Taming Topic Instability For Reasoning Over Unstructured Data in Software Engineering

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***Abstract*—Topic Modeling has been widely used to identify patterns in a corpus across various fields. The Latent Dirichlet Allocation (LDA) algorithm is a widely used topic modeling algorithm which in practice is called using its defaults. We report that these defaults can lead to highly misleading results in Software Engineering. It is very important to generate stable topics using the Non-Deterministic LDA method. But one of the curse is setting the right parameters that control the LDA. We ran differential evolution (DE) as an optimizer to explore the tuning space (as a first step) then tested it against the default parameter settings. We found that these tunings were remarkably simple, and took hundreds, not thousands of evaluations to obtain very good results. Since the improvements are so large, and (2) the tuning is so simple, that many industries, who are using LDA, should change the standard methods for better throughput and accuracy of their products. The implication for other kinds of topic modeling algorithms is now an open and pressing issue. Even we can improvise the actual clusters to get better results.**

***Keywords*—Topic modeling, Stability, LDA, tuning, differential evolution.**

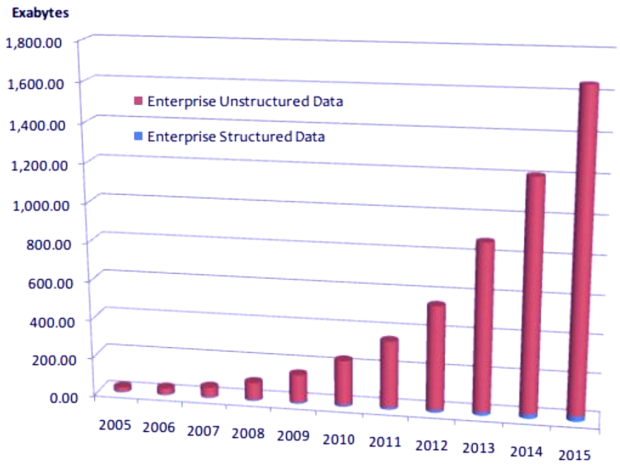

Figure 1: Data Growth 2005-2015

I. Introduction

In the 21st century, we have now access a mount of data about software engineering. International Data Corporation (IDC), figure 1, shows the number to be 1600 Exabytes. Most of these data is in an unstructured format [50]. Unstructured data does not have a pre-defined data model and is typically text-heavy. Finding insights among unstructured text is extremely difficult unless we can search, characterize, and classify their text data in a meaningful way.

One of the common algorithm for finding related topics within unstructured text (an area called topic modeling) is Latent Dirichlet Allocation (LDA) as shown in the next section. It is usually used using off-the-shell default parameters. But what we found is due to the algorithms non-deterministic behaviour, the topics generated are not stable. In the next section, we will be exploring this problem more and the workaround given by other researchers.

There are various libraries which provide LDA implementation and each library comes with a set of parameters. It is very impractical to get the right combination of parameters due to larger search space. To tackle the above problem, we observed that the parameters taken by LDA can be tuned. In the next coming sections, we will show that many researchers have agreed to the idea of using different configurations for generating topics using LDA. But, we have seen rare work done when it comes to tune the important parameters of LDA for getting stable topics. Most people have went ahead with LDA's default parameters and have not searched the whole configurations space.

To tackle the problem of how to tune, we have seen that one of the simplest ***multiobjective optimizers (differential evolution*** [62]) works very well for tuning in certain kinds of software analytics [18]. There has been success stories where DE has helped in tuning the parameters [18], [8], [14]. Prior to this work, our intuition was that tuning would change the behavior of LDA, to some degree. Also, we suspected that tuning would take so long time and be so CPU intensive that the benefits gained would not be worth the effort. We have found large instability in 2 data miners, namely, defect predictors and LDA. Results have shown that we can contain the instability to a large extent using Differential Evolution (DE). So, this makes us wonder Search-Based Software Engineering techniques can help us.

The results of this paper show that the above points are false since:

1) Tuning LDA is remarkably simple;
2) And can dramatically improve stability in the topic generation.

We can say that now, we can mitigate stability of non-deterministic LDA. We are talking about model instability itself rather than results instability. Many industries, working

on a product development in text analytics have been widely using LDA. This gives them a chance to incorporate better throughput and accuracy in their product. Menzies et al. [45] showed how model instability can give rise to different effort estimations across various projects.

Those results were found by exploring six research questions:

- **RQ1**: *Do the default settings lead to misleading results?* We will show that topics generated are more stabled with tuned parameters rather with the default settings.
- **RQ2**: *Does tuning improve the stability scores of LDA?* In our work, we will show dramatic improvement in the stability scores with the tuned parameters rather than going for default parameters.
- **RQ3**: *Does different data need different configurations to make LDA stable? Does it change some predefined parameter values of lda?* We will show that different sets of configurations are found out by DE. For one of the results, we showed that we need topic size of less than 30 rather than 67 [21].
- **RQ4**: *Is tuning easy?* We have seen that one of the simpler multiobjective optimizers (differential evolution [62]) works very well for tuning in major software analytics.
- **RQ5**: *Is tuning impractically slow?* We achieved dramatic improvements in the stability scores of LDA in less than 300 evaluations (!); i.e., very quickly.
- **RQ6**: *Should data miners be used "off-the-shelf" with their default tunings?* Wei et al. [18] showed that for defect prediction from static code measures, their answer is an emphatic "no". And we also say that for LDA, it is a "no".

Topic Modeling have been used in various spheres of Software Engineering. Sun et al. reported a survey of LDA's usage to support various SE tasks between 2003 and 2015 [64]. The number of papers published across top major conferences and journals are listed in figure 2. The survey in figure 3 show that there is an increasing concern in this area.

