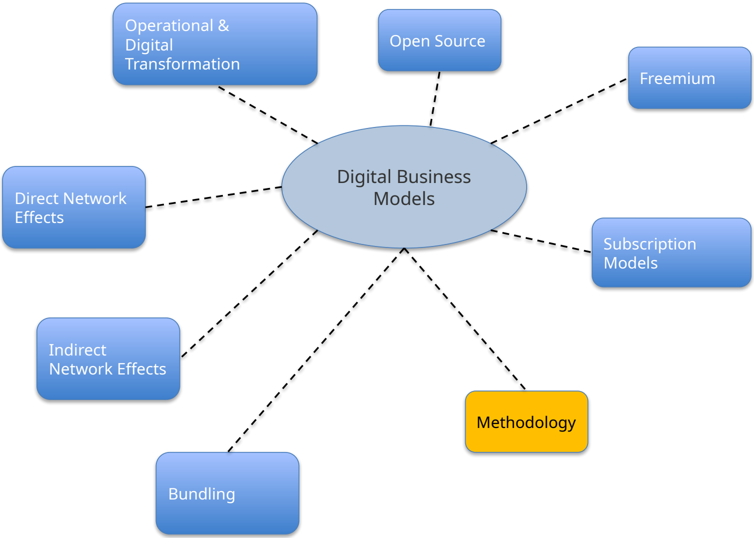
Research Overview

Vineet Kumar

Yale School of Management

Presenting at:
University of Texas
McCombs School of Business
November 2025

Research Overview



Digital Economy – Business Models

Digital Business Models

Operational & Digital Transformation

Designing Pricing Strategy for Operational and Technological Change (*Management Science*) (2020)

Open Source

Competitive Product Strategy for Open Source Software (*Marketing Science*) (2011)

Freemium

Making Freemium Work. (*Harvard Business Review*) (2014)

Designing Freemium: Strategic Balancing of Growth and Monetization. (Revision, Marketing Science)

Monetizing Serialized Content: How ``Wait for Free" Impacts Paid and Free Consumption, (*Working Paper*)

Direct Network Effects

On the Friendship Paradox and Inversity: A Network Property with Applications to Privacy-sensitive Network Interventions, with David Krackhardt and Scott Feld, (PNAS) (2024)

Can Random Friends Seed More Buzz and Adoption? Leveraging the Friendship Paradox, (Management Science) Forthcoming

Indirect Network Effects

Subscription Models

Estimating Demand for Subscriptions: Identifying Willingness to Pay without Price Variation, (*Marketing Science*) Forthcoming

Bundling

The Dynamic Effects of Bundling as a Product Strategy (Marketing Science, Lead Article) (2013)

Methodology

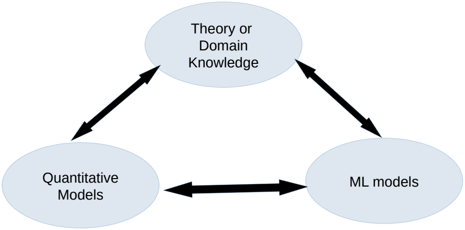
Linear Estimation of Aggregate Dynamic Discrete Demand for Durable Goods without the Curse of Dimensionality. (*Marketing Science*) (2019)

Estimating Dynamic Discrete Choice Models with Aggregate Data: Properties of the Inclusive Value Approximation (*Quantitative Marketing and Economics*, Lead Article) (2019)

Overview: Structural models of Complementary Choices (*Marketing Letters*) (2014)

Role of Human Knowledge in Research

ML has typically been atheoretical



- One view of ML – advanced form of *statistical pattern matching*
  - Similar model (CNN) used both for detecting lung cancer (medicine) and for detecting stars (astronomy)

My Take

Our **domain knowledge (theory)** has a lot to add

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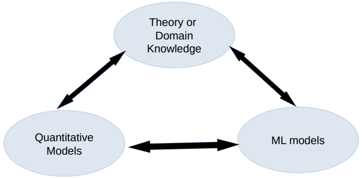
Why add domain knowledge?

