# High-Productivity and High-Performance Analysis of Filtered Semantic Graphs

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# Key Contributors (past and present)

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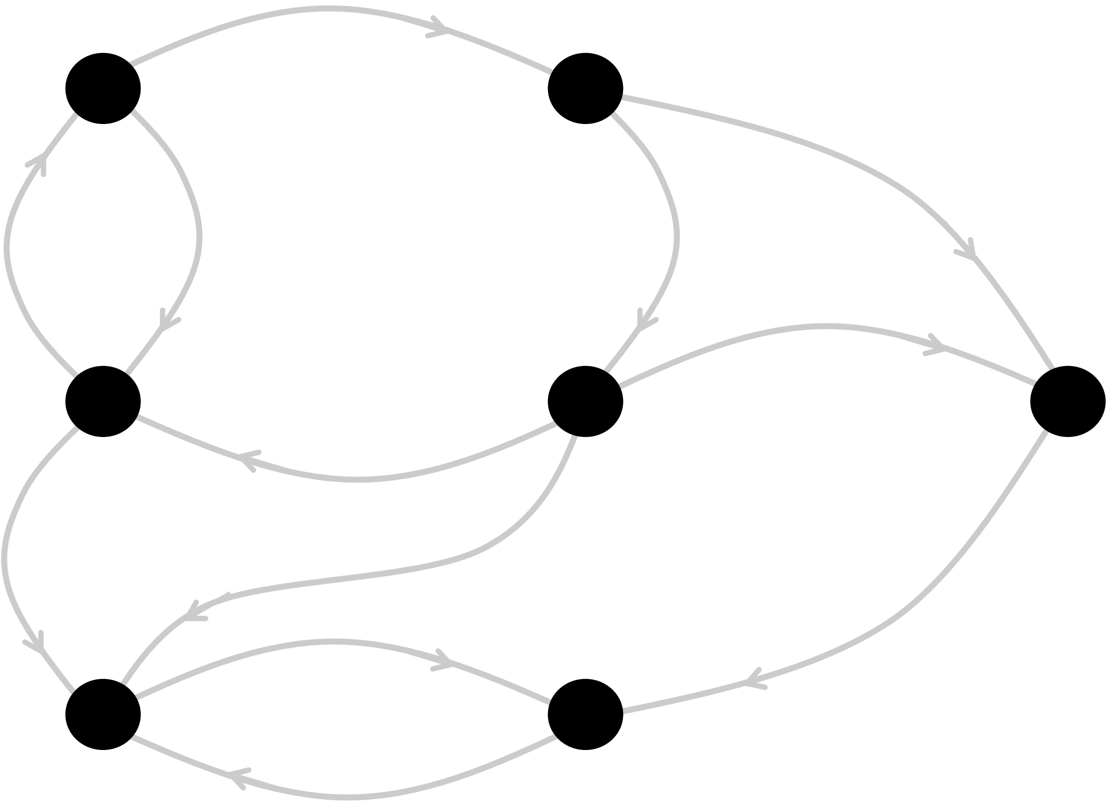
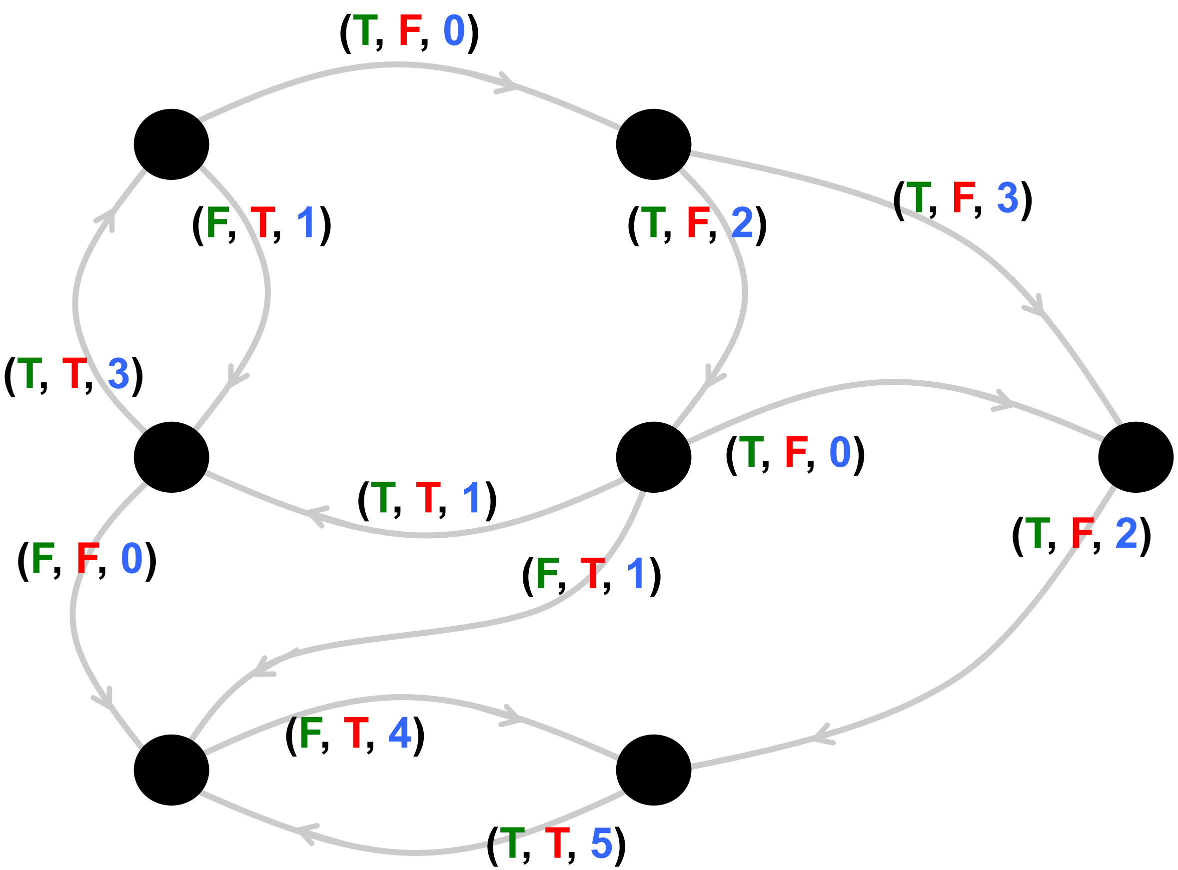
# A useless binary graph

Good for benchmarking though
(i.e. Graph500)



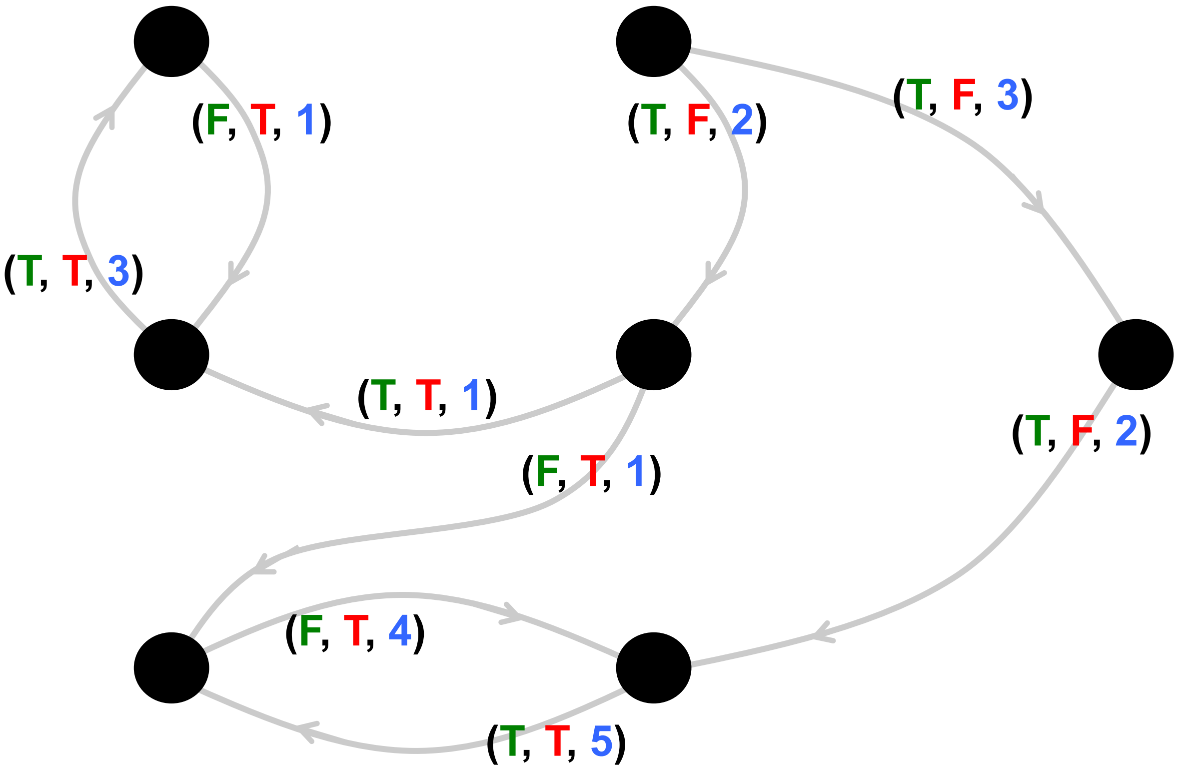
# A useful semantic graph




```
class edge_attr:
    isText
    isPhoneCall
    weight
```

