

PREDICTING SATELLITE CLOSE APPROACHES USING STATISTICAL PARAMETERS IN THE CONTEXT OF ARTIFICIAL INTELLIGENCE

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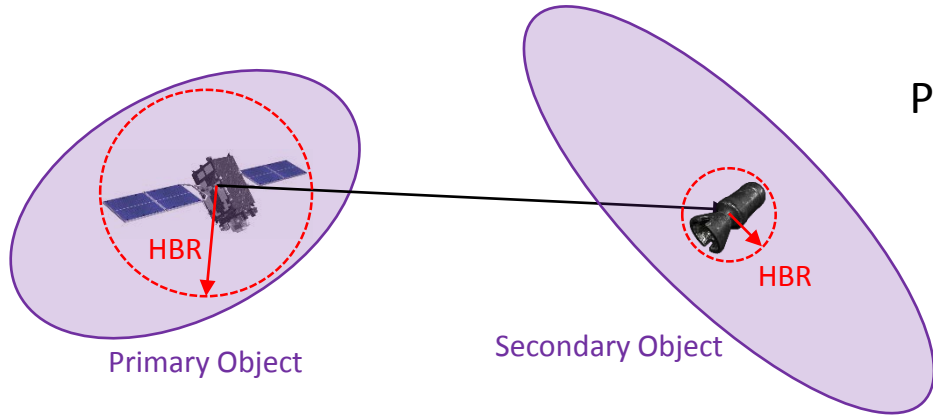
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***NASA Goddard Space Flight Center, [†] Purdue University and [‡] Tufts University**

AGENDA

- Background and Motivation
- Objective
- Approach and Results
 - Parameter set considerations
 - Data Wrangling : Unsupervised Machine Learning
 - Fuzzy Inference Systems
 - Deep Neural Networks
- Summary
- Future Work

Background and Motivation

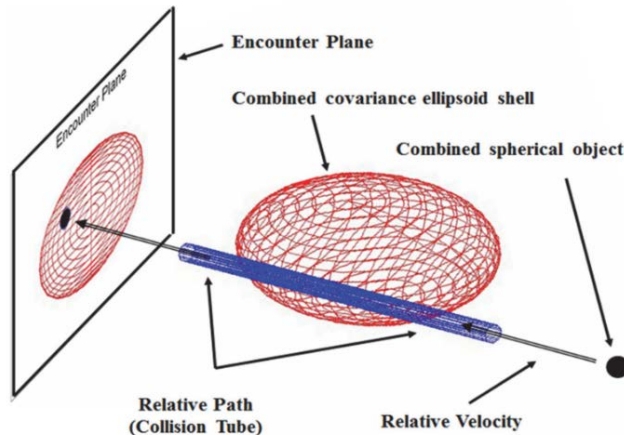


Primary and Secondary objects in a close encounter are described by:

- Position (Relative Position)
- Velocity
- Covariance matrix (region of uncertainty)
- Hard-body radius (HBR) (circumscribing radii)

$$P_c = \frac{1}{\sqrt{8\pi^3} \sigma_x \sigma_y \sigma_z} \int_{V_{ti}}^{V_{tf}} \int \int \exp \left[\frac{-x^2}{2(\sigma_x)^2} + \frac{-y^2}{2(\sigma_y)^2} + \frac{-z^2}{2(\sigma_z)^2} \right] dx dy dz$$

Probability of collision (Pc) computed from integrating the combined covariance matrix over the total HBR volume swept.



