Temporal Analysis of Literary and Programming Prose

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ABSTRACT

Literary works reference a variety of globally shared themes including well-known people, events, and time periods. It is particularly interesting to locate patterns that are either invariant across time or exhibit a characteristic change across time, as they could imply something important about society that those works record. This paper suggests the use of Google n-gram viewer as a fast prototyping method for examining time-based properties over a rich sample of literary prose. Using this method, we find that some repeating periods of time, like Sunday, are referenced disproportionally, allowing us to pose questions such as why a day like Thursday is so unpopular. Furthermore, by treating software as a work of prose, we can apply a similar analysis to open-source software repositories and explore time-based relations in commit logs. Doing a simple statistical analysis on a few temporal keywords in the log records, we reinforce and weaken a few beliefs on how college students approach open source software. Finally, we help readers working on their own temporal analysis by comparing the fundamental differences between literary works and code repositories, and suggest blog or wiki as recently-emerging works.

Categories and Subject Descriptors

D.2.7 [Software Engineering]: Distribution, Maintenance, and Enhancement—Version control; G.3 [Mathematics of Computing]: Probability and Statistics—Multivariate statistics

General Terms

Measurement

Keywords

Temporal Mining, Software Repository Mining, Sampling

1. INTRODUCTION

In the past, discovery of issues recorded in written works depended on lots of manpower reading through printed or even hand-written scripts. Nowadays, the task is made easier with digitization: it has become easier to look for particular keywords from e-books circulated in digital format. It is also much easier to work with old literary works after digitizing them with the scanning and optical character recognition (OCR) technology.

This paper brings our readers’ attention to temporal analysis of literary works, in which we look for characteristic patterns across time. It could be an invariance which stands the test of time. It could be a trend which is changing. Below are some examples:

- Appearance of temporal indicators (such as the days of the week) across prose: In novels, it could mean the time of a setting. In news reports, their appearance indicates the time instances at which interesting events occurred.

- Evolution across the same prose - when the book/article is published, any invariance/change in the word used.

In an age in which digital content is evolving at an increasingly rapid pace, we look back at the seemingly analog form of literary repositories and look to extrapolate ideas that may also hold true for extremely technical prose, that of software repositories. Software source code written in a programming language such as Ruby, C, or Python code may not read like the work of Shakespeare to an average reader; however, the additional data stored in repository history logs provides a level of evolutionary detail that we are not fortunate enough to access in the traditional literary world.

Literature and software code share many of the same characteristics and lend them well to being compared. Both works, in a general sense, need to be compiled or interpreted on a per-processor basis to be used in their intended form; the two forms follow well developed patterns; in software those patterns are validated by a compiler and in literature they may be validated by a dictionary or grammar guide. By treating literature and software as fundamentally the same type of repository, we conduct several experiments and infer the properties that may be shared between the literary and software sources.

We start out by presenting an analysis of both literary and programming prose. The approach is mainly hypothesis testing, which depends on researchers initiating certain proposals. We then attempt to use statistics to see if they are statistically significant or not. It is unlike data mining, in which
we mainly ask the computer program to cluster the items to
discover possible patterns itself. This simpler practice allows
us to obtain statistics using existing tools, so as to inspire
those without programming knowledge to initiate their own
creative designs. We also present a few interesting results
that are worth further thinking. This paper is organized as
follows. In Section 2, we detail the methodology. In Section
3, we present the interesting findings that we have found
from literary and programming prose, before we conclude
and discuss possible future works in Section 4.

2. METHODOLOGY

2.1 Literary Works

For literary works, we chose measurable components such as
due to the digital nature of the source material, may
numbers to years and English week day names.

By choosing generally universal search terms, we focus our
efforts away from the parsing and extraction to the inferences
and comparisons between samples of repositories and that
of the whole. We can fit those queries in the web interface
described below.

To look for recurring keywords in literary writings, we
make use of the n-gram viewer [2] in Google Books. The
company has precompiled the set of one- to five- grams from
over a million of books that they scanned and were published
between the years 1800 and 2000. It keeps a representative
sample of literary works and provides a precompiled dataset
for fast queries. It also offers a web page [1] where amateurs
and non-fiction, temporal keywords are seldom mentioned in
the week:

| Years    | Number of books |
|----------|-----------------|
| 1520 - 1699 | 1,243          |
| 1700 - 1799 | 44,059         |
| 1800 - 1899 | 5,518,213      |
| 1900 - 2008 | 31,823,074     |

2.2 Software

Keyword search in source code can be done through specialized
search engines [7] where one can search for code snippets.
In a sense, code search is more similar to book search or
literature search, as search is carried out based more on key
words than on links.

