Quantitative Analysis of Learning Object Repositories

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Learning Object Repositories (LOR) are the backbone of the Learning Object Economy. However, little is known about how big they are, how they grow over time, what are the distribution of the contribution among their users or the popularity of their contents. This paper is a first step to measure these operational aspects of Learning Object Repositories and Referatories through a series of quantitative analysis. Measuring key aspects of the production and consumption of Learning Objects is a new sub-field of Informetrics that we call "Learnometrics". The analyses are performed on current data from widely used LOR's. The results confirm some long held beliefs, but also point out some new issues: LORs grow linearly, contribution distribution follows a power law and popularity of objects follows a log-normal distribution. The paper discusses the implications of these findings for the LOR community.

1. Introduction

A Learning Object Repository (LOR) is digital library containing primarily educational material. Its main purpose is to enable the sharing of material for reuse. LOR's are the backbone of the "Learning Object Economy" (Campbell, 2003), where learning objects are created, shared, reused, remixed, enriched and shared again. Technically, they are a computational system containing some type of metadata database, a content store and a user interface for indexation and search. A special and popular form of LOR is the Learning Object Referatory. The referatory does not store digital documents, it only contains metadata and links to material hosted elsewhere (generally on the Web).

Most of the research on Learning Object Repositories has focused on technical issues like their architecture (Hatala et al, 2002) or their interoperability (Simon et al, 2004). On the other hand, little is known about more operational aspects of LOR's. Some questions for which the literature does not provide an answer yet are: What is the typical size of a LOR? How do LORs grow? What is the productivity of the average contributor? How many objects are accessed and how many times? Is there a Long Tail effect (Anderson, 2006) in the popularity of learning objects? Is the productivity of a contributor related to the popularity of her objects? These questions are relevant not only to measure the progress of the "Learning Object Economy", but also to provide empirical information on which decisions about architecture, interoperability strategies and planning for growth should be based. This type of questions, formally called metrics, has been decisive for the advancement of other fields of knowledge. For example, software metrics make it easier to compare different strategies for project development (Sharble, 1996), Scientometrics lead to schemas that measure the progress and impact of scientific research (Garfield, 2006), Webometrics enable the creation of PageRank (Page, 1998), the most famous metric for ranking Web sites. In the same line, Learnometrics, a proposed sub-field of Informetrics to study the production and consumption of Learning Objects, could help the research community to compare different system implementations (Ochoa & Duval, 2006), measure the impact that contributors or learning objects have in the learning community (Duval, 2006) and to develop smarter tools to lower the barriers for Learning Object creation and reuse (Ochoa & Duval, 2006b).

To our knowledge, the most prominent attempts to characterize LORs and measure their characteristics are made by McGreal in (McGreal, 2007). He provides a comprehensive survey of existing LORs and classifies them in various typologies. Unfortunately, his analysis is mostly qualitative and cannot be used to answer the questions mentioned before. Other relevant studies are (Neven, 2002) and (Sicilia, 2005) where different LORs are also qualitatively compared. In contrast with these earlier studies, this paper will quantitatively analyze and compare representative LOR's. The structure of this paper is as follows: Section 2 presents an analysis of the size distribution. Section 3 analyzes the growth rate. Section 4 presents the outcomes of a study of the contribution distribution and segmentation of LORs. Section 5 focuses on the popularity distribution among learning objects and contributors. The paper ends with conclusions from the analysis.

LOR's were selected for each study based on their representativeness and the availability of the required information. For example, while most LOR's provide information about their size, just few of them present the number of hits each learning object had. Nevertheless a core set of 4 LOR's (Ariadne, Merlot, Connexions and Maricopa Learning Exchange) is used through all the analyses.

2. Size Analysis

In order to conduct an analysis of the size of LOR's, 25 repositories and 14 referatories were studied. These LORs were selected from the list compiled by McGreal in (McGreal, 2007). Only LOR's that are not the result of the federation of other repositories, that are publicly available and that contain or link to learning objects of small granularity (raw material or lessons) were analyzed. While McGreal already reported an estimate of the size, we measured each LOR through direct observation, on November 3rd – 4th 2007. Some inconsistencies, not due to natural growth, were found between the data reported by McGreal and the LORs size obtained from our observation. For example, Exploratorium Digital Library is reported in (McGreal, 2007) to have 100+ objects, while its web site presents 13886 objects in the general search. The new compiled list of LORs and their size can be seen in Table 1 and 2. For a complete description of other characteristics, such as web address, granularity, metadata standard and level, we refer the reader to (McGreal, 2007).

