



# SIX MILLION CREDIT APPLICATIONS LATER

What We've Learned About  
AI-Driven Lending



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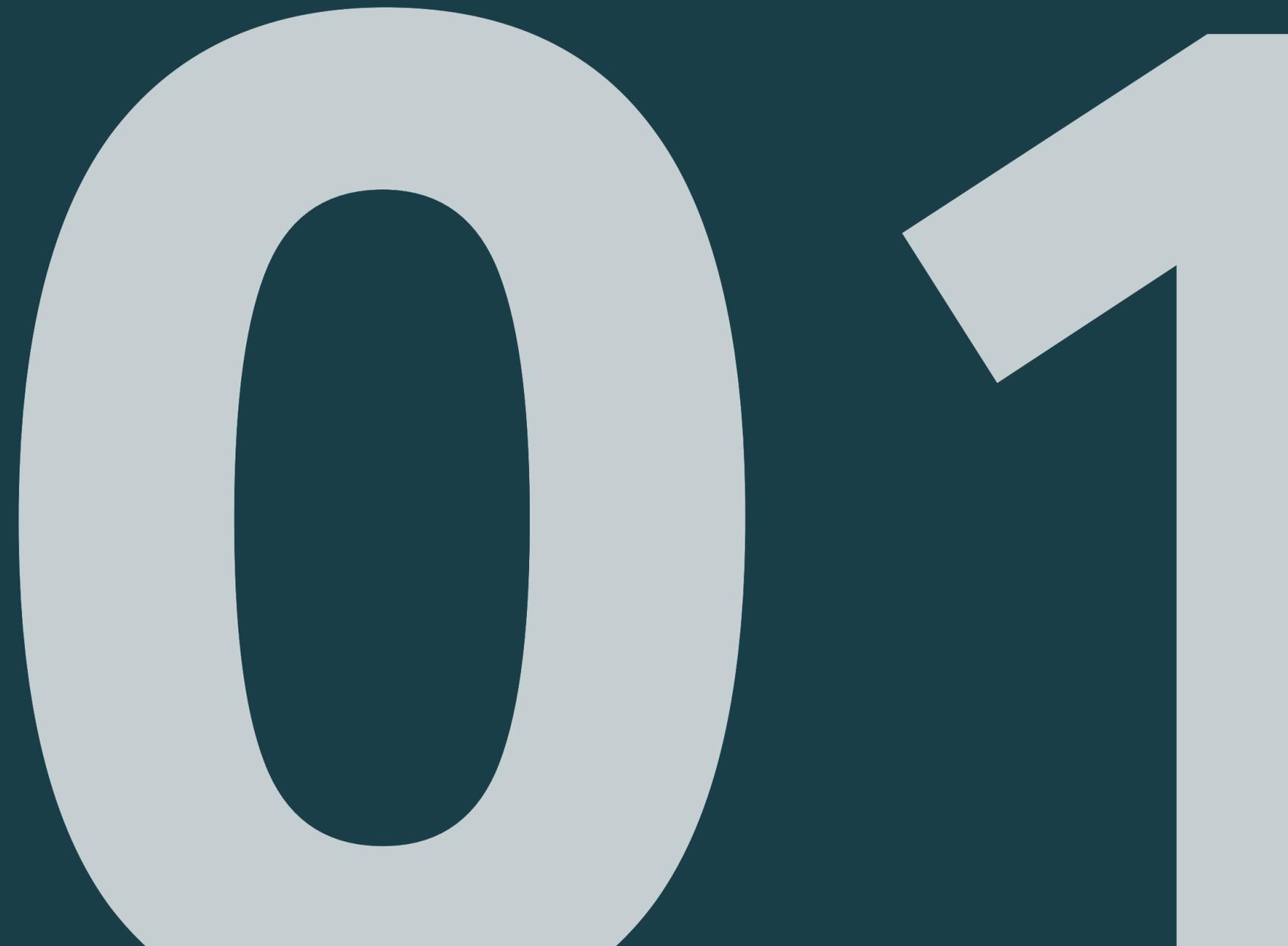
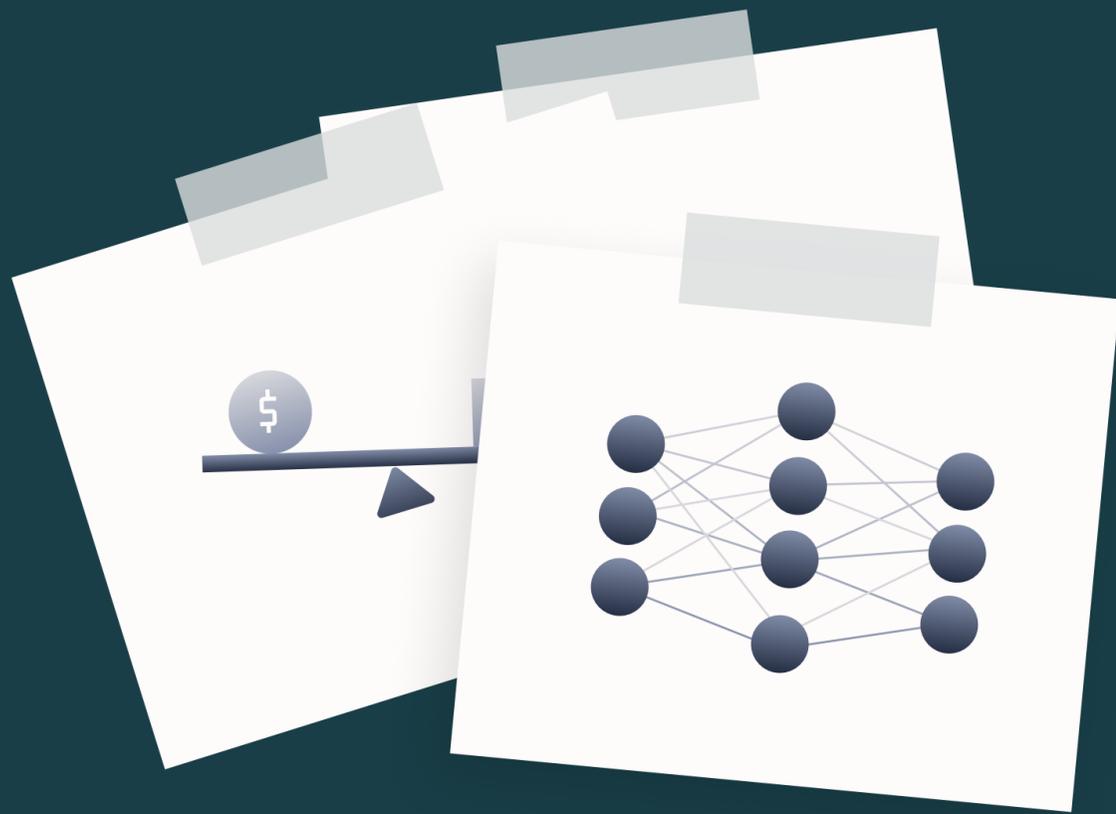
SIX MILLION CREDIT APPLICATIONS LATER

