Automatic Labelling of Topic Models

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Abstract

We propose a method for automatically labelling topics learned via LDA topic models. We generate our label candidate set from the top-ranking topic terms, titles of Wikipedia articles containing the top-ranking topic terms, and sub-phrases extracted from the Wikipedia article titles. We rank the label candidates using a combination of association measures and lexical features, optionally fed into a supervised ranking model. Our method is shown to perform strongly over four independent sets of topics, significantly better than a benchmark method.

1 Introduction

Topic modelling is an increasingly popular framework for simultaneously soft-clustering terms and documents into a fixed number of "topics", which take the form of a multinomial distribution over terms in the document collection (Blei et al., 2003). It has been demonstrated to be highly effective in a wide range of tasks, including multi-document summarisation (Haghighi and Vanderwende, 2009), word sense discrimination (Brody and Lapata, 2009), sentiment analysis (Titov and McDonald, 2008), information retrieval (Wei and Croft, 2006) and image labelling (Feng and Lapata, 2010).

One standard way of interpreting a topic is to use the marginal probabilities $p(w_i|t_j)$ associated with each term w_i in a given topic t_j to extract out the 10 terms with highest marginal probability. This results in term lists such as:[1]

stock market investor fund trading investment firm exchange companies share

[1]Here and throughout the paper, we will represent a topic t_j via its ranking of top-10 topic terms, based on $p(w_i|t_j)$.

which are clearly associated with the domain of stock market trading. The aim of this research is to automatically generate topic labels which explicitly identify the semantics of the topic, i.e. which take us from a list of terms requiring interpretation to a single label, such as STOCK MARKET TRADING in the above case.

The approach proposed in this paper is to first generate a topic label candidate set by: (1) sourcing topic label candidates from Wikipedia by querying with the top-N topic terms; (2) identifying the top-ranked document titles; and (3) further post-processing the document titles to extract sub-strings. We translate each topic label into features extracted from Wikipedia, lexical association with the topic terms in Wikipedia documents, and also lexical features for the component terms. This is used as the basis of a support vector regression model, which ranks each topic label candidate.

Our contributions in this work are: (1) the generation of a novel evaluation framework and dataset for topic label evaluation; (2) the proposal of a method for both generating and scoring topic label candidates; and (3) strong in- and cross-domain results across four independent document collections and associated topic models, demonstrating the ability of our method to automatically label topics with remarkable success.

2 Related Work

Topics are conventionally interpreted via their top-N terms, ranked based on the marginal probability $p(w_i|t_j)$ in that topic (Blei et al., 2003; Griffiths and Steyvers, 2004). This entails a significant cognitive load in interpretation, prone to subjectivity. Topics are also sometimes presented with manual post-hoc labelling for ease of interpretation in research publications (Wang and McCallum, 2006; Mei et al.,

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2006). This has obvious disadvantages in terms of subjectivity, and lack of reproducibility/automation.

The closest work to our method is that of Mei et al. (2007), who proposed various unsupervised approaches for automatically labelling topics, based on: (1) generating label candidates by extracting either bigrams or noun chunks from the document collection; and (2) ranking the label candidates based on KL divergence with a given topic. Their proposed methodology generates a generic list of label candidates for *all* topics using only the document collection. The best method uses bigrams exclusively, in the form of the top-1000 bigrams based on the Student's t-test. We reimplement their method and present an empirical comparison in Section 5.3.

In other work, Magatti et al. (2009) proposed a method for labelling topics induced by a hierarchical topic model. Their label candidate set is the Google Directory (gDir) hierarchy, and label selection takes the form of ontological alignment with gDir. The experiments presented in the paper are highly preliminary, although the results certainly show promise. However, the method is only applicable to a hierarchical topic model and crucially relies on a pre-existing ontology and the class labels contained therein.

Pantel and Ravichandran (2004) addressed the more specific task of labelling a semantic class by applying Hearst-style lexico-semantic patterns to each member of that class. When presented with semantically homogeneous, fine-grained near-synonym clusters, the method appears to work well. With topic modelling, however, the top-ranking topic terms tended to be *associated* and not lexically *similar* to one another. It is thus highly questionable whether their method could be applied to topic models, but it would certainly be interesting to investigate whether our model could conversely be applied to the labelling of sets of near-synonyms.

