Supplementary Document for 'A Survey on Hypergraph Mining: Patterns, Tools, and Generators'

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In this document, we discuss future applications and directions of hypergraph mining, especially hypergraph patterns. We mainly review and discuss existing applications and research topics related to graph mining and graph patterns, especially the graph counterparts of what we have discussed in this survey. Since most hypergraph patterns are generalized from graph patterns, we expect many existing applications and directions of graph mining and graph patterns will also be extended and generalized to hypergraphs in the future.

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1 DATASETS

Table 1 summarizes the basic statistics of a number of publicly available and frequently used hypergraph datasets from the real world. The datasets are grouped by their domains, and we provide brief descriptions for the nodes and hyperedges in each dataset.

2 APPLICATIONS TO ALGORITHMIC DESIGN

First, we discuss the possible applications of hypergraph mining to algorithmic design. Many results of graph mining, especially graph patterns, have inspired the design of innovative graph algorithms for real-world applications. These algorithms have proved to be highly practical, demonstrating excellent efficiency and/or effectiveness. We expect that such applications can be generalized to hypergraphs in the future using the corresponding hypergraph patterns, and they can be useful for hypergraph algorithms and hypergraph mining, especially considering the high natural complexity of hypergraphs [46, 55, 80, 148].

Degree distributions and singular value distributions. The observation that real-world graphs usually exhibit heavy-tailed degree distributions has been used for the design of graph algorithms, including distributed graph algorithms [62, 138], degree distribution estimation algorithms [51],

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Table 1. The basic statistics of real-world hypergraph datasets. For temporal hypergraphs, $|V|$ is the number of nodes, $|E|$ is the number of temporal hyperedges counting repetitions, and $|E^*|$ is the number of unique hyperedges (i.e., repeated hyperedges are counted only once). For static hypergraphs, $|E^*|$ is the number of hyperedges, and we put "-" for $|E|$. The statistics are obtained from the original data sources. Some datasets are converted to hypergraphs from the original form of bipartite graphs or simplicial complexes.

