

# Advancing Database Mining: Integrative Approaches of Machine & Deep Learning for Sequential Pattern Analysis

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## Abstract

*In the vast expanse of data science, database mining has secured itself as an essential thread, allowing organizations to weave patterns amidst billows of bytes. This study examines the combination of machine learning and deep learning methods for heavy-duty sequential pattern discovery in database mining applications. The first targets are to investigate whether it is more efficient to extract sequential patterns using hybrid frameworks combining traditional machine learning algorithms with other deep learning architectures, detect suitable methods for developing efficient hybrid frameworks for SP extraction, and evaluate effectiveness against efficiency in different database environments. I applied a mixed-methods research design using secondary data analysis from benchmark databases including UCI Machine Learning Repository datasets. Finally, we propose that such integrative approaches (using ML preprocessing pipeline for data preparation and DL for pattern recognition) can provide better accuracy comparing to DL alone approaches. Using the hybrid Long Short-Term Memory networks combined with Random Forest preprocessing, results show sequential pattern detection accuracy of 94.7%, a 12.3% improvement compared to using Long Short-Term Memory networks and Random Forest alone. Explains how attention mechanisms improve recognition of patterns in sequences over time. It is concluded that combinational machine and deep learning frameworks are the best way forward for enhancing the database mining of sequential pattern analysis applied settings.*

**Keywords:** Database Mining, Sequential Pattern Analysis, Machine Learning, Deep Learning, Hybrid Algorithms

## 1. Introduction

The rapid digitalization of every living aspect has resulted in an overwhelming increase of information, which has much-altered the way of finding knowledge by organizations. Specifically, we define Data Mining, also known as knowledge discovery in databases, is a computer based process of discovering patterns in large datasets including technique at the

intersection of artificial intelligence, machine learning, statistic, and database (Han et al.2012) to identify patterns, associations, or anomalies in the data (to predict outcomes). The journey from basic statistical approaches to advanced computing ones has allowed researchers and practitioners to discover useful sequential patterns from complex temporal databases that were too complicated to analyze before. Sequential pattern mining deals with the task of finding all sequential subsequences that appear frequently in a sequence database. This area is especially important for applications such as predicting customer behaviour and market basket analysis, as well as genomic sequence analysis and network intrusion detection (Fournier-Viger et al., 2017). The complexity of sequential data with its temporal dependencies, variable-length sequences, and high dimensionality requires a sophisticated computational methodology with the ability to model both local and global patterns in the data structure.

The field of pattern recognition in database mining applications has been dominated by machine learning for the longest time. Decision Trees, Support Vector Machines and ensemble methods have been quite effective in classification and clustering problems (Witten et al., 2016). But the conventional machine-learning methodology relied heavily on feature engineering and may find difficulty in capturing long-range dependencies that exist in sequential data. One of the major bottlenecks that hampers their scalability and generalization to different application domains is having to manually extract relevant features from raw sequential data. Deep learning has become a game-changer for many of the shortcomings of traditional machine learning. Introduction Recurrent neural networks and their more advanced architectures like the Long Short-Term Memory networks and the Gated Recurrent Units, have an inherent ability to model sequential dependencies without the need for elaborate feature engineering(LeCun et al., 2015). For example, convolutional neural networks have also shown that layered features can be extracted from structured data. Deep learning architectures hold strong benefits for sequential pattern analysis in complex databases due to their automatic feature learning capability.

A machine learning or deep learning-based approach is a relatively new frontier for database mining

research. The sequential data analysis community has recently leveraged the representational power of deep learning with hybrid frameworks incorporating both deep learning and traditional machine learning which exploit the interpretability and computational efficiency of traditional methods (Zhang et al., 2019). These integrative approaches can potentially integrate preprocessing and dimensionality reduction based on machine learning, with advanced recognition of patterns based on deep neural architectures. So, To sum up again, this research is a part one as foundational systematized evaluation of integrative machine and deep learning methods for sequential pattern analysis have become more pressing. Combining these methodological paradigms can make the pattern discovery process more accurate, computationally efficient, and generalizable to different types of database mining applications.

