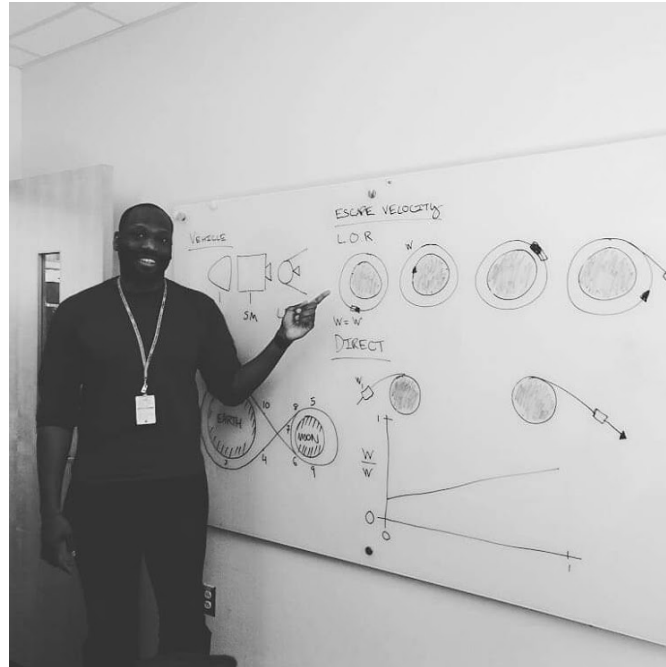


**Dr. Newton Campbell** is a Computer Scientist specializing in artificial intelligence. Through SAIC, he currently serves as an Artificial Intelligence subject matter expert on the NASA Langley Research Center OCIO Data Science Team. Prior to NASA, Dr. Campbell spent 10 years doing research and development in support of the US Department of Defense and Intelligence Communities. In that capacity, he served as the Principal Investigator and technical lead of multiple cybersecurity and artificial intelligence projects, with specific focus on Internet Privacy and Cyber-Physical Systems. Dr. Campbell completed his PhD in Computer Science at Nova Southeastern University.

He regularly coordinates STEM activities with schools and media groups in the Baltimore-Washington Metropolitan area. He is an active member of the Planetary Society, the Philosophical Society of Washington, and IEEE. He is a Technology Fellow at American University Washington College of Law, member of the Schusterman Foundation REALITY network, and both the French-American Foundation and Australian-American Leadership Dialogue, representing US technology leaders as part of the Young Leadership Dialogue contingent.





# Use of Design of Experiments in Determining Neural Network Architectures for Loss of Control Detection

**Dr. Newton Campbell**

NASA LaRC OCIO Data Science Team

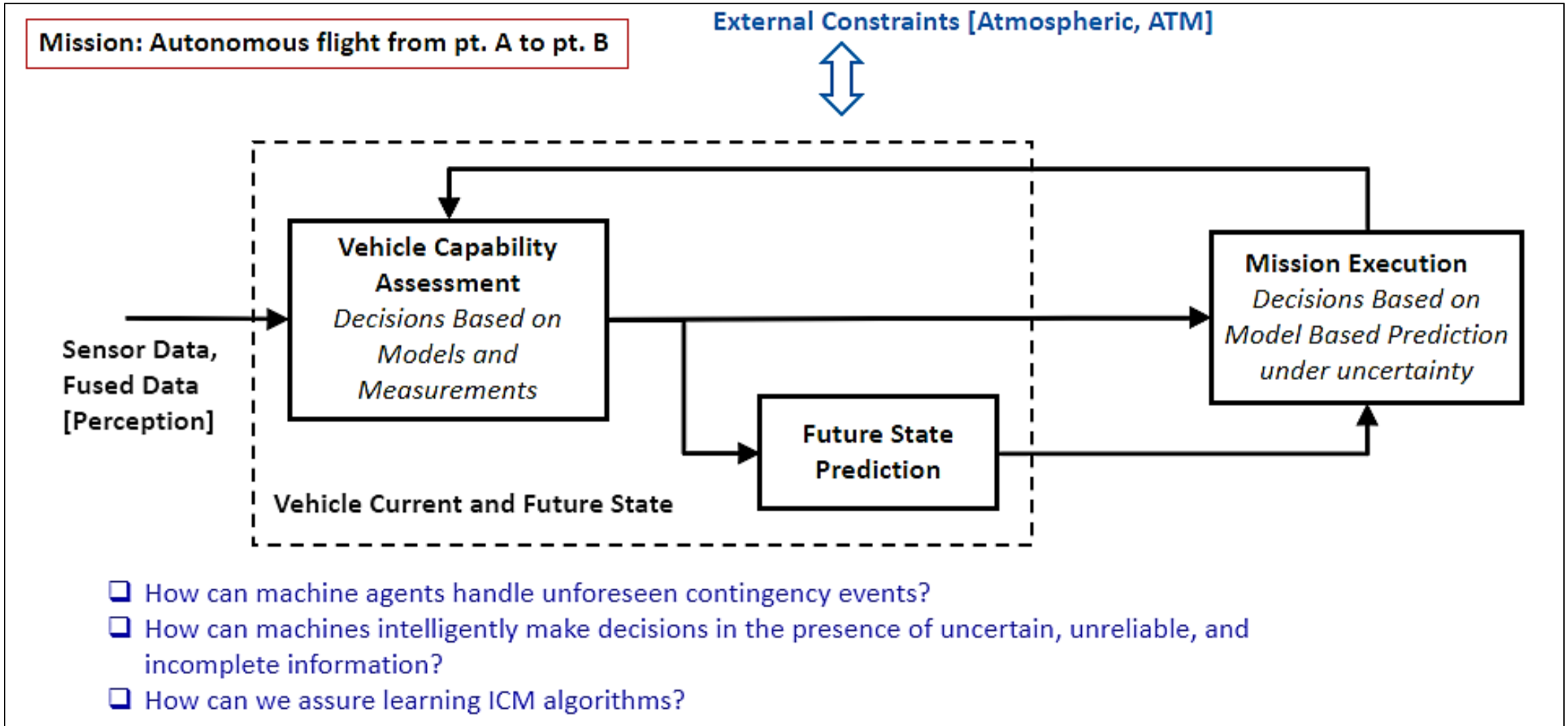
**Dr. Irene Gregory, Dr. Jared Grauer**

NASA LaRC Dynamic Systems and Controls Branch

IEEE Aerospace Conference 2021

Section: Implementing Artificial Intelligence for Aerospace

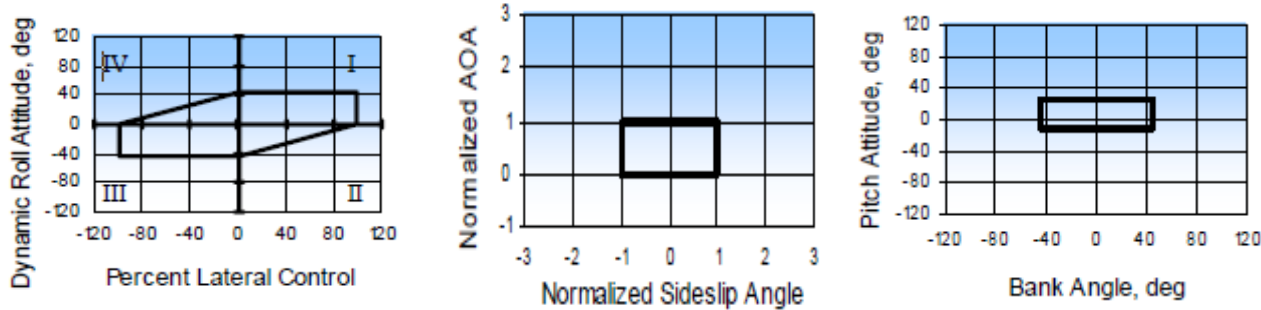
[newton.h.campbell@nasa.gov](mailto:newton.h.campbell@nasa.gov)



\* I. M. Gregory *et al.*, "Intelligent contingency management for urban air mobility," in *AIAA Scitech 2021 Forum*, 2021. doi: [10.2514/6.2021-1000](https://doi.org/10.2514/6.2021-1000)

