Momentous Brands

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

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Springboard Jan '21 Cohort
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> “ Products are made in the factory, but brands are created in the mind. ”
>
> *-Walter Landor*

Background

Brands exist all around us. While not tangible, their value does change over time. Companies and brand owners measure this value in the form of consumer perception. Just like the stock market, every news report, customer interaction, and celebrity tweet has the power to impact a brand’s perceived value. Unlike the stock market, this perceptual change isn’t tracked every day but rather once per year.

This annual brand perception data is known as the Brand Asset Valuator (BAV) survey. This 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 study quantifies this relationship by ranking brands among 48 common personality attributes: things like ‘kindness,’ ‘uniqueness,’ ‘authenticity,’ and ‘trendiness.’ This framework allows for a category agnostic view of brands. For example, an attribute like ‘kindness’ can be compared apples-to-apples for a shoe retailer, hotelier, phone network, and bank.

BAV is viewed as a veritable goldmine of consumer data—tracking the perception of 57,000 brands across 50 global markets—and is in fact the largest quantitative consumer study of brands in the world. To my client and employer, Landor & Fitch, the world’s largest brand consultancy, BAV plays an important role in its work for current and prospective clients. It is so important that it has garnered over 160 million investment dollars from the company since its inception. However, even with all of that investment, the survey’s 48 attributes make reports of the data complex to interpret, explain, and understand. And when you’re in the business of communication, the understandability of your recommendations is everything.

Goal & Objectives

The goal of this work is to identify additional business value within the BAV by defining a new or simplified understanding of the attributes that most impact a brand's strength in culture. A more interpretable BAV will:

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

Data and Scope

This analysis focuses solely on the last 2 years of BAV data. The data is limited to the United States study only, which consists of about 3,500 brands. The data are collected via online or pen-and-paper surveys with 1.9 million consumers. The study tracks consumer sentiment on brands, usage, and advocacy. Each of these attributes are reported in the dataset as both raw and scaled (percentile) values. The target variable of the dataset is a brand's "Recommend to a Friend" score—a BAV attribute used as a proxy for brand strength.

Summary of Results

Factor analysis was conducted to reduce the dataset's dimensionality. This reduced the 48 brand character features down to 8 factors. Four regression models, SGD, Random Forest, Lasso Regression, and XGBoost were then fit on the reduced dataset (Table 1). The Random Forest model proved to be the most performative against the key metrics of Validation Score & Mean Absolute Error (Table 1).

Table 1. Initial results of four regression models

Model	Train Score (R^2)	Validation Score (R^2)	Mean Squared Error	Mean Absolute Error
SGD	0.7063	0.6783	24.87	3.56
Random Forest	0.9716	***0.7938***	15.94	***2.78***
Lasso Regression	0.7068	0.6783	24.87	3.55
XGBoost	0.9691	0.7194	22.51	3.45

Thusly, The Random Forest model was taken into further optimization. A large discrepancy between the Baseline (default) model's Train Score and Validation Score suggested the model may be overfitting to the training data. To solve for this finding, the model was put through parameter tuning (Table 2).

Table 2. Parameter tuning results of the Random Forest Regression model

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***

All of the optimization methods were run a dataset that excluded the '0' target value observations. The absent data led to prediction anomalies observed during the visualization of the initial Random Forest model (Figure 6). Overall, the hand tuned Random Forest model using a grid search method was the most performative model on both key metrics.

Data Wrangling

The original brand datasets contained ~3600 rows and 185 columns each for 2017, 2018 & 2019. The decision was made to focus only on the 2018 and 2019 brand perception datasets because of inconsistent attributes between 2017 and the following years.

For the 2018 and 2019 datasets, the following changes were made to clean the information. Duplicate brands (those appearing in multiple sectors) were reconciled, whitespaces in Brand IDs were stripped, and approximately 30 null columns were deleted. The only imputation made on the dataset was for one missing sector value (WeLive). This company's sector was manually imputed using domain knowledge to 'Travel & Entertainment' which matched the observation both above and below.

The end state of the data at this stage was one data frame for 2018 and one data frame for 2019. Each set contained 155 columns and ~3400 observations. Brands not present in both years were observed and retained.

Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted on the raw, 'pct' columns of the BAV data. This measure was selected because it displayed truer variability from year-to-year than the percentile scores. Additionally, this measure further reduced the number of features in the dataset from 155 to 58. The data was then scaled to be representative of the survey responses with all remaining features stored as floating point values ranging between 0-100.

The target variable was likelihood to 'Recommend [the brand] to a Friend' as a proxy for brand strength. In the BAV dataset, these value scores ranged from 0 to 50.5 (Figure 1).

