ONLINE RESOURCE ALLOCATION EQUITY IN A NON-PROFIT ENVIRONMENT

REPRODUCED RESEARCH IN A SIMULATED ENVIRONMENT
CS 488 - INDEPENDENT STUDY

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1. INTRODUCTION

The paper "Equity Promotion in Online Resource Allocation" written by Pan Xu and Yifan Xu investigated a critical issue faced by many Americans during the COVID-19 pandemic: healthcare equity. Americans have been trying to push the concept of "racial equality" for all sectors of life – with the objective to treat everyone fairly without any prejudice. However, this concept is biased due to factors such as income, housing, and other financial burdens that make life much harder for underrepresented and lower-income groups such as Blacks and Hispanics. This was the exact scenario for the COVID-19 vaccine rollout in Minnesota in a non-profit environment. There were stark disparities between the absolute served ratio and the population parameters, as the White population had claimed 88% of the resources – while representing 83% of the population ratio. Thus, limiting the vaccine availability for other races such as Black, Asian, and American Indians. This was just one state's issue with healthcare discrimination, a problem that was amplified throughout the rest of the country.

In theory, as the researchers mentioned an inter-serving ratio should have been followed which would have matched each group to their population ratio. However, an intra-serving ratio was found that tried to compare opposing groups against one another, not considering Minnesota's overall population proportions. The researchers focused on an internal-equity model, which generalizes the external reasons for pursuing the resource and analyzes the internal factors of the subject such as race, gender, and age. They created a model called EPORA which attempted to focus on the intra-serving ratio by distributing the vaccines based on the absolute-serving ratio. The objective of this model was to create a more equitable allocation of vaccine rollouts to rectify any amplified societal prejudice. Our project attempts to recreate EPORA within a simulated environment and test cases, culminating in the Xu model.

2. PROBLEM STATEMENT

The Xu model depicts an equitable allocation model that aims to prevent minority populations from being overlooked and beaten out by majority populations for online resource allocation – such as the COVID-19 vaccines. Our simulated environment is a mix between assumptions and real data to balance the complexities of the real world and effectiveness. First, we focused on the arrival rates of the population and assumed that the people in our town's population represented the American population demographics in 2021 (Figure 1), and the arrival rates of our "town" were equivalent to those from the racial demographics of the fully vaccinated US population in all of 2021(Figure 2). We took the entire calendar year of 2021 to limit any irregularities with specific phases of people only being eligible for the vaccine to get a more realistic arrival population. Another assumption our model makes is that if a particular member of the group (example: White Male Town A) is rejected from one provider they do not attempt to access a different provider. This was an assumption we developed and asserted in our code to lower the complexity of our simulated town. To keep our simulated environment on a smaller and more manageable scale we kept a district population of 5,000 people and had 5 towns: 1, 2, 3 ,4, or 5. Our bipartite graph only served people within 2 towns of the person's home. For example, if the resident lived in town 1 or 2 they could only be served at CVS etc for the rest of the towns. This was an attempt to simulate transportation and commute issues that demand agents faced.

The Xu model focuses on an arrival population following the arrival rates of the fully vaccinated US population, to display the slight advantages some races had over others in accessing the vaccine. We believed that the fully vaccinated population in 2021(Figure 2) indicated the accessibility of resources specific races had in being vaccinated and wanted to properly showcase this advantage/disadvantage. From here, the Xu model had the town's population arrive at these specific rates for the vaccine. The model first checks what town the person was from to understand which provider was within their distance. After identifying the provider available to the person, the model checked the pharmacy's stock. If the pharmacy had a non-negative stock and the pharmacy's served ratio of that race was under the population racial demography the vaccine was distributed. Otherwise, the person was rejected and as stated above they did not attempt to visit other pharmacies.