In recent work, Lau et al. (2010) proposed to approach topic labelling via best term selection, i.e. selecting one of the top-10 topic terms to label the overall topic. While it is often possible to label topics with topic terms (as is the case with the stock market topic above), there are also often cases where topic terms are not appropriate as labels. We reuse a selection of the features proposed by Lau et al. (2010), and return to discuss it in detail in Section 3.

While not directly related to topic labelling, Chang et al. (2009) were one of the first to propose human labelling of topic models, in the form of synthetic intruder word and topic detection tasks. In the intruder word task, they include a term w with low marginal probability $p(w|t)$ for topic t into the top-N topic terms, and evaluate how well both humans and their model are able to detect the intruder.

The potential applications for automatic labelling of topics are many and varied. In document collection visualisation, e.g., the topic model can be used as the basis for generating a two-dimensional representation of the document collection (Newman et al., 2010a). Regions where documents have a high marginal probability $p(d_i|t_j)$ of being associated with a given topic can be explicitly labelled with the learned label, rather than just presented as an unlabelled region, or presented with a dense "term cloud" from the original topic. In topic model-based selectional preference learning (Ritter et al., 2010; Ò Séaghdha, 2010), the learned topics can be translated into semantic class labels (e.g. DAYS OF THE WEEK), and argument positions for individual predicates can be annotated with those labels for greater interpretability/portability. In dynamic topic models tracking the diachronic evolution of topics in time-sequenced document collections (Blei and Lafferty, 2006), labels can greatly enhance the interpretation of what topics are "trending" at any given point in time.

3 Methodology

The task of automatic labelling of topics is a natural progression from the best topic term selection task of Lau et al. (2010). In that work, the authors use a reranking framework to produce a ranking of the top-10 topic terms based on how well each term – in isolation – represents a topic. For example, in our *stock market investor fund trading ...* topic example, the term *trading* could be considered as a more representative term of the overall semantics of the topic than the top-ranked topic term *stock*.

While the best term could be used as a topic label, topics are commonly ideas or concepts that are better expressed with multiword terms (for example STOCK MARKET TRADING), or terms that might not be in the top-10 topic terms (for example, COLOURS would be a good label for a topic of the form *red green blue cyan ...*).

In this paper, we propose a novel method for automatic topic labelling that first generates topic label candidates using English Wikipedia, and then ranks the candidates to select the best topic labels.

3.1 Candidate Generation

Given the size and diversity of English Wikipedia, we posit that the vast majority of (coherent) topics or concepts are encapsulated in a Wikipedia article. By making this assumption, the difficult task of generating potential topic labels is transposed to finding relevant Wikipedia articles, and using the title of each article as a topic label candidate.

We first use the top-10 topic terms (based on the marginal probabilities from the original topic model) to query Wikipedia, using: (a) Wikipedia's native search API; and (b) a site-restricted Google search. The combined set of top-8 article titles returned from the two search engines for each topic constitutes the initial set of *primary* candidates.

Next we chunk parse the primary candidates using the OpenNLP chunker,[2] and extract out all noun chunks. For each noun chunk, we generate all component n-grams (including the full chunk), out of which we remove all n-grams which are not in themselves article titles in English Wikipedia. For example, if the Wikipedia document title were the single noun chunk *United States Constitution*, we would generate the bigrams *United States* and *States Constitution*, and prune the latter; we would also generate the unigrams *United*, *States* and *Constitution*, all of which exist as Wikipedia articles and are preserved.

In this way, an average of 30–40 *secondary* labels are produced for each topic based on noun chunk n-grams. A good portion of these labels are commonly stopwords or unigrams that are only marginally related to the topic (an artifact of the n-gram generation process). To remove these outlier labels, we use the RACO lexical association method of Grieser et al. (2011).

