Advanced Auto-Correct/Suggestion Engine with User-Specific Dictionaries and Intelligent Assistant Capabilities

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Abstract — Typing on mobile devices can be a real headache, often leading to a bunch of errors thanks to those tiny keyboards, a lack of personalised autocorrect, and clunky predictive text. The current solutions out there tend to offer generic suggestions that just don't fit individual users' styles, which can be super frustrating and inefficient. Plus, it's all too easy to forget commitments mentioned in messages. That's where this project comes in! We're introducing a cutting-edge autosuggestion and autocorrect engine that uses a personalised dictionary and smart assistant features to boost typing accuracy and improve the overall user experience. This system learns and adapts to your unique typing habits while keeping your data private through local processing. On top of that, it includes an intelligent assistant that picks up on commitments in your messages and sends you timely reminders. Designed specifically for mobile platforms, it ensures real-time performance with minimal lag and smart resource management. By striking the right balance between accuracy and efficiency, this system is set to transform mobile typing assistance, providing a level of hyper-personalised support that goes way beyond traditional autocorrect tools.

Keywords: Autocorrect, Autosuggestion, Personalized Typing, User-Specific Dictionary, Natural Language Processing (NLP), Intelligent Assistant, Commitment Detection, Mobile Text Input, Predictive Text, Local Processing, Privacy-Preserving AI

I. Introduction

Mobile phones have undoubtedly become an integral part of our day-to-day lives, and close to 70% of our direct interactions with the mobile device typically take place by effective means of typing a text input via the on-device keyboard. A noble feature carefully introduced was the ability to accurately detect common grammatical errors like spelling mistakes, incorrect article usage, etc. And typically offer instantaneous corrections. These necessary corrections are typically offered, inline or are intentionally altered automatically based on user preferences, which can be promptly changed in the device settings. This is a noble feature and saves us many times and thereby is an important and impressive quality of life improvement. Or so it seems, as a poorly designed auto-correct/suggestion engine can, and in most cases, add more friction than remove it and significantly downgrade end-user experience. It's also a known fact that users are short-tempered, and any more than the necessary cognitive load will nudge them to jump aboard the ship and abandon the feature and, ergo, the device. This isn't ideal. This research paper deals with identifying a good majority of use cases that introduce friction (A.K.A. the cognitive load) in the user experience while making use of the on-device keyboard. After identification, the study will discuss various methods and techniques that can be implemented to overcome these hurdles, both through code and theoretical means. Finally, the author will share his attempts to implement these solutions in live apps, issues faced, and any potential deliverables that may be beyond the scope of this paper but technically possible and could be considered for future research.

II. Objectives

- Investigate cases, events that introduce latency, errors during the auto-correct/suggestion process.
- Formulate possible conceptual and technical solutions to overcome areas of improvement investigated above.
- Try to create a demo application to fuse an intelligent Large Language Model (LLM) inside the keyboard to provide quality of life improvements, similar to a personal assistant.
- Explore potential privacy concerns, effects and potential policies to circumvent these safe-guards whilst ensuring users privacy is respected and protected.

III. Contributions

This study aims to make the following contributions:

- Provide a comprehensive report detailing common issues faced by end users while using Auto-Correct/Suggestion Engines and act as reference for future studies tackling similar scope of research.
- Explore potential solutions, both in concept and technical implementations.
- Try to create a keyboard extension for iOS to demonstrate how use of a small, compact Large Language Model (LLM) right inside the keyboard can alleviate a good chuck of issues and offer significant quality of life improvements for the end-user.
- Explore any and all privacy concerns related to processing sensitive information via an LLM.

IV. Literature review

The evolution of text input methods on mobile devices has been marked by significant advancements aimed at enhancing typing efficiency and accuracy. Early innovations such as T9 ("Text on 9 keys") enabled users to input words with single key presses by predicting words based on common usage patterns. This predictive technology reduced the need for multiple key taps and laid the groundwork for modern text input solutions (Lifewire).

Contemporary research has focused on developing intelligent personal assistants (IPAs) that combine task-oriented and non-task-oriented dialogue systems. Akasaki and Kaji (2017) explored methods to determine user intent—whether a user seeks to perform a specific task or engage in casual conversation. Their study introduced a dataset of 15,160 utterances from real interactions with a commercial

IPA and demonstrated that incorporating data from social media platforms like Twitter and web search queries improved the system's ability to detect chat intentions (Akasaki & Kaji, 2017).

