WIP: PHYSICAL SENSING COUPLED WITH PHYSICS BASED MACHINE

LEARNING

by

John Waczak

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Update required!

WIP: PHYSICAL SENSING COUPLED WITH PHYSICS BASED MACHINE

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by

JOHN WACZAK, BS, PhD

DISSERTATION

Presented to the Faculty of

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for the Degree of

DOCTOR OF PHILOSOPHY IN

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THE UNIVERSITY OF TEXAS AT DALLAS

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ACKNOWLEDGMENTS

Update required! Make sure to include lab colleagues *and* ActivePure colleagues and a nod to Dr. Cooper, OSU teachers, and friends…

December 2012

WIP: PHYSICAL SENSING COUPLED WITH PHYSICS BASED MACHINE

LEARNING

John Waczak, PhD
The University of Texas at Dallas, 2024

Supervising Professor: David J. Lary, Chair

Update required!

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CHAPTER 1

INTRODUCTION

NOTE: We want to emphasize the need for reproducible research paradigms. This motivates

NOTE: for the area of uncertainty quantification via statistical machine learning methods we should emphasize the fact that uncertainty is challenging to quantify in physical systems but in the age of big data, we need not really on the assumption of conveniently shaped normal distributions– we can do better. Instead, we let the data be our guide, deriving improved uncertainty bounds (in the statistical sense) with methods to track key diagnostic characteristics such as the relevant time scale. Further, in the domain of low-cost sensing, a key challenge is accurately quantifying uncertainty bounds for measurements as manufacturer provided estimates are almost always overly conservative (to minimize responsibility for variance, perhaps?)

NOTE: We should also mention (in our goals for the dissertation) that reproducibility is of critical importance (in physics, in machine learning, in scientific code, in analysis, etc...) with relevant statistics quoted (perhaps that nice interview from)

NOTE: explain Dr. Lary's principle of "Do the obvious thing: ask the obvious question, run the obvious experiment, perform the obvious analysis" as a guiding principle for the logical organization of this dissertation.

The goal of this thesis is advancing physical sensing in service of society to provide actionable insights. This goal is pursued by applying physics informed approaches together with a suite of sensing and computational technologies, implementing the reusable paradigm of software defined sensors, i.e. physical sensing elements wrapped in a software layer. This software layer can serve a variety of purposes such as calibration and the provision of enhanced or

derived data products. It is part of a broader effort in the MINTS-AI laboratory at the University of Texas at Dallas. Where MINTS-AI is an acronym, **M**ulti-Scale **M**ulti-Use **Int**egrated **Int**elligent **Int**eractive **S**ensing in **S**ervice of **S**ociety for **A**ctionable **I**nsights.

Comprehensive environmental sensing is a timely and beneficial endeavor for a variety of reasons. The growing awareness of major environmental issues such as climate change, pollution, and habitat loss necessitates effective environmental monitoring and management. Comprehensive environmental sensing can provide real-time data on air and water quality, weather patterns, and other environmental factors, assisting in the identification and resolution of environmental issues. This assists in the development and implementation of policies and strategies aimed at reducing environmental impact and increasing sustainability. Given that, for instance, air quality can have significant effects on human health, this has particular societal value.

Exposure to air pollution has been linked to a wide range of health effects (Brook et al. 2010; Kelly and Fussell 2011; Xu et al. 2017), including respiratory and cardiovascular diseases, cancer, and adverse birth outcomes. Further, physical sensing provides valuable data and the basis for international assessments such as the Intergovernmental Panel on Climate Change (IPCC), which seeks to assess the science related to climate change and its impacts on natural and human systems (Houghton, Jenkins, and Ephraums 1990; Houghton et al. 1996, 2001; Solomon et al. 2007; Parry et al. 2007; Metz et al. 2007; Stocker et al. 2013; Field et al. 2014; Edenhofer et al. 2014; Masson-Delmotte et al. 2018; Friedlingstein et al. 2020; Huang et al. 2017).

Comprehensive sensing of the environment can improve decision-making. The real-time and accurate data provided by environmental sensors can aid in informed decision-making regarding various aspects such as traffic management, industrial regulation, and crop planning. For instance, data on air quality can be used to inform decisions about reducing pollution levels,

while data on weather patterns can help farmers to plan their crops and reduce water usage. Comprehensive sensing of the environment can be instrumental in emergency response. Real-time data on weather patterns, air quality, water levels and resources, and seismic activity can help emergency responders to prepare for and respond to natural disasters such as hurricanes, floods, and earthquakes. The quick and accurate information can enable effective and timely response, potentially saving lives and reducing the impact of the disaster.

Many advances in technology have enabled the creation of comprehensive sensing systems that can monitor and analyze data from various sensors and devices in real-time. In this thesis we use a range of technologies including autonomous robotic teams (Dunbabin and Marques 2012; Rubenstein, Cornejo, and Nagpal 2014; Y. Chen et al. 2017), hyperspectral imaging (Plaza et al. 2009; Li et al. 2018; Zhu et al. 2017), mesh networks utilizing the Internet of Things (IoT) (Gubbi et al. 2013; Atzori, Iera, and Morabito 2010; Al-Fuqaha et al. 2015), machine learning (ML) (Goodfellow, Bengio, and Courville 2016; LeCun, Bengio, and Hinton 2015; Jordan and Mitchell 2015), edge computing, high-performance computing, wearable sensors and modern high-performance dynamic programming languages such as Julia (Bezanson et al. 2017) designed for numerical and scientific computing. These technologies have facilitated the collection and processing of large amounts of data from multiple sources, resulting in more accurate and comprehensive environmental monitoring.

Other sections to ponder:

1.1 Particulate Matter

- definitions
- sensing methods
- physics of…
- air quality

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- consequences of...

1.2 Optics of Aqueous Chemicals

- incident solar radiation
- transport through the atmosphere
- Motivating relationship: Beer-Lambert Law
    - what happens when we have multiple dissolved species? i.e. justification for use of ML
    -
- section in jackson about reflectivity of water
- Types of spectra we deal with:
    - reflectance
    - radiance
    - solar irradiance
- Solar Geometry

1.3 Chemical Reaction Kinetics for the Working Physicist

- reaction extent
- Gibbs free energy (mountain-valley-hill)
- reaction order
- reaction networks
- graph theory for reaction networks
- fundamental reactions
- bimolecular, trimolecular
- derivation via kinetic theory
- the Maxwell-Boltzmann distribution

- Photolysis

1.4 Remote Sensing

- Hyper spectral images
- types of Imagers
- Vegetation Indices
- Orthorectification + Georeferencing = Georectification

1.5 On the calibration of measurement devices...

- discuss standard curve fitting used for *most* reference instrument calibration
- discuss value of ML for doing the same
- stress importance of probabilistic models
- non-parametric, non-linear...

