

Taxonomy Builder: a Data-driven and User-centric Tool for Streamlining Taxonomy Construction

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Abstract

An existing domain taxonomy for normalizing content is often assumed when discussing approaches to information extraction, yet often in real-world scenarios there is none. When one does exist, as the information needs shift, it must be continually extended. This is a slow and tedious task, and one that does not scale well. Here we propose an interactive tool that allows a taxonomy to be built or extended *rapidly* and with a *human in the loop* to control precision. We apply insights from text summarization and information extraction to reduce the search space dramatically, then leverage modern pretrained language models to perform contextualized clustering of the remaining concepts to yield candidate nodes for the user to review. We show this allows a user to consider as many as 200 taxonomy concept candidates an hour to quickly build or extend a taxonomy to better fit information needs.

1 Introduction

Information extraction (IE), or the extraction of structured information from free text, is a sub-field of natural language processing (NLP) that is of keen interest to those outside of the NLP community. Practitioners who desire to mine information from text often set this up as a two-part task: (1) extracting the structured information from each document, and then (2) normalizing the extractions to be able to aggregate across a given corpus.

For this second step, often referred to as *grounding*, there are several approaches, but in industry and many domain-specific applications, the standard method for grounding is linking to a relevant ontology or taxonomy (Friedman et al., 2001; Srinivasan et al., 2002; Shen et al., 2014; Sevgili et al., 2020), i.e., a set of domain concepts and their hierarchical organization (and additional relations in

the case of an ontology). However, the task of creating or maintaining these resources is laborious and never complete; as new documents are added or the use case shifts, there are concepts that are not well covered by the current taxonomy. As a result, typically a user must manually add new, relevant concepts to the taxonomy – a process which is both time-consuming and expensive.

Here we present a tool that is designed to streamline this process by using automatically gleaned text summarization analytics from the corpus itself, coupled with the power and expressivity of recent contextualized embeddings, to suggest candidate concepts to a human user during an interactive session. The user can accept, reject, or manipulate the suggested concept, then determine where it belongs in relation to other existing nodes. Taxonomies can be persisted for downstream use or a subsequent editing session. Our contributions are:

(1) We propose a data-driven approach to interactively build or augment a taxonomy with new concepts derived from the corpus of interest. The human user is at the center of our workflow and retains full control. Our approach first ranks and then clusters corpus concepts to provide the user with highly salient and coherent suggestions for new taxonomy nodes. In a web application, the user can act on the suggestions by adding, editing, deleting, or skipping them as desired. The tool is designed to be domain agnostic and interactive, with expensive steps performed in advance.

(2) We provide two case studies to demonstrate the utility of our approach, first, focused on a causal analysis of the drivers of food insecurity, and second, managing regional security (Section 5). We show that a user was able to process an average of 200 nodes per hour, 16% of which were added to the taxonomy. We find that the extended taxonomy results in an overall consistently higher grounding

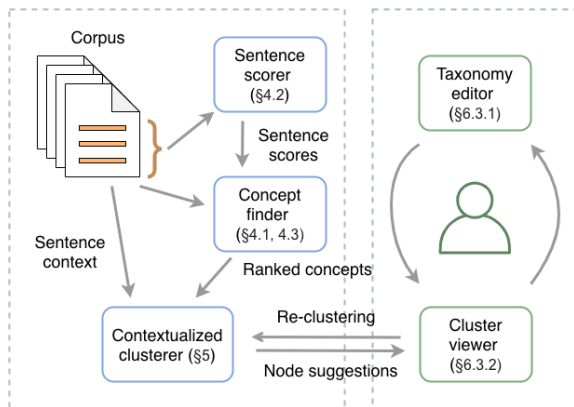


Figure 1: Overall architecture of our Taxonomy Builder, which combines offline pre-processing steps (the components in the left panel) with online user sessions (right panel).

confidence. We show that this increased confidence correlates with an increase in grounding correctness. Further, the updated taxonomy results in an increase in the number of causal relations between high-confidence grounded concepts.

2 Related work

There are several large, ontological resources, e.g., WordNet (Miller, 1995; Fellbaum, 2010), Cyc (Lenat, 1995), UMLS (Bodenreider, 2004), and SNOMED CT (Donnelly et al., 2006). However, resources such as these, even in aggregate, do not have coverage of all domains; instead, they need to be perpetually extended to cover new concepts (Powell et al., 2002; Ceusters, 2011).

