Extending Functional Dependency to Detect Abnormal Data in RDF Graphs

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Outline

- Motivation
- Functional Dependency (FD)
- Value-clustered Graph Functional Dependency (VGFD)
- System
  - Clustering
    - Pre-clustering
    - Optimal k-Means clustering
  - Handling multi-valued properties
  - Static pruning
  - Runtime pruning
- Conclusion and future work

Motivation

- Low data quality is a pressing problem for information integration
- Numerous problems could occur during the data generation process using a variety of tools
- Question answering needs to be more accurate and reliable
- Trust or other assessments require foundational input

Functional Dependency in DB

- It is by far the most common integrity constraints for databases.
- It is devised to specify missing semantics in mere syntactic definitions of database relations.
- Definition
  - **Given a relation *R*, a set of attributes *X*** in *R* is said to functionally determine another attribute *Y*, also in *R*, (written $X \rightarrow Y$) if, and only if, **each *X* value** is associated with precisely **one *Y* value**.
- E.g. {Course, Semester} → Instructor

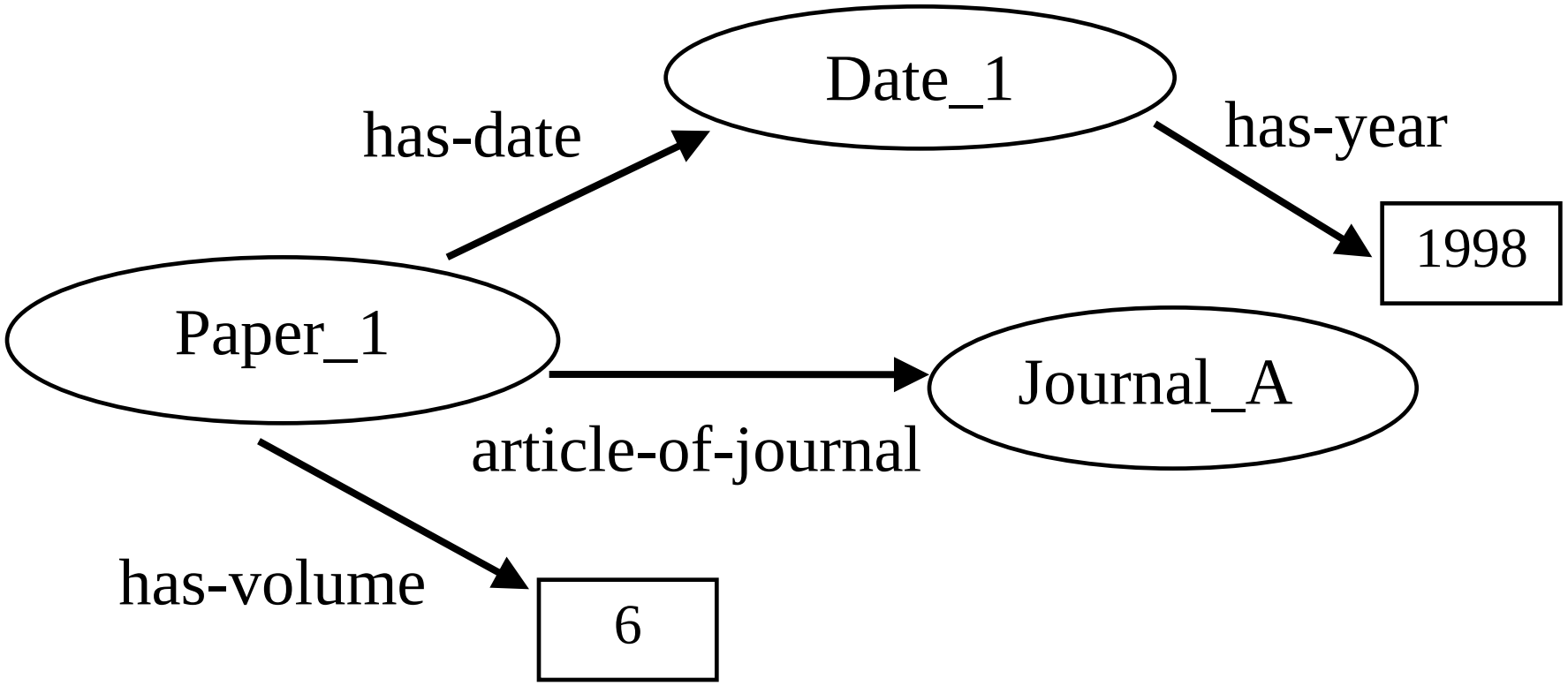
  {postalCode} → province

Challenges

- RDF data can be viewed as extremely decomposed relational tables
- More forms of combinations of properties convey latent semantics
  - E.g. *advisorOf* ∘ *studentOf* $^{-}$, *father* ∘ *brother*
- Multi-valued properties make it harder to determine value correlations
  - E.g. *city* and *province*
- Different syntactic values could be (almost) logically equivalent
  - E.g. 1.000001 vs. 1.0; “blue & red” vs. “red & blue”

