Research Statement

Vineet Kumar, *Yale School of Management*

My overall research focus is at the intersection of technology and business & society.[1] Given my background in both engineering and business, I am especially interested in two focus areas.

(A) *Digital business models:* My research focuses on distinct strategic long-run choices relevant to digital firms, a topic of interest to multiple fields. I study this area using methods based on microfoundations of agents' preferences, typically empirical structural models.

(B) Building *theory-based machine learning (ML)* methods incorporating structured knowledge (theory) developed from first principles to be human interpretable, and provide representations satisfying required properties (e.g. monotonicity).

Methodological Overview: Theory or structured knowledge is central to my microfounded models. In empirical studies, the structural approach yields estimates with clear economic interpretations, enabling the counterfactual evaluation of firm or regulatory policies, as well as exogenous changes in technology or the market.

(A) Digital Business Models

I examine firms' strategic choices that drive performance in the marketplace. With traditional products, these models are well established. Digital offers new possibilities (e.g. versioning, social etc.), and these choices and their alignment drive marketplace outcomes. Within digital business models, my research can broadly be themed as focusing on three different sources of connections: between *products*, *consumers* and *data*.

1) Connections across Products – Product Line

I detail the connections between products, with a research overview and agenda provided in [P1].

Bundling Hardware and Software: What is the long-run value of mixed bundling (products+bundles) relative to pure bundling, or no bundling? Is bundling more effective with stronger network effects? Is bundling more impactful when product valuations are negatively correlated? In [P4], I empirically investigate these questions using data on videogame consoles (hardware) and game titles (software). Prior to this research, almost all of the literature had focused on the static impacts of bundling. I find that in dynamic settings with intertemporal tradeoffs, bundling is more effective with *positive correlation* of valuation across products. Bundles act by pulling demand forward, i.e. consumers buy now rather than wait – a new mechanism only possible in a dyanmic setting – and higher sales obtain with positive correlation. Prior research had found bundling to be more effective with negative correlation of valuations. I also show that bundling is more effective when indirect network effects are weaker, which was not known earlier. The paper also develops a novel

[1] For simplicity of exposition, this document is written stylistically in the first person singular, although most of my work is in collaboration with a wonderful set of co-authors.

identification strategy for correlation in valuations based on the tying ratio, leveraging the feature that consumers purchase one hardware but many software units.

Follow-up Methodological Studies: The work on the bundling project also led me to investigate methods for estimating dynamic demand models in technology markets. Examining the commonly used inclusive value approach, I show that it can lead to highly biased estimates of economically important quantities like elasticity and profits [P5]. Motivated by the need for models to flexibly accommodate dynamics with large state spaces, I develop a new method with lower computational complexity that can be easily estimated [P2]. Specifically, for a large class of problems (with terminating or renewal choice) using market-level data, we can obtain consumer preferences with the computational complexity of a linear regression. Identification is proven formally and the method can be used for counterfactual analysis.

Versioning: Freemium is the most popular digital business model (e.g. app stores, cloud storage, SaaS). I provide an overview of issues in Freemium for a general audience in [P11]. Few consumers (typically <5%) migrate to the paid version, so product design is of critical importance. I undertake a deep dive into designing freemium for a storage service, examining the growth-monetization tradeoff. In [P16], I evaluate product design (value of free version) and referral incentives, which impact the value of the free product, and therefore, upgrades. In counterfactuals, I find that offering a greater referral bonus relative to the firm's bonus can increase growth but reduce monetization, while beyond a threshold, it can decrease both growth and monetization. I study how to optimally structure dynamic referral incentives.

I examine the strategic use of time as a versioning and monetization strategy (wait for free) in [P18]. This strategy is commonly employed by platforms publishing content (e.g. novels as serialized episodes), with consumers having complementary value for content across episodes. I leverage a natural experiment – wait time is reduced by the platform – to study the impact on downstream consumer choices. Existing consumers were found to increase paid consumption, and more new consumers start reading, increasing aggregate consumption. I show how a microfounded mechanism with complementarity can rationalize these data patterns. Overall, this demonstrates the strategic role of temporal versioning in driving choices, which has not been shown earlier.

(Digital) Transformation: The transformation process is an important, but inherently risky and challenging one for firms. However, empirical structural studies of transformation are relatively rare. In [P10], I evaluate the transformation strategy for a firm moving a product based on an older technology (physical) to one based on newer technology (digital). Using a panel from a firm using the "Netflix" model, I first estimate microfounded consumer preferences for viewing content in physical form. I evaluate optimal pricing for the product line, comprising multiple versions, showing how the firm prices to extract surplus from heterogeneous consumers. Next, in counterfactuals with reduced service time, I find the value created increases, but differentiation across versions also decreases. I uncover novel mechanisms demonstrating how a transformation that enables more value to be created for all consumers results in lower profits and even lower revenue for the firm. This research identifies and quantifies a new mechanism by which transformation risk is created.

