



*Reshaping*  
***Consumer Lending*** *with*  
***ARTIFICIAL INTELLIGENCE***

*White paper*

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# ABSTRACT

The lending ecosystem around the world has been at the center of significant changes in the last decade. From financial technology disrupting the financial services sector industry with highly efficient and cost-effective processes to stringent regulations following the 2008 global financial crisis, the burgeoning technological intervention has played a dominant role in the rapid expansion of the lending industry. One such technology is Machine Learning, which has begun to create new and highly promising avenues in the lending market.

While much of data analytics revolves around understanding and analyzing the past, Machine Learning can go a step a few steps further and find many hidden relationships, classify data and most importantly be predictive. ML, by very quickly crunching through large amounts of data can predict future performance or recommend a course of action, sometimes at a transaction level that even expert humans would be unable to provide.

Fintech organizations are progressively augmenting the applications of Machine Learning algorithms in their operations to build efficient and effective systems, better insight for decision making, enhanced customer service, meaningful user experience, cost reduction, revenue enhancement, and market share gains.

**In this white paper, we will put aside the grandiose and instead highlight what we firmly believe are ML's more immediate and practical applications in the data-rich consumer lending industry. We emphasize here, solutions and applications applicable to the lending industry that can be implemented in short development cycles with the right technological framework and expertise by using data that either already exists or can be sourced.**

In many instances, with enhancements to current systems, valuable data that was otherwise being ignored may be easily captured. This should provide, in short to medium term, a combination of one or more of the following: better insight for decision making, enhanced customer service, meaningful user experience, cost reduction, revenue enhancement and market share gains.

Far from the enslavement of humankind and without prognosticating the state of humanity in 2050, our plan instead, is to enslave the machines for our clients to make their businesses more productive, increase profits and gain market share - the holy trinity of capitalism and familiar goal of almost every corporate technology initiative.

**To us, it is not humanity vs. the machines but instead, our clients' machines vs. their competitors' machines - i.e., if their competitors are smart enough to have any trained machines whatsoever. That simple. To paraphrase Elon Musk, if your machines aren't learning and your competitors are then they will crush you. The stakes this time are high. Who will win? The race is on ...**

