KERT: Automatic Extraction and Ranking of Topical Keyphrases from Content-Representative Document Titles

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Abstract

We introduce KERT (Keyphrase Extraction and Ranking by Topic), a framework for topical keyphrase generation and ranking. By shifting from the unigram-centric traditional methods of unsupervised keyphrase extraction to a phrase-centric approach, we are able to directly compare and rank phrases of different lengths. We construct a topical keyphrase ranking function which implements the four criteria that represent high quality topical keyphrases (coverage, purity, phraseness, and completeness). The effectiveness of our approach is demonstrated on two collections of content- representative titles in the domains of Computer Science and Physics.

1 Introduction

Keyphrases have traditionally been defined as terms or phrases which summarize the topics in a document (Turney, 2000). Keyphrase extraction is an important step in many tasks, such as document summarization, clustering, and categorization (Manning and Schütze, 1999). More recently, the definition has been expanded to include the notion of topical keyphrases - groups of keyphrases which summarize the topics in a given document, or document collection (Liu et al., 2010). Most existing work on keyphrase extraction identifies keyphrases from either individual documents or an entire text collection (Tomokiyo and Hurst, 2003; Liu et al., 2010). However, recently there has been some interest in working with documents consisting of very short text, such as a collection of tweets (Zhao et al., 2011), in order to summarize the document collection.

Our framework also targets short texts - in particular, collections of *content-representative titles*. Document titles are content-representative if they may serve as concise descriptions of the content of the document. The words in a content-representative title can therefore be thought of as probabilistic priors for which words are the most likely to generate keyphrases describing the document. Scientific publications and newspaper articles generally have content-representative titles, whereas fiction books generally do not. As we address the task of representing the topics present in a document collection, content-representative titles are cleaner and more efficient to deal with than entire documents.

Most current approaches to topic construction yield lists of unigrams to represent topics. However, it has long been known that unigrams account for only a small fraction of human-assigned index terms (Turney, 2000). Therefore, in order to construct high quality keyphrases for a given topic, it is important to provide n-gram keyphrases rather than unigram keywords. However, it is inappropriate to discard all unigrams when approaching this task. For instance, consider that the unigram 'classification' and the trigram 'support vector machines' are both high quality topical keyphrases for the Machine Learning topic in the domain of Computer Science. We should therefore be able to perform integrated ranking of mixed-length phrases in a natural way.

Such a ranking function must successfully represent human intuition for judging what constitutes a high quality topical keyphrase. We propose that this is best represented by four criteria: coverage, purity, phraseness, and completeness. As an example, consider the task of constructing and ranking

keyphrases for various topics in Computer Science:

- **Coverage:** A representative keyphrase for a topic should cover many documents within that topic. *Example:* 'information retrieval' has better coverage than 'cross-language information retrieval' in the Information Retrieval topic.
- **Purity:** A phrase is pure in a topic if it is only frequent in documents belonging to that topic and not frequent in documents within other topics. *Example: 'query processing' is more pure than 'query' in the Database topic.*
- **Phraseness:** A group of words should be combined together as a phrase if they co-occur significantly more often than the expected chance co-occurrence frequency, given that each term in the phrase occurs independently. *Example: 'active learning' is a better phrase than 'learning classification' in the Machine Learning topic.*
- Completeness: A phrase is not complete if it is a subset of a longer phrase, in the sense that it rarely occurs in a title without the presence of the longer phrase. Example: 'support vector machines' is a complete phrase, whereas 'vector machines' is not because 'vector machines' is almost always accompanied by 'support'.

Our aim is to construct topics represented by a ranked list of keyphrases of various lengths where more highly ranked keyphrases are considered to be better index phrases for that topic. The main contributions of this work are:

- We introduce KERT (Keyphrase Extraction and Ranking by Topic), a framework for topical keyphrase generation and ranking. By altering the steps in the traditional methods of unsupervised keyphrase extraction, we can directly compare of phrases of different lengths, resulting in a natural integrated ranking of mixed-length keyphrases.
- We construct a topical keyphrase ranking function which implements the four criteria that intuitively represent high quality topical keyphrases (coverage, purity, phraseness, and completeness).
- We demonstrate the effectiveness of our approach on two collections of content-representative titles in the domains of Computer Science and Physics.

