Momentous Brands

Finding New Value in WPP's Brand Asset Valuator (BAV)

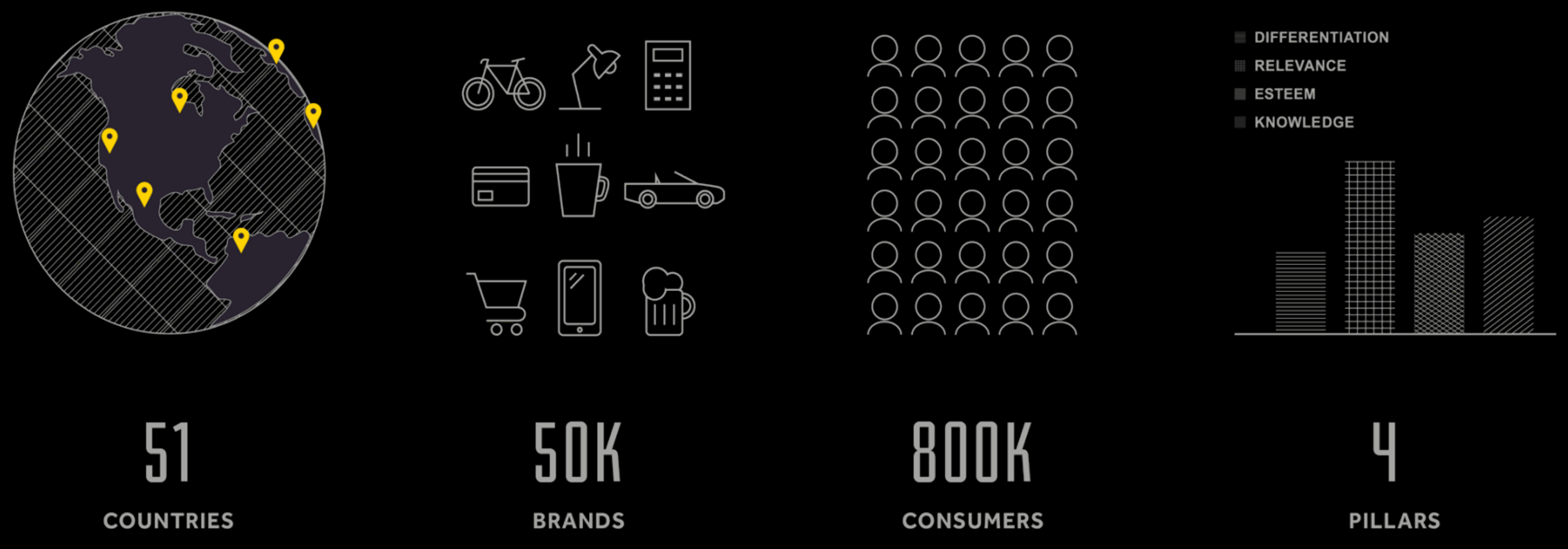
LANDOR & FITCH


“Products are made in the factory, but brands are created in the mind”
-Walter Landor

BRAND ASSET VALUATOR

Measuring what's in the mind

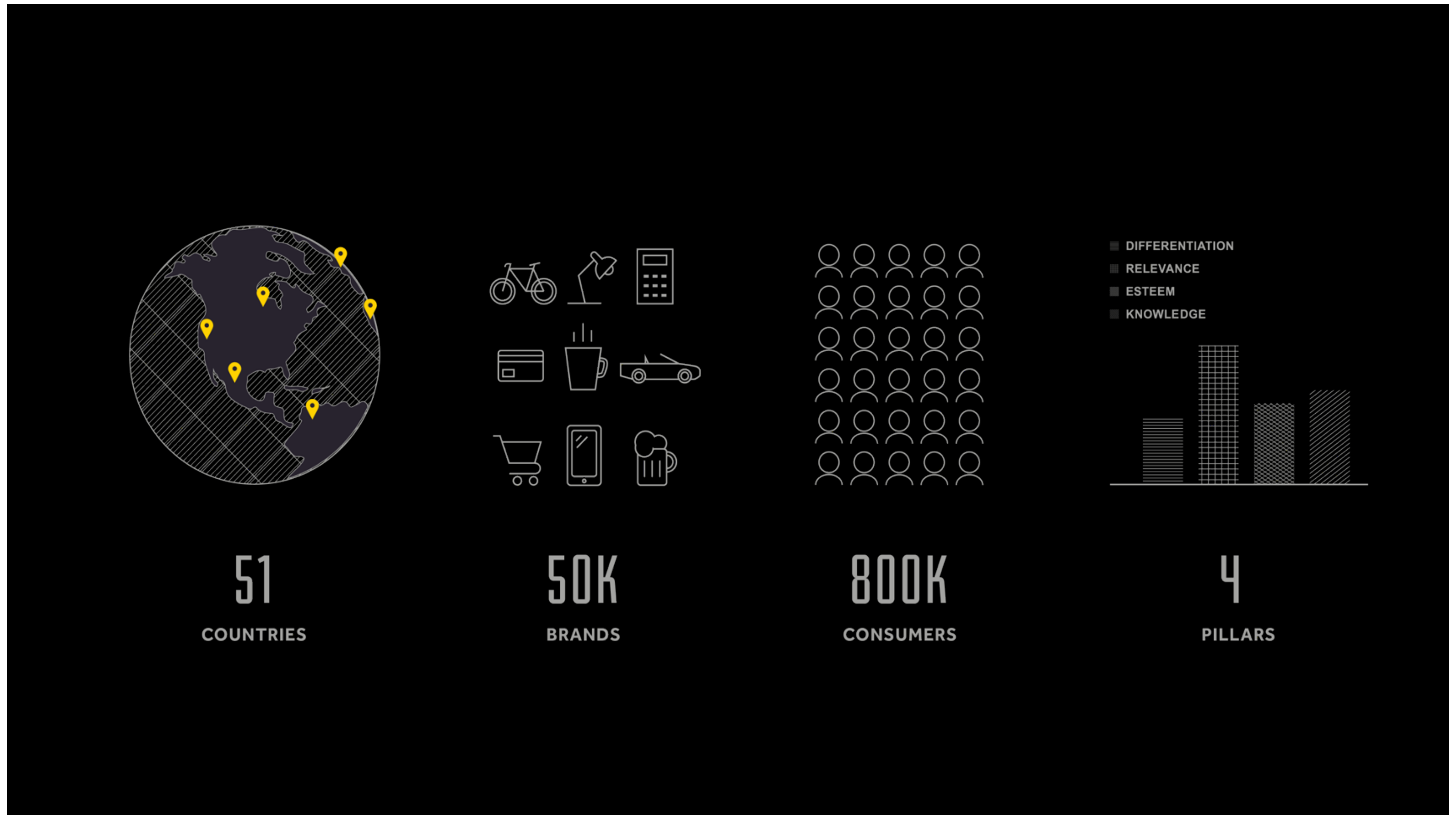
WPP's Brand Asset Valuator (BAV) tool has been tracking the shifting perception of brands in the minds of consumers annually since 1993. Grounded in psychology, the philosophy behind the study is that consumer relationships with brands can be defined similarly to those with people.



