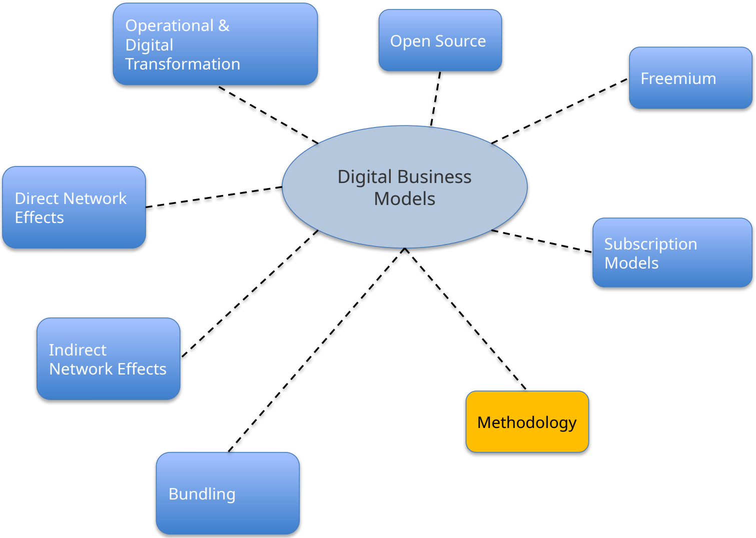
Research and Teaching Overview

Vineet Kumar

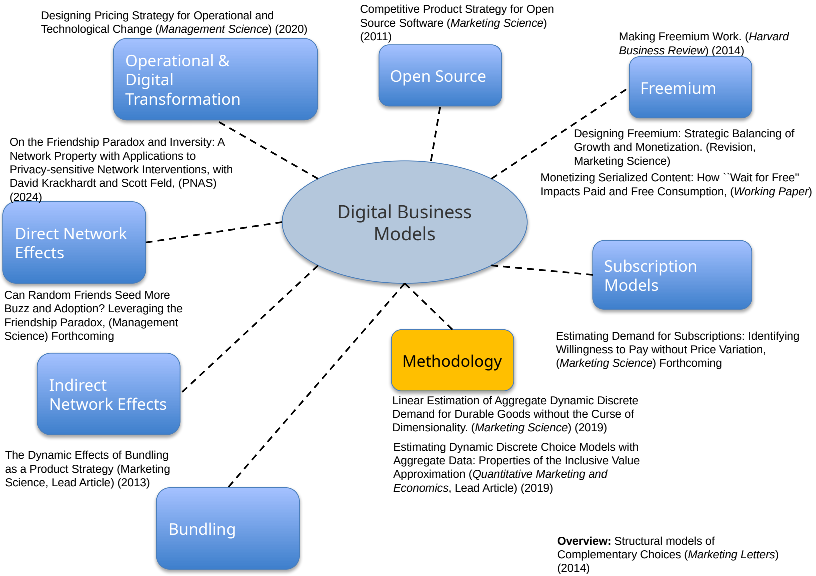
Yale School of Management

Presenting at:
Boston University Questrom School of Business
September 2025

Research Overview

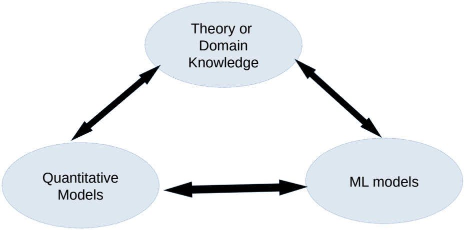


Digital Economy – Business Models



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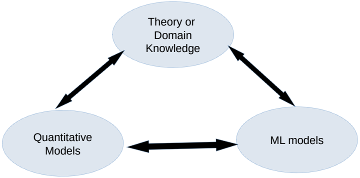
Can improve predictive *accuracy*, *explainability*, provide *guarantees*



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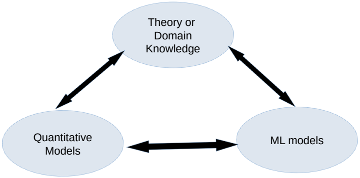

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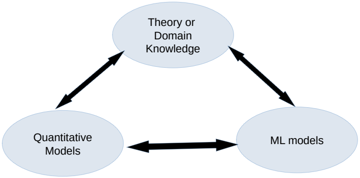

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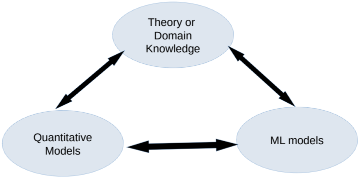

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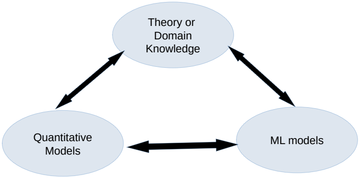

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- Nonparametric Bandits Leveraging Informational Externalities to Learn the Demand Curve. Forthcoming at *Marketing Science*
- Market Structure Mapping with Visual Characteristics. (Research in progress)

Generative Interpretable Visual Design

Sisodia, Burnap and Kumar

Presenting at:
Boston University Questrom School of Business
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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*

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)

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What about preferences in visual space?

Cannot do this because characteristics for visual design are unknown!

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Research Goals

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

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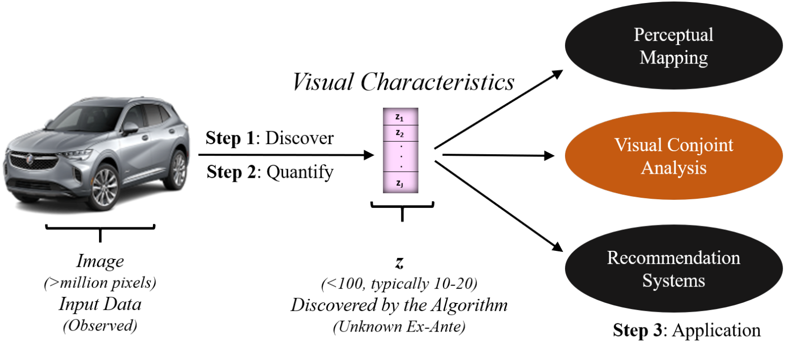
Hyundai: $(3, 8, 5, 9)$ compared to BMW: $(1, 3, 10, 1)$