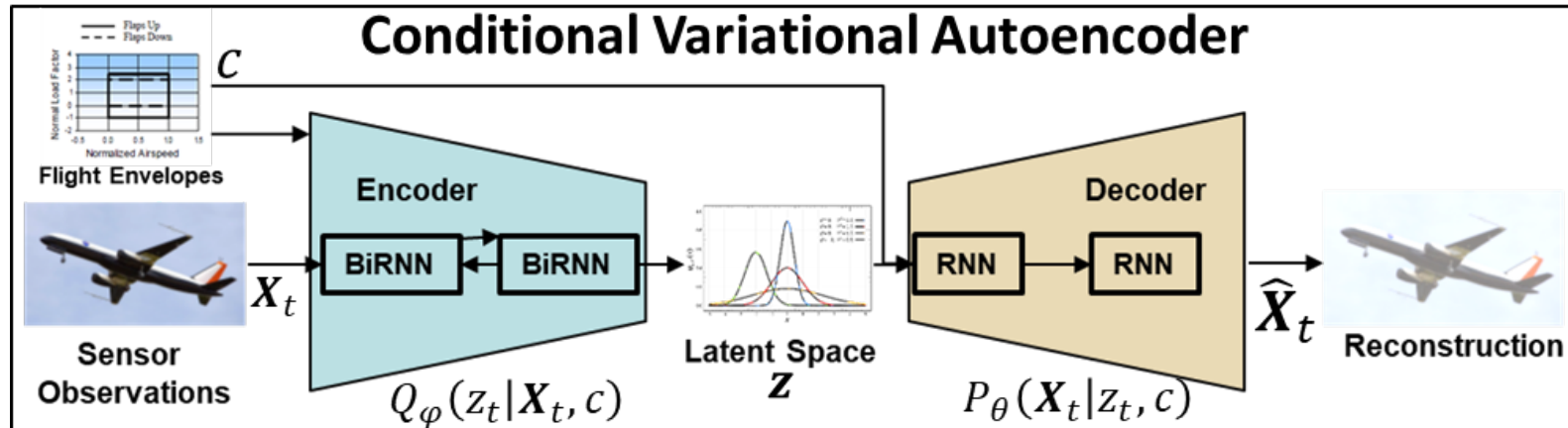
## Flight Envelopes and Loss-of-Control

\*Wilborn, J., & Foster, J. (2004, August). Defining commercial transport loss-of-control: A quantitative approach. In *AIAA atmospheric flight mechanics conference and exhibit* (p. 4811).



## Previous Work

- Demonstrated an ability to distinguish operational control conditions from loss-of-control (LOC) conditions using a **conditional variational autoencoder (CVAE)**
- Characterized the algorithm for Gated Recurrent Unit (GRU) and Long-Term Short-Term Memory (LSTM) architectures
- The most significant of CVAE anomalies (dips in reconstruction probability) indicates an LOC disturbance signal
- Large shifts in the latent space indicate movement toward envelope limits



\* N. H. Campbell, J. A. Grauer, and I. M. Gregory, “Loss of control detection for commercial transport aircraft using conditional variational autoencoders,” in *AIAA SciTech 2021 Forum*, 2021. doi: [10.2514/6.2021-0778](https://doi.org/10.2514/6.2021-0778)



# Design Optimization of Neural Networks for Aerospace Applications

## Objective

Apply Design of Experiments (DOE) analyses to characterize neural network architectural choices for LOC and envelope limit detection

Baseline Neural Network Architecture



Apply NN architecture factors for experimentation



Investigate effects of changing NN factors on LOC and Envelope Limit Detection

# LOC Detection through Reconstruction Probability

$\mathbf{X}_t$ : Vector of measurements from on-board sensors

$\hat{\mathbf{X}}_t$ : CVAE Reconstruction of measurements

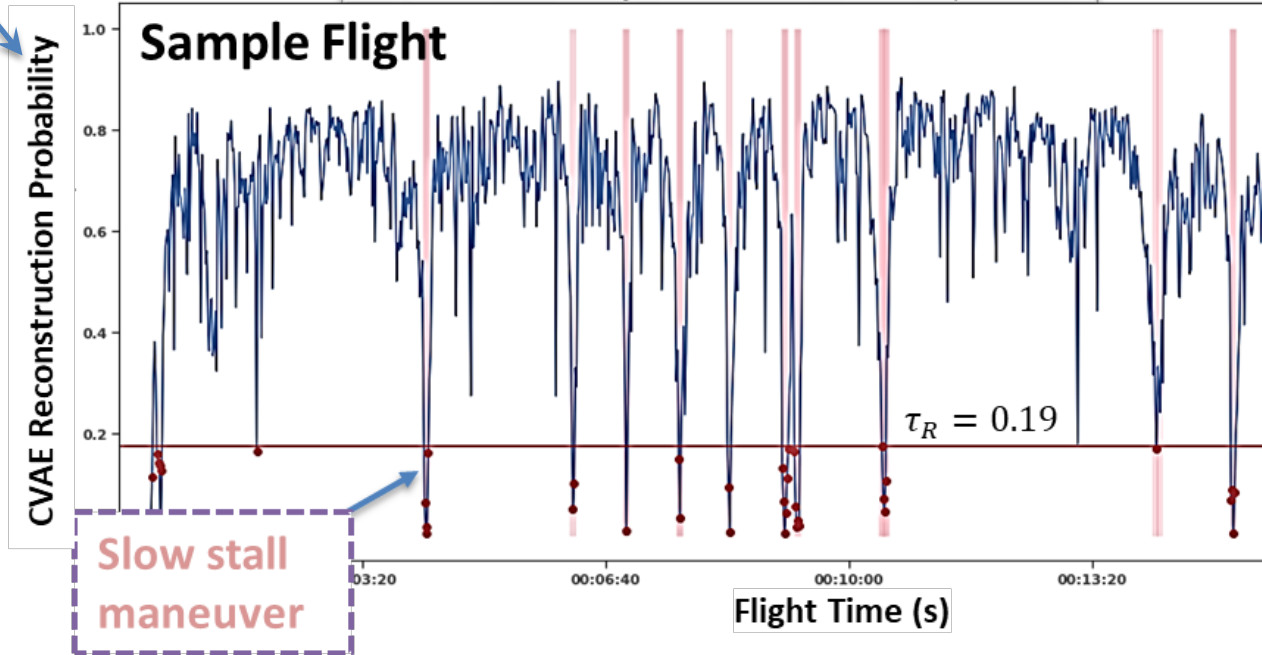
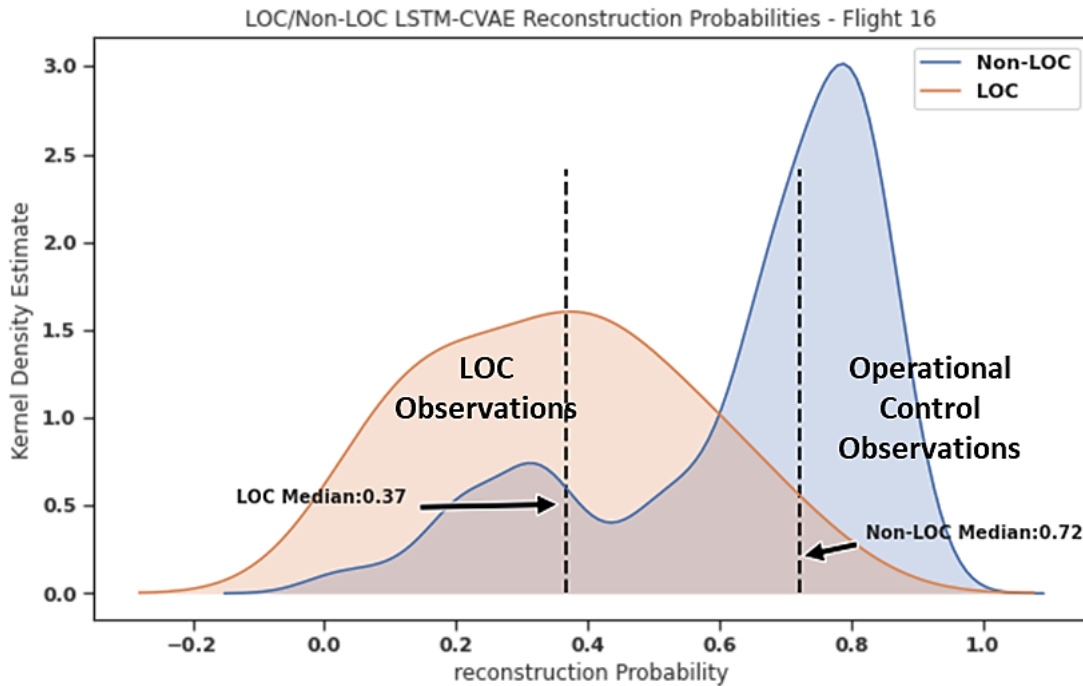
Reconstruction Probability (for  $L$  reconstructions)

$$R(\mathbf{X}|\hat{\mathbf{X}})_{[t]} = E_{Q_\phi(z_t|\mathbf{X}_t, c)}[\log P_\theta(\mathbf{X}_t|z_t, c)] \approx \frac{1}{L} \sum_{l=1}^L e^{(\hat{x}_t - x_t)^2}$$

LOC anomaly threshold:  $\tau_R$

LOC detection:  $R(\mathbf{X}|\hat{\mathbf{X}})_{[t]} < \tau_R$

NASA AirSTAR  
T-2



\* N. H. Campbell, J. A. Grauer, and I. M. Gregory, "Loss of control detection for commercial transport aircraft using conditional variational autoencoders," in *AIAA Scitech 2021 Forum*, 2021. doi: [10.2514/6.2021-0778](https://doi.org/10.2514/6.2021-0778)

$\mu_{z_t}$ : Means of the latent space at time  $t$

$\sigma_{z_t}$ : Standard deviations of the latent space at time  $t$

KL-Divergence: How much information is lost when  $z_t$  is used to approximate  $z_{t+1}$ ?

