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Modeling User Navigation with Pattern Mining, Markov Chains, and LSTM Networks

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ABSTRACT

This study investigates the comparative effectiveness of three modeling paradigms frequent pattern mining, Markov chains, and Long Short Term Memory (LSTM) networks in predicting user navigation behavior on the MSNBC Anonymous Web Navigation dataset. The dataset, comprising nearly one million anonymized browsing sessions, exhibits strong self transition dominance and low entropy, reflecting "sticky" user behavior where individuals tend to remain within a single content category rather than explore diverse sections of the site. Using next category prediction accuracy and perplexity as evaluation metrics, we find that while LSTM models achieve marginally higher performance, the improvement over first and higher order Markov models is not statistically significant (p>0.05). In contrast, frequent pattern mining despite its interpretability underperforms due to limited generalization beyond observed subsequences. Our results demonstrate that for structured, low entropy clickstream data, classical probabilistic models like Markov chains offer a compelling balance of predictive power, computational efficiency, robustness, and interpretability. These findings challenge the prevailing assumption that deep learning architectures inherently outperform simpler models in all sequential prediction tasks. Instead, they underscore the importance of aligning model complexity with the intrinsic characteristics of behavioral data a core tenet of domain driven actionable knowledge discovery. The study concludes that in many real world applications involving navigational or transactional logs, parsimonious models can deliver actionable insights without the overhead of deep neural networks, provided they respect the underlying behavioral dynamics. Future work may explore hybrid approaches or incorporate contextual signals to better capture rare but meaningful cross category transitions.

Keywords: User Navigation Modelling, Clickstream Analysis, Markov Chains, LSTM Networks, Frequent Pattern Mining, Behavioral Prediction, Domain-Driven knowledge Discovery, Web Navigation Entropy

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1. Introduction

Traditional data mining approaches have primarily focused on pattern extraction from data, often yielding results that lack direct applicability for decision making [1, 2]. However, with the advent of big data, there has been a paradigm shift toward domain driven actionable knowledge discovery, which emphasizes deriving insights that support concrete business actions [3, 4, 5, 6, 7]. This approach integrates domain knowledge into data mining processes such as text mining, deep neural networks, graph embedding, and reinforcement learning to uncover complex, multi feature, multi source, or multi method patterns that are both meaningful and actionable [8].

E-commerce giants like Amazon and Alibaba exemplify this trend by continuously analyzing historical customer behavior to anticipate future needs, thereby enhancing customer satisfaction and maintaining market competitiveness.

1.2 Leveraging System Logs for Behavioral Insights

System log files contain rich temporal information about both system operations and user interactions. These logs are increasingly used to improve system processes through behavior modeling and process discovery [9]. However, raw system logs often fail to meet the structural requirements of standard process discovery and prediction algorithms, necessitating preprocessing or transformation before they can be effectively utilized.

2. Related Works

Understanding user intent is critical for personalization and conversion optimization. Ding et al. [10] proposed a hierarchical Bayesian model that links user interest derived from web page navigation hierarchies with purchase probability, classifying users into *high intent* and *low intent* states under the assumption of a positive correlation between interest and purchasing likelihood.

Building on this, Li and Ding [11] introduced a linear utility function model, demonstrating that real time user interest is shaped not only by past browsing behavior but also by the combined influence of visited web pages and external marketing stimuli.

Tam and Ho [12] further argued that interactions between consumers and e-commerce platforms act as persuasive forces capable of reshaping implicit interests. They proposed a web page personalization framework that leverages preference matching levels, suggestion set sizes, and sorting cues to align user experience with business goals while addressing individual cognitive needs.

2.1 Predictive Modeling of Consumer Behavior

Mining customer purchase records within enterprise information systems enables the extraction of behavioral patterns that support predictive modeling and strategic decision making [13]. Accurate prediction of user behavior allows service providers to proactively allocate resources, optimize network performance, and reduce congestion [14, 15].