- Topic modeling is applied in various SE tasks, including source code comprehension, feature location, software defects prediction, developer recommendation, traceability link recovery, re-factoring, software history comprehension, software testing and social software engineering.
- There are works in Requirements Engineering where it was necessary to analyze the text and come up with the important topics [5], [66], [43].
- People have used topic modeling in prioritizing test cases, and identifying the importance of test cases [27], [76], [73].
- Increasingly, it has also become very important to have automated tools to do a Systematic Literature Review (SLR) [69]. We found these papers [61], [2], [40] who have used clustering algorithms (topic modeling) to do SLR.

Venue	Full name	Count
ICSE	International Conference on Software Engineering	4
CSMR-WCRE / SANER	International Conference on Software Maintenance, Reengineering, and Reverse Engineering / International Conference on Software Analysis, Evolution, and Reengineering	3
ICSM / ICSME	International Conference on Software Maintenance / International Conference on Software Maintenance and Evolution	3
ICPC	International Conference on Program Comprehension	3
ASE	International Conference on Automated Software Engineering	3
ISSRE	International Symposium on Software Reliability Engineering	2
MSR	International Working Conference on Mining Software Repositories	8
OOPSLA	International Conference on Object-Oriented Programming, Systems, Languages, and Applications	1
ESEC/FSE	International Symposium on the Foundations of Software Engineering / European Software Engineering Conference	1
TSE	IEEE Transaction on Software Engineering	1
IST	Information and Software Technology	3
SCP	Science of Computer Programming	2
ESE	Empirical Software Engineering	4

Figure 2: Survey Venue and Statistics

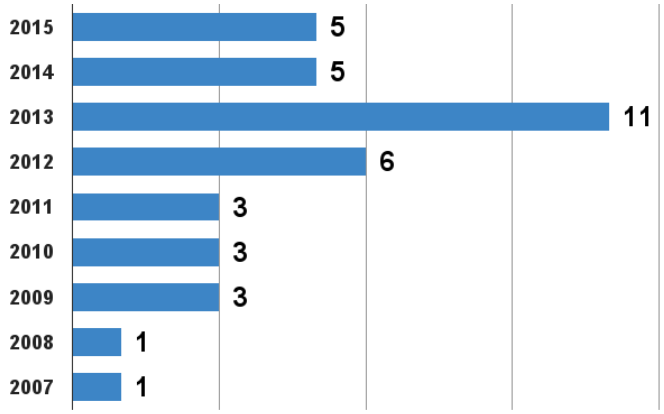

Figure 3: The distribution of the papers published in different years

This gives us the motivation of generating stable topics in software engineering which will make product development faster, cheaper and accurate.

II. Previous Work

Are the impacts of instability in LDA addressed in the text analytics? To answer that question, in April 2016, we searched scholar.google.com for the conjunction of "lda" and "topics" or "stable" or "unstable" or "coherence". At the time of writing this paper, we got 475 results. We selected for papers since 2012, we got to 189 results. After discarding the non-SE papers, we read over this sample of 57 highly-cited SE text analytics papers. 28 papers talk about instability in LDA (more details can be found at *https://goo.gl/Bpc6Vb*). Also, we found in that sample was that only two authors acknowledged the impact of tunings. About 35% papers in our sample did not adjust the "off-the-shelf" configuration of the LDA. Among the other 65%, 83% papers, explored the configurations space with brute force. Their was not an effective and faster way of choosing the right set of parameters. Those papers, which accepted the problem of instability in LDA, came to some conclusions which can be found in Table I. The literature review for rest of the papers are categorized in the following subsections.

Reference ID	Citations	Mentions instability in LDA?	Talks about using off the shell parameters?	Does tuning?	Conclusion
[60]	112	Y	Y	N	Explored Configurations without any explanation
[54]	108	Y	Y	N	Explored Configurations without any explanation Reported their results using multiple experiments
[7]	96	Y	Y	N	Explored Configurations without any explanation Choosing right set of parameters is a difficult task
[58]	75	Y	Y	Y	Uses GA to tune parameters. They determine the near-optimal configuration for LDA in the context of only some important SE tasks
[20]	61	Y	Y	N	Explored Configurations without any explanation
[29]	45	Y	Y	N	They validated the topic labelling techniques using multiple experiments.
[26]	44	Y	Y	N	Explored Configurations without any explanation
[65]	44	Y	Y	N	Open issue to choose optimal parameters
[13]	35	Y	Y	N	Choosing the optimal number of topics is difficult
[66]	35	Y	Y	N	Explored Configurations without any explanation
[67]	31	Y	Y	N	Choosing right set of parameters is a difficult task
[6]	29	Y	Y	N	Explored Configurations without any explanation and accepted to the fact their results were better because of the corpus they used
[37]	27	Y	Y	Y	Explored Configurations using LDA-GA
[36]	20	Y	Y	N	In Future, they planned to use LDA-GA
[32]	15	Y	Y	N	Explored Configurations without any explanation
[28]	13	Y	Y	N	Explored Configurations without any explanation (Just with no. of topics)
[24]	13	Y	Y	N	Their work focused on optimizing LDA's topic count parameter
[19]	6	Y	Y	N	Explored Configurations without any explanation. Choosing right set of parameters is a difficult task
[21]	5	Y	Y	N	Explored Configurations without any explanation
[35]	5	N	Y	N	Explored Configurations without any explanation
[53]	3	Y	Y	N	They improvised LDA into ISLDA which gave stability across different runs
[63]	2	Y	Y	Y	Explored Configurations using LDA-GA
[12]	0	N	Y	N	Explored Configurations without any explanation. Choosing right set of parameters is a difficult task
[74]	2	Y	N	N	Uses modified frameworks of LDA. This is for classified datasets.