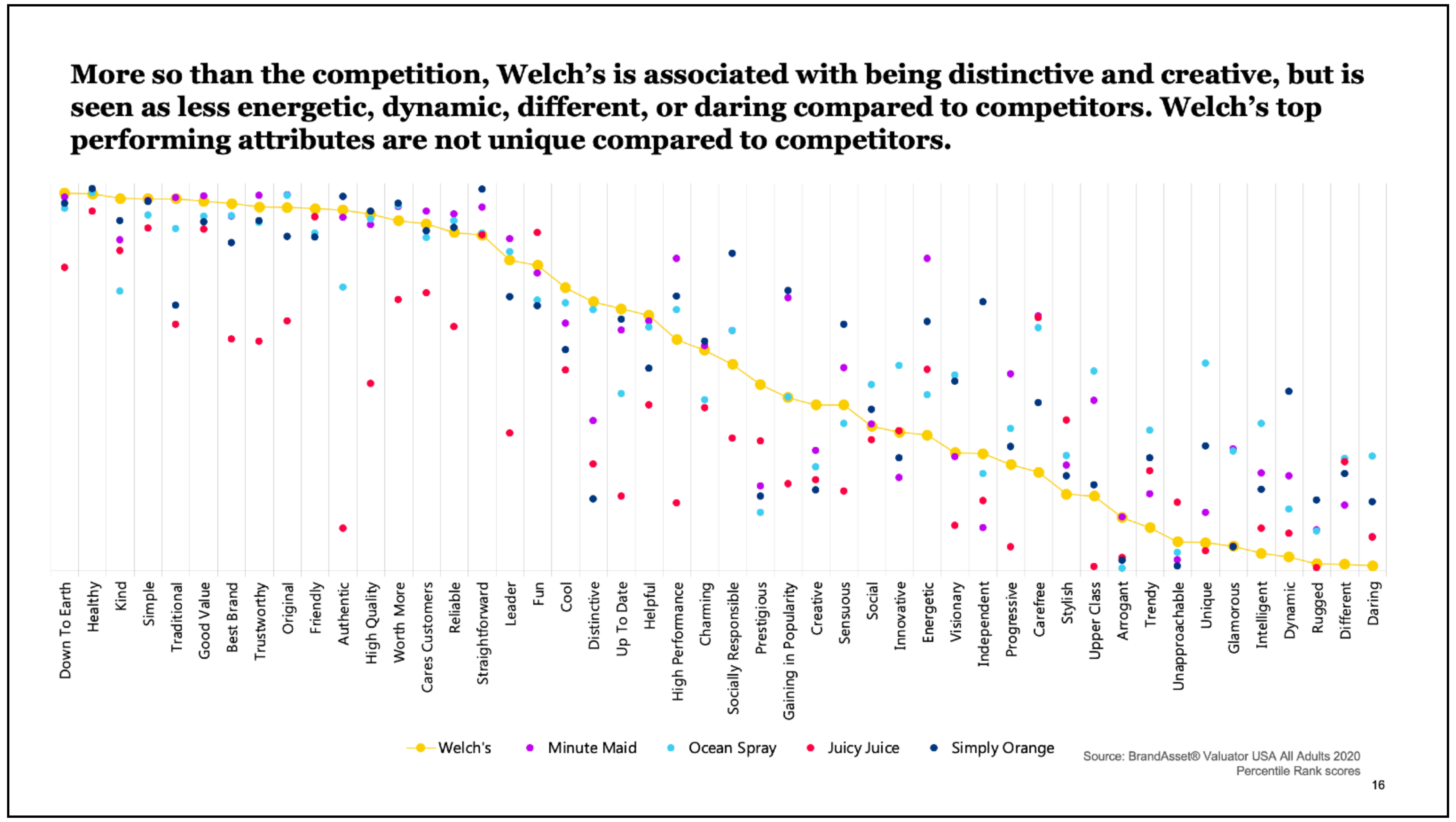
THE PROBLEM

Sounds impressive.
Feels overwhelming.

BAV ········· WTF?



How we sell it



How we share it

HYPOTHESIS

The data isn’t complicated. Our analysis is.

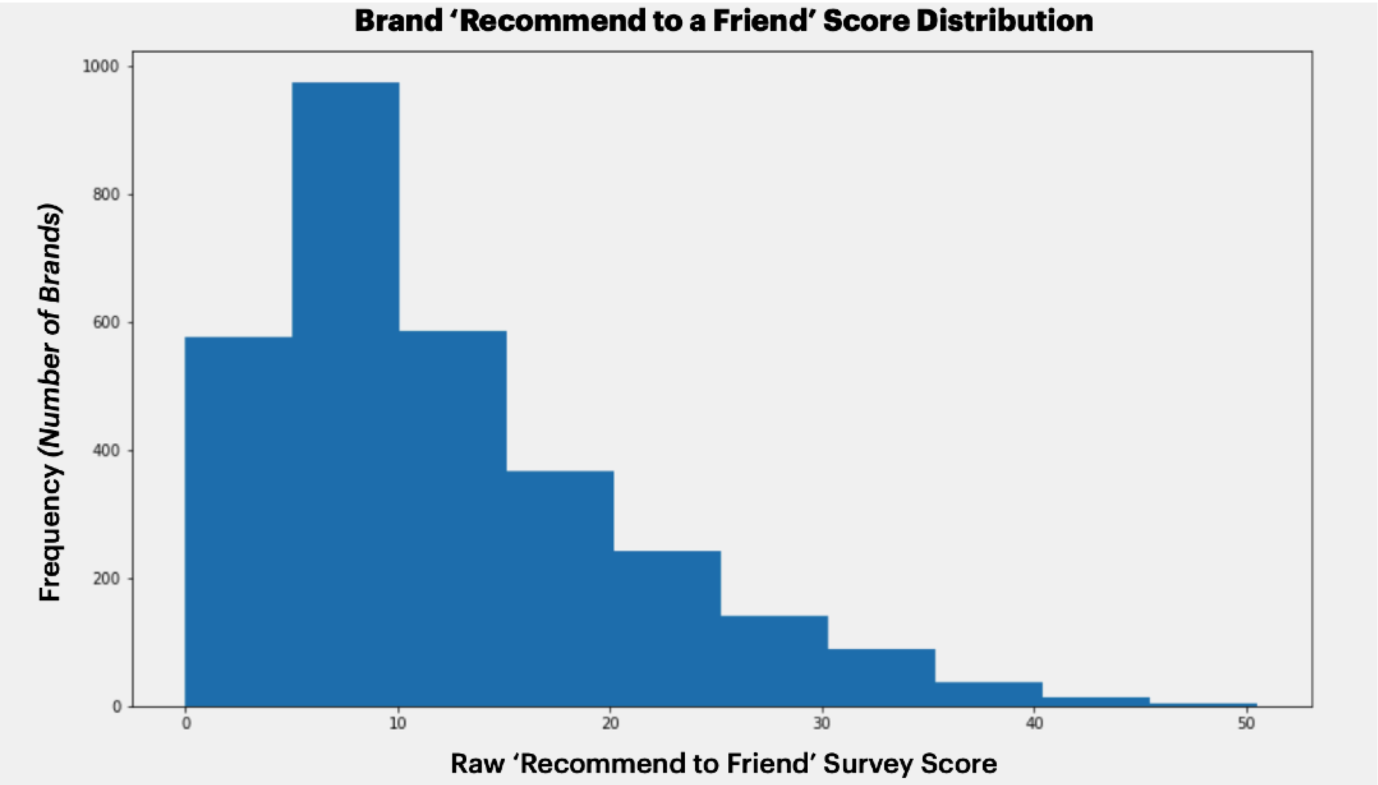
There’s additional business value within the BAV. Defining a new or simplified understanding of the attributes that most impact a brand’s strength in culture will:

- Help Landor & Fitch sell its services and demonstrate value to clients
- Lead to stronger and more actionable brand recommendations
- Impact how clients direct their brand strategies in the short term

APPROACH

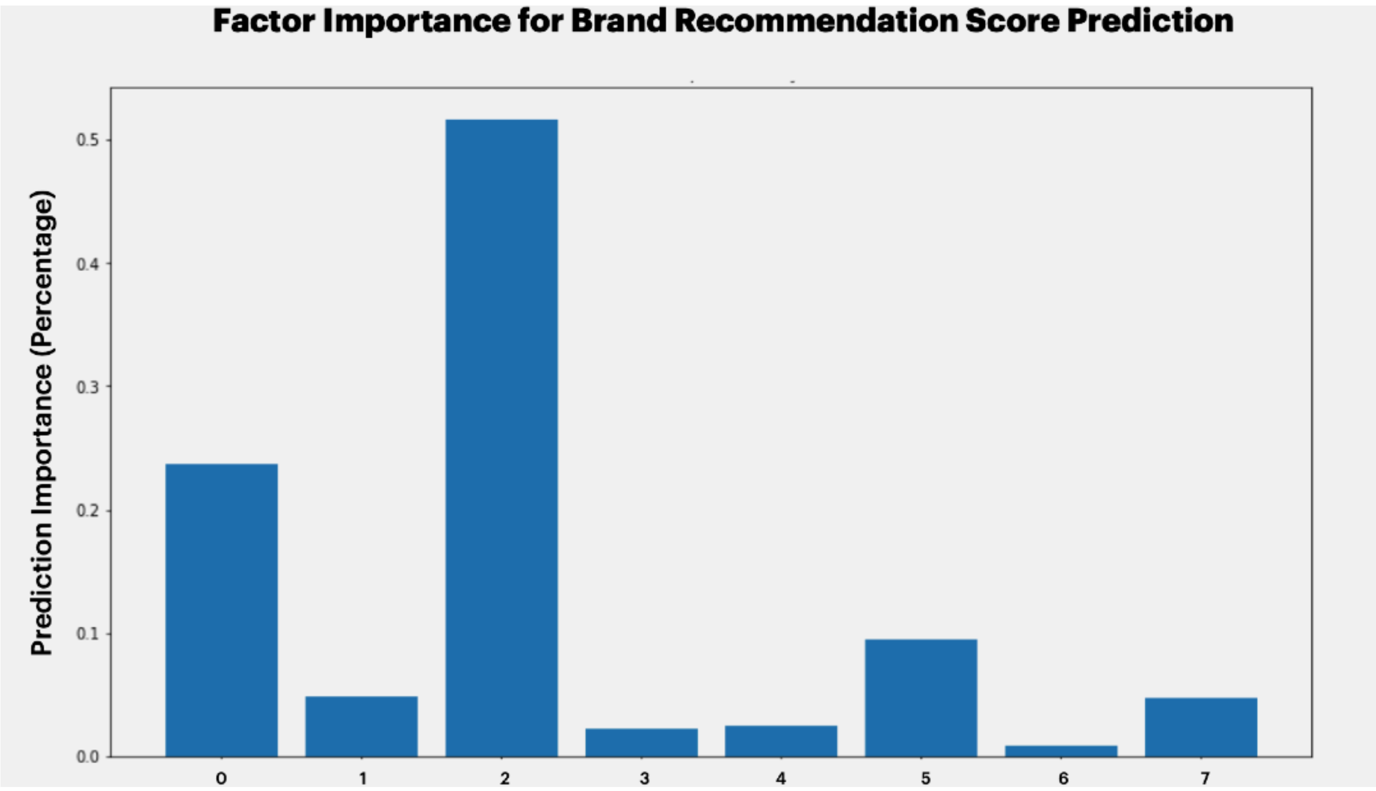
Three parts to a simplified BAV

1. Understand



Before diving deep, we need to understand what makes up brand strength. Here we use the likelihood to 'recommend the brand to a friend' as a proxy for strength and seek to understand any patterns that already exist in the data.