Domain	Dataset	Node	Hyperedge	Source	$\|V\|$	$\|E\|$	$\|E^*\|$
Co-authorship	DBLP [22]	Author	Publication	D1 (link)	1,924,991	3,700,067	2,599,087
	MAG-Geology [22, 149]	Author	Publication	D1 (link)	1,256,385	1,590,335	1,207,390
	MAG-History [22, 149]	Author	Publication	D1 (link)	1,014,734	1,812,511	895,668
	MAG-10 [8, 149]	Author	Publication	D1 (link)	80,198	-	51,889
	OGBN-MAG [169]	Author	Publication	D3 (link)	736,389	1,134,649	751,927
	AMiner [160]	Author	Publication	D3 (link)	13,262,573	22,552,647	10,923,507
	MAG [149]	Author	Publication	D3 (link)	27,320,375	30,175,013	21,016,440
	Cora-CA [179]	Author	Publication	D4 (link)	2,708	-	1,072
	DBLP-CA [179]	Author	Publication	D4 (link)	41,302	-	22,363
Co-citation	Cora [179]	Co-cited Paper	Citing Paper	D4 (link)	2,708	-	1,579
	Citeseer [179]	Co-cited Paper	Citing Paper	D4 (link)	3,312	-	1,079
	Pubmed [179]	Co-cited Paper	Citing Paper	D4 (link)	19,717	-	7,963
Q&A	Tags-SO [22]	Tag	Question	D1 (link)	49,998	14,458,875	5,675,497
	Tags-MSE [22]	Tag	Question	D1 (link)	1,629	822,059	174,933
	Tags-AU [22]	Tag	Question	D1 (link)	3,029	271,233	151,441
	Threads-SO [22]	User	Thread	D1 (link)	2,675,955	11,305,343	9,705,709
	Threads-MSE [22]	User	Thread	D1 (link)	176,445	719,792	595,778
	Threads-AU [22]	User	Thread	D1 (link)	125,602	192,947	167,001
	Answers-SO [166]	Answer	User	D1 (link)	15,211,989	-	1,103,243
	Answers-MO [166]	Answer	User	D1 (link)	73,851	-	5,446
	Questions-Algebra [10]	User	Tag	D1 (link)	423	-	1,268
	Questions-Geometry [10]	User	Tag	D1 (link)	580	-	1,193
Co-purchase	Walmart-1 [8]	Product	Shopping Trip	D1 (link)	88,860	-	69,906
	Walmart-2 [8]	Product	Shopping Trip	D1 (link)	88,837	-	65,898
	Amazon [125]	Product	User	D1 (link)	2,268,231	-	4,285,363
Review	Music-Blues [125]	Reviewer	Music Type	D1 (link)	1,106	-	694
	Madison-Restaurant [9]	Reviewer	Restaurant Type	D1 (link)	565	-	601
	Vegas-Bars [9]	Reviewer	Bar Type	D1 (link)	1,234	-	1,194
Drug	Substances [22]	Substance	Drug	D1 (link)	5,311	112,405	10,025
	Classes [22]	Class	Drug	D1 (link)	1,161	49,724	1,222
	DAWN-1 [22]	Drug	Patient	D1 (link)	2,558	2,272,433	143,523
	DAWN-2 [8]	Drug	Patient	D1 (link)	2,109	-	87,104
Congress	Bills-Congress [22, 57, 58]	Sponsor	Bill	D1 (link)	1,718	260,851	85,085
	Bills-Senate [36, 57, 58]	Sponsor	Bill	D1 (link)	294	-	29,157
	Bills-House [36, 57, 58]	Sponsor	Bill	D1 (link)	1,494	-	60,987
	Committees-Senate [36]	Member	Committee	D1 (link)	282	-	315
	Committees-House [36]	Member	Committee	D1 (link)	1,290	-	341
Social contact	Email-Eu [22, 104, 185]	Sender/Recipient	Email	D1 (link)	998	234,760	25,791
	Email-Enron [22]	Sender/Recipient	Email	D1 (link)	143	10,883	1,542
	Primary-School [36, 152]	Student	Interaction	D1 (link)	242	106,879	12,799
	High-School [36, 120]	Student	Interaction	D1 (link)	327	172,035	7,937
	Directors [142]	Director	Company	D2 (link)	522	-	102
	Crime [47]	Criminal	Crime Event	D2 (link)	510	-	256
User behavior	Trivago [36]	Clicked Hotel	User	D1 (link)	172,738	-	233,202
	Foursquare [182]	Visited Restaurant	User	D2 (link)	2,334	-	1,019
	Yelp [33]	Visited Restaurant	User	D4 (link)	50,758	-	679,302
Biology	Host-Virus [127]	Virus	Host	D2 (link)	466	-	218
	Zoo [49]	Animal	Biological Attributes	D4 (link)	101	-	43
	Mushroom [49]	Mushroom	Biological Attributes	D4 (link)	8,124	-	298
	Florida Bay [106]	Species/Organism	Carbon Exchange	D5 (link)	125	-	141,233
Computer vision	NTU2012 [27]	Visual Objects	Similar Objects	D4 (link)	2,012	-	2,012
	ModelNet40 [178]	Visual Objects	Similar Objects	D4 (link)	12,311	-	12,311
Text	20News [49]	News Article	Word	D4 (link)	16,242	-	100
Recipe	Cooking [8]	Ingredient	Recipe	D1 (link)	6,714	-	39,774

D1: https://www.cs.cornell.edu/~arb/data.
D2: https://github.com/Abel0828/supervised_hypergraph_reconstruction [174].
D3: https://github.com/kswoo97/pcl [92].
D4: https://github.com/jianhao2016/AllSet [33].
D5: https://sites.google.com/view/panli-purdue/datasets.

graph traversal algorithms [196], knowledge graph completion [147], and triangle counting algorithms [97]. Similarly, skewed singular values in real-world graphs have been used for optimizing triangle counting [93, 164]. Skewed degree distributions and singular value distributions are also observed in real-world hypergraphs (see P1 and P14). Therefore, the above applications are possibly extendable to hypergraphs, for the counterpart algorithmic problems on hypergraphs.

