

DineWise: AI-Powered Personalized Menu Recommendation And Dynamic Pricing System

Deekshitha Navuluri¹, Bhavya Panguluri², Phanindhr Thota³, Manoj Kumar Ambavarapu⁴,
Sai Mahesh Sandeboina⁵,

Seidenberg School of Computer Science and Information Systems

Pace University, New York, NY, USA

¹dn60422n@pace.edu, ²bp44114n@pace.edu, ³pt23858n@pace.edu, ⁴ma40457n@pace.edu,
⁵ss91507n@pace.edu

Abstract— DineWise is an AI-powered web application, which caters to restaurants with their menu items, dynamically priced in real time, considering real-time demand and user preferences. By unleashing the powers of NCF for personalized recommendation and DRL for dynamic pricing, DineWise presents a data-driven methodology that optimizes the twin objectives of user satisfaction and revenue for restaurants. The following presents the architecture of the system, machine learning methodologies, test results, and possible future enhancements that illustrate exactly how DineWise reimagines the dining experience through a preference-and-demand-personalized menu.

Keywords— AI in dining, dynamic pricing, personalized recommendations, machine learning, customer experience

I. INTRODUCTION

As the world rapidly embraces digital transformation, the dining industry is poised for a revolutionary shift to meet the evolving demands of modern customers. Traditional static menus and rigid pricing structures are becoming obsolete, as diners now seek personalized, flexible, and dynamic experiences. Restaurants that fail to adapt risk losing relevance in an increasingly competitive landscape. DineWise emerges as the ultimate solution, leveraging cutting-edge AI to deliver tailored menu recommendations and dynamic pricing that adapts to real-time demand.

DineWise combines the power of Neural Collaborative Filtering (NCF) for personalized dish suggestions and Deep Reinforcement Learning (DRL) for real-time pricing optimization. By analyzing individual customer preferences, dining history, and contextual factors, DineWise ensures that each diner receives recommendations aligned with their tastes. Simultaneously, its dynamic pricing mechanism adjusts prices based on demand patterns, ensuring profitability for restaurants while maintaining fairness and value for customers. This dual approach enhances customer satisfaction and maximizes operational efficiency for dining establishments.

With DineWise, the dining experience is transformed into a seamless blend of personalization and adaptability. Customers are presented with intuitive menu options tailored to their preferences, while restaurants benefit from optimized revenue

streams and reduced resource wastage. By addressing the shortcomings of traditional dining practices, DineWise empowers restaurants to thrive in a rapidly changing market, setting a new standard for innovation and excellence in the culinary world.

II. LITERATURE REVIEW

The existing body of literature has highlighted the effectiveness of machine learning models, particularly Neural Collaborative Filtering (NCF) and Deep Reinforcement Learning (DRL), in addressing challenges related to personalized recommendation and dynamic pricing. NCF, a state-of-the-art recommendation technique, combines the principles of collaborative filtering with the power of deep neural networks to create elastic, scalable systems capable of capturing intricate user preferences. By leveraging both user and item interaction data, NCF builds comprehensive profiles that adapt over time, delivering highly relevant and personalized suggestions. Meanwhile, DRL has emerged as a powerful tool for dynamic pricing, enabling systems to adjust prices in real time based on demand fluctuations, inventory levels, and external market conditions. Together, these models provide a robust foundation for tailoring user experiences while optimizing profitability.

Despite their proven success in domains such as e-commerce and online streaming services, these advanced AI techniques remain underutilized in the dining industry. For example, NCF has revolutionized the way platforms like Netflix and Amazon personalize content and product recommendations, while DRL has powered sophisticated pricing strategies in industries like travel and ride-sharing. However, when it comes to dining, the reliance on static menus and fixed pricing mechanisms persists, leaving a significant gap in the application of these transformative technologies. This disconnect represents a missed opportunity for the dining industry to harness AI-driven systems that could drastically improve customer engagement and operational efficiency.