2 Related Work

The state-of-the-art approaches to unsupervised keyphrase extraction have generally been graphbased, unigram-centric ranking methods, which first extract unigrams from text, rank them, and finally combine them into keyphrases. TextRank (Mihalcea and Tarau, 2004) constructs keyphrases from the top ranked unigrams in a document collection. Topical PageRank (Liu et al., 2010) splits the documents into topics and creates keyphrases from top ranked topical unigrams. Some previous methods have used clustering techniques on word graphs for keyphrase extraction (Liu et al., 2009; Grineva et al., 2009), relying on external knowledge bases such as Wikipedia to calculate term importance and relatedness. Barker and Cornacchia (2000) use natural language processing techniques to select noun phrases as keyphrases. Tomokiyo and Hurst (2003) take a language modeling approach, requiring a document collection with known topics as input and training a language model to define their ranking criteria.

Unlike most of these methods which extract keyphrases from documents, we aim to extract keyphrases from a corpus of short texts. Zhao et al (2011) also uses short text - microblogging data from Twitter - but we work with content-representative document titles.

Topic modeling techniques such as PLSA (probabilistic latent semantic analysis) (Hofmann, 2001) and LDA (latent Dirichlet allocation) (Blei et al., 2003) take documents as input, model them as mixtures of different topics, and discover word distributions for each topic. Some previous work has developed topic modeling to discover topical phrases comprised of consecutive words (Wang et al., 2007). Our framework also uses topic modeling - an extension of LDA - to perform the initial word clustering into topics, but does not restrict phrases to only those word sequences explicitly found in the text.

Since we aim to transform a collection of short texts into sets of ranked keyphrases, the top-K keyphrases for each topic may also serve as that topic's labels. Therefore our work is tangentially related to automatic topic labeling (Mei et al., 2007).

3 KERT Framework

A key aspect of our framework is that we do not follow the traditional unigram-centric approach of keyphrase extraction, where words are first extracted and ranked independently, and then combined to create phrases. Instead, we construct topical phrases immediately after clustering the unigrams. By shifting from a unigram-centric to a phrase-centric ap-

proach, we are able to extract topical keyphrases and implement a ranking function that can directly compare keyphrases of different lengths, as we explain in Section 3.3.

Our steps for topical keyphrase generation and ranking are as follows:

- **Step 1.** Cluster words in the document dataset into T foreground topics and one background topic, using background LDA.
- **Step 2.** Extract candidate keyphrases for each topic according to the word topic assignment.
- **Step 3.** Rank the keyphrases in each foreground topic $z \in 1, \ldots, k$ by integrating the criteria of Coverage, Purity, Phraseness, and Completeness.

In the subsequent sections we give detailed explanations of each step.

3.1 Clustering Words using Topic Modeling

Content-representative titles exhibit several characteristics that guide our clustering approach:

- Short and well-formed. Most titles are composed of a few key technical words and background words. Background words are found across titles belonging to different topics.
- Ambiguous Unigrams. A single word (e.g. 'vector') may appear in different topics, while phrases (e.g. 'support vector machines') are overall less topic-ambiguous.
- Mix of Topics. A title may comprise a sparse mixture of different topics, in spite of its short length.

LDA (Blei et al., 2003) and its extensions have been shown to be effective for modeling textual documents. We therefore use a modified LDA model which includes an additional background topic z = 0. Each title is modeled by a distribution over the foreground topics $z = 1, \ldots, k$ and the background topic. For each word in a title, we decide if it belongs to the background topic or one of the foreground topics, and then choose the word from the appropriate distribution.

Formally, let ϕ^t denote the word distribution for topic $t=0,\ldots,k$. Let θ^d be the topic distribution of document d. Let λ denote a Bernoulli distribution that chooses between the background topic and foreground topics. The generative process is as follows:

- 1. Draw $\phi^t \sim Dir(\beta)$, for $t = 0, \dots, k$.
- 2. For each title $d \in D$,
 - (a) draw $\theta^d \sim Dir(\alpha)$.

- (b) for each word position i in d
 - i. draw $y_{d,i} \sim Bernoulli(\lambda)$
 - ii. if $y_{d,i} = 0$, draw $w_{d,i} \sim Multi(\phi^0)$, otherwise
 - A. draw topic $z \sim \theta^d$
 - B. draw $w_{d,i} \sim Multi(\phi^z)$

where α and β are Dirichlet prior parameters for θ and ϕ respectively.

