

# *Learning from Noisy Out-of-Domain Corpus Using Dataless Classification*

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## Abstract

In real-world applications, text classification models often suffer from a lack of accurately labelled documents. The available labelled documents may also be out-of-domain, making the trained model not able to perform well in the target domain. In this work, we mitigate the data problem of text classification using a two-stage approach. First, we mine representative keywords from a noisy out-of-domain dataset using statistical methods. We then apply a dataless classification method to learn from the automatically selected keywords and unlabelled in-domain data. The proposed approach outperformed various supervised learning and dataless classification baselines by a large margin. We evaluated different keyword selection methods intrinsically and extrinsically by measuring their impact on the dataless classification accuracy. Last but not least, we conducted an in-depth analysis of the behaviour of the classifier and explained why the proposed dataless classification method outperformed supervised learning counterparts.

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## 1 Introduction

Text classification has been extensively studied within the NLP community, and modern neural networks models achieve promising accuracy of higher than ninety per cent on some well-studied benchmark datasets (Yogatama et al., 2017; Howard and Ruder, 2018). However, when we apply text classification models to real-world problems, the accuracy is often much lower. There are a few reasons.

Firstly, the text classification models are often trained on a fixed set of training documents. The data labelling process is usually a one-time effort. The static set of training documents does not cover emerging topics or keywords, and there is no guarantee that the model will maintain a decent accuracy after having been deployed for a prolonged period.

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Secondly, off-the-shelf text classification models for a specific domain is often not available, and people settle with a general-purpose classifier or a classifier built for a similar domain. Previous work showed that applying text classification models directly on out-of-domain data will cause a drastic performance drop (Mudinas et al., 2018).

The third challenge for applying text classification in real-world applications is the lack of accurate training data. Industry projects usually run on a much shorter timeline. Researchers do not have the luxury of time and resources to build a large, high-quality dataset (Dahlmeier, 2017). They need to settle with either a small dataset or use noisy labels obtained from crowd-sourcing or user-generated content such as hashtags (Wang et al., 2011).

Last but not least, the Internet contains heterogeneous textual data in the form of static HTML pages or dynamic pages generated using various web frameworks. Different types of web pages such as home pages, forums and product list pages are ubiquitous and have very different characteristics (Nguyen-Hoang et al., 2018). This is in contrast to popular benchmark datasets where the data come from a single source. The heterogeneous input may affect the accuracy of the text classification models. However, its impact has not been well-studied and quantified.

This work was motivated by our experience building text classifiers for contextual advertising (Jin et al., 2017). The goal of contextual advertising is to display ads on only web pages which are related to the ad. We apply text classifiers to categorise all the web pages in the user browsing history. To facilitate the integration with various ad exchanges and publishers, we need to classify the web content into the category taxonomy defined by Interactive Advertising Bureau (IAB), the organisation which develops industry standards for online advertising<sup>1</sup>. The taxonomy consists of twenty-three tier-1 categories and more than 300 tier-2 categories. It covers a broad range of sectors such as automotive, education and travel. The large number of categories, the heterogeneous content on the Internet together pose a great challenge for advertisers to build and maintain highly accurate text classifiers.

We began building text classifiers for contextual advertising a few years ago by crawling categorised newswire websites such as Reuters<sup>2</sup> and Star Online<sup>3</sup> and mapping their categories to IAB categories. This saved us a huge effort to create the corpus by labelling web pages manually. However, it suffers some significant drawbacks. Namely, the training data does not resemble the actual user browsing data, and there exists label noise due to human error or imperfect category mapping.

In this work, we propose a method to mitigate the data problem and improve the accuracy of the classifier drastically. We first mine keywords for each category from a noisy labelled training corpus using statistical methods. This is based on the assumption that the label noise of individual documents may offset each other when we calculate the distribution of keywords among a large collection of documents. A robust statistical method shall be able to separate the representative keywords for a category from random words that appear

<sup>1</sup> <https://www.iab.com/guidelines/iab-quality-assurance-guidelines-qag-taxonomy/>

<sup>2</sup> <https://www.reuters.com/>

<sup>3</sup> <https://www.thestar.com.my/>

due to noise. Using the keywords, we apply a state-of-the-art dataless text classification model (Li et al., 2016) which requires only a handful of seed words for each category and no labelled documents to train. We mitigate the problem of the noisy labels by letting the dataless model figure out the correct label by itself. The dataless paradigm also allows us to learn from unlabelled in-domain documents, which can yield further performance improvement.

Our contributions in this work are threefold. Firstly, we use the automatically mined keywords as the bridge and address the noisy label problem with a dataless learning method. The proposed two-stage approach drastically outperformed various baselines, including a state-of-the-art supervised learning model on datasets for contextual advertising. Secondly, we conducted a thorough intrinsic and extrinsic evaluation on various keyword extraction methods and their impact on the dataless classifier’s accuracy. The proposed method yields both more meaningful keywords and better accuracy for the induced dataless classifier. Lastly, we conducted an in-depth analysis of the working of the classifiers to explain why the proposed method yields superior performance. This provides the basis for further theoretical and empirical studies.

## 2 Related Work

We present three areas of related work which are closely related to this paper, namely text classification with label noise, domain adaptation and dataless classification.

### 2.1 Text Classification With Label Noise

There are three main approaches to perform text classification with the presence of label noise: *label noise-robust models*, *data cleansing methods* and *noise-tolerant methods* (Fré- nay and Verleysen, 2014).

Label noise-robust models are the simplest among all approaches. It neither tries to cleanse nor to model the noise. Certain types of classifiers are more robust to the label noise, such as ensembles using bagging (Dietterich, 2000). On the other hand, despite being a strong baseline for many classification tasks, SVM is not robust to label noise (Nettleton et al., 2010). The model relies on a few support vectors close to the decision boundary and wrongly labelled data can have a large impact on the model’s accuracy. Label noise-robust models are relatively effective when the amount of label noise is small.

Data cleansing methods aim first to identify the label noises, then either remove the wrongly labelled data or try to reassign the correct label. Researchers favour data cleansing methods because they can be combined with any standard classification algorithm as an additional preprocessing step. Data cleansing methods are relatively easy to implement. We can either use anomaly detection methods (Sun et al., 2007) or model prediction-based filtering with either voting (Brodley et al., 1996) or k-fold cross-validation (Gamberger et al., 1999).

Last but not least, Noise-tolerant methods try to learn a label noise model simultaneously with a classifier. This approach models the label noise explicitly using often a Bayesian prior (Gerlach and Stamey, 2007; Swartz et al., 2004). In the same spirit, Breve and others (Breve et al., 2010) proposed a novel particle walk semi-supervised learning method

which is robust to the noise of the label. Their method first converts the dataset into a similarity graph, then apply a label propagation algorithm to correct the wrongly labelled instances.

## 2.2 Domain Adaptation

There are two scenarios for domain adaptation, depending on whether there is in-domain labelled data (usually a small amount compared to the original dataset) available.

When we have a small amount of in-domain labelled data, transfer learning is the standard approach (Pan and Yang, 2010). Transfer learning was popularised through the ImageNet challenges (Krizhevsky et al., 2012). Recently, researchers replicated the success of transfer learning to the field of NLP and achieved new state-of-the-art results for text classification (Howard and Ruder, 2018; Peters et al., 2018). These approaches first pre-train a language model on a large corpus, then fine-tune the language model using the in-domain unlabelled data. While in-domain labelled data are usually expensive to obtain, unlabelled data such as movie reviews or web pages are often available in abundance. The final step is to train a classifier for the target classification task using the fine-tuned encoder from the previous step. Transfer learning significantly reduced the labelled data needed to train classifiers with decent accuracy. Howard and Ruder (Howard and Ruder, 2018) demonstrated that with 100 labelled examples, they could match the performance of training from scratch on 100x more data.

When there is no in-domain labelled data at all, we need to build models that are “domain-robust” or tap on unsupervised learning methods. Sachan and others (Sachan et al., 2018) investigated various models’ reliance on key lexicons by carefully constructing training and testing datasets with not key lexicon overlap. They found out while sophisticated deep learning models can theoretically capture non-local semantic features, they still rely heavily on the presence of keywords in practice. On the lexicon dataset, the accuracy of various models dropped on average ten to twenty per cent. To reduce this gap, Sachan and others (Sachan et al., 2018) proposed two methods, namely keyword anonymisation and adaptive word dropout to regularise the model and make it rely less on the keywords. Similarly, Li and others (Li et al., 2018b) performed adversarial training with Gradient Reversal Layer (Ganin et al., 2016) to remove category-specific information and to make the model generalise to unseen categories.

Mudinas and others (Mudinas et al., 2018) proposed a novel unsupervised method to bootstrap domain-specific sentiment classifiers. They observed that the positive/negative sentiment words form distinct clusters in the in-domain embedding space. To this end, they trained a simple linear model to classify words into positive or negative sentiment based on their word embedding alone. Then, they used the induced lexicon to assign pseudo-labels to the unlabelled documents. Finally, the pseudo-labelled documents were used to train a supervised LSTM model which achieves accuracy comparable to fully-supervised approaches.

### 2.3 Dataless Classification

Dataless classification (Chang et al., 2008) denotes the family of learning protocols which can induce classifiers without any labelled data (document). Instead, dataless classification algorithms make use of labelled keywords and unlabelled corpus to train the classifier. There are various approaches for dataless classification, such as hand-crafted rules, constraint optimisation, injecting the keywords as priors to the model and semantic representation of the documents and the labels.

Chang and others (Chang et al., 2008) made use of *Explicit Semantic Analysis (ESA)* (Gabrilovich et al., 2007) to embed both the documents and the labels into a shared semantic space representing concepts inferred from Wikipedia. The classification is performed by calculating the cosine similarity between the document and label representation. They also considered the impact of dataless classification on domain adaptation. However, differ from this work, they only considered the binary classification between two categories “baseball” and “hockey” and their source and target dataset (20NG and Yahoo! Answers dataset) are both manually curated and do not contain label noise. Subsequent work on dataless classification extended the ESA approach to both hierarchical classification (Song and Roth, 2014; Zheng et al., 2016) and cross-lingual classification (Song et al., 2016; Song et al., 2019).

