

Using Machine Learning to Demystify Startups Funding, Post-Money Valuation, and Success

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Using Machine Learning to Demystify Startups Funding, Post-Money Valuation, and Success

Yu Qian Ang, Andrew Chia, and Soroush Saghafian

Abstract This chapter develops a novel approach to predict post-money valuation of startups across various regions and sectors, as well as their probabilities of success. Using startup funding data and descriptions from Crunchbase over a ten-year period, we develop two models linking information such as description, region, and venture capital funding to successful outcomes such as the achievement of an acquisition or IPO. The first model utilizes latent Dirichlet allocation, a generative statistical model in natural language processing, to organize the startups in the dataset into clusters representing various sectors in the typical economy. An optimized distributed gradient boosting regressor (XGBoost) is subsequently deployed to make use of the resultant feature set to predict post-money valuation, with Bayesian optimization used to find the optimal hyperparameters. Our model consistently achieves an accuracy of over 95% on hold-out test sets, even with some continuous features removed. The second model is a feed-forward neural network constructed using TensorFlow, with the final layer providing probabilities of success. We find that post-money valuations across regions are typically log-normally distributed, and startups in regions such as San Francisco Bay Area typically witness higher valuations across most sectors. We also find that startups operating in specific geographical regions and sectors of economy (e.g., regions and sectors with higher number of investors) typically have higher predicted probabilities of success. Our approach offers an empirical perspective to startups, policymakers, and venture funds to benchmark and predict valuation and success, clearing some opacity in the modern startup economy.

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1 Introduction

In the modern economy, startups and entrepreneurship are viewed almost synonymously, both resulting in technological innovation, economic growth, and jobs creation. Touted as both a panacea for solving unemployment and a catalyst for growth, it is unsurprising that major cities are vying to be the next silicon valley, competing to attract innovative ideas, entrepreneurial talents, technology-driven startups, and venture capital (VC) funding. Globally, startups have become an increasingly prominent feature in the world economy, both as creators of economic value and disruptors of existing industries. They also play significant roles in major cities as important drivers of innovation and sources of next-generation ideas, in a myriad of sectors, including healthcare, manufacturing, transportation, logistics, and finance. Having a vibrant startup ecosystem, thus, increases the attractiveness of a city for business investments that spur job growth or rejuvenate existing industries. It is, therefore, unsurprising that the popular media is often filled with against-all-odds success stories of startups. But are such startup success stories really against-all-odds? Or are there measurable factors that can help to correctly predict the future success of startups?

In recent years, academic research aimed at understanding the dynamics of entrepreneurship have proliferated due to the growing role that startups play (Shane and Ulrich, 2004), and financing/funding has been identified as a crucial factor in any successful startup ecosystem. On one hand, startups—especially technology-based firms—are often financially constrained (Carpenter and Petersen, 2002) requiring significant funding for research and development, customer acquisition, and marketing, among others. Startups that are well funded or VC-backed have been reported to outperform their non-funded counterparts (Gompers and Lerner, 2001; Denis, 2004). Obtaining financing such as VC investments or follow-up funding also contributes to the so-called “signalling effect” (Islam et al., 2018) helping early-stage startups gain credibility as they progress from conceptualization to commercialization. On the other hand, obtaining sufficient funding without early signs of traction is often impossible. Funding and startup success, hence, can be viewed as a chicken and egg problem.

This chicken and egg problem makes it often difficult to comprehend valuation of startups, and identify the key factors contributing to their success. For example, will a startup with a given amount of Series A funding be eventually successful? Is it possible to predict such startups likelihood of success with reasonable confidence, given that success stories are typically rare events with about 90% of startups failing on average? Answers to these types of questions can significantly assist various players and decision-makers in the startup ecosystem, including entrepreneurs, venture capitalists, policymakers, and researchers. For example, VCs are often perceived as entities that fill the void in the innovation and commercialization process. However, to ensure viability, VCs need to generate consistently superior returns on investments, a significant challenge given the inherently risky nature of early-stage companies. Since as high as 75% of venture-backed deals typically fail to return the investment

(Hoque, 2020), VCs rely on a small number of portfolio investments to achieve outstanding paybacks—enough to cover for losses and still produce substantiate profits. Therefore, any data-driven method that can yield superior investment decisions can be significantly valuable.

In this study, we review the entrepreneurial ecosystems and take stock of the key fundraising activities in major cities around the world. We then construct two models using modern machine learning approaches to predict startups' potential post-money valuation and probability of success using a dataset of funding activities across different regions, sectors of the economy, and funding stages, observed over a 10-year period (2009–2018).

Our study makes several contributions to the existing literature on startup and entrepreneurship. First, we examine the startup financing landscape in the context of different geographical regions and funding stages. In the ubiquitous, globalized nature of modern technology-based startups and their products and services, there is a need for research to shed light on how fundraising activities vary across cities. This will also be beneficial for startups seeking funding as part of their internationalization strategy, and for venture funds targeting specific geographical regions and financing stages. We also provide insights into statistical aspects of funding raised in different regions and sectors of economy, including their distributional properties. Second, we make use of some machine learning approaches to develop strong prediction models that can (a) augment the myriad analysis and benchmarking typically done by venture funds, startups, or policymakers, and (b) serve as basis for further academic studies.

In what follows, we first review the startup financing landscape and introduce our data set. We then describe the methodology and approach behind our machine learning models, and discuss the insights gained by making use of them on our data set. Finally, we conclude by (a) providing recommendations for various entities involved in the startup ecosystem, including entrepreneurs and policymakers, (b) identifying limitations of our work, and (c) summarizing potential avenues for future work.

1.1 Financing

Funding is a vital resource for startups; financing and equity investments through government grants, accelerators/incubators, angel investors, and venture funds are key resources that can shape a startup's development trajectory. These funds are typically utilized to support critical activities such as product development, marketing, research and development, and staffing. Recognizing the importance of financing, governments and policymakers around the world have developed their own funding programs, such as independent government-sponsored funds (Alperovych et al.,

2015), co-investment/co-financing vehicles, and grants, among the many instruments designed to catalyze the startup ecosystem. These accompany private entrepreneurial investments by venture capitalist, corporate venture capital funds, startup accelerators/incubators and angels, as well as relatively newer financing modalities such as equity crowdfunding (Drover et al., 2017). Naturally, most of the financing activities gravitates and converges towards major cities. The geographical region in which a startup is located, hence, can play an important role in the investment amounts it can attract.

Besides the geographical region, the investment amounts a startup can attract typically vary significantly across funding stages. In most geographical regions and entrepreneurial ecosystems, seed funding is usually the first institutional funding received by a startup, although many venture funds are now looking at pre-seed due to the competitive nature of seed investments. The name of this round, seed funding, is self-explanatory: seed funding is used to take a startup from ideation to some early traction, such as initial product development, market research, or validation for product-market fit. A seed funding round typically ranges between \$100,000 to \$2 million, depending on the type of startup and the geographical region. The typical valuation for a startup raising seed ranges between \$3 million and \$6 million (Reiff, Nathan, 2020). Unfortunately, many startups run out of seed funding before they can gain sufficient traction. For example, data from the market research firm CB Insights obtained by tracking a cohort of 1,100 startups that raised seed rounds in the United States shows that less than 50% managed to raise a second round of funding. Furthermore, only 15% of these startups eventually raised a fourth round (which corresponds to Series C), and 67% either ended up dead or became self-sustaining (Insights, 2017).

