

TiFi: Taxonomy Induction for Fictional Domains [Extended version]*

Cuong Xuan Chu
Max Planck Institute for Informatics
Saarbrücken, Germany
cxchu@mpi-inf.mpg.de

Simon Razniewski
Max Planck Institute for Informatics
Saarbrücken, Germany
srazniew@mpi-inf.mpg.de

Gerhard Weikum
Max Planck Institute for Informatics
Saarbrücken, Germany
weikum@mpi-inf.mpg.de

ABSTRACT

Taxonomies are important building blocks of structured knowledge bases, and their construction from text sources and Wikipedia has received much attention. In this paper we focus on the construction of taxonomies for fictional domains, using noisy category systems from fan wikis or text extraction as input. Such fictional domains are archetypes of entity universes that are poorly covered by Wikipedia, such as also enterprise-specific knowledge bases or highly specialized verticals. Our fiction-targeted approach, called TiFi, consists of three phases: (i) category cleaning, by identifying candidate categories that truly represent classes in the domain of interest, (ii) edge cleaning, by selecting subcategory relationships that correspond to class subsumption, and (iii) top-level construction, by mapping classes onto a subset of high-level WordNet categories. A comprehensive evaluation shows that TiFi is able to construct taxonomies for a diverse range of fictional domains such as Lord of the Rings, The Simpsons or Greek Mythology with very high precision and that it outperforms state-of-the-art baselines for taxonomy induction by a substantial margin.

1 INTRODUCTION

1.1 Motivation and Problem

Taxonomy Induction: Taxonomies, also known as type systems or class subsumption hierarchies, are an important resource for a variety of tasks related to text comprehension, such as information extraction, entity search or question answering. They represent structured knowledge about the subsumption of classes, for instance, that electric guitar players are rock musicians and that state governors are politicians. Taxonomies are a core piece of large knowledge graphs (KGs) such as DBpedia, Wikidata, Yago and industrial KGs at Google, Microsoft Bing, Amazon, etc. When search engines receive user queries about classes of entities, they can often find answers by combining instances of taxonomic classes. For example, a query about “left-handed electric guitar players” can be answered by intersecting the classes left-handed people, guitar players and rock musicians; a query about “actors who became politicians” can include instances from the intersection of state governors and movie stars such as Schwarzenegger. Also, taxonomic class systems are very useful for type-checking answer candidates for semantic search and question answering [27].

Taxonomies can be hand-crafted, examples being WordNet [13], SUMO [32] or MeSH and UMLS [4], or automatically constructed by *taxonomy induction* from textual or semi-structured cues about type instances and subtype relations. Methods for the latter include text

mining using Hearst patterns [20] or bootstrapped with Hearst patterns (e.g., [48]), harvesting and learning from Wikipedia categories as a noisy seed network (e.g., [8, 14, 16, 36–38, 45, 47]), and inducing type hierarchies from query-and-click logs (e.g., [18, 33, 35]).

The Case for Fictional Domains: Fiction and fantasy are a core part of human culture, spanning from traditional literature to movies, TV series and video games. Well known fictional domains are, for instance, the Greek mythology, the Mahabharata, Tolkien’s Middle-earth, the world of Harry Potter, or the Simpsons. These universes contain many hundreds or even thousands of entities and types, and are subject of search-engine queries – by fans as well as cultural analysts. For example, fans may query about Muggles who are students of the House of Gryffindor (within the Harry Potter universe). Analysts may be interested in understanding character relationships [3, 24, 44], learning story patterns [5, 6] or investigating gender bias in different cultures [1]. Thus, organizing entities and classes from fictional domains into clean taxonomies (see example in Fig. 1) is of great value.

Challenges: While taxonomy construction for encyclopedic knowledge about the real world has received considerable attention already, taxonomy construction for fictional domains is a new problem that comes with specific challenges:

1. State-of-the-art methods for taxonomy induction make assumptions on entity-class and subclass relations that are often invalid for fictional domains. For example, they assume that certain classes are disjoint (e.g., living beings and abstract entities, the oracle of Delphi being a counterexample). Also, assumptions about the surface forms of entity names (e.g., on person names: with or without first name, starting with Mr., Mrs., Dr., etc.) and typical phrases for classes (e.g., noun phrases in plural form) do not apply to fictional domains.
2. Prior methods for taxonomy induction intensively leveraged Wikipedia categories, either as a content source or for distant supervision. However, the coverage of fiction and fantasy in

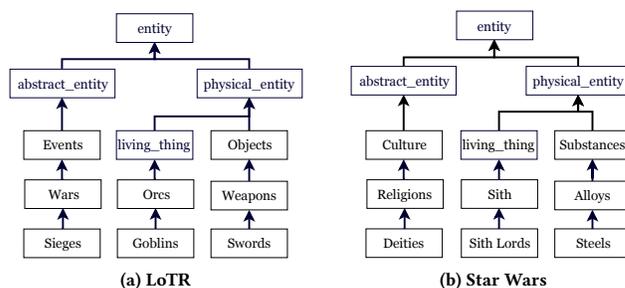


Figure 1: Excerpts of LoTR and Star Wars taxonomies.

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Wikipedia is very limited, and their categories are fairly ad-hoc. For example, Lord Voldemort is in categories like `Fictional cult leaders` (i.e., people), `J.K. Rowling characters` (i.e., a meta-category) and `Narcissism in fiction` (i.e., an abstraction). And whereas Harry Potter is reasonably covered in Wikipedia, fan websites feature many more characters and domains such as `House of Cards` (a TV series) or `Hyperion Cantos` (a 4-volume science fiction book) that are hardly captured in Wikipedia.

- Both Wikipedia and other content sources like fan-community forums cover an ad-hoc mixture of in-domain and out-of-domain entities and types. For example, they discuss both the fictional characters (e.g., Lord Voldemort) and the actors of movies (e.g., Ralph Fiennes) and other aspects of the film-making or book-writing.

The same difficulties arise also when constructing enterprise-specific taxonomies from highly heterogeneous and noisy contents, or when organizing types for highly specialized verticals such as medieval history, the Maya culture, neurodegenerative diseases, or nano-technology material science. Methodology for tackling such domains is badly missing. We believe that our approach to fictional domains has great potential for being carried over to such real-life settings. This paper focuses on fiction and fantasy, though, where raw content sources are publicly available.

1.2 Approach and Contribution

In this paper we develop the first taxonomy construction method specifically geared for fictional domains. We refer to our method as the **TiFi** system, for **T**axonomy **i**nduction for **F**iction. We address Challenge 1 by developing a classifier for categories and subcategory relationships that combines rule-based lexical and numerical contextual features. This technique is able to deal with difficult cases arising from non-standard entity names and class names. Challenge 2 is addressed by tapping into fan community Wikis (e.g., `harrypotter.wikia.com`). This allows us to overcome the limitations of Wikipedia. Finally, Challenge 3 is addressed by constructing a supervised classifier for distinguishing in-domain vs. out-of-domain types, using a feature model specifically designed for fictional domains.

