Probabilistic Aircraft Trajectory Prediction Considering Weather Uncertainties Using Dropout As Bayesian Approximate Variational Inference

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Outline

1. Introduction
2. Preliminaries
3. Data Source
4. Network Architecture
5. Experimental Results
6. Conclusion

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.

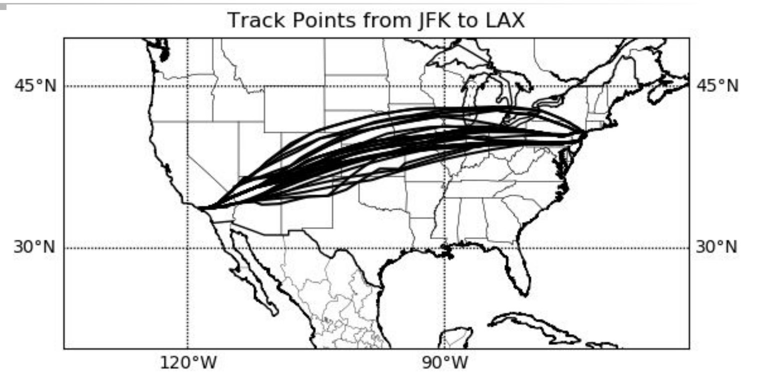


Fig.1 Flight Tracks from JFK to LAX on Dec 19, 2018

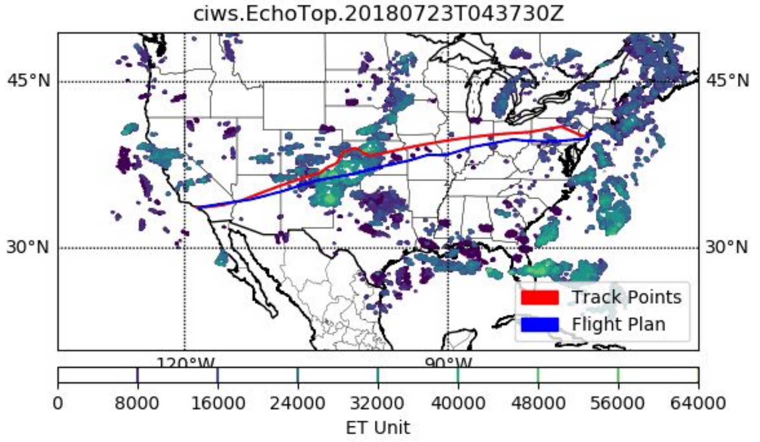


Fig.2 Convective Weather Conditions during the Flight Period from 04:45:00 to 11:47:30 on July 23, 2018

