Generative Interpretable Visual Design: Application to Visual Conjoint

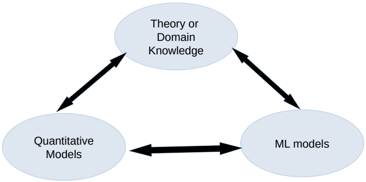
The Making of a Paper

Vineet Kumar

Yale School of Management

Presenting at:
Marketing Science Doctoral Consortium
June 2025

Overview



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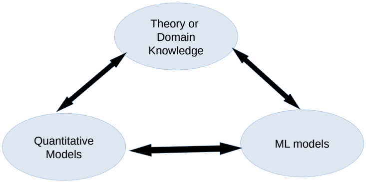

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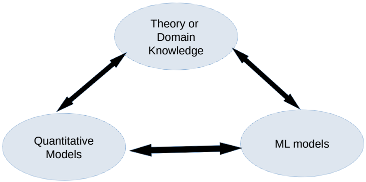

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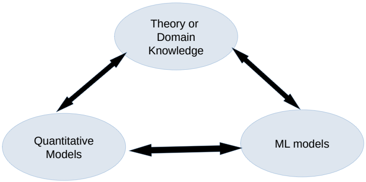

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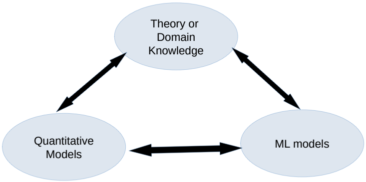

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- Generative Interpretable Visual Design: Using Disentanglement for Visual Conjoint Analysis. (Journal of Marketing Research)
- Market Structure Mapping with Visual Characteristics. (Research in progress)

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Cars

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Fashion

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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

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What about preferences in visual space?

Cannot do this because characteristics for visual design are unknown!

Lesson 1

Exploring the Space of Research Questions

- Don't be afraid to ask hard questions where there is little academic research.

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  - Why?

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  - Need to educate the reader / audience that this is something worth studying.

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

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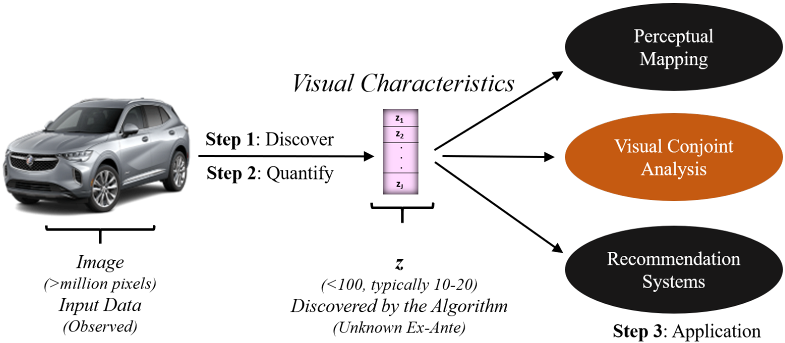
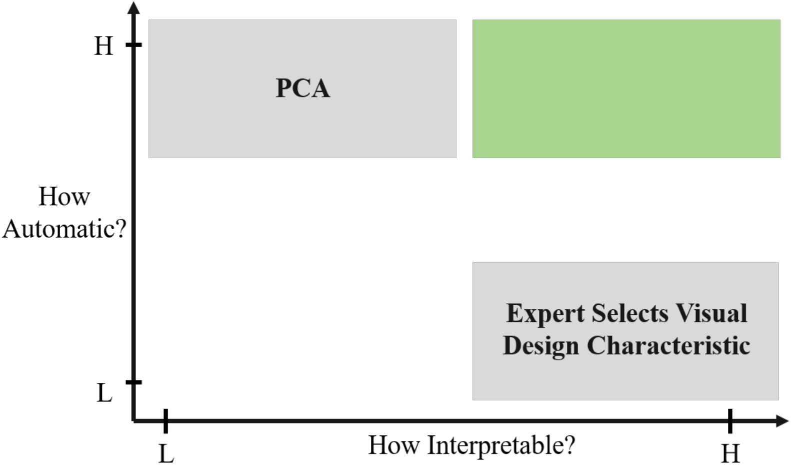
Hyundai: $(3, 8, 5, 9)$ compared to BMW: $(1, 3, 10, 1)$

Why Visual Characteristics?



