Localization versus Standardization:

Websites vs. Products

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Introduction

Corporations constantly wonder how they should grow. There are two major methods for growth: through number of customers or through share of each customer's wallet[1]. But once the cost of gaining an additional customer outweighs their expected value, or current customers no longer have extra income to spend on your product, companies begin considering the international marketplace.

Entering international markets seem very appealing because the increase in sales means a possible increase in net profit. But entering a new country is also a risky venture. A host of problems can arise from a poor choice in international expansion.

To guide executives' choice of where to expand, strategists can use a combination of the CAGE model[2] and a costs and benefits chart. The cage model consists of four distances by which a country is compared to the originating country: Cultural, Administrative, Geographic, and Economic. Cultural distance discusses how each culture is different in terms of metrics such as managements' styles, customs, and holidays. Administrative distance refers to how government policies differ between countries. This includes differences such as political climate and currency. Geographic distance refers to differences between countries on geographic features such as mountains, arable terrain, and the physical distance between countries. Economic distance refers to differences between countries on metrics such as poverty and economic size.

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[1] Moorman, Christine. "How Does Your Company Grow?" Forbes. Forbes Magazine, 02 July 2012. Web. 21 Nov. 2016.

[2] Ghemawat, Pankaj."Distance Still Matters: The Hard Reality of Global Expansion." Harvard Business Review 79, no. 8 (September 2001): 137-147.

While each of these metrics is important, it is pertinent to remember that the importance of each varies from industry to industry. Cement companies would consider Geographic distances more important than cultural distances, while a makeup company would be more concerned with cultural norms surrounding beauty. But once a country has been picked for expansion based on CAGE distances, the company must decide how to market their product in the new country.

In addition, the competitive landscape must be analyzed. Many corporations use Porter's Five Forces Framework [3] to analyze countries to look for potential openings. The Five Forces include: Threat of New Entrants, Bargaining Power of Buyers, Bargaining Power of Suppliers, Threat of Substitute Products and Services, and Rivalry Among Existing Competitors. Threat of New Entrants refers to how easy it would be for new companies to the market. Bargaining Power of Buyers refers to consumers' ability to set price in the market. Conversely, Bargaining Power of Suppliers refers to the power of suppliers of raw inputs to bargain in the market. Threat of Substitutes refers to the ability for customers to switch to different products or services, even out of the traditional market. Rivalry Among Existing Competitors refers to existing competitors and how they compete. These forces are rated as high or low, and the first four help feed into Rivalry Among Existing Competitors. By doing this analysis for each country, corporations are able to decide whether or not a country is worth the entrance risk.

Upon selecting the country to enter and thoroughly understanding the differences between the home and selected countries, companies must decide if they would like the product to be standardized or localized. A standardized product is one that is very similar

[3] Porter, Michael E. The Five Competitive Forces That Shape Strategy. Tampa, FL: Harvard Business Review, 2008. Print.

among the markets it is sold. Conversely, a localized product is one that resembles the original product in concept and function, but has been modified to fit the entering country. Realistically, this choice lies on a spectrum, and companies must decide where on the spectrum to place their product. For example, McDonald's operating in Japan will sell products localized to the market, such as the えびフィレオ (shrimp burger) and the てりやきマックバーガー (teriyaki burger)[4]. While they sell these products tailored to the local audience, they also sell many of the same products they sell around the world. This means that they are neither a standardized or localized company, but somewhere in the middle.

Each option has its benefits and weaknesses. A more standardized product will benefit from economies of scale, as fewer modifications will need to be made to production. However, the company risks alienating consumers who may have a hard time understanding a standardized product and disagree how it fits into their lives. Standardizing works well for low-touch products like concrete, where the product more closely resembles a commodity. A localized product means that sales may increase as consumers more easily resonate with a product tailored to their tastes. The cost to do this, however, may be very high as a separate department may need to be formed specifically for this country, and care has to be taken not to modify the product beyond recognition. Localization is usually used for companies dealing in high-touch products such as therapy and clothing, where consumer tastes play a large role in purchase behavior.

To help guide the decision to standardize or localize, professionals might use STP analysis to organize consumers. STP stands for Segment, Targeting, and Position.

[4]"バーガーメニュー（レギュラー） | メニュー情報 | McDonald's マクドナルド." Welcome to McDonald's Japan. McDonald's, n.d. Web. 17 Apr. 2017.

Segmentation means finding different types of consumers and grouping them based on certain tastes, abilities, or educations. These segments are further developed to discuss important attributes of each. Once segments are developed, targeting is done to evaluate segments and pick one or more. Following this, positioning includes creating a product mix (Product, Price, Place, Promotion) surrounding this segment. Each potential position will have a SWOT (Strengths, Weaknesses, Opportunities, and Threats) Analysis consisting of internal and external factors that will lead to the success or failure of the product.

Companies understand that even the best option comes with some risk, and have different ways of entering into these countries, ranging from indirect exporting to greenfield expansion (direct investment where a company grows its operations from the ground up)[5]. As entrance goes from indirect exporting to greenfield expansion, control increases, but so does risk. This means that companies must debate the importance of control of their operations, while also weighing the possible risk involved in expansion. While exporting indirectly, many products are still standardized in that companies do not necessarily consider their sales in the country part of major operations. Once the company begins direct exporting, the question of localization versus standardization may begin being considered.

As we move towards the singularity, companies are beginning to understand the importance of their digital presence. Having a place for customers to view and purchase products, leave feedback, and learn about the brand is important for any company hoping to make long-term customers who will be loyal to the brand for years. Social media sites like Facebook and Twitter are good for building buzz about deals and to promote products,

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[5] Hubbard, Nancy A. "Greenfield Expansion." Conquering Global Markets: Secrets from the World's Most Successful Multinationals. Houndmills, Basingstoke, Hampshire: Palgrave Macmillan, 2013. 132-48. Print.

but when customers want to know about all offerings, they will visit the company's website. With customers from around the world visiting your website, do you want everyone seeing the same thing? Will a customer in China find the American website fits their needs as a consumer? Should companies be expanding their website presence to have a variety of websites targeted at different geographic locations? How much should be invested in these websites?

Research Questions

The aim of this project is to answer a few questions, namely:

1. Are the websites for current multinationals more standardized or more localized?
2. Do companies with standardized products have standardized websites, and do companies with localized products have localized websites?
3. Do non-website factors of corporations influence the similarity/difference of their websites?
4. How do people perceive websites as being similar or different?

Past Research

Little research has been done into the localization and standardization of websites in the past. When discussing online presence, most companies default to their social media presence. Companies find it more important to be active through sources such as Facebook and Twitter than their corporate websites.

