An Inside Peek at AI Use in Private Equity

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KEY FINDINGS

- The number of private equity firms that have started to use AI is rising rapidly.
- Use of AI will greatly transform the deal-making process.
- By increasing efficiency, AI will likely cause an industry shakeout.

ABSTRACT

The number of private equity (PE) firms that have started to use artificial intelligence (AI) in investment decisions has risen rapidly over the past 10 years. This article provides a detailed account that can serve as a template for others in the industry who wish to make better investment decisions using AI. The news is both good and bad. The increased use of AI in PE and venture capital will greatly increase operational efficiency and transform the ways in which partners perform their work. It will allow for the entry of new firms but will also lead to a technological arms race and is predicted to cause an eventual industry shakeout.

TOPICS

Private equity, big data/machine learning, performance measurement*

The number of private equity/venture capital (PE/VC) firms that have started to use artificial intelligence (AI) in investment decisions has risen rapidly over the past 10 years. Although not everyone is interested in revealing the secret sauce involved, four firms that use AI have shared relevant information: EQT Ventures, SignalFire, Hone Capital, and Jolt Capital. This article provides a detailed account that can serve as a template for others in the industry who wish to make better investment decisions using AI. The news is both good and bad. Increased use of AI by PE/VC firms will greatly increase their operational efficiency, eliminate junior-level tasks and those juniors themselves, transform the ways in which partners perform their work, reduce travel and meetings, increase long-distance deals, diversify investment portfolios, and allow for the launching of new firms. However, it may very well lead to a technological arms race and eventually cause an industry shakeout.

PE/VC firms use AI support that ranges in scope from simple standalone screening models to end-to-end decision support systems (DSS). For some, such as Kleiner Perkins and Sequoia, data-driven VC simply means tracking how many times a startup is mentioned on Twitter. For others, such as Jolt Capital, it leads to a complete

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*All articles are now categorized by topics and subtopics. View at PM-Research.com.

1 Trocha (2019) counted 83 data- and AI-driven VCs. Corea (2019) reported more than 25 VC funds using AI. Although 64% of the respondents to a 2018 survey by Pitchbook did not use AI, 50% planned to adopt AI in the future (Pitchbook 2019).
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Summer 2021

redesign of the workflow and deal-making process. Finally, 645 Ventures and Daphni are examples of firms that have used data-driven VC methods to enter the VC industry, overcoming entry barriers created by wealth, experience, and personal networks. First, we examine two firms that have built in-house end-to-end DSS.

EQT Ventures, with operating funds totaling $1.2 billion, launched Motherbrain in 2016, the year it was founded. Motherbrain compiles data from about 40 data sources, including third-party databases and data scraped from websites. Algorithms use app store downloads, investor information, website traffic, entrepreneur résumés, and other details to rank order prospects. Unstructured data, such as emails and text messages between partners, also pass through Motherbrain. These data are combined with traditional structured data from databases such as PitchBook to build predictive models. The platform enables EQT Ventures to identify startups before receiving a pitch, which has been a major benefit for the firm. The predictive models also make the efforts of the 30-person team more efficient by immediately eliminating the least promising startups. The system then supports the due diligence process by generating notifications that include summaries of past meetings with prospects. Even so, only around 30% of EQT Venture’s investment decisions come through Motherbrain, which monitors around 2 million companies daily (Palmer 2017; Trocha 2019).

A second firm, SignalFire, founded in 2013 by Chris Farmer, was also started with the goal of applying AI methods to the full range of VC decision making. The firm has funds of $375 million; it took eight years and tens of millions of dollars to build its software, called Beacon. Beacon tracks 8 million startups around the world, supporting deal generation, investment decisions, and portfolio monitoring. ItBrowse academic publications, patent filings, and K12 reports, to name but a few. Companies that deviate from expectations are flagged on a dashboard. The system helps SignalFire discover companies that it would not have seen otherwise and pass up companies that everyone else is looking at. In addition to being a market intelligence platform, Beacon serves as a communication tool for various stakeholders: Advisors, limited partners, founders, and partners are connected by various versions of Beacon that are targeted toward their tasks. Data scientists and engineers are vital to SignalFire and own shares in the company. “They are the heart of the business,” Farmer says. SignalFire is said to spend an astounding $10 million a year running Beacon (Palmer 2017; Trocha 2019).

