Fields from online form

1 In 100 words or less, describe your startup, venture, technology, or concept

Enterprise retailers in the US are rapidly adopting Machine Learning (ML) to increase revenue and customer satisfaction in their online operations. However, ML is still very expensive and complex for a growing number of smaller businesses.

AI POW integrates automation and interpretability into ML. Our goal is to reduce the ML development complexity to accelerate its adoption for smaller businesses and help them thrive in the digital-first economy. Our team has already developed the #1 automated ML software on GitHub that allows our current users to access business monitoring software but at a fraction of current time and cost.

2 Has your startup had any sales revenue? Please Explain:

While AI POW is still at the beginning stage of commercializing our technologies, we have already had $55,000 of revenue at the time of submission.

3 YouTube elevator pitch link

https://www.youtube.com/watch?v=mNwi9_tP62M

Information above goes into submission form. Information below should be uploaded independently using the follwojng format: ES_AIPOW_TexasA&MUniversity.pdf

Rice Business Plan Competition - Executive Summary [five pages max] Deadline: February 2, 2021.

AI POW - ***Non-Confidential Executive Summary***

Contact Person & Cell Phone: Daochen 'Frank' Zha, 979-721-1408 **Website:** www.powtech.ai **Address:** 503 Southwest Parkway, College Station TX, 77840. **Corporate Directors:** Xia 'Ben' Hu and Alfredo Costilla-Reyes. **Capital Seeking:** $2 Million USD. **Uses of funding:** Increase sales, marketing and engineering teams along with expansion of computation resources.

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1 Business summary

The US's retail industry is currently looking to improve its online operations to serve a market shifting to buy mainly on the web. Data monitoring is a valuable tool in e-commerce because anomalies in data often point to areas that need attention. For example, a common problem reflected in real-time business data are drops in sales due to human typos that mistakenly indicate that a product is out of stock. Therefore, if this error goes undetected, it can substantially harm the online business' sales and leave disappointed customers who may never come back. An equally important issue is that while large retailers are quickly adopting machine Learning (ML)-based business monitoring software, these advanced tools are still costly and complicated, limiting smaller retailers' ability to benefit from their data assets.

AI POW integrates automation and interpretability into ML. Our goal is to reduce the ML development speed and complexity to accelerate its adoption by smaller businesses and help them thrive in the digital-first economy. Our team has already developed the #1 open-source Automated ML software on GitHub that allows our current users to obtain comparable business monitoring tools like those designed by human experts in large enterprises but at a fraction of current time and cost.

2 Customer Problem

The retail and subsequently the e-commerce industries heavily depend on business monitoring measures to detect anomalies in real-time data, which are visible symptoms of underlying problems in a business, affecting relevant metrics such as revenue and customer satisfaction. Figure 1 contrasts how small businesses have approached this problem; for example, managers who monitor their data **manually** find this method costly, poor to scale, and the slowest to detect anomalies when handling significant amounts of data. Similarly, while hard-programmed **statistical** thresholds have improved scale and anomaly detection speed, their accuracy is still insufficient because such techniques can't easily 'self-adapt' to the ever-changing online environment.

On the other hand, large retailers are currently adopting complex business analytics tools to monitor their online businesses automatically and promptly detect issues that need immediate attention [1]. In particular, Machine Learning software has shown staggering results because of its ability to predict malfunctions beyond just detecting errors in past transactions. However, **current enterprise ML** still involves considerable computer science background and substantial budget sizes, not to mention that the output results are hardly understandable by business owners due to its 'black-box' nature.

Based upon our team's sponsored research projects with industrial partners, including Amazon and Facebook, we observed a pressing need for business managers to detect and resolve problems that negatively affect their revenue as quickly as possible. We see a growing opportunity in creating better business monitoring tools as the Small Specialty Retail Stores in the US alone already spends more than **$3.3 billion dollars yearly on business analytics tools** [2]. Specifically, our customer discovery efforts suggest that by reducing the engineering complexity of business analytic tools, we can accelerate its adoption as more business owners are enabled to create and deploy custom-made business monitoring tools.