A study conducted by Troestler and Lee at the Institutionen för ekonomisk och industriell utveckling [6] studied how internal factors influence the appearance of a company's website among three companies. They found that some companies do change their website appearance to fit local consumers. For example, they found that car companies changed their website's aesthetics to match local tastes and preferences. Each Ford website was made to appear "trendy" in the target market as to draw upon local consumer preferences for trendy vehicles. The principal researchers were primarily interested not with the fact that companies had difference sites, but how their categorization into global, multinational, and transnational influences these differences.

Another study, conducted by Singh, Furrer, and Ostinelli[7] showed that consumers prefer highly adapted websites, and that attitudes toward local country websites are more favorable than that of foreign websites.

Hypotheses

The following hypotheses are based off of the combination of the research questions and past research.

Hypothesis 1: The websites for current multinationals are more localized than standardized.

[6] Troestler, Andrea, and Hsin Ping Lee. The adaptation and standardization on websites of international companies: Analysis and comparison from websites of United States, Germany and Taiwan. Thesis. Institutionen för ekonomisk och industriell utveckling, 2007. N.p.: n.p., n.d. Print.
[7] Singh, Nitish, Olivier Furrer, and Massimiliano Ostinelli. "To Localize or to Standardize on the Web: Empirical Evidence from Italy, India, Netherlands, Spain, and Switzerland." Multinational Business Review 12.1 (2004): 69-88. Web.

Hypothesis 2: Companies that have more localized products also have more localized websites. Companies that have more standardized products also have more standardized websites.

Hypothesis 3: The standardization/localization of a company's websites can be determined based on factors unrelated to their website.

Hypothesis 4: There exists a model that can accurately predict how similar/different websites are based off of their metrics.

Methodology

The list of the top 100 companies by market capital were collected from online resources. Market capital was chosen as the organizing variable because it represents an ordering in terms of simple valuation for the companies.

From here, search was done to collect the nationalized addresses for each company in a variety of countries (United States, China, Japan, Australia, UK, Germany, Russia, Nigeria, Kenya, Brazil, México, and Argentina). This was done by searching various combinations of the company and the country on Google, or by modifying the domain name of the site based off expected patterns.

This list was used with a prototype Mechanical Turk survey to create 55 unique surveys (shown in **Appendix 2**). Respondents were asked to visit two different websites and compare them on a scale of 1 to 7 (1 being most similar) with regards to overall similarity, similarity of media on the website, similarity of the physical web address, language similarity, similarity of navigation, and the similarity of the purveyed message. Surveys were constructed so that no pair of websites for the same company appeared twice on the same survey. The list of companies, along with the websites looked at, can be found in **Appendix 1**. Mechanical Turk was chosen because of its ability for a community of respondents to complete surveys quickly, combined with a history of providing reliable data[8]. It should be stated that other researchers have noted that the survey conditions for Mechanical Turk surveys are not well maintained, and respondents could be doing activities such as cooking or watching TV[9]. In addition, respondents have a profit incentive, which could lead to large amounts of random clicking.

To collect information about the localization/standardization of products, professionals from the top 100 companies were contacted via LinkedIn. They were asked to connect, and upon connection, an email was sent to them with the survey. Upon return of the survey, the data were recorded.

The collected data were manipulated into multiple forms to make analysis easier, and information such as number of employees, industry, and 2015 revenue was added to aide data analysis.

From the analysis, conclusions were drawn to either accept or reject the hypotheses.

Analysis

Data Analysis Methods

Collected data were analyzed using a variety of packages in R by means of RStudio and Microsoft Excel. Some data needed to be cleaned/added by hand, but a majority of the cleaning, combining, and analyzing was done using popular R packages. Values greater

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[8] Rand, David G. "The Promise of Mechanical Turk: How Online Labor Markets Can Help Theorists Run Behavioral Experiments." Journal of Theoretical Biology 299 (2012): 172-79. Print.
[9] Crump, Matthew J. C., John V. Mcdonnell, and Todd M. Gureckis. "Evaluating Amazon's Mechanical Turk as a Tool for Experimental Behavioral Research." PLoS ONE 8.3 (2013): n. pag. Print.

than 4 were determined to say that a website is more localized, and values less than 4 were said to represent metrics that were more standardized.

A Note on Terminology

The data were broken down and combined in three different ways. For ease of understanding, these data sets will be termed:

Individual Survey Responses: The results of the survey. This is the set of data containing each comparison made by a respondent. This set can be found in **Appendix 4** and looks like:

Table 1

Example of Individual Survey Responses

Input.1	Input.2	Overall	Language	Media	Navigation	Message	Web.Address
https://apple.com/	http://www.apple.com/hk/	4	2	3	4	3	4
https://apple.com/	http://www.apple.com/hk/	2	7	1	1	2	1
https://apple.com/	http://www.apple.com/hk/	1	2	3	4	5	6
https://apple.com/	http://www.apple.com/hk/	1	7	1	1	1	3
https://apple.com/	http://www.apple.com/hk/	1	7	1	1	1	4
https://apple.com/	http://www.apple.com/hk/	6	3	5	3	6	4

Combined Data: The results of Survey Data being combined for each unique pair of Input.1 and Input.2. This set can be found in **Appendix 5** and looks like (some columns removed for size):

Table 2

Example of Combined Data

Input1	Input2	Industry	overall	language	media	navigation	message	web.Address
https://apple.com/	http://www.apple.com/hk/	Manufacturing	2.50	4.65	2.30	2.70	3.00	3.50
https://apple.com/	http://www.apple.com/jp/	Manufacturing	2.65	5.30	2.80	2.85	2.95	3.15
https://apple.com/	http://www.apple.com/au/	Manufacturing	2.65	2.85	2.60	2.80	2.60	3.05
https://apple.com/	http://www.apple.com/uk/	Manufacturing	2.65	2.45	2.55	2.80	3.05	3.75
https://apple.com/	http://www.apple.com/de/	Manufacturing	3.20	4.10	2.85	2.65	2.90	3.80
https://apple.com/	http://www.apple.com/ru/	Manufacturing	2.40	5.10	2.50	2.30	2.45	2.85

Final Classifications: The results of Combined Data being combined by unique Input1. This set also contains data about Revenue, Market Capital, Number of Employees, and Country of Origin. For completeness, this data set contains companies that did not have websites to compare. In analysis, this data set was modified to remove items where there was nothing to compare. This set can be found in **Appendix 6** and looks like (some columns removed for size):

