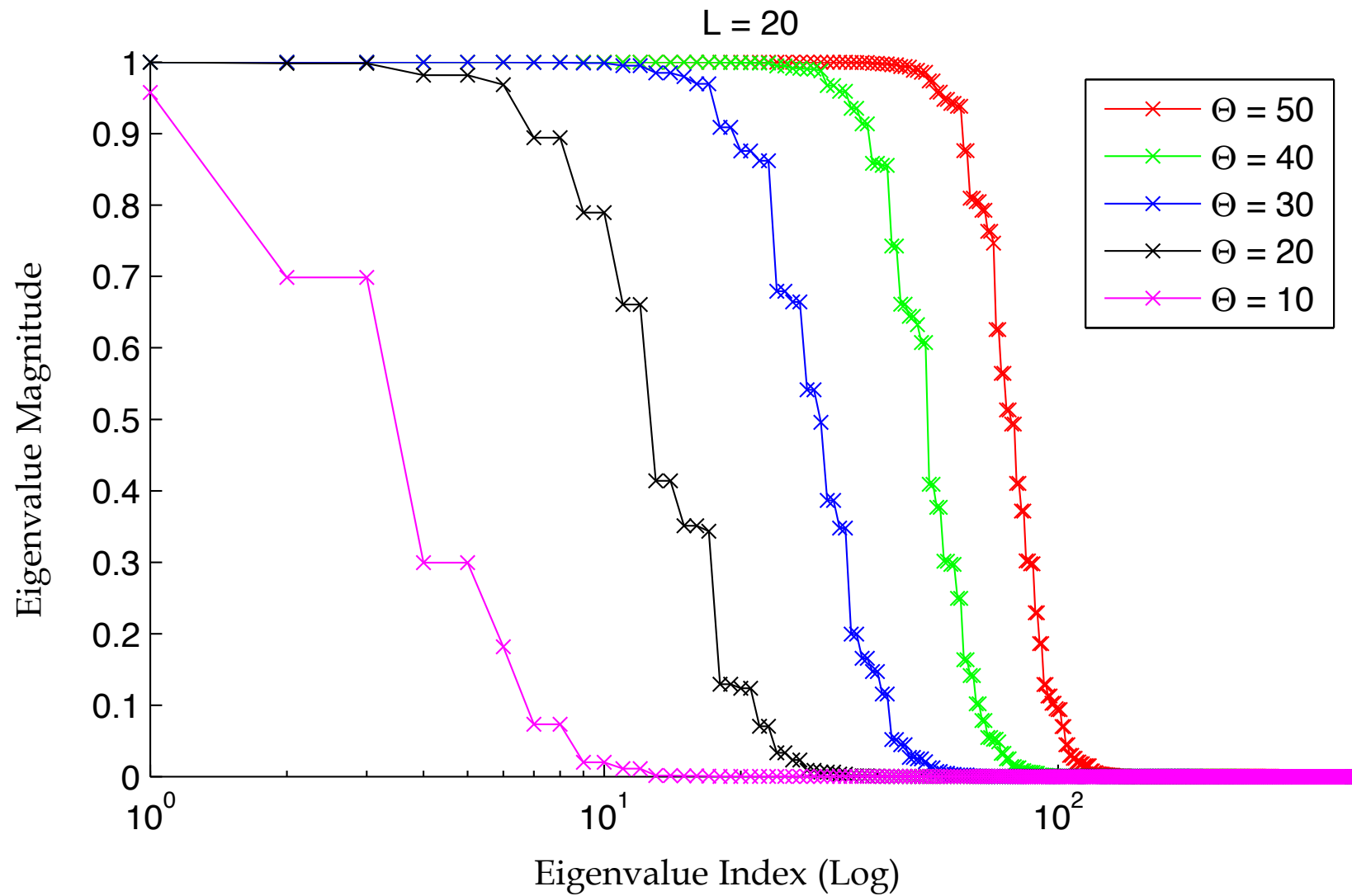
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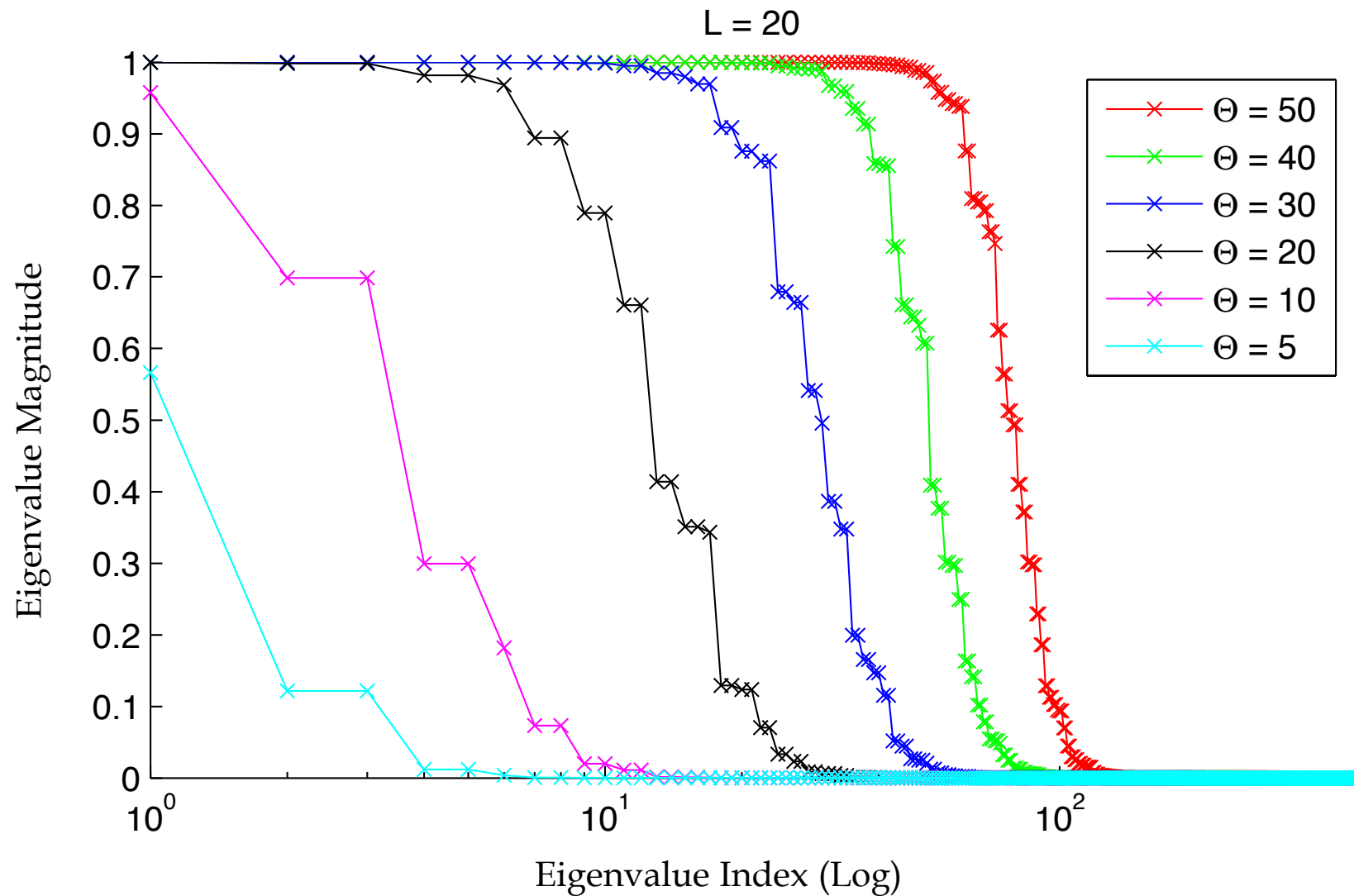
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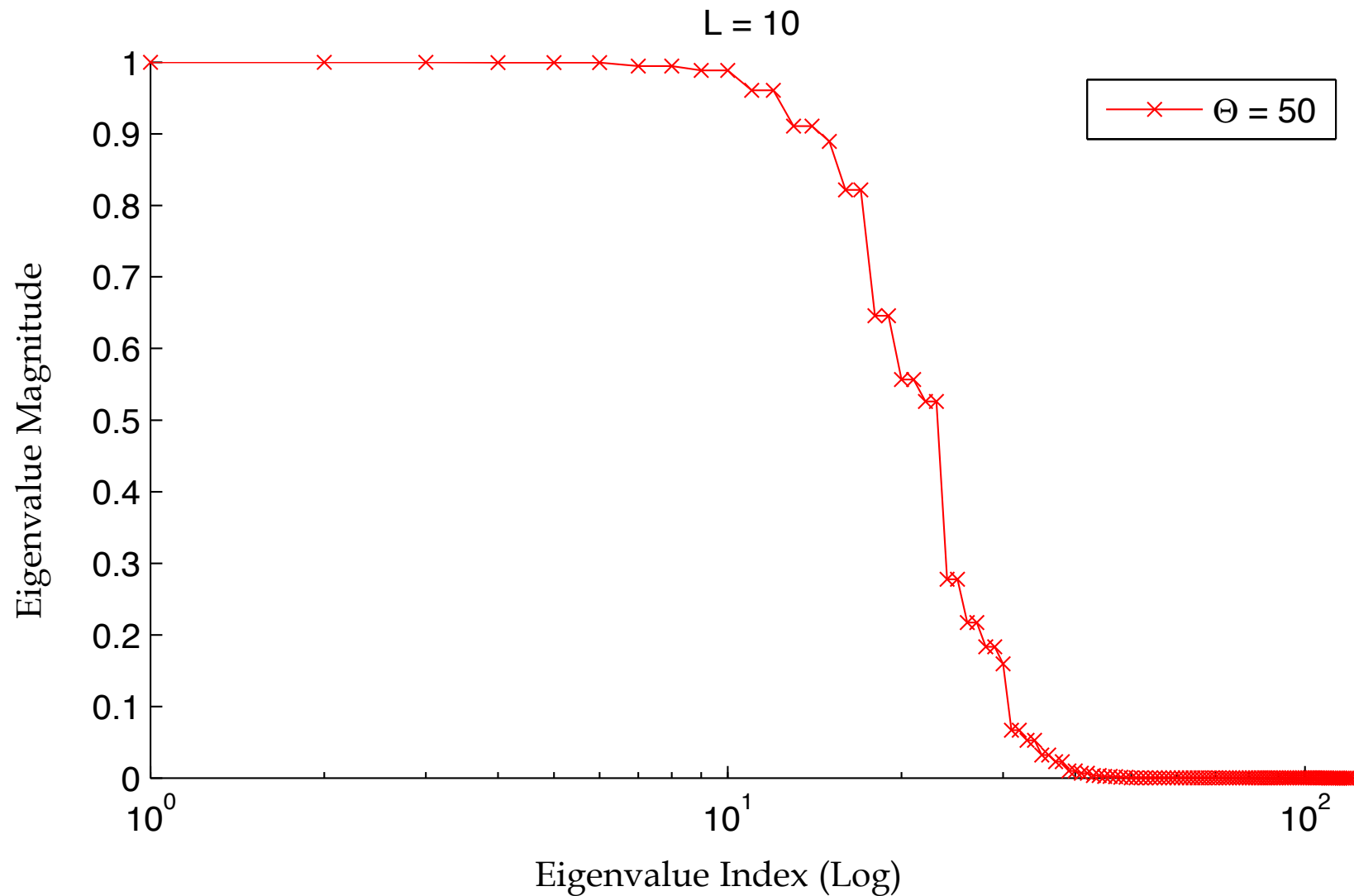
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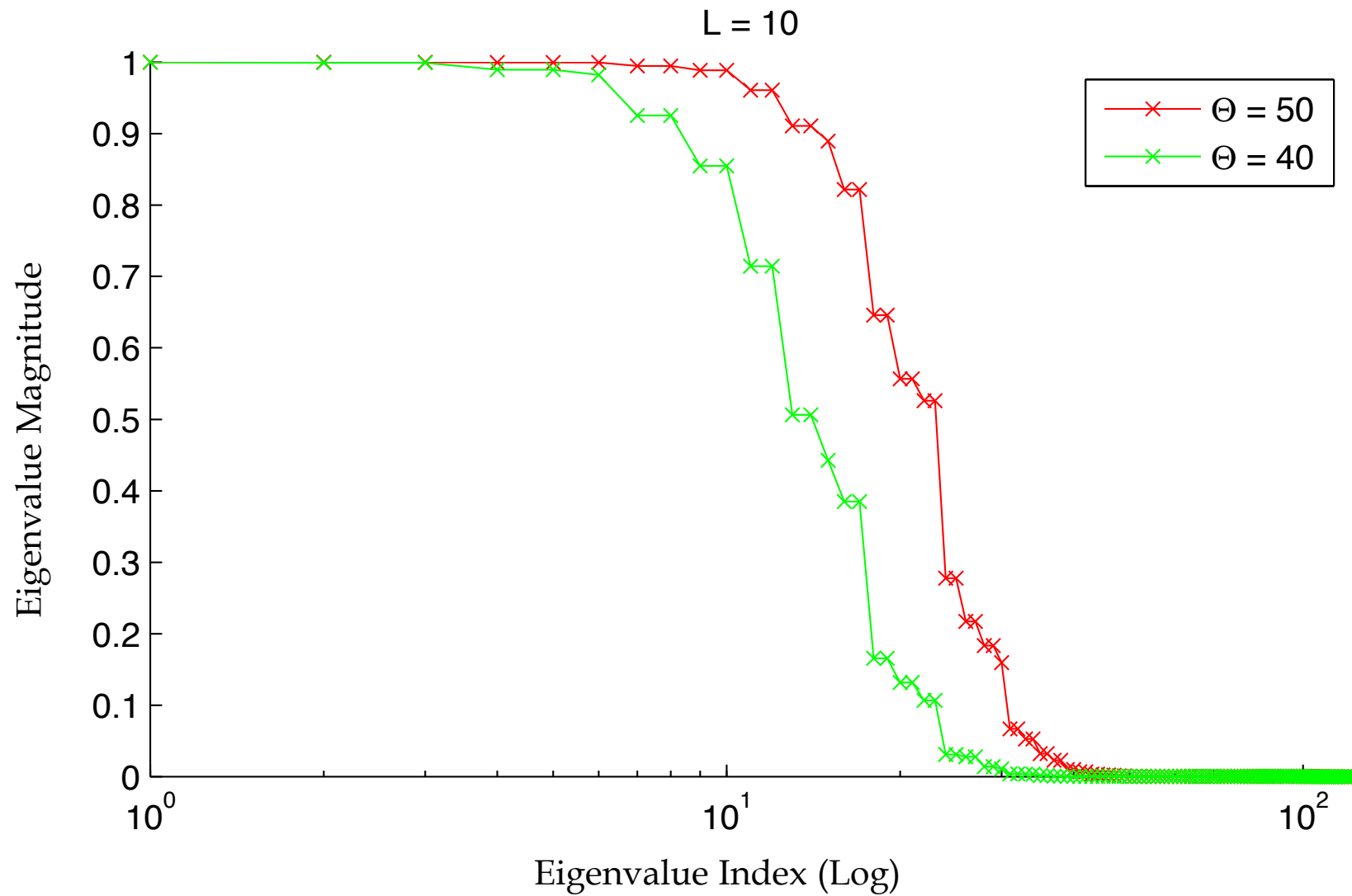
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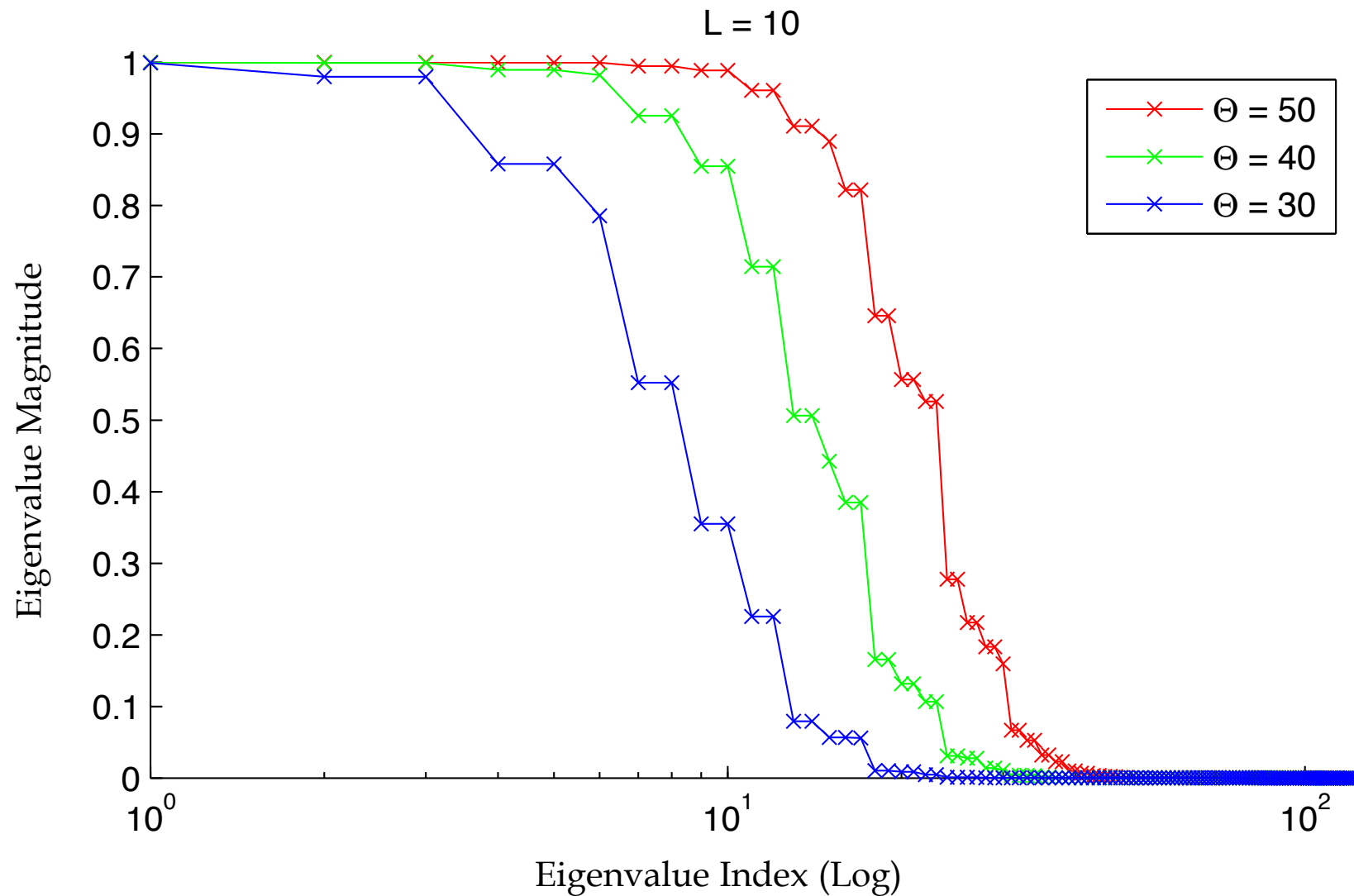
