

Project A6 Resource-Efficient Graph Mining

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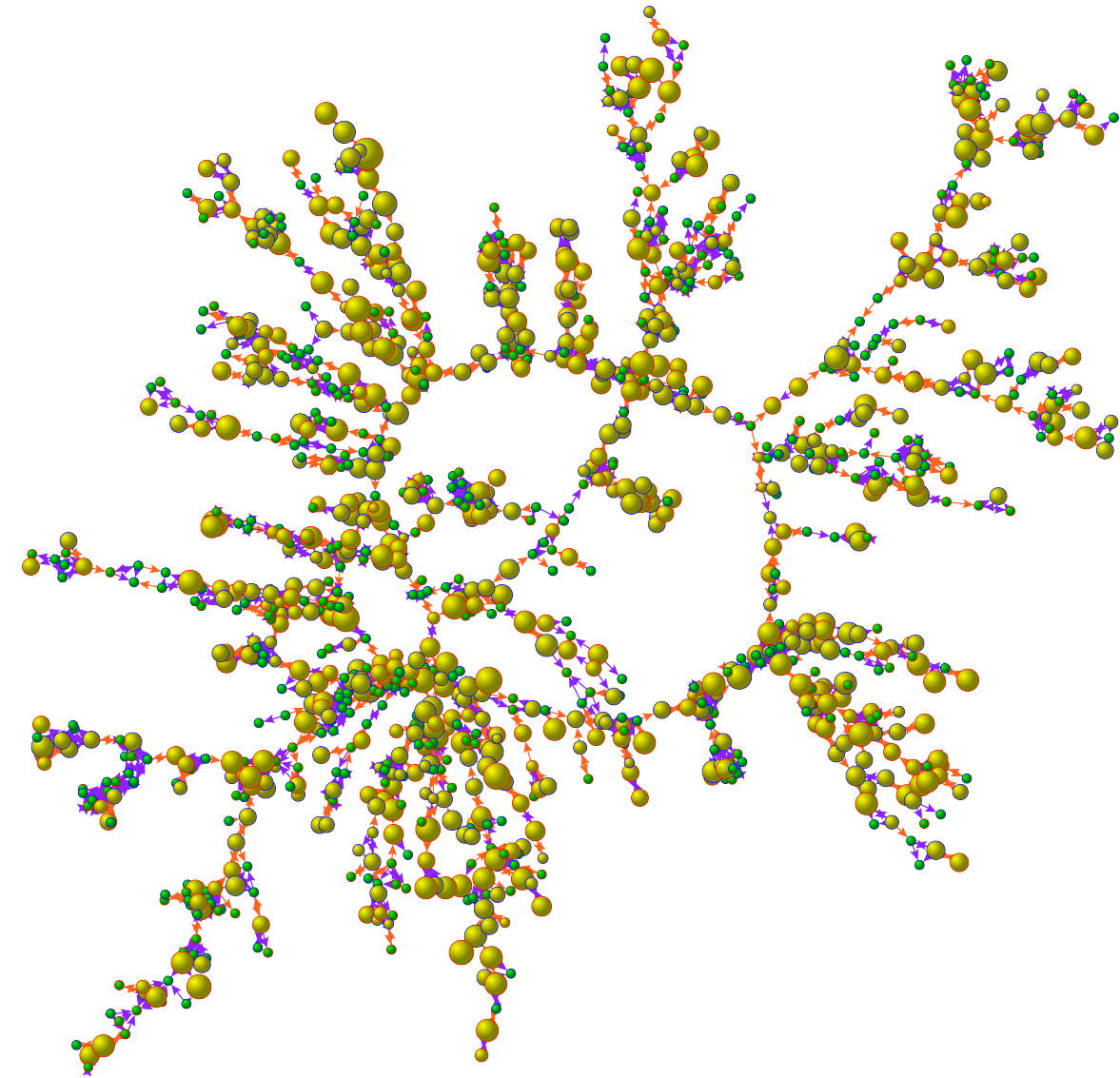
Problem