[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

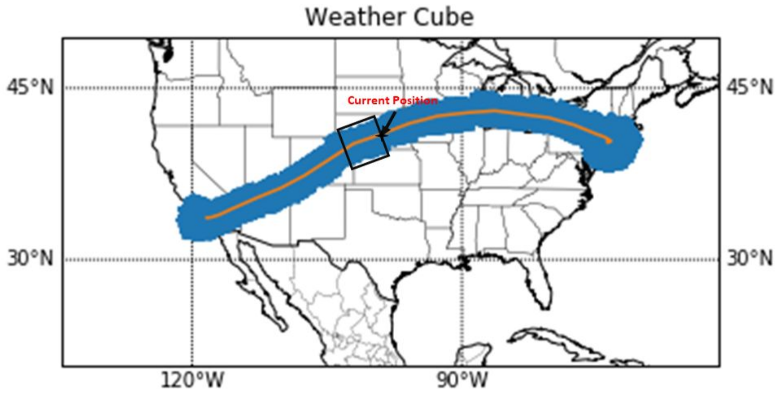


Fig.3 Weather cube generating algorithm

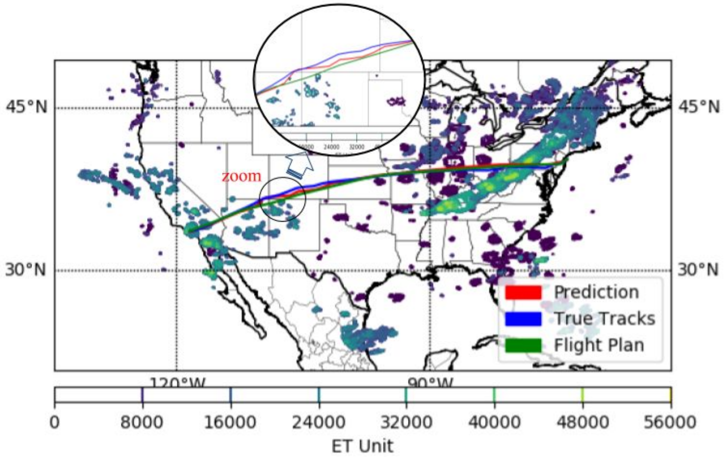


Fig.4 A prediction result

- 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.
  - No prediction uncertainties.

[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 control sectors.
  - incorporate Bayesian framework to introduce uncertainties into the prediction.

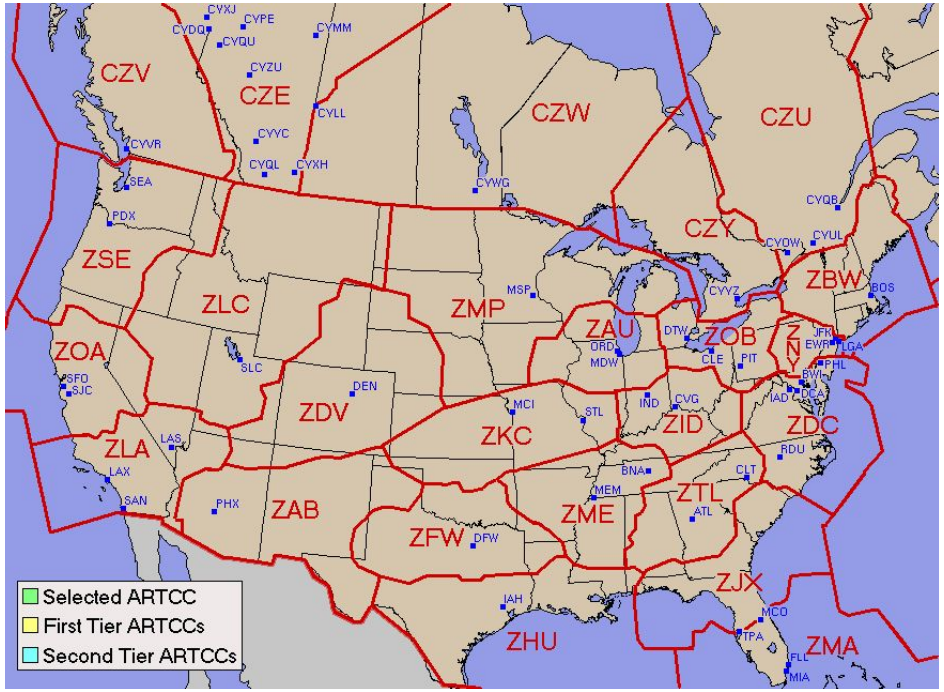
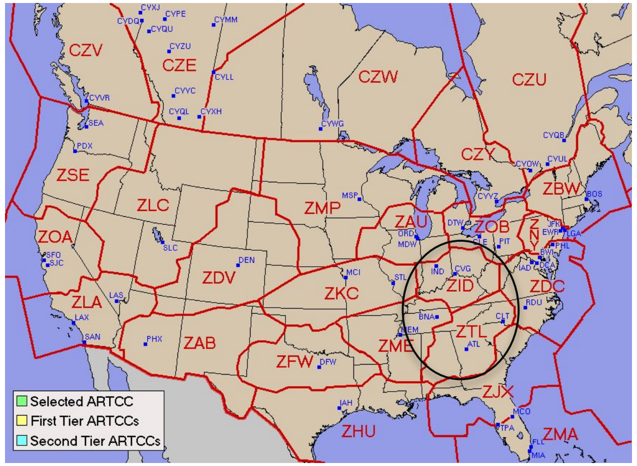


Fig.5 United States Air Route Traffic Control Center (ARTCC)
Source: https://www.fly.faa.gov/ois/tier/themap.html

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.



