

Automatic Discovery and Generation of Visual Design Characteristics

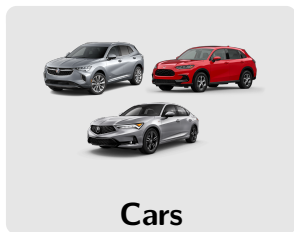
Application to Visual Conjoint

Vineet Kumar

Yale School of Management

UIUC Gies College of Business
May 2023

Visual (or aesthetic) design matters across many product categories . . .



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Cars



Fashion

Visual (or aesthetic) design matters across many product categories . . .



Cars



Fashion



Furniture

...even for mundane categories like yogurt



“We worked hard to *get the packaging right* ... American yogurt has always been sold in containers with relatively narrow openings. In Europe yogurt containers are *wider and squatter*, and that’s what I wanted for Chobani.”

—Hamdi Ulukaya, Founder & CEO, Chobani

Visual design matters



Visual design matters



“Exterior look/design is the top reason shoppers avoid a particular vehicle (30%), followed by cost (17%).”

—JD Power Avoider Study 2015

What this paper seeks to do

Research Goals

Our research aims to obtain interpretable visual characteristics directly from unstructured product images

- *automatically discover* (extract) characteristics

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- *quantify* these characteristics

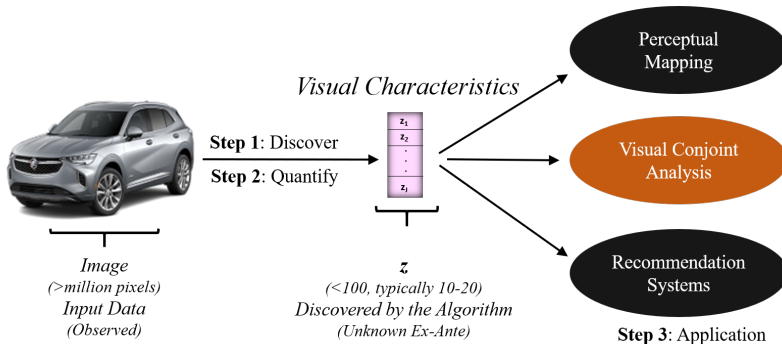
What this paper seeks to do

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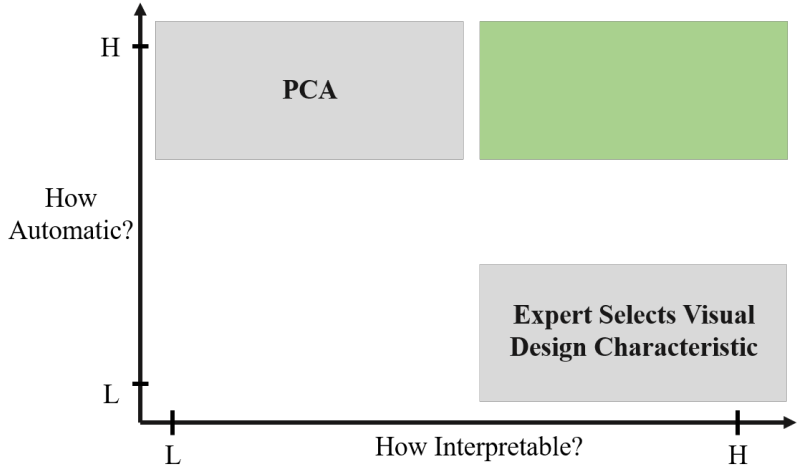
Our research aims to obtain interpretable visual characteristics directly from unstructured product images

- *automatically discover* (extract) characteristics
- *quantify* these characteristics
- *generate visual design that span the space of visual characteristics*

