

A note on line and total directed superhypergraphs, line bidirected graphs, line multidirected graphs, and related structures

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Abstract

Hypergraphs extend classical graphs by allowing *hyperedges* to connect any nonempty subset of vertices, thereby capturing complex group-level relationships. Superhypergraphs advance this framework by introducing recursively nested powerset layers, enabling the representation of hierarchical and self-referential links among hyperedges. A *line graph* encodes the adjacencies between edges of an original graph by transforming each edge into a vertex and connecting two vertices if their corresponding edges share a common endpoint. A *total graph* incorporates both the vertices and edges of the original graph as its own vertices, with edges representing adjacency or incidence between these entities.

Various extensions of these graph concepts exist that incorporate directional information, such as *Directed Graphs*, *Bidirected Graphs*, and *Multidirected Graphs*. In this paper, we investigate the notions of line graphs and total graphs within the settings of *Directed HyperGraphs*, *Directed SuperHyperGraphs*, *Bidirected Graphs*, and *Multidirected Graphs*.

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1. Introduction

Classical graph theory provides a fundamental mathematical language for modeling entities and pairwise relations among them[36]. In an ordinary graph, vertices represent objects and edges represent binary interactions. This framework is powerful and widely applicable, but it is not

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always sufficient for systems in which a single relation may involve several objects simultaneously, or in which relations themselves are organized in nested, hierarchical, or multi-level forms. Such situations arise naturally in collaborative networks, molecular systems, decision-making structures, engineering systems, and learning models based on higher-order interactions.

To overcome the restriction to pairwise relations, the notion of a *HyperGraph* has been introduced and extensively studied [13, 16]. A HyperGraph generalizes an ordinary graph by allowing each edge, called a *hyperedge*, to connect an arbitrary nonempty subset of vertices. Hence, HyperGraphs provide a direct way to represent higher-order relations involving more than two entities [1, 6, 7, 23, 38]. This expressive capacity has made HyperGraphs useful in several areas, including graph neural networks [19, 20, 43, 65, 66], decision-making [35, 48], fuzzy hypergraph theory [46, 59, 60], neutrosophic hypergraph theory [22, 28, 29], and chemistry [47, 58].

Although HyperGraphs capture multiway interactions, they do not by themselves fully describe structures in which vertices, hyperedges, or relational units are arranged through several nested levels. For this purpose, the concept of a *SuperHyperGraph* has been developed. A SuperHyperGraph extends the hypergraph framework by using iterated powerset constructions, so that supervertices and superhyperedges may represent sets, sets of sets, and more generally hierarchically nested objects. This makes it possible to model multi-level dependencies, recursive groupings, and interactions among higher-order units rather than only among ordinary vertices. Recent studies have investigated foundational aspects of SuperHyperGraphs and related structures [31, 39, 62]. Their potential applications have also been discussed in contexts such as graph neural networks, engineering, and decision-making [3, 37, 40].

A comparison of Graphs, HyperGraphs, and SuperHyperGraphs is presented in Table 1.

Table 1: Comparison of Graphs, HyperGraphs, and SuperHyperGraphs

Structure	Basic objects	Type of relation	Main modeling capability
Graph	Vertices and edges	Each edge connects two vertices.	Models pairwise relations between ordinary objects.
HyperGraph	Vertices and hyperedges	Each hyperedge connects a nonempty subset of vertices.	Models multiway interactions involving several objects simultaneously.
SuperHyperGraph	Supervertices and superhyperedges built through iterated powersets	Relations may occur among nested objects such as sets, sets of sets, or higher-level units.	Models hierarchical, multi-level, and recursively grouped interactions.

Alongside these developments, classical graph theory contains several important graph transformations. Among them, the *line graph* and the *total graph* are particularly fundamental. The line

graph of a graph transforms edges of the original graph into vertices and records adjacency between original edges. Thus, it shifts the viewpoint from vertices to relations. The total graph, on the other hand, incorporates both vertices and edges of the original graph as vertices of a new graph, and it records both adjacency and incidence among these objects. These constructions are useful because they allow one to study relational behavior, incidence patterns, and edge-based connectivity through ordinary graph-theoretic tools.

However, when direction, higher-order incidence, or hierarchical nesting is introduced, the classical notions of line graphs and total graphs require careful reformulation. In directed settings, adjacency must respect the orientation of edges or hyperedges. In HyperGraphs, one must specify how hyperedges are adjacent through shared vertices, tails, or heads. In SuperHyperGraphs, the situation becomes even richer, because the objects being connected may themselves be nested sets or higher-level relational units. Consequently, line and total constructions for directed hypergraph-like and superhypergraph-like structures should preserve not only incidence, but also directional and hierarchical information.

Motivated by this observation, this paper investigates line and total graph constructions in several generalized directed frameworks. In particular, we consider *Directed HyperGraphs*, *Directed SuperHyperGraphs*, *Bidirected Graphs*, and *Multidirected Graphs*. We introduce corresponding notions of line directed HyperGraphs, line directed SuperHyperGraphs, line bidirected graphs, and line multidirected graphs, and we examine how these constructions relate to their classical counterparts. Furthermore, we discuss total directed and total SuperHyperGraph constructions, together with iterated versions of line and total transformations.

The main contribution of this paper is to provide a unified viewpoint for extending classical line and total graph operations to directed, higher-order, and hierarchically nested settings. In addition to defining these generalized constructions, we also clarify several structural properties that are preserved or transformed by them. In particular, we discuss how directed edge-composability is converted into adjacency in the corresponding line structure, how directed paths and cycles in the transformed object correspond to compatible sequences of original edges or hyperedges, and how superhypergraph-level nesting produces structural behavior that has no direct analogue in ordinary graph or hypergraph settings. The proposed constructions preserve the core intuition of classical line and total graphs while adapting it to hyperedges, superhyperedges, and directional incidence relations. In this way, the paper clarifies how familiar graph transformations can be lifted from ordinary graphs to HyperGraphs, SuperHyperGraphs, and related directed structures.

2. Preliminaries

In this section, we review the key concepts and notation used throughout this paper. All graphs and HyperGraphs considered here are finite.

2.1. Hypergraphs and Superhypergraphs

The definitions of hypergraphs and Superhypergraphs are presented below.

Definition 2.1 (n -th Powerset). [63]. Let H be a set. The n -th powerset $\text{POWS}^n(H)$ is defined recursively by

$$\text{POWS}^0(H) = H, \quad \text{POWS}^{k+1}(H) = \text{POWS}(\text{POWS}^k(H)), \quad k \geq 0.$$

The *nonempty* n -th powerset $\text{POWS}^{*n}(H)$ is defined similarly but removes the empty set at each stage:

$$\text{POWS}^{*0}(H) = H, \quad \text{POWS}^{*(k+1)}(H) = \text{POWS}^*(\text{POWS}^{*k}(H)),$$

where $\text{POWS}^*(X) = \text{POWS}(X) \setminus \{\emptyset\}$

Example 2.2 (n -th powerset in everyday planning: nested menu design). Let $H = \{\text{salad}, \text{soup}, \text{pasta}\}$ be the set of available dishes. Then $\text{POWS}^1(H)$ lists all possible menus (any subset of dishes). An element of the second powerset,

$$M = \{\{\text{salad}\}, \{\text{soup}, \text{pasta}\}\} \in \text{POWS}^2(H),$$

may be read as a *menu of menus*: the caterer offers either the single-dish menu $\{\text{salad}\}$ or the two-dish menu $\{\text{soup}, \text{pasta}\}$. Likewise, a collection $C = \{M, M'\} \in \text{POWS}^3(H)$ encodes a *catalog* of alternative menu packages. This illustrates how POWS^n captures nested choice structures (choices, choices of choices, etc.).

Definition 2.3 (HyperGraph). [13, 16] A finite *HyperGraph* $H = (V, E)$ is specified by:

- A nonempty vertex set V .
- A collection E of hyperedges, where each $e \in E$ is a nonempty subset of V .

HyperGraphs generalize ordinary graphs by permitting edges to join any number of vertices, making them ideal for modeling higher-order relationships. In this work, we assume both V and E are finite.

Example 2.4 (Hypergraph in practice: coauthorship network). Let $V = \{\text{Rika}, \text{Yuya}, \text{Chen}, \text{Dee}\}$ be a set of researchers. Define hyperedges by papers:

$$E = \{\{\text{Rika}, \text{Yuya}\}, \{\text{Yuya}, \text{Chen}, \text{Dee}\}, \{\text{Rika}, \text{Chen}\}\}.$$

Then $H = (V, E)$ is a hypergraph where each paper (hyperedge) connects *all* of its coauthors simultaneously, naturally representing a group collaboration that cannot be reduced to pairwise links without loss of information.

Definition 2.5 (Level- n SuperHyperGraph (incidence form)). (cf.[24]) Fix a finite base set V_0 and an integer $n \geq 0$. Let $V_n \subseteq \text{POWS}^n(V_0)$ be a finite set, whose elements are called n -supervertices. A *level- n SuperHyperGraph* is a pair

$$\mathcal{H}^{(n)} = (V_n, \mathcal{E}), \quad \text{with} \quad \emptyset \neq \mathcal{E} \subseteq \text{POWS}(V_n) \setminus \{\emptyset\}.$$

Thus each n -superedge $E \in \mathcal{E}$ is a nonempty subset of the vertex set V_n . (When $n = 0$, this is an ordinary finite hypergraph; when, additionally, every $E \in \mathcal{E}$ has size 2, it is an ordinary graph.)

Example 2.6 (Level-2 SuperHyperGraph in organizations: programs of teams). Let the base set of people be

$$V_0 = \{a, b, c, d, e\}.$$

Form teams (level 1 supervertices)

$$T_1 = \{a, b\}, \quad T_2 = \{c, d, e\}, \quad T_3 = \{a, c\},$$

and set

$$V_1 = \{T_1, T_2, T_3\} \subseteq \text{POWS}^1(V_0).$$

Create programs (level 2 supervertices) as collections of teams

$$P_1 = \{T_1, T_2\}, \quad P_2 = \{T_2, T_3\},$$

and let

$$V_2 = \{P_1, P_2\} \subseteq \text{POWS}^2(V_0).$$

Define a level-2 SuperHyperGraph

$$\mathcal{H}^{(2)} = (V_2, \mathcal{E})$$

with superedges

$$\mathcal{E} = \{ \{P_1, P_2\}, \{P_1\} \} \subseteq \text{POWS}(V_2) \setminus \{\emptyset\}.$$

Here, $\{P_1, P_2\}$ models a joint milestone linking both programs, while the singleton $\{P_1\}$ models an internal review of P_1 alone. This realizes the incidence-form definition: level-2 supervertices are elements of $\text{POWS}^2(V_0)$, and superedges are nonempty subsets of V_2 .

Notation 2.7 (Stars). For $\mathcal{H}^{(n)} = (V_n, \mathcal{E})$ and $v \in V_n$, the *star* of v is

$$\text{Star}_{\mathcal{H}}(v) := \{ E \in \mathcal{E} : v \in E \} \subseteq \mathcal{E}.$$

We also write $\mathcal{E}^{\neq \emptyset}(v) := \text{Star}_{\mathcal{H}}(v)$ and $\mathcal{E}^{(\geq 2)}(v) := \{ E \in \mathcal{E} : v \in E \text{ and } |E| \geq 2 \}$ when we wish to exclude size-1 edges in the star.

2.2. directed hypergraph

A directed hypergraph is a hypergraph generalization of a directed graph. Similar to undirected hypergraphs, directed hypergraphs have been extensively studied for their various derivatives and applications (cf. [17, 51, 54, 55]). Its definition is provided below.

Definition 2.8 (Directed Hypergraph). [5, 32] A *Directed Hypergraph* H is a pair $H = (V, E)$, where:

- V is a finite set of vertices (or nodes).
- E is a finite set of hyperarcs. Each hyperarc $e \in E$ is an ordered pair $e = (\text{Tail}(e), \text{Head}(e))$, where:
 - $\text{Tail}(e) \subseteq V$ is a non-empty subset of vertices, called the *tail* of the hyperarc.
 - $\text{Head}(e) \in V$ is a single vertex, called the *head* of the hyperarc.
- A hyperarc $e = (\text{Tail}(e), \text{Head}(e))$ connects all vertices in $\text{Tail}(e)$ to the vertex $\text{Head}(e)$.

- When $|\text{Tail}(e)| = 1$ for all $e \in E$, the directed hypergraph reduces to a standard directed graph.

Remark 2.1 (On the single-head convention). In this paper, the basic directed hypergraph model is introduced using the single-head convention, where each hyperarc has the form

$$e = (\text{Tail}(e), \text{Head}(e)), \quad \emptyset \neq \text{Tail}(e) \subseteq V, \quad \text{Head}(e) \in V.$$

This convention is useful for modeling many-to-one dependencies, such as production rules, prerequisite systems, workflow transitions, and inference rules, where several input objects jointly produce or activate one output object. It also makes the connection with ordinary directed graphs transparent: when every tail is a singleton, the model reduces directly to a classical digraph.

However, this choice is not essential for the proposed line and total constructions. A more general many-to-many directed hypergraph may be defined by allowing each hyperarc to have the form

$$e = (\text{Tail}(e), \text{Head}(e)), \quad \emptyset \neq \text{Tail}(e) \subseteq V, \quad \emptyset \neq \text{Head}(e) \subseteq V.$$

The single-head model is then recovered as the special case $|\text{Head}(e)| = 1$ for every $e \in E$. Thus the single-head convention should be viewed as a mathematically convenient base case rather than as a restriction on the possible scope of the proposed framework.

Example 2.9 (Directed Hypergraph: Course Prerequisite System). Let V be the set of courses at a university (each element is a single course). Define a directed hypergraph $H = (V, E)$ where a hyperarc $e = (\text{Tail}(e), \text{Head}(e))$ encodes a prerequisite rule that *all* courses in the tail must be completed before enrolling in the head course. For example, with

$$V = \{\text{Math101}, \text{Phys101}, \text{CS101}, \text{Data201}, \text{AI301}\},$$

the rules

$$(\{\text{Math101}, \text{CS101}\}, \text{Data201}), \quad (\{\text{Data201}, \text{Phys101}\}, \text{AI301})$$

mean that *Data201* requires both *Math101* and *CS101*, while *AI301* requires both *Data201* and *Phys101*. Here each tail is a subset of V and the head is a single course in V , exactly matching the directed-hypergraph definition.

Define the *Directed n -SuperHypergraph* and examine its relationships with other graph classes. The definition and basic properties are given below.

Definition 2.10 (Directed n -SuperHypergraph). [25, 26] Let V be a finite, nonempty set of vertices, and let the iterated powersets be defined recursively by

$$\text{POWS}^0(V) = V, \quad \text{POWS}^{k+1}(V) = \text{POWS}(\text{POWS}^k(V)) \quad (k \geq 0).$$

A *Directed n -SuperHypergraph* is a tuple

$$\text{DSH}_n = (V, E),$$

where $E \subseteq \text{POWS}^n(V) \times \text{POWS}^n(V)$ is a set of *directed n -superhyperedges*. Each $e = (T, H) \in E$ consists of

- $T \in \text{POWS}^n(V)$: the **tail object** (a nested “source” collection), and
- $H \in \text{POWS}^n(V)$: the **head object** (a nested “target” collection).

When convenient, we require $T, H \neq \emptyset$ for $n \geq 1$ (nonemptiness of the outer level).

Remark 2.2. • For $n = 0$, one has $\text{POWS}^0(V) = V$, so $E \subseteq V \times V$; thus DSH_0 is an ordinary directed graph (digraph).