Druck and others (Druck et al., 2008) proposed generalised expectation (GE) criteria, which induce a classifier by performing constraint optimisation over the distribution of labelled words among documents predicted into each category. GE has been successfully applied on different tasks, such as text categorization (Druck et al., 2008) and language identification in mixed-language documents (King and Abney, 2013). Similarly, Charoenphakdee and others (Charoenphakdee et al., 2019) proposed a theoretically grounded risk minimisation framework that directly optimises the area under the receiver operating characteristic curve (AUC) of a dataless classification model.

Settles (Settles, 2011) and Li and Yang (Li and Yang, 2018) both used multinomial naïve Bayes (MNB) for dataless classification. Settles (Settles, 2011) extended MNB to allow labels for words by increasing their Dirichlet prior. His method consists of three steps: firstly to estimate the initial parameters using only the priors; secondly to apply the induced classifier on unlabelled documents; lastly to re-estimate the model parameters using both labelled and probabilistically-labelled documents. Using an interactive approach to query document and word labels from the user, the system can achieve ninety per cent of state-of-the-art performance after a few minutes of annotation. In contrast, Li and Yang (Li and Yang, 2018) used the labelled keywords to provide pseudo labelled documents. They then performed standard semi-supervised learning using EM algorithm.

Li and others (Li et al., 2016) proposed Seed-Guided Topic Model (STM) for dataless text classification. Different from the standard LDA, STM models two sets of topics: *category-topics* and *general-topics*. Category-topics contains specific words which are representative of a category. General-topics are words which frequently occur in a category, but they alone do not indicate the category. For example, if a document contains the keyword “mammogram”, it is almost certainly related to cancer. However, it is not the case for keywords like “breast” and “prostate” although they do frequently occur in documents about “cancer”. The inference of STM consists of two stages: they first initialise

the category word probability and the document category distribution by counting the co-occurrence with seed words belonging to each category. Then, they apply joint Gibbs sampling to infer all the hidden parameters. STM is demonstrated to drastically outperform various baselines, including GE and a naïve Bayes model similar to Settles (Settles, 2011). STM has also been extended to perform multi-label classification (Zha and Li, 2019) and joint document filtering and classification (Li et al., 2018a).

Recently, Meng and others (Meng et al., 2018) proposed WESTCLASS, a novel weakly-supervised text classification method. It consists of two steps: pre-training and self-training. Firstly, it generates pseudo documents for each category from various sources of supervision, such as labelled keywords or documents. A generative mixture model is used to repeatedly generate a number of terms from a background distribution and the class-specific distribution to form pseudo documents. The pseudo documents are used to *pre-train* a neural model. To adapt to real-world input documents, it performs self-training on unlabelled real documents and automatically add the most confident predictions to the training set. The method drastically outperformed baselines such as IR with tf-idf, Chang and others (Chang et al., 2008) and CNN trained on pseudo-labelled documents.

Another task closely related to dataless classification is zero-shot text classification (OSHOT-TC) (Yin et al., 2019). Besides allowing no labelled training documents, it requires the model to generalise to *unseen labels*. For example, the classifier is trained on “hockey” and “baseball” category using either a supervised or dataless learning method, and it needs to classify documents belonging to the “badminton” category which occurs only at test time. The main approach to OSHOT-TC is to calculate the interaction between the document and category embeddings and model it as either a ranking or classification problem.

Li and others (Li et al., 2018b) calculated the element-wise difference and element-wise product between the category embedding and each word in the document. The document-level relevance is aggregated using convolutional layers. Nam and others (Nam et al., 2016) applied a bilinear function  $f(x, y)$  in the form of  $x^T W y$ , where  $x$  is the document representation,  $y$  is the label representation, and  $W$  is a matrix with learnable parameters capturing the interaction between the two representations. Pappas and Henderson (Pappas and Henderson, 2019) proposed Generalised Input-Label Embedding (GILE), which extends the bilinear interaction with a more generalised interaction with a non-linear activation function and a controllable parameter capacity. They demonstrated that GILE outperformed the model proposed by Nam and others (Nam et al., 2016) drastically for both seen and unseen labels.

We believe OSHOT-TC is a promising research direction. However, its requirement of generalising to any unseen labels limits the accuracy it can achieve with the current state of research. The state-of-the-art model’s performance on unseen labels is 243% to 1,062% worse than on seen labels based on different evaluation metrics (Pappas and Henderson, 2019). In contrast, dataless classification models can often yield performance that is close to a fully-supervised model. Besides, it is reasonable to assume that we know the categories in advance before we deploy the classifier. Even if the list of categories is non-static, we can easily retrain the dataless classifier with the new list of category names and keywords. Therefore, we limit the scope of this work to dataless classification and do not consider the zero-shot learning setting.

### 3 Proposed Method

Our proposed method consists of two steps: we first mine keywords for each category from a noisy labelled training corpus, then use a dataless learning algorithm to induce a text classifier with the keywords and unlabelled documents. We provide details of these two steps in Subsection 3.1 and 3.2.

Our method was remotely inspired by two well-known principles: the law of large numbers (Hsu and Robbins, 1947) and the principle of least effort (Zipf, 1949). While individual document labels may contain some random noise, when we collect keyword statistics from a large corpus, we expect the noise to be averaged out, and we can still obtain a set of high-quality keywords representing each category. On the other hand, by focusing only on keywords, we abstract out the syntactic and contextual information. The induced classifier is less likely to overfit the training corpus and may generalise better to other domains or genres of text. As commented by Settles (Settles, 2011), learning from keywords is closer to human’s learning process and requires much less effort than learning from a large number of labelled documents.

#### 3.1 Mining Keywords From (Noisy) Labelled Corpus

The selection of keywords makes a significant impact on the accuracy of the induced dataless classifier (Li et al., 2018a). While keyword (or keyphrase) extraction from text has been extensively studied, how the selection of keywords impacts dataless classification was rarely if ever discussed. Previous work used either hand-picked keywords (Druck et al., 2008; Settles, 2011; Meng et al., 2018), or relied on only the category name or category description (Chang et al., 2008; Li et al., 2016; Li et al., 2018b). The problem of extracting keywords from a (noisily) labelled corpus is defined formally as follows:

We have a corpus  $(D_1, \dots, D_C)$ , where  $D_c = (d_1, \dots, d_k)$  is the set of documents (noisily) labelled as category  $c$ . Each document  $d_i$  contains a list of terms  $(w_1, \dots, w_l)$ . We want to generate a list of representative terms  $t_1, \dots, t_n$  from the vocabulary  $V = [w_1, \dots, w_N]$  for each category. This is related to the measurement of association in information theory. Therefore, we try to apply pointwise mutual information between keyword  $w$  and category  $c$ .  $pmi(w; c)$  is defined as follows:

$$pmi(w; c) \equiv \log \frac{p(w, c)}{p(w)p(c)} = \log \frac{df(w, c) \sum_{c \in C} df(c)}{df(w)df(c)} \quad (1)$$

where  $df(w, c)$  is the number of documents belong to category  $c$  and contain word  $w$  and  $df(w)$  is the number of documents that contain word  $w$ .  $df(c)$  is the number of documents belonging to category  $c$ . Correspondingly,  $\sum_{c \in C} df(c)$  is the total number of documents in the corpus. We notice that  $pmi$  tends to favor rare words. E.g. when a word occurs only once in the corpus, it will have high  $pmi$  score in the category where it occurs. This makes the mined keywords unreliable, especially in the presence of the label noise. We therefore introduce  $pmi-freq$  with two modifications: firstly, we multiple the  $pmi$  score with the log term frequency of word  $w$ . Secondly, we set a threshold of minimum term frequency of 5. The  $pmi-freq$  will be set to zero if the term frequency is below the threshold.

$$pmi-freq(w; c) = \begin{cases} \log df(w) \log \frac{df(w, c) \sum_{c \in C} df(c)}{df(w) df(c)}, & \text{if } df(w) \geq 5 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

While *pmi* ensures that there is a strong association between the top keywords and the category, we also want the keywords for different categories to have little or no overlap. We apply maximal marginal relevance (MMR) (Carbonell and Goldstein, 1998) to achieve this.

$$mmr \equiv \arg \max_{w_i \in S_{c_m}} [\lambda Sim_1(w_i, c_m) - (1 - \lambda) \max_{w_j \in S_{c_n} \& m \neq n} Sim_2(w_i, w_j)] \quad (3)$$

In Equation 3, the first term measures the similarity between candidate word  $w_i$  and category  $c_m$ . The second term measures the maximum similarity between candidate word  $w_i$  and any seed word from another category  $c_n$ . The parameter  $\lambda$  controls the weights of the two terms. A higher  $\lambda$  favours keywords that are strongly associated to category  $c_m$ . A smaller  $\lambda$  favours keywords that occur exclusively in category  $c_m$  but not in other categories. We use a default  $\lambda$  of 0.5 and *pmi-freq* as the similarity measure for both  $Sim_1$  and  $Sim_2$ .

We want to study the impact of different label noise rate on the quality of the mined keywords. Since the label noise rate for a corpus is fixed, we synthesise label noise using the following mechanism:

1. Choose the label noise rate  $\epsilon$  to generate noise;
2. Calculate the # of docs with corrupted label:  $n_{corrupt} = \text{math.floor}(n_{docs} \cdot \epsilon)$ ;
3. Randomly select  $n_{corrupt}$  docs and randomly shuffle their labels;

We use the well-known 20 newsgroups dataset (Lang, 1995) and vary the percentage of label noise from zero percent up to seventy percent. We manually examine the top ten keywords to evaluate the quality of the keyword mining algorithm. We count a keyword to be correct if it unambiguously represents the category. E.g. while the word ‘‘Israeli’’ represents the category ‘‘talk.politics.mideast’’, the word ‘‘territories’’ does not. Due to the space limit, we only show the results for three randomly selected categories (talk.politics.mideast, rec.autos, rec.sport.baseball) while the other categories follow the same trend.

