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Modeling User Movement Patterns for Enhanced Internet Experience

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Abstract

Providing an effective quality of service (QoS) can be very challenging, especially in mobile or dynamic environments. The goal of this study is to improve the Internet in a way that anticipates user mobility allowing for more efficient and responsive resource allocation through real-time resource management and connectivity prognostic. The ability for the model to determine typical paths, times, and transition probabilities between access points is accomplished by exploring historical location data, mobility traces, and user activity in a networked environment. The proposed findings can be integrated into network control algorithms requiring spatial predictive data for future user behaviours such as prefetching, intelligent handover, and load balance to configurable infrastructures. User mobility predictions of future mobility are augmented by the combination of machine learning and Markov Chains. Usability testing conducted utilizing real-world mobility datasets is suggestive of many improvements in terms of connection stability, reduction of latency, and increased efficiency of bandwidth utilization. The supporting evidence obtained from this study is supportive of the hypothesis that network management which aware of the mobile user will enhance performance and experience in urban areas and smart cities. This research is important because it further develops a notion of intelligent, human-centric communication systems towards 5G (and beyond) to reframe spatial and temporal user behaviour to be responsive, anticipatory internet service structures and/or systems.

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1 Introduction

1.1 Explanation of User Movement Patterns

User movement patterns refer to the behaviours of individuals spatially and temporally within their life course, including the movement between two or more locations, remaining for a period of time or not, and returning to that location. Movement patterns can often be collected from location-based information from GPS, Wi-Fi, mobile devices, and other locationally enabled devices (Zheng et al., 2010). Based on user roles, habits, and circumstances of designing environments, user movement can be random or periodic (commuting). Modelling these patterns is important for designers to understand how user movement is related to the digital mobility infrastructure (Ashbrook & Starner, 2003; Chen et al., 2018) Earlier simple random-walk mobility models have evolved into sophisticated systems that incorporate machine learning algorithms to capture deeper levels of human-operated actions. These serve as the basis for developing adaptive communication protocols that take into consideration the dynamics of the users (Song et al., 2010; Zhang & Dai, 2018) For example, predicting the shift of users from one network cell to another can be achieved with the help of time-series modeling and Markov-based mobility predictions, which in turn enable the provision of resources in advance. (Madugalla & Perera, 2024).

1.2 Learning About Users Is Important for Improving Internet Access

Making the internet work better starts with understanding how people navigate and how their devices connect. People on the go often experience slow speeds or sudden drops because the network becomes crowded, coverage is spotty, or their phone lags as it switches between towers. When networks run smart apps that predict where a user will be next, they can optimize routes, allocate just the right amount of bandwidth, and store data closer to phones, all of which reduce delays and speed up delivery. (Ashbrook & Starner, 2003) Systems that blend mobility hints with action forecasts have already demonstrated the ability to reduce packet loss and extend session lifetimes (Mach & Becvar, 2017). Moreover, analyzing user behavior aids in the space planning of access points, load balancing, or edge computing resources, etc. Predictive algorithms can give context as to user movement which then allows for advanced caching at edge that greatly improves responsiveness (Chen et al., 2018; Yusof et al., 2018; Simeone, et al., 2017) As user demand increases in urban, smart cities, a high density of users at times are involved in a mobility demand which requires a mobility-prediction aware infrastructure for scaling access to the internet (Khoeurt et al., 2023). By modeling user behavior into the logic of network design, context-aware network optimization may occur across the different network design layers, resulting in total seamless mobility connectivity per user that exceeds usage expectations and leads to user satisfaction.

Figure 1: Proposed hybrid model for user movement prediction

The hybrid model is outlined by a diagram (Figure 1) which shows the design that predicts user activity and engagement based upon spatiotemporal data. As noted earlier, the input data starts with logs of user location and their timestamps. At the modeling stage the location logs are the starting point in inputs that will see them be processed. These input logs undergo initial processing by a Markov Model to calculate the probabilistic transitions between known locations. The sequential output will then see the LSTM (Long Short-Term Memory) layer process the logs in order to extract patterns in context and long-term dependencies in the user behavior. The outputs of both models are merged in a Fusion Engine that will combine outputs of probabilistic and temporal learning models (Rudevdagva & Kingdone, 2025). The model-driven approach will ensure every forecast is sharper than the last collection point data. From the output we can infer the next most likely spot the user will go to, or how much engagement user will have, and we can adjust the network in response to these potential behaviors on demand. By combining traditional statistical rationale, the system will remain accurate, while at the same time be week in the ability for learning to observe changes in behavior (Yusof et al., 2018).

