L-Università ta' Malta

Analyzing Topic Prevalence in Popular Hacker News Stories

ICS5115 - Statistics for Data Scientists

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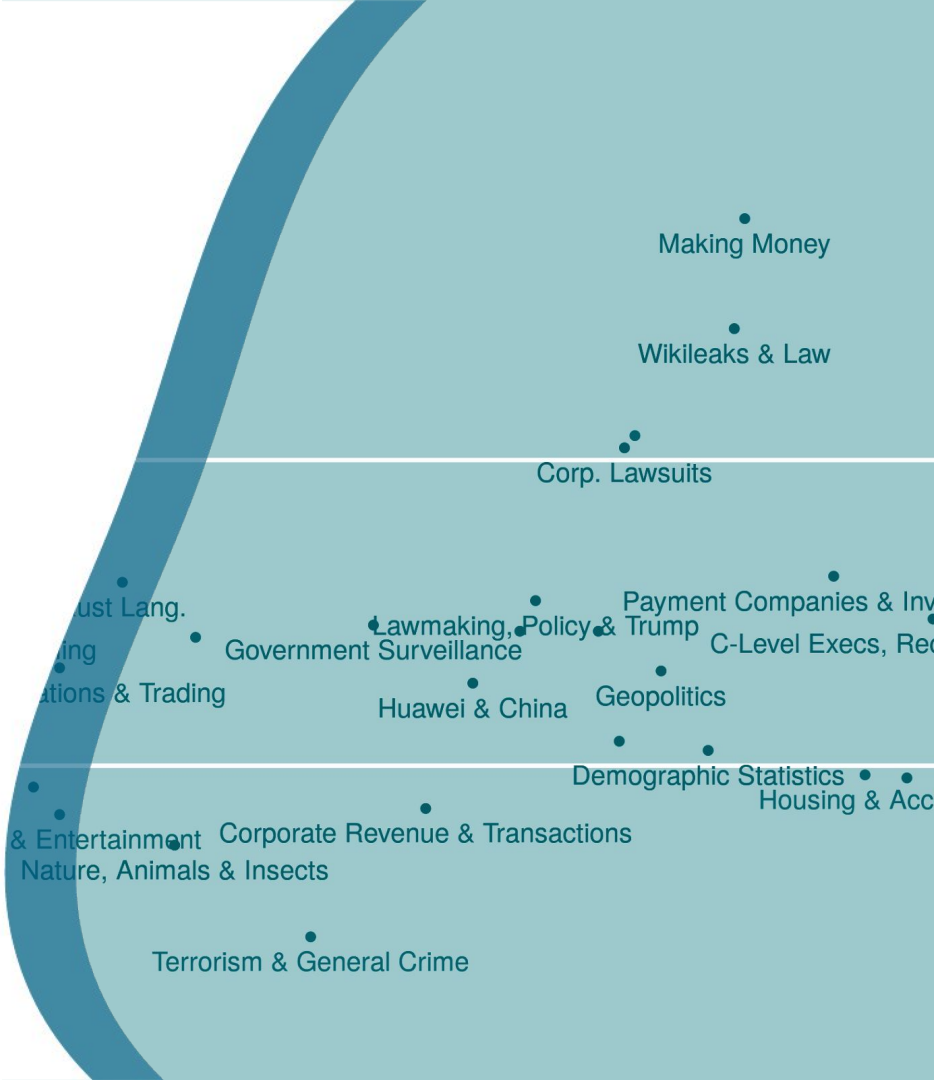

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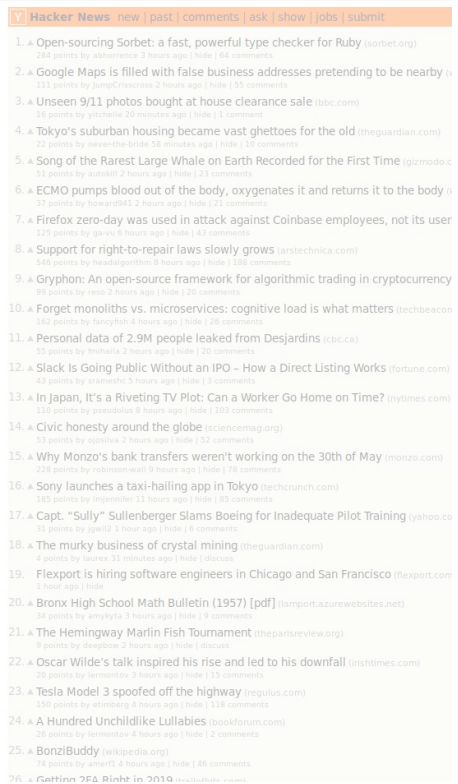
Data Collection