# Edge filter illustration

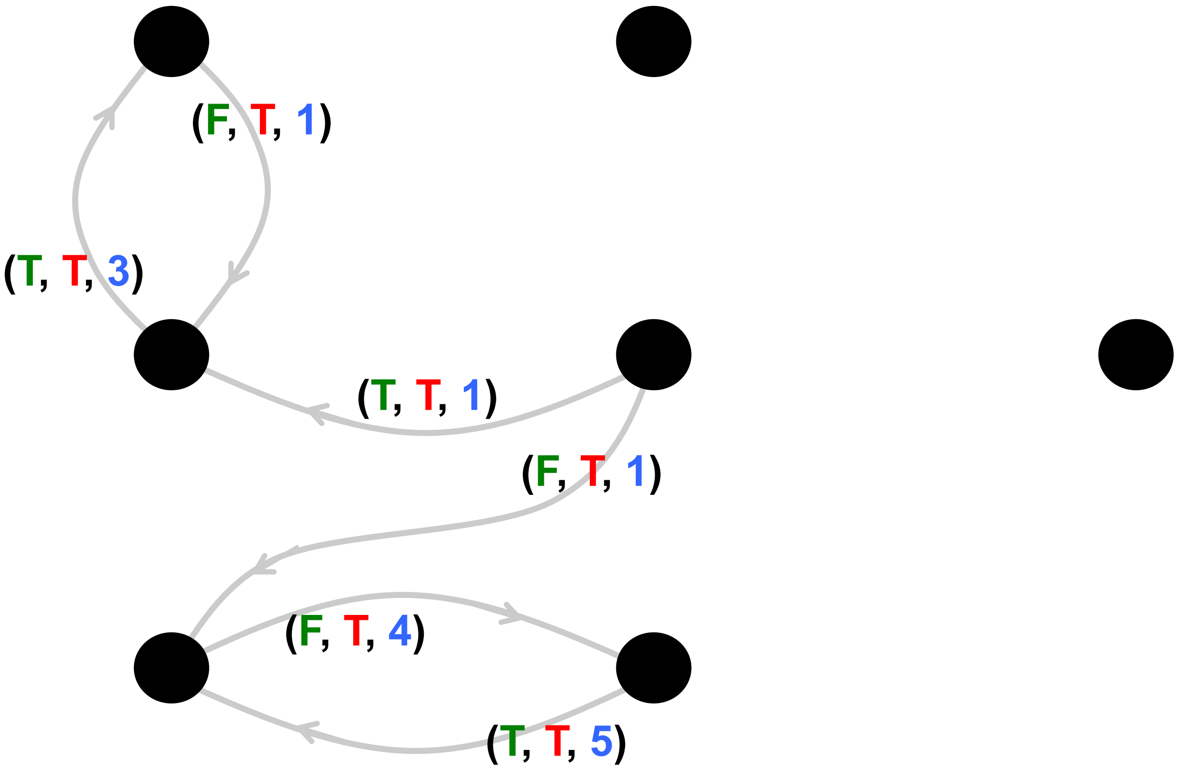
```
G.addEFilter(lambda e: e.weight > 0)
```




```
class edge_attr:
    isText
    isPhoneCall
    weight
```

# Edge filter illustration

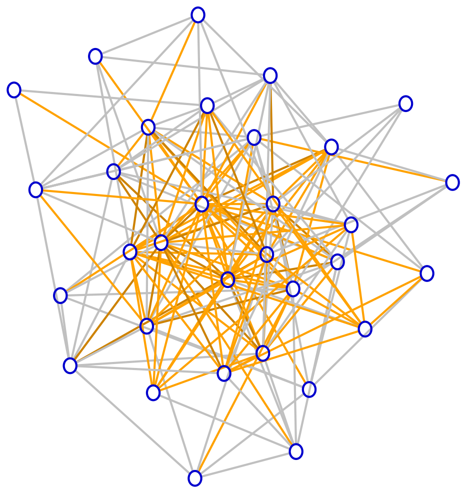
```
G.addEFilter(lambda e: e.weight > 0)
G.addEFilter(lambda e: e.isPhoneCall)
```



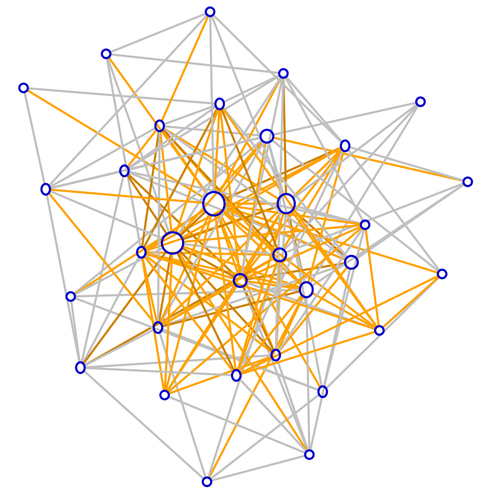

```
class edge_attr:
    isText
    isPhoneCall
    weight
```

