Automatic Discovery and Generation of Visual Design Characteristics

Application to Visual Conjoint

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Yale School of Management

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

Cars

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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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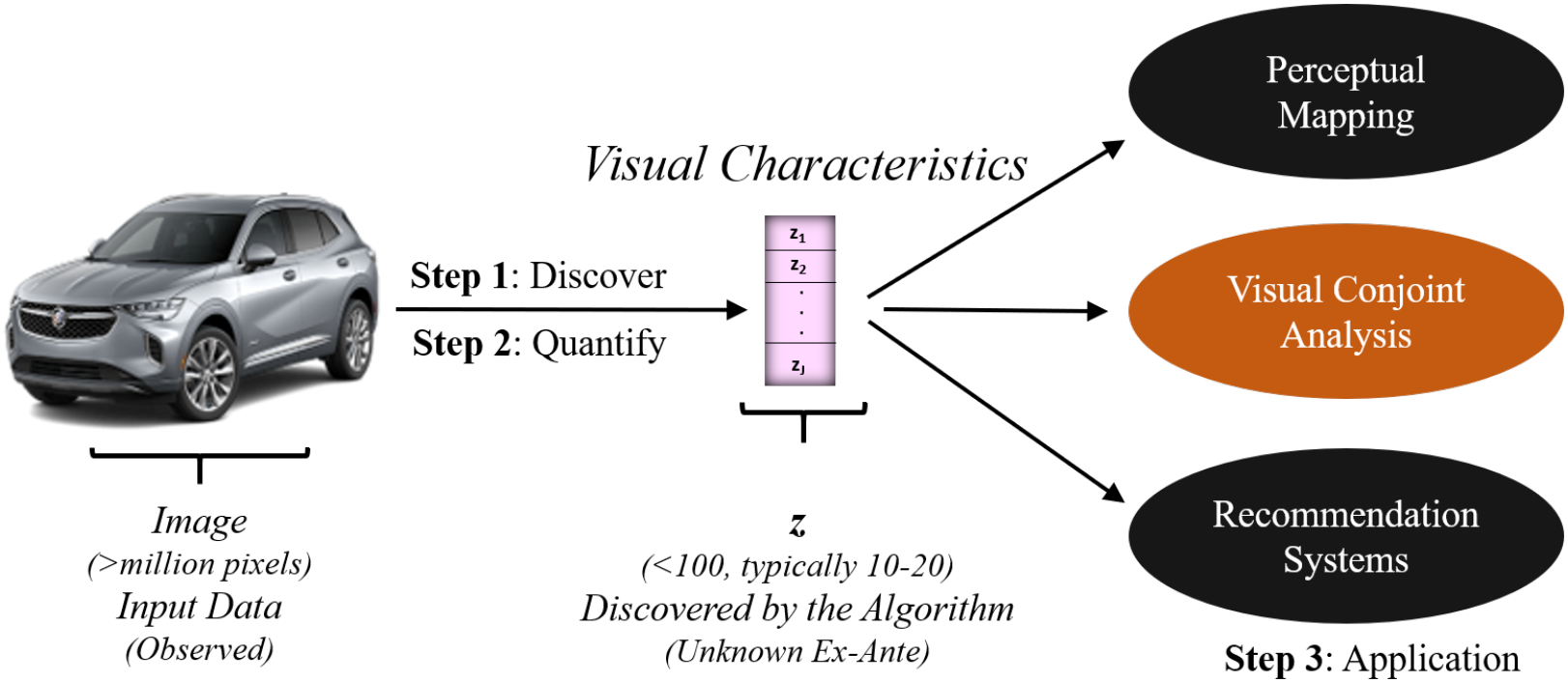
Research Goals

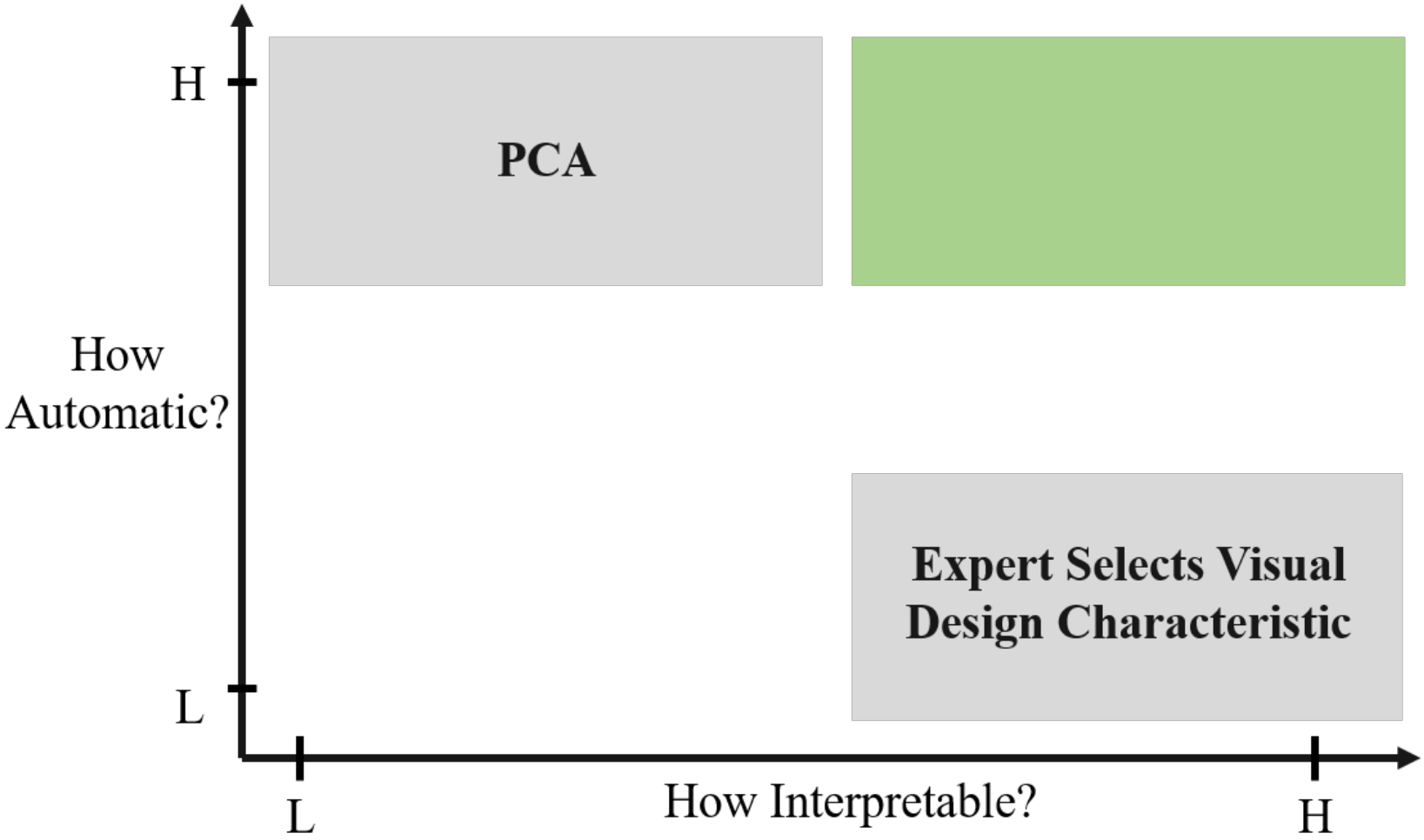
Our research aims to obtain **interpretable** visual characteristics directly from unstructured product images

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

Research Goals



Modeling Visual Characteristics: A comparison of methods



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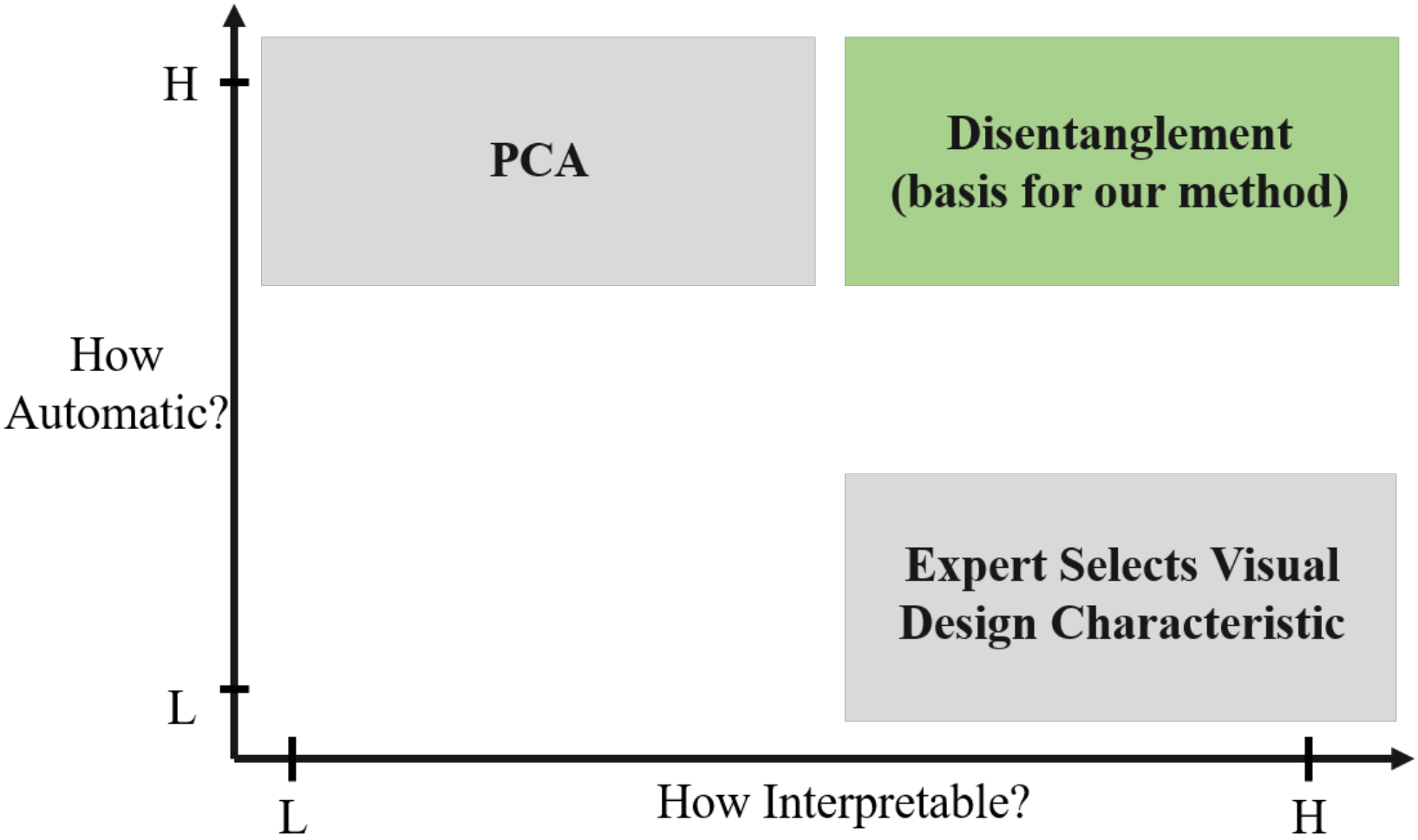

