Predicting Aircraft Trajectories
– A Deep Generative Neural Networks Approach

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Joint work with Prof. Michael Ball, and Prof. David Lovell

Outline

- Introduction
- Data Sources and Feature Engineering
- Methodology
- Numerical Experiments
- Summaries

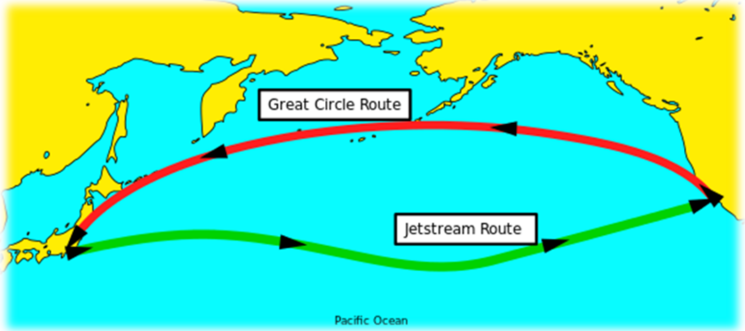
Background (I)

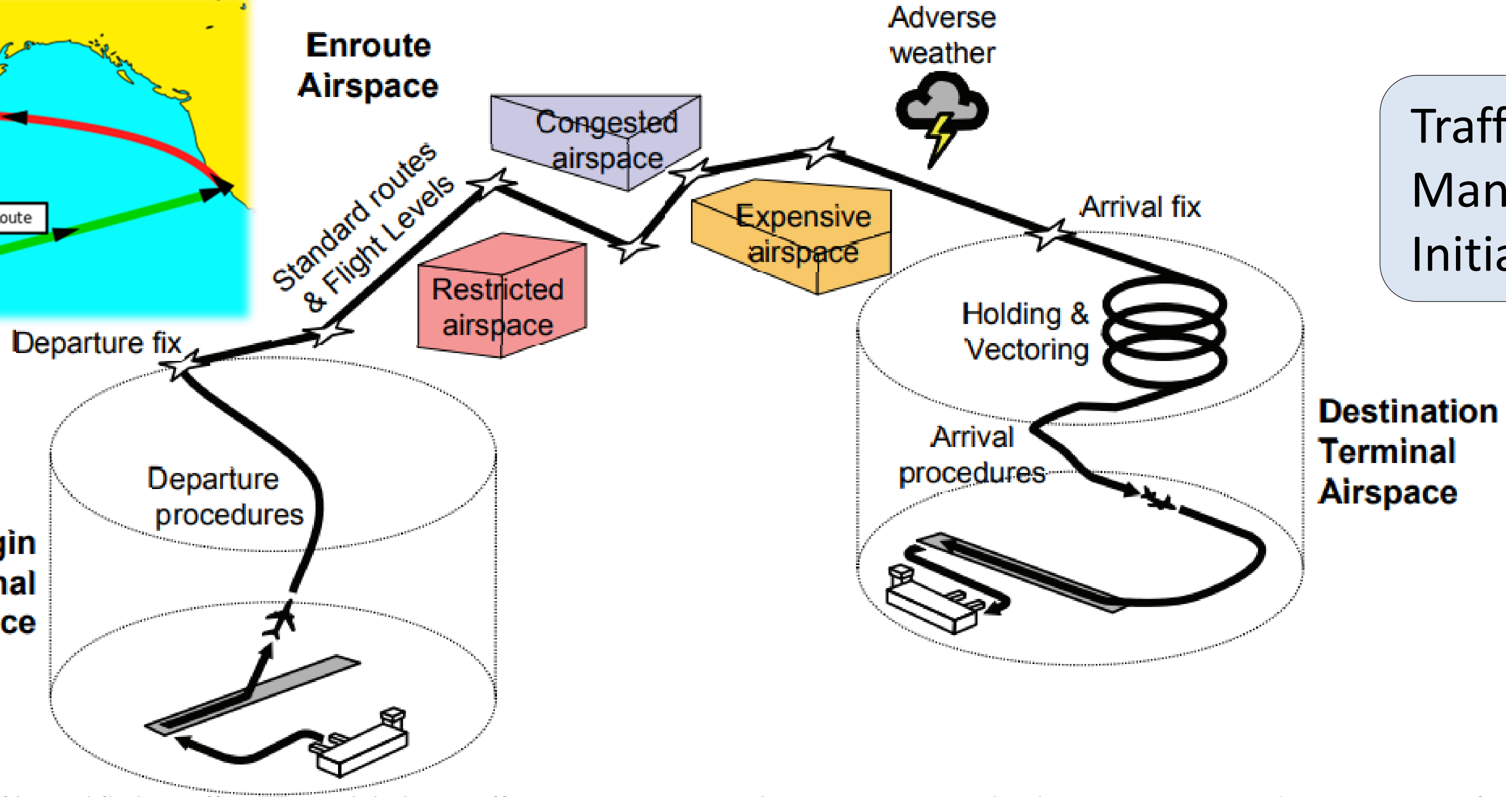
- FAA and EUROCONTROL published metrics to evaluate the flight en route inefficiency, and FAA is seeking to understand the causal factors behind the inefficiency.
- Observe rich variety of route choices that differ drastically with respect to en route inefficiency.
- Models have been proposed to understand the features that affect the choice of route for a flight, and further, the **overall** contributions of different factors to flight en route inefficiencies.

Reference:
Y. Liu, M. Hansen, D. Lovell, C. Chuang, M. Ball and J. Gulding, "Causal Analysis of En Route Flight Inefficiency--the US Experience," in 12th USA/Europe Air Traffic Management Research and Development Seminar (ATM 2017), Seattle, WA, USA, 2017

Background (II)

- Interests towards individual flights have been widely recognized in recent years.
- Trajectory prediction tools fit well into this domain.



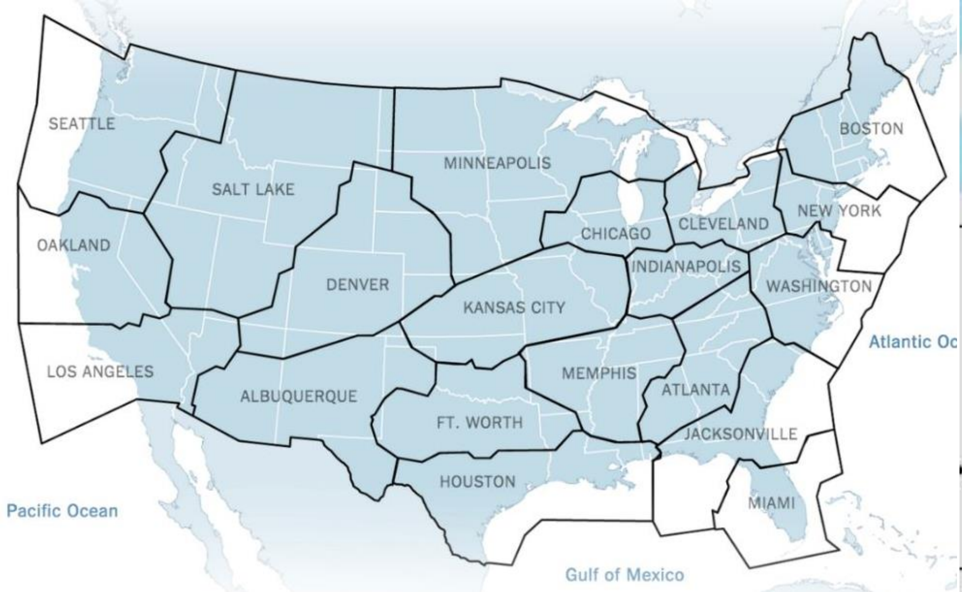


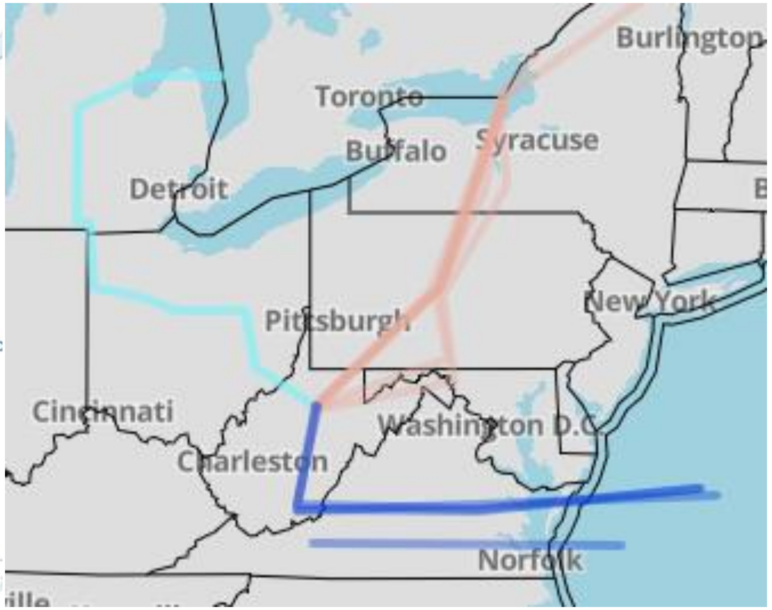
Traffic Management Initiatives (TMIs)

Source:
https://en.wikipedia.org/wiki/Jet_stream
Reynolds, T. G. (2008, September). Analysis of lateral flight inefficiency in global air traffic management. In 8th AIAA Aviation Technology, Integration and Operations Conference, Anchorage, Alaska, US.

Applications (I)

- Traffic Management Initiatives (TMI) Planning
  - Sector based operations.
  - Deterministic flight trajectory predictions: historical flight tracks/ filed flight plans.
  - Drawbacks: unable to capture uncertainties.





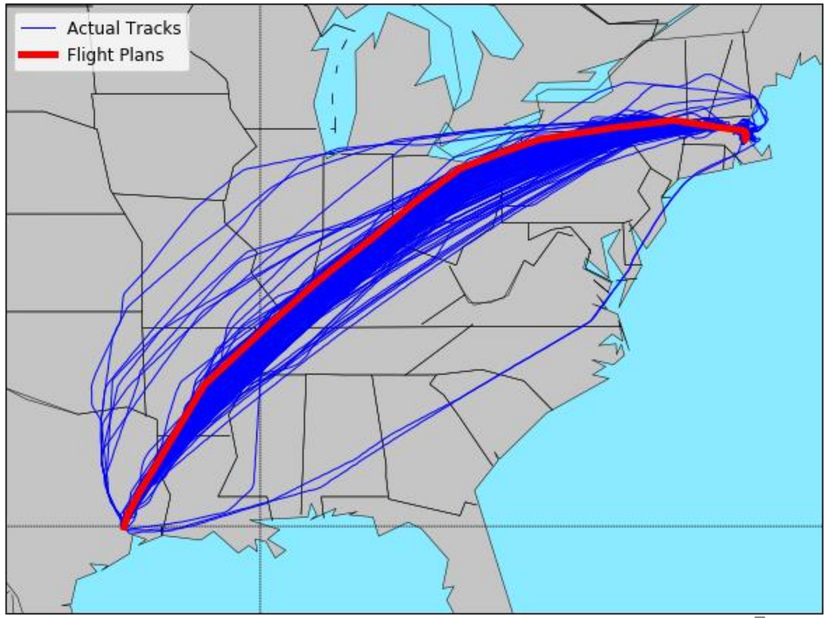


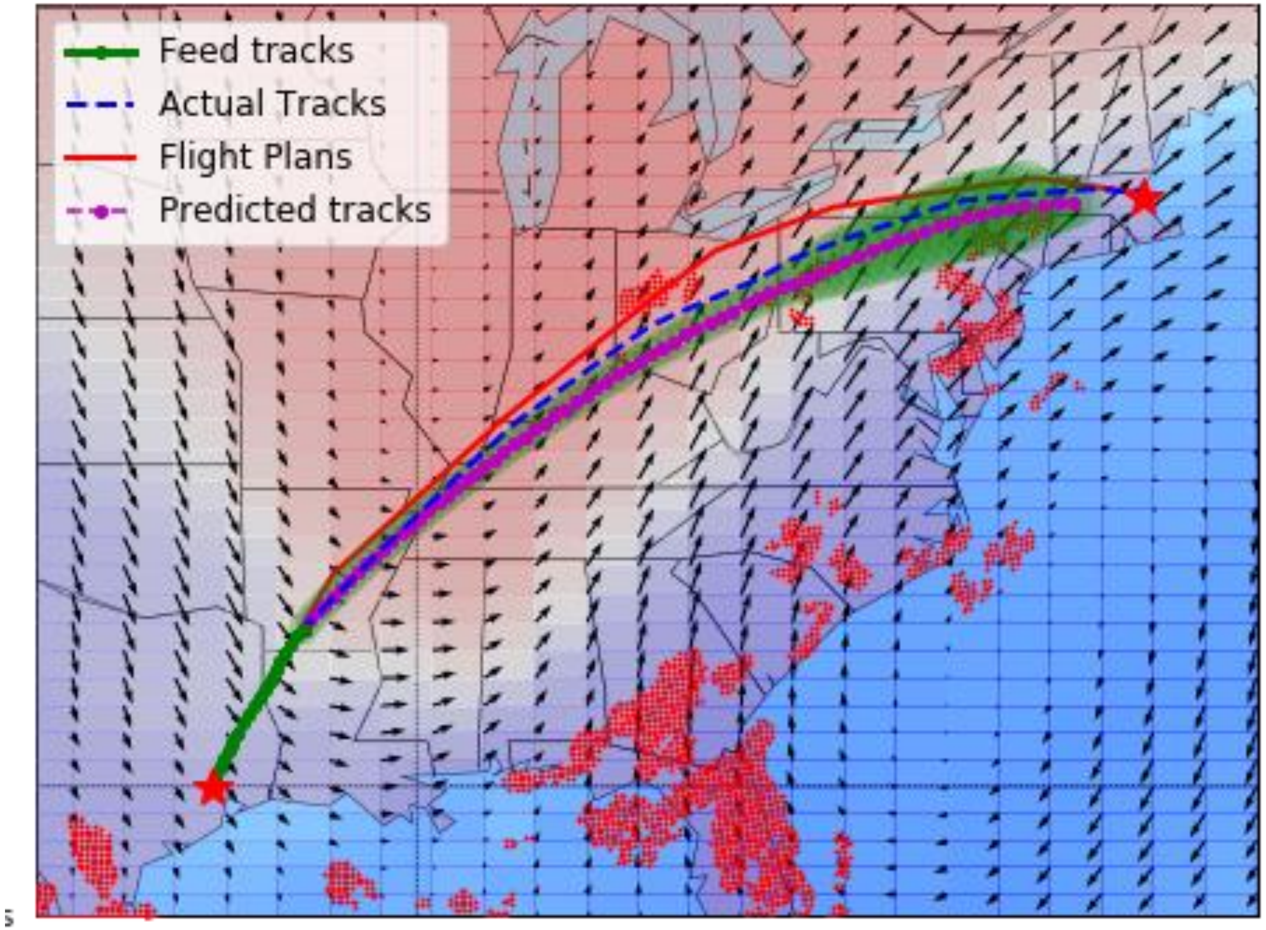
Image courtesy of: [fly8ma.com]() and Alex Estes.

