Using Interactions in the Quantification of Media Bias

Diogo F. Pacheco[1], Dillon Rose[1], Fernando B. Lima-Neto[2], Ronaldo Menezes[1]

[1]BioComplex Laboratory, Computer Science, Florida Institute of Technology, USA
[2]Escola Politécnica, University of Pernambuco, Brazil

dpacheco2013@my.fit.edu, drose2010@my.fit.edu, fbln@ecomp.poli.br, rmenezes@cs.fit.edu

Abstract

It is hard to describe how strong most people feel about the favoritism of the media towards certain political parties, events and people. Our world is not short of anecdotal accounts of how this or that media outlet demonstrate favoritism and perhaps reports the so called "truth". But what is the truth? Media outlets are packed with what we call "spin"—a type of propaganda used to sway public opinion in favor or against an organization or public figure. So an obvious question arises: *Can this favoritism be quantified?* Many of the works published on media bias look at historical reasons for the media to take sides. One clear example of favoritism happens in politics; the Pew Research Center has shown that different media outlets attract audiences with different political ideology, which in turn can put pressure on outlets to satisfy what they want to hear leading to spinning the news: a typical vicious cycle. This paper proposes a mechanism to quantify media bias based on the analysis of relationships between people or organizations in the real world. We demonstrate the validity of our approach by looking at US politicians and how these relationships are reported by outlets. We propose a metric called *coverage* that indicates how much the media outlet can be trusted and then we show how the coverage can be applied to the case of party and individual favoritism. We apply our proposed approach to the US Senate using collaborations between senators in bills' co-sponsorships as the ground truth; the assumption is simple, Senators working more should get more coverage on the media. Our results indicate that most media outlets favor the Democrats and only one favors the Republicans.

1 Introduction

If we ask people who are interested in news, it is hard to find an individual who will argue that media outlets are unbiased. Despite their attempts to portray themselves as "nonpartisan" or "neutral", most of us feel quite the opposite about the media outlets. But does this bias really exist? And if yes, can it be quantified? The quantification of media bias could help us understand the effect it has on the public's opinion. For instance, could media bias explain public opinion about parties or politicians?

In this paper, we introduce the concept of coverage of a media outlet that may be used to evaluate media bias. One example we use in this paper has to do with politics because it is easy to find examples of polarization in politics. The USA is a good case because theirs politics are highly polarized between the Republicans (conservatives) and Democrats (liberals) which leads to a hypothesis that the media may have to reflect this polarization given they generally cater to the public of particular locations. In this paper, we attempt to quantify media coverage and apply the proposed concept to the idea of politics, more specifically the politics of the US Senate. Our proposed approach may be used in other examples beyond politics as long as we know the "truth"; after all, we can not evaluate anything if we do not know what is "correct". For instance, we can not evaluate beauty unless we have a definition of what beauty is, but knowing the ground truth would allow us to rank individuals on the beauty scale.

Politics is a nice case study because media outlets are perceived to have preferences towards certain political parties and individuals. In the USA, we have many accounts of media favoritism. For instance, Povich [9] who is herself a Washington correspondent, published a book with alarming numbers demonstrating that in Washington, D.C., the vast majority of reporters are liberals and, when asked, were many times more likely to vote for John Kerry (democrat) than George W. Bush (republican) in the 2004 presidential election. Yet, the favoritism of correspondents may not necessarily trickle down to the news outlets themselves, and if they do, the favoritism may appear at different scales in each of the outlets—this is where our work comes in.

The approach we propose in this paper is based on three factors that represent "true reports", "false reports" and "lack of reports". These factors will compose what we call the newspaper *coverage*. We concentrate on newspapers and selected 10 of the largest in the USA (by circulation numbers). As we said before, in order to quantify the coverage, we needed a ground truth. In the case of politics, there are many sources of ground truth, we have decided to look at newspaper coverage about the US Senate and use the information from the Senate itself as the ground truth. The nature of collaborations within the Senate give us a "truth" target. Our premise is that we should expect that if two senators collaborate in the Senate, their collaboration should also be depicted in the newspapers if the coverage of the newspaper is adequate. It is clear that this approach may be controversial because one could easily argue certain bills are more popular or more important and hence the senators involved in the proposal of a popular bill will naturally get more coverage than senators working on less popular bills. Although this is possible, the counter-argument would be to say that popularity may actually be a byproduct of the media coverage and not the cause of the coverage. Our proposed approach assumes some independence of other variables because that is the only way to move forward on the discussion of media bias quantification. In Section 3.2 we describe the specific way the metrics are computed.

For our case study with the US Senate, our findings demonstrate that the Dallas Morning News is the only newspaper favoring the Republicans, but only very slightly; in fact, this is the closest to what we would call unbiased. On the other side of the spectrum the NY Post favors Democrats the most. The NY Times bias is uncertain as it favors Republicans in party level, but favors Democrats in individual level. All other newspapers are slightly biased towards the Democrats. The importance of our results is twofold: *(i)* citizens can use such metrics to evaluate the quality of the news they read, and *(ii)* newspapers could use our approach to gauge themselves and adjust their coverage as necessary. Last, we have also evaluated the site *senate.gov* as if it was a newspaper and found that the official US Senate website bias is also uncertain for the same reasons we cited above for the NY Times case.

This paper is divided as follows. In Section 2 we describe some of the works published on media bias and their relation to the approach we propose here; most work on media bias use politics as a case because politics is naturally polarized. In Section 3 we describe our methodology to quantify coverage; we start with the description of the data we collected for the US Senate, how the coverage is actually computed, and how the bias is classified. We follow in Section 4 with the analysis of the level of bias of 10 newspapers in the USA compared to the ground truth of the US Senate. We finish this work in Section 5 with some discussion on the proposed approach and some indication of future works.

2 Related Work

Media bias has always been a topic of interest because it is a subject everyone feels a little passionate about. Most people have an opinion about how the media possibly sway public opinion. Interestingly, no matter who you select, they believe the media tends favors the other side, in politics that would be the other candidates, parties, ideology, etc. In the USA, liberals say the media is conservative [5] and conservatives say the media is liberal [1]. Who is right?

