Conditional Generative Adversarial Network (CGAN) for Aircraft Trajectory Prediction Considering Weather Effects

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outline

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Introduction – Motivations

- ❖ Weather-related safety concerns and huge uncertainties exist during daily aviation operations.
  - ➢ Unforeseeable: The convective weather conditions can develop rapidly [1].
  - ➢ Frequent: 30% ~ 40% of the delayed flights are caused by weather related reasons [2].
- ❖ The workload of controllers can increase significantly during certain extreme climatic events.
- ❖ The development of flight trajectory planning tools help reduce these concerns.
- ❖ NextGen requires an accurate and automatic flight trajectory planning tool to update the flight route.
- ❖ To achieve this, researchers focus on,
  - ➢ System-level trajectory planning and dynamic weather reroutes.
  - ➢ Deterministic prediction and probabilistic prediction.

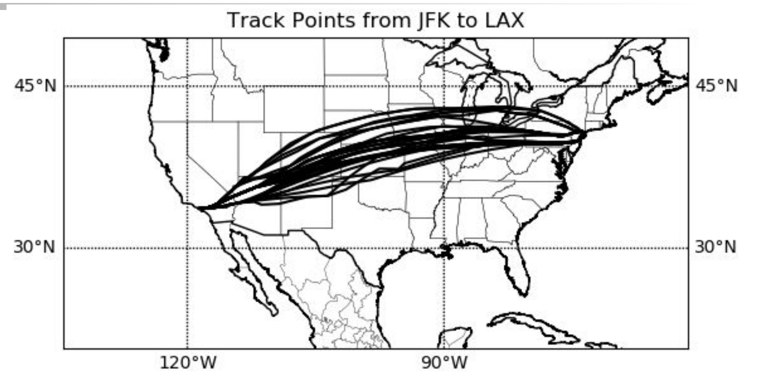


Fig.1 Flight Tracks from JFK to LAX on Dec 19, 2018

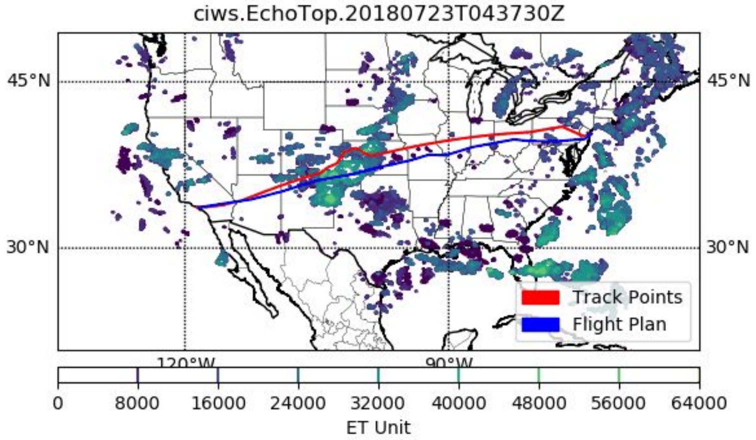


Fig.2 Convective Weather Conditions during the Flight Period from 04:45:00 to 11:47:30 on July 23, 2018

[1] Erzberger, H., Lauderdale, T., and Chu, Y., "Automated conflict resolution, arrival management, and weather avoidance for air traffic management," Journal of aerospace engineering, Vol.226, No. 8, 2012, pp. 930–949.

[2] Belcastro, L., Marozzo, F., Talia, D., & Trunfio, P. (2016). Using scalable data mining for predicting flight delays. ACM Transactions on Intelligent Systems and Technology (TIST), 8(1), 5.