Table I: Literature Survey

A. Problems with LDA

- In LDA, learning the various distributions is a problem of Bayesian inference. It also use the alternative inference techniques like Gibbs sampling [71] and expectation propagation (VEM) [48]. These techniques gave rise to non deterministic ways which are responsible for the instability in the topic modeling. Different inference techniques in LDA try to maximize the resulting lower bound on the log likelihood [11]. The expected complete log likelihood of the data can have many local maximas, which leads to different distributions and in turn leads to instability in the output. The distributions which are found with the help of LDA, resulting from the same dataset with the same vocabulary and model parameters, any differences between them are entirely due to the randomness in inference techniques [32]. This randomness affects perplexity variations, word and document ratios. There is a problem of finding the optimal number of clusters, but different configuration parameters may lead us to the stable topics.

- The topics learned by LDA sometimes are difficult to interpret by end users [74], [58]. We want topics to be finer grained (more number of topics) or coarse grained (less number of topics) according to the use case. Rationality about the topics instability is impor-

tant if an industry is using topic modeling in all their use cases [34], [56].

- Online learning [30] for LDA uses constant memory requirements and empirically converges faster than batch collapsed Gibbs sampling. However, it still requires a full pass through the entire corpus each iteration. It can therefore be slow to apply to very large datasets, and is not naturally suited to settings where new data is constantly arriving.
- We saw that this is just not happening with only particular programming language or particular library. This instability is happening irrespective of the tools in which LDA has been implemented. Some of the papers mentioned using GibbsLDA++ written in C++ and they observed the same instability [38], [68], [26]. Some papers mentioned about using Python implementation of LDA and observed the same instability [26]. LDA implemented in JAVA language produced the same incoherent topics [41], [29]. And, we observed this problem is in the Scikit-Learn version of LDA, implemented in Python, as well as Spark Mllib library.

B. Tuning: Important and Ignored

This section argues that tuning is an under-explored software analytics. The impact of tuning is well understood [10]. Yet issues of tuning are rarely or poorly addressed in the defect prediction literature. When we tune a data miner, what we are really doing is changing how a learner applies its heuristics. This means tuned data miners use different heuristics, which means they ignore different possible models, which means they return different models; i.e. how we learn changes what we learn.

Wei et al. [18] shows that only few authors acknowledged the impact of tunings. A few other papers did acknowledge that one data miner may not be appropriate for all data sets. Those papers tested different "off-the-shelf" data miners on the same data set. For example, Elish et al. [16] compared support vector machines to other data miners for the purposes of defect prediction. Those papers tested different "off-the-shelf" data miners on the same data set. Wei et al. [18] showed that finding useful tunings is very easy. This result is both novel and unexpected. Learners are very amenable to tuning. Hence, they are also very amenable to significant performance improvements. Given the low number of evaluations required, they asserted that tuning should be standard practice for anyone using data miners.

C. WorkAround to LDA Instability Problem

1) ***Unsupervised****:*

Solution 1: To evaluate the stability of topics, most papers [42], [41], [26] manually accessed the topics and then used for further experiments. Some made use of Amazon Mechanical Turk to create gold-standard coherence judgements [34].

This workaround will take a lot of manual effort and time which is not feasible for many. In the age of automation, we need an efficient way of making LDA stable.

Solution 2: Users have external knowledge regarding word correlation, which can be taken into account to improve the semantic coherence of topic modeling methods. SCLDA [74] can handle different kinds of knowledge such as word correlation, document correlation, document label and so on. One advantage of SCLDA over existing methods is that it is very fast to converge.

We do not have enough resources to have a user knowledge for the type of datasets we used, and that's the reason we are not using this solution to improve stability.

Solution 3: The most common parameters in the LDA are number of clusters (k), number of iterations (n), document topic prior (α), and word topic prior (β). The other solution is tuning these parameters of LDA. Tuning the parameters and using different configurations were used by [58], [37], [54]. They [20], [68] achieved higher stability by just increasing the number of cluster size.

We found this to have better advantage than the other solutions based on the tuning work done by Wei [18]. And in our work, we have used this solution.

2) ***Supervised****:*

Solution 3: We found so many improvised frameworks of LDA namely, *Labeled LDA* [59], *Dirichlet Forest LDA* [3], *Logic LDA* [4], *Quad-LDA* [52], *NMF-LDA* [72], *Interactive Topic Modeling* (ITM) [31], *MRTF* [15] and many more, helping in generating better stable topics.

We will not be able to use any of the above supervised solutions as our datasets are not labeled. And these all frameworks work best with the classified datasets. This is going to be our future work which we will be addressing next.

D. Evaluation

To evaluate the topics coherence or the cluster stability using LDA, there has been number of evaluation measures proposed. There is a direct approach, by asking people about topics, and an indirect approach by evaluating *pointwise mutual information (PMI)* [34], [56] between the topic words. PMI being an automatic method, we are not sure of exact details of it which made us to not use this measure. We could not use direct approach, due to resource limitation to ask an expert for the type of datasets we used, and that's the reason we are not using this criteria to evaluate.

Perplexity is monotonically decreasing in the likelihood of the data, and is algebraically equivalent to the inverse of the geometric mean per-word likelihood. It shows how well topic-word and word-document distributions predict new test samples. The smaller the perplexity, the better (less uniform) is the LDA model. The usual trend is that as the value of

perplexity drops, the number of topics should grow [32]. But problem with perplexity is that the value of perplexity doesn't remain constant with different topic size and with dictionary sizes [32], [77]. A lot depend on the code implementation of perplexity and the type of datasets used. Since, we are using different implementations of LDA as well as different datasets, we are not using Perplexity as evaluation measure.

