# International Workshop on Machine Learning for Space Weather: Fundamentals, Tools and Future Prospects International Centre for Theoretical Physics

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022



On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment

## Renato Filjar,

Laboratory for Spatial Intelligence,
University of Applied Sciences Hrvatsko Zagorje Krapina,
Krapina, CROATIA

# International Workshop on Machine Learning for Space Weather: Fundamentals, Tools and Future Prospects Pugget Airco Argenting 7th November 2022 11th November 2022

Buenos Aires, Argentina, 7th November, 2022 - 11th November, 2022

- Content
- Machine learning-based model development
- Model performance assessment
- Case study of GNSS ionospheric delay correction model performance assessment
- Discussion

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

## All models are wrong, but some are useful.

G E P Box

Box, G E P. (1979). Robustness in the strategy of scientific model building (report).

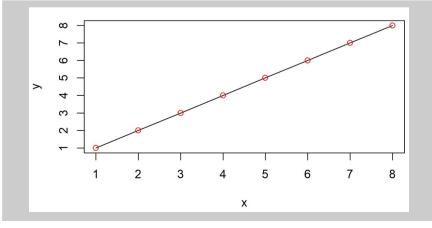
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

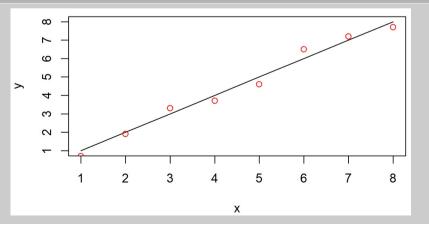
- Rationale and nature of statistical modelling
- A model of a phenomenon or a system is a main outcome of every research. → description, or prediction

Ideal world (Mathematics)

$$y = ax + b$$



Real world (Statistics)  $y=ax+b+\epsilon$  $\hat{y}=\hat{a}x+\hat{b}$ 



Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

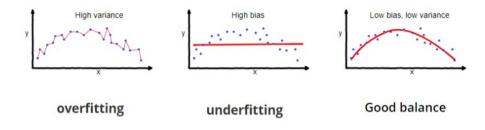
## Machine learning

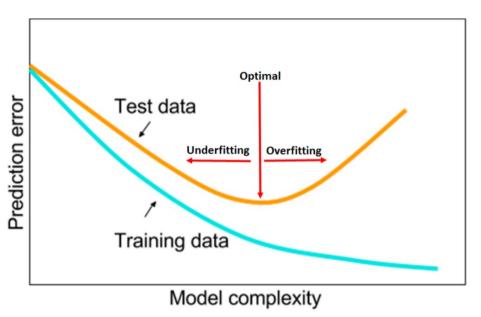
- A set of statistics-based methods for predictive or descriptive model development based on observations (a sample of population) of a statistical variable, or variables
- Original observations set split randomly into: training, and testing sub-sets (Pareto principle, or other)
- Supervised, unsupervised, and reinforcement learning
- Scientific methodology (a common-sense methodology): problem statement, data selection, statistical analysis of data (properties), model structure and model development method definition (hypothesis), model development, model performance assessment → decision on the model to solve the problem in the most efficient manner (optimisation, inference)

Buenos Aires, Argentina, 7th November, 2022 - 11th November, 2022

- Underfitting and overfitting
- Statistics as a tool for detection, identification, and extraction of hidden knowledge in data
- Statistics as the means for 'finding the signal in the noise'.
- Silver, N. (2015). The Signal and the Noise: Why So ManyPredictions Fail – but Some Don't. Penguin Books. New York, NY.







Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

- Bias vs Variance the need for a balance
- Bias as a representation of systematic error

Variance as a representation of a random error Source: https://medium.com/ almabetter/bias-variancetradeoff-c8c2a0fb643e **Model Complexity** Trade-off fit Overfit Underfit Medium Bias - Medium variance High Bias - Low variance Low Bias - High variance

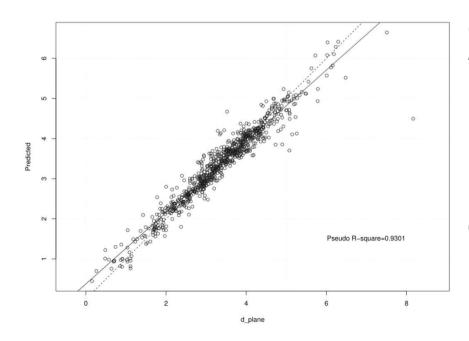
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

- Model performance assessment Goodness of fit
- Predicted vs observed target values of the testing sub-set

# Predicted vs Observed (P-O) diagram

Source: Filić, M, Filjar, R. (2018). ISBN 978-613-9-90118-0.