Introduction – Previous Work

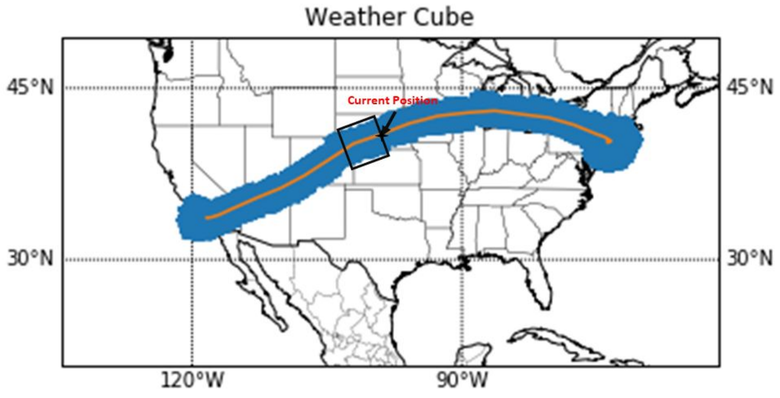


Fig.3 Weather cube generating algorithm

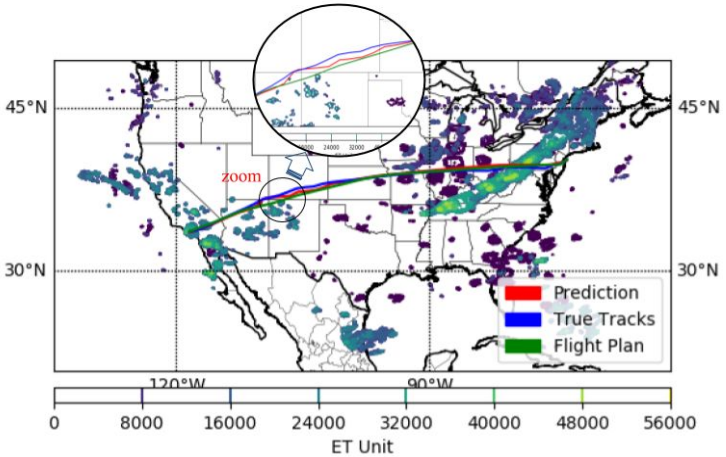


Fig.4 A prediction result

- Previous work [3] use recurrent neural network to predict the flight trajectory from JFK to LAX.
  - Extract weather data along each track point.
  - Modify the recurrence of RNN cell to incorporate weather features into the model.
- Issues,
  - A long prediction (6 hours flight) is untrustworthy.
  - Needs better prediction accuracy with prediction uncertainties.
  - Limited data.

[3] Pang, Y., Yao, H., Hu, J., & Liu, Y. (2019). A Recurrent Neural Network Approach for Aircraft Trajectory Prediction with Weather Features From Sherlock. In AIAA Aviation 2019 Forum (p. 3413).

Introduction – Solutions

- To accommodate these, we
  - perform sector-specific prediction rather than prediction across multiple sectors.
  - adopt semi-supervised generative model.

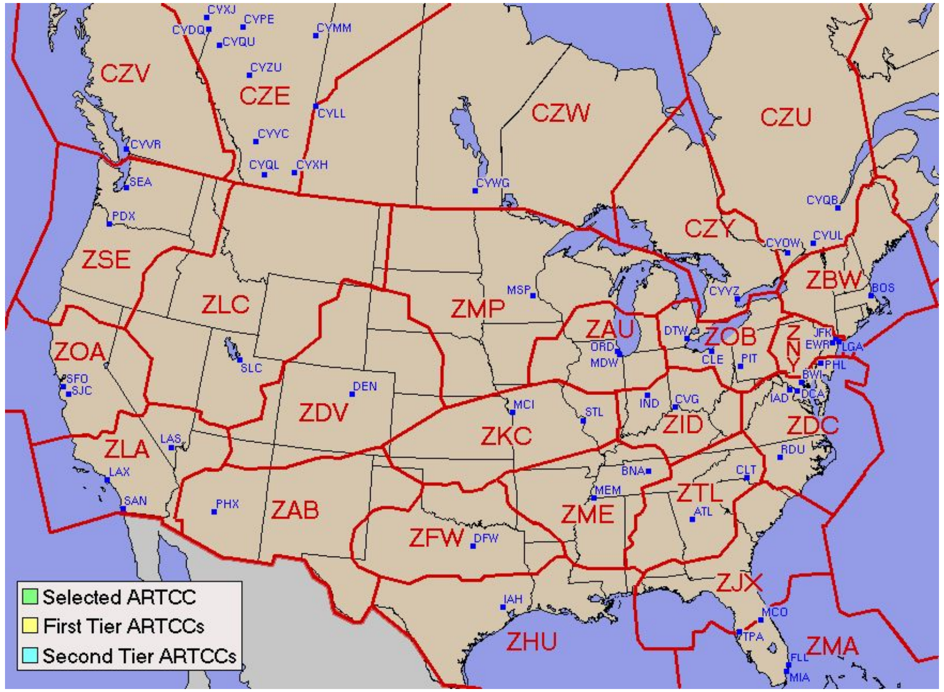
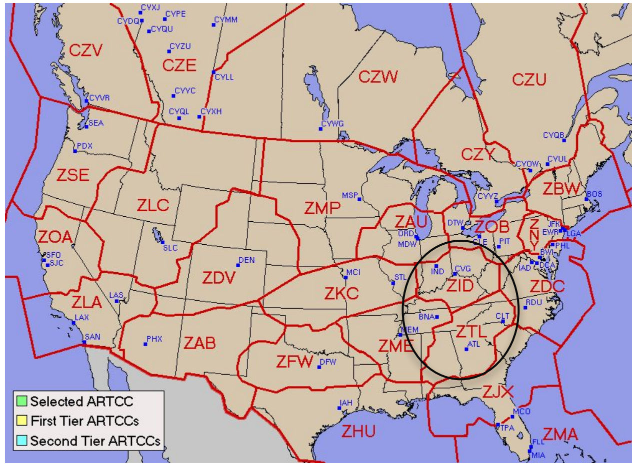


Fig.5 United States Air Route Traffic Control Center (ARTCC)
Source: https://www.fly.faa.gov/ois/tier/themap.html

Introduction – Case Study

- Start from data analysis.
  - It's reported to have severe weather condition on 06/24/2019* within the United States airspace.
  - Tornado and high wind are reported at numerous locations in the east.
- Sector ZID (Indianapolis) and ZTL (Atlanta) roughly cover the area of interest.



