Analysing the Burstiness of U.S. Supreme Court Topics on Wikipedia

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1 Introduction

In this paper, I analyse the dynamics of editorial wars in U.S. Supreme Court articles on Wikipedia (WP) using the concept of Burstiness (B). The question I focus on is whether the characteristics of a case cited in the WP article about the case or in an article which the case is key affects the B of the article. The concept of B is not new and has been used to model many systems to determine the extent to which events are random. I use the B measure as a proxy for editorial wars rather than total edits and editors because each article has existed for various periods so comparing sums does not give an accurate depiction of the dynamics of edits. By using the *bursty* measure we can compare like-with-like using the distribution of the edits for each article.

The structure of the paper is as follows: (i) I first outline the concept of B and my methodology for calculating it by comparing the deviation from a Poisson distribution; (ii) I then briefly describe the sources for the data used and data wrangling methods, which can be seen in full in the Appendix; and (iii) I conduct some descriptive and statistical analysis as a way to explore the data obtained to see if there are underlying causes of editorial wars for these articles. From the review, we see that while there may be some correlation with and effects from the case characteristics, the results are not conclusive. This is expected as any open socio-technical environment that supports communities of humans and bots that update and contest information (Al Tamime, Giordano, & Hall, 2018), is highly complex and does not readily lend itself to modelling. As such, the exploratory results in this paper should be seen as stepping stone to further analysis on the causes of editorial wars in U.S. Supreme Court WP articles — and more generally, legal articles on WP.

2 Analysing Burstiness

2.1 What is Burstiness?

Statisticians have long tried to model systems for decades but not always with good results. The general idea is that since human interaction is random, we should be able to model interactions with random statistical models. However, the world is not that simple, and many different systems have very different behaviours — hence the use of B. Burstiness (B) can be described as the sudden increase in activity, particularly for a short period, i.e. a measure of how regular, random, or '*bursty*' interactions in a system are. Many systems exhibit some of form of B, such as markets, games, networks, and even our environment, for example with earthquakes (Al Tamime et al., 2018). In our case, the concept can be used to describe unexpected surges of online activities or interactions, for example on WP. If WP activity is *bursty*, we should observe long periods of inactivity, followed by short bursts of activity. On the opposing end, non-*bursty* systems have regularly timed interactions, such as time between heartbeats at rest; and on the middle of the scale, we have completely random behaviour, such as the time between winnings on a slot machine (Al Tamime et al., 2018). On WP, getting a measure for how *bursty* edits or revisions are, indicates to us how contentious a topic might be — thereby signalling potential *'editorial wars'* (Sumi & Yasseri, 2011; Yasseri, Sumi, Rung, Kornai, & Kertész, 2012). *Editorial wars* have long been recognised by the WP community and are seen as extreme cases of disagreement over the contents of an article (Sumi & Yasseri, 2011).

2.2 Methodology for Measuring Burstiness

Moving away from the theory, much research has been done on mathematically measuring B. In this paper, I use the formula derived for measuring B to study the system of article editing/revisions for U.S. Supreme Court topics and cases on WP (Goh & Barabási, 2008; Yasseri et al., 2012). To measure the B of WP editing, I obtain the distributions of edits using the timestamps on the revisions, i.e. the mean and standard deviation, which gives us the distribution of the time between events in the system (inter-event times). I then analyse how different the distribution of inter-event times is from a Poisson distribution, which expresses the probability of some events occurring in a fixed interval of time or space at a constant rate, independent of each other (Goh & Barabási, 2008; Yasseri et al., 2012). The math is relatively straightforward as we take the difference between the standard deviation and the mean of inter-event times over the sum of the standard deviation and the mean of a Poisson distribution. The range of this formula is $1, -1$. The $\lim_{\sigma \to 0} B = -1$, because as the data deviates less, the system is less likely to be *bursty*. As $B \to 0$, the distribution of inter-event times more closely resembles the Poisson distribution, meaning that they are random. Finally as $B \to 1$, the *burstier* the data. Our equation can be formalised as:

$$\mathbf{B} \triangleq \frac{\sigma_\tau - m_\tau}{\sigma_\tau + m_\tau}, \tag{1}$$

Noting that our output is a number from 1 to -1, the lower the number is, the less *bursty* it is, and the higher it is, the *burstier*. If it is close to 0, this means that the system represented by the data is random.