We use a collapsed Gibbs sampling method for model inference. We iteratively sample the topic assignment $z_{d,i}$ for every word $w_{d,i}$ in each document until convergence. In traditional topic modeling tasks, the sampled topic assignments are mainly used to estimate the topic distribution ϕ^z . In our case, we are more interested in the topic assignments for the words in each title, because these values are the foundation of our topical keyphrase generation step, as described in the next section. We use the maximum a posteriori (MAP) principle to label each word: $z_{d,i} = \arg\max_{z_{d,i}=0,\dots,k} P(z_{d,i}|W)$.

3.2 Candidate Keyphrase Generation

There are two ways to discover keyphrases: either extract them from the text (sequences of words) which actually occur in the text, or to automatically construct them (Frank et al., 1999), an approach which is regarded as both more intelligent and more difficult (Hammouda et al., 2005; Manning and Schütze, 1999).

In a dataset of content-representative titles, extracting phrases directly from the text is quite limiting as this approach is too sensitive to the caprices of various writing styles. For instance, consider that two computer science papers titles, one containing 'mining frequent patterns' and the other containing 'frequent pattern mining,' are clearly discussing the same topic, and should be treated as such. A keyphrase may also be separated by other words: 'mining top-k frequent closed patterns' also belongs to the topic of frequent pattern mining, in addition to incorporating secondary topics of top-k frequent patterns, and closed patterns. Therefore, we define a phrase to be an order-free set of words appearing in the same title, and must therefore construct our phrases.

After the clustering step described in Section 3.1 is completed, each word $w_{d,i}$ in each title d has a topic label $z_{d,i} \in \{0, \dots, k\}$. If a set of words in a title d are assigned a common foreground topic t > 0,

these words may comprise a topical phrase in t (e.g. {'frequent', 'pattern', 'mining'} in the topic of 'Data Mining'). If this set occurs in many titles with the topic label t, it is likely a good candidate keyphrase for that topic.

We use frequent pattern mining approaches to mine the candidate topical phrases. For each topic t, we construct a topic-t word set $p_d^t = \{w_{d,i}|z_{d,i} = t\}$ consisting of the words with the topic label t for each document d. We unite all the topic-t word sets into the topic-t set $D_t = \{d|p_d^t \neq \emptyset\}$. We may then mine frequent word sets from $p_{D_t}^t = \{p_d^t|d \in D_t\}$ using any efficient pattern mining algorithm, such as FP-growth (Han et al., 2004). We require a good topical keyphrase to have enough topical support $f_t(p) > \mu$ in order to filter out some coincidental co-occurrences (where $f_t(p)$ denotes the frequency of the word set p in topic t).

We thus define a candidate topical keyphrase for topic t to be a set of words $p = \{w_1 \dots w_n\}$ which are simultaneously labeled with topic t in at least μ titles, as discovered by the frequent pattern mining step. We then move on to evaluating the quality of the candidate topical keyphrases in order to rank them within each topic.

3.3 Ranking Measures and Function

As discussed in Section 1, a ranking function must compare topical keyphrases with respect to the four criteria of Coverage, Purity, Phraseness, and Completeness. This implies that the function should be able to directly compare keyphrases of mixed lengths, which we refer to as having the **comparability property**. For example, the keyphrases 'classification,' 'decision trees,' and 'support vector machines' should all be ranked highly in the integrated list of keyphrases for the Machine Learning topic, in spite of having different lengths.

Traditional probabilistic modeling approaches such as language models or topic models do not have the comparability property. They can model the probability of seeing an n-gram given a topic, but the probabilities of n-grams with different lengths (unigrams, bigrams, etc) are not well comparable. These approaches simply find longer n-grams to have much smaller probability than shorter ones, because the probabilities of seeing every possible unigram sum up to 1, and so do the probabilities of seeing every possible bigram, trigram, etc. But the

total number of possible n-grams grows following a power law $(O(v^n))$ where v is the vocabulary size), and therefore ranking functions based on these traditional approaches invariably favor short n-grams. While previous work has used various heuristics to correct this bias during post-processing steps, (Tomokiyo and Hurst, 2003; Zhao et al., 2011), our approach is cleaner and more principled.