2. Reduce



Have you ever felt like there may be some overlap between the specific BAV attributes? How distinct visionary from innovative, for example? This exercise shrinks the 48 attributes into 8 distinct factors.

3. Predict

To test how accurate our simplified understanding is, we can model our ability to 'predict' a brand's recommendation score using its scores in for our eight factors. This exercise was conducted on 3600 BAV brands in the two most recent surveys.

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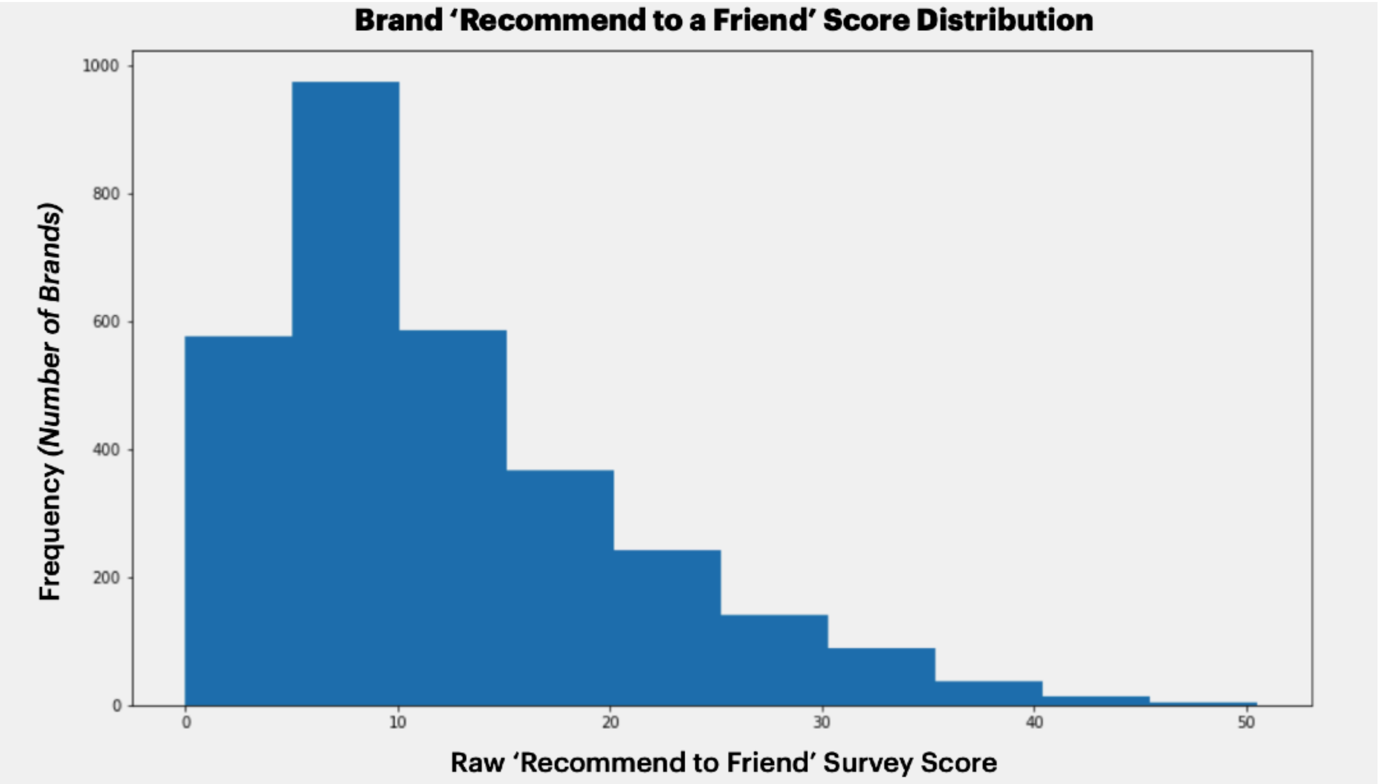

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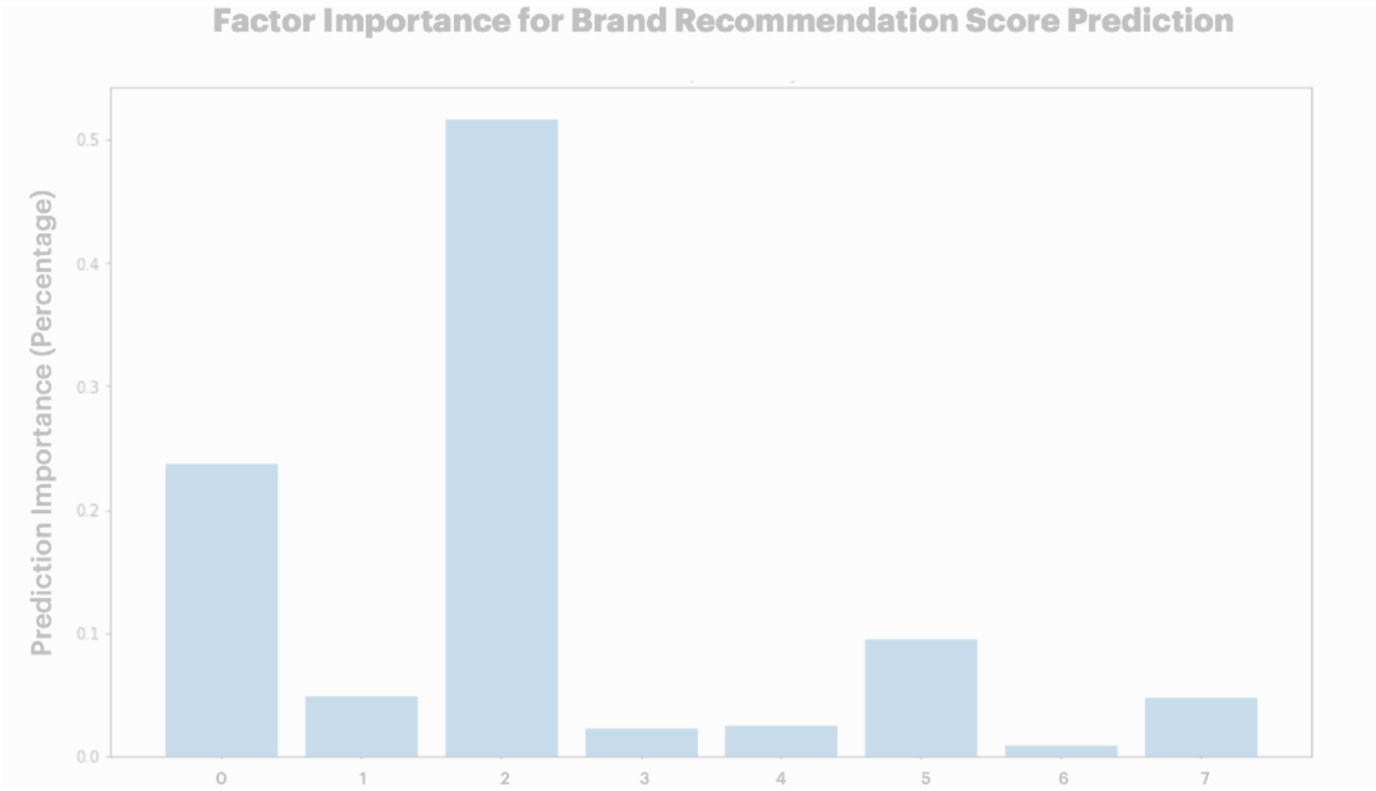

