Algorithmic Insurance: A Conformal Prediction Framework

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Joint project with:
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Motivation

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Algorithmic Torts: A Prospective Comparative Overview

Transnational Law & Contemporary Problems, Vol. 29, No. 1, Forthcoming

69 Pages • Posted: 16 Aug 2018

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Date Written: August 3, 2018

A recently released white paper, "Artificial Intelligence and Algorithmic Liability - A technology and risk engineering perspective" points out that unleashing the power of data and artificial intelligence creates "endless business opportunities to ultimately improve the quality of our lives." But with those opportunities, the report warns, comes a "broad spectrum of risks encompassing not only regulatory compliance, but also liability and reputational risk if algorithmic decision-making triggers unintended and potentially harmful consequences."

Employed Algorithms: A Labor Model of Corporate Liability for AI

72 Duke L.J. 797 (2023)
U Iowa Legal Studies Research Paper No. 2022-27

63 Pages • Posted: 12 Nov 2021 • Last revised: 4 Jan 2023

Mihailis Diamantis
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Date Written: October 19, 2021

Abstract

The workforce is digitizing. Leading consultancies estimate that algorithmic systems will replace 45 percent of human-held jobs by 2030. One feature that algorithms share with the human employees they. are replacing is their capacity to cause harm. Even today, corporate algorithms discriminate against loan applicants, manipulate stock markets, collude over prices, and cause traffic deaths. Ordinarily, corporate employers would be responsible for these injuries, but the rules for assessing corporate liability arose at a time when only humans could act on behalf of corporations. Those rules apply awkwardly, if at all, to silicon. Some corporations have already discovered this legal loophole and are rapidly automating business functions to limit their own liability risk.

This Article seeks a way to hold corporations accountable for the harms of their digital workforce: some algorithms should be treated, for liability purposes, as corporate employees. Drawing on existing functional characterizations of employment, the Article defines the concept of an "employed algorithm" as one over which a corporation exercises substantial control and from which it derives substantial benefits. If a corporation employs an algorithm that causes criminal or civil harm, the corporation should be liable just as if the algorithm were a human employee. Plaintiffs and prosecutors could then leverage existing, employee-focused liability rules to hold corporations accountable when the digital workforce transgresses.

Keywords: Corporate Liability, Law and Tech, AI, Algorithms, Consumer Protection, Labor Law, Labor Theory, Jurisprudence, Corporate Crime, Tort, Gig Workers, Independent Contractors, Employment

Previous Work

Algorithmic Insurance

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As machine learning algorithms start to get integrated into the decision-making process of companies and organizations, insurance products are being developed to protect their owners from liability risk. Algorithmic liability differs from human liability since it is based on a single model compared to multiple heterogeneous decision-makers and its performance is known a priori for a given set of data. Traditional actuarial tools for human liability do not take these properties into consideration, primarily focusing on the distribution of historical claims. We propose, for the first time, a quantitative framework to estimate the risk exposure of insurance contracts for machine-driven liability, introducing the concept of *algorithmic insurance*. Specifically, we present an optimization formulation to estimate the risk exposure of a binary classification model given a pre-defined range of premiums. We adjust the formulation to account for uncertainty in the resulting losses using robust optimization. Our approach outlines how properties of the model, such as accuracy, interpretability, and generalizability, can influence the insurance contract evaluation. To showcase a practical implementation of the proposed framework, we present a case study of medical malpractice in the context of breast cancer detection. Our analysis focuses on measuring the effect of the model parameters on the expected financial loss and identifying the aspects of algorithmic performance that predominantly affect the risk of the contract.

Key words: Algorithmic Insurance; Machine Learning; Algorithmic Risk; Insurance Contracts

- Presented the first-ever quantitative framework for algorithmic insurance
  - Only covers binary classification losses.
  - The method is not generalizable or scalable to other forms of supervised learning algorithms.
  - Assumes liability arises as per litigation but does not establish a non-legal operational business model.
- This work aims to :
  - Propose a generalizable and scalable business model.
  - Risk exposure estimation framework that applies to both regression and classification.
  - Considers pricing at a portfolio as well as individual level.

Pricing regression

Pricing regression liability

Expected Claims Cost = $\boxed{\text{Claim Frequency}}$ X Claim Severity

May or may **not** depend on model's performance.