In 2000, D'Alessio and Allen [3] set out to answer the question above. They investigated three kinds of bias namely: *gatekeeping bias*, the preference for selecting stories about one party or the other; *coverage bias*, or the amount of coverage each party gets; and *statement bias* which deals with the favorability of coverage towards one party. The authors looked at bias in newspapers, magazines, and television and of these only the television had slight coverage bias and statement bias.

Druckman and Parkin [6] showed that the effect of a newspaper tone towards a candidate can impact the voters' decision and they found some good evidence that the slanted editorials indeed can achieve this goal. They also raised the question of whether readers are to blame or the victims for not looking for diversity in their media activities (reading, watching TV, etc.)

Groseclose and Mulyo [8] have proposed an interesting measure of media bias and applied it to print and television media outlets. Their metric is based on a count of mentions to specific think tanks. Think tanks themselves are assigned a score from conservative to liberal based on the mentions of their names by members of congress. The starting point is the ADA metric (Americans for Democratic Actions) of members of congress, which is used to calculate an ADA-like for each think tank which will then be used to calculate another ADA-like score for media outlets. The authors found that most media outlets are left-leaning (liberal), except for the Fox News' Special Report and the Washington Times.

Media bias may also be related to voting patterns. DellaVigna and Kaplan [4] have done a study specifically with the Fox News Channel in more than 9,000 towns in the USA and found that their pro-right approach accounted for a significant gain of the republican party between the years 1996 and 2000. On average the party gained 0.4 to 0.7 percentage points in the towns where the Fox News Channel was available.

Nowadays we live in the decade of the big data. Scientists today have the ability to collect data about virtually anything and certainly politics is one area of interest. This availability should yield more reliable results on bias, be it on politics or any other issue worth studying. Moreover, all the studies above provide absolute results and not based on a "truth". This can be a concern because favoritism refers to doing something abnormal and not just a count. As a simple example, assume two brands of cars: brand X has 80% of the market share and brand Y has 20% of the market share. If this is the case, one should expect that 80% of the car accidents will involve Brand X and any deviation of this would be abnormal. In fact, if we find that there is a 50–50 situation in car accidents between Brand X and Y, that would be anomalous and indicate some issue with Brand Y. We believe the same should apply to politics. If a party or individual work more and is more involved in congress, that person or party should get more attention and that would be considered normal if this imbalance is proportional to the activity of the party/individual.

3 Methodology

The contribution of this paper falls on the idea of *coverage* explained later, but in order for us to get there we are forced to intertwine the general idea of coverage to the case of bias in politics. This makes the description of the work easier to follow. However, we must highlight that our contribution *is independent of politics and can be applied to other subjects*; politics are used here to demonstrate the effectiveness of the method proposed.

3.1 Data Collection: Congress and Newspapers

The discussion on bias automatically brings the question of what is the truth? To argue that a newspaper favors a particular topic or person one has to know the number of times that a topic or person is *expected* to be mentioned.

Although politics is a multi-facet subject and politicians many times become popular on the media due to characteristics other than their performance as a politician, we decided to evaluate our proposed method entirely from the angle of "collaborativeness". We define the "collaborativeness" of a politician (in our case, a senator) as the number of times this politician has collaborated with other senators (absolute collaborativeness) and the rate of each of those collaborations (weighted collaborativeness). The true level of collaboration of a senator is given by the concept of co-sponsorships. In the US Senate, bills can be introduced by any of the senators and others generally demonstrate their support by co-signing the introduced bill. Furthermore, according to Campbell [2], co-sponsorship is actively sought by the bill proponent because they can use the number of co-sponsorships on speeches as an indication of broad support to the bill's idea. Given this market of co-sponsorships, one could be inclined to say that they take place quite often but Fowler [7] has observed that the average legislator cosponsors only 2-3% of the bills—meaning they are quite selective.

We used the New York Times Congress API[1] to gather data from the 113$^{\text{th}}$ US Senate, i.e. senators' names and the amount of collaboration (co-sponsorship bills) among them. We identified 104 senators which is 4 over the normal 100. The additional names are: Jeffrey Chiesa (1), Republican, in replacement to Frank Lautenberg (died), then replaced by Democrat Cory Booker (2); William Cowan (3), Democrat, the interim for John Kerry (Secretary of State), then replaced by Democrat Edward Markey (4).

One of the challenges when it comes to doing analysis of newspapers' bias relates to the data collection. Most newspapers are not keen on giving their data for analysis and request us not to use Web crawlers to collect data either. Therefore we decided to abandon our initial thought of using Web crawlers in lieu of using information from Google search queries because Google has already done the parsing of the pages on each site and can provide us with just the count we need.

Figure 1 shows how data was extracted using Google. In the figure, we can see that the Google's search on the New York Post domain (nypost.com) has found 4 pages in the newspaper where senators "John McCain" and "Mark Begich" are mentioned together. The number 4 is then used to quantify the strength of the social relation between the two senators according to the New York Post. Each newspaper yields a social graph between senators. We have used 104 names which means that 5,356 queries were executed to generate a network for one particular newspaper. We have chosen the top-10 newspapers in the USA based on their circulation[2]—in reality only one newspaper in the top-10 list was not considered which was the New York Daily News because we already had 2 newspapers from New York. We added the Dallas Morning News (11$^{\text{th}}$ in the list). Table 1 shows the characteristics of each newspaper considered and some of the information related to the senator's social network extracted from each of them. We have, for comparison purposes, also collected data from the website *senate.gov*. This website is a portal for the US Senate and publishes the senators' activities. We wanted to verify the bias of that portal because it could also help us to better understand newspaper bias.