- For $n = 1$, one has $E \subseteq \text{POWS}(V) \times \text{POWS}(V)$; hence DSH_1 is a directed hypergraph (tails/heads are vertex *sets*).
- For $n \geq 2$, T, H are *nested* collections (sets of sets, etc.), enabling multi-level grouping of sources and targets and capturing hierarchical/aggregated interactions.
- If $T = \{v_1\}$ and $H = \{v_2\}$ at $n = 0$ (or $T = \{\{v_1\}\}$, $H = \{\{v_2\}\}$ at $n = 2$, etc., via singleton lifts), the edge behaves like a standard directed edge $v_1 \rightarrow v_2$.

Remark 2.3 (Compatibility with directed SuperHyperGraphs). The many-to-many viewpoint is also consistent with the definition of a directed n -SuperHypergraph. Indeed, a directed n -superhyperedge has the form

$$e = (T, H), \quad T, H \in \text{POWS}^n(V),$$

so both the source object and the target object may already be nested collections. For $n = 1$, this gives a directed hypergraph whose tail and head are subsets of V . For $n \geq 2$, it gives a genuinely hierarchical many-to-many relation between nested objects. Hence the single-head directed hypergraph used in the preliminary section is a convenient base convention, whereas the directed SuperHyperGraph framework naturally supports more general many-to-many and nested many-to-many relations.

Example 2.11 (Directed n -SuperHypergraph ($n = 2$): Multi-Team Approval Workflow). Let V be the set of individual staff members in an organization. Level-1 collections are *teams* (nonempty subsets of V), i.e., elements of $\text{POWS}^1(V) = \text{POWS}(V)$. Level-2 collections are *consortia of teams*, i.e., elements of $\text{POWS}^2(V) = \text{POWS}(\text{POWS}(V))$.

Suppose three teams are

$$G_1 = \{a, b\}, \quad G_2 = \{c\}, \quad G_3 = \{d, e, f\} \subset V,$$

and consider the consortia

$$C_{\text{approve}} = \{G_1, G_2\} \in \text{POWS}^2(V), \quad C_{\text{handoff}} = \{G_3\} \in \text{POWS}^2(V).$$

Create a directed 2-superhyperedge

$$e = (C_{\text{approve}}, C_{\text{handoff}}) \in \text{POWS}^2(V) \times \text{POWS}^2(V).$$

This models the real-life rule: an approval may be issued by either team G_1 or team G_2 , after which the work is handed to team G_3 . Thus both the tail and the head are elements of $\text{POWS}^2(V)$, so the construction is a concrete instance of a directed n -superhypergraph with $n = 2$.

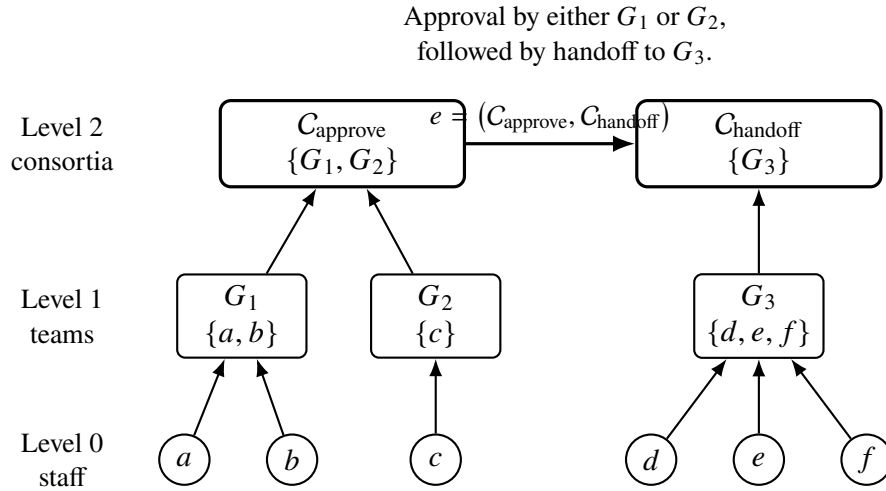


Figure 1: A directed 2-SuperHyperGraph representing a multi-team approval workflow. The tail object is the level-2 consortium $C_{\text{approve}} = \{G_1, G_2\}$, and the head object is the level-2 consortium $C_{\text{handoff}} = \{G_3\}$.

Theorem 2.12 (Reduction ladder). *Let $\text{DSH}_n = (V, E)$ be a Directed n -SuperHypergraph.*

1. *If $n = 0$, DSH_0 is exactly a directed graph.*
2. *If $n = 1$, DSH_1 is exactly a directed hypergraph.*
3. *For any $n \geq 1$, restricting to singleton-lifted edges*

$$E' = \left\{ (\{S\}, \{T\}) \in E \mid S, T \in \text{POWS}^{n-1}(V) \right\}$$

yields a Directed $(n-1)$ -SuperHypergraph on V (after identifying $\{S\} \mapsto S$). Iterating this identification reduces any DSH_n to a directed hypergraph ($n=1$), and further to a digraph ($n=0$) when tails/heads are singletons.

Proof. (1) and (2) are immediate from $\text{POWS}^0(V) = V$ and $\text{POWS}^1(V) = \text{POWS}(V)$. For (3), observe that if every tail/head at level n is a singleton $\{S\}$ with $S \in \text{POWS}^{n-1}(V)$, then the map $\{S\} \mapsto S$ is a bijection between the allowed tails/heads and $\text{POWS}^{n-1}(V)$. Thus E' corresponds to a subset of $\text{POWS}^{n-1}(V) \times \text{POWS}^{n-1}(V)$, i.e., a Directed $(n-1)$ -SuperHypergraph. Repeating the argument establishes the stated reductions. $\square$

3. Line Directed HyperGraph

3.1. Line Directed Graph

A line graph represents adjacencies between edges of a graph, forming vertices connected when edges share an endpoint[9, 14, 61]. Line directed graphs transform a directed graph into another whose vertices represent edges, preserving directed adjacency relationships (cf.[11, 45]).

Definition 3.1 (Line Directed Graph). (cf.[21]) Let $D = (V, A)$ be a finite directed graph (*digraph*), where V is the vertex set and $A \subseteq V \times V$ is the arc set. The *line directed graph* of D , denoted $L(D)$, is the digraph whose

- vertices are the arcs of D , i.e., $V(L(D)) = A$;
- there is an arc in $L(D)$ from $e_1 = (u, v) \in A$ to $e_2 = (x, y) \in A$ if and only if $v = x$, i.e., the head of e_1 equals the tail of e_2 :

$$A(L(D)) = \{ ((u, v), (v, y)) \in A \times A \mid (u, v) \in A, (v, y) \in A \}.$$

This is the standard definition: “ $L(D)$ has the arcs of D as vertices; there is an arc from pq to uv iff $q = u$.”

Remark 3.1 (Many-to-many extension of the line construction). The line directed hypergraph construction extends naturally to the many-to-many setting. Let $H = (V, E)$ be a directed hypergraph whose hyperarcs are of the form

$$e = (\text{Tail}(e), \text{Head}(e)), \quad \emptyset \neq \text{Tail}(e) \subseteq V, \quad \emptyset \neq \text{Head}(e) \subseteq V.$$

Then one may define the line directed hypergraph by

$$\text{LDHG}_{\text{mm}}(H) = (E, E_{\text{mm}}^{\text{line}}),$$

where

$$E_{\text{mm}}^{\text{line}} = \left\{ (\{e_1\}, e_2) \mid e_1, e_2 \in E, \text{Head}(e_1) \cap \text{Tail}(e_2) \neq \emptyset \right\}.$$

Thus there is a line hyperarc from e_1 to e_2 whenever at least one output vertex of e_1 is an input vertex of e_2 . This is a weak composability condition. If the intended semantics requires that all outputs of e_1 be available before e_2 can occur, one may instead use the stronger condition

$$\text{Head}(e_1) \subseteq \text{Tail}(e_2).$$

Therefore, the single-head condition

$$\text{Head}(e_1) \in \text{Tail}(e_2)$$

used earlier is exactly the special case of the many-to-many condition when $\text{Head}(e_1)$ is a singleton.

3.2. Line Directed HyperGraph

Line directed hypergraphs map a directed hypergraph into a hypergraph where vertices represent hyperedges, maintaining directed incidence structure.

Definition 3.2 (Line Directed HyperGraph). Let $H = (V, E)$ be a directed hypergraph. Its *Line Directed HyperGraph* is the directed hypergraph

$$\text{LDHG}(H) := (E, E^{\text{line}})$$

whose vertex set is the hyperarc set E of H , and whose hyperarc set is

$$E^{\text{line}} := \left\{ (\{e_1\}, e_2) \mid e_1, e_2 \in E, \text{Head}(e_1) \in \text{Tail}(e_2) \right\}.$$

Thus, for every admissible composable pair $e_1 \rightarrow e_2$ in H (i.e. the head of e_1 belongs to the tail of e_2), we place in $\text{LDHG}(H)$ a (singleton–tail) hyperarc from the vertex e_1 to the vertex e_2 .

Example 3.3 (Line Directed HyperGraph: Manufacturing Flow of a PCB). Consider a directed hypergraph $H = (V, E)$ whose vertices V are *artifacts* in a printed–circuit–board (PCB) production line and whose hyperarcs encode *process steps*: the tail lists all required inputs and the head is the produced output. Let

$V = \{\text{RawBoard}, \text{SolderPaste}, \text{SolderedBoard}, \text{Components}, \text{AssembledBoard}, \text{TestFixture}, \text{TestedBoard}\},$

and define the process steps (hyperarcs)

$$\begin{aligned} e_1 &= (\{\text{RawBoard}, \text{SolderPaste}\}, \text{SolderedBoard}), \\ e_2 &= (\{\text{SolderedBoard}, \text{Components}\}, \text{AssembledBoard}), \\ e_3 &= (\{\text{AssembledBoard}, \text{TestFixture}\}, \text{TestedBoard}). \end{aligned}$$

In the *line directed hypergraph* of H , the vertices are the process steps $\{e_1, e_2, e_3\}$, and we add a (singleton–tail) hyperarc from e_i to e_j exactly when the *output* of e_i (its head) is among the *inputs* of e_j (its tail). Hence

$$E^{\text{line}} = \left\{ (\{e_1\}, e_2), (\{e_2\}, e_3) \right\},$$

because $\text{Head}(e_1) = \text{SolderedBoard} \in \text{Tail}(e_2)$ and $\text{Head}(e_2) = \text{AssembledBoard} \in \text{Tail}(e_3)$. The resulting line directed hypergraph compactly captures which manufacturing steps can follow which others.

Theorem 3.4 (LDHG is a directed hypergraph and generalizes the line digraph). *Let $H = (V, E)$ be a directed hypergraph and let $\text{LDHG}(H) = (E, E^{\text{line}})$ be as in Definition 3.2. Then:*

- (a) (**Well-defined directed hypergraph**). *LDHG(H) is a directed hypergraph: every element of E^{line} has a nonempty tail (a singleton $\{e_1\}$ with $e_1 \in E$) and a head in the vertex set E .*
- (b) (**Reduction to the line directed graph**). *Suppose H comes from a digraph $D = (V, A)$ by identifying each arc $a = (u, v) \in A$ with the hyperarc $e_a = (\{u\}, v) \in E$. Then $\text{LDHG}(H)$ is canonically isomorphic to the classical line directed graph $L(D)$:*

$$V(\text{LDHG}(H)) = A, \quad (\{(u, v)\}, (v, w)) \in E^{\text{line}} \iff ((u, v), (v, w)) \in A(L(D)).$$

In particular, LDHG is a strict generalization of the line directed graph.

Proof. (a) By construction, vertices of $\text{LDHG}(H)$ are the elements of E . Given $e_1, e_2 \in E$ with $\text{Head}(e_1) \in \text{Tail}(e_2)$, the pair $(\{e_1\}, e_2)$ has a nonempty tail $\{e_1\} \subseteq E$ and its head e_2 is a vertex of $\text{LDHG}(H)$; hence it is a valid hyperarc. Therefore $E^{\text{line}} \subseteq \{(\emptyset \neq S \subseteq E, \text{head} \in E)\}$, so $\text{LDHG}(H)$ is a directed hypergraph.

(b) Let $D = (V, A)$ be a digraph and form $H = (V, E)$ with $E = \{ (\{u\}, v) \mid (u, v) \in A \}$. Define a bijection $\varphi : A \rightarrow V(\text{LDHG}(H))$ by $\varphi((u, v)) = (\{u\}, v)$. For arcs, we have

$$(\{(\{u, v\}), (v, w)) \in E^{\text{line}} \iff \text{Head}((\{u\}, v)) = v \in \text{Tail}((\{v\}, w)) = \{v\},$$

which holds exactly when $v = v$, i.e. always for the composable pair $(u, v) \rightarrow (v, w)$. Thus $(\{(\{u, v\}), (v, w)) \in E^{\text{line}}$ if and only if $((u, v), (v, w)) \in A(L(D))$. Transporting arcs through φ identifies $\text{LDHG}(H)$ with $L(D)$ (note that every tail in $\text{LDHG}(H)$ is a singleton, hence $\text{LDHG}(H)$ is a digraph in this special case). Therefore the construction reduces to the classical line directed graph, proving the claim. $\square$

3.3. Line Directed SuperHyperGraph

Line directed superhypergraphs convert a directed superhypergraph into one whose vertices are superhyperedges, preserving hierarchical directed connections.

Definition 3.5 (Line Directed SuperHyperGraph). Let $\text{DSH}_n = (V, E)$ be a Directed n -SuperHypergraph. Its *Line Directed SuperHyperGraph* is the Directed 1-SuperHypergraph

$$\text{LDSH}(\text{DSH}_n) := (E, E^{\text{line}}),$$

with base set E (the n -superhyperedges of the original object) and

$$E^{\text{line}} := \left\{ (\{e_1\}, \{e_2\}) \in \text{POWS}(E) \times \text{POWS}(E) \mid e_1 = (T_1, H_1), e_2 = (T_2, H_2) \in E, H_1 \subseteq T_2 \right\}.$$

That is, there is a *line superhyperedge* from the vertex e_1 to the vertex e_2 (we write $e_1 \rightarrow e_2$) precisely when the head object of e_1 is contained in the tail object of e_2 at level n , i.e. $H_1 \subseteq T_2$ as elements of $\text{POWS}^n(V)$.

Example 3.6 (Line Directed SuperHyperGraph: Multi-Team Approval and Handoff). Let V be the set of *individuals* in an organization. Level-1 objects $\text{POWS}(V) \setminus \{\emptyset\}$ represent *teams*, and Level-2 objects $\text{POWS}(\text{POWS}(V))$ represent *consortia of teams*. Consider a directed 2-superhypergraph $\text{DSH}_2 = (V, E)$ with

$$\begin{aligned} e_A &= (\{G_{\text{Design}}\}, \{G_{\text{QA}}\}), \\ e_B &= (\{G_{\text{QA}}, G_{\text{Mfg}}\}, \{G_{\text{Mfg}}\}). \end{aligned}$$

Since the head object of e_A is $\{G_{\text{QA}}\}$ and this is contained in the tail object of e_B , the line directed superhypergraph has a line superhyperedge from e_A to e_B . Thus, the vertices of the line object are the policy edges $\{e_A, e_B\}$, and the line superhyperedge records a valid composition of policies.

