2021 ISEF Project Summary

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Title: Crysis Outcome Prediction Based on Human Behavior

ISEF 2021

Rationale:

Predicting how outcomes of an Emergency situation will be affected by certain human behaviors is important to understanding what safety protocols are most effective and what measures to have in place if people were to not follow those protocols in an emergency situation.

Engineering Goal:

Using two adversarial reinforcement learning algorithms, create a program that simulates the possible outcomes of a scenario to find the best solution to the problem accounting for rogue agents that act against the best solution.

Procedures:

- Create a simulation that to a degree accurately depicts the challenges of surviving the zombie apocalypse i.e. finding supplies, fighting zombies, possibly fighting off rival humans.
- Implement and train learning algorithms with different weights on rewards to create variability in the agents.
- Collect data on the survival rate of people over time in the simulation along with the overall outcome.
- Graph the data and draw meaningful conclusions about how the program responded to the problem it was given and the complications along the way.

Risk and Safety:

All work can be done with just a standard laptop, no inherent risks.

Data Analysis:

Using a spreadsheet data will be recorded on the weight of certain variables affecting actions such as the reward of gathering supplies rather than fighting zombies. Data will also be collected on how individuals survive compared to their group survival time. The data will then be graphed with a line graph to show how the changing behavior variables affected average survival time among individuals and groups. All data will be generated via the simulations that will be run a multitude of times. All of the data will help to benchmark the AI.

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