Ai SPARK

The leading AI solution for credit risk analysis

Methodology

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Powered by the continual evolution of machine learning technologies and backed by over 90 years' collective experience, Ai SPARK redefines the Structured Products industry by producing instant, objective, and continuous risk and credit results.

The company's Transparent Autonomous Risk Algorithm (TARA™) is the leading artificial intelligence (AI) software for credit risk analysis. A continual iterative machine learning process allows TARA™ to produce clear, concise, and objective risk assessments, allowing its users—Structured Products debt and equity professionals— to enhance their processes effectively and effortlessly.

Background

Individual loan analysis is hard. Debt investment professionals face a monumental task providing real-time investment decisions, for a subject whose performance is impacted by innumerable fast changing factors.

They operate in a chaotic and open system, with near infinite dimensions; multi-layered factors that impact properties: submarket performance, industry classification, covenants, crime, tenants, financial leverage, environmental concerns, macro-economic disturbances, pandemics, inflation, the behavior of the Fed, global supply disruptions, war, borrower/guarantor attitudes and behavior, the special servicer, the list goes on.

The complexity of this challenge was at the root of the Great Financial Crisis and many, if not all major Fixed Income market industry disruptions in the past.

Furthermore, while analyzing debt instruments is intensive, costly, and requires sector specific skillsets, the work is done under crushing time constraints with market participants needing to make decisions impacted by 100's of loans in just hours. This presents an enormous challenge but also an equally large opportunity to leverage technology for debt investing and analysis.

Against this backdrop we consider how to leverage machine learning and TARA™ to meet the challenge of investment analysis.

TARA™ at a Glance

TARA™'s aim is to optimize predictions of future collateral performance, by learning and tracking which factors influence historical (and current) loan performance.

Leveraging machine learning for securitized debt investments offers the industry:

- Unprecedented accuracy: TARA™ autonomously risk rates loans' future performance with unparalleled accuracy and speed, without the distortion of bias.
- Higher returns: TARA™ provides forward looking results, while accepting the users' assumptions as well, to generate custom stresses, enabling users to buy higher yield bonds lower in the stack, with confidence.
- Ease of use: Cloud-based AI that integrates seamlessly into clients' technologies of choice.
- AI powered: The continual iterative machine learning process allows TARA™ to produce clear, concise, and objective risk assessments effectively and effortlessly in real-time.
- Maintain quality standards: During phases of staff turnover, TARA™ helps ensure credit work accuracy and high-quality standards.
- Increase productivity: TARA™ enables teams to refocus and better prioritize by directing Human Resources to their highest and best use. Allowing teams to free up time for deeper credit analysis and/or platform expansion translates into greater accuracy and alpha.

B-piece buyers are naturally sensitive to minimal losses, so for any given set of bond offerings, being able to quickly compare credit pools, relative tail risk, and individual loan sensitivities can help triage deal flow and improve credit monitoring. Underwriting a whole pool takes a lot of time with few resources, or a lot of resources with little time. TARA helps those resources. to be allocated more efficiently.

Leading Asset Manager
West Coast Firm

Machine Learning vs. Deep Learning

Machine learning is a branch of AI that gives computers the ability to learn and improve with experience, without explicitly being programmed, by using data and algorithms to imitate intelligent human behavior. Algorithms use historical and present data as inputs to predict new values.

Deep Learning is a subset of machine learning that uses vast volumes of data and complex algorithms to train a model, teaching computers to do what comes naturally to humans, to learn by example.

The machine learning process looks for patterns in data to later make inferences based on the examples provided, allowing computers to learn autonomously without human intervention and adjusting actions accordingly.

The Need for AI in Securitized Products

Investment analysis today is widely conducted using a bottom-up approach, on a loan basis, to assess the value—an approach that involves gathering granular loan information to form an opinion of prospective health and future performance.

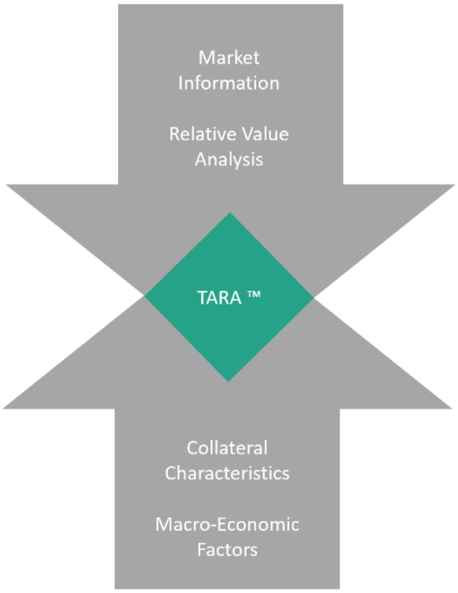
Often, debt market participants additionally employ a “model” which converts certain important performance metrics into a quantitative answer that informs investment actions and/or accounting—a model which can then be adjusted to bring in factors not captured explicitly within it; qualitative adjustments informed by the “bottom-up” analysis of the analyst.

