Motilal Nehru National Institute of Technology, Allahabad

Major Project

Aerial Base Stations(ABS)-Assisted 5G-Networks Through Human Mobility Prediction

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Motivation

- Utilizing Unmanned Aerial Vehicles (UAVs) as Aerial Base Stations (ABS) alongside traditional cellular infrastructure that offers a promising and cost-effective approach for on-demand communications in next generation networks.

Some of the motivations are specified below :

1. Better coverage and higher quality of service for more users.

2. A quick, flexible and on-demand wireless communication.

3. Less expensive and better recovery feasible for future.

Introduction

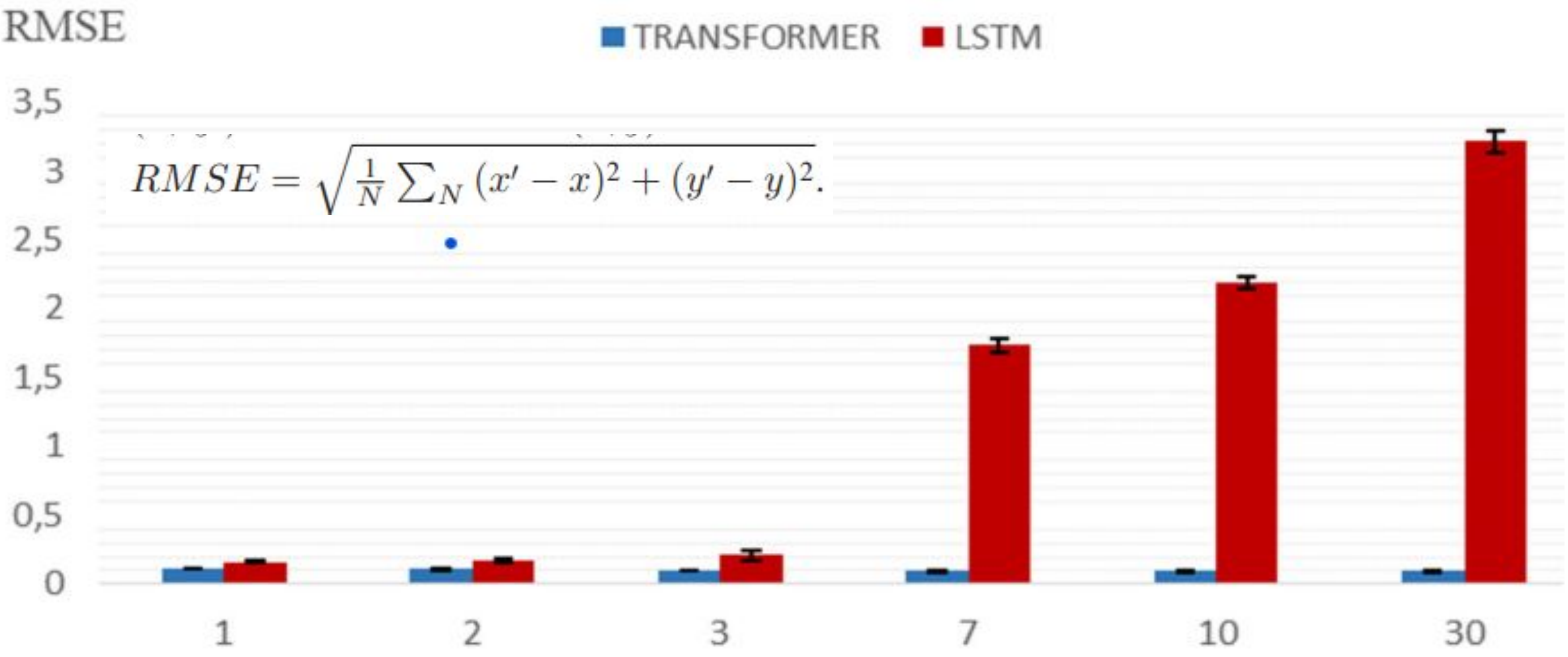
- Accurately estimating the spatio-temporal distribution of mobile users.
- 3D placement of Aerial Base Station(ABSs) by predicting human mobility.

Overview

- Implementation of Human Mobility Prediction for ABS's placement.

- It uses Transformer model and Long Short Term Memory (LSTM) as a reference model.

Prediction error of the user's location as a function of the size of input series.



$$RMSE = \sqrt{\frac{1}{N}\sum_N (x' - x)^2 + (y' - y)^2}.$$

Fig 1. RMSE error v/s input sequence length

Overview

- A transformer model uses encoder-decoder architecture.

- The self-attention mechanism allows the transformer to capture long range dependencies.

