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The Causal AI / ML Revolution in Education

www.cmlinsight.com
info@cmlinsight.com

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Causal AI & ML Overview

Artificial Intelligence (AI) and Machine Learning (ML) have become ubiquitous in our everyday lives from consumer applications to enterprise systems. Predictive analytics, a field of machine learning, has gone from a nascent concept over ten years ago in student success to now a critical component to improving outcomes in all areas of education.

While predictive analytics has “grown-up”, there still remains questions and concerns about its use in education. Specifically, concerns around black-box algorithms, trust in prediction scores, using past data to model the future in an ever changing world of pandemics and demographic shifts in Higher Education. As such, the activity of solely using machine learning to train and test models puts into many questions its ability to truly shed a light on the right key drivers for student success.

Today, however, we are witnessing a new development in AI / ML that has been around for nearly two decades but is just now emerging as a new tool to help education achieve the outcomes it has been searching for. It's called Causal AI / ML and it may offer us a major advance in understanding the cause and effect of student success initiatives and the efficacy of edtech investments, and do it affordably.

While Causal AI / ML has quietly been used in scientific pursuits for years, it's no secret to advanced start-ups in the world including the likes of Google, Lyft, Netflix, and Uber. It is emerging as a proven analytics approach that can be used at scale. Most importantly, it is now being used to improve student success.

And unlike predictive analytics, which imparts a sense of finality or inevitability, Causal AI / ML helps students and educators improve their lives and prevent negative outcomes through interventions and feedback that produce a high return on investment. Institutions or businesses that are adept at using evidence from both retrospective and prospective data are gaining an advantage.

Causal AI identifies the underlying web of causes of a behavior or event and furnishes critical insights that predictive models fail to provide.

StanfordSOCIAL
INNOVATIONReview
Informing and inspiring leaders of social change

Why Now?

For the last ten years institutions have been working hard to help students perform better during challenging times. Expensive predictive analytics tools have unfortunately not delivered what they once promised. Once heralded as the core of machine learning, risk predictions neither impact student persistence materially nor do they engage overworked student success teams.

Causal AI / ML is a new innovative approach to help institutions go beyond risk predictions and impact student success with high precision. This approach fuses salient concepts from economics, healthcare, sensor signal processing, and machine learning to infer the true causal impact of interventions. This causal knowledge is the foundation of resource allocation and student success portfolio optimization by funneling students to interventions with the greatest impact likelihood and harnessing human capital for continuous process innovation.

The roots of Causal AI/ML can be traced over a decade ago by leading researchers like Judea Pearl, Gary Marcus, and Yoshua Benigo. However, it's only been due to recent advances in technology innovation and research breakthroughs that Causal AI/ML has been nudged into the spotlight. Take for example, the Economics Nobel Prize awarded last year to three professors on labor economics and education research “for their methodological contributions to the analysis of causal relationships”.



Joshua Angrist
MIT

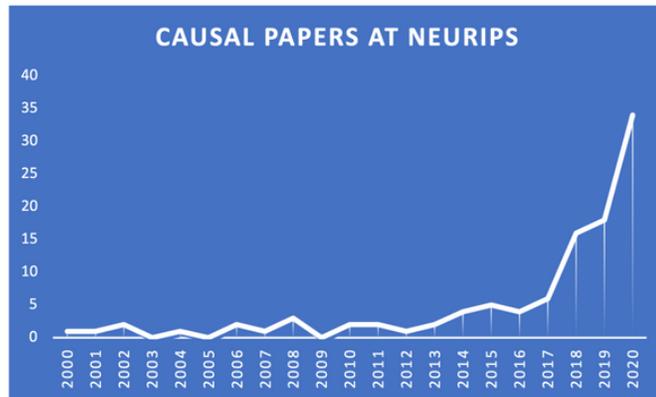
Guido Imbens
Stanford University

David Card
UC Berkeley

This year’s Laureates have provided us with new insights and shown what **conclusions about cause and effect can be drawn from natural experiments.** Their approach has spread to other fields and revolutionized empirical research.

2021 Nobel Committee

It's also worth noting that Causal AI / ML research has dramatically increased in the last few years indicating more interest and potential for new use cases.



The history of papers presented at NeurIPS with 'causal', 'causation' or 'causality' in the title.
Source: Rich Carter

Finally, both [Stanford](#) and [Gartner](#) have recently published the evolution of this space and its potential impact on society:

A closer look at causal AI will show how it can open up the black box within which purely predictive models of AI operate. Causal AI can move beyond correlation to highlight the precise relationships between causes and effects.



