Machine Learning and Snow Science.

Oral Presentation

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Outline

Background

Why do we care about snow?

- Seasonal snow is an important part of the Earth's climate system because:
    1. It helps regulate the temperature of the Earth's surface because of its high albedo.
    2. Snow acts like an insulating blanket
        - i. It prevents moisture from escaping from the ground beneath it.
        - ii. The soil and organisms beneath 1 foot of snow are protected from changes in the air temperature above the snow surface.

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Background

Why do we care about snow?

- Many regions of the world depend on water from snowmelt to support life. Water from snowmelt flows back into rivers and reservoirs, serving as the major source of water in many regions of the world.
    1. About one-sixth of the world's population depend on water from snow melt.
    2. In the western United States, mountain snowmelt is the primary source of water.

Motivation

What is the problem?

- The earth is warming up, altering the historical pattern of snow accumulation and snowmelt. Methods that work in the past are becoming less accurate.
- Snow cover is often located in mountainous regions making it difficult to monitor snow cover change using manual techniques. As a result, we often resort to "looking at it from the space" (space-borne remote sensing).
- When we fly over the mountains, what we observe is whether there is snow/no snow. We do not know how deep it is or how fast it is melting.

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Aim and Objectives

- **Aim**: review previous articles which have applied machine learning for estimating snow properties.
- **Objectives**: concentrate on the application of Machine Learning to understanding;
  1. Fractional Snow Cover
  2. Snow Depth
  3. Snow Water Equivalent

Fractional Snow Cover

Background

- The spatial extent of snow (snow cover area) is crucial in the management of hydrological regimes, forest fire risk assessment, and recreational demands.
- Fractional snow cover (FSC) is the percentage of a pixel covered by snow.
- We often get snow cover data from two systems:
    i. Landsat remote sensing system
    ii. Moderate Resolution Imaging Spectroradiometer (MODIS)

Note: there are many satellites out there but you have to pay for them

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Fractional Snow Cover

- Sample Landsat imagery

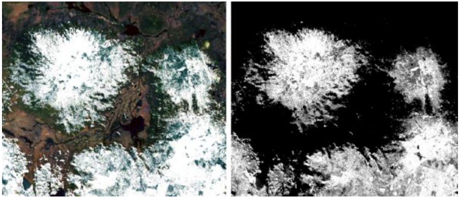

Figure: Landsat Imagery, Source: United States Geological Survey

- Sample MODIS imagery can be found on NASA Videos YouTube page.

Fractional Snow Cover

Problems with Satellite Imagery

- **Spatial Resolution**

  i. Landsat system provides snow-covered area estimates at 30 m spatial resolution (one pixel on the Landsat image corresponds to a square of 30 by 30 meters on the ground).

  ii. MODIS system provides snow-covered area estimates at 500 m spatial resolution

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Fractional Snow Cover

Problems with Satellite Imagery

- **Temporal Resolution**
  1. Landsat system has a 16-day return return time.
  2. MODIS has a daily return time
- **Main Problem:** We want images taken at Landsat's spatial resolution and MODIS' temporal resolution ☹.
- **Possible Solutions:**
  1. Downscale MODIS
  2. Use Machine Learning (focus) for FSC mapping

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Fractional Snow Cover

Machine Learning for FSC Mapping

- **Frequently ML techniques:**
  1. Artificial Neural Networks (ANN)
  2. Random Forest (RF)
  3. Support Vector Regression (SVR)

Random Forest

It is an ensemble learning technique based on the concept of Bagging.

- Ensemble → combining multiple learning machines to obtain an improved version of the constituting ones.
- Bagging → Bootstrap + Aggregation. Given $\mathcal{D}_n^{(tr)}$, obtain bootstrapped samples and then $\hat{f}^1(\mathbf{x}), \hat{f}^2(\mathbf{x}), \cdots, \hat{f}^B(\mathbf{x})$.

$$\hat{f}_{\text{bag}}(\mathbf{x}) = \frac{1}{B}\sum_{b=1}^{B}\hat{f}^b(\mathbf{x}). \tag{1}$$

This is bagging!

RF → Bagging + random feature selection. Note: Eq (1) is for regression, majority vote is for classification.