Theorem 3.7 (LDSH is a Directed SuperHyperGraph). *For every Directed n -SuperHypergraph $\text{DSH}_n = (V, E)$, the construction $\text{LDSH}(\text{DSH}_n) = (E, E^{\text{line}})$ of Definition 3.5 is a Directed 1-SuperHypergraph on the base set E .*

Proof. By definition $E^{\text{line}} \subseteq \text{POWS}(E) \times \text{POWS}(E)$, so edges of $\text{LDSH}(\text{DSH}_n)$ are pairs of level-1 objects over E (singleton tails and heads). Thus $\text{LDSH}(\text{DSH}_n)$ is a Directed 1-SuperHypergraph on base set E . $\square$

Theorem 3.8 (Generalizes the line directed graph). *Let $D = (V, A)$ be a finite digraph and consider the Directed 1-SuperHypergraph $\text{DSH}_1(D) = (V, E)$ obtained by identifying each arc $(u, v) \in A$ with the superhyperedge $e_{(u,v)} = (\{u\}, \{v\}) \in \text{POWS}(V) \times \text{POWS}(V)$. Then $\text{LDSH}(\text{DSH}_1(D))$ is canonically isomorphic to the classical line directed graph $L(D)$.*

Proof. Vertices of LDSH are $E = \{e_{(u,v)} : (u, v) \in A\}$; identify $e_{(u,v)}$ with the arc (u, v) . By Definition 3.5, a line edge from $e_{(u,v)}$ to $e_{(x,y)}$ exists iff $H_1 = \{v\} \subseteq T_2 = \{x\}$, i.e. $v = x$. Thus there is an arc $(u, v) \rightarrow (x, y)$ in LDSH exactly when there is the standard line-graph arc in $L(D)$. This gives a canonical isomorphism. $\square$

Theorem 3.9 (Generalizes the line directed hypergraph). *Let $H = (V, E)$ be a directed hypergraph in the single-head convention ($E \subseteq \{(T, h) : \emptyset \neq T \subseteq V, h \in V\}$). Embed H as a Directed 1-SuperHypergraph $\text{DSH}_1(H) = (V, \widehat{E})$ by*

$$(T, h) \mapsto \widehat{e} = (T, \{h\}) \in \text{POWS}(V) \times \text{POWS}(V).$$

Then $\text{LDSH}(\text{DSH}_1(H))$ agrees with the usual Line Directed HyperGraph (after the obvious identification of a singleton head $\{\widehat{e}_2\}$ with the vertex $\widehat{e}_2$).

Proof. Vertices of LDSH are the (embedded) hyperarcs $\widehat{e} = (T, \{h\})$ of H . By Definition 3.5, there is a line edge from $\widehat{e}_1 = (T_1, \{h_1\})$ to $\widehat{e}_2 = (T_2, \{h_2\})$ iff $\{h_1\} \subseteq T_2$, i.e. $h_1 \in T_2$. This is exactly the standard composability condition used in the line directed hypergraph: the head of the first hyperarc lies in the tail of the second. If one identifies the singleton head $\{\widehat{e}_2\}$ with the vertex $\widehat{e}_2$, the edge set coincides with that of the usual LDHG. $\square$

3.4. Algebraic representations and spectral viewpoint

Line graph constructions are closely related to incidence and adjacency matrices in classical algebraic graph theory. We therefore record a basic matrix representation of the generalized line constructions introduced above. This provides a first algebraic viewpoint on these structures and clarifies how spectral methods may be developed for them.

Let $H = (V, E)$ be a finite directed hypergraph in the single-head convention, where

$$V = \{v_1, \dots, v_p\}, \quad E = \{e_1, \dots, e_m\},$$

and each hyperarc is written as

$$e_j = (\text{Tail}(e_j), \text{Head}(e_j)).$$

Define the *tail incidence matrix*

$$B_T \in \{0, 1\}^{p \times m}$$

and the *head incidence matrix*

$$B_H \in \{0, 1\}^{p \times m}$$

by

$$(B_T)_{ij} = \begin{cases} 1, & v_i \in \text{Tail}(e_j), \\ 0, & v_i \notin \text{Tail}(e_j), \end{cases} \quad (B_H)_{ij} = \begin{cases} 1, & v_i = \text{Head}(e_j), \\ 0, & v_i \neq \text{Head}(e_j). \end{cases}$$

Then the matrix

$$W_L(H) := B_H^\top B_T \in \mathbb{N}^{m \times m}$$

records directed hyperarc composability. Indeed,

$$(W_L(H))_{ij} = 1 \iff \text{Head}(e_i) \in \text{Tail}(e_j)$$

in the single-head setting. Thus $W_L(H)$ is a weighted adjacency matrix of the line directed hypergraph $\text{LDHG}(H)$. The corresponding unweighted adjacency matrix may be obtained by taking the support:

$$A_L(H)_{ij} = \begin{cases} 1, & (W_L(H))_{ij} > 0, \\ 0, & (W_L(H))_{ij} = 0. \end{cases}$$

If self-transitions are excluded, one may additionally impose

$$A_L(H)_{ii} = 0 \quad (i = 1, \dots, m).$$

Proposition 3.1 (Adjacency representation of the line directed hypergraph). *Let $H = (V, E)$ be a finite directed hypergraph in the single-head convention. Then the adjacency matrix $A_L(H)$ defined above is precisely the adjacency matrix of the line directed hypergraph $\text{LDHG}(H)$, after identifying each hyperarc $e_i \in E$ with a vertex of $\text{LDHG}(H)$.*

Proof. By definition of $\text{LDHG}(H)$, there is a line hyperarc from e_i to e_j if and only if

$$\text{Head}(e_i) \in \text{Tail}(e_j).$$

On the other hand,

$$(B_H^\top B_T)_{ij} = \sum_{r=1}^p (B_H)_{ri} (B_T)_{rj}.$$

Since e_i has a single head, this sum is equal to 1 exactly when the head vertex of e_i belongs to the tail of e_j , and is 0 otherwise. Therefore the support of $B_H^\top B_T$ gives exactly the adjacency relation of $\text{LDHG}(H)$. $\square$

The same idea extends to directed n -SuperHyperGraphs. Let

$$\text{DSH}_n = (V, E), \quad E = \{e_1, \dots, e_m\},$$

where

$$e_i = (T_i, H_i), \quad T_i, H_i \in \text{POWS}^n(V).$$

Choose a compatibility relation

$$C_n(H_i, T_j)$$

between the head object H_i and the tail object T_j . For example, in the subset-based convention used above, one may take

$$C_n(H_i, T_j) \iff H_i \subseteq T_j.$$

Define the line compatibility matrix

$$A_L^{(n)} = (a_{ij}^{(n)})_{1 \leq i, j \leq m}$$

by

$$a_{ij}^{(n)} = \begin{cases} 1, & C_n(H_i, T_j) \text{ holds,} \\ 0, & C_n(H_i, T_j) \text{ does not hold.} \end{cases}$$

Then $A_L^{(n)}$ is the adjacency matrix of the line directed n -SuperHyperGraph. Thus, in the SuperHyperGraph setting, adjacency is not only a relation between ordinary edges, but a matrix representation of composability between nested head and tail objects.

Remark 3.2 (Spectral viewpoint). The spectrum of a generalized line construction can be studied through the eigenvalues of its adjacency matrix A_L , or through a weighted version such as

$$W_L(H) = B_H^\top B_T.$$

In the weighted setting, the nonzero eigenvalues of

$$B_H^\top B_T$$

coincide, with algebraic multiplicities, with the nonzero eigenvalues of

$$B_T B_H^\top.$$

Hence the weighted line-transition matrix on hyperarcs is spectrally related to a vertex-level transition matrix. This observation provides a bridge between the original directed hypergraph and its line directed hypergraph.

For the unweighted line adjacency matrix, one usually applies a support or threshold operation to $B_H^\top B_T$. Since thresholding may change the spectrum, a complete spectral characterization requires additional assumptions. Nevertheless, the matrices B_T , B_H , $W_L(H)$, and $A_L(H)$ provide a natural starting point for defining adjacency spectra, Laplacian spectra, and spectral clustering methods for generalized line directed hypergraphs and directed SuperHyperGraphs.

For spectral clustering and related applications, one may define the out-degree matrix of the line object by

$$D_L^{\text{out}} = \text{diag} \left(\sum_{j=1}^m A_L(H)_{1j}, \dots, \sum_{j=1}^m A_L(H)_{mj} \right),$$

and the corresponding directed line Laplacian by

$$\mathcal{L}_L^{\text{out}} = D_L^{\text{out}} - A_L(H).$$

Alternatively, for undirected spectral methods, one may use the symmetrized matrix

$$A_L^{\text{sym}} = \frac{1}{2} (A_L(H) + A_L(H)^\top)$$

and define

$$\mathcal{L}_L^{\text{sym}} = D_L^{\text{sym}} - A_L^{\text{sym}},$$

where D_L^{sym} is the diagonal degree matrix of A_L^{sym} . These matrices make it possible to apply standard spectral tools to edge-transition patterns, hyperarc-composability, and nested superhyperedge interactions.

4. Iterated line directed graphs

4.1. Iterated line directed graphs

Iterated line directed graphs repeatedly apply the line graph operation to a directed graph, preserving directional adjacency structure [41, 42, 50].

Definition 4.1 (Iterated line digraph). [8, 10] Define $L^0(G) := G$ and, recursively, $L^{k+1}(G) := L(L^k(G))$ for each integer $k \geq 0$. We call $L^k(G)$ the k -iterated line digraph of G .

Example 4.2 (Iterated line digraph of a short path). Let $G = (V, A)$ be the directed path $1 \rightarrow 2 \rightarrow 3$, i.e.,

$$V = \{1, 2, 3\}, \quad A = \{(1, 2), (2, 3)\}.$$

Then the line digraph $L(G)$ has

$$V(L(G)) = A = \{e_{12}, e_{23}\}, \quad A(L(G)) = \{(e_{12}, e_{23})\}$$

since the head of e_{12} equals the tail of e_{23} . Iterating once more, $L^2(G) = L(L(G))$ has

$$V(L^2(G)) = A(L(G)) = \{(e_{12}, e_{23})\}, \quad A(L^2(G)) = \emptyset.$$

Thus $L(G)$ is a single directed edge, and $L^2(G)$ is a single isolated vertex.

Proposition 4.1 (Walk model and adjacency in $L^k(G)$). *For every $k \geq 1$:*

(i) *The vertices of $L^k(G)$ are in one-to-one correspondence with directed walks*

$$(v_0, v_1, \dots, v_k) \text{ in } G, \text{ i.e., } (v_{i-1}, v_i) \in A(G) \text{ for } i = 1, \dots, k.$$

(ii) *Under this correspondence, there is an arc in $L^k(G)$ from the walk $(v_0, \dots, v_k)$ to the walk $(v_1, \dots, v_k, v_{k+1})$ for each $(v_k, v_{k+1}) \in A(G)$.*

Proof. The statement is immediate for $k = 1$ from the definition of $L(G)$. For $k \geq 2$, a vertex of $L^k(G) = L(L^{k-1}(G))$ is an arc of $L^{k-1}(G)$, hence a pair of consecutive vertices of $L^{k-1}(G)$. By the induction hypothesis, vertices of $L^{k-1}(G)$ correspond to length- $(k-1)$ walks in G , and an arc of $L^{k-1}(G)$ corresponds to sliding a length- $(k-1)$ window by one step in G . Therefore vertices of $L^k(G)$ correspond to length- k walks, and adjacency corresponds to the one-step shift $(v_0, \dots, v_k) \rightarrow (v_1, \dots, v_k, v_{k+1})$ whenever $(v_k, v_{k+1}) \in A(G)$. $\square$

4.2. Iterated line directed hypergraphs

Iterated line directed hypergraphs repeatedly form line hypergraphs from a directed hypergraph, maintaining directed incidence between hyperedges.

Definition 4.3 (Iterated line directed hypergraphs). Let $H = (V, E)$ be a directed hypergraph. Define

$$L^1(H) := L(H), \quad L^{k+1}(H) := L(L^k(H)) \quad (k \geq 1).$$

We call $L^k(H)$ the k -iterated line directed hypergraph of H .

Example 4.4 (Iterated line directed hypergraphs: a small production workflow). Consider a (finite) directed hypergraph $H = (V, E)$ that models a toy food production line. The vertices are ingredients and intermediates

$$V = \{\text{Flour, Water, Yeast, Dough, Sauce, Cheese, PizzaBase, Pizza}\}.$$

Hyperarcs encode *operations* that consume several inputs (tail) to produce one output (head):

$$\begin{aligned} e_1 &: (\{\text{Flour, Water, Yeast}\}, \text{Dough}), \\ e_2 &: (\{\text{Dough}\}, \text{PizzaBase}), \\ e_3 &: (\{\text{Sauce, Cheese, PizzaBase}\}, \text{Pizza}). \end{aligned}$$

The line directed hypergraph $L(H)$ has the *operations* e_1, e_2, e_3 as its vertices. There is a (singleton–tail) hyperarc from e_i to e_j exactly when the head of e_i is an element of the tail of e_j . Hence

$$\begin{aligned} (\{e_1\}, e_2) &\in E(L(H)) \quad \text{since } \text{Dough} \in \{\text{Dough}\}, \\ (\{e_2\}, e_3) &\in E(L(H)) \quad \text{since } \text{PizzaBase} \in \{\text{Sauce, Cheese, PizzaBase}\}. \end{aligned}$$

There is no hyperarc $(\{e_1\}, e_3)$, because $\text{Dough} \notin \{\text{Sauce, Cheese, PizzaBase}\}$.

Iterating once more, the second line hypergraph $L^2(H) = L(L(H))$ has as vertices the hyperarcs of $L(H)$, i.e. $\{(\{e_1\}, e_2), (\{e_2\}, e_3)\}$. Since the head of $(\{e_1\}, e_2)$ equals e_2 and the tail of $(\{e_2\}, e_3)$ is $\{e_2\}$, we obtain

$$(\{(\{e_1\}, e_2)\}, (\{e_2\}, e_3)) \in E(L^2(H)),$$

which compactly represents the two–step operation chain $e_1 \rightarrow e_2 \rightarrow e_3$ (“make dough $\rightarrow$ press base $\rightarrow$ bake pizza”). In general, $L^k(H)$ encodes directed chains of k composable operations as vertices, with adjacency corresponding to a one–step shift along such chains.

Remark 4.1. For $k \geq 1$ define the set of *compatible k -sequences of hyperarcs*

$$W_k(H) := \left\{ (e_1, \dots, e_k) \in E^k \mid h(e_i) \in T(e_{i+1}) \text{ for all } i = 1, \dots, k-1 \right\}.$$

Intuitively, $(e_1, \dots, e_k)$ is a directed *walk of hyperarcs* in which the head of each step belongs to the next tail.

Theorem 4.5 (Basic properties and walk correspondence). *Let $H = (V, E)$ be a directed hypergraph.*

- (a) $L(H)$ is a directed hypergraph in the sense above. Moreover, by Definition, all hyperarcs of $L(H)$ have singleton tails and single-vertex heads:

$$E(L(H)) \subseteq \{ (\{x\}, y) : x, y \in V(L(H)) \}.$$

- (b) For every $k \geq 1$, $L^k(H)$ is a directed hypergraph and there is a natural bijection

$$\iota_k : \mathbf{W}_k(H) \xrightarrow{\cong} V(L^k(H))$$

satisfying the recursion

$$\iota_1(e_1) := e_1, \quad \iota_{k+1}(e_1, \dots, e_{k+1}) := (\{ \iota_k(e_1, \dots, e_k) \}, \iota_k(e_2, \dots, e_{k+1})).$$

Under this identification, adjacency in $L^k(H)$ is the one-step shift: there is a hyperarc

$$(\{ \iota_k(e_1, \dots, e_k) \}, \iota_k(e_2, \dots, e_{k+1})) \in E(L^k(H))$$

for each $(e_1, \dots, e_{k+1}) \in \mathbf{W}_{k+1}(H)$.

