Explaining Mixtures of Sources in News Articles

Anonymous ACL submission

Abstract

Writers often use different informational sources to inform storytelling, yet little is understood about *why* different sources are chosen. Are sources chosen primarily because they disagree? Because they represent different groups? In this work, we seek to explain why humans combine sources in news articles by comparing different schemas for information categorization. We adapt five existing schemas to the new task of source categorization, and introduce three novel ones. For a given document, our goal is to identify the schema best describing its sources. We do so by viewing the categorization implied by a schema as a latent variable assignment, and choosing the assignment that maximizes the probability of observing the document. We find two schemas: *stance* (Hardalov et al., 2021) and *social affiliation* (a schema we introduce) best explain sourcing in the most documents, but other schemas explain for certain topics (e.g. *NLI* (Dagan et al., 2005) best describes fact-heavy topics like "Science"). Finally, we find we can predict the optimal schema given just the headline of an article with moderate accuracy. This hints an application to *planning* source retrieval in areas such as retrieval-augmented generation.

1 Introduction

Human writers synthesize different groups of informational sources in news articles. Consider the following news article, shown in Figure 1. The author shares her planning process[1]:

> *NJ schools are teaching climate change in elementary school. We wanted to understand: how are **teachers** educating children? How do **parents** and **kids** feel? Is there **pushback**?*

Headline: NJ Schools Teach Climate Change at all Grade Levels
Michelle Liwacz asked her first graders: what can penguins do to adapt to a warming Earth? ← *labels:* Academic, Neutral
Gabi, 7, said a few could live inside her fridge. ← *labels:* Unaffiliated, Neutral
Tammy Murphy, wife Governor Murphy, said climate change education was vital to help students. ← *labels:* Government, Agree
Critics said young kids shouldn't learn disputed science. ← *labels:* Unaffiliated, Refute
A **poll** found that 70 percent of state residents supported climate change being taught at schools. ← *labels:* Media, Agree

Table 1: Informational sources synthesized in a single news article. *How would we choose sources to tell this story?* We show two different source-type "plans", annotated under two competing schema: affiliation and stance. Our central questions: (1) *Which schema best explains the sources used in this story?* (2) *Can we predict, given a topic sentence, which schema to use?*

As can be seen, the journalist identified different groups of sources (e.g. teachers, kids, parents) based the topic she wished to explore. Why did she choose these groups, or source-categories? Was it to capture different sides of an issue (i.e. *stance*-based axis of difference)? Was it to include different social groups (i.e. *affiliation*-based axis)?

Different theoretical schemas have been developed which all, at the core, describe ways information is synthesized (Dagan et al., 2005). Yet, little work has been done to unify or compare them. In this work, we *seek to answer these questions and lay the groundwork for deeper explorations into how humans select sources*. We introducing a task, *source-categorization*, and unify 8 schemas from different domains for this task: five of which we curate and adapt from parallel tasks, and three novel

[1]Plan: https://nyti.ms/3Tay92f [paraphrased]. Final article: https://nyti.ms/486I11u, see Table 1.

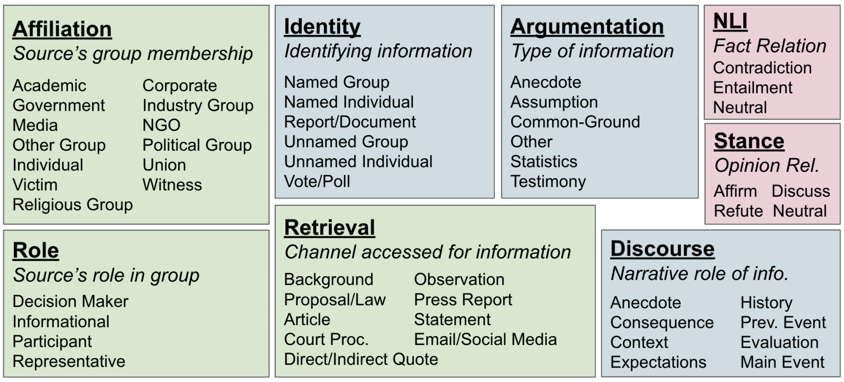

Figure 1: Label sets of each of the 8 schemas we use to study source categorization. **Extrinsic Source Schemas** Affiliation, role and retrieval-method (Spangher et al., 2023) capture characteristics of sources *extrinsic* to their usage in the document. **Functional Source Schemas:** Argumentation (), Discourse () and Identity capture functional role of sources for conveying an overall narrative. **Debate-Oriented Source Schemas**: Natural Language Inference (NLI) (Dagan et al., 2005) and Stance (Hardalov et al., 2021) capture the role of sources in broadening the story to encompass multiple sides. Definitions for each label in Appendix C.

schemas that we introduce. These schemas capture broad aspects of how information relates both *within* a document (e.g. stance detection (Hardalov et al., 2021), natural language inference (NLI) (Dagan et al., 2005), argumentation (Al Khatib et al., 2016), discourse (Choubey et al., 2020)) as well *extrinsically*: (e.g. retrieval (Spangher et al., 2023), social affiliation, organizational role, identity). We annotate 4,922 sourcees across 600 articles and build classifiers for these schema, showing that we can model them with reasonable accuracy.

Having curated these different approaches, we seek to compare them against each other. By viewing a document's source-categorization under different schemas as different latent-variable assignments, we find the optimal schema for that document on the following basis: *a labeling schema, or latent variable assignment, is more useful if it gives more information about the completed document*. We adapt simple metrics for this goal: conditional perplexity (Airoldi and Bischof, 2016), and posterior predictive likelihood (Spangher et al., 2023).

We find that a source's *social affiliation* and *stance* optimally explain most documents. However, for certain kinds of documents, other schemas are more informative. For example, for factually dense topics like "Science", the *NLI* schema provides a useful latent structure. The choice of schema, we find, can be predicted with moderate accuracy (ROC=.67) using only the headline of the article, opening the door to different planning approaches for source selection. Finally, *are these 8 schemas enough?* We extensively baseline against multiple latent variable models, which we build, and show that we cannot beat these schemas.

Our contributions are threefold:

- We frame *source-type categorization* as a framework unifying prior work in information categorization, and study it in the lens of nonfiction story telling.
- We build an accurate pipeline to extract sources from news articles and label them under 8 different *source-type schemas* (including 5 existing schema and 3 novel schema we develop in conjunction with journalists). We annotate a large dataset of 4 million news articles, called *NewsSources*, which we release.
- We use conditional perplexity to compare these schema, showing that different schemas are optimal for different topics. Further, we show that the optimal schema can be predicted given just the headline with .67 ROC, opening the door to advances in generative planning.

We see a broad impact in this line of work. Understanding source selection can aid in plan-based natural language generation (Yao et al., 2019; Yang et al., 2022) and multi-document retrieval tasks (e.g. multi-document QA (Pereira et al., 2023), multi-document summarization (Shapira et al., 2021)). We can take steps towards computational journalism goals like a source recommendation system (Spangher et al., 2023) and aid in critical media studies (Hernández and Madrid-Morales, 2020).

2 Source Categorization

2.1 Problem Statement

Our central question is: why did the writer select sources s_1, s_2, s_3... for document d? Intuitively, let's say we observe a document on a controversial topic containing many opposing viewpoints. We are able to label the one source as "agreeing" and another as "disagreeing", etc. Then, the *stance* (Hardalov et al., 2021) schema likely describes why the writer chose these sources better than the *discourse* schema (which is more about story-telling).

