TECHNISCHE UNIVERSITÄT BERLIN

AIM-3: SCALABLE DATA ANALYSIS & DATA MINING

Trend and Topic Detection on Hacker News

USING LDA AND A COMBINATION OF WORD2VEC AND K-MEANS

Authors:

Bram LEENDERS & Marc ROMEYN

bcleenders@gmail.com marc.romeyn@gmail.com

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1 Introduction

1.1 What is Hacker News

Hacker News is a social news site: it aggregates news by allowing users to submit stories. Interesting submissions can be upvoted by other users and all submissions are ranked by popularity.
The content on Hacker News is mostly related to science, in particular computer science. The guidelines for what content can be posted are very broad; the guidelines specify on topic as "*anything that gratifies one's intellectual curiosity*"[1].
Hacker News started in February 2007, eight years ago at the time of writing, and has experienced rapid growth, resulting in a daily 2.6 million pageviews and 3.5 unique visitors per month[2]. One of the reasons suggested for this popularity is Hacker News' similarity to how Reddit used to be[3]: user-submitted content with a very minimalistic, terminal-like interface.

1.2 Research Question

A lot happened and changed during the last eight years, especially in the field of computer science. This research is ment to demonstrate how these real-life events are correlate with the activity on Hacker News.
This lead to the following research question:

Research Question: what correlation can we find between real-world events and the popularity of corresponding topics on Hacker News?

This question depends on two other questions, since we have not yet specified what we mean by popular nor what topics we mean exactly. These subquestions are:

SubQuestion 1: what topics does the Hacker News content consist of?
SubQuestion 2: how does one quantify the popularity of a topic?

1.3 Outline

We start this paper with a description of the dataset and our data processing steps in section 2. In section 3 we give the results of some exploratory research with the dataset to give a feeling what data is like.
After the exploratory research, we describe how we clustered the articles. We used two methods to divide the articles into categories: Latent Dirichlet allocation and a combination of Word2Vec and k-means. Both methods and their implementations are explained in section 4. The results of the classification and the trends are shown in section 5.

[1] `https://news.ycombinator.com/newsguidelines.html`
[2] `https://news.ycombinator.com/item?id=9219581`
[3] `http://techcrunch.com/2013/05/18/the-evolution-of-hacker-news/`

2 Dataset

As explained in the previous section, our analysis is on the set of all stories posted on Hacker News. It is a large set of news articles, blog posts, essays, tutorials and other types of mostly textual media. Nearly all of it is English, although there are a few other languages used as well. Let us first describe what exactly we refer to when we use the word story. To do this, we will describe the four catagories of content on Hacker News:

- Stories: the majority of submissions are stories. A story can be either a link to another webpage or a relatively short text by the submittor.
- Jobs: companies sponsored by YCombinator (the seed investor behind Hacker News) can post job offers on Hacker News. The percentage of jobs is very small: under one percent of the total volume.
- Polls: users can submit multiple choice questions for other users to answer.
- Comments: the three types mentioned above can receive comments by other users.

Since this research focuses only on the stories, we have left out the other three types. The dataset used in our research contains all stories between February 19th 2007 (the date Hacker News was launched[4]) and June 10th 2015 (the day we ran our crawler). This is a time span of 3033 days, during which a total of over 1.5 million stories were submitted.

2.1 Data Processing Steps

The following steps were taken in the data processing:

1. **Data retrieval** (section 2.2): crawl all data from the Hacker News API and the respective websites. We extracted the text from the HTML and wrote the result to disk as JSON files, split on days (one file contains one day of articles).
2. **Exploratory research** (section 3): to get a better understanding of the dataset
   - Postgres: to allow for more versatile access to the data, we stored the dataset in a Postgres database.
   - Tableau: to visualize the results of our data analysis, we used Tableau.
3. **Train and apply clustering models** (section 4): we used two ways of clustering the articles. Since our implementation of LDA did not scale properly, we only used the results of Word2Vec and k-means for the next steps.
4. **Popularity calculation**: using the article and topic information, we can plot the popularity of a topic over time. We did this using Zeppelin[5], an Apache project for data analysis. We used Spark jobs and SparkSQL to analyze the data. This is a very scalable approach, but it requires some effort from the developer.