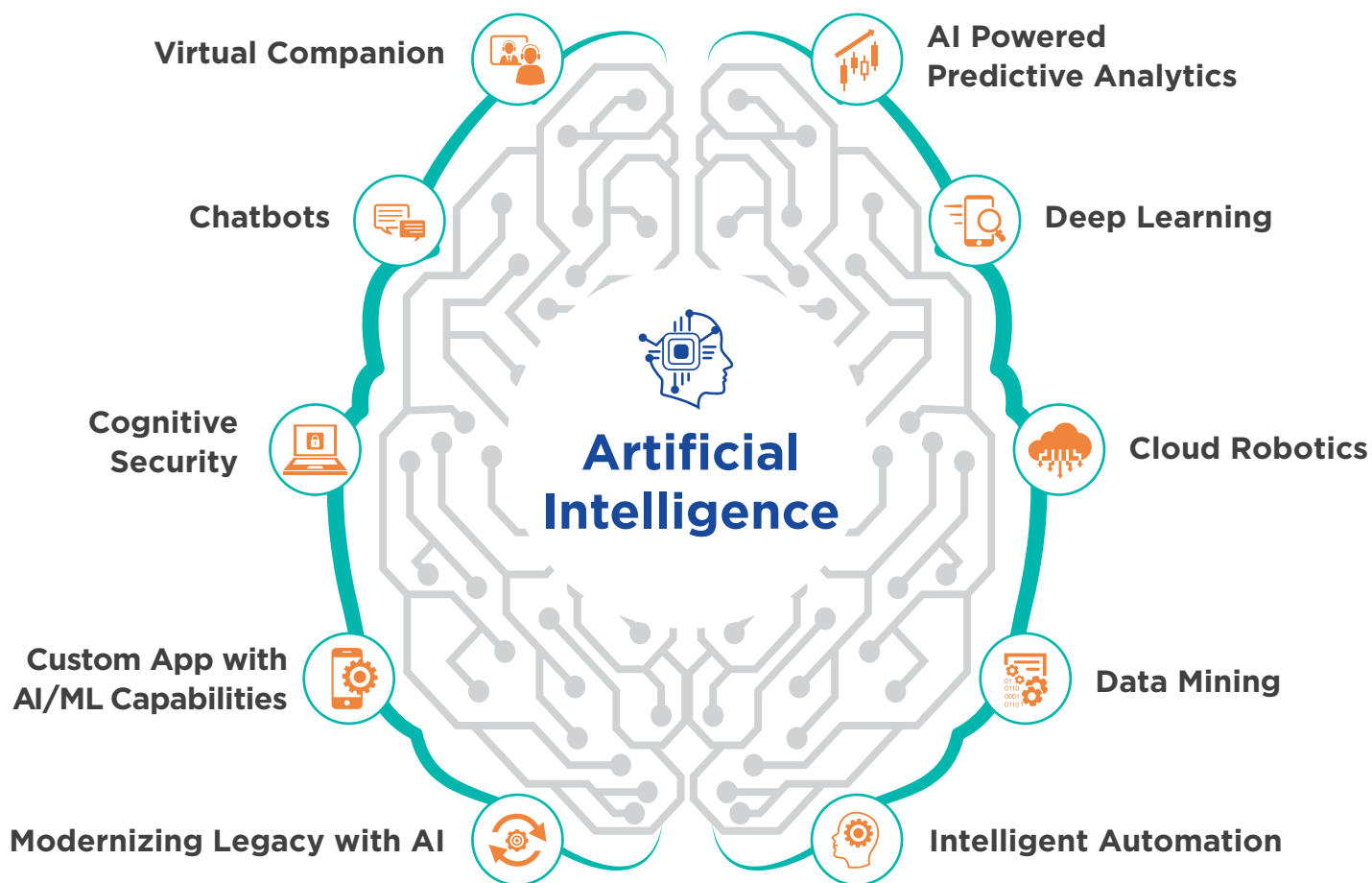
# INTRODUCTION

Machine Learning, or ML, is a sub-field of Artificial Intelligence (AI) and is one of the most promising technological innovations in recent years. ML has definitely captured the imagination of a very broad audience. ML is riding especially high with the media, technology analysts, stock analysts, slideware strategy consultants, matrix spewing management gurus and even politicians and talk show hosts. Some have even hailed it as the single greatest technological invention ever and predicted that it will change humanity as we know it thereby completely putting sliced bread to shame.

As with most promising technologies, one always enters a hype phase where the expectations of the technology far outpace the realizable benefits in a reasonable timeframe thus setting up a trough of disillusionment from a lack of broader commercial success. While we have not yet entered the disillusionment phase and hopefully, may never. To that end we have outlined approaches for our clients to avoid the usual traps by taking a focused approach that involves working with domain experts.

We believe there is indeed much hype and misinformation in the case of ML mainly due to its association with Artificial Intelligence (AI) and consequently to its association with many Hollywood science fiction movies depicting robots taking over the earth and controlling people's minds and lives. There are many forecasts from the usual thinkers, philosophers, and prognosticators that have people worried about massive job losses and even a Hollywood ending with humanity being enslaved by robots.

**Artificial Intelligence is a powerful cluster of advanced technologies that enables machines to sense, envision, act, and learn.**



The technology industry is pushing ML hard. What is lacking, if anything, within the technology industry with respect to ML? In our opinion, it is the availability of technical talent in the form of experienced machine learning engineers that also have deep domain expertise with intimate knowledge of data sources in those domains that can be used to train the machines. This is the boundary where hype separates from reality.

Why do we think there is much substance to ML? Once you get away from the hyped prognostications, there is a mature core to the technology. Notwithstanding the above hype, our goal in this white paper has been to separate reality from science fiction. We firmly believe the technology; the science and the math underlying ML is sound and fairly mature with many tool-sets that have been around for at least a decade and some even longer. Some of the most popular toolkits are actually available as open source libraries, languages and programming environments giving us a much lower cost entry point for adoption for our clients.