Models are sometimes (but not always) calibrated using historical performance data. Other times, models are calibrated by the industry experience and qualitative judgement of the investment professionals who built them. The model calibration is when the investment professional looks at historical records or their own judgement and experience. This is where DATA – whether explicitly or implicitly – inescapably comes to bear on credit risk analysis.

Typical man-made credit risk models in the industry are NOT "bottom-up" but better described as "top-down", due to their relatively blunt nature when compared to granular manual "bottom-up" analysis. A man-made credit risk model may have several highly impactful risk drivers complemented by several secondary inputs. However, the top-down model, while limited by the number of model inputs, provides a stable measuring stick and reliable tool which the professional uses to translate his/her overall analysis into a quantitative value that is actionable. In addition, when time is short and the number of line items is large, the model can fill in where the qualitative "bottom-up" analysis can't reach.

> Ai SPARK is pioneering the next step forward in credit analysis. Its AI based platform is built FOR and BY Securitized Products professionals and helps our team assess risk and adapt to changes in the macro environment faster than ever before.
>
> No other platform comes close.
>
> Asset Manager
> Large US Bank

Why AI?



The application of AI in investment analysis cannot be described as "top-down", at least not in the same way as a man-made credit risk model, because of the sheer amount of granular information that it considers. Neither can it be described as "bottom-up" because, after all, it is built using data.

It is in between the "bottom-up" and "top-down" approaches as seen in the diagram (left). It is "bottom-up" when set next to a man-made credit risk model, and "top-down" when set next to an investment analyst's qualitative approach.

The granular nature of AI will make it more dynamic and accurate relative to man-made credit risk models. Its accuracy will be driven by exponentially more data than a regular model, and as such has the capacity to speed up the analyst, focus analytical efforts, and fill in with greater reliability than a regular model. This allows the analyst to get on with more in-depth analysis with confidence.

In addition, AI has a superior ability to draw inferences in data. It can mimic any model, decision tree, or mathematical function known to man, when/if it deems it necessary to do so. This ability gives it an inherent advantage over typical man-made models.

Platform Expansion

The virtues of technology make analysts more powerful and gives them back more time, enabling the team to push into other areas of the market and cover exponentially more assets with the same number of analysts. Such platform expansion provides debt platform owners with immediate value and increased potential, specifically for CRE, syndicated bank loans and CLOs.

Model Governance

AI by its nature is a continuous feedback loop into its own performance, as it tracks results and continuously attempts to improve accuracy. This task is rarely accomplished by qualitative heavy platforms nor by quantitative man-made credit risk models, and when this task of re-assessing performance is tracked, it is very time-consuming and expensive to do manually.

Knowledge Capture

In addition, due to its granularity, AI has the flexibility to accept the "bottom-up" approach qualitative analysis in a more explicit and less abstract way than credit-risk models often do. As such, it robustly supports the debt professionals' qualitative work and stores knowledge in a much more interpretable way.

Data Relationships

The value of procuring more, and different types, of data for use in any platform is limited by how well the data is used. There is always a race to have data, but of course, just having the data is meaningless without somehow bringing it into the answer which informs action (or inaction).

The usefulness of any data source is dependent upon the answer to two questions:

(1) How does this data source influence my answer?
(2) How does this data source influence (and how is it influenced by) other data points?

To the extent that we are not equipped to arrive at and/or retain the answers to these two questions on our own, we fail to capture the true meaning of the data that we have. It could be that we are inundated by new data sources, and yet we do not use them optimally.

AI can swiftly pull together and track an astounding number of dimensions. It will draw relationships where confirming data is robust, all while incorporating uncertainty in areas where not enough data is available.

Its ability to build relationships is mathematically very powerful, indeed – if optimal – it could mimic any man-made credit risk model.