Thanks to our customers, Zest AI has helped put more AI-based credit underwriting models into production than any software vendor in the industry. Models built using Zest now score close to \$125 billion in lending portfolios across all credit products and we've generated more than six million scores to date. So we've learned a few things (some the hard way) about doing AI-driven lending.

We still get the same basic questions over and over again. Yes, the tech is legit. Yes, you will make significantly more money through higher underwriting profits and efficiency gains. No, you won't have a problem complying with federal and state banking regulations. Beyond this basic set of fundamental concerns and questions, we've put together this special FAQ based on more specific common questions we get from banks and credit unions. Hopefully, this will help fill in the gaps in your knowledge about AI-driven lending and lead you to some fruitful answers.

INTRODUCTION

# The six lessons



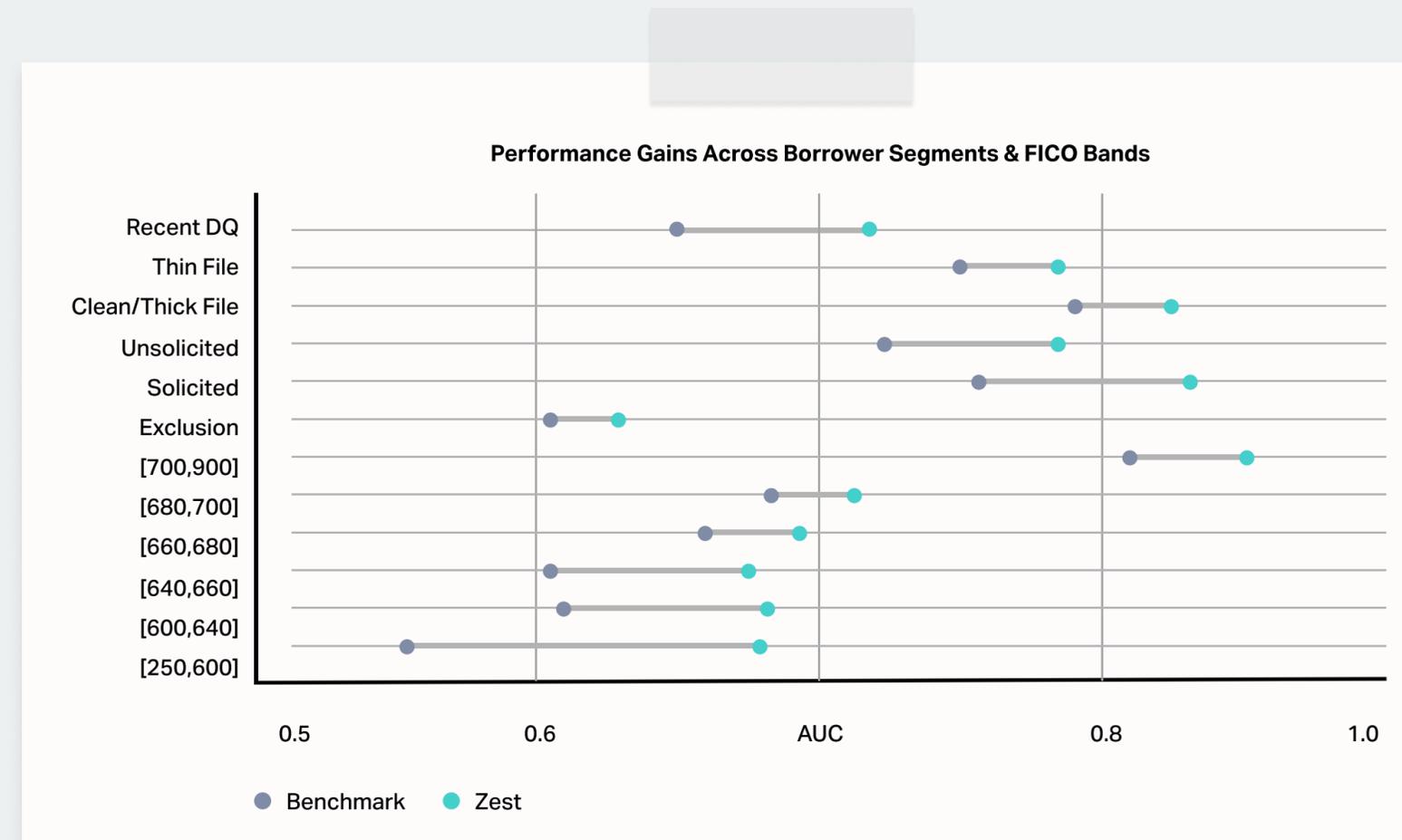
## INTRODUCTION: THE SIX LESSONS

Zest is a software and services company transforming how the consumer finance industry makes its biggest decision: who do lend to? We enable lenders to build and deploy powerful and compliant AI credit models swiftly and easily. Models built using Zest leverage more data and better math to deliver more profit and more inclusive lending for our customers.

Among the challenges lenders face today is how to safely provide credit to the 45 million Americans that are either impossible to score (aka "credit invisible") or too difficult to score due to them having thin files at the major credit reporting agencies. Another 80 million more Americans are considered sub-prime, a category that national generic credit scores have a difficult time assessing. In our work with lenders, FICO and VantageScore-based methods are barely better than a coin toss at predicting the creditworthiness of non-prime applicants. Add it all up and you're talking about nearly 40% of the country which presents a pretty big challenge to everybody in this space.

