

# Tagging Scientific Publications using Wikipedia and Natural Language Processing Tools. Comparison on the ArXiv Dataset

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**Abstract.** In this work, we compare two simple methods of tagging scientific publications with labels reflecting their content. As a first source of labels Wikipedia is employed, second label set is constructed from the noun phrases occurring in the analyzed corpus. We examine the statistical properties and the effectiveness of both approaches on the dataset consisting of abstracts from 0.7 million of scientific documents deposited in the ArXiv preprint collection. We believe that obtained tags can be later on applied as useful document features in various machine learning tasks (document similarity, clustering, topic modelling, etc.).

**Keywords:** tagging document collections, natural language processing, Wikipedia

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## 1 Introduction

In this work, we present a study of two methods for contextualizing scientific publications by tagging them with labels reflecting their content. First method is based on Wikipedia and second approach relies on the noun phrases detected by the natural language processing (NLP) tools. The motivation behind this study is threefold.

First, we would like to develop new meaningful features for document content representation, which will go beyond basic bag of words approach. The tags can serve as such features, which later on can be employed for various applications, e.g., determining document similarity, clustering, topic modelling, and other machine learning tasks. After the appropriate filtering and ranking, obtained tags can also be used as keyphrases, summarizing the document.

Our second goal is the comparison of the two approaches to tagging publications with labels reflecting their content. We employed two methods, abbreviated hereafter NP and WIKI. The NP approach relies on the tags' dictionary generated from *noun phrases* detected in analyzed corpus using NLP tools. Similar approaches based on NLP techniques were used, e.g., for keyphrase extraction [1,2]. Conversely, the WIKI method relies on readily available dictionary of meaningful tags coming from filtered Wikipedia entries. Wikipedia was already applied in many studies on conceptualizing and contextualizing document collections. To name just a few recent examples, applications include clustering [3,4], assigning readable labels to the obtained document clusters [5,6], facilitating classification [7], or extracting keywords [8]. However, not much is known about the effectiveness of Wikipedia when it comes to processing scientific texts. Especially, in the case of collections covering broad range of disciplines, there is a lot of domain-specific vocabulary involved, usually beyond the scope of interest of the average Internet user, i.e., Wikipedia reader and author. Example of such a broad collection is the ArXiv preprint repository [9]. Manually creating the "gold standard" dictionary of meaningful tags is a difficult task, as it would require a large team of highly qualified experts from different disciplines. Therefore, we find that it is insightful to compare the results obtained using the WIKI method with the independent competitive NP approach. Interesting questions include the relative effectiveness of the WIKI/NP methods for different fields of science, the average number of tags per document in both methods, the typical tags missed by one of the methods and included in the other, etc. Such a comparison can also show if the methods are complementary or if one is superior than the other.

The third goal of this work is the analysis of statistical properties for obtained tags. We look at distributions of number of different tags per document. We also examine, if the Zipf's law is valid for the rank-frequency curves of labels detected by both methods. It is also interesting to check, if the aforementioned statistical properties are qualitatively similar for the NP and WIKI tags.

The paper is organized as follows. In Sect. 2, the employed datasets are described. Afterwards, in Sect. 3, we provide the details of both tagging procedures — the one based on Wikipedia (WIKI) and the complementary approach based on the noun phrases (NP). Comparison of both methods is the subject of Sect. 4. Statistical properties of the obtained tags are investigated in Sect. 5. The paper is summarized in Sect. 6.

## 2 Employed Datasets

The ArXiv repository [9] was started in 1991 by a physicist Paul Ginsparg. Originally, it was intended to host documents from the domain of physics. However, later on it gained popularity in other areas. Currently, it hosts entries from physics, mathematics, computer science, quantitative biology, quantitative finance, and statistics. The content is not peer-reviewed, however, many documents are simply preprints, published later on in scientific journals or presented

on conferences. In this work, we analyze the ArXiv publications metadata harvested via OAI/PMH protocol up to the end of March 2012. This made up to over 0.7 million of documents. For our study, the distribution of the manuscripts across domains is of high interest. For this purpose, we used `<setSpec>` field of the ArXiv XML format, which gives a coarse-grained information about the field of document. All the ArXiv coarse-grained categories together with their full-names are presented in Table 1. The percentage of documents in each category is displayed in Fig. 1. The presented values do not add up to 100% since multiple categories per document are allowed. In this study, we have also employed Wikipedia. We have used raw data available from the Wikipedia dump website, dated 2013.01.02.

