Collective Attention on the Web

Christian Bauckhage
University of Bonn
Fraunhofer IAIS
christian.bauckhage@iais.fraunhofer.de

Kristian Kersting
TU Dortmund University
kristian.kersting@cs.tu-dortmund.de

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Christian Bauckhage
University of Bonn
Fraunhofer IAIS
christian.bauckhage@iais.fraunhofer.de

Kristian Kersting
TU Dortmund University
kristian.kersting@cs.tu-dortmund.de

Contents

Abstract

Understanding the dynamics of collective human attention has been called a key scientific challenge for the information age. Tackling this challenge, this monograph explores the dynamics of collective attention related to Internet phenomena such as Internet memes, viral videos, or social media platforms and Web-based businesses. To this end, we analyze time series data that directly or indirectly represent how the interest of large populations of Web users in content or services develops over time. Regardless of regional or cultural contexts, we generally observe strong regularities in time series that reflect attention dynamics and we discuss mathematical models that provide plausible explanations as to what drives the apparently dominant dynamics of rapid initial growth and prolonged decline.

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1

Introduction

The Web has evolved to be many things: a network, a service, a means of social interaction, a marketplace, a source of news, a repository of knowledge, a database of multimedia content, and an integral part of human activity. This raises the need to investigate how the Web will further evolve as a social-, commercial-, and technical platform and has given rise to the new discipline of Web science [Berners-Lee et al., 2006, Hendler et al., 2008].

By its very nature, Web science is an interdisciplinary endeavor that involves aspects of sociology, psychology, economics, computer science, and data science and the content of this monograph illustrates this. We will investigate an apparently widespread sociological or psychological Web phenomenon from the point of view of data science. In particular, we will discuss how to harness data scientific methods in order to develop an understanding of the dynamics of collective attention on the Web. In fact, our motivation behind this monograph is perfectly summarized by the following quote:

> The subject of collective attention is central to an information age where millions of people are inundated with daily messages. . . . It is thus of interest to understand how atten-

> tion to novel items propagates and eventually fades among large populations. [Wu and Huberman, 2007]

We first encountered the peculiar dynamics of collective attention processes when we began studying Internet memes a couple of years ago [Bauckhage, 2011].

The term *Internet meme* refers to the phenomenon of content that spreads rapidly among Web users. It alludes to a theory by Dawkins [1976] who postulated *memes* as a cultural analogon of biological genes so as to explain how rumors, catch-phrases, melodies, or fashion trends replicate through a population.

Correspondingly, Internet memes are catch phrases or humorous or repugnant pictures or video clips that "go viral" on the Web. While the phenomenon of viral content can be traced back to the early days of the Web, it is because of the interactive and participatory nature of modern social media such as content sharing platforms or social networking sites that Internet memes have become a staple of contemporary Web culture. They typically originate from platforms like *4chan*, *tumblr*, or *youtube*, gain notoriety via social news and entertainment sites such as *reddit*, *failblog*, *memegenerator*, or *quickmeme* and then spread through the social Web at large [Bauckhage, 2011, Coscia, 2013, Shifman, 2013].

Internet memes are *dynamic media objects* that evolve through commentary or parody. Consider, for example, the "y u no" meme shown in Figure 1.1. It first appeared on *tumblr* in 2010 and quickly found its way to *memegenerator* from where it spread virally. In its basic form, the meme consists of an image of a stick figure whose angry face was copied from the Japanese anime series Gantz (Figure 1.1(a)). It typically contains a text in short messaging style that poses mundane questions as to modern life and culture (Figure 1.1(b)). Mutations include self-referential variants that allude to *meme culture* (Figure 1.1(c)) as well as versions that deviate from the original phenotype (Figure 1.1(d)). Also, the meme occasionally occurs in media outside of the Internet but is then reported back on the Web, for instance on social networking sites (Figure 1.1(e)). Internet memes therefore transgress media and cultural boundaries and can be characterized as inside jokes that many people are in on.