# The need for filters

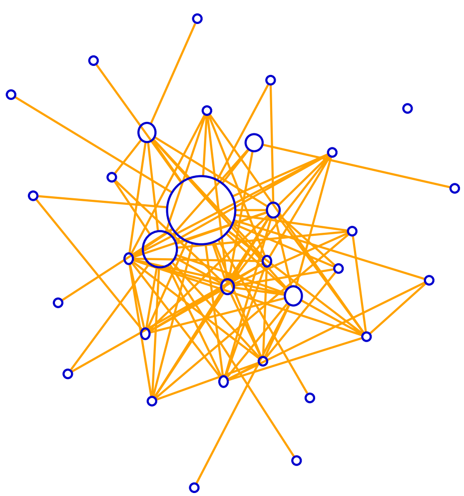
Graph of text & phone calls



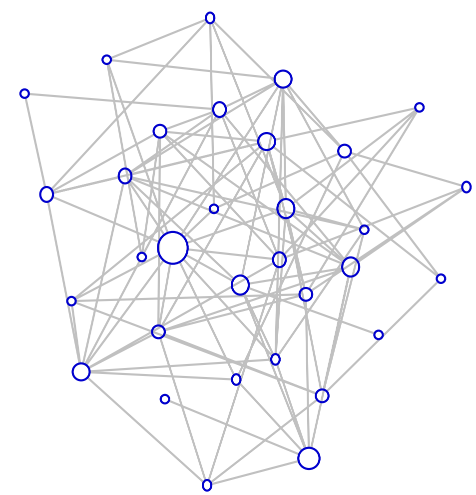
Betweenness centrality



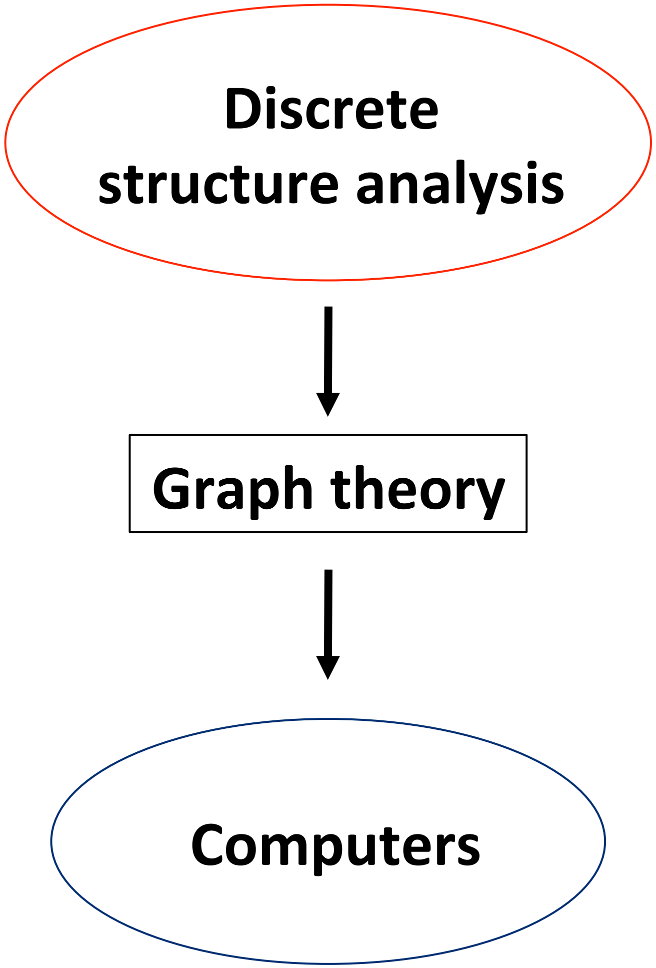
Betweenness centrality on text messages



Betweenness centrality on phone calls



# Parallel Graph Analysis Software



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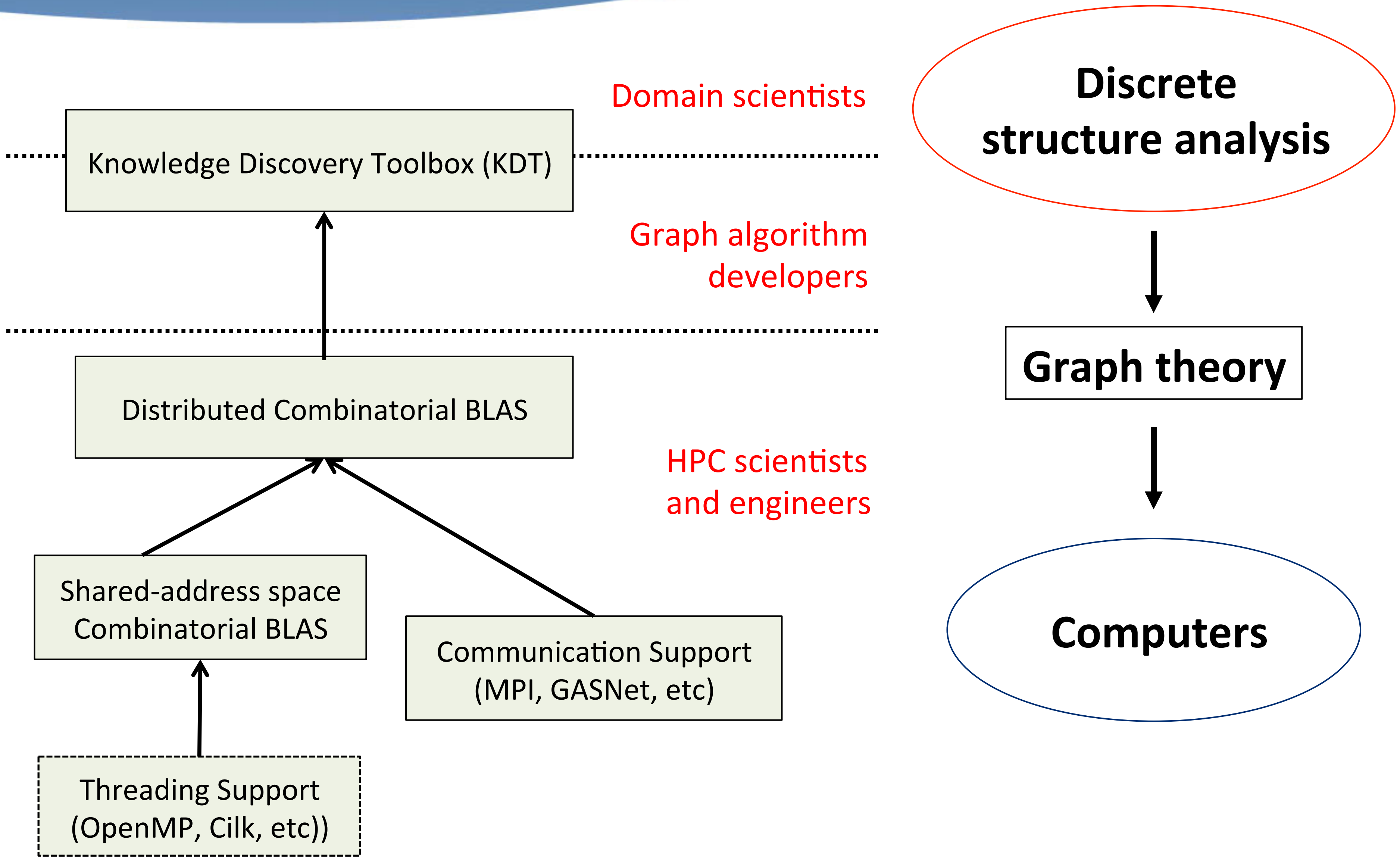
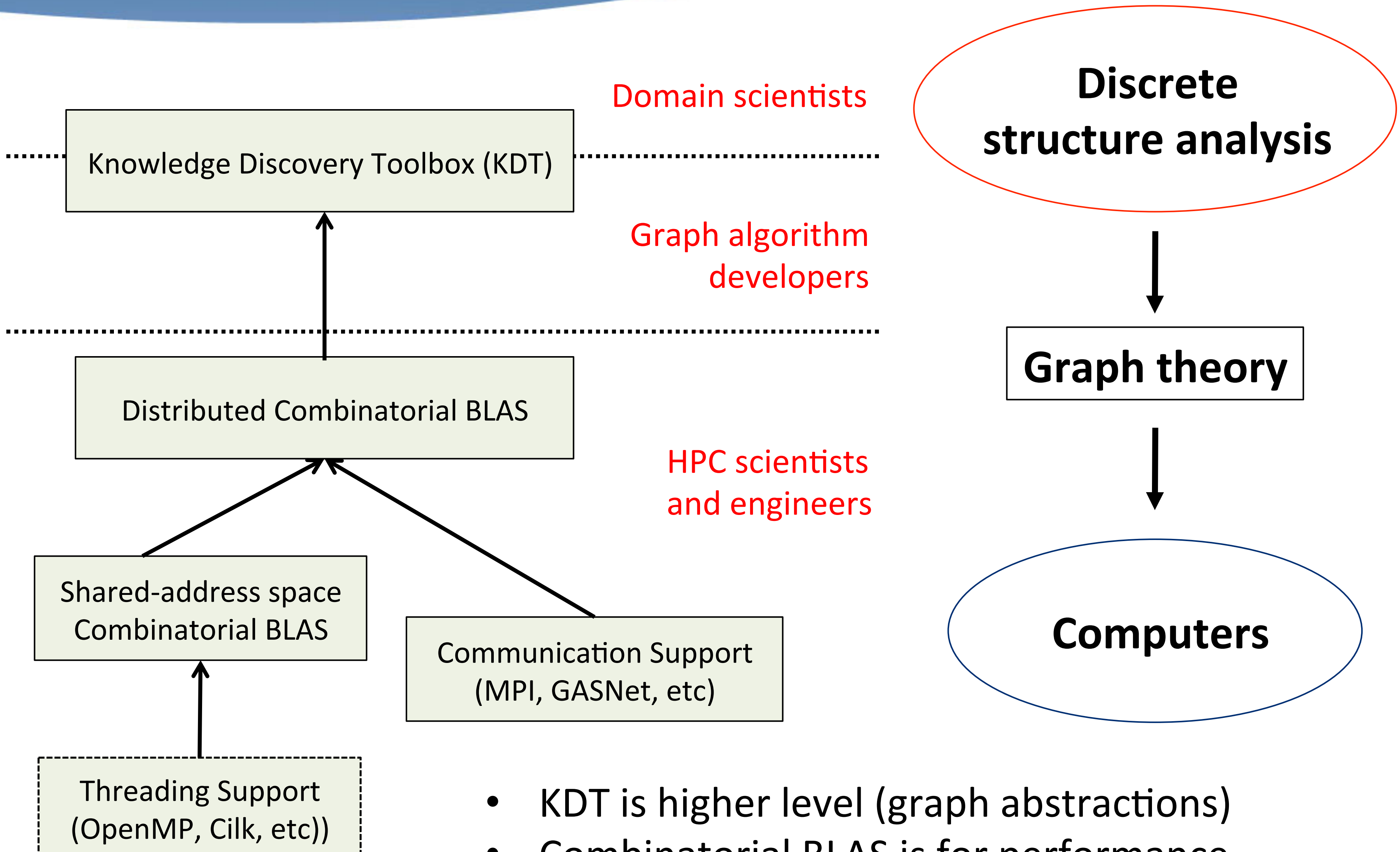
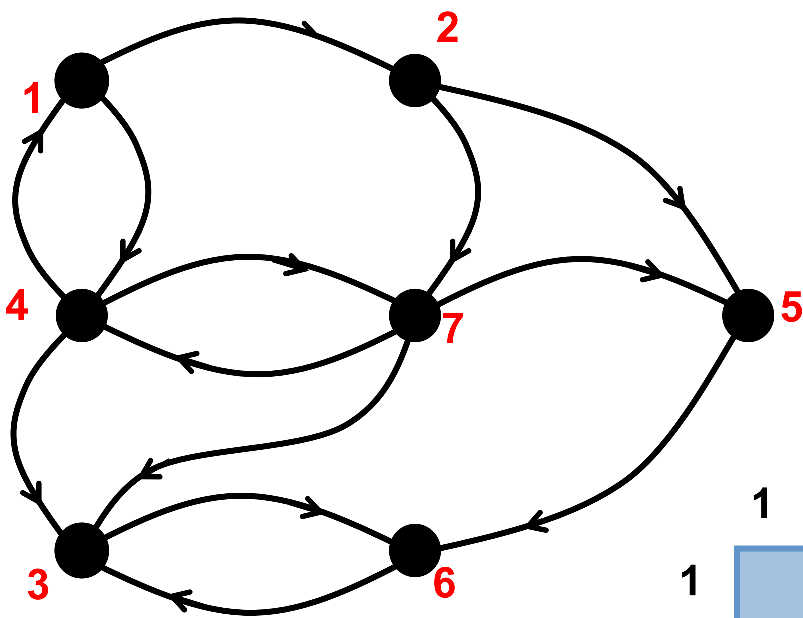


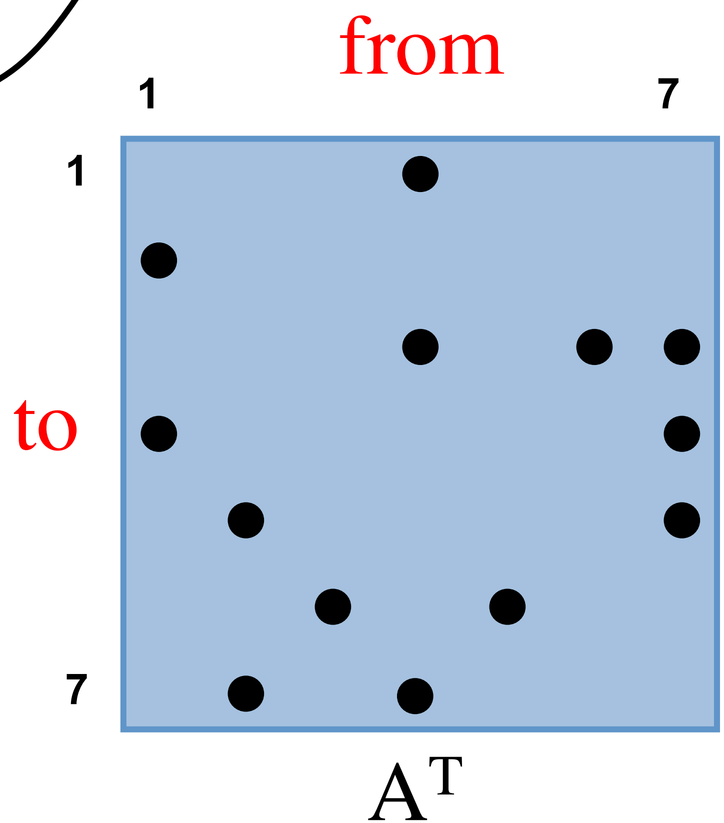
# Parallel Graph Analysis Software

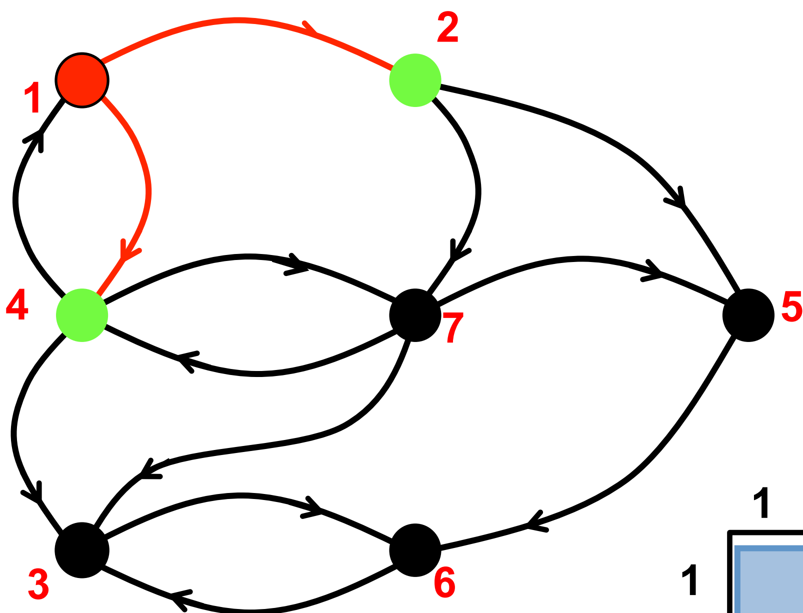



- KDT is higher level (graph abstractions)
- Combinatorial BLAS is for performance

# Breadth-first search in the language of linear algebra



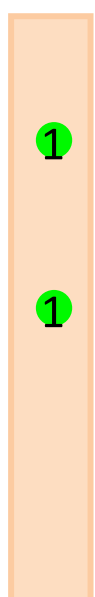


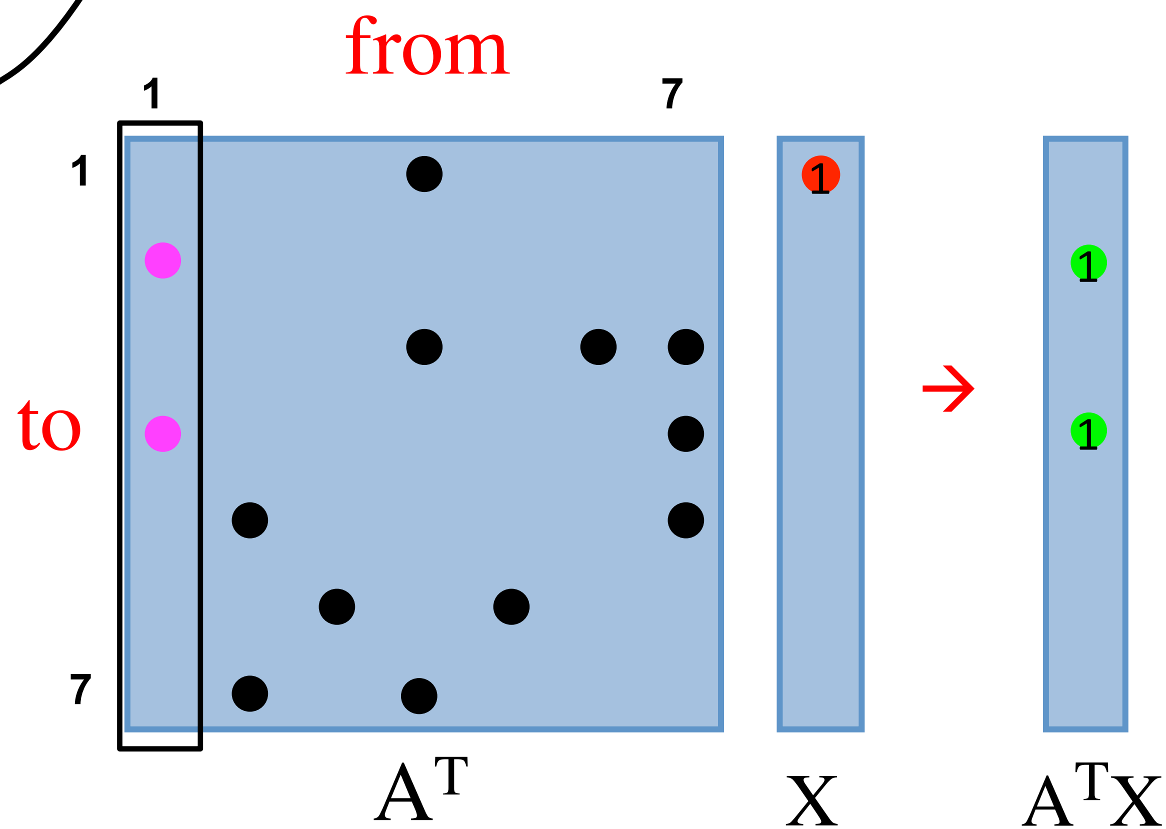

Particular semiring operations:

**Multiply:** select

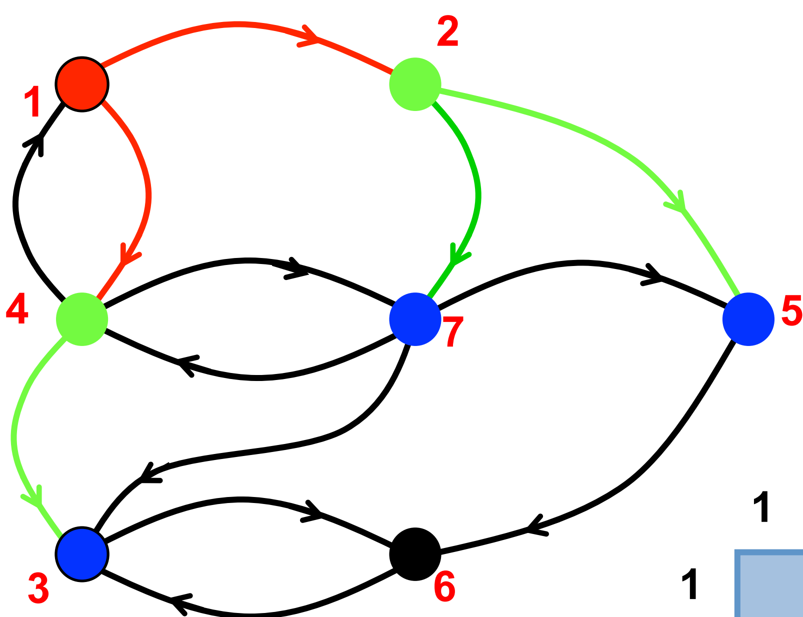
**Add:** minimum

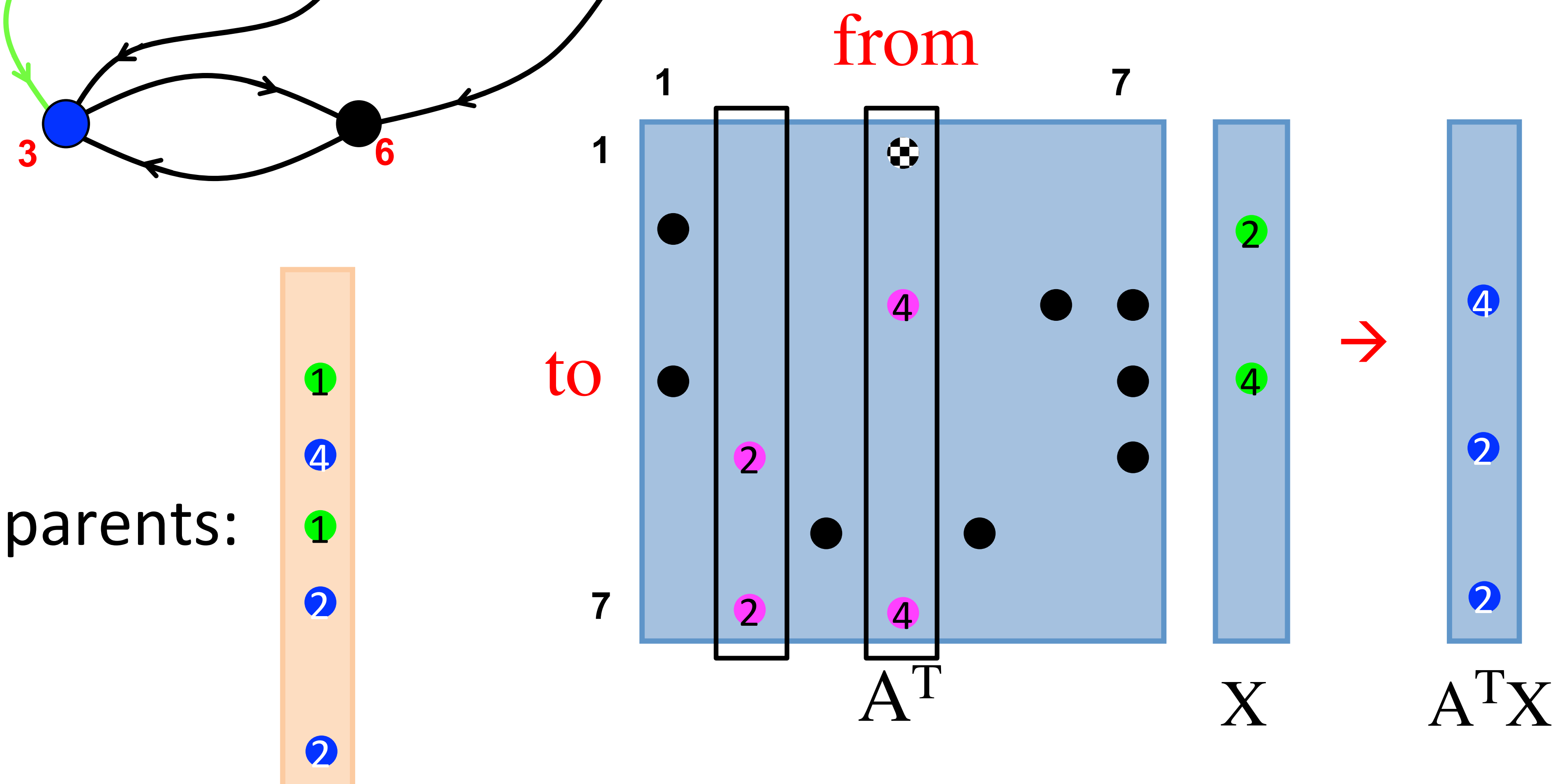
parents:



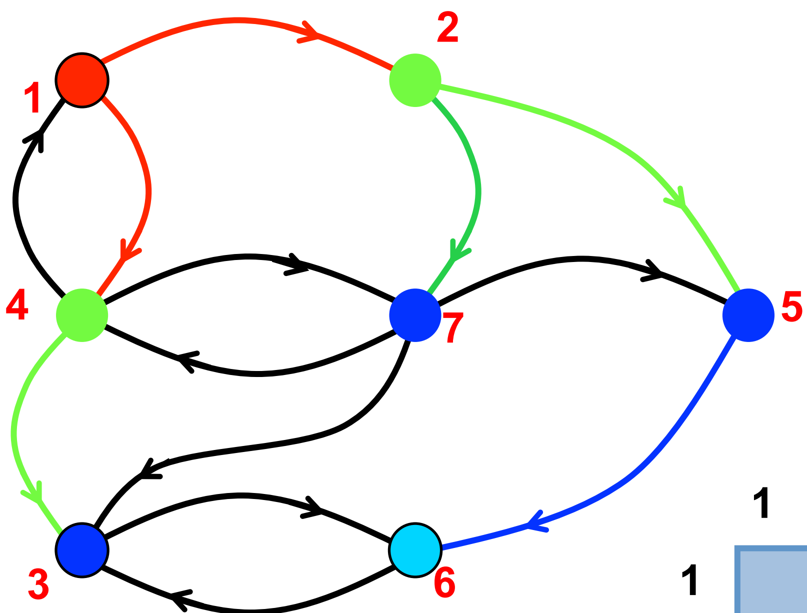



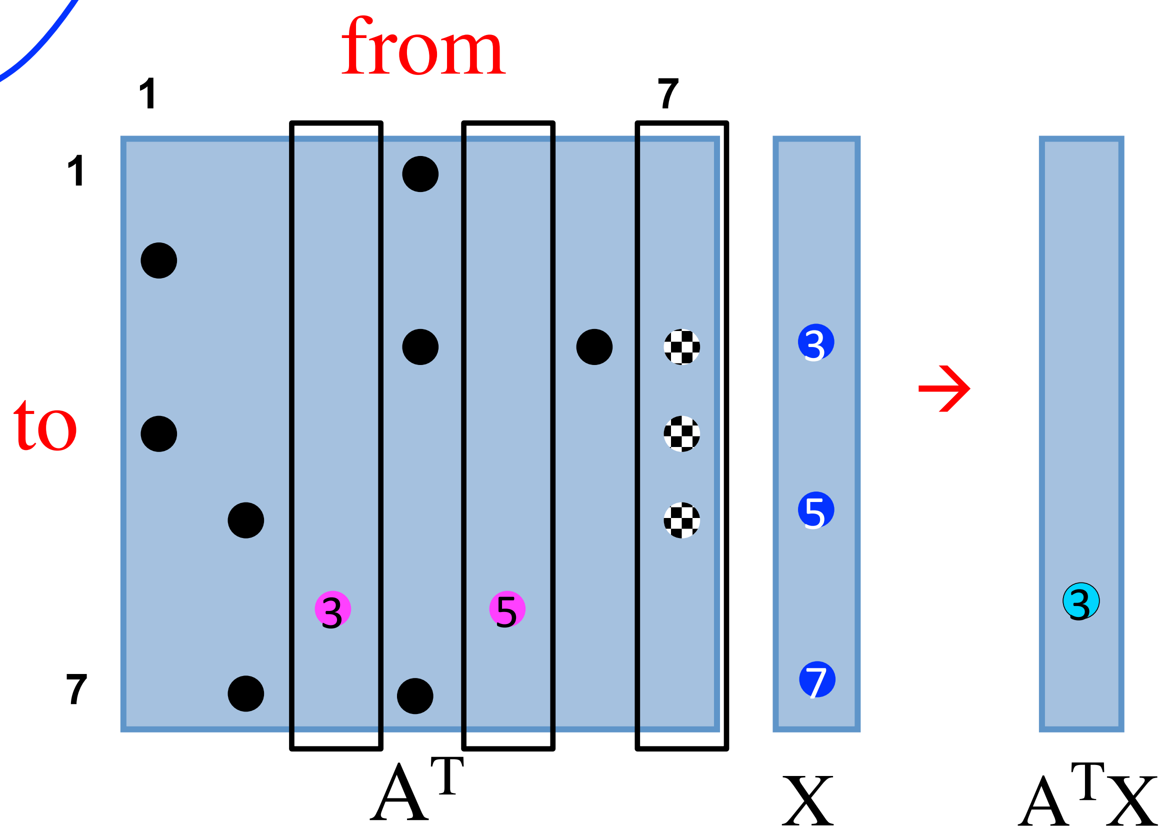
**Multiple** traverses outgoing edges
**Add** chooses among incoming edges