Can improve predictive *accuracy*, *explainability*, provide *guarantees*



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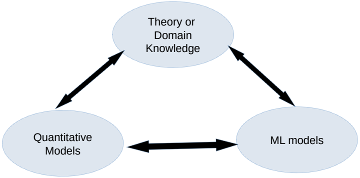

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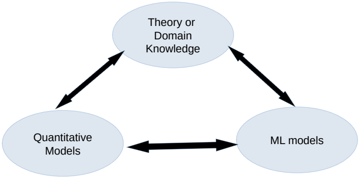

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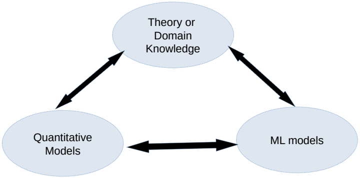

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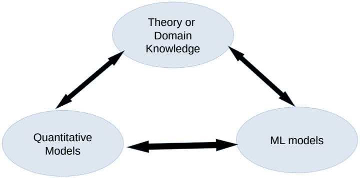

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- Nonparametric Bandits Leveraging Informational Externalities to Learn the Demand Curve. Forthcoming at *Marketing Science*
- Market Structure Mapping with Visual Characteristics. (Research in progress)

Generative Interpretable Visual Design

Sisodia, Burnap and Kumar

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

Cars

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

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*

Consumer Preferences for Visual Design

Demand Estimation: Big Picture

Goal:

Obtain consumer preferences for visual design (conjoint or market data)

Demand Estimation for Products in Differentiated Product Markets in Economics and Marketing

- Builds on foundation of Lancaster (1966), Kotler (1967)

Demand Estimation: Big Picture

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What about preferences in visual space?

Cannot do this because characteristics for visual design are unknown!

What this research seeks to do

Research Goals

Obtain **human-interpretable** visual characteristics (not outliers) directly from unstructured product image data:

- *automatically discover* and extract characteristics for products

What this research seeks to do

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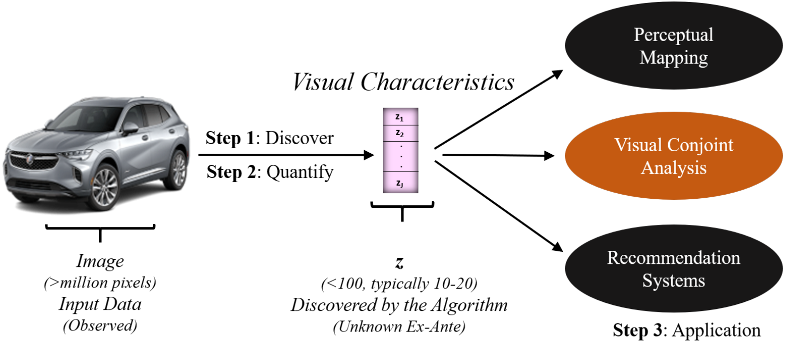
Hyundai: $(3, 8, 5, 9)$ compared to BMW: $(1, 3, 10, 1)$

Research Goals

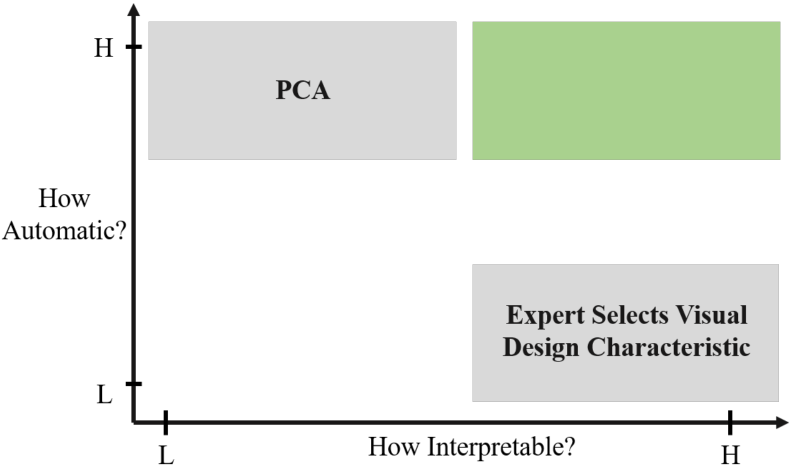
Hyundai: $(3, 8, 5, 9)$ compared to BMW: $(1, 3, 10, 1)$
Several questions come to mind:

- What does the first number represent? Does 3 mean something different from 1?
- Can humans interpret these numeric values?
- What domain knowledge does the model need to have?

Why Visual Characteristics?