RACO (Related Article Conceptual Overlap) uses Wikipedia's link structure and category membership to identify the strength of relationship between articles via their category overlap. The set of categories related to an article is defined as the union of the category membership of all outlinks in that article. The category overlap of two articles (a and b) is the intersection of the related category sets of each article. The formal definition of this measure is as follows:

$$|(\cup_{p\in O(a)} C(p)) \cap (\cup_{p\in O(b)} C(p))|$$

where $O(a)$ is the set of outlinks from article a, and $C(p)$ is the set of categories of which article p is a member. This is then normalised using Dice's coefficient to generate a similarity measure. In the instance that a term maps onto multiple Wikipedia articles via a disambiguation page, we return the best RACO score across article pairings for a given term pair. The final score for each secondary label candidate is calculated as the average RACO score with each of the primary label candidates. All secondary labels with an average RACO score of 0.1 and above are added to the label candidate set.

Finally, we add the top-5 topic terms to the set of candidates, based on the marginals from the original topic model. Doing this ensures that there are always label candidates for all topics (even if the Wikipedia searches fail), and also allows the possibility of labeling a topic using its own topic terms, which was demonstrated by Lau et al. (2010) to be a baseline source of topic label candidates.

3.2 Candidate Ranking

After obtaining the set of topic label candidates, the next step is to rank the candidates to find the best label for each topic. We will first describe the features that we use to represent label candidates.

3.2.1 Features

A good label should be strongly associated with the topic terms. To learn the association of a label candidate with the topic terms, we use several lexical association measures: pointwise mutual information (PMI), Student's t-test, Dice's coefficient, Pearson's χ^2 test, and the log likelihood ratio (Pecina, 2009). We also include conditional probability and reverse conditional probability measures, based on the work of Lau et al. (2010). To calculate the association measures, we parse the full collection of English Wikipedia articles using a sliding window of width

[2] http://opennlp.sourceforge.net/

20, and obtain term frequencies for the label candidates and topic terms. To measure the association between a label candidate and a list of topic terms, we average the scores of the top-10 topic terms.

In addition to the association measures, we include two lexical properties of the candidate: the raw number of terms, and the relative number of terms in the label candidate that are top-10 topic terms.

We also include a search engine score for each label candidate, which we generate by querying a local copy of English Wikipedia with the top-10 topic terms, using the Zettair search engine (based on BM25 term similarity).[3] For a given label candidate, we return the average score for the Wikipedia article(s) associated with it.

3.2.2 Unsupervised and Supervised Ranking

Each of the proposed features can be used as the basis for an unsupervised model for label candidate selection, by ranking the label candidates for a given topic and selecting the top-N. Alternatively, they can be combined in a supervised model, by training over topics where we have gold-standard labelling of the label candidates. For the supervised method, we use a support vector regression (SVR) model (Joachims, 2006) over all of the features.

4 Datasets

We conducted topic labelling experiments using document collections constructed from four distinct domains/genres, to test the domain/genre independence of our method:

BLOGS : 120,000 blog articles dated from August to October 2008 from the Spinn3r blog dataset[4]

BOOKS : 1,000 English language books from the Internet Archive American Libraries collection

NEWS : 29,000 New York Times news articles dated from July to September 1999, from the English Gigaword corpus

PUBMED : 77,000 PubMed biomedical abstracts published in June 2010

[3] `http://www.seg.rmit.edu.au/zettair/`
[4] `http://www.icwsm.org/data/`

The BLOGS dataset contains blog posts that cover a diverse range of subjects, from product reviews to casual, conversational messages. The BOOKS topics, coming from public-domain out-of-copyright books (with publication dates spanning more than a century), relate to a wide range of topics including furniture, home decoration, religion and art, and have a more historic feel to them. The NEWS topics reflect the types and range of subjects one might expect in news articles such as health, finance, entertainment, and politics. The PUBMED topics frequently contain domain-specific terms and are sharply differentiated from the topics for the other corpora. We are particularly interested in the performance of the method over PUBMED, as it is a highly specialised domain where we may expect lower coverage of appropriate topic labels within Wikipedia.