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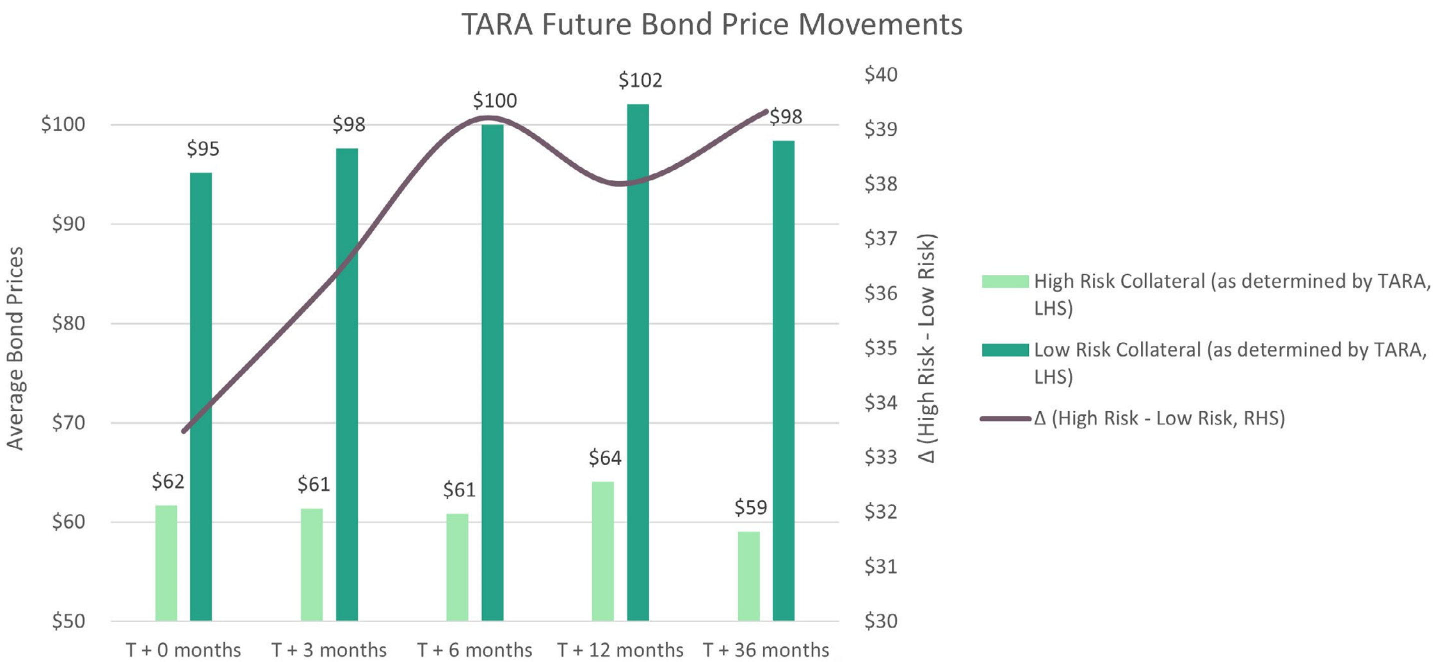
We are inundated by new data sources, and yet we do not use them optimally. In short, TARA™ can use the data that we have...optimally.

TARA™ identifies alpha opportunities to drive greater returns by leveraging latest available technologies. By providing unprecedented accuracy and immovable principles through enhanced modelling and deep logic, TARA™ provides the platform for precise and unwavering risk analysis. It is therefore able to clear one of the industry's biggest hurdles by completely removing any ability to skew or manipulate market participant behavior, providing a constantly improving level of precision.

This precision is evident in empirical observation of TARA™'s performance in assessing market bond prices.

The explanation of bond prices is consistent through time – and most significant.
during times of market dislocation, also as shown in the below chart.

Last, and most importantly, TARA™ predicts future bond price movements.



T + 0 months is January 2019 in the chart above, which examines bonds flagged by TARA™ as having higher quality collateral, compared to bonds flagged by TARA™ as having lower quality collateral.

Given the effectiveness of TARA™ at leveraging available data to predict strength of underlying bond collateral, it should be expected that TARA™ will be able to build portfolios that outperform in the future, and that any deviance would be under pressure to be corrected (i.e., the bonds that TARA™ flags as containing higher risk collateral will underperform against bonds that TARA™ flags as lower collateral).

This bond pricing pressure is most evident in two situations: (i) when the market experiences a large dislocation, and (ii) when the market experiences an inversion of the relationship (wherein for a short period of time, what TARA™ deems as higher quality bonds are priced lower than comparable lower quality bonds).