Table 3

Example of Final Classifications

Company	overall	language	media	navigation	message	web.Address
Berkshire Hathaway Inc.	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Comcast Corporation	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Ping An Insurance (Group) Company Of China Ltd	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Procter and Gamble	3.522727	4.218182	3.768182	3.759091	3.694727	3.868182
Total SA	3.304545	4.118182	3.463636	3.322727	3.381818	3.631818
3M Company	3.340909	4.068182	3.554545	3.254545	3.350000	3.681818

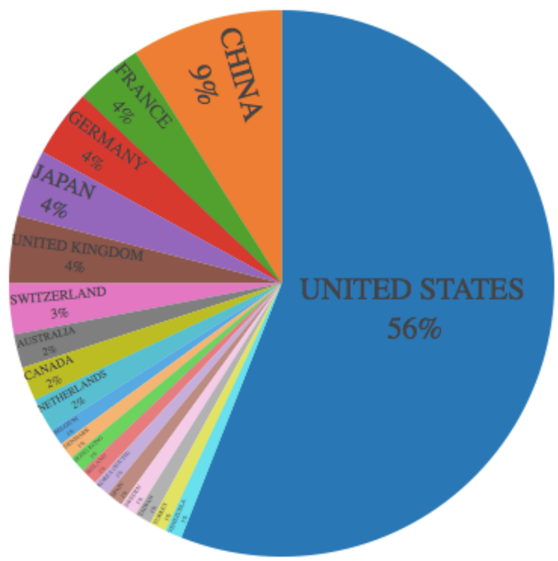
Overall Factor: To maintain clarity, the metric that measures the overall similarity/difference of the websites will be termed “overall factor”. This is to remove confusion between overall as a general sense and overall as a measured metric. In figures and tables, the word “overall” still refers to the measured metric, not any combination of other factors.

Background on Collected Data

The top 100 companies came from one of 20 different countries. The most popular country was the United States with 56 companies, followed by China with 9.

Figure 1

Country of Origin for Companies



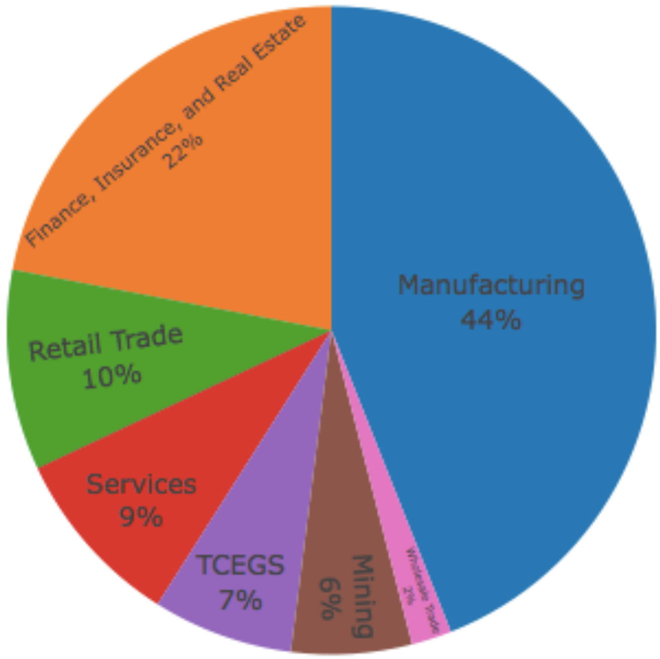
These companies were divided into one of 10 classifications based on their Standard Industrial Classification[10]. Of the 12 possible classifications, only 7 were used. This was a matter of chance, as none of the top 100 companies fell into any of 5 classifications. Manufacturing represented the largest of these classifications at 44 companies, followed by Finance, Insurance, and Real Estate. Transportation,

[10] "SEC Info - U.S. Standard Industrial Classification (SIC)." SEC Info - U.S. Standard Industrial Classification (SIC). N.p., n.d. Web. 08 Mar. 2017.

Communications, Electric, Gas and Sanitary service (TCEGS) was shortened in all analysis due to its long name.

Figure 2

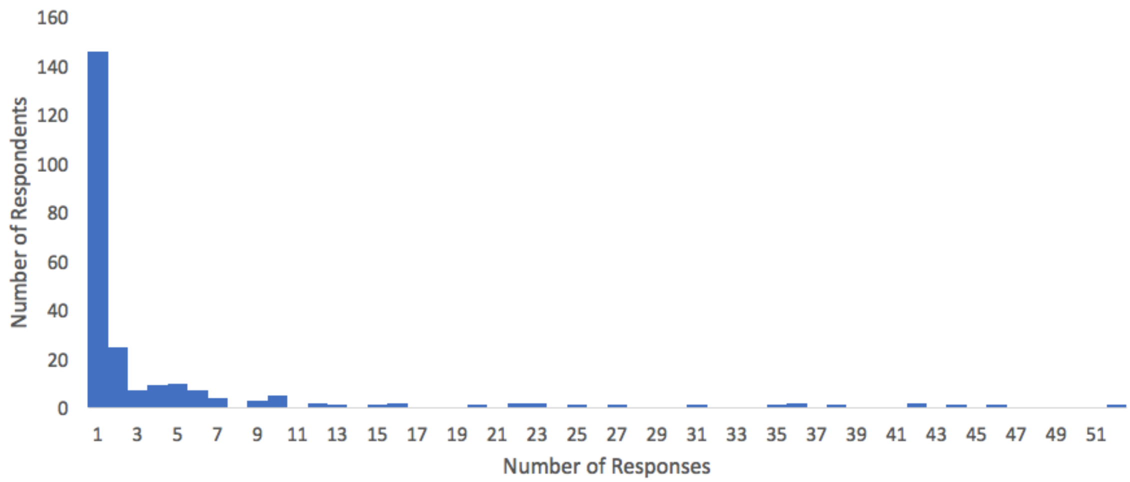
Industry of Companies



There were 1098 approved surveys taken by 240 unique workers, averaging 4.58 different surveys per respondent. The survey was live less than 3 days before the correct number of surveys were accepted. 60.5% of respondents only took 1 survey, while 12.08% took 10 or more surveys. The average time to complete a survey was 15.01 minutes, and the standard deviation was 14.29 minutes. 187 submitted surveys had to be rejected. A few of them were because the data were obviously faked - workers submitted the same number for each data point - but a majority of rejects were because the workers did not answer all the questions.

