Microblogs Structure. Challenges and Opportunities

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In recent years, microblog services such as Twitter have gained increasing popularity, leading to active research on how to effectively exploit its content. Microblog documents such as 'tweets' differ in morphology to more traditional documents such as web pages. Particularly, tweets are considerably shorter (140 characters) than web documents and contain contextual tags regarding the topic (hashtags), intended audience (mentions) as well as links to external content (URLs). Unfortunately, state of the art retrieval models perform rather poorly in capturing the relevance of microblogs, due to the previously unforeseen conditions in which they operate.

In this work, first we focus on investigating the problems that state of the art retrieval models suffer when handling microblogs, then we provide a number of solutions to adapt to the new medium. Initially we simulate the behaviour of such retrieval models under microblog retrieval conditions. Based on our findings we devised a retrieval model, namely **MBRM**, which significantly outperforms the state of the retrieval models in the microblog context.

Furthermore we look at microblog documents as a high-dimensional entity and study the structural differences between those documents which are deemed relevant against those non-relevant. Moreover we leverage these statistical differences in experiments to enhance the behaviour of retrieval models. Additionally we study the interactions between the different dimensions in terms of their order within the documents by modelling relevant and non-relevant tweets as state machines. These state machines are then utilised to produce scores which in turn are used for re-ranking. Our evaluation results show statistically significant improvements over the baseline in terms of precision at different cut-off points for both approaches. These results confirm that the relative presence of the different dimensions within a document and their ordering are connected with the relevance of microblogs.

Categories and Subject Descriptors: C.2.2 [**Computer-Communication Networks**]: Network Protocols

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1. INTRODUCTION

Microblogs have grown in popularity in recent years, gradually transforming the way we find out about the latest events and communicate. Twitter is the most prominent service [1], as it is used by millions, posting over 340 million tweets every day[2]. Microblog services are used for various purposes including: (i) self promotion, (ii) advertising, (iii) real-time news broadcasting, (iv) social discussions etc. The most important aspect of

[1] https://twitter.com/
[2] http://blog.twitter.com/2012/03/twitter-turns-six.html

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Twitter is that it provides unique insight into real-time events, such as first hand reports of events as they are developing, along with the opinion of those discussing them. This information makes Twitter a uniquely valuable media source, which led to obtaining much attention by research and industrial communities.

Retrieving documents in Twitter can be extremely challenging because of their morphology. The content is limited to 140 characters per messages (known as *Tweets*). This constraint leads to varied linguistic quality [Teevan et al. 2011] due to colloquialisms and users efforts to fit their content within the limitations. More importantly tweets pose new challenges for which state of the art retrieval models were not designed for[3].

Whilst few recent works have identified some features as possibly being detrimental in microblog ad-hoc retrieval [Naveed et al. 2011], no study has been carried out to determine the concrete effect of the different features on state of the art retrieval models. Therefore we are set to investigate the connection of the structure of microblog documents with their relevance during an ad-hoc search task. This whole work revolves around the following main question:

What are the reasons behind the underperformance of state of the art retrieval models in the context of microblogs? And what can we do about it?

To this end, firstly we observe the performance of state of the art retrieval models in the context of Twitter corpora selecting the best retrieval model as a baseline. Then we perform a series of experiments which simulate the behaviour of a number of state of the art retrieval models in order to identify possible shortcomings in their design with respect to microblog documents. This initial experiment is completed with the creation of a retrieval model which takes into account all previous findings, namely MBRM. MBRM demonstrates that the scope hypotheses still holds within microblog documents, and that microblog document statistics can be leveraged to significantly improve ad-hoc retrieval performance.

Secondly, we study the behaviour of inherent features of microblog documents and evaluate their suitability for enhancing the behaviour of state of the art retrieval models. Moreover, we demonstrate which microblog specific features are most indicative of the relevance of microblogs by reporting statistically significantly improved retrieval performance for ad-hoc search when taking them into account.

Finally, we extend our analysis by considering the ordering of the different component that make up microblog documents. In order to do so, we encode the structure of observed relevant and non-relevant documents into state machines. These are in turn used to produce scores for re-ranking. We utilise the 2013 microblog collection to construct such state machines, and we test on the 2011 and 2012 microblog collections combined. Our results show statistically significantly improved results over the selected baseline, demonstrating the connection of microblog structure with relevance.

This work will be driven by the following research questions:

RQ1. Are there structural differences between relevant and non-relevant microblog documents? Can we exploit them for ad-hoc retrieval?
RQ1.1 Does document length have any connection with the relevance of microblogs?
RQ1.2 Does term frequency of query terms relate to the relevance of microblogs?
RQ1.3 Can we adapt state of the art retrieval models to better handle microblogs?

[3]Models such as: Okapi BM25 [Robertson and Zaragoza 2009]; Divergence From Randomness (DFR) [Amati et al. 2003]; Hiemstra's Language Model (HLM) [Hiemstra 2001]; and Dirichlet Language Model (DLM) [Zhai and Lafferty 2001]

RQ1.4 Can we devise a retrieval model to better capture the relevance of microblogs?
RQ2. Can microblog features be exploited to help retrieval models better capture relevance than current retrieval models?
RQ3. Is the order of the different elements in a microblog document connected with relevance? Can it be utilised for ad-hoc retrieval?

The rest of the chapter is organised as follows. First, we cover relevant literature regarding microblog searches and introduce the concepts utilised throughout this work (Section 2). Section 3 sets the evaluation environment in which our experimentation is carried out, giving way to our main analysis (Section **??**). Finally Section 6 concludes the work and points future research directions.

2. BACKGROUND

In this Section we will introduce concepts and related literature to this work.

2.1. Retrieval Models

The first part of this work revolves around retrieval models and how their design affects their performance when retrieving microblogs. In our experimentation we include retrieval models such as: Okapi BM25 [Robertson and Zaragoza 2009]; Divergence From Randomness (DFR) [Amati et al. 2003]; Hiemstra's Language Model (HLM) [Hiemstra 2001]; and Dirichlet Language Model (DLM) [Zhai and Lafferty 2001]. These models are introduced in more details in Section 4, and their behaviour described individually against microblog conditions. However we first introduce some basic background to ease the understanding of the following sections.

2.1.1. Probability of Relevance Framework. For many years researchers have developed their understanding on estimating the relevance of documents, thus leading to many models and definitions of relevance. One of the most representative works in this area of research is the Probability of Relevance Framework (PRF) [Roelleke 2013]. PRF is formulated by $P(r|\hat{d}, q)$, where r refers to relevance, q a given query and $\hat{d}$ represents a document as a vector of features $\hat{d} = (f_1, ...f_n)$. Note that vector features can be any imaginable data. The main importance of this framework is the formalisation of relevance as a function of a given query and document vectors. This can be utilised as a framework for any probabilistic retrieval model, thus becoming the basis of numerous research works.

2.1.2. Document length normalization. [Singhal et al. 1996] has been employed by retrieval models to counterbalance the effects of longer documents, which may not necessarily add any new information to a topic, but are prone to contain higher term frequencies. In line with this effort, the design of BM25 by [Robertson and Zaragoza 2009] involved the study of document characteristics, resulting in the definition of the **scope** and **verbosity** hypotheses. The **verbosity** hypotheses supports that some authors are more verbose than others, thus applying length normalization by dividing by the length of the document is beneficial to better capture relevance, as repetition of terms is superfluous. On the other hand, the **scope** hypotheses states that some authors simply have more to say, thus adding more relevant information to the topic and occupying more space. BM25 applies a soft normalisation that takes into account both cases.

