Generative Interpretable Visual Design

Application to Visual Conjoint

Ankit Sisodia[1], Alex Burnap[2] and Vineet Kumar[2]

[1]Purdue University

[2]Yale School of Management

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November 2023

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

Cars

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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 (not surprising / outlier) directly from unstructured product images

- *automatically discover* (extract) characteristics

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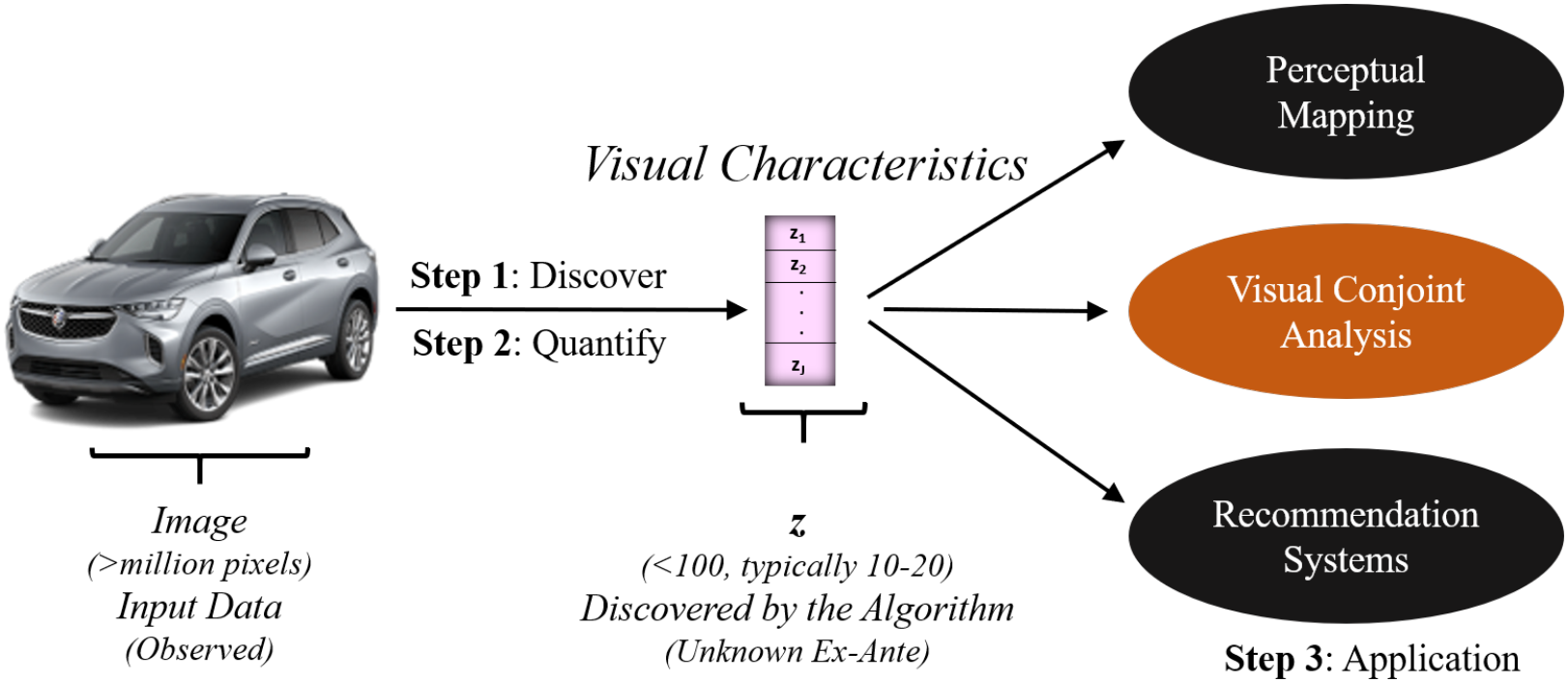
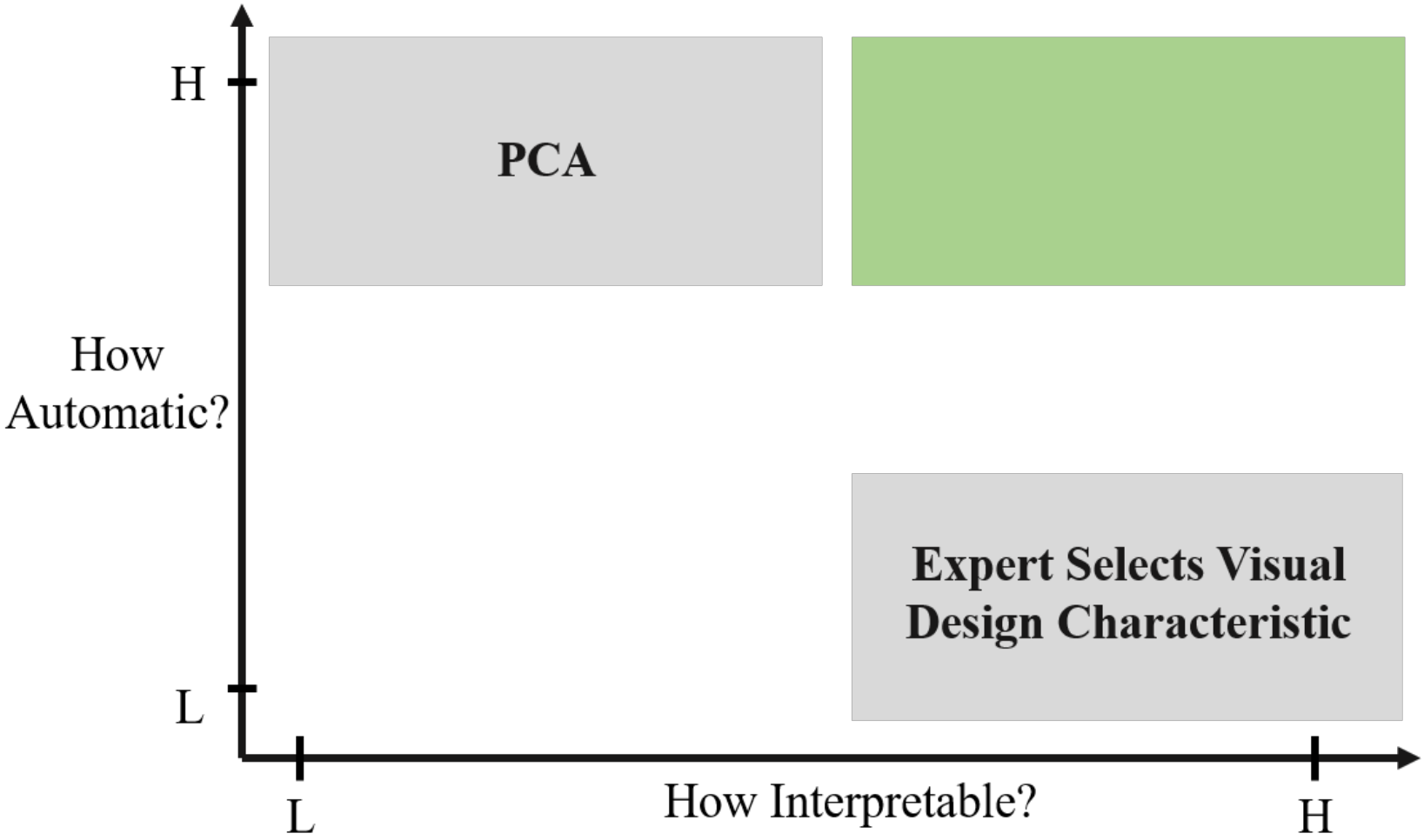
Hyundai: $(3, 8, 5, 9)$ compared to BMW: $(1, 3, 10, 1)$

Why Visual Characteristics?



Modeling Visual Characteristics: A comparison of methods



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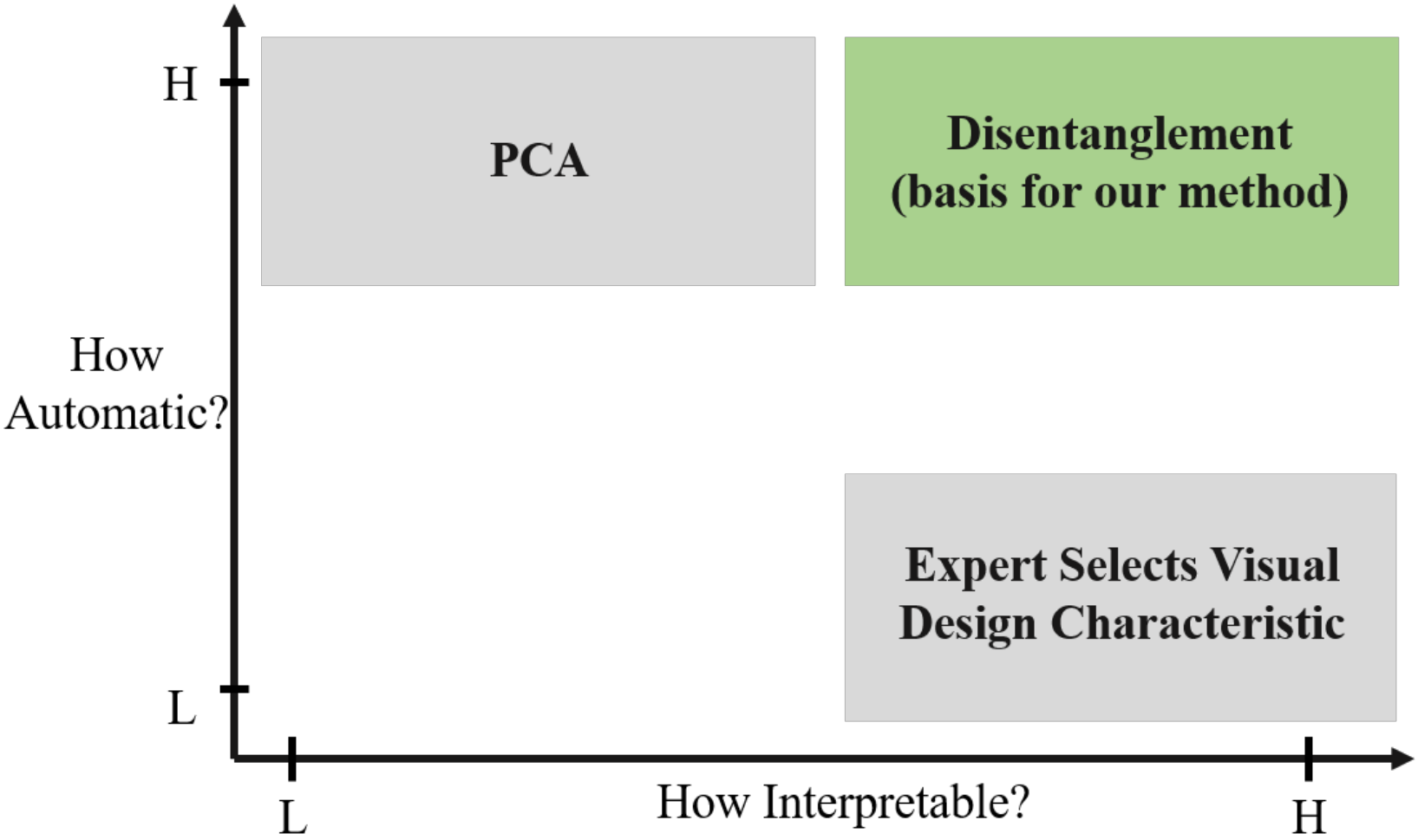