The potential for AI-driven dining solutions to disrupt the traditional dining model is immense. By integrating NCF for personalized menu recommendations and DRL for real-time pricing, restaurants can move beyond the one-size-fits-all approach to deliver highly customized, adaptive experiences.

These technologies can not only elevate the customer journey by aligning offerings with individual tastes and preferences but also empower restaurants to respond dynamically to demand patterns, maximizing revenue while minimizing resource wastage. The untapped application of these proven methodologies in the dining industry marks an exciting frontier for innovation, poised to redefine the way restaurants operate and interact with their customers in the era of digital transformation.

III. CURRENT SOLUTIONS

Most restaurant management systems today offer only basic functionalities when it comes to personal recommendations and pricing flexibility. While some systems provide elementary filtering options, such as categorizing menu items based on dietary preferences or common allergens, they lack the sophistication of machine learning algorithms to deliver truly personalized recommendations. This limitation means that customer preferences are often generalized, failing to address the nuanced and dynamic expectations of individual diners. The absence of advanced personalization not only hampers the customer experience but also leaves restaurants at a competitive disadvantage in an increasingly customer-driven market.

Additionally, the inability of most restaurant systems to implement dynamic pricing further restricts opportunities for revenue optimization. Static pricing models do not account for real-time factors such as fluctuating demand, seasonal variations, or the popularity of specific dishes. This rigidity prevents restaurants from capitalizing on high-demand periods or incentivizing the purchase of less popular items during slower times. As a result, profitability is often constrained, and restaurants are unable to fully leverage their potential for strategic pricing.

DineWise bridges these critical gaps by introducing state-of-the-art machine learning models that revolutionize both personalization and pricing strategies. Its AI-driven approach employs advanced algorithms such as Neural Collaborative Filtering (NCF) for menu recommendations, ensuring that suggestions are tailored to each customer's unique preferences, dining history, and context. In parallel, DineWise's dynamic pricing system, powered by Deep Reinforcement Learning (DRL), adapts pricing in real-time based on customer demand and external factors. This dual capability not only enhances the customer experience by providing highly relevant menu options but also empowers restaurants to maximize revenue and efficiency. By combining personalized recommendations with adaptive pricing, DineWise sets a new standard for innovation and operational excellence in the dining industry.

IV. SYSTEM REQUIREMENTS

A. Functional Requirements

1. **User Personalization:** personalizing menu recommendations by considering a user's profile and food preference.
2. **Dynamic Pricing:** Dynamic pricing would achieve immediate alteration due to demand, with a view to optimizing returns with inventory intact.
3. **User Authentication:** Allow the creation of accounts and subsequent login to store information securely for customized data.
4. **Menu Management:** This allows restaurant managers to add, update, and modify menu items, including setting up pricing for each.
5. **Order History and Analytics:** The ordering history of customers is visible while the managers get access to the usage analytics.

B. Non-Functional Requirements

1. **Machine Cross-Platform Compatibility:** This application should be made available on desktops, and it should also be accessible on mobile.
2. **Scalability:** Design the system to handle the high volume of users' requests and data during peak hours.
3. **Data Security and Privacy:** Securely handle and store user data to comply with privacy standards and regulations.
4. **Performance:** It should be a high-performance system, responding to every request pertaining to its primary roles in under 2 seconds on average.
5. **Reliability and Availability:** The application should always be on to support smooth, non-intermittent business operations.

These are the minimum number of requirements for making such a website as DineWise responsive and friendly concerning every customer's and restaurant manager's needs.

V. METHODOLOGY

A. User Interface

DineWise incorporates a ReactJS-based frontend designed to deliver an exceptional and seamless user experience for both customers and restaurant managers. For diners, this modern interface provides an intuitive platform to explore personalized menu recommendations tailored to their preferences. Customers can easily review suggested dishes, complete with real-time updates on pricing influenced by demand trends and other contextual factors. The interface ensures that the entire process—from browsing the menu to

making informed choices—is smooth, engaging, and dynamic, enhancing the overall dining experience.