Proof. (a) By Definition, $V(L(H)) = E$ and each listed pair $(\{e\}, f)$ has a nonempty tail $\{e\} \subseteq V(L(H))$ and a head $f \in V(L(H))$, so $L(H)$ is indeed a directed hypergraph.

(b) We proceed by induction on k . For $k = 1$ the statement is immediate: $V(L(H)) = E = \mathbf{W}_1(H)$ via $\iota_1(e_1) = e_1$.

Assume the claim holds for k . Then $L^{k+1}(H) = L(L^k(H))$ has vertex set $V(L^{k+1}(H)) = E(L^k(H))$. By the definition of the line operator, a hyperarc of $L^k(H)$ is any pair

$$(\{ u \}, v) \quad \text{with } u, v \in V(L^k(H)) \text{ and } h_{L^k}(u) \in T_{L^k}(v).$$

By the induction hypothesis, every $u \in V(L^k(H))$ is of the form $u = \iota_k(e_1, \dots, e_k)$ and every $v \in V(L^k(H))$ is of the form $v = \iota_k(e_2, \dots, e_{k+1})$ for some $(e_1, \dots, e_{k+1}) \in \mathbf{W}_{k+1}(H)$. Moreover, by construction of ι_k one checks directly that

$$h_{L^k}(\iota_k(e_1, \dots, e_k)) = \iota_{k-1}(e_2, \dots, e_k), \quad T_{L^k}(\iota_k(e_2, \dots, e_{k+1})) = \{ \iota_{k-1}(e_2, \dots, e_k) \}.$$

Hence the line condition $h_{L^k}(u) \in T_{L^k}(v)$ is satisfied iff $u = \iota_k(e_1, \dots, e_k)$ and $v = \iota_k(e_2, \dots, e_{k+1})$ for a compatible sequence, i.e., $(e_1, \dots, e_{k+1}) \in \mathbf{W}_{k+1}(H)$. This shows that

$$\iota_{k+1}(e_1, \dots, e_{k+1}) := (\{ \iota_k(e_1, \dots, e_k) \}, \iota_k(e_2, \dots, e_{k+1}))$$

parametrizes all vertices of $L^{k+1}(H)$ bijectively, and the displayed hyperarc is present *exactly* for $(e_1, \dots, e_{k+1}) \in \mathbf{W}_{k+1}(H)$. Thus the adjacency in $L^{k+1}(H)$ is the stated one-step shift, completing the induction. $\square$

Theorem 4.6 (Generalization ladder). *Let $H = (V, E)$ be a directed hypergraph.*

- (A) ($k=1$ gives the line directed hypergraph). For $k = 1$, $L^1(H) = L(H)$ is exactly the line directed hypergraph of H .

(B) (**Reduction to iterated line digraphs**). Suppose H comes from a digraph $D = (V, A)$ by replacing each arc $(u, v) \in A$ with the hyperarc $e_{uv} = (\{u\}, v)$. Then, for every $k \geq 1$, there is a natural digraph isomorphism

$$L^k(H) \cong L^k(D),$$

obtained by identifying a vertex $\iota_k(e_{v_0v_1}, \dots, e_{v_{k-1}v_k}) \in V(L^k(H))$ with the directed walk $(v_0, \dots, v_k) \in V(L^k(D))$.

(C) (**LDH generalizes line digraphs**). In particular, when all hyperarcs of H have singleton tails ($|T(e)| = 1$) and distinct heads, $L(H)$ coincides with the classical line digraph on the arc set: there is an arc from e_{uv} to e_{vw} in $L(H)$ iff v is the common endpoint, i.e., iff $h(e_{uv}) = v \in T(e_{vw}) = \{v\}$.

Proof. (A) is immediate from the definition $L^1(H) := L(H)$.

For (B), by construction $V(L(H)) = E = \{e_{uv} : (u, v) \in A\}$ and

$$(\{e_{uv}\}, e_{vw}) \in E(L(H)) \iff h(e_{uv}) = v \in T(e_{vw}) = \{v\} \iff (u, v) \rightarrow (v, w) \text{ in } D,$$

so $L(H) \cong L(D)$. Iterating and using Theorem 4.5(b), the vertices of $L^k(H)$ are in bijection with compatible sequences $(e_{v_0v_1}, \dots, e_{v_{k-1}v_k})$, equivalently with directed walks $(v_0, \dots, v_k)$ in D , and adjacency is the one-step shift on walks in both constructions. Hence $L^k(H) \cong L^k(D)$.

For (C), take $k = 1$ in (B). The displayed equivalence shows $L(H)$ agrees with the usual line digraph when every $T(e)$ is a singleton, as claimed. $\square$

4.3. Iterated line directed superhypergraphs

Iterated line directed superhypergraphs repeatedly build line superhypergraphs from a directed superhypergraph, preserving hierarchical directed incidence patterns.

Remark 4.2. For $n \geq 0$ define the *compatibility* predicate C_n between $X, Y \in \text{POWS}^n(V)$ by

$$C_0(x, y) \Leftrightarrow x = y \quad (x, y \in V), \quad C_n(X, Y) \Leftrightarrow X \cap Y \neq \emptyset \quad (n \geq 1).$$

For a set W and $x \in W$, define the n -fold singleton lift $\sigma_0(x) := x$ and $\sigma_{k+1}(x) := \{\sigma_k(x)\}$, so that $\sigma_n(x) \in \text{POWS}^n(W)$ is the n -times nested singleton of x .

For $k \geq 1$, define the set of n -compatible k -walks of superhyperedges

$$W_k^{(n)}(\mathcal{H}^{(n)}) := \left\{ (e_1, \dots, e_k) \in E^k : C_n(H(e_i), T(e_{i+1})) \text{ for } i = 1, \dots, k-1 \right\}.$$

Definition 4.7 (Iterated line directed n -superhypergraphs). Let $\mathcal{H}^{(n)}$ be as above. Define $L_n^1(\mathcal{H}^{(n)}) := L_n(\mathcal{H}^{(n)})$ and, for $k \geq 1$,

$$L_n^{k+1}(\mathcal{H}^{(n)}) := L_n\left(L_n^k(\mathcal{H}^{(n)})\right).$$

We call $L_n^k(\mathcal{H}^{(n)})$ the k -fold (or iterated) line directed n -superhypergraph of $\mathcal{H}^{(n)}$.

Example 4.8 (Iterated line directed superhypergraphs: programs composed of teams). Let V_0 be a finite set of people in an organization. At level 1, form *teams* as subsets of people:

$$\text{teams } M_1 = \{a, b\}, \quad M_2 = \{c, d\}, \quad M_3 = \{b, c\} \subseteq \text{POWS}^1(V_0).$$

At level 2, form *programs* as collections of teams (elements of $\text{POWS}^2(V_0)$):

$$P_1 = \{M_1\}, \quad P_2 = \{M_3\}, \quad P_3 = \{M_2\}.$$

Consider a directed 2-superhypergraph $\mathcal{H}^{(2)} = (V_2, E)$ with vertex set $V_2 = \{P_1, P_2, P_3\}$ and superhyperedges

$$e_A : (\{P_1\}, \{P_2\}), \quad e_B : (\{P_2\}, \{P_3\}), \quad e_C : (\{P_3\}, \{P_1\}).$$

Each $e_\bullet$ expresses a *program-level dependency*: the (level-2) head of one superhyperedge (a collection of teams) must be contained in the (level-2) tail of the next for the workflow to proceed. The line directed 2-superhypergraph $L_2(\mathcal{H}^{(2)})$ has $\{e_A, e_B, e_C\}$ as vertices and singleton-tail superhyperedges

$$(\{e_A\}, \{e_B\}), \quad (\{e_B\}, \{e_C\}), \quad (\{e_C\}, \{e_A\}),$$

because, e.g., the head of e_A is $\{P_2\}$ and the tail of e_B is $\{P_2\}$ at the same level, so the composability condition is satisfied. Iterating once more, $L_2^2(\mathcal{H}^{(2)}) = L_2(L_2(\mathcal{H}^{(2)}))$ has as vertices the above three superhyperedges, and contains

$$(\{(\{e_A\}, \{e_B\})\}, (\{e_B\}, \{e_C\})),$$

which encodes the two-step program chain $e_A \rightarrow e_B$ (“handoff from program P_1 to P_2 , then from P_2 to P_3 ”). In this way, $L_2^k(\mathcal{H}^{(2)})$ summarizes length- k hierarchically consistent handoff sequences between program-level dependencies, preserving the nested (teams-within-programs) structure.

Theorem 4.9 (Well-definedness and walk correspondence). *Let $\mathcal{H}^{(n)} = (V, E)$ be a directed n -superhypergraph.*

- (A) $L_n(\mathcal{H}^{(n)})$ is a directed n -superhypergraph (in particular, $E' \subseteq \text{POWS}^n(E) \times \text{POWS}^n(E)$). Hence each iterate $L_n^k(\mathcal{H}^{(n)})$ is a directed n -superhypergraph.
- (B) For every $k \geq 1$ there is a canonical bijection

$$\iota_k^{(n)} : \mathbf{W}_k^{(n)}(\mathcal{H}^{(n)}) \xrightarrow{\cong} V(L_n^k(\mathcal{H}^{(n)})),$$

given recursively by

$$\iota_1^{(n)}(e_1) := e_1, \quad \iota_{k+1}^{(n)}(e_1, \dots, e_{k+1}) := (\sigma_n(\iota_k^{(n)}(e_1, \dots, e_k)), \sigma_n(\iota_k^{(n)}(e_2, \dots, e_{k+1}))).$$

Under this identification, there is an arc from $\iota_k^{(n)}(e_1, \dots, e_k)$ to $\iota_k^{(n)}(e_2, \dots, e_{k+1})$ in $L_n^k(\mathcal{H}^{(n)})$ for each $(e_1, \dots, e_{k+1}) \in \mathbf{W}_{k+1}^{(n)}(\mathcal{H}^{(n)})$, i.e., adjacency is the one-step shift of walks.

Proof. (A) By the Definition, vertices of $L_n(\mathcal{H}^{(n)})$ are elements of E . For each ordered pair $(e_1, e_2) \in E \times E$ with $C_n(H(e_1), T(e_2))$, the arc we add has tail $\sigma_n(e_1) \in \text{POWS}^n(E)$ and head $\sigma_n(e_2) \in \text{POWS}^n(E)$, so $E' \subseteq \text{POWS}^n(E) \times \text{POWS}^n(E)$ as required.

(B) For $k = 1$ this is the identity $E \cong V(L_n(\mathcal{H}^{(n)}))$. Assume the claim for k . Then $V(L_n^{k+1}(\mathcal{H}^{(n)})) = E(L_n^k(\mathcal{H}^{(n)}))$. By the Definition, an arc of $L_n^k(\mathcal{H}^{(n)})$ has the form $(\sigma_n(u), \sigma_n(v))$ with $u, v \in V(L_n^k(\mathcal{H}^{(n)}))$ and $C_n(H_k(u), T_k(v))$, where T_k, H_k are the tail/head maps in $L_n^k(\mathcal{H}^{(n)})$. By the induction hypothesis each u and v is *uniquely* represented as $u = \iota_k^{(n)}(e_1, \dots, e_k)$ and $v = \iota_k^{(n)}(e_2, \dots, e_{k+1})$ for a walk $(e_1, \dots, e_{k+1}) \in \mathbf{W}_{k+1}^{(n)}$. A direct unwinding of the definitions shows that the compatibility condition for the line step is *equivalent* to $C_n(H(e_i), T(e_{i+1}))$ at the base level, i.e., exactly the walk condition. Hence every vertex of L_n^{k+1} is of the displayed recursive form, giving the bijection and the shift adjacency. $\square$

Theorem 4.10 (Generalization ladder). *Let $n \geq 0$, $k \geq 1$, and $\mathcal{H}^{(n)} = (V, E)$ be a directed n -superhypergraph.*

- (i) **Directed superhypergraph:** $L_n^k(\mathcal{H}^{(n)})$ is a directed n -superhypergraph for all k (closure under iteration), by Theorem 4.9 (A).
- (ii) **Iterated line digraphs ($n=0$):** If $n = 0$, then $\mathcal{H}^{(0)}$ is a digraph $D = (V, A)$ and $L_0^k(\mathcal{H}^{(0)})$ is naturally isomorphic to the classical k -iterated line digraph $L^k(D)$: vertices on both sides correspond bijectively to directed length- k walks $(v_0, \dots, v_k)$, and adjacency is one-step shift.
- (iii) **Iterated line directed hypergraphs ($n=1$):** If $n = 1$, then $L_1^k(\mathcal{H}^{(1)})$ is (canonically) isomorphic to the iterated line directed hypergraph obtained by iterating the standard line operator that declares an arc $\{e_1\} \rightarrow e_2$ whenever $H(e_1) \cap T(e_2) \neq \emptyset$. (The two versions differ only by the singleton identification $e \leftrightarrow \{e\}$.)
- (iv) **Line directed superhypergraph ($k=1$):** For general $n \geq 0$, $L_n^1(\mathcal{H}^{(n)}) = L_n(\mathcal{H}^{(n)})$ is exactly the line directed n -superhypergraph of the Definition.

Proof. (i) is Theorem 4.9 (A).

(ii) When $n = 0$ we have $E \subseteq V \times V$, and C_0 is equality of the shared vertex: (u, v) is compatible with (v, w) . Vertices of L_0^k are in bijection with length- k walks $(v_0, \dots, v_k)$; an arc exists from $(v_0, \dots, v_k)$ to $(v_1, \dots, v_{k+1})$ iff (v_i, v_{i+1}) consecutively match—precisely the rule for $L^k(D)$.

(iii) For $n = 1$, $T(e), H(e) \subseteq V$ and C_1 is nonempty intersection. By Definition, L_1 adds an arc from $\sigma_1(e_1) = \{e_1\}$ to $\sigma_1(e_2) = \{e_2\}$ exactly when $H(e_1) \cap T(e_2) \neq \emptyset$. Identifying $\{e\} \leftrightarrow e$ yields the usual line directed hypergraph. Iteration respects this identification, giving the stated isomorphism for all k .

(iv) is tautological from Definition 4.7. $\square$

5. Total Directed HyperGraph

A Total Directed HyperGraph represents vertices and directed hyperedges as nodes, linking them by directed adjacency and incidence to encode complete hypergraph structure faithfully and compactly.

5.1. Total Directed Graph

A total directed graph connects every vertex pair in a directed graph, respecting possible edge orientations between them (cf.[12, 18, 52]).

Definition 5.1 (Total Directed Graph). Let $D = (V, A)$ be a finite digraph. The *total directed graph* of D , denoted $T(D)$, is the digraph defined as follows:

$$\begin{aligned} V(T(D)) &= V \cup A, \\ A(T(D)) &= A_{VV} \cup A_{AA} \cup A_{VA} \cup A_{AV}, \end{aligned}$$

where

$$\begin{aligned} A_{VV} &:= \{ (u, v) \in V \times V \mid (u, v) \in A \}, & (\text{vertex--vertex adjacency as in } D) \\ A_{AA} &:= \{ ((x, u), (u, y)) \in A \times A \}, & (\text{consecutive arcs in } D) \\ A_{VA} &:= \{ (u, (u, v)) \in V \times A \mid (u, v) \in A \}, & (\text{tail--to--arc incidence}) \\ A_{AV} &:= \{ ((u, v), v) \in A \times V \mid (u, v) \in A \}. & (\text{arc--to--head incidence}) \end{aligned}$$

Equivalently: the vertices of $T(D)$ correspond to the *elements* of D (vertices and arcs), and two vertices of $T(D)$ are adjacent precisely when the corresponding elements of D are adjacent (either as adjacent vertices, consecutive arcs, or incident vertex/arc in the appropriate direction).