Applications (II)

- Trajectory Based Operations (TBO)
  - Uses the 4D trajectories to both strategically manage and tactically control surface and airborne operations.
  - It is essentially asking, where the flight is going to be at the time of interest.
- Trajectory Prediction Tool
  - Central to TBO analysis.
  - Estimate sector demands and plan TMI.
  - Performance analysis.

Research Goal

- Develop aircraft trajectory prediction tools that can
  - Incorporate uncertainties such as adverse weather and wind.
  - Predict flight tracks given initial conditions.
  - Provide prediction intervals.



Highlights

- Generative Model
  - Inputs related to convective weather, winds, and temperature in the vicinity of the aircraft, as well as the flight plan information.
  - Outputs flight coordinates modeled as Gaussian Mixtures.
- Feature Engineering
  - Efficient tree-based spatiotemporal matching algorithm.
  - Batch mode matching during training.
  - Recursive matching during inference.

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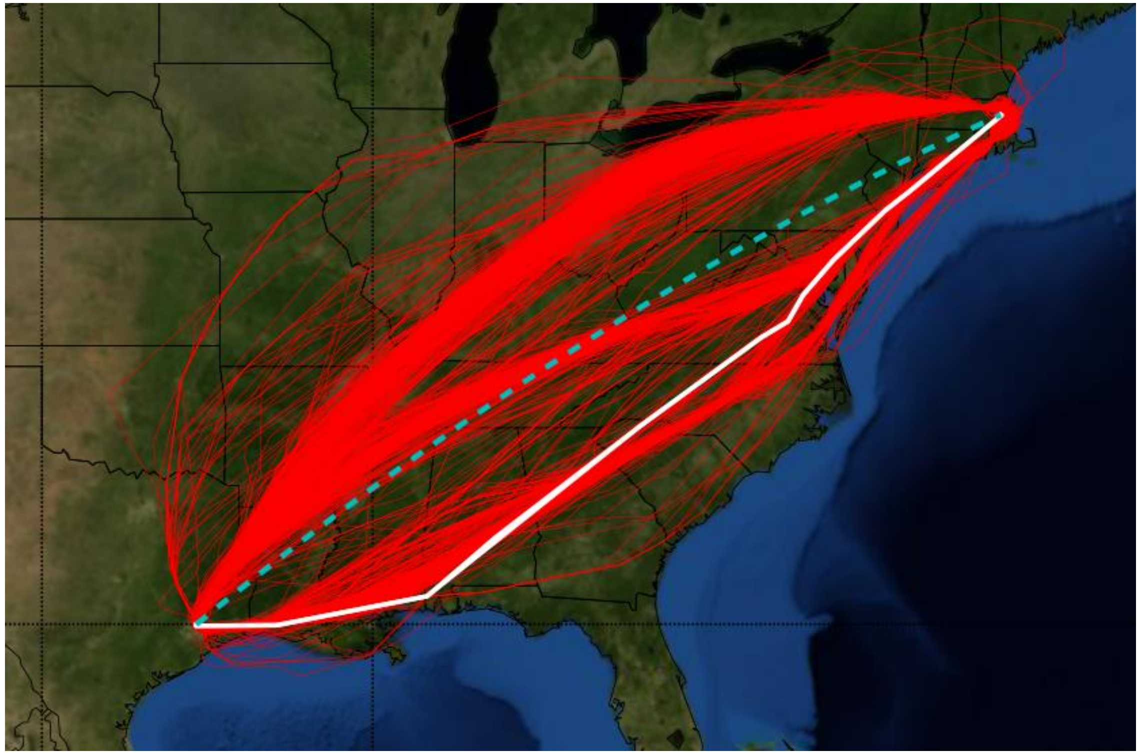
Data Sources

- Flight Track Data
- National Convective Weather Data
- Wind Speed Data
- Temperature Data

Data Sources – TFMS

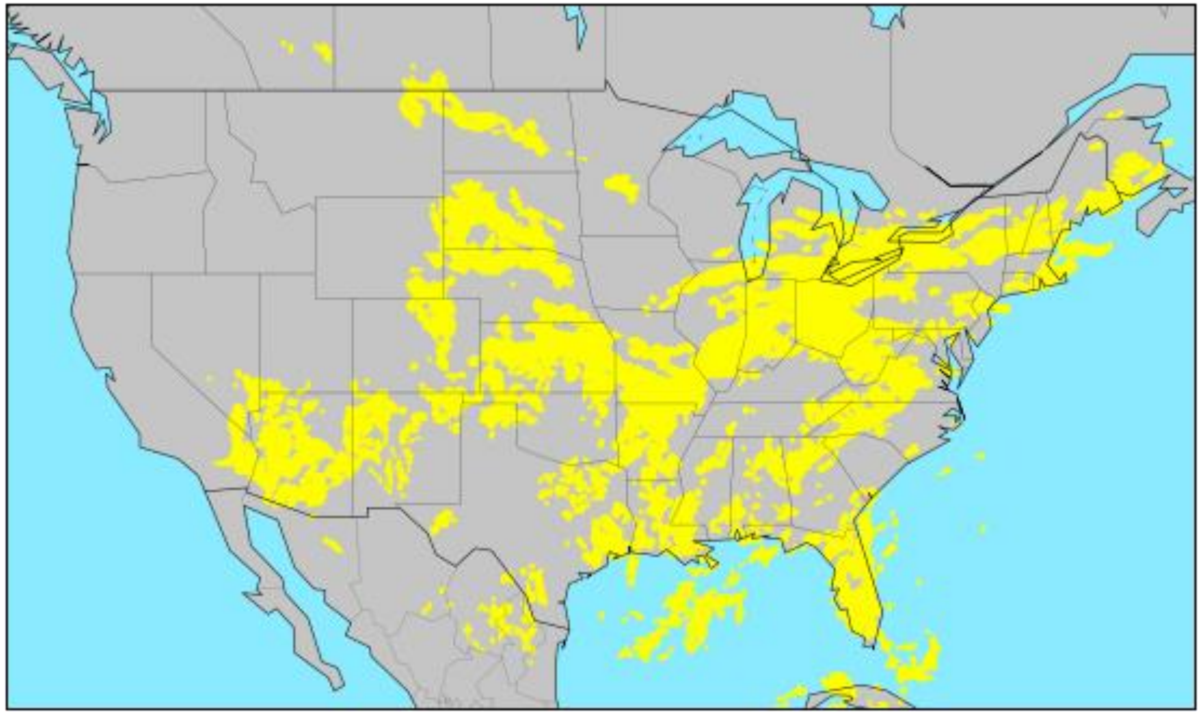
- Flight Track/ Plan Data
  - Come from FAA Traffic Flow Management System.
  - Typically 60-second update.
  - Latitude, longitude, altitude, time
  - Derived the vertical and horizontal speeds.



Data Sources – NCWF

- National Convective Weather Data (NCWF)
  - 5-minute update nowcast.
  - Convective weather polygons with altitude (flight level) and speed.

NCWF convective weather polygon

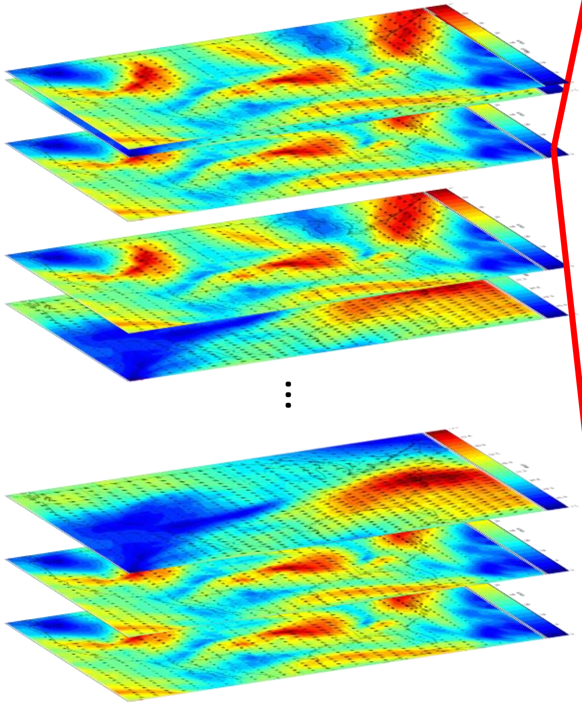


Data Sources – NAM

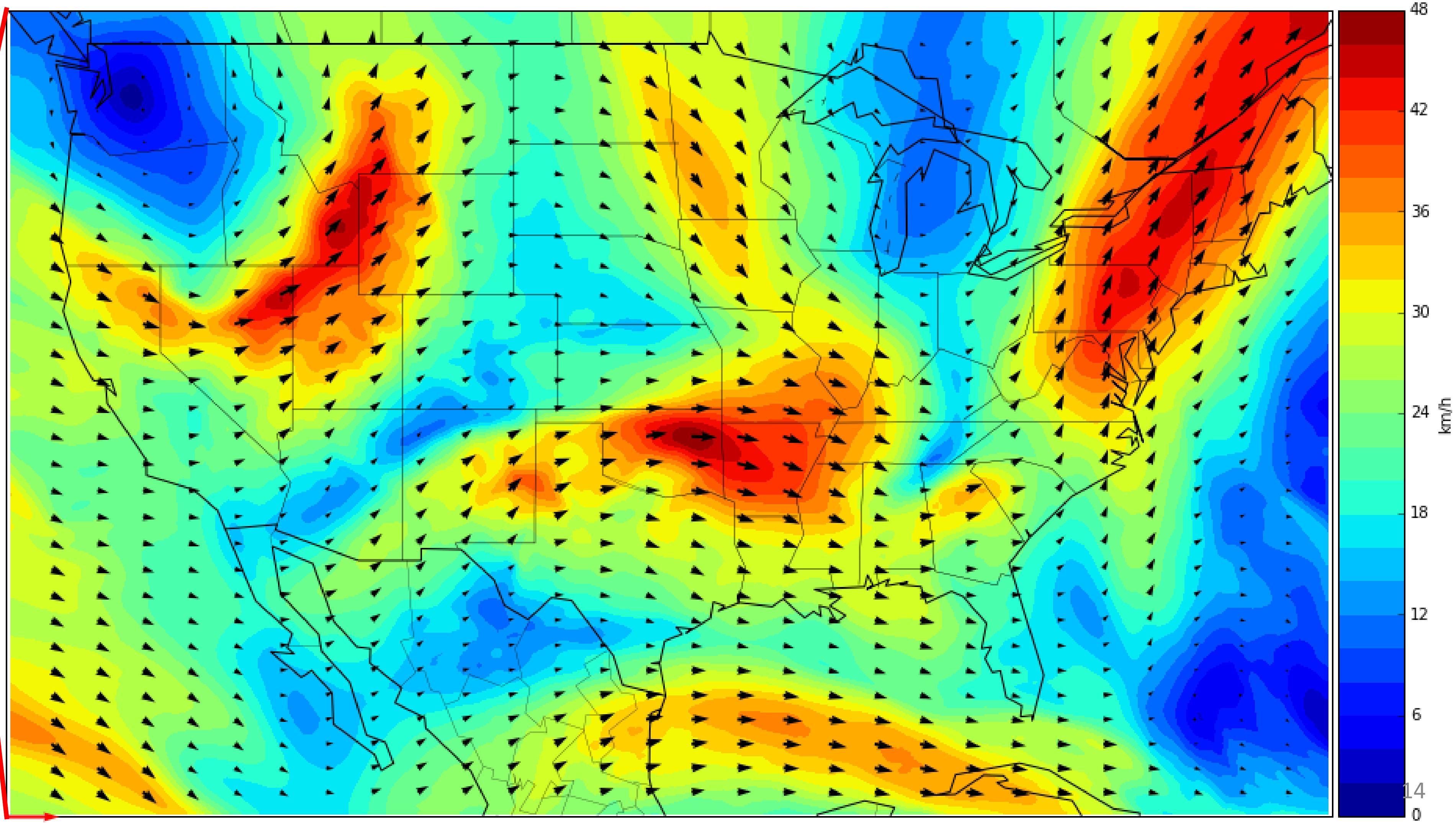
- North American Mesoscale Data (NAM)
  - Updated 4 cycles per day: 00:00; 06:00; 12:00; 18:00.
  - Each cycle produced 5 datasets at 0 hour, 1 hour, 2 hour, 3 hour and 6 hour.
  - Wind speed and temperature.
  - $0.1° \times 0.1°$
  - 39 altitude levels: 50 mbar (~68000 ft) to 1000mbar (~0 ft).

