## Automated Topical Component Extraction Using Neural Network Attention Scores from Source-based Essay Scoring

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#### Abstract

While automated essay scoring (AES) can reliably grade essays at scale, automated writing evaluation (AWE) additionally provides formative feedback to guide essay revision. However, a neural AES typically does not provide useful feature representations for supporting AWE. This paper presents a method for linking AWE and neural AES, by extracting Topical Components (TCs) representing evidence from a source text using the intermediate output of attention layers. We evaluate performance using a feature-based AES requiring TCs. Results show that performance is comparable whether using automatically or manually constructed TCs for 1) representing essays as rubric-based features, 2) grading essays.

#### 1 Introduction

Automated essay scoring (AES) systems reliably grade essays at scale, while automated writing evaluation (AWE) systems additionally provide formative feedback to guide revision. Although neural networks currently generate state-of-the-art AES results (Alikaniotis et al., 2016; Taghipour and Ng, 2016; Dong et al., 2017; Farag et al., 2018; Jin et al., 2018; Li et al., 2018; Tay et al., 2018; Zhang and Litman, 2018), non-neural AES create feature representations more easily useable by AWE (Roscoe et al., 2014; Foltz and Rosenstein, 2015; Crossley and McNamara, 2016; Woods et al., 2017; Madnani et al., 2018; Zhang et al., 2019). We believe that neural AES can also provide useful information for creating feature representations, e.g., by exploiting information in the intermediate layers.

Our work focuses on a particular source-based essay writing task called the response-to-text assessment (RTA) (Correnti et al., 2013). Recently, an RTA AWE system (Zhang et al., 2019) was built by extracting rubric-based features related to the

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use of *Topical Components (TCs)* in an essay. However, manual expert effort was first required to create the TCs. For each source, the TCs consist of a comprehensive list of topics related to evidence which include: 1) important words indicating the set of evidence topics in the source, and 2) phrases representing specific examples for each topic that students need to find and use in their essays.

To eliminate this expert effort, we propose a method for using the interpretable output of the attention layers of a neural AES for source-based essay writing, with the goal of extracting TCs. We evaluate this method by using the extracted TCs to support feature-based AES for two RTA source texts. Our results show that 1) the feature-based AES with TCs manually created by humans is matched by our neural method for generating TCs, and 2) the values of the rubric-based essay features based on automatic TCs are highly correlated with human Evidence scores.

#### 2 Related Work

Three recent AWE systems have used non-neural AES to provide rubric-specific feedback. Woods et al. (2017) developed an influence estimation process that used a logistic regresion AES to identify sentences needing feedback. Shibani et al. (2019) presented a web-based tool that provides formative feedback on rhetorical moves in writing. Zhang et al. (2019) used features created for a random forest AES to select feedback messages, although human effort was first needed to create TCs from a source text. We automatically extract TCs using neural AES, thereby eliminating this expert effort.

Others have also proposed methods for preprocessing source information external to an essay. Content importance models for AES predict the parts of a source text that students should include when writing a summary (Klebanov et al.,

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Source Excerpt: Today, Yala Sub-District Hospital has medicine, free of charge, for all of the most common diseases. Water is connected to the hospital, which also has a generator for electricity. Bed nets are used in every sleeping site in Sauri...
Essay Prompt: The author provided one specific example of how the quality of life can be improved by the Millennium Villages Project in Sauri, Kenya. Based on the article, did the author provide a convincing argument that winning the fight against poverty is achievable in our lifetime? Explain why or why not with 3-4 examples from the text to support your answer.
Essay: In my opinion I think that they will achieve it in lifetime. During the years threw 2004 and 2008 they made progress. People didnt have the money to buy the stuff in 2004. The hospital was packed with patients and they didnt have alot of treatment in 2004. In 2008 it changed the hospital had medicine, free of charge, and for all the common dieases. Water was connected to the hospital and has a generator for electricity. Everybody has net in their site. The hunger crisis has been addressed with fertilizer and seeds, as well as the tools needed to maintain the food. The school has no fees and they serve lunch. To me thats sounds like it is going achieve it in the lifetime.

Table 1: A source excerpt for the  $RTA_{MVP}$  prompt and an essay with score of 3.

Prompt	$RTA_{MVP}$	$RTA_{Space}$
Score 1	852	538
	(29%)	(26%)
Score 2	1197	789
	(40%)	(38%)
Score 3	616	512
	(21%)	(25%)
Score 4	305	237
	(10%)	(11%)
Total	2970	2076

Table 2: The Evidence score distribution of RTA.

2014). Methods for extracting important keywords or keyphrases also exist, both supervised (unlike our approach) (Meng et al., 2017; Mahata et al., 2018; Florescu and Jin, 2018) and unsupervised (Florescu and Caragea, 2017). Rahimi and Litman (2016) developed a TC extraction LDA model (Blei et al., 2003). While the LDA model considers all words equally, our model takes essay scores into account by using attention to represent word importance. Both the unsupervised keyword and LDA models will serve as baselines in our experiments.