More abstractly, we assume each source belongs to 1-of-k categories. Different categorizations, or explanations, are possible (e.g. see Figure 1), and the "right" explanation is the one that best predicts the final document. Each of these categorizations, or explanations, is specified by a *schemas* (for the 8 schema used in this work, see Figure 1).

To apply a schema to a document, we frame a supervised approach consisting of two components: (1) an attribution function, a, introduced in Spangher et al. (2023):

$$a(s) = q \in Q_d \text{ for } s \in d \tag{1}$$

which maps each sentence s in document d to a source $Q_d = \{q_1^{(d)}, ...q_k^{(d)}\}$[2] and (2) a classifier, c:

$$c_Z(s_1^{(q)}, ...s_n^{(q)}, h) = z \in Z \tag{2}$$

which takes as input a sequence of sentences attributed to source $q^{(d)}$ (and optionally h, a headline or summary of the article) and assigns a type $z \in Z$ for schema Z. Taken together, c_Z and a give us a learned estimate of the posterior $p(z|x)$.

This supervised framing is not typical in latent-variable settings, where the choice of z and the *meaning* of Z are typically jointly learned without supervision. However, learned latent spaces often do not correspond well to theoretical schemas (Chang et al., 2009), and supervision has been shown to be helpful with planning (Wei et al., 2022). On the other hand, supervised models trained on different schema are challenging to compare, especially when different architectures are optimal for each schema. A latent-variable framework here is ideal: comparing different graphical models (Bamman et al., 2013; Bamman and Smith, 2014) *necessitates* comparing different schemas, as each run of a latent variable model produces a different schema.

[2] These sources are referenced in d. There is no consideration of document-independent sources.

2.2 Schema Criticism

We can compare schemas in two ways: (1) how well they explain each observed document and (2) how structurally consistent they are.

Explainability A primary criterion for a schema is for it to explain the observed data well. To measure this, we use *conditional perplexity*[3]

$$p(x|z) \tag{3}$$

which measures the uncertainty of observed data, x, given a latent structure, z. Measuring $p(x|z)$ for different z (fixing x) allows us to compare z. Conditional perplexity was originally introduced by Zhou and Lua (1998) as a way of comparing machine-translation pairs (in their case, both x and z are observable), and is an equivalent formulation to the "left-to-right" algorithm introduced in (Airoldi and Bischof, 2016), for evaluating unsupervised models.

Structural Likelihood: A second basic criterion for a latent structure to be useful is for it be consistent, which is a predicate for learnability. We assess the consistency of a set of assignments, z, by calculating the *posterior predictive*:

$$p(z|z_{-}, x) \tag{4}$$

Deng et al. (2022) exploring using full joint distribution, $p(z)$, *latent perplexity*, to evaluate the structure text x produced by generative language models ("*model criticism*"). Spangher et al. (2023) simplified this by using posterior predictive to study document structure, which is easier to learn and thus helps us differentiate different Z better ("*schema criticism*").[4] Now, we describe our schemas.

2.3 Source Schemas

Our schemas, shown in Figure 1, can be divded into three categories: **debate-oriented**, **functional**, and **extrinsic**. We describe the higher-level goals of each category of schemas, see Appendex C for more details and definitions for each label.

Debate-Oriented Schemas Both *Stance* and *NLI* capture the relation between two spans of text: a *premise* (**p**) and a *hypothesis* (**h**). *NLI* (Dagan et al., 2005) is primarily factual while *Stance*

[3] We abuse notation here, using p as both probability and perplexity: $p(x) = \exp\{-\mathbb{E} \log p(x_i|x_{<i})\}$.

[4] In Spangher et al. (2023)'s work, z was the choice of source, rather than the choice of source-type. They had no concept of a "schema" to describe sources

Schema	Macro-F1	Schema	Macro-F1
Argumentation	68.3	Retrieval	61.3
NLI	55.2	Identity	67.2
Stance	57.1	Affiliation	53.3
Discourse	56.1	Role	58.1

Table 2: Classification f1 score, macro-averaged, for the 8 schemas. We achieve moderate classification scores for each of schema. In Section 2, when we compare schemas, we account for differences in classification accuracy by introducing noise to higher-performing classifiers.

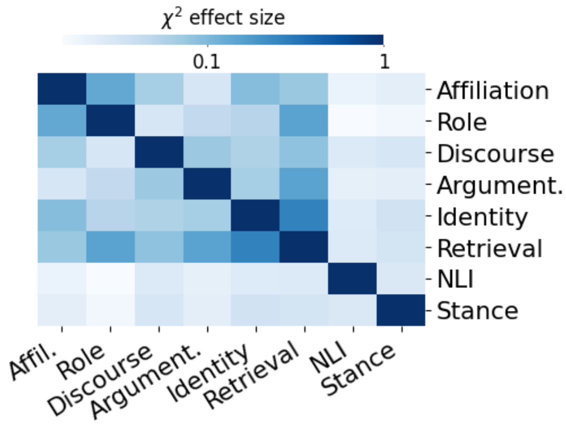

Figure 2: Correlation between 8 schemas, measured as Cramer's V (Cramér, 1999), or the effect-size measurement of the χ^2 test of independence.

(Hardalov et al., 2021) is opinion-based[5]. A text pair may be factually consistent, and thus be classified as "Entailment" under a *NLI* schema, but express different opinions and be classified as "Refute" under *Stance*. In our setting, the article's headline is **p** and a source's attributable information is **h**. According to these schemas, a writer uses sources for the purpose of expanding or rebutting information in the narrative.

Functional Source Schemas *Argumentation*, *Discourse* and *Identity* all capture the role a source plays in the overall narrative construction of the article. For instance, a source might provide a "Statistic" for a well-formed argument (*Argumentation* (Al Khatib et al., 2016)), or "Background" for a reader to help contextualize (*Discourse* (Choubey et al., 2020)). Under these schemas, the writer includes sources based on how the information they offer supports narrative construction. *Identity*, a novel schema, captures how the reader identifies the source. For example, an "Unnamed Individual" is not identifiable by the reader. This has a narrative function: some stories are about such sensitive topics that journalists include unnamed sources, despite being against norms (Sullivan, 2016), because the information provided is vital to the story.

Extrinsic Source Schemas *Affiliation*, *Role* and *Retrieval* schemas serve to characterize attributes of sources external to the news article. Stories often implicate social groups (McLean et al., 2019), such as "academia" or "government." Those group identities are extrinsic to the story's architecture but important for the selection of sources. Sources may be selected because they represent a group (i.e. *Affiliation*) or because their group position is important within the story's narrative (e.g. "participants" in the events, i.e. *Role*). *Retrieval*, introduced by Spangher et al. (2023), captures the channel through which the information was found. Although these schema are news-focused, similar ideas can be applied to other fields. For instance, a research article in machine learning might include models from the *open-source*, *academic* and *industry research* communities.

[5]Reddy et al. (2021) views these as the same.

Schema	n	H	% Maj.	% Min.
Affiliation	14	2.2	32.9	0.46
Role	4	1.0	53.3	4.61
Identity	6	1.3	52.2	0.69
Argument.	6	1.1	62.9	0.22
NLI	3	1.1	40.4	22.6
Stance	4	1.3	34.8	15.5
Discourse	8	1.9	30.0	1.09
Retrieval	10	2.0	21.4	0.05

Table 3: Description of the size of each schema (n) and the class imbalance inherent in it, shown by: Entropy (H), % Representation of the Majority class (% Maj.) and % Representation of the Minority class (% Min.).

