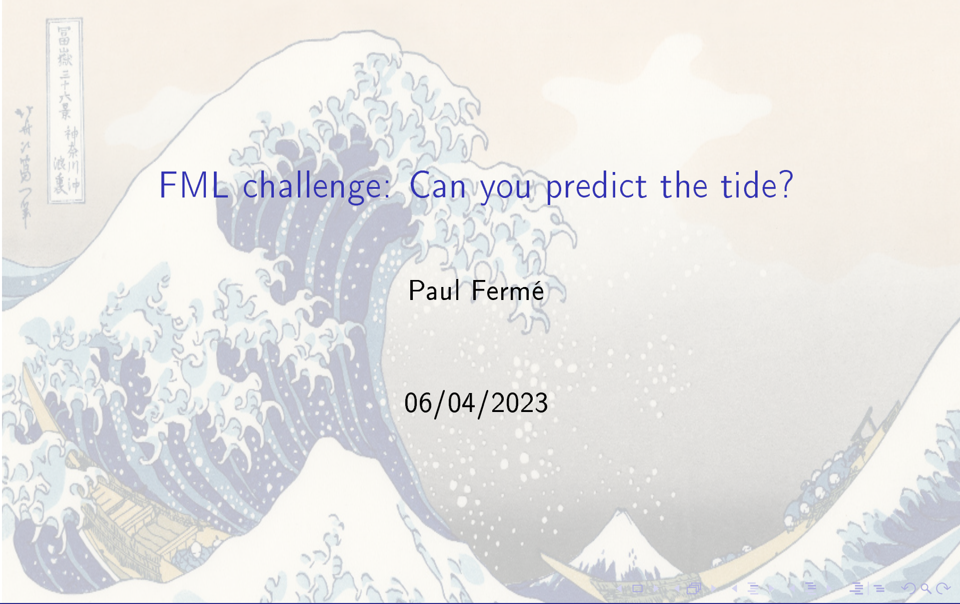

FML challenge: Can you predict the tide?

Paul Fermé

06/04/2023

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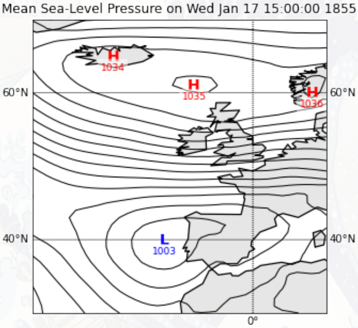
- *Tide* composed of astronomical tide and radiational tide. *Easily predicted.*
- *Surge* is the difference between observed sea level and *tide*. *Critical importance for safety reasons.*

Data description



- Sea-level pressure field (SLP).
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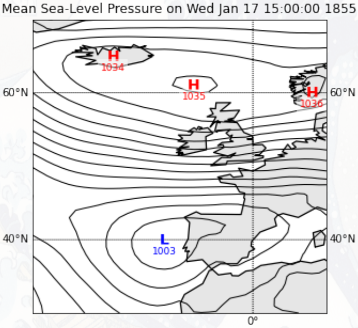

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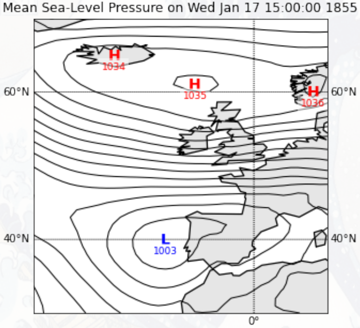

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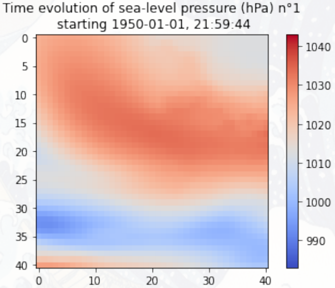
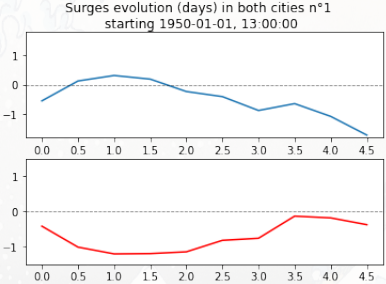
- Output: Surges on next five days.

Example data

Input:





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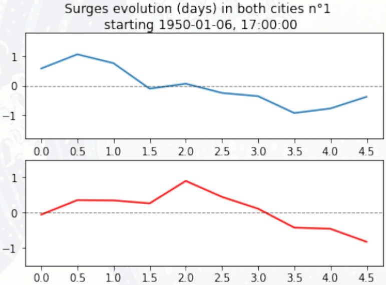

Benchmark: K-nearest neighbors

- Metric: L^2 loss function, weight $(1, 0.9, \ldots, 0.1)$.

