AI for Collision Avoidance — Go/No Go Decision-Making

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Motivation

- 7,500 active satellites as of Mar 2023 [1]
  - This is expected to grow to 58,000 by 2030 [2]
- 36,500 space debris objects larger than 10 cm[1]
- Increasing density of objects in orbit → more conjunctions
- 43,000 conjunctions with probability of collision (PoC) > 1E-6 occur monthly in LEO [3]
  - Results in approx. two actionable alerts per week per satellite [4]
- On-call personnel needs to be available 24 hrs/day, year-round

How will this scale, when conjunctions are to rise exponentially?
-> Automation is necessary!

LEO: Low Earth Orbit

Why isn't the Go/No Go decision automated?

Simple PoC/miss distance thresholds result in unnecessary maneuvers.

Analysts also consider:

- Trustworthiness of the source of the data
- Conjunction Data Message (CDM) evolution for the event
- Inconsistency in orbit determination process resulting in jumping values
- K factor — indicates if dilution region is reached
- Prior experience/intuition

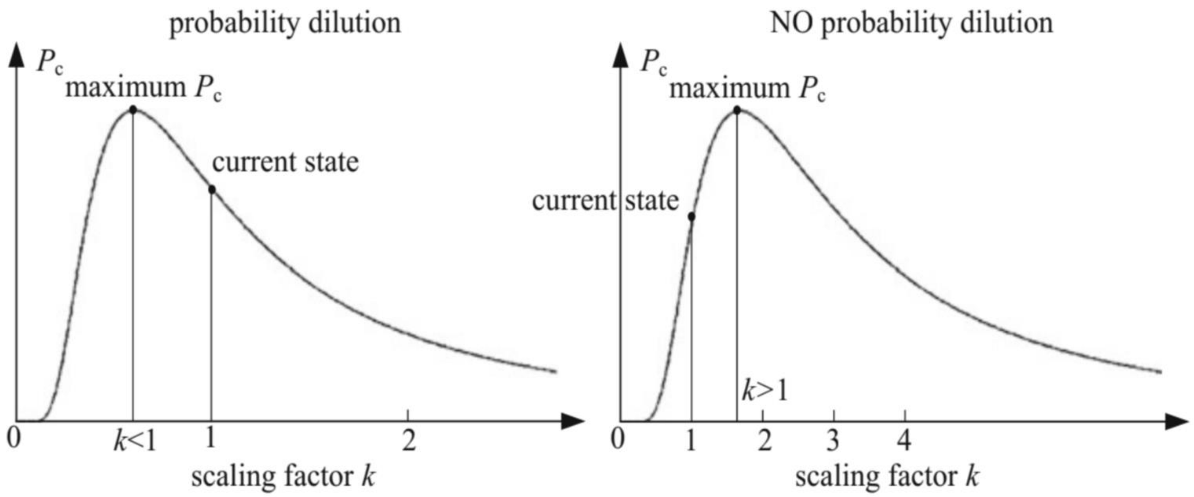

Fig. 1: Probability dilution occurs when K < 1 [5]

Can AI capture the complexity of this decision-making process?

K: Covariance scaling factor

PoC: Probability of Collision

Key contents

GSOC CDM classification project

- Synthetic CDM series generation
- Classification by analysts
- Results on human decision-making

AI for time series classification

- AI model selection
- Model architecture
- Results from AI classification

CDM: Conjunction Data Message

GSOC: German Space Operations Center

GSOC CDM classification project: studying decision-making

- 20 high risk events classified by GSOC analysts
- 4-5 CDMs per event, go/no go decision made by 4 analysts
- Survey conducted to understand rationale behind decisions
- Limitation: analysts are working with foreign objects

Data source:

- Privateer[6]
    - Only 1 CDM per event, time to TCA < 1 hour
    - Radial component of covariance larger than along-track component
    - No hard body radius info

Synthetic generation of time series and covariance manipulation necessary

TCA: Time of closest approach

CDM: Conjunction Data Message

GSOC: German Space Operations Center

Synthetic CDM series generation

Nominal trends across CDM series as TCA nears:

- Covariance decreases
- Covariance ellipses converge
- Mean position (X,Y,Z) in new CDM lies within covariance of previous CDM

Monte Carlo simulation used to generate 1000 CDMs per event. 4-5 CDMs selected.

Median values of the 20 events:

- Probability of collision: 6.855E-5
- Miss distance: 720 m

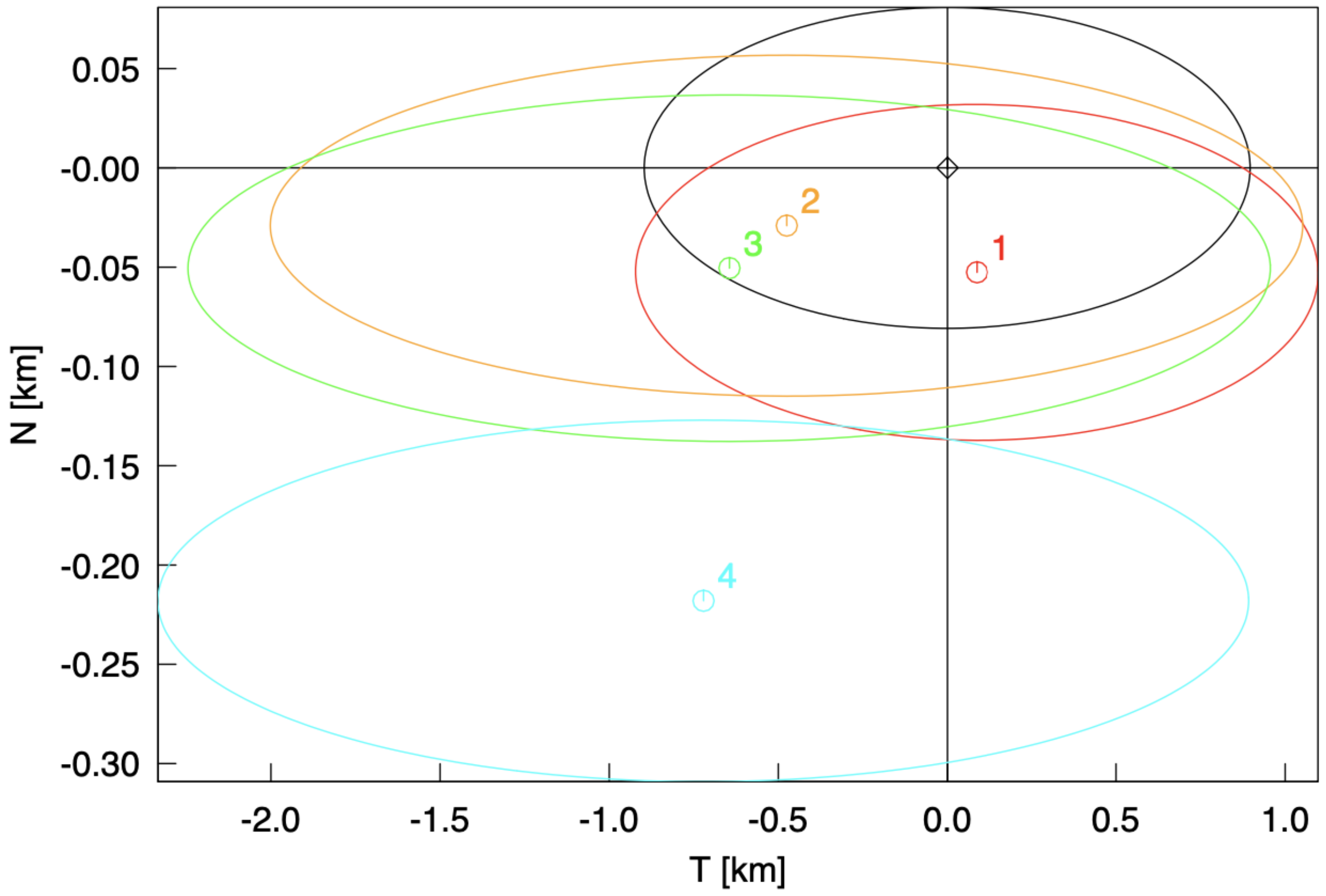

Fig. 2: Covariance evolution. 4 is furthest from TCA.

TCA: Time of Closest Approach

CDM: Conjunction Data Message

GSOC CDM processing tool

- For each CDM, the TCA is recomputed
  - Recalculating miss distance by propagating objects around original TCA
  - Covariance is the same as in the CDM, but PoC is updated

- Outputs seen by analysts
  - Summary text file
  - Approach geometry
  - PoC in the B-plane
  - Maneuver cost (delta-V) and impact on PoC
  - Covariance history

PoC: Probability of Collision

TCA: Time of Closest Approach

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CDM processing – summary text file

DT [d]	DATA		TCA [UTC]	DIST [km]
1.0	CDM	2023-02-28	10:16:08.624	0.723
	GSOC	2023-02-28	10:16:08.624	0.723
1.4	CDM	2023-02-28	10:16:08.624	0.886
	GSOC	2023-02-28	10:16:08.620	0.884
1.7	CDM	2023-02-28	10:16:08.624	1.006
	GSOC	2023-02-28	10:16:08.625	1.006
2.0	CDM	2023-02-28	10:16:08.624	0.873
	GSOC	2023-02-28	10:16:08.689	0.566
2.4	CDM	2023-02-28	10:16:08.624	1.731
	GSOC	2023-02-28	10:16:08.637	1.726

