

Random template banks and relaxed lattices

or: why it's efficient to be lazy

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Albert-Einstein-Institut

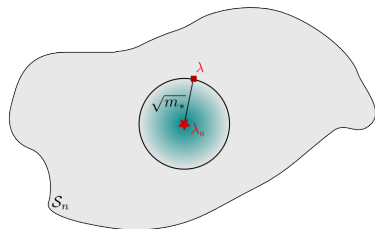
Golm-Han Group meeting, 02 Sep 2008

Paper for comment: [LIGO-P080090-00-Z](#)



Introduction: metric & template banks

Matched filtering with templates $h(t; \lambda)$



Signal in $\lambda_s \in \mathcal{S}_n$

targeting $\lambda = \lambda_s + \Delta\lambda$

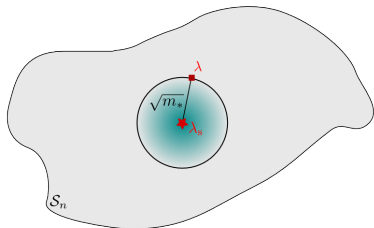
loss: $\text{SNR}(\lambda) < \text{SNR}(\lambda_s)$

mismatch $m \equiv 1 - \frac{\text{SNR}(\lambda)}{\text{SNR}(\lambda_s)}$



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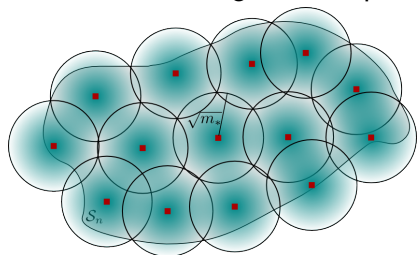
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Template bank of given mismatch m_*

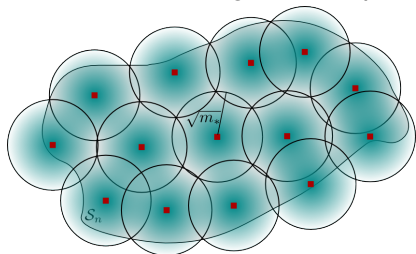
Each template $\lambda_{(k)}$ covers a sphere $|\lambda - \lambda_{(k)}|^2 \leq m_*$

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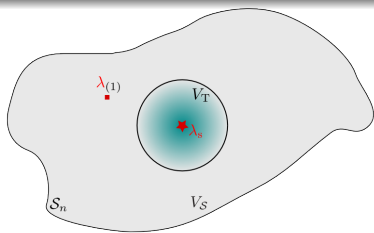
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Number of templates: $N = \theta m_*^{-n/2} V_S$
(normalized thickness θ of a covering)



Random template bank construction



Place **one** template randomly

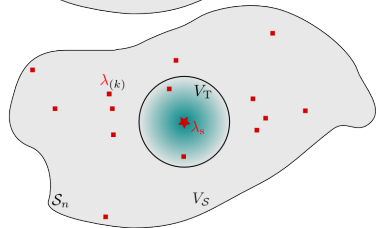
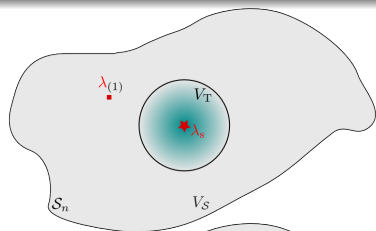
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(covered volume $V_T = m_*^{n/2} V_n$)



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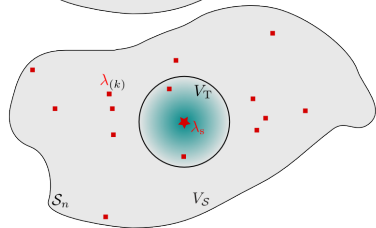
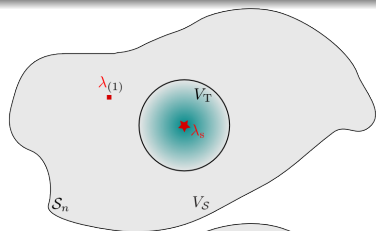
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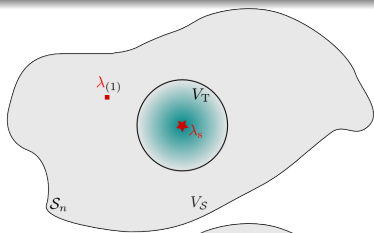
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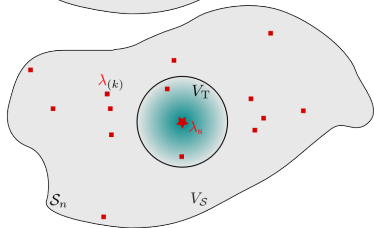