- We perform a one-time extract from the HN archive HckrNews, which includes the top 50% articles by points between **1st December 2018 and 31st May 2019**
- The extract is parsed to create a CSV file containing all information on the bulletin board (headline, link, points, comments, date, domain)
- The top 30 posts by points by day are filtered, associating a rank number to the post
- We iteratively scrape the page for each source and store the source as an HTML document within a folder using the RVest R Library
- *Output dataset: hackernews_board.csv*



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Methodology & Key Assumptions

- **Descriptive Analysis:** Visual & Correlation
  - What is the relationship between points and comments?
  - Do temporal factors affect ranking?
- **Topic Analysis:** Detect Topics from the Corpus
  - Using a *Bayesian Generative Model* to detect topics
  - We find out which topics occur most frequently together
  - Which topics occur more in the top rank than other ranks
- We assume that the top page is adequately represented by the top 30 articles by points from the archive, and also disregard videos, pdfs and obscure web applications

Data Sources
https://hckrnews.com/
Several News Websites

Source Datasets
hackernews_board.csv
hackernews_board_content.csv

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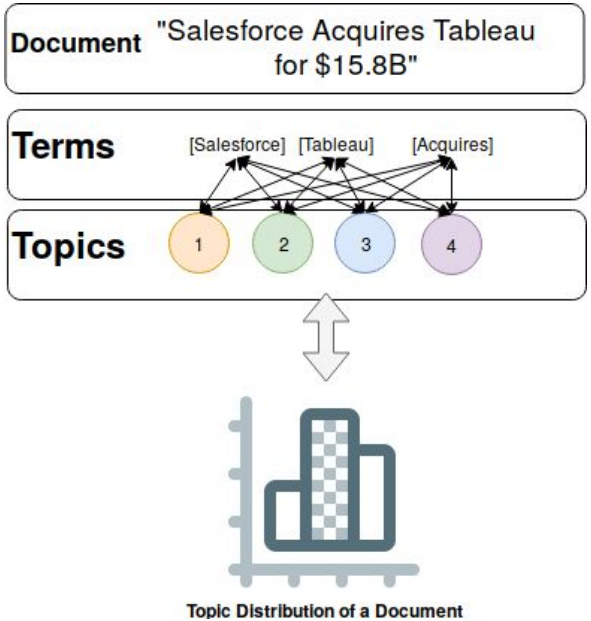
Latent Dirichlet Allocation

- Represents documents as mixtures of latent topics by term distributions
- Assumes prior knowledge of *K* (number of topics to detect).
- Therefore tightly coupled with a *parameter estimation problem*
- We evaluate the mixture by calculating the *Maximum Log Likelihood*