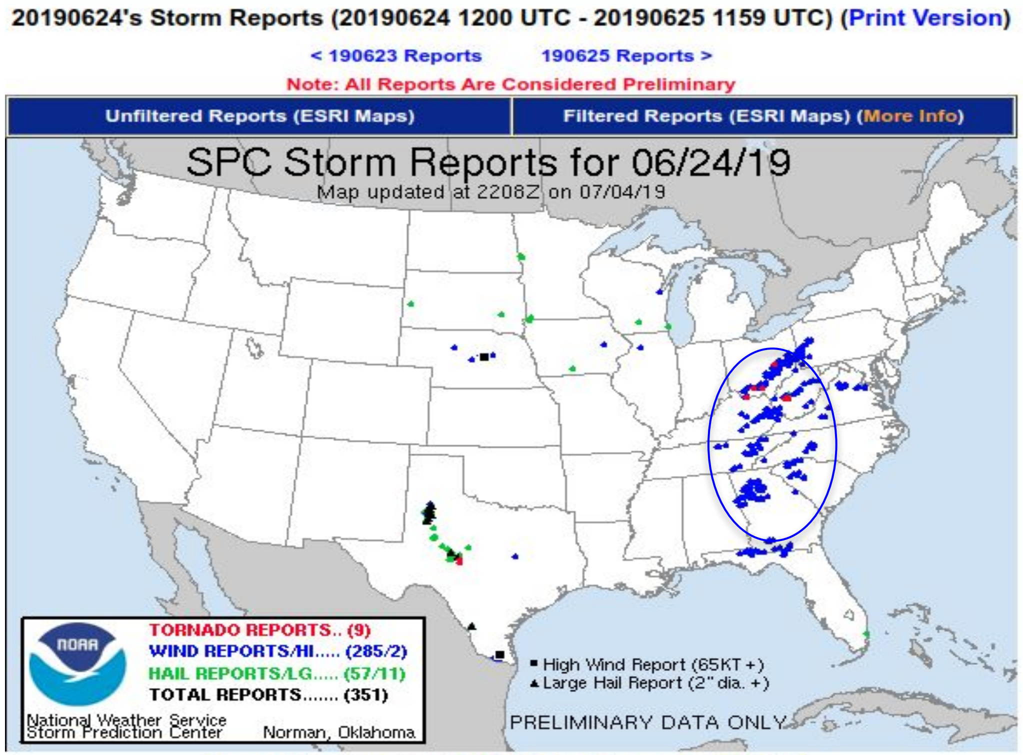


Fig.6 SPC Storm Reports for 06/24/19

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

Preliminaries – Variational Inference

- Bayesian theorem,
$$p(\omega|X,Y) = \frac{p(Y|X,\omega)p(\omega)}{p(Y|X)}$$
- Bayesian inference,
$$p(y^*|x^*,X,Y) = \int p(y^*|x^*,\omega)p(\omega|X,Y)d\omega$$
- Approximating variational posterior,
$$KL(q_\theta(\omega)||p(\omega|X,Y)) = \int q_\theta(\omega)log\frac{q_\theta(\omega)}{p(\omega|X,Y)}d\omega$$
- Minimizing KL divergence is equivalent to maximizing the evidence lower bound (ELBO) w.r.t. $q_\theta(\omega)$
$$\mathcal{L}_{VI}(\theta) := \int q_\theta(\omega)\,log(p(Y|X,\omega))\,d\omega - KL(q_\theta(\omega)||p(\omega))$$