Modeling Visual Characteristics

A comparison of methods



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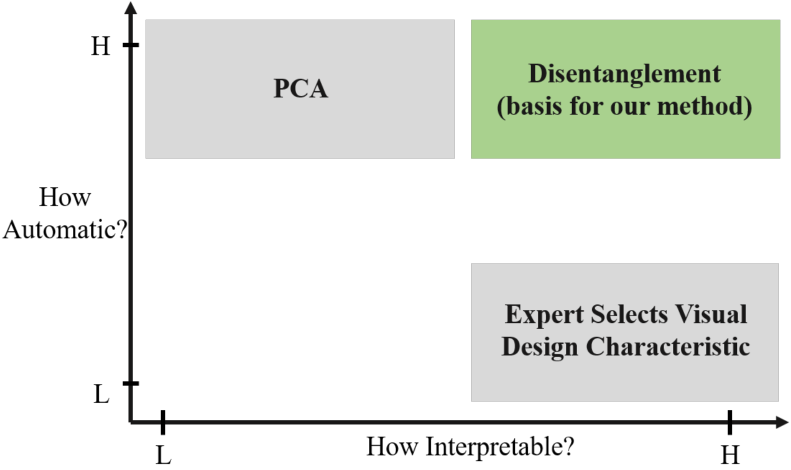

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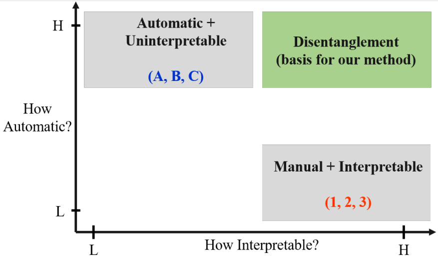

Automatic + Uninterpretable

- 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)*
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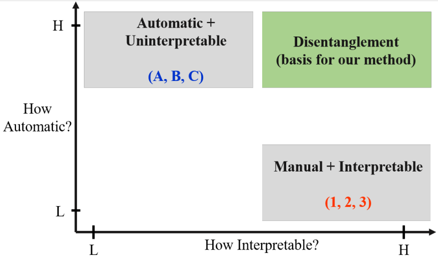

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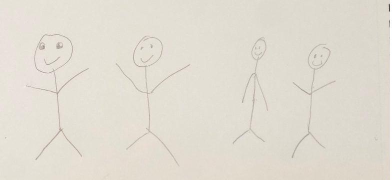
Manual + Interpretable

- 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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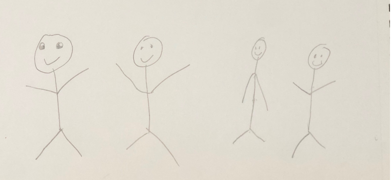

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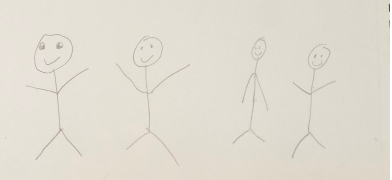

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Goal: One to one mapping between $z \Leftrightarrow c$

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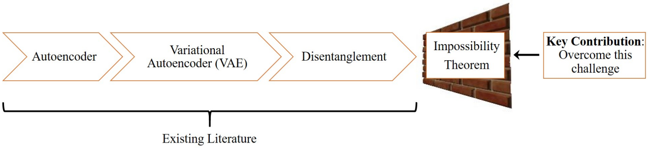
- Do not be afraid to be critical of your own project.
  - Many think it is like their (intellectual) baby and needs protection!

Roadmap: Impossibility Theorem



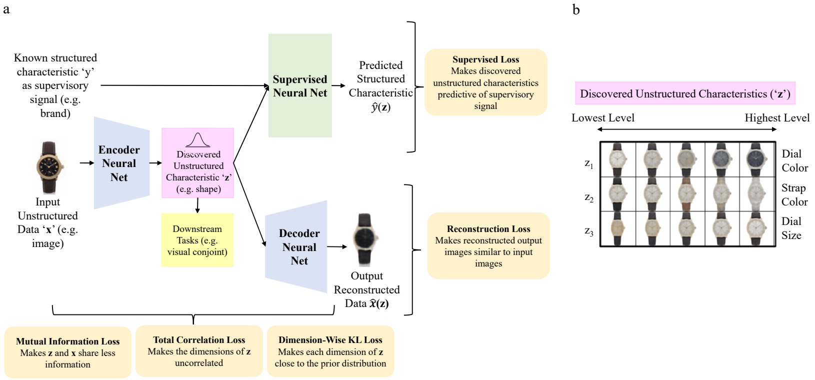
Impossibility Theorem

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.

Schematic of Proposed Approach



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

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- In this case, conjoint versus demand model. Make sure one of them is clearly feasible.