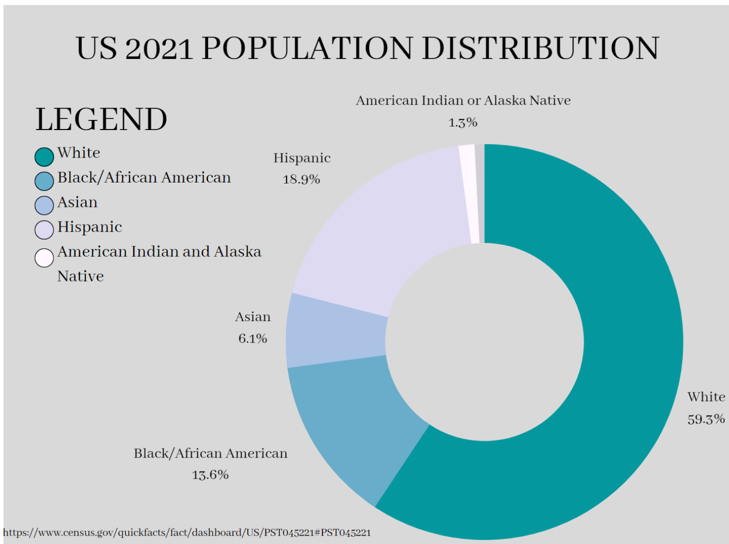

Figure 1: US 2021 Population Distribution

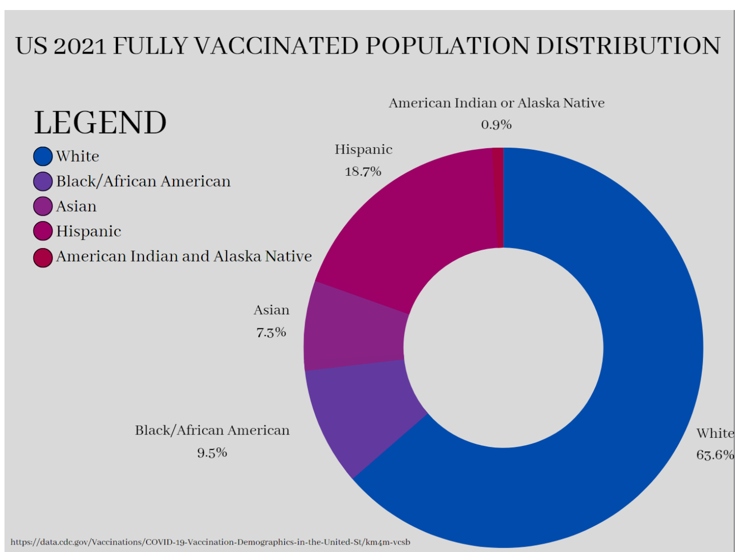

Figure 2: US 2021 Fully Vaccinated Population Distribution

3. ALGORITHMS

Similar to the original paper, our input was also based on the vector I = $\{G = (I, J, E), \{b_i\}, \{\lambda_j\}$, G = $\{g\}, \{\mu_g\}\}$. For reference, the I represents the total providers and J is the total number of users in our bipartite graph which had E (edges) for when an agent was within range of a specific provider. In our simulation, this corresponded with the different towns and our three providers: Walgreens (1 or 2), Rite-Aid (3), CVS (4 or 5). The chosen range for our simulated project was 1-2 towns, thus if a person was in Town 1 they could only visit providers in Town 1 or Town 2. *bi* was the specified capacity of the vaccines at these locations since scarcity would affect the equitable distribution of the resources. The next metric is $\lambda\ j$ the arrival rate of the demand agents which was heavily based on {g} the specific group the user belongs to. In our algorithm, the people were classified by race (African American, White, Hispanic, Asian, American Indian/Alaska Native) and gender (Male or Female). The groups were based on the following racial distinctions: African American/Black, White, Hispanic, American Indian/Alaska Native. Based on the specific group, there was a target serving ratio to depict equitable distribution given as input. These metrics culminated the input data into the Xu model to create the equitable resource allocation of the vaccines– over varied scarcity. It is important to note that there was an "Other" racial group with 0.9% of the US population that we eliminated from our simulated data set because of a lack of data and vaccination information.

In the Xu Model, we try our best to simulate the real world by generating "people" based on real-life parameters. Using a uniform distribution of each identifier and matching them to their true parameters, such as gender, race, and town location, we would randomly assign each "person" their qualities. However, the randomness algorithm was based on the racial distribution of Americans in 2021, while the gender and towns were evenly split. For the simplicity of our algorithm, we said there are a total of 1000 vaccinations available per day with 300 located at CVS, 500 located at Walgreens, and 200 located at Rite Aid. We keep track of how many vaccinations are left at each location as well as how many people in each race are vaccinated. Our algorithm generates a "person" one by one in a stream to simulate randomness, then they visit their respective supplier(s) depending on their town for a vaccine. If they have options regarding providers, they randomly select one. As stated above, if the location provider is out of vaccines we assumed the demand agent (person) did not visit another provider. Our allocation method is based on a constantly updating population ratio for each race. When a person comes for a vaccination, we check if their specific race's vaccination ratio has crossed the threshold of the population race ratio. If not, we decrement the number of vaccinations at that certain location and increment the vaccinated person counter for the race that was just vaccinated. We continue this method until all resources have been exhausted. Another large aspect of our experiment was Stochastic Modeling, so the simulation would not be heavily skewed due to randomness. We utilized a Monte Carlo simulation to run each model and its three separate scarcity levels 100 times each to average and find the true allocation percentage of each race from our model.

To measure the effectiveness of the Xu model, we implemented a greedy heuristic algorithm. In this algorithm, we followed a "first-come-first-served" allocation method based on the race of the "person" generated. However, the distribution of the races was based on the fully vaccinated population of the US in 2021 to reflect the arrival rate. Thus, we served demand agents based on the order they came in which was skewed to represent arrival rates until all resources were exhausted. This heuristic was similar to the actual procedure that occurred with the first year of vaccination rollouts. There was no specific cap for races, or an equitable distribution everyone was served until the capacity was reached. The next section of the paper will showcase our experimental results that depicts how inequitable the greedy heuristic algorithm was and how it mirrors the CDC data recorded from 2021.

