NASA Project Quarterly Report

Progress on Traffic Flow Density and Safety related event prediction

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Introduction

- From individual level to systemic level:
  - The previous work study the individual level impact of convective weather on flight trajectories.
  - The current objective is to do systemic level flight event and traffic density prediction.

Table 1. Meaning of different event types

Event Type	Counts	Meaning
EV_MOF	279645	Mode of flight. A flight record in vertical domain such as descending level, climbing level. Also known as vertical trajectory.
EV_XING	250173	Crossing event from one sector to another sector. Indicate which space volume are you in and which one are you crossing to other column.
EV_USER	134956	User event. The definition is flexible includes times you go into a center, different volume definitions. It's a user based concept.
EV_TRNS	75086	Transition from above or below altitude. Not often used.
EV_PXCP	52892	Unknown.
EV_INIT	50934	Detail on the begin of flight tracks. Smaller set on facility recorded by the surveillance system.
EV_STOP	50934	The last track point of the aircraft.
EV_LOOP	41118	Indication of holding pattern. The flight circle around in the trajectory.
EV_TOC	25467	Top of climb. Reach cruise altitude. Overlap with MOF.
EV_TOD	25467	Top of descend. Start to descent from cruise altitude
EV_RRT	20692	Reroute. New flight plan change compared to old flight plan.
EV_LND	19526	Landing event. Recorded when arrival aircraft pass the arrival runway threshold.
EV_TOF	14697	Take off event. It's defined geometrically when the aircraft cross the departure runway threshold (wheels come off the pavement).
EV_STOL	5174	Stop holding. Finish EV_LOOP Event.
EV_GOA	1814	Go around. About to land but pull up and circle back, turn around again. A possible safety concern.

