Ontology-based Methods for Classifying Scientific Datasets into Research Domains: Much Harder than Expected

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Abstract: Scientific datasets are increasingly stored, published, and re-used online. This has prompted major search engines to start services dedicated to finding research datasets online. However, to date such services are limited to keyword search, and provide little or no semantic guidance. Determining the scientific domain for a given dataset is a crucial part in dataset recommendation and search: "Which research domain does this dataset belong to?". In this paper we investigate and compare a number of novel ontology-based methods to answer that question, using the distance between a domain-ontology and a dataset as an estimator for the domain(s) into which the dataset should be classified. We also define a simple keyword-based classifier based on the Normalized Google Distance, and we evaluate all classifiers on a hand-constructed gold standard. Our two main findings are that the seemingly simple task of determining the domain(s) of a dataset is surprisingly much harder than expected (even when performed under highly simplified circumstances), and that (again surprisingly), the use of ontologies seems to be of little help in this task, with the simple keyword-based classifier outperforming every ontology-based classifier. We constructed a gold-standard benchmark for our experiments which we make available online for others to use.

1 INTRODUCTION

Scientific datasets play a crucial role in scientific research. Dataset search engines collect many scientific datasets online, and provide these to researchers. Some existing dataset search engines that aim to satisfy this demand are Google DataSet Search[1], Mendeley Data[2] and Elsevier DataSearch[3].

Determining the research domain of a dataset is a key point for researchers when reusing this dataset, because topical relevance is a very import information to consider for secondary data (Gregory et al., 2020). If we represent each candidate domain by a domain-specific ontology, the task of domain-classification turns into the task of ontology-selection: which ontology (and therefore which domain) should be selected based on the description of the dataset? Ontology selection is the process of selecting and ranking a list of ontologies, sorted by how well they meet a certain ontology evaluation task (Sabou et al., 2006). Existing ontology selection approaches can be classified into three types: based on popularity (Patel et al., 2003) (Ding et al., 2005) (Buitelaar et al., 2004), based on richness of knowledge (Alani and Brewster, 2005) and based on topic coverage (Lopez et al., 2006). We provide a new ontology selection task. In this paper, the ontology selection task is to find the ontology which best describes a given dataset. Ontology selection becomes a process of finding an ontology for a given dataset, which is why our new task is called "ontology classification".

We develop and test a number of ontology-based methods for classifying a dataset into a particular domain, using ontology-based similarity measures. There are many existing ontology-based similarity measures to calculate similarity between terms, such as (Wu and Palmer, 1994) and (Resnik, 1995), Lin (Lin et al., 1998). We develop and test a number of ontology-based classification methods, and compare them against a simple domain-name classifier using Normalized Google Distance. To our surprise, the simple keyword-based classifier outperforms all the ontology-based approaches.

[1] https://toolbox.google.com/datasetsearch
[2] https://data.mendeley.com/
[3] https://datasearch.elsevier.com/

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2 MOTIVATION

A number of existing dataset search engines exist to find datasets provided by other researchers. Users of such dataset search engines often want to classify datasets by research domain, and then explore the datasets from the particular domain which they are interested in. The most obvious approach would be to rely on domain-labelling provided by the author of the dataset. However, user-provided labels are known to be notoriously unreliable (Hovy and Lavid, 2010). For datasets from scientific papers, the domain of the paper or the domain of the journal or conference of the paper could be a good way to determine the domain of a dataset. However, this approach obviously only applies to datasets that have an associated publication in a journal or conference.

An inspection of three popular dataset search engines, Google Dataset Search, Mendeley Data and Elsevier DataSearch reveals that we can easily sort datasets by source, data type, date and so on. However, none of them consider the domain of datasets. This is because many dataset providers do not annotate their dataset with a clear domain. Consequently, in this paper we aim to find an effective approach to automatically classify scientific datasets into the right domain.

3 PRELIMINARIES

In this section, we introduce our approach to keyword extraction from the dataset description, as well as the similarity measures used in our classifiers.

3.1 Keyword Extraction Approach

In this paper, we will extract keywords from text (the description of the dataset), without having any pre-training model for keywords extraction available. Consequently, unsupervised keyword extraction approaches are our only choice. There are many popular unsupervised keywords extraction approaches, such as TextRank (Mihalcea and Tarau, 2004), Rake (Rose et al., 2010), TF-IDF (Salton and Buckley, 1988) and so on. We choose to use TextRank because it considers not only context but also recursive information of text, and we use the TextRank implementation from Gensim [4].