3 Service

AI POW's intuitive business monitoring platform has the potential to eliminate the engineering complexity and allow retail and e-commerce managers to build and deploy advanced business analytics tools for their businesses efficiently. The benefits from these advanced technologies include better understanding their customers' online habits, forecasting product demand, and better understanding problems that may affect their revenue. But most importantly, the AI POW's mission aims to help our customers, or decision-makers in a company, to quickly identify and understand anomalies and opportunities in their businesses and take more reliable data-driven decisions.

Our **existing open-source systems** [3, 4, 5] have already been used in industrial scenarios and helped demonstrate the feasibility and potential market demand of a simpler and more affordable platform. Specifically, reducing the engineering complexity of business analytic tools can accelerate its adoption as more subject matter experts with a basic programming background can quickly utilize business monitoring technologies.

AI POW's AutoML helps business owners automate the business monitoring task while intuitively understanding the origin of the anomalies to improve revenue and customer experience. An automatic way to detect sub-optimal conditions in e-commerce will enable supervisors to have a general top view over the entire online store and precision anomaly prediction per customer and product. Our tool also offers business owners the ability to visualize anomalies in context to ensure the best management judgment when finding fast and effective actionable tasks for time-sensitive e-commerce problems. Figure 1 highlights AI POW's competitive advantages compared to the current solutions in the market.

Comparison metric	Manual	Statistical	Current enterprise ML	**AI POW's AutoML**
Scale	**Low**	Medium	High	**High**
Anomaly detection speed	**Very Low**	High	High	**High**
Accuracy	Medium-high	**Low**	High	**High**
Cost of implementation	Low-medium	Medium	**High**	**Low**
Cost to maintain	**High**	Medium	Low	**Low**
Interpretability	High	Medium	**Low**	**High**

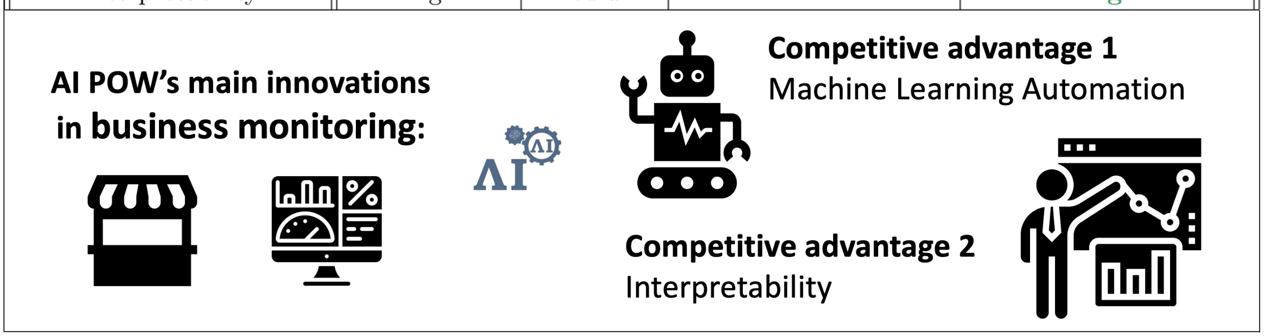

Figure 1: Current business monitoring solutions compared to **AI POW's** competitive advantages: ML automation, and interpretability.

We want to highlight that our team has protected the intellectual property generated in current libraries under the open software license. This license type allows us to open-source our core system with basic functionalities to enable potential customers to build their business monitoring system upon our trial version. Specifically, the system's core functions allow users to create basic functionality. On the other hand, we are publishing advanced functions, such as automated machine learning, interpretable machine learning, and anomaly detection, under the GPL v3 license, which forbidden unauthorized commercialization of products based on our protected modules. Our goal with the aforementioned intellectual property is to encourage academic researchers to conduct research based on our libraries and attract more users while protecting our product from unlicensed business usage.