Safety Concern

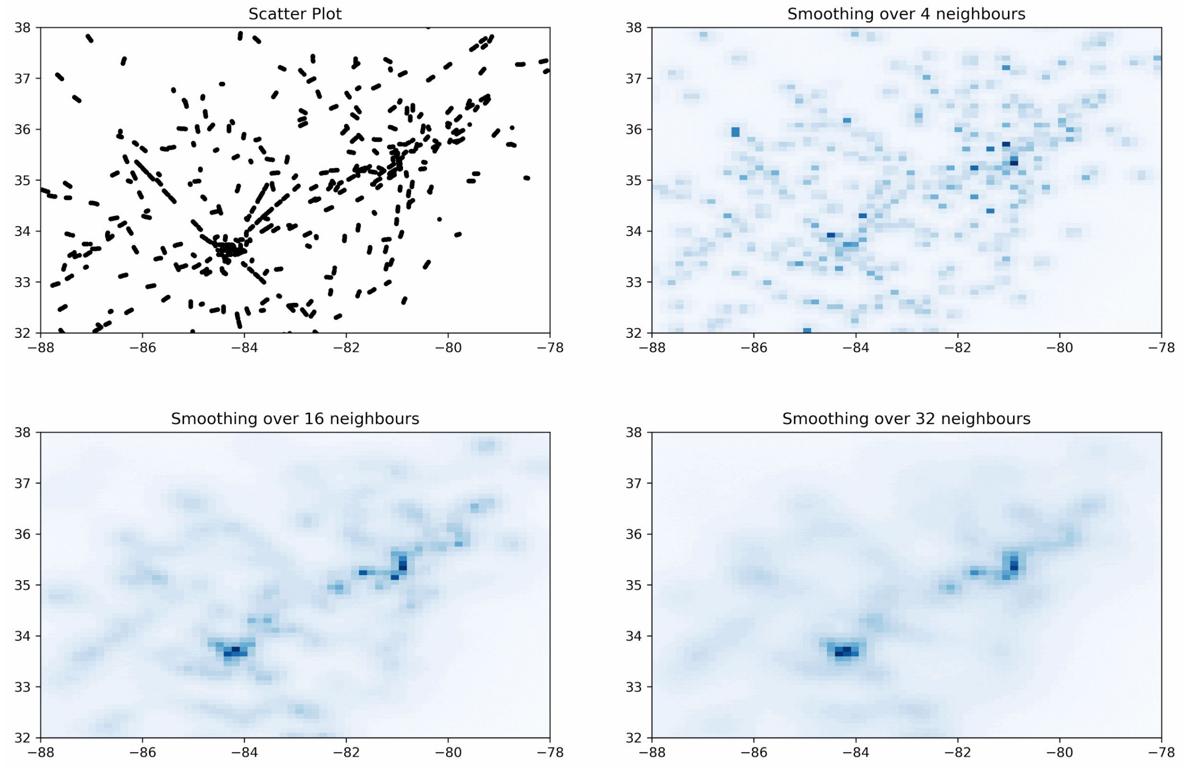
Data Preparation

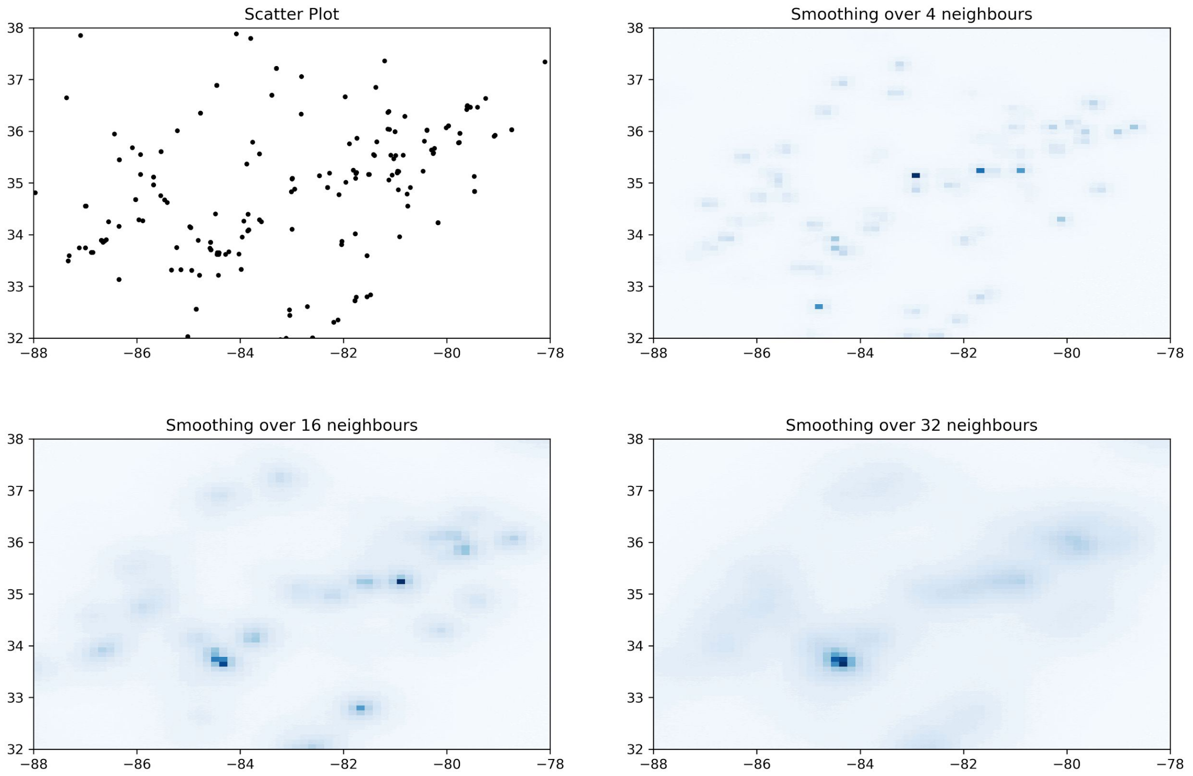
- Two types of data in Sherlock Data Warehouse.
  - Flight recording: ZTL from Aug 1st, 2019 to Aug 28th, 2019
  - Flight event occurrence recording: ASDEX+ATL from Aug 1st, 2019 to Aug 28th, 2019
- Data processed:
  - Traffic flow heatmap generator:
    - time_interval = 60s, size = 64x64, range_latlon=[[-88, -78], [32, 38]], range_time=[12pm, 4pm]
  - Event occurrence generator for all flight event types and only safety-related event types:
    - time_interval = 60s, size = 64x64, range_latlon=[[-88, -78], [32, 38]], range_time=[12pm, 4pm]
  - Smoothing the discrete scatter plot around its nearest neighbors.
- Large-scale data processing techniques deployed:
  - SparkSQL, SparkRDD for efficient querying of the flight recordings.
  - GeoSpark extensions for efficient geospatial query.
  - Reduce computational complexity with R-tree/KD-tree for accelerated query indexing with amortized cost O(logn).

```
rectangular_query = "SELECT COUNT(acId) " \
                    "FROM spatialdf " \
                    "WHERE ST_Contains(ST_PolygonFromEnvelope({}, {}, {}, {}), geom)" \
    .format(lat[index_lat], lon[index_lon], lat[index_lat+1], lon[index_lon+1])
```

