Fast graph kernel with optical random features

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1: Summary

The **graphlet kernel**is a classical method in graph classification. It however suffers from a high computation cost due to the isomorphism test it includes.

We propose to leverage kernel random features within the graphlet framework, and establish a theoretical link with the MMD metric. If this method can still be prohibitively costly for usual random features, we then incorporate optical random features that can be computed in *constant time*.

3: Efficiency of $GSA - \varphi$ with φ_{RF} w.r.t. the MMD metric.

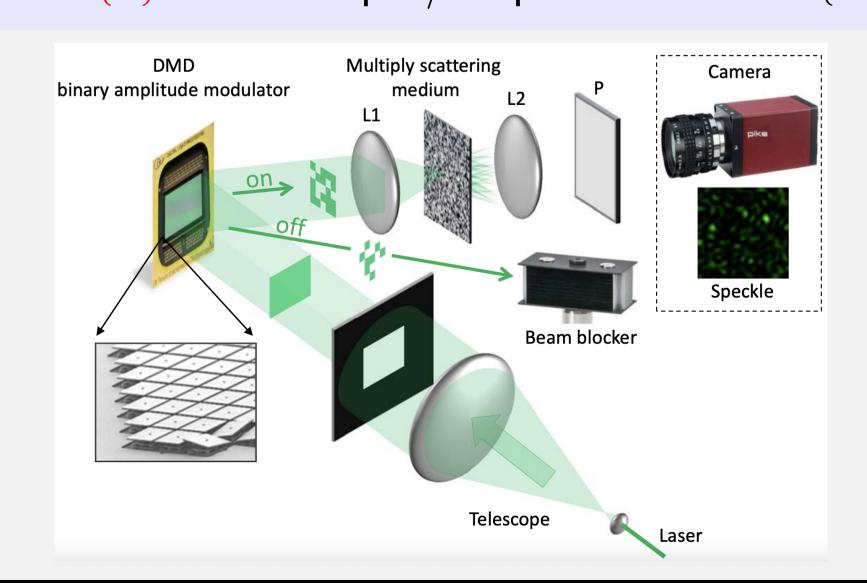
- $ightharpoonup \kappa(\mathbf{x}, \mathbf{x}') = \mathbb{E}_{\mathbf{w} \sim p} \ \xi_{\mathbf{w}}(\mathbf{x})^* \xi_{\mathbf{w}}(\mathbf{x}') \ \text{(kernels with RFs)}.$
- $\kappa_{GS}(\mathbf{x}, \mathbf{x}') = \exp^{-\frac{\|\mathbf{x} \mathbf{x}'\|^2}{2\sigma^2}} \Rightarrow \varphi_{GS}(\mathbf{x}) = \frac{\sqrt{2}}{\sqrt{m}} cos(\mathbf{W}^T \mathbf{x} + b)$

Theorem Let \mathcal{G} and \mathcal{G}' be two graphs. Assume that $|\xi_{\mathbf{w}}(F)| \leq 1$. Then, for all $\delta > 0$, with probability at least $1 - \delta$:

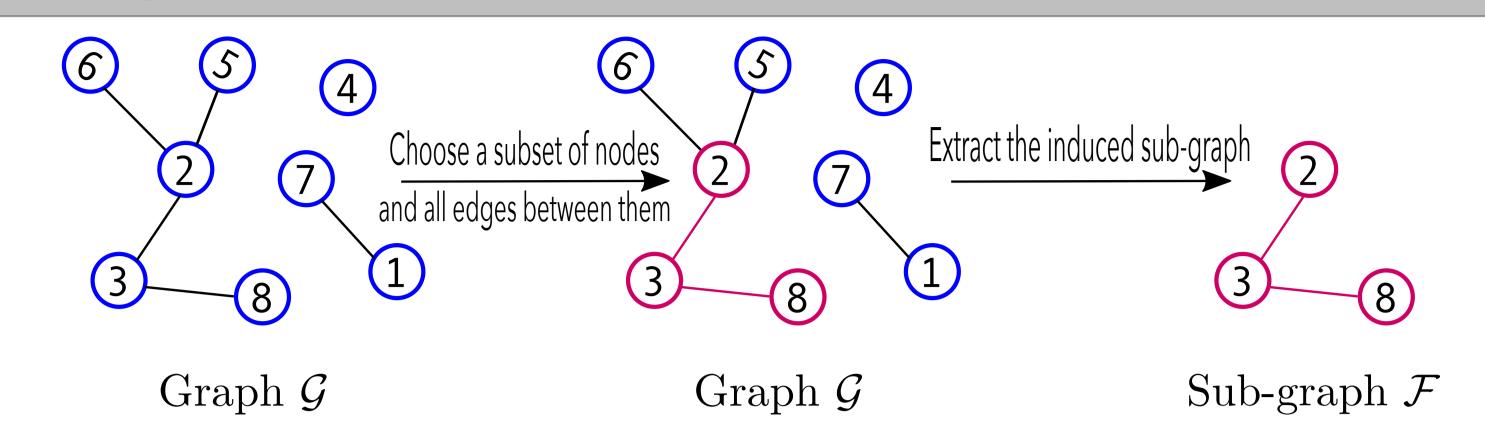
$$\frac{\left|\left|\mathbf{z}_{g}-\mathbf{z}_{g'}\right|^{2}-MMD(\mathbf{f}_{g},\mathbf{f}_{g'})^{2}\right| \leq 4\sqrt{\log(6/\delta)}}{\sqrt{m}} + \frac{8\left(1+\sqrt{2\log(3/\delta)}\right)}{\sqrt{s}}$$

