Faceted Hierarchy: A New Graph Type to Organize Scientific Concepts and a Construction Method

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Abstract
On a scientific concept hierarchy, a parent concept may have a few attributes, each of which has multiple values being a group of child concepts. We call these attributes facets: classification has a few facets such as application (e.g., face recognition), model (e.g., svm, knn), and metric (e.g., precision). In this work, we aim at building faceted concept hierarchies from scientific literature. Hierarchy construction methods heavily rely on hyponym detection, however, the faceted relations are parent-to-child links but the hyponym relation is a multi-hop, i.e., ancestor-to-descendent link with a specific facet “type-of”. We use information extraction techniques to find synonyms, sibling concepts, and ancestor-descendent relations from a data science corpus. And we propose a hierarchy growth algorithm to infer the parent-child links from the three types of relationships. It resolves conflicts by maintaining the acyclic structure of a hierarchy.

1 Introduction
Concept hierarchies play an important role in knowledge discovery from scientific literature. Concepts are expected to be organized in a hierarchical structure like chapters-to-sections-to-subsections in textbooks. In this work, we propose a new representation of scientific concept hierarchy, called faceted concept hierarchy. Under this hierarchy, the links should not only carry parent-child relations but also the semantic relations (facets) between the concepts. Figure 1 presents a part of the faceted hierarchy in Data Science. The parent node is “classification” and the child concepts of it are expected to be grouped into three facets, each of which has three child-concepts. One example of the faceted relation we define is as follows:

parent(“classification”, “svm”): “models”,

Figure 1: The idea of faceted concept hierarchy from Data Science publications: For student learning, concepts are expected to be organized in a hierarchical structure. For example, here the nine child-concepts of “classification” (in dashed line blocks) should be grouped into three facets (“models”, “applications”, and “metrics”).

which is more complete than “type-of” relations in the works that focused on taxonomy or ontology induction (Liang et al., 2017; Gupta et al., 2017; Zhang et al., 2018; Liu et al., 2018) like this:
type-of(“svm”, “classification model”).

The basic units of the hierarchy include concept nodes and their parent-to-child relations. Three types of essential structural relations are expressed in paper texts and can be used to infer the parent-to-child relations. The relation types include (1) synonym (concept names on the same node), (2) sibling (concept nodes having the same parent), and (3) ancestor-to-descendant (nodes on the direct descending line). The task of hierarchy construction has three challenges. First, there is no sufficient human annotated data or available distant supervisory sources to feed into (deep) learning models. It is necessary to extract the concepts and relations in an unsupervised manner. Second, the extracted relations could be noisy at the long tail of the frequency distribution. When inferring the parent-to-child relations, the algorithm should consider the trustworthiness of the synonym, sib-
ling, and ancestor relations. Also, it is important to
detect redundant or conflicting relations (links) on
the hierarchy. Third, it requires a joint process of
clustering child-concepts into the parent concept’s
facets and identifying words as facet indicators.

We propose a novel framework $\text{HiGrowth}$ that
grows faceted hierarchies from literature data. The
framework has five modules: (M1) scientific concept
extraction, (M2) concept typing, (M3) hierar-
chical relation extraction, (M4) hierarchy growth, and (M5) facet discovery. The M1–M3 NLP mod-
ules were implemented in an unsupervised man-
er. First, we use two complementary keyphrase
mining tools to extract concepts: one is rule-based
and the other is a statistical learning method. Sec-
ond, we use a KNN-based method, simple and ef-
effective, to assign types (e.g., $\$\text{Problem}$, $\$\text{Method}$)
to the concepts. Third, we use textual patterns
to extract the hierarchical relations (i.e., synonym,
sibling, and ancestor). To address the second chal-
lenge, we design an efficient algorithm that grows
a concept hierarchy by scanning the set of relation
tuples (sorted by their frequency from the high-
est to the lowest) just once and inferring parent-
to-child relations. This algorithm will be able to
identify unnecessary, invalid, and redundant links
during the process of hierarchy growth in spite of
serious noise at the long tail. Finally, we use a
word clustering method to discover the facets of
every parent concept and assign child concepts to
each of the facets.

Thirty-two junior/senior students who took the
Data Science course in Spring 2018 were asked
to manually label the parent-child concept pairs.
We finalize a set as ground-truth if the pair was la-
belled by more than half of the participants. The
F1 score of building the parent-to-child links is
0.73. The F1 score of 2-hop paths is 0.69. Both
precision values are above 0.99, showing that the
links in the hierarchy are precise because of the
careful design of the growth algorithm, but the
pattern-based methods have limitations of finding
all possible relations.