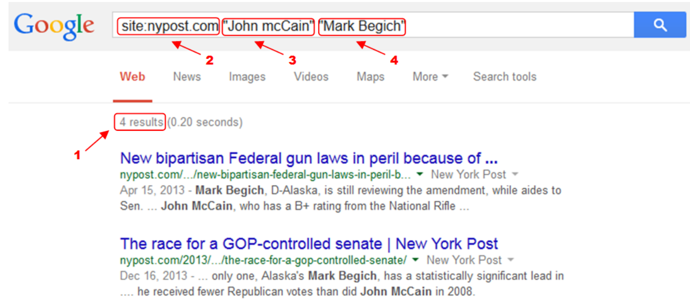

Figure 1: Screenshot of a Google search used to collect data related to the relationship between senators. (1) is the main result of the search and the number we use to relate the two senators used in the search. In this example we have the relationship between (3) John McCain and (4) Mark Begich, restricted for (2) the New York Post (a single domain).

Table 1: Information related the top 10 newspapers in the USA, the senate.gov portal, and the amount of data we collected about each of them. The social network of all newspapers and senate.gov have 104 nodes (n). TIM stands for "total individual mentions" for the senators while TNR stands for "total number of relations" for pairs of senators.

Newspaper	Circulation[a]	# edges (network density)	TIM[b]	TNR[c]
Chicago Sun Times	470,548	3,115 (0.582)	30,245	27,880
Chicago Tribune	414,930	3,165 (0.591)	42,113	21,642
Dallas Morning News	409,265	1,929 (0.360)	25,179	23,056
Denver Post	416,676	3,533 (0.660)	91,750	56,980
Los Angeles Times	653,868	3,671 (0.685)	90,878	74,309
New York Post	500,521	1,587 (0.296)	18,513	5,277
New York Times	1,865,318	5,003 (0.934)	218,282	814,110
USA Today	1,674,306	4,657 (0.869)	71,181	88,109
Wall Street Journal	2,378,827	4,664 (0.871)	124,145	84,539
Washington Post	474,767	5,184 (0.968)	427,264	1,886,195
Senate.gov	—	4,555 (0.850)	425,918	1,614,389

Correlation coefficients between circulation and citations are $\rho^{a,b} = 0.14$, $\rho^{a,c} = 0.00$, and $\rho^{a,b+c} = 0.03$.

Table 1 is quite informative because it shows that the circulation of a newspaper has almost no direct correlation to how much it talks about politics. For instance, we see that the Washington Post has one of the lowest circulation numbers but it has enough mentions of senators' collaboration to yield almost a complete network (i.e. the network density is 0.968). One can also notice that newspapers differ significantly on the number of times senators are mentioned (TIM, Total Individual Mentions) and the number

[1]http://developer.nytimes.com/docs/read/congress_api

[2]According to the information available from Alliance for Audited Media. www.auditedmedia.com

of relations found in the newspaper (TNR, Total Number of Relations) for all pairs of senators. This means that some newspapers are more "social" than others as they depict a higher number of social relationships.

3.2 Quantifying Coverage

Given the data in Table 1, we can now describe how to calculate the coverage of a newspaper using the example from the US Senate. The idea is that the Senate information on co-sponsorship of bills is a ground truth on how senators collaborate. In other words, the co-sponsorship of bills forms a social network between senators that we argue to be a good representation of the senators' activities. Our metrics are based on the fact that the Social Network formed from newspapers have to be similar to the one from the co-sponsorship. It is very important to point out that our contribution is *not* dependent on data from US Senate bill co-sponsorship being the best representation the truth. Although we believe it is a good representation, the technique proposed works with any ground truth because it is analogous to trying to find the distance between a feature vector for the ground truth and the feature vector for a newspaper—the value of such distance would represent the bias.

The similarity between these networks is very particular to our approach. One should not be satisfied in doing a simple network matching (like graph matching) because the lack of information (few citations) is also important for comparison. We propose metrics for quantifying the coverage (and type of coverage) based on three criteria described below. First, consider **M** and **S** as the adjacency matrices of a newspaper and the Senate, respectively; **S** represents the truth that we want **M** to be compared against, i.e. S_{ij} is the number of bills co-sponsored by senators i and j, while M_{ij} is the number of pages they appear together (see Figure 1-1). The three metrics below lead to three other matrices, each of which quantifies the criteria in question. These matrices will be further used to classify the coverage of each newspaper with regards to US Senate politics:

Legitimacy: If senators collaborate in the Senate, we believe this collaboration has to be represented in the newspapers. If the amount of pairs' collaboration in the Senate is proportional to the amount of pairs' citation in the newspaper (plus or minus a threshold), these relations are considered as part of the legitimacy of the newspaper. Newspapers should aim for high legitimacy values.

Fabrication: refers to reporting on relationships that do not exist in the social network of the ground truth or to report excessively (above the legitimacy threshold). Newspapers should aim for low fabrication values.

Negligence: Negligence is the dual of fabrication and refers to the fact that many times a relationship that is represented by the ground truth is not discussed at all by the newspapers or is poorly reported (bellow the legitimacy threshold). This negligence affects the reliability of the newspaper because it suggests the newspaper reports only of part of the truth. Newspapers should aim for low negligence values.

We propose two approaches to calculate the matrices **L** (Legitimacy), **F** (Fabrication), and **N** (Negligence): considering the weight of relations and ignoring it. Note that these matrices are computed for each newspaper in this study. Each newspaper has these three matrices associated with it.

3.2.1 Naive Coverage

In the naive approach to compute legitimacy, fabrication, and negligence one should consider only the existence/absence of relations between senators, i.e. the collaborations' weights are ignored. The matrices of Legitimacy (**L**), Fabrication (**F**), and Negligence (**N**) are defined as:

$$L_{i,j} = \begin{cases} 1, & \text{if } S_{i,j} > 0 \wedge M_{i,j} > 0 \\ 1, & \text{if } S_{i,j} = 0 \wedge M_{i,j} = 0 \\ \varnothing, & \text{otherwise.} \end{cases} \quad (1)$$

$$F_{i,j} = \begin{cases} 1, & \text{if } S_{i,j} = 0 \wedge M_{i,j} > 0 \\ \varnothing, & \text{otherwise.} \end{cases} \quad (2)$$

$$N_{i,j} = \begin{cases} 1, & \text{if } S_{i,j} > 1 \wedge M_{i,j} = 0 \\ \varnothing, & \text{otherwise.} \end{cases} \quad (3)$$

In all equations above and throughout this paper, the value $\varnothing$ is used to represent that nothing is stored in that location in the matrices; that is, it represents a *null* in that position. Later we show how this can be used in the definition of *coverage*.