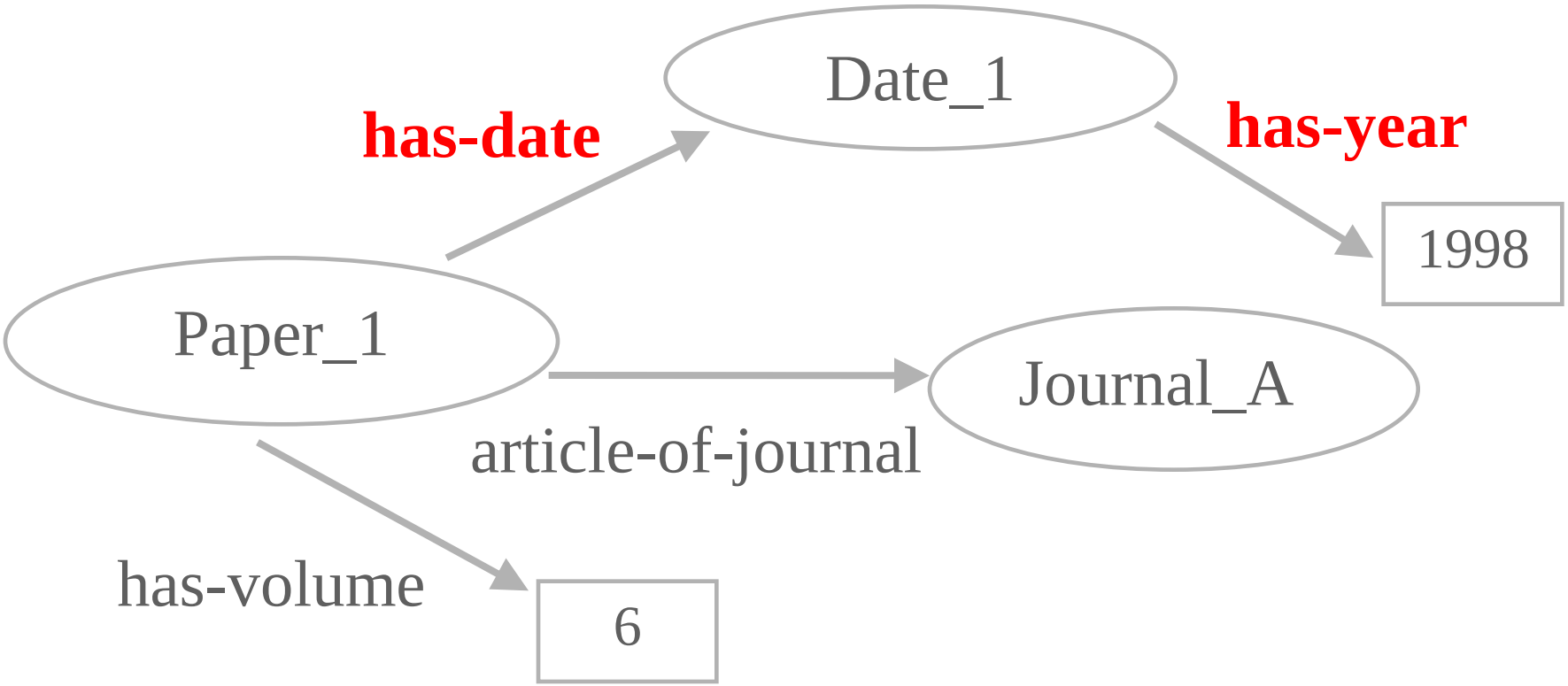
    upper ages of a certain type of school are in a small range