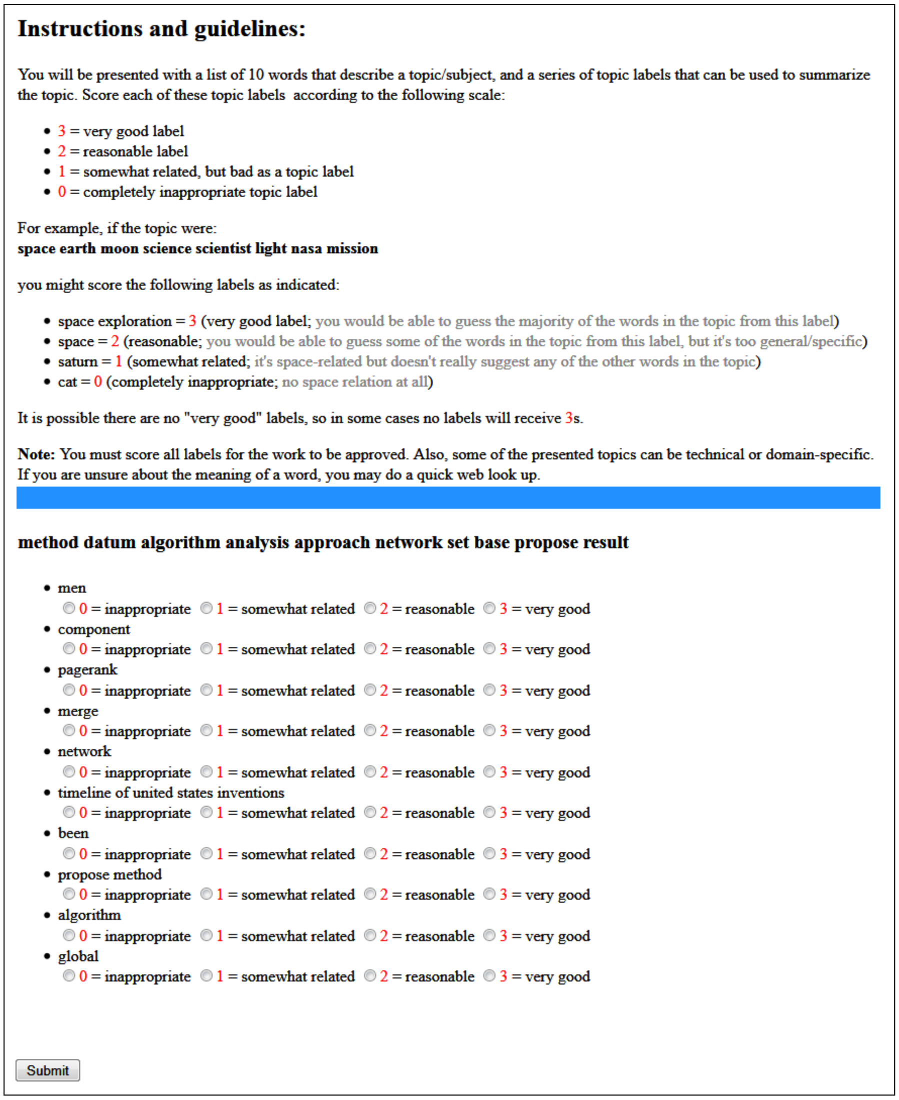
We took a standard approach to topic modelling each of the four document collections: we tokenised, lemmatised and stopped each document,[5] and created a vocabulary of terms that occurred at least ten times. From this processed data, we created a bag-of-words representation of each document, and learned topic models with $T = 100$ topics in each case.

To focus our experiments on topics that were relatively more coherent and interpretable, we first used the method of Newman et al. (2010b) to calculate the average PMI-score for each topic, and filtered all topics that had an average PMI-score lower than 0.4. We additionally filtered any topics where less than 5 of the top-10 topic terms are default nominal in Wikipedia.[6] The filtering criteria resulted in 45 topics for BLOGS, 38 topics for BOOKS, 60 topics for NEWS, and 85 topics for PUBMED. Manual inspection of the discarded topics indicated that they were predominantly hard-to-label junk topics or mixed topics, with limited utility for document/term clustering.

Applying our label candidate generation methodology to these 228 topics produced approximately 6000 labels — an average of 27 labels per topic.

[5] OpenNLP is used for tokenization, Morpha for lemmatization (Minnen et al., 2001).

