
# VFR Trajectory Forecasting using Deep Generative Model for Autonomous Airspace Operations

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# Outline

Background and Preliminaries

Model Development and Training Process

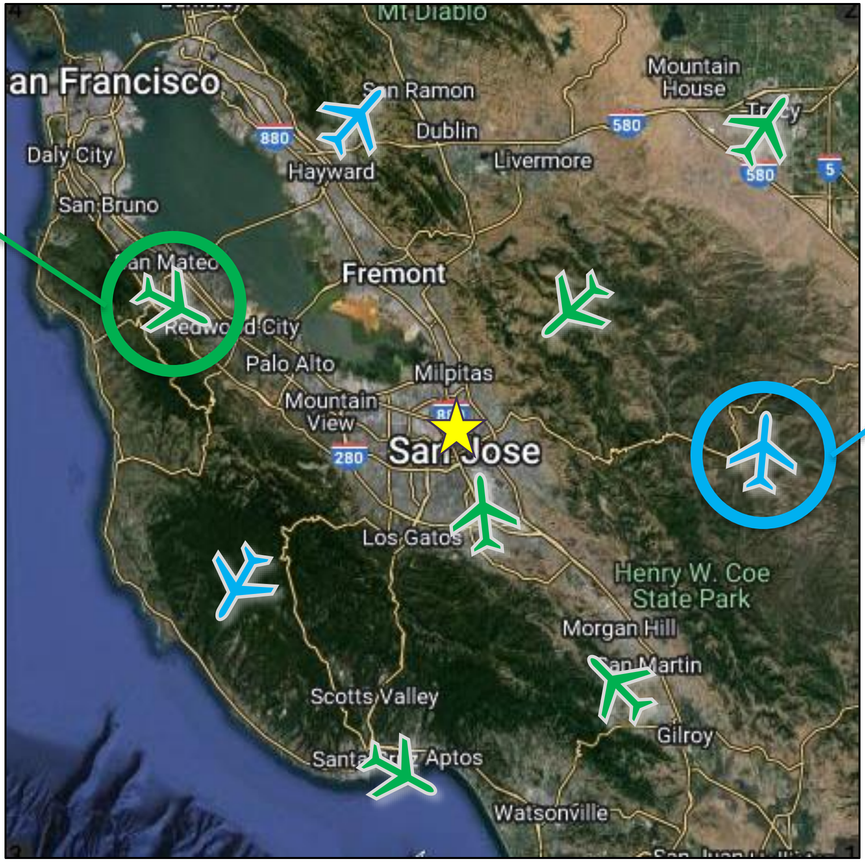
Results and Conclusions

# Background

Current airspace traffic consists of two categories of flights: VFR and IFR

- Airspace operations impacted by traffic from both VFR and IFR

Instrument Flight Rules (IFR)
- ➢ Flight plans available
- ➢ Easy to forecast

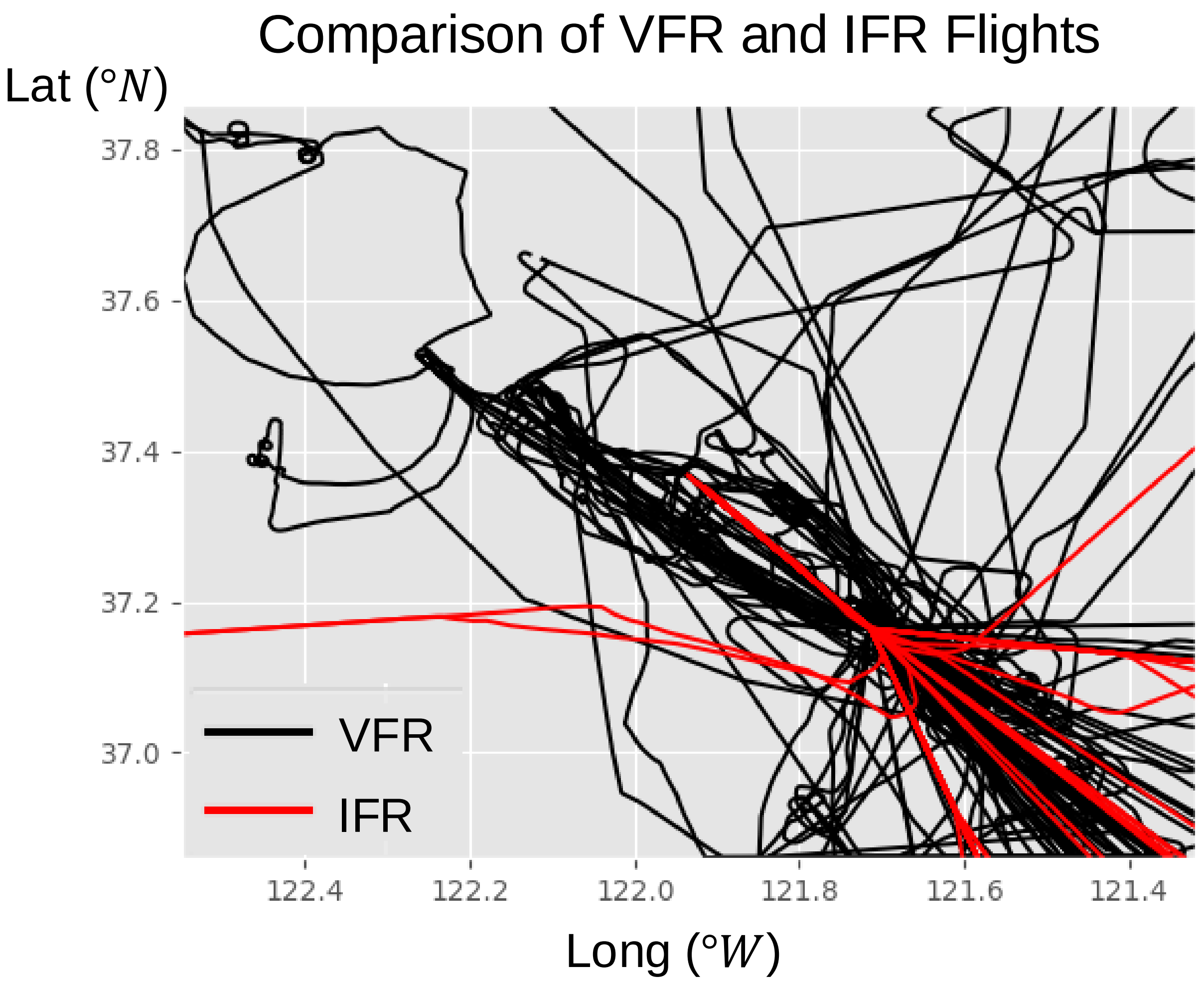



Visual Flight Rules (VFR)
- ➢ Visual based flights
- ➢ High uncertainty

# Background

Visual Flight Rules (VFR) flights have significant trajectory uncertainties due to:

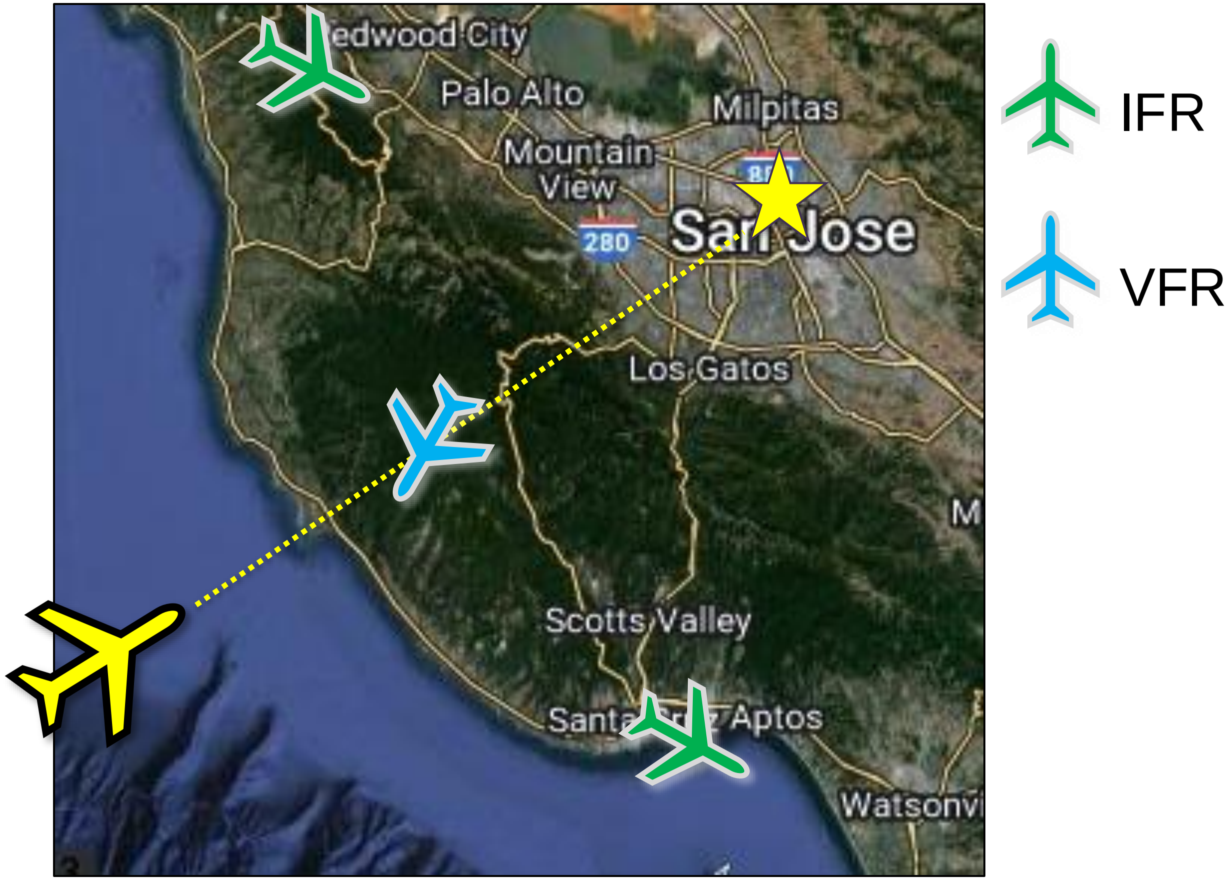
- Lack of flight plans
- Gaps in surveillance
- Less-structured flight paths
- Mission and region-specific behavior




Uncertainty in the VFR flights makes traffic prediction challenging

# Motivation

- Future airspace will see integration of uncrewed aircraft (UA)
- Requires seamless integration of UA with all existing traffic, both VFR and IFR



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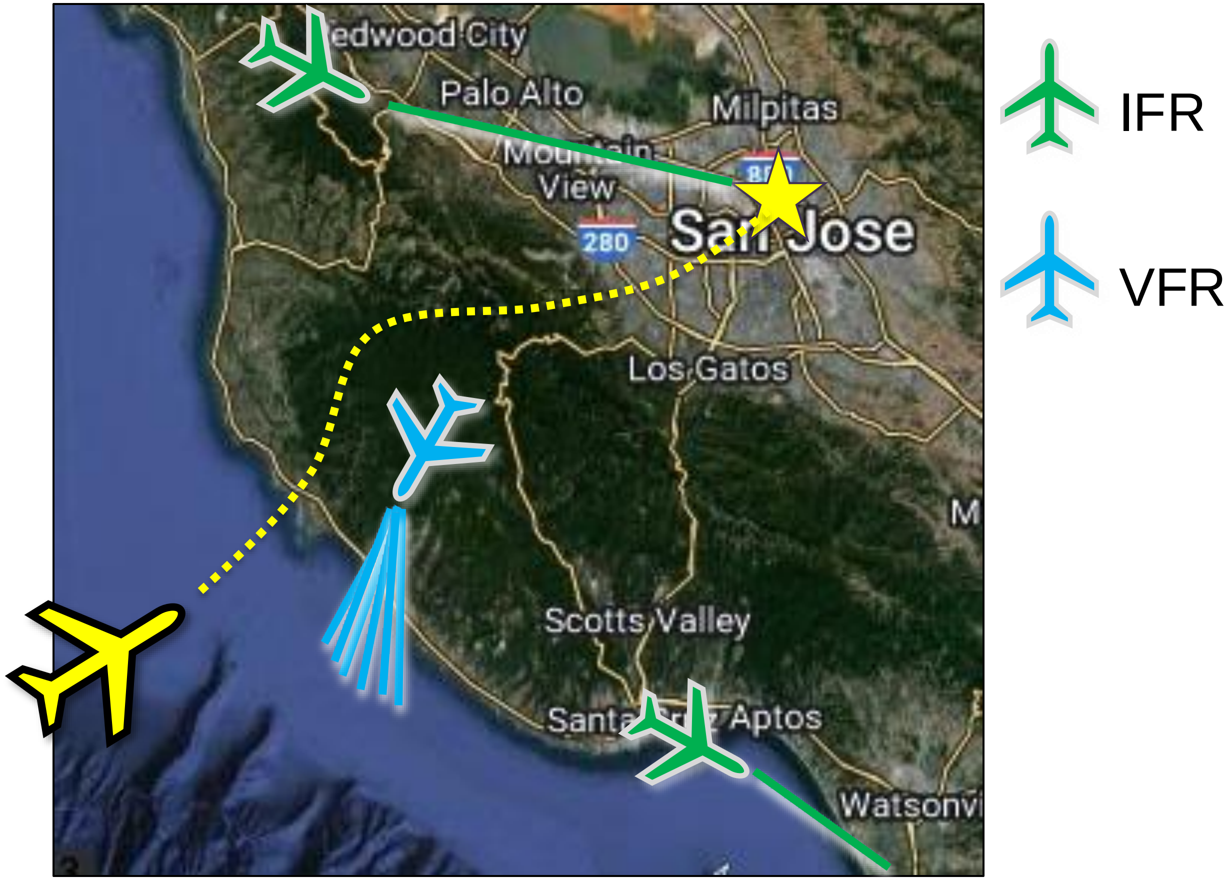


# Previous Works

## Trajectory forecasting works

- State-space based methods: unsuitable for data driven optimization; typically limited to certain distribution types [Jiang, et al 2021]

- Machine learning based methods: discriminative models produce deterministic results which don't capture uncertainty [Ayhan, et al. 2016; Dong, et al. 2023]