Modeling Visual Characteristics: A comparison of methods



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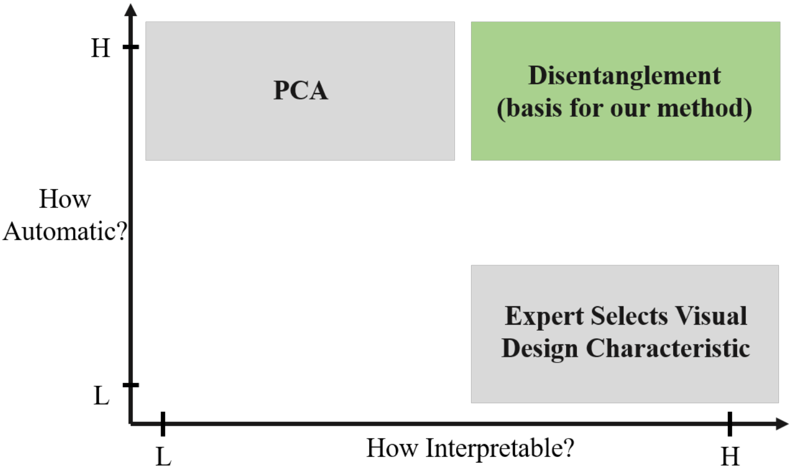

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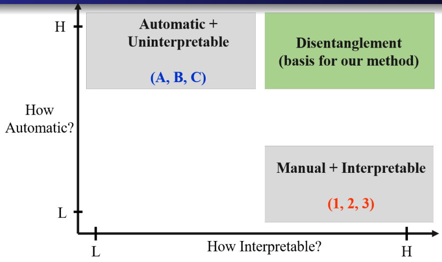

Automatic + Uninterpretable

- 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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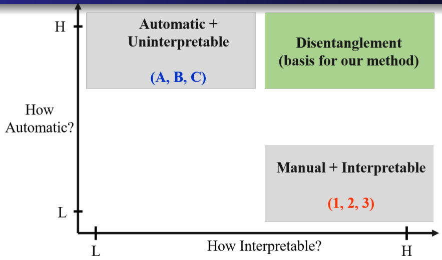

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Manual + Interpretable

- 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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Bengio et al (2013)

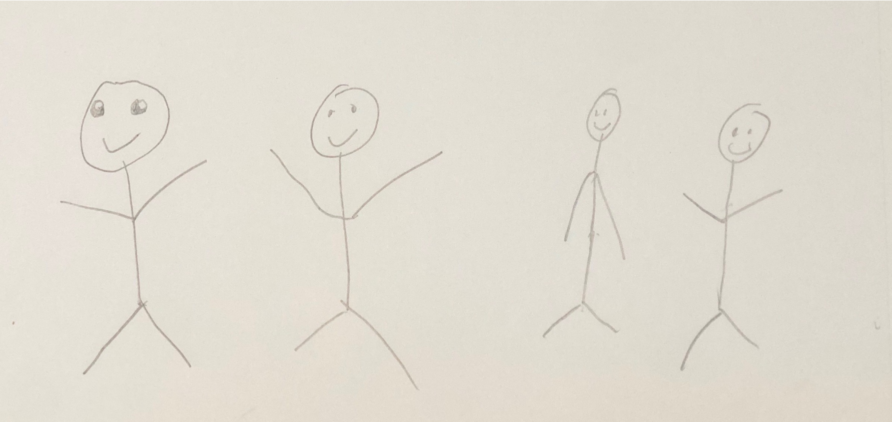
> *"A disentangled representation can be defined as one where* **single latent units** *are sensitive to changes in single generative factors, while being relatively invariant to changes in other factors"*

- Latent Units ($\mathbf{z}$): Dimensions in the model's latent space
- Generative factors ($\mathbf{c}$): Human-interpretable true characteristics

Idea: Reality or Data generating process is compositional based on generative factors.

What is disentanglement?

Stick



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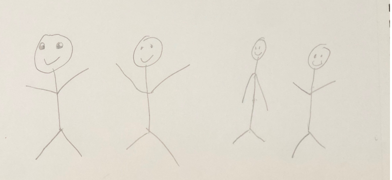

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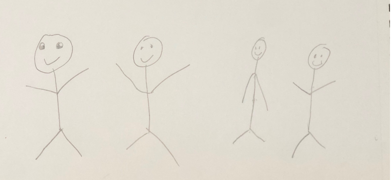

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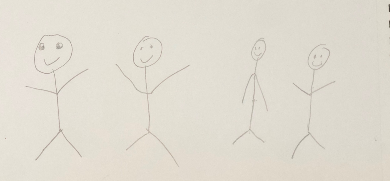
- Latent Units ($\mathbf{z}$): What algorithm discovers – dimensions in the model's latent space
- Generative factors ($\mathbf{c}$): Human-interpretable

What is disentanglement?