[6] As determined by POS tagging English Wikipedia with OpenNLP, and calculating the coarse-grained POS priors (noun, verb, etc.) for each term.



Instructions and guidelines:

You will be presented with a list of 10 words that describe a topic/subject, and a series of topic labels that can be used to summarize the topic. Score each of these topic labels according to the following scale:

- 3 = very good label
- 2 = reasonable label
- 1 = somewhat related, but bad as a topic label
- 0 = completely inappropriate topic label

For example, if the topic were:
space earth moon science scientist light nasa mission

you might score the following labels as indicated:

- space exploration = 3 (very good label; you would be able to guess the majority of the words in the topic from this label)
- space = 2 (reasonable; you would be able to guess some of the words in the topic from this label, but it's too general/specific)
- saturn = 1 (somewhat related; it's space-related but doesn't really suggest any of the other words in the topic)
- cat = 0 (completely inappropriate; no space relation at all)

It is possible there are no "very good" labels, so in some cases no labels will receive 3s.

Note: You must score all labels for the work to be approved. Also, some of the presented topics can be technical or domain-specific. If you are unsure about the meaning of a word, you may do a quick web look up.

method datum algorithm analysis approach network set base propose result

- men
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- component
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- pagerank
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- merge
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- network
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- timeline of united states inventions
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- been
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- propose method
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- algorithm
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good
- global
  0 = inappropriate 1 = somewhat related 2 = reasonable 3 = very good

Submit

Figure 1: A screenshot of the topic label evaluation task on Amazon Mechanical Turk. This screen constitutes a *Human Intelligence Task* (HIT); it contains a topic followed by 10 suggested topic labels, which are to be rated. Note that *been* would be the stopword label in this example.

4.1 Topic Candidate Labelling

To evaluate our methods and train the supervised method, we require gold-standard ratings for the label candidates. To this end, we used Amazon Mechanical Turk to collect annotations for our labels.

In our annotation task, each topic was presented in the form of its top-10 terms, followed by 10 suggested labels for the topic. This constitutes a *Human Intelligence Task* (HIT); annotators are paid based on the number of HITs they have completed. A screenshot of a HIT seen by annotator is presented in Figure 1.

In each HIT, annotators were asked to rate the labels based on the following ordinal scale:

3: Very good label; a perfect description of the topic.

2: Reasonable label, but does not completely capture the topic.

1: Label is semantically related to the topic, but would not make a good topic label.

0: Label is completely inappropriate, and unrelated to the topic.

To filter annotations from workers who did not perform the task properly or from spammers, we ap-

Domain	Topic Terms	Label Candidate	Average Rating
BLOGS	china chinese olympics gold olympic team win beijing medal sport	2008 summer olympics	2.60
BOOKS	church arch wall building window gothic nave side vault tower	gothic architecture	2.40
NEWS	israel peace barak israeli minister palestinian agreement prime leader palestinians	israeli-palestinian conflict	2.63
PUBMED	cell response immune lymphocyte antigen cytokine t-cell induce receptor immunity	immune system	2.36

Table 1: A sample of topics and topic labels, along with the average rating for each label candidate

plied a few heuristics to automatically detect these workers. Additionally, we inserted a small number of stopwords as label candidates in each HIT and recorded workers who gave high ratings to these stopwords. Annotations from workers who failed to passed these tests are removed from the final set of gold ratings.

Each label candidate was rated in this way by at least 10 annotators, and ratings from annotators who passed the filter were combined by averaging them. A sample of topics, label candidates, and the average rating is presented in Table 1.[7]

Finally, we train the regression model over all the described features, using the human rating-based ranking.

5 Experiments

In this section we present our experimental results for the topic labelling task, based on both the unsupervised and supervised methods, and the methodology of Mei et al. (2007), which we denote MSZ for the remainder of the paper.

5.1 Evaluation

We use two basic measures to evaluate the performance of our predictions. **Top-1 average rating** is the average annotator rating given to the top-ranked system label, and has a maximum value of 3 (where annotators unanimously rated all top-ranked system labels with a 3). This is intended to give a sense of the *absolute* utility of the top-ranked candidates.