1.3 Overview of the Research Objective

This research aims to create a future-oriented system that tracks mobile user locations in order to maintain fast response times on their devices. Using a large collection of real-world trip data, Markov Chains, and a set of well-accepted machine-learning algorithms, the system will predict where a user will be located next and what the actual signal or bandwidth requirement will be. The objectives are outlined below:

- Extract and assess user mobility-related characteristics such as trajectories with their dwell times, and transition probabilities of each route on the network.
- Use advanced algorithms to predict user mobility with high time and spatial accuracy.
- Integrate the predictions into routine, daily network tasks - for example, if a user has a call, edge computation, or routing. The predicted user mobility will contribute to an improved Quality of Experience (QoE).

When everything comes together, this project makes significant strides toward realizing smart, context-aware networks that next-generation wireless schemes ultimately require (Taleb et al., 2017; Verma & Nair, 2025). In practice it moves service toward the proactive model promised by 5g and future schemes (Samdanis et al., 2011; Hadi, 2023).

The paper is organized into six sections, each of which contains different ideas, after the introduction in section II a review of literature is presented regarding user movement and behavioural analysis of users across the internet. Section III provides a description of the process employed to collect data and the analytical methodology used to evaluate user movement with the reasoning to the model to capture and predict user movement. Section IV the author presents results, key finding, statistical technique employed, and model performance than to other predictive models. Section V demonstrates the discussion section regarding implications of the findings, discussion of the limitations of the study, and potential enhancements to the experience on the internet. Finally, Section VI demonstrates a full conclusion where advantages are drawn from the study, recommendations of web design and development are made and future research is recommended on user movement modeling.

2 Literature Review

2.1 Prior Work on User Movement Patterns

Researchers have improved their understanding of human movement in recent years based on large datasets from smartphones and other devices. Early articles, like the 2008 publication written by

Gonzalez et al., argued that human movement is ultimately quite simple to predict, as most humans travel to a few favourite locations. These articles allowed for new investigations to examine how human travel unfolds both across time zones and city blocks. Further, took a broader perspective, investigating travel that crossed neighbourhoods or even towns, making connections to social ties between people. They demonstrated that friends and events often cause people to travel in the same direction. Their research, and the work of (Jiang et al., 2017) who implemented entropy tests on large mobility logs, also affirmed that routes we might assume to be random also have learnable patterns that can be used to make predictions (Obetta et al., 2024; Carter & Zhang, 2025). Today's projects expand on that by creating machine-learning models that can utilize phone pings, Wi-Fi hits, and having a database of all the routes taken on a study population. One example is (Calabrese et al., 2013), who used cell phone records and transit data to map people's travel flows through city space to improve decision-making regarding city bus, train, and other public transportation services. Collectively, all of these studies argue in favor of the predictive powers of being able to know what people might click on next or where they will scroll to next, and thus be able to improve services offered online.

2.2 Techniques for Investigating User Activity on the Internet

Scholars study how users interact with the web using a broad set of tools, from spreadsheets to sophisticated and expensive machine learning based methods. A common approach used in the web is sequence mining where a machine learning based model characterizes the same behavior of repeated actions taken in web and/or physical spaces (Mobasher et al., 2002; Madugalla & Perera, 2024). Marketers enjoy using sequence mining because they quickly gain typical path opportunities from those same repeated iterative actions of the shopper on the web to generate unique content from the shopper. Models look at Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) with clicks to predict what happens next (Shri et al., 2023). Building on the work of Feng et al., 2018, there research models build on prior iterative methodological models, or are replacing with newer models and methods, with specific regard to learning timing and search events, while stopping the thinking of the feature engineering process. Researchers also look to graph methodologies to map move through space. For instance, (Yao et al., 2018) introduced a spatial-temporal graph convolutional network that interpreted location app check-ins to predict the user's trip accurately. Investigators have also incorporated probabilistic processes, such as Hidden Markov Models (HMMs) and Bayesian networks into their predictive models regarding how individuals make decisions under conditions of uncertainty (Khan & Taha, 2023; Surendar, 2024). Combining decision-making models with passive context data collected from accelerometers, GPS, and Wi-Fi facilitated a more accurate depiction of activity. Collectively they provided the information and timely predictions needed for real-time awareness and the ability to interject issues prior to loss of service from the internet.