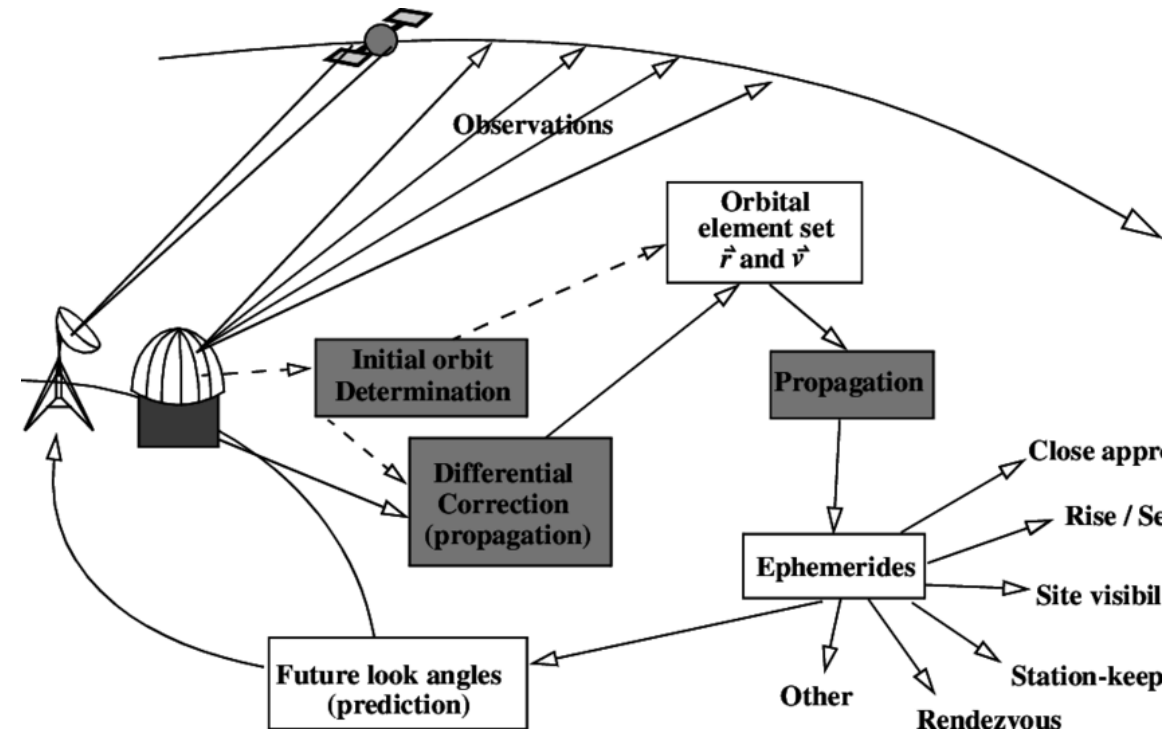
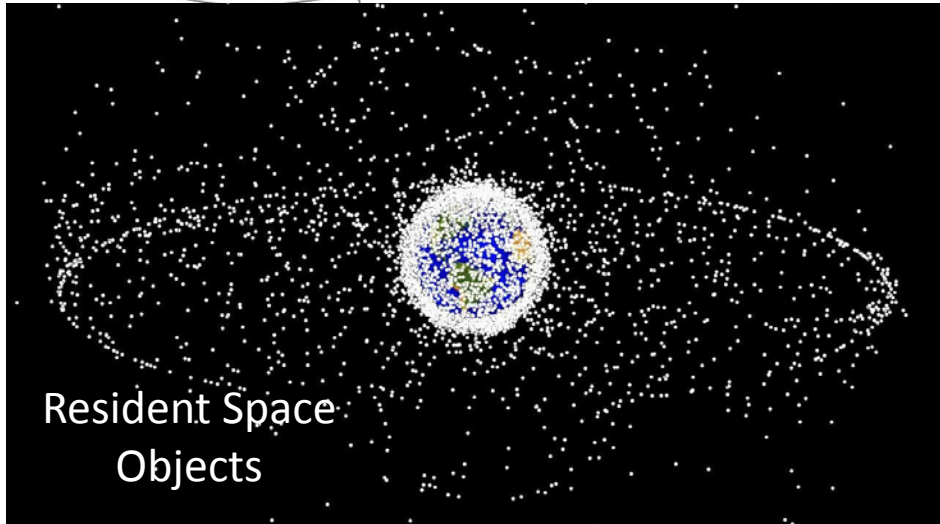
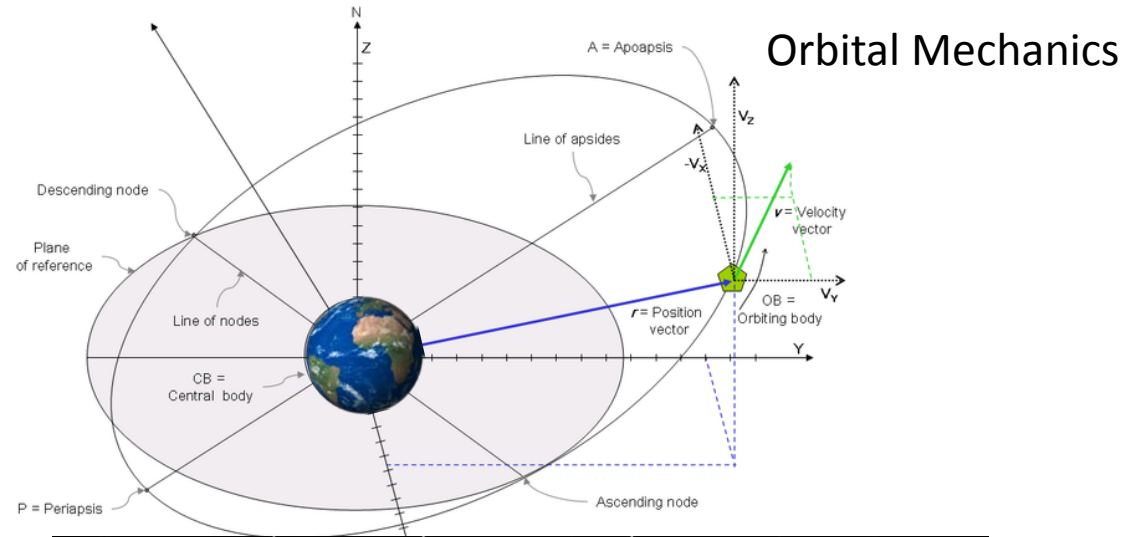
If relative motion in the encounter region is linear, the problem can be reduced to a two-dimensional integral by integration and projection.

$$P_c = \frac{1}{2\pi\sigma_x\sigma_y} \int_{-HBR}^{HBR} \int_{-\sqrt{HBR^2-x^2}}^{\sqrt{HBR^2-x^2}} \exp \left[\left(-\frac{1}{2}\right) \left\{ \left(\frac{x+x_m}{\sigma_x}\right)^2 + \left(\frac{y+y_m}{\sigma_y}\right)^2 \right\} \right] dx dy$$

-This "2D" Pc is the primary method currently used in the field of space situational awareness.

Background and Motivation

Newton's laws of universal gravitation
and laws of motion



Sensor tasking

Navigation OR
Orbit
Determination

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Objective

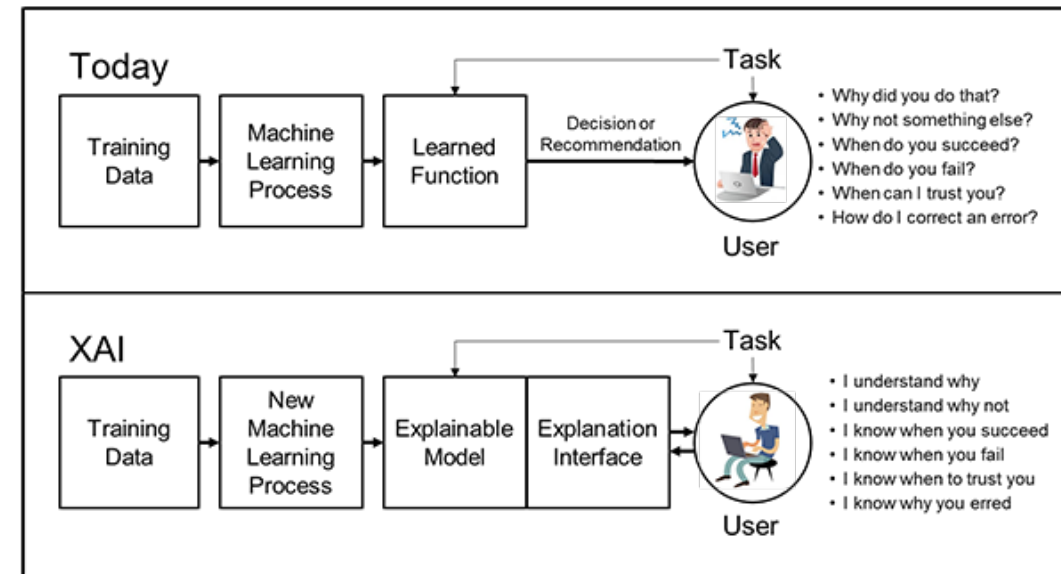
- **Goal:** Investigate and construct an architecture using physics-based statistical parameters via machine learning and deep neural networks for *intelligent and reliable rapid satellite collision avoidance decision-making*.