Graphs are ubiquitous and complex

Graphs occur, e.g., in chem-, bioinformatics, and social network analysis

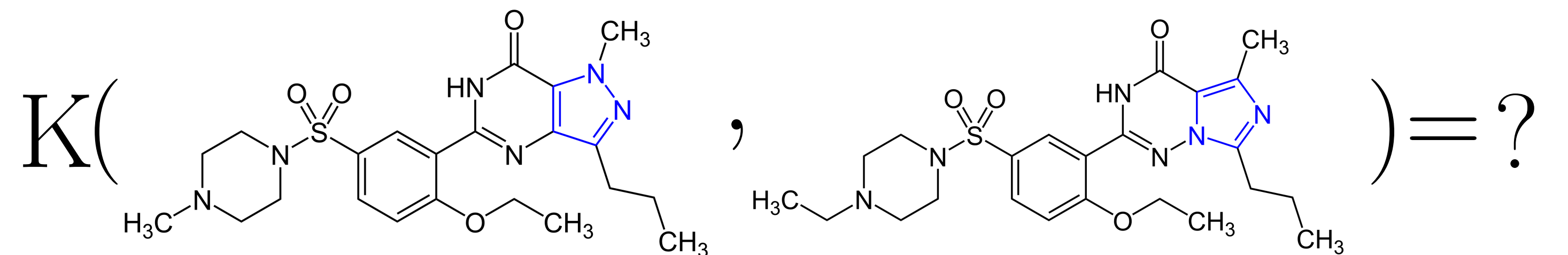
Real-world graphs ...

- ▶ are **large**
- ▶ are **irregular**
- ▶ are **sparse**
- ▶ have a **hierarchical structure**
- ▶ have **rich information** attached to **nodes and edges**



Graph classification

How similar are two graphs?

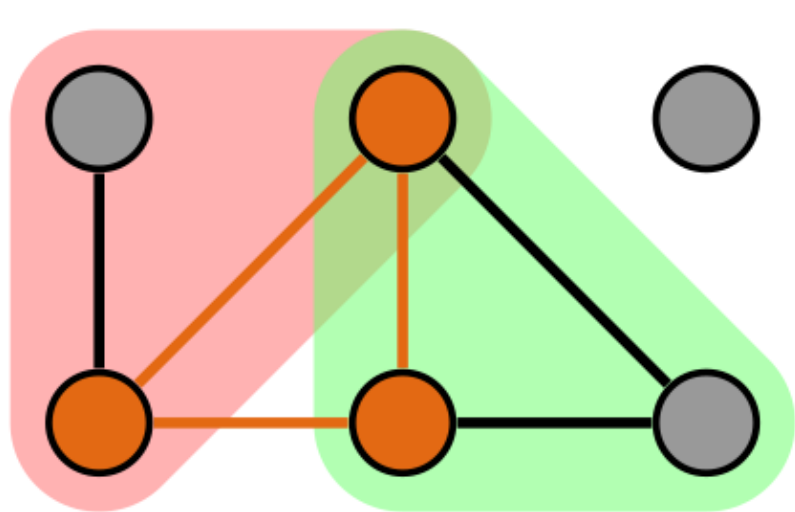


- ▶ **No obvious vector representation for graphs**
- ▶ **Standard machine learning approaches cannot be applied directly**

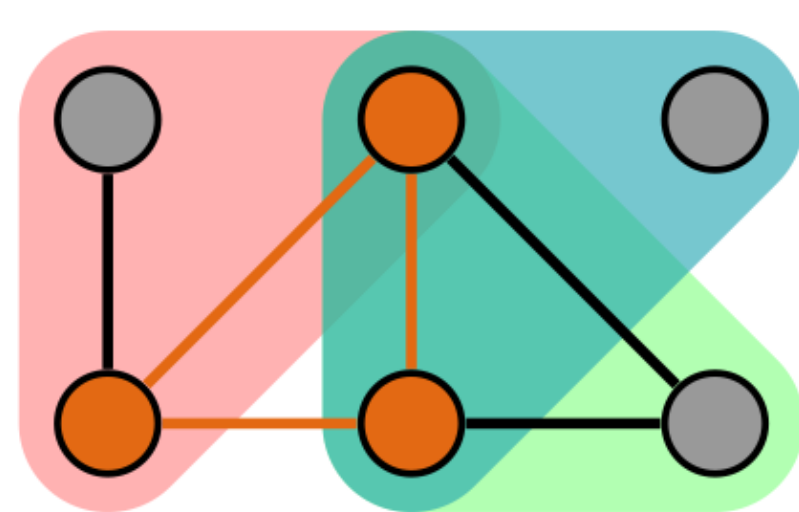
Methodology

Vertex refinement

Local k -dimensional Weisfeiler-Lehman kernel [ICDM 2017]