[4]https://radimrehurek.com/gensim/summarization/keywords.html

3.2 Similarity Measures

We use several similarity metrics for calculating the similarity between a dataset and an ontology. The *coverage* metric is a simple measure, which just considers the intersection of two sets. The *Jaccard* metric considers not only the intersection but normalises this by the union of the two sets. The Normalized Google Distance (NGD) is a semantic similarity measure based on the number of co-occurences in the Google search engine. Word2vec measures are based on a text corpus converted into a set of vectors and returns the cosine similarity between two word vectors.

Jaccard Similarity. Given two sets of keywords A and B, the Jaccard similarity between A and B is:

$$Jaccard(A,B) = \frac{A \cap B}{A \cup B} \tag{1}$$

Google Distance. The Google Distance between a dataset and an ontology is based on the Normalized Google Distance (NGD) (Cilibrasi and Vitanyi, 2007), which is a semantic similarity measure computed from results of the Google search engine. The NGD between two terms a and b is defined as:

$$NGD(a,b) = \frac{\max\{\log f(a), \log f(b)\} - \log f(a,b)}{\log M - \min\{\log f(a), \log f(b)\}} \tag{2}$$

where $f(a)$ is the number of Google hits of a; $f(a,b)$ is the number co-occurences of a and b on the same web page; and M is the total number of web pages searched by Google times the average number of search terms occurring on pages (estimated to be $25x10^9$). Roughly speaking this computes the normalised probability of two terms co-occurring on a web-page (adjusted logarithmically for scale). Using NGD, we can provide the definition of the Google Distance GD between two sets of keywords A and B as:

$$GD(A,B) = \frac{\{\sum NGD(a,b) | a \in A, b \in B\}}{|A| * |B|} \tag{3}$$

where $|A|$ and $|B|$ is the size of A and B, respectively.

Word2Vec. Word2Vec (Mikolov et al., 2013) is a very popular NLP algorithm, which produces a vector space of words based on a given corpus. With the help of this vector space, similarity measures between two vectors can be calculated, such as the Cosine distance or Euclidean distance. We use the DL4J-Word2Vec library[5] for learning the word embedding of all the

[5]http://deeplearning4j.org/docs/latest/deeplearning4j-nlp-word2vec

keywords in our experiments. The training corpus we used for word2vec is the Google News corpus[6] enriched with a corpus trained on the Mendeley datasets that we used in this paper. We use the cosine similarity measure to calculate the similarity between terms.

4 ONTOLOGY CLASSIFIER AND DOMAIN-NAME CLASSIFIER

We will now introduce our approaches to classify the research domain for scientific datasets. The domain classifier is a simple baseline method that finds the domain for a dataset by calculating the similarity between the dataset and the name of the domain (e.g. "Computer Science"). Beyond this baseline method, the ontology classifiers will consider the ontology of a research domain, in other words we will reduce the problem of domain classification to the problem of ontology classification.

4.1 Domain-name Classifier Approach

As baseline, we use a simple classifier that calculates the Google Distance between the keywords from the metadata of the dataset and a single term that represents the domain name (e.g. "Computer Science"). To allow comparison with the ontology classifiers, we ensure that this domain name includes everything that is covered by the ontology. Therefore, the definition of domain in this paper is the broadest term for each scientific domain, which means that "Semantic Web" or "Machine Learning" are not domain names in this paper but "Computer Science" and "Physics" are, ensuring that the domain name has the same coverage as the corresponding ontology. We use this very simple approach as a baseline to compare with all the ontology-based approaches. Different from the ontology-based classifiers, the domain-name classifier just considers keywords from (the meta-data of) the datasets and the domain names. Intuitively, the Google search engine can be considered as a huge "knowledge source", which covers most concepts and relationships across every research field. Using the Google search engine, the domain-name classifier can show how close a dataset is to each domain by calculating the similarity between the description of the dataset and the name of the domain.

Def. 1 (Google Distance between Dataset and Domain-name). *Given a set of keywords K_D extracted from dataset D and a domain which has name $Domain_N$, the Google Distance between these is:*

$$GD(D, Domain_N) = \frac{\{\sum NGD(d, Domain_N) | d \in K_D\}}{|K_D|} \tag{4}$$

where $|K_D|$ is the number of keywords extracted from dataset D.