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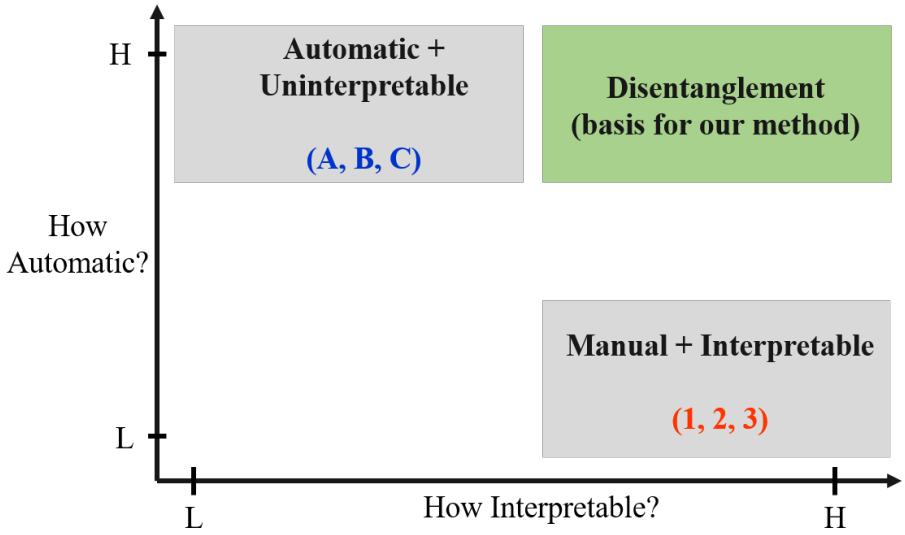

Automatic + Uninterpretable

- 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)*
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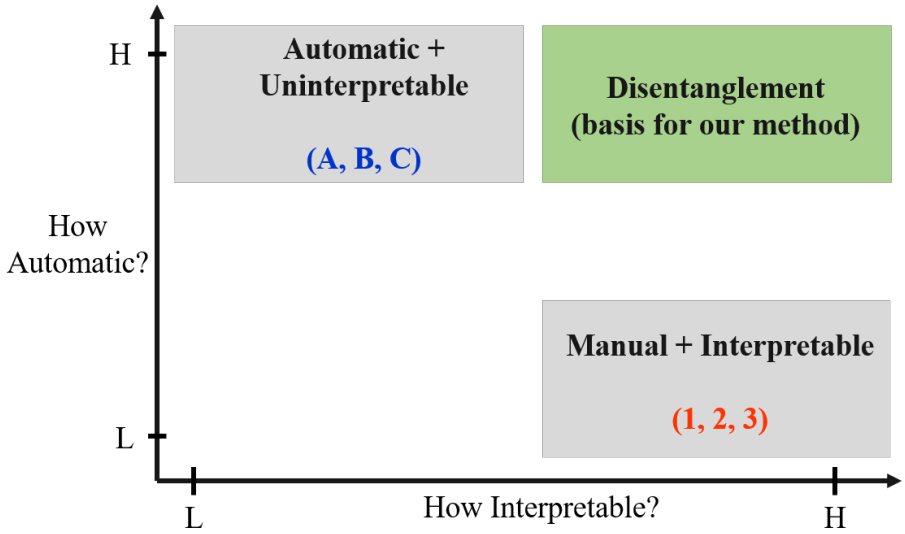

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Manual + Interpretable

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

Is Human Interpretability always necessary?

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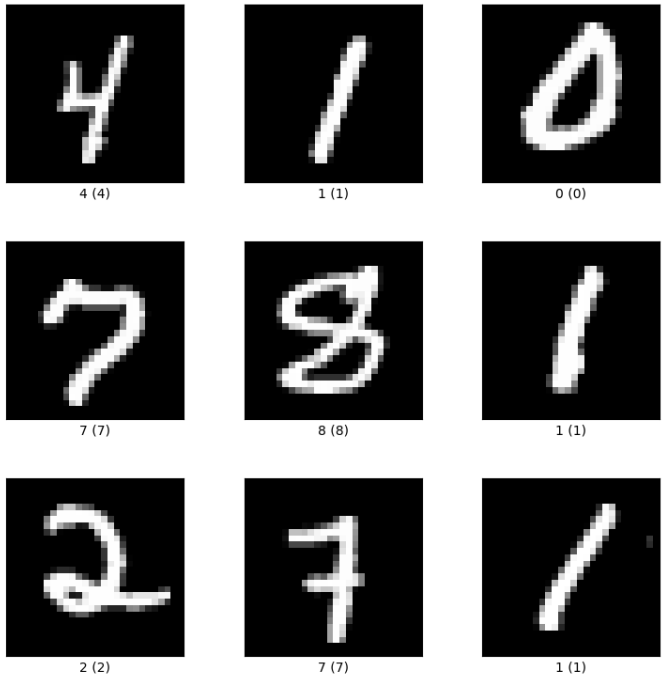
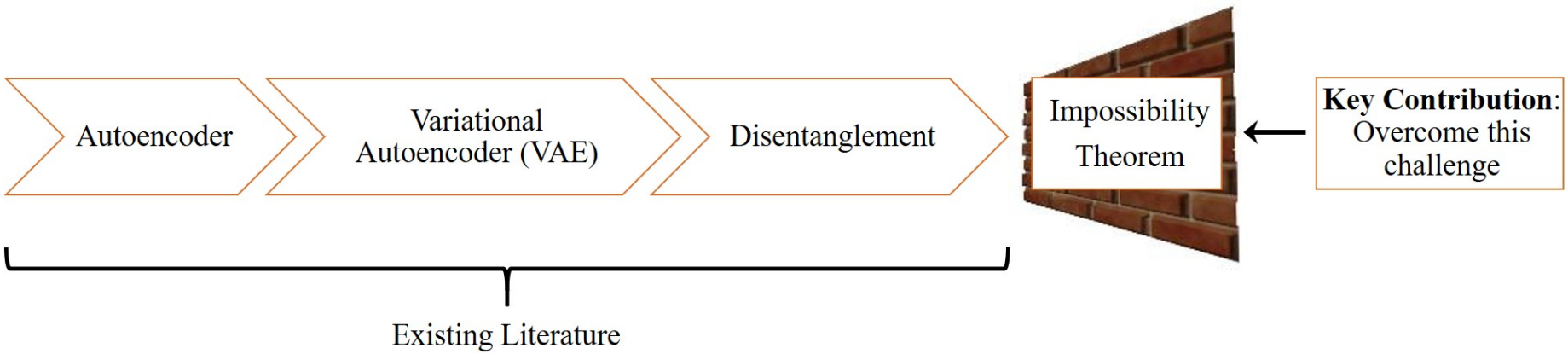


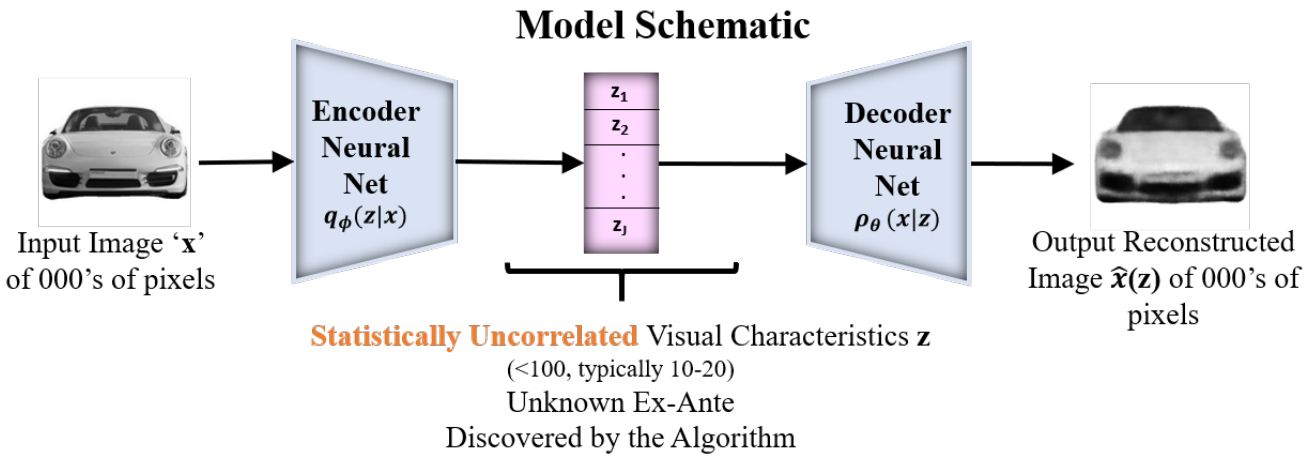
Roadmap of Our Approach



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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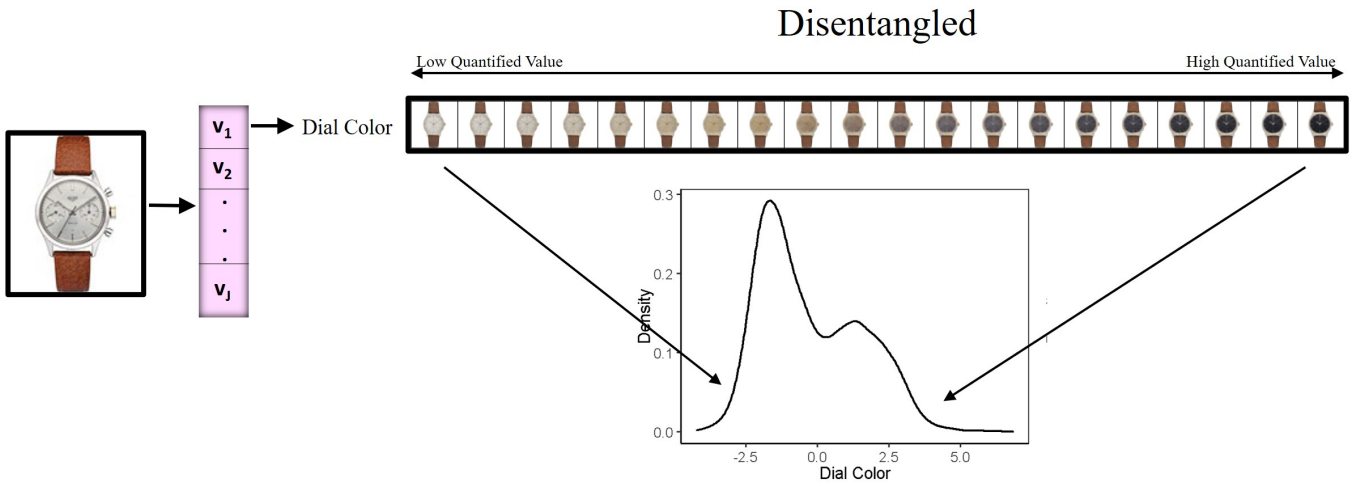
Disentangled v Entangled Representation