Rank	Repository	Size (LO)
1	HEAL	22,347
2	Exploratorium Digital Library	13,886
3	PBS Teacher Source	11,942
4	BioDiTRL	8,949
5	Curriki	8,201
6	CITIDEL	5,992
7	Connexions	4,872
8	ARIADNE	4,798
9	LearnNC	3,138
10	Wisconsin Online Resource Center	2,445
11	National Learning Network UK	1,825
12	Illumina	1,755
13	Maricopa Learning Exchange	1,609
14	Apple Interchange	938
15	Explore Learning with Gismos	420
16	Science WebLinks	335
17	Free-ed Net	126
18	Fathom archive	96
19	LOLA Exchange: Wesleyan U	84
20	Exploratories	71
21	PhET U. of Colorado	67
22	General Physics Java Applets	59
23	ESCOT	44
24	UC Berkeley Interactive University	36
25	Harvey Project	31

Table 1: Rank and Size of the 25 Repositories studied

The 25 repositories have in total circa 100,000 learning objects, with an average size of circa 4000 objects. However, as can be seen in the semi-log plot in Figure 1, the function that relates the rank of the repository and its size is not linear, it behaves exponentially (fitted exponent -0.29). This skewed distribution of size concentrates the majority of learning objects in a few big repositories while a lot of small repositories contribute only a small percentage. As Figure 1 shows, 20% of the repositories (the biggest 5) contribute almost 70% of the total number of learning objects. Repositories ranked from 15 to 25, combined, contribute less than 3% of the number of learning objects in all the surveyed repositories.

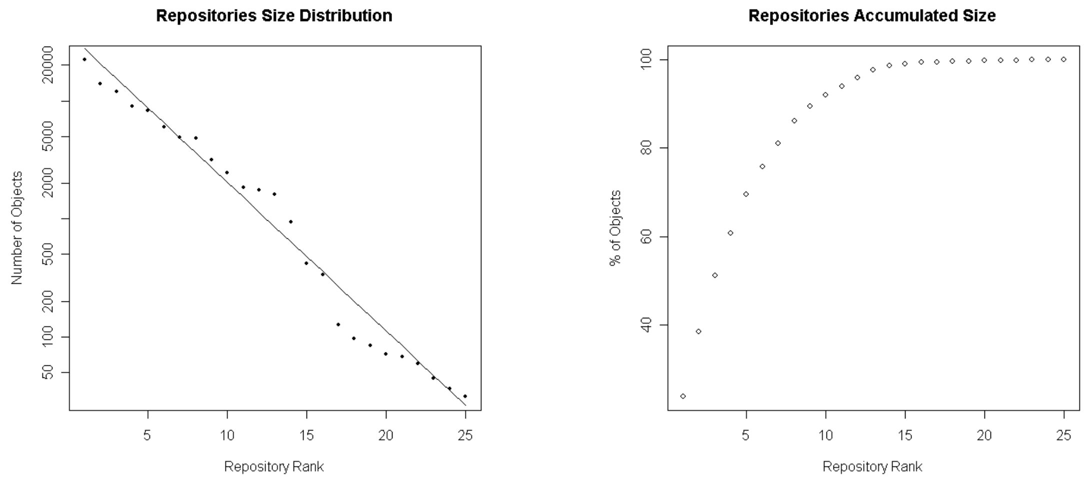

Figure 1: Size distribution and accumulated size for the 25 repositories

The 14 studied referatories offer in total circa 300,000 learning objects, with an average of circa 21,000 objects per referatory. Again, when plotted in a semi-log graph, the exponential relation is apparent (fitted exponent -0.31). The biggest 20% (3 referatories) concentrate 66% of the 300.000 objects. The lower half (rank 8 to 14) contribute only 10% of the total.