To address the human cost of creating or maintaining taxonomies, many proposed approaches either rely on supervised data (Bordea et al., 2016; Mao et al., 2018; Espinosa-Anke et al., 2016, e.g.) or perform unsupervised term extraction and clustering (Bisson et al., 2000; Drymonas et al., 2010, e.g.). As supervised training cannot be assumed in real-world settings, our approach is more similar to the latter; we use unsupervised methods for concept discovery, ranking, and clustering. However, we keep the human in the loop to guide the process, critical for sensitive use cases such as military events, medical emergencies, etc.

Maedche and Staab (2001) similarly propose a tool that allows a user to guide a semi-automatic ontology creation process. However, our approach uses techniques from text summarization to filter candidate concepts and modern contextualized embeddings to more robustly handle multiple word senses and multi-word phrases to minimize the work that must be done by the user.

3 Architecture

Our approach for rapid data-driven taxonomy generation combines insights from several layers of text understanding to suggest highly relevant candidate concepts to a user, who decides how to use them (or not) to build the taxonomy they need. The architecture is shown in Figure 1.

Specifically, given a corpus of documents and optionally an existing taxonomy, we assign saliency scores to each sentence based on keyword occurrence (Appendix A.1). From sentences with a sufficiently high saliency, we extract multi-word expressions (noun and verb phrases) as potential phrases of interest. These are ranked with respect to each other using an extension of the TextRank algorithm (Mihalcea and Tarau, 2004) (Appendix A.3). The top-ranked concepts are encoded with contextualized word embeddings and clustered (Appendix B). Resulting clusters are presented to the user as suggested novel concepts; the phrases in the clusters can be thought of as *examples* of that concept. To ensure interactivity, these computationally expensive steps are done ahead of time, and the user need only load the pre-computed initial clusters.

Once loaded, clusters are exposed to the user through our interactive web application. The user can then decide between a series of actions (Section 4); specifically, they can *accept*, *edit*, *skip*, or *discard* the node. Accepted nodes are then inserted into the current working taxonomy. The user continues to work through the system’s suggestions until they are satisfied with the taxonomy.

4 Taxonomy builder workflow

Once phrases are ranked and clustered, they are passed to the user-facing interface, which implements a two-part workflow: (a) cluster curation and (b) concept organization.

4.1 Cluster curation workflow

We frame the **cluster curation** workflow as a potentially iterative process, where the user adds novel nodes to the taxonomy from the suggested clusters and then, if desired, submits unused phrases for re-clustering and a subsequent iteration of curation. By eliminating phrases that are irrelevant or have already been associated with a taxonomy node, each iteration provides an improved basis for organizing the remaining phrases into new, potentially usable clusters. The workflow for a curation iteration is illustrated in Figure 2:

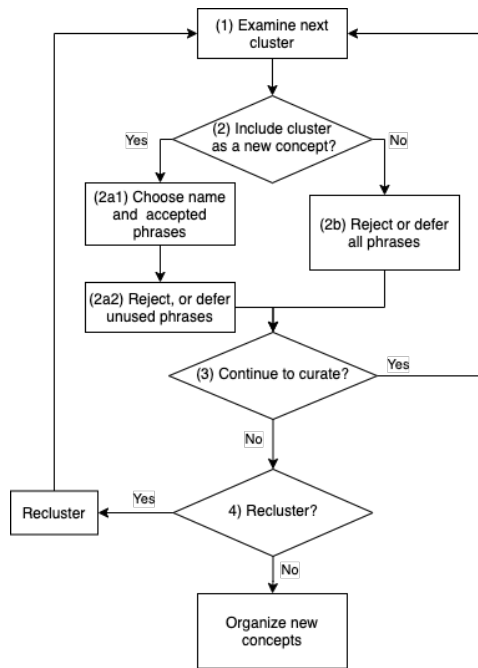


Figure 2: Cluster curation workflow.

