CPSC 768:
Scalable and Private Graph Algorithms

Lecture 23: Algorithms Engineering: Theory-in-Practice

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Announcements

- **Final project report and presentation: April 24th (last day of class)**
  - Final project presentation is a 30 min presentation
- **Last day of Open Problem Sessions: April 26th** (last week of classes)
  - Will be turned into a reading group/continue with OPS, stay tuned!

Continued: Parallel Low Diameter Decomposition

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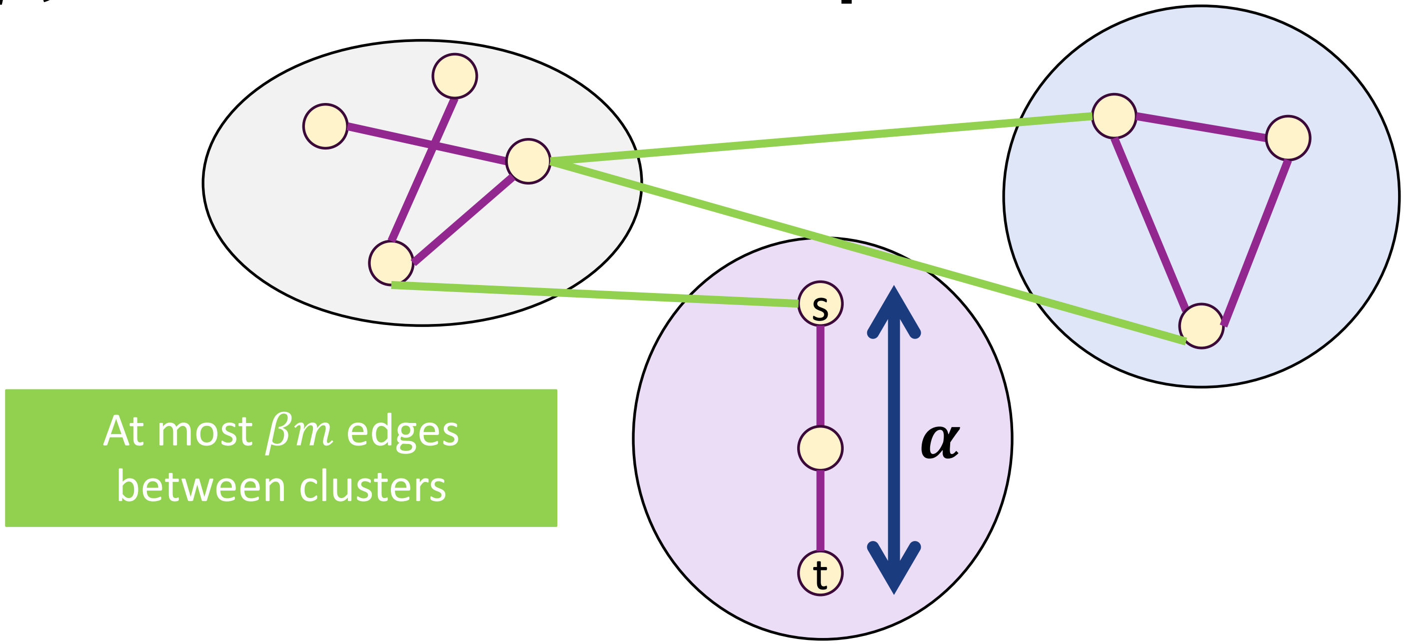

Parallel Low Diameter Decomposition [MPX SPAA ‘13]

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    - Vertex assigned to first edge that hits it

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  - $p(x) = \beta e^{-\beta x}$
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- Use start time $T_v = \delta_{\max} - \delta_v$ where $\delta_{\max} = \max_{v \in V}(\delta_v)$

Backwards Exponential Distribution: very few to start, more towards the end

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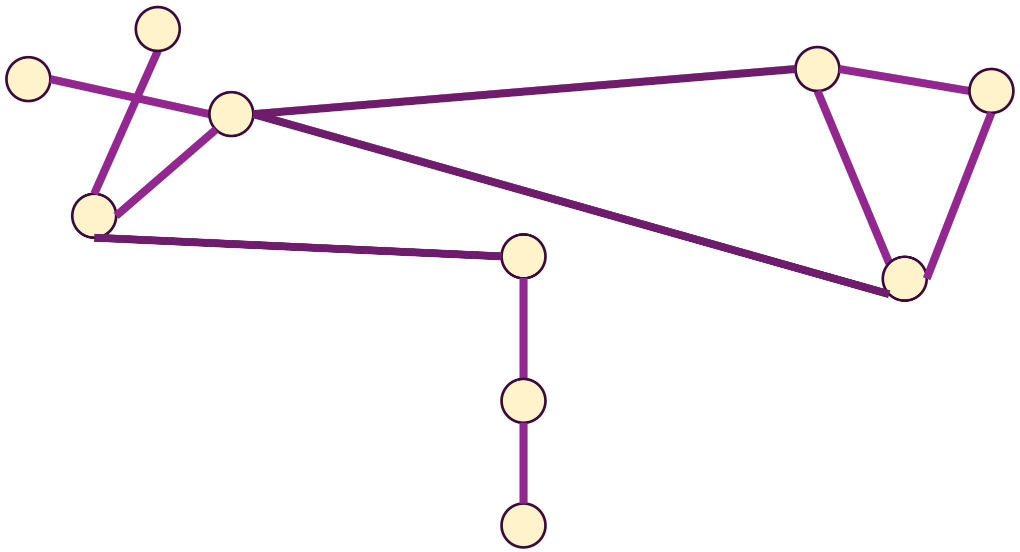