For restaurant managers, the ReactJS-powered platform offers robust tools to track and analyze demand trends in real time. The system features an interactive dashboard that visualizes key metrics such as dish popularity, customer preferences, and pricing effectiveness. These insights empower managers to make data-driven decisions, such as adjusting menu items to align with changing demand or leveraging dynamic pricing strategies to optimize revenue. By providing a clear and actionable overview of operational performance, DineWise enables restaurants to respond proactively to market trends and customer behavior.

The ReactJS framework ensures that the platform is not only visually appealing but also highly responsive and scalable. Its modular architecture allows for smooth integration of additional features, ensuring that the system evolves alongside the restaurant's needs. By bridging advanced AI capabilities with a user-friendly interface, DineWise sets a new benchmark for restaurant management tools, delivering value to both diners seeking a personalized experience and managers aiming for operational excellence and profitability.

B. *API Gateway and Backend Services*

DineWise leverages a robust API gateway that serves as the backbone for secure and efficient data communication between the frontend and backend components. This gateway is designed to ensure the safe transit of data, protecting sensitive customer information and operational insights while maintaining high-performance standards. Its architecture is built to support real-time interactions, enabling seamless integration between the user-facing ReactJS interface and the complex backend processes.

The backend, powered by Flask and Node.js, is engineered for scalability and optimized for handling high-volume requests. It efficiently processes incoming data from the API gateway, fetches the relevant information from databases, and routes it to the underlying machine learning models. These models, responsible for generating personalized recommendations and dynamic pricing, rely on precise and timely data inputs to deliver accurate outputs. By facilitating smooth data flow and computation, the backend ensures that users experience minimal latency, even during peak usage periods.

This architecture is designed with future growth in mind, allowing for modular upgrades and the incorporation of additional services as needed. The combination of Flask and Node.js provides a flexible and adaptable foundation that supports a wide range of machine learning frameworks and data sources. Together with the API gateway, this system ensures that DineWise can handle complex, real-time computations without compromising on security, reliability, or speed, making it a powerful solution for modern restaurants aiming to deliver personalized and dynamic experiences at scale.

C. *Machine Learning Models*

The two major machine learning models implemented into DineWise will be:

1. **Neural Collaborative Filtering:** NCF combines the strengths of collaborative filtering with neural networks that distill user preferences for menu item recommendations that best fit individual tastes.
2. **Deep reinforcement learning:** DRL adjusts price dynamically to demand, with a view to optimizing revenue while managing inventory simultaneously. Repeated learnings by DRL amply accommodate fluctuations in customer demand and hence are quite suitable for dynamic pricing.

D. *Database*

MongoDB plays a pivotal role in DineWise's architecture as the active repository for storing and managing critical information related to users, menu items, and pricing data. Its document-based, NoSQL design ensures flexibility in handling diverse and dynamic data structures, making it ideal for a system like DineWise that requires scalability and speed. By serving as the central repository, MongoDB enables the platform to store large volumes of structured and unstructured data efficiently, supporting both current operations and future growth.

The use of MongoDB allows DineWise to access historical data rapidly, which is essential for driving its AI-powered features. For personalized recommendations, the system draws on user-specific data, such as dining history, preferences, and interaction patterns, stored within MongoDB. This data is seamlessly integrated with machine learning algorithms like Neural Collaborative Filtering (NCF), enabling the platform to deliver highly accurate and contextually relevant suggestions. Similarly, menu item

data, including descriptions, availability, and associated demand patterns, is maintained in MongoDB to support dynamic pricing strategies and inventory optimization.

Beyond recommendations, MongoDB enhances inventory management by providing a real-time view of stock levels and usage trends. Restaurant managers can leverage this data to make informed decisions, such as identifying which items are underperforming or ensuring popular dishes are adequately stocked to meet demand. With its robust querying capabilities and support for horizontal scaling, MongoDB ensures that DineWise remains fast, reliable, and adaptable to the evolving needs of restaurants, helping to drive operational excellence and superior customer experiences.

VI. TESTING AND EVALUATION

Performance validation of DineWise involved intensive use in testing its core functionalities: the recommendation engine, dynamic pricing, and responsiveness of its user interface.

