eMoksha
A DATA SCIENCE COMPANY

WHITE PAPER

IMPROVING PRE-TRIAL OUTCOMES BY APPLYING MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

INTRODUCTION

Pre-Trial manages bond information in a case management system which could be a vendor-provided system, statewide system, or home-grown system. These systems typically output some reporting which provides basic information about the number of bonds issued, types of bonds issued, etc. The reports could look like simple text tables (see Fig. 1, Fig 2) or someone in the office doing some basic graphs/charts (see Fig. 3) to make sense of the bond data. This type of reporting is also generated for annual reporting purposes as well. This is how Pre-Trial is used to looking at their data and making sense of it. However, with the recent arrival of machine learning and Artificial Intelligence, a fundamental shift needs to take place regarding how we look at historical Pre-Trial data (we will use sample bond data in this white paper) to discern more than what Pre-Trial is used to. We will examine in this white paper how AI/ Machine Learning can be put to use for better outcomes for Pre-Trial.

If we look at sample bond data reporting, the bond data can answer important questions at a high level e.g. how many bonds were issued for Caucasians vs African Americans, how many FTA's were there, and what %age of defendants were FTAs etc. The questions do answer what is happening but they don't tell the whole story e.g. what's driving FTAs. This type of reporting and analysis approach does not go deep enough to identify why the metrics are where they are and how they can be improved. We will demonstrate in this white paper how using AI/Machine Learning, we can quickly gather actionable information to turn some sample bond data into actions for impact. Our focus will be from Pre-Trial perspective to increase bond concurrency rate so Pre-Trial recommendations have more likelihood of being accepted by the Judge.

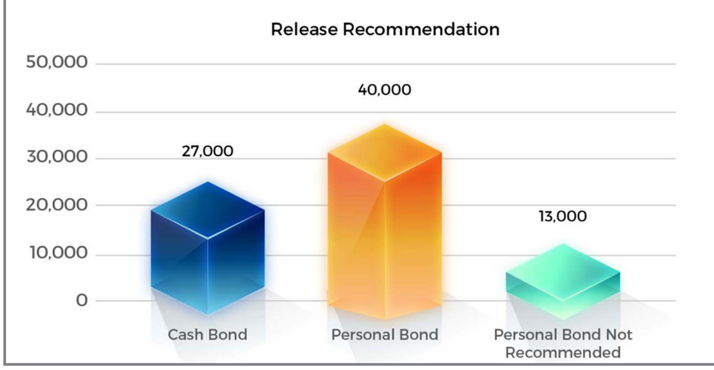
Fig. 1 Example of Typical Bond Reporting

RACE	PERSONAL BOND	CASH BOND
White	2,200	700
Black	1,500	500
Others	96	18
Total	**3,796**	**1,218**

Fig. 2 Examples of Typical Bond Reporting

BOND RELEASE OUTCOMES	PERSONAL BOND	CASH BOND
No. of Defendants	2,000	700
Charged with Failure to Appear (FTA)	13%	17%
NEW OFFENSE ARRESTS		
Misdemeanor Arrests	17%	25%
Felony Arrest	6%	12%

Fig. 3 Example of Typical Bond Reporting



CONCURRENCE RATE

Concurrence rate is the number of instances where pre-trial recommendation by a Probation Officer is accepted by a judge so that the supervision level or detention status ordered corresponds with the assessed risk of pretrial misconduct by a Probation Officer.

MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

We will not go deep into definitions of Machine Learning/AI. Our focus on this white paper is not on mechanics and process of Machine Learning but on practical implications of applying Machine Learning for Courts. For simplicity purpose, Machine Learning focuses on utilizing historical data to do pattern recognition and make future predictions based on past trends in data. Artificial Intelligence takes this one step further and enables machine learning to be used in a user-friendly automated way e.g., letting an algorithm augment our understanding regarding what drives bond concurrency rate and who can help increase concurrency rates.

BOND DATA AVAILABILITY

We will use some very basic meaningful bond data which is easily available in any court system.