Once a seed stage startup gains sufficient traction—measured in terms of common key performance indicators such as revenue or user acquisition—it moves to raise Series A funding. In this round, startups are expected to have a viable business model and sufficient traction, since investors want to assure more substantive development and growth. As the name suggests, series funding, consists of a series of startup funding rounds that follow one after the other (Yuen, 2020), generally with increased valuation in each subsequent round. Typical rounds include Series A, B, C, D and sometimes E and F, and these rounds of funding is typically raised through venture capital firms (or other institutional investors). The different rounds are intended to also reflect the startup's status, performance, and valuation (Williams et al., 2013). A prospering and well-performing startup will have its company stock valued higher in a Series B round than A, and higher still in a Series C round. A startup not performing well may still obtain Series financing rounds, but subsequent Series rounds will often value the company at a lower stock price (a “downround”). Currently, the mean Series A funding round is valued at around \$10 to \$15 million in the United States, a figure that has been growing steadily (Fundz Research, 2020). The mean Series B round currently stands at around \$32 million, with a median pre-money valuation of \$58 million (Fundz Research, 2020). However, these overall

averages are highly contextualized and differ significantly across countries, different regions (even within the same country), and startup types.

Although the exact juncture is not specifically defined, typically after the second and/or third capital injection, startups enter a growth stage where funding serves to propel rapid growth and expansion rather than ignition. This usually entails internationalization (e.g., expansion to additional markets), diversification of product lines, aggressive marketing, or new manufacturing and production locations. With a commercially viable product and product-market-fit, a startup at this stage should have a good source of revenue and continue to attract new users/customers at breakneck speed. Very few startups eventually reach the Series D stage, and the amount raised by them as well as their valuations vary widely among them.

Finally, mezzanine financing and bridge loans are hybrid loan and equity financing mechanisms that prepare the startup for the final push for an exit. Mezzanine financing is typically perceived as being riskier than other types of startup financing due to higher interest rates. An initial public offering (IPO) is often the final stage of funding that a startup goes through before it becomes an established company. A startup may also be acquired along the way, regardless of funding stage, especially if it has new technologies or has established significant user base or data that are of high value to the acquirer.

1.2 Post-Money Valuation

In the startup ecosystem, valuation is the process of quantifying the worth of a company at specific junctures. Valuation is important to founders for various reasons, including the fact that it determines the amount of equity they must give to investors in exchange for funds. Similarly, for investors, valuation helps to set the shares they should receive in lieu of their investments during a financing round (Miloud et al., 2012).

Valuation often has two stages: pre-money and post-money valuation. Pre-money valuation typically refers to the value of a company before—and not including—the latest funding round in question. Thus, pre-money valuation can be roughly described as how much a startup is worth prior to the current round of investments. Post-money valuation, however, refers to the value of the startup after receiving investments (Frei and Leleux, 2004). Both pre- and post-money valuation are usually affected by a variety of factors, including the sector of the economy the startup belongs to, its technology, revenue, reputation, and level of traction. Valuation methods can be broadly grouped into two main categories: qualitative and quantitative. The former—qualitative method—is more prevalent in assessing early-stage startups due to the lack of sufficient information at that point early on. The—quantitative method—is used more often in later stages, as more information (e.g., financial)

becomes available at such stages.

One common method in valuation is the discounted cash flow method (Festel et al., 2013), which estimates how much cash flow the company is slated to produce. This estimation is obtained by making use of a reasonable, expected rate of investment return. A higher discount rate is typically associated with startups that have higher risks. This method relies partly on an investment analyst’s ability to make sound and accurate assumptions on a startup’s growth trajectory. A second popular method, which is usually utilized for pre-revenue and early-stage startups, is the Berkus Method, named after investor David Berkus (Berkus, 2016). This approach makes use of a general rule of thumb to estimate the value of the startup, since current pre-revenue forecasts rarely turned out to be accurate. Other commonly used methods include the First Chicago method, the venture capital method, the Comparables method, the Book Value method, the Scorecard method, and the Risk Factor Summation method (Nasser, 2017). As many valuation exercises are subjective, especially in early-stage investment, and the exact method utilized are often undisclosed, we avoid developing models that rely on any of these methods of valuation. Instead, we make use of machine learning algorithms and train them on actual post-money values in our data. These algorithms then learn to predict the post-money valuation of startups using their early stage raw data.

1.3 Success

The definition of a successful startup is in general elusive and subjective. For investors, however, the notion of success is relatively straightforward, because they usually value return on investment. Thus, from an investor’s perspective, the holy grail is a profitable exit, such as a successful acquisition or IPO. An exit is also often the only realistic way for professional or institutional investors to significantly profit from an investment. However, success is more complicated from the founders’ perspective. Some founders, and especially serial entrepreneurs, seek financial gain, and pursue profitable exits after gaining significant trajectories. Others value success on more introspective terms, such as creating social good. Moreover, there can be a long incubation time between the founding of a startup and its acquisition or IPO. Thus, labelling startups that are on their way to success but have not achieved it as unsuccessful is often an unfair assessment of their potential. These make studying success among startups a perplexing task.

For the goals of this study, we start by considering the conventional, investor-based definition of success: whether a startup will be acquired or will launch IPO. We then expand our definition of success to also include startups that are able to raise follow-on funding amounts that are greater than their previous funding rounds, since such startups tend to grow over time. We make use of this definition of success to train a neural network to classify startups into two categories: successful

and unsuccessful. This classification is done based on predicting the probability of success using features such as geographic region, sector, stage, and funding, among others. Once it is trained, our neural network algorithm is able to accurately predict if a startup (not included in the training data) will eventually be successful given its features.

2 Data

The primary dataset for this study comprises startup funding instances obtained from Crunchbase, with supplementary data on the companies, IPOs, and acquisitions. Crunchbase is a platform that aggregates business information about private and public companies. Originally built to track startups, Crunchbase now contains information on startups, venture funds, and companies on a global scale. Crunchbase sources their data through many channels, including an in-house data team, their venture program, and community. We accessed Crunchbase data using a REpresentational State Transfer (REST) Application Programming Interface (API) user-key, to access compressed Tape Archive Files (TAR) that contains various raw data on companies and funding rounds globally, starting from 1915. The data from various files were matched using the unique identifier generated for each startup and investor. The resultant dataset reflects a ten-year period from 2009 to 2018, with a total of 290,707 observations of startups funding instances around the world. From these 290,707 observations, we retained 46,025 observations after (a) filtering for empty fields, mismatching, or corrupted data, and (b) focusing on observations related to one of the top 15 cities that have the highest number of startups. These allowed us to maintain a reasonable number of datapoints in each region, and consequently, perform analysis that are robust (and not affected by issues such as sparsity).

While there are other platforms and databases that tracks startup financing, including Pitchbook, AVCF, and CB Insights, the data aggregating methodologies used in them are different. It is, therefore, unfeasible to simply merge data from different sources, especially if consistency is to be maintained. Furthermore, global financing data can never be complete in practice, since a significantly number of transactions are undisclosed, and many startups operate in stealth mode for confidentiality. Therefore, we consider our Crunchbase dataset as relatively representative, even as the final dataset, after data wrangling, is a relatively small sub-sample of the entire startup population.

Figure 1 shows the top 15 major cities with the highest number of startups in our dataset. In these cities, most startups are still operational, ranging from 83% of the startups in the San Francisco Bay Area to 92% in New Delhi. Figure 2 shows the status of startups in these major cities. Unsurprisingly, we see that San Francisco Bay Area not only has the largest number of startups, but also the highest percentage of startups that are either acquired or have launched IPO (11%). Other cities with

relatively high percentages of startups that were acquired or launched IPO include Toronto (11%) and Paris (10%).

