Market Structure Mapping with Interpretable Visual Characteristics

Ankit Sisodia [1] and Vineet Kumar [2]

[1]Purdue University
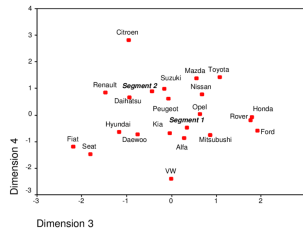
[2]Yale School of Management

Presenting at:
University of Notre Dame Marketing Seminar
May 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)

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)
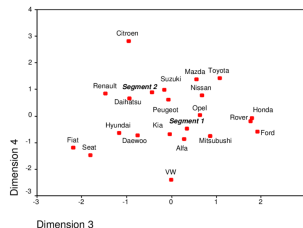
- Graphical representations of product positioning (e.g. Multidimensional Scaling)
- Strategic tools for understanding competitive landscape that enable companies to:

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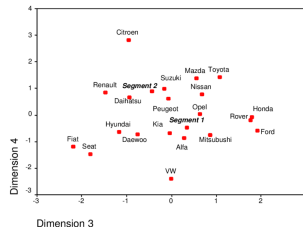
- Graphical representations of product positioning (e.g. Multidimensional Scaling)

- Strategic tools for understanding competitive landscape that enable companies to:
  - Identify market gaps

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)
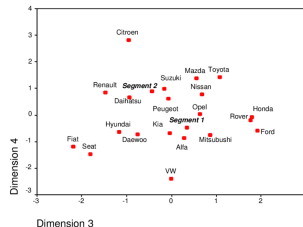
- Graphical representations of product positioning (e.g. Multidimensional Scaling)
- Strategic tools for understanding competitive landscape that enable companies to:
  - Identify market gaps
  - Spot new opportunities

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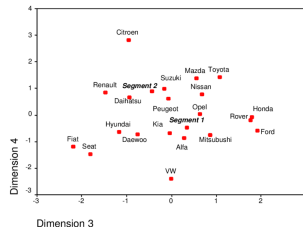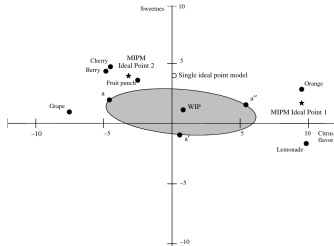
- Graphical representations of product positioning (e.g. Multidimensional Scaling)

- Strategic tools for understanding competitive landscape that enable companies to:
  - Identify market gaps
  - Spot new opportunities
  - Identify substitutes (competitors) and evaluate positioning

Market Structure Map: Examples
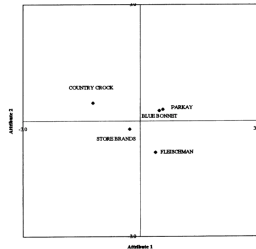Compositional (Left) & Decompositional (Right)

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

Erdem (1996), *Marketing Science*

Market Structure Mapping
Sources of Data

Compositional (Building up)

- **Product characteristics (functional, psychological, aesthetic / visual?)**

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices

Market Structure Mapping
Sources of Data

Compositional (Building up)

- **Product characteristics (functional, psychological, aesthetic / visual?)**

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices
- Sales data (cross-elasticity of demand)

Market Structure Mapping
Sources of Data

Compositional (Building up)

- **Product characteristics (functional, psychological, aesthetic / visual?)**

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices
- Sales data (cross-elasticity of demand)
- User comments and reviews

Market Structure Mapping
Sources of Data

Compositional (Building up)

- **Product characteristics (functional, psychological, aesthetic / visual?)**

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices
- Sales data (cross-elasticity of demand)
- User comments and reviews
- Search Co-occurrence

Compositional (Building up)

- **Product characteristics (functional, psychological, aesthetic / visual?)**

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices
- Sales data (cross-elasticity of demand)
- User comments and reviews
- Search Co-occurrence

Compositional (Building up)

- **Product characteristics (functional, psychological, aesthetic / visual?)**

Decompositional (Breaking down)

- Survey data by asking 1st and 2nd choices
- Sales data (cross-elasticity of demand)
- User comments and reviews
- Search Co-occurrence

What's common?

Neither of these approaches have considered visual characteristics.