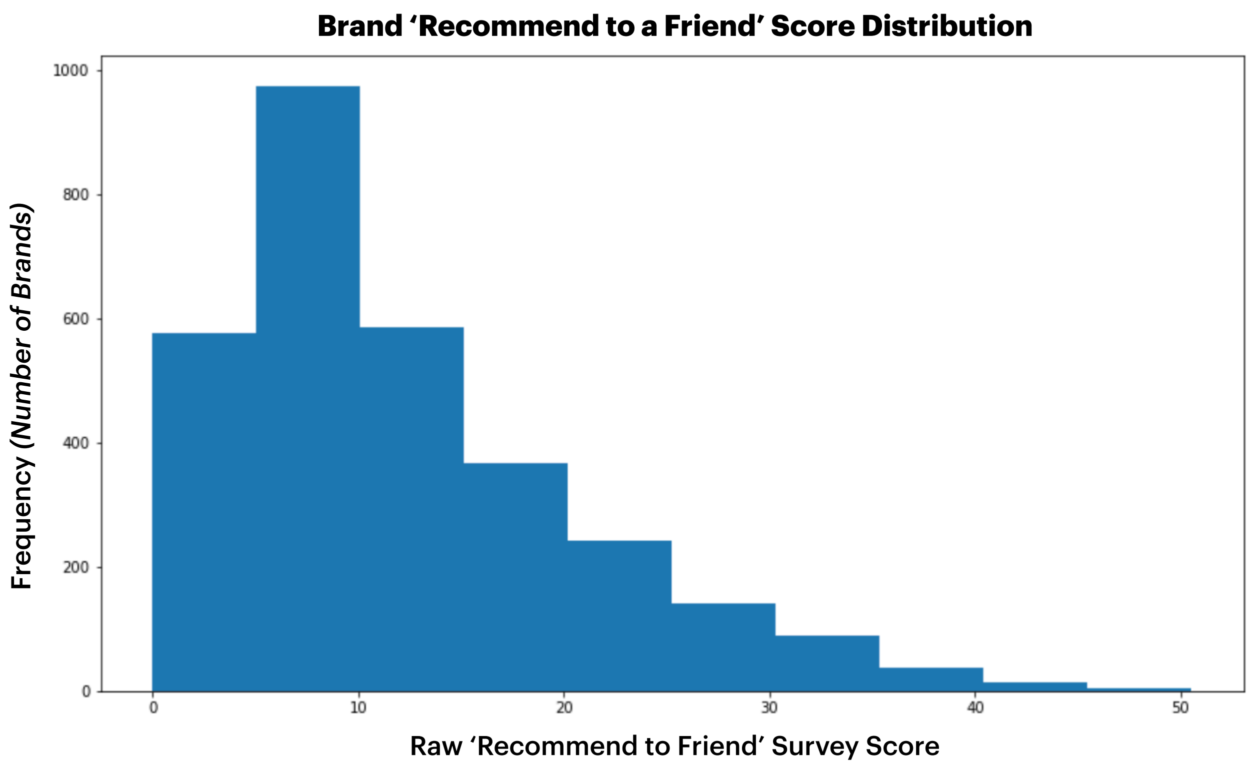

Figure 1. Distribution of Brand 'Recommend to a Friend' Scores

Correlation between features was evaluated next. It was hypothesized that many of the 55 remaining features would move together (Figure 2) resulting in groupings or clusters identifiable through heat-mapping a correlation plot (Figure 3).