2.2. Retrieval of Microblogs is Hard

Retrieval models are designed to rely on term frequency and document length as the variables to quantify whether a document is more important than other. From a very

Table I: TREC Tracks results in terms of precision@30

2011		2012		2013		2014	
Best	Median	Best	Median	Best	Median	Best	Median
0.502	0.298	0.470	0.362	0.560	0.370	0.722	0.629

simplified perspective, a retrieval model will give more importance to a document that contains query terms more frequently than another document (Assuming similar document lengths). Likewise, when query terms appear the same number of times, a document will be deemed less or more informative based on the document lengths.

However, as stated before, microblog documents are limited in length to 140 characters in the case of Twitter. This limitation obviously challenges the abovementioned assumptions, which unfortunately form the basis of the workings of most retrieval models in a way or another.

The new medium and the low retrieval performance achieved by state of the art retrieval models gave way to an extensive area of research spearheaded by the Text Retrieval Conference (TREC) through its microblog track. Over recent years, numerous approaches have been proposed which significantly improve retrieval performance in diverse ways.

2.3. TREC Microblog Retrieval Tracks

TREC organised a number of tracks over four consecutive years 2011-2014 in order to organise the research community and jointly address this retrieval problem. In order to evaluate the performance of the prospective solutions and allow for comparability they agreed on a collection of documents and a set of topics, as well as relevance judgements on those topics provided by NIST obtained through pooling.

To this end they sampled two collections of documents from a Twitter stream over two different periods of time. The first collection was gathered in 2011 but was used for during both the 2011 and 2012 microblog tracks. Similarly, the second collection was gathered in 2013 and was used for both the 2013 and 2014 microblog tracks. Finally the number of topics varied between 50 and 60, but are 225 in total.

The summary results for each of the tracks are presented in Table I for reference. Amongst the top performing participants we can find [Amati et al. 2011; Li et al. 2011; Metzler and Cai 2011] for microblog 2011 and [Kim et al. 2012; Aboulnaga et al. 2012; Han et al. 2012] for 2012, which mostly employed query and document expansion techniques as well as learning to rank (L2R) approaches. Additionally, the 2013 track followed a similar trend producing works in the same categories L2R [Siming Zhu 2013; Gao et al. 2013], query expansion [Pre-Processing 2013; Perez et al. 2013] and document expansion [Jabeur et al. 2013].

Moreover, the work by [Damak et al. 2013] produced a comprehensive summary of the features used by different approaches, and demonstrated how to successfully combine them using naive bayes as an L2R approach combining a number of features including hashtags, mentions, url presence, recency, etc.

Work by [Thomas 2012] studied the effects that preprocessing had on retrieval performance. Their findings showed that the best performance was achieved when applying all preprocessing steps, which include (i) language detection, (ii) Emotion removal, (iii) Lexical normalization, (iv) Mention Removal and (v) Link Removal. Additionally, works by [Ferguson et al. 2012; Naveed et al. 2011] have identified that problems affecting retrieval models in microblogs are related to *term frequency* and *document length normalization*.

2.4. Making Sense Of Microposts

The MSM workshop [Basave et al. 2013] presented participants with a challenge. The objective was to build systems able to identify and extract concepts from microblog documents, in a semi-supervised manner. The participant systems were to categorise concepts as belonging to the categories: person, organisation, location and miscellaneous. A similar task is that of microblog summarisation [Sharifi et al. 2010] in that tweets have to be processed and made sense of in order to produce a richer representation.

Amongst the works submitted to this workshop, we can highlight the work by Tao, Ke et al. [Tao et al. 2012]. In their work they perform an in depth analysis of both topic dependent and independent features for the MSM task. Some of the topic independent features consider the presence of hashtags, urls and the length of the documents to be in connection with the relevance of documents. In our work, we pay attention to the same features, but from a different angle, by looking how much space relative to the total characters in the document is dedicated to each of the microblogs elements.

2.5. Other Microblog retrieval features

Work by [Massoudi et al. 2011] explored the use of other features to improve ad-hoc retrieval. These features include emoticons, hyperlinks, shouting, capitalization, retweets and followers. Work by [Nagmoti et al. 2010] extended the study concerning the use of social features such as the number of followers and followees to enhance ad-hoc retrieval performance. While all these works attempt to exploit some microblog features or augment them with external resources, they do not try to explain how these features relate to the relevance of microblog documents. In our work, we consider features based purely on microblog characteristics, explain their relationship with relevance, and finally use those features that seem beneficial to improve the behaviour of a state of the art retrieval model.

2.6. Understanding Microblogs

We believe that no significant progress has been made to understand *why are retrieval models failing* in microblogs. Due to their limited size, document length and term frequencies are often loosely blamed with the underperformance of retrieval models. We believe it is important to explore, and properly assess the interaction of such features. Better understanding could lead to better performance of retrieval models, or new models altogether, which are the starting point for many techniques commonly used in microblog retrieval (E.g. Automatic Query Expansion).

3. EXPERIMENTAL SETTING

Datasets. In this evaluation we have used the four collections from the TREC Microblog track. The 2011 and 2012 collections share the same corpus but have different topics and relevance assessments. On the other hand the 2013 and 2014 collections share the same corpus. The later corpus is an order of magnitude bigger than previous collections. However, the 2013 and 2014 relevance assessments are statiscally comparable to the 2012 track. Moreover, the ratio of documents $\frac{relevant}{non-relevant}$ is much higher for the 2013, which can result in generally better retrieval performance than previous tracks by default. The 2014 on the other hand is closer in this ratio to the 2012 collection. In fact it has a considerably lower number of relevant documents per topic.

In total there are 225 topics with query lengths ranging from 2 to 3 tokens, in line with the literature [Teevan et al. 2011]. Refer to Table II for an extended overview of these collections.

Table II: Descriptive statistics for the collections being used in this study

TREC Microblog track collection year	2011	2012	2013	2014
Number of topics	50	60	60	55
# documents	16M		260M	
# assessed documents	40855	73073	71279	57985
# assessed non-relevant documents	38124	66893	62268	47340
# assessed relevant documents	2731	6180	9011	4753
Ratio $\frac{Relevant\ Docs}{Non-Relevant\ Docs}$	0.07	0.09	0.14	0.10
Avg. relevant documents per topic	58.45	106.54	150.18	79.22

Table III: Evaluation results for the state of the art models considered. (Bold denotes the best performing system)

(a) 2011 collection

	Precision				
	@5	***@10***	***@15***	***@20***	***@30***
BM25	0.54	0.48	0.45	0.41	0.38
DFRee	0.61	**0.58**	**0.54**	**0.50**	0.45
DLM	0.50	0.47	0.45	0.42	0.37
HLM	0.54	0.48	0.45	0.42	0.38
IDF	**0.63**	0.56	0.52	0.49	**0.46**