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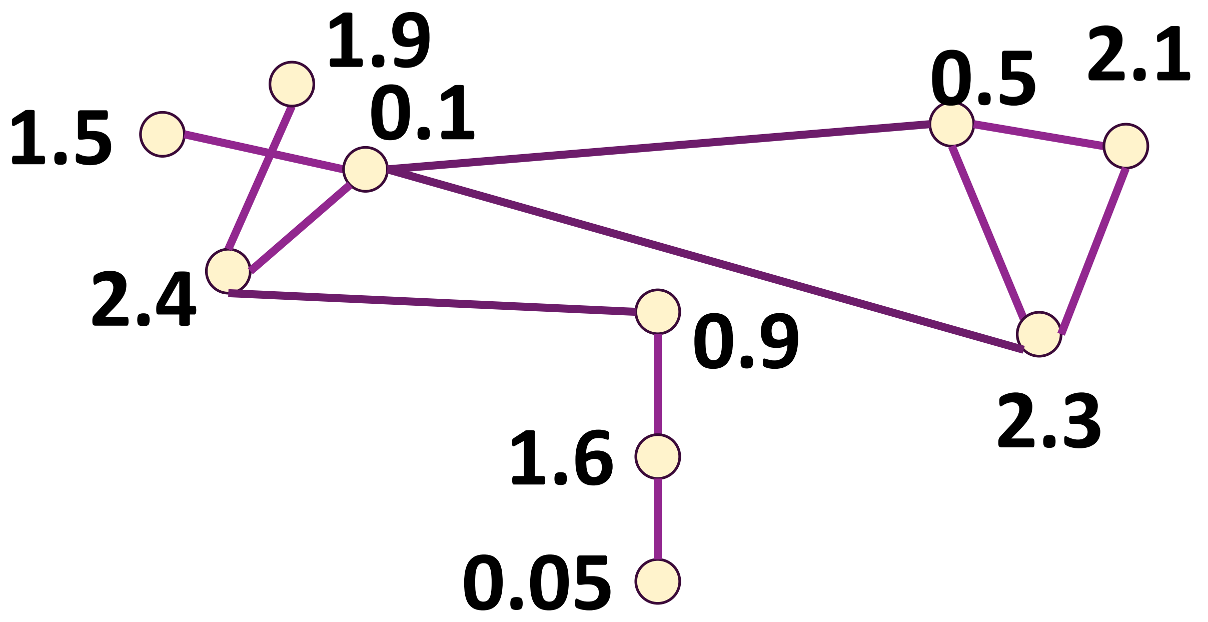

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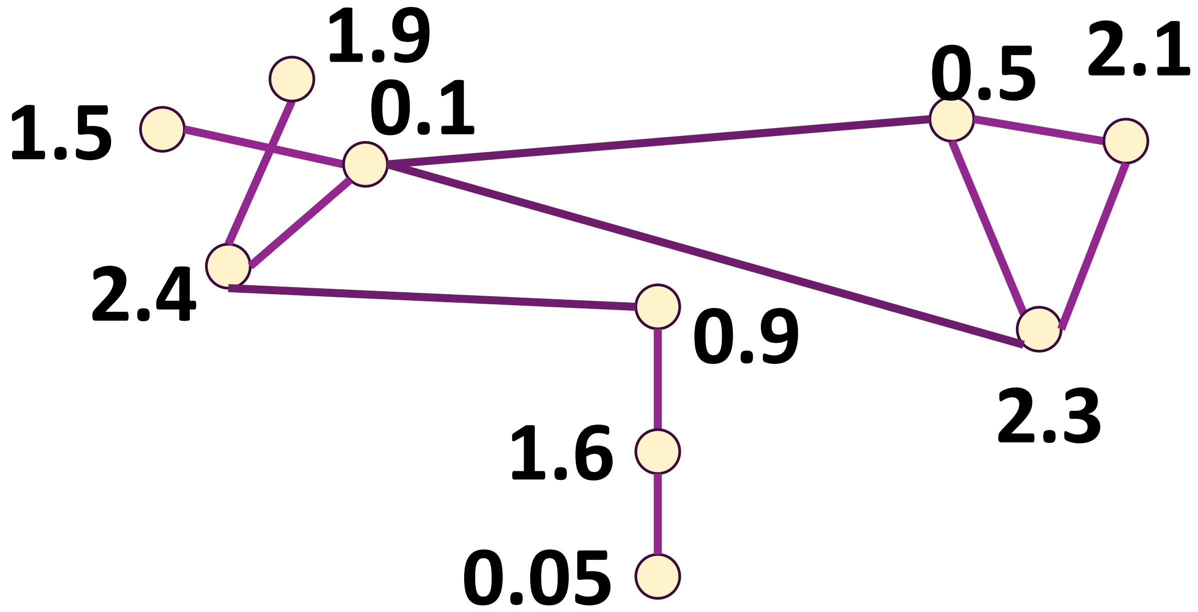