3.2.2 General Coverage

In this approach we consider the weight of collaborations and because of that we create the matrix of relative differences **D** that represents how many times a relationship between 2 senators were cited in a newspaper more or less than expected when comparing with the true collaboration matrix of the Senate. For instance, suppose that the relation between senators a and b in the Senate is twice as frequent as the relation between senators c and d. Thus, the newspaper is expected to talk about a and b (as a pair) twice as more as it talks about c and d (also as a pair). However, it is unlikely that both kinds of networks (Senate **S** and newspapers **M**) present collaborations in the same scale. For that reason, we should calculate the adjustment factor (ε) to scale **S** to be comparable to **M** as:

$$\varepsilon = \frac{z}{\max_{i,j}(S_{i,j})}, \quad (4)$$

where z is given by the mean value of all $M_{i,j}$ such that the relation of i and j is maximum in **S**. Note that the maximum relationship in **S** can be made by more than one pair. For instance, we could have various pairs of senators that have the same number of relationships (collaborations) in the Senate and that number can be maximum compared to all other relationships. The matrix of relative differences **D** is defined as:

$$D_{i,j} = \begin{cases} \frac{M_{i,j}}{\varepsilon}, & \text{if } S_{i,j} = 0 \\ -\varepsilon S_{i,j}, & \text{if } M_{i,j} = 0 \\ 1 - \varepsilon \frac{S_{i,j}}{M_{i,j}}, & \text{if } M_{i,j} \leq \varepsilon \frac{S_{i,j}}{2} \\ \varepsilon \frac{M_{i,j}}{S_{i,j}} - 1, & \text{otherwise.} \end{cases} \quad (5)$$

As the elements of **D** represent the number of times a relationship is over/under covered, if an expected value is zero, but the real observation is different from zero, then, this ratio is infinity. These special cases happen when there is no collaboration in the Senate ($S_{i,j} = 0$)—maximum fabrication—or when no citations appear in a newspaper ($M_{i,j} = 0$)—maximum negligence. These conditions are represented in the first two cases of equation 5.

Once we have measured the differences in ratio for each relation, now we can calculate **L**, **F**, and **N** by filtering **D**. Note that we tolerate the legitimacy in ±10% deviation (threshold) from the real expected value.

$$L_{i,j} = \begin{cases} D_{i,j}, & \text{if } -0.1 < D_{i,j} < 0.1 \\ \varnothing, & \text{otherwise.} \end{cases} \quad (6)$$

$$F_{i,j} = \begin{cases} D_{i,j}, & \text{if } D_{i,j} \geq 0.1 \\ \varnothing, & \text{otherwise.} \end{cases} \quad (7)$$

$$N_{i,j} = \begin{cases} |D_{i,j}|, & \text{if } D_{i,j} \leq -0.1 \\ \varnothing, & \text{otherwise.} \end{cases} \quad (8)$$

Furthermore, we expect that the density distribution function of **D** from a fair newspaper follows a normal distribution with mean zero. The variance explains behaviors apart legitimacy, while positive or negative skew indicates dominance of fabrication or negligence, respectively.

3.2.3 Coverage Composition

The coverage of a newspaper is defined by the composition of all reports, i.e. those classified as legitimate, fabricated, or neglected. Consider **X** as being one of criteria matrices (**L**, **F**, or **N**). The contribution to the coverage is the number of relations of **X** divided by the total number of possible collaboration relations (i.e. self-relation is ignored) and is given by e^X. Total coverage is calculated as:

$$e^X = \frac{1}{n(n-1)} \sum_i^n \sum_j^n 1 : (X_{i,j} \neq \varnothing) \quad (9)$$

$$e^L + e^F + e^N = 1 \quad (10)$$

Although Equation 10 appears to be intertwined with politics, it is being used in this context just as an example. Coverage allows us to investigate favoritism of any subject with a social relationship. The metric is based on differences between social relationships that are expected versus measured.

3.3 Bias Classification

As argued earlier, the coverage metric proposed here can be applied to many different subjects. However, it may be useful sometimes to have a finer granularity of this coverage. One example is the case of politics being used in this paper. One can talk about negligence, fabrication and legitimacy of a newspaper as a whole but these values could be skewed to a particular party which would be considered bias towards an ideology (high level) or skewed towards particular individuals (low level). We introduce the bias classifications and detail them through a simple example, illustrating since the coverage measure until the bias interpretation.

We propose an evaluation of bias at party level considering fabrication as a factor and negligence as a contra-factor. In order to understand the effect for each party, we interpret the density distribution function of the matrix of differences **D** - it is a composition of negligence, legitimacy, and fabrication criteria. First, we calculate the mean for relations between Republicans and between Democrats (μ^{Rep} and μ^{Dem}). Then, the greatest mean determines the party who is being favored through newspaper coverage, by being more fabricated ($\mu > 0$) or being less neglected ($\mu < 0$). If the means are even then the newspaper is balanced regarding party position.

In addition, we consider favoritism in a lower level. We should account exclusively to fabrication values, i.e. check who is being more reported than expected. In other words, we add the amount of times relations between two Democrats senators were fabricated (f^{Dem}) and add the amount of fabricated relations between Republicans (f^{Rep}). This calculation is defined as:

$$f^{\text{party}} = \frac{1}{2} \sum_i^n \sum_j^n F_{i,j} : \left(i^{\text{party}} = j^{\text{party}}\right), \quad (11)$$

We can now compare the values of f^{Dem} to f^{Rep} determining whether a group of individuals are being favored or not, and if the case, from whose party they are. Note that with two levels of bias, if a newspaper skews to the same party in both levels, this clearly suggest bias toward this party. However, if a newspaper switches parties into these levels, then bias classification becomes subjective. In other words, it favors the coverage of a party as a whole, but favors even more specific individuals from the other party.