Notes,
X – training inputs
Y – training labels
x* – testing inputs
y* – testing labels
ω – model parameters

Preliminaries – Bayesian Neural Nets

- The gradient descent of BNN can be achieved by minimizing the Negative ELBO,

$$\mathcal{L}_{VI}(\theta) := KL(q_\theta(\omega)||p(\omega)) - \mathbb{E}_{q_\theta(\omega)}[log(X,Y|\omega)]$$

- Bayes By Backprop uses the chain rule to calculate the gradient,

$$\frac{\partial}{\partial\theta}\mathbb{E}_{q_\theta(\omega)}[f(\omega,\theta)] = \mathbb{E}_{q(\epsilon)}[\frac{\partial f(\omega,\theta)}{\partial\omega}\frac{\partial\omega}{\partial\theta} + \frac{\partial f(\omega,\theta)}{\partial\theta}]$$

- A neural network with arbitrary depth and non-linearities, with Bernoulli dropout applied before every weight layer, is mathematically equivalent to an approximate variational inference which results in uncertainty estimates [4].

[4] Gal, Y., and Ghahramani, Z., "Dropout as a Bayesian approximation: Representing model uncertainty in deep learning," international conference on machine learning, 2016, pp. 1050–1059.

Preliminaries – Bayesian Convolutional Neural Nets

- To perform approximate VI to convolutional layers,
  - Place a prior distribution over each kernel and approximately integrate them with Bernoulli variational distributions.
  - Sample the Bernoulli random variables and multiply with the weight matrix.
- This approximating distribution is also equivalent to applying the dropout after every convolution layer as well as inner-product layers [5].

- <u>The implementation of the Bayesian CNN is as simple as using dropout after every convolution layer before pooling [6].</u>

[5] Gal, Y., "Uncertainty in deep learning," Ph.D. thesis, PhD thesis, University of Cambridge, 2016.

[6] Gal, Y., and Ghahramani, Z., "Bayesian convolutional neural networks with Bernoulli approximate variational inference," arXiv:1506.02158, 2015.

Preliminaries – Bayesian Recurrent Neural Nets

- Variational dropout,

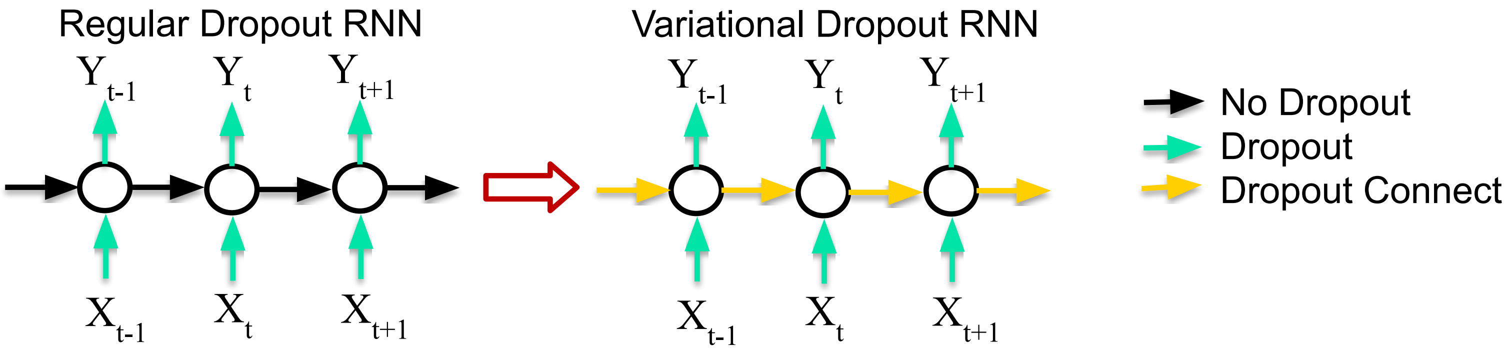


Fig.7 Variational Dropout

- Variational dropout can drop the connection between each state of RNN folds by randomly mask each row of the approximating distribution to zero as,

$$q(\omega_k) = pN(\omega_k; 0, \sigma^2 I) + (1-p)N(\omega_k; m_k, \sigma^2 I)$$

  - where k is the row index, p is the dropout probability and σ^2 is the small noise.
- We optimize over m, the variational parameters of the random weight matrices, or RNN weight matrices in standard view.