Transformer

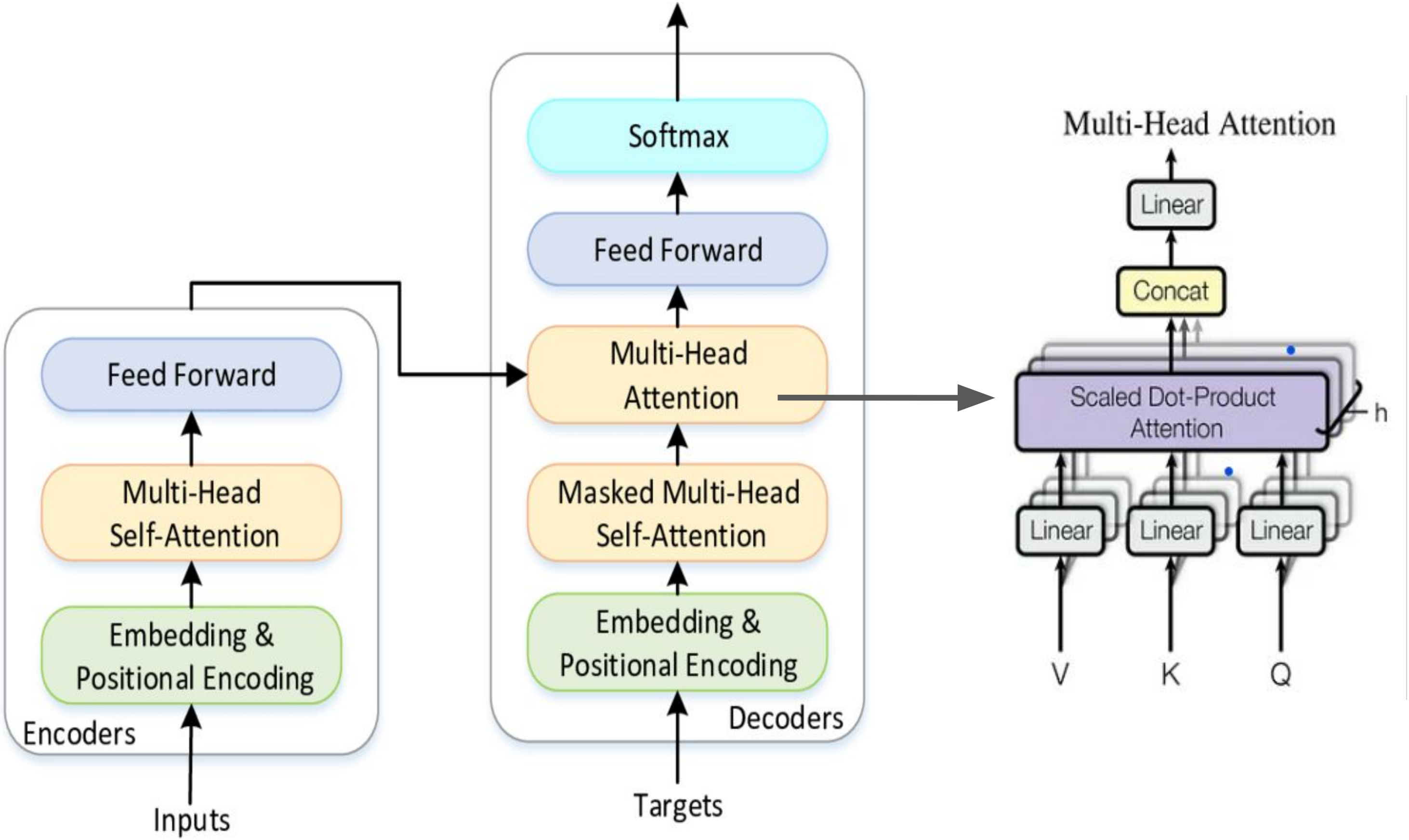


Fig 2. Transformer architecture

Main factors of using a transformer -

- Transformers allow for better parallelization of training due to their self-attention mechanism. This can lead to faster training times compared to sequential processing in LSTMs.

- Transformers are designed to capture long-range dependencies in sequences effectively. They use self-attention mechanisms to weigh the importance of different parts of the input sequence when making predictions.

- Transformers are more scalable to larger datasets and can handle sequences of varying lengths more efficiently. This can be beneficial when dealing with the diverse time intervals between mobility data points.