Rank	Referatory	Size (LO)
1	Intute	120,278
2	Edna	36,530
3	GEM Exchange Gateway	34,946
4	MERLOT	18,106
5	AMSER	16,666
6	SMETE	14,251
7	DLESE	13,530

Rank	Referatory	Size (LO)
8	Internet Mathematics Library	10,482
9	Nime-Glad	8,879
10	AT&T Blue Web'n	6,371
11	Ideas	5,622
12	FerlFirst	3,938
13	EducaNext	760
14	Learning about Learning Objects	250

Table 2: Rank and Size of the 14 referatories studied

From this analysis three main conclusions can be obtained.

1. Learning Object Referatories are almost an order of magnitude larger in size than Learning Object Repositories. The biggest repository, HEAL, has the size of the average referatory. This can be explained by the fact that contributing links is much easier than contributing complete learning material. To upload a learning object to a repository, the contributor needs to have some kind of right over the material (for example, being the author), while to contribute a link to a referatory does not require any ownership or permission over the content. A dedicated referatory contributor can just search the Web for material and add as many links as she wants.
2. The relation between the repository or referatory size and its rank seems to be exponential with an exponent near -0.30. This result is consistent with the data reported by (Brody, 2007) for the analysis of the size of institutional publication repositories. In his data, an exponential function with an exponent of -0.20 can be found. This behavior indicates that there is not a stable or "average" size for a repository.
3. Due to the exponential distribution of the size, most of available learning objects are concentrated in a few big repositories or referatories. Although small repositories could have relevant material for specific areas, it is hardly worth to visit them in general. This finding is a strong case for the federation of repositories (Ternier, 2006) or metadata harvesting (Hatala, 2004), where objects can be easily found in one (or several) centralized places, even if they are stored in small or obscure repositories.

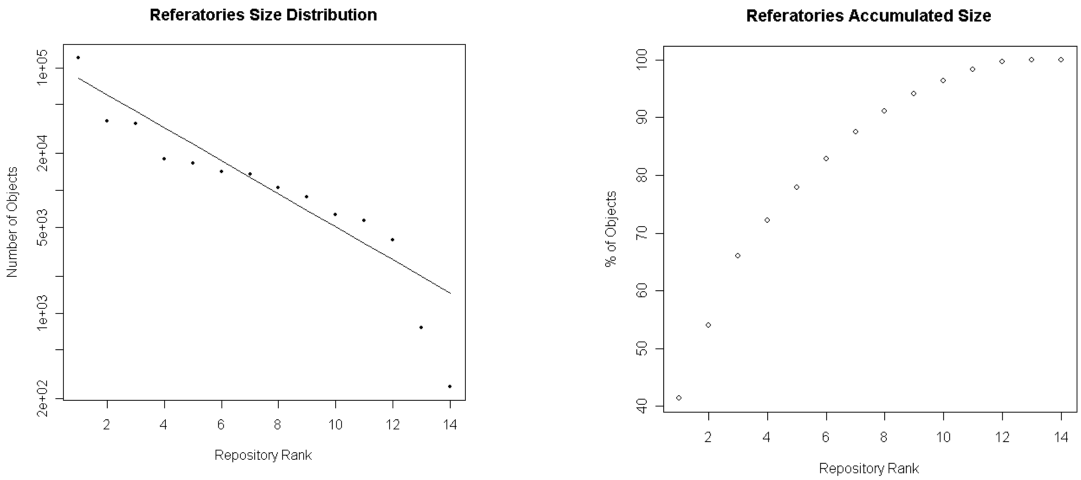

Figure 2: Size distribution and accumulated size for the 14 referatories

3. Growth Analysis

To understand how the repositories and referatories grow, three of each type were studied. The selection was based on how representative they are in terms of size, time they have existed and the availability of the publication date of the objects. ARIADNE, Maricopa Learning Exchange and Connexions were selected for the repositories. Intute, Merlot and FerlFirst were included for the referatories. For all of them, except Intute, the date of publication of all their objects were obtained. In the case of Intuite, a sample with all the objects containing the word "Science" (approximately 10% of the repository) was made. The data were collected trough web scraping of the sites during the period between the 5th and the 8th of November 2007. The characteristics of each LOR can be found in Table 3.