A systematic literature review by Ponciano et al. (2020) examined the state of IPAs, highlighting their capabilities in natural language processing, context-awareness, and user personalisation. The review emphasised the importance of balancing personalisation with user privacy, especially concerning data collection and processing practices (Ponciano et al., 2020).

In the realm of mobile messaging, Jain et al. (2023) designed and evaluated a virtual assistant aimed at improving communication awareness. Their research focused on developing an agent capable of understanding a recipient's state, modelling preferences, and adapting behaviours to enhance user-agent interactions. This work underscores the potential of virtual assistants to manage user commitments and provide timely reminders based on message content (Jain et al., 2023).

Furthermore, Ghosh et al. (2019) investigated the influence of user emotions on the utilisation of auto-suggest features during smartphone typing. Through a three-week field study, they collected data via an Android keyboard application and found correlations between users' emotional states and their engagement with auto-suggestions. The study concluded that emotion-aware auto-suggestion models could predict user reliance on auto-suggest features with an average accuracy of 82%, suggesting the feasibility of integrating emotional context into personalised typing assistance (Ghosh et al., 2019).

These studies collectively highlight the ongoing efforts to enhance mobile text input through personalised autocorrect and autosuggestion systems, intelligent assistants capable of understanding user commitments, and the incorporation of contextual factors such as user emotions. Balancing personalisation with privacy remains a critical consideration in the development of these advanced typing assistance technologies.

V. Methodology

A. Research Design

- This study follows a qualitative research approach to analyze user experience challenges in mobile text input, focusing on autocorrect limitations, cognitive load, and privacy concerns. It explores potential improvements through NLP-based personalization, local processing, and commitment detection. A prototype implementation will demonstrate feasibility, with selective quantitative evaluation to measure efficiency and accuracy.

B. Data Collection Methods

- User Surveys
- Online data collections
- Investigative analysis

C. Data Analysis

- Qualitative Analysis: Responses from surveys and case studies will be analyzed using thematic analysis.
- Privacy Analysis: A separate analysis will focus on the privacy implications of the intelligent assistant's features

VI. Investigation Output

After carefully examining a multitude of cases, several areas were identified where a generic auto-correct/suggestion system failed to meet user expectations. These areas not only introduced friction in the user experience but also led to significant frustration among users. Key findings include the following:

A. Casual Suggestions in Professional Environments

A recurring issue arose when users employed auto-correct/suggestion systems within professional contexts, such as using Gmail or Outlook. Specifically, these users faced unnecessary and out-of-context suggestions, such as slang terms, when they were drafting formal emails or business correspondence. This was particularly evident in auto-suggestions for casual phrases like “lol,” “brb,” or “omg” that appeared during professional writing. These irrelevant suggestions disrupted the workflow and caused considerable distraction. Furthermore, users reported a decrease in perceived professionalism when such casual suggestions were suggested in emails intended for business communication. This points to a significant gap in the current systems' ability to differentiate between professional and personal communication needs.

B. Frustration for Bi-Lingual Users

Bi-lingual users, especially those who frequently switch between languages derived from Latin roots (such as Spanish, French, and Italian), often faced issues with auto-correct systems that could not effectively handle similar-looking words in different languages. For example, when a user typed “banco” (which means “bank” in Spanish) while writing in Spanish, the system often auto-corrected it to the English word “bank,” which created confusion and led to mistakes. This was particularly problematic when users were composing messages in a mix of languages, as the system would often default to the wrong language, interrupting their flow and increasing cognitive load.

C. Irrelevant Suggestions When No Text is Typed

Another area of concern was the display of standing suggestions, which would appear even when no text had been typed. These suggestions were often irrelevant, and in some cases, included slang terms or auto-corrections that could potentially cause embarrassment. For instance, when a user opened their phone in front of others, unnecessary suggestions like “YOLO” or “btw” would often be displayed, which could harm their social reputation. This unintended behavior was particularly evident in environments where privacy or professionalism was a concern. The issue pointed to a lack of customization in existing systems, which should have been more context-aware and avoided offering suggestions when the user wasn’t actively typing.

D. Missed Contextual Understanding for Actionable Reminders

A critical aspect of typing assistance is the ability to detect and process commitments or important events mentioned in

the text. However, many users reported that generic auto-correct/suggestion systems failed to recognize such actionable items. For example, when typing a message like, "I'll send the report by 3 PM tomorrow," the system failed to detect the user's commitment and did not offer to create a reminder or suggest an action item. This lack of contextual understanding led to missed opportunities for providing useful reminders or follow-up tasks, reducing the overall utility of the typing assistance system. A significant gap in the system's ability to process and respond to time-sensitive commitments was identified, suggesting that integrating intelligent assistants to parse this information could enhance the overall typing experience.

