AI FOR SCIENCE: DEEP LEARNING FOR IMPROVED SATELLITE OBSERVATIONS AND NUMERICAL MODELING

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AI CAN DO IMPRESSIVE THINGS

DEFEAT WORLD CHAMPION STRATEGISTS

OPERATE VEHICLES AUTONOMOUSLY

COMMUNICATE IN NATURAL LANGUAGE

GENERATE ORIGINAL CONTENT
DEEP LEARNING BUILDS FUNCTIONS FROM DATA

Find $f$, given $x$ and $y$

INPUTS

OUTPUTS

SUPERVISED DEEP LEARNING
A NEW TOOL FOR SOFTWARE DEVELOPMENT

TEMP, PRESSURE, MOISTURE

FUNCTION 1
FUNCTION 2
FUNCTION 3
FUNCTION 4
FUNCTION 5

PROBABILITY OF RAIN

HAND-WRITTEN FUNCTION

Function1(T,P,Q)
update_mass()
update_momentum()
update_energy()
do_macrophysics()
do_microphysics()
y = get_precipitation()
return y

LEARNED FUNCTION

Function1(T,P,Q)
A = relu(w1 * [T,P,Q] + b1)
B = relu(w2 * A + b2)
C = relu(w3 * B + b3)
D = relu(w4 * C + b4)
E = relu(w5 * D + b5)
y = sigmoid(w6 * E + b6)
return y

Convert expert knowledge into a function
Reverse-engineer a function from inputs / outputs
LEARNED FUNCTIONS ARE GPU ACCELERATED
ENHANCE EXISTING APPLICATIONS

Improve all stages of numerical weather prediction

COLLECTION    THINNING    ASSIMILATION    EMULATION    PARAMETRIZATION    COMMUNICATION
BUILD NEW CAPABILITIES

- Real-time weather detection
- Environmental monitoring
- Disaster planning, search and rescue
- Near-Earth object detection
- Accelerated data assimilation
- Autonomous sensors and rovers
- Data enhancement and repair
- Faster / more accurate parameterizations
An interesting application of AI is the real-time detection of features of interests, such as tropical storms, hurricanes, tornados, atmospheric rivers, volcanic eruptions, and more. Using AI we can rapidly process the data streaming in from multiple satellites around the globe, enabling us to examine every pixel in detail for important information.
FEATURES OF INTEREST

- Tropical Cyclones
- Extra-tropical Cyclones
- Atmospheric Rivers
- Storm Fronts
- Tornados
- Convection Initiation
- Cyclogenesis
- Wildfires
- Blocking Highs
- Volcanic Eruptions
- Tsunamis
TROPICAL STORM DATASET FROM IBTRACS AND GFS

Extract positive and negative examples for supervised learning
U-NET

Multi-scale Convolutional Neural Net for Image Segmentation

GFS WATER VAPOR FIELD

TARGET SEMENTATION

Key:
- Green: Residual Skip Connection
- Orange: 3x3x3 Convolution
- Red: Strided Convolution
- Green: Transposed Convolution
RESULTS: TROPICAL STORMS

NOAA ESRL
Mark Govett
Jebb Stewart
Christina Bonfonti

NVIDIA
David Hall

SOURCE
GFS Water Vapor

TARGET
IBTRACS Storm Locations
RESULTS: TROPICAL STORMS
GOES SATELLITE OBSERVATIONS
UPPER-TROPOSPHERIC

NOAA ESRL
Mark Govett
Jebb Stewart
Christina Bonforti

NVIDIA
David Hall

SOURCE
GOES 12-15 Upper Tropospheric
Water Vapor Band

TARGET
IBTRACS Storm Locations
RESULTS: CONVECTION INITIATION

GROUND TRUTH

PREDICTION

NOAA ESRL
Mark Govett
Jebb Stewart
Christina Bonfonti

NVIDIA
David Hall

SOURCE
Himawari8 band 8,13

TARGET
Composite Radar
Reflectivity DBZ>35

2018-05-20T00:00:00
In cases where a 1-1 map is not possible, we can employ conditional generative adversarial networks in order to generate a single, physically plausible state from a distribution of possible states. This prevents the dilution or blurring caused by under-constrained output.
FORWARD AND INVERSE OPERATOR APPROXIMATION

SATELLITE RADIANCES

MODEL VARIABLES
RESULTS:
SATELLITE TO MODEL CONDITIONAL GAN

NVIDIA
David Hall

SOURCE
GOES-15 Band 3
GFS Water Vapor

TARGET
GFS Water Vapor
GOES-15 Band 3
“REGRESS THEN GAN”