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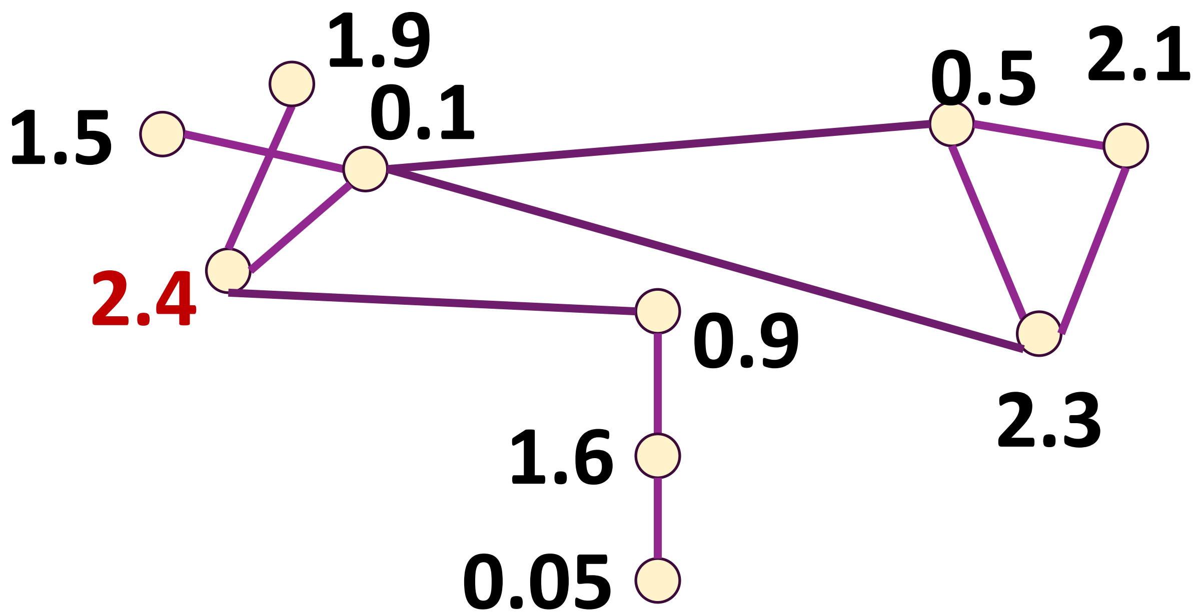

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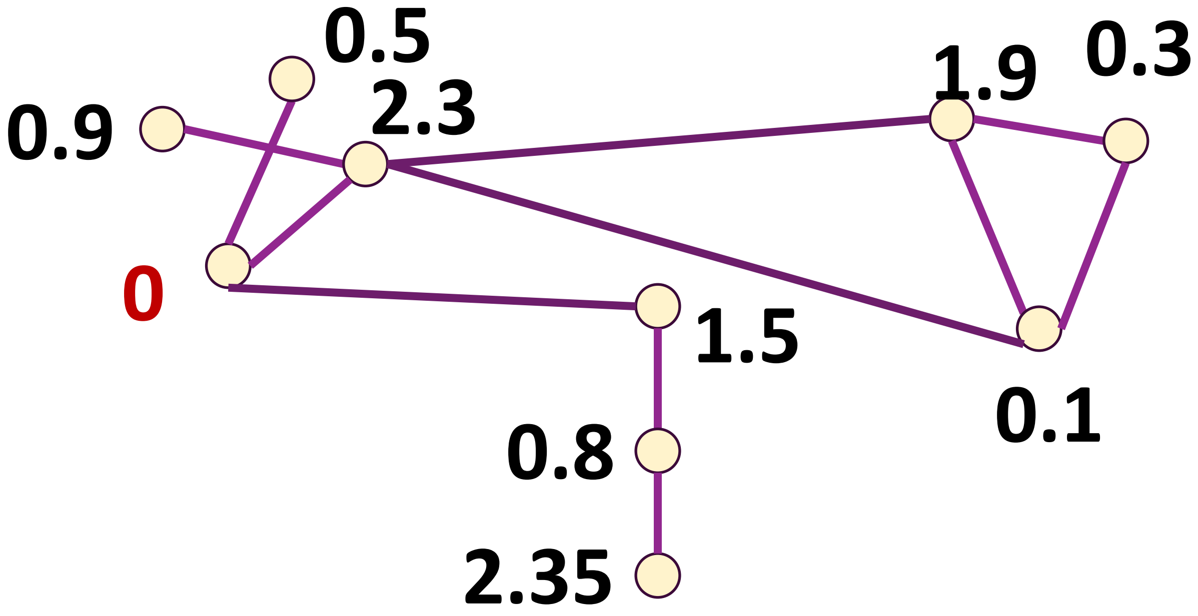