VGFD Definitions



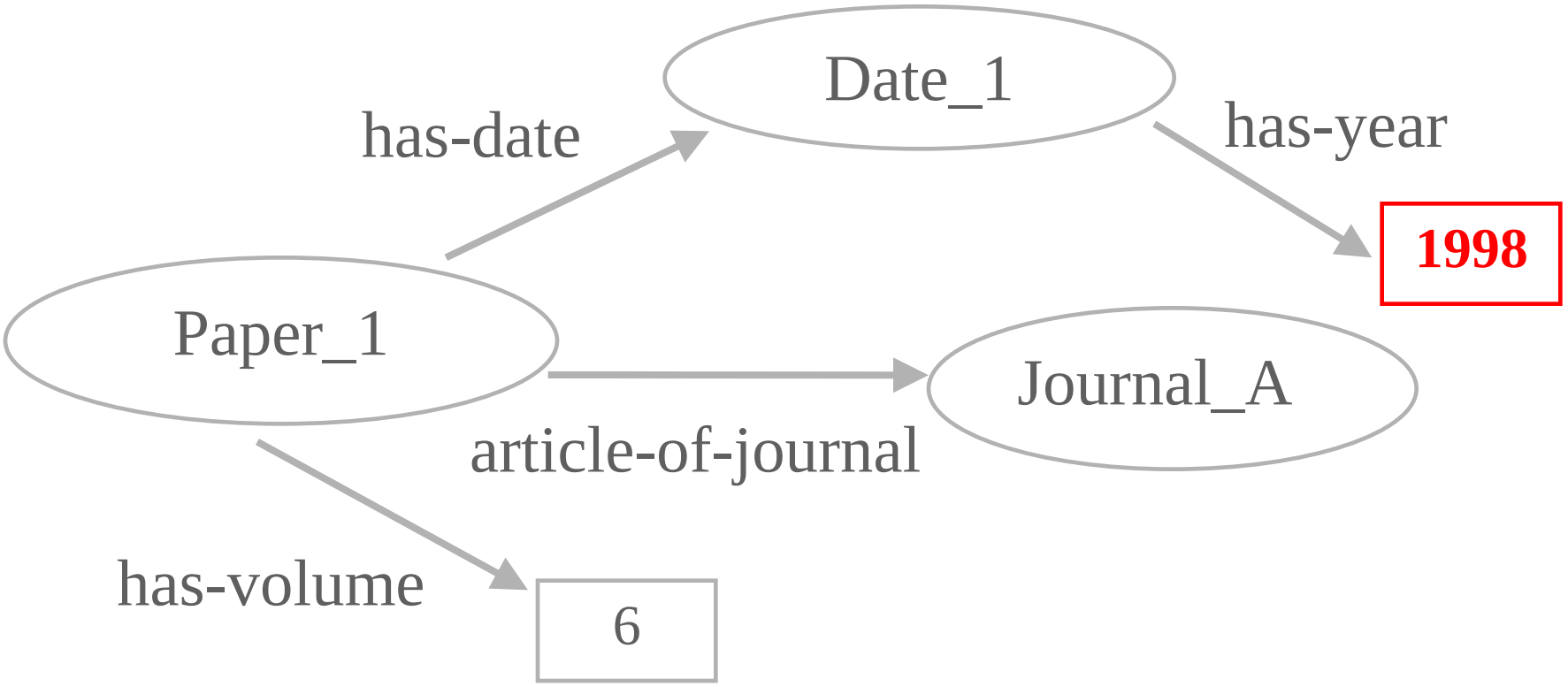
An RDF graph: directed, labeled graph

VGFD Definitions



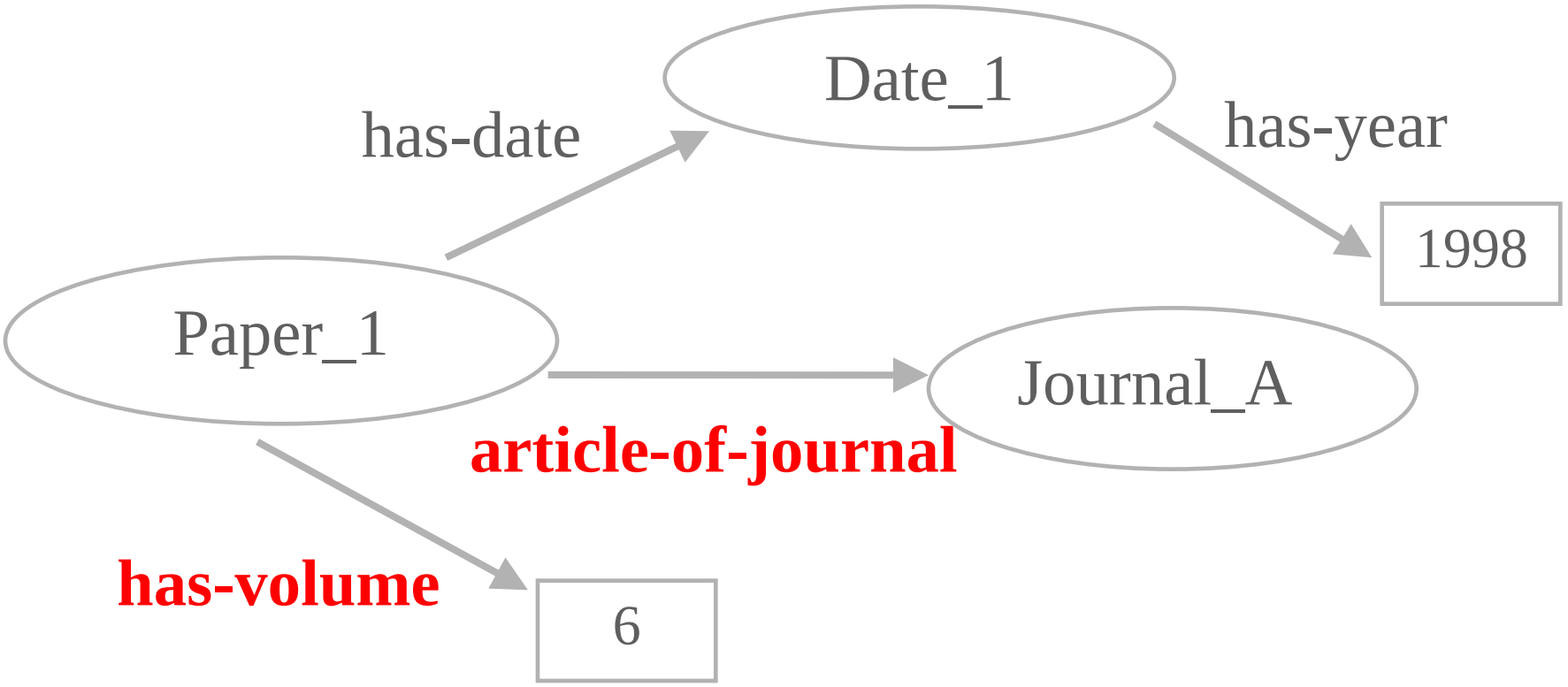
An example Composite Property: has-date ◦ has-year