In the next section we present a simple example to illustrate this application.

3.3.1 A Simple Example

Given the amount of computations described so far, we believe it is didactic to show on a simple example how these values are calculated (see Table 2). To keep it simple, instead of handling 2-dimension matrices we use one-dimension where each element represents the relationship between a pair of senators in the Senate or citations in a newspaper. We illustrate two newspapers named **M1** and **M2** in comparison to a hypothetical Senate **S**. Of the 5 relations defined, A and B are between Democrats, and C, D and E among Republicans. The bi-partisan relations were

Table 2: Simple example depicting how the coverage is calculated.

Relation	Party	**S**	**M1**	**D1**	**L1**	**F1**	**N1**	**M2**	**D2**	**L2**	**F2**	**N2**
A	Dem	10	11	0.1	∅	0.1	∅	15	0.125	∅	0.125	∅
B	Dem	20	18	-0.1	∅	∅	0.1	20	-0.25	∅	∅	0.25
C	Rep	15	5	-2	∅	∅	2	0	-20	∅	0	20
D	Rep	30	30	0	0	∅	∅	40	0	0	∅	∅
E	Rep	5	15	2	∅	2	∅	50	6.5	∅	6.5	∅

Newspaper	z	ε	e^L	e^F	e^N	f^{Dem}	f^{Rep}	μ^{Dem}	μ^{Rep}	$bias^{party}$	$bias^{ind.}$	$bias^{global}$
M1	30	1	1/5	2/5	2/5	0.1	2	0	0	Balanced	Rep.	Uncertain
M2	40	1.33333	1/5	2/5	2/5	0.125	6.5	-0.0625	-4.5	Dem.	Rep.	Uncertain

not consider in this example since they do not affect on bias evaluation.

In order to compare media and Senate networks, we must calculate the adjustment factor ε in order to make **S** comparable to **M1**. We follow with the identification for the relation with maximum collaboration in **S** given by $S_D = 30$. Find the value for the same relation in the newspaper, $M1_D$ which gives us $z = 30$. In this case, the number of citations in **M1** is the same in **S**, then $\varepsilon = 1$. Observe that relation A indicates two Democrats that collaborate in the Senate 10 times and by multiplying by the adjustment factor the expected value for $M1_A = 10$. However, the observed value is $M1_A = 11$ which is 10% more than expected and the difference matrix assumes $D1_A = 0.1$. In a similar way one can notice that relation $M1_B$ is 10% less than expected and making $D1_B = -0.1$. After all calculation one observe that in 2 occasions **M1** over cites relations and this is why 2/5 of coverage is classified as fabricated (e^F).

To analyze the bias at party level of **D1**, we must compare the means for both parties. Accounting to Democrats we have values 0.1 and -0.1, giving $\mu^{\text{Dem}} = 0$. For the Republicans, we compute values -2, 0, and 2, also reaching $\mu^{\text{Rep}} = 0$. As the means are even and equal to zero, we can say that **M1** is balanced concerning parties, because it reports fairly both sides. The fabricated reports are compensated by the neglected ones to each party. If we take **D2** parties' means, however, both are negative, but $\mu^{\text{Dem}} > \mu^{\text{Rep}}$. This means both parties are not reported as they should, but since μ^{Dem} is greater, the democrat party is favored.

Considering the lower level bias of **D1** and **D2**, we can see that there are much more fabrication in favor to Republicans as $f^{Rep} \gg f^{Dem}$. This means that, apart from party level bias behavior, there are some republican individuals being much more fabricated than they should. In this way, if one analyzes bias through people, one confirms a favoritism towards republican pairs. In the combined evaluation, neither **D1** and **D2** can be seen as biased since there is no evident favoritism.

4 Experimental Results

4.1 Coverage Quantification

In this section we describe the application of the proposed media coverage evaluation. First we applied the naive coverage model to 10 newspapers and the senate.gov website and compared their coverage against the true Senate collaboration network. Then, we applied the general model to the same data set to observed the differences between models. Finally, we utilized the coverage model to evaluate if medias are biased to Democrats or Republicans, or if they are neutral.

At the top of Figure 2(a)(b) the naive approach results are shown. We observe small amounts of Fabrication (in red) - the highest value is 1.90% for the Washington Post and the Wall Street Journal. Because of the density of the Senate network, it is hard to find pairs of senators that never collaborated together. There is also a huge difference in the negligence of the New York Post and the Dallas Morning News from others which we believe be the result of the fact that these journals have smaller political sessions (as it can be confirmed in the value of TIM and TNR in Table 1).

There is a high correlation between Legitimacy and Negligence as observed in Figure 2(b) when we ignore Fabrication. Indeed, this approach may be too naive because it disregards the weight of the relationships between two senators. However, it is described here to show that the coverage approach could be used regardless of the weight of relations. The reliability of the results provided by our coverage method is directly related to the quality of the ground truth (matrix **S** in this example) and the quality of the matrices to compare (matrices **M** for each newspaper in this example).