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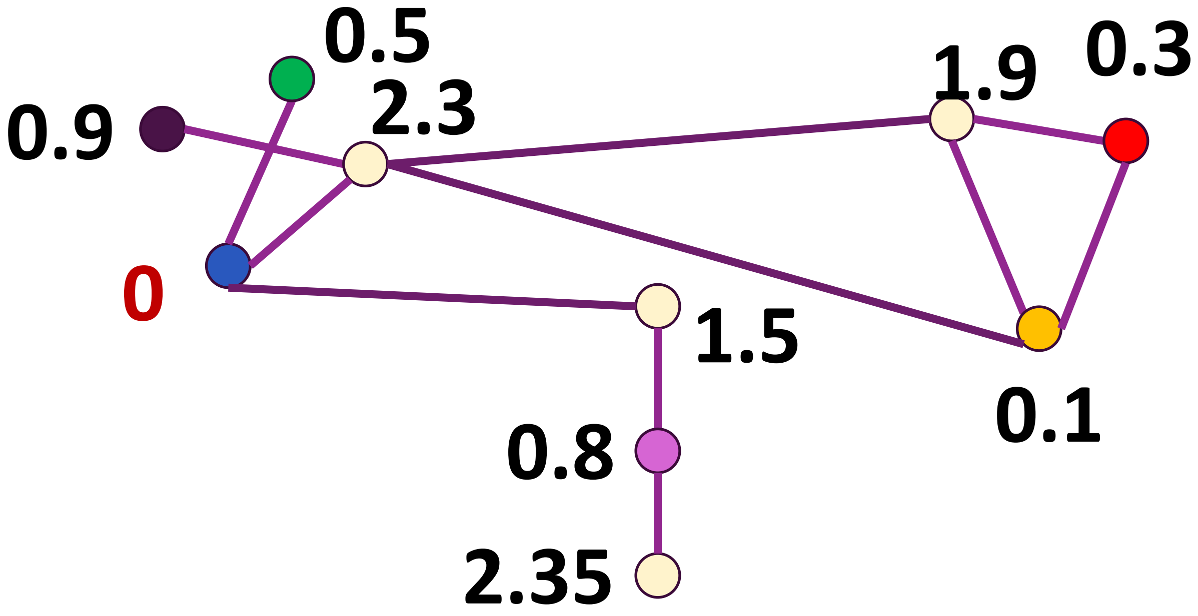

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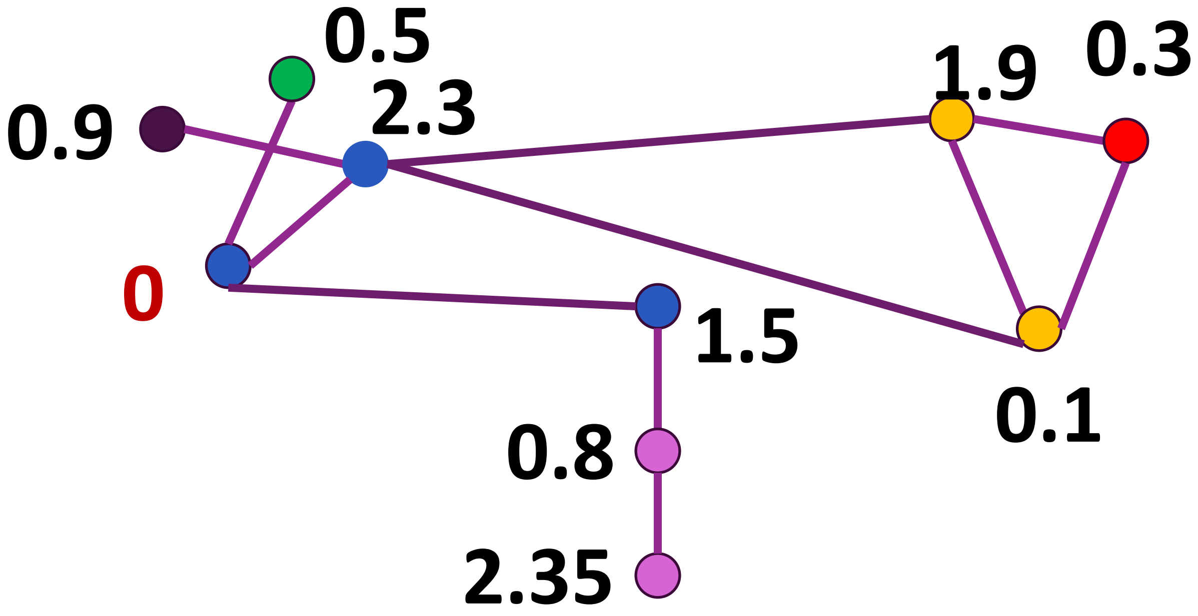