Then we can introduce our domain-name classifier algorithm, denoted as $DnC(D, List_{Domain})$.

Algorithm 1: $DnC(D, List_{Domain})$.

Input : D: a dataset, $List_{Domain}$: a list of domain names
Output : Most similar domain $Domain_D$
$Sim_{max} \leftarrow 0.0$;
$Domain_D \leftarrow empty$;
foreach $Domain\ name\ DN \in List_{Domain}$ **do**
    $Sim_{D,DN} \leftarrow GD(D, DN)$;
    if $Sim_{D,DN} > Sim_{max}$ **then**
        $Domain_D \leftarrow DN$;
        $Sim_{max} \leftarrow Sim_{D,DN}$;
    end
end
return $Domain_D$;

4.2 Ontology Classifier Approaches

Different from the ontology selection introduced in (Sabou et al., 2006), our approach to ontology selection is to find a suitable ontology based on the similarity between the keywords from a dataset and the keywords from the ontology. We use the keywords extraction method from the Gensim implementation of TextRank introduced above to extract keywords from the title and the description of datasets.

In order to apply the similarity metrics defined above, we need to extract the keywords of the candidate ontologies (each representing a particular scientific domain). However, for an ontology with rich concepts, it's not a good choice to consider all the concepts as keywords because especially for large ontologies, many concepts from the ontology will be irrelevant for any specific dataset, adversely affecting the distance metric even for datasets belonging to the same domain as the ontology. Additionally, the calculation of the similarity between a dataset and an ontology will be more efficient when not all the concept from the ontology will be considered. We therefore introduce a new notion called an "*ontology specific view*", to calculate the similarity between an ontology and a dataset more effectively and efficiently. Given a dataset D and an ontology O, the *ontology specific view of D on O* is the set of keywords from D which match with the name of some concepts in O. To retrieve such names, we used the commonly used semantic web vocabulary

[6]https://code.google.com/archive/p/word2vec/

"rdfs:label". In other words, the *ontology specific view* gives a way to recognize keywords that match with the concepts from an ontology.

Informally, just like looking at the world with colored glasses, we consider the ontology specific view as the "colored glasses". The ontology we use determines the "color of the glasses", and we see the set of keywords only through this "ontological color". The "coloured glasses" that give the best view of the set of keywords is the best selection.

Def. 2 (**Ontology Specific View**). *Given a dataset D and an ontology O, the ontology specific view $OSV_{D,O}$ of D based on O is a set of concepts which are both concepts from the ontology O as well as keywords appearing in the dataset D:*

$$OSV_{D,O} = \{c | c \in W_D \cap C_O\} \tag{5}$$

where C_O is the set of concepts from ontology O and W_D is the set of keywords from dataset D.

We consider the ontology specific view as the "domain-specific keywords of a dataset". Then, we can calculate similarity between a dataset and an ontology using the keywords of dataset and the ontology specific view.

Def. 3 (**Similarity between Dataset and Ontology**). *Given a dataset D and an ontology O, the similarity $sim_{D,O}$ between D and O is the average of the similarity between the keywords from D and $OSV_{D,O}$:*

$$sim_{D,O} = \frac{\{\sum_{i=1}^{|K_D|} \sum_{j=1}^{|OSV_{D,O}|} sim(d_i, o_j) | d_i \in K_D, o_j \in OSV_{D,O}\}}{|K_D||OSV_{D,O}|} \tag{6}$$

where K_D is the set of keywords of dataset D.

Before we introduce the definition of ontology classifier, we first look back at the similarity measures introduced in the last section. All the similarity measures are defined between two sets of terms, and can be applied to determine the similarity between a dataset (reduced to the ontology-specific view of its extracted keywords) and an ontology. This is because both the keywords from a dataset and from the ontology specific view are sets of terms. This results in the following definitions of similarity measures:

Def. 4 (**Jaccard Similarity between Dataset and Ontology**). *Given a dataset D and an ontology O, the Jaccard similarity between D and O is:*

$$Jaccard(K_D, OSV_{D,O}) = \frac{K_D \cap OSV_{D,O}}{K_D \cup OSV_{D,O}} \tag{7}$$

where K_D is the set of keywords from D, and $OSV_{D,O}$ is the ontology specific view of D based on O.