- Use statistical representation of the random vector (state) and the uncertainties (covariance) to construct the parameters
- CA (collision avoidance) decision making involves mostly P_c , however in operations additional constructs are considered as well ex. Miss-distance, OD quality etc.
- Sensor tasking is also a key component/contributor to the CA decision making. How can we incorporate this qualitatively and quantitatively?

- **Key points to consider:**

- In Machine Learning, quality data is imperative.
- Must have a clear goal for the outcome
- Can we explain the outcome?

Explainable AI (XAI) Concept



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Approach

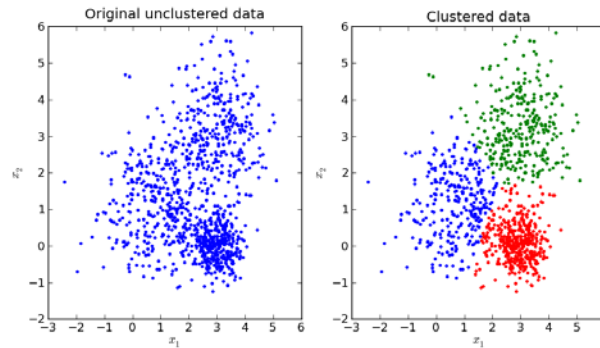
(1) Obtain Data

(2) Data Wrangling

(3) Train Model

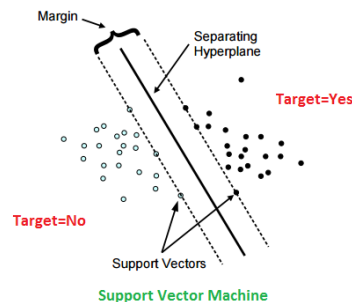
Unsupervised Machine Learning Methods: Clustering and Classification

K-means



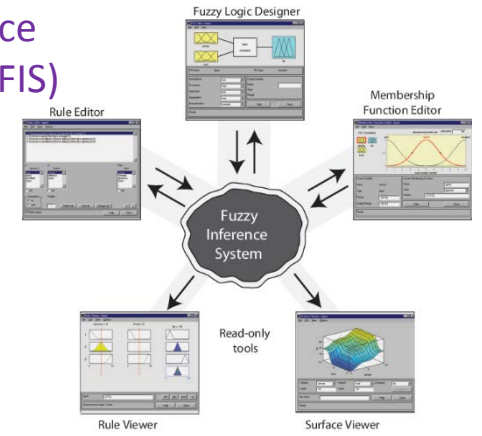
Partition N observations into K clusters.

SVM-Support Vector Machines



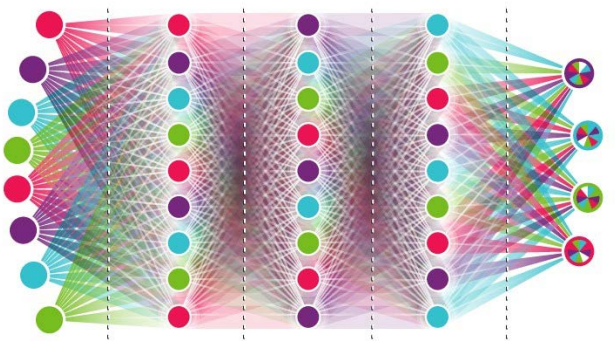
Separation into K groups with the widest gap possible

Fuzzy Inference System (FIS)



DEEP NEURAL NETWORK

Input layer → Hidden layer 1 → Hidden layer 2 → Hidden layer 3 → Output layer



Deep Neural Network (DNN)



Two spacecraft at Time of close approach (TCA)



Statistical Parameters

Probability of Collision

Miss Distance

Mahalanobis Distance

Bhattacharyya Distance

Kullback-Leibler Distance etc.

Parameter set considerations

- Investigate statistical parameters using the available information that could provide additional insight into conjunction events.
- Developed a set of “ statistical information parameters” (and their variations) derived from some of the same information used to compute P_c .

Probability of Collision (P_c)

Mahalanobis Distance (MHD)

Miss Distance (MD)

Bhattacharyya Distance (BD)

Angle between two orbit planes(OA)

Kullback-Leibler Distance (KLD)

Other?

(Both Primary and Secondary)

-Position and Velocity

-Covariance matrix

-Other?