VGFD Definitions



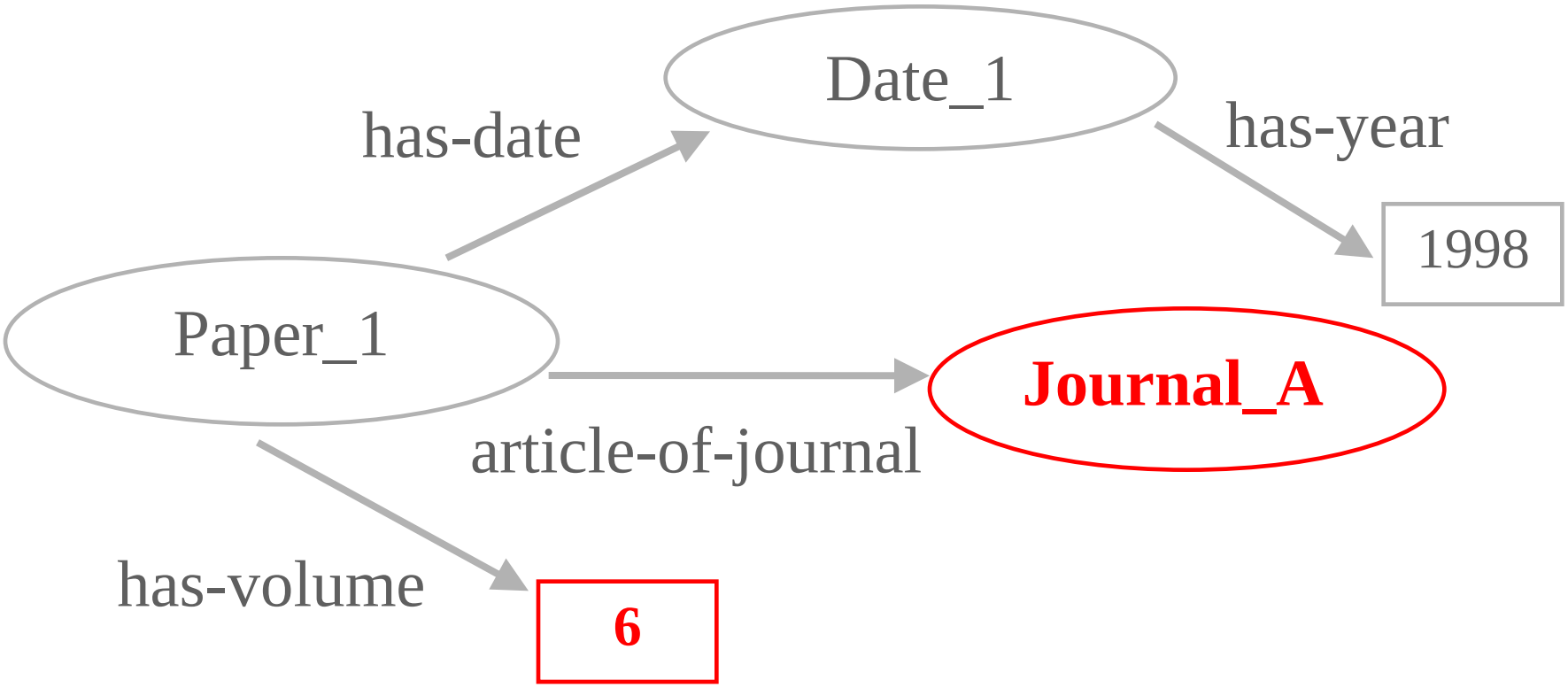
Value(Paper_1, has-date ◦ has-year) = 1998