We will try to accomplish the following with the above bond data:

- Explore bond data and build important bond metrics
- Understand what's driving these metrics
- Maximize our chances for a higher concurrency rate
- Choose actions needed to achieve maximum concurrency rates

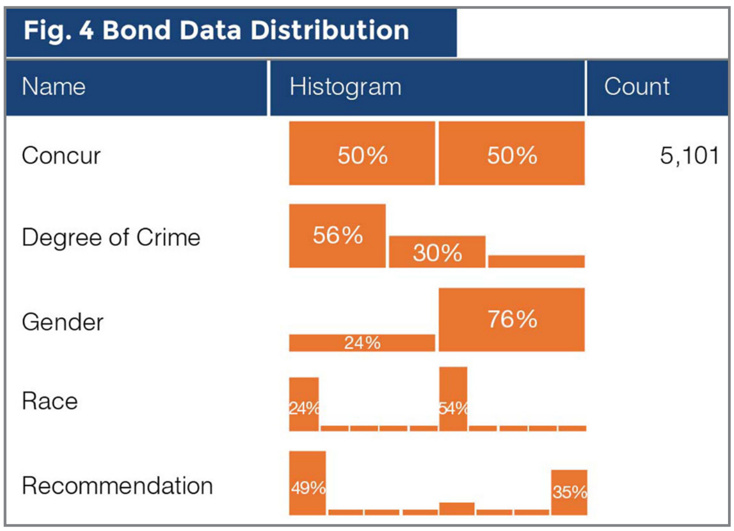


Fig. 4 Bond Data Distribution

UNDERSTANDING BOND DATA

By utilizing the bond data, first, we will develop some understanding of the data distribution. We can look at some data fields and make some exploratory observations such as:

- 56% of bond entries are felony related and 30% misdemeanour related.
- 76% of entries are male and 24% female.
- 54% of bond entries are Caucasian and 24% are African American.
- 39% are personal bond recommendations and 49% are cash bonds

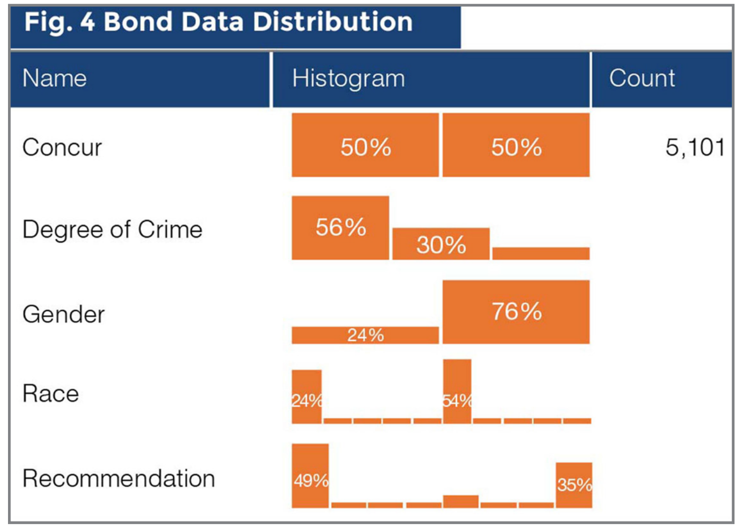


Fig. 4 Bond Data Distribution

We will calculate Bond Concurrency rate as the next step. Concurrency rate can be presented in the form of a dashboard shown below. We notice that bond concurrency fluctuates month to month and most current concurrency rate is 39%. This means judge agrees 39% of time with PO recommendations while 61% of times those recommendations are rejected.