However, unlike books which often mention temporal indica-
tors such as days of the week as events in both fiction
and non-fiction, temporal keywords are seldom mentioned in
the programs (as variable names or functions) unless they
are doing calendrical computations.

In contrast, we can often extract much richer development
history of code than literarcy counterparts. A version control
system [5] is often used in large code development projects to
manage changes to code stored in digital format. It associates
each change with a specific date and time. For program code,
such change logs are named commits. A commit refers to the
idea of making an often subject-based grouping of tentative
changes, in this context changes of code in a developer’s local
computer, permanent by uploading the changes to a code
repository [4]. This is the final step that a programmer does
when he is satisfied with the modifications he has made on
the local code. As a result, a commit can be treated as a
record of progress.

One may access the commit logs to explore this temporal
feature of code at the commit level. For example, with git
version control system, he can use the git log functionality
[2] With a simple command, he can obtain the date, time and
author of each commit.

3. FINDINGS

3.1 Literary Works

To test the consistency property of certain temporal key-
words over an extended period of time given a reasonably
static social factor, we explore the specific references to those
keywords in a data set that spans hundreds of years. We
accomplish this through use of the Google Books 1-grams
English data set mentioned in the previous section. Table
2 suggests the distribution of the publication years of the
books being used to compile the statistics.

3.1.1 Days of the week

This involves accessing the number of references by case
insensitive listings for the singular form of the seven days of
the week: Sunday, Monday, Tuesday, Wednesday, Thursday,
Friday, and Saturday. The resulting relative frequency plot
is shown in Figure 1.

Leaving aside speculations regarding the literary signifi-
cance of Sundays at nearly double frequency or the lack of

Table 1: Books with multiple editions in a sample of
1000 books

| Number of Editions | Books |
|--------------------|------|
| 2                  | 29   |
| 3                  | 6    |
| 4                  | 3    |
| 5                  | 1    |
| 10                 | 1    |

Table 2: Distribution of publication years of the
books

1http://books.google.com/ngrams

2For example, http://www.google.com/codesearch
3http://learn.github.com/p/log.html
popularity Tuesday through Thursday hold in our sample to our literary counterparts, our data indicates much broader trends that hold true for a significant period of time. The consistent result indicates the effect of sampling by century was minimal, despite the significant differences caused by spelling or optical character recognition challenges, notably the medial s that declined significantly in the 1800s.

3.1.2 Months of the year

We find their relative frequencies remain consistent, as shown in Figure 2, across centuries and in the overall distribution. While our repository of English literature spans over 450 years, this specific trend and presumably many others remains remarkably consistent given the wide variety and literary development during that time period.

Relative frequencies of the months show similar consistency over time too. Check Figure 2. Excluding May and June which could also be used as names and verbal auxiliary and thus expected to show up more often, we observe a few months that are consistently occurring more than other months, such as July.

3.1.3 Relative temporal indicators

Finally, we look at relative temporal indicators including “today”, “yesterday” and “tomorrow”. See Figure 3. Before around 1800, “yesterday” dominated. Afterwards, the usage of “today” boomed and outnumbered the others. We also observe a similar rise of “tomorrow”. Though the premium is not as large as that of “today”, it also consistently outnumbers “yesterday”.

3.2 Software

In this section, we analyze the git repositories maintained by the Rensselaer Center of Open Source software (RCOS) in Rensselaer Polytechnic Institute (RPI)\(^4\). RCOS is a group of RPI students who work on a variety of self-initiated open source projects. They participate for course credits or a stipend. We pick a set of eight repositories as shown in Table 3. The chosen projects are under active developments as indicated by their large numbers of commits.

3.2.1 Hours of the day

We start by looking at the distribution of the commits over the 24 hours of the day. We are interested in the time of the day when the students work, so we take the programmers’ commit time without converting them to time corresponding to the time zone of the school. Instead of summing up the actual number of commits, we add up the proportion of commits of all the projects in the same hour together and compile Figure 4. This prevents projects with huge total number of commits from dominating the statistics and thus equalizes the influence of individual projects.

As shown in Figure 4, the proportion of commits remains at a relatively high level from the afternoon till early morning the next day. A trough is observed at around 6 a.m. This matches our expectation that students tend to stay late at night or even till early in the morning to code. This also confirms the importance of shifting actual time to honor the concept of a day of a typical person. Students usually define that a day ends when they go to bed, and it can be extended beyond chronological midnight.

