Ahmedabad University

CSE541: Computer Vision

Weekly Report 1

Group - 9

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Predicting Spatio-temporal temperature variations using Machine learning models

Introduction:

The purpose of this report is to outline the development and implementation of a deep learning model for predicting spatio-temporal temperature variations within a rectangular enclosure. The model utilizes machine learning techniques, including Proper Orthogonal Decomposition (POD), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks, to analyze fluid dynamics and heat transfer phenomena.

Problem Statement:

- Develop a deep learning model for the problem of Predicting Spatio temporal temperature variations using Machine Learning models
- Train the model using spatio-temporal data available from CFD for a small time duration.
- Predict temporal data and compare with CFD model results available for higher time duration.

Literature Survey:

Title	Algorithm and Methodologies
Hybrid deep-learning POD-based parametric reduced order model for flow around wind-turbine blade	The NIROM methodology incorporates a Grassmann manifold interpolation approach for obtaining basis functions corresponding to new Reynolds numbers and utilizes a long short-term memory (LSTM) recurrent neural network for predicting temporal coefficients associated with these basis functions.
A non-intrusive parametric reduced order model for urban wind flow using deep learning and Grassmann manifold.	It includes LSTM for sequential data, Grassmann interpolation for subspace interpolation, in a non-intrusive ROM framework, predicting unsteady velocity fields and kinetic energy, offering computational efficiency.
A novel framework for spatio temporal prediction of environment data using deep learning.	Decomposes spatio-temporal processes into temporally referenced basis functions and stochastic spatial coefficients.Reconstructs spatio-temporal fields on a regular grid from spatially irregularly distributed time series data. Utilizes deep learning to capture spatial, temporal, and spatio-temporal dependencies.
Non-Linear Proper Orthogonal Decomposition for Convection-Dominated flows	Integration of POD with LSTM networks improves performance over existing methods, paving the way for Galerkin-free models in convection-dominated flows.The versatility of the NLPOD approach, can be combined with various techniques beyond LSTMs with physics-guided machine learning to reduce model uncertainty.

Approach:

- We will first do the data filtering and that filtered data will be used.
- We decided to use POD/CNN for reducing the size of the data and extract the features which are useful for our model.
- So, the work of POD/CNN is going to be the spatial features extraction.
- Then we have to do a temporal analysis and this model is semi supervised so we have to provide the output data to the model.
- So this approach is going to be the recurrent approach.
- So, for a recurrent approach we decided to use LSTM as we have the control to fetch a particular data and we can discard the particular data.
- So we decided to use LSTM and recurrent neural networks to process our data.
- Then we will evaluate the model with the data provided.

Datasets Discussions:

The dataset contains information about fluid flow properties and temperature distribution within a rectangular enclosure.

It includes data such as pressure, velocity magnitude, temperature, heat flux, and gradients at different locations within the enclosure.

This data can be used to analyze fluid dynamics and heat transfer phenomena.

