Aircraft Trajectory Prediction using LSTM Neural Network with Embedded Convolutional Layer

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The 11th annual conference of the prognostics and health management society 2019
Scottsdale, AZ, USA
September 21-26

outline

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3. Data Acquisition
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Introduction

1. Weather-related delay of commercial operations are one of the most frequently encountered problems in the en-route airspace.
2. It's also shown that the workload of controllers can increase significantly during certain extreme climatic events.
3. NextGen requires an automatic flight trajectory planning tool to update the flight route thus release the workload of controllers and pilots.
4. Huge uncertainties exist during daily aviation operations.
5. The development of trajectory prediction tools help reduce safety concerns.

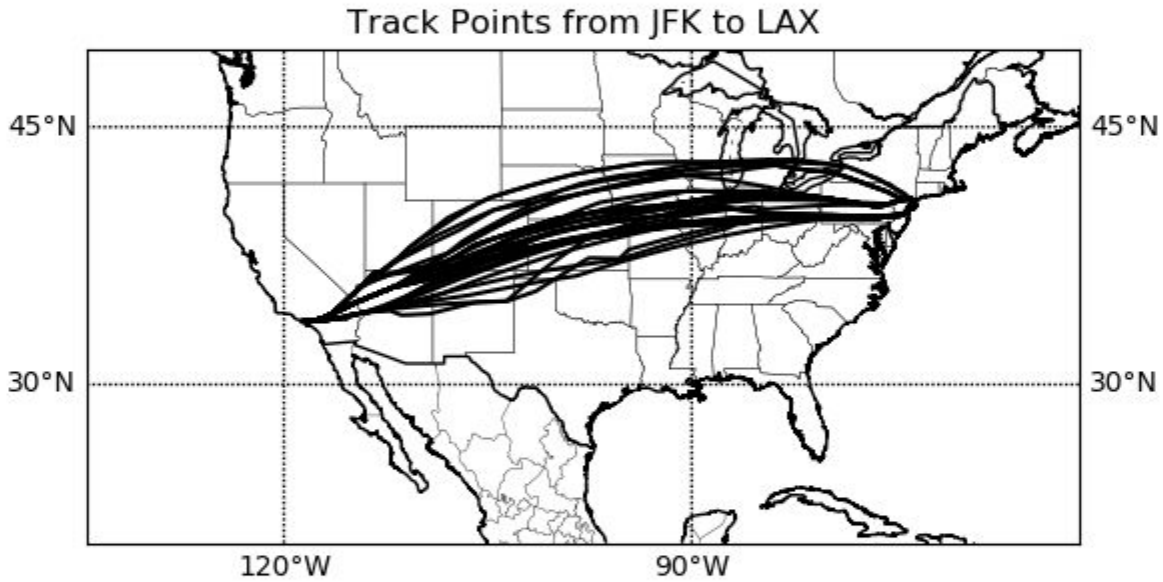


Fig.1 Flight Tracks from JFK to LAX on Dec 19, 2018

Introduction

1. The convective weather conditions can develop rapidly and pose safety concerns to aviation operations.
2. Multiple prediction models are purposed, and can conclude into two categories, dynamic weather reroutes (DWR) and strategic trajectory prediction (TP).
3. Recurrent Neural Network (RNN) has been shown as an effective tool to peform sequential learning tasks.
4. The regression model is formulated by modifying the recurrence of the RNN.