Data Wrangling: Unsupervised Machine Learning

- Unsupervised learning methods classify data into groups based on features within the dataset that may not be immediately obvious to a human operator.
- Clustering algorithms fall into two broad groups:
 - Hard Clustering: each data point belongs to only one cluster ex. K-means and Support Vector Machines
 - Soft Clustering: each data point belongs to more than one cluster ex. Fuzzy C-means and Gaussian Mixture Models

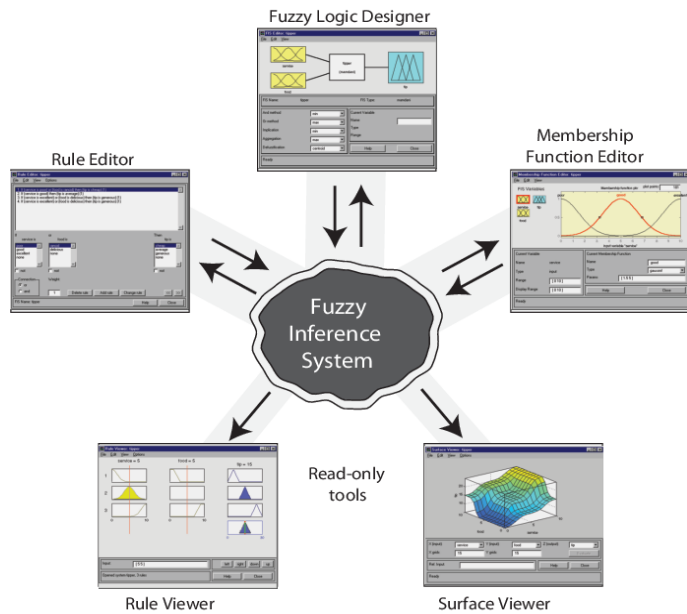
- Two clusters/classifications were defined:
 - “safe” or “not safe”**
- The performance metric was compared to a Monte Carlo computation for the ground truth based on P_c
 - **1 – ensemble’s correct assignment**
 - **0 – ensemble’s incorrect assignment**
- These performance values were used as input weights for the decision making tools

Clustering Performance Methods for K-means and SVM using the Performance Metric

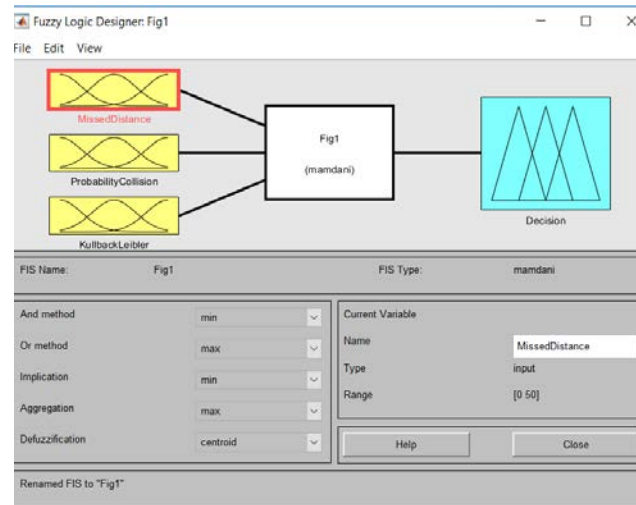
Parameter	K-means	SVM
Probability of Collision (P_c)	0.7742	0.9995
Miss Distance (MD)	0.6389	0.8314
Mahalanobis Distance (MHD)	0.6983	0.8810
Bhattacharyya Distance (BD)	0.7611	0.8864
Kullback-Leibler Distance (KLD)	0.7736	0.8459
Orbit Angle (OA)	0.5387	0.8711

Fuzzy Inference Systems

- Fuzzy inference systems map input to output using fuzzy logic, which is able to express partial membership of variables or parameters to certain sets using Fuzzy Membership functions (FMF).
- Using the Mamdani FMF, we investigated the decision making tool's output using three informational parameters: Miss-Distance, Probability of Collision and the Kullback-Leiebler Divergence



Define FMF in the Membership Editor and the decisions rules in the Rule Editor ex. $\{0,1\} = (\text{unsafe}, \text{safe})$

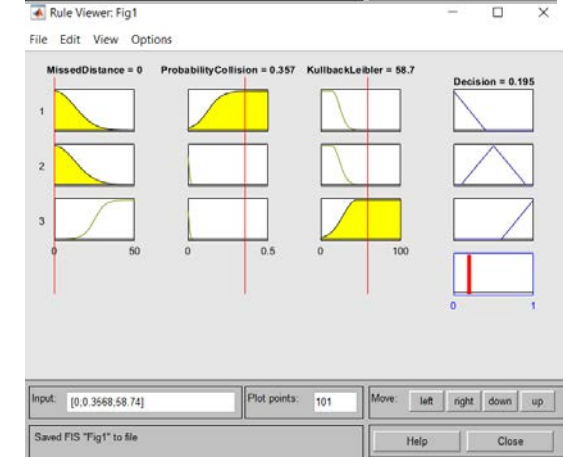


Fuzzy Logic Designer GUI using MATLAB[®] defining the FMFs MD, Pc and KLD.

High – MD
Low – Pc
Mid – KLD
Output : 0.837



Low – MD
High – Pc
Mid – KLD
Output : 0.195



Deep Neural Networks

- For comparison we designed and implemented a Deep Neural Network (DNN) model for decision making augmentation with Pc.
- In this context of using DNN for decision making, we considered a few informational parameters: Pc, KLD, MHD, BD, MD and the OA. We grouped the informational parameter into arbitrary assignments of 4 groups:

-Group 1 = {KLD, MD, BD, Pc, MHD}

-Group 2 = {KL, MD, MHD, Pc}

-Group 3 = {Pc, MHD, OA}

-Group 4 = {Pc}

Group 3 and Group 4 will be presented.

- DNN model design considerations:
 - Three sets for number of hidden layers: {10, 20 and 40}
 - Backpropagation training functions: Scaled-conjugate gradient (SCG) and Levenberg-Marquardt (LM)
 - Training, Validation and Testing ratios: 0.7, 0.15 and 0.15 respectively
- Used a sample data set of 1000 samples of simulated data containing both safe and unsafe encounter classifications.