In the computer vision area, attention cropped images have been used for further image classification or object detection (Cao et al., 2015; Yuxin et al., 2018; Ebrahimpour et al., 2019). In the NLP area, Lei et al. (2016) proposed to use a generator to find candidate rationale and these are passed through the encoder for prediction. Our work is similar in spirit to this type of work.

#### **3** RTA Corpus and Prior AES Systems

The essays in our corpus were written by students in grades 4 to 8 in response to two RTA source texts (Correnti et al., 2013):  $RTA_{MVP}$  (2970 essays) and  $RTA_{Space}$  (2076 essays). Table 1 shows an excerpt from  $RTA_{MVP}$ , the associated essay writing prompt, and a student essay. The bolding in the source indicates evidence examples that experts manually labeled as important for students to discuss (i.e., TC phrases). Evidence usage in each essay was manually scored on a scale of 1 to 4 (low to high). The distribution of Evidence scores is shown in Table 2. The essay in Table 1 received a score of 3, with the bolding indicating phrases semantically related to the TCs from the source text.

To date, two approaches to AES have been proposed for the RTA:  $AES_{rubric}$  and  $AES_{neural}$ . To support the needs of AWE,  $AES_{rubric}$  (Zhang and Litman, 2017) used a traditional supervised learning framework where rubric-motivated features were extracted from every essay before model training - Number of Pieces of Evidence (NPE)<sup>1</sup>, Concentration (CON), Specificity (SPC)<sup>2</sup>, Word Count (WOC). The two aspects of TCs introduced in Section 1 (topic words, specific example phrases) were used during feature extraction.

Motivated by improving stand-alone AES performance (i.e., when an interpretable model was not needed for subsequent AWE), Zhang and Litman (2018) developed  $AES_{neural}$ , a hierarchical neural model with the co-attention mechanism in the sentence level to capture the relationship between the essay and the source. Neither feature engineering nor TC creation were needed before training.

#### 4 Attention-Based TC Extraction: TC<sub>attn</sub>

In this section we propose a method for extracting TCs based on the  $AES_{neural}$  attention level outputs. Since the self-attention and co-attention mechanisms were designed to capture sentence and phrase importance, we hypothesize that the attention scores can help determine if a sentence or

<sup>&</sup>lt;sup>1</sup>An integer feature based on the list of *topic words* for each topic.

<sup>&</sup>lt;sup>2</sup>A vector of integer values indicating the number of *specific example phrases* (semantically) mentioned in the essay per topic.

No.	Sentences	$attn_{sent}$	$attn_{phrase}$
1	People didn't have the money to	0.00420	0.23372
	buy the stuff in 2004.		
2	The hunger crisis has been addressed	0.08709	0.62848
	with fertilizer and seeds, as well as		
	the tools needed to maintain the food.		
3	The school has no fees and they	0.10686	0.63369
	serve lunch.		

Table 3: Example attention scores of essay sentences.

phrase has important source-related information.

To provide intuition, Table 3 shows examples sentences from the student essay in Table 1. Bolded are phrases with the highest self-attention score within the sentence. Italics are specific example phrases that refer to the manually constructed TCs for the source.  $Attn_{sent}$  is the text to essay attention score that measures which essay sentences have the closest meaning to a source sentence.  $Attn_{phrase}$  is the self-attention score of the bolded phrase that measures phrase importance. A sentence with a high attention score tends to include at least one specific example phrase, and vice versa. The phrase with the highest attention score tends to include at least one specific example phrase if the sentence has a high attention score.

Based on these observations, we first extract the output of two layers from the neural network: 1) the  $attn_{sent}$  of each sentence, and 2) the output of the convolutional layer as the representation of the phrase with the highest  $attn_{phrase}$  in each sentence (denoted by  $cnn_{phrase}$ ). We also extract the plain text of the phrase with the highest  $attn_{phrase}$  in each sentence (denoted by  $text_{phrase}$ ). Then, our  $TC_{attn}$  method uses the extracted information in 3 main steps: 1) filtering out  $text_{phrase}$  from sentences with low  $attn_{sent}$ , 2) clustering all remaining  $text_{phrase}$  based on  $cnn_{phrase}$ , and 3) generating TCs from clusters.

The first filtering step keeps all  $text_{phrase}$  where the original sentences have  $attn_{sent}$  higher than a threshold. The intuition is that lower  $attn_{sent}$ indicates less source-related information.

The second step clusters these  $text_{phrase}$  based on their corresponding representations  $cnn_{phrase}$ . We use k-medoids to cluster  $text_{phrase}$  into Mclusters, where M is the number of topics in the source text. Then, for  $text_{phrase}$  in each topic cluster, we use k-medoids to cluster them into Nclusters, where N is the number of the specific example phrases we want to extract from each topic. The outputs of this step are M \* N clusters.

The third step uses the topic and example clus-

Layer	Parameter Name	Value
Embedding	Embedding dimension	50
Word-CNN	Kernel size	5
	Number of filters	100
Sent-LSTM	Hidden units	100
Modeling	Hidden units	100
Dropout	Dropout rate	0.5
Others	Epochs	100
	Batch size	100
	Initial learning rate	0.001
	Momentum	0.9

Table 4: Hyper-parameters for neural training.



