SHORT-TEXT CLASSIFICATION USING UNSUPERVISED KEYWORD EXPANSION

MANUSCRIPT

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ABSTRACT

Short-text classification, like all data science, struggles to achieve high performance using limited data. As a solution, a short sentence may be expanded with new and relevant feature words to form an artificially enlarged dataset, and add new features to testing data. This paper applies a novel approach to text expansion by generating new words directly for each input sentence, thus requiring no additional datasets or previous training. In this unsupervised approach, new keywords are formed within the hidden states of a pre-trained language model and then used to create extended pseudo documents. The word generation process was assessed by examining how well the predicted words matched to topics of the input sentence. It was found that this method could produce 3-10 relevant new words for each target topic, while generating just 1 word related to each non-target topic. Generated words were then added to short news headlines to create extended pseudo headlines. Experimental results have shown that models trained using the pseudo headlines can improve classification accuracy when limiting the number of training examples.

Keywords Short-Text Analysis · Document Expansion · Text Classification · Pre-Trained BERT

1 Introduction

The web has provided researchers with vast amounts of unlabeled text data, and enabled the development of increasingly sophisticated language models which can achieve state of the art performance despite having no task specific training [1, 2, 3]. It is desirable to adapt these models for bespoke tasks such as short text classification.

Short-text is nuanced, difficult to model statistically, and sparse in features, hindering traditional analysis [4]. These difficulties become further compounded when training is limited, as is the case for many practical applications.

This paper provides a method to expand short-text with additional keywords, generated using a pre-trained language model. The method takes advantage of general language understanding to suggest contextually relevant new words, without necessitating additional domain data. The method can form both derivatives of the input vocabulary, and entirely new words arising from contextualised word interactions and is ideally suited for applications where data volume is limited.

Extended Headlines Improve Classification Accuracy for Small Training Sizes

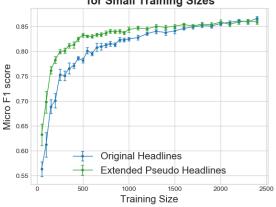


Figure 1: Binary Classification of short headlines into 'World-Post' or 'Crime' categories, shows improved performance with extended pseudo headlines when the training set is small. Using: Random forest classifier, 1000 test examples, 10-fold cross validation.

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2 Literature Review

Document expansion methods have typically focused on creating new features with the help of custom models. Word co-occurrence models [5], topic modeling [6], latent concept expansion [7], and word embedding clustering [8], are all examples of document expansion methods that must first be trained using either the original dataset or an external dataset from within the same domain. The expansion models may therefore only be used when there is a sufficiently large training set.

Transfer learning was developed as a method of reducing the need for training data by adapting models trained mostly from external data [9]. Transfer learning can be an effective method for short-text classification and requires little domain specific training data [10, 11], however it demands training a new model for every new classification task and does not offer a general solution to sparse data enrichment.

Recently, multi-task language models have been developed and trained using ultra-large online datasets without being confined to any narrow applications [1, 2, 3]. It is now possible to benefit from the information these models contain by adapting them to the task of text expansion and text classification.

This paper is a novel approach which combines the advantages of document expansion, transfer learning, and multitask modeling. It expends documents with new and relevant keywords by using the BERT pre-trained learning model, thus taking advantage of transfer learning acquired during BERT's pretraining. It is also unsupervised and requires no task specific training, thus allowing the same model to be applied to many different tasks or domains.

3 Procedures

3.1 Dataset

The News Category Dataset² [12] is a collection of headlines published by HuffPost [13] between 2012 and 2018, and was obtained online from Kaggle [14]. The full dataset contains 200k news headlines with category labels, publication dates, and short text descriptions. For this analysis, a sample of roughly 33k headlines spanning 23 categories was used. Further analysis can be found in table 9 in the appendix.