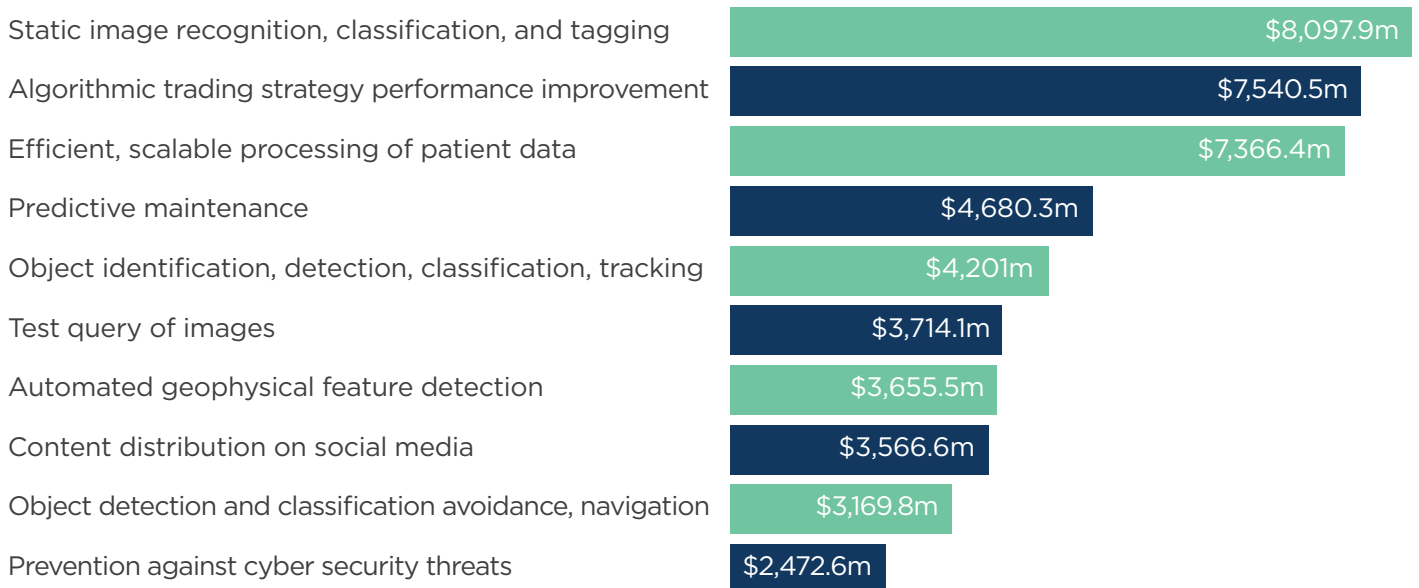
**Andrew Ng, adjunct professor at Stanford University and former chief scientist at Baidu, says, “Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don’t think AI will transform in the next several years,”**

In a similar vein, Andrej Karpathy, Director of AI at Tesla, writes in his [blog](#) that neural networks, arguably the most powerful of machine learning techniques, represent the beginning of a fundamental shift in how we write software, “They are Software 2.0”. It will soon be rare to see any impactful software in the industry which does not leverage the power of machine learning for its intelligence.



# THE FUTURE OF AI

Forecasted cumulative global artificial intelligence revenue 2016-2025, by use case (U.S. dollars)







# What Exactly is **MACHINE LEARNING?**

While there are many confusing and self-serving definitions of Machine Learning (ML) being circulated, here are two that get to the heart of what ML is all about without using esoteric buzzwords:

The oldest and somewhat informal definition is from Arthur L. Samuel who in 1959 described ML as "the field of study that gives computers the ability to learn without being explicitly programmed." Samuel is considered a pioneer in the field of Artificial Intelligence (AI) and widely recognized as having developed the Samuel Checkers - the first self-learning computer program.

A more nuts and bolts definition came in the mid-90s from Tom Mitchell as, "A computer program is said to learn from Experience E concerning some class of Tasks T and Performance measure P if its performance at Tasks in T, as measured by P, improves with Experience E."

**One key takeaway from these definitions is the notion of learning from experiences (historical data, interactions with the environment) to make intelligent inferences, and not by a human expert providing explicit logic or rules to affect that intelligence.**

In situations where behaviors change over time (consumer preferences, fraud attacks, etc.), ML can learn continually and adapt to those changes by refreshing the learned model autonomously. Rules-based systems, on the other hand, would require human experts to periodically update the rules manually.

As an academic field of study, Machine Learning is considered to be the love child of Computer Science and Computational Statistics. Due to its inherent goal of creating computer systems that learn, it is also considered a sub-field, the broader field of Artificial Intelligence (AI). In the present context, at academic institutions, ML is taught within the computer science departments but with many collaborations with math, physical and life sciences.

It is widely agreed that difficult computational problems in data analytics that cannot be solved analytically are best solved with machine learning algorithms using training data.

## CROSSING THE CHASM

Until a few years, only 'digital companies,' the so-called FAANGs - Facebook, Amazon, Apple, Netflix, Google and additionally Microsoft were aggressive adopters of ML. Today ML has gone mainstream throughout the digital industries with widespread applications in automotive (self-driving cars), healthcare (predicting and diagnosing diseases), meteorology (weather forecasting), manufacturing (analyzing IoT data to predict component failure), insurance (forecasting losses and risk analysis) and banking (credit card fraud prediction, credit scoring).



# What are the Different Types of **ML METHODOLOGIES?**

**ML fundamentally is the practice of using algorithms to parse the data, detect the latent signal in it, and use that to decide or predict about something in the world.**

So instead of hand-coding software routines with a specific set of instructions to accomplish a task, the machine is ‘trained’ using large amounts of data using algorithms that give it the ability to learn how to perform the task.

1

## Supervised learning

The program is ‘trained’ on a pre-defined set of ‘training examples,’ which then facilitate its ability to reach an accurate conclusion when given new data. Its two major subcategories are:

### Regression

The Machine Learning system where the value being predicted falls somewhere on a continuous spectrum. These systems enable us with questions of or ‘How many?’ or ‘How much?’. Examples: ‘What will this stock be worth?’ ‘What is the value of this house?’ ‘How much is this loan worth?’

