MIDS W207
Applied Machine Learning

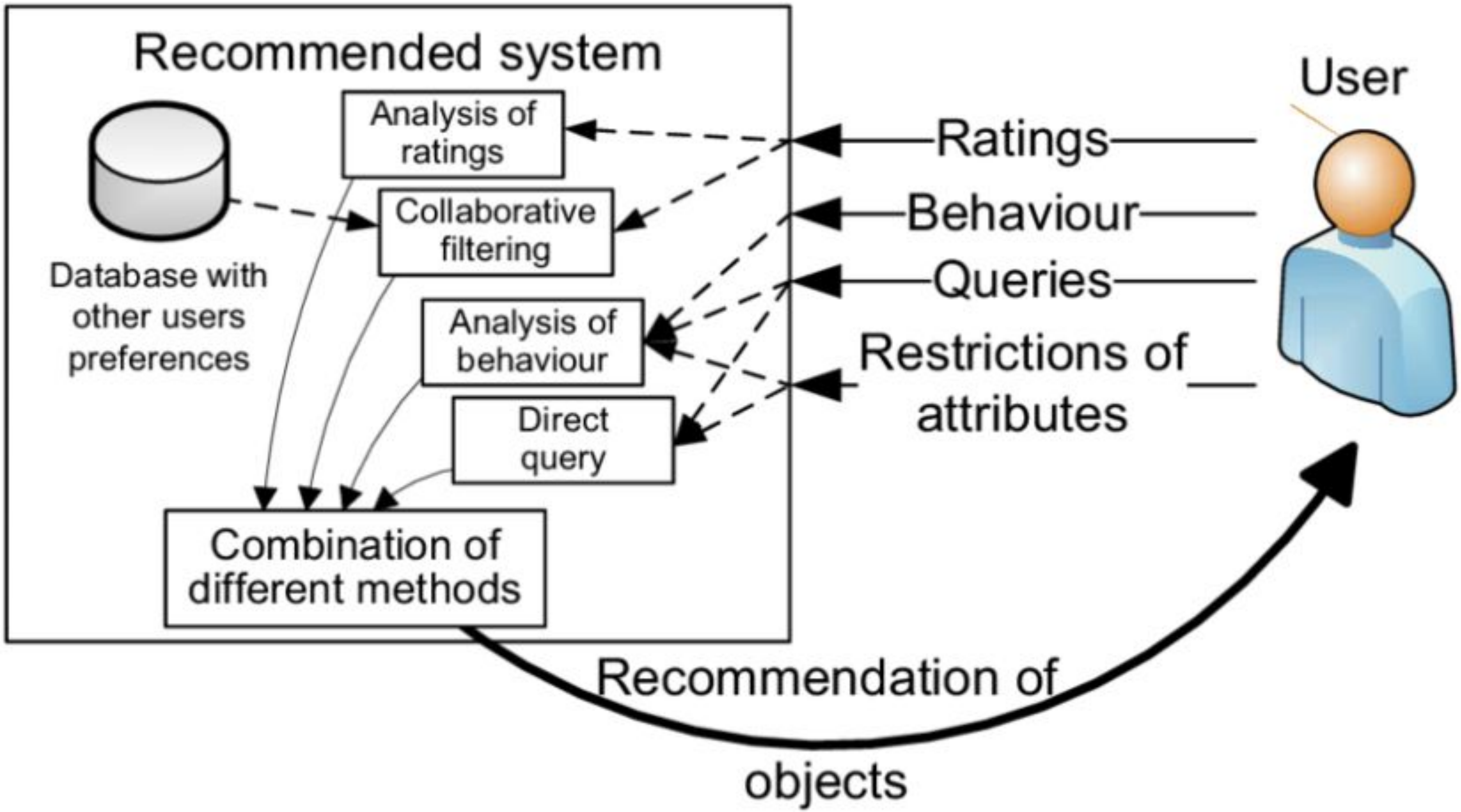
Week 11
Live Session Slides

Topics

- Recommender Systems
- Graph neural Networks
- Long Short Term Memory (LSTM)
- Stable Diffusion

Recommendation Systems

Recommender Systems



Recommender Systems Types

Recommender systems

- **Content based methods**

  Define a model for user-item interactions where users and/or items representations are given (explicit features).