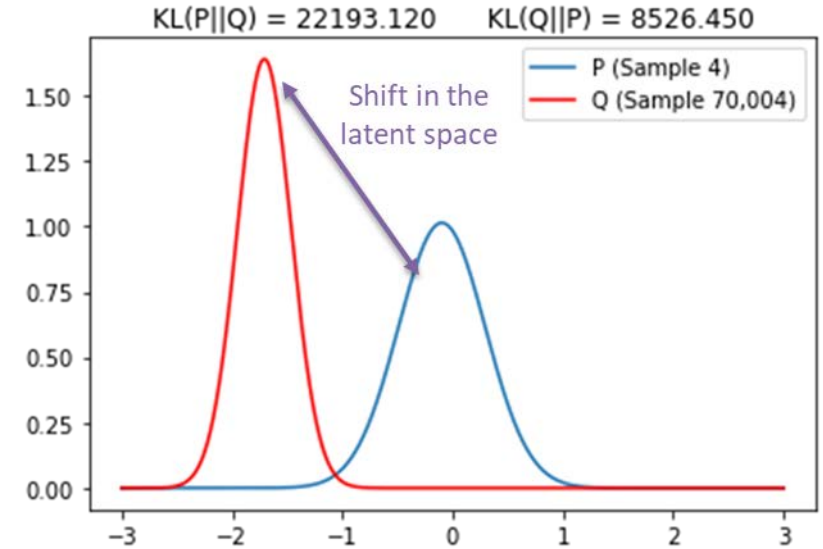
$$D_{KL}(z_t || z_{t+1}) = \frac{1}{2} \left[ \log \frac{|\sigma_{z_{t+1}}|}{|\sigma_{z_t}|} - d + \text{tr}(\sigma_{z_{t+1}}^{-1} \sigma_{z_t}) + (\mu_{z_{t+1}} - \mu_{z_t})^T \sigma_{z_{t+1}}^{-1} (\mu_{z_{t+1}} - \mu_{z_t}) \right]$$

JS-Divergence: How much information is lost when  $z_t$  is used to approximate  $z_{t+1}$  or  $z_{t+1}$  is used to approximate  $z_t$ ?

$$D_{JS}(z_t || z_{t+1}) = \frac{D_{KL}(z_t || z_{t+1}) + D_{KL}(z_{t+1} || z_t)}{2}$$

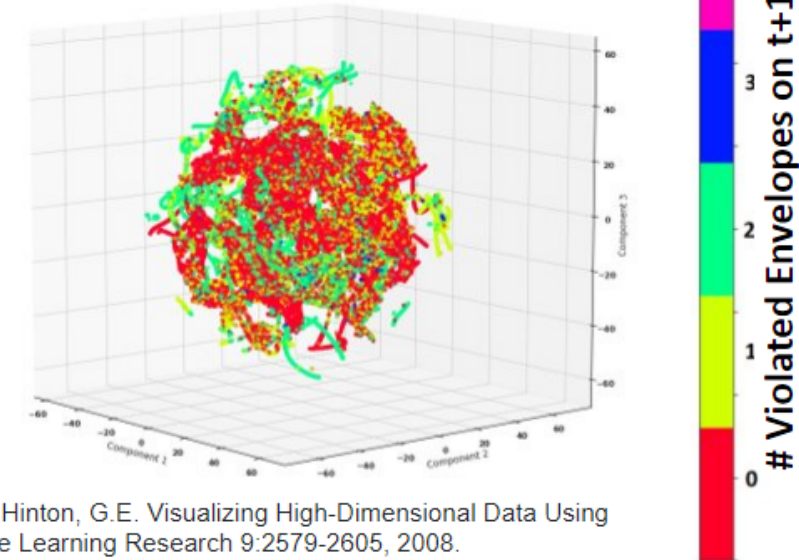
Envelope limit approach:  $|\nabla \sqrt{D_{JS}(z_t || z_{t+1})}| > \tau_z$

\* N. H. Campbell, J. A. Grauer, and I. M. Gregory, "Loss of control detection for commercial transport aircraft using conditional variational autoencoders," in *AIAA Scitech 2021 Forum*, 2021. doi: [10.2514/6.2021-0778](https://doi.org/10.2514/6.2021-0778)



GRU-CVAE Latent Space(means) t-SNE\*

Means of the 11-dimension latent space compressed to 3 dimensions



\* van der Maaten, L.J.P.; Hinton, G.E. Visualizing High-Dimensional Data Using t-SNE. *Journal of Machine Learning Research* 9:2579-2605, 2008.



# Design of Experiments



## Factors

### Discrete

- $x_1$ : Layer Type ([Gated Recurrent Unit](#), [Long Short-Term Memory](#))
- $x_2$ : Activation Function ([elu](#), [linear](#), [relu](#), [selu](#), [softplus](#), [softsign](#), [tanh](#))
- $x_3$ : Optimization Function ([Adaptive Moment Estimation](#)(ADAM), [Stochastic Gradient Descent](#), [Adadelta](#))
- $x_4$ : Dropout on intermediate layers(0,0.1)

### Continuous

- $x_5$ : Number of epochs used in training
- $x_6$ : Final training loss measure  
$$E_{Q_\varphi(z|p)}[\log P_\theta(z|p, c)] - D_{KL}(Q_\varphi(z|p, c)||P_\theta(z, c))$$
- $x_7$ : Final validation loss measure  
$$E_{Q_\varphi(z|p)}[\log P_\theta(z|p, c)] - D_{KL}(Q_\varphi(z|p, c)||P_\theta(z, c))$$

**Purpose:** Determine the effect of neural network architectural decisions and necessary training on conditional variational inference of commercial transport loss-of-control and state change.

## Responses (Outcomes)

\*Text in green indicates preferred value for belief state detection

- $y_1$ : Average KL Loss over all Flights (**Low**)
- $y_2$ : Average Reconstruction Loss over all Flights (**Low**)
- $y_3$ : Average KL Loss over Maneuvers (**Low**)
- $y_4$ : Average Reconstruction Loss over Maneuvers (**Low**)
- $y_5$ : Area of Intersection for Reconstruction Probabilities of Loss-Of-Control and Normal Flight Observations (**Low**)
- $y_6$ : Area of Intersection for Gaussian Shift of State Change and Normal Flight Observations (**Low**)
- $y_7$ : Balanced accuracy for reconstruction probability-based anomaly detection (**High**)
- $y_8$ : Difference in Average Reconstruction Probability for Loss-of-Control observations and Normal observations (**High**)
- $y_9$ : Difference in Average value of gradient of Jensen-Shannon distance when entering or exiting an envelope and average value with no envelope state change (**High**)

**Number of Observations: 84 = 2<sup>2</sup> × 7 × 3**

\*Montgomery, D. C. (2017). *Design and analysis of experiments*. John Wiley & Sons.