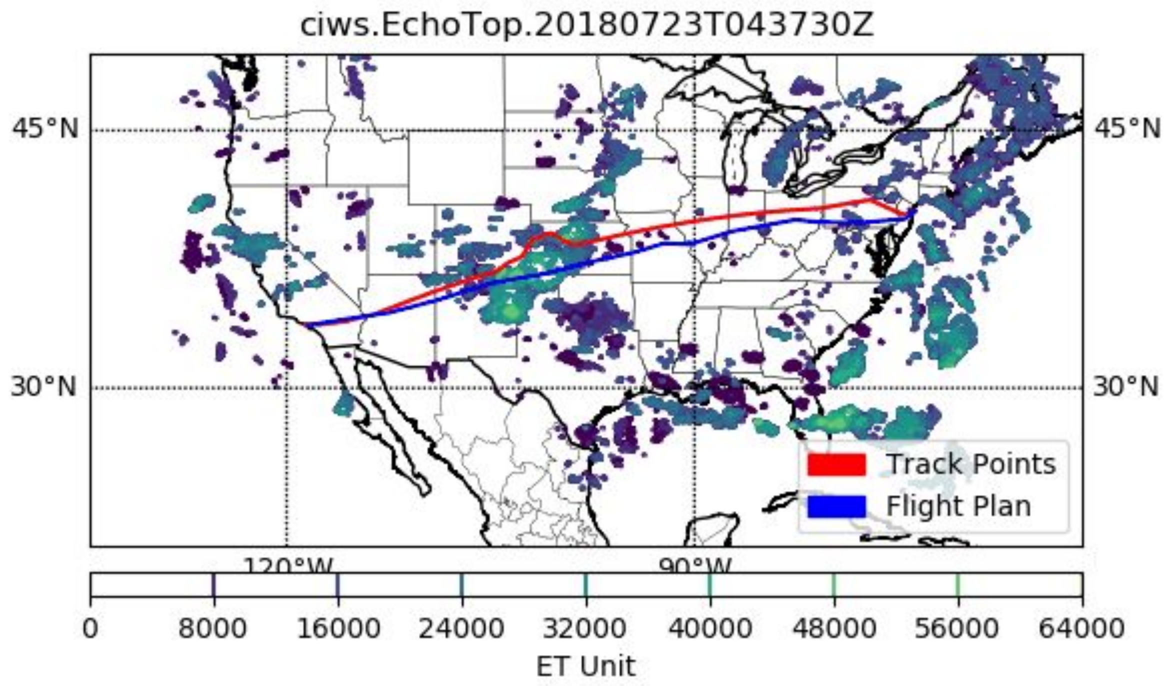


Fig.2 Convective Weather Conditions during the Flight Period from 04:45:00 to 11:47:30 on July 23, 2018

Related Work - DWR

- Dynamic Weather Reroutes (DWR) - Online
  - DWR was raised by domain experts as a ground-based concept.
  - It’s a computer aided tool to automatically analyzes in-flight aircraft and propose time and fuel corrections to the weather avoidance routes [1].
  - Terminal AutoResolver [2] was developed for conflict resolution and weather cells avoidance. Real experiments based on this has been conducted on AA flights since July 2012 [3].
  - Results shows that congestions could be reduced by 19-38% if all flights fly based on DWR rather than other routes [4].

Related Work - TP

- Strategic Trajectory Prediction (TP) - Offline
  - TP in both spatial and temporal space is a popular research topic for researchers with different backgrounds.
  - Multiple tools such as Hidden Markov Model (HMM) [5], Recurrent Neural Network (RNN) [6] and Generalized Linear Model (GLM) [7] has been applied, incorporates with weather features.
  - HMM is a deterministic approach which only allows prediction among historical trajectory candidates.
  - The RNN approach uses a deep generative encoder-decoder framework for 4D trajectory prediction.

Data Acquisition - SDW

- 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 Integrate Flight Format (IFF) data for flight plans and real tracks, and Convective Integrated Weather Service (CIWS) for EchoTop (ET) weather data.

Data Acquisition - IFF

- ➢ Raw IFF data for one day is a csv of 5-10 gigabytes with around 50 million rows each.
- ➢ It contains all the flight records within the national air space.
- ➢ Flight tracks include flight records, 4D coordinates and flight procedures.
- ➢ 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*).
- ➢ We have collected the data over the range from Nov 1, 2018 to Feb 5, 2019 of 2737 flight tracks and flight plans.