Def. 5 (**Google Distance between Dataset and Ontology**). *Given a dataset D and an ontology O, the Google Distance $GD_{D,O}$ of D and O is:*

$$GD(D,O) = \frac{\{\sum NGD(d,o) | d \in K_D, o \in OSV_{D,O}\}}{|K_D| * |OSV_{D,O}|} \tag{8}$$

We also provide a simple ontology classifier approach with coverage similarity. Coverage similarity just considers the size of the ontology specific view, which means that it only considers the coverage of the ontology concepts.

Def. 6 (**Coverage Similarity between Dataset and Ontology**). *Coverage similarity between a dataset D and an ontologyO measures the size of the ontology specific view $OSV_{D,O}$ of D and the size of O:*

$$Cover(D,O) = \frac{|OSV_{D,O}|}{|O|} \tag{9}$$

where $|O|$ is the number of concepts in ontology O.

Using these similarity measures between dataset and ontology, we can now provide the definition of an ontology classifier.

Def. 7 (**Ontology Classifier Task**). *Given a dataset D and a list of ontology candidates $List_O$, an ontology classifier should find the suitable ontology O_i so that $Sim_{D,O_i} \geq Sim_{D,O_j}$ for each $O_i, O_j \in List_O$.*

Based on the ontology classifier task, we can introduce our algorithm $OC(D, List_O, Sim)$ for an ontology classifier, in which the similarity measure *Sim* could be any one of the similarity measures between dataset and ontology.

Algorithm 2: $OC(D, List_O, Sim)$.

```
Input  : D: a dataset, List_O: a list of ontology
         candidates, Sim: similarity measure
         between dataset and ontology
Output : most similar ontology O
Sim_max ← 0.0;
O ← empty;
foreach ontology O' ∈ List_O do
    if Sim_{D,O} > Sim_max then
        O ← O';
        Sim_max ← Sim_{D,O};
    end
end
return O
```

5 EXPERIMENTS AND RESULTS

In this section we will introduce the datasets and ontology candidates used in experiments, pipeline of experiment, evaluation method for experiment and results.

5.1 Experiments Setup

Dataset. The datasets we used in our experiments are from Mendeley Data[7]. We choose from Mendeley Data 960 datasets, which are associated with a published paper in a known journal. The distribution of research domains across all the datasets are:

- 60 datasets from the **biomedical** domain.
- 33 datasets from the **computer science** domain.
- 180 datasets from the **physics** domain.
- 683 datasets from the **finance** domain.
- 4 datasets from the **environment** domain.

The URI's of all of these datasets are made available by us [8].

We chose these these 960 datasets for the following reason. First, all of these datasets are retrieved from Mendeley, which means these are scientific datasets actually shared by scientists; secondly, these datasets are all annotated with a link to an associated paper in their metadata, which means we can retrieve the gold standard label through the link to the journal of the paper associated with the dataset. The first reason ensures the ecological validity of our benchmark, the second reason ensures that we have a gold standard to evaluate our results against.

On inspection of the 960 datasets in our gold standard, we find that there is a strong bias on the distribution of the domains of these datasets, with 70% labelled with "finance". To compensate for this, we add a balanced-distribution experiment to check whether this bias influences experiment results or not. In the balanced-distribution experiment, we choose 217 datasets (60 from biomedical, 60 from physics, 60 from finance, 33 from computer science and 4 from environment).


```
id: 1095312112254118121119119998:MENDELEY_DATA,
title: "Data for: Distribution network prices and
        solar PV: Resolving rate ...",
description: "Abstract of associated article:
        1-in-4 detached households in ...",
subjectAreas: Finance,
Keywords_CSO: [article, household, rate, ...],
Keywords_Physics: [article, rate, distribution, ...],
Keywords_FINANCE: [article, household, rate, ...],
Keywords_Envo: [article, solar, rate, distribution, ...],
Keywords_Bio: [signal recognition particle 7s rna, ...],
Keywords: [rate, tariff, household, network, ...],
dataset_url: https://data.mendeley.com/datasets/bwwyv6zy5m,
DOI: 10.17632/bwwyv6zy5m.1,
licence: "CC BY NC 3.0"
```


Figure 1: Meta-Data of Mendeley Dataset in JSON.