Figure 3

Answer Frequency of Respondents

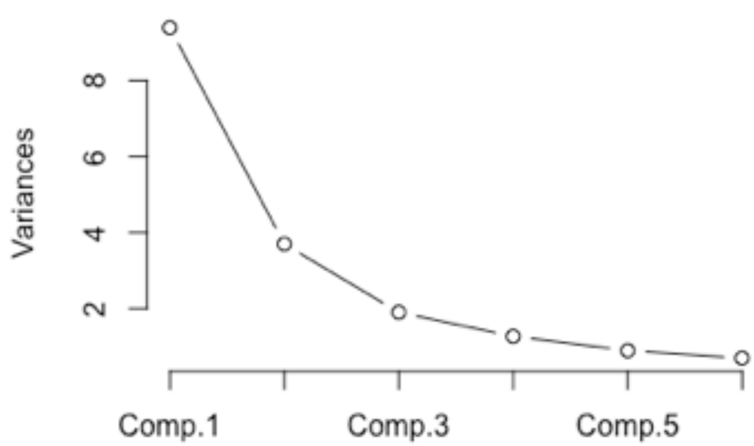


Reliability of Data

Individual Survey Responses were first put through factor analysis to determine if there were underlying groupings in the data. **Figure 4** gives a line plot that shows how variances change with the number of factors.

Figure 4

Number of Factors vs. Variances



Visual Analysis of **Figure 4** shows that the data is likely comprised of two factors. **Figure 5** shows the results of basic factor analysis using 2 factors.

Figure 5

Results of Factor Analysis - Individual Survey Responses

```
Uniquenesses:
    Overall    Language       Media  Navigation     Message Web.Address 
      0.477       0.837       0.279       0.301       0.194       0.630 

Loadings:
            Factor1 Factor2
Overall     0.504   0.518  
Language            0.396  
Media       0.486   0.696  
Navigation  0.686   0.478  
Message     0.861   0.254  
Web.Address 0.584   0.171  

               Factor1 Factor2
SS loadings      2.050   1.232
Proportion Var   0.342   0.205
Cumulative Var   0.342   0.547

Test of the hypothesis that 2 factors are sufficient.
The chi square statistic is 307.54 on 4 degrees of freedom.
The p-value is 2.56e-65
```

Because the SS loadings for both of these factors are greater than 1, we can say that they are both significant. The p-value also supports the fact that the model accurately predicts the number of factors. Further, the large chi-square statistic means that either there are two factors or that the data is very strange. By choosing the columns which have the highest loadings, we see that Factor 1 consists of Navigation, Message, and Web Address, and that Factor 2 consists of Overall Factor, Language, and Media. These groupings will be used to check internal consistency.

Cronbach's Alpha values were collected from the two factor sets to check for internal consistency. **Figure 6** shows reliability analysis on Factor 1. **Figure 7** shows internal consistency analysis on Factor 2.

Figure 6

Reliability Analysis – Factor 1

```
Reliability analysis
Call: psych::alpha(x = raw_data[c(6, 7, 8)])

  raw_alpha std.alpha G6(smc) average_r S/N    ase mean  sd
       0.8       0.8    0.75      0.58 4.1 0.0033  3.4 1.4

 lower alpha upper     95% confidence boundaries
0.8 0.8 0.81

 Reliability if an item is dropped:
            raw_alpha std.alpha G6(smc) average_r S/N alpha se
Navigation       0.71      0.71    0.55      0.55 2.4   0.0055
Message          0.64      0.64    0.48      0.48 1.8   0.0068
Web.Address      0.83      0.83    0.71      0.71 4.9   0.0032
```

Figure 7

Reliability Analysis – Factor 2

```
Reliability analysis
Call: psych::alpha(x = raw_data[c(3, 5, 6)])

  raw_alpha std.alpha G6(smc) average_r S/N    ase mean  sd
      0.83      0.83    0.77      0.62 4.9 0.0028  3.4 1.4

 lower alpha upper     95% confidence boundaries
0.82 0.83 0.83

 Reliability if an item is dropped:
           raw_alpha std.alpha G6(smc) average_r S/N alpha se
Overall         0.81      0.81    0.68      0.68 4.2   0.0037
Media           0.75      0.75    0.60      0.60 3.0   0.0048
Navigation      0.74      0.74    0.59      0.59 2.9   0.0049
```

Because raw_alphas for both factors are at or above the recommended .7-.8 to determine consistency, it can be said that each factor in internally consistent. When looking at each figure under “Reliability if an item is dropped”, we see that only in Factor 1 does there exist a raw_alpha value that is higher than the overall raw_alpha. Dropping Web.Address from analysis only increases Factor 1's raw_alpha to .82, so it will be kept in for all analysis.

Basic Combined Data Analysis - Websites

Summary statistics about Individual Survey Responses were created and can be seen in **Figure 8**.

Figure 8

Summary of Individual Survey Responses

Overall	Language	Media	Navigation	Message	Web.Address
Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000	Min. :1.000
1st Qu.:2.000	1st Qu.:2.000	1st Qu.:2.000	1st Qu.:2.000	1st Qu.:2.000	1st Qu.:2.000
Median :3.000	Median :4.000	Median :3.000	Median :3.000	Median :3.000	Median :3.000
Mean :3.323	Mean :4.176	Mean :3.467	Mean :3.369	Mean :3.374	Mean :3.549
3rd Qu.:5.000	3rd Qu.:6.000	3rd Qu.:5.000	3rd Qu.:4.000	3rd Qu.:5.000	3rd Qu.:5.000
Max. :7.000	Max. :7.000	Max. :7.000	Max. :7.000	Max. :7.000	Max. :7.000
NA's :4	NA's :5	NA's :8	NA's :10	NA's :10	NA's :8

Combined Data were analyzed to look for values greater than 4 (the middle of the survey scale). **Figure 9** below represents the overall factor for Combined Data by Industry. There were 46 cases where the overall factor was greater than 4, representing 8.37% of the comparisons.

Figure 9

Overall Difference – Combined Data

Final Classifications were analyzed on simple metrics. **Appendix 6** shows the individual background information, averages, and standard deviations for each company on the list. The most important figures are shown in **Figure 10** below.

