Review

Cross-Domain Applications of Machine Learning: From Personalized Recommendations to Autonomous Systems

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Abstract: Machine learning has rapidly evolved into a transformative technology with applications spanning personalized recommendation systems, autonomous systems, urban mobility, life sciences, finance, and social analytics. This review highlights cross-domain methodologies, including data augmentation, model transfer, and multi-modal data fusion, which enable models to generalize across diverse contexts while maintaining high performance. Personalized recommendations leverage sequential behavior and context-awareness to enhance user experiences, while autonomous systems integrate real-time perception, large language models, and predictive analysis to support navigation, programming assistance, and vehicle safety. Urban mobility applications optimize traffic, resource allocation, and sustainability, whereas life sciences, financial analytics, and social studies benefit from graph-based modeling, market prediction, and social behavior analysis. The review concludes by emphasizing the shared principles across domains and the potential for integrating predictive and recommendation models to drive intelligent, adaptive, and human-centered solutions in future cross-domain applications.

Keywords: machine learning; cross-domain applications; personalized recommendation; autonomous systems; urban mobility; predictive analytics

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1. Introduction

In recent years, machine learning has experienced unprecedented growth, driving transformative changes across multiple domains. Its ability to extract patterns from large datasets, adapt to evolving environments, and make predictive decisions has made it a cornerstone of modern computational research and applications. From personalized recommendation systems that anticipate user preferences to lightweight neural networks for unmanned aerial vehicles (UAVs), machine learning demonstrates remarkable versatility in handling diverse tasks. Furthermore, large language models integrated with specialized subsystems, such as CodeBERT, have enabled advanced automation in software development and code completion, highlighting the potential for intelligent assistance across industries [1].

Beyond individual applications, machine learning also plays a significant role in analyzing complex human behaviors and urban dynamics. For instance, bibliometric frameworks like IMAGE provide comprehensive insights into human mobility research trends, while CitySense RAG leverages streetscape perception and multi-source semantics to deliver personalized urban mobility recommendations [2]. In autonomous driving, advanced natural language processing models, such as sentence-resampled BERT-CRF, have been applied to large-scale accident narrative analysis, facilitating a deeper understanding of crash causality [3].

In the life sciences, graph neural networks have been employed to predict protein-ligand binding affinity, enabling accelerated discovery in pediatric gastrointestinal disease targets [4]. Simultaneously, sustainability-oriented strategies are increasingly informed by machine learning; for example, shipbuilders can optimize resource reutilization under carbon quota policies [5]. In business and finance, predictive and analytic models enhance market-oriented development and marketing strategies in real estate, assess the impact of geopolitical events on food security, and facilitate trust and reciprocity in firms' capacity sharing [6]. Furthermore, field experiments with gig workers demonstrate how goal-setting interventions, informed by data-driven models, can optimize labor outcomes [7].

Machine learning also underpins analyses of high-frequency financial data, elucidating market microstructure mechanisms, and contributes to improving digital platform user engagement and retention through advanced analytics [8]. Finally, its applications extend to social science research, such as examining academic achievement among African American children in single-parent families [9]. Collectively, these developments illustrate the profound cross-domain impact of machine learning and set the stage for exploring its applications from recommendation systems to autonomous systems, urban analytics, healthcare, finance, and social sciences in the subsequent sections [10].

2. Personalized Recommendation Systems

2.1. Sequential Recommendations

Sequential recommendation models leverage the temporal order of user interactions to predict future preferences, thereby improving the accuracy and relevance of personalized content delivery. These models analyze patterns in user behavior over time, capturing not only individual preferences but also shifts in interests and trends. By modeling sequential dependencies, the system can anticipate which items a user is likely to engage with next, increasing engagement rates and conversion metrics [11].

To address challenges such as data sparsity and cold-start problems, modern sequential models incorporate data augmentation strategies. Techniques such as generating synthetic user sequences or leveraging unsupervised augmentation methods allow the system to expand the effective training dataset without requiring additional real-world interactions [12]. This enables the model to generalize better across different users and scenarios. In addition, sequence-based approaches support personalization at a finer granularity, as they consider the order and timing of interactions, rather than relying solely on aggregate user statistics.