3.2.2 Days of the week

After adjusting for the extended night hours, we can then analyze the commit data by the unit of days. The students are asked to report their progress every Friday at 4 P.M. during regular semester and at noon during summer. A question is to see if students’ work (and hence commits) are concentrated on the few days before the project progress presentations. Statistically, we need to check if the number of commits is significantly larger on Wednesdays and Thursdays.
To do this, we compile the proportion of commits at different days of the week, as shown in Table 4.

Then we compute how these figures are deviated from the expected value $1/7 = 14.29\%$, which is the expected proportion if the commits are distributed evenly across the seven days of the week. All the 95% confidence intervals (C.I.) include 0, which means we are not confident to say any deviation is significant relative to the expected evenly-distributed case.

3.2.3 Coding session length

When interpreting commit, note that a commit just means a confirmation. The hours of work behind it are impossible to tell. However, it makes sense to cluster consecutive commits which are temporarily close with their immediate neighbor and estimate approximate session length. Table 5 shows the average length of the sessions. The grand mean is around 4.5 hours.

This grand mean may provide an idea on the scale of the programming tasks one should be assigned to do, as very likely the software project one can achieve could depend on the attention span one can put into the project. Analyzing the average session of successful projects may provide recommended coding time for projects of different scales.

4. CONCLUSIONS

Sentences and lines of code are rarely grouped together outside of a pseudo code lecture or alike, but the wealth of information they and the meta-data surrounding them provide show that despite their differences in appearance and structure there are many similarities. We have presented the methodology for temporal analysis of literary and pro-

| Project name  | Duration    |
|---------------|-------------|
| Briefcase     | 3 hr 5 min  |
| Convalot      | 4 hr 1 min  |
| Milkyway      | 4 hr 55 min |
| MobileNotifer | 4 hr 2 min  |
| Notebook      | 6 hr 17 min |
| RPIDirectory  | 7 hr 29 min |
| ShuttleTracking | 2 hr 2 min |
| YACS          | 3 hr 32 min |
Figure 4: Relative frequencies of commits at different time of a day

Table 4: Proportion of commits in different days of the week (a day starts at 6.00am and ends at 5.59am the next day)

| Project name  | Mon     | Tue    | Wed    | Thurs  | Fri    | Sat    | Sun     |
|---------------|---------|--------|--------|--------|--------|--------|---------|
| Briefcase     | 19.70%  | 13.64% | 11.36% | 15.13% | 6.82%  | 21.97% | 11.36%  |
| Convalot      | 13.79%  | 10.34% | 14.29% | 12.07% | 20.20% | 20.69% | 8.62%   |
| Milkyway      | 14.70%  | 16.17% | 15.60% | 15.15% | 14.57% | 12.97% | 10.84%  |
| MobileNotifier| 12.44%  | 22.44% | 8.44%  | 14.67% | 11.11% | 17.78% | 13.11%  |
| Notebook      | 10.74%  | 10.43% | 19.63% | 16.26% | 15.34% | 14.42% | 13.19%  |
| RPIDirectory  | 3.63%   | 31.61% | 14.51% | 25.39% | 17.62% | 1.04%  | 6.22%   |
| ShuttleTracking| 8.21%  | 13.04% | 31.40% | 6.76%  | 16.43% | 8.21%  | 15.94%  |
| YACS          | 15.02%  | 12.82% | 11.72% | 19.05% | 16.48% | 7.69%  | 17.22%  |

Mean deviation from 14.29%: -2.01%, 2.03%, 1.58%, 1.28%, 0.53%, -1.19%, -2.22%

Standard deviation: 4.85%, 7.29%, 7.10%, 5.34%, 4.14%, 7.16%, 3.62%

Standard error: 1.71%, 2.58%, 2.51%, 1.89%, 1.47%, 2.53%, 1.28%

95% CI max: 1.35%, 7.08%, 6.50%, 4.98%, 3.41%, 3.77%, 0.29%

95% CI min: -5.37%, -3.02%, -3.33%, -2.43%, -2.34%, -6.15%, -4.14%

As for further work, first we assume occurrence is equivalent popularity. We have not accounted for duplicates that are unrelated to popularity. For more complex analysis, we probably need further programming. We may make use of the APIs offered by Google, for instance, to expand.

In literary works, we are interested in occurrences of temporal keywords across multiple works. Changes across editions of the same work are generally not considered due to the rather limited number of samples with multiple editions. In contrast, temporal keywords seldom occur in source code which makes analysis of their occurrences uninteresting. Rather, we are provided more temporal information such as commit timestamps which make it feasible and meaningful to look into the commit patterns and the changes across different commits. Meanwhile, we are aware of something in-between those two extremes, namely blogs and wiki web pages. They contain not only text but also rich revision information as code repository.

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