

idealized user. Therefore, we recommend that further research into sequential decision-making for inline text autocomplete should *not* pursue the goal of solely increasing text entry speed, but rather aim to make real users enjoy the text entry experience.

There are several important directions for future work, to address some of the limitations of this paper. (1) It would be interesting to perform our theoretical analysis on the outputs of a real language model, to connect better with practice. (2) On the computational side, we hope to experiment with feeding the LM probability values as part of the input into the PPO and DQN agents. (3) Our user study only considered prompted writing tasks, where our software told users what sentences to write. The results may be different if users were asked to do freeform writing. (4) Most importantly, we believe that introducing more realistic conditions into our simulations would provide greater scope for RL-based agents to improve over threshold-based methods. Examples include stochasticity in the user suggestion acceptance behavior, typos in their text input, or deciding suggestion acceptance based on semantic matching with the target sentence rather than hard matching. This research would align well with other work that has found users to prefer autocomplete suggestions due to lower cognitive and physical burden, even when text entry speed is impaired (Quinn & Zhai, 2016).

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A Reward Derivation

Our objective is to minimize the total time it takes for the user to enter the input. Hence, the instantaneous reward will be proportional to the *saved time* due to a correct suggestion that the user accepted minus the *lost time* due to cognitive load imposed on the user. For simplicity, we assume all characters take the same amount of time to write ($\Delta t_{char-write}$) and to be read ($\Delta t_{char-read}$). We also associate an additional fixed time loss for every suggestion, where the user has to pause and move their gaze ($\Delta t_{distraction}$). Hence we will have:

$$r \propto \text{Saved Time} - \text{Lost Time} \quad (1)$$

$$\propto \text{len}(a) \times \text{accepted} \times \Delta t_{char-write} - \text{len}(a) \times \Delta t_{char-read} - \Delta t_{distraction} \times (\text{len}(a) \neq 0) \quad (2)$$

$$\propto \text{len}(a) \left(\text{accepted} - \frac{\Delta t_{char-read}}{\Delta t_{char-write}} \right) - \frac{\Delta t_{distraction}}{\Delta t_{char-write}} \times (\text{len}(a) \neq 0) \quad (3)$$

$$\propto \text{len}(a)(\text{accepted} - \alpha) - \beta \times (\text{len}(a) \neq 0), \quad (4)$$