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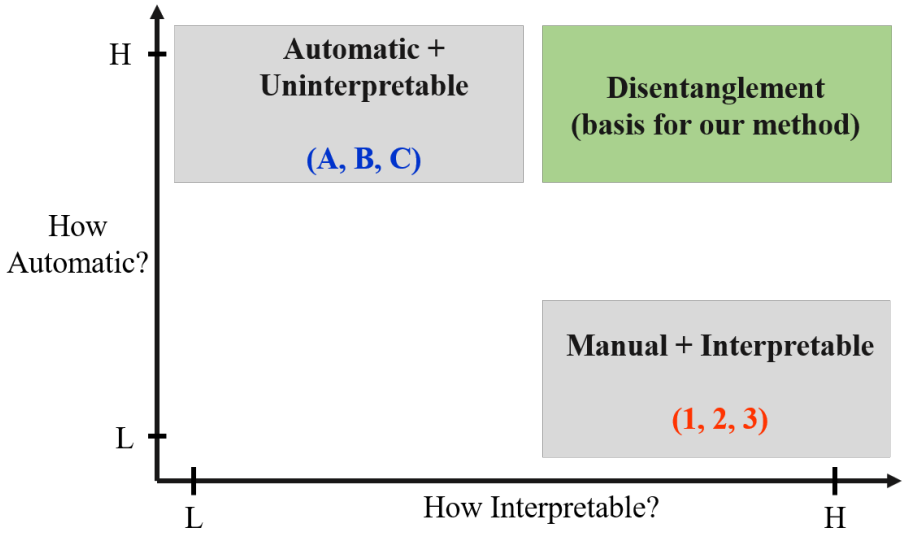

Automatic + Uninterpretable

- 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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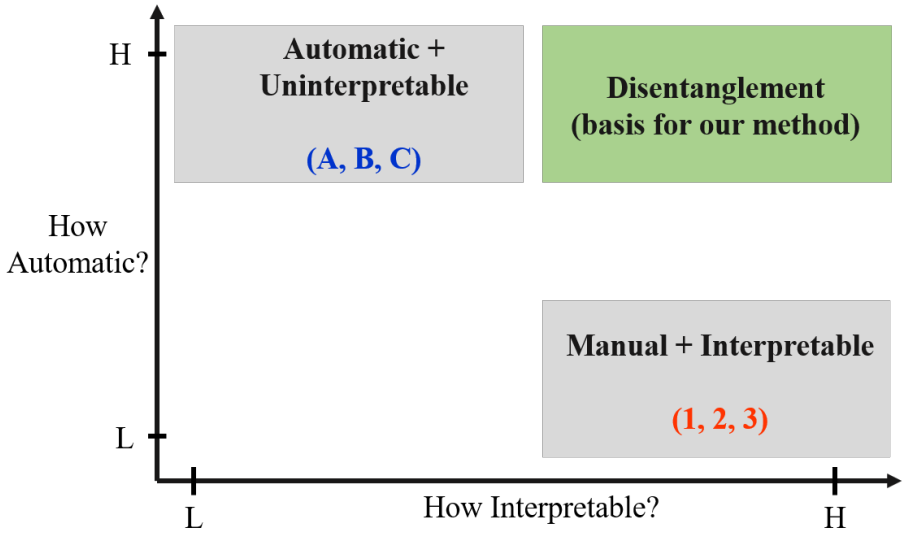

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Manual + Interpretable

- 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*

Is Human Interpretability always necessary?

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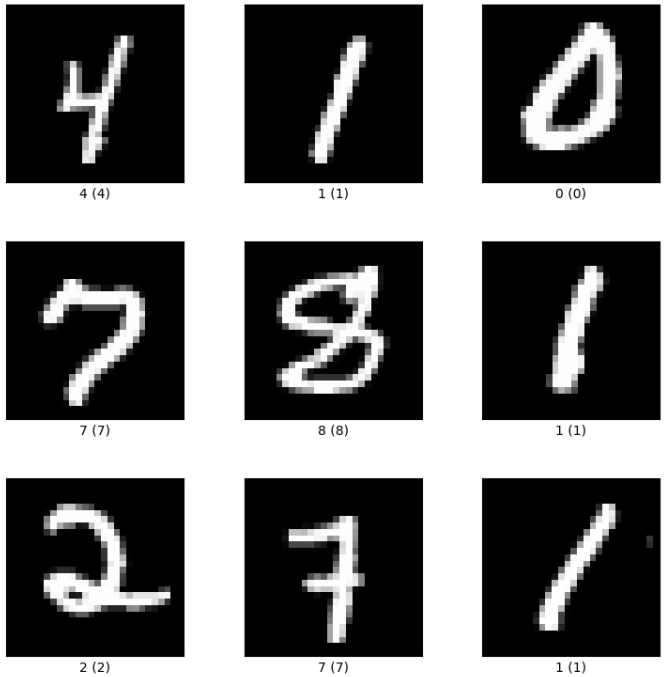

What is disentanglement?

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

What is disentanglement?

Stick

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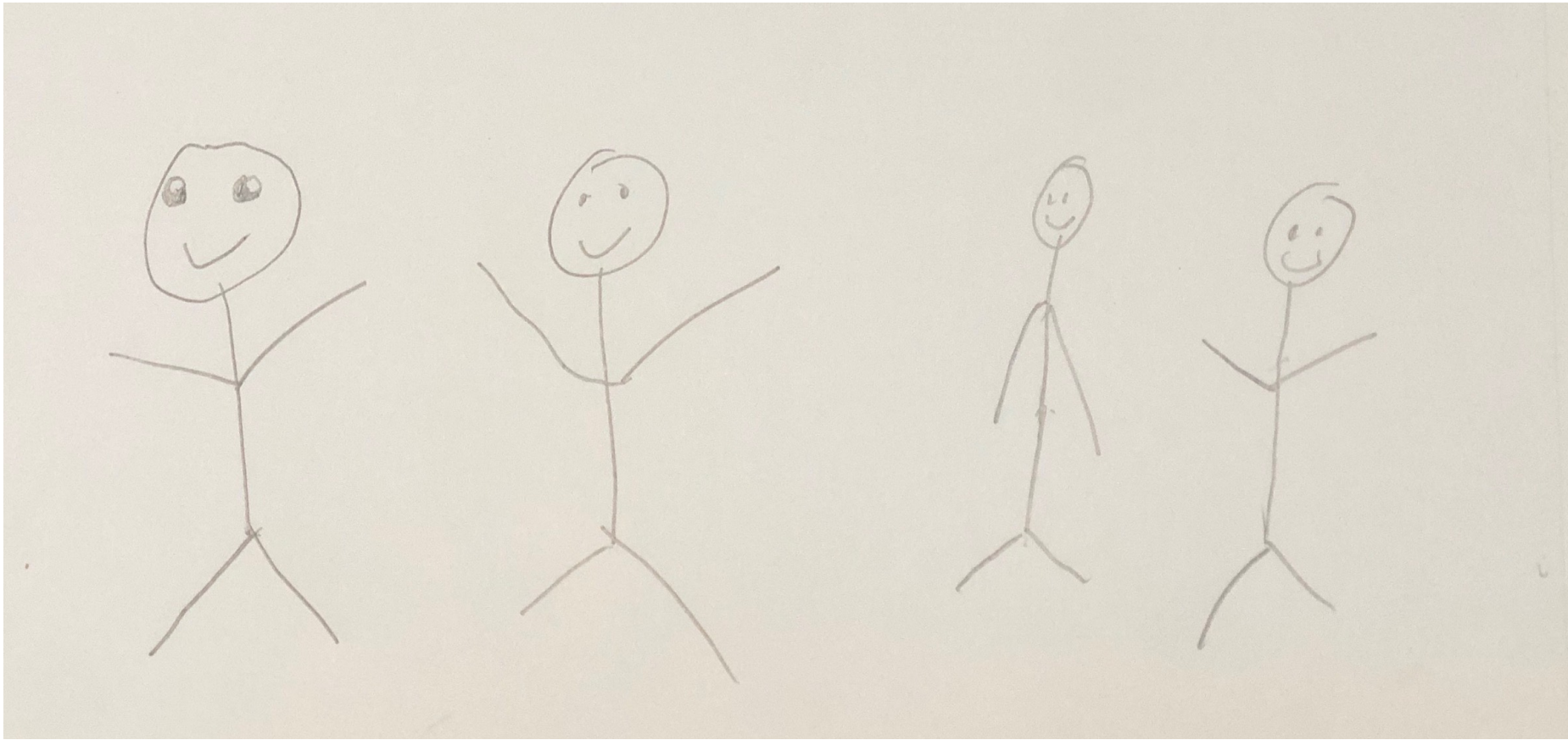

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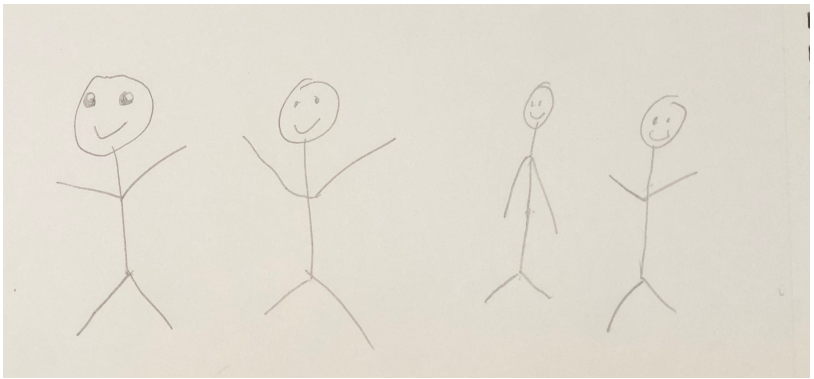

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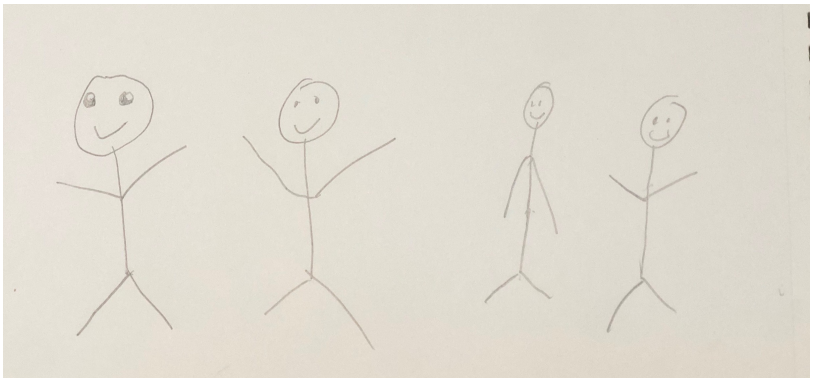

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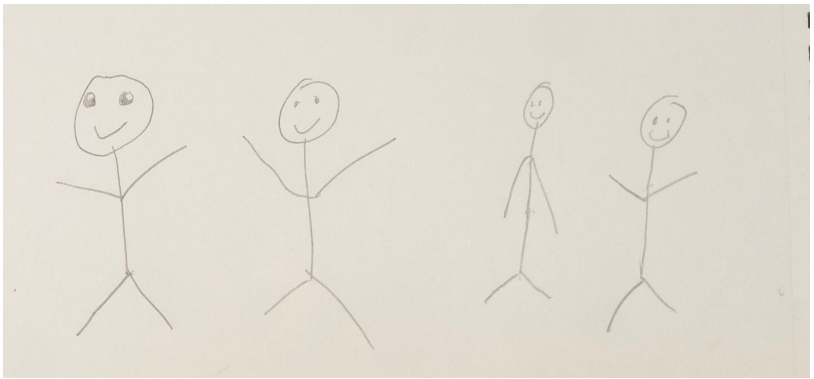