## Factors

### Discrete

- $x_1$ : Layer Type ([Gated Recurrent Unit](#), [Long Short-Term Memory](#))
- $x_2$ : Activation Function ([elu](#), [linear](#), [relu](#), [selu](#), [softplus](#), [softsign](#), [tanh](#))
- $x_3$ : Optimization Function ([Adaptive Moment Estimation](#)(ADAM), [Stochastic Gradient Descent](#), [Adadelata](#))
- $x_4$ : Dropout on intermediate layers(0,0.1)

### Continuous

- $x_5$ : Number of epochs used in training
- $x_6$ : Final training loss measure

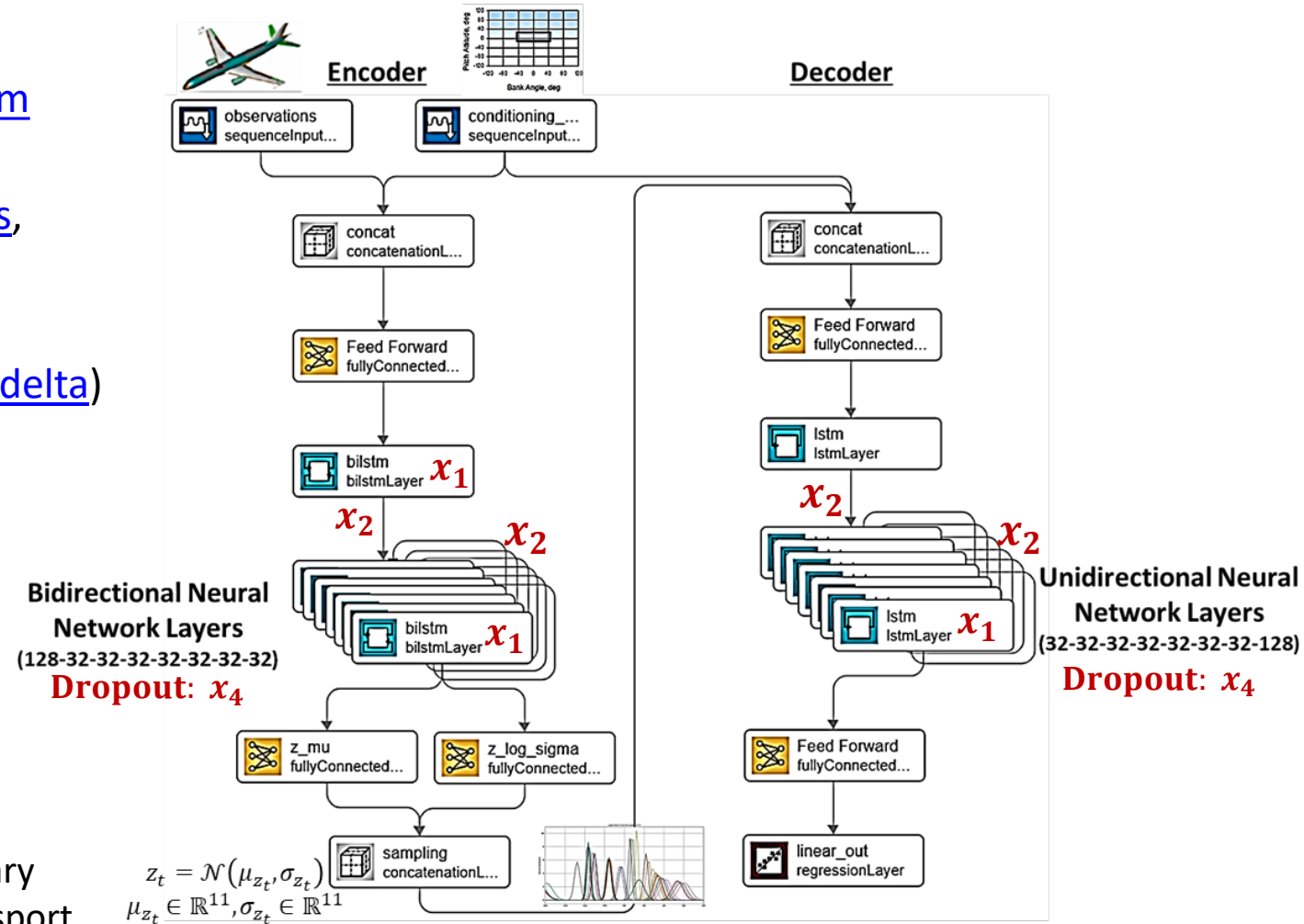
$$E_{Q_\phi(z|p)}[\log P_\theta(z|p, c)] - D_{KL}(Q_\phi(z|p, c)||P_\theta(z, c))$$

- $x_7$ : Final validation loss measure

$$E_{Q_\phi(z|p)}[\log P_\theta(z|p, c)] - D_{KL}(Q_\phi(z|p, c)||P_\theta(z, c))$$

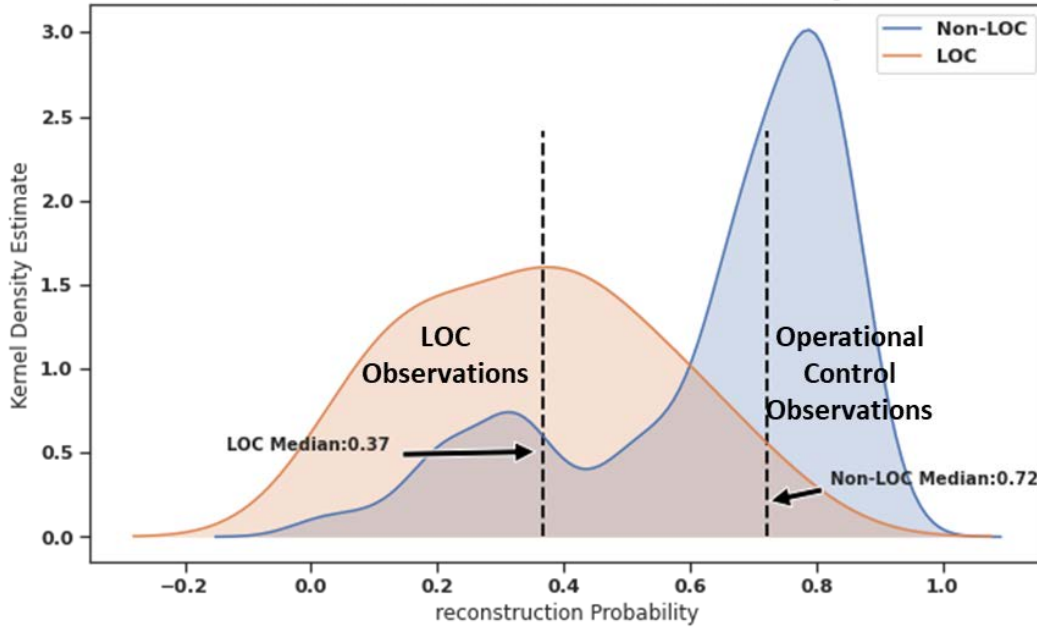
**Purpose:** Determine the effect of Hyperparameters and necessary training on conditional variational inference of commercial transport loss-of-control and state change.