## VFR specific works

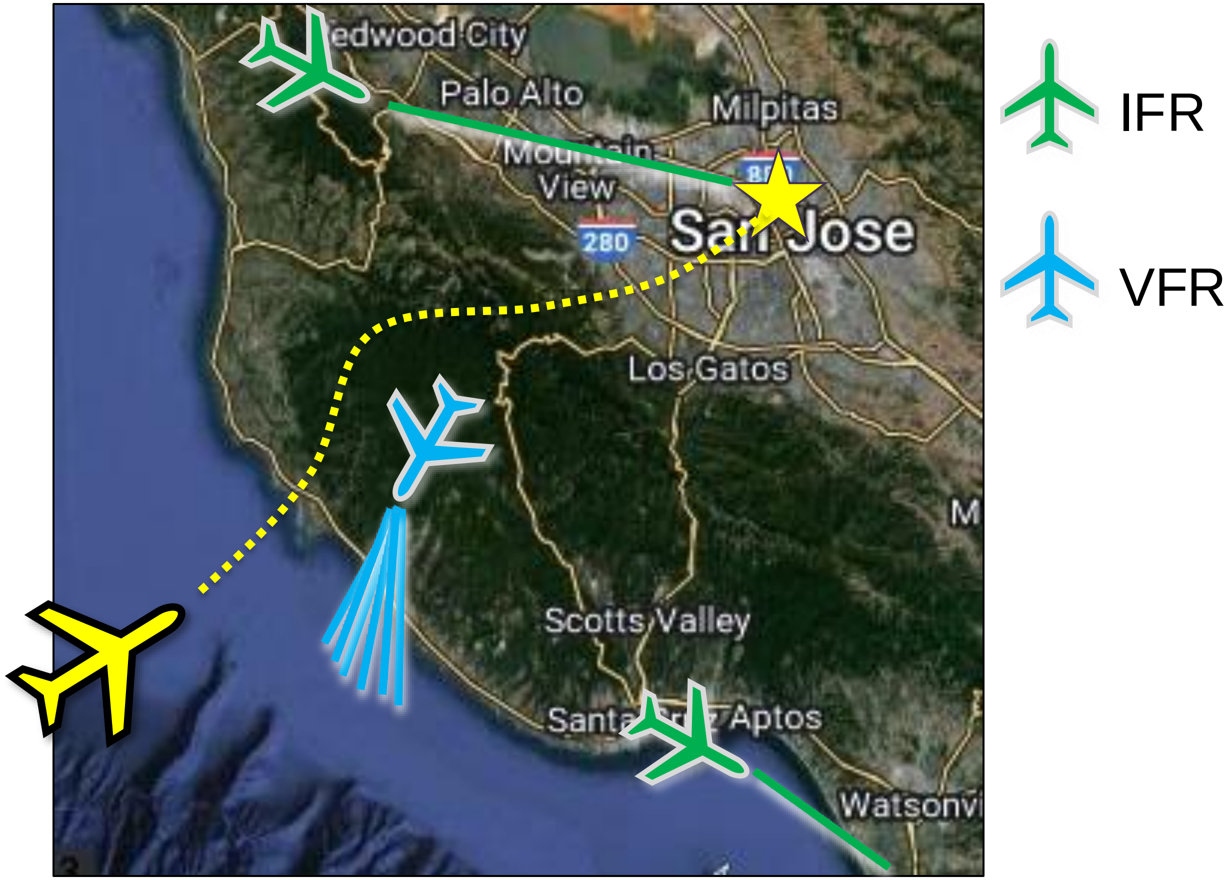
- VFR trajectory prediction modelling: limited to mission specific scenarios (i.e. reconnaissance flights only) [Andreeva-Mori, et al. 2022]

- VFR traffic prediction occupancy maps: grid-based heat maps that provide probability of VFR interaction [Bulusu, et al. 2023, Bulusu, et al. 2024]

# Motivation

- Traditional methods are not sufficient for predicting VFR traffic

- Generative model presents a novel opportunity to forecast probabilistic trajectories that characterize varied VFR behavior



# Contributions

Use deep generative model, in the form of Variational Autoencoder (VAE), to perform VFR trajectory forecasting

- Development of variational autoencoder (VAE) architecture suitable for trajectory forecasting
  - Includes data processing steps to prepare real-world flight trajectories
- Empirical results showing:
  - Comparison of VAE to classical machine learning (XGBoost)
  - Results over both towered and non-towered airports
  - Forecasting over increasing time horizons

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# Problem Formulation

## Forecasting of VFR flights using trajectories

- Trajectory: collection of states and any conditioning variables

$$T = \{\boldsymbol{s}_0, \boldsymbol{a}_0, \boldsymbol{s}_1, \boldsymbol{a}_1, \boldsymbol{s}_2, \boldsymbol{a}_2, \dots, \boldsymbol{a}_{T-1}, \boldsymbol{s}_T\}$$

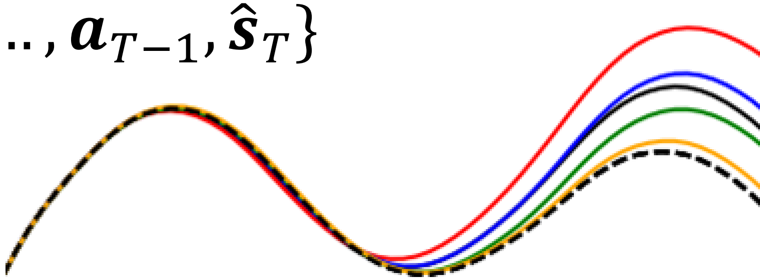
$\boldsymbol{s}_t: states\ of\ the\ agent$

$\boldsymbol{a}_t: any\ available\ conditioning\ variables$

$e.g. environmental\ conditions\ or\ actions$

- Forecasted trajectory: $T_{forecasted} = \{\boldsymbol{s}_0, \boldsymbol{a}_0, \hat{\boldsymbol{s}}_1, \boldsymbol{a}_1, \hat{\boldsymbol{s}}_2, \boldsymbol{a}_2, \dots, \boldsymbol{a}_{T-1}, \hat{\boldsymbol{s}}_T\}$

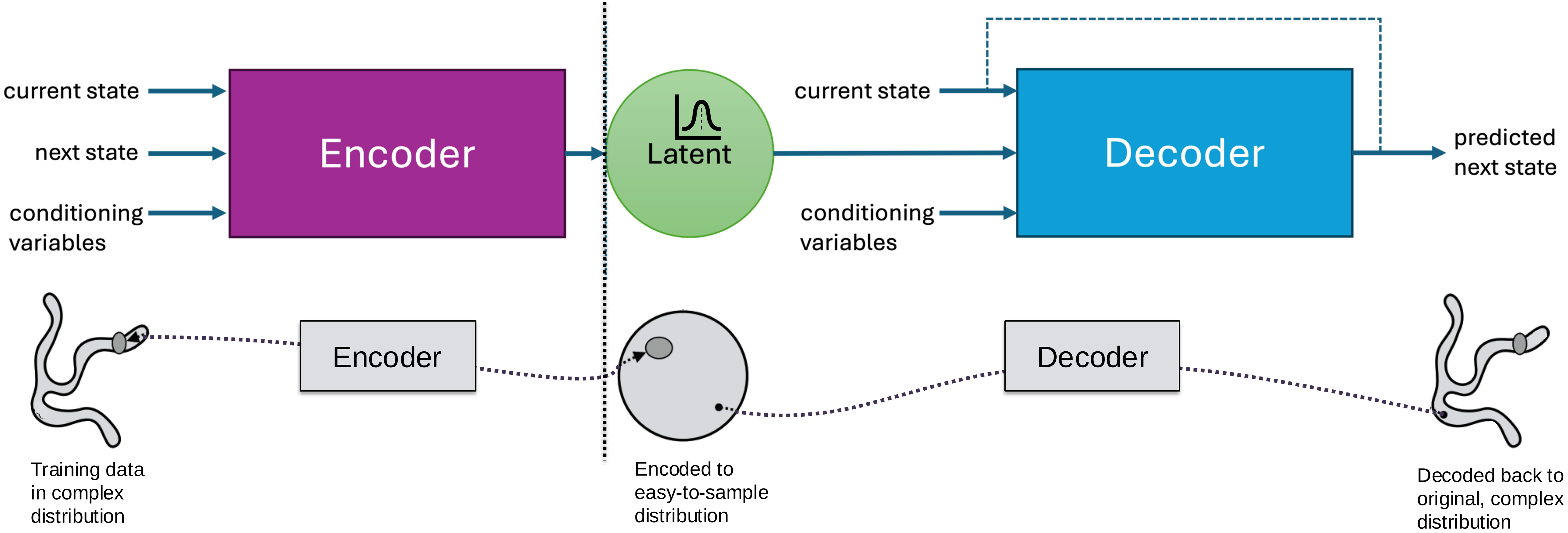
where $\boxed{\hat{\boldsymbol{s}}_{t+1} \sim p(\boldsymbol{s}_{t+1} | \boldsymbol{s}_t; \boldsymbol{a}_t)}$