Are these cars close substitutes?

(A)
$179,000-$243,000, 553 HP,
16-23 MPG

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

Are these cars close substitutes?

(A)
$179,000-$243,000, 553 HP,
16-23 MPG

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

Ferrari California

Bentley Continental GT

Importance of Visual Design

Functional characteristics alone are *not sufficient* to even place the car in an appropriate segment (submarket), let alone determines substitution patterns

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

Challenges in using visual images for market structure mapping

Three Challenges:

1. Inputs from Raw Images: Backgrounds, lighting, and camera angles overshadow actual product design, causing mis-clusters.

Challenges in using visual images for market structure mapping

Three Challenges:

1. Inputs from Raw Images: Backgrounds, lighting, and camera angles overshadow actual product design, causing mis-clusters.

2. Scalability: Need to work with hundreds or thousands of product models / images, so challenging to have human intervention

Challenges in using visual images for market structure mapping

Three Challenges:

1. Inputs from Raw Images: Backgrounds, lighting, and camera angles overshadow actual product design, causing mis-clusters.

2. Scalability: Need to work with hundreds or thousands of product models / images, so challenging to have human intervention

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

Challenges in using visual images for market structure mapping

Three Challenges:

1. Inputs from Raw Images: Backgrounds, lighting, and camera angles overshadow actual product design, causing mis-clusters.

2. Scalability: Need to work with hundreds or thousands of product models / images, so challenging to have human intervention

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[1]
- **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

---

[1] 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

Seg A (Minicar)

Seg B (Subcompact)

Seg C (Compact)

Seg D (Mid-Sized)

Seg E (Mid-Sized Luxury)

Seg J (SUV)

Seg 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 × 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

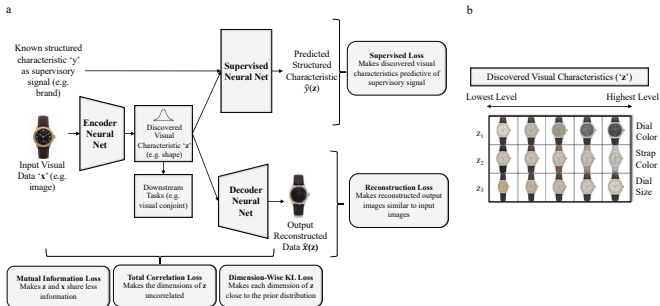# We match each make-model with its front-facing image

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*

Disentanglement → Visual Characteristics

a

Known structured characteristic 'y' as supervisory signal (e.g. brand)

Input Visual Data 'x' (e.g. image)

Encoder Neural Net

Discovered Visual Characteristic 'z' (e.g. shape)

Downstream Tasks (e.g. visual conjoint)

Supervised Neural Net

Predicted Structured Characteristic $\hat{y}(z)$

Supervised Loss Makes discovered visual characteristics predictive of supervisory signal

Decoder Neural Net

Output Reconstructed Data $\hat{x}(z)$

Reconstruction Loss Makes reconstructed output images similar to input images

Mutual Information Loss Makes z and x share less information

Total Correlation Loss Makes the dimensions of z uncorrelated

Dimension-Wise KL Loss Makes each dimension of z close to the prior distribution

b

Discovered Visual Characteristics ('z')

Lowest Level   Highest Level

z_1 Dial Color
z_2 Strap Color
z_3 Dial Size

Loss Function & Supervisory Signals

$$\underbrace{L(\theta, \phi; \mathbf{m}, \mathbf{v})}_{\text{Disentanglement Loss}} = \underbrace{-\mathbf{E}_{q_\phi(\mathbf{v}|\mathbf{m})}\left[\log p_\theta(\mathbf{m}|\mathbf{v})\right]}_{\substack{\text{Reconstruction} \\ \text{Loss}}} + \underbrace{I_q(\mathbf{v}, \mathbf{m})}_{\substack{\text{Mutual} \\ \text{Information} \\ \text{Loss}}} + \lambda_1 \underbrace{KL\left[q(\mathbf{v})||\prod_{j=1}^{J}q(v_j)\right]}_{\substack{\text{Total Correlation} \\ \text{Loss}}} + \underbrace{\sum_{j=1}^{J} KL\left[q(v_j)\right]}_{\substack{\text{Dimension-W} \\ \text{KL Divergence}}}$$