### Classification

The Machine Learning system where we explore to anticipate a class or category, such as ‘Will this loan default in the first 60 days?’ a Yes/No classification; ‘Which house pet is visible in an image?’, multi-way classification cat, dog, bird; and so on.

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2

## Unsupervised learning

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The program is given a cluster of data and must seek patterns and relationships therein. Clustering is a classic application of unsupervised machine learning where data is not labeled but is divided into groups based on similarity and other measures of natural structure in the data. Another critical application is classifying items, events, observations that are not disparate from others in the data (anomaly detection), this is applicable in use cases such as fraud detection, fault detection, etc.

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3

## Reinforcement Learning

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The program interacts with some system (e.g., a car, a consumer) and learns to perform actions that maximize a cumulative measure of success. Examples: a self-driving car learning to perform a maneuver while maximizing the safety margins, an intelligent mailer system learning to reach out to consumers at the right times with offers and promotions to maximize her life-time value, a game playing software learning to select the right move at each turn in the game of Go to maximize the odds of winning.

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ML now can take millions of rows of data to build predictions using thousands of attributes. Older statistical regression techniques ran into severe limitations after a few dozen variables.



# What are the Steps in Building an **ML MODEL?**

**The most typical scenario in supervised ML involves creating a data set from various sources that have been scrubbed to remove errors.**

This is the data set that we believe could be ‘predictive,’ i.e., we have a hypothesis that there are relationships between this data and some business outcome or value that we are interested in knowing more.

Examples: The probability of loan fraud, the likelihood of loan default, the value of a house, etc.

1

## Data Set Creation

Collect and extract data from various sources. This could be in millions of rows with hundreds of attributes. Scrub the data to ensure it is free of errors and anomalies.

2

## Split Data Sets

Split the data set into a training data set and a testing data set. The ratio used is typically 80%-20% ; but may vary.

3

## Data Set Manipulation

This is an optional and iterative step, and depends on the domain knowledge of the data scientist as well. Often it involves normalizing each attribute to make it easier for the computers to solve and even creating derivative and higher order variables from the base attributes.

4

## Run the Algorithms

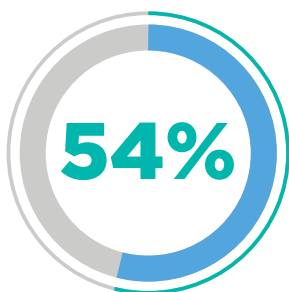
Data scientists will choose to run some algorithms against the training data set to see which algorithm performs better. Some examples of ML algorithms in the financial domain are neural networks, random forest, and logistic regression. Often, they will use a combination of algorithms to come up with the best model. It is known as ensemble learning and produces by far the best results.

5

## Test the Model Against the Training Data Set

This step involves testing the model derived in Step 4 against data that was not used to develop the model. In the test data set, the outcomes or values are known. This gives us a reasonable means to assess how good model is regarding foreseeability.

### What are the main benefits



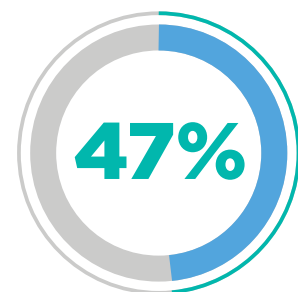
#### **EFFICIENT**

completing tasks faster



#### **PRODUCTIVE**

doing tasks for us



#### **PREDICTIVE**

making lives easier





# How are **EMERGING TECHNOLOGIES** changing the consumer lending industry?

Lending industry's dynamics are transforming rapidly. A whole breed of lenders is fundamentally changing the industry and revamping its modus operandi. However, most financial institutions are still performing the traditional way and grappling with the challenges of the legacy systems, and inertia to change.

While Cloud, SaaS, and API technologies help mobile banking and expand the horizons of innovation and enable organization who are skeptical to take the risk of opening access outside of the firewall. It seems safer and more comfortable to adhere to the legacy systems that are at the core of most financial companies. Nevertheless, the modern marketplace - not merely the financial services marketplace but the contemporary economy - will not allow banks to survive with closed systems anymore. To stay competitive, the lending companies need to respond quickly to meet emerging challenges.

**This paper examines the critical drivers for the financial institutions to reinvent themselves, challenges in the current lending industry and ML applications in the consumer lending industry.**

**For borrowers,** lending so far has typically meant a cumbersome process, manually filling up lengthy application forms, submission of volumes of documents, a couple of them are not even readily available which meant spending many hours preparing them. This is followed by months-long due diligence with some complex methods and no specific status updates and eventually, a decision with no justifications and sometimes too late to be of any use.