That's why we've got so many lenders ringing up asking about using AI and machine learning to power their credit underwriting models.

AI/ML is proven to boost the accuracy of risk models over simplistic FICO-type models. As this graphic shows, ML models outperform generic credit scores in every borrower segment and every credit band, even superprime, but especially among the higher-yielding segments below prime.

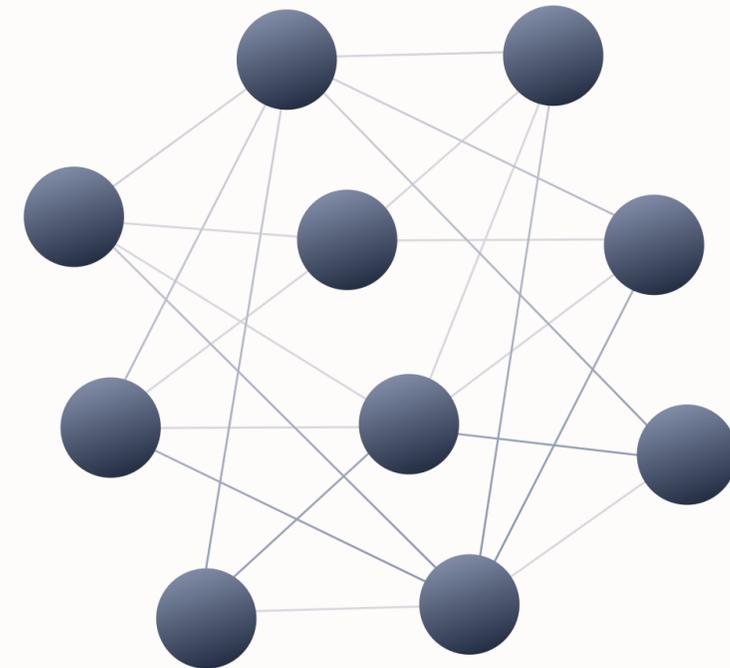


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## INTRODUCTION: THE SIX LESSONS

As the status quo in credit scoring crumbles, lenders are stepping past their doubts about ML and starting to assess how to make it happen. While top 10 or 20 banks are well-resourced enough to develop and automate their own AI lending tools and models, there are plenty of firms, about 14,000 or so, that could use the help from vendors such as Zest AI in building highly predictive and explainable AI/ML models that meet fair lending and compliance obligations.

The pandemic scrambled a lot of bank and credit union tech upgrades as firms wrestled with the transition to remote work and the rush of customers and members onto digital channels. But through the pandemic and even a bit before, models built using Zest have delivered millions of scores while our teams have helped dozens of lenders make the transition to AI-driven lending. What have we learned? Let's get into the key lessons.



LESSON #1

Financial  
inclusion is  
sound  
business

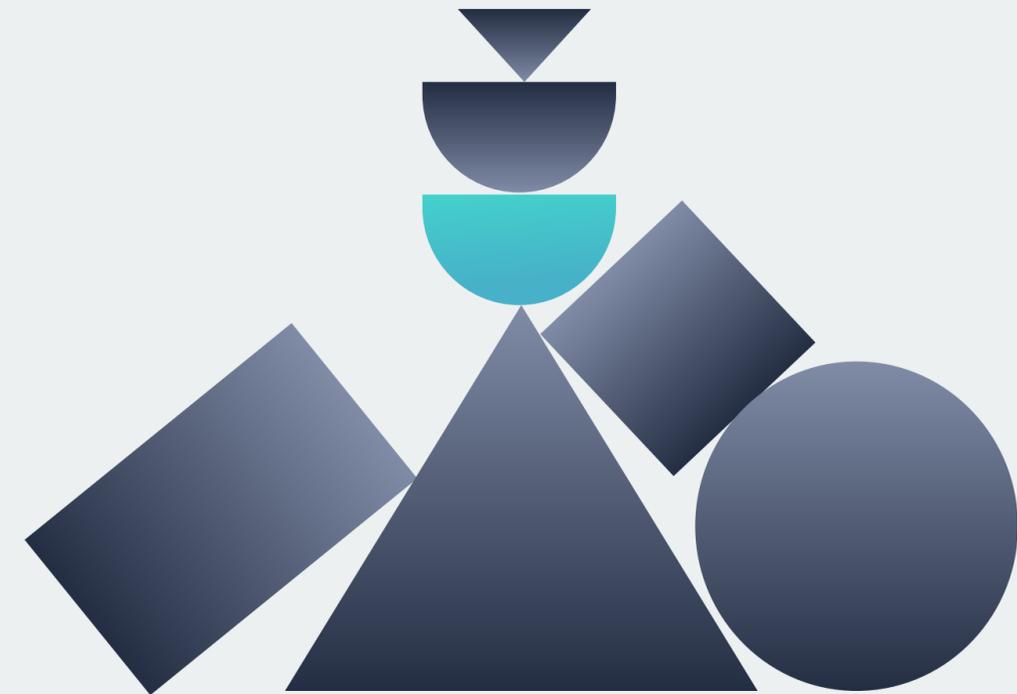
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## LESSON #1: FINANCIAL INCLUSION IS SOUND BUSINESS