VGFD Definitions



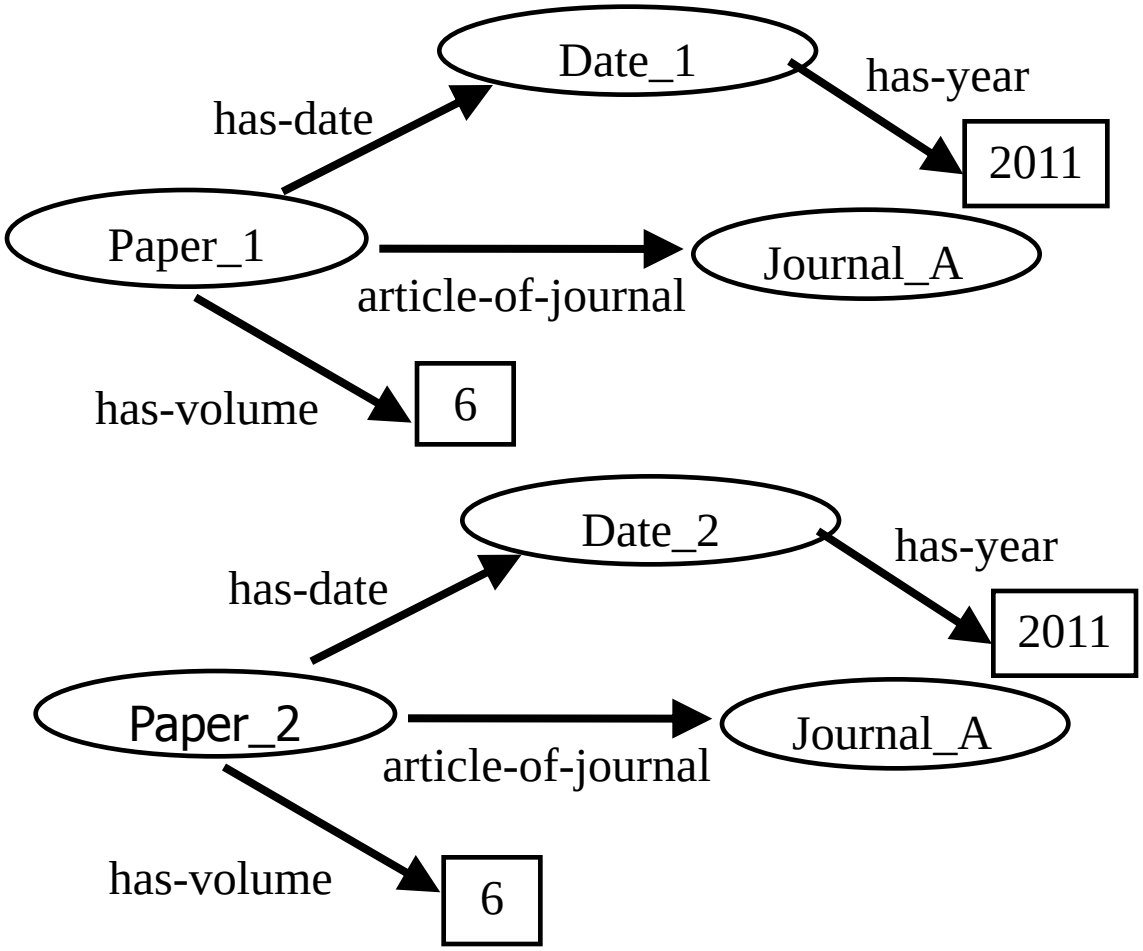
An example Conjunctive Property:
article-of-journal + has-volume

VGFD Definitions



Value(Paper_1, article-of-journal + has-volume) = (Journal_A, 6)

VGFD Definitions



A possible example VGFD:

article-of-journal + has-volume → has-date ◦ has-year

Handling Multi-valued Property

deptNo		deptName	
subject	object	subject	object
A	1	A	CS
A	2	A	EE
B	1	B	EE
C	2	C	CS
D	2	D	EE

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Candidate Value Mapping	Count
1→ EE	2
2→ EE	2
2→ CS	2
1→ CS	1

