"Don’t quote me on that": Finding Mixtures of Sources in News Articles

Alexander Spangher  Nanyun Peng  Jonathan May  Emilio Ferrara
Information Sciences Institute / University of Southern California
{spangher, peng, jonmay, ferrarae}@isi.edu

Abstract
Journalists publish statements provided by people, or sources to contextualize current events, help voters make informed decisions, and hold powerful individuals accountable. In this work, we construct an ontological labeling system for sources based on each source’s affiliation and role. We build a probabilistic model to infer these attributes for named sources and to describe news articles as mixtures of these sources. Our model outperforms existing mixture modeling and co-clustering approaches and correctly infers source-type in 80% of expert-evaluated trials. Such work can facilitate research in downstream tasks like opinion and argumentation mining, representing a first step towards machine-in-the-loop computational journalism systems.

1 Introduction
A dominant form of information published in news articles is derived from people, called sources. Through direct conversation, statements or written correspondence, journalists interact with sources to obtain quotations that inform news consumers’ understanding of current events, facilitate the voting decisions we make in our democracy and hold powerful individuals accountable. Journalists are trained to think formulaically about the sources they include in their text. Consider the following scenario:

A reporter is assigned a piece by her editor, who says: “The government is struggling to pass a budget. Find me two congressmen holding up the budget, and three White House officials who will talk about their plans.”.

This scene illustrates a common formula by which one type of news coverage (“budget coverage”) is conceived and executed, the result of which, for one named source, is shown in Box 1. In fact, this scene should not sound at all foreign to readers from a journalistic background. Although news corpora are standard in linguistics research, little attention is given to the highly formulaic, generative process by which these corpora are written.

Here we introduce a taxonomy and a model for one of many generative processes in newsmaking: the inclusion of named sources, or named-entities associated with quotations, in news articles. Researchers have noted challenges in analysing quotes in news articles in fields like sentiment analysis (Hussein, 2018), discourse analysis (Vessey, 2013) and opinion mining (Balahur et al., 2009). A common challenge across these domains involves the interdependent nature of quotations: quotes from sources are not included independently in news articles, as is often assumed, but are based on the mixture of voices journalists choose to tell a story.

Computational journalism is an emerging discipline that seeks to apply computational techniques to enhance journalists’ ability to seek new information (Cohen et al., 2011). Researchers in this field attempt to build models for machine-in-the-loop systems to aid journalistic inquiry and pro-
duce more robust news coverage.

In light of that, our motivation is two-fold: an understanding of how sources are used in news articles can inform downstream linguistics tasks that are dependent on mining sources’ quotes for information. It is also a first-step towards tools that can help journalists identify gaps in pieces, find sources more quickly and produce more robust coverage.

1.1 Contributions of this work

Our research advances three distinct directions:

1. We propose a problem definition for the analysis of named sources, as well as an ontology of named sources that categorizes sources into different source-types by their affiliation and role (cf., Section 2).

2. We implement a probabilistic graphical model that captures the mixture of source-types in each news article as a function of news-article type and the words that are associated with each source (cf., Section 4). We evaluate our model with expert annotators and show a predictive accuracy of 80%, well above existing baselines (cf., Section 6).

3. We present analytical insights that (1) lay the groundwork for future studies aimed at helping journalists find sources more quickly; (2) show how our model can be used to analyze trends in news. For instance, we find that between 1999-2002 in New York Times front page articles, high-level government officials were quoted less frequently while academic experts were quoted more.1 (cf., Section 7)

Our work can be helpful for journalists and our broader society: insofar as journalism is a form of information-sharing formalized over centuries of practice, the methods and models that journalists follow can inspire other forms of information-sharing in society.

2 Problem Statement

We seek to model news stories as mixtures of sources (eqn 1), where each source is labeled by a source-type. A sample labeled article is shown in Box 2.

\[
a_i = [s_1, s_2, ..., s_n] \quad (1)
\]

\[
type(s_j) = r(s_j) \cdot a(s_j) \quad (2)
\]

\[
type(a_i) \in \{1, 2, 3, ...T\} \quad (3)
\]

The source-type is defined as a concatenation of a source’s identified affiliation and role (eqn 2). A source’s affiliation refers to the kind of organization a source belongs to while role represents their role in that organization.3

Each news article is defined by a document-type (eqn 3), which influences the mixture of source-types present in the article. We next present the source ontology, shown in Table 1, based around the notion of affiliation and role. We leave to future work a similar explication of news-article types – in this work, we model them as latent variables to be inferred (cf. Section 4).