Pair Plot Correlation of Key Features

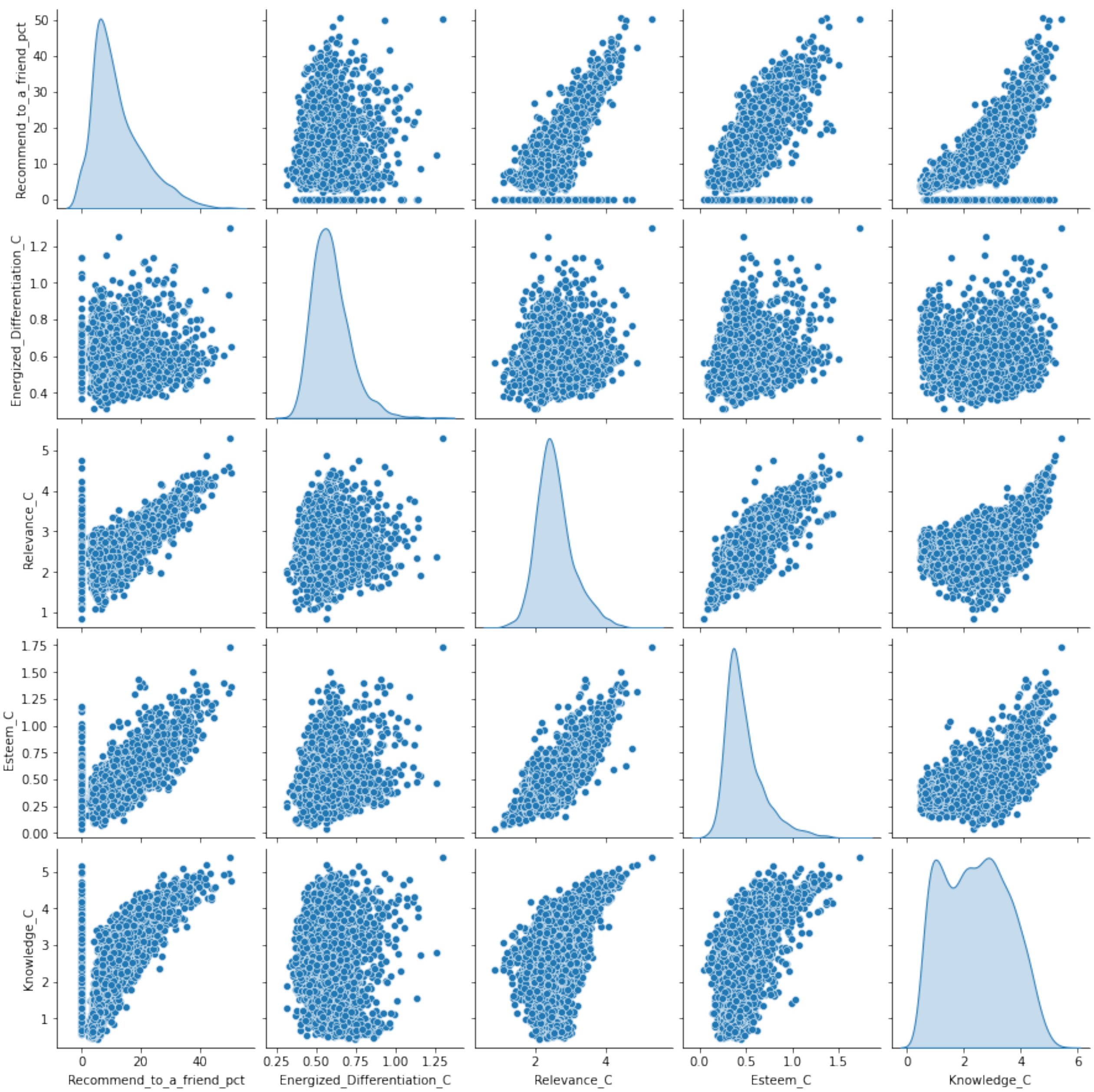

Figure 2. Pair Plot Correlation of Key Features (KDE density plot on the diagonal)

Correlation Heat Map of Remaining Features

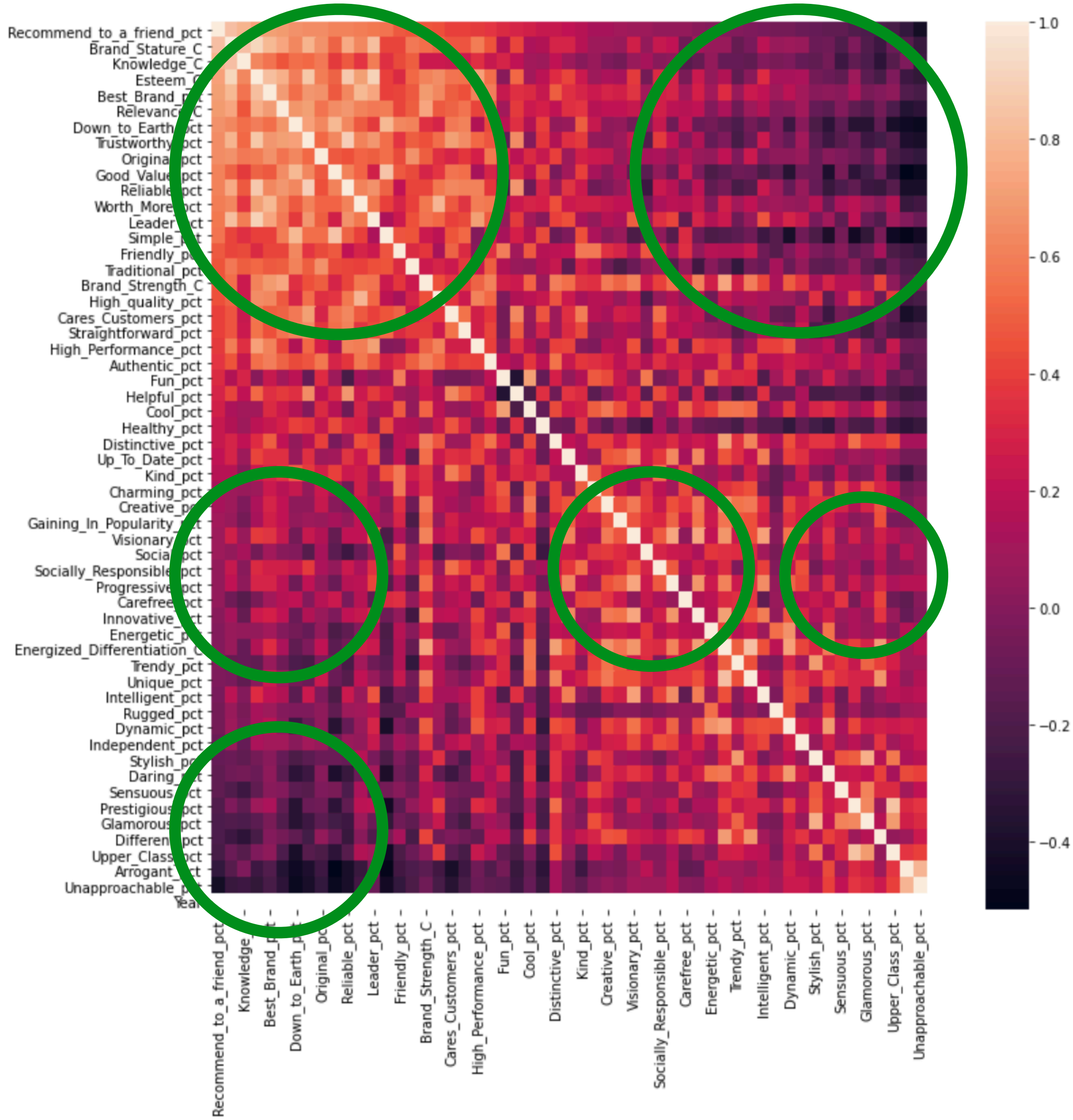

Figure 3. Correlation Heat Map of Remaining Features *(Sorted by Correlation with Target Variable)*

Seen in Figure 3, the groupings circled in green show that there are a number of feature clusters that correlate similarly with the target variable. The results of the observed correlation suggested there was potential for further dimensionality reduction in an effort to reduce the number of features and to better understand them.