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Union bound over all vertices: $P\left[\delta_{\max} > \frac{c \log n}{\beta}\right] \leq \frac{1}{n^{c-1}}$

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    - Fix time for one endpoint, probability other endpoint within one of that time is at most $1 - e^{-\beta}$
    - $1 - e^{-\beta} < \beta$ for $\beta > 0$ using Taylor series
    - Hence, for **any edge marginal probability edge is in cut is $\boldsymbol{\beta}$**
    - Expected number of edges in cut: βm

Algorithms Engineering: Theory-in-Practice

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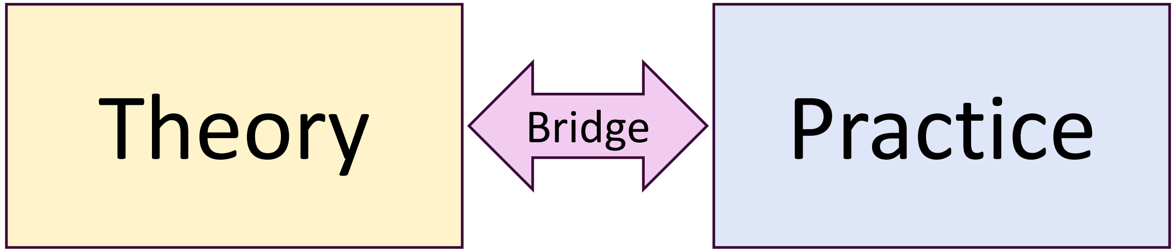

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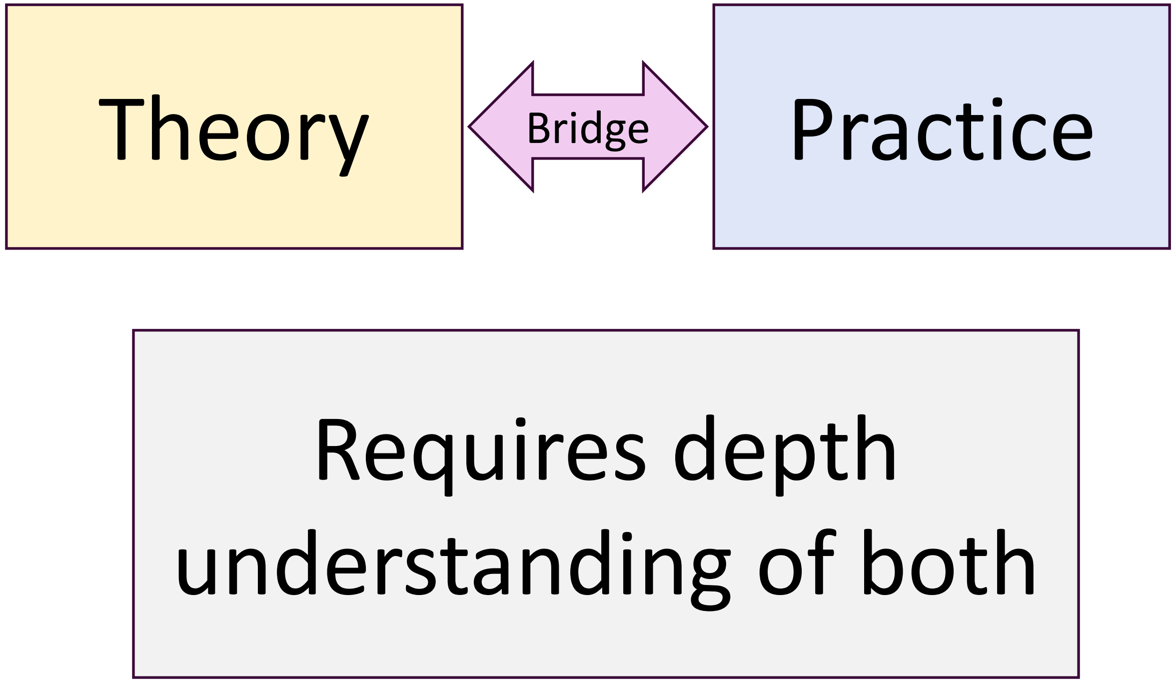