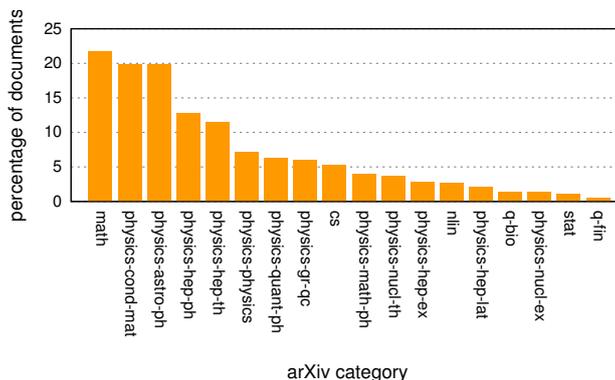
**Table 1.** The ArXiv categories and their abbreviations.

Abbreviation	Category Full Name
cs	Computer Science
math	Mathematics
nlin	Nonlinear Sciences
physics-astro-ph	Astrophysics
physics-cond-mat	Condensed Matter Physics
physics-gr-qc	Physics — General Relativity and Quantum Cosmology
physics-hep-ex	High energy Physics — Experiment
physics-hep-lat	High energy Physics — Lattice
physics-hep-ph	High energy Physics — Phenomenology
physics-hep-th	High energy Physics — Theory
physics-math-ph	Mathematical Physics
physics-nucl-ex	Nuclear Physics — Experiment
physics-nucl-th	Nuclear Physics — Theory
physics-quant-ph	Quantum Physics
physics-physics	Physics — Other Fields
q-bio	Quantitative Biology
q-fin	Quantitative Finance
stat	Statistics

### 3 Processing Methods

Our processing methods consisted of three phases — generating the preliminary dictionary, cleaning the dictionary and tagging. Only the first phase differentiated the two analyzed methods that is, the the approach employing Wikipedia (WIKI) and the procedure making use of the noun phrases (NP).

1. **Generating the preliminary dictionary.** During this stage the preliminary version of the dictionary used later on for labeling was obtained. For the WIKI case, simply all multi-word entries from Wikipedia dump were extracted. For the NP method all the abstract from ArXiv corpus were analyzed



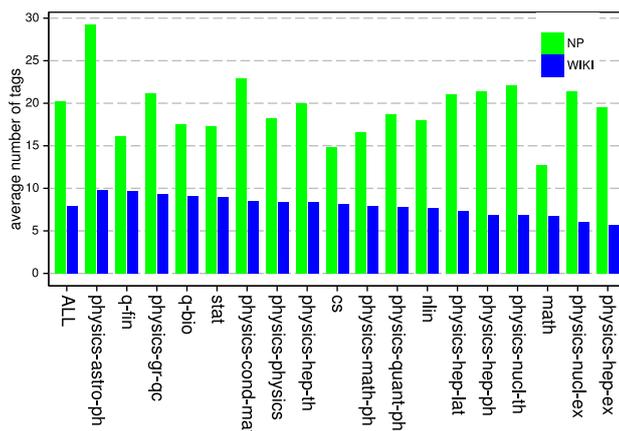
**Fig. 1.** The percentage of documents marked with various ArXiv categories. Note that, since multiple categories per paper are possible, the sum of the numbers above exceeds 100%. The labels for categories are explained in Table 1.

using general purpose natural language processing library OpenNLP [10], detecting all the noun phrases containing two or more words. Noun phrases occurring in fewer than 4 documents were excluded from the dictionary.