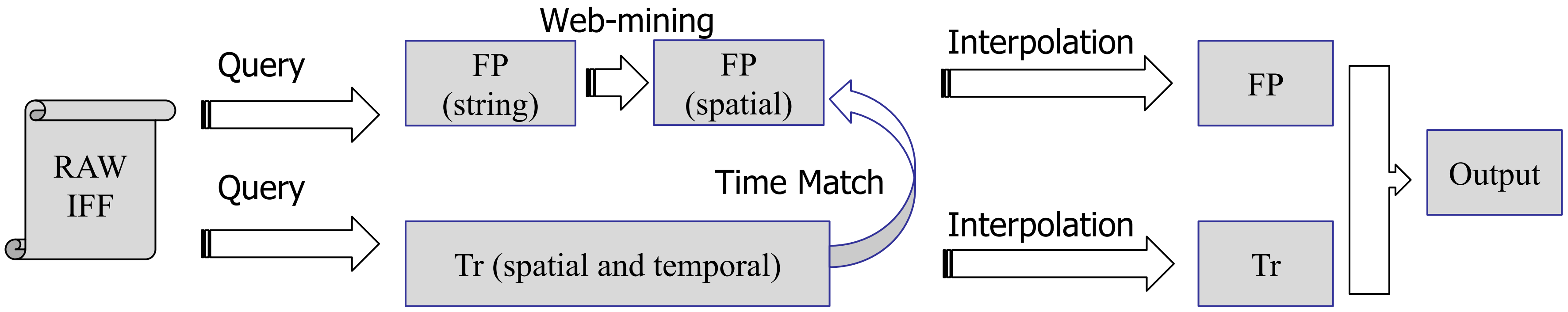


Fig.3 Flowchart: Raw IFF data processing

Data Acquisition - CIWS

- The two key features of CIWS, Echo Top (ET) and Vertically Integrated Liquid (VIL), both come with current and forecast datasets in Sherlock.
- A Lincoln Laboratory's study [9] shows that vertically integrated liquid (VIL) is a better indicator of storm severity and new growth and is less susceptible than other precipitation representations to anomalous propagation and other anomalies.
- CIWS for one day is 576 .nc files, update every 150 seconds,
- Create an algorithm to take out feature cubes (20x20), rotate w.r.t. the heading angle.
- The blue area is the weather of interest in for this flight track.
- 2528/2737 tracks have complete weather data.

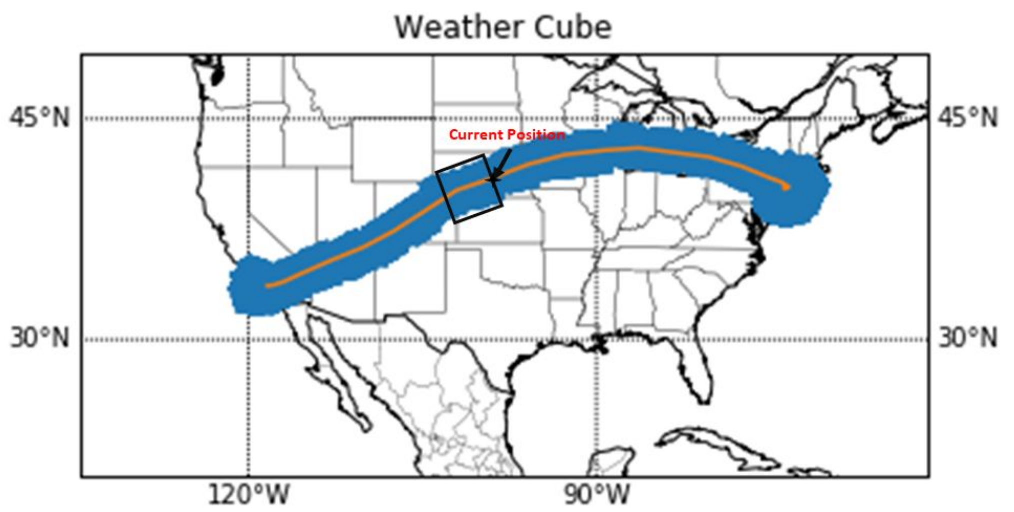


Fig.4 Weather area of interest by the purposed algorithm

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

Network Architecture-LSTM

- The objective is to predict trajectories with the last on-file flight plan, with weather features as calibration.
- Recurrent Neural Network has been shown successful in sequential learning and time series forecasting tasks.
- The task can be classified as a Seq2Seq learning task.
- Classical Long short-term memory (LSTM) as a special form of RNN, doesn't take spatial correlations into consideration.
- We embed convolutional layers into the recurrence to incorporate weather features.