Open Source: I examine the market for open source software [P14], where products made by competing firms share common elements. Open source contributions made either by developers or by any firm are available to all competing firms (e.g. Linux or Android). It is puzzling that encouraging free-riding can lead to high quality products; my model with interconnected markets (developer and product) explains how this happens. Developers signal their capabilities by making contributions of features to the open source software (public good). My research shows how free-riding is sustained in equilibrium. Firms can build on features to differentiate on another complementary dimension (usability), and a greater degree of open source contributions can enhance the differentiation value of usability. I show that, in contrast to what research and even industry leaders believed, allowing free-riding can even increase product quality.[2]

2) Connections across Data – Linking Purchase and Usage

The third connection that I examine is the linkage between types of data, i.e. purchase data and usage data. In digital settings, usage data is uniquely available, and valuable in obtaining insights about consumer preferences. However, most studies in marketing and economics involve only purchase data. I connect usage and purchase data across several settings, including [P16, P10]. In [P3], I demonstrate how usage data is conceptually distinct, and is critically important for identification, not just estimation. Specifically, I show that identification of the Willingness to Pay (WTP) distribution for subscriptions without price variation is possible by leveraging usage data, but impossible without it. The key insight is that combining high-frequency usage data with purchase data allows for a conceptual leap in identification of the distribution of consumer willingness-to-pay (WTP), which was not thought to be possible without price variation. I combine usage data with exogenous factors impacting usage to first estimate usage utility, then aggregate this stream, combined with purchase data to obtain the WTP distribution. I can then conduct counterfactual analyses, such as product design. The framework is flexible in accommodating a large class of usage utility models, making it widely applicable.

3) Connections across Consumers – Networks

Word-of-mouth and referral effects can impact business models. However, my research here is broadly applicable to a wide class of network interventions beyond that.

I investigate privacy-sensitive methods for leveraging network structure to obtain higher-degree nodes in unknown networks [P15], e.g. for word-of-mouth. The literature focuses on obtaining the entire network structure (not privacy-friendly!), and also does not offer provable guarantees. I examine two strategies (ego-based and alter-based), based on the friendship paradox, asking individuals to nominate random friends. I show that these strategies have distinct mathematical properties, and also propose a new network property called Inversity, which determines which strategy obtains better connected seeds, based on network structure. The strategies are simple to implement and offer provable guarantees of obtaining higher-degree individuals.

I empirically study whether using friendship paradox strategies can achieve greater adoption in

[2] https://www.zdnet.com/article/ballmer-i-may-have-called-linux-a-cancer-but-now-i-love-it/

[P13]. Using a model of communication and adoption across social networks estimated on data, I evaluate counterfactual seeding strategies. I show that ego-based friendship seeding outperforms random seeding, and surprisingly, obtains higher adoption than even leader-based seeding. The results hold across a range of specifications and networks, demonstrating robustness and empirical value, and have implications for referral design. In contrast to prior work, my research proves that it is possible to leverage networks to impact interventions with guarantees for *any* network, without knowing the network.

(B) Theory-based Machine Learning

My research focus in ML is based on integrating structured knowledge to develop better ML methods, which in turn, enables us to obtain insights about consumer responses. First, there is a growing set of important research questions where ML is required. Marketing in practice involves important elements that impact consumers that cannot be appropriately captured by structured data (e.g. text, visual design, music, videos). Yet, the vast majority of research has focused on structured data, since they are more available and have standardized methods to analyze them. Traditional non-ML quantitative methods are not great at capturing the nuances of unstructured data. Moreover, ML also makes it feasible to generate novel unstructured data like text or images.

Given their growing capabilities, ML models are being increasingly used in academia and industry. However, they are typically opaque black box models (e.g. ChatGPT), leading to significant problems. First, these models are highly complex (with billions of parameters) and humans don't know the interpretation of these parameters. We also don't know the data on which they are trained. Second, they do not have a true understanding of the consumer.[3] Third, they are typically not interpretable – we don't know *why* they work. They are prone to failure (e.g. hallucinations), and we cannot know *when* this will happen because we have little visibility.[4]

My focus is on solving these challenges, developing better ML methods based on theory or structured knowledge.[5] My background, being fluent with both microfounded theory-based models and in ML, has enabled me to bring a unique perspective to this research. My research is focused around three aspects: (a) developing methods to incorporate structured knowledge into ML models, (b) provide complete model and data transparency, and (c) improve explainability and interpretability along with performance. Rather than using commercially available black box models, I develop models from basic elements. All of my ML research is transparent with the open source code publicly available for others to examine, critique and build on. I believe this approach can improve stakeholder trust and acceptance of AI systems.