Preliminaries – Bayesian Recurrent Neural Nets

- Implementing the approximate inference to RNN is identical to implementing dropout in RNNs with the same network units dropped at each time step, randomly dropping inputs, outputs, and recurrent connections [7].

- <u>The final Bayesian framework is simply applying regular dropout after each convolutional layers and variational dropout to recurrent cells.</u>

- Uncertainty estimates: MC dropout

$$p(y^*|x^*, X, Y) \approx \int p(y^*|x^*, \omega)q(\omega)d\omega \approx \frac{1}{K}\sum_{k=1}^{K} p(y^*|x^*, \hat{\omega_k})$$

[7] Gal, Y., and Ghahramani, Z., “A theoretically grounded application of dropout in recurrent neural networks,” Advances in neural information processing systems, 2016, pp. 1019–1027.

Data Source – Database

- Sherlock Data Warehouse (SDW)
  - SDW [8] 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.
  - ZTL on June 24th, 2019.

[8] 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 tool to parse it into WGS84 coordinates using online database (*opennav.com*).

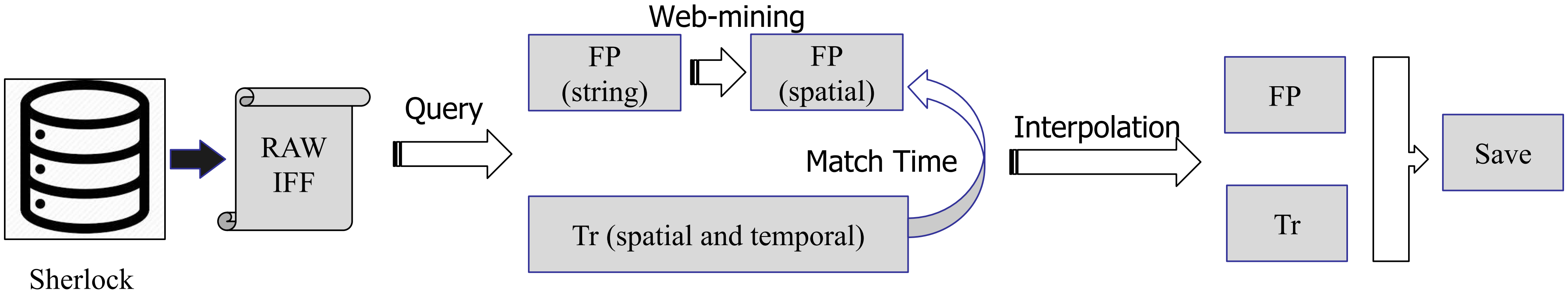


Fig.8 Flowchart: Raw IFF data processing

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 6255×50×2.

