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Autor

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Autor

TITULO

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Orientador: Prof. Dr. Romulo Gonçalves Lins

Coorientador: Prof. Dr. Ricardo Gaspar

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Profa. Dra. Franciane Freitas Silveira - Examinadora Interna Suplente

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Obrigado a todos

Epígrafe

*“Learn from the mistakes of those who followed your advice”
(Unknown author)*

Abstract

Machine learning methods have become a powerful tool for the academic community in recent decades. In the field of computational fluid and thermodynamics, these methods have been used to perform fast inferences on unseen parameters, reducing the computational burden associated with traditional numerical methods. Most works in this field focus on predicting scalar global or integrated parameters. However, this work introduces a new machine learning data-driven flow reconstruction method that can reconstruct entire flow fields using singular value decomposition as a dimensionality reduction technique. Additionally, we conducted a study on the impact of the number of selected modes for dimensionality reduction on the overall performance metrics and other hyperparameters for neural network performance. We also compared the performance of neural networks with the Kriging method. The main results showed that shallow neural networks with sigmoid activation functions performed better than deep neural networks, and the Kriging method was faster and more accurate than the neural networks. The best models obtained so far have demonstrated their viability as accurate surrogate models.

Keywords: Fourth Industrial Revolution; Data-Driven Culture; Computer Vision systems; Quality control; Statistical process control

Resumo

Métodos de aprendizado de máquina tornaram-se uma ferramenta poderosa para a comunidade acadêmica nas últimas décadas. No campo da fluidodinâmica computacional e da termodinâmica, esses métodos têm sido usados para realizar inferências rápidas sobre parâmetros não vistos, reduzindo a carga computacional associada aos métodos numéricos tradicionais. A maioria dos trabalhos nesse campo concentra-se em prever parâmetros globais ou integrados escalares. No entanto, este trabalho introduz um novo método de reconstrução de fluxo baseado em dados de aprendizado de máquina que pode reconstruir campos de fluxo inteiros usando a decomposição de valores singulares como técnica de redução de dimensionalidade. Além disso, conduzimos um estudo sobre o impacto do número de modos selecionados para redução de dimensionalidade nas métricas de desempenho geral e em outros hiperparâmetros para o desempenho de redes neurais. Também comparamos o desempenho de redes neurais com o método de Krigagem. Os principais resultados mostraram que redes neurais rasas com funções de ativação sigmoide tiveram um desempenho melhor do que redes neurais profundas, e o método de Krigagem foi mais rápido e preciso do que as redes neurais. Os melhores modelos obtidos até agora demonstraram sua viabilidade como modelos substitutos precisos.

Palavras-chave: Indústria 4.0; Cultura de Dados; Sistemas de visão computacional; Qualidade; Controle estatístico de processo