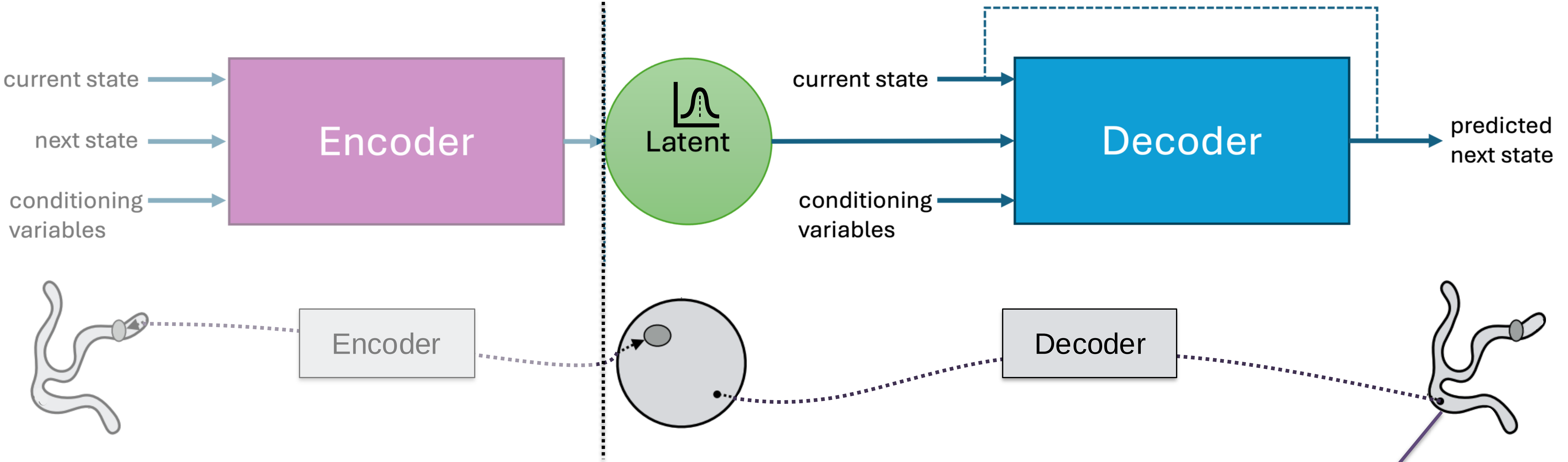
*Use deep generative model to learn the distribution of next state given current state and conditioning variables*

# Variational Autoencoder (VAE)

- Deep generative model learns the underlying distribution of the training data
- Variational auto-encoder (VAE): latent space based representation that can capture diverse behaviors
  - Provides the ability to do probabilistic sampling



# Variational Autoencoder (VAE)



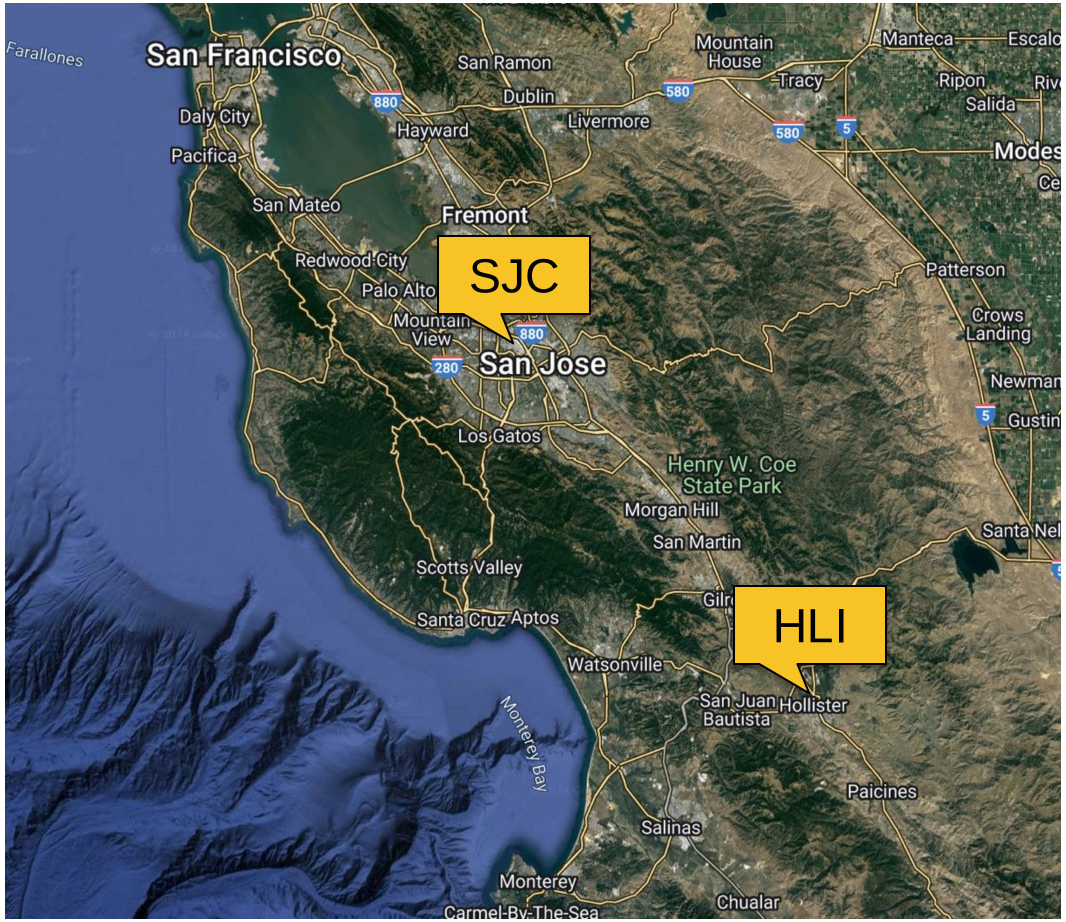

$$\hat{\boldsymbol{s}}_{t+1} \sim \boxed{p(\boldsymbol{s}_{t+1} \mid \boldsymbol{s}_t; \boldsymbol{a}_t)}$$