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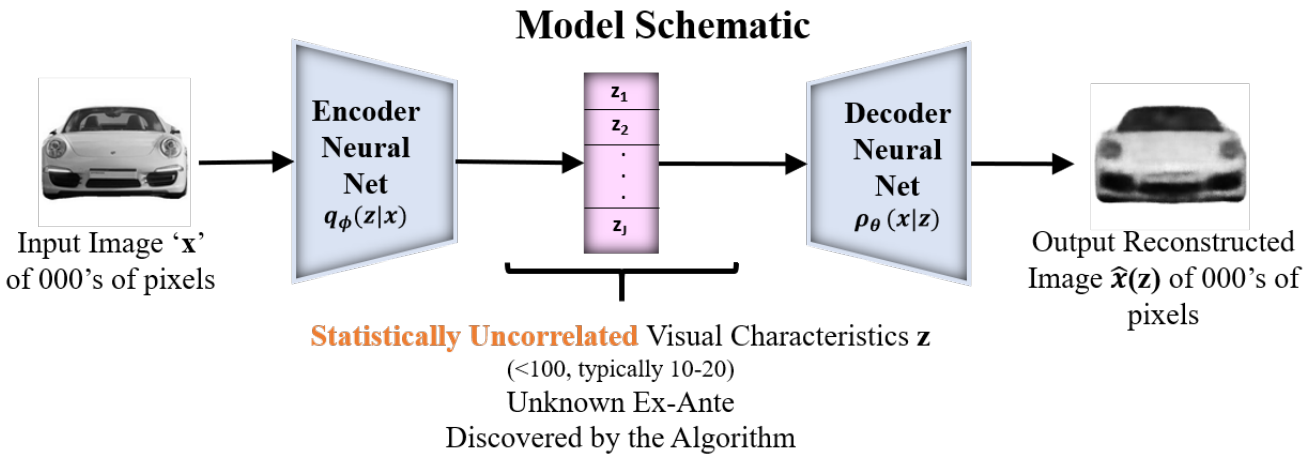
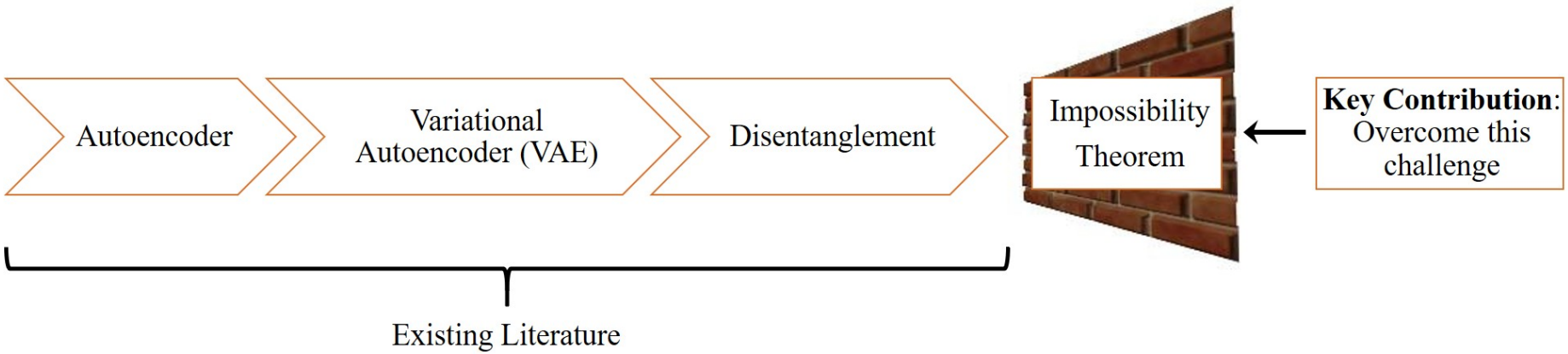
Goal: One to one mapping between $z \Leftrightarrow c$

Models in Existing Literature



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

Roadmap of Our Approach

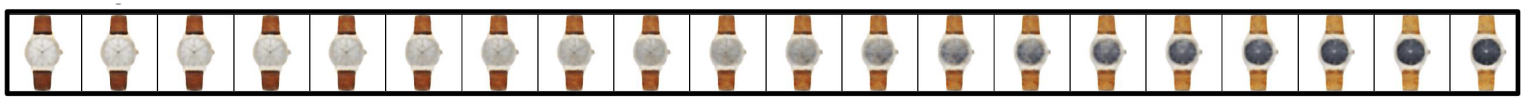


Contribution

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

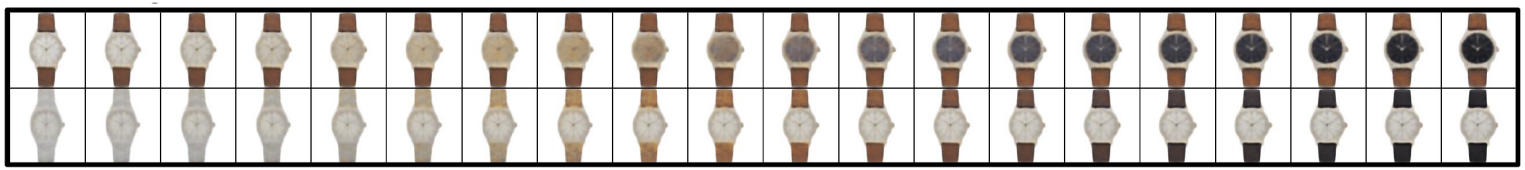
Disentangled and Entangled Representations

Example of *Entangled* Visual Characteristics



Entangled
Dial Color and
Strap Color

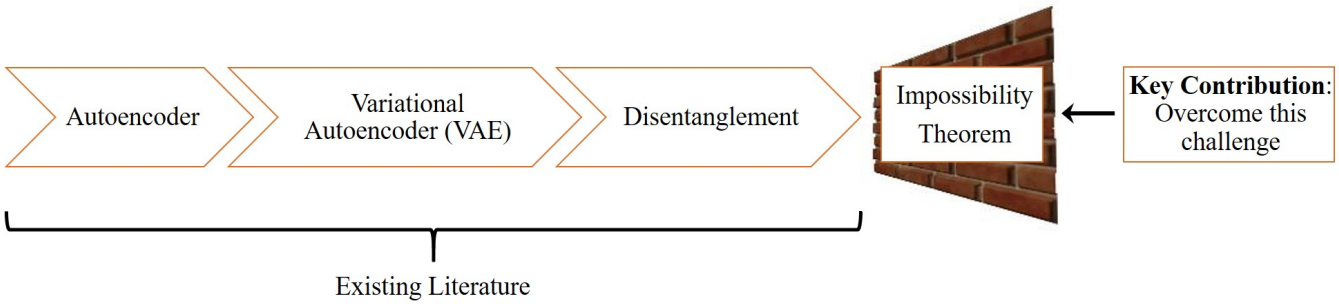
Example of *Disentangled* Visual Characteristics



Dial Color

Strap Color

Impossibility Theorem



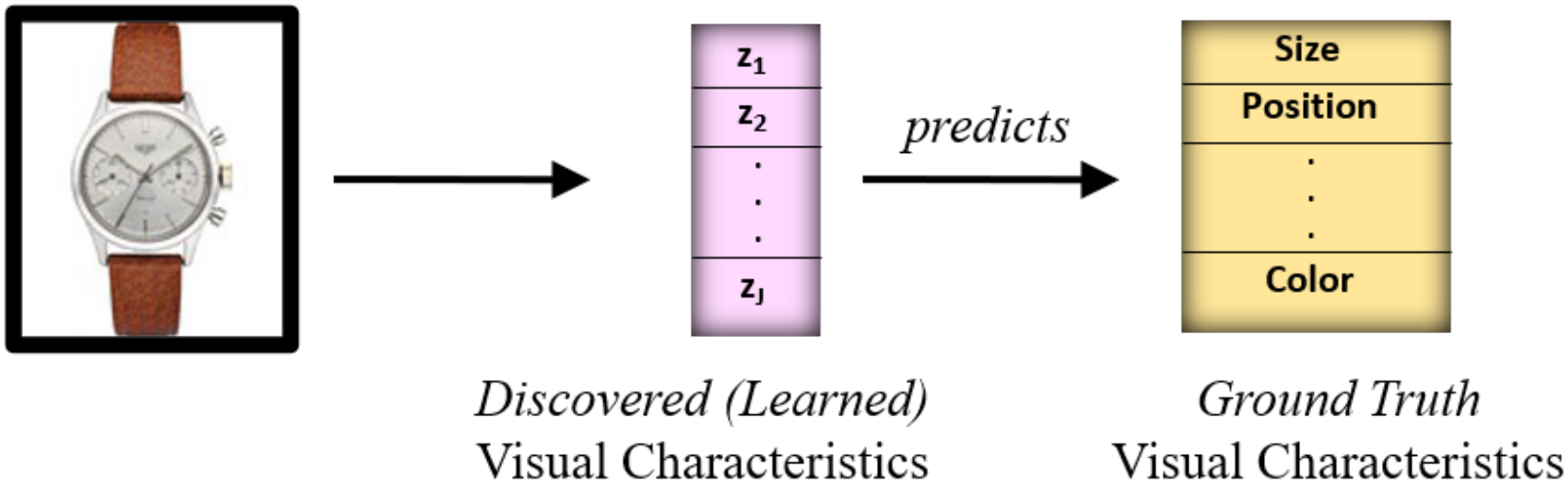
Impossibility Theorem

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.

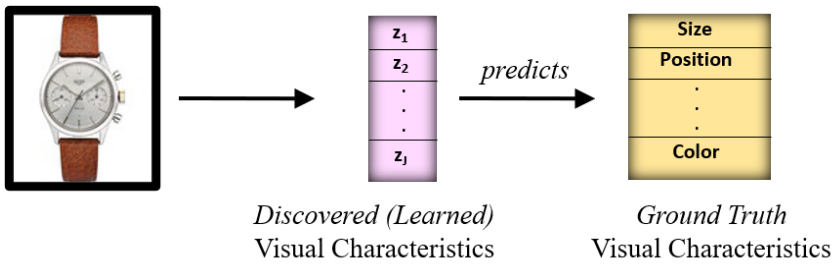
Implication: Every disentangled representation can have other *infinite* equivalent entangled representations.