**For lenders,** this was characterized by enormous data requirements for underwriting, weeks-long data collection, experiential data collection, non-digitized data, manual and subjective underwriting processes, data scattered across files and systems and consequently; less than optimum decisions.

Apparently, this is the age of the customer, and the pressure is invariably on the financial companies to keep their customers delighted with speed and ease while dealing with Rising Customer Expectations, Regulatory Compliance, Operational Challenges, and Fragmented View of the Customer.





# Key Drivers of **BUSINESS CHANGE**

## Rising Customer Expectations



Customers have become more demanding as there are many providers in the market. They do not need standard product offerings; rather they need customized solutions for their problems. They need convenient and simple lending experiences with quick fund delivery. They need highly personalized services with implicit assumptions that their providers know them well with their past interactions.

## Stringent Regulatory Requirements



Financial companies are working to remain competitive by fully monetizing the immense quantity of data available to them; however, the industry is under greater regulatory scrutiny. These companies can harness data ensuring compliance with data governance restrictions.

## Operational Challenges



Organizations deploy multiple systems processing, and data is scattered across systems with no single source of truth and face challenges that include legacy systems, inefficient process, and data integration.

## Fragmented View of the Customer



Eventually, the silos that exist between legacy accounting systems and new applications are leading to a fragmented view of the customer. Fragmented customer data makes it difficult to achieve a 360-degree customer view.

# ML Applications in **CONSUMER LENDING**



# ML Applications in **CONSUMER LENDING**

Consumer Lending (CL) of all kinds including mortgages, autos, credit cards, student loans, etc., is a data-rich environment. For example, in a typical mortgage lending scenario, we estimate that between the borrower's credit history, property, employment, income, tax, and insurance information, more than five thousand data attributes are captured during the lending process. This is a time-consuming and expensive process and in the case of many lenders, a very manual one. How much of this data is even relevant? How much of it is useful in predicting borrower behavior during the application, closing, post funding and servicing stages? As such these are questions that are perfect applications for ML to answers. Given that many financial institutions have many years of this data stored or accessible makes it perfect to train using ML algorithms to devour and tell us what is useful, predictive and how. Most companies infer only a small fraction of the vast potential of what is helpful from this data. This is primarily because they are mostly using traditional reporting techniques to analyze it, if at all.



# Applications for ML are broadly classified into the following main functional areas:



# ML Application **CREDIT SCORING**





# ML Application

## CREDIT SCORING

In a study of data from over five years, including the financial crisis, MIT researchers found that machine learning could be used to reduce a bank's losses on delinquent customers by up to 25%. Additionally, some early adopters in the industry have used ML to predict the credit performance of borrowers with limited credit (aka 'thin file').

Credit scoring is the crux of loan management. Through machine learning, an algorithm for the predictive model is built to process credit scoring. Machine learning tools access data through extensive mining from various sources such as online transactional behavior, purchasing behavior with e-commerce, social media activity, etc. to evaluate the creditworthiness of borrowers. This assures unbiased play with interest rates as per their creditworthiness, and the borrower getting listed in risk buckets.

The biggest opportunity that exists for lenders in this area is the ability to score the applicant's creditworthiness numerically by combining credit bureau data with the property, income, employment, tax, assets into an overall score that predicts the creditworthiness considering the complex variety of factors and not just the credit bureau data.

**Data Sources:** Credit Bureau, Property, Income, Assets, Tax, Utilities, Rent

### Benefits:

- > Lower underwriting/origination costs by machine or machine assisted decisioning
- > Reduced credit losses
- > Lower agency recourse risk
- > Better risk-adjusted margins
- > Lower servicing costs



# ML Application **MARKETING**



# ML Application **MARKETING**

Lenders looking to expand their Consumer Direct channels have a large amount of anonymized credit data and data from other marketing sources available to build models. Typically, these scores run through the universe of borrowers on a monthly or biweekly basis and calculate their LTA 'likelihood to apply'. Those that score above a profitable threshold are then contacted through various channels typically mail, e-mail, call-centers.

Standard models have been available from the credit bureaus for a while. With the accessibility of ML, it is now possible to build a more responsive and accurate custom model by using data sources to match-up with lenders own experience and 'borrower characteristics' data.

**Data Sources: Credit Bureau, other transaction data sources**

## **Benefits:**

- > **Lower marketing cost**
- > **Higher response rate from direct marketing efforts**
- > **Better close rates**





# ML Application

# **LEAD MANAGEMENT**



# ML Application

## LEAD MANAGEMENT

Once lenders have gone through the process (and often high expense) of getting a person to apply for a loan, it is imperative for them to convert as many of these leads into funded loans as possible.