$$L(W) = logP(d|\Upsilon, \alpha) = \sum_t logP(d_t|\Upsilon, \alpha)$$



Descriptive Analysis

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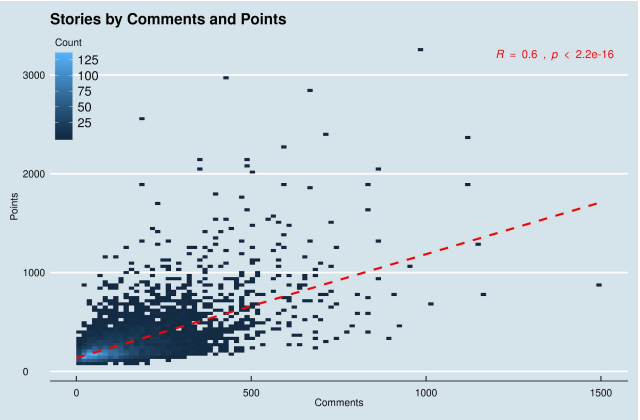
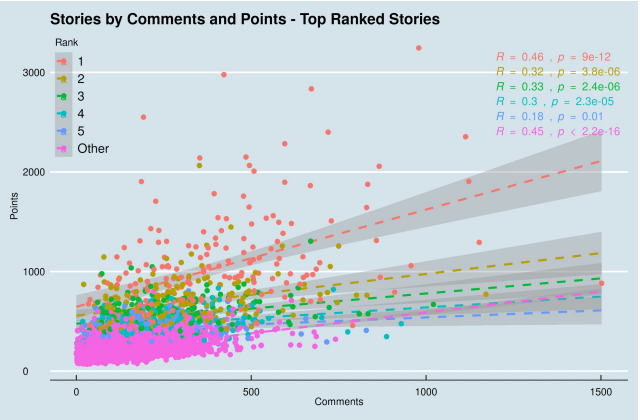
Distribution by Points and Comments

- Perhaps unsurprisingly, points and comments are **moderately to strongly correlated** with a Pearson's R of 0.6
- This correlation decreases slowly, when grouped by rank
- High density at the zero-axis
- Gentle horizontal and vertical skews - sometimes users comment without upvoting and vice-versa





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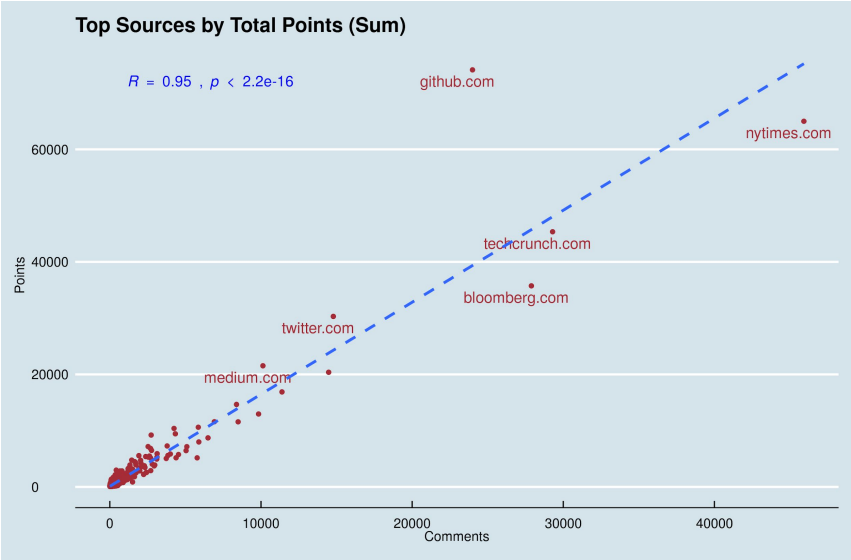
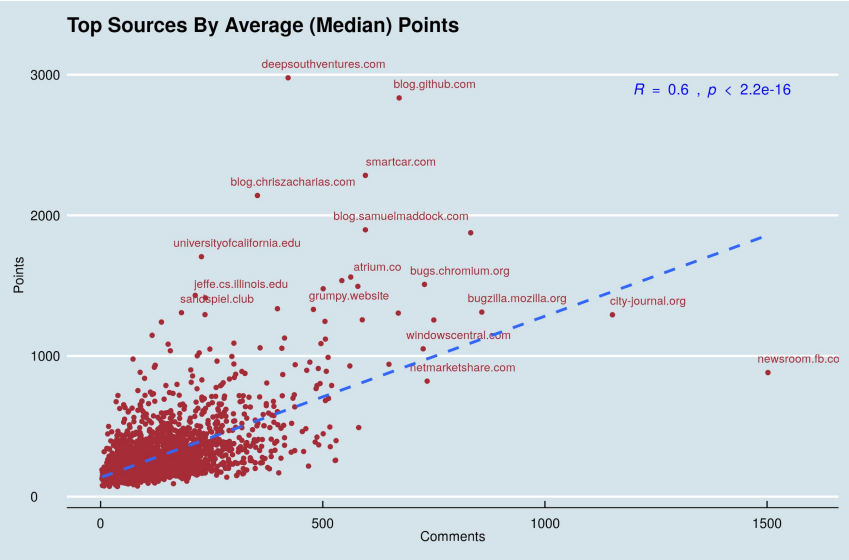
Sources by Points and Comments