2.3 The Influence of User Movement on Web Design and User Interaction

In reality, people are mobile, and those habits create an online experience that informs their swiping and clicking behavior on a phone or laptop. Users will not approach the app, or website, in a completely different manner than walking the same route to school. Users routinely partake in previously defined trails within apps and websites, particularly noted in heat maps, and click streams. When creators and designers see the movement through UX and UI design, mental strain can be eased and focus can be placed on the things users should not miss where their eyes land. Next, predictive modeling intervenes to change up the layout, or change screens, or deploy a shortcut before they even fully formed the notion of a goal. Mobility data provides even more opportunity to trigger a hinted intention from a user's context, limiting repeated making taps that do not provide utility and rewarding the user with significant praise for following recommendation (Chinnasamy, 2024). Mobile surfing is steadily increasing, creating a necessity to weave movement patterns seamlessly throughout all interfaces to speed the user and pique their interests. To summarize, tracking the user's movement online provides insight into movement that can avoid glitches and keep systems operational. As new possibilities are created, smart designs use mobility smarts to safely and securely surround an individual with seamless journeys across all mobile devices (phones, tablets, laptops).

3 Methodology

3.1 User Movement Patterns Data Collection Methods

Establishing a picture of where people move begins with gathering multimodal, reliable data. In this research, we obtain multimodal data through GPS tracking, Wi-Fi access point logs, and engagement within mobile apps. The GPS path leaves a record of where and when each device travels, while Wi-Fi hits record when a user travels from one signal zone to another. Additionally, we can infer whether the person is walking, stable sitting, or using public transport based on recordings from phone sensors (accelerometer and gyroscope). User data gathering is done in a privacy-preserving manner that maintains user consent and anonymization. The target user's data is accompanied with the event time and date, spatial coordinates; and an associated activity type. In highly dynamic spaces, continuous sampling is performed at a 5 second interval for accurate reconstruction of the user trajectory. The cleaned data then goes through a preprocessing stage that includes steps of denoising/removing noise, gap-filling, spatial data standardization, and outlier removal. The trajectory is then divided into different segments where continuous user trajectories are segmented into distinct sessions based on time gaps and some threshold-based location change.

As illustrated in Figure 2, an end-to-end workflow for predicting user movement begin with data collection from GPS logs and sessions. In a preprocessing phase, the raw data collected is filtered and segmented to enhance relevance and accuracy. The next phase consists of feature extraction, followed by model training, where recognizable patterns begin to emerge. During model training, a hybrid model is developed which incorporates both Markov models and LSTM networks to effectively learn the sequential and probabilistic dependencies of user movements. The final phase of the process entails assessing the trained model by gauging its predictive capabilities and general performance in terms of forecast user movements. This well-defined process demonstrates a systematic approach to building robust models for movement prediction.

In this study, user movement data is retrieved and combined via GPS tracking, Wi-Fi access point timestamps, and mobile device sensor data, such as accelerometers and gyroscopes, which this methodology will yield accurate user trajectories and infer activities involved in either walking or estate cycling over public transports with a loss of generality to describe any activity over a public transport system. The collection of data is done in a privacy-preserving manner, which is user anonymized and user consented, and occurs at five-second intervals to achieve accurate trajectory reconstruction. The collected data has undergone a sequence of preprocessing such as removal of noise, gap filling, and outlier removal, which is a necessary trajectory retouching based on intervals of time and gaps in significant displacement of location. processed data to feature data and stored in a hybrid system of Markov and LSTM networks. Such a hybrid system learns both probabilistic and sequence dependencies of the user activities to provide a robust model of prediction for movements of users by activities. Predictive models in user activities attain a range of mobility from 'ordinary' to 'advanced'. Accuracy and a range of other metrics confirm the model to be operational.