We propose a different ranking model which exhibits the comparability property. The key idea is to represent the random event $e_t(p)=$ 'seeing a phrase p in a random title with topic t'. With this definition, the events of seeing n-grams of various lengths in different titles are no longer mutually exclusive, and therefore the probabilities no longer need to sum up to 1. Formally, the probability of $e_t(p)$ is defined to be $P(e_t(p)) = \frac{f_t(p)}{|D_t|}$. In the subsequent sections we define our measures representing the 4 criteria of coverage, purity, phraseness, and completeness using quantities related to this probability.

3.3.1 Coverage

A representative keyphrase for a topic should cover many documents within that topic. For example, 'information retrieval' has better coverage than 'cross-language information retrieval' in the topic of Information Retrieval. We directly quantify the coverage measure of a phrase as the probability of seeing a phrase in a random topic-t word set $p_d^t \in D_t$:

ing a phrase in a random topic-
$$t$$
 word set $p_d^t \in D_t$:
$$\pi_t^{cov}(p) = P(e_t(p)) = \frac{f_t(p)}{|D_t|} \tag{1}$$

3.3.2 Purity

A phrase is pure in topic t if it is only frequent in documents about topic t and not frequent in documents about other topics. For example, 'query processing' is a more pure keyphrase than 'query' in the Databases topic.

We measure the purity of a keyphrase by comparing the probability of seeing a phrase in the topic-t collection of word sets and the probability of seeing it in any other topic-t' collection ($t' = 0, 1, \ldots, k, t' \neq t$). A reference collection $D_{t,t'} = D_t \cup D_{t'}$ is a mix of of topic-t and topic-t' titles. If there exists a topic t' such that the probability of $e_{t,t'}(p)$ = 'seeing a phrase p in a reference collection $D_{t,t'}$ is similar or even larger than the probability of seeing p in D_t , the phrase p indicates confusion about topic t and t'. The purity of a keyphrase compares the probability of seeing it in the topic-t collection and the maximal

probability of seeing it in any reference collection:

$$\pi_t^{pur}(p) = \log \frac{P(e_t(p))}{\max_{t'} P(e_{t,t'}(p))}$$

$$= \log \frac{f_t(p)}{|D_t|} - \log \max_{t'} \frac{f_t(p) + f_{t'}(p)}{|D_{t,t'}|}$$
(2)

3.3.3 Phraseness

A group of words should be grouped into a phrase if they co-occur significantly more frequent than the expected co-occurrence frequency given that each word in the phrase occurs independently. For example, while 'active learning' is a good keyphrase as in the Machine Learning topic 'learning classification' is not, since the latter two words co-occur only because both of them are popular in the topic.

We therefore compare the probability of seeing a phrase $p = \{w_1 \dots w_n\}$ and seeing the n words $w_1 \dots w_n$ independently in topic-t documents:

$$\pi_t^{phr}(p) = \log \frac{P(e_t(p))}{\prod_{w \in p} P(e_t(w))}$$

$$= \log \frac{f_t(p)}{|D_t|} - \sum_{w \in p} \log \frac{f_t(w)}{|D_t|}$$
(3)

3.3.4 Completeness

A phrase p is not complete if a longer phrase p'which contains p usually co-occurs with p. For example, 'vector machines' is not a complete phrase but 'support vector machines' is, because 'support' almost always accompanies 'vector machines'.

We thus measure the completeness of a phrase pby examining the conditional probability of observing p' given p in a topic-t title:

$$\pi_t^{com}(p) = 1 - \max_{p' \supseteq p} P(e_t(p')|e_t(p))$$

$$= 1 - \max_w P(e_t(p \cup \{w\})|e_t(p))$$

$$= 1 - \frac{\max_w f_t(p \cup \{w\})}{f_t(p)}$$

3.3.5 **Combined Ranking Function**

We combine these 4 measures into a comprehensive function for ranking a topical keyphrase:

$$r_t(p) = \begin{cases} 0 & \pi_t^{com} \le \gamma \\ \pi_t^{cov}[(1-\omega)\pi_t^{pur} + \omega \pi_t^{phr}](p) & \text{o.w.} \end{cases}$$
(5)

where $\gamma, \omega \in [0, 1]$ are two parameters.

The completeness criterion is used as a filtering condition to remove incomplete phrases, where γ controls how aggressively we prune. $\gamma = 0$ corresponds to ignoring the criteria and retaining all max*imal* phrases, where no supersets have the same topical support. As γ approaches 1, more phrases will be filtered and only *closed* phrases (where no supersets are sufficiently frequent) will remain. The other three criteria then calculate the ranking score for the keyphrases which pass the completeness filter.