Local neighbourhood

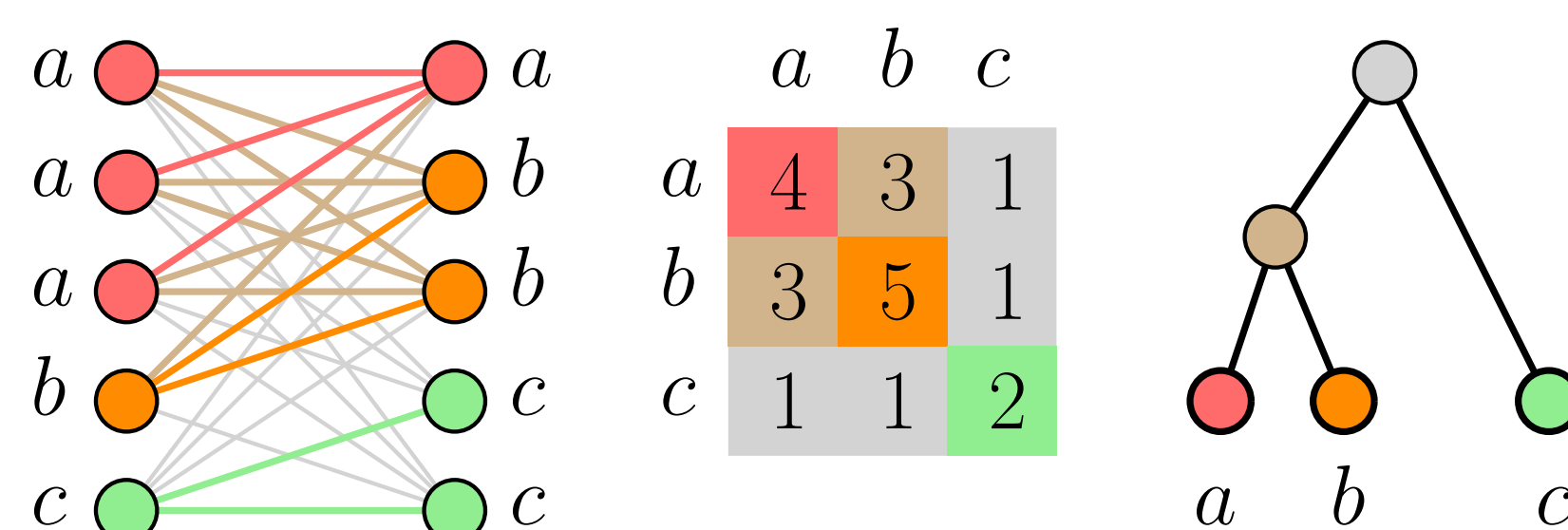


Global neighbourhood

- ▶ **Parallel sampling algorithm with provable approximation guarantees**
- ▶ Considers **local** as well as **global** properties

Assignments via trees

Kernels from optimal assignments [NIPS 2016]