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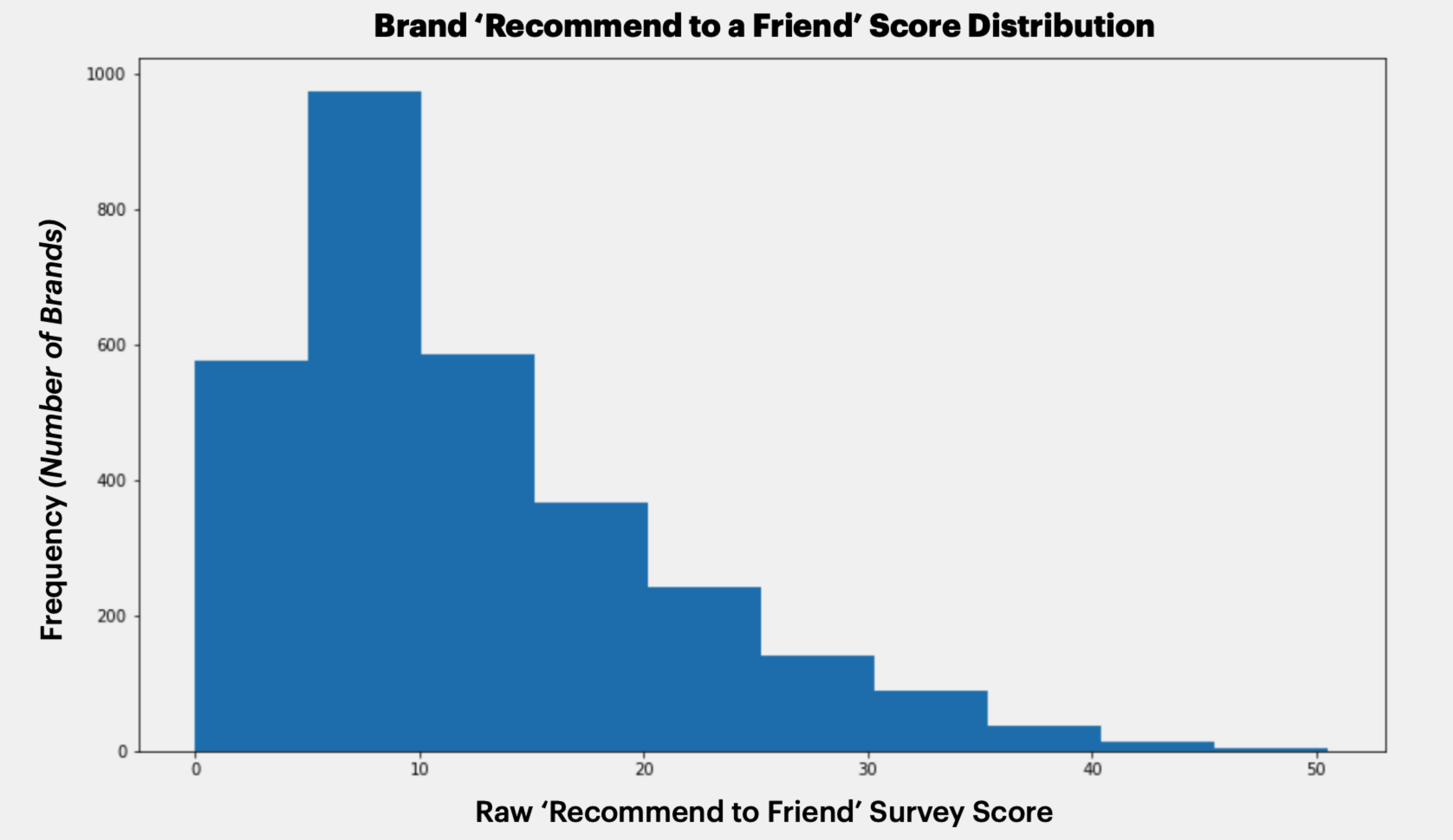
UNDERSTAND

The ‘raw’ truth

We’re used to communicating the percentile scores from BAV to our clients. However, that effort alone is skewing our understanding.

The breakdown of the raw scores tells a more nuanced story. The raw (unscaled) ‘recommend to a friend’ scores for example have a long tail to the right—**with the top percentile representing raw scores anywhere from 36 - 50.**



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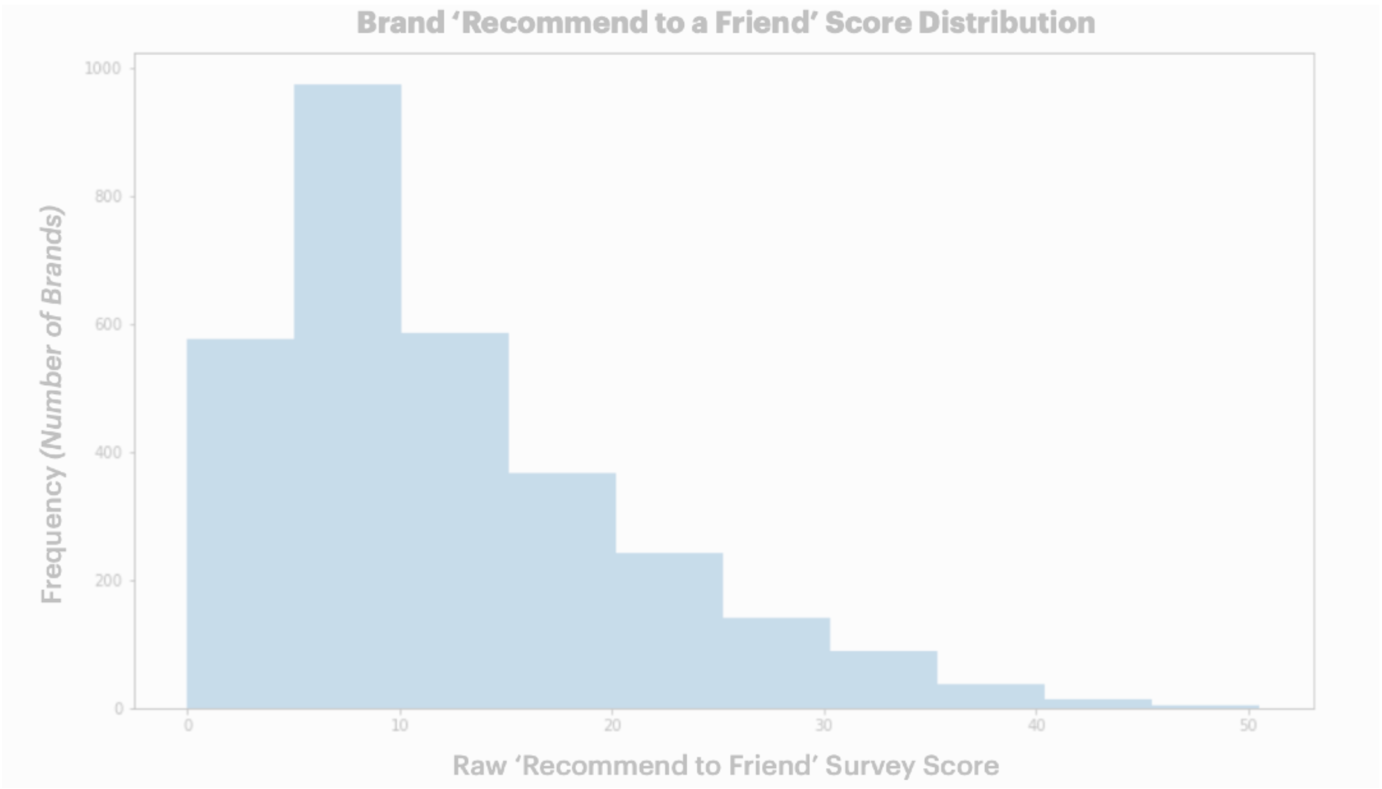

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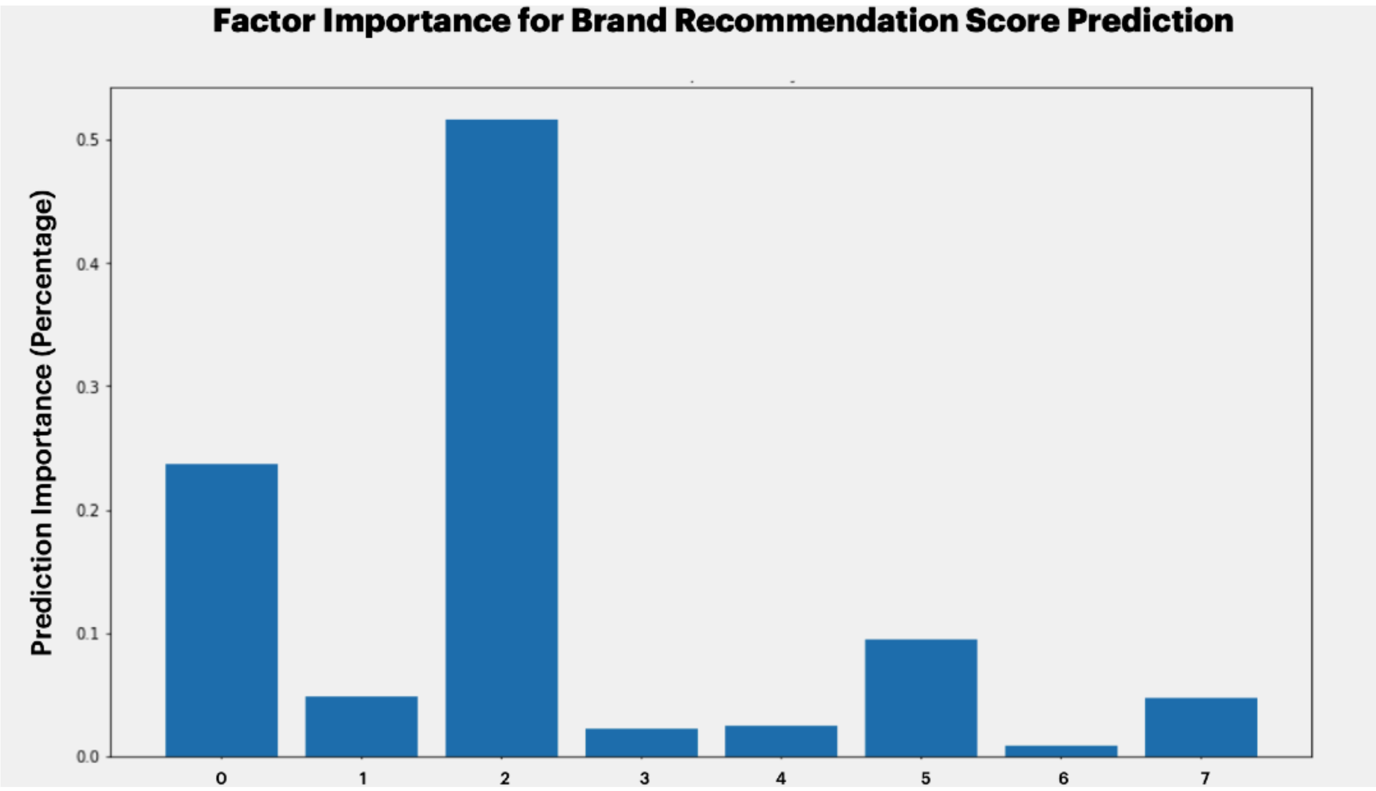