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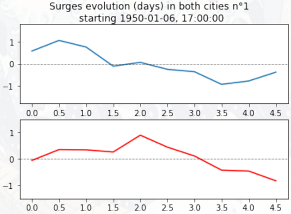
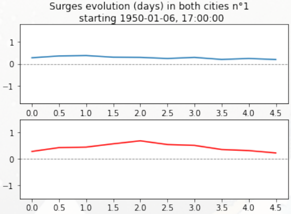


True surges



Benchmark prediction

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- Normalize the data:
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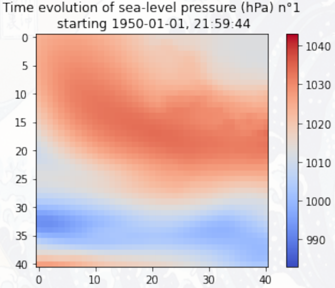
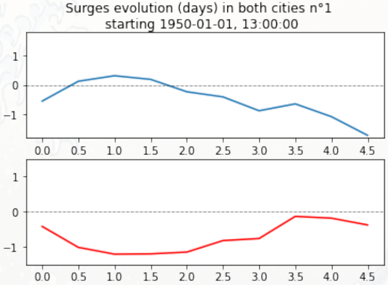
- $<6\%$ difference with the best solution online (0.4419).

On an example





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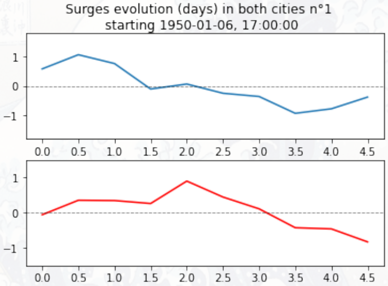

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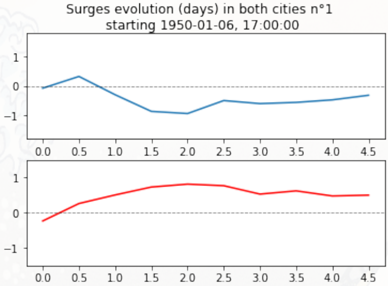

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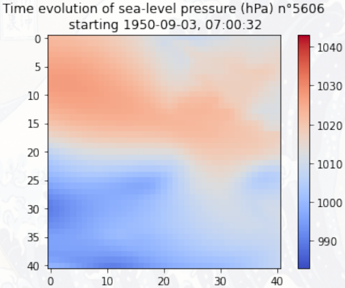

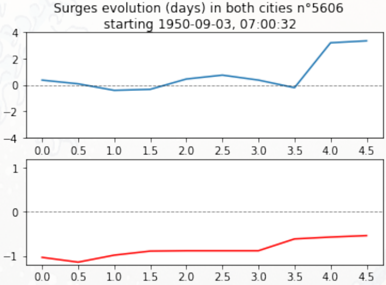

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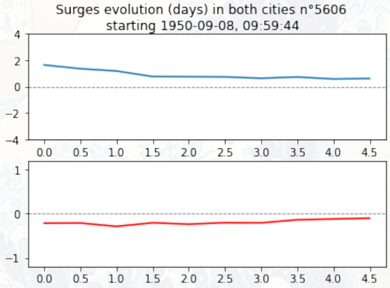

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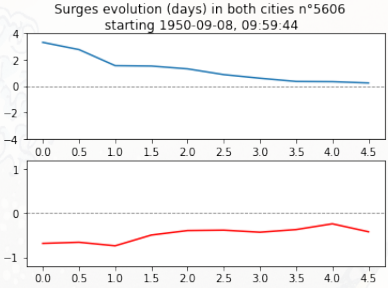

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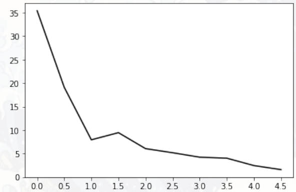
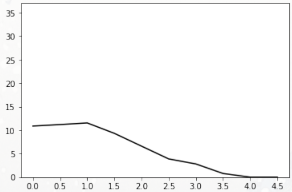


Second to last surge input influence (%var) on the surge evolution (days) in city 1



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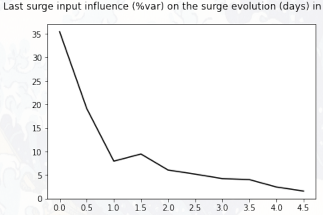

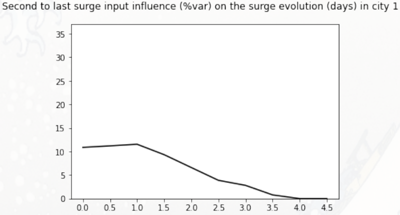

- Time: 6.6% (resp. 5.3%) variance increase every 10 years in city 1 (resp. 2). *Global warming?*

Issues and other attempted methods

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  1. Windows of data over 5 days, but samples every day.
  2. If one takes only unoverlapped data, test efficiency decreases.
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- Neural Network instead of Lasso regression? Either overfits or behaves poorly compared to Lasso.

Conclusion and further directions

- We have developped a simple method, using only PCA and Lasso regression, to predict sea surges.
- Explains $> 50\%$ of variance (benchmark 23%, best 56%).
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- *Thank you!*


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