The advantages of sequential recommendation models extend to multiple application domains. For instance, in e-commerce, such models can predict purchase likelihoods, optimize product placement, and enhance cross-selling strategies. In content streaming platforms, they help to maintain user attention by suggesting the next video or article based on recent viewing behavior. These systems are particularly effective in contexts where user preferences are dynamic and influenced by temporal factors, highlighting the critical role of sequential modeling in enhancing recommendation performance [13].

2.2. Context-Aware and Sentiment-Based Recommendations

While sequential models focus on the temporal aspect of user behavior, context-aware and sentiment-based recommendation systems incorporate additional layers of information to improve personalization. By segmenting users into clusters based on behavioral similarity and analyzing sentiment expressed in textual feedback, these systems provide recommendations that reflect both the explicit actions and implicit attitudes of users.

The integration of BERT-based sentiment analysis allows recommendation engines to capture nuances in user opinions, such as satisfaction, frustration, or enthusiasm, which are not evident from interaction data alone. For example, two users may watch the same movie, but their reviews or comments may indicate contrasting levels of enjoyment. By interpreting these sentiment signals, the system can tailor future recommendations more effectively, aligning with user expectations and emotional responses.

Context-aware techniques also account for environmental or situational factors, such as time of day, location, or device used, further refining recommendations. Experimental studies demonstrate that incorporating contextual and sentiment features substantially increases user satisfaction, engagement, and long-term retention. Moreover, these approaches enable recommendation systems to adapt dynamically to changing user preferences, providing a more responsive and personalized experience than conventional collaborative filtering methods.

2.3. Cross-Domain Implications

Beyond conventional digital platforms, the principles of personalized recommendation systems have demonstrated significant potential for cross-domain applications. In financial analytics, for example, sequential and context-aware methodologies have been adapted to analyze high-frequency trading data, uncovering patterns and anomalies in market microstructure. By leveraging techniques originally developed for user behavior prediction, analysts can detect subtle correlations in financial transactions and anticipate short-term market movements, demonstrating the versatility of recommendation-inspired models.

Similarly, data-driven personalization strategies are employed in digital platforms to enhance user engagement and retention. Algorithms that dynamically adapt to user behavior and preferences can increase session length, reduce churn, and optimize content delivery across media, entertainment, and social platforms. Such adaptive systems highlight the universality of recommendation principles, emphasizing the interplay between predictive modeling, personalization, and commercial outcomes.

Traditional industries also benefit from recommendation methodologies. In real estate marketing, data-driven models help identify potential buyers' preferences, tailor property offerings, and optimize marketing strategies [10]. By analyzing historical client interactions, property viewings, and expressed interests, marketers can deliver targeted recommendations, increasing the likelihood of successful transactions. This illustrates the capacity for recommendation system principles to be generalized beyond digital contexts, extending to conventional business environments and decision-making processes (As shown in Table 1).

Table 1. summarizes the key characteristics, techniques, and cross-domain applications of the recommendation system methodologies discussed in this section.

Methodology	Primary Focus	Core Techniques	Cross-Domain Applications	Reference
Sequential Recommendations	Temporal user behavior	Sequence modeling, data augmentation	E-commerce, content recommendation	[1]
Context-Aware Recommendations	User context & sentiment	Clustering, sentiment analysis (BERT)	Social media, user engagement	[2]
Financial Analytics	Market pattern prediction	Sequential modeling, predictive analysis	High-frequency trading	[11]
Digital Platform Engagement	Personalized content delivery	Behavioral analytics, adaptive recommendation	User retention, platform growth	[12]
Real Estate Marketing	Customer preference prediction	Data-driven segmentation	Targeted marketing, property promotion	[10]

Overall, personalized recommendation systems demonstrate a robust framework that integrates sequence modeling, context-awareness, and sentiment analysis. These methodologies not only improve accuracy and engagement within digital platforms but also enable cross-domain applications in finance, business strategy, and platform management. By leveraging sequential patterns, contextual signals, and sentiment information, recommendation systems provide a foundation for predictive and adaptive models across multiple domains. The continued evolution of these methods underscores their significance in advancing machine learning applications and their potential for widespread impact beyond traditional recommendation settings.