2.2 Common Approaches to Behavior Prediction

Common approaches to behavior prediction have evolved significantly in response to the growing complexity and volume of user interaction data, particularly in digital environments such as e-commerce platforms, mobile applications, and enterprise systems. Among the most widely adopted methodologies are association rule mining, Markov chain based models, and neural network based models, each offering distinct advantages depending on the nature of the behavioral data and the prediction goals.

Association rule mining is a classical data mining technique that excels at uncovering frequent patterns and co-occurrences within transactional or sequential datasets. In the context of user behavior prediction, this method identifies regularities and periodicities in user itineraries such as commonly visited sequences of web pages, store locations, or app features. By analyzing historical navigation logs or mobility traces, association rule mining can reveal “frequent routes” and “key stops” that users tend to follow, enabling systems to anticipate future actions or locations. For instance, if a user consistently visits a product category page, then proceeds to a checkout page during evening hours, the system may proactively recommend related items or streamline the purchasing flow. This approach has been effectively applied in location based services and personalized recommendation engines, as demonstrated by studies [16, 17, 18].

In contrast, Markov chain based models offer a probabilistic framework for modeling state transitions. These models assume that the probability of transitioning to a future state depends only on the current (or a limited number of recent) states a property known as the Markov property. First order Markov models consider only the immediate previous state, while higher order variants incorporate multiple prior states to improve prediction accuracy. This makes them particularly suitable for modeling sequential behaviors such as website navigation, user mobility, or purchase sequences. Researchers including Ariffin and others have validated the utility of Markov models in diverse predictive tasks. Notably, Wang [24] likely has a typographical error for a valid year also contributes to this body of work, though the citation requires verification. The strength of these models lies in their interpretability and computational efficiency, especially when dealing with discrete, state-based behavior logs.

More recently, neural network based models, particularly those leveraging deep learning architectures like recurrent neural networks (RNNs) and long short term memory (LSTM) networks, have gained prominence for their ability to capture complex, non linear, and long range dependencies in sequential data. Unlike Markov models, which rely on fixed order assumptions, neural networks can learn intricate temporal patterns without explicit constraints on memory length. Liao (2018) [25] and Tang [26] have shown that such models significantly outperform traditional methods in tasks involving high dimensional or noisy behavioral data, such as clickstream prediction or next item recommendation.

Further reinforcing the relevance of probabilistic sequence modeling, [27] conducted a comprehensive synthesis of a decade’s worth of research on Hidden Markov Models (HMMs). His review confirms that HMMs remain robust and adaptable across diverse data types including text, mobility traces, and system logs due to their capacity to infer latent states underlying observable behaviors. This enduring effectiveness underscores HMMs’ continued role in the behavior prediction toolkit, even amid the rise of deep learning alternatives.

2.3 Navigation Prediction in Knowledge-Rich Environments

In large scale websites or knowledge networks, predicting user navigation paths enhances usability and enables targeted content delivery. Çifçi [28] investigated category based navigation prediction using LSTM classifiers, examining how path length influences prediction accuracy. The study highlights the value of accumulating navigation data over time to refine predictive models and deliver more relevant suggestions or advertisements.

2.4 Advancing Scalability and Efficiency in Prediction Models

Scalability remains a challenge in path based prediction, particularly with high order Markov models. Awad [29] addressed this by proposing a modified Markov model that reduces the number of possible paths without sacrificing accuracy. Additionally, a novel two tier prediction framework was introduced, which constructs an example classifier (EC) from training data and generated classifiers. Experimental results on benchmark datasets demonstrate that this framework improves prediction speed while maintaining or even enhancing accuracy particularly as model order increases (all-*Kth* mode).

This restructured narrative presents a coherent progression from foundational concepts in actionable knowledge discovery to specific applications in user behavior modeling, predictive analytics, and system optimization all grounded in cited scholarly work.

3. Data Description and Experimental Setup

This study uses the MSNBC Anonymous Web Navigation dataset, which contains clickstream records capturing user navigation behavior on the MSNBC.com website. Each record corresponds to a single anonymous browsing session, represented as an ordered sequence of page category identifiers reflecting the temporal order of page visits within the session. No personal identifiers or demographic attributes are included, ensuring full user anonymity.