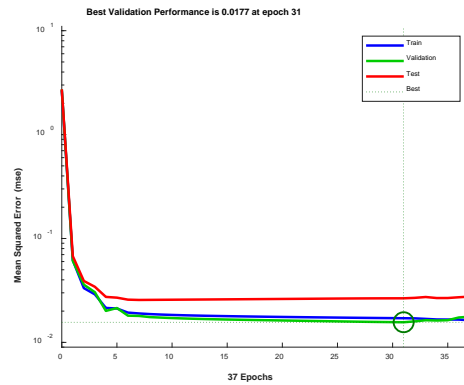
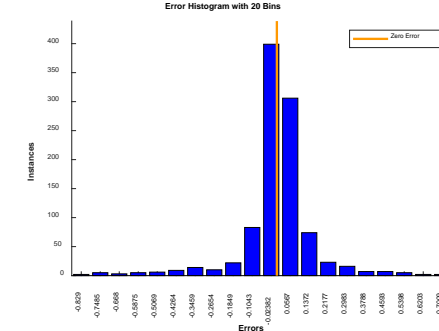
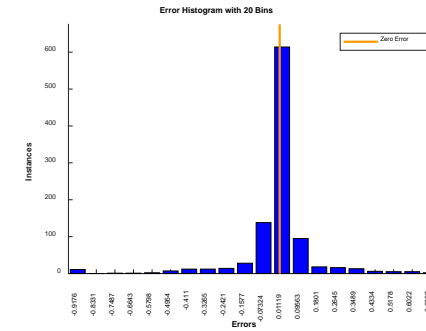
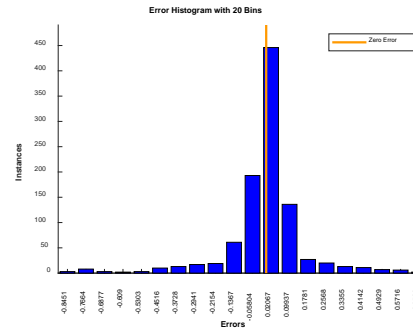
(Note the binary outputs assignments for the DNN are not the same assignments as for the FIS, but bear similar theoretical meaning and representation).

Deep Neural Networks: Group 3

- This was the best performing Group of all 4 considered here.
- The best performing DNN model used the LM algorithm with 10 hidden layers

Performance Metrics for Group 3.

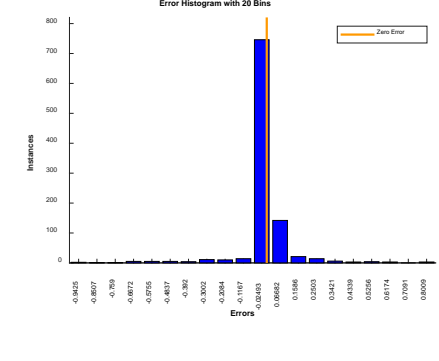
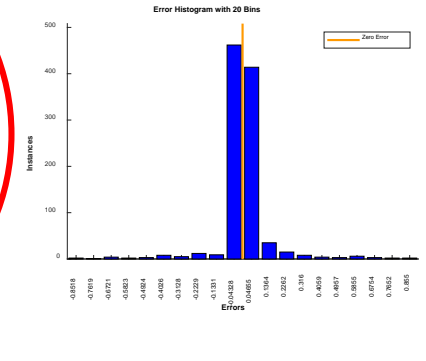
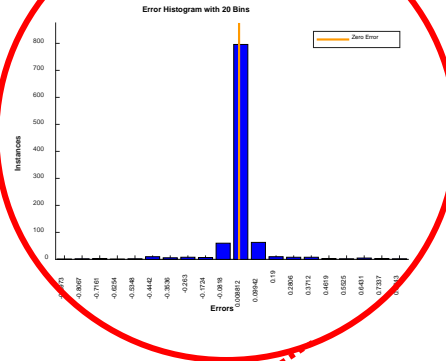
		Group 3		
		10 layers	20 layers	40 layers
Scaled Conjugate Gradient	Regression	0.93	0.93	0.94
	RMSE: Perf	0.0293	0.0284	0.0245
Levenberg-Marquardt	Regression	0.96	0.96	0.96
	RMSE: Perf	0.0177	0.0179	0.0179



SCG 10 Hidden Layers

SCG 20 Hidden Layers

SCG 40 Hidden Layers



LM 10 Hidden Layers

LM 20 Hidden Layers

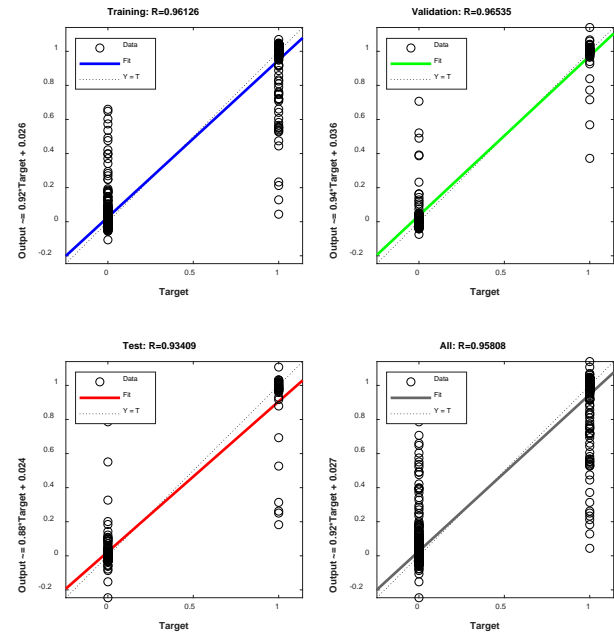
LM 40 Hidden Layers

Performance Plot

DNN Performance analysis after training and testing.

Error histograms for SCG (top) and LM (below). The vertical red line is the zero error mark.