Data Sources – NAM

39 isobaric pressure levels
For each level: 614 x 428

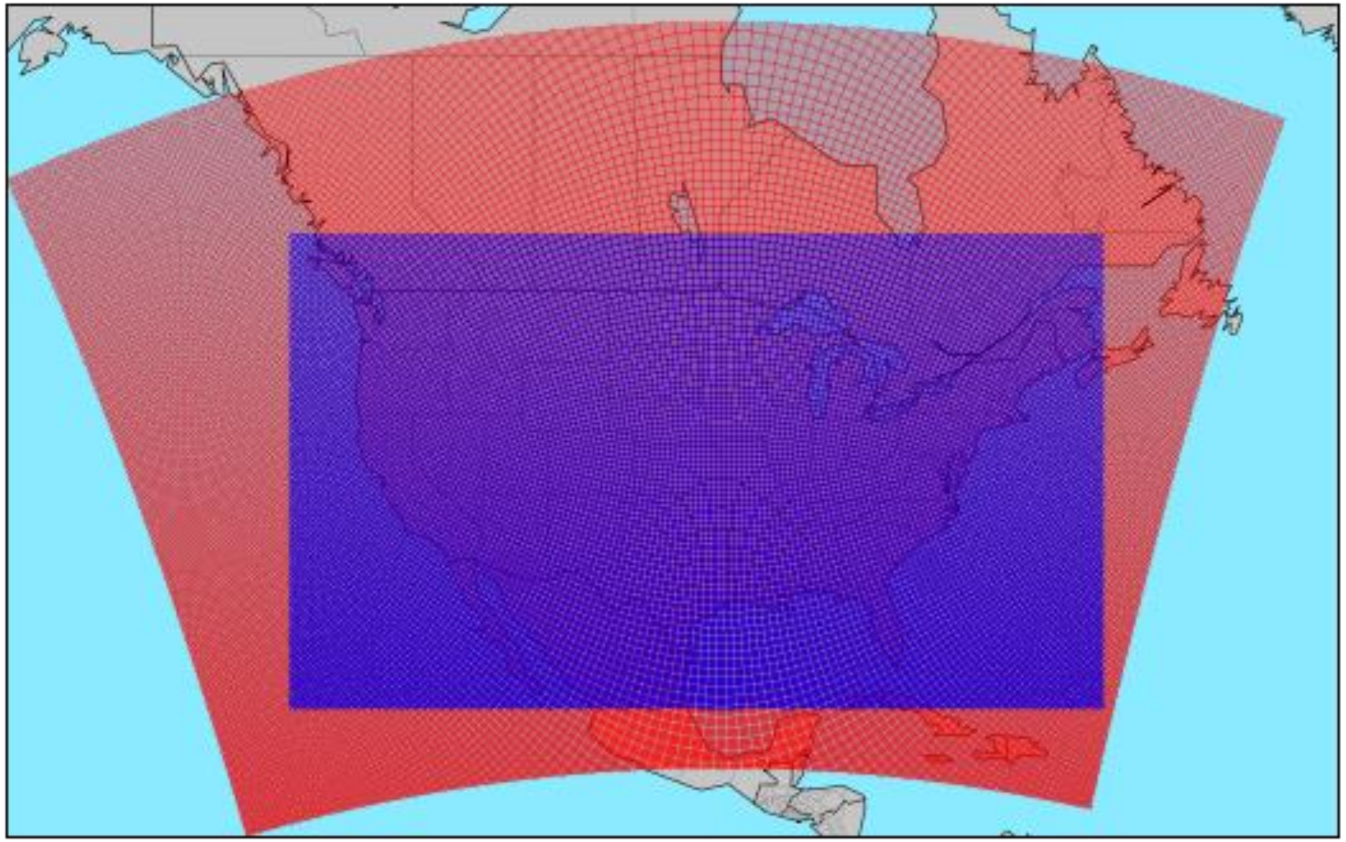


Wind Field Diagram (km/h) @ 200 mbar (~ 38,000 ft.); 02/04/2013 18:00 Zulu



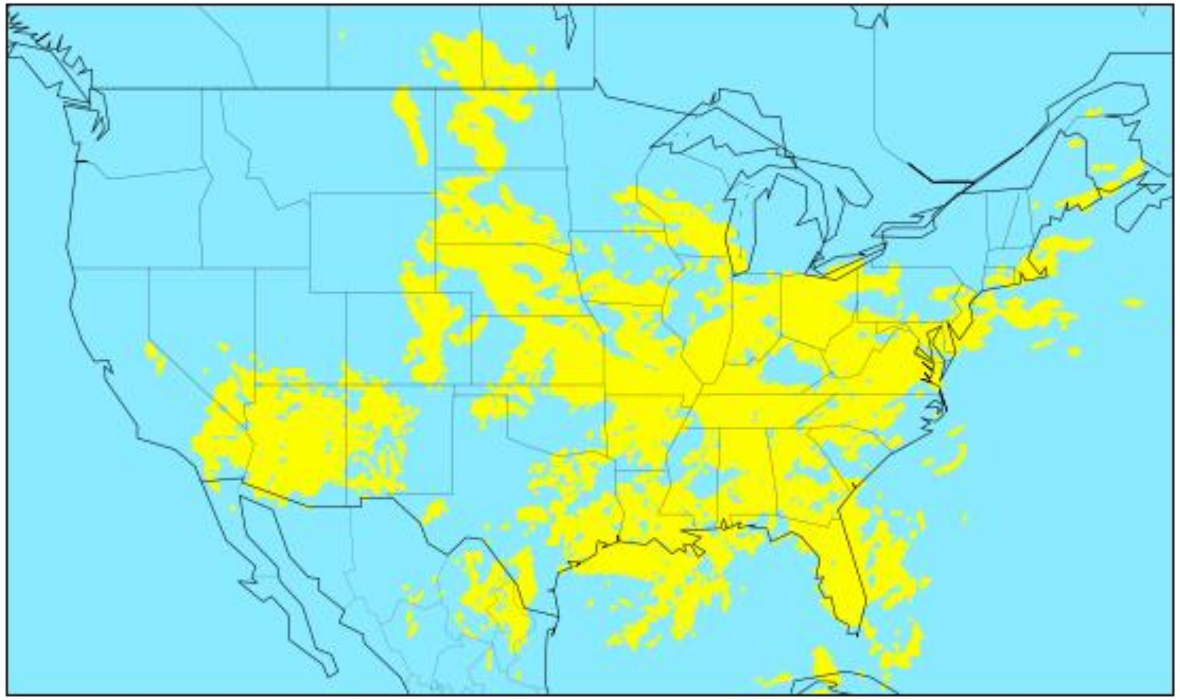
Feature Engineering – Georeferencing

- Based on NAM weather data
- Red
  - Original georeferencing grid
  - 428×614
- Blue
  - Cropped georeferencing grid
  - Latitude: $22° \sim 52°$
  - Longitude: $-130° \sim -64°$
  - $\sim 336 \times 413$



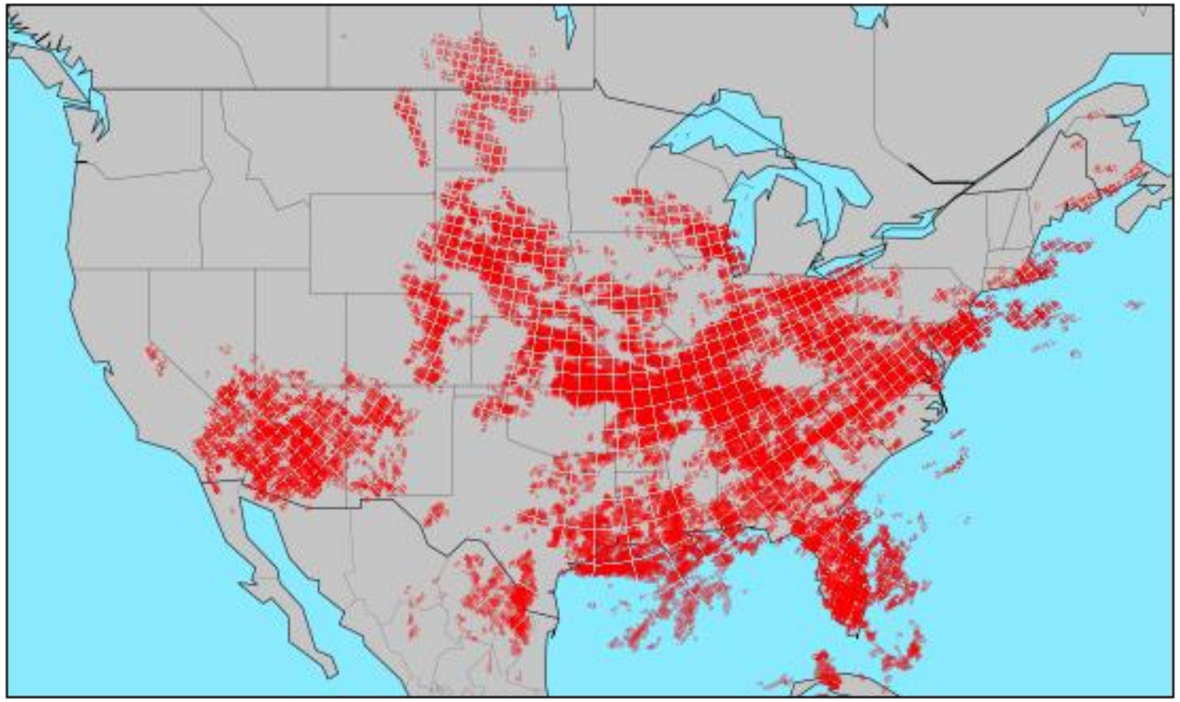
Feature Engineering – Discretize Weather Data

Original (2D projection)



Original data describe the boundary and altitude of convective weather polygons

Discretized (2D projection)

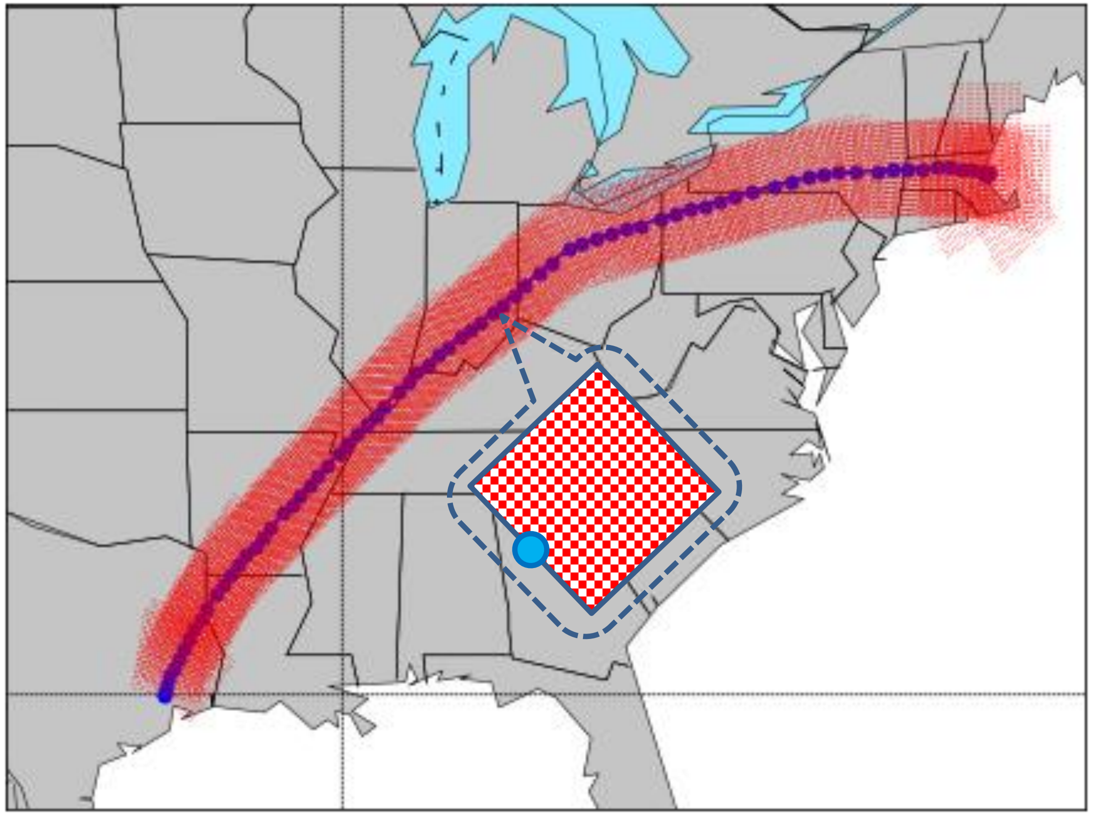


Discretized weather information will be stored as binary variables in a matrix spanned by our georeferencing grid. The red points on the graph are the nonzero elements.

Feature Engineering – Feature Cube Path

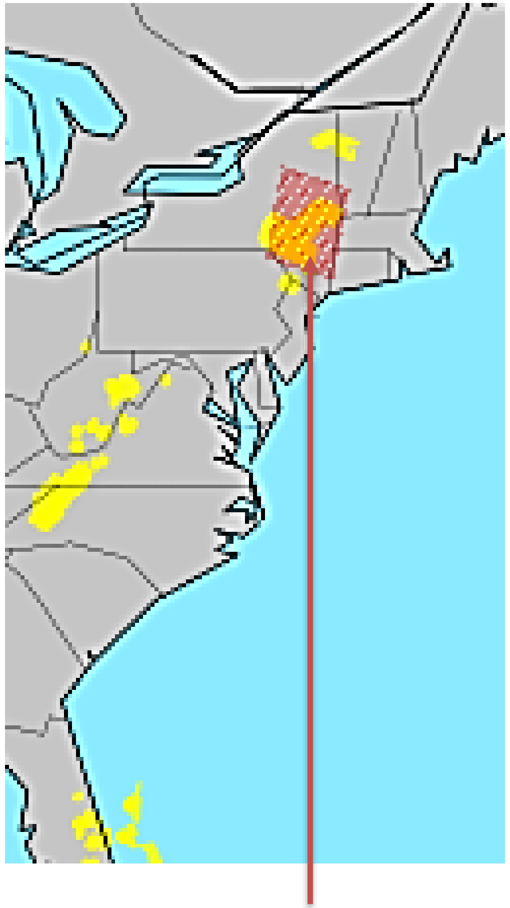
- 2D grid
  - For each track point, create a 20x20 grid matrix with one side centered at the track point, and oriented by the azimuth.
- Altitude buffer
  - NAM: flight level → pressure altitude.
  - NCWF: flight level $\pm$ 200 FL
- Time buffer
  - NAM: track time $\pm$ 3 hours
  - NCWF: track time $\pm$ 1 hour

Flight grid path is oriented by the azimuth.



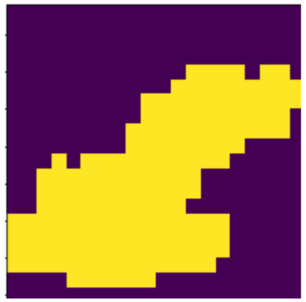
Feature Engineering – Matching

- Batch Mode Tree-based 4D Matching
  - Temporal trees: query to find the closest time instances to the flight tracks.
  - Spatial trees: query to find the closest location instances to the flight grid path.