$$h_x = h_t \oplus x_t$$

$$f_t = Sigmoid(W_f \cdot h_x + b_f)$$

$$i_t = Sigmoid(W_i \cdot h_x + b_i)$$

$$\hat{c}_t = Tanh(W_c \cdot h_x + b_c)$$

$$c_t = f_t \cdot c_t + i_t \cdot \hat{c}_t$$

$$o_t = Sigmoid(W_o \cdot h_x + b_o)$$

$$h_t = o_t \cdot Tanh(c_t)$$

Network Architecture - Graph

Conv layers

$$x_{conv1} = Relu(K_1 \otimes x_{weather})$$
$$x_{conv2} = Relu(K_2 \otimes x_{conv1})$$
$$x_{dense1} = Relu(Dense(flatten(x_{conv2}), n_1))$$
$$x_{dense2} = Relu(Dense(x_{dense1}, n_2))$$

Gates

$$h_x = h_t \oplus x_t \oplus x_{dense2}$$
$$f_t = Sigmoid(W_f \cdot h_x + b_f)$$
$$i_t = Sigmoid(W_i \cdot h_x + b_i)$$
$$\hat{c}_t = Tanh(W_c \cdot h_x + b_c)$$
$$c_t = f_t \cdot c_t + i_t \cdot \hat{c}_t$$
$$o_t = Sigmoid(W_o \cdot h_x + b_o)$$
$$h_t = o_t \cdot Tanh(c_t)$$

Expand h_t Dimensions

$$h_t = Relu(Dense(dim_{h_t}, dim_{hidden} - dim_{input} - n_2))$$
$$h_{out} = Relu(h_t)$$