AI use can also be more limited in scope but still offer a nascent firm a competitive advantage over incumbents. An example is Hone Capital, the VC arm of the Chinese PE firm CSC Group. With the help of a single AI screening model, it broke into Silicon Valley, where it had no prior experience, in 2017 and became one of its most active seed investors. Managing partner Veronica Wu has described how it succeeded (Wu and Gnanasambandam 2017). The firm first partnered with AngelList—a US-based deal-making, job seeker, and angel investor platform focused on startup deal syndication—to obtain data on deal flow. Using AngelList’s data on more than 30,000 deals, paired with more data on deals and entrepreneurs from sources including Crunchbase, Mattermark, and PitchBook, Wu created a machine-learning model to predict whether a venture would make it to a series A round of funding (a similar approach using Crunchbase data alone is described by Arroyo et al. 2019). The database initially contained 400 characteristics on each deal; these were filtered down to a model with 20 characteristics that were most predictive of making it to a series A round. Hone’s model includes predictors such as investors’ historical conversion rates, total money raised, the founding team’s background, and the syndicate lead’s area of expertise. The model recommends close to 20 deals a week. Investment committee work then takes over, and about 80% of the model-based recommendations are rejected.
Although prediction models have been employed in banking since the 1960s (in which they are called credit scoring models), PE/VC firms have started adopting AI-enhanced prediction models only recently for a couple of reasons. First, competitive pressure has been created by newcomers such as SignalFire, based on its strong use of AI. Second, the technology to merge and analyze large amounts of unstructured data has become widely available only recently. Third, VC partners long rejected the idea that their gut instincts could be replaced by something better. In the early 2000s, however, it became apparent that even simple prediction models could beat VC partners’ intuition (Zacharakis and Meyer 2000; Åstebro 2002). In general, prediction models rarely fail to beat human predictions (Dawes, Faust, and Meehl 1989; Grove and Meehl 1996; Thorngate, Dawes, and Foddy 2009; Jung et al. 2020). However, at that time, the arguments on why VCs should adopt AI fell on deaf ears. Most of the VCs who met with the author argued that they did not trust algorithms. Those who accepted the statistical evidence still wanted to make decisions based on their own gut instincts. However, the main argument for the initially slow adoption rate might be that VCs need to see how the nature of their work could significantly shift from the old ways of doing things. This has now been done by new entrants, such as EQT Ventures, SignalFire, and Hone Capital, which have all grown quickly in volume and deal making at the expense of existing firms. The accuracy of prediction has turned out to be only a side issue.

Two facts stand out about AI’s impact on VC deal making. First, firms that have adopted AI seem to be making a fair number of deals and different deals than before. This has completely changed internal operations, and the next example shows how. Second, their deals primarily concern the early funding stages: seed and series A. Apparently, when a deal involves more unreliable information, it is more likely to have been completed with AI support. This can be explained in part by the limits of human cognition. People have the greatest difficulty in making unbiased decisions when confronted with a great deal of uncertainty and conflicting information. We have a hard time combining information in making judgments and tend to assign excessive weight to salient information (Åstebro 2002; Kahneman 2011). For example, in an experiment, Andrew Zackarakis and Dale Meyer (2000) showed that when practicing and experienced VCs were successively shown increasing amounts of credible information about ventures (e.g., the track record of the team, the degree of competition), their ability to predict venture success successively and considerably declined. Another reason for the additional power now provided by AI in VC decision making is that new and primarily text-based sources of information have become available online in the past decade (e.g., LinkedIn, AngelList, Kickstarter, Crunchbase). These new data can be mined by natural process language tools in powerful analytical engines to augment decision making.

Let us take a closer look at how one firm uses AI in making its decisions. We will learn about its thinking in designing its technology stack, the full range of decisions that can be supported with AI at PE/VC firms, and how AI enabled the firm to raise operational efficiency significantly.

**JOLT CAPITAL AND NINJA**

Ninja is Jolt Capital’s DSS. In 2016, Philippe Laval, partner, member of the investment committee, and CTO at Jolt Capital, initiated its development, which continued with a three-member team over three years. The design was based on three key insights Laval had into what a PE/VC firm’s daily work routine looks like and how using AI can change ingrained traditions.
First Insight

PE/VC partners traditionally do not use digital/collaborative tools. Much of their time is spent in meetings and on the phone, so important data are not recorded systematically or sometimes at all. Partners spend a lot of time traveling to meetings to collect information. Therefore, Laval argued that to be accepted, DSS must be applicable to all possible decision-making situations, from research through the decision funnel to final acceptance or rejection. It should also be so easy to use that it will beat alternatives at each stage in the workflow. Although it does not substitute the process for any tasks, it should support all decision-making tasks. As staff search for information or make decisions, they should prefer not to go outside the DSS, and the DSS should have the granularity to compete with personal meetings and thereby reduce the time needed to travel to and from those meetings.