Word embedding in transformer

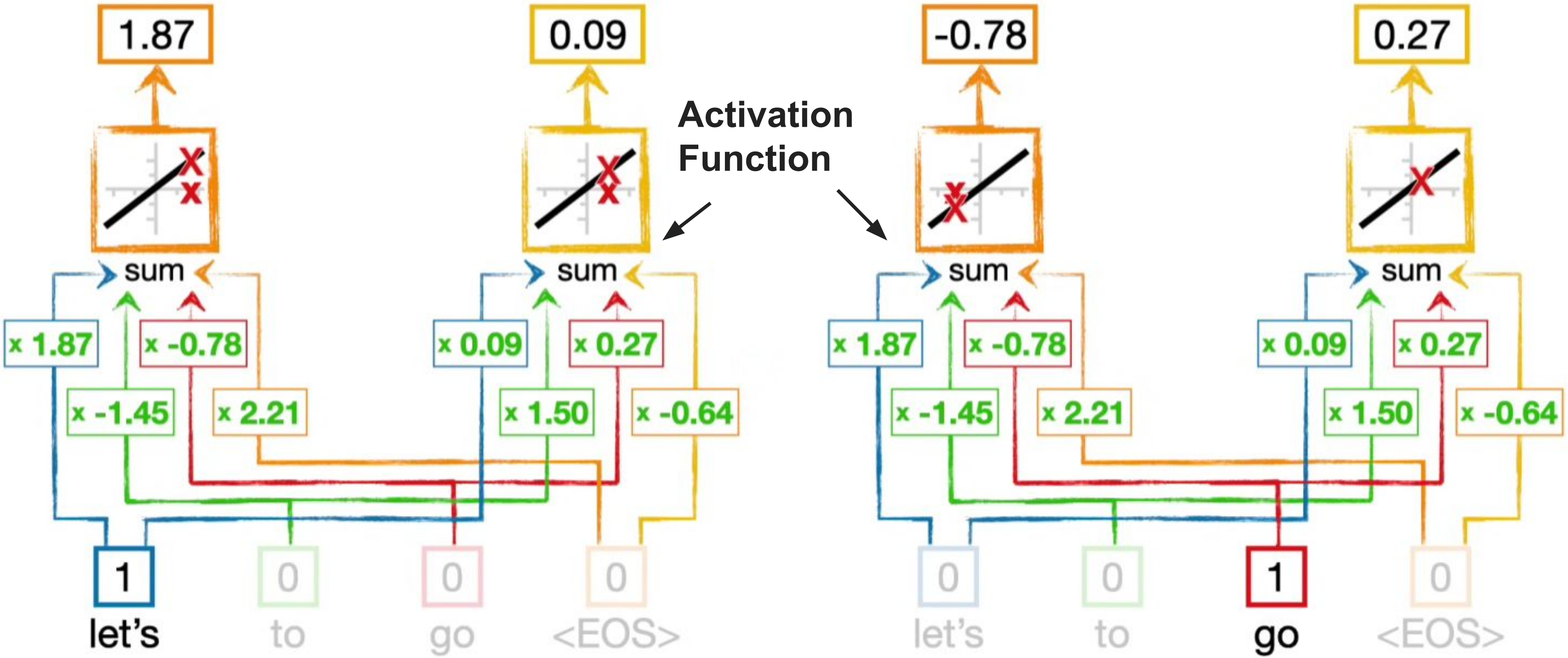


Fig 3. Word embedding [13]