(b) 2012 Collection

	Precision				
	@5	***@10***	***@15***	***@20***	***@30***
BM25	0.40	0.37	0.34	0.34	0.31
DFRee	**0.46**	**0.45**	**0.42**	**0.39**	**0.36**
DLM	0.34	0.33	0.32	0.29	0.27
HLM	0.38	0.37	0.35	0.33	0.31
IDF	0.44	0.39	0.36	0.36	0.34

(c) 2013 collection

	Precision				
	@5	***@10***	***@15***	***@20***	***@30***
BM25	0.58	0.51	0.46	0.42	0.38
DFRee	**0.67**	0.60	0.55	0.51	**0.45**
DLM	0.27	0.28	0.26	0.26	0.24
HLM	0.44	0.38	0.35	0.33	0.31
IDF	0.66	**0.62**	**0.56**	**0.52**	**0.45**

(d) 2014 collection

	Precision				
	@5	***@10***	***@15***	***@20***	***@30***
BM25	0.69	0.62	0.58	0.57	0.52
DFRee	0.73	0.68	0.65	0.63	0.60
DLM	0.35	0.35	0.34	0.34	0.33
HLM	0.55	0.49	0.46	0.44	0.41
IDF	**0.75**	**0.73**	**0.69**	**0.67**	**0.62**

(e) All collections

	Precision				
	@5	***@10***	***@15***	***@20***	***@30***
BM25	0.55	0.49	0.46	0.43	0.39
DFRee	**0.62**	**0.57**	**0.54**	**0.51**	**0.46**
DLM	0.36	0.35	0.34	0.32	0.30
HLM	0.47	0.43	0.40	0.38	0.35
IDF	**0.62**	**0.57**	0.53	**0.51**	**0.46**

Evaluation measures. We pay attention to precision at different ranks, with a maximum cut-off point at rank 100. Future evidence is accepted only at the collection statistics level as agreed by TREC organisers disregarding any documents after the query issuing time when computing evaluation measures [4].

Baseline selection. Table III contains evaluation results for the considered state of the art retrieval models when applied to Twitter corpora from the 2011, 2012 and 2013 Trec microblog collections. The models considered in this evaluation are TF-IDF (IDF)[5], BM25, DFRee, Hiemstra's LM (HLM) and Dirichlet's LM (DLM) since it was the baseline for the Microblog Tracks in 2013 and 2014. Moreover, we adhere to the implementation and default settings found within the Terrier IR platform [Ounis et al. 2005]. Finally, since DFRee and IDF are generally the best performing models we will use them as our baselines.

4. INVESTIGATING RETRIEVAL MODEL PROBLEMS

The literature has identified **document length normalization** as the main culprit for the under-performance of retrieval efforts in microblogs. The work by [Naveed et al. 2011] suggests that the **Verbosity** and **Scope** hypotheses do not hold for microblog retrieval.

The **verbosity** hypothesis supports that some authors are more verbose than others, thus applying length normalization by dividing by the length of the document is beneficial to better capture relevance, as repetition of terms is superfluous. On the other hand, the **scope** hypotheses states that some authors simply have more to say, thus naturally adding more relevant information to the topic. As a result documents are longer but more extensive and rigorous in their content than shorter ones. The added value should be accounted for and thus the documents should promoted over shorter ones should not be normalised w.r.t their length.

In the context of Microblog retrieval, [Naveed et al. 2011] carried out a number of experiments using a logistic regression model over a number of tweet features as the retrieval methodology. They showed significant improvements in performance when their algorithm did not perform document length normalization over its normalised counterpart. However, since in their work their ranking approach takes into consideration multiple other features, it is not clear if their finding about document length normalization is generalisable.

Furthermore, although it is been often assumed, it is not known if length normalisation is bad altogether for microblog retrieval, or maybe is just how it is interpreted in this particular case what makes it harmful.

Intuition tell us that document length normalization as we know it does not interact well with the limitations characterised by microblogs. The **Verbosity** and **Scope** hypotheses seem not to model the behaviour of users publishing microblogs. Microblog users generally have the challenge of fitting their messages within the strict character limit. Consequently, retrieval models designed under scope and verbosity or similar premises, such as BM25 [Robertson and Zaragoza 2009] are likely to exhibit unexpected behaviour.

To aid in developing our understanding of the behaviour of retrieval models we formalise their composition. To this end we have compiled Table IV to show the different components involved in the score computation of a variety of state of the art retrieval models. The top row of the table indicates whether the component relies on collection

[4]https://github.com/lintool/twitter-tools/wiki/TREC-2013-Track-Guidelines

[5]$Where\ TF = 1$. Results worsen considerably if we do not set TF to a constant.

statistics (I.e. Collection feature) or the document itself (Document feature). The second row contains acronyms for each of the features, which are expanded as:

- **AverageDocumentLength (ADL):** This is the average document length, in number of tokens, for the whole collection.
- **DocumentLength (DL):** This is the document length, in number of tokens, for the document being scored.
- **NumberOfDocuments (ND):** Total number of documents in the collection.
- **DocumentFrequency (DF):** Number of documents in which the term appears (I.e. A term's posting list size).
- **NumberOfTokens (NT):** Number of different tokens in the collection.
- **CollectionTermFrequency (CTF):** Frequency of a term in the whole collection. (I.e. Total number of occurences of a term in the collection)
- **TermFrequency (TF):** Frequency of the term in the document being evaluated.

Table IV: Features involved in the computation of retrieval models.

	Collection Features					Document Features	
	ND	***DF***	***ADL***	***NT***	***CTF***	***TF***	***DL***
IDF	*	*					
DFRee				*	*	*	*
BM25	*	*	*			*	*
HLM				*	*	*	*
DLM				*	*	*	*

Each of the remaining rows contain the name of the retrieval model as well as whether a component involved in its computation (Denoted by *). For example, DFRee uses NumberOfTokens (NT), CollectionTermFrequency (CTF), TermFrequency (TF) and Document Length (DL).

4.1. The BM25 Case

The work by [Ferguson et al. 2012] examined the performance of BM25 when used under a microblog retrieval scenario. Their findings showed how the closer to zero the free parameters were set in BM25, the better the performance achieved. However, they did not connect this finding to the design of BM25 and what these settings meant in terms of the affected components. In this section we exemplify and connect these findings to the theory by simulating the behaviour of BM25 under microblog retrieval conditions.

First, we observe in Table IV how BM25 relies on document length by using both ADL and DL components in its computation. Furthermore, BM25 has two free parameters, namely b and k_1, which control the effects of the "saturation function" over the final score. The saturation function in BM25 encodes the document length evidence as part of the score as follows:

The first version of the saturation function is given by:

$$\text{Version 1: } \frac{f(q_i, D)}{f(q_i, D) + k_1} \text{ for some k\_1} > 0 \tag{1}$$

Once we take into consideration the Verbosity and Scope hypotheses, we derive the following saturation function:

$$\text{Version 2: } \frac{f(q_i, D)}{f(q_i, D) + k_1 * ((1-b) + b * dl/avdl)} \text{ for some k\_1} > 0 \tag{2}$$

The main difference between these equations is that **Version 2** reduces the effect of term frequency with respect to the document length and its collection average, whilst **Version 1** only relies on the k_1 free parameter. Secondly, the free parameter b ponders between the Verbosity and Scope hypotheses. Setting b to 0 effectively disables the Verbose hypothesis, giving full weight to Scope, in other words, the longer the document the better. Thus when b is set to 0, *Version 2* of the saturation function becomes *Version 1*.