Source by sum gives a clear picture of the top sources -
but by median, we see some sources are *one-hit-wonders*

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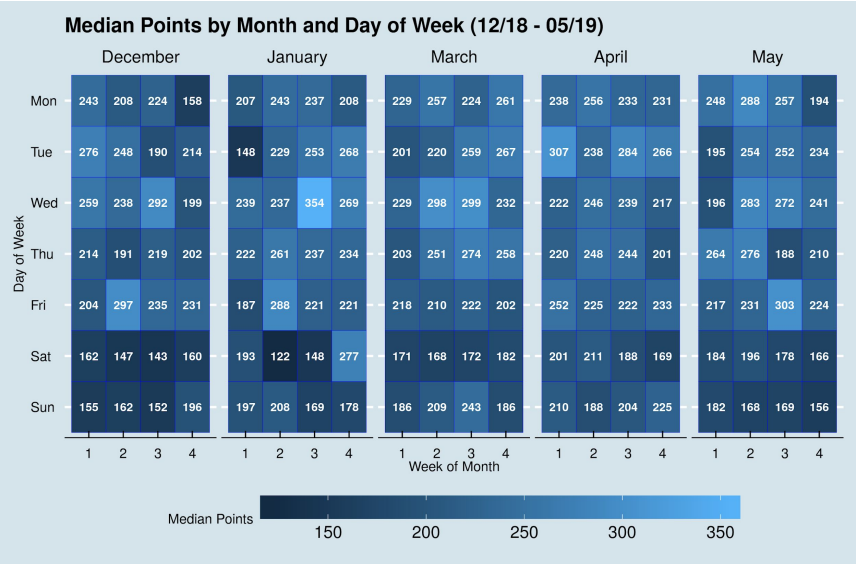
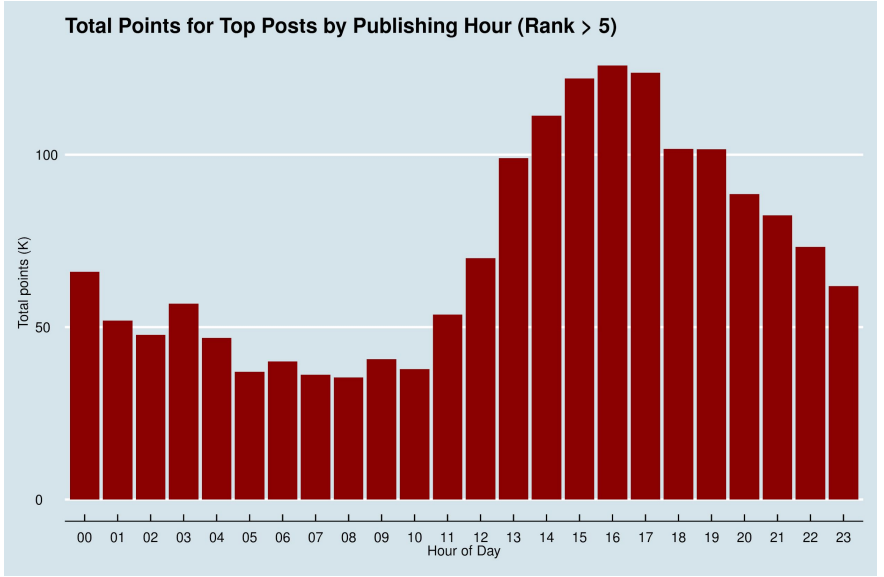
Date & Time of Day





Stories Published on Weekdays and between 2pm and 7pm tend to be assigned more points