3.2 Word Generation

Words were generated using the BERT pre-trained model developed and trained by Google AI Language [1]. BERT creates contextualized word embedding by passing a list of

word tokens through 12 hidden transformer layers and generating encoded word vectors. To generate extended text, an original short-text document was passed to pre-trained BERT. At each transformer layer a new word embedding was formed and saved. BERT's vector decoder was then used to convert hidden word vectors to candidate words, the top three candidate words at each encoder layer were kept.

Each input word produced 48 candidate words, however many were duplicates. Examples of generated words per layer can be found in table 10 and 11 in the appendix. The generated words were sorted based on frequency, duplicate words from the original input were removed, as were stop-words, punctuation, and incomplete words. The generated words were then appended to the original document to create extended pseudo documents, the extended document was limited to 120 words in order to normalize each feature set. Further analysis can be found in table 9 in the appendix.

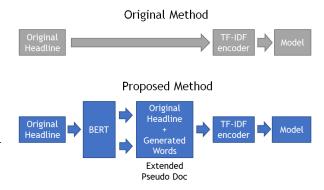


Figure 2: The proposed method uses the BERT pre-trained word embedding model to generate new words which are appended to the original text creating extended pseudo documents.

3.3 Topic Evaluation

To test the proposed methods ability to generate unsupervised words, it was necessary to devise a method of measuring word relevance. Topic modeling was used based on the assumption that words found in the same topic are more relevant to one another then words from different topics [15]. The complete 200k headline dataset [12] was modeled using a Naïve Bayes Algorithm [16] to create a word-category co-occurrence model. The top 200 most relevant words were then found for each category and used to create the topic table 7. It was assumed that each category represented its own unique topic.

The number of relevant output words as a function of the headline's category label were measured, and can be found in figure 3. The results demonstrate that the proposed method could correctly identify new words relevant to the input topic at a signal to noise ratio of 4 to 1.

²Further information related to the dataset and its author can be found here: https://rishabhmisra.github.io/publications/

Generated Words Based on Labeled Category 12 2000 8 8 Off Target Headline Category

Figure 3: The number of generated words within each topic was counted, topics which matched the original headline label were considered 'on target'. Results indicate that the unsupervised generation method produced far more words relating to the label category then to other topics. Tested on 7600 examples spanning 23 topics.

3.4 Binary and Multi-class Classification Experiments

Three datasets were formed by taking equal length samples from each category label. The new datastes are 'Worldpost vs Crime', 'Politics vs Entertainment', and 'Sports vs Comedy', a fourth multiclass dataset was formed by combining the three above sets.

For each example three feature options were created by extending every headline by 0, 15 and 120 words. Before every run, a test set was removed and held aside. The remaining data was sampled based on the desired training size. Each feature option was one-hot encoded using a unique tfidf-vectorizer [17] and used to train a randomforest classifier [18] with 300-estimators for binary predictions and 900-estimators for multiclass.

Random forest was chosen since it performs well on small datasets and is resistant to overfitting [19]. Each feature option was evaluated against its corresponding test set. 10 runs were completed for each dataset.

4 Results and Analysis

4.1 Evaluating word relevance

It is desirable to generate new words which are relevant to the target topics and increase predictive signal, while avoiding words which are irrelevant, add noise, and mislead predictions.

The strategy, described in section 3.3, was created to measure word relevance and quantify the unsupervised model performance. It can be seen from fig 3 and 8 in the appendix that the proposed expansion method is effective at generating words which relate to topics of the input sentence, even from very little data. From the context of just a single word, the method can generate 3 new relevant words, and can generate as many as 10 new relevant words from sentences which contain 5 topic related words 8. While

the method is susceptible to noise, producing on average 1 word related to each irrelevant topic, the number of correct predictions statistically exceed the noise.

Furthermore, because the proposed method does not have any prior knowledge of its target topics, it remains completely domain agnostic, and can be applied generally for short text of any topic.

4.1.1 Binary Classification

Comparing the performance of extended pseudo documents on three separate binary classification datasets shows significant improvement from baseline in the sparse data region of 100 to 1000 training examples.