## 2. Literature Review

The roots of sequential pattern mining originate from the seminal work of Agrawal and Srikant in 1995, which proposed the Apriori All algorithm for isolating sequential patterns from customer transaction databases. The paper introduced key ideas such as support thresholds, candidate generation, and pattern pruning, all of which are still considered in current approaches. Afterward, there are more advances such as SPADE, Prefix Span and GSP algorithms that tested the computational cost but durable discovery of accuracy (Zaki, 2001). Over the last twenty years, the use of machine learning and other applications of data mining in the database have grown significantly. The use of Random Forests introduced by Breiman (2001) marked the advent of ensemble methods as potent classifiers of patterns in high-dimensional spaces. Its capability of managing missing values, delivering feature importance rankings and being disliked for overfitting made it very appropriate for database mining applications. As formalized by Cortes and Vapnik (1995), support vector machines have been shown to be powerful for binary and multiclass classification (auto\_2018), especially when combined with kernels.

The wave of deep learning that began from Krizhevsky et al. Among the works that have revolutionized the way we compute pattern recognition is (2012). The success of their ImageNet classification showed that deep convolutional networks can learn hierarchical feature representations that go beyond hand-engineered features. This discovery launched a flurry of deep learning research in areas such as natural language processing, speech recognition, and sequential data processing. Since Hochreiter and Schmidhuber introduced Long Short-Term Memory networks

(1997), recurrent neural network architectures, tailored for sequential data, have undergone a rapid evolution. LSTM architectures solve the vanishing gradient problem that affected previously designed recurrent networks, allowing LSTMs to learn long-range dependencies in sequence data. Cho et al. In 2014 they proposed Gated Recurrent Units, which were shown to be as performant as LSTMs for sequence based tasks while being easier to compute. Deep learning to database mining generates a lot of research. Mikolov et al. Neural network language models were shown by (2013) to distribute representations that reflect semantic relationships in natural sequential text data. Following their word2vec approach, research on embedding-based representations for various forms of sequential data became widespread. Vaswani et al. Attention Is All You Need (2017) presented the Transformer architecture and showed that attention only can reach state-of-the-art performance for sequence transduction problems without using recurrence.

A new productive line of research is hybrid approaches with machine learning and deep learning. XGBoost A Scalable Tree Boosting System Chen and Guestrin (2016) proposed XGBoost, a scalable gradient boosting framework, that has been used together with neural network architectures to improve prediction nervousness. Research by Zhang et al. Traditional machine learning algorithms have been previously shown to improve deep learning performance over sequential classification tasks (2019) by reducing noise and dimensionality in the data. With the ubiquitous data of networks recently, graph neural networks have shifted the paradigms of sequential pattern analysis to network data structures. In data-scarce environments, transfer learning methods have shown promise in enhancing sequential patterns. The work of Howard and Ruder (2018) demonstrated that pretrained language models can be fine-tuned to a downstream classification task with a few labelled examples, which suggests that similar approaches may be possible for mining databases. Having access to such a tremendous amount of knowledge by means of large-scale pretraining is a major benefit for niche domains such as sequential pattern analysis.

## 3. Objectives

1. To evaluate the comparative performance accuracy of traditional machine learning algorithms versus deep learning architectures in sequential pattern detection within benchmark databases.
2. To identify and develop optimal hybrid frameworks integrating machine learning preprocessing with deep learning pattern recognition for enhanced sequential analysis.

3. To assess computational efficiency metrics including training time, inference speed, and memory utilization across integrative approaches for database mining applications.
4. To examine the generalization capability of integrative machine and deep learning models across diverse sequential pattern analysis domains and database structures.

#### 4. Methodology

This research is quantitative and related to the analysis of data using secondary data analysis and computational experimentation conducted in the course of this research, to discover integrative sequential pattern analysis approaches in database mining. This work is based on comparative experiments with different machine learning and deep learning setups on widely used benchmark datasets, allowing for a systematic assessment of algorithm performance under identical application conditions. This sample consists of five benchmark datasets sourced from the UCI Machine Learning Repository and Kaggle open data platform, picked due to the prominence of use in sequential pattern mining literature and the presence of ground truth labels for evaluating accuracy. These datasets include: the Online Retail Dataset with 541,909 transaction records, the MSNBC Anonymous Web Data with 989,818 sequential page visits, the Retail Market Basket Data with 88,163 transactions, the E-commerce Behavior dataset with 285,129 customer sequences and the Web Log Sequential Data with 149,639 session records. These datasets contain various characteristics of sequential patterns on sequence lengths, vocabularies and temporal granularities span from trivial to real-world database mining relevant applications.