A. Test Cases

1. Accuracy of Recommendations: The dishes recommended are relevant for the user's preference.
2. Dynamic Price Optimization: The basis of pricing, considering demand for obtaining the highest revenues during peak periods.
3. Cross-Device Compatibility: Ensured the user interface works equally well across different devices.
4. Data Security Compliance: It ensures that the users' data is very safe and confidential with regards to set privacy.

B. EVALUATION METRICS

Key evaluation metrics would be recommendation accuracy, revenue optimization with respect to pricing, user engagement, and system response time. Initial tests indicated that users were very satisfied with the personal recommendations, while demand-based pricing adjustments did well in improving profitability.

VII. PRODUCT RESULTS

Pilot testing of DineWise demonstrated outstanding performance, achieving high accuracies in both personalized recommendations and dynamic price adjustments. The platform's AI-driven mechanisms effectively tailored dish suggestions to individual user preferences, creating a dining experience that resonated deeply with customers. Feedback

from users during the testing phase highlighted the accuracy and relevance of the recommendations, with many expressing satisfaction at how well the platform aligned with their tastes and dining habits. This personalized approach not only enhanced the overall dining experience but also fostered customer loyalty by addressing their unique preferences.

Dynamic pricing, another cornerstone of DineWise, proved equally successful during the pilot phase. By adjusting prices in real-time based on demand fluctuations and contextual factors, the system demonstrated its capability to balance profitability and customer value. For example, during peak demand periods, popular items were priced slightly higher, whereas less in-demand dishes were attractively priced to encourage sales. This adaptive pricing strategy resulted in better revenue optimization for participating restaurants, showcasing the potential for DineWise to maximize profitability without compromising the customer experience.

Furthermore, dynamic pricing contributed to operational efficiency by aligning pricing with inventory levels and reducing food wastage. The system's ability to analyze real-time data allowed restaurants to optimize menu offerings and inventory management, ensuring that excess stock was minimized while maintaining sufficient availability of popular items. Overall, the pilot test validated DineWise's ability to transform traditional dining operations into a more dynamic, customer-centric, and profitable model, setting the stage for its wider adoption in the industry.

VIII. CONCLUSION

DineWise presents a groundbreaking approach to modernizing the dining experience by integrating AI-optimized personalized recommendations and dynamic pricing. By continuously adapting to evolving customer preferences and real-time demand patterns, DineWise sets a new benchmark for customer satisfaction and operational efficiency. Its AI-driven capabilities enable restaurants to offer tailored dining experiences that resonate deeply with individual diners, while simultaneously optimizing revenue and reducing resource wastage. This dual focus on personalization and profitability positions DineWise as a transformative force in the dining industry, bridging the gap between traditional practices and the demands of a data-driven world.

Looking ahead, the potential for further innovation and refinement in DineWise is immense. Future development efforts

may focus on enhancing the machine learning algorithms that power its recommendations and dynamic pricing, ensuring even greater accuracy and adaptability. Expanding dietary filters to include more nuanced preferences, such as detailed nutritional requirements or cultural cuisines, could further enrich the user experience. Additionally, advanced analytics features for restaurant managers, such as predictive demand forecasting and customer behavior insights, would empower them to make smarter, data-informed decisions to improve operations and customer satisfaction.

DineWise represents a forward-looking vision for the dining industry, reimagining it as a space driven by data intelligence and customer-centric solutions. By seamlessly integrating advanced technology into every aspect of the dining experience, DineWise has the potential to redefine how restaurants operate, engage with customers, and achieve sustainable growth. As the platform continues to evolve, it paves the way for a future where dining is not just about food but about delivering exceptional, personalized, and adaptive experiences that cater to the needs of every individual diner.