Research Goals

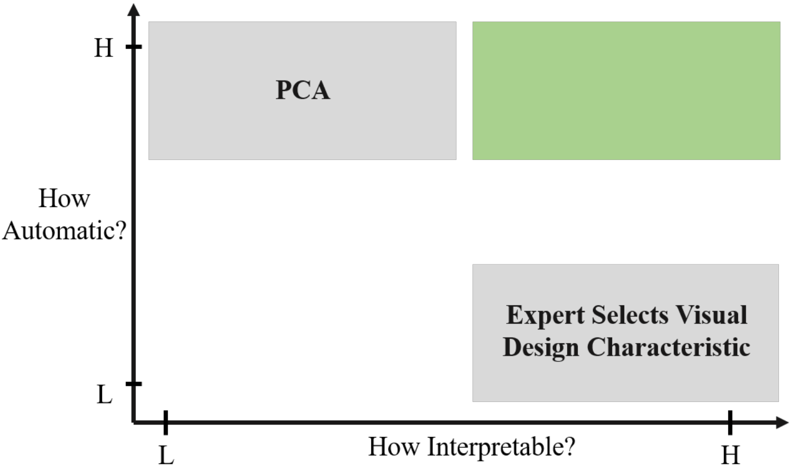
Hyundai: $(3, 8, 5, 9)$ compared to BMW: $(1, 3, 10, 1)$
Several questions come to mind:

- 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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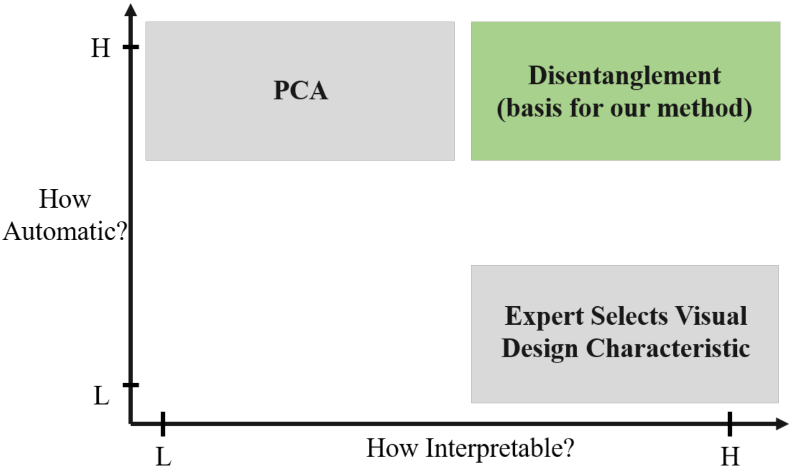

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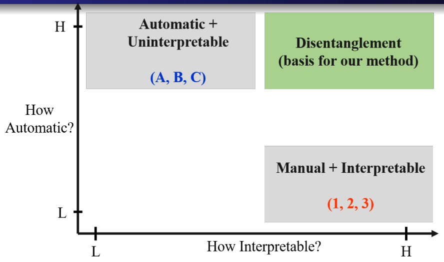

Automatic + Uninterpretable

- 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)*
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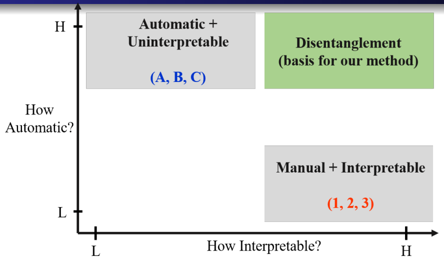

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Manual + Interpretable

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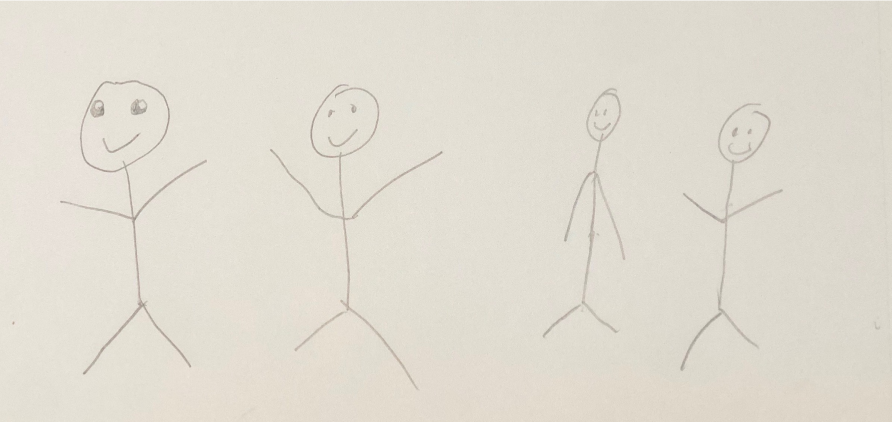
- Latent Units ($\mathbf{z}$): Dimensions in the model's latent space
- Generative factors ($\mathbf{c}$): Human-interpretable true characteristics

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

What is disentanglement?

Stick



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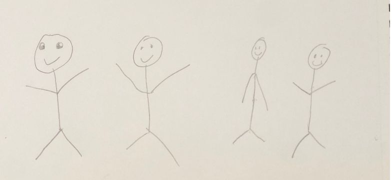

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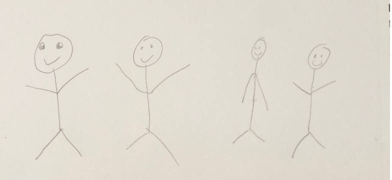

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- Latent Units ($\mathbf{z}$): What algorithm discovers – dimensions in the model's latent space
- Generative factors ($\mathbf{c}$): Human-interpretable

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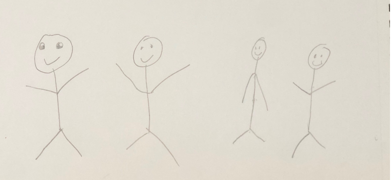

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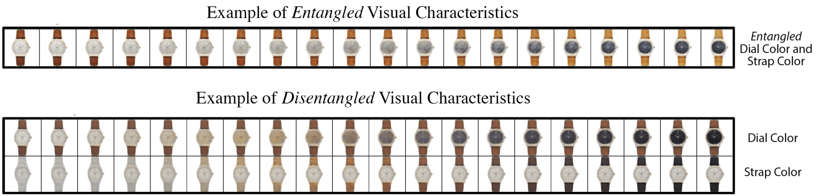
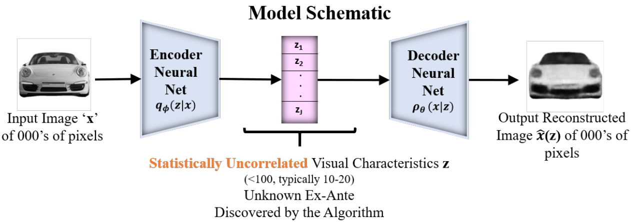
$\boxed{\text{Goal: One to one mapping between } z \Leftrightarrow c}$