PRJ	DT [d]	ANGL [deg]	OBJ1_SIGMA [km]			OBJ2_SIGMA [km]			PMAX (K<1)	PTRUE (K>1)	K
TST	1.0	0.0	(0.116	0.896	0.081)	(0.307	1.882	0.320)	0.00e+00	6.73e-05	0.0
TST		85.0	(0.116	0.896	0.081)	(0.307	1.882	0.320)	2.80e-04	2.18e-04	0.7
TST	1.4	0.0	(0.127	1.010	0.085)	(0.312	2.133	0.321)	0.00e+00	5.95e-05	0.0
TST		85.0	(0.127	1.010	0.085)	(0.312	2.133	0.321)	6.53e-04	2.54e-04	0.4
TST	1.7	0.0	(0.131	1.527	0.086)	(0.326	2.292	0.329)	0.00e+00	3.00e-05	0.0
TST		85.0	(0.131	1.527	0.086)	(0.326	2.292	0.329)	2.12e-04	1.61e-04	0.7
TST	2.0	0.0	(0.132	1.601	0.087)	(0.331	2.961	0.329)	0.00e+00	2.98e-05	0.0
TST		85.0	(0.132	1.601	0.087)	(0.331	2.961	0.329)	3.43e-04	1.59e-04	0.5
TST	2.4	0.0	(0.155	1.613	0.091)	(0.338	3.192	0.342)	0.00e+00	7.89e-06	0.0
TST		85.0	(0.155	1.613	0.091)	(0.338	3.192	0.342)	3.00e-04	1.44e-04	0.5

Fig. 3: Summary of event evolution. Entries followed by 'GSOC' pertain to those computed by the processing tool.

CDM processing — approach geometry

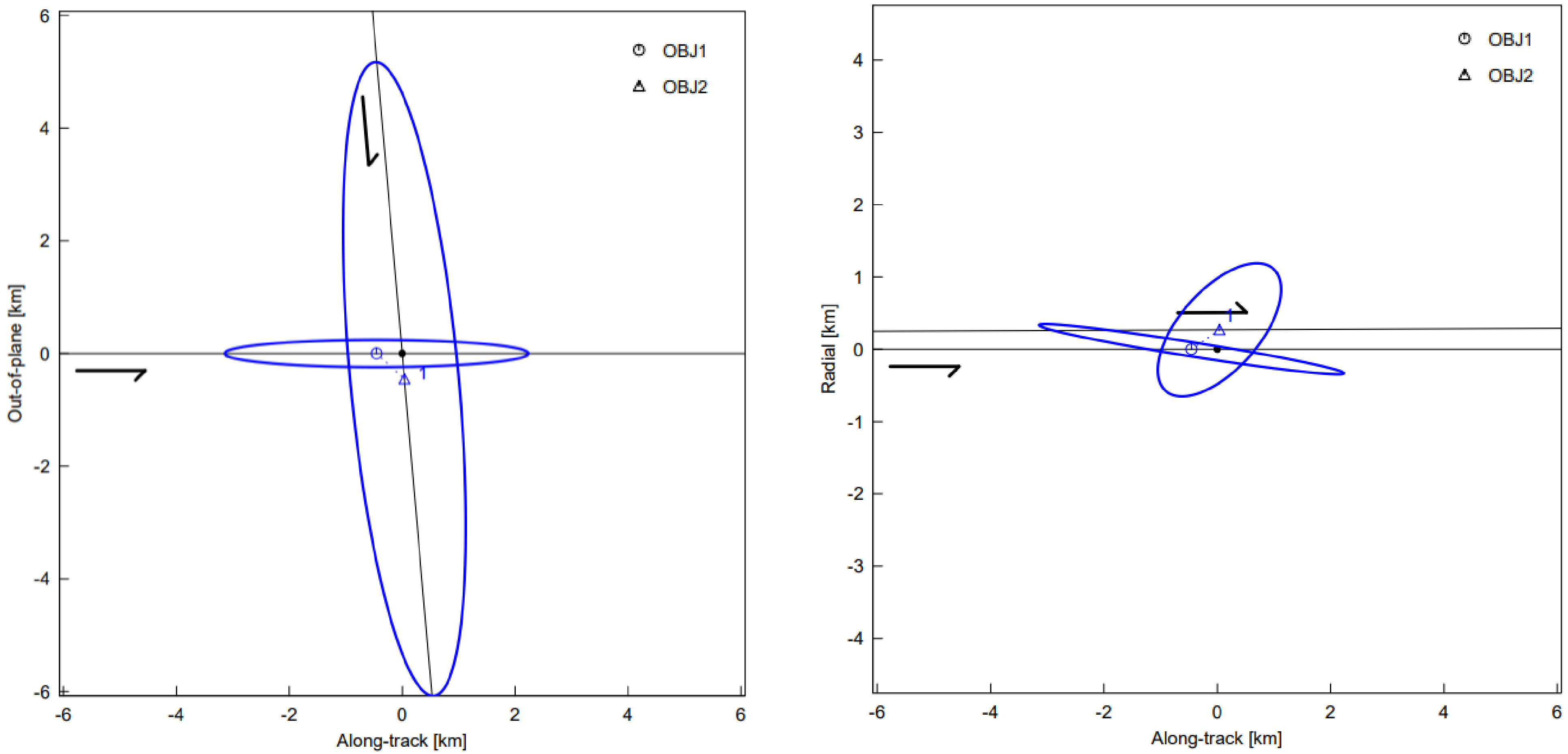

Fig. 4: Conjunction approach geometry in N-T and R-T frames.