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Miss Match

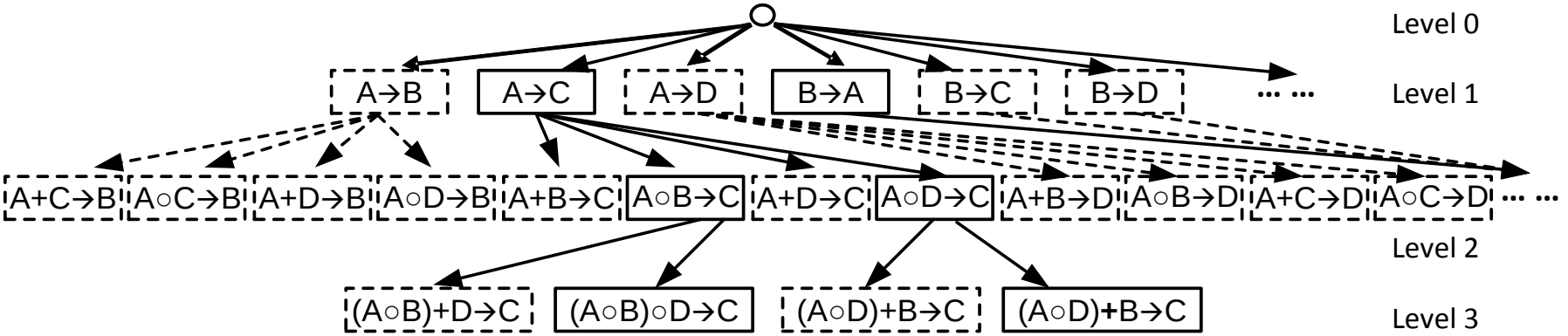
Candidate Value Mapping	Count
1→ EE	2
2→ EE	2
2→ CS	2
1→ CS	1

Confidence of VGFD deptNo → deptName = 4/5 = 0.8

Static Pruning Heuristics

- Insufficient subject/object overlap between properties to be composed or between the LHS and the RHS
- The discriminability of the LHS is less than that of the RHS
  - Discriminability of a property = # distinct values / the size of property extension
- The LHS or RHS has too high a discriminability
- The discriminability of a Composite Property (Conjunctive Property resp.) is no greater than (no less than resp.) that of each property involved.

Level-wise Discovering Process



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In this example, we suppose:

a. *A* and *B* have few common subjects
b. the discriminability of *B* is less then that of *C*
c. *D* has a high discriminability

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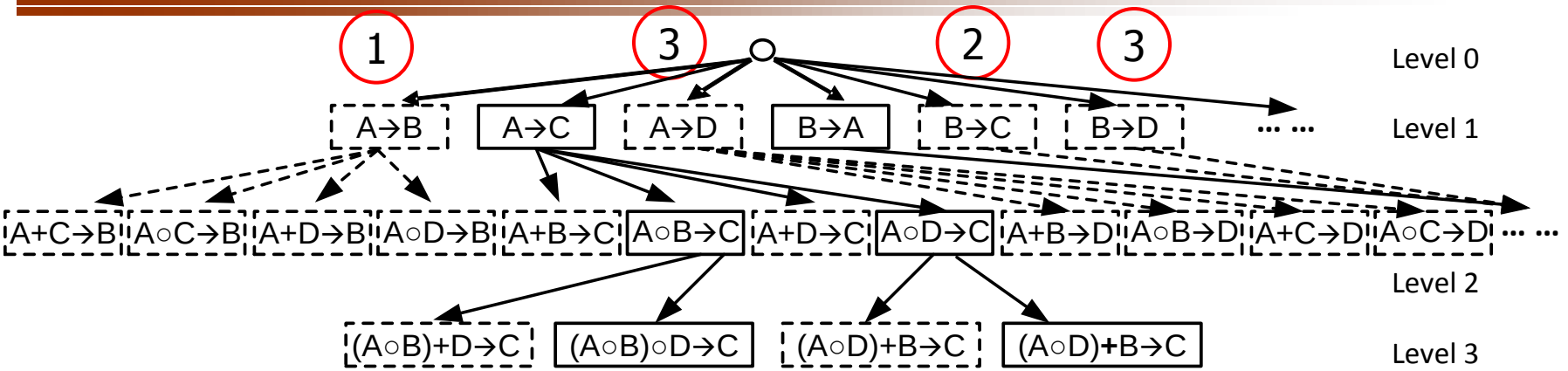