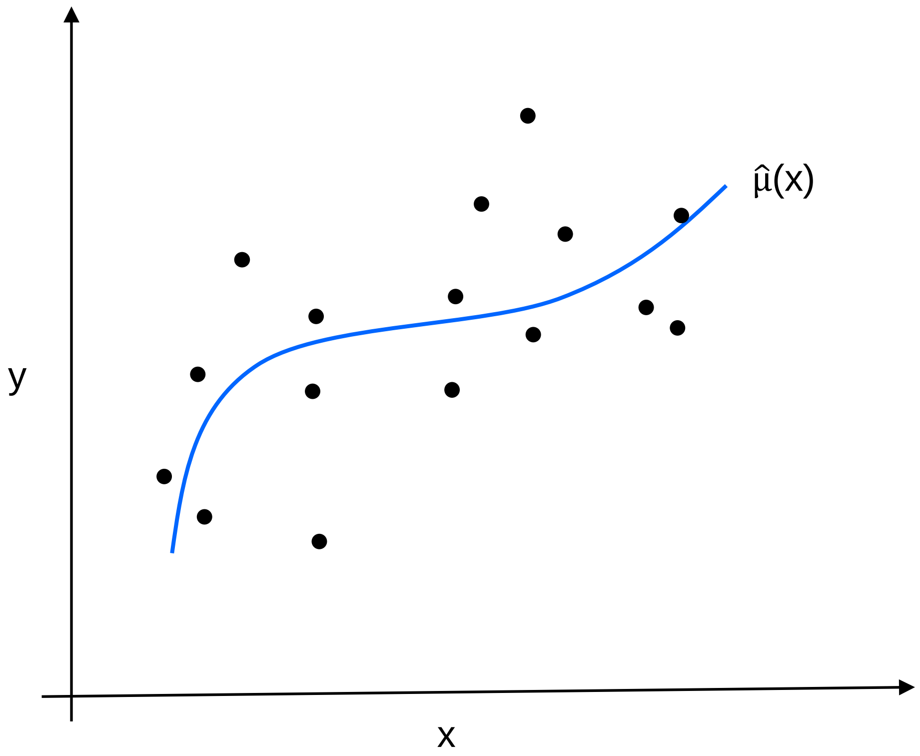
Claim Frequency = Number of instances of model under-performance

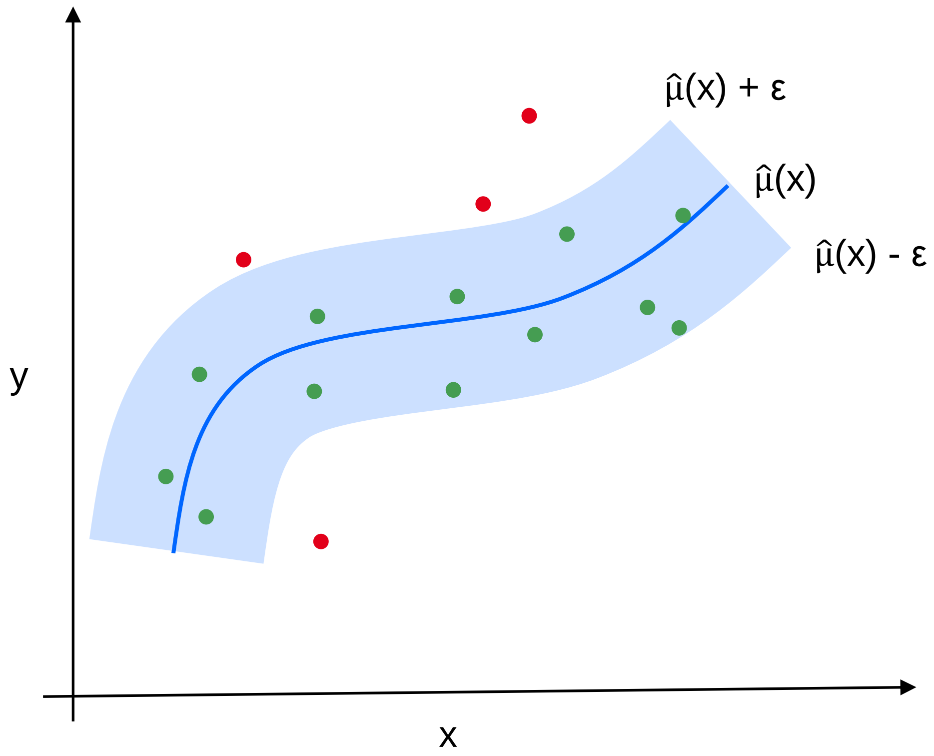
= Number of times model is used X $\boxed{\text{Probability of under-performance}}$