nodenumber	x-coordinate	y-coordinate	pressure	dynamic-pressure	total-pressure	velocity-magnitude	temperature	total-temperature	wall-temperatu
1	0.000000000E+00	0.000000000E+00	-3.289589076E-04	2.065594629E-07	2.065594629E-07	0.000000000E+00	3.004808960E+02	3.003679199E+02	3.003866272E+02
2	2.711297420E-04	0.000000000E+00	-5.551265203E-04	1.934296705E-07	-7.995281521E-06	0.000000000E+00	3.002555847E+02	3.002609558E+02	3.002609558E+02
3	5.693724379E-04	0.000000000E+00	-5.096629029E-04	1.391373843E-07	-1.762314059E-05	0.000000000E+00	3.001263123E+02	3.001271057E+02	3.001271057E+02
4	8.974394295E-04	0.000000000E+00	-5.201669992E-04	8.266521689E-08	-1.450958189E-05	0.000000000E+00	3.000975037E+02	3.000980530E+02	3.000980835E+02
5	1.258313074E-03	0.000000000E+00	-3.931043611E-04	6.863636770E-08	-6.040190783E-06	0.000000000E+00	3.000767212E+02	3.000771790E+02	3.000771179E+02
6	1.655274071E-03	0.000000000E+00	-2.772968728E-04	7.104272726E-08	3.322387101E-06	0.000000000E+00	3.000608521E+02	3.000611877E+02	3.000611877E+02
7	2.091931179E-03	0.000000000E+00	-1.976463682E-04	7.667495083E-08	1.382648134E-05	0.000000000E+00	3.000484619E+02	3.000487061E+02	3.000487061E+02
8	2.572254045E-03	0.000000000E+00	-1.379890746E-04	8.214894365E-08	2.615990888E-05	0.000000000E+00	3.000386963E+02	3.000389099E+02	3.000389099E+02
9	3.100609174E-03	0.000000000E+00	-8.886527939E-05	8.641730176E-08	4.051345968E-05	0.000000000E+00	3.000310059E+02	3.000311584E+02	3.000311890E+02
10	3.681799863E-03	0.000000000E+00	-4.595065548E-05	8.918801342E-08	5.690383841E-05	0.000000000E+00	3.000249939E+02	3.000250854E+02	3.000250854E+02
11	4.321109504E-03	0.000000000E+00	-7.125893717E-06	9.041654891E-08	7.524525427E-05	0.000000000E+00	3.000202942E+02	3.000203857E+02	3.000204163E+02
12	5.024350248E-03	0.000000000E+00	2.870051503E-05	9.013224656E-08	9.553925338E-05	0.000000000E+00	3.000167236E+02	3.000167847E+02	3.000167847E+02
13	5.797915161E-03	0.000000000E+00	6.272514293E-05	8.839494114E-08	1.179250539E-04	0.000000000E+00	3.000140076E+02	3.000140381E+02	3.000140381E+02
14	6.648836192E-03	0.000000000E+00	9.623090591E-05	8.536162710E-08	1.424569491E-04	0.000000000E+00	3.000119324E+02	3.000119934E+02	3.000119934E+02
15	7.584849838E-03	0.000000000E+00	1.296770643E-04	8.125262241E-08	1.690927311E-04	0.000000000E+00	3.000104065E+02	3.000104370E+02	3.000104370E+02
16	8.614464663E-03	0.000000000E+00	1.635287335E-04	7.630451648E-08	1.977609645E-04	0.000000000E+00	3.000092468E+02	3.000092468E+02	3.000092468E+02
17	9.747040458E-03	0.000000000E+00	1.981181849E-04	7.077397157E-08	2.283805370E-04	0.000000000E+00	3.000083313E+02	3.000083618E+02	3.000083618E+02
18	1.099287439E-02	0.000000000E+00	2.335925092E-04	6.489607074E-08	2.608195355E-04	0.000000000E+00	3.000076599E+02	3.000076599E+02	3.000076294E+02
19	1.236329135E-02	0.000000000E+00	2.700869809E-04	5.890150945E-08	2.948909241E-04	0.000000000E+00	3.000070801E+02	3.000070801E+02	3.000071106E+02
20	1.387075055E-02	0.000000000E+00	3.076337744E-04	5.302519668E-08	3.304338898E-04	0.000000000E+00	3.000065918E+02	3.000065918E+02	3.000066223E+02
21	1.552895550E-02	0.000000000E+00	3.461495799E-04	4.742842918E-08	3.673051833E-04	0.000000000E+00	3.000061646E+02	3.000061646E+02	3.000061646E+02
22	1.735297963E-02	0.000000000E+00	3.855873074E-04	4.220049732E-08	4.053417942E-04	0.000000000E+00	3.000057983E+02	3.000058289E+02	3.000058289E+02
23	1.935940795E-02	0.000000000E+00	4.258531553E-04	3.740188248E-08	4.443871148E-04	0.000000000E+00	3.000054626E+02	3.000054626E+02	3.000054626E+02
24	2.156647854E-02	0.000000000E+00	4.668816109E-04	3.306528029E-08	4.843233619E-04	0.000000000E+00	3.000051575E+02	3.000051575E+02	3.000051575E+02
25	2.399425581E-02	0.000000000E+00	5.086374586E-04	2.919340858E-08	5.250844406E-04	0.000000000E+00	3.000048523E+02	3.000048828E+02	3.000048828E+02
26	2.666481212E-02	0.000000000E+00	5.511079216E-04	2.575798597E-08	5.666327197E-04	0.000000000E+00	3.000046082E+02	3.000046082E+02	3.000046082E+02
27	2.960242331E-02	0.000000000E+00	5.942849675E-04	2.270786759E-08	6.089431117E-04	0.000000000E+00	3.000043335E+02	3.000043640E+02	3.000043335E+02
28	3.283379599E-02	0.000000000E+00	6.381619605E-04	1.998982313E-08	6.519895396E-04	0.000000000E+00	3.000041199E+02	3.000041199E+02	3.000041199E+02
29	3.638830408E-02	0.000000000E+00	6.827652687E-04	1.755568846E-08	6.957944133E-04	0.000000000E+00	3.000039063E+02	3.000039368E+02	3.000038757E+02
30	4.029826447E-02	0.000000000E+00	7.281053695E-04	1.534488447E-08	7.403774071E-04	0.000000000E+00	3.000037231E+02	3.000037231E+02	3.000037231E+02
31	4.459922016E-02	0.000000000E+00	7.741203881E-04	1.330643240E-08	7.856721641E-04	0.000000000E+00	3.000035095E+02	3.000035095E+02	3.000035400E+02
32	4.933027178E-02	0.000000000E+00	8.206808707E-04	1.140448713E-08	8.315549931E-04	0.000000000E+00	3.000033569E+02	3.000033569E+02	3.000033569E+02
33	5.453442782E-02	0.000000000E+00	8.675241261E-04	9.599909312E-09	8.777727489E-04	0.000000000E+00	3.000032043E+02	3.000032043E+02	3.000032043E+02
34	6.025899947E-02	0.000000000E+00	9.141495102E-04	7.864694673E-09	9.238320636E-04	0.000000000E+00	3.000030518E+02	3.000030518E+02	3.000030823E+02
35	6.655602902E-02	0.000000000E+00	9.597734897E-04	6.196668068E-09	9.689599974E-04	0.000000000E+00	3.000029297E+02	3.000029602E+02	3.000028992E+02

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