REFERENCES

1. HE, X., LIAO, L., ZHANG, H., NIE, L., HU, X., & CHUA, T. (2017). "NEURAL COLLABORATIVE FILTERING." PROCEEDINGS OF THE 26TH INTERNATIONAL CONFERENCE ON WORLD WIDE WEB, 173-182.
2. WANG, H., ZHANG, F., ZHAO, M., LI, W., XIE, X., & GUO, M. (2019). "MULTI-TASK NEURAL NETWORKS FOR PERSONALIZED PRODUCT RECOMMENDATIONS." PROCEEDINGS OF THE ACM SIGIR CONFERENCE ON RESEARCH AND DEVELOPMENT IN INFORMATION RETRIEVAL.
3. SILVER, D., HUANG, A., MADDISON, C. J., ET AL. (2016). "MASTERING THE GAME OF GO WITH DEEP NEURAL NETWORKS AND TREE SEARCH." NATURE, 529(7587), 484-489.
4. CHOI, S., HE, X., & LEE, H. (2021). "DYNAMIC PRICING WITH REINFORCEMENT LEARNING: A SURVEY." IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, 32(12), 5257-5274.
5. ZHANG, Y., & YANG, Q. (2021). "A SURVEY ON MULTI-TASK LEARNING." IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, 34(2), 558-576.
6. GOODFELLOW, I., BENGIO, Y., & COURVILLE, A. (2016). DEEP LEARNING. MIT PRESS.
7. SUTTON, R. S., & BARTO, A. G. (2018). REINFORCEMENT LEARNING: AN INTRODUCTION (2ND ED.). MIT PRESS.
8. KINGMA, D. P., & BA, J. (2015). "ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION." INTERNATIONAL CONFERENCE ON LEARNING REPRESENTATIONS (ICLR).
9. VASWANI, A., SHAZEER, N., PARMAR, N., ET AL. (2017). "ATTENTION IS ALL YOU NEED." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS), 30.
10. LECUN, Y., BENGIO, Y., & HINTON, G. (2015). "DEEP LEARNING." NATURE, 521(7553), 436-444.
11. MIKOLOV, T., CHEN, K., CORRADO, G., & DEAN, J. (2013). "EFFICIENT ESTIMATION OF WORD REPRESENTATIONS IN VECTOR SPACE." ARXIV PREPRINT ARXIV:1301.3781.
12. HE, K., ZHANG, X., REN, S., & SUN, J. (2016). "DEEP RESIDUAL LEARNING FOR IMAGE RECOGNITION." IEEE CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR), 770-778.
13. HOCHREITER, S., & SCHMIDHUBER, J. (1997). "LONG SHORT-TERM MEMORY." NEURAL COMPUTATION, 9(8), 1735-1780.
14. CHEN, T., & GUESTRIN, C. (2016). "XGBOOST: A SCALABLE TREE BOOSTING SYSTEM." PROCEEDINGS OF THE ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING (KDD).
15. DEVLIN, J., CHANG, M. W., LEE, K., & TOUTANOVA, K. (2019). "BERT: PRE-TRAINING OF DEEP BIDIRECTIONAL TRANSFORMERS FOR LANGUAGE UNDERSTANDING." PROCEEDINGS OF THE NORTH AMERICAN CHAPTER OF THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS (NAACL), 4171-4186.
16. RADFORD, A., NARASIMHAN, K., SALIMANS, T., & SUTSKEVER, I. (2018). "IMPROVING LANGUAGE UNDERSTANDING BY GENERATIVE PRE-TRAINING." OPENAI TECHNICAL REPORT.
17. BROWN, T. B., MANN, B., RYDER, N., ET AL. (2020). "LANGUAGE MODELS ARE FEW-SHOT LEARNERS." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS), 33, 1877-1901.
18. KIPF, T. N., & WELLING, M. (2017). "SEMI-SUPERVISED CLASSIFICATION WITH GRAPH CONVOLUTIONAL NETWORKS." INTERNATIONAL CONFERENCE ON LEARNING REPRESENTATIONS (ICLR).
19. ZHOU, J., CUI, G., ZHANG, Z., ET AL. (2020). "GRAPH NEURAL NETWORKS: A REVIEW OF METHODS AND APPLICATIONS." AI OPEN, 1, 57-81.
20. YANG, Z., DAI, Z., YANG, Y., ET AL. (2019). "XLNET: GENERALIZED AUTOREGRESSIVE PRETRAINING FOR LANGUAGE UNDERSTANDING." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS).
21. TANG, J., QU, M., WANG, M., ET AL. (2015). "LINE: LARGE-SCALE INFORMATION NETWORK EMBEDDING." PROCEEDINGS OF THE ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING (KDD).
22. SUN, Y., & HAN, J. (2012). "MINING HETEROGENEOUS INFORMATION NETWORKS: A STRUCTURAL ANALYSIS APPROACH." ACM SIGKDD EXPLORATIONS NEWSLETTER, 14(2), 20-28.
23. BENGIO, Y., SIMARD, P., & FRASCONI, P. (1994). "LEARNING LONG-TERM DEPENDENCIES WITH GRADIENT DESCENT IS DIFFICULT." IEEE TRANSACTIONS ON NEURAL NETWORKS, 5(2), 157-166.
24. GRAVES, A., & SCHMIDHUBER, J. (2005). "FRAMEWISE PHONEME CLASSIFICATION WITH BIDIRECTIONAL LSTM AND OTHER NEURAL NETWORK ARCHITECTURES." NEURAL NETWORKS, 18(5-6), 602-610.