The second measure is normalized discounted cumulative gain (nDCG: Jarvelin and Kekalainen (2002), Croft et al. (2009)), computed for the top-1 (**nDCG-1**), top-3 (**nDCG-3**) and top-5 ranked system labels (**nDCG-5**). For a given ordered list of scores, this measure is based on the difference between the original order, and the order when the list is sorted by score. That is, if items are ranked optimally in descending order of score at position N, nDCG-N is equal to 1. nDCG is a normalised score, and indicates how close the candidate label ranking is to the optimal ranking within the set of annotated candidates, noting that an nDCG-N score of 1 tells us nothing about absolute values of the candidates. This second evaluation measure is thus intended to reflect the *relative* quality of the ranking, and complements the top-1 average rating.

Note that conventional precision- and recall-based evaluation is not appropriate for our task, as each label candidate has a real-valued rating.

As a baseline for the task, we use the unsupervised label candidate ranking method based on Pearson's χ^2 test, as it was overwhelmingly found to be the pick of the features for candidate ranking.

5.2 Results for the Supervised Method

For the supervised model, we present both in-domain results based on 10-fold cross-validation, and cross-domain results where we learn a model from the ratings for the topic model from a given domain, and apply it to a second domain. In each case, we learn an SVR model over the full set of features described in Section 3.2.1. In practical terms, in-domain results make the unreasonable assumption that we have labelled 90% of labels in order to be able to label the remaining 10%, and cross-domain results are thus the more interesting data point in terms of the expected results when applying our method to a novel topic model. It is valuable to compare the two, however, to gauge the relative impact of domain on the results.

We present the results for the supervised method in Table 2, including the unsupervised baseline and an upper bound estimate for comparison purposes. The upper bound is calculated by ranking the candi-

[7] The dataset is available for download from http://www.csse.unimelb.edu.au/research/lt/resources/acl2011-topic/.

Test Domain	Training	Top-1 Average Rating				nDCG-1	nDCG-3	nDCG-5
		All	1°	2°	Top5			
BLOGS	Baseline (unsupervised)	1.84	1.87	1.75	1.74	0.75	0.77	0.79
	In-domain	1.98	1.94	1.95	1.77	0.81	0.82	0.83
	Cross-domain: BOOKS	1.88	1.92	1.90	1.77	0.77	0.81	0.83
	Cross-domain: NEWS	1.97	1.94	1.92	1.77	0.80	0.83	0.83
	Cross-domain: PUBMED	1.95	1.95	1.93	1.82	0.80	0.82	0.83
	Upper bound	2.45	2.26	2.29	2.18	1.00	1.00	1.00
BOOKS	Baseline (unsupervised)	1.75	1.76	1.70	1.72	0.77	0.77	0.79
	In-domain	1.91	1.90	1.83	1.74	0.84	0.81	0.83
	Cross-domain: BLOGS	1.82	1.88	1.79	1.71	0.79	0.81	0.82
	Cross-domain: NEWS	1.82	1.87	1.80	1.75	0.79	0.81	0.83
	Cross-domain: PUBMED	1.87	1.87	1.80	1.73	0.81	0.82	0.83
	Upper bound	2.29	2.17	2.15	2.04	1.00	1.00	1.00
NEWS	Baseline (unsupervised)	1.96	1.76	1.87	1.70	0.80	0.79	0.78
	In-domain	2.02	1.92	1.90	1.82	0.82	0.82	0.84
	Cross-domain: BLOGS	2.03	1.92	1.89	1.85	0.83	0.82	0.84
	Cross-domain: BOOKS	2.01	1.80	1.93	1.73	0.82	0.82	0.83
	Cross-domain: PUBMED	2.01	1.93	1.94	1.80	0.82	0.82	0.83
	Upper bound	2.45	2.31	2.33	2.12	1.00	1.00	1.00
PUBMED	Baseline (unsupervised)	1.73	1.74	1.68	1.63	0.75	0.77	0.79
	In-domain	1.79	1.76	1.74	1.67	0.77	0.82	0.84
	Cross-domain: BLOGS	1.80	1.77	1.73	1.69	0.78	0.82	0.84
	Cross-domain: BOOKS	1.77	1.70	1.74	1.64	0.77	0.82	0.83
	Cross-domain: NEWS	1.79	1.76	1.73	1.65	0.77	0.82	0.84
	Upper bound	2.31	2.17	2.22	2.01	1.00	1.00	1.00

Table 2: Supervised results for all domains

dates based on the annotated human ratings. The upper bound for top-1 average rating is thus the highest average human rating of all label candidates for a given topic, while the upper bound for the nDCG measures will always be 1.