3 Data

3.1 Wikipedia

Using a combination of Python libraries, I obtain the data for calculating B from WP. Specifically, from MediaWiki, we can get the revision data of an article. For this paper, I focus on the list of the most popular articles on the U.S. Supreme Court (Wikipedia contributors, 2018). Using the table provided, which gives us the 250 most popular articles, I query WP's database to get the revisions, timestamps of the revisions and the editor who revised it. One obstacle obtaining this data was the request limit imposed by MediaWiki which only allows 500 objects to be returned at a time. However, using *while loop*, we can continue the query after the first 500 results are returned. By putting the value continue into our next *get* call, we return the next set of objects, and it continually does this until it gets all results. I also extract the first case citation mentioned on the page which I will later merge with the U.S. Supreme Court Case dataset. Having perused a few articles, the first case citation on an article is either the citation for the case the article is about or the citation of a case important to the article.

3.2 U.S. Supreme Court Dataset

The Supreme Court Database, provided by Spaeth et al., spans all four centuries of the Court's decisions, from its first decision in 1791 to the Court's recent decisions in 2017 (arold J. Spaeth & Benesh, n.d.). The specific dataset I use is case-centred data which provides case level information; i.e., each row in the database corresponds to a dispute (arold J. Spaeth & Benesh, n.d.). This data is merged with the data obtained from WP using the citation for the case. I use this to provide a bit more insight into whether any factors surrounding the case which the WP article refers to affect the likelihood for it to be *bursty*. I also provide some descriptive statistics which give us an idea of the types of cases that make onto WP articles.

3.3 Issues with Data

As expected, we have some missing data for our citation which causes some data loss when the datasets are merged. Most of this results from the inconsistency in citation. For example, in the case of *Obergefell v. Hodges* the article uses the U.S. citation, while the case centred dataset does not include one. Also, as some of the WP articles are event focused or centred around an individual's nomination, for example Associate Justice Brett Kavanaugh, the articles do not include a citation for which it can be merged with.

In addition, as the Wikipedia data obtained includes details of the editors (usernames and timestamps of edits) and users (pageviews), care was taken not to display or reveal any of this information in this analysis — as we are focused on the phenomenon of B, not the patterns of specific individuals. This is one benefit of using aggregate statistics as they allow us observe systems without compromising privacy. As for the data obtained from the Supreme Court Database, while this is publicly available information, we still have to be sensitive of the type of knowledge, or more particularly the wisdom, we derive from the analysis below. As such, I take care not to make any insinuation or causal inference as this is an exploratory analysis.

4 Analysis

4.1 Descriptive Statistics

Below I provide some summary statistics for variables obtained from the merge. First, we have a summary of the cases that were represented in the WP articles and the relevant chief justices that presided over the cases. From table 1 and figure 1, We see a prevalence of cases tried by the most recent chief justices, i.e. Rehnquist Court (September 26, 1986 – September 3, 2005), Burger Court (June 23, 1969 – September 26, 1986) and Warren Court (October 5, 1953 – June 23, 1969). This may be a result of the fact that WP is a recent phenomenon, so the cases that make it onto legal articles are more likely to be relatively recent — except when they are landmark cases. Concerning popularity measured by the average page views of the articles which included a case tried by each chief justice, we see that the cases tried by Burger (17,725 pageviews), Warren (16,643 pageviews) and Roberts (12,219 pageviews) are included in more popular articles. While there might also be potentially interesting trends between the B of an article and the chief justice overseeing the cited case (see table 1), I believe it is best to hold of making any inferences until further analysis is conducted.

	Rank	Page Views	Burstiness	Count
Burger	133.92	17725.54	0.68	39
Rehnquist	140.30	7845.66	0.67	50
Roberts	136.35	12218.55	0.73	20
Vinson	140.63	6136.63	0.65	8
Warren	98.12	16642.64	0.70	25

Table 1: Descriptive Statistics, Means by Chief Justice

Next, we analyse the issues tried in the Supreme Court using the same metrics above to see how they fair (see table 2 and figure 2). We see that regarding frequency, First Amendment (42 cases), Civil Rights (34 cases) and Criminal Procedure (29 cases) issues have a higher representation. Considering the contention around these issues, it should not come as a surprise that they are cited more often in these articles. Interestingly, however, concerning popularity, we see that the issue of Privacy — though only represented in a few articles — appears in more popular articles (25,476 pageviews). This may partly be a result of the recent

