Shapes as Product Differentiation:

Neural Network Embedding in the Analysis of Font Markets

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Markets for Products with High-Dimensional Attributes

Many products considered in economic analyses have key attributes that are *unstructured* and thus high-dim

Examples:

- design: automobiles, houses, furniture, clothing
- text, audio and video: books, musics and movies

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More generally, products are often presented to consumers in visual/textual forms (along with structured attributes)

- packages in supermarket
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Important decision factors for consumers and thus key decision variables for producers

Traditional Economic Models

Economic models with product attributes

- Lancasterian characteristics (Lancaster (1966, 1971))
- Discrete-choice models (McFadden (1973), Berry, Levinsohn & Pakes (1995))
- Hedonic models (Rosen (1974), Bajari & Benkard (2005))

These models include

- low-dim observed attributes

  and

- scalar unobserved attributes

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Q: unstructured attributes as scalar unobservable vs. high-dim observables?

- may depend on policy questions

Possible Policy Questions

...that can be answered by "quantifying" high-dim attributes:

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- policies that protects the originality of artistic features
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Quantification amounts to constructing embedding (and a low-dim space) of the attributes

This Project: Markets for Fonts

Considers a particular design product: fonts

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Why font market?

1. font is one of the simplest visually-differentiated products
2. such visual info can be a strong predictor for functionality and value of the product (unlike fine art products)
3. fonts market is typically large (unlike fine art markets)
   - frequent productions and transactions
4. font is a stylized product that captures a key aspect many products in the market have in common: design attributes

Embedding and Low-Dimensional Characteristics Space

We represent font shapes as low-dim embeddings (and construct a characteristics space) by neural network embedding

Specifically, we adapt a state-of-the-art method in deep convolutional neural network

- the network directly learns embedding,
- i.e., a mapping from font images to a compact Euclidean space

Embedding and Low-Dimensional Characteristics Space

Why convolutional neural network (CNN)?

- for visual/textual data considered in this project, NN outperforms (by large margin) other machine learning methods (e.g., LASSO, random forest)
- esp. CNN is known to be appropriate to capture the "spatial" dependence, e.g., of pixels or musical notes

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Drawback of NN: interpretability

Still, the resulting characteristics space can be a basis for various economic analyses

- distance metric has clear interpretation of shape similarity

Economic Analyses Using Embedding

We conduct two analysis:

1. a simple trend analysis of font style (in the paper)
2. a causal analysis of merger effects using synthetic control method

Key insight: given the characteristics space constructed via embedding...

- firms engage in spatial competition
- main decision variable of this competition is font design (as product differentiation)

Contributions of This Paper

1. First to use of neural network embedding for visual data in the empirical analysis of markets
   - Glaeser et al. (2018): Google Street View
   - Gross (2016): Logo design competition
2. Merger and product differentiation with unstructured attributes
   - Berry & Waldfogel (2001), Hastings (2004), Ashenfelter & Hosken (2008), Sweeting (2013), Fan (2013):
     - use structured data for product offerings (e.g., number of products, product spec's) or price
     - we show traditional measures for product offerings do not capture the merger effect in this market

I. Online Marketplace for Fonts

Background: Online Marketplace for Fonts

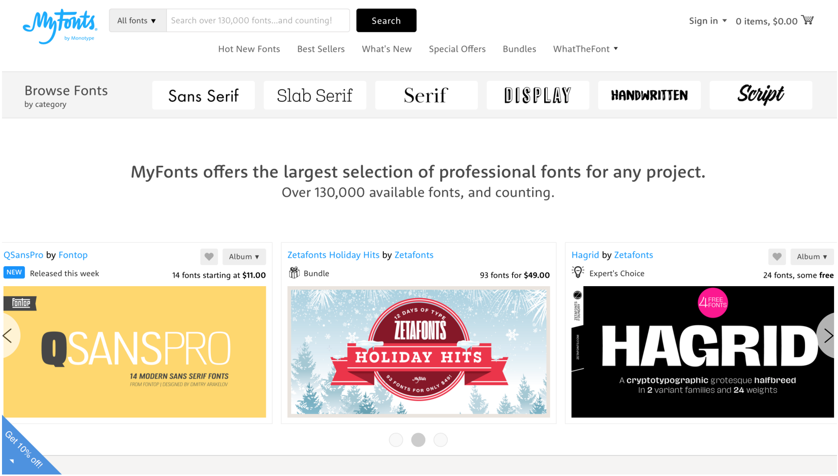
We consider the world's largest online market place "MyFonts.com" that sell around 28,000 different fonts

The marketplace sells...