This relationship demonstrates the alpha of using TARA™ relative to the bottom-up qualitative analysis and top-down man-made credit risk modeling widely used in the debt space today. This accuracy/result does NOT consider the fact that present-day users of TARA™ tend to also incorporate qualitative analysis to further boost the TARA™ signal.

The result on bond prices is impacted by controlling for duration and seniority, wherein senior bonds are most heavily affected by TARA™'s tail risk result (see TARA™ Results, Tail Risk), and Mezz and sub bonds are most impacted by TARA™'s loss expectations (see TARA™ Results, Ratings).

TARA™

TARA™ is an AI built for the purpose of tracking tranche and collateral performance.

Typical usage (by function) for teams using TARA™ can be broadly broken down as follows:

Use Cases

- Portfolio Management / Trading
- Credit Analysis
- Risk and Surveillance
- Marketing / Fundraising / Training

Across all asset types, TARA ™ combines loan level attributes with Economic indicators. Within each asset, there are specific nuances that are also considered and that is described below.

Collateral fields

The entire history of property and loan information as provided by the CREFC IRP (Commercial Real Estate Finance Council Investor Reporting Package) and INTEX™.

- Investor Reporting Package history
- Historical Loan Pricing
- Reference Data
- Both collateral and bond model Intex support files.

Data Sources & Curation

Ai SPARK continuously seeks to improve the data that is being exposed to TARA™. There are 5 major sources of data that feed into TARA™. These are: external market fields, collateral fields, submarket fields, percentile fields and "Sparks", as described below.

External market fields

The fields are generally related to economic factors from publicly available sources:

- Bank for International Settlements
- Board of Governors of the Federal Reserve System (US)
- Producer Price Indices
- Commodity Levels
- Department of Housing and Urban Development
- Federal Financial Institutions Examination Council
- Federal Reserve Bank of Chicago
- Federal Reserve Bank of Kansas City
- Federal Reserve Bank of New
- Federal Reserve Bank of Philadelphia
- Federal Reserve Bank of St. Louis
- Freddie Mac
- Haver Analytics
- ICE Benchmark Administration Limited
- International Monetary Fund
- National Bureau of Economic Research
- Administration
- U.S. Federal Housing Finance Agency
- University of Oregon
- Organization for Economic Co-operation and Development

- U.S. Bureau of Economic Analysis
- U.S. Bureau of Labor Statistics
- U.S. Bureau of the Census
- U.S. Bureau of Transportation Statistics
- U.S. Department of Housing and Urban Development
- U.S. Employment and Training

Asset Class Overview

Ai SPARK developed proprietary algorithms by which it selects the most promising fields and configurations (as well as the priority) which are exposed for consideration to TARA™. This process is continuous, in that Ai SPARK endeavors to continually improve the feeds that are exposed to TARA™ as well as their configurations.

Terms:

Submarket fields

Fields derived from collateral information provided by INTEX™. These fields track a statistic, usually descriptive of collateral performance (e.g., occupancy) tracking a cohort (or peer group) of loans, e.g., the cap rates (statistic) of a peer group based on property type, loan size and MSA.

Percentile fields

Like the submarket fields, these are fields derived from collateral information provided by INTEX™. These fields track the percentile rank of a collateral loan's statistic, usually descriptive of collateral performance (e.g., occupancy, industry) against a cohort (or peer group) of loans.

Sparks

Fields derived by Ai SPARK using afore mentioned sources. Indices are designed to address specific concerns and shortcomings within the data, e.g., the fact that prior to 2022, most of Securitized Products history has taken place in a declining interest rate environment.

Data sets

Data sets are largely comprised of the historical data as provided by INTEX™. This consists of:

- Approximately 15,000 CLO tranches (Debt and Equity), which is over 99% of the market, and all related syndicated loan level information for each deal.

- Over 10,000 CMBS conduit, Agency and SASB transactions, with reporting beginning in the 1990's.