The coverage criterion is in some sense the most important, since a keyphrase with low coverage will be obviously of low quality. In $r_t(p)$, $\pi_t^{cov}(p)$ is a probability $P(e_t(p))$ and multiplies both π_t^{pur} and π_t^{phr} . This is desirable because when $P(e_t(p))$ is small, phrase p will have low support, and thus the estimates of purity and phraseness will be unreliable and play a minor role.

The tradeoff between purity and phraseness is controlled by ω . Both measures are log ratios on comparable scales, and can thus be balanced by a weighted summation. As ω increases we expect more topic-independent but common phrases to be ranked higher.

The ranking function can also be nicely explained in an information theoretic framework. In fact, the product of coverage and purity, $\pi_t^{cov}(p)\pi_t^{pur}(p) = P(e_t(p))\log\frac{P(e_t(p))}{P(e_{t,t^*}(p))}$ is equal to the pointwise KLdivergence between the probability of $e_t(p)$ and $e_{t,t^*}(p)$. Pointwise KL-divergence is a distance measure between two probabilities that takes the absolute probability into consideration, and is more robust than pointwise mutual information when the relative difference between probabilities need to be supported by sufficiently high absolute probability. Likewise, the product of coverage and phraseness, $\pi_t^{cov}(p)\pi_t^{phr}(p)$ is equivalent to pointwise KLdivergence between the probability of $e_t(p)$ under different independence assumptions. Therefore, Eq. (5) can also be interpreted as a weighted summation of two pointwise KL-divergence metrics.

Experiments

We use two collections of content-representative ti $r_t(p) = \begin{cases} 0 & \pi_t^{com} \leq \gamma \\ \pi_t^{cov}[(1-\omega)\pi_t^{pur} + \omega\pi_t^{phr}](p) & \text{o.w.} \end{cases}$ tles in our evaluation. The first - the DBLP dataset - is a set of titles of recently published computer science papers in the areas related to Databases. Data tles in our evaluation. The first - the DBLP dataset -Mining, Information Retrieval, Machine Learning,

kpRelInt*	kpRel	KERT-cov	KERT _{-pur}	KERT _{-phr}	KERT-com	KERT
learning	learning	effective	support vector machines	learning	learning	learning
classification	classification	text	feature selection	classification	support vector machines	support vector machines
selection	learning classification	probabilistic	reinforcement learning	selection	support vector	reinforcement learning
models	selection	identification	conditional random fields	feature	reinforcement learning	feature selection
algorithm	selection learning	mapping	constraint satisfaction	decision	feature selection	conditional random fields
feature	feature	task	decision trees	bayesian	conditional random fields	classification
decision	decision	planning	dimensionality reduction	trees	vector machines	decision trees
bayesian	bayesian	set	constraint satisfaction problems	problem	classification	constraint satisfaction
trees	feature learning	subspace	matrix factorization	reinforcement learning	support machines	dimensionality reduction
problem	trees	online	hidden markov models	constraint	decision trees	matrix factorization

Table 1: Top 10 ranked keyphrases in the Machine Learning topic by different methods.

and Natural Language Processing. These titles come from DBLP¹, a bibliography website for computer science publications. The second collection - the arXiv dataset - is a sample of titles of physics papers published within the last decade, and labeled by their authors as belonging to the subfields of Optics, Fluid Dynamics, Atomic Physics, Instrumentation and Detectors, or Plasma Physics. This collection of titles comes from arXiv², an online archive for electronic preprints of scientific papers.³

Both datasets were minimally pre-processed by removing all stopwords from the titles. After pre-processing, the DBLP dataset contained 33,313 titles consisting of 18,598 unique words, and the arXiv dataset contained 9,722 titles evenly sampled from the specified 5 physics subfields, and consisting of 9,648 unique words.

4.1 DBLP Dataset Experiments

We use the DBLP dataset to evaluate the ability of our method to construct topical keyphrases that appear to be high quality to human judges, via a user study. We will first describe the methods we used for comparison, and then present a sample of the keyphrases actually generated by these methods and encountered by participants in the user study. We then explain the details of our user study, and present quantitative results.