- **Collaborative filtering methods**

  - **Model based**

    Define a model for user-item interactions where users and items representations have to be learned from interactions matrix.

  - **Memory based**

    Define no model for user-item interactions and rely on similarities between users or items in terms of observed interactions.

- **Hybrid methods**

  Mix content based and collaborative filtering approaches.

Recommender Systems: Recent Advancements and State of the Art

Patel, R., Thakkar, P., & Ukani, V. (2024). **CNN Rec: Convolutional Neural Network based recommender systems-A survey.** Engineering Applications of Artificial Intelligence, 133, 108062.

Ahmadian Yazdi, H., Seyyed Mahdavi, S. J., & Ahmadian Yazdi, H. (2024). **Dynamic educational recommender system based on Improved LSTM neural network**. Scientific Reports, 14(1), 4381.

Sohafi-Bonab, J., Aghdam, M. H., & Majidzadeh, K. (2023). **DCARS: Deep context-aware recommendation system based on session latent context.** Applied Soft Computing, 143, 110416.

Jeong, S. Y., & Kim, Y. K. (2023). **Deep Learning-Based Context-Aware Recommender System Considering Change in Preference.** Electronics, 12(10), 2337.

Recommender Systems: Recent Advancements and State of the Art

Deep neural networks

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Context Aware

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Recommender Systems: Recent Advancements and State of the Art

Federated learning

Huang, J., Ma, B., Wang, M., Zhou, X., Yao, L., Wang, S., ... & Chen, Y. (2023). **Incentive mechanism design of federated learning for recommendation systems in MEC**. IEEE Transactions on Consumer Electronics.

Jie, Z., Chen, S., Lai, J., Arif, M., & He, Z. (2023). **Personalized federated recommendation system with historical parameter clustering.** Journal of Ambient Intelligence and Humanized Computing, 14(8), 10555-10565.

Wu, Y., Cao, J., & Xu, G. (2023). **Fairness in recommender systems: evaluation approaches and assurance strategies.** ACM Transactions on Knowledge Discovery from Data, 18(1), 1-37.

Chizari, N., Tajfar, K., & Moreno-García, M. N. (2023). **Bias Assessment Approaches for Addressing User-Centered Fairness in GNN-Based Recommender Systems.** Information, 14(2), 131.

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Bias and Fairness

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Recommender Systems: Recent Advancements and State of the Art