Will **not** depend on model's performance

Function of model performance to be estimated

Defining under-performance for regression





Under-performance =
Y_{test} is outside $[\hat{\mu}(X_{test}) - \varepsilon, \hat{\mu}(X_{test}) + \varepsilon]$ → *What is the appropriate size of this interval?*

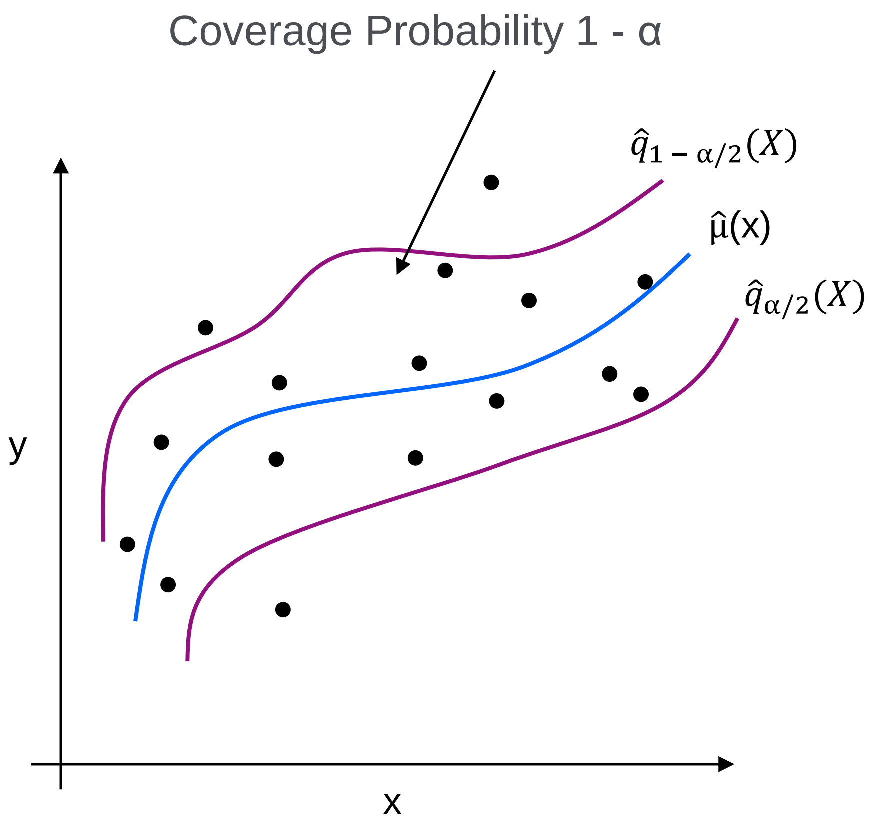
Conformal prediction

Conformal Prediction

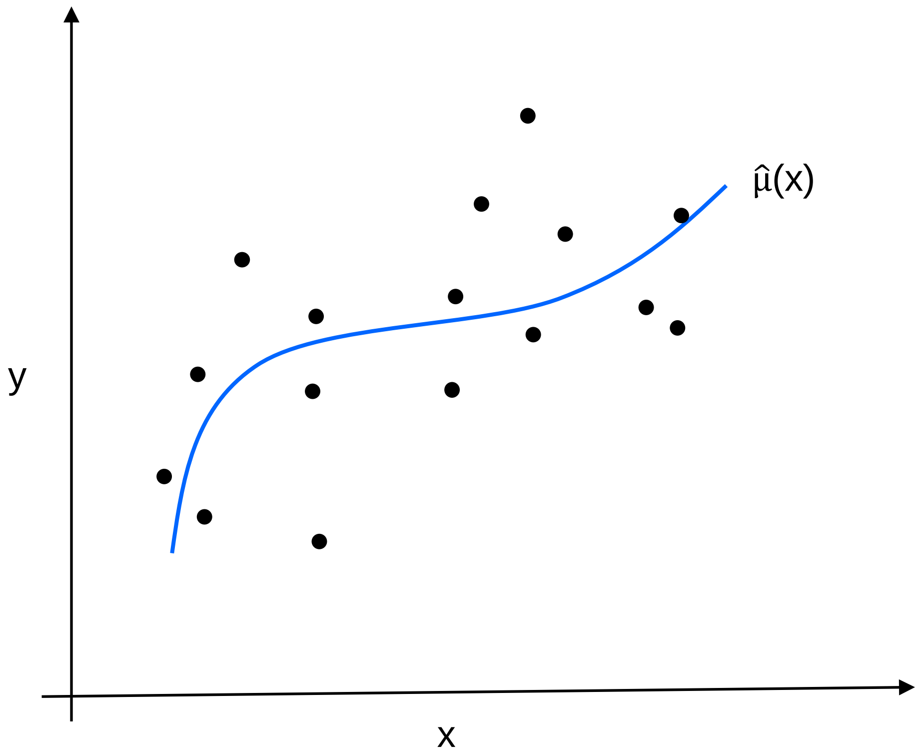
Input features (X) → Target variable (Y)

