# EN.625.692.81.SP22 PROBABILISTIC GRAPHICAL MODELS PROJECT OUTLINE AND BIBLIOGRAPHY: A PROBABILISTIC GRAPHICAL MODEL FOR CREDIBILITY

NICHOLAS LINES

## 1. Introduction

1.1. **Why credibility?** Nearly all adults old enough to have a social media account and internet connection are bombarded by information, opinions, and news. On an individual level, accumulating important news information is overwhelmingly done through passive online activities. Five years ago the Pew Research Center found that 67% of Americans learned about news on social media, and this year they added that 23% got their news from podcasts [1][8]. Interestingly, this movement toward digitally-fed news has also brought on increased concern about legitimacy: Pew also asked their 2021 respondents if they would support Federal internet censorship, and 48% said yes, compared with 39% in 2018. How to use existing systems to find credible information is a vital question each individual must answer. More generally, any actor involved in distilling news data into factual reports must perform a similar credibility analysis using a network of dubious sources. Self-filtering news data is a difficult challenge, involving both bias in the sources consulted, bias introduced by those sources, and bias in credibility assessment introduced by the actor.

In this project we will introduce a probabilistic graphical framework in which we can explore information fusion tasks. While this approach is fairly simple and extremely clinical, we claim that it has the potential to aid (not replace) human coordination of news information review and digestion. We note that the goal of our investigation is to improve in recognition of net credibility of sources in terms of *consensus*, not *truth*.

1.2. **A probabilistic graphical representation of news reporting.** Consider a newspaper reporter $B$ who is required to stay abreast of current events in each of $N_E \in \mathbb{N}$ news topics. We will assume (naïvely, of course) that these news topics are all independent (i.e. content from one topic carries no significant intersection with content from another topic). To aid in this, the reporter has established $N_O \in \mathbb{N}$ distinct sources that observe some subset of world events and pass on their opinions to the reporter. For the purposes of this project, the reporter has no independent verification system outside of this set of observers $O = \{O_1, O_2, \ldots, O_{N_O}\}$. The overall goal of the reporter is to understand the world events as well as possible using the available sources.

The first task toward this end will be for the reporter to identify consensus in each topic and decide on a set of sources that are most trustworthy regarding that topic.

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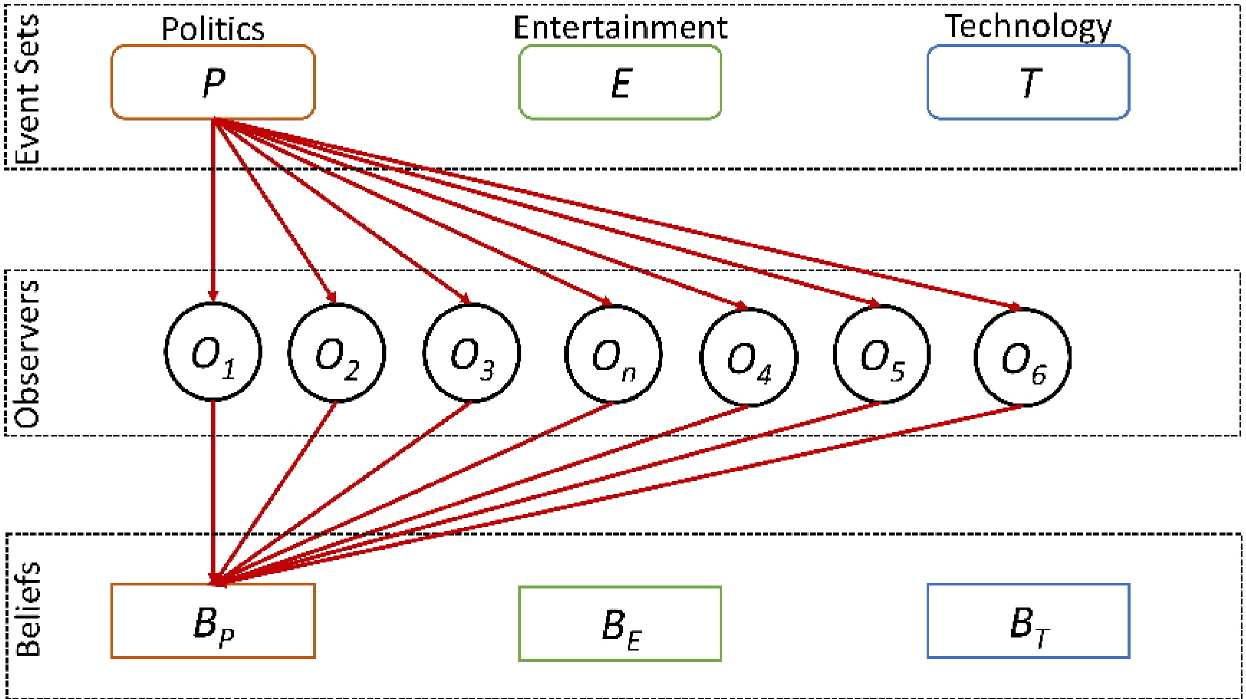


FIGURE 1. An illustration of the trust network described in the Details subsection. The directed edges from the Politics variable to the observers and from the observers to the Reporter's current belief about the Political variable are shown. In the full model, directed edges like these flow from each of the Event Sets to each Observer and from each Observer to each Belief.