The first variable analyzed was the "Average Growth" rate, measured in objects inserted per day. This value is obtained by dividing the number of objects in the LOR by its age in days (Table 3). From the results, it can be concluded that the difference in size of the LORs is not due only to their different age, but also to the difference in productivity of their contributors. While the average growth rate in the repositories is uniform (from 1.1 to 1.8), in the referatories, it varies significantly (from 1.7 to 26.2).

The average growth rate pictures the growth as constant. To test this assumption the number of objects in the LOR versus time was plotted (Figure 5). The graph shows that the increase in the number of objects is, in general, linear, but the rate is not constant. Two different growth rates are clearly identifiable in all the LORs. There is a linear "Early Growth" rate that is maintained during the first 1 to 3 years until an "Inflection Point" is reached and then, an also linear, "Mature Growth" rate starts. Table 3 reports the growth rates for each of these stages. This change in the growing rate can be explained as the end of a test or bootstrap period (Early Growth) and the beginning of the stable and sustainable life of the repository (Mature Growth).

	Learning Objects	Age of Repository (years)	Average Object Age (years)	Average Growth (objects/day)	Inflection Point (days)	Early Growth (objects/day)	Mature Growth (objects/day)
Repositories							
Ariadne	4,798	11.0	6.0	1.1	~ 1,000	2.1	0.7
Connexions	4,872	7.7	2.9	1.8	~ 1,100	0.8	2.0
Maricopa	1,609	4.2	1.9	1.4	~ 1,000	0.8	2.2
Referatories							
Intute	120,278	12.3	4.6	26.2	~ 1,700	8.0	41.0
Merlot	18,106	10.7	4.2	4.6	~ 1,100	0.8	5.6
FerlFirst	3,938	6.2	3.7	1.7	~ 300	5.1	1.0

Table 3: Size analysis of 6 LORs

Another interesting finding arises from the comparison between the "Early" and "Mature" growth. In most cases (Connexions, Maricopa, Intute and Merlot), the Early growth is lower than the Mature growth. In two cases (Ariadne and FerlFirst), the contrary is true. This behavior can be explained by the increase and decrease of the number of contributors. In open communities as Merlot, Connexions and Maricopa where the membership is open and anybody can upload materials, the inflection point could mark the time when the site became "popular" and attracted new members to help the initial user base. Maturity is reached when the arrival of newcomers compensates users leaving the community. In closed communities or projects as Ariadne, Intute and FerlFirst, where learning objects can only be uploaded by authorized members and the membership is not open, it is more difficult to establish the reason for the inflection point. In the case of Ariadne, the inflection point is the moment when the focus from the community shifted from evangelization to attract new members towards interconnection with other repositories through the GLOBE consortium, decreasing the number of active submissions to the core repository. As such, Ariadne is moving from primarily being a repository to primarily being an integrator of repositories. Intute has a closed project with an rather fixed number of contributors, but its early growth is lower than its mature growth. The explanation is that, while Intute (previously known as RDN) has objects inserted before 1999, these objects originate from previous projects (Hiom, 2006). The inflection point in Intute marks the launch of RDN 8 years ago. What is reflected in the maturity rate is a constant growth from the beginning of the repository, fueled by continuous funding.

The direction of change (increase or decrease) of the growth rate is also reflected in the average age of the learning objects in the LOR (Table 3). When the rate increases, the average object age is less than the half of the repository age. This is an indication that, comparatively, most of the objects are produced in the Maturity phase.

The growth analysis confirms the commonly held belief that LOR growth is linear. The existence of two linear phases in the life of LOR's cannot be confirmed with any research publication, but an examination of the growth graphics produced by ROAR tool for OAI institutional repositories (Hitchcock, 2007), reveals that most of them also present this dual-linear behavior. This phenomenon warrants further research.

