Could algorithms help create a better venture capitalist?

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Venture capitalists have long used subjective methods to make investments. Could a Moneyball-inspired approach help?

Ask anyone in venture capital about their business model and they will probably tell you it's all about the "hits."In the VC world, a hit is a startup that makes it big, returning many multiples of a venture fund's initial investment. Hits are great for everyone-investors, entrepreneurs, job seekers-but the problem is they don't happen very often. William Hambrecht, a legendary venture capitalist who made early investments in Apple, Genentech, and Google, says the odds of a big hit are about one in 10. "A few others will work out, and you're going to lose in a lot," he says.

But what if venture capital could boost its odds to 50-50, or even two out of three? With $48 billion in VC investment in 2014, such an improvement would prevent huge amounts of money from being lost on startups that never had much of a chance of surviving the harsh competitive environment. The challenge is to identify those likely laggards well before the market rejects their idea and, perhaps more importantly, to see the big hits before anyone else. Venture capital has long relied on subjective, intuitive methods of assessing startups, but that's changing as more firms are bringing data science and consistency into their decision-making.

Hambrecht, who started an investment bank in 1968, isn't the first venture capitalist you'd expect to be investing according to the results of an algorithm, but that's exactly what he's doing these days. As a partner at WR Hambrecht Ventures, the VC arm of the IPO specialist

WR Hambrecht and Company, Hambrecht works closely with managing director Thomas Thurston on an investment strategy that combines predictive modeling and Clayton Christensen's disruption theory. Thurston, a former business development manager at Intel, is also the founder of Growth Science, a three person company he calls a for-profit think tank that's "trying to do the science, build the tools, and do the research all around this one question: How can we better predict when innovations will survive or fail, both for startups and when corporations launch new products or do acquisitions?" he says. The company uses proprietary databases and data harvesting, along with algorithms, to bring innovations into the world of statistics, delivering probabilities on the success of business models and new technology. Hambrecht and Thurston join forces in a very specific way: Each company that WR Hambrecht Ventures invests in has gone through the Growth Science prediction engine and passed. "There's no human subjectivity involved anywhere along the line," Thurston explained. "All the algorithms converge on a discrete yes or no."

That yes or no depends on a lot of factors, and Thurston declined to be very specific about what they are. But he did separate them into two categories: those inside the startup, and those external to the startup. "We've found only around 20% of the predictive value to come from details specific to the startup itself (e.g., the team)," he says, "whereas 80% comes from things outside of the startup," which he listed as the market, customers, competitors, technology trends, and timing. The model is also designed to be dynamic rather than static: "we care more about how things are likely to change, rather than how things are today," he says.

So how are Hambrecht's funds doing? It's too early to say for certain. VC funds typically take 10 to 15 years to return money to investors, and Hambrecht has been using the Growth Science method for eight. (Among the firm's investments: Tango, a mobile messaging service worth $1.5 billion.) With that said, the signs are positive. According to Hambrecht, "the portfolios are up five times, just based on subsequent offerings, and nothing has gone public or sold out big yet, so we think these funds are going to have very high returns. We have several we think will go into the public market, probably within the next year."

Another facet of Growth Science is its work with "member" companies, such as Intel, 3M, Cray Computer, and a few others. These firms pay Growth Science for access to its prediction engine; they can log in to a website, answer a set of questions about an innovation or a new business, and Growth Science sends them a report on its likelihood of success.

Ron Hoffner is a senior manager in the strategic business development group at 3M **MMM** -0.54°/o , and the company's liaison with Growth Science. Prior tojoining 3M, Hoffner worked in UnitedHealth' s innovation lab, researching techniques to decrease uncertainty in markets. When he learned of Growth Science'sbusiness model simulation, it made perfect sense to him as a risk management tool. Before using it to guide real decisions, 3M did a few tests with the model in different environments, such as new ventures, mergers and acquisitions, and innovations. Satisfied with its accuracy, 3M has put the predictive model to use in its health care business group, where it's used frequently to manage a portfolio of innovations. To Hoffner, the simulation answers three key questions about a new product or innovation: Is the market going to be big? Is this the right technology? Does the approach align with the company'sbusiness model?

On that last question, Peter Ungaro, the CEO of Cray Computer, provided a concrete example of how the simulation changed the company's direction with a new product rollout. Cray, which makes supercomputers, data-storage, and analytics platforms, was a new entrant in a particular market, introducing a product with an increase in performance, but also a reduced total cost of ownership. Based on the company's status as a new entrant, the model recommended positioning the product as the one with the lowest cost of ownership, instead of playing up its high performance. "That's a really interesting thing, especially for a company like Cray, which is built on providing our customers with the most performance possible," Ungaro says. "The product still does that, but we position it in the market in a different way.So far, the outcome has been really good."

This approach, Hoffner says, boils down to an options-based form of decision-making, where the right information can translate into various courses of action and their likely outcomes. The result, he says, is strategic flexibility. "I really think it is the next level," Hoffner says. "If you look at the future of management, this is something people will look back on as the first tool to introduce data-driven management."