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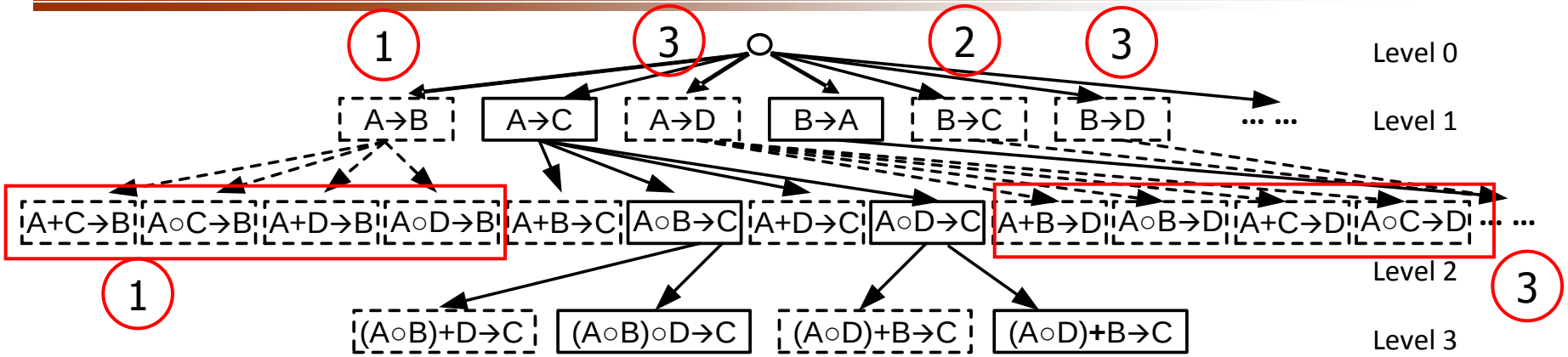

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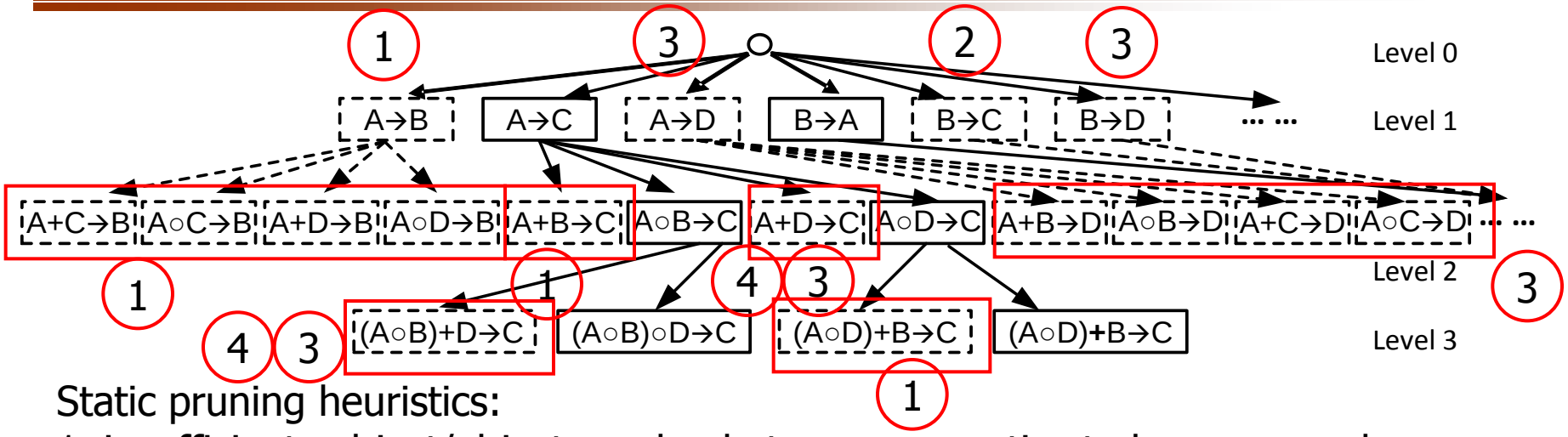

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Runtime Pruning

- Mutual Information

$$I_{XY} = \sum_i \sum_j p_{i,j} \log (p_{i,j}/p_i p_j)$$

$$\begin{aligned} E_X + E_Y - E_{XY} &= \sum_i p_i \log 1/p_i + \sum_j p_j \log 1/p_j - \sum_i \sum_j p_{i,j} \log 1/p_{i,j} \\ &= \sum_i \sum_j p_{i,j} [\log p_{i,j} - \log p_i - \log p_j] = \sum_i \sum_j p_{i,j} \log (p_{i,j}/p_i p_j) \end{aligned}$$

- Entropy coefficient (EC)

$$EC(X|Y) = I_{XY}/E_Y$$

- Sampling a subset of instances for a VGFD to compute EC

Clustering

- Pre-clustering
  - Light-weight computation provides two benefits for finer clustering
    - The minimum number of clusters
    - Reserves expensive distance calculation for pairs of points within the same pre-cluster
  - Process
    - Pick a point that is closest to the center
    - Cluster points that are close to this center
    - Repeat the above two steps until all points are clustered

Clustering

- Optimal k-Means Clustering
  - Improved from Gap Statistic,
    - Estimating the number of clusters in a data set via the gap statistic, R. Tibshirani, G. Walther, T. Hastie, *Journal of the Royal Statistical Society*, Vol. 63, No. 2. (2001), pp. 411-423.
  - Without the input of k, automatically find the optimal number of clusters
  - Variation of normal k-Means clustering by restricting the distance calculation only on the pairs that within the same pre-cluster