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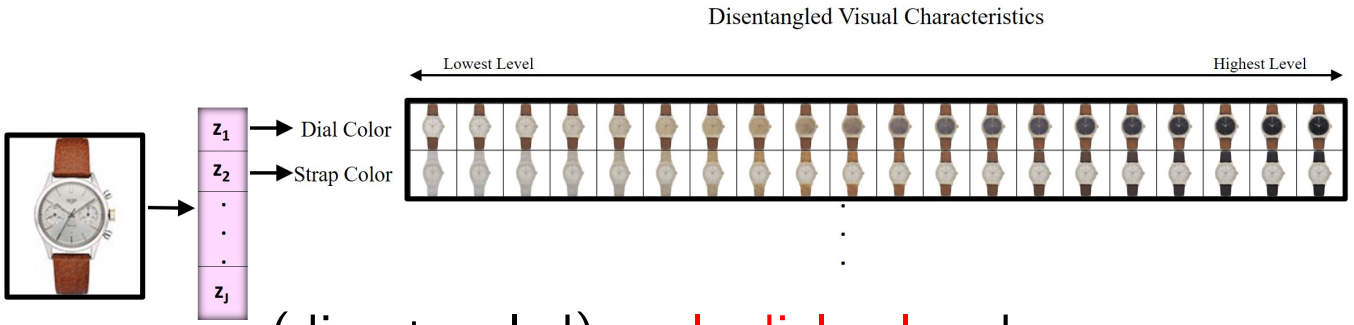
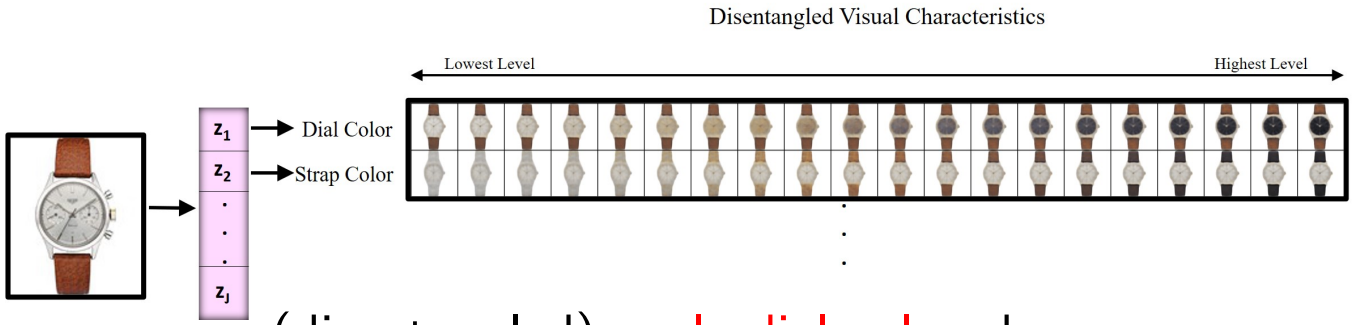


v_1 (disentangled): only dial color changes

v_2 (disentangled): only strap color changes

Disentangled v Entangled Representation



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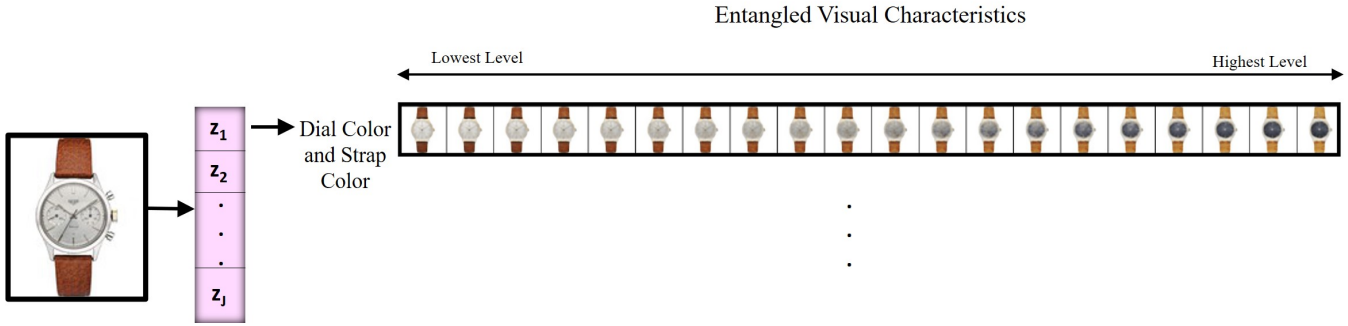

v_1 (entangled): both dial color and strap color changes

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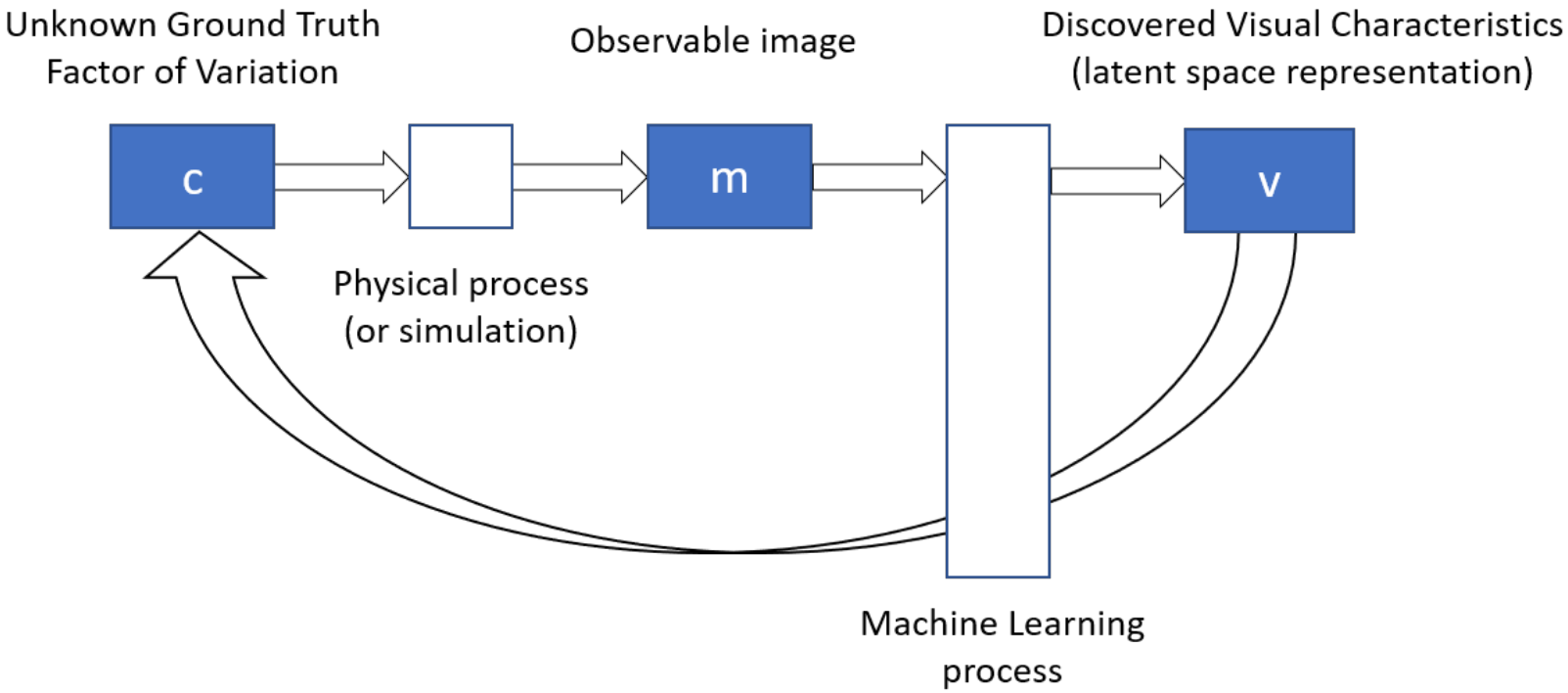

Goal of machine learning process: Recover latent space $\mathbf{v}(\mathbf{m}(\mathbf{c}))$ and make correspondence $\boxed{\mathbf{c} \longleftrightarrow \mathbf{v}}$

