Name: Yu Song

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Graduate Studies Overview:

- Program: Ph.D. in Marketing, Stephen M. Ross School of Business, University of Michigan, Ann Arbor, MI
- Entering Year: 2020
- Selected Graduate Courses
    - Marketing / Business
        - Choice Theory and Modeling (Fred Feinberg)
        - Structural Models (S. Sriram)
        - Empirical Models in Marketing (Puneet Manchanda)
        - Empirical Modeling Using Bayesian Methods (Anocha Aribarg)
        - Cognition, Memory and fMRI (Carolyn Yoon; Richard Bagozzi)
        - Judgement and Decision Making (Scott Rick)
        - Advertising and Branding (Rajeev Batra)
        - Applied Sensation and Perception (Aradhna Krishna)
        - Empirical Methods in Operations Management (Jun Li)
        - Empirical Research Methods (Maggie Yue Zhou)
    - Economics
        - Microeconomics Theory (Shaowei Ke)
        - Game Theory (David Miller)
        - Applied Microeconometrics I (Melvin Stephens)
        - Applied Microeconometrics II (Yuehao Bai)
        - Industrial Organizations and Public Policy (Ying Fan)
    - Statistics / Computer Science
        - Probability Theory (Jinho Baik)
        - Discrete State Stochastic Processes (Joseph Conlon)
        - Causal Inference (Kevin Quinn)
        - Bayesian Modeling (Long Nguyen)
        - Machine Learning (Clayton Scott)
        - Natural Language Processing (Joyce Chai)
        - Reinforcement Learning (Lei Ying)

Research Interests:

My research interests center on economics of digitization, specifically focusing on social media platforms and two-sided marketplace. I use a combination of econometric models and state-of-art machine learning methods to understand platform strategy and customer behavior and inform marketing and policy decision making.

Project Summary:

- "Does Carrying News Increase Engagement with Non-News Content on Social Media Platforms?" with Puneet Manchanda
- "The Effects of Platform Suggested Prices: Experimental Evidence from E-commerce" with Jessica Fong and Puneet Manchanda
- "Customer Feedback and Product Improvement" with Mainak Sarkar and S. Sriram

Project Descriptions:

In my project with Puneet Manchanda, we study the impact of news on non-news user engagement and content generation on Facebook. This research question is motivated by the debate on whether news aggregators like Facebook should pay news publishers for including their content. On the one side, news publishers argue that news aggregators, especially tech giants, cannibalize the advertising dollars from news websites. On the other side, news aggregators claim that they provide a channel that connects people to news websites and helps news publishers reach a wider audience, thereby actually boosting their advertising revenues. When the debate comes to an extreme, Facebook shut down all its news content from being shared and viewed in Australia in February 2021. Our study takes advantage of this exogenous shock and uses difference-in-differences to measure how the news shutdown affected non-news user engagement and content generation on Facebook. We find that after Facebook shut down its news, both user engagement and content generation of non-news content decreased. These results suggest the positive spillover effects of news on non-news content. We also find that these effects were more pronounced for more influential, socially active, experienced, and verified accounts. We use Natural Language Processing (NLP) to understand the content generation. We run a simple quantification exercise to show that carrying news has economically significant impact on Facebook advertising revenues. Our results provide timely and relevant implications for regulators and social media platforms.

In another project with Jessica Fong and Puneet Manchanda, we explore the impact of price suggestion on listing price and adoption behaviors. Our study focuses on a peer-to-peer secondhand marketplace. To address the challenge of pricing, especially for inexperienced sellers, many online platforms have introduced price suggestion tools. Despite the growing popularity of these tools, there is a lack of understanding about their impact on the listing price and downstream selling outcomes. To fill this gap, we design and implement a large-scale field experiment on a peer-to-peer second-hand online marketplace. To test and identify the inference bias—sellers look at other sellers' prices before listing—we employ a random density treatment level design based on the sellers' listing category. This involves randomly assigning each category to one of several treatment levels, with varying probabilities of assignment to the control group or one of treatment groups. Based on the listing category's treatment probability assignment, we then randomly assign sellers into either the control group in which sellers do not receive price suggestion or one of the eight treatment groups in which sellers receive various deviations from the usual price suggestion. The experiment lasts for five weeks from May to June 2023 and consists of all sellers with their listings in categories that support the price suggestion feature on the platform. We compare the listing prices of sellers across different treatment groups, and explore when and why sellers adopt the suggested prices. We find that sellers who receive a lower suggested price tend to list their items at a lower price, and are more likely to sell out their items. We are designing a follow-up experiment to test the optimal suggested price that maximizes both individual-level and aggregate-level GMV in both short run and long run. The results of our study have important implications

for firms considering the deployment of price suggestion tools and provide insight into the decision-making process of sellers' price setting.

In the project with Mainak Sarkar and S. Sriram, we study how listening to customer feedback impacts subsequent content generation on a podcast platform. We first identify the attributes that mentioned largely in the reviews, such as speaking speed, the volume of background music, and so on. We then use deep learning models to measure the attributes in these reviews and check whether these attributes change based on the review. We aim to quantify whether and when producers respond to reviews and whether it will improve the subsequent podcasts in terms of total engagement, and study which review the content generators should listen to.