Dimensionality Reduction

Principal Component Analysis (PCA) was performed in an attempt to reduce dimensionality. PCA explained more variance in the dataset; however, reporting on data in this form would be difficult to explain and impossible to interpret. As a result, the components were abandoned in favor of Factor Analysis.

Factor Analysis was performed on the original, unscaled data. The parameter of 10 was initially selected by plotting a scree plot of the Eigen values and using the elbow method to identify 10 factors with significance, defined as Eigen values >1 (Figure 4). This explained about 71% of the variance with 10 factors.

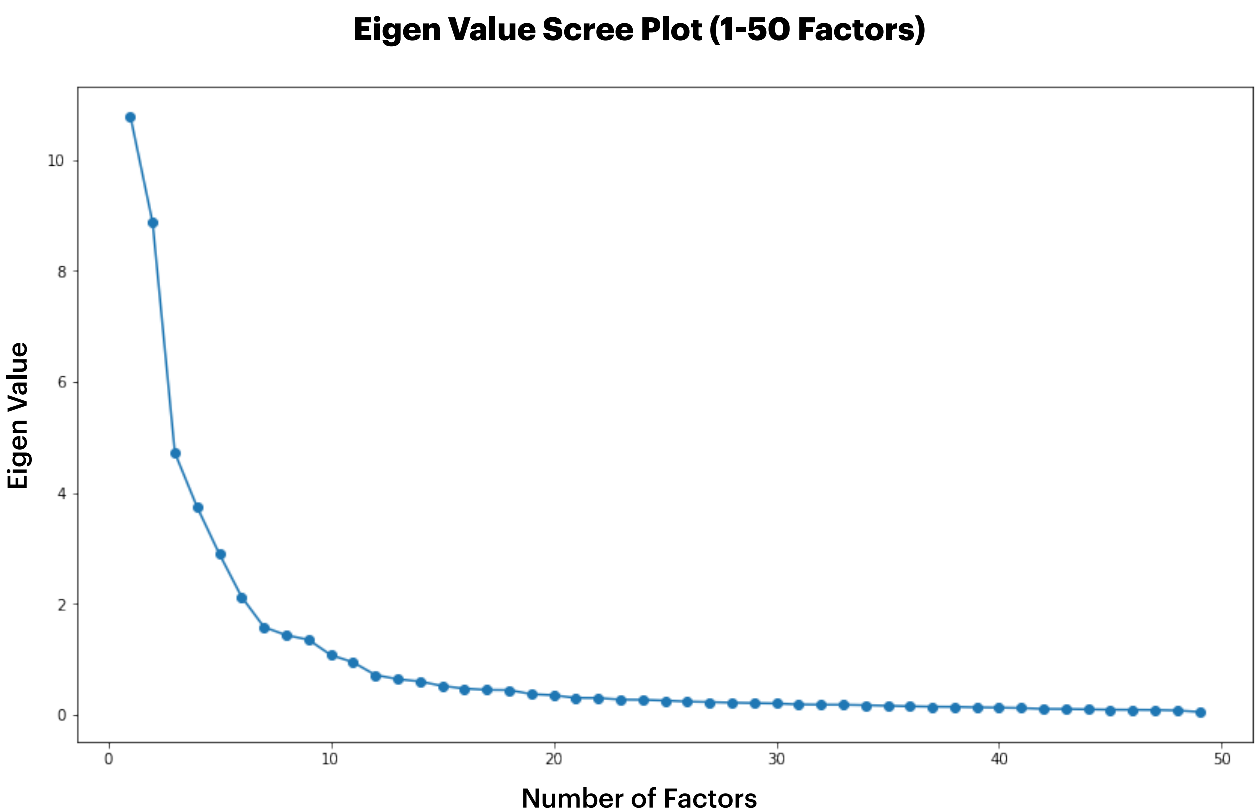

Figure 4. Scree Plot of Eigen Values (1-50 Factors)

After charting the 10 factor scenario, it was discovered that the last two factors had no practical significance as they were comprised of mainly duplicated brand attributes. Rerunning the analysis on the remaining 8 factors explained ~69% of the variance and improved interpretability. Because of potential data leakage, a second round of Factor Analysis was run on a reduction of 6 features from the raw dataset. The features removed were the '_C' columns of "Esteem", "Knowledge", "Relevance", "Differentiation", "Strength", and “Stature.” This removal improved the clarity and increased the Proportional Variance of the remaining factors (Table 3).

Table 3. Explained Variance of Dataset Factors

	Factor 0	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
SS Loadings	7.170663	5.975130	5.095241	4.237310	3.667243	3.299887	2.304192	1.979373
Proportion Variance	0.146340	0.121941	0.103985	0.086476	0.074842	0.067345	0.047024	0.040395
Cumulative Variance	0.146340	0.268282	0.372266	0.458742	0.533583	0.600928	0.647952	0.688348

