Release Early, Release Often: Predicting Change in Versioned Knowledge Organization Systems on the Web

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\textbf{Abstract.} The Semantic Web is built on top of Knowledge Organization Systems (KOS) (vocabularies, ontologies, concept schemes) that provide a structured, interoperable and distributed access to Linked Data on the Web. The maintenance of these KOS over time has produced a number of KOS version chains: subsequent unique version identifiers to unique states of a KOS. However, the release of new KOS versions pose challenges to both KOS publishers and users. For publishers, updating a KOS is a knowledge intensive task that requires a lot of manual effort, often implying deep deliberation on the set of changes to introduce. For users that link their datasets to these KOS, a new version compromises the validity of their links, often creating ramifications. In this paper we describe a method to automatically detect which parts of a Web KOS are likely to change in a next version, using supervised learning on past versions in the KOS version chain. We use a set of ontology change features to model and predict change in arbitrary Web KOS. We apply our method on 139 varied datasets systematically retrieved from the Semantic Web, obtaining robust results at correctly predicting change. To illustrate the accuracy, genericity and domain independence of the method, we study the relationship between its effectiveness and several characterizations of the evaluated datasets, finding that predictors like the number of versions in a chain and their release frequency have a fundamental impact in predictability of change in Web KOS. Consequently, we argue for adopting a release early, release often philosophy in Web KOS development cycles.

\textbf{Keywords:} KOS change, Linked Data versioning, Ontology evolution

1 Introduction

\textbf{Motivation.} Knowledge Organization Systems (KOS), such as SKOS taxonomies and OWL ontologies, play a crucial role in the Semantic Web. They are at the core of any Linked Data vocabulary and provide structured access to data, formalize the semantics of multiple domains, and extend interoperability across the Web. Concepts are central entities in KOS and represent objects with common
characteristics. However, with time, objects are continuously subject to change. As the world changes, our understanding of it evolves. Consequently, concepts in KOS change over time.

**Problem definition.** Curation of KOS is a manual, knowledge intensive and arduous task. To adapt their systems to domain changes, data publishers update their KOS through *versioning*, mostly using their expert knowledge. This creates *KOS version chains*: subsequent unique version identifiers to unique states of a KOS. Changes in the domain positions publishers and users of KOS in a great dilemma. For publishers, the continuous evolution of knowledge has a severe impact on their update work. Users create links in their datasets to well-known KOS, but the validity of these links is compromised when the KOS is updated to a new version. Automatic detection of concept change would be a great aid towards proactivity for publishers and users of KOS. Unfortunately, there is currently hardly any tool to help dealing with concept change.

**Use cases.** To enhance comparability studies in the history of work, social scientists and historians have developed the Historical International Standard Classification of Occupations (HISCO), a historical taxonomy of occupations since the 16th century. Many historical datasets need to update their links to HISCO concepts across their different versions. The Gene Ontology (GO) standardizes the representation of gene attributes across species and datasets. A new version is released every month. DBpedia, an RDF version of Wikipedia, is frequently updated to improve cross-domain knowledge access. Linked Open Vocabularies (LOV) gathers versions of vocabularies used in the Linked Open Data (LOD) cloud linking Web resources. Librarians, social scientists, historians, biologists and webmasters have a dire need to assess this versioning processes by identifying, and predicting, when a concept will change in the forthcoming release. This will reduce time spent in manual data exploration or requirements gathering, on publishers’ side; and will lower ramifications (i.e. simultaneous use of old and new versions) on users’ side.

**Contribution.** We describe a generic approach to predict change in version chains. Previous approaches have proven to be effective in (i) predicting *enrichment*; (ii) of *OBO/OWL* ontology classes; and (iii) in the *biomedical domain* [1,2]. Our interest is to investigate if a more generic approach works for predicting *when and where* a Web KOS of any domain will change. We extend this idea in a *generic KOS change prediction framework* based on supervised learning on past versions of Linked Datasets, that (I) predicts *change* (i.e. estimates if a concept will change its meaning); (II) in arbitrary RDF graphs; and (III) in a domain-independent manner. We evaluate this approach in 139 KOS in social history, encyclopedic knowledge, Web ontologies and Web vocabularies. We study the properties of these KOS that favour better change predictions.