Product Images and Parts of Watch

Disentangled and Entangled Representations

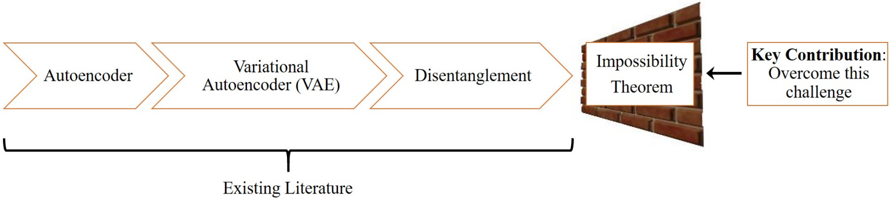


Models in Existing Literature



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

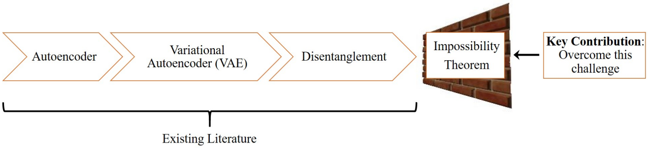
Roadmap of Our Research Approach



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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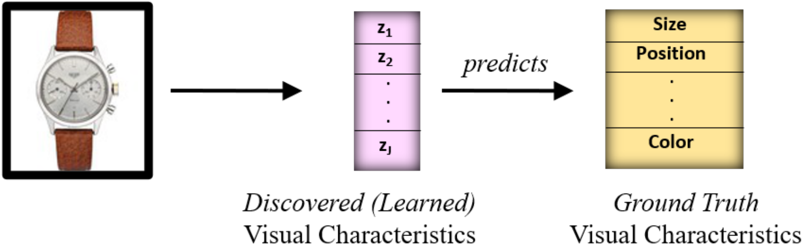
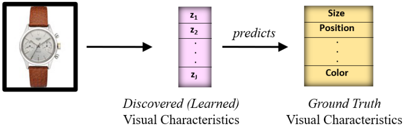
  - Human labeling
- Can we use this approach to discover visual characteristics?

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*.

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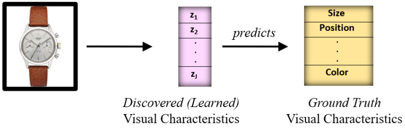

What's the Problem?

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

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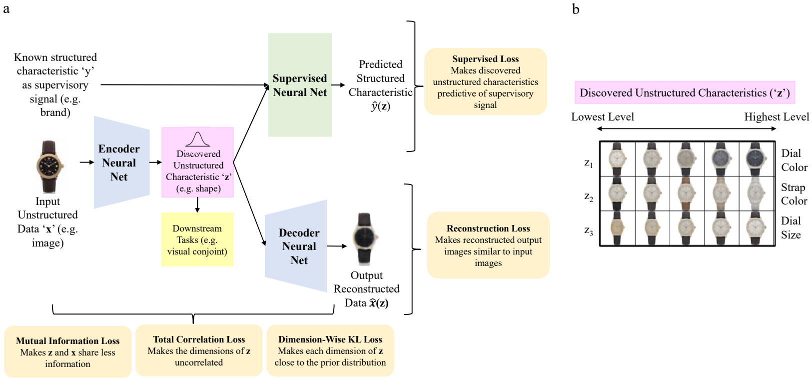
Schematic of Proposed Approach



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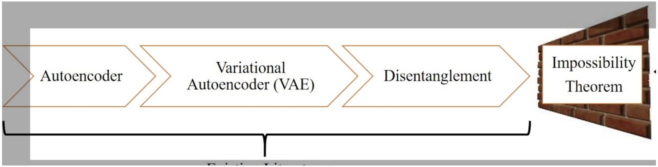

- **Solution** without ground truth on visual characteristics:
- Leverage **structured product characteristics** to provide a supervisory signal for disentanglement

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

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

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

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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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- Can use structured product characteristics as signals: brand, price, material etc.

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)

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

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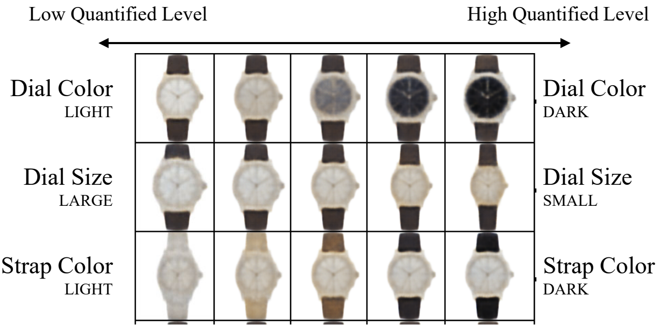

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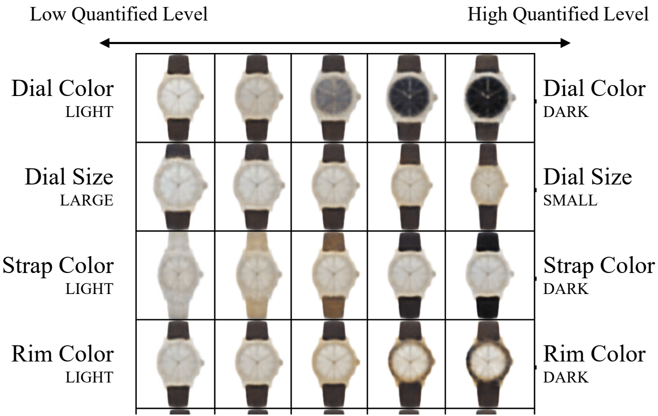

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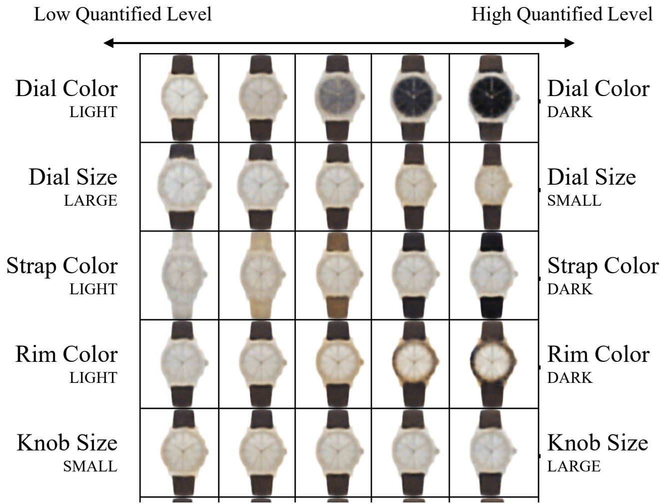