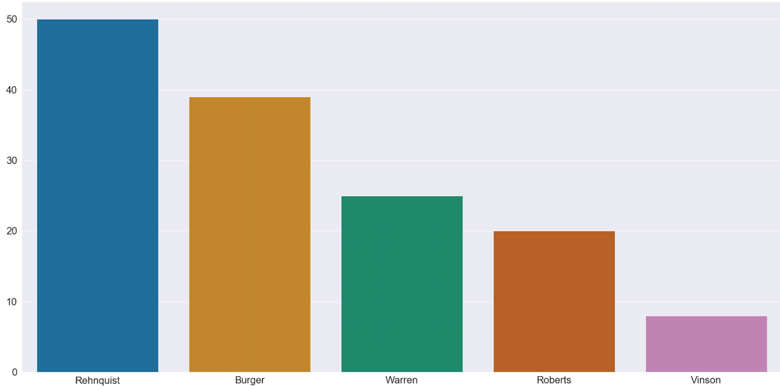

Figure 1: Bar Plot of WP Article Count by Chief Justice

rise in the privacy issues, but looking a bit deeper, we see that older landmark cases which do not necessarily reflect current privacy concerns, such as *Roe v. Wade*, are included in this category. Cases such as *Roe v. Wade* are disproportionately popular articles on WP and much older so it may just be skewing the mean popularity score as our sample size is nine.

	Rank	Page Views	Burstiness	Count
Criminal Procedure	112.17	12103.52	0.71	29
Civil Rights	136.56	18446.41	0.67	34
First Amendment	132.14	9693.76	0.69	42
Due Process	138.00	9650.20	0.69	5
Privacy	95.56	25476.22	0.70	9
Unions	94.00	8207.00	0.74	1
Economic Activity	149.20	6256.40	0.65	10
Judicial Power	182.00	3796.33	0.65	3
Federalism	153.80	5838.80	0.70	5
Miscellaneous	161.50	4725.00	0.61	4

Table 2: Descriptive Statistics, Means by Issue Area

We are also interested in seeing what affects the B of an article, so I produce the categorical plot in figure 3 to see if the type of issues affect the likelihood for an article to be *bursty*. Intuitively, we should expect the more contentious issues to be more *bursty* or less random. From table 2 and figure 3, we see that there is no significant deviation across issues as the mean B varies between 0.6 to 0.75. However, we can still discern what issues

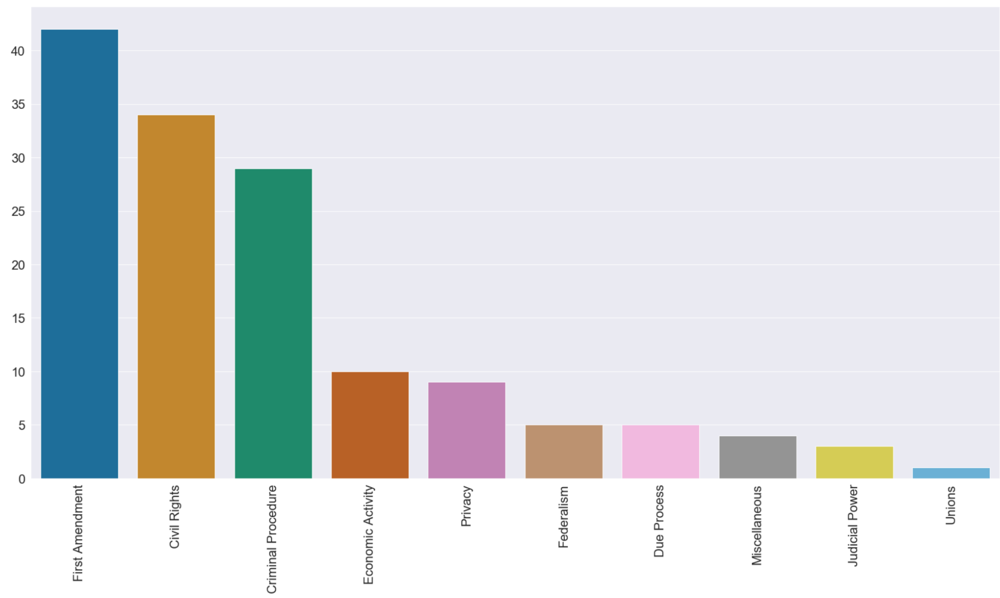

Figure 2: Bar Plot of WP Article Count by Issues

are more *bursty* than others. In particular, the mean B for articles that refer to cases on Privacy (mean B, 0.70), Unions (mean B, 0.74), Federalism (mean B, 0.70), Criminal Procedure (mean B, 0.71), First Amendment (mean B, 0.69) and Due Process (mean B, 0.69) cases appear more *bursty*. Given that we only have a small sample for some of these issues, the B observed in articles that include Criminal Procedure and First Amendment Issues are more compelling — a likely a result of the *editorial wars* on WP.

Given this insight, I use the next section to test whether we can explain or predict the B of an article by the issue area the case relates to using a univariate linear regression.