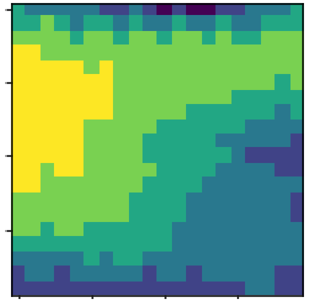


One grid on the flight grid path

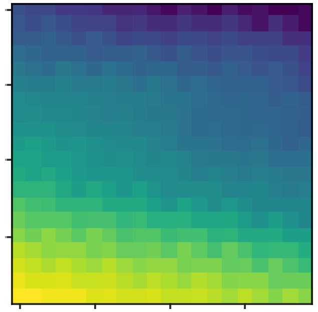
NCWF weather



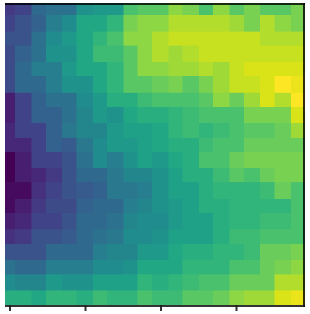
Temperature



Westly wind speed



Southerly wind speed



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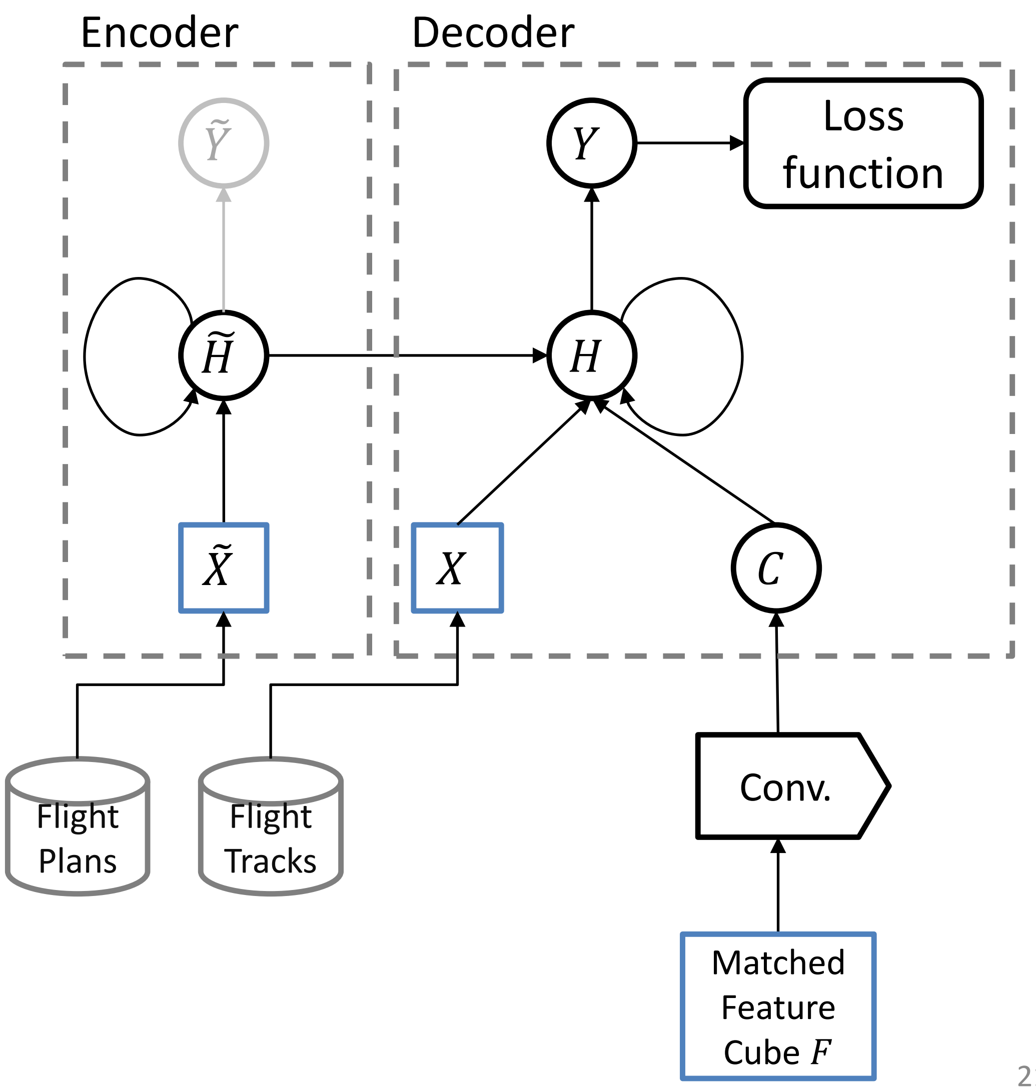
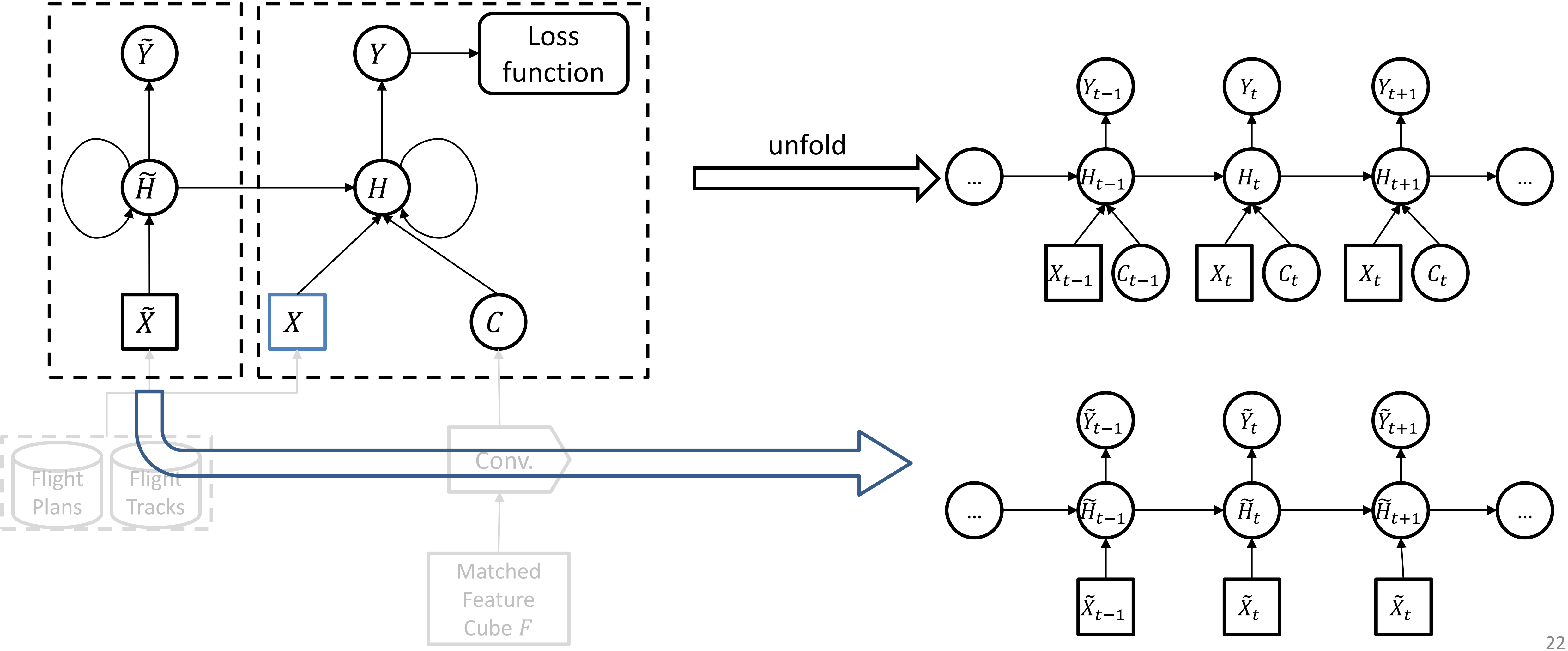
Methodology

- Training framework
  - Encoder LSTM network: embed flight plan sequence information.
  - Decoder LSTM network: learn the spatiotemporal correlation from flight tracks.
  - Convolutional layers: learn feature representations from high-dimensional meterological feature cubes.
- The predicted flight tracks are modeled as **Mixture of Gaussians** whose parameters are learned by the decoder network.

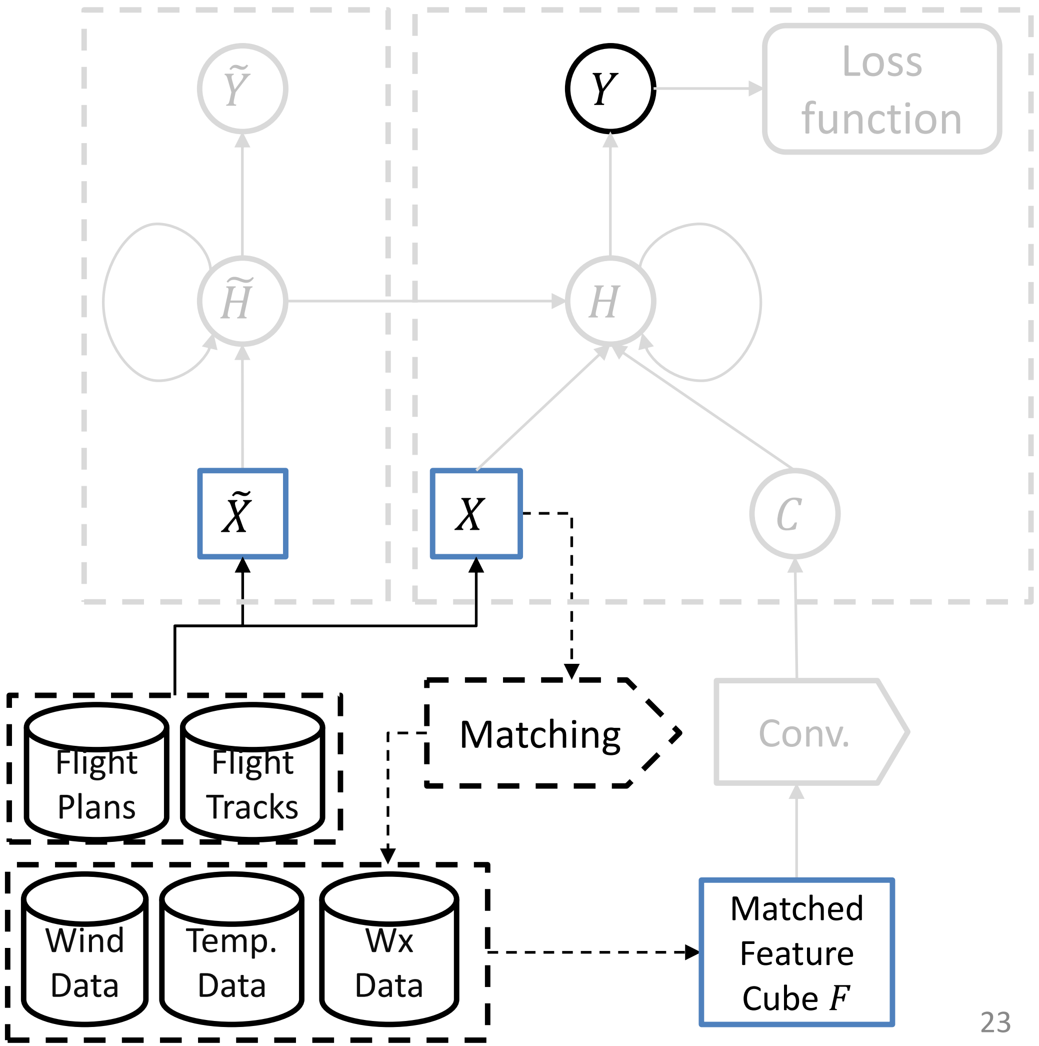


Framework – Training



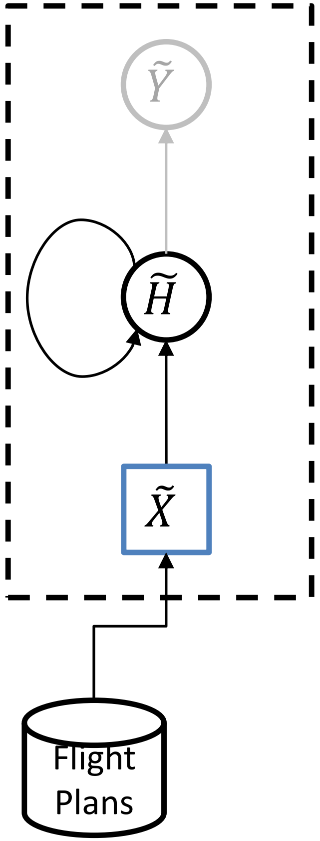
Framework – Training

- Inputs
  - $\tilde{X}$: Sequence of 2D coordinate (Lat, Lon) of flight plans.
  - X: Sequence of state variables of flight tracks.
  - $X_t = (Lat, Lon, Alt, Time, Lat\ speed, Lon\ speed)_t = (x, y, z, t, \dot{x}, \dot{y})_t$.
  - F: Sequence of matched feature cubes that correspond to X.
- Outputs
  - Y: Sequence of Gaussian mixture parameters
  - $Y_t = \left(\pi_i, \mu_x^i, \mu_y^i, \mu_z^i, \mu_{\dot{x}}^i, \mu_{\dot{y}}^i, \Sigma_{(x,y,z)}^{\mathrm{i}}, \Sigma_{(\dot{x},\dot{y})}^{\mathrm{i}}\right)_{\mathrm{t}}$