Recurrence

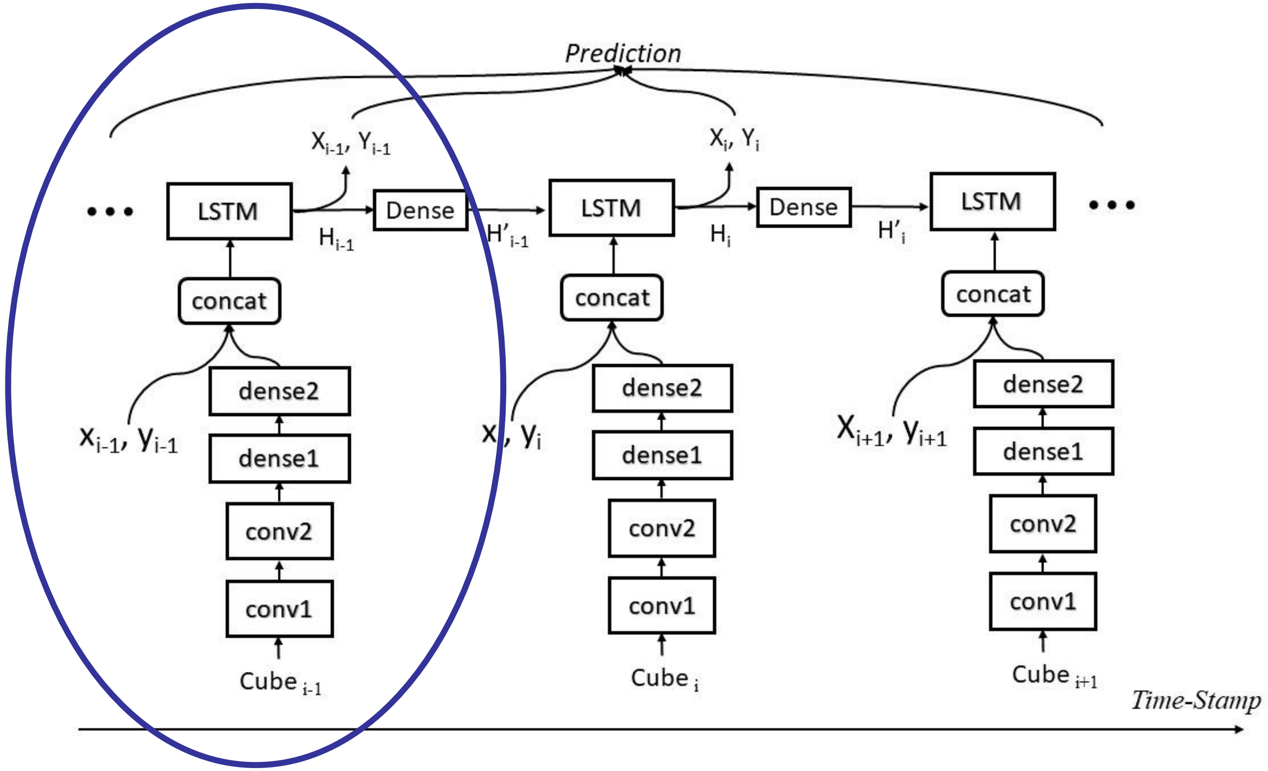


Figure 5. Graphic View of unfolded Network Architecture

Network Architecture - Details

- Normalization is performed.
- Hidden dimension is set to be the fix number 100.
- Hidden tensor and cell state are initialized with the start point.
- The convolutional layers have a stride of 2, kernel size of 6x6x2 and 3x3x4, respectively.
- A mean squared error loss is used.

$$L(W_x, b_x) = \frac{1}{n}\sum_{i}^{n}(Y_i^{pred} - Y_i^{true})^2$$

Experimental Results

- Training is performed on a workstation with Intel Xeon E5-1620 v4 @3.50 GHz and Nvidia GTX 1080 with tensorflow-gpu version 1.6.0.
- Training data and testing data are separated with a weight of 0.75 and 0.25.
- Adam optimizer is used for backpropagation.
- 3D prediction is conducted with the fold number of 50.