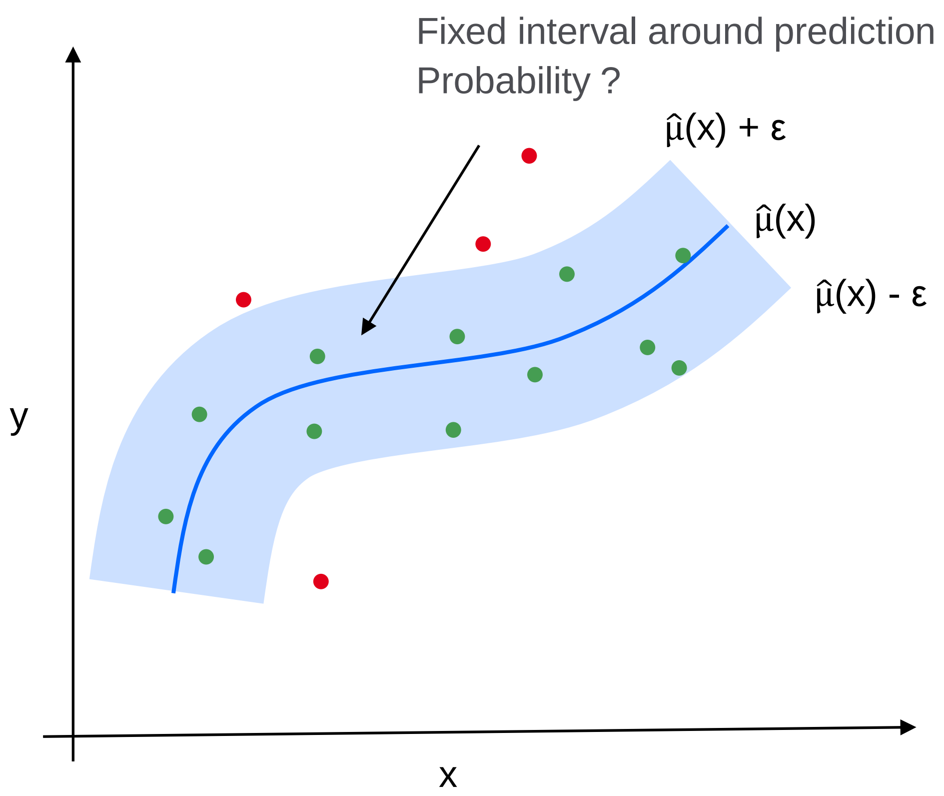
Input features (X) → Model → Prediction ($\hat{\mu}(X)$)

Prediction ($\hat{\mu}(X)$)
Confidence level (α) → Conformal Prediction → Confidence interval around $\hat{\mu}(X)$