Position encoding

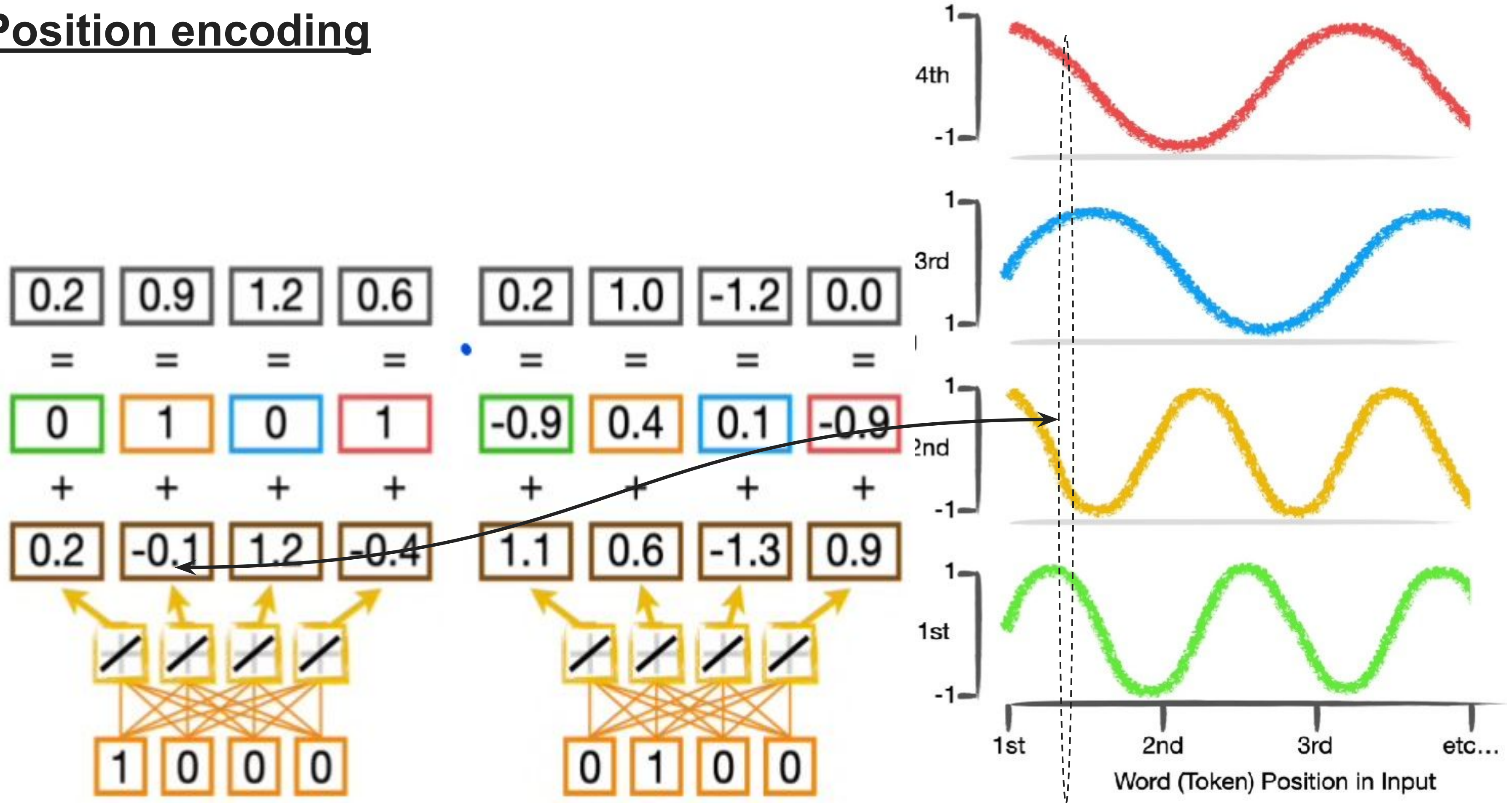


Fig 4. Locational encoding [13]