Experimental Results - 1

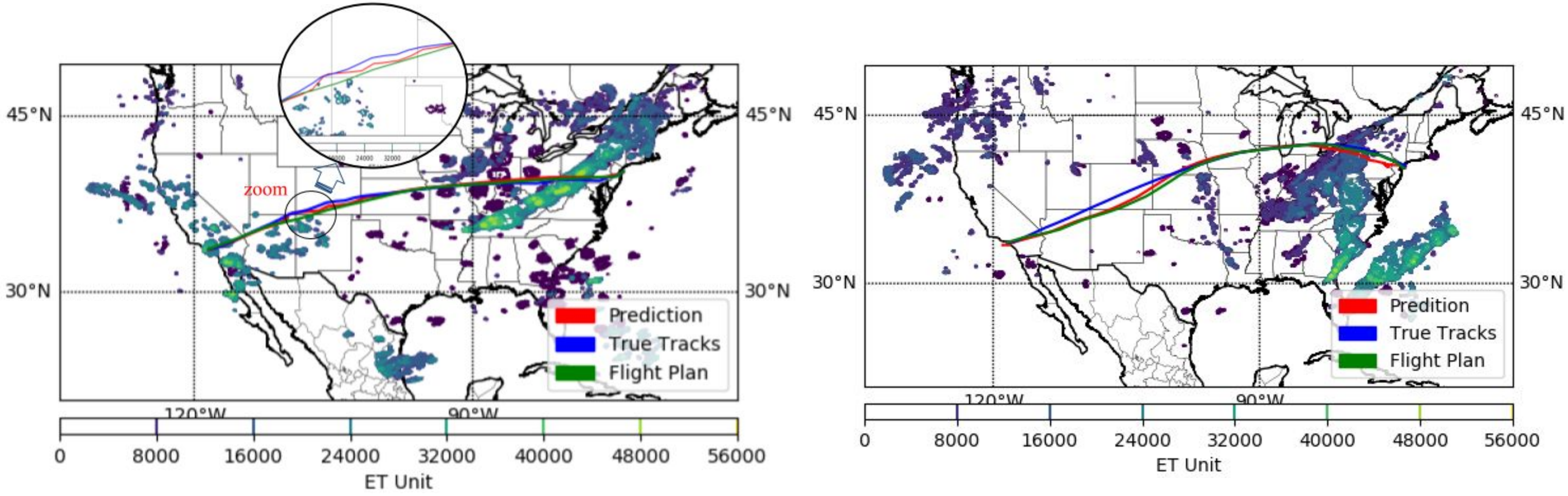


Figure 6a. Variance Reduced

Experimental Results - 2

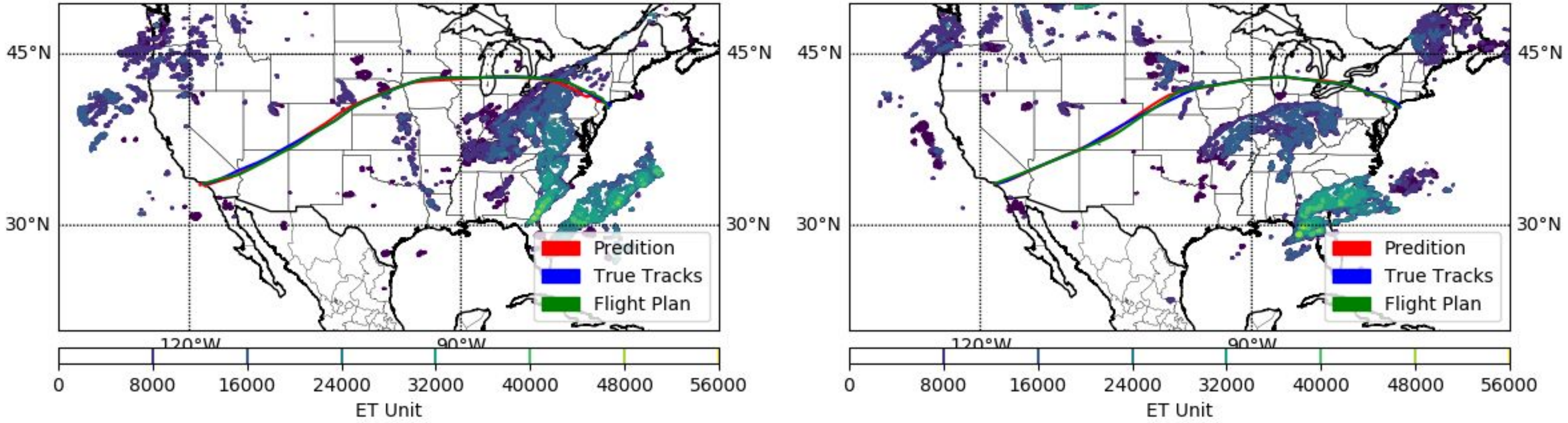


Figure 6b. Performance not clear

Statistical Analysis

- To numerically measure the model prediction improvements. We calculate the L2 norm of two trajectory differences.
  - The difference between original flight plan and true trajectory
  - The difference between predicted flight tracks and true trajectory

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

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

  - Then we compare the two L2 norms and calculate variance reduction.