TOY PROBLEM: TRAINING A 2D CONDITIONAL GAN

NVIDIA
David Hall

SOURCE
1d parametric coordinate

TARGET
Synthetic point distribution distribution
RESULTS: CGAN CLOUD GENERATION

NASA Goddard
Tianle Yuan
Hua Song
Victor Schmidt
Kris Sankaran

MILA
Yoshua Bengio

NVIDIA
David Hall

SOURCE
Hadcrut4, cmip, 20cr

TARGET
Hadcrut4, cmip, 20cr
Using NVIDIA’s super-slow motion and inpainting techniques, we can repair missing or damaged pixels in satellite and model data, or create high quality interpolations of the data in space and time.
USE DEEP LEARNING TO PREDICT OPTICAL FLOW

U-COMPONENT OF WIND

2D OPTICAL FLOW

0

20m/s
RESULTS:
SLOW MOTION ADVECTION

NVIDIA
David Hall

SOURCE
GOES-15 Band 3

TARGET
GFS u,v wind fields
IN-PAINTING

Use partial-convolutions to fill in missing data
RESULTS: INPAINTING MISSING HADCRUT4 CLIMATE DATA

FREI UNIVERSITAT BERLIN
Christopher Kadow

NVIDIA
David Hall

SOURCE
Hadrut4, cmip, 20cr

TARGET
Hadrut4, cmip, 20cr
INPAINTING MISSING GOES-17 OBSERVATIONS

NOAA STAR
E. Maddy\textsuperscript{(RTI)}
N. Shahroudi\textsuperscript{(RTI)}
R. Hoffman\textsuperscript{(UMD)}
T. Connor\textsuperscript{(AER)}
S. Upton\textsuperscript{(AER)}
J. Ten Hoeve\textsuperscript{(NWS)}

SOURCE
GOES-17

TARGET
GOES-17

AI-BASED IMAGE CORRECTION ALGORITHM
Correction based on NVIDIA’s inpainting algorithm but applied for 256 x 256 pixel ABI thermal band images

AI-based correction produces realistic images in corrupted bands.
Corrections can be applied when all thermal bands are corrupted or when only a subset of bands are corrupted. In the latter case, image reconstruction improved due to spatial/spectral redundancy.
Climate models are able to predict changes in precipitation, but how will this effect streamflow rates? To answer this question one can build a detailed physical model, or train a neural network to predict time series data. In this case, we find a simple network performs just as well.
STREAMFLOW FROM PRECIPITATION
Predicting streamflow probabilities under climate change

UC Davis
Paul Ullrich, Lele Shu, Shiheng Duan

NVIDIA
David Hall

Source
PRISM

Target
Stream Gauge Data
Deep Learning is another way to write software
DL functions are created from data
Can enforce conservation with Lagrange multipliers or hard constraints
An alternative route to GPU optimization
Can automate or improve many tasks
Build functions too unintuitive / complex for humans
Regression returns a single value (the mean)
GANs randomly sample states from a distribution
DL functions are limited by data + model expressiveness
Hand-written functions can be limited by imagination + programming language
SUMMARY

UNETs for weather and space-weather detection

Slow motion interpolation via optical flow prediction

Inpainting for imputing missing HadCRUT4 and GOES-17 data

Conditional GANs for data assimilation and cloud generation

Convolutions in time for streamflow prediction

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Feature detection can be applied to detect features on the Sun and other astrophysical bodies. In particular, we can apply AI to solar flares and coronal mass ejections in order to predict the influx of highly charged particles on Earth’s atmosphere.
SOLAR DYNAMICS OBSERVATORY

- 1.5 TB Data / Day
- Operational Since 2010
- AIA: 10 Wavelength Channels
- 150M Images To Be Labelled
- 30k Images Labelled so far

- Coronal Holes
- Active Regions
- Sunspots
- Solar Flares
- Coronal Mass Ejections
- Filaments
RESULTS: CORONAL HOLES

NASA Goddard
Michale Kirk, Barbara Thompson, Jack Ireland, Raphael Attie

NVIDIA
David Hall

Altamira
Matt Penn, James Stockton,

SOURCE
Solar Dynamics Observatory
AIA Imager

TARGET
Hand-crafted detection algorithm
SUNSPOT PREDICTIONS
Highly imbalanced dataset. Needs special care.

Predicts all 0s unless special care is taken
• Super-sample minority class
• Under-sample majority class
• Use focal loss

Select small crops from high-res imagery
Pos : crops w/large fraction sunspot pixels
Neg : randomly selected crops

Train conv net on small crops only
Predict on full-resolution images
RESULTS: SUNSPOTS

NASA Goddard
Michale Kirk, Barbara Thompson, Jack Ireland, Raphael Attie

NVIDIA
David Hall

Altamira
Matt Penn