- 1 User examines clusters in descending order of cluster score.
- 2 For each cluster, the user decides whether to include it as a taxonomy node, informed by its perceived relevance to the use case and its perceived added value, relative to existing nodes.
 - 2a1 If the cluster is included, one phrase is selected for the node *name* and one or more phrases are chosen as concept *examples*; this can be done in bulk.
 - 2a2 User can also *reject* or *defer* unused phrases from this cluster. Rejected phrases are excluded from reclustering, whereas deferred phrases are included if the user chooses to recluster.
 - 2b If the cluster is not included in (2), the user can either reject or defer the entire cluster, or some of its phrases.
- 3 User decides whether to continue to curate or, if remaining clusters appear to be unlikely candidates for inclusion, to *defer* the remaining clusters.
- 4 Having completed an iteration of curation, the user either reclusters or moves on to the concept organization workflow.

4.2 Concept organization workflow

The **concept organization** workflow is: Examining each of the newly generated concepts in turn, the user 1) searches for an existing taxonomy node that would be a suitable parent to the new concept, 2) adds the concept to an existing branch if one is found or a new branch if none exists, and 3) updates any additional required concept metadata. Once all concepts have been organized within the taxonomy, the user publishes the new or augmented taxonomy.

4.3 User interface

The above workflows are carried out using a web application that includes a cluster viewer and a

taxonomy editor. The **cluster viewer** displays the clustered concepts and allows the user to include or exclude clusters. The **taxonomy editor** allows the user to traverse the taxonomy tree, add or remove nodes, move existing nodes to different branches, and make changes to node metadata. The user can toggle between these at any time.

4.3.1 Cluster viewer

The cluster viewer consists of 1) reclustering controls, 2) a cluster list, and 3) a target node editor. The reclustering controls allow the user to submit new clustering jobs and access previously submitted jobs. The cluster list displays all clusters in descending order of score and contains controls for adding clusters to the taxonomy as concept nodes. The target node editor permits directly editing a new or existing taxonomy node corresponding to the given cluster (see Figure 3).

Each displayed cluster has a panel showing a) a node selector tool allowing a user to select an existing node or create a new node in the taxonomy as the "target" for the current cluster, b) a recommended concept name, initially populated by the first phrase within the cluster, c) a switch to either reject or curate the cluster (*curate* by default), d) the list of cluster phrases, e) phrases selected for inclusion, f) rejected phrases. Each cluster phrase has an option to *accept* it as an example, *reject* it, or *select it as the concept name*. The target node can be updated in the target node editor panel (3) and even moved in the taxonomy by updating its "parent" field. Through the inclusion of defaults, we ensure that the user does not need to treat all phrases, saving them time.

When the user first enters the cluster viewer, the application fetches and displays the initial clustering results. Once the user has included at least one cluster as a new concept by accepting a phrase, the option to recluster is enabled. When the user executes this option, the application submits a clustering job including all deferred phrases, clears the cluster results, and polls the clustering service for the job status. When the new clustering job is finished, the new cluster results are displayed and the job id is persisted in the application state for that user, allowing the user to follow the curation workflow over multiple iterations despite interruptions. Accepted clusters are automatically added to a top-level branch in the taxonomy named "clusters." Any changes to a cluster's name and accepted phrases automatically propagate to the

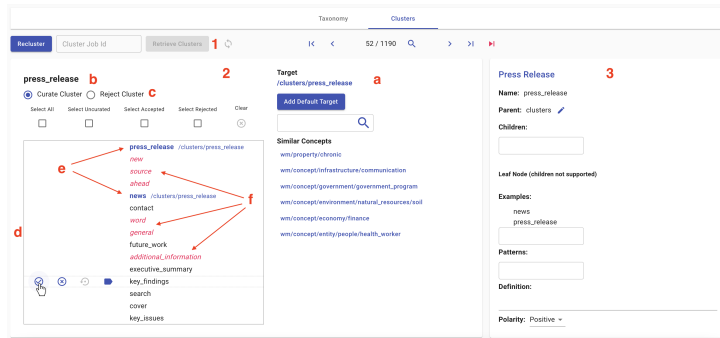


Figure 3: Cluster viewer user interface. Number and letter labels refer to the elements as described in Section 4.3.1.

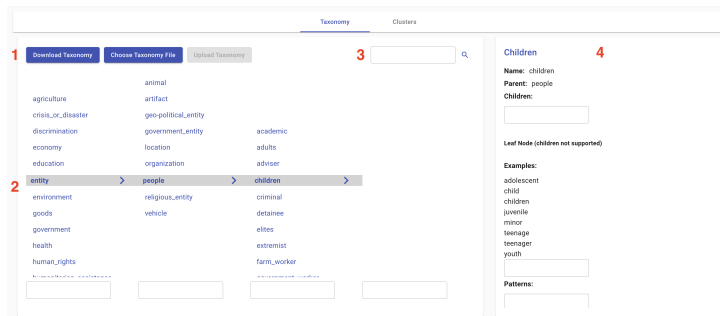


Figure 4: Taxonomy editor user interface. Number labels refer to the elements as described in Section 4.3.2.

corresponding concept’s name and examples.