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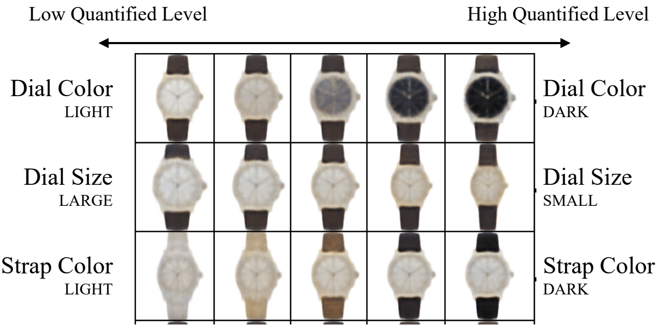

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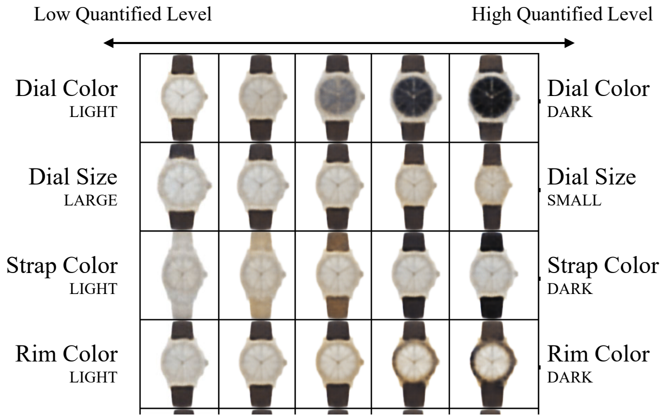

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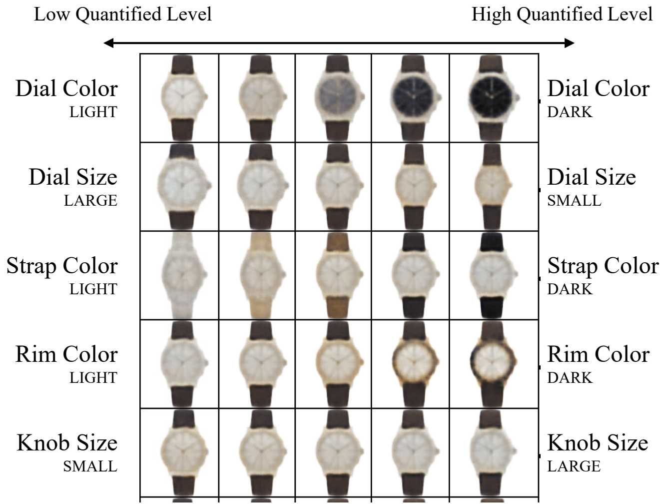

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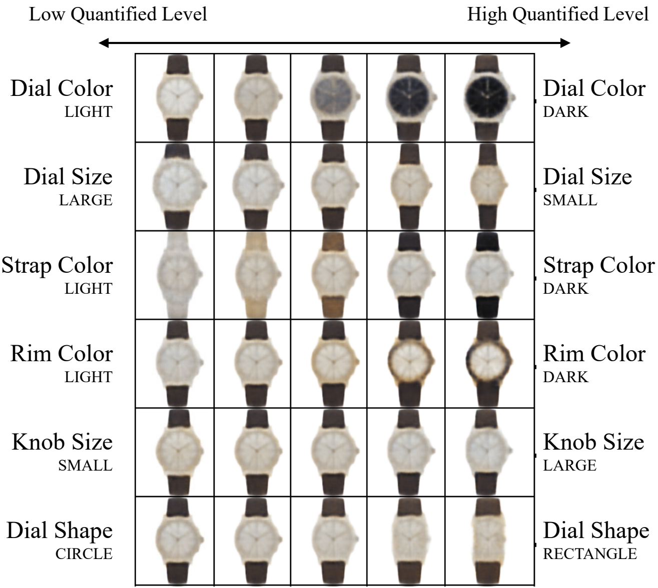

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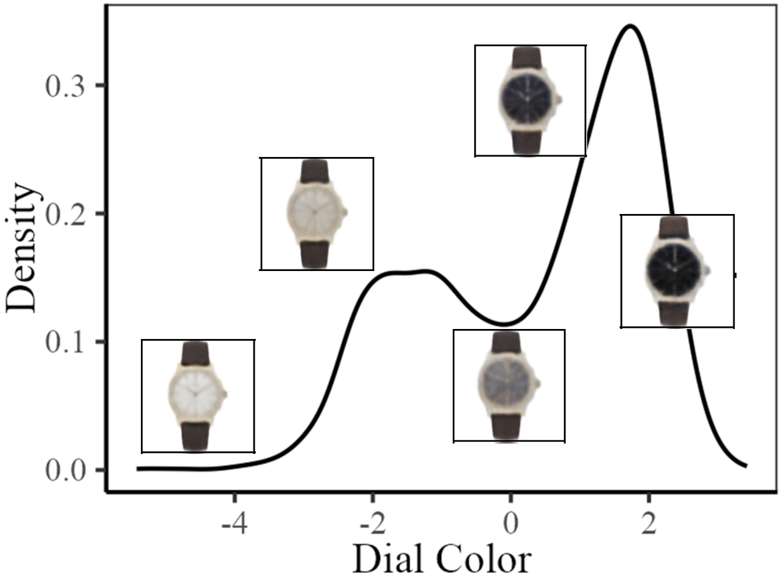