Among previous work, only Druck and others (Druck et al., 2008) proposed an automatic algorithm to mine keywords from oracle labelled documents based on mutual information (*mi*). Therefore, we compare the three aforementioned methods *pmi*, *pmi-freq*, *mmr* together with *mi*. Besides, we also show the result of a naive baseline *freq*, which outputs the most frequent word for each category after stop word removal. *mi* is expressed as:

$$mi(w; C) \equiv \sum_{c \in C} p(w, c) \log \frac{p(w, c)}{p(w)p(c)} \propto \sum_{c \in C} df(w, c) \log \frac{df(w, c) \sum_{c \in C} df(c)}{df(w) df(c)} \quad (4)$$

*mi* is independent from the category since it sums up all the categories. Therefore, Druck and others (Druck et al., 2008) first selected the most predictive  $k$  features based on *mi* and then assigned the word to the category where it occurs with most often, and other categories that it occurs with at least half as often.



Figure 1 shows the number of correct keywords output by each algorithm for different noise rate  $\epsilon$ . We can observe that *pmi-freq* and *mmr* almost always generate better keywords than *pmi* except for the automotive category when the label noise rate is relatively low. This is because *pmi* generates specific automotive brand names which are relatively unambiguous. *pmi-freq* and *mmr* remain effective even when the label noise rate is 0.5. They also tend to be more robust against the change of the noise rate and the generated keywords remain relatively static. On the other hand, *pmi* sometimes generates completely different keywords when the noise rate is increased by 0.1.

Table 1 shows the generated keywords of various algorithms for the category “rec.sport.baseball” with label noise rate of 0.3. We underline the ambiguous keywords. We can see that almost all keywords generated by *pmi* are person or team names. Six out of ten keywords are ambiguous. In contrast, *pmi-freq* and *mmr* generate specific keywords related to the baseball game. They generate much fewer ambiguous keywords and will likely generalise better. The two baselines *freq* and *mi* both perform poorly. While *freq* tends to generate common words like “bad” and “actually”, *mi* tends to generate words that occur frequently in multiple categories (because it sums up the mutual information score for all categories) and therefore have less discriminative power.

The full list of keywords generated by each algorithm at different label noise rate is presented in Appendix A. *Pmi-freq* and *mmr* perform on par with each other. Therefore, we choose to use *pmi-freq* as the final algorithm to mine keywords due to its simplicity.

PMI	PMI-FREQ	MMR	FREQ	MI
royals	pitcher	pitcher	baseball	<u>season</u>
<u>hernandez</u>	baseball	braves	<u>games</u>	<u>team</u>
dodgers	braves	pitching	<u>team</u>	baseball
marlins	pitching	pitchers	<u>hit</u>	pitcher
<u>lankford</u>	pitchers	hitter	pitcher	<u>players</u>
braves	hitter	batter	<u>play</u>	braves
<u>fielder</u>	batter	<u>gant</u>	<u>lot</u>	<u>stats</u>
cardinals	<u>gant</u>	inning	<u>league</u>	<u>player</u>
<u>ws</u>	inning	batting	<u>bad</u>	<u>games</u>
<u>winfield</u>	<u>league</u>	jays	<u>actually</u>	<u>hitter</u>

Table 1: Automatically mined keywords for the category “rec.sport.baseball” with 0.3 label noise. The ambiguous keywords are underlined.

### 3.2 Training Dataless Classifiers

We apply the Seed-Guided Topic Model (STM) (Li et al., 2016) to train dataless classifiers. The architecture of STM is depicted in Figure 2. STM takes labelled seed words and unlabelled documents as input. In the first step, the initial document category distribution is estimated from the term frequency of seed words with a Dirichlet smoothing prior. It also calculates the category word probability of unlabelled words based on their co-occurrence with the labelled seed words as follows:

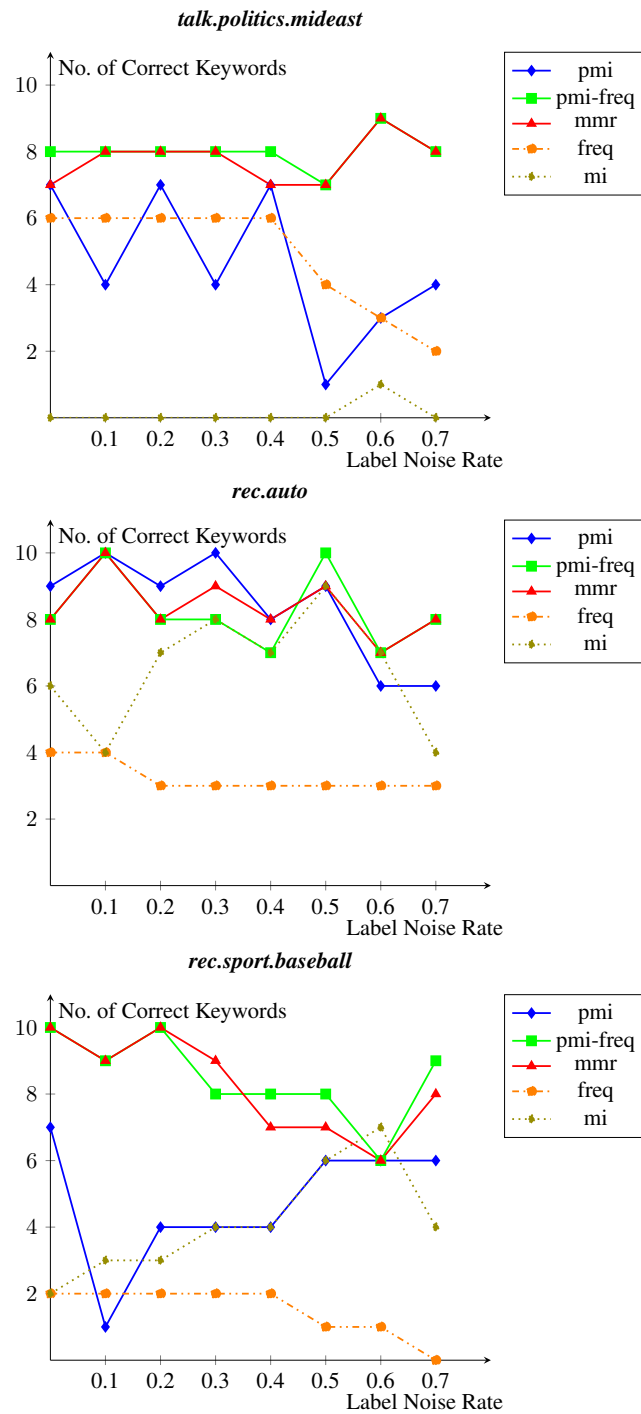


Fig. 1: Number of correct keywords generated by each algorithm varying the percentage of label noise.

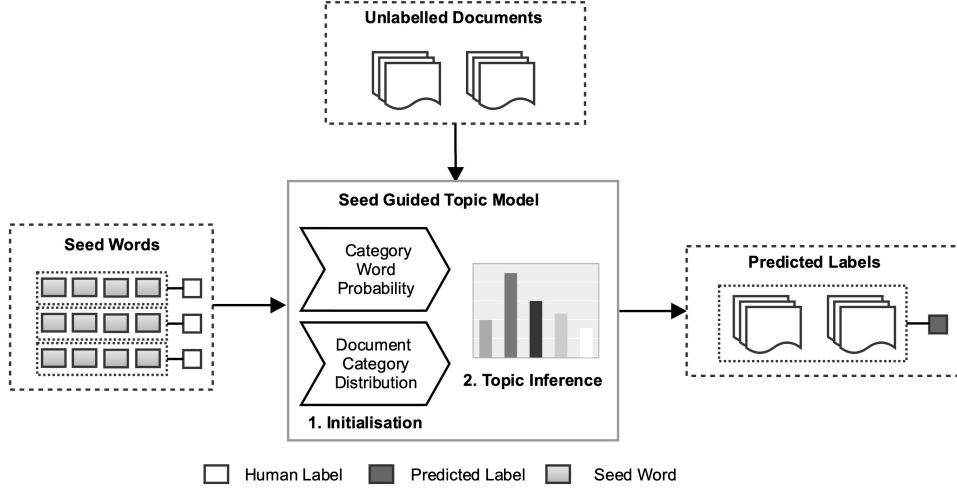


Fig. 2: The architecture of the seed-word guided topic model.

We first calculate the conditional probability  $p(w|s)$  using Equation 5, where  $df(w, s)$  is the number of the documents containing both unlabelled word  $w$  and seed word  $s$ . The relevance of word  $w$  to category  $c$  is then calculated as the average conditional probability of  $w$  with respect to each seed word in  $S_c$  (Equation 6).

$$p(w|s) = \frac{df(w, s)}{df(s)} \quad (5)$$

$$rel(w, c) = \frac{1}{|S_c|} \sum_{s \in S_c} p(w|s) \quad (6)$$

Lastly, the relevance score is normalised by summing over each category  $c$  and each word  $w$  in the vocabulary in Equation 7 and Equation 8 respectively. The final  $\nu_c$  values are used to initialise the category word probability before the inference process.

$$\nu(w, c) = \max\left(\frac{rel(w, c)}{\sum_c rel(w, c)} - \frac{1}{c}, 0\right) \quad (7)$$

$$\nu_c(w, c) = \frac{\nu(w, c)}{\sum_w \nu(w, c)} \quad (8)$$

The model differentiates two types of underlying topics: the category-topic and the general-topic. General-topics capture the global semantic information and are shared by all the documents. A category-topic is associated with a single category and captures the relevant keywords of the category. STM model introduces a binary variable  $x_{d,i}$  which indicates whether the associated word  $w_{d,i}$  is generated from document  $d$ 's category-topic  $c_d$  or from one of the general-topics. The parameter inference is carried out using Gibbs Sampling, and the generative process is described below:

1. For each category  $c \in \{1..C\}$

- (a) draw a general-topic distribution  $\varphi \sim \text{Dirichlet}(\alpha_0)$ ;
- (b) draw a category word distribution  $\vartheta \sim \text{Dirichlet}(\beta_0)$ ;
- 2. For each general-topic  $t \in \{1 \dots T\}$ :
  - (a) draw a word distribution for the general-topic  $\phi_t \sim \text{Dirichlet}(\beta_1)$ ;
- 3. For each document  $d \in \{1 \dots D\}$ :
  - (a) generate an initial category distribution  $\eta_d$ ;
  - (b) draw category  $c_d \sim \text{Multinomial}(\eta_d)$ ;
  - (c) draw a general-topic distribution  $\theta_d \sim \text{Dirichlet}(\alpha_1 \cdot \varphi_{c_d})$ ;
  - (d) for each word  $i \in \{1 \dots |d|\}$ :
    - i draw  $x_{d,i} \sim \text{Bernoulli}(\delta_{w_{d,i}, c_d})$ ;
    - ii if  $x_{d,i} = 0$ : draw word  $w_{d,i} \sim \text{Multinomial}(\vartheta_{c_d})$ ;
    - if  $x_{d,i} = 1$ :
      - A draw general-topic assignment  $z_{d,i} \sim \text{Multinomial}(\theta_d)$ ;
      - B draw word  $w_{d,i} \sim \phi_{z_{d,i}}$ ;

During the inference/prediction, the model first jointly samples each pair of  $x_{d,i}$  and  $z_{d,i}$  conditioned on every possible category  $c$ . It then estimates the conditional probability distribution  $p(c_d = c | \mathbf{z}, \mathbf{x}, \mathbf{c}_{-d}, \mathbf{w})$ , where  $-d$  denotes the collection of documents excluding document  $d$ . We observe that STM tends to predict inconsistent labels for the same input. In the work of Li and others (Li et al., 2016), they predict the category as the category sampled from the category probability distribution in the last iteration. Instead, we predict  $\text{argmax } p(c_d = c | \mathbf{z}, \mathbf{x}, \mathbf{c}_{-d}, \mathbf{w})$  in the last iteration as the document category.