Feature Correlation with Each Factor

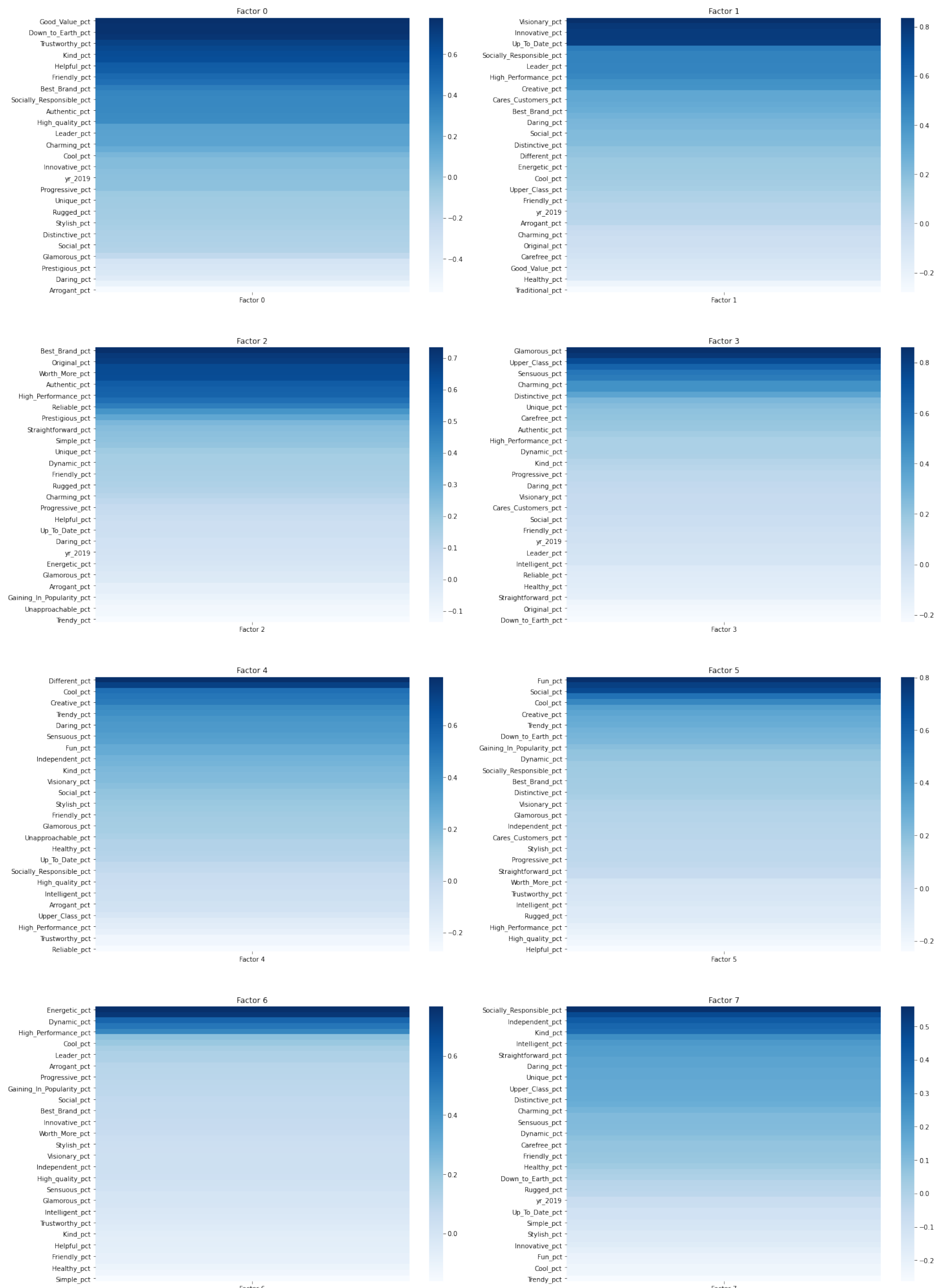

Figure 5. Feature Correlation with Each Factor (0-7)

The last step was to understand the makeup of each factor. This makeup was visualized by correlating the brand attributes against each factor (Figure 5). The darker the color the stronger the positive correlation.

In some cases the lighter color signified a negative correlation with the factor (Table 4). New names were then generated using domain knowledge to further contextualize each of the eight factors (Table 4).

Factor Name Generation

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***

Table 4. Factor Name Generation Based on Brand Attribute Makeup

Machine Learning Approach

The two key metrics for model selection were Mean Absolute Error and Validation score. Because the model is intended for infrequent use in a business setting, metrics of training time and testing time were excluded. Initial regression modeling was conducted on the newly factor reduced dataset. The four methods used were Stochastic Gradient Decent (SGD), Random Forest Regression, Lasso Regression, and XGBoost. The Random Forest model was most performative against the key metrics and was brought forward into further optimization.