Figure 1: An overview of four TC extraction systems.

tering to extract TCs. As noted earlier, TCs include two parts: topic words, and specific example phrases. Since our method is data-driven and students introduce their vocabulary into the corpus, essay text is noisy. To make the TC output cleaner, we filter out words that are not in the source text. To obtain topic words, we combine all  $text_{phrase}$ from each topic cluster to calculate the word frequency per topic. To make topics unique, we assign each word to the topic cluster in which it has the highest normalized word frequency. We then include the top  $K_{topic}$  words based on their frequency in each topic cluster. To obtain example phrases, we combine all  $text_{phrase}$  from each example cluster to calculate the word frequency per example, then include the top  $K_{example}$  words based on their frequency in each example cluster.

#### 5 Experimental Setup and Results

Figure 1 shows an overview of four TC extraction methods to be evaluated.  $TC_{manual}$  (upper bound) uses a human expert to extract TCs from a source text.  $TC_{attn}$  is our proposed method and automatically extracts TCs using *both* a source text and student essays.  $TC_{lda}$  (Rahimi and Litman, 2016) (baseline) builds on LDA to extract TCs from student essays only, while  $TC_{pr}$  (baseline) builds on PositionRank (Florescu and Caragea, 2017) to instead extract TCs from only the source text.

Since PositionRank is not designed for TC ex-

Prompt	Component	Parameter	$TC_{lda}$	$TC_{pr}$	$TC_{attn}$
	Tania Wanda	Number of Topics	9	19	16
$RTA_{MVP}$	Topic Words	Number of Words	30	20	25
$h_{MVP}$	Example Phrases	Number of Topics	20	1	18
	Example Phrases	Number of Phrases	15	20	15
	Topic Words	Number of Topics	15	20	10
$DTA_{-}$	Topic words	Number of Words	10	10	20
$RTA_{Space}$	Example Phrases	Number of Topics	10	1	9
	Example Phrases	Number of Phrases	20	50	20

Table 5: Parameters for different models.

traction, we needed to further process its output to create  $TC_{pr}$ . To extract topic words, we extract all keywords from the output. Next, we map each word to a higher dimension with word embedding. Lastly, we cluster all keywords using k-medoids into  $PR_{topic}$  topics. To extract example phrases, we put them into only one topic and remove all redundant example phrases if they are subsets of other example phrases.

We configure experiments to test two hypotheses: H1) the  $AES_{rubric}$  model for scoring Evidence (Zhang and Litman, 2017) will perform comparably when extracting features using either  $TC_{attn}$ or  $TC_{manual}$ , and will perform worse when using  $TC_{lda}$  or  $TC_{pr}$ ; H2) the correlation between the human Evidence score and the feature values (NPE and sum of SPC features)<sup>3</sup> will be comparable when extracted using  $TC_{attn}$  and  $TC_{manual}$ , and will be stronger than when using  $TC_{lda}$  and  $TC_{pr}$ . The experiment for H1 tests the impact of using our proposed TC extraction method on the downstream  $AES_{rubric}$  task, while the H2 experiment examines the impact on the essay representation itself.

Following Zhang and Litman (2017), we stratify essay corpora: 40% for training word embeddings and extracting TCs, 20% for selecting the best embedding and parameters, and 40% for testing. We use the hyper-parameters from Zhang and Litman (2018) for neural training as shown in Table 4. Table 5 shows all other parameters selected using the development set.

**Results for H1.** H1 is supported by the results in Table 6, which compares the Quadratic Weighted Kappa (QWK) between human and  $AES_{rubric}$  Evidence scores (values 1-4) when  $AES_{rubric}$  uses  $TC_{manual}$  versus each of the automatic methods.  $TC_{attn}$  always yields better performance, and even significantly better than  $TC_{manual}$ .

**Results for H2.** The results in Table 7 support H2.  $TC_{attn}$  outperforms the two automated base-

Prompt	$TC_{manual}(1)$	$TC_{lda}$ (2)	$TC_{pr}$ (3)	$TC_{attn}$ (4)
$RTA_{MVP}$	0.643 (2,3)	0.614 (3)	0.525	0.648 (1,2,3)
$RTA_{Space}$	0.609 (3)	0.615 (3)	0.559	0.622 (1,3)

Table 6: The performance (QWK) of  $AES_{rubric}$  using different TC extraction methods for feature creation. The numbers in the parentheses show the model numbers over which the current model performs significantly better (p < 0.05). The best results between automated methods in each row are in bold.

Prompt	Feature	$TC_{manual}$	$TC_{lda}$	$TC_{pr}$	$TC_{attn}$
	NPE	0.542	0.482	0.587	0.639
$RTA_{MVP}$	SPC (sum)	0.689	0.585	0.365	0.679
DT A	NPE	0.484	0.513	0.494	0.625
$RTA_{Space}$	SPC (sum)	0.601	0.574	0.533	0.598

Table 7: Pearson's r comparing feature values computed using each TC extraction method with human (gold-standard) Evidence essay scores. All correlation values are significant ( $p \le 0.05$ ). The best results between automated methods in each row are in bold.

lines, and for NPE even yields stronger correlations than the manual TC method.

