Our team set out to determine whether or not it was possible to use the adversarial network structure proposed in **\cite{zhang2018mitigating}**to mitigate bias in a dataset related to a continuous variable. Many examples of this technique used binary predictions and binary protected classes or attribute, so we wanted to explore if the technique would be successful in other applications. Overall, we were successful in mitigating some bias related to age as an influencing predictor of whether or not an employee would leave (attrition). We achieved an acceptable level of demographic parity among the age groups we defined, and did not trade-off too much prediction accuracy for improved fairness. To expand on the work in this experiment, we see several possible avenues to pursue.  While we were pleased with the results, there would be added value to achieving a more balanced distribution across age groups. This could entail pre-processing work to over- and under-sample from the employee population. Another avenue to consider would be additional tuning of the prediction models for more balanced outcomes. Additionally, technical aspects of the code could be refined to create a “stop” in the models when the adversary has sufficiently removed bias and correlation is no longer detected in the adversarial model for \emph{Z}(\emph{X}. Not only might this improve results, it may increase the architecture’s capacity to handle larger data sets. Lastly, we could redesign the adversarial architecture to specifically achieve a different type of fairness, such as equality of opportunity or equality of odds. This would dictate different variables to be shared with the adversarial network for prediction purposes. Ultimately, the opportunity to mitigate bias in continuous variables using adversarial network architecture shows promise. However, these opportunities cannot allow practitioners to become complacent and confident that systems are unbiased and fair. The myriad of tool kits, packages, process interventions, new techniques, or improved data collection cannot – and must not – replace the inquisitiveness, skepticism, mortal imagination, and compassion that humans bring to bear to on machine learning. (edited)