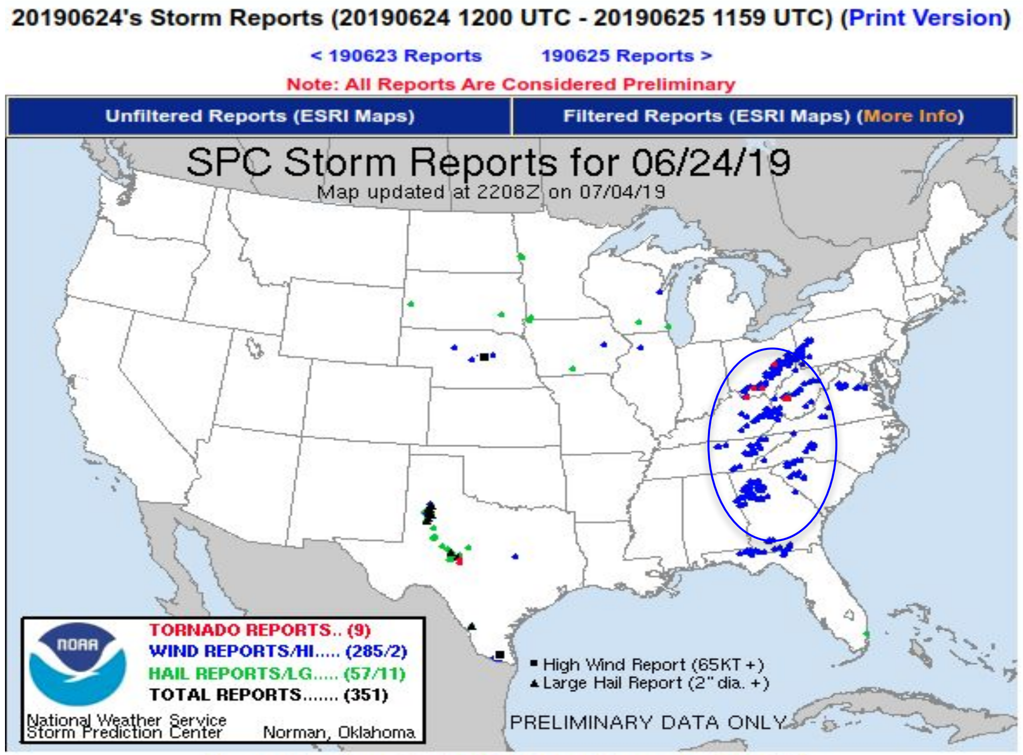


Fig.6 SPC Storm Reports for 06/24/19

*NOAA Storm Prediction Center: *https://www.spc.noaa.gov/exper/archive/events/*

Data Source – Database

- Sherlock Data Warehouse (SDW)
  - SDW [4] is a big data system for data visualization to support air traffic management (ATM) research, which includes a database, a web-based graphical user interface (GUI) and other services.
  - Data of SDW primarily comes from the FAA and the National Oceanic Atmospheric Administration (NOAA).
  - We use sector Integrate Flight Format (IFF) data for flight plans and real tracks, and Convective Integrated Weather Service (CIWS) for EchoTop (ET) weather data.
  - ZID on June 24th, 2019.

[4] Arneson, H. M., Hegde, P., La Scola, M. E., Evans, A. D., Keller, R. M., & Schade, J. E. (2019). Sherlock Data Warehouse.

Data Source – Flight Data

- Sector IFF data for each day is around 200 MB with over 10 million rows.
- Flight Records includes flight tracks, flight plan and flight information.
  - Flight tracks includes spatial and temporal coordinates.
  - Flight Plan comes as a string of waypoints. We create a web-based mining code to parse it into WGS84 coordinates using online database (*opennav.com*).