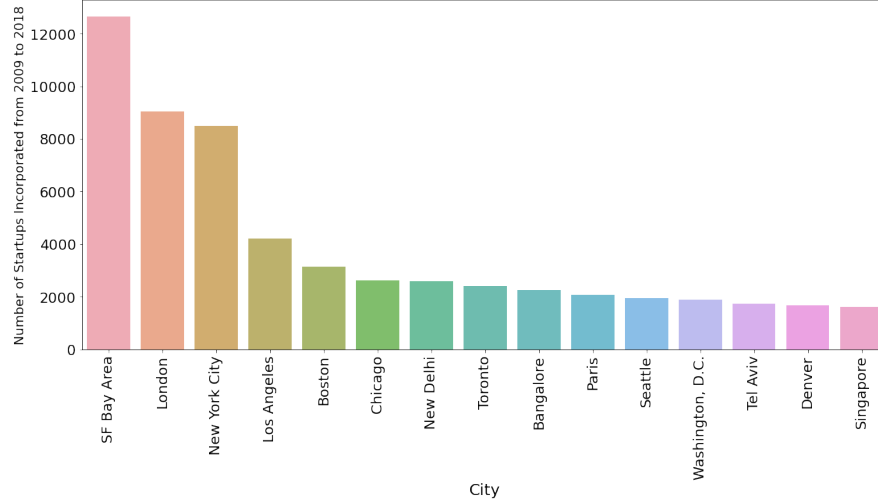


Fig. 1: Top 15 cities with the highest number of startups in our dataset

Our preliminary exploratory analysis of the investment stage of startups revealed over 25 funding stages in our dataset, ranging from pre-seed stage to Series J and even post-IPO. Much of the data in many regions and in the later stages are sparse, containing very few data points. For consistency and rigor of our machine learning models, we used a subset of the overall data comprising funding information for the top 15 regions, as well as the following stages: grant, angel round, seed, series A, series B, series C, series D, and series E. Figure 3 shows the amount of funding raised based on region and funding stage.

To better understand the nature and properties of post-money valuations, we assessed their distributional properties across regions and funding stages using kernel density estimation (KDE). KDE is a non-parametric method commonly employed to approximate the probability density function (PDF) of continuous values (Parzen, 1962) such as funding (Carayannis et al., 2018) or startup valuation (Quintero, 2019). Figures 4 and 5 show the KDE for the amount raised (on a logarithmic scale) based on region and funding stage respectively. Funding amount raised and post-money valuation in venture capital are typically power-law distributed (Korver, 2018), and may be subject to the Babe Ruth effect (Dixon, 2015). While most funding raised and valuations are situated at lower values, there may exist a long tail of exceptionally high funding amount raised or post-money valuations (Quintero, 2019). Thus, the natural logarithm of these quantities is typically normally distributed. This also



Fig. 2: Status of startups in the top 15 cities

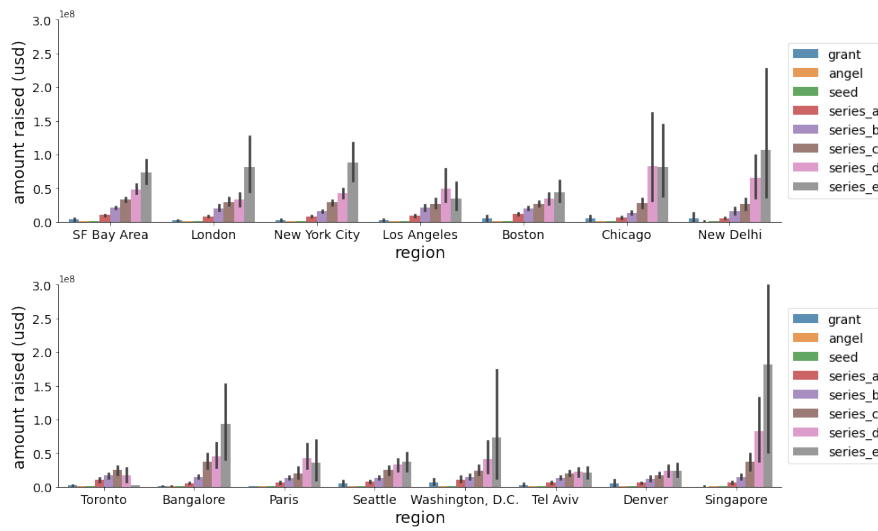


Fig. 3: Funding amount (USD) based on stage and region

exemplifies the known fact that returns are highly concentrated on “home run” investments.