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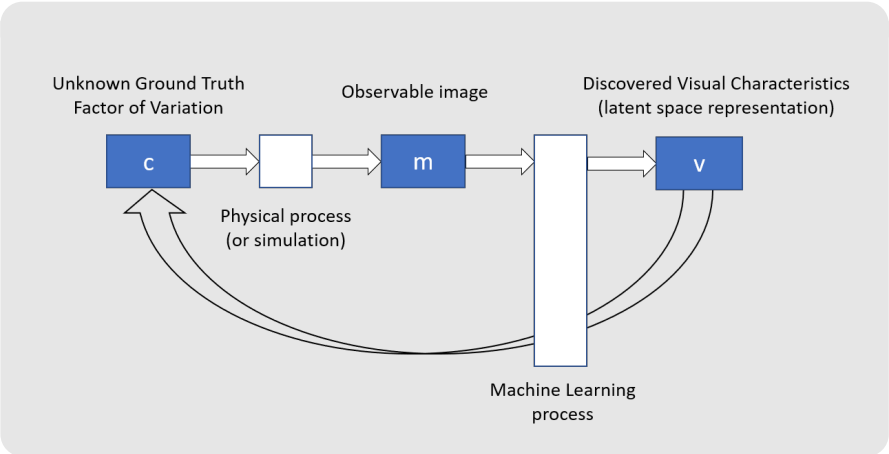
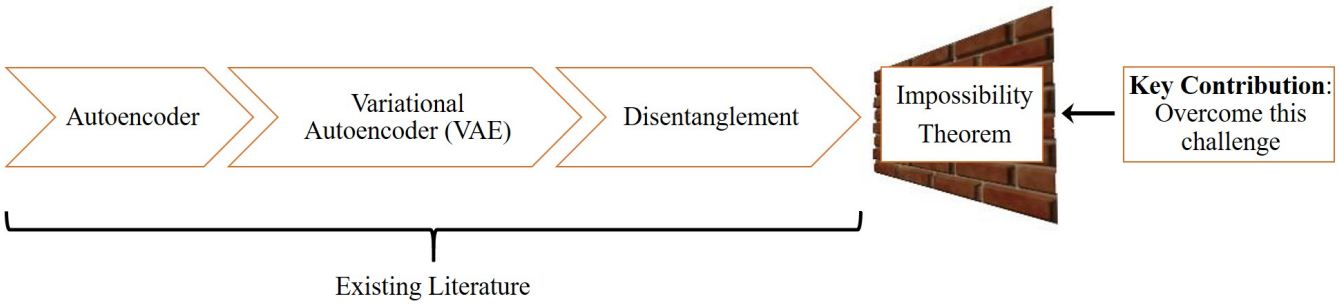


Impossibility Theorem



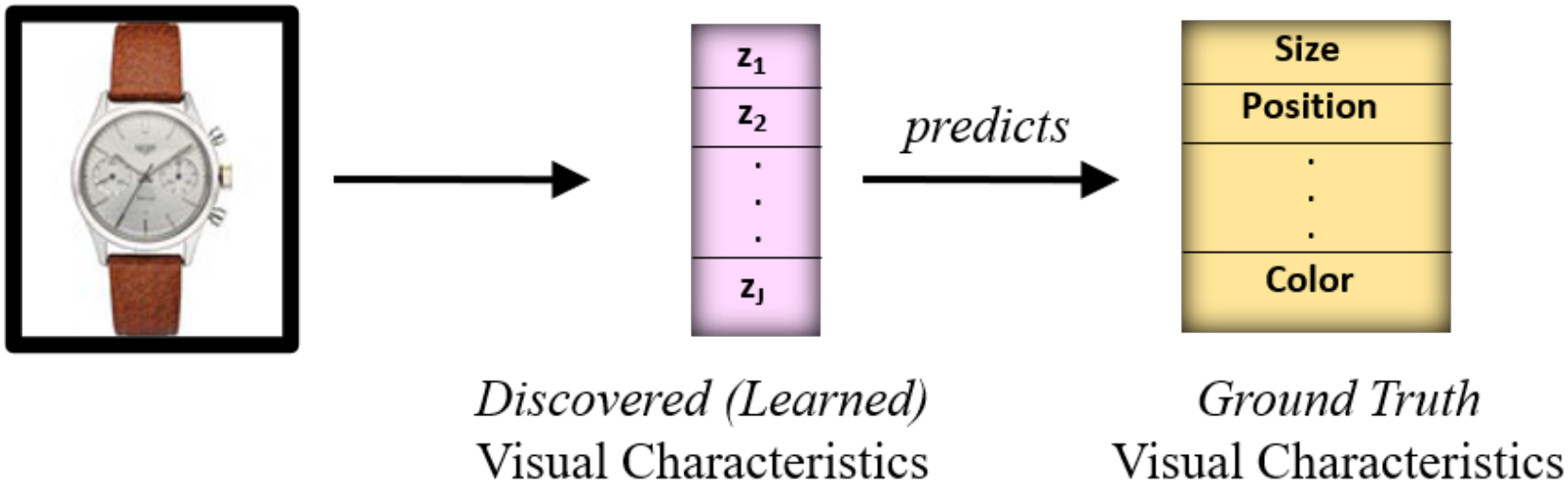
Impossibility Theorem

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

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

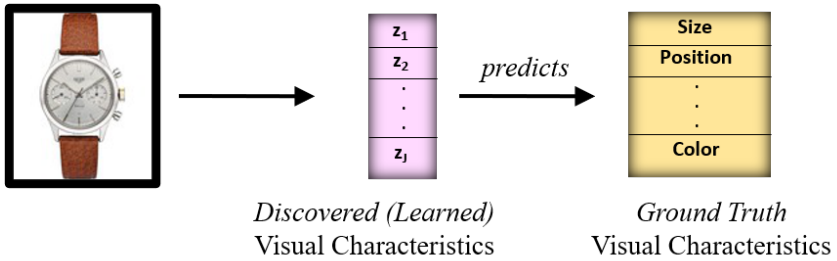
Implication: Every disentangled representation can have other *infinite* equivalent entangled representations.

Overcoming Impossibility Theorem



Overcoming Impossibility Theorem

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. In fact, these are precisely what we want to find.

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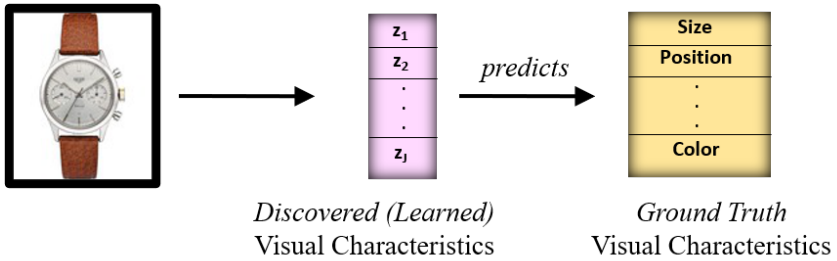

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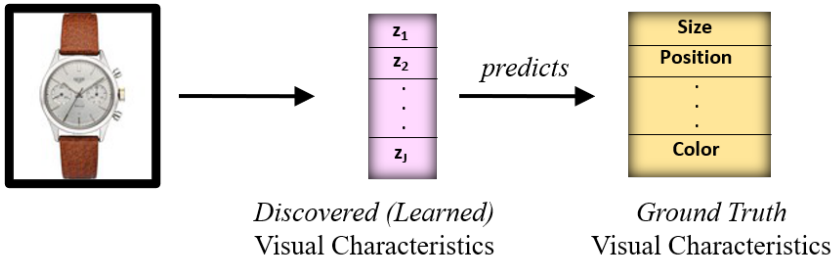

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- Researcher needs to determine what are the true characteristics to focus on
- Need to ensure humans understand what these labels are and how to quantify them for each image

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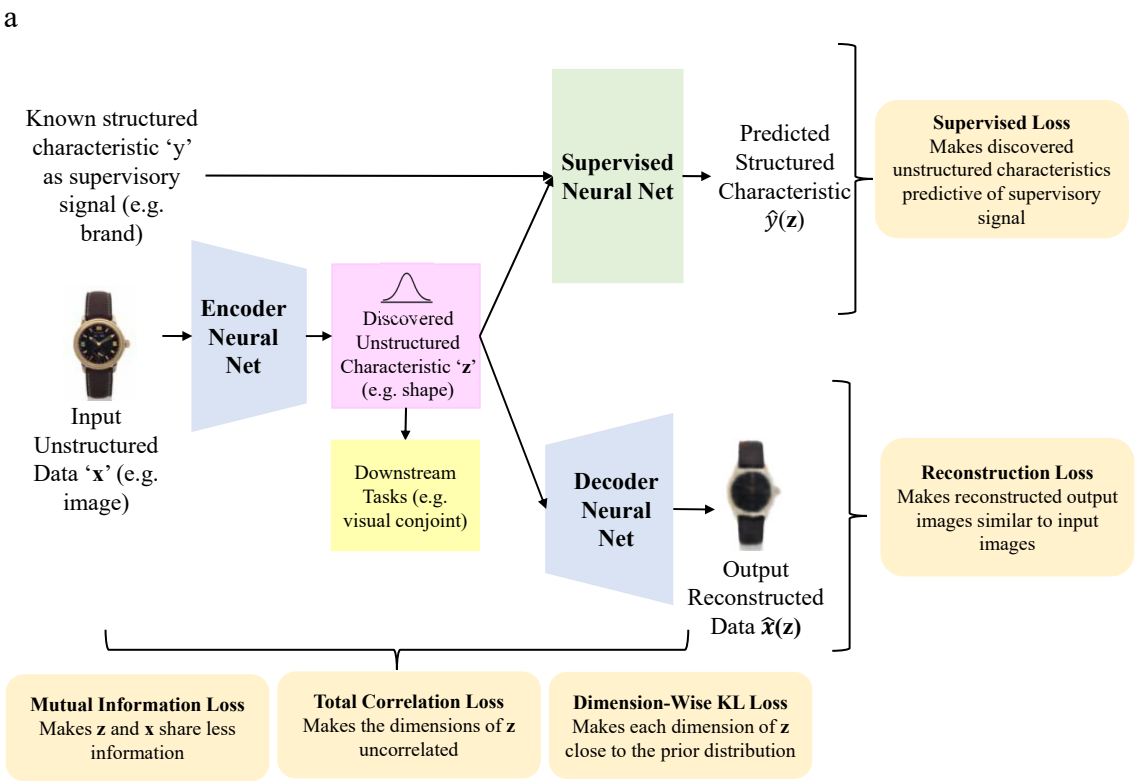
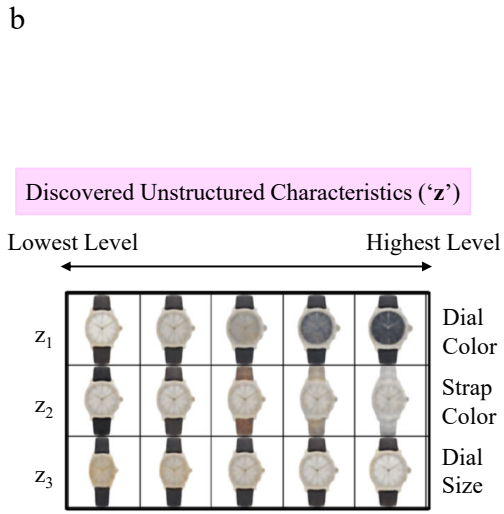
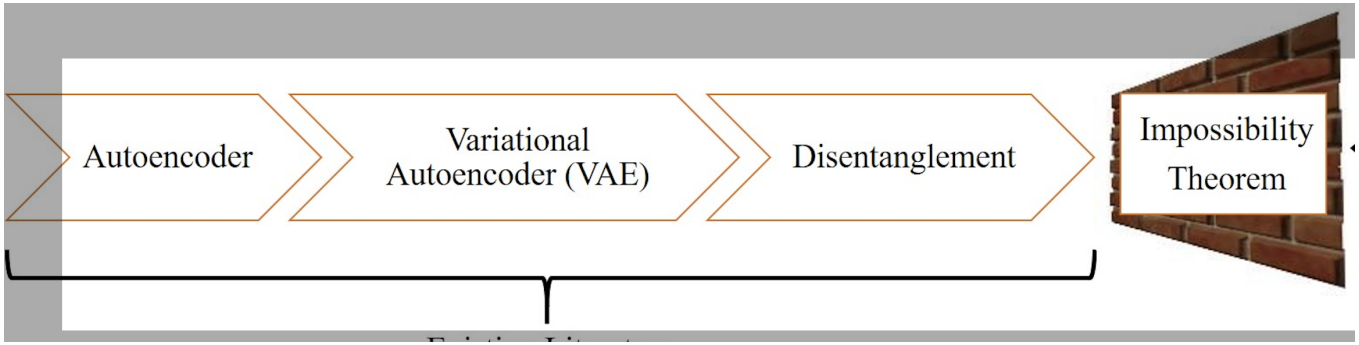
Schematic of Proposed Approach