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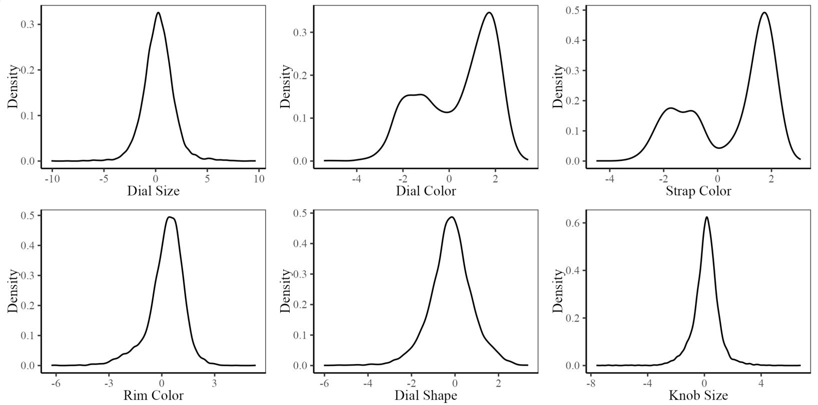
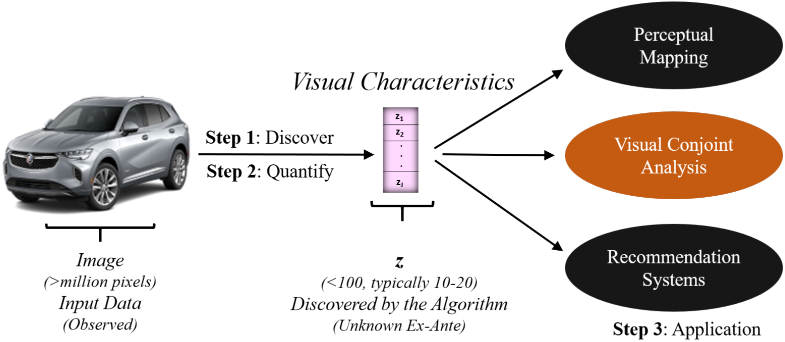
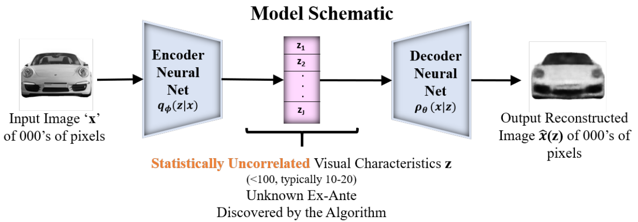


Research Goals



Visual Conjoint Analysis: Background



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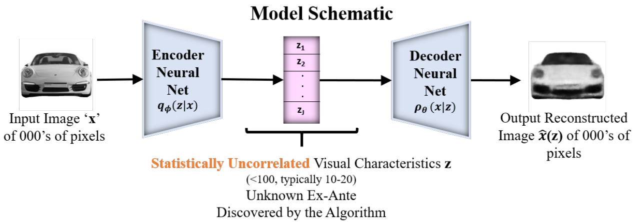

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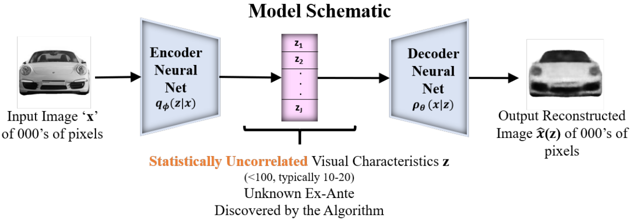

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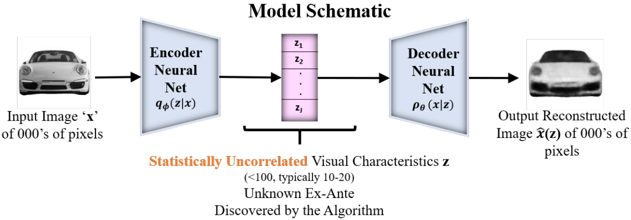

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- Can span the entire space of visual designs *without being bound by the correlations in the data.*

Ongoing Research

Market Structure Mapping with Interpretable Visual Characteristics

- Sunday, June 15, 8:30 am – 8:52 am, Meeting Room 10

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