**Qualitative Analysis.** The manually-created topic words for  $RTA_{MVP}$  represent 4 topics, which are "hospital", "malaria", "farming" and "school"<sup>4</sup>. Although Table 5 shows that the automated list has more topics for topic words and might have broken one topic into separate topics, a good automated list should have more topics related to the 4 topics above. We manually assign a topic for each of the topic words from the different automated methods.  $TC_{lda}$  has 4 related topics out of 9 (44.44%),  $TC_{pr}$  has 6 related topics out of 19 (31.58%), and  $TC_{attn}$  has 10 related topics out of 16 (62.50%). Obviously,  $TC_{attn}$  preserves more related topics than our baselines.

Moving to the second aspect of TCs (specific example phrases), Table 8 shows the first 10 specific example phrases for a manually-created category that introduces the changes made by the MVP project<sup>5</sup>. This category is a mixture of different topics because it talks about the "hospital", "malaria", "school", and "farming" at the same time.  $TC_{attn}$  has overlap with  $TC_{manual}$  on different topics. However,  $TC_{lda}$  mainly talks about "hospital", because the nature of the LDA model doesn't allow mixing specific example phrases about different topics in one category. Unfortunately,  $TC_{pr}$ 

<sup>&</sup>lt;sup>3</sup>These features are extracted based on TCs.

<sup>&</sup>lt;sup>4</sup>All Topic Words generated by different models can be found in the Appendix A.1.

<sup>&</sup>lt;sup>5</sup>All Specific Example Phrases generated by different models can be found in the Appendix A.2.

TC <sub>manual</sub>	$TC_{lda}$	$TC_{pr}$	$TC_{attn}$
progress just four years	running water electricity	brighter future hannah	electricity running water irrigation set
medicine most common diseases	water connected hospital generator electricity	millennium villages project	poor showed treatment school supplies
water connected hospital	patients afford	unpaved dirt road	farmers could crops afford bed
hospital generator electricity	rooms packed patients probably	bar sauri primary school	electricity hospital
bed nets used every sleeping site	share beds	future hannah	better fertilizer medicine enough also
hunger crisis addressed fertilizer seeds	recieve treatment	sauri primary school	rooms packed patients
tools needed maintain food supply	doctor clinical officer running hospital	villages project	food fertilizer crops get supply
no school fees	doctors clinical	millennium development goals	five net costs 5
school attendance rate way up	water fertilizer knowledge	village leaders	nets net bed free
kids go school now	receive treatment	dirt road	running water supplies schools almost

Table 8: Specific example phrases for the  $RTA_{MVP}$  progress topic.

does not include any overlapped specific phrase in the first 10 items; they all refer to some general example phrases from the beginning of the source article. Although there are some related specific example phrases in the full list, they are mainly about school. This is because the PositionRank algorithm tends to assign higher scores to words that appear early in the text.

## 6 Conclusion and Future Work

This paper proposes  $TC_{attn}$ , a method for using the attention scores in a neural AES model to automatically extract the Topical Components of a source text. Evaluations show the potential of  $TC_{attn}$  for eliminating expert effort without degrading  $AES_{rubric}$  performance or the feature representations themselves.  $TC_{attn}$  outperforms baselines and generates comparable or even better results than a manual approach.

Although  $TC_{attn}$  outperforms all baselines and requires no human effort on TC extraction, annotation of essay evidence scores is still needed. This leads to an interesting future investigation direction, which is training the  $AES_{neural}$  using the gold standard that can be extracted automatically.

One of our next steps is to investigate the impact of TC extraction methods on a corresponding AWE system (Zhang et al., 2019), which uses the feature values produced by  $AES_{rubric}$  to generate formative feedback to guide essay revision.

Currently, the  $TC_{lda}$  are trained on student essays, while the  $TC_{pr}$  only works on the source article. However,  $TC_{attn}$  uses both student essays and the source article for TC generation. It might be hard to say that the superior performance of  $TC_{attn}$  is due to the neural architecture and attention scores rather than the richer training resources. Therefore, a comparison between  $TC_{attn}$  and a model that uses both student essays and the source article is needed.

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## **A** Appendices

## A.1 Topic Words Results

Table 9 shows all topic words for the  $RTA_{MVP}$  from  $TC_{manual}$ . Table 10 shows all topic words for the  $RTA_{MVP}$  from  $TC_{lda}$ . Table 11 shows all topic words for the  $RTA_{MVP}$  from  $TC_{pr}$ . Table 12 shows all topic words for the  $RTA_{MVP}$  from  $TC_{attn}$ .

## A.2 Specific Example Phrases Results

Table 13 shows all specific example phrases for the  $RTA_{MVP}$  from  $TC_{manual}$ . Table 14 shows all specific example phrases for the  $RTA_{MVP}$  from  $TC_{lda}$ . Table 15 shows all specific example phrases for the  $RTA_{MVP}$  from  $TC_{pr}$ . Table 16 shows all specific example phrases for the  $RTA_{MVP}$  from  $TC_{attn}$ .

