CS 744: BIG DATA SYSTEMS

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ADMINISTRIVIA

- Midterm grades up today
- Pick up papers office hours today or Tuesday class
- Course Projects: round 2 meetings

GRAPH MINING

WHATS DIFFERENT ?

Graph Analytics

Examples

- PageRank
- Shortest path
- Connected components
- …

Graph Mining

Examples

- Counting motifs
- Frequent sub-graph mining
- Finding cliques
- …

GRAPH MINING: DEFINITIONS

Graph G = (V, E) Vertices and edges have unique ids.

Embedding sub-graph of G, i.e., subset of vertices and edges

- Vertex-induced – start from vertices, include all edges for vertices
- Edge-induced – start from edges, include all endpoint vertices

Pattern any arbitrary graph

Pattern is a template, embedding is an instance

AUTOMORPHISM, ISOMORPHISM

Embedding is isomorphic to pattern iff

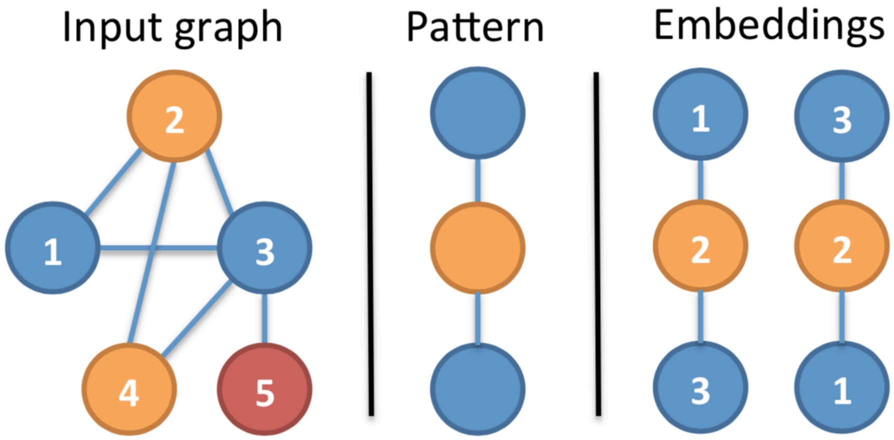
one-to-one mapping between vertices, edges

vertex mapped has same label

edges connect matching vertices

Embedding e is automorphic to e' iff

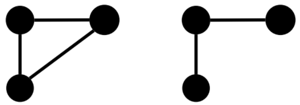
contain same edges and vertices



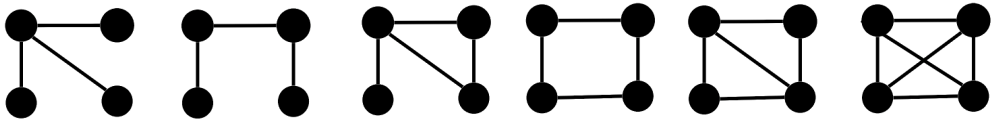
EXAMPLE: MOTIF COUNTING

Motifs: Connected patterns that are non-isomorphic

k=3 – two patterns



k=4 – six patterns



Goal:

Find counts of each pattern in graph

FILTER PROCESS MODEL

Two UDFs: Filter embedding Φ and Process embedding π

Algorithm

```
Initial embedding set I
For each embedding in set
    C <- generate embeddings(add one vertex)
    For each embedding e in C
        If Φ(e):
            F <- F U π(e)
Terminate if F is empty
else loop with I <- F
```

BSP Execution by parallelizing this loop

AGGREGATION FUNCTIONS

Aggregation functions:

Filter function α , Aggregate function β

Similar to groupByWindowAndApply ?

Consistency properties

If embeddings are automorphic, all UDFs return same value

Anti-monotonicity – filter return same values for extensions

OTHER APPROACHES

Think like Vertex

- Vertex has local embedding
- "Push" message to border vertex

Cons

- Highly connected vertex → hotspot
- Duplicate messages, one per border

Think like Pattern

- Don't materialize embeddings
- Store patterns, recompute embeddings on the fly

Cons

- Partition by pattern (fewer ?)
- Popular pattern, load imbalance

ARABESQUE API: EXAMPLE

```
boolean filter(Embedding e){
  return (numVertices(e) <= MAX_SIZE);
}
void process(Embedding e){
  mapOutput (pattern(e),1);
}
Pair<Pattern,Integer> reduceOutput (
    Pattern p, List<Integer> counts){
  return Pair (p, sum(counts));
}
```

Counting Motifs

DISTRIBUTED EXECUTION

Apache Giraph based distributed implementation

Synchronous super-steps (BSP)

- Workers receive messages sent previously [Embeddings]
- Process messages [Filter Process]
- Send new messages to be delivered [Aggregate output?]

Can be implemented in any BSP system ? (e.g., Spark)

EXPLORATION STRATEGY

Goals

- Prune embeddings that are "identical" (i.e. automorphic)
- Need to do this without coordination (why ?)

Approach

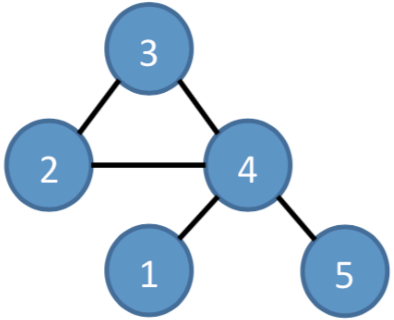
- Determine a "canonical" embedding (unique and extensible)
- Canonical property
    - Start with smallest id
    - Add the neighbor with smallest id not visited yet
- Incremental check while adding vertex to embedding

EFFICIENT STORAGE: ODAG

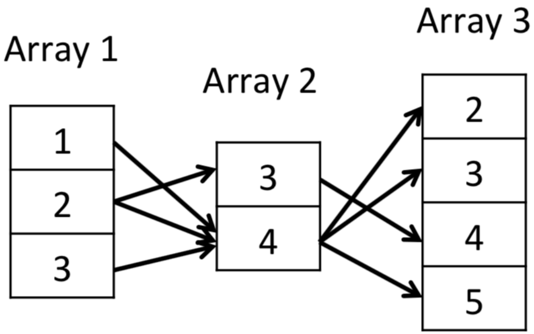
Storage model: Ordered lists of vertex / edge ids (integers)

ODAG format

- Store all first elements of embeddings in one array (and so on)
- Links between array indices if embedding has a such link
- Could lead to spurious embeddings



Canonical embeddings		
1	4	2
1	4	3
1	4	5
2	3	4
2	4	5
3	4	5



EFFICIENT STORAGE: ODAG

ODAG benefits

- N vertices can have up to N^k embeddings of size k
- ODAG upper bound $O(k \cdot N^2)$ ($k \ll N$)

Using ODAGs

- Avoid spurious embeddings using `filter, aggregateFilter`
- Merging ODAGs
  - Every worker creates ODAG outputs
  - Use map-reduce to do the merge!
  - Map each entry based on position to worker

OTHER OPTIMIZATIONS

Partitioning Embeddings

- Performed at start of every iteration
- Round-robin scheme with block size b
- Estimate embeddings that start from a vertex

Two-level aggregation

- Need to aggregate by pattern. Equality requires isomorphism check
- *Quick pattern* calculated locally and aggregated
- Use canonical pattern to do second level aggregation

SUMMARY

Graph Mining: new workload that is compute and data intensive

First system to do distributed graph mining

Challenges: Lots of intermediate state (trillions of embeddings)

Key ideas:

- Filter / prune embeddings using canonical definition
- Efficient storage using ODAGs