Contribution



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

Table of Notation

Symbol	Category	Meaning
$\mathbf{x}$	Input Data	Product image
$\mathbf{y}$	Input Data	Supervisory signal(s)
$\hat{\mathbf{x}}$	Output Data	Reconstructed image
$\hat{\mathbf{y}}$	Output Data	Predicted Supervisory Signal(s)
$\mathbf{z}$	Latent Space	Visual characteristic vector
$\mathbf{z}_{\text{inf}}$	Subset of Latent Space	Informative visual characteristic
$p(\mathbf{z})$	Model	Prior distribution
$p_\theta(\mathbf{x}\|\mathbf{z})$	Decoder Neural Net	Conditional Probability of Generating Image Data given Latent Space
$q_\phi(\mathbf{z}\|\mathbf{x})$	Encoder Neural Net	Conditional Probability of Latent Space given Image Data
$p_w(\mathbf{y}\|\mathbf{z})$	Supervisory Neural Net	Conditional Probability of Supervisory Signal given Latent Space
θ	Weights of Neural Net	Decoder's parameters
ϕ	Weights of Neural Net	Encoder's parameters
w	Weights of Neural Net	Supervisory Net's parameters
$\mathbf{E}_{q_\phi(\mathbf{z}\|\mathbf{x})}\left[\log p_\theta(\mathbf{x}\|\mathbf{z})\right]$	Loss Function	Reconstruction Loss
$I_q(\mathbf{z},\mathbf{x})$	Loss Function	Mutual Information Loss
$KL\left[q(\mathbf{z})\|\|\prod_{j=1}^{J} q(z_j)\right]$	Loss Function	Total Correlation Loss
$\sum_{j=1}^{J} KL\left[q(z_j)\|\|p(z_j)\right]$	Loss Function	Dimension KL Divergence Loss
$P(\hat{y}(\mathbf{z}), y)$	Loss Function	Supervised Loss
$\mathcal{L}(\theta,\phi,\beta;\mathbf{x},\mathbf{z})$	Loss Function	Total Loss
J	Hyperparameter	Dimensionality of latent space
α	Hyperparameter	Weight on Mutual Information Loss
β	Hyperparameter	Weight on Total Correlation Loss
γ	Hyperparameter	Weight on Dimension KL Divergence Loss
δ	Hyperparameter	Weight on Supervised Loss

Model Estimation

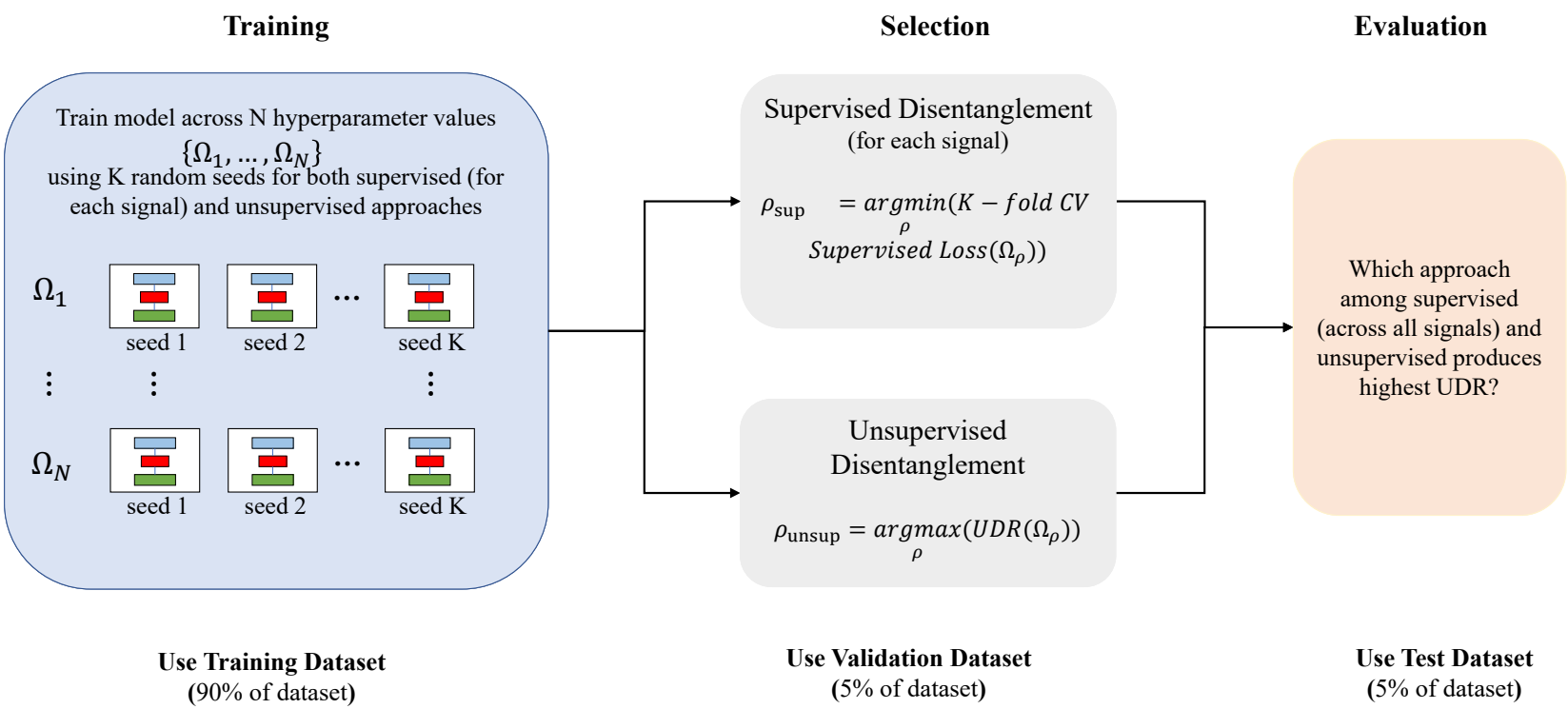
- Learn model parameters by minimizing loss $L(\theta, \phi; \mathbf{x}, \mathbf{z})$ of integrated model
- θ and ϕ are encoder and decoder parameters; $\mathbf{x}$ are images

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

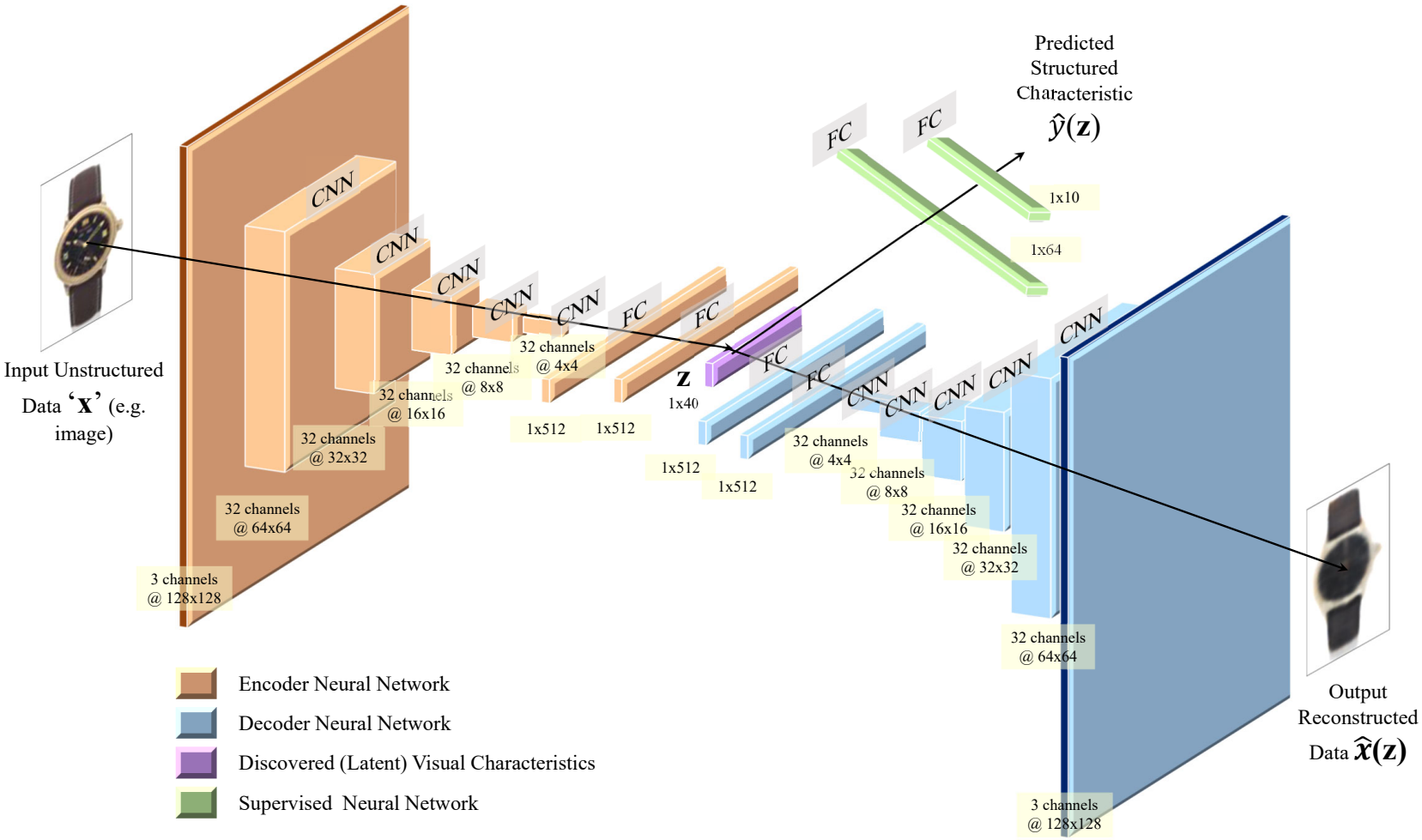
$$+\gamma \underbrace{\sum_{j=1}^{J} KL\left[q(z_j)||p(z_j)\right]}_{\text{Dimension-Wise KL Divergence Loss}} + \delta \underbrace{P(\hat{\mathbf{y}}(\mathbf{z}), \mathbf{y})}_{\text{Supervised Loss}}$$