The STM model has two main advantages that allow it to achieve high accuracy for dataless classification. Firstly, the model explicitly calculates the correlation of unlabelled words to the seed words and uses it to initialise the category word probability. This makes the inference process much easier compared to using a randomly initialised probability distribution. Secondly, by separating the topics into general-topics and category-topics, the model can focus on only the reliable signals and “skim-through” the rest of the document by assigning it to a general-topic.

We apply the STM model with the keywords mined using the algorithm described in Section 3.1 and a large unlabelled corpus to train the final classifier.

## 4 Experiments

### 4.1 Datasets

We use three datasets to carry out experiments in this work. One is a legacy large labelled dataset crawled from newswire sites. We refer to this dataset as *news-crawl dataset*. The label was obtained by mapping the news categories to IAB categories. Therefore, we expect the presence of label noise in the dataset. We also crawled another evaluation dataset with roughly one hundred documents per category following similar methodology. We refer to it as *news-crawl-v2 dataset*. These two datasets differ in two ways. Firstly, *news-crawl dataset* was collected before April 2015 and *news-crawl-v2 dataset* was collected during May 2019. Secondly, they are crawled from different websites. These differences allow

us to study the behaviour of the models when applied to a slightly different domain. The details of constructing the dataset as well as the websites where the two datasets were collected are presented in Appendix B.

The third dataset is a small manually labelled evaluation dataset. We crawled the documents from URLs in the real-time-bidding (RTB) requests we logged. The RTB traffic contains URLs in the user browsing history where there is an opportunity for us to display ads. It contains heterogeneous web pages, such as forums, blogs and even social network sites. This dataset is more realistic to our application domain. We refer to this dataset as *browsing dataset*. All datasets contain the same twenty-two categories (all IAB tier-1 categories <sup>4</sup> except for “News” because “News” can cover any topic). We release the evaluation datasets publicly for researchers to reproduce our results and to facilitate future research in contextual text classification <sup>5</sup>.

For the browsing dataset, we found out during the annotation that some documents may belong to multiple categories. Therefore, we did not limit to one category per document but labelled all the correct categories. Table 2 summarises the number of labels assigned to documents. Sixty per cent of the documents were assigned only one label, and ninety-four per cent of the documents have two or fewer labels. Multi-label classification is beyond the scope of this work. We are only interested in predicting one of the correct labels which have been annotated.

# of labels	# of documents
1	892
2	516
3	84
4	9

Table 2: The number of labels assigned to documents in the browsing dataset.

The number of documents in the three corpora is shown in Table 3. We can see that the number of documents for each category is imbalanced, especially for the news-crawl dataset. We did not downsample the majority categories but kept all the documents that we crawled. Another observation is that the categories with the most number of documents in the news-crawl dataset and browsing dataset are very different. While the news-crawl dataset contains many documents related to business or politics, in the user-browsing dataset, there are more documents related to entertainment, food&drinks and shopping. Besides, there is also a difference in the document length in the datasets. The average document lengths for news-crawl dataset and news-crawl-v2 dataset are 503 and 1,470 words while in the user-browsing dataset, it is 350 words. This evidence suggests a potential mismatch between the training data and the real-world data where the model is applied.

<sup>4</sup> <https://www.iab.com/guidelines/iab-quality-assurance-guidelines-qag-taxonomy/>

<sup>5</sup> <https://github.com/YipingNUS/nle-supplementary-dataset>

Category label	news-crawl	news-crawl-v2	browsing
Business	44,343	100	50
Society	25,460	89	71
Technology & Computing	16,466	100	178
Health & Fitness	16,171	100	132
Law, Government & Politics	14,374	97	44
Science	11,863	100	96
Sports	11,055	100	92
Art & Entertainment	10,746	100	207
Education	8,321	100	80
Personal Finance	5,693	80	56
Automotive	5,522	91	109
Food & Drinks	4,408	100	173
Family & Parenting	4,204	118	44
Style & Fashion	4,191	100	62
Travel	3,995	100	135
Hobby & Interest	3,710	100	117
Pets	3,246	100	22
Religion & Spirituality	2,936	95	57
Home & Garden	2,427	100	66
Real-estate	2,056	100	86
Careers	1,685	65	49
Shopping	1,611	92	152
Total	204,483	2,127	1,501

Table 3: Statistics of datasets. The categories are sorted by the number of documents in the news-crawl corpus.

## 4.2 Experimental Setup

We split news-crawl dataset randomly into a 0.9/0.1 training and testing set. The fixed test set is only used for evaluation and not included during training and keyword mining. News-crawl-v2 and browsing dataset are reserved for evaluation only.

### 4.2.1 Parameter Setting

For the first step of mining keywords from the labelled dataset, we select the top fifteen unigram keywords for each category based on the *pmi-freq* score. All the documents have been lowercased and we remove keywords that are less than four characters, contain numbers or contained in NLTK stopword list<sup>6</sup>. The remaining keywords and the training data (labels removed) are used to train the STM model. We use the parameters recommended in Li and others (Li et al., 2016) with the total number of topics  $T$  being three times the

<sup>6</sup> <https://www.nltk.org/data.html>

number of categories. We set  $\alpha_0 = 50/T$ ,  $\beta_0 = \beta_1 = 0.01$ ,  $\alpha_1 = 100$  and  $\rho = 0.8$ . We stop the inference after the 5th iteration.

#### 4.2.2 Methods in Comparison

We compare our proposed method against various supervised learning and dataless classification baselines and a recent transfer learning-based state-of-the-art model. All the models use word unigrams as features and weight using term frequency when applicable.

##### Supervised Learning Baselines:

- **Multinomial Naïve Bayes (MNB):** MNB model is a competitive baseline for text classification tasks (Wang and Manning, 2012). We train a supervised MNB model with Laplace smoothing ( $\alpha = 1$ ). We use the implementation in scikit-learn <sup>7</sup>.
- **Support Vector Machines (SVM):** SVM is a versatile model used widely across different domains. It is also one of the most commonly used ML models in the industry. We train a linear SVM classifier using stochastic gradient descent with the default parameter settings in scikit-learn ( $\alpha = 1e - 4$ ). We use term frequency as the weighting scheme.
- **K-Nearest Neighbours (KNN):** We train a KNN model with a relatively small  $k = 3$ . In practice, KNN’s prediction time is at least two magnitudes slower than the other models, making it not applicable for production usage. We show the results of this model for comparison purpose only.
- **Universal Language Model Fine-tuning (ULMFiT):** <sup>8</sup> ULMFiT (Howard and Ruder, 2018) is a recent model applying transfer learning to induce a text classifier from a language model. It reported state-of-the-art performance on various topic and sentiment classification benchmarks. We use the implementation of ULMFiT in fastai library <sup>9</sup> and apply the optimisation tricks such as discriminative fine-tuning and gradual unfreezing as proposed by Howard and Ruder (Howard and Ruder, 2018). We use the default parameters and fine-tune the classification model for fifteen iterations using our training data.

##### Dataless Classification Baselines:

- **Generalised Expectations (GE):** GE (Druck et al., 2008) is a dataless classification method using user-labelled keywords to constrain the training of a discriminative model. We use the same user labelled keywords as our proposed method. The GE implementation is from the Mallet library <sup>10</sup>.
- **Multinomial Naïve Bayes with priors (MNB/Priors):** MNB/Priors (Settles, 2011) is another dataless classification baseline which increases priors for labelled keywords and learns from an unlabelled corpus using EM algorithm. We use the open-source MNB/Priors implementation provided by the author <sup>11</sup>.

<sup>7</sup> <https://scikit-learn.org>

<sup>8</sup> Though ULMFiT is pretrained on unlabelled corpus, it still requires labelled documents in the fine-tuning step. Therefore, we count it as supervised method.

<sup>9</sup> <https://github.com/fastai/fastai>

<sup>10</sup> <http://mallet.cs.umass.edu/>

<sup>11</sup> <https://github.com/burrsettles/dualist>

- **Doc2vec:** Doc2vec (Le and Mikolov, 2014) learns distributed embedding representation of documents. We concatenate the keywords for each category to form a “document” and infer its document vector as the “category vector”. When predicting the category of a document, we simply take the category of the nearest category vector. We use the doc2vec implementation in gensim<sup>12</sup> with default parameters. We set the embedding size to 100 and train the model for ten epochs.
- **WESTCLASS:** WESTCLASS (Meng et al., 2018) is a weakly-supervised neural model for text classification. Although WESTCLASS can take various types of supervision, we limit to the keywords for a fair comparison with other dataless classification methods. We use the implementation by the original authors<sup>13</sup>. We generate 500 pseudo documents per category for pre-training<sup>14</sup> and the entire unlabelled training corpus for self-training. We also use the CNN architecture as recommended in the paper.

#### 4.2.3 Performance Metrics

For the news-crawl dataset, we report the accuracy and Macro- $F_1$  scores. Because the categories are highly imbalanced, Macro- $F_1$  is more meaningful than Micro- $F_1$  to indicate the average performance across different categories.