Regression Plot

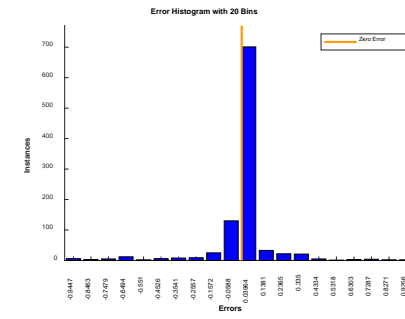
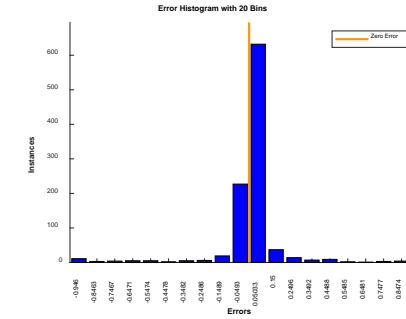


Deep Neural Networks: Group 4

- This was the least performing Group of all 4 considered here.
- The best performing DNN model used the LM algorithm with 10 hidden layers

Performance Metrics for Group 4.

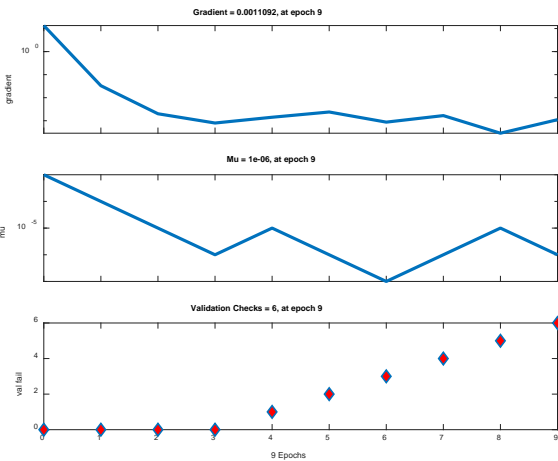
		Group 4		
		10 layers	20 layers	40 layers
Scaled Conjugate Gradient	Regression	0.93	0.92	0.93
	RMSE: Perf	0.0313	0.0342	0.032
Levenberg-Marquardt	Regression	0.93	0.93	0.93
	RMSE: Perf	0.0309	0.0303	0.0303



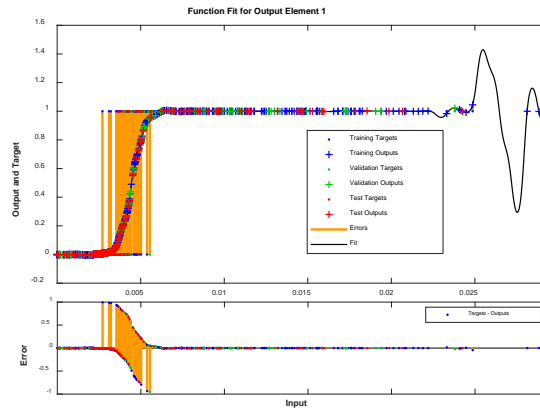
SCG 10 Hidden Layers

SCG 20 Hidden Layers

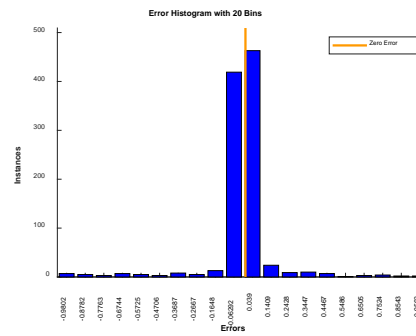
SCG 40 Hidden Layers



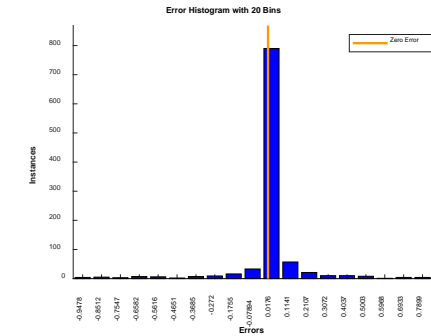
Training State



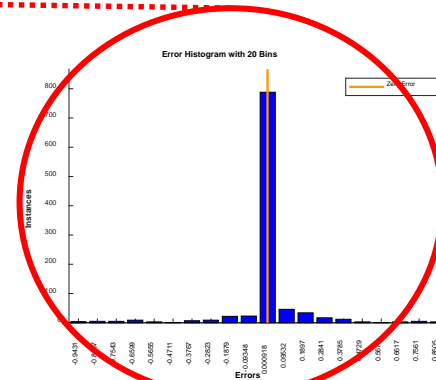
Output and Target Function Fit



LM 10 Hidden Layers



LM 20 Hidden Layers



LM 40 Hidden Layers

Training state output and function fit (target vs output) with an error subplot

Error histograms for SCG (top) and LM (below). The vertical red line is the zero error mark.