- 2. Cleaning the dictionary.** Clearly, on this level both dictionaries contain a lot of non-informative entries. Therefore, we apply a cleaning procedure to both preliminary tag sets. For each tag we remove initial and final words, if they belong to the set of stopwords. The labels which contain only one word after such filtering are removed. Then we use a simple heuristic observation that good label candidates usually do not contain stopword in the middle, see the study [11] for more details. One notable exception here is the word *of*. We drop all entries according to this heuristic rule. Naturally, many far more sophisticated algorithms can be employed here, e.g., matching grammatical pattern devised to select true keywords, which could be employed, when the knowledge about the part-of-speech classification is available [12,13]. However, the simple stopword method worked well enough for us, especially that we are mostly aiming at labels for further applications in machine learning and hence we can afford having certain fraction of "bogus labels". The generated dictionaries after the cleaning procedure contained around 5 million entries for the WIKI method and 0.3 million for the NP case.
- 3. Tagging.** Finally we tag the analyzed corpus of ArXiv abstracts with the obtained filtered dictionaries. In the process of tagging, we make use of the Porter stemming [14], to alleviate the problem of different grammatical forms. All abstracts that contain sequence of words that stems to the same roots as label contained in the WIKI/NP dictionary are tagged with it.

## 4 Comparison of the WIKI and NP Tags Across Domains

As a first step in the comparison of the WIKI and NP methods we calculated the average number of tags per document. This quantity was examined across different disciplines, the results are presented in Fig. 2. The disciplines in Fig. 2

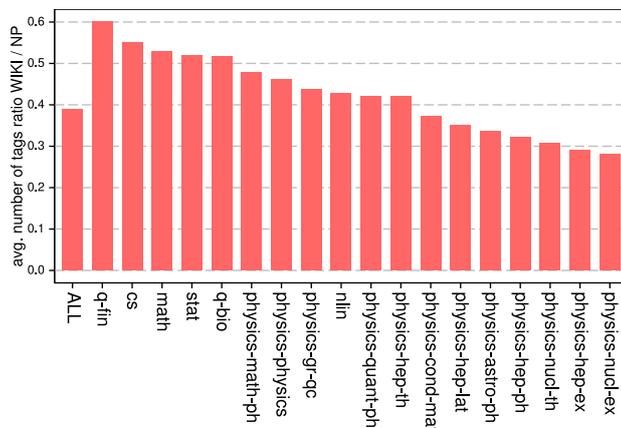


**Fig. 2.** Average number of tags per article for the WIKI and NP cases separated into ArXiv categories. Note that categories are sorted according to the average number of WIKI tags in the descending order.

are sorted according to the average result for the WIKI method in ascending order. This allows us to observe that both methods are weakly correlated. In other words, if the WIKI method gives high number of tags for certain category, it does not imply that the NP approach yields high average as well. This observation can be quantified by calculating the correlation coefficient between the average number of the WIKI and NP tags for each category, which indeed turns out to have very low value of  $\rho = 0.13$ . Another conclusion from Fig. 2 is that clearly the NP method yields higher number of tags across all the domains. The average number of WIKI tags is roughly in the range from 0.3 to 0.6 of the NP result. The exact ratios for all the domains are visualized in Fig. 3. The bar chart is sorted according to the descending ratios. The sequence of disciplines can be, to a certain extent, intuitively understood. The leading categories, such as computer science and quantitative finance, are probably more familiar to the average Internet user than experimental nuclear physics or high-energy physics. Thus the coverage of the WIKI labels is also better in these domains. This indicates that various methods, relying on the knowledge from Wikipedia and verified on the computer science texts (such as, e.g., keyphrases in [8]) can have considerably lower performance when applied to documents from different scientific field.