As we introduced before, the study carried by [Ferguson et al. 2012] explored the best parameters for b and k_1 concluding that best performance is achieved as both parameters tend to 0. However, the authors did not mention is that by setting those parameters close to 0, we are disregarding the document length normalisation component altogether. Thus for all intents and purposes BM25 becomes IDF. This can be proved mathematically by substituting b and k_1 by 0 as follows 3.

$$\begin{aligned}
\text{BM25}(D,Q) &= \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f(q_i, D) \cdot (k_1 + 1)}{f(q_i, D) + k_1 \cdot (1 - b + b \cdot \frac{|D|}{\text{avgdl}})} \\
&= \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f(q_i, D) \cdot (0 + 1)}{f(q_i, D) + 0 \cdot (1 - 0 + 0 \cdot \frac{|D|}{\text{avgdl}})} \\
&= \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f(q_i, D)}{f(q_i, D)} \\
&= \sum_{i=1}^{n} \text{IDF}(q_i)
\end{aligned} \tag{3}$$

Initially it would seem that the **Scope** and **Verbosity** hypotheses do not hold for microblogs. The reasoning behind being that these hypotheses were developed for documents that were unbounded in terms of their length such as web pages or books. However, since document length has an upper bound in microblogs, authors express their ideas in a very constrained space where verbosity and scope hypotheses do not seem to hold. However we will later observe that this conclusion is partially true[6].

Furthermore, terms in microblog documents have very low document frequencies. In fact, more often than not, query terms appear at most once in each document unless dealing with spam. Thus a query term appearing more than once within a document can have a dramatic effect over the score produced by BM25. In other words, the very low document frequencies result in unreliable estimations of the informativeness of a query term. Consequently, in this particular case, it is better to rely on features outside the document such as collection features.

Finally, Figure 1 shows the possible BM25 scores for a range of Term Frequency (TF) and Doc. Length (DL) values.[7]. We can extract two interesting behaviours which we can compare later to other retrieval models. Firstly the increase of document length is regarded as negative. In other words the more information in number of terms is encoded in the document the less relevant it is regarded. Secondly the increasing term frequency results in increased scores. This would seem counter-intuitive in a document

[6]We later demonstrate that **scope** does hold, but not **verbosity**
[7]Where $ND = 100k$ and $DF = 100$

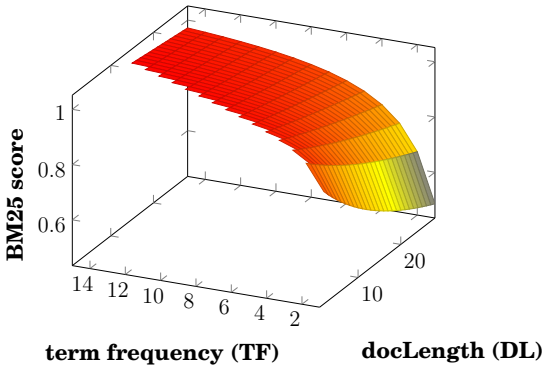


Fig. 1: Term Frequency (TF) vs, Doc. Length (DL)

with such a limited length, as users normally struggle to fit their messages. Additionally, there is a danger of promoting spam messages which may only contain the query terms.

4.2. The Hiemstra's Language Model (HLM) Case

Table IV shows that HLM utilises both CollectionTermFrequency (CTF) and TermFrequency (TF) together with the total number of different tokens in the collection (NT) and document length (DL). Furthermore, if we pay attention to Table III we can observe that whilst DFR and HLM utilize the same components, HLM exhibits a more erratic performance under microblog conditions. HLM's performance for the 2013 collection is considerably lower than that of DFR or IDF, whereas it remains close to the top performing models for the 2011, 2012 and 2014 collections. HLM is formulated as follows:

$$\text{HLM}(D,Q) = \sum_{i=1}^{n} \log_2 \left[1 + \frac{c \cdot f(q_i, D) \cdot ntoks}{(1-c) \cdot f(q_i, C) \cdot |D|} \right] \tag{4}$$

where $ntoks$ refers to the number of unique tokens in the collection (NT), c is a free parameter, and C represents the set of all documents in the collection. $f(q_i, D)$ represents the TF of a query term q_i in document D, whereas $f(q_i, C)$ is CTF of term q_i. The free parameter c regulates how HLM satisfies the conditions of **coordination level ranking (CLR)**) [Hiemstra and De Vries 2000]. CLR is a rule enforced in the design of HLM which ensures that documents containing n query terms are ranked higher than those with $n-1$ terms.

Similarly to BM25, the assumption where higher term frequencies should be regarded positively, can easily result in the promotion of spam and undesired results. And this is rooted in the fact that query terms occur normally 1-2 times in a microblog document, due to length limitations.

Figure 2a shows a plot of the possible scores produced by HLM in its default configuration ($c = 0.15$)[8]. We can observe that for documents where the length is lower than 5 the differences between the scores are very marked. Above length 5 the progression of scores is much more subtle. In other words, shorter documents are subject to high differences between their scores due to small changes in their limited length.

[8]Where $ND = 100k$, $DF = 100$ and $NT = 1000$

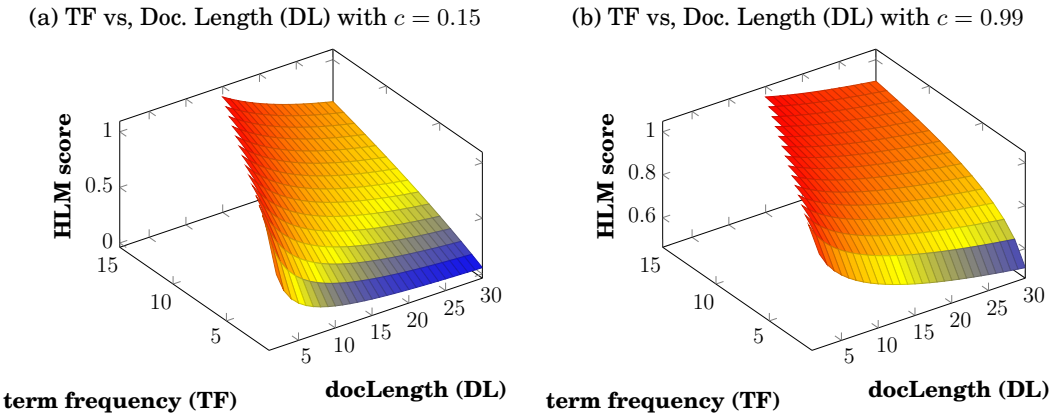


Fig. 2: HLM analysis

Furthermore, we can observe in Formula 4, how the high sensitivity to low document length is a result of the model's design, since document length acts as a multiplier in the denominator. Additionally, term frequency can be found within the nominator as a multiplying component. Consequently, when higher than 1 it will result in an unreasonable boost of the score. In the case of microblog documents this can be problematic due to the scarce frequencies which average around 1.17 (± 0.48)[9].