2 $\text{HiGrowth}$ – Part I: Information
Extraction Components (M1 – M3)

2.1 Data Description

We collected full text, all sections including ab-
stract, introduction, and experiments, of 5,850 pa-
pers in the proceedings of ACM SIGKDD 1994–
2015, IEEE ICDM 2001–2015, The Web Confer-
ence 2001–2015 and ACM WSDM 2008–2015.

2.2 M1: Scientific Concept Extraction

We use phrase mining tools, $\text{AutoPhrase}$ (Shang et al., 2018) & $\text{SCHBase}$ (Adar and Datta, 2015),
to extract scientific concepts from data science
papers. $\text{AutoPhrase}$ adopted distant supervision
and large-scale statistical techniques; $\text{SCHBase}$
focused on a tendency to expand keyphrases by
adding terms, coupled with a pressure to abbrevi-
ate to retain succinctness in academic writing.

2.3 M2: Concept Typing

We use a simple but effective method to clas-
sify the concepts into four types: $\$\text{Problem}$ (e.g.,
“fraud_detection”), $\$\text{Method}$ (e.g., “svm”), $\$\text{Object}$
(e.g., “frequent_patterns”), and $\$\text{Metric}$ (e.g.,
“accuracy”). We assume that the neighboring non-
stop word indicates the concept’s type, for exam-
ple, the trigger word “problem” in the sentence
“... the problem of fraud detection” suggests that
“fraud_detection” is a $\$\text{Problem}$. We manually se-
lect a set of 20 trigger words that indicate concept
types when they appear left/right next to the con-
cepts. Table 1 shows a few examples. If in the text
one concept has a left/right neighboring word in
the set, the corresponding type gets one vote. For
each concept, we count the votes on every type
and use the strategy of majority voting (MajVot) to
determine the predicted type (i.e., the most voted).

2.4 M3: Hierarchical Relation Extraction

In order to find the relations in an unsupervised
manner on the scientific text, we use textual pat-
tterns, mainly Hearst Patterns (Hearst, 1992), to

| Type      | Triggers on the left | Triggers on the right |
|-----------|----------------------|-----------------------|
| $\$\text{Problem}$ | problem, problems | task, tasks, demands |
| $\$\text{Method}$ | methods | method, model, algorithm |
| $\$\text{Object}$ | number | function |
| $\$\text{Metric}$ | measure, terms | measures, scores, values |

Figure 2: Three types of hierarchical relations.

Table 1: Neighboring words for concept typing.
accurately extract three types of hierarchical relations, where X and Y are two concept names:

- **synonym** \((X, Y)\), if \(X\) and \(Y\) will be included in the same concept node on the hierarchy;
- **sibling** \((X, Y)\), if the concept nodes of \(X\) and \(Y\) will have the parent node;
- **ancestor** \((X, Y)\), if there will be a path from the concept node of \(X\) to the node of \(Y\).

Note that **synonym** and **sibling** relations are symmetric, while **ancestor-to-descendant** is asymmetric (see Figure 2).

**Find synonym** \((X, Y)\). Two ideas to find synonym concepts: First, the plural form of a noun or noun-phrase concept can be considered as a synonym, for example, we have **synonym** (“SVM”, “SVMs”) and **synonym** (“decision_tree”, “decision_trees”). Second, the abbreviation inside of parentheses can be considered as a synonym of the full name preceding the parenthesis. We have **synonym** (“support_vector_machines”, “SVMs”) from text “... Support Vector Machines (SVMs)...”.

**Find ancestor** \((X, Y)\). Heuristic patterns such as

- \(X\) such as \(\{Y_1, Y_2, \ldots, (\text{and}|\text{or})\} Y_n\),
- \(X\{\}\) including \(\{Y_1, Y_2, \ldots, (\text{and}|\text{or})\} Y_n\),

have been often used to find “isA” relation or called hypernym for taxonomy construction: \(Y_i\) (e.g., “dog”) is a kind of \(X\) (e.g., “mammal”). However, we expect to extract **facet hierarchical relations** such as

- **ancestor** (“machine_learning”, “SVM”): models;
- **ancestor** (“machine_learning”, “classification”): tasks;
- **ancestor** (“classification”, “SVM”): models;

instead of

- **isA** (“machine_learning_models”, “SVM”);
- **isA** (“machine_learning_tasks”, “classification”);
- **isA** (“classification_models”, “SVM”),

if the text contains

- . . . machine learning models such as SVM. . . ;
- . . . machine learning tasks such as classification. . . ;
- . . . classification models such as SVM. . . ;

especially when “machine_learning” has been extracted as a concept. Note that we are not confident to say every relation given by pattern matching is **parent-to-child**. We denote the relation as **ancestor**. We expect that “machine_learning” connects to “SVM” through “classification” on the hierarchy instead of a direct connection.