For the browsing dataset, because some documents contain multiple labels, we cannot apply standard multi-class classification metrics directly. Therefore, we use accuracy<sup>+</sup> and  $maF_1$  for multi-label classification following Nam and others (Nam et al., 2017).

Accuracy<sup>+</sup> is defined as the total correct predictions divided by the total predictions. Since all the models are multi-class classification models and predict only one label, we count the prediction to be correct if the predicted label is one of the labels that has been annotated by the human annotator.  $maF_1$  for multi-label classification is defined as:

$$maF_1 = \frac{1}{L} \sum_{j=1}^L \frac{2tp_j}{2tp_j + fp_j + fn_j} \quad (9)$$

where  $L$  is the number of categories and  $tp_j$ ,  $fp_j$ ,  $fn_j$  denote the number of true-positive, false-positive and false-negative of category  $j$ . We note that to obtain a perfect  $maF_1$  score of 1, the model needs to predict all the correct label(s) for each document. Since all the models in comparison predict only one label for each document, the  $maF_1$  score is strictly lower than 1, but the comparison is still fair nevertheless.

### 4.3 Results and Discussion

#### 4.3.1 Mined Keywords from Labelled Corpus

Table 4 shows the generated keywords for each category, which will be used by all dataless classification models.

<sup>12</sup> <https://radimrehurek.com/gensim/models/doc2vec.html>

<sup>13</sup> <https://github.com/yumeng5/WESTClass>

<sup>14</sup> Meng and others (Meng et al., 2018) demonstrated that generating more than 500 documents per category will not yield any performance improvement.



<b>Category</b>	<b>Generated keywords</b>
Business	<i>aircraft railways ridership airframe airbus commuters aviation harvesting railroads roofing marketers boeings</i>
Society	<i>skout matchcom okcupid friendships transgender samesex lesbian marriages flirt lgbt dating lesbians heterosexual</i>
Technology & Computing	<i>android scan apps firmware samsung os leftright device smartphones keyboard snapdragon 64bit usb smartphone</i>
Health & Fitness	<i>symptoms inflammation medications disease vitamin disorders diabetes diet chronic diagnosis nutrition infections</i>
Law, Government & Politics	<i>immigration passport uscis embassy attorney lawyers consular citizenship consulate lawyer legal citizens immigrants</i>
Science	<i>horoscpe astrology atoms earths jupiter planets nasa molecules electrons telescope particles forecast orbit</i>
Sports	<i>olympics medal league semifinal finals midfielder freestyle championship semifinals football stadium athletes</i>
Art & Entertainment	<i>bollywood actress actor films film song album singer actors songs lyrics comedy costar drama movie hollywood</i>
Education	<i>colleges universities students exam academic undergraduate admissions faculty examination cbse campus education</i>
Personal Finance	<i>stocks investors securities nasdaq equity dividend investor bse earnings trading nse volatility bluechips intraday</i>
Automotive	<i>torque tires honda brakes wheels v8 exhaust transmission chevrolet steering engine cylinder dealership mileage sedan</i>
Food & Drinks	<i>recipe sauce bake preheat recipes flour butter delicious flavor ingredients vanilla baking cheese stir garlic</i>
Family & Parenting	<i>babys babycenter pregnancy babies trimester baby uterus pregnant breastfeeding placenta midwife newborn</i>
Style & Fashion	<i>calories tattoo weightloss fat waistline dieting menswear acne sneaker carbs cardio dresses slimming moisturizing</i>
Travel	<i>kayak booking rentals airline hotels attractions beaches resorts reservation reservations couchsurfing hotel</i>
Hobby & Interest	<i>minecraft armor gameplay quests puzzle ingame multiplayer rpg enemies crossword weapons pokemon monsters</i>
Pets	<i>puppies vet puppy breeds dogs veterinarian breed dog pups breeders kennel pet terrier cats canine</i>
Religion & Spirituality	<i>christians christ jesus bible religious worship islam christianity quran muslims church prayer scriptures muslim</i>
Home & Garden	<i>diy wood soil gardeners cabinets backsplash mulch planting compost plants fertilizer decor watering screws potting</i>
Real-estate	<i>furnished rent condo bedrooms rental sqft apartments apartment bedroom spacious trulia renovated vrbo rentals</i>
Careers	<i>vacancies recruitment candidates interviewer resume qualification employers employer freshers vacancy interviewers</i>
Shopping	<i>coupons coupon pricepony discount scoopon cashback freebies storewide</i>

Table 4: Generated keywords using pmi-freq.

## 4.3.2 Text Classification Performance

Table 5 shows the performance of various models on the three datasets. All the supervised learning models are trained on the full news-crawl training set with class labels. All the dataless classification models are trained using the same list of keywords in Section 4.3.1. They also access the full news-crawl training set but without the class labels.

All the supervised models performed reasonably well on the news-crawl test set. However, their performance degraded drastically on the other two datasets. This shows that while supervised learning methods can learn important features from the training data and predict accurately on similar documents, there is no guarantee that the model will perform well when the input document looks very different, although they are about the same topics. The recent state-of-the-art ULMFiT model outperformed the other baselines by a large margin on news-crawl test set and achieved a high accuracy of 0.922. Its performance on the other datasets is still competitive among the supervised baselines but lags behind the best dataless classification models.

While MNB’s performance on the news-crawl test set lagged behind SVM, its performance on the other two datasets was superior, suggesting that it generalises better to a new domain different from the training data. This is consistent with the finding of Sachan and others (Sachan et al., 2018), where a discriminative Logistic Regression model suffered more than a Naïve Bayes model when applying on a corpus without important lexicon overlap. The KNN model obtained a slightly inferior yet still reasonable performance on the news-crawl test set. However, it failed on the other two datasets. Suggesting the differences between the datasets are large, and a similarity-based classification algorithm will not work.

Model	news-crawl test set		news-crawl-v2		browsing dataset	
	Accuracy	Macro- $F_1$	Accuracy	Macro- $F_1$	Accuracy <sup>+</sup>	ma $F_1$
Random	.045		.045		.067	
Most frequent	.217		.055		.146	
MNB	.817	.766	.524	.466	.660	.504
SVM	.850	.811	.489	.470	.471	.381
KNN	.751	.679	.189	.159	.166	.103
ULMFiT	<b>.922</b>	<b>.892</b>	.541	.496	.564	.431
GE	.510	.483	.596	.587	.777	.617
MNB/Priors	.533	.411	.439	.366	.631	.493
Doc2vec	.391	.383	.480	.461	.557	.424
W <sub>E</sub> STCLASS	.187	.163	.190	.158	.177	.121
STM	.544	.527	<b>.623</b>	<b>.607</b>	<b>.794</b>	<b>.625</b>

Table 5: Performance of various models on three datasets: news-crawl test set, news-crawl-v2 dataset and on browsing dataset.

It is interesting to observe that while dataless classification models lagged behind all

the supervised learning models on the news-crawl test set, they yielded competitive performance on the other two datasets. This confirms our intuition that by abstracting the semantics using keywords, we can obtain better transferability.

STM achieved the best performance on all three datasets compared to other dataless baselines. GE is the second best model and its performance is consistently 1-3 per cent lower than STM. Despite the two models have completely different architectures, they both explicitly exploit the word-cocurrence information, suggesting that it is an important strategy to bootstrap knowledge in a dataless learning process.

The doc2vec baseline has a mediocre performance on all datasets and is consistently 15-20 per cent lower than STM. WESTCLASS’s performance was surprisingly very low. Meng and others (Meng et al., 2018) demonstrated that the model performed well on binary sentiment classification and topic classification with a small number of categories (four or five). However, our task has twenty-two categories. The core assumption of WESTCLASS that the keywords and documents of each category lie in disjoint clusters in a low-dimensional space may not hold when the number of categories get larger. This is partially validated by the poor performance of doc2vec, where the average of the keyword embeddings is used to represent the category. After pretraining with pseudo labelled documents, WESTCLASS has a poor macro- $F_1$  score of 0.104, suggesting the poor quality of the pseudo documents. The self-training does improve macro- $F_1$  by nearly six per cent, but WESTCLASS’s performance remains very poor compared to other baselines.

Two questions arose naturally when we were analysing the result:

1. Why STM performs well on different datasets but not so well on the test set which is most similar to the data which it is trained on?
2. What caused ULMFiT’s performance to degrade drastically when applied on another domain?

To answer the first question, we plot the confusion matrix of STM model on news-crawl test set in Figure 3. We can see that the misclassifications are not random. While we anticipate misclassifications among closely related categories such as “business” and “personal-finance”, some other cases are worth investigating, such as misclassifying a large proportion of “pets” documents to “family-parenting”.

To this end, we did further analysis on the documents belonging to the “pets” category that are misclassified as other categories. Tabel 6 shows the top five categories STM model predicted for documents belonging to the “pets” category. Our first impression is that these categories are somehow related to “pets”, such as pets are part of the family and important especially to children. Some articles may also talk about veterinary medicine or pet-related diseases, thus making it related to “health & fitness” category.

We inspected the documents which are “misclassified” as “family & parenting” and found that almost all of them are related to children and pets or pets in a family/relationship. Table 7 shows some example snippets. These documents naturally belong to both categories, but only one label was assigned in the news-crawl dataset. This explains why STM’s performance on the news-crawl test set is poor while it performs well on the browsing dataset, where all correct categories are labelled.