Moreover, we integrate our taxonomies with an upper-level taxonomy provided by WordNet, for generalizations and abstract classes. This adds value for searching by entities and classes. Our method outperforms the state-of-the-art taxonomy induction system for the first two steps, HEAD [16], by 21-23% and 6-8% percentage points in F1-score, respectively. An extrinsic evaluation based on entity search shows the value that can be derived from our taxonomies, where, for different queries, our taxonomies return answers with 24% higher precision than the input category systems. Along with the code of the TiFi system, we will publish taxonomies for 6 fictional universes.

2 RELATED WORK

Text Analysis and Fiction. Analysis and interpretation of fictional texts are an important part of cultural and language research, both for the intrinsic interest in understanding themes and creativity [5, 6], and for extrinsic reasons such as predicting human behaviour [12] or measuring discrimination [1]. Other recurrent

topics are, for instance, to discover character relationships [3, 24, 44], to model social networks [3, 9], or to describe personalities and emotions [10, 26]. Traditionally requiring extensive manual reading, automated NLP techniques have recently lead to the emergence of a new interdisciplinary subject called *Digital Humanities*, which combines methodologies and techniques from sociology, linguistics and computational sciences towards the large-scale analysis of digital artifacts and heritage.

Taxonomy Induction from Text. Taxonomies, that is, structured hierarchies of classes within a domain of interest, are a basic building block for knowledge organization and text processing, and crucially needed in tasks such as entity detection and linking, fact extraction, or question answering. A seminal contribution towards their automated construction was the discovery of Hearst patterns [20], simple syntactic patterns like “*X is a Y*” that achieve remarkable precision, and are conceptually still part of many advanced approaches. Subsequent works aim to automate the process of discovering useful patterns [39, 43]. Recent work by Gupta et al. [15] uses seed terms in combination with a probabilistic model to extract hypernym subsequences, which are then put into a directed graph from which the final taxonomy is induced by using a minimum cost flow algorithm. Other approaches utilize distributional representations of types [31, 40, 46, 50], or aim to learn them pairwise [50] or hierarchically [31].

Taxonomy Construction using Wikipedia. A popular structured source for taxonomy construction is the Wikipedia category network (WCN) for taxonomy induction. The WCN is a collaboratively constructed network of categories with many similarities to taxonomies, expressing for instance that the category `Italian 19th century composers` is a subcategory of `Italian Composers`. One project, WikiTaxonomy [37, 38] aims to classify subcategory relations in the WCN as *subclass* and *not-subclass* relations. They investigate heuristics based on lexical matching between categories, lexico-syntactic patterns and the structure of the category network for that purpose. YAGO [22, 45] uses a very simple criterion to decide whether a category represents a class, namely to check whether it is in plural form. It also provides linking to WordNet [13] categories, choosing in case of ambiguity simply the meaning appearing topmost in WordNet. MENTA [8] learns a model to map Wikipedia categories to WordNet, with the goal of constructing a multilingual taxonomy over both. MENTA creates mean edges and subclass edges between categories and entities across languages, then uses Markov chains to rank edges and induce the final taxonomy. WiBi (Wikipedia Bitaxonomy) [14] proceeds in two steps: It first builds a taxonomy from Wikipedia pages by extracting lemmas from the first sentence of pages, and heuristically disambiguating them and linking them to others. In the second step, WiBi combines the page taxonomy and the original Wikipedia category network to induce the final taxonomy. The most recent effort working on taxonomy induction over Wikipedia is HEAD [16]. HEAD exploits multiple lexical and structural rules towards classifying subcategory relations, and is judiciously tailored towards high-quality extraction from the WCN.

Domain-specific Taxonomies. TAXIFY is an unsupervised approach to domain-specific taxonomy construction from text [2].

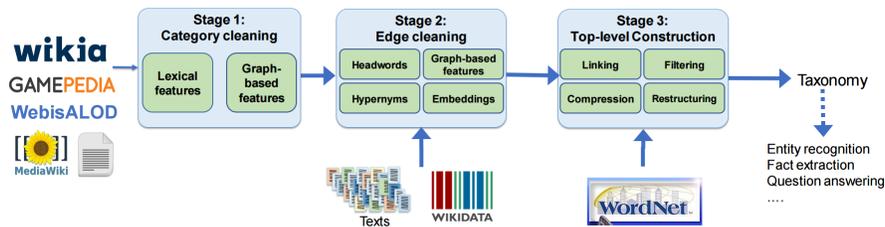


Figure 2: Architecture of TiFi.

Relying on distributional semantics, TAXIFY creates subclass candidates, which in a second step are filtered based on a custom graph algorithm. Similarly, Liu et al. [28] construct domain-specific taxonomies from keyword phrases augmented with relative knowledge and contexts. Compared with taxonomy construction from structured resources, these text-based approaches usually deliver comparably flat taxonomies.

Fan Wikis. Fans are organizing content on fictional universes on a multitude of webspaces. Particularly relevant for our problem are fan Wikis, i.e., community-built web content constructed using generic Wiki frameworks. Some notable examples of such Wikis are *tolkiengateway.net/wiki*, with 12k articles, *www.mariowiki.com* with 21k articles, or *en.brickimedia.org* with 29k articles. Particularly relevant are also Wiki farms, like Wikia¹ and Gamepedia², which host Wikis for 380k and 2k different fictional universes, and have Alexa rank 49 and 340, respectively.

In these Wikis, like on Wikipedia, editors collaboratively create and curate content. These Wikis come with support for categories, the *The Lord of the Rings* Wiki, for instance, having over 900 categories and over 1000 subcategory relationships, the *Star Wars* Wiki having 11k and 14k of each, respectively. Similarly as on Wikipedia, these category networks do not represent clean taxonomies in the ontological sense, containing for instance meta categories such as 1980 films, or relations such as Death in Battle being a subcategory of Character.

3 DESIGN RATIONALE AND OVERVIEW

3.1 Design Space and Choices

Input: The input to the taxonomy induction problem is a set of entities, such as locations, characters and events, each with a description in the form of associated text or tags and categories. Entities with textual descriptions are easily available in many forums incl. Wikipedia, wikis of fan communities or scholarly collaborations, and other online media. Tags and categories, including some form of category hierarchy, are available in various kinds of wikis – typically in very noisy form, though, with a fair amount of uninformative and misleading connections. When such sites merely provide tags for entities, we can harness subsumptions between tags (e.g., simple association rules) to derive a *folksonomy* (see, e.g., [11, 23, 25]) and use this as an initial category system. When

only text is available, we can use Hearst patterns and other text-based techniques [7, 20, 41] to generate categories and construct a subsumption-based tree.