2.1 Source Ontology

One function of journalism is to interrogate the organizations powering our society. Thus, many sources are from Institutions: Government, Corporations, Universities, Non-Governmental Organizations (NGOs). Journalists first seek to quote decision-makers: presidents, CEOs, or senators. Sometimes decision-makers only comment though Representatives: advisors, lawyers or spokespersons. These sources all typically provide knowledge of the inner-workings of an organization.

Broader views are often sought from Informational sources: experts in government or analysts in corporations; scholars in academia or researchers in NGOs. These sources usually provide broader perspectives on topics.

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1This coincides with the invasion of Afghanistan, a period in history during which Chivers and Kelly (2018) notes the Pentagon became far less accessible to journalists.

3We emphasize that the focus of the role category is on the source’s role in the organization, not the story itself.
A different category of sources do not belong to formal organizations. They are Individuals: Actors, Victims and Witnesses. These sources differ based on how active a role they take in the events around them: actors affect events around them, while witnesses and victims are neutral or affected by the events around them. Often, these sources cannot be directly reached and journalists seek proxies: family members, lawyers, doctors or spokespeople.

2.2 Source Identification and Representation

We define sources, formally, as PERSON named-entities that are quoted: i.e., they are the governor in an nsubj dependency with a speaking verb: “say”, “recall”, “continued”, “add”, “tell”, “according to”. Each source is linked to all of her coreferences throughout the text. We represent documents as combinations of source-words as well as background-words. Source-words are all words in the first sentence that mentions a source, as these usually contain identifying information (e.g.: “Mick Mulvaney, the president’s chief of staff.”) as well as all sentences that contain a quote by that source (e.g.: “‘Get over it’, said Mulvaney.”). Background words are all other words.

3 Related Work

This work focuses on people quoted in news articles and is part of a broader field of character-based analysis in text. **Persona Modeling** Our work builds off Bamman et al. (2013) – which was extended by Card et al. (2016). Authors model characters in text as mixtures of topics, which are themselves influenced by latent “personas.” Both their work and ours seek to learn latent character-types.

There are key differences between our work and theirs: Bamman et al. (2013) view their characters as doers. Their characters are villains or heroes who have substantive roles in a plotline. As such, the text associated with characters is verb focused.4 Our work, in contrast, views characters as information providers, not necessarily active participants in the story.5 Thus, we build a different set of rules for associating text with characters. Additionally, there are differences in model structure which we will discuss in Section 4.

**Opinion Mining** Another strain focuses on characterizing voices in a text by opinion (O’Keefe et al., 2013). Such work has been applied in computational platforms for journalists (Radford et al., 2015) and in fake news detection (Conforti et al., 2018). This strain of research might benefit from the current work: role and affiliation are as important as other processes in journalistic inquiry. Identifying “supporters” and “opposers” is a very difficult task while analysing role and affiliation is closer to the journalistic process, as well as an easier task; there are specific keywords and appositive structures journalists use to identify role and affiliation.

**Computational Journalism** This work also falls into the field of Computational Journalism, which seeks to apply computational techniques to enhance the news environment. One vein in this field aims at improving the readers’ experience with news. Researchers have sought to improve detection of incongruent information (Chesney et al.,...
The key variables in our model, which we wish to infer, are the document type $T_d$ for each document, and the source-type $(S_{d,n})$ for each source. It is worth noting a key difference in our model architecture: Bamman et al. (2013) assume that there is an unbounded set of mixtures over person-types. In other words, in step 2, $S_s$ is drawn from a document-specific Dirichlet distribution, $P_S^{(d)}$. While followup work by Card et al. (2016) extends Bamman et al. (2013)’s model to ameliorate this, Card et al. (2016) do not place prior knowledge on the number of document types, and rather draw from a Chinese Restaurant Process.\footnote{Card et al. (2016) do not make their code available for comparison.} We constrain the number of document-types, anticipating in later work that we will bound news-article types into a set of common archetypes, much like we did for source-types.

Additionally, both previous models represent documents solely as mixtures of characters. Ours, on the other hand, allows the type of a news article, $T$, to be determined both by the mixture of sources present in that article, and the other words in that article. For example, a crime article might have sources like a government official, a witness, and a victim’s family member, but it might also include words like “gun”, “night” and “arrest” that are not included in any of the source words.

The model then infers source-type, $S$, document type $T$, and word-topic $z$. These variables are all categorical. All of the variables labeled $P$, in the diagram represent Dirichlet Priors, while all of the variables labeled $H$, in the diagram represent Dirichlet Hyperpriors.