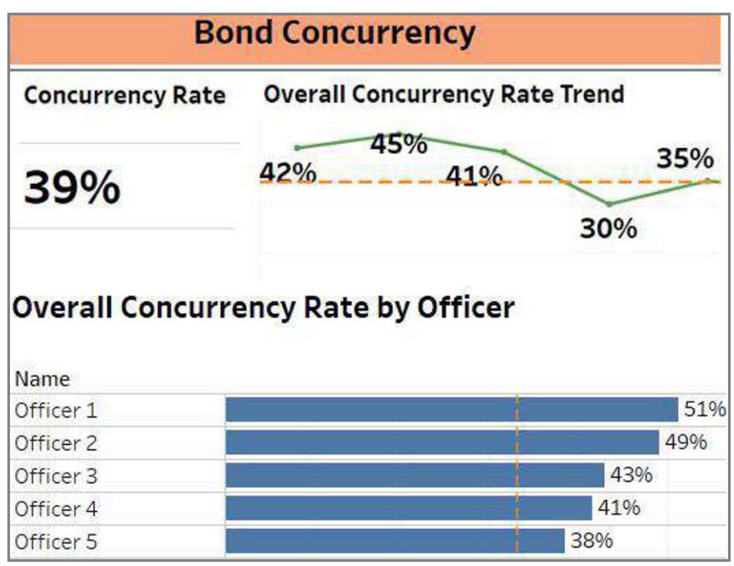
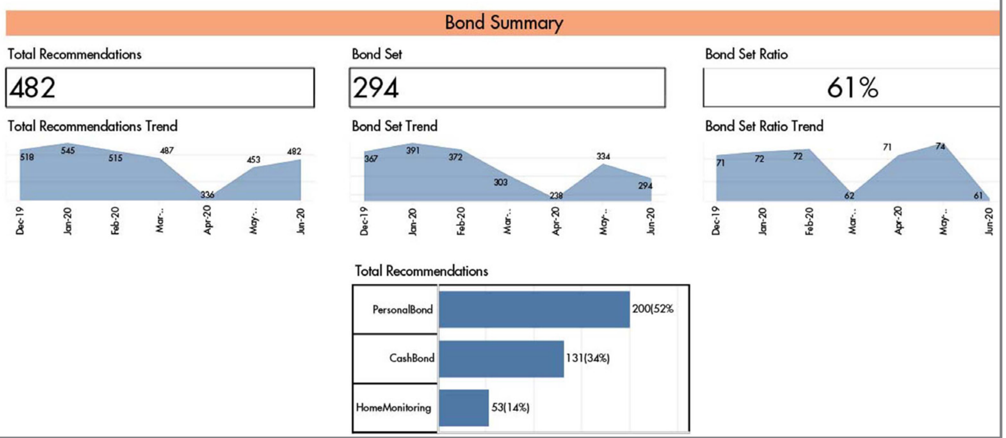


Fig. 5 Bond Summary Dashboard



We can also build trends about Total Recommendations; Bond set by Probation Officer etc.The dashboard enables us to see general trends over time and is useful information at a high level. The matrices dashboards can answer questions such as:

Count of Recommendations	How many recommendations were made?
Concurrence Rate	What is the concurrence rate?
Concurrence Trend	How the concurrence rate changes over time?
Jurisdiction Trend	How the concurrence rate changes over time?
Probation Officer Trend	How many bonds were recommended by each officer?

The information in dashboards tells us what is happening with metrics but it is not necessarily helping us understand why the concurrency rate is low (39%). Naturally this leads to next question how can the rate be improved? What should be changed to make it better? What is the impact of that change? This is where we start to focus on applying machine learning and AI to answer such questions.

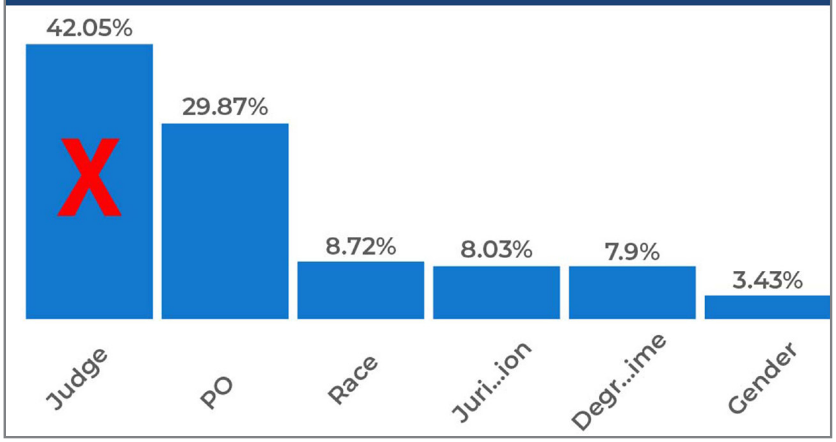
MACHINE LEARNING IN ACTION – DRIVER ANALYSIS