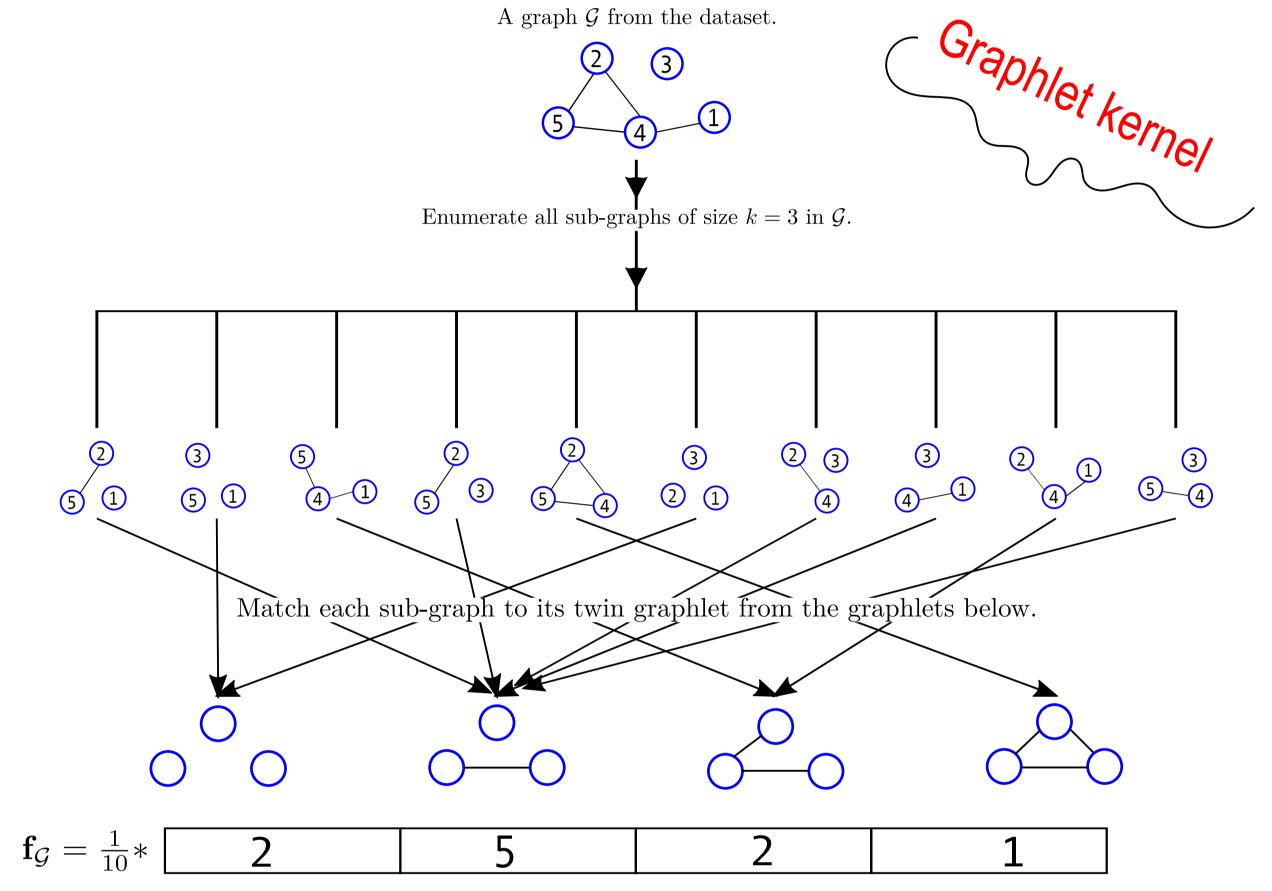
4: Incorporating Optical random featurs

- $ightharpoonup \phi_{OPU}(\mathbf{x}) = |\mathbf{W}\mathbf{x} + \mathbf{b}|^2; \ \mathbf{W} \in \mathbb{R}^{m \times d}, \mathbf{x} \in \mathbb{R}^d$
- $m \mapsto \infty \Rightarrow$ $\phi_{OPU}(\mathbf{x_1})^T \phi_{OPU}(\mathbf{x_2}) \approx \kappa_{OPU}(\mathbf{x_1}, \mathbf{x_2})$
- ► Optical Processing Units (OPUs) evaluate φ_{OPU} in O(1) in both input/output dimensions (d, m).