The U.S. suffers from broad and deep gaps in wealth and access to affordable credit, especially in Black and Latinx communities. A disproportionate number of them are among that 40% of the country who are hard to score, credit invisible, or have artificially depressed credit scores because of the way the system is set up today.

In the past couple of years there has been a greater focus on bringing more of the country into the mainstream financial system, yet many lenders are hesitant to lend down the spectrum because their current tools and methods cannot assess non-prime risk accurately. This is a missed opportunity to end the perpetuation of generations of financial and economic inequality.

[Citibank estimates](#) that a lack of lending to black entrepreneurs over the past 20 years has cost the U.S. \$13 trillion in business revenue and 6.1 million new jobs per year. A lack of equal access to housing credit has cost \$218 billion over the same period. If racial inequality gaps were addressed today, \$5 trillion could be added to the economy over the next five years.



LESSON #2

Bet on the  
trend, not a  
point in time

03

SCORE  
20

JANE

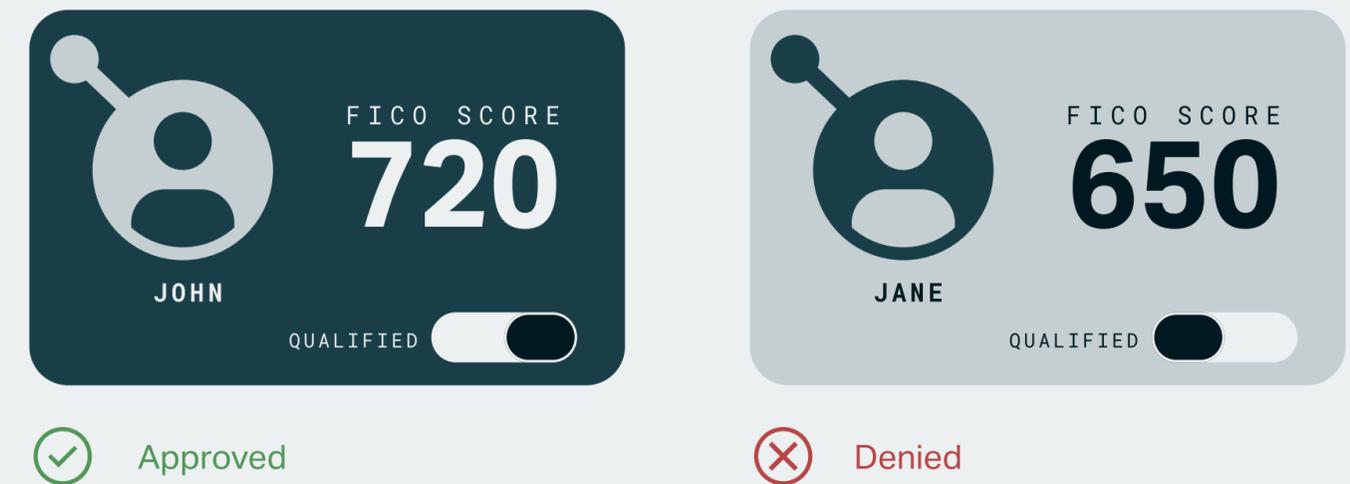
FICO SCORE  
650

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## LESSON #2: BET ON THE TREND, NOT A POINT IN TIME

The hesitancy to lend deeper down the credit spectrum is, in large part, caused by an inability to trust legacy credit scores to make an accurate risk assessment of the middle band of borrowers, who often fall into a gray area. That's especially true now with [the Covid economy scrambling scores](#). Two borrowers with the same score may represent completely different risk profiles to a lender. One applicant with a 650 score might be on her way from 600 to 700, while the other may be heading in the opposite direction. You can't spot these distinctions by using generic scores that rely on only a handful of data points pulled at a specific point in time. You need to use a richer set of trended data, including as many tradelines as feasible, to better assess the creditworthiness of through-the-door applicants. ML models generate their advantage over generic scores by incorporating hundreds of more variables than traditional models. They excel at handling trended data and tapping into millions of correlations to provide more nuanced views of consumers that lead to increased approvals and fewer losses.

Here's an illustration of what we're talking about. A traditional model would look at applicants John and Jane and almost certainly approve John over Jane based on their traditional, generic scores.



But is John the more creditworthy applicant?

## LESSON #2: BET ON THE TREND, NOT A POINT IN TIME

**Not exactly.** Machine learning models built using Zest leverage more data and correlations, especially among trended variables, to uncover more than enough red flags to indicate John is a riskier applicant than his credit score would indicate.