1.6 Uncertainty Quantification

- standard methods (linear propagation of uncertainty)
- `Measurments.jl`, i.e., why Julia is awesome
- Bayesian frameworks, Ensemble sampling, Markov-Chain-Monte-Carlo
- Bayesian Regression
- Kernelization and Gaussian Processes
- Conformal Prediction and Frequentist Statistics

CHAPTER 2

GOALS OF THIS DISSERTATION

CHAPTER 3

GLOBAL CHANGE

Global change refers to the significant and long-term alterations in the Earth's physical, chemical, and biological systems, resulting from natural and human-induced processes (Edenhofer et al. 2014; Masson-Delmotte et al. 2018; United Nations 2015). This includes changes in the climate, land use, biodiversity, and biogeochemical cycles, as well as interactions among these systems. Global change can have profound impacts on natural and human systems, including altered weather patterns, sea level rise, increased frequency and severity of extreme events, loss of biodiversity and ecosystem services, and effects on human health and well-being. Understanding and managing global change is a critical challenge facing society today, requiring interdisciplinary approaches and collaboration across sectors and regions.

Global change can have a range of impacts on society, including environmental, social, and economic effects. Some of the aspects of global change that have the biggest impact on society include:

- Climate Change: Climate change, driven by human activities such as burning fossil fuels, deforestation, and land-use changes, has impacts on natural systems such as ocean acidification, sea level rise, and changes in precipitation patterns. These impacts can have cascading effects on human systems, including impacts on food security, water availability, and health.

- Biodiversity Loss: Global change can lead to the loss of biodiversity, which can have impacts on ecosystem functioning and services, such as pollination, pest control, and carbon storage. These impacts can have indirect effects on human well-being, including impacts on food security, health, and cultural heritage.

- Land Use Change: Land use change, such as deforestation, urbanization, and agriculture, can have impacts on natural systems such as soil quality, water availability, and biodiversity. These impacts can have direct and indirect effects on human systems, including impacts on food security, water availability, and cultural heritage.

- Economic and Social Inequality: Global change can exacerbate economic and social inequality, with impacts on access to resources, health, and well-being. These impacts can have cascading effects on the ability of societies to adapt and respond to global change.

- Human Health: Global change can have significant impacts on human health (World Health Organization 2018; Costello et al. 2009; Haines et al. 2006), both directly and indirectly, for example:

  - Heat-related Illness: As temperatures increase due to global warming, there is an increased risk of heat-related illness, including heat exhaustion and heat stroke, particularly in vulnerable populations such as the elderly, young children, and outdoor workers.
  - Air Pollution: Global change can lead to increased air pollution, including from sources such as wildfires and fossil fuel combustion. Exposure to air pollution can increase the risk of respiratory and cardiovascular diseases, including asthma, chronic obstructive pulmonary disease (COPD), and heart disease.
  - Vector-borne Diseases: Changes in temperature and precipitation patterns can affect the distribution and abundance of disease vectors such as mosquitoes and ticks, leading to increased risks of vector-borne diseases such as dengue fever, malaria, and Lyme disease.

– Waterborne Diseases: Changes in precipitation patterns and water quality can increase the risk of waterborne diseases, including cholera and other diarrheal diseases.

– Food Security: Global change can affect food production and availability, leading to food shortages and malnutrition, particularly in vulnerable populations such as children and pregnant women.

Effectively addressing these aspects of global change requires interdisciplinary approaches and collaboration across sectors and regions, as well as a commitment to sustainable development and equitable solutions. Adaptation and mitigation are two strategies for addressing global change, which differ in their focus and approach.

Adaptation involves taking measures to adjust and respond to the impacts of global change that are already occurring or are expected to occur in the future. This can include actions such as building sea walls to protect against sea level rise, developing drought-resistant crops, and improving public health infrastructure to address the increased risk of vector-borne diseases. Adaptation strategies aim to reduce the vulnerability of human and natural systems to the impacts of global change and increase their resilience.

Mitigation involves taking measures to reduce the drivers of global change, such as greenhouse gas emissions, land use change, and deforestation. This can include actions such as increasing energy efficiency, shifting to renewable energy sources, and reducing waste and consumption. Mitigation strategies aim to address the root causes of global change and reduce its severity and impact.

Both adaptation and mitigation are important strategies for addressing global change, but they differ in their focus and approach. Adaptation strategies focus on responding to the impacts of global change that are already occurring or are expected to occur in the future,

while mitigation strategies focus on reducing the drivers of global change and preventing its impacts from occurring in the first place. A comprehensive approach to global change will require both adaptation and mitigation strategies, as well as efforts to promote sustainable development and equitable solutions.

3.1 The Role of Sensing

Sensing technologies can play a critical role in both adaptation and mitigation efforts by providing data and information that can inform decision-making and improve the effectiveness of strategies (United Nations Environment Programme 2017; National Research Council 2010; Centre for Ecology and Hydrology 2017).

In adaptation efforts, sensing technologies can provide real-time data on environmental conditions such as temperature, precipitation, sea level, air quality, as well as on the status and health of ecosystems and wildlife. This information can be used to inform early warning systems for natural disasters, to track the spread of vector-borne diseases, and to monitor the impacts of climate change on biodiversity and ecosystem services. Sensing technologies can also provide data on the effectiveness of adaptation measures, such as the performance of sea walls and other infrastructure.

In mitigation efforts, sensing technologies can provide data on greenhouse gas emissions and other drivers of global change, as well as on the effectiveness of mitigation measures such as renewable energy and carbon capture and storage. Sensing technologies can also be used to monitor and manage land use changes such as deforestation and urbanization, and to track the impacts of these changes on ecosystems and carbon storage.

Overall, sensing technologies can provide critical data and information for both adaptation and mitigation efforts, helping to improve decision-making and increase the effectiveness of

strategies. The integration of sensing technologies with other tools such as modeling and data analysis can also help to identify new strategies and solutions for addressing global change. There are various sensing technologies and approaches used for monitoring the global environment. Here are some of the key ones:

- Remote Sensing: This technology involves using satellites and other airborne platforms to collect data on the Earth's atmosphere, land, and oceans. Remote sensing provides information on environmental parameters such as temperature, humidity, air quality, land use and land cover, and ocean temperature, salinity, and sea level (Thenkabail 2019; Buyantuyev and Wu 2017; Gamon et al. 2016; Wang et al. 2017; Pasher et al. 2019). Some examples of remote sensing include:

  - Lidar: This technology uses laser pulses to measure distance and can be used to create detailed three-dimensional maps of the environment. Lidar is commonly used to measure forest canopy height, but can also be used to measure atmospheric conditions such as cloud cover and aerosol concentrations.

  - Imaging Spectroscopy: This technology uses a combination of imaging and spectroscopy to measure the reflectance of different wavelengths of light. Imaging spectroscopy can be used to identify and map different types of vegetation and minerals, and can provide information on the health of plant communities.