In order to obtain a more critical judgment of medias, we submitted the 10 newspaper and the senate.gov website to the second approach (general coverage). The Figure 2(c)(d) shows clearly how the scenario has changed for the naive approach. By definition, only $D_{i,j} = 0$ should represent legitimacy, but as a model of approximation, we considered also true reports, those which deviate up to 10% (towards negligence or fabrication). In this scenario, there is no more linear correlation between legitimacy and negligence. The previous high scores of legitimacy have disappeared in the

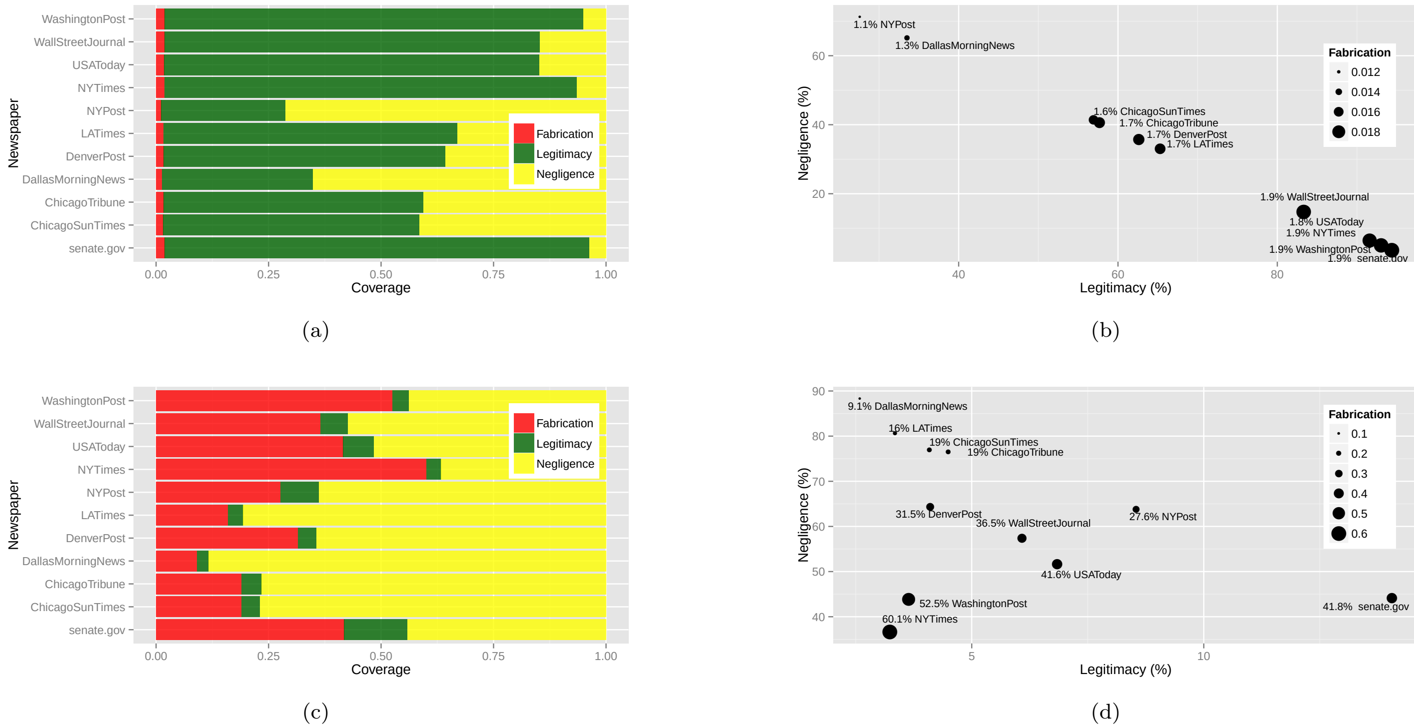

Figure 2: On the left, coverage of each media outlet is formed by Fabrication (red), Legitimacy (green), and Negligence (yellow) - the naive (a) and the general (c) approaches. On the right, values of each media for Fabrication (point size), Legitimacy (x axis), and Negligence (y axis). In naive approach (b): from left to right, and from top to bottom, we can see newspaper rank position, with the NY Post being the worst and the Washington Post being the best. In general approach (d) there is no best newspaper, for example, the NY Times is the best (lowest) in negligence coverage 37%, but is the worst in fabrication 60%.

general approach. The major player in the results is negligence. There is no best newspaper option because readers may use different criteria to express what is important: negligence, fabrication, or legitimacy.

4.2 Bias Application

Once concepts of bias were explained and established by the example in Section 3.3.1, we discuss some possible wrong bias evaluation concerning the US Senate by lack of data. It is well known that the Senate has been evenly distributed between Republicans and Democrats for several years. If one tries to evaluate bias considering mainly the total individual mentions (TIM) to each party per media outlet, then one has to make some assumptions:

- Parties work/collaborate in the same proportion as they are divided in the Senate; or,
- Newspapers are unbiased.

If one believes in the first assumption and check the TIMs (see Table 3), one would classify the Dallas Morning News, the Chicago Sun Times, the Washington Post, and the NY Post as biased towards Republicans (group R) because they over-mention Democrats in more than 10%. On the other hand, the NY Times, the Denver Post, and also the senate.gov website would be classified as Democrats (group D) for the same reason. Finally, the LA Times, the USA Today, the Chicago Tribune, and the Wall Street Journal would be bounded unbiased (group U). In contrast, those that believe in the second assumption and are readers of group R's papers, would claim that Republicans has more active senators. Similarly, readers of group D would argue in favor of Democrats. At last, readers of group U would believe both parties work evenly.

The fact is collaboration in the 113$^{\text{th}}$ Senate is not evenly distributed (25% +Dem) and to get accurate evaluation of bias we should compare not only citations, but confront to a more formal ground truth.

In Table 3 the results from application of general coverage and bias classification for 10 newspaper and the senate.gov website are shown. Also, there is collaboration information related to the ground truth network (113$^{\text{th}}$ Senate) and values for general coverage which was already observed in Figure 2. Analyzing each criterion individually, one can notice all newspapers fabricate, neglect, and are legitimate more towards Democrats, with the Dallas Morning News fabrication being the only exception. Figures 3, 4 and 5 depicts the density distribution functions for fabrication, negligence and legitimacy. This general behavior reflects on μ^{Rep} assuming negative values for major newspaper meaning Republicans are constantly neglected. When compared with μ^{Dem}, one can see that Democrats are even more neglected in the Dallas Morning News and in the NY Times. This

Table 3: Total individual mentions (TIM) per party; Coverage scores for Fabrication, Legitimacy, and Negligence from 10 medias and *senate.gov* according to the general approach. For each criterion, one can see the percentage of party dominance in the coverage, e.g. considering only the fabricated relations from the Dallas Morning News, there are 9% more fabrication for Republicans. Medias are sorted according to bias classification.