The experimental tools include the well-known machine learning libraries Scikit-learn 1.2.0 for

classical algorithms, Tensor Flow 2.11.0 and PyTorch 1.13.0 for deep learning implementations, and MLxtend for sequential pattern mining utilities. In order to obtain reproducible timings, all computational experiments were performed in a standardized hardware environment consisting of a NVIDIA Tesla V100 GPU (32GB mem.), a Intel Xeon processor and 128GB RAM. Hyperparameter tuning using grid search with 5-fold cross-validation based on established best practices was performed across all implementations. The data preprocessing techniques performed were sequence tokenization, padding (to make the sequences of equal length), and finally the split of training, testing, and validation sets using the proportions of 70–15–15. Machine learning baselines utilize n-grams, sequence length, and frequency-based transformations as feature engineering. Neural-network models use embedding layers to learn features automatically from the non-vectorized raw sequential inputs. An overview of the analytical framework<sup>3</sup>The analytical framework makes use of the following metrics and measures: accuracy, precision, recall, F1-score and area under the receiver operating characteristic curve as evaluation metrics; training time, and inference latency as efficiency measures. To assess whether performance differences between algorithmic approaches are statistically significant, we apply paired t-tests and Wilcoxon signed-rank tests at alpha level 0.05.

#### 5. Results

Through experimental evaluation, ample performance metrics are provided for machine learning, deep learning, and the hybrid integrative approaches for sequential pattern analysis. Presentation of results through methodical analysis in tabular format with statistical interpretation of results.

**Table 1: Classification Accuracy Comparison Across Algorithmic Approaches**

Algorithm	Online Retail	MSNBC Web	Market Basket	E-commerce	Web Log	Mean
Random Forest	81.2%	78.4%	79.8%	80.1%	77.9%	79.5%
SVM	76.8%	74.2%	75.6%	77.3%	73.8%	75.5%
XGBoost	83.4%	80.7%	82.1%	81.9%	79.6%	81.5%
LSTM	89.7%	86.3%	88.4%	87.8%	85.9%	87.6%
GRU	88.9%	85.7%	87.6%	87.2%	85.1%	86.9%
Hybrid RF-LSTM	94.7%	91.8%	93.2%	92.6%	90.4%	92.5%

For each of six algorithmic configurations, Table 1 provides classification accuracy on five benchmark datasets. Hybrid RF-LSTM achieved the best performance with mean accuracy of 92.5%, 12.3% better than Random Forest alone, and 4.9% higher than LSTM alone. Statistical analysis indicates

significance at  $p < 0.001$  for hybrid versus non-hybrid comparisons For the integrative approach, the Online Retail dataset gave the best accuracy at 94.7%, due to its relatively clear sequential transaction patterns, which make it suitable for combined feature engineering and deep pattern recognition.

**Table 2: Precision, Recall, and F1-Score Performance Metrics**

Algorithm	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.782	0.768	0.775	0.847
SVM	0.741	0.729	0.735	0.812
XGBoost	0.804	0.791	0.797	0.869
LSTM	0.863	0.851	0.857	0.924
GRU	0.854	0.842	0.848	0.918
Hybrid RF-LSTM	0.918	0.907	0.912	0.967

Table 2 shows overall classification metrics averaged against all experimental datasets. This Hybrid RF-LSTM setup achieved an F1-score of 0.912 – indicative of an appropriate balance between precision and recall required for effective practical applications in database mining. An AUC-ROC value of 0.967 indicates an excellent ability to discriminate the two

classes for sequential pattern classification. These precision increases – ~ 5.5% when compared with LSTM only continue to suggest that Random Forest preprocessing provides a means of reducing false positives, either through better feature selection or noise reduction procedures.

**Table 3: Computational Efficiency Metrics**

Algorithm	Training Time (min)	Inference Time (ms)	Memory Usage (GB)	Parameters
Random Forest	12.4	2.3	4.2	847,293
SVM	28.7	4.8	6.8	412,847
XGBoost	15.6	2.8	5.1	923,184
LSTM	67.3	8.4	12.7	2,847,296
GRU	54.2	7.1	10.4	2,134,472
Hybrid RF-LSTM	71.8	9.7	14.2	3,128,489

Table 3 summarizes the computational resource requirements for each of the algorithmic approaches. It takes 71.8 minutes to train the Hybrid RF-LSTM which is modest 6.7% overhead compared to training standalone LSTM as no extra stages in preprocessing was involved. Its 9.7 ms inference latency is still reasonable for real time applications. The mem usage

of 14.2 GB depicts the size of the merged model parameters, but there is a possibility to implement batching efficiently in practice The hybrid approaches are justifiable on account of their significant accuracy gains illustrated in prior analyses at the expense of extra computational overheads.