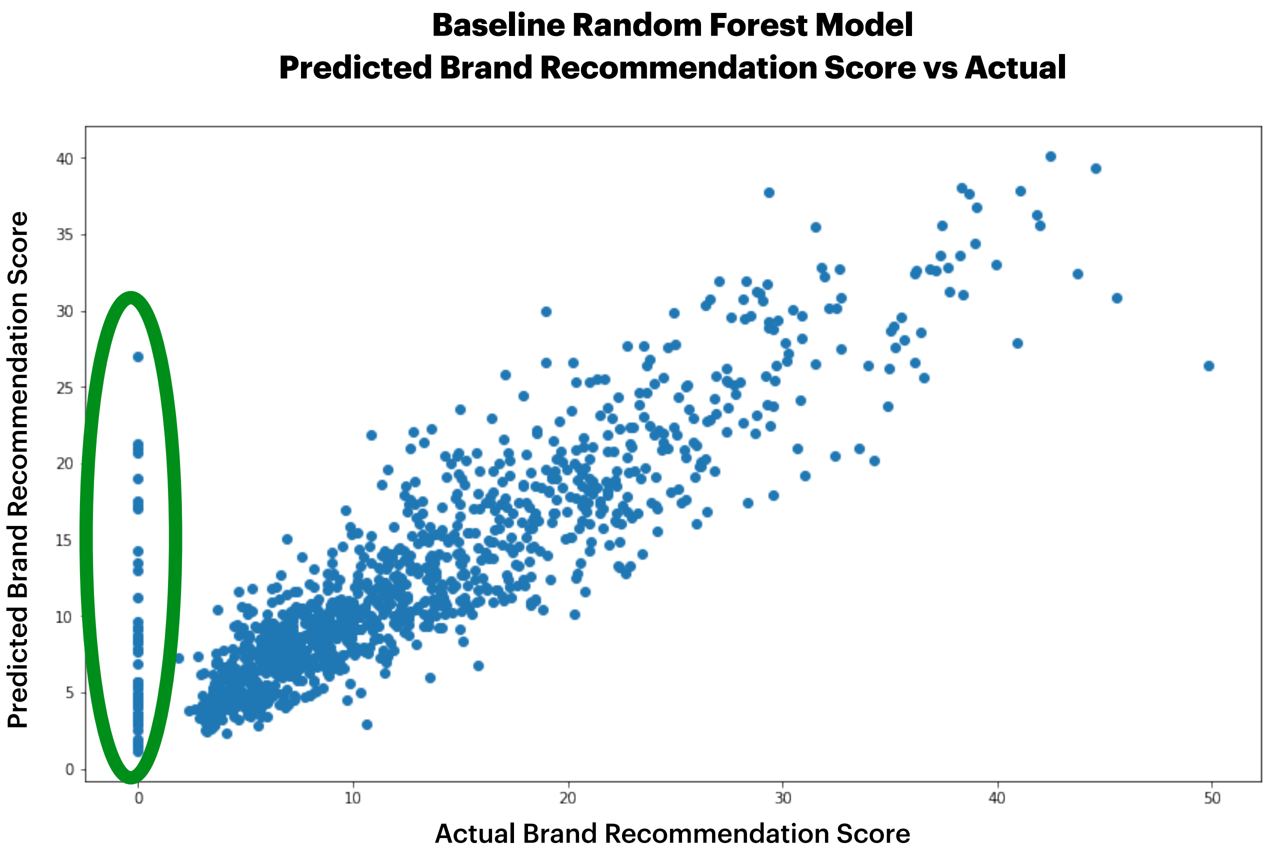

Figure 6. Baseline Random Forest Model, Predicted Brand Recommendation Scores vs. Actual

The Baseline (default) Random Forest model recorded a 96% training score and a 79% validation score. This large discrepancy suggested the model was overfitting to the training data and that the model would benefit from additional parameter tuning. It was also seen that the absent zero values in the target variable were leading to prediction anomalies in the initial Random Forest model (Figure 6). The zeros (circled in green) showed a wide prediction distribution and contributed to significant amount of the error in the baseline model. These zeros were dropped in conjunction with additional model fine tuning.

Fine tuning began with random search and Bayesian optimization methods. The results from both the methods showed signs of less overfit as the training results were generalizing better and trending closer o the validation set (Table 5).

With the optimal parameters from both methods, an additional round of hand tuning using grid search was performed to further optimize for validation scores. The parameters identified from the hand tuned optimization method (Figure 7) proved the most performative on all metrics (Table 2).

```
Best Training Score: 0.8213192857078934
Best Params: {'bootstrap': True, 'ccp_alpha': 0.0, 'criterion': 'mse', 'max_depth': None, 'max_features': 'auto', 'ma
x_leaf_nodes': 120, 'max_samples': None, 'min_impurity_decrease': 0.0, 'min_impurity_split': None, 'min_samples_lea
f': 2, 'min_samples_split': 5, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 400, 'n_jobs': None, 'oob_score': Fal
se, 'random_state': None, 'verbose': 0, 'warm_start': False}
```

Figure 7. Optimized parameters resulting from hand tuned grid search

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Performance and Shortcomings

The Hand Tuned Random Forest model shows additional predictive accuracy on the lower range of scores (Figure 8), but struggles to accurately predict values in the highest range (Figure 9).