R: Radial direction in RTN frame

T: Along-track direction in RTN frame

N: Normal direction in RTN frame

CDM processing – B-plane analyses

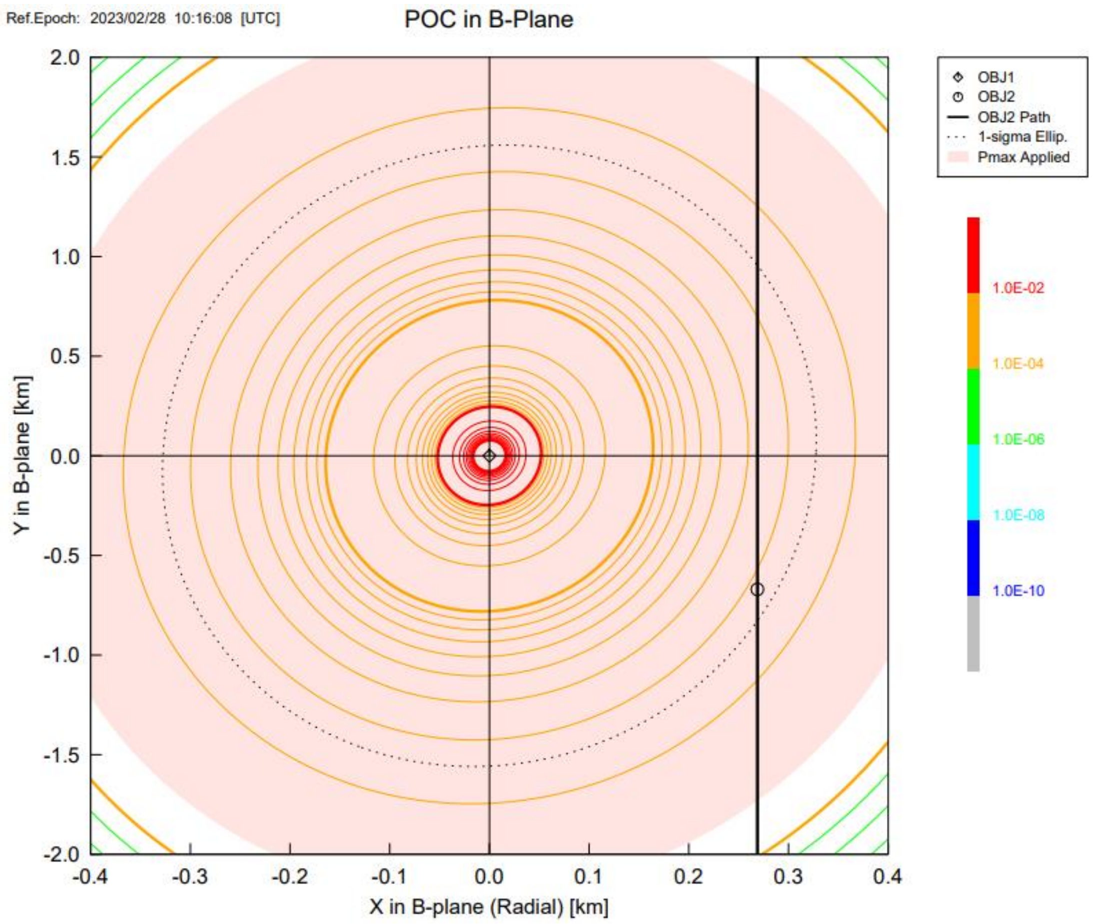

Fig. 5: Probability of Collision in B-plane. Centered on Obj 1.