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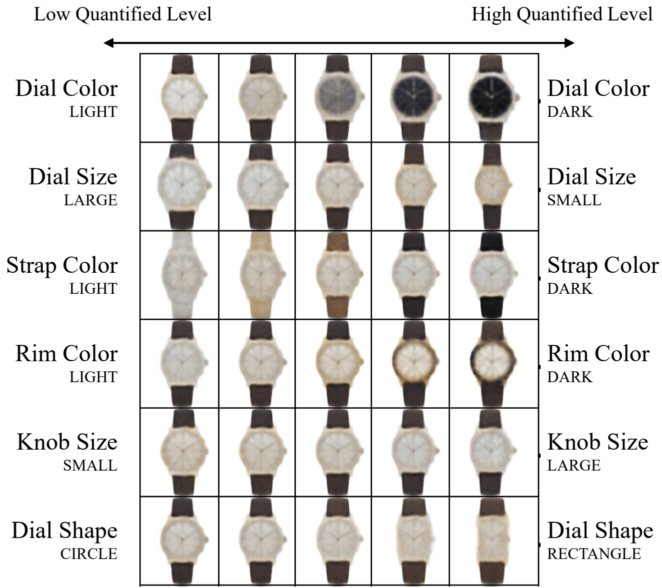
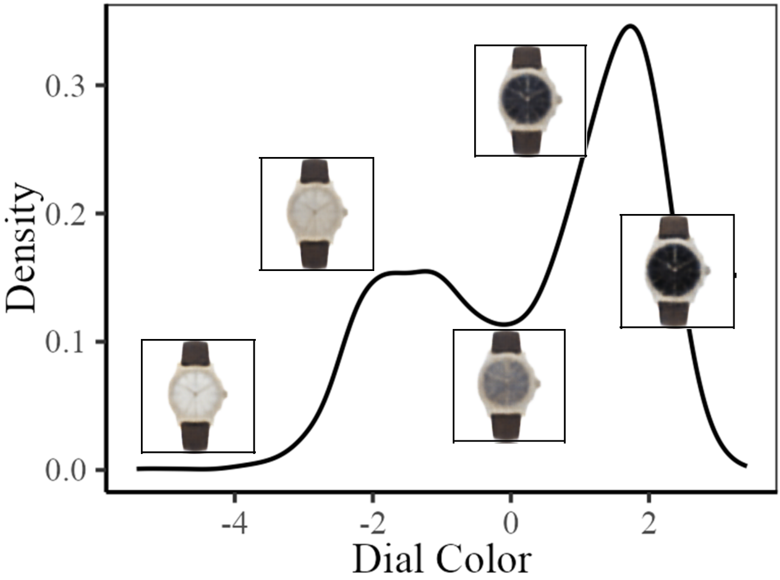


Density of Discovered Visual characteristics



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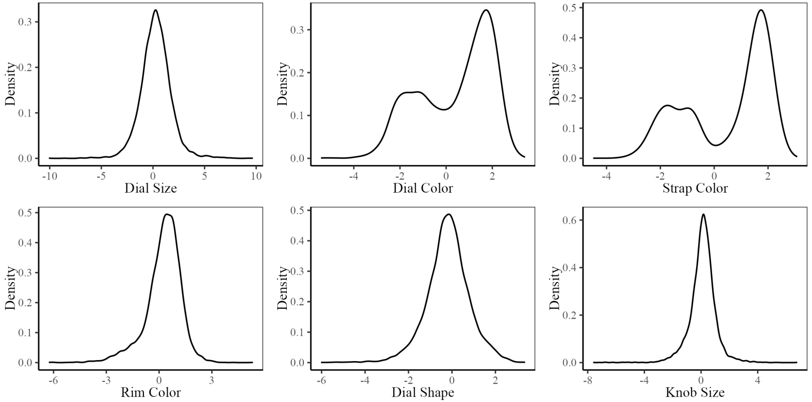
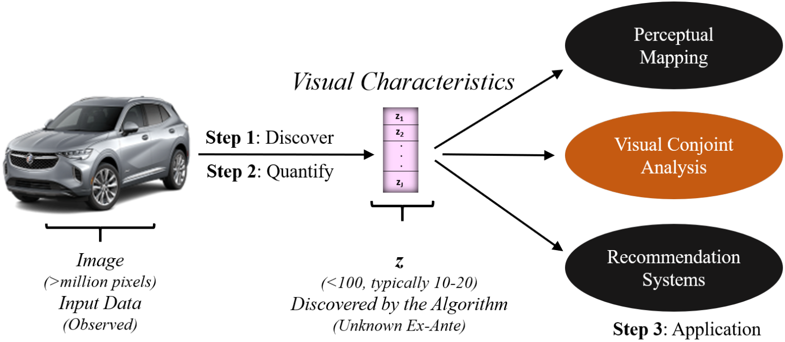


Research Goals



- 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

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

Market Structure Mapping with Interpretable Visual Characteristics

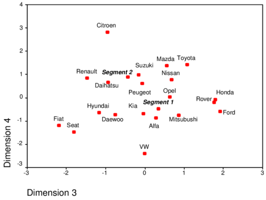
Sisodia and Kumar

Presenting at:
Boston University Questrom School of Business
September 2025

What is a Market Structure Map?