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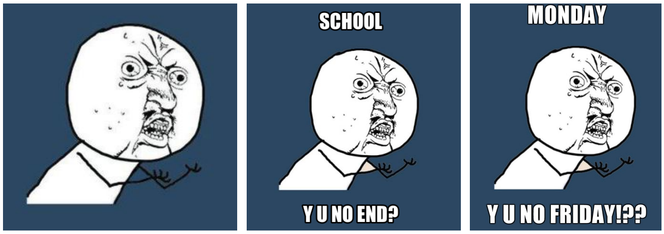
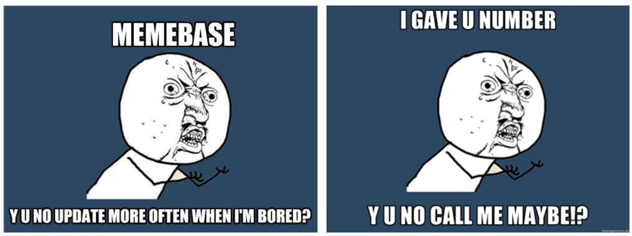


(a) the “y u no” guy (b) instances of the “y u no” meme

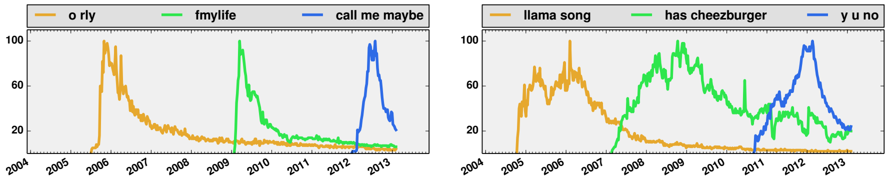


(c) the “y u no” meme with references to the Web site *memebase* and to the “call me maybe” meme

(d) mutations of the “y u no” meme alluding to pop cultural items such as an anime movie or a game franchise

(e) the “y u no” meme appearing on a birthday cake and on the front page of a printed news paper

Figure 1.1: Example of an Internet meme. Instances of the “y u no” meme consist of a simple image macro and a grammatically carefree piece of text that calls to attention questions of everyday life and contemporary culture. The meme first appeared on *tumblr* in 2010; as of this writing, querying the Google search engine for “y u no” yields more than a million results.



(a) positively skewed, narrow peaks, rather long tails

(b) positively skewed, broad peaks, rather short tails

Figure 1.2: Prototypical examples of meme related time series retrieved from Google Trends. While details are chaotic, there appear to be common, general trends as to how collective interest in individual Internet memes grows and declines.

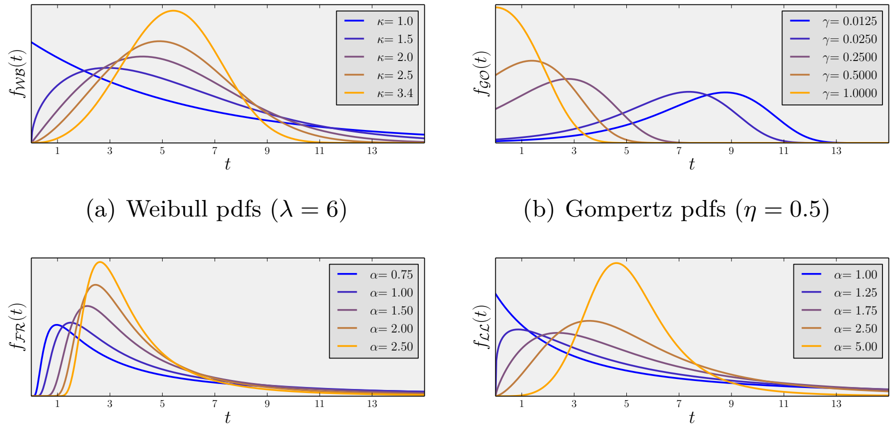
In addition to their content dynamics, Internet memes also show characteristic properties regarding their life cycles. While some were observed to go in and out of popularity in just a matter of weeks, others attract collective attention for extended periods of time. This is exemplified in Figure 1.2 which shows meme related time series retrieved from Google Trends. The graphs indicate how worldwide interest in individual memes (measured in terms of relative search frequencies) grew and declined over time. Although the short term dynamics of these time series appear chaotic, there are characteristic *general trends*: after a point of onset, public interest in a meme grows rapidly but once a meme has reached peak popularity, interest begins to fade more or less quickly.