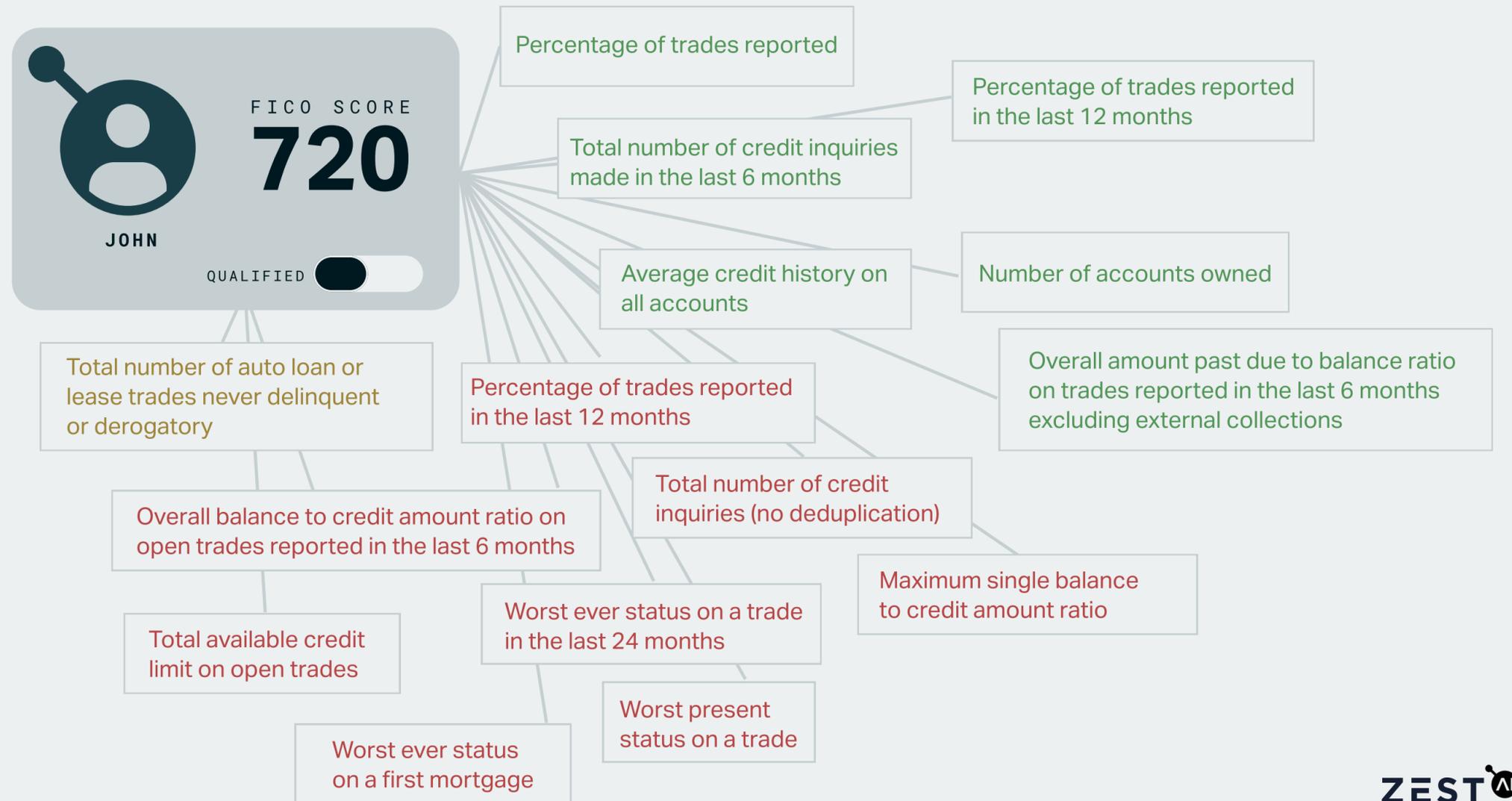
40 accounts owned

12 late payments 30-60 days

0 new credit accounts

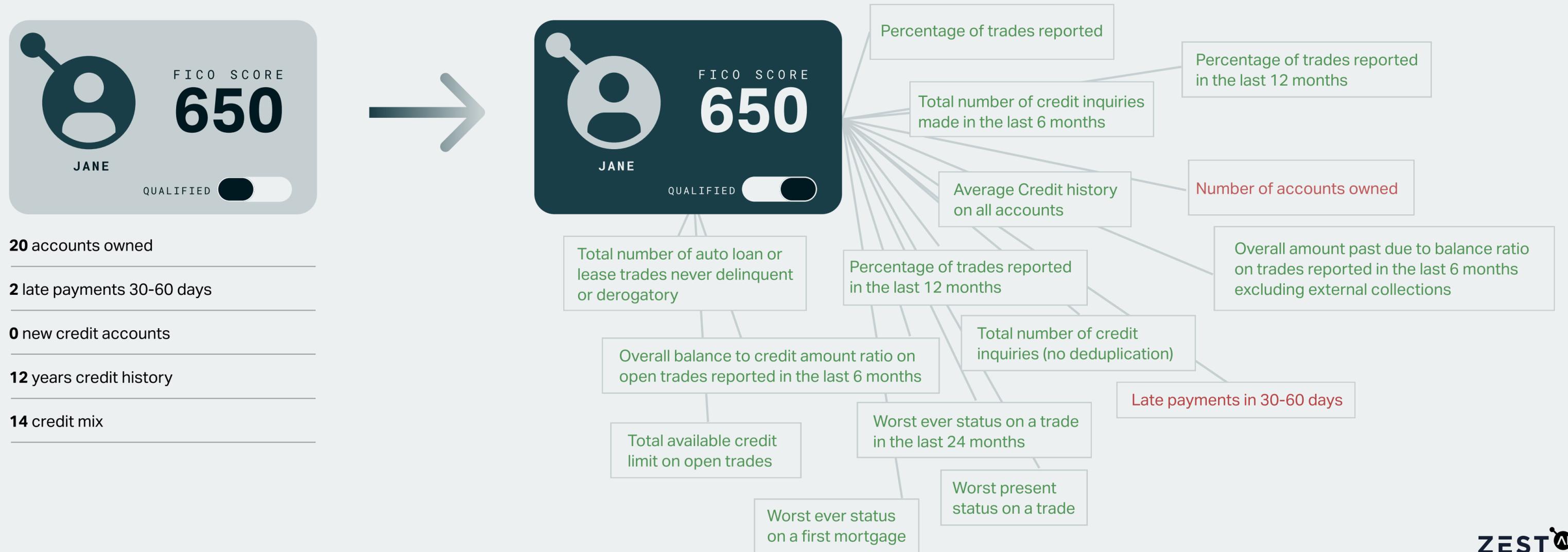
20 years credit history

10 credit mix



## LESSON #2: BET ON THE TREND, NOT A POINT IN TIME

By using far more trended variables from Jane's credit file, the model built using Zest extracts a lot more insight from fewer accounts. It turns out she has more high-quality current accounts such as her mortgage.



## LESSON #2: BET ON THE TREND, NOT A POINT IN TIME

The Result? John is denied and Jane is approved.



One question we often get: **How do you get trended data for down-spectrum borrowers without a lot of credit history?**

Certainly, if there's no history, we're not going to make it up with synthetic data. That would be far from compliant.

But ML models are better able to draw signal even from a thin credit file because they're more tolerant of missing data. They can also more easily accommodate alternative data sources such as cash flow data from rent, cell phone bills, utility bills, and first-party savings or checking accounts. You can get a lot of predictive signals from looking at how people use their money. The industry is [already moving in this direction](#) because it produces better models than simplistic generic scores.

LESSON #3

# Counterfactuals matter

# 04

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## LESSON #3: COUNTERFACTUALS MATTER

Building reliable, accurate, and resilient statistical models very often requires reject inference, a method for improving the quality of a scoring model based on the use of rejected or unfunded loan application data. For those unfamiliar with reject inference, it's designed to tackle the blind-spot problem. If you train a model to predict defaults based only on the performance of your own borrowers, you're missing the behavior of everyone else. Training your all-important underwriting model using only a fraction of the potential population of applicants should make you very worried. The people that you don't have performance data on look different from your approved population. Some that were denied or walked away may have ended up performing quite well with a different lender. If you exclude them from your risk model, your credit policy will reflect an incomplete understanding of your addressable population. Studying only your funded population results in a model that will behave in unexpected ways when scoring people who look different than what it has seen before.

There are a number of reject inference techniques out there. Beware of the ones that rely on model-based methodologies such as fuzzy data augmentation, parceling, or re-weighting. These methods use the underwriting model itself to generate performance targets for the declined population. These methods assume the funded and unfunded populations are the same and make arbitrary (often wrong) assumptions about the default rate of the unfunded population. The result is often little to no improvement in model performance (and, in some cases, worse performance).