## Conditional Variational Autoencoder Architecture

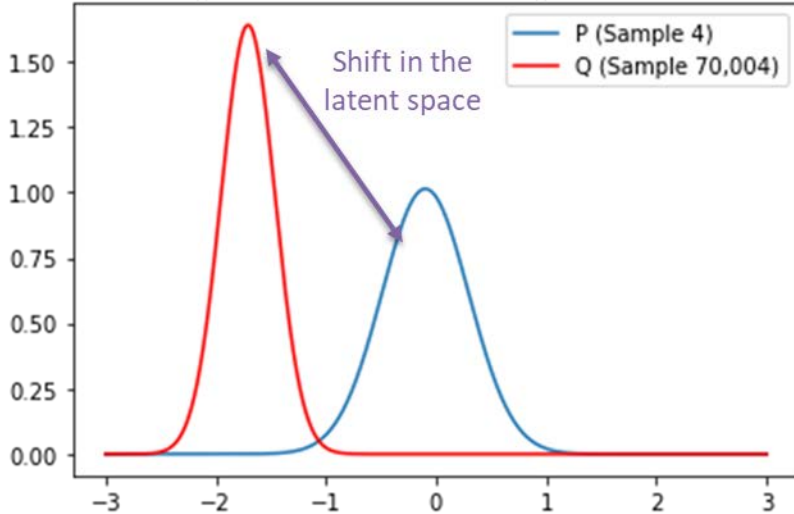


# Design of Experiments

LOC/Non-LOC LSTM-CVAE Reconstruction Probabilities - Flight 16



$KL(P||Q) = 22193.120$      $KL(Q||P) = 8526.450$



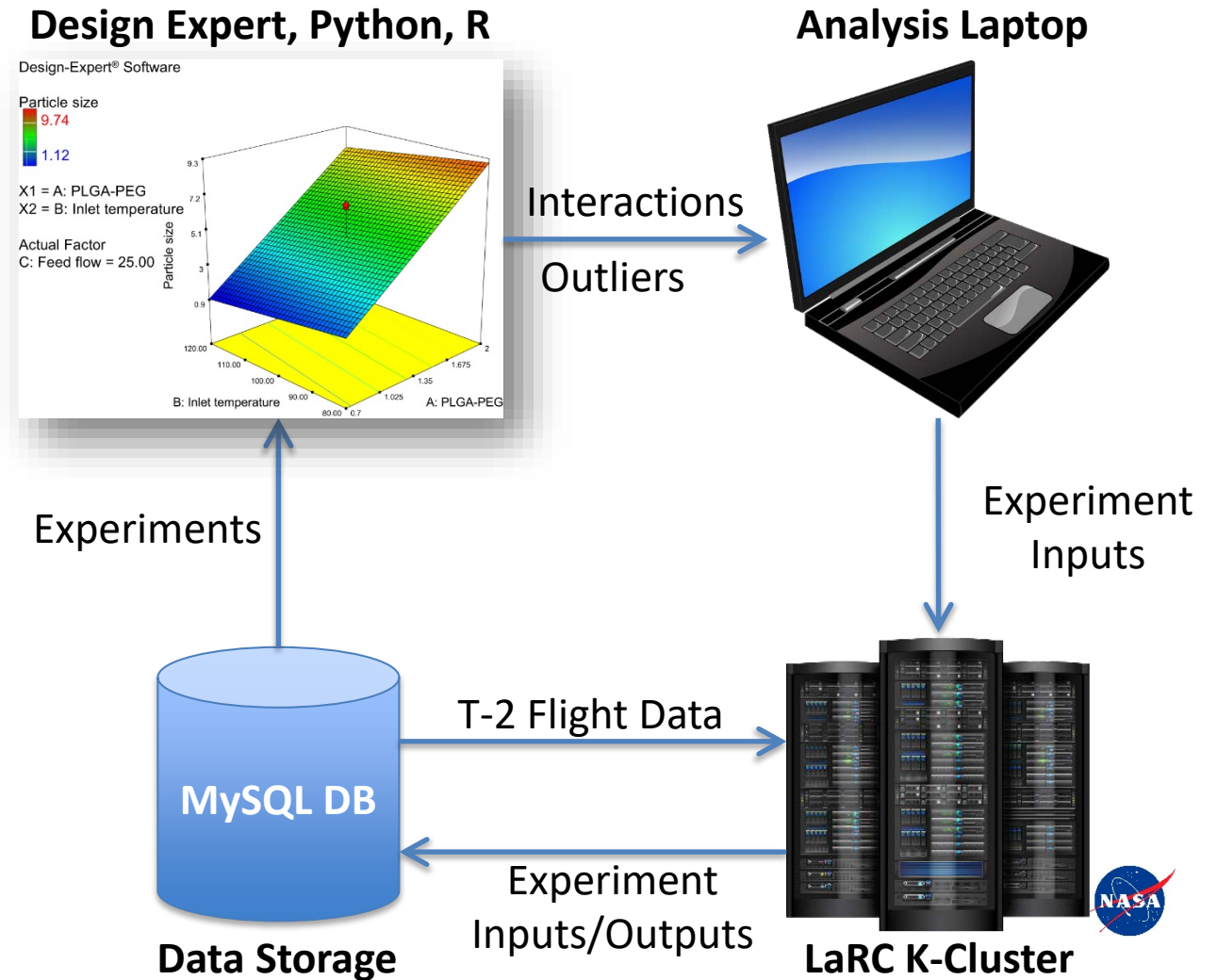
\*Text in green indicates preferred value for belief state detection

## Responses (Outcomes)

- $y_1$ : Average KL Loss over all Flights (**Low**)
- $y_2$ : Average Reconstruction Loss over all Flights (**Low**)
- $y_3$ : Average KL Loss over Maneuvers (**Low**)
- $y_4$ : Average Reconstruction Loss over Maneuvers (**Low**)
- $y_5$ : Area of Intersection for Reconstruction Probabilities of Loss-Of-Control and Normal Flight Observations (**Low**)
- $y_6$ : Area of Intersection for Gaussian Shift of State Change and Normal Flight Observations (**Low**)
- $y_7$ : Balanced accuracy for reconstruction probability-based anomaly detection (**High**)
- $y_8$ : Difference in Average Reconstruction Probability for Loss-of-Control observations and Normal observations (**High**)
- $y_9$ : Difference in Average value of gradient of Jensen-Shannon distance when entering or exiting an envelope and average value with no envelope state change (**High**)

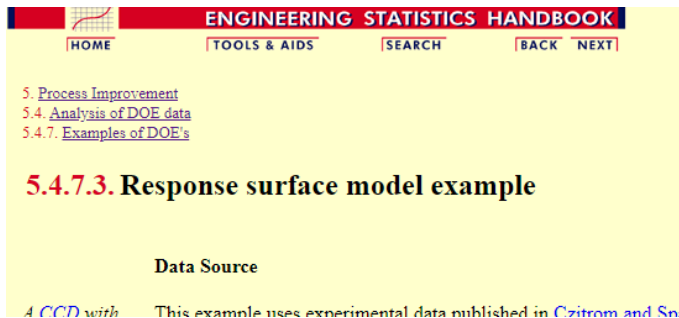
# Running the Experiments

- Trained on 46 independent flights, validated on 12 flights
- Training for maximum of 10,000 epochs
  - Early stopping if validation loss does not decrease over 1,000 epochs
- One NVIDIA Tesla K40 GPU per Experiment
  - NASA Langley Research Center K-Cluster
  - NASA Langley Research Center OCIO Database



Model the template specified in [NIST/SEMATECH e-Handbook of Statistical Methods Section 5.4.7.3](#) for response surface modeling:

1. Fit the full model to response  $y_i$ .
2. Use stepwise regression, forward selection, or backward elimination to identify important variables.
3. When selecting variables for inclusion in the model, follow the hierarchy principle and keep all main effects that are part of significant higher-order terms or interactions, even if the main effect p-value is larger than you would like .
4. Generate diagnostic residual plots for the model selected.
  - a) Histograms, box plots, normal plots, etc.
5. Examine the fitted model plot, interaction plots, and ANOVA statistics
  - a) R<sup>2</sup>, adjusted R<sup>2</sup>, lack-of-fit test, etc.
6. Use contour plots of the response surface to explore the effect of changing factor levels on the response.
7. Repeat all the above steps for the second response variable.
8. After satisfactory models have been fit to both responses, you can overlay the surface contours for both responses.
9. Find optimal factor settings.

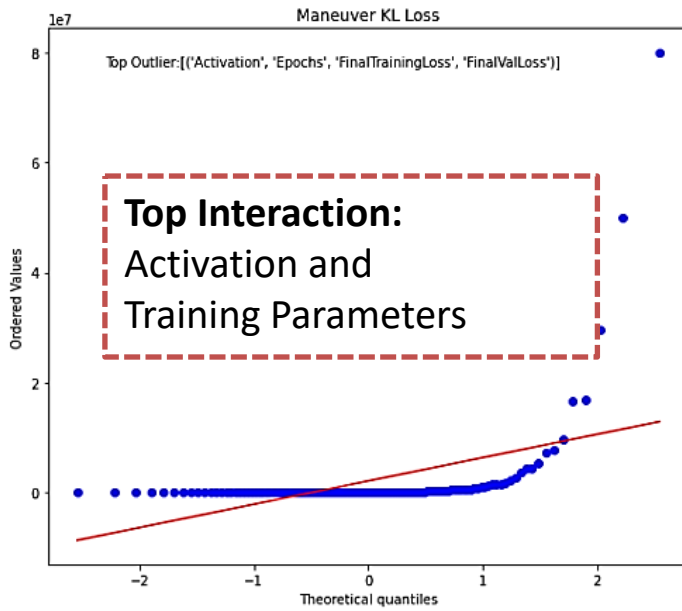


$$y_i = \beta_0 + \sum_{j=1}^7 \beta_j x_j + \sum_{1 \leq j < k \leq 7} \beta_{jk} x_j x_k + \sum_{j=1}^7 \beta_{jj} x_j^2 + \epsilon$$

