Jaywalk! for all I care...

Exploring pedestrian path planning and route selection

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Introduction: Automated driver assistance systems (ADAS) face challenges with pedestrians, especially in complex urban environments where pedestrians exhibit diverse and unpredictable behaviors. The uncertainty exhibited by these road users - in addition to the can-of-worms in collecting it (Feng et al., 2021) - is magnified in automated driving systems (ADS) designed to execute both the dynamic driving task (DDT) and strategic tasks (i.e., trip planning, route selection). However, this off-loading of the driving task requires an adequately scaled system that can handle a myriad of ambiguous pedestrian behaviors (Mitman and Ragland, 2007). Herein lies the gap between the amount of training possible to provide such systems and the training necessary to ensure *some* level of safe deployment in multimodal contexts.

Background: Reinforcement learning (RL) has gained significant popularity on this front for its flexibility to explore a state space independently, providing resiliency towards unseen events and environments. Reasonably, a lack of interpretability becomes concerning in high-risk domains, where agents act according to learned optimal policies not entirely understood (Armstrong and Mindermann, 2018; Glanois et al., 2021). Mistrust leads to distrust: before real-world applications of RL models are statistically real test-beds for them. However, creating such simulations with distribution-level accuracy is difficult for sparse events struggling with dimensionality (i.e., safety-critical driving events, Yan et al. (2023)). At scale, such is also the case for pedestrians, whom inherently and indefinitely add complexity to their environments through interaction (autocirricula, Leibo et al. (2019)). But fear not! Wang et al. (2022a,b, 2020), Wang et al. (2016, 2021), ..., have made significant efforts developing human-like driving models to exhibit socially compatible behaviors. In light, socially compatible behaviors for various kinds of road agents must be learned (i.e., vulnerable road users (pedestrians) require more sensitivity in interaction terms of space and time).

Research question: How do we walk? Due to collection costs and privacy concerns, robust (and granular) pedestrian behavior data is scarce, which limits the amount of knowledge we have about pedestrian path planning at a microenvironment scale. Johora and Müller (2021) suggests pedestrians often path plan irrationally. It may be interesting to use observed expert demonstrations to simulate, for example, how pedestrians avoid re-routes due to construction (flexibility to new tasks), or what running to the bus looks like (robustness to goal specification). Because there are multiple expert demonstrations per participant, it would also be interesting to explore preferences among pedestrians.

Analysis plan: Let's explore walking. Maybe potentially with deep imitation learning and expert demonstration. These demonstrations are provided via previously collected GIS-linked walking activity from pedestrians in Seattle, WA. Of note, this dataset contains multiple traversals for ~ 300 pedestrians.

I would be remiss to not mention some recent work. What initially sparked interest into expert demonstration for intelligent planning was Rhinehart et al. (2018), who model continuous-state, discrete-time, partially-observed Markov processes in a deep imitative learning model (an exact target no longer, cars can avoid pot-holes). Vozniak et al. (2020) uses deep imitation learning to explore pedestrian behaviors in critical safety scenarios, and Trinh et al. (2020) employed a PPO-based path planning model that followed common walking conventions and human behaviours such as walking on the left side of the road and staying away from dangerous obstacles. Honorable mention to a devil's advocate, Lake et al. (2017), who kinda thinks the whole things a joke.
Next steps: Will need help scaling scope/focus. Get feedback from EV, meet to discuss scope and brainstorm implementation. Please reach out if you have significant concerns!

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