Our generative story is as follows:

For each document $d = 1, ..., D$:

1. Sample a document type $T_d \sim Cat(P_T)$
2. For each source $s = 1, ..., S_{d,n}$ in document:
   (a) Sample source-type $S_s \sim Cat(P_S^{(T_d)})$
3. For each word $w = 1, ..., N_w$ in document:
   (a) If $\gamma_{d,w} = \text{“source word”}$, sample word-topic $z_{d,w} \sim Cat(P_z^{(S_s)})$
   (b) If $\gamma_{d,w} = \text{“background”}$, sample word-topic $z_{d,w} \sim Cat(P_z^{(T_d)})$
   (c) Sample word $w \sim Cat(z_{d,w})$

Within this broad field, our work aims at aiding journalists by leading towards machine-in-the-loop systems. Overview, for instance, is a tool that helps investigative journalists comb through large corpora (Brehmer et al., 2014). Workbench is another tool by the same authors aiming to facilitate web scraping and data exploration (Stray). Workbench is also used by Diakopoulos et al. (2010) to assist in social media posts that are unique and relevant. Our work is especially relevant in this vein. We envision characterizations of source types being combined with knowledge graphs to lead to similar tools for finding relevant sources, and suggesting sources to add to a story.
4.1 Inference

We construct the joint probability and collapse out the Dirichlet variables: $P_w, P_z, P_S, P_T$ to solve a Gibbs sampler. Next, we discuss the document-type, source-type, and word-topic inferences.

4.1.1 Document-Type Inference

First, we sample a document-type $T_d \in 1, ..., T$ for each document:

$$
p(T_d|T_{-d}, s, z, \gamma, H_T, H_S, H_Z) \propto (HT_d + c_{T_d,s}) \times \prod_{i,j=1}^{S_d} \left( \frac{(H_{S_d} + c_{T_d,s}) + (SH_S)}{c_{T_d,s} + \gamma + KH_z} \right)
$$

where the first term in the product is the probability attributed to document-type: $c_{T_d,s}$ is the count of all documents with type $T_d$, not considering the current document $d$'s assignment. The second term is the probability attributed to source-type in a document: the product is over all sources in document $d$. Whereas $c_{T_d,s}$ is the count of all sources of type $s$ in documents of type $T_d$, and $c_{T_d,s}$ is the count of all sources of any time in documents of type $T_d$. The third term is the probability attributed to word-topics associated with the background word: the product is over all background words in document $d$. Here, $c_{k,s,T_d,s}$ is the count of all words with topic $k$ in document type $T_d$, and $c_{s,s,T_d,s}$ is the count of all words in documents of type $T_d$.

4.1.2 Source-Type Inference

Next, having assigned each document a type, $T_d$, we sample a source-type $S_{(d,n)} \in 1, ..., S$ for each source:

$$
p(S_{(d,n)}|S_{-(d,n)}, T_d, z, \gamma, H_T, H_S, H_Z) \propto (H_{S_d} + c_{(d,n)}) \times \prod_{i,j=1}^{S_{d,n}} \left( \frac{(H_{S_d} + c_{(d,n)}) + (SH_S)}{c_{(d,n)} + \gamma + KH_z} \right)
$$

The first term in the product is the probability attributed to the source-type: $c_{(d,n)}$ is the count of all sources of type $S_{(d,n)}$ in documents of type $T_d$, not considering the current source's source-type assignment. The second term in the product is the probability attributed to word-topics of words associated to the source: the product is over all words associated with source $n$ in document $d$. Here, $c_{z,j,s,S_{(d,n)},s}$ is the count of all words with topic $z_j$ and source-type $S_{(d,n)}$, and $c_{z,j,s,S_{(d,n)},s}$ is the count of all words associated with source-type $S_{(d,n)}$.

4.1.3 Word-topic Inference

Finally, having assigned each document a document-type and source a source-type, we sample word-topics. For word $i, j$, if it is associated with sources ($\gamma_{i,j} = \text{Source Word}$), we sample:

$$
p(z_{(i,j)}|z^{-{(i,j)}}, S, T, w, \gamma, H_w, H_S, H_T, H_Z) \propto (c_{z_{(i,j)},s,T_{(d,n)},s} + H_{zi,j}) \times \left( \frac{c_{z_{(i,j)},s,T_{(d,n)},s} + V H_w}{c_{z_{(i,j)},s,T_{(d,n)},s} + VH_w} \right)
$$

The first term in the product is the word-topic probability: $c_{z_{(i,j)},s,T_{(d,n)},s}$ is the count of word-topics associated with source-type $S_{(d,n)}$, not considering the current word. The second term is the word probability: $c_{z_{(i,j)},s,T_{(d,n)},s}$ is the count of words of type $w_{i,j}$ associated with word-topic $z_{i,j}$, and $c_{z_{(i,j)},s,T_{(d,n)},s}$ is the count of all words associated with word-topic $z_{i,j}$.

