Who Writes Wikipedia?: An Investigation from the Perspective of Ortega and Newton Hypotheses

Anamika Chhabra
Dept. of CSE,
Indian Institute of Technology Ropar, India
anamika.chhabra@iitrpr.ac.in

S. R. S. Iyengar
Dept. of CSE,
Indian Institute of Technology Ropar, India
sudarshan@iitrpr.ac.in

ABSTRACT

In any collaborative system, people do not contribute equally. This is particularly observed to be true for systems seeking to gather contributions from a large, diverse group of people. In such settings, it is seen that a sizable amount of contribution comes from a small group of highly-active users. While it is well-understood that such users are instrumental in the system's progress, the contribution made by a large group of less-active users is not sufficiently understood. Popularly called *masses*, these users comprise of the majority of the system's user base. It is, therefore, important to examine their worth in the system. The literature in this direction points towards two contradicting points of view with one acknowledging masses' contribution (*Ortega Hypothesis*) while the other deeming them unnecessary in the system (*Newton Hypothesis*). Given the large-scale collaboration facilitated by Wikipedia where a large crowd with a diverse skill-set and hence unequal contribution participates, a detailed investigation of the worth of masses becomes necessary for informed policy-making.

In this work, we examine whether masses help or hamper the knowledge-building in Wikipedia. We specifically consider their contribution across different contribution types pertaining to the insertion of new content as well as the administrative activities. We observe that although the individual contribution by masses is small, yet they contribute important pieces of knowledge to Wikipedia articles. The results indicate that the overall contribution of masses across several parameters even exceeds the contribution by elites. We also find that as compared to masses, highly-active users dominate the edits where no new content is inserted and only activities involving the up-keeping of the existing content such as restructuring or formatting take place. The results of the study may help in devising appropriate incentivization policies for Wikipedia and the collaborative systems in general.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**; *Collaborative and social computing design and evaluation methods.*

KEYWORDS

Masses, Ortega Hypothesis, Newton Hypothesis, Contribution inequality, Wikipedia

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1 INTRODUCTION

Advancements in the Internet have resulted in faster and easier means of sharing knowledge and solving problems. Successful crowdsourced portals such as Wikipedia, StackOverflow and Github are a testimony to this development. These portals are driven by voluntary contributions by a large online crowd. Further, the users in this crowd are guided by diverse psychological, social and cognitive reasons for using these portals. This diversity leads to differences in *how* as well as *how much* they use these portals [23, 43, 48]. As a result, a small group of users contributes a lot while a large number of users contribute very less [29, 41, 42, 48]. This inequality has been observed on many portals including Wikipedia [8, 43], Wikis [47], Usenet Newsgroups [59], Stackoverflow [58, 61], FLOSS communities [19, 52], Amazon [42] and blogs. Research has also shown that such inequality automatically emerges in collaborative settings [36, 40, 60]. Although the contribution inequality in collaborative settings has been observed, a question of general importance pertaining to inequality has not been sufficiently explored, particularly in knowledge-building communities: Given that a large fraction of contribution is made by a small number of users, what is the worth of the remaining less-active users? Popularly called *masses*, these users constitute the majority of the user base. Therefore, it is important to examine their relative worth in the system and the kind of contribution made by them. Alternatively, whether they lead to unnecessary noise in the system or do they render useful contribution. Knowing an answer to this question seems essential for making decisions regarding the system's incentivization policies and resource allocation.

1.1 Ortega vs Newton Hypotheses

There are two different schools of thought when it comes to attributing value to people with a low contribution in systems of collaborative nature. The first one, known as *Ortega Hypothesis*, regards a mass of low and medium-level contributors as being instrumental in the system's overall functioning [17]. The hypothesis is attributed to *Ortega Y. Gasset*, who in his book 'The Revolt of the Masses' [44] highlighted the importance of *masses* in any field.

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Ortega defines masses as average people who are not 'specially qualified'. The importance of masses was also supported by Florey [21] who asserted that there is nothing called a *breakthrough* in science, rather coming up with an excellent piece of work requires small inputs by a large number of people. Many other studies also support the capabilities of masses for doing good science [53]. On the other hand, an opposing hypothesis called *Newton Hypothesis* supports the view that only a bunch of top-level contributors, i.e., *elites* are sufficient for making progress in any field and the remaining mass of medium and low-level contributors may be safely discarded [17]. These opposing hypotheses have been examined in the scientific domain using bibliometric analyses [10, 17, 18, 33, 37], with most of them supporting Newton Hypothesis. At the same time, these bibliometric analyses are argued to suffer from several inaccuracies and limitations owing to the *non-uniform* citation practices of researchers [12, 33, 39]. The existing literature, therefore, reflects a lack of agreement regarding the worth of masses in collaborative systems in general.

With the recent development of online knowledge-building and problem-solving portals that rely on the contribution by a large number of users in the online crowd, it becomes necessary to appropriately examine and reward the contribution made by users at different levels. Our inability to understand and acknowledge users' importance with respect to their contribution has implications for incorrect and sub-optimal policies on collaborative portals.