[4] `https://news.ycombinator.com/hackernews.html`
[5] `http://zeppelin-project.org/`

5. **Interpretation** (section 5): since we had no automated way of linking the behaviour of the popularity (e.g. spikes or long-term in-/decrease) with real-world events, we interpreted this ourselves. We looked, for example, at the most popular articles in the months where popularity of a topic spiked.

In the rest of this paper, we will further explain these steps and discuss the results of each step.

2.2 Data Retrieval

To crawl all stories, we used the official Hacker News API[6]. This API returns some basic metadata about the story, such as the submitter, title, points (upvotes), a (possibly empty) story text and a (possibly empty) url. Stories generally either have a story text or a url, most only have a url.
For the stories with a non-empty story text field, fetching the story from the API is enough. For other stories, we also fetched the content linked to by the url. An important remark here is that some urls (especially the old ones) have become invalid over the course of time. Whenever the content was no longer available, we set the text to an empty string: the metadata (title, submitter, upvotes, etc.) is included in the statistics.
To crawl all stories (including the linked content), we used a homemade crawler that fetches the content, strips out meaningless text and html and saves the result in chunks of 1 day's worth of content. The code for this crawler is publicly available on GitHub[7].
The algorithm used for the extraction of meaningfull content is GoOse[8]. It uses heuristics to rank the importance and relevance of html elements on a webpage. For example: if it detects a `<div>...</div>` block with many words inside, then that is likely to be important. If, on the other hand, it finds an html block `<button>Login</button>`, then it will remove the block for it is probably not a relevant part of the text of the page.
The resulting dataset is about 4.4 GB in size.

3 Exploratory Research

We have now established some semantics of the data gathered for our research. Before diving into the data analysis, we will first quantify the data by providing the reader with some statistics.

3.1 Overall Activity

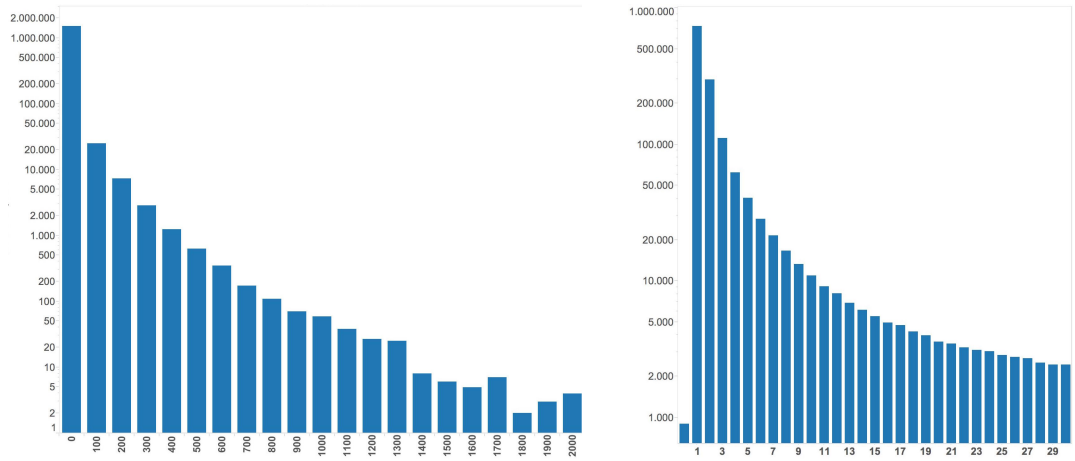
Statistics	
Stories	1,544,261
Submitters	165,126
Upvotes	16,668,848
Comments	7,383,865

[6] `https://hn.algolia.com/api`
[7] `https://github.com/bcleenders/AIM/tree/master/crawler`
[8] `https://github.com/advancedlogic/GoOse`

An interesting remark, is that January 6th 2014 did not have any submissions. The reason for this was a long downtime of the Hacker News website [9].