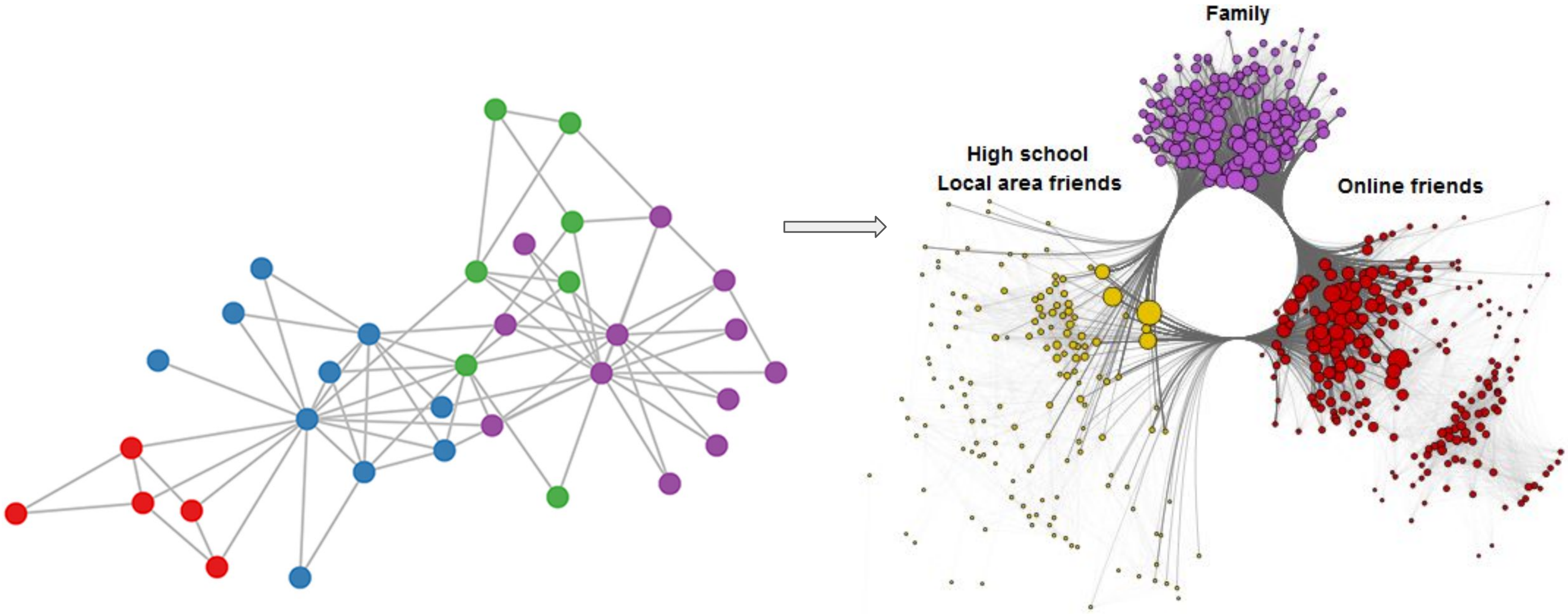
Explainable AI

Wang, Y. C., Chen, T. C. T., & Chiu, M. C. (2023). **An improved explainable artificial intelligence tool in healthcare for hospital recommendation**. Healthcare Analytics, 3, 100147.

Shams, M. Y., Gamel, S. A., & Talaat, F. M. (2024). **Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making.** Neural Computing and Applications, 1-20.

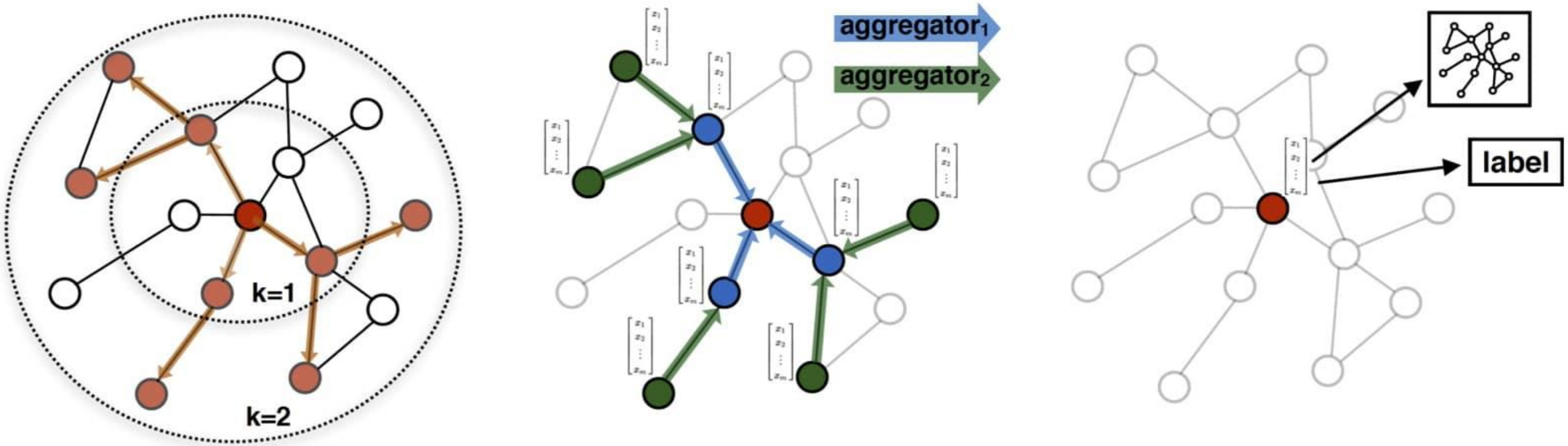
Graph Neural Networks

Graph Neural Networks



Graph Neural Networks Working

Initialization → Message Passing → Aggregation Function → Neighborhood Aggregation → Output



1. Sample neighborhood

2. Aggregate feature information from neighbors

3. Predict graph context and label using aggregated information

Graph Neural Network Types

- Graph Convolutional Networks (GCNs)
- Graph Attention Networks (GATs)
- Graph Recurrent Networks (GRNs)
- Graph Autoencoders
- Graph Attention Mechanisms
- Graph Neural ODEs
- Graph Pooling Networks

Graph Neural Networks: Recent Advancements and State of the Art

Applications

Truong-Quoc, C., Lee, J. Y., Kim, K. S., & Kim, D. N. (2024). **Prediction of DNA origami shape using graph neural network.** Nature Materials, 1-9.