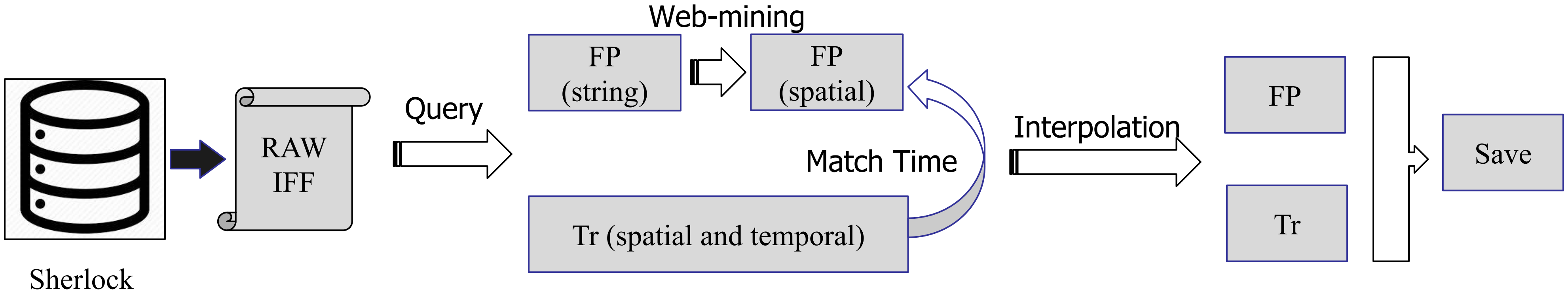


Fig.7 Flowchart: Raw IFF data processing

Data Source – Flight Data

- The processing of sector IFF data follows a similar procedure as the previous work and can be conclude as,
  - <u>Query → Match → Interpolate → Equalize</u>
- The dimension of the processed flight data is 4103×50×2.

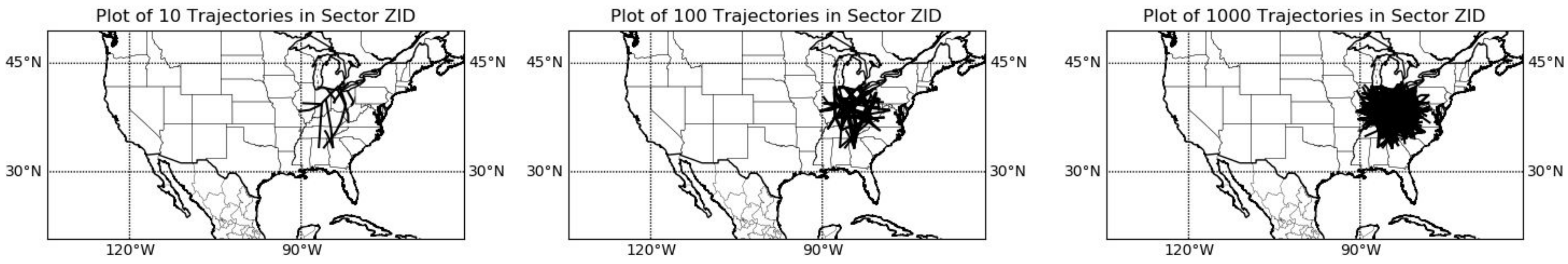
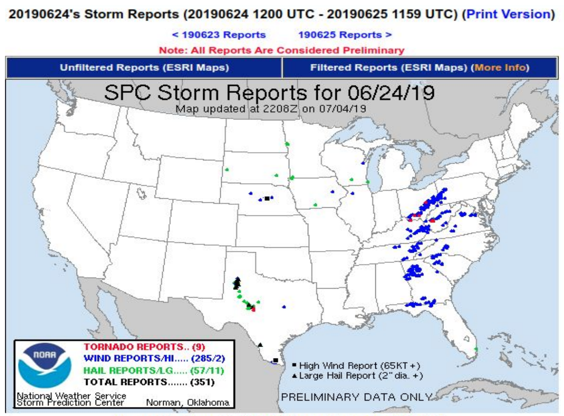


Fig.8 Flights in sector ZID on 06/24/2019



Data Source – Weather Data

- The two key features of CIWS are EchoTop (ET) and Vertically Integrated Liquid (VIL), both come with current and forecast dataset in Sherlock. We only use current ET for demonstration.
- At each track point, we take out the weather tensor of size 32×32×1 except for the starting point. The orientation of the weather tensor is rotated with the aircraft heading angle.
- The processed weather tensor has size 4103×49×32×32×1.

Table 1 EchoTop Key Features

Parameters	Current	Forecast
Dimension	1x1x3520x5120	24x1x3520x5120
Range Latitude / °	[19.36, 48.90]	
Range Longitude / °	[-134.35, -61.65]	
Update Frequency / s	150	300