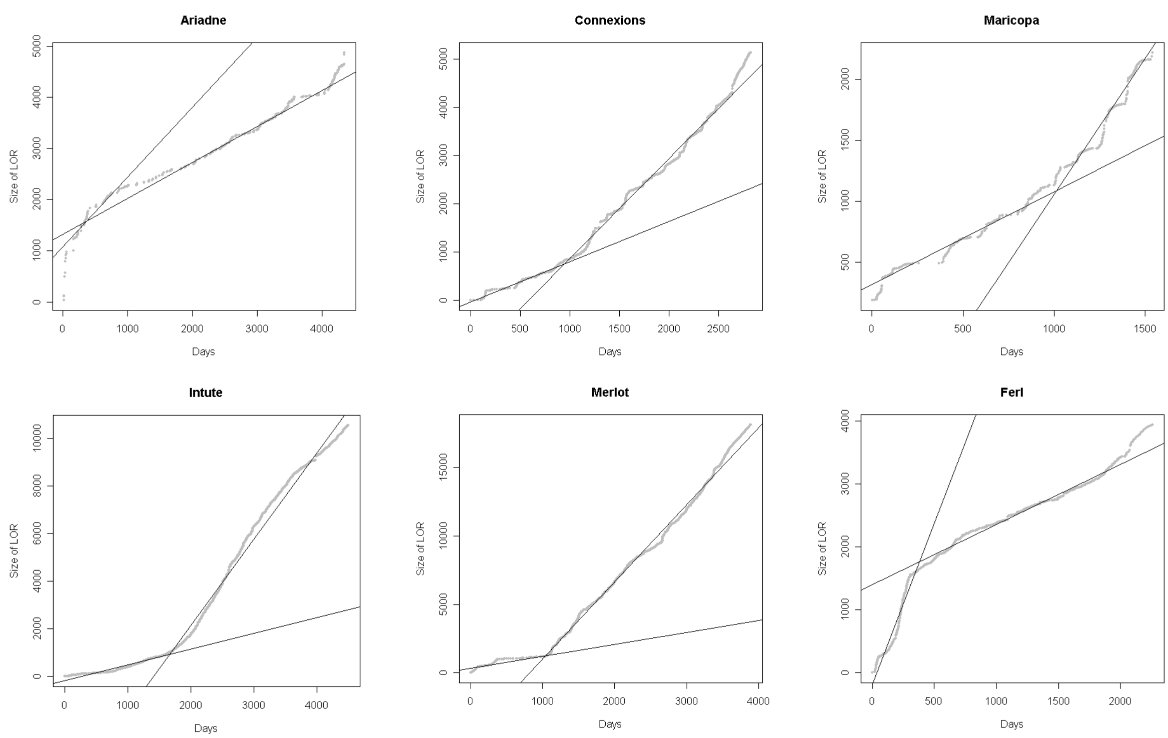

Figure 3: Growth graphs for the 6 studied LORs

4. Contributors Analysis

The LORs are filled with learning objects by a group of individuals that we will call "contributors". The contributor of a learning object can be its author or not. To understand the contribution behavior in different LOR's, five of them were studied: Ariadne, Merlot, BioDiTRL, Connexions and Maricopa Learning Exchange. These LOR's were selected because they publicly present information about the contributor of each object and represent different community sizes. The contributor information of all the objects in the mentioned LORs was extracted through web scraping during the period between the 5th and the 8th of November 2007. Table 4 presents a summary of the data collected.

	Contributors	Objects	Average Contribution (objects)	Power Law α	20% of Contributos (% of objects)
Ariadne	832	4,798	5.8	1.76	75%
Merlot	2,675	18,106	6.8	1.89	82%
BioDiTRL	97	8,949	92.2	1.43	95%
Connexions	714	4,872	6.8	1.58	78%
Maricopa	698	1,609	2.3	2.17	64%

Table 4: Contribution Analysis of 5 LORs

The average contribution is easily obtained as the number of objects divided by the number of contributors. This value is very similar for all LOR's except for BioDiTRL, were a small group of contributors (97) produced a large quantity of elements. Being mostly a repository of photographs, it is easy to have a high average contribution. For comparison, in Scribd, a PDF document sharing site, an average user contributes 7 documents. In Flickr, a photo sharing Web site, a free user posts 300 photos in average.