Figure 10

Basic Analysis – Final Classifications

```
    overall          language          media           navigation        message         web.Address
 Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000
 1st Qu.:2.945   1st Qu.:3.828   1st Qu.:3.114   1st Qu.:3.006   1st Qu.:3.067   1st Qu.:3.270
 Median :3.253   Median :4.170   Median :3.460   Median :3.265   Median :3.330   Median :3.461
 Mean   :3.006   Mean   :3.748   Mean   :3.122   Mean   :3.038   Mean   :3.041   Mean   :3.202
 3rd Qu.:3.583   3rd Qu.:4.410   3rd Qu.:3.670   3rd Qu.:3.656   3rd Qu.:3.518   3rd Qu.:3.705
 Max.   :4.800   Max.   :5.550   Max.   :4.650   Max.   :5.000   Max.   :4.450   Max.   :5.000
```

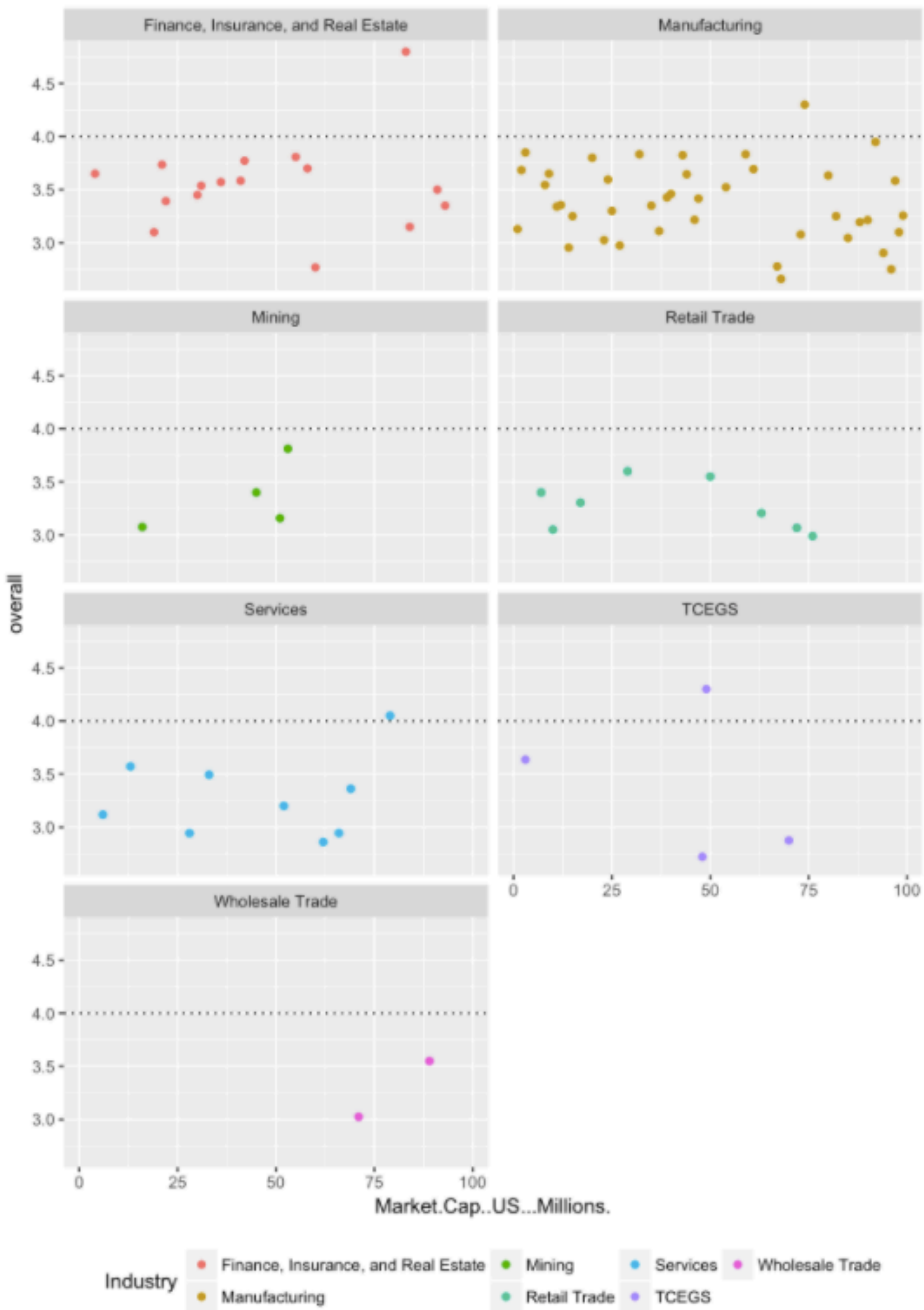
Figure 11

Overall Factor versus Market Capital – Final Classifications

Figure 11 represents the overall factor plotted against market capital in millions, with dot color representing the company's industry. **Figure 12** below shows each industry on a different graph. Visual examination of these graphs shows no correlation between market capital and overall factor within industries.

Figure 12

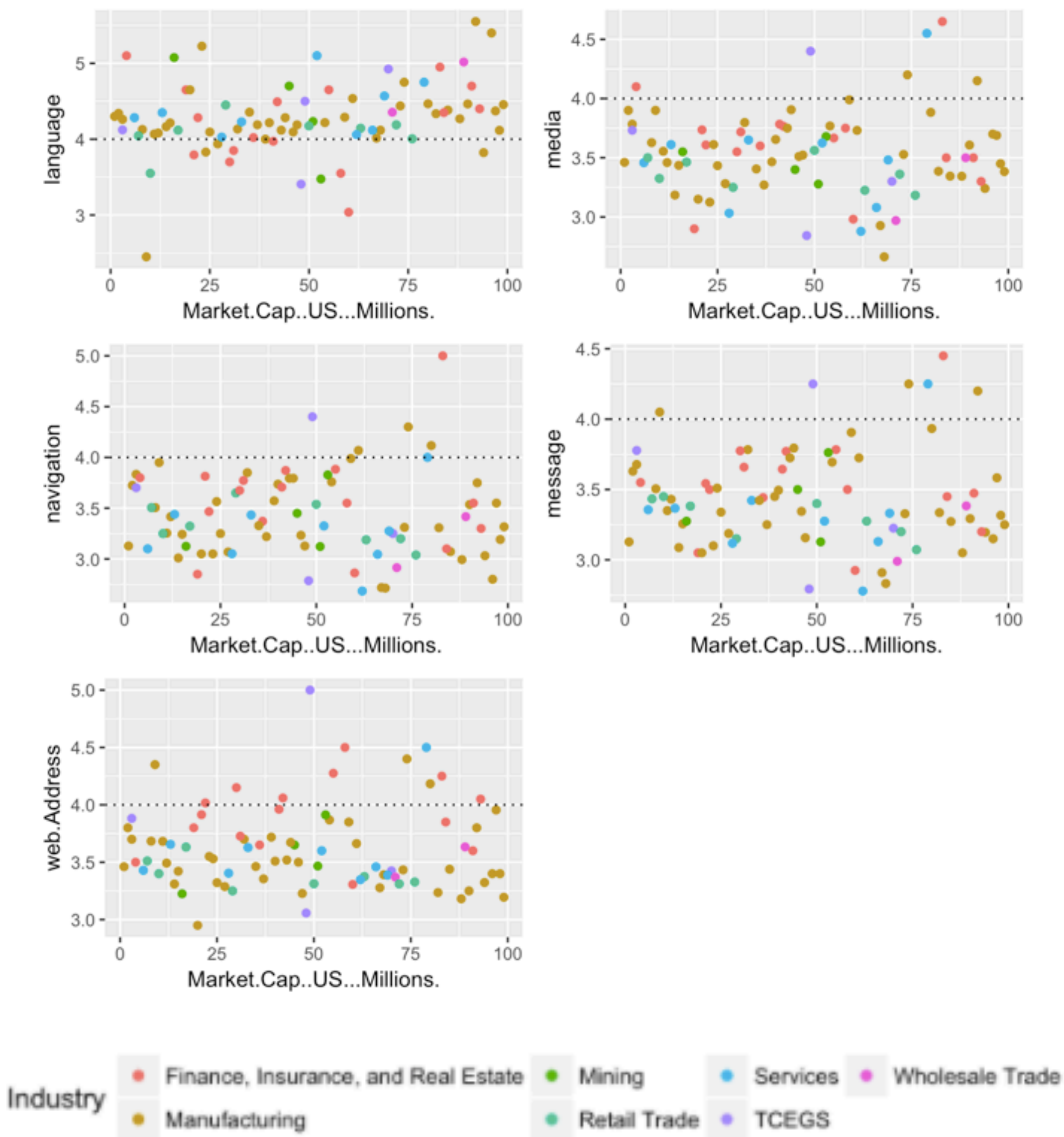
Overall Factor Difference versus Market Capital by Industry