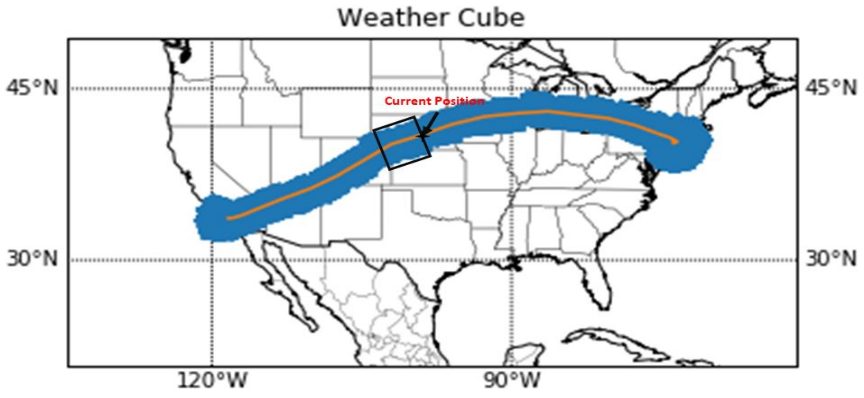


Fig.9 Weather cube generating algorithm

Preliminaries – Generative Adversarial Network

- The Generative Adversarial Network is proposed by *Ian J. Goodfellow* in 2014 [5].
- It composes two deep neural nets, the generator *G*, and the discriminator *D*.
- GAN is about counterfeiters.
  - G produce fake data to imitate the ground truth.
  - D detect the counterfeits.
- The competition between the generator and the discriminator forces them to keep improving their methods to make the counterfeits indistinguishable from the ground truth data. (semi-supervised learning model)
- This is called a mini-max game on the cross-entropy loss,

$$\min_{G}\max_{D} V(D,G) := \mathbb{E}_{x\sim P_{data}(x)}[log(D(x))] + \mathbb{E}_{x\sim P_{z}(z)}[log(1-D(G(z)))]$$

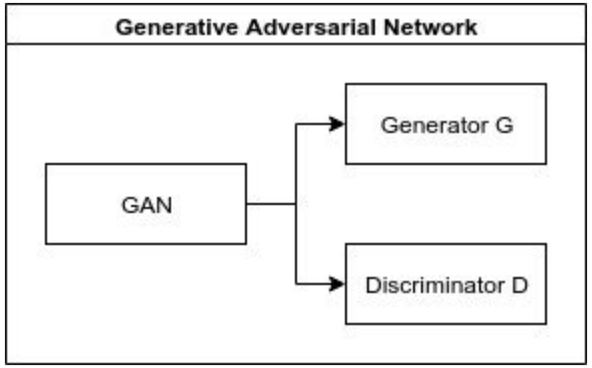


Fig.10 Generative Adversarial Network (GAN)

[5] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y., “Generative Adversarial Nets,” Advances in Neural Information Processing Systems 27, edited by Z. Ghahramani, M. Welling, C. Cortes,N. D. Lawrence, and K. Q. Weinberger, Curran Associates, Inc., 2014, pp. 2672–2680.

Preliminaries – GAN

- GAN applications have increased rapidly.
  - image/face generation
  - model reconstruction
  - speech and text generation

- An image generated by a StyleGAN [6] that looks deceptively like a portrait of a young woman. This image was generated by a StyleGAN based on an analysis of portraits.

- Regression?

Fig.11 Face Generation with style GAN

[6] Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 4401-4410).

Preliminaries – Conditional GAN

- Conditional GAN (CGAN) is as simple as adding an additional input to the generator and discriminator [7].
- The objective changes to,

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\underline{\boldsymbol{y}})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\underline{\boldsymbol{y}})))].$$

- A few papers use CGAN to perform regression task [8, 9].
- <u>In our model, the condition would be the last on-file flight plan and the weather conditions.</u>
- The model can be formulated as, $f(x, z|\underline{\{p, w\} \in \mathbf{y}})$
  - where x is the true trajectory, z is random noise as input to G, p is the flight plan tensor and w is the weather tensor.
- z follows truncated normal distribution $N(0.5,\ 1.0)$ with a lower bond 0 and upper bond 1.