Results in forecasted trajectory: $T_{forecasted} = \{\boldsymbol{s}_0, \boldsymbol{a}_0, \hat{\boldsymbol{s}}_1, \boldsymbol{a}_1, \hat{\boldsymbol{s}}_2, \boldsymbol{a}_2, \ldots, \boldsymbol{a}_{T-1}, \hat{\boldsymbol{s}}_T\}$

Image sources: adapted from *Variational auto-encoder (Kingma and Welling, 2019)*

# Data Processing

- Data source: 1 year of data over towered (SJC) and non-towered (HLI) airports
  - Variability in trajectories observed
  - Increased VFR traffic for non-towered
  - More training data for towered
- Data pre-processing steps:
  - Delta time for inconsistent time steps
  - Cos and sin of heading angle to prevent angular discontinuities
  - Standard pre-processing steps
- State vector for training:




$$s_t = [\Delta time, lat, long, alt, groundSpeed, climbRate, \cos Heading, \sin Heading]$$

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# Results

- Comparison of three models:
  - XGBoost: classical state-of-the-art machine learning
  - VAE: developed model for towered airport
  - VAE – Non-towered: developed model for non-towered airport

- Forecasting over three increasing time horizons:
  - Each horizon = 1 time step
  - Time step may be varying lengths, e.g. 4 s or 12 s

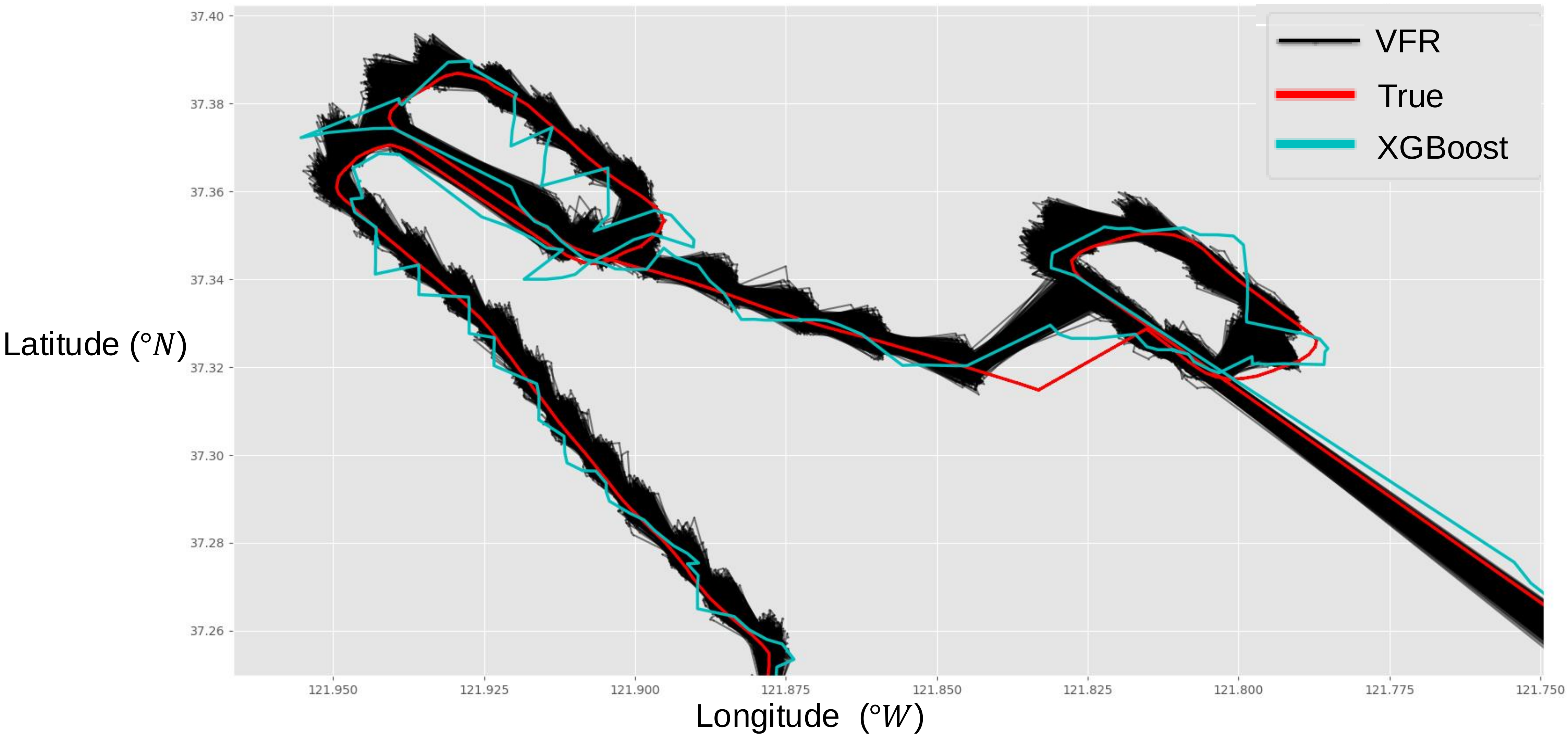
- Analysis of latitude, longitude, altitude, and total (averaged) errors

# Mean Absolute Error (MAE) Values Between True and Forecast

| Horizon (Time Steps) | Model Type | Total MAE | Latitude MAE | Longitude MAE | Altitude MAE |
|---|---|---|---|---|---|
| 1 | XGBoost | 0.0994 | 0.0010 | 0.0013 | 0.2959 |
| | VAE (Towered) | 0.1091 | 0.0033 | 0.0032 | 0.3209 |
| | VAE (Non-towered) | 0.1546 | 0.0020 | 0.0043 | 0.4577 |
| 5 | XGBoost | 0.5386 | 0.0047 | 0.0085 | 1.603 |
| | VAE (Towered) | 0.3409 | 0.0091 | 0.0089 | 0.8967 |
| | VAE (Non-towered) | 0.4014 | 0.0047 | 0.0124 | -1.187 |
| 10 | XGBoost | 1.008 | 0.0043 | 0.0050 | 3.014 |
| | VAE (Towered) | 0.5714 | 0.0156 | 0.0151 | 1.683 |
| | VAE (Non-towered) | 0.7239 | 0.0083 | 0.0226 | 2.141 |

- XGBoost performance similar to VAE for time horizon of 1
- VAE outperforms XGBoost for increased time horizons