Topic Analysis

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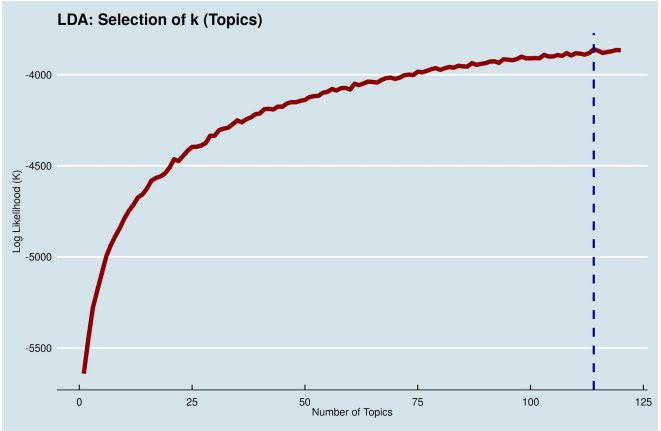
Detecting Topics

- We perform punctuation removal and stemming on our corpus
- *Gibbs Sampling* is used to find the conditional probability distribution of a word's topic assignment
- Our model is run at 700 iterations, discarding the first 200 iterations to increase accuracy
- We re-train the model for $1 < K > 121$, calculating the Maximum Log Likelihood at each iteration - selecting k when the value MLL begins to taper off
- Ideal K for our model is 114 topics (detected)

Document Term Matrix	
Documents	5,939
Terms	7,947
Sparsity	99%

TABLE I
DOCUMENT TERM MATRIX FOR LDA TRAINING



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Topics Detected

- A total of 114 topics were detected
- We evaluated each topic, assigning an annotation to each one
- The topics are of generally high quality, 15% of topics were identified to be noisy.

Topic Id	Keywords	Human-Readable Annotation
1	point view channel youtub content	Youtube
2	flight plane air boe pilot	Boeing 737 & Aviation
3	countri india germani europ world	Geopolitics
4	phone devic call android smartphon	Mobile Devices & Apps
5	life friend mind world advic	Self Improvement
6	rust webassembl red swift runtim	Rust Lang.
7	materi glass plastic wast wood	Environmental Concerns
8	earth moon land planet star	Space Exploration
9	compani fund investor capit founder	VC,IPOs & Money
10	editor edit guid emac studio	IDEs
11	money peopl dollar million thousand	Making Money
12	peopl decis lot problem fact	Quitting Jobs & Toxic SV Culture
13	ve lot ll note	Noisy Topic 1
14	perform intel cpu processor core	CPUs, Performance & Advances
15	market busi industri compani sale	Corporate Revenue & Transactions

TABLE II
EXAMPLES OF HUMAN-READABLE ANNOTATIONS ASSIGNED TO LDA TOPICS

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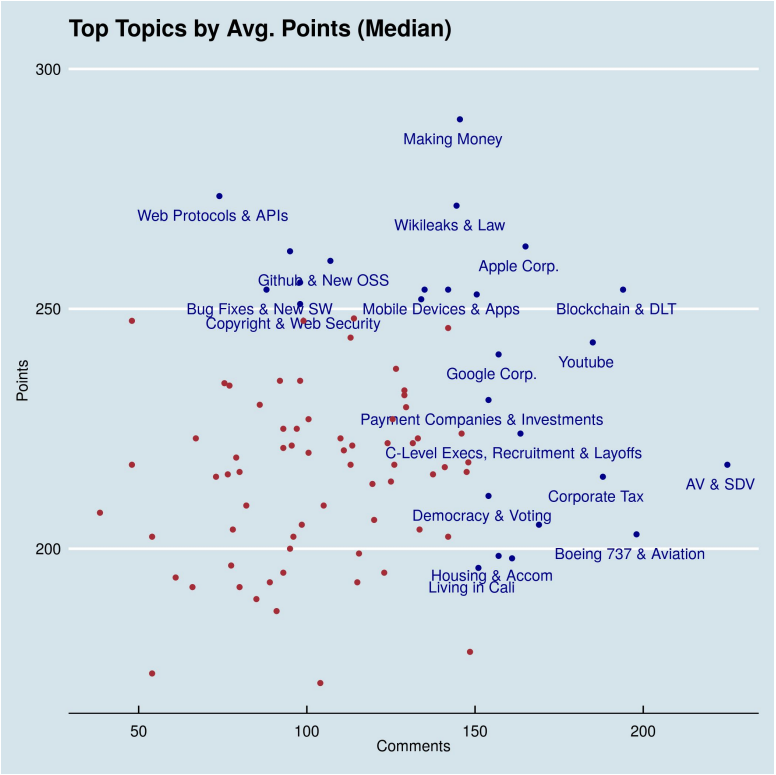
Top Topics