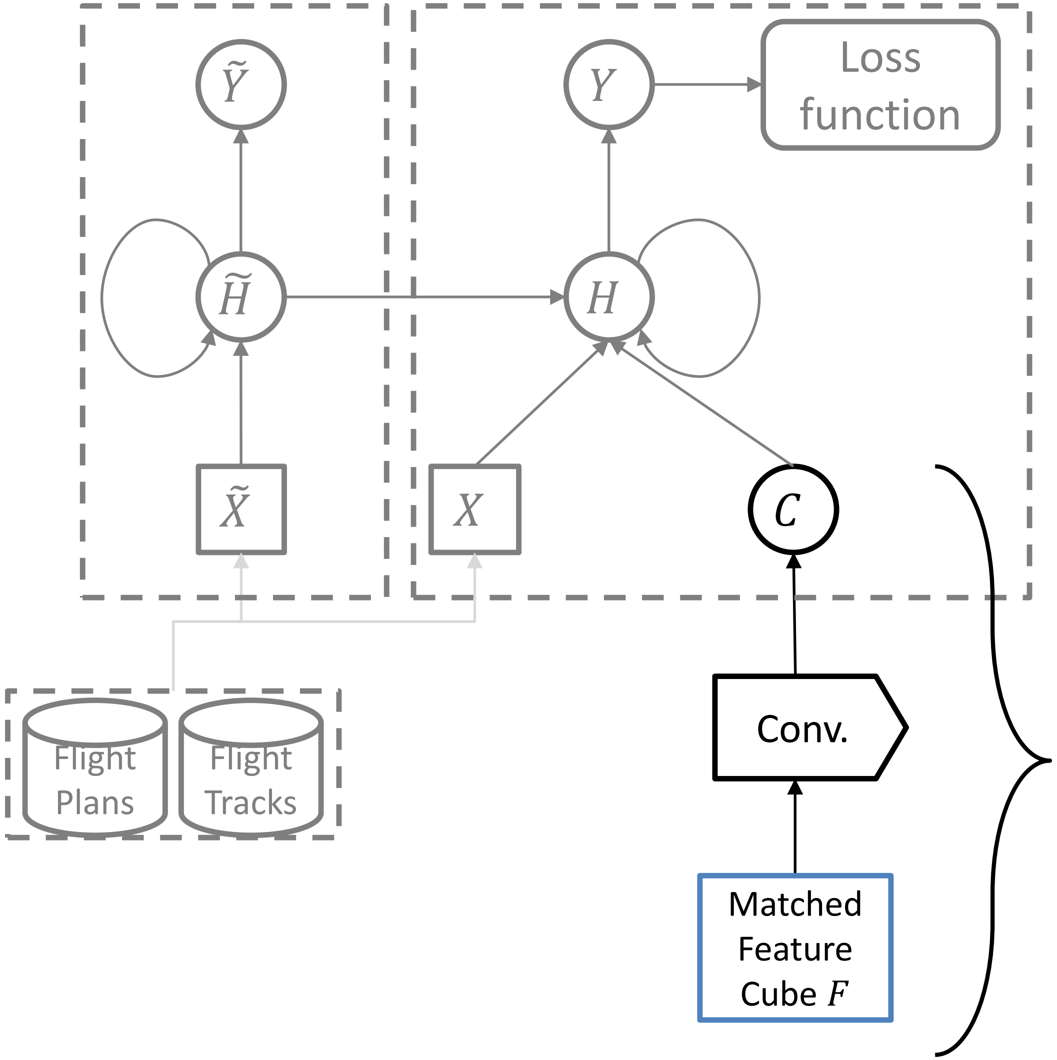


Framework – Training

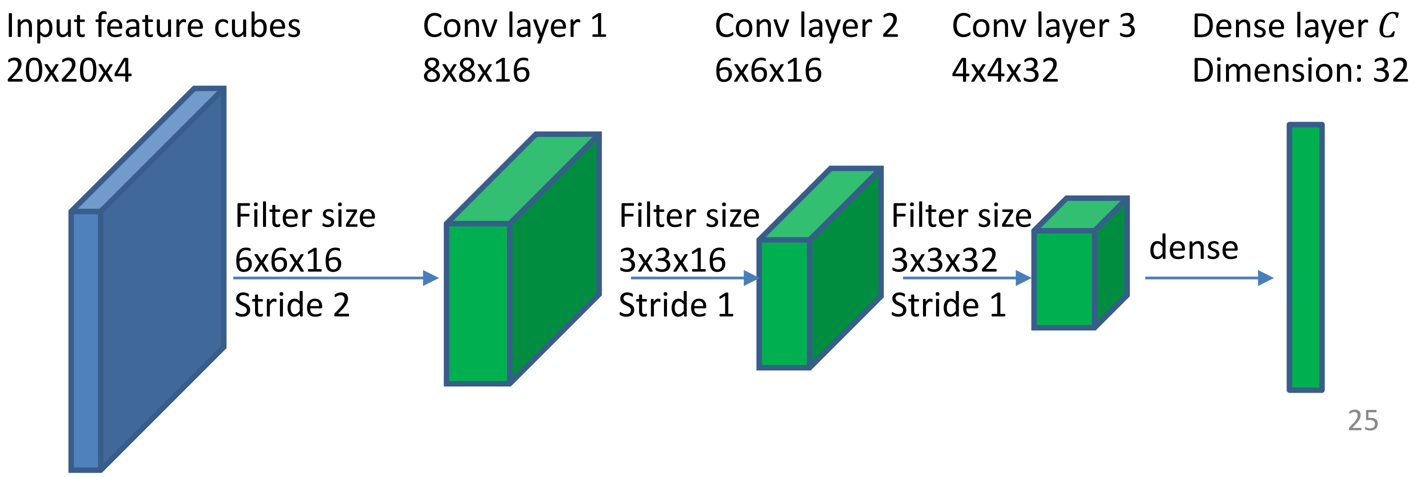
- Encoder LSTM
  - $\tilde{X}$: Sequence of 2D coordinate (Lat, Lon) of flight plans.
  - $\widetilde{H}$: hidden layers of a two-layer LSTM with 128 neurons.
  - Flight plan information $\tilde{X}$ is therefore embedded by encoder LSTM into a fixed-length variable $\widetilde{H}$.



Framework – Training



- Convolutional Layers
  - Three convolutional layers and one dense layer.
  - No pooling layers, and no padding operations.
  - Dense layer has 32 neurons that act as the feature representations from the high-dimensional meteorological feature cubes (20x20x6=2400).

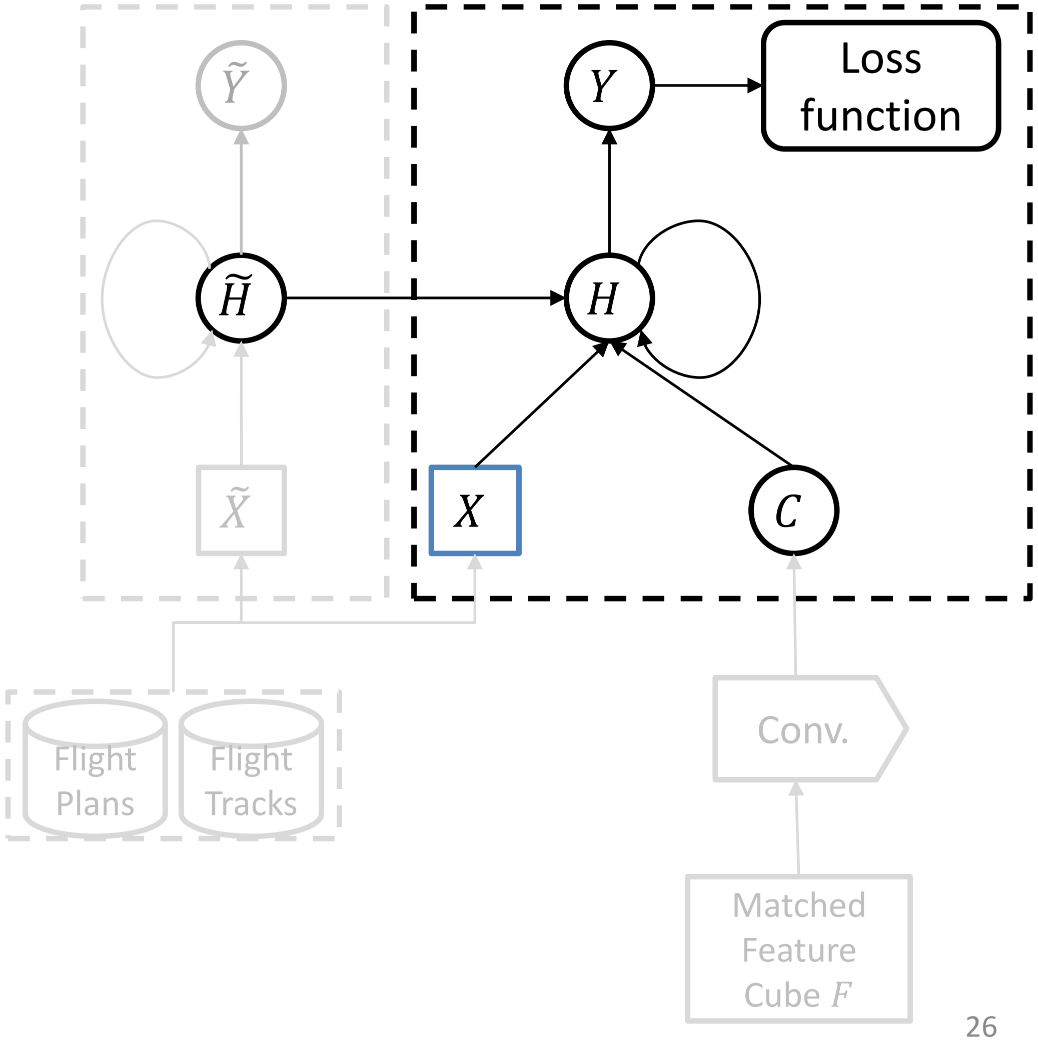


Framework – Training

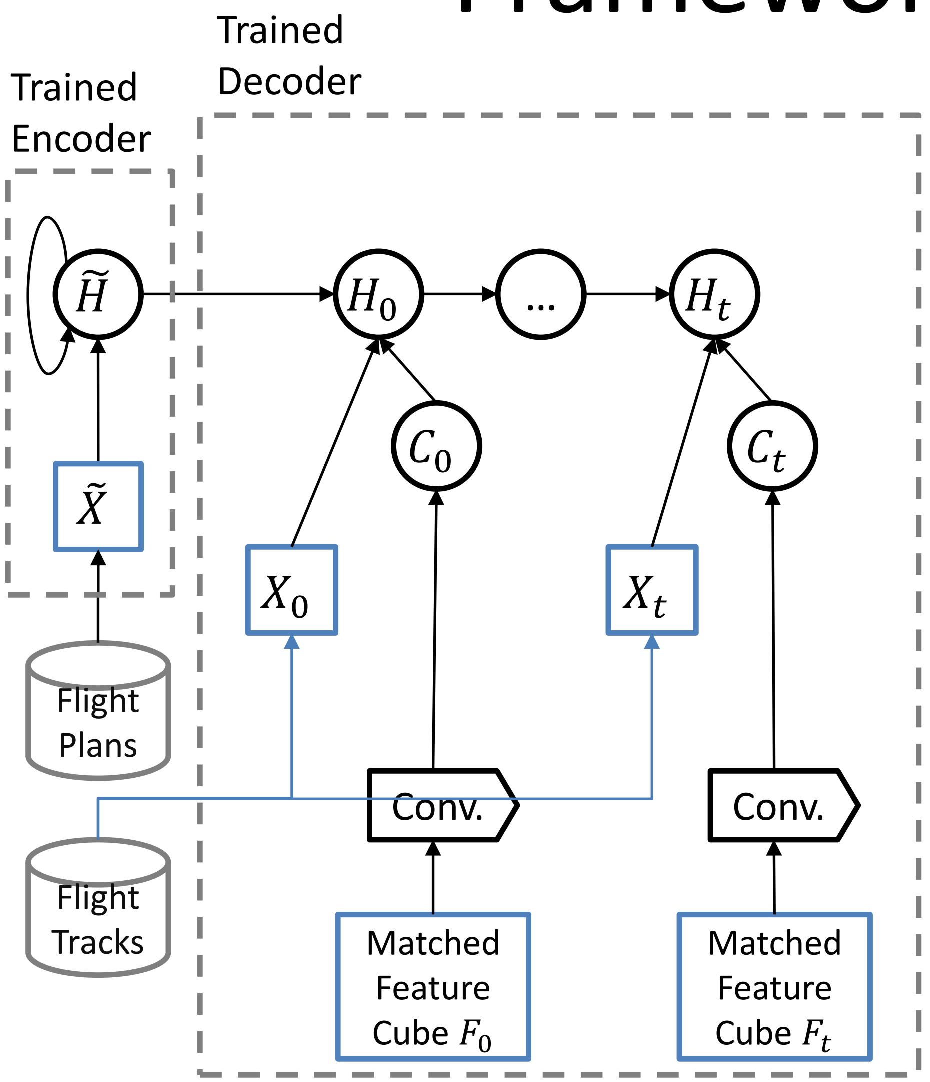
- Decoder LSTM
  - C: fixed-length feature vector learned by CNN (dense layer) from high-dimensional weather data.
  - Both X and C are fed into an embedding layer with 64 neurons before entering the decoder network.
  - Y: gaussian mixture parameters: $\pi_i, \mu^i_{lat}, \mu^i_{lon}, \mu^i_{alt}, \mu^i_{latspd}, \mu^i_{lonspd}$ $\Sigma^i_{(lat,lon,alt)}, \Sigma^i_{(latspd,lonspd)}$.
  - Loss function

$$L = -\sum_t^T \log\left[\sum_i \pi_i P_i\left(\widehat{X_{t+1}} \middle| Y_t, X_t, X_{t-1}, \ldots\right)\right]$$

$$P_i\left(\widehat{X_{t+1}} \middle| Y_t, X_t, X_{t-1}, \ldots\right) \sim N\left(\begin{bmatrix}\mu^i_{lon}\\ \mu^i_{lat}\\ \mu^i_{alt}\end{bmatrix}, \Sigma^i_{(lat,lon,alt)}\right) N\left(\begin{bmatrix}\mu^i_{latspd}\\ \mu^i_{lonspd}\end{bmatrix}, \Sigma^i_{(latspd,\,lonspd)}\right)$$