Data Visualization

- Processed 28 days data. Each plot has time interval 60s.





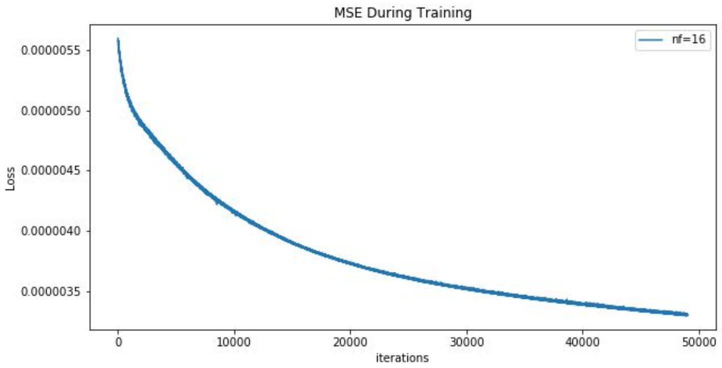
Proposed Methodology

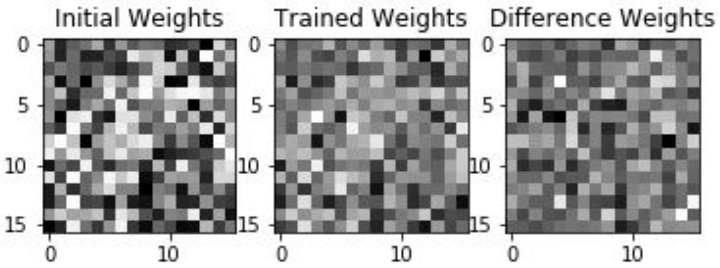
- We proposed three substudies:
  - a) Safety-Related Events:
    - Predict the occurrence of EV_LOOP and EV_GOA based on the traffic flow density
  - b) All Flight Events:
    - Predict the occurrence of all types of flight event based on the traffic flow density
  - c) Traffic Flow Prediction:
    - Next frame prediction of the traffic flow density video.
- a) and b) classified as same task but with different dataset
  - Autoencoder (AE): finished
  - Deep-convolutional general adversarial networks (DCGAN)[1]: no good result
- c) is a sequenced image learning task (video learning):
  - Eidetic 3D LSTM (E3D-LSTM)[2]: State-of-art video learning framework
    - Training is slow as it requires extensive CUDA calculation.