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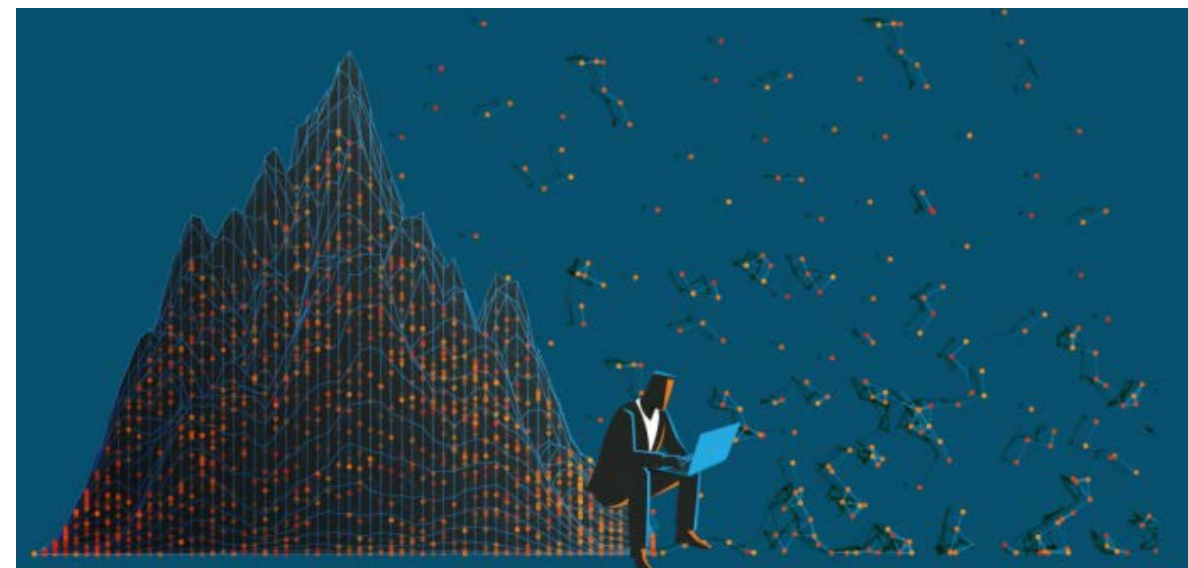
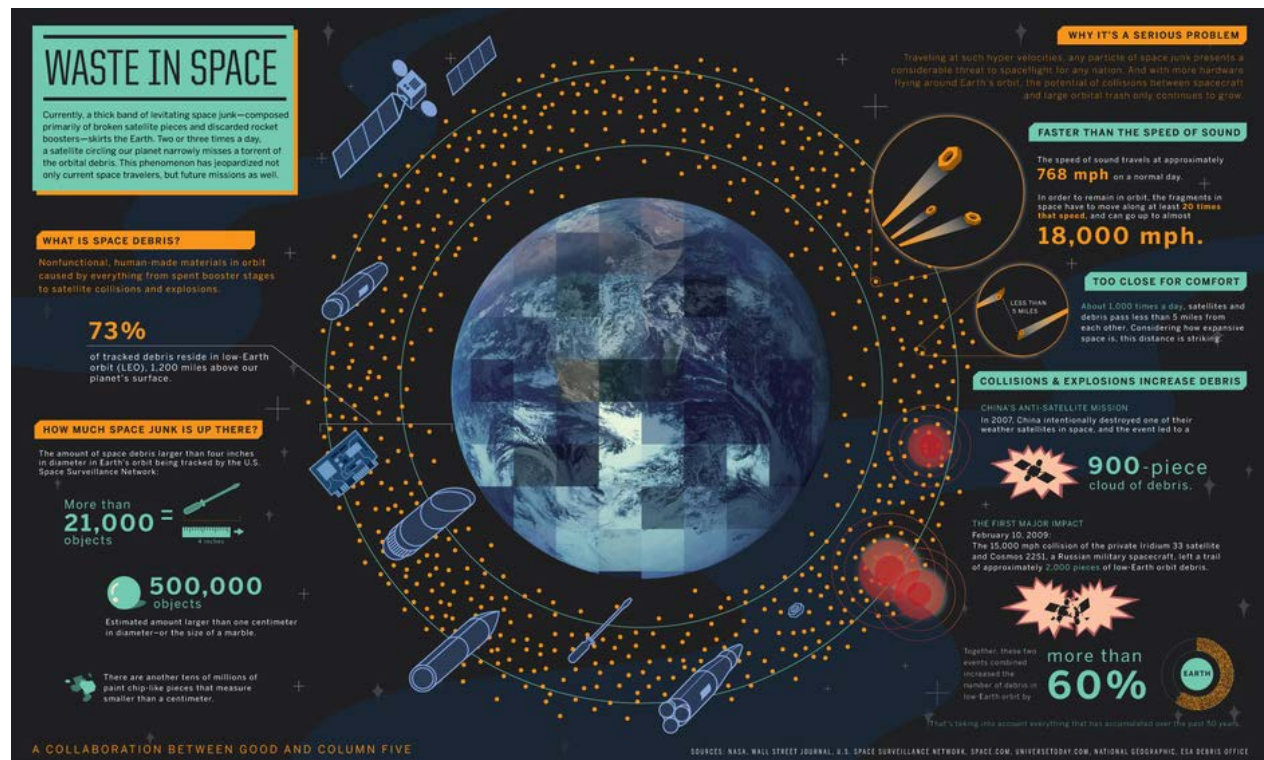
Summary

- Fuzzy Inference Systems generated a decision space that may not be able to successfully capture the classifications made by unsupervised or supervised techniques for this application.
 - It provided an aggregated output based on the weights of the Fuzzy-membership functions.
- Deep Neural Networks presented more promising results compared to the Fuzzy Inference System for a collision avoidance decision-making tool.
- An augmented or exclusive satellite collision avoidance decision-making construct based on preliminary machine learning performance, and ongoing research suggests a favorable architecture with modeled binary or tertiary decisional outputs.

Ongoing & Future Work

- Ongoing research is being implemented to determine an optimal and representative physics-derived adaptive set of parameters for each conjunction case.
- Consider parameters beyond state and covariance such as information available in a Conjunction Data Message (CDM) or space weather data, example:
 - Number of Observations used
 - Energy Dissipation Rate (EDR)
 - Radio Flux and Geomagnetic Indices etc.
- Incorporate Recurring Neural Network (RNNs) model to ingest time-series based information sequentially incorporated to provide predictions at TCA.
- Potential for these models to be extended to perform collision avoidance for large-constellations semi-autonomously.