Similar plotting was done on the Final Classifications data set with the other recorded metrics. **Figure 13** shows how each of these metrics relate to market capital for the 100 companies.

Figure 13

Market Capital versus Various Factors for Companies

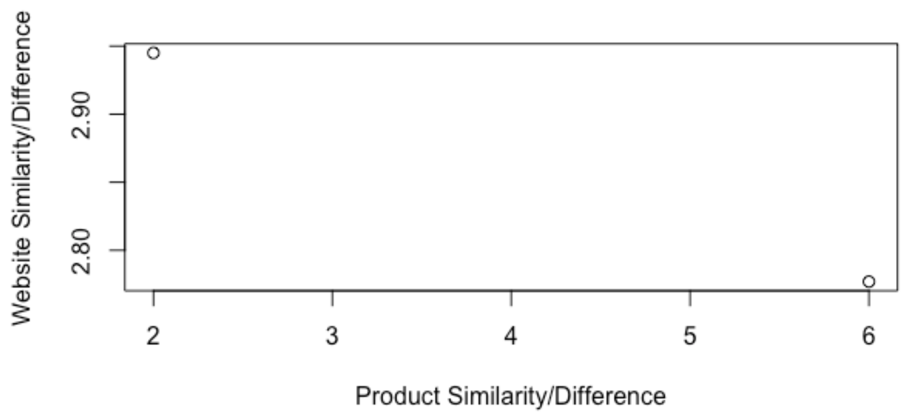


Basic Combined Data Analysis – Websites and Products

Only two surveys requesting information on product similarity/difference were returned. From this, **Figure 14** was made.

Figure 14

Product Differentiation vs. Website Differentiation



Logistic Regression – External Factors to Predict Components of Similarity

A Logistic Regression was done to test how external components (Industry, Country of Origin, Market Capital, Number of Employees, Revenue) related to components of similarity. Logistic Regressions were completed for each factor tested. **Figure 15** shows output of the logistic regression for overall similarity. Similar to overall similarity, no other factor had many significant independent variables.

Figure 15

Sample Logistic Regression Output

```
Call:
glm(formula = overall ~ Industry + Country + Market.Cap..US...Millions. +
    X2015.Revenue..US...Billions. + Employees, data = lm.train)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.92065  -0.19548   0.05798   0.26824   0.77788

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   5.156e-01  3.546e-01   1.454   0.1510
IndustryManufacturing         1.530e-01  1.744e-01   0.878   0.3835
IndustryMining                1.866e-01  2.555e-01   0.730   0.4679
IndustryRetail Trade         -6.696e-03  2.346e-01  -0.029   0.9773
IndustryServices              8.922e-02  2.247e-01   0.397   0.6927
IndustryTCEGS                -4.380e-01  2.483e-01  -1.764   0.0826 .
IndustryWholesale Trade       2.739e-01  4.131e-01   0.663   0.5097
CountryBELGIUM                4.952e-01  5.948e-01   0.833   0.4083
CountryCANADA                 8.177e-02  4.803e-01   0.170   0.8654
CountryCHINA                  4.633e-01  3.935e-01   1.177   0.2435
CountryDENMARK                4.316e-01  5.924e-01   0.729   0.4690
CountryFRANCE                 4.432e-01  4.484e-01   0.989   0.3267
CountryGERMANY                1.437e-01  4.478e-01   0.321   0.7493
CountryHONG KONG              1.089e+00  6.287e-01   1.732   0.0882 .
CountryIRELAND                4.189e-01  6.175e-01   0.678   0.5000
CountryJAPAN                  3.127e-01  4.720e-01   0.662   0.5102
CountryKOREA (SOUTH)          5.627e-01  6.122e-01   0.919   0.3616
CountryNETHERLANDS           -1.121e-02  4.893e-01  -0.023   0.9818
CountrySPAIN                  5.843e-01  6.102e-01   0.958   0.3420
CountrySWITZERLAND            5.196e-01  4.616e-01   1.126   0.2646
CountryTAIWAN                 4.970e-01  5.938e-01   0.837   0.4059
CountryTURKEY                 6.706e-01  5.823e-01   1.152   0.2539
CountryUNITED KINGDOM         5.081e-01  4.566e-01   1.113   0.2701
CountryUNITED STATES          2.122e-01  3.672e-01   0.578   0.5654
CountryVENEZUELA              6.353e-01  5.813e-01   1.093   0.2787
Market.Cap..US...Millions.   -1.153e-06  5.668e-07  -2.034   0.0463 *
X2015.Revenue..US...Billions. -3.417e-05 7.496e-04  -0.046   0.9638
Employees                     1.911e-07  2.529e-07   0.756   0.4527
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

<u>Decision Tree – External Factors to Predict Components of Similarity</u>

Decision Tree models with were made using the C5.0 package in R. A random sample of 90 rows were used to train the tree, and 10 rows were used to test the model. Columns were modified so that values greater than 4 were evaluated to Different, and any values less than 4 were evaluated to Similar. Models were made with factors as response variables and the corporation's Industry, Country of Origin, Market Capital, Revenue, and number of Employees as independent variables. **Table 4** shows the accuracy of these models when tested with the same 10 rows.

Table 4

Prediction Accuracies of Factors - Decision Trees

	Overall	Media	Language	Web Address	Message	Navigation
Accuracy	80%	70%	90%	80%	70%	80%

Summaries and Cross Tables were examined for each decision tree, examples of which are shown in **Figure 16** and **Figure 17**. Similar to **Figures 16 and 17**, all summaries showed that the decision tree categorized all training data into one category, causing the results of the prediction to only go one way. This further causes the accuracy of the models to be dependent on the values on the test set, not by classifications based on company metrics.

Figure 16

Summary Data for Overall Decision Tree