For word $i, j$, if it is associated with background word-topic ($\gamma_{i,j} = \text{Background}$), we sample:

$$
p(z_{(i,j)}|z^{-{(i,j)}}, S, T, w, \gamma, H_w, H_S, H_T, H_Z) \propto (c_{z_{(i,j)},s,T_{(d,n)},s} + H_{zi,j}) \times \left( \frac{c_{z_{(i,j)},s,T_{(d,n)},s} + V H_w}{c_{z_{(i,j)},s,T_{(d,n)},s} + VH_w} \right)
$$

Equation 7 is nearly identical to 6, with the exception of the first term, the word-topic probability term, where $c_{z_{(i,j)},s,T_{(d,n)},s}$ refers to the count of words associated with word-topic $z_{i,j}$ in document-type $T_d$, not considering the current word. The second term, the word probability term, is identical.

5 Data

We use the New York Times Annotated Corpus for training and evaluation, which contains 1.8 million articles published during 1987–2007, as well as metadata information for each article, including the date of publication and the page of the newspaper the article was printed on. We take all articles that appeared on the front-page (A1) of the New York Times on Monday-Friday. This results in approximately 30,000 articles. When training our model, we focus on weekday front-page stories.

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7https://catalog.ldc.upenn.edu/LDC2008T19
8Stories published on weekend days tend to be longer, investigative pieces or analysis pieces that have significantly different structure from typical daily news stories. Thus, to bound our analysis we focus on weekday front-page stories.
we further restrict the set of articles we consider to those that include at least one source. This leaves us with approx. 25,000 articles in our corpora.

6 Experiments

We run our topic model over a range of latent topics, $K$. We display results for $K = 25$. We specify a set of 26 source-types defined by our source-ontology. Our subject-matter experts manually tag 1,000 source-types as training data (out of 125,000 source-types total), which we use to train our topic model in a semi-supervised setting.

After the model completes, we examine the latent source-types assigned to each source in our dataset and our subject-matter experts manually check the labels assigned to 1,000 of these sources as validation data.

We have an overall accuracy-rate of 79%, with an inter-annotator agreement $> 80\%$ by two annotators. We compare our model against 4 baseline models, shown in Figure 2. The models are: 

- **SM+L** is our semi-supervised source topic-model.
- **SM-L** is our source topic model run without labels.
- **PM** is Bamman et al. (2013)’s Persona topic model run on news corpora with our text-processing rules (described in Section 2)$^9$. 
- **VPM** is a vanilla version of the Persona topic model run on our news corpora with Bamman et al. (2013)’s text-processing rules. Finally, **BC** is a Spectral co-clustering approach (Dhillon, 2001)$^{10}$

We use the same hyperparameters for each of the models, and for the unsupervised models, we assign cluster index with source role by examining the PMI between labels and cluster index for data in the labeled training dataset. 

The overall accuracy of both **SM-L** and **SM+L**, as shown in Figure 2a beats the other baselines, indicating that our modeling choices provide necessary signal.

According to Figure 2b, **SM+L** outperforms other models by a large margin for all the Institutional source-types (scoring a maximum accuracy of .90 for source-types of “NGO” affiliation). **SM+L** underperforms on the Individual categories, scoring a minimum of .33 for “Victim” affiliation.

Interestingly, for the Actor category, the **VPM** outperforms other models. This might be due to the emphasis on verbs **VPM** places on the words it associates with characters during text-preprocessing (see Section 3). Although many source-types are not specifically associated with verbs, **Actors** are appear to be generally defined by their action, which allows this model to perform well.

As shown in Figure 2c, **SM+L** outperforms all other models on roles, scoring above 80% accuracy for all categories, although the semi-supervision plays a large role, as **SM-L** is one of the worst-performers. A different modeling approach, or perhaps more supervision (or weak supervision) might help us yield even more improvements in performance.

7 Analytical Insights

We show two analyses from our **SM+L** model: (1) the description of source-types, and (2) the break-
7.1 Description of Source-Types

We examine how often different types of sources are used. Table 2 shows the aggregate count of source-types throughout our corpus. Academic-Informational are used the most, followed by Government Representatives and Decision-Makers, while Victims, Actors and Witnesses are used the least.