4 Target Market

IBISWorld analysts indicate that the business monitoring industry will generate 86.7 billion US dollars in revenue in 2021 in the US; as shown in Fig. 2 the Online Business monitoring market represents 17% of the market with a reported 11.3% annual growth over the past five years [2]. This industry heavily focuses on large enterprises with the data requirements and budget sizes necessary to take full advantage of anomaly detection software, leaving an unmet need for smaller firms. **However, IBISWorld's report indicates**

that smaller businesses will become more critical to this industry over the next five years as they adopt enterprise technologies, that will eventually become the standard. We see an opportunity to serve this market by developing easy-to-use ML tools with intuitive user interfaces tailored to retail and e-commerce managers with a basic programming background.

We want to highlight that retailers, including online businesses, are already heavy users of enterprise software. Online businesses are particularly prepared to adopt enterprise software because they already heavily use information technology as a core part of their business. The e-commerce market segment is relatively mature due to its early adoption of enterprise software and will continue growing as online businesses displace traditional competitors. Altogether, retailers generated more than 4.0% of industry revenue in 2020 of the business analytics market [2].

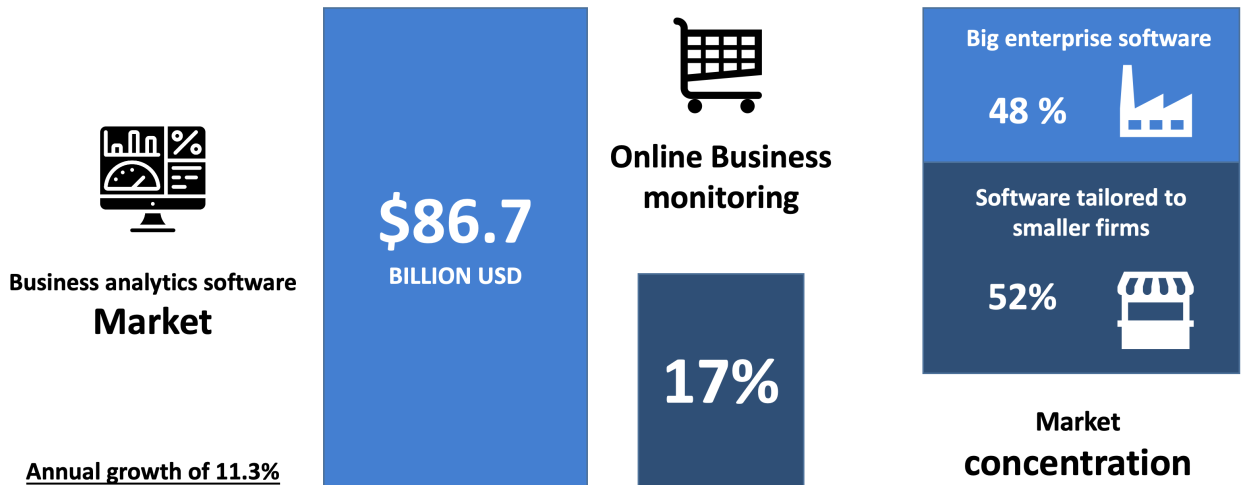

Figure 2: Business analytics market and online business monitoring concentration breakdown

5 Customers

As a result of our extensive collaborations with industry partners, we have experienced the existing online economy problems from a practical and realistic perspective. We recognize that a missing component between scientific research in business analysis and the current e-commerce industry's demands are the computational elements to bridge the gap between sophisticated algorithms and the technologies tailored to assist humans in taking full advantage of advanced ML-tools. AI POW's solutions aim to integrate automation and interpretability components into recent state-of-the-art research for retailers with mature data assets. Businesses that fit our current customer profile are retailers and e-commerce businesses with at least 100 employees.

Our current ML solutions have successfully targeted smaller firms that do not have the budget sizes to hire a computer scientist team. Additionally, we have built a strong user-base for the past three years with our open-source software, and we have seen a substantial increase in adoption in the past 12 months due to the rise in e-commerce traffic due to current stay-at-home restrictions. As we reach our critical mass adoption target, we are confident in securing funds to help capitalize on the confidence we have built in our products.