Second Insight

In making decisions, PE/VC firms gather a lot of information from many different sources. In the process of researching a company, partners might make several calls, search Google and LinkedIn, read a report from an investment analyst, and check Bloomberg. To analyze a financial plan, they might use Excel or perhaps switch to Crystal Ball. Laval argued that partners should not have to leave the DSS to complete a particular task because that would undermine the value of the DSS and might mean that the training of its algorithms could lack important data. Laval therefore designed Ninja to gather all of the relevant data used by Jolt Capital, both structured and unstructured, and present the information in more organized ways than its alternatives can.

Third Insight

Laval explained that partners generally do not have a high rate of learning from investments because investments occur infrequently. This advantages senior partners at PE/VC firms and leads decision-making power to be concentrated in the hands of only a few. Laval wanted to find a way for the DSS to learn to imitate the preferences and decisions of experienced partners more quickly and distribute that experience to help all involved at the firm.

Building on these three insights, Laval designed Ninja to gather information from the web, meeting notes, internal usage statistics by Jolt staff, and paid data sources. Ninja is a graphical database connecting people, news, and businesses and information about them. Conversations are carried out within Ninja, obviating the need for other methods (e.g., email, SMS texts). Notes from phone calls are added. Staff can also upload data or documents. Notes and other text are then scanned and converted to data using text-parsing techniques.

Laval said that user experience (U/X) and workflow design were two key considerations in building Ninja. A partial solution or a design with a poor U/X interface would have been easily rejected. Ninja was designed to become the preferred method for collecting data and recording the entire decision-making process. Finally, two machine learning algorithms learn rules about which objects (businesses, people) partners prefer and do not prefer as they sift through prospects and click on a “like” button, which occurs hundreds of times more often than eventual deals. This enables rapid algorithm training through supervised learning.

By the spring of 2020, Ninja had collected data on over 600,000 companies that had been automatically identified, stored, and liked at various stages of decision making. The data included details on 15,000 algorithm-recommended companies.
that had been reviewed and rejected, an average of 6 per day. Ultimately, Jolt Capital invested in 17 companies during the 2019–2020 period in which it used Ninja.

A PEEK UNDER THE ML HOOD

Ninja has two algorithms, both of which build on creating similarities/distances between a focal company and other companies. The first algorithm compares the distance between companies based on short narratives. This information is scraped from websites, LinkedIn, Crunchbase, and other public sources. The second algorithm compares the distance between companies using a topology-based distance measure applied to a graph plotting the companies.

1. The first algorithm produces semantic graphs based on text similarity. The algorithm uses natural language processing (NLP) to create links. The text is a brief paragraph about the company (see Exhibit 1). Similar paragraphs are matched in a 512-dimensional semantic space that is then reduced to a single dimension score: the percentage of match between paragraphs on two companies.

2. Ninja also matches companies based on information obtained on their patents, employees, personnel, and investors from several data feeds and extracts from news reports. These pieces of information are tags associated with each company, not free text. Tags are specified by outsourced data providers and are scraped from the web or generated by performing NLP on news articles. All of those tags become nodes and relationships, generating a large multidimensional vector driving the generation of a second graph. Tags that are well connected are co-quoted. A company is then presented as a function of its position in the ecosystem with these two graphs.
DAILY WORK

The investment committee’s daily work runs through Ninja. Partners each spend about three to four hours per day on Ninja. Ninja contains a set of key figures and displays for their daily work, as companies move from the research stage to decisions about accepting or rejecting an investment target. As explained, one type of display is a map of the company landscape, which shows investment targets that are similar versus distant—in this case the potential target company Sinequa (in blue). The area is indicated by color (e.g., Europe in gray, and non-Europe in red). The target is located in the lower-right quadrant at the center of Exhibit 1. Exusia and Altilia are located the closest to Sinequa. The size of the bubble indicates the number of employees.

By default, Ninja lists and maps 40 comparable companies, with the closest ranked first. Exhibit 2 lists the top two companies closest to Sinequa: Exusia and Altilia. A partner can select or deselect a company to confirm or reject it as close. This trains the matching algorithm. The text drives the NLP matching.