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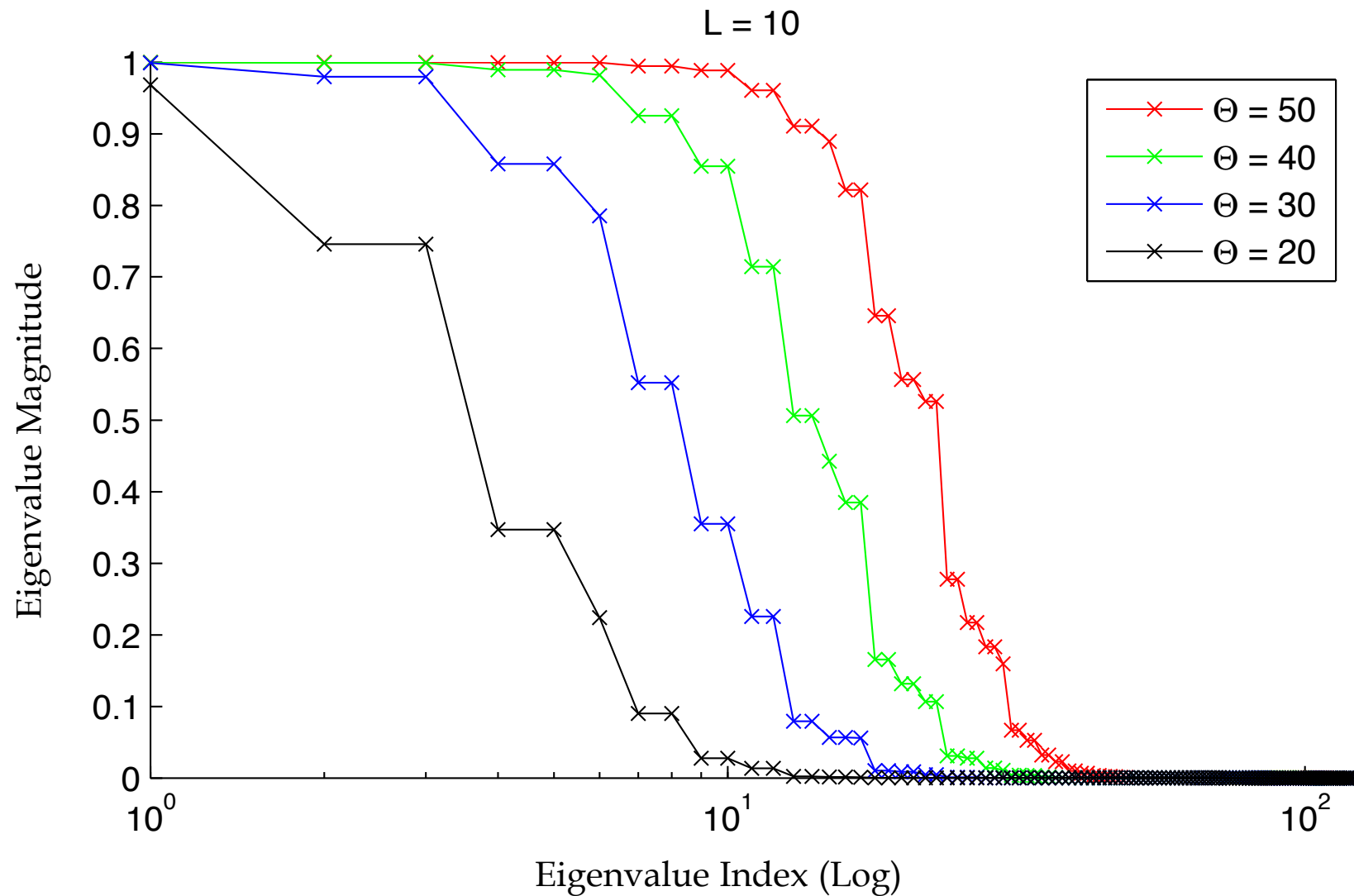
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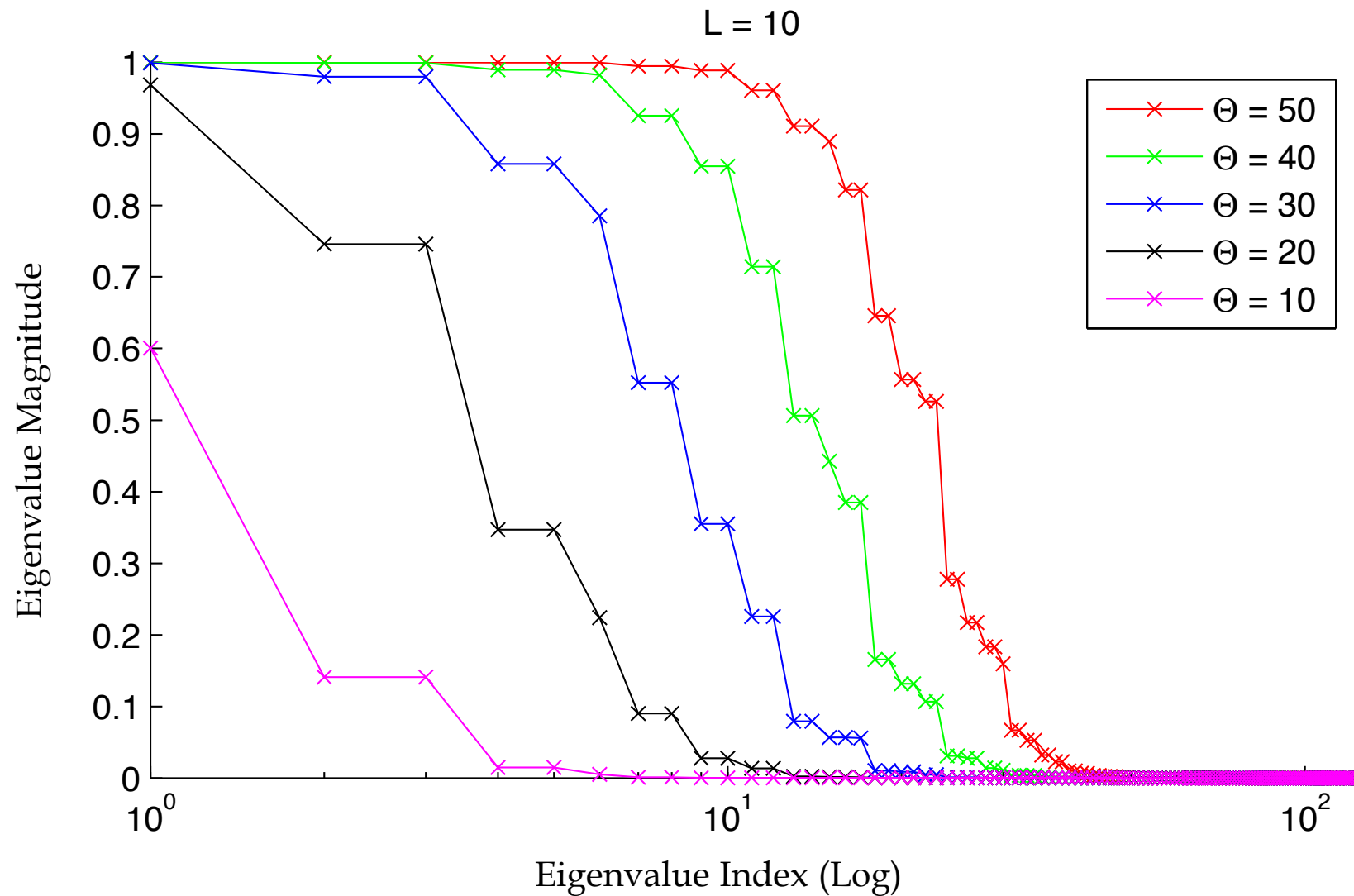
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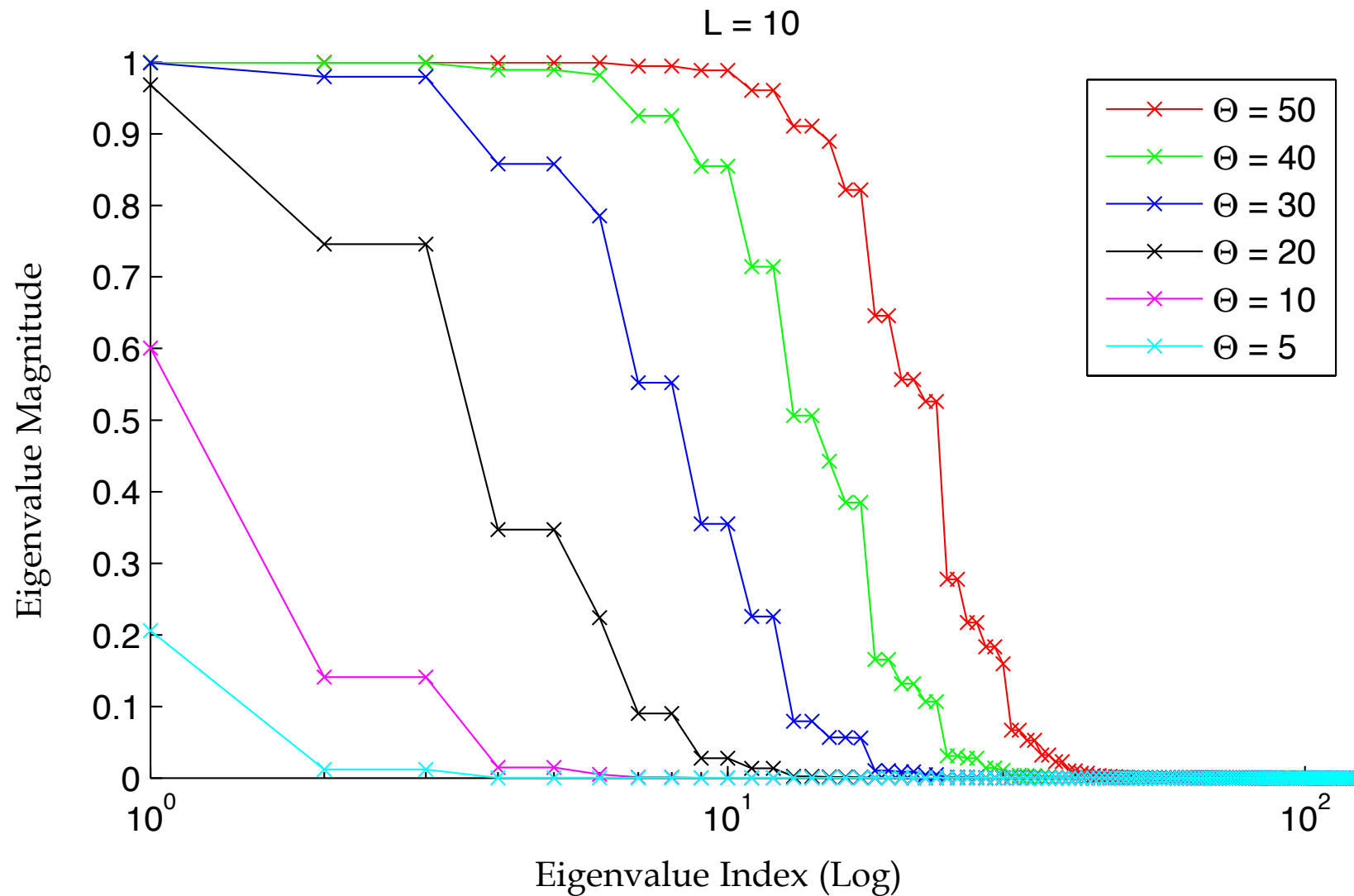
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Spatio-Spectral Concentration Theory