Self Attention

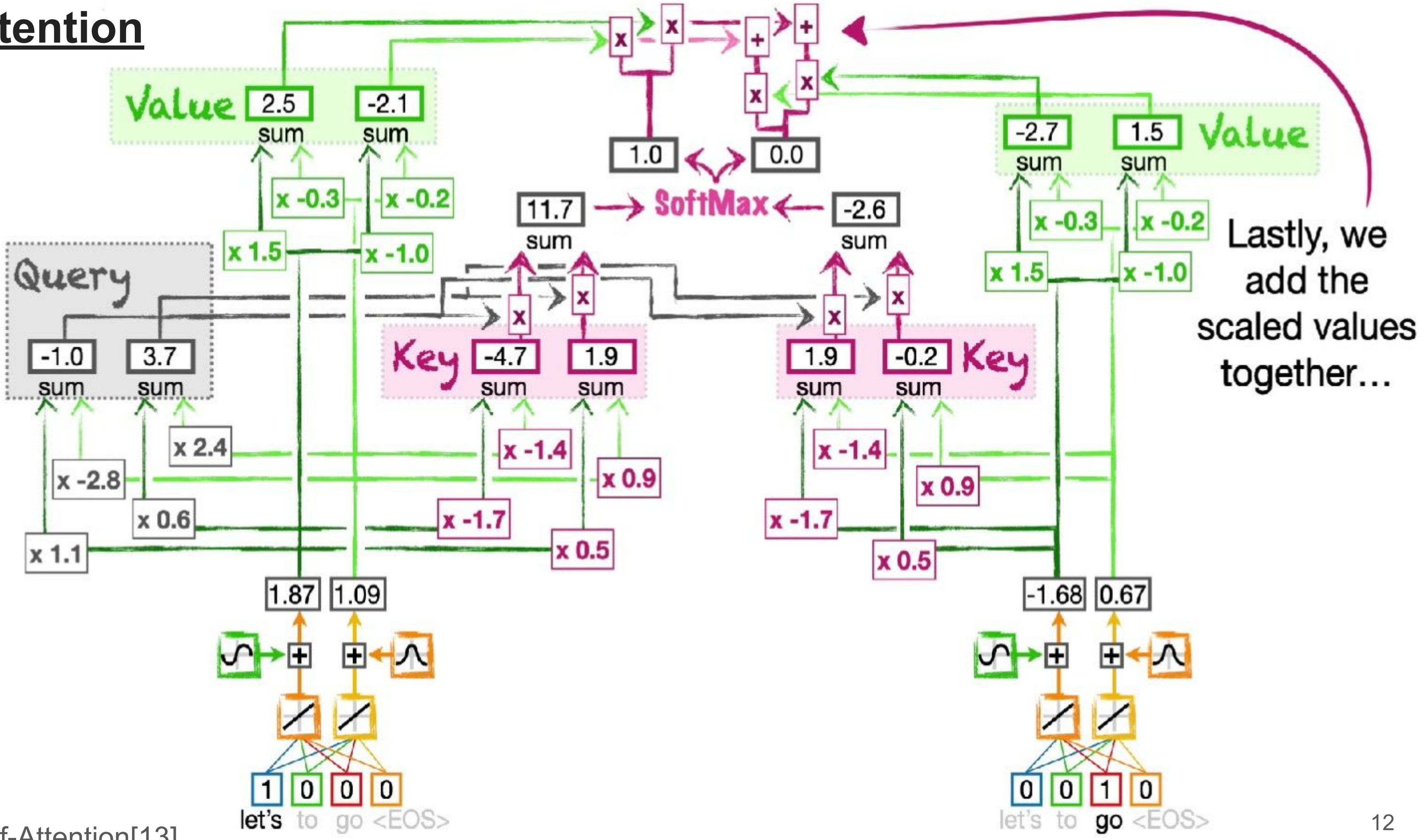


Fig 5. Self-Attention[13]

Decoder Architecture

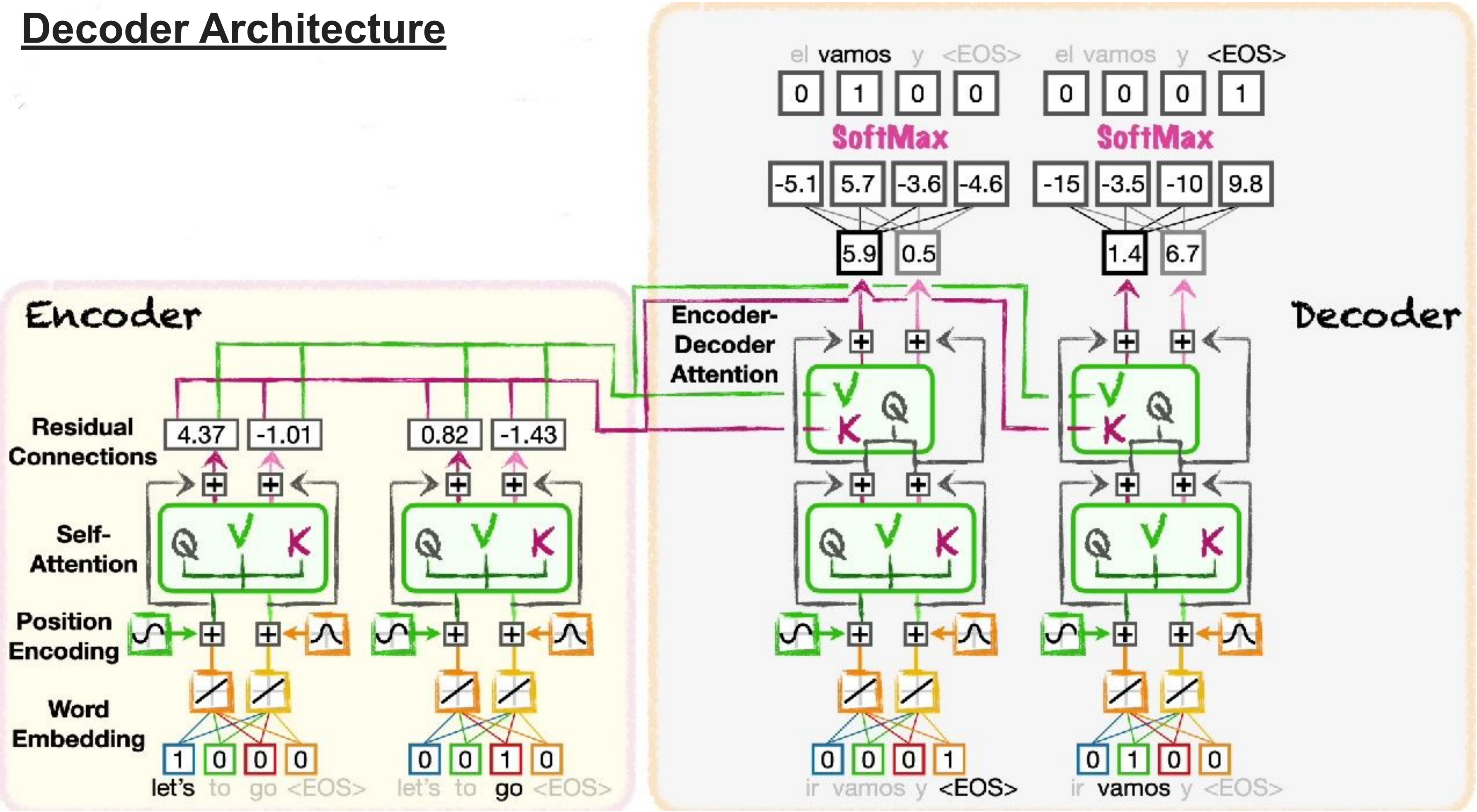


Fig 6. Encoder-decoder architecture [13]

Problem Description

1. **Predicting human mobility:** Given the geolife dataset represented by a sequence of stamped points,predicting user location within 5G networks.
2. **Modeling human mobility patterns:** This involves analyzing data about how people move around in a particular area or population, and identifying patterns or trends.
3. **ABS placement:** predicting the UE mobility pattern and place the UAVs to get best coverage using SSO based framework.