Impossibility Theorem – Implications



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

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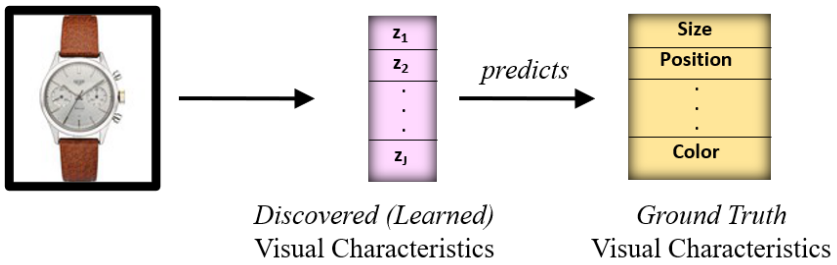

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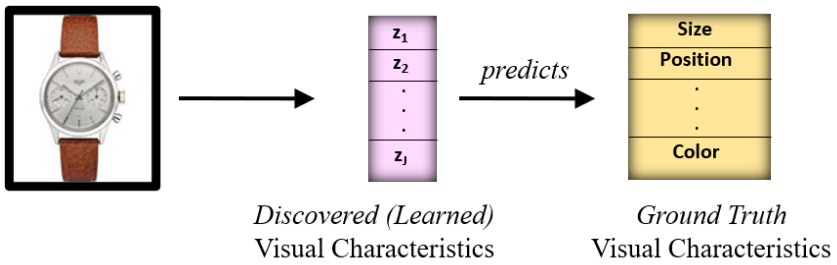

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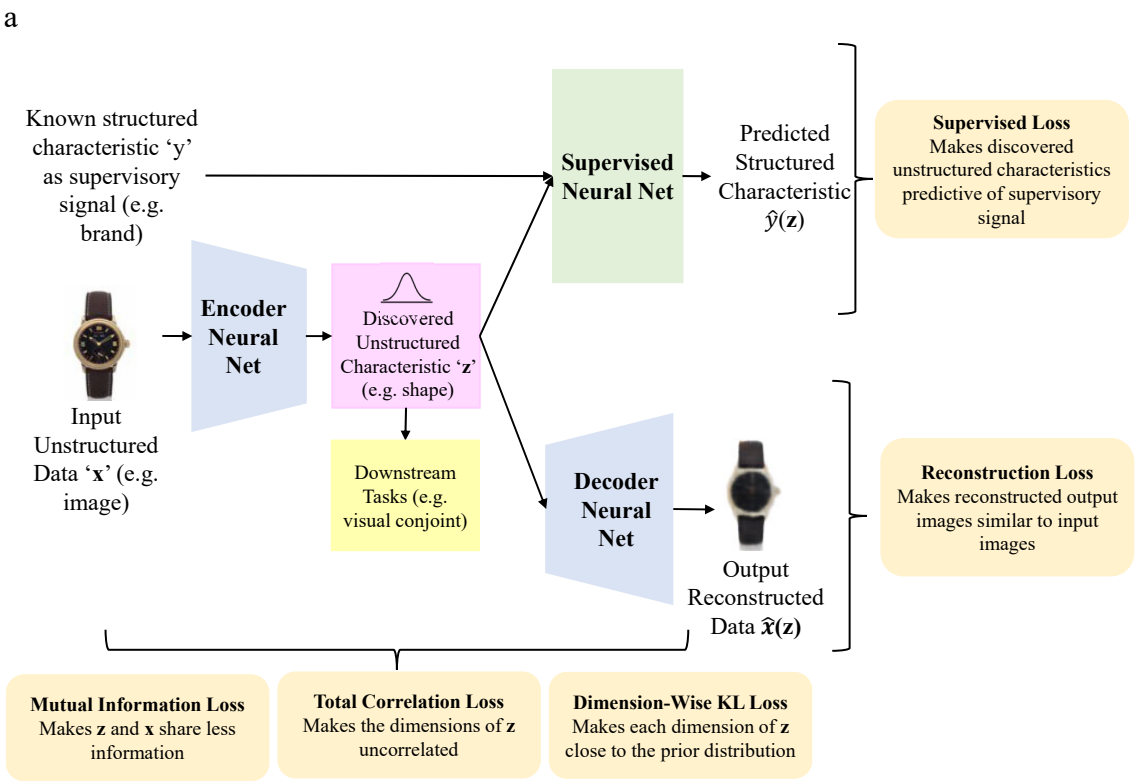
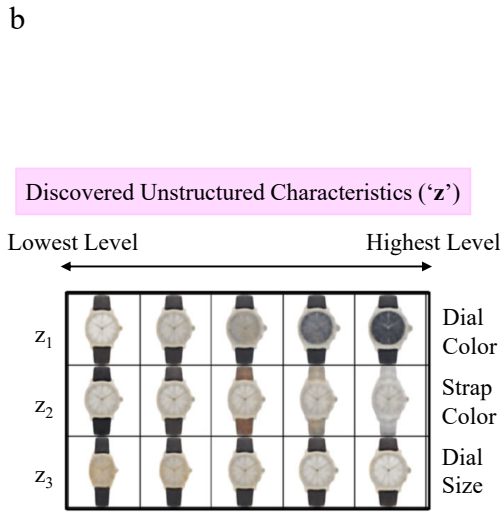
- Researcher needs to determine what are the *true characteristics* to focus on $\implies$ not Automatic
- Need to ensure humans understand what these labels are and *how to quantify them* for each image

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

Schematic of Proposed Approach





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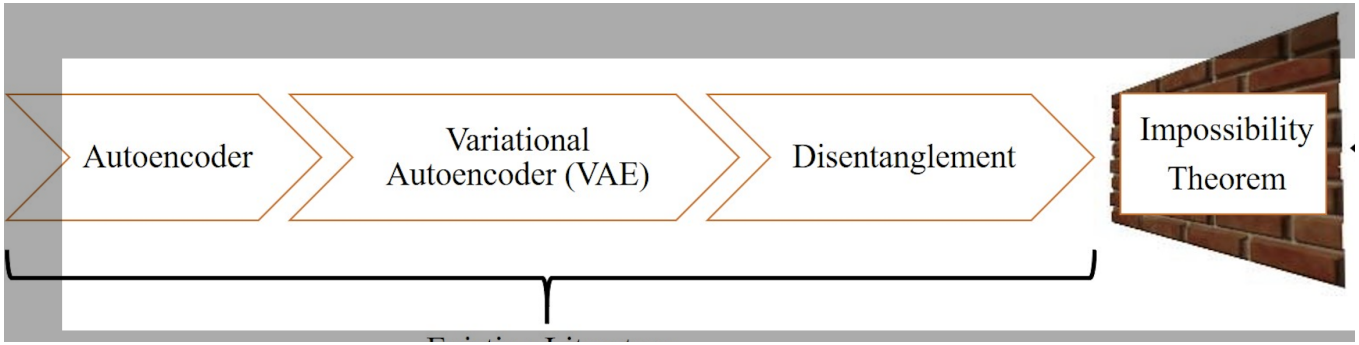

- **Solution** without ground truth on visual characteristics:
- Leverage **structured product characteristics** to provide a supervisory signal for disentanglement

Model

- 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

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

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

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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 – Role of Supervised 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?

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Brand Perception

- . . . Cartier has many case shapes from round and oval to cushion-shaped, tonneau, and of course, the many square-shaped or rectangular-shaped Tank watches.[a]

[a] https://www.prestigetime.com/blog/rolex-vs-cartier.html
[b] https://www.prestigetime.com/blog/audemars-piguet-vs-patek-philippe.html
[c] https://www.bobswatches.com/rolex-blog/watch-101/patek-philippe-better-rolex.html

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- Rolex is much more well-known for its highly-functional and iconically-designed sports and tool watches . . . [c]

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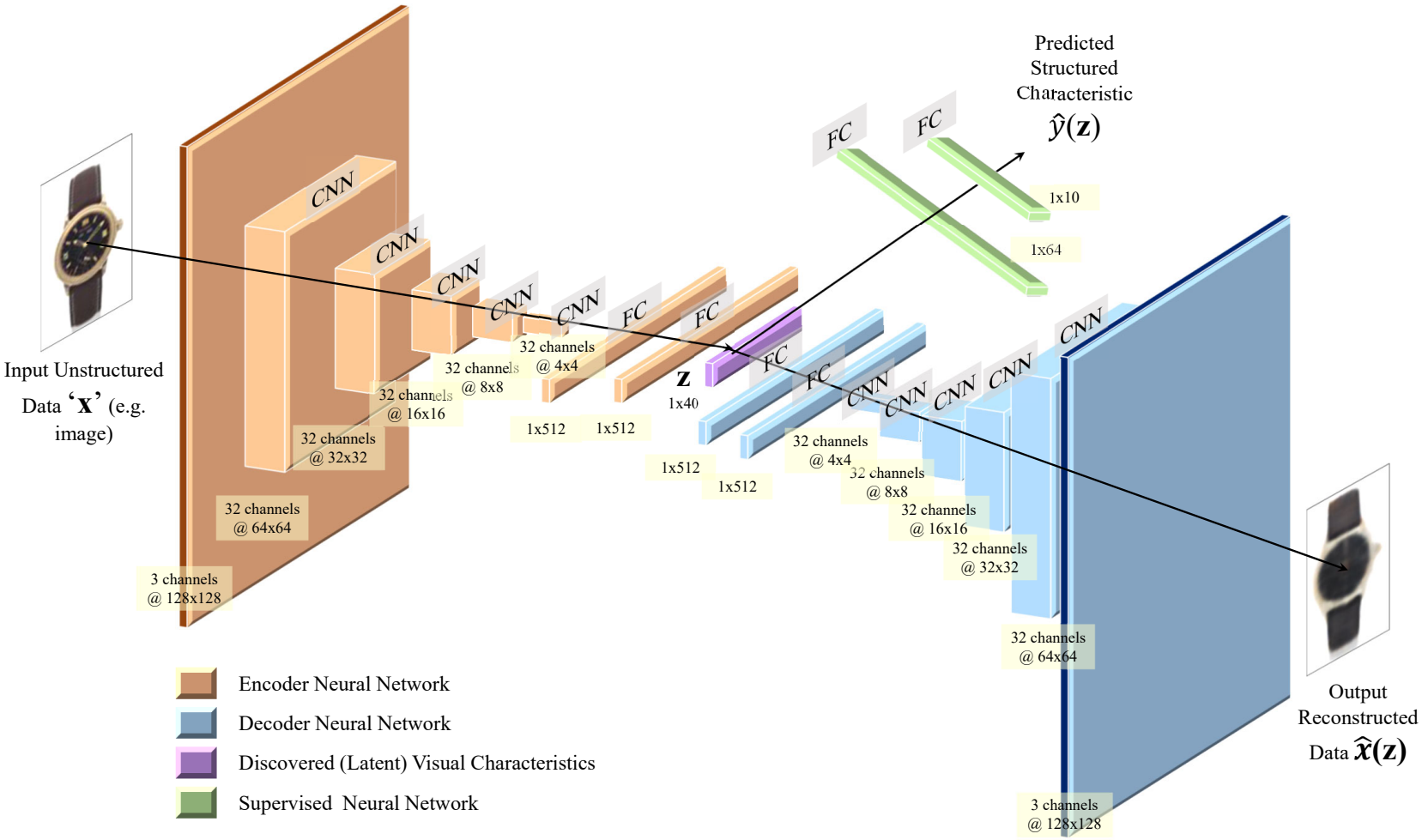
Model Architecture



Disentanglement Evaluation Metric

How to evaluate?

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]

[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.

Disentanglement Evaluation Metric

Unsupervised Disentanglement Ranking (UDR)

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(higher is better)

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Key Idea

"Models that disentangle well are more likely to be similar to each other than the ones that do not disentangle" [a]

Disentanglement Evaluation Metric

Unsupervised Disentanglement Ranking (UDR)

UDR measures disentanglement, ranges from 0 to 1 (higher is better)

- Perturbed Models (different seed) i and j
- Define UDR at the pairwise level as UDR_{ij}
- Average across all possible combinations of i and j

$$UDR_{ij} = \frac{1}{d_a + d_b} \left[\sum_b \frac{r_a^2}{\sum_a R(a,b)} I_{KL}(b) + \sum_a \frac{r_b^2}{\sum_b R(a,b)} I_{KL}(a) \right]$$

where a is a visual characteristic in model i and b in model j

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UDR

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1. $\frac{r_a^2}{\sum_a R(a,b)}$: ratio of the (squared) correlation of the visual characteristic a in model i that is most similar to b, to the sum of the correlations across *all the visual characteristics* in model i
2. It will be higher if there is a one-to-one mapping between one visual characteristic in model i and another in model j.
3. Add across all informative visual characteristics b of model j, which are represented by $I_{KL}(b)$ using a threshold for KL divergence between the characteristic's posterior and the prior.
4. $\sum_a \frac{r_b^2}{\sum_b R(a,b)} I_{KL}(a)$: Counterpart to the first term

Human Interpretable Characteristics?