1.2 Masses versus Elites in Wikipedia

Wikipedia is the best example of large-scale collaboration for building knowledge by volunteering crowd where an investigation of masses' contribution may provide helpful insights. Moreover, the scientific developments environment resembles the Wikipedia environment at a high level such that insertion, deletion, updation of new content is akin to a new research development adding to the existing developments, refuting them, or providing more on top of them [12]. Therefore, the debates prevalent in the former also apply to the latter setup. In addition to this, the need to evaluate the worth of masses on Wikipedia is also evident from the lecture delivered by Jimmy Wales back in 2005 at Stanford [57] where he discussed the need to examine 'who exactly is writing Wikipedia'. Although old, this lecture serves as one of the classic sources of the motivation behind this study. Wales spoke about a preliminary analysis made on Wikipedia as per which half of all the edits were made by just 2.5% of all the users. It was also expressed that this observation was entirely based on the number of edits only and detailed analysis in this context was yet to be conducted. However, at the same time, it was also speculated that this small group of 100 or 1000 users was possibly responsible for creating Wikipedia. This view is opposed to the common belief as per which, Wikipedia is the best example of large-scale collaboration demonstrating the *Wisdom of Crowds* effect [7, 50]. That is, it is written by a large number of users each providing a small amount of input. While Wales' lecture may provide surface-level inequality details with respect to edits, there are a few noteworthy points. Firstly, the *kind* of the contribution made to the articles in these edits was not considered in this preliminary analysis. Apart from variability in the amount of change that the article goes through in an edit, the edits could constitute a variety of activities ranging from the insertion of new content to fixing typos to reorganizing content. Therefore, the number of edits may not be the appropriate measure of contribution. This is supported by our analysis on the most-edited article 'George W. Bush' where we find that the number of edits made by the user who had added the maximum number of non-stop words - that also stayed till the final version - was merely one. Further, the value of the correlation between the number of edits by users and the number of non-stop words contributed by them was very low ($\sigma = 0.203$). Therefore, it is required to examine the kind of contribution made by users in their edits rather than the number of edits while investigating their worth. Secondly, to write a comprehensive piece of information, it is generally not possible for a small bunch of people to have all the knowledge about any given topic. Hence, a detailed analysis of the actual contribution made to the articles by the users' edits is required to evaluate their worth. A related rule in connection with participation inequality on the web is *1% rule*, also called *90-9-1 rule* [38, 42, 54]. As per this rule, only 1% of the users in an online community actively contribute content, the next 9% of the users sparingly contribute, while the remaining 90% do not contribute much and mainly lurk.

The above arguments incline towards the validity of the Newton Hypothesis. However, the contradiction between the Newton Hypothesis and the well-accepted 'Wisdom of Crowds' concept prevalent in collaborative settings sets the motivation for our exploration of masses' worth in Wikipedia.

1.3 Our Contribution

In this work, we explore the contribution of masses in Wikipedia articles to learn about their value in the system. We define masses to be users with a limited engagement as compared to the bunch of highly-active elites where the engagement is measured in terms of the number of edits made in the articles. We employ a percentile stratification strategy to split users by their engagement level. Specifically, this work handles the following research questions:

RQ1: How does the contribution of masses and elites differ when it comes to different contribution types in Wikipedia pertaining to the new content insertion?

RQ2: Low-contributing users are known to be responsible for a large number of edits that vandalize the articles' content. Apart from vandalism, what is the proportion of good content contribution by masses?

RQ3: Is there any distinction in the contribution by masses and elites with respect to activities involving up-keeping of the existing content such as restructuring and formatting of the content?

To handle RQ1, we measure the contribution of users belonging to different percentile classes across different contribution types such as words, images, references etc (Section 4). For answering RQ2, we use ORES [30] technique that provides real-time scoring of wiki edits using machine learning classifiers to know whether they were intended for vandalism or not. (Subsection 5.1). Finally, for handling RQ3, we examine users' contribution across different administrative activities that do not involve bringing in new information to the articles, rather focus on presenting the existing content well (Subsection 5.2). While working on these research questions, we particularly compare the contribution made by masses with that of the elite bunch. If Newton Hypothesis is to be true, the useful contribution made by masses should be negligible as compared to the elites. On the other hand, a substantial amount of helpful contribution by masses will indicate the claims of the Ortega Hypothesis to be true.

Our analysis presents useful insights with respect to the masses' contribution in Wikipedia. It shows that although the individual contribution by masses is small, they collectively provide an unignorable proportion of the useful contribution. In particular, we observe that the masses' contribution towards bringing in new information in the articles is even more than by the elites across several contribution types. Moreover, we find a higher inclination of elites towards performing activities such as restructuring and formatting as compared to masses. Overall, the results indicate that if the policies are built considering the views of Newton Hypothesis, i.e., a large mass of low contributing users may be safely discarded without any damage to the system, they may not be able to function well. The results suggest devising appropriate policies to harness the potential of masses.

2 RELATED WORK

The relative contribution of masses and elites concerning the kind of contribution that they make has not been sufficiently explored in fields other than a few studies in the scientific domain and open-source software communities. In FLOSS communities, masses and elites have been referred to as core and peripheral users and the focus of most work has been towards either the communications among these users or the shift of users from core to periphery and vice-versa [19, 22, 46, 56]. In these communities, both core and peripheral members have been found to be important for the success of the project, where core members make contributions such as writing functions for the software, while peripheral users perform tasks such as bug fixing etc [46].