- The 'Worldpost vs Crime' dataset showed the most improvement as seen in figure 2. Within the sparse data region the extended pseudo documents could achieve similar performance as original headlines with only half the data, and improve F1 score between 13.9% and 1.7%
- The 'Comedy vs Sports' dataset, seen in figure 5, showed an average improvement of 2% within the sparse region.
- The 'Politics vs Entertainment' dataset, figure 4, was unique. It is the only dataset for which a 15-word extended feature set surpassed the 120-words feature set. It demonstrates that the length of the extended pseudo documents can behave like a hyper parameter for certain datasets, and should be tuned according to the train-size.

4.1.2 Multiclass Classification

The Extended pseudo documents improved multiclass performance by 4.6% on average, in the region of 100 to 3000 training examples, as seen in figure 6. The results indicate the effectiveness of the proposed method at suggesting relevant words within a narrow topic domain, even without any previous domain knowledge.

In each instance it was found that the extended pseudo documents only improved performance on small training sizes. This demonstrates that while the extended pseudo docs are effective at generating artificial data, they also produce a lot of noise. Once the training size exceeds a certain threshold, it becomes no longer necessary to create additional data, and using extended documents simply adds noise to an otherwise well trained model.

Performance Varies with Number of Added Words 0.85 0.85 0.80 0.70 Original Headlines 15 added words 120 added words 120 added words Training Size

Figure 4: Binary Classification of 'Politics' or 'Entertainment' demonstrates that the number of added words can behave like a hyper paremeter and should be tuned based on training size. Tested on 1000 examples with 10-fold cross validation

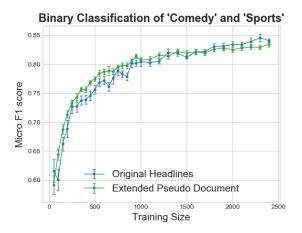


Figure 5: Binary Classification of 'Politics' vs 'Sports' has less improvement compared to other datasets which indicates that the proposed method, while constructed to be domain agnostic, shows better performance towards certain topics. Tested on 1000 examples with 10-fold cross validation.

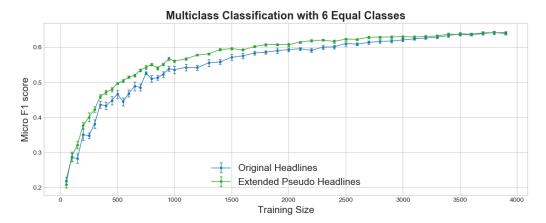


Figure 6: Added Words improve Multiclass Classification between 1.5% and 13% in the range of 150 to 2000 training examples. Tests were conducted using equal size samples of Headlines categorized into 'World-Post', 'Crime', 'Politics', 'Entertainment', 'Sports' or 'Comedy'. A 900 Estimator Random Forest classifier was trained for each each data point, tested using 2000 examples, and averaged using 10-fold cross validation.

5 Discussion

Generating new words based solely on ultra small prompts of 10 words or fewer is a major challenge. A short sentence is often characterized by a just a single keyword, and modeling topics from such little data is difficult. Any method of keyword generation that overly relies on the individual words will lack context and fail to add new information, while attempting to freely form new words without any prior domain knowledge is uncertain and leads to misleading suggestions.

This method attempts to find balance between synonym and free-form word generation, by constraining words to fit the original sentence while still allowing for word-word and word-sentence interactions to create novel outputs. The word vectors must move through the transformer lay-

ers together and therefore maintain the same token order and semantic meaning, however they also receive new input from the surrounding words at each layer. The result, as can be seen from table 10 and 11 in the appendix, is that the first few transformer layers are mostly synonyms of the input sentence since the word vectors have not been greatly modified. The central transformer layers are relevant and novel, since they are still slightly constrained but also have been greatly influenced by sentence context. And the final transformer layers are mostly non-sensical, since they have been completely altered from their original state and lost their ability to retrieve real words.