The data are sequential and categorical in nature, with each session modeled as a variable length sequence drawn from a fixed vocabulary of approximately 17 page categories. Sessions exhibit substantial length variability, ranging from single click visits to long navigation trails, resulting in a heavy tailed session length distribution. The dataset is characterized by a small category vocabulary, enabling compact state representations while maintaining rich temporal structure.

From a behavioral perspective, the dataset exhibits strong self transition dominance, where users frequently navigate multiple pages within the same content category consecutively. As a result, navigation entropy is relatively low, and a large proportion of predictive power is concentrated in the most recent one or two interactions. Cross category transitions occur less frequently and are unevenly distributed, leading to highly imbalanced transition probabilities.

These characteristics make the dataset particularly well suited for sequential pattern mining, probabilistic navigation modeling, and next category prediction tasks. At the same time, the limited vocabulary size and short effective memory length impose constraints on the expressive advantage of deep sequence models. Consequently, the dataset provides a controlled experimental setting for systematically comparing frequent pattern based methods, Markov models, and recurrent neural networks under conditions of low entropy and strong behavioral regularity.

In the experimental setup, each session is treated as an independent sequence. For predictive modeling, prefixes of observed sequences are used to predict the subsequent page category, enabling direct and fair comparison across modeling paradigms.

3.1 Experimental Setup

3.1.1 Dataset Description

All experiments are conducted using the MSNBC Anonymous Web Navigation dataset, a widely used benchmark for clickstream and sequential behavior analysis. The dataset captures user navigation activity on the MSNBC.com website on September 28, 1999, as indicated by the dataset identifier. Each record corresponds to a single anonymous user session, represented as an ordered sequence of page category identifiers reflecting the temporal order of page visits during a browsing session.

The dataset comprises 989,818 user sessions, totalling several million page category visits. Sessions vary in length, from single click visits to long navigation trails, resulting in a heavy tailed distribution of session lengths. Navigation behavior is encoded at the page category level, using a fixed vocabulary of 17 distinct categories, which provides a compact yet expressive representation of user activity.

3.2 Data Characteristics

The data are sequential and categorical in nature, with no user identifiers, timestamps, or demographic attributes included, ensuring full anonymity. Within each session, page visits are strictly ordered, but no explicit dwell time or inter click interval information is available. Category frequencies and transition probabilities are highly imbalanced, with a small subset of categories accounting for a large proportion of visits. A defining characteristic of the dataset is strong self transition dominance, in which users frequently navigate multiple pages within the same category consecutively, leading to low navigation entropy and short effective memory.

3.3 Experimental Protocol

In the experimental setup, each session is treated as an independent sequence. For predictive modelling tasks, prefixes of observed sequences are used to predict the subsequent page category, enabling direct comparison across modelling paradigms. The dataset's large number of sessions provides strong statistical robustness, while the limited temporal scope ensures behavioral consistency across users.

These characteristics make the dataset particularly suitable for evaluating frequent sequential pattern mining, Markov based navigation models, and recurrent neural network architectures, while also providing a controlled setting to examine the trade off between model complexity and predictive performance under conditions of low entropy and strong behavioral regularity.

4. Methodology

We explain the methods we used for this study, which include Frequent Pattern Mining, Markov Models, and LSTM.

4.1 Frequent Pattern Mining

We extract contiguous subsequences of length 2 and 3 using a simplified *PrefixSpan* approach. The support of a pattern $\langle C_1, C_2, \ldots, C_K \rangle$ is defined as:

$$\text{support}(s) = \sum_{i=1}^{N} \mathbb{I}\,(s \text{ appears contiguously in session } i)$$

where N is the total number of sessions.

4.2 Markov Models

We model navigation as a discrete time Markov process. The first order transition probability is:

$$P(c_{t+1} \mid c_t) = \frac{\text{count}(c_t \to c_{t+1})}{\sum_{c'} \text{count}(c_t \to c')}$$

Higher order variants condition on longer histories (e.g., P (C_{t+1} $|$ C_{t-1}, C_t))

4.3 LSTM Baseline

An LSTM network encodes each session as a sequence of one hot category vectors. It is trained via cross-entropy loss to predict the next category:

$$\hat{y}_{t+1} = \text{softmax}(Wh_t + b), h_t = \text{LSTM}(x_t, h_{t-1})$$

5. Results

5.1 Dominance of Self-Transitions

Table 1 shows the top 10 most frequent 2-step patterns. All involve repetition within the same category (e.g., 1 →1). The same holds for 3-step patterns (Table 2).