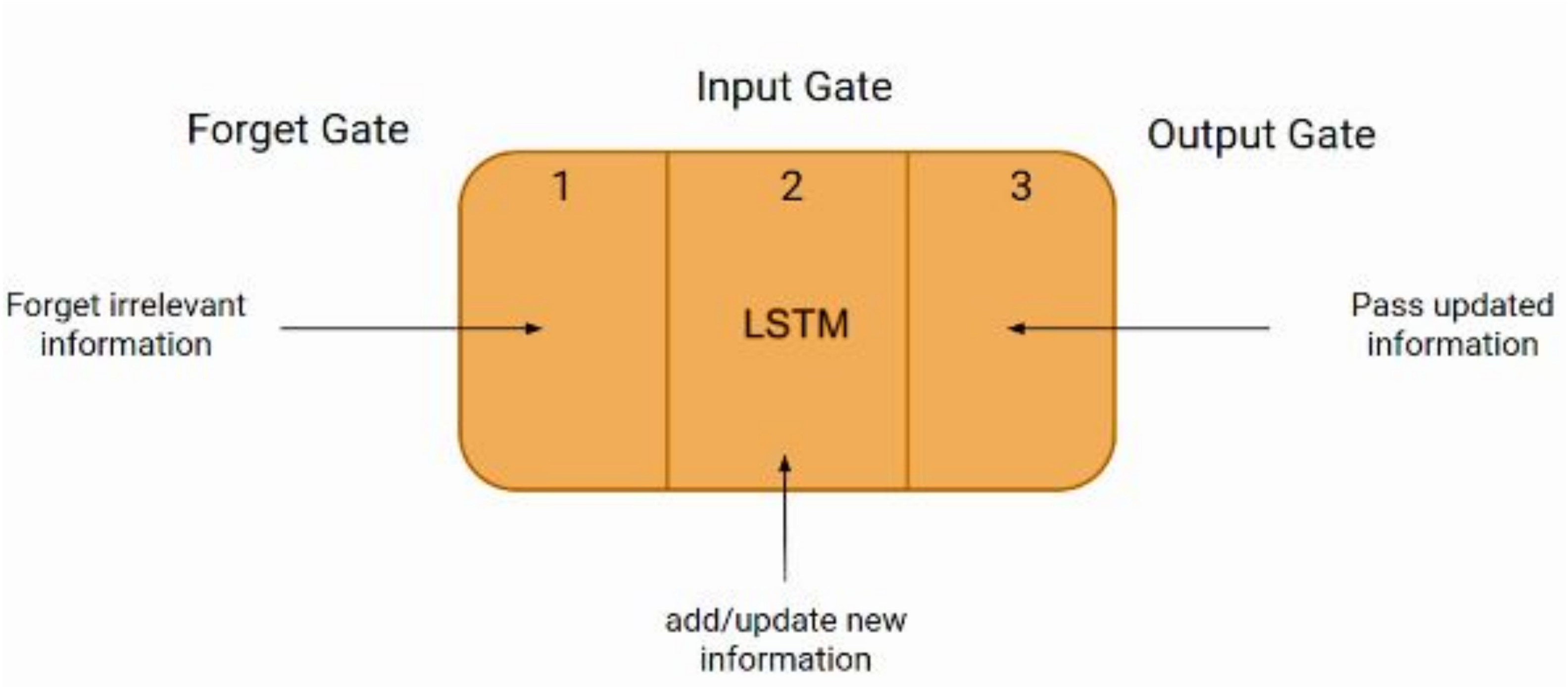
Jiang, W., Luo, J., He, M., & Gu, W. (2023). **Graph neural network for traffic forecasting: The research progress.** ISPRS International Journal of Geo-Information, 12(3), 100.

Phan, H. T., Nguyen, N. T., & Hwang, D. (2023). **Fake news detection: A survey of graph neural network methods.** Applied Soft Computing, 110235.

DeZoort, G., Battaglia, P. W., Biscarat, C., & Vlimant, J. R. (2023). **Graph neural networks at the Large Hadron Collider.** Nature Reviews Physics, 5(5), 281-303.