**Table 2.** Comparison of the top 10 most frequent tags in four categories. The first column (Top WIKI) denotes labels occurring in the WIKI method. The second column (Top NP) includes results produced by the NP method. The third column (Top WIKI-only) displays most frequent tags generated by the WIKI method, but not by the NP. Finally, the fourth column shows the most frequent NP results, not detected by the WIKI (Top NP-only).

Top WIKI	Top NP	Top WIKI-only	Top NP-only
<b>cs</b>			
lower bound	lower bound	state of art	large scale
upper bound	upper bound	degrees of freedom	interference channel
polynomial time	polynomial time	point of view	time algorithm
et al	et al	object oriented	proposed algorithm
sensor network	sensor network	quality of service	proposed method
logic programming	logic programming	order of magnitude	hoc network
wireless network	wireless network	game theory	considered problem
real time	real time	Reed Solomon	wireless sensor
network coding	network coding	multi agent system	channel state
ad hoc	ad hoc	multi user	capacity region
<b>math</b>			
Lie algebra	Lie algebra	Calabi Yau	give rise
differential equation	differential equation	Navier Stokes	higher order
moduli space	moduli space	point of view	initial data
lower bound	lower bound	non negative	infinitely many
field theory	field theory	Cohen Macaulay	new proof
finite dimensional	finite dimensional	algebraically closed	over field
sufficient condition	sufficient condition	degrees of freedom	value problem
upper bound	upper bound	self dual	large class
Lie group	Lie group	Gromov Witten	time dependence
two dimensional	two dimensional	answered question	mapping class
<b>physics-nucl-ex</b>			
cross section	cross section	equation of state	heavy ion
Au Au	heavy ion	center of mass	Au collisions
heavy ion collision	Au Au	order of magnitude	ion collision
form factor	Au collisions	degrees of freedom	Au Au collision
beta decay	ion collision	ultra relativistic	transversal momentum
elliptic flow	Au Au collision	Drell Yan	200 GeV
high energies	heavy ion collision	time of flight	relativistic heavy
experimental data	transversal momentum	presented first	relativistic heavy ions
charged particle	200 GeV	long lived	low energies
nuclear matter	form factor	national laboratory	Pb Pb



**Fig. 3.** The ratio of the average number of the WIKI tags to the number of the NP tags for different ArXiv categories. The categories are sorted in the order of ascending ratio.

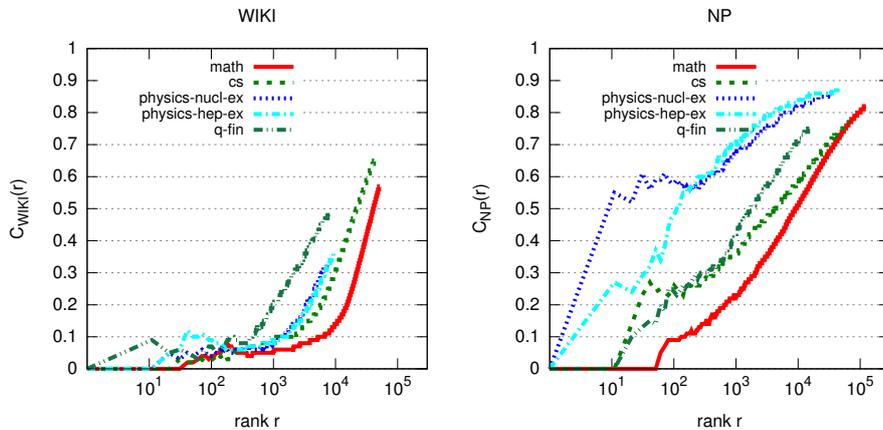
To further investigate the differences between the two methods we displayed the most frequent tags generated by both methods in Table 2. In addition, we also included the most frequent tags generated uniquely by each method, to be able to better judge the differences. We have performed this analysis for three different ArXiv categories. We have selected `cs` and `math` as they have high ratio of the WIKI/NP average number of tags (we have neglected here `q-fin` since there is very low number of documents from this field, see Fig. 1). We have also included `physics-nucl-ex`, as it is at the other end of the spectrum, having very low aforementioned ratio of the WIKI/NP average number of tags. There are a couple of interesting observations, which can be made from Table 2. Note that Top WIKI and Top NP categories are identical for `cs` and `math` categories, whereas for `physics-nucl-ex` there are much different. In the latter case, the top four WIKI tags occur also in the NP results, however, the NP adds a lot of additional labels. They are mostly related to various kinds of nuclei collision processes, which apparently are too specific to be described in Wikipedia. Interestingly, the *Au-Au* tag from the WIKI corresponds to the article about one of the online auction portals and has nothing to do with gold nuclei. Another interesting property is that the WIKI method is much better at detecting surnames related to various theories, equations, etc. In particular, this is visible for `math` and the WIKI-only category, where four out of ten tags are related to surnames. Clearly, not all of the above tags are perfect. It can be observed that noun-phrases detector sometimes yields the fragments of actual noun phrase, e.g., *hoc network* is a fragment of correct phrase *ad hoc network*, *time algorithm* comes from complexity statements, such as *polynomial time algorithm*, etc. There are also a few tags which do not yield any information, e.g., *et al*, *point of view*,