4.1.1 Methods for Comparison

We use background LDA introduced in Section 3.1 for the word clustering step in order to create input for all the methods that we compare. We resort to a Newton-Raphson iteration method (Minka, 2000) to learn the hyperparameters, and empirically set $\lambda=0.1$, which leads to generally coherent results for our dataset.⁴

To evaluate the performance of KERT, we implemented several variations of the function, as well as two baseline functions. The baselines come from Zhao et al (2011), who focus on topical keyphrase extraction in microblogs, but claim that their method can be used for other text collections. We implement their two best performing methods: kpRe-IInt* and kpRel.⁵ We also construct variations of KERT where the keyphrase extraction steps are the same, but each of the four ranking criteria is ignored in turn. We refer to these versions as KERT_cov, KERT_pur, KERT_phr, and KERT_com, respectively.

¹http://www.dblp.org/

²http://arxiv.org

³Both datasets will be online available

⁴The learned $\alpha=1.0$ is smaller than the typical setting due to the nature of our short text, and $\beta=0.07$ is larger because in our dataset, different topics often share the same words.

⁵Their main ranking function kpReIInt considers the heuristics of phrase interestingness and relevance. As their interestingness measure is represented by re-Tweets, a concept that is not appropriate to our dataset, we reimplement the interestingness measure to be the relative frequency of the phrase in the dataset instead, and we therefore refer to our reimplementation as kpReIInt*. kpRel considers only the relevance heuristic.

These variations nicely represent the possible settings for the parameters $\gamma \in [0,1]$ and $\omega \in [0,1],$ which are described in Section 3.3.5. In KERT we set $\gamma = \omega = 0.5$. KERT_com sets $\gamma = 0$ to demonstrate what happens when we retain all *maximal* phrases. As γ approaches 1, more phrases will be filtered but a very small number of *closed* phrases (no supersets are frequent) will not be. KERT_phr sets $\omega = 0$ and KERT_pur sets $\omega = 1$, which demonstrates the tradeoff between ignoring phraseness for the sake of maximizing purity, and ignoring purity to optimize for phraseness, respectively.

4.1.2 Qualitative Results

Table 1 shows the top 10 ranked topical keyphrases generated by each method for the topic of Machine Learning. kpRel and kpRelInt* yield very similar results, both clearly favoring unigrams. However, kpRel also ranks several keyphrases highly which are not very meaningful, such as 'learning classification' and 'selection learning.' Removing coverage from our ranking function yields the worst results, confirming the intuition that a high quality keyphrase must at minimum have good coverage. Without purity, the function favors bigrams and trigrams that all appear to be very meaningful, although several high quality unigrams such as 'learning' and 'classification' no longer appear. Removing phraseness, in contrast, yields meaningful unigrams but very few bigrams, and looks quite similar to the kpRelInt* baseline. Finally, without completeness, phrases such as 'support vector' and 'vector machines' are ranked highly, although they should not be, as both are sub-phrases of the high quality trigram 'support vector machines.'

4.1.3 User Study and Quantitative Results

To quantitatively measure keyphrase quality, we invited people to judge the generated topical keyphrases generated by the different methods. Since the DBLP dataset generates topics in computer science, we recruited 10 computer science graduate students - who could thus be considered to be very knowledgeable judges - for a user study. We generated 5 topics from the DBLP dataset and found 4 of them were clearly interpretable as Machine Learning, Databases, Data Mining, and Information Retrieval. For each of the four topics, we retrieved the top 20 ranked keyphrases by each method. These keyphrases were gathered together per topic and pre-

sented in random order, and users were asked to evaluate the quality of each keyphrase on a 5 point Likert scale.

To measure the performance of each method given the user study results, we adapt the **nKQM@K measure** (normalized keyphrase quality measure for top-K phrases) from (Zhao et al., 2011), which is itself a version of the *nDCG* metric from information retrieval (Järvelin and Kekäläinen, 2002). We define nKQM@K for a method *M* using the top-K generated keyphrases as:

$$nKQM@K = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{j=1}^{K} \frac{score_{aw}(M_{t,j})}{log_2(j+1)}}{IdealScore_K}$$

Here T is the number of topics, and $M_{t,j}$ refers to the j^{th} keyphrase generated by method M for topic t. Unlike in (Zhao et al., 2011), we have more than 2 judges, so we define $score_{aw}$ as the agreement-weighted average score for the $M_{t,j}$ keyphrase, which is a weighted mean of the judges' score by the weighted Cohen's κ . This gives a higher value to a keyphrase with scores of (3,3,3) than to one with scores of (1,3,5), though the average score is identical. Finally, $IdealScore_K$ is calculated using the scores of the top K keyphrases of all judged ones.

