Project Proposal

AI Project group 5

1. Team name and team members

- Team name : 5Zone

- Team member :

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2. Project background & Related work

Project background :

The ozone layer in the stratosphere protects the biosphere from harmful solar ultraviolet radiation. In the troposphere, it acts as an efficient purifier, but high concentrations can be harmful to the health of humans, animals, and plants. Ozone is also a significant contributor to ongoing climate change as a potent greenhouse gas. Since the discovery of the Antarctic ozone hole in the 1980s and the subsequent implementation of the Montreal Protocol to regulate the production of ozone-depleting substances, ozone has been regularly monitored both on the ground and in space.

Related work :

- **Air Quality Forcasting**

Existing air quality forecasting models can be divided into two categories: physical models and machine learning models. Physical models, such as street canyon and Gaussian plume models, simulate the emission and diffusion processes of air pollutants based on air motion and matter diffusion theories. However, these models require accurate pollution source data and have limited generalization ability. On the other hand, machine learning models learn the relationship between input features and Air Quality Index (AQI) values from data.

Deep learning models automate feature learning by stacking multiple neural networks to fit the nonlinear transformation from inputs to outputs. These models capture complex spatial-temporal relationships and dependencies among monitoring stations, with recent advances utilizing Graph Neural Networks (GNNs) to model non-Euclidean distributed entities.

However, most models focus on predicting air quality at specific locations and do not consider dependencies between regions.

- GNN

Incorporating temporal dynamics into Graph Neural Networks (GNNs) poses a significant challenge in many applications. While GNNs excel at capturing spatial relationships and dependencies within graph-structured data, they often struggle to effectively model temporal dynamics. This limitation arises due to the inherent nature of GNNs, which typically operate on fixed graph structures and lack mechanisms to explicitly handle temporal changes. Consequently, in tasks where temporal aspects play a crucial role, such as dynamic graph analysis and time-series prediction, traditional GNNs may not provide satisfactory performance. As a result, there has been growing interest and research efforts aimed at extending GNNs to better accommodate temporal information, leading to the development of various temporal graph neural network models and methodologies.

3. Goal

The goal is to predict changes in ozone conditions based on data obtained from satellite observations.

4. Dataset

open-source emissions data (from Sentinel-5P satellite observations)
link: https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S5P_NRTI_L3_O3?hl=en#description

5. Evaluation methods and baselines for comparison.

Evaluation Method:

- The evaluation method consists of assessing the accuracy of ozone density predictions.

Baselines:

- Predictions using an RNN after embedding (without considering spatial features).
- Predictions using a GNN trained with GCN (Graph Convolutional Network) but not considering temporal features.
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- predictions made by a GNN model that considers both temporal and spatial features.

6. Team github link

: https://github.com/2024-AIP-Group5