

Workshop on Collision Avoidance Challenge Results

Introduction

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ESA UNCLASSIFIED – Releasable to the Public





https://kelvins.esa.int/collision-avoidance-challenge/



Motivation

Recap Challenge

Challenge Preparation



Motivation





From manual expert work....





... to machine learning





ESOC: database of > 250 000 close approach events

Predict "criticality", e.g. final separation, mimic past decisions

The Challenge

Public challenge held late 2019 running 2 months First ever public release of a large set of CDMs

- Only mildly anonymised

Pilot to assess whether ML can help assessing conjunctions

- Engage/attract data scientists
- (i.e. not necessarily experts in debris / flight dynamics)

96 participants, 862 submissions



Results





Today, active **collision avoidance** among orbiting satellites has become a routine task in space operations, relying on validated, accurate and timely space surveillance data. For a typical satellite in Low Earth Orbit, hundreds of alerts are issued every week corresponding to possible close encounters between a satellite and another space object (in the form of **conjunction data messages CDMs**). After automatic processing and filtering, there remain about 2 actionable alerts per spacecraft and week, requiring detailed follow-up by an analyst. On average, at the European Space Agency, more than one collision avoidance manoeuvre is performed per satellite and year.

In this challenge, you are tasked to build a model to predict the final collision risk estimate between a given satellite and a space object (e.g. another satellite, space debris, etc). To do so, you will have access to a database of real-world conjunction data messages (CDMs) carefully prepared at ESA. Learn more about the challenge and the data.



This competition is organized by ESA's Advanced Concepts Team (ACT) in partnership with ESA's Space Debris Office

Experts from both teams are available for interactions via the competition discussion page.

Results

Challenge

Best Last

Kelvins About Competitions Collision Avoidance Challenge



Home

Challenge Data Submission Rules Rules Scoring Results Leaderboard

Discussion

Challenge Preparation



How data looks like?

event_id	time_to_tca	mission_id	risk	max_risk_ r	max_risk_scaling	miss_distance	relative_speed	relative_position_r	relative_position_t	relative_position_n	relative_velocity_r	relative_velocity_t	relative_velocity_n t_tim
(1.566798229	5	-10.205	-7.83476	8.602100967	14923	13792	453.8	5976.6	-13666.8	-7.2	-12637	-5525.9
	1.207493507	5	-10.3558	-7.84894	8.956373809	14544	13792	474.3	5821.2	-13319.8	-7	-12637	-5525.9
(0.952192743	5	-10.3456	-7.84741	8.932195119	14475	13792	474.6	5796.2	-13256.1	7	-12637	-5525.9
(0.579669363	5	-10.3378	-7.84588	8.913444064	14579	13792	472.7	5838.9	-13350.7	-7	-12637	-5525.9
(0.257806042	5	-10.3913	-7.85294	9.036838245	14510	13792	478.7	5811.1	-13288	-7	-12637	-5525.9
1	6.530455104	5	-7.5613	-7.2543	2.746781823	2392	3434	74.3	2317.1	-589.4	25.9	-847.8	-3328.2
1	5.561646088	5	-9.31569	-7.4689	7.223137485	3587	3434	99	3475.4	-885.1	. 24.7	-847.8	-3328.2
1	5.226503738	5	-7.42251	-7.051	2.956639138	7882	3434	-50	-7638.3	1945.7	36.8	-847.7	-3328.2
1	3.570013079	5	-9.24811	-7.32753	7.425994268	26899	3434	-82	-26067	6638.2	56.8	-847.8	-3328.2
2	6.983473519	2	-10.8162	-6.60171	13.29315867	22902	14348	-1157.6	-6306.2	21986.3	15.8	-13792	-3957.1
2	6.691610521	2	-10.8505	-6.60345	13.3742415	22966	14348	-1161.1	-6330.2	22046.3	15.8	-13792	-3957.1
1	6.269979225	2	-30	-6.21796	426.8085319	18785	14347	-698.8	-5176.4	18044.8	14.4	-13791.4	-3957.2
2	6.04235213	2	-30	-6.27108	181.4967781	18842	14347	-700	-5192.1	. 18099.4	14.4	-13791.4	-3957.2
2	5.711715972	2	-30	-6.27745	187.5253596	19015	14347	-709.9	-5242.1	18264.8	14.5	-13791.4	-3957.2
2	5.377642257	2	-30	-6.27827	190.0905681	. 19137	14347	-710.3	-5273.6	18382.8	14.5	-13791.4	-3957.2
2	5.02891463	2	-30	-6.28325	188.2700588	18918	14347	-714.8	-5213.9	18172	14.5	-13791.4	-3957.2
2	4.724354919	2	-30	-6.28358	192.1005632	19152	14347	-717.5	-5277.4	18397.2	14.5	-13791.4	-3957.2
2	4.334353623	2	-30	-6.52462	1984.965171	18635	14347	-704.3	-5134.8	17900	14.4	-13791.4	-3957.2
1	4.055291782	2	-30	-6.27051	404.8873209	18789	14347	-700.7	-5177.3	18048.3	14.4	-13791.4	-3957.2
2	3.692814988	2	-30	-6.27165	408.1050061	18826	14347	-698.8	-5187.4	18084.4	14.4	-13791.4	-3957.2
1	3.358613426	2	-30	-6.26313	393.7434614	18715	14347	-690.8	-5155.7	17978.5	14.4	-13791.4	-3957.2
1	2 2.886460741	2	-30	-6.26344	397.1047409	18748	14347	-686.8	-5171.4	18008.5	14.4	-13791.4	-3957.2
2	2.340627465	2	-30	-6.26624	401.442549	18763	14347	-692.9	-5175.6	18022.2	14.4	-13791.4	-3957.2
1	1.883868252	2	-30	-6.26809	403.494416	18753	14347	-700.1	-5172.4	18012.1	. 14.4	-13791.4	-3957.2
1	1.68578941	2	-30	-6.26737	399.2433736	18709	14347	-703	-5160.9	17970	14.4	-13791.4	-3957.2
2	1.363231435	2	-30	-7.1943	6711.316427	18686	14347	-733.1	-5153.3	17947	14.4	-13791.4	-3957.2
2	1.042884213	2	-30	-7.19017	6592.133467	18666	14347	-732.2	-5146.1	17928.3	14.4	-13791.4	-3957.2
2	0.602016169	2	-30	-7.19736	6804.742777	18692	14347	-727	-5148.4	17954.6	14.4	-13791.4	-3957.2
2	0.40194684	2	-30	-7.44928	37296.16821	18708	14347	-717.9	-5159	17968.9	14.4	-13791.4	-3957.2 7