**Table 4: Performance Across Varying Sequence Lengths**

Sequence Length	RF Accuracy	LSTM Accuracy	Hybrid Accuracy	Improvement
Short (1-10)	84.2%	82.7%	91.3%	7.1%
Medium (11-50)	79.8%	87.4%	93.8%	6.4%
Long (51-100)	72.4%	89.2%	94.6%	5.4%
Very Long (>100)	68.1%	88.7%	93.2%	4.5%

Table 4 shows algorithm performance based on input sequence length categories Accuracy decays from 84.2% at short sequences to 68.1% at very long sequences due to the Vanishing Gradient Problem. Random Forest was shown to be limited in learning long temporal dependencies. In contrast, LSTM consistently among length groups owing to its

recurrent structure. Hybrid approach delivers close-to perfect performance on all categories utilizing maximum accuracy of 94.6% (for long sequences), implying that significant synergy is achieved using a combination of feature preprocessing at the top-level and deep sequential modeling in the body of the pipeline.

**Table 5: Cross-Domain Generalization Performance**

Training Domain	Testing Domain	RF Transfer	LSTM Transfer	Hybrid Transfer
Retail	E-commerce	71.4%	79.8%	86.3%
Web Logs	MSNBC	68.7%	77.2%	84.1%
E-commerce	Retail	73.2%	81.4%	87.8%

MSNBC	Web Logs	67.9%	76.8%	83.6%
Market Basket	Retail	74.8%	82.1%	88.4%

Cross-domain generalization is subsequently evaluated, with the transfer learning experiments presented in table 5 where models trained in one dataset are evaluated on other domains. This Hybrid RF-LSTM achieves better generalization, maintaining transfer accuracy between 83.6% and 88.4%, which is 6–8 percentage points higher than any standalone

approach. But most importantly, these findings demonstrate integrative preprocessing makes model robustness to domain shift, which is a key consideration for practical organelle proteomic database mining that must work across heterogeneous data sources.

**Table 6: Ablation Study of Hybrid Architecture Components**

Configuration	Accuracy	F1-Score	Training Time
LSTM Only	87.6%	0.857	67.3 min
RF Preprocessing + LSTM	92.5%	0.912	71.8 min
PCA Preprocessing + LSTM	88.4%	0.869	64.2 min
RF + Attention LSTM	94.1%	0.928	78.4 min
RF + Bidirectional LSTM	93.7%	0.921	82.6 min
Full Hybrid (RF + Attention BiLSTM)	95.2%	0.941	89.3 min

In Table 6, we conduct ablation analysis to isolate the contributions of individual architectural components in hybrid frameworks. Preprocessing with Random Forest yields 4.9% better accuracy than baseline LSTM, a significant contrast to PCA preprocessing gains of 0.8%. The attention mechanism helps further by improving it by 1.6%, by only attending to the relevant parts of the input sequence. The hyper-performance embedding fusion of RF preprocessing with attention-based bidirectional LSTM yields the highest peak accuracy (95.2%) and F1 of 0.941, and thus confers the best-fit integrative architecture for the sequential pattern analysis in database mining.

## 6. Discussion

The experimental results in this work show that integrative machine learning and deep learning methods may be useful for promoting sequential pattern analysis for database mining applications. As a result, the systematic evaluations on multiple benchmark datasets, algorithmic configurations, and performance metrics allows more nuanced interpretations of the results with implications for both theorizing and practical implementations. Hybrids RF-LSTM architectures outperformed standalone LSTM (mean 87.6%) and isolated Random Forest (mean 79.5%) by substantial margins (92.5% mean accuracy), confirming the main hypothesis that the integrative approaches provide better pattern recognition ability. This result corroborates theoretical assumptions about the complementary nature of the preprocessing role of the machine learning models and the pattern extraction role of the deep learning models (Chen & Guestrin, 2016). Random Forest preprocessing seems to also help by performing

important tasks such as feature selection, noise removal and dimensionality reduction that prepare the sequential data for a lower-dimensional and easier deep learning process. The hybrid approaches show some very interesting features when we look at the precision-recall analysis. This does 5.5% better than using an LSTM alone, which suggests that the preprocessing with machine learning is successful in filtering out spurious patterns that could contribute to false positive classifications. This improvement has a considerable practical impact in database mining applications since that precision has a direct bearing on expenditure of resources and downstream analytical validity. The balanced F1-score of 0.912 shows that improving precision does not compromise on recall performance, this ensures a good ability to capture patterns.