give rise, initial data, etc. If there is a need, their impact can be reduced by improving the filtering procedure described in Sect. 3.

As a final stage of the analysis we decided to address a question, to what extent the tags generated by the WIKI and NP methods are different? Table 2 suggests that in many categories top rank labels might be similar. Larger deviations may get introduced for the less frequent tags. To examine this phenomenon, we propose the following measures that describes the percentage of unique tags detected by each method up to rank  $r$

$$C_{\text{WIKI}}(r) = \frac{\#(T_{\text{WIKI}}(r) \setminus T_{\text{NP}}(\infty))}{r}, \quad C_{\text{NP}}(r) = \frac{\#(T_{\text{NP}}(r) \setminus T_{\text{WIKI}}(\infty))}{r}, \quad (1)$$

where  $T_{\text{WIKI}}(r)$  denotes the set of all tags up to rank  $r$  assigned by the WIKI method,  $T_{\text{WIKI}}(\infty)$  refers to the set of all tags assigned by the WIKI method. The meaning of  $T_{\text{NP}}(r)$  and  $T_{\text{NP}}(\infty)$  is analogous, but refers to the NP approach. The  $C_{\text{WIKI}}(r)$  function describes the percentage of tags up to rank  $r$ , obtained from the WIKI method that were not detected by the NP approach (independently of rank). The  $C_{\text{NP}}(r)$  has analogous meaning for the NP case. The plots of the above quantities for a few sample ArXiv categories are presented in Fig. 4. We have selected the categories in a way that the edge cases of the fastest and the slowest growing dependencies are included. The figures clearly show that for the WIKI case the percentage of the unique tags is low, i.e. around 10%, up to relatively high ranks, mostly  $\sim 10^3$ – $10^4$ . This confirms the intuition that the relevant WIKI tags are indeed in majority noun phrases. On the other hand, the curves for the NP case show a different behaviour, the percentage of the unique tags grows much faster in this case, indicating that they might yield much richer



**Fig. 4.** The dependence of  $C_{\text{WIKI}}$  (left panel) and  $C_{\text{NP}}$  (right panel) on rank  $r$ , i.e., the percentage of tags up to rank  $r$  for the WIKI/NP method that were not detected by the other approach. Only a few sample categories were selected, including edge cases with the fastest and the slowest growing dependencies. See Eq. (1) and the main text for details .

information. The 10% level of unique tags is exceeded for the ranks lower than  $10^2$  for the most categories. However, to give the definitive statement about the quality of the above tags, the domain experts should be consulted.