Most lenders, especially mortgage lenders, have dismal closing ratios. Loan applications that result in actual loan findings tend to average around 10%. This results in a tremendous amount of wasted labor input for the 90% that do not result in a loan. The ability to identify various traits of a lead that result in a higher likelihood of closing can drive better resource allocation and timely intervention to prevent pipeline leakage.

### Benefits:

- > **Increase app to fund ratios which are traditionally dismal (~10%) we believe this benefit is even significant than the cost side.**
- > **Greater engagement through every step of the buyer's journey.**



# ML Application **USER EXPERIENCE**



# ML Application

## USER EXPERIENCE

The number of steps in the lending process and the longer each step takes is directly proportional to the drop-off rate of customers.

The User Experience (UX) layer of the origination process has to be enhanced to capture telemetry data from various UX triggers - what screen, how long, etc. to measure the stage by stage dropout rate. After a period, this would create the training data set for an ML model with the forecast event being the act of dropping out. Monthly, new models incorporating the 'learning' from recent data would continue. This would trigger action on the part of the originator to prevent loans from falling out.

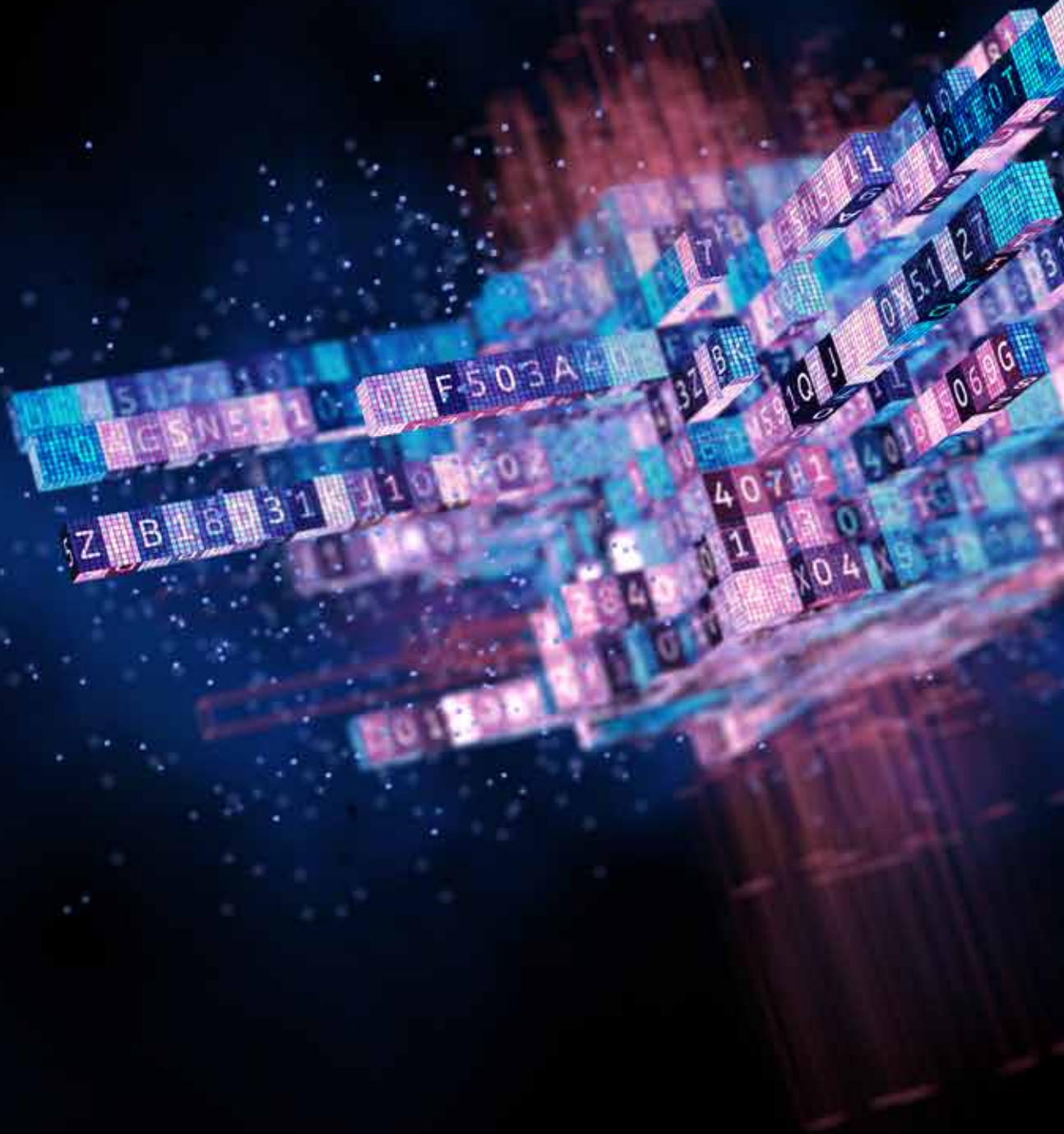
### Benefits:

- > **Increase percentage of self-service (which reduces LO commissions cost)**
- > **Immersive omnichannel experience from home discovery to loan funding**





# ML Application **ROBO-ADVISING**



# ML Application

## **ROBO-ADVISING**

We are all familiar with recommendation engines in our daily lives. The most famous examples are those of Netflix and Amazon. Both look at past viewership or purchases and recommend new ones. This is an interesting problem in that it looks at the behavior of others in addition to your own to recommend products to you. The hypothesis is that, a) If you have something in common with others on one product, then you might like what they also additionally watched or purchased and b) Recommend products/movies that are similar to ones that you have consumed in the past.

The same context is extensible in the lending domain where there are numerous products on offer that the borrower may qualify for but how to know which is the best overall? The idea is to create a 'robo-advisor' similar to what is becoming prevalent in the case of the wealth management industry where 'bots' now recommend investments. The lending advisor would recommend products based on past choices made by borrowers in conjunction with loan officers and yet combine it with product rules and guidelines.

**Data Sources: Full loan origination data set**

**Benefits:**

- > **Enhanced customer self-service**
- > **Lower LO (loan officer) cost**



# ML Application **FRAUD DETECTION**

# ML Application

## FRAUD DETECTION

Fraud in lending is estimated to cost billions to the industry. Fraud comes in many forms - fraud due to misrepresentation by borrowers, falsification of documents, brokers and loan officers corrupting the process, borrowing using false identities, falsified appraisals, collusion with intermediaries and service providers - all lead to significant financial losses to the lender.

Account takeover fraud in banking is nearly up by 300% year over year, web application fraud is up by 200%, and fraud of government services and payments are up by 30%.

ML is a great way to develop models to flag loans that have a risk of having fraud and pass them on to a 'second look' review. These models are built using comprehensive data available during loan origination and triggered at many stages and at least once right before closing.

**Data Sources: Complete origination data with training on known 'bad outcomes' i.e., known fraud cases over the years**

### **Benefits:**

- > **Reduced write-offs**
- > **Lower legal costs**





# ML Application **LOAN SERVICING AND COLLECTIONS**

# ML Application

# **LOAN SERVICING AND COLLECTIONS**

## Call Prioritization Models

In a typical mortgage, loan payments are due on the first of the month with a 15-day grace period before a late charge is assessed. Most borrowers typically pay on the same day of the month. Using the servicers own historical payment pattern data, ML models can be built to prioritize who to call and when is the best day of the month to start sending them reminders and calling them. In the case of other types of loans such as credit cards, personal loans, auto loans, and the due dates can be all over the months making ML-based call prioritization models even more effective.

**Data Sources:** Historical payment data from servicing system

### **Benefits:**

- > Reduction in collection calls made
- > Higher customer satisfaction
- > Lower delinquencies



# ML Application **PROPENSITY TO PREPAY MODEL**

# ML Application

## **PROPENSITY TO PREPAY MODEL**

Servicing can be a significant source of ongoing steady revenue for lenders. Lenders of all kinds have it in their best interests to ensure that customers have no reason to leave. Especially mortgage customers sometimes have reasons that make it necessary to pay off their mortgages and get new ones. These reasons include refinancing to lower payments, refinancing to consolidate debts or purchase of a new home. It is the lender who owns the servicing rights to retain these customers because they already have a business relationship and losing them would deprive them of years of steady servicing revenue.

Prudent lenders can use payment pattern data, credit bureau data, and other transactional data feeds to build ML models that can predict the likelihood of prepaying within the next 30 days and prompt them to take defensive measures such as pre-emptive refinance offers using sweeteners such as rebates and zero-cost refinances.

This is more convenient and cost-effective for the customer and lender to retain the long-term servicing revenue stream. By creating a dedicated low cost 'defensive refi' unit that does not have the sales compensation structure of typical loan officers, the lender can make an origination profit as well.

**Data Sources: Historical payment data from servicing system, housing data feeds, credit bureau data**

### **Benefits:**

- > **Customer retention**
- > **Greater customer satisfaction**
- > **Higher origination revenue**
- > **Greater servicing revenue**





# ML Application

# **LOSS MITIGATION**



# ML Application

## LOSS MITIGATION

In mortgage servicing, one of the main sources of losses and high servicing costs is from the borrower defaults resulting in foreclosure. Due to the long time-line of foreclosure in most states, the resulting lost interest during the non-performing stage and the administrative/legal costs of going through foreclosure are usually not in the best interest of either the borrower or the lender. As such workouts, payment plans, and short-sales are almost always a better strategy. Machine learning models built on payment pattern data, credit bureau, and other feeds to create a 'likelihood of default' model which can give the servicer a heads-up. The servicer can then assign the loan to a 'work-out' unit to work proactively with the borrower to explore non-foreclosure strategies. It is a win-win situation-best for the borrower and best for the lender/servicer/loan investor.