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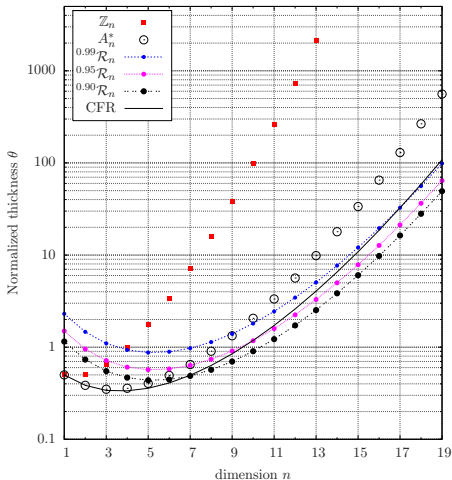
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☞ determines $N_{\mathcal{R}}(\eta, m_*) \approx \underbrace{\frac{1}{V_n} \ln \left(\frac{1}{1 - \eta} \right)}_{\text{thickness } \theta(\eta)} m_*^{-n/2} V_S$



Properties of random template banks

$\eta\mathcal{R}_n(m_*)$: Random-template bank for mismatch m_* and covering confidence η : thickness $\theta(\eta) = \frac{1}{V_n} \ln\left(\frac{1}{1-\eta}\right)$

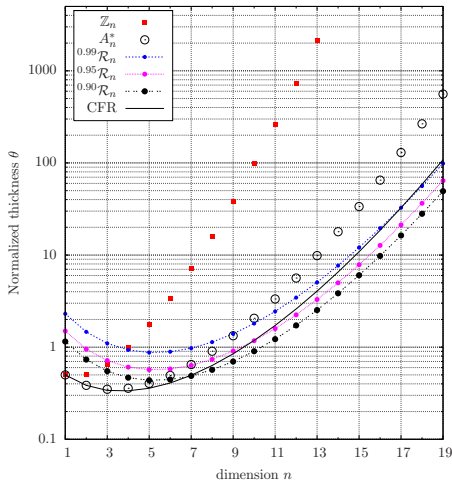


- $\eta\mathcal{R}_n$ beats best lattice covering at higher dimensions
- beats theoretical lower limit (CFR) on covering thickness
- possible because **not** strictly a covering
- major practical advantage: simplicity
- if non-constant metric $g_{ij}(\lambda)$: sampling density $\propto \sqrt{\det g_{ij}}$



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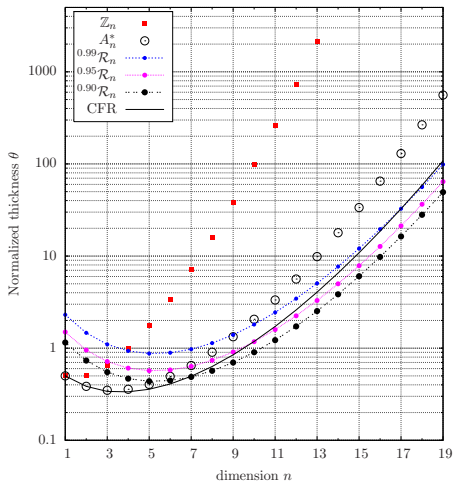


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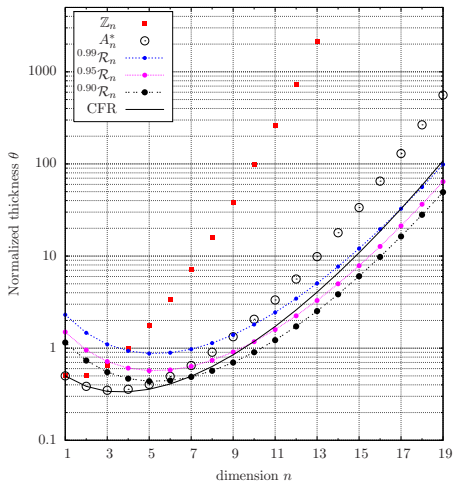


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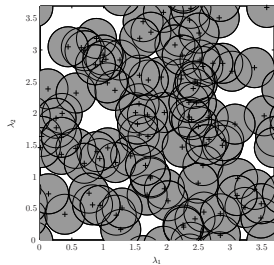