Output: Starting with a noisy category tree or graph for a given set of entities, from a domain of interest, the goal of TiFi is to construct a clean taxonomy that preserves the valid and appropriate classes and their instance-of and subclass-of relationships but removes all invalid or misleading categories and connections. Formally, the output of TiFi is a directed acyclic graph (DAG) $G = (V, E)$ with vertices V and edges E such that (i) non-leaf vertices are semantic classes relevant for the domain, (ii) leaf vertices are entities, (iii) edges between leaves and their parents denote which entities belong to which classes, (iv) edges among non-leaf vertices denote subclass-of relationships.

There is a wealth of prior literature on taxonomy induction methods, and the design space for going about fictitious and other non-standard domains has many options. Our design decisions are driven by three overarching considerations:

- We leverage *whatever input information is available*, even if it comes with a high degree of noise. That is, when an online community provides categories, we use them. When there are only tags or merely textual descriptions, we first build an initial category system using folksonomy construction methods and/or Hearst patterns.
- For the output taxonomy, we *prioritize precision over recall*. So our methods mostly focus on removing invalid vertices and edges. Moreover, to make classes for fictitious domains more interpretable and support cross-domain comparisons (e.g., for search), we aim to align the domain-specific classes with appropriate upper-level classes from a general-purpose ontology, using WordNet [13]. For example, dragons in Lord of the Rings should be linked to the proper WordNet sense of dragons, which then tells us that this is a subclass of mythical creatures.
- It may seem tempting to cast the problem into an end-to-end machine-learning task. However, this would require sufficient training data in the form of pairs of input datasets and gold-standard output taxonomies. Such training data is not available, and would be hard and expensive to acquire. Instead, we break the overall task down into focused steps at the granularity of individual vertices and individual edges of category graphs. At this level, it is much easier to acquire labeled training data, by crowdsourcing (e.g., mturk). Moreover, we can more easily devise features that capture both local and global contexts, and we can harness external assets like dictionaries and embeddings.

¹www.wikia.com/fandom

²www.gamepedia.com

3.2 TiFi Architecture

Based on the above considerations, we approach taxonomy induction in three steps, (1) category cleaning, (2) edge cleaning, (3) top-level construction. The architecture of TiFi is depicted in Fig. 2. Fig. 3 illustrates how TiFi constructs a taxonomy.

The first step, *category cleaning* (Section 4), aims to clean the original set of categories V by identifying categories that truly represent classes within the domain of interest, and by removing categories that represent, for instance, meta-categories used for community or Wikia coordination, or concern topics outside of the fictional domain, like movie or video game adaptations, award wins, and similar. Previous work has tackled this step via syntactic and lexical rules [34, 37, 45]. While such custom-tailored rules can achieve high accuracy, they have limitations w.r.t. applicability across domains. We thus opt for a supervised classification approach that combines rules from above with additional graph-based features. This way, taxonomy construction for a new domain only requires new training examples instead of new rules. Moreover, our experiments show that, to a reasonable extent, models can be reused across domains.

The second step, *edge cleaning* (Section 5), identifies the edges from the original category network E that truly represent subcategory relationships. Here, both rule-based [17, 37] and embedding-based approaches [31] appear in the literature. Each approach has its strength, however, rules again have limitations wrt. applicability across domains, while embeddings may disregard useful syntactic features, and crucially rely on enough textual content for learning. We thus again opt for a supervised approach, allowing us to combine existing lexical and embedding-based approaches with various adapted semantic and novel graph-based features.

For the third step, *top-level construction* (Section 6), basic choices are to aim to construct the top levels of taxonomies from input category networks [17, 37], or to reuse existing abstract taxonomies such as WordNet [45]. As fan Wikis (and even Wikipedia) generally have a comparably small coverage of abstract classes, we here opt for the reuse of the existing WordNet top-level classes. This also comes with the additional advantage of establishing a shared vocabulary across domains, allowing to query, for instance, for *animal species appearing both in LoTR and GoT* (with answers such as dragons).

4 CATEGORY CLEANING

In the first step, we aim to select the categories from the input that actually represent classes in the domain of interest. There are several reasons why a category would not satisfy this criterion, including the following:

- *Meta-categories*: Wiki platforms typically introduce metacategories related to administration and technical setup, e.g., Meta or Administration.
- *Contextual categories*: Community Wikis usually contain also information about the production of the universes (e.g., inspirations or actors), about the reception (e.g., awards), and about remakes and adaptations, which do not related to the real content of the universes.
- *Instances*: Editors frequently create categories that are actually instances, e.g., ARDA or MORDOR in *The Lord of The Rings*).

- *Extensions*: Wikis sometimes also contains fan-made extensions of universes that are not universally agreed upon.

Previous works on Wikipedia remove either only meta-categories or instances by using crafted lexical rules [34, 37, 38]. As our setting has to deal with a wider range of noise, we instead choose the use of supervised classification. We use a logistic regression classifier with binary (0/1) lexical and integer graph-based features, as detailed next.

A. Lexical Features.

- *Meta-categories*: True if a categories' name contains one of 22 manually selected strings, such as wiki, template, user, portal, disambiguation, articles, administration, file, pages, etc.
- *Plural categories*: True if the headword of a category is in plural form. We use shallow parsing to extract headwords, for instance, identifying the plural term Servants in Servants of Morgoth, a strong indicator for a class.
- *Capitalization*: True if a category starts with a capital letter. We introduced this feature as we observed that in fiction, lowercase categories frequently represent non-classes.

B. Graph-based Features.

- *Instance count*: The number of direct instances of a category.
- *Supercategory/subcategory count*: The number of super/subcategories of a category, e.g., 0/2 for Characters in Fig. 3 (left). Categories with more instances, superclasses or subclasses have potentially more relevance.
- *Average depth*: Average upward path length from a category. Categories with short paths above are potentially more likely not relevant.
- *Connected subgraph size*: The maximal size of connected subgraphs which a given category belongs to. Each connected subgraph is extracted by using depth first search on each root of the input category network. Meta-categories are sometimes disconnected from the core classes of a universe.

While the first two are established features, all other features have been newly designed to especially meet the characteristics of fiction. As we show in Section 7, this varied feature set allows to identify in-domain classes with 83%-85% precision.

5 EDGE CLEANING

Once the categories that represent classes in the domain of interest have been identified, the next task is to identify which subcategory relationships also represent subclass relationships. While most previous works rely on rules [8, 14, 16, 37], these are again too inflexible for the diversity of fictional universes. We thus tackle the task using supervised learning, relying on a combination of syntactic, semantic and graph-based features for a regression model.