Causal AI is a key enabler of the next wave of AI. Causal AI benefits include:

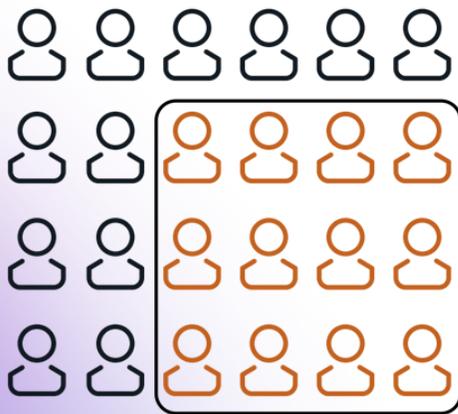
- **Efficiencies** from adding domain knowledge to bootstrap causal AI models
- **Greater decision augmentation** and autonomy in AI systems
- **Better explainability** by capturing easy-to-interpret cause-and-effect relationships
- **More robustness and adaptability** by leveraging causal relationships in changing environments
- **Reduced bias in AI systems** by making causal links more explicit

Gartner

Better Decision Making

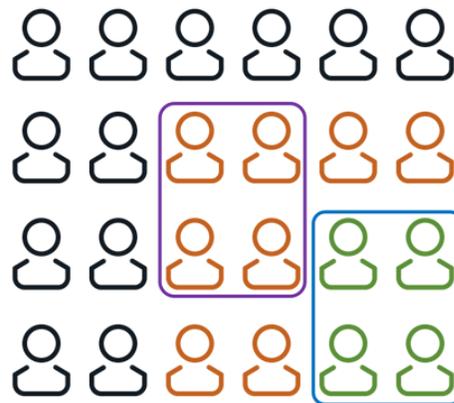
Based on the decades of collective experience at CML Insight, one of the most effective ways to achieve student success and lower achievement gaps is to maximize the synergy between humans and AI systems with the causal AI/ML layer serving as a bridge.

Correlation ML Approach (Predictive Analytics)



at-risk population with no insight into intervention recommendations

Causal ML Approach



specific groups that have the highest likelihood to benefit from available interventions

The Causal AI / ML methods highlight which students will benefit from which interventions based on real-world evidence as shown above. The approach is focused on student success impact, not just knowing who is at risk.

Moving Beyond Predictions

As the saying goes, correlation does not imply causation—but in the past the field of analytics has poured an enormous amount of resources into correlation analysis, trying to produce highly accurate predictions. This step is still important to the Causal AI/ML revolution, but if we don't understand the relationship between treatments and outcomes it offers us little guidance on how to actually fix our problems.

Causal AI/ML finally lifts the lid on these limitations and allows us to use causality to truly understand which interventions or initiatives have the largest impact and effect on populations. To understand the problem, let's represent the 18-20 million students enrolled in U.S. institutions with a model of a hundred students. Based on traditional graduation rates at fifty percent, we then assume that fifty of these students are at risk of dropping out.

Before predictive analytics, we didn't know who those fifty at-risk students were. Now we can confidently identify them with a high degree of accuracy, just within the first week of a term. But, despite this amazing advance, we still don't know what interventions will work for these students. How should an institution maximize its limited resources?

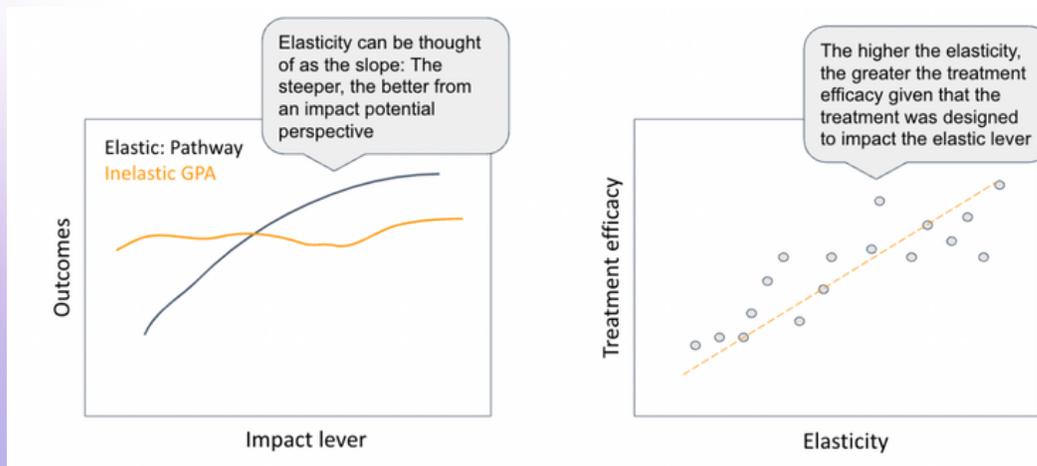
Without knowing the causal relationships, schools have been throwing everything but the kitchen sink at the problem, trying to support students at-risk through many supports like supplemental instruction, mentoring, advising, learning communities, the list goes on. But that scattershot approach is neither highly effective nor a good use of resources. With Causal AI/ML we can finally understand what works and for whom.