Therefore, we modify the patterns as below:

- \(X \text{ pl} >\) such as \(\{Y_1, \ldots, (\text{and}|\text{or})\} Y_n\),
- \(X \text{ pl} >\) including \(\{Y_1, \ldots, (\text{and}|\text{or})\} Y_n\),

where \(<\text{pl} >\) is the plural form of a noun or noun phrase, e.g., “models” and “tasks”. We extract **ancestor** \((X, Y)\) from the above patterns. We will infer concrete **parent-to-child** relations and parent concept’s facets in the next section.

**Find sibling** \((X, Y)\). Shorter patterns in which the ancestor concept names are missing occur more frequently in the text, for example:

- \(\langle \text{pl} >\) such as \(\{Y_1, Y_2, \ldots, (\text{and}|\text{or})\} Y_n\),
- \(\langle \text{pl} >\) including \(\{Y_1, Y_2, \ldots, (\text{and}|\text{or})\} Y_n\),

and other patterns like

- \(Y_1, Y_2, \ldots, \text{ and|or}(\text{other}) <\text{pl} >\).

We extract **sibling** \((Y_i, Y_j)\) from these patterns. The number of **sibling** relations is more than the number of the **ancestor** relations, and the **sibling** relations, e.g., **sibling** (“precision”, “recall”), bring useful information to hierarchy induction, say, \(Y_i\) and \(Y_j\) have the same **parent** concept node.

We use the strategy of majority voting to choose one relation type for each pair of concepts. We assume that a pair of concepts can have no or only one relation among **synonym**, **sibling**, and **ancestor**. However, the relational extractions may still be noisy due to the long tail. Next we discuss how to construct a high-quality concept hierarchy from a set of the three types of relations with noise.

3 **HiGrowth – Part II**: Hierarchy Growth (M4) and Facet Discovery (M5)

3.1 M4: The Hierarchy Growth Algorithm

Given a set of relations \(\text{rel}(X, Y)\) and their support (i.e., frequency), construct a hierarchy \(\mathcal{H}\) in which the links are directional indicating **parent-
When adding a new sibling relation into the hierarchy:

- Grow the hierarchy $\mathcal{H}$ with this relation (see Figure 4).
- Remove redundant links when the relation is ancestor (see Figure 5).
  - Narrow down ancestor relations to parent-to-child when the scan completes (see Figure 6).

We denote different sets of connected nodes given a concept node $X$ as below (see Figure 3):
- $\mathcal{P}_X$ is the set of parent nodes of $X$: there is at least one direct link from $\forall Z \in \mathcal{P}_X$ to $X$;
- $\mathcal{C}_X$ is the set of child nodes of $X$: there is at least one direct link from $X$ to $\forall Z \in \mathcal{C}_X$;
- $\mathcal{A}_X$ is the set of ancestor nodes of $X$: there is at least one path but no direct link from $\forall Z \in \mathcal{A}_X$ to $X$;
- $\mathcal{D}_X$ is the set of descendant nodes of $X$: there is at least one path but no direct link from $X$ to $\forall Z \in \mathcal{D}_X$.

Check if a relation is invalid (Figure 3). Given a new relation synonym($X$, $Y$), if there has been any other relation between $X$ and $Y$ such as ancestor (i.e., $X \in \mathcal{D}_Y$ or $Y \in \mathcal{D}_X$) or sibling (i.e., $\mathcal{P}_X \cap \mathcal{P}_Y \neq \emptyset$), this new relation is invalid to be added to the $\mathcal{H}$. Given sibling($X$, $Y$), if $X$ and $Y$ have at least one parent, we skip; if there has been an ancestor relation between $X$ and $Y$, the sibling relation is invalid. Given ancestor($X$, $Y$), if there has been path from $X$ to $Y$ (i.e., $Y \in \mathcal{D}_X$), we skip it; if there has been a sibling relation (i.e., $\mathcal{P}_X \cap \mathcal{P}_Y \neq \emptyset$) or a descendant relation (i.e., $X \in \mathcal{D}_Y$), the ancestor relation is invalid.