A common element of market structure analysis is the derivation of a **market structure map**, *that is, a spatial representation of firms' competitive positions relative to one another based on some measure of their competitive relationships (DeSarbo et al. 1993)*

- Graphical representations of product positioning (e.g. Multidimensional Scaling)



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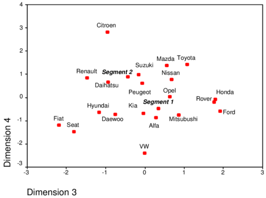

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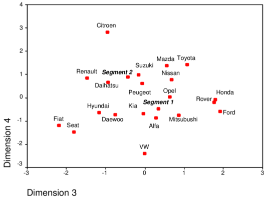

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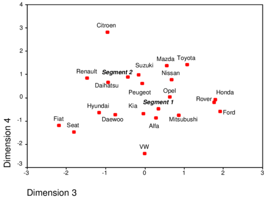

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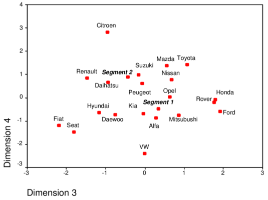
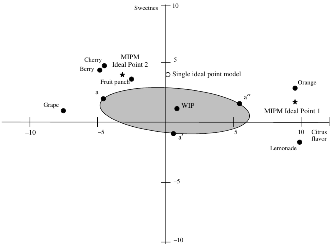


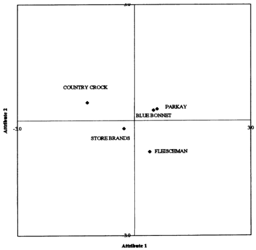
  - Identify market gaps
  - Spot new opportunities
  - Identify competitors and evaluate positioning

Market Structure Map: Examples

Compositional (Left) & Decompositional (Right)



Lee, Sudhir and Steckel (2002), *Journal of Marketing Research*



Erdem (1996), *Marketing Science*

Compositional (Building up)

- Product characteristics – functional, psychological

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices

Market Structure Mapping

Sources of Data

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What's common?

Neither of these approaches have considered visual characteristics.

Are these cars close substitutes?

First, consider *functional* product characteristics:

(A)	**(B)**
\$179,000-\$243,000, 553 HP, 16-23 MPG	From \$242,700, 542-650 HP, 14-22 MPG

Are these cars close substitutes?

First, consider *functional* product characteristics:

(A)

$179,000-$243,000, 553 HP, 16-23 MPG

Ferrari California

(B)

From $242,700, 542-650 HP, 14-22 MPG

Bentley Continental GT

Importance of Visual Design

Functional characteristics alone are *not sufficient* to even place the car in an appropriate segment (submarket)

Visual design matters *a lot* for cars

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

—JD Power Avoider Study 2015

Challenges in using visual images for market structure mapping

Three Challenges:

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3. Black-Box (Un)interpretable Embeddings: Pretrained networks may focus on brand logos or color, complicating interpretation of true style.
    - We need to be able to choose what visual characteristics matter for market structure
    - Does color matter? Does angle matter?

Should Color be included in Visual Characteristics Maps?

- Should a red Ferrari California be close substitute to a red Toyota Corolla?

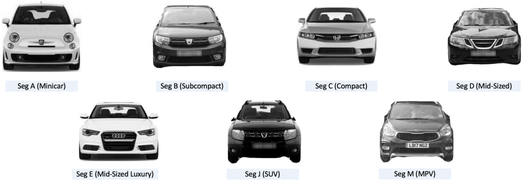
Data

- **UK Automobile Market**
  - 2,439 make-model-year observations from 2008 to 2017
  - 379 unique models from 49 unique makes
- **Sales and Auto Characteristics:**
  - Characteristics (price, MPG, horsepower, weight, dimensions, etc.) from Parker's
  - Sales from DVM-CAR[2]
- **Images:**
  - Front-facing automobile images from DVM-CAR
  - Converted from color to grayscale to *focus on shape* rather than color.
  - (very) Low-resolution: 128×128 pixels

[2] Huang, Jingmin, et al. (2022), *IEEE International Conference on Big Data*

Segments in the UK automobile market

Segment	Description
A	Minicars
B	Subcompact
C	Compact
D	Mid-size
E	Mid-size Luxury
J	SUV
M	MPV



Summary Statistics of the 2013 UK Auto Market

Variable	Mean	St. Dev.	Min.	Max.
Total Quantity Sold	8,074.834	13,714.100	1	113,390
Price (in £000 units)	26.333	14.668	7.868	108.624
MPG (tens of miles per gallon)	4.999	1.058	2.250	7.200
Weight (in 10 lbs)	327.704	2.444	324.506	332.106
HP/Wt (in HP per 10 lbs.)	0.461	0.169	0.060	1.347
Length (in 1000 inches)	1.724	0.178	1.062	2.054
Width (in 1000 inches)	0.756	0.063	0.580	0.899
Height (in 1000 inches)	0.616	0.054	0.537	0.780
Wheelbase (in 1000 inches)	1.046	0.081	0.735	1.266
Space (length $\times$ width)	1.310	0.215	0.697	1.759
Vehicle Segment (Proportion):				
Segment A (Minicars)	0.112	0.316	0	1
Segment B (Subcompact)	0.120	0.326	0	1
Segment C (Compact)	0.162	0.369	0	1
Segment D (Mid-Size)	0.129	0.335	0	1
Segment E (Mid-Size Luxury)	0.071	0.257	0	1
Segment J (SUV)	0.241	0.428	0	1
Segment M (MPV)	0.166	0.373	0	1
Country of Origin (Proportion):				
France	0.108	0.311	0	1
Germany	0.241	0.428	0	1
Japan	0.220	0.415	0	1
South Korea	0.091	0.289	0	1
UK	0.108	0.311	0	1
USA	0.058	0.234	0	1

Match each model with front-facing image

Is this sufficient?

"Market research studies have shown that 70% of consumers identify and judge automobiles by the appearance of headlights and grille located on the *face of the automobile."*

– The Wall Street Journal 2006

Loss Function & Supervisory Signals

$$\underbrace{L(\theta, \phi; \mathbf{m}, \mathbf{v})}_{\text{Disentanglement Loss}} = \underbrace{-\mathbf{E}_{q_\phi(\mathbf{v}|\mathbf{m})}\left[\log p_\theta(\mathbf{m}|\mathbf{v})\right]}_{\text{Reconstruction Loss}} + \underbrace{I_q(\mathbf{v}, \mathbf{m})}_{\text{Mutual Information Loss}} \tag{1}$$

$$+ \lambda_1 \underbrace{KL\left[q(\mathbf{v})\,||\prod_{j=1}^{J} q(v_j)\right]}_{\text{Total Correlation Loss}} + \underbrace{\sum_{j=1}^{J} KL\left[q(v_j)||p(v_j)\right]}_{\text{Dimension-Wise KL Divergence Loss}} + \lambda_2 \underbrace{P(\widehat{\mathbf{y}(\mathbf{v})}, \mathbf{y})}_{\text{Supervised Loss}}$$

Number of Signals	Supervisory Signals	λ_1	λ_2	UDR
3	Wheelbase, Width, Height	50	10	0.739
3	HP/Weight, MPG, Space	50	30	0.710
1	Price	50	30	0.708
1	Weight	50	40	0.708
1	Wheelbase	50	30	0.690
1	Width	50	5	0.689
3	Length, Width, Height	50	40	0.678
1	Length	50	40	0.666
0	Unsupervised β-TCVAE	50	0	0.658
1	Height	30	20	0.378
1	Country of Origin	10	10	0.139
1	Segment	10	10	0.134
1	Unsupervised VAE	1	0	0.073
1	Unsupervised AE	0	0	0.074
1	Make	1	1	0.072

$\lambda_1 \in [1, 5, 10, 20, 30, 40, 50]$ and $\lambda_2 \in [0, 1, 5, 10, 20, 30, 40, 50]$.