Assignment

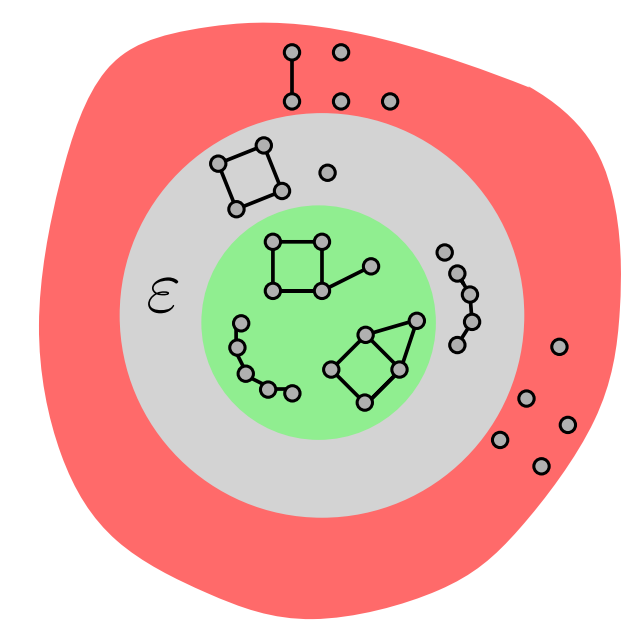
Base-kernel

Tree

- ▶ **Base kernels** that induce PSD assignment kernels
- ▶ **Linear running time**
- ▶ Weisfeiler-Lehman **Optimal Assignment kernel**

Theoretical expressivity

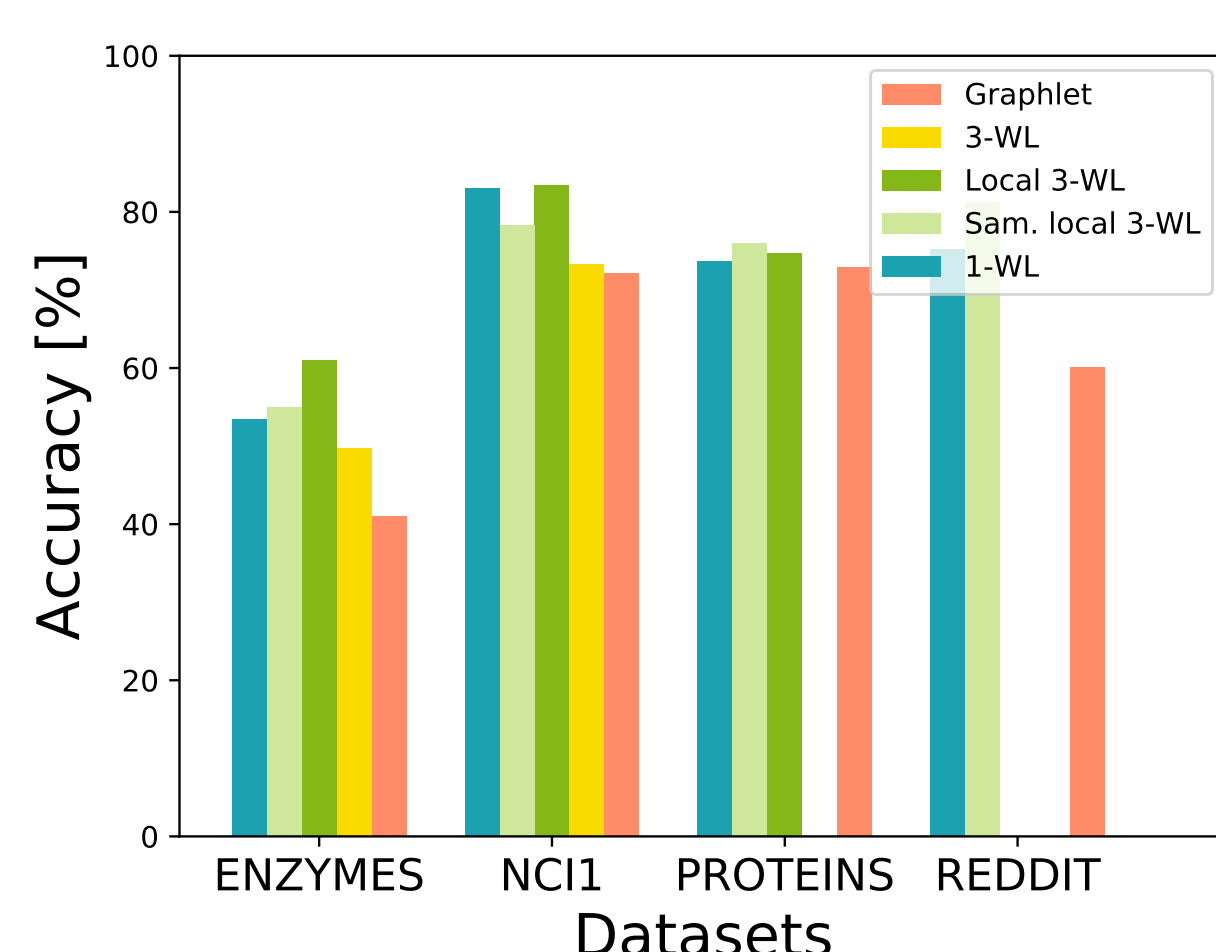
Property testing framework for graph kernels [IJCAI 2018]