25. CHEN, X., & ZITNICK, C. L. (2015). "MIND'S EYE: A RECURRENT VISUAL REPRESENTATION FOR IMAGE CAPTION GENERATION." IEEE CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR).
26. KRIZHEVSKY, A., SUTSKEVER, I., & HINTON, G. E. (2012). "IMAGENET CLASSIFICATION WITH DEEP CONVOLUTIONAL NEURAL NETWORKS." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS), 25.
27. GIRSHICK, R., DONAHUE, J., DARRELL, T., & MALIK, J. (2014). "RICH FEATURE HIERARCHIES FOR ACCURATE OBJECT DETECTION AND SEMANTIC SEGMENTATION." IEEE CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR).
28. SIMONYAN, K., & ZISSERMAN, A. (2015). "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION." INTERNATIONAL CONFERENCE ON LEARNING REPRESENTATIONS (ICLR).
29. REN, S., HE, K., GIRSHICK, R., & SUN, J. (2015). "FASTER R-CNN: TOWARDS REAL-TIME OBJECT DETECTION WITH REGION PROPOSAL NETWORKS." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS).
30. SZEGEDY, C., LIU, W., JIA, Y., ET AL. (2015). "GOING DEEPER WITH CONVOLUTIONS." IEEE CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR).
31. ZHANG, H., GOODFELLOW, I., METAXAS, D., & ODENA, A. (2019). "SELF-ATTENTION GENERATIVE ADVERSARIAL NETWORKS." INTERNATIONAL CONFERENCE ON MACHINE LEARNING (ICML).
32. RADFORD, A., METZ, L., & CHINTALA, S. (2015). "UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS." ARXIV PREPRINT ARXIV:1511.06434.
33. GOODFELLOW, I., POUGET-ABADIE, J., MIRZA, M., ET AL. (2014). "GENERATIVE ADVERSARIAL NETS." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS).
34. SRIVASTAVA, N., HINTON, G., KRIZHEVSKY, A., ET AL. (2014). "DROPOUT: A SIMPLE WAY TO PREVENT NEURAL NETWORKS FROM OVERFITTING." JOURNAL OF MACHINE LEARNING RESEARCH, 15, 1929-1958.
35. IOFFE, S., & SZEGEDY, C. (2015). "BATCH NORMALIZATION: ACCELERATING DEEP NETWORK TRAINING BY REDUCING INTERNAL COVARIATE SHIFT." INTERNATIONAL CONFERENCE ON MACHINE LEARNING (ICML).
36. ZHOU, B., KHOSLA, A., LAPEDRIZA, A., ET AL. (2016). "LEARNING DEEP FEATURES FOR DISCRIMINATIVE LOCALIZATION." IEEE CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR).
37. LI, J., MONROE, W., RITTER, A., ET AL. (2016). "DEEP REINFORCEMENT LEARNING FOR DIALOGUE GENERATION." EMPIRICAL METHODS IN NATURAL LANGUAGE PROCESSING (EMNLP).
38. TIELEMAN, T., & HINTON, G. (2012). "LECTURE 6.5—RMSPROP: DIVIDE THE GRADIENT BY A RUNNING AVERAGE OF ITS RECENT MAGNITUDE." COURSERA: NEURAL NETWORKS FOR MACHINE LEARNING.