Topic 1Topic 2Topic 3Topic 4carebedfarmerschoolhealthnetfertilizersupplieshospitalmalariairrigationfeetreatmentinfectdyingstudentdoctorbednetcropmiddayelectricitymosquitoseedmealdiseasebugwaterlunchwatersleepingharvestsupplysickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingtenergyfreekidtenergydiekidpatientgoattendofficerrunningsetset				
healthnetfertilizersupplieshospitalmalariairrigationfeetreatmentinfectdyingstudentdoctorbednetcropmiddayelectricitymosquitoseedmealdiseasebugwaterlunchwatersleepingharvestsupplysickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingtestfreekidtestfreekidbedtestgoattendofficertesttestattend	Topic 1	Topic 2	Topic 3	Topic 4
hospitalmalariairrigationfeetreatmentinfectdyingstudentdoctorbednetcropmiddayelectricitymosquitoseedmealdiseasebugwaterlunchwatersleepingharvestsupplysickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingenergyfreekidstingstingkidbedstinggoclinicalsedattendofficerstingsting	care	bed	farmer	school
treatment infect dying student doctor bednet crop midday electricity mosquito seed meal disease bug water lunch water sleeping harvest supply sick die hungry book medicine cheap feed paper generator infect food pencil no biting tenergy die free kid free kid go clinical go attend	health	net	fertilizer	supplies
doctorbednetcropmiddayelectricitymosquitoseedmealdiseasebugwaterlunchwatersleepingharvestsupplysickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingtenergyfreekidtenergykidkidbedtenergygoattendofficertenergytenergy	hospital	malaria	irrigation	fee
electricitymosquitoseedmealdiseasebugwaterlunchwatersleepingharvestsupplysickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingenergydiefreekidbedstidkidpatientgoattendofficerinfectstid	treatment	infect	dying	student
diseasebugwaterlunchwatersleepingharvestsupplysickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingenergydiefreekidchildrenbedkidgoattendofficerinfectsupply	doctor	bednet	crop	midday
watersleeping dieharvestsupply booksickdiehungrybookmedicinecheapfeedpapergeneratorinfectfoodpencilnobitingenergydiefreekidbedkidchildrenbedgoattendofficerintertgo	electricity	mosquito	seed	meal
sick die hungry book medicine cheap feed paper generator infect food pencil no biting energy die free kid children bed kid patient go clinical attend	disease	bug	water	lunch
medicinecheapfeedpapergeneratorinfectfoodpencilnobitingenergydiefreekidchildrenbedkidpatientgoclinicalattend	water	sleeping	harvest	supply
generatorinfectfoodpencilnobitingenergydiefreekidchildrenbedkidpatientgoclinicalattendofficerit	sick	die	hungry	book
no biting energy die free kid children bed kid patient go clinical attend officer	medicine	cheap	feed	paper
die free kid children bed kid patient go clinical attend officer	generator	infect	food	pencil
kid children bed kid patient go clinical attend officer	no	biting		energy
bedkidpatientgoclinicalattendofficer	die			free
patient go clinical attend officer	kid			children
clinical attend officer	bed			kid
officer	patient			go
	clinical			attend
running	officer			
	running			

Table 9: Topic words of  $TC_{manual}$ .

TOPIC 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9
help	kenya	poverty	food	money	school	people	hospital	years
poor	like	think	fertilizer	need	kids	sauri	medicine	africa
world	better	author	crops	nets	supplies	malaria	hospitals	project
good	know	lifetime	water	thing	children	sick	water	villages
things	life	article	farmers	afford	schools	2008	free	sauri
time	help	possible	needed	donate	lunch	disease	electricity	village
work	think	convinced	grow	right	education	2004	diseases	helped
hard	sauri	fight	dying	dollar	afford	nets	medicines	change
going	live	proverty	problem	treatment	energy	mosquitoes	doctors	lives
alot	clothes	said	family	survive	learn	getting	2008	goals
reason	states	achievable	families	needs	students	says	gave	improved
happen	place	time	stop	stuff	went	years	doctor	2015
helping	health	convince	lack	person	adults	progress	examples	help
goal	important	believe	hunger	cause	fees	died	2004	changed
believe	feel	hannah	tools	patients	parents	text	shape	year
problems	happy	shows	seeds	provide	2004	away	cure	changes
countries	tell	reasons	plants	cost	lunches	mosquitos	running	started
difference	care	convincing	fertilizers	beds	books	prevent	treat	great
places	shoes	fighting	farming	means	home	treated	support	millennium
change	story	wrote	able	dont	wanted	dieing	common	progress
little	america	story	solved	dollars	chores	said	beds	came
improve	ways	agree	supply	medical	meal	come	patients	girl
country	wants	saying	irrigation	jobs	wood	night	said	2025
achieve	makes	opinion	wont	everyday	materials	bite	generator	place
hope	clothing	winning	afford	gone	learning	death	clean	program
helps	community	sachs	hungry	doctors	able	sleep	electricty	tells
everybody	economy	progress	plant	lots	suplies	impoverished	giving	small
start	history	conclusion	look	sickness	meals	living	drink	millenium
easy	paragraph	says	farms	live	paper	amazing	cures	read
making	thats	future	feed	fact	attendance	easily	evidence	happened

Table 10: Topic words of  $TC_{lda}$ .