**Data Sources:** Full servicing data set, credit bureau data, housing data, macro feed, income data

### Benefits:

- > Greater customer cure rate
- > Home retention and satisfaction
- > Lower losses and charge-offs
- > Lower delinquencies
- > Higher servicing revenue



# ML Application

# **PORTFOLIO MANAGEMENT**



# ML Application

## PORTFOLIO MANAGEMENT

While many loan originators, especially in the mortgage business, do not retain long-term credit risk by immediately selling to government-sponsored enterprises (GSEs) such as FannieMae, FreddieMac, and FHA/VA, there are many institutions that do retain credit risk. These include financial institutions such as money center banks, super-regional banks, mortgage insurers, REITS, insurance companies, bond funds, fixed income funds, and mutual funds. This could include jumbo loans, non-conforming loans and sub-prime loans - loans that are typically not purchased by the pseudo-government agencies.

Risk and portfolio managers at these institutions that retain credit risk are always concerned about future loan performance. ML models trained on historical loan data and macro-economic data can be used to value and hedge the portfolio. The models used here are typically default and prepayment models, which may then be used to forecast and hedge the value of the portfolio using the most appropriate hedging securities instruments.

**Data Sources:** Historical loan performance data, macroeconomic data

### Benefits:

- > Better loss and prepayment forecasting
- > Portfolio valuation
- > Servicing rights valuation
- > Loan loss reserve calculations &
- > Lower hedging mismatch losses





# ML Application

# **THIRD PARTY ORIGINATIONS**



# ML Application

## THIRD PARTY ORIGINATIONS

Many mortgage lenders supplement their retail and wholesale origination volumes by purchasing closed loans. For some, this is a significant source of lending volume that allows them to spread their infrastructure costs over a larger loan volume, albeit, at a lower margin. For many mortgage REITs lacking a captive origination channel, this is the only way to acquire loans for their investment portfolio. ML models trained on historical loan performance data and optionally on macro-economic & housing data can significantly improve credit quality and flag loans with issues up front. For long-term loan investors such as REITs and various investment funds, this can be a great way to improve long-term loan performance by filtering out the loans with the highest likelihood of default or fraud.

**Data Sources:** Historical loan performance data, macroeconomic data

### Benefits:

- > Lower due-diligence cost
- > Reduced credit losses
- > Decreased put-back from GSEs
- > Lower losses from fraud





# ML Application **CAPITAL MARKETS**



# ML Application

## CAPITAL MARKETS

A vast majority of non-bank lenders do not retain credit risk by selling their originated loans. In case of mortgage lenders, the loans are typically sold off to government agencies such as FannieMae, FreddieMac, and FHA/VA. Some lenders who originate non-agency loans in significant volumes may also choose to securitize their origination. Securitization involves the originator/issuer having to retain a substantial amount of credit and performance risk in the long-term. Thus, for securitizers, it is imperative to ensure that credit quality is sustained in the long-term as that is how they make money, essentially earning a net interest margin over time. Therefore, in addition to applying standard rules-based guidelines, these lenders could significantly improve long-term performance by implementing ML models to filter out loans with a high propensity for early payment default and fraud risk.

**Data Sources:** Full origination data (including credit, income, property, employment, and assets), macro-economic data

### Benefits:

- > Lower early payment defaults
- > Reduced long-term credit losses







# FINAL THOUGHTS

## Investing in Artificial Intelligence is the need of the hour

It is apparent that AI and ML are the future of consumer lending. Consumers no longer want the same old experience; they want convenient, secure solutions that meet their lending needs. Machine Learning is remarkably a cost-effective solution since the task of lending and monitoring fintech activities such as investments are undertaken by machines.

AI and ML applications should be top business priorities for consumer lending companies to embark on the digital transformation journey for better decision-making, cost reduction, streamline operations, and increase operational efficiencies.

Considering this, consumer lending companies must make a concerted effort to implement ML applications such as Fraud Detection, Lead Management, User Experience, Marketing/Lead Generation, Credit Scoring, Robo-Advising, Capital Markets/Secondary Marketing, Loss Mitigation, Risk Management, Loan Servicing, and Collections to improve the customer experience while reducing costs and stay better positioned for the future changes in the consumer lending ecosystem.



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AI powered digital lending platform



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