3 Learning Categorization Schemas

In this section, we describe how we extracted sources from news articles, annotated data and built classifiers for these schema.

3.1 Source Extraction

Before classifying sources, we first need to learn an attribution function (Equation 1) to identify the set of sources in news articles. Spangher et al. (2023) introduced a large source attribution dataset, but their models are either closed (i.e. GPT-based) or underperforming. So, we train a high-performing open-source model using their dataset. We fine-tune GPT3.5-turbo [6], achieving a prediction accuracy of 74.5% on their test data[7]. Then, we label a large silver-standard dataset of 30,000 news articles and distill a BERT-base span-labeling model, described in (Vaucher et al., 2021), with an accuracy of 74.0%.[8] We use this model to score a large corpus of $90,000$ news articles from the NewsEdits corpus (Spangher et al., 2022). We find that 47% of sentences in our documents can be attributed to sources, and documents each contain an average of 7.5 +-/5 sources. These statistics are comparable to those reported by Spangher et al. (2023).

3.2 Annotation

We annotate data for our new schemas and evaluate model performance on all schemas. We recruited two annotators, one an undergraduate and the other a former journalist. The former journalist trained the undergraduate for 1 month to identify and label sources, then, they independently labeled 425 sources in 50 articles with each schema to calculate agreement, scoring $\kappa = .63, .76, .84$ on *Affiliation*, *Role* and *Identity* labels. They then labeled 4,922 sources in 600 articles with each schema over 9 months, labeling roughly equal amounts. Finally, they jointly labeled 100 sources in 25 documents with the other schemas for evaluation data over 1 month, with $\kappa \geq .54$.

3.3 Training Classifiers for Source Schemas

We train classifiers to assign labels sources under each schema. Unless specified, we use a sequence classifier using RoBERTa-base with self-attention pooling, like in Spangher et al. (2021a); we chose a smaller model that could scale to processing large amounts of articles.

Affiliation*, *Role*, *Identity We use our annotations to train classifiers $p(t|s_1^{(q)} \oplus ... \oplus s_n^{(q)})$, which take as input sentences attributable to source q and output a category in each schema.

Argumentation*, *Retrieval*, *Discourse are labeled on a sentence-level by authors on news and opinion datasets. We use datasets provided by the authors without modification and train classifiers to labels each sentence s. For each source q, we assign the label y with the most mutual information[9] across attributed sentences $s_1^{(q)}, ...s_n^{(q)}$.

NLI We use an NLI classifier trained by Williams et al. (2022) to label each sentence attributed to source q as a separate hypothesis, and the article's headline as the premise. We use mutual information to assign a single label as above.

Stance We create a news-focused stance dataset by aggregating news and news-topic-related stance datasets: FNC-1 (Pomerleau and Rao, 2017), Perspectrum (Chen et al., 2019), ARC (Habernal et al., 2017), Emergent (Ferreira and Vlachos, 2016) and NewsClaims (Reddy et al., 2021)[10]. We filter these training sets to include premises and hypothesis $\geq$ 10 words and ≤ 2 sentences, and train a classifier. We fine-tune GPT3.5-turbo[11] to label news data similarly to *NLI*, and label 60,000 news articles. We distill a $T5$ model with this data and achieve comparable performance (Table Table 2 shows T5's performance).

3.4 Classification Results and EDA

We briefly describe the results of our classification trials. As shown in Table 2, we model schemas within a range of f1-scores $(53.3, 67.2)$, showing moderate success in learning each schema. In the next section, we introduce noise (i.e. random label-swapping), to the outputs of these classifiers so that that all have the same accuracy.

We do not observe a strong correlation between the number of labels in the schema and the classification accuracy ($\rho = -.16$). As seen in Table 3, many schema are highly skewed, with, for example, the minority class in Argumentation ("common ground") being present in less than .22% of sources. Using our classifiers to label the news articles compiled in Section 3.1, we find that the schemas all offer different information. Figure 2 shows the effect size of the χ^2 independence test, a test ranging from $(0, 1)$ which measures the relatedness of two sets of categorical variables (Cramér, 1999). The schemas are largely uncorrelated, with the highest correspondence being $\nu = .34$ between "Identity" and "Retrieval". We were surprised that NLI and

[6] As of November 30th, 2023.

[7] Lower than the reported 83.0% accuracy of their Curie model. We formulate a different, batched prompt aimed at retrieving more data, see Appendix ??

[8] All models will be released.

[9] $\arg\max_y p(y|q)/p(y))$

[10] Data aggregation is common in stance detection (Hardalov et al., 2021; Schiller et al., 2021)

[11] We use OpenAI's GPT3.5-turbo fine-tuning endpoint, as of November 16, 2023.

		Conditional Perplexity $p(x\|z)$			Posterior Predictive $p(\hat{z}\|z_{-}, x)$		
Schema	n	PPL	Δ kmeans (↓)	Δ rand (↓)	F1	÷ kmeans (↑)	÷ rand (↑)
NLI	3	22.8	0.62	-0.08	58.0	1.02**	1.01 **
Stance	4	21.5	-1.71	-3.21**	39.1	0.88**	0.83 **
Role	4	22.3	-0.06	-0.33**	38.7	1.11**	1.10 **
Identity	6	21.8	-0.42	-0.94	25.0	1.00	1.15 **
Argumentation	6	21.7	-0.52	-1.04	30.7	1.10 **	1.12 **
Discourse	8	22.3	0.54	-0.75	19.2	1.06 **	1.08 **
Retrieval	10	23.7	1.47	0.36	15.8	1.10 **	1.12 **
Affiliation	14	20.5	-2.11**	-3.04**	10.5	1.26 **	1.16 **
latent var. model	14	22.06	-0.58	-1.51			

Table 4: Comparing our schemas against each other. In the first set of experiments, we show *conditional perplexity* results, which tell us how well each schema explains the document text. Shown is PPL (the mean perplexity per schema), $\Delta kmeans$ (PPL - avg. perplexity of kmeans) and $\Delta random$ (PPL - avg. perplexity of the random trial). Statistical significance ($p < .05$) via a t-test calculated over perplexity values is shown via **.In the second set of experiments, we show *posterior predictive* results, measured via micro F1-score. We show F1 (f1-score per schema), ÷ kmeans (F1 / f1-score of kmeans), ÷ random (F1 / f1-score of random trial). Statistical significance ($p < .05$) via a t-test calculated over 500-sample bootstrapped f1-scores is shown via **.

Stance were not very related, as they have similar labelsets and have been used interchangeably (Reddy et al., 2021). This indicates that significant semantic differences exist between fact-relations and opinion-relations, resulting in different application of tags. We explore this in Appendix A.

4 Comparing Schemas

We are now ready to explore how well these schemas explain source selection in documents. We start by describing our experiments, then baselines, and finally results. All experiments in this section are based on $90,000$ news articles from NewsEdits (Spangher et al., 2022), described in the previous section. We split $85,000/5,000$ train/eval.

4.1 Experiments

We run two experiments based on the approaches introduced in Section 2.2: (1) *conditional perplexity* and (2) *posterior predictive*.

Each experiment requires us to learn the probability density function over a set of latent types. For *conditional perplexity*, or $p(x|z)$ (Equation 3), we train an autoregressive model that takes as a prompt a sequence of latent variables, each for a different source, and we assess perplexity on the article text.[12] Specifically, the prompt template is:

⟨headline⟩ [HEADLINE]
⟨labels⟩ (1) label_1
(2) label_2...⟨text⟩ (1)
$s_1^{(q_1)} ... s_n^{(q_1)}$ (2)...