Mechanistic basis of integration sequence length analysis provides insights into complementary functioning of integrated approaches. Expectedly, machine learning algorithms would perform worse with longer sequence runs after a certain length, not due to the temporal trend necessarily, but because traditional algorithms are not as well-honed to model large explicit temporal dependencies without explicit recurrent mechanisms (Witten et al., 2016). While deep learning architectures are still fairly invariant to the sequence length due to recurrent processing, they may not efficiently leverage local features in shorter sequences. Our hybrid approach delivers best-of-both-worlds performance by utilizing machine learning to extract local features and deep learning to model global sequential information. These cross-domain generalization experiments are a key contribution with important real-world impact.

Arbitrary application of database mining solutions to any given database can be invalidated by the real structural and domain differences among the vast majority of database sources due to the nature of model deployment in practice [29]. An shown 6-8 percent point generalization edge of hybrid approaches over standalone solutions translates to number of domain shift-resistant nature which makes retraining less complicated and deployment extra versatile. This result indicates that the domain-invariant features selected by machine learning preprocessing contribute to generalization ability in deep learning.

Analysis of computational efficiency shows that hybrid approaches have a small overhead with respect to the performance benefits they provide. A 6.7% increase is acceptable in training time in comparison to baseline LSTM due to the 4.9% increase in accuracy: Nonetheless, it is not a dealbreaker. Real-time applicability for interactive database mining systems is maintained with an inference latency of 9.7 milliseconds. All these efficiency traits lend to allowing for practical deployment across various application domains from high-throughput transaction processing to real-time behavioral profiling systems. The ablation study serves as architectural guidance for integrative approaches designing. The large performance gain of Random Forest preprocessing over PCA alternatives suggests that ensemble-based feature selection provides benefits beyond dimensionality reduction. They provide a complementarity like enhancement through an adaptive use of an attention mechanism on sequentially relevant components, in line with theoretical approaches that describe selective processing acting on complex patterns (Vaswani et al., 2017). The best performing full hybrid model with RF pre-processing and attention-augmented bidirectional LSTM provides an architectural framework to derive optimal value from sequential data.

There are some limitations of this work that need to be acknowledged and could be investigated in future work. While the use of benchmark datasets facilitates a standard comparison, it may not adequately capture the data richness and noise nature of production database environment. Understanding these lessons is important, but should be investigated further as, to date, the majority of the data presented has come from scientific studies and research that focused on ideal and experimental set-ups rather than real-world deployments. Future investigations should replicate studies through industry relevant case studies with real-world deployment constraints. In addition, the study presented here addressed supervised sequential pattern classification, but unsupervised and semi-supervised variants also deserve evaluation in the

case of an unavailability of labeled data. This research contributes to the increasingly diverse landscape of how algorithms can be integrated for mining applications directly on a database. The variety of synergies between machine learning and deep learning approaches demonstrated so far highlight some excellent opportunities for further research on how we can best combine these approaches, whether adaptively, mechanistically or through domain adaptation. These performance baselines and architectural guidelines, give practitioners a baseline they could build from as they implement their own advanced sequential pattern analysis systems.

## 7. Conclusion

This study has contributed systematically to the integrative methods for database mining applications involving sequential patterns using machine learning and deep learning approaches. Through the experimental evaluation over five benchmark datasets, we show that hybrid RF-LSTM architectures yield 92.5% mean classification accuracy which are significant gains of 12.3% over stand-alone Random Forest and 4.9% over stand-alone LSTM networks. Performance analysis confirmed that ensemble machine learning methods which enact integrative preprocessing of sequential data allows for more effective low dimensional embedding helping with deep learning pattern formation; yielding well balanced precision-recall characteristics F1-score of 0.912. Hybrid methods are significantly more robust to domain shift, providing 83-88% transfer accuracy compared to 67-82% for the non-integrated option, evident in cross-domain generalization experiments. After performing ablation analysis, we found that bidirectional LSTM with attention on top of Random Forest output as preprocessing gives the best results, reaching an accuracy of 95.2%. Despite the heavy training overhead (6.7%) and an extremely limited inference latency (under 10 milliseconds), its computational efficiency is still practical for deployment. This evidence demonstrates that integrative machine and deep learning frameworks are the most efficient methodological choice for advancing database mining in sequential pattern analysis, offering both theoretical contributions to the field of algorithms integration research and practical guidance to apply in real life applications.

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