However, the average number of objects is a good measurement to characterize the behavior of contributors only if the contribution distribution is not skewed. To establish the real distribution a size-frequency plot with the data of each LOR is generated (Figure 6). The x-axis of the size-frequency plot represents the number of objects (size) and the y-axis, the number of contributors that have published exactly x objects (frequency). The size frequency plot is analog to a histogram. The result for all the LORs is an L shaped curve. If this same data is plotted on a log-log scale, it follows the tale-telling decreasing line of the power law distribution. This is a highly skewed distribution where the mean or standard deviation values have limited meaning. This distribution is characterized instead by alpha (α), the slope of the line in the log-log plot. This alpha value (reported in Table 4) determines the "fairness" of the distribution. A low alpha implies that the distribution is dominated by few hyper-productive individuals. On the other hand, a high alpha value is characteristic of distributions were a high proportion of elements are published by casual contributors (contributors that provide just 1 or 2 objects at most). This difference in distribution is easier to see in the percentage of objects that the most productive 20% of users have contributed (reported in the last column of Table 4). For the LOR with the lowest alpha, BioDiTRL, the 19 most productive users are responsible of 95% of the content. In the case of the LOR with the highest alpha, Maricopa Learning Exchange, 25% of objects have been published by users that have contributed just 1 object.

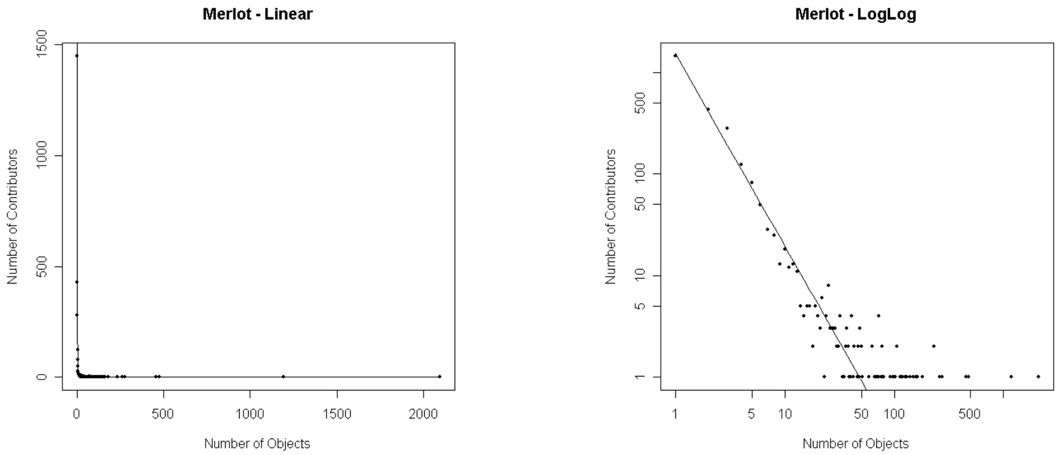

Figure 4: Distribution of Contribution of Merlot LOR

The publishing of learning objects in LORs seems to have a similar distribution to that of publishing papers (Coile, 1977) or contributing comments in online forums (Whittaker, 1998). The main implication of a power law distribution is that there is no such thing as an "average" contributor. The best way to describe them should be as a pyramid: a few highly productive users at the top, a slightly bigger amount of medium-productive users in the middle and the majority of users, producing just a few objects each, at the base. Depending on the value of alpha, the majority of the objects will be contributed by the top or the bottom of the pyramid.

5. Popularity Analysis

The purpose of LOR's is not just to store learning objects, but to provide access to them in order to make them available for reuse. The number of times that objects have been accessed is a proxy measurement of how well this purpose is reached. Six LORs were used to establish the popularity of their contained learning objects: Connexions, FerlFirst, Maricopa Learning Exchange, Learning with Learning Objects (LWLO), Merlot and Ariadne. The main criteria for their selection were to be representative for a size of repository or referatory and to provide information about the access for each object in the repository. The popularity information of all the objects in the LOR's was extracted through web scraping during the period between the 9th and the 10th of November 2007. In the case of ARIADNE, the popularity information was extracted from server logs from the period between February 2004 and December 2005. The first four selected LORs presented the number of times that the object (or its metadata) has been viewed. Merlot has a counter of the number of times that each object has been added to a personal collection (bookmarked). Ariadne logs contain information about the number of times that an object has been downloaded from the repository.