Additionally, we examine the breakdown of source-type over time. Figure 3 shows the count of a selected group of source-types during 1987–2008 in the New York Times. One startling shift is the sharp drop in Government Decision-Makers relative to other source-types shown. In 1999–2002, Government Decision-Makers went from having one of the largest presences in the press to having one of the smallest. This indicates a sharp change in the accountability of government.

Finally, we examine the top three topics associated with a selection of source-types, shown in Table 3. For example, academic-expert sources are most commonly associated with a “research/student” topic, a “hospital/study” topic and a care-giving topic.

This kind of analysis can be useful in future work for identifying the types of sources used implicitly (Pareti et al., 2013). We envision an additional computational journalism application for this work in being able to compile and categorize source-types from external knowledge bases for journalists to use.

| Source Role                  | Count   |
|------------------------------|---------|
| academic-expert              | 30,626  |
| government-representative    | 26,521  |
| government-decision-maker    | 25,432  |
| corporate-decision-maker     | 23,620  |
| corporate-representative     | 6,037   |
| ngo-expert                   | 2,983   |
| witness-individual           | 529     |
| actor-individual             | 505     |
| victim-individual            | 403     |

Table 2: Counts of selected source types throughout the corpus.

7.1.1 Source-Types by Document Type

Finally, we can interrogate the relationship between different document types and the source-types used in them. This direction is an active area of ongoing work: presently, we lack a collaborative understanding of the generative news-article types that newsrooms produce. However, we can still glean some interesting insights.

Table 4 shows the top source-types associated with the document-types our model learns. We show several interesting combinations learned by our model. For example, news articles of type Document Type 3 tend to contain more Government Decision-Makers, Victim-Lawyers and Corporate Victims than other document types: this category includes stories about corporate fraud or misconduct being litigated in courts, and draw in those affected by corporations and government actors involved in resolving disputes. News articles of type Document Type 16 tend to contain more Corporate Analysts, Government Experts and Academic Experts than other categories of news: these articles tend to be analysis pieces about the state of the world that draw in experts to comment.

We envision a promising future direction for this kind of analysis: A system could check a half-finished piece and recognize the source-gaps that exist before a first-draft is shown to an editor. An editor could check summary statistics about various story types to decide to include more Witness-type sources in relevant types of coverage. These and others are directions we hope this research can follow in the future.
### Table 3: Top topics associated with selected source types. Top three topics are weighted by PMI.

| Source-Type       | Top Topics                                      | Source-Type       | Top Topics                                      |
|-------------------|------------------------------------------------|-------------------|------------------------------------------------|
| academic-expert   | research, child, student; like, hospital, study; care, come, time | actor-individual | year, include, agree; time, issue, party; make, woman, family |
| corporate-decision-maker | work, think, add; official, program, come; make, woman, family | corporate-spokesman | price, month, yesterday; official, program, come; try, government, support |
| government-advisor | staff, today, force; add, case, adviser; win, include, tax | government-decision-maker | interview, committee, member; make, election, lead; force, come, statement |
| government-lawyer | add, case, adviser; office, investigate, counsel; work, member, record | government-spokesman | try, government, support; add, case, adviser; office, investigation, counsel |
| ngo-expert        | research, child, student; like, hospital, study; make, work, million | victim-individual | year, include, agree; make, woman, family; official, program, come |
| victim-lawyer     | win, include, tax; make, work, million; like, hospital, study | witness-casual | like, far, percent; make, election, lead; work, member, record |

### Table 4: Topic Source-types associated with each document-type, ordered by PMI. Possibly relevant combinations selected for display by journalist collaborators.

| Doc-Type | Top Source-Types |
|----------|------------------|
| 0        | actor-doctor     |
| 1        | witness-casual   |
| 3        | government-decision-maker |
| 8        | academic-decision-maker |
| 10       | academic-decision-maker |
| 11       | government-decision-maker |
| 16       | corporate-analyst |
| 17       | corporate-victim |

### 8 Conclusions

In conclusion, we have shown a more nuanced way of thinking about the voices used in journalism. We have developed a model that shows news articles as mixtures of sources, and have begun to explore the different types of news articles that would require different types of sources. We have used this model to predict source-types present in unlabeled articles, with promising degrees of accuracy. Furthermore, our model yields useful analytical insights that allow us to interrogate various relationships including how different types of sources are referenced, portraying editorial norms that vary in time and context; and how different document types use different sources.

Future work holds promise both for (1) improving our categorization schemes, (2) improving our modeling approach and (3) finding downstream applications both in news production and news analysis for such an approach. Overall, we intend this work to serve as a demonstration of how the types of generative processes behind news can be quantified, and the results of such an effort.
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