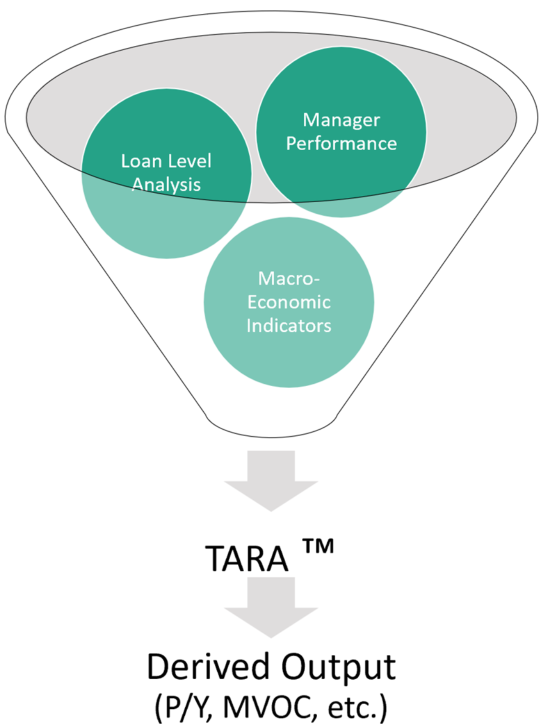
The sector has experienced at least three large systemic crises in that time, which disrupted. new issuance, refinance liquidity, as well as top line collateral performance.

Ai SPARK attempts to correct for aspects that are not captured by this history, by creating "SPARKS" or indices aimed at specific concerns, e.g., the fact that CMBS history took place in a predominantly declining interest rate environment.

Collateralized Loan Obligations

Coverage

	Debt	Equity
USD	7,500	2,000
EUR	3,000	1,000
Private (estimate)	1,000	250



Macro-Economic Indicators

- Interest Rate Curves
- Bureau of Labor Statistics
- Industry Specific Variables

Manager Performance

Our Manager performance input is calculated using a broad range of inputs.

- Equity Returns
- Experience and Performance
- Assets Under Management
- Portfolio Performance

Asset Level Analysis

- Historical Price History
- Delinquency
- Industry Analysis
- Cohort Performance
- Rating
- Loan Attributes: 2nd Lien, Covenant Lite

Commercial Real Estate

Coverage

Conduit	12,000
SASB	2,500
CRE CLO	500

Tail Risk (CRE)

The tail risk module exposes concentration risk within CRE debt portfolios.

CMBS and CRE pools tend to be non-homogeneous with individual collateral loans having lopsided impacts on portfolio performance, due to wide-ranging differences in collateral loan sizes.

Tail risk is especially relevant for bonds that have higher credit support, which may (in other asset classes) be safe due to diversification, but in CMBS, be subject to increased risk due to pool concentrations.

A sound means of assessing this concentration risk is through scenario analysis which considers edge ("tail") scenarios where a number of larger loans fall into default and creates a loss to the CMBS Trust or any investor portfolio.

Two portfolios may have the same risk when considering what is expected to happen but have wildly different risk when considering the worst-case scenarios of what could happen.

The tail risk module of TARA™ applies the following algorithm.

(1) Get expected performance of each collateral loan: Ask TARA™ for the expected loss of each collateral loan expressed as the TARA™ Rating letter grade (i.e. A+, A, A-, B+, B, B-, C+, C, C-, D+, D, D-)

(2) Get TARA™ rating performance: Look up the historical performance of each TARA™ Rating letter grade, and express these as cumulative distribution curve of losses experienced for each rating historically.

(3) Generate (over 10,000+) scenarios of correlated performance results for each loan in the pool according to their rating.

(4) Generate pool losses across scenarios according to collateral performance and loan size (% of pool).

(5) Sort scenarios from worst possible observed scenario to best.

(6) Examine implied tail of the sorted scenario distribution.

In this way, the tail risk module considers the worst to best possible outcomes for a pool, incorporating TARA™'s signal of individual loan risk, in addition to the composition or concentration of the pool.

TARA™ can communicate the worst-case scenarios, their likelihood, and point to the collateral loans most responsible for the tail risk.

After the inputs go through a vigorous data integrity and cleansing process to ensure accuracy, TARA ™ analyzes the fields and produces current and forward-looking metrics. As new information is integrated, the process repeats to create a continuous loop of learning and outputs.

Model Overview

Objective

The objective of training TARA™ is to provide the most accurate out-of-sample, forward-looking predictive AI possible. Equally, the objective is to provide an AI that is usable, and interpretable, thus enabling robust interaction with a user.

Learning Architecture

The Learning architecture is defined as both (i) the mathematical equations which define the learning process, and (ii) the algorithms that govern the inflow of data as part of the learning process. These form the core of TARA™'s learning ability.

Ai SPARK constantly seeks to improve the learning architecture of TARA™. This is an iterative process in which we review end results with investment professionals.