Grow the hierarchy $\mathcal{H}$ with a new relation (Figure 4). We sort valid relations by their frequencies. For synonym($X$, $Y$), we merge node $X$ and $Y$ in $\mathcal{H}$: if neither was in $\mathcal{H}$, we create a new isolated node named “$X$, $Y$” if one of them existed in $\mathcal{H}$, we update the name of the existing node as “$X$, $Y$”; if both existed, we merge their ancestor nodes as the new ancestor node $\mathcal{A}_X \cup \mathcal{A}_Y$, and we
merge their descendant nodes as the new descendant node \( D_X \cup D_Y \).

For sibling \((X, Y)\), if neither of the concepts existed, we create a “NIL” node as the parent node to each concept node; if one of them existed, for each parent node in \( D_X \), we add \( Y \) as a child node of it; if both existed, we merge their parent nodes as the parent node of each and eliminate the NILs.

For ancestor \((X, Y)\), we add a descendant link from \( X \) to \( Y \). When \( X \) and \( Y \) are in \( H \), we eliminate the NILs and remove the redundant links.

When adding a new relation sibling \((X, Y)\), we merge their parent nodes. If there has been at least one non-NIL node in the set of parent nodes, we remove the NILs. When adding an ancestor node of either \( X \) or \( Y \), if they share a NIL parent node, we remove the NIL node.

Remove redundant links when growing with ancestor \((X, Y)\) (Figure 5). On the concept hierarchy, we allow only one path from an ancestor node to a descendant node. Therefore, when we add a new ancestor \((X, Y)\), there are three situations of having a redundant link. First, if there has been a path from \( X \) to \( Y \), the new relation is redundant. For example, suppose on \( H \), \( A \) (“svm”) is a descendant node of \( X \) (“classification”) and \( Y \) (“ls-svm”) is a descendant node of \( A \) (“svm”). Then a new relation ancestor (“classification”, “ls-svm”) is actually infeasible so it is redundant. We do not add it to the hierarchy. For the other two situations, we also remove the existing, redundant link in the hierarchy.

### 3.2 M5: Facet Word Discovery using Context Word Clustering

For each parent node, we decompose a 3-order tensor, child node by type of child node by context word, in which each entry is the count of the context word (e.g., “models”) used in the patterns (e.g., “$Problem$classification models such as $Method$ naïve_bayes and $Method$ svm”) that indicate the semantic relation between the parent node (e.g., “classification”) and child node (e.g., “svm”). The decomposition assigns a cluster of context words to each group of child nodes. We consider the most frequent context word in the cluster as the facet of the child nodes group.

We conduct experiments to answer three questions: (1) Are the three NIP modules effective in extracting hierarchical relations? (2) Does the hierarchy growth algorithm generate a hierarchy of better quality than existing methods? Are NIL nodes and redundant link removal necessary? (3) What does the result hierarchy look like?

### 4 Experiments

#### M1: Scientific concept extraction. Table 2 shows examples of data science concepts extracted. The learning module in AutoPhrase can segment words and phrases of good statistical features like high frequency. There is often no ambiguity when we lowercase them but the phrase lengths tend to be short. SchBase has a different philosophy: it looks for abbreviation expansions that could be long and of very low frequency. We show some case studies in Table 2. For result of

### Table 2: Data science concept examples extracted by two complementary phrase mining tools.

| Keyword       | Count  | Keyphrase       | Count  |
|---------------|--------|-----------------|--------|
| clustering    | 22,607 | data_mining     | 8,120  |
| classification| 19,488 | machine_learning| 4,195  |
| accuracy      | 18,108 | feature_selection| 3,320 |

(a) AutoPhrase finds quality keywords/phrases of good statistical features (e.g., frequency, concordance).

| Keyword       | Count  | Keyphrase       | Count  |
|---------------|--------|-----------------|--------|
| SVM           | 5,774  | least           | 3,548  |
| LDA           | 3,542  | 3               | 4      |
| AUC           | 2,542  | root-mean-square| 3      |

(b) Some typical examples of acronyms and abbreviation expansions found by SCHBase.

#### Table 3: Performance of concept typing.

| Concept         | Prediction | Ground Truth |
|-----------------|------------|--------------|
| MajVot          | 0.874 (188/27) |              |
| MajVot+Grouping | 0.963 (207/8)  |              |

#### Table 4: False type predictions in red.

| Concept              | Prediction | Ground Truth |
|----------------------|------------|--------------|
| frequent_patterns    | $\$Object$ | $\$Object$ |
| principal_components | $\$Method$ | $\$Object$ |
| information_gain     | $\$Metric$ | $\$Object$ |
| cluster_analysis     | $\$Method$ | $\$Problem$ |

(a) MajVot: 27 false predictions.