Zest's patented reject inference approach combines model-based methods with rules-based methods that can help identify if an unfunded applicant has taken out a similar loan elsewhere, and their corresponding loan status, using post-application bureau data (and third party data where possible). Our hybrid technique delivers double-digit statistical improvement on top of the boost machine learning already provides.

LESSON #4

Lenders want  
fairer lending  
outcomes



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## LESSON #4: LENDERS WANT FAIRER LENDING OUTCOMES

Nearly every lender we work with is making social and racial equity a priority, and earmarking funds for financial inclusion initiatives in their communities. But even the most forward-thinking lenders are frustrated at the lack of proper tools to achieve their goals through lending alone. They're stuck making the traditional trade-off between model accuracy and fairness. They need better math. To the rescue: Zest's patented technique for double-optimizing models for accuracy and fairness.

**How does it work?** Instead of training a single credit risk model, you train it alongside an identical twin. This twin "helper" model has access to protected class information and its only job is to predict the protected class status of the applicant based only on the score of the risk model.

If the helper model finds that scores are coming out highly correlated with race or gender, you have a biased model. The helper then passes back information to help retrain the original risk model -- over and over again -- until it comes back with a score distribution that is hard to distinguish along racial or gender lines.

The technique, called adversarial debiasing, produces the most optimal trade-off between accuracy and fairness. We're already seeing some remarkable results in credit fairness. One credit card model built using Zest closed the approval rate disparity gap between women and men by 25% without significantly impacting performance. And the best part is that this automated de-biasing application comes standard with Zest's Model Management System software.

LESSON #5

Scoring is no longer set and forget

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## LESSON #5: SCORING IS NO LONGER SET AND FORGET

We saw, and continue to see, a lot of uncertainty around traditional credit scores. They went up after Covid-19 tanked the economy and, more than a year later, they continue to rise even though the economy is not out of the woods. What sort of reliability or stability do we have from those scores?

In times of change, using the same generic scores or waiting one to two years to revisit your score card could put you in a world of hurt. Lending teams need to be able to respond quickly when change accelerates. Formulating the right response means having real transparency or interpretability in your current credit models.

What we've been saying for a number of years now -- and hopefully it's catching on -- is that legacy credit models dependent on logistic regression (like FICO) are not as straightforward as they seem.