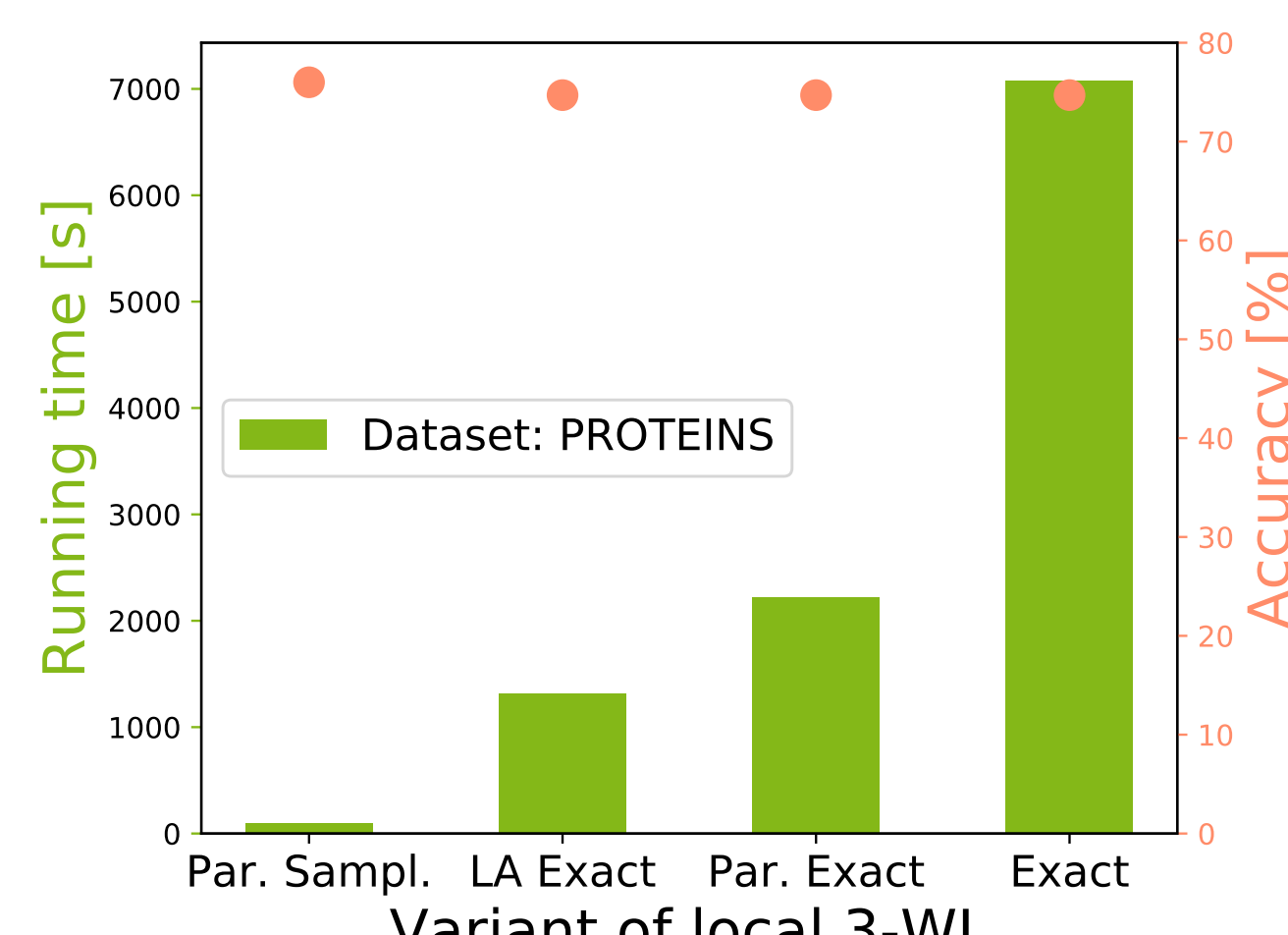
Graph property: connectivity

- ▶ Current kernels **cannot discriminate** between **simple graph properties**
- ▶ **More expressive kernel** based on k -disks