- fonts designed by foundries owned by Monotype, as well as
- fonts from third parties foundries

Background: Online Marketplace for Fonts

Main page in MyFonts.com



Background: Online Marketplace for Fonts

Example of a font family page in MyFonts.com

Gilroy Light Italic *Gilroy Light Italic*	from **$25.00**	Buying Choices
Gilroy Regular Gilroy Regular	from **$25.00**	Buying Choices
Gilroy Regular Italic *Gilroy Regular Italic*	from **$25.00**	Buying Choices
Gilroy Medium Gilroy Medium	from **$25.00**	Buying Choices
Gilroy Medium Italic *Gilroy Medium Italic*	from **$25.00**	Buying Choices
Gilroy Semi Bold **Gilroy Semi Bold**	from **$25.00**	Buying Choices

Background: Online Marketplace for Fonts

In this market, consumers are typically other designers who use fonts as intermediate goods to produce...

- prints (posters, pamphlets, cards)—desktop license
- webpages—web license

Between 2012 and 2017, around 2,400,000 purchases were made

Data from the Marketplace

Product attributes: unstructured and structured

- images of typefaces
- tags (descriptive words assigned by producers or consumers)
- price
- license type (desktop, web, apps, ePub, digital ads)
- number of languages/glyphs supported, foundry/designer info
- date introduced

Also transcation and consumer data

The dataset is shared by Monotype

Visual Attributes

Fonts are displayed on the webpage using pangrams

- effectively capture important design elements (spacing, deep-height, up-height, ligature)

Format of pangram images: bitmap (200 $\times$ 1000 pixels)

We use (crops of) pangrams as direct inputs in CNN

- try to mimic consumer's perception

Examples of Pangram Images

Quick zephyrs blow, vexing daft Jim.

Quick zephyrs blow, vexing daft Jim.

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II. Construction of Embedding and Characteristics Space

Construction of Embedding

We employ a method where the network directly learns a mapping from pangram images to a compact Euclidean space

- this mapping is called embedding
- we map each pangram to 128-dim embedding
- L^2 distance corresponds to measure of similarity of font shape

Developed by Schroff et al. (2015) for face recognition

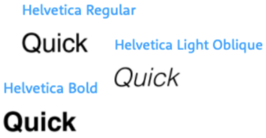
- triplet loss

We adapt their approach for our purpose

- not interested in classification of font identity
- but embedding and resulting characteristics space is our interest

Triplets of Faces

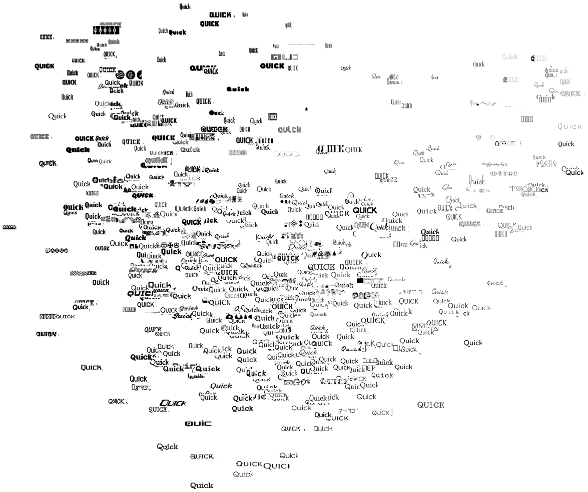
Triplets of Typeaces



Constructed Characteristics Space

128-dim space, projected in 2-dim for visualization

- each point corresponds to embedding of each font family



External Verification Using Word Embedding

Want to verify that visual attributes captured in the resulting embedding are relevant to economic agents' perception

"Perceived" attributes:

- tags assigned to each font family by font designers and consumers
- also high-dim: nearly 30,000 different words in the tags
  - e.g., curly, flowing, geometric, organic, decorative, contrast
- apply standard word embedding "Word2vec" (2-layer NN)

Show shape embeddings contains substantial info about word embeddings

- measured by mutual information
- industry-defined product category contains only limited info