A. Syntactic Features.

Head Word Matching. Head word matching is arguably the most popular feature for taxonomy induction. Categories sharing the same headword, for instance Realms and Dwarven Realms are natural candidates for hypernym relationships.

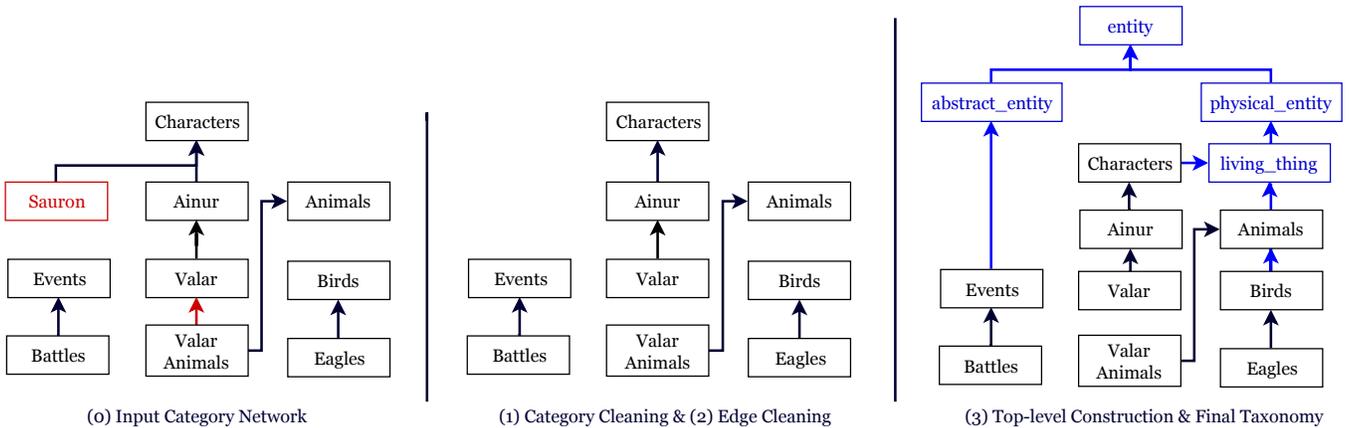


Figure 3: Example of three-stage taxonomy induction.

We use a shallow parsing to extract, for a category c , its headword $head(c)$, its prefix $pre(c)$, and its suffix (postfix) $pos(c)$, that is, $c = pre(c) + head(c) + pos(c)$. Consider a subcategory pair (c_1, c_2) :

1. If $head(c_1) = head(c_2)$, $head(c_1) + pos(c_1) = head(c_2) + pos(c_2)$ and $pre(c_2) \subseteq pre(c_1)$ then c_2 is a superclass of c_1 .
2. If $head(c_1) = head(c_2)$, $pre(c_1) + head(c_1) = pre(c_2) + head(c_2)$ and $pos(c_2) \subseteq pos(c_1)$ then c_2 is a superclass of c_1 .
3. If $head(c_1) \neq head(c_2)$ and $head(c_2) \subseteq pre(c_1)$ or $head(c_2) \subseteq pos(c_1)$ then there is no subclass relationship between c_1 and c_2 .

Case (1) covers the example of Realms and Dwarven Realms, while case (2) allows to infer, for instance, that Elves is a superclass of Elves of Gondolin. Case (3) allows to infer that certain categories are not superclasses of each other, e.g., Gondor and Lords of Gondor. Each of subclass and no-subclass inference are implemented as binary 0/1 features.

Only Plural Parent. True if for a subcategory pair (c_1, c_2) , c_1 has no other parent categories, and c_2 is in plural form [16].

B. Semantic Features.

WordNet Hypernym Matching. WordNet is a carefully handcrafted lexical database that contains semantic relations between words and word senses (synsets), including hypo/hypernym relations. To leverage this resource, we map categories to WordNet synsets, using context-based similarity to identify the right word sense in the case of ambiguities. To compute the context vectors of categories, we extract their definitions, that is, the first sentence from the Wiki pages of the categories (if existing), and their parent and child class names. As context for WordNet synsets we use the definition (gloss) of each sense. We then compute cosine similarities over the resulting bags-of-words, and link each category with the position-adjusted most similar WordNet synset (see Alg. 1). Then, given categories c_1 and c_2 with linked WordNet synset s_1 and s_2 , respectively, this feature is true if s_2 is a WordNet hypernym of s_1 .

Wikidata Hypernym Matching. Similarly to WordNet, Wikidata also contains relations between entities. For example, Wikidata knows that Maiar is an instance (P31) of Middle-earth races in the

Algorithm 1: WordNet Synset Linking

Data: A category c

Result: WordNet synset s of c

$c = pre + head + pos$, $l = null$;

$l =$ list of WordNet synset candidate for c ;

if $l = null$ **then**

$l =$ list of WordNet synset candidates for $pre + head$;

if $l = null$ **then**

$l =$ list of WordNet synset candidates for $head$;

if $l = null$ **then**

\perp return null;

$max = 0$, $s = null$;

for all WordNet synset s_i in l **do**

$sim(s_i, c) = cosine(V_{s_i}, V_c)$ with V : context vector;

$sim(s_i, c) = sim(s_i, c) + 1/(2R_{s_i})$ where R : rank in WordNet;

if $sim(s_i, c) > max$ **then**

$max = sim(s_i, c)$;

$s = s_i$;

return s ;

The Lord of the Rings. While Wikidata’s coverage is generally lower than that of Wordnet, its content is sometimes complementary, as WordNet does not know certain concepts, e.g., Maiar.

Page Type Matching. One interesting contribution of the WiBi system [14] was to use the first sentence of Wikipedia pages to extract hypernyms. First sentences frequently define concepts, e.g., “*The Haradrim, known in Westron as the Southrons and once as the “Swertings” by Hobbits, were a race of Men from Harad in the region of Middle-earth directly south of Gondor.*”. For categories having matching articles in the Wikis, we rely on the first sentence from these. We use the Stanford Parser [29] on the definition of the category to get a dependency tree. By extracting `nsubj`, `compound` and `conj` dependencies, we get a list of hypernyms for the category. For example, for Haradrim we can extract the relation `nsubj(race-13, Haradrim-2)`, hence `race` is a hypernym of Haradrim. After getting

hypernyms for a category, we link these hypernyms to classes in the taxonomies by using head word matching, and set this feature to true for any pair of categories linked this way.

WordNet Synset Description Type Matching. Similar to page type matching, we also extract superclass candidates from the description of the WordNet synset. For instance, given the WordNet description for Werewolves: “a monster able to change appearance from human to wolf and back again”, we can identify Monster as superclass.