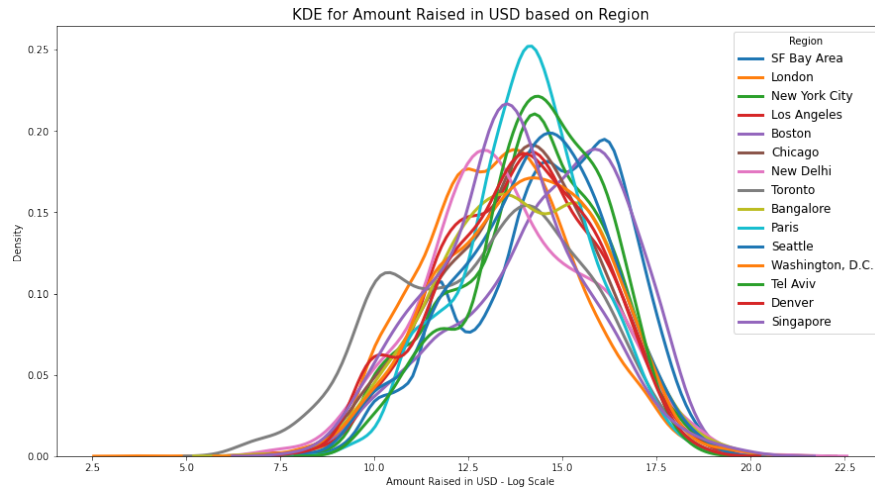


Fig. 4: KDE for funding amount raised (logarithmic scale) based on region

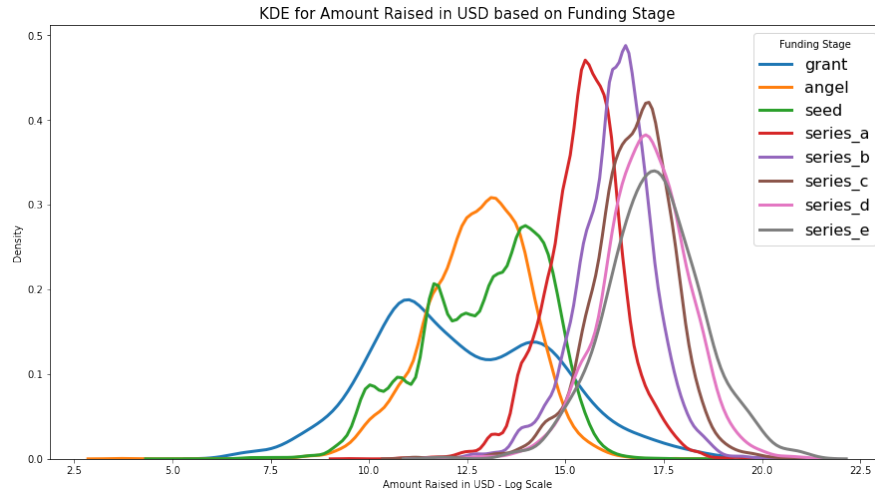


Fig. 5: KDE for funding amount raised (logarithmic scale) based on funding stage

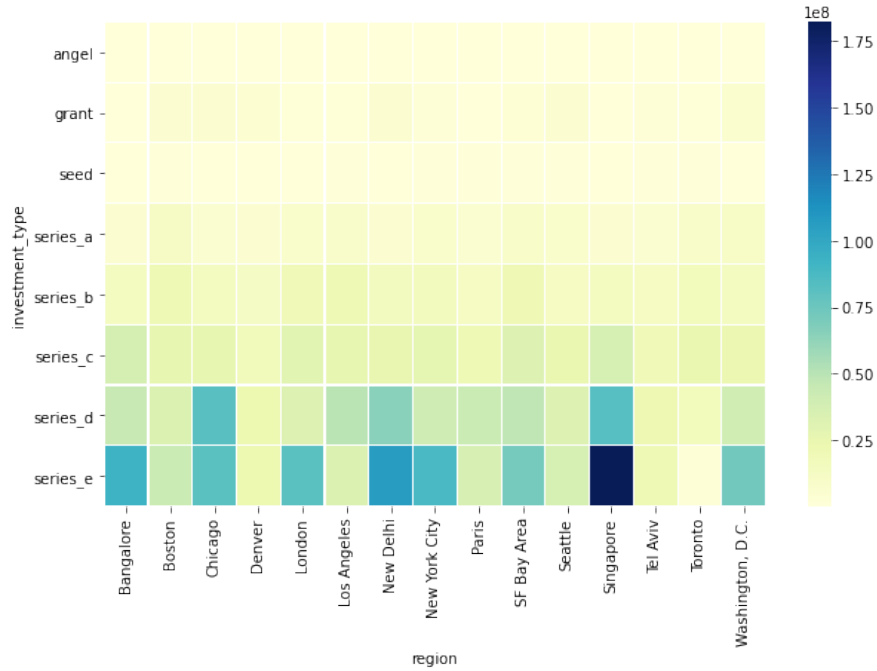


Fig. 6: Heatmap for funding amount (logarithmic scale) based on region and funding stage

Figure 6 illustrates the heatmap (in logarithmic scale) of funding stage and region. The darker colors represent higher funding amounts raised. As can be seen, the early stage rounds are approximately similar, with New Delhi having more funding in terms of grants. Boston and San Francisco have more Series A funding, while Chicago, London, Singapore, and Bangalore have higher Series E funding compared to other cities. However, since the heatmap aggregates total funding over stages, the results could be dominated by outliers, e.g., a few companies raising significantly higher funding of startups based on the region and funding stage, respectively.

Figures 7 and 8 present the KDE of post-money valuations. First, most regions have a bimodal log-normal distribution, but it is evident that the second mode in San Francisco Bay Area has relatively higher density than the other regions. Second, there is significant overlap in post-money valuations between angel and seed rounds, as well as series C, series D, and series E. This suggests that while the differentiations between seed, and A and B funding rounds seem to be relatively clear, subsequent rounds for growth stage companies are relatively difficult to differentiate based on valuation alone. Quintero (2019) also provides a similar observation regarding the overlap between post-money valuation of startups in angel, pre-seed, and seed rounds. As Quintero (2019) discusses, this phenomenon is likely due to the

changing definition of a seed round, and/or more institutional VCs participating in early stage pre-seed rounds.

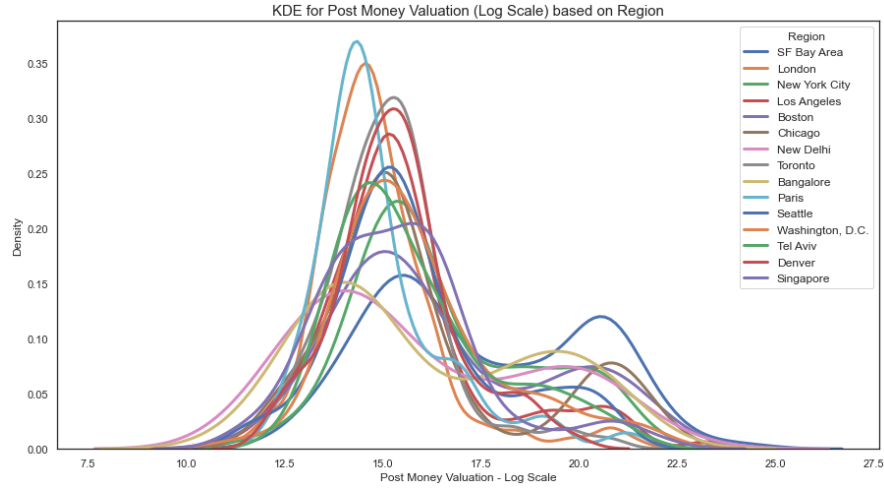


Fig. 7: KDE for post-money valuation (logarithmic scale) based on region

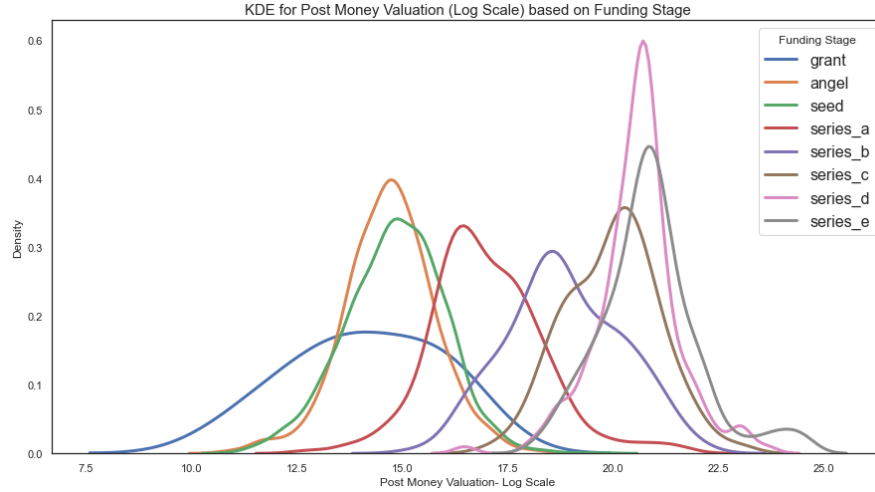


Fig. 8: KDE for post-money valuation (logarithmic scale) based on funding stage

Finally, Figure 9 illustrates the relationship between the post-money valuations (logarithmic scale) and the funding amount raised (logarithmic scale) separately for each region. Beyond the power-law connection, we observe from Figure 9 that in general there is a positive relationship between the post-money valuation and funding amount, and that the magnitude of this relationship is relatively consistent across different regions.



Fig. 9: Plots of funding amount raised with post-money valuations based on region, both on logarithmic scale

3 Methodology

3.1 Sectoral Clustering – Latent Dirichlet Allocation

While the dataset provides us with information on the sectors of economy each startup belongs to, the data in the category and description columns are manually entered or selected, with inconsistencies across the entire dataset. To overcome this issue, we employed a commonly used unsupervised learning approach in Natural Language Processing (NLP), topic modelling, and related fields: the Latent Dirichlet Allocation (LDA) method (Blei et al., 2003). LDA was first used in the context of population genetics (Pritchard et al., 2000). In machine learning, it is often viewed as a generative probabilistic model of a collection of composites of discrete parts/data such as text corpora. In particular, it is a three-level hierarchical Bayesian model, where each item in a collection is modelled as a finite mixture over an underlying set of topics, which is in turn modelled as an infinite mixture over an underlying set of topic probabilities (Blei et al., 2003).