Topic 1	Topic 2	Topic 3		Topic 4 Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10	Topic 11	Topic 12	Topic 13	Topic 14	Topic 15	Topic 15 Topic 16 Topic 17 Topic 18	Topic 17	Topic 18	Topic 19
rrigation	road	diseases	adults	fight	development	joyful	people	midday	village	millennium	backs	plenty	doctor	thing	paper	end	work	sleeping
fertilizer	brighter	medicine		lifetime	villages	dirt		school			women	access	hospital		supplies		world	bed
farmers	future	malaria			project	jump		fees			ground	care	shape		chores			net
crops	hannah	disease			goals	bar		students			bananas	medicines	patients		books			nets
plant	car	mosquitoes			plan	music		meal			cloth	schools	treatment		pencils			site
seeds	sauri	charge			economy	singing		energy			mothers	today	officer					
outcome	market				quality	everyone		lunch			feet	supply	water					
lack	year				supporters	dancing					clothing	areas	electricity					
tools	time					help					day	kind	generator					
	place					health					rooms							
	years					advice					family							
	poverty					items												
	life					targets												
C	communities					death												
	leaders					night												
	glimpse					costs												
	africa					die												
	chemicals					knowledge												
	solutions					food												
	millions					parents												

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Topic 16	fertilizer	seeds	addressed	irrigation	necessary	tools	lack	plenty	plant	nomme	become														
Topic 15 To	supply fe	naintain		hunger irr	-		life			away co	_														
		Г	Č.			a					-														
Topic 14	project	world	millennium	village	across	work	end	worry	supporters	time	2025	history	selling												
Topic 13	bed	nets	used	every	sleeping	site	midday	meal	dramatic	change	clinical	officer	tattered	clothing	chemicals	malarial	preventable	treatable	costs						
Topic 12	hospital	2004	disease	yala																					
Topic 11	school	schools	fees	students																					
Topic 10	free	medicine	crops	charge	farmers	medicines																			
Topic 9	many	people	kenya	sauri	pencils	africa	yet	sachs	though	feed	two	health	set	crisis	areas	items									
Topic 8	afford	lifetime	could	achievable	together	malaria	take	future	worked	care	family	hard	poog	doctor	either	whole	save	millions	easy	met	ever	around	mosquitoes	easily	
Topic 7	supplies	food	net	rooms	packed	patients	needed	5	keep	poor	five	like	come	little	treatment	minimal	almost	harvest	showed	cheap					
Topic 6	electricity	water	generator	also	running	energy	connected																		
Topic 5	goals	problems	day	cloth	three	made	books	2015	knowledge	learn	one														
Topic 4	lunch	serves	parents	attend	passed																				
Topic 3	years	four	villages	80	progress	last	occurred	year	changes	outcome	today	first	along												
Topic 2	way	would	rate	attendance	help	kids	enough	better	go	get	place	solutions	really	targets	see	die	hungry	dancing	walked	bare	feet	hannah	impoverished	encouraging	probably
Topic 1	poverty	fight	winning																						

Table 12: Topic words of  $TC_{attn}$ .

Category I	Category 2	Category 3	Category 4
unpaved roads	united nations intervention	yala sub district hospital	malaria common disease preventable treatable
tattered clothing	safer healthier better life	three kids bed two adults rooms packed patients	mosquitoes carry malaria infect people biting
bare feet	out poverty stabilize economy quality life communities	not medicine treatment could afford	kids die malaria adults sick 20 000 day
less than 1 dollar day	africa kenya sauri	no doctor only clinical officer running hospital	bed nets mosquitoes away people save millions lives
	goals met 2015 2025	no running water electricity	bed nets cost 5 dollar
	80 villages across sub-sahara africa	sad people dying near death preventable	cheap medicines treat malaria
Category 5	Category 6	Category 7	Category 8
crops dying	kids not attend go school	progress just four years	progress encouraging supporters
not afford fertilizer irrigation	not afford school fees	yala sub district hospital has medicine	solutions problems keep people impoverished
outcome poor crops	kids help chores fetching water wood	medicine free charge	change poverty stricken areas good
lack fertilizer water	schools minimal supplies books paper pencils	medicine most common diseases	poverty history not easy task hard
enough food crops harvest feed whole family hungry sick	concentrate not energy	water connected hospital	winning against poverty possible achievable lifetime
	no midday meal lunch	hospital generator electricity	
		bed nets used every sleeping site	
		hunger crisis addressed fertilizer seeds	
		tools needed maintain food supply	
		kids go school now	
		no school fees	
		now serves lunch students	
		school attendance rate way up	

Table 13: Specific example phrases of  $TC_{manual}$ .