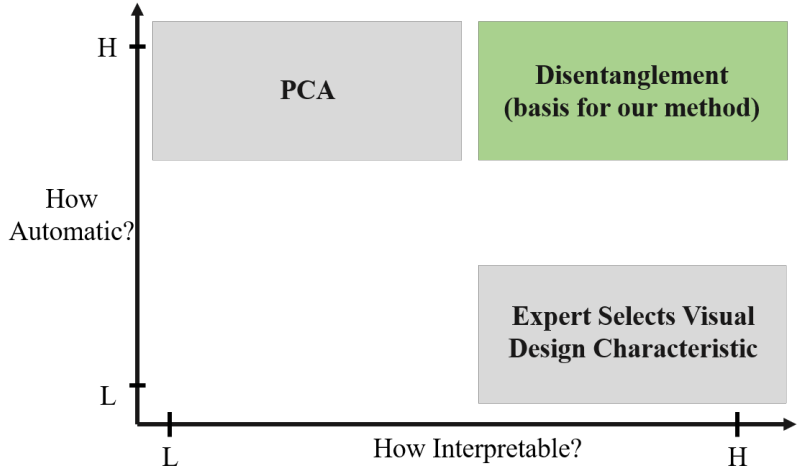
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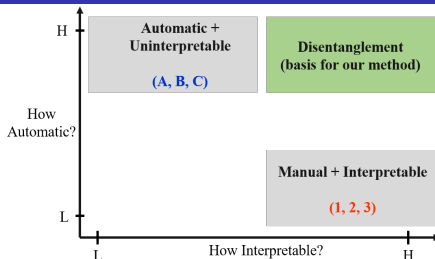
Modeling Visual Characteristics: A comparison of methods



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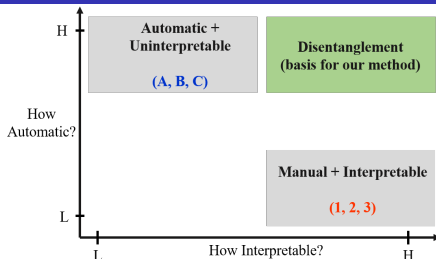
Modeling Visual Characteristics: A comparison of methods



Automatic + Uninterpretable

- A - Bajari, P. L. et al. (2021) : Hedonic prices and quality adjusted price indices powered by AI, *CENMAP working paper*
- B - Law, S., et al. (2019) : Take a look around: using street view and satellite images to estimate house prices. *ACM Transactions on Intelligent Systems and Technology (TIST)*
- C - Aubry, S., et al. (2019) : Machine learning, human experts, and the valuation of real assets. *CFS Working Paper Series*

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Manual + Interpretable

- 1 - Zhang, M. et al. (2022) : Can consumer-posted photos serve as a leading indicator of restaurant survival? Evidence from yelp. *Management Science*
- 2 - Liu, Y., et al. (2017) : The effects of products' aesthetic design on demand and marketing-mix effectiveness: The role of segment prototypicality and brand consistency. *Journal of Marketing*
- 3 - Zhang, S., et al. (2021) : What makes a good image? Airbnb demand analytics leveraging interpretable image features. *Management Science*

What is disentanglement?

Bengio et al (2013)

*“A disentangled representation can be defined as one where **single latent units** are sensitive to changes in **single generative factors**, while being relatively invariant to changes in other factors”*

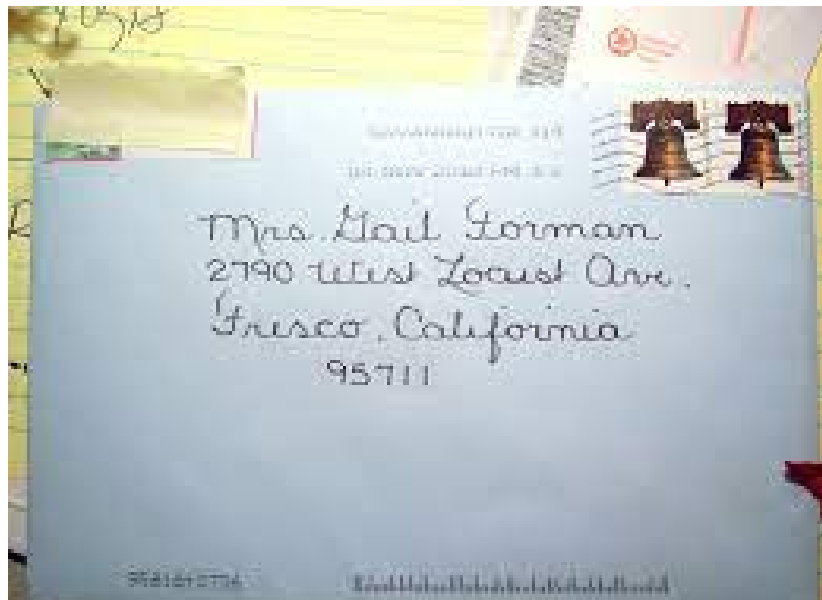
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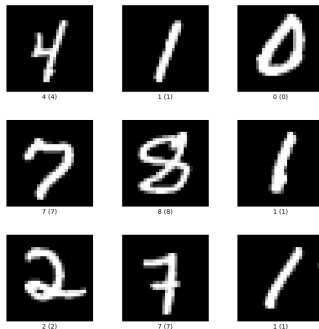
*“A disentangled representation can be defined as one where **single latent units** are sensitive to changes in **single generative factors**, while being relatively invariant to changes in other factors”*