This method is unique since it avoids needing a prior dataset by using the information found within the weights of a general language model. Word embedding models, and BERT in particular, contain vast amounts of informa-

tion collected through the course of their training. BERT Base for instance, has 110 Million parameters and was trained on both Wikipedea Corpus and BooksCorpus [1], a combined collection of over 3 Billion words. The full potential of such vastly trained general language models is

still unfolding. This paper demonstrates that by carefully prompting and analysing these models, it is possible to extract new information from them, and extend short-text analysis beyond the limitations posed by word count.

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6 Appendix

6.1 Additional Tables and Figures

Sample of the Topic Table

WORLDPOST	CRIME	POLITICS	ENTERTAINME	NT SPORTS	COMEDY	COLLEGE	EDUCATION	SCIENCE	WOMEN
aleppo	suspect	gop	trailer	nba	maher	campus	education	nasa	feminism
korea	shooter	democrats	swift	nfl	colbert	colleges	charter	mars	funniest
migrants	fatally	republicans	netflix	lebron	meyers	college	teachers	scientists	feminist
pakistan	allegedly	senate	thrones	ncaa	trevor	frat	teacher	spacecraft	metoo
mosul	cops	sanders	taylor	player	conan	university	schools	astronomers	women
syria	murder	huffpollster	album	mlb	seth	fraternity	devos	space	sexist
yemen	officer	bernie	teaser	football	snl	grads	classroom	pluto	abortion
minister	gunman	democratic	movie	touchdown	fallon	faculty	tenure	rover	steinem
syrian	charged	clinton	kylie	championship	stephen	uva	educational	telescope	tweets
turkish	accused	rubio	khloe	soccer	kimmel	universities	teaching	asteroid	female

Figure 7: A Topic table, created from the category labels of the complete headline dataset, can be used to measure the relevance of generated words.

An original headline was analyzed by counting the number of words which related to each topic. The generated words were then analyzed in the same way. The change in word count between input topics and output topics was measured and plotted as seen in figure 8.

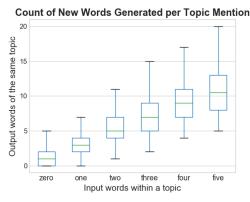


Figure 8: Box plot of the number of generated words within a topic as a function of the number of input words within the same topic. Results indicate that additional related words can be generated by increasing the signal of the input prompt. Tested on 7600 examples spanning 23 topics.

Data Statistics							
Original F	leadline	Generated Words					
count	33779	count	33779				
mean	10.2	mean	111.4				
std	2.7	std	32.2				
min	1	min	4				
25%	9	25%	91				
50%	10	50%	110				
75%	12	75%	131				
max	28	max	317				

Figure 9: Information regarding the original headlines, and generated words used to create extended pseudo headlines.