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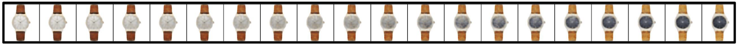
- Latent Units ($\mathbf{z}$): What algorithm discovers – dimensions in the model's latent space
- Generative factors ($\mathbf{c}$): Human-interpretable

Goal: One to one mapping between $z \Leftrightarrow c$

Product Images and Parts of Watch

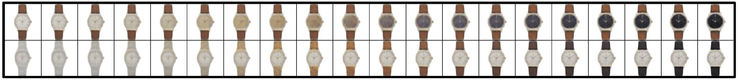
Disentangled and Entangled Representations

Example of *Entangled* Visual Characteristics



Entangled
Dial Color and
Strap Color

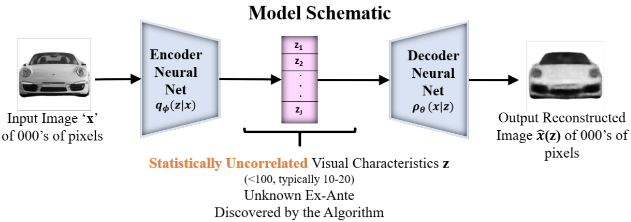
Example of *Disentangled* Visual Characteristics



Dial Color

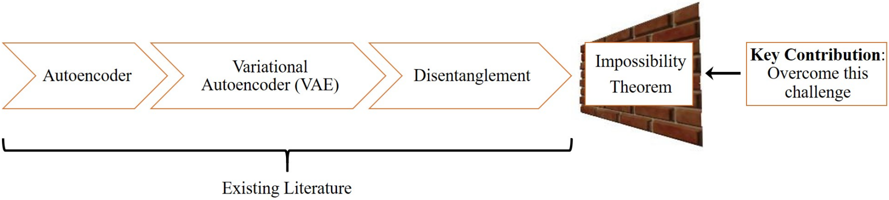
Strap Color

Models in Existing Literature



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

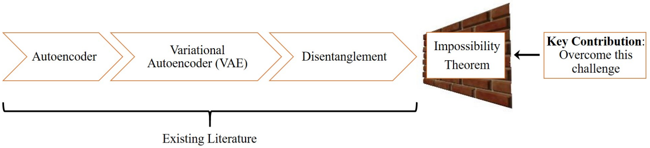
Roadmap of Our Research Approach



Contribution

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

Impossibility Theorem



Impossibility Theorem

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

[a] Locatello, Francesco, et al. "Challenging common assumptions in the unsupervised learning of disentangled representations." ICML. PMLR, 2019.

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

ML Approach to Impossibility Theorem

Impossibility: Without Supervision, every disentangled representation can have other *infinite* equivalent entangled representations.

- ML researchers recognize the challenge of impossibility

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    - Human labeling

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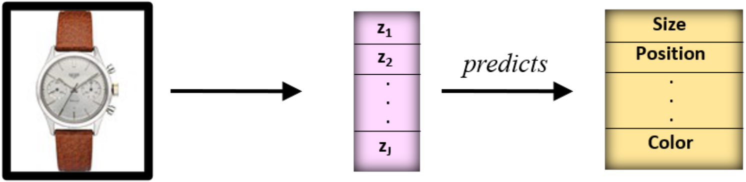
Impossibility: Without Supervision, every disentangled representation can have other *infinite* equivalent entangled representations.

- ML researchers recognize the challenge of impossibility
- Need a supervisory signal
- ML methods assume that ground truth is known by researchers
    - Human labeling
- Can we use this approach to discover visual characteristics?

Impossibility Theorem – Implications

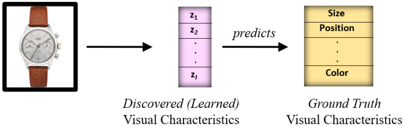


Discovered (Learned)
Visual Characteristics

Ground Truth
Visual Characteristics

Impossibility Theorem – Implications

Common approach to ground truth in ML is to get humans to label[1]



What's the Problem?