2: From the graphlet kernel to $GSA - \phi$

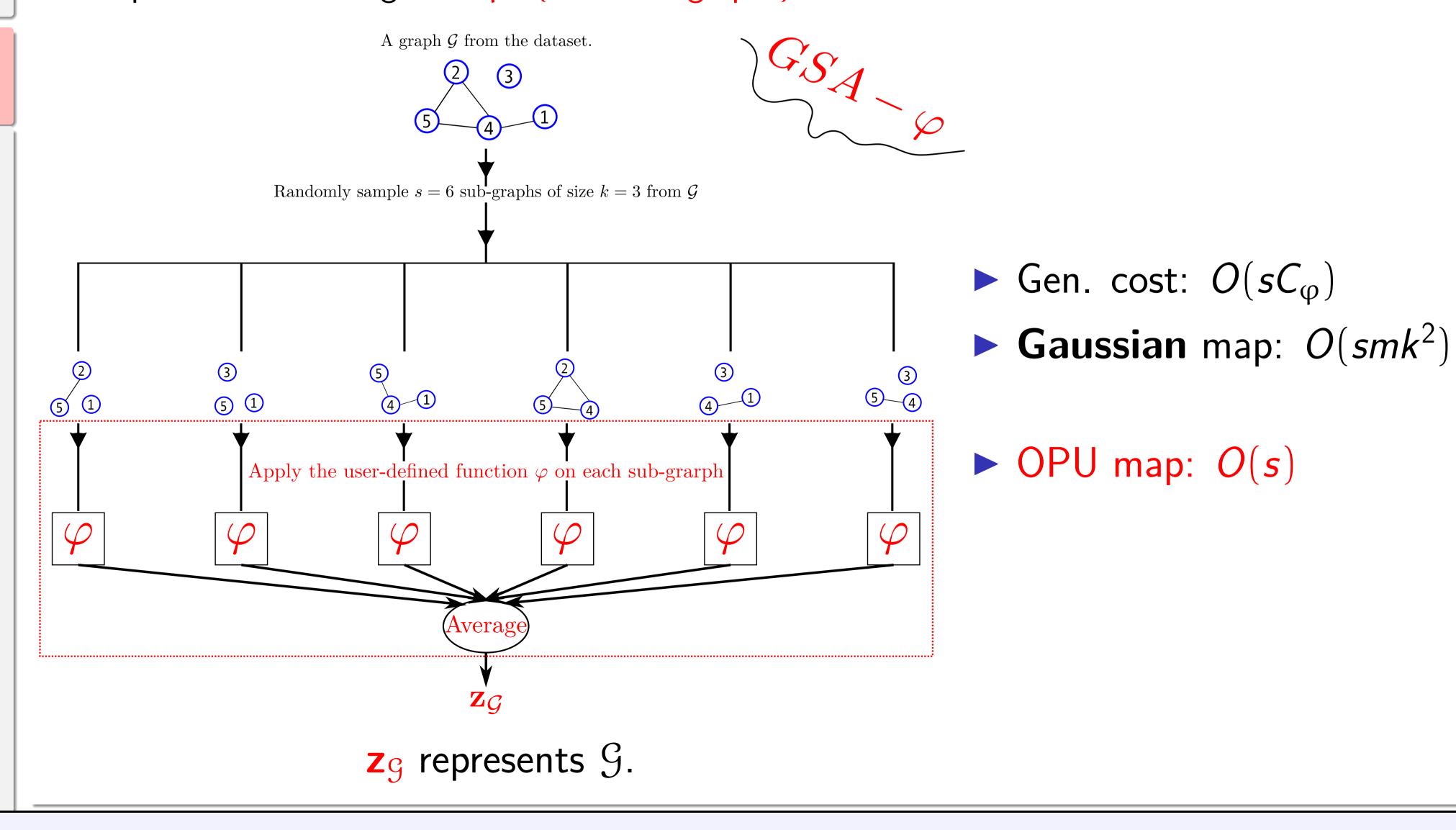




- Exp. cost: $O(\binom{v}{k}N_kC_k^{\cong})$
- Can be a bit reduced: $O(sN_kC_k^{\cong})$
- Still exponential.

► Replace the matching with φ : {size-k subgraphs} $\mapsto \mathbb{R}^m$

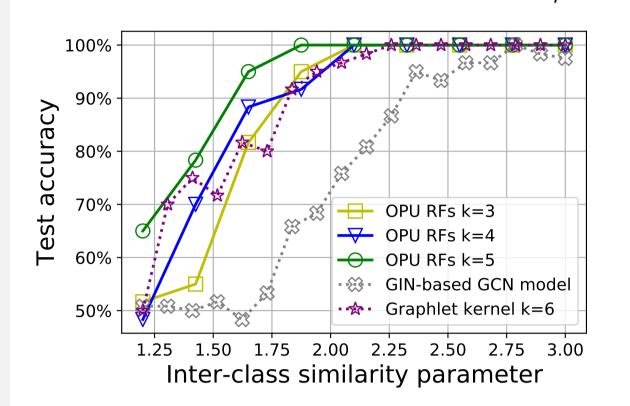
The normalized historgram $\mathbf{f}_{\mathcal{G}}$ is the representation vector for \mathcal{G} .

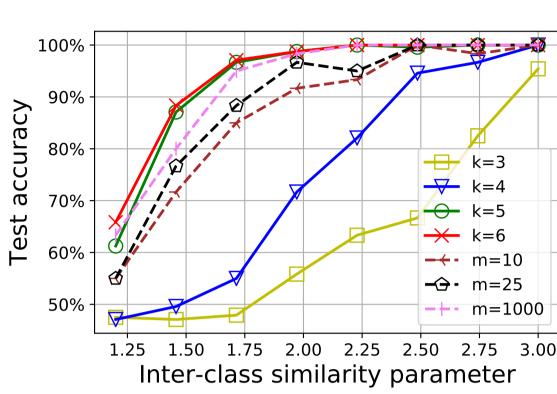


5: Experiments

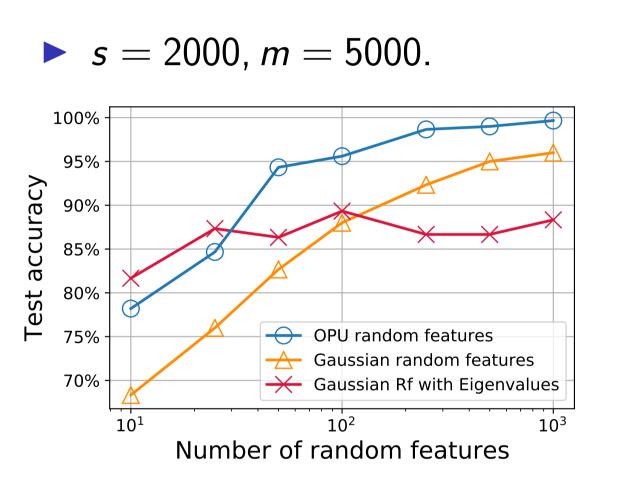
$GSA - \phi_{OPU}$ Vs. graphlet kernel and GCNs