Inverse Conformal Prediction

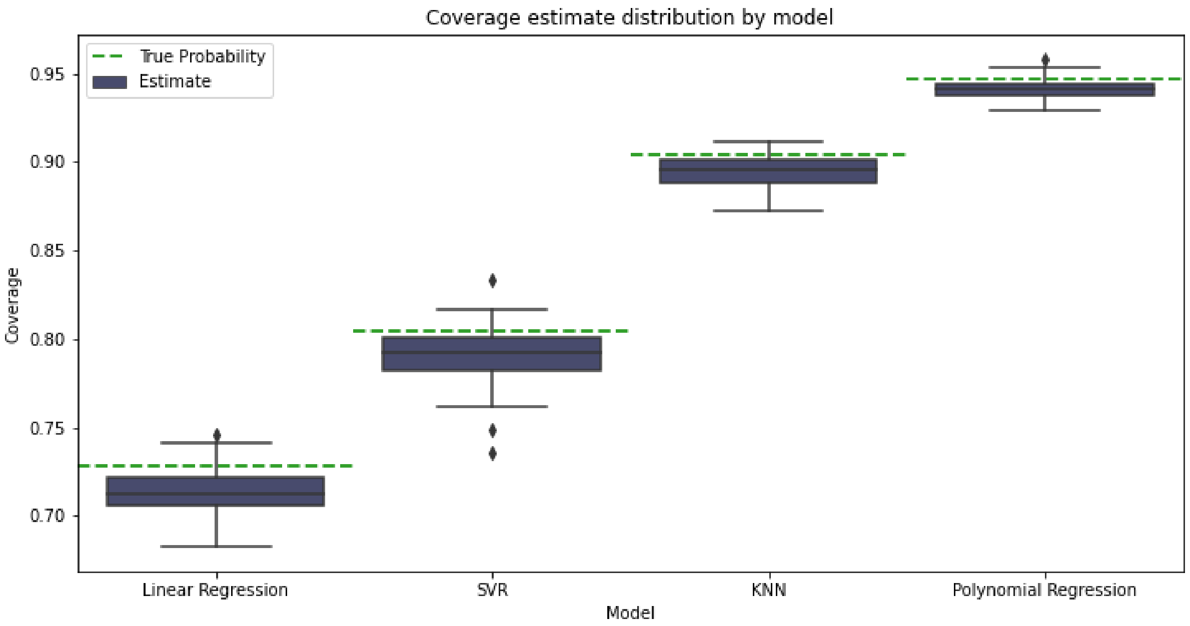


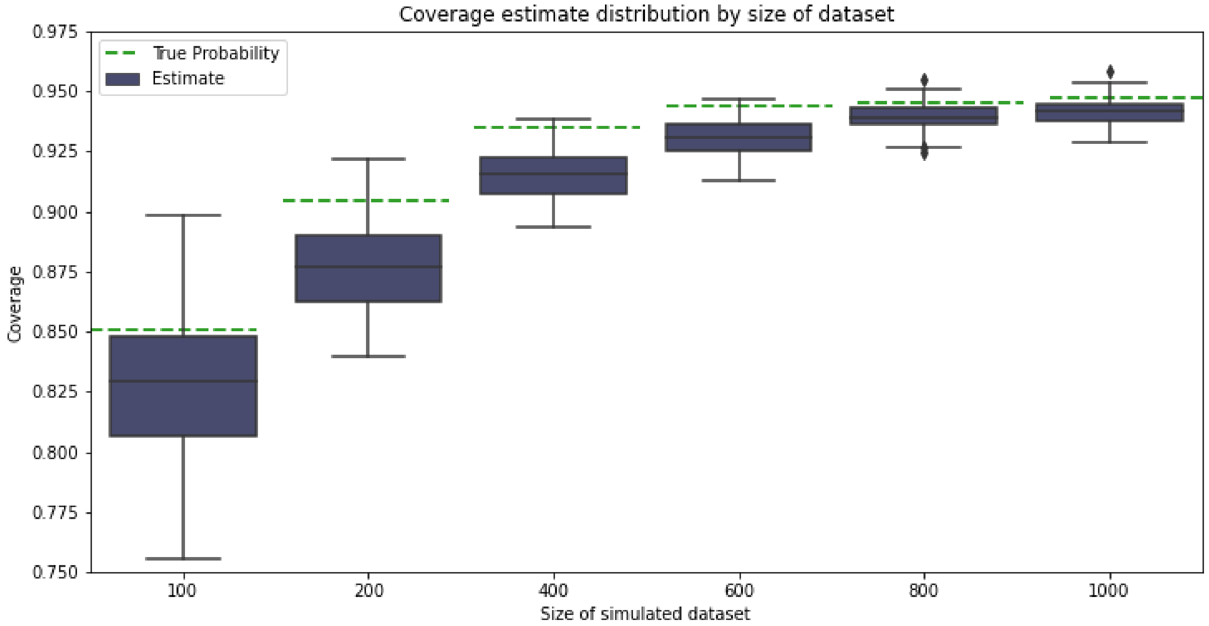


Given prediction interval width ε,
Find coverage probability

Key Results

Results





- Estimates are a reasonable indication of the true value.
- The estimate is conservative/prudent compared to the true value.
- Variability in estimates is lower for more superior models and larger datasets.
- The difference between the average estimate and true value is lower for superior models and larger datasets.