Temporal locality. In many real-world temporal graphs, the temporal locality is observed, where edges appearing within a smaller temporal window are more likely to interact. This property has been used for designing efficient algorithms for triangle counting [100] and graph traversal [96]. Several patterns related to temporal locality have been observed in hypergraphs (see P16 and P20), and we expect such patterns to be useful in the design of algorithms for temporal hypergraphs.

Diameters. Small diameters in real-world graphs have been considered in designing algorithms for large-scale graph mining [88]. Therefore, shrinking diameters observed in real-world hypergraphs (see P26) are also possibly useful for large-scale hypergraph mining.

Core-periphery structures. Several algorithms leverage core-periphery structures in real-world graphs for efficient graph compression [110] and the rapid retrieval of similar nodes [85, 146], and thus we expect such structures in hypergraphs (see P3) to be useful in related tasks [39].

Treewidth. Bounded treewidth in real-world graphs has been used for optimizing graph queries [118], designing graph clustering algorithms [19], and Bayesian inference [141]. Although the study of treewidth in hypergraphs is still mainly limited to the theoretical field [115, 121, 161], we expect more patterns regarding treewidth will be discovered in real-world hypergraphs and those patterns will be used in many applications.

3 APPLICATIONS TO MACHINE LEARNING

In addition to algorithmic design, graph patterns have also been widely used in machine learning, especially machine learning on graphs. This suggests the potential usefulness of observed patterns within real-world hypergraphs across hypergraph-related applications, as discussed below.

Graph neural networks and general feature representation. One of the most common topics in machine learning on graphs is feature representation, where graph neural networks (GNNs) are often used. Many graph properties and patterns have been considered for enhancing the performance of GNNs, including degree distributions [108, 112, 184, 193], assortativity [159], graph motifs [20, 29, 45, 60, 83, 123, 131, 190, 199, 200], ego-networks [128, 139]. Structural patterns can also be used as additional node features to enrich the features used for graph learning [43, 68]. Recently, a line of research focused on using graph patterns for the theoretical analysis of GNNs. For example, graph motifs have been used to explain the learning process and the outcomes produced by GNNs [130], and ego-networks have been used for designing a theoretically and practically transferable GNN model [203]. Besides, graph patterns, especially graph motifs, can be used for general feature representation at both the node level and the graph level. Typically, graph motifs are extensively used for the comprehensive analysis and representation of whole graphs [13, 15, 122, 176], as well as for comparing multiple graphs [133, 186]. Moreover, graph motifs are also used for modeling the evolution of temporal graphs [42, 140]. We expect hypergraph patterns to be useful, as their graph counterparts, not only in GNNs (e.g., a straightforward generalization of k-cores in hypergraphs has been utilized for the initialization of GNNs [111]), but also in increasingly popular hypergraph neural networks [18, 33, 55, 61, 64, 69, 71, 79, 90, 109] and general feature representation in hypergraphs [14] for applications including educational management [105] and fake news detection [77].

Link prediction and community detection. Link prediction [98, 114] and community detection [56] are two traditional machine-learning problems on graphs. Many graph patterns have been used in those two problems, including assortativity [6, 40], graph motifs [1, 137, 170, 177], the structure of ego-networks [3, 162], and structural similarity (especially neighborhood homogeneity) [21, 31, 153, 172, 188]. Link prediction (i.e., hyperedge prediction) [30, 74, 99, 165, 168, 180, 183, 187] and community detection in hypergraphs [34, 41, 53, 86, 87, 89, 202] have gained more and more attention recently. Specific applications where they have been employed include (1) recognizing unique sets of items to be purchased together [107], (2) proposing new combinations of ingredients for recipes [198], (3) suggesting novel collaborations among researchers [113], and (4) uncovering clusters of genes that collaborate for specific biological functions [124]. We look forward to seeing hypergraph patterns be used for these two tasks.

Anomaly detection. Anomaly detection [26] is another traditional machine-learning problem, and graph-based anomaly detection [5] is a popular subtopic. Many graph patterns have been used in graph-based anomaly detection, including graph motifs [126], the structure of ego-networks [4], k-cores [145], and structural similarity (especially neighborhood homogeneity) [25]. Recently, anomaly detection in hypergraphs has also been studied [101, 171], and Do and Shin [48] have considered a simple heuristic of anomaly detection on nodes by comparing the hypercoreness values and degrees of nodes. We anticipate more usage of hypergraph patterns for this application.