Versioning / Releases / Back-Testing

TARA™ versions are cited as a number followed by an 8-digit numerical which signifies an update.

Major release

A major release is denoted as a whole number (e.g., Version 3). A major release signifies:

(a) Important changes in TARA™'s learning architecture.
(b) Important changes in dimension reduction techniques (see Data).
(c) Important changes in TARA™ output (learning targets).

Minor release

A minor release is denoted by the decimal values preceding the major release number (e.g., version 3.11). Minor releases signify important changes in data fields and/or data field configuration (see Data).

Update release

An update is an 8-digit numerical code which references its date of release formatted as yyyymmdd (e.g., version 3.11 (20231001)). An update signifies a refresh of its version incorporating all performance data experienced up to the date of the revision.

Back-Testing

Testing is done continuously as the mind of TARA™ either (i) grows its experience, (ii) changes its fields/dimensions or (iii) has its learning architecture changed by Ai SPARK.

Phase I – Statistical Tests

The first phase of back-testing involves monitoring TARA™ predictions using baseline statistics. This consists of:

(i) Testing statistical accuracy of TARA™ predictions using various definitions for false positives, true positives, false negatives, and true negatives, tracked against new issuance loans, term loans, maturing loans and all loans, using such statistics as:

(a) Accuracy, Precision, Recall/Sensitivity, F1, Specificity and Correlation.

(ii) Tracking anomalies and/or counter intuitive decisions by TARA™

(iii) Heuristics: Verification that the shape of the result loss curves are similar to actual observed losses, and lack evidence of over and under fitting data.

Ai SPARK must observe broad confirmation in these three areas for a version of TARA™ to pass its first phase.

Phase II – Model Comparisons

Any version which passes into phase II is already highly optimized and performs well. Phase II determines where the version lies when compared to other predictive tools, using publicly available model predictions from leading rating agencies, banks, and analytics vendors, in addition to past versions of TARA™.

Versions which consistently outperform these models are passed into the next phase of testing.

Phase III – Out of Sample Back-Testing

In phase III, we conduct out of sample back-testing to ensure that TARA™'s results will be robust going forward out of sample. We explore loss vs. prediction delta across vintages, time and within transactions known to have anomalous collateral (e.g., aggressively sized regional malls / same manager).

We ensure that results are robust for both non-distressed, new issuance, seasoned and distressed loans alike.

Phase IV – User Tests

The final phase of testing is comprised of our user tests. Does the version make sense when an investment professional interacts with it?

We conduct sensitivity analysis to ensure that the new version is interpretable for an end-user.

Ai SPARK positions, if a version does not make sense or is not intuitive enough to an end-user, it is less likely to maintain its predictive power going forward.

In this phase, multiple real estate professionals look for "non-sensical" behavior(s) of the version. Finding non-sensical behaviors in the edge cases of the AI is not always, but sometimes, indicative of a version that has overfit (or underfit), or otherwise failed to learn and be applicable out of sample.

FAQs

What is TARA™?

TARA™, the Transparent Autonomous Risk Algorithm delivers an unbiased look into collateral-level risk for CLOs, bank loans, commercial real estate debt and CMBS. Utilizing machine-learning to distill 30+ years of data and more accurately forecast future performance.

How is TARA™ different?

TARA™ is the first AI assisted risk analysis service for Structured Products, giving you a superior way to instantly assess a portfolio, compare pools, and triage teamwork effort. It integrates with current team workflows, direct data feeds, Excel add-in, data provider integration, or web application.

Who built TARA™?

Ai SPARK spent 5+ years of development with a team of researchers, programmers, data scientists, modelers, and investment professionals to create TARA™. Out of the box, TARA™ brings your team the power of Artificial Intelligence.

What if I already have a model?

Keep using your model. TARA™ is different, being the first AI assisted analyst helper that supports Bank Loans and CRE CLO's, SASB, and conduit. TARA™ is inherently more dynamic and is used alongside or in conjunction to regular credit risk models.

How does the model work, and how was it structured?

First and foremost, TARA™ is different than a "model". Models tend to behave linearly when reacting to user inputs and are backwards looking. TARA™ is more like an analyst in that how it reacts to user inputs will be reliant on the particulars of a collateral loan. It is as if TARA™ provides an individualized "model" for each collateral loan that it looks at and predicts future performance.

Second, a model is fixed, having been built upon the statistical relationships/regressions that were observed in the data. TARA™ continuously brings in new information and learns from new remittance.

Is TARA™ really unbiased and autonomous?