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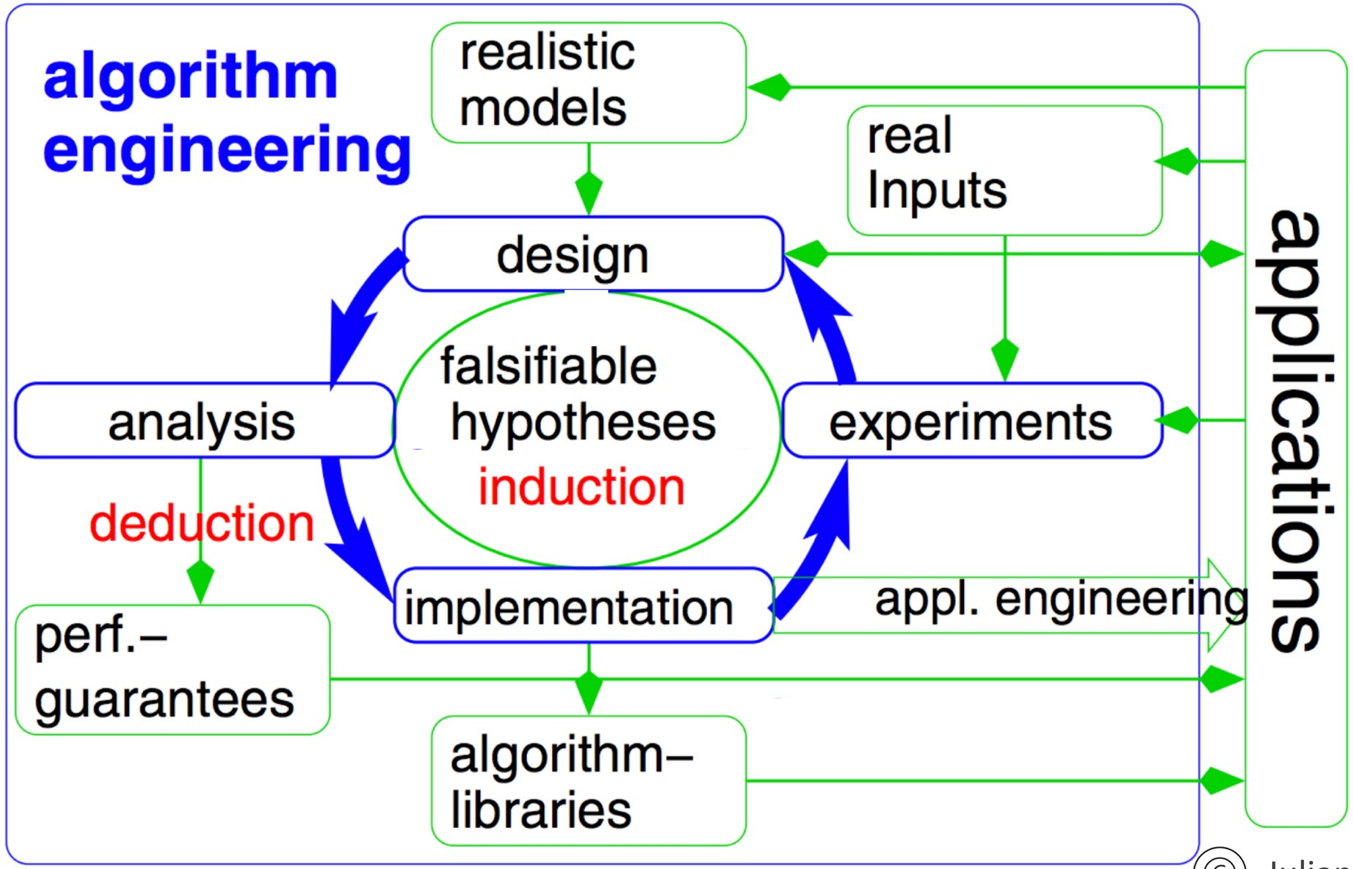

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Source: "Algorithm Engineering – An Attempt at a Definition", Peter Sanders

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  - Asymmetric read-write costs in non-volatile memory

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Algorithm Design and Analysis

- **Difference in asymptotic complexities:**
  - **Algorithm 1:** $N \log_2(N)$
  - **Algorithm 2:** $1000\,N$
  - **Which one is practically better?**

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  - **Simplicity** improves practicality and leads to better performance

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  - Time vs. space tradeoffs
  - Work vs. parallelism tradeoffs

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- **Write clean, modular code**
- **Write correctness checkers**
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Implementations

- **Write clean, modular code**
  - Easier to experiment with different methods, and save a lot of development time when adding new features
- **Write correctness checkers**
  - Especially important in numerical and geometric applications because of floating-point arithmetic errors and non-determinism, different results from different runs!
- **Save previous versions of your code!**
  - Version control always! If you need to rollback changes!