- Latent Units (**v**): Dimensions in the model's latent space
- Generative factors (**c**): Human-interpretable true characteristics

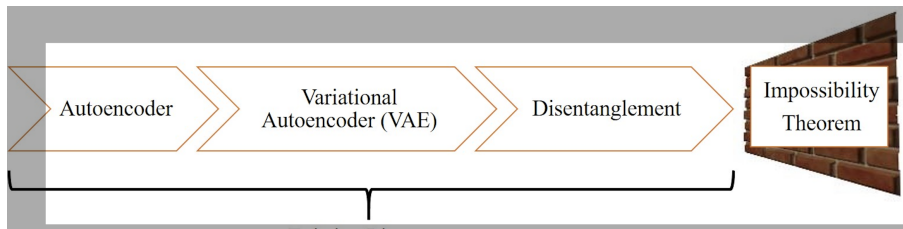
Is Interpretability always necessary?



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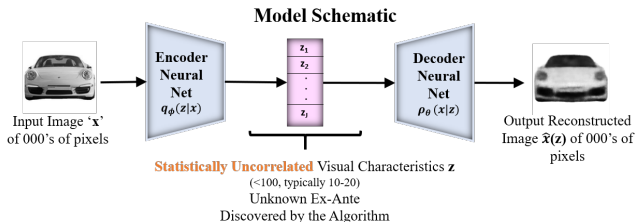
Roadmap of Our Approach



Contribution

We aim to overcome this impossibility theorem with a simple approach of using structured product characteristics.

Models in Existing Literature



Model	Goal
Autoencoder (AE)	Reconstruction accuracy
Variational Autoencoder (VAE)	... + structured latent space
Disentanglement	... + ... + statistically independent latent space

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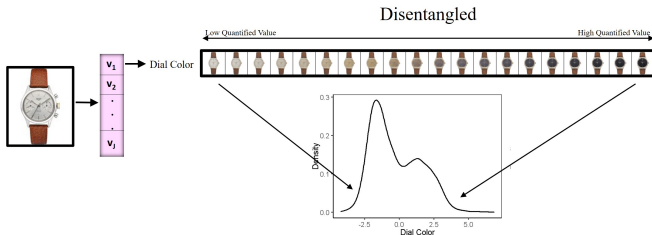
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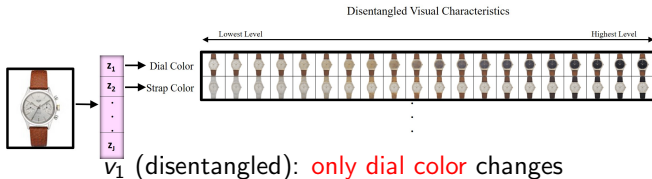
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Disentangled v Entangled Representation