In addition to results for the combined candidate set, we include results for each of the three candidate subsets, namely the primary Wikipedia labels ("1°"), the secondary Wikipedia labels ("2°") and the top-5 topic terms ("Top5"); the nDCG results are over the full candidate set only, as the numbers aren't directly comparable over the different subsets (due to differences in the number of candidates and the distribution of ratings).

Comparing the in-domain and cross-domain results, we observe that they are largely comparable, with the exception of BOOKS, where there is a noticeable drop in both top-1 average rating and nDGC-1 when we use cross-domain training. We see an appreciable drop in scores when we train BOOKS against BLOGS (or vice versa), which we analyse as being due to incompatibility in document content and structure between these two domains. Overall though, the results are very encouraging, and point to the plausibility of using labelled topic models from independent domains to learn the best topic labels for a new domain.

Returning to the question of the suitability of label candidates for the highly specialised PUBMED document collection, we first notice that the upper bound top-1 average rating is comparable to the other domains, indicating that our method has been able to extract equivalent-quality label candidates from Wikipedia. The top-1 average ratings of the supervised method are lower than the other domains. We hypothesise that the cause of the drop is that the lexical association measures are trained over highly diverse Wikipedia data rather than biomedical-specific data, and predict that the results would improve if we trained our features over PubMed.

The results are uniformly better than the unsupervised baselines for all four corpora, although there is quite a bit of room for improvement relative to the upper bound. To better gauge the quality of these results, we carry out a direct comparison of our proposed method with the best-performing method of MSZ in Section 5.3.

Looking to the top-1 average score results over the different candidate sets, we observe first that the upper bound for the combined candidate set ("All") is higher than the scores for the candidate subsets in all cases, underlining the complementarity of the different candidate sets. We also observe that the top-5 topic term candidate set is the lowest performer out of the three subsets across all four corpora, in terms of both upper bound and the results for the supervised method. This reinforces our comments about the inferiority of the topic word selection method of Lau et al. (2010) for topic labelling purposes. For NEWS and PUBMED, there is a noticeable difference between the results of the supervised method over the full candidate set and each of the candidate subsets. In contrast, for BOOKS and BLOGS, the results for the primary candidate subset are at times actually higher than those over the full candidate set in most cases (but not for the upper bound). This is due to the larger search space in the full candidate set, and the higher median quality of candidates in the primary candidate set.

5.3 Comparison with MSZ

The best performing method out of the suite of approaches proposed by MSZ method exclusively uses bigrams extracted from the document collection, ranked based on Student's t-test. The potential drawbacks to this approach are: all labels must be bigrams, there must be explicit token instances of a given bigram in the document collection for it to be considered as a label candidate, and furthermore, there must be *enough* token instances in the document collection for it to have a high t score.

To better understand the performance difference of our approach to that of MSZ, we perform direct comparison of our proposed method with the benchmark method of MSZ.

5.3.1 Candidate Ranking

First, we compare the candidate ranking methodology of our method with that of MSZ, using the label candidates extracted by the MSZ method.

We first extracted the top-2000 bigrams using the N-gram Statistics Package (Banerjee and Pedersen, 2003). We then ranked the bigrams for each topic using the Student's t-test. We included the top-5 labels generated for each topic by the MSZ method in our Mechanical Turk annotation task, and use the annotations to directly compare the two methods.

To measure the performance of candidate ranking between our supervised method and MSZ's, we re-rank the top-5 labels extracted by MSZ using our SVR methodology (in-domain) and compare the top-1 average rating and nDCG scores. Results are shown in Table 3. We do not include results for the BOOKS domain because the text collection is much larger than the other domains, and the computation for the MSZ relevance score ranking is intractable due to the number of n-grams (a significant shortcoming of the method).