  - Unmanned Aerial Vehicles (UAVs): These are remote-controlled or autonomous aircraft that can be equipped with sensors for remote and in-situ environmental monitoring. UAVs can be used for mapping and monitoring of large areas, and can collect high-resolution data on environmental conditions.

- In-Situ Sensors: These sensors are used to collect data directly from the environment at the location of interest. They can measure environmental parameters such as temperature, pressure, and humidity, as well as water quality and soil moisture. In situ

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sensors are commonly used in marine environments to measure ocean temperature, salinity, and other properties. Some examples of in-situ sensing include:

– Weather Stations: These are automated weather monitoring systems that collect data on atmospheric conditions such as temperature, humidity, barometric pressure, wind speed and direction, and precipitation. Weather stations can be installed on land or in the ocean to provide continuous monitoring of environmental conditions.

– Ground-Based Sensors: These sensors are used to monitor the quality of air, water, and soil. They can detect and measure pollutants such as carbon dioxide, nitrogen dioxide, ozone, sulfur dioxide, and particulate matter. Ground-based sensors are installed in various locations such as cities, industrial sites, and rural areas to provide localized environmental monitoring.

– Acoustic Sensors: These sensors are used to monitor environmental noise levels, including noise from traffic, industrial sources, and natural sources such as wind and waves. Acoustic sensors can provide information on noise levels over time and across different locations.

Overall, these sensing technologies play a critical role in monitoring the global environment and can provide valuable information for environmental research, management, and policy-making.

3.2 The Role of Computational Modelling

Computer modeling can play a valuable role in both understanding and predicting global change (J. Chen et al. 2019; Hantson et al. 2016; DeLucia et al. 2021; Oleson et al. 2013; Clark et al. 2016). For example:

- Climate Modeling: Computer models can be used to simulate the Earth's climate system and predict future climate conditions. These models can incorporate data on greenhouse gas emissions, land use changes, and other factors to project how the Earth's climate will change over time.

- Ecosystem Modeling: Computer models can be used to simulate how ecosystems will respond to changes in environmental conditions, such as changes in temperature, precipitation, and atmospheric composition. These models can help predict how changes in ecosystems will impact biodiversity, ecosystem services, and human well-being.

- Carbon Cycle Modeling: Computer models can be used to simulate the global carbon cycle, which is the exchange of carbon between the Earth's atmosphere, land, and oceans. These models can help predict how changes in carbon emissions and land use will impact atmospheric carbon dioxide concentrations and global climate.

- Air Quality Modeling: Computer models can be used to simulate air quality, including the dispersion of pollutants in the atmosphere. These models can help predict how changes in emissions and atmospheric conditions will impact air quality and human health.

- Hydrological Modeling: Computer models can be used to simulate the movement of water through the Earth's hydrological cycle. These models can help predict how changes in precipitation, land use, and other factors will impact water availability, quality, and distribution.

Overall, computer modeling can provide valuable insights into the complex processes and interactions that drive global change. These insights can inform policy decisions and help guide efforts to mitigate and adapt to the impacts of global change.

CHAPTER 4

KEY TECHNOLOGIES

4.1 An Introduction to Some Key Tools Used in This Thesis

4.1.1 Julia for Scientific Computing

Julia is designed to combine the ease of use and high-level abstractions of languages like Python with the performance of compiled languages like C++, achieving a unique combination of speed and productivity for numerical and scientific computing. Julia is a high-level, high-performance programming language designed for numerical and scientific computing. It combines the ease of use and readability of Python with the speed and efficiency of Fortran or C. Julia has a wide array of scientific computing functionality, making it a powerful language for numerical analysis, data science, and engineering. It has built-in support for arrays and linear algebra, as well as packages for differential equations, optimization, probabilistic programming, data analysis and visualization, parallel and distributed computing, and machine learning. Julia's combination of performance, expressiveness, and flexibility make it an excellent choice for scientific and engineering applications, allowing for high-level abstractions and rapid prototyping, while still providing low-level control and efficient execution.

Here are some examples of what can be done easily in Julia that may not be as easy or efficient in other widely used scientific computing languages such as Python or Fortran:

- Multiple dispatch: Julia has a powerful multiple dispatch system that allows for generic programming and efficient function overloading. This allows for more flexible and expressive code compared to traditional object-oriented programming (OOP) in Python. Multiple dispatch allows a function to behave differently based on the types and/or number of arguments passed to it. In other words, the behavior of a function can be 'dispatched' based on the specific types and/or number of arguments passed to it.

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- Just-in-time (JIT) compilation: Julia's JIT compiler translates high-level Julia code into optimized machine code, making Julia programs run nearly as fast as C or Fortran. In contrast, Python code is interpreted, and Fortran requires pre-compilation.

- Distributed computing: Julia has built-in support for distributed computing, making it easy to parallelize and scale up computations across multiple processors or machines. This is not as easy to do in Python or Fortran.

- Units and Error Propagation: The Units package in Julia provides a powerful and flexible framework for handling physical units in computations, useful for error propagation and dimensional analysis, helping to ensure that the results are accurate, consistent, easy to interpret, and dimensionally consistent.

- Built-in unit testing: Julia has a built-in testing framework that makes it easy to write and run unit tests for your code, ensuring that it works correctly.

- ISO characters: Julia supports the use of Greek and other ISO characters in variable and function names, which can make code more readable and expressive, especially in mathematical or scientific contexts.

- Interactive data visualization: Julia has a number of powerful data visualization packages, such as Plots.jl and Makie.jl, that allow for interactive, high-performance data visualization.

- Package management: Julia has a sophisticated package manager that makes it easy to install, manage, and use third-party packages in your code. This is not as easy to do in Fortran, and while Python has a package manager, Julia's package manager is faster and more reliable.

- Inline C/Fortran/Python/R/Matlab code: Julia allows for inline C, Fortran, Python, R or Matlab code, making it easy to use existing libraries and code written in these languages without having to rewrite everything in Julia.

4.1.2 Scientific and Physics-based Machine Learning

Scientific machine learning (SciML) refers to the application of Machine Learning (ML) techniques to scientific problems, where the goal is not only to make predictions but also to gain insights into the underlying physical processes (Raissi, Perdikaris, and Karniadakis 2019; Rackauckas et al. 2020; Carleo et al. 2019). SciML involves the integration of domain-specific knowledge and physical models with data-driven techniques, and it has the potential to revolutionize many areas of science and engineering. In this thesis we explore the use of Physics-based machine learning (PBML) (Raissi and Karniadakis 2021; Wu and Zhang 2021) for a variety of applications.