4.3.2 Taxonomy editor

The taxonomy editor consists of 1) import/export controls, 2) taxonomy explorer, 3) concept search widget, and 4) node editor (Figure 4). The import/export controls permit the user to upload a taxonomy and download the current state of a taxonomy as a taxonomy file. The taxonomy explorer provides a collapsed tree view of the taxonomy similar to multi-directory views common to many operating systems. This permits users to see a selected node, its siblings, its children, and its closest three ancestors and their siblings. Visible nodes can be clicked to become the new selection, allowing users to traverse the taxonomy in any “direction.” This format was chosen because it displays a relatively broad cross-section of the taxonomy without sacrificing intelligibility and navigability. The concept search widget allows users to search for concept names and navigate to them without having to click through the explorer. The node editor allows users to update the concept name, update its parent, add and remove children, and update node metadata.

5 Usage Scenarios

We evaluate our tool through two use cases, both of which are motivated by DARPA’s World Modelers

program:¹ food insecurity and regional security. We detail both evaluations in Appendix C. The take-home messages from this evaluation were: (a) the users were able to process 200 candidates for taxonomy concepts per hour using the tool; (b) the updated taxonomies yielded increased grounding confidence scores, which indicate that the new taxonomies fit the data better, and (c) the new grounding confidence scores have increased correlation with grounding correctness.

6 Conclusions

We introduced a tool to streamline taxonomy construction and extension. Using techniques from text summarization alongside the benefits of modern pretrained language models, we automatically glean cohesive taxonomy node suggestions from the corpus itself. The user interface then allows users to quickly review suggestions and decide whether to accept or reject part or all of each. Through two case studies, we showed that this tool can be used to rapidly extend an existing taxonomy in a matter of hours, and further that the resulting taxonomy is a better fit to the domain of interest.

The software is included in the DART framework at: <https://github.com/twosixlabs-dart/dart-ui>.

¹<https://www.darpa.mil/program/world-modelers>

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A Concepts

For the process of selecting phrases from the corpus to serve as potential concepts of interest (or examples of those concepts), we use filters to both improve the speed of clustering and reduce the noise in the final clusters themselves.

A.1 Sentence salience

To prevent candidate phrases that are not salient to the core content of the documents, we use a simple *extractive text summarization* technique to identify the most salient or important sentences and assign each a score (Luhn, 1958; Allahyari et al., 2017).

We first lowercase document text and tokenize with `spaCy`,² ignoring stopwords and punctuation. We then extract keywords by calculating the frequency of all words, normalizing such that the most frequent has a value of 1. Finally, we calculate sentence salience scores by identifying the occurrence of keywords within a sentence, summing their frequency values, and normalizing these sums such that the most salient sentence in a document, i.e., the one with the highest sum, has a score of 1.

The sentence salience score quality was evaluated against a human rater. We selected random pairs of sentences, and for each asked our rater to determine which sentence was more important to the meaning of the document. A preliminary analysis with 10 news articles found that the human judgment agreed with the assigned scores 80% of the time. In cases of disagreement, typically the human chose a headline or summary sentence, whereas the algorithm chose a sentence with detailed but relevant information. From this preliminary analysis, we made two minor changes that made the model more robust to irregularities in documents: disregarding bullet points and subheadings. After making this change, rater judgments were nearly 100% aligned with the assigned salience scores.

A.2 Candidate phrases

To get candidate phrases from the sufficiently salient sentences, we process them with the CLU lab processors library.³ We then select noun and verb chunks, splitting on coordinating conjunctions and trimming determiners from the edges. We note frequency and where they occur, keeping the 10k most frequent.

²<https://spacy.io>

³<https://github.com/clulab/processors>
We use FastNLPPProcessor, based on CoreNLP (Manning et al., 2014).