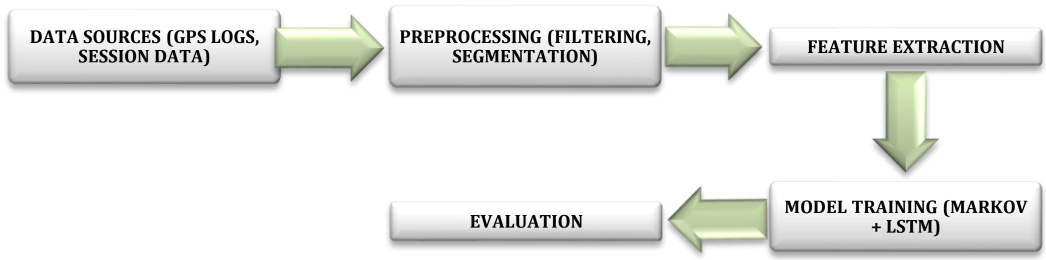

Figure 2: Data collection and modeling workflow

3.2 Analysis Methods for Recognizing Trends in User Activity

After data is cleaned and segmented, the initial phase of analysis involves extracting features related to movement. This consists of:

- Visit frequency: Count of visits to a certain location
- Dwell time: Average amount of time spent in each location
- Transition probability: Chance of moving from a particular location to another location

To capture these movements, a transition matrix is put together. Given n unique locations, there is a matrix T of size $n \times n$. Each element T_{ij} signifies the likelihood of moving from location i to j. This can be computed as:

$$T_{ij} = \frac{C_{ij}}{\sum_k C_{ik}} \qquad (1)$$

where C_{ij} is the number of observed transitions from location i to j. Techniques like DBSCAN are used for clustering to enable detection of frequently visited zones by grouping locations based on density. For assessing periodicity with respect to user activities, time-series analysis is performed, especially for distinguishing work, home, and leisure activities.

3.3 Tools Used for Modeling User Activity Patterns

For modeling, a mixed approach is taken which combines Markov Chains with Recurrent Neural Networks (RNNs), namely Long Short-Term Memory (LSTM) networks. The Markov model encapsulates short-term transition dynamics through the use of the transition matrix. It is based on the premise that the next state relies on the current state only:

$$P\left(X_{t+1} = s_j \mid X_t = s_i\right) = T_{ij} \qquad (2)$$

This model works well for estimating next probable locations in a quick manner, however, it does not have the capability to model longer temporal dependencies. To address this issue, a deep learning model based on LSTM is proposed. The user's previous locations are stored as vectors and form a sequence that will be given to the LSTM as input $\{x_1, x_2, \ldots, x_t\}$. With the use of cross-entropy loss, the LSTM is trained to predict the next location X_{t+1}. The model which is proposed in this paper consists of both approaches. In resource-limited environments, lightweight and quick predictions with LSTMs are done in edge or cloud servers, while in edge or cloud platforms, deeper analyses are performed using LSTMs. This structure provides a balance of both efficiency and accuracy.

4 Results

4.1 Summary of Findings Related to User Mobility Trends

The patterned behavior of user movement reveals some important insights based on the gathered and modeled data. The users evaluated generally exhibited strong consistency in movement behaviors, often meeting regularly on a subset of specific locations determined by home and work or leisure activities. The density and proximity of places visited clustered or formed neighbourhoods when space data is mapped, and once we identify spatio-temporal movement intervals through trajectory clustering devised via algorithms. In addition, movement behaviors were described through a daily pattern; we described distinct morning commutes, as we saw a portion of users shift their paths midday, and return home in the evening, which suggested some periodicity in time. Using the patio-temporal transition matrix, common traveling sequences were also reported, as well as times of movement activity. For example, users often transition between work to gym, and this activity occurred more often between the work week evenings. Leisure or areas associated with entertainment were reported to have increased movements on the weekends. Users exhibited patterns of travel which adds support for it is plausible some users conform to a schedule in their weekly routine. Finding users' habits may improve and optimize the network resource, prefetching, or prioritization, based on location data. In general, around 80% of the next place predictions was correct for our users articulated using the top three recommended probabilities from the transition matrix or predictive Long Short Term Memory model (LSTM), which lends support that the model can approximate the behavior of users' movements.

