Words have meaning: language choice and startup success

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Introduction

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Background

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Hypothesis

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Data

Y Combinator startup company descriptions

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Figure 1 − histogram of words per company description

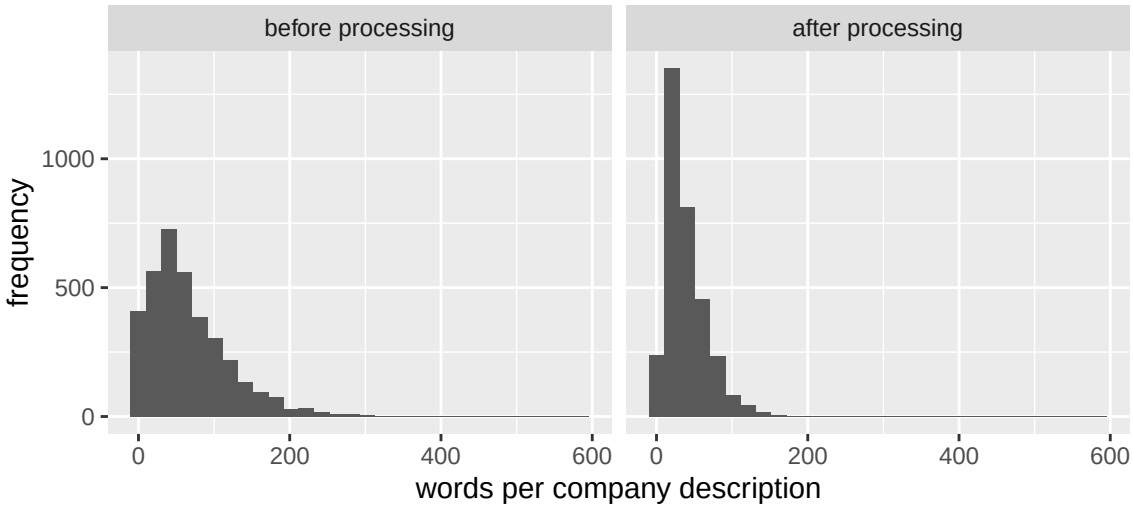

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Figure 2 − top five locations where companies are founded