Some vendors of logistic regression models such as FICO or VantageScore lay claim to using machine learning in the upfront process of building model variables. But in doing so they're making some pretty strong assumptions about the lack of correlation between features in these models. What they're saying is, "Well, we can't make an ML model so we'll just use ML to build a new variable, and then stick it into a logistic regression model. But it's still a logistic regression model, so I'm okay." This is absurd. We've taken to calling these models "LRINO," or logistic regression in name only.

A real ML model that's built properly will almost always outperform logistic regression models. If you're going to use an algorithm to score people, you might as well use the best one you can.

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## LESSON #5: SCORING IS NO LONGER SET AND FORGET

No matter what kind of algorithm you decide to use for your credit underwriting, one of your paramount concerns should be the ability to monitor that model once it's in production. Some lenders we work with have been using the same legacy credit scores or scorecards for years, and are sacrificing better returns just because they aren't prepared to take on a model that might require a bit more surveillance to make sure that the model and loan performance are as expected. Zest's Model Management System, for example, delivers better performance with adequately sensitive monitors that tell you when features are drifting or score distributions are changing, or when it's time for model or policy adjustments due to changes in the market.

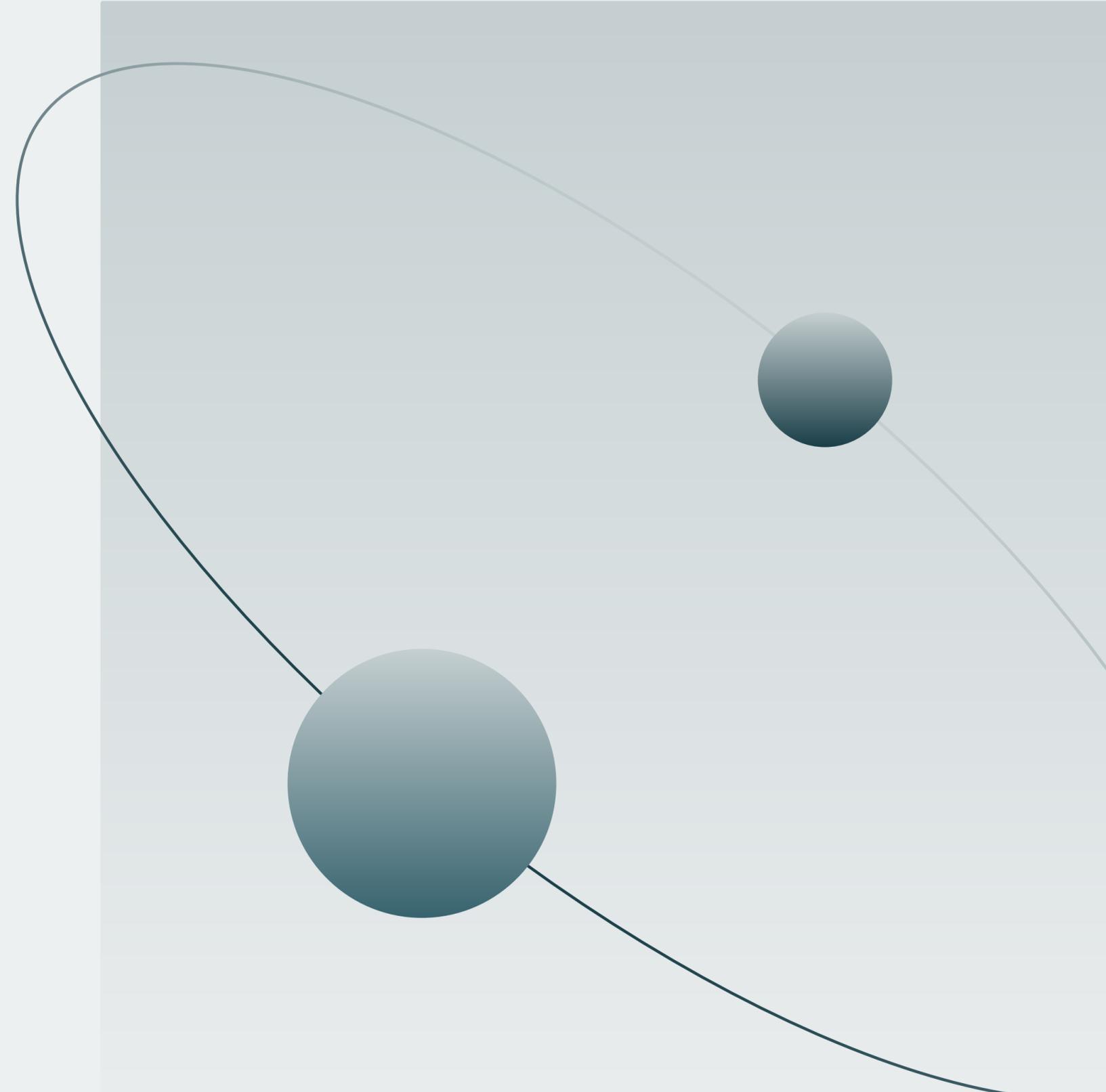
For example, even before the pandemic, one of our long-time customers, Akbank, one of the largest banks in Turkey, was using Zest model monitoring and caught indications of a looming currency-driven recession. The bank was able to make adjustments proactively to its credit policy prior to the economy hitting a rough spot. Fast forward a couple of years to early 2020 when a personal loans customer in the U.S. saw a sudden and dramatic spike in credit-line drawdowns. With the naked eye it could have been a sign of bust-out fraud, but more sensitive multivariate ML monitors showed it was merely customers with solid credit taking out funds just as the pandemic was hitting. The model's approvals had been fine. The model was behaving as it was intended during the period of development.