Table III shows that HLM is the second worst model overall for microblog retrieval. We hypothesise that the reason for this under-performance lies in the substantial scoring differences above-mentioned, resulting from the specific morphology of microblog documents which HLM does not account for. Thus reducing de differences in the scoring, should yield improved retrieval performance.

4.2.1. Offsetting experiment. In order to test this hypotheses we simulate the behaviour of longer documents with higher term frequency by offsetting the values of TF and DL. We do this by a simple addition $TF = TF + dTF$, in this case dTF being the pondering value to offset TF. Likewise, we utilise $DL = DL + dDL$ where dDL is the variable to offset DL.

Table V shows the performance of HLM measured by Precision@30 with different configurations. The first row shows the performance of HLM with a default configuration of $c = 0.15$.

The second row with $dTF = 20$ so that $TF = TF + 20$ which denotes the offsetting of TF by +20. As stated before, the reason behind this offsetting is to reduce the differences between possible scores with respect to the actual values of TF. As we can observe only offsetting TF does no result in any significant improvement. Similarly, the third row shows the performance of HLM when offsetting DL by +20 in order to reduce the possible score differences. Consequently the results are much better than before with a Precision@30 increase of +11.76%. Finally, we experiment with the offsetting of TF and DL together to achieve yet another +15.79% Precision@30 increase over the previous combination and a very substantial increase of +29.41% over the baseline (no offsets) configuration).

It is interesting to notice how only the increase of TF does not help in retrieval, however only increasing DL does produce better results. Yet more importantly, by in-

[9]Computed for query terms in all TREC microblog topics up to 2014 and our baseline DFR

Table V: P@30 scores for HLM as we consider different combinations of dTF and dDL, and c (All collections together)

c	***dTF***	***dDL***	***P@30***
0.15			0.3475
0.15	20		0.3486
0.15		20	**0.3839**
0.15	20	20	**0.4462**
0.05			**0.2824**
0.40			**0.4009**
0.70			**0.4281**
0.99			**0.4492**
0.99	20	20	**0.4532**

crementing both TF and DL we obtain the best performance over all previous configurations. These results hint to a very subtle relationship between DL and TF values of microblog documents.

Rows 5 to 8 in Table V show the performance of HLM with different values of c. As c is increased performance increases as well, reaching comparable performance to the approach which offsets DL and TF.

Finally, we compare Figures 2a and 2b which show scores produced by HLM w.r.t. TF and DL with different values of c. Figure 2a sets $c = 0.15$ whereas Figure 2b sets $c = 0.99$. It is easily observed how Figure 2a shows more differences across the spectrum of scores with respect to TF and DL than Figure 2b. We can also observe how offsetting DL and TF forces the possible values of HLM to lie in the more stable area of the Figures. Furthermore, Figure 2b produces the most stable scores.

From these experiments we can conclude that retrieval models require a conservative and delicate relationship with DL and TF, taking especial care to reduce the differences across the spectrum of possible scores, in order to reduce any unfair weighting differences due to scarcity in DL and TF.

4.3. The DLM Case

Dirichlet Smoothed language model (DLM), was the baseline retrieval model for the 2013 and 2014 instances of the microblog track. DLM was used within the "Microblog track as a service" client which managed a Lucene index in its core. DLM has a smoothing parameter named μ, which was set to 2500 by default during the 2013 and 2014 microblog tracks. Moreover, DLM scores are produced [10] by the following equation:

$$\text{DLM}(D,Q) = \sum_{i=1}^{n} \log_2 \left[1 + \frac{f(q_i, D)}{\mu \cdot \frac{f(q_i, C)}{ntoks}} \right] + \log_2 \left[\frac{\mu}{|D| + \mu} \right] \tag{5}$$

where $ntoks$ refers to the number of unique tokens in the collection (NT), μ is a free parameter, and C represents the set of all documents in the collection. $f(q_i, D)$ represents the TF of a query term q_i in document D, whereas $f(q_i, C)$ is the collection document frequency (CTF) of term q_i.

Figures 3a and 3b show DLM scores in terms of the μ parameter, w.r.t. document frequency and document length respectively. Figure 3c on the other hand demonstrates the relation between document frequency and document length.

[10] As implemented in the Terrier IR platform

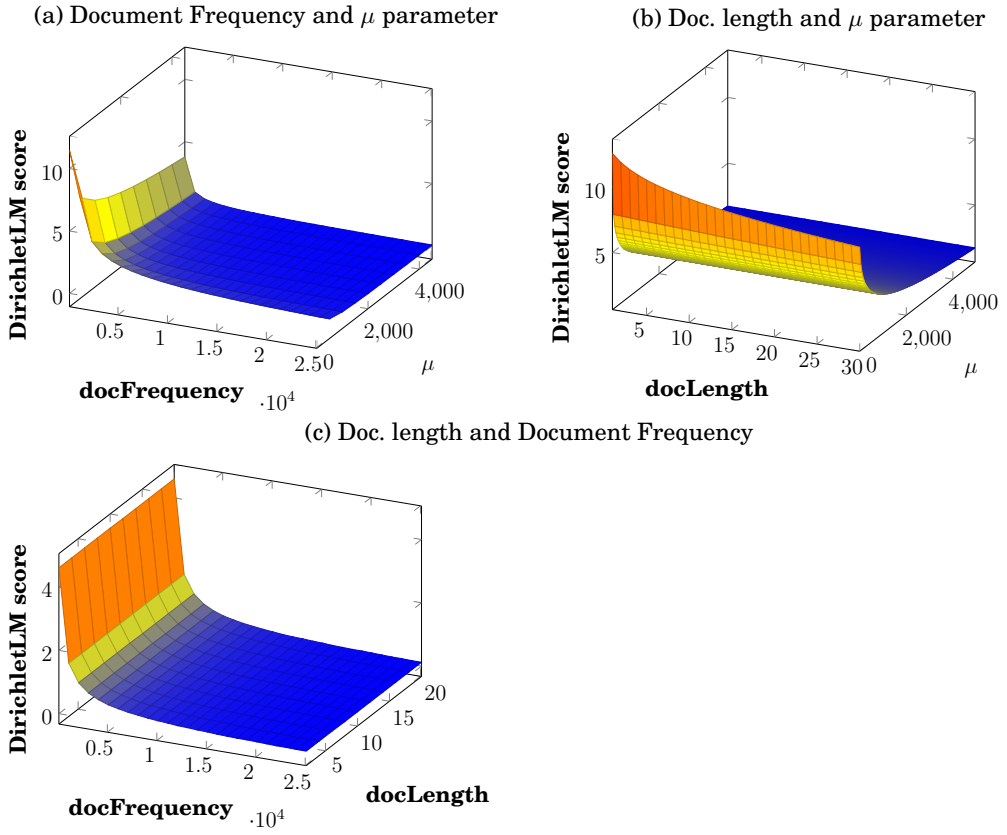


Fig. 3: DLM evaluation figures

As we can observe from Equation 4.3 the parameter μ is closely related to the collection statistics, and the length normalization component of the equation. Moreover the lower the values of μ the higher the score differences for similar document frequencies as shown in Figure 3a. Similarly, we can observe in Figure 3b how μ interacts with document length. For low values of μ we can observe how the scores are reduced at the same time that documents become larger, as expected for normal documents. Interestingly, this behaviour is dampened with higher values of μ, as score differences are heavily reduced w.r.t. the different document lengths. Since the default value for μ is 2500, it is no surprise that document length has virtually no effect over the scores for DLM as seen in Figure 3c, contrary to other retrieval models.