Statistical tests Pearson  $\chi^2$  test

$$\chi^2 = \frac{\sum_{i=1}^{N} (O_i - E_i)^2}{E_i}$$

 $O_i$  denotes observed count of bin I  $E_i$  denotes en expected count of bin I, defined as:

$$E = [F(Y_u) - F(Y_l)]N$$

Determined  $\chi^2$  value is then examined for conformance with  $\chi^2$  statistical distribution

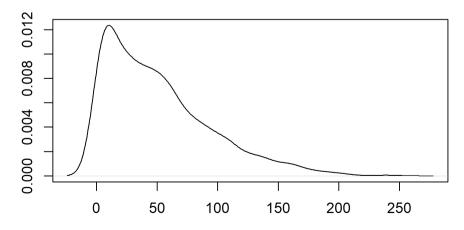
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

- Model performance assessment Statistical distribution of residuals
- residual = predicted value observed value (for the same set of predictors values)
- A new statistical variable

# Box-plot diagram

#### **Experimental probability density function**



Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

 Model performance assessment - Is my model good (enough)?

```
Call:
lm(formula = y \sim x2 + x3)
Residuals:
            10 Median
    Min
                           30
                                 Max
-4818.1 -2745.4 -639.2 2035.2 7487.4
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) -7507.67
                       695.51 -10.795 < 2e-16 ***
              28.04
x2
                        40.23 0.697
                                        0.487
                        32.73 6.835 7.27e-10 ***
x3
             223.70
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 3243 on 97 degrees of freedom
Multiple R-squared: 0.9426, Adjusted R-squared: 0.9414
F-statistic: 796.4 on 2 and 97 DF, p-value: < 2.2e-16
```

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

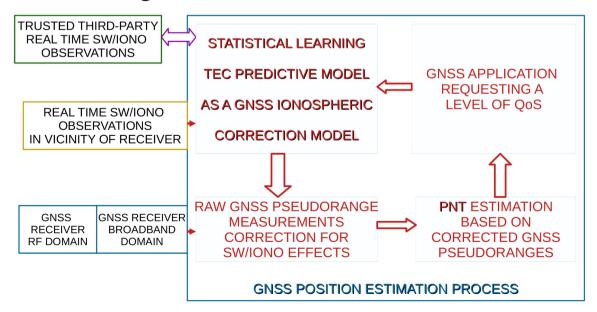
- Model performance assessment Essential model performance indicators
- P-O diagram
- RMSE
- adjR2
- statistical significance of predictors
- comparison with bechmark/reference model preformance in the same scenario/case study

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

# Case study of GNSS ionospheric delay correction model performance assessment

- Self-adaptive environment-aware Software-Defined Radio (SDR) GNSS position estimation algorithm
- Adaptive GNSS ionospheric delay correction model for shortterm rapidly developing geomagnetic storm in sub-equatorial region



#### Reference:

Filjar, R. (2022). Statistical learning TEC predictive model for GNSS ionospheric delay mitigation in self-adaptive environment - aware SDR GNSS position estimation algorithm. The United Nations/Azerbaijan Workshop on the International Space Weather Initiative: The Sun, Space Weather and Geosphere. Baku, Azerbaijan.