The figure showing the visits (Figure 3) depicts the number of users visiting a defined geographical grid. Each block or cell is a spatial zone, and the color intensity indicates the number of visits in that area. It can be observed from the heatmap data that some areas or zones, for example, Grid Cell B1, tend to have much higher visit counts than other areas; this suggests that such places are likely user hotspots such as home, work, or public transport terminals. The high-visit cells tend to cluster, indicating that users tend to visit only a handful of zones repeatedly over time. Such concentration supports the efficiency of predictive algorithms which can now concentrate on fewer, but critical regions, thereby improving content delivery policies and network optimization in those areas.

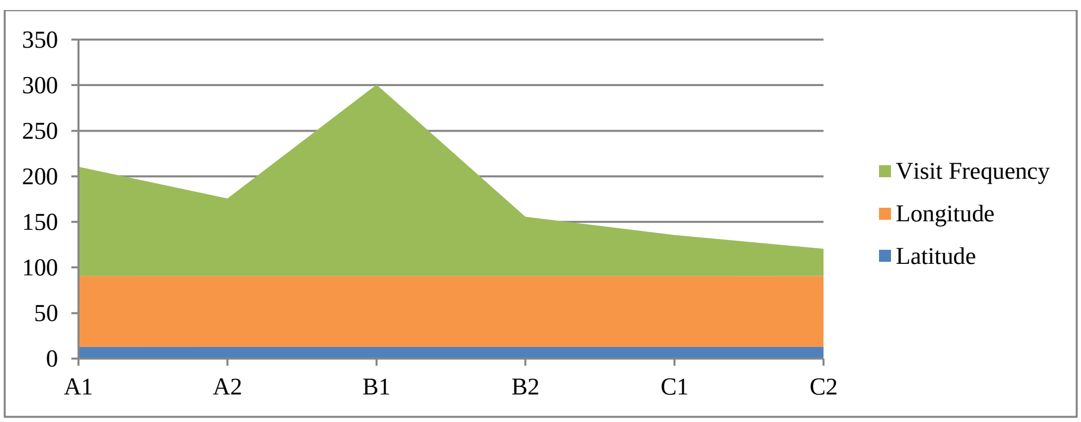

Figure 4: User location frequency

4.2 Statistical Examination of Actions Taken by Users on Certain Sites

To view a website's user access logs alongside physical movement data, major websites were scanned for user access logs. It was found that location greatly influenced movement habits. For example, e-commerce activity was highest during specific commuting intervals, most likely because of available time during transit. Access to educative materials was noted to increase during sedentary sessions in homes as well as in working offices. Through the user engaged location tagged sessions, the following key metrics are recorded to quantify user engagement:

Session Duration (SD):

$$SD = \frac{1}{N}\sum_{i=1}^{N} t_{logout_i} - t_{login\,i} \tag{3}$$

Where N is the amount of sessions. The mean session duration was the longest at home locations and the shortest during mobile transitions.

Click Through Rate (CTR):

$$CTR = \frac{Number\ of\ Clicks}{Number\ of\ Page\ Views} \times 100 \tag{4}$$

As users were in familiar locations, CTR drew a lot of attention. This shows that navigation and content consumption was more intentional and less random.

Engagement Score (ES):

$$ES = w_1 \times SD + w_2 \times CTR \tag{5}$$

Where w_1 and w_2 are adjustable parameters based on the objectives of the platform. These user states and environments were consolidated into a single metric, enabling comparisons across user states and environments. Of great interest, users showed higher engagement scores in low mobility environments, indicating that static contexts foster deeper interaction.