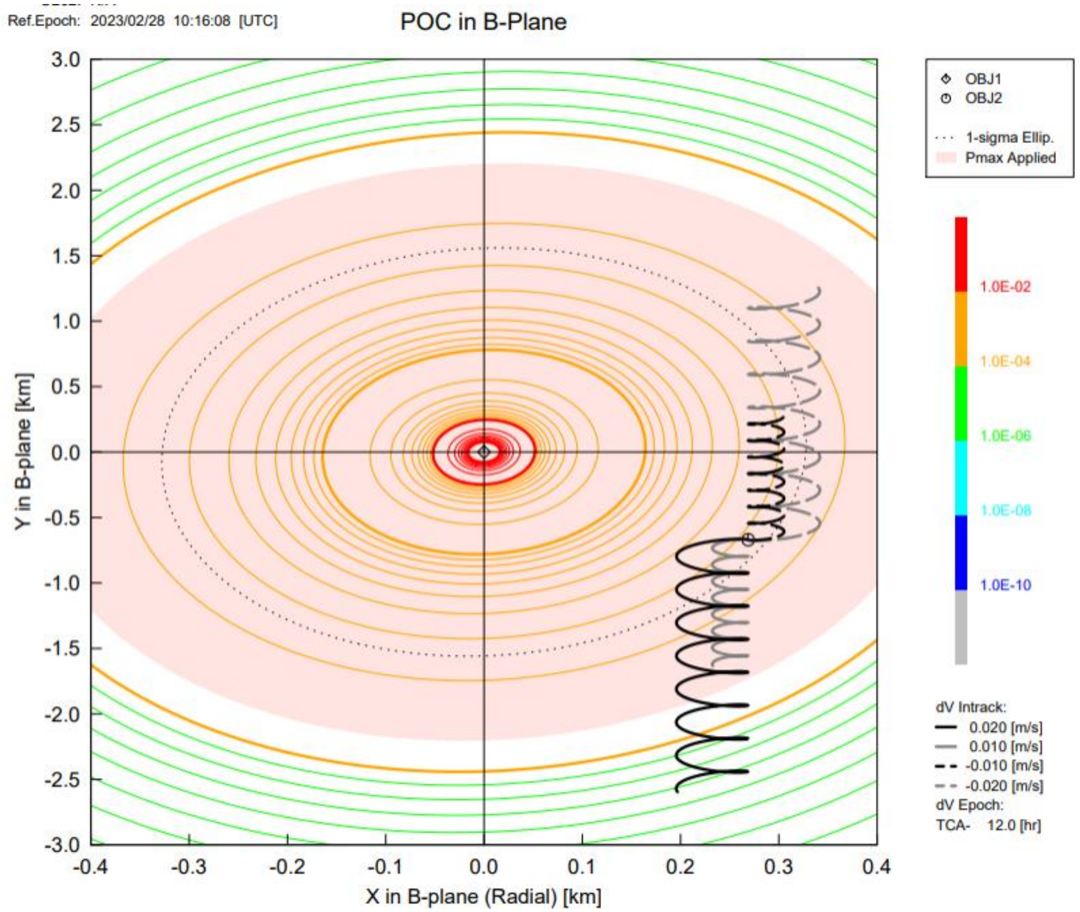

Fig. 6: Maneuver cost in B-plane. Centered on Obj 1.

CDM processing – covariance history

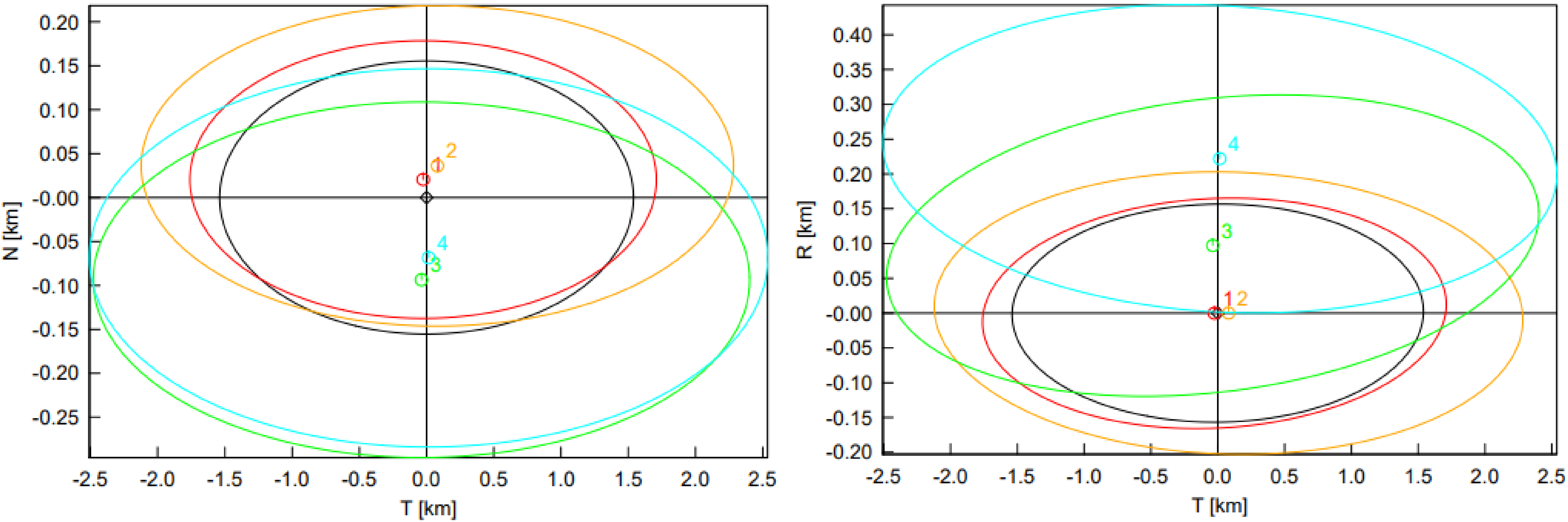

Fig. 7: Covariance history in N-T and R-T frames. Centered on final CDM.

R: Radial direction in RTN frame

T: Along-track direction in RTN frame

N: Normal direction in RTN frame

CDM: Conjunction Data Message

Survey specifics

- Time taken to make decision

- Impression of mission
    - Definitely maneuver
    - Wait for another CDM if possible
    - Maneuver not necessary, but close call
    - Not a concerning event

- Why did you make this decision?

- Rank importance of each feature in text file/plots for decision-making

CDM: Conjunction Data Message

Which features affect decision-making?