Visual Characteristic 1: Body Shape

Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Body Shape	0.30	0.33	0.39	-0.28	0.25	-0.42

- Hatchback-like profiles → smaller wheelbase, lower length, and lighter
- Hatchback-like profiles → taller and narrower

Visual Characteristic 2: Boxiness

Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Boxiness	0.05	-0.07	0.14	-0.59	0.02	-0.49

- Higher degree of boxiness $\rightarrow$ Taller and upfront from the front
- Lower degree of boxiness $\rightarrow$ Flatter and sleeker
- Boxiness captures cabin “uprightness” (not related to length or wheelbase)

Visual Characteristic 3: Grille Height

Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Grille Height	0.04	0.02	0.05	-0.04	0.03	-0.05

- Reflects stylistic design choices
- Unrelated to size-related factors

Visual Characteristic 4: Grille Width

Correlation Between Discovered Visual Dimensions and Physical Vehicle Measures

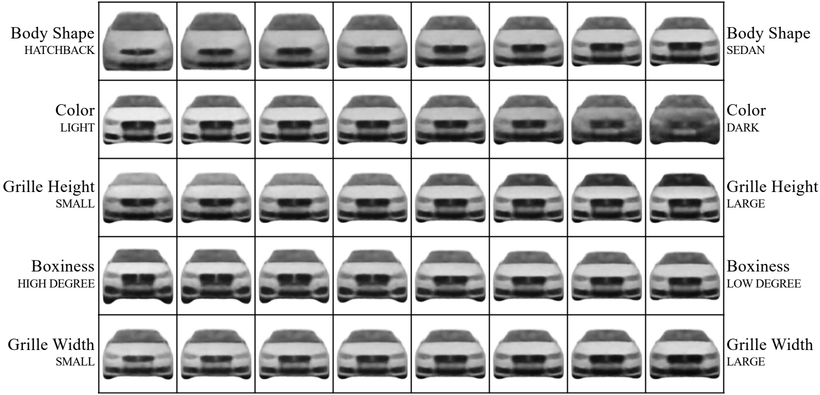
	Wheelbase	Weight	Length	Height	Width	Height/Width Ratio
Grille Width	0.12	0.08	0.12	0.03	0.15	-0.09

- Reflects stylistic design choices
- Unrelated to size-related factors

Visual Characteristic 5: Color

- We find the visual characteristic of *Color*.
- Color should not impact market structure because a car is available in many colors.
- We, therefore, exclude it when we create market structure maps.
- This is only possible because of disentanglement.

Disentanglement obtains four interpretable visual characteristics



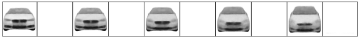
Left to Right: Vary one visual characteristic, keeping all others fixed

Human Understanding of Visual Characteristics

- Showed respondents sequence of car images

Q1/4: Look at the below image to see the various parts of a car.

Now, carefully examine each car image below from 1 to 5, going from left to right.
Note: Images are low-quality on purpose. Be sure to see all the images 1 to 5.



1 2 3 4 5

LEFT RIGHT

How does the car change the <u>most</u> as you go from image 1 to 5? Go through each part of the car one by one before deciding your response. Write it in a few words.

Human Understanding of Visual Characteristics

- Showed respondents sequence of car images
- Asked respondents open-ended questions about visual changes

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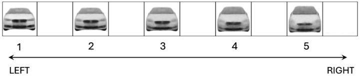

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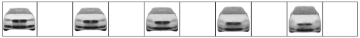

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- Example: LLM summarizes that respondents are saying that cars becoming lower, flatter, and wider can be thought of as boxiness

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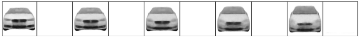

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LEFT RIGHT

How does the car change the <u>most</u> as you go from image 1 to 5? Go through each part of the car one by one before deciding your response. Write it in a few words.

Quantification Validation Survey Question

Which pair of cars in your judgment are visually more similar? Carefully check both large and small visual aspects. Do not consider any non-visual features like brand or price.

Left Pair

Right Pair

Correlation Between Different Characteristics

	Functional Characteristics				Visual Characteristics			
	Price	MPG	HP/Weight	Space	Boxiness	Body Shape	Grille Height	Grille Width
Price	1.00							
MPG	-0.60	1.00						
HP/Weight	0.74	-0.48	1.00					
Space	0.67	-0.47	0.36	1.00				
Boxiness	0.06	0.04	0.29	0.09	1.00			
Body Shape	0.50	-0.25	0.54	0.36	0.13	1.00		
Grille Height	0.11	0.03	0.12	0.05	0.04	-0.02	1.00	
Grille Width	0.07	-0.05	0.04	0.15	0.01	-0.12	-0.05	1.00

Does Form Follow Function? Insight 1: Products close in functional space are differentiated visually

- *Operationalization*: Calculate correlation between distances in functional product characteristics and visual product characteristics for each pair of make-models within each segment

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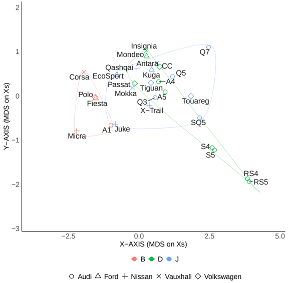
Segment	Correlation	Std. Error
A (Minicars)	-0.08	0.05
B (Subcompact)	-0.05	0.05
C (Compact)	-0.05	0.04
D (Mid-size)	0.02	0.04
E (Mid-size Luxury)	0.13	0.10
J (SUV)	0.09	0.03
M (MPV)	0.11	0.04

Market Structure Maps

Market Structure Map using only functional characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV



Market Structure Map using only visual characteristics

Segment	Description
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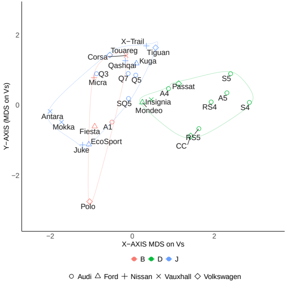
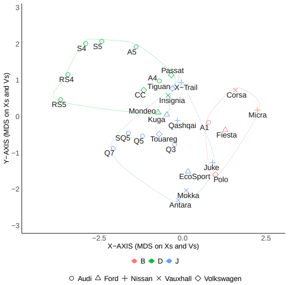
D	Mid-size
J	SUV