**Research Questions.** We focus on the following research questions:

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[3] See [http://historyofwork.iisg.nl/](http://historyofwork.iisg.nl/)

[4] See [http://www.geneontology.org/](http://www.geneontology.org/)

[5] See [http://lov.okfn.org/](http://lov.okfn.org/)
– **RQ1.** Can past knowledge be used to predict concept change in Web KOS? Can this be done by extending a class-enrichment prediction method into a concept change prediction method?

– **RQ2.** What features encoding past knowledge have a greater influence on future changes? What classifier performs best to predict these changes?

– **RQ3.** Can this new method predict change in KOS independently of the domain of application? What features characterize the Web KOS where this method works best?

**Findings.** We run our pipeline in 139 different KOS version chains in RDF, including the Dutch historical censuses, the DBpedia ontology, in-use ontologies in the SPARQL endpoints of the LOD cloud, and Linked Open Vocabularies used all over the Web. We obtain solid evaluation performances, with f-measures of 0.84, 0.93 and 0.79 on predicting test data with learnt models. We characterize the datasets in which our approach works best. We find that features such as dataset size, the number of versions in the chain, the time gap between each version, the complexity of their schemas or the nature of the edits between versions have a strong influence in the quality of the predictive models of change.

The rest of the paper is structured as follows. In Sections 2 and 3 we survey previous efforts to address change in KOS, and define our target problem and formalism. Section 4 describes our approach, pipeline and feature set. In Section 5 we perform an experimental evaluation in 139 Web KOS version chains, describing the input data, process, results and dataset characterization. In Section 6 we discuss these results with respect to our research questions, before we conclude.

**2 Related Work**

In Machine Learning changes in the domain are related with the phenomenon of concept drift. It is difficult to learn in real-world domains when “the concept of interest may depend on some hidden context, not given explicitly in the form of predictive features. (...) Changes in the hidden context can induce more or less radical changes in the target concept, which is generally known as concept drift” [19]. Hence, drift occurs in a concept when the statistical properties of a target variable (the concept) change over time in unforeseen ways. Multiple concept drift detection methods exist [6].

With the advent of the Semantic Web, changes in concepts have been investigated by formally studying the differences between ontologies in Description Logics [7]. [1] propose a method based on clustering similar instances to detect concept change. [20] define the semantics of concept change and drift, and how to identify them, in a Semantic Web setting. The related field of ontology evolution deals with “the timely adaptation of an ontology and consistent propagation of changes to dependent artifacts” [1]. As stated by [18], the first step for any evolution process consists in identifying the need for change; change capturing can then be studied as structure-driven, data-driven or usage-driven. Accordingly,
change is only a step in the evolution process, although the definition of the goal of ontology change ("deciding the modifications to perform upon an ontology in response to a certain need for change as well as the implementation of these modifications and the management of their effects in depending data, services, applications, agents or other elements") suggests that the overlap between the two fields is considerable. [16] propose a method based on supervised learning on past ontology versions to predict enrichment of classes of biomedical ontologies, using guidelines of [18] to design good predictors of change. The need of tracing changes in KOS in application areas of the Semantic Web has been stressed, particularly in the Digital Humanities [14] and Linked Statistical Data, where concept comparability [3] is key.

3 Problem Definition

We base our definition of change in Web KOS on the framework proposed by [20].

Definition 1. The meaning of a concept \( C \) is a triple \((\text{label}(C), \text{int}(C), \text{ext}(C))\), where \( \text{label}(C) \) is a string, \( \text{int}(C) \) a set of properties (the intension of \( C \)), and \( \text{ext}(C) \) a subset of the universe (the extension of \( C \)).

All the elements of the meaning of a concept can change. To address concept identity over time, authors in [20] assume that the intension of a concept \( C \) is the disjoint union of a rigid and a non-rigid set of properties (i.e. \( \text{int}_r(C) \cup \text{int}_n(C) \)). Then, a concept is uniquely identified by some essential properties that do not change. The notion of identity allows the comparison of two variants of a concept at different points in time, even if a change on its meaning occurs.

Definition 2. Two concepts \( C_1 \) and \( C_2 \) are considered identical if and only if, their rigid intensions are equivalent, i.e., \( \text{int}_r(C_1) = \text{int}_r(C_2) \).

If two variants of a concept at two different times have the same meaning, there is no concept change. We define intensional, extensional, and label similarity functions \( \text{sim}_\text{int}, \text{sim}_\text{ext}, \text{sim}_\text{label} \) in order to quantify meaning similarity. These functions have range \([0, 1]\), and a similarity value of 1 indicates equality.