Many researchers [56], [20] uses Jaccard Similarity for evaluating stability. We define our measure similar to it. We say topics are stable, when there are x times n% of terms overlap in a topic across m runs. We can see an example of 5 terms overlap in figure 4. We take median of all the scores generated by evaluating topic. In this example, figure 4, median score is 1.0 for each run. So overall median score comes out to be 1.0. We always select top 10 terms within a topic suggested by some researchers [58], [39]. It makes sense to us that to have a successful topic modeling, to define each topic you need top few terms which will completely define that topic. *If we get different words then it will mean different topics which will put any product based on topic modeling at risk.*

To understand our results, we have defined some terminologies. We call the above median score as ***Raw score*** which is 1.0. This *Raw Score* can come from tuning and untuned results defined similarly. We also define a ***Delta Score*** which is the absolute difference between **Raw Score**$_{tuned}$ − **Raw Score**$_{untuned}$.

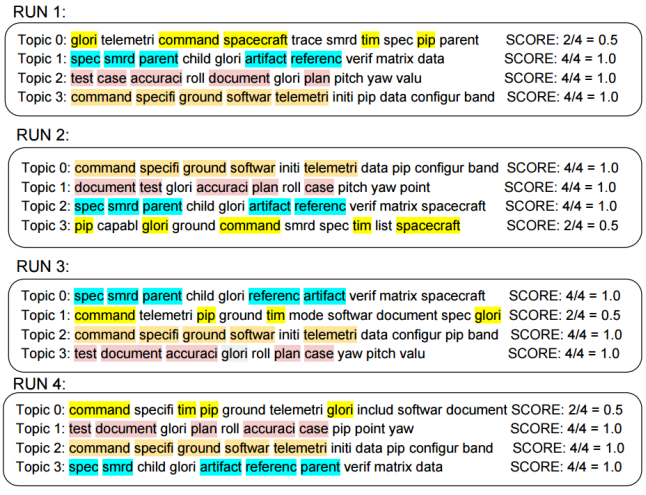

Figure 4: Example of 5 terms overlap across 4 runs and its stability score

E. Notes on LDA

Latent Dirichlet Allocation (LDA) is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. It learns the various distributions (the set of topics, their associated word probabilities, the topic of each word, and the particular topic mixture of each document) and is a problem of Bayesian inference. The original method used is a variational Bayes approximation of the posterior distribution [11], alternative inference techniques use Gibbs sampling [25] and Variational Expectation Maximisation (VEM) [48].

Regardless of the methods, all these attempts to fit the model to data using maximum likelihood. Lesser the likelihood, more the convergence of the model and expected to achieve better results. The perplexity, used by convention in topic modeling, is monotonically decreasing in the likelihood of the data.

The pseudocode for untuned LDA is shown in Algorithm 1 with the default set of parameters. In the following description, superscript numbers denote lines in the pseudocode. The data is shuffled everytime LDA is run^{L5}. Data is in the form of term frequency scores of each word per document. Shuffling is done in order to induce maximum variance among different runs of LDA. Topics^{L6} is a list of list which contains topics from all the different runs. A stability score is evaluated on every 10 runs, and this process is continued 10 times. At the end, median score is selected as the untuned final score^{L3-L11}.

Algorithm 1 Pseudocode for untuned LDA with Default Parameters

Input: $no.ofterms$, $Data$
Output: $Final\_Score$
1: **function** LDASCORE($no.ofterms$, $Data$)
2: $Score \leftarrow \emptyset$
3: **for** $j = 0$ to 10 **do**
4: **for** $i = 0$ to 10 **do**
5: $data \leftarrow$ **shuffle**($Data$)
6: $Topics$.append(lda($k = 10$,$\alpha = none$,$\beta = none$))
7: **end for**
8: $Score$.append($Overlap$(Topics, $no.ofterms$, l[0]))
9: **end for**
10: $Final\_Score \leftarrow$ median(Score)
11: **return** $Final\_Score$
12: **end function**

F. Tuning Algorithms

The other solution which we discussed was tuning the parameters of LDA. Here is a list of optimizers used widely in research: simulated annealing [17], [46]; various genetic algorithms [23] augmented by techniques such as differential evolution [62], tabu search and scatter search [22], [9], [49], [51]; particle swarm optimization [57]; numerous decomposition approaches that use heuristics to decompose the total space into small problems, then apply a response surface methods [33], [78]. Of these, the simplest are simulated annealing (SA) and differential evolution (DE), each of which can be coded in less than a page of some highlevel scripting language. Our reading of the current literature is that there are more advocates for differential evolution than SA. For example, Vesterstrom and Thomsen [70] found DE to be competitive with particle swarm optimization and other GAs. DEs have been applied before for parameter tuning (e.g. see [55], [14], [18]) but this is the first time they have been applied to tune the configurations of LDA.

We will tune hyperparameters of LDA using DE. DE also comes up with parameters like number of iterations, mutation, crossover rate, population size, and different selection strategies. The objective of LDA is to maximize the stability scores. Based on the literature review, we found that we don't need to have topics more than 10 terms. We also found the important parameters that need to be tuned. See Table II. We also used online variational Bayesian approximation as well as gibbs sampling for LDA, with random input row order of data to

make sure that in each run the learning is different. This gave us more concrete results as few tuned set of parameters which we found performed good across each run.

The pseudocode for differential evolution is shown in Algorithm 2. In the following description, superscript numbers denote lines in the pseudocode. DE evolves a *NewGeneration* of candidates from a current Population. Our DE will terminate after a certain number of evaluations. We ran initial experiments to define this constant. We will talk about this in section V. Each candidate solution in the Population is a pair of (Tunings, Scores). Tunings are selected from Table II and Scores come from the stability score after running our LDA experiment$^{L23-L30}$.

