# Regularities in bisimulation reductions of big graphs 

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## Bisimulation reduction of graphs

- Bisimulation partitioning is an important concept in many fields (computer science, modal logic, etc.), in DB research as well (structural index, graph reduction)
- It can be seen as a way of clustering nodes



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- Reduce graph size while preserving structural properties (e.g., reachability)
- Result can be seen as a (PB) graph
- What properties does the PB graph have?


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- Do results under bisimulation reduction (e.g., PB graph) also have such properties?
- How would that knowledge help us?


## Experimental setup for investigation

- Big graphs, from 1 Million to 1.4 Billion edges (Twitter, DBPedia, etc.)
- State-of-the-art external-memory algorithm for computing bisimulation reductions
- We use cumulative distribution function (CDF) to present distributions


## Regularities - bisimulation result

Power-law also exists in many attributes for bisimulation partition results for real graphs. But this is not the case for synthetic graphs.

## Regularities - partition block size distribution


synthetic graphs

$\rightarrow$ Jamendo $\rightarrow$ LinkedMDB $\rightarrow$ DBLP $\rightarrow$ DBPedia $\rightarrow$ WikiLinks - - Twitter - Flickr-Grow - BSBM - SP2B - Power $\rightarrow$ Random

## Regularities - PB graph in-degree distribution


synthetic graphs

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## A close look at Social Intelligence Benchmark (old)

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- What structure is exhibited by graphs generated by the Social Intelligence Benchmark?
- Use s3g2130313.tar, downloaded from sourceforge.net/projects/sibenchmark/ (thanks to Minh-Duc Pham)
- Number of nodes: 2.6M, Number of edges: 12.6M
- Configuration: numtotalUser: 10000, 2010-1-1 to 2012-1-1


## In-degree and out-degree of original graph



## Partition block size \& signature length distribution



## In-degree and out-degree of PB graph



## Insights

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- Some more work remains to be done for synthetic graph generators towards exhibiting the reduction properties of real graphs.
- Bisimulation result/graph grows when original graph grows, which calls for scalable/adaptive algorithms (e.g., choose different $k$ for different parts of the graph, different node/edge labeling)


## Thank you! Q\&A

For more information, just google seeqr project or visit: bit.ly/seeqr

## Definition of $k$-bisimilar

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Let $k$ be a non-negative integer and $G=\left\langle N, E, \lambda_{N}, \lambda_{E}\right\rangle$ be a graph. Nodes $u, v \in N$ are called $k$-bisimilar (denoted as $u \approx^{k} v$ ), iff the following holds:
(1) $\lambda_{N}(u)=\lambda_{N}(v)$,
(2) if $k>0$, then for any edge $\left(u, u^{\prime}\right) \in E$, there exists an edge $\left(v, v^{\prime}\right) \in E$, such that $u^{\prime} \approx^{k-1} v^{\prime}$ and $\lambda_{E}\left(u, u^{\prime}\right)=\lambda_{E}\left(v, v^{\prime}\right)$, and
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In this example graph, nodes 1 and 2 are 0 - and 1 - bisimilar but not 2-bisimilar.

## In-degree distribution of original graphs


synthetic graphs

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## Out-degree distribution of original graphs


synthetic graphs


## Signature length


synthetic graphs


| - Jamendo - - LinkedMDB - Ditter - Flickr-Grow - BSBM - SP2B $\rightarrow$ Power $\rightarrow$ RikiLinks |  |
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|  |  |
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## Out-degree of PB graph


synthetic graphs

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- How fast does it grow?
- Linearly with respect to the original graph.