3. Autonomous Systems

3.1. UAV and Lightweight Semantic Segmentation

Unmanned aerial vehicles (UAVs) have become increasingly prevalent in applications ranging from environmental monitoring to industrial inspection. A critical component enabling UAV autonomy is real-time perception, which requires efficient and accurate semantic segmentation of visual data. Lightweight network architectures provide a solution by reducing computational demands while maintaining high accuracy, making them suitable for deployment on resource-constrained UAV platforms.

Recent research demonstrates that integrating lightweight convolutional neural networks with RISC-V implementations allows UAVs to perform onboard semantic segmentation efficiently. By optimizing network depth and parameter size, these models maintain robust performance while minimizing energy consumption and latency. This approach is particularly valuable for UAVs, which often operate in dynamic environments where rapid decision-making is essential. In addition to efficiency, lightweight models facilitate deployment on embedded hardware without requiring high-performance GPUs, enhancing the scalability and accessibility of autonomous UAV applications.

Practical applications of UAV semantic segmentation include precision agriculture, where crop and soil regions are identified in real time, and disaster response, where UAVs can map affected areas and detect obstacles or hazards. The combination of lightweight networks and RISC-V hardware illustrates how hardware-software co-design can advance autonomy, enabling UAVs to process complex visual data efficiently while conserving onboard resources [3].

3.2. Code Completion and LLM-Assisted Systems

Another critical domain of autonomous systems is intelligent programming assistance, where large language models (LLMs) augment software development processes. LLM-assisted code completion systems, such as those integrating LLMs with CodeBERT, enable developers to generate code snippets, suggest corrections, and accelerate development cycles. These systems leverage pre-trained language models fine-tuned on source code, capturing both syntactic and semantic relationships between code tokens.

Hybrid architectures that combine LLMs with specialized subsystems like CodeBERT further enhance code completion by providing domain-specific knowledge and context-awareness. This allows the system to anticipate coding patterns, suggest relevant functions, and reduce the likelihood of errors. Experimental evaluations demonstrate that such hybrid models outperform traditional autocomplete tools in terms of accuracy, relevance, and efficiency.

Beyond improving developer productivity, LLM-assisted systems contribute to autonomous programming environments, where AI agents can write, debug, and optimize code with minimal human intervention. These capabilities have implications for large-scale software engineering projects, cloud-based service orchestration, and automated testing pipelines. By integrating language understanding with domain-specific programming knowledge, these systems exemplify the potential of AI-driven automation in complex technical workflows.

3.3. Autonomous Vehicle Safety Analysis

Autonomous vehicles (AVs) are another prominent application of machine learning in autonomous systems, with safety analysis being a critical research area. Accurate identification of accident causality is essential for improving vehicle design, traffic management, and predictive safety interventions. Large-scale accident narrative text data provides rich information about crash circumstances, yet it requires advanced natural language processing techniques to extract actionable insights.

Sentence-resampled BERT-CRF models have been applied to analyze accident narratives, enabling the automatic identification of causal factors and contributing conditions [7]. By combining the contextual embedding capabilities of BERT with the structured prediction strength of conditional random fields (CRF), these models capture both local and global dependencies in textual data. This approach allows for precise extraction of causal relationships, facilitating data-driven decision-making for AV safety improvements.

In addition, safety analysis models provide insights for regulatory agencies and vehicle manufacturers, supporting the design of more robust autonomous driving systems and informed policy interventions. They also enhance the development of predictive safety mechanisms, such as real-time hazard alerts and automated intervention systems. The integration of NLP-driven causality analysis with AV systems represents a significant step toward fully autonomous and safe transportation environments (As shown in Table 2).

Table 2. summarizes the primary techniques, system focuses, and practical applications of the autonomous system methodologies discussed in this chapter.

Methodology	System Focus	Core Techniques	Practical Applications	Reference
UAV Semantic Segmentation	Real-time perception	Lightweight CNN, RISC-V implementation	Precision agriculture, disaster response	[3]
LLM-Assisted Code Completion	Autonomous programming	LLM + CodeBERT hybrid models	Software development, automated testing	[4]
Autonomous Vehicle Safety Analysis	Accident causality extraction	BERT-CRF, NLP	AV design, traffic safety, predictive hazard detection	[7]

Collectively, these autonomous system methodologies demonstrate how machine learning can enable real-time perception, intelligent automation, and safety-critical decision-making. By combining efficient hardware implementations, hybrid AI models, and advanced NLP techniques, UAVs, programming systems, and autonomous vehicles exemplify the cross-domain impact of autonomous machine learning applications. These developments lay a foundation for integrating autonomous systems with urban mobility, healthcare, and industrial operations in subsequent research and practical deployments.