Spectrum (conjecture):

$$K(\epsilon) = \frac{C}{4\pi} + \left(\log \left(\frac{1 - \epsilon}{\epsilon} \right) \mathcal{B}(\partial\mathcal{U}) \right) \log(C) + o(\log C)$$

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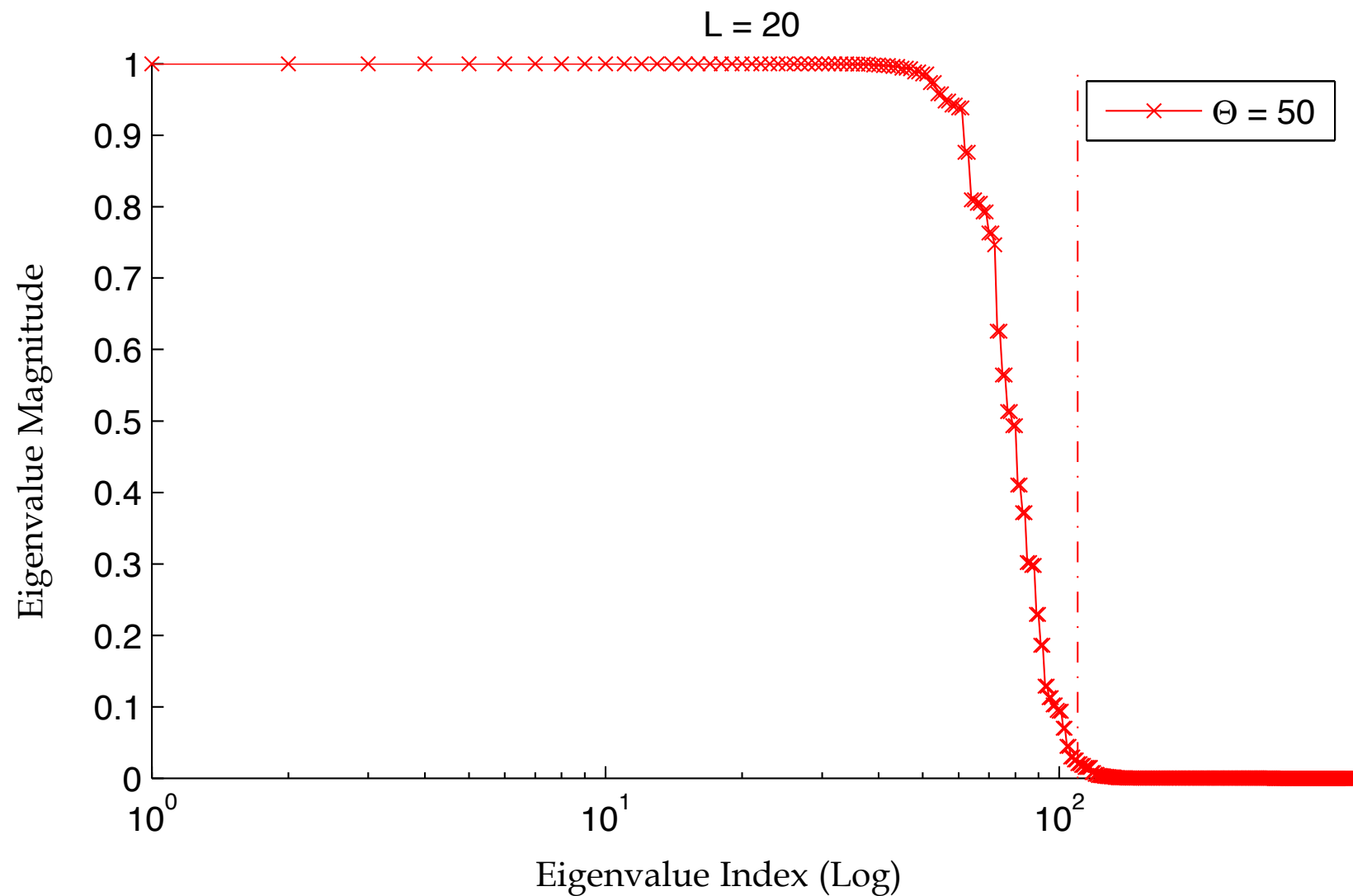
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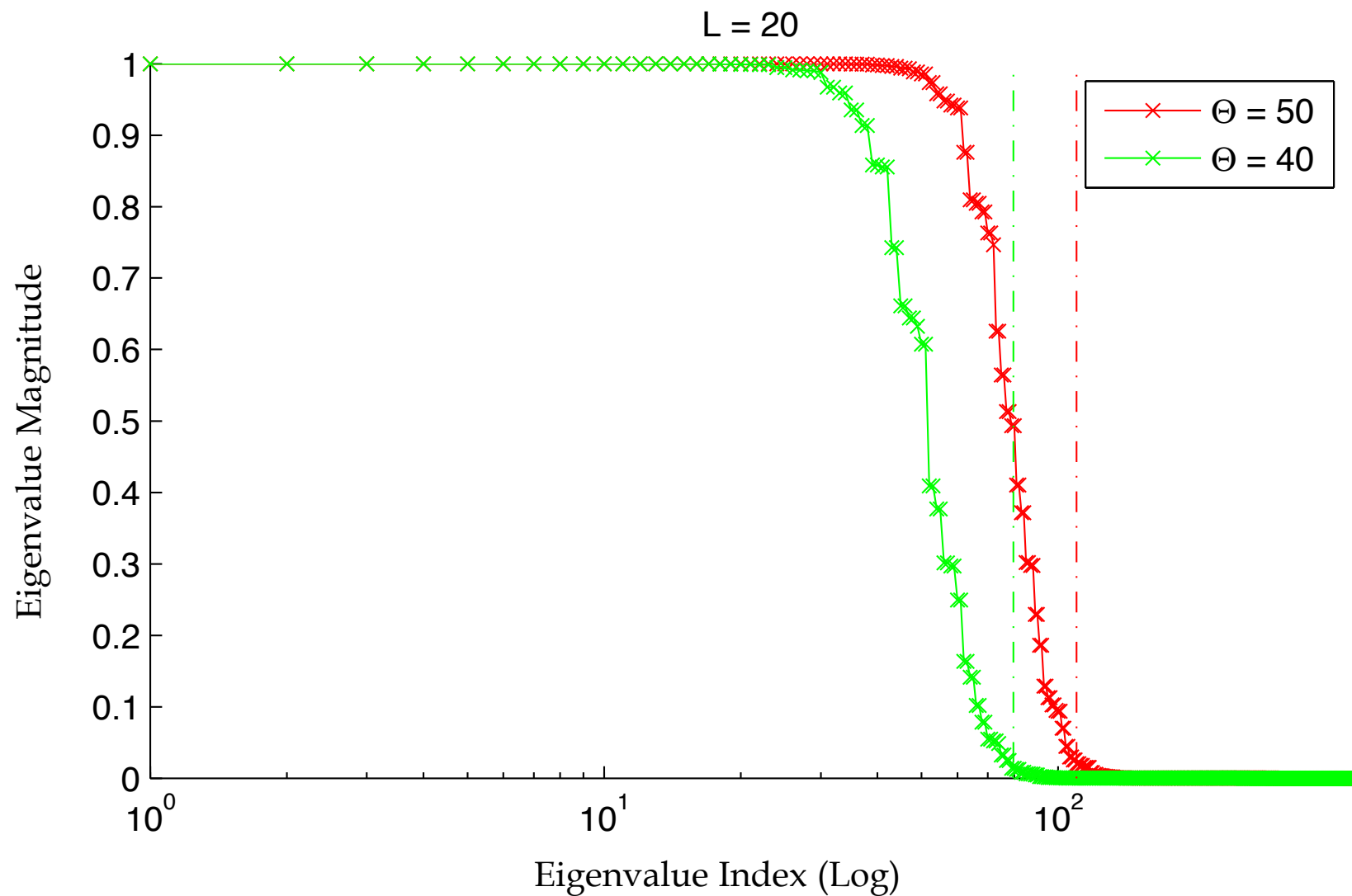