Definition 3. A concept has extensionally changed in two of its variants \( C' \) and \( C'' \), if and only if, \( \text{sim}_\text{ext}(C', C'') \neq 1 \). Intensional and label change are defined similarly.

We implement this framework as our definition of concept change between two KOS versions in a version chain.

4 Approach

The basic assumption of our proposed approach is that the knowledge encoded in past versions of a Linked Dataset can be used to faithfully predict which
parts of it will suffer changes in a forthcoming version. Features that have an influence in changing an ontology have been previously studied and classified as: **structure-driven**, derived from the structure of the ontology (e.g. if a class has a single subclass, both should be merged); **data-driven**, derived from the instances that belong to the ontology (e.g. if a class has many instances, the class should be split); and **usage-driven**, derived from the usage patterns of the ontology in the system it feeds (e.g. remove a class that has not been accessed in a long time).

[18] have successfully proven the use of these features (i) to predict **class enrichment**, that is, to estimate if a class will be extended (e.g. with new children or properties) in the future; (ii) in (OBO/OWL) ontologies; and (iii) in the biomedical domain. However, it remains unclear if supervised learning and features of [18] can be generally applied (I) to predict **general change**, that is, to estimate if a concept will experience change in its meaning; (II) in any Linked Dataset (i.e. generic RDF graphs); and (III) in a domain-independent manner.

In order to investigate these, we present a pipeline that includes: (a) an abstraction of the input parameters required for the learning process; (b) an abstraction of features that apply not only to OBO/OWL ontologies, but to any Linked Dataset; and (c) a pre-learning optimization technique to merge features of identical versioned concepts into single training/test individuals.

### 4.1 Pipeline

Figure 1 shows the pipeline of our proposed approach. Taking input \{Feature generation parameters, change definition, version chain, learning parameters\}, the system returns output \{Feature selection, classifier performance\}.

First, the **Feature Generator (FG)** generates \(k\) training datasets and one test dataset, according to the following input set elements: (a) **version chain** containing \(N\) versions of a KOS, in any RDF serialization, where the change prediction is to be performed; (b) several user-set **feature generation parameters** that control the feature generation process (the \(\Delta_{FC}\) parameter, setting the version to be used to decide if a concept of the training data has changed; and the \(\Delta_{TT}\) parameter, setting the version to be used to decide if a concept of the test data has changed); and (c) a customizable **definition of change** that...
Fig. 2: A KOS version chain. Training and test datasets for $N = 7$, $\Delta FC = 1$ and $\Delta TT = 2$.

determines the value of the target variable. The last element of the input set, learning parameters, is passed further to be used in a later stage. Once all set, $k$ training datasets and the test dataset are built by the FG as shown in Figure 2. The parameters $N$, $\Delta FC$ and $\Delta TT$ are used to determine which versions will play the role of $\{V_t\}$, $V_r$ and $V_e$. $\{V_t\}$ is the set of training versions, which are used to build the training dataset. $V_r$ is the reference version, against which all versions in $\{V_t\}$ are compared, using the definition of change provided as input, to determine whether there is concept change or not. $V_e$ is the evaluation version and is used to build the test dataset, following a similar procedure as with $\{V_t\}$ and $V_r$, this time comparing $V_r$ with $V_e$. $V_e$ is set by default to the most recent version. While extracting features, each concept is labeled depending on whether change happened between one version of the concept and the next, using definitions of Section 3. Since versions can only be compared pairwise, the FG produces $k$ training datasets. In order to preserve identity of learning instances, the Identity Aggregator (IA) matches concepts in the $k$ training datasets and merges their features into one individual, modifying the dataset dimensionality accordingly. The training and test datasets are then ingested by the Normalizer (Norm), which adjusts value ranges, recodes feature names and types, and discards outliers. Finally, the training and test datasets are used by the Machine Learning Interface (MLI) as an input for the feature selection and classification tasks. These are done in a generic and customizable way, building on top of the implementation of state-of-the-art machine learning algorithms contained in the WEKA API [9]. The last element of the pipeline’s input set, learning parameters, is used here to achieve this and contains: (a) a feature selection algorithm to rank features according to their influence on conceptual change; (b) a relevance threshold $t$ to filter these selected features; and (c) the list of classifiers to be trained. First, the MLI runs the chosen feature selection algorithm. Second, it trains the chosen subset of WEKA classifiers (all by default). Last, it evaluates the trained models and stores results.
4.2 Feature Set