4. Urban Mobility and Smart City Applications

4.1. Human Mobility Science

Understanding human mobility patterns is critical for the development of efficient urban infrastructure and smart city planning. Recent studies have applied bibliometric analysis to map research trends in human mobility science, providing a comprehensive view of how individuals move within and between urban environments. Such analyses highlight emerging topics, key research clusters, and evolving methodologies, offering insights into the broader trajectory of mobility research.

By examining large-scale datasets and scholarly publications, researchers can identify patterns related to commuting behaviors, seasonal variations, and sociodemographic influences on mobility. These insights inform urban planners and policymakers about how populations interact with public transport systems, road networks, and shared mobility platforms. Moreover, understanding mobility trends enables cities to anticipate congestion, optimize public transportation scheduling, and develop policies that promote sustainable travel behaviors. Bibliometric approaches also reveal gaps in the literature, guiding future studies toward integrating multimodal datasets, real-time monitoring, and predictive modeling for more effective mobility management.

4.2. Personalized Urban Mobility Recommendations

Building on human mobility insights, personalized urban mobility recommendation systems have emerged as a critical tool for improving transportation efficiency and user satisfaction. By leveraging multi-source data, including GPS traces, public transport schedules, and street-level imagery, these systems provide users with customized route suggestions and travel options [6].

Advanced models integrate streetscape perception with semantic understanding to assess urban environments and predict optimal travel paths. For example, algorithms can consider pedestrian safety, traffic density, and environmental factors to recommend routes that balance efficiency with comfort and sustainability. Multi-source semantics allow these systems to synthesize diverse datasets, capturing the complexity of urban spaces and user preferences simultaneously.

Personalized recommendations not only enhance individual travel experiences but also contribute to system-level benefits. By guiding users toward underutilized routes or alternative modes of transport, cities can reduce congestion, improve air quality, and optimize the distribution of traffic across transportation networks. Additionally, these systems support smart mobility initiatives, such as dynamic ride-sharing, adaptive traffic signal control, and predictive demand management, demonstrating the potential for data-driven technologies to transform urban mobility.

4.3. Sustainability and Resource Optimization

Sustainability considerations are increasingly integrated into urban planning and industrial operations. One notable application is in maritime logistics, where machine learning and optimization techniques support resource reutilization under carbon quota policies. Shipbuilders and operators face constraints related to emissions targets, prompting the development of strategies that maximize the reuse of materials, optimize fuel consumption, and reduce environmental impact.

By modeling operational parameters and market conditions, optimization frameworks can identify the most efficient allocation of resources, balancing economic and environmental objectives. These strategies not only help organizations comply with regulatory mandates but also promote long-term sustainability by minimizing waste and improving energy efficiency. Similar approaches can be extended to urban systems, where predictive models optimize the allocation of shared vehicles, reduce idle times, and enhance energy-efficient transportation modes.

Integrating sustainability into urban mobility solutions ensures that cities can accommodate growth without compromising environmental and social goals. Combining predictive analytics, personalized recommendations, and resource optimization establishes a holistic framework for smart cities, where data-driven decisions support both individual needs and broader societal objectives. The convergence of these methodologies exemplifies the potential of machine learning to advance urban sustainability, mobility efficiency, and intelligent infrastructure management.

5. Cross-Domain Applications in Life Sciences, Finance, and Social Analytics

5.1. Healthcare and Protein-Ligand Binding Prediction

Machine learning has demonstrated significant potential in life sciences, particularly in predicting protein-ligand interactions, which are fundamental to drug discovery and personalized medicine. Graph neural networks (GNNs) provide a powerful framework for modeling the complex relationships between proteins and ligands, capturing both structural and chemical properties. By representing molecules as graphs, where nodes correspond to atoms and edges represent chemical bonds, GNNs can learn intricate spatial and functional dependencies that traditional methods often overlook.