Algorithm 2 Pseudocode for DE with a constant number of evaluations

Input: np= 10, f= 0.7, cr= 0.3, iter= 3, Goal ∈ Finding maximum score
Output: $S_{best}, final\_generation$

1: **function** DE($np, f, cr, iter, Goal$)
2: $Cur\_Gen \leftarrow \emptyset$
3: $Population \leftarrow$InitializePopulation(np)
4: **for** $i = 0$ to $np - 1$ **do**
5: Cur_Gen.append($Population$[i],ldascore($Population$[i], $term$, $Data$)
6: **end for**
7: **for** $i = 0$ to $iter$ **do**
8: $NewGeneration \leftarrow \emptyset$
9: **for** $j = 0$ to $np - 1$ **do**
10: $S_i \leftarrow$Extrapolate($Population$[j],Population,cr,f,np)
11: **if** ldascore(S_i) $\geq$ Cur_Gen[j][1] **then**
12: $NewGeneration$.append(S_i,ldascore($S_i, term, Data$))
13: **else**
14: $NewGeneration$.append(Cur_Gen[j])
15: **end if**
16: $Cur\_Gen \leftarrow NewGeneration$
17: **end for**
18: **end for**
19: $S_{best} \leftarrow$ GetBestSolution(Cur_Gen)
20: $final\_generation \leftarrow Cur\_Gen$
21: **return** $S_{best}, final\_generation$
22: **end function**
23: **function** LDASCORE(l, $term$, $Data$)
24: $Topics \leftarrow \emptyset$
25: **for** $i = 0$ to 10 **do**
26: $data \leftarrow$ **shuffle**($Data$)
27: $Topics$.append(lda($k = l$[0],$\alpha = l$[1],$\beta = l$[2]))
28: **end for**
29: **return** $Overlap$(Topics, $term$,l[0])
30: **end function**
31: **function** EXTRAPOLATE(old, pop, cr, f, np)
32: $a, b, c \leftarrow threeOthers$(pop, old)
33: $newf \leftarrow \emptyset$
34: **for** $i = 0$ to $np - 1$ **do**
35: **if** $cr \leq$ random() **then**
36: $newf$.append($old[i]$)
37: **else**
38: **if** typeof(old[i])== bool then **then**
39: $newf$.append(not $old[i]$)
40: **else**
41: $newf$.append(trim(i,(a[i]+$f*$(b[i] − c[i]))))
42: **end if**
43: **end if**
44: **end for**
45: **return** $newf$
46: **end function**

The premise of DE is that the best way to mutate the existing tunings is to Extrapolate^{L31} between current solutions. Three solutions a, b, c are selected at random. For each tuning parameter i, at some probability cr, we replace the old tuning x_i with y_i. For booleans, we use $y_i = x_i$ (see line 39). For numerics, $y_i = a_i + f \times (b_i - c_i)$ where f is a parameter controlling crossover. The trim function^{L41} limits the new value to the legal range min..max of that parameter.

The main loop of DE^{L9} runs over the Population, replacing old items with new Candidates (if new candidate is better). This means that, as the loop progresses, the Population is full of increasingly more valuable solutions. This, in turn, also improves the candidates, which are Extrapolated from the Population.

The data is shuffled everytime LDA is run^{L26}. Data is in the form of term frequency scores of each word per document. Shuffling is done in order to induce maximum variance among different runs of LDA. Topics^{L27} is a list of list which contains topics from all the different runs. A stability score is evaluated on every 10 runs. At the end, median score is selected as the final score$^{L23-L30}$.

III. EXPERIMENTATION

A. Data Sets

To answer our research questions, we will be working on couple of open source datasets to verify that tuning does help the stability scores. All these datasets have been preprocessed using the normal steps of stopwords removal, stemming, and then considering the top 5% of tf-idf scores. More details about the statistics of datasets can be found in the table III. The datasets used are:-

- **PITS**: This is a text mining data set generated from project and issue tracking system (PITS) reports [44], [47]. This data is about the bugs and changes in the code, to submit and review patches, to manage quality assurance, to support communication between developers, etc. The aim is to identify the top topics which can identify each severity separately. The dataset can be downloaded from this repository [1] [1].
- **StackOverflow**: StackOverflow is a privately held website, the flagship site of the Stack Exchange Network. It features questions and answers on a wide range of topics in computer programming. The data can be downloaded from various sources [2] [3]. This dataset is so big that it can only be run on Spark with a cluser of nodes to reduce the runtime. Results of this dataset is only coming from Spark mllib implementation.
- **Citemap**: A citation, also called a reference, uniquely identifies a source of information. Citemap can be used to create citations for the map. Dataset can be downloaded from [4].

Size before preprocessing Size after preprocessing

[1] http://openscience.us/repo/issues
[2] http://data.stackexchange.com
[3] http://blog.stackoverflow.com/tags/cc-wiki-dump/
[4] https://github.com/ai-se/citemap/blob/master/citemap.csv

Parameters	Default	Tuning Range	Description
n_topics (k)	10	[10,100]	Number of topics or cluster size
doc_topic_prior (α)	None	[0,1]	Prior of document topic distribution. This is called alpha
topic_word_prior (β)	None	[0,1]	Prior of topic word distribution. This is called beta

Table II: List of parameters tuned by this paper

Datasets	Size	
	Before Preprocessing	After Preprocessing
PitsA	1.2MB	292 KB
PitsB	704KB	188KB
PitsC	143KB	37KB
PitsD	107KB	26KB
PitsE	650KB	216KB
PitsF	549KB	217KB
Ciemap	8.6MB	3.7MB
Stackoverflow	7GB	527MB

Table III: Statistics on the datasets

IV. Experimental Results

All the subsequent results are coming after running on Local machine. These results are implemented using Variational Expectation Maximisation (VEM) method of LDA in Python (Scikit-learn). The StackOverflow dataset is so big that it can only be run on Spark cluster. We have specifically mentioned if any of the other results are coming from Gibbs Implementation or Spark platgorm.