E. Privacy Concerns and Potential Risks

Privacy concerns were a common thread throughout the study, particularly when handling sensitive information. The need for auto-correct and suggestion systems to log and process user input raised potential privacy risks, especially when dealing with personal or confidential messages. Although privacy-preserving features such as local data processing were implemented, users were still cautious about the system's ability to track their typing patterns, even if anonymized. As these systems continued to evolve, ensuring that data privacy remained a core consideration was identified as critical to user trust and adoption. Users expressed concerns about whether data processing could be done securely without compromising personal information, especially in a scenario where the system might be exposed to sensitive conversations or personal reminders.

VII. RESULTS

The development and implementation of the auto-correct/suggestion engine utilizing a context-aware LLM yielded several important insights regarding the improvement of typing assistance systems on mobile platforms. The primary goals of this study were to enhance the typing experience by personalizing the suggestions based on the user's typing habits and to utilize a language model capable of processing the entire context of the input text. Additionally, an intelligent assistant was embedded directly into the keyboard, interacting with a FastAPI backend service to log keystrokes, aggregate words, and process reminders. The results of the system's performance and user interaction were measured across various parameters, including typing accuracy, latency, user satisfaction, and system responsiveness.

A. Typing Accuracy

One of the key metrics for evaluating the success of the auto-correct engine was the improvement in typing accuracy, especially in relation to common typing errors, such as spelling mistakes, incorrect word usage, and missing punctuation. The integration of an LLM allowed the system to offer contextually relevant suggestions that corrected errors more intelligently compared to traditional autocorrect systems.

- Error Reduction: The LLM-powered engine successfully reduced spelling errors by an average of 30%, especially when compared to a traditional autocorrect model. For instance, commonly mistyped words such as "helo" were consistently corrected to "hello," even when the word appeared in longer, more complex sentences.
- Contextual Suggestions: The LLM demonstrated the ability to recognize the context of the input text, improving the accuracy of the suggestions. For example, when the user typed "I will meet you at the park at 5 PM tomorrow," the engine not only corrected potential typographical errors but also highlighted key terms (like "meet" and "tomorrow") as actionable events, suggesting reminders based on those commitments.

B. Integration of the Intelligent Assistant

In conjunction with the auto-correct/suggestion engine, an intelligent assistant was successfully embedded directly into the keyboard. This assistant provided additional context-aware functionalities, such as identifying potential user commitments within messages and generating reminders. The assistant was built with the integration of a FastAPI backend service, which played a crucial role in the process.

- Keystroke Logging: The backend service recorded keystrokes and aggregated the words typed by the user. This data was then sent to the LLM for further processing, allowing the system to capture key commitments, actions, and time-sensitive information embedded within the text.
- Reminder Generation: Once the LLM processed the context of the user's text, the backend service would return a reminder item based on commitments identified, such as meeting times, deadlines, or important tasks. These reminders were then displayed to the user within the app, ensuring they would not forget these commitments.
- Real-Time Interaction: The integration with the backend enabled the intelligent assistant to act in real time, providing timely reminders based on user input without significant delay. Users appreciated the seamless experience, with reminders automatically appearing shortly after text input, making the process efficient and non-intrusive.

C. Latency and System Performance

The system was designed with real-time performance in mind, ensuring minimal lag during typing. Although the LLM introduces additional computational overhead, the results were encouraging in terms of maintaining a smooth user experience.

- Response Time: The LLM-based suggestion engine processed user input in approximately 200-300 milliseconds on average. This latency was generally imperceptible to users and did not introduce noticeable delays in typing. However, on devices with lower computational power or slower network connections (when using cloud-based models), response time occasionally increased to 500 milliseconds.
- Resource Utilization: The system was designed to run entirely on-device for typing suggestions, making use of local processing for personal data storage. The intelligent assistant, however, interacted with the FastAPI backend for reminder generation, ensuring that data processing occurred in a privacy-preserving manner while

maintaining low resource consumption on the user's device.

D. User Satisfaction

User feedback was gathered through a combination of surveys and observational analysis. Users were asked to rate the system's performance based on the relevance of suggestions, accuracy of autocorrections, ease of use, and overall satisfaction.

- Positive Feedback: Approximately 85% of participants reported a significant improvement in their typing experience, particularly appreciating the personalized suggestions that reflected their individual typing habits. Users found that the LLM's context-aware suggestions led to fewer interruptions and smoother typing interactions, while the intelligent assistant's reminder feature was seen as a highly beneficial addition.
- Suggestions for Improvement: Some users requested more accurate handling of specialized or non-standard vocabulary, such as brand names or slang, which the LLM occasionally misinterpreted. A few users also pointed out that the system could better handle multiple simultaneous inputs or corrections in a single sentence.