In the direction of inequality of contribution on Wikipedia, Arazy and Nov. [8] examined local and global inequality on Wikipedia where the terms local and global refer to article-specific inequality and Wikipedia-wide inequality respectively. The authors concluded that both these inequalities impact the quality of articles and facilitate coordination. Hence they argued that both these inequalities are important for Wikipedia. A study that was carried out on Wikipedia in the context of the worth of different kinds of users was performed by Anthony et al. [5] who compared the quality of contribution made by registered and anonymous users. The authors observed that the highest quality contributions in Wikipedia articles come from a huge number of one-time contributors who do not even create an account. The authors call these infrequent anonymous users as 'Good Samaritans' and the registered, frequent users as 'Zealots'. The focus of this study was on whether the users were registered or anonymous rather than the amount of their contribution. Another initial study performed for checking who contributes to Wikipedia was a preliminary analysis of a few articles by Aaron Swartz that he published on his blog [51]. The author counted the number of characters contributed to a given article by its users and showed that many of the top contributors - as per the number of characters contributed - were not even registered. Moreover, most of them had made very few edits in the given article. Further, the contributors with the most edits had added the least number of characters to the articles. In comparison to this preliminary work, our study provides an in-depth analysis of articles where we examine users' contribution not only in terms of words but also across other contribution types such as images, references as well as administrative activities. Kittur et al. [34] studied the temporal distribution of edits made on Wikipedia by *elite* users and *common* users. They characterized all admin users as well as those making more than 10K edits on Wikipedia as elite users. The authors modeled contribution as the number of words added and removed. Apart from having a core group of high activity editors, the authors also highlighted the importance of having a periphery of many low activity editors in articles. They also observed a shift in workload from elite users to common users with time. Given a diverse set of ways in which the users can contribute to Wikipedia, instead of examining contribution only in terms of the number of words, our study provides a multi-dimensional perspective by exploring several other contribution types as well. Further, Priedhorsky et al. [45] studied who contributes value to Wikipedia where the value was measured in terms of *Persistent Word Views (PWV)*. These PWV were used as a proxy to determine the number of times any given word introduced by an edit is viewed. The authors concluded that less active contributors add very little over the overall value (PWV) in Wikipedia while a small proportion of contributors add the vast majority. However, the authors' notion of PWV is based on an article view. It is based on the assumption that each time an article is viewed, each of its words is also viewed. Our analysis, on the other hand, examines users' contribution to a given Wikipedia article where such a notion of the value of content may not be applicable. Our analysis based on measuring content's importance with respect to quantification across contribution types thus differs from this work in methods as well as goals and provides a different perspective.

The contrasting conclusions made in the existing studies on Wikipedia - where a few studies acknowledge masses' contribution while the others deem their contribution to be negligible - indicate the persisting debate regarding who writes Wikipedia as well as the importance of more in-depth analyses on this topic. In contrast with the previous studies, our work examines the contribution of users in Wikipedia across several dimensions and provides a fresh perspective to the ongoing debate of the contribution by elites and masses in Wikipedia. The study highlights certain aspects of the contribution by masses in Wikipedia that were not explored by the previous studies, that is, the contribution across different contribution types. Additionally, while highlighting the damage introduced by masses, the study underlines a large proportion of good contribution coming from masses, thus emphasizing the employment of improved filtering techniques to gather more contribution by less-active users.

3 DATA SET

The unit of contribution in Wikipedia has been considered to be the number of edits in many past studies[1] [24], except a small number of studies considering other parameters such as the amount of time

[1]https://en.wikipedia.org/wiki/Wikipedia:Editcountitis

spent [27], views' count [45] and whether the edits are preserved or rolled back subsequently [1]. However, our analysis will reveal that the number of edits may not be the sole indicator of the amount of contribution made by users in Wikipedia and that the kind of changes made to the articles in these edits need to be considered.

To perform a detailed investigation involving the changes made at the level of revisions, we gathered the complete revision history of 100 most-edited articles of Wikipedia. For this, we used KDAP library[2] which provides tools to extract and analyze the data of Wikipedia articles. This study performs article-specific analyses, i.e., each article is considered as a representation of a community of users working towards a common goal. This has been done by several past studies and helps in estimating larger-scale scenarios [35, 51]. We did not consider 'List' articles such as 'List of Impact Wrestling personnel' that contain links to other Wikipedia articles due to a different article structure and a disparate method of creation. The data consists of articles from a wide range of topics such as people, countries, religions etc. The data about each article comprises of their complete revision history since their inception to the date of data collection in XML format. For each revision, it contains details such as username or IP address, userid, revision id, the content of the article after the edit, timestamp of the revision, the article size in bytes etc. Descriptive statistics of the data set are presented in Table 1. All the articles (except '*Syrian Civil War*' that started in 2011) were created before 2006, with precisely 65 articles that started in Wikipedia's inception year, i.e., 2001. Despite being the top-edited articles, many of them belonged to 'B' and 'C' quality grades, indicating that the number of edits may not be the sole criterion for judging the quality of the content.

Measure	Statistics
Total Revisions Analyzed	19,60,251
Total Users Analyzed	6,16,750
Maximum Number of Revisions per article	46,408
Minimum Number of Revisions per article	15,459
Maximum Number of Users per article	14,629
Minimum Number of Users per article	3,232
Number of FA Articles	20
Number of GA Articles	33
Number of B Articles	36
Number of C Articles	11

Table 1: Wikipedia Data Set Basic Statistics. (FA, GA, B and C are articles' quality grades.)

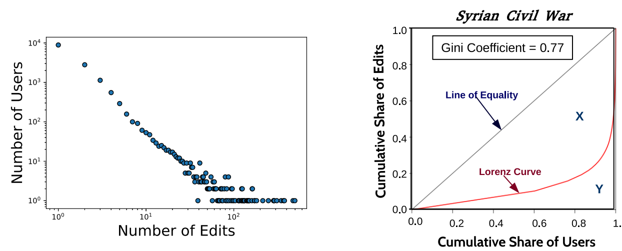
We computed the Pearson correlation coefficient (ρ) between a few parameters corresponding to the articles (See Table 2). The intuition that more users are likely to lead to more revisions, was confirmed by a high correlation ($\rho = 0.73$) between the number of users and the number of revisions. However, a low correlation of 0.26 between the number of revisions and the article size indicates that more revisions might not lead to more content in the article. This supports the fact that many of the revisions in Wikipedia articles improve the quality of the content, rather than increasing the content size. Further, as shown in Table 2, a very low correlation was found between the number of users and the size of the article; the article age and the number of users; and the article age and the size of the article.