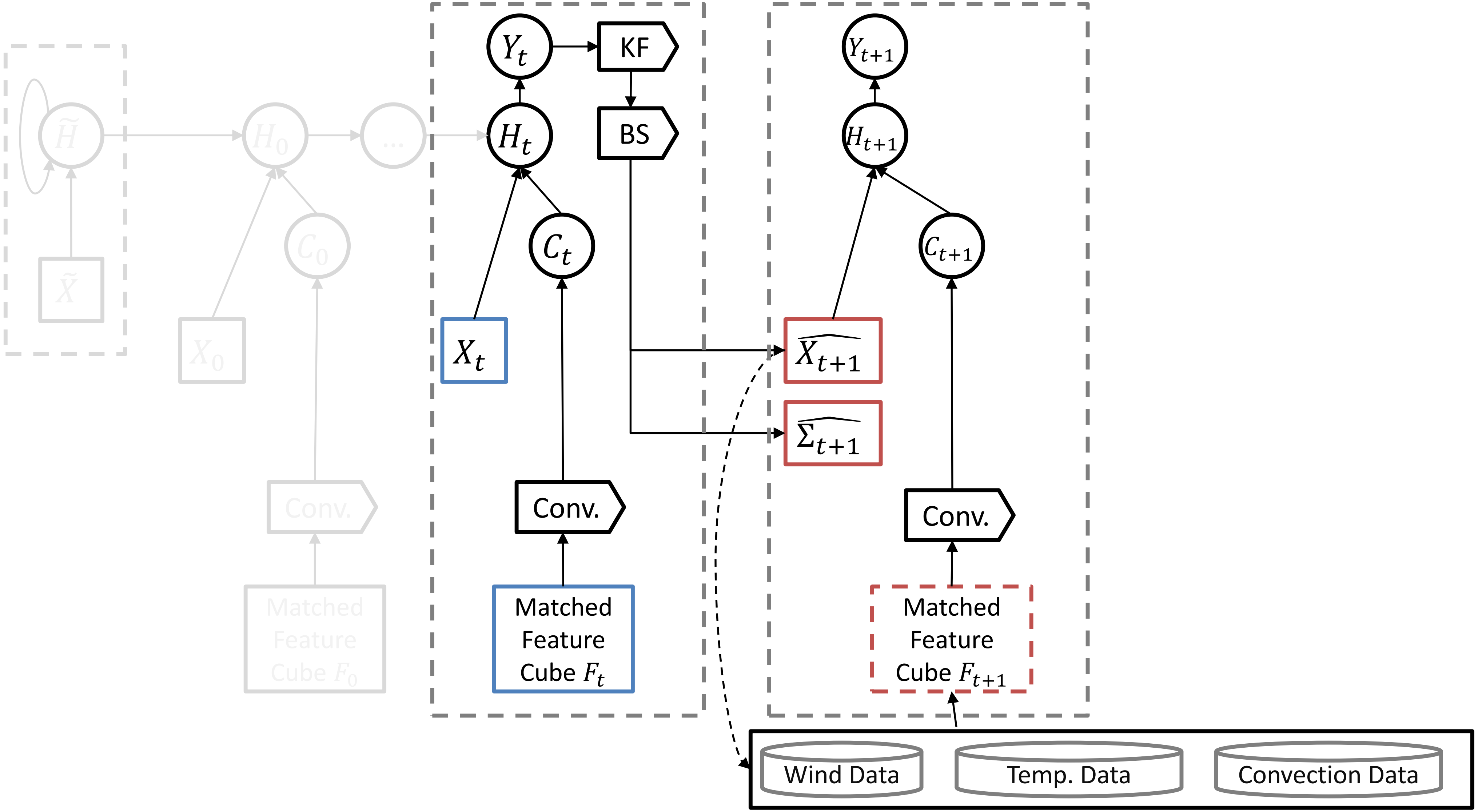
Framework – Inference/ Sampling



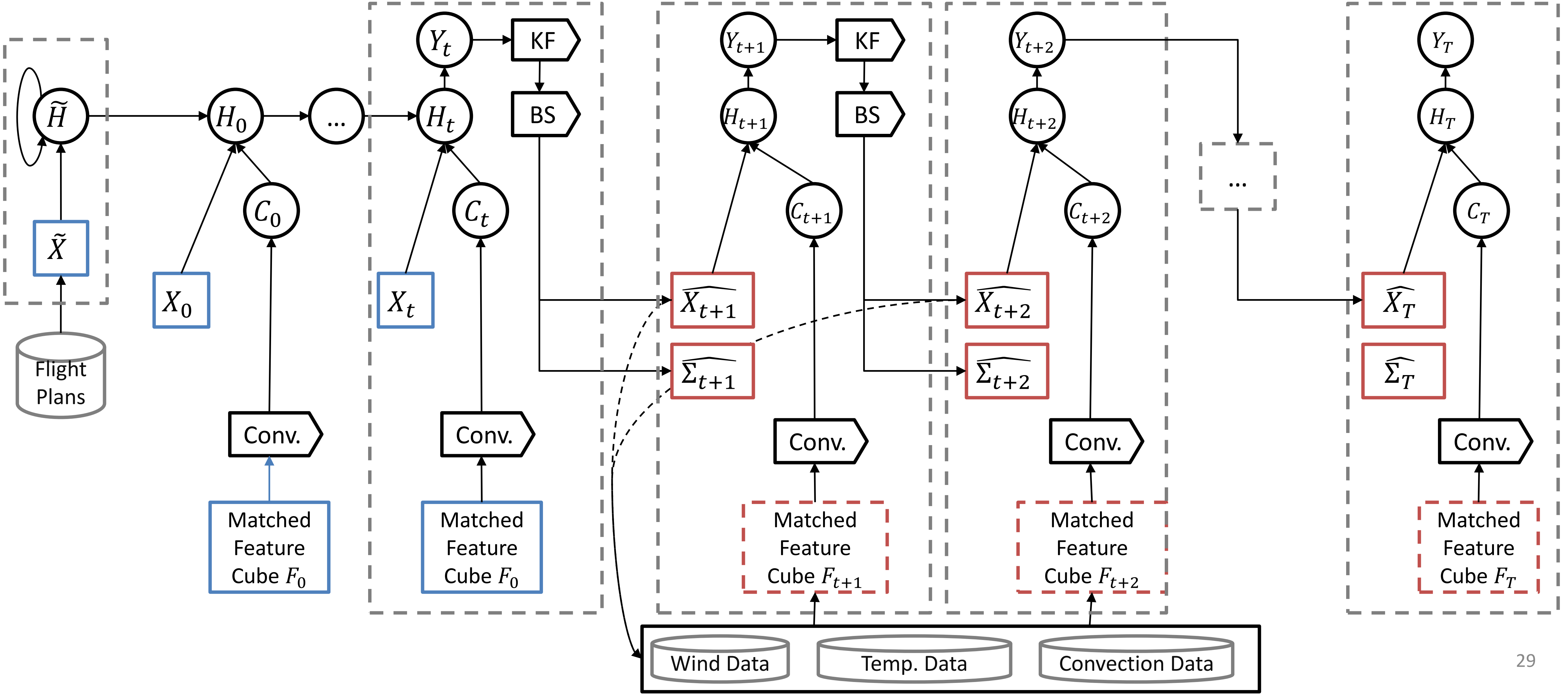
- Inputs
  - Trained networks
  - Sequence of flight plans
  - Sequence of first t flight coordinates
- Outputs
  - The predicted flight coordinates after time t.
  - Confidence interval of every predicted flight coordinates.

Framework – Inference/ Sampling

$$Y_t = \left(\pi_i, \mu_x^i, \mu_y^i, \mu_z^i, \mu_{\dot{x}}^i, \mu_{\dot{y}}^i, \Sigma^{\mathrm{i}}_{(x,y,z)}, \Sigma^{\mathrm{i}}_{(\dot{x},\dot{y})}\right)_{\mathrm{t}}$$



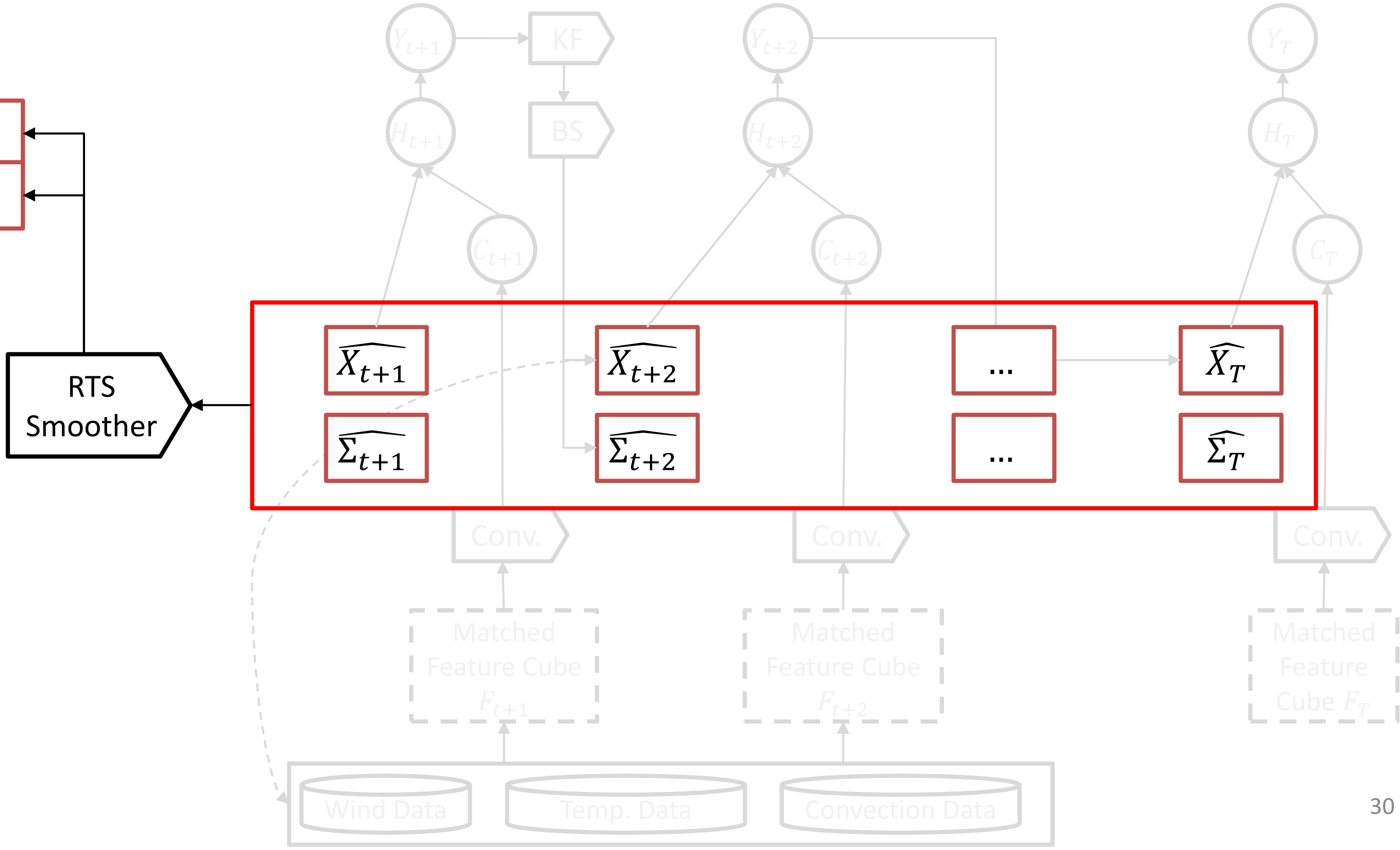
Framework – Inference/ Sampling



Framework – Inference/ Sampling

Best k sampled sequences

$\widehat{X_{t+1}}$	$\widehat{X_{t+2}}$	$\widehat{X_{t+3}}$	…	$\widehat{X_T}$
$\widehat{\Sigma_{t+1}}$	$\widehat{\Sigma_{t+2}}$	$\widehat{\Sigma_{t+3}}$	…	$\widehat{\Sigma_T}$



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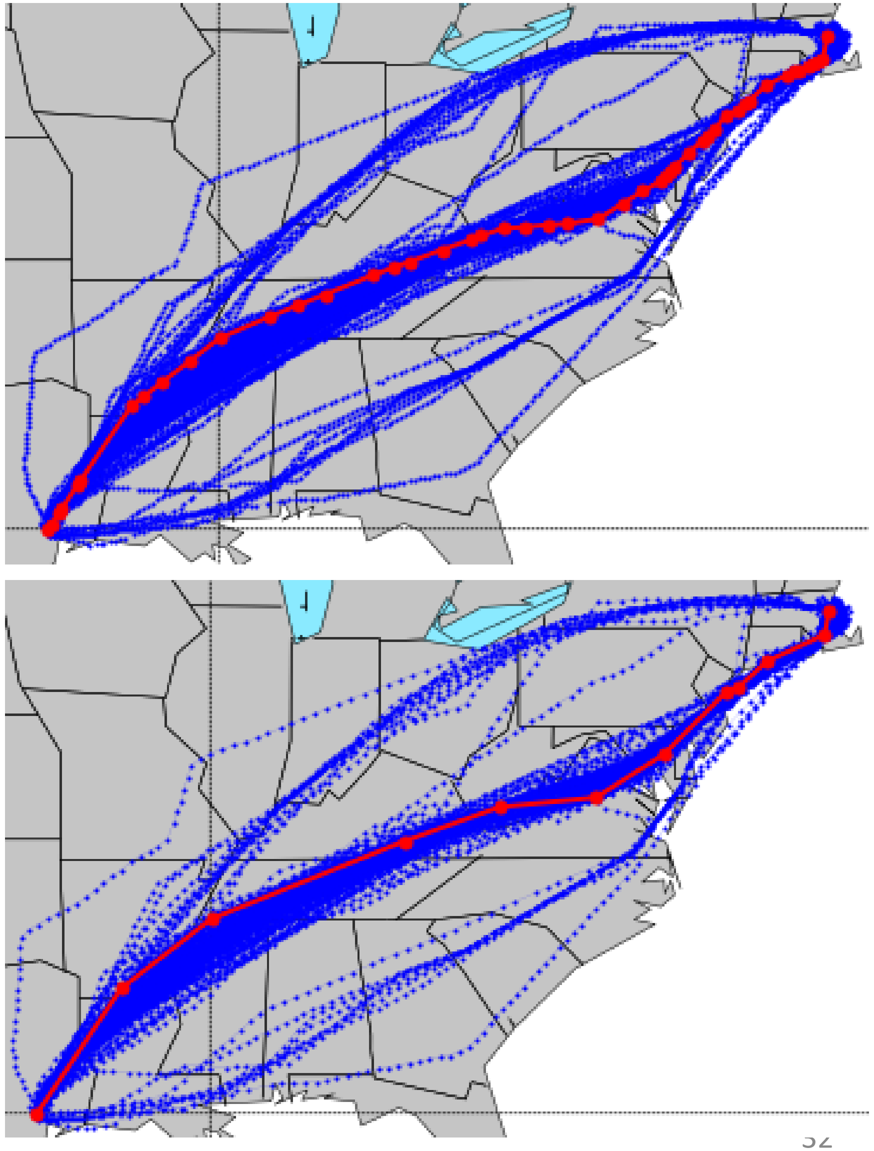
Numerical Experiments