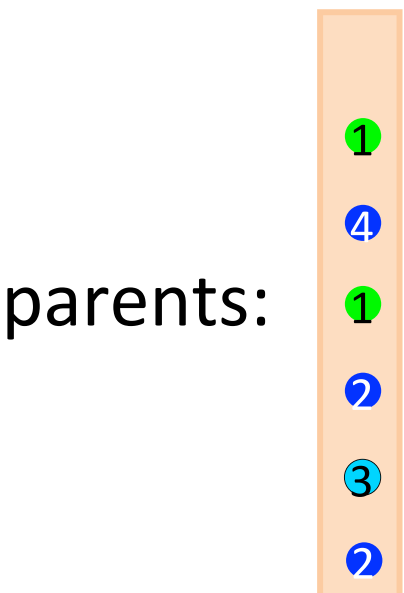


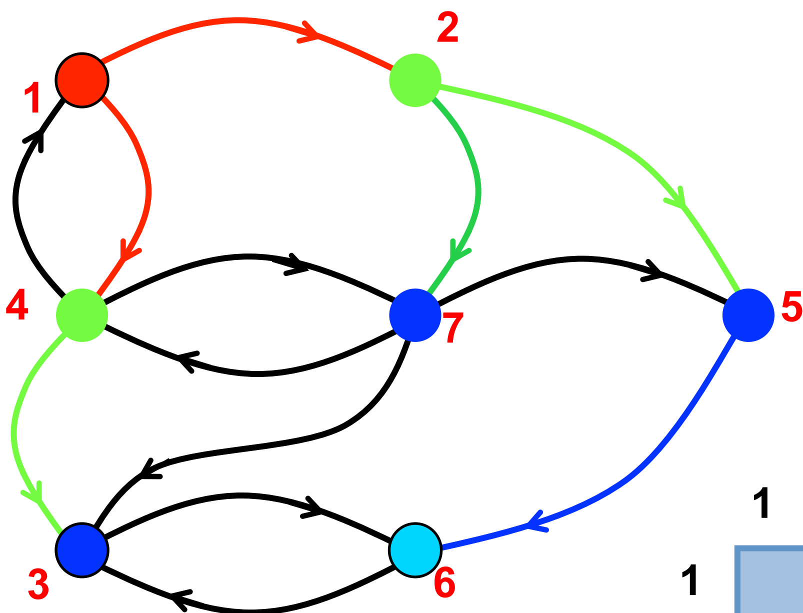



Select vertex with <u>minimum</u> label as parent

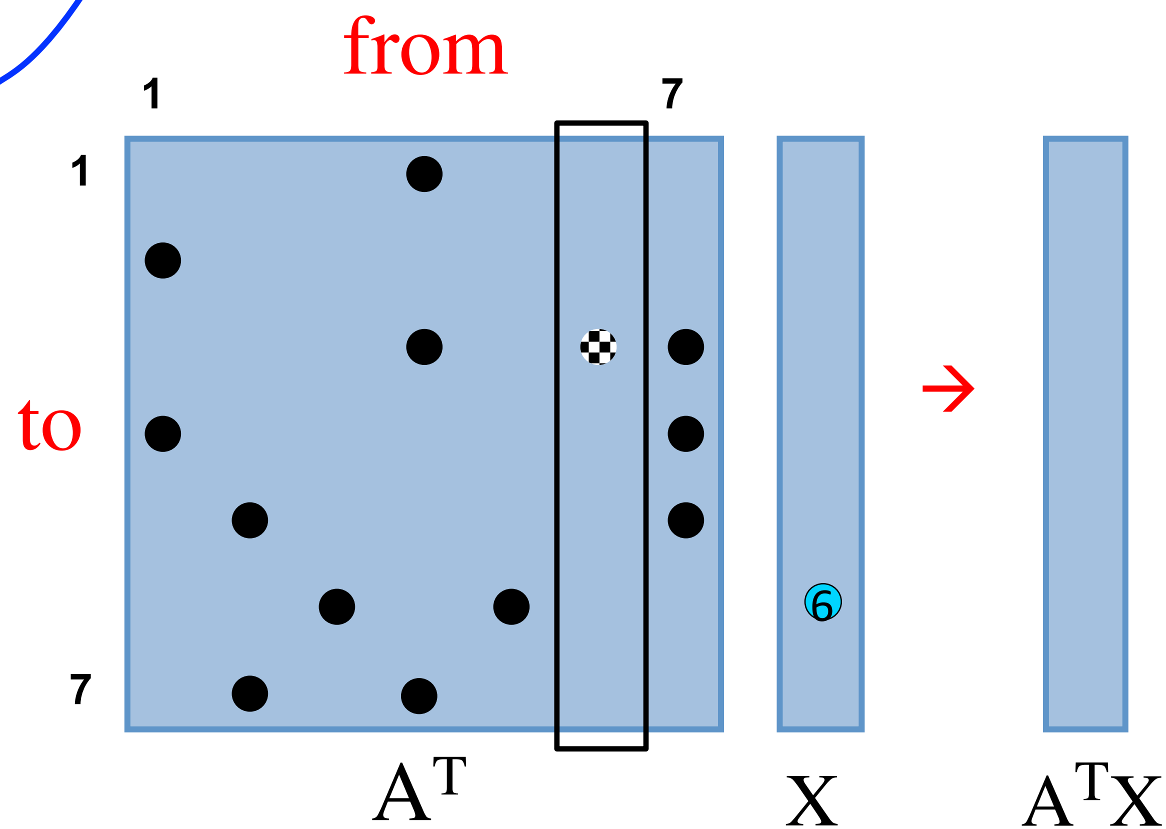


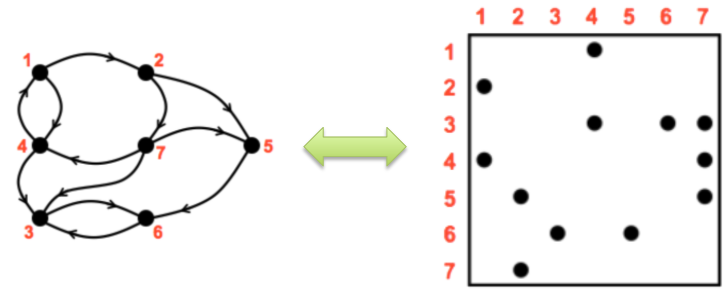



**Result:** Deterministic breadth-first search



# Knowledge Discovery Toolbox

http://kdt.sourceforge.net/




A general graph library with operations based on linear algebraic primitives

- Aimed at domain experts who know their problem well but don't know how to program a supercomputer
- Easy-to-use Python interface
- Runs on a laptop as well as a cluster with 10,000 processors
- Version 0.2 released in March 2012; Version 0.3 expected in a month

BERKELEY LAB
UCSB
The Parallel Computing Laboratory
NSF
Office of Science U.S. Department of Energy
intel
Microsoft

Lugowski, Alber, **B.**, Gilbert, Reinhardt, Teng, and Waranis. A flexible open-source toolbox for scalable complex graph analysis. *SIAM Conference on Data Mining (SDM)*,2012

# Attributed semantic graphs and filters

Example:

- Vertex types: Person, Phone, Camera, Gene, Pathway
- Edge types: PhoneCall, TextMessage, CoLocation, Sequence Similarity
- Edge attributes: StartTime, EndTime

- Calculate centrality just for emails among engineers sent between times sTime and eTime

```
def onlyEngineers(self):
    return self.position == Engineer

def timedEmail (self, sTime, eTime):
    return ((self.type == email) and
            (self.Time > sTime) and
            (self.Time < eTime))

start = dt.now() - dt.timedelta(days=30)
end = dt.now()

# G denotes the graph
G.addVFilter(onlyEngineers)
G.addEFilter(timedEmail(start, end))

# rank via centrality based on recent
email transactions among engineers
bc = G.rank('approxBC')
```

**Algorithm implementation is agnostic to the filters applied** →

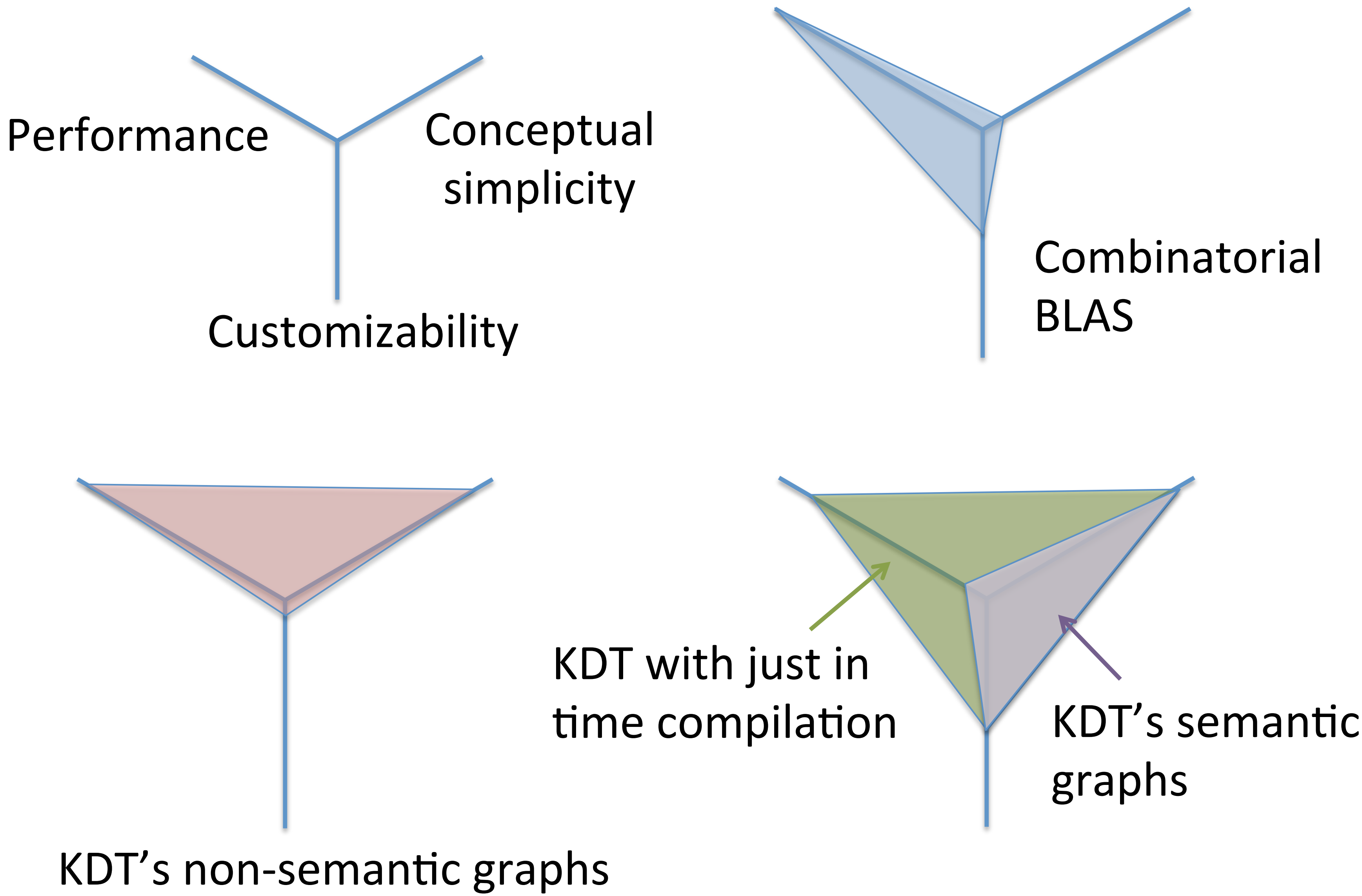
Lugowski, **B.**, Gilbert, Reinhardt. Scalable complex graph analysis with the knowledge discovery toolbox. In *ICASSP*, 2012