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## LESSON #5: SCORING IS NO LONGER SET AND FORGET

Many lenders we work with recognize there's a new approach needed to model management, one that's more proactive and agile and driven by better monitoring. We're not talking about free-wheeling AI that's changing all the time. Far from it. Models built using Zest are rigorously documented and locked-down once they're trained and validated. What we're talking about is giving you the ability to do model refits as market conditions warrant and doing them within a matter of weeks, not a year.

A software-driven approach is the key to managing the complexity that comes with better models so that overstretched risk teams know what to keep their eyes on. You don't need to dread the next model refit or rebuild. With software automation throughout the model lifecycle, like the kind that comes standard with Zest's Model Management System, you've got the agility you need to unlock additional value in your lending business.



LESSON #6

# Innovation requires change management



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## LESSON #6: INNOVATION REQUIRES CHANGE MANAGEMENT

The shift to AI-driven lending will change the economics of your business in a positive way. Along with that comes a good bit of culture change -- not just for credit risk teams, but for executive leadership, loan underwriting, and loan operations teams, as well. The firms that have enjoyed the most success and reaped the full potential of these investments see AI-driven lending as an opportunity to improve the way they do business.

At the same time, it's fair to say that we've encountered quite a bit of people who are feeling lost or skeptical, especially with all the changes across nearly every aspect of our lives in the past 18 months. There's a lot of technical detail even in this short guide you're reading today! People are naturally inclined to ask, "**Do we need to completely reinvent the one thing that I'm super comfortable doing?**"

Take a breath. Any innovation requires change but what we've also seen, especially at small or mid-sized financial institutions, is that the re-education required is pretty straightforward. You're just answering questions such as, "What does a double-digit increase in model accuracy mean for my business?" Or, "What can I have my underwriting teams do better now that most of the easier credit decisions are automated?"

Analysts are accustomed to delivering these kinds of insights to their lending leaders and it's not too hard to draw a straight line from better model accuracy to the results that accompany those gains. The insights and outputs that you get from Zest software fit directly into existing business processes.

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## LESSON #6: INNOVATION REQUIRES CHANGE MANAGEMENT

For example, in fair lending, Zest's automated approach to identifying disparate impact and generating less discriminatory alternative models is not replacing, appending, or subverting a process. It's simply supercharging and automating the work people already do. If your software is capable of producing high quality analysis and reports, it spares your talented people from grunt work. Nobody wants to be an Excel monkey. They want to focus on higher value tasks and start asking more interesting questions of the data and do the fun sleuthing work that builds confidence in a new decisioning system.

The changes that come with AI-driven lending have downstream implications for your loan operations and underwriting team, as well. Can they spend more time cross selling or upselling? Can they improve efficiency in other aspects of their workflow?

We've had customers who've been pleasantly surprised after moving to AI-driven lending that instead of spending a bulk of their time doing monotonous or rote decisioning, they get to spend more time with customers and members, they get to chat about products or services, helping them find what's right for them, which, is certainly more engaging than click, point, drag, drop. And a lot of their managers and business line leaders have been pleased as well, since they get growth without having to scale head count, which certainly comes in handy in times like this when so many employers are struggling to hire good workers.

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## LESSON #6: INNOVATION REQUIRES CHANGE MANAGEMENT

We'd be remiss if we didn't touch on the IT issues that hold financial firms back from moving to AI-driven lending. According to [a 2020 report](#) by the Economist Intelligence Unit, one-third of US financial firms cite the cost of technology as a main barrier to adoption. Given the immediate value-creation we've seen with Zest clients, we often challenge prospective customers to think about how AI-driven lending can be solved independently of other tech projects (and end up funding them, as well). Are there areas where systems can be integrated to increase value? An investment that will contribute immediately to revenue ought to jump up in the queue of IT priorities.

Something counterintuitive we've found: Nearly all the big banks have built and tested ML credit underwriting models, but many struggle or fail to put them into production (often over IT issues) whereas we've seen smaller institutions and credit unions get ML models up and running more quickly to gain an advantage.

The game doesn't go to who has the best AI, but to those who can implement, integrate and manage it most effectively.

We've helped dozens of banks, credit unions and specialty finance companies make the switch to AI-based lending without having to bring on massively expensive data science teams. There are thousands more who will need to make that journey, and we're here for them. Every lending operation wants to be more financially inclusive in a measurable way, and we're here to make that happen, too.

# Conclusion

AI-driven lending can transform your organization's growth and bottom line. Putting in the time to understand the results and properly prepare your organization will reap outsized rewards. First, you'll need to start rallying internal stakeholders around the potential opportunities early in the process. Then, take advantage of outside resources to learn.

We have tons of reading material at Zest, including a [six-step guide to adopting machine learning underwriting](#) and a team of analysts and experts that can address any questions you might have.

# Thank You

Schedule a demo today to learn how AI can help your organization make better and faster lending decisions.

[hello@zest.ai](mailto:hello@zest.ai)

## About Zest AI

Zest AI makes the power of machine learning safe to use in credit underwriting. Lenders using Zest AI software make better decisions and better loans—increasing revenue, reducing risk, and automating compliance. Zest AI was founded in 2009 with the mission of making fair and transparent credit available to everyone and is now one of the fastest-growing fintech software companies. The company is headquartered in Los Angeles, California. Learn more at [www.zest.ai](http://www.zest.ai) and connect with us on [Twitter](#) and [LinkedIn](#).