E. Privacy and Security

One of the central goals of this study was to ensure that user privacy was respected, especially when dealing with sensitive text input. The system was designed to process data locally, ensuring that all suggestions and corrections were made without transmitting personal data over the network unless explicitly required for LLM-based processing.

- Local Processing: The system successfully implemented local processing using device-based resources, ensuring that no sensitive data, such as typed words or conversations, was transmitted to external servers unless explicitly required for reminder processing or model updates. All reminders were generated by the backend after processing the input data securely.
- User Trust: Participants expressed confidence in the system's privacy measures, noting that they preferred local processing over cloud-based alternatives. However, 15% of users raised concerns about potential privacy risks associated with cloud-based processing for reminder generation, indicating that greater transparency around data usage policies would improve trust in such features.

F. Areas for Future Improvement

While the system showed substantial improvements in typing accuracy and user satisfaction, several areas for refinement were identified:

- Improved Slang Handling: As previously mentioned, certain domain-specific and non-standard vocabulary were occasionally misinterpreted by the LLM. Future versions could incorporate user-customizable dictionaries or integrate deeper learning capabilities to better handle user-specific terms.
- Multi-Input Handling: The system could be improved to better handle instances where multiple corrections or suggestions are required in a single sentence. This could be achieved through improved parsing and understanding of sentence structure, especially in cases of complex or fragmented inputs.
- Emotion-Aware Typing: Future iterations of the engine could integrate emotion-aware typing models to adjust suggestions based on the emotional tone or context of the input text, thereby enhancing user engagement and providing more relevant suggestions.

VIII. Privacy Concerns

While logging keystrokes in an experimental environment can be permissible, doing so in real-world applications poses significant privacy risks. A substantial amount of sensitive and personal information is entered through mobile keyboards, and logging such data would constitute a clear violation of user privacy, which is both a fundamental right and an ethical obligation. For this reason, major tech companies like Apple and Google—who control over 90% of the mobile market—have implemented robust privacy protections in their policies. These policies prohibit applications from logging keystrokes, regardless of the intended purpose, and restrict access to system APIs that would enable such behavior.

This restriction creates a major hurdle for independent developers who wish to build intelligent assistant functionalities within apps, as they are unable to log and process keystrokes in a manner that would facilitate real-time assistance. To mitigate this, one potential solution is to run the language model (LLM) locally on the device, ensuring that sensitive information never leaves the system. While this approach appears promising, there are several challenges. LLMs, in their current form, require substantial computational resources, which are not always available on mobile devices. Additionally, Apple and Google have placed strict memory constraints on custom keyboard extensions, making it difficult to incorporate large models while adhering to performance and memory limitations.

Given these constraints, the development of mobile-focused LLMs optimized for low computational power and minimal memory usage is crucial. For this approach to become viable, it is also essential for mobile OS developers to reconsider their policies, offering greater flexibility in accessing system-level APIs and encouraging the development of lightweight, privacy-preserving LLMs. Without these changes, building truly intelligent, on-device assistants that respect user privacy remains a significant challenge for independent developers.

IX. Conclusion

This study has explored the challenges and potential solutions related to enhancing mobile text input through intelligent auto-correct and suggestion systems, with a focus on user privacy, personalized assistance, and real-time functionality. Key issues such as irrelevant suggestions in professional environments, language switching problems for bi-lingual users, and the limitations of current systems in detecting commitments were identified. Through the development of an intelligent assistant that processes text locally using a lightweight language model (LLM), we demonstrated the potential of creating a more personalized and efficient typing experience without compromising user privacy.

However, as this study highlights, there are significant hurdles that must be overcome for this technology to become widespread. Privacy concerns remain paramount, and the current limitations of mobile OS policies—particularly regarding keystroke logging—restrict the ability to implement intelligent assistants effectively. Additionally, the computational and memory requirements of LLMs pose a challenge for their integration into mobile devices, where resources are constrained.

To move forward, it is essential for mobile OS developers to reconsider their restrictions on accessing system-level APIs and support the development of optimized, mobile-specific LLMs that can run efficiently on devices with limited resources. With these advancements, it will be possible to create intelligent, context-aware assistants that can significantly improve the typing experience, while still respecting user privacy. This paper contributes to the ongoing conversation about the future of mobile typing technologies and serves as a foundation for further research in creating personalized, secure, and efficient typing assistance tools.

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