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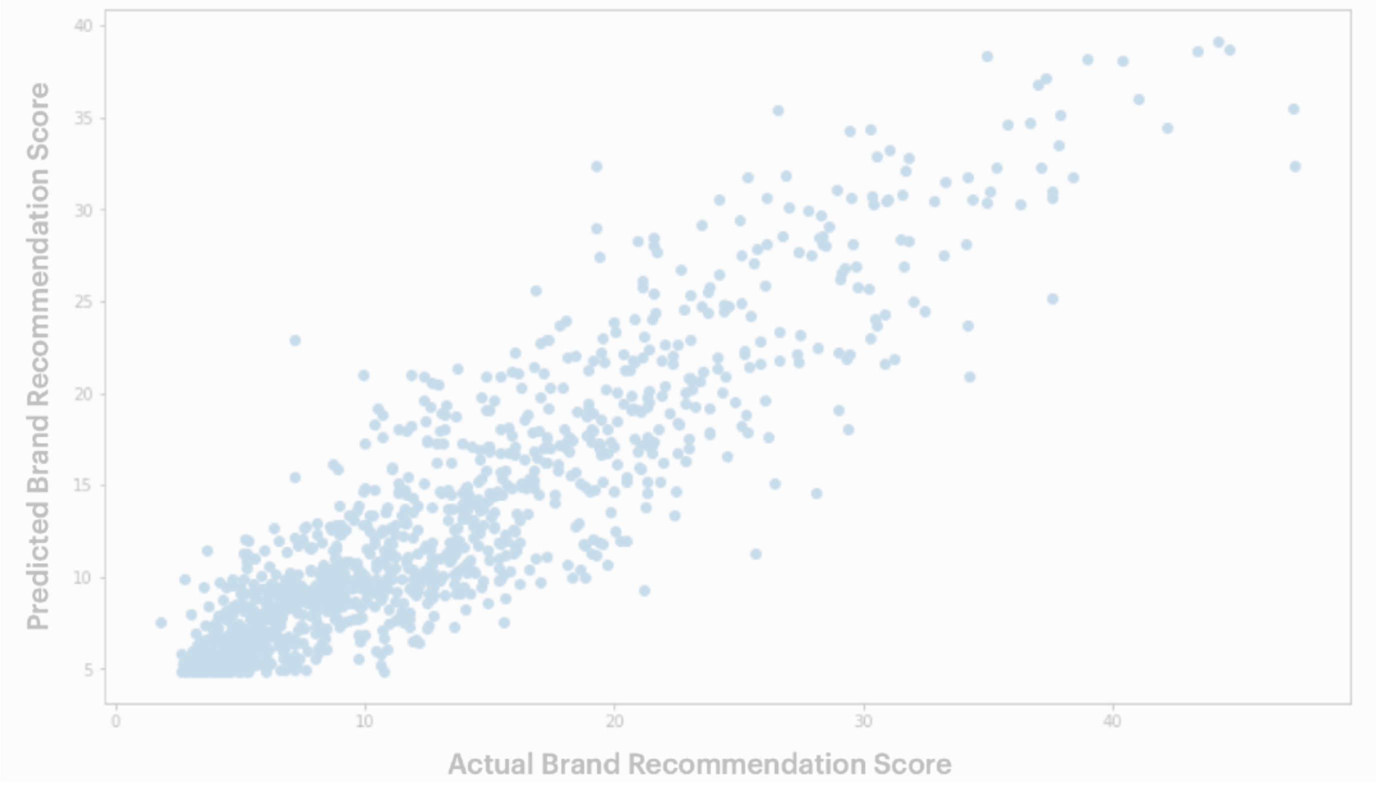

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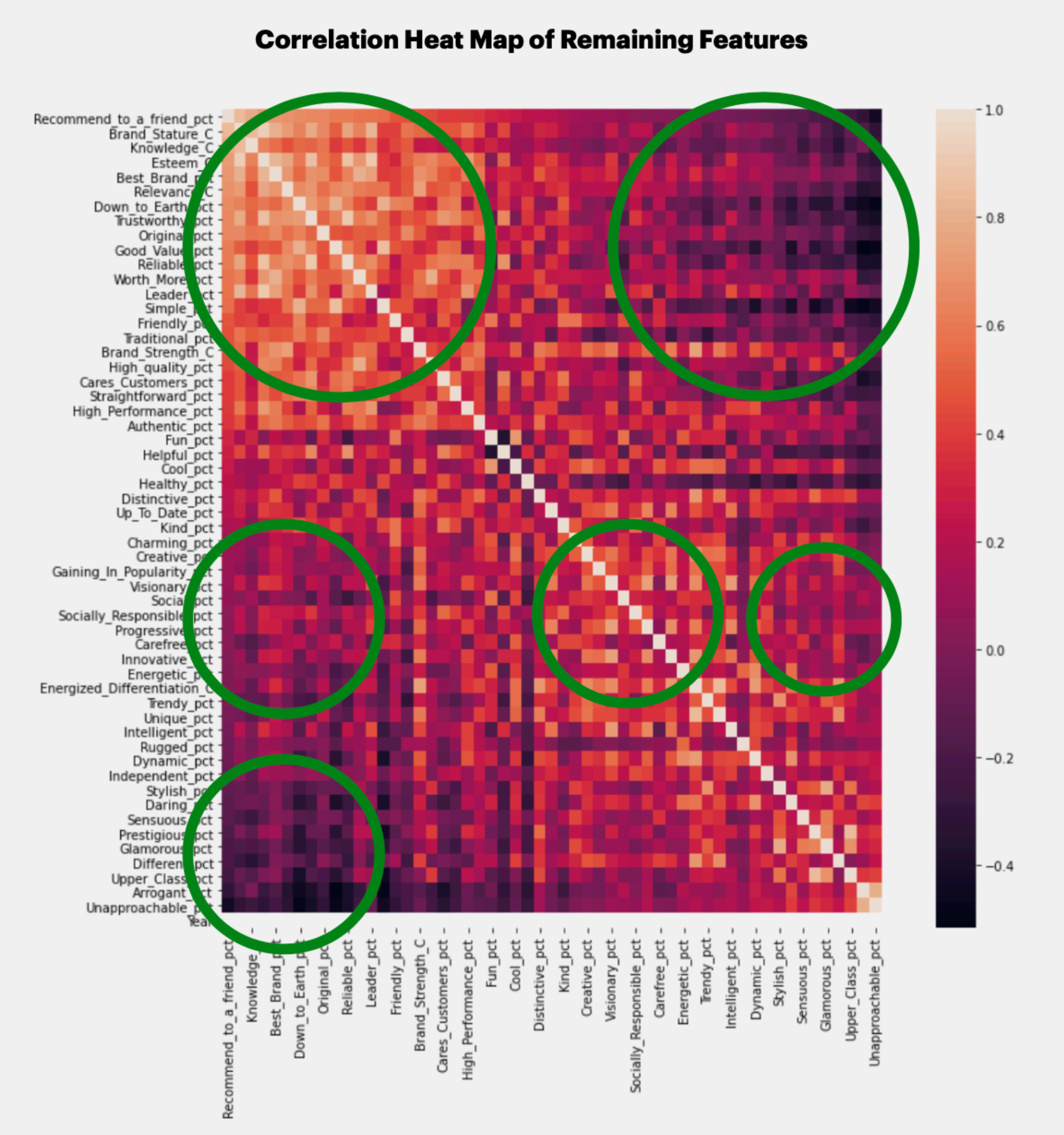
REDUCE

Attributes do group together

Plotting and sorting the correlation of the 48 brand attributes suggested that there is some redundancy among the BAV attributes.

Statistically, it's important to eliminate as much of that overlap as possible, by grouping or clustering these attributes together. And practically, it's worth the effort to make sense of what those groupings (factors) may be.