3.2 Upvote Distribution

If users like a story, they can express their approval by upvoting it. These upvotes are then used to rank the stories by popularity and calculate the (currently) most popular submissions. Since the formula for determining a posts "score" strongly favours newly submitted stories, even stories with few upvotes can spike to the frontpage.
To enter the frontpage (the top 30), a story often needs at least ten upvotes, stories that stay on the frontpage for a longer period of time will often have over a hundred upvotes. The distribution of upvotes per story can be seen in figure 3.1. Stories placed in buckets of size 100 based on the number of upvotes they received. The graph plots the size of each bucket Note that these graphs are scaled logarithmically: in the graph showing all posts (figure 3.1a), 97.5% of the stories are in the first bucket, i.e. only 2.5% of the stories get over 100 upvotes. The second graph (3.1b) is a zoomed in version with a bucket size of 1, and shows the distribution for points with 30 upvotes or less, a set of over 1.4 million stories.



(a) Distribution over all stories
Bucket size 100

(b) Distribution over low-ranked stories
Bucket size 1

Figure 3.1: Distributions of upvotes over posts (log scale)

There are only six stories with over 2100 upvotes. For completeness' sake, these are the stories whose popularity is quite literally "off the charts":

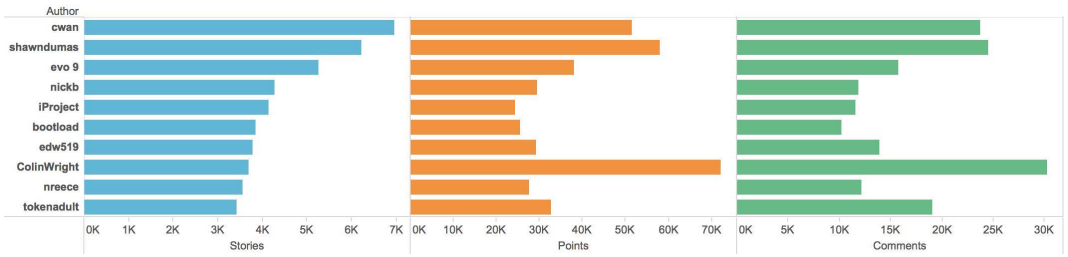
[9] `https://twitter.com/hackernewsonion/status/420068968464789505` - "Hacker News is DOWN, but your chances of getting into YC if you know how to scale a plain text website are UP."

Most upvoted stories	
Title	Points
Steve Jobs has passed away	4271
Tim Cook Speaks Up	3086
2048	2732
Don't Fly During Ramadan	2617
Hyperloop	2549
Microsoft takes NET open source and cross platform	2376

3.3 Top Users

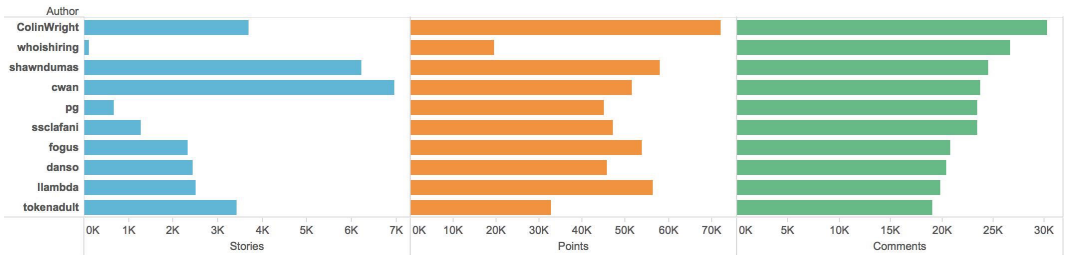
In figure 3.2, we show the statistics for some of the most active submitters. These statistics illustrate that Hacker News has a very active group of users. Together, this top 10 submitted 45,190 stories, which equals an average of 1.5 stories per user per day over the last 7 years.