[2]www.github.com/descentis/kdap

Variables	Pearson Correlation
#Revisions and #Users	0.73
#Revisions and Size	0.26
#Users and Size	-0.03
Age_in_days and #Users	0.09
Age_in_days and Size	0.07

Table 2: Correlation values between various data set parameters.

3.1 Inequality of Contribution



(a) **(b)**

Figure 1: (a) Distribution of the number of users with respect to the number of edits made by them. (X and Y axis are log-scaled). (b) Lorenz Curve for the article Syrian Civil War showing Gini coefficient of 0.77. Both the plots depict highly unequal contribution made by users in Wikipedia articles.

To examine the contribution inequality present in the articles of the data set, we plotted the number of users with respect to the number of edits made by them in the given article. It was found that a large number of users were making only very few edits. On the other hand, only a small bunch of users were making a large number of edits. As an example, Figure 1(a) shows the distribution obtained for the article 'George W. Bush' exhibiting a power-law behavior, where the axes are log-scaled. In this article, around 61% of the users made only one edit each. Another measure to compute inequality among values of a frequency distribution is *Gini Coefficient (G)* which ranges from 0 ('perfect equality') to 1 ('maximum inequality'). The method of computation of G may be understood using *Lorenz Curve* that plots the cumulative share of edits with respect to the cumulative share of users. G is computed as the ratio $(X/X+Y)$ where X is the area between the line of equality (i.e., when everyone contributes equally) and the Lorenz curve, and Y is the area between the Lorenz curve and the X-axis. This method has been employed by a few past studies for computing inequality of contribution in Wikipedia articles [34, 47]. The average G for the articles in our data set was found to be 0.61 with a maximum of 0.76 for the article *'Syrian Civil War'* (See Figure 1(b)). High values of G further confirm a high inequality present in Wikipedia articles and point towards a setting where a small bunch of users is making a sizable fraction of edits.

3.2 Users' Division into Percentile Classes

To examine users' contribution across a spectrum, we divided the users of each article into six percentile rank classes based on the number of edits made by them. The method of percentile classes has been used by many works in the past to identify the activity level of users in the system. For example, Bornmann et. al [10] and

Green [28] used it in their work on bibliometric analysis where they divided the research papers into percentile classes based on their citation count. We named the percentile classes as lt_{50}, bt_{50-75}, bt_{75-90}, bt_{90-95}, bt_{95-99} and gt_{99} which contained users with less than 50, 50 to 75, 75 to 90, 90 to 95, 95 to 99 and greater than 99 percentile as sorted based on the number of edits made by them. Clearly, these classes reflect the extent of users' interaction with the portal, with highly-active top 1% of the users belonging to the class gt_{99}.

Category	Average of Min edits (SD)	Average of Max edits (SD)
lt_{50}	1 (σ = 0)	1 (σ = 0)
bt_{50-75}	1 (σ = 0)	2 (σ = 0.14)
bt_{75-90}	2 (σ = 0.14)	4 (σ = 0.76)
bt_{90-95}	4 (σ = 0.78)	7 (σ = 1.66)
bt_{95-99}	7 (σ = 1.66)	32 (σ = 11.55)
gt_{99}	32 (σ = 11.79)	1091 (σ = 834.99)

Table 3: Average of minimum and maximum number of edits made by the users belonging to each percentile class across the articles. More than 90% of the users had made less than 4 edits.

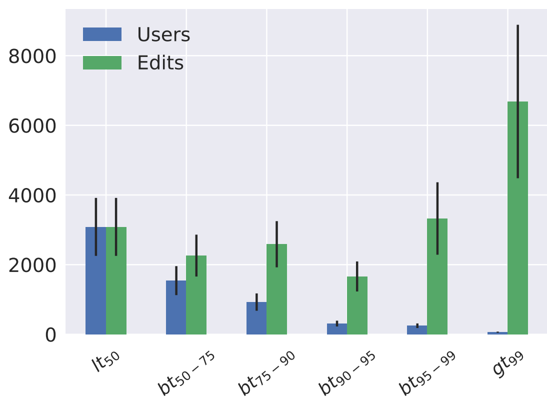


Figure 2: Number of users and the total number of edits made by the users of each percentile class. From left to right, the number of users decreases, while the number of edits increase, with the right-most class containing the highly-active 1% users.

Table 3 shows the average of the minimum and the maximum number of edits made by the users in each class. As can be seen, the number of edits made by the users of the class lt_{50} - that contains 50 percent of the least contributing users - was only 1. We also see that more than 90% of the users had made less than 4 edits. The last class, i.e., gt_{99} contains the most-active 1% of the users. The maximum number of edits made by a single user in any article was observed to be as high as 4768 (for the article '*Ulysses S. Grant*'). Figure 2 further shows the total number of users belonging to each class as well as the edits made by them averaged across the articles. As each user of the class lt_{50} is making a single edit, the number of users and edits in this class are equal. Further, towards the right of the spectrum, the class gt_{99} has only 1% of the users, while the number of edits made by them is quite high. These 1% users are considered the most prolific [9] while the bottom 90% of the users are considered the least active in the system. Additionally, considering the 90-9-1 rule [38, 41, 54] as well as for the purpose of checking the Ortega hypothesis, it will be helpful to have a higher-level categorization on top of the spectrum obtained through the percentile classes. We, therefore, define the bottom 90% of the users (i.e., from classes lt_{50} to bt_{75-90}) as masses, top 1% users as elites (i.e, the gt_{99} class) and the middle 9% users (i.e., the classes bt_{90-95} and bt_{95-99}) to be 'Medium-Level Contributors (MLC)' to enable an efficient comparison. This categorization on top of the percentile classes will help in obtaining a broader perspective apart from a comparison across a finer-grained spectrum. It is important to remark that the delineation between masses and elites is a subjective decision. Although there are a few subjective measures devised for the identification of masses (or core members) in FLOSS communities [20], there are no quantitative measures in general. We have used the existing theories and practices to divide the spectrum of users into categories. As per our categorization, it can be seen that the users in masses are making less than 4 edits while the number of edits made by the users in the elites category goes up to as high as 1091 on an average. For better visualization, we would be showing a comparison of various parameters among the categories masses, MLC and elites, especially focusing on the comparison of users on the two extremes, i.e., masses and elites.