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Introduction

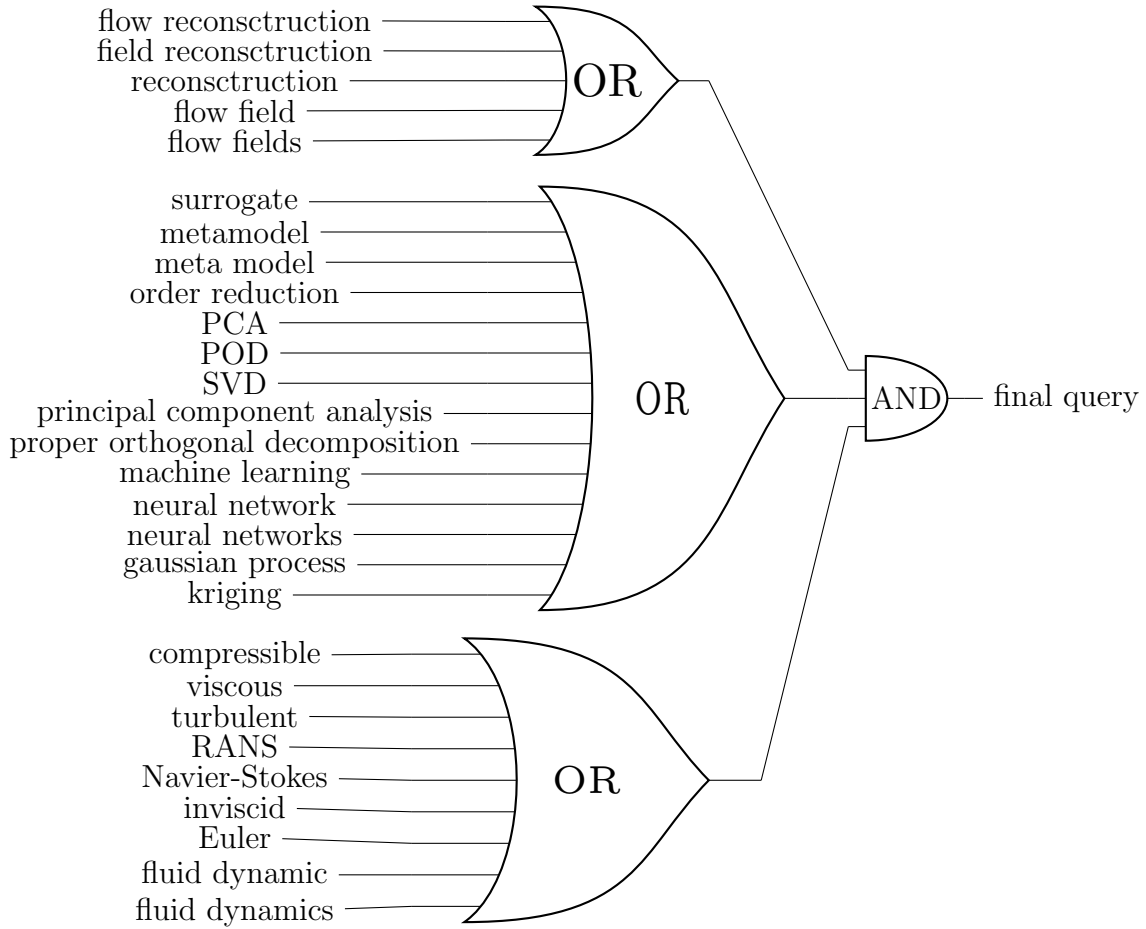
Definition of ML method

"ML is a subfield of AI. It can be defined as a set of methods and algorithms for estimating the relationship between some inputs and outputs with the help of a number of trainable parameters. The learning of these parameters, that is, their optimization with respect to a given metric, is achieved in an iterative manner by comparing the model predictions against ground truth data or evaluation of the model performance."?

1.1 Bibliography Review

A bibliometric review was conducted by search for the most relevant (to the authors knowledge) keywords in the field of present work scopus. These keywords were properly organized using the boolean operators in order to avoid returning uncorrelated works and to be broader as possible. They are:

```
( "flow reconstruction" OR "field reconstruction" OR "reconstruction"
OR "flow field" OR "flow fields") AND ("surrogate" OR "metamodel" OR
"meta model" OR "order reduction" OR "reduced order" OR "PCA" OR "POD"
OR "SVD" OR "principal component analysis" OR "singular value
decomposition" OR "proper orthogonal decomposition" OR "machine
learning" OR "neural network" OR "neural networks" OR "gaussian
process" OR "kriging" ) AND ( "compressible" OR "viscous" OR "
turbulent" OR "RANS" OR "Navier-Stokes" OR "inviscid" OR "Euler" OR "
fluid dynamic" OR "fluid dynamics" ) AND ( "data-driven" OR "data
driven" )
```



Numerical methods for multiphysics simulations of fluid dynamics are mature and widely used in industrial and academic applications. However, reducing the computational costs associated with these methods is still a must. Machine learning techniques like Kriging and Neural Networks have emerged as viable alternatives to build surrogate models for traditional numerical methods, with direct applications in tasks such as optimization, inverse problems, and uncertainty quantification. In this work, we explore a data-driven flow reconstruction method that can predict high-fidelity multiphysics flows using low-fidelity flow simulations as input.