To understand why ULMFiT’s performance dropped significantly when applied on a different domain, we want to understand what features the model learns and whether these

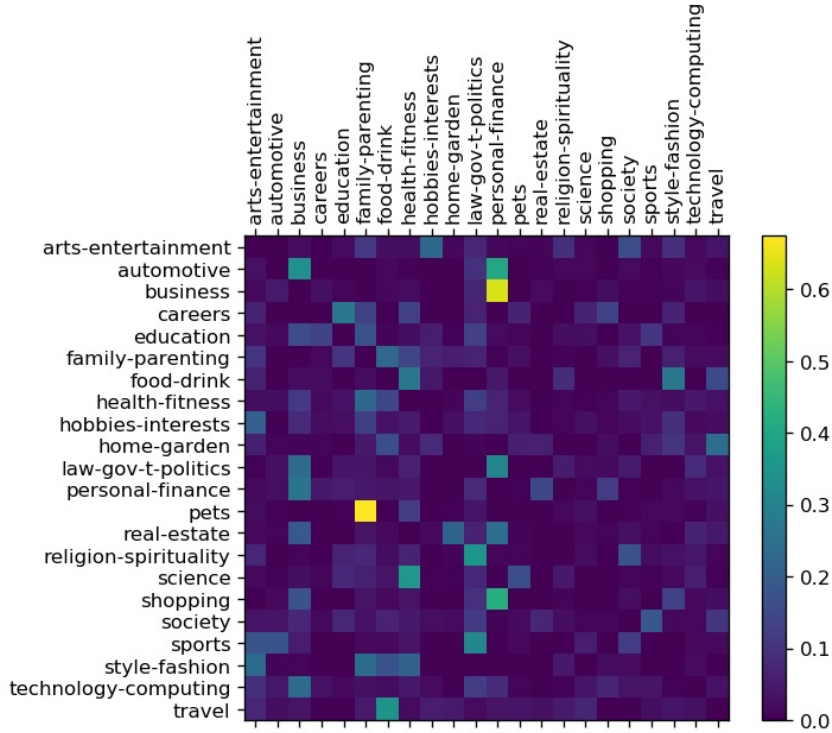


Fig. 3: The confusion matrix of STM model prediction on the news-crawl test set. The diagonal entries (correct predictions) have been removed to surface the misclassifications.

Category	# of predictions
Pets	194
Family & Parenting	89
Health & Fitness	16
Law, Government & Politics	5
Travel	4

Table 6: Top five categories the STM model predicts for documents belonging to pets category.

features can be easily transferable across domains. Therefore, we used LIME<sup>15</sup> (Ribeiro et al., 2016), a model-agnostic interpretation technique to explain the predictions of ULM-FiT on sample text drawn from different datasets. LIME perturbs the input instance  $X$  slightly and probes the classifier for prediction. It then fits a linear interpretation model

<sup>15</sup> <https://github.com/marcotcr/lime>

#	Text
1	poll Do you think it's important for children to have pets? No, pets only make messes Yes, it teaches them responsibility. Share your vote on facebook so your friends can take this poll
2	Babies vs pets in viral advertising posted which do you prefer? Pets or babies? They're everywhere in social media pulling views sparking massive followings rising to the top of every hit list it's a massive love fest huh? what's going on? have we gone cute crazy? why do these characters work so well? ...
3	'The dog is (by which you mean, 'I want a divorce!') ... The dog is bored is my husband projecting? transferring? planning on taking the dog for a romantic tropical vacation? Am I right? Am i crazy? You decide. Relationships are full of mystery and are open to interpretation, wild speculation and deep neurosis ...

Table 7: Example documents with label “pets” and are classified as “family & parenting”.

that approximates the classifier locally in the vicinity of  $X$ . LIME can output a list of features contributing to predicting each category with their feature importance.

Figure 4 shows LIME’s explanations for both ULMFiT and STM on a sample document from news-crawl dataset <sup>16</sup>. While both models predict close to 1.0 probability for the correct category “home-garden”, the interpretation for STM is obviously more plausible. In contrast, Figure 5 depicts an example from browsing dataset where STM predicts the correct label with high confidence but ULMFiT predicts the wrong label. In general, we found that ULMFiT tends to focus on more “fuzzy” features. This may due to the nature of deep learning models which capture complex interactions of non-local features. While these features helped ULMFiT to achieve a very high accuracy on a random-split test set, they may not remain reliable when the input data differ significantly from the training data.

### 4.3.3 Impact of Keyword Selection Strategy

In Section 3.1, we manually evaluated the quality of the mined keywords using different algorithms. In this section, we try to answer the question how much different keyword selection strategies affect the accuracy of the induced dataless classifier and whether our proposed keyword selection method improves the final accuracy.

To this end, we trained STM with different set of keywords and evaluated them on the same evaluation datasets. The keyword selection strategies we compared with are  $S_{label}$ , which uses only the words occurring in the category name. It is one of the systems used in Li and others (Li et al., 2016). We also compare with  $S_{freq}$  and  $S_{mi}$ , which use frequency-based and mutual information-based keyword selection mentioned in Section 3.1. For  $S_{freq}$  and  $S_{mi}$ , we generate fifteen top keywords for each segment, making the number

<sup>16</sup> The document has been truncated due to space limit but sufficient information is left for the models to make the correct prediction.

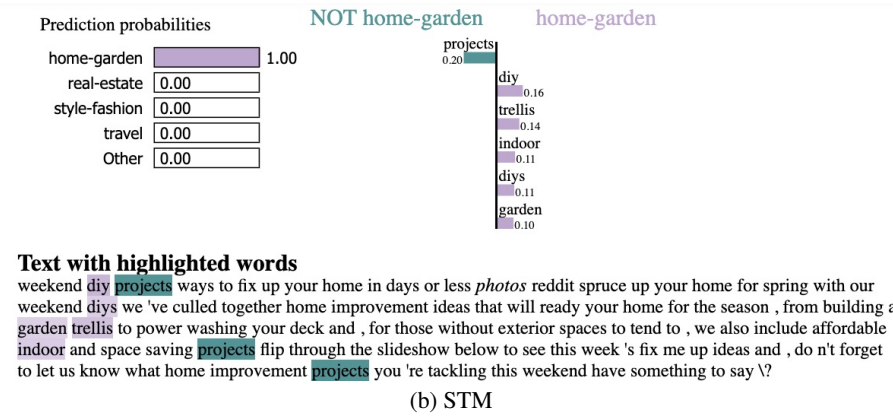
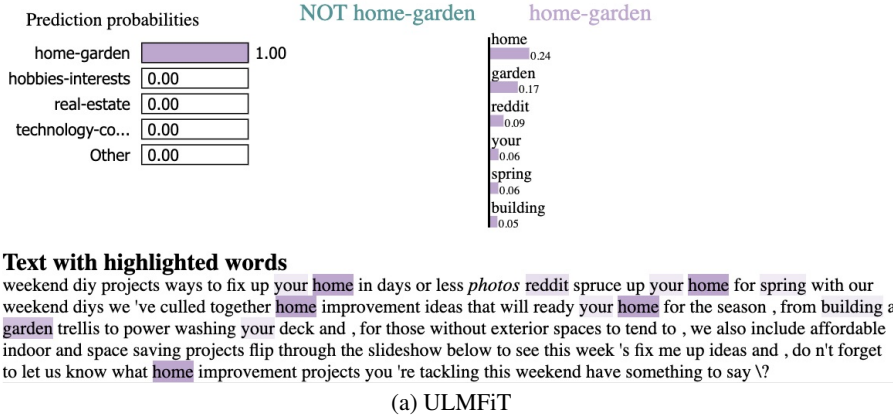


Fig. 4: LIME explanations on a sample document from news-crawl dataset.

of keywords equal to  $S_{pmi-freq}$ . We publish the keywords selected using each method to facilitate replication of our results <sup>17</sup>.

Model	news-crawl test set		news-crawl-v2		browsing dataset	
	Accuracy	Macro- $F_1$	Accuracy	Macro- $F_1$	Accuracy <sup>+</sup>	ma $F_1$
STM + $S_{pmi-freq}$	.544	.527	.623	.607	.794	.625
STM + $S_{label}$	.270	.243	.332	.259	.405	.340
STM + $S_{freq}$	.284	.257	.425	.359	.500	.358
STM + $S_{mi}$	.301	.265	.434	.344	.565	.385

Table 8: Performance of STM using different set of keywords on three datasets: news-crawl test set, news-crawl-v2 dataset and browsing dataset.

Table 8 shows the result. Firstly, using the seed words occurring in the category name

<sup>17</sup> <https://github.com/YipingNUS/nle-supplementary-dataset>

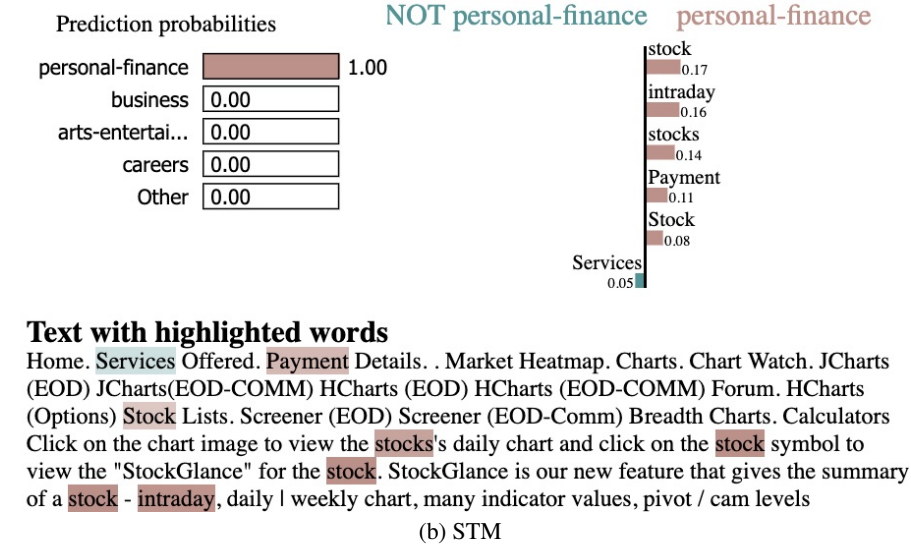
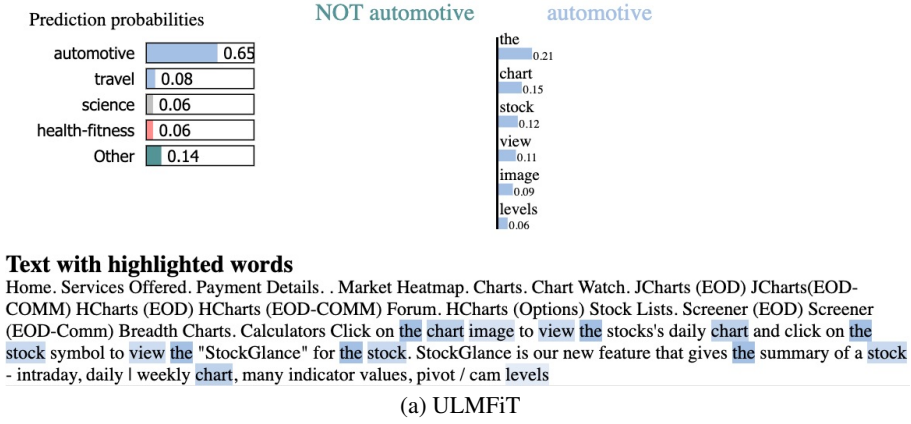


Fig. 5: LIME explanations on a sample document from browsing dataset.

alone resulted in the poorest performance, indicating that the category name does not provide sufficient supervision to train an accurate classifier. Some category names are covering terms which might not frequently occur in the text, such as “technology & computing”, where people might talk much more about “mobile phones” and “laptops” than “computing”. The baseline seed word selection methods  $S_{freq}$  and  $S_{mi}$  improved from  $S_{label}$ . However, their performance still far lagged behind the proposed  $S_{pmi-freq}$ , demonstrating the importance of the seed word selection method on the final accuracy of the dataless classifier.