4 CONTRIBUTION ACROSS DIFFERENT CONTRIBUTION TYPES (RQ1)

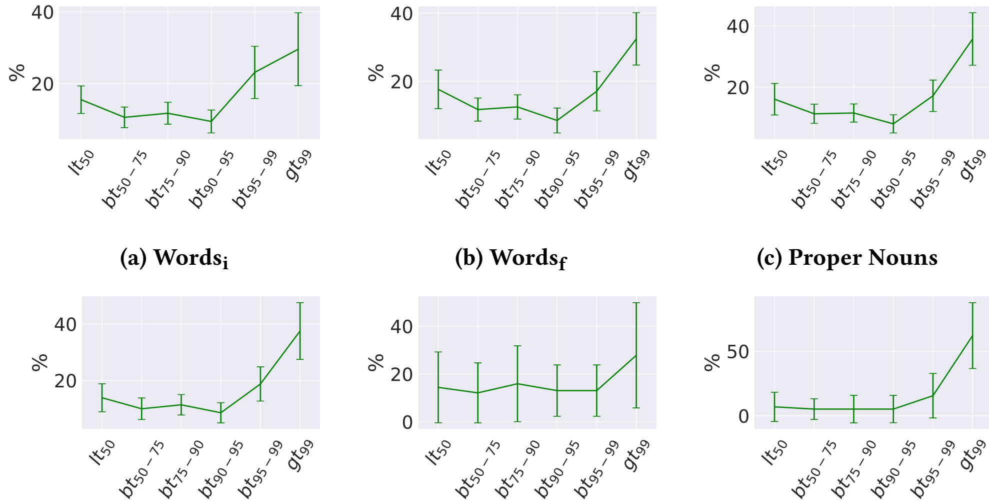
The freedom of editing is at times misused by Wikipedia editors by some of them indulging in different forms of vandalism, one of them being *Mass Deletion (MD)*[3] [2, 25, 45, 55]. Vandalism is difficult to avoid in a crowdsourced environment. Further, the cases of vandalism are observed to be mostly attempted by *common* users [34] as compared to elite users, where common users are low-edit users. However, on Wikipedia, they are observed to be handled within no time [55] by watchful users by reverting the objectionable or irrelevant edits. In the articles of our data set, we find that masses are involved in 84.57% of all the MD cases. Further, out of all the reverts[4], 69.01% were made on the edits of masses.

A high proportion of cases of vandalism by masses indicates that they seem to misuse the resources available on the portal and hence the system might possibly do better by discouraging their participation. However, given that masses are a sizable fraction of the total user base, both altruistic, as well as destructive elements, are likely to be present. Therefore, while there may be a few vandals trying to create damage, there is also a possibility of masses comprising of users that provide constructive contribution as well. This requires us to check for parameters pertaining to the useful contribution to the articles. Since, the creation of a Wikipedia article involves different kinds of activities such as insertion of text, images, references, etc, we examine the contribution by the users across the parameters as given below:

Words Inserted ($Words_i$): Insertion of knowledge in terms of new words is one of the most important contributions to an encyclopedia. We, therefore, analyze each revision and track the new (non-stop) words inserted into the articles by each user.

[3] Converting an article to a version that is at least 90% smaller than the previous version.

[4] We analyzed reverts by computing the MD5 checksum of the revisions' content which is a common method of finding reverts in Wikipedia articles [49].



(a) Words$_i$ **(b) Words$_f$** **(c) Proper Nouns**

(d) Factoids **(e) References** **(f) Images**

Figure 3: Percentage contribution across various parameters over the spectrum obtained by percentile classes.

Words that stay in the final revision ($Words_f$): Wikipedia articles are always in-flux, with new content added on top of the existing content. In doing so, the content that is not relevant is quickly removed in the subsequent revisions. Therefore, a piece of text that stays till the final revision, indicates its quality [3]. Hence, for each word in the final version of each article, we trace the user who adds this word *first* in the article.

Proper Nouns (PN):. Words in any piece of text may carry varying importance. For example, for an encyclopedia, proper nouns are more important words than the verbs, adjectives, etc as they introduce new subjects into the article connected to its topic. Therefore, we track the users who first introduce the proper nouns in the articles.

Factoids (Internal Links): Every Wikipedia article is composed of details about some key pieces of information related to its topic. We term these pieces as *factoids*. When one factoid is introduced, more information connected to it is added subsequently [15]. However, automatic identification of these factoids in a piece of text may not be straightforward.

Wikipedia articles are connected to each other through *internal links*, which point to other Wikipedia articles. The fact that a Wikipedia article has been created for a term or phrase indicates its importance. Therefore, the internal links in a Wikipedia article may be used as a proxy for finding important pieces of information. We, therefore, harness this property to identify the factoids in an article. For each factoid, we then trace the user by whom it was introduced in the article for the first time.

Images: Apart from the textual contribution, Wikipedia users contribute in the form of images. We, therefore, record the users' contribution with respect to the insertion of images.

References: Another useful contribution made by Wikipedia users is the insertion of sources of the information present in the articles in the form of references. The presence of a reference for a given piece of information also maintains *Neutral Point of View* (NPOV)[5] and verifiability[6] policy of Wikipedia. Hence, they are an important form of meta-knowledge in the articles.