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  - Perf, gprof, valgrind

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- **Useful benchmarking tools:** Cilkscale, Cilksan

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- **Easier development in the future—no wasted work in development**
- **Service to the community to develop your own for your needs and potential other needs in the future**

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Libraries and Frameworks are Very Important!

- **Example frameworks:**

ParlayLib - A Toolkit for Programming Parallel Algorithms on Shared-Memory Multicore Machines

Build passing | codecov 97% | License MIT

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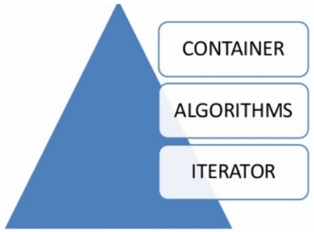
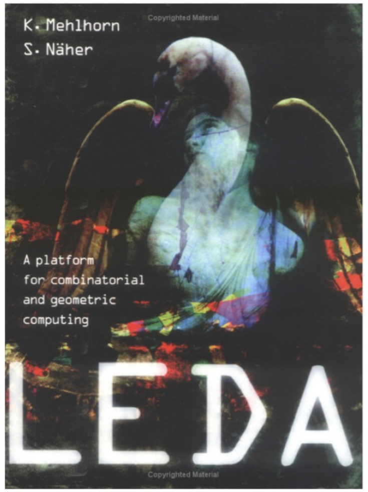
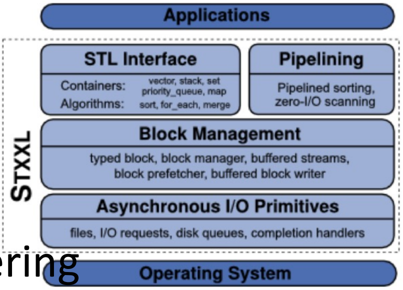


CGAL





boost C++ LIBRARIES

Problem Based Benchmark Suite

Home | Benchmarks/Code | Inputs | License | People | Publications

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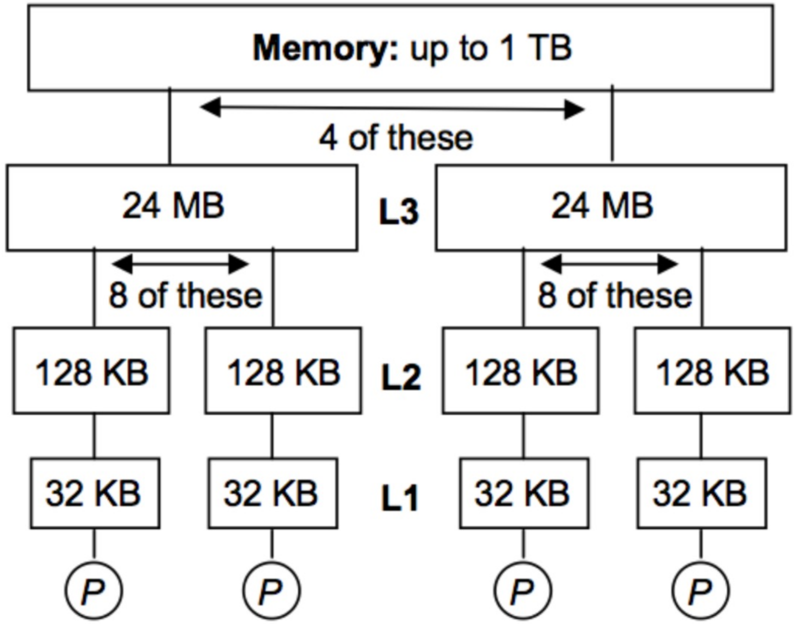
Cache Hierarchies



Design cache-efficient and cache-oblivious algorithms to improve locality

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Memory level	Approx latency
L1 Cache	1-2ns
L2 Cache	3-5ns
L3 cache	12-40ns
DRAM	60-100ns

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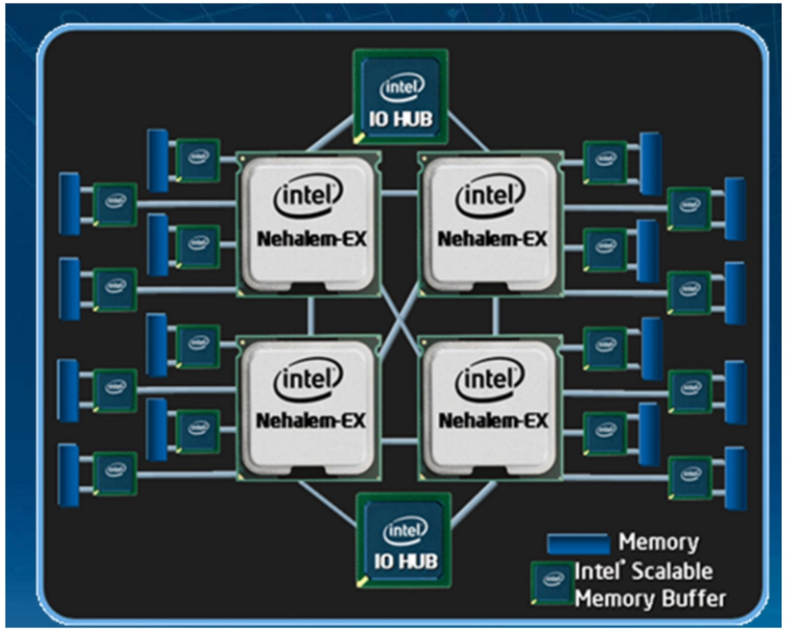
Non-Uniform Memory Access (NUMA)