- Ground truth on visual characteristics is *unknown*.

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

Impossibility Theorem – Implications

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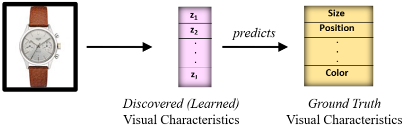
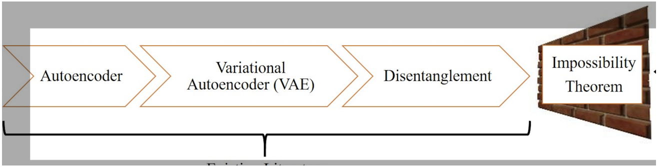


What's the Problem?

- Ground truth on visual characteristics is *unknown*.
- Need to ensure humans understand what these labels are and *how to quantify them* for each image

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

Contribution



- **Solution** without ground truth on visual characteristics:
- Leverage **structured product characteristics** to provide a supervisory signal for disentanglement

Model

- ϕ encoder and θ decoder parameters; $\mathbf{x}$ are images and $\mathbf{z}$ are visual characteristics
- Learn model parameters by minimizing loss $L(\theta, \phi; \mathbf{x}, \mathbf{z})$ of

$$\underbrace{L(\theta, \phi, \mathbf{w}); \mathbf{x}, \mathbf{z})}_{\text{Total Loss}} = \underbrace{\mathbf{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[\log p_\theta(\mathbf{x}|\mathbf{z})\right]}_{\text{Reconstruction Loss}} + \alpha \underbrace{I_q(\mathbf{z}, \mathbf{x})}_{\text{Mutual Information Loss}} + \beta \underbrace{KL\left[q(\mathbf{z}) || \prod_{j=1}^{J} q(z_j)\right]}_{\text{Total Correlation Loss}}$$

$$+ \gamma \underbrace{\sum_{j=1}^{J} KL\left[q(z_j) || p(z_j)\right]}_{\text{Dimension-Wise KL Divergence Loss}} + \delta \underbrace{P(\hat{\mathbf{y}}(\mathbf{z}), \mathbf{y})}_{\text{Supervised Loss}}$$

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Loss Term	Why is this term included?
Reconstruction	Promotes accurate reconstruction of images
Mutual Information	Minimizes redundant information
Total Correlation	Promotes statistical independence between visual characteristics
Dimension-Wise KL	Penalizes deviations from a prior
Supervised	Provides a signal to address the impossibility theorem

Model: Reconstruction Loss

- ϕ encoder and θ decoder parameters; $\mathbf{x}$ are images and $\mathbf{z}$ are visual characteristics
- Learn model parameters by minimizing loss $L(\theta, \phi; \mathbf{x}, \mathbf{z})$ of integrated model
- Reconstruction Loss (pixel level):

$$E_{q_\phi(z|x)}[\log p_\theta(x|z)]$$

- Given latent representation z, can decoder accurately obtain the x in the data?
- $p_\theta(x|z)$ high probability if reconstruction is good
- Encoder produces z probabilistically, so need to take expectations $E_{q_\phi(z|x)}$
- Both encoder and decoder are learning here

Model: Mutual Information Loss

- ϕ encoder and θ decoder parameters; $\mathbf{x}$ are images and $\mathbf{z}$ are visual characteristics
- Learn model parameters by minimizing loss $L(\theta, \phi; \mathbf{x}, \mathbf{z})$ of integrated model
- Mutual Information:

$$I_q(X; Z) = \mathbb{E}_{q(x,z)}\Big[\log \left(\frac{q(x,z)}{q(x)q(z)} \right) \Big]$$

- Each input x produces a distinct z, retains lot of information

Model

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- ϕ encoder and θ decoder parameters; $\mathbf{x}$ are images and $\mathbf{z}$ are visual characteristics
- Learn model parameters by minimizing loss $L(\theta, \phi; \mathbf{x}, \mathbf{z})$ of

$$\underbrace{L(\theta, \phi, \mathbf{w}); \mathbf{x}, \mathbf{z})}_{\text{Total Loss}} = \underbrace{\mathbf{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})]}_{\text{Reconstruction Loss}} + \alpha \underbrace{I_q(\mathbf{z}, \mathbf{x})}_{\text{Mutual Information Loss}} + \beta \underbrace{KL\left[q(\mathbf{z}) || \prod_{j=1}^{J} q(z_j)\right]}_{\text{Total Correlation Loss}}$$

$$+ \gamma \underbrace{\sum_{j=1}^{J} KL\left[q(z_j) || p(z_j)\right]}_{\text{Dimension-Wise KL Divergence Loss}} + \delta \underbrace{P(\hat{\mathbf{y}}(\mathbf{z}), \mathbf{y})}_{\text{Supervised Loss}}$$