LDA Algorithm

LDA (as introduced in Blei et al. 2003) involves the following generative process for each document in a corpus:

1. Choose $N \sim \text{Poisson}(\xi)$
2. Choose $\theta \sim \text{Dir}(\alpha)$
3. For each of the N words w_n :
 - a. Choose a topic $z_n \sim \text{Multinomial}(\theta)$
 - b. Choose a word w_n from $p(w_n|z_n, \beta)$, a multinomial probability conditioned on the topic z_n and model parameter β .

In the context of topic modelling, the composites are typically documents and the parts are words and/or phrase. Thus, LDA represents documents as mixtures of topics that churn out observable words based on random variables drawn from specific distributions (see the LDA algorithm above). For this study, we use LDA to group the startups into various sectoral clusters, based on (a) keywords in their categories or descriptions, and (b) probabilities of the key-words being associated with specific sectoral clusters. The optimal number of clusters is decided based on coherence scores for number of clusters (between 5 to 50). We then assign each startup to a cluster based on the LDA results and keyword probability assignments.

3.2 Predicting Post-money Valuation – ElasticNet

ElasticNet (Zou and Hastie, 2005) is a regularized linear model that employs both l_1 -norm and l_2 -norm penalization to achieve better mean-square prediction error performance compared to either pure Least Absolute Shrinkage and Selection Operator (LASSO) or Ridge regression. We use it to form a baseline model for predicting post-money valuations. The relative weight between l_1 -norm and l_2 -norm penalization as well as the overall penalization factor in ElasticNet are hyperparameters that we tune using 5-fold cross-validation.

3.3 Predicting Post-money Valuation–XGBoost

XGBoost (Chen and Guestrin, 2016), short for eXtreme Gradient Boosting, is a recent optimized distributed gradient boosting technique that has been widely used in applied machine learning and online data science competitions, especially for structured or tabular data. XGBoost is an implementation of gradient boosted decision trees which is designed for enhanced speed and performance by making use of parallel tree boosting.

In this study, we deploy the XGBoost regressor to model the post-money valuation of startups in logarithmic scale. The feature set includes sector (obtained from LDA), region, funding amount raised, number of investors in the round, and funding stage as well as engineered features representing lag and growth.

3.3.1 Hyperparameter Tuning for XGBoost Using Bayesian Optimization

Common techniques for obtaining optimal hyperparameters include random search and grid search, but these techniques can be inefficient and slow. One reason is that they typically do not take advantage of the information learned during previous optimization rounds. For this study, we make use of Bayesian optimization (Snoek et al., 2012), which constantly learns from previous optimization stages to find the best set of hyperparameters. This gives Bayesian optimization the ability to require fewer samples and iterations to obtain the best set of hyperparameter values compared to some other methods (e.g., random search or grid search).

Bayesian optimization involves constructing a posterior distribution that improves as the number of observations grows. When used for hyperparameter tuning, the algorithm gets closer to the optimized set of hyperparameter values as the parameter space worth exploring shrinks. Bayesian optimization for hyperparameter tuning takes into account the classic exploration versus exploitation paradigm, and seeks to balance needs between both. A typical method is to fit a Gaussian process to the known samples for every iteration. The posterior distribution is then utilized to

determine the next point to be explored.

In our test runs, where we used Bayesian optimization on XGBoost, our models generally converged in less than 10 iterations, compared with much longer search durations for cross-validated grid-based or randomized search. The resultant model accuracies were, however, approximately similar across cities. Nevertheless, we chose Bayesian optimization instead of typical methods of tuning such as cross-validated grid-based or randomized search due to its clear advantage in computational efficiency.

3.4 Predicting Success – Neural Network

To predict success of startups, we make use of a feed-forward neural network and train in it using our dataset. Mindful of the size of our dataset, we restrict our neural network to two hidden layers. We also employ drop-out layers (Srivastava et al., 2014) between the dense layers to regularize our model and avoid over-fitting.

To train our neural network, we use two measures of startup success (as noted earlier). The first measure is based on whether a startup eventually makes it to an exit by being acquired or by launching IPO. However, we also recognize that many startups in our study period may still be on their way being acquired or launching IPO. Thus, we augment our definition of success by considering startups that are continuing to grow in terms of the amount of funding that they are able to raise. This second definition of success covers all firms that meet the first definition (being acquired or launching IPO), but also includes all firms that have not exhibited signs of stagnation.

4 Results

4.1 Sectoral Clustering

Our LDA model found 16 sectoral clusters to be the optimal number of clusters. Figure 10 provides a wordcloud visualization of each sectoral cluster using the Python WordCloud package (Mueller, 2020). Words in this figure represent keywords with the highest probability of being in each sector cluster (generated by the LDA analysis) and the size of the font is proportional to this probability.

The sectors obtained using LDA and visualized in Figure 10 are rather evident. For example, sectoral cluster one comprises startups in retail, fashion, and e-commerce. Similarly, sectoral cluster four comprises startups mainly in the domains of artificial intelligence, machine learning, and data analytics, while sectoral cluster fourteen

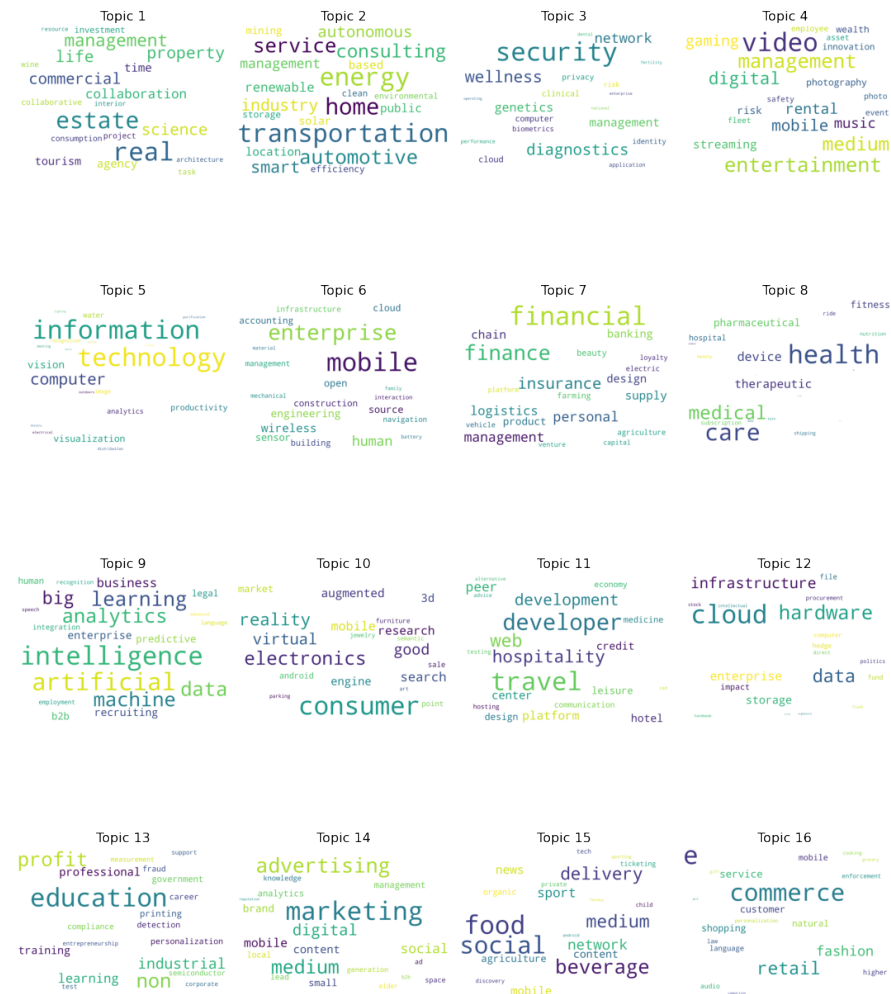


Fig. 10: Wordcloud for sectoral clusters found, with the larger fonts representing higher probabilities

comprises startups in medical technology, healthcare, and pharmaceuticals. However, since LDA is primarily an unsupervised approach, the results contain some keywords which do not fit quite well in particular clusters. An example is the inclusion of the word “insurance” in sector cluster six, which comprises primarily “energy” and “industrial” related startups.