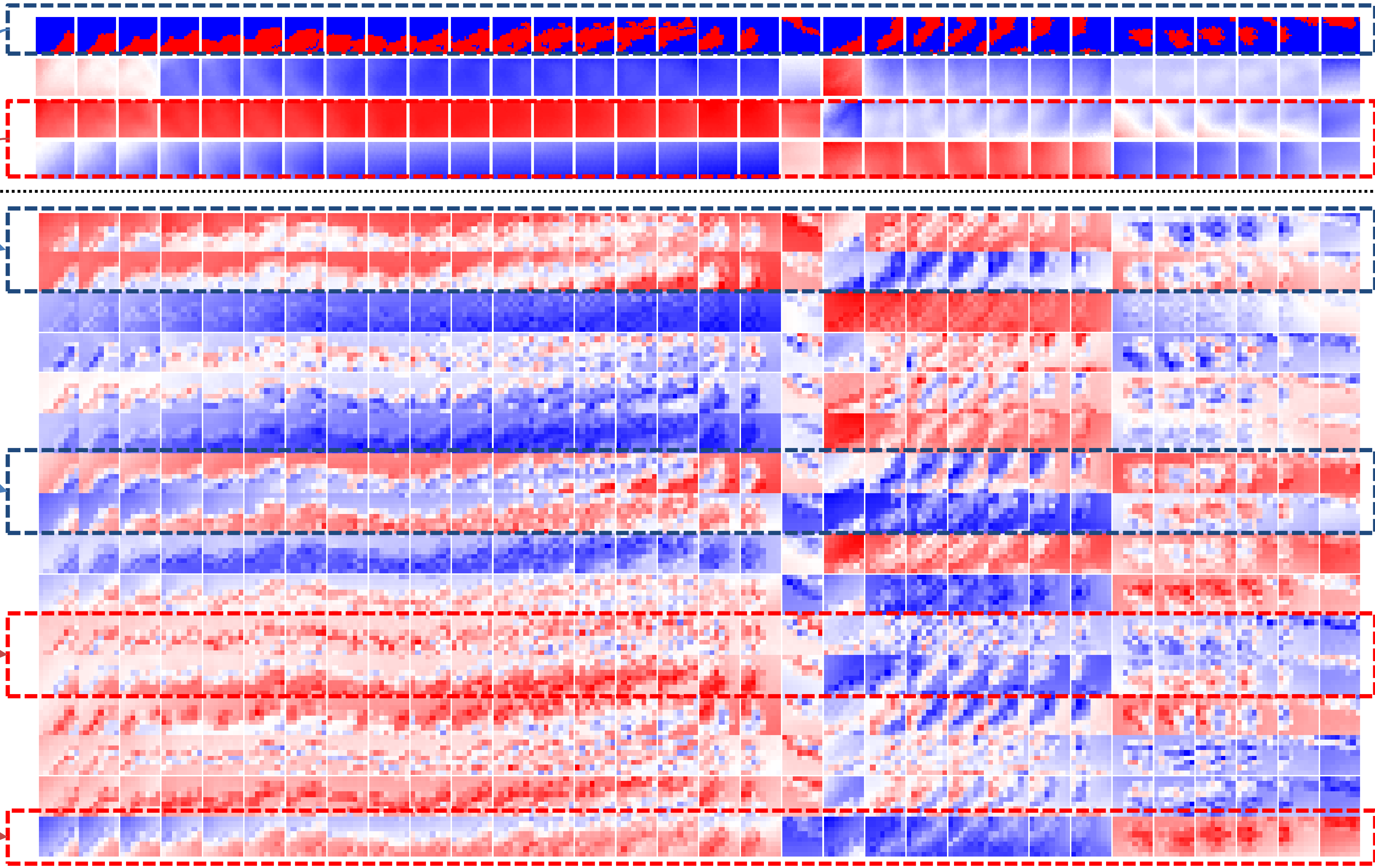
- Training Set
  - 1342 flights from IAH to BOS in 2013.
- Testing Set
  - 337 flights from IAH to BOS in 2013.
- Preprocessing
  - Downsample flight plans by identifying significant points.
  - Downsample flight tracks by half (Avg. sequence length = 94).
  - Normalize feature maps to 0 mean and unit variance.
- Training Specifics
  - Nesterov Momentum SGD.
  - Gradient clipping.
  - 3 Gaussian mixtures.
  - Dropout rate: 0.5