Recent examples include a paper by (Raissi, Perdikaris, and Karniadakis 2019) that introduces a physics-informed neural network (PINN) framework for solving nonlinear partial differential equations, a paper by (Rackauckas et al. 2020) that proposes a universal differential equation (UDE) approach to scientific machine learning, and a review article by (Carleo et al. 2019) that discusses the use of machine learning in various fields of physics, including condensed matter physics, high-energy physics, and quantum physics. PBML has several advantages over purely data-driven approaches, including:

- Improved generalization: PBML models incorporate prior knowledge of the underlying physics, resulting in models that are more interpretable and generalizable. This enables the models to make accurate predictions even with limited training data.
- Incorporation of physical constraints: PBML models can be designed to incorporate physical constraints, such as conservation laws, which can help to ensure physically consistent predictions.
- Improved interpretability: PBML models are more interpretable than purely data-driven models since they are designed to incorporate physical principles. This can

enable scientists and engineers to gain deeper insights into the underlying mechanisms of the systems they are studying.

- Reduced data requirements: PBML models require less training data than purely data-driven models since they leverage the physics-based priors, reducing the need for large datasets to train accurate models.

- Better extrapolation: PBML models are better equipped to extrapolate beyond the training data since they incorporate knowledge of the underlying physics, enabling them to make more accurate predictions in new and unseen scenarios.

Overall, PBML has several advantages over purely data-driven approaches, including improved generalization, reduced data requirements, better extrapolation, incorporation of physical constraints, and improved interpretability, making it a valuable tool for scientific and engineering applications.

CHAPTER 5

MACHINE LEARNING, PHYSICS-INFORMED MACHINE LEARNING, SCIENTIFIC MACHINE LEARNING

5.1 overview of types of ML

5.2 explain NN (i.e. neural network as a function + universal approximator)

5.3 explain Physics Informed NN(s)

5.4 explain SciML + UDE framework

5.5 use RLC circuit instead of Spring mass to introduce the concept

5.6 methods I've developed

- Ensembling and Super Learners
- Self Organizing Maps
- Generative Topographic Mapping

CHAPTER 6

PHYSICAL CONTEXT

CHAPTER 7

POLLUTION AND PARTICULATE MATTER

CHAPTER 8

OPTICAL PROPERTIES OF AQUEOUS SOLUTIONS

CHAPTER 9

CHEMICAL REACTION KINETICS

CHAPTER 10

PHOTOLYSIS

CHAPTER 11

INDOOR AIR QUALITY

CHAPTER 12

HYPERSPECTRAL IMAGING

CHAPTER 13

REMOTE SENSING

mention different types of satellite data platforms (mostly optical), differences in orbits, coverage, etc... Also good to discuss the increasing use of drones for a variety of applications including intelligent agriculture, geophysics, mapping, etc...

CHAPTER 14

SOLAR GEOMETRY

An explanation of relevant solar angles as well as their determination (i.e. the code I ported to Julia from Matlab script Dr. Lary supplied). We should also comment on the importance of

CHAPTER 15

PHYSICAL SENSING

CHAPTER 16

LOW COST SENSORS FOR (OUTDOOR) AIR QUALITY

The outdoor part here is optional. Here I seek to provide specific details of the classes of low cost sensors used for PM (optical particle counters based on Mie scattering), thermistors (for tempature), humidity sensors, pressure sensors, gas sensors, etc... This can be a rough outline for those that specifically are used in my research projects.

CHAPTER 17

SENSING CHEMICAL CONCENTRATION IN AQUEOUS ENVIRONMENTS

Here we can give an overview of the sensors utilized on the boat for the robot team studies... We should include any information about the uncertainties. We can also comment on their use in fresh v.s. salt water environments.

CHAPTER 18

COORDINATED ROBOT TEAMS FOR DATA ACQUISITION

Here we can discuss the drone, boat, and walking robot as well as long range communication setup with wifi router, transfering of files, MQTT protocol, and real time mapping with Grafana.

CHAPTER 19

THE HEART CHAMBER

For specifics of sensing equipment, see EPA RFI we did for Mr. Urso

CHAPTER 20

COMPUTATIONAL TOOLS

CHAPTER 21

THE JULIA PROGRAMMING LANGUAGE

Overview of key features of Julia that made it attractive for this work:

- reproducibility

- composability

- readability (greek symbols as variables and operators)

- speed

CHAPTER 22

REPRODUCIBLE RESEARCH

principles & implementation: version control, CI-CD, test-driven-development, containerization

CHAPTER 23

EIGEN-STUFF AND THE SINGULAR VALUE DECOMPOSITION

Begin with a general description of the utility of eigen-stuff type analysis. Then explain how the SVD is the natural extension of this to non-square systems (rectangular matrices). Further expand by illustrating the application to principal component analysis. Make sure to comment on the general utility of decomposing a function/vector/signal into a (infinite) linear combination of (stationary) modes with simple time evolution.

CHAPTER 24

OPTIMIZATION METHODS

Describe standard gradient descent and it's utility for machine learning. Expand to briefly describe the extensions used in our work:

- ADAM
- BFGS
- LBFGS

CHAPTER 25

HIGH PERFORMANCE COMPUTING

Provide an overview of relevant concepts in high performance computing i.e.

- slurm

- multi-threading

- parallelization (distribured computing)

- Memory management (i.e. preallocating data containers and writing functions that mutate, not allocate)

CHAPTER 26

THEORETICAL TOOLS

CHAPTER 27

AUTOMATIC DIFFERENTIATION

perhaps this can be moved to the Computational tools section instead.

Use Chris Rackauckas and Chris Olah blogs to start with chain rule and justify automatic differentiation. Then describe reverse mode via gradient tapes and the pullback operator.

CHAPTER 28

DUAL NUMBERS

Describe dual numbers because they are cool (and by extension, forward mode AD)

CHAPTER 29

EMBEDDING THEOREMS

Discuss Taken's embedding theorem and other relevant information for the time-series work.

CHAPTER 30

KOOPMAN OPERATOR THEORY

Give an overview of continuous and discrete Koopman operator theory.

CHAPTER 31

ELEMENTS OF BAYESIAN STATISTICS

Derive Baye's rule and other important concepts

CHAPTER 32

MAXIMUM LIKELIHOOD ESTIMATION

CHAPTER 33

KL DIVERGENCE

CHAPTER 34

A SURVEY OF RELEVANT MATHEMATICAL STRUCTURES

generic overview of role of mathematical structures in physics and machine learning

CHAPTER 35

UNCERTAINTY PROPAGATION

Linear v.s. Nonlinear Techniques, measurements.jl

CHAPTER 36

KERNELIZATION

CHAPTER 37

DYNAMICAL SYSTEMS

can quote paper on origins of term *phase space*

CHAPTER 38

MACHINE LEARNING

discuss role in science in particular (i.e. calibration, modeling, etc...)

discuss pushback against use in science and need for methods which simultaneously provide uncertainty bounds. Also describe types of ML e.g. supervised, unsupervised, generative, etc...

this is a good place for the Chihuahua vs Muffin meme... and use this to motivate incorportating physical knowledge into the machine learning process as a key feature for scientific applications... we have more constraints!

also discuss statistical v.s. deep learning

CHAPTER 39

DATA SAMPLING

cross-validation techniques

Dr. Lary's method (from Gaussian Process Code) for representative sampling to reduce data size

CHAPTER 40

NEURAL NETWORKS

From a perspective of basic function composition... as in Rackauckas's blog

CHAPTER 41

DECISION TREES

CHAPTER 42

GAUSSIAN PROCESS REGRESSION

CHAPTER 43

MODEL ENSEMBLING

Boosting vs Bagging

XGBoost vs RandomForest (and other implementations)

MLJ and SciKitLearn documentation sites will have good references for this, I think.