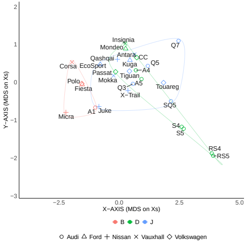
Market Structure Map using both type of characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV



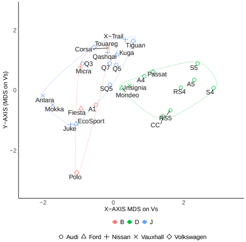
Insight 2: Visual increases differentiation and helps separate segments

Only Functional Characteristics



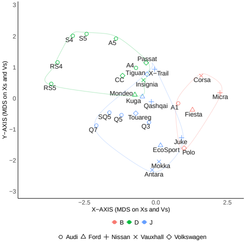
24.3% segment overlap

Only Visual Characteristics



32.9% segment overlap

Both Characteristics

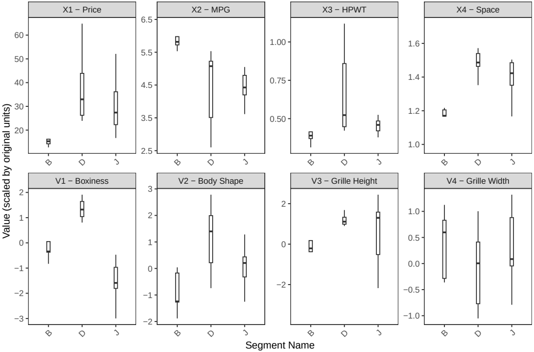


8.3% segment overlap

Does Disentanglement Provide Further Insights?

Insight 2D: Which visual characteristics increase differentiation?

- Disentanglement identifies interpretable characteristics contributing to differentiation



Insight 2D: Which visual characteristics increase differentiation?

- Disentanglement identifies interpretable characteristics contributing to differentiation
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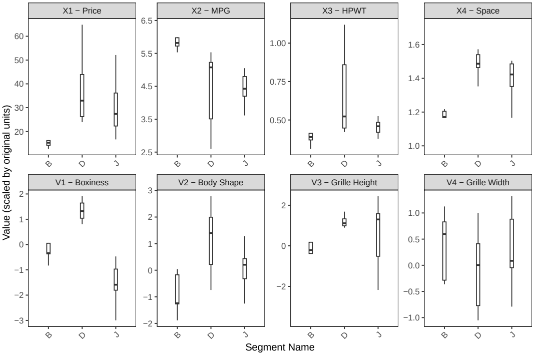
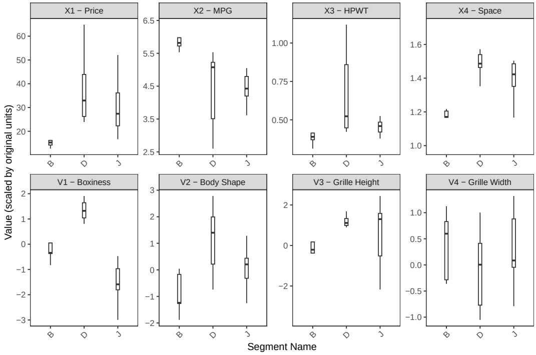


Insight 2D: Which visual characteristics increase differentiation?

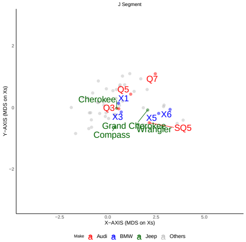
- Disentanglement identifies interpretable characteristics contributing to differentiation
- Seg D & J overlap on most of the functional characteristics but Seg B is different
- Seg D & J are different in boxiness and grille



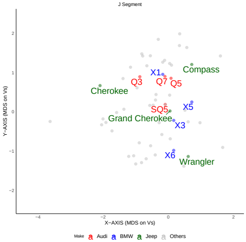
Insight 3: Different Visual Strategy Across Brands

Segment J – SUVs

Only Functional Characteristics



Only Visual Characteristics



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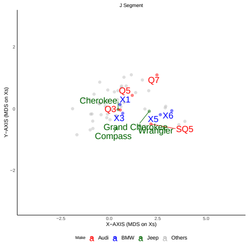

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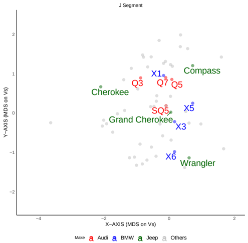


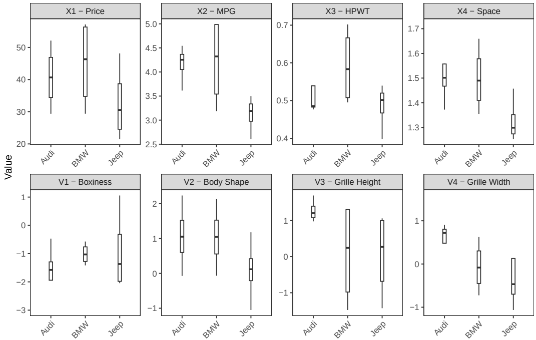
Area Share of a Make in Functional Space & Visual Space (Segment J: SUVs)

Make	Models	Area Share (Functional)	Area Share (Visual)	Ratio
Audi	4	17.90%	2.96%	6.05
BMW	4	6.35%	6.48%	0.98
Jeep	4	9.38%	28.42%	0.33

Insight 3D: Different Visual Strategy Across Brands

Disentanglement identifies interpretable characteristics

- Audi is very tight on some visual characteristics, notably, grille height and grille width $\Longrightarrow$ *distinctive look*



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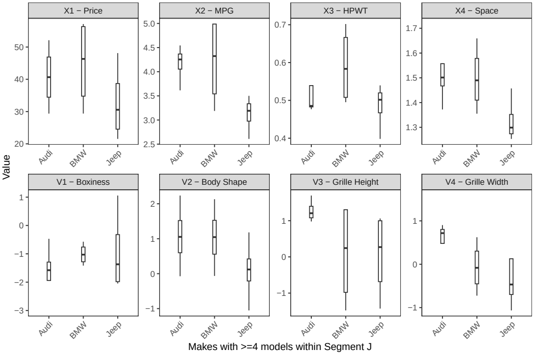