Elasticity and Efficacy

Advisors want to know what they can do to help students so their time can be spent wisely. Today they go through multiple screens, collect necessary data from multiple systems, get predictions on which students are likely to drop out, prepare for student conversations, not knowing exactly how to help students.

What's needed is to make it easy to get to the most valuable information in an evidence-based manner to help spur the right actions most effective for each student. Leveraging decades of experience in deploying AI systems in multiple verticals to impact business outcomes, the key knowledge that cuts across all the noise is the evidence on which student group will be most responsive to which treatment type. There is a strong association between impact elasticities and treatment efficacies. The elasticity is defined as the change in outcomes given change in impact lever, which is a set of malleable attributes derived from data through feature engineering. The figure below illustrates this point.



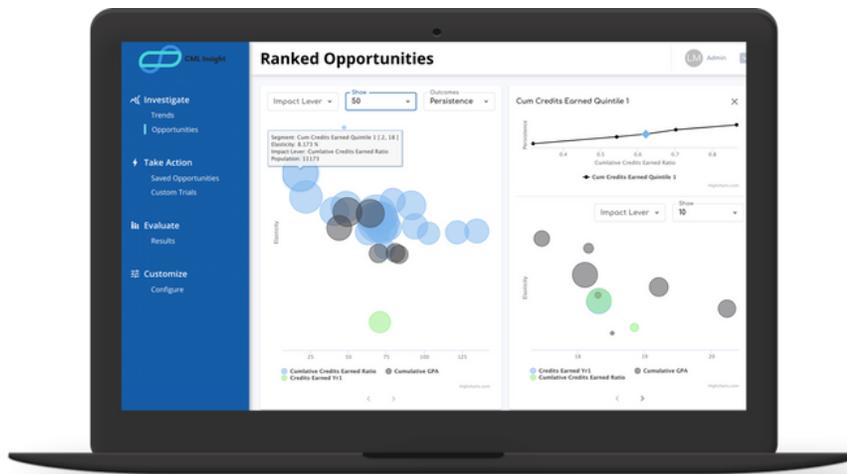
The key concepts are impact lever, elasticity, and treatment efficacy. Intentional intervention design should focus on elastic impact levers, which depend on population heterogeneities.

Once intentional interventions are executed, they can be evaluated to identify the relative sweet spots of each program and to zero in on the areas of improvement for continuous process innovation. During this process, student success teams are highly engaged and immersed in “flow” activities that form the core of crowdsourced intervention knowledge creation.

CML Insight Platform

The core philosophy of the CML Platform is to highlight key trends in institutional student health metrics ranked from the best. Next, the user can see which student groups are most responsible for trends going in the wrong direction.

Given the strong association between impact elasticity and treatment efficacy, the user can then see the list of student groups ranked by various impact elasticities and student success metrics in the trend charts. This view gives the user a succinct yet comprehensive understanding of what treatments should be run.



In short, the CML Insight Platform is designed to:

- Provide trends on student success metrics that matter so institutions can pinpoint which metrics to improve
- Prioritize which student subgroups (including segments traditionally associated with equity or achievement gaps) based on elasticities associated with high-value impact levers on persistence and academic performance
- Help build real-world evidence (RWE) on multiple metrics by running causal impact analyses on as many student success programs and initiatives as possible.

This is the beginning of a repeating cycle of causal insights leading to high-precision process innovations, which can lead to improved student success and highly-engaged students and staff.

