Developing fine-scale snow cover fraction estimates using Deep Learning

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Introduction and overall goals

• Need fine-resolution, gap-free, satellite-based data (e.g., snow cover fraction, or SCF) for evaluating local hydrology
  • MODIS MOD10A1 v5 SCF @ 500 m: gaps in spatial coverage
  • MOD10C1 v5 SCF daily @ 5-km: near-complete spatial coverage
• Downscale / super-resolution regression from MOD10C1 to obtain MOD10A1 SCF- like product without gaps
• Demonstration of this Deep Learning prototype for a target 1-km resolution
Background

- Computer vision: simple super-Resolution Convolutional Neural Network (SRCNN): for fast, state-of-the-art image restoration
- Emerging geoscientific super-resolutioning applications
  - Use serially stacked SRCNNs etc.;
    - Augmented with auxiliary data channels (e.g., terrain elevation)
  - Cannot adequately handle input data gaps (e.g., at coastal pixels)
- Computer vision innovations in image inpainting: partial convolution
  - Handles gaps consistent across input channels (e.g., RGB in image)
Spatial domain and data

- 3° X 3° over Central California & Nevada
- 3-year training period (2009-2011)
- Similar development (dev) / validation and test set distributions
  - Alternate days of an year (2012) form these 2 sets
- MOD10C1 SCF input has 3 channels to be considered together: SCF, cloud cover fraction (CCF) and Confidence Index
- Different auxiliary channel types:
  1. Static terrain-related: elevation, slope, aspect
  3. Dynamic LSM-based (land surface model): precipitation, snow water equivalent (SWE), surface radiative temperature, leaf area index (LAI)
Our infrastructure

• Developing infrastructure called MENSA (Machine learning Environment for NASA Scientific data Applications) coded in Python
• Modified to handle and fill gaps that vary across the input / auxiliary channels
• Successfully implemented on NCCS ADAPT GPUs
• Following accomplishments till date:
  • Keras API layer for modified partial convolution
  • Loss functions in Tensorflow / Keras that consider only valid spatiotemporal data values in target image, e.g., RMSE
• Ongoing work:
  • Additional modified Keras API layers, e.g., batch normalization, activation, addition, pooling.
  • Other loss functions, e.g., that consider visual semantics
Data flow schematic through SRCNN

- Augmentation of traditional Dong et al* [2014] SRCNN
- ‘Same’ padding throughout during convolution

Input stack: MOD10C1 + Auxiliary

Activation stack 1: 64 channels

Activation stack 2: 32 channels

Output MOD10A1 SCF-like grid

* Dong et al [2014]: Learning a deep convolutional network for image super-resolution
Spatiotemporal valid-data percentage

Maskings
- Self
- PConv
- Modified PConv

Availability for our modified partial conv-based prediction
Upper limit for traditional partial conv-based training and prediction
Upper limit for our modified partial conv-based training

Data channel/s

Valid-data percentages

MOD10C1  MOD10A1 SnoAlb  MOD11A1 LST  LIS dynamic  Static  MOD10A1 SCF
Sample winter day’s prediction vs. target

Batch RMSE [%]
- Training: 5.7
- Dev: 5.1
- Test: 5.3
Sample summer day’s prediction vs. target

Batch RMSE [%]
- Training: 5.7
- Dev     : 5.1
- Test    : 5.3
Sample day’s gap-filling w.r.t input and target
Sample winter / summer days’ prediction after further masked training

- Training: 5.7
- Dev      : 5.5
- Test      : 5.6
Sample winter day after further masked training: spatial components

(a) 2011/2/10 target

9.0% valid-data

(b) 2011/2/10 prediction
masked to target

8.5% RMSE,
97.9% binary accuracy

(c) 2011/2/10 complement
of target

88.4% valid-data

(d) 2011/2/10 prediction
masked to complement of target

7.2% RMSE,
98.4% binary accuracy
Sample summer day after further masked training: spatial components

(a) 2011/6/24 target

(b) 2011/6/24 prediction masked to target

(c) 2011/6/24 complement of target

(d) 2011/6/24 prediction masked to complement of target
Discussion and ongoing work

- The simple SRCNN shows good skill in estimating SCF with RMSE estimates around or below 10%.
- Preparation of Keras layers that enable using other types of convolutional network architectures:
  - Parallel SRCNN stacking (ResNet-style)
  - Encoder-decoder type: e.g., U-Net
- MENSA data processing environment will include for hydrology:
  - Applications (e.g., super-resolution, regression, classification, segmentation)
  - Data analytics