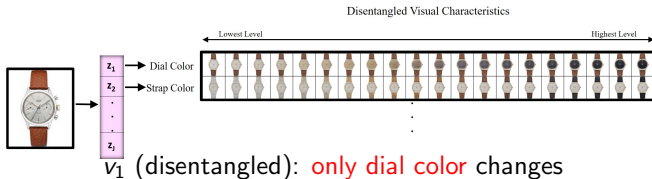


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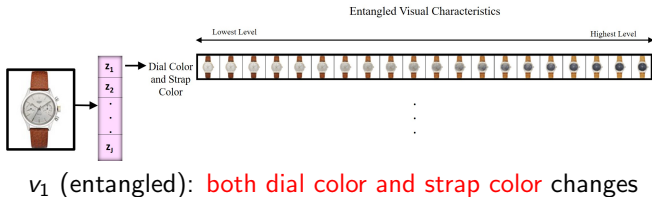


v_2 (disentangled): **only strap color** changes

Disentangled v Entangled Representation



v_2 (disentangled): **only strap color** changes



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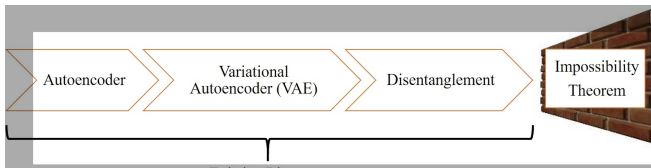
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Impossibility Theorem

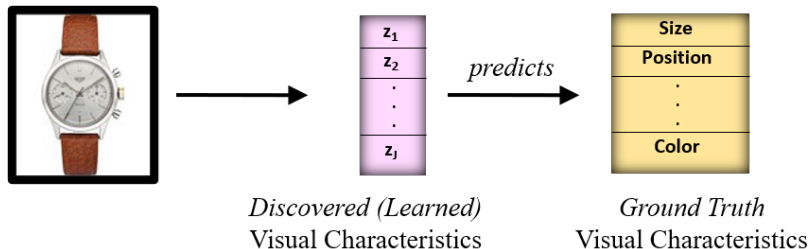


Impossibility Theorem

Unsupervised (*i.e. only images*) learning of disentangled representations is *fundamentally impossible* except under certain restrictive conditions.

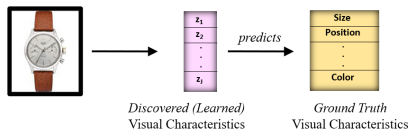
Implication: Every disentangled representation can have other equivalent entangled representations.

Overcoming Impossibility Theorem



Overcoming Impossibility Theorem

Common approach to ground truth in ML is to get humans to label¹



What's the Problem?

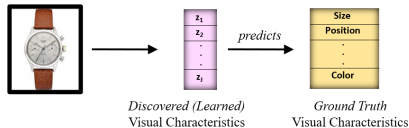
- Ground truth on visual characteristics is unknown. In fact, these are precisely what we want to find.

¹ Locatello, Francesco, et al. "Disentangling factors of variation using few labels." ICLR. 2020.

Gyawali, Prashnna K. et al. "Learning to disentangle inter-subject anatomical variations in electrocardiographic data." IEEE Transactions on Biomedical Engineering. 2021.

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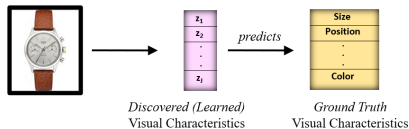
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Overcoming Impossibility Theorem

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What's the Problem?

- Ground truth on visual characteristics is **unknown**. In fact, these are precisely what we want to find.
- Researcher needs to determine what are the **true characteristics** to focus on
- **Need to ensure humans understand what these labels are and how to quantify them for each image**

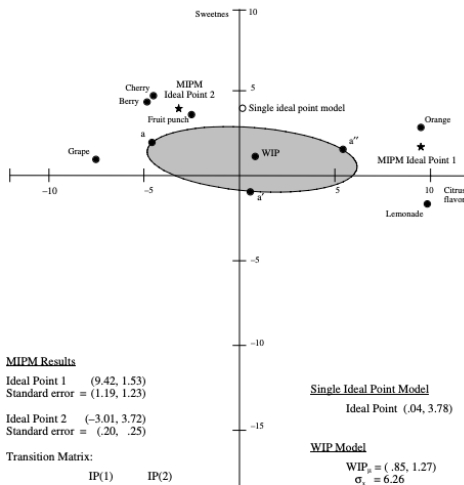
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Ideal Point