The sources of knowledge that I examine include ideas and concepts from fields like marketing and economics, but is not limited to these. However, building in theoretical foundations within ML methods is typically quite challenging. The question is how to incorporate theory into complex deep

[3] The same CNN deep net models used for marketing applications are also used in biology.

[4] Consider the algorithms for self-driving vehicles illustrating these points – only now are we beginning to get some idea about the inner workings. See The Hidden Autopilot Data That Reveals Why Teslas Crash (Wall Street Journal, 07/30/2024).

[5] Other researchers are trying to integrate theory from their academic fields into ML, e.g. in physics [O1].

learning models with unstructured data. Such a challenge holds even in the case of reinforcement learning with structured data. Below, I detail the specifics of my research in ML to illustrate the approach.

Visual Characteristics: I aim to quantify consumer preferences for visual characteristics in [P19]. Visual appearance is high-dimensional and hard to characterize and explain, without human input. I develop a theory-based algorithm to automatically discover and quantify visual characteristics of products. Theory plays a crucial role in the following ways. First, the objective function is designed to incentivize low-dimensional and orthogonal representations, based on the idea that the product designs satisfy that property. Second is the idea that products often have a distinct look tied to the brand, with recognizable "visual signatures" like LV handbags or BMW cars. Brands typically have a consistent aesthetic, and consumers form expectations around this. The method extracts visual characteristics from product images using brand and other characteristics to supervise disentanglement. The method obtains significantly better performance *and* interpretability, and importantly, can *generate* counterfactual visual designs without human judgment.

Music and Emotion: In the music emotion research [P7], the ideas about consonance and dissonance of music, and how that connects to the listener's emotion is aided by using domain knowledge (theory) from multiple fields. Specifically, the knowledge is based on both: (a) the mathematics of sound waves and (b) psychology of human music perception. Explaining why a listener feels a specific emotion when listening to music was a black box earlier. Here, theory is used as the basis for creating flexible and non-contiguous consonance filters, helping obtain a representation that enables explainability, so we can visualize the features of music impacting listener responses. The application also enables a form of contextual targeting for ads, without using any consumer data (aiding privacy).

Learning Unknown Demand Curves: To learn an unknown demand curve by experimentation, I develop a reinforcement learning model with nonparametric multi-armed bandits (MAB) [P20]. Economic theory informs us that demand curves are downward sloping.[6] The classic experiment (A/B testing) benchmark is inefficient since it explores all prices equally, whereas MABs provide a more sophisticated approach ("learning while earning"). However, *how* to incorporate theory here is not quite obvious. I find that monotonicity adds two sources of value. First, it improves the performance of the algorithm substantially since it learns not just from each individual price (or arm) experimented, but across arms (an informational externality). Second, including theoretical guarantees that the resulting demand curve obtained is monotonic is especially important when algorithms are trusted and used to make automated pricing decisions. Without monotonicity, we can get an upward sloping demand curve, and the algorithm would choose unrealistically high prices, increasing the risk of failure.

Overall, all the ML-based research I have undertaken brings in the power of structured knowledge to enhance the capability of ML along several aspects: performance, interpretability / explainability, and providing representations satisfying desirable properties. In turn, these ML methods are useful

[6] There are exceptions (e.g. Veblen goods).

to help us gain valuable insights into consumer and firm behavior, leading to a symbiotic process. I plan to continue to explore theory-based ML methods and new business models enabled by ML.

Teaching

I have developed and taught elective courses at the masters and doctoral levels, and have also contributed to the executive MBA and executive education. I use a mix of lectures to help with learning principles, complemented with discussions featuring case studies by the Socratic method. In *Digital Strategy*, I explore digital business models (e.g. Dropbox), and evaluate models used by disruptors and complementors. I investigate the drivers and barriers of platform success, and examine digital transformation and emerging technologies. Given the connection to my research, I've incorporated exercises based on research into the course material. Digital transformation has been used in custom executive education programs at Yale, e.g. YGELP.

I recently developed and taught a masters-level elective course titled *Artificial Intelligence: Strategy & Marketing*. The objective is to help students understand the ideas, gain familiarity with the methods and their business applications. I introduce the primary ML methods (supervised, supervised, reinforcement and generative), followed by an examination of how organizations obtain value from AI, through case studies. I also demonstrate how fairness (and bias) can be and are often designed into algorithms, whether intentionally or not, and the resulting implications for all stakeholders. In my pedagogical experiments, I've found that assigning students to present (carefully selected) academic papers can be effective, with faculty guidance.

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