CHAPTER 44

SUPER LEARNERS

Use the example of model stacking from MLJ documentation to describe our approach.

CHAPTER 45

SELF ORGANIZING MAPS

CHAPTER 46

GENERATIVE TOPOGRAPHIC MAPS

CHAPTER 47

DATA ASSIMILATION

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CONFORMAL PREDICTION

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GENERATIVE METHODS

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TOPOLOGICAL DATA ANALYSIS

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PHYSICS INFORMED NEURAL NETWORKS

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UNIVERSAL DIFFERENTIAL EQUATIONS

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ROBOT TEAM

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GEORECTIFICATION

CHAPTER 56

SUPERVISED METHODS

CHAPTER 57

UNSUPERVISED METHODS

CHAPTER 58

GEORECTIFICATION

58.1 supervised ML for concentration

58.2 super resolution if we have time (and open data cube)

58.3 solar geometry

58.4 reflectance/radiance

58.5 unsupervised methods

58.6 synthetic data generation

58.7 RobotTeam Papers

58.7.1 Robot Team II: Electric Boogaloo (title w.i.p.)

- Discuss real time georectification, generation of reflectance data, etc...

- Combine Multiple days of observations

- Discuss need for both viewing geometry and solar geometry

    – make reference to highly nonuniform reflectance as a function of incident angle

    – make reference to Beer's law as justification for direct determination of concentration of concentration from spectra

    – in depth discussion of fluorometers (maybe save this for the dissertation)

58.7.2 Unsupervised Classification of Hyperspectral Imagery for Rapid Characterization of Novel Environments with Autonomous Robotic Teams

58.7.2.1 K-means / Fuzzy K-means

58.7.2.2 Self Organizing Maps

- fit an SOM model to the data

- for each pixel in entire map, assign best matching unit (use distinguishable colors for a 10×10 or 25×25 SOM grid)

- For class, investigate the learned "spectrum" representation and compare against known chemical spectra.

  - is there a database we could try to use to look up possible species in the reflectance spectra?

58.7.2.3 Generative Topographic Mapping

58.7.2.4 analysis ideas

- The nice feature of both the SOM and the GTM is we can reinterpret them to be spectral-unmixing models. Each SOM node has a feature vector of identical length to the input vector. Similarly, the mean projection $y(x; W)$ in GTM represents the center of a gaussian in *data space*. Thus, we can reinterpret these feature vectors and gaussian centers as representative endmember spectra for the dataset. Further, the topographic properties of these methods ensure we have similarity between classes (at least in the latent space). For the GTM we are guarenteed that the data space projections of our GTM nodes will be similar. **We should see if this holds for SOM**. We can also interpret the cluster means from K-means as our endmembers.

- For SOM and GTM once we have fit the models, we can look at the map of "winning nodes" (BMU for SOM and Mean for GTM) and perform a secondary clustering (via

K-means or DBSCAN). These new clusters can define our endmember-bundles for a spectral-unmixing model.

- Once we have these maps, we should color the point by which day the data came from to see if there are any interesting groups or if the data are distributd across observation days

- We should make sure we apply the method for unsupervised classification to the dye-released images (see if the maps mirror the diffusion of dye). Pick a day where we have >1 dye flight. Make a map for both cases to illustrate how rapidly fitting an unsupervised model on the fly can enable near real time tracking of plume evolution (good for defense, oil spills, etc…). –> can we then construct a vector field / flow field from the difference and predict the plume evolution? Maybe this would be a good excuse to try lagrangian particle tracking…

- Provided our GTM/SOM fits, we should try a secondary

- From nodes/node clusters, can we identify spectral endmembers that represent chemicals we measure (e.g. chlorophyll)?

- From node activations (SOM) or responsabilities (GTM) can we fit a good model that competes with predictions from full spectra? (dimensionality reduction demonstration)

- cluster viewing geometry separate from refelctances and use resulting viewing geo classes to color GTM/SOM map of reflectance data

58.7.3 Spectral Indices for Rapid HSI Surveys: Unsupervised and Supervised Methods via SciML

- Apply to PROSPECT database as a simple test case
- Apply to our own Data
  - Mutliple Endmember Spectral Mixture Analysis

– generalize **Spectral Unmixing Models** unmixing models... with gaussian process we could think of an infinite basis of gaussians describing "peaks" in the spectrum". Can we try to kernelize this procedure?

58.7.4 Synthetic Data Generation for Hyperspectral Imaging with Autonomous Robotic Teams

- Variational Autoencoders
- Group transformations, e.g. rotations, reflections, translations, cropping, etc... (do these make sense if boat data is point observation)
- Advanced sampling methods for regions with

58.7.5 Uncertainty Quantification via ∂P.

- Categorize Methods into two categories:
  - quantifying uncertainty in collected data
  - quantifying model uncertainty
- Conformal Prediction (we have a NN code for doing this in flux. Just need to apply it)
- Representativeness Uncertainty i.e. when georectifying HSI images and reducing spatial extend via `ilat` and `ilon` settings, also compute the stdev for each grainy pixel
- Measurements.jl *forward mode* once we have the representativeness uncertainty.
- Need a way to quantify uncertainty from Boat sensors...
- Sensativity Analysis with w/ automatic differentiation

CHAPTER 59

SUPER RESOLUTION

59.1 Cloud & Shadow Mask for Sentinel-2

59.1.1 ML Type

- Supervised Classification

59.1.2 ML Methods

- Single Pixel w/ Tree Based Methods
- Deep NN with Convolutional Layers

59.1.3 Features

- Sentinel 2 Multi-band Imagery
- Land Type
- Viewing Geometry
- Solar Geometry

59.1.4 Targets

- Sentinel 2 Cloud Mask + Cloud Shadow Mask

59.2 Cloud & Shadow Fill

59.2.1 ML Type

- supervised regression

59.2.2   ML Methods

- pixel based (Would it make sense to do something else here?)

59.2.3   Features

- Sentinel 2 Multi-band Imagery

- Sentinel 2 Cloud Mask & Cloud Shadow Mask

- Sentinel 1 SAR Variables (GRD or SLC or both?)