Long Short Term Memory (LSTMs)

LSTM Structure



Description	Recurrent Neural Network (RNN)	Long Short Term Memory (LSTM)	Gated Recurrent Unit (GRU)	Transformers
Overview	RNNs are foundational sequence models that process sequences iteratively, using the output from the previous step as an input to the current step.	LSTMs are an enhancement over standard RNNs, designed to better capture long-term dependencies in sequences.	GRUs are a variation of LSTMs with a simplified gating mechanism.	Transformers move away from recurrence and focus on self-attention mechanisms to process data in parallel
Key characteristics	- Recurrent connections allow for the retention of "memory" from previous time steps.	- Uses gates (input, forget, and output) to regulate the flow of information. - Has a cell state in addition to the hidden state to carry information across long sequences.	- Contains two gates: reset gate and update gate. - Merges the cell state and hidden state.	- Uses Self-attention mechanisms to weigh the importance of different parts of the input data. - Consists of multiple encoder and decoder blocks. - Processes data in parallel rather than sequentially.
Advantages	- Simple structure. - Suitable for tasks with short sequences.	- Can capture and remember long-term dependencies in data. - Mitigates the vanishing gradient problem of RNNs.	- Fewer parameters than LSTM, often leading to faster training times. - Simplified structure while retaining the ability to capture long-term dependencies.	- Can capture long-range dependencies without relying on recurrence - Highly parallelizable, leading to faster training on suitable hardware.
Disadvantages	- Suffers from the vanishing and exploding gradient problem, making it hard to learn long-term dependencies - Limited memory span	- More computationally intensive than RNNs - Complexity can lead to longer training times.	- Might not capture long-term dependencies as effectively as LSTM in some tasks.	- Requires a large amount of data and computing power for training. - Can be memory-intensive due to the attention mechanism, especially for long sequences.
Use Cases	Due to its limitations, plain RNNs are less common in modern applications. Used in simple language modeling, time series prediction	Machine translation, speech recognition, sentiment analysis, and other tasks that require understanding of longer context.	Text generation, sentiment analysis, and other sequence tasks where model efficiency is a priority.	- State-of-the-art performance in various NLP tasks, including machine translation, text summarization. - Forms the backbone for models like BERT and GPT.
Model variants	Vanilla RNN, Bidirectional RNN, Deep (Stacked) RNN	Vanilla LSTM, Bidirectional LSTM, Peephole LSTM, Deep (Stacked) LSTM	GRU	Original Transformer (Seq-to-Seq), Encoder only (Eg: BERT), Decoder only (Eg: GPT), Text to Text (Eg: T5)

LSTMs: Recent Advancements and State of the Art

Applications

Lu, S., Yang, J., Yang, B., Li, X., Yin, Z., Yin, L., & Zheng, W. (2024). **Surgical instrument posture estimation and tracking based on LSTM.** ICT Express.