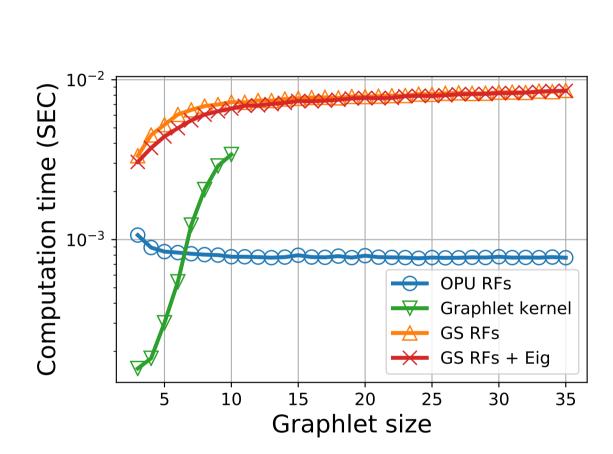
- ▶ Dataset: 300 graphs based on the stochastic block model.
- ► Lft: $GSA \varphi_{OPU}$ with uniform sampling.
- ▶ Rgt: $GSA \varphi_{OPU}$ with random walks, graphlet kernel, and GIN model.
- If not mentioned: s = 2000, m = 5000.





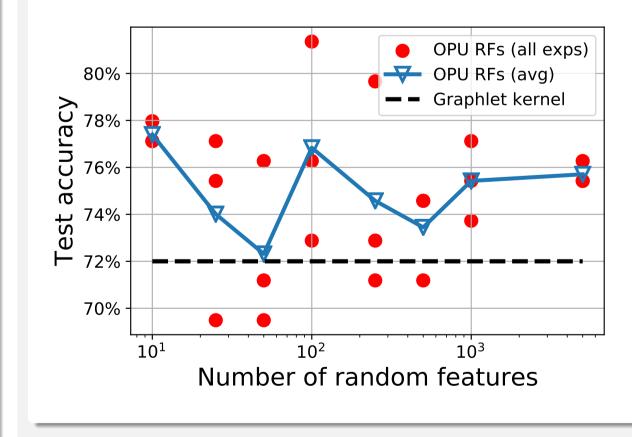
$GSA - \varphi$ with different φ_{RF} + comp. cost

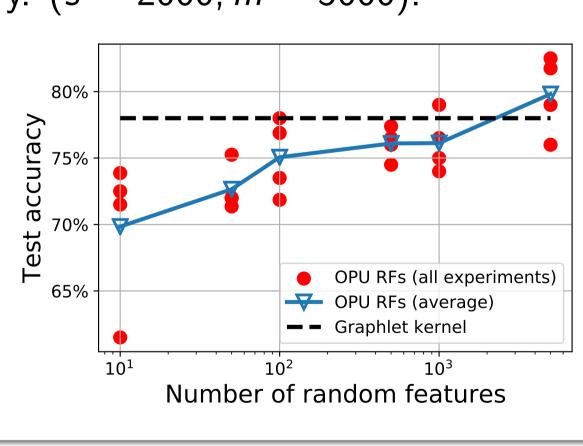




Results on real world datasets.

▶ Lft: D&D dataset, rgt: Reddit-Binary. (s = 2000, m = 5000).





- [1] Saade et al. Random projections through multiple optical scattering: Approximating kernels at the speed of light. *ICASSP*, 2016.
- [2] Shervashidze et al. **Efficient graphlet kernels for large graph comparison**.

 International Conference on Artificial Intelligence and Statistics, 2009.
- [3] Rahimi et al. Random features for large-scale kernel machines. NIPS, 2007.