We fine-tune GPT2-base models (Radford et al., 2019) to perform conditional language modeling. Initial experiments show that text markers (e.g. "(1)", "⟨text⟩") are essential for the model to learn structural cues. However, they also provide their own signal (e.g. on the number of sources) – vanilla modeling shows that even baselines have reduced perplexity. To reduce the effects of these artifacts, we use a technique called *negative prompting* (Sanchez et al., 2023). Specifically, we calculate perplexity on the *altered* logits, $P_\gamma = \gamma \log p(x|z) - (1-\gamma) \log p(x|\hat{z})$, where $\hat{z}$ is a shuffled version of the latent variables. Since textual markers remain the same in the prompt for z and $\hat{z}$, this removes markers' predictive power.

To learn the *posterior predictive* (Equation 4), we train a BERT-based classification model (Devlin et al., 2018) to take the article's headline and a sequence of source-types *with a one randomly held out*. We then seek to predict *that one*, and evaluate using f1-score. Additionally, we follow Spangher et al. (2023)'s observation that some sources are *more important* (i.e. have more information attributed). We model the 4 sources per article with the most sentences attributed to them.

[12] We note that this formulation has overlaps with recent work seeking to learn latent plans (Deng et al., 2022; Wang et al., 2023; Wei et al., 2022).

4.2 Baselines

Both evaluations described might be unduly affected by the dimensionality of each schema's latent space (Lu et al., 2017); larger latent spaces tend to assign lower probabilities to each point. Thus, we benchmark each schema against baselines with similar latent dimensions.

Random We generate a series of k unique identifiers[13], and randomly sample one for each source in each document. k is set to match the number of labels in the schema being compared against.

Kmeans We cluster all sources across all documents into k clusters using kmeans (Likas et al., 2003). We represent sources for clustering as paragraph-embeddings, which we derive using Sentence BERT (Reimers and Gurevych, 2019) [14].

Latent Variable Model We hypothesize that kmeans may be a poor unsupervised baseline, as cluster assignment might be confounded by topical aspects of the documents, rather than the functional role of the sources. We adapt a Bayesian hierarchical model introduced by (Spangher et al., 2021b) designed to separate topical and functional components in text. We fully specify the model and variations we tested in Appendix F, including the Gibbs-sampler samplers derived. Because of the slow run-time, we do not run multiple trials.

4.3 Results and Discussion

As shown in Table 4, the supervised schemas mostly have have lower conditional perplexity than their random and unsupervised kmeans baselines. However, only the *Stance*, *Affiliation* and *Role* schemas improve significantly (at $p < .001$), and the *Role* schema's performance increase is minor. *Retrieval* has a statistically significant *decrease* in explainability. There are two reasons for this: (1) a small number of examples are very high perplexity, and this shifts the distribution significantly (when considering median statistics, as shown in Appendix A, the difference disappears.) (2) We examine examples and find that *Retrieval* does not impact wording as expected: writers make efforts to convey information similarly whether it was obtained via a quote, document or a statement.

[13]Using MD5 hashes, from python's `uuid` library.

[14]Specifically, `microsoft/mpnet-base`'s model `https://www.sbert.net/docs/pretrained_models.html` given all sentences associated with the source.

Interestingly, we *do* observe statistically significant improvements of kmeans over random baselines in all cases (except $k = 3$). In general, our baselines have lower variance in perplexity values than experimental schemas. This is not unexpected: as we will explore in the next section, we expect that schemas will be optimal for certain articles and suboptimal for others, resulting in a greater range in performance. For more detailed comparisons, see Appendix A.

Posterior predictive results generally show improvement across trials, with the *Affiliation* trial showing the highest improvement over both baselines. This indicates that most tagsets are, to some degree, internally consistent and predictable. *Stance* is the only exception, showing significantly lower f1 than even random baselines. This indicates that, although Stance is able to explain observed documents well (as observed by it's impact on conditional perplexity), it's not always predictable how it will applied. Perhaps this is indicative that writers do not know a-priori what sources will agree or disagree on any given topic before talking to them, and writers do not always actively seek out opposing sides.

The latent variable model does not perform well. We show in Appendex F that the latent space learned by the model is sensible. Bayesian models are attractive for their ability to encode prior belief, and ideally they would make good baselines for a task like this, which interrogates latent structure. However, more work is needed to better align them to modern deep-learning baselines.

5 Predicting Schemas

Taken together, our observations from (1) Section 3.4) indicate that schemas are largely unrelated and (2) Section 4.3 indicate that *Stance* and *Affiliation* both have similar explanatory power (although *Stance* is less predictable). We next ask: which kinds of articles are better explained by one schema, and which are better explained by the other?

In Table 5, we show topics that have low perplexity under the *Stance* schema, compared with the *Affiliation* schema (we calculate these by aggregating document-level perplexity across keywords assigned to each document in our dataset). As we can see, topics requiring greater degrees of debate, like "Artificial Intelligence", and "Taylor Swift" are favored under the *Stance* Topic, while broader topics requiring many different social perspectives, like

Stance	*Affiliation*
Bush, George W	Freedom of Speech
Swift, Taylor	2020 Pres. Election
Data-Mining	Jazz
Artificial Intelligence	Ships and Shipping
Rumors/Misinfo.	United States Military
Illegal Immigration	Culture (Arts)
Social Media	Mississippi

Table 5: Top keywords associated with articles favored by stance or affiliation. Keywords are manually assigned by news editors

Affiliation	41.7%	Argument.	1.2%
Identity	22.7%	Discourse	1.1%
Stance	17.7%	NLI	1.1%
Role	13.4%	Retrieval	1.1%

Table 6: Proportion of our validation dataset favored by one schema, i.e. $\hat{Z} = \arg\max_Z p(x|z)$

"Culture" and "Freedom of Speech" are favored under *Affiliation*. We set up an experiment where we try to predict $\hat{Z} = \arg\min_Z p(x|z)$, the schema for each datapoint with the lowest perplexity. Using perplexity scores calculated in the prior section[15], we calculate the lowest-perplexity schema. Table 6 shows the distribution of such articles. We downsample the articles until the classes are balanced, and train a simple linear classifier[16] to predict $\hat{Z}$. We get .67 ROC-AUC (or .23 f1-score). These results are tantalizing and offer the prospect of being able to *better plan source retrieval*, in RAG, and computational journalism settings, by helping decide an axis on which to seek different sources. More work is needed to validate these results.

6 Related Work

Latent Variable Persona Modeling Our work is inspired by earlier work in persona-type latent variable modeling (Bamman et al., 2013; Card et al., 2016; Spangher et al., 2021b). Authors model characters in text as mixtures of topics. We both seek to learn and reason about about latent character-types, but their line of work takes an unsupervised approach. We show that supervised schemas outperform unsupervised.

Multi-Document Retrieval In multiple settings – e.g. multi-document QA (Pereira et al., 2023), multi-document summarization (Shapira et al., 2021), retrieval-augmented generation (Lewis et al., 2020) – information *from a single source* is assumed to be insufficient to meet a user's needs. In typical information retrieval settings, the goal is to retrieve a single document closest to the query (Page et al., 1998). In settings where *multiple sources are needed*, on the other hand, retrieval goals are not clearly understood[17]. Our work attempts to clarify this, and can be seen as a step towards better retrieval planning.

