My primary research interest is to develop and use statistical machine learning methods to identify influences on human behavior.

Human behavior, either at an individual or collective level, is complex. This complexity warrants a myriad of disciplines dedicated to the study of human behavior, each with a unique perspective. Investigators from disparate fields find themselves interested in identical or overlapping data—for example, both economists and socialists analyze consumer purchases; both historians and linguists study written records. And now with the deluge of data emanating from the digital era, investigators find themselves relying on massive unstructured data. Computational methods assist investigators with the analysis of such data; these methods are sufficiently generic to expose patterns in the data that are of interest across disciplines. My research is concerned with all aspects of these computational approaches, from developing statistical machine learning models of human behavior to building tools to explore and interpret model results.

General Methodology I rely on Bayesian latent variable models, which are well-suited to exploratory data analysis because variables can map to intuitive concepts such as the "topic" of a document or the "influence" of one person on another. These variables represent assumptions about some hidden structure that was involved in the creation of the data—we do not directly observe the "topics" of a document, only the resulting words. Given a joint probability model of latent and observed variables, the central computational task is to compute or estimate the posterior distribution of the latent variables, given the observed data. The goal of exploratory tools is to then translate this posterior distribution into a visualization, browser, or navigator that is accessible to an investigator; this allows the model to be a lens through which to view the data. My research involves every stage of this process: first, working with domain experts to develop models of human behavior, then deriving, implementing, and applying scalable inference algorithms to estimate the posterior given real-world data, and finally building visualizations of the results to help interpret, validate, and critique the original models.

Modeling text Written text is a rich and abundant source of data that can tell us about human behavior, relationships, and influences. Probabilistic topic models discover the underlying themes in collection of documents; these themes can be used to summarize, organize, explore, and analyze the corpus.

Topic models, however, are high-level statistical tools—a user must scrutinize numerical distributions to understand their results. To make these results accessible, David Blei and I developed a method for visualizing topic models. Our method creates a navigator of the documents, allowing users to explore the hidden structure that a topic model discovers and understand the collection in new ways. This work included the release of open-source software; the method and its accompany software have been influential in shaping the exploration of topic models and in their application to a variety of domains.

Historians face a related problem: they read many documents to identify significant events that influence individuals and agencies. Hanna Wallach, David Blei, and I developed methods to help historians identify possible events from diplomatic messages or similarly structured text (such as email). We built on topic modeling to distinguish between topics that describe "business-as-usual" and event topics that deviate from these patterns during particular periods of time. We developed a scalable variational inference algorithm for this model, as well as a visualization pipeline; both have corresponding open-source software. As an example application, we analyzed over two million diplomatic messages from the 1970s, as provided by Matt Connelly's History Lab at Columbia; this analysis highlighted historical events of which our expert historian had previously been unaware. We anticipate that our methods will be used by historians, political scientists, and journalists who wish to explore and understand large corpora of documents.

Modeling user behavior Logged user actions, such as clicks on web posts, can also help us understand influences on behavior. Algorithmic recommendation systems use this data to uncover latent "preferences" for items and form personal recommendations based on the activity of others with similar tastes.

With David Blei and Tina Eliassi-Rad, I developed the *social Poisson factorization* (SPF) recommendation model. Prior work represents users only in terms of general preferences; these models do not capture that a user may like an item because her friend likes that item. SPF models both signals, discovering both latent preferences and unobserved influence between pairs of connected users; these learned parameters can then be used to explore data. We developed scalable algorithms for analyzing data with SPF and demonstrated that it outperforms competing methods on six real-world datasets.

With Mike Gartrell, Jake Hofman, and others, I explored how group settings influence users by performing a large-scale study of television viewing habits. Our analysis revealed how engagement in group viewing varies by viewer and content type, and how viewing patterns shift across various group contexts. We then constructed a simple model of how individual preferences are combined in group settings.

Disentangling convolved observations With Young-suk Lee, Olga Troyanskaya, and Babara Engelhardt, I considered the problem of modeling collections of convolved observations. Specifically, each feature of an observation is the sum of particles that originate from distinct factors. This structure exists in data from many disciplines, including political voting among different demographics, RNA gene expression across cell types, fMRI scans of neuron activity, and financial investment across stocks and investors. We are currently working on a manuscript to present generalized nonparametric deconvolution models (NDMs), a family of Bayesian nonparametric models for data with this structure, and study its performance on data from a variety of domains. NDMs learn 1) the features of global factors shared among all observations and the number and global proportions of these factors; 2) for each observation, the proportion of particles that belong to each factor; and 3) the features of observation-specific (or local) factors for each observation. While the first two objectives are fulfilled by existing models, the final objective, which we call deconvolution, is unique to our model, and allows us to ask scientific questions that are difficult to address with other models.

Algorithms as a source of influence Algorithms have transformed how users consume information and interact with retailers and other users. I am beginning a research trajectory to investigate the complex influence effects of algorithms on user behavior. I am starting with the study of recommendation systems (including their interfaces) applied to text content (e.g., online news and opinion articles), and plan to expand this work to search algorithms, text correction and prediction, and automatic personal assistants. This research will bridge the gap between formal causal inference and deployed algorithms that influence human behavior, and reveal the capacity for these algorithms to be used to manipulate the decisions of billions of users; this analysis may, in turn, lead to superior long-term user experiences or even motivate policies and regulation to protect users and improve algorithmic transparency.

In the first phase, I am investigating an inherent feedback loop in most live recommender systems, typical of explore/exploit dilemmas: a recommendation system is trained and deployed using an initial set of behavior data, the recommendation system then influences user behavior, and the model is then re-trained based on the new algorithmically confounded behavior data. This feedback loop may result in a narrowing of personalized recommendations or community-wide effects. I plan to characterize this influence, formalize how to account for it, and build new recommendation systems that address these dynamics.

This research builds off of my previous experience analyzing text, modeling user behavior to improve recommendation systems, and building visualizations, as well as my expertise in modeling influences on human behavior more broadly. In pursuing these research interests, I anticipate collaborating with faculty and students interested in machine learning, visualization, human-computer interaction, sociology, and political science. I would also be interested in investigating other sources of influence on human behavior, including applications involving voting and censorship, understanding social network dynamics, and improving education.