Available at: https://www.unoosa.org/documents/pdf/psa/activities/2022/ISWI2022/s6 01.pdf

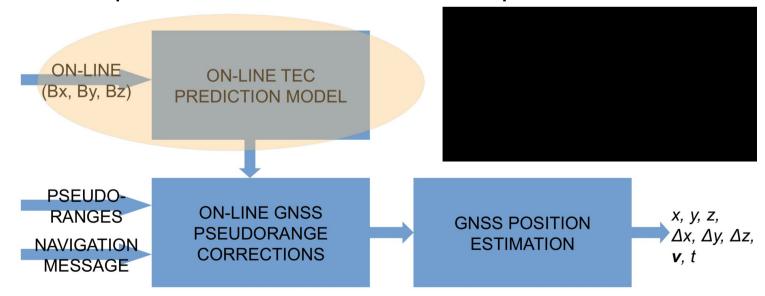
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

#### Case study reference:

Filjar, R, Weintrit, A, Iliev, T, Malčić, G, Jukić, O, Sikirica, N. (2020). doi: https://doi.org/10.23919/FUSION45008.2020.9190264

- Case study of GNSS ionospheric delay correction model performance assessment
- Positioning environment situation awareness → geomagnetic field observation in the time and the place of positioning
- Self-adaptivness → S/M L-based TEC prediction model

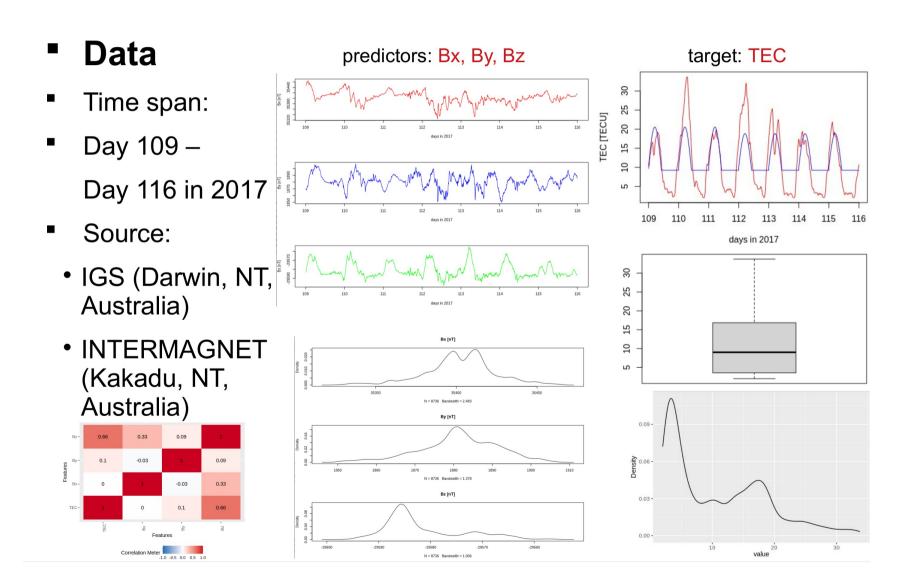


Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

- Case study of GNSS
   ionospheric delay correction
   model performance
   assessment
- Geomagnetic field observations taken at the Intermagnet Kakadu, NT, Australia reference station
- GNSS pseudorange observations taken at the IGS Darwin, NT, Australia reference station
- A short-term rapidly developing geomagnetic storm, identified by its Dst patterns



Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022



Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

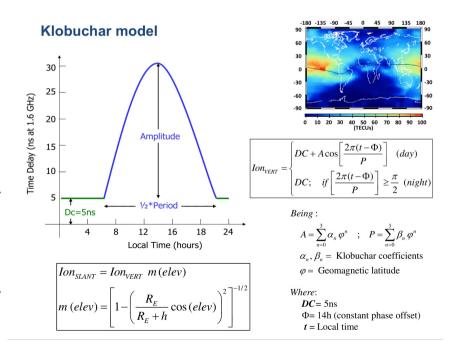
- Case study of GNSS
   ionospheric delay
   correction model
   performance assessment
- Source:

Sanz Subirana, J, Juan Zornoza, J M, Hernández-Pajares, M. (2013). GNSS Data Processing, Volume I: Fundamentals and Algorithms. ESA. Noordwijk, The Netherlands. ISBN 978-92-9221-886-7.