(b) MajVot+Grouping: 8 false predictions.
AutoPhrase, some 1-gram and n-gram high-quality phrase are in Table 2a. For results of SchBase, some acronyms and typical abbreviation expansions we selected are in Table 2b. With these two complementary tools, we harvest a collection of 215 data science concepts.

**M2: Concept typing.** Table 3 shows that the accuracy of concept typing (a 4-class classification task) is 0.874. Table 4a gives two of the 27 MajVot’s false predictions. We observe that some synonym/sibling concept names like “topic_model” and “topic_models” have inconsistent predicted types due to the sparsity of their neighboring words. Therefore, we leverage the synonym/sibling relations discovered in the next subsection to group the related concept names together and determine their type based on the neighboring words of all the concepts in the group (called MajVot+Grouping). The accuracy is improved significantly to 0.963. Table 4b shows three of the 8 false cases among 215 predictions. Table 5 shows the number of concepts of each type we have for hierarchy induction.

**M3: Hierarchical relation extraction.** Table 6 gives the number of relation tuples we extracted for each type. The relation synonym has the highest number of extractions while sibling gives the most unique concept pairs.

### 4.2 Results on Hierarchy Quality Evaluation

**Evaluation metrics.** Based on the manually labelled parent-to-child relations, we evaluate the quality of the resulting hierarchy with three standard IR metrics, precision, recall, and F1 score, on extracting concept pairs that have a 0-hop path (i.e., synonyms), a 1-hop path (i.e., “parent-to-child” relation), and a 2-hop path (i.e., ancestor relation as parent’s parent). A higher score means better performance.

**Baseline method.** It is not fair to compare with taxonomy construction methods because we are targeting a different problem, that is to generate a concept hierarchy of facets with three kinds of hierarchical relations. Therefore, we choose to compare with a hierarchy induction method, called TAXI (Panchenko et al., 2016), and we feed it with all the relations we mined so that we only compare on the performance of hierarchy induction algorithms. However, TAXI has no module to consider the sibling relations but we have the “NIL” mechanism. TAXI goes through all the relations several times, removes cycles, and links disconnected components to the root, while we consider the relation weights and generate the hierarchy in a growth manner for one scan. Therefore, compared with TAXI, HiGrowth is a more efficient algorithm on generating a facet concept hierarchy.

**Quality analysis.** As shown in Table 7, HiGrowth consistently outperforms TAXI on all three kinds of paths: it improves synonym detection by 3.4%, parent relation extraction by 27.8%, and 2-hop ancestor relation extraction by from 0.31 to 0.69. Actually, the HiGrowth variant that disabled the generation and removal of “NIL” node can still outperform TAXI because the hierarchy grows with relations from the most confident to the least confident. With the “NIL” nodes, HiGrowth improves the 1-hop relation by 18.3% and 2-hop relation by 49.6%. This shows that it is important to carefully consider the sibling relations.

### 4.3 Results on Removing Redundant Links

Figure 7 presents redundant links that HiGrowth skipped or removed when adding a new relation ancestor(X, Y) for each of the three situations, respectively. The most common situation is that, we have ancestor(A, X) and ancestor(A, Y) in the hierarchy, and now we have a new link to specify the relation between X and Y, two descendants of A.

If X is an ancestor of Y, we remove the redundant link ancestor(A, Y). We can see a few examples of the 93 redundant relations. A is a more gen-

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### Table 5: Number of concepts of each type.

| Method | Problem | Method | Object | Metric |
|--------|---------|--------|--------|--------|
| Count (predicted) | 932 | 104 | 9 | 50 |
| Count (ground truth) | 933 | 100 | 13 | 49 |

### Table 6: Number of relations for each type.

| Type | Synonym | Sibling | Ancestor |
|------|---------|---------|----------|
| # unique concept pairs | 41 | 234 | 138 |
| # extractions | 1,966 | 1,379 | 381 |