We propose sets of concept structural features and membership features. Structural features measure the location and the surrounding context of a concept in the dataset schema, such as children concepts, sibling concepts, height of a concept (i.e. distance to the leaves), etc. Since classification schemas are graphs in general and may contain cycles, these properties are defined with a maxDepth threshold that indicates the maximum level at which the property will be calculated (e.g. direct children, children at depth one, two, etc.). A concept is considered to be a child of another if they are connected by a user-specified property (e.g. skos:broader, skos:narrower or rdfs:subClassOf). We use direct children (descendants at distance 1) [dirChildren], children at depth ≤ maxDepth [dirChildrenD], direct parents (concepts this concept descends from) [parents], and siblings (concepts that share parents with this concept). Membership features measure to what extent a concept in the classification is used in the data. A data item in a Linked Dataset is considered to be using a concept of the classification if there is a user-defined membership property linking the data item with the concept (e.g. dc:subject or rdf:type). We use members of this concept [dirArticles] and total members considering all children at depth ≤ maxDepth [dirArticlesChildrenD] as membership features. Finally, we define a set of hybrid features that combine the previous into a single one (e.g. ratio of members per number of direct children) [ratioArticlesChildren, ratioArticlesChildrenD]. These sets of features map conveniently to the different types of change discovery described by [18]: structural features implement structure-driven change discovery; and membership features can be seen both as data-driven (since they describe instances belonging to the ontology) and usage-driven (since users querying these are indirectly using their classes).

These features are computed for each concept in all versions as indicated by the training and test dataset building parameters (see FG module, Section 4.1). However, not all of them may be used for predicting change. [16] show that similar features based on [18] are good candidates for modelling class enrichment. We only select those that prove to be good predictors of concept change in arbitrary domains, as chosen by the feature selection (see MLI module, Section 4.1).

5 Evaluation

We apply our proposed approach to 139 KOS version chains retrieved from the Web. We describe the properties of such version chains, the experiment setup and the evaluation criteria. We report on our results, providing evidence to RQ2 and RQ3, evaluating: (a) the performance of the feature set as a generic predictor of change in KOS version chains (see Section 4.2); (b) the performance of the classifiers at the predicting task; and (c) characteristics of the KOS version chains where our approach works best.
5.1 Input Data

In order to study the genericity of our approach and its applicability in a domain-independent setting, we use a set of 139 multi- and interdisciplinary KOS version chains represented as Linked Data. We classify these 139 version chains in four groups: (1) a version chain of the DBpedia ontology with its latest 8 versions ([DBpedia]); (2) a version chain of the Dutch historical censuses dataset with its latest 8 versions ([CEDAR])\(^6\); (3) 3 version chains of ontologies retrieved from SPARQL endpoints in the Linked Data cloud, with at least 3 versions each ([SPARQL]); and (4) 134 version chains from Linked Open Vocabularies\(^7\), with at least 3 versions each ([LOV]). Each version within these chains consists of (a) schema information expressed using vocabularies such as SKOS, RDFS or OWL; (b) instance data making use of such schema; and (c) labels describing the nodes of the schema and the instances.

The version chain of the DBpedia ontology [DBpedia] is a community-curated formalization of all classes and properties describing DBpedia content. Instances are resources of DBpedia which have some class of the ontology as rdf:type. The set of labels are the rdfs:label literals attached to the classes of each versioned ontology. In the version chain of the Dutch historical censuses dataset ([CEDAR]), the classification is a SKOS hierarchy of HISCO occupations reported in each version. Instances are census observations of people having one of these HISCO occupations as cedar:occupation. The set of labels are the skos:prefLabel (Dutch) literals used in the census to describe these occupations in each specific version. The version chains containing ontologies retrieved from the Linked Data cloud ([SPARQL]) are retrieved by querying the 637 public SPARQL endpoints listed in [http://datahub.io/](http://datahub.io/). This returns 49 379 ontologies with at least one previous version (owl:priorVersion), and we use this property to reconstruct their version chains. We discard all non-dereferenceable and non-parseable version URIs, and we prune all chains with less than 3 versions, resulting in 3 ontology chains (geonames, fao and lingvoj). Finally, we obtain 134 version chains containing versions of Linked Open Vocabularies ([LOV]), a repository of all known versions of all known vocabularies in the Semantic Web. A detailed breakdown of these 4 groups, the 139 version chains and their characteristics is available at [http://bit.ly/kos-change](http://bit.ly/kos-change).

