**Abstract:**

Every March, sports enthusiasts and analysts attempt to craft the perfect NCAA March Madness bracket. While some rely on gut feeling, personal bias, or betting odds, others turn to statistical analysis and machine learning for a competitive edge. This paper explores the challenges of building machine learning models to predict men's tournament outcomes more accurately than a seeding-based baseline (always choosing the higher seed to win). The focus lies in engineering features that better reflect tournament dynamics.

To address this, the author examines the empirical relationship between the number of teams a conference sends to the tournament and their collective performance. This relationship is used to scale traditional team statistics (offensive rating, blocks, field goals made, etc.) from the 2003 to 2024 seasons. These adjusted features aim to account for conference strength and variability in competition quality. Using this curated dataset, three models are trained to predict game outcomes as binary win or loss results: an XGBoost regressor, a logistic regression model, and a simple artificial neural network.

Preliminary results indicate that while seed-based predictions provide for a strong baseline, incorporating scaled, contextualized features leads to modest performance improvements. The models, however, still struggle with unpredictable, high-variance matchups and upsets, a consequence of the tournament's single-elimination, high stakes format.

These findings emphasize the value of domain-specific feature engineering and thoughtful data scaling in basketball prediction tasks. While machine learning models can offer measurable gains, they are ultimately constrained by the erratic nature of the tournament itself.