Loss Term	Why is this term included?
Reconstruction	Promotes accurate reconstruction of images
Mutual Information	Minimizes redundant information
Total Correlation	Promotes statistical independence between visual characteristics
Dimension-Wise KL	Penalizes deviations from a prior
Supervised	Provides a signal to address the impossibility theorem

Model – Role of Supervised Loss

$$\underbrace{L(\theta,\phi,\mathbf{w});\mathbf{x},\mathbf{z})}_{\text{Total Loss}} = \underbrace{\mathbf{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[\log p_\theta(\mathbf{x}|\mathbf{z})\right]}_{\text{Reconstruction Loss}} + \alpha \underbrace{I_q(\mathbf{z},\mathbf{x})}_{\text{Mutual Information Loss}} + \beta \underbrace{KL\left[q(\mathbf{z})||\prod_{j=1}^{J} q(z_j)\right]}_{\text{Total Correlation Loss}}$$

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Idea to Overcome Impossibility Theorem

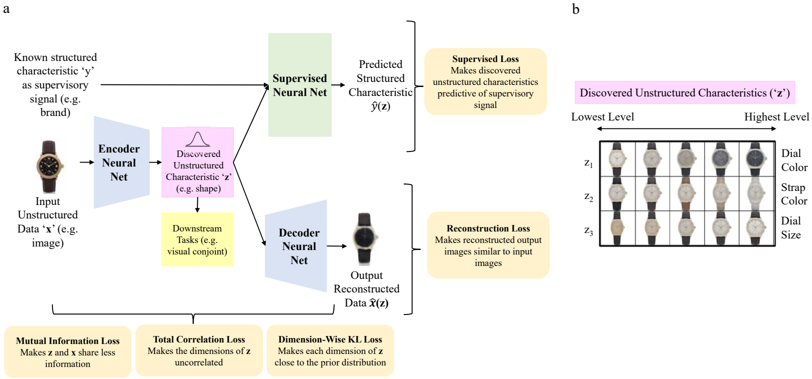
If the supervisory signal is sufficiently correlated with visual characteristics, then it can help obtain the unique (true) disentangled representation

Why might brand aid the disentanglement model?

Brand as a Supervisory Signal

Idea: Brands have a specific "look" that can be correlated with visual appearance (and therefore visual characteristics)

Schematic of Proposed Approach



Evaluating Visual Characteristics

Visual Characteristics: Human Interpretable?

- Are these visual characteristics human interpretable?

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Starting from the image on the left, **what part of the watch changes the <u>most</u>** as you go from left to right? Carefully check both large and small visual aspects. Go through each part of the watch one by one before selecting any option. Refer to the above image to see parts of the watch.

Note: Images are low-quality on purpose

- ○ Bezel
- ○ Crown
- ○ Date Window
- ○ Dial
- ○ Hands
- ○ Hour Marker
- ○ Lug
- ○ Strap

How is that part of the watch changing?

Visual Characteristics: Quantification?

Interpretability and Quantification

Visual characteristic	Interpretability Survey	Quantification Survey
Dial Size	76%	83%
Dial Color	80%	92%
Strap Color	88%	92%
Rim (Bezel) Color	79%	88%
Dial Shape	87%	68%
Knob (Crown) Size	70%	85%