Distributional Similarity. The distributional hypothesis states that similar words share similar contexts [19], and despite the subclass relation being asymmetric, symmetric similarity measures have been found to be useful for taxonomy construction [42]. In this work, we utilize two distributional similarity measures, a symmetric one based on the structure of WordNet, and an asymmetric one based on word embeddings. The symmetric Wu-Palmer score compares the depth of two synsets (the headwords of the categories) with the depth of their least common subsumer (*lcs*) [49]. For synsets s_1 and s_2 , it is computed as:

$$Wu\text{-Palmer}(s_1, s_2) = \frac{2 * \text{depth}(lcs(s_1, s_2)) + 1}{\text{depth}(s_1) + \text{depth}(s_2) + 1} \quad (1)$$

The HyperVec score [31] not only shows the similarity between a category and its hypernym, but is also directional. Given categories c_1 and c_2 , with stemmed head words h_1, h_2 respectively, the HyperVec score is computed as:

$$HyperVec(c_1, c_2) = \text{cosine}(E_{h_1}, E_{h_2}) * \frac{\|E_{h_2}\|}{\|E_{h_1}\|}, \quad (2)$$

where E_h is the embedding of word h . Specifically, we are using Word2Vec [30] to train a distributional representation over Wikia documents. The term $\text{cosine}(E_{h_1}, E_{h_2})$ represents the cosine similarity between two embeddings, $\|E_h\|$ the Euclidean norm of an embedding. While WordNet only captures similarity between general concepts, embedding-based measures can cover both conceptual and non-conceptual categories, as often needed in the fantasy domain (e.g. similarity between Valar and Maiar).

C. Graph-based Features.

Common Children Support. Absolute number of common children (categories and instances) of two given categories. Presumably, the more common children two categories have, the more related to each other they are.

Children Depth Ratio. The ratio between the number of child categories of the parent of the edge, and its average depth in the taxonomy. This feature models the generality of the parent candidate.

The features for edge cleaning combine existing state-of-the-art features (Head word matching, Page type matching, HyperVec) with adaptations specific to our domain (Wikidata hypernym matching, WordNet synset matching), and new graph-based features. Section 7 shows that this feature set allows to surpass the state-of-the-art in edge cleaning by 6-8% F1-score.

6 TOP-LEVEL CONSTRUCTION

Category systems from Wiki sources often rather resemble forests than trees, i.e., do not reach towards very general classes, and miss useful generalizations such as man-made structures or geographical features for fortresses and rivers. While works geared towards Wikipedia typically conclude with having identified classes and subclasses [8, 14, 16, 37, 38], we aim to include generalizations and abstract classes consistently across universes. For this purpose, TiFi employs as third step the integration of selected abstract WordNet classes. The integration proceeds in three steps:

- (1) Given the taxonomy constructed so far, nodes are linked to WordNet synsets using Algorithm 1. Where the linking is successful, WordNet hypernyms are then added as superclasses. For example, the category Birds is linked to the WordNet synset `bird%1:05:00::`, whose superclasses are `wn_vertebrate` \rightarrow `wn_chordate` \rightarrow `wn_animal` \rightarrow `wn_organism` \rightarrow `wn_living_thing` \rightarrow `wn_whole` \rightarrow `wn_object` \rightarrow `wn_physical_entity` \rightarrow `wn_entity`.
- (2) The added classes are then compressed by removing those that have only a single parent and a single child, for instance, `abstract_entity` and `physical_entity` in Fig. 3 (right) would be removed, if they really had only one child.
- (3) We correct a few WordNet links that are not suited for the fictional domain, and use a self-built dictionary to remove 125 top-level WordNet synsets that are too abstract to add value, for instance, `whole`, `sphere` and `imagination`.

Note that the present step can add subclass relationships between existing classes. In Fig. 3, after edge filtering, there is no relation between Birds and Animals, while after linking to WordNet, the subclass relation between Birds and Animals is added, making the resulting taxonomy more dense and useful.

7 EVALUATION

In this section we evaluate the performance of the individual steps of the TiFi approach, and the ability of the end-to-end system to build high-quality taxonomies.

Universes. We use 6 universes that cover fantasy (LoTR, GoT), science fiction (Star Wars), animated sitcom (Simpsons), video games (World of Warcraft) and mythology (Greek Mythology). For each of these, we extract their category networks from dump files of Wikia or Gamepedia. The sizes of the respective category networks, the input to TiFi, are shown in Table 1.

7.1 Step 1: Category Cleaning

Evaluation data for the first step was created using crowdsourcing, which was used to label all categories in LoTR, GoT, and random 50

Universe	# Categories	# Edges
Lord of the Rings (LoTR)	973	1118
Game of Thrones (GoT)	672	1027
Star Wars	11012	14092
Simpsons	2275	4027
World of Warcraft	8249	11403
Greek Mythology	601	411

Table 1: Input categories from Wikia/Gamepedia.

Method	Universe	Precision	Recall	F1-score
Pasca 2018 [34]	LoTR	0.33	0.75	0.46
	GoT	0.57	0.85	0.68
Ponzetto & Strube 2011 [38]	LoTR	0.44	1.0	0.61
	GoT	0.45	1.0	0.62
Pasca + Ponzetto & Strube	LoTR	0.41	0.75	0.53
	GoT	0.64	0.85	0.73
TiFi	LoTR	0.84	0.82	0.83
	GoT	0.85	0.85	0.85

Table 2: Step 1 - In-domain category cleaning.

Train	Test	Precision	Recall	F1-score
LoTR	GoT	0.81	0.85	0.83
GoT	LoTR	0.64	0.88	0.74
LoTR	Star Wars	0.63	0.94	0.75
LoTR	Simpsons	0.91	0.63	0.74
LoTR	World of Warcraft	0.95	0.63	0.75
LoTR	Greek Mythology	0.86	0.6	0.71

Table 3: Step 1 - Cross-domain category cleaning.

from each of the other universes. Specifically, workers were asked to decide whether a given category had instances *within* the fictional domain of interest. We collected three opinions per category, and chose majority labels. Worker agreement was between 85% and 91%.

As baselines we employ a rule-based approach by Ponzetto & Strube [38], to the best of our knowledge the best performing method for general category cleaning, and recent work by Marius Pasca [34] that targets the aspect of separating classes from instances. Furthermore, we combine both methods into a joint filter. The results of training and testing on LoTR/GoT, respectively, each under 10-fold crossvalidation, are shown in Table 2. TiFi achieves both superior precision (+40%) and F1-score (+22%/+23%), while observing a smaller drop in recall (-18%/-15%). On both fully annotated universes the improvement of TiFi over the combined baseline in terms of F1-score is statistically significant (p-value $2.2 \cdot 10^{-16}$ and $1.9 \cdot 10^{-13}$, respectively). The considerable difference in precision is explained largely by the limited coverage of the rule-based baseline. Typical errors TiFi still makes are cases where categories have the potential to be relevant, yet appear to have no instances, e.g., song in LOTR. Also, it occasionally misses out on conceptual categories which do not have plural forms, e.g., Food.