Planning in Language Models Along the line of the previous point, chain-of-thought reasoning (Wei et al., 2022) and few-shot prompting, summarized in (Sanchez et al., 2023), can be seen as latent-variable processes. Indeed, work in this vein is exploring latent-variable modeling for shot selection (). Our work, in particular the *conditional perplexity* formulation and it's implementation, can be seen as a way of comparing different chain-of-thought plans as they relate to document planning.

Computational Journalism seeks to apply computational techniques to assist journalists in reporting. Researchers have sought to improve detection of incongruent information (Chesney et al., 2017), detecting misinformation (Pisarevskaya, 2017), and detecting false claims made in news articles (Adair et al., 2017). Such work can improve readers' trust in news and enhance news aggregation systems online. If our work is one step towards better yield better planning, then we can

7 Conclusions

In conclusion, we explore ways of thinking about sourcing in human writing. We compare 8 schemas of source categorization, and adapt novel ways of comparing them. We find, overall, that *affiliation* and *stance* schemas help explain sourcing the best, and we can predict which is most useful with moderate accuracy. Our work lays the ground work for a larger discussion of retrieval aims in multi-document retrieval settings, it also takes us steps towards tools that might be useful to journalists.

Naturally, though, our work is a simplification of the real human processes guiding source selection; these categories are non-exclusive and inexhaustive. We hope by framing these problems we can spur further research in this area.

[15] across the dataset used for validation, or 5,000 articles
[16] Bag-of-words with logistic regression
[17] As Pereira et al. (2023) states, *"retrievers are the main bottleneck"* for well-performing multi-document systems.

8 Limitations

A central limitation to our work is that the datasets we used to train our models are all in English. As mentioned previously, we used English language sources from Spangher et al. (2022)'s *NewsEdits* dataset, which consists of sources such as nytimes.com, bbc.com, washingtonpost.com, etc.

Thus, we must view our work with the important caveat that non-Western news outlets may not follow the same source-usage patterns and discourse structures in writing their news articles as outlets from other regions. We might face extraction and labeling biases if we were to attempt to do such work in other languages.

9 Ethics Statement

9.1 Risks

Since we constructed our datasets on well-trusted news outlets, we assumed that every informational sentence was factual, to the best of the journalist's ability, and honestly constructed. We have no guarantees that our classification systems would work in a setting where a journalist was acting adversarially.

There is a risk that, if planning works and natural language generation works advance, it could fuel actors that wish to use it to plan misinformation and propaganda. Any step towards making generated news article more human-like risks us being less able to detect and stop them. Misinformation is not new to our media ecosystem, (Boyd et al., 2018; Spangher et al., 2020). We have not experimented how our classifiers would function in such a domain. There is work using discourse-structure to identify misinformation (Abbas, 2022; **?**), and this could be useful in a source-attribution pipeline to mitigate such risks.

We used OpenAI Finetuning to train the GPT3 variants. We recognize that OpenAI is not transparent about its training process, and this might reduce the reproducibility of our process. We also recognize that OpenAI owns the models we fine-tuned, and thus we cannot release them publicly. Both of these thrusts are anti-science and anti-openness and we disagree with them on principle. We tried where possible to train open-sourced versions, as mentioned in the text.

9.2 Licensing

The dataset we used, *NewsEdits* (Spangher et al., 2022), is released academically. Authors claim that they received permission from the publishers to release their dataset, and it was published as a dataset resource in NAACL 2023. We have had lawyers at a major media company ascertain that this dataset was low risk for copyright infringement.

9.3 Computational Resources

The experiments in our paper required computational resources. We used 64 12GB NVIDIA 2080 GPUs. We designed all our models to run on 1 GPU, so they did not need to utilize model or data-parallelism. However, we still need to recognize that not all researchers have access to this type of equipment.

We used Huggingface models for our predictive tasks, and will release the code of all the custom architectures that we constructed. Our models do not exceed 300 million parameters.

9.4 Annotators

We recruited annotators from our educational institutions. They consented to the experiment in exchange for mentoring and acknowledgement in the final paper. One is an undergraduate student, and the other is a former journalist. Both annotators are male. Both identify as cis-gender. The annotation conducted for this work was deemed exempt from review by our Institutional Review Board.

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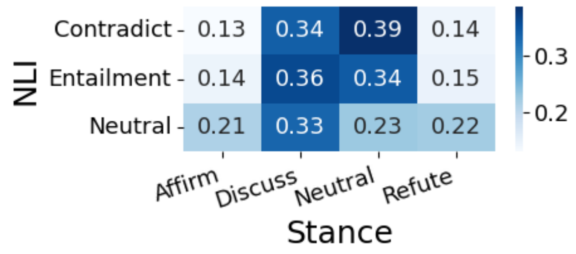


Figure 3: Stance and NLI schema definitions are not very aligned. We show conditional probability of labels in each category, $p(x|y)$ where x = Stance and y = NLI.

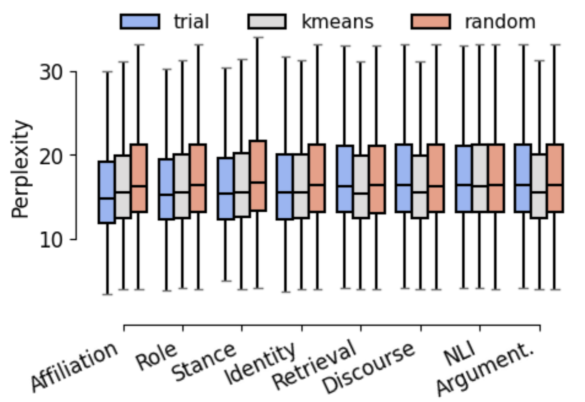


Figure 4: Distribution of conditional perplexity measurements across different experimental groups.

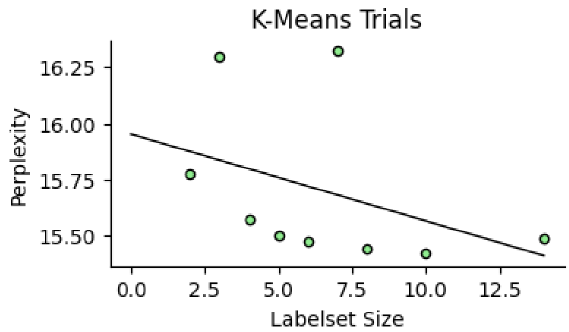
The map of our appendix is as follows. First, in Appendix A, we include more exploratory analysis to support our experiments, including comparisons between schemas. In Appendix C, we give a more complete set of definitions for the labels in each schema. In Appendix F, we define the unsupervised latent variable models we use as baselines, including providing details on their implementation.

Before we start, here is another example of a news article along with the description, by the journalist, of the sources categories they started to investigate.

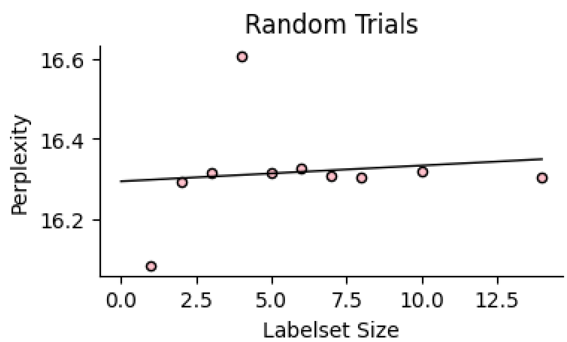
A Exploratory Data Analysis

We explore more nuances of our schemas, including comparative analyses. We start by showing a deeper view of $\hat{Z}$, or the conditions under which a schema best explains the observed results. In Tables 7 and 8, we show an extension of Table 5 in the main body: we show favored keywords across all schemas. (Note that in contrast to Table 5, we restrict the keywords we consider to a tighter range). When topics require a mixture of different information types, like statistics, testimony, etc. *Argumentation* is favored. When story-telling is on topics like “Travel”, “Education”, “Quarantine (Life and Culture)”, where it incorporates background, history, analysis, expectation, *Discourse* is favored. In Table 9, we show the top *Affiliations* per section of the newspaper, based on the NYT LDC corpus (Sandhaus, 2008).