Looking at the results for the other domains, it is clear that our ranking system has the upper hand: it consistently outperforms MSZ over every evaluation metric.[8] Comparing the top-1 average rating results back to those in Table 2, we observe that for all three domains, the results for MSZ are below those of the unsupervised baseline, and well below those of our supervised method. The nDCG results are more competitive, and the nDCG-3 results are actually higher than our original results in Table 2. It is important to bear in mind, however, that the numbers are in each case relative to a different label candidate set. Additionally, the results in Table 3 are based on only 5 candidates, with a relatively flat gold-standard rating distribution, making it easier to achieve higher nDCG-5 scores.

5.3.2 Candidate Generation

The method of MSZ makes the implicit assumption that good bigram labels are discoverable within the document collection. In our method, on the other hand, we (efficiently) access the much larger and variable n-gram length set of English Wikipedia article titles, in addition to the top-5 topic terms. To better understand the differences in label candidate sets, and the relative coverage of the full label candidate set in each case, we conducted another survey where human users were asked to suggest one topic label for each topic presented.

The survey consisted, once again, of presenting annotators with a topic, but in this case, we gave them the open task of proposing the ideal label for

[8]Based on a single ANOVA, the difference in results is statistically significant at the 5% level for BLOGS, and 1% for NEWS and PUBMED.

Test Domain	Candidate Ranking System	Top-1 Avg. Rating	nDCG-1	nDCG-3	nDCG-5
BLOGS	MSZ	1.26	0.65	0.76	0.87
	SVR	1.41	0.75	0.85	0.92
	Upper bound	1.87	1.00	1.00	1.00
NEWS	MSZ	1.37	0.73	0.81	0.90
	SVR	1.66	0.88	0.90	0.95
	Upper bound	1.86	1.00	1.00	1.00
PUBMED	MSZ	1.53	0.77	0.85	0.93
	SVR	1.73	0.87	0.91	0.96
	Upper bound	1.98	1.00	1.00	1.00

Table 3: Comparison of results for our proposed supervised ranking method (SVR) and that of MSZ

the topic. In this, we did not enforce any restrictions on the type or size of label (e.g. the number of terms in the label).

Of the manually-generated gold-standard labels, approximately 36% were contained in the original document collection, but 60% were Wikipedia article titles. This indicates that our method has greater potential to generate a label of the quality of the ideal proposed by a human in a completely open-ended task.

6 Discussion

On the subject of suitability of using Amazon Mechanical Turk for natural language tasks, Snow et al. (2008) demonstrated that the quality of annotation is comparable to that of expert annotators. With that said, the PUBMED topics are still a subject of interest, as these topics often contain biomedical terms which could be difficult for the general populace to annotate.

As the number of annotators per topic and the number of annotations per annotator vary, there is no immediate way to calculate the inter-annotator agreement. Instead, we calculated the MAE score for each candidate, which is an average of the absolute difference between an annotator's rating and the average rating of a candidate, summed across all candidates to get the MAE score for a given corpus. The MAE scores for each corpus are shown in Table 4, noting that a smaller value indicates higher agreement.

Corpus	MAE
BLOGS	0.50
BOOKS	0.56
NEWS	0.52
PUBMED	0.56

Table 4: Average MAE score for label candidate rating over each corpus

As the table shows, the agreement for the PUBMED domain is comparable with the other datasets. BLOGS and NEWS have marginally better agreement, almost certainly because of the greater immediacy of the topics, covering everyday areas such as lifestyle and politics. BOOKS topics are occasionally difficult to label due to the breadth of the domain; e.g. consider a topic containing terms extracted from Shakespeare sonnets.

7 Conclusion

This paper has presented the task of topic labelling, that is the generation and scoring of labels for a given topic. We generate a set of label candidates from the top-ranking topic terms, titles of Wikipedia articles containing the top-ranking topic terms, and also a filtered set of sub-phrases extracted from the Wikipedia article titles. We rank the label candidates using a combination of association measures, lexical features and an Information Retrieval feature. Our method is shown to perform strongly over four independent sets of topics, and also significantly better than a competitor system.

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