Recommendation. Recommendation [76, 143] is a long-standing research topic in machine learning. Graphs are an important tool for building recommendation systems [28, 67, 157], and many graph patterns, including graph motifs [44, 63, 156, 201] and the structure of ego-networks [52], have been used in graph-based recommendation models. Furthermore, many challenges and remedies in recommendation systems are closely linked to graph patterns, such as addressing popularity bias stemming from heavy-tailed degree distributions [116, 175]. Hypergraphs are also useful for this task, especially bundle recommendation [158, 204] and group recommendation [11, 192], which can be modeled using hypergraphs [78, 119, 191, 195]. We await more applications of hypergraph patterns for recommendation systems.

Subgraph sampling. In machine learning on graphs, subgraph sampling is a useful technique for, e.g., better representation [7] and higher time efficiency [32, 144, 194]. A line of works exists on representative subgraph sampling [73, 103, 117], where the target is to sample subgraphs with similar characteristics as a given graph. Subgraph sampling has also been used for estimating quantities of a given graph [81, 189], where the estimation algorithms exploit the skewed degree distribution [2] and fast mixing time [65] of real-world graphs. Recently, this task has been considered on hypergraphs [38]. Hopefully, hypergraph patterns can be proven useful on related tasks, just like their graph counterparts.

4 ANALYSIS AND MINING OF GENERALIZED HYPERGRAPHS

In this survey, we have mainly discussed simple hypergraphs (i.e., undirected and unweighted ones). Below, we would like to discuss several types of generalized hypergraphs.

Directed hypergraphs. Directed hypergraphs, where nodes within each hyperedge are partitioned into a source set and a destination set, have been studied in the fields of theoretical mathematics and theoretical computer science with researchers paying continuous attention [16, 17, 59, 136]. Directed hypergraphs are applied to many tasks, including expert systems [134], image segmentation [50], music composition [70], metabolic network analysis [163], chemical reaction modeling [84], and objects retrieval [12]. Ranshous et al. [135] studied patterns in real-world directed transaction hypergraphs, and applied the observed patterns to transaction classification. Recently, Kim et al. [91] extended the concept of reciprocity to directed hypergraphs and studied related patterns within real-world directed hypergraphs. We expect more patterns to be explored on directed hypergraphs.

Weighted hypergraphs. Most works mentioned in this survey deal with unweighted real-world hypergraphs or explicitly preprocess the datasets into unweighted ones, although some take the repetition of hyperedges into consideration [23, 102]. At the same time, weighted hypergraphs provide a more general and expressive way to represent systems. Weighted hypergraphs, particularly those with each hyperedge associated with a numerical value, have been used for biological studies [75], image retrieval [72], concept-to-text generation [94, 95], and object classification [154]. Recently, there also has been a growing interest in hypergraphs with edge-dependent vertex weights (where a node can have different weights in different hyperedges) [35, 37, 66, 206]. We expect more patterns to be explored on weighted hypergraphs.

Heterogeneous hypergraphs. Heterogeneous hypergraphs are another type of generalized hypergraphs, where nodes can belong to different classes (or types, labels, etc.). Some theoretical studies have been conducted on heterogeneous hypergraphs [151, 167]. Recently, heterogenous hypergraphs have also been considered for hypergraph representation learning [54, 155, 181, 205]. More patterns await discovery on heterogeneous hypergraphs.

Uncertain hypergraphs. Generalized hypergraphs also include uncertain hypergraphs, where the presence or absence of hyperedges is not deterministic but governed by probabilities or uncertainty measures. Uncertainty naturally arises in real-world scenarios, and it is important to consider uncertainty when modeling real-world systems into graphs or hypergraphs [24, 82, 132]. The studies on uncertain hypergraphs are still mainly limited to theoretical ones [129, 150, 173, 197], and we expect that more patterns can be discovered on uncertain hypergraphs.

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