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 Training, Selection, & Evaluation



Model Architecture



Disentanglement Evaluation Metric

Esterman details the value of UDR, which we quote below:

> *"There are no labels available for many real-life applications and for some data, generative factors of interest are hard or impossible for humans to annotate.*

Disentanglement Evaluation Metric

Unsupervised Disentanglement Ranking (UDR) measures disentanglement

- **Why UDR?**: "There are no labels available for many real-life applications and for some data, generative factors of interest are hard or impossible for humans to annotate."[2]
- **Key Idea**: "Models that disentangle well are more likely to be similar to each other than the ones that do not disentangle"[3]

[2] Estermann, B., Marks, M., & Yanik, M. F. (2020). Robust Disentanglement of a Few Factors at a Time using rPU-VAE. Advances in Neural Information Processing Systems, 33, 13387-13398.

[3] Estermann, B., Marks, M., & Yanik, M. F. (2020). Robust Disentanglement of a Few Factors at a Time using rPU-VAE. Advances in Neural Information Processing Systems, 33, 13387-13398.

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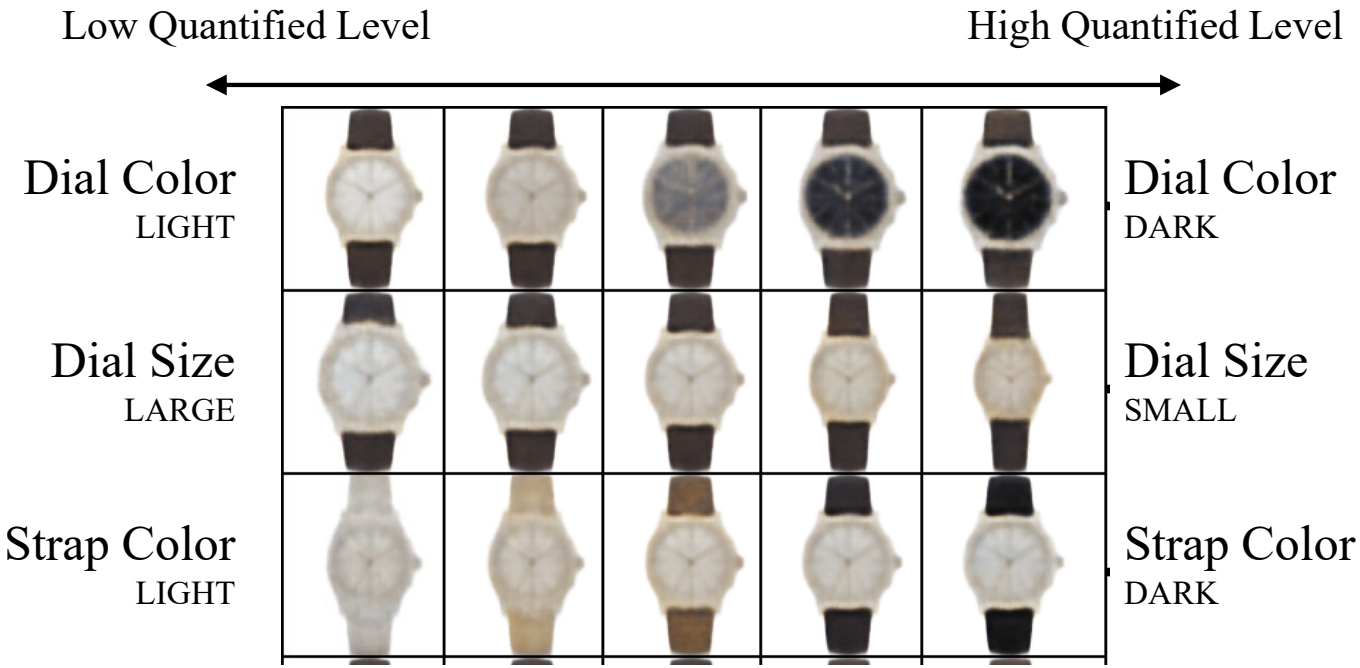

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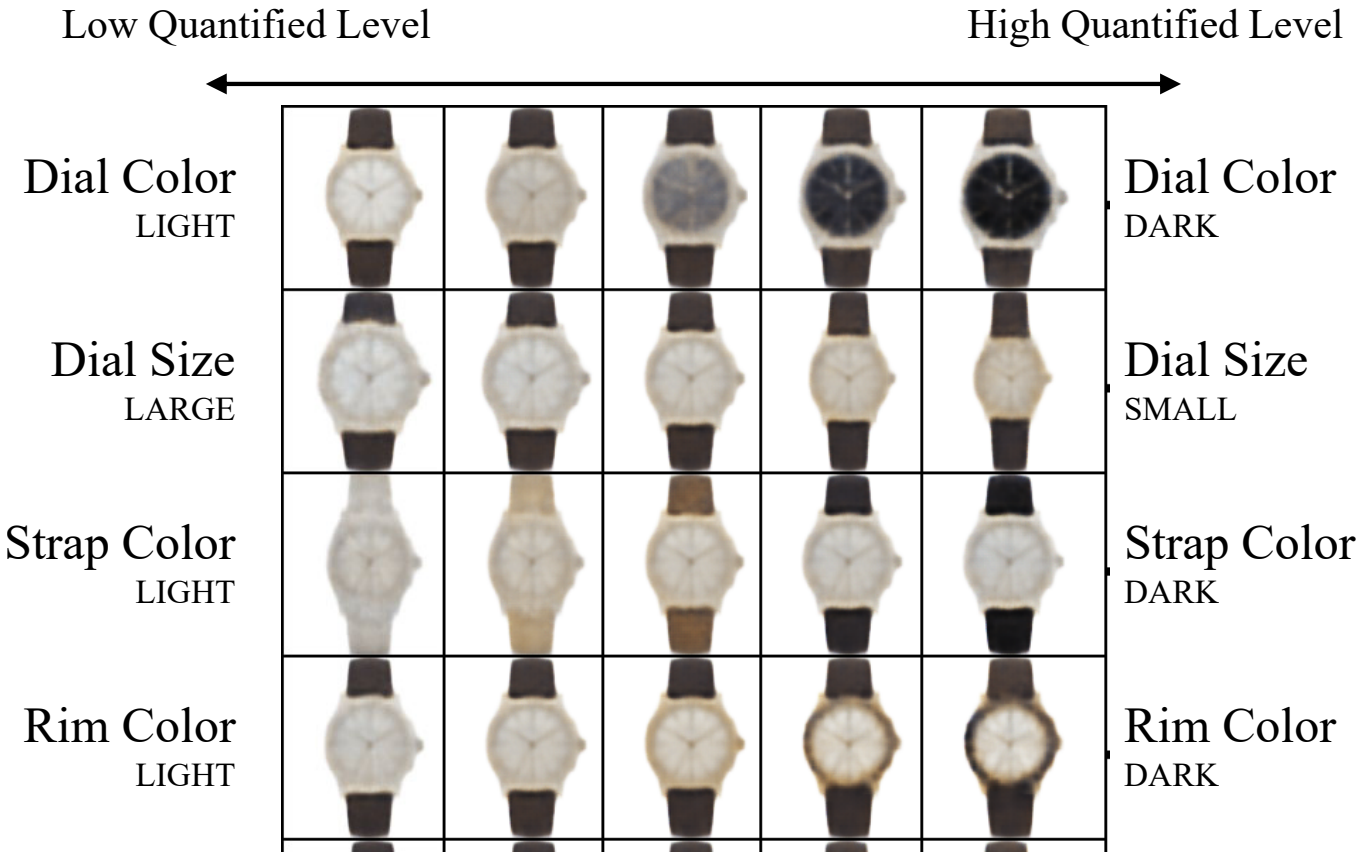