Fruit Punch: Example from Lee, Sudhir and Steckel (2002)

Figure 2
MIPM RESULTS FOR HOUSEHOLD 057



Research Overview – Substantive

Digital
Business
Models

Research Overview – Substantive

Competitive Product Strategy
for Open Source Software,
with B. Gordon and K.
Srinivasan

Marketing Science, 30(6)

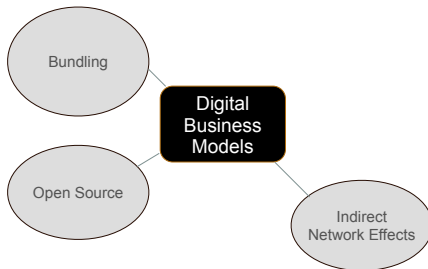


Open Source

Digital
Business
Models

Research Overview – Substantive

The Dynamic Effects of
Bundling as a Product
Strategy, with *T. Derdenger*
Marketing Science, 32(6)

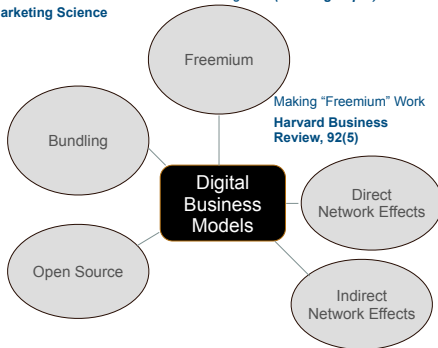


Research Overview – Substantive

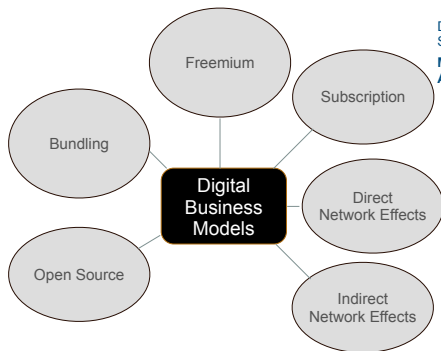
Designing Freemium: Strategic
Balancing of Growth and Monetization,
with C. Lee and S. Gupta

Revision at **Marketing Science**

Designing Plans on Digital
Platforms, with I. Weaver and S.
Jonnalagedda (**Working Paper**)

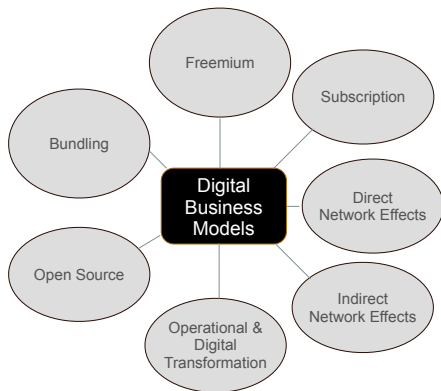


Research Overview – Substantive



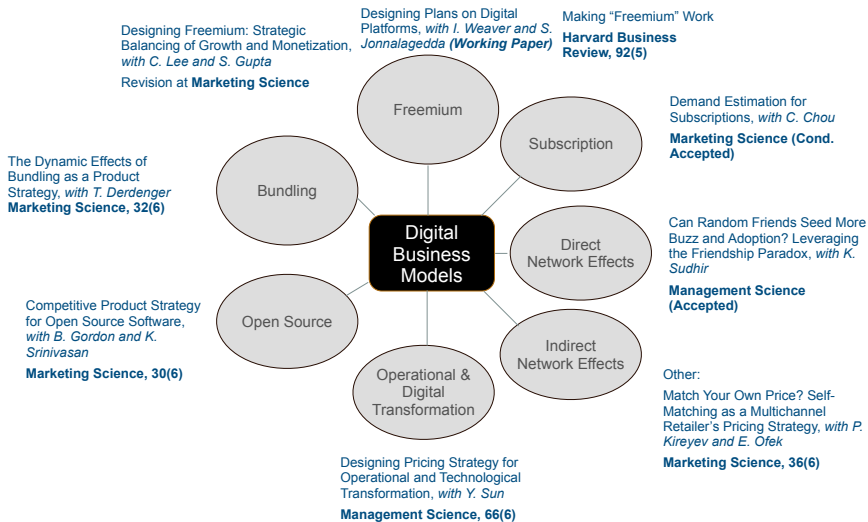
Demand Estimation for
Subscriptions, *with C. Chou*
**Marketing Science (Cond.
Accepted)**