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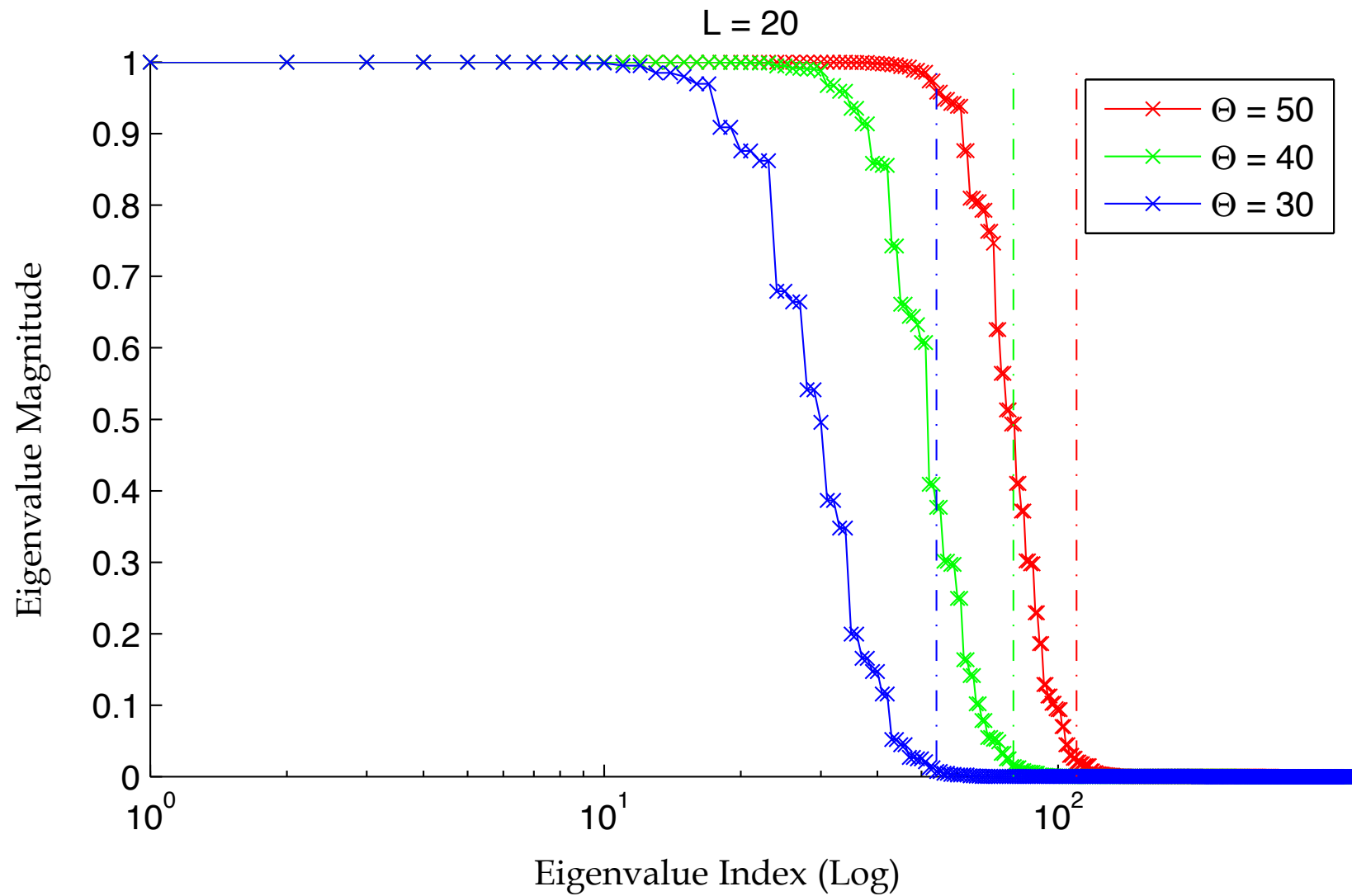
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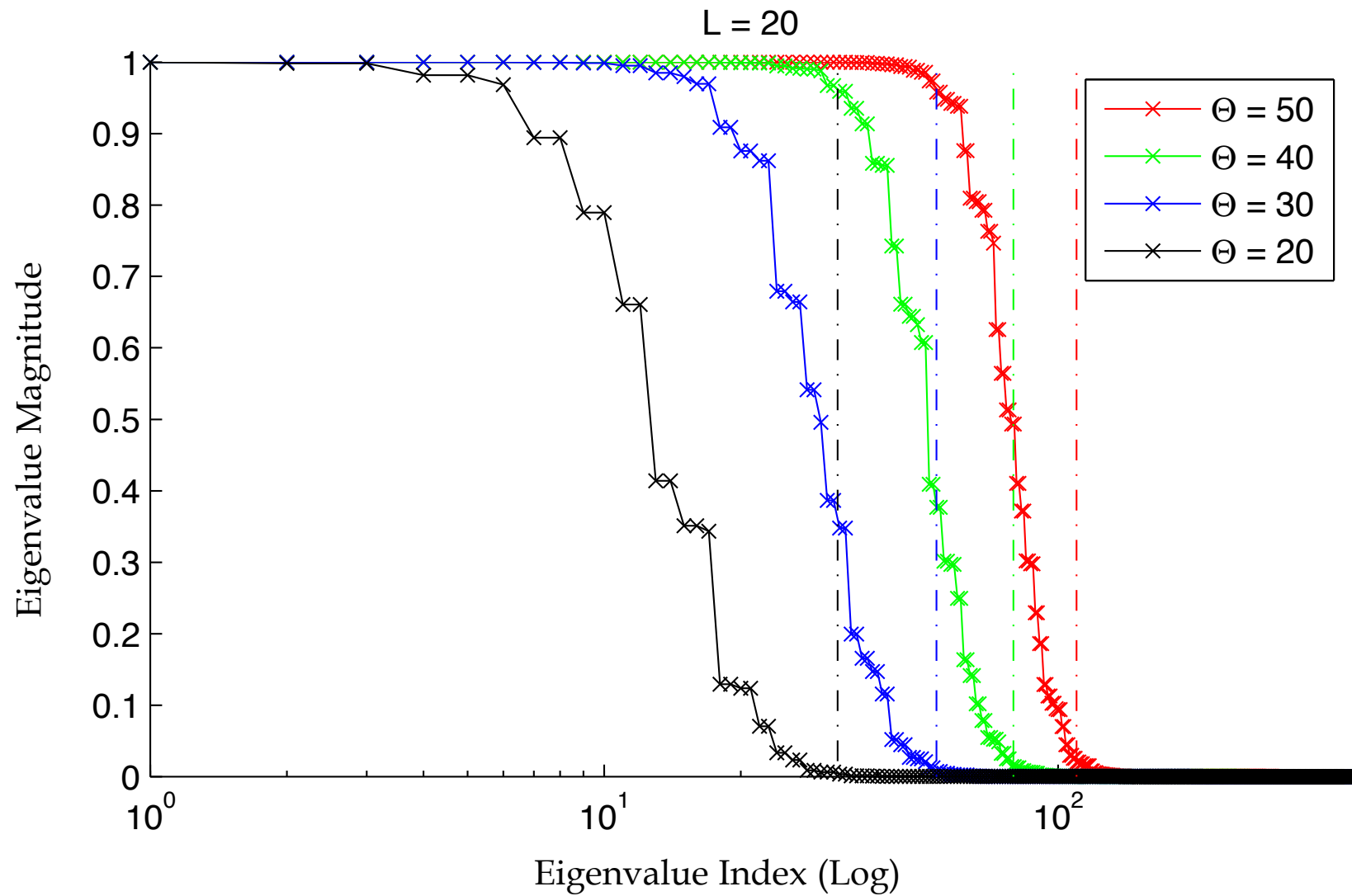
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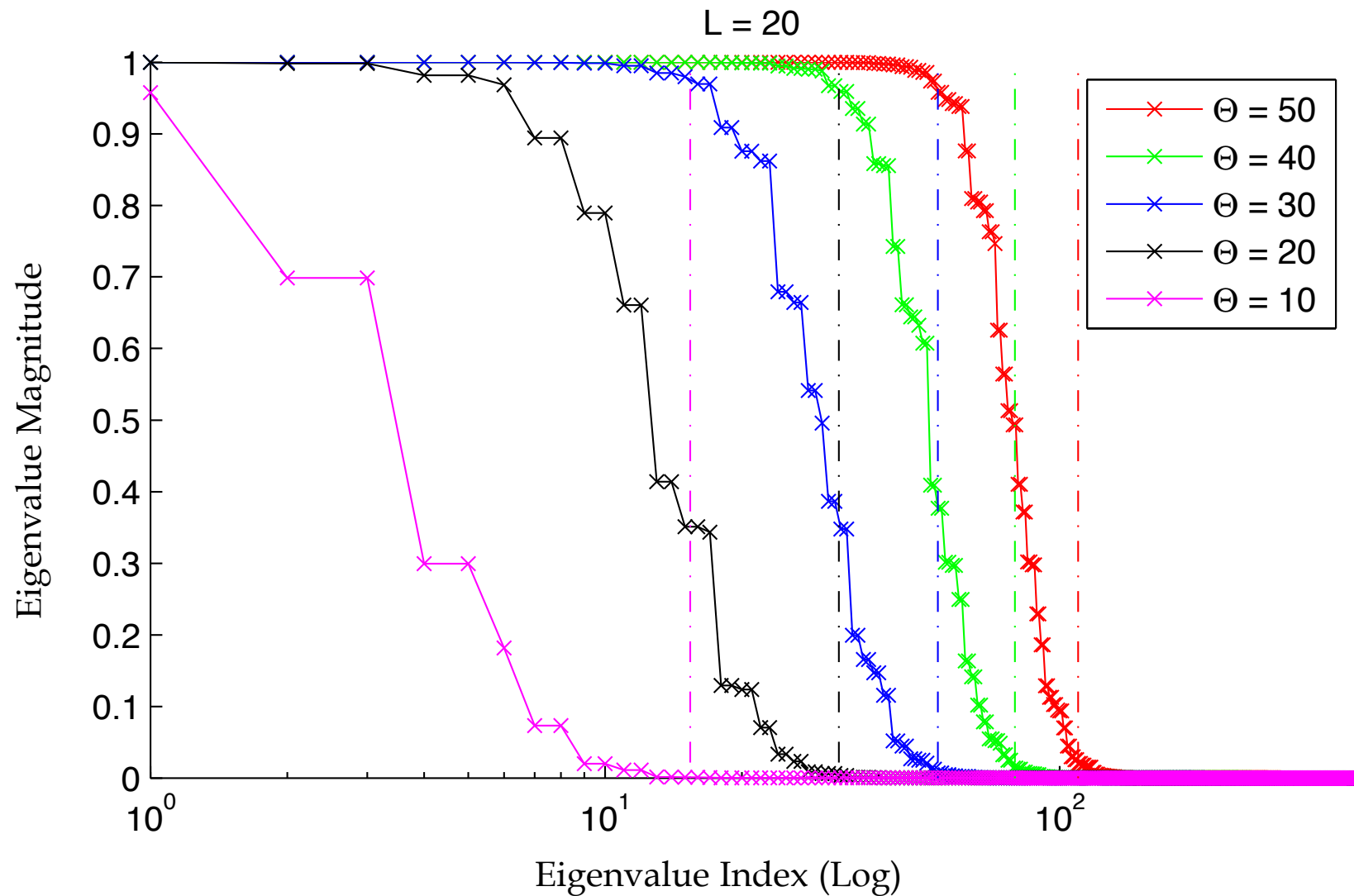