III. Merger Analysis

Measures for Degree of Product Differentiation

We propose two measures for design differentiation:

1. Distance to "Averia": For image x_i of font i,

$$D_i^A \equiv \|f(x_i) - f_{averia}\|_2$$

   - $f(\cdot) \in \mathbb{R}^d$ is the embedding
   - f_{averia} is the average embedding of all font images

2. Gravity measure:

$$D_i^G \equiv -\sum_{j \neq i} \frac{1}{\|f(x_i) - f(x_j)\|_2}$$

   - cf. Hotelling's competition

Results are robust to the choice of measure

Causal Analysis of Merger

In June 2014, one of the major font foundries, FontFont, is acquired by Monotype

- Monotype (i.e., MyFonts.com) sells fonts from foundries it owns as well as third-party foundries
- and before the merger, FontFont has sold its fonts on MyFonts.com as a third party

FontFont Is Merged to Monotype

Monotype Inc.

myfonts.com

Monotype

FontFont (fontfont.com) ← FontFont (fontfont.com)

Linotype (linotype.com)

Bitstream

3rd Party Foundries:

FontFont (fontfont.com)

Effect of Merger on Product Differentiation

We study the causal effect of this merger on product differentiation decisions of the merging firm (FontFont)

- major channel for product differentiation is the design of fonts

The outcome of interest is the degree of design differentiation by each foundry

We take average of D_i^A or D_i^G of all new fonts created by a foundry in given period

Effect of Merger on Product Differentiation

Want to estimate how FontFont's design decision has changed by the merger

Challenges:

- only single treated unit (FontFont), multiple untreated (control) units
- difficult to find a single control unit that matches treated unit

Synthetic Control Method

Synthetic control method addresses these challenges:

- Abadie & Gardeazabal (2003), Abadie et al. (2010)

Compare treated unit with a "synthetic control unit"...

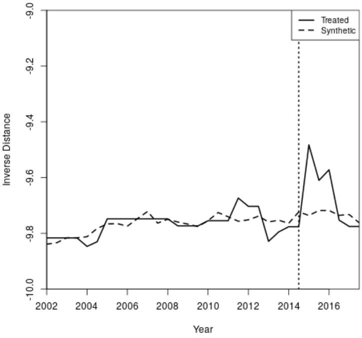
- = a weighted average of all control units

Weights W: estimated by minimizing $\|X_1 - \boldsymbol{X}_0 W\|$

- vector X_1: treated unit's observed characteristics (including pre-trt outcomes)
- matrix $\boldsymbol{X}_0$: control units' characteristics
- we use: embeddings (pre-trt), glyph count, sales, order count, age

Treated Unit vs. Synthetic Control

Trends of treated unit vs. synthetic control (left), vs. naive control avg. (right)



Estimated Treatment Effects

Years (After Merger)	2015/1–2015/2	2016/1–2016/2	2017/1–2017/2
Treatment Eeffect	0.107**	0.0576*	-0.019
p-value (block)	0.037	0.0741	1
p-value (all)	0.0022	0.0522	0.9978

* *p*-values above and in placebo tests (in the paper) are calculated using Chernozhukov et al. (2019)

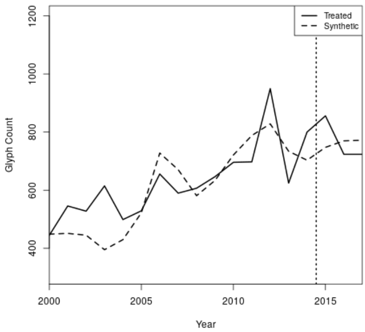
FontFont creates more experimental fonts (i.e., increases product variety), at least for two years

Possible reasons:

1. increases visual variety to diversify, as merger promotes efficiency
2. avoids cannibalization, i.e., competition of their own

Effects of Merger on Traditional Product Offering Measures

Glyph counts (left), and the number of new fonts (right)



Conclusions

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Consider simplest design product, fonts, and quantify shapes using deep neural network embedding

The resulting low-dim characteristics space can be a basis for various economic analyses

- its distance measures product similarity

Illustrate the usefulness with two economic analyses

- trend analysis of font style
- merger analysis with causal interpretation using synthetic control method

On-going projects

1. Product differentiation as spatial competition
2. Consumer's bundle choice and complementarity

Thank You