Example 5.2 (Total Directed Graph: a two-step workflow). Let the digraph be $D = (V, A)$ with

$$V = \{A, B, C\}, \quad A = \{(A, B), (B, C)\}.$$

Then the total directed graph $T(D)$ has vertex set

$$V(T(D)) = V \cup A = \{A, B, C, (A, B), (B, C)\}.$$

Its arc set splits into the four canonical families:

$$\begin{aligned} A_{VV} &= \{(A, B), (B, C)\}, & (\text{original vertex--vertex arcs}) \\ A_{AA} &= \{((A, B), (B, C))\}, & (\text{consecutive arcs}) \\ A_{VA} &= \{(A, (A, B)), (B, (B, C))\}, & (\text{tail--to--arc incidence}) \\ A_{AV} &= \{((A, B), B), ((B, C), C)\}. & (\text{arc--to--head incidence}) \end{aligned}$$

Thus $T(D)$ simultaneously records adjacency of vertices, adjacency of arcs, and both directions of vertex--arc incidence.

5.2. Total Directed HyperGraph

A total directed hypergraph connects every vertex subset in a directed hypergraph, preserving directed incidence between subsets.

Definition 5.3 (Total directed hypergraph). Let $H = (V, E)$ be a directed hypergraph. Its *total directed hypergraph* $T(H)$ is the directed hypergraph defined by

$$V(T(H)) := V \cup E, \quad E(T(H)) := E_{VV} \cup E_{EE} \cup E_{VE} \cup E_{EV},$$

where the four families of hyperarcs are

$$E_{VV} := \left\{ (\{u\}, \{v\}) : \exists e \in E \text{ with } u \in T(e), v \in H(e) \right\}, \quad (\text{vertex-to-vertex adjacency via a hyperarc}),$$

$$E_{EE} := \left\{ (\{e_1\}, \{e_2\}) : e_1, e_2 \in E, H(e_1) \cap T(e_2) \neq \emptyset \right\}, \quad (\text{consecutive hyperarcs}),$$

$$E_{VE} := \left\{ (\{u\}, \{e\}) : e \in E, u \in T(e) \right\}, \quad (\text{tail-vertex to incident hyperarc}),$$

$$E_{EV} := \left\{ (\{e\}, \{v\}) : e \in E, v \in H(e) \right\}. \quad (\text{hyperarc to head-vertex}).$$

Thus every hyperarc of $T(H)$ has singleton tail and head, so $T(H)$ is a directed hypergraph whose hyperarcs encode vertex-vertex reachability through a hyperarc, hyperarc composition, and the two directions of vertex-hyperarc incidence.

Remark 5.1 (Many-to-many extension of the total construction). The total directed hypergraph construction also extends to many-to-many directed hypergraphs. If every hyperarc $e \in E$ has nonempty tail and head sets

$$\text{Tail}(e) \subseteq V, \quad \text{Head}(e) \subseteq V,$$

then the total directed hypergraph may again be defined on the vertex set

$$V(T(H)) = V \cup E.$$

Its hyperarcs may be decomposed into the four families

$$E(T(H)) = E_{VV} \cup E_{EE} \cup E_{VE} \cup E_{EV},$$

where

$$E_{VV} = \left\{ (\{u\}, \{v\}) \mid \exists e \in E, u \in \text{Tail}(e), v \in \text{Head}(e) \right\},$$

$$E_{EE} = \left\{ (\{e_1\}, \{e_2\}) \mid e_1, e_2 \in E, \text{Head}(e_1) \cap \text{Tail}(e_2) \neq \emptyset \right\},$$

$$E_{VE} = \left\{ (\{u\}, \{e\}) \mid e \in E, u \in \text{Tail}(e) \right\},$$

and

$$E_{EV} = \left\{ (\{e\}, \{v\}) \mid e \in E, v \in \text{Head}(e) \right\}.$$

Thus the total construction simultaneously records vertex-to-vertex transitions induced by hyperarcs, hyperarc-to-hyperarc composability, tail incidences, and head incidences. The single-head version is recovered by imposing $|\text{Head}(e)| = 1$ for all $e \in E$.

Example 5.4 (Total Directed HyperGraph: a simple multi-input production). Let $H = (V, E)$ be a directed hypergraph with

$$V = \{x, y, z, w\}, \quad E = \{e_1, e_2\},$$

where

$$e_1 : (T(e_1), H(e_1)) = (\{x, y\}, \{z\}), \quad e_2 : (T(e_2), H(e_2)) = (\{z\}, \{w\}).$$

The total directed hypergraph $T(H)$ has vertex set

$$V(T(H)) = V \cup E = \{x, y, z, w, e_1, e_2\},$$

and hyperarcs

$$\begin{aligned} E_{VV} &= \{(\{x\}, \{z\}), (\{y\}, \{z\}), (\{z\}, \{w\})\}, \\ E_{EE} &= \{(\{e_1\}, \{e_2\})\} \quad \text{since } H(e_1) \cap T(e_2) = \{z\} \neq \emptyset, \\ E_{VE} &= \{(\{x\}, \{e_1\}), (\{y\}, \{e_1\}), (\{z\}, \{e_2\})\}, \\ E_{EV} &= \{(\{e_1\}, \{z\}), (\{e_2\}, \{w\})\}. \end{aligned}$$

Hence $T(H)$ captures (i) vertex-to-vertex reachability through one hyperarc, (ii) composability of hyperarcs, and (iii) both vertex–hyperarc incidences.

Theorem 5.5 (Well-definedness). *For every directed hypergraph $H = (V, E)$, the structure $T(H)$ of Definition 5.3 is a directed hypergraph.*

Proof. By construction $V(T(H)) = V \cup E$ is a finite nonempty set. Each element of $E_{VV} \cup E_{EE} \cup E_{VE} \cup E_{EV}$ is an ordered pair $(\{x\}, \{y\})$ of nonempty subsets of $V \cup E$, hence is a valid hyperarc. Therefore $T(H)$ meets the definition of a directed hypergraph. $\square$

Theorem 5.6 (Generalization of the total directed graph). *Let $D = (V, A)$ be a finite digraph and regard D as a directed hypergraph $H_D = (V, E)$ by identifying each arc $(u, v) \in A$ with the hyperarc $e_{(u,v)} = (\{u\}, \{v\}) \in E$. Then $T(H_D)$ is naturally isomorphic to the classical total directed graph $T(D)$:*

$$\Phi : V(T(H_D)) = V \cup E \longrightarrow V(T(D)) = V \cup A, \quad \Phi(v) = v \ (v \in V), \quad \Phi(e_{(u,v)}) = (u, v),$$

and $(\{x\}, \{y\}) \in E(T(H_D))$ if and only if $(\Phi(x), \Phi(y)) \in A(T(D))$.

Proof. The map Φ is a bijection by construction. We check the four arc families.

(i) *Vertex–vertex:* $(\{u\}, \{v\}) \in E_{VV}$ for $T(H_D)$ iff there exists $e \in E$ with $u \in T(e)$ and $v \in H(e)$. Since every $e \in E$ has the form $e_{(x,y)} = (\{x\}, \{y\})$, this is equivalent to $(u, v) \in A$. Thus $(\Phi(u), \Phi(v)) = (u, v) \in A_{VV}$ of $T(D)$.

(ii) *Hyperarc–hyperarc:* $(\{e_{(x,u)}\}, \{e_{(u,y)}\}) \in E_{EE}$ for $T(H_D)$ iff $H(e_{(x,u)}) \cap T(e_{(u,y)}) = \{u\} \cap \{u\} \neq \emptyset$, i.e., the head of the first equals the tail of the second. Under Φ this becomes $((x, u), (u, y)) \in A_{AA}$ of $T(D)$.

(iii) *Vertex–hyperarc incidence:* $(\{u\}, \{e_{(u,v)}\}) \in E_{VE}$ for $T(H_D)$ iff $u \in T(e_{(u,v)})$, which corresponds to $(u, (u, v)) \in A_{VA}$ of $T(D)$.

(iv) *Hyperarc–vertex incidence:* $(\{e_{(u,v)}\}, \{v\}) \in E_{EV}$ for $T(H_D)$ iff $v \in H(e_{(u,v)})$, which corresponds to $((u, v), v) \in A_{AV}$ of $T(D)$.

Thus Φ preserves and reflects all arcs, yielding an isomorphism $T(H_D) \cong T(D)$. $\square$

5.3. Total Directed SuperHyperGraph

A total directed superhypergraph connects all vertex collections in a directed superhypergraph, maintaining directed incidence across hierarchical levels. We will need two canonical constructions: the n -fold *singleton lift* into $\text{POWS}^n(X)$, and the *atom map* that flattens an n -level object over V to the set of base vertices it contains.

Definition 5.7 (Singleton lift and atom map). For a set X and $n \geq 0$, define the n -fold singleton lift $\sigma_n : X \rightarrow \text{POWS}^n(X)$ recursively by

$$\sigma_0(x) = x, \quad \sigma_{k+1}(x) = \{\sigma_k(x)\} \quad (k \geq 0).$$

For a finite base set V define the atom map $\text{At}_n : \text{POWS}^n(V) \rightarrow \text{POWS}(V)$ recursively by

$$\text{At}_0(v) = \{v\}, \quad \text{At}_{k+1}(X) = \bigcup_{Y \in X} \text{At}_k(Y) \quad (k \geq 0).$$

Thus At_n collects all level-0 (i.e. base) vertices appearing inside a nested object in $\text{POWS}^n(V)$.

Definition 5.8 (Total directed n -superhypergraph). Let $S = (V, E)$ be a directed n -superhypergraph as in the Definition. Form its *total directed n -superhypergraph* $T^{(n)}(S)$ as follows.

Vertex set. Let $\tilde{V} := V \cup E$, i.e., treat every original edge $e \in E$ as a new atomic vertex. Set $V(T^{(n)}(S)) := \tilde{V}$.

Edge set. Define four families of directed n -superhyperedges, each given by an ordered pair in $\text{POWS}^n(\tilde{V}) \times \text{POWS}^n(\tilde{V})$ using the n -fold singleton lift σ_n :

$$\begin{aligned} E_{VV}^{(n)} &:= \left\{ (\sigma_n(u), \sigma_n(v)) : \exists e \in E \text{ with } u \in \text{At}_n(T(e)), v \in \text{At}_n(H(e)) \right\}, \\ E_{EE}^{(n)} &:= \left\{ (\sigma_n(e_1), \sigma_n(e_2)) : e_1, e_2 \in E, \text{At}_n(H(e_1)) \cap \text{At}_n(T(e_2)) \neq \emptyset \right\}, \\ E_{VE}^{(n)} &:= \left\{ (\sigma_n(u), \sigma_n(e)) : e \in E, u \in \text{At}_n(T(e)) \right\}, \\ E_{EV}^{(n)} &:= \left\{ (\sigma_n(e), \sigma_n(v)) : e \in E, v \in \text{At}_n(H(e)) \right\}. \end{aligned}$$

The edge set of $T^{(n)}(S)$ is the union

$$E(T^{(n)}(S)) := E_{VV}^{(n)} \cup E_{EE}^{(n)} \cup E_{VE}^{(n)} \cup E_{EV}^{(n)} \subseteq \text{POWS}^n(\tilde{V}) \times \text{POWS}^n(\tilde{V}).$$

Example 5.9 (Total Directed SuperHyperGraph (level $n = 2$): programs built from teams). Let the base set be $V = \{a, b, c, d\}$. Consider a directed 2-superhypergraph $S = (V, E)$ with two 2-superhyperedges

$$e_A : (T(e_A), H(e_A)) = (\{\{a, b\}\}, \{\{c\}\}), \quad e_B : (T(e_B), H(e_B)) = (\{\{c\}\}, \{\{d\}\}),$$

where elements of $\text{POWS}^2(V)$ are sets of subsets of V . Write $\sigma_2(x) = \{\{x\}\}$ for the double singleton lift and At_2 for the atom map (which flattens to base vertices), so $\text{At}_2(T(e_A)) = \{a, b\}$,

$\text{At}_2(H(e_A)) = \{c\}$, $\text{At}_2(T(e_B)) = \{c\}$, $\text{At}_2(H(e_B)) = \{d\}$. The total directed 2-superhypergraph $T^{(2)}(S)$ has vertex set

$$\tilde{V} = V \cup E = \{a, b, c, d, e_A, e_B\}.$$

Its 2-level edges are the following four families (all tails/heads live in $\text{POWS}^2(\tilde{V})$ via σ_2):

$$\begin{aligned} E_{VV}^{(2)} &= \{ (\sigma_2(a), \sigma_2(c)), (\sigma_2(b), \sigma_2(c)), (\sigma_2(c), \sigma_2(d)) \}, \\ E_{EE}^{(2)} &= \{ (\sigma_2(e_A), \sigma_2(e_B)) \} \quad \text{since } \text{At}_2(H(e_A)) \cap \text{At}_2(T(e_B)) = \{c\}, \\ E_{VE}^{(2)} &= \{ (\sigma_2(a), \sigma_2(e_A)), (\sigma_2(b), \sigma_2(e_A)), (\sigma_2(c), \sigma_2(e_B)) \}, \\ E_{EV}^{(2)} &= \{ (\sigma_2(e_A), \sigma_2(c)), (\sigma_2(e_B), \sigma_2(d)) \}. \end{aligned}$$

Thus $T^{(2)}(S)$ elevates both base vertices and 2-level edges to vertices and encodes vertex-vertex reachability through a single 2-edge, composition of 2-edges, and both directions of incidence, all placed coherently at level 2.

Intuitively, $T^{(n)}(S)$ makes both *objects* of S (the base vertices V and the n -level edges E) into vertices, and then creates four types of directed n -superhyperedges encoding: (i) vertex-to-vertex reachability through a single original edge; (ii) composition of original edges; (iii) incidence from tail-vertices to an edge; and (iv) incidence from an edge to its head-vertices. The use of At_n ensures these are decided at the level of base vertices even when $T(e), H(e)$ are nested ($n \geq 1$). The lift σ_n places these incidences at the correct superlevel.

Theorem 5.10 (Well-definedness: $T^{(n)}(S)$ is a directed n -superhypergraph). *For any directed n -superhypergraph $S = (V, E)$, the structure $T^{(n)}(S) = (\tilde{V}, E(T^{(n)}(S)))$ of Definition 5.8 is a directed n -superhypergraph on the base set $\tilde{V}$.*

Proof. By construction $\tilde{V} = V \cup E$ is finite and nonempty. Each edge of $T^{(n)}(S)$ has the form $(\sigma_n(x), \sigma_n(y))$ with $x, y \in \tilde{V}$; hence its tail and head lie in $\text{POWS}^n(\tilde{V})$ by the definition of σ_n . Therefore $E(T^{(n)}(S)) \subseteq \text{POWS}^n(\tilde{V}) \times \text{POWS}^n(\tilde{V})$, as required in the Definition. $\square$

Theorem 5.11 (Generalization of the total directed graph). *Let $D = (V, A)$ be a finite digraph and regard it as a directed 0-superhypergraph $S_0 = (V, E_0)$ with $E_0 = A \subseteq V \times V$. Then the total directed 0-superhypergraph $T^{(0)}(S_0)$ is (canonically) isomorphic to the classical total directed graph $T(D)$.*

Proof. Here $n = 0$, σ_0 is the identity, and $\text{At}_0(v) = \{v\}$. The vertex set of $T^{(0)}(S_0)$ is $\tilde{V} = V \cup E_0 = V \cup A$, which equals the vertex set of $T(D)$. We verify the four edge families coincide:

- (i) $E_{VV}^{(0)}$ consists of (u, v) whenever $\exists (x, y) \in A$ with $u \in \{x\}$ and $v \in \{y\}$, i.e. precisely when $(u, v) \in A$. This is A_{VV} in the definition of $T(D)$.
- (ii) $E_{EE}^{(0)}$ contains $((x, u), (u, y))$ whenever $(x, u), (u, y) \in A$, i.e. consecutive arcs; this equals A_{AA} in $T(D)$.
- (iii) $E_{VE}^{(0)}$ contains $(u, (u, v))$ for each $(u, v) \in A$ (tail incidence), i.e. A_{VA} .
- (iv) $E_{EV}^{(0)}$ contains $((u, v), v)$ for each $(u, v) \in A$ (head incidence), i.e. A_{AV} .