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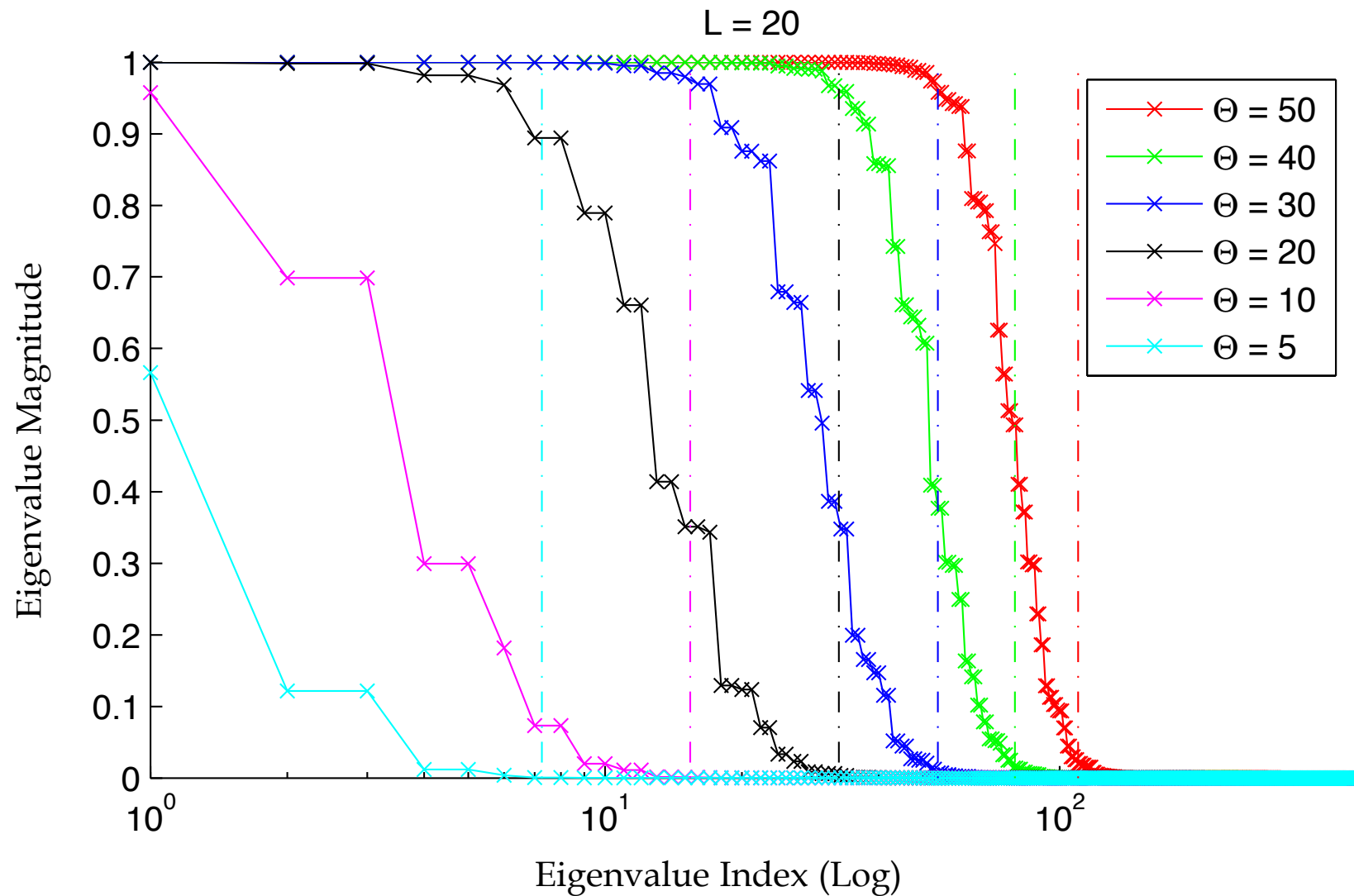
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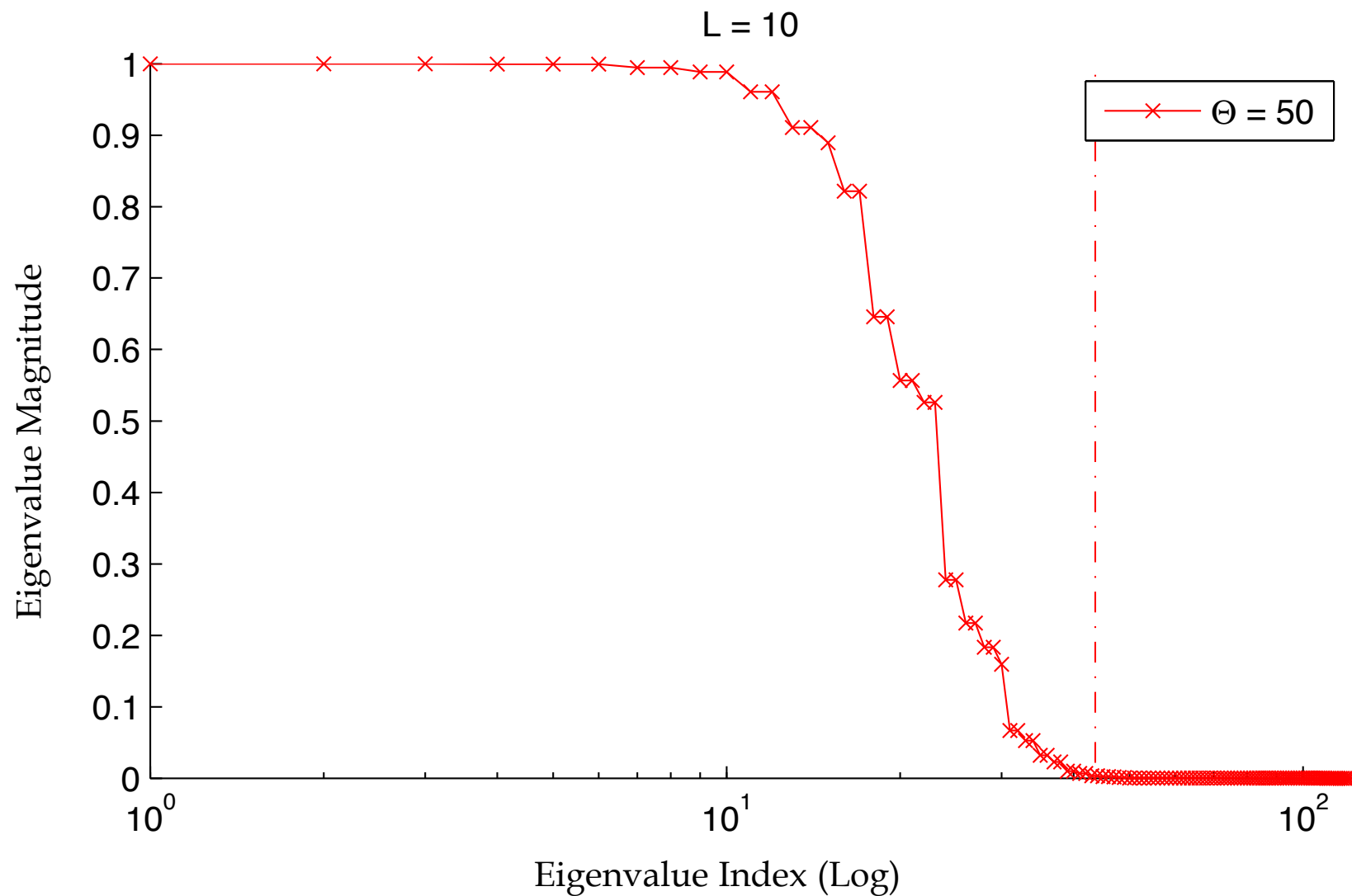
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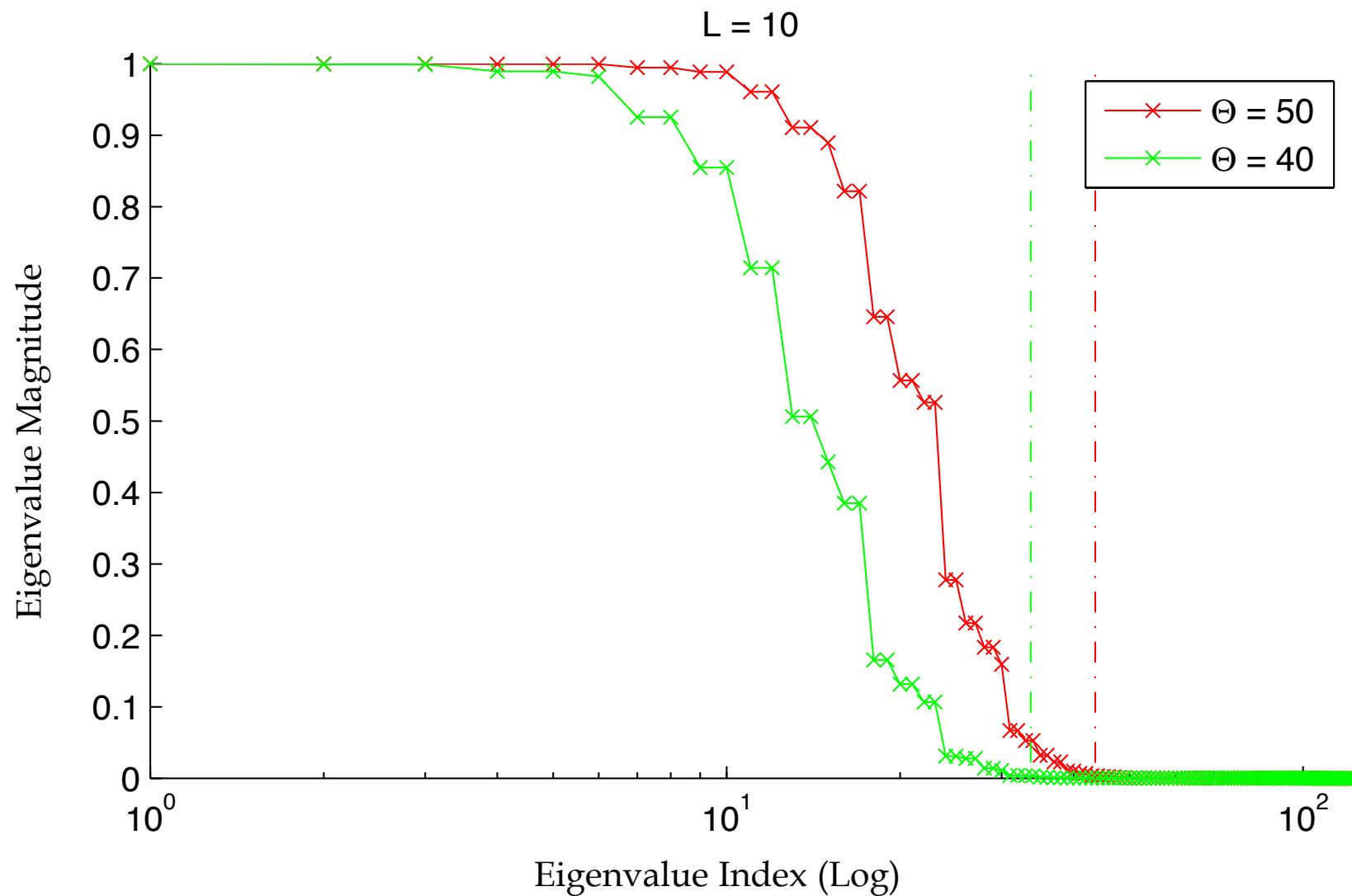
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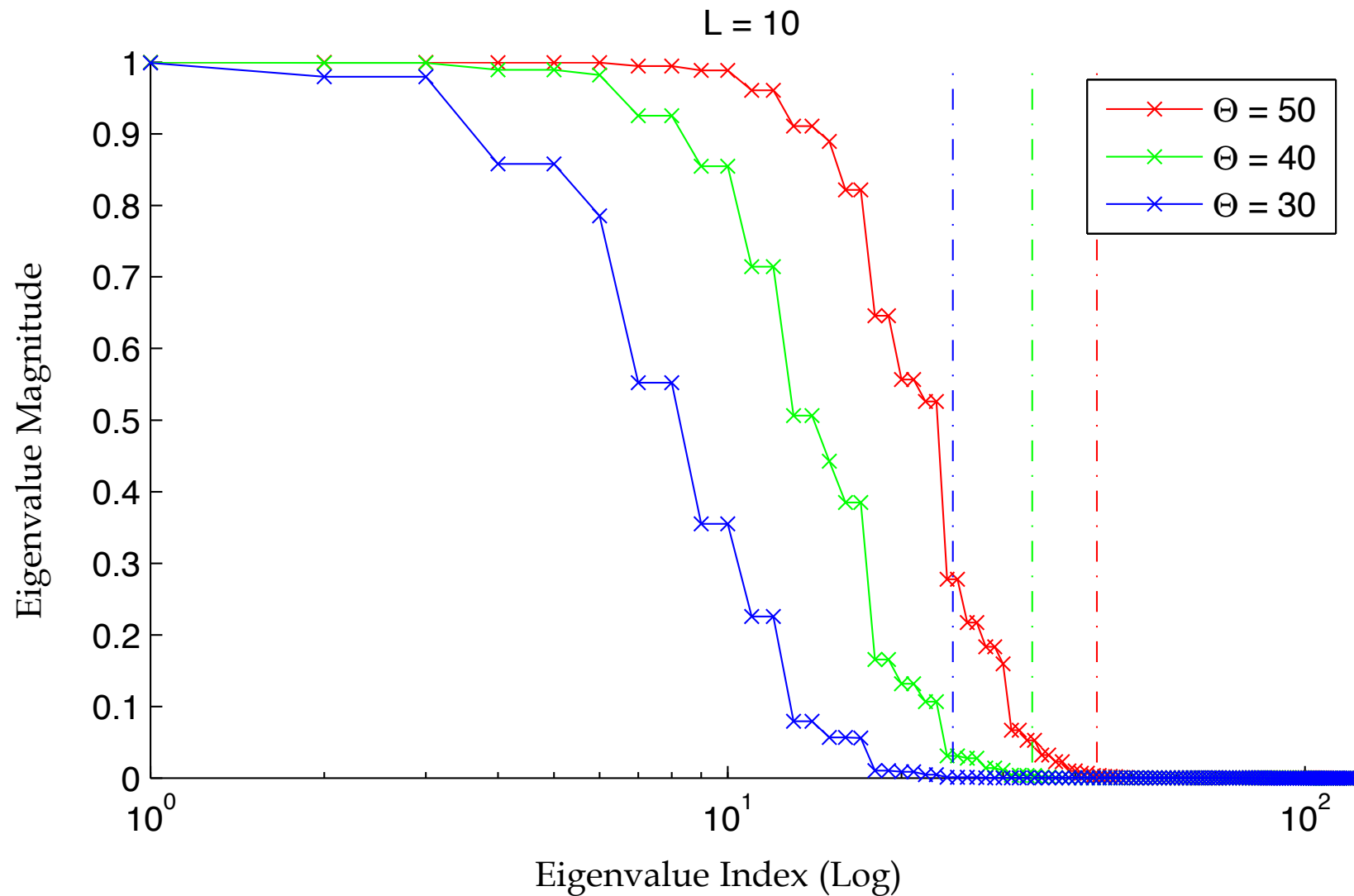