Interestingly, attention dynamics like these are not exclusive to the phenomenon of Internet memes. Among others, we also observed them to manifest in

- Web search frequency data related to buzz words from the area of information technology [Bauckhage et al., 2013a]

- Web search frequency data related to social media services or e-commerce websites [Bauckhage et al., 2014]

- time series of view counts of popular *youtube* videos [Bauckhage et al., 2015a]



(a) Weibull pdfs ($\lambda = 6$)

(b) Gompertz pdfs ($\eta = 0.5$)

(c) Frechet pdfs ($\beta = 3$)

(d) Log-Logistic pdfs ($\beta = 5$)

Figure 1.3: Examples of probability density functions (pdfs) whose shapes resemble those of the empirical time series in Figure 1.2.

- time series indicating daily playing times people spent on online games [Bauckhage et al., 2012]
- time series reflecting the buying behaviors of players of freemium games [Sifa et al., 2015].

Taken together, all these observations suggest that the dynamics of collective attention on the Web seem to be governed by common latent principles or processes. The obvious question therefore is, if data collected from the Web will allow us to identify or at least to reliably characterize the nature of these hidden, *i.e.* not directly observable, processes.

Seen from the point of view of data science, answering this question seems but a mere exercise in model fitting. Indeed, there are well established scientific tools for time series analysis and it should be easy to fit more or less flexible mathematical models such as shown in Figure 1.3.

However, the crucial point we are trying to bring forward in this monograph is that *the problem we are dealing with is first and foremost a problem of model selection rather than a problem of mere model fitting.*

To clarify this claim, we note that, when properly parametrized, the examples of various probability distributions shown in Figure 1.3 all seem to be able to account for the general behavior of the time series in Figure 1.2. In other words, it will generally be no problem whatsoever to devise more or less sophisticated mathematical functions that capture the attention dynamics we are interested in. The real problem is whether every such model makes sense, or, to paraphrase once more, whether every such model is plausibly interpretable in terms of *physical* processes.

Note that by using the term *physical*, we do not necessarily refer to mechanisms studied in *physics* but express the fact that a convincing mathematical model of Web phenomena should not just fit observed data but should also allow for explaining them in terms of concepts that are grounded in the real world. In our context, this is to say that any model of the dynamics of collective attention on the Web should only be deemed appropriate if it can be tied in with psychological or social phenomena.

Alas, much of the literature on data analytics for Web science is agnostic of this reasonable requirement; rather, the focus often seems to be on the aspect of goodness of fit than on the aspect of plausibility. This has previously been noted by Lazer et al. [2014] who vehemently criticized the lack of interpretability and the "big data hubris" of purely data driven approaches to Web data analytics for their potential of over-fitting and misleading results.

Given these preliminaries, we can summarize our contributions in this monograph as follows: We are interested in the temporal dynamics of collective attention on the Web and our object of study are discrete time series such as in Figure 1.2 which reflect how the interest of large populations of Web users in a topic evolves over longer periods of time. We analyze data like these using mainly statistical tools, however, our methodology follows a model driven rather than a data driven paradigm and therefore adheres to the criticism brought forth by Lazer et al. [2014].

To be more specific, we explore to what extent collective attention dynamics on the Web can be understood in terms of

- growth processes that are known from the study of fads in fields like sociology or cultural studies
- diffusion processes that are studied by economists trying to understand the diffusion of innovations or goods
- spreading processes that are known to occur in (social) networks and are frequently studied in physics
- epidemic processes that characterize viral outbreaks and are of major interest in medicine and mathematical epidemiology.

This is to say that we will propose and investigate different models that can account for the noticeably skewed nature of attention related time series such as in Figure 1.2. Admittedly, this will be a mathematical endeavor but in order not to lose our focus on the topic of collective attention on the Web, we defer more technical material to the appendix. Nevertheless, we very much encourage our mathematically inclined readers to work through the appendix so as to fully appreciate the depth of the approaches we consider.

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