Thus $T^{(0)}(S_0) = T(D)$. $\square$

Theorem 5.12 (Generalization of the total directed hypergraph). *Let $H = (V, E)$ be a directed hypergraph (i.e. a directed 1-superhypergraph). Then the total directed 1-superhypergraph $T^{(1)}(H)$ is naturally isomorphic to the total directed hypergraph $T(H)$ of Definition (Total directed hypergraph).*

Proof. Now $n = 1$, so $\sigma_1(x) = \{x\}$ and At_1 reduces a subset of V to itself. The vertex set of $T^{(1)}(H)$ is $\tilde{V} = V \cup E$, which is the vertex set used in $T(H)$. For edges, note that every edge in $T^{(1)}(H)$ has singleton tail and head, so it corresponds to an ordered pair of *atoms* in $V \cup E$.

(i) $E_{VV}^{(1)}$ contains $(\{u\}, \{v\})$ iff there exists $e \in E$ with $u \in T(e)$ and $v \in H(e)$, i.e. exactly the vertex–vertex arcs in $T(H)$. Identifying $\{u\} \leftrightarrow u$ and $\{v\} \leftrightarrow v$ yields the same arcs as in E_{VV} of $T(H)$.

(ii) $E_{EE}^{(1)}$ contains $(\{e_1\}, \{e_2\})$ iff $H(e_1) \cap T(e_2) \neq \emptyset$, precisely the consecutive-hyperarc condition in $T(H)$. Under $\{e\} \leftrightarrow e$ this is E_{EE} of $T(H)$.

(iii) $E_{VE}^{(1)}$ contains $(\{u\}, \{e\})$ iff $u \in T(e)$, matching E_{VE} of $T(H)$.

(iv) $E_{EV}^{(1)}$ contains $(\{e\}, \{v\})$ iff $v \in H(e)$, matching E_{EV} of $T(H)$.

Hence the identification of singleton lifts gives a canonical isomorphism $T^{(1)}(H) \cong T(H)$. $\square$

6. Line Bidirected Graph and Total Bidirected Graph

The Line Bidirected Graph transforms each bidirected edge into a vertex and preserves edge adjacencies through bidirectional incidence and orientation relationships in the original graph. The Total Bidirected Graph represents both original vertices and bidirected edges as vertices, encoding vertex adjacency, edge adjacency, and incidence while retaining bidirectional structure.

6.1. Bidirected Graph

A bidirected graph is a graph where each edge endpoint has an independent orientation, allowing bidirectional incidence representation [49, 67].

Definition 6.1 (bidirected graph). [15, 33, 67] A *bidirected graph* is a directed graph with independent orientations at each endpoint of an edge. Formally, a bidirected graph is defined as:

$$G = (V, E, \tau),$$

where:

- V is the set of vertices.
- E is the set of edges, each connecting two vertices.
- $\tau : V \times E \rightarrow \{-1, 0, 1\}$ is the bidirection function:
 - $\tau(v, e) = 1$: Edge e is directed toward vertex v .
 - $\tau(v, e) = -1$: Edge e is directed away from vertex v .
 - $\tau(v, e) = 0$: Vertex v is not incident to edge e .

6.2. Line Bidirected Graph

A line bidirected graph represents edges of a bidirected graph as vertices, connecting them if they share an endpoint in the original.

For $v \in V$ write

$$E^+(v) := \{ e \in E : \tau(v, e) = +1 \}, \quad E^-(v) := \{ e \in E : \tau(v, e) = -1 \},$$

the incident edges that *enter* (resp. *leave*) v .

Definition 6.2 (Line bidirected graph). Let $G = (V, E, \tau)$ be a finite bidirected graph. Its *line bidirected graph* is the bidirected graph

$$L_{\text{bi}}(G) = (E, E_L, \tau_L),$$

defined as follows.

- **Vertices:** $V(L_{\text{bi}}(G)) = E$; that is, each edge of G becomes a vertex of $L_{\text{bi}}(G)$.
- **Edges:** For each $v \in V$ and each *ordered* pair $(e_{\text{in}}, e_{\text{out}}) \in E^+(v) \times E^-(v)$ with $e_{\text{in}} \neq e_{\text{out}}$, introduce a new edge $\ell = \ell_v(e_{\text{in}}, e_{\text{out}})$ of $L_{\text{bi}}(G)$ incident with the two vertices e_{in} and e_{out} and with endpoint signs

$$\tau_L(e_{\text{in}}, \ell) = -1, \quad \tau_L(e_{\text{out}}, \ell) = +1, \quad \tau_L(e, \ell) = 0 \text{ for } e \notin \{e_{\text{in}}, e_{\text{out}}\}.$$

(If desired, parallel edges created by different v or by different ordered pairs may be kept, yielding a bidirected multigraph; otherwise identify parallel copies.)

Intuitively, each $\ell_v(e_{\text{in}}, e_{\text{out}})$ encodes a *feasible turn at v* from the incoming end of e_{in} to the outgoing end of e_{out} .

Example 6.3 (Line Bidirected Graph of the above instance). For $v \in V$, set

$$E^+(v) := \{ e \in E : \tau(v, e) = +1 \}, \quad E^-(v) := \{ e \in E : \tau(v, e) = -1 \}.$$

With the τ from the previous example we have

$$E^+(A) = \{e_3\}, E^-(A) = \{e_1\}; \quad E^+(B) = \{e_1\}, E^-(B) = \{e_2\}; \quad E^+(C) = \{e_2\}, E^-(C) = \{e_3\}.$$

The *line bidirected graph* $L_{\text{bi}}(G) = (E, E_L, \tau_L)$ has vertex set E and, for each $v \in V$ and ordered pair $(e_{\text{in}}, e_{\text{out}}) \in E^+(v) \times E^-(v)$ with $e_{\text{in}} \neq e_{\text{out}}$, an edge $\ell_v(e_{\text{in}}, e_{\text{out}})$ such that

$$\tau_L(e_{\text{in}}, \ell_v) = -1, \quad \tau_L(e_{\text{out}}, \ell_v) = +1, \quad \tau_L(e, \ell_v) = 0 \text{ for } e \notin \{e_{\text{in}}, e_{\text{out}}\}.$$

Thus here

$$E_L = \{ \ell_A(e_3, e_1), \ell_B(e_1, e_2), \ell_C(e_2, e_3) \}.$$

If we orient each line edge from its -1 endpoint to its $+1$ endpoint, we obtain the directed 3-cycle $e_3 \rightarrow e_1 \rightarrow e_2 \rightarrow e_3$, which coincides with the classical line digraph of $A \rightarrow B \rightarrow C \rightarrow A$.

Theorem 6.4 (Well-definedness). *For every finite bidirected graph $G = (V, E, \tau)$, the structure $L_{bi}(G) = (E, E_L, \tau_L)$ in Definition 6.2 is a (finite) bidirected graph.*

Proof. By construction the vertex set is E (finite). Each edge $\ell = \ell_v(e_{in}, e_{out})$ is incident with exactly two vertices e_{in} and e_{out} and has $\tau_L(e_{in}, \ell) = -1$, $\tau_L(e_{out}, \ell) = +1$ and zero elsewhere. Thus $\tau_L : E \times E_L \rightarrow \{-1, 0, +1\}$ is a valid bidirected incidence function, and $L_{bi}(G)$ is bidirected by Definition. $\square$

Theorem 6.5 (Generalizes the line digraph). *Let $D = (V, A)$ be a finite digraph and view it as a bidirected graph $G = (V, E, \tau)$ by taking $E = A$ and, for each arc $e = (u, v)$,*

$$\tau(u, e) = -1 \quad (\text{tail}), \quad \tau(v, e) = +1 \quad (\text{head}).$$

Orient each edge ℓ of $L_{bi}(G)$ from its -1 endpoint to its $+1$ endpoint. Then the resulting digraph is canonically isomorphic to the classical line digraph $L(D)$.

Proof. Fix arcs $e_1 = (x, v)$ and $e_2 = (v, y)$ of D with $\text{head}(e_1) = v = \text{tail}(e_2)$. In the bidirected encoding, $\tau(v, e_1) = +1$ and $\tau(v, e_2) = -1$, so by Definition 6.2 there is an edge $\ell_v(e_1, e_2)$ with $\tau_L(e_1, \ell) = -1$ and $\tau_L(e_2, \ell) = +1$. Under the “ $- \rightarrow +$ ” orientation rule, this yields an arc $e_1 \rightarrow e_2$. Conversely, any edge ℓ of $L_{bi}(G)$ arises from some v and ordered pair (e_1, e_2) with $\tau(v, e_1) = +1$, $\tau(v, e_2) = -1$, which in the digraph corresponds exactly to $\text{head}(e_1) = v = \text{tail}(e_2)$, i.e. a directed adjacency $e_1 \rightarrow e_2$ in $L(D)$. This gives a bijection between arcs of $L(D)$ and oriented edges of $L_{bi}(G)$, preserving incidence, hence a canonical isomorphism of digraphs. $\square$

6.3. Total Bidirected Graph

A total bidirected graph extends a bidirected graph by adding edges between all vertex pairs with any endpoint orientation relationship present.

Definition 6.6 (Total bidirected graph). Let $G = (V, E, \tau)$ be a finite bidirected graph. The *total bidirected graph* of G is the bidirected graph

$$T_{bi}(G) = (V_T, E_T, \tau_T),$$

defined as follows.

Vertices. $V_T := V \cup E$; thus both original vertices and original edges of G are vertices of $T_{bi}(G)$.

Edges. $E_T := E_{VV} \cup E_{EE} \cup E_{VE}$, where

$$\begin{aligned} E_{VV} &:= \{ \kappa_e \mid e \in E \text{ with endpoints } u, v \in V \text{ (possibly } u = v) \}, \\ E_{EE} &:= \{ \lambda_v(e_{in}, e_{out}) \mid v \in V, e_{in} \in E^+(v), e_{out} \in E^-(v), e_{in} \neq e_{out} \}, \\ E_{VE} &:= \{ \iota(v, e) \mid v \in V, e \in E, \tau(v, e) \in \{\pm 1\} \}. \end{aligned}$$

Incidence signs. The signed incidences $\tau_T(\cdot, \cdot)$ are given by

(V–V edges) if e has endpoints u, v in G , then $\kappa_e \in E_{VV}$ with

$$\tau_T(u, \kappa_e) = \tau(u, e), \quad \tau_T(v, \kappa_e) = \tau(v, e), \quad \tau_T(x, \kappa_e) = 0 \quad \forall x \in V_T \setminus \{u, v\};$$

(E–E edges) $\lambda_v(e_{\text{in}}, e_{\text{out}}) \in E_{EE}$ is incident with $e_{\text{in}}, e_{\text{out}}$ via

$$\tau_T(e_{\text{in}}, \lambda_v(e_{\text{in}}, e_{\text{out}})) = -1, \quad \tau_T(e_{\text{out}}, \lambda_v(e_{\text{in}}, e_{\text{out}})) = +1, \\ \tau_T(x, \lambda_v(e_{\text{in}}, e_{\text{out}})) = 0 \quad \forall x \notin \{e_{\text{in}}, e_{\text{out}}\};$$

(V–E edges) $\iota(v, e) \in E_{VE}$ is incident with v and e via

$$\tau_T(v, \iota(v, e)) = \tau(v, e), \quad \tau_T(e, \iota(v, e)) = -\tau(v, e), \quad \tau_T(x, \iota(v, e)) = 0 \quad \forall x \notin \{v, e\}.$$

(If desired, parallel edges created by distinct witnesses may be kept, producing a bidirected multi-graph.)

Example 6.7 (Total Bidirected Graph of the same instance). Let $G = (V, E, \tau)$ be the bidirected graph in the first example. The *total bidirected graph* $T_{\text{bi}}(G) = (V_T, E_T, \tau_T)$ has

$$V_T = V \cup E = \{A, B, C, e_1, e_2, e_3\},$$

and three edge families: vertex–vertex (E_{VV}), edge–edge (E_{EE}), and vertex–edge (E_{VE}).

(i) Vertex–vertex edges. For each $e \in E$ with endpoints u, v in G , add κ_e incident to u, v with

$$\tau_T(u, \kappa_e) = \tau(u, e), \quad \tau_T(v, \kappa_e) = \tau(v, e).$$

Here:

$$\tau_T(A, \kappa_{e_1}) = -1, \quad \tau_T(B, \kappa_{e_1}) = +1; \quad \tau_T(B, \kappa_{e_2}) = -1, \quad \tau_T(C, \kappa_{e_2}) = +1; \quad \tau_T(C, \kappa_{e_3}) = -1, \quad \tau_T(A, \kappa_{e_3}) = +1.$$

(ii) Edge–edge edges. For each $v \in V$ and $(e_{\text{in}}, e_{\text{out}}) \in E^+(v) \times E^-(v)$, add $\lambda_v(e_{\text{in}}, e_{\text{out}})$ incident with $e_{\text{in}}, e_{\text{out}}$ by

$$\tau_T(e_{\text{in}}, \lambda_v) = -1, \\ \tau_T(e_{\text{out}}, \lambda_v) = +1.$$

Thus:

$$\tau_T(e_1, \lambda_B(e_1, e_2)) = -1, \quad \tau_T(e_2, \lambda_B(e_1, e_2)) = +1; \\ \tau_T(e_2, \lambda_C(e_2, e_3)) = -1, \quad \tau_T(e_3, \lambda_C(e_2, e_3)) = +1; \\ \tau_T(e_3, \lambda_A(e_3, e_1)) = -1, \quad \tau_T(e_1, \lambda_A(e_3, e_1)) = +1.$$

(iii) Vertex–edge incidence edges. For each incident pair (v, e) with $\tau(v, e) \in \{\pm 1\}$, add $\iota(v, e)$ with

$$\tau_T(v, \iota(v, e)) = \tau(v, e), \\ \tau_T(e, \iota(v, e)) = -\tau(v, e).$$

Concretely:

$$\begin{aligned} \tau_T(A, \iota(A, e_1)) &= -1, \tau_T(e_1, \iota(A, e_1)) = +1; & \tau_T(B, \iota(B, e_1)) &= +1, \tau_T(e_1, \iota(B, e_1)) = -1; \\ \tau_T(B, \iota(B, e_2)) &= -1, \tau_T(e_2, \iota(B, e_2)) = +1; & \tau_T(C, \iota(C, e_2)) &= +1, \tau_T(e_2, \iota(C, e_2)) = -1; \\ \tau_T(C, \iota(C, e_3)) &= -1, \tau_T(e_3, \iota(C, e_3)) = +1; & \tau_T(A, \iota(A, e_3)) &= +1, \tau_T(e_3, \iota(A, e_3)) = -1. \end{aligned}$$

Hence $T_{bi}(G)$ elevates both original vertices and edges to vertices and connects them by (a) vertex–vertex edges respecting the original endpoint signs, (b) edge–edge edges encoding feasible turns at intermediate vertices, and (c) vertex–edge edges encoding signed incidence.