# Comparison of VAE and XGBoost (Time Horizon = 5)



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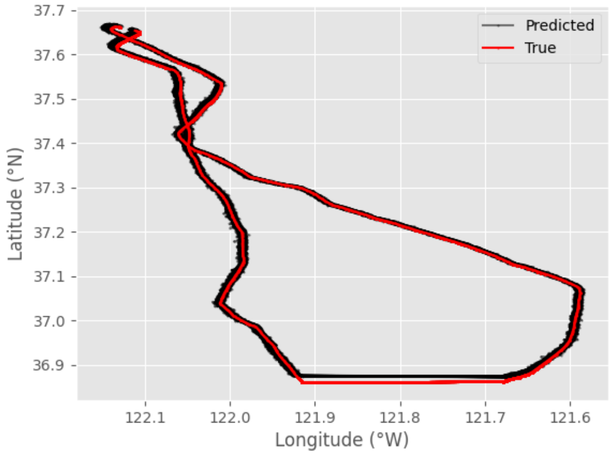
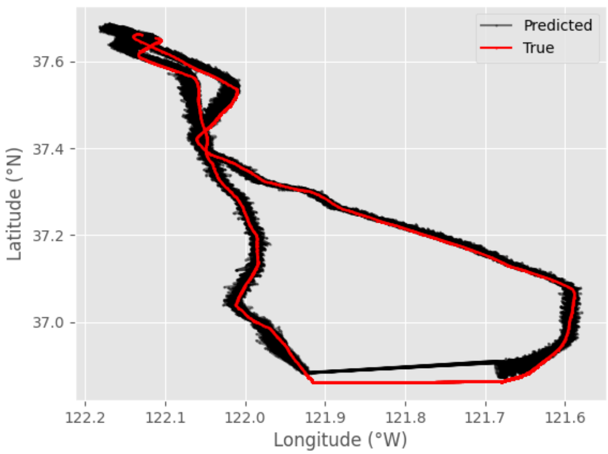
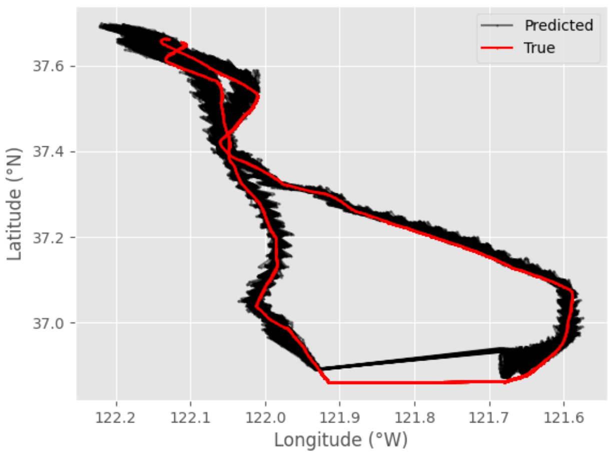
- MAE increases with increasing time horizons
- Non-towered shows higher MAE than towered

# Results over Towered Airport

<table>
<tr><th>Ex</th><th>Time Horizon = 1</th><th>Time Horizon = 5</th><th>Time Horizon = 10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>
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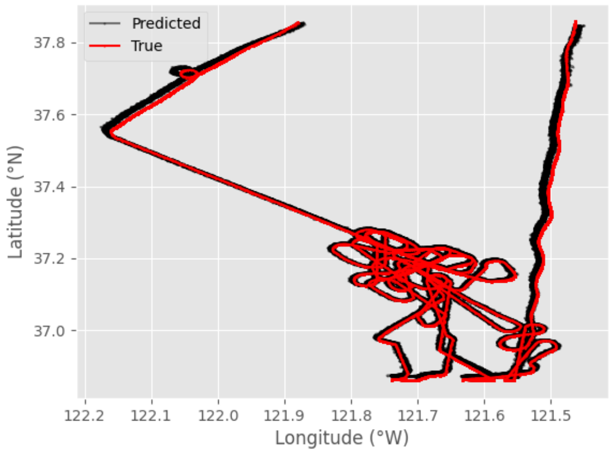
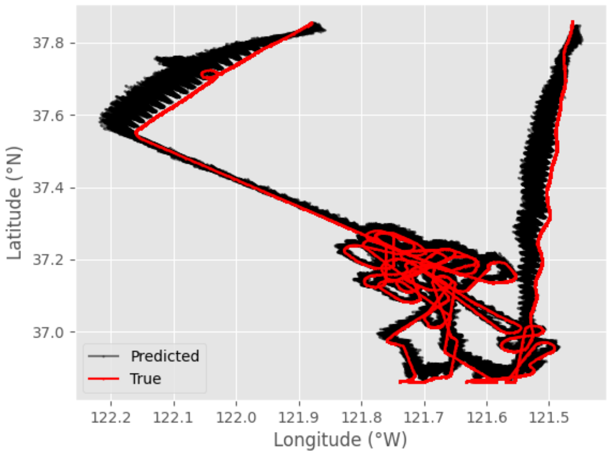
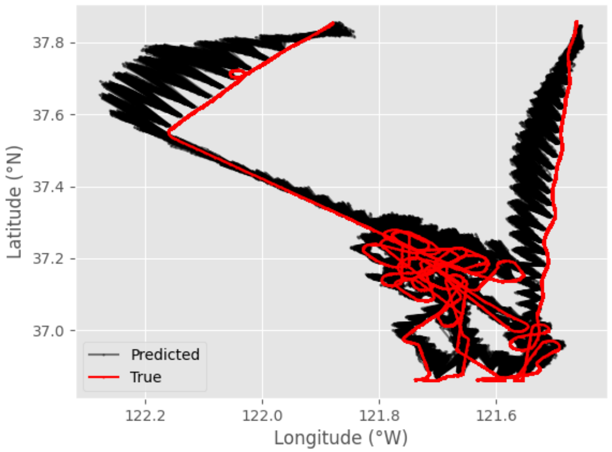
<tr><td>2</td><td>
</td><td>
</td><td>
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# Results over Non-towered Airport