Interestingly, we observed that  $mi$  did generate good keywords for some categories but failed for some other categories. We show two sample categories with their corresponding keywords selected by  $mi$  and their P/R/ $F_1$  score on the news-crawl-v2 dataset. Most keywords  $mi$  selected for the category “real estate” turned out to be location names in Singapore. This might due to the bias in the data collection. As a result, the category did not

Category	Generated keywords	P/R/F <sub>1</sub>
Family & Parenting	<i>pregnancy babys breastfeeding uterus babycenter vaginal fetus trimester cervix pediatrician</i>	.76/.91/.83
Real Estate	<i>clicked movingcom realtorcom hdb blk eunos yishun kio lebar foreclosures</i>	0/0/0

Table 9: Sample generated keywords using *mi* and the P/R/F<sub>1</sub> on news-crawl-v2 dataset.

generalise at all and had a zero F<sub>1</sub> score on the news-crawl-v2 dataset. On the other hand, *mi* generates good keywords for the category “family & parenting”, and the F<sub>1</sub> score is also high. It demonstrates that *mi* is to some extent effective to detect meaningful keywords. However, it is not robust enough to guarantee good-quality keywords for each category.

Putting together the result in this section and Section 4.3.2, we want to highlight that the selection of seed words has at least as much impact on the dataless classification accuracy as the selection of different algorithms. However, it has not received due attention from the research community.

#### 4.4 Experiment on Sentiment Classification Datasets

To demonstrate the effectiveness of the proposed method on other tasks and datasets, we conduct an experiment on a pair of publicly available sentiment classification datasets. We train the supervised and dataless classifiers on IMDB dataset (Maas et al., 2011) and evaluate the model on both IMDB and Yelp test set (Zhang et al., 2015). Both datasets consists of evenly distributed binary polarity classes. IMDB dataset contains 25,000 training documents, 25,000 testing documents and an additional 50,000 unlabelled documents. Yelp test set contains a total of 38,000 documents. Compared to the previous datasets for contextual advertising, these datasets are easier for three reasons: they contain only two classes; the classes are balanced and the document labels are free from noise.

We use IMDB training set to train all the supervised classifiers<sup>18</sup>. We also use the training set to automatically mine thirty keywords for each class, which are used by all dataless classifiers. The list of keywords are shown in Table 10. We then use the combination of the training set and the unlabelled set to train the dataless classifiers. Table 11 shows the results of all the competing models. Since the datasets contain only two evenly distributed classes, we report only the accuracy score.

We can make a few observations from the result. Firstly, some dataless classification models perform on par with simple supervised learning baselines. This is encouraging because the supervised models are trained using 25,000 labelled documents while the dataless classification models use only thirty automatically mined keywords per category. Secondly, ULMFiT performs the best on both datasets. This is probably because the training data is free from noise and the two datasets are relatively similar (both are user reviews).

While dataless classification models do not perform as well as a state-of-the-art supervised model on sentiment classification datasets, they do demonstrate better robustness

<sup>18</sup> We use the combination of training set and unlabelled set to fine-tune the language model for ULMFiT.



Category	Generated keywords
negative	<i>worst waste awful poorly pointless terrible worse horrible lame stupid crap laughable redeeming unfunny wasted bad boring badly pathetic mess ridiculous dull atrocious incoherent lousy poor supposed garbage sucks unwatchable</i>
positive	<i>excellent wonderful superb wonderfully beautifully amazing perfect touch- ing captures fantastic flawless delightful favorite terrific refreshing superbly perfection outstanding gem underrated breathtaking brilliant loved finest excellently highly favorites friendship brilliantly matthau</i>

Table 10: Generated keywords using pmi-freq from IMDB training set.

Model	IMDB		Yelp	
	Original	Curated	Original	Curated
MNB	.814	-	.745	-
SVM	.840	-	.773	-
KNN	.611	-	.539	-
ULMFiT	<b>.944</b>	-	<b>.856</b>	-
GE	.813	.810	.767	.781
MNB/Priors	.802	.802	.777	.774
Doc2vec	.645	.613	.661	.636
WESTCLASS	.698	.696	.653	.684
STM	.792	.792	.713	.705

Table 11: Accuracy of various models on IMDB and Yelp test set.

when applied to a different domain. On average, supervised models' accuracy dropped 7.5 per cent when applied to Yelp dataset compared to IMDB test dataset. On the other hand, dataless classification models' accuracy dropped only 3.6 per cent.

We believe the performance of dataless classification models versus supervised models is related to the bias-variance tradeoff. Dataless classification models have high bias resulting from the labelled keywords, but low variance and can generalise better to samples that look different. Supervised models, especially deep learning models, have much lower bias but high variance. It gives us the hint that dataless classification models might perform better than supervised learning models when the document labels contain a lot of noise or the training and testing samples look very different (high covariate shift).

In this set of experiments, STM does not perform as well as GE and MNB/Priors. STM applies topic modelling to capture latent topics in the background corpus. It might be more suitable for topic classification rather than sentiment classification. In the previous topic classification experiments on contextual advertising datasets, despite the input source changes, the underlying topics remain similar and therefore the inferred topics are useful across different datasets. However, IMDB dataset consists of movie reviews and Yelp dataset consists of reviews for points of interest such as restaurants and hotels. The

topics in the two datasets are completely different, suggesting that the latent topics STM inferred from IMDB dataset are not transferable to the Yelp dataset. This explains why STM’s accuracy dropped close to eight per cent on the Yelp dataset.

The underlined keywords in Table 10 are considered low-quality. They consist of movie or actor names (“redeeming” and “matthau”), movie-specific words (“captures” and “un-watchable”) and general words (“supposed” and “friendship”). Mentioning a movie or an actor may be a signal whether the review is positive or negative, but they are mostly irrelevant in another domain. Therefore, we want to study the impact of curating the automatically mined keywords on the accuracy of dataless classification models. In Table 11, we show the result with both the original list of keywords in Table 10 and the curated keywords after removing all the underlined domain-specific and noisy keywords. As we expected, there is no improvement on IMDB test set after curating the keywords. On Yelp dataset, GE and WESTCLASS’s accuracy improved while the other models’ accuracy either remained the same or decreased. No conclusion can be drawn but we believe in a real-world application setting, it is worthwhile curating the keywords, especially when the original list of keywords is noisy.

## 5 Domain Adaptation Performance

Our models are trained using the news-crawl dataset and aim to be applied to the data similar to the user browsing dataset. Since there is a clear sign of mismatch between the two domains, we are interested in studying how can unlabelled in-domain user browsing data help to train more accurate models. While labelling a large amount of in-domain data can be prohibitively expensive, unlabelled in-domain data are often available in abundance.

To this end, we crawled an additional 280 thousand URLs from the user browsing history in the RTB log and created the *browsing-unsup* dataset (without overlap with the browsing dataset). Applying the STM model on the unlabelled dataset is straight-forward. We used the same set of keywords and the new unlabelled in-domain dataset to train the new model. For ULMFiT, we applied two different strategies, namely *mix-domain* and *cross-domain*. In the *mix-domain* setting, we used the (unlabelled) in-domain data to fine-tune the language model and used the original news-crawl dataset to train the classifier. In the *cross-domain* setting, we used self-training similar to Meng and others (Meng et al., 2018). We first applied the previous ULMFiT model trained on news-crawl dataset to predict labels on browsing-unsup dataset. We then used the pseudo-labelled documents to train a new ULMFiT classifier<sup>19</sup>. In this way, both the data to fine-tune the language model and the data to train the final classifier are from in-domain data. We compare the accuracy of the classifiers being trained on the news-crawl and the in-domain browsing-unsup data in Table 12 (with the relative percentage of change in the bracket).

We can clearly observe that the STM model benefited from unlabelled in-domain data. This is because while the representative keywords may occur in both datasets, the context they appear may differ. By tapping on the unlabelled in-domain data, the model can capture features which are useful in the target domain.

<sup>19</sup> We used only documents with a label probability higher than 0.8 to ensure the labels are relatively clean while we have at least 1,000 documents for each category.

Model	news-crawl test set		browsing dataset	
	Accuracy	Macro- $F_1$	Accuracy <sup>+</sup>	ma $F_1$
ULMFiT	<b>.922</b>	<b>.892</b>	.564	.431
ULMFiT mix-domain	-	-	.508 (-9.9%)	.433 (+0.4%)
ULMFiT cross-domain	-	-	.665 (+17.9%)	.506 (+17.4%)
STM	.544	.527	.794	.625
STM cross-domain	-	-	<b>.814 (+2.5%)</b>	<b>.647 (+3.5%)</b>

Table 12: Impact of unlabelled in-domain data on the model performance.

As we expected, the ULMFiT mix-domain model did not improve the performance. This is possibly because we had to use different sources of data to fine-tune the language model and to train the final classifier. The fine-tuned language model might have been “unlearned” when training the classifier with a different dataset. We also observed a higher perplexity when finetuning the language model using the browsing-unsup dataset compared to using the news-crawl dataset, indicating that the browsing dataset might be more different from the WikiText-103 dataset (Merity et al., 2016), where the language model was pre-trained.

On the other hand, the cross-domain method improved the performance of ULMFiT drastically with a more than seventeen percent improvement in both accuracy and macro  $F_1$ . This demonstrated the importance of in-domain labelled documents for supervised learning methods and that self-training can effectively bootstrap an in-domain dataset from an out-of-domain classifier without any manual labelling. However, ULMFiT model still lagged behind the original STM model without domain adaptation.