Annotation	Story Headline
Hiring & Careers	Absolute truths I unlearned as junior developer (monicalent.com)
Hiring & Careers	I interviewed at six top companies in Silicon Valley in six days (blog.usejournal.com)
Hiring & Careers	When hiring senior engineers, youre not buying, youre selling (hiringengineersbook.com)
Making Money	How to Be Successful (blog.samaltman.com)
Making Money	Firefox desktop market share now below 9% (netmarketshare.com)
Making Money	Open Source Doesnt Make Money Because It Isnt Designed to Make Money (www.ianbicking.org)
Web Protocols & APIs	Remote Code Execution on Most Dell Computers (d4stiny.github.io)
Web Protocols & APIs	HTTP headers for the responsible developer (www.twilio.com)
Web Protocols & APIs	HTTP/3 explained (http3-explained.haxx.se)
Wikileaks & Law	Julian Assange arrested in London (www.bbc.co.uk)
Wikileaks & Law	U.S. Supreme Court Puts Limits on Police Power to Seize Private Property (www.nytimes.com)
Wikileaks & Law	If Software Is Funded from a Public Source, Its Code Should Be Open Source (www.linuxjournal.com)
Apple Corp.	Spotify to Apple: Time to Play Fair (www.timetoplayfair.com)
Apple Corp.	FaceTime bug lets you hear audio of person you are calling before they pick up (9to5mac.com)
Apple Corp.	Apple Sign In (techcrunch.com)



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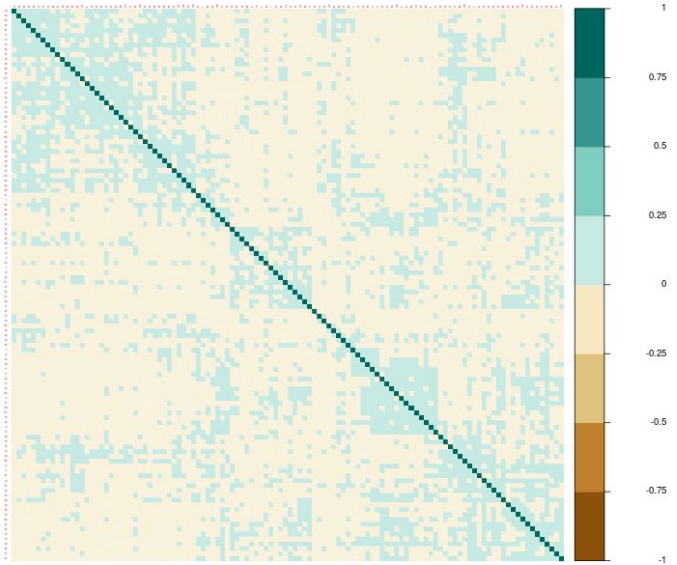
Covariance Matrix:
Do certain topics occur more often than others?

- We observe that the concept of a topic does not occur in isolation - topics are frequently inter-related.
- The most frequently occuring topics are those which occur most frequently together.
- We build a document-topic probability covariance matrix, displaying the covariance of two topics occurring together.
- The matrix is clustered hierarchically - we can see that topic clusters clearly exist