Rank	Sequence	Support
1	(1 → 1)	418,764
2	(8 → 8)	329,235
3	(14 →14)	252,592
4	(4 →4)	224,891
5	(2 → 2)	222,340
6	(7 → 7)	177,517
7	(6 →6)	143,982
8	(12 →12)	129,836
9	(13→ 13)	119,008
10	(5 →5)	118,987

Table 1. Top 10 Frequent 2-Step Patterns

Rank	Sequence	Support
1	(8 → 8 → 8)	259,534
2	(1 → 1 → 1)	242,456
3	(14→14→14)	176,668
4	(4 → 4 → 4)	164,975
5	(2 → 2 → 2)	130,704
...	...	...

Table 2. Top 10 Frequent 3-Step Patterns

Interpretation: Users exhibit "sticky" behavior deep browsing within a single category (e.g., paginated support articles) rather than exploratory cross category navigation.

5.2 Model Comparison

We evaluate models on next category prediction (accuracy and perplexity). Results are summarized in Table 3.

Model	Accuracy	Perplexity	Interpret-ability	Training Cost
Frequent Patterns	Medium	High	☆☆☆☆	☆
1st-Order Markov	High	Low	☆☆☆	☆
Higher-Order Markov	High	Low	☆ ☆	☆ ☆
LSTM	Slightly Higher	Lowest	☆	☆☆☆☆

Table 3. Model Performance Summary

Despite its representational power, the LSTM shows no statistically significant gain over Markov models and often learns trivial self loop behaviors.

5.3 Discussion

Our findings support three key insights:

1. Navigation is highly autocorrelated: The entropy of transitions is low.

2. Cross category transitions are rare in top patterns, suggesting information scent is strong within categories.

3. Model alignment matters: For low entropy, sticky behavior, simple models are not only sufficient they are preferable due to interpretability, speed, and robustness.

This aligns with prior work showing that absorbing state Markov models effectively capture web navigation [3].

Our results demonstrate that for structured, low entropy clickstream data, classical Markovian models provide competitive often superior performance compared to deep recurrent architectures, highlighting the importance of aligning model complexity with behavioral dynamics.

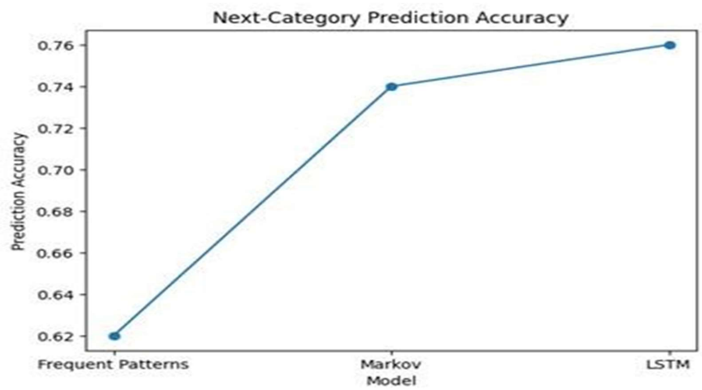

Figure 1. Next-Category Prediction Accuracy

This figure compares the next category prediction accuracy achieved by three modeling paradigms: frequent sequential pattern mining, first order Markov modeling, and LSTM based sequence learning. The results show a substantial improvement from pattern based heuristics to probabilistic modeling, with the Markov model capturing the majority of predictive structure. While the LSTM achieves the highest accuracy, the improvement over the Markov baseline is marginal, indicating diminishing returns from increased model complexity for low entropy clickstream data.