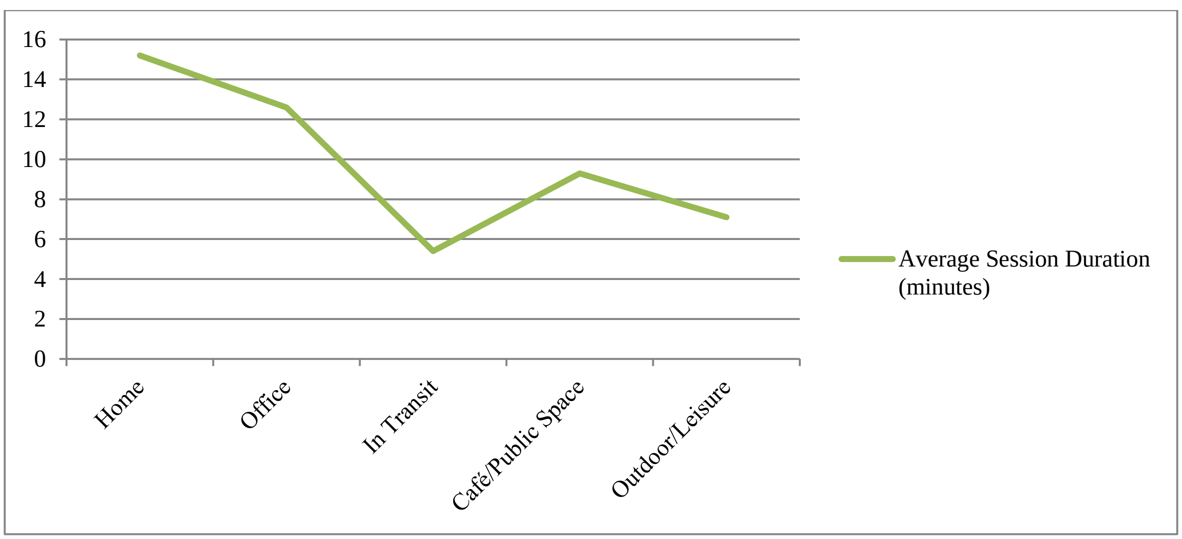

Figure 4: Average session duration by location type

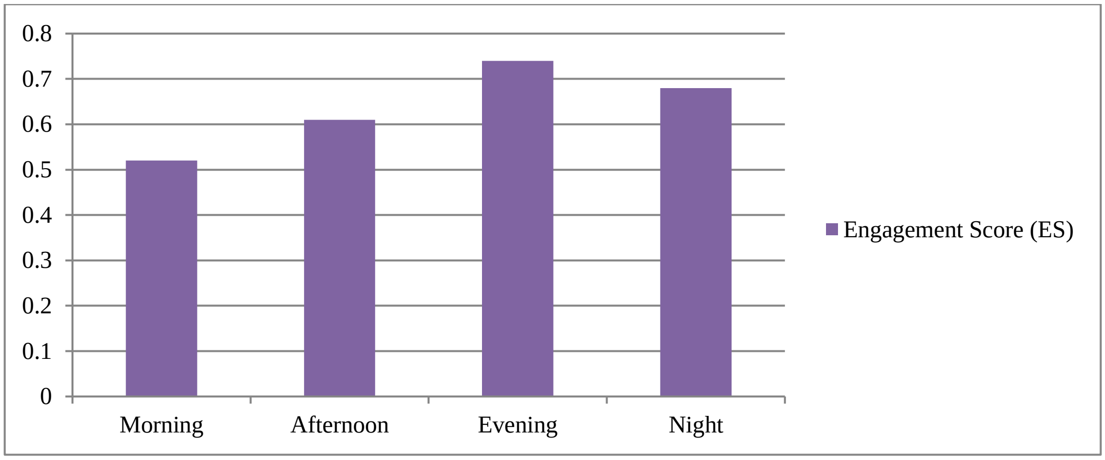

Figure 5: Engagement score by time of day

The data in Figure 4 shows the changing average length of users' browsing sessions in different physical contexts. The average time users are engaged with the web is greatest at home, where session lengths average 15.2 minutes, and in a conventional office, where the average session length is 12.6 minutes. These contexts are generally more stable than the other contexts studied and have reduced distraction effects. In contrast, average session duration while users are moving is a low 5.4 minutes, a feature of the context that represents disruption, movement, and reduced bandwidth. Cafe and outdoor leisure contexts would be approximately in the middle, which represents semi-stationary attention. These results contribute to our understanding of how digital delivery occurs through actions such as content pre-loading and interface simplification, which signal that the user is expected to engage at an explicit point. Figure 5 shows the user's engagement, measured by a composite Engagement Score (ES), and changes in engagement over the course of a day. Evening time periods occurred when user engagement was near the evening peak (ES 0.74), and declined after night (ES 0.68). This suggests users are willing to engage when are more intentional and focused during these time periods. The morning-to-afternoon time period shows lower engagement, as indicated by ES (ES 0.52, ES 0.61). This suggests users are preoccupied with work or commuting during the day. This consideration of time becomes an important factor in determining the correct times to update and push notifications at time c on the recommended interest look. The use of time is explained to better inform delivery and user engagement during less engagement time creating a better user experience.