	Strategy 1	Strategy 2	Strategy 3
Expert 1	55%	30%	25%
Expert 2	70%	45%	25%

Table 1: Manual evaluation results (P@20) for three different strategies (Section A.3) for edge weights in the phrase graph. Strategy 1 uses *similarity* alone, Strategy 2 uses *similarity* \times *PMI*, and Strategy 3 uses *similarity* \times *PMI* \times *frequency*. P@20 indicates what percentage of the concepts ranked in the top 20 were considered relevant for the use case by the corresponding expert.

A.3 Ranking candidates

These 10k phrases are ranked using an extension of TextRank (Mihalcea and Tarau, 2004), an algorithm inspired by PageRank (Page et al., 1999) that treats text as a graph and applies a graph-based ranking algorithm to surface keywords or phrases. The key extension in this effort is that nodes in the constructed graph are the phrases previously extracted, rather than full sentences, as in the original algorithm.

The algorithm consists of four steps: (1) Identify text units that best fit the task to be nodes in the graph; (2) Identify relations between units and draw the corresponding edges; (3) Iterate the graph-based ranking algorithm until convergence; (4) Sort nodes based on ranking scores.

As mentioned, in our implementation of TextRank, we consider our extracted chunks to be the text units (i.e., nodes in the graph) rather than complete sentences. We experimented with several options for defining edge weights, including word embedding similarity, Point-wise Mutual Information (PMI), and frequency of co-occurrence in the same sentence. (Mahata et al., 2018). For the embedding similarity, we represent each phrase as its GloVe embedding (Pennington et al., 2014), averaging embeddings of multi-word expressions, and compare with cosine similarity. Building on these three information sources, we compared three edge similarity strategies:

$$strategy_1 = cosine_similarity(c_1, c_2) \quad (1)$$

$$strategy_2 = strategy_1 \times PMI(c_1, c_2) \quad (2)$$

$$strategy_3 = strategy_2 \times log(cooccur(c_1, c_2)) \quad (3)$$

where c_1 and c_2 are the phrases to be compared.

Using a small set of documents, we had two domain experts do a blind evaluation of the top-ranked phrases produced by the different strategies. As shown in Table 1, strategy 1 produces the best TextRank overall,⁴ and so was chosen. To avoid a

⁴Post-hoc analysis showed that strategy 2 prefers infre-

fully connected graph, which slows down the Text-Rank algorithm dramatically, we set a threshold for the similarity scores⁵ and for each phrase, we keep only edges for the 100 most similar neighbors.

After ranking the extracted phrases, the highest-ranked 5k are used for generating the node suggestion clusters (Section B).

B Clustering

After extraction, phrases are clustered into semantically cohesive groups to serve as taxonomy node suggestions. We use Huggingface transformers (Wolf et al., 2020) to obtain contextualized DistilBERT (Sanh et al., 2020) embeddings of each occurrence of each phrase. We then use Annoy⁶ to perform time-efficient nearest neighbor search over these embeddings. For each phrase, we obtain a ranked list (in terms of cosine similarity) of the top- k most similar phrases as input to the clustering.

To cluster the phrases, we employ an algorithm based on the CBC algorithm (Clustering By Committee) (Pantel and Lin, 2002), which uses average link agglomerative clustering (Schütze et al., 2008, Ch. 17) to recursively form cohesive clusters that are dissimilar to one another. For each cluster c that is formed, the algorithm assigns a score: $|c| \times \text{avgsim}(c)$, where $|c|$ is the number of members of c and $\text{avgsim}(c)$ is the average pairwise cosine similarity between members. This score reflects a preference for larger and cohesive clusters. We then rank the clusters in decreasing order of their cluster scores, prioritizing the most effective and cohesive clusters to the user for selection and addition to the taxonomy.

C Usage Scenarios and Discussion

We evaluate our tool through two use cases, both of which are motivated by DARPA’s World Modelers program.⁷ The first use case focuses on food insecurity, which is a complex domain, spanning several disciplines including economics, government policy, agriculture, etc. The second use case addresses regional security, an equally complex domain.

quent phrases that aren’t descriptive of the overall topic, e.g., *intergovernmental panel* and *environ*, whereas strategy 3 oppositely adds frequent phrases, e.g., names of countries, which the experts deemed not useful for taxonomy construction.

⁵We found 0.0 to be both a useful and intuitive threshold.