By building a preliminary predictive model (Random Forest Modeling) to understand what is driving concurrency rate, we observe that Judge (42% driving strength) and Probation Officer (29%) (See Fig 6, next page) involved have a very significant impact on the concurrence rate as compared to the other factors such as Race, Jurisdiction, Type of Crime, and Gender. Even though Judge is the most important driving factor statistically, Pre-Trial has no influence over Judge's decision-making actions. We need to focus on the next important driver of concurrency rate, Probation Officer. Machine Learning is guiding us and identifying important factors impacting outcome that need to be analyzed. This is extremely important otherwise we would have spent plenty of time trying to find statistically significant relationships that concurrency rate has.

Machine Learning enables you to know where the focus of analysis should be so

you are not spending time on discovering relationships in data which could be meaningless and not useful to solve the problem at hand.

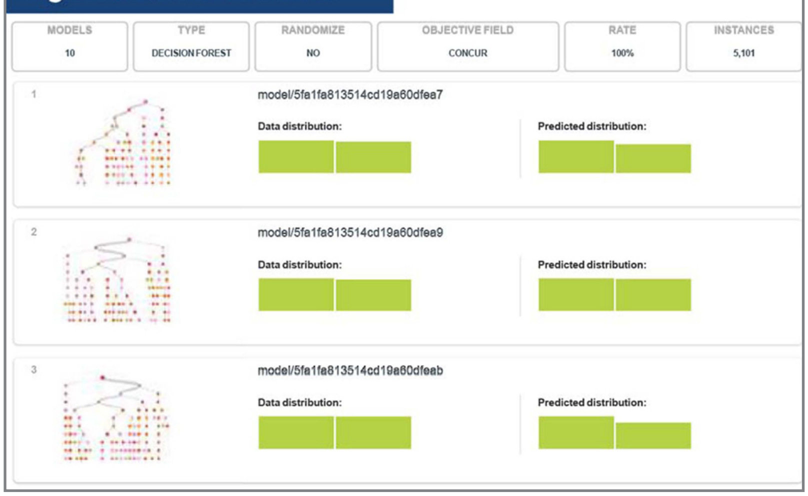
Fig. 6 Driving Factors for Bond Concurrence



MACHINE LEARNING/AI ANSWERS: WHY IS IT HAPPENING?

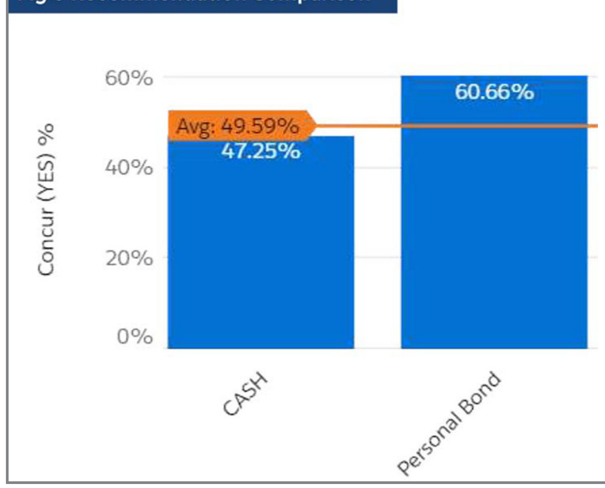
After developing an understanding of our data and metrics, what we know so far is that statistically Judge/- PO are main drivers of concurrency rate and concurrency rate is low. How can we improve it then? Let us set the goal to maximize our concurrency rate and we will build another predictive model to help with maximizing the rate.