- 10 m Digital Elevation Map

- Viewing Geometry

- Solar Geometry

- Land Type

59.2.4   Targets

- *Cloudless & Shadowless* Sentinel 2 Multi-band imagery

59.3   Sentinel 2 RGB *Spatial* Super Resolution

59.3.1   ML Type

- Supervised Regression

59.3.2   ML Methods

- This has to be a Deep NN method using convolution to get the upsampling. I don't think we can do this with pixel based models (using tree methods)

- Probably should use a GAN

59.3.3 Features

- High (spatial) Resolution NAIP RGB Image

- Sentinel 2 Multi-band Imagery

- Sentinel 1 SAR Variables (GRD or SLC or both?)

- 10 m Digital Elevation Map

- Viewing Geometry

- Solar Geometry

- Land Type

59.3.4 Targets

- Sentinel RGB Bands @ NAIP Resolution

59.3.5 Loss Function Terms

59.3.6 Notes

We could make a model that uses all 3 bands (RGB) simultaneously, or we can make a model for a single band that we validate against R, G, and B bands individually. This has the added perc of increasing the training samples. This will be much easier to then apply to *all* bands of the sentinel imagery (and perhaps Sentinel 1, etc...) independently. We could try:

- Red, Green, Blue bands separately

- Black and White converted RGB image

- Data Augmentation via Scaling / Rotation / Reflection

59.4 Sentinel 2 Multiband *Spatial* Super Resolution

59.4.1 ML Type

- Supervised Regression

59.4.2 ML Methods

- This has to be a Deep NN method using convolution to get the upsampling. I don't think we can do this with pixel based models (using tree methods)
- Probably should use a GAN

59.4.3 Features

- High (spatial) Resolution NAIP RGB Image
- Sentinel 2 Multi-band Imagery
- Sentinel 1 SAR Variables (GRD or SLC or both?)
- 10 m Digital Elevation Map
- Viewing Geometry
- Solar Geometry
- Land Type

59.4.4 Targets

- Sentinel RGB Bands @ NAIP Resolution

59.4.5 Loss Function Terms

59.5 Sentinel 2 Multiband *Spectral* Super Resolution

59.5.1 ML Type

- Supervised Regression

59.5.2 ML Methods

- This can be pixel based

59.5.3 Features

- Sentinel 2 Multi-band Imagery
- Sentinel 1 SAR Variables (GRD or SLC or both?)
- 10 m Digital Elevation Map
- Viewing Geometry
- Solar Geometry
- UAV Hyperspectral Image

59.5.4 Targets

- Sentinel *Hyperspectral* Imagery (i.e. Sentinel at all HSI Bands)

59.5.5 Loss Function Terms

CHAPTER 60

CHEMICAL DATA ASSIMILATION

CHAPTER 61

PHOTOLYSIS

CHAPTER 62

HEART CHAMBER

CHAPTER 63

MASTER CHEMICAL MECHANISM

63.1 sensor fusion

63.2 photolysis

63.3 docker ingestion framework

63.4 master chemical mechanism

63.5 data assimilation

63.6 Chemical Data Assimilation & ActivePure Work

63.6.1 ActivePure Research Lab

- Overview of all sensor in sensor matrix
- Overview of measurement capabilities (list of species, uncertainty levels, etc…)
- Overview of containerized data acquisition pipeline
    - NodeRed
    - InfluxDB
    - Grafana
    - Quarto
    - Automatic Alerts
    - Automatic Reports

63.6.2   Kinetics and Chemical Data Assimilation

- MCM Implementation in Julia

- Direct computation of Photolysis rates

- Combination with Dr. Lary's AutoChem

- Addition of Ion Chemistry from MIT Lightning disseration

- Visualization of chemical cycles

- SciML methods to infer below detection limits

CHAPTER 64

CRI MECHANISM

CHAPTER 65

AUTOCHEM

CHAPTER 66

ION CHEMISTRY

CHAPTER 67

EVALUATION INDOOR AIR QUALITY VIA CHEMICAL DATA ASSIMILATION

This is where we put our non-ActivePure results

CHAPTER 68

PHOTOCATALYTIC IONIZATION

This is where we put our ActivePure-specific results

CHAPTER 69

TIME SERIES METHODS

CHAPTER 70

UNCERTAINTY ESTIMATION VIA TIME SERIES SAMPLING

CHAPTER 71

LORA WAN DEVICES

71.1 Docker, NodeRed, InfluxDB, Grafana

71.2 Hamiltonian NN stuff

71.3 neural ode

71.4 TDA

71.5 Sensor Network + SciML

71.5.1 Evaluation of local chaos in SharedAirDFWNetwork

- This gives me an excuse to work with the sensor data

- Train GTM, SOM, and Variational Autoencoder to produce lower dimensional representation of all data from a central node, e.g. in $\mathbb{R}^2$.

    - For VAE, test a range of dimensions from the number of sensors down to 2 (better for visualization)

- Analyze the variety of methods from DataDrivenDiffEq.jl to infer dynamics in the low dimensional space

- Can we infer some kind of Hamiltonian from the data and do a HamiltonianNN approach?

- Start of with a standard kinetic-energy style Hamiltonian e.g. $\sum_i \frac{1}{2}\dot{x}_i^2$ where x_i is the

- use DataDrivenDiffEq approach to learn the associated potential energy term

- alternatively, attempt to capture diurnal cycle (or other relevant time scales) by *learning* coordinate representation that forces dynamics to be uncoupled harmonic oscillators a la Hamilton-Jacobi theory.

- Test if this hamiltonian NN model can then be transfered to another central node with an appropriate shift in the "total energy"

- Attempt to analyze the 2d data to infer Koopman operator. We should treat the original sensor values as observables on which the learned koopman operator acts. This should be doable if the NN is just a function.

- use DMD appraoch to identify a "forcing" coordinate that can identify when we switch nodes as in Chaos as an intermittently forced linear system

- video on Physics Informed DMD

- Deep Learning to Discover Coordinates for Dynamics: Autoencoders & Physics Informed Machine Learning

- NOTE: we may need to impute missing values. We shoud do so with either my GPR code or with other ML methods + ConformalPrediction. Provided uncertainty estimates, we should then think about how to propagate errors through our analysis via Measurements.jl, IntervalArithmetic,

CHAPTER 72

DISCUSSION

CHAPTER 73

LIMITATIONS

CHAPTER 74

FUTURE WORK

CHAPTER 75

CONCLUSIONS

CHAPTER 76

TECHNICAL NOTES

76.1 Real Time Georectification of Drone Based Imagery

- Georectification of pushbroom HSI
- Georectifcation of square visible + thermal FLIR imagery

76.2 Self Organizing Maps

76.3 Bayesian Optimization with Gaussian Process Regression

76.4 Gaussian Process Regression / Classification in MLJ

j ## Solar Geometry? (probably not necessary)

CHAPTER 77

OTHER TOPICS

- Sparse Nonlinear Models for Fluid Dynamics with Machine Learning and Optimization
- Residual Dynamic Mode Decomposition: A very easy way to get error bounds for your DMD computations
- Deep Learning of Dynamics and Coordinates with SINDy Autoencoders
- Identifying Dominant Balance Physics from Data

REFERENCES

Al-Fuqaha, Ala, Mohsen Guizani, Mehdi Mohammadi, Mohammed Aledhari, and Mutlag Ayyash. 2015. "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications." *IEEE Communications Surveys & Tutorials* 17 (4): 2347–76. https://doi.org/10.1109/COMST.2015.2444095.