$y_1$ : Average KL Loss over All Missions

$y_3$ : Average KL Loss over Specific Maneuvers

## DOE Insight

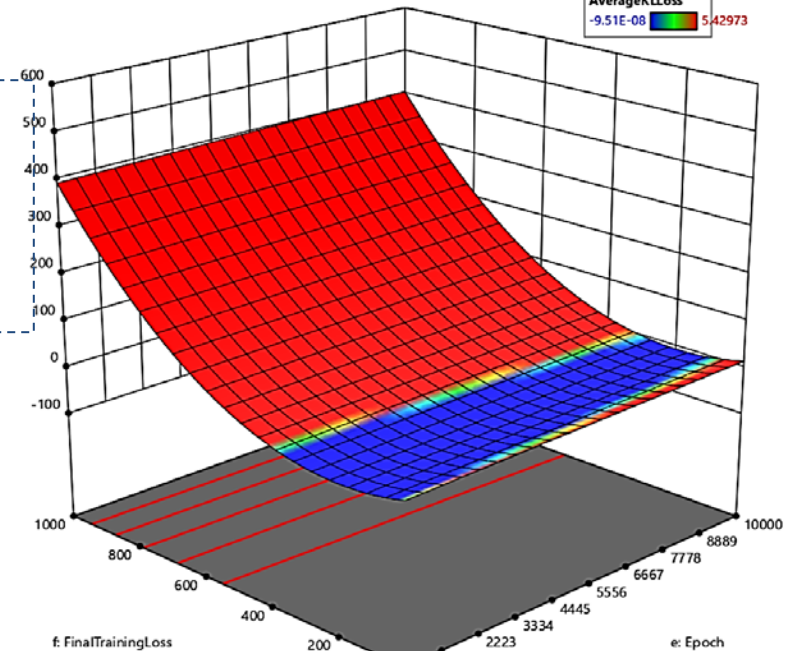
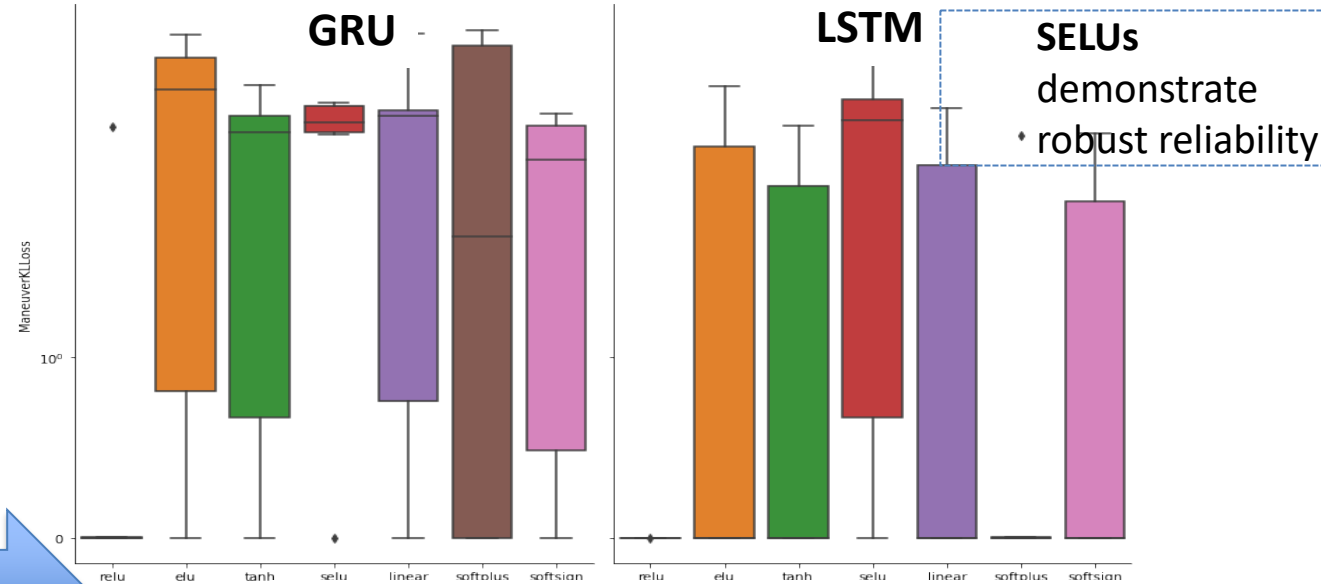


### Training:

Outcomes have smooth relationship with training loss function and epochs



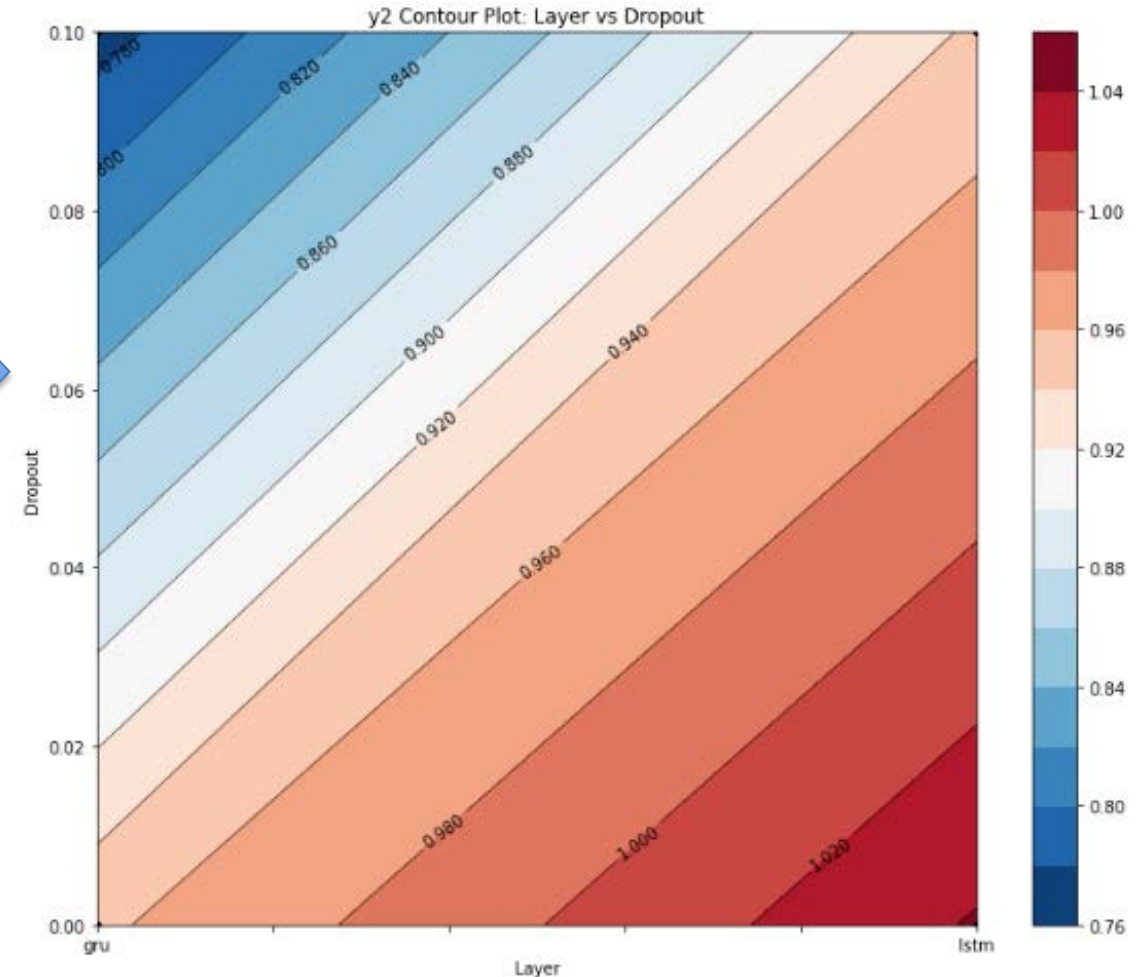
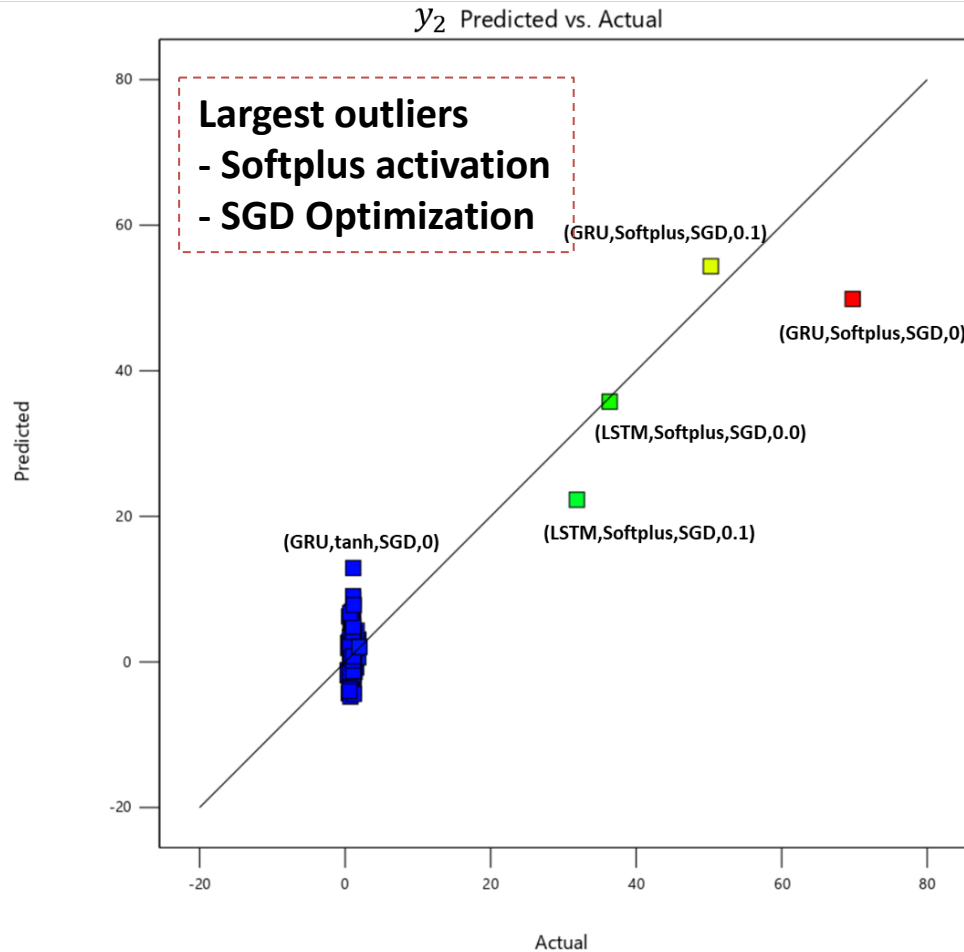
Latent space learning for our T-2 flights architecture is stable under CVAE