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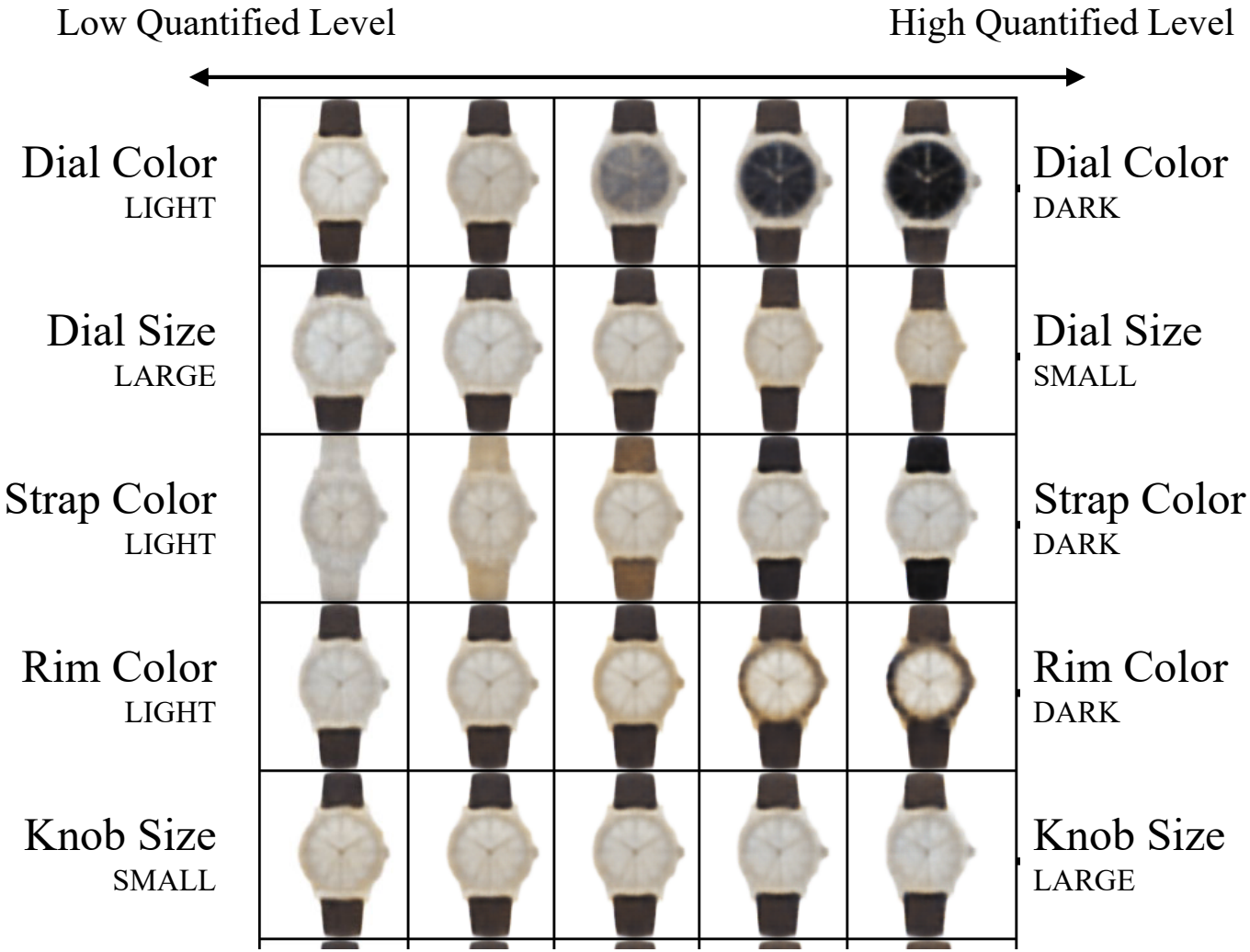

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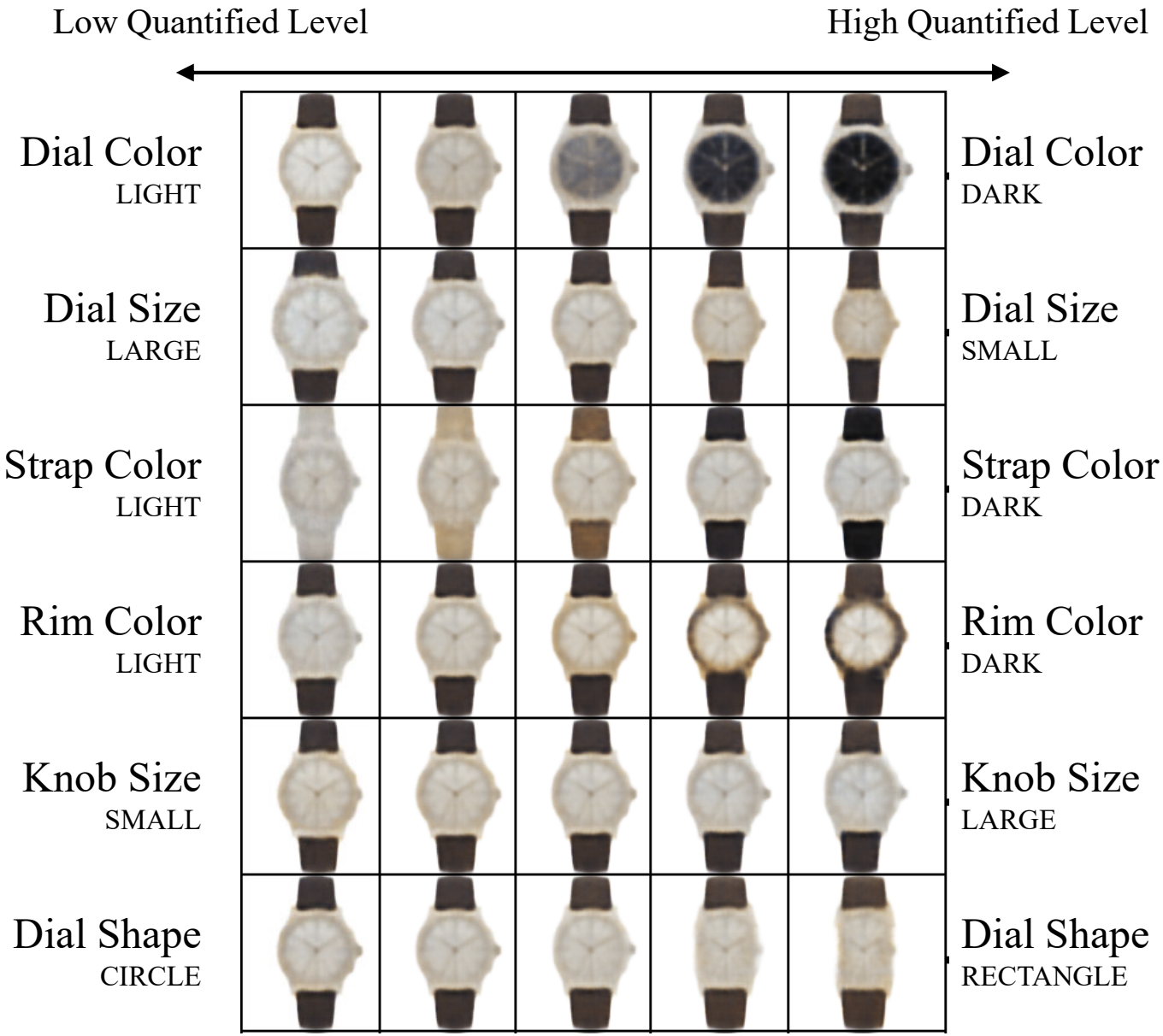
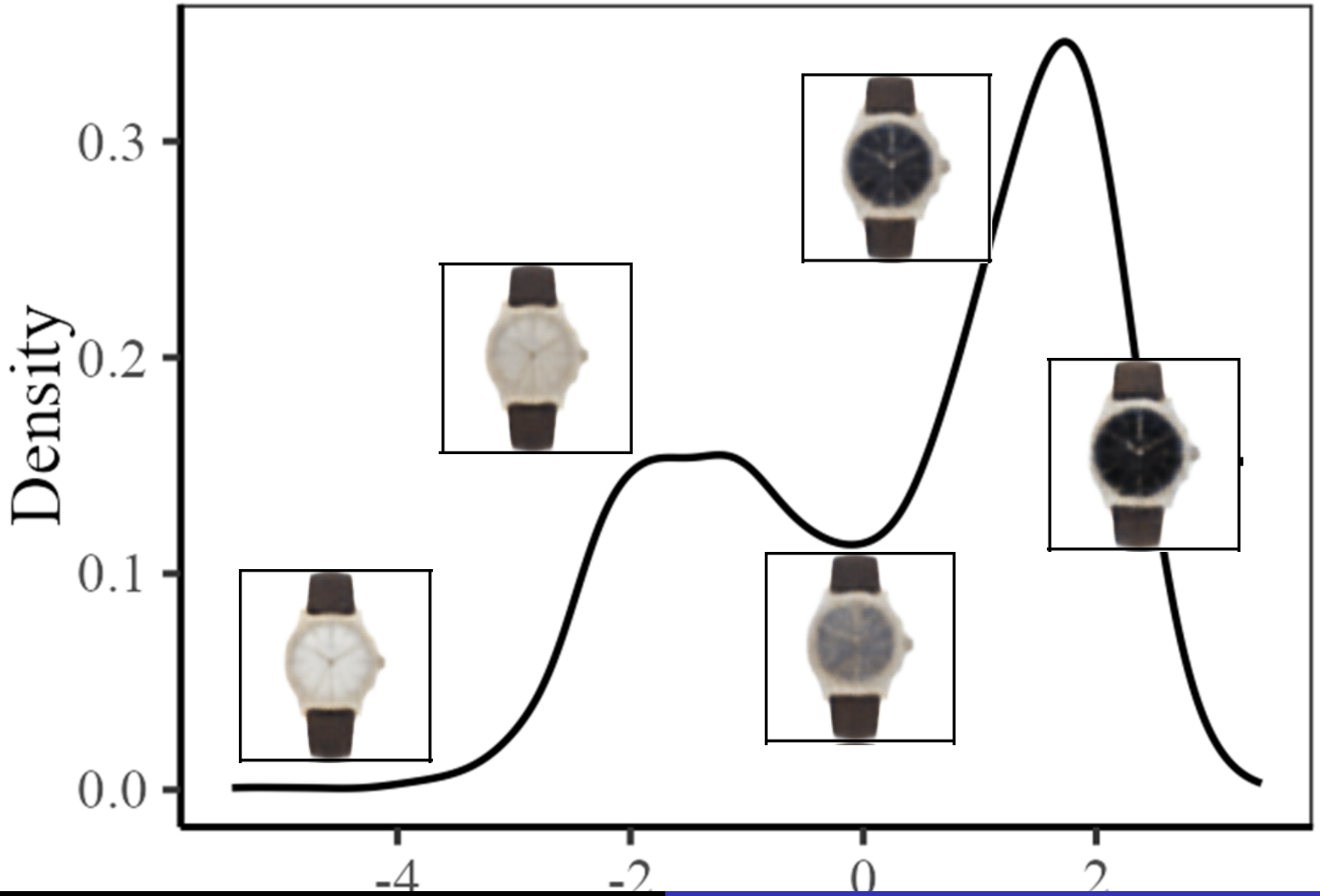