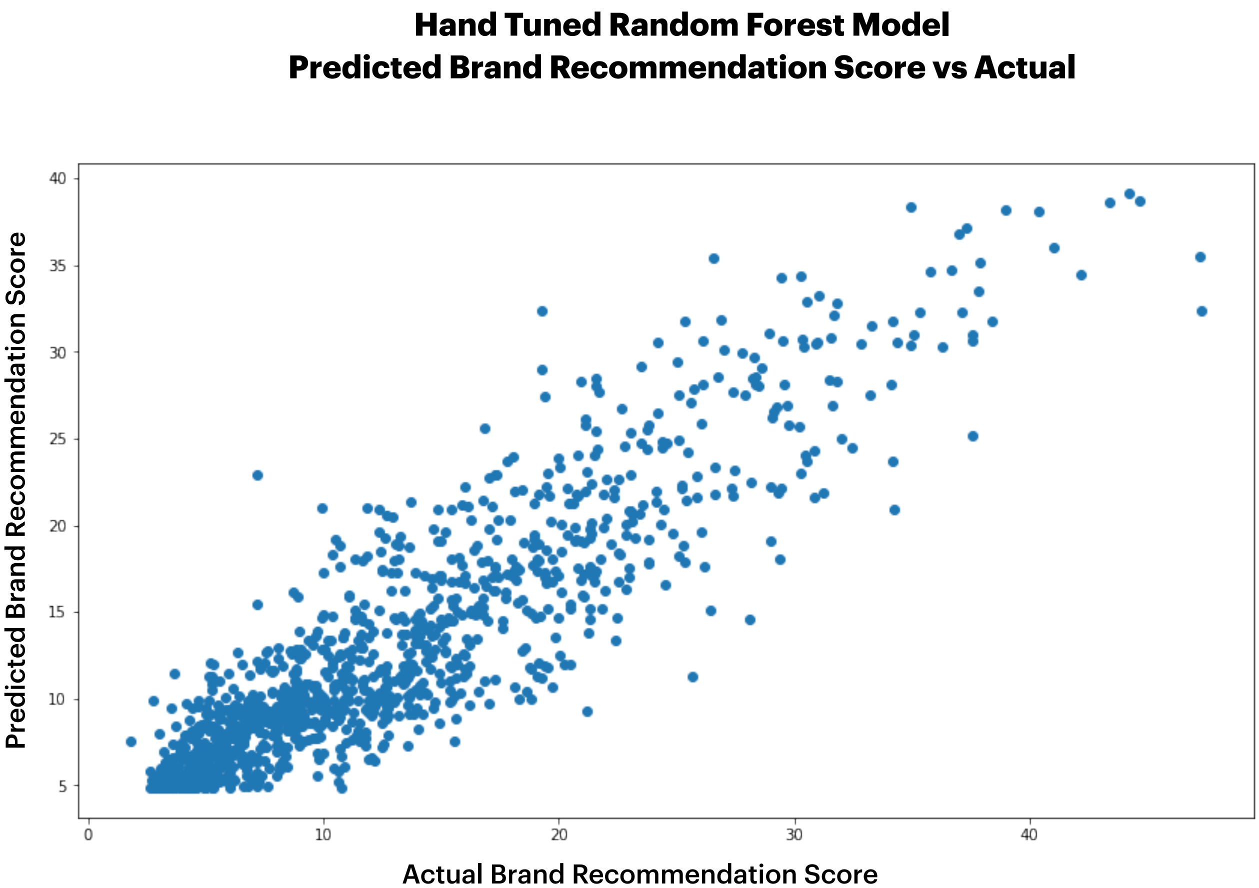

Figure 8. Hand Tuned Random Forest Model, Predicted Brand Recommendation Scores vs. Actual

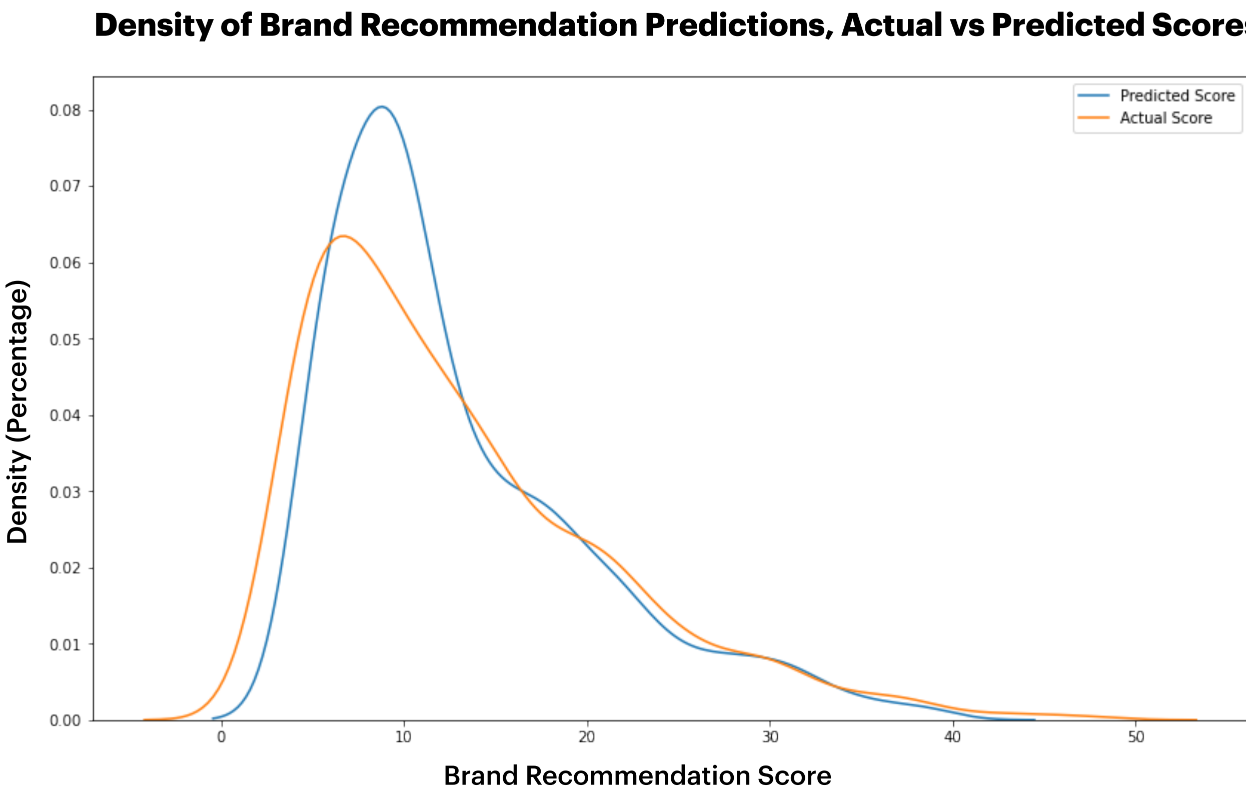

Figure 9. Density of Brand Recommendation Predictions, Actual vs Predicted Scores

Factor Importance

Based on our U.S. BAV data, the factors of 'Timeless' and 'Approachable' are most strongly associated with the predictability of Brand Recommendation Score. While 'Powerful' and 'Prestigious' are least important (Figure 10).