Available at:

https://gssc.esa.int/navipedia/GNSS\_Book/ESA\_GNSS-Book\_TM-23\_Vol\_I.pdf

- Geomagnetic field observations-based candidate models:
- LRM ... Linear Regression Model
- MMLPNN ... Monotone Multi-layer Perceptron Neural Network Model
- RFM ... Random Forest Model,
- Klobuchar ... standard GPS Klobuchar Model



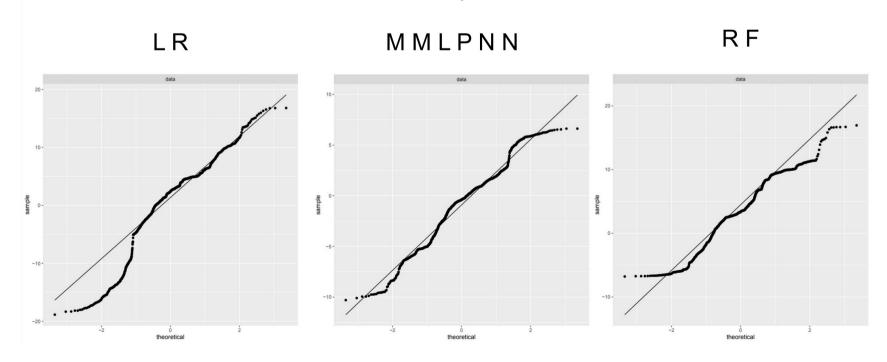
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

- Case study of GNSS ionospheric delay correction model performance assessment
- Machine learning-based methods for model development

LINEAR REGRESSION (LR)	MONOTONE MULTI-LAYER PERCEPTRON NEURAL NETWORK (MMLPNN)	RANDOM FOREST (RF)
$\hat{y} = \beta_0 + \sum_{i=1}^{3} \beta_i x_i$ $\hat{x} = (x_1 = B_x, x_2 = B_y, x_3 = \hat{B}_z)$	$ \hat{y}(x) = w_b + \sum_{l=1}^{L} w_l \tanh \cdot \left( w_{b,l} + \sum_{h=1}^{H} w_{l,h} \tanh \left( w_{b,h} + \sum_{i=1}^{I} w_{h,i} x_i \right) \right) $ $ \frac{\partial \hat{y}}{\partial x_j} = \sum_{l=1}^{L} w_l \cdot (1 - \theta_1^2) \cdot \sum_{l=1}^{H} w_{l,h} \cdot (1 - \theta_2^2) \cdot w_{h,j} \ge 0 $ $ \theta_1 = \tanh \left( w_{b,l} + \sum_{h=1}^{H} w_{l,h} \tanh \left( w_{b,h} + \sum_{i=1}^{I} w_{h,i} x_i \right) \right) $ $ \theta_2 = \tanh \left( w_{b,h} + \sum_{i=1}^{I} w_{h,i} x_i \right) $	DECISION

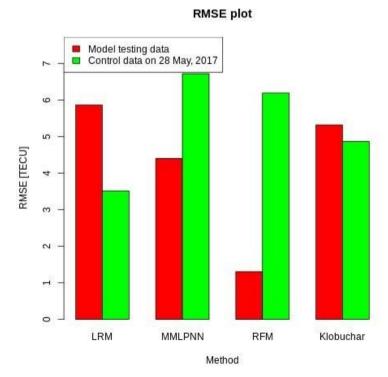
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

- Case study of GNSS ionospheric delay correction model performance assessment
- Model performance assessment q-q diagrams (conformity of residuals to normal distribution)



Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

- Case study of GNSS ionospheric delay correction model performance assessment
- Model performance assessment bias
- Root Means Square Error (RMSE)
- LRM ... Linear Regression Model
- MMLPNN ... Monotone Multi-layer Perceptron Neural Network Model
- RFM ... Random Forest Model,
- Klobuchar ... standard GPS Klobuchar Model



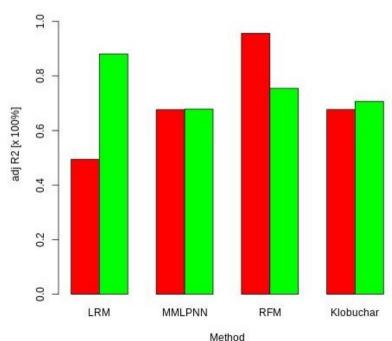
Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