- UDR indicates disentanglement, but are these visual characteristics human interpretable?
- Without any domain knowledge about the product category?

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Starting from the image on the left, **what part of the watch changes the most** 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: Interpretability?

Do humans agree with the model's quantification?

- Show two pairs of visual designs: (A, B) and (C, D)
- If the model says pair (A, B) are more similar than pair (C, D), do humans agree?

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

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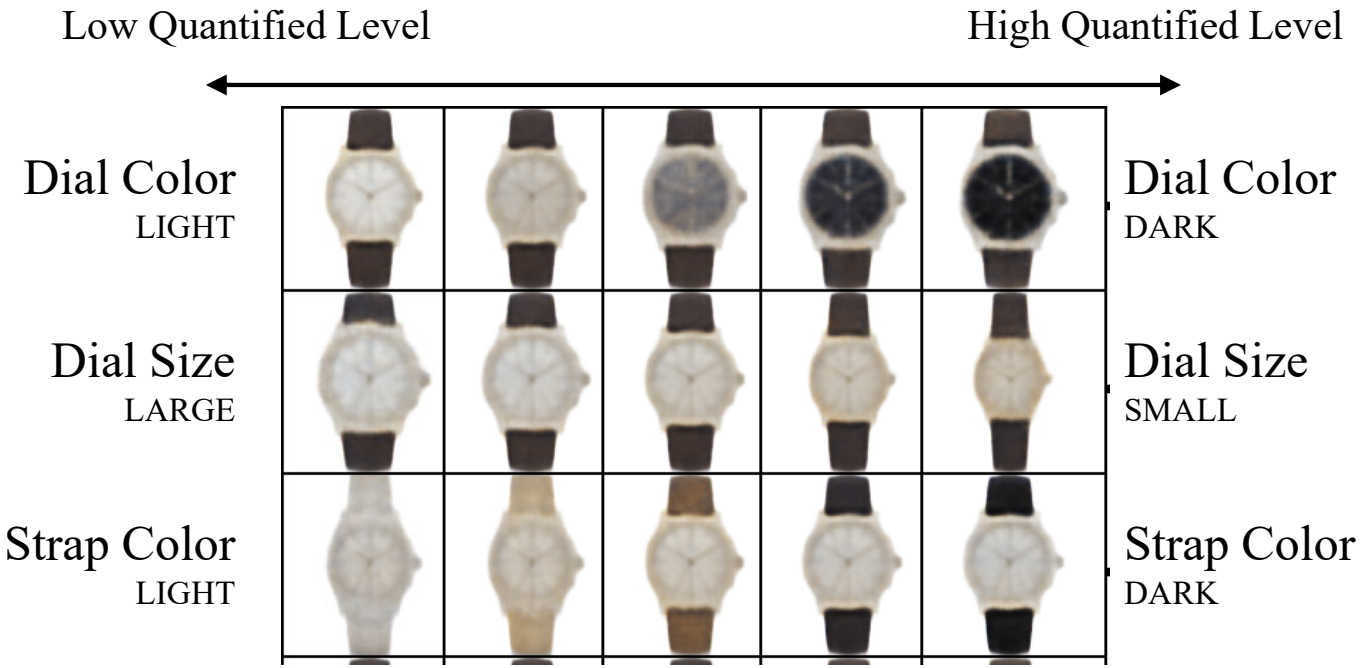
Discovered Visual characteristics



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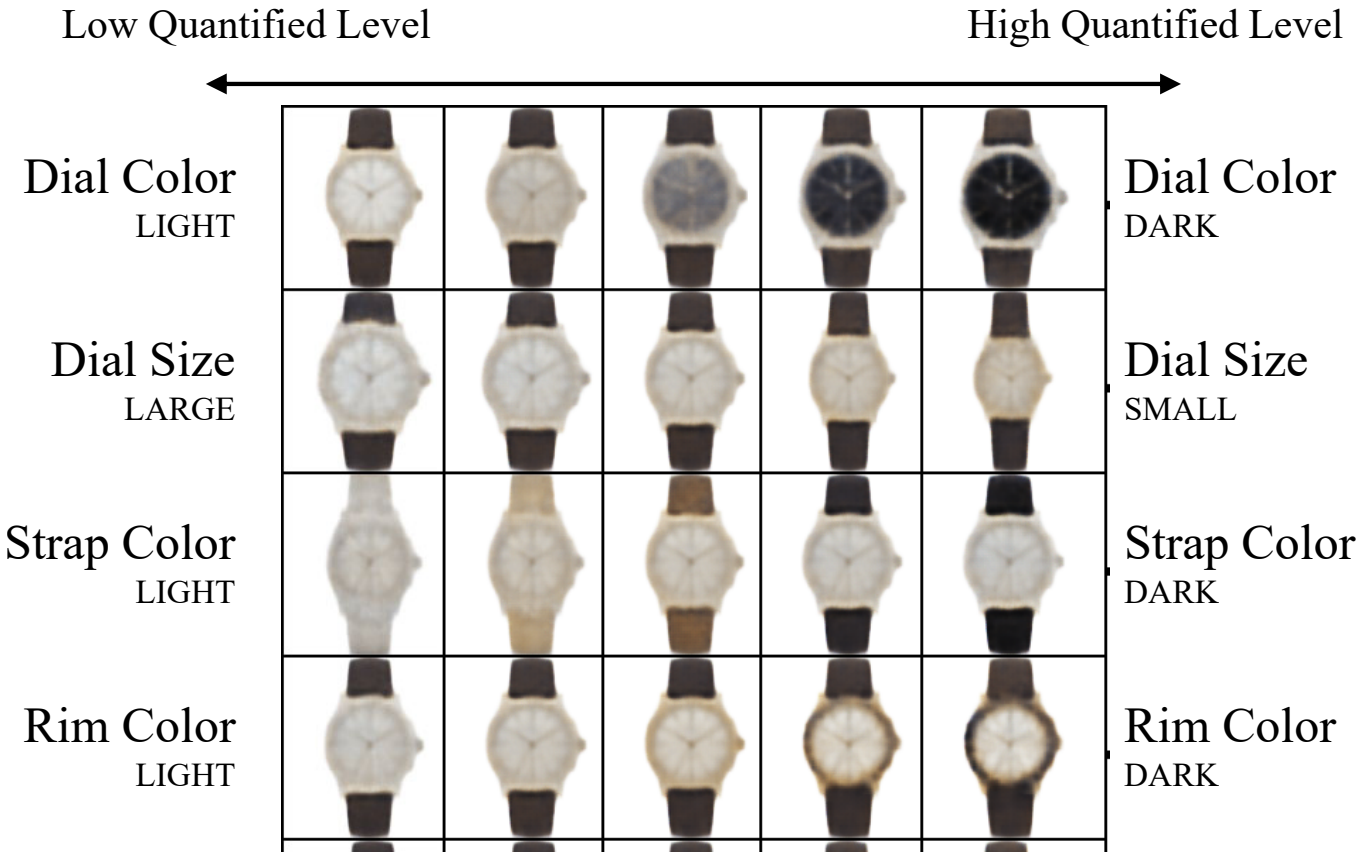

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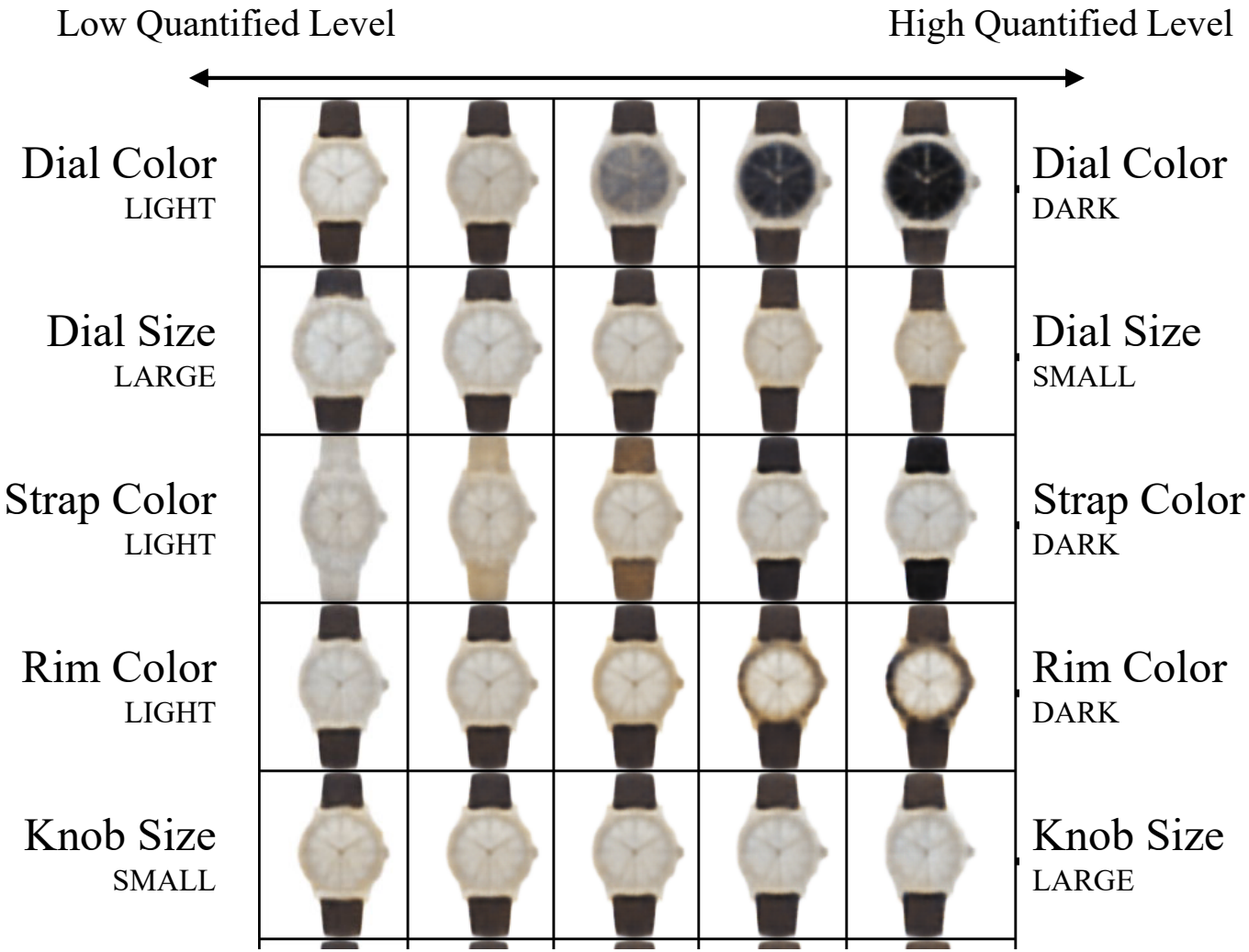