Media	TIM			Fabrication		Legitimacy		Negligence		μ^{Dem}	μ^{Rep}	Bias		
	Dem	Rep	%	e^F	Coverage	e^L	Coverage	e^N	Coverage			party	ind.	global
Dallas Morning News	4,376	20,791	-79%	9%	27% +Rep	3%	18% +Dem	88%	41% +Dem	-9.42	-7.73	Rep	Rep	Rep
NY Times	128,294	88,627	30.9%	60%	84% +Dem	3%	47% +Dem	37%	53% +Dem	-19.40	-14.76	Rep	Dem	Uncertain
LA Times	45,196	45,412	-0.5%	16%	75% +Dem	3%	45% +Dem	81%	33% +Dem	-7.19	-9.10	Dem	Dem	Dem
Chicago Sun Times	8,594	21,630	-60.3%	19%	68% +Dem	4%	38% +Dem	77%	27% +Dem	1.27	-1.28	Dem	Dem	Dem
USA Today	33,839	37,104	-8.8%	42%	88% +Dem	7%	48% +Dem	52%	53% +Dem	2.33	-1.38	Dem	Dem	Dem
Chicago Tribune	20,816	21,146	-1.6%	19%	90% +Dem	4%	31% +Dem	77%	22% +Dem	0.72	-3.45	Dem	Dem	Dem
Washington Post	143,316	280,964	-49%	53%	88% +Dem	4%	36% +Dem	44%	43% +Dem	-3.56	-8.16	Dem	Dem	Dem
Wall Street Journal	62,167	61,737	0.7%	37%	84% +Dem	6%	39% +Dem	57%	40% +Dem	3.83	-1.19	Dem	Dem	Dem
Denver Post	57,242	34,350	40%	32%	79% +Dem	4%	50% +Dem	64%	43% +Dem	6.71	0.59	Dem	Dem	Dem
NY Post	8,392	10,108	-17%	28%	88% +Dem	9%	22% +Dem	64%	19% +Dem	21.90	3.52	Dem	Dem	Dem
Senate.gov	255,062	167,436	34.4%	42%	81% +Dem	14%	43% +Dem	44%	75% +Dem	-15.69	-5.87	Rep	Dem	Uncertain
113th Senate*	137,364	102,246	25.6%											

* For the Senate numbers represent collaboration inter party instead of party mention.

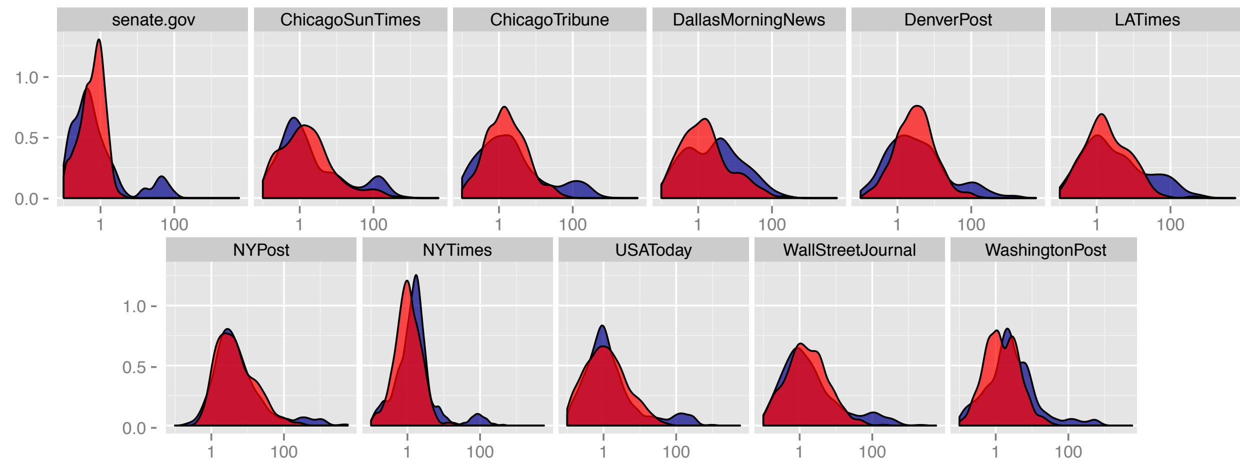

Figure 3: Density distribution of fabrication (log scale) for 10 newspapers and senate.gov. Apart from the senate.gov, medias are sorted alphabetically from left to right.

classifies both as party biased to Republicans because they neglect more Democrats collaboration.

Therefore, as mentioned above, fabrication is mainly towards Democrats, so applying the bias composition (party and individual levels) we find the Dallas Morning News as the unique republican biased newspaper. The NY Times and the senate.gov are uncertain as they favor different parties in each level, while all 8 other newspapers favor Democrats by reporting more about them than expected. The quantification of bias is given by the differences in means (μ^{Dem}-μ^{Rep}). Finally, the NY Post is the most biased while the Dallas Morning News is the closest to an unbiased classification.

5 Conclusion

In this paper, we proposed the coverage metric with two approaches, naive and general, based on social interactions and inspired by three criteria (fabrication, legitimacy and negligence) to understand media coverage more broadly. We tested our hypothesis with 10 major USA newspapers (by circulation numbers) comparing them to the US Senate network of collaboration (bills co-sponsorship). The data set was collected data using Google search for citation networks (newspapers) and using the NY Times Congress API for the co-sponsorship network (US Senate).