Previous research mostly focused on scalar and integrated quantities. In contrast, our work focuses on predicting entire flow fields, allowing the method to capture flow structures such as shock formation and highly non-linear heat flux distributions over supersonic Convergent-divergence nozzle walls.

The number of variables required to represent multidimensional flow fields can be very large, resulting in impractically large neural networks or Kriging methods. To tackle this issue, we employ principal component analysis (PCA) decomposition as an order reduction technique. An important aspect of this work is studying the impact of the chosen reduced dimensionality on the accuracy of the surrogate model.

In ? the authors addresses the problem of select the best rank k of a SVD decomposition to accurately reconstruct a given dataset. Some methods ranges from evaluation of variance

or entropy content in the latent space. The authors also introduced new criteria known as Kullback-Leibler and anomaly detection. This highlights the importance of appropriate selection of reduced basis rank. In this work we focus on studying the model sensitivity with respect to basis dimension by evaluating the NRMSE, R2 and MAPE for the overall reconstruction strategy.

In [?] used convolutional adversarial networks to predict the flow rate of a gas-liquid multiphase flow, surpassing the performance of state-of-art flow rate prediction methods. Although MAPE metric achieved good performance, as low as 8.36 % we emphasize the method was made to predict the scalar quantity of mass flow rate, being flow reconstruction methods more capable, being able to predict the entire flow field.

In [?] the authors used neural networks to identify the dynamics of a 2-D PDE Burger's equations. The authors work entirely in full dimensional, without any dimensionality reduction technique. The results, accounts for Lyapunov stability test, and show the model is stable and accurate. In our view, the lack of dimensionality reduction, could be a severe issue when dealing with high dimensional problems, as the one we are dealing with.

In [?] have developed mathematical rigorous upper bound error for the solution of a PDE using neural networks (PINNs). The method can't be directly applied to non-linear PDEs, and also can't be used to determine the lower limit for error. This highlights the importance, difficulty and necessity to more rigorous error analysis for machine learning methods.

In [?], the practical implications of Reynolds number in the coefficient discharge of flow in critical nozzles is studied. The Reynolds number for this machine was estimated as $Re = \frac{4\dot{m}_{th}}{\pi D_{th}\mu_0}$, since in our design experiment, the boundary conditions forced the flow to be sonic at throat, no appreciable impact regarding Re number is expected.

In [?] the authors used a data-driven approach for flow reconstruction in the context of identification of nonlinear dynamical systems. The approach consists in using auto-encoder to reduce the model dimensionality, then discover the underlying equations based on a restricted number of measurements data. Although not exactly in the same context of present study, auto-encoders have shown superior ability to deal with the latent variables, surpassing proper orthogonal decomposition methods.

The advantages of dimensionality reduction for machine learning method to predict fluid dynamic systems was also investigated by [?]. The authors used auto-encoder to reduce system dimensionality and have reported superior performance for the system identification when compared to full dimensional inferences.

Despite recent advances in machine learning methods and its applications, the flow reconstruction technique can also be applied using traditional numerical solvers, in [?] the authors apply the flow reconstruction technique to reconstruct microstructures of a gas diffusion layer and its anisotropic transport properties, the method used sparse measurements and traditional numerical solvers to achieve the reconstruction, it is a good

example of opportunity to use machine learning methods to reduce the computational cost of traditional numerical methods in flow reconstruction problems.

In [?] the authors applied the principal component analysis (PCA) as a dimensionality reduction technique to represent PDEs's solutions. To represent complex geometries and boundary conditions with ease, the methodology also made use of a novel mesh morphing technique to map the domain into a common morphed mesh and a Gaussian process as a regression technique. As novelty, the method used finite element interpolation and shape embedding into low dimensional coordinates.

In the work of [?] a multiresolution reconstruction of hypersonic heat flux was performed using sparse measurements data at Mach 0.8 and Mach 6.

[?] Used proper orthogonal decomposition (POD) combined with linear discriminant analysis on a clustering framework to identify the best sensor placement for identify the unsteady dynamic in the wake of wind turbines. The results show only evolution of point measurements and not the entire flow field, although it highlights how a small number of sensor can be selected to best reconstruct a flow field using projection based techniques.