A characteristic of fiction is variety. As our approach requires labeled training data, a question is to which extent labeled data from one domain can be used for cleaning categories of another domain. We thus next evaluate the performance when applying models trained on LoTR on the other 5 universes, and the model trained on GoT on LoTR. The results are shown in Table 3, where for universes other than LoTR and GoT, having annotated only 50 samples. As one can see, F1-scores drop by only 9%/2% compared with same-domain training, and the F1-score is above 70% even for quite different domains.

To explore the contribution of each feature, we performed an ablation test using recursive feature elimination. The most important feature group were lexical features (30%/10% F1-score drop if

Method	Universe	Precision	Recall	F1-score
HyperVec [31]	LoTR	0.82	0.8	0.81
	GoT	0.83	0.81	0.82
HEAD [16]	LoTR	0.85	0.83	0.84
	GoT	0.81	0.78	0.79
TiFi	LoTR	0.83	0.98	0.90
	GoT	0.83	0.91	0.87

Table 4: Step 2 - In-domain edge cleaning.

Train	Test	Precision	Recall	F1-score	MAP
LoTR	GoT	0.81	0.79	0.80	0.92
GoT	LoTR	0.89	0.87	0.88	0.89
GoT	Star Wars	0.92	0.92	0.92	0.91
GoT	Simpsons	0.86	0.86	0.86	0.92
GoT	World of Warcraft	0.72	0.71	0.72	0.76
GoT	Greek Mythology	0.92	0.92	0.92	0.92

Table 5: Step 2 - Cross-domain edge cleaning.

removed in LoTR/GoT), with plural form checking being the single most important feature. In contrast, removing the graph-based features lead only to a 10%/0% drop, respectively.

7.2 Step 2: Edge Cleaning

We used crowdsourcing to label all edges that remained after cleaning noisy categories from LoTR, GoT, and random 100 edges in each of the other universes. For example, we asked Turker whether in LOTR, Uruk-hai are Orc Man Hybrids. Inter-annotator agreement was between 90% and 94%.

We compare with two state-of-the-art systems: (1) HEAD [16], the most recent system for Wikipedia category relationship cleaning, and (2) HyperVec [31], a recent embedding-based hypernym relationship learning system. The results for in-domain evaluation using 10-fold crossvalidation are shown in Table 4. As one can see, TiFi achieves a comparable precision (-2%/+2%), and a superior recall (+15%/+13%), resulting in a gain in F1-score of 6%/8%. Again, the F1-score improvement of TiFi over HyperVec and HEAD on the two fully annotated universes is statistically significant (p-values $7.1 \cdot 10^{-9}$, 0.01 , $5.8 \cdot 10^{-5}$ and $6.5 \cdot 10^{-5}$, respectively).

To explore the scalability of TiFi, we again perform cross-domain experiments using 100 labeled edges per universe. The results are shown in Table 5. In all universes but *World of Warcraft*, TiFi achieves more than 80% F1-score, and the performance is further highlighted by mean average precision (MAP) scores above 89%, meaning TiFi can effectively separate correct from incorrect edges.

As mentioned earlier, taxonomy induction on real-world domain can leverage a lot of semantic knowledge like WordNet synsets, while fiction frequently contains non-standard categories such as Valar and Tatyar. We further evaluate the performance of TiFi by distinguishing two types of edges:

- *Concept edges*: Both parent and child exist in WordNet.
- *Proper-name edges*: At least one of parent and child does not exist in WordNet.

In *The Lord of the Rings*, there are 145 proper-name edges and 407 concept edges, while in *Game of Thrones*, there are 61 and 329 of each, respectively. Table 6 reports the performance of TiFi, comparing to HEAD and HyperVec on both types of edges. As

Method	Universe	Proper-name edges			Concept edges		
		Precision	Recall	F1-score	Precision	Recall	F1-score
HyperVec [31]	LoTR	0.88	0.59	0.71	0.80	0.88	0.84
	GoT	1.0	0.16	0.27	0.83	0.9	0.87
HEAD [16]	LoTR	0.91	0.74	0.81	0.83	0.87	0.85
	GoT	0.72	0.68	0.70	0.82	0.8	0.81
TiFi	LoTR	0.92	0.79	0.85	0.88	0.89	0.88
	GoT	0.96	0.68	0.8	0.90	0.91	0.91

Table 6: Step 2 - Edge cleaning: Proper-name vs. concept edges.

Universe	#New Types	#New Edges	Precision
LoTR	43	171	0.84
GoT	39	179	0.84
Starwars	373	3387	0.84
Simpsons	115	439	0.92
World of Warcraft	257	2248	0.84
Greek Mythology	22	76	0.84

Table 7: Step 3 - WordNet integration.

one can see, for proper-name edges, TiFi achieves a very high precision of 92%/96%, outperforms HEAD by 4%/10% and HyperVec by 14%/53% in F1-score, respectively.

We again performed an ablation test in order to understand feature contribution. We found that all three groups of features have importance, observing a 1-4% drop in F1-score when removing any of them. The individually most important features were *Only Plural Parent*, *Headword Matching*, *Common Children Support* and *Page Type Matching*.

7.3 Step 3: Top-level Construction

The key step in top-level construction is the linking of categories to WordNet synsets (i.e. category disambiguation), hence we only evaluate this step. For this purpose, in each universe, we randomly selected 50 such links and evaluated their correctness, finding precisions between 84% and 92% (see Table 7). Overall, this step is able to link 30-72% of top-level classes from Step 2, and adds between 22 to 373 WordNet classes and 76 to 3387 subclass relationships to our universes.

7.4 Final Taxonomies

Table 8 summarizes the taxonomies constructed for our 6 universes, with the bottom 4 universes built using the models for GoT. Reported precisions refer to the weighted average of the precision of subclass edges from Step 2, and the precision of WordNet linking.

Universe	# Types	# Edges	Precision
LoTR	353	648	0.88
Game of Thrones	292	497	0.83
Star Wars	7352	12282	0.90
Simpsons	1029	2171	0.88
World of Warcraft	4063	7882	0.76
Greek Mythology	139	313	0.91

Table 8: Taxonomies produced by TiFi.

Figure 4 shows the resulting taxonomy for Greek Mythology, rendered using the R layout *fruchterman.reingold*. All taxonomies will be made available both as CSV and graphically.