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

Boxiness HIGH DEGREE ... Boxiness LOW DEGREE

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

Grille Width
SMALL

Grille Width
LARGE

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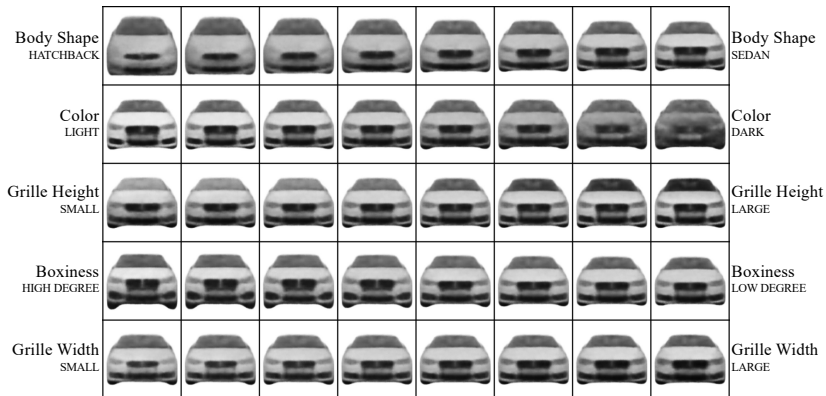
Left to Right: Vary one visual characteristic, keeping all others fixed

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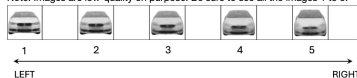
How does the car change the most as you go from image 1 to 5? Go through each part of the car one by one before deciding your response. Write it in a few words.

Human Understanding of Visual Characteristics

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

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.

How does the car change the _most_ 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
- Used LLMs (GPT-4, Claude) to identify *common themes* in respondent responses

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.

How does the car change the most 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
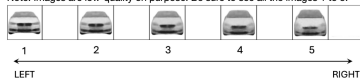
- Used LLMs (GPT-4, Claude) to identify *common themes* in respondent responses

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

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.

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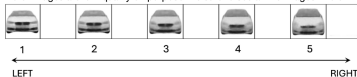
How does the car change the most as you go from image 1 to 5? Go through each part of the car one by one before deciding your response. Write it in a few words.

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 Characterist | | |
	Price	MPG	HP/Weight	Space	Boxiness	Body Shape	Grille He
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

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

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

- *Result*: Low correlation
  between functional and
  visual similarity

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

- *Result*: Low correlation between functional and visual similarity

- *Implication*: Makes use

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

- *Result*: Low correlation between functional and visual similarity

- *Implication*: Makes use

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

- *Result*: Low correlation between functional and visual similarity

- *Implication*: Makes use

Segment	Correlation	St
A (Minicars)	-0.08	
B (Subcompact)	-0.05	
C (Compact)	-0.05	
D (Mid-size)	0.02	
E (Mid-size Luxury)	0.13	
J (SUV)	0.09	
M (MPV)	0.11	

Market Structure Maps

Market Structure Map using only functional characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV
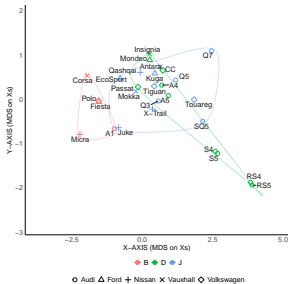
Market Structure Map using only visual characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV
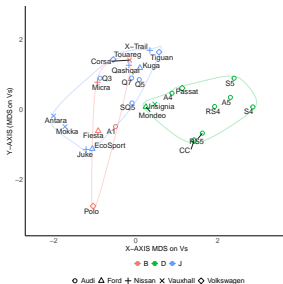
Market Structure Map using both type of characteristics

Segment	Description
B	Subcompact
D	Mid-size
J	SUV
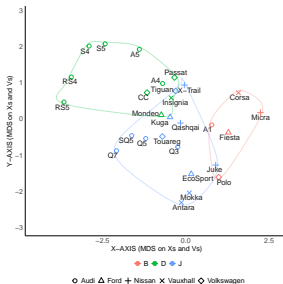
Insight 2: Visual increases differentiation and helps separate segments