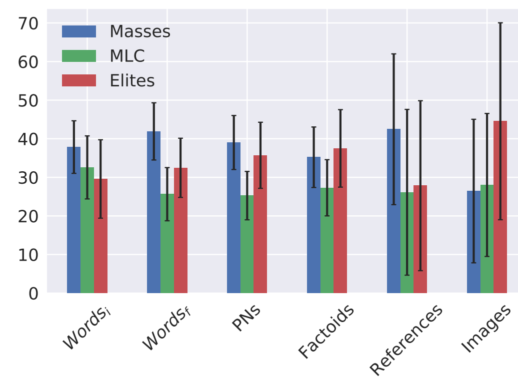
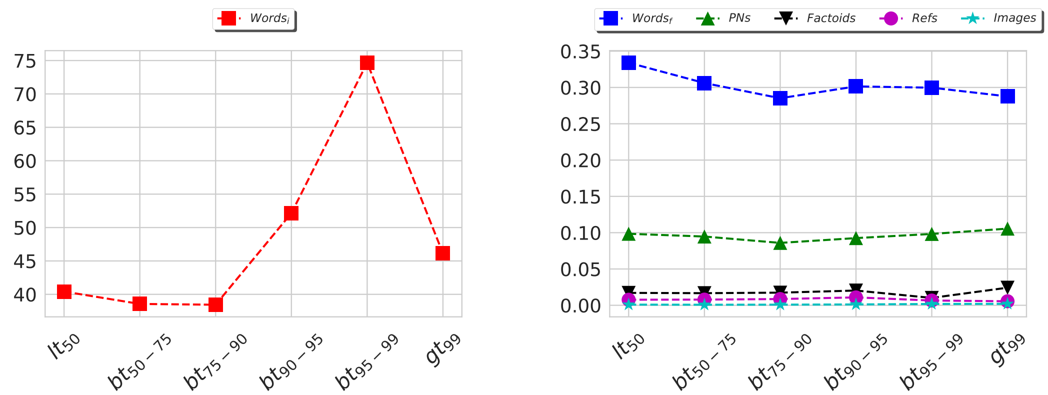


Figure 4: Overall proportion of contribution across various parameters made by the users of masses, MLC and elite categories. Except for images, the contribution by masses is found to be significantly higher than the bunch of highly-active elites with $p < 0.001$ for all parameters.

These are a few parameters pertaining to the new content insertion in the articles and may help in examining the contribution of users belonging to different classes. It may be noted that for tracking the users responsible for contributing to the above parameters, we gave the authority to the user who introduced the corresponding content first in the articles.

[5]https://en.wikipedia.org/wiki/Wikipedia:Neutral_point_of_view
[6]https://en.wikipedia.org/wiki/Wikipedia:Verifiability



(a) **(b)**

Figure 5: (a) Average Number of words inserted per edit of each class. The per-edit contribution by users of class gt_{99} was not very high indicating a possibility of their edits being more towards administrative activities. (b) The average number of $Words_f$ (i.e., Words that stay till the final version), PNs (i.e., Proper Nouns), $Factoids$, $References$ and $Images$ inserted by each edit made by users of each class. The per-edit contribution by users of less-active classes across these parameters was either higher or comparable to that of highly-active classes.

Figure 3 shows the percentage contribution by each percentile class for the above parameters. For the purpose of Ortega hypothesis, we need these values aggregated with respect to masses, MLC and elites. Therefore, the bar plot in Figure 4 shows the aggregated values. It is interesting to see that masses' contribution across all parameters except images was observed to be either comparable or more than the contribution by elites ($p < 0.001$). Only in the case of images, elites were found to be making a higher contribution (44.53 ± 25.52, $p < 0.001$) than masses (26.44 ± 18.60, $p < 0.001$). This is expected to be due to the annual photo competitions[7] that Wikipedia conducts regularly to balance the lack of visual representation. Figure 4 shows that although the individual contribution by the users in masses is very small (< 4 edits), put together they are providing a good proportion of useful contribution, which in most cases even surpasses the contribution by elites.

As the number of edits made by each class is variable (See Figure 2), checking the per edit contribution of users from the six classes may provide additional insights. We, therefore, computed the average contribution across these parameters by each edit of the users of the classes as shown in Figure 5. Figure 5(a) shows the per-edit contribution in the insertion of new non-stop words, and Figure 5(b) shows the per-edit contribution in the remaining five parameters. In Figure 5(a), we see that the users of class bt_{95-99} are adding the maximum number of words per edit. However, the contribution per-edit of class gt_{99} is not as high. Fig 5(b) shows that in the rest five parameters, the difference between per-edit contribution by users of different classes is not very high. Moreover, lt_{50} users' contribution is even higher than gt_{99} users across parameters such as $Words_f$, i.e., words that stay till the final version and the references. This shows that,

> Although masses indulge in vandalism, they also provide a large proportion of the useful contribution. In other words, they bring in new pieces of knowledge into the articles in different forms such as text, references etc., which across most parameters, is even more than the contribution by elites.

5 CASE STUDY

We further performed a case-study on the top-edited article 'George W. Bush' that involves two in-depth analyses in the direction of examining the quality and the contribution towards administrative activities by different classes.

5.1 ORES (Objective Revision Evaluation Service) analysis (RQ2)

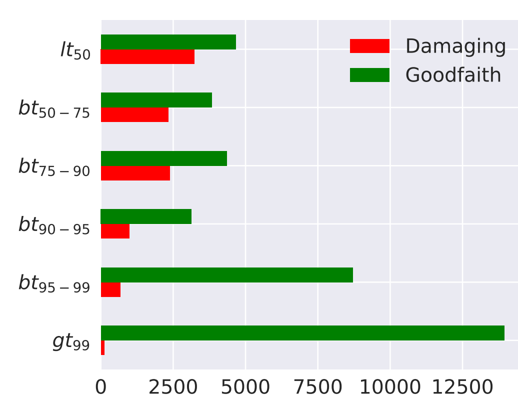


Figure 6: ORES analysis of the article 'George W. Bush' showing the total number of damaging and goodfaith edits made by users of each class. Although the number of damaging edits by lower contributing classes is high, they also contribute a large number of goodfaith edits.