- Accessing **remote memory** is more expensive than accessing local memory of a socket
  - Latency depends on the number of hops



Design NUMA-aware algorithms to improve locality

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I/O Efficiency

- Need to read input from disk at least once
- Need to read many more times if input doesn't fit in memory

Memory	Latency	Throughput
DRAM	60–100 ns	Tens of GB/s
SSD	Tens of μs	500 MB–2 GB/s (seq), 50–200 MB/s (rand)
HDD	Tens of ms	200 MB/s (seq), 1 MB/s (rand)

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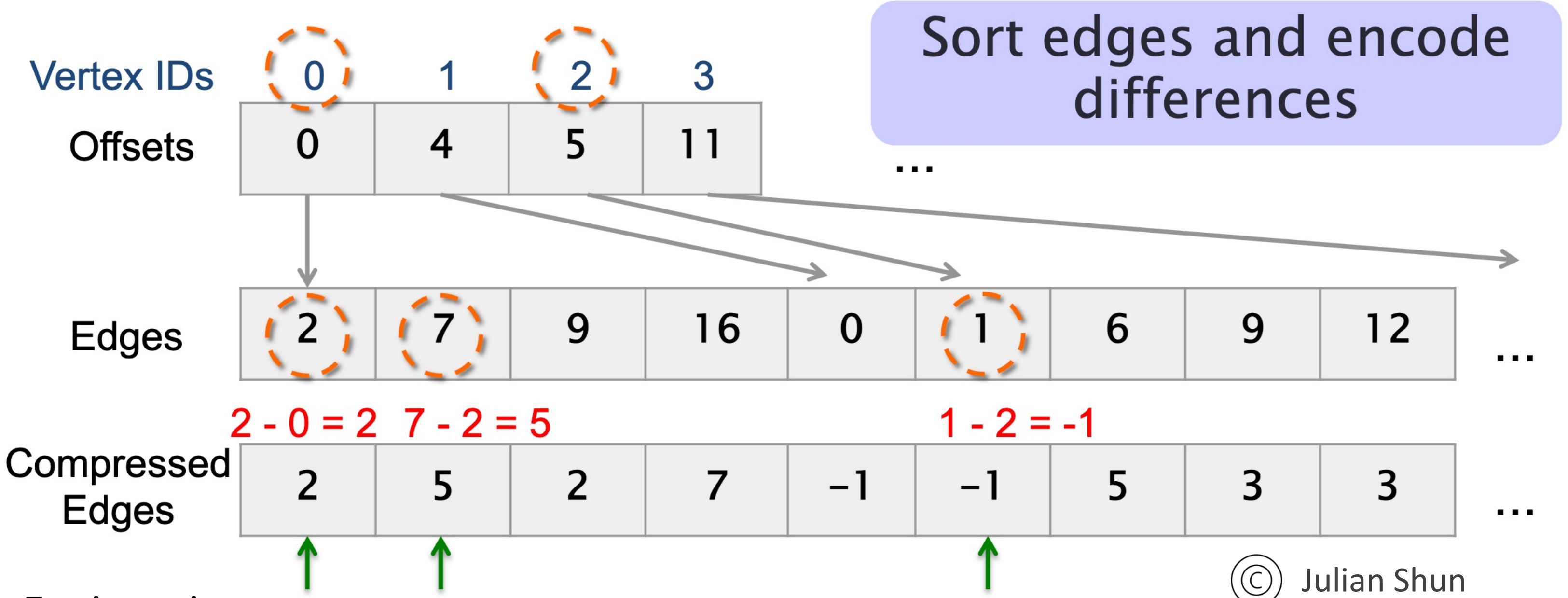
Very Large Graphs!

- Need **graph compression** if graph cannot fit on machine

Very Large Graphs!

- Need **graph compression** if graph cannot fit on machine
- **Compressed Sparse Row (CSR), Compressed Row Storage (CRS), Yale format**



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Many Things in Theory and Practice

- Many things to learn in theory and practice
- **Lots of knowledge in between**
- **Communication between the communities important**
  - **Will lead to practical impact!**