Dataset - Geolife GPS trajectory

- A GPS trajectory dataset collected in (Microsoft Research Asia) GeoLife project by 182 users in a period of over three years (from April 2007 to August 2012).

- This dataset contains 17,621 trajectories with a total distance of about 1.2 million kilometers and a total duration of 48,000+ hours.

- These trajectories were recorded by different GPS loggers and GPS-phones, and have a variety of sampling rates. 91 percent of the trajectories are logged in a dense representation, e.g. every 1~5 seconds or every 5~10 meters per point.

Optimizer

Adam

- Each weight in the neural network receives a personalized learning rate, leading to enhanced optimization by considering the unique characteristics of each weight.
- Adam effectively handles sparse gradients encountered in human mobility prediction tasks and makes the data to be convergent faster.

Automatic Learning Rate Tuning

Efficiency in Sparse Gradients

Result

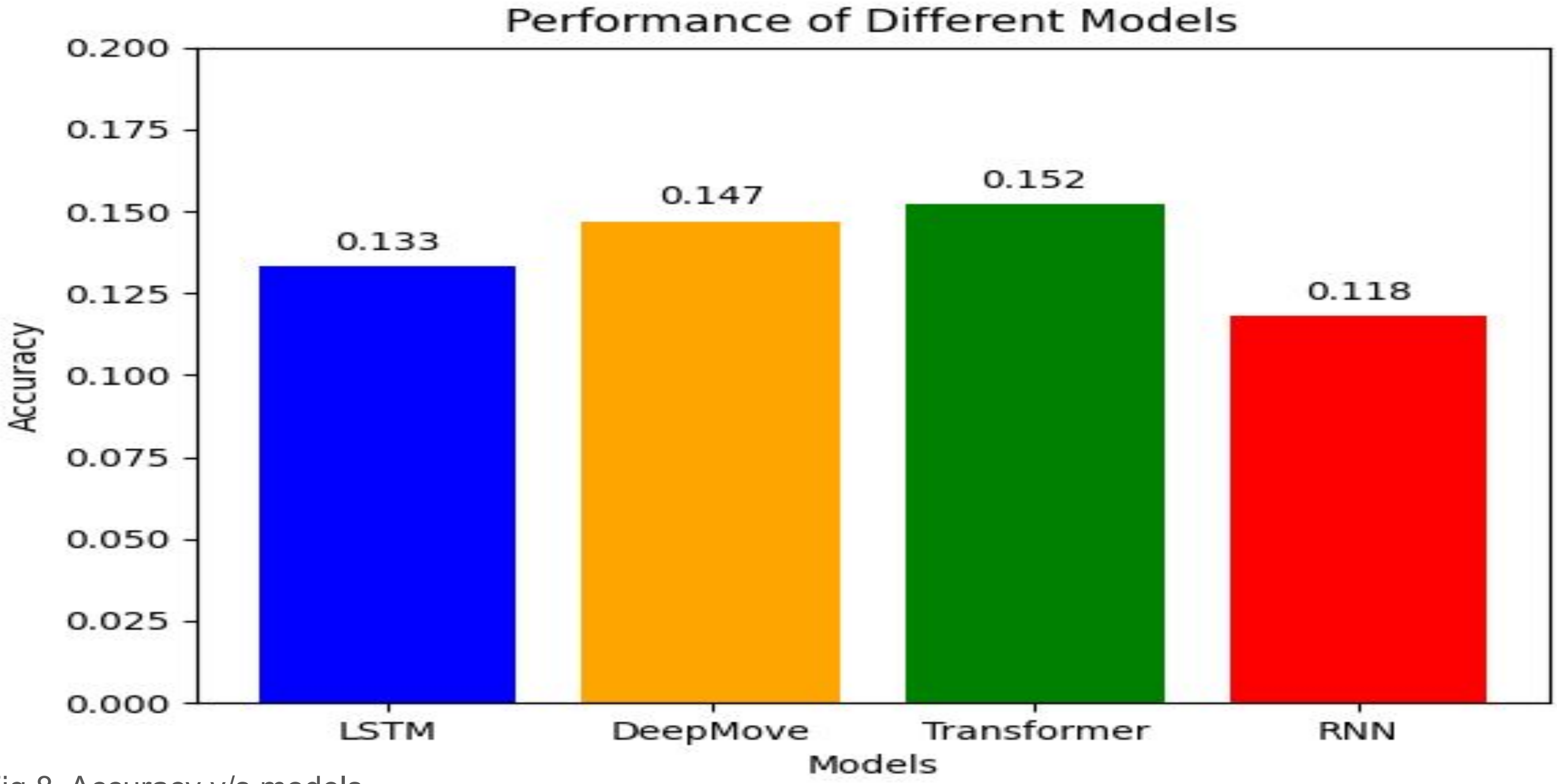


Fig 8. Accuracy v/s models

Result

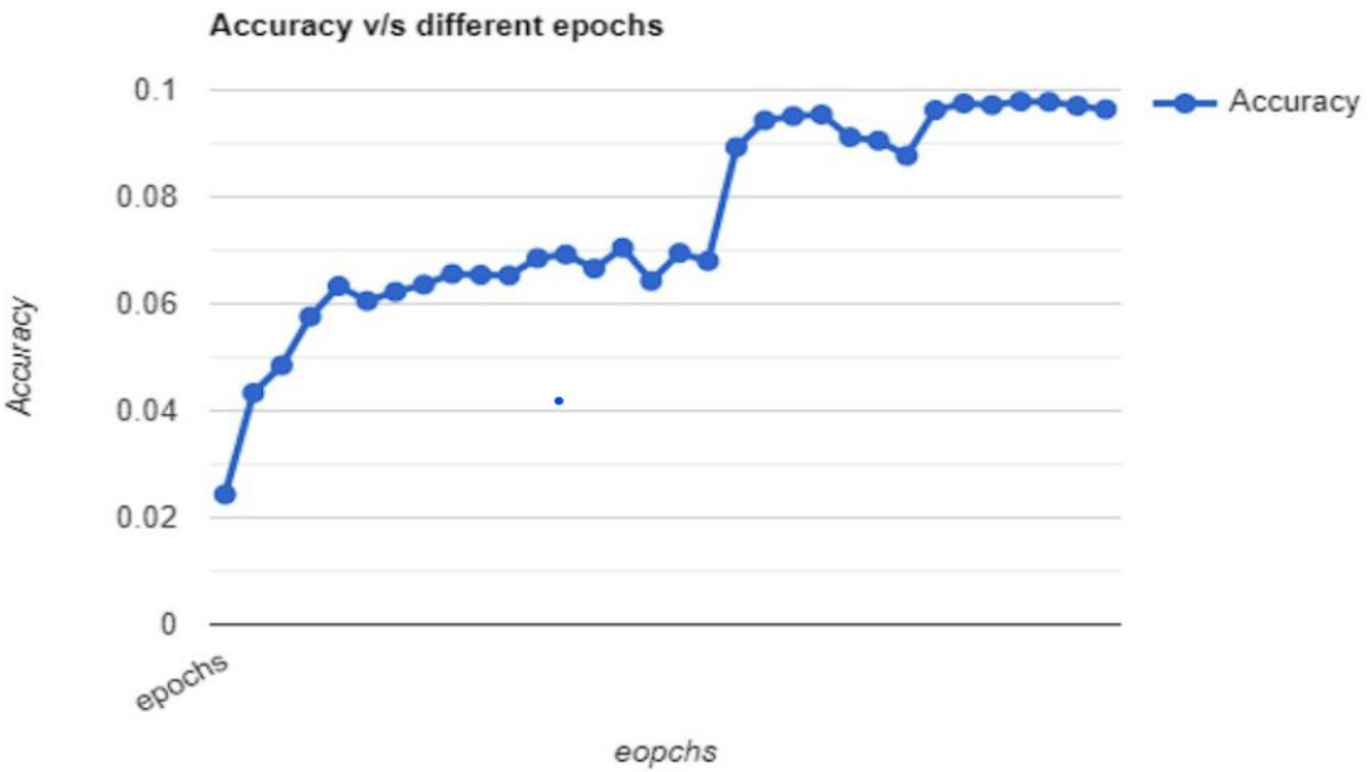