[7] https://commons.wikimedia.org/wiki/Commons:Photo_challenge

Category	Total damaging	Total Goodfaith
Masses	7955 (81.78%)	**12849 (33.26%)**
MLC	1653 (16.99%)	11835 (30.64%)
Elites	119 (1.22%)	**13941 (36.09%)**

Table 4: Summary of ORES analysis of the article 'George W. Bush' for the high-level categories. (The values to be read column-wise.) For example, out of all good-faith edits, masses contributed 33.26%, MLC contributed 30.64% and the elites contributed 36.09% depicting that a large proportion of good contribution coming from masses.

ORES [30] is a web-service that uses machine learning models and provides an estimate of the quality of a given revision. The service provides probability scores for whether a given revision is potentially *damaging* or was made in *goodfaith*. Edits that are likely to be eventually reverted are termed as damaging, where the probability of a given edit to be reverted is computed based on the sample data of edits that were reverted. We performed the ORES analysis on all the revisions of the article 'George W. Bush' to compute the number of damaging and goodfaith revisions made by the users belonging to each class. As shown in Figure 6, the number of damaging edits by the lower classes are quite higher than by the top classes. Contrasting values were observed for the number of goodfaith edits. However, aggregating the values as shown in Table 4, we find that

> Despite a large proportion of damaging edits by masses, there is also a high proportion of goodfaith edits from the masses (33.26%), which is comparable to the proportion of goodfaith edits made by the elites (36.09%).

These observations suggest setting the right policies to filter the contribution from masses, while also encouraging more contribution from them, as it constitutes a large portion of the good contribution.

5.2 Contribution Across Administrative Activities (RQ3)

It has been observed that in collaborative set-ups, out of all the activities available to contribute, users tend to choose a subset of them [13, 14, 16]. Therefore, it may be possible that a user who is contributing heavily in one of the activities, is contributing infrequently to the others and vice-versa. In Section 4, we observed that despite a large number of edits, the amount of contribution towards the insertion of new knowledge by elites is not very high. Therefore, it may be helpful to investigate that other than the activities involving new content insertion, what other kinds of activities are performed by elites. Performing the structuring and formatting of the existing content is one of the activities that is sometimes performed by Wikipedia contributors. The detailed revision history of the articles enables us to examine the edits at the level of such changes. We, therefore, computed the contribution made by the users of the two extreme classes, i.e. lt_{50} and gt_{99} across the activities not involving the insertion of new content. For each revision made by the users of these two classes, we particularly examined how many of them were of the following types:

(1) **No insertion (*No_in*)**: In such revisions, no new content was inserted. Only the removal of content took place.
(2) **Only Structuring (*Struct*):** In these revisions, new content was not inserted, however, positioning of the existing content was changed to enhance the structuring of the existing content.
(3) **Only Formatting (*Format*)**: In such revisions, various cases of formatting were observed. These cases included introducing links to other Wikipedia articles, links to other websites, making text bold or italic, introducing headlines and sub-headlines, introducing enumerated or unordered lists, indentations etc.

We checked for the above cases of revisions out of the edits made by the users of two extreme classes, viz. lt_{50} and gt_{99} for 'George W. Bush' article. There were 7,315 lt_{50} users contributing the same number of revisions and 146 gt_{99} users contributing 13,999 revisions for this article. Figure 7 shows the proportion of the above three types of revisions obtained for the two classes. We see that the above types of revisions by the users of the class gt_{99} were found to be more in proportion than the lt_{50} users. In particular, out of all the edits made by gt_{99} users, 26.49% of them did not insert anything into the articles and only removed content from the articles. Further, 5.33% of the revisions only restructured content, with no new insertions or removals, while 28.77% of the revisions made by them only focused on improving the formatting of the existing content. The cases of revisions involving such activities by the lt_{50} users were found to be quite lesser, i.e., 11.22%, 4.70% and 22.35% respectively. These observations provide a possible reason for a low contribution to the new content insertion by elites as observed in Figure 4.

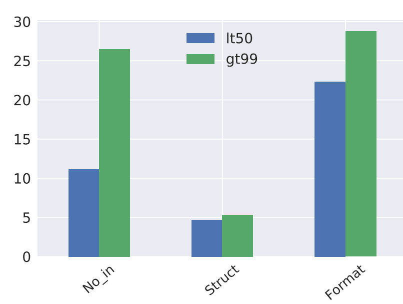


Figure 7: Proportion of edits made by the users of two extreme classes, i.e., lt_{50} and gt_{99} belonging to the types: No_In: (i.e., No Insertion, only removal), Struct: (i.e., Structuring) and Format: (i.e., Formatting). It shows highly-active users making more edits where no new insertion happened and only formatting or restructuring was done.

This analysis along with the ORES analysis indicates that,

> The elites make lasting edits, which are mostly not reverted as often as the edits by masses. However, a good proportion of their contribution is in performing the activities that help in maintaining the article structure, removing irrelevant information and up-keeping of the articles.

The contribution involving maintenance activities is unequivocally essential for the quality as well as the readability of the content. However, when it comes to the creation of an encyclopedia, such contribution clearly seems secondary. The primary contribution, i.e., the introduction of the new information, is made in a good proportion by a large number of users in masses as observed in Figure 4.