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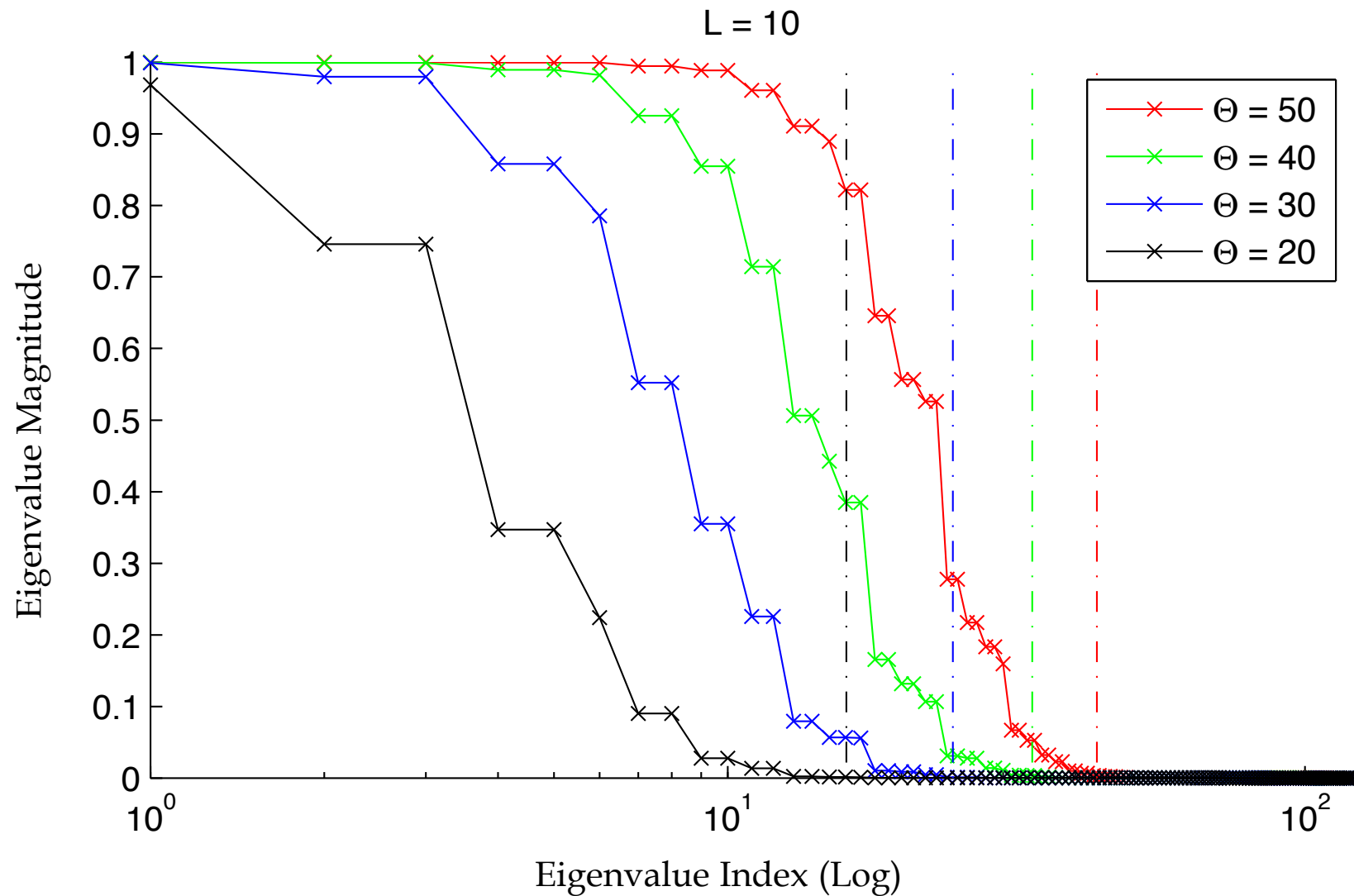
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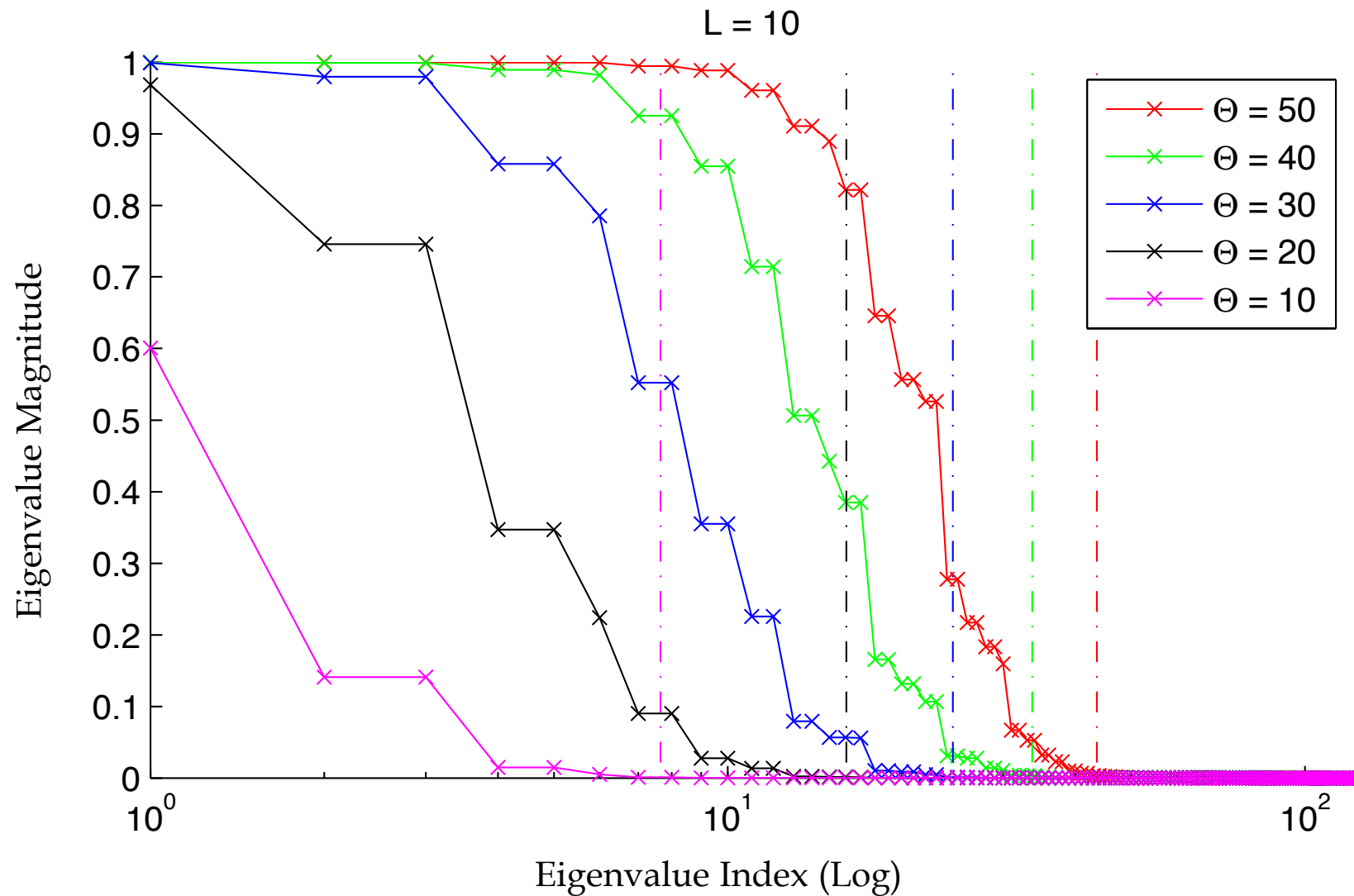
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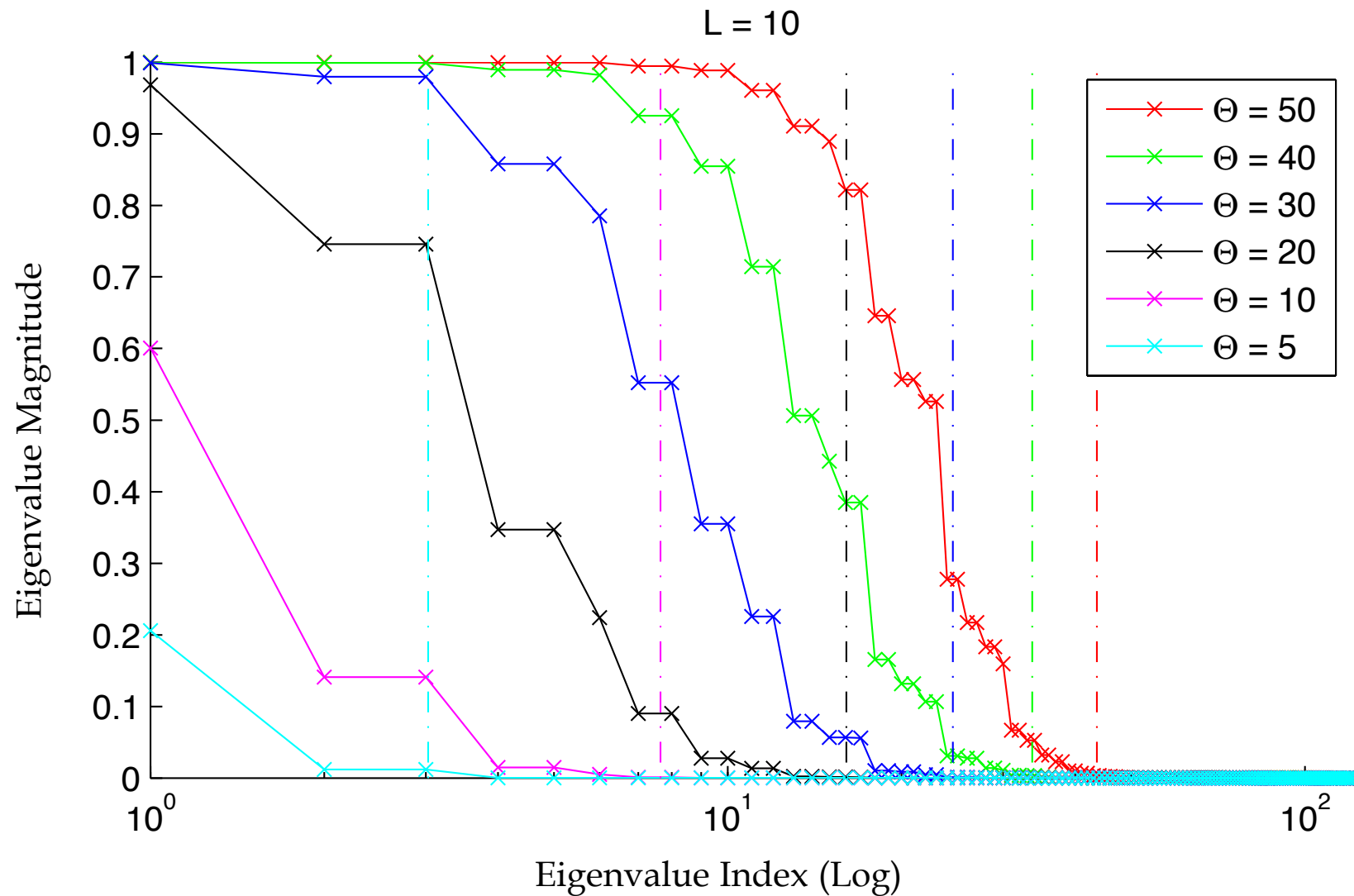
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Effective Dimension