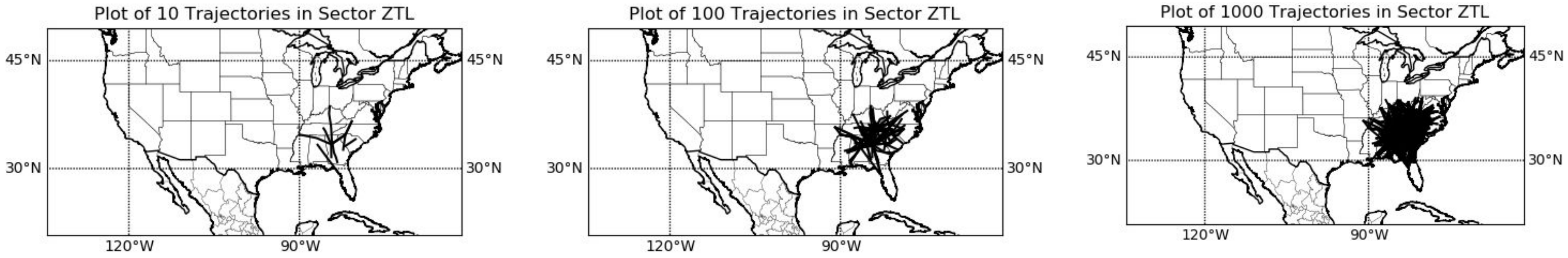


Fig.9 Flights in sector ZTL on 06/24/2019

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 6255×49×32×32×1.

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

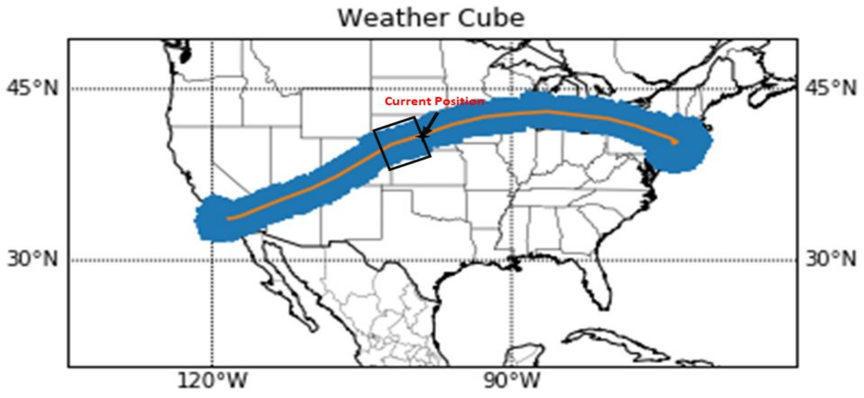


Fig.10 Weather cube generating algorithm

Network Architecture – Details

Table 2 Model Layer Setup

Layers	Input Size	Output Size	Dimension	Others
Conv3d_1	[N, 49, 32, 32, 1]	[N, 49, 10, 10, 3]	[1, 5, 5, 3]	Strides: [1, 3, 3, 1], No Padding
Conv3d_2	[N, 49, 10, 10, 3]	[N, 49, 4, 4, 1]	[1, 3, 3, 1]	Strides: [1, 3, 3, 1], Zero Padding
Flatten	[N, 49, 4, 4, 1]	[N, 49, 16]		
Dense_1	[N, 49, 16]	[N, 49, 4]	4	
Dense_2	[N, 49, 4]	[N, 49, 1]	1	
Concat	[N, 49, 1]	[N, 49, 3]		Concatenate with Flight Plan *p*
LSTM	[N, 49, 3]	[N, 49, 128]	128	Variational Dropout
Dense_3	[N, 49, 128]	[N, 49, 64]	64	
Dense_4	[N, 49, 64]	[N, 49, 32]	32	
Dense_5	[N, 49, 32]	[N, 49, 2]	2	No Dropout

Network Architecture – Details

- Dropout,
  - Regular dropout is applied after each dense layer.
  - Variational dropout is applied to LSTM cell.
  - Dropout ratio is 0.5 for all layers.

- Model,
  - Zero initialization is used to LSTM cell.
  - Root mean squared error.
  - Training with momentum optimizer with value of 0.9.
  - Weight decay is set to the learning rate.

Experimental Results

- We perform *K=100* MC dropout tests and evaluate the mean and variance of the prediction.
- Mean and variance are the key parameters to determine the confidence ellipses at each prediction point.