5.2 Experimental Setup

Our evaluation process is two-fold. First, we assess the quality of our features as concept change predictors, and we choose the most performing ones. We do this via feature selection (see Section 4.1). Second, we use these selected features for learning, and we evaluate quality of the resulting classifiers on predicting concept change. To evaluate classifiers we follow a simple approach: we compare the predictions made by the classifiers with the actual concept change going on

\(^6\)See [http://www.cedar-project.nl/](http://www.cedar-project.nl/)

\(^7\)See [http://lov.okfn.org/dataset/lov/](http://lov.okfn.org/dataset/lov/)
Table 1: Top selected features in CEDAR and DBpedia.

| CEDAR feature      | DBpedia feature      |
|--------------------|----------------------|
| 1 siblings         | dirChildren          |
| 2 dirArticlesChildrenD2 siblings | dirChildrenD2       |
| 3 ratioArticlesChildren dirChildrenD2 | dirChildrenD3 |
| 4 dirArticles dirChildrenD3 | dirChildrenD4       |
| 5 dirArticlesD1 dirArticlesD2 | dirArticlesChildrenD2 |

in a next dataset version. To do this, we use the test dataset $V_e$ (see Section 4.1) produced after setting the parameter $\Delta TT$. Since we compare predictions with unseen labeled data, we know whether the predictions are correct or not.

Since more versions are available in the version chains of [CEDAR] and [DBpedia], we execute several learning tasks adding more past versions to $\{V_t\}$ incrementally. We study how this impacts prediction of change in $V_i$. We also run a learning task considering all versions, and we use the trained classifiers to predict change in the most current version.

For assessing model quality, we use standard performance measures: precision, recall, $f$-measure, and area under the ROC curve. We perform a two-fold evaluation. On one hand, we evaluate the quality of the models produced without making any predictions and using 10-fold cross-validation with the training data. On the other hand, we use the same indicators to evaluate the classifiers’ prediction performance using the unseen test datasets $V_e/V_i$. We compare our results to a random prediction baseline.

5.3 Results

Table 1 shows the top selected features by the Relief algorithm [10], included in the WEKA API. The features are ordered according to their selection frequency. We observe that membership features (dirArticles, dirArticlesChildren) are systematically selected in the CEDAR data instead of structural properties (siblings, dirChildren). Conversely, we observe a clear preference for structural properties (dirChildren, dirChildrenD, siblings) in the DBpedia data. We execute our approach six times in the Dutch historical censuses (1) and the DBpedia (2) version chains, adding one Linked Dataset version to $\{V_t\}$ and shifting $V_i$ forward once each time. We identify each experiment with the year/timestamp of the version to be refined. Figure 5 shows the results. We also predict the most recent version of the DBpedia ontology, using all available versions as training set $\{V_t\}$, and leaving the last for testing ($V_e$). Table 2 shows the results.

Selected features for the 3 version retrieved from the SPARQL endpoints ([SPARQL]) and the 134 version chains of the Linked Open Vocabularies ([LOV]) are available at [http://bit.ly/kos-change](http://bit.ly/kos-change). Predictive models for these datasets are learnt with different results, as shown in Table 2. The quality of the prediction using learnt models for [SPARQL] is very high in the fao and
Table 2: 10-fold CV scores in the version chains from LOD SPARQL endpoints and Linked Open Vocabularies.

|        | fao | geonames | lingvoj | LOV (avg.) |
|--------|-----|----------|---------|------------|
| Precision | .751 | .438     | .95     | -          |
| Recall   | .765 | .662     | .947    | -          |
| F-measure| .744 | .527     | .937    | .922       |
| ROC area | .844 | .792     | .566    |            |

The lingvoj version chains, but almost as bad as random in geonames. Explanation for such results are detailed in the next section. Results for version chains in the LinkedOpenVocabularies can be found in detail at [http://bit.ly/kos-change](http://bit.ly/kos-change).