Error is minimized if

$$B(\omega) \approx \tilde{B}(\omega) = \sum_{i=1}^K \tilde{b}_i \varphi_i \quad , \quad K \ll N$$

is approximated with $\varphi_i(\omega)$ for which

$$\|\varphi_i(\omega)\|_{\mathcal{U}}^2 \quad , \quad i = K + 1 \dots N$$

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is approximated with $\varphi_i(\omega)$ for which

$$\|\varphi_i(\omega)\|_{\mathcal{U}}^2 \quad , \quad i = K + 1 \dots N$$

\Rightarrow *Optimal basis functions are Slepian functions.*

Effective Dimension

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$$\|\varphi_i(\omega)\|_{\mathcal{U}}^2 \quad , \quad i = K + 1 \dots N$$

\Rightarrow *Optimal basis functions are Slepian functions.*

\Rightarrow *Effective dimension is given by $K(\epsilon)$.*

Effective Dimension

$$K(\epsilon) = \frac{C}{4\pi} + \left(\log \left(\frac{1 - \epsilon}{\epsilon} \right) \mathcal{B}(\partial\mathcal{U}) \right) \log(C).$$

Applications

- Transport Matrix compression.
 - Optimal cluster size.
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- Exploitation of coherence of light transport in sampling-based algorithms.