# Filter options and implementation

- Filter defined as unary predicates, checked in order they were added
- **Each KDT object** maintains **a stack of filter predicates**
- All operations respect filters, enabling **filter-agnostic algorithm design**

| On-the-fly filters | Materialized filters |
|---|---|
| Edges are retained | Edges are pruned on copy |
| Check predicate on each edge/vertex traversal | Check predicate once on materialization |
| Cheap but done on each run | Expensive but done once |

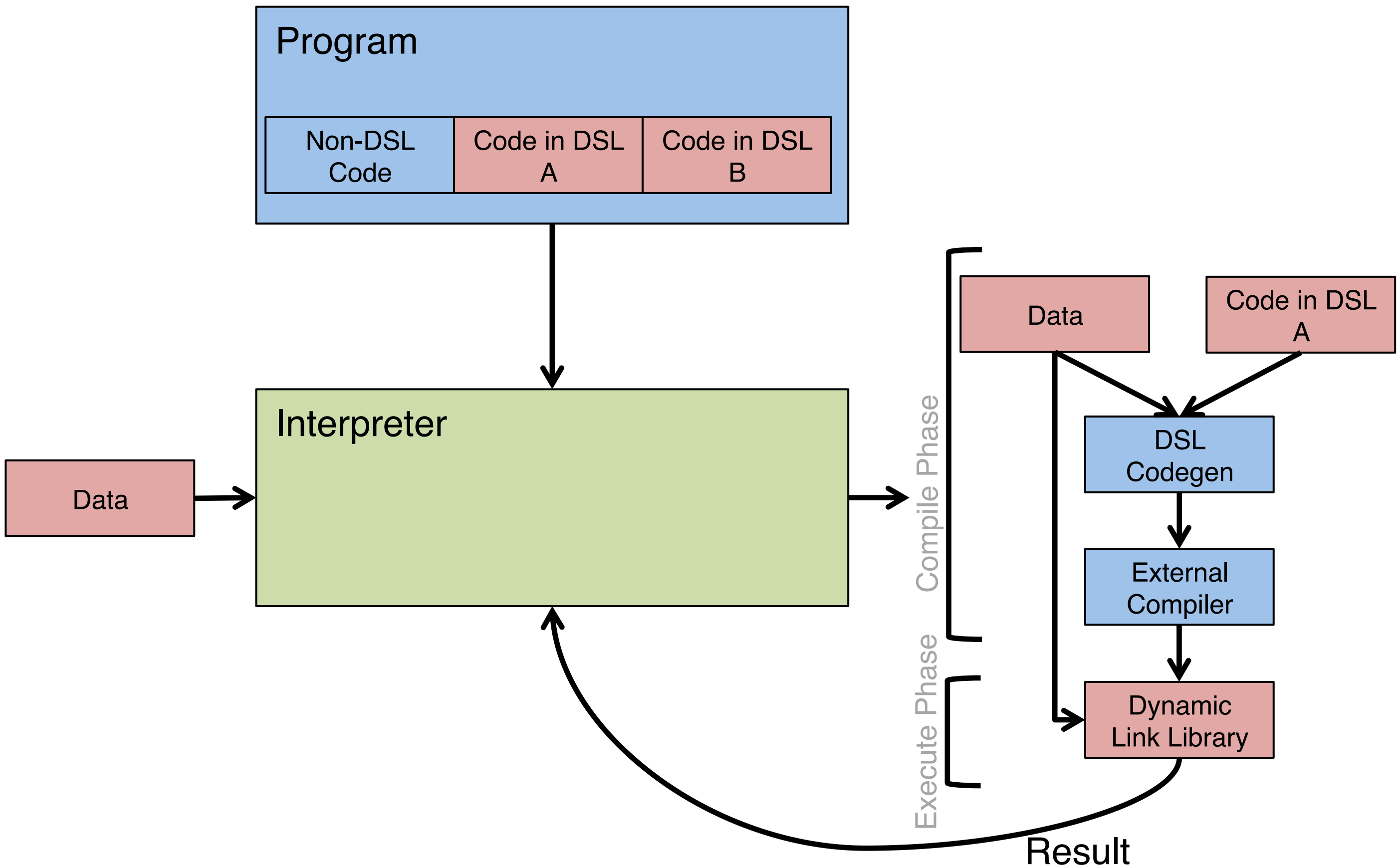
# Targeting "domain experts"



# Problems with Customizing in KDT

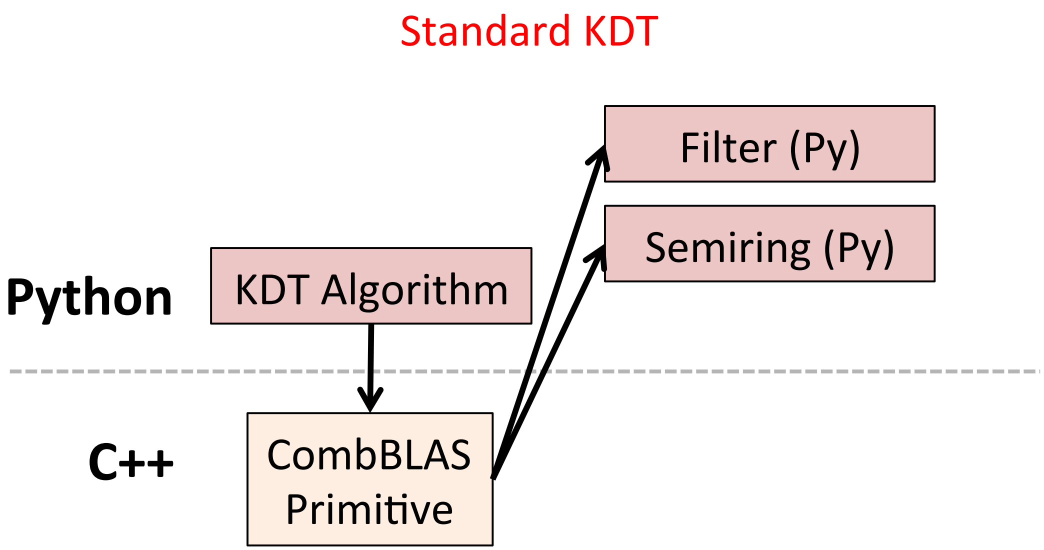
- Filtering on attributed semantic graphs is slow
  - In plain KDT, filters are pure Python functions.
  - Requires a per-vertex or per-edge upcall into Python
  - Can be as slow as 80X compared to pure C++
- Adding new graph algorithms to KDT is slow
  - A new graph algorithm = composing linear algebraic primitives + customizing the *semiring* operation
  - *Semirings* in Python; similar performance bottleneck

# Review: Selective Embedded Just In Time Specialization (SEJITS)

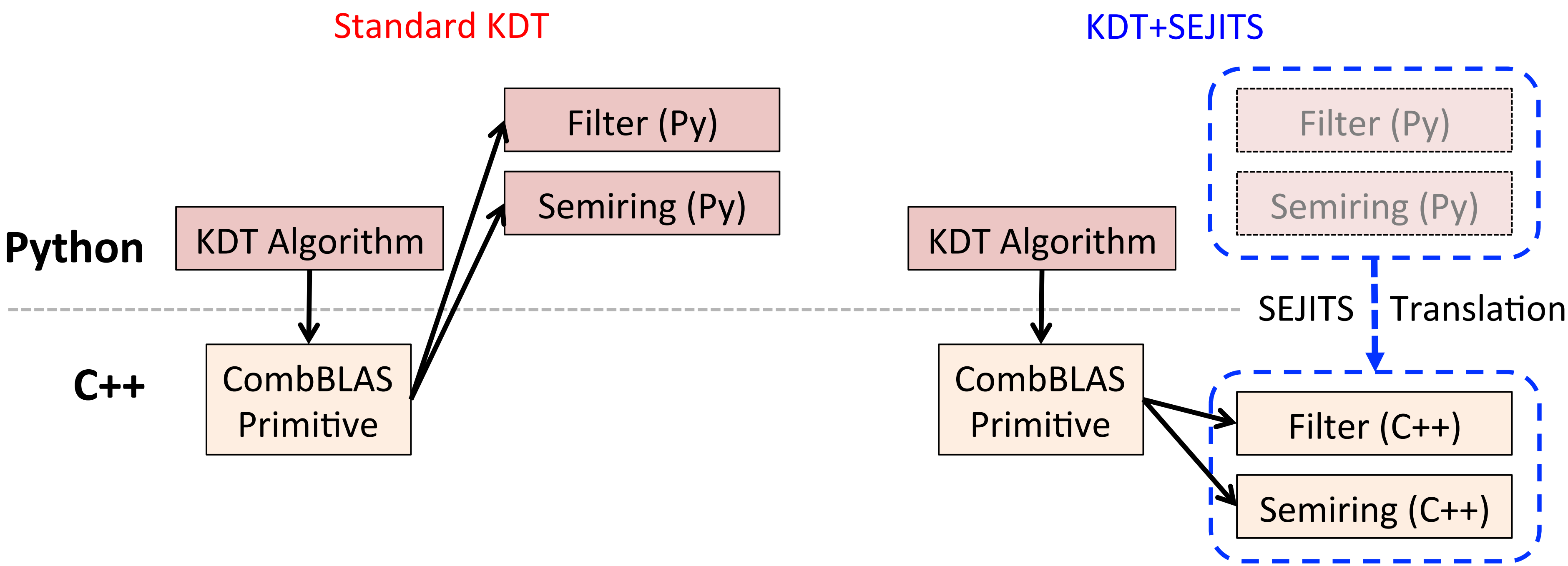



Catanzaro, Kamil, Lee, Asanovic, Demmel, Keutzer, Shalf, Yelick, Fox. SEJITS: Getting productivity and performance with selective embedded JIT specialization. *PMEA,* 2009

# SEJITS for filter/semiring acceleration



# SEJITS for filter/semiring acceleration




Embedded DSL: Python for the whole application

- Introspect, translate Python to equivalent C++ code
- Call compiled/optimized C++ instead of Python

**B.**, Duriakova, Gilbert, Fox, Kamil, Lugowski, Oliker, Williams. High-Performance and High-Productivity Analysis of Filtered Semantic Graphs, *IPDPS*, 2013

# Details about the experimental setting

- Filtered breadth-first search and maximal independent set
- Edge values are generated to guarantee a particular filter permeability by weighting the random number generator.