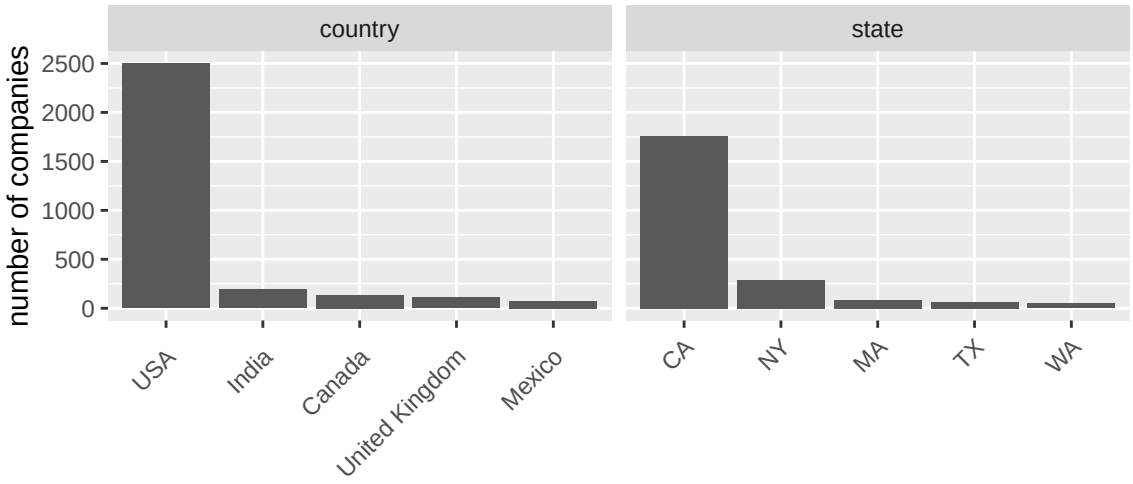

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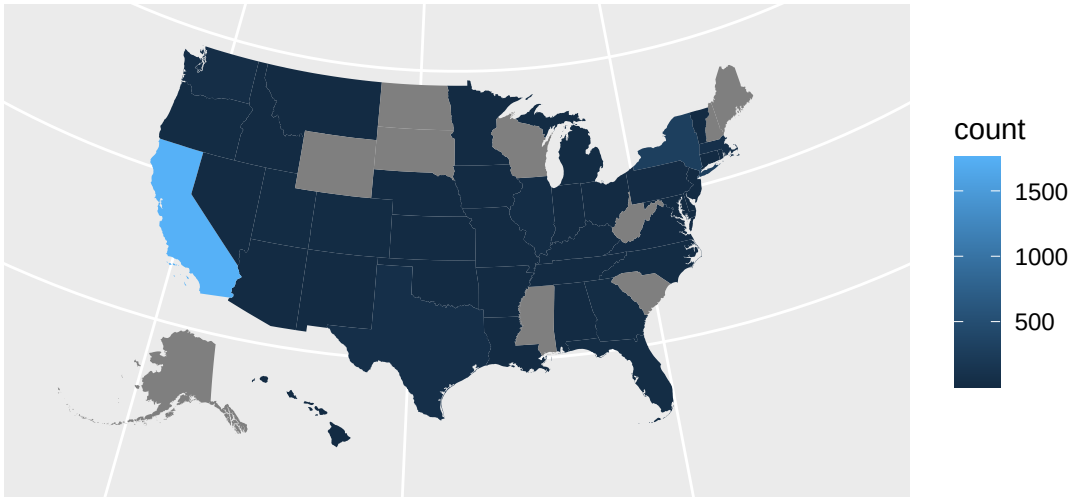
Figure 3 − geographic distribution of Y Combinator companies



Open source textbook extracts

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Table 1 - textual data summary statistics

data	document count	words per document						
		minimum	lower quartile	mean	median	upper quartile	maximum	standard deviation
companies, pre-processing	3586	1	28	66.45901	53	93	586	55.06245
companies, post-processing	3251	1	19	38.47155	31	52	287	27.17250
textbooks, pre-processing	5	344	2039	3009.60000	2841	3583	6241	2170.63627
textbooks, post-processing	5	181	1067	1676.80000	1918	2065	3153	1117.73396

Crunchbase startup funding data

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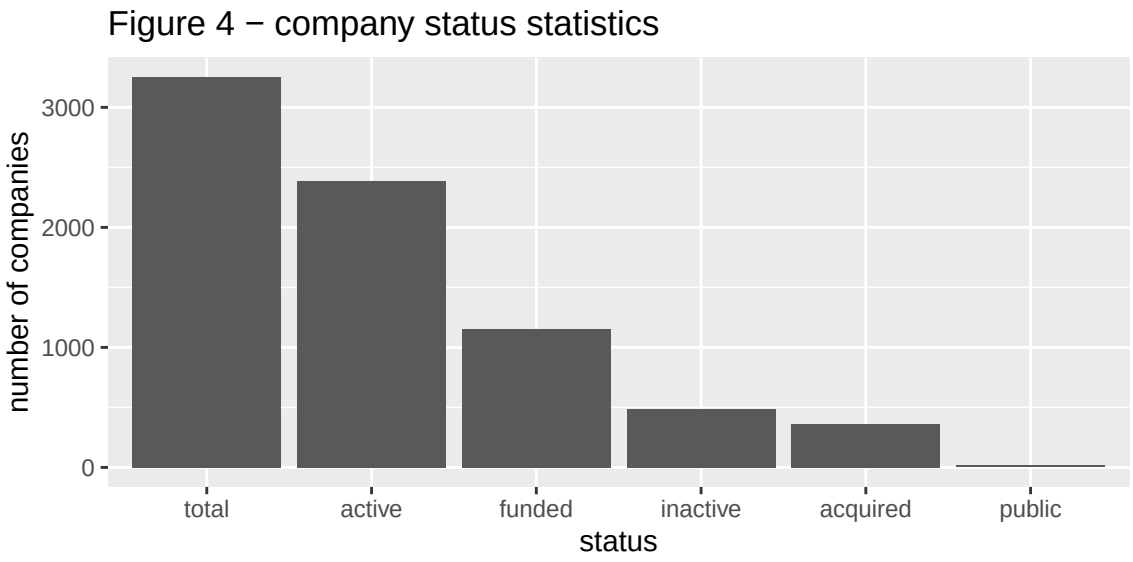
Table 2 - funding and exit data for Y Combinator companies

status	count
total	3251
active	2386
funded	1153
inactive	488
acquired	362
public	15



Methodology

Once we obtained the required data, our methodology followed three main steps: (1) processing the data into useable form, (2) calculating cosine and Jaccard similarity scores between each company description and each textbook, and (3) use ordered and multivariate regressions to analyse the relationship between the calculated similarity scores and company outcomes. These steps are discussed in detail in the following sections.