Fig 9. Accuracy variation through different epochs

Adaptive SSO- based framework for ABS placement

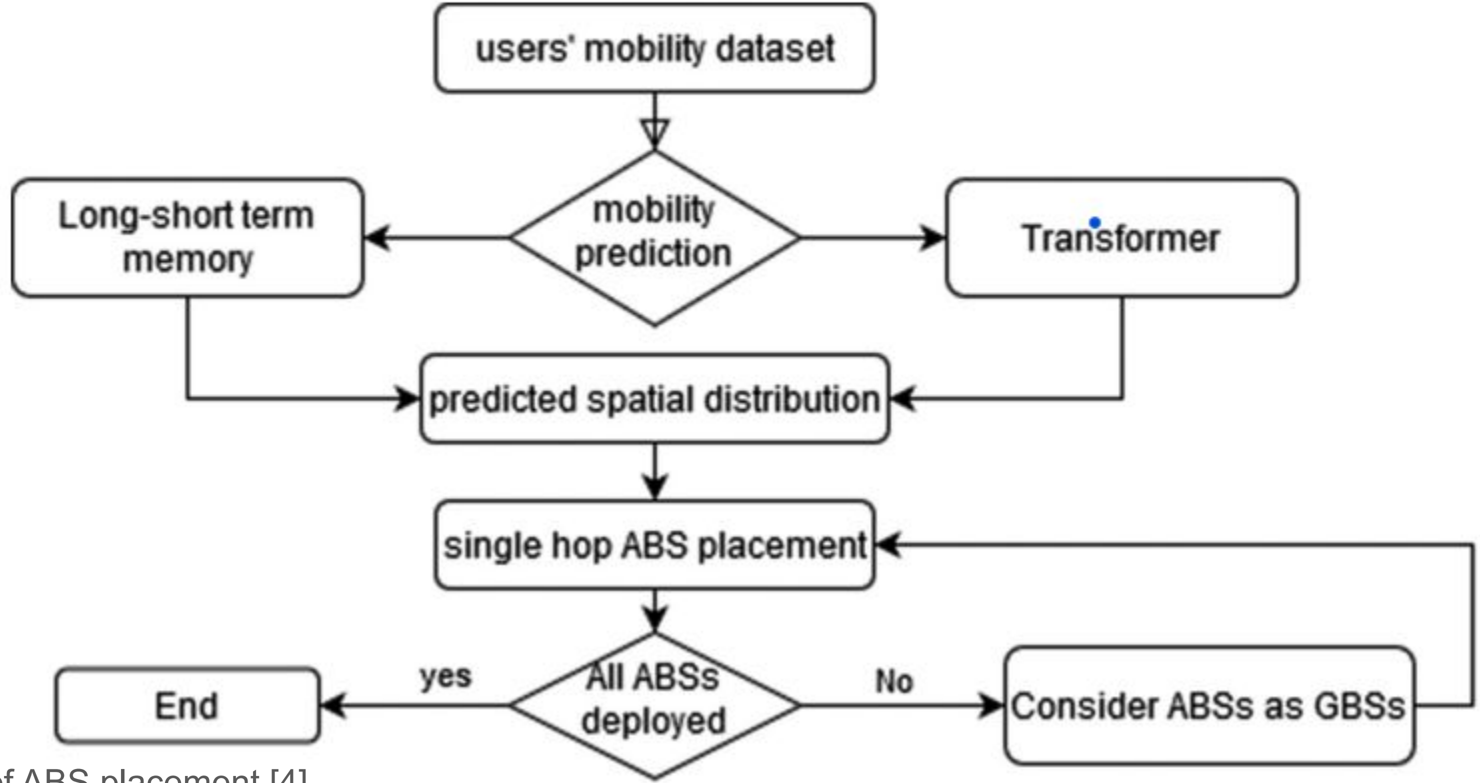


Fig 7. Flow of ABS placement [4]

Related CourseWork

1) **Efficient 3-D placement of an ABS**

Studied the 3-D placement problem of a drone-cell

- Revised as a 3-D placement challenge, the objective is to enhance revenue by maximizing the coverage of users through the drone-cell.
- Discussed the characteristics of the air-to-ground channel, and observed that they can be captured only by considering both the altitude of the drone-cell, and locations of the drone-cell and the users in the horizontal dimension

[1]R. I. Bor-Yaliniz, A. El-Keyi, and H. Yanikomeroglu, “Efficient 3-D placement of an aerial base station in next generation cellular networks,” in Proc. IEEE Int. Conf. Commun., 2016, pp. 1–5.

Related CourseWork

2) Channel modeling for UAV communications

Problem:- UAV channel modelling

- Categorized the UAV channel measurement campaigns in low altitude platform based on the narrowband or wideband channel sounder, low–cost and low–power channel sounding solution, and widely deployed ground infrastructure
- A comprehensive survey of the UAV channel characterization with measurement campaigns and statistical channel models.

[2] A. A. Khuwaja, Y. Chen, N. Zhao, M.-S. Alouini, and P. Dobbins, “A survey of channel modeling for UAV communications,” IEEE Commun. Surv. Tut., vol. 20, no. 4, pp. 2804–2821, Oct.–Dec. 2018.

Future Aspect

Multi-hop ABSs placement to achieve the optimized coverage and improve the user 5G experience by connecting the UAVs and moving them by predicting locations.

Design of a system to achieve real-time mobility tracking.

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[11] G. Zhang, Q. Wu, M. Cui, and R. Zhang, “Securing UAV communications via trajectory optimization,” in Proc. IEEE Glob. Commun. Conf., 2017, pp. 1–6.

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[13]https://www.youtube.com/watch?v=AsNTP8Kwu80&list=PLblh5JKOoLUIxGDQs4LFFD--41Vzf-ME1&index=15&t=42s&ab_channel=StatQuestwithJoshStarmer