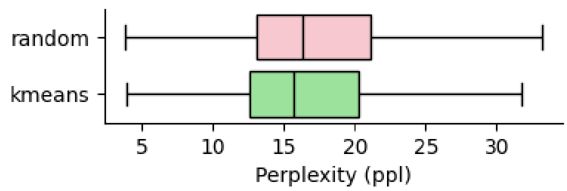
Next, we further explore the relation between different labelsets. In Figure 4, we show the same story as in Table 4 in the Main Body, except with a broader view of the distributional shifts. As can be seen, by comparing differents between the means in Table 4 and the medians in 4, we see that the effect



(a) Relationship between the size of the labelset and perplexity for kmeans trials



(b) Relational between the size of the labelset and perplexity for random trials.



(c) Distribution over perplexity scores for all random trials and kmeans trials, compared.

Figure 5: To explore the effects of labelset size, and confirm that conditional perplexity does align with basic intuitions, we compare Random trials and Kmeans trials across all of our labelset sizes.

Affiliation	Argumentation	Discourse	NLI
Inflation (Economics)	Race and Ethnicity	Travel and Vacations	Deaths (Fatalities)
Writing and Writers	Books and Literature	Quarantine (Life and Culture)	Murders, Homicides
United States Economy	Demonstrations, Protests and Riots	Education (K-12)	Law and Legislation
Race and Ethnicity	Travel and Vacations	Fashion and Apparel	States (US)
Disease Rates	Suits and Litigation	Murders, Homicides	Science
Real Estate and Housing (Residential)	Senate	Great Britain	Politics and Government
China	United States International Relations	Deaths (Fatalities)	Personal Profile
Supreme Court (US)	Deaths (Fatalities)	Pop and Rock Music	Children/ Childhood
Ukraine	Labor and Jobs	Demonstrations, Protests and Riots	China

Table 7: Keyword topics that are best explained (i.e. have the lowest conditional perplexity) by the following schemas: Affiliation, Discourse, NLI. Broader topics, like "Inflation" which require sources from different backgrounds, favor Affiliation-based source selection, while topics integrating many different, possibly conflicting, facts, favor NLI-based selection.

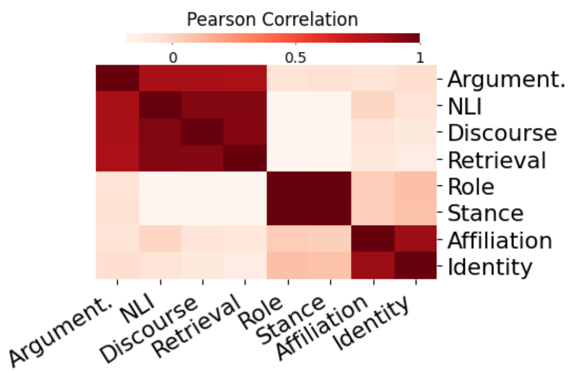


Figure 6: Pearson Correlation between conditional perplexity per document under different schemas.

of outliers is quite large, which reduces the significance we observe. In 6, we show the correlation between perplexities across labelsets. We observe clusters in our schemas of particularly high correlation. Interestingly, this stands in contrast to Figure 2, which showed almost no relation between the tagsets. We suspect that outlier effects on perplexity (e.g. misspelled words, strange punctuation) has a high effect on relating different conditional perplexities, swamping the effects of the schema. This points to the caution in using perplexity as a metric; it must be well explored and appropriately baselined.

In Figure 3, we explore more why NLI and Stance are not very related. It turns out that many of the factual categories can fall in any one of the opinion-based categories. A lot of "Entailing" facts under NLI, for example, might be the the basis of "Discussion" under Stance. This points to the need to be cautious when using NLI as a stand-in for Stance, as in (Reddy et al., 2021).

In Figures 5, we compare random and kmeans perplexities across the latent dimension size. Our experiments show that indeed, we are learning important cues about perplexity. As expected, "Random" assignments have almost no affect on the perplexity of the document, while "kmeans" assignments do. Increasing the dimensionality space of Kmeans, interestingly, *decreases* the median perplexity, perhaps because the Kmeans algorithm is allowed to capture more and more meaningful semantic differences between sources.

B Article Example

Here is an article example, annotated with different schema definitions, along with a description by the journalist of why they pursued the sources they did.

We mined state and federal court paper-

Retrieval	Role	Identity	Stance
Actors and Actresses	Inflation (Economics)	United States Economy	Midterm Elections (2022)
Fashion and Apparel	House of Representatives	Disease Rates	Presidential Election of 2020
Pop and Rock Music	Presidential Election of 2020	Real Estate and Housing (Residential)	California
Elections	United States Economy	Movies	Storming of the US Capitol (Jan, 2021)
Personal Profile	Trump, Donald J	Education (K-12)	Vaccination and Immunization
Deaths (Fatalities)	Education (K-12)	Race and Ethnicity	News and News Media
Primaries and Caucuses	Elections, House of Representatives	Ukraine	United States Economy
Politics and Government	Supreme Court (US)	Trump, Donald J	Defense and Military Forces
Regulation and Deregulation of Industry	Computers and the Internet	Presidential Election of 2020	Television

Table 8: Keyword topics that are best explained (i.e. have the lowest conditional perplexity) by the following schemas: Retrieval, Role, Identity, Stance. Political topics, like "House of Representatives" which often have a mixture of different roles, favor Role-based source selection, while polarizing topics like "Storming of the US Capitol" favor Stance.

work. We went looking for [previous] stories. We called police and fire communications people to determine [events]. We found families for interviews about [the subjects'] lives.[18]

C Further Schema Definitions

Here we provide a deeper overview of each of the schemas that we used in our work, as well as definitions that we presented to the annotators during annotation.

- **Affiliation:** Which group the source belongs to.
  - **Institutional:** The source belongs to a larger institution.
    1. **Government:** Any source who executes the functions of or represents a government entity. *(E.g. a politician, regulator, judge, political spokesman etc.)*
    2. **Corporate:** Any source who belongs to an organization in the private sector. *(E.g. a corporate executive, worker, etc.)*
    3. **Non-Governmental Organization (NGO):** If the source belongs to a nonprofit organization that operates independently of a government. *(E.g. a charity, think tank, non-academic research group.)*
    4. **Academic:** If the source belongs to an academic institution. Typically, these are professors or students and they serve an informational role, but they can be university administrators, provosts etc. if the story is specifically about academia.
    5. **Other Group:** If the source belongs or is acting on behalf of some group not captured by the above categories (please specify the group).