Percentage of Flight Deviation Reduced	Overall Variance Reduction
47.0%	12.3%

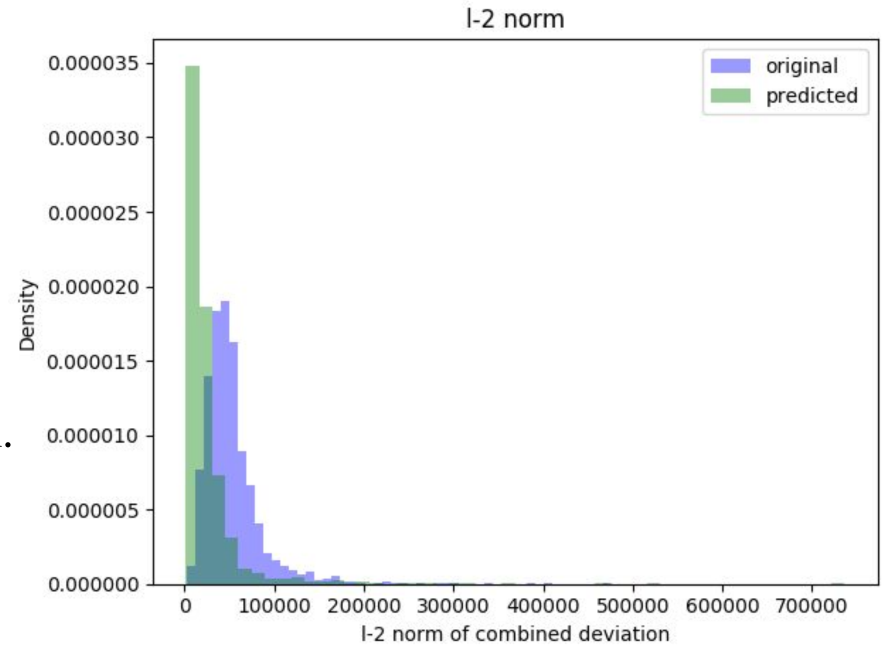


Figure 7. Distribution of deviation L_2

Conclusion

- The trained model is able to calibrate the last on-file flight plan given convective weather conditions. The population statistical study shows that a 3D TP has a better performance and is capable of reduce deviation for 47.0% of the flights. The overall deviation reduction reaches 37.3%

- Innovations
  - Developed tools to generate 4D flight plan from the text format string of FPs.
  - Developed algorithms to take out the weather feature cube of a given coordinates.
  - Embed convolutional layers into the LSTM recurrence and omit pooling layers to keep location information in the loop.
  - Expand hidden tensor dimensions by adding additional fully-connected layers.

Discussion

- The data processing is labor intensive.
- Difficulties in preparing the data,
  - Extreme weather conditions is the most useful data source to get for our training, but flights tend to be canceled during this kind of weather conditions.
    - A typical date is Sep 5, 2017 where it's reported to have severe weather conditions but there are only 2 flights flying from JFK to LAX found in the database.
    - There is reported to have severe weather conditions right above DFW but the weather data is not available for that date.
  - For those moderate severe weather conditions, the flight plan has been found to take care of them appropriately thus the real tracks follow the flight plan all the time.
  - The CIWS data in Sherlock is not complete for quite a few days.
- We downloaded terabytes of data but only got 2528 training data which is still a relatively small number for a deep learning model.

Future Work

- Better Prediction Power
  - Build better predictive models to reduce overall variance.
    - Adversarial learning.
    - Physics-based learning.
- Non-deterministic Approach
  - Bayesian deep learning.