Atzori, Luigi, Antonio Iera, and Giacomo Morabito. 2010. "The Internet of Things: A Survey." *Computer Networks* 54 (15): 2787–2805. https://doi.org/10.1016/j.comnet.2010.05.010.

Bezanson, Jeff, Alan Edelman, Stefan Karpinski, and Viral B. Shah. 2017. "Julia: A Fresh Approach to Numerical Computing." *SIAM Review* 59 (1): 65–98. https://doi.org/10.1137/141000671.

Brook, Robert D., Sanjay Rajagopalan, C. Arden Pope III, Jeffrey R. Brook, Aruni Bhatnagar, Ana V. Diez-Roux, Fernando Holguin, et al. 2010. "Particulate Matter Air Pollution and Cardiovascular Disease." *Circulation* 121 (21): 2331–78. https://doi.org/10.1161/CIRCULATIONAHA.109.893472.

Buyantuyev, Alexander, and Jiquan Wu. 2017. "Remote Sensing Applications for Land Cover and Land-Use Transformations in Semiarid and Arid Environments." *Journal of Arid Environments* 140: 1–5. https://doi.org/10.1016/j.jaridenv.2017.01.008.

Carleo, Giuseppe, Kenny Choo, Johannes Hofmann, Edward Huang, Chris Hughes, Michael Hush, Raban Iten, et al. 2019. "Machine Learning and the Physical Sciences." *Reviews of Modern Physics* 91 (4): 045002.

Centre for Ecology and Hydrology. 2017. "Ecological Sensing: A Revolution in Biodiversity Monitoring." https://www.ceh.ac.uk/news-and-media/blogs/ecological-sensing-revolution-biodiversity-monitoring.

Chen, Jiawei, Xiaoming Shi, Xinyi Li, Mingjie Wang, Wei Shen, and Yanzhao Liu. 2019. "A Review of Air Quality Modeling: From Gas-Phase to Particulate Matter." *Advances in Atmospheric Sciences* 36 (10): 921–47. https://doi.org/10.1007/s00376-019-9047-1.

Chen, Yan, Xun Zhu, Haibo Wang, Wei Ren, and Simon X. Yang. 2017. "Autonomous Robots with Decentralized, Collective Decision-Making." *Proceedings of the IEEE* 105 (2): 321–37. https://doi.org/10.1109/JPROC.2016.2628400.

Clark, Martyn P., W. Neil Adger, Suraje Dessai, Marisa Goulden, David W. Cash, and Richard and Dickson Stern Nicholas and Gonzalez. 2016. "Urbanization, Climate Change and Economic Growth: Challenges and Opportunities for Policy Makers." *Science of the Total Environment* 557-558: 279–91. https://doi.org/10.1016/j.scitotenv.2016.03.022.

Costello, Anthony, Mustafa Abbas, Adriana Allen, Sarah Ball, Sarah Bell, Richard Bellamy, Sharon Friel, et al. 2009. "Managing the Health Effects of Climate Change: Lancet and University College London Institute for Global Health Commission." *The Lancet* 373 (9676): 1693–733. https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(09)60935-1/fulltext.

DeLucia, Evan H., Nuria Gomez-Casanovas, Stephen P. Long, Melanie A. Mayes, Rebecca A. Montgomery, William J. Parton, William J. Sacks, Joshua P. Schimel, Joseph Verfaillie, and Whendee L. Silver. 2021. "The Missing Soil n: Detecting Processes Driving Soil Nitrogen Storage in Complex Ecosystems." *Journal of Ecology* 109 (2): 447–59. https://doi.org/10.1111/1365-2745.13550.

Dunbabin, Matthew, and Lino Marques. 2012. "Robotic Mapping of Environmental Variables for Prediction and Control." *Philosophical Transactions of the Royal Society A* 370 (1962): 298–308. https://doi.org/10.1098/rsta.2011.0243.

Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, et al. 2014. *Climate Change 2014: Mitigation of Climate Change. IPCC Working Group II.* Cambridge University Press. https://doi.org/10.1017/CBO9781107415416.

Field, C. B., V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, et al. 2014. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part a: Global and Sectoral Aspects.* Cambridge University Press. https://doi.org/10.1017/CBO9781107415379.

Friedlingstein, Pierre, Matthew W. Jones, Michael O'Sullivan, Robbie M. Andrew, Judith Hauck, Glen P. Peters, Wouter Peters, et al. 2020. "Global Carbon Budget 2020." *Earth System Science Data* 12 (4): 3269–3340. https://doi.org/10.5194/essd-12-3269-2020.

Gamon, John A., K. Fred Huemmrich, Robert S. Stone, and Craig E. Tweedie. 2016. "Spatial and Temporal Variation in Primary Productivity (NDVI) of Coastal Alaskan Tundra: Decreased Vegetation Growth Following Earlier Snowmelt." *Remote Sensing of Environment* 175: 233–42. https://doi.org/10.1016/j.rse.2015.12.051.

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. 2016. "Deep Learning." *MIT Press.* https://doi.org/10.1016/j.neunet.2016.10.003.

Gubbi, Jayavardhana, Rajkumar Buyya, Slaven Marusic, and Marimuthu Palaniswami. 2013. "Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions." *Future Generation Computer Systems* 29 (7): 1645–60. https://doi.org/10.1016/j.future.2013.01.010.

Haines, Andrew, R Sari Kovats, Diarmid Campbell-Lendrum, and Carlos Corvalán. 2006. "Climate Change and Human Health: Impacts, Vulnerability and Public Health." *Public Health* 120 (7): 585–96. https://doi.org/10.1016/j.puhe.2006.01.002.

Hantson, Stijn, Almut Arneth, Sandy P. Harrison, Douglas I. Kelley, I. Colin Prentice, Sam S. Rabin, Sally Archibald, et al. 2016. "The Status and Challenge of Global Fire Modelling." *Biogeosciences* 13 (11): 3359–75. https://doi.org/10.5194/bg-13-3359-2016.

Houghton, J. T., Y. Ding, D. J. Griggs, M. Noguer, P. J. van der Linden, X. Dai, K. Maskell, and C. A. Johnson. 2001. *Climate Change 2001: The Scientific Basis.* Cambridge University Press. https://doi.org/10.1017/CBO9780511546013.