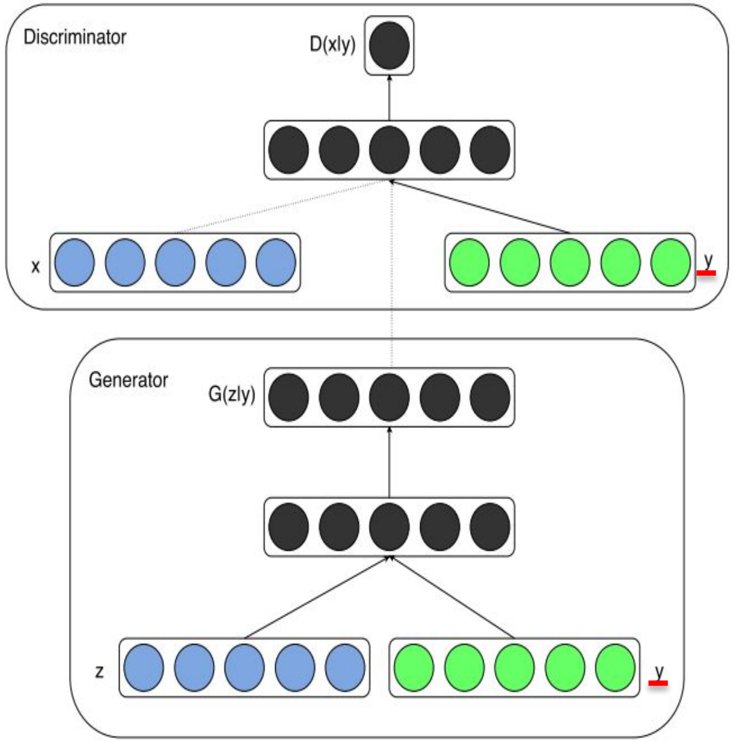


Fig.12 CGAN architecture [7]

[7] Mirza, M., & Osindero, S. (2014). Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784.

[8] Aggarwal, K., Kirchmeyer, M., Yadav, P., Keerthi, S. S., & Gallinari, P. (2019). Regression with Conditional GAN. arXiv preprint arXiv:1905.12868.

[9] Yu, Y., Harscoët, F., Canales, S., Reddy, G., Tang, S., & Jiang, J. (2020, January). Lyrics-Conditioned Neural Melody Generation. In International Conference on Multimedia Modeling (pp. 709-714). Springer, Cham.

Network Architecture - Details

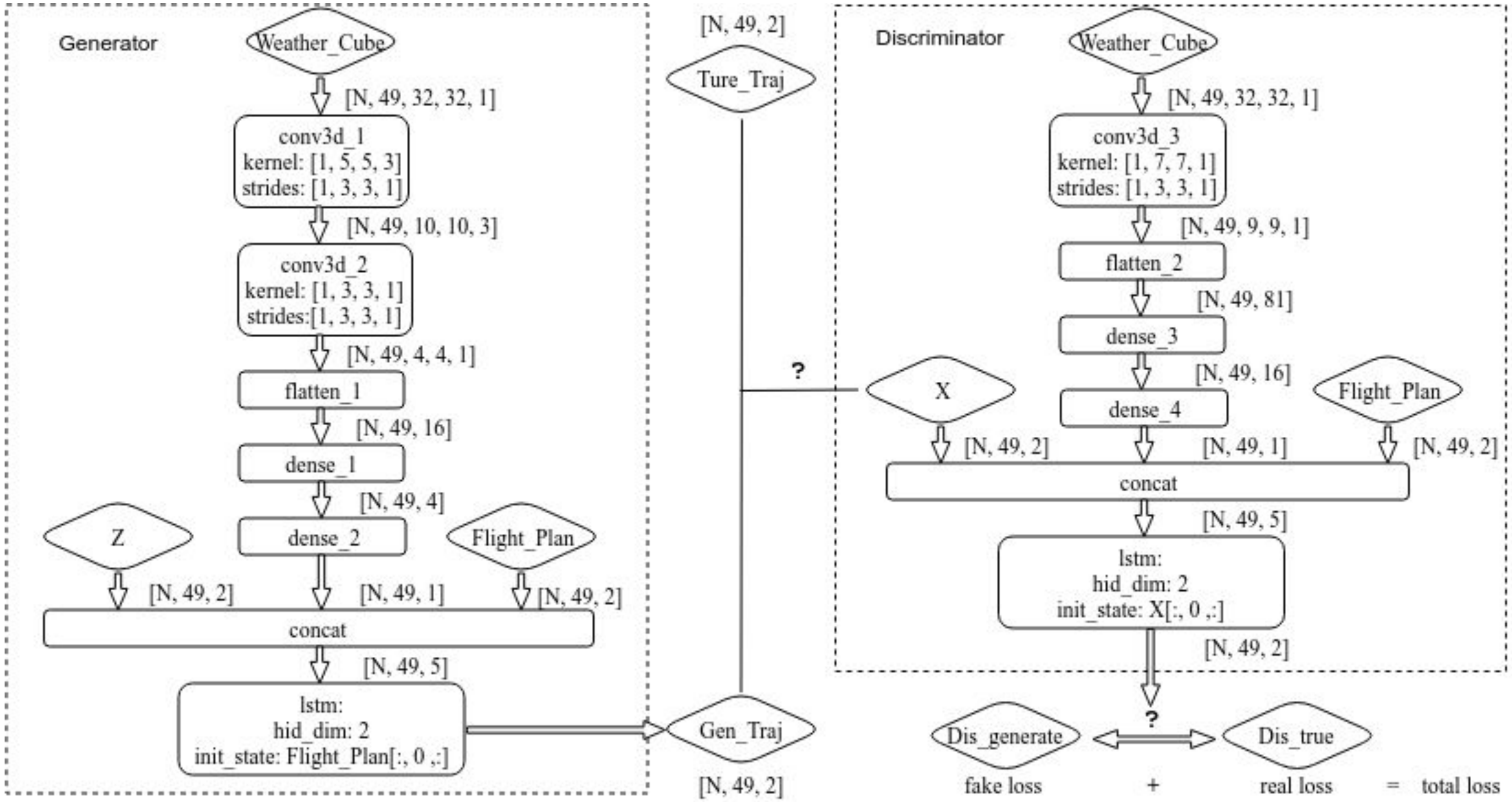


Figure 13. Flow of Tensor

Network Architecture - Details

- Optimization objective,

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim P_{data}(x)}[log(D(x|w,p))] + \mathbb{E}_{x\sim P_z(z)}[log(1 - D(G(z|w,p)))]$$