Feature Maps

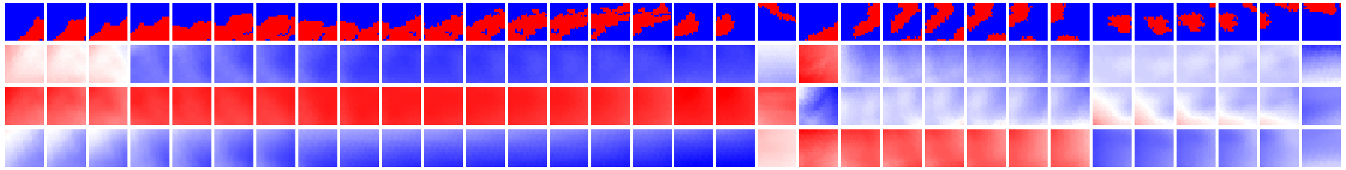
Input feature cubes

Conv. layer 1

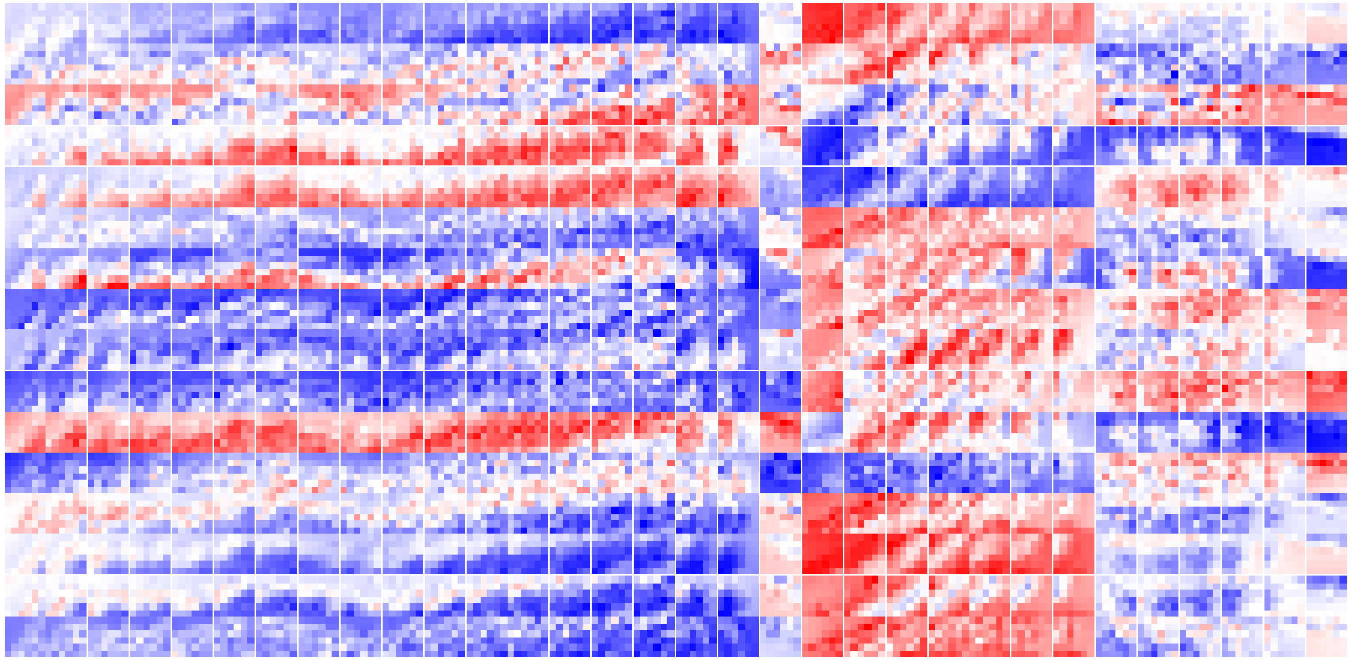


Feature Maps

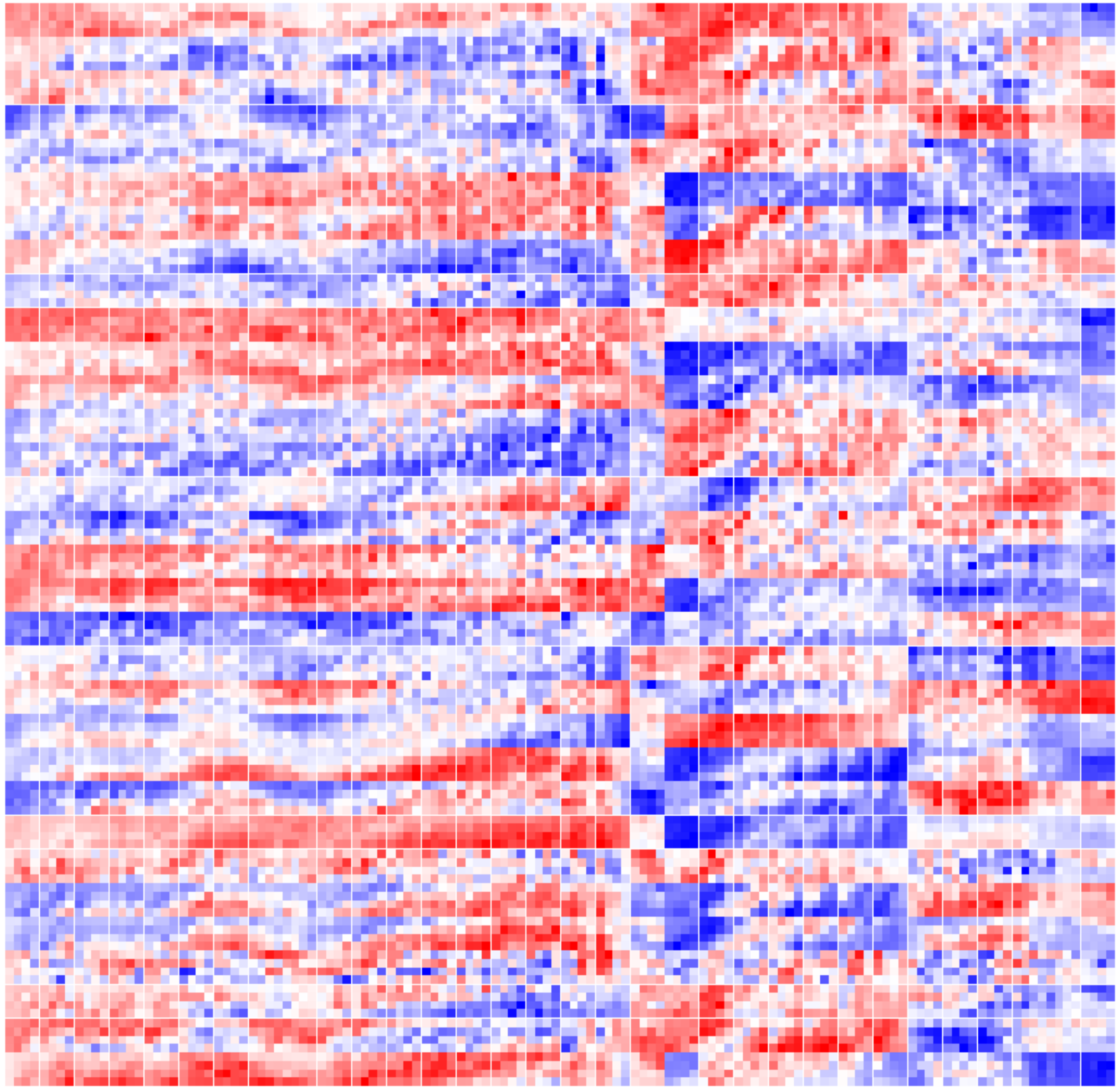
Input feature cubes



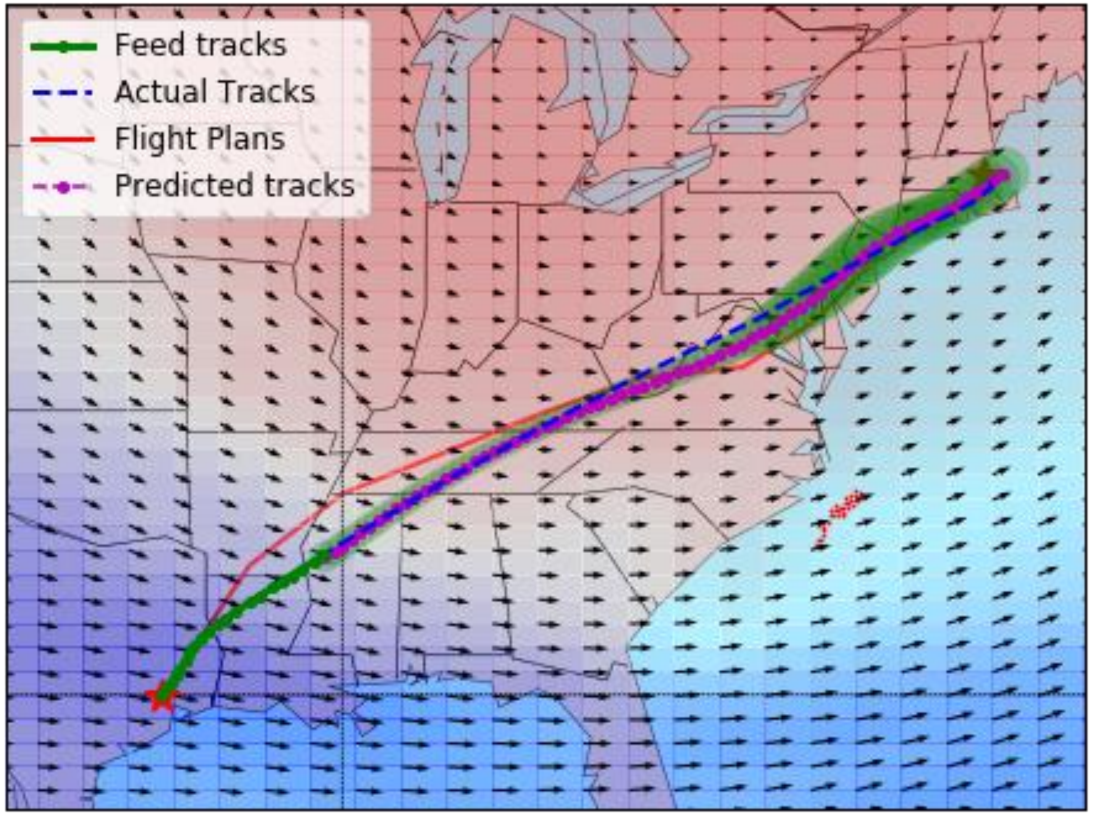
Conv. layer 2

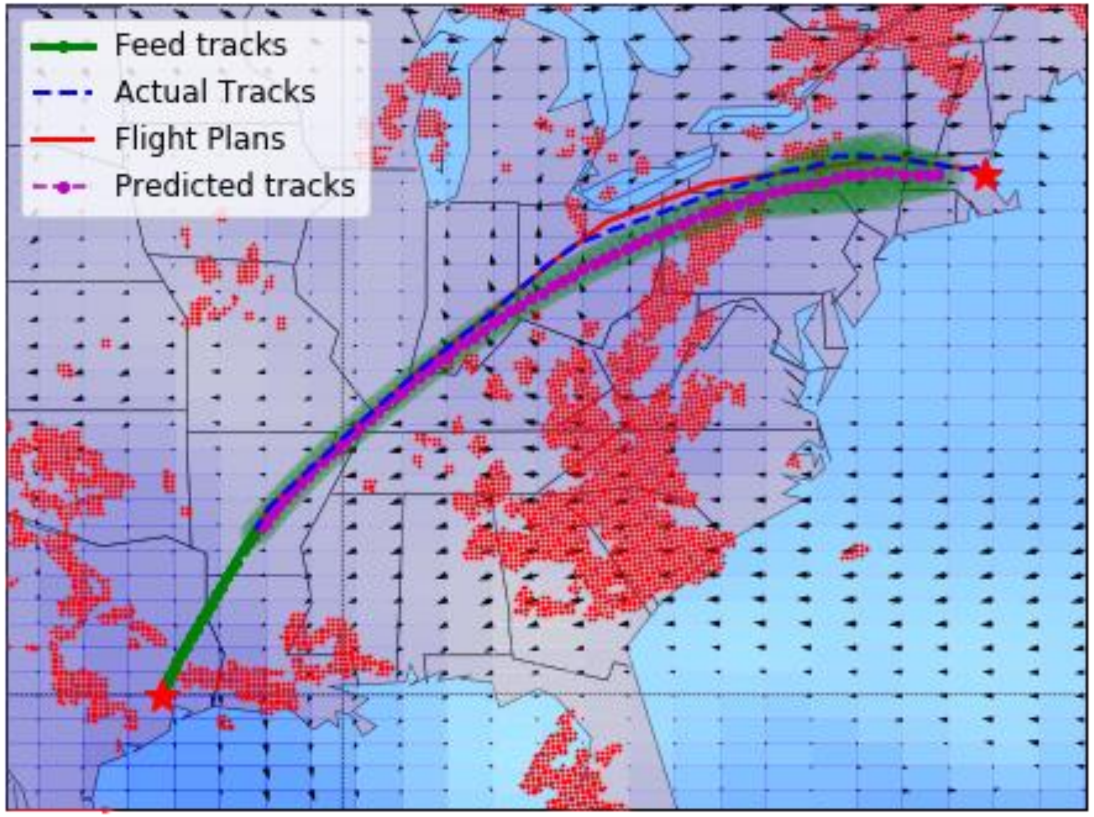


Conv. layer 3



Evaluation


Feed tracks
Actual Tracks
Flight Plans
Predicted tracks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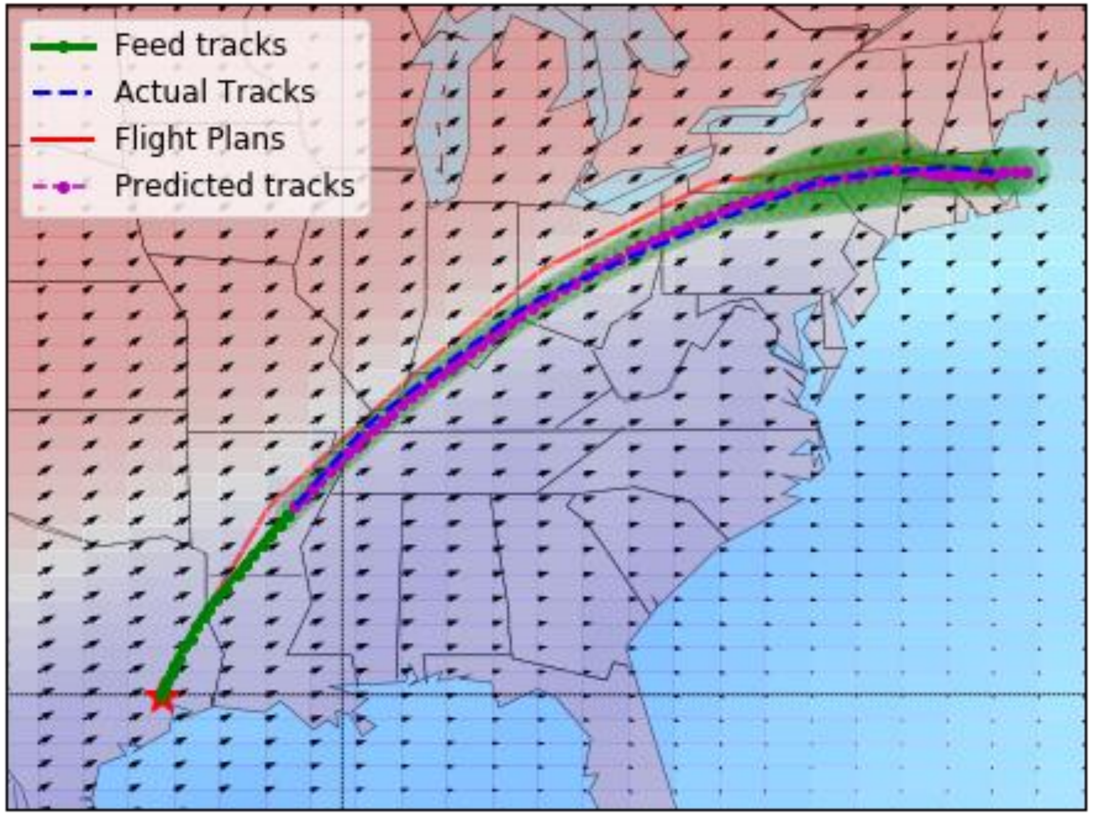
Feed tracks
Actual Tracks
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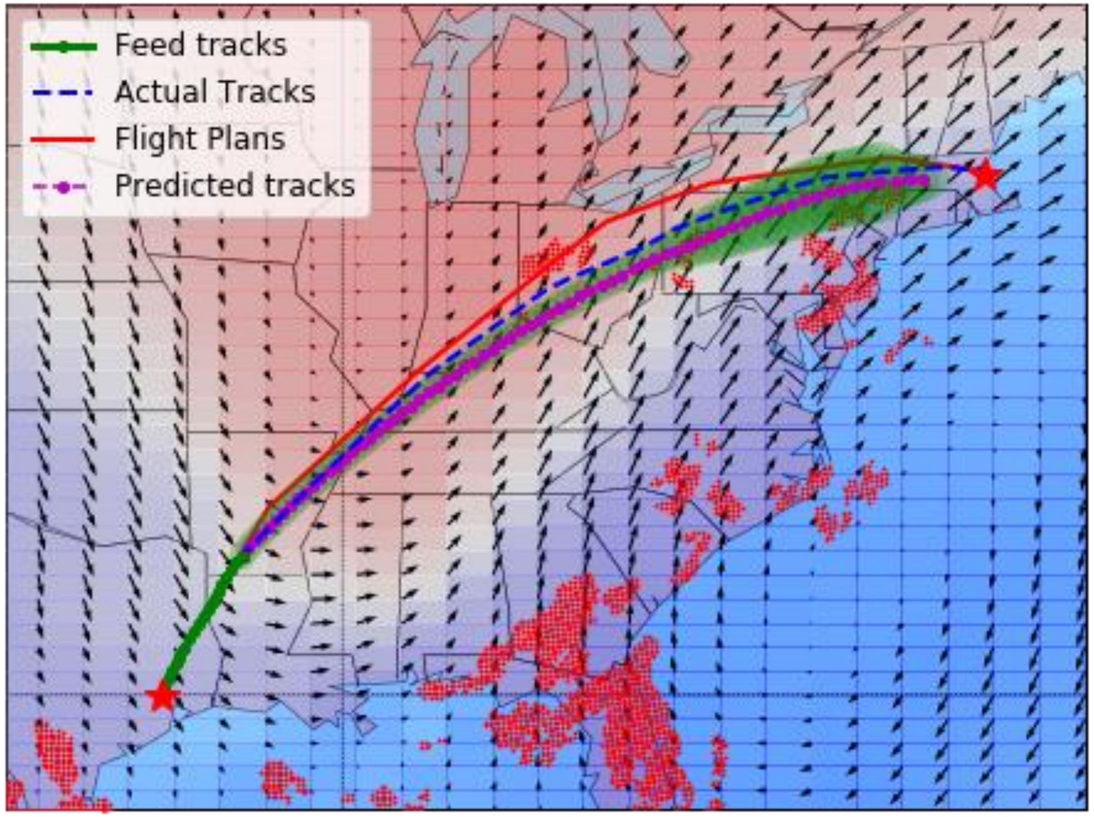
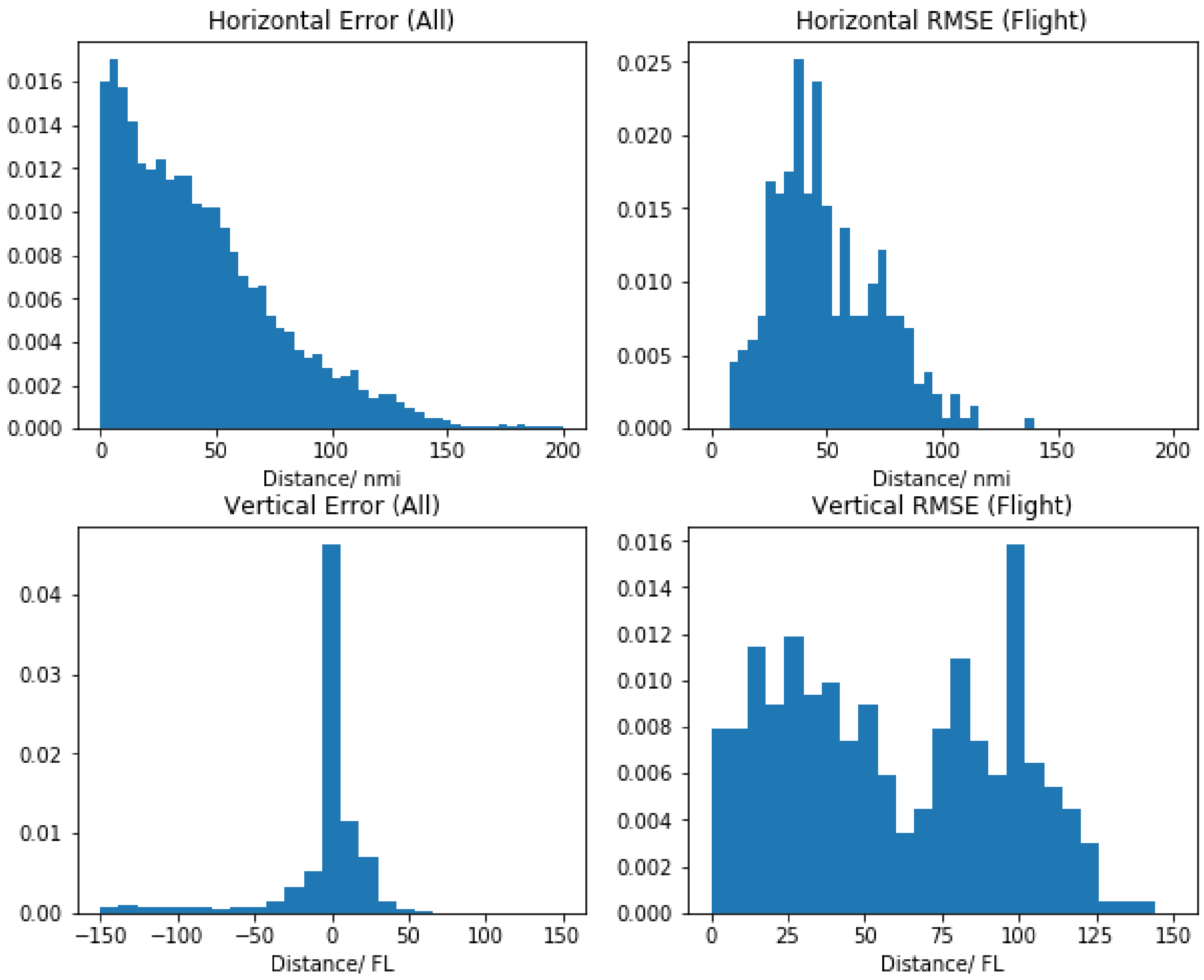

Feed tracks
Actual Tracks
Flight Plans
Predicted tracks

Evaluation

- Horizontal Error
  - All: $\left|X_{i,pred} - X_{i,act}\right|$ (nmi)
  - Flight: $\sqrt{\sum_{i \in J} \frac{\left(X_{i,pred} - X_{i,act}\right)^2}{J}}$ (nmi)
- Vertical Error
  - All: $Z_{i,pred} - Z_{i,act}$ (FL)
  - Flight: $\sqrt{\sum_{i \in J} \frac{\left(Z_{i,pred} - Z_{i,act}\right)^2}{J}}$ (FL)



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Summaries

- Propose an end-to-end deep neural network framework to predict actual flight trajectories.
- Convolutional layers are deployed to extract feature representations from high-dimensional weather features.
- The model is generative and can predict/ generate flight track distributions given initial conditions and weather information.
- Adaptive Kalman Filter, beam search, and RTS smoother are implemented to prune the prediction intervals.

Thank you!

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