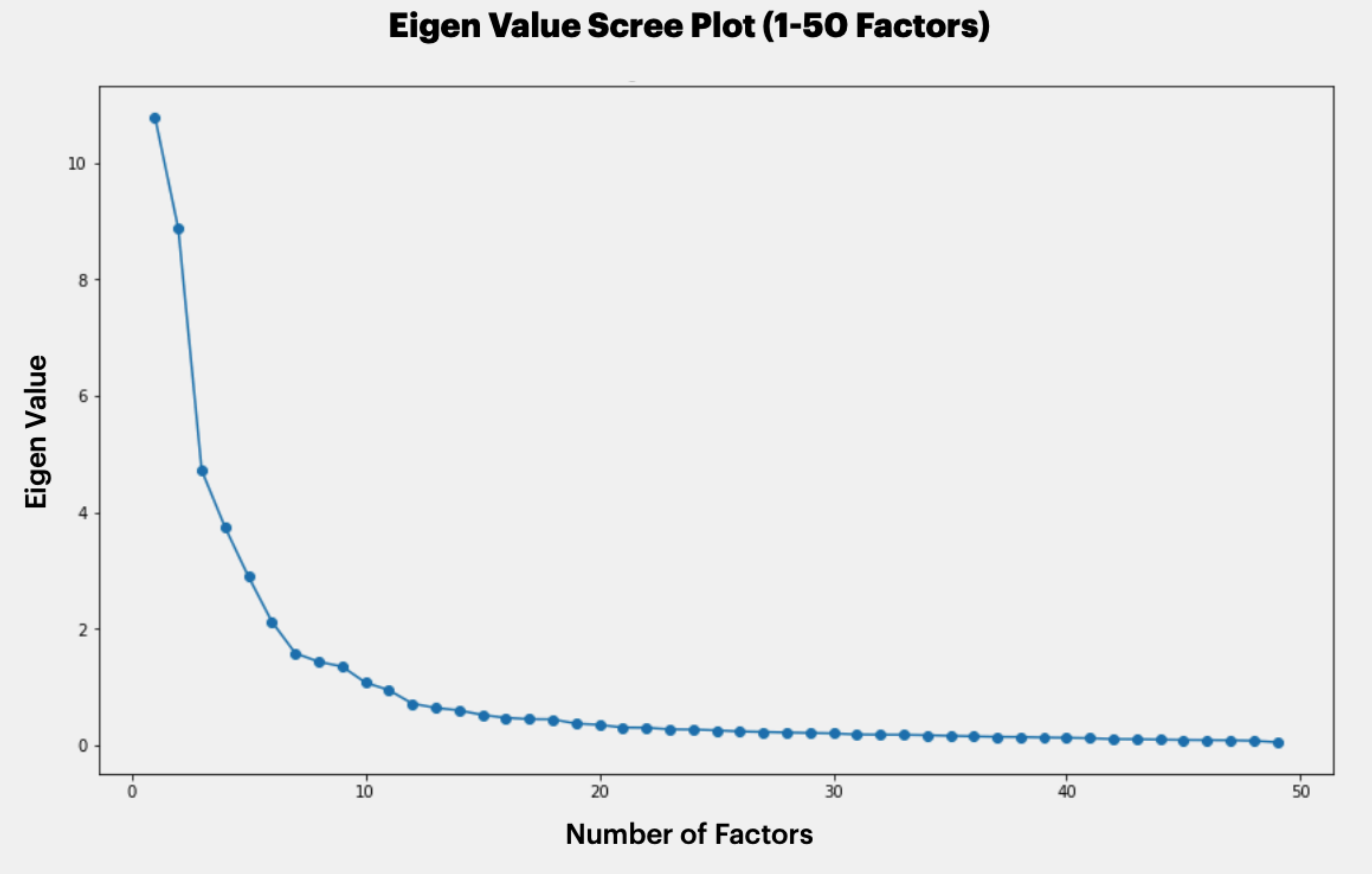


REDUCE

Taking BAV from 48 - 8

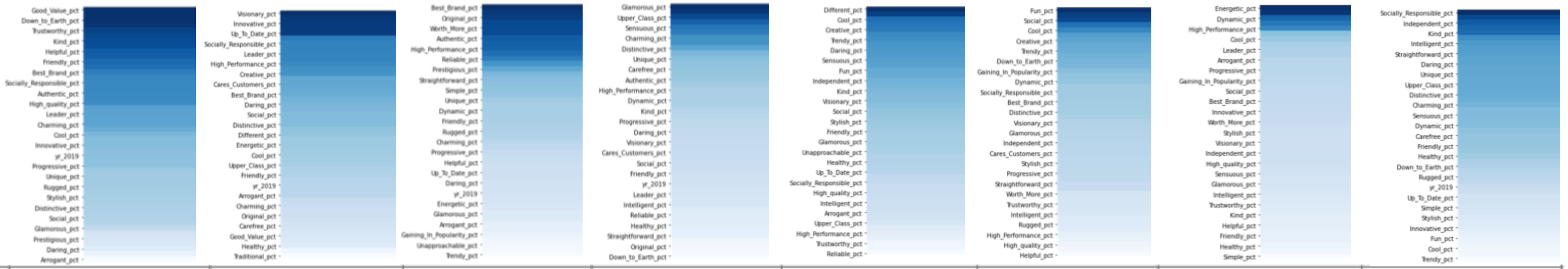
While a few types of clustering methods were conducted, factor analysis proved the most beneficial for our work as it retained an understanding of the underlying makeup of each grouping.

Arriving at the number 8 was a bit science and a bit art. The science suggested 10 factors as a starting point, but digging into the makeup of each, suggested that there were really 8 distinct factors explaining about ~70% of the variance

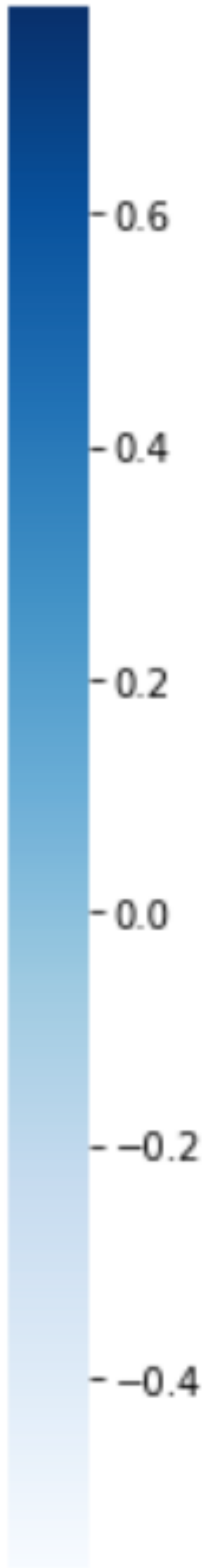


REDUCE

The big 8



Factor	0	1	2	3	4	5	6	7
Attr 1	Good Value	Visionary	Original	Glamorous	Different	Fun	Energetic	Socially Responsible
Attr 2	Down to Earth	Up to Date	Worth More	Stylish	Cool	Social	Dynamic	Independent
Attr 3	Cares for Customers	Innovative	Best Brand	Upper Class	Creative	Cool	High Performance	Kind
Attr 4	Kind	Intelligent	Traditional	Distinctive	Trendy	Friendly	Rugged	Intelligent
Attr 5	Reliable	Leader	Authentic	Sensuous	Carefree		Daring	
Attr 6	Friendly	Socially Responsible						
NOT	Arrogant		Trendy	Down to Earth	Reliable			
Name	***Approachable***	***Progressive***	***Timeless***	***Prestigious***	***Free-Spirited***	***Charismatic***	***Powerful***	***Thoughtful***