$$G^* = \arg\min_G \max_D \mathcal{L}_{GAN}(G,D)$$

  - A root mean squared error loss is used instead of cross-entropy loss.

- Training details,
  - LSTM is initialized with the starting point of the input.
  - The data is separated into training set and testing set.
  - Train with Adam optimizer with learning rate of 0.001 running 100 epochs.

Experimental Results

- The testing result is the output from the generator G where,
  - The random input z is sampled randomly during each test.
- We perform 100 tests and calculate the mean and variance.

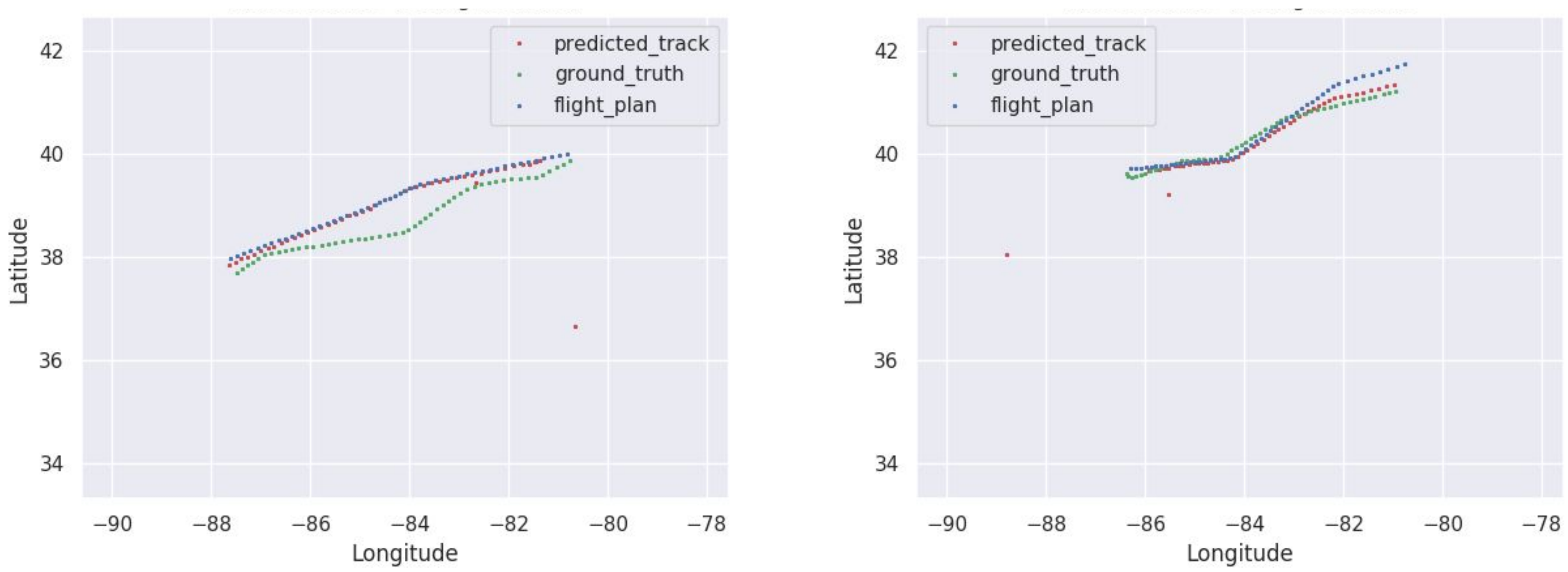


Fig.14 CGAN Mean Prediction

Experimental Results

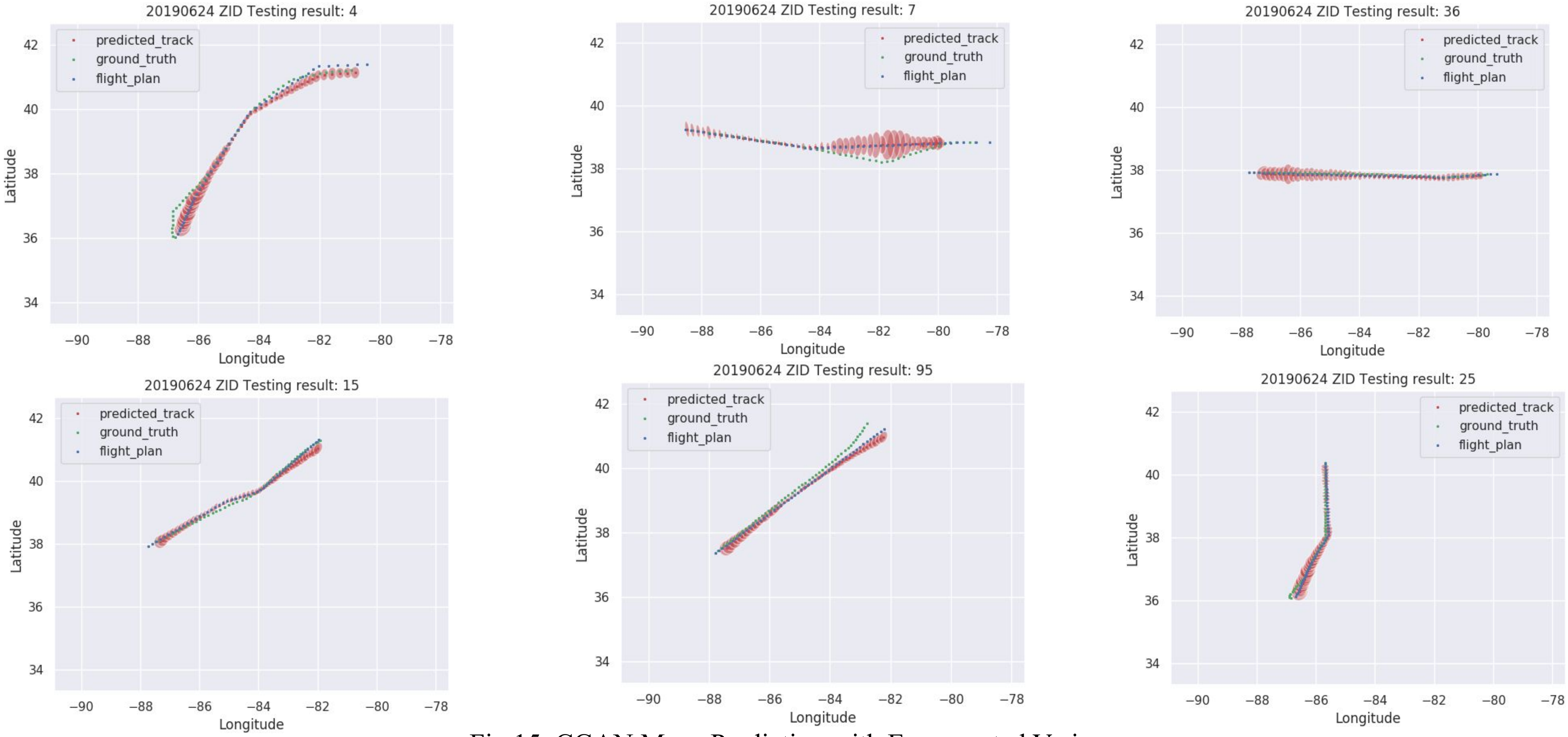


Fig.15 CGAN Mean Prediction with Exaggerated Variance

Variance Reduction

- Model performance evaluation metrics,

$$L2_k^{ori} = \sum_i^n \sum_j^d (Y_{k,i,j}^{true} - Y_{k,i,j}^{fp})^2$$

$$L2_k^{new} = \sum_i^n \sum_j^d (Y_{k,i,j}^{true} - Y_{k,i,j}^{pred})^2$$

$$reduction = \frac{Var(L2_k^{ori}) - Var(L2_k^{new})}{Var(L2_k^{ori})}$$

- CGAN has better prediction power.

Table 2 Comparison to Previous Work

Models	Percentage of Flights Reduced	Overall Variance Reduction
Conv-LSTM	47.0%	12.3%
Generative Model	55.2%	22.1%
Dropout as Bayesian	26.2%	16.8%

Conclusion

- The proposed CGAN can achieve better predicting performance compared to the previous Conv-LSTM model in the statistical study.
- The model outputs a confidence interval to the prediction by doing many tests.
  - Randomness comes from the randomly sampled input z to the generator.
- Reduce the amount of data needed for training but increase training difficulties.

- Future work,
  - Model with better uncertainty estimates.
  - Knowledge discovery of the current dataset.

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References

[1] Erzberger, H., Lauderdale, T., and Chu, Y., “Automated conflict resolution, arrival management, and weather avoidance for air traffic management,” Proceedings of the Institution of Mechanical Engineers, Part G: Journal of aerospace engineering, Vol.226, No. 8, 2012, pp. 930–949.

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Questions?

Thanks.