```
Evaluation on training data (90 cases):

	    Decision Tree
	  ----------------
	  Size      Errors

	     1    2( 2.2%)   <<


	   (a)   (b)    <-classified as
	  ----  ----
	    88          (a): class 0
	     2          (b): class 1
```

Figure 17

Cross Table for Overall Decision Tree

```
   Cell Contents
|-------------------------|
|                       N |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  10


             | dt.test$overall
     dt.pred |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |         8 |         2 |        10 |
             |     0.800 |     0.200 |           |
-------------|-----------|-----------|-----------|
Column Total |         8 |         2 |        10 |
-------------|-----------|-----------|-----------|
```

Linear Regression - Components of the Overall Factor

A linear regression was completed on Combined Data to see if there was a relationship between the components of the overall factor. It was found that Language and Web.Address were insignificant in the model at $P < .001$. After readjusting the model, the intercept was still insignificant. The model was centered, and the intercept was found to be significant. The model found from this data is: Overall Factor = 3.322 + .34981 (media - 3.467) + .38707 (navigation - 3.369) + .2271 (message - 3.373). This simplifies to:

Overall Factor = .0392 + .3481 * Media + .38707 * Navigation + .2271 * Message

Figure 18

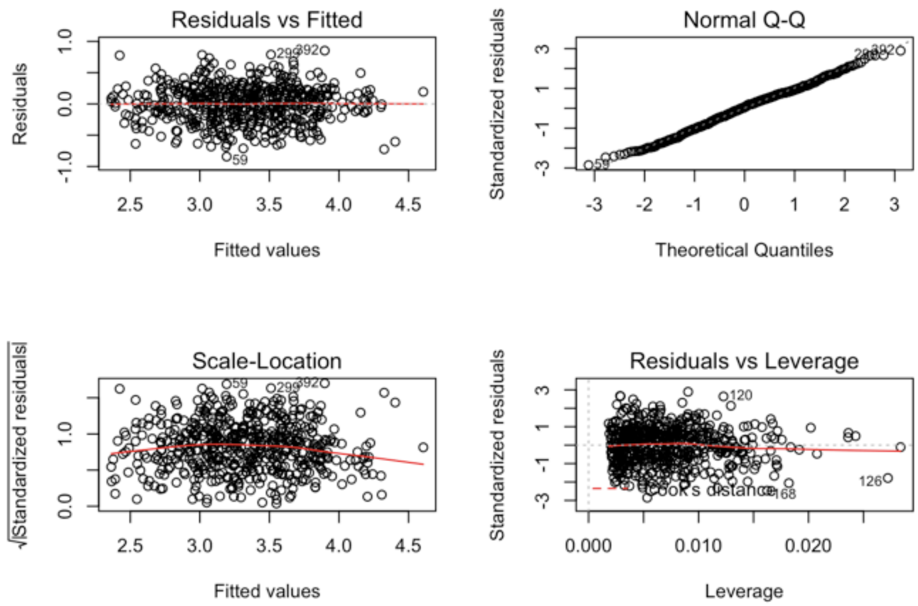
Linear Model for Overall Factor