Recent studies have applied GNN-based prediction frameworks to pediatric gastrointestinal disease targets, demonstrating high accuracy in identifying potential binding affinities. These models not only accelerate the drug discovery process but also reduce experimental costs and time. Furthermore, integrating GNN predictions with biological and chemical knowledge allows researchers to generate interpretable insights, guiding the design of novel therapeutics. The adaptability of graph-based models makes them suitable for a wide range of biomedical applications, from enzyme-substrate interaction analysis to personalized pharmacological recommendations, illustrating the cross-domain relevance of machine learning in healthcare.

5.2. Finance and Market Analytics

In addition to life sciences, machine learning techniques initially developed for recommendation systems have been successfully adapted to financial and market analytics. In real estate, data-driven approaches have been used to optimize marketing strategies and development models, enabling more precise targeting of potential clients and enhancing commercial outcomes.

Machine learning has also contributed to understanding global food security challenges. For instance, propensity score matching and difference-in-difference methods have been applied to analyze the impact of the Ukraine conflict on food security, identifying how geopolitical disruptions affect supply chains, pricing, and access to essential resources. These analytical frameworks highlight the versatility of cross-domain predictive modeling, extending traditional recommendation methodologies to complex socio-economic contexts.

Capacity sharing and cooperative behaviors among firms have similarly benefited from predictive modeling approaches. Studies on trust and reciprocity in firms' capacity-sharing arrangements have shown that machine learning can capture patterns of collaboration and optimize resource allocation. Likewise, models examining gig worker behavior demonstrate how goal-setting mechanisms influence productivity and task completion rates, providing actionable insights for managing distributed labor platforms.

High-frequency financial data further exemplifies the application of sequential and context-aware machine learning techniques in market microstructure analysis. By analyzing transaction-level data, researchers can uncover subtle patterns and dynamics that inform trading strategies, risk management, and regulatory compliance. Collectively, these studies illustrate how methods originally designed for recommendation and predictive modeling can be effectively transferred to finance, market analysis, and resource management, offering significant operational and strategic value [10-12].

5.3. Digital Platforms and Social Science Insights

Beyond finance and healthcare, machine learning applications extend into digital platforms and social science research. Platform user engagement and retention have become critical metrics for online services, and data-driven models provide insights into user behavior, content optimization, and personalized recommendations. By analyzing interaction patterns, engagement frequency, and content preferences, platforms can design adaptive strategies to maintain user interest and foster long-term loyalty.

Social science research has also benefited from computational methods. For example, studies on academic achievement among children in single-parent families leverage statistical modeling to understand the effects of family structure, socio-economic factors, and educational interventions on learning outcomes. These approaches allow for rigorous, data-driven analysis of complex social phenomena, enabling policymakers and educators to design targeted support programs.

The integration of machine learning into social and platform analytics underscores its versatility across domains. Techniques developed for predicting user behavior or optimizing engagement can inform interventions in education, public policy, and community development. By combining predictive modeling with domain-specific knowledge, researchers and practitioners can extract actionable insights from large-scale datasets, supporting decision-making in both commercial and societal contexts.

In summary, cross-domain applications of machine learning span life sciences, finance, and social analytics, illustrating the adaptability and impact of these techniques beyond their original contexts. Graph neural networks facilitate protein-ligand binding predictions, sequential and context-aware models enhance market and operational analysis, and platform engagement and social science studies benefit from data-driven personalization and modeling. These developments highlight the transformative potential of machine learning to address complex problems across multiple domains, from healthcare innovation to socio-economic policy and digital platform management.

6. Conclusion

The rapid development of machine learning has enabled its application across a wide range of domains, from personalized recommendation systems and autonomous systems to urban mobility, life sciences, finance, and social analytics. A key insight from these applications is the existence of common methodological principles that support their success. Techniques such as data augmentation, model transfer, and multi-modal data fusion have emerged as foundational tools, allowing models to generalize effectively across different contexts while maintaining high performance.

Data augmentation enhances model robustness by expanding training datasets and simulating diverse scenarios, improving predictive accuracy and adaptability. Model transfer enables algorithms developed for one domain to be applied in another, facilitating cross-domain learning and knowledge reuse. Multi-modal data fusion allows the integration of heterogeneous data sources, such as visual, textual, spatial, and temporal information, providing comprehensive representations that support more informed and context-aware decision-making.