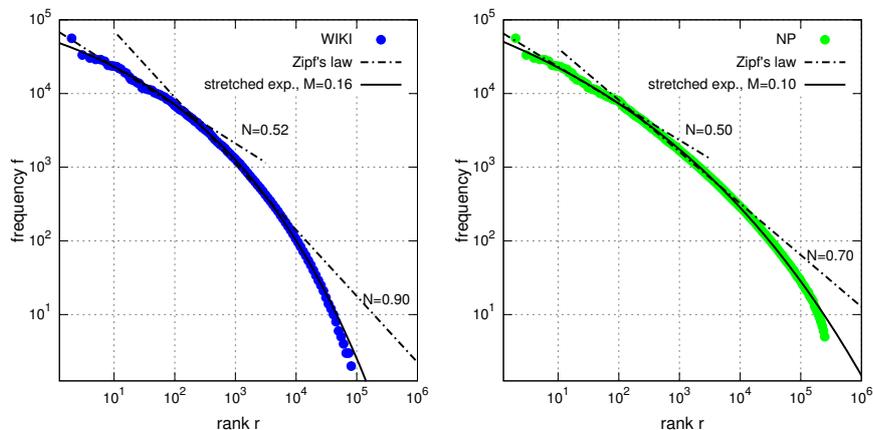
## 5 Statistical Properties of the WIKI and NP Tags

Tags can be expected to have similar statistical properties as ordinary words. One of the universal properties observed for words is the so-called Zipf's law, which states that the word frequency  $f$  as a function of its rank  $r$  in the frequency table should exhibit power-law behaviour

$$f(r; A, N) = A r^{-N}, \quad (2)$$

where  $A$  and  $N$  are parameters. This type of simple dependency was observed not only for words, but also keyphrases, e.g., in the PNAS Journal bibliographic dataset [15]. However, the detailed investigation reveals that for large corpora, in particular when many different authors and hence different styles are involved, the simple model (2) might be insufficient to describe the frequency-rank dependence throughout the whole  $r$  variability range [16]. Sometimes a few curves of the type (2) are necessary in order to accurately describe the observed distribution throughout the whole rank domain.

In the case of our tags, the observed rank-frequency dependencies are presented in Fig. 5. In both cases (WIKI and NP), the crude approximation for



**Fig. 5.** Comparison of the frequency dependence on rank observed for tags obtained from both approaches — the WIKI (left panel) and the NP (right panel). The models fitted to the observed distributions are Zipf's law, see Eq. (2), and stretched exponential model, see Eq. (3).

the observed data was obtained using a combination of two Zipf type curves for

different rank regimes. It turned out that up to rank 100, the values of exponent  $N$  were very similar in both cases and approximately equal to 0.5. However, for larger values the WIKI case showed more rapid decay with  $N = 0.95$ , as opposed to  $N = 0.73$  in the NP case. Nevertheless, it is easily observed that a simple combination of the Zipf type curves does not fit the data very well. It turns out that the observed rank-frequency dependencies are much better approximated by one of the alternatives to the power-law (2), namely the stretched exponential distribution. This type of distribution is used to describe large variety of phenomena from physics to finance [17]. It was observed, e.g., for rank distributions of radio/light emission intensities from galaxies, French and US agglomeration sizes, daily Forex US-Mark price variation, etc. The stretched exponential model yields the following dependence of frequency on rank

$$f(r; C, D, M) = C \exp(-D r^M), \quad (3)$$

with  $C$ ,  $D$ , and  $M$  being parameters. As can be observed in Fig. 5, this model fits the data much better. Similarly to the Zipf's law, the value of the exponent for the NP case, which reads  $M = 0.12$ , is lower than for the WIKI, where  $M = 0.19$ . This indicates slower decay and "fatter tail" for the NP tags case.