Density of Discovered Visual characteristics (from 'Brand+Material' Signal)



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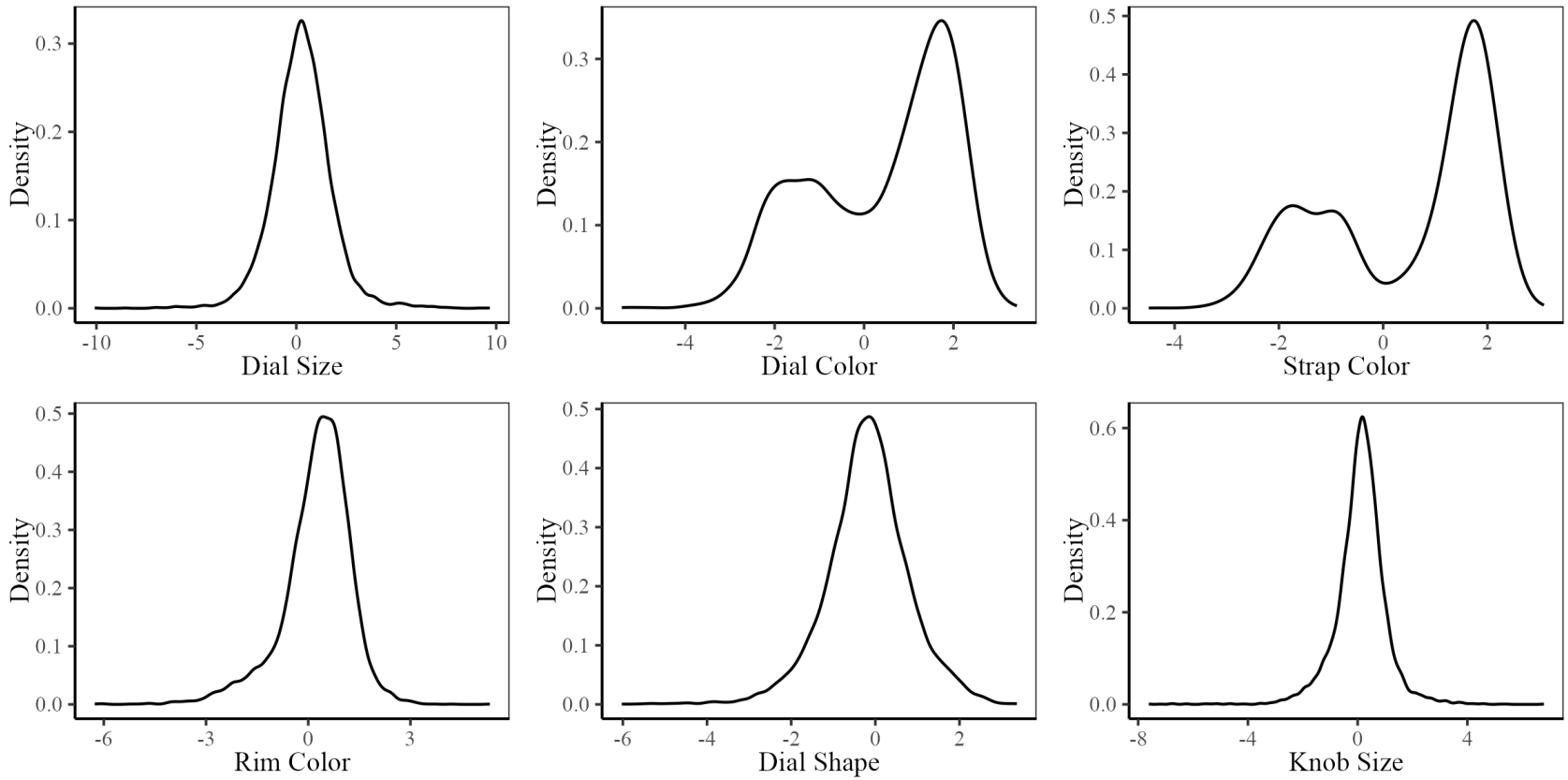


Example choice-based conjoint (CBC) question in conjoint survey.

Consider the two watches below that vary **only on visual style**. Of these two, which watch would you prefer more (for yourself)?

Select

Select

Next

Utility: Hierarchical Bayesian Model

$$u(\mathbf{z}; \beta_i) = \beta_1 z_1 + \ldots + \beta_K z_K$$

$$\begin{aligned}
\mu_\Theta &\sim \mathcal{N}(\mathbf{0}, \sigma_\Theta^2) \\
\boldsymbol{\Theta} &\sim \mathcal{N}(\mu_\Theta, \boldsymbol{\Lambda}_\Theta) \\
\boldsymbol{\Omega}_\beta &\sim \mathrm{LKJ}(\eta) \\
\boldsymbol{\Lambda}_\beta &= \mathbf{D}(\sigma_\beta)\boldsymbol{\Omega}_\beta\mathbf{D}(\sigma_\beta) \\
\beta_i &\sim \mathcal{N}(\boldsymbol{\Theta}^T\mathbf{r}_i, \boldsymbol{\Lambda}_\beta) \\
u_i^j &= z_j\beta_i + \epsilon_{ij} \\
y_i^{j,j'} &\sim \mathrm{Bernoulli}(\omega_i(j,j')) \\
\text{where} \quad \omega_i(j,j') &= \frac{\exp(u_i^j)}{\exp(u_i^j) + \exp(u_i^{j'})}
\end{aligned}$$

where $\mathrm{LKJ}(\eta)$ is a Cholesky factorization of the correlation matrix $\boldsymbol{\Omega}_\beta$ of the individual "part-worth" preference vector over visual characteristics. $\mathbf{D}(\cdot)$ denotes a diagonal matrix, $\mathbf{r}_i$ are consumer covariates, u_i^j is the utility customer i gets from watch design j, and ϵ_{ij} is a Gumbel random variable. The Bernoulli probability parameter $\omega_i(j,j')$ is specified by the logit function, and $\{j,j'\}_i$ denotes the set of all pairwise choice comparisons for watches $j, j' \in J$ that customer i chose over in the conjoint survey. Note that σ_Θ^2, $\boldsymbol{\Lambda}_\Theta$, η are researcher-defined hyperparameters chosen via model selection using prediction accuracy on the validation data split as the evaluation metric.

Conjoint Model Accuracy (Generated Watches)

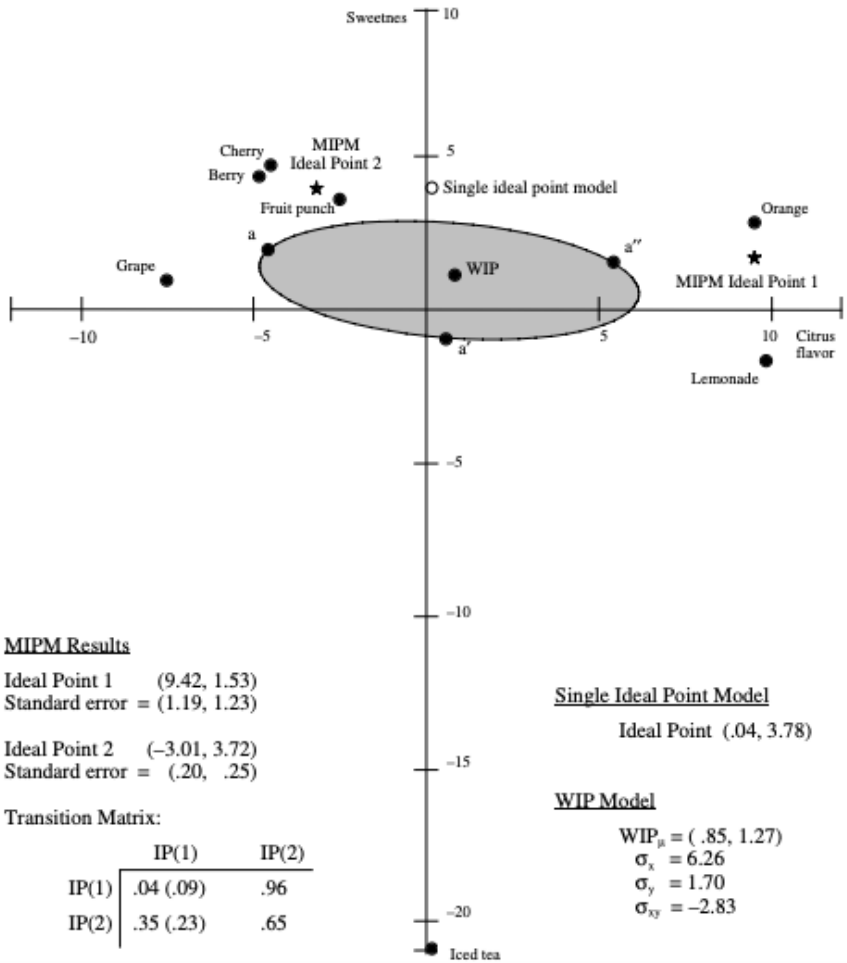
Model	Hit Rate	(Std. Dev.)
Disentangled Embedding + Logit Model (Homogeneous)	63.16%	(2.34%)
Disentangled Embedding + Neural Net (Homogeneous)	65.81%	(2.22%)
Disentangled Embedding + Neural Net (Observable Heterogeneity)	67.52%	(0.92%)
Pretrained Deep Learning Model (Observable Heterogeneity)	68.31%	(1.54%)
Disentangled Embedding + HB Model (Observable + Unobservable Heterogeneity)	71.61%	(1.87%)

- Pretrained Deep learning model is trained on millions of images, and has millions of parameters
- Our HB model also has a small number parameters, and all predictions are based on only 6 visual characteristics

Ideal Point

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

Figure 2
MIPM RESULTS FOR HOUSEHOLD 057



Generated Ideal Point Watches for Two Segments

Ideal Point: Optimal positioning of a product in characteristic space based on preferences of a selected consumer segment.

Segment 1:
"Ideal Point" Watch Design

Segment 2:
"Ideal Point" Watch Design