The analysis of the total amount of hits of the first 4 LORs (2 Referatories and 2 Repositories) suggests that the popularity of the LOR is positively correlated with its size. This correlation is maintained even if the values are divided by the number of objects and the LOR age (Average hits in Table 5). Users are more attracted to big repositories. The difference in the average hits per day, as well as the percentage of objects being hit in Merlot and Ariadne suggest that the probability of downloading or bookmarking is at least 3 orders of magnitude smaller than just viewing the object.

	Hit Meaning	Size	Total Hits	% of Objects being hit	Average Hits (hits/day per object)	Meanlog	Sdlog	alpha	xmin	20% of Objects (% of total hits)
Connexions	Object viewed	4,872	39,167,202	100	7.67	8.2	1.3	-	-	59%
FerlFirst	Link clicked	3,938	15,073,625	100	4.14	8.1	0.6	-	-	55%
Maricopa	Metadata viewed	1,609	3,017,049	100	1.75	7.4	0.6	-	-	44%

LWLO	Link clicked	250	20,405	100	0.10	4.2	0.8	-	-	40%
Merlot	Object bookmarked	18,106	26,532	43	0,0014	-6.4	1.0	2.22	0,002	86%
Ariadne	Object downloaded	4,798	2,626	10	0,00015	-6.8	0.7	2.64	0,001	100%

Table 5: Popularity analysis of 6 LORs

To measure the distribution of the popularity inside each repository first the number of hits that an object has received is divided by the number of days that the object has been published. For Ariadne only the time during the sampled period is considered. This division reduces the effect that object age has in the object popularity. The final measurement of popularity for each object is hits per day. To obtain a meaningful graphical representation of the popularity distribution, the inverse cumulative probability of an object being hit versus the object rank is plotted (Figure 5). This plot represent for each object, the number of objects that have received more hits. The best fitting distribution for the first four LORs is the log-normal (Table 5 reports the fitted parameters). The popularity distribution of Merlot and Ariadne follows the log-normal distribution for small number of hits, but then deviates to a more straight line behavior characteristic of a power law distribution. The fitted values for alpha and xmin (the point where power distribution starts) are shown in Table 5 for Merlot and Ariadne. Figure 5 (right) shows the double fitting of the Merlot data by the log-normal and power-law distributions.

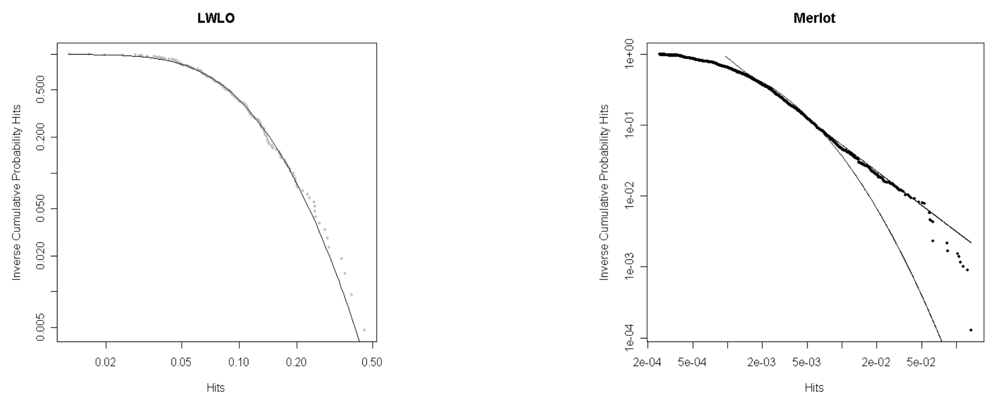

Figure 5: Popularity Distribution of Learning with Learning Object and Merlot LORs

This distribution of probability is similar to what is found in (Sinha, 2006) where the popularity distribution of several user-selected elements is also found to follow a log-normal distribution. (Egghe, 2006) suggests that the finding of a power law tail with an exponential or log-normal head is an indication of a system in transition from power-law to log-normal distributions.