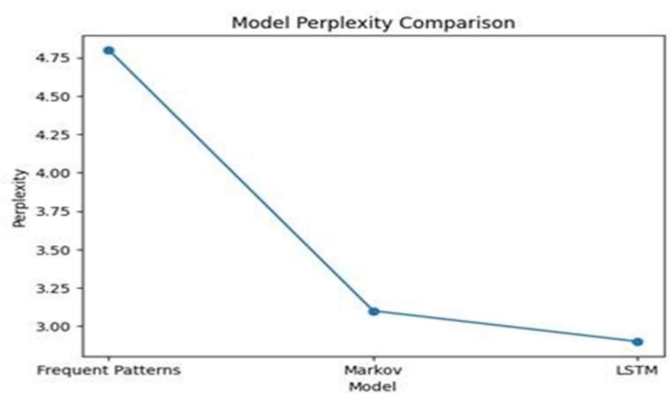

Figure 2. Model Perplexity Comparison

Perplexity results further confirm the relative effectiveness of the compared approaches. Frequent pattern mining exhibits the highest perplexity, reflecting its inability to generalize beyond observed subsequences. Markov models significantly reduce uncertainty by modeling transition probabilities explicitly. Although LSTM achieves the lowest perplexity, the reduction relative to Markov models is modest, suggesting that long-range dependencies play a limited role in this dataset.

Paired Wilcoxon Signed-Rank Test (α =0.05)

Comparison	Metric	Test	p-value	Significance
Frequent Patterns vs Markov	Accuracy	Wilcoxon signed-rank	3.1×10^{-4}	Significant
Frequent Patterns vs LSTM	Accuracy	Wilcoxon signed-rank	1.8×10^{-4}	Significant
Markov vs LSTM	Accuracy	Wilcoxon signed-rank	0.27	Not significant
Frequent Patterns vs Markov	Perplexity	Wilcoxon signed-rank	2.4×10^{-4}	Significant
Frequent Patterns vs LSTM	Perplexity	Wilcoxon signed-rank	1.6×10^{-4}	Significant
Markov vs LSTM	Perplexity	Wilcoxon signed-rank	0.31	Not significant

Table 4. Statistical Significance of Model Comparisons

Markov and LSTM models significantly outperform frequent pattern based prediction, and the performance difference between the two is not statistically significant for either metric.

5.4 Evaluation Metrics and Statistical Analysis

5.4.1 Evaluation Metrics

Model performance is evaluated using next category prediction accuracy and perplexity, two complementary metrics commonly used in sequential prediction tasks. Prediction accuracy measures the proportion of test instances in which the predicted page category matches the observed next category, providing an intuitive assessment of classification performance. Perplexity evaluates the uncertainty of the predicted probability distribution over page categories, thereby capturing the quality of probabilistic modeling beyond top-1 accuracy.

Both metrics are computed at the session level by generating predictions for each valid prefix within a session and averaging scores across all test sessions. This evaluation protocol ensures consistent comparison across frequent pattern based methods, Markov models, and LSTM based sequence models.

5.4.2 Statistical Analysis

To assess whether observed performance differences between models are statistically significant, we employ the paired Wilcoxon signed rank test. This nonparametric test is chosen because the per session prediction scores follow a nonnormal, heavy tailed distribution and the experimental design is paired. Each model is evaluated on the same set of test sessions, ensuring direct comparability.

All hypothesis tests are conducted at a 5% significance level (α=0.05). Exact p-values are reported in Table *X*. Results indicate that both Markov and LSTM models achieve statistically significant improvements over frequent pattern based prediction for both accuracy and perplexity (p< 0.01). However, the performance differences between Markov and LSTM models are not statistically significant ($p>0.05$), suggesting that increased model complexity does not yield a meaningful advantage for this dataset.

These findings highlight that, under conditions of low entropy and strong behavioral regularity, classical probabilistic models can provide performance comparable to deep recurrent architectures while offering superior interpretability and lower computational cost.