Figure 11 shows the topic model visualization using the pyLDAvis package. The left visualization depicts the clustering of each of the topics, where the size of the circle is proportional to overall prevalence of the topic in the corpus. The distance be-

tween each of the topics is measured by calculating the Jensen-Shannon divergence, a measure of similarity between two probability distributions. Multidimensional scaling is used to project the distances onto two dimensions. It is desirable to have little to no overlap of the topic circles. The visualization on the right depicts the most important words of each topic.

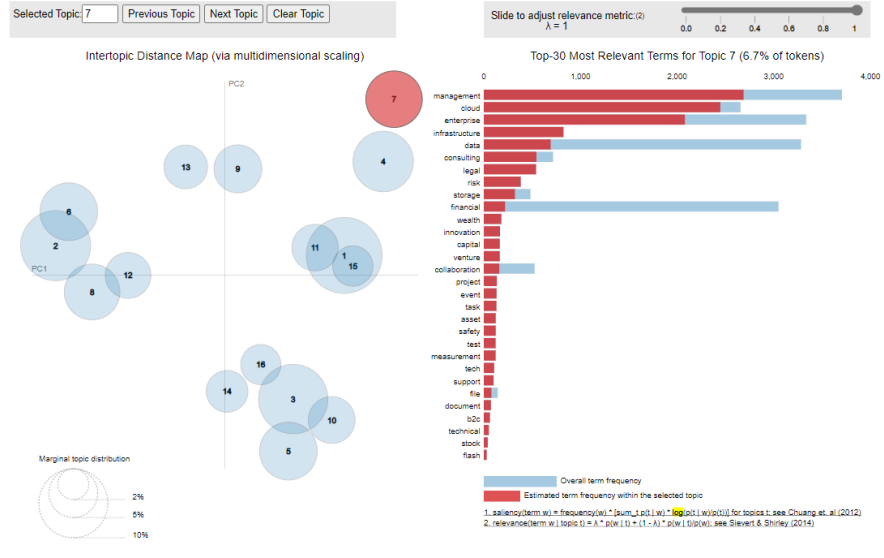


Fig. 11: pyLDavis topic model visualization

4.2 Predicting Post-Money Valuation

Our ElasticNet model (tuned using cross-validation) chose an l_1 -norm to l_2 -norm ratio of 1.0, effectively representing a LASSO regression model. In addition, it chose a relatively low penalization rate of 0.00652. With these hyperparameters, the model was able to achieve an excellent accuracy of 96.275% and a mean absolute error of 0.589 on our test (i.e., out-of-sample) data.

We examined the coefficients of the predictors in our ElasticNet model to gain an initial understanding of the predictors that were the most important for the model. Figure 12 shows that (log) raised amount was the most decisive factor within the ElasticNet model, followed by the investment type. We also observe that the later series rounds types of investments have a positive association with post-money evaluation, while the earlier rounds investments have a negative association. Furthermore, the growth in raised amount as well as employee count seem to be positively associated

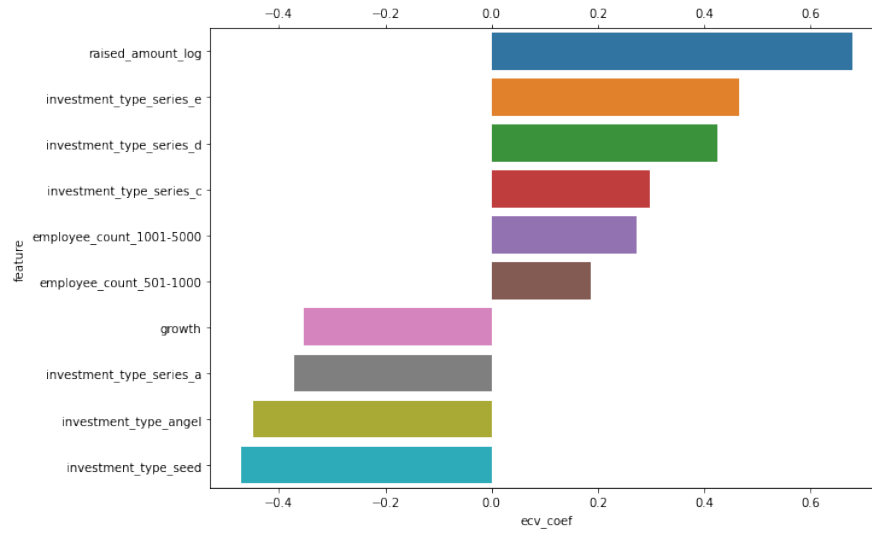


Fig. 12: Top 10 ElasticNet coefficients by size

with post-money valuation. However, the size of the coefficients depicted in Figure 12 suggests that past performance and growth have a higher influence on the post-money valuation of a startup compared to the startups size (measured by employee count).

Our tuned XGBoost model achieved an outstanding accuracy score of 96.45% and low mean absolute error of 0.550 on our test (i.e., out-of-sample) data. Figure 13 shows the plot of the true values (logarithm scale) and predicted values (logarithmic scale) in the test set (using our XGBoost model), with a high R^2 value of 0.9 when fitting a linear function. Our results indicate that our XGBoost model outperforms the ElasticNet approach. The increased accuracy and decreased mean absolute error achieved by the XGBoost model compared to ElasticNet suggest that the relationship between post-money valuation and its determinants is rather complex and most likely non-linear.

Using our XGBoost model, we next generate insights into the most important factors in predicting post-money valuation of startups. In Figures 14 and 15, we illustrate a representative boosted tree and the feature importance of the predictors in the model, respectively. These figures show that funding amount raised is the most important predictor of post-money valuation, followed by the investor count. The observation that funding amount raised is the most important feature is consistent with the findings of our baseline ElasticNet model. The difference in second-most important feature (i.e., investor count in the XGBoost model versus the investment stage in the ElasticNet approach) could be due to a high correlation between invest-

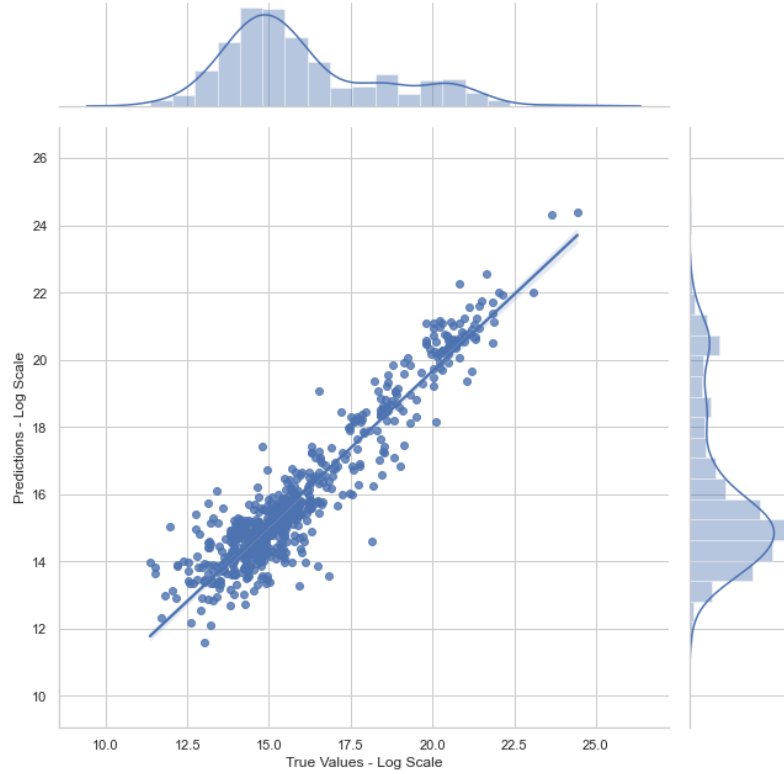


Fig. 13: True versus model predicted values in the test set

ment stage and funding amount, which is accounted for in the XGBoost model in a non-parametric manner.