Figure 3.2: Top 10 submitters by submitted stories



If we take the top 10 not by the number of stories a user has submitted but by the number of comments his or her stories have received, we get the rankings in figure 3.3.

Figure 3.3: Top 10 submitters by received comments



The interesting second place in this top 10 is user "_whoishiring". This user has almost no posts (a mere 114) but received 26,649 comments. Experienced Hacker News readers may have already expected this, for this user starts a monthly thread where companies can post job offers and others can respond to these. As such, the user only posts one story per month but its stories are discussed very actively.

3.4 Top Domains

As already stated in the description of the dataset, many of the stories are links to external sites. To provide some insights into which sites attract a lot of attention from the Hacker News community, we made three top ten lists that rank the sites by the same criteria as we did in the previous section: by number of stories, by points and by number of comments.

Most popular domains		
By Number of Stories	By Points	By Comments
techcrunch.com (27.711)	github.com (400.373)	techcrunch.com (172.854)
github.com (26.596)	techcrunch.com (365.207)	nytimes.com (153.471)
youtube.com (21.977)	nytimes.com (287.234)	github.com (127.812)
nytimes.com (18.125)	arstechnica.com (176.633)	arstechnica.com (80.666)
medium.com (14.172)	wired.com (161.698)	wired.com (75.406)
arstechnica.com (12.657)	medium.com (132.468)	washingtonpost.com (56.257)
wired.com (10.867)	bbc.co.uk (98.031)	medium.com (53.924)
bbc.co.uk (8.118)	washingtonpost.com (97.537)	bbc.co.uk (51.828)
en.wikipedia.org (7.058)	youtube.com (96.339)	theatlantic.com (41.530)
businessinsider.com (6.877)	theatlantic.com (77.628)	online.wsj.com (36.729)

These rankings provide some insights into what types on news are popular. The big geeky news sites (Techcrunch, Ars Technica and Wired) are present and are about as popular as the big newspapers (NY Times, BBC, Washington Post).
The high ranking of github.com (a code hosting site, *not* a news site) can be explained by the large number of open source projects hosted on GitHub that submit links to new versions and press releases on Hacker News. Some examples of these projects are Facebook's React framework, Twitter's Bootstrap, SQLite and io.js.
Notably, GitHub's competitors (e.g. BitBucket, GitLab and Beanstalk) do not show up in these rankings. This demonstrates GitHub's overpowering popularity in the code hosting market, at least in the open source community.
In the top lists given above, we have provided the number of articles, points and comments on groups of articles. The strong similarity between the different methods of ranking indicates a strong correlation between how well a story scores on various features. This is in line with what one might expect: people post, like and comment most of things they consider most interesting.

4 Clustering Articles Into Topics

In order to cluster the articles into topics we chose two different unsupervised approaches:

- **Latent Dirichlet Allocation**: clusters based on the content of the articles. This algorithm represents articles as a bag of words: order of words does not matter. Every article consists of words, and these words are linked to different topics with some probability.

- **Word2Vec combined with k-means**: clusters the articles based on the titles. With a trained Word2Vec-model it is possible to transform every word into a vector. Transforming an article title into a vector is simply adding up the vectors of all words in the title. The vector-representations of the titles can be used as input for k-means, which will cluster the titles.

4.1 Latent Dirichlet Allocation

LDA is a generative probabilistic model of a set of documents. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words [1]. The input parameters are the number of topics (k) and the number of iterations (N) the algorithm will run. For each document in the collection, the words are generated in a two-stage process:

1. Temporary topics are assigned to each word in a semi-random manner (using the *Dirichlet distribution*).

2. Repeat N times: for every word w in the set of documents, do:

   a) For each topic t: re-assign w to t with probability $P(t \mid d) \cdot P(w \mid t)$

After running LDA, we can calculate the probability that a document d is in a topic by looking at the probabilities words in d occur in the topic. If an article can only be in one topic, simply pick the topic with the highest probabilty.