This could be a desired feature for microblog retrieval, however let us look at the performance achieved for a range of μ values in Table VI. As we can observe generally the higher the value of mu the worse the performance obtained, with the exception of μ within the 1 to 20 range.

In order to further understand the behaviour of DLM in the case of Microblog retrieval, we perform an analogous experiment to the previously performed for HLM. Since DLM was also designed for longer documents than microblogs, offsetting the statistics of TF and DL can be interesting experiment as it would better resemble its standard behaviour in term of the numerical values produced as scores.

Table VI: P@30 scores for DLM for a range of μ values (All collections together)

μ	***P@30***
1	0.4028
5	0.4164
20	0.4241
50	0.4099
100	0.3933
500	0.3396
1000	0.3227
2500	0.2988

Table VII: P@30 scores for DLM as we consider different combinations of dTF and dDL, and μ, (All collections together)

μ	***dTF***	***dDL***	***P@30***
20			0.4241
20	20		0.4558
20		20	0.3901
20	20	20	0.4547
2500			0.2988
2500	20		0.4468
2500		20	0.2892
2500	20	20	0.4466

The results of the evaluation are presented in Table VII. The first four lines contain the P@30 values for different combinations where μ is set to 20. As we can observe offsetting TF by +20 results in a substantial +7.47% increase of P@30 with respect to the default configuration. On the other hand offsetting DL by +20 results in a 8.02% decrease of performance in terms of P@30. Finally, combining the offsetting of both TF and DL results in comparable performance than that obtained by only increasing TF.

The same behaviour is obtained across all combinations when we set the $\mu = 2500$. To further develop our understanding of the behaviour, and to draw conclusions for such results, we devised Figures 4a and 4b. Figures 4a and 4b present the DLM scores produced with respect to Doc. Length (DL) and Term Frequency (TF) when $\mu = 2500$ and $\mu = 20$ respectively.

Let us analyse the results from Table VII in connection with Figures 4a and 4b. As we can observe incrementing DL will result in an increased differentiation of DLM scores with respect to TF as more values are closer to the minimum and maximum values. In other words there are less intermediate values (Light coloured areas), which ultimately reflects on heightened sensitivity to differences across the TF spectrum. Furthermore, we can also observe in Table VII how incrementing DL values, results in worse performance in all cases. Consequently the increased differentiation of DLM scores with respect to the TF parameter, produced by the increment of DL is detrimental and in line with the findings in the previous section.

Additionally, Figure 4a shows an almost linear progression of DLM scores with respect to TF, whereas Figure 4b ($\mu = 20$) exhibits a logarithmic behaviour with respect to TF. The latter behaviour is more desirable because there should be a saturation point when incrementing TF at which there is very little value added to the score of the document, or could be even counter productive. In fact, if we take into considera-

(a) Doc. length (DL) and Term Frequency (TF) when $\mu = 2500$

(b) Doc. length (DL) and Term Frequency (TF) when $\mu = 20$

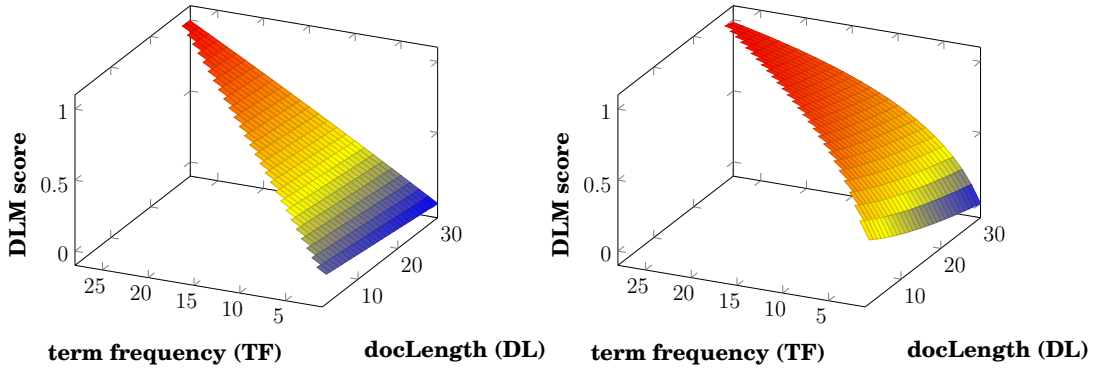


Fig. 4: Evaluating DLM's behaviour

tion that term frequencies within microblogs are in the range 1-2, the pivoting value w.r.t TF should be very low, to avoid promoting spam microblogs.

The better behaviour with respect to TF is rewarded with increased performance whether the value of μ is 20 or 2500. In fact the offsetting of TF seems to overrule the effects of μ as similar results are obtained in both $\mu = 20$ and $\mu = 2500$ conditions. The effects of offsetting TF are most visually evident when looking at Figure 4b as differences amongst the different scores become very small, when $TF > 20$.

Extending on the findings by [Naveed et al. 2011] who showed how length normalization was detrimental to microblog retrieval in an L2R retrieval framework. Our experiments have so far indicated the existence of a particular relationship between TF and DL that is most appropriate for Microblog retrieval. We believe that the score progressions with respect to *DL should modelled by a very gentle slope*, whereas there should be a pivoting point with respect to *TF where scores should decay* in order to account for spam. In the following sections these ideas will be further elaborated.

4.4. The DFRee Case

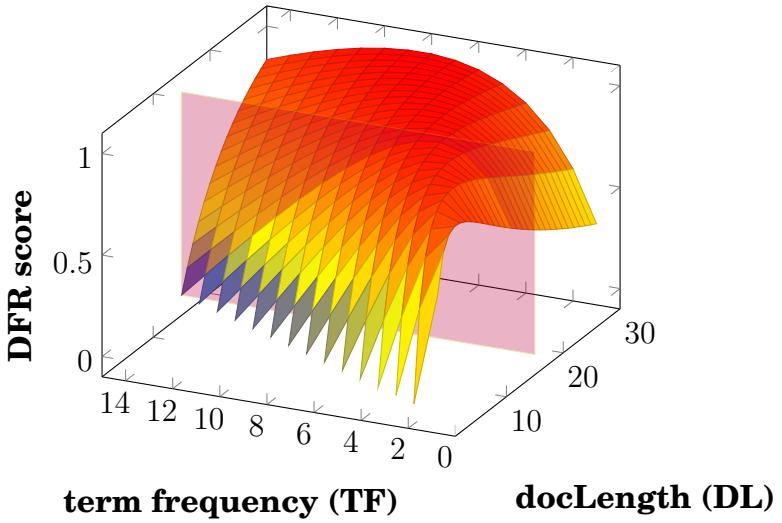
DFRee[11] is a Divergence From Randomness model implemented in the Terrier IR platform [Ounis et al. 2006]. DFRee has been designed as a parameter-free model and adheres to the following implementation:

$$prior = \frac{f(q_i, D)}{|D|}, posterior = \frac{f(q_i, D) + 1}{|D| + 1} \tag{6}$$

$$InvPriorColl = \frac{ntoks}{f(q_i, C)}, norm = f(q_i, D) * log_2 \frac{posterior}{prior} \tag{7}$$

[11] http://terrier.org/docs/v2.2.1/javadoc/uk/ac/gla/terrier/matching/models/DFRee.html

Fig. 5: Evaluating DFR's behaviour: Doc. length (DL) and Term Frequency (TF)



$$DFRee(q_i, D, C) = norm * [\\ f(q_i, D) * (-log_2(prior * InvPriorColl)) \\ + (f(q_i, D) + 1) * log_2(posterior * InvPriorColl) \\ + 0.5 * log_2(posterior/prior)], \quad (8)$$

where $f(q_i, D)$ represents the frequency of query term q_i within document D. Similarly $f(q_i, C)$ holds the collection C frequency for query term q_i. Furthermore $ntoks$ is the total number of unique terms within collection C and $|D|$ represents the document length of document D.