7.5 Wikipedia as Input

While our method is targeted towards fiction, it is also interesting to know how well it does in the traditional Wikipedia setting. To this end, we extracted a specific slice of Wikipedia, namely all categories that are subcategories of Desserts, resulting in 198 categories connected by 246 subcategory relations, which we fully labeled.

Using 10-fold crossvalidation, in the first step, category cleaning, our method achieves 99% precision and 99% recall, which puts it on par with Ponzetto & Strube [38], which achieves 99% precision and 100% recall. The reason for the excellent performance of both systems is that noise in Wikipedia categories concerns fairly uniformly meta-categories, which can be well filtered by enumerating them. In the second step, edge cleaning, TiFi also achieves comparable results, with a slightly lower precision (83% vs. 87%) and a slightly higher recall (92% vs. 89%), resulting in 87% F1-score for TiFi vs. 88% for HEAD.

7.6 WebIsALOD as Input

WebIsALOD [21] is a large collection of hypernymy relations extracted from the general web (Common Crawl). Relying largely on pattern-based extraction, the data from WebisALOD is very noisy, especially beyond the top-confidence ranks. Being text-based, several features based on category systems become unavailable, making this source an ideal stress test for the TiFi approach.

Data: To get data from WebisALOD, we selected the top 100 most popular entities from two universes, *The Lord of the Rings* and *Simpsons*, 100 per each, based on the frequency of their mentions in text. We then queried the hypernyms of these entities and took the top 3 hypernyms based on ranking of confidences cores (minimum confidence 0.2). We iterated this procedure once with the newly gained hypernyms. In the end, with *The Lord of the Rings*, we get 324 classes and 312 hypernym relations, meanwhile, with *Simpsons*, these numbers are 271 classes and 228 hypernym relations. We fully manual label these datasets by checking whether classes are noisy and hypernym relations are wrong. From the labeled data, only 217 classes (67%) and 167 classes (62%) should be kept in *The Lord of the Rings* and *Simpsons*, respectively. In the case of hypernym relations, only 42% and 47% of them are considered to be correct relations in *The Lord of the Rings* and *Simpsons*, respectively. These statistics confirm that the data from WebisALOD is very noisy.

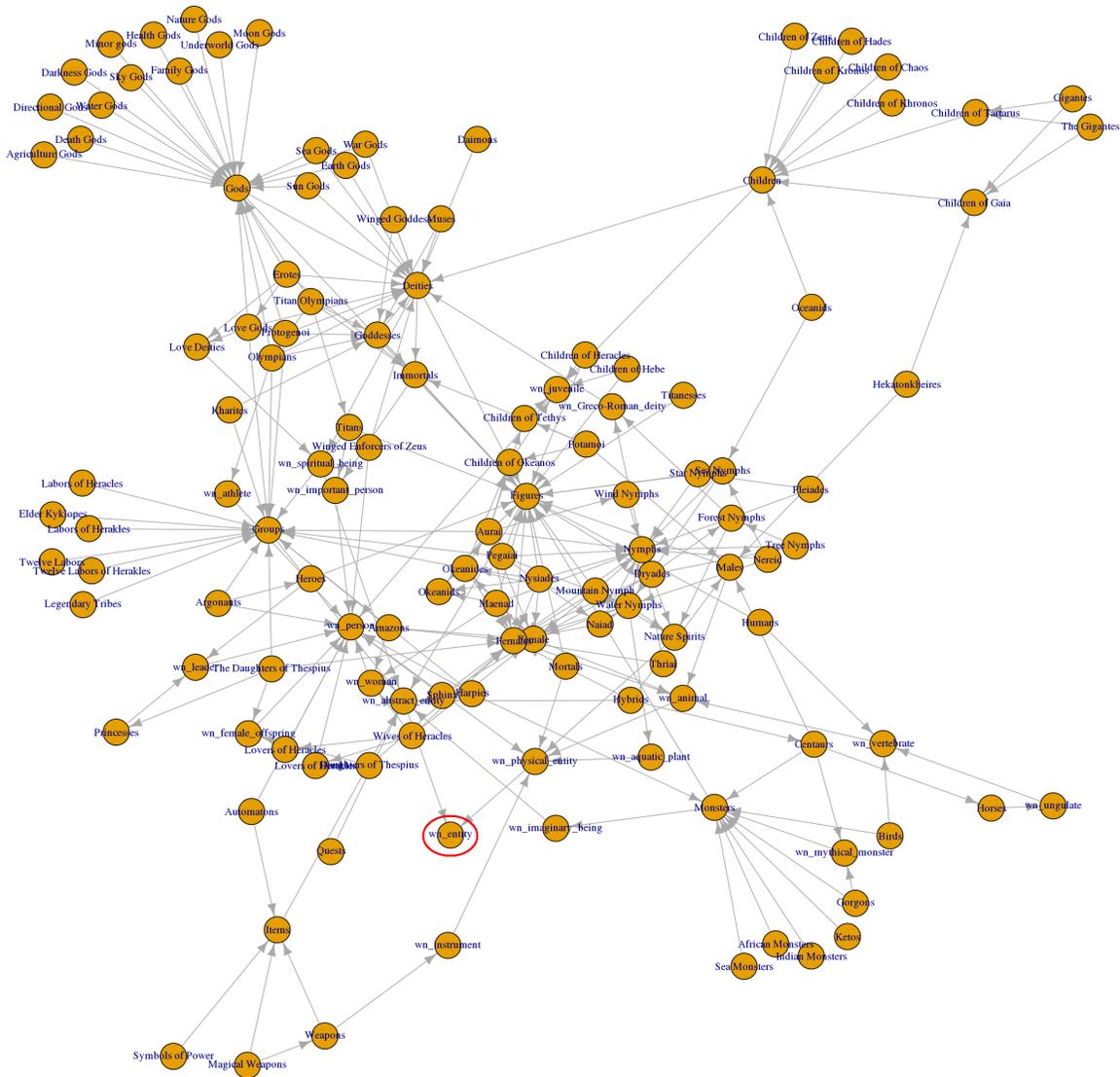


Figure 4: Final TiFi taxonomy for Greek Mythology.

Results: In Step 1, Ponzetto & Strube [38] use lexical rules to remove meta-categories, while Pasca [34] uses heuristics which are based on information extracted from Wikipedia pages to detect entities that are classes. To enable comparison with Pasca’s work, we used exact lexical matches to link classes from WebIsALOD to Wikipedia pages titles, then used Wikipedia pages as inputs. In fact, classes from WebIsALOD are hardly meta-categories and the additional data from Wikipedia is also quite noisy. Table 9 shows that TiFi still performs very well in category cleaning, and significantly outperforms the baselines by 10%/20% F1-score.