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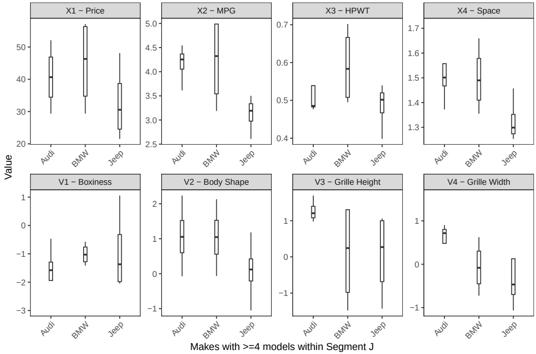
- Jeep varies on most visual characteristics



Insight 3: Different Visual Strategy Across Brands

Audi Q3

Audi Q5

Audi Q7

Audi SQ5

BMW X1

BMW X3

BMW X5

BMW X6

Jeep Cherokee

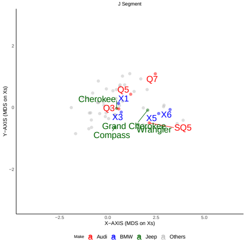
Jeep Compass

Jeep Grand Cherokee

Jeep Wrangler

Insight 4: Product-Level

Only Functional Characteristics



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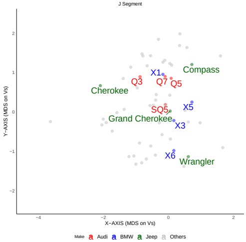

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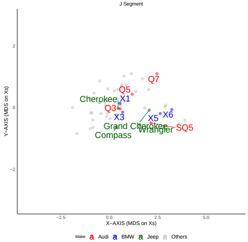
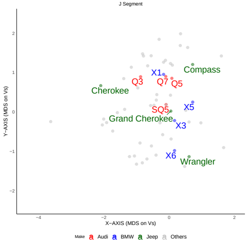


Only Visual Characteristics



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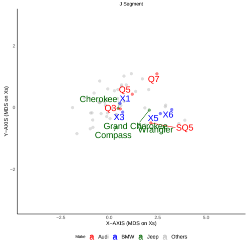

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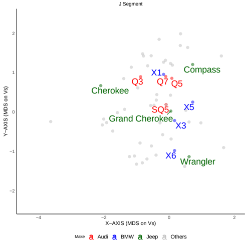

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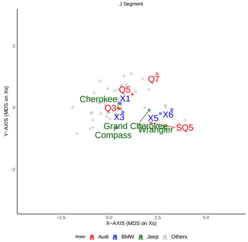

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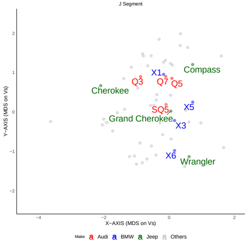

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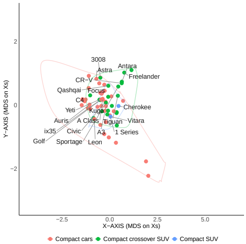
  - Looking at visual, we can see that they are now separated more
- Positioning BMW X3: Should I focus on Cherokee (which is what functional map suggests)?
  - Visual map suggests the Grand Cherokee is closer instead

Insight 5: Leaping to Another Category

Only Functional Characteristics



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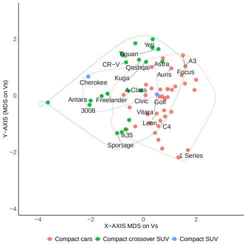
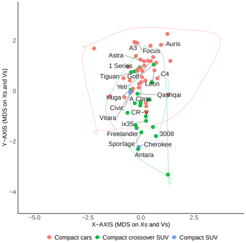
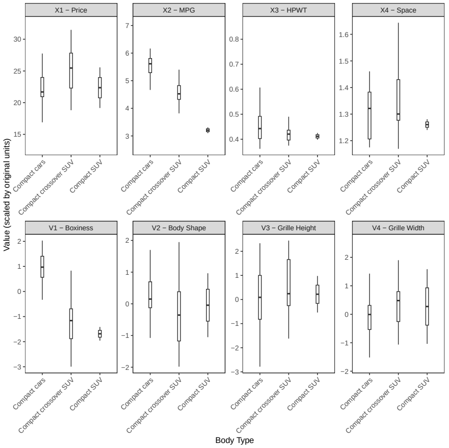


Both Characteristics



Insight 5D: Leaping to Another Category

- Compact cars and compact crossover SUVs differ in boxiness
- Compact cars and compact crossover SUVs overlap across most functional characteristics
- Compact crossover SUVs and compact SUVs are similar in visual characteristics
- Compact crossover SUVs and compact SUVs differ in some



Connecting Consumer Search to Market Structure Maps

Consumer Search $\Longleftrightarrow$ Market structure maps?

We use Google Trends to look for consumers searching pairs of models

- Consumer searching for "Honda Civic" and "Toyota Corolla" more likely to be comparing

$$\log_{10}(Y_{AB}+1) = \beta_0 + \beta_1(|X_A - X_B|) + \beta_2(|V_A - V_B|) + \epsilon_{AB}$$

[3] Raw Google Trend values are scaled by each pair's segment sales share

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Consumer Search ⟺ Market structure maps?

	(1)	(2)	(3)	(4)
Constant	2.778***	9.509***	2.974***	8.871***
	(0.205)	(1.425)	(0.291)	(1.479)
Δ HP/Weight	−2.395	−3.761**	−2.886*	−4.021***
	(1.691)	(1.460)	(1.638)	(1.453)
Δ Space	−1.685	1.200	−1.444	1.431*
	(1.068)	(0.851)	(1.031)	(0.853)
Δ MPG	−0.601***	−0.407**	−0.599***	−0.432***
	(0.199)	(0.163)	(0.196)	(0.165)
Δ Price	−0.214***	−0.188***	−0.203***	−0.194***
	(0.037)	(0.031)	(0.036)	(0.032)
Δ Boxiness			−0.263	0.249
			(0.161)	(0.154)
Δ Bodyshape			0.149	−0.361**
			(0.108)	(0.144)
Δ Grille Height			−0.284***	−0.007
			(0.072)	(0.065)
Δ Grille Width			0.324**	−0.001
			(0.138)	(0.145)
Make Fixed Effects	No	Yes	No	Yes
Observations	306	306	306	306
R^2	0.168	0.590	0.247	0.602
Adjusted R^2	0.157	0.559	0.227	0.566
Note:	*p<0.1; **p<0.05; ***p<0.01			

Consumers search for visually similar cars even after accounting for functional similarity

Conclusion and Takeaways

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