Graphlets over Time: A New Lens for Temporal Network Analysis

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Graphs are Everywhere!

- A graph consists of a set of nodes and a set of edges
- Graphs are used to represent various types of data



Real-world Graphs are Evolving over Time

- Many real-world graphs evolve over time, especially with newly arriving nodes and edges
- They are naturally represented as a stream of edges

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Time t	1	2	3	4	•••	Т
Arriving Edge	a → b	b → c	$c \rightarrow b$	a → c		
Graph (Directed)	a b	a b	a b	a b		

Real-world Graphs are Evolving over Time

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• Consider a snapshot of an edge stream





• There are induced subgraphs that are isomorphic to each other





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Graphlet

- A graphlet is a class (set) of isomorphic induced subgraphs
- Graphlets are used to analyze "higher-order" connectivity of graphs
- This work focuses on 13 (weakly) connected graphlets of size 3 defined on directed graphs









• An induced subgraph corresponding to a graphlet is called instance

















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Summary of Our Contributions

- Research questions: "How do real-world graphs evolve over time?"
 - We focus on local structures rather than global structures (e.g., diameter)
- Method: to examine the changes of graphlet instances over time
- Outcome: patterns and analysis tools





• How does the graphlet instance distribution change as a graph grows?



Snapshot at time t



• How does the graphlet instance distribution change as a graph grows?



Snapshot at time t + 1



• How does the graphlet instance distribution change as a graph grows?



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Snapshot at time t + 1



- For each newly arriving edge $v_1 \rightarrow v_2$:
 - For each neighbor v_3 of v_1 or v_2



- For each newly arriving edge $v_1 \rightarrow v_2$:
 - For each neighbor v_3 of v_1 or v_2 :
 - If v_1 , v_2 , v_3 is previously connected:
 - num_prev_graphlet_instance--
 - num_new_graphlet_instance++



- For each newly arriving edge $v_1 \rightarrow v_2$:
 - For each neighbor v_3 of v_1 or v_2 :
 - If v₁, v₂, v₃ is previously connected:
 num_prev_graphlet_instance-num_new_graphlet_instance++
 - Else:

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• num_new_graphlet_instance++





• Our algorithm achieves the lowest complexity possible for any enumeration-based method

• **Theorem**. Given an edge stream, the time complexity of counting the instances of every graphlet in all snapshot by our algorithm is

 $\Theta\left(\Sigma_{v\in\mathcal{V}}(d(v))^2\right) = \Theta(\#graphlet\ instances\ in\ the\ last\ snapshot),$

where d(v) is the degree of node v in the last snapshot

Graphlets over Time: Observations

- We examine the graphlet instance distribution change in real graphs
- Example: a citation network (ArXiv HepPh)

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Graphlets over Time: Observations

- We can observe domain-based patterns
- Graphs from the same domain share similar patterns in their evolution
- Example: citation networks

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- Example: online Q/A networks

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- We can observe domain-based patterns
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- Example: email/message networks

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Graphlet Transition Graph: Motivation

- How can we compare evolutionary patterns in greater detail?
- Idea: to count the occurrences of graphlet transitions
 - Our counting algorithm is easily extended to count the transitions under the same time complexity



Graphlet Transition Graph: Definition

- Graphlet transition graph (GTG) of an edge stream is a graph where
 - Nodes: graphlets

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- Edges: transitions between graphlets
- Weight: ratio of the transitions occurring in the edge stream





Graphlet Transition Graph: Example



Graphlet Transition Graph: Observations

- We can observe domain-based patterns in GTGs
- Graphs from the same domain share similar edge-weight distributions
- Example: citation networks



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- How can we compare graphlet-transition patterns numerically?
- Can we compare them for graphs with different scales?
- Idea: to measure the significance of graphlet transitions

dataset	# nodes	# edges
HepPh	18,477	136,190
Patent	3,774,362	16,512,782

Characterization Profile: Definition

• Significance of a graph transition *i* is defined as:

$$SP_i \coloneqq \frac{w_i - \widetilde{w_i}}{w_i + \widetilde{w_i} + \epsilon}$$

- w_i : occurrences of *i* in a given edge stream
- $\widetilde{w_i}$: (expected) occurrences of *i* in a randomized edge stream
- ϵ : a small constant
- $SP_i > 0$: the transition *i* is more frequent than expectation
- $SP_i < 0$: the transition *i* is less frequent than expectation



Characterization Profile: Definition

• Characteristic profile (CP) of an edge stream is the normalized significance vector of all transitions

$$[CP_1, CP_2, \dots, CP_{28}], \quad where \quad CP_i \coloneqq \frac{SP_i}{\sqrt{\sum_{i=1}^{|E|} SP_i^2}}$$

• CP is a 28-diemensional vector that summarizes the evolutionary pattern of an edge stream



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- We can observe domain-based patterns in GTGs
- Example: citations networks vs email/messaging networks





- We measure the numerical similarity between two edge streams using the correlation coefficients between their CPs
- Similarity is higher within each domain and lower across domains



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Characterization Profiles: Numerical Similarity

- How well do our CPs characterize evolutionary patterns?
- We need a comparison with competitors

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Comparison with Competitors

- Competitors compute CPs based on the following statistics
 - Graphlet count [1]: count of graphlet instances in the last snapshot
 - OTA & GoT [2]: count of transitions between multiple snapshots



1971

Domain-based similarity was less clear in the competitors



Graphlet count [1]

1971

- Domain-based similarity was less clear in the competitors
- GoT [2] and OTA [2] run out of memory on large-scale streams



- Consider a binary classification problem:
 - Given: two edge streams
 - Classify: whether they belong to the same domain or not
- With the best similarity threshold:
 - Ours correctly classifies 97.2% of the pairs
 - Graphlet count [1], GoT [2], and OTA [3] correctly classify 83.3%, 81.0, 85.7% of the pairs, respectively

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- Ours is up to 10 times faster than GoT [2] and OTA [2]
 - GoT and OTA involve duplicated counting in multiple snapshots
 - They also need to store graphlet instances and track their changes





Conclusions

- Research questions: "How do real-world graphs evolve over time?"
- Method: to examine the changes of graphlet instances over time
- **Outcome**: patterns (e.g., domain-based similarity) & analysis tools (e.g., graph transition graphs)

https://github.com/deukryeol-yoon/graphlets-over-time