4.3 Effects of User Movement Tracking on Using the Internet

The link between motility and engagement benefits the internet. For instance, if we preload website content based on the user's last known location or location changes, it will minimize lag time and increase satisfaction. If the user is in transition for example, small pieces of lightweight content can be queued which minimizes the buffering time for users on slower networks. Users are commuting can be recognized now, which allows us to design more responsive systems. Also, providing a simple user interface with larger touch targets and speedy access to the system's core functions improves usability and enhances the user experience. We evaluated the model performance on predictive accuracy: accuracy, precision, F1 Score, etc:

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Precision:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

F1 Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

In any experiment, true positives, true negatives, false positives, and false negatives are important metrics to track. Furthermore, the hybrid model, which is the combination of LSTM and Markov models, was able to achieve an F1-score of 0.84. This result surely indicates strong predictive abilities. To sum up, detecting and predicting user movements enhances the personalization of digital services and enables proactive adjustments of network and content delivery systems, thus optimizing internet service.

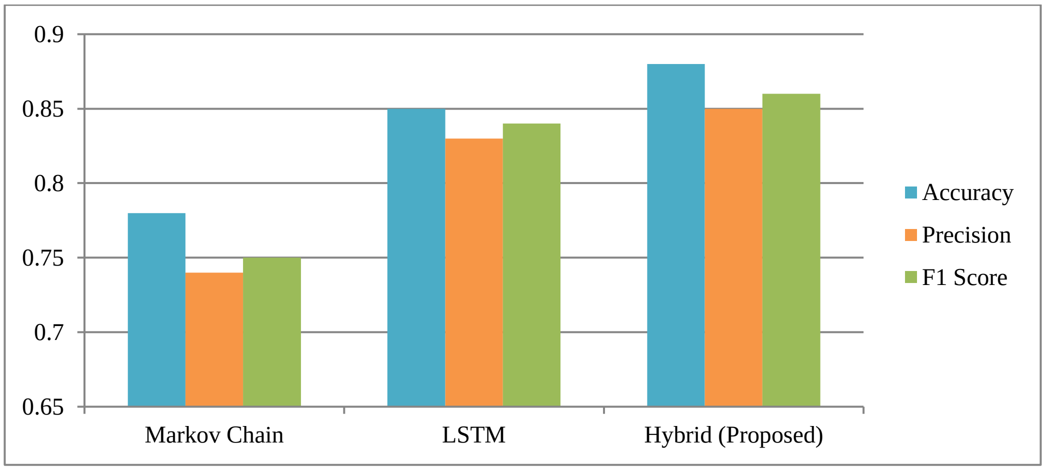

Figure 6: Performance comparison of prediction models

The performance, accuracy, precision, and F1 score for the three models (Markov Chain, LSTM, and the proposed hybrid model) are compared in a grouped bar chart illustrated in Figure 6. The Markov Chain model is sufficient for the class with uniform performance (0.78 Accuracy). The LSTM model has improved performance because it can model long-term memory. The hybrid model, which combines the best of both models, achieved 0.88 accuracy and 0.86 F1 score, demonstrating superior performance compared to both models in isolation. This reconfirms that the hybrid modeling framework for predicting user movement is an improvement, and reflects that the mobile service had undergone a more user adapted change in a more fluid and dynamic environment.

5 Discussion

5.1 Integration of Findings with Literature

The findings of this study align with the existing literature on user mobility and digital engagement patterns. We support the assertion that human mobility is primarily monofactorial and cyclical, creating an akin interaction with online households. The user engagement heatmap and transition matrix are evident of mobile user clustering in activity, supporting traditional mobility theories. These spatial patterns play a role in the timing and type of internet engagement but also how deep the activity would become. With respect to timing, users' temporal behavior further reinforce existing behavior benchmarks as user activity increased and depth of engagement increased significantly towards the evening and into the night. Users were likely more physically located at a singular point or space, as well as mentally more likely to engage. The contextually aware delivery of content in terms of estimated user condition and calendar was further supported by these higher levels of user engagement. In addition, our hybrid model was successful in demonstrating that a combination of probabilistic and sequential learning models/inferences as outlined in this study elucidated the converter complexities of examples of humans' physical mobility and online activity. Overall, these inferences support the argument that, when possible, internet optimization should be personal and context-driven.