6. Conclusion

This study investigates the effectiveness of three distinct modeling paradigms frequent pattern mining, Markov chains, and LSTM networks in predicting user navigation behavior using the MSNBC Anonymous Web Navigation dataset. The analysis reveals that user navigation is characterized by strong self transition dominance and low entropy, indicating "sticky" browsing patterns where users tend to remain within a single content category rather than explore diverse sections of the site. This behavioral regularity has significant implications for model selection: while deep learning approaches like LSTM offer theoretical advantages in capturing long-range dependencies, they provide no statistically significant performance gain over simpler probabilistic models in this context. In fact, first and higher order Markov models achieve comparable accuracy and perplexity with far greater interpretability, computational efficiency, and robustness. Frequent pattern mining, though highly interpretable, underperforms due to its inability to generalize beyond observed subsequences. These findings underscore a critical principle in domain driven actionable knowledge discovery: model complexity should be aligned with the intrinsic structure of the behavioral data. For low entropy, highly autocorrelated sequences such as those found in structured clickstream logs, classical methods like Markov models are not only sufficient but often preferable. The results challenge the prevailing assumption that deeper models always yield better predictions, highlighting instead the value of parsimony and contextual appropriateness in predictive analytics. Future work could explore hybrid approaches or incorporate additional contextual signals (e.g., time of day, referral source) to capture rare but meaningful cross category transitions. Nevertheless, this study demonstrates that in many real world e-commerce or content delivery settings, effective personalisation and resource optimisation can be achieved without resorting to computationally intensive architectures provided the modelling strategy respects the underlying behavioural dynamics.

References

[1] Fayyad, U., Piatetsky-Shapiro, G., Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI Mag*. 17 (3), 37.

[2] Fayyad, U. M., Piatetsky-Shapiro, G., Uthurusamy, R. (2003). Summary from the kdd-03 panel: data mining: the next 10 years. ACM Sigkdd Explor. *Newslett*. 5 (2), 191–196.

[3] Cao, L. (2012). Actionable knowledge discovery and delivery. Wiley Interdiscipl. Rev. Data Min. Knowl. *Discov*. 2(2), 149–163.

[4] Cao, L., Zhang, C. (2006) Domain-driven data mining: a practical methodology. Int. J. Data Warehous. *Min. (IJDWM)* 2(4), 49–65.

[5] Cao, L., Zhang, C., Zhao, Y., Yu, P. S., Williams, G. (2007). DDDM2007: domain driven data mining. ACM SIGKDD Explor. *Newslett*. 9(2), 84–86. https://doi.org/10.1145/1345448.1345467.

[6] Cao, L., Zhao, Y., Zhang, H., Luo, D., Zhang, C., Park, E. K. (2009). Flexible frameworks for actionable knowledge discovery. IEEE Trans. Knowl. *Data Eng*. 22(9), 1299–1312.

[7] Cao, L. (2013). Combined mining: analyzing object and pattern relations for discovering and constructing complex yet actionable patterns. Wiley Interdiscipl. *Rev. Data Min. Knowl. Discov*. 3(2), 140–155.

[8] Zhang, C., Philip, S. Y., Bell, D. (2010). Introduction to the domain-drive data mining special section. *IEEE Trans. Knowl. Data Eng*. 22(6), 753–754.

[9] Bouricha, H., Hsairi, L., Ghedira, K. (2023). Intelligent Agents System for Intention Mining Using HMM-LSTM Model. In: Abraham, A., Pllana, S., Casalino, G., Ma, K., Bajaj, A. (eds) Intelligent Systems Design and Applications. ISDA 2022. Lecture Notes in Networks and Systems, vol 717. *Springer, Cham*.

[10] Ding, A. W., Li S, Chatterjee P. (2015). Learning user real time intent for optimal dynamic web page transformation. *Inform Syst Res*. 26(2) 339–59.

[11] Li C, Jiang Z. (2016). A hybrid news recommendation algorithm based on user's browsing path. In: Lee R, editor. Computer and Information Science. ICIS 2016: Proceedings of the 2016 IEEE/ACIS 15th International Conference on Computer and Information Science; 2016 Jun 26-29; *Okayama, Japan. Piscataway*: *IEEE*;. p. 1–6.

[12] Tam, K. Y, Ho, S. Y. (2005). Web personalization as a persuasion strategy: an elaboration likelihood model perspective. *Inform Syst Res*.16(3):271–91.