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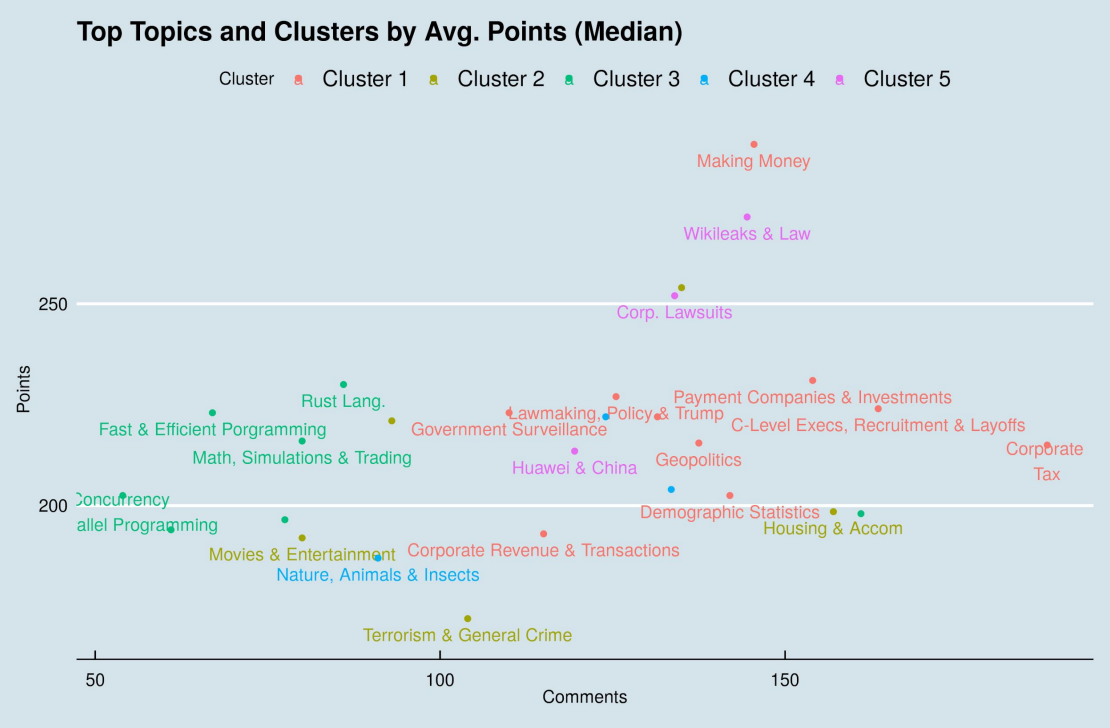
Topic Clusters:
Do certain topics occur more often than others?



Topic Id	Topic Annotation	Cluster Name
11	Making Money	Cluster 1
15	Corporate Revenue & Transactions	Cluster 1
37	Corporate Tax	Cluster 1
23	C-Level Execs, Recruitment & Layoffs	Cluster 1
3	Geopolitics	Cluster 1
17	Lawmaking, Policy & Trump	Cluster 1
43	Payment Companies & Investments	Cluster 1
9	VC,IPOs & Money	Cluster 1
50	Government Surveillance	Cluster 1
30	Demographic Statistics	Cluster 1
51	Nosiy Topic G	Cluster 1
48	Housing & Accom	Cluster 2
22	Japanese Tech.	Cluster 2
35	Problems & The Past	Cluster 2
21	Noisy Topic B	Cluster 2
20	Movies & Entertainment	Cluster 2
12	Quitting Jobs & Toxic SV Culture	Cluster 2
27	Terrorism & General Crime	Cluster 2
47	Math, Simulations & Trading	Cluster 3
53	Functional Lagnuages	Cluster 3
44	Noisy Topic E	Cluster 3
6	Rust Lang.	Cluster 3
31	Noisy Topic C	Cluster 3
40	Ruby Lang.	Cluster 3
33	Interpreted Prog. Languages	Cluster 3
57	Concurrency & Parallel Programming	Cluster 3
26	Fast & Efficient Porgramming	Cluster 3
77	Nature, Animals & Insects	Cluster 4
113	Family Issues & Happiness	Cluster 4
94	Chess & Games & Board Games	Cluster 4
85	Noisy Topic K	Cluster 4
110	Noisy Topic Q	Cluster 5
89	Huawei & China	Cluster 5
58	Wikileaks & Law	Cluster 5
71	Corp. Lawsuits	Cluster 5

TABLE IV
CLUSTERS EXTRACTED FROM COVARIANCE MATRIX

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Rank Correlation:
Are specific topics over-represented in the top post?