⁶<https://github.com/spotify/annoy>

⁷<https://www.darpa.mil/program/world-modelers>

C.1 Use case 1: food insecurity

For this use case, the user⁸ was provided with an initial taxonomy⁹ created for the DARPA World Modelers program, and used the tool to perform cluster curation and taxonomy editing for 2 hours. In this time, the user was able to curate 400 clusters. Of those 400, 65 were chosen for inclusion as taxonomy nodes, 18 were *deferred* for reclustering, and the remaining 317 were *rejected* entirely. After this curation, the resulting taxonomy was compared against the original.

For this case study, we use a corpus of 472 documents from the food insecurity domain (government and NGO reports, news articles, etc.). We perform IE using the Eidos causal information extraction system (Sharp et al., 2019), resulting in 209,352 extracted concepts related to food security.

We then attempt to ground each concept mention to the taxonomy, assigning a grounding confidence score. There are many ways of assigning a confidence score. Here, we create a vector representation for the mention to be grounded and of each node in the taxonomy by averaging the GloVe embeddings for each non-stop word in the mention’s text span and the taxonomy node’s examples, respectively. We then assign each mention to the node that is closest in terms of cosine similarity.

We analyze extracted mentions and their grounding before and after the taxonomy update. Of the 209,352 concepts extracted, 170,488 were grounded before the update and 170,539 were grounded after.¹⁰ Further, after the update, 48,404 concepts (28% of grounded concepts), were grounded to a different taxonomy term. For example, the phrase *ethnic-religious divisions* was originally grounded to the taxonomy concept `crisis_or_disaster/conflict/hostility` (with a score of 0.48), but after the update, it is grounded to `ethnic_conflicts` (with a higher score of 0.56).

Of the groundings that changed, for 47,518 the confidence increased after the taxonomy update (98% of those that changed). Figure 5 shows the distribution of the changes in grounding scores attributed to the taxonomy update. Importantly, we observed that this increase in grounding confi-

⁸One of the authors served as the tool’s user.

⁹<https://github.com/WorldModelers/Ontologies>

¹⁰The Eidos system has an internal filter that doesn’t produce groundings when the confidence is below 0.2.

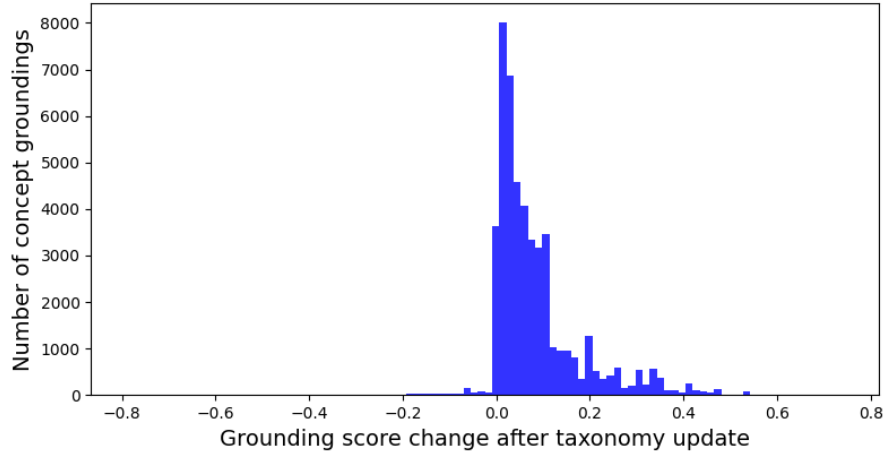


Figure 5: Histogram of changes in grounding scores associated with specific concepts after the taxonomy update in use case 1.

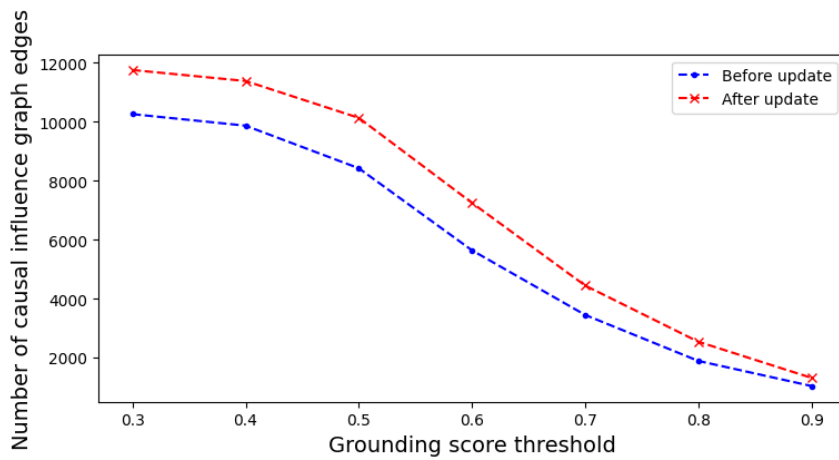


Figure 6: The number of causal influence graph edges over concepts obtained before and after the taxonomy update at a given grounding score threshold in use case 1.