We give an example of the meta-data of a Mendeley dataset in Figure 1. There are the descriptive metadata (id, title, description, etc.) and administrative metadata (licence) in the Mendeley collection. The metadata "id" is the unique identifier used to index the dataset. The metadata-fields "title" and "description" give a description of the content and usage of the dataset. We use these to extract keywords of datasets and in order to compute the ontology specific view. The metadata-field "extractedKeywords" is the set of keywords of a dataset given in Mendeley. We compute five other metadata fields for ontology-specific "extractedKeywords", such as "extractedKeywords_CSO", where for example "extractedKeywords_CSO" is the ontology specific view of the computer science ontology CSO for this dataset, and similar for the other ontologies. The metadata-field "dataset_url" is the URL linked to the Mendeley Data search engine. Through this URL, one can find the description of the dataset (such as title, associated paper, etc.).

We only use the title and description of datasets for our classification task, without considering any other information from the dataset itself. This is because that we treat the dataset itself as a "black box" from which we cannot get any information except for the title and description. Many scientific datasets have highly specialised data formats (gene sequences, images, geo-coordinates, etc.), and these are not suitable for extracting information in a general purpose search engine. So we chose to take the hardest case possible, namely assuming that no information can be gained from the dataset itself, and all we have are the human readable descriptions.

Ontology Candidates. We use five ontology candidates from five domain for our ontology selection task: FIBO[9] (Finance), UMLS[10] (Biomedical), CSO[11] (Computer Science), ENVO[12] (Environment) and OPB[13]+physics[14] (Physics). We chose these ontology candidates because they are the richest or most popular ontologies in their domain. For the physics domain, since there is not any existing ontology that can cover most concepts in physics domain, we combined physics for biology ontology with a physics for astronomy ontology.

[7] https://data.mendeley.com/

[8] https://github.com/eva01wx/WISE_ClassifiactionPaper_Datasets

[9] https://spec.edmcouncil.org/fibo/

[10] https://www.nlm.nih.gov/research/umls/

[11] https://cso.kmi.open.ac.uk/home

[12] http://environmentontology.org/

[13] https://sites.google.com/site/semanticsofbiologicalprocesses/projects/the-ontology-of-physics-for-biology-opb

[14] http://www.astro.umd.edu/~eshaya/astro-onto/owl/physics.owl

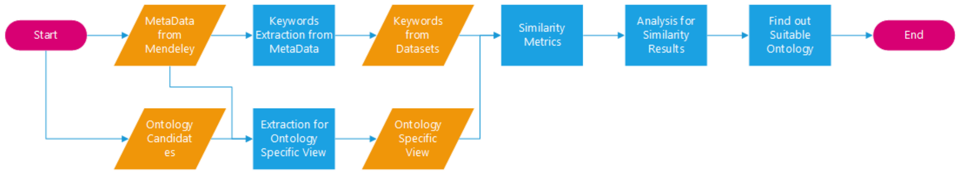


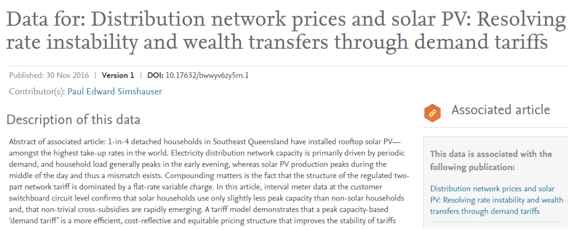
Figure 2: Pipeline for Ontology Classifier Experiemnt.

Pipeline for Ontology Classifier Experiment. The whole pipeline for the ontology classifier experiment is depicted in Figure 2. Given a list $List_D$ of Mendeley datasets and a list $List_O$ of ontology candidates the process of the ontology classifier experiment is as follows:

1. Extract keywords K_D from Mendeley datasets $D \in List_D$.
2. For each ontology $O \in List_O$, extract the ontology-specific view $OSV_{O,D}$ based on O from $D \in List_D$.
3. Calculate the similarity between K_D and $OSV_{O,D}$ by using different similarity metrics, and consider this as the similarity between dataset D and ontology O.
4. Choose the most suitable ontology from $List_O$ for $D \in List_D$ based on the similarity between D and each $O \in List_O$.