The log-normal distribution generates a Long Tail (Anderson, 2006) effect in the access to LORs. The last column of Table 5 presents the percentage of hits produced by the 20% most popular objects of each LOR. The four first distributions (that follow more closely the log-normal) have a low concentration of hits (60% to 40%). On the other hand, in Merlot and Ariadne, the majority of objects have not been bookmarked or downloaded. In those cases, the majority or the complete amount of hits is concentrated in the most popular 20% and consequently there is no Long Tail effect.

Another interesting measurement is the popularity of each contributor and how the number of objects published is related with her popularity. A proxy to measure the contributor popularity is to average the popularity of all the objects that she has published. Four LORs that provide contributor and popularity information are selected for this analysis. Table 6 presents the result. There is no correlation between the number of objects inserted by a user and her average popularity.

	Hits per Day per Contributor	Average Objects per Contributor	p Correlation Coefficient

Connexions	61.8	6.8	0.19
Maricopa	5.0	2.3	-0.09
Merlot	0.002	6.8	-0.01
Ariadne	0.004	5.8	-0.16

Table 6: Analysis of the Popularity by Contributor

6. Conclusions

The analysis of the previous sections provided answers to the questions presented in the introduction. Following is a summary of those questions, the answers we have identified and their implications:

- **What is the average size of a LOR?**
  The average size of a repository is 4,000 learning objects. The size of referatories is one order of magnitude larger and averages at 20,000 objects. The relationship between size and rank is exponential, not linear. Few LORs are responsible for the majority of content. Federation or harvesting seem to be the only viable approaches to provide access to small repositories.
- **How do LORs grow?**
  They grow linearly. However different linear growing rates can be observed in the lifetime of a LOR. An "early" and a "mature" rate can be observed. The change in growth (increase or decrease) seems to be related to the way that new members become part of the contributor community. In open communities a positive change is observed maybe due to the increase in the number of contributors.
- **What is the productivity of the average contributor?**
  The simple but erroneous answer would be 2 to 7 objects per contributor, but the power-law distribution of the contribution makes the correct answer a little more complex. All repositories have a few hyper-productive users, more medium-level contributors and many infrequent contributors. The amount of importance of each group is dictated by the alpha of the power-law distribution. In low alpha repositories, the majority of the content is created by the hyper-producers, while in high alpha repositories, most objects are contributed by casual users. LOR administrators should know their alpha and treat the different segments of the community accordingly, retaining big producers or encouraging casual submissions.
- **How many objects are accessed?**
  The simple access rate seems to be 100 percent. All objects are visited at least once. The same is not true for more committing user activities, such as bookmarking or downloading, which has happened to less than half of the objects of old and known repositories. This suggests that when a user does not find a suitable object in a repository, the problem is the relevance of the content, not the findability of the objects themselves. Objects can be found as it is demonstrated by the 100% access but are not always bookmarked or downloaded meaning that they have not be found relevant.

- **How many times do objects get a hit?**
  While an average could be obtained (four times a day), a much better estimation of the middle point is given by the inverse logarithm of the meanlog. Given that the distribution is log-normal, 50% of the objects will receive less hits than this value, while the remaining 50% will receive more. In the studied cases, that value is around eigth times a day. We can expect to have a few very popular objects and a lot of objects that are downloaded few times. The same rules that applied to other types of popularity are also valid for LOR's.
- **Is there a Long Tail effect in the popularity of learning objects?**
  When dealing with object views, yes. The objects that are infrequently accessed, thanks to their volume, contribute importantly to the total popularity of the repository. When dealing with more committing activities, there is no Long Tail effect. The reasons for the lack of interaction with a considerable amount of objects in the repository deserve further investigation.
- **Is the productivity of a contributor is related to the popularity of its objects?**
  No. The popularity of a learning object is completely independent from the number of objects inserted by its contributor. In other words, the quality of learning object is unrelated to the quantity that a contributor publishes.

There are much more relevant questions that need to be answered about the operation and usage of LORs. This work is a first attempt to measure key aspects of the "Learning Object Economy" through small calculations or metrics. This paper is intended to start a discussion on what in the future could be called "Learnometrics" or metrics for Learning Objects.

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