Experimental Results

- Example VGFDs

VGFD	Description
genus→family	Organisms in the same genus also have the same family.
writer→genre	A work's writer determines the work's genre.
teamOwner→chairman	The teams with the same owner also have the same chairman.
composer→mediaType	The works by the same composer have the same media type.
militaryRank→title	The people of the same military rank also have the same title.
location→nearestCity	The things on the same location have the same nearest city.
topic→primaryTopic	The papers with the same topic have the same primary topic.
manufacturer+oilSystem →compressionRatio	The manufacturer and oil system determine the engine's compression ratio.
publisher ∘ country →language	The publisher's country determines the language of that published work.
article-of-journal+has-volume →has_date	The volume number of a journal where an article is published determines the published date of this article.
faculty→budget	The size of the faculty determines the budget range.
militaryRank→salary	The military rank determines the range of salary.
occupation→salary	The occupation determines the range of salary.
type→upperAge	A school's type determines the range of upper age.

Experimental Results

- Example Erroneous Data

1	<r:Shanghai_Jiao_Tong_University, o:university/undergrad, 194323445>
2	<r:Harrow_College, o:School/upperAge, 2009.0>
3	<r:Melbourne_Grammar_School, o:School/ranking, 2006.0>
4	<r:Google_Maps, o:Work/language, r:Coverage_details_of_Google_Maps>
5	<r:Wiktionary, o:Work/language, r:History_and_development>
6	<r:Dembela, o:Place/coordinates, coord|N|W>
7	<r:Hutt_Valley_High_School, o:EducationalInstitution/principal, r:2008>
8	<r:Wake_Island, o:Island/country, r:United_States_Air_Force>
9	<r:Albuquerque_Plaza, o:Building/floorCount, 2221>
10	<r:varedo, o:City/province, r:Province_of_Milan>
11	<i:796511, p:has-date, to-10-01>
12	<i:journals/jair/DarwicheP97, p:has-date, 1998>
13	<s:person/bastian-quilitz, s:ns/swc/ontology#affiliation, research assistant>
14	<s:person/ulf-leser, s:ns/swc/ontology#affiliation, professor>

- System performance

Dataset	SWRC	DBPedia	RKB
Precision	55%	86%	62%

Conclusion and Future Work

- Conclusion
  - Finding corroboration patterns in the form of Value-clustered Graph Functional Dependency
  - Detect abnormal data by checking conflicts with patterns
  - Experiments on different real world data sets that validate the system
- Future work
  - Further generalize the VGFDs
  - Apply system on knowledge acquisition areas

Thank you

Questions and comments?

Integrity Constraints

- Valuable in checking and enforcing data consistency
- Providing further semantics on data, and promoting semantic query optimization
- Open World Assumption (OWA) and the Non-Unique Name Assumption (NUNA) make them harder to be enforced
- How to automatically discover approximate integrity constraints?

System Process Overview

- 1. Find natural clusters of property values
- 2. List all possible combinations of properties on the LHS and RHS of VGFDs
- 3. Static pruning on all possible VGFDs
- 4. Runtime pruning of VGFDs
- 5. Compute the candidate VGFDs

Optimal k-Means Clustering

Algorithm 7 $Optimal\_kMeans(L, groups)$, L is a set of literal values; $groups$ is a set of pre-clustered groups of L.

1: $k = |groups|$
2: $Gap(k) = Gap\_Statistic(groups)$
3: $tmpC \leftarrow groups$
4: **repeat**
5: $k = k + 1$, $C \leftarrow tmpC$, $tmpC \leftarrow \emptyset$ //$tmpC$ is the set of k clusters
6: **for each** $i \leq k$ **do**
7: $Init(m_i), c_i \leftarrow c_i \cup m_i, tmpC \leftarrow tmpC \cup c_i$ //m_i is the center of each cluster
8: **repeat**
9: **for each** $x \in L$ **do**
10: $c_i \leftarrow c_i \cup \arg\min_{m_i \in Group(x)} Distance(x, m_i)$
11: **for each** $i \leq k$ **do**
12: $m_i = Mean(c_i)$
13: **until** $\forall i \leq k, m_i$ converges
14: $Gap(k) = Gap\_Statistic(tmpC)$
15: **until** $Gap(k) < Gap(k-1)$
16: **return** C

Initialize the estimated cluster center

Find the closest center within the same pre-cluster

Re-compute the center

Check if the gain of this clustering is slower than the expected rate

Pre-clustering

- Pre-clustering on strings
  - The weight of a word is based on its frequency in the values of the property
  - The string that has the largest sum of weights divided by the number of words in it is the center
  - Example pre-cluster results:

    {Coach, First Team Coach, Head coach, Senior Coach, Acting head coach, Reserve team coach, Chief Coach},

    {Director, Sports Director, Technical Director, Director general}