Only Functional Characteristics
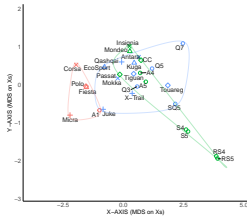
24.3% segment overlap

Only Visual Characteristics
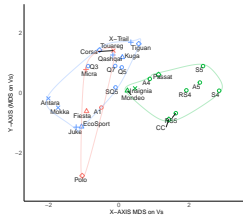
32.9% segment overlap

Both Characteristics
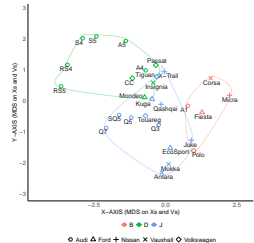
8.3% segment overlap

Does Disentanglement Provide Further Insights?

Insight 2**D**: Which visual characteristics increase differentiation?

- Disentanglement identifies interpretable characteristics contributing to differentiation
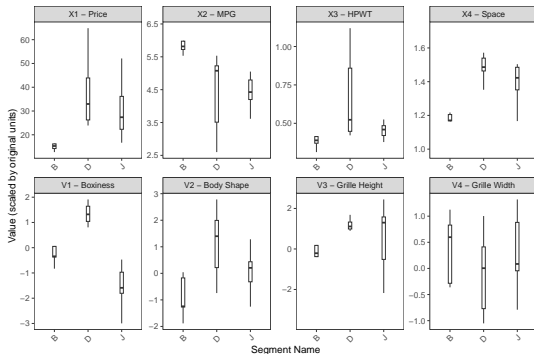
Insight 2**D**: Which visual characteristics increase differentiation?

- Disentanglement identifies interpretable characteristics contributing to differentiation
- Seg D & J overlap on most of the functional characteristics but Seg B is different
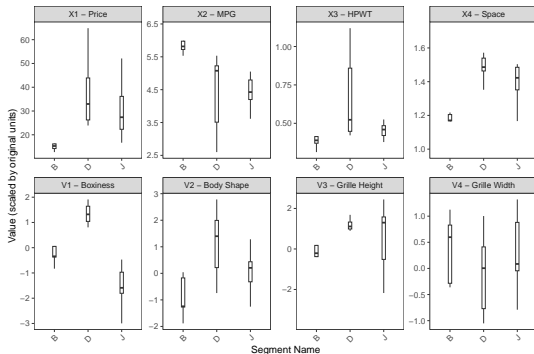
Insight 2**D**: Which visual characteristics increase differentiation?

- 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
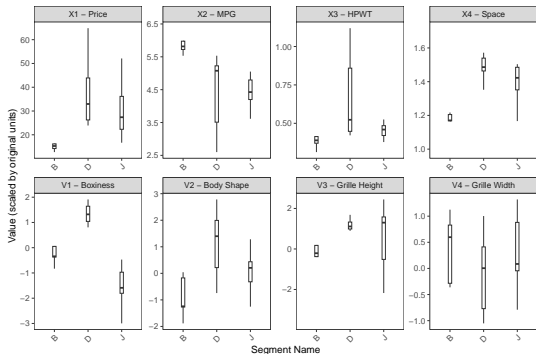
Segment J – SUVs

Insight 3: Different Visual Strategy Across Brands

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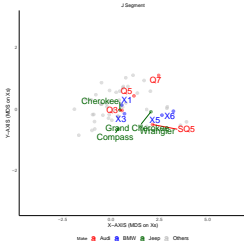
	Only Functional Characteristics	Only Visual Characteristics
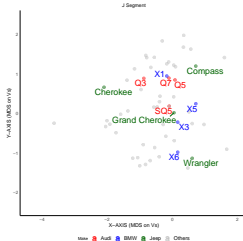
Area Share of a Make in Functional Space & Visual Space (Segment J: SUVs)

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 $\implies$ *distinctive look*
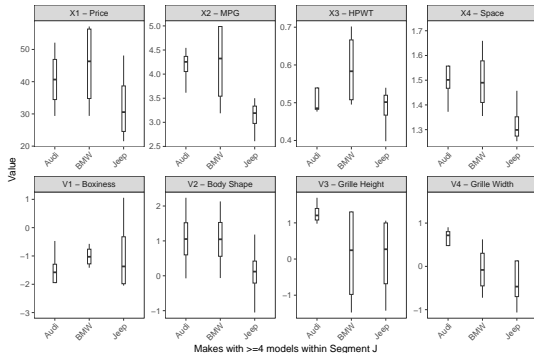
Insight 3D: Different Visual Strategy Across Brands