Yes and no. Like almost all AI under the very strictest sense of the word, it is not. Ai SPARK chooses which data to expose to TARA™ in the data procurement process. Ai SPARK sets the learning architecture of TARA™ at the very beginning of a major version release, thereby addressing issues noticed in one or more of the testing phases, but that is where the line is drawn.

Ai SPARK never tells TARA™ what to think of a particular field, never injects its bias into the opinion formulation process, and limits itself strictly to creating, improving, or procuring the data fields that TARA™ looks at, after which TARA™ learns autonomously of any intervention.

I would like to understand more about how AI is being used in TARA™.

TARA™ is a deep learning neural network using mathematics and algorithms from the fields of Artificial Intelligence and Machine Learning. Ai SPARK designs the learning architecture that TARA™ uses to learn and formulate itself.

What data does TARA™ use?

TARA™ incorporates 1,000's of data points broken into several categories; submarket, economic, geographic, property, performance, status, and loan. From there TARA™ learns which data most frequently contributes to historical loan losses and uses that information to predict future performance.

See Training TARA™, Data Sources.

How does TARA™ help my team?

TARA™ handles the heavy computational work and frees people to perform the deeper dives into collateral, and gather knowledge which can then be incorporated and combined with the power of TARA™. Under all economic conditions, use TARA™ to optimize portfolios and identify opportunities in the market.

Who else is using TARA™?

TARA™ is used by investment professionals at leading due diligence providers, B-piece buyers, investment grade buyers, researchers, insurance companies, and top-tier asset managers.

Which inputs are adjusted in TARA™'s standard stress scenarios; base; recession, bearish, very bearish?

The stress scenarios that we apply "out of the box" are described in TARA™ Results, Stress Scenarios.

How do you treat TARA™ for business cycles?

TARA™ has experienced the dotcom bubble, 9-11, the Great Financial Crisis, a market liquidity crisis in the wake of the Great Financial Crisis, and the Coronavirus. These events keep building its long-term memory. We therefore do not explicitly treat or adjust TARA™ for business cycles outside of the creation of "SPARKS"; indices that we create to address particular shortcomings in the dataset (e.g., the fact that all of the history has largely been in a declining interest rate environment).

What is your test performance? What is its correlation to historical results?

Ai SPARK provides the actual results alongside TARA™'s predictions, for the entirety of asset level history. Thus, enabling a user to view test performance for themselves under all cuts of the data.

What data is driving statistics/results?

Unlike man-made credit risk models the key drivers of TARA™ results will change for each collateral loan. The inputs that drive TARA™ can be viewed using the "Illumination" feature. See TARA™ Results, Illumination.

What does a loss expectation showing less than .1% mean?

It means that TARA™ has no expectation that the collateral loan will take a significant loss.

Does TARA™ do timing ofloss?

Yes. Loss expectation within the next 12 months, next 36 months, and lifetime of the collateral are all provided in the Bond Cash Flow section of the tara_sheet, in addition to being evident in the CDR's in INTEX calc, and the INTEX Global Asset Level outputs produced by TARA™.

In version 3.0+, loss timing is expressed (in months) for each distressed collateral loan.

What dials are available to vary the scenarios under which the AI can predict outcomes?

Any fields within the TARA™ tara_sheet are available to change and adjust. This is where users apply their overrides and "Ask TARA" for updated results. The "Illumination" feature will graphically show which fields are most impactful for each collateral loan.

How do we interpret the results TARA™ provides?

TARA™ provides a loss estimate for each collateral loan (in addition to CDR vectors which can be used in a cash flow engine). TARA™ also provides a letter rating grade tied to the loss estimate. The track record or prevailing performance of each letter grade is viewable in the 'committee docs' report. TARA™ ranks the TARA™ sheet by loans which are most impactful to any specific portfolio – providing a priority list for deep dives on loan collateral. TARA™ shows the user which fields are driving its ratings. This allows users to change those field values and ask TARA™ to update collateral results considering individual qualitative input.

What happens as a deal seasons?

As a deal seasons, TARA™ will react and provide end to end loss guidance from new issue to surveillance. The more track records a loan has as it moves through its life, the stronger TARA™ will be in its opinion.

Why should we trust TARA™?