5.2 Evaluation

We use the associated paper of each of our datasets as the gold standard for our evaluation. This is because Mendeley does not list a domain for the datasets in the above collection. Instead, we constructed a gold standard by following for each of the listed datasets the link to the journal in which the paper was published that is mentioned in the dataset's metadata, and then determining by hand what is the appropriate domain based on the information about the journal.


Data for: Distribution network prices and solar PV: Resolving rate instability and wealth transfers through demand tariffs

Published: 30 Nov 2016 | **Version 1** | **DOI:** 10.17632/bwwyv6zy5m.1

Contributor(s): Paul Edward Simshauser

Description of this data

Abstract of associated article: 1-in-4 detached households in Southeast Queensland have installed rooftop solar PV—amongst the highest take-up rates in the world. Electricity distribution network capacity is primarily driven by periodic demand, and household load generally peaks in the early evening, whereas solar PV production peaks during the middle of the day and thus a mismatch exists. Compounding matters is the fact that the structure of the regulated two-part network tariff is dominated by a flat-rate variable charge. In this article, interval meter data at the customer switchboard circuit level confirms that solar households use only slightly less peak capacity than non-solar households and, that non-trivial cross-subsidies are rapidly emerging. A tariff model demonstrates that a peak capacity-based 'demand tariff' is a more efficient, cost-reflective and equitable pricing structure that improves the stability of tariffs

Associated article

This data is associated with the following publication:

Distribution network prices and solar PV: Resolving rate instability and wealth transfers through demand tariffs

Figure 3: Mendeley dataset (https://data.mendeley.com/datasets/bwwyv6zy5m).

As we can see in Figure 1, each Mendeley dataset used in our experiment is associated with a Mendeley dataset link. Through the Mendeley dataset link, we can find the associated paper (Figure 3). Then we find the associated journal which the associated paper is published in. It's easy to decide which domain a journal belongs to through the link to the journal of the associated paper. So with the help of the associated journal, we can decide the gold standard domain of all Mendeley datasets. We publish this gold standard online[15].

According to the gold standard above, we use two measures to evaluate the experiment results. The first one is simple accuracy, which means that we just consider the score of the number of datasets, which are classified to right domain, divided by the total number of datasets as accuracy. The second one is F1-measure (Chinchor, 1992), which is always used to evaluate the accuracy of results of classification measures. In our experiments, F1-measure is used to evaluate results for each domain.

For F1-measure in our experiments, given a particular domain, we define True-Positive, True-Negative, False-Positive and False-Negative as follow:

- **True-Positive:** The list of datasets which are not only classified to given domain in gold standard but also are classified to given domain by classification measures.
- **True-Negative:** The list of datasets which are not classified to given domain by both gold standard and classification measures.
- **False-Negative:** The list of datasets which are classified to given domain by gold standard but not by classification measures.
- **False-Positive:** The list of datasets which are classified to given domain by classification measures but not by gold standard.

We also introduce a novel approach to evaluate the result of F1 measure. In classification task, there are always several classification targets, which are the candidates the given data/datasets would be classified into. For instance, if we want to classify dataset into research domain, and we have three domain candidates. Then we can say that these three domain candidates are the classification targets.

Based on the number of classification targets, we can have the random accuracy. For example, if we have

[15]https://github.com/eva01wx/WISE_ClassifiactionPaper_Datasets

Table 1: Simple Accuracy Results.

Measures	UnBalanced	Balanced
Google Distance (with Domain Name)	72.5%	63.5%
Coverage	76.8%	47.5%
Jaccard	22.4%	31.8%
Coverage + Jaccard	48.9%	30.2%
Word2Vec(Google News)	30.6%	27.5%
Word2Vec(Self-training)	29.6%	16.4%
Google Distance	36.1%	26.2%

three classification targets, we have random accuracy 33.3% (1/3) for classifying dataset into right domain.

With the help of random accuracy, we can compute the random F1 score:

$$Random\_F1 = 1/n \tag{10}$$

where n is the number of classification targets. Let's continue the example above. When we have random accuray 33.3% (1/3) with three classification targets, we have random F1 socore 33.3% (1/3). This is because if random accuracy is 33.3% (1/3), then we can know that True positive, True negative, False negative and False positive is 11.1% (1/9), 44.4% (4/9), 22.2% (2/9) and 22.2% (2/9), respectively. Then we can easily know that precision is 33.3% (1/3) and recall is 33.3% (1/3). With precision and recall, we can compute that F1 score is 33.3% (1/3). We compare the F1 scores of our experiments against this random F1 score.