Disentanglement identifies interpretable characteristics

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

- BMW is typically a more "boxy" look
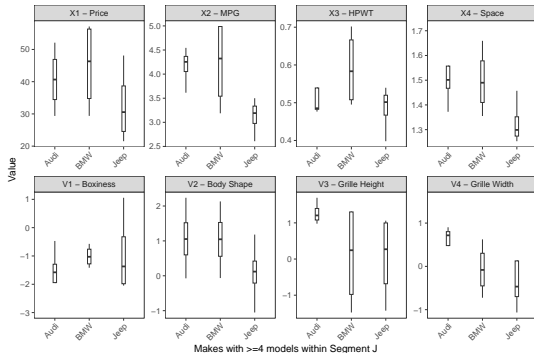
Insight 3D: Different Visual Strategy Across Brands

Disentanglement identifies interpretable characteristics

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

- BMW is typically a more "boxy" look

- Jeep varies on most visual characteristics

Makes with >=4 models within Segment J
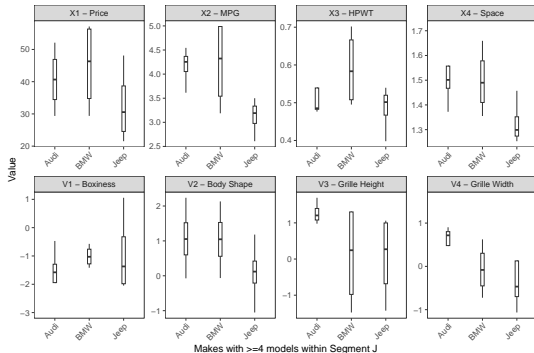
Insight 3: Different Visual Strategy Across Brands

Audi Q3   Audi Q5   Audi Q7   Audi SQ5

BMW X1   BMW X3   BMW X5   BMW X6

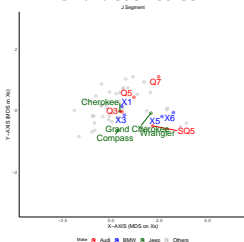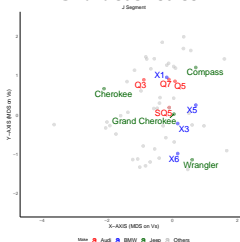Jeep Cherokee   Jeep Compass   Jeep Grand Cherokee   Jeep Wrangler

Insight 4: Product-Level
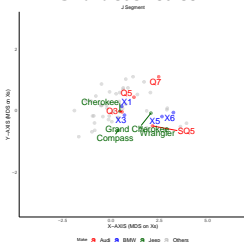

Only Functional Characteristics
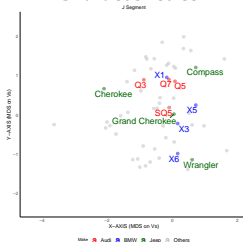
Only Visual Characteristics

- Looking only at functional characteristics, BMW seems to be positioning X5 and X6 too close (cannibalization risk)

Insight 4: Product-Level
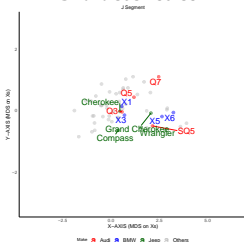

Only Functional Characteristics

Only Visual Characteristics

- Looking only at functional characteristics, BMW seems to be positioning X5 and X6 too close (cannibalization risk)
  - Looking at visual, we can see that they are now separated more

Insight 4: Product-Level

Only Functional Characteristics
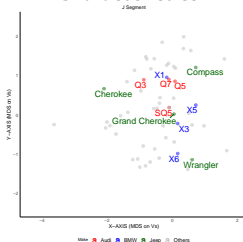
Only Visual Characteristics

- Looking only at functional characteristics, BMW seems to be positioning X5 and X6 too close (cannibalization risk)
  - 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)?