Another interesting statistical property of the generated tags is the distribution for number of distinct labels per document. It turns out that, even though the average tag counts per document are quite different for the WIKI and NP methods (see Sect. 4), the distributions in both cases come from the same family. Observed histograms can be approximated with the negative binomial distribution. According to this model, the probability of finding document with  $k$  tags reads

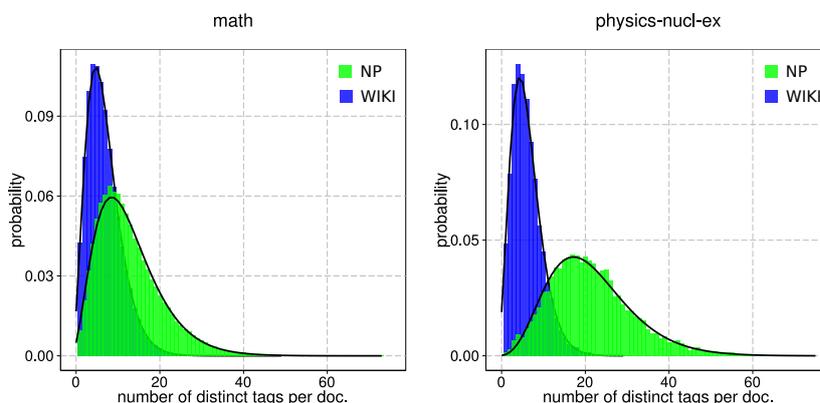
$$\text{Prob}(k; P, R) = \binom{k + R - 1}{k} P^R (1 - P)^k, \quad (4)$$

where  $R > 0$  and  $P \in (0, 1)$  are the parameters of the distribution. The comparison of the above model with the observed histograms can be found in Fig. 6.

## 6 Summary and Outlook

In this paper, we have compared two methods of tagging scientific publications. First, abbreviated WIKI, was based on the multi-word entries from Wikipedia. Second, referenced as NP, relied on the multi-word noun phrases detected by the NLP tools. We have focused on the effectiveness of each method across domains and on the statistical properties of the obtained labels.

When it comes to the effectiveness of the above methods, it turned out that the NP approach yields higher average number of tags per document. The difference is by a factor between two and three with respect to the WIKI case. This strongly depends on domain. The WIKI tags coverage is better in the areas more relevant to the Internet community, such as computer science or quantitative finance than in more exotic domains such as nuclear experimental physics.



**Fig. 6.** Distribution for the number of tags per document within two sample ArXiv categories `math` (left panel) and `physics-nucl-ex` (right panel). The distribution can be well approximated by the negative binomial distribution, see Eq. (4). The black line represents the fits of this model to the observed data.

In addition, there is almost no correlation between the average number of labels generated by the NP and WIKI methods, when separated to different scientific domains. This signals that results of both methods are to a certain extent complementary. When it comes to the differences in the obtained tags, it turns out that high-rank labels from the WIKI method are usually also detected by the NP. The notable, easy to understand exceptions are tags containing the complex of surnames, such as *Navier-Stokes*. Depending on the category, within the first  $10^3 - 10^4$  most frequent WIKI tags the percentage of the unique labels is lower than 10%. Conversely, for the NP method the number of unique tags is much higher. Usually in the top 100 labels, there is already more than 10% cases not found by the WIKI method. However, the average level of "bogus tags" seems higher for this method. In particular, sometimes it yields broken phrases such as *hoc network* instead of *ad hoc network*. The development of more accurate filters for such cases or better part-of-speech taggers/chunkers trained on scientific corpora could improve the method.

As far as the statistical properties are concerned, it turned out that both the WIKI and NP methods exhibit qualitatively very similar behaviour. The dependence of the tag frequency on the tag rank can be approximated by the Zipf's law, however, only in the limited rank range. To be able to cover the whole rank domain the so-called stretched exponential model has to be employed. It constitutes a good fit for both the WIKI and NP. Obtained curve parameters indicate much slower decay ("fatter tail") for the NP method. The investigation of the distribution for the number of tags per document revealed that in both the WIKI and NP cases it follows quite closely the negative-binomial model.

Overall, in our opinion, both the WIKI and NP methods seem useful, and to a certain extent complementary. In future we plan to apply the generated

tags as features, extending the simple bag of words document representation, in various types of machine learning tasks (document similarity, clustering, etc.). Verifying the performance on such tasks will enable for more definite statement on the usefulness of both methods.

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