Similarly to the evaluations carried out in previous sections, we simulated the scores produced by DFRee given a range of TF and DL values. The objective is studying its behaviour in microbloging conditions, and draw conclusions about its performance. These simulated values are shown in Figure 5.

As we traverse the Document Length axis we can observe an interesting behaviour which is not present in any model observed so far.

For low values of TF, incrementing DL from 1 to ~ 16 results in also a higher score. This behaviour aligns with the scope hypotheses as longer documents are regarded as more informative. However, when DL reaches high enough values the scores start to decline. The latter behaviour is in line with the verbose hypotheses which assumes the extra length is due to superfluous information. Particularly when the extended document length is not accompanied by higher query term frequencies.

When dealing with documents as short as microblogs it is very difficult assert their informativeness or relevance in terms of the verbose or scope hypotheses. In fact all retrieval models observed so far follow these to some degree and perform worse than a simply using IDF as a retrieval model. Additionally, the premises in which they are built seem not to hold as they fail to perform better than simple IDF. However DFRee is an interesting exception as it performs better than all the studied retrieval models, and it performs better than IDF in some cases (Table III).

Table VIII: Behaviour when harmonising score differences.(All collections together.)

Model	***configuration***	***stdev***	***P@30***
DLM	$c = 2500$	0.2639	0.2988
DLM	$c = 50$	0.2479	0.4099
DLM	$c = 20$	0.2384	0.4241
HLM	$c = 0.15$	0.2553	0.3475
HLM	$c = 0.40$	0.2365	0.4009
HLM	$c = 0.99$	0.1135	0.4492
BM25	$b = 0.75, k = 1.2$	0.1274	0.3948
BM25	$b = 0.75, k = 0.7$	0.0927	0.4399
BM25	$b = 0.9, k = 0.1$	0.0181	0.4580
PEARSON	-0.70		
KTau	-0.66		

We believe that the *saturation point* observed in Figure 5 in terms of TF and DL is responsible for DFRee outperforming other retrieval models in this task (And sometimes IDF). The score produced by DFRee can only be higher if both TF and DL increase. Thus, incrementing the value of a single component will increase the score to a saturation point after which the score will then decrease. As an example, consider an average microblog document of length 15 (blue plane in Figure 5). The score is maximised when TF approaches 3, after which higher TF values result in a significant reduction to the score.

This behaviour opposed to that of BM25, HLM and DLM which exhibit a positive correlation between TF and the score produced. Note that in this case a document made up of repeating query terms would be valued over others with richer, and more informative content. This behaviour is obviously problematic as it promotes spam-like documents. Fortunately DFRee has a pivoting point which attempts to alleviate this possibility, thus reducing the value of increasing TF in short documents.

Recall that users of microblog services such as Twitter, strive to fit their messages within the character limit. It stands to reason, that the more terms they fit within the character limit the higher the chances of it being informative. The pivoted behaviour of DFRee does not completely match this premise, however it does match it better than all other observed retrieval models (Including BM25, HLM and DLM) where longer documents are simply less relevant under microblog conditions.

Summarising, we believe that DFRee's behaviour is key to better understand why most retrieval models fail to capture the relevance of microblogs. Particularly important is the *saturation point* behaviour as a function of TF and DL. We can observe that promoting documents that are longer, whilst penalising documents with higher TF values than 2 may be a better fit to capture microblogs' relevance.

4.5. Harmonising Score differences

So far we have introduced a set of representative retrieval models, and discussed how they behave when facing microblog-like conditions. We have mainly simulated the spectrum of scores produced w.r.t. TF and DL by each model when fixing all other parameters. Moreover we have observed that retrieval models performance seems to increase when we overestimate the values of TF and DL, thus forcing the models to return values of lesser score differences.

Table VIII holds a summary of the results for all retrieval models with various configurations with respect to Precision@30. Additionally the third column holds the stan-

Table IX: Retrieval models performance with log-smoothed scores (All collections)

	Precision @ 30		
	Default	$log_2(Ret.Model)$	% difference
DLM	0.2988	0.3977	+33.10%
HLM	0.3475	0.4489	+29.18%
$BM25$	0.3948	0.4336	+9.83%
$DFRee$	0.4614	0.4531	-1.80%
IDF	0.4626	0.4626	0%

dard deviation of the simulated scores produced by the retrieval models in microblog conditions[12].

As it can be easily observed, the possible document scores are much closer together for those configurations that improve a retrieval model's performance. In fact there is a strong statistical correlation (last two columns) between reducing the standard deviation and improving the retrieval performance of the models. This observation motivates the following hypothesis:

The range of scores produced by retrieval models can be unfairly different due to its behaviour w.r.t. the scarcity of TF and DL values in microblog conditions.

If this hypothesis is true, we should be able to achieve similar positive results if we reduce the scoring differences of a retrieval model by means of any other technique. To this end we decided to apply a base two logarithm, to the scoring function of each retrieval model. As an example, the formulation of HLM would be as follows:

$$\text{HLM}(D,Q) = \sum_{i=1}^{n} \mathbf{log_2}\left[\log_{\mathbf{2}}\left[\mathbf{1} + \frac{\mathbf{c}\cdot\mathbf{f(q_i,D)}\cdot\mathbf{ntoks}}{(\mathbf{1}-\mathbf{c})\cdot\mathbf{f(q_i,C)}\cdot|\mathbf{D}|}\right]\right] \tag{9}$$

where the added logarithm function can be found next to the summation sign.

Table IX holds a comparison between the default P@30 achieved by each model and the same model with the log function applied to it. As we can observe the results for DLM, HLM and BM25 perform significantly better than their standard, whereas DFRee performs marginally worse and IDF remains unaffected.

From these experiments we can conclude that state of the art retrieval models produce unfair scores due to the scarcity of TF and DL during microblog retrieval. This effect can be mitigated by employing techniques to reduce possible score differences such as applying a log function. To conclude, when ranking microblog documents our models should consider the existing TF and DL evidence, but should also be conservative when managing the overall effects on the produced scores.