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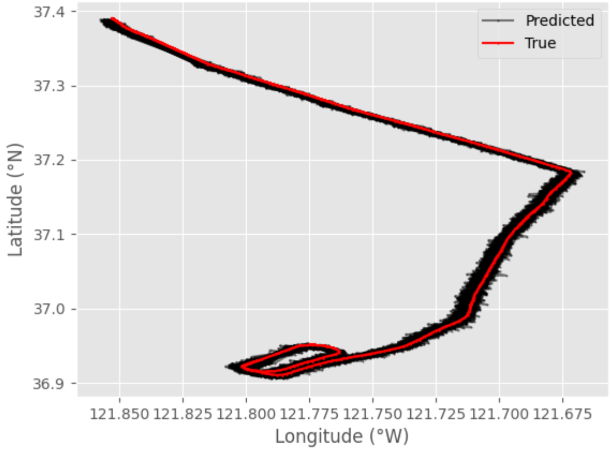
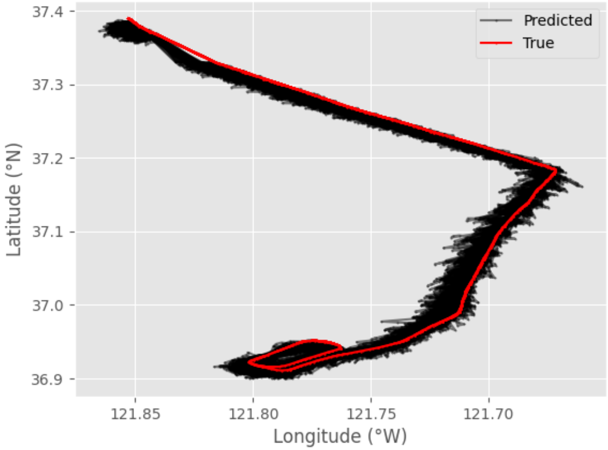
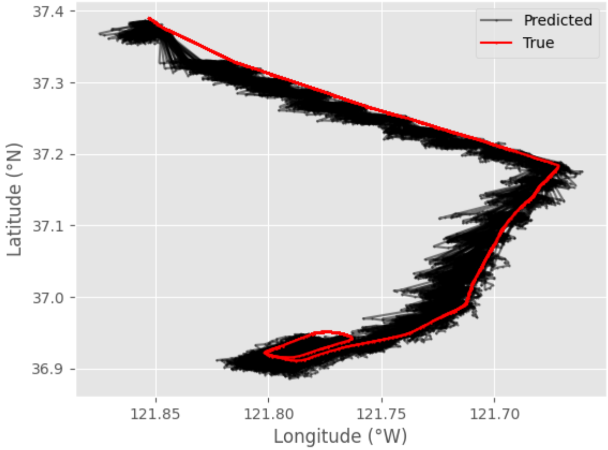
<tr><td>1</td><td>
</td><td>
</td><td>
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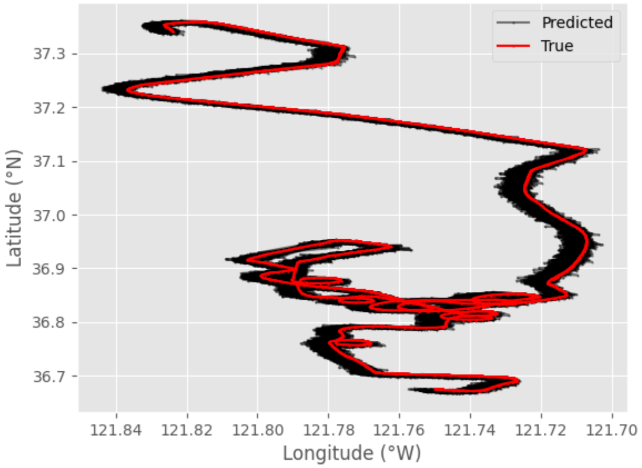
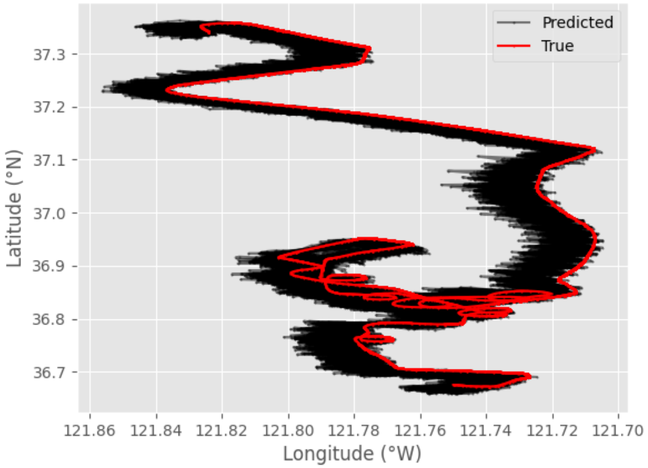
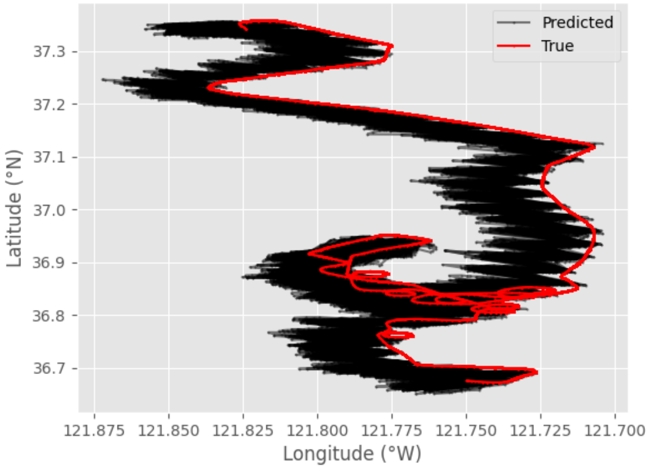
<tr><td>2</td><td>
</td><td>
</td><td>
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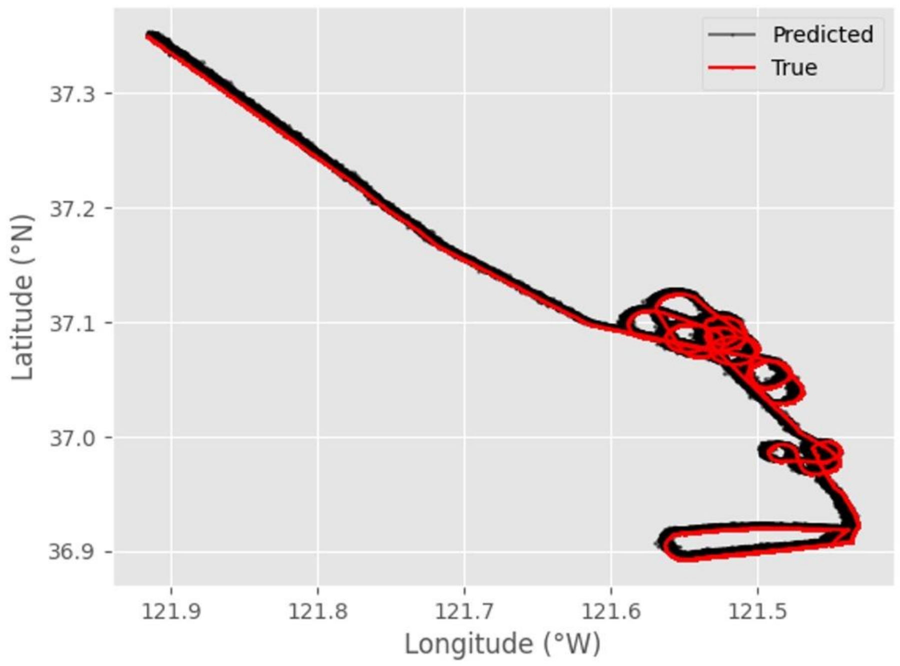
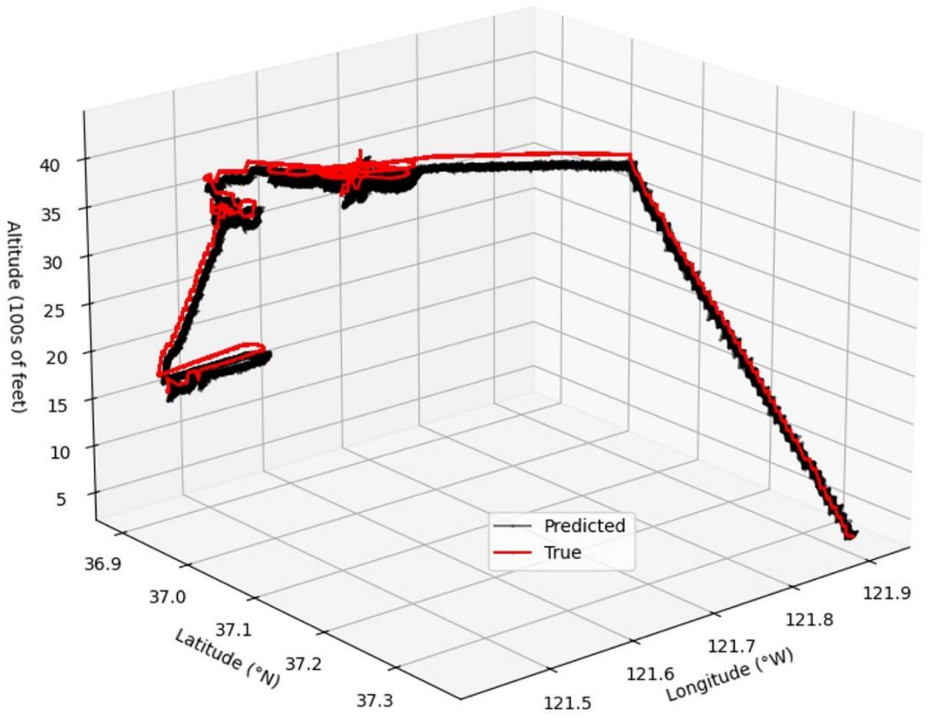
- Altitude shows higher MAE values than latitude and longitude