In [?] Used convolutional neural networks (CNN) to reconstruct particle image velocimetry (PIV) steady velocity fields in a gas turbine pre mixed swirl combustor. The model is purely data driven and used experimental data of hydroxyl(OH) planar laser induced Fluorescence (OH-PLIF) and PIV for training. No dimensionality reduction technique was used in the training process, some kind of compression is embedded in the encode-decoding process is embedded in the convolutional layers of the CNN.

In [?] Turbulence is a highly complex and yet to be fully understood phenomena, this research paper review some of advances in using machine learning methods to model such complex multiscale problem. Some of the outlined models are methods for parameter identification, system identification and reconstruction of closure model. The ML models showed promising results, with high accuracy subgrid scale terms prediction. Focused on incompressible turbulence modeling. Closure terms prediction and field deconvolution are key areas pointed.

[?] used 2D data from high-resolution ocean model, to emulate the real achievable quality of satellite images, a low pass filter was applied in the training data. A convolutional neural networks were then trained, to predict subsurface flow fields and eddy momentum forcing term from the degraded data. Showing possible application to improve model accuracy and also infer data from sparse observations.

[?] used data from limited pressure measurements of the viscous flow around a cylinder to perform a flow field reconstruction. POD was used for dimensionality reduction and optimal basis construction. The performance metrics although was not reported in terms of whole field data reconstruction, but only scalar quantity such as the Reynolds number prediction.

[?] used POD for low dimensional projection and convolutional neural networks to

extract low-dimensional features. The ground truth data was numerically generated by a finite element method to solve the unsteady navier stokes equation in compressible regime. The models investigated for system identification or inverse problem was proper orthogonal decomposition-recurrent neural network (POD-RNN) and convolutional recurrent autoencoder network (CRAN). The recurrent neural network in question was a long short-term memory network (LSTM). The criteria for basis selection was the traditional energy preservation. The CRAN models were found to surpass the POD-RNN in terms of accurately representation of highly nonlinear problems such as the flow around two side-by-side cylinders. The computational cost of training the CRAN model was however 16 times higher. Although tailored to unsteady flow reconstruction, this work has many similarity with ours since, a low dimensional representation of flow features must be established prior to build a regressor model, in our case to predict flow fields for new unseen design parameters and in the case of the referenced study to extrapolate in time.

? is focused on the 2D unsteady flow around attached airfoils. Sparse sensor data are used to reconstruct the flow field. POD was used for dimensionality reduction and, some strategies were used to recover the basis from sparse measurements, simple linear approaches and also a shallow (3 -layers) fully connected neural network. The results showed neural network performed better, no considerations about computation time however were discussed.

? is also another work focused on unsteady flow. The method is data-driven and used generative adversarial networks to encode and predict the flow field for unseen parameter. The model only uses one parameter to characterize the boundary conditions. The result and reconstructed flow field agreed well with high fidelity generated data with a significant computational cost reduction.

? used an interpolation method to perform a parametric dimensionality reduction using POD and then reconstruct the incompressible flow around a cylinder and the stress tensor field on double-T beam. The active subspace method proposed outperformed traditional methods when using small number of principal components but have worse performance when using large number of principal components. No details about the interpolation method were given and the performance of the model in predictive regime should be highly affected by this interpolation technique.

? applied standard POD, and improved version of POD using ridge regression and a shallow decoder (SD) to reduce dimensionality and reconstruct 2D spatial and temporal flow fields from sparse measurements. From natural nonlinearity nature of SD, it outperforms both POD methods in terms of accuracy. The studied cases include numerical flow around a cylinder, experimental data for mesoscale sea surface temperature and numerical turbulent isotropic flow.

? used deep learning to predict fully-turbulent systems. The proposed approach uses data from low-fidelity simulations to infer high fidelity flow fields. Physical information of

in the form of a loss function with PDE residual was also used, so this technique can be seen as a hybrid model using both data and physical information.