[18] https://www.nytimes.com/2017/01/23/insider/on-the-murder-beat-times-reporters-in-new-yorks-40th-precinct.html

Newspaper Sections	Proportion of Sources in each Category		
Arts	Individual: 0.29	Media: 0.19	Witness: 0.17
Automobiles	Corporate: 0.41	Witness: 0.17	Media: 0.11
Books	Individual: 0.26	Media: 0.19	Witness: 0.18
Business	Corporate: 0.51	Government: 0.2	Industry Group: 0.06
Dining and Wine	Witness: 0.28	Individual: 0.18	Media: 0.17
Education	Government: 0.36	Academic: 0.19	Witness: 0.1
Front Page	Government: 0.5	Political Group: 0.09	Corporate: 0.08
Health	Government: 0.33	Academic: 0.19	Corporate: 0.12
Home and Garden	Individual: 0.21	Witness: 0.19	Corporate: 0.17
Job Market	Corporate: 0.26	Individual: 0.15	Witness: 0.14
Magazine	Witness: 0.23	Media: 0.2	Individual: 0.18
Movies	Individual: 0.28	Media: 0.18	Witness: 0.18
New York and Region	Government: 0.36	Witness: 0.13	Individual: 0.12
Obituaries	Government: 0.18	Individual: 0.18	Media: 0.16
Opinion	Government: 0.43	Media: 0.14	Witness: 0.12
Real Estate	Corporate: 0.33	Government: 0.21	Individual: 0.12
Science	Academic: 0.4	Government: 0.19	Corporate: 0.1
Sports	Other Group: 0.38	Individual: 0.15	Witness: 0.14
Style	Individual: 0.23	Witness: 0.2	Corporate: 0.17
Technology	Corporate: 0.41	Government: 0.17	Academic: 0.09
The Public Editor	Media: 0.44	Individual: 0.16	Government: 0.16
Theater	Individual: 0.34	Witness: 0.18	Media: 0.14
Travel	Witness: 0.25	Corporate: 0.21	Government: 0.15
U.S.	Government: 0.44	Political Group: 0.12	Academic: 0.08
Washington	Government: 0.6	Political Group: 0.1	Media: 0.08
Week in Review	Government: 0.37	Academic: 0.11	Media: 0.1
World	Government: 0.54	Media: 0.09	Witness: 0.09

Table 9: Distribution over source-types with different *Affiliation* tags, by newspaper section.

- **Individual:** The source does **NOT** belong to a larger institution.
  1. **Actor:** If the source is an individual acting on their own. *(E.g. an entrepreneur, main character, solo-acting terrorist.)*
  2. **Witness:** A source that is ancillary to events, but bears witness in either an active *(e.g. protester, voter)* or inactive *(i.e. bystander)* way.
  3. **Victim:** A source that is affected by events in the story, typically negatively.
  4. **Other:** Some other individual (please specify).

- **Role:**
  1. **Participant:** A source who is either directly making decisions on behalf of the entity they are affiliated with, or taking an active role somehow in the decision-making process.
  2. **Representative:** A source who is speaking on behalf of a *Participant*.
  3. **Informational:** A source who is giving information on ongoing decisions or events in the world, but is not directly involved in them.
  4. **Other:** Some other role that we have not captured (please specify).

- **Role Status:**
  1. **Current:** A source who is currently occupying the role and affiliation.
  2. **Former:** A source who *used* to occupy the role and affiliation.
  3. **Other:** Some other status that we have not captured (please specify).

Headline: Services failed to prevent crime
__'s voice became a preoccupation of __, who told the police that he heard her calling his name at night. ← Government, Neutral
"Psychotic Disorder," detectives wrote in their report. ← *labels:* Government, Refute
"She had a strong voice," said Carmen Martinez, 85, a neighbor. ← Witness, Neutral
Records show a string of government encounters failed to help __ as his mental health deteriorated. ← *labels:* Government, Agree
"This could have been able to be avoided," said __'s lawyer. ← *labels:* Actor, Agree

Table 10: Informational sources synthesized in a single news article[19]. Source categorizations under two different schema: affiliation and stance. Our central question: *which schema best characterizes the kinds of sources needed to tell this story?*

We note that **Rote Status** was a schema that we collected, but ultimately did not end up modeling.

D Example GPT Prompts

We give more examples for prompts.

D.1 Source Attribution Prompts

In Section 3.1, we discuss training a GPT3.5-Turbo model with Spangher et al. (2023)'s source attribution dataset to create more labeled datapoints, which we then distil into a BERT model. We train a batched model to save on costs. The prompt takes the following form:

```
Input:
1. <sent 1>
2. <sent 2>
3. <sent 3>...
Response:
1. <attribution 1>
2. <attribution 2>
...
```

Here is an example:

```
System Prompt:
You are a journalist's
fact-checker who identifies
sources providing information
for each sentence. The user
will show you a sentences in
an article and you'll respond
with the source of the sentences.
Consider the whole article and be
sure to answer every question.
Answer either by directly
copying text in the article
OR with "passive-voice" when
a canonical source is clearly
consulted OR "journalist" when
a direct observation is made OR
"No source" when no source is
referenced, the information is
vague, or the source is unclear.
Do not make up names, or say
anything that is not in the
article besides those phrases
above.
User Input: 1: BANGKOK | A
plane carrying key senior Laotian
government officials crashed
Saturday morning, leaving at
least four people dead, Laotian
diplomats said Saturday.
2: Killed in the crash were
two top figures in the security
apparatus of the authoritarian
Lao government: the deputy prime
minister, Douangchay Phichit,
and Thongbane Sengaphone, the
minister of public security,
according to two Lao diplomats.
3: For a Communist party that
relies on force and intimidation
to stay in power, the loss of
what were arguably the two most
powerful people in the security
apparatus was a significant blow.
4: The governor of Vientiane
province was also killed in the
crash.
5: In addition to his post
as deputy prime minister Mr.
Douangchay was defense minister
and a member of the Politburo
, the highest decision - making
body of the Communist party.
6: Mr. Thongbane, the public
security head, was feared in the
country and was said to be one of
the officials leading a crackdown
against dissent over the past
year and half.
Response:
1: Laotian diplomats
```

```
2: No Source
3: No Source
4: No Source
5: No Source
6: No Source
```

D.2 Stance-Based Prompts

In Section 3.3 we discuss the prompts we formulated to do appropriate transfer learning from the stance datasets others have annotated to our news setting. Because in Stance detection, there are usually many claims made for each hypothesis, we used batched prompts to save costs, in the following form:

```
Premise: <premise>
Claim:
1. <claim 1>
2. <claim 2>
Response: 1. <label 1>
2. <label 2>
...
```

Here is an example:

```
System Prompt: You are a
journalist's assistant who spots
opposing claims. The user will
give you a premise and 5 claims.
Respond to each one, in numbered
order from 1 to 5, with a choice
from: ['Neutral', 'Affirm',
'Discuss', 'Refute'].
Don't say anything else, and be
sure to answer each one.
User Prompt
Premise: 3-D printing will
change the world.
Claims:
1: I can see 3D printing for
prototypes, and some custom work.
However manufacturing industries
use thousands of plastics and
thousands of metal alloys...
2: Flash backwards to 1972,
Colorado, where the newly
enfranchised...
3: This is precisely the way I
feel about 3D printers...another
way to fill the world with
plastic junk that will end up
in landfills, beaches, and yes,
mountains and oceans. ...
4: I am totally terrified with
the thought of 3-D printed,
non-traceable, guns and bullets
in every thugs hands. May that
never happen. But then Hiroshima
did (bad thing)...
5: Hate to point out an obvious
solution is to tie the tax rate
to unemployment....
Response:
1: Refute
2: Neutral
3: Refute
4: Affirm
5: Neutral
```