39. DOSOVITSKIY, A., BEYER, L., KOLESNIKOV, A., ET AL. (2020). "AN IMAGE IS WORTH 16x16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE." INTERNATIONAL CONFERENCE ON LEARNING REPRESENTATIONS (ICLR).
40. LIU, Z., LIN, Y., CAO, Y., ET AL. (2021). "SWIN TRANSFORMER: HIERARCHICAL VISION TRANSFORMER USING SHIFTED WINDOWS." PROCEEDINGS OF THE IEEE/CVF INTERNATIONAL CONFERENCE ON COMPUTER VISION (ICCV).
41. HE, J., MCAULEY, J., & LESKOVEC, J. (2016). "UPS AND DOWNS: MODELING THE VISUAL EVOLUTION OF FASHION TRENDS WITH ONE-CLASS COLLABORATIVE FILTERING." INTERNATIONAL WORLD WIDE WEB CONFERENCE (WWW).
42. CHO, K., VAN MERRIËNBOER, B., GULCEHRE, C., ET AL. (2014). "LEARNING PHRASE REPRESENTATIONS USING RNN ENCODER-DECODER FOR STATISTICAL MACHINE TRANSLATION." EMPIRICAL METHODS IN NATURAL LANGUAGE PROCESSING (EMNLP).
43. LIANG, X., XU, T., ZHANG, H., ET AL. (2018). "SYMBOLIC GRAPH REASONING MEETS CONVOLUTIONS." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS).
44. WU, Y., SCHUSTER, M., CHEN, Z., ET AL. (2016). "GOOGLE'S NEURAL MACHINE TRANSLATION SYSTEM: BRIDGING THE GAP BETWEEN HUMAN AND MACHINE TRANSLATION." ARXIV PREPRINT ARXIV:1609.08144.
45. DONG, Y., CHAWLA, N. V., & SWAMI, A. (2017). "METAPATH2VEC: SCALABLE REPRESENTATION LEARNING FOR HETEROGENEOUS NETWORKS." PROCEEDINGS OF THE ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING (KDD).
46. BORDES, A., USUNIER, N., GARCIA-DURAN, A., ET AL. (2013). "TRANSLATING EMBEDDINGS FOR MODELING MULTI-RELATIONAL DATA." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS (NEURIPS).
47. YANG, B., YIH, W. T., HE, X., ET AL. (2015). "EMBEDDING ENTITIES AND RELATIONS FOR LEARNING AND INFERENCE IN KNOWLEDGE BASES." INTERNATIONAL CONFERENCE ON LEARNING REPRESENTATIONS (ICLR).
48. PEI, J., TANG, H., & ZHOU, C. (2017). "LEARNING DYNAMIC NETWORK EMBEDDING WITH JOINTLY MODELING THE EVOLUTIONARY RELATIONSHIPS OF NODES." PROCEEDINGS OF THE ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING (KDD).
49. HAMILTON, W. L., YING, R., & LESKOVEC, J. (2017). "REPRESENTATION LEARNING ON GRAPHS: METHODS AND APPLICATIONS." IEEE DATA ENGINEERING BULLETIN, 40(3), 52-74.
50. NIE, L., ZHANG, H., & CHUA, T. (2019). "MULTIMODAL RECOMMENDATION IN CONTEXTUAL SCENARIOS." PROCEEDINGS OF THE ACM INTERNATIONAL CONFERENCE ON MULTIMEDIA RETRIEVAL (ICMR).