Fig. 7 Ensemble Models



After building our predictive model, we make some additional observations. We learn that making a personal bond recommendation result in a better concurrence rate (60.66%) as compared to a cash bond recommendation (47.25%)

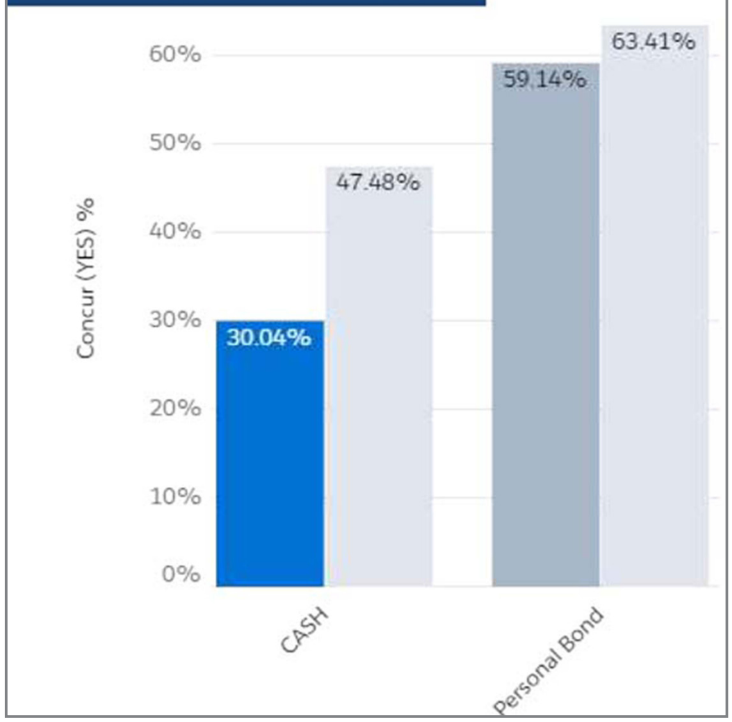
Fig 8 Recommendation Comparison



We learned that the personal bond recommendation helps maximize the concurrency rate. This is very useful information but it does not go deep enough yet to tell who can help drive more personal bond recommendations. We want to dig deeper and find out what brings down the concurrency rate. One of the primary drivers we understood from predictive factor analysis was Probation Officer. (See Fig. 5).We will take a deeper look at that probation officer concurrency rate. Model informs us that Officer 5, has one of the lowest concurrency rates among all the officers (41.03%).

Fig. 9 Officer Concurrency Rate

Fig.10 Officer 5 Concurrency Rate



This naturally leads to our next question why is the rate for this officer low as compared to other officers? Further analysis of drivers of concurrence from our model gives us an explanation regarding why the rate is low. When Officer 5 is recommending cash bond, the concurrence rate drops significantly. The drop is not that much for personal bond but for cash bond the rate drop is so significant (30.04% for Officer 5 vs 47.48% for all others) so almost 18% difference between officer 5 and the rest.

IMPROVING OUTCOME

At this point, we have concluded that:

- Personal bond recommendation gets a better concurrence rate than a cash bond
- Officer 5 has the lowest concurrence rate and the primary reason for that low rate is cash bond recommendations being made by the officer.

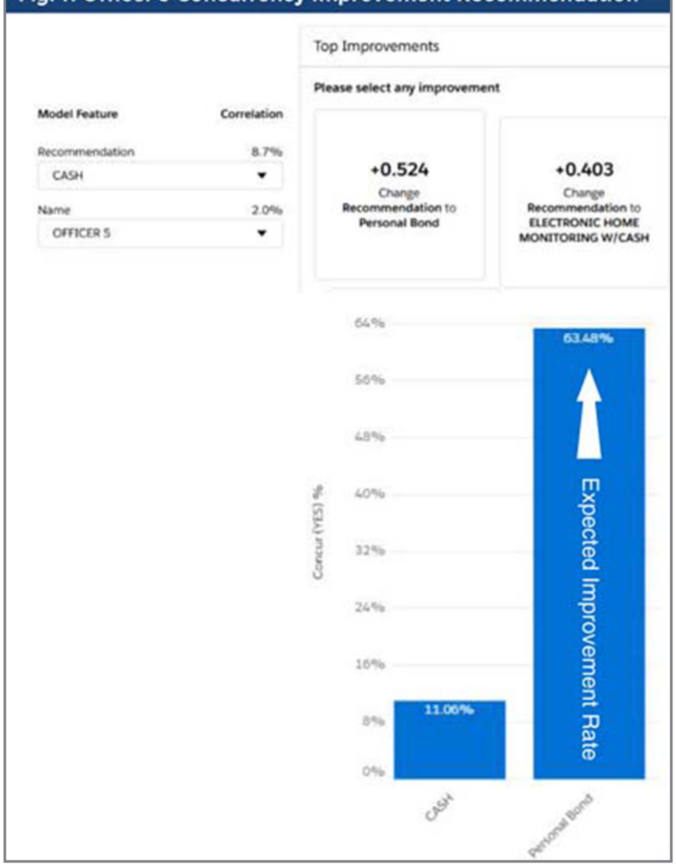
This leads to our next questions how can we improve the low rate then? We want to understand the impact of asking Officer 5 using reasonable assumptions to make more personal bond recommendations as compared to the cash bond. This is where we will run a scenario analysis from our model to tell the officer what to expect if she makes this change. Our model shows that the concurrence rate goes up from 59.14% (See