We showed the importance of considering relations' weights in coverage evaluation and how the perception of legitimacy can be changed into fabrication or negligence. We reveal that the main activity of medias is negligence, i.e. to ignore or to report real situations bellow expectations. Therefore, there is no best newspaper since readers can have different concerns over the importance of legitimacy, fabrication and negligence. We also demonstrated that coverage is not correlated to circulation.

To demonstrate the applicability of coverage as a metric, we proposed a bias classification in two levels: party and individuals. We highlighted a common wrong bias evaluation as a result of weak assumptions (lack of data or benchmarks). Then we evaluated ten major newspapers. Despite claiming themselves as balanced and fair, the results revealed that most newspapers evaluated are biased towards

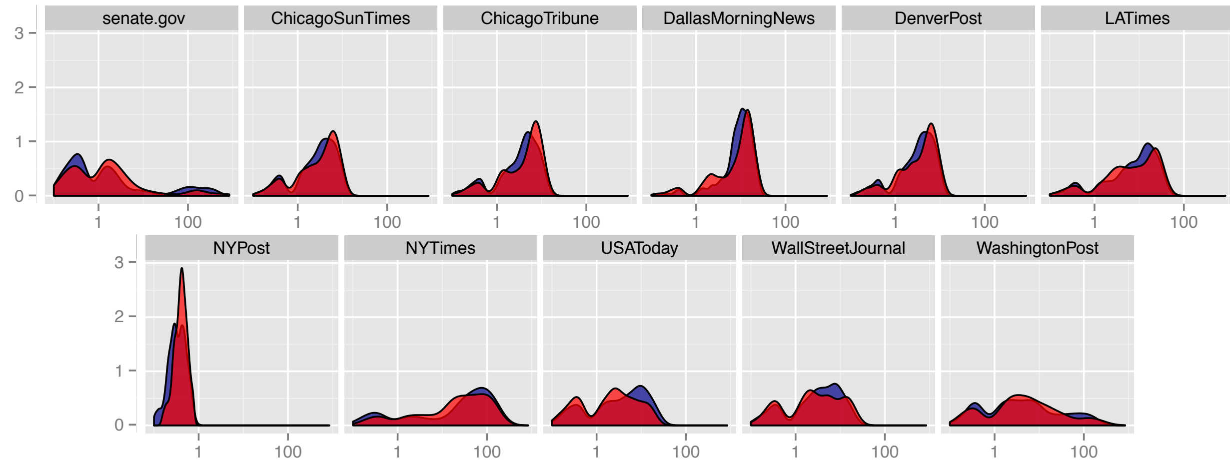

Figure 4: Density distribution of -negligence (log scale) for 10 newspapers and senate.gov. Apart from the senate.gov, medias are sorted alphabetically from left to right.

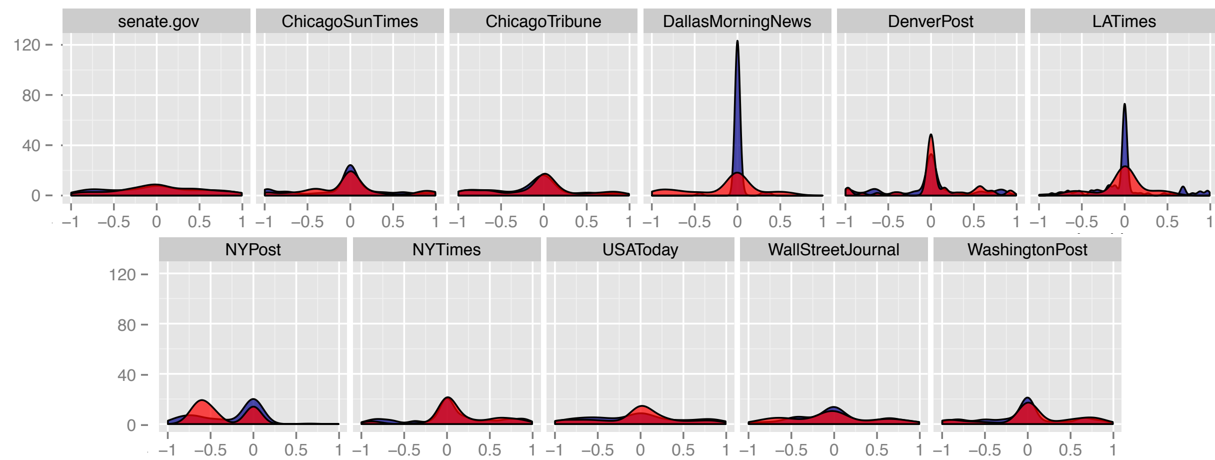

Figure 5: Density distribution of legitimacy for 10 newspapers and senate.gov. Apart from the senate.gov, medias are sorted alphabetically from left to right.

the Democrats, being the NY Post the foremost. The exceptions are the Dallas Morning News, which favors the Republicans and the NY Times whose global bias is inconclusive, because they favor Republicans at the party level, but promote individual Democrats. We also submitted the senate.gov website to our evaluation and its bias was also inconclusive.

Overall, we can conclude that coverage is an effective and powerful tool to compare media bias without requiring the use of Natural Language Processing (NLP) tools such as sentimental analysis.

Motivated by these findings we intend to investigate more types of medias which may include television and radio. The ground truth of the senate.gov website may need to be evaluated. In fact, one of the points in the paper that requires further study is how to define what is "true". We have chosen an option we believe is reasonable, but the approach proposed can take other "ground truths" as input. This may lead to interesting ways to compare media outlets. For instance, if we take CNN as the ground truth, we may be able to show how all the other media outlets compare to CNN (right or left of it).

Last, our approach has some unresolved issue related to the irrelevance given to NLP. It is most certain that NPL could help us contextualize the mention of individuals as positive or negative. The use of sentiment analysis on the text could generate different matrices **M**. However our approach for coverage would continue to work. Also, the **S** matrix only considered co-sponsorship in the 113^{th} Senate, as newspaper citations are not time constrained, if we consider every collaboration between those pairs in their entire political life, our ground truth may even be more representative of the reality.

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