Research Overview – Substantive

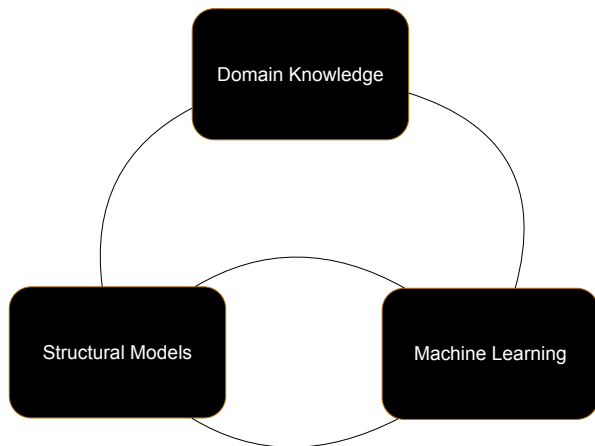


Designing Pricing Strategy for
Operational and Technological
Transformation, with Y. Sun
Management Science, 66(6)

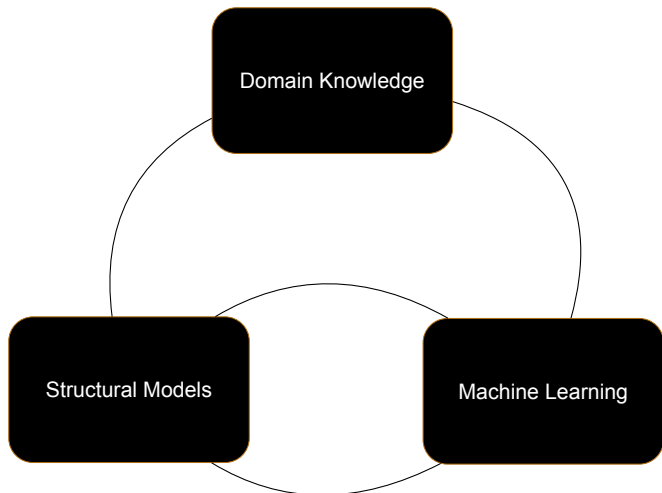
Research Overview – Substantive



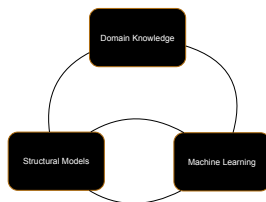
Research Overview – Substantive



Research Overview – Methodological

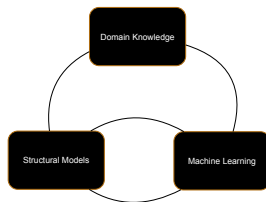


Research Overview – Methodological



- Structural Models:
 - Linear Estimation of Aggregate Dynamic Discrete Demand for Durable Goods without the Curse of Dimensionality, with C. Chou and T. Derdenger
Marketing Science
 - Estimating Dynamic Discrete Choice Models with Aggregate Data: Properties of the Inclusive Value Approximation, with T. Derdenger, **Quantitative Marketing and Economics**

Research Overview – Methodological



- Machine Learning:
 - Nonparametric Bandits Leveraging Informational Externalities to Learn the Demand Curve, with I. Weaver, *Major Revision* at **Marketing Science**
 - A Theory-Based Interpretable Deep Learning Architecture for Music Emotion, with H. Fong and K. Sudhir, *Major Revision* at **Marketing Science**
 - Automatically Discovering Unknown Product Attributes Impacting Consumer Preferences, with A. Sisodia and A. Burnap, *Revision* at **Journal of Marketing Research**

The End