- Case study of GNSS ionospheric delay correction model performance assessment
- Model performance assessment variance
- Adjusted coefficient of determination
- adjR2 parameter → for objective comparison of described original

$$R^{2} = 1 - \frac{\sum_{i=1}^{N} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i=1}^{N} (y_{i} - \bar{y})^{2}}$$

$$adjR2 = 1 - (1 - R^{2}) \cdot \frac{s_{N} - 1}{s_{N} - p}$$



adj R2 plot

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

## **Discussion**

- Essential practical methodology for a machine learning-, and observations-based predictive model performance assessment is outlined, for the purpose of GNSS-related ionospheric delay correction model development
- A case study of a machine learning self-adaptive positioning (i. e. geomagnetic) environment-aware GNSS ionospheric delay model development, and its performance assessment is presented in the scenario of short-term raoidly developing geomagnetic storm in sub-equatorial region
- Future research: model development for classes of short-term rapidly developing storms, battery of statistical tests to be selected for usage in model performance assessment, computational requirements to be defined in distributed positioning environment

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

### Reference list

- Filjar, R. (2022). An application-centred resilient GNSS position estimation algorithm based on positioning environment conditions awareness. Proc ION ITM 2022, 1123 1136. Long Beach, CA. doi: 10.33012/2022.18247
- Filjar, R, Weintrit, A, Iliev, T, Malčić, G, Jukić, O, Sikirica, N. (2020). Predictive Model of Total Electron Content during Moderately Disturbed Geomagnetic Conditions for GNSS Positioning Performance Improvement. Proc FUSION2020, 256-262. Sun City, South Africa. doi: https://doi.org/10.23919/FUSION45008.2020.9190264
- Filić, M, Filjar, R. (2019). On correlation between SID monitor and GPS-derived TEC observations during a massive ionospheric storm development. URSI AP-RASC 2019 Meeting. New Delhi, India. doi: 10.23919/URSIAP-RASC.2019.8738664
- Filić, M, and Filjar, R. (2018). Forecasting model of space weather-driven GNSS positioning performance (monograph). Lambert Academic Publishing. Riga, Latvia. ISBN 978-613-9-90118-0.
- Filić, M, Filjar, R. (2018). Modelling the Relation between GNSS Positioning Performance Degradation, and Space Weather and Ionospheric Conditions using RReliefF Features Selection. Proc of 31st International Technical Meeting ION GNSS+ 2018, 1999-2006. Miami, FL. doi: https://doi.org/10.33012/2018.16016
- Filić, M, Grubišić, L, Filjar, R. (2018). Improvement of standard GPS position estimation algorithm through utilization of Weighted Least-Square approach. Proc of 11th Annual Baška GNSS Conference, 7-19. Baška, Krk Island, Croatia. Available at: <a href="https://www.pfri.uniri.hr/web/hr/dokumenti/zbornici-gnss/2018-GNSS-11.pdf">https://www.pfri.uniri.hr/web/hr/dokumenti/zbornici-gnss/2018-GNSS-11.pdf</a>

Buenos Aires, Argentina, 7th November, 2022 – 11th November, 2022

On performance assessment of machine learning-based GNSS ionospheric delay correction model based on space weather predictors in immediate positioning environment (R Filjar, *Croatia*)

## Reference list

- Maindonald, J, John Brown, W. (2010). Data Analysis and Graphics Using R: An Example-Based Approach (3rd). Cambridge University Press. Cambridge, UK. ISBN 9781139194648
- Lindholm, A, Wahlström, N, Lindsten, F, and Schön, T B. (2022). Machine Learning – A First Course for Engineers and Scientists. Cambridge University Press. Cambridge, UK. ISBN: 9781108843607. Available at: http://smlbook.org/
- James, G, Witten, D, Hastie, T, Tibshirani, R. (2021). An Introduction to Statistical Learning with Applications in R. Springer Verlag. ISBN 978-1071614174. Available at: https://www.statlearning.com/
- Efron, B, Hastie, T. (2016). Computer Age Statistical Inference: Algorithms, Evidence and Data Science. Cambridge University Press. Cambridge, UK. ISBN 9781107149892. Available at: https://hastie.su.domains/CASI/order.html
- Biecek, P, Burzykowski, T. (2020). Explanatory Model Analysis: Explore, Explain, and Examine Predictive Models. With examples in R and Python. CRC Press. Boca Raton, FL. ISBN 9780367135591. Available at: https://ema.drwhy.ai/