Rank	Analyst A	Analyst B	Analyst C	Analyst D
1	PoC	PoC	PoC, position uncertainty, B-plane plot	PoC
2	Miss distance	Miss distance, position uncertainty	-	Position uncertainty
3	B-plane plot	-	-	Relative position in RTN
4	Position uncertainty	Cov. history plot	Relative position in RTN	Collision geometry
5	Relative position in RTN, relative velocity	Relative position in RTN	Miss distance	B-plane plot
6	-	B-plane plot	Collision geometry	Miss distance
7	Collision geometry	Collision geometry	Cov. history plot	Cov. history plot
8	Cov. history plot	Relative velocity	Relative velocity	Relative velocity

PoC: Probability of Collision

Key findings from GSOC CDM Classification Project

- With tie-breaker: 10 Go’s and 10 No-Go’s
- Analysts disagreed on 4 out of 20 cases
- Tricky cases characterized by
  - Inconsistent CDM trends
  - Covariance — how much uncertainty is acceptable to make a decision?
- Elements of subjectivity — risk averseness varies
- Time taken
  - 2 minutes per event, 40 minutes for 20 events

Can AI mimic human decision-making in this context?

CDM: Conjunction Data Message

Selecting an AI model

- Model needs to
    - Learn from multiple features (PoC, miss distance, etc.)
    - Accept a time series input
    - Produce many-to-one classification result
- Long Short-Term Memory (LSTM)
    - Type of recurrent neural network (RNN)
    - Avoids vanishing gradient problem
    - Information flows through cell states
    - Forget gate, Input gate, Output gate — manipulate stored memory

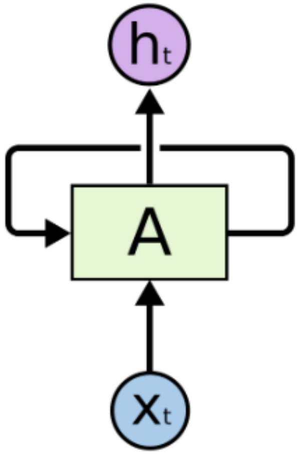

Fig. 8: Recurrent Neural Network. x_t is an input, h_t is an output [7].

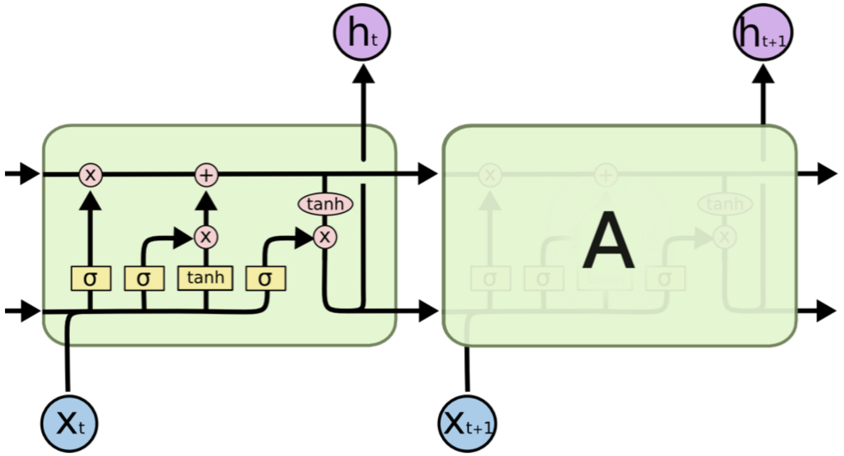

Fig. 9: LSTM model with 2 time steps [7].

LSTM architecture

- Built using Keras in Python
- 20 samples, 5 time steps, 10 features
- Feature scaling using Z-normalization
- Hyperparameter optimization (KerasTuner)
- Performance metric: test accuracy
    - evenly split classes
- 4 layers

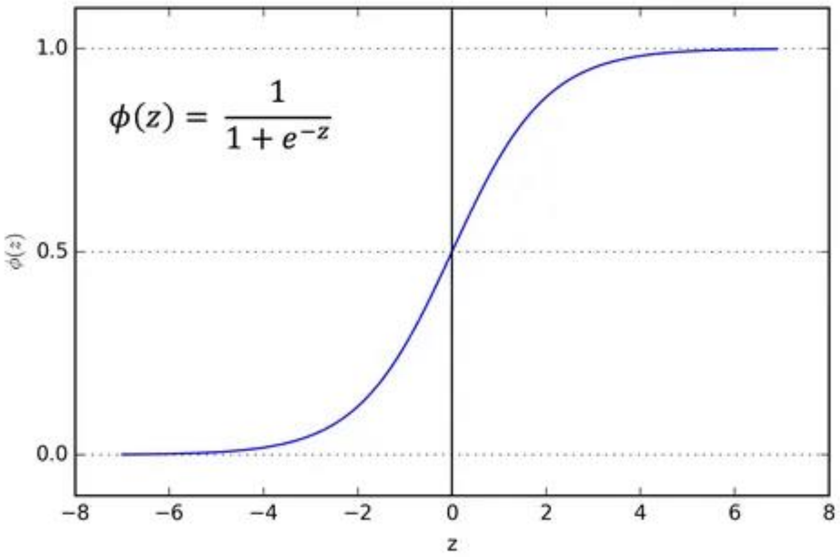

Fig. 10: Graph of sigmoid function [8].