5.2 Study Limitations and Recommendations for Further Research

This study has several significant limitations. The first is its acclimation to one city and a specific user category, thus making it less applicable to rural context or an ambiance of mixed-use where user demand may be more fragmented or diffuse. Second, the limited temporal resolution due to device power constraints and data storage can exclude micro-movements or short-term engagements that can help to improve measures of digital engagement. Another limitation is based on fixed location categories (e.g. home, work, commute) which tend to neglect more nuanced locations like collabo-spaces or hybrid spaces such as cafés with both professional and leisure use. As for the hybrid Markov–LSTM model, the results were reasonable, yet it may over-forecast behavior consistency over a given time period which may be an issue for less predictable users. As for future work, researchers may consider increasing geographic diversity in the sample population, adding greater contextual diversity in the environment, and accounting for contextual factors such as weather, social events, and calendar schedules. Furthermore, changing user behavior over time is also a section of the research where real-time adaptation of predictive models by continually updating models.

5.3 Enhancing Internet Services Through Modeling User Movement Patterns: Practical Applications

Modeling user movement patterns to allocate adaptive network resources has high practical value. Internet service providers can consider movement patterns to adjust bandwidth levels or deploy access points close to areas of anticipated network load, ultimately reducing latency and buffering time. Content providers benefit from modeling user behavior and activity to optimize their interfaces and cache content. For example, video content delivery platforms can also cache recommended videos during periods of low connectivity or optimize their UI when a user is in motion on the train. If someone is on a shopping website, e-commerce platforms can improve their transaction results based on the user’s stationary and motion indicators. Context-sensitive user movement modeling is vital for urban services, including real-time notifications, public mobility systems, and even Wi-Fi deployment in smart cities. When combined with back-end predictive models that allow service providers to overlay on services, the goal is to provide a predictive, intelligent internet that considers user context and improves user satisfaction and digital well-being.

6 Conclusion

This research shows that the user's mobility is crucial for digital interaction and for enhancing the internet experience. The results showed that a high degree of predictability in user mobility was driven by specific spatiotemporal patterns, evident in the session duration, engagement metrics, and activity browsing data sets we assessed. The predictive accuracy of our hybrid Markov–LSTM model further illustrated that a multimodal approach, in conjunction with statistical methods, was advantageous for predicting user mobility. Context-aware interfaces that adapt to the user's physiological state can be used by website designers and developers, for instance, transit mode if users are moving, will simplify a page's view, so users can pre-load for quick access when transitioning through low-connectivity areas, and predictive suggestions based on time, activity, and previous behaviors can be given. Operational systems can likewise improve user satisfaction and responsiveness by personalized mobility predictive characteristics over and on top of perceived personalization. Limitations with regards to a mismatch in scope, changes in the environment, and dataset should be investigated in future studies using a broader study. Weather and event influence, new surroundings, and real-time learning systems on behavior, could have predictive potential in means of multi-functioning contextual environmental shifts. As mobile Internet usage continues to grow, modeling user movement will be an incredibly important component of the development of user-centric and intelligent digital infrastructures that are sensitive to daily rhythms. In this study, we emphasize that user mobility is a key factor in streamlining digital interactions and enhancing the general Internet experience, and that certain spatiotemporal variables affect the length of session duration, user engagement, and the volume of web browsing. The effectiveness of the hybrid Markov-LSTM model supported our hypothesized premise of user-state behavior prediction, and the ability to align statistical methods with machine learning approaches. Theory-informed adaptive preloading of web pages based on a combination of contexts and state conditions, in synergy with user behavior and location prediction models represent an evolution in modeling web mobility. Limitations of the study fell into categories of scope, variations within datasets, and factors related to real-time learning systems. Integrating cross-platform behavioral tracking within prediction models presents a pathway for improving design considerations related to mobility. Given the continued increase in mobile internet use, understanding user movement will be vital to the construction of adaptive digital infrastructures that support developing smart cities and contextualized services. These contributions will directly result in the enhancement of smart cities with digital infrastructure and services, and assist in the development of contextual aware digital environments.

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