```
##
## Call:
## lm(formula = data$overall ~ adjmedia + adjnav + adjmessage)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.84237 -0.19857  0.01766  0.20582  0.85255
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.32254    0.01263 263.033  < 2e-16 ***
## adjmedia     0.34981    0.04794   7.296 1.05e-12 ***
## adjnav       0.38707    0.05349   7.237 1.57e-12 ***
## adjmessage   0.22171    0.05129   4.323 1.83e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.296 on 545 degrees of freedom
## Multiple R-squared:  0.6595, Adjusted R-squared:  0.6577
## F-statistic: 351.9 on 3 and 545 DF,  p-value: < 2.2e-16
```

The R^2 for the model is .6577, meaning it explains approximately 65.77% of the overall factor. Visual examination of the diagnostic plots in **Figure 19** was done. This analysis showed no signs that the model is skewed.

Figure 19

Diagnostic Plots for Linear Model



Discussion

<u>Data Collection - Websites</u>

The data acquisition process held some interesting information. There were 3 major ways that a company would have websites in different countries. The first was that they would have their site be a .com address, but use some variation after the '/' to change the language and visibly change the site. The second is to change the top-level domain to match the area that the site is about. For example, Google uses domains like .com, .jp, and .de to reference the language that the site is in. The third way is that companies will blanket websites for regions that they are in. this was especially popular for companies in Africa where a company might have a section that simply explains their operations in these countries, or has one website dedicated to the entire area.

Interestingly, some websites didn't have US (.com) addresses. This was the case for the Commonwealth Bank of Australia, Ping an Insurance (Group) Company of China Ltd, and U.S. Bancorp. The Commonwealth Bank of Australia only had Australian and Japanese websites. Ping an Insurance (Group) Company of China only had a Chinese website, which was interesting because it had a '.com' ending, but was completely in Chinese. U.S. Bancorp does not have a corporate website, only usbank.com, a subdivision of U.S. Bancorp.

Because Google is now a subsidiary of Alphabet Inc., abc.xyz was looked for in the context of other countries, but nothing could be found. Since their largest player in the market is Google, its websites were used for analysis.

Using Amazon Mechanical Turk for the first time was also interesting. The time from survey submission to complete answers was very short, and the overall process was fairly painless. In future studies, per emailed requests, buttons and counters could be added to help respondents verify that information is completely filled out, lowering the number of rejects needed. There were also many people upset with rejects who would email their frustrations about being rejected for not completing the work.

Data Collection - Products

While many people were contacted through LinkedIn, very few decided to connect back, and even fewer responded to the email that was sent as part of this project. With only two replies, it is difficult to analyze the data in any way to draw conclusions. It was originally believed that LinkedIn provided email addresses as open information, but this was recently changed so that you must be connected with a person to see their email.

Factor and Reliability Analysis

When examining the results of the factor analysis, it was interesting to see that the uniqueness for Language is very high. This might mean that it should not be considered as one of the two factors and should be in a category by itself. A similar statement might be made about Web Address, but to a much lesser extent. If a reasonable cutoff of .4 is made when displaying the loadings table, this becomes more reasonable as Language would not have any values on the table.

It is interesting that the two factors came out the way they did. Factor analysis is usually done to create "bundles" of metrics that are related. The combination of Navigation, Message, and Web.Address seems to portray more back-end and infrastructure based metrics, while Language and Media are more front-facing metrics. These could be the two categories that were actually being measured through these questions.

The alpha values were also within tolerance levels. It was originally assumed that Mechanical Turk might provide subpar data because of the profit incentive of workers. While it is nearly impossible to filter out all the bad responses, this consistency was higher than was expected.

Basic Combined Data – Websites

With 1 being very similar and 7 being very different, values greater than 4 (the average) would show where people feel sites are different.

Figure 8 shows summary data for Individual Survey Responses. Language is the only variable whose average was greater than 4. This should be expected as the language barrier is a major reason why a company should create a localized website. With the other factors having means in the 3s, it can be said that individual respondents thought the websites were fairly standardized on these metrics.

Viewing the Combined Data information in **Figure 9**, we see that most of the data points lie below the 4-line. Of the values that are above the 4-line, many of them are manufacturing, as expected. It is interesting that the highest value goes to Finance, Insurance, and Real Estate. This industry seems to be one that would be more standardized, but Akelius seemed to have the largest difference. Each of the pair of websites is very simple, so even small changes mean that the websites can be very different. This is what the high data point might be saying.

Figure 10 is a basic analysis of Final Classifications on analyzed metrics. Results are similar to **Figure 8**, where Language is the only factor with a mean greater than 4.

When simply viewing **Figure 11**, there did not seem to be any relationship between factors of overall comparison and overall comparison. Only 4 values were greater than 4, meaning that 4% of the top 100 websites are more different than similar. Breaking this graph down by industry, we see that these companies each come from a different industry.

By looking at **Figure 13**, we see that many sites have very different languages, but are mostly similar on the other metrics. There also seems to be no obvious trend relating Market Capital to any factors of overall similarity. A quick linear regression on these metrics shows that none of these variables directly relate to market capital.

<u>Basic Combined Data Analysis – Websites and Products</u>

With only two data points collected, there is little room to create any kind of model about the relationship between these metrics.

Logistic Regression – External Factors to Predict Components of Similarity

The logistic regression was done on the Final Classifications data set. Primary results showed no promise for tuning the model. Variations on this were done for each tested response variable, using a continuous dependent variable and linear regression, as well as removing dependent variables that had probabilities greater than .1. The results of all these tests were the same, resulting in no good model to fit extra-website factors to similarity using a logistic regression.

Decision Tree – External Factors to Predict Components of Similarity

Decision Tree models were made to predict tested components. When the models were tested for accuracy, they were found to be relatively accurate, but when the results were compared to the actual answers, it was found that for each model, the predictions would be the same. This was tested with a larger test set, which resulted in the same outcome. A boosted model was also tested, but it was found that the function defaulted to one trial. This means that the models will always predict the factor to be either one or zero not depending on the non-website factors, but by the one or zero it will always use. This also make decision trees a poorly fitted model for factors.

Linear Regression - Components of overall similarity

The Combined Data set was used for the linear regression. Therefore, this represents a model that can be applied to any two websites, not the average of the company, to predict the overall similarity.

The Residuals vs. Fitted plot shows a fairly straight line near 0, an indicator of a good model. The Normal Q-Q plot maintains that the residuals of the model are fairly normally distributed. The pattern begins deviating closer to the poles, but this is expected. The Scale-Location plot, which shows if residuals are spread equally along the predictor variables, shows some signs of widening and then narrowing, but not enough to worry about homoskedacity. The Residuals vs. Leverage plot shows that there are no influential cases as all are within Cook's lines. Removing points noted in these plots improved the Adjusted R-Squared by .0054. With these things being true, we can say that this model does a good job of predicting overall similarity.

Conclusions

Hypothesis 1 - The websites for current multinationals are more localized

Given the data from the Basic Combined Data Analysis – Websites section, we must reject the hypothesis and claim that websites are more standardized than localized. The fact that at every level the overall factor is below 4, combined with the factors (besides language) being below 4, we cannot prove Hypothesis 1 and must claim that current multinationals are more localized.

Hypothesis 2 - Companies that localize their products also localize their websites. Companies that standardize their products also standardize their websites.

Because enough data could not be collected on this metric for any analysis, no testing could be done. Therefore, we cannot test the hypothesis.

Hypothesis 3 – The standardization/localization of a company's websites can be determined based on factors unrelated to their website.

The data collected from the Logistic Regression and Decision Tree models do not support the hypothesis that standardization/localization of a company's websites can be determined based on factors unrelated to their websites. With a logistic regression model that contains no significant variables and decision tree models that only predict one way or the other, Hypothesis 3 cannot be supported.

Hypothesis 4 – There exists a model that can accurately predict how similar/different websites are based off of their metrics.

This question was answered by the last linear regression. The regression model was able to predict the function for overall similarity. The variables are significant, and the diagnostic plots portray the model as being good, thus we can accept the hypothesis.

Implications

The results of this study have wide applicability. We see that current multinationals are more standardized than localized. This is in the face of research stating that people prefer highly localized websites. Businesses will have to work to localize their sites more so that they can realize a larger, happier customer base.

The fact that two models could not accurately predict factors of standardization/localization of these companies based on their non-website related metrics does not mean that a model does not exist. With more data points, it may be easier for a model to accurately predict factors of similarity. This also includes more factors to aide prediction.

Being able to predict the overall similarity of websites using the logistic model means that there exists a model that should be able to show how different factors affect overall website similarity. Because the R^2 value was .6577, there is room for growth as other variables help constitute overall similarity.

Limitations and Possible Sources of Error

With any research comes the possibility for sources of error. The first possible error comes from the method used to collect data. Amazon's Mechanical Turk is known to be a reliable source of data collection for companies, with various studies showing the reliability of the method. Respondents do have a profit incentive to complete as many surveys as possible as quickly as possible. While the data were shown to be fairly reliable, it is impossible to tell if this was by random chance or not. There is always a chance for human error in data analysis. A wrong click or copy could have altered the data. There were also time and financial limitations with this experiment. Given more resources, more data could have been collected, leading to more widespread results.

Future Research

Future research would include an expansion of the research completed for this project. In theory, this means using a larger number of websites to collect data, using in-lab studies with respondents that do not have as strong of a profit incentive, and asking respondents more detailed questions about the comparison of these websites. Future research also includes finding alternate ways to collect data about the localization/standardization of products. A last expansion would be to try a larger variety of models to make predictions about standardization/localization of websites.

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