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Spatial coverage and worst-case mismatch

example: ${}^{0.9}\mathcal{R}_n(0.1)$



$\eta\mathcal{R}_n$ provide **incomplete coverage**

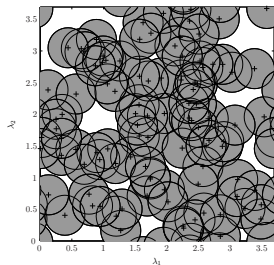
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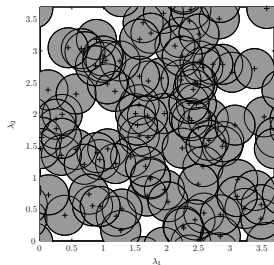
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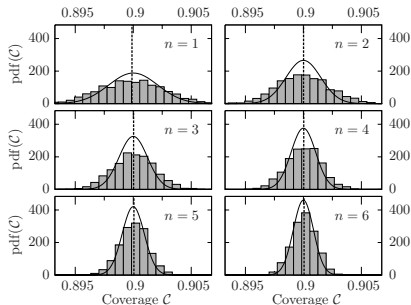
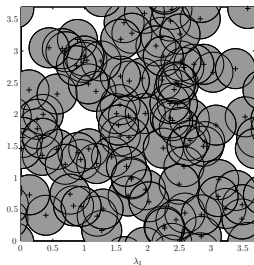
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${}^{0.9}\mathcal{R}_n$ Monte-Carlo simulations for $N_{\mathcal{R}} = 10^4$



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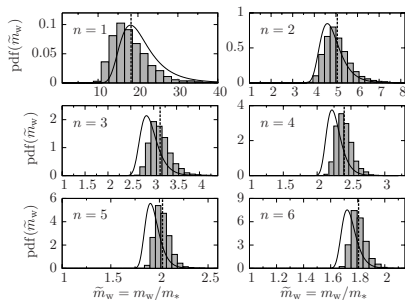
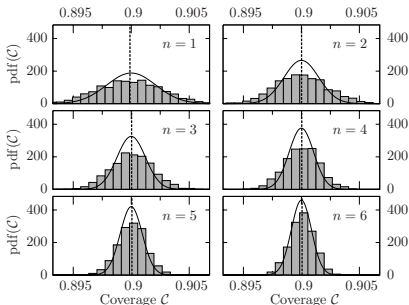
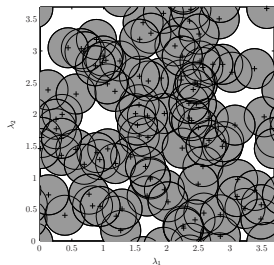
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Relaxed lattice coverings

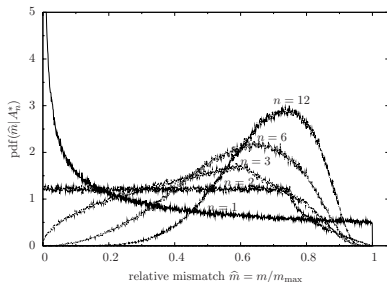
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☞ give up complete coverage for lattices



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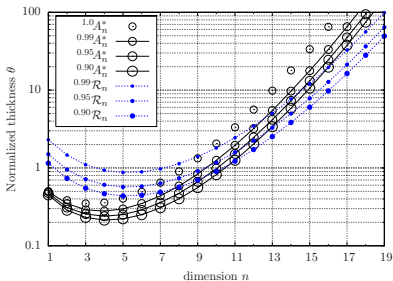
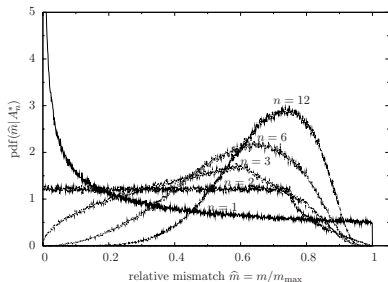
Use MC-simulation to find $\text{pdf}(m|\Lambda_n)$: find “relaxed” mismatch m_* such that $P(m \leq m_*) = \eta \implies$ allows to use coarser lattice



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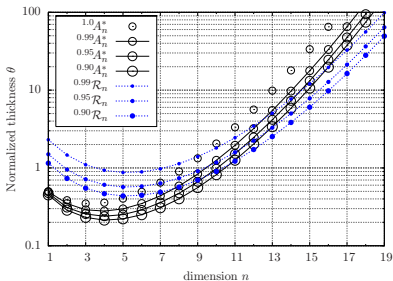
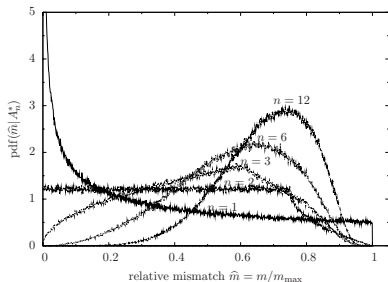
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- 👉 Very efficient, but only at lower dimensions ($n \lesssim 10$)
- 👉 more difficult than $\eta\mathcal{R}_n$, especially with varying metric $g_{ij}(\lambda)$