6 Sales/Marketing Strategy

The open-source community has highly praised the AI POW's libraries in academia and the GitHub platform. **This open-source initiative has also become AI POW's primary marketing tool as our open-source software adoption has brought several hundreds of users and, lately, our first paying customers**. Specifically, A significant part of the audience we have created around our open-source solutions requests premium features tailored to their specific needs. AI POW is currently channeling such demand using a direct distribution channel through our website, www.powtech.ai.

It is important to highlight that while we are looking forward to growing our open-source-based marketing strategy, part of our fundraising plan includes a significant investment in strengthening and expanding our sales strategy tailored to paying customers.

7 Business model

Our business model follows conventional practices in the business intelligence industry, divided into non-recurring and recurring revenue streams. **Non-recurring revenue streams** involve setup infrastructure costs such as AI & ML model building, platform installation, operator training, deployment expenses, and data preprocessing. Our **recurring revenue streams** follow standard models of cloud container companies [6] such as AWS®. They include ML deployment operation, license fees, data volume analyzed, and extra premium features related to security and data encryption. While our software as a service (SaaS) expected margin is 80 to 85%, our projected monthly burn rate is expected to be $21,000 for the first year.

Also, we are currently focusing on expanding our growing customer base of small retailers. For this, we are designing intuitive business monitoring tools to serve small companies with diverse e-commerce needs such as outlier detection, recommendation systems, and automated ML, to name a few. We want to highlight that companies such as Amazon and LinkedIn have used our open-source packages in the past, and we are currently looking to continue our business and research collaboration.

8 Competitors

As shown in Fig. 3, **AI POW's current open source** in ML Automation [5] and Outlier detection [3, 4] has helped us validate the market need for advanced business monitoring and attract our early adopters. **But even more importantly, the open-source tools we currently provide also helped us understand that current solutions in the market still lack enough automation and interpretability to be adopted by most small retailers with limited programming expertise**.

Direct competitors such as Anodot [7], Databricks [8, 9], H2O [10, 11], and DataRobot [12, 13], respectively, aare increasingly investing in ML automation techniques. We are looking to complement these efforts by further expanding our human-centered explainability technologies that are already visible in our published research and our popular open-sourced projects. **We firmly believe that our competitive advantage is our strong focus on ML automation, which we inherently combine with explainable AI to maximize human knowledge with intelligent machine support**.

On the other hand, our indirect competitors also include the **Open Source** libraries Keras [14, 15, 16] and Tensor Flow [17, 18, 19]. While they offer elements to build anomaly detection tools, both libraries are not flexible for business managers. Nevertheless, our goal is to push forward this effort by minimizing the industry experts' learning curve and accelerating our business monitoring platform adoption. We do so by building proprietary software dedicated to ML automation on top of open-sourced neural architectures widely used by the AI community.

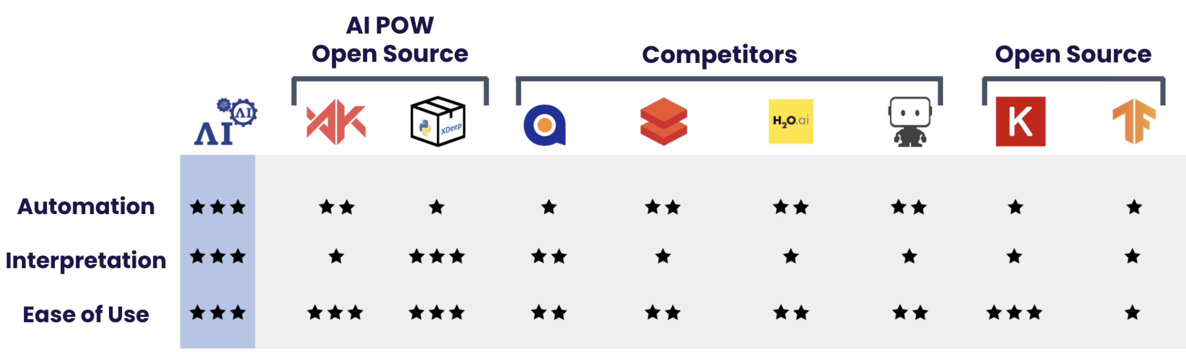

Figure 3: Current business monitoring solutions in the market.