Measure	Masses	Elites
Total Words Inserted	37.84%	29.57%
Words in Final Revision	41.90%	32.46%
Proper Nouns	39.02%	35.71%
Factoids	35.20%	37.50%
References	42.52%	27.83%
Images	26.44%	44.53%

Table 5: Comparative Summary of masses' and elites' contribution. All the values are statistically significant with $p < 0.001$. Masses' contribution across many parameters was found to be more than elites.

6 DISCUSSION

Investigating the worth of masses in a system is a question of general importance as masses dominate the system's user base. This question has relevance not only for knowledge-building systems like Wikipedia, rather for any system driven by the contribution of a large number of users. In case it is observed that they do not provide any useful contribution, the administrators may focus on directing the resources towards a much smaller bunch of highly active elites. On the other hand, if masses provide such value to the system that is otherwise difficult to be achieved through the bunch of elites, they are required to be encouraged through the right policies. Ignorance of the actual picture may lead to skewed incentivization policies and an improper resource allocation thus obstructing in harnessing the users' full potential.

Our study on Wikipedia shows that although the individual contribution of a majority of users on these portals may be small, put together they provide a large fraction of useful contribution. Table 5 shows a comparative summary of the results obtained from the analysis. It shows that in many aspects, masses outperform the bunch of highly-active elites on Wikipedia. They are observed to be providing a large fraction of the new content, which is one of the most important kinds of contribution for an encyclopedia. The reason for such behavior is understandable. It is difficult for a small bunch of expert users to be having all possible knowledge about any particular article. Small pieces of diverse and lesser-known knowledge about the articles are more likely to come from a large group of users, i.e., masses. Our findings, thus, incline towards the validity of the Ortega hypothesis in knowledge-building systems. Further, if these systems are built following only the claims of the Newton Hypothesis, they might not be able to achieve their intended purpose. This being said, it is important to remark that the study, while highlighting the importance of masses, does in no way attempt to undermine the focused contribution made by elites. Unequivocally, the elites manage and set the direction for other users to contribute (e.g. in Wikipedia [35] and FLOSS [19]) which is crucial for the system to function. Therefore, it seems that clear support or rejection of the existence of any one of the hypotheses might be an over-claim; it may be possible that the two hypotheses are not mutually exclusive and that a combination of these may be true in practice.

There may be a few limitations of the study. Firstly, the analysis considers each Wikipedia article as a standalone community. Therefore, there may be cases where a user is making a large number of edits overall, but very few edits in the article under consideration. This might reflect a need to examine the entire English Wikipedia to judge each user's overall contribution, thereby, considering the English Wikipedia to be a community. However, it may further be possible that a user who is making a small amount of contribution in English Wikipedia, is making more contribution in other languages Wikipedias or for that matter in other knowledge-sharing portals, thus cascading the initial concern of what should represent a community. Nevertheless, given that the users contributing to a given Wikipedia article in a way share similar domain knowledge and work towards a common goal of improving the article's content, they may be considered a sufficient proxy for a community. Moreover, the users contributing to each Wikipedia article engage in a large number of complex interactions with the article's content[8]. Wikipedia articles, thus, may be safely used for examining the signatures and behavior of users in a community at a comparatively larger scale. Further, considering that the most-edited articles are likely to provide a detailed testing-ground for an article-specific analysis than the articles with a small number of edits, this work examines the most-edited articles. The contribution patterns of elites and masses may or may not differ when we move away from the most-edited articles.

In general, the study highlights that online communities are not egalitarian and hence suggests tapping the potential of users through stratified mechanisms. Most of the collaborative portals employ various incentivization procedures that award points, badges or special privileges to users based on their contribution [4, 11, 26]. These procedures are known to affect users' engagement level and style [6, 31, 32]. Therefore, they need to be carefully drafted, as inappropriate incentivization policies may hamper the portal's functioning [39, 61]. The existing policies have largely been built acknowledging only the contribution by elites, while not giving much weight to the majority of mass users [26]. For instance, Amazon and Yahoo Answers employ a *relative* reward mechanism by acknowledging the top contributors. Such policies discourage a huge cohort of users who may not be able to reach these standards with their little piece of contribution. This may result in inefficient utilization of the potential of contributors making the 'Wisdom of crowds' [50] effect fade away. To handle this, the progress monitoring mechanisms may bracket the users in different strata as per their contribution and may incentivize them differently. This may be achieved through milestones with gradually scaling difficulty rather than a uniform and an evenly-spread reward system. A relatively easily achievable reward system for beginners may encourage them to contribute more. A few measures could be taken at the interface level as well. For instance, the interface design should be such that it eases usage for users visiting less often as well as facilitates advanced tools and features for more active and dedicated users. Another guideline requiring both interface and policy level changes

[8]The number of revisions for the article 'George W. Bush' was found to be more than 46,000.

involves highlighting not only the top users on the interface but also those that are doing well out of the low contributing cohort. Such a space on the interface dedicated for pacing up newcomers may help in retaining useful information providers in these portals. Additionally, as we have seen in Table 4, apart from the useful contribution, masses also cause some amount of damage to the system. Therefore, it is required that automatic filtering mechanisms be employed to inspect the contribution made by less-active users as well as newcomers on the portals. Further, an encouragement of supervisory roles - such as *watchers* in Wikipedia - will help in minimizing the damage due to destructive contribution while still encouraging the constructive contribution by masses.

7 CONCLUSION

The study revisits the prevalent belief that *only* top 1% of the users in peer-production communities are sufficient for running the system, as proclaimed by the existing rules such as 1-9-90 rule and Newton Hypothesis. The analysis highlights that in Wikipedia, the masses who interact with the portal very infrequently, are *also* required in the system for their small but useful pieces of contribution in bringing new pieces of knowledge to the articles. The results endorse the claims of the Ortega hypothesis in Wikipedia and recommend examining and reconsidering system policies made solely based on Newton Hypothesis.

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