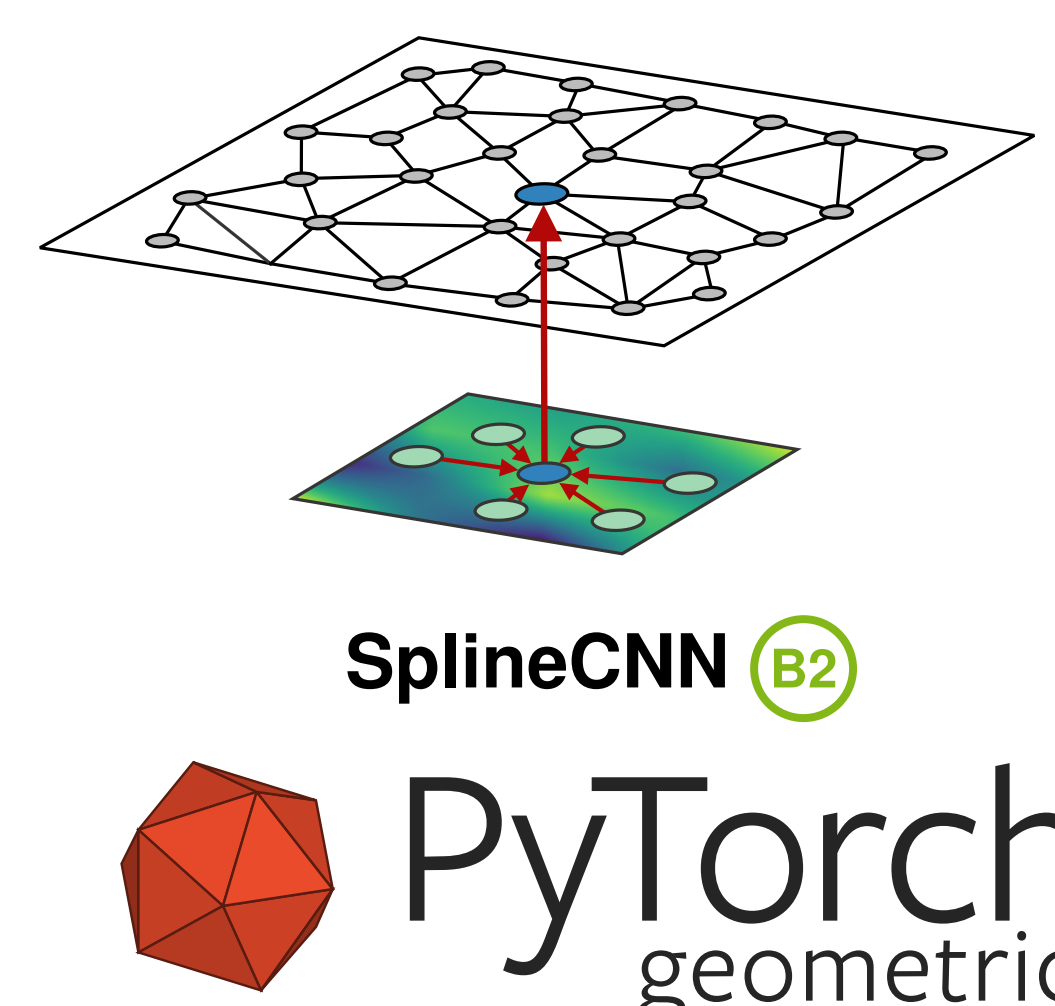
Results



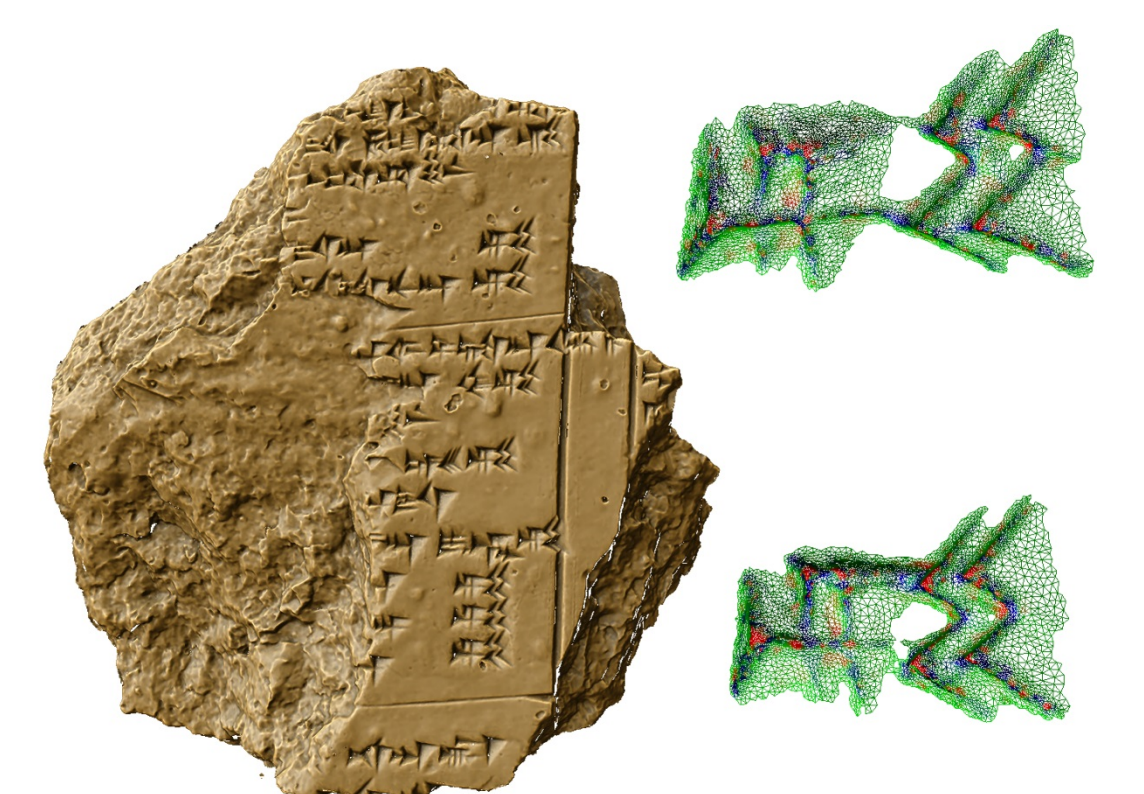
Local 3-WL accuracy



Speed-up by sampling and parallelism



Geometric deep learning framework (B2)



Cuneiform classification (B2)

Additional selected results

Scalability

- ▶ **Spectrum approximation** via random walks [KDD 2018]
- ▶ **Scalable kernels** for graphs with **continuous labels** [ICDM 2016]
- ▶ **Scalable kernels** via **propagation** [Machine Learning 2016]
- ▶ **Scaling lifted probabilistic inference and learning** via graph databases [SDM 2016]

Expressivity

- ▶ **Counting cycles** of large graphs [Algorithmica 2018]
- ▶ Parameterizing the **distance distribution** of undirected networks [UAI 2015]
- ▶ Architecture for **tractable multivariate Poisson distributions** [AAAI 2017] (B4)
- ▶ **Machine Learning** meets **data-driven journalism** [#Data4Good@ICML 2016] (A1)

Towards the third phase

- ▶ **Cuneiform classification** on limited data [COST@SDM 2018] (B2)
- ▶ **Hierarchical pooling** [NIPS 2018]
- ▶ **Fast deep graph learning** via **B-spline kernels** [CVPR 2018] (B2)
- ▶ **Protein complex similarity** [Preprint] (C1)
- ▶ **Group equivariant deep learning** [NIPS 2018] (B2)