Category 1	Category 2	Category 3	Category 4	Category 5
work hard	life time	author convince winning fight poverty achievable lifetime	children adults	easy task
better place	united nations	author convinced winning fight poverty achievable lifetime	mosquitoes carry malaria	lived dollar
hetter health	united states	author wants	disease called malaria	thin a history
beichten future	life communities	author continue tribuing fight measured.	uisease cantou manana oomo aicht	truef mond
unings like	IIKe DOOKS paper pencits	winning light proverty achievable include	matariat mosquitoes	carn money
unings need		winning ngin poverty acmevable me ume	easily adults sick	
ugnung poverty work change	IIII portant KIUS thinks immortant	aruce ongrier fuure wining fight novienty ochievolda	solutions problems people impovensneu meenitees avor	
work cliange hard work	unitiks inipot tant	wining ngin poverty acinevance arricle states	infect records biting	
	WAILUS MILOW	al ucie states $-1$		
agree author		winning ii ght poverty acheivable	away sleeping	
working hard		author provided		
better life 2008		author thinks		
better life 2008		based article author convince		
reading article		convinced poverty		
things changed		poverty acheivable lifetime		
Category 6	Category 7	Category 8	Category 9	Category 10
attendance rate	amazing progress years	good shape	kids adults	donate money
midday meal	text says	good education	2015 2025	tattered clothes
serves lunch students	text said	went school	hungry sick	tattered clothing
midday meals	year girl	areas good	cheap medicines	bare feet
served lunch	year 2004	trying help	goals supposed	donating money
students wanted learn	paragraph says	worked hard		save millions lives
books pencils	progress shows winning fight poverty achievable	second reason		
kids attend school	treated chemicals	second example		
schools minimal	paragraph states	girl went		
schools hospitals	progress encouraging supporters millennium villages	hannah sachs convinced winning		
school school fees		wentkenya		
practical items				
kids sauri attend school parents afford school fees				
attendence rate				
parents money				
Category 11	Category 12	Category 13	Category 14	Category 15
clean water	grow crops	millennium village project	stop poverty	running water electricity
water wood	feed family	millenium village project	long time	water connected hospital generator electricity
fresh water	needed help	millennium villages project helped	world work change	patients afford
needs help	farmers worry	change dramatically	beat poverty	rooms packed patients probably
medicines free charge	crops dying afford necessary fertilizer irrigation	dramatic changes occured villages subsaharan africa	ending poverty	share beds
chores fetching	fertilizer knowledge	place live	want learn	recieve treatment
fetching water	hunger crisis addressed fertilizer seeds tools needed maintain food supply	happened years	places like	doctor clinical officer running hospital
	feed families	dramatic changes occurred villages	shows winning fight poverty achievable lifetime	doctors clinical
	hunger crisis adressed	millennium development goals	want kind poverty	water fertilizer knowledge
	family plant seeds outcome poor	change povertystncken areas good	poverty assure access	receive treatment
	farmers worried	coming years		running bare
		encouraging supporters minennium vinages project occurred villages subsaharan		arrord treatment
Category 16	Category 17	Category 18	Category 19	Category 20
yala subdistrict hospital medicine free charge common diseases	nets	plan people poverty	achieve goal	years later
free lunch		stabilize economy quality life communities	reach goal	took years
yala district		assure access health care help	going school	started 2004
preventable treatable		people people	story says	
common africa		near death	achieve goals	
diseases like		poor crops lack		
common disease africa		homeless people		
hospital good shape				
district hospital				

## Table 14: Specific example phrases of $TC_{lda}$ .

Category 1 brighter future hannah millennium villages project unpaved dirt road bar sauri primary school future hannah sauri primary school villages project millennium development goals village leaders dirt road car jump little kids preventable diseases people many kids diseases people kids die school supplies primary school school fees infect people

Table 15: Specific example phrases of  $TC_{pr}$ .