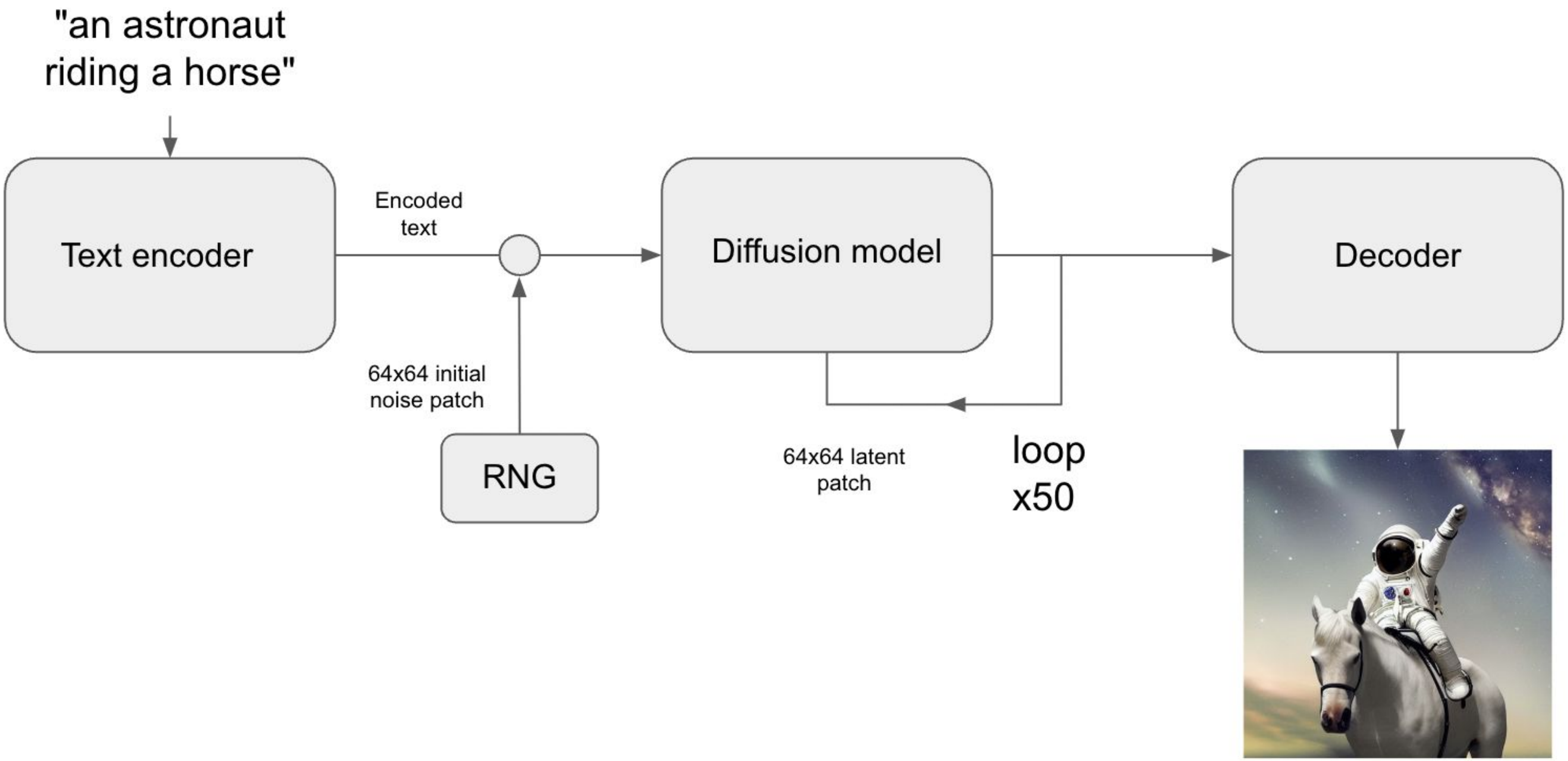
Nanjappan, M., Pradeep, K., Natesan, G., Samydurai, A., & Premalatha, G. (2024). **DeepLG SecNet: utilizing deep LSTM and GRU with secure network for enhanced intrusion detection in IoT environments.** Cluster Computing, 1-13.