Finally, to test the robustness of our XGBoost model and its potential over-reliance on particular predictor(s), we first removed the top continuous predictors, and reran it.. Between several runs, the resultant model only showed an accuracy decline of around 3% to 5%, with the LDA sectors remaining as the most important features. The resultant plot of true and predicted values in our test data is shown in Figure 16, with a R^2 of 0.8 for the fitted linear function. As can be seen from this figure, the points are more widely scattered and dispersed across the values compared to our original XGBoost model (see Figure 13, and compare with 16). Nonetheless, the low level of degradation in predictive power suggests that our XGBoost model can be used as an effective tool even in other datasets in which some of the important variables are not available.

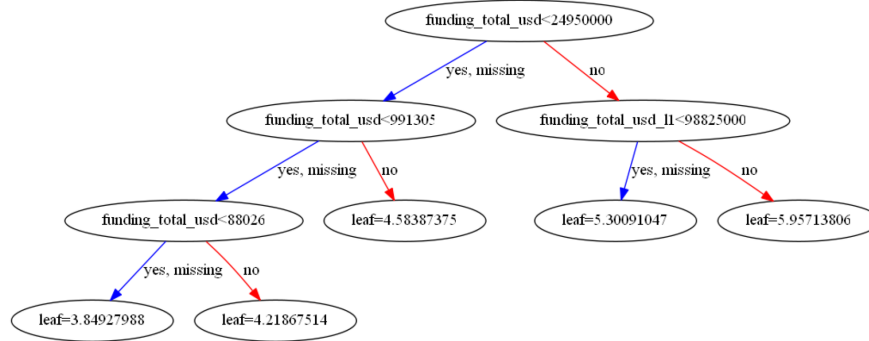


Fig. 14: Boosted tree example

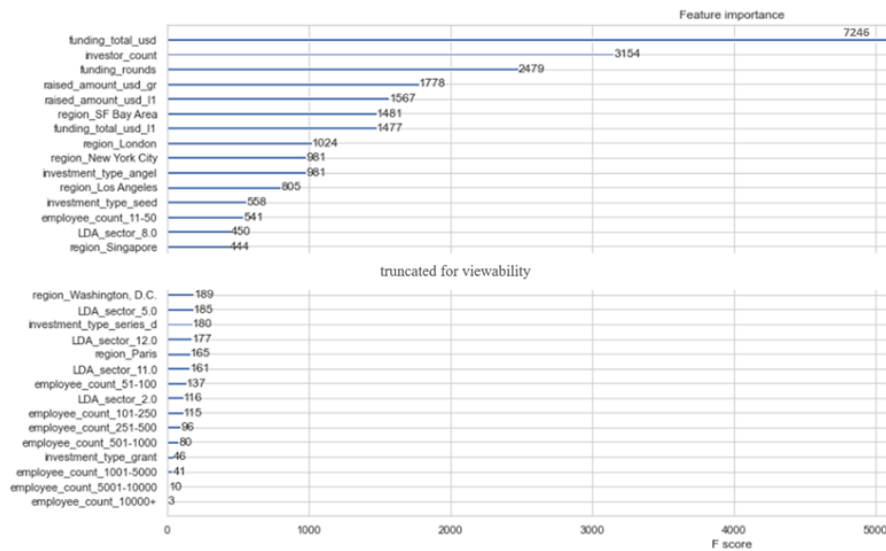


Fig. 15: Feature importance of XGBoost model

4.3 Predicting Success

To test the performance of our neural network in predicating success, we first performed a random training/validation split of 80-20 on our data. After training our neural network on the training part, we gauged its prediction accuracy on the validation set. We observed an accuracy of 92.48% when we used the first, stricter definition of success (i.e., defining success only based on acquisition or IPO). However, when we broadened the definition of success to startups that were still growing, we observed a prediction accuracy (on the validation set) of 81.21%. This reduction in prediction accuracy highlights the challenge of evaluating startup success.

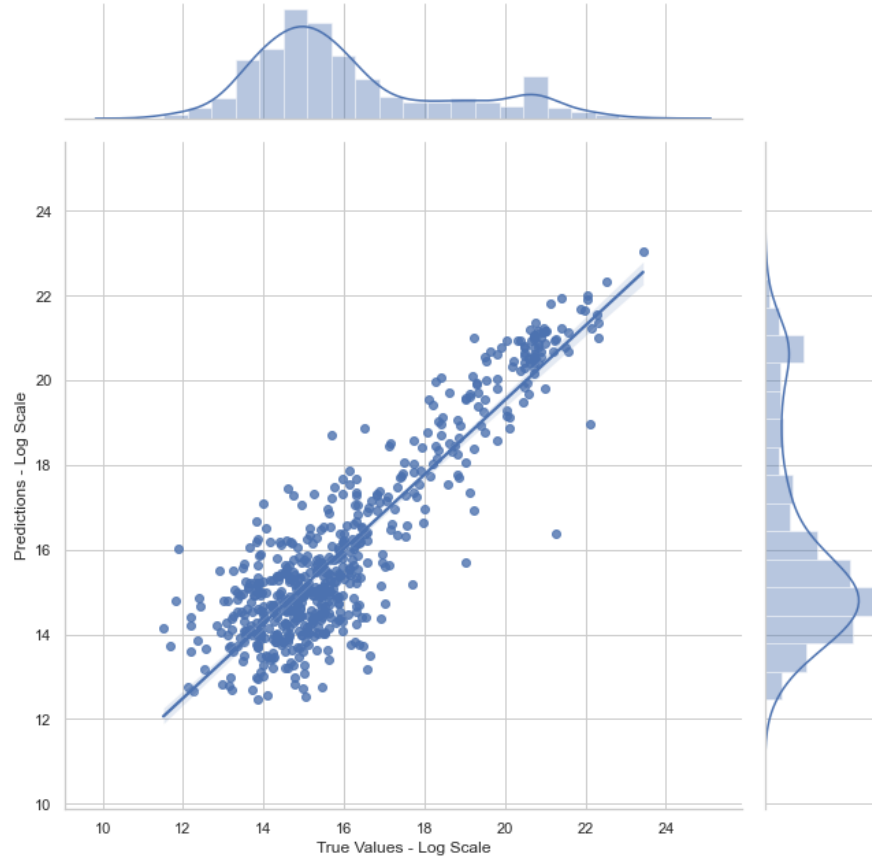


Fig. 16: True versus model predicted values in the test set with top predictors removed

Specifically, focusing only on startups that eventually exit via an IPO or acquisition makes it difficult to make use of data on early-stage startups, and broadening the definition of success does not seem to help since the prediction performance suffers. This alludes to our earlier discussion in Section 1.3 that startup success is typically less straightforward to define.