In Step 2, HEAD uses heuristics to clean hypernym relations between classes, mostly based on lexical and information from class pages (e.g. Wikipedia pages). Although TiFi also uses the information from class pages, its supervised model uses also a set of other features and is thus more versatile. Table 10 reports the

Method	Universe	Precision	Recall	F1-score
Pasca, 2018 [34]	LoTR	0.67	1.0	0.80
	Simpsons	0.62	1.0	0.76
Ponzetto & Strube 2011 [38]	LoTR	0.67	1.0	0.80
	Simpsons	0.62	1.0	0.76
TiFi	LoTR	0.89	0.94	0.91
	Simpsons	0.95	0.97	0.96

Table 9: WebIsALOD input - step 1 - In-domain cat. cleaning.

results of TiFi, comparing with HEAD in edge cleaning, with TiFi outperforming HEAD by 28%-53% F1-score.

Both steps were also evaluated in the cross-domain settings, with similar results (90%/91% F1-score in step 1, 53%/55% F1-score in step 2).

Query	Text		Structured Sources	
	Google	Wikia	Wikia-categories	TiFi
Dragons in LOTR	Glaurung, Túrin, Turambar, Eärendil, Smaug, Ancalagon	Dragons, Summoned Dragon, Spark-dragons	Urgost, Long-worms, Gostir, Drogoth the Dragon Lord, Cave Drake, War of the Dwarves and Dragons, Dragon-spell, Stone Dragons, Fire-drake of Gondolin, Spark-dragons, Were-worms, Summoned Dragon, Fire-drakes, Glaurung, Ancalagon, Dragons, Cold-drakes, Sea-serpents, User blog:Alex-Lioce/Kaldrache the Dragon, Smaug, Dragon (Games, Workshop), Drake, Scatha, The Fall of Erebor	Long-worms, War of the Dwarves and Dragons, Dragon-spell, Stone Dragons, Fire-drake of Gondolin, Spark-dragons, Were-worms, Fire-drakes, Glaurung, Ancalagon, Dragons, Cold-drakes, Sea-serpents, Smaug, Scatha, The Fall of Erebor, Gostir
Which Black Numenoreans are servants of Morgoth	-	Black Númenórean	Men of Carn Dûm, Corsairs of Umbar, Witch-king of Angmar, Thrall Master, Mouth of Sauron, Black Númenórean, Fuinur	Men of Carn Dûm, Corsairs of Umbar, Witch-king of Angmar, Mouth of Sauron, Black Númenórean, Fuinur
Which spiders are not agents of Saruman?	-	-	Shelob, Spider Queen and Swarm, Saenathra, Spiderling, Great Spiders, Wicked, Wild, and Wrath	Shelob, Great Spiders

Table 12. Example queries and results for the entity search evaluation.

Method	Universe	Precision	Recall	F1-score
HEAD [16]	LoTR	0.27	0.05	0.09
	Simpsons	0.31	0.09	0.14
TiFi	LoTR	0.79	0.55	0.62
	Simpsons	0.61	0.32	0.42

Table 10: WebIsALOD - step 2 - In-domain edge cleaning.

Query	Text		Structured Sources	
	Google	Wikia	Wikia-categories	TiFi
t	2 (52%)	7 (65%)	10 (62%)	8 (87%)
$t_1 \cap t_2$	1 (23%)	2 (11%)	8 (40%)	3 (70%)
$t_1 \setminus t_2$	1 (20%)	4 (36%)	8 (63%)	6 (79%)
Average	1 (32%)	4 (37%)	9 (55%)	6 (79%)

Table 11: Avg. #Answers and precision of entity search.

8 USE CASE: ENTITY SEARCH

To highlight the usefulness of our taxonomies, we provide an extrinsic evaluation based on the use case of entity search. Entity search is a standard problem in information retrieval, where often, textual queries shall return lists of matching entities. In the following, we focus on the retrieval of correct entities only, and disregard the ranking aspect.

Setup. We consider three universes, *The Lord of the Rings*, *Simpsons* and *Greek Mythology*, and manually generated 90 text queries belonging to the following categories (10 of each per universe):

- (1) Single type: Entities belonging to a class, e.g., *Orcs in the Lords of the Rings*;
- (2) Type intersection: Entities belonging to two classes, e.g., *Humans that are agents of Saruman*;
- (3) Type difference: Entities that belong to one class but not another, e.g., *Spiders that are not servants of Sauron*.

We utilize the following resources:

- Unstructured resources: (1) Google Web Search and (2) the Wikia-internal text search function;
- Structured resources: (3) the Wikia category networks and (4) the taxonomies as built by TiFi.

Evaluation. For the unstructured resources, we manually checked the titles of the top 10 returned pages for correctness.

For the structured resources, we matched the classes in the query against all classes in the taxonomy that contained those class names as substrings. We then computed, in a breadth-first manner, all subclasses and all instances of these classes, truncating the latter to maximal 10 answers, and manually verified whether returned instances were correct or not.

Results. Table 11 reports for each resource the average number of results and their precision. We find that Google performs worst mainly because its diversification is limited (returns distinct answers often only far down in the ranking), and because it cannot well process conjunction and negation. Wikia performs better in terms of answer size, as by design it contains each entity only once.

Still, it struggles with logical connectors. The Wikia categories produce more results than TiFi (9 vs. 6 on average), though due noise, they yield a substantially lower precision (~24%). This corresponds to the core of the TiFi approach, which in step 1 and 2 is cleaning, i.e., leads to a lower recall while increasing precision.

Table 12 lists three sample queries along with their output. Crossed-out entities are incorrect answers. As one can see, text search mostly fails in answering the queries that use boolean connectives, while the original Wikia categories are competitive in terms of the number of answers, but produce many more wrong answers.

9 CONCLUSION

In this paper we have introduced TiFi, a system for taxonomy induction for fictional domains. TiFi uses a three-step architecture with category cleaning, edge cleaning, and top-level construction, thus building holistic domain specific taxonomies that are consistently of higher quality than what the Wikipedia-oriented state-of-the-art could produce.

Unlike most previous work, our approach is not based on static rules, but uses supervised learning. This comes with the advantage of allowing to rank classes and edges, for instance, in order to distinguish between core elements, less or marginally relevant ones, and totally irrelevant ones. In turn it also necessitates the generation of training data, yet we have shown that training data can be reasonably reused across domains.

Mirroring earlier experiences of YAGO [45], it also turns out that a crucial step in building useful taxonomies is the incorporation of abstract classes. For TiFi we relied on the established WordNet hierarchy, nevertheless finding the need to adapt a few links, and to remove certain too abstract concepts.

So far we only applied our system to fictional domains and one slice of Wikipedia. In the future, we would like to explore the construction of more domain-specific but real-world taxonomies, such as gardening, Maya culture or Formula 1 racing.

Code and taxonomies will be made available on Github.

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