A. *RQ1: Do the default settings lead to misleading results?*

In figure 5, X-axis represents number of terms overlap. Y-axis represents the raw stability score. For definition of *Raw Scores* and *Delta Scores*, you can refer to Section II-D. Different lines are for the different datasets. From the figure 5, it can be clearly seen that instability occurs in the untuned results. Researchers [58], [39] said that, 10 terms per topic are ideal to define a topic of interest but we can see raw score starts dropping after 5 terms. With default settings, it can surely lead to misleading results.

Result 1
Prior Papers who reports LDA may have been severly compromised.

B. *RQ2: Does tuning improve the stability scores of LDA?*

In figure 6, x-axis represents number of terms overlap. Y-axis represents the Raw scores. Different lines are for the different datasets. We can see that tuning results are either always above the default settings (untuned) or stayed the same. Since figure 6 is hard to read, we have augmented the results into figure 7. In figure 7, x-axis represents number of terms overlap. Y-axis represents the delta improvement which is ($tuning - untuned$) results. If the lines are above x-axis, that means tuning performed better than the untuned. Different lines are for the different datasets. It clearly shows that the

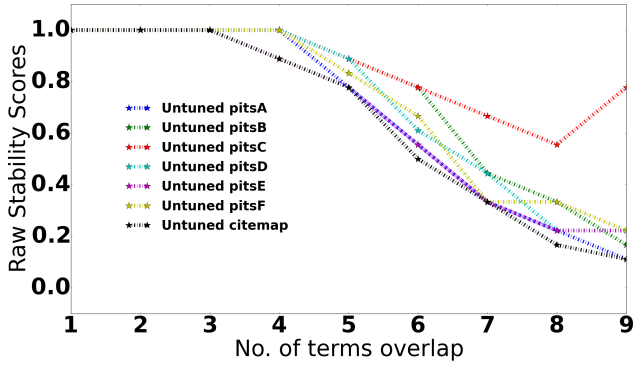

Figure 5: Terms vs Raw Scores between tuning and default parameters

answer to RQ2 is "yes" - tuning has a positive effect on stability scores. Tuning either helped it or remained the same but it never had any negative effect. The dramatic improvement started showing after 5 terms overlap. The most improvement which we observed was in PitsD dataset for 8 terms overlap of about 80%. That's why we recommend that we shouldn't list more than 5 terms per topic, as stability starts dropping.

Result 2
Based on Figure 7, we highly recommend tuning in future LDA.

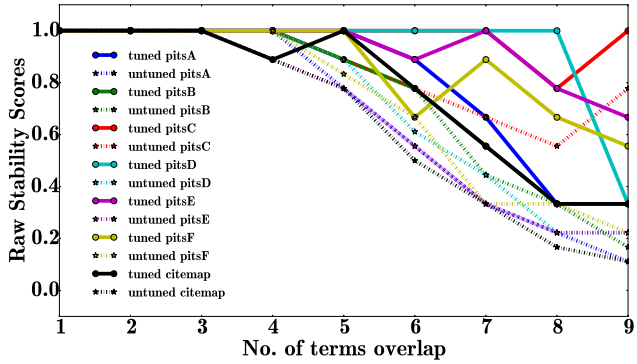

Figure 6: Terms vs Raw Scores between tuning and default parameters

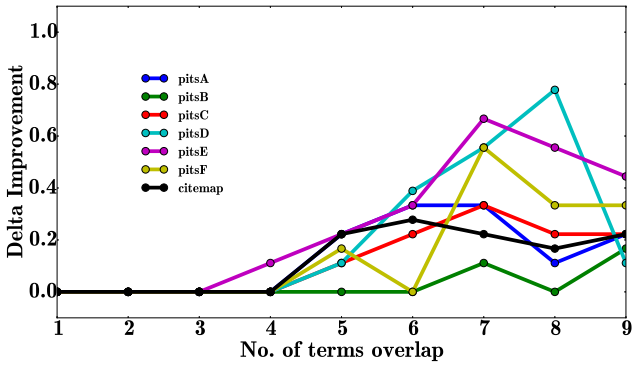

Figure 7: Terms vs Delta Improvement between tuning and default parameters

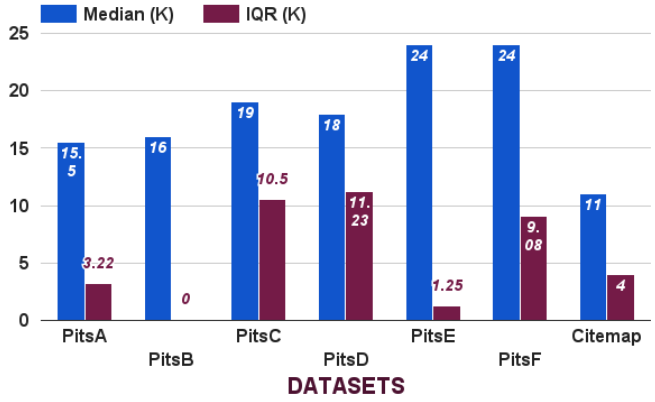

Figure 8: Datasets vs Parameter (k) variation

C. *RQ3: Does different data need different configurations to make LDA stable? Does it change some predefined parameter values of lda?*

Figures 8, 9, and 10, x-axis represents different datasets and y-axis represents values of median and IQR. Each figure shows the variation in the values of number of topics (k), alpha (α) and beta (β). These results are for 5 terms overlap. From these figures, it clearly shows how tuning selects the different ranges of values of parameters. These figures represent a very high Median Score and as well as very high interquartile range (IQR) for different datasets. This means that tuning helped us to arrive at different sets of configurations making the topic generation more constant. In figure 8 for pitsB dataset, we are seeing 0 IQR, that means tuning helped us to find only 1 set of configurations which got us to that Stable score. We found many such similar number throughout the results. (Refer this link at *https://goo.gl/Nin5pV* for elaborate results).