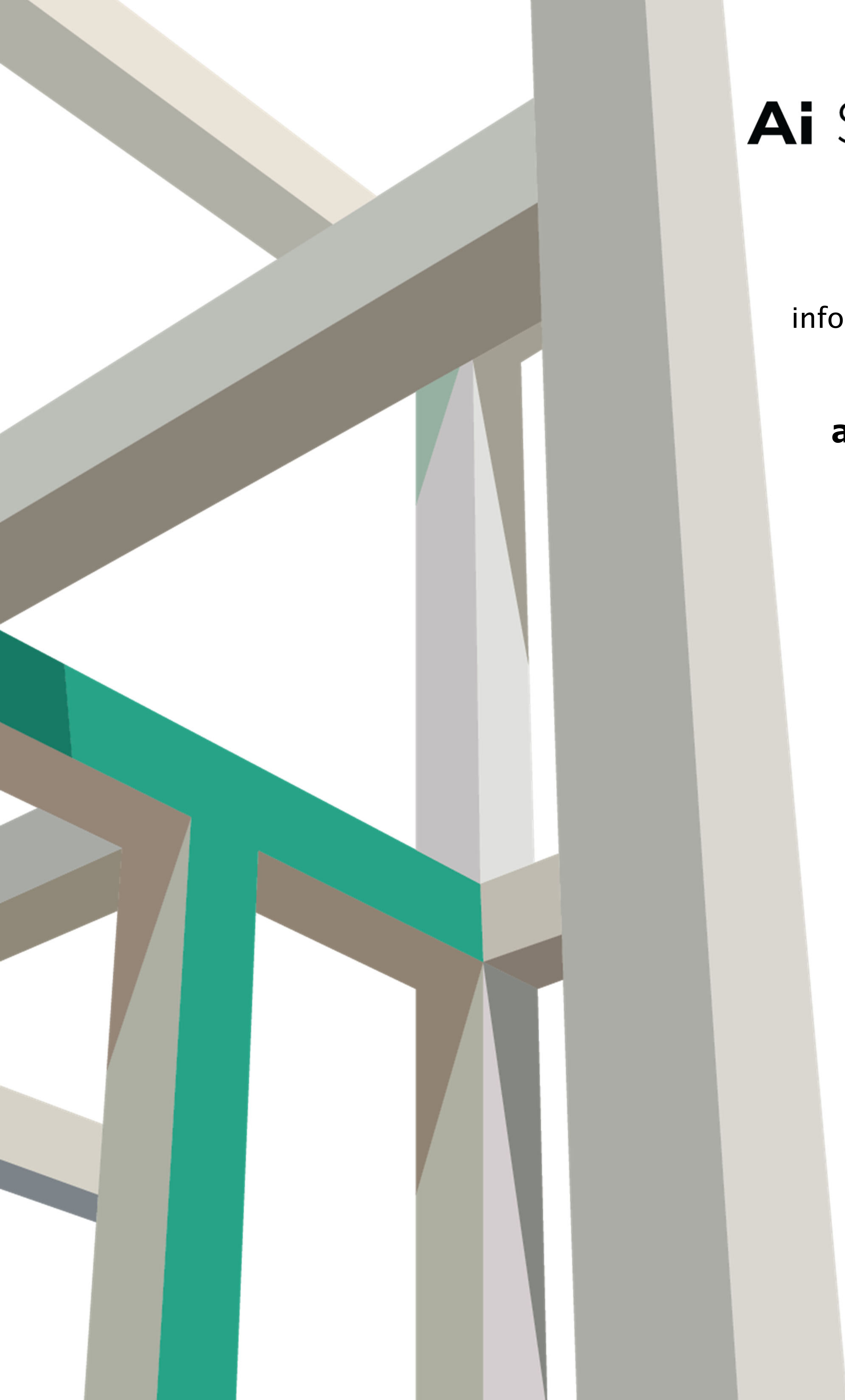
The principles, testers, and advisors behind the AI have over 100 years' experience in the Structured Products industry and some of the best track records in model creation through the Great Financial Crisis and subsequent recovery. TARA™ was built to provide participants with an unbiased view into collateral credit risk, with humility and experience to know its limitations— to know where to hand off to users—to provide the most accurate loss guidance.

We already have all the same data as you. Why should we use TARA™?

The technology excels at compiling various data sources into a cohesive loss guidance. TARA™ is able to continuously reinvent itself in an effort to provide the most accurate guidance possible for CRE debt. Even if you have the same data, TARA™ offers the best way of pulling it all together into a single answer for each collateral loan.

Do we need an INTEX subscription to use TARA™?

No. TARA™ can be used without an INTEX subscription through Ai SPARK.



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