Policy Memo 3 (1024 words)

TO: Boston Director of Public Transportation

FROM: Ethics Consultant

SUBJECT: Street Bump Value Concerns

1. **Background:**

Street Bump is an app that was developed as part of an effort by the Boston's Mayor's office to improve neighborhood streets through crowd-sourced data collected by the accelerometer in a user's smartphone (Simon 2014). Street Bump works as follows: before a user starts driving, they start the app and put their phone in their cupholder or on the dashboard. The app analyzes the incoming data from the accelerometer, recording the GPS location to an Amazon Web Services (AWS) remote server when the analyzed signal indicates a bump in the road was hit. Road inspectors are then sent to bumps that have been repeatedly logged by a dedicated team in the Department of Transportation, and they flag the locations with damaged roadways for repair. Although performance has improved since InnoCentive was contracted by the Department of Transportation (Simon 2014), questions remain about the values embedded in the Street Bump system.

2. **Theoretical Framework:**

To better think about the values embedded in Street Bump's algorithm, the ideas offered by Biddle regarding the judgment calls that lead to tradeoffs reflecting such values in machine learning algorithms will be summarized. Since it is impossible to avoid all epistemic failings because one cannot achieve all epistemic goals in tandem, choices must be made about which failures to avoid (Biddle 2020). Over the course of developing a ML system, such decisions must be made, reflecting value judgments – ethical or political – that impact users in different ways. The tradeoffs at each step, as proposed by Biddle, follow.

The first step of the ML development cycle, problem identification, is deciding what factors do and do not constitute the scope of the identified problem or task. The algorithm developers must decide how to quantify this problem so that it can be measured, which involves specifying evaluation metrics, leading to tradeoffs that reflect value judgments based on which criteria they choose as important to fulfill. Arguably the most critical step in the development of a ML system is deciding the data on which the model is trained since it impacts the performance of the model at all levels. The criticality of this step ensures it is the most value-laden step, where the features deemed important when constructing a data set depend on values and interests related to the represented target audience. After a data set is created, the next step of designing an ML system is deciding the tradeoff between accuracy and explainability based on algorithm and learning method, where the prioritized option highlights the values present in the tradeoff. In addition to the tradeoffs between accuracy and explainability, designers must also make tradeoffs between accuracy and error among different groups. In other words, designers must make conscious decisions about the types of fairness that they are or are not willing to violate. The last actual part of ML development cycle is deciding how and what outputs are generated. The values reflected in this decision once again relates to whom the designers would like to affect with their algorithm. Lastly, after the ML development cycle is finished, the system must then be deployed, which involves the concepts of transparency and opacity around the algorithm. The several decisions surrounding transparency are all value-laden with each judgment reflecting values of the designers.

3. Analysis of Values:

Now that Biddle's framework has been summarized, the values embedded in Street Bump will be analyzed using it. The analysis of values will focus mainly on the accuracy and fairness values embedded in Street Bump. As it currently stands, Street Bump's designers made the decision to prioritize users with cellphones since the system requires data from an application available exclusively on phones. This choice to capture data from a specific source that isn't available equally to everybody, such as cellphones and cars, shows a priority for those who can afford such things and live those lifestyles.

Although many people own cellphones, not everybody owns or can afford a car. Street Bump's semi-exclusivity warrants concern as it may exacerbate existing injustices. Since the more impoverished will be misrepresented in Street Bump's dataset as they lack equal access to phones and cars, these impoverished citizens are likely to be overlooked due to the lack of representation in the dataset, leading to skewed conclusions drawn from analysis of the data (Barocas & Selbst 2016). Thus, the roads in poorer communities will continue to degrade as the more affluent neighborhoods continue to stay maintained.

In addition to valuing those more fortunate, another aspect of Street Bump that must be questioned is whether an AI and ML system needed to be developed to address the problem in the first place. Street Bump tracks a user's location while in use with the location of bumps recorded to a remote AWS server, showing a design tradeoff of user's privacy for ease of data access and storage. Relating back to the problem identification step of Biddle's framework, one may wonder if the app is needed to solve the problem at all because there is still a human component of Street Bump that could do the job of the app anyway. Hence, solving Street Bump's possible discrimination against minority classes might not even be required as Street Bump itself may be unnecessary despite its cost-effectiveness.

4. **Practical Recommendation(s):**

In this section I will attempt to offer a practical recommendation to alleviate the discrimination concern that exists within Street Bump's data collection. As the main issue comes about due to discrepancies in smartphone ownership between poorer communities and other populations in the city, a possible solution involves having Street Bump running on public transit, such as busses, as it is used by protected classes more than other groups (Anderson 2020). This approach would help get data from those underserved communities that may not have been recorded in the dataset before. Additionally, this recommendation could alleviate the privacy concern since the location is no longer tied to an individual and rather tied to public units whose locations are already known. One downside to this approach, however, is that busses follow preset routes, so it's likely many potholes in those poorer neighborhoods would still go unrecorded, but more representation in those areas would be achieved than if the recommendation remained unimplemented.

5. **References:**

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