Factor Importance for Brand Recommendation Score Prediction

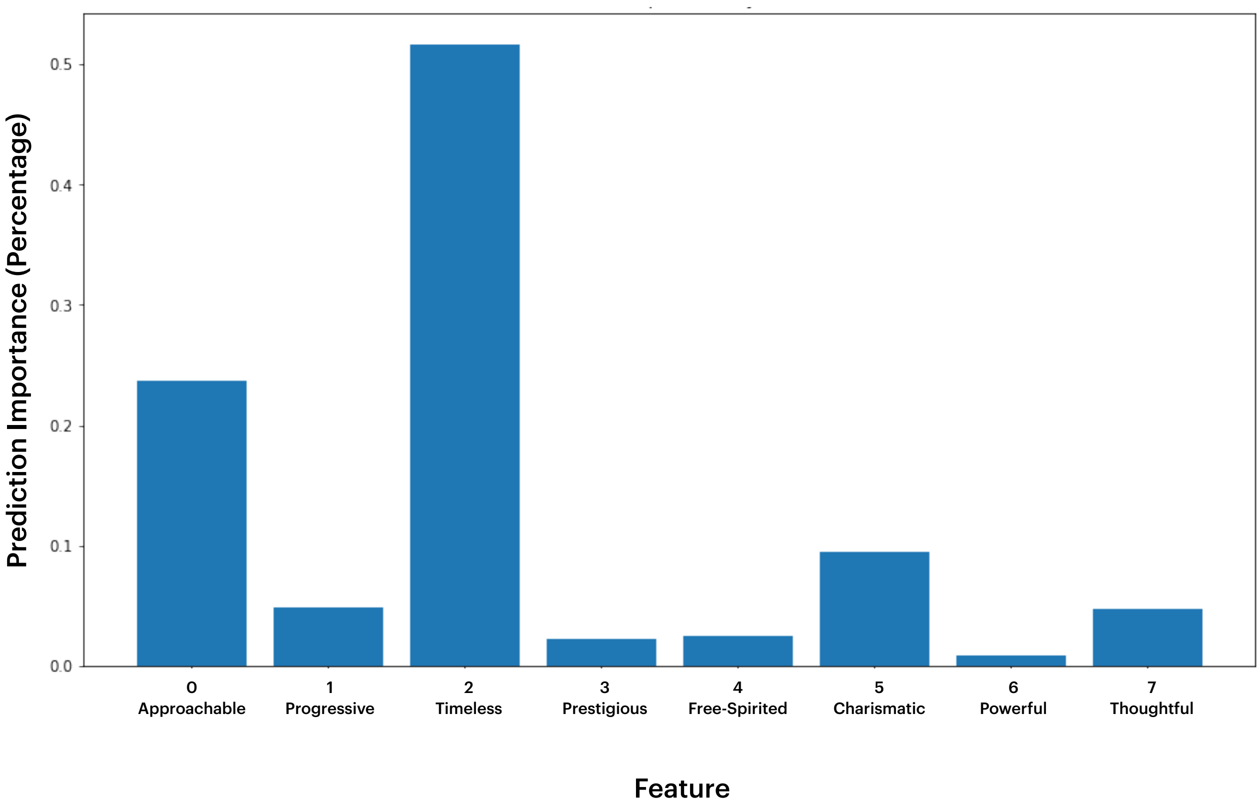

Figure 10. Final Model Feature Importance on Brand Recommendation Score Prediction

Conclusion

The goal of this report was to determine if there is a simpler way to interpret and report on the responses of the Annual BAV survey. The results of this report suggest that there is a simpler way by using a combination of Factor Analysis for dimensionality reduction and a Hand Tuned Random Forest model for Brand Strength prediction.

Conducting this analysis has simplified our understanding of the attributes that most impact a brand's perceived strength in culture. This understanding can help Landor & Fitch sell its services and demonstrate value to clients, lead to stronger and more actionable brand recommendations, and impact how clients direct their brand strategies over the next few years.

The reduction in dimensionality greatly improves the interpretability of the results. The clarity of the factors was surprisingly strong and applicable to Landor & Fitch's business needs. These 8 named factors (reduced from 48) will be much easier to interpret and explain in future engagements with U.S. clients.

The >81% accuracy (Validation R^2) of the final Random Forest model is very appropriate for use in a marketing context. Brand strength predictability at this level will speed client decision making and help inform the strategies of future brand consulting work in the U.S.

Limitations & Future Research

This report had multiple limitations. It only looked at the BAV study conducted in the U.S. This limits Landor & Fitch to using these results with U.S. clients only. Because Landor & Fitch is a global brand consultancy, it could have been beneficial to include BAV data from other key global markets to determine if these results could be applied to brands outside of the U.S. Secondly, this report only looked at two years of the BAV study. This could have weakened the power of the results. More years could have been included had the brand attributes been consistent or made consistent over additional survey years. Thirdly, this study did not investigate the longevity of the identified factors. Future research should investigate appropriate time intervals on how frequently to run this method of analysis to keep pace with consumer culture. Finally, because the business sector in which the brand operates was removed, the results may be over-generalized. Adding back in the brand sector could improve the model's accuracy based on the category of interest. In conclusion, further research is needed in this area of study.