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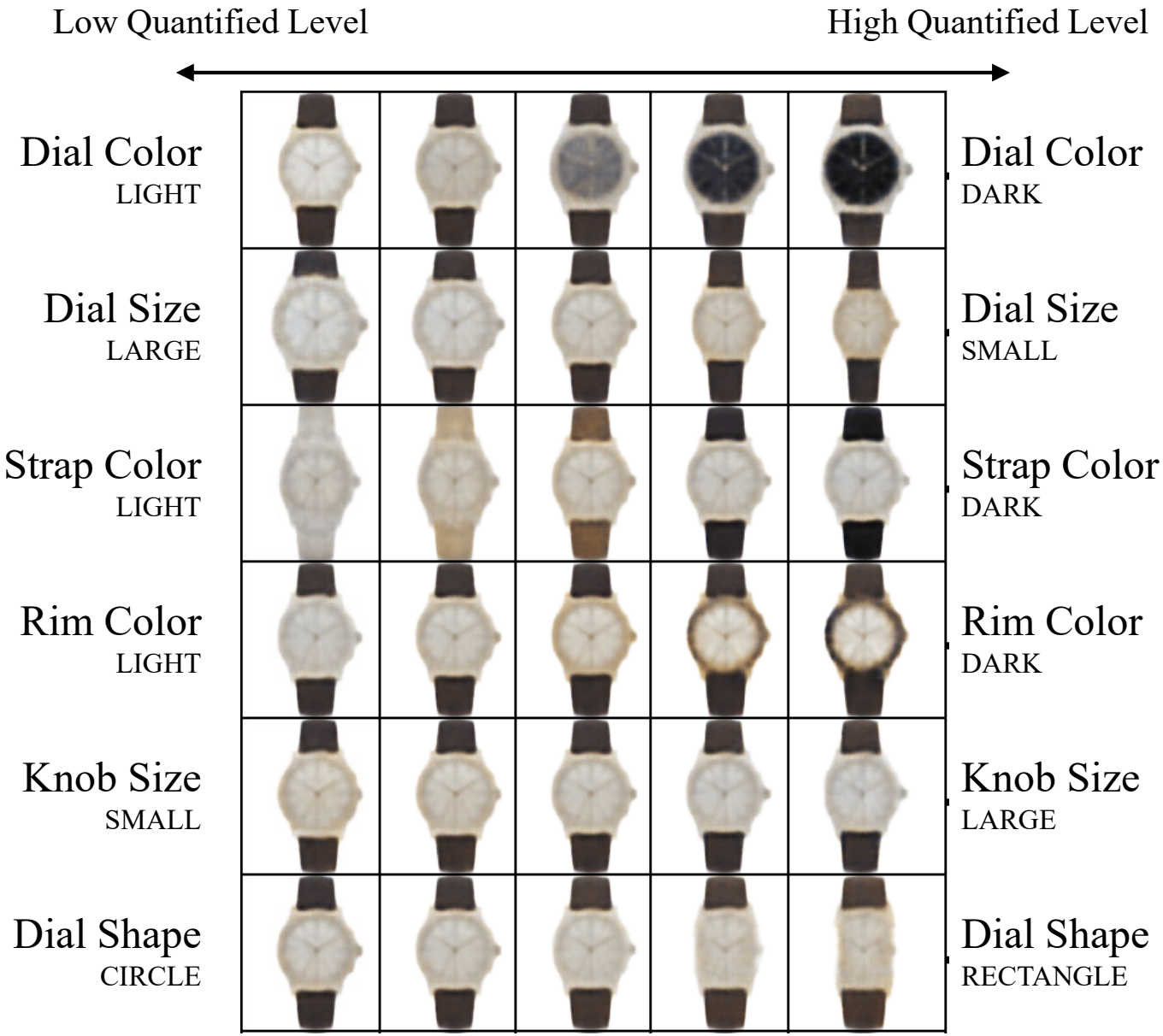
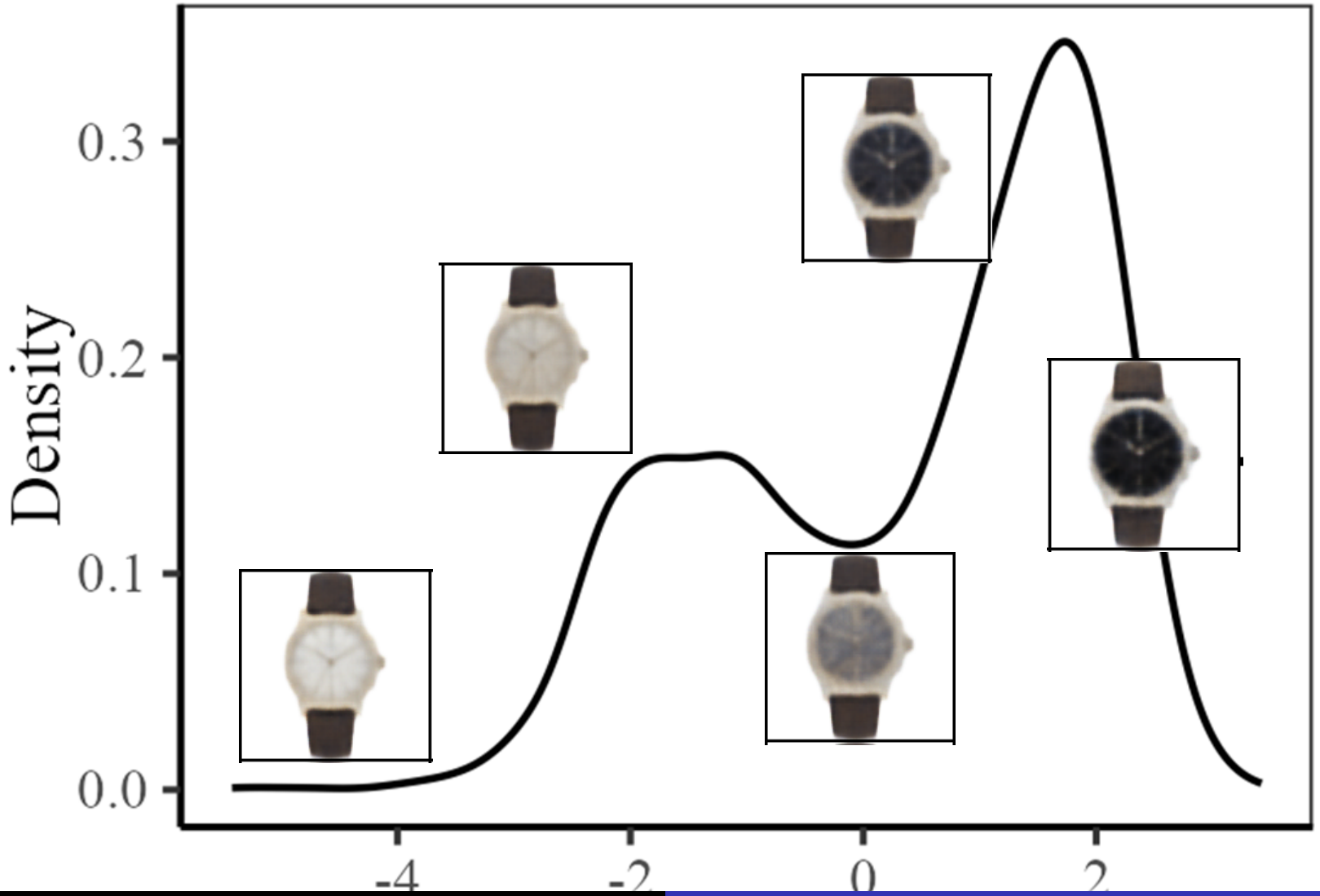


Density of Discovered Visual characteristics (from 'Brand+Material' Signal)