The second task will be to introduce $N_n \in \mathbb{N}$ new sources of unknown trustworthiness, and determine their trustworthiness and assign them to informative groups as appropriate.

1.3. **Details.** We'll now begin to provide assumptions that will limit the scope of the problem to enable us to perform meaningful experiments. Let $N_E = 3$, that is, we limit ourselves to three topic sets, specifically $P$ for Politics, $E$ for Entertainment, and $T$ for Technology. We will assume hard boundaries between these topics, i.e. knowledge about Politics will be independent of knowledge about Entertainment, etc. Moving forward from instantiation, we will assign to each topic set a new value $P_t \sim D_P, E_t \sim D_E, T_t \sim D_T$ for $t = 1, 2, 3...$, sampled from $\{0, 1\}$ according to a binomial probability distribution unique to each topic. This value represents a fact related to that topic area at time $t$. Note that the value held by each topic variable is binary, and each value is independent from those held at other time steps and by other variables within the same time step.

1.3.1. *What do we observe?* Let's discuss the observers. Let $N_O = 6$. We define three Dirichlet distributions

$$\begin{aligned} D_{O,P} &= Dir\left([0.8, 0.1, 0.1]\right) \\ D_{O,E} &= Dir\left([0.1, 0.8, 0.1]\right) \\ D_{O,T} &= Dir\left([0.1, 0.1, 0.8]\right) \end{aligned}$$

so that each is biased towards a single topic, and sample from these the multinomial parameters for each observer node

$$\begin{aligned} p_{O_1}, p_{O_2} &\sim D_{O,P} = Mult\left(n_{O,P}, p_{O,P}\right) \\ p_{O_3}, p_{O_4} &\sim D_{O,E} = Mult\left(n_{O,E}, p_{O,E}\right) \\ p_{O_5}, p_{O_6} &\sim D_{O,T}. = Mult\left(n_{O,T}, p_{O,T}\right). \end{aligned}$$

For each time step $t$ and each observer node $i = 1, 2, ..., 6$, we draw a sample

$$O_{i,t} \sim Mult\left(n_{O_i}, p_{O_i}\right)$$

which will serve to tell us how the observer will pass on their observations to the reporter. We'll start with $n_{O_i} = 5$ for all nodes, and crank this up as needed to make learning faster.

1.3.2. *When do we observe?* For each observer $O_i$, during our initialization we'll draw $t_{O_i,P}, t_{O_i,E}, t_{O_i,T}$ ~$Uniform((0,1))$, which will serve as the parameters for the Bernoulli decision to report or not report about each topic each round.

Each observer takes note of the three event values and retransmits them to the reporter according to the following system:

$$\begin{aligned} &\text{For} && \text{each topic } j = 1, 2, 3: \\ &\text{If } \tau && > \mathit{threshold} \text{ for } \tau \sim \ Bernoulli(t_{O_i,j}): \\ & && \text{If } O_{i,t}[j] > 0, \text{ pass on the true event value} \\ & && \text{Otherwise, pass on 1 or 0 with equal probability.} \end{aligned}$$

## 2. Outline

Task 1 is to learn the trustworthiness of each node $O_i$ with respect to each topic by forming clusters that agree by consensus.

For Task 2 after Task 1 is complete at time step $t_k$ we introduce a new observer $O_n$ whose bias has been sampled randomly according to one of the three strategies described above. The task will be to learn the bias of $O_n$ in as few time steps as possible.

The following steps are necessary.

(1) Construct a Python environment using PyMC and other relevant libraries.
(2) Create the model described above.
(3) Using a simple Monte Carlo approach, repeatedly propagate information through the network and observe how many iterations are required to be run before the reporter learns the correct credibility information up to a given threshold, completing Task 1.
(4) Similarly simulate Task 2.

Once these have been completed, if extra time is available, we will investigate how sensitive this model is to changes in the various parameters and thresholds employed.

## 3. Related work and Bibliographic Notes

1. In recent years, efforts to understand how news information propagates in a network have largely focused on social networks. In [10] we find this problem approached in a way that explicitly admits that ground truth is unavailable, which inspired our consensus-based approach. In general, ground truth is so rarely available in real-world settings that it is somewhat irrelevant in the context of news reporting. Social media analysis has seen some success in this area of analysis. Examples of successful work include trust explorations like [2], and uncovering social dynamics essential to adoption of new technology, like in [4].

2. Analysis of how credibility is changed within a network of communicating agents is often connected to the concept of belief propagation, a term used both for the idea in general of spreading beliefs, but also specifically applied to the sum-product algorithm for this purpose pioneered by Judea Pearl. A useful survey on this subject is provided in [9].

3. Storing and using knowledge in a probabilistic graphical framework is usually the realm of knowledge graphs. For a fairly thorough source that introduces knowledge graphs and their applications, we refer to [3]. Another name this problem falls under is "information fusion," which has begun to be applied to text-based problems as well, making it an important keyword for this project. We are still investigating [6] and [7] to better understand how these concepts fold into this project.

For general information about Probabilistic Graphical Models, we will refer to the course text, [5].

## References

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*E-mail address*: nicholasalines@gmail.com