4.2 Basic Regression Analysis

A categorical linear regression was performed to estimate the model. The dependent variable (burstiness) ranges from -1 (non-*bursty*) to 1 (*bursty*), where 0 is considered random. The predictor or independent variable used are the issues the case pertains to (issueArea). Table 3 summarises the results of the univariate regression model for the B of edits. It displays the coefficient estimates of issueArea, as well as the corresponding standard errors. Statistically significant coefficients at the 99%, 95%, and 90% confidence levels are identified with ***, **, and *, respectively. The overall pooled model explained 15.8% variation of the B measures.

As the scope of this paper is limited and exploratory, I will not conduct a full interpre-

Table 3: Model of Burstiness and Issue Area

	Dependent Variable: Burstiness	
	Model: OLS Categories	Results
Issues (issueArea)	Civil Rights	-0.046***
		(0.014)
	First Amendment	-0.026*
		(0.013)
	Due Process	-0.024
		(0.027)
	Privacy	-0.013
		(0.021)
	Unions	0.027
		(0.056)
	Economic Activity	-0.061***
		(0.020)
	Judicial Power	-0.062*
		(0.034)
	Federalism	-0.016
		(0.027)
	Miscellaneous	-0.102***
		(0.030)
Intercept		0.713***
		(0.010)
N		134
R^2		0.158

Standard errors in parentheses. Two-tailed test.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

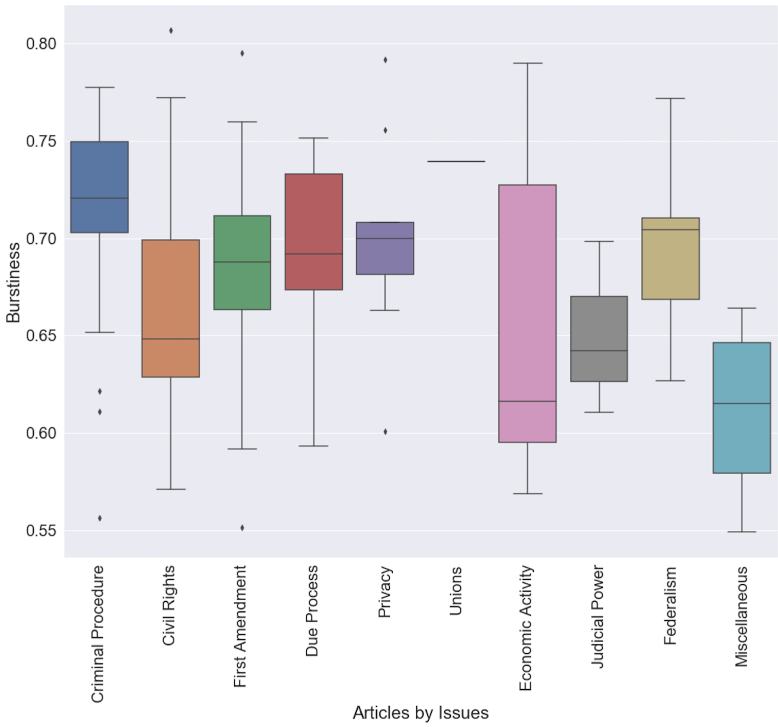

Figure 3: Categorical plot of WP Articles Burstiness by Issue

tation of the model produced. Nonetheless, it is worth noting that while the model helps identify possible effects of case characteristics on the likelihood of a U.S. Supreme Court WP article to be *bursty*, it does not give us a full picture of the underlying causes of the editorial wars surrounding these articles — especially because our sample size is relatively small. It is also clear from a skim of the list of cases returned from WP (Wikipedia contributors, 2018) that other external factors such as economic, social and political events also affect the behaviour of editors in this system.

5 Conclusion

The exploratory analysis conducted shows that there are some underlying links between the characteristics of the cases cited and the B of an article. For example, we see that relatively recent cases (post-1953) are more represented in the articles. While this may be a result of WP being a recent phenomenon and data on older cases being sparse, we also see that the contentious issues tried by the Supreme Court are more *bursty*. Also of note is that Criminal Procedure, Civil Rights and First Amendment issues are most represented in the data obtained, again pointing to the fact that the controversy surrounding these issues might make the articles they link to both more popular and *bursty*. Finally, we see from the regression analysis that a model for B — while limited in explanation — can be created to see what characteristics explain B and in turn editorial wars around an article. The results obtained are not conclusive as this paper is limited in scope, but we see that it serves as a preliminary step to determining the causes of editorial wars in U.S. SC topics on WP — and perhaps, more generally, legal topics on WP.

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