9 Competitive advantage

To validate the competitive advantages claims of Fig. 1, our team has developed highly praised open-source packages such as AutoKeras [5], which has advanced to become # 1 automated deep learning software on GitHub. Its impressive growing user adoption is reflected through over 7,700 stars in 1,300 forks, not to mention that leading global companies such as LinkedIn, Amazon, and Apple have validated AI POW's business monitoring open-source packages through heavily funded AI published research.

10 Management team

AI POW LLC is a young startup established in 2019 with its origins in academia and the open-source community. Our team brings together the technical expertise with validated AI experience and the entrepreneurial skills to materialize our vision into a business reality. We are planning additional key hires that involve an experienced operations officer and expanding our programmer workforce.

Daochen "Frank" Zha is a Ph.D. student from the Department of Computer Science and Engineering at Texas A&M University. His research mainly centers on machine learning and data mining, particularly in optimizing data mining solutions with reinforcent learning. He is leading the RLCard project, an open-source platform for reinforcement learning in card games. He is also the major contributor to several other machine learning open-source projects, including PyODDS, an end-to-end system for automated outlier detection, and TODS, an AutoML framework for time series outlier detection. The projects deveoped by Mr. Zha have attracted more than 1,000 stars in total on Github.

Kwei-Herng "Henry" Lai is a Ph.D. student from the Department of Computer Science and Engineering at Texas A&M University. He worked at Academia Sinica and established joint researches with KKBOX, KKTIX, and Cathay United Bank, providing cutting-edge and large-scale machine learning solutions for the industry. Mr. Lai has led several industrial collaborative research projects on Anomaly Detection funded by Trane and General Motors. He has developed SMORE, a large-scale modularized graph embedding toolkit for recommender systems, and contributed to AutoKeras, the most popular automated machine learning package on gitHub. He is also the co-author of RLCard, a toolkit for reinforcement learning in card games.

Advisor, Xia "Ben" Hu is an Associate Professor and Lynn '84 and Bill Crane '83 Faculty Fellow at Texas A&M University in the Department of Computer Science and Engineering. He has published more than 100 papers in major data mining venues. His articles have received seven Best Paper Award (candidate), and he is the recipient of the JP Morgan AI Faculty Award, the Adobe Data Science Award, and the NSF CAREER Award. An open-source package developed by his group, namely AutoKeras, has become the most used automated deep learning system on Github (with over 7,600 stars and 1,200 forks). Dr. Hu's work on deep collaborative filtering, anomaly detection, and knowledge graphs is part of the TensorFlow package, Apple production system, and Bing production system. Hu's work has been cited more than 7,000 times, with an h-index of 38. He was the conference General Co-Chair for WSDM 2020.

Management team, Alfredo Costilla-Reyes is a postdoctoral researcher at Texas A&M University in the Department of Computer Science and Engineering. He graduated from both the Entrepreneurship and Technology Commercialization program at Mays Business School and the doctorate program in Electrical Engineering, both from Texas A&M University. Dr. Alfredo has been a recipient of the NSF I-Corps Site, the McFerrin-Entrepreneurship Fellowships, and the prestigious Mexico National Youth Award for his contributions in science, technology, and entrepreneurship. Specifically. His entrepreneurial endeavors have participated in venues such as YCombinator's YC120 event, and Silicon Valley Bank Trek, to name a few.

11 Goals

Our central motivation to participate at the Rice Business Competition is, first and foremost, **to find mentoring that can help us refine our SaaS-focused business model**. Equally important is to raise our Series A round of 2 Million dollars. Our team will allocate the investment to increase our team and expand our Automatic Data Processing Equipment capabilities and better serve our current users and customers.

It is essential to highlight that we have formed a team to commercialize our technology, and we have finalized and submitted one SBIR application. Our team will designate any potential non-dilutive funding to move forward our internal research and technology commercialization agenda.