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Random Forest

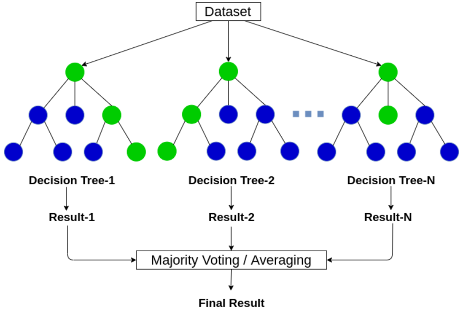

Figure: Ensemble of Decision Trees , Source: AI Pool

Decision Tree Regression: $\hat{y} = \hat{f}(\mathbf{x}) = \frac{1}{|R_j|}\sum_{i=1}^{n} y_i 1(\mathbf{x}_i \in R_j).$

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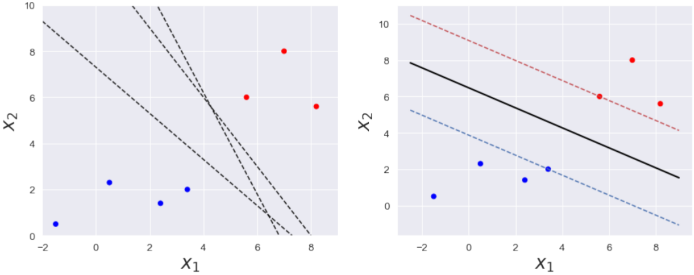
Support Vector Machine

- **Linear Support Vector Machine (SVM)**



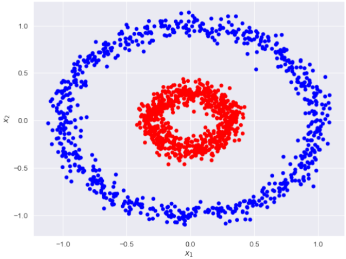
- **Optimization Problem:**

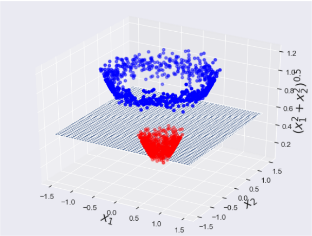
$$\min_{\mathbf{w},b} f(\mathbf{w}, b) = \frac{1}{2}\|\mathbf{w}\|^2, \tag{2}$$

$$\text{subject to: } y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 \;\; \forall i = 1, \cdots, n. \tag{3}$$

Support Vector Machine

- **Nonlinear SVM**





- **Prediction function**

$$f(\mathbf{x}) = \text{sign}\left(b + \sum_{i=1}^{n} \alpha_i y_i \mathcal{K}(\mathbf{x}, \mathbf{x}_i)\right). \tag{4}$$

- **Artificial Neural Networks (ANNs)**

  Inspired by biological neurons but not models of the brain!

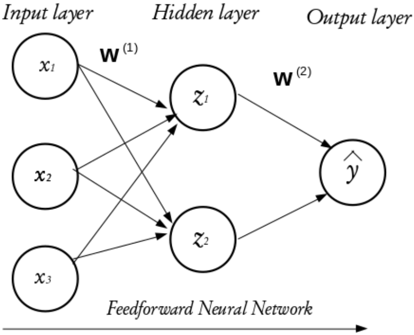


Figure: Feedforward NN.

Artificial Neural Networks

- **Artificial Neural Networks (ANNs)**

Consider the NN in Figure above, each neuron in the hidden layer does the follow computation

$$z_j = w_{0,j}^{(1)} + \mathbf{w}_j^{T(1)} \mathbf{x}_i, \tag{5}$$

The final output (predicted value) is

$$\hat{y}_i = \hat{f}(\mathbf{x}_i; \mathbf{w}) = h(w_{0,j}^{(2)} + \mathbf{w}_j^{T(2)} g(\mathbf{z}_i)). \tag{6}$$

$h(\cdot)$ and $g(\cdot)$ are activation functions and $\mathbf{w}_j^{(1)}$, $\mathbf{w}_j^{(2)}$ are weights as defined above. Hence, the loss optimization problem is

$$\mathbf{w}^* = \underset{\mathbf{w}}{\operatorname{argmin}} \left\{ \widehat{\mathcal{R}}_n(\mathbf{w}) \right\}.$$

where $\widehat{\mathcal{R}}_n(\mathbf{w}) = \frac{1}{|\mathcal{D}_n|} \sum_{i=1}^{n} (f(\mathbf{x}_i; \mathbf{w}) - y_i)^2$..