Masking layer	LSTM layer	Dropout layer	Dense layer
Pads shorter sequences	270 units	Dropout_rate = 0.2	1 unit, sigmoid activation

LSTM: Long Short-Term Memory

Model results

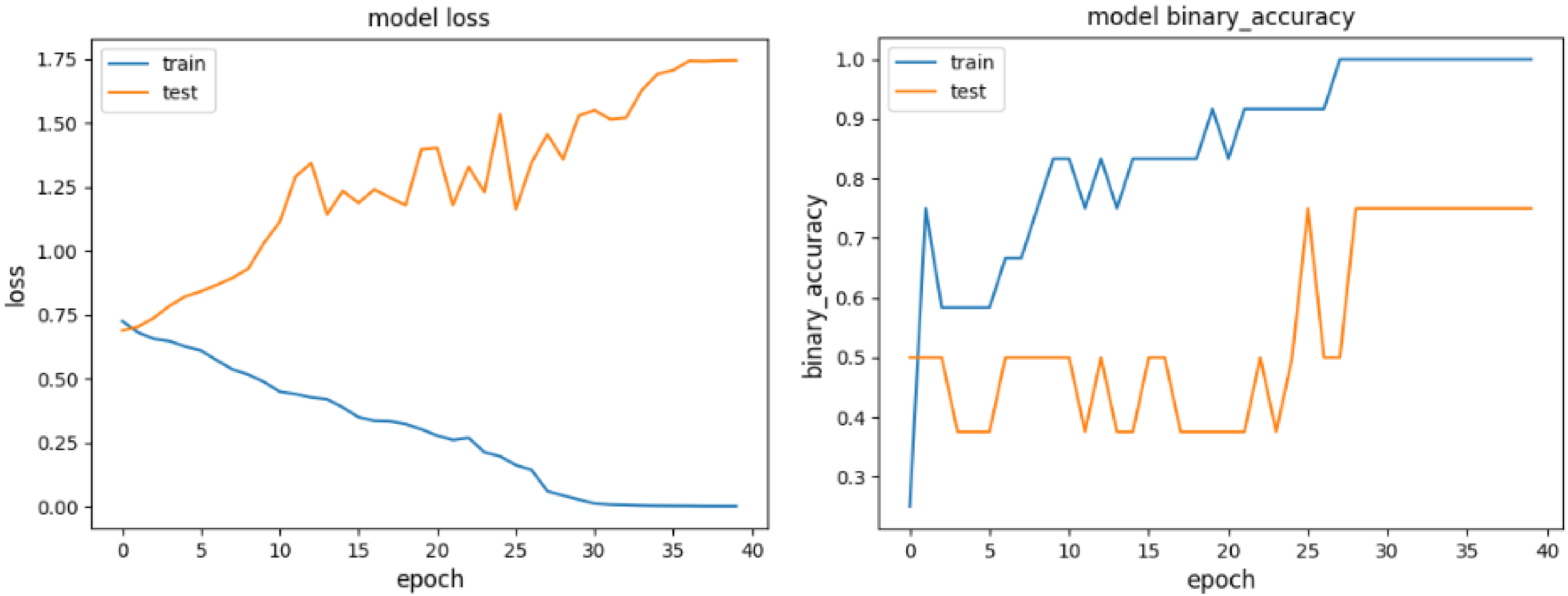

Fig. 11: Loss and Accuracy performance on training (12 samples) and test (8 samples) sets.

High Test Loss with High Test Accuracy: high prediction error on misclassified cases!

LSTM application findings

- Model is learning from training data and improving predictions
- Tendency to overfit — perfect training accuracy
- More training data needed
- Test set accuracy is 75%

Scope for model improvement:

- Feature selection
- Different feature scaling methods
- Explainable AI with ranked feature importance

LSTM: Long Short-Term Memory

Next steps: scaling!

- **Critical CDM time-series generation**
  - Cases which would typically involve humans
  - Database for training both humans/AI decision-makers
  - Work with GSOC analysts to classify events

- **Train LSTM model with more samples (~1000 events)**
  - How well can AI learn from time series data in this context?
  - Can it adapt to new target labels?

- **AI needs to be reliable and explainable**
  - Hybrid AI-human decision-making systems

LSTM: Long Short-Term Memory

CDM: Conjunction Data Message

GSOC: German Space Operations center

Thank you!

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Always open to questions, feedback, collaborations! 😊

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APPENDIX

Synthetic CDM series generation

1. Assume TCA stays constant across CDMs
   - Time to TCA ~ T-1 for last CDM, other CDMs ‘created’ at 8 hour intervals
2. Obtain ‘difference factors’ for CDM parameters
   - Trends from CDM series in the Kelvin dataset & GSOC events
3. Apply these to parameters that change over CDM series, for each object:
   - State vector (X, Y, Z, XDOT, YDOT, ZDOT)
   - 21 covariance terms
4. Convert states to RTN frame and calculate miss distance, relative state vector

Covariance needs to be symmetric and positive semi-definite!