The DSS also provides information about patents, key people working in the field, relevant investors, a list of events (e.g., conferences and meetings attended by people from the top 40 companies), the top matched Fortune 5,000 corporations, and an automatically generated investment report.

Ninja is primarily a data presentation engine and a workflow support system. The workflow dashboard is at the heart of the system for a user. The dashboard (Exhibit 3) shows a company called XMOS. A company goes through the following stages: mined, liked, contacted, in contact, allocated, and, finally, invested. Arrows (inserted by the author) point to a few highlights on this dashboard: the number of patents, a verbal description of the firm, graphs on growth and financing, tags, and social profiles. When a partner likes a company, the algorithms are trained at both the partner and aggregate level. The chat channel streams on the right-hand side of the window (comments in the chat have been redacted). This company has been assigned to a partner to prepare it for an investment committee meeting.
THE FUTURE OF AI IN PE/VC DECISION MAKING

Al adoption by established PE/VC firms is expected to accelerate, first by incorporating AI piecemeal into various tasks; sometimes, as in the case of Jolt, AI will completely disrupt old ways of thinking and working. We will continue to see the entry of new firms that specialize in using AI.

The screening of new prospects is one task that is certain to become more AI driven across the board—not just through algorithmic screening but also with various data visualization techniques. The old approach to finding unique deals involved hiring research assistants, typically MBA graduates, and teaching them how to find great deals in all of the inbound messages. According to Jean Schmitt, partner and CEO at Jolt Capital, this approach was never very fruitful: “As an investor, I don’t want a junior to filter my deals, because they have their own biases, and often won’t see the real opportunity.”

Another method employed is discarding all inbound requests and instead relying exclusively on referrals. This approach predictably creates a lemmings-type problem for PE/VC firms, in which the price of good deals is bid up to the marginal cost of investment. It can also lead to sentiment investment, which might explain the sometimes-large swings in valuation in the industry. Schmitt said, “It’s as if I was hiring a journalist to do my selection of deals. It’s based on gossip; you end up selecting based on what people say. Finding outlier opportunities requires a totally different approach.”

Algorithmic screening gives PE/VC firms the ability to fine-tune their search for odd but potentially high-value candidates, as illustrated by EQT Ventures, SignalFire, and Hone Capital. Many others have followed, including Quake Capital, Correlation...
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Ventures, WR Hambrecht Ventures, Connetic Ventures, and Fly Ventures. At least two approaches are employed in this screening. In the first, the algorithm gathers what is hoped to be unique data and constructs a prediction model based on observable success outcomes, such as raising $100 million or launching an initial public offering. This is what Hone Capital did. The second, the approach taken by Jolt, uses supervised training by the decision makers. Schmitt explains how the screening algorithm is trained at Jolt Capital: “The learning part is critical, because after a while, the system can tell me what I like and what I don’t like. A junior isn’t filtering these deals; my digital self is. So, the point is to train the system to understand what I like and don’t like, and then the system can show me what I would normally like.” It also helps to make the initial selection more efficient. “The system keeps discovering companies from all over the place, every week we are looking at 70 opportunities brought up by the system. This thing is a productivity tool, so there’s no idle time,” says Schmitt.

Al-based decision support is not limited to the screening stage—any stage of the decision funnel can be supported by AI. More comprehensive DSSs are needed for this purpose, such as the DSS selected by InReach Ventures, FF Venture Capital, and Hatcher+. Pierre Garnier, a partner at Jolt Capital, gave an example: “In a few seconds, we can get a pre–due diligence report and look at the people of interest, the potential competitors, and partners in the ecosystems.” He then described the benefits from doing this that were not obvious from the start:

Let’s imagine that Ninja has discovered a company which looks interesting to me. I get in touch with the CEO, and when I’m talking to him, I have in front of me the report. I end up looking smarter in front of a CEO: “wow, this guy really knows the sector … I’m engaging with smart investors.” The relationship with big corporates is also really interesting. It can give us a map of who could be potential buyers down the road. And it’s important to know who the key people in the industry are: opinion leaders, influencers, technical gurus, etc. The platform allows us to identify them very quickly. It can help us to source our board members. So, this is not only a deal-sourcing tool, even though it’s a big part of it.