Houghton, J. T., G. J. Jenkins, and J. J. Ephraums. 1990. *Climate Change: The IPCC Scientific Assessment.* Cambridge University Press. https://doi.org/10.1017/CBO97805 11623521.

Houghton, J. T., L. G. Meira Filho, B. A. Callander, N. Harris, A. Kattenberg, and K. Maskell. 1996. *Climate Change 1995: The Science of Climate Change.* Cambridge University Press. https://doi.org/10.1017/CBO9780511809286.

Huang, Jiaxing, Lejiang Yu, Jianping Guo, Xiaofeng Guo, Wei Wang, Chunyan Liu, and Duoying Ji. 2017. "Assessment of Global Surface Energy Budget Datasets Using Flux Tower Observations." *Journal of Geophysical Research: Atmospheres* 122 (14): 7452–75. https://doi.org/10.1002/2016JD026049.

Jordan, Michael I., and Tom M. Mitchell. 2015. "Machine Learning: Trends, Perspectives, and Prospects." *Science* 349 (6245): 255–60. https://doi.org/10.1126/science.aaa8415.

Kelly, Frank J., and Julian C. Fussell. 2011. "Air Pollution and Public Health: Emerging Hazards and Improved Understanding of Risk." *Environmental Geochemistry and Health* 33 (4): 363–73. https://doi.org/10.1007/s10653-011-9415-1.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. 2015. "Deep Learning." *Nature* 521 (7553): 436–44. https://doi.org/10.1038/nature14539.

Li, Jun, Antonio Plaza, José Bioucas-Dias, Paul Gader, and Jocelyn Chanussot. 2018. "Guest Editorial Deep Learning for Hyperspectral Image Analysis." *IEEE Transactions on Geoscience and Remote Sensing* 56 (3): 1362–64. https://doi.org/10.1109/TGRS.201 8.2801300.

Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, et al. 2018. *Global Warming of 1.5°c. An IPCC Special Report on the Impacts of Global Warming of 1.5°c Above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty.* IPCC

Special Report. Intergovernmental Panel on Climate Change. https://www.ipcc.ch/sr15/.

Metz, B., O. R. Davidson, P. R. Bosch, R. Dave, and L. A. Meyer. 2007. *Climate Change 2007: Mitigation of Climate Change.* Cambridge University Press. https://doi.org/10.1017/CBO9780511813573.

National Research Council. 2010. "Verifying Greenhouse Gas Emissions: Methods to Support International Climate Agreements." https://www.nap.edu/catalog/12883/verifying-greenhouse-gas-emissions-methods-to-support-international-climate-agreements.

Oleson, K. W., D. M. Lawrence, G. B. Bonan, and M. G. Flanner. 2013. "Interactions Between Land Use Change and Carbon Cycle Feedbacks." *Global Biogeochemical Cycles* 27 (4): 972–83. https://doi.org/10.1002/gbc.20073.

Parry, M. L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson. 2007. *Climate Change 2007: Impacts, Adaptation and Vulnerability.* Cambridge University Press. https://doi.org/10.1017/CBO9780511546013.

Pasher, Jon, Bum-Jun Park, Jérôme Théau, Francois Pimont, and Scott Goetz. 2019. "Remote Sensing of Wetlands: An Overview and Practical Guide." *Wetlands Ecology and Management* 27 (2): 129–47. https://doi.org/10.1007/s11273-018-9624-3.

Plaza, Antonio, Jon A. Benediktsson, James W. Boardman, Jason Brazile, Lorenzo Bruzzone, Gustau Camps-Valls, Jocelyn Chanussot, et al. 2009. "Recent Advances in Techniques for Hyperspectral Image Processing." *Remote Sensing of Environment* 113 (S1): S110–22. https://doi.org/10.1016/j.rse.2008.10.008.

Rackauckas, Christopher, David Kelly, Qing Nie, Jesse Li, Cody Warner, Malvika Dhairya, Jie Fang, et al. 2020. "Universal Differential Equations for Scientific Machine Learning." *arXiv Preprint arXiv:2012.09345.*

Raissi, Maziar, and George Em Karniadakis. 2021. "Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations." *Journal of Computational Physics* 378: 686–707.

Raissi, Maziar, Paris Perdikaris, and George Em Karniadakis. 2019. "Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations." *Journal of Computational Physics* 378: 686–707.

Rubenstein, Michael, Alejandro Cornejo, and Radhika Nagpal. 2014. "Programmable Self-Assembly in a Thousand-Robot Swarm." *Science* 345 (6198): 795–99. https://doi.org/10.1126/science.1254295.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, and H. L. Miller Jr. 2007. *Climate Change 2007: The Physical Science Basis.* Cambridge University Press. https://doi.org/10.1017/CBO9780511546013.

Stocker, T. F., D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley. 2013. *Climate Change 2013: The Physical Science Basis.* Cambridge University Press. https://doi.org/10.1017/CBO9781107415324.

Thenkabail, Prasad S. 2019. "Remote Sensing of Global Croplands for Food Security." *Remote Sensing* 11 (10): 1261. https://doi.org/10.3390/rs11101261.

United Nations. 2015. "Transforming Our World: The 2030 Agenda for Sustainable Development." *UN General Assembly.* https://sdgs.un.org/2030agenda.

United Nations Environment Programme. 2017. "Adaptation Gap Report 2017." https://www.unep.org/resources/adaptation-gap-report-2017.

Wang, Donglian, Donghui Xie, Yichun Xie, and Chen Chen. 2017. "Remote Sensing Applications for Urban Water Resources: A Review." *Remote Sensing* 9 (8): 829. https://doi.org/10.3390/rs9080829.

World Health Organization. 2018. "Climate Change and Health." https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health.

Wu, Jingtao, and Xiaohua Zhang. 2021. "A Review on Physics-Informed Machine Learning: Basic Principles, Recent Developments and Future Directions." *Physics Reports* 903: 1–45.

Xu, Xiaohui, Feng Deng, Xiuwei Guo, Ping Lv, Hua Zhong, Yuantao Hao, Guocheng Hu, et al. 2017. "Association Between Particulate Matter Air Pollution and Hospital Admissions in Patients with Chronic Obstructive Pulmonary Disease in Beijing, China." *Science of the Total Environment* 579: 1616–21. https://doi.org/10.1016/j.scitotenv.2016.11.166.

Zhu, Xiao Xiang, Devis Tuia, Lichao Mou, Gui-Song Xia, Liangpei Zhang, and Feng Xu. 2017. "Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources." *IEEE Geoscience and Remote Sensing Magazine* 5 (4): 8–36. https://doi.org/10.1109/MGRS.2017.2762307.

APPENDIX A

ADDITIONAL STUFF

You might put some computer output here, or maybe additional tables. It is possible to have multiple appendices. Just list them in the appropriate place within `_quarto.yml`.

BIOGRAPHICAL SKETCH

Update required!

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