$y_2$ : Average Reconstruction Loss over all Flights

$y_4$ : Average Reconstruction Loss over Maneuvers

## DOE Insight



LSTMs average better reconstruction loss than GRUs



# Analysis – LOC Detection Performance

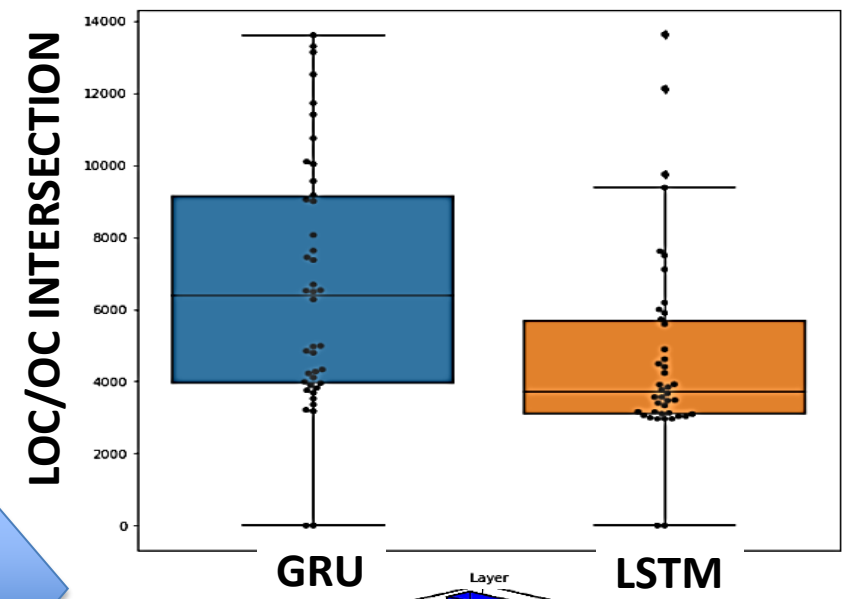
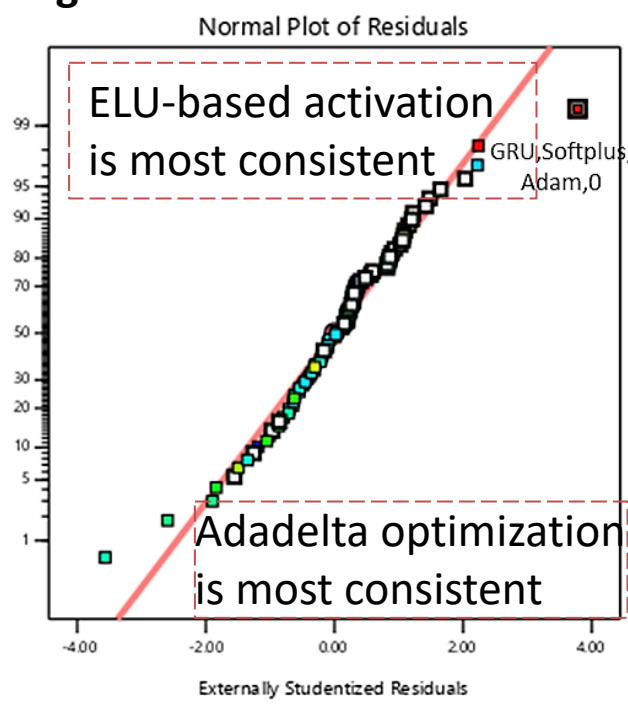
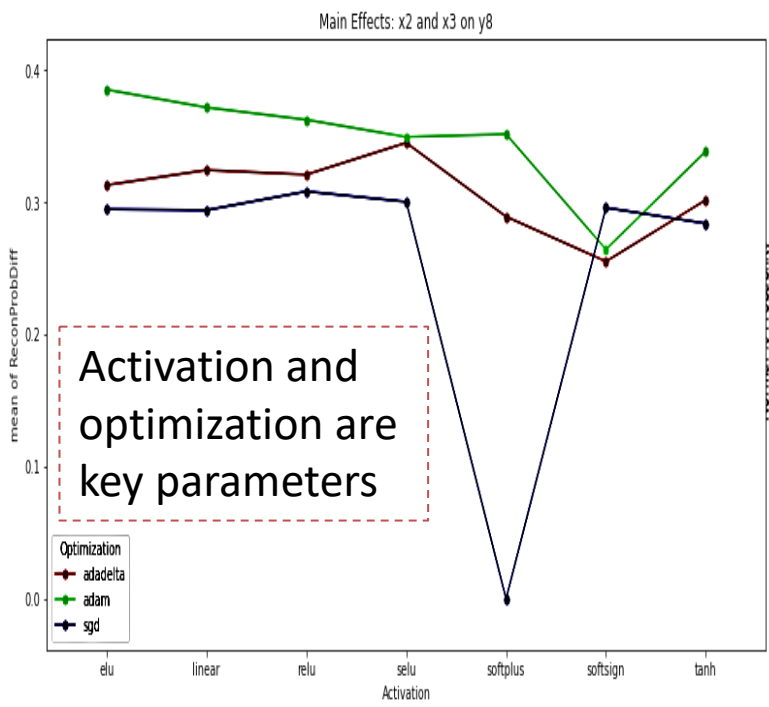


$y_5$ : Area of Intersection for Reconstruction Probabilities of Loss-Of-Control and Normal Flight Observations

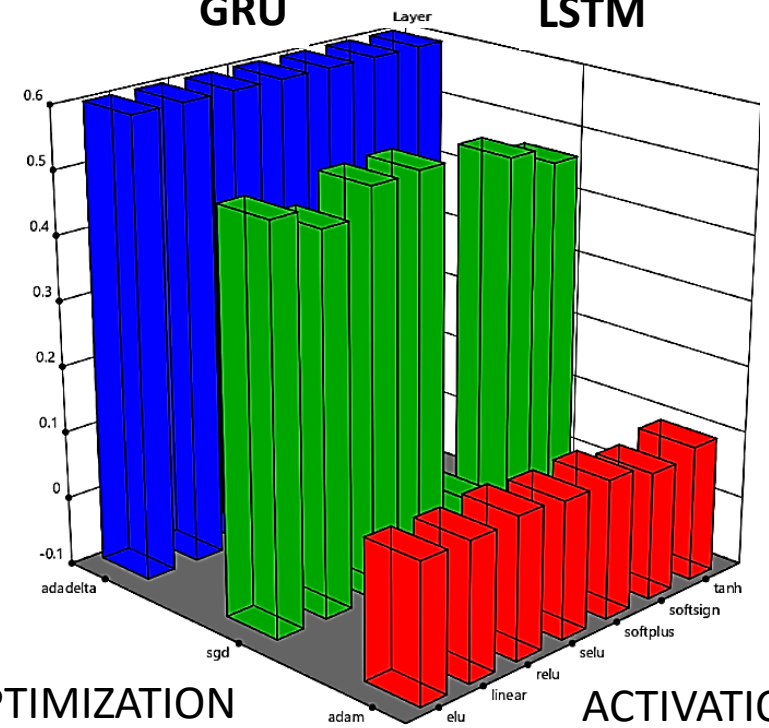
$y_7$ : Balanced accuracy for reconstruction probability-based anomaly detection

