	Dataset	<b>F-score</b>	
	Dataset	Original	Ours
CofeTata	DUC	2514	2517
TextRank	Inspec	3612	11010
<u>SingleRank</u>	DUC	2712	2419
<b>ExpandRank</b>	DUC	31117	26.14
KeyOluster	Inspec	4616	3819

Mable 3: Original vs. re-implementation scores

of Mexikank<sup>6</sup>, and are confident that our implementation is correct. It is also worth mentioning that using our re-implementation of SingleRank, we are able to match the best scores reported by Mihalcea and Marao (2004) on Vasoea.

We score 2 and 5 points less than Wan and Xiao's (2008) implementations of SingleRank and ExpandRank, respectively. We speculate that document presprocessing (e.g., stemming) has constributed to the discrepancy, but additional expertiments are needed to determine the reason.

SingleRank vs. TextRank Figure () shows that StingleRank behaves very differentily from Text tiRanki. As mentioned in Section 3.2.31 the two algorithms differ in three major aspects. To determine which aspect is chiefly responsible for the targe difference in their performance, we conduct three fabilation experiments. Each experiment modifies exactly one of these aspects in SingleR1 ank so that it behaves tike TextRank, effectively ensuring that the two algorithms differ only in the remaining two aspects. More specifically in the three experiments, we (11) change SingleRank's window size to 21 (2) build an unweighted graph for SingleRank, and (3) incorporate TextRank's way of forming keyphrases into SingleRank, respectively. Figure 2 shows the resultant curves allong with the SingleRank and TextRank curves on thisped taken from Frigure (ib.) As we can see, the way of forming phrases, rather than the window size or the weight assignment method, has the largest impact on the scores. In fact, after incorporating TextRank's way of forming phrases. SingleRank exhibits a remarkable drop in perfort mance, vielding a curve that resembles the flext tiRank curve. Also note that SingleRank achieves better recali values than flextikank. To see the real son, recall that flextRank requires that every word of a gold keyphrase must appear among the top-

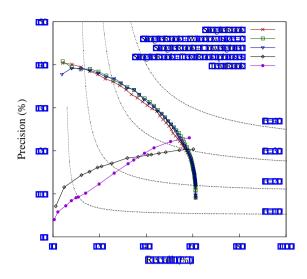


Figure 2: Abiation results for SingleRank on Val spec

ranked unigrams. This is a fairly strict criterion, especially in comparison to SingleRank, which does not require all unigrams of a gold keyphrase to be present in the top-ranked list. We observe similar trends for the other datasets.

## 5 Conclusions

We have conducted a systematric evaluation of five state-off-the-art unsupervised keyphrase extraction algorithms on datasets from four diffferent domains. Several conclusions can be drawn from our experimental results. First, to fully understand the strengths and weaknesses of a keyphrase extractor it is essential to evaluate it on multipie datasets. In particular, evaluating it on a singie dataset has proven inadequate, as good performance can sometimes be achieved due to certrain statistical characteristics of a dataset. Second, as demonstrated by our experiments with TextiRank and SingleRank, post-processing steps such as the way of forming keyphrases can have a large impact on the performance of a keyphrase extractor Hence it may be worthwhile to investipare alternative methods for extracting candidate kevohrases (e.g., Kumar and Srinathan (2008)). You et all ((2009))). Finally, despite the large amount of recent work on unsubervised keyphrase extractor, our results indicated that (If-lidf remains a strong baseline offering very robust performance across different datasets.

<sup>&</sup>lt;sup>6</sup>http:///github.com/sharethis//textrank