4.2 Word2Vec

Word2Vec is an algorithm that computes vector representations of words based on co-occurrences. The spatial distance between two word-vectors corresponds to word similarity. In order to achieve this it combines two different algorithms: skip-gram and continuous bag of words (CBOW).
Skip-gram model is an method for learning distributed vector representations that capture a large number of syntactic and semantic word relationships [2]. Given a a word w, the skip-gram model predicts the n neighboring words. The CBOW model works the other way around: it predicts w, given the n neighboring words.
Word2Vec is an example of "shallow" learning and can be trained as a simple neural network. This neural network has a single hidden layer with no non-linearities and no unsupervised pre-training of layers is needed [3].

4.3 Measuring popularity of a topic

First and foremost, our popularity must account for different lengths of months and a smaller userbase in the early years of Hacker News. To do so, we must use relative scores per month, rather than comparing absolute numbers.
We have decided to base our popularity measure on all three features we used for the rankings above: number of articles, number of upvotes and number of comments. If a topic receives

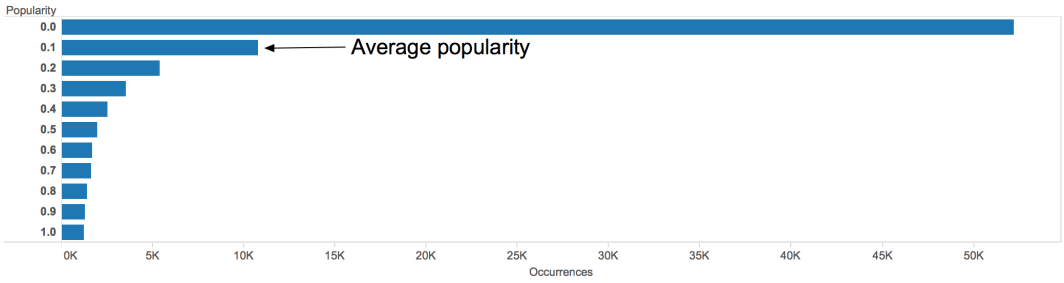
2% of the arcticles, 2% of the upvotes and 5% of the comments, the popularity score is 3% (the average of the three).
To give a formal definition: let S_m be the set of all stories in month m and T_i all stories in the topic number i. With these two definitions, $S_m \cup T_i$ is the set of all stories on a topic i in month m. Furthermore, let s_u (resp. s_c) be the number of upvotes (resp. comments) story s has received. Then, given a topic id i and a month m, the score for that topic in that month is:

$$score(i,m) = \frac{1}{3}\frac{|S_m \cup T_i|}{|S_m|} + \frac{1}{3}\frac{\sum_{s \in S_m \cup \in T_i} s_u}{\sum_{s \in S_m} s_u} + \frac{1}{3}\frac{\sum_{s \in S_m \cup \in T_i} s_c}{\sum_{s \in S_m} s_c}$$