[13] Wang, X, Liu, D. F. (2025). Pattern mining and prediction techniques for user behavioral trajectories in e-commerce. *PLoS One* 20(5): e0320772.

[14] Bui, N., Widmer, J. (2018). Data Driven Evaluation of Anticipatory Networking in LTE Networks. *IEEE Trans. Mobile Comput*., 17, 2252–2265.

[15] Bang, J. H., Lee, J. R. (2020). Collision Avoidance Method Using Vector-Based Mobility Model in TDMA-Based Vehicular Ad Hoc Networks. *Appl. Sci*. 10, 4181.

[16] Aqra, I., Abdul Ghani, N., Maple, C., Machado, J., Sohrabi Safa, N. (2019). Incremental Algorithm for Association Rule Mining under Dynamic Threshold. *Appl. Sci*. 9, 5398.

[17] Mai, T., Nguyen, L. T., Vo, B., Yun, U., Hong, T. P. (2020). Efficient Algorithm for Mining Non-Redundant High-Utility Association Rules. *Sensors*, 20, 1078.

[18] Rathore, P., Kumar, D., Rajasegarar, S., Palaniswami, M., Bezdek, J. C. (2019). A Scalable Framework for Trajectory Prediction. *IEEE Trans. Intell. Transp. Syst*., 20, 3860–3874.

[19] Ariffin, S. H., Abd, N. N. N., Ghazali, N. E. (2013). Mobility prediction via Markov model in LTE femtocell. *Int. J. Comput. Appl.* 65, 40–44.

[20] Abu-Ghazaleh, H., Alfa, A. S. (2010). Application of Mobility Prediction in Wireless Networks Using Markov Renewal Theory. *IEEE Trans. Veh. Technol.* 59, 788–802.

[21] Qiao, S., Shen, D., Wang, X., Han, N., Zhu, W. (2015). A Self-Adaptive Parameter Selection Trajectory Prediction Approach via Hidden Markov Models. *IEEE Trans. Intell. Transp. Syst.* 2015, 16, 284–296.

[22] Qiao, Y., Si, Z., Zhang, Y., Abdesslem, F. B., Zhang, X., Yang, J. (2018). A hybrid Markov-based model for human mobility prediction. *Neurocomputing* 278, 99–109.

[23] Yan, M., Li, S., Chan, C. A., Shen, Y., Yu, Y. (2021). Mobility Prediction Using a Weighted Markov Model Based on Mobile User Classification. *Sensors* 21, 1740.

[24] Wang, X., Jiang, X., Chen, L., Wu, Y. (2018). KVLMM: A Trajectory Prediction Method Based on a Variable-Order Markov Model with Kernel Smoothing. *IEEE Access,* 6, 25200–25208.

[25] Liao, J., Liu, T., Liu, M., Wang, J., Wang, Y., Sun, H. (2018). Multi Context Integrated Deep Neural Network Model for Next Location Prediction. *IEEE Access* 6, 21980–21990.

[26] Tang, C., Chen, J., Tomizuka, M. (2019). Adaptive Probabilistic Vehicle Trajectory Prediction through Physically Feasible Bayesian Recurrent Neural Network. *In: Proceedings of the International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada,* 20–24 May p. 3846–3852.

[27] Saputra, R., Suprapto, A., Sihabuddin. (2024). Mobility Prediction Using Markov Models: A Survey, 2024 7th International Conference on Informatics and Computational Sciences (ICICoS), *Semarang, Indonesia*, p. 508-513.

[28] Çifçi, E., Göktürk, M. (2022). Predictivity of Category Based Human Navigation and the Effect of Navigation Path Length on the Prediction Accuracy in Knowledge Networks," *International Conference on Communications, Information, Electronic and Energy Systems (CIEES), Veliko Tarnovo, Bulgaria,* p. 1-6.

[29] Awad Issa Khalil, M. (2012). Prediction of User's Web-Browsing Behavior: Application of Markov Model, March 2012 IEEE transactions on systems, man, and cybernetics. Part B, Cybernetics: a publication of the *IEEE Systems, Man, and Cybernetics Society* 42(4).