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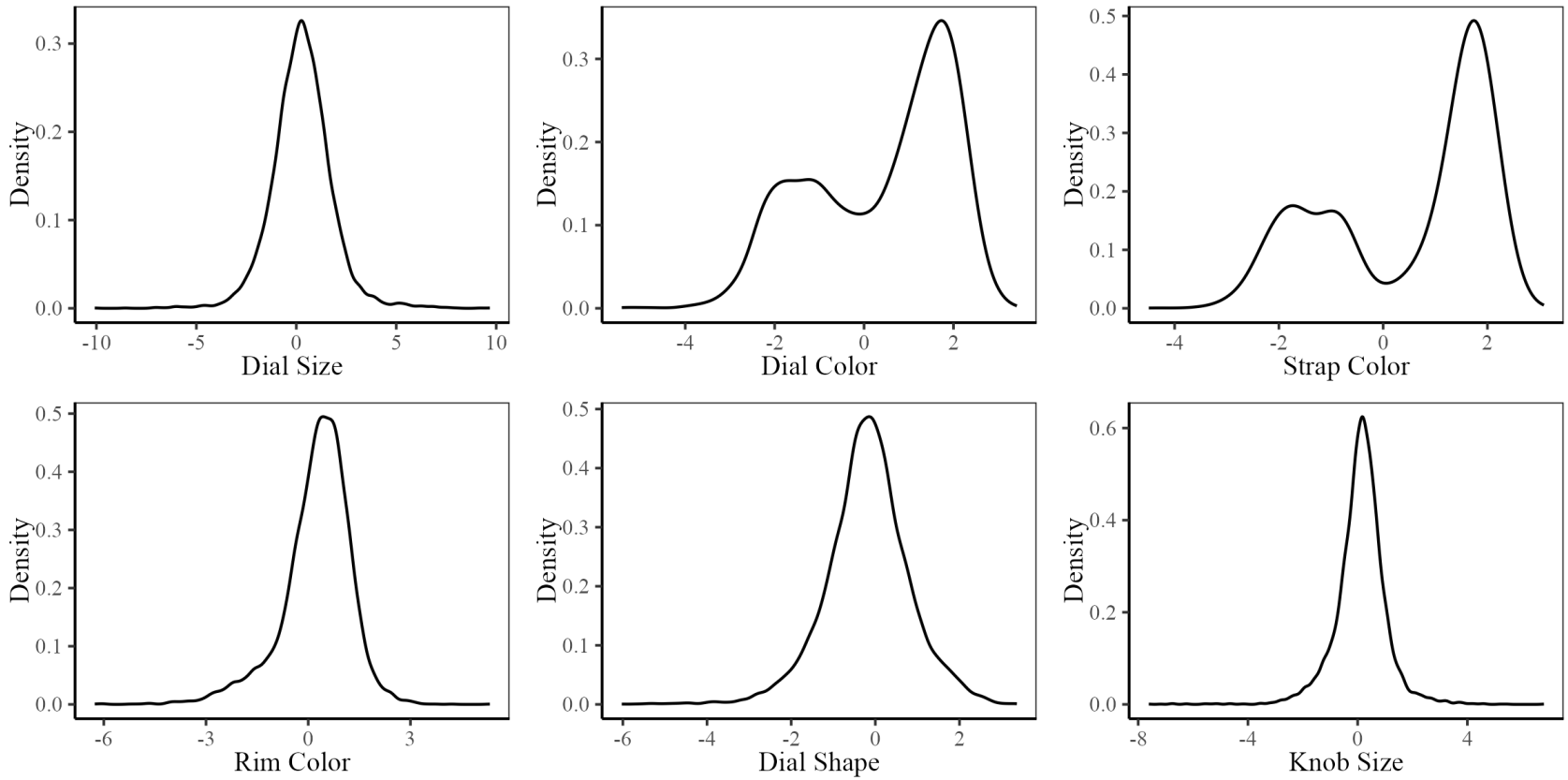
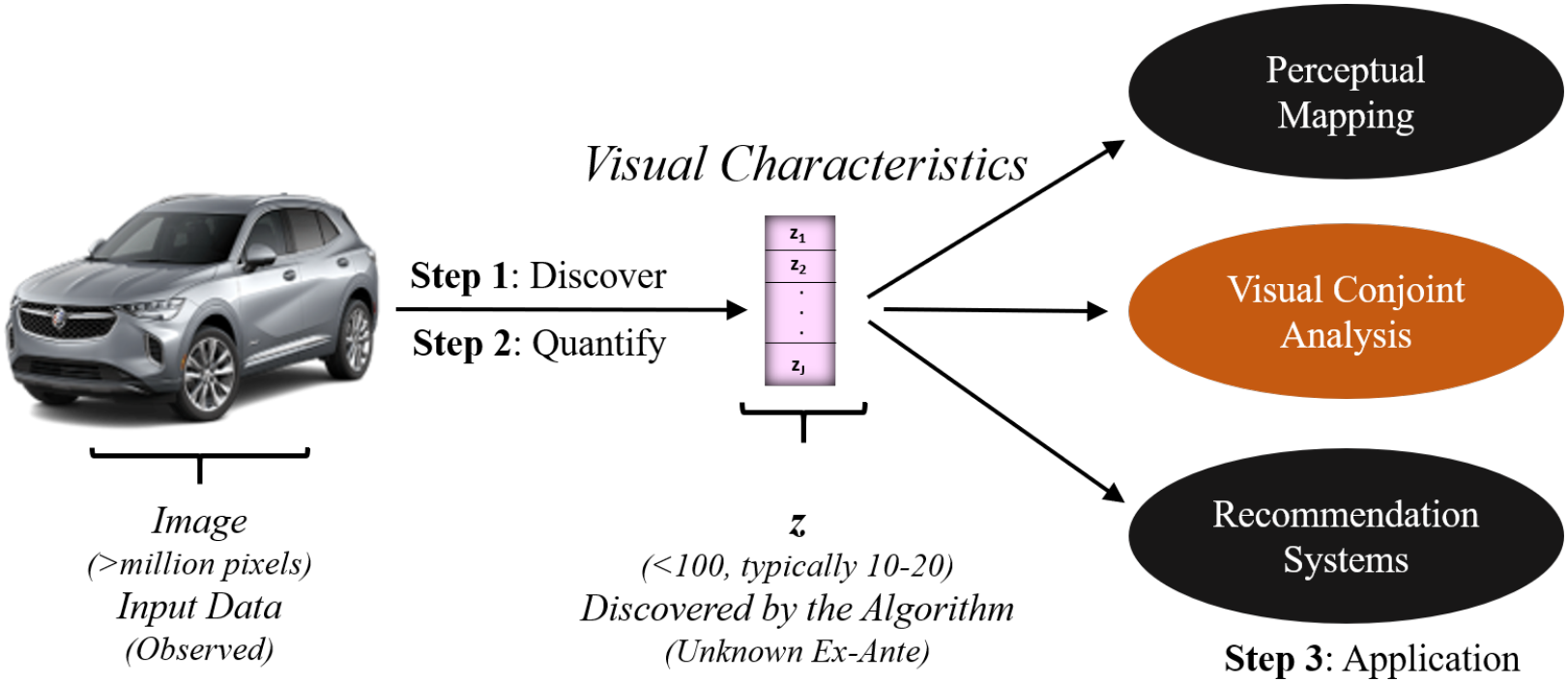
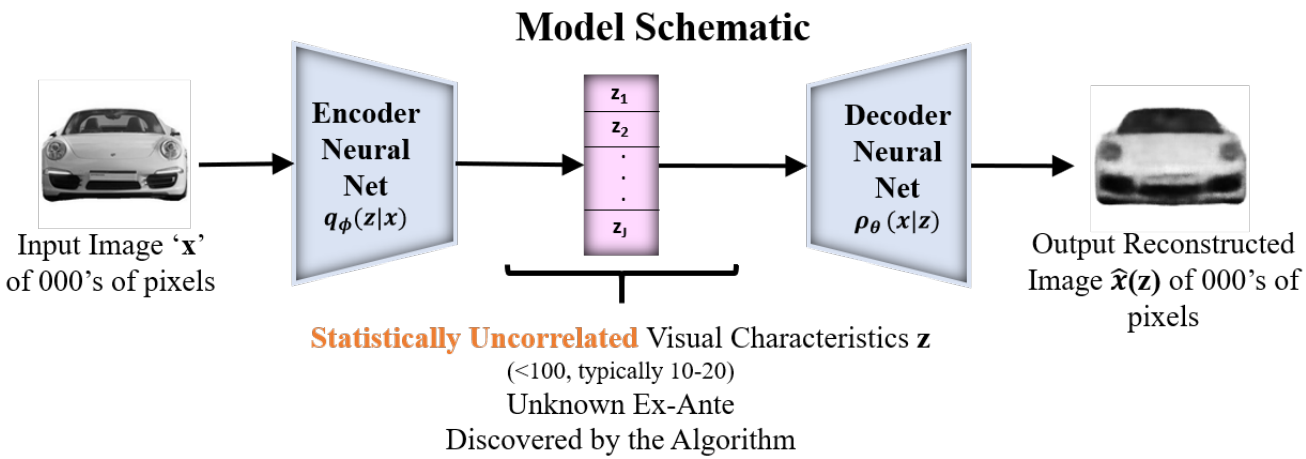


Research Goals



Visual Conjoint Analysis: Background



- Visual conjoint has been challenging to do because elements of visual space are correlated

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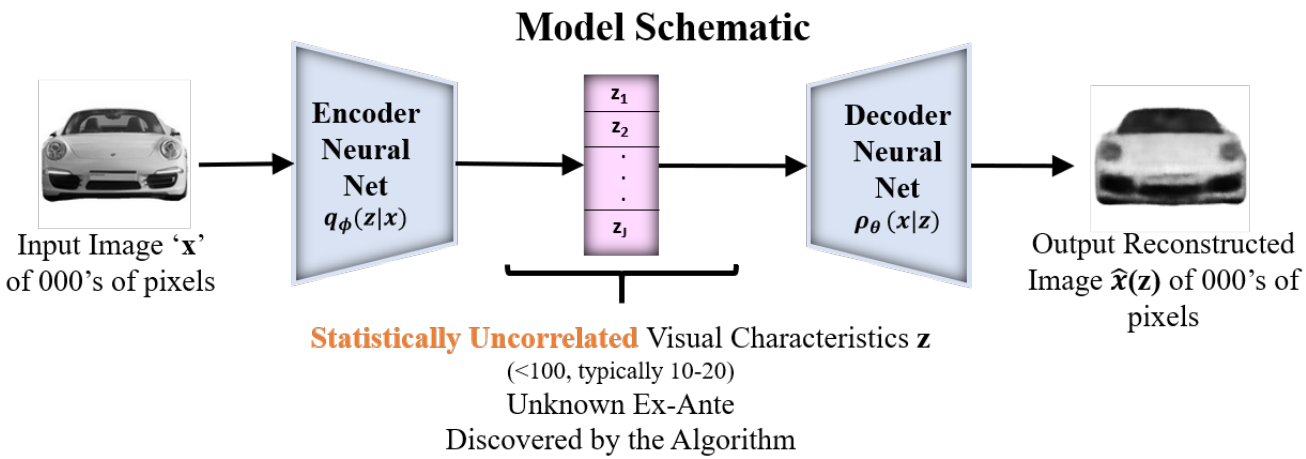

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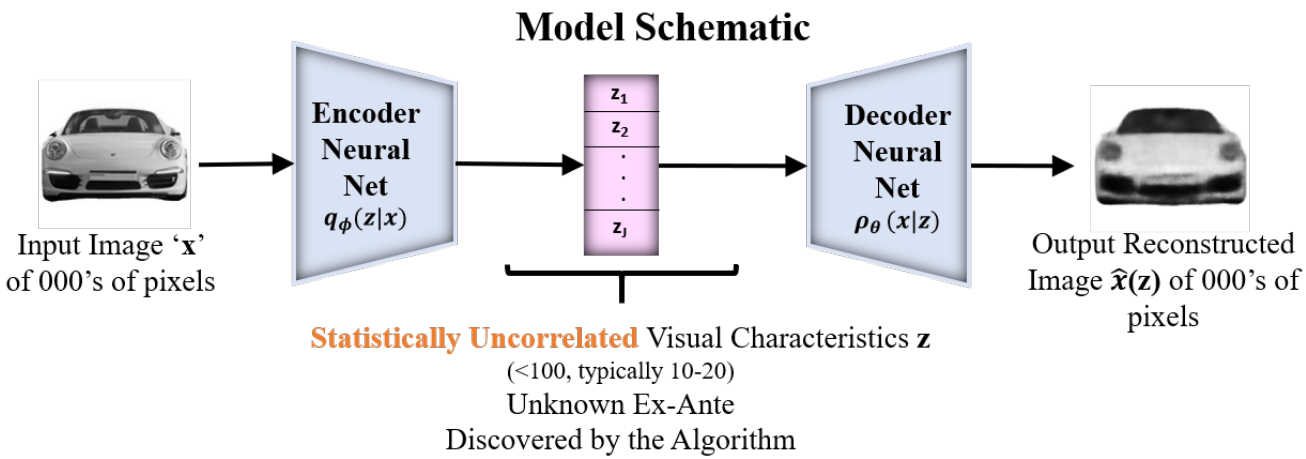

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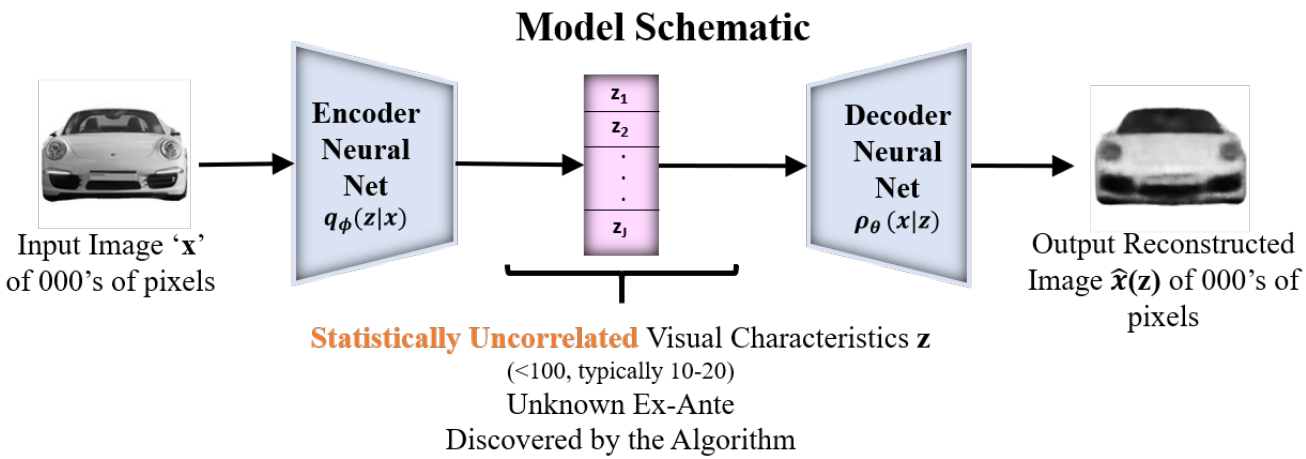

- Visual conjoint has been challenging to do because elements of visual space are correlated
- Designs have always been manually generated by product designers (prototypes)
- Our approach generates new never-seen visual designs (counterfactual)
- Can span the entire space of visual designs *without being bound by the correlations in the data*.