[1] Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.
[2] Wang, Y., Jiang, L., Yang, M. H., Li, L. J., Long, M., & Fei-Fei, L. . Eidetic 3d lstm: A model for video prediction and beyond. ICLR 2019

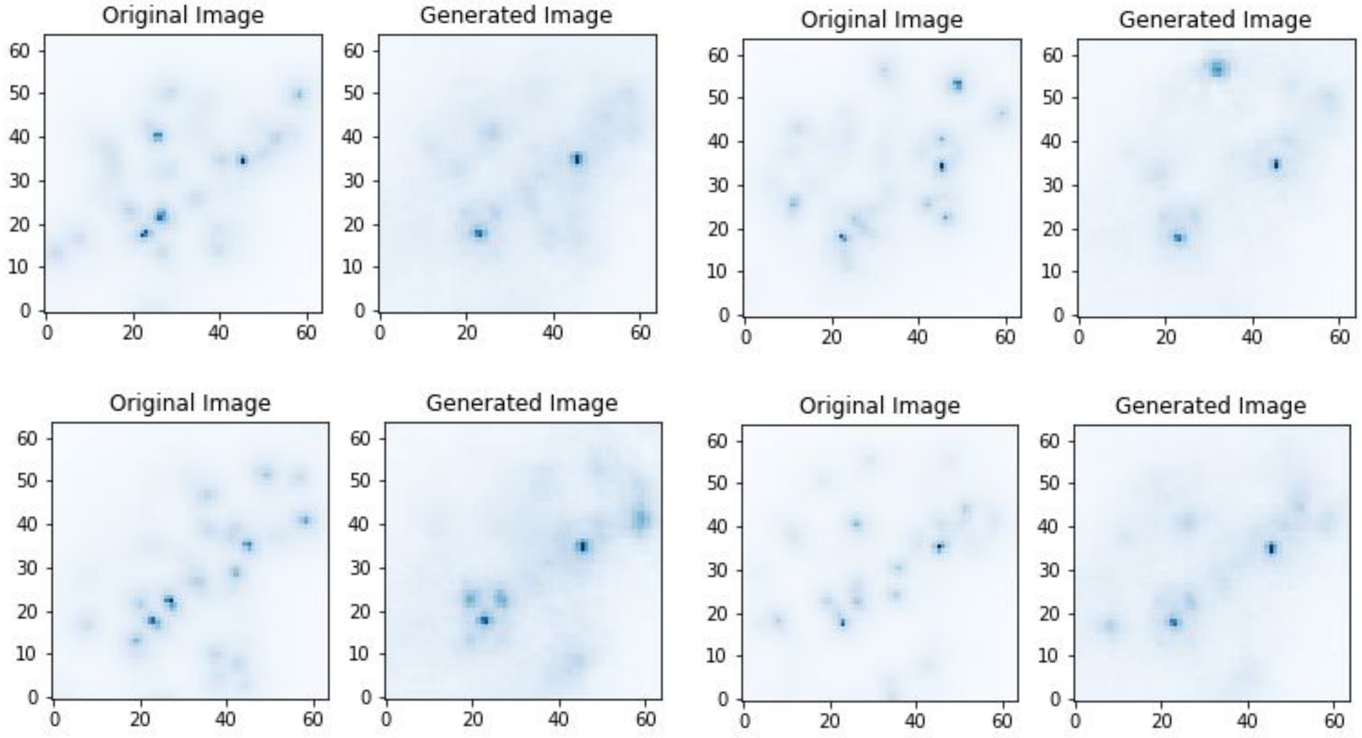
All Flight Events

- Autoencoder



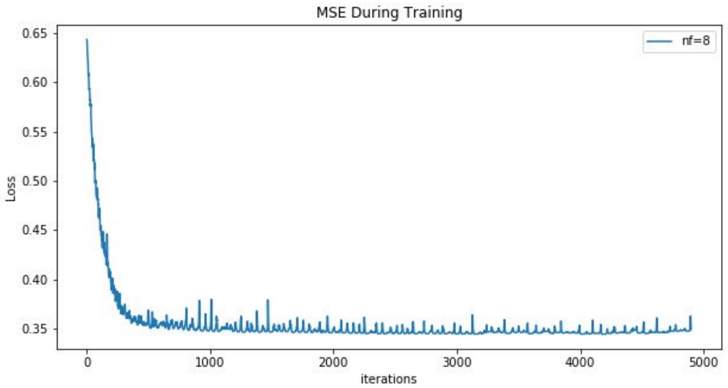


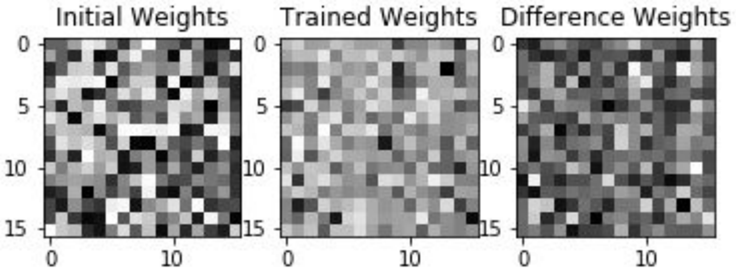