'Crime' Headline with generated Words at each hidden layer

Sentence:		- 2	noonlo	injured	in	Indiana	school	Chaoting
Layer	Guess		people	injureu	""	mulana	SCHOOL	Shooting
0	0	site	people	hurt	in	##ety	school	shoots
0	1	\$	##rbin	injured	across	infancy	##ent	shooting
0	2	##led	##mel	##iard	defending	fending doe		tia
1	0		people	injured	in	lehigh	school	shooting
1	1	2	caps	##hed	across	indiana	##en	shoots
1	2		##els	##wr	by	##ety	##ian	##if
2	0		people	injured	in	indiana	school	shooting
2	1	,	then	wounded	across	##open	##ent	shoots
2	2	of	##fer	engaged	en	łodz	saw	shoot
3	0	,	people	injured	in	indiana	school	shooting
3	1		caps	wounded	by	##mark	##en	shoots
3	2	-	person	built	en	oman	##ent	shoot
4	0	-	person	wounded	in	##sl	pacific	shooting
4	1	ladies	people	bush	major	wales	##aja	shot
4	2		first	standing	the	indiana	the	shoot
5	0	late	*	wounded	in	indiana	school	shooting
5	1	##um	‡	injured	##els	purdue	church	shoots
5	2	lost	†	##ided	maj	##ook	bed	shoot
6	0	non	race	wounded	paralyzed	##og	elf	shooting
6	1	blinded	marine	injured	disabled	ac	school	shoot
6	2	reflection	mangrove	disabled	fighting	the	##mouth	disaster
7	0	dam	*	injured	in	lip	school	explosion
7	1	eye	also	defeated	during	sun	dam	shooting
7	2	ocean	and	dressed	on	little	water	disaster
8	0	music	##s	##ide	in	a	##an	shooting
8	1	:	:	##ides	inland	2012	##land	shot
8	2	-	an	up	ac	##ede	elf	slash
9	0	:	family	lost	in	oregon	school	shooting
9	1	dam	group	gained	at	the	office	hills
9	2	ok	notable	cross	for	ac	village	artillery
10	0	name	people	made	in	car	school	shooting
10	1	unknown	only	introduced	into	school	student	shot
10	2	date	not	used	for	band	summer	summer
11	0	often	or	thus	in	these	bodies	or
11	1	sometimes	1	so	or	or	or	and
11	2	or	thus	often	as	and	and	often

Figure 10: Top 3 guesses for each token position at each later of a BERT pretrained embedding model. Given the input sentence '2 peoplpe injured in Indiana school shooting', the full list of generated words can be obtained from the values in the table.

'Politics' headline with generated words at each hidden layer

Sente	nce:	- House	republicans	Damantad					deal
Layer	Guess	House republicans		Reported progress		on	an	immigration	ueai
0	0	house		report	progress	on	an	immigration	deal
0	1	##nea	republicans	reported	##oc	##plate	a	ska	deals
0	2	the	recess	##i	progression	responsibilit	##cala	saxe	trade
1	0	the	republicans	report	progress	on	a	immigration	deal
1	1	door	republican	reported	##ed	in	an	family	deals
1	2	house	swat	correctly	field	upon	the	##ia	contract
2	0	the	republicans	report	progress	on	an	immigration	deal
2	1	leg	also	reported	field	upon	the	ed	deals
2	2	to	alla	reports)	##ced	a	border	contract
3	0	tab	republican	report	progress	on	a	immigration	deal
3	1	review	date	reported	##ed	upon	the	##osta	deals
3	2	2018	##osta	poll	quincy	quo	an	sep	contract
4	0	re	republicans	report	progress	on	an	immigration	deal
4	1	also	democrats	reported	##s	##ced	the	ed	transaction
4	2	the	republican	commissione	liv	prisoner	a	est	deals
5	0	and	democrats	report	progress	on	a	immigration	deal
5	1	thomas	##ges	state	emissions	recording	an	relations	deals
5	2	##ke	republicans	reported	decisions	##de	the	intelligence	contract
6	0	the	republican	report	progress	on	the	new	deal
6	1	and	republicans	sensor	report	about	a	advent	reform
6	2	tooth	critics	state	reflection	concerning	an	milk	deals
7	0	##con	congress	:	,	on	a	milk	deal
7	1	(the	report	progress	about	an	eye	•
7	2	review	:	review	##et	of	the	new	reform
8	0	##es	##s	and	progress	on	the	civil	and
8	1	##s	##gs	to	,	in	an	new	-
8	2	-	##ist	:	aid	for	a	a	to
9	0	bay	would	to	to	on	whose	whose	"
9	1	for	to	for	on	for	"	to	to
9	2	by	can	(for	with	or	or	(
10	0	nos	as	dry	"	:	if	if	ok
10	1	,	and	report	for	for	an	(if
10	2	##ce	for	panel	(how	what	0	(
11	0		for	for	for	and	an		and
11	1	and	and	•	•	for	and	the	or
11	2	as	as	as	as	on	a	and	all

Figure 11: Top 3 guesses for each token position at each later of a BERT pretrained embedding model.