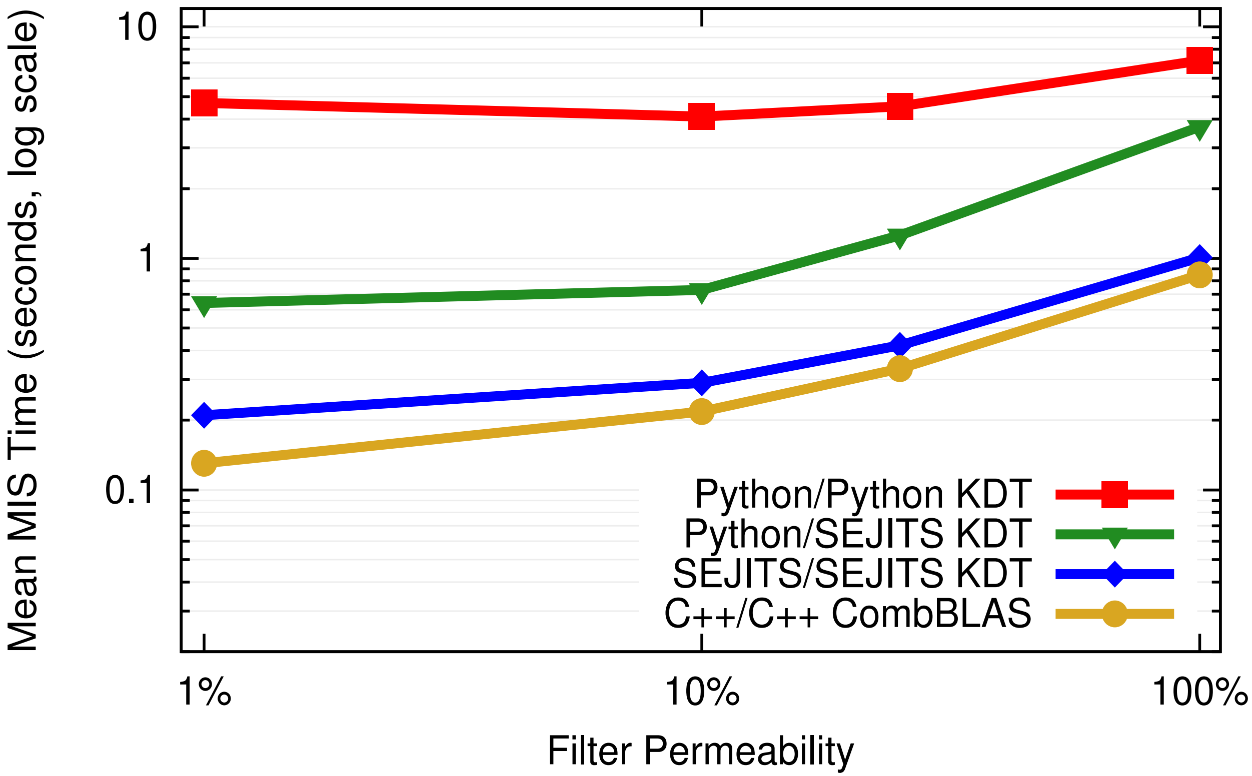
```
struct TwitterEdge {
  bool follower;
  time_t latest; // set if count > 0
  short count; // number of retweets
};
```

The edge filter written in Python :
(translated to C++ on the fly by SEJITS)

```
class MyFilter(PcbFilter):
  def __init__(self, target_date):
    self.target = strtoftime(target_date)

  def filter(e):
    # if it is a retweet edge
    if (e.count > 0 and
        # and it is before the target date
        e.latest < self.target):
      return True
    else:
      return False
```

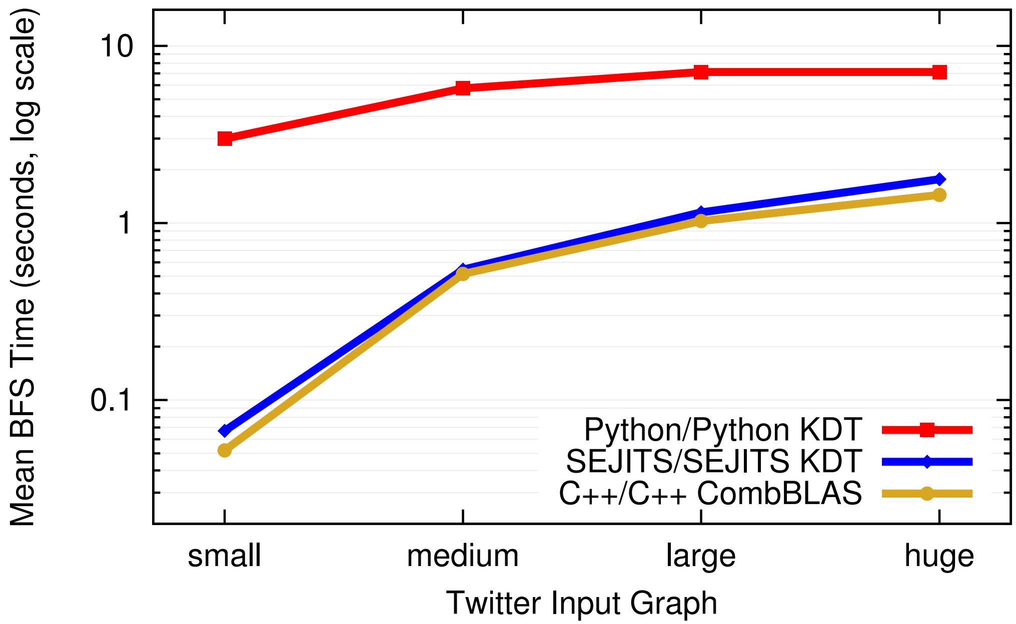
# SEJITS+KDT multicore performance




- MIS= Maximal Independent Set
- 36 cores of Mirasol (Intel Xeon E7-8870)
- Erdős-Rényi (Scale 22, edgefactor=4)

Synthetic data with weighted randomness to match filter permeability
Notation: [semiring impl] / [filter impl]

# SEJITS+KDT real graph performance




- Breadth-first search
- 16 cores of Mirasol (Intel Xeon E7-8870)

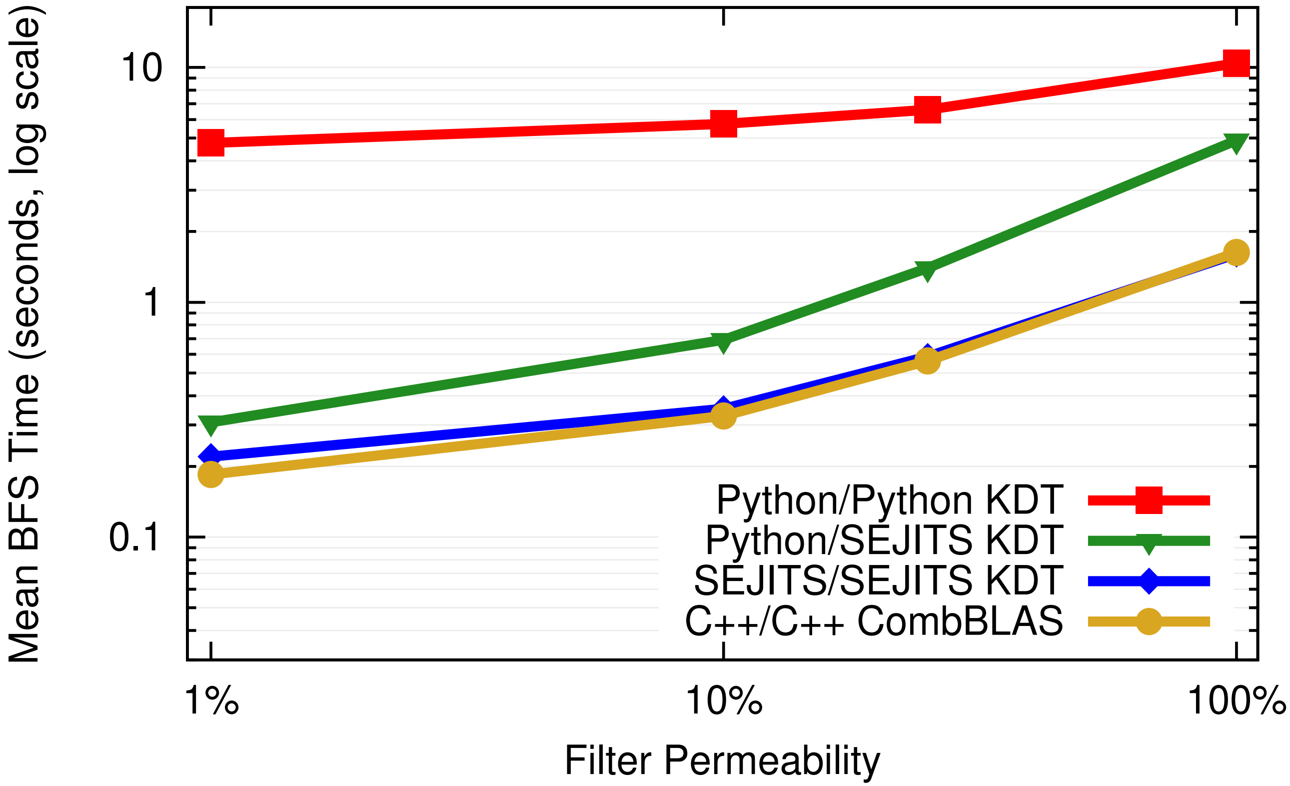
SIZES (VERTEX AND EDGE COUNTS) OF DIFFERENT COMBINED TWITTER GRAPHS.

| Label | Vertices (millions) | Edges (millions) | | |
|---|---|---|---|---|
| | | Tweet | Follow | Tweet&follow |
| Small | 0.5 | 0.7 | 65.3 | 0.3 |
| Medium | 4.2 | 14.2 | 386.5 | 4.8 |
| Large | 11.3 | 59.7 | 589.1 | 12.5 |
| Huge | 16.8 | 102.4 | 634.2 | 15.6 |

