

Identifying Successful Investors in the Startup Ecosystem

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ABSTRACT

Who can spot the next Google, Facebook, or Twitter? Who can discover the next billion-dollar startups? Measuring investor success is a challenging task, as investment strategies can vary widely. We propose **InvestorRank**, a novel method for identifying successful investors by analyzing how an investor’s collaboration network change over time. **InvestorRank** captures the intuitions that a successful investor achieves increasingly success in spotting great startups, or is able to keep doing so persistently. Our results show potential in discovering relatively unknown investors that may be the success stories of tomorrow.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous

Keywords

investor, startup, success metric, network analysis

1. INTRODUCTION

Who can spot the next billion-dollar startup? How can we discover talented investors who can find such hidden gems? Conventional measures of an investor’s success is frequently measured by the proportion of startup firms in his or her investment portfolio that filed for initial public offering (IPO), were acquired, or merged with another firm [2, 4], or a combination thereof. However, no prior work has proposed a measure that leverages *network effects* to quantify how the relationships among *venture capitalists* (VC) and *angel investors* may lead to successful investments. *Angel investors* or *angels* are influential investors who contribute in early rounds of funding. Among them, the most successful ones are called *super angels*. But, again, there is no objective measure that suggests why they are so [5, 6, 8]. This is a significant gap, because recent research showed that investor networks are valuable source of information in startup financing [1]. Our paper fills this gap. Our overarching goal

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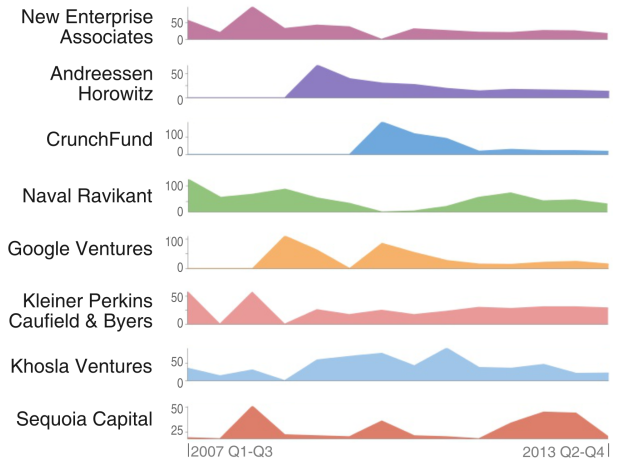


Figure 1: Example investors with increasing or persistently-good **InvestorRanks**. Each chart shows how the investor ranks over time among all investors (lower is better), each value computed from a collaboration network snapshot of a 3-quarter window (2007 Q1-Q3, Q2-Q4, ..., 2013 Q2-Q4).

is to formulate an effective network-centric metric for measuring successful investor behavior, irrespective of investor type (individual vs. firm) or the number of investments.

2. OUR APPROACH: INVESTORRANK

Intuitively, investors do not become hugely successful overnight — this takes time, possibly years, by judiciously selecting their co-investors. That is, we want to measure if an investor becomes increasingly “close” to some known exemplar successful investors over time, such as by co-investing with a super angel, or with another successful investor who co-invested with a super angel.

We propose **InvestorRank**, a network-centric approach that captures this intuition, by analyzing an investor’s time-varying collaboration network to mine successful co-investment behavior. It gauges the similarity in an investor’s behavior with that of a set of successful firms or angels, such that new investors with investment behavior similar to that of super angels are ranked higher.

Time-varying Investor Collaboration Network. We use a time-varying bipartite graph containing nodes for investors and startups to represent the change in their co-investment over time. A link between an investor and a



Figure 2: Investor A’s InvestorRank improves at time T_1 , thanks to the new investment (orange edge) that brings A closer to the super angel.

startup represents an investment. This graph includes the exemplar investors, the startups they invested in and any other investor that invested in those startups. We generate this time-varying graph using data from CrunchBase¹, a socially-curated website containing information on startups and funding, obtained in December 2013. This dataset contains 56,847 investments made in 19,375 startups by 11,096 investors. We take snapshots of the graph at regular intervals, using a sliding window of width ω (e.g., 3 quarters). Thus, an edge in a snapshot represents an investment made in that time window. Together, these snapshots form the time-varying investor collaboration network. Figure 3 shows an example subgraph in a snapshot.

Angels as Exemplar Successful Investors. We collected 19 exemplar investors from a combination of online articles [5, 6] and the Wikipedia super angel list [8]. Some of them are firms, some are super angels². Our list was then examined by an experienced researcher familiar with the VC ecosystem, who deemed their investment behavior and structure of co-investments as highly successful.

The InvestorRank Algorithm. The central idea of InvestorRank is to measure if an investor becomes increasingly “close” to some known exemplar successful investors over time, such as by directly co-investing in a startup with a super angel or another successful investor, or indirectly by investing alongside other investors who are investing with the exemplar investors. Figure 2 shows how an example investor’s increasing success is captured by its increasing closeness to a super angel.

InvestorRank adapts the *personalized PageRank algorithm* [3, 7] with a damping factor of 0.85, to compute such a closeness score for each investor, based on how far they are relative to the exemplar investors in the graph. Personalized PageRank has been used to solve many real-world problems, such as ranking webpages based on personal preferences or recommending products to customers. Adapting it for measuring investor success is novel.

In detail, investors’ closeness scores are computed against these 19 exemplar investors that are ranked the highest by design (with a score of 1); an investor having a closeness score closer to 1 means he or she is closer to, or more similar to, becoming an exemplar investor, thus more successful.

We compute and track an investor’s InvestorRank over time, using a 3-quarter sliding window. Thus, each graph snapshot describes the investments made in a period of 3

¹www.crunchbase.com

²Exemplar investors: Scott Banister, Cyan Banister, Ron Conway, David Lee, SV Angel, Keith Rabois, Reid Hoffman, Greylock Partners, Peter Thiel, Sean Parker, Ken Howery, Founders Fund, Founder Collective, Chris Dixon, Bill Trenchard, Caterina Fake, David Frankel, Mark Gerson, Zach Klein

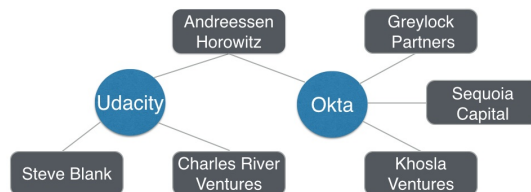


Figure 3: Example collaboration subgraph for 2012 Q2-Q4. Circles are startups. Rectangles are investors. An edge denotes an investment.

quarters; its first quarter overlaps with its preceding snapshot, and its last quarter overlaps with its succeeding snapshot (e.g., 2007 Q1-Q3, 2007 Q2-Q4, ..., 2014 Q2-Q4).

3. OUR FINDINGS & FUTURE WORK

InvestorRank provides us with a quantifiable method to identify successful investors. We are currently using two heuristics for identification. We flag an investor if his or her InvestorRank: (1) is consistently below 100, exceeding that for at most twice; or (2) follows a general trend of improvement when comparing to its preceding snapshot, with up to 8 times going the other way. Interestingly, the second rule flags potentially successful investors effectively out of the 1524 unlabeled investors in our Crunchbase data; all flagged investors have ranks under 200, and usually under 50. Figure 1 shows several such successful investors. In addition, InvestorRank also discovers successful, but less well-known, investors who may be rising stars, e.g., Paul Buchheit, General Catalyst Partners. Our next step is verify our findings through expert interviews. We also plan to incorporate the effect of funding amount and time of funding in the life cycle of a startup into InvestorRank.

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