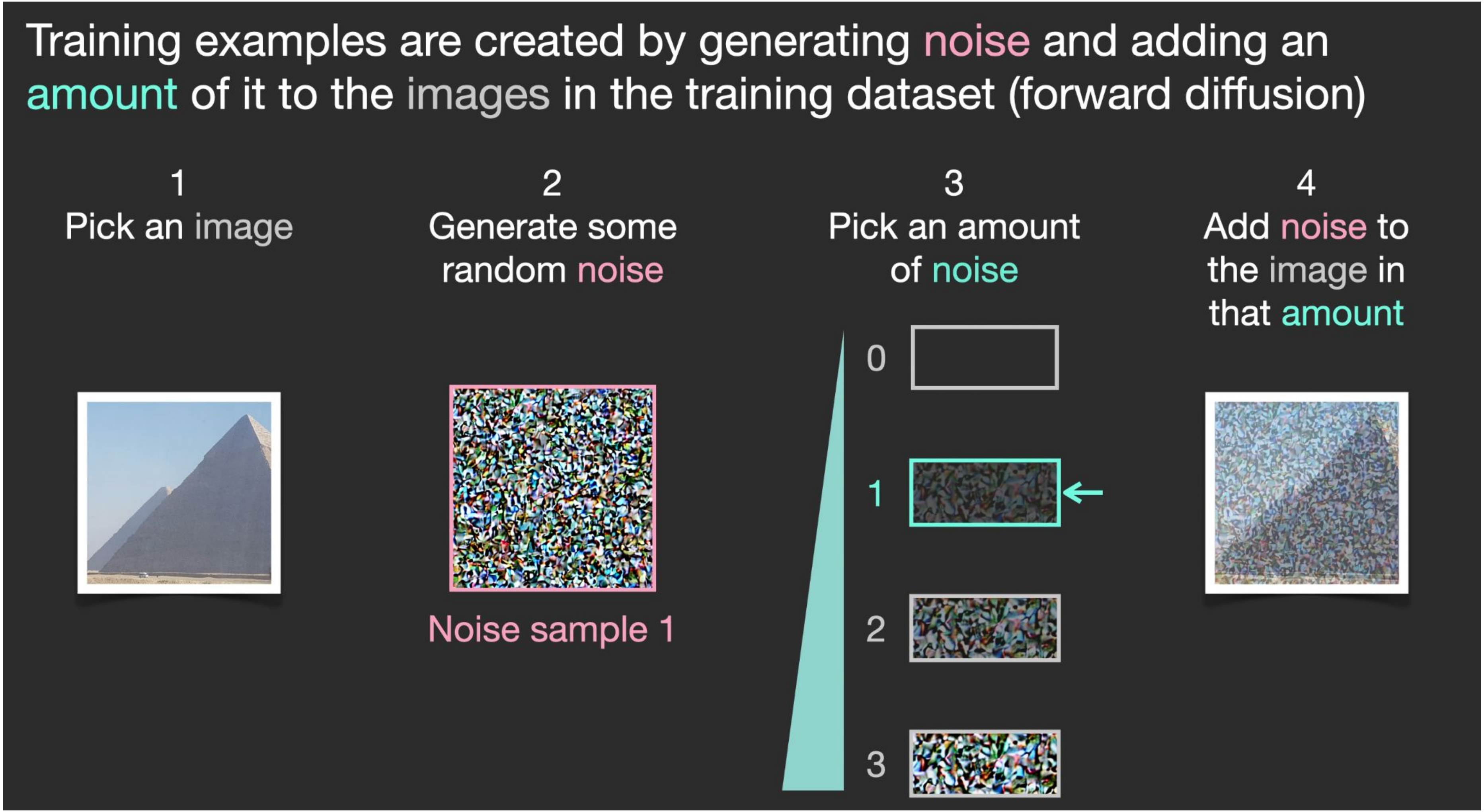
Zhang, C., Ma, L., Luo, Z., Han, X., & Zhao, T. (2024). **Forecasting building plug load electricity consumption employing occupant-building interaction input features and bidirectional LSTM with improved swarm intelligent algorithms**. Energy, 288, 129651.

Jhong, Y. D., Chen, C. S., Jhong, B. C., Tsai, C. H., & Yang, S. Y. (2024). **Optimization of LSTM parameters for flash flood forecasting using genetic algorithm**. Water Resources Management, 1-24.

Stable Diffusion

Stable Diffusion




Training examples are created by generating noise and adding an amount of it to the images in the training dataset (forward diffusion)
1
Pick an image
2
Generate some random noise
3
Pick an amount of noise
4
Add noise to the image in that amount
Noise sample 1
0
1
2
3

Stable Diffusion: Recent Advancements and State of the Art

Applications

Arshed, M. A., Mumtaz, S., Ibrahim, M., Dewi, C., Tanveer, M., & Ahmed, S. (2024). **Multiclass AI-Generated Deepfake Face Detection Using Patch-Wise Deep Learning Model.** Computers, 13(1), 31.

Liang, Y., Feng, S., Zhang, Y., Xue, F., Shen, F., & Guo, J. (2024). **A stable diffusion enhanced YOLOV5 model for metal stamped part defect detection based on improved network structure.** Journal of Manufacturing Processes, 111, 21-31.

Shavlokhova, V., Vollmer, A., Zouboulis, C. C., Vollmer, M., Wollborn, J., Lang, G., ... & Saravi, B. (2023). **Finetuning of GLIDE stable diffusion model for AI-based text-conditional image synthesis of dermoscopic images.** Frontiers in Medicine, 10.

Dehouche, N., & Dehouche, K. (2023). **What's in a text-to-image prompt? The potential of stable diffusion in visual arts education.** Heliyon, 9(6).