# Results over Towered Airport – 2D and 3D Views

## 2D Latitude-Longitude View

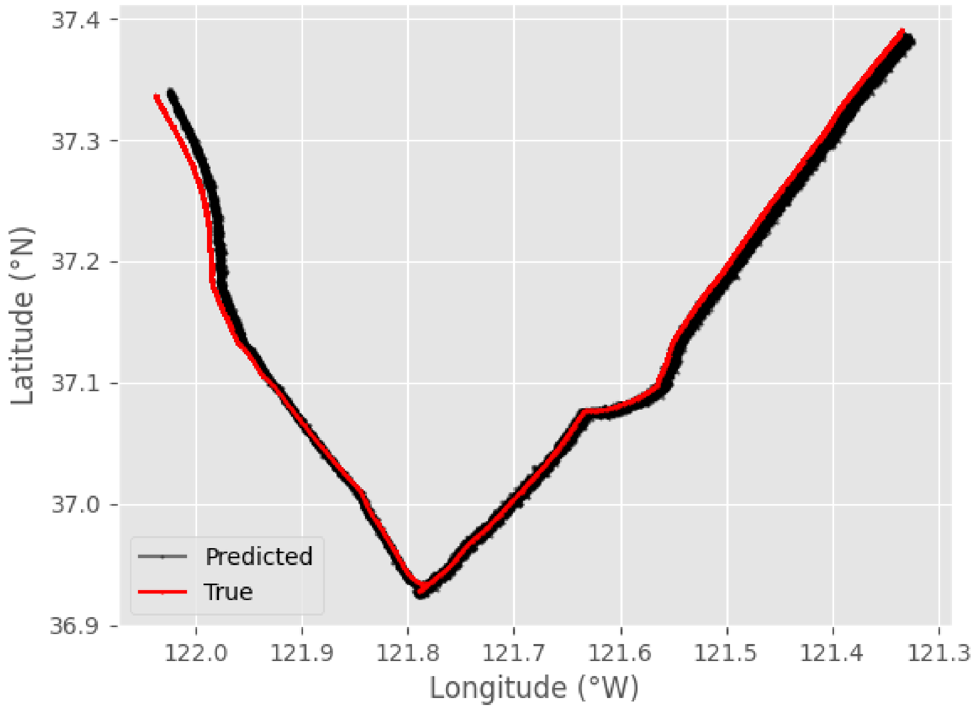



## 3D Latitude-Longitude-Altitude View



# Results over Non-towered Airport – 2D and 3D Views

2D Latitude-Longitude View

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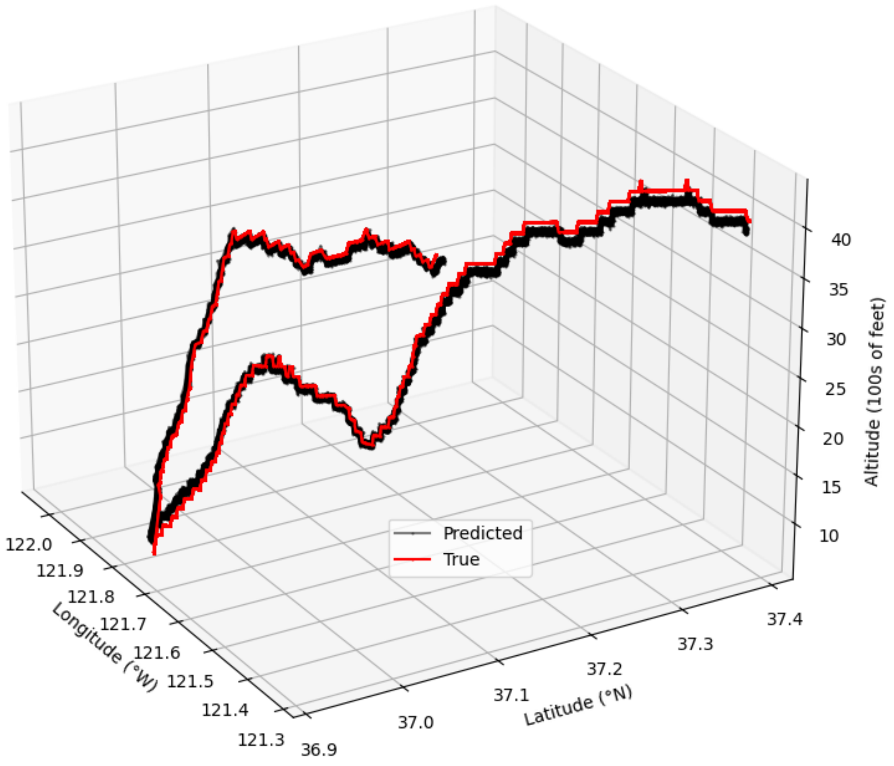
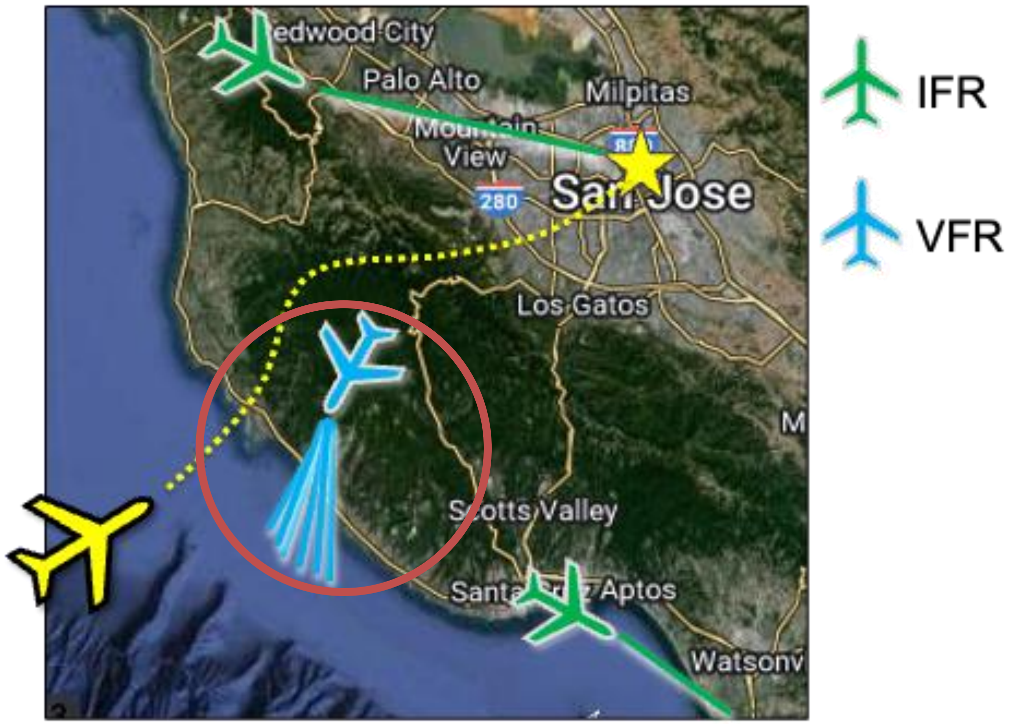


# Conclusions

- Developed VAE model suitable for forecasting of VFR trajectories
  - Probabilistic results showed the uncertainty distribution of VFR trajectories

Future work:

- Expand forecasting region to en route trajectories
- Add conditioning variables, such as environmental conditions and metrics, to measure impact on forecasted trajectories
- Assess the effectiveness on other applications



# Thank you!

Questions?