dence correlates with grounding correctness. To verify this, we measured the Pearson correlation between grounding confidence and correctness (which is represented as a Boolean variable, i.e., correct/incorrect grounding) for 42 randomly selected concepts. The Pearson correlation values were 55.15% for the original taxonomy vs. 59.37% for the updated one, a relative increase of 7.6%.

Next, we use INDRA (Gyori et al., 2017; Sharp et al., 2019), an automated model assembly system, to assemble each set of causal influence relations (before and after taxonomy updating) into a causal influence graph by aggregating relations with matching groundings. We find that the number of edges in the causal influence graph increased from 11,072 to 12,720 after the taxonomy update, and further, we show in Figure 6 the number of edges in each influence graph between nodes whose grounding scores are above a given threshold. As shown, after the taxonomy update, the influence

graph is consistently larger and covers more taxonomy terms compared to before, with higher confidence.

C.2 Use case 2: regional security

This use case was performed by a group of expert analysts outside the tool’s developer team as part of a DARPA program evaluation. The analysis attempted to model a complex regional crisis scenario, using IE from documents to construct models of causal influences of security concerns surrounding Kenya’s 2022 elections.

Users started from an initial taxonomy¹¹. 10k documents relevant for the use case were identified by the organizers of the evaluation to seed the taxonomy extension process. Users were then given access to the tool to perform cluster curation and

¹¹<https://github.com/WorldModelers/Ontologies>

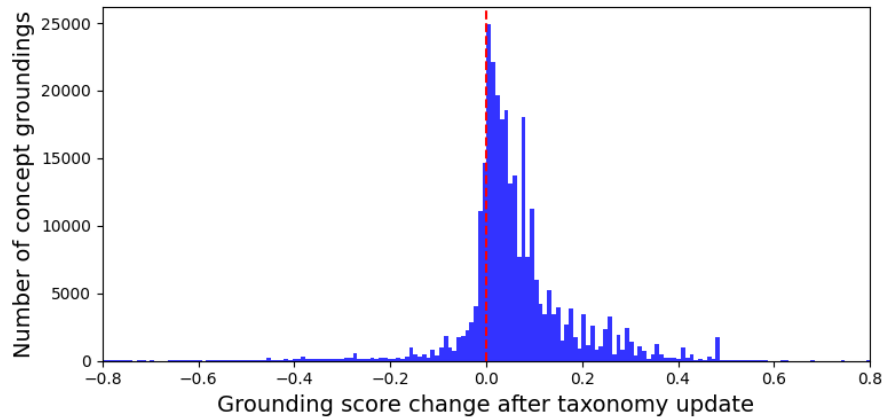


Figure 7: Histogram of changes in grounding scores associated with specific concepts after the taxonomy update in use case 2 (the red line provides vertical axis at 0 score change for clarity).

taxonomy editing over the course of multiple days.

Similar to use case 1, to evaluate the effect of taxonomy changes, we performed IE using Eidos on the seed corpus. This resulted in a total of 1,205,628 concepts extracted from the 10k document corpus. We then grounded each extracted concept – using the approach described for use case 1 – with respect to the taxonomy both before and after the update. We found that 297,405 of the extracted concepts (24.6% of all extracted) were grounded to different taxonomy entries after the update. Of these, 247,113 (83%) were grounded with a higher score compared to before (see Figure 7 for the distribution of score changes).

Using INDRA, we then assembled causal relations that were extracted between concepts from the corpus into a causal influence graph before and after the taxonomy update. In both cases, we applied a grounding score threshold of 0.6 to retain concepts grounded to a taxonomy term with high-confidence. We found that the number of nodes in the graph increased from 337 to 451 (an increase of 33.8%) and the number of edges grew from 23,274 to 29,562 (a 27.6% increase) after the update. Overall, we again found that the taxonomy update resulted in a larger causal influence graph at a given level of confidence.