Textual data Our two separate sources of textual data required different means to extract and then process into usable formats. We extracted the company descriptions using the rvest package, looping through each company's individual website and scraping the required information. For the five textbooks, we manually extracted just the table of contents, index, or glossary (as available, it varied per textbook) and then imported them into R using the pdftools package.

The initial textual data, once imported into R, was still not in a format useful for analysis. We followed several steps to convert the data into a usable format:

(1) We removed all numbers, whitespace, punctuation, and any blank or "NA" rows to reduce the data to just words.

(2) Next, we "lemmatized" each word using the textstem::lemmatize_words function. This function uses a dictionary based on the Mechura 2016 English lemmatization list. This step reduced the words to common base forms, reducing the complexity of the data and making it easier to analyze.

(3) Finally, we calculated term frequencies for each document, and then used this information to build a document-term matrix of all the company descriptions, textbook extracts, and terms. The matrix contains a set of vectors for each textbook extract and company description, with each value corresponding to a specific term and the frequency it is found in each document.

Funding and exit data We based the current status of each company based on information scraped from the Y Combinator website - each company is described as either "Inactive" (gone out of business), "Active", "Acquired", or "Public". We were fortunate in this project in that the Y Combinator and Crunchbase websites use a similar naming convention for companies, making joining the textual data with the funding data an easy step. We filtered the Crunchbase funding data down to the company name and the number of funding rounds received and joined this data to the list of companies using the dplyr::left_join function. The Crunchbase data only included companies that have received startup funding, enabling us to define a second logical variable for whether or not a company had received funding.

Similarity scores The final processing step required was to calculate the similarity between each company description and the textbook extracts, i.e. how similar a company's initial descriptive language is to a business topic. We did this using two measures, the cosine and Jaccard similarity scores between each company description and each textbook.

We calculated the cosine similarity score for each company description using the lsa::cosine function. This function takes two arguments, the respective vectors for each company description and textbook, and returns a cosine similarity score. In mathematical terms, this score is the dot product of the two vectors divided by the product of their lengths.

The Jaccard similarity score is similar to the cosine similarity score, but only considers unique words per document instead of frequency. To calculate this score, we first converted each vector into a logical vector, based on whether or not the term was present in the respective document. The Jaccard similarity score is then calculated as the intersection of the two vectors divided by the union of the two vectors.

The mean cosine and Jaccard similarity scores for each company, grouped by company status, are listed in the below table.

Table 3 - similarity scores by company status

Data integration and regression analysis Combining these sources of data gave us a table with X independent variables (the cosine and Jaccard similarity scores for each company - how closely a company's

		Mean cosine similarity scores				
status	count	entrepreneurship	finance	leadership	marketing	strategy
Acquired	362	0.0738666	0.0255525	0.0403263	0.0272614	0.0498762
Active	2386	0.0784647	0.0298825	0.0418272	0.0335066	0.0526428
Inactive	488	0.0651645	0.0222868	0.0358728	0.0272202	0.0461308
Public	15	0.1074728	0.0321027	0.0614199	0.0352015	0.0725202

		Mean Jaccard similarity scores				
status	count	entrepreneurship	finance	leadership	marketing	strategy
Acquired	362	0.0004728	0.0002122	0.0002551	0.0000659	0.0002961
Active	2386	0.0004464	0.0002053	0.0002590	0.0000649	0.0002824
Inactive	488	0.0003831	0.0001778	0.0002160	0.0000570	0.0002429
Public	15	0.0006702	0.0002840	0.0004078	0.0001092	0.0004442

description matched a business topic) and two dependent variables. The first dependent variable was logical: whether or not a company received funding. The second dependent variable was ordinal, based on a company's exit status: "Inactive", "Active", "Acquired", or "Public", in that order. We ran two regressions using this data to determine if there was a relationship between the textual data and (1) whether a company received funding and (2) its viability as a company as measured by exit status.

Results

It is difficult to draw robust conclusions from our two regressions. The results of each regression are listed in the below tables, with p-value .05 statistically significant independent variables in bold.

For the first regression, similarity scores versus a company's exit status, the estimates of the coefficient for each variable in the regression formula varied widely in both sign and value. Only one variable, the marketing cosine similarity score, was statistically significant at a p-value of .05. We could interpret this as with an one unit increase in the marketing cosine similarity score, the log odds of a company progressing through each status increases by 0.30. However, due to the wide variety in the rest of the results it is impossible to draw a solid conclusion from this.