Future Work

- Boundary function for $K(\epsilon)$.

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- Slepian functions for Riemannian manifolds.

Conclusion

- Characterization of effective dimension of light transport in a local neighborhood.
 - Improved estimate for dimensionality.
 - Closed form expression for basis functions.

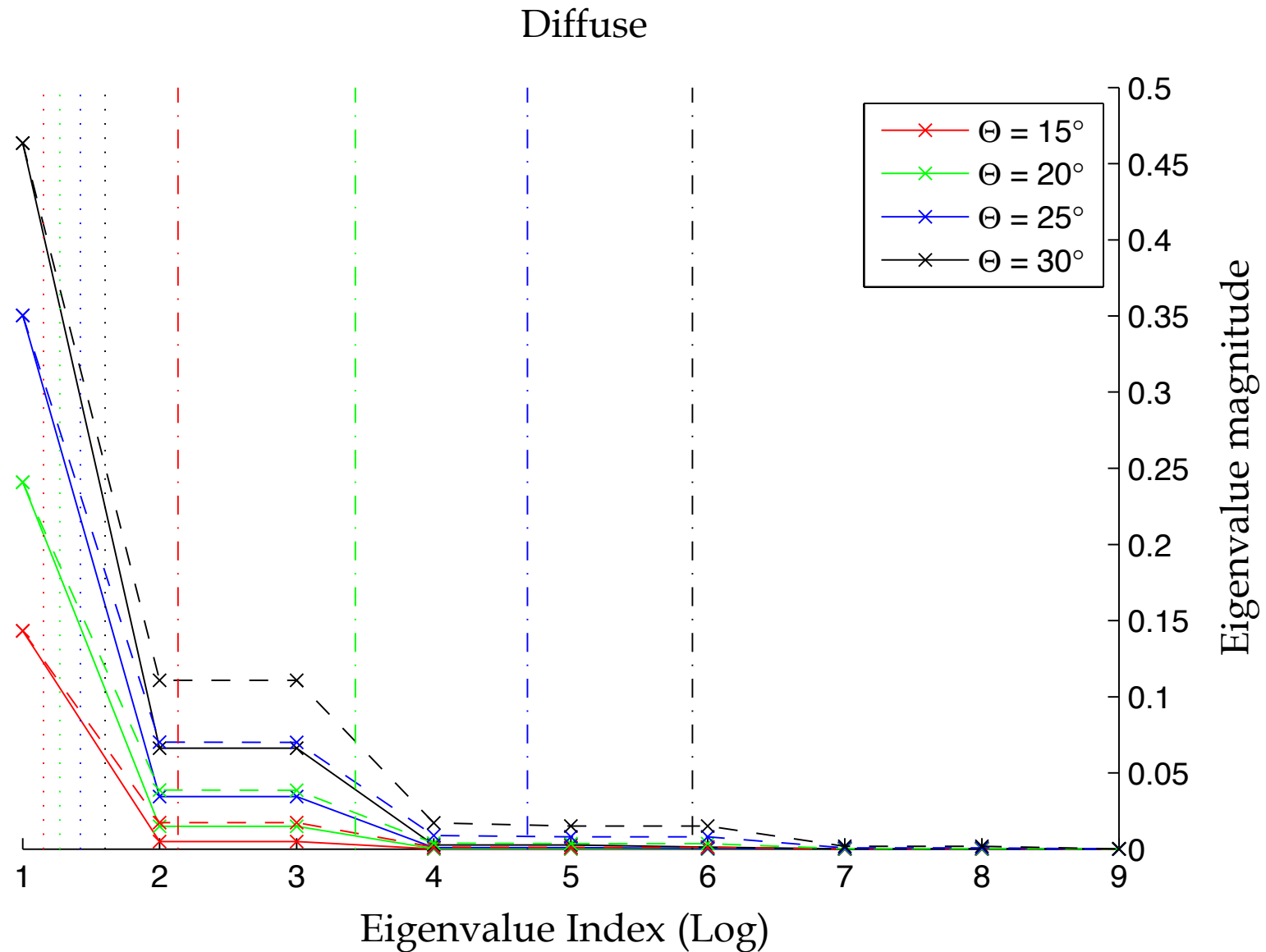
Conclusion

- Characterization of effective dimension of light transport in a local neighborhood.
 - Improved estimate for dimensionality.
 - Closed form expression for basis functions.
- Introduction of Slepian functions.
 - Efficient representation of localized signals.
 - Advantages of Spherical Harmonics.

More information and source code:

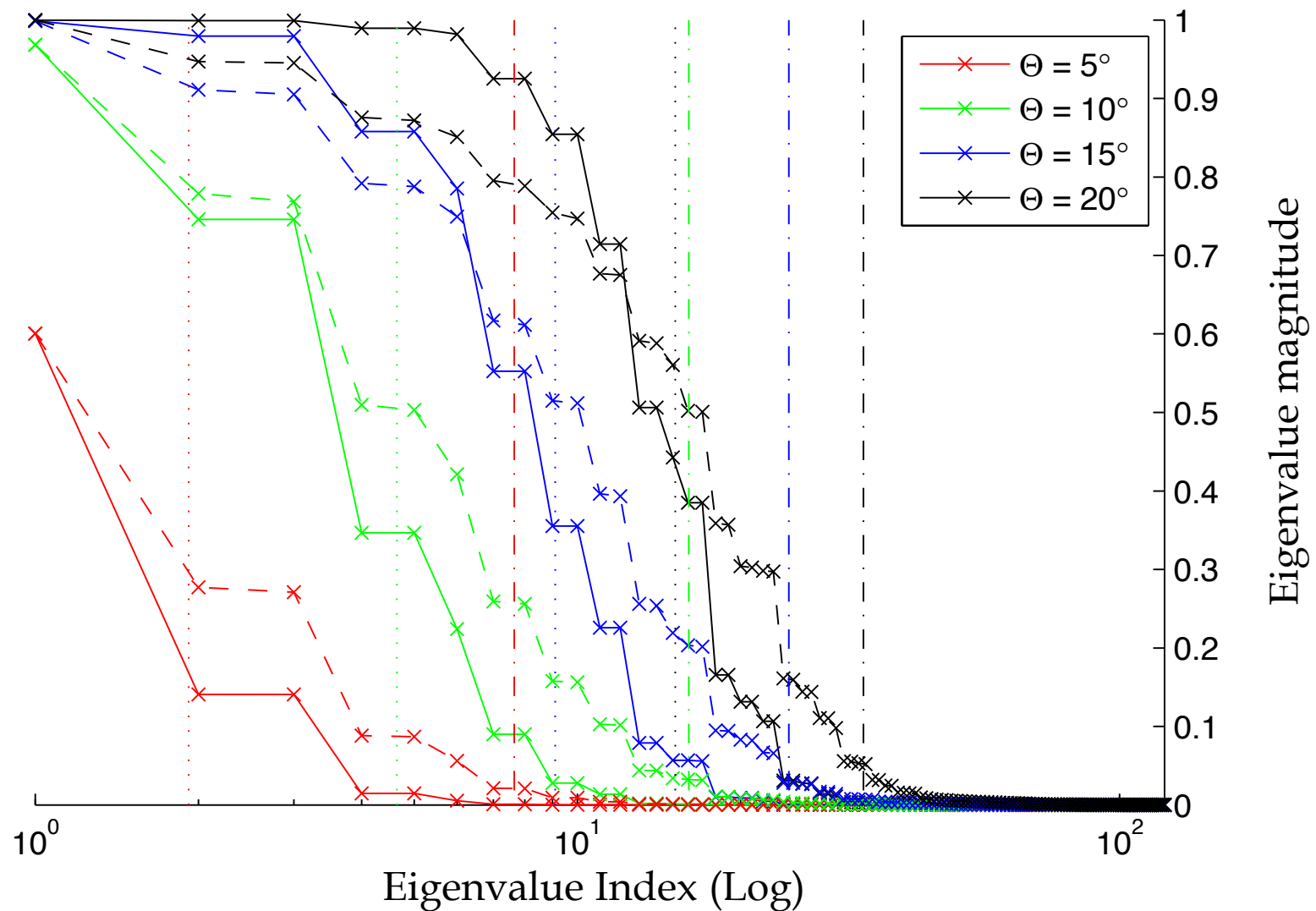
www.dgp.toronto.edu/people/lessig/effective-dimension/

Effective Dimension



Effective Dimension

Phong, $s = 132$



Related Work

- Coherence has been exploited in precomputed radiance transfer for some time.¹
- Mahajan et al.² studied the effective dimension in flatland and discussed extension to 3D.
- Shading equation has been studied previously by Ramamoorthi and co-workers³ using assumptions similar to ours.

¹ Liu X, Sloan P, Shum H, Snyder J. *All-Frequency Precomputed Radiance Transfer for Glossy Objects*. In: Eurographics Symposium on Rendering 2004.; 2004.; Sloan P, Hall J, Hart J, Snyder J. *Clustered Principal Components for Precomputed Radiance Transfer*. In: SIGGRAPH '03: ACM SIGGRAPH 2003 Papers. New York, NY, USA: ACM Press; 2003:382-391.

² Mahajan D, Shlizerman IK, Ramamoorthi R, Belhumeur P. *A Theory of Locally Low Dimensional Light Transport*. ACM Trans. Graph. 2007;26(3) (Proceedings of ACM SIGGRAPH 2007):1-9.

³ Ramamoorthi R, Hanrahan P. *A Signal-Processing Framework for Inverse Rendering*. International Conference on Computer Graphics and Interactive Techniques. 2001. Available at: <http://portal.acm.org/citation.cfm?id=383271>; Ramamoorthi R, Hanrahan P. *A Signal-Processing Framework for Reflection*. ACM Transactions on Graphics (TOG). 2004;23(4).; Ramamoorthi R, Koudelka M, Belhumeur P. *A Fourier Theory for Cast Shadows*. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2005;27(2).