Category 1	Category 2	Category 3	Category 4	Category 5	Calegory o
winning fight	could feed bed net afford	four vears progress lifetime vear	fees students school supplies schools	sauri knowledge	supplies medicines
poverty winning world villages	people school work hard books	villages occurred 80 across along	school fees supplies afford fertilizer	afford school fees	better medicine water energy
winning fight poverty	also every diseases kids health	net 5	tools crops school fees seeds	bed nets help keep	hospital electricity connected
winning poverty	preventable family people care	vears many villages sauri project	farmers rooms patients crops people	food attendance rooms end many	bed nets 5 also
fight poverty	afford school fees bed nets	outcome poor crops	school lunch meal midday supplies	problems also people energy many	water electricity hospital fertilizer
poverty fight winning	also would energy leam help	progress vears kenva africa todav	lunch students serves midday	food supply maintain electricity supplies	electricity water energy
fight poverty winning	people fees school farmers could	rate people	medicine 2004 5 vears keep	school fees	bed showed
2	lunch could work electricity medicine	villages kenva 80 farmers manv	school lunch schools also fees	2004 also year rate school	bed nets used
	could afford fertilizer	four vears lifetime poverty vear	vears school showed hospital water	farmers needed food supply villages	generator energy
	school supplies little afford enough	years four last five day	school parents attend		bed nets free
	food also	famers two many poverty	school medicine fertilizer hospital bed		water electricity also fertilizer supplies
	also tools	years changes fertilizer addressed	school schools fees free two		electricity water running also generator
	supply maintain food also tattered	years villages kenya project attendance	school fees schools lunch free		generator electricity
		energy poverty hunger electricity	lunch school crops food farmers		fertilizer bed net water
			water fertilizer energy school medicines		fertilizer addressed school supplies crisis
Category 7	Category 8	Category 9	Category 10	Category 11	Category 12
electricity running water irrigation set	bed showed diseases	help students supplies people schools	years four free schools medicine	medicine electricity tools fertilizer medicines	schools also school students attendance
poor showed treatment school supplies	lunch meal energy	people years four three though	school schools free supplies fees	water electricity connected schools running	free charge school maintain supply
farmers could crops afford bed	dramatic change bed nets	villages years 80 poverty many	crops fertilizer farmers tools plant	students lunch serves school 2004	crops farmers 2004 first food
electricity hospital	poverty better lives made many	worked to gether end	water electricity supplies school energy	medicine crops free hospital also	lack fertilizer school bed nets
better fertilizer medicine enough also	achievable lifetime sauri	pencils students supplies yet	medicine school supplies years hunger	school supplies farmers attendance crops	bed nets years hospital
rooms packed patients	malaria good bed net used	villages many kenya sauri 80	fertilizer crops lack farmers water	water supplies schools free hospital	hospital disease four years 2004
food fertilizer crops get supply	bed net	vears food supply hunger crisis	fertilizer irrigation crops medicine water	schools crops supplies free charge	every sleeping site
five net costs 5	common diseases	sauri net	medicines school medicine fertilizer free	school schools lunch also free	school hed also occurred 80
nets net hed free	work together poverty	net 5	free charve medicine school medicines	school fees schools	vears four schools last students
runing water cumiliae echoole almost	homital as school could afford	echool sumuliae itame	neede alout crone fartilizar	school faar hund	school sumiliae schools des 2004
	nioim minor iooire og mildeoi	survoi suppres rucius		SCHOOL LCCS HILDL	
bed supplies knowledge medicines afford	project progress made 1000 good	sachs many	Iree schools lunch school charge	Iunch schools school seeds food	crops ranners schools project also
supplies food supply farmers water	also hospital doctor clinical showed		bed nets water fertilizer medicines	school fees schools free lunch	hospital years medicine school water
supplies midday school food hunger	years made malaria take changes		free charge medicine school fertilizer	schools supplies electricity farmers fertilizer	free charge schools years meal
many food	could better future people lunch		crops farmers fertilizer electricity knowledge	students lunch	medicine hospital made
			school fees schools free medicines	schools school farmers crops bed	free charge school years hunger
Category 13	Category 14	Category 15	Category 16	Category 17	Category 18
bed nets	villages africa millennium 80 across	supply books	seeds fertilizer addressed food medicine	enough would work hard better	water connected hospital
water running medicine medicines supplies	80 villages across	electricity water	seeds supply fertilizer crops plenty	people world sauri kids poverty	nets bed used crops afford
bed nets medicine crops electricity	poverty fight people kenya end	poverty many lives hunger every	fertilizer seeds crops	many people poverty could take	midday meal
sauri free bed nets	world 2015	diseases lack water day every	tools fertilizer	kenya would better walked bare	midday meal lunch
crops fertilizer plant food irrigation	poor village sauri	adults one bed two last	crops farmers also water could	poverty problems crisis though many	bed nets used
bed nets every water medicine	well project villages poor end	people food work many energy	crops seeds water needed	people kenya targets 80 villages	bed every sleeping site net
fertilizer crops water keep tools	achievable kenya	villages village school people many	addressed fertilizer seeds	almost kids die people	bed nets every used school
kenya bed nets	many villages people problems kenya	school food schools hospital people	seeds fertilizer food also water	rate way progress better africa	hospital water running clinical officer
bed nets also adults	project villages kenya village people	years changes four free occurred	seeds fertilizer water	attendance rate way	water hospital bed nets
sauri bed nets	goals four years met needed	water every work school fees	fertilizer food	see world	bed nets could keep
every bed nets	poverty village fight africa sauri	years hospital villages charge connected	fertilizer irrigation necessary farmers tools	go hungry get people could	bed nets used every sleeping
diseases medicine medicines common preventable	attendance rate way selling come	food maintain supply electricity supplies	fertilizer seeds irrigation farmers lack	get food work would probably	hospital charge bed nets preventable
nets bed water sauri years	work world help last together	2015 2025 dying hunger death	fertilizer lack crops become sauri	world winning fight way place	
crops fertilizer enough farmers	poverty many 2015 millennium progress	diseases malaria		people easily sauri history way	

# Table 16: Specific example phrases of $TC_{attn}$ .