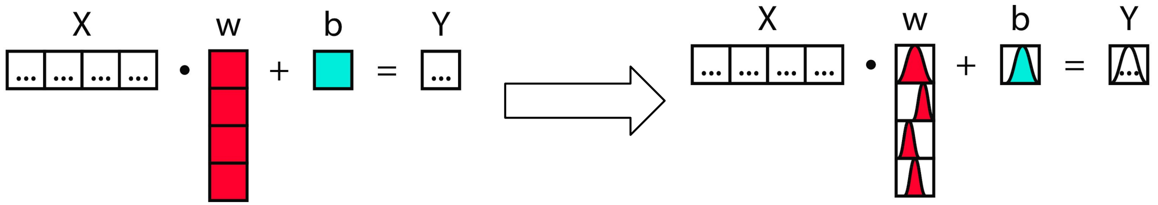
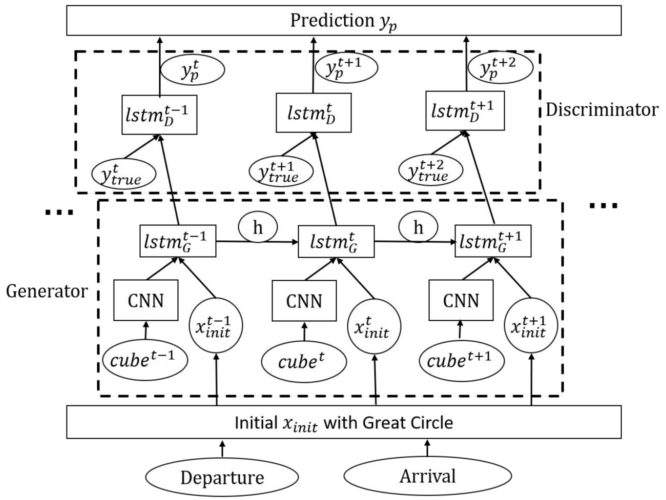
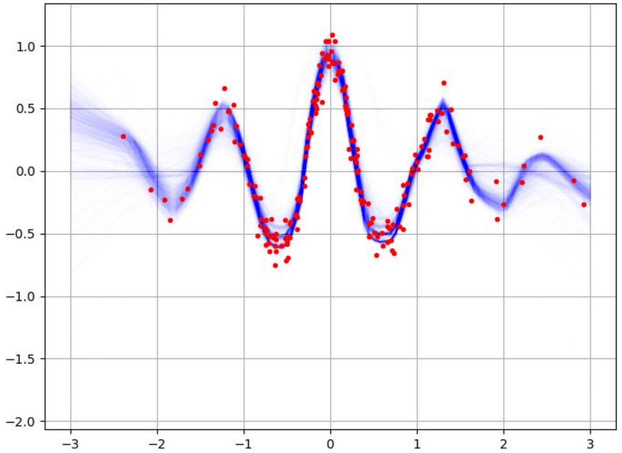


Fig 9. Understanding Bayesian Deep Learning
Credit to Eric J. Ma's talk " *An Attempt At Demystifying Bayesian Deep Learning*" at PyData NYC, 2017





Acknowledgements

The work related to this research were performed at the Prognostic Analysis and Reliability Assessment Lab at Arizona State University. The research reported in this paper was supported by funds from NASA University Leadership Initiative program (Contract No. NNX17AJ86A, Project Officer: Dr. Kai Geobel and Dr. Anupa Bajwa, Principal Investigator: Dr. Yongming Liu). The support is gratefully acknowledged.

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Questions?

Thanks

Appendix - IFF Parser

Algorithm 1 Flight Tracks and Flight Plans

Data: IFF raw data path
Input: Key1, Key2, DateList, n
Output: Tr_{new}, FP_{new}

for date in DateList **do**
  Load IFF raw data file of given date
  Query the file departing at Key1 and arriving at Key2
  Create a folder named with date
  Save 4D Tr and last on-file FP named with flight call sign and date in the datefolder
  for callsign in datefolder **do**
    Parse FP into WGS84 coordinates
    Match FP from Tr for the time column
    Interpolate FP and Tr with 1 second interval
    Equally sample n points from FP and Tr as Tr_{new} and FP_{new}
    Save Tr_{new} and FP_{new}
  end for
end for

Appendix - CIWS Parser

Algorithm 2 Weather Cube Generation

Data: True Trajectory Data, Weather Data
Input: TrajectoryPoints, CubeSize, Weather
Output: $WeatherCube_{coord}$, $WeatherCube_{Value}$

Convert weather data coordinates to Mercator's Projection Coordinates
Convert trajectoryPoints coordinate to Mercator's Projection Coordinates
for Points in TrajectoryPoint **do**
    Determine the flight direction
    Find a line perpendicular to the current position normal line
    Generate 20 points along this perpendicular line
    for Step in the CubeSize **do**
        From every right of these 20 points move to the next point which passed through a perpendicular line parallel to the previous line with distance of Step
        Generate 20 points along the new perpendicular line
        Move another step from very right of these new 20 points
    end for
end for
Save $WeatherCube_{coord}$ and $WeatherCube_{Value}$