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Fractional Snow Cover

Sample Literature

Kuter (2021) employed SVR and RF for estimating FSC from MODIS Terra data and compared the performance of these algorithms with previously proposed artificial neural networks (ANNs) and multivariate adaptive regression splines (MARS). For fair comparison, same data and experimental design were employed.

Normalized Difference Snow Index (NDSI) and Normalized Difference Vegetation Index (NVDI), land cover type. Min-max normalization was used for pre-processing the data.

Random forest (500 trees, min_sample = 5). SVR (both polynomial and rbf kernel were used).

Random Forest was found to be more superior based on RMSE (0.13) and R(0.9).

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Snow Depth

- How deep is the snow we saw from above?

Figure: Measuring Snow Depth, Source: Eurac Research

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Snow Depth

Background

- Knowing the spatial of snow is not as important as knowing the depth for reasons such as weather forecast, disaster management, water delay planning, and hydrology in general.
- Despite its importance, there is an enormous void in our quantitative knowledge of mountain snowpack.
- Onsite measurement is hard, expensive, challenging, time-consuming, and potentially dangerous to field crews.

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Snow Depth

Background

- Can we look from space and know the snow depth (SD)?

  Not by just looking.

  Two commonly used remote sensing instruments for collecting snow depth data are:

  - Airborne Light Detection and Ranging (Lidar)
  - Passive Microwave Remote Sensing

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Snow Depth

Problem

- **What is the problem?**
  1. Lidar
     - Lidar is expensive
     - Not enough historical data
     - Might be inaccurate if laser hits grass.
  2. Passive Microwave
     - Coarse Spatial Resolution (25 km)
     - Signal Loss in Wet Snow
     - Doesn't work well in the mountains

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Computing Artifact

- My computing Artifact consists of a brief Introduction to Machine Learning presented at the SnowEx Hackweek, held on July 12 - 16, 2021. Hackweeks are organized by the eScience Institute at the University of Washington, and it is a participant-driven event designed to meet the needs of emerging data science communities.
- The artifact demonstrates how Machine Learning can be used to predict Snow Depth.
- About 100 people in attendance.
- Tutorial was prepared and delivered by me.
- Available on Github.

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Snow Water Equivalent

Background

- Snow water equivalent (SWE) is the amount of water that will be produced by completely melting a snowpack.
- This is mostly our ultimate goal except for few cases.
- Can't be measured directly, but if we know how dense and how deep our snowpack is, we can know how much water will be available downstream when it melts.
- We rely on field-based measurement to know SWE.

Snow Water Equivalent

Background

Figure: Measuring SWE Using Federal Snow Sampler, Source: USDA

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Snow Water Equivalent

Problem

- Traditionally, at any given point, SWE can be estimated as follows;

$$\text{SWE} = h_s \cdot \frac{\rho_s}{\rho_w} \tag{7}$$

where h_s is the snow depth, ρ_s is the snow density, and ρ_w is the density of water.

- Problem is that we don't know the snow density and snow depth everywhere.

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Snow Water Equivalent

Application of Machine Learning Techniques to SWE Estimation

- *Bair et al. (2018)* developed two machine learning models (bagged regression trees and feed-forward neural networks) for predicting SWE in Afghanistan's watershed.
- The trained models were evaluated using the bias and RMSE metrics. For the bagged regression tree, the RMSE ranged between 6 mm - 45 mm and for the feed-forward neural network, it ranged from 9 mm - 58 mm leaving the bagged regression the most preferred in this study.

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Gaps in ML Application and Open Questions

- **Gaps in Machine Learning Applications:**
  1. Lack of details for reproducible results.
  2. Lack of baseline models.
- **Open Questions:**
  1. Would time series techniques (e.g. ARIMA and Recurrent Neural Network) improve our ability to predict snow products?
  2. Would a convolutional neural network produce more accurate predictions of snow products since it is used principally for image analysis?

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Acknowledgments

A huge thanks to my advisors (Dr. Mead and Dr. Marshall) for their helpful comments and suggestions leading to the improvement of my synthesis and artifact!

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Gratitude

Thank you for

Listening!