What do we want to predict?





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What do we want to predict?





Max Risk 3 days in advance

Max Risk 2 days in advance

Max Risk 1 day in advance

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How are we Scoring submissions?





Score



How we came up with ...

$scoring = \frac{MSE}{F2}$

- Classification: probability above or below 10⁻⁶: F2 value
- Regression for those above 10⁻⁶: MSE

Long story short: it took us 5 iterations

Log10(risk) ... if log10(risk) > -30





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→ THE EUROPEAN SPACE AGENCY

Scoring Function (I)



MSE(log(risk)): Mean Squared Error

Issues

- All errors are equally important
- -6 → -3 >>> -26 → -23



Scoring Function (II)





MSE * true_risk

Higher risk events are more important

Issues

- candidates could always predict high risk and not being penalized appropriately
- Would lead to false alarms

Scoring Function (III)





Scoring Function (IV)





- Need to tell the difference between:
 - High risk events (risk > 1e-6)
 - Low risk events (risk < 1e-6)

Classification	
F1	

Scoring Function (IV)



$scoring = \frac{MSE}{F1}$

But ... F1 gives equal importance to False Positive & False Negatives

For collision avoidance we can accept false positives but don't want to miss potential risks

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Scoring Function (V)



$scoring = \frac{MSE}{F2}$

F2 penalises (more than F1) the false negatives

Details see also <u>https://link.springer.com/article/10.1007/s42064-021-0101-5</u>

There is more to it ...

- Lots of data preparation (data cleaning, missing data, deciding which data ...)
- Data Anonymization
- Code / Version control (gitlab.esa.int)
- Permissions to release the data
- Meetings / Telecons / presentations / mails

https://www.m eetup.com/Fra

nkfurtDataScie

nce/events/255

952732/

• Media outreach

FRANKFURT DATA SCIENCE



ENABLING & SUPPORT

AI challenged to stave off collisions in space



Interested in taking part in a rubbish challenge? 🔧 🕅

To manoeuvre or not to manoeuvre... that's the question posed by ESA's **#SpaceDebris** Office and Advanced Concepts Team.

Find out more: esa.int/Our_Activities...

#MachineLearning #AI @ESAcleanspace



5:03 PM · Oct 9, 2019 · Twitter Web App

https://www.esa.int/Enabling_Support/Space_Engineering_Techn ology/AI_challenged_to_stave_off_collisions_in_space

Team Work



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Collision Avoidance Challenge

To manoeuvre or not to manoeuvre ... that is the question.

https://kelvins.esa.int/collision-avoidance-challenge/

👤 Take Part

16:30 \rightarrow 16:50 Introduction (ESA)

16:50 \rightarrow 17:10 Engineered Decision Tree for Judging Spacecraft Collision Risks, Sven Rehban (Honda Research Institute Europe)

17:10 \rightarrow 17:30 Learning from an imbalanced dataset of conjunction data messages, Rasit Abay (NeuraSpace)

17:30 \rightarrow 17:50 Machine learning-powered algorithms for predicting the risk of satellite collisions, Michal Myller (KP Labs)

17:50 → 18:10 **Outlook (ESA)**