Test Data



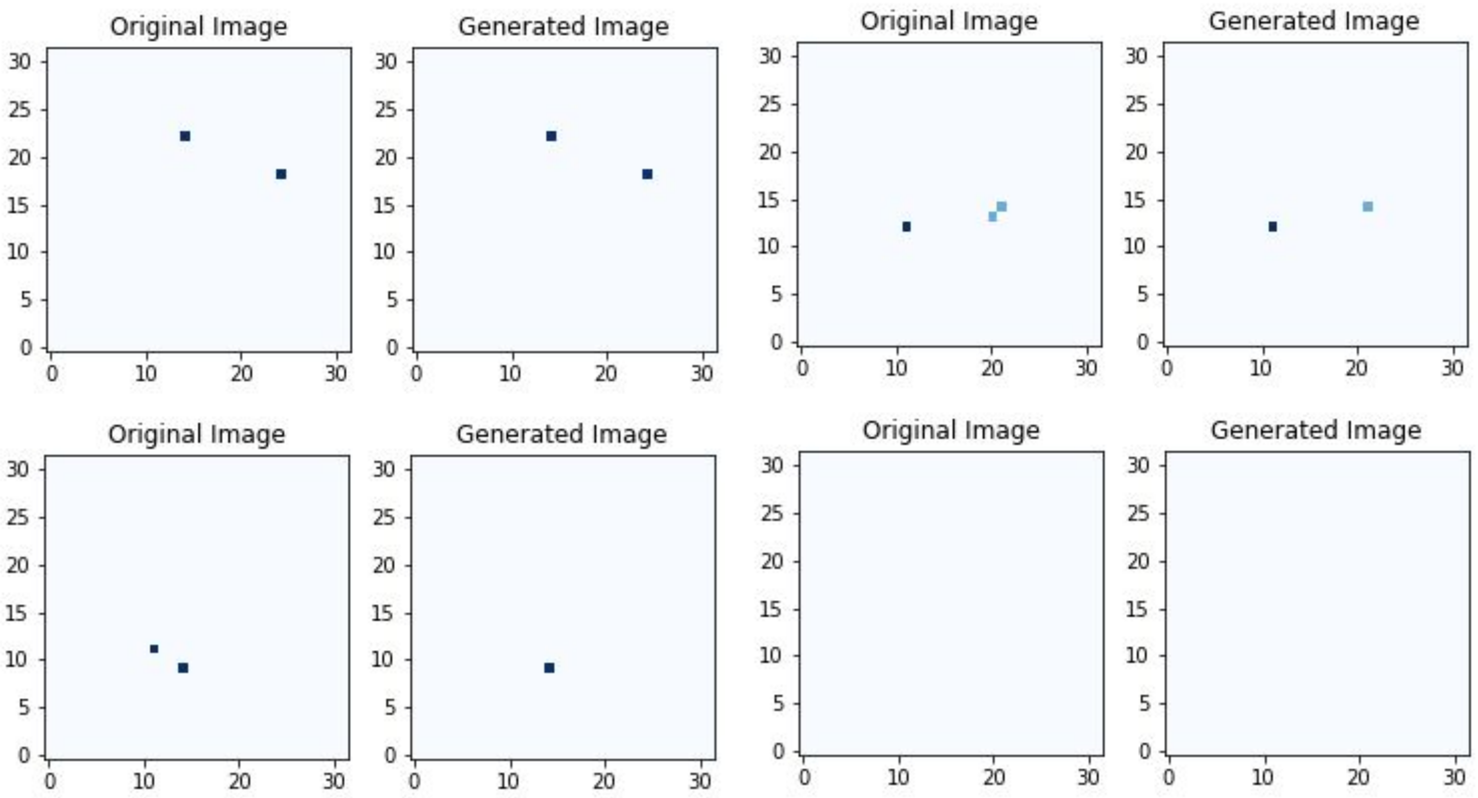
Safety-Related Events

- Autoencoder



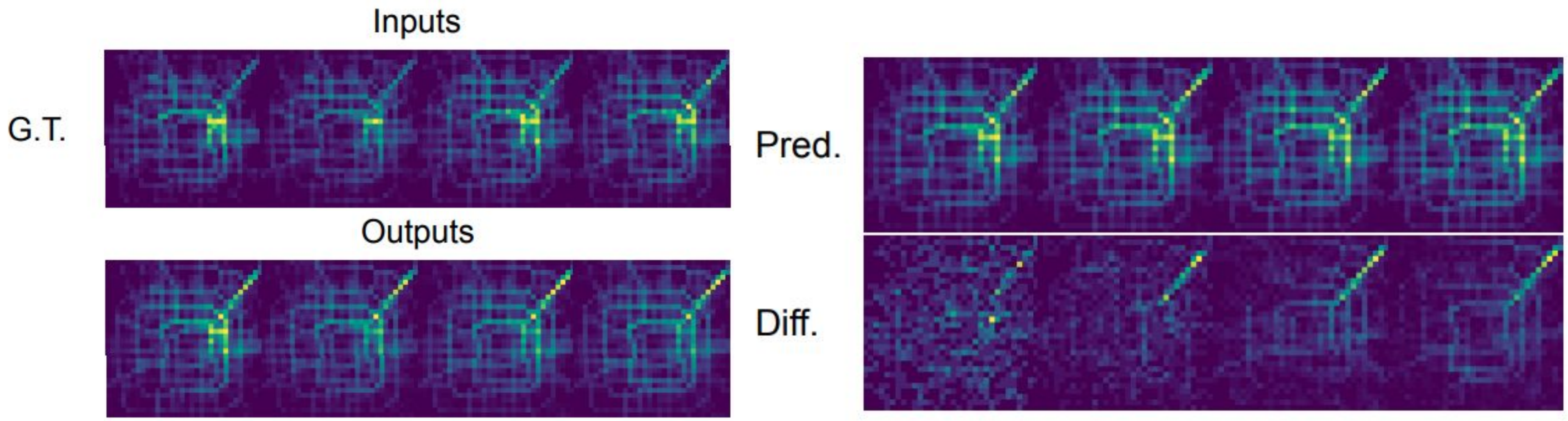


Test Data



Traffic Flow Prediction

- E3D-LSTM:
  - Add *Scaled Dot-Product* attention[3].
  - Add more *LayerNorm*[4] for faster training.
  - Demo with TaxiBJ dataset[2]



[3]Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In Advances in neural information processing systems (pp. 5998-6008).
[4]Ba, J. L., Kiros, J. R., & Hinton, G. E. (2016). Layer normalization. arXiv preprint arXiv:1607.06450.

- Future work:
  - Parameter tuning for better evaluation result
  - Finish E3D-LSTM with the traffic flow data from Sherlock
- Also consider the suggestions and comments.