Table 4 - exit status regression table

For the second regression, similarity scores versus whether or not a company received startup funding, the results were marginally more clear. Four variables, the entrepreneurship, finance, and marketing cosine similarity scores and the entrepreneurship Jaccard similarity score had statistically significant estimates of their coefficient. This could be interpreted as a one unit increase in these similarity scores corresponding to a respective increase or decrease in the log odds of a company receiving funding. Again however, the wide variance in results makes it difficult to draw solid conclusions. If there were truly a strong relationship,

term	estimate	log odds	std.error	t statistic	p value	coef.type
ent_c	1.4308724	4.182347e+00	1.3944003	1.026156e+00	0.3048180	coefficient
fin_c	-0.5290431	5.891685e-01	1.4805517	-3.573283e-01	0.7208460	coefficient
ldr_c	**3.1763422**	**2.395896e+01**	**1.5903768**	**1.997226e+00**	**0.0458006**	**coefficient**
mkt_c	-1.2159323	2.964335e-01	0.8584770	-1.416383e+00	0.1566634	coefficient
str_c	-3.2406770	3.913740e-02	1.9529217	-1.659399e+00	0.0970354	coefficient
ent_j	1267.7589882	Inf	0.0037398	3.389887e+05	0.0000000	coefficient
fin_j	419.0829791	1.012571e+182	0.0030495	1.374271e+05	0.0000000	coefficient
ldr_j	-2442.6144174	0.000000e+00	0.0041386	-5.902061e+05	0.0000000	coefficient
mkt_j	745.5850996	Inf	0.0013264	5.621172e+05	0.0000000	coefficient
str_j	1078.0305844	Inf	0.0043240	2.493123e+05	0.0000000	coefficient
Inactive|Active	-1.3724071	2.534960e-01	0.0779986	-1.759528e+01	0.0000000	scale
Active|Acquired	2.4571785	1.167183e+01	0.0868109	2.830496e+01	0.0000000	scale
Acquired|Public	5.8110501	3.339696e+02	0.2673527	2.173552e+01	0.0000000	scale

one would expect to see similar results for each cosine or Jaccard similarity score. Instead, they again vary greatly in both sign and value, leading to inconclusive results.

Table 5 - funded regression table

term	estimate	std.error	statistic	p.value
(Intercept)	**-0.6021217**	**0.075806**	**-7.9429338**	**0.0000000**
ent_c	**-3.1122222**	**1.462765**	**-2.1276304**	**0.0333677**
fin_c	**-7.7819262**	**1.848884**	**-4.2089853**	**0.0000257**
ldr_c	1.7989371	1.750830	1.0274768	0.3041960
mkt_c	**-2.6269333**	**1.027653**	**-2.5562452**	**0.0105809**
str_c	3.6325517	2.087376	1.7402482	0.0818154
ent_j	**1027.8160713**	**357.883129**	**2.8719322**	**0.0040797**
fin_j	-482.8442896	541.929932	-0.8909718	0.3729443
ldr_j	-963.1932609	500.930394	-1.9228086	0.0545041
mkt_j	-129.7534025	1015.312243	-0.1277966	0.8983100
str_j	590.4033507	517.827425	1.1401547	0.2542219

Conclusion

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References

R libraries

We used the below libraries in our analysis and to develop this report:

tidyverse / tm / MASS / xml2 / rvest / urbnmapr / here / dplyr / broom / kableExtra

tidytext / textstem / sjPlot / pdftools / textclean / widyr / text2vec / lsa

Company descriptions

All company descriptions were scraped from their respective pages at ycombinator.com/companies

Textbook extracts

We extracted the table of contents, indices, and glossaries (availability varied by textbook) from the below open source textbooks to build our dictionaries:

–Burnett, J. (n.d.). Introducing marketing. Open Textbook Library. Retrieved April 21, 2022, from https://open.umn.edu/opentextbooks/textbooks/introducing-marketing

–Coleman, W., & Halbardier, A. (n.d.). Principles of Management. openstax.org. Retrieved April 21, 2022, from https://openstax.org/details/books/principles-management

–Laverty, M., & Littel, C. (n.d.). Entrepeneurship. OpenStax. Retrieved April 21, 2022, from https://openstax.org/details/books/entrepreneurship

–Reed, K. B. (n.d.). Strategic management. Open Textbook Library. Retrieved April 21, 2022, from https://open.umn.edu/opentextbooks/textbooks/mastering-strategic-management

–Taylor, J., Robison, L., Hanson, S., & Black, J. R. (2021, January 28). Financial Management for small businesses, 2nd Oer edition. Financial Management for Small Businesses 2nd OER Edition. Retrieved April 21, 2022, from https://openbooks.lib.msu.edu/financialmanagement/

Funding data

Crunchbase funding data provided by Katie Moon, Professor of Finance at University of Colorado Boulder.