Artificial Intelligence for Space Situational Awareness and Collision Avoidance Decision Making

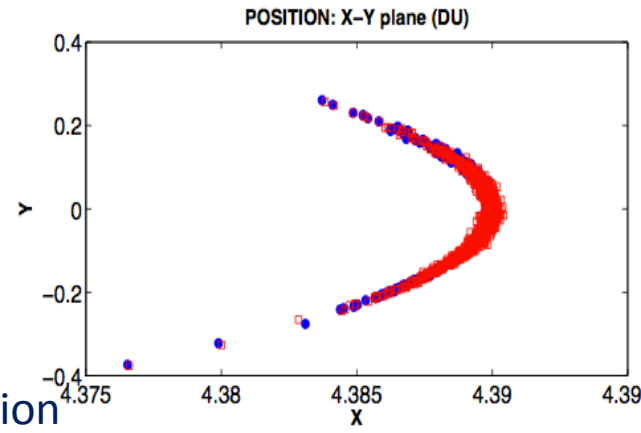
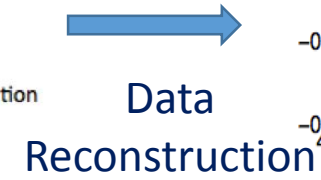
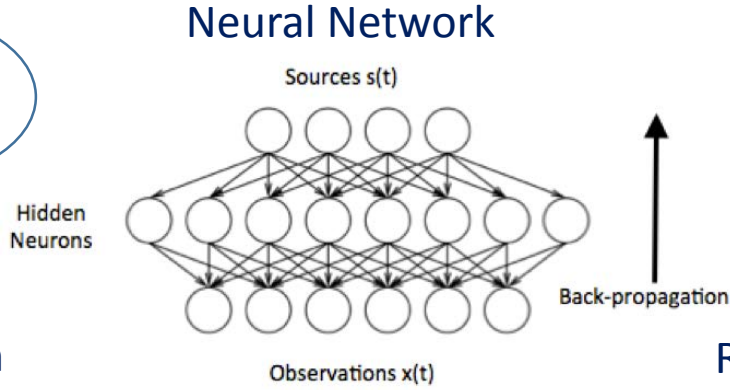
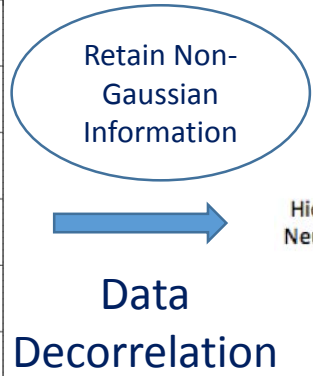
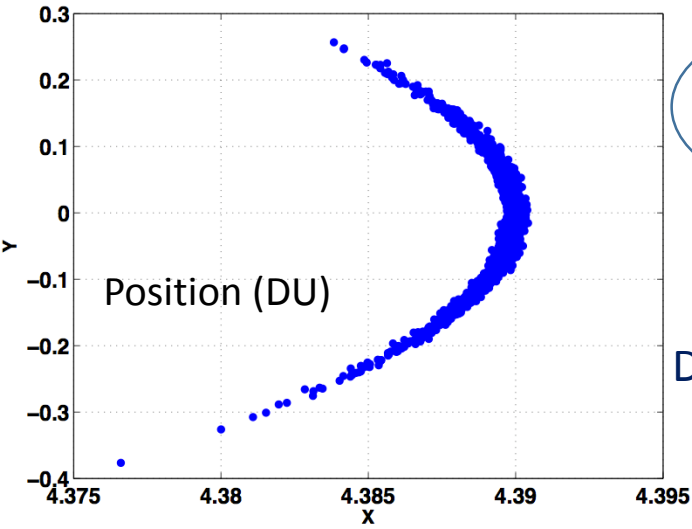


Intelligent data analytics can help us understand and augment problem-solving techniques beyond our current capabilities.

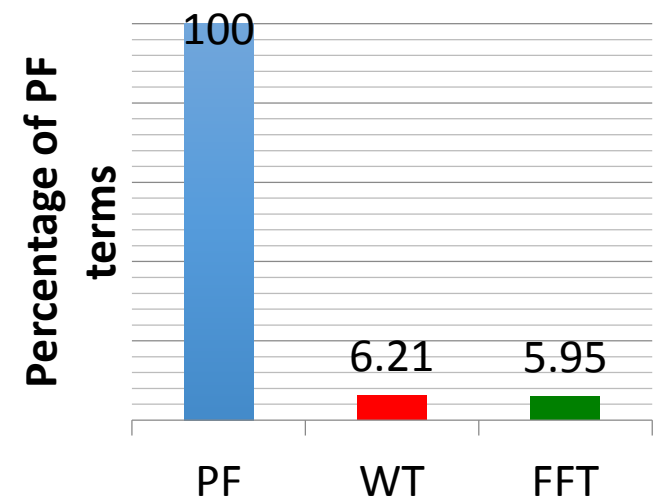
THANK YOU

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 - PI: Dr. Alinda Mashiku, NASA GSFC Navigation and Mission Design Branch (595)
 - Co-PI: Prof. Carolin Frueh, Purdue University School of Aeronautics and Astronautics and
 - Co-PI: Dr. Nargess Memarsadeghi, NASA GSFC Science Data Management Branch (586)
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 - CARA performs SSA and CA for uncrewed NASA missions and other agencies
- Summer interns:
 - Evana Gizzi : Tufts University
 - Mitch Zielinski : Purdue University
- Special Thank you to the TEMPO (Technology Enterprise and Mission Pathfinder Office, Code 450.2) their support.

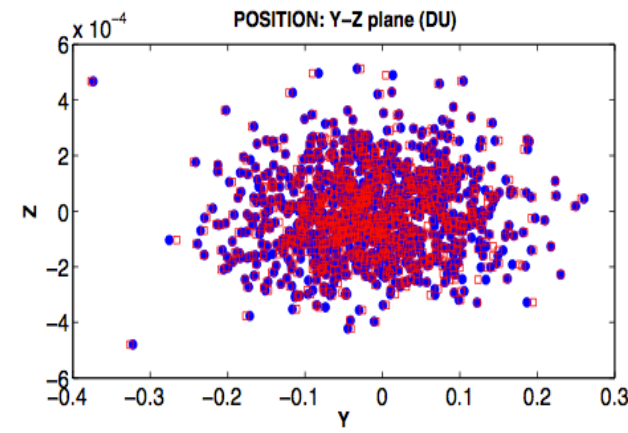
Machine Learning for State Uncertainty Characterization



Fast-Fourier and Wavelet Transforms and Inverses



- PF
- WT
- FFT



Compressed data with retained information content

Monte Carlo samples for a spacecraft's position uncertainty characterization (Generated using a Particle Filter (PF))