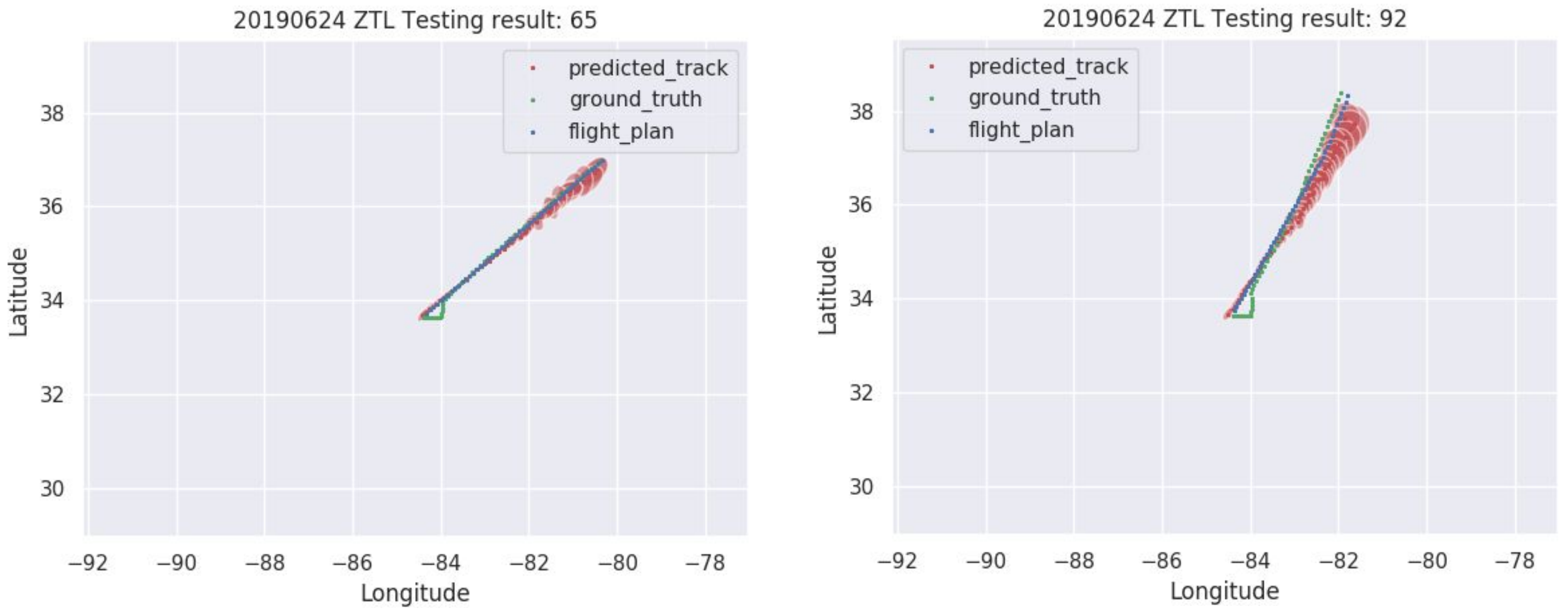


Figure 11. Model Prediction

[9] Wang, Y., Pang, Y., & Liu, Y. (2020). A Voice-Communication Augmented Simulation Framework for Aircraft Trajectory Simulation. In AIAA SciTech 2020 Forum.

Variance Reduction

- ❖ To numerically evaluate the mean model performance, we define the following quantities,

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

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

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

- ❖ Dropout is good at deviation variance reduction but less competitive in prediction accuracy.

Table 3 Comparison of Result

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

- ❖ Generative Model.

Conclusion

- The formulation of Bayesian Neural Network is as simple as applying regular dropout after each fully-connected layer and performing variational dropout to RNN cells.
- The experimental result shows that the model can predict the aircraft trajectory as well as outputting an uncertainty bound when performing MC dropout during testing.

Future Work

- Exact Variational inference for Bayesian NNs.
- Knowledge discovery of the current dataset.

Acknowledgements

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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.