STATISTICS ABOUT THE LARGEST STRONGLY CONNECTED COMPONENTS OF THE TWITTER GRAPHS

| | Vertices | Edges traversed | Edges processed |
|---|---|---|---|
| Small | 78,397 | 147,873 | 29.4 million |
| Medium | 55,872 | 93,601 | 54.1 million |
| Large | 45,291 | 73,031 | 59.7 million |
| Huge | 43,027 | 68,751 | 60.2 million |

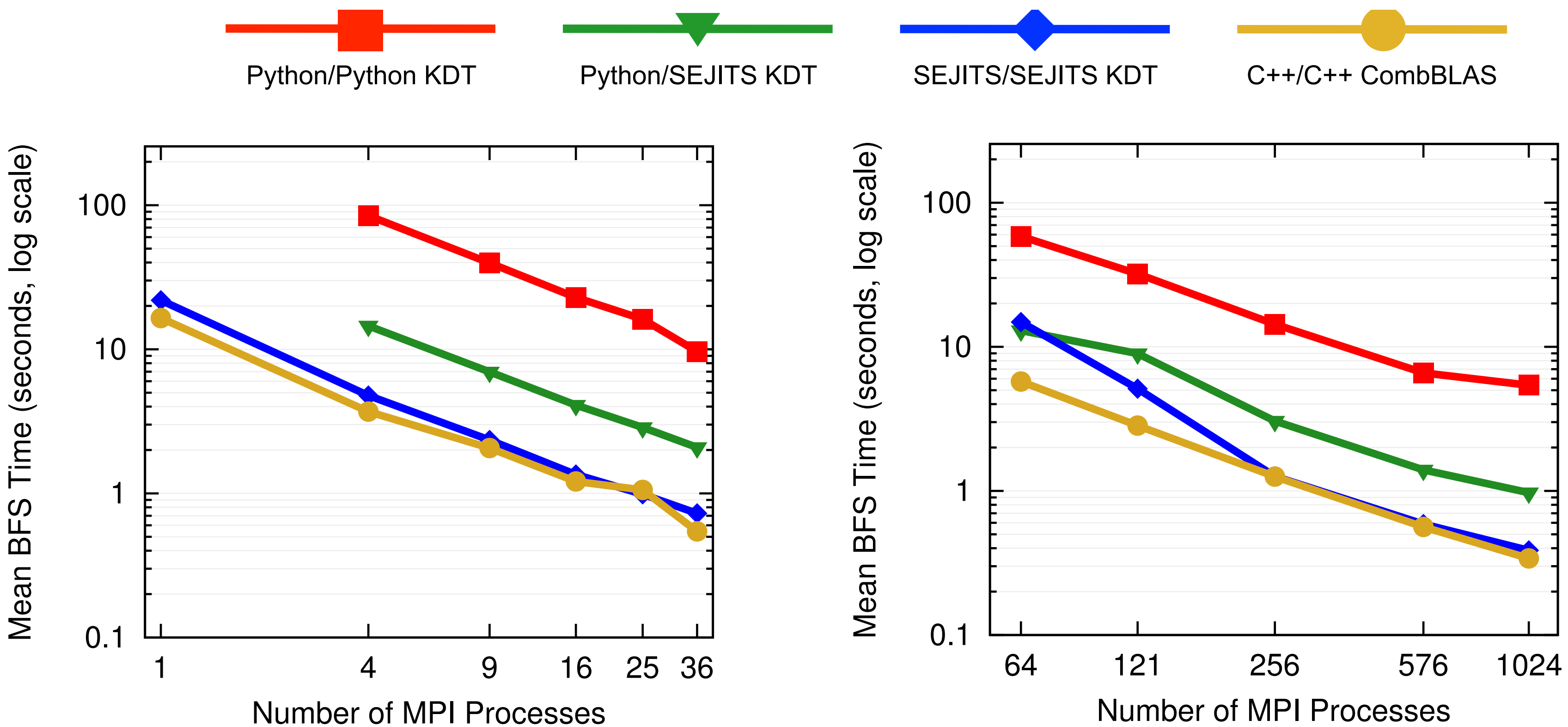
# SEJITS+KDT cluster performance




- Breadth-first search
- 576 cores of Hopper (Cray XE6 at NERSC with AMD Opterons)
- R-MAT (Scale 25, edgefactor=16, symmetric)

A ***roofline model*** for shows how SEJITS moves KDT analytics from being Python ***compute bound*** to being ***bandwidth bound***.

# SEJITS does not impede scaling

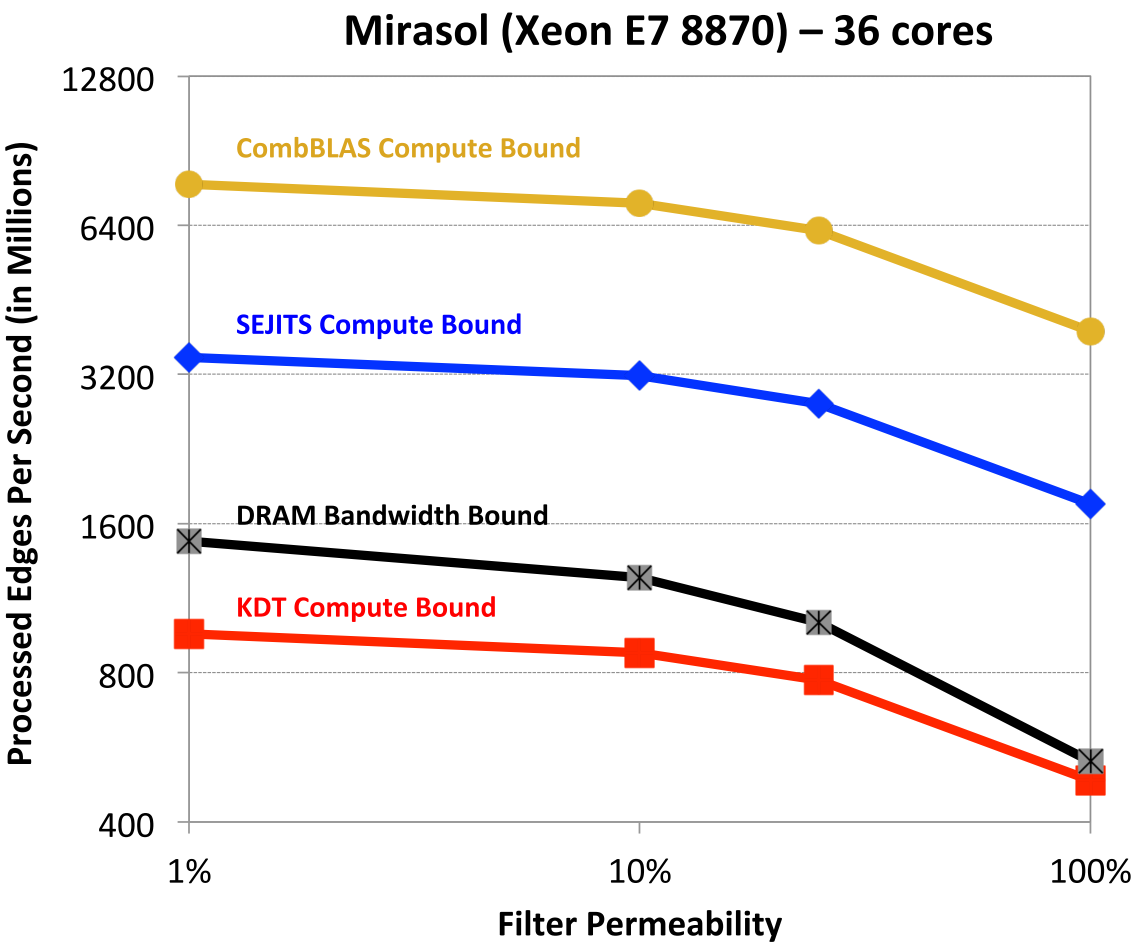



R-MAT Scale 22, 25% permeable

R-MAT Scale 25, 25% permeable

As the compute limitations are lifted, parallel scaling gets **harder** due to higher bandwidth/sec requirements of the computation.

# Roofline analysis: Why SEJITS+KDT works?




Even with SEJITS, there are run-time overheads with function calls via pointers.

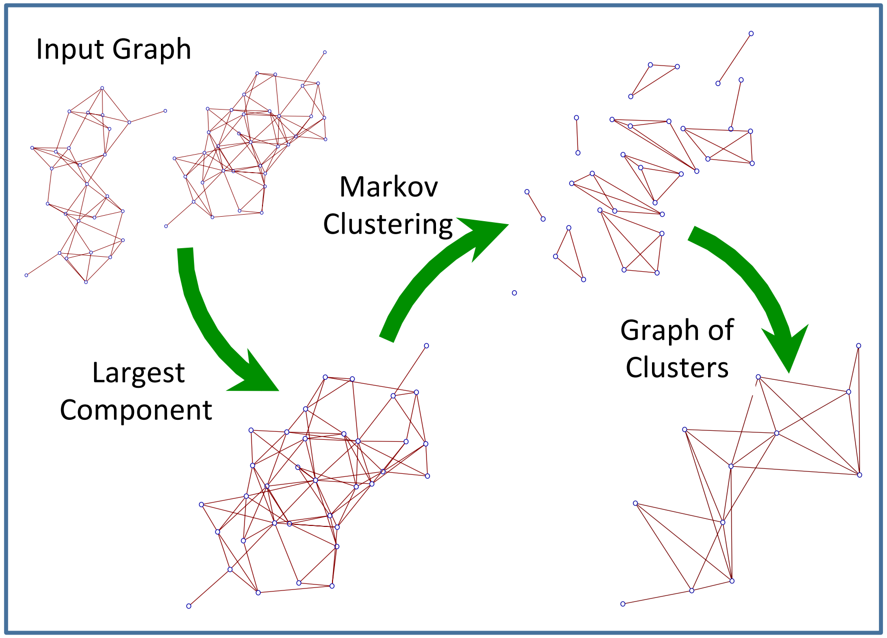
How is it so close to the Combinatorial BLAS performance?

Because once we are bandwidth bound, additional complexity does not hurt.

# Main contribution

- Both Boost Graph Library (BGL) and Parallel Boost Graph Library (PBGL) implement the filtered graph abstraction.
- Why do we re-invent the wheel?

✓ **High-productivity programming**
✓ **Targeting domain scientists**




```
# bigG contains the input graph
comp = bigG.connComp()
giantComp = comp.hist().argmax()
G = bigG.subgraph(comp==giantComp)

clus = G.cluster('Markov')

clusNedge = G.nedge(clus)

smallG = G.contract(clus)

# visualize
```

# Conclusions

- **KDT + Combinatorial BLAS**: Making parallel graph analysis accessible to domain scientists.
- Layered **software architecture** allows concurrent advances in performance and functionality.
- High-performance **filtered semantic graph processing** is possible without changes from the graph algorithm developer.
- Possible to write callbacks in high-level language while retaining low-level language performance
- Possible to define datatypes at runtime [Ongoing work]