$y_8$ : Difference in Average Reconstruction Probability for Loss-of-Control observations and Normal observations

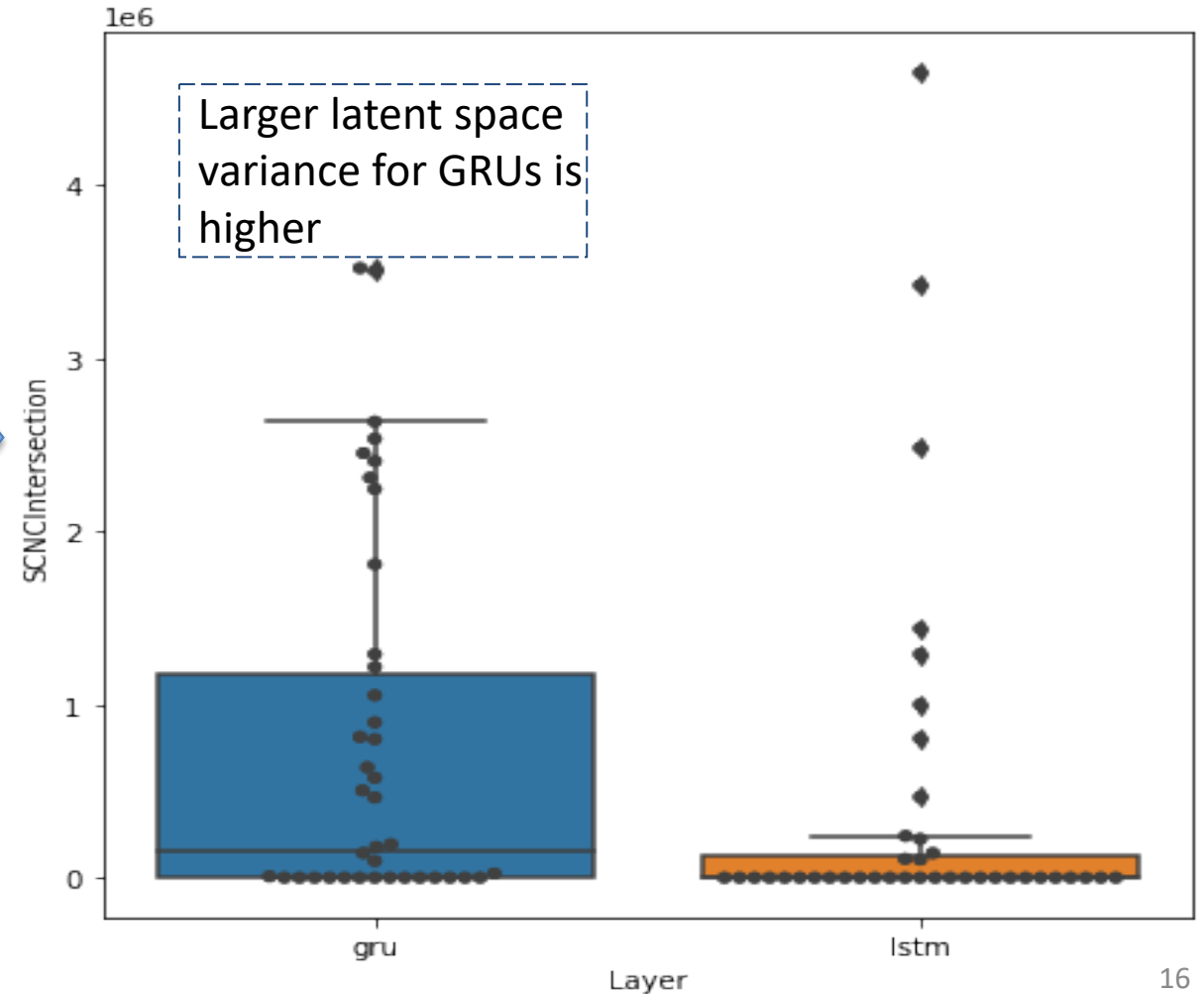
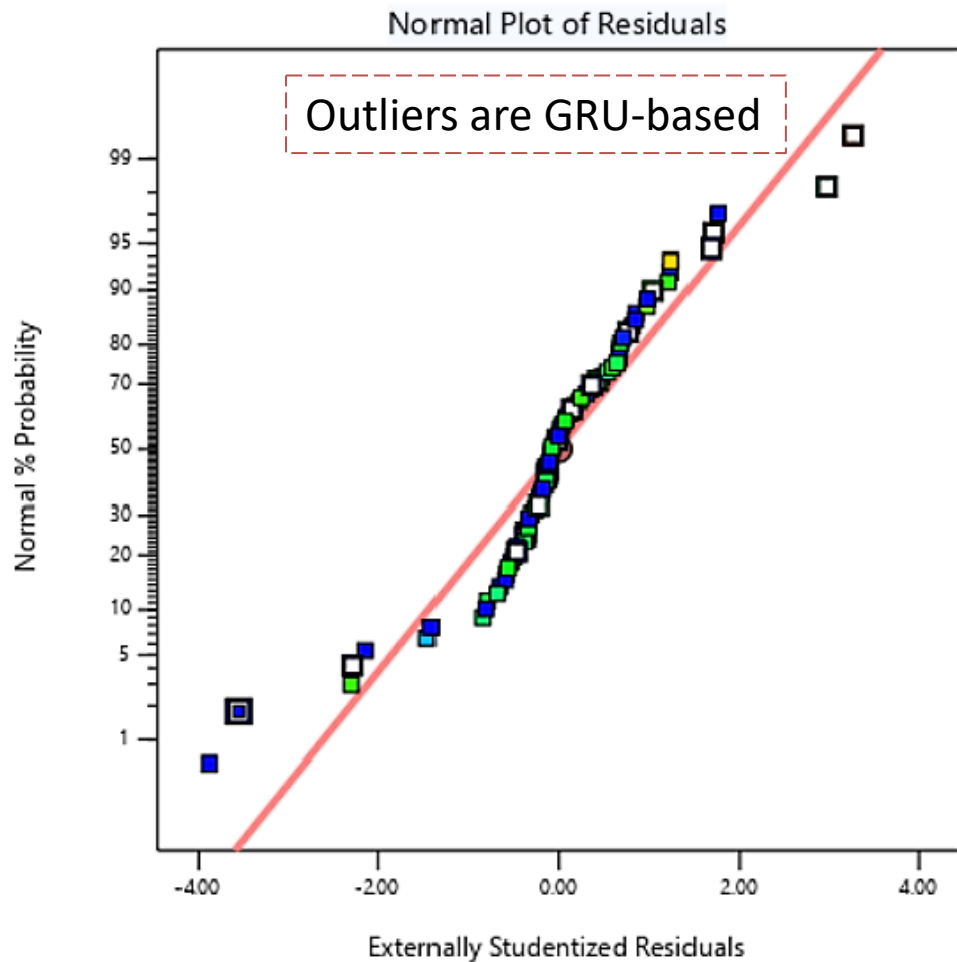
## DOE Insights

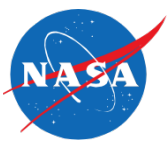


LOC/OC DIFFERENCE



- $\gamma_6$ : Area of Intersection for Gaussian Shift of State Change and Normal Flight Observations
- $\gamma_9$ : Difference in Average value of gradient of Jensen-Shannon distance when entering or exiting an envelope and average value with no envelope state change





# Architectural Recommendations from DOE Analysis



- Recommendations for distinguishing LOC from non-LOC observations (Avg Adj. R-squared: 0.759)
  - **Activation Function: elu, relu, selu, tanh**
  - **Optimization Function: Adam**
- Recommendations for determining that the vehicle is approaching envelope limits (Avg Adj. R-squared: 0.911)
  - **Activation Function: elu, selu**
  - **Optimization Function: Adadelata**
- Additional recommendations for other factors in paper



# Conclusions



- Template specified in [\*NIST/SEMATECH e-Handbook of Statistical Methods Section 5.4.7.3\*](#) for response surface modeling
- Demonstrated use of DOE in design optimization of neural network architecture for aerospace engineering (first study)
- Future studies:
  - Screening study for all architectural factors prior to response surface study
  - Repeated experimentation to account for random weight initialization



## Main Author

Newton Campbell Jr., PhD

[newton.h.campbell@nasa.gov](mailto:newton.h.campbell@nasa.gov)