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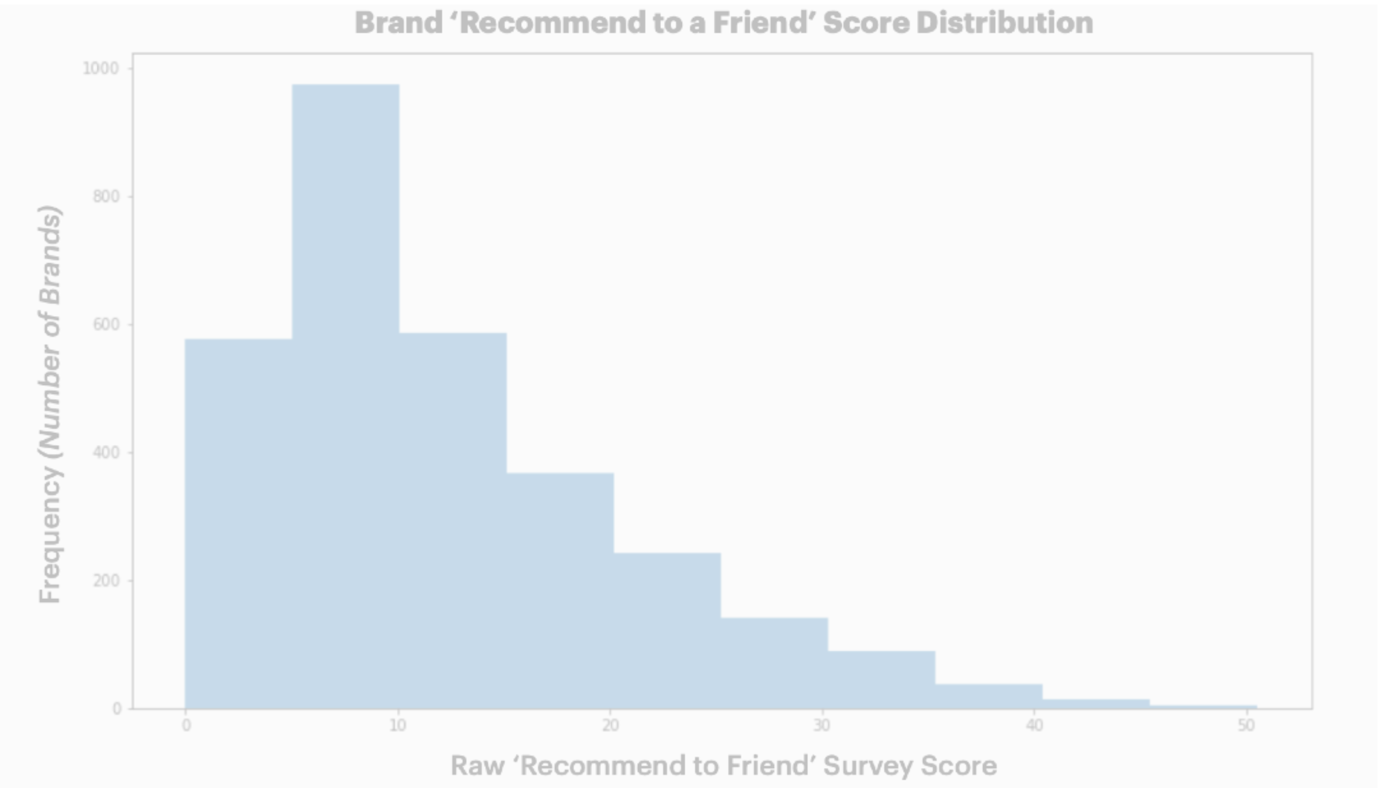

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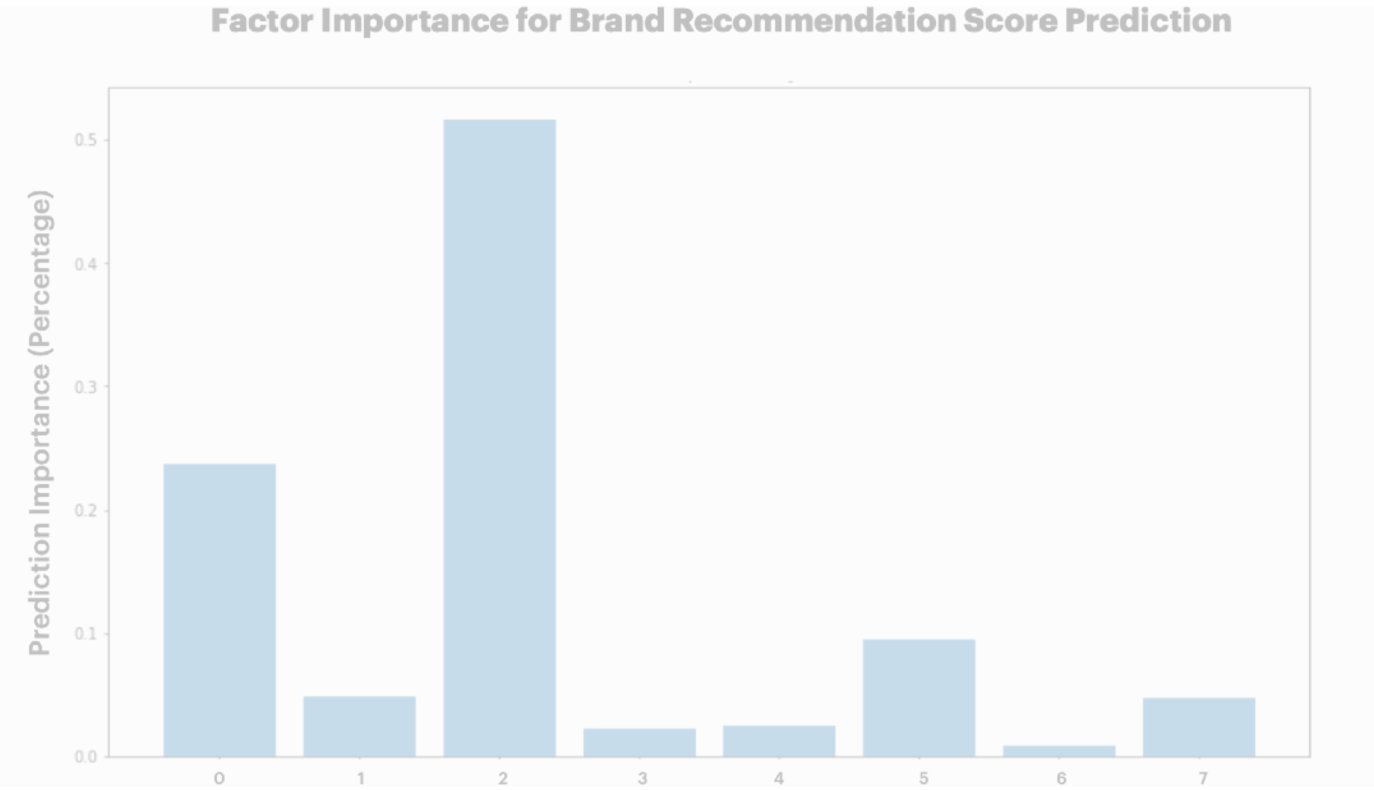

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PREDICT

‘Training’ a ‘model’

The importance of training a model is understanding how well it performs on unseen or unknown data.

In our case, this was done by testing a handful of architectures and fine tuning the most performative model. The accuracy of the model is measured by holding back 20% of the brands in the dataset, and using them to ‘predict’ their recommendation scores.

The final random forest model used our big 8 brand factors and resulted in an 81% Validation Score (R^2) and a Mean Absolute Error of 2.67 points.

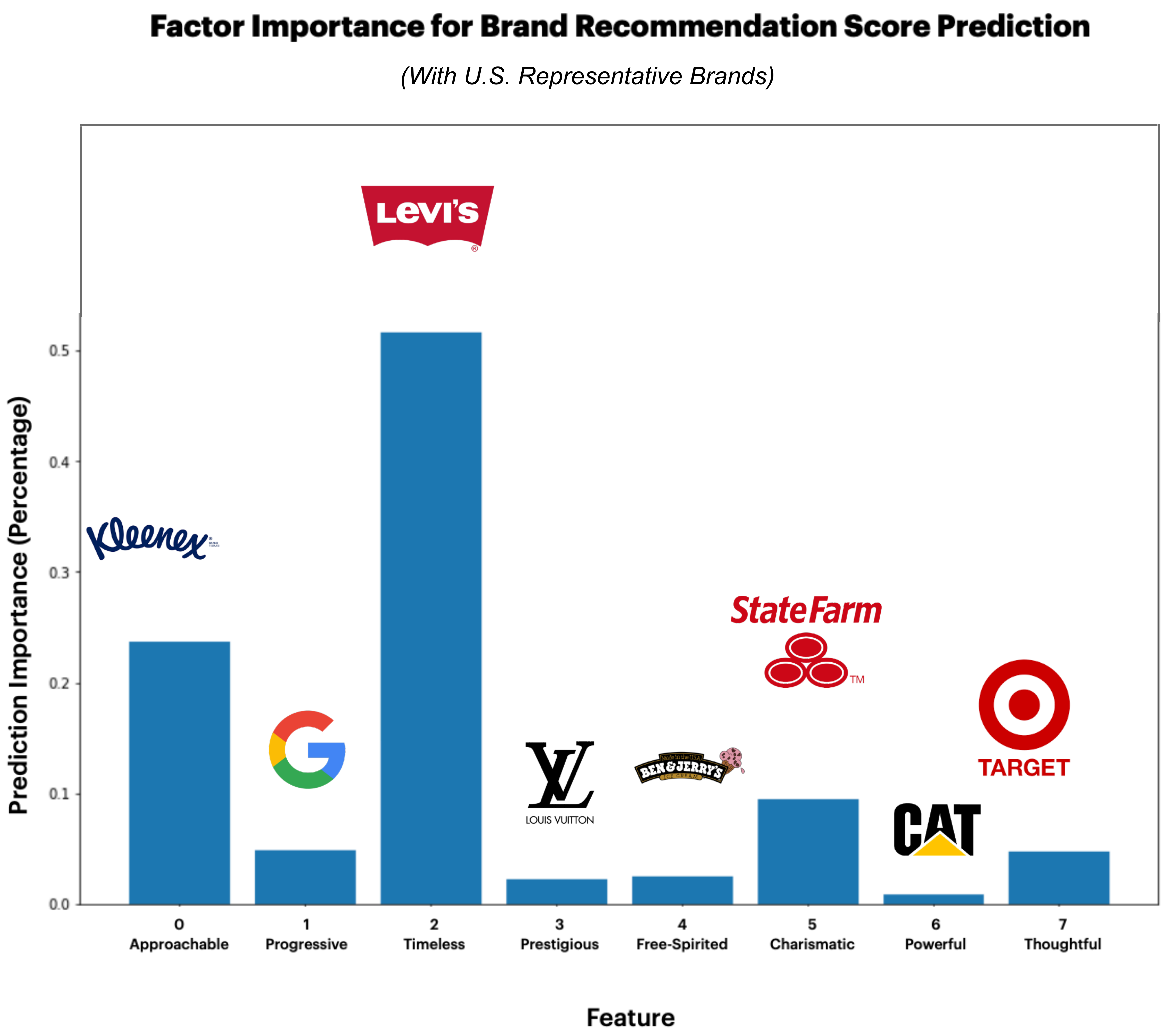
Hand Tuned Random Forest Model
Predicted Brand Recommendation Score vs Actual