## 6 Conclusions and Future Work

In this work, we mitigated the lack of accurate in-domain documents for text classification by proposing a novel two-stage approach. We firstly mine keywords from a noisy out-of-domain corpus, then use the keywords and unlabelled documents to train a dataless classifier. The proposed approach outperformed various supervised learning and dataless classification baselines by a large margin on a corpus of user browsing dataset. By tapping on unlabelled in-domain documents, the model yields another three per cent performance gain.

During the experiments, we identified that the multi-label problem is one of the main reason why supervised learning methods failed. The proposed dataless method does not exploit the document labels and is thus more robust. In future work, we plan to explicitly model the multi-label classification problem and identify the segments of the document which represent different topics.

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**A Automatically Mined Keywords at Different Label Noise Rate**

$\epsilon$	PMI	PMI-FREQ	MMR	FREQ	MI
.1	diaspora	arab	arab	israel	<u>govt</u>
	<u>sarajevo</u>	israel	israeli	jews	<u>agnostic</u>
	<u>karabag</u>	israeli	arabs	<u>war</u>	<u>suspects</u>
	<u>millet</u>	muslims	<u>serdar</u>	muslims	<u>infer</u>
	rabin	arabs	<u>argic</u>	jewish	<u>testify</u>
	gaza	jews	israel	arab	<u>excuses</u>
	<u>shostack</u>	<u>serdar</u>	armenian	muslim	<u>reminded</u>
	agdam	<u>argic</u>	turkish	<u>during</u>	<u>arrogance</u>
	<u>davidsson</u>	muslim	turks	<u>state</u>	<u>salem</u>
	<u>barbarism</u>	jewish	armenians	<u>history</u>	<u>examine</u>
.4	yitzhak	muslims	armenian	israel	<u>inquisition</u>
	hamas	israel	arab	<u>war</u>	<u>paradox</u>
	azerbaijanis	armenian	<u>argic</u>	jews	<u>agnostic</u>
	<u>settlements</u>	muslim	genocide	muslims	<u>ponder</u>
	<u>balkan</u>	jewish	<u>serdar</u>	jewish	<u>reward</u>
	<u>lehi</u>	jews	arabs	<u>during</u>	<u>dragging</u>
	erzurum	arab	armenians	muslim	<u>affair</u>
	gaza	<u>argic</u>	<u>serbs</u>	<u>state</u>	<u>thy</u>
	plo	genocide	israel	arab	<u>overlooked</u>
	azerbaijan	<u>serdar</u>	armenia	actually	<u>prophecies</u>
.7	iraqis	muslim	armenians	jews	<u>fundamentally</u>
	<u>bayonets</u>	armenians	<u>serdar</u>	israel	<u>mittchell</u>
	plo	<u>serdar</u>	<u>argic</u>	<u>ever</u>	<u>elvis</u>
	<u>memoirs</u>	<u>argic</u>	muslim	<u>state</u>	<u>meters</u>
	<u>arf</u>	arab	moslem	<u>others</u>	<u>tricky</u>
	azeris	moslem	armenian	<u>during</u>	<u>cent</u>
	moslem	armenian	turkish	<u>actually</u>	<u>holland</u>
	<u>asala</u>	turkish	jew	<u>put</u>	<u>affects</u>
	<u>sdpa</u>	jew	arabs	<u>group</u>	<u>mysteries</u>
	<u>exterminated</u>	jews	genocide	<u>give</u>	<u>pan</u>

Table 13: Keywords for the category “talk.politics.mideast” with .1/.4/.7 label noise.



€	PMI	PMI-FREQ	MMR	FREQ	MI
.1	geico	car	cars	car	car
	camaro	cars	car	cars	engine
	corvette	ford	ford	engine	cars
	rotors	engine	mustang	ford	<u>insurance</u>
	diesels	mustang	camaro	<u>buy</u>	<u>clutch</u>
	mustang	nissan	geico	<u>price</u>	<u>manual</u>
	sunroof	engines	nissan	<u>miles</u>	wheel
	tach	camaro	diesels	<u>big</u>	<u>design</u>
	nissan	geico	corvette	<u>speed</u>	<u>sports</u>
	shifter	suspension	suspension	<u>put</u>	<u>bought</u>
.4	diesels	car	car	car	car
	corvette	cars	cars	cars	cars
	odometer	ford	ford	engine	ford
	lexus	engine	mustang	<u>price</u>	engines
	camaro	engines	camaro	<u>actually</u>	<u>brake</u>
	audi	mustang	<u>cylinder</u>	<u>buy</u>	wheels
	convertible	<u>exhaust</u>	<u>tranny</u>	<u>every</u>	<u>clutch</u>
	<u>liter</u>	camaro	coupe	<u>big</u>	wheel
	geico	<u>cylinder</u>	diesels	<u>put</u>	mph
	<u>tranny</u>	<u>tranny</u>	engine	<u>miles</u>	<u>design</u>
.7	traction	engine	<u>gt</u>	car	engine
	convertible	cars	mustang	<u>little</u>	ford
	wagon	<u>gt</u>	engine	<u>best</u>	<u>cult</u>
	<u>gt</u>	ford	wagon	<u>called</u>	<u>alot</u>
	mustang	car	traction	<u>every</u>	camaro
	mazda	mustang	cars	<u>price</u>	mustang
	<u>seats</u>	wagon	<u>seats</u>	engine	<u>raised</u>
	ford	traction	convertible	cars	<u>represent</u>
	<u>exhaust</u>	<u>seats</u>	car	<u>big</u>	<u>conversion</u>
	<u>pulse</u>	convertible	ford	<u>probably</u>	<u>taxes</u>

Table 14: Keywords for the category “rec.autos” with .1/.4/.7 label noise. The ambiguous keywords are underlined.

$\epsilon$	PMI	PMI-FREQ	MMR	FREQ	MI
.1	<u>royals</u>	pitcher	pitcher	baseball	<u>team</u>
	batters	baseball	batting	<u>games</u>	<u>games</u>
	<u>alomar</u>	batting	pitching	<u>team</u>	baseball
	<u>larkin</u>	pitching	pitches	<u>hit</u>	<u>season</u>
	<u>sandberg</u>	pitches	batters	<u>players</u>	<u>players</u>
	<u>platoon</u>	hitter	hitter	pitcher	<u>player</u>
	<u>ws</u>	batter	batter	<u>league</u>	pitcher
	<u>mattingly</u>	braves	braves	<u>season</u>	<u>win</u>
	<u>boggs</u>	jays	jays	<u>lot</u>	<u>league</u>
	<u>sabo</u>	<u>sox</u>	<u>sox</u>	<u>play</u>	hitting
	.4	yankees	pitcher	pitcher	baseball
<u>hirschbeck</u>		hitter	hitter	<u>team</u>	pitcher
<u>phillies</u>		batter	batter	<u>hit</u>	<u>player</u>
<u>padres</u>		<u>sox</u>	<u>sox</u>	<u>games</u>	<u>win</u>
orioles		jays	jays	pitcher	<u>season</u>
mets		batting	batting	<u>player</u>	hitter
<u>bosio</u>		baseball	pitchers	<u>best</u>	<u>games</u>
<u>sabo</u>		pitchers	yankees	<u>probably</u>	batter
pitched		yankees	<u>hirschbeck</u>	<u>players</u>	<u>teams</u>
<u>rbi</u>		<u>hirschbeck</u>	<u>ball</u>	<u>ball</u>	batting
.7		<u>dl</u>	batting	batting	<u>probably</u>
	<u>winfield</u>	hitting	jays	<u>little</u>	<u>cult</u>
	<u>martinez</u>	jays	batter	<u>day</u>	<u>stats</u>
	umpires	batter	bat	<u>lot</u>	innings
	<u>sabo</u>	bat	pitcher	<u>try</u>	pitches
	batting	baseball	<u>morris</u>	<u>kind</u>	<u>player</u>
	<u>hirschbeck</u>	pitcher	inning	<u>enough</u>	<u>season</u>
	jays	<u>morris</u>	umpires	<u>actually</u>	pitch
	batter	inning	hitter	<u>post</u>	symptoms
	inning	umpires	<u>stats</u>	<u>give</u>	<u>homosexuals</u>

Table 15: Keywords for the category “rec.sport.baseball” with .1/.4/.7 label noise. The ambiguous keywords are underlined.

### B Construction of News-Crawl Datasets

In this section, we describe the method we used to crawl the labelled datasets from newswire sites without manually labelling the articles so that researchers can reproduce our results or create datasets for other categories.

Many websites, especially newswire sites, categorise their content into a list of predefined categories. An example is shown in Figure 6.



Fig. 6: Screenshot from The New York Times homepage.

Some of these sites encode the category name in the URL like the case in Figure 7. We can apply regular expressions on the URLs to extract the category of the article. An example is shown in Table 16.



Fig. 7: Sample URL and its different components.

Regular Expression for URL	Category
<code>nytimes.com/([^\d][0-9]*)/([^\d][0-9]*)/([^\d][0-9]*)/(arts   books   movies   theater)</code>	Arts & Entertainment
<code>pethelpful.com/(rabbits   dogs   birds   cats   misc)</code>	Pets

Table 16: Sample regular expression to extract the category of news articles.

The other websites which do not include the category in the URL usually have a list page where we can crawl the list of URLs related to a category, such as [www.reuters.com/news/archive/entertainmentNews](http://www.reuters.com/news/archive/entertainmentNews) and <https://www.dw.com/en/auto-industry/t-17282970>. Tabel 17 shows the full list of domains where *news-crawl dataset* and *news-crawl-v2 dataset* are crawled.

news-crawl dataset	news-crawl-v2 dataset
reuters.com	cooking.nytimes.com
nytimes.com	nytimes.com
theguardian.com	instructables.com
independent.co.uk	community.babycenter.com
thestar.com.my	pethelpful.com
alphamom.com	olx.ph
ultimate-guitar.com	biblegateway.com
dailynews.com	coupons.com
dallasnews.com	groupon.com
cheatsheet.com	shopback.sg
dailyfinance.com	psychologytoday.com
pawntation.com	independent.co.uk
religionnews.com	marriage.com
	helpguide.org

Table 17: Domains from where the news-crawl datasets were crawled.