Pricing regression liability

Expected Claims Cost = $\boxed{\text{Claim Frequency}}$ X Claim Severity

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= Number of times model is used X $\boxed{\text{Probability of under-performance}}$

Will **not** depend on model's performance

Function [illegible] model perform[illegible]ce to be es[illegible]nated

For regression =

$P(Y_{test}$ is outside $[\hat{\mu}(X_{test}) - \varepsilon, \hat{\mu}(X_{test}) + \varepsilon])$

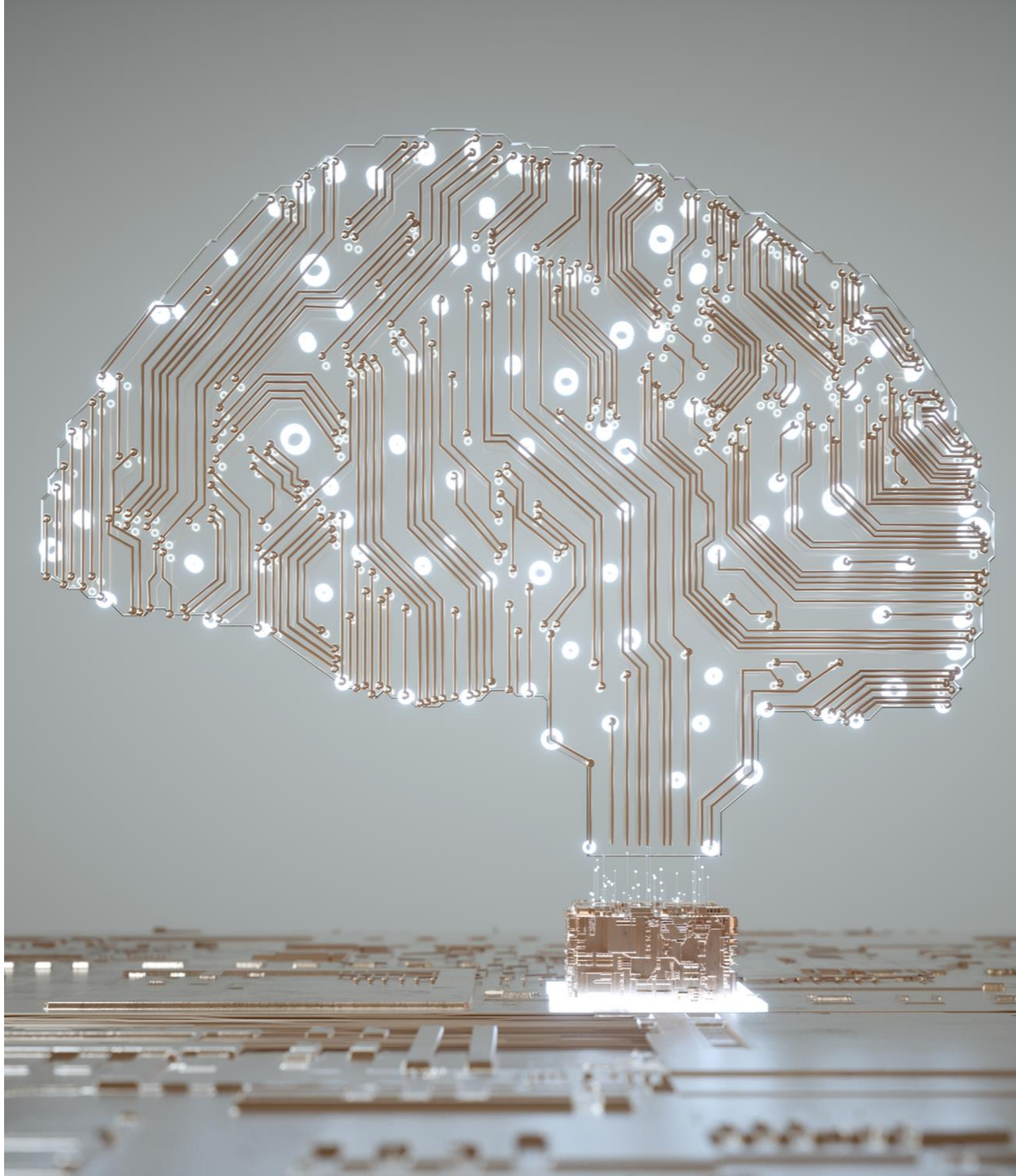
Summary

Primary Contributions

- Proposed quantitative framework for regression (+ classification) algorithmic insurance pricing using inverse conformal prediction
- Evaluated Inverse CP method effectiveness for different
    - Model Complexity
    - Size of datasets

Next Steps

- Extend the framework beyond supervised learning models
- Relax the assumption that AI output is used directly for decision-making to capture human-AI interaction
- Consider algorithmic fairness and ethical considerations.



Thank you!

Questions?

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