Theorem 6.8 (Well-definedness). *For every finite bidirected graph $G = (V, E, \tau)$, the structure $T_{bi}(G) = (V_T, E_T, \tau_T)$ of Definition 6.6 is a finite bidirected graph.*

Proof. By construction, V_T is finite. For each edge of E_T there are exactly two nonzero incidences, each in $\{\pm 1\}$, and all other incidences are 0:

- For $\kappa_e \in E_{VV}$, only the endpoints u, v of e have nonzero incidence, with $\tau_T(u, \kappa_e) = \tau(u, e)$ and $\tau_T(v, \kappa_e) = \tau(v, e)$.
- For $\lambda_v(e_{in}, e_{out}) \in E_{EE}$, only e_{in} and e_{out} have nonzero incidence, with values -1 and $+1$ respectively.
- For $\iota(v, e) \in E_{VE}$, only v and e have nonzero incidence, with $\tau_T(v, \iota(v, e)) = \tau(v, e)$ and $\tau_T(e, \iota(v, e)) = -\tau(v, e)$.

Thus $\tau_T : V_T \times E_T \rightarrow \{-1, 0, +1\}$ satisfies the bidirected axioms of Definition. $\square$

Theorem 6.9 (Generalizes the total directed graph). *Let $D = (V, A)$ be a finite digraph and view it as a bidirected graph $G = (V, E, \tau)$ by taking $E = A$ and, for each arc $e = (u, v)$,*

$$\tau(u, e) = -1 \quad (\text{tail}), \quad \tau(v, e) = +1 \quad (\text{head}).$$

Orient each edge of $T_{bi}(G)$ from its -1 endpoint to its $+1$ endpoint. The resulting digraph is canonically isomorphic to the classical total directed graph $T(D)$ of Definition (Total Directed Graph).

Proof. We show a bijection between the four arc classes of $T(D)$ and the oriented edges of $T_{bi}(G)$.

(VV-class). For each arc $e = (u, v) \in A$, the edge $\kappa_e \in E_{VV}$ satisfies $\tau_T(u, \kappa_e) = -1$ and $\tau_T(v, \kappa_e) = +1$, hence orients as $u \rightarrow v$. This yields exactly the arc set $A_{VV} = \{(u, v) \in V \times V : (u, v) \in A\}$.

(EE-class). For consecutive arcs $e_1 = (x, u)$ and $e_2 = (u, y)$ in D ($\text{head}(e_1) = u = \text{tail}(e_2)$), we have $\tau(u, e_1) = +1$ and $\tau(u, e_2) = -1$, so $\lambda_u(e_1, e_2) \in E_{EE}$ satisfies $\tau_T(e_1, \lambda) = -1$, $\tau_T(e_2, \lambda) = +1$, hence orients as $e_1 \rightarrow e_2$. This yields exactly $A_{AA} = \{((x, u), (u, y)) \in A \times A\}$.

(VA-class). If $e = (u, v) \in A$, then $\tau(u, e) = -1$, so $\iota(u, e) \in E_{VE}$ satisfies $\tau_T(u, \iota(u, e)) = -1$, $\tau_T(e, \iota(u, e)) = +1$, hence orients as $u \rightarrow e$. This yields exactly $A_{VA} = \{(u, (u, v)) : (u, v) \in A\}$.

(AV-class). If $e = (u, v) \in A$, then $\tau(v, e) = +1$, so $\iota(v, e) \in E_{VE}$ satisfies $\tau_T(v, \iota(v, e)) = +1$, $\tau_T(e, \iota(v, e)) = -1$, hence orients as $e \rightarrow v$. This yields exactly $A_{AV} = \{((u, v), v) : (u, v) \in A\}$.

These four correspondences are bijective on their respective classes and preserve incidence. Therefore the orientation of $T_{bi}(G)$ from -1 to $+1$ produces a digraph canonically isomorphic to $T(D)$. $\square$

7. Line Multidirected Graph

7.1. Multidirected Graph

A multidirected graph is a graph that allows multiple directed edges between vertices, each assigned a specific multiplicity, thereby extending the standard directed graph representation [27, 57].

Definition 7.1 (Multidirected Graph). [56, 57] A *multidirected graph* is a tuple

$$G = (V, E, s, t, m),$$

where

- V is a finite set of vertices,
- E is a finite set of edges,
- $s, t : E \rightarrow V$ assign to each edge its source and target,
- $m : V \times V \rightarrow \mathbb{N}_0$ gives the multiplicity of edges from one vertex to another.

Example 7.2 (Multidirected Graph: parallel shipments in a small logistics hub). Let $V = \{A, B, C\}$ denote depots. Consider four directed shipments (edges)

$$E = \{e_1, e_2, e_3, e_4\}, \quad s(e_1) = A, t(e_1) = B; \quad s(e_2) = A, t(e_2) = B;$$

$$s(e_3) = B, t(e_3) = C; \quad s(e_4) = B, t(e_4) = B \text{ (a loop at } B \text{)}.$$

The multiplicity function $m : V \times V \rightarrow \mathbb{N}_0$ records how many parallel edges exist from one depot to another:

$$m(A, B) = 2, \quad m(B, C) = 1, \quad m(B, B) = 1,$$

and $m(u, v) = 0$ for all remaining ordered pairs (u, v) . Then $G = (V, E, s, t, m)$ is a multidirected graph: there are two parallel edges $A \rightarrow B$ (namely e_1, e_2), one edge $B \rightarrow C$ (e_3), and one loop at B (e_4).

7.2. Line Multidirected Graph

A line multidirected graph is constructed from a multidirected graph by taking its vertices to represent the edges of the original, with edges indicating consecutive incidence in the original graph.

Definition 7.3 (Line Multidirected Graph). Let $G = (V, E, s, t, m)$ be a finite multidirected graph. The *line multidirected graph* of G , denoted $L_{\text{md}}(G)$, is the multidirected graph

$$L_{\text{md}}(G) = (V_L, E_L, s_L, t_L, m_L)$$

defined as follows.

- **Vertices.** $V_L := E$. Thus each edge of G becomes a vertex of $L_{\text{md}}(G)$.

- **Edges.** Set

$$E_L := \{ \epsilon = (e_1, e_2) \in E \times E : t(e_1) = s(e_2) \}.$$

Each ordered pair of *consecutive* edges in G is an edge of $L_{\text{md}}(G)$.

- **Source/Target.** For $\epsilon = (e_1, e_2) \in E_L$ put

$$s_L(\epsilon) := e_1, \quad t_L(\epsilon) := e_2.$$

- **Multiplicity.** For $x, y \in V_L = E$, define

$$m_L(x, y) := \# \{ \epsilon \in E_L : s_L(\epsilon) = x, t_L(\epsilon) = y \}.$$

Equivalently, $m_L(e_1, e_2) = 1$ if $t(e_1) = s(e_2)$ and 0 otherwise (so multiplicities count parallel line-edges should a modeling choice create them).

Loops in G are permitted and induce the natural loops in $L_{\text{md}}(G)$ when $t(e) = s(e)$.

Example 7.4 (Line Multidirected Graph of the logistics hub). Let $G = (V, E, s, t, m)$ be as above. Its line multidirected graph $L_{\text{md}}(G) = (V_L, E_L, s_L, t_L, m_L)$ has

$$V_L = E = \{e_1, e_2, e_3, e_4\}.$$

By definition,

$$E_L = \{ \epsilon = (e_i, e_j) \in E \times E : t(e_i) = s(e_j) \}.$$

Since $t(e_1) = t(e_2) = B$, and the edges starting at B are e_3 and e_4 , while $t(e_3) = C$ (no outgoing edge from C in this instance) and $t(e_4) = B$ (with outgoing e_3, e_4 again), we obtain

$$E_L = \{ (e_1, e_3), (e_1, e_4), (e_2, e_3), (e_2, e_4), (e_4, e_3), (e_4, e_4) \}.$$

For each $\epsilon = (e_i, e_j) \in E_L$ we set $s_L(\epsilon) = e_i$ and $t_L(\epsilon) = e_j$. The multiplicity on $V_L \times V_L$ counts how many such ordered pairs realize the same ordered pair of vertices:

$$m_L(e_i, e_j) = \# \{ \epsilon \in E_L : s_L(\epsilon) = e_i, t_L(\epsilon) = e_j \}.$$

In this concrete example all listed pairs are distinct, so $m_L(e_i, e_j) = 1$ for the six pairs above and $m_L(x, y) = 0$ otherwise. Operationally, a vertex of $L_{\text{md}}(G)$ represents a shipment, and an edge of $L_{\text{md}}(G)$ represents a feasible two-leg itinerary where the destination of the first shipment equals the origin of the second (including chaining through the loop e_4 at depot B).

Theorem 7.5 (Well-definedness). *For every finite multidirected graph $G = (V, E, s, t, m)$, the structure $L_{\text{md}}(G) = (V_L, E_L, s_L, t_L, m_L)$ of Definition 7.3 is a finite multidirected graph.*

Proof. Finiteness is immediate because $V_L = E$ and $E_L \subseteq E \times E$ are finite. By construction, $s_L, t_L : E_L \rightarrow V_L$ are well-defined maps, and $m_L : V_L \times V_L \rightarrow \mathbb{N}_0$ counts (possibly zero) how many edges of E_L go from one line-vertex to another. Hence $L_{\text{md}}(G)$ satisfies Definition ??.

Theorem 7.6 (Generalizes the line directed graph). *Let $D = (V, A)$ be a (multi)digraph, and view it as a multidirected graph by $G_D = (V, E, s, t, m)$ with $E = A$ and $m(u, v) = \#\{a \in A : s(a) = u, t(a) = v\}$. Then the underlying digraph of $L_{\text{md}}(G_D)$ is canonically isomorphic to the classical line directed graph $L(D)$: its vertices are the arcs of D , and there is an arc $(a_1 \rightarrow a_2)$ iff $t(a_1) = s(a_2)$.*

Proof. In $L_{\text{md}}(G_D)$ we have $V_L = E = A$. By definition, $E_L = \{(a_1, a_2) \in A \times A : t(a_1) = s(a_2)\}$, and the source/target maps are $s_L(a_1, a_2) = a_1$ and $t_L(a_1, a_2) = a_2$. Forgetting the multiplicity bookkeeping recovers exactly the arc set of the line digraph $L(D)$. $\square$

Definition 7.7 (Orientation functor Φ). Let $G_{\text{bi}} = (V, E, \tau)$ be an *orientable* bidirected graph, i.e., each $e \in E$ is incident with exactly two vertices u, v and $\{\tau(u, e), \tau(v, e)\} = \{-1, +1\}$. Define a multidirected graph

$$\Phi(G_{\text{bi}}) = (V, E, s, t, m)$$

by setting $s(e)$ to be the unique vertex with $\tau(s(e), e) = -1$, and $t(e)$ the unique vertex with $\tau(t(e), e) = +1$, while $m(u, v)$ again counts parallel edges.

Theorem 7.8 (Generalizes the line bidirected graph (orientable case)). *Let G_{bi} be an orientable bidirected graph and let $\Phi(G_{\text{bi}})$ be as in Definition 7.7. Consider the underlying (unsigned) digraph of the line bidirected graph $L_{\text{bi}}(G_{\text{bi}})$ obtained by directing each “turn” from e_{in} to e_{out} and forgetting endpoint signs. Then there is a natural digraph isomorphism*

$$U(L_{\text{bi}}(G_{\text{bi}})) \cong \text{underlying digraph of } L_{\text{md}}(\Phi(G_{\text{bi}})).$$

Proof. Vertices on both sides are the edges E of the original structure. (1) If in $L_{\text{bi}}(G_{\text{bi}})$ there is a turn $e_{\text{in}} \rightarrow e_{\text{out}}$ at v with $e_{\text{in}} \in E^+(v)$ and $e_{\text{out}} \in E^-(v)$, then by the definition of Φ , $t(e_{\text{in}}) = v = s(e_{\text{out}})$. Hence $(e_{\text{in}}, e_{\text{out}}) \in E_L$ of $L_{\text{md}}(\Phi(G_{\text{bi}}))$, i.e., there is a line edge $e_{\text{in}} \rightarrow e_{\text{out}}$. (2) Conversely, if $(e_1, e_2) \in E_L$ of $L_{\text{md}}(\Phi(G_{\text{bi}}))$, then $t(e_1) = s(e_2) =: v$. In the bidirected signs, this means $\tau(v, e_1) = +1$ and $\tau(v, e_2) = -1$, hence there is a turn $e_1 \rightarrow e_2$ at v in $L_{\text{bi}}(G_{\text{bi}})$. Thus we have a bijection on arcs preserving incidence, which gives the claimed isomorphism. $\square$

7.3. Computational Interpretation: Hierarchical Message Passing

The generalized structures considered in this paper also have a natural computational interpretation in the context of graph machine learning. In ordinary graph neural networks, message passing is usually performed between adjacent vertices. Hypergraph neural networks extend this idea by allowing messages to be aggregated through hyperedges, so that information can be exchanged among all vertices participating in the same higher-order relation. For SuperHyperGraphs, the same principle can be lifted to a hierarchical setting: messages may be passed not only between vertices and hyperedges, but also among supervertices, superhyperedges, and higher-level nested relational objects.

More concretely, a hierarchical message-passing scheme on a SuperHyperGraph may be organized in several stages. First, vertex-level features are aggregated inside hyperedges or level-1 supervertices. Second, the resulting hyperedge-level representations are passed to higher-level supervertices or superhyperedges, such as sets of hyperedges or groups of groups. Third, information may be

propagated back from these higher-level objects to lower-level objects, thereby allowing global or hierarchical context to influence local vertex representations. Symbolically, one may consider update rules of the form

$$h_v^{(t+1)} = \Phi_V\left(h_v^{(t)}, \text{AGG}_{e \ni v} h_e^{(t)}\right),$$

$$h_e^{(t+1)} = \Phi_E\left(h_e^{(t)}, \text{AGG}_{v \in e} h_v^{(t)}, \text{AGG}_{\mathcal{E} \ni e} h_{\mathcal{E}}^{(t)}\right),$$

and

$$h_{\mathcal{E}}^{(t+1)} = \Phi_{\mathcal{E}}\left(h_{\mathcal{E}}^{(t)}, \text{AGG}_{e \in \mathcal{E}} h_e^{(t)}\right),$$

where $h_v^{(t)}$, $h_e^{(t)}$, and $h_{\mathcal{E}}^{(t)}$ denote the features of vertices, hyperedges, and superhyperedges at layer t , respectively. The maps Φ_V , Φ_E , and $\Phi_{\mathcal{E}}$ are learnable update functions, and AGG denotes a permutation invariant aggregation operator, such as summation, averaging, maximum, or attention-based aggregation.

From this viewpoint, the line and total constructions studied in this paper provide useful auxiliary structures for message passing. A line construction transforms hyperedges or superhyperedges into vertices of a new object, making it possible to perform message passing directly among relations. Thus, adjacency in a line directed hypergraph or line directed SuperHyperGraph can be interpreted as a valid transition channel between hyperedge-level or superhyperedge-level representations. A total construction, on the other hand, places vertices, hyperedges, and incidence relations in a single unified structure. This is particularly useful when a computational model needs to update vertex features and relation features simultaneously.

Therefore, the proposed generalized line and total constructions are not only formal extensions of classical graph transformations. They also provide a mathematical basis for hierarchical message-passing architectures in which information flows across multiple levels of organization: from vertices to hyperedges, from hyperedges to superhyperedges, and back again. Such a viewpoint may be useful for modeling multi-level systems in decision-making, engineering networks, workflow analysis, knowledge representation, and higher-order graph machine learning.