5 Results

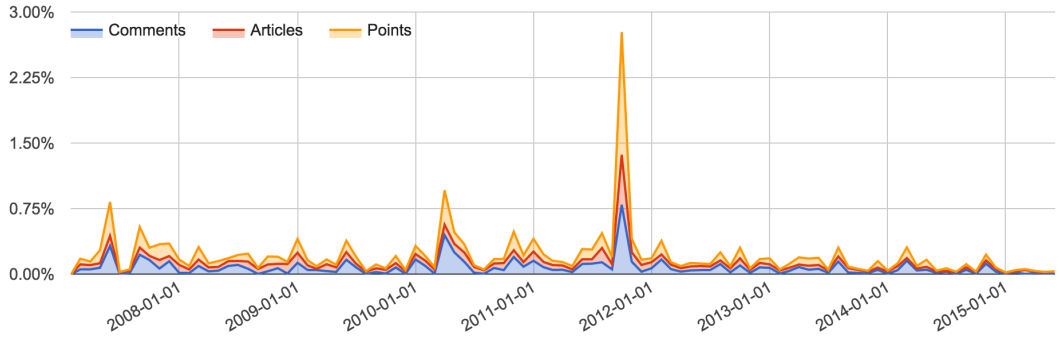
In this section, we will show and discuss some of the results of the research described in the earlier sections. More specifically: we show how exactly the popularity of various topics changed over time. Since we have a thousand topics, we cannot show charts for every individual topic. Instead, we hand-picked a few topics we consider to be interesting and show these.
Note that, since there are 1,000 topics, the average popularity is 0.1%. The popularity is positively skewed, however: roughly a third of the month/topic combinations have a popularity below one basis point (0.01%). To stress this point we include figure 5.1, which shows the distribution of monthly popularity from 0.0% to 1.0% in steps of 0.1%.

Figure 5.1: Popularity distribution - distribution of popularity (in percent) per month/topic combination



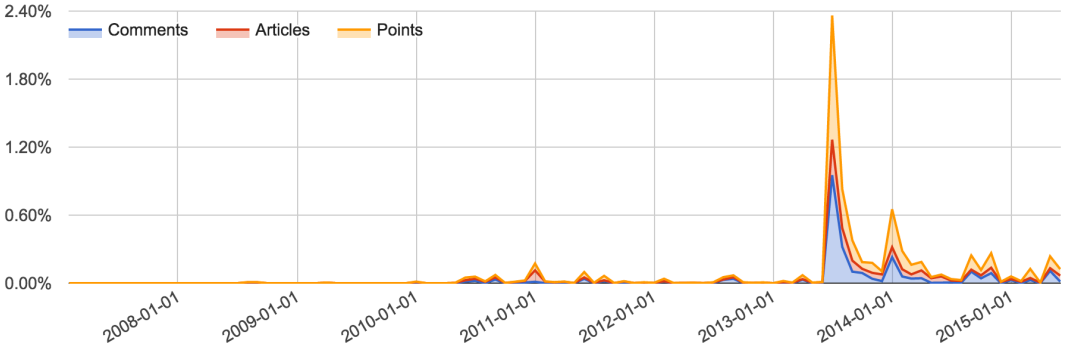
The first chart shows the popularity of the topic with Steve Jobs. As stated before, the news article about his death was the most upvoted article in Hacker News history. As such, one might expect a spike around the time of his death (October 5, 2011). Figure 5.2 shows one enormous spike, which matches our expectations perfectly.
Steve Wozniak (Jobs' cofounder) is also in this topic, but stayed too much in the background to cause big spikes.

Figure 5.2: Popularity of Apple founders Steve Jobs and Wozniak



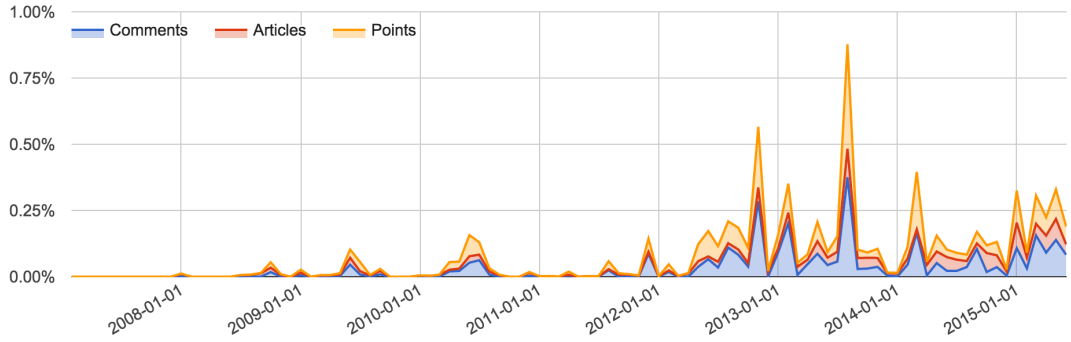
Another big event in the computer science community was the identification of Edward Snowden. The identity of the famous NSA whistleblower was revealed by the Guardian at June 9, 2013. As with Steve Jobs, we see a huge spike in the popularity of this topic for the same month.
Earlier (small) peaks are caused by other usages of the word whistleblower and/or Wikileaks. After his public identification, he gave a few more interviews which attracted some attention and explain the sustained popularity.