Discovered Visual characteristics

Discovered Visual characteristics

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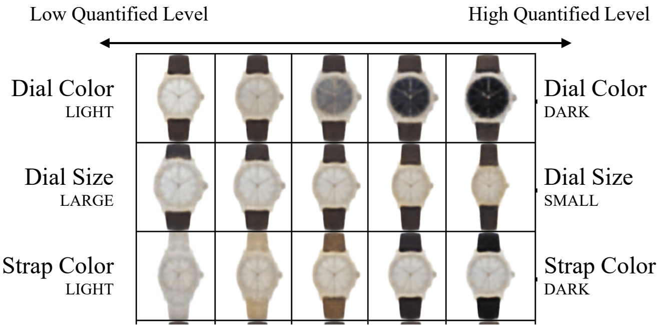
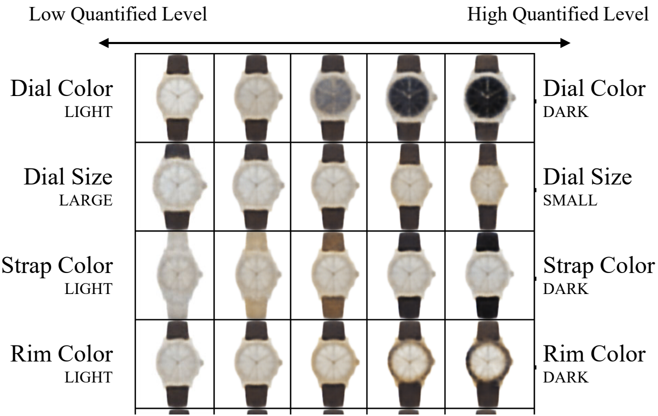


Discovered Visual characteristics



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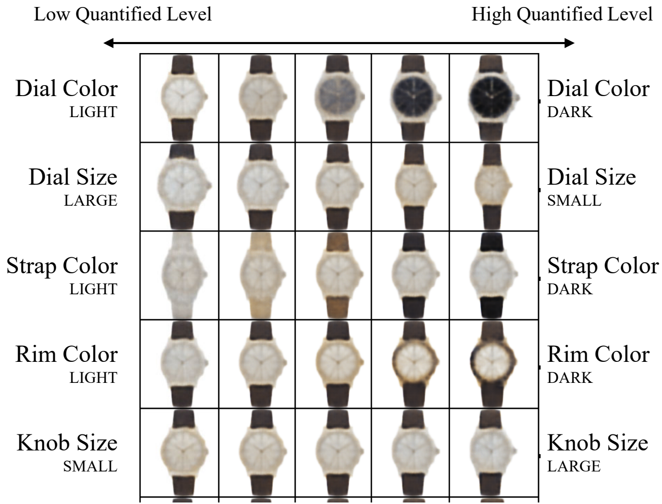

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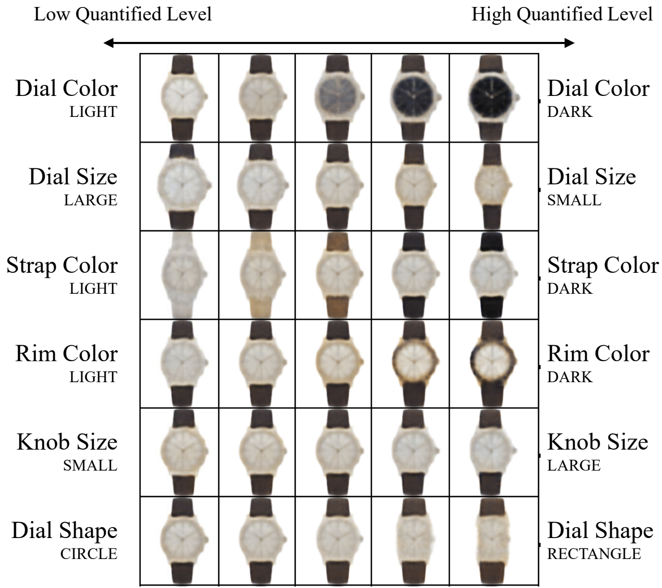
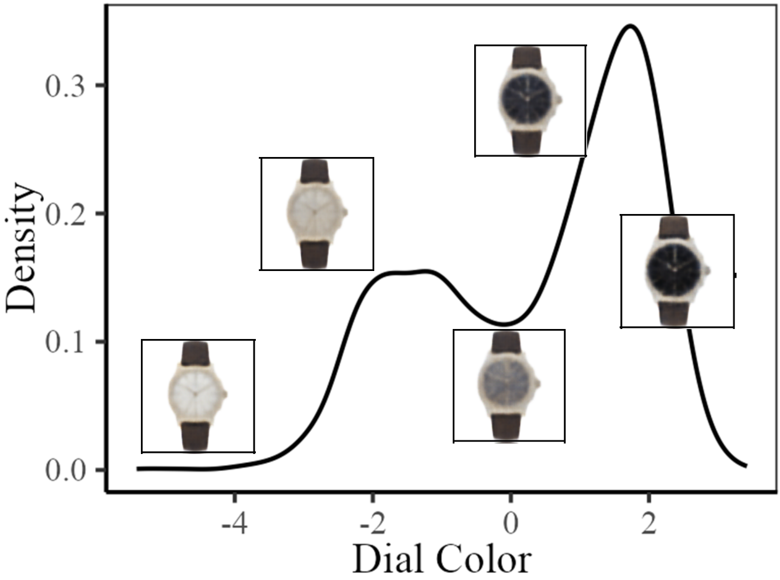