While AI POW is still at the beginning stage of commercializing our technologies, we have already had $55,000 of revenue at the time of submission, and we are projecting $300,000.00 of revenue in 2021.

Financials ($0 US)	2019	2020	2021 (projected)	2022 (projected)	2023 (projected)
Revenue	0	55k	300k	1.2M	4M
Expenditures	0	3k	256k	1M	3M
Net	0	52k	44k	200k	1M

References

[1] Tractica. *Revenues from the artificial intelligence software market worldwide from 2018 to 2025, by region (in billion U.S. dollars) [Graph]*, April 22, 2019 (Accessed October 6, 2020). https://www.statista.com/statistics/721747/worldwide-artificial-intelligence-market-by-region/.

[2] Dan Cook. *IBISWorld US Industry (NAICS) Report 51121C. Business Analytics Enterprise Software Publishing in the US*, July 2020. Retrieved from IBISWorld database.

[3] Kwei-Harng Lai, Daochen Zha, Guanchu Wang, Junjie Xu, Yue Zhao, Devesh Kumar, Yile Chen, Purav Zumkhawaka, Minyang Wan, Diego Martinez, and Xia Hu. Tods: An automated time series outlier detection system, 2020.

[4] Yuening Li, Daochen Zha, Praveen Venugopal, Na Zou, and Xia Hu. Pyodds: An end-to-end outlier detection system with automated machine learning. In *Companion Proceedings of the Web Conference 2020*, WWW '20, pages 153–157, New York, NY, USA, 2020. Association for Computing Machinery.

[5] Haifeng Jin, Qingquan Song, and Xia Hu. Auto-keras: An efficient neural architecture search system. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1946–1956, 2019.

[6] Donna L Hoffman and Thomas P Novak. A conceptual framework for considering web-based business models and potential revenue streams. *International Journal of Marketing Education*, 1(1):7–34, 2005.

[7] PitchBook Data. *Anodot — Private Company Profile*, January 2021. Retrieved from PitchBook database.

[8] PitchBook Data. *Databricks — Private Company Profile*, January 2021. Retrieved from PitchBook database.

[9] Robert Ilijason. Spark and databricks. In *Beginning Apache Spark Using Azure Databricks*, pages 15–25. Springer, 2020.

[10] PitchBook Data. *H2O.ai — Private Company Profile*, August 2020. Retrieved from PitchBook database.

[11] Patrick Hall, Navdeep Gill, Megan Kurka, and Wen Phan. Machine learning interpretability with h2o driverless ai. *H2O. ai. URL: http://docs. h2o. ai/driverless-ai/latest-stable/docs/booklets/MLIBooklet. pdf*, 2017.

[12] PitchBook Data. *DataRobot — Private Company Profile*, August 2020. Retrieved from PitchBook database.

[13] Ahmad P Tafti, Eric LaRose, Jonathan C Badger, Ross Kleiman, and Peggy Peissig. Machine learning-as-a-service and its application to medical informatics. In *International Conference on Machine Learning and Data Mining in Pattern Recognition*, pages 206–219. Springer, 2017.

[14] Nikhil Ketkar. Introduction to keras. In *Deep learning with Python*, pages 97–111. Springer, 2017.

[15] Antonio Gulli and Sujit Pal. *Deep learning with Keras*. Packt Publishing Ltd, 2017.

[16] Jojo Moolayil, Jojo Moolayil, and Suresh John. *Learn Keras for Deep Neural Networks*. Springer, 2019.

[17] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. Tensorflow: A system for large-scale machine learning. In *12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16)*, pages 265–283, 2016.

[18] Nishant Shukla. *Machine learning with TensorFlow*. Manning Publications Co., 2018.

[19] Joshua V Dillon, Ian Langmore, Dustin Tran, Eugene Brevdo, Srinivas Vasudevan, Dave Moore, Brian Patton, Alex Alemi, Matt Hoffman, and Rif A Saurous. Tensorflow distributions. *arXiv preprint arXiv:1711.10604*, 2017.