Figure 5.3: Popularity of Edward Snowden, Whistleblower, leaks, Reddit



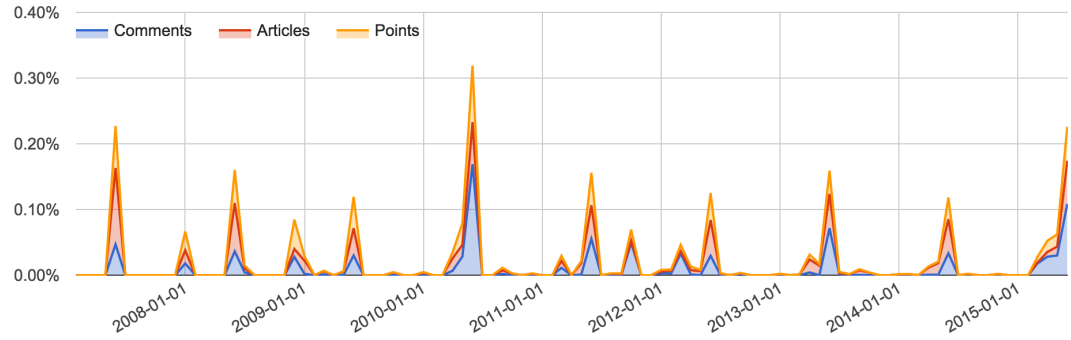
Elon Musk is described by Wired.com as a ”maverick entrepreneur" due to his big and risky projects. We see this reflected in the chart of his popularity (figure 5.4). Halfway 2010, Elon was out of cash (despite a 200 million dollar buyout from PayPal), which sparked some curiousity. The big spike late 2012 marks his expressed intent to have SpaceX (his spacecraft company) fly to Mars. The biggest spike in the chart, halfway 2013, marks the introduction of Hyperloop, a project for high-speed transportation, owned by Musk.

Figure 5.4: Popularity of Elon Musk, SpaceX, Tesla, Hyperloop



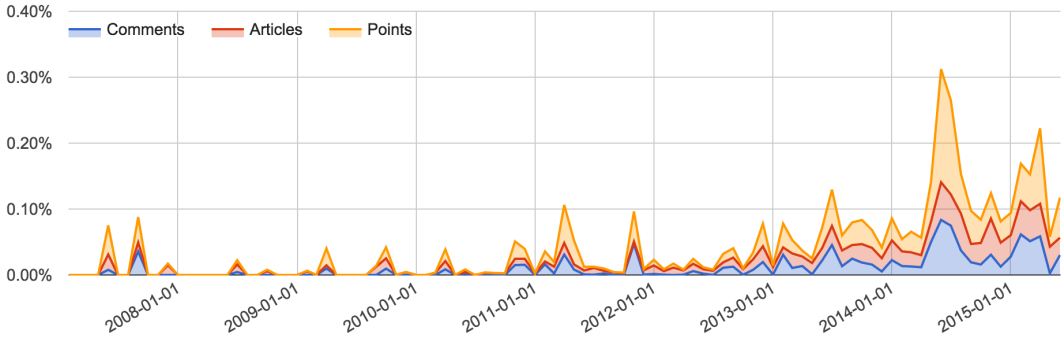
In the popularity charts of keynote-related topics (figure 5.5), one can see yearly patterns of spiking popularity. Each June has a spike of over 0.1%, which corresponds to Apple's annual WWDC (Worldwide Developers Conference). The spikes smaller than 0.1% are just noise.