5.3 Results

We run two versions of our experiments: with the unbalanced distribution of the datasets (with a strong bias in favour of the finance domain), and a balanced distribution of datasets which compensates for this bias, as described in the section on our experimental setup. Both experiments aim to find out the best metric to use for classifying datasets into right domain. The balanced experiment is to see if the bias of distribution will impact the performance of these metrics.

All results are given as the accuracy of the domain-classification by comparing it with the results from the gold standard. As we can see in Table 1, we tested 7 different approach for both the balanced and the unbalanced scenario, including both the domain-name classifier and the different ontology-based classifiers. In the unbalanced experiment, two measures reach a high accuracy (>70%). In the balanced experiment, only one measure reaches 60% accuracy.

We also split out these results for each of the different domains, again for both the balanced and the unbalanced scenario, in tables 2 and able 2, comparing against the random f-1 score, which is 20% in our experiment.

Unsurprisingly, in the unbalanced scenario in Table 2, all methods have a good F1-score on the finance domain and outperform the random F1 score. But disappointingly, for any of the other domains only the Google Distance (distance from the domain name) and the Coverage metric have a better than random F1 score an any of the other domains. For the balanced scenario, which is shown in Tabel 2, the scores are even lower: only the Google Distance from the Domain Name performed reasonably well, outperforming the random score in three domain. The coverage metric managed to do this in two domains, as did the mixture measure of Coverage+Jaccard in the same domains.

Summarising, across both the unbalanced and the balanced scenario, the simple domain-name classifier based on Google Distance outperforms the Coverage-based ontology classifier approach, which by itself was already the best performing among all the ontology-based approaches.

6 CONCLUSION

In this paper we have defined the novel task of domain classification for research datasets. We ran several experiments not only with ontology-based classifiers, but also with a simple domain-name classifier, to test the performance of these classifier approaches. Our surprising finding is that our experimental results show that the simple domain classifier approach outperforms all the ontology-based approaches when classifying the research domain for a collection of datasets for which we had obtained gold standard answers. This is contrary to our initial intuition, where we had expected that a rich vocabulary as contained in a high quality domain-specific ontology would provide a better classifier then simply the single word name of the research domain.

There are some possible improvements in future work. In this paper we just considered title and description of datasets for classification. Other parts of the content of datasets could be considered in future work, such as other metadata of datasets and the actual underlying data in datasets (such as a figure or a table). Considering these additional information would improve the outcome of classification. In this paper we ran experiments with 960 datasets from Mendeley, and only 217 datasets in the balanced scenario. In future work, we aim to do our classification experiments with large scale datasets.

We intended to use this domain classification for further steps in future work. Users often publish their datasets without mentioning the domain (as is clear from the dataset on Mendeley). A service that reliably determines the domain of dataset (our currents score is over 70%) will make datasets much easier to find by

Table 2: F1-Score Results for Unbalanced and Balanced Scenario.

	Unbalanced scenario					Balanced scenario				
Measure	CS	Physics	Finance	Bio	Environment	CS	Physics	Finance	Bio	Environment
Google Distance (Domain Name)	0.03	**0.24**	**0.71**	0.05	0.01	0.11	**0.31**	**0.37**	**0.26**	0.02
Coverage	0.0	**0.27**	**0.76**	0.01	0.0	0.0	**0.38**	**0.38**	0.02	0.0
Jaccard	0.04	0.06	**0.25**	0.05	0.0	0.16	0.12	0.09	0.21	0.0
Coverage Jaccard	0.01	0.18	**0.55**	0.01	0.01	0.03	**0.21**	**0.24**	0.03	0.03
Word2Vec (Google News)	0.01	0.13	**0.36**	0.02	0.0	0.03	0.19	0.18	0.10	0.0
Word2Vec (Self-trained)	0.0	0.10	**0.38**	0.01	0.01	0.0	0.08	0.15	0.05	0.03
Google Distance	0.01	0.14	**0.43**	0.02	0.01	0.02	0.17	0.19	0.09	0.01

other scientists. Once we have classified a dataset into the correct domain, we can try to find similar datasets from the same domain. This will be an important support function to help researchers find more datasets for their research.

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