5.4 Characterization of Version Chains

The last part of our evaluation consists of studying what specific characteristics of the input version chains have a relationship with the quality of the learnt models and their predictive power (RQ3). To investigate this, we compute, for each version chain, a set of version chain characteristics that include: size of the chain (totalSize) in number of triples; number of versions in the chain (nSnapshots); average time gap (in days) between the release date of each version (avgGap); average size of each version (avgSize); number of inserted new statements between versions (nInserts); number of deletes (nDeletes); number of common statements (nComm); is the KOS a tree or a graph (isTree); maximum tree depth among versions (maxTreeDepth); average tree depth (avgTreeDepth); number of instances (totalInstances); ratio of instances over all statements (ratioInstances); number of structural relationships (totalStructural); and ratio of structural relationships over all statements (ratioStructural). First, we use regression to analyse which dataset characteristics are good predictors of the performance of the best selected classifier in our approach, using the area under the ROC curve as a response variable. The best model is shown in Figure 3. In these models we find that, under the null hypothesis of normality and non-dependence, the predictors nSnapshots, avgTreeDepth, ratioStructural, ratioInserts and ratioComm are good explanatory variables with respect to the performance of change detection in KOS version chains. The model in Figure 3, which includes ratioInserts discarding ratioDeletes and ratioComm due to multi-collinearity, shows the best model fit with respect to the data. Secondly, we use multinomial logistic regression to analyse what dataset characteristics are good predictors of the classifier type selected as best in our approach. A simulation with the best model is shown in Figure 4. In this model we find that avgGap is influential at selecting a tree.
classifier instead of a bayes one. We also find that totalSize is influential at selecting functions and rules based classifiers instead of bayes ones. In Figure 4, we show a simulation on how these predictors\textsuperscript{11} influence the choice of the different classifier families. Observe that all classifier families will be less likely chosen for the task when the time gap between KOS versions decreases, except for tree-based classifiers; in other words, more frequent releases will favours most models predicting change. Interestingly, ratios on instance and schema data will influence the best classifier type in an inverse way: more instance data will favour tree-based and rules classifiers, while more schema data will favour bayes classifiers. We discuss consequences of these results in the next section.

6 Discussion and Lessons Learned

In this Section we discuss our findings, by (1) observing specific correctly predicted changing concepts; (2) arguing the different classifier performances; and (3) claiming that the relationship found between some predictors in KOS version chains and their predictability empirically supports the release early, release often philosophy in KOS development.

\textsuperscript{11}Additional details at http://bit.ly/kos-change
We first explore some particular concepts predicted to change. For instance, http://cedar.example.org/ns#hisco-06 is an example concept of [CEDAR] predicted to change which in fact did: the class of “medical, dental, veterinary and related workers”. Most of its features present high stability across the versions; except those related to its instances. These vary from 841 sets of observations, to 68, 143, 662 and 110, while structural properties like number of children (4) or siblings (9) remain relatively stable. In the [DBpedia] version chain we find that http://dbpedia.org/ontology/CollegeCoach is a concept also expected to change. The number of Wikipedia articles pointing to it increases linearly (2787, 3520, 4036, 4870...); it always remains a leave with a unique parent, so its children subhierarchy does not change either. Interestingly, its siblings remain stable (21, 21, 23, 23) until it gets a new parent and its siblings suddenly explode (23, 344). Therefore, it is easy to see why membership and structural features are influential in modelling changes in [CEDAR] and [DBpedia].

More generally, we discuss the performance of classification and the selection of classifiers. Although the Logistic, the MultilayerPerceptron and the tree-based algorithms have good performance in specific situations, the NaiveBayes classifier shows consistent results in all change prediction experiments. Similar behavior and results have been described \[10\]. Interestingly, we observe how the non-overfitting tendency of NaiveBayes is an advantage if the classifier is trained with more past versions (nSnapshots): MultilayerPerceptron, for instance, pre-
(a) 10-fold CV scores on the CEDAR training dataset.

(b) Prediction scores on the CEDAR test dataset.