5 Recommendations

In this section, we leverage our findings to provide broad recommendations for (a) entrepreneurs, (b) venture capital or investors, and (c) policymakers or governments seeking to improve the startup ecosystem. First, our results suggest that entrepreneurs seeking to maximize their post-money valuation should avoid trend-chasing (e.g.,

targeting a specific sector of economy) and instead focus on ideas or efforts that can generate the most amount of funding. Specifically, our findings suggest that trend-chasing may not maximize post-money valuation: no specific sector of economy is specifically significant in predicting post-money valuation, at least not compared to the total funding and investor counts. Besides the idea behind the startup, our findings suggest that fundraising efforts can also be significantly important in achieving high post-money valuation. Startups that are unable to gain and maintain momentum via fundraising activities are likely to suffer in their post-money valuation. Second, we observe that the investor count has a significant impact on post-money valuation, as exemplified by its high feature importance. A closer examination of some startups which raised significant amounts of funding also suggests that having “branded” investors can have a positive impact. This is most likely due to a “signaling effect:” investors often follow their high profile counterparts, since financial commitments from high profile investors are often interpreted by other investors as a sign of a startups probable future success. Having a high profile investor on board or even leading the round leads to an increased probability of success and higher expected post-money evaluation. Finally, we also observe that there are significant agglomeration effects from being in top startup regions such as the San Francisco Bay Area or New York, although the effect of being in a particular region shows a diminishing rate of return as one moves through the list of top performing cities.

In the same vein as the above, we broadly recommend for startups to develop an internationalization strategy and consider expanding internationally at a relatively early stage, primarily for enhanced exposure, market access, and traction. It can be inferred from our exploratory data analysis and findings that domestic markets in most regions serve to be particularly advantageous only for certain sectors and for startups of certain sizes (or at certain stages). With the increasingly open nature of most startup ecosystems around the world, innovative companies backed by technology will be able to gain foothold quickly in different regions that place particular emphasis on the sector(s) that they belong to, and thereby obtain an early competitive advantage. Domestically, startups should gain access to credible reference customers in their respective sector(s) as early as possible, especially if they are developing innovative products or providing innovative services that require early adopters. Regions with a large base of multinational corporations and even small and medium-sized enterprises in the same sector can provide the necessary network effect to catalyze traction, which can in turn result in rapid revenue growth.

On the contrary, we recommend that venture funds (especially those dedicated to early stage startups) focus their investments on specific areas/sectors of interest or expertise, rather than adopting a broad mandate which may potentially result in “thinning out” and subsequently hurt returns. Venture funds can be broadly classified as generalist, thesis-driven or sector-focused. With the increased competition across funding stages and regions, it may be advantageous—especially for early stage funds—to be sector specific. This coincides with our observation and analysis that apart from top startup hubs such as San Francisco Bay Area, different regions seem

to “favor” different sectoral clusters. The key benefits of focusing on specific sectors are threefold. First, sector-specific domain expertise and intelligence allow the fund to source for higher quality deal flows, and maximize value capture with the same dollar value. Within-sector network effects such as partnerships with corporates may also give these funds an edge over broad-based generalist VCs, and provide the fund an edge in sourcing for high potential startups to invest in. Second, unless the fund has celebrity or renowned General Partners (GP) or investors, having sector-specific domain intelligence and expertise will help the fund establish credibility and gain confidence from Limited Partners (LP)—a factor crucial in the hyper-competitive nature of this industry. Third, our feature importance analysis shows that the ability to predict startup success does not improve when we broaden our definition of success to take advantage of available data points related to early stage startups. This suggests that it is difficult to assess the merits of early stage startups using purely quantitative measures, which necessitates deeper subject matter or sectoral analysis.

In providing recommendations for policymakers (and more broadly, governments) we note that they often would like to develop vibrant ecosystems, boost job creation, and catalyze economic growth. Thus, they typically seek to promote the creation or attraction of startups that have high potential and can grow to provide substantial employment and/or value-add activities. Considering this, our results have a few implications for them. First, policymakers should consider setting up co-investment instruments or mechanisms with the private sector—while allowing the private sector to take the lead in investing—especially in areas where there are gaps in specific funding stages, or sectors which serve as important nodes linking various economic activity or supply chains. Similarly, our KDE plots show that there is some overlap between government grants and other funding mechanisms along the same angel and seed stage(s). It can be a signal that government grants are directed to the same space as private investments, which might not be the most efficient use of resources, and might not result in desirable outcomes. It will be worthwhile for policymakers and policy analysts to conduct further detailed analyses in this regard. Second, policymakers should design policy levers to further entrench well-performing (or priority) sectors, and anchor major players in the domain, including not just multinational corporations but also small and medium-sized startups with high-growth potential. Combining the two recommendations, policymakers should develop a strategy or implement a program to systematically cultivate top global entrepreneurial, technology, and investment talents, and attract them to establish startups or investment vehicles. The incentives to do these do not necessarily have to be directly monetary. For example, they could include a combination of market or technology access, financing, network, or other forms of support.

Finally, our findings on predicting post-money valuation indicate that in some cases, there may exist a disconnect between startup size and valuation. This can have a few different implications for public policy decisions depending on policymakers’ objectives. If policymakers want to attract and encourage startups as a means of job creation, they must bear in mind that startups that generate the most jobs may not

necessarily be those that are the most valued by the market. On the other hand, if their objective is to target high-value startups that can serve as anchors for a vibrant startup ecosystem, policymakers must accept that such a targeting strategy may not yield as many jobs, at least in the short-term.

6 Conclusions, Limitations, and Future Work

In this chapter, we analyzed the global startup landscape. We did so first by providing descriptive statistical analyses and visualizations, and then by building predictive models using machine learning techniques. Our contribution lies in (a) a novel processing of sectoral level data through collating text-based descriptions into sectors of the economy, (b) making use of machine learning methods to predict post-money valuation and startup success, and (c) identifying the most important predictors of startups' performance.

Our machine learning models enable predicting (within reasonable confidence) a startups post-money valuation and success based on various variables such as region, sector, and funding amount raised. Through our analysis of variable importance, we find that startups across different regions performed relatively similar in terms of post-money valuation. Thus, region is not a significant predictor of startup performance. In contrast, however, startups' post-money valuations differ based on some other important features. Specifically, our results indicate that two most important predictors of post-money valuation are the amount of funding raised and investor count. As is expected, we also observe that startups' post-money valuation mildly differ based on the sector of economy and the funding stage. However, we find that these variables (sector of economy and funding stage) are not strong predictors of future performance of startups.

An entrepreneur, venture capital analyst, or policymaker can use our models to predict the post-money valuation and success of a startup by simply specifying features such as the region, sector, and funding amount raised. This prediction, in turn, can be used to make better investment decisions, design more appropriate economic policies, and/or implement superior evidence-based mechanisms that can boost the overall startup ecosystem.

In closing, we note that our work has some important limitations that future research can address. First, as we noted earlier, measuring performance of startups, defining what success is, and how it can be quantified are perplexing tasks. We used a few measures of performance and success that we could quantify based on our data. We leave it to future work to validating our findings using other measures of startup performance. Second, our work is focused on developing predictive methods. Future research can combine our methods with prescriptive analyses to develop strong tools aimed at identify the causal drivers of startups' success. Third, we used a single

source of data. Future work can enhance our analyses as well as the predictive power of our models by first combining this data with other sources, and then training our models on the resultant larger data set. Finally, as more information about patents and the technical competency of startups become available, future work can (a) assess the role that different startups play in the technology translation process (e.g., from basic research to commercialization), and (b) determine mechanisms through which this translation process impacts their post-money valuation and success.

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