Optimization Method	Train Score (R^2)	Validation Score (R^2)	Mean Squared Error	Mean Absolute Error
Baseline	0.9716	0.7938	15.94	2.78
Random Search	0.9729	0.7956	15.78	2.77
Bayesian	0.8102	0.7709	16.62	2.95
Hand Tuned (Grid Search)	0.8945	***0.8141***	12.51	***2.67***

IN PRACTICE

What this means in practice

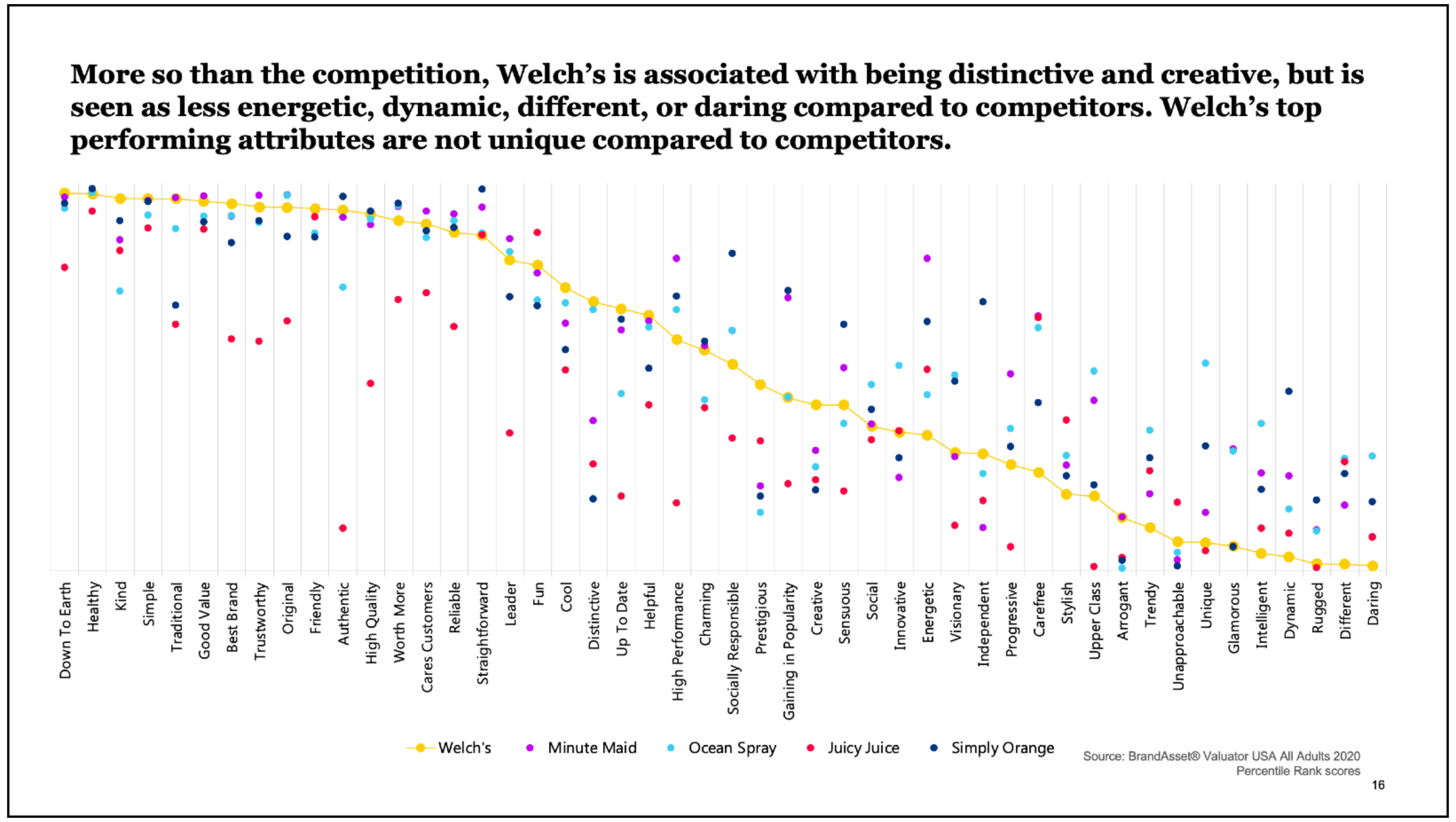
We can communicate a brand's perceived strength in culture in a quicker and more intuitive way—for our clients and ourselves.



IN PRACTICE

Where we started.
Where we ended.

WTF? .... **NOW**



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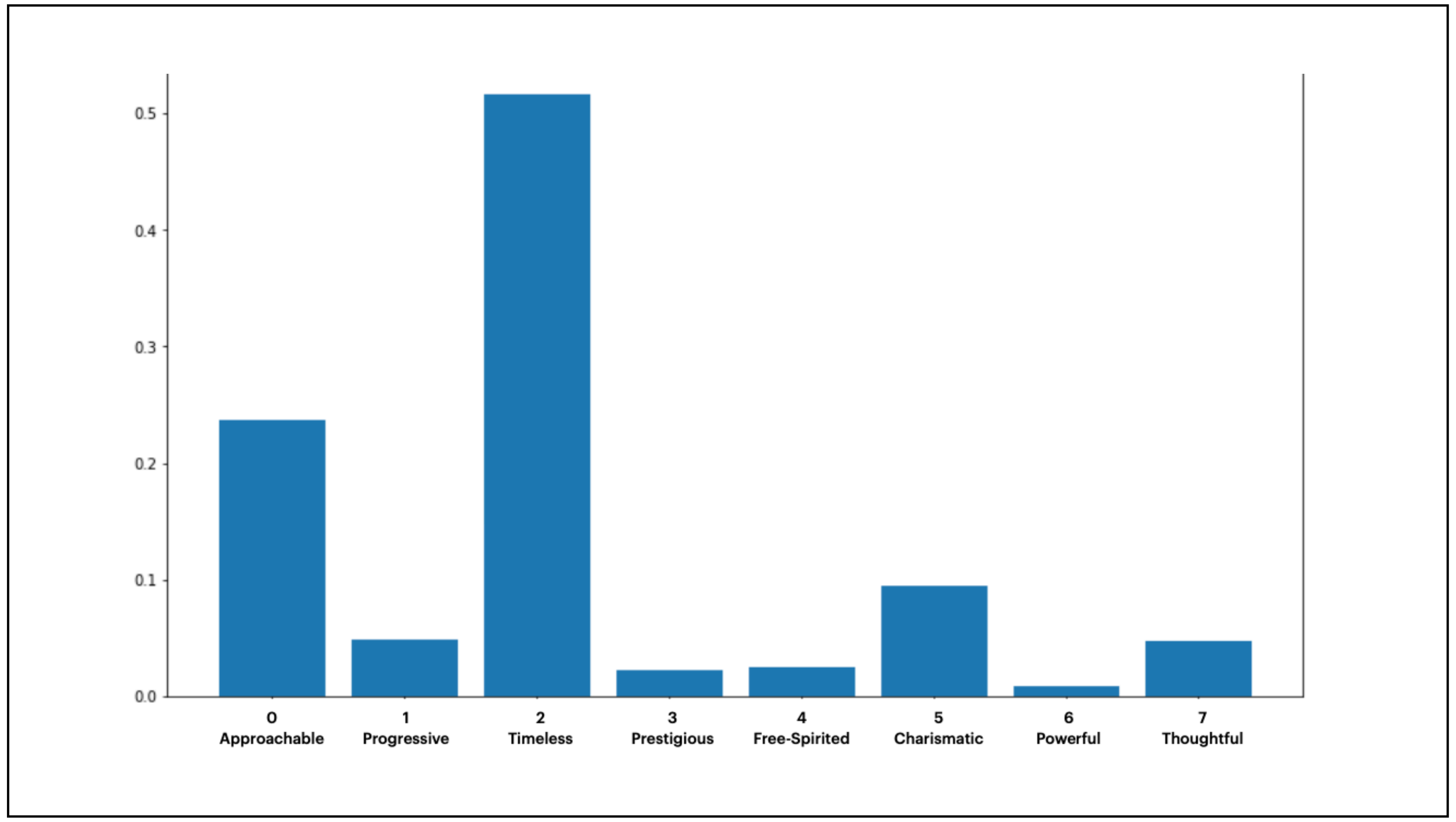

Where we ended

Thanks.

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