The other result which we found is in the citemap dataset. If we look in the spreadsheet, from Row 121-129, we see that we are getting good stable scores within 30 topic size. But in the [21] paper, they found that we will need a topic size of 67. Definitely, it can change predefined parameters of LDA. We also observed the similar trend for other term overlaps as well as other sampling methods.

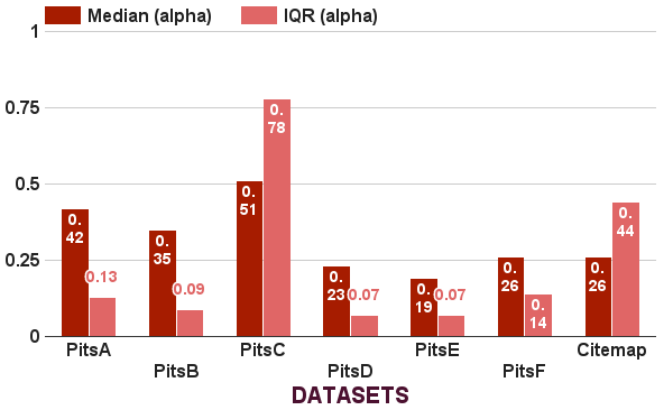

Figure 9: Datasets vs Parameter (alpha) variation

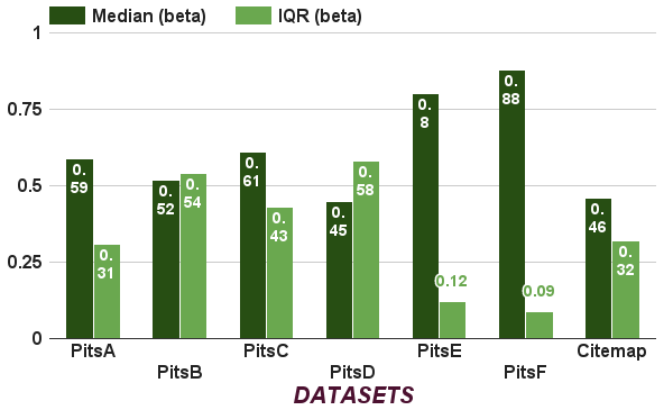

Figure 10: Datasets vs Parameter (beta) variation

D. *RQ4: Is tuning easy?*

In terms of the search space explored via tuning, is much smaller. To see this, recall from Algorithm 2 that DE explores a Population of size np = 10. This is a very small population size since Rainer Storn (one of the inventors of DE) recommends setting np to be ten times larger than the number of parameters being optimized. We also ran experiments with different sets of F, CR, and population size (*np*), and we see that it didn't change much.

We have shown results only for Citemap dataset which can be referred in Figure 11. For other datsets, we can refer at *https://goo.gl/HQNASF*. In Figure 11, different lines show different combinations of F, CR and Population size. F is selected either 0.3 or 0.7, and similarly CR is selected 0.3 or 0.7, and population size is selected either 10 or 30 (which is 10 times the number of parameters being optimized). These numbers are according to the original Rainer Storn [62]

recommended settings.

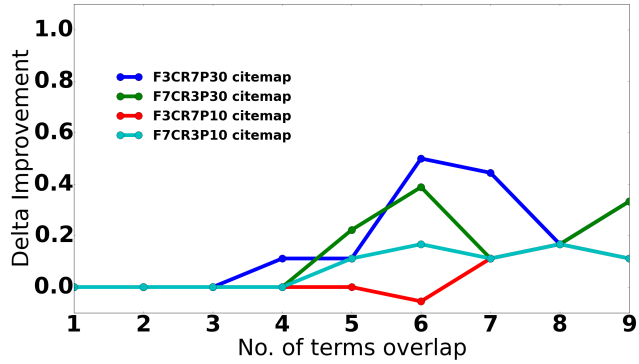

Figure 11: Terms vs Delta Improvement using Different settings of DE

After reviewing the results from all the datasets, we can say that there isn't much of an improvement by using different F, CR, and Population size. So our all other experiments used $F = 0.7$, $CR = 0.3$ and $Popsize = 10$

E. RQ5: Is tuning impractically slow?

Figure 12 and 13, x-axis represents different datasets and y-axis represents the runtimes in seconds (Log_{10}). From the table IV, we will show that we just need 300 evaluations to do tuning. Using this criteria, we can see that tuning runtimes is only about 5 times the runtimes without tuning. Figure 12 is with Gibbs implemented in Python, and figure 13 is with VEM implemented in Python.

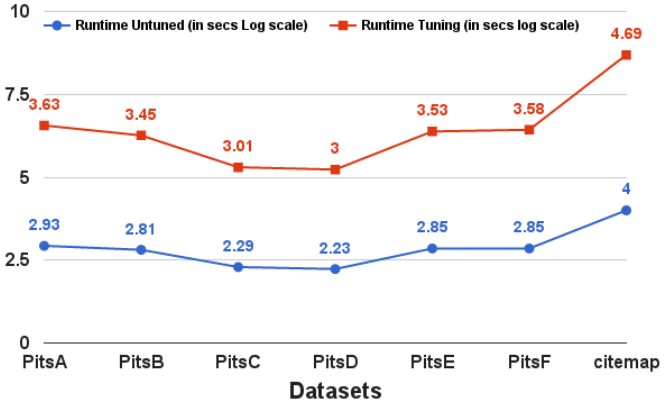

Figure 12: Gibbs: Datasets vs Runtimes

F. RQ6: Should data miners be used "off-the-shelf" with their default tunings?

From figures 8, 9, and 10, we can easily see that for different datasets, we need different parameters. Such large IQRs