4. EXPERIMENTAL RESULTS

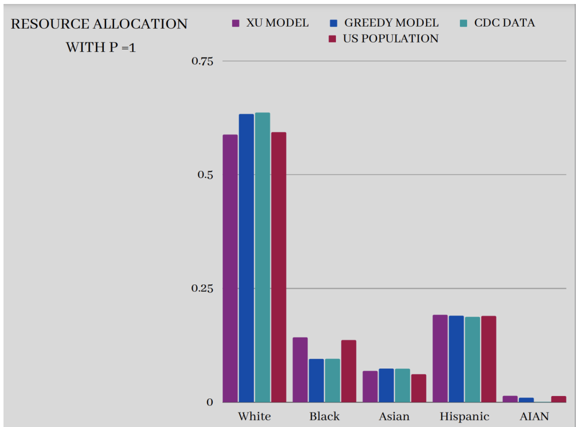

Figure 3: Results of the Simulation at P =1

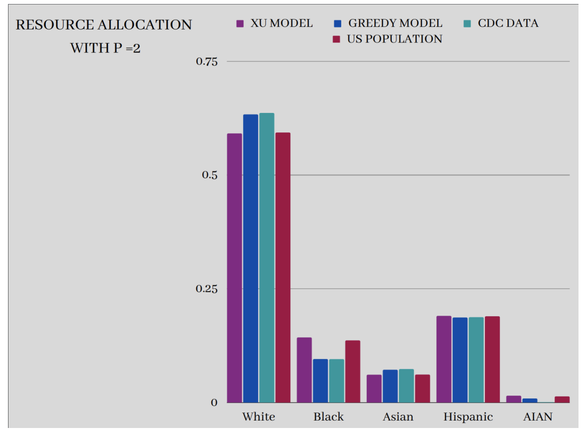

Figure 4: Results of the Simulation at P = 2

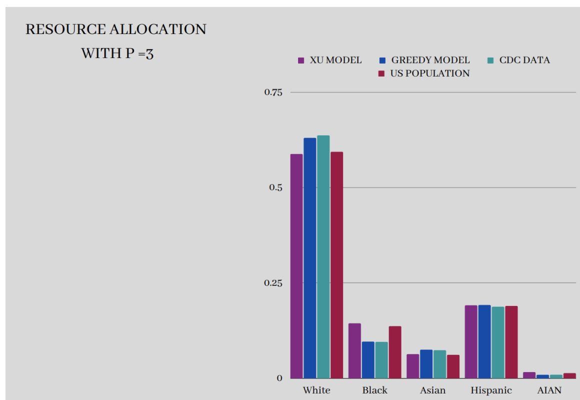

Figure 5: Results of the Simulation at P = 3

Our results of the Stochastic modeling demonstrated the effectiveness and accuracy of the Xu model in distributed resources according to the inputted ratio, even when the arrival rate does not reflect the population. This is largely due to the algorithm which turned away demand agents when the serving ratio for that group was over the inputted target serving ratio. This metric was recalculated after every iteration/arrival to ensure that the target ratio was achieved. As in the original paper, we decided to test out our algorithm on varying degrees of scarcity to make sure that even when resources are low – equitable allocation is not compromised.

Figures 3,4, and 5 depict the allocation of vaccines per race at a scarcity level of 1, 2, and 3 respectively. Our objective was to make the Xu Model as close as the target ratio of the US population, while we see that our greedy model heuristic matches the CDC data. This indicates how the greedy model accurately portrays the true allocation that occurred during 2021 because of the skewed arrival rates. We can see that for all three figures even as vaccines become more scarce (p = 3) whites are still continuously overserved by the greedy model by approximately 4%. This limits the vaccines available for minority races who arrive at a less frequent rate due to distance and socioeconomic issues that prevent them from easily accessing the vaccine. However, in the Xu model we see that no matter how the scarcity levels change, our model is always on par with the US population. No matter how skewed the arrival rates become with a disproportionate amount of vaccines, the Xu model ensures every racial group is treated equitably.

4. CONCLUSION

This paper presents a linear programming-based strategy to aid in the equitable distribution of resources in a non-profit environment. We were successful in creating an algorithm that administers vaccines according to the target ratio of the entire population instead of based on a “first come first serve basis”. The Xu model depicts our allocation algorithm and the greedy heuristics displayed the latter strategy. Time was a major constraint of the project as we had one semester to research the past work, understand the problem, create our own model, and test it. If given further time, our next step would have been to delve into a real data set to analyze how effective the Xu model truly is. We would also like to explore other factors of vaccination allocation that could have led to a non-equitable distribution such as political affiliation, socioeconomic status, and geographic location.

Our research allowed us to understand the importance of healthcare equity, particularly within underrepresented races. By understanding the impact of healthcare disparities, we can work towards improving inclusion in medicine to ensure a fair distribution of resources for all. Overall, as newcomers to research this was an enriching learning experience for us both. It has allowed us to apply our data science principles taught in the classroom to real-world scenarios we all face. This project allowed us to delve into the research world and creatively apply our knowledge of data science to solve real-world problems and see the power of computing in action.

5. REFERENCES

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