Thurston views Growth Science's VC and enterprise work as two sides of the same coin. In each case, managers are trying to predict the future before investing money in it. According to Thurston's analysis of data from the Small Business Administration, and his own data on startups, between 20% and 30% of new businesses survive to their 10th birthday. Startups with VC-backing, he says, aren't doing much better than new Thai restaurants, dry cleaners, or spin-offs from large corporations. "Have we [the entrepreneurship economy] gotten any better at predicting any business?" Thurston asked. "Our data suggest no, not in any statistically significant amount." Growth Science, however, claims it is turning that around. When it comes to predicting survivorship of companies after a 10-year period, Thurston says Growth Science has been right 67% of the time, and totally wrong on the remaining third.

That raises the question: If Growth Science has vastly improved the odds of investing in new technologies and businesses, why isn't the entire VC world knocking on its door? Thurston's answer: "A lot of venture capitalists, like the scouts in Moneyball reacting to sabermetrics, are skeptical."

Count Ian Sigalow among the skeptics. Sigalow is a co-founder and partner at Greycroft Partners, a venture capital firm with offices in New York and Los Angeles. Sigalow, of course, isn't skeptical of technology-his firm invests mainly in Internet and mobile companies-but of the idea of using data to judge what's going to happen in 10 years. "Nobody is that prescient, where you can figure out how an entrepreneur is going to pivot his or her business," he says. "Nor can you capture the value of having a good strategic partner in your VC. Any science that tries to reduce this to a number-regardless of who funds it or who's involved – I think is actually missing a lot."

Unlike Thurston, Sigalow doesn't see quants taking over VC, even in the distant future, but he does see the potential of using data to help venture capitalists make decisions. Greycroft, for example, has employed a graduate student in data science for the past two summers.One project she's working on is performing due diligence on companies using machine learning as part of their software, analyzing algorithms for efficacy and novelty. Greycroft is also having her analyze data from some portfolio companies to asses whether changes in the market are temporary or more lasting. More specifically, Sigalow explained that a company pitched his firm recently, touting that its app was at the top of app charts for a few weeks. "The question was: Is this company the next Snapchat or the next dud?" he says. "We looked at the persistence, the usage data, the behavior in terms of session length and frequency...and came up with the conclusion that this was unlikely to be the next Snapchat because it did not exhibit the characteristics that Snapchat did at that time in its lifecycle."

Data analytics are undoubtedly creeping into venture capital-Google Ventures uses an algorithm to help with investment decisions, and a Silicon Valley firm called Correlation Ventures is built upon an algorithmic investing strategy.But the old-fashioned process of detailed research and human judgment still has a lot going for it. Just ask the people at Lux Research, an emerging-technology consulting firm in Boston. For the past 10 years, Lux's science-trained analysts have been scouring the business landscape for new technology firms, interviewing employees of those firms, and slowly compiling their own database of companies that succeeded or failed. Lux rates each company it profiles according to nine key factors, which are available to the public on its website in a report called "Measuring and Quantifying Success in Innovation." The result of that rating is a company profile with a "Lux Take," which ranges from "strong positive" to "strong caution."

The company recently looked back at five years worth of profiles and found that 50% of the companies that earned a "positive" rating went on to be successful, an outcome which Lux defines as an IPO, acquisition, or transition to standalone profitability. Given the usual odds of new business survival, the Lux system seems to inject a significant amount certainty into the process of evaluating startups. For Chris Hartshorn, Lux's chief research officer, the company's high rate of accuracy is attributable to two things: capability and methodology. Lux's analysts are scientists with Ph.Ds who are familiar with the most advanced technology in their area of expertise. In other words, "they understand if a startup is trying to break the laws of thermodynamics," Hartshorn says. And the Lux methodology, which rates companies on nine factors, has been in place for 10 years, allowing the firm to compare the companies it profiles in a consistent way.

People talk a lot about the importance of innovation to economic growth. In a recent survey of voters in swing states by the Economic Innovation Group, 75% of those surveyed agreed that America needs more entrepreneurs and investors in order to improve long-standing economic problems. Hartshorn considers this a call to action. "The innovation economy has an information problem," he says. "The information that drives it isn't good. How can countries become innovation economies in a more efficient way? Let's get better at funding the startup companies that will grow and drive employment. For every dollar that goes in the wrong place, that's a shitty dollar. And it should matter."

Big data may indeed be able to help, but it's more likely to be a piece of the puzzle, not the solution. For instance, academic studies have shown that serial entrepreneurs successful in the past are more likely to do well in new ventures. That implies there is some explanatory power in looking backwards for guidance on what's ahead."But the nature of entrepreneurship is always changing," says Josh Lerner, the Jacob H. Schiff Professor of Investment Banking at Harvard Business School. "Most regressions predicting entrepreneurial success in the literature have very low goodness of fit CR-squared), which suggests the limits of a 'Moneyball' approach here. Predicting which startup is going to be successful is much harder than [predicting] which baseball player is. Itis as if the baseball rules are being changed every year in unpredictableways."