Al is not likely to make the decisions for most partners, although Deep Knowledge Ventures and Social Capital have switched to fully automated decisions. Prediction algorithms do just that—make predictions. This gives the experts a good lead, and then they can make the ultimate call. For example, even though Ninja picked 15,000 firms out of 600,000 as attractive, only 3,000 were eventually liked by a partner, and only 300 were passed on to the investment committee at Jolt for review.

Operational Efficiency

Al is used most efficiently when it reduces routine and time-consuming work for PE/VC firms. As an industry, they will no longer need to have a throng of juniors calling CEOs to ask whether they are interested in getting funding, nor will they need research assistants to sort through incoming pitch decks. Partners can spend more time making deals, as long as they trust the algorithms doing the screening. What is not to like about an algorithm that is your digital self and relieves you from spending hours in planes and meetings and sifting through websites?

PE/VC firms will shrink their back-office staff but spend more on information technology, and decisions will be made much more quickly. For example, Kima, one of the world’s most active early-stage investors and an AI user, invests in two to
three startups a week, despite having only three investment committee members. These trends are already visible. The author’s analyses show a median of seven deals per year made by firms that adopt AI support versus two by non-adopters. The 90th percentile is 39 deals per year for adopters versus 10 for non-adopters. Over the past 10 years, AI-supported firms have dramatically increased their operational efficiency, from an average of 0.5 deals per employee per year in 2000 to 1.3 in 2019.²

**Beating Others to the Punch**

PE/VC firms are always trying to beat one another to the punch. Predictably, they will increasingly do so, driven by a technological arms race. For example, Fly Ventures claims to be able to reveal startups that have not even started looking for investment. However, algorithms built differently pick different prospects, so it is possible that investment will become more democratized. For example, Connetic Ventures uses its prediction algorithm to assemble a portfolio in which 42% of investments is led by women or minorities. This is good news for the industry.

**Add-On Services**

PE/VC firms can easily build value-added services that are data and algorithm driven. For example, Bloomberg beta, Entrepreneur First, NFX, and Dorm Room Fund have developed predictive tools for finding and matching talent and PE/VC firms.

**Changing Investment Models**

Right Side Capital Management (RSCM) uses a standard web form and rule-based tools to adopt an investment strategy involving heavy portfolio diversification. It limits investment to the following: “Anything in tech. But you must be doing real engineering.” RSCM makes hundreds of pre-seed investments of $50,000 to $200,000. This strategy, sometimes dubbed spray and pray, can be executed only with minimal human capital due diligence. Indeed, it promises a reply “within a few waking hours. Never more than 2 business days.” Since its founding in 2012, the firm has invested in more than 800 startups, and in 2020, it made more than 60 investments. Others following a similar strategy are Social Capital and Kima Ventures.

**Syndication of Data, Platforms, and Algorithms**

This is an exciting area of development. Project A offers its business intelligence infrastructure called Mara to the public. The software, a library for integrating a business’s data into a data warehouse, was released via Github. First Round built multiple pieces of custom software, including something like “a private Quora” in which its portfolio entrepreneurs can share lessons with one another. Entrepreneurs looking for funding from Follow The Seed are asked to incorporate a tracking algorithm into their product. The algorithm analyzes how customers interact with a given product, looking for signs of viral growth. Follow The Seed shares its algorithm with other VCs, angels, and family offices in exchange for deal flow. Jolt Capital shares its data warehouse with other PE firms. Perhaps this trend will lead to a winner-takes-all contest based on data and technology.

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² Data collected by matching firms with and without AI use, using Venture Expert and other data.
THE FUTURE OF PE/VC WITH AI SUPPORT

For a while, the acceleration of AI adoption among PE/VC firms will enable the continued entry of firms with new investment approaches as well as the rapid growth of new and small PE/VC firms. For example, the founding partner of Inreach, Roberto Bonanzinga, claims that his firm can analyze around 2,500 startups every month. This will lead to increased competition based on efficiency and the uniqueness of deals generated. “Compared to other firms, and in particular very large firms, we believe that we are much more efficient in originating new opportunities, since Ninja is doing it for us,” says Pierre Garnier, a partner at Jolt.

However, the expansion of new firms based on AI also will have clear negative effects on competition. Most industries that experience a radical business-transforming innovation such as this one demonstrate a familiar pattern of evolution: The increased competition focused on new technology eventually squeezes out new entrants and accelerates the exit of those that cannot remain at the technological frontier. This dynamic typically leads to industry shakeouts (see, e.g., Klepper 2015; Klepper and Simons 2000).

REFERENCES


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