TCA: Time of closest approach

CDM: Conjunction Data Message

GSOC: German Space Operations center

Synthetic CDM series generation

5. Ensure covariance is symmetric and positive semi-definite

- Covariance_posdef = Covariance x Covariance^{Transpose}
- Rescale to keep magnitudes realistic, with *Cov(T,T)* >> *Cov(R,R)* and *Cov(N,N)*

6. Calculate probability of collision with these perturbed CDM parameters

- PoC is a function of: states, covariances, and hard body radius of the 2 objects
- Hard body radius used in Privateer CDM found using optimization algorithm

Run Monte Carlo simulation with 1000 trials using the *randn* function on the difference factors

R: Radial direction in RTN frame

T: Along-track direction in RTN frame

N: Normal direction in RTN frame

CDM: Conjunction Data Message

Survey results

- Analysts did not agree on a maneuver decision for 4 out of 20 cases
- Characteristics of 4 'problem' cases:

	Analyst A	Analyst B	Analyst C
Case 1	(G) PoC above threshold, and is consistent	(N) Position uncertainties too high to decide	(G) PoC slightly above threshold
Case 2	(G) PoC slightly above threshold, consistent over CDMs	(N) PoC is critical, but wait for better position uncertainty	(G) Low normal separation
Case 3	(G) Critical PoC, PoC and radial separation are consistent	(N) PoC is critical, but wait for better position uncertainty	(G) Critical PoC, consistent over CDMs

PoC: Probability of Collision

CDM: Conjunction Data Message

Survey results

	Analyst A	Analyst B	Analyst D (not C)
Case 4	(G) Critical PoC	(N) High PoC, but high radial uncertainty in both objects	(G) Critical PoC

Analysts disagree when faced with:

- High position uncertainties
- Inconsistent CDM trends

Additional insights:

- With tie-breaker: 10 go's - 10 no-go's
- PoC maneuver threshold is 1E-4, but no covariance threshold
- 80% agreeability between analysts

PMAX: Maximum PoC

PoC: Probability of Collision

CDM: Conjunction Data Message

K value: Covariance scaling factor

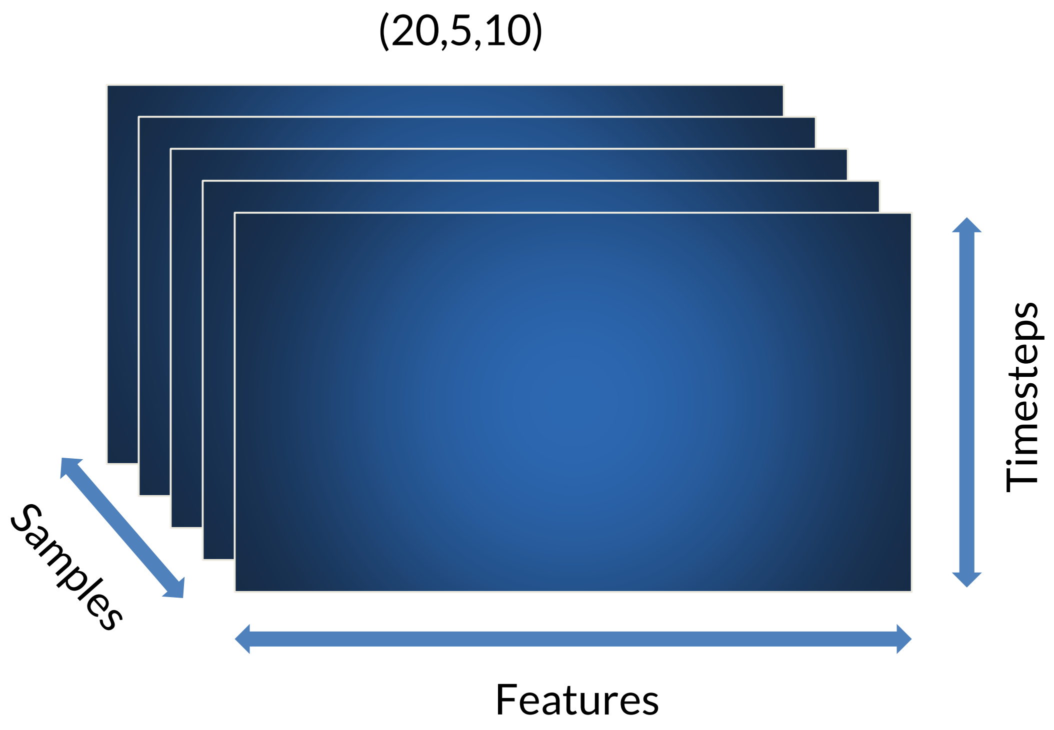
Data preparation

- Input data
    - n_samples = 20, number of cases to process
    - n_timesteps = 5, max. number of CDMs
    - n_features = 10 (PoC, miss distance, etc.)

- Feature scaling
    - Z-normalization

$$x_{scaled} = \frac{x - \mu}{\sigma}$$

- Pad shorter sequences with '9's — to be ignored by model



x : value from series
μ : mean of series
σ : standard deviation of series

Parameter selection and model setup

- Hyperparameter tuning
  - KerasTuner
- Gradient-based optimization: Adam optimizer
  - Fast convergence
  - Adaptive learning rate
- Loss function: Binary cross-entropy
  - $-[\, y * \log(p) + (1 - y) * \log(1-p)]$
  - y: true label, p: prediction
- Performance metric: test accuracy
  - Evenly split classes

Parameter	Value
LSTM layer units	270
Learning rate	0.001
Dropout rate	0.2
Epochs	35
Batch size	2

LSTM: Long Short-Term Memory
Adam: ADAptive Moment estimation