- We pose the null hypothesis H_0:
  - *Achieving the top rank from within the front page is unrelated to the story topic*
- We perform a **Chi-Squared test** between two categorical values: topic name and binned rank (Top Rank/Not Top Rank):
  - **The top rank is highly dependent on the topic p-value of 0.002634**
- We perform a One-Way ANOVA test between the numeric rank *(ordinal)* and the topic name *(categorical)*:
  - **The top rank is highly dependent on the topic with Pr(>F) 2.97-e09**
- We **reject** the null hypothesis, **the top rank is highly dependent on the topic.**

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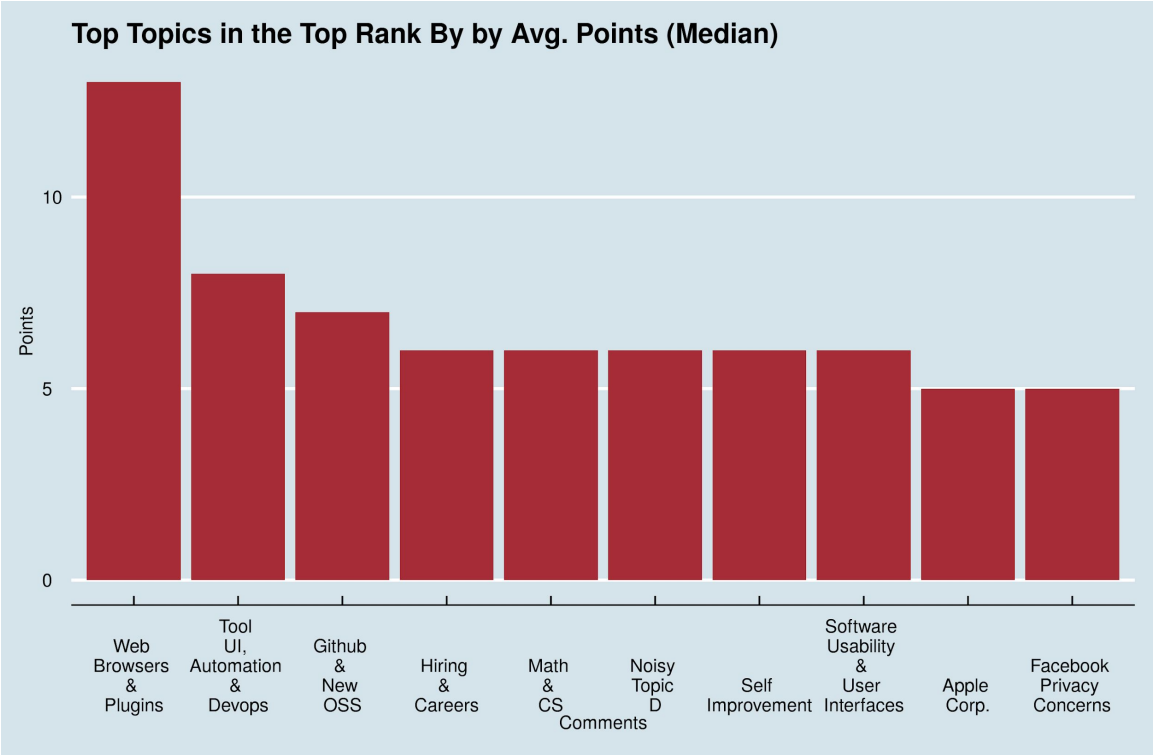
Top Topics within the Top Post



Conclusion

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Key Findings

- Points and comments are moderately to strongly correlated with a Pearson's R of 0.6
- Stories posted between 2pm and 7pm tend to rank higher than others.
- Certain topics tend to be over-represented on the front page such as:
  - These include topics related to companies and revenue growth (such as making money, recruitment)
  - Programming Niches (Ruby/Rust Programming, Concurrency and Parallel Programming)
- There is strong evidence which states that achieving the top rank is dependent on the topic ($p=0.002634$)
  - Stories on "Web Browsers & Plugins" are over-represented within the top rank.

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Evaluation

- The detected topics are of a high quality mainly due to our decision represent documents as collections of *Noun Phrases and Verb Phrases*
- We observe a very low p-value in our top rank analysis, noting that the chi-squared test may be unreliable due to low frequency counts. A Fisher's exact test rendered similar results
  - For this reason we also performed a One-Way ANOVA on the full rank value
- It may be interesting to further investigate the temporal aspect of the data