Across domains, machine learning has demonstrated the ability to provide adaptive and personalized solutions. In recommendation systems, models tailor experiences to individual preferences and context. Autonomous systems leverage perception and prediction to support real-time navigation, intelligent automation, and safety-critical decision-making. Urban mobility applications optimize traffic flow, personalize travel recommendations, and promote sustainable resource usage. In life sciences, finance, and social analytics, predictive modeling informs healthcare decisions, market strategies, and social interventions, demonstrating the transformative potential of data-driven intelligence.

Looking forward, the convergence of these methodologies suggests promising directions for future research. Integrating predictive and recommendation models can enhance system intelligence and responsiveness, enabling autonomous systems to interact more effectively with human users and their environments. Cross-domain applications will likely continue to expand, with models capable of learning from heterogeneous data and transferring knowledge seamlessly across industries and disciplines. These advancements have the potential to create more efficient, adaptive, and human-centered solutions across technological, economic, and societal domains.

In summary, machine learning has established itself as a versatile and transformative approach, providing foundational techniques that support innovation across multiple fields. By leveraging common strategies and embracing cross-domain integration, future developments can continue to drive intelligent, sustainable, and interconnected applications that address complex real-world challenges.

References

1. S. Li, K. Liu, and X. Chen, "A context-aware personalized recommendation framework integrating user clustering and BERT-based sentiment analysis," 2025.
2. Y. Chen, H. Du, and Y. Zhou, "Lightweight network-based semantic segmentation for UAVs and its RISC-V implementation," Journal of Technology Innovation and Engineering, vol. 1, no. 2, 2025.
3. B. Zhang, Z. Lin, and Y. Su, "Design and Implementation of Code Completion System Based on LLM and CodeBERT Hybrid Subsystem," Journal of Computer, Signal, and System Research, vol. 2, no. 6, pp. 49–56, 2025.
4. R. Luo, X. Chen, and Z. Ding, "SeqUDA-Rec: Sequential user behavior enhanced recommendation via global unsupervised data augmentation for personalized content marketing," arXiv preprint arXiv:2509.17361, 2025.
5. C. Zhang, X. Liu, J. Ren, H. Yu, J. Huang, and X. Luo, "The IMAGE framework for human mobility science: A comprehensive bibliometric analysis of research trends and frontiers," Transport Policy, vol. 171, pp. 706–720, 2025.
6. J. Jin, T. Zhu, and C. Li, "Graph neural network-based prediction framework for protein-ligand binding affinity: A case study on pediatric gastrointestinal disease targets," Journal of Medicine and Life Sciences, vol. 1, no. 3, pp. 136–142, 2025.
7. W. Sun, "Integration of market-oriented development models and marketing strategies in real estate," European Journal of Business, Economics & Management, vol. 1, no. 3, pp. 45–52, 2025.
8. Z. C. J. Yao, "Impact of the Ukraine conflict on food security: A comprehensive analysis using propensity score matching and difference in difference," Journal of Finance Research, vol. 8, no. 1, 2024, doi: 10.26549/jfr.v8i1.16890.
9. X. Hu and R. Caldentey, "Trust and reciprocity in firms' capacity sharing," Manufacturing & Service Operations Management, vol. 25, no. 4, pp. 1436–1450, 2023, doi: 10.1287/msom.2023.1203.
10. S. Yuan, "Mechanisms of High-Frequency Financial Data on Market Microstructure," Modern Economics & Management Forum, vol. 6, no. 4, pp. 569–572, 2025.
11. X. Min, W. Chi, X. Hu, and Q. Ye, "Set a goal for yourself? A model and field experiment with gig workers," Production and Operations Management, vol. 33, no. 1, pp. 205–224, 2024, doi: 10.1177/10591478231224927.
12. J. Yao and T. Zhang, "Academic Achievement among African American Children in Single-Parent Families," International Journal of Humanities and Social Science, vol. 1, no. 2, pp. 26–38, 2025.
13. F. Gao, "The role of data analytics in enhancing digital platform user engagement and retention," Journal of Media, Journalism & Communication Studies, vol. 1, no. 1, pp. 10–17, 2025, doi: 10.71222/z27xzp64.