Figure 5.5: Popularity of keynote, Apple, @scale, developers conference



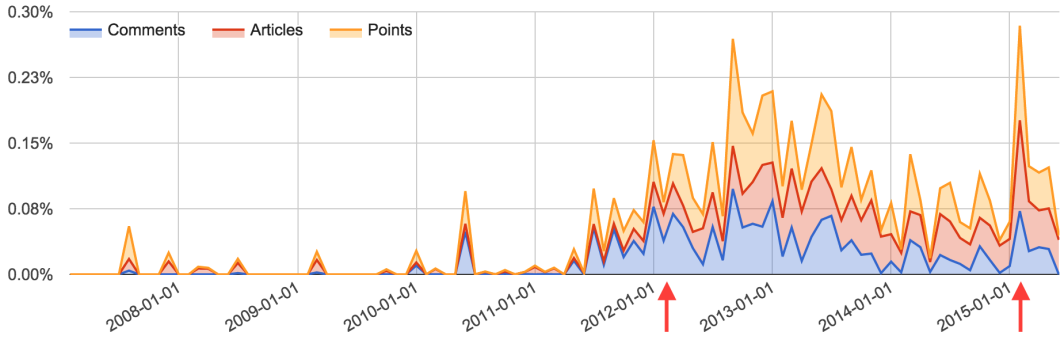
The next chart (figure 5.6) shows the increasing popularity of a new and upcoming technique: containerization. Before the releases Docker (2013) and CoreOS (2014) and before that, containerization was already used as a term for seperating Linux processes (which explains earlier peaks). The chart show how the release of Docker 1.0 (June 2014) created a lot of buzz, and the sustained popularity afterwards.
Interestingly, the initial release of Docker did not receive much attention. We think this is because the usecases were a bit vague and the software was not production-ready.

Figure 5.6: Popularity of Docker, CoreOS, etcd, containers, OpenStack



In the last chart we provide here (figure 5.7), we added two red arrows. These point at the release dates of the Raspberry Pi (version 1 and 2). Before the first release, we already see a growing attention. Since the Raspberry Pi is a crowd-funded project, its creaters already promoted it before the release.

Figure 5.7: Popularity of Raspberry Pi, Kindleberry



6 Conclusion

The goal of this research was to find out how the popularity of topics on Hacker News evolves over time. To answer this question, we defined a popularity measure based on the percentage of articles, upvotes and comments in a topic.
We then continued by dividing the dataset of 1.5 million articles into a thousand topics using two unsupervised clustering algorithms: Word2Vec in combination with k-means and Latent Dirichlet allocation. Through manual inspection, we have verified that the topics formed by these algorithms are coherent and sensible.
The resulting distribution of stories over these topics allowed us to determine the popularity of topics. Looking at the popularity plotted over time, we have seen three types of “trends":

- Single events, e.g. deaths and product releases (Steve Jobs, Hyperloop). These cause big spikes during the month of the event, but don’t have long-lasting effects.

- Recurring evens, e.g. annual conferences (WWDC). These clearly show up in the results, although they are generally not as extreme compared to single-time events.
- Long-lasting trends, e.g. concepts or technologies (Raspberry Pi, Docker/CoreOS). These topics attract attention over a longer span of time, but even within these time spans the months with big news (product releases) generally have a much higher (by a factor of two or three) popularity. Only really big topics have such a long-lasting trend.

We have demonstrated that many topics show a strong correlation between real world events and increased activity on Hacker News. Not all topics are equally clear defined and not all have such clearly visible trends, but many do. Unfortunately, this paper does not offer enough space to show charts for all thousand topics. As a solution this, we will publish all our data online so interested readers can easily create their own charts.

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