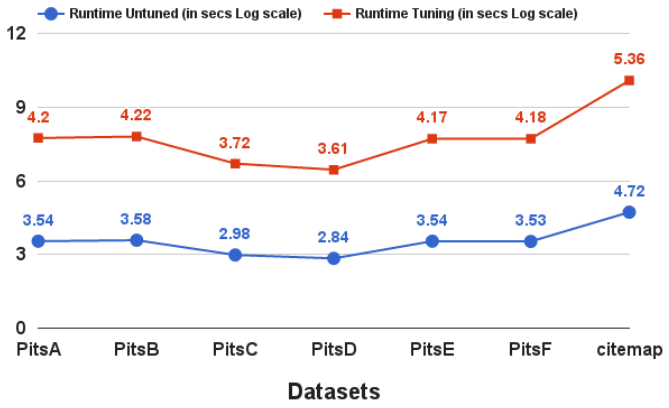

Figure 13: VEM: Datasets vs Runtimes

show that we get quite varied ranges of parameters. Hence, we answer RQ6 as "no" since, to achieve the improvements seen in this paper, tuning has to be repeated whenever the goals or data sets are changed. Given this requirement to repeatedly run tuning, it is fortunate that (as shown above) tuning is so easy and so fast.

V. Threats to Validity

Is it a quirk of the implementation? This instability problem remained the same across any implementation of LDA. Figure 14, is with VEM method implemented in Spark. In this figure, x-axis represents different term overlaps and y-axis represents the raw stability scores. Dashed lines represents the untuned results and the solid lines represents the tuned results. We can see that tuning helped in achieving stable topic generation. The results of other datasets, can be referred at *https://goo.gl/UVaql1*. So it is not a quirk of implementation.

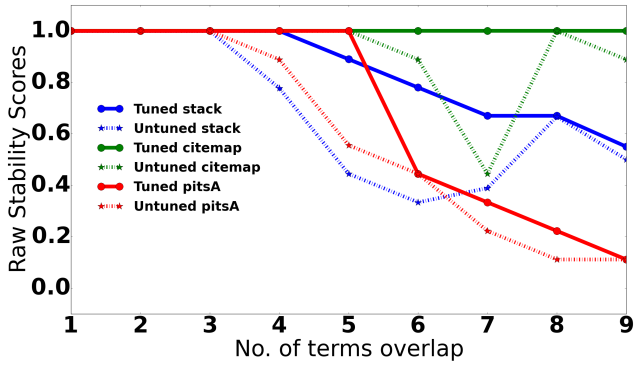

Figure 14: Spark Results

Is it a quirk of the sampling method used? In Figure 15, dashed lines represents the Gibbs implementation and solid line represents the tradition VEM method. The y-axis represents the delta improvement between tuning and untuned results. We can see that even after 5 terms, the stability score went down in both Gibbs Sampling and VEM. We also saw the same magnitude of improvements. So it is not

a quirk of a particular sampling method. Here results of only 3 datasets are shown. For other datasets, results can be referred at *https://goo.gl/faYAcg*. So it is not a quirk of implementation.

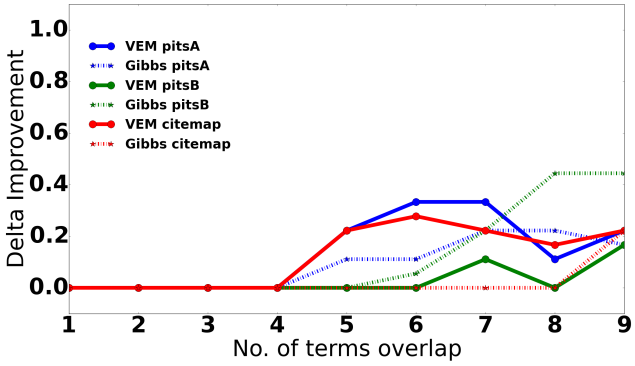

Figure 15: GIBBS vs VEM

Terminating criteria for DE From table III, we can see that after 300 evaluations, there was no improvement in the stability scores across all the datasets and it stayed the same.

Datasets\Evaluations	100	200	300	400
PitsA	0.9	0.9	1.0	1.0
PitsB	0.9	0.9	0.9	1.0
PitsC	0.9	1.0	1.0	1.0
PitsD	0.9	1.0	1.0	1.0
PitsE	0.9	0.9	1.0	1.0
PitsF	0.9	0.9	0.9	0.9
Ciemap	0.67	0.67	0.77	0.77
Stackoverflow	0.6	0.7	0.8	0.8

Table IV: Evaluations vs Stability Scores

VI. Conclusion and Future Work

Our exploration of the six research questions listed in the introduction show that when doing topic modeling, analytics without parameter tuning are considered harmful and misleading. As more data getting generated day by day, it is really necessary to do accurate topic modeling. Now, with the help of tuning, we can generate stable topics to quite a good extent.

This paper showed that tuning improved the stability scores of LDA, sometimes the improvement is quite dramatic (about 80%). This paper also highlighted that we can now select the right set of parameters for different datasets to get stable topics. This paper combined with Wei et al. [18] suggests that data miners should not be used off-the-shell with their default tunings. Now, we can use the more stable LDA to find features and fed into a classifer to get improved precision and recall [12], [61]

As to future work, it is now important to explore the implications of these stable topics generated by LDA in a product development. We can now actually work with other workarounds mentioned in the section II-C2 with classified datasets. To improve stability, we can even try to improvise the actual clusters to get better results.

This paper just investigated on stability of LDA using one optimizer. Hence, we can make no claim that DE is the best optimizer for all data miners. There are various other unstable data miners like Decision Tree Learning, Neural Networks, and Bayesian Learning [75] where optimizer can mitigate stability into all these miners.

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