Fig 9 -Officer Concurrency Rate) existing concurrence rate for officer 5 to 63% predicted concurrence rate by switching to the personal bond recommendation instead of cash recommendation. Similarly reviewing other Probation Officers e.g. Officer 3, we predict an incremental increase from 54% to 59%.

We learn that by applying this to each officer, our approach will result in almost 16% concurrence rate increase for personal bond recommendation from 60% to 76%. Although in the real world there are several limiting conditions that could prohibit an officer to recommend personal bond however having visibility into the impact of a personal bond recommendation on the ordered supervision level is very actionable and could result in keeping more individuals out of jail.

Machine Learning can help us further dissect the data for more probation officers to identify opportunities to improve the rate.

Fig. 11 Officer 5 Concurrency Improvement Recommendation



CONCLUSION

We were able to show in this white paper that utilizing the power of AI/Machine Learning, we can take the leap to move beyond statistical reporting/dashboard building to discover insights such as:

What Happened: Measure important bond metrics by doing exploratory statistical analysis and metrics trending analysis e.g. reviewing concurrency rates of officers and understanding monthly trends of overall concurrency rate

Why Happened: Answer questions regarding what drives outcome (e.g. what drives concurrency rate) and what is the root cause for the state of the outcome (e.g. why low concurrency rate)

Actions: What actions can we take to improve the metrics (e.g. switch the recommendation to personal bond instead of cash bond)

By diving deep into the data with AI/ Machine Learning, we were able to detect signals and turn them into actions which otherwise would have remained hidden with traditional approaches of reporting and dashboarding.

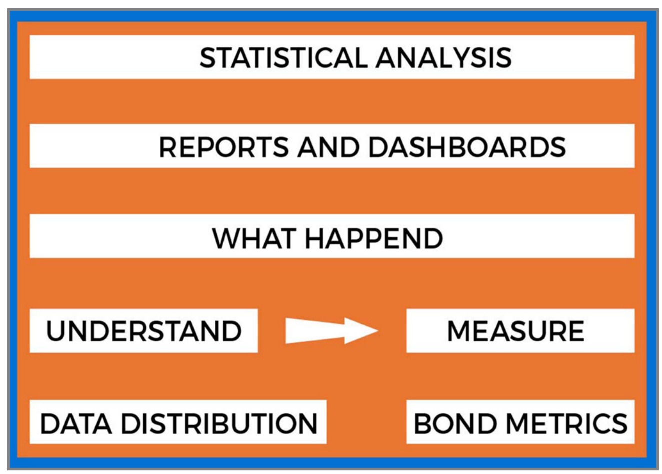
WHERE TO GO FROM HERE

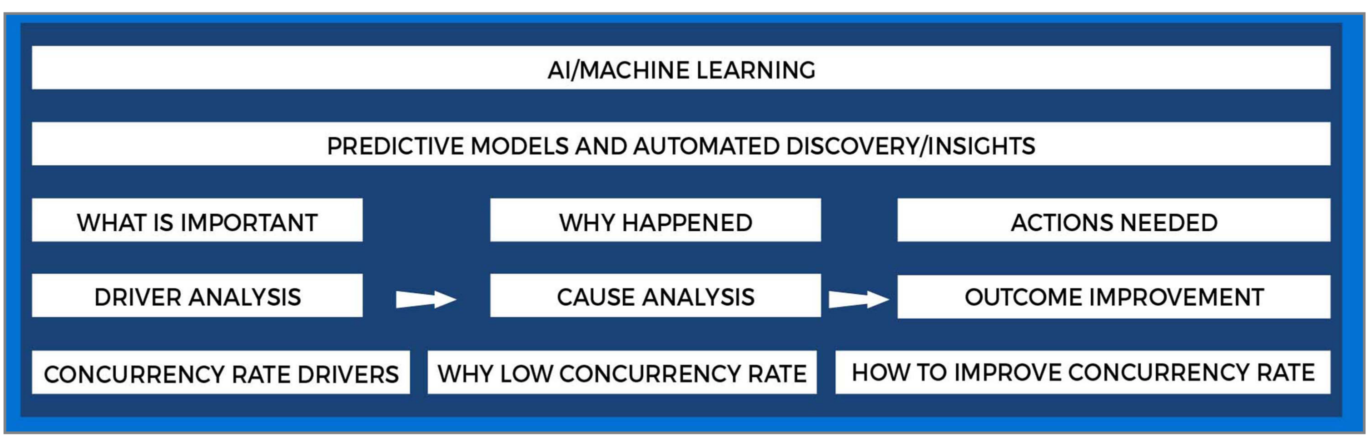
What should we do with all this analysis? We need a tangible and objective way to use our analysis rather than keeping our findings in a power point slide deck or an excel file for discussion. We need to provide tools in the hands of the recommending officers to help them do an effective job. We can achieve this by scoring the incoming new bond data and applying the predictive model to give us a prediction about the probability of concurrence (See Fig. 12) when a recommendation is being made. A good example of this will be an officer looking at a predicted concurrence outcome (e.g. 40% chance that a specific Judge could agree) will help the officer re-evaluate the recommendation being made.

Fig. 12 Concurrence Prediction Probability

DEGREE OF CRIME	GENDER	JUDGE	NAME	RACE	RECOMMENDATION	CONCURRENCE PREDICTION	PREDICTION PROBABILITY
FELONY	Male	Judge1	Officer 1	C	Cash	NO	80%
MISDEMEANOR	Male	Judge2	Officer 1	C	Personal Bond	YES	95%
FELONY	Male	Judge1	Officer 1	A	Cash	YES	40%
FELONY	Female	Judge4	Officer 1	A	Personal Bond	YES	88%
MISDEMEANOR	Male	Judge1	Officer 2	C	Cash	YES	82%
FELONY	Female	Judge1	Officer 2	A	Cash	YES	94%
MISDEMEANOR	Male	Judge2	Officer 2	C	Personal Bond	NO	60%
MISDEMEANOR	Female	Judge2	Officer 2	C	Personal Bond	NO	98%

A key point to note here is that in this process, we are not replacing human judgement with an algorithm but rather we are augmenting human understanding of data with the help of an algorithm to dig deeper and strive for the best possible outcome.





ABOUT VIK MEHTA, AUTHOR

Vik Mehta is the Founder and Managing Principal at eMoksha Consulting. Vik has provided data science thought leaderships, consulting, project management and analysis services for several data science initiatives in multiple court areas such as Adult Probation, Pre-Trial, Juvenile Delinquency/Dependency and Court Administration. Vik has been working in Courts and Justice area for over 20 years and is also helping customers in Private Sector by leveraging data science and machine learning solutions. Vik holds an MBA from University of Michigan and has earned PMP certification by Project Management Institute. He can be reached at vmehta@emokshallc.com

ABOUT eMOKSHA CONSULTING

eMoksha Consulting is digital transformation company which provides advance Machine Learning and Artificial Intelligence solutions to multiple industries including Courts. Our Data Science as a service for Courts enables Courts to discover insights needed to guide policy making, decisions and actions. We utilize powerful machine learning algorithms to find correlations and patterns in data to help solve court problems and assist with evidence-based management.

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WWW.EMOKSHALLC.COM I 440-455-9307 I SALES@EMOKSHALLC.COM

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