Fig. 5: Average classifier performance in the CEDAR refinement experiment with 6 incremental learning runs. Lines show performance measures varying along them.

\[ V_e = 2013 \]

#### Table 3: Average DBpedia prediction performance.

|                | \( V_e = 2013 \) | \( V_e = 2013 \) |
|----------------|------------------|------------------|
| Precision      | .98              | .66              |
| Recall         | .98              | .75              |
| F-measure      | .98              | .67              |
| ROC area       | .81              | .58              |
| Base precision | .48              | .52              |

(a) 10-fold CV scores, training dataset. (b) Prediction scores, test dataset.

dicts better with less data (f-measures from 0.82 to 0.30), but with more versions NaiveBayes wins (0.72 to 0.84). However, performance is poorer in some versions (e.g. 1889 and 1930 of CEDAR, 2010 and 2011 of DBpedia). This can be due to several reasons. First, the version to predict may contain unexpected changes that have not been learnt from previous versions (e.g. historical research suggests that those specific CEDAR versions suffered major revision almost from scratch [12]), making their changes harder to predict. Second, corner cases of conceptual change might not be captured with the feature set. Third, these CEDAR versions contain scarce member data that might insufficiently describe uncommon changes. Still, our refinement approach proves to be useful on detecting these coherence data-issues. Figure 5 shows that classification, in general, outperforms the random baseline.

After observing that past knowledge allows building predictive models for change in KOS, a meaningful question to discuss is: what characteristics of KOS version chains make changes in these chains more predictable? In Section 5.4
we build regression models to understand the genericity of our approach, by observing what characteristics of our evaluated 139 KOS version chains have an influence on (a) the performance of the change prediction; and (b) the selection of one or another classifier (RQ3). According to our findings (see Figure 3), the predictors nSnapshots, avgTreeDepth, ratioStructural, ratioInserts and ratioComm are good explanatory variables of the performance of change prediction in KOS version chains. This leads to three important observations: (1) a longer version history in a KOS makes its changes more predictable; (2) schema information is more important than instance information for change modelling; and (3) inserting new statements and leaving the existing ones in a new release helps more in preserving change consistency than removing old statements. Good practices in the maintenance life cycle of Web ontologies, schemas and vocabularies can be built on top of these observations. For instance, it is important to stimulate the design of vocabularies and practices for dataset versioning, explicitly describing and linking the change history of KOS versions as Linked Data. Guidelines should encourage the inclusion of as much structural and schema triples in datasets as possible, by making their count explicit (e.g. extending the VoID vocabulary [2] to include ratios of schema and instance data) and rewarding such datasets with more visibility. In addition, the behaviour of predictor avgGap (see Figure 4) suggests that a majority of classifiers will predict change better if the time between KOS releases is short. Hence the evidence that supports this paper’s title: we encourage KOS publishers to release early, release often [17]. As in the software development philosophy, we emphasize the importance of early and frequent KOS releases. Besides the empirical evidence shown in this paper, we believe this will create a tighter feedback loop between KOS publishers and KOS users, allowing ontologies and vocabularies to progress faster, and enabling
users to help define the KOS to better conform to their requirements and avoid their disuse. An early, frequent, and consistent KOS update will lead, under the assumptions of this paper, to a more consistent and meaningful Web towards change.

7 Conclusions and Future Work

Changes in KOS pose challenges to Linked Data publishers and users. Releasing new KOS versions is a knowledge-based and labor-intensive task for publishers, and compromises the validity of links from users’ datasets. We automatically detect which parts of a Linked Dataset will undergo change in a forthcoming version using supervised learning and leveraging change knowledge contained in past versions. Recalling back our research questions, our approach tackles RQ1 by providing generic and customizable change definition functions; generic and customizable features, including free choice of predicates to use in their generation; customizable learning algorithms (feature selection and classification); and fully automated executions—from input Linked Data KOS version chains to output feature/classifier performances. The assumption that change in KOS version chains can be predicted using past knowledge is acceptable considering intensional, extensional and label changes. We predict change accurately (f-measures of 0.84, 0.93 and 0.79 in test data) in 139 different KOS by generalizing the state of the art methods and features in a Machine Learning pipeline for Linked Data (RQ1). We study the variance in relevant features from our feature set, and how classifiers behave using these features to predict change (RQ2). With respect to its domain-independent applicability and the features that characterize Web KOS where our method works best (RQ3), we study the characteristics of these KOS version chains, and we find that specific features such as the number of snapshots, the time gap between versions, the complexity and amount of schema statements and the number of inter-version insertions characterize KOS with good change predictability, and we suggest research lines to foster a more meaningful and consistent Web towards change. Multiple challenges are open for the future. First, we will study how different definitions of concept change affect the predictive models. Second, we plan to apply our approach to additional domains for the sake of genericity. Finally, we plan to scale up our approach in a distributed environment to cope with larger datasets and detect change in real time.

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