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	**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 Point

- Marketing Literature has conceptualized the notion of ideal point (DeSarbo, Ramaswamy, and Cohen 1995).
- Optimal positioning of a product in the space of characteristics
  - In this study, visual characteristic space
- Can also do this across researcher-defined segments

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

Segment 1	Young moderately-affluent females
Segment 2	Older males

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

Big Picture

- Potential for domain knowledge (what we as researchers know) to help in machine learning

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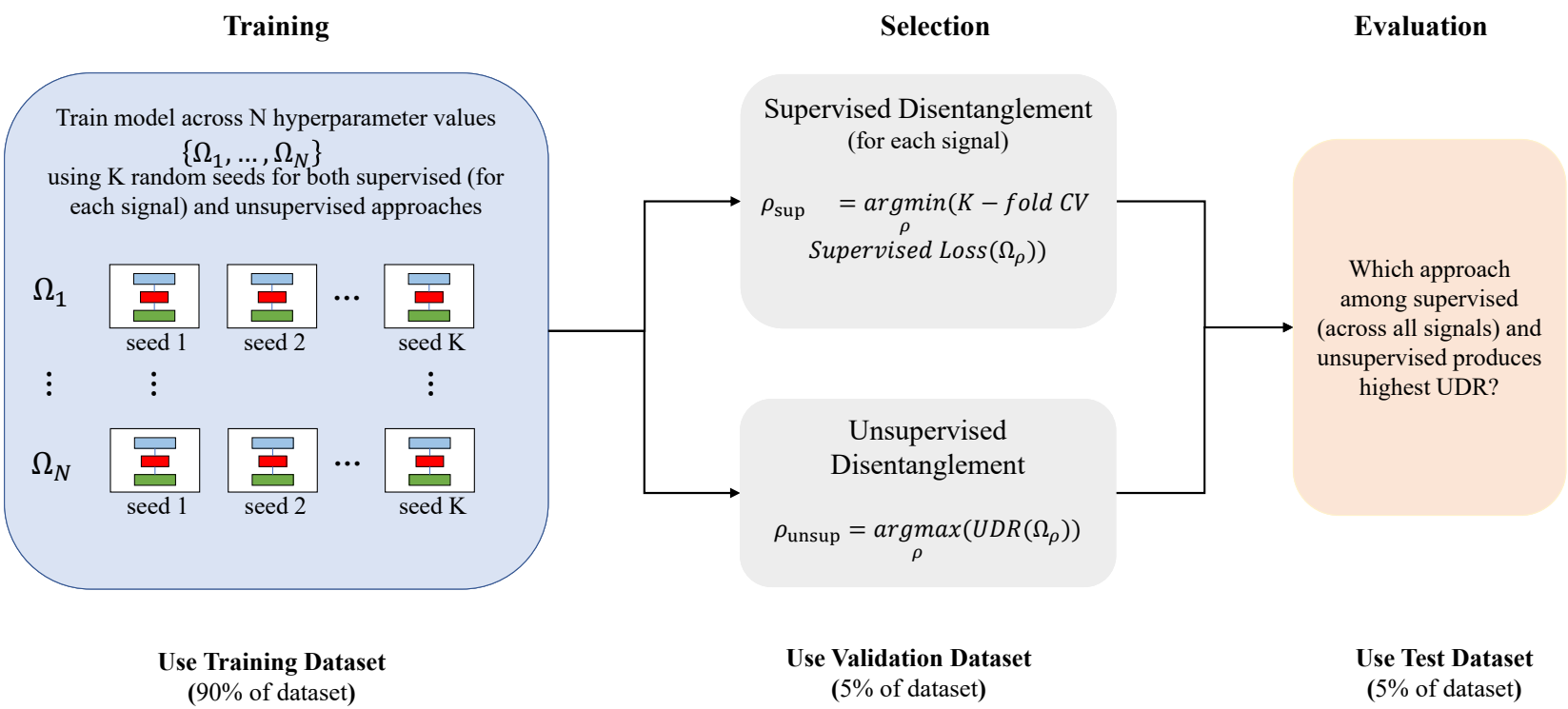
- ML has typically been quite atheoretical (more general?)
- Worth asking *where* and *how* domain knowledge can be incorporated in ML models
- Could be lots of complementarities

The End

vineet.kumar@yale.edu

Additional Slides

Model Training, Selection, & Evaluation



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.*

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

Why does brand aid the disentanglement model?

Cartier

Patek Philippe

Rolex

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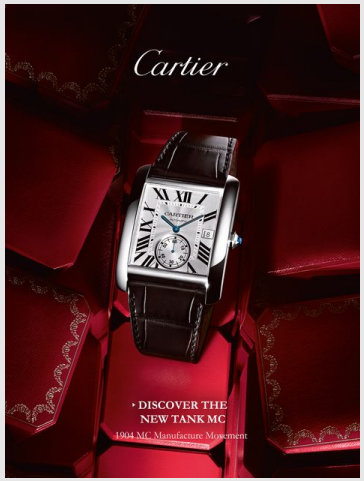
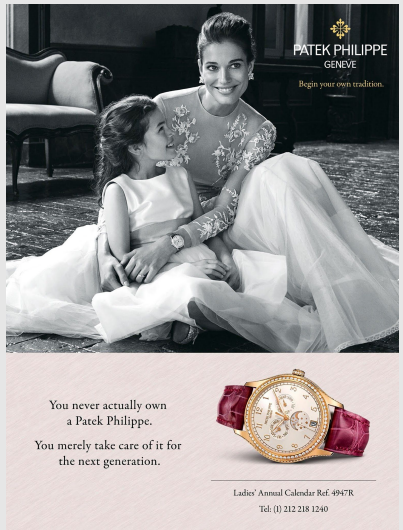


Cartier



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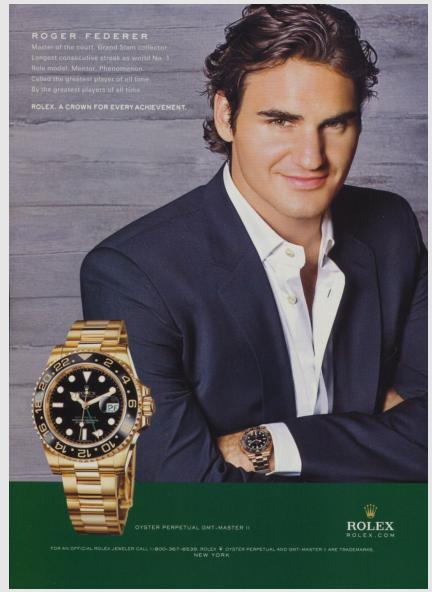

Rolex

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Brand Perception

- . . . Cartier has many case shapes from round and oval to cushion-shaped, tonneau, and of course, the many square-shaped or rectangular-shaped Tank watches.[a]

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[b] https://www.prestigetime.com/blog/audemars-piguet-vs-patek-philippe.html
[c] https://www.bobswatches.com/rolex-blog/watch-101/patek-philippe-better-rolex.html

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- Patek (Philippe) is more conservative and classic on the design front, which is great since most people looking for a Patek (Philippe) are looking for a dress watch.[b]

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- Rolex is much more well-known for its highly-functional and iconically-designed sports and tool watches . . . [c]

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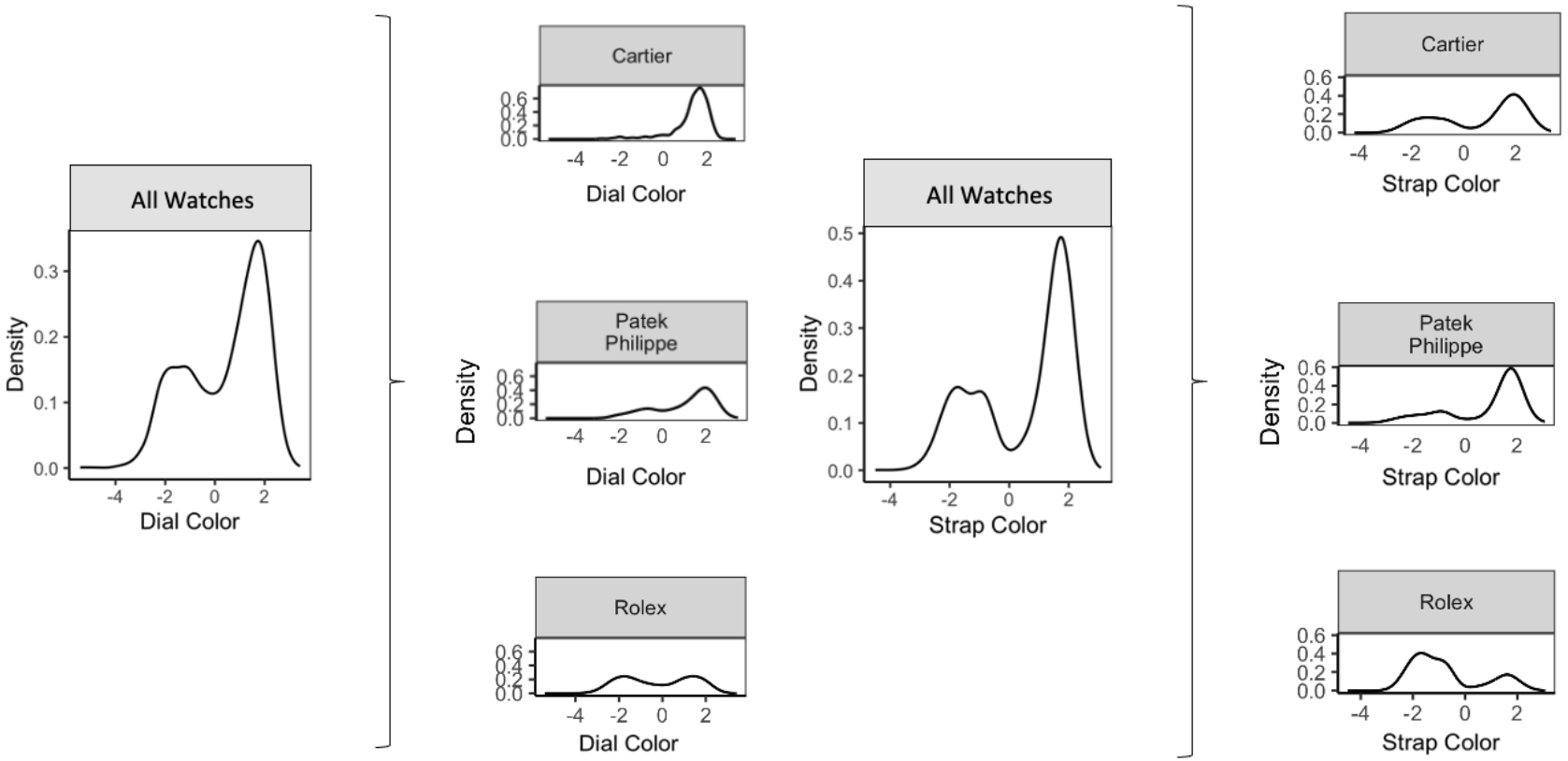

Our method is able to quantify these differences across brands from the visual product images.

Why does brand aid the disentanglement model?

Average of pairwise JS Divergence Of a visual characteristic across different brands is much higher than across different price points.

Visual Characteristic	Brand	2 Discrete Prices	3 Discrete Prices	5 Discrete Prices	10 Discrete Prices
Dial Color	6.28	1.62	1.77	1.91	1.91
Dial Size	9.71	2.13	3.24	4.13	4.86
Strap Color	6.16	0.56	1.76	1.85	2.08
Rim Color	9.07	3.61	6.56	6.57	8.34
Dial Shape	5.97	0.29	0.66	0.75	3.16
Knob Size	8.20	6.02	5.76	13.08	13.46
Across All 6 Char	7.56	2.37	3.29	4.71	5.63