? used nonlinear Laplacian spectral analysis (NLSA) to build a weak formulation for the Koopman operator for the low dimensional representation of the dynamics of a fully turbulent 3D convection flow. Data was generated using DNS for the Rayleigh Bernard convection problem. NLSA can be viewed as POD in a delay-coordinate space.

? used a convolutional neural network to predict results of a 2D CFD zone fire model. The surrogate model reconstructed the temperature and velocity fields given scalar parameters for the simulations. The model is completely data-driven and no dimensionality reduction beyond the convolutional operations was performed.

? used volumetric tomographic Networks (VT-Nets) to perform a three dimensional tomographic reconstruction of turbulent flame flows. The performance of the machine learning method was compared with traditional algebraic reconstruction techniques (ART), showing the convolutional neural networks were able to outperform traditional methods when a reduced number of 2D projections are used to reconstruct the whole 3D flame. It is also insanely faster than traditional algorithms for inference tasks.

? used proper orthogonal decomposition (POD) to reduce dimensionality and then used sparse measurements to perform a flow field reconstruction. The sensor placement, quantity and system dimension was investigated to characterize the sparse reconstruction performance.

? performed a velocity field prediction on a scramjet isolator using deep learning. The data-driven model used a convolutional neural network to establish a relationship between wall pressure and velocity field. Experimental data was used for comparison and 3D RANS simulations were performed to build the datasets, although the simulations were 3D only 2D slices of flow field were used to train and test the model. Despite the model being compressible with a lot of oblique shock formations, no attempt to recover the shock structures were made.

? used a symmetrical deep convolutional neural network to reconstruct the 2D steady state supersonic flow field in a cascade channel. The model is data-driven and used discrete pressure data to reconstruct 2D flow field. The model was able to accurately reconstruct flow structures present in the form of shock wave formation under unseen parameters.

? show surrogate model can replace costly traditional solvers in a heat transfer problem, they effectively used fully connected convolutional neural networks to perform flow field reconstruction of 2D heat transfer problem with nanofluid flowing in a microchannel with grooves. The data driven model used design parameters such as groove radius, relative depth, boundary conditions and a fluid parameter to infer 2D physical fields of pressure, temperature and velocity components. Neural networks showed superior performance when compared with traditional surrogate models.

1.2 POD

The POD reduction, perhaps in a slightly modified form, is known throughout the literature alternatively as principal component analysis (PCA), empirical orthogonal functions (EOF), the Hotelling transform, or a Karhunen-Loeve expansion. Here, we will simply refer to it as POD.

Fundamentação Teórica

2.1 Impactos financeiros de um produto defeituoso

2.1.1 O valor de uma marca

$$\nabla^2 f_{ij} = 4f_{ij} - (f_{(i+1)j} + f_{(i-1)j} + f_{i(j+1)} + f_{i(j-1)}) \quad (2.1)$$

Outra forma simples de apresentar esta expressão consiste em fornecer uma *matriz* contendo os coeficientes dos *pixels*:

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

3.1 Numerical Methods

The present flow reconstruction method is purely data-driven and should work seamlessly with experimental data. For the sake of cost and time, in this work, the data was synthetically generated using numerical solvers.

3.2 POD

POD, also known as principal component analysis (PCA), empirical orthogonal functions (EOF), the Hotelling transform, or a Karhunen-Loeve expansion in various domains, is a technique to reduce the dimensionality of complex data sets. This method is extensively used in numerical simulations and physical experiments to extract dominant patterns of variability from a high-dimensional dataset.

Aplicação da Metodologia

4.1 Determinação do caso a ser estudado

Resultados**5.1 Determinação do caso a ser estudado**

Etapa concluída.

Referências Bibliográficas

Anexos

Este é um anexo.

Não há renumeração para os anexos neste modelo.

Não parece ser útil ter distinção entre apêndices e anexos.

Anexo 01

Este é um anexo.

Não há renumeração para os anexos neste modelo.

Não parece ser útil ter distinção entre apêndices e anexos.

Se fizer passar para a versão 1.0.