### Table 7: Comparing HiGrowth with baselines on building hierarchy from data science literature.

| Method | Path   | Precision | Recall | F1  |
|--------|--------|-----------|--------|-----|
| TAXI   | 0-hop  | 1.0       | .5034  | .6697 |
|        | 1-hop  | 1.0       | .4004  | .5719 |
|        | 2-hop  | 1.0       | .1831  | .3095 |
| HiGrowth w/o “NIL” | 0-hop | 1.0 | .5294 | .6923 |
|        | 1-hop | .9482 | .4583 | .6179 |
|        | 2-hop | .9499 | .3038 | .4603 |
| HiGrowth | 0-hop | 1.0 | .5294 | .6923 |
|        | 1-hop | .9926 | .5781 | .7307 |
|        | 2-hop | .9987 | .5253 | .6885 |
eral (ancestor-level) concept. The frequency of $A$ is often higher than the frequency of $X$ or $Y$. The weights of $\text{ancestor}(A, X)$ and $\text{ancestor}(A, Y)$ are bigger than the weight of $\text{ancestor}(X, Y)$. So the latter relation will be added to the hierarchy when the other two have been on the hierarchy.

### 4.4 Visualizing the Concept Hierarchy

Figure 8 presents the concept hierarchy that HiGrowth extracted from the Data Science publications. The hierarchy is not very large but still not visible in one page, so we enlarge three parts of the hierarchy, including (1) a set of concepts as the “measures” facet of “binary_classification,” (2) the “applications” and “algorithms” facets of the concept “classification,” and (3) the “algorithms” of “community_detection,” the “techniques” of “matrix_factorization,” and the “methods” of “feature_extraction” and “dimensionality_reduction.” We represent the relations of synonyms by adding different surface names for same entities in one node. For example, “topic_models” and “topic_model” are merged into one node in Figure 8 because they have the same semantic meaning.

### 5 Related Work

#### 5.1 Scientific Concept Extraction

Scientific concept extraction is a fundamental task (Yu et al., 2019; Jiang et al., 2019). It has been widely studied on multiple kinds of text sources such as web documents (Parameswaran et al., 2010), business documents (Ménard and Ratté, 2016), clinical documents (Jonnalagadda et al., 2012), material science documents (Kim et al., 2017), and computer science publications (Upadhyay et al., 2018). The phrase mining technologies have been evolving from noun phrase analysis (Evans and Zhai, 1996) to recently popular representation learning methods (Mikolov et al., 2013; Pennington et al., 2014). Here we combined...
two methodologies that have been demonstrated to be effective in Science IE (Gábor et al., 2018).

5.2 Hierarchical Relation Extraction

There has been unsupervised methods on hypernym discovery and synonym detection (Weeds et al., 2014). In this work, we combine precise textual patterns, not only the syntactic patterns (Snow et al., 2005) but also the typed patterns (Nakashole et al., 2012; Li et al., 2018; Wang et al., 2019) to find synonyms and hypernyms. We consider hypernyms carefully as ancestor-to-descendant instead of parent-to-child relations. Synonyms are on the same node, and hypernyms are connected via one- or multi-hop path. Moreover, we extract the sibling relations which precisely describe the nodes on the same level. All the three types of relation tuples are important for inferring concept hierarchies.

5.3 Hierarchy Construction and Population

There are two kinds of hierarchy construction methods: one is taxonomy or ontology induction that infers “isA” relations by machine learning models (Kozareva and Hovy, 2010; Wu et al., 2012; Yang et al., 2015; Cimiano and Staab, 2005), and the other is topical hierarchy discovery that organizes phrases into topical groups and then infers hierarchical connections between the topical groups (Wang et al., 2015; Jiang et al., 2017). For the first kind of approaches, researchers used syntactic contextual evidence (Anh et al., 2014), belief propagation for population (Bansal et al., 2014), and embedding-based inference (Fu et al., 2014; Nguyen et al., 2014). For the second part, poincaré embedding and ontology embedding methods have been proposed to learn node representations from existing hierarchies (Nickel and Kiela, 2017; Chen et al., 2018).

None of the existing approaches aimed at inferring parent-to-child relations based on the three types of hierarchical relations (i.e., synonym, ancestor-to-descendant, and sibling). We propose a novel hierarchy growth algorithm that addresses the issues of noisy, redundant, and invalid links.

6 Conclusions

This paper presented the HiGrowth method that constructs a faceted concept hierarchy from literature data. The major focus is on growing a hierarchy from three kinds of hierarchical relations that were extracted by pattern-based IE and weighted by their frequency. The hierarchy growth algorithm handles unnecessary, invalid and redundant links, even the relation set is noisy at the long tail.

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Figure 8: The resulting faceted concept hierarchy we extracted from Data Science publications, nodes mean the entities with different surface names (synonyms).
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