D.3 GPT-2 Conditional Perplexity Prompts

In Section 4.1, we discuss crafting prompts for GPT2-base models in order to calculate conditional perplexity. We give the outline of our prompt. Here is an example:

```
Revelations from the artist's
autobiography threaten to cloud
her new show at the San Francisco
Museum of Modern Art.
<labels>
(1): NGO,
(2): Media,
(3): Media,
(4): Media,
(5): Corporate
<text>
(1): In a telephone interview
on Tuesday, the museumś current
director, Christopher Bedford ,
said he welcomed the opportunity
to "be very outspoken about
the museumś relationship to
antiracism" and ...
(2): Last week a Chronicle
critic denounced the museumś
decision to proceed with the
show.
(3): Its longest-serving
curator, Gary Garrels, resigned
in 2020 soon after a post quoted
him saying, "Dont́ worry, we will
definitely continue to collect
white artists."
(4): The website Hyperallergic
surfaced those comments in June .
```

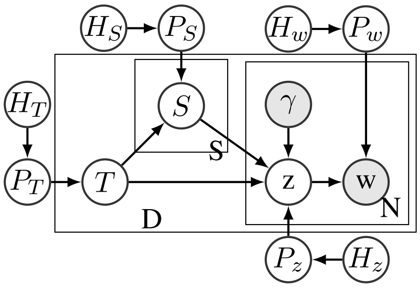


Figure 7: Plate diagram for Source Topic Model

```
(5):  And its previous director,
Neal Benezra, apologized to
employees after removing critical
comments from an Instagram post
following the murder of George
Floyd.
(6):  And the San Francisco
Museum of Modern Art has been
forced to reckon with what
employees have called structural
inequities around race.
(7):  The popular Japanese artist
Yayoi Kusama, whose " Infinity
Mirror Rooms " have brought
lines around the block for one
blockbuster exhibition after
another, has...'
```

E Combining Different Schema

We show how two schema, *Role* and *Affiliation* may be naturally combined. One function of journalism is to interrogate the organizations powering our society. Thus, many sources are from Affiliations: *Government*, *Corporations*, *Universities*, *Non-Governmental Organizations* (NGOs). And, they have different *Roles* in these places. Journalists first seek to quote *decision-makers* or *participants*: presidents, CEOs, or senators. Sometimes decision-makers only comment though *Representatives*: advisors, lawyers or spokespeople. 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. Table 11 shows the intersection of these two schema.

F Latent Variable Models

As shown in Figure 7, our model observes a switching variable, γ and the words, w, in each document. The switching variable, γ is inferred and takes one of two values: "source word" for words that are associated with a source "background", for words that are not.

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 *P*riors, while all of the variables labeled $H_{.}$ in the diagram represent Dirichlet *H*yperpriors.

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 $\gamma_{d,w}$ = "source word", sample word-topic $z_{d,w} \sim Cat(P_z^{(S_s)})$
   (b) If $\gamma_{d,w}$ = "background", sample word-topic $z_{d,w} \sim Cat(P_z^{(T_d)})$
   (c) Sample word $w \sim Cat(z_{d,n})$

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.[20] We constraint 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

[20] Card et al. (2016) do not make their code available for comparison.

			Role		
			Decision Maker	*Representative*	*Informational*
Affiliation	*Institutional*	*Government*	President, Senator...	Appointee, Advisor...	Expert, Whistle-Blower...
		Corporate	CEO, President...	Spokesman, Lawyer...	Analyst, Researcher...
		NGO	Director, Actor...	Spokesman, Lawyer...	Expert, Researcher...
		Academic	President, Actor...	Trustee, Lawyer...	Expert, Scientist...
		Group	Leader, Founder...	Member, Militia...	Casual, Bystander...
	Individ.	*Actor*	Individual...	Doctor, Lawyer...	Family, Friends...
		Witness	Voter, Protestor...	Spokesman, Poll...	Bystander...
		Victim	Individual...	Lawyer, Advocate...	Family, Friends...

Table 11: Our source ontology: describes the affiliation and roles that each source can take. A *source-type* is the concatenation of *affiliation* and *role*.

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.

F.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.

F.1.1 Document-Type inference

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

$$\begin{aligned} p(T_d|T_{-d}, s, z, \gamma, H_T, H_S, H_Z) \propto \\ (H_{TT_d} + c^{(-d)}_{T_d,*}) \times \prod_{s=1}^{S_d} \frac{(H_{Ss} + c_{T_d,s,*,*})}{(c_{T_d,*,*,*} + SH_S)} \\ \times \prod_{j=1}^{N_T} \frac{(H_{zk} + c_{k,*,T_d,*})}{(c_{*,*,T_d,*} + KH_z)} \end{aligned} \quad (5)$$

where the first term in the product is the probability attributed to document-type: $c^{(-d)}_{T_d,*}$ 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 $c_{T_d,*,*,*}$ 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, $c_{k,*,T_d,*}$ is the count of all words with topic k in document type T_d, and $c_{*,*,T_d,*}$ is the count of all words in documents of type T_d.

F.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.

$$\begin{aligned} p(S_{(d,n)}|S_{-(d,n)}, T, z, H_T, H_s, H_z) \propto \\ (H_{SS_d} + c^{-(d,n)}_{T_d,S_{(d,n)},*,*}) \\ \times \prod_{j=1}^{N_{S_{d,n}}} \frac{(H_z + c_{z_j,*,S_{(d,n)},*,*})}{(c_{*,*,S_{(d,n)},*,*} + KH_z)} \end{aligned} \quad (6)$$

The first term in the product is the probability attributed to the source-type: $c^{-(d,n)}_{T_d,S_{(d,n)},*,*}$ 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 assigned to the source: the product is over all words associated with source n in document d. Here, $c_{z_j,*,S_{(d,n)},*,*}$ is the count of all words with topic z_j and source-type $S_{(d,n)}$, and $c_{*,*,S_{(d,n)},*,*}$ is the count of all words associated with source-type $S_{(d,n)}$.

F.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 ($\gamma_{i,j}$ = Source Word), we sample:

$$\begin{aligned} p(z_{(i,j)}|z^{-(i,j)}, S, T, w, \gamma, H_w, H_S, H_T, H_z) \propto \\ (c^{-(i,j)}_{z_{i,j},*,S_d,*,*} + H_{zz_{i,j}}) \times \frac{c^{-(i,j)}_{z_{i,j},*,w_{i,j},*} + H_w}{c^{-(i,j)}_{z_{i,j},*,*,*} + VH_w} \end{aligned} \quad (7)$$

The first term in the product is the word-topic probability: $c^{-(i,j)}_{z_{i,j},*,S_d,*,*}$ is the count of word-topics associated with source-type S_d, not considering the current word. The second term is the word probability: $c^{-(i,j)}_{z_{i,j},*,w_{i,j},*}$ is the count of words of type $w_{i,j}$ associated with word-topic $z_{i,j}$, and $c^{-(i,j)}_{z_{i,j},*,*,*}$ 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 ($\gamma_{i,j}$ = Background), we sample:

$$p(z_{(i,j)}|z^{-(i,j)}, S, T, w, \gamma, H_w, H_S, H_T, H_z) \propto \\ (c^{-(i,j)}_{z_{i,j},*,T_d,*} + H_{z z_{i,j}}) \times \frac{c^{-(i,j)}_{z_{i,j},*,w_{i,j},*} + H_w}{c^{-(i,j)}_{z_{i,j},*,*,*} + VH_w} \tag{8}$$

Equation 8 is nearly identical to 7, with the exception of the first term, the word-topic probability term, where $c^{-(i,j)}_{z_{i,j},*,T_d,*}$ 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.