Density of Discovered Visual characteristics



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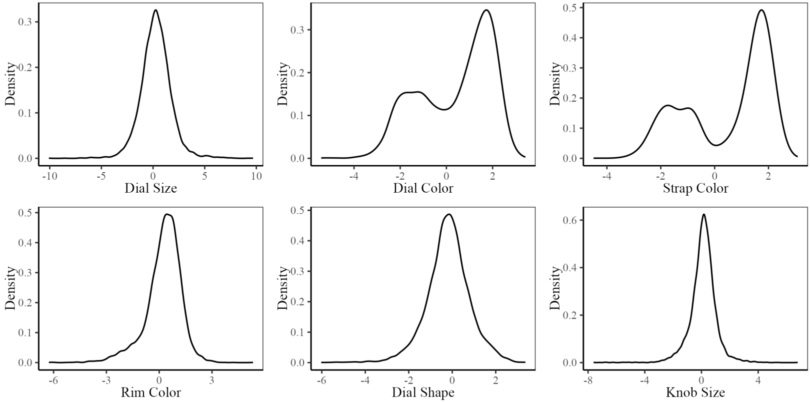
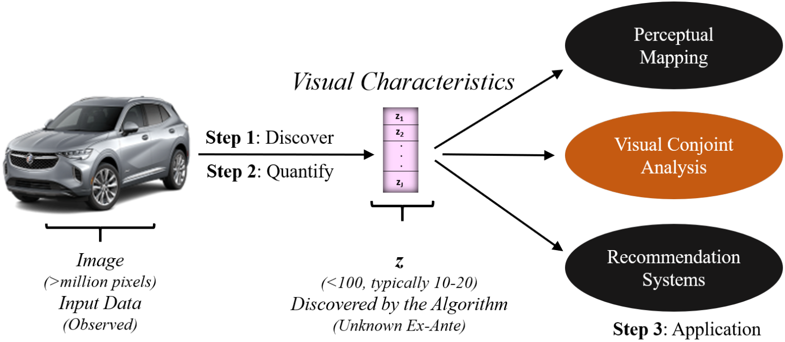


Research Goals



- Visual conjoint has been challenging to do. With disentanglement we can create counterfactual designs to span the space.

Conjoint Model Accuracy

Generated Watches

Model	Out-of-Sample Hit Rate (SD)
Disentangled Embedding + Logit Model (–)	63.16% (2.34%)
Disentangled Embedding + Neural Net (–)	65.81% (2.22%)
Pretrained Deep Learning Model Embedding (O)	68.31% (1.54%)
Disentangled Embedding + Neural Net (O)	67.52% (0.92%)
Disentangled Embedding + Random Forest (O)	68.77% (0.90%)
Disentangled Embedding + XGBoost (O)	69.10% (0.41%)
Disentangled Embedding + HB Model (O + U)	**71.61% (1.87%)**
Disentangled Embedding + HB Model + Interactions (O + U)	70.68% (1.35%)

- Pretrained Deep learning model is trained on *millions of images*, and has millions of parameters
- Our Hierarchical Bayes (HB) model has a small number parameters, and all predictions are based on only 6 visual characteristics
- With 6 visual characteristics, our HB model outperforms the pretrained deep neural net

Ideal Points for Segments

- Discover 2 segments with distinct and differentiated preferences

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Segment 1:
“Ideal Point” Watch Design

Segment 2:
“Ideal Point” Watch Design

Conclusion

We obtain interpretable visual characteristics directly from unstructured product images

- *automatically discover* (extract) characteristics

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Applications

We then used the model to:

- generate new counterfactual designs to obtain consumer preferences over visual characteristics.
- obtain ideal point visual designs corresponding to different consumer segments