Method	nKQM@5	nKQM _{@10}	nKQM@20
KERT_cov	0.2605	0.2701	0.2448
kpRelInt*	0.3521	0.3730	0.3288
KERT_phr	0.3632	0.3616	0.3278
kpRel	0.3892	0.4030	0.3767
KERT_com	0.5124	0.4932	0.4338
KERT	0.5198	0.4962	0.4393
KERT_pur	0.5832	0.5642	0.5144

Table 2: nKQM@K values for different methods (ordered by their performance from low to high)

Table 2 compares the performance across different methods. The top performances are clearly variations of KERT with different parameter settings. As expected KERT_{-cov} exhibits the worst performance. The baselines perform slightly better, and it is interesting to note that kpRel, which is smoothed purity, performs better than kpRelInt*, and even slightly better than KERT_{-phr}. This is because kpRelInt* adds in a measure of *overall* keyphrase coverage in the entire collection, which hurts rather than helps for this task. Removing completeness

appears to have a very small negative effect, and we hypothesize this is because high-ranked incomplete keyphrases are relatively rare, though very obvious when they do occur (e.g. 'vector machines'). KERT_pur performs the best - which may reflect human bias towards longer phrases - with an improvement of at least 50% over the kpRelInt* baseline for all reported values of K.

4.2 arXiv Dataset Experiments

We use the arXiv dataset, which contains labeled titles, to explore which method maximizes the mutual information between phrase-represented topics and titles. As the collection has 5 categories, we set T=5.

For each method, we do multiple runs for various values of K (the number of top-ranked phrases per topic considered), and calculate the mutual information MI_K for that method as a function of K. To calculate MI_K , we label each of the top K phrases in every topic with the topic in which it is ranked highest. We then check each paper title to see if it contains any of these top phrases. If so, we update the number of events "seeing a topic t and category c" for t = 1...T, with the averaged count for all those labeled phrases contained in the title; otherwise we update the number of events "seeing a topic t and category c" for $t = 1 \dots T$ uniformly, where c is the Primary Category label for the paper title in consideration. Finally, we compute the mutual information at K:

$$MI_K = \sum_{t,c} p(t,c) \log_2 \frac{p(t,c)}{p(t)p(c)}$$

We compare the baselines (kpRelInt* and kpRel), KERT, and variations of KERT where only coverage ($KERT_{cov}$), only purity ($KERT_{pur}$), and only coverage and purity ($KERT_{cov+pur}$) are used in the ranking function. We feed them the same input by background LDA with the same parameter settings as discussed above. Figure 1 shows MI_K for each method for a range of K.

It is clear that for MI_K , coverage is more important than purity, since $KERT_{pur}$ is by far the worst performer. Both baselines perform nearly as well as $KERT_{cov}$, and all are comfortably beaten by $KERT_{cov+pur}$ (> 20% improvement for K between 100 and 600), which uses our coverage and purity measure. It is interesting to note that adding in the phraseness and completeness measures yields

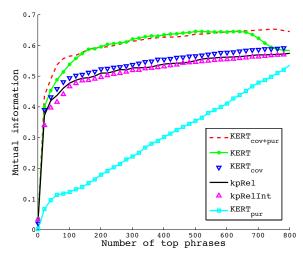


Figure 1: MI_K values for various methods (methods in legend are ordered by performance, high to low)

no improvement in MI_K . However, the experiments with the DBLP dataset demonstrate that these measures are very helpful in the eyes of expert judges. In contrast, while MI_K is definitely improved with the addition of the purity measure, people prefer for it to be removed. Although we outperform other approaches in both evaluations, these observations show interesting differences between theory-based and human-based evaluation metrics.

5 Conclusion

In this work we introduce KERT (Keyphrase Extraction and Ranking by Topic), a framework for the automatic extraction and ranking of topical keyphrases using collections of content-representative document titles. Unlike existing techniques, our phrasecentric approach is able to construct candidate topical keyphrases in such a way as to allow our ranking function to directly compare the quality of keyphrases of different lengths. Our method yields high quality topical keyphrases, with over 50% improvement over a baseline method according to human judgement and over 20% improvement according to mutual information. In the future we would like to further explore why human judgement appears to be consistently biased against the purity criteria, in contrast to quantitative metrics such as mutual information. We are also interested in extending our approach to working with longer texts.

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