Insight 4: Product-Level
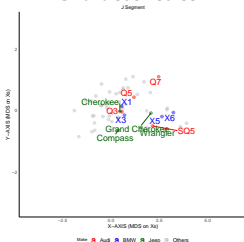

Only Functional Characteristics
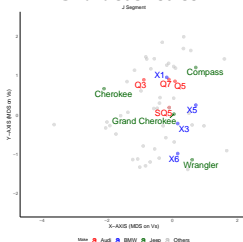
Only Visual Characteristics

- Looking only at functional characteristics, BMW seems to be positioning X5 and X6 too close (cannibalization risk)
  - 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
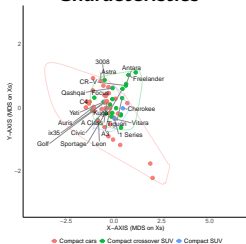
Only Visual Characteristics
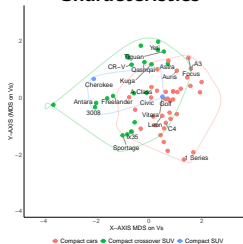
Both Characteristics
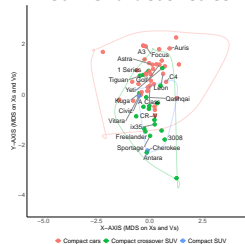
Insight 5D: Leaping to Another Category

- 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
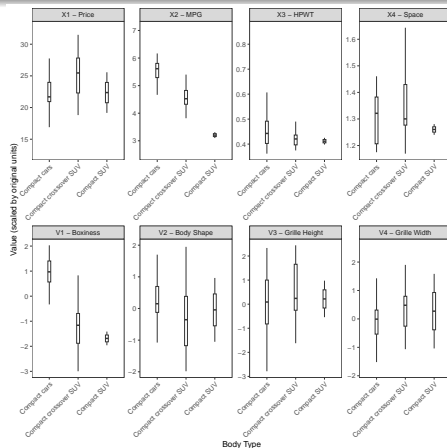
Connecting Consumer Search to Market Structure Maps

Consumer Search ⟺ 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

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

---

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

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
- Models likely in consideration set

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

---

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

Consumer Search ⟺ 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
- Models likely in consideration set

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

- $\log_{10}(Y_{AB} + 1)$ is the log-transformed normalized Google Trends score for the pair (model A, model B) belonging to the same segment[2]

---

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

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
- Models likely in consideration set

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

- $\log_{10}(Y_{AB} + 1)$ is the log-transformed normalized Google Trends score for the pair (model A, model B) belonging to the same segment[2]
- (X_A, X_B) are standardized functional characteristics

---

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

Consumer Search $\iff$ 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
- Models likely in consideration set

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

- $\log_{10}(Y_{AB} + 1)$ is the log-transformed normalized Google Trends score for the pair (model A, model B) belonging to the same segment[2]
- (X_A, X_B) are standardized functional characteristics
- (V_A, V_B) are standardized visual characteristics

---

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

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

- We quantify human-interpretable visual design characteristics and obtain market structure maps

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics

- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics
- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level
- Visual design increases differentiation across segments

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
    - Method allows us to select only *relevant* visual characteristics
- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level
- Visual design increases differentiation across segments
- Different visual strategy across brands

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics
- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level
- Visual design increases differentiation across segments
- Different visual strategy across brands
  - Brand consistency (e.g. Audi)

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics
- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level
- Visual design increases differentiation across segments
- Different visual strategy across brands
  - Brand consistency (e.g. Audi)
  - Within-brand differentiation (e.g. Jeep) in design

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics

- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level

- Visual design increases differentiation across segments

- Different visual strategy across brands
  - Brand consistency (e.g. Audi)
  - Within-brand differentiation (e.g. Jeep) in design

- Product close in functional space often differentiated visually and the other way around

Conclusion and Takeaways

- We quantify human-interpretable visual design characteristics and obtain market structure maps
  - Method allows us to select only *relevant* visual characteristics
- (Interpretable) Visual characteristics can provide an entirely new set of insights at segment (submarket) level, brand level and product level
- Visual design increases differentiation across segments
- Different visual strategy across brands
  - Brand consistency (e.g. Audi)
  - Within-brand differentiation (e.g. Jeep) in design
- Product close in functional space often differentiated visually and the other way around
- Consumers search for visually similar cars even after accounting for functional similarity