8. Conclusion

In this paper, we examined the concepts of line graphs and total graphs in the contexts of *Directed HyperGraphs*, *Directed SuperHyperGraphs*, *Bidirected Graphs*, and *Multidirected Graphs*. In particular, we considered how classical line and total graph constructions can be reformulated when edges carry directions, when hyperedges connect multiple vertices, and when superhyperedges involve hierarchically nested objects. The proposed viewpoint shows that these constructions preserve the essential ideas of adjacency and incidence while extending them to more general directed and higher-order structures.

We also provided illustrative examples to clarify how the proposed constructions operate in concrete settings, such as directed hyperedge interactions, multi-level superhypergraph relations, bidirected edge incidences, and multidirected connections. These examples indicate that line-type constructions are useful for studying adjacency among edges or superhyperedges, whereas total-type constructions are useful for simultaneously representing vertices, edges, incidence relations,

and adjacency relations within a single framework. Some basic mathematical properties were also discussed, including the consistency of these generalized constructions with their classical counterparts in suitable special cases.

Looking ahead, we expect that the concepts introduced here will be further enriched by incorporating advanced frameworks such as the Fuzzy Set [68], Intuitionistic Fuzzy Set [4], Neutrosophic Set [2], HyperFuzzy Set [34], Soft Set [53], Plithogenic Set [64], and Quadripartitioned Neutrosophic Set [44], among others. Such extensions may make it possible to treat uncertainty, indeterminacy, multi-valued membership, parameterized information, and contradictory relational data within line and total graph constructions. Moreover, we expect further investigations into extended frameworks based on multidirected hypergraphs and multidirected superhypergraphs[30], among others.

We also anticipate further progress in the design of graph algorithms for these structures. For example, future work may investigate recognition problems, connectivity measures, traversal algorithms, shortest-path-type problems, incidence-based centrality measures, and computational complexity for the generalized line and total constructions studied here. In addition, computational experiments and case studies may help validate the usefulness of these models in applications such as decision-making systems, workflow networks, engineering systems, knowledge representation, and higher-order network analysis. Finally, deeper mathematical investigations may reveal additional structural relationships among directed hypergraphs, directed superhypergraphs, bidirected graphs, multidirected graphs, and their corresponding line and total forms.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this work.

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Use of Generative AI and AI-Assisted Tools

We use generative AI and AI-assisted tools for tasks such as English grammar checking, and We do not employ them in any way that violates ethical standards.

Disclaimer

The ideas presented here are theoretical and have not yet been validated through empirical testing. While we have strived for accuracy and proper citation, inadvertent errors may remain. Readers should verify any referenced material independently. The opinions expressed are those of the authors and do not necessarily reflect the views of their institutions.

References

- [1] M. Akram and G. Shahzadi, Hypergraphs in m-polar fuzzy environment, *Mathematics*, **6**(2), 2018, 28.
- [2] M. Al Tahan, S. Al-Kaseasbeh, and B. Davvaz, Neutrosophic Quadruple Hv-modules and their fundamental module, *Neutrosophic Sets and Systems*, **72**, 2024, 304–325.
- [3] M. Alqahtani, Intuitionistic fuzzy quasi-supergraph integration for social network decision making, *International Journal of Analysis and Applications*, **23**, 2025, 137–137.
- [4] K. T. Atanassov, Circular intuitionistic fuzzy sets, *Journal of Intelligent & Fuzzy Systems*, **39**(5), 2020, 5981–5986.
- [5] G. Ausiello and L. Laura, Directed hypergraphs: Introduction and fundamental algorithms? a survey, *Theoretical Computer Science*, **658**, 2017, 293–306.
- [6] M. A. Bahmanian and M. Šajna, Hypergraphs: connection and separation, *arXiv preprint arXiv:1504.04274*, 2015.
- [7] M. A. Bahmanian and M. Sajna, Connection and separation in hypergraphs, *Theory and Applications of Graphs*, **2**(2), 2015, 5.
- [8] C. Balbuena, X. Marcote, and D. Ferrero, Diameter vulnerability of iterated line digraphs in terms of the girth, *Networks: An International Journal*, **45**(2), 2005, 49–54.
- [9] D. Bauer and R. Tindell, The connectivities of line and total graphs, *Journal of Graph Theory*, **6**(2), 1982, 197–203.
- [10] L. W. Beineke and J. S. Bagga, Iterated Line Digraphs, In *Line Graphs and Line Digraphs*, 2021, Springer, pages 173–199.
- [11] L. W. Beineke and J. S. Bagga, Super line graphs and super line digraphs, In *Line graphs and line digraphs*, 2021, Springer, pages 233–256.
- [12] L. W. Beineke and J. S. Bagga, Total Graphs and Total Digraphs, In *Line Graphs and Line Digraphs*, 2021, Springer, pages 203–217.
- [13] C. Berge, *Hypergraphs: combinatorics of finite sets*, volume 45, 1984, Elsevier.
- [14] L. Boro, M. M. Singh, and J. Goswami, Line graph associated to the intersection graph of ideals of rings, *J. Math. Comput. Sci.*, **11**(3), 2021, 2736–2745.
- [15] A. Bouchet, Nowhere-zero integral flows on a bidirected graph, *Journal of Combinatorial Theory, Series B*, **34**(3), 1983, 279–292.
- [16] A. Bretto, Hypergraph theory, *An introduction. Mathematical Engineering. Cham: Springer*, **1**, 2013.

- [17] J. Burke, A. Akbari, R. Bailey, K. Fasusi, R. A. Lyons, J. Pearson, J. Rafferty, and D. Schofield, Representing multimorbid disease progressions using directed hypergraphs, In *medRxiv*, 2023.
- [18] G. Chartrand and M. J. Stewart, Total digraphs, *Canadian Mathematical Bulletin*, **9**(2), 1966, 171–176.
- [19] J. Chen and P. Schwaller, Molecular hypergraph neural networks, *The Journal of Chemical Physics*, **160**(14), 2024.
- [20] E. Chien, C. Pan, J. Peng, and O. Milenkovic, You are AllSet: A Multiset Function Framework for Hypergraph Neural Networks, *ArXiv*, **abs/2106.13264**, 2021.
- [21] C. Dalfó and M. Fiol, Cospectral digraphs from locally line digraphs, *Linear Algebra and its Applications*, **500**, 2016, 52–62.
- [22] P. Dhanya and P. Ramkumar, Text Analysis Using Morphological Operations on a Neutrosophic Text Hypergraph, *Neutrosophic Sets and Systems*, **61**, 2023, 337–364.
- [23] Y. Feng, H. You, Z. Zhang, R. Ji, and Y. Gao, Hypergraph neural networks, In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, 2019, 3558–3565.
- [24] T. Fujita, Exploration of Graph Classes and Concepts for SuperHypergraphs and n-th Power Mathematical Structures, *Advancing Uncertain Combinatorics through Graphization, Hyperization, and Uncertainization: Fuzzy, Neutrosophic, Soft, Rough, and Beyond*, **3**(4), 2024, 512.
- [25] T. Fujita, Review of Some Superhypergraph Classes: Directed, Bidirected, Soft, and Rough, In *Advancing Uncertain Combinatorics through Graphization, Hyperization, and Uncertainization: Fuzzy, Neutrosophic, Soft, Rough, and Beyond (Second Volume)*, 2024, Biblio Publishing.
- [26] T. Fujita, Directed acyclic superhypergraphs (dash): A general framework for hierarchical dependency modeling, *Neutrosophic Knowledge*, **6**, 2025, 72–86.
- [27] T. Fujita, Extensions of multidirected graphs: Fuzzy, neutrosophic, plithogenic, rough, soft, hypergraph, and superhypergraph variants, *International Journal of Topology*, **2**(3), 2025, 11.
- [28] T. Fujita, Hesitant Neutrosophic Network Models for Operations Research: Graphs, Hypergraphs, and Superhypergraphs, *Advances in Neutrosophic Mathematics and Informatics*, **1**(2), 2026, 25–38.
- [29] T. Fujita and F. Smarandache, Fuzzy and Neutrosophic Directed Superhypergraphs: Definitions, Properties, and Illustrative Real-World Applications in Decision-Making., *IAENG International Journal of Applied Mathematics*, **56**(5), 2026, 1681.
- [30] T. Fujita and F. Smarandache, *HyperGraph and SuperHyperGraph Theory with Applications (VII): About Directed SuperHyperGraph*, 2026, Infinite Study.
- [31] T. Fujita and F. Smarandache, Representing higher-order networks: A survey of graph-based frameworks, 2026.
- [32] G. Gallo, G. Longo, S. Pallottino, and S. Nguyen, Directed hypergraphs and applications, *Discrete applied mathematics*, **42**(2-3), 1993, 177–201.
- [33] L. Gellert and R. Sanyal, On degree sequences of undirected, directed, and bidirected graphs, *European Journal of Combinatorics*, **64**, 2017, 113–124.
- [34] J. Ghosh and T. K. Samanta, Hyperfuzzy sets and hyperfuzzy group, *Int. J. Adv. Sci. Technol*, **41**, 2012, 27–37.

- [35] Z. Gong and J. Wang, Hesitant fuzzy graphs, hesitant fuzzy hypergraphs and fuzzy graph decisions, *Journal of Intelligent & Fuzzy Systems*, **40**(1), 2021, 865–875.
- [36] J. L. Gross, J. Yellen, and M. Anderson, *Graph theory and its applications*, 2018, Chapman and Hall/CRC.
- [37] M. Hamidi and M. Taghinezhad, *Application of Superhypergraphs-Based Domination Number in Real World*, 2023, Infinite Study.
- [38] M. Hamidi, M. Rahmati, and A. Rezaei, *Boolean expression based on hypergraphs with algorithm*, 2021, Infinite Study.
- [39] M. Hamidi, F. Smarandache, and E. Davneshvar, Spectrum of superhypergraphs via flows, *Journal of Mathematics*, **2022**(1), 2022, 9158912.
- [40] M. Hamidi, F. Smarandache, and M. Taghinezhad, *Decision Making Based on Valued Fuzzy Superhypergraphs*, 2023, Infinite Study.
- [41] T. Hasunuma, Embedding iterated line digraphs in books, *Networks: An International Journal*, **40**(2), 2002, 51–62.
- [42] T. Hasunuma, Queue layouts of iterated line directed graphs, *Discrete applied mathematics*, **155**(9), 2007, 1141–1154.
- [43] J. Huang and J. Yang, UniGNN: a Unified Framework for Graph and Hypergraph Neural Networks, *ArXiv*, **abs/2105.00956**, 2021.
- [44] S. Hussain, J. Hussain, I. Rosyida, and S. Broumi, Quadripartitioned neutrosophic soft graphs, In *Handbook of Research on Advances and Applications of Fuzzy Sets and Logic*, 2022, IGI Global, pages 771–795.
- [45] Q. Japhet, D. Watel, D. Barth, and M.-A. Weissner, Maximal Line Digraphs, *arXiv preprint arXiv:2406.05141*, 2024.
- [46] S. Jiang, M. Kang, X. Xu, J. Xiao, and L. Lü, A Multi-Scale Evolutionary Framework for Fuzzy Hypergraph Community Detection, *IEEE Transactions on Fuzzy Systems*, 2026.
- [47] H. Kajino, Molecular hypergraph grammar with its application to molecular optimization, In *International Conference on Machine Learning*, 2019, PMLR, 3183–3191.
- [48] W. A. Khan, W. Arif, H. Rashmanlou, and S. Kosari, Interval-valued picture fuzzy hypergraphs with application towards decision making, *Journal of Applied Mathematics and Computing*, **70**(2), 2024, 1103–1125.
- [49] N. Kita, Bidirected Graphs I: Signed General Kotzig-Lovász Decomposition, *arXiv: Combinatorics*, 2017.
- [50] M. Knor and L. Niepel, Connectivity of iterated line graphs, *Discrete applied mathematics*, **125**(2-3), 2003, 255–266.
- [51] S. Krieger and J. D. Kececioğlu, Shortest Hyperpaths in Directed Hypergraphs for Reaction Pathway Inference, *Journal of computational biology : a journal of computational molecular cell biology*, 2023.
- [52] Z. Liu and Z. Zhang, Restricted connectivity of total digraph, *Discrete Mathematics, Algorithms and Applications*, **8**(02), 2016, 1650022.
- [53] D. Molodtsov, Soft set theory-first results, *Computers & mathematics with applications*, **37**(4-5), 1999, 19–31.

- [54] H. Moon, H. Kim, S. Kim, and K. Shin, Four-set Hypergraphlets for Characterization of Directed Hypergraphs, *ArXiv*, **abs/2311.14289**, 2023.
- [55] K. Oko, S. Sakaue, and S. ichi Tanigawa, Nearly Tight Spectral Sparsification of Directed Hypergraphs, In *International Colloquium on Automata, Languages and Programming*, 2023.
- [56] S. Pardo-Guerra, V. K. George, V. Morar, J. Roldan, and G. A. Silva, Extending undirected graph techniques to directed graphs via category theory, *Mathematics*, **12**(9), 2024, 1357.
- [57] S. Pardo-Guerra, V. K. George, and G. A. Silva, On the Graph Isomorphism Completeness of Directed and Multidirected Graphs., *Mathematics (2227-7390)*, **13**(2), 2025.
- [58] J. Park, F. Chen, and J. Park, A molecular hypergraph convolutional network with functional group information, 2021.
- [59] T. Pramanik, R. Mahapatra, T. Allahviranloo, L. Mrcic, A. Kalampakas, and S. Samanta, Spherical fuzzy hypergraph in decision making, *Scientific Reports*, 2026.
- [60] S. Samanta and M. Pal, Bipolar fuzzy hypergraphs, *International Journal of Fuzzy Logic Systems*, **2**(1), 2012, 17–28.
- [61] D. Sastry and B. S. P. Raju, Graph equations for line graphs, total graphs, middle graphs and quasi-total graphs, *Discrete Mathematics*, **48**(1), 1984, 113–119.
- [62] F. Smarandache, *Extension of HyperGraph to n-SuperHyperGraph and to Plithogenic n-SuperHyperGraph, and Extension of HyperAlgebra to n-ary (Classical-/Neutro-/Anti-) HyperAlgebra*, 2020, Infinite Study.
- [63] F. Smarandache, Foundation of SuperHyperStructure & Neutrosophic SuperHyperStructure, *Neutrosophic Sets and Systems*, **63**(1), 2024, 21.
- [64] F. Sultana, M. Gulistan, M. Ali, N. Yaqoob, M. Khan, T. Rashid, and T. Ahmed, A study of plithogenic graphs: applications in spreading coronavirus disease (COVID-19) globally, *Journal of ambient intelligence and humanized computing*, **14**(10), 2023, 13139–13159.
- [65] B.-L. Wang, G. Shen, D. Li, J. Hao, W. Liu, Y. Huang, H. Wu, Y. Lin, G. Chen, and P.-A. Heng, LHNN: lattice hypergraph neural network for VLSI congestion prediction, *Proceedings of the 59th ACM/IEEE Design Automation Conference*, 2022.
- [66] Y. Wang, Q. Gan, X. Qiu, X. Huang, and D. Wipf, From hypergraph energy functions to hypergraph neural networks, In *International Conference on Machine Learning*, 2023, PMLR, 35605–35623.
- [67] R. Xu and C.-Q. Zhang, On flows in bidirected graphs, *Discrete mathematics*, **299**(1-3), 2005, 335–343.
- [68] L. A. Zadeh, Fuzzy sets, *Information and control*, **8**(3), 1965, 338–353.