5. MBRM: A MICROBLOGS RETRIEVAL MODEL

In the previous section, we discussed a number of problems faced by state of the art retrieval models when dealing with microblogs. We presented scarcity of TF and DL as a source of high scoring differences amongst the spectrum of possible scores for a retrieval model. Additionally we started defining the requirements for a retrieval model to effectively handle microblog documents by better capturing their informativeness. These requirements can be summarised as:

[12]where $DL <= 30$ and $TF <= 15$

(1) Higher DL should be regarded positively as authors of microblogs strive to fit as much content as possible within the character limits
(2) Higher TF should be regarded negatively as high TF could be a result of spam messages, and normally TF revolves around 1-2
(3) Score differences with respect to DL and TF should produce gentle slopes, to not penalise/promote unfairly documents with very little differences.

Following these premises, we have designed a "MicroBlogs Retrieval Model", namely MBRM. MBRM is composed of two parts to deal with document based evidence. Then we attach the aforementioned part to an IDF component which represents the collection's information. Similarly to the formulation of BM25, the two main components of MBRM deal with document length and query term frequency. The first component deals with the document length and is given by the following logistic distribution:

$$DLComp(DL) = \frac{c_1}{1 + a_1 \mathrm{e}^{-b_1 DL}} \tag{10}$$

where a_1, b_1 and c_1 are parameters to control the growth, maximum and starting point of the distribution. Secondly, the following component given by a gaussian distribution deals with the effect of TF over the final score produced by MBRM:

$$TFComp\,(TF) = a_2 e^{-\frac{(TF-b_2)^2}{2c_2^2}} \tag{11}$$

where a_2, b_2 and c_2 are similar parameters to those found in the previous function. These functions were chosen as they offer good control over the curves, and their values can be bound between 1 and 0 and we do not need to normalise them. The final formulation for MBRM is given by:

$$MBRM(D,Q) = \sum_{i=1}^{|Q|} (1-\alpha) * \mathbf{IDF}(q_i) + \alpha * DLComp(|D|) * TFComp(q_i) \tag{12}$$

which can be also expressed as:

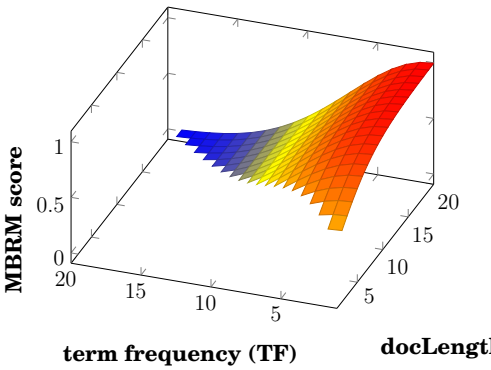
$$MBRM(D,Q) = \sum_{i=1}^{|Q|} (1-\alpha) * \mathbf{IDF}(q_i) + \alpha * \left(\frac{c_1}{1 + a_1 \mathrm{e}^{-b_1 DL(|D|)}} \right) * \left(a_2 e^{-\frac{(TF(q_i)-b_2)^2}{2c_2^2}} \right) \tag{13}$$

Figure 6a shows a simulation of the behaviour of MBRM in terms of TF and DL. The parameters used to for both components (DLComp and TFComp) are shown in Table X. In Figure 6a we can observe how the values obtained on the TF axis decrease slowly for the initial values of TF, but rapidly accelerate in their descent to then settle near

Table X: MBRM recommended parameter settings

Parameter	Recommended values
a_1	1.5
b_1	0.3
c_1	1.0
a_2	1.0
b_2	2.0
c_2	6.0

(a) Doc. length (DL) and Term Frequency (TF)



(b) MBRM effects of α on each fold.

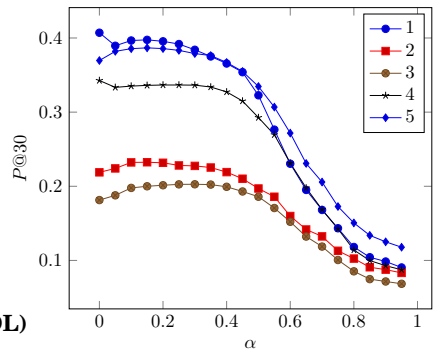


Fig. 6: MBRM: A Microblog Retrieval Model

Table XI: Performance of MBRM on all collections (Where * $p < 0.05$ and ** $p < 0.01$ respectively, with respect to IDF and DFRee)

	Precision				
	@5	***@10***	***@15***	***@20***	***@30***
DFRee	0.62	0.57	0.54	0.51	0.46
IDF	0.62	0.57	0.53	0.51	0.46
MBRM ($\alpha = 0.20$)	**0.64***	**0.59***	**0.56****	**0.53****	**0.48***

0. This behaviour is similar to that of DFRee (Albeit smoother) in which the highest importance is given to low TF values ~ 2 and then it is reduced.

In terms of DL we produce a soft increasing slope to account for increasing value assigned to more informative documents. Unlike $DFRee$, the slope is always incremental. The idea behind it being that the more terms in the microblog the more comprehensive it should be, as more information is encoded regardless of the character limitation.

In order to find the optimal value for the pondering value of α we divided the all the collections into 5 folds. For each of the folds we produced a P@30 result for a number of α values in the 0-1 range. These can be found in Figure 6b. It can very easily be observed that the most optimal values for the mixing parameter α are near 0.20.

Finally Table XI shows the evaluation results obtained for MBRM in terms of Precision at different levels in comparison with IDF and DFRee. As it can be observed, the performance is always significantly superior than the baselines. The main difference with respect to IDF is obviously that it takes advantage of document statistics, where IDF does not. However the main difference with respect to DFRee is that documents longer than 15 terms are not penalised following the aforementioned rationale.

These results not only demonstrate that we can make effective use of document statistics unlike previously thought by other authors [Naveed et al. 2011], but also that the scope hypotheses still holds for small documents. In other words, the authors of the documents will attempt to encode as much information as possible even with the obvious document limitations.

The verbose hypotheses however seems not to hold, as authors are simply capped by the character limitation with very little length variations. Thus documents are not generally longer due to style differences, or the verbosity of the author, but it is rather

a reflection of the author's capacity to encode rich information in such limited constraints, which again aligns better with the scope hypotheses. And this is what we ultimately attempted to capture with our MBRM retrieval model.

6. CONCLUSIONS

In this work, we verified whether the scope and verbosity hypotheses still hold for microblog document retrieval. We initially hypothesise that since microblog documents have a character limit the scope and verbosity hypotheses could not hold, as it is assumed that the author of the document is able to produce documents of any length.

We then proceeded to analyse the behaviour of a number of state of the art retrieval models. The models chosen were BM25, HLM, DLM, DFRee and IDF. Our experimentation led to a better understanding of what could be the shortcomings experienced by such models under microblog retrieval constraints. Particularly, we isolated the fact that longer documents should be promoted to account for effort of microblog authors to encode their messages into the character limit. Then we identified that higher term frequencies than 1-2 should be penalised as they are more likely to be less informative and more reminiscent of spam. Based on these observations we concluded that the scope hypotheses does hold in microblog retrieval, however verbosity does not.

Finally we built a retrieval model optimised for microblog retrieval, namely MBRM, which significantly outperforms the best baselines, by making better use of document-encoded evidence.

Future work will demonstrate how MBRM can be used to push further the current performance of approaches that rely on the initial results such as Automatic Query Expansion.

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