About Us

CML Insight is pioneering Causal AI/ML for education. Its platform is used to improve student success for Higher Education, K12, and edtech companies. Our platform goes beyond predictions, providing transparent causal insights and suggesting actions that directly improve educational outcomes. CML Insight is run by scientists and engineers.

Contact us at info@cmlinsight.com or follow us on [LinkedIn](#).



Dave Kil
FOUNDER & CEO



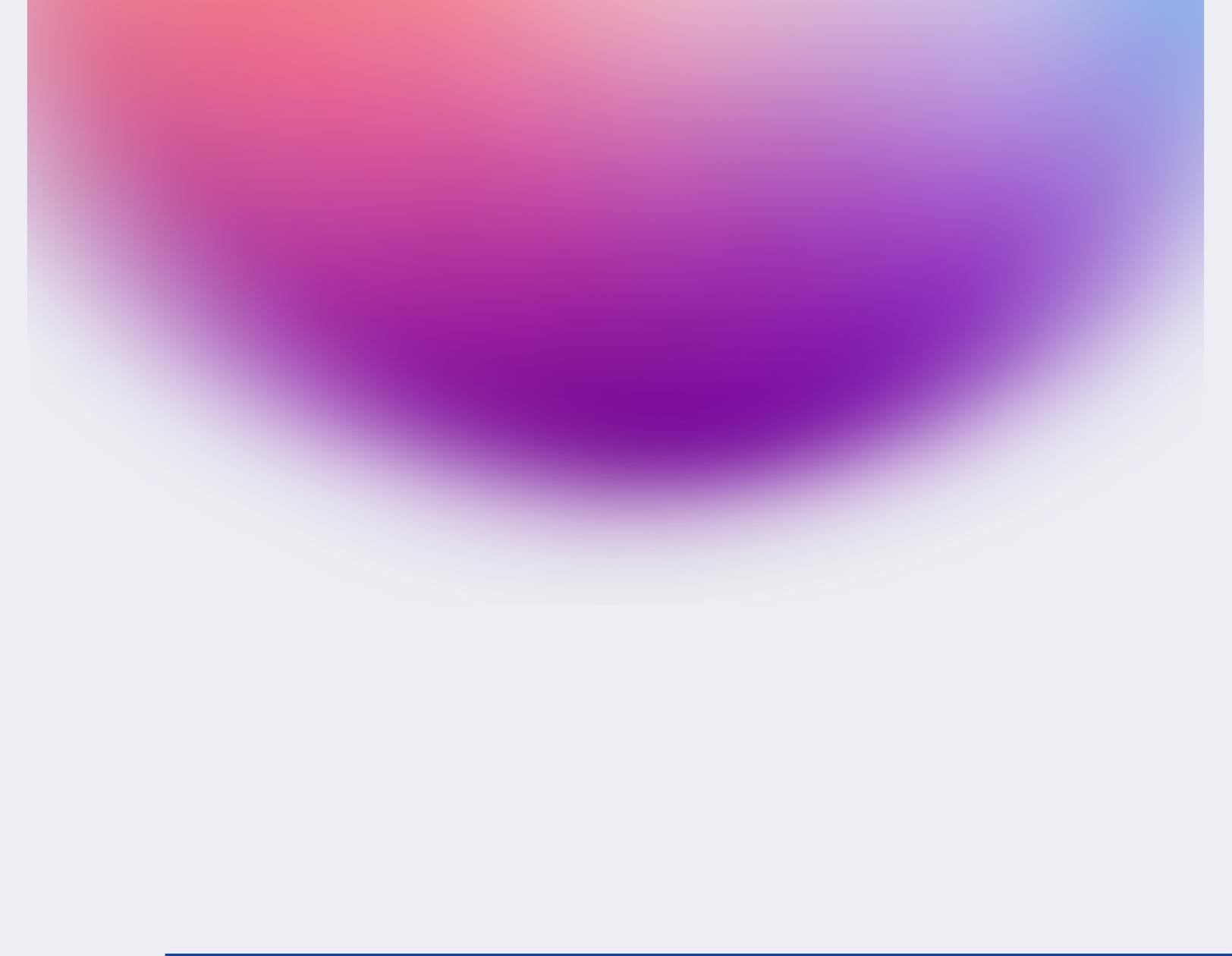
Daya
CO-FOUNDER & CTO



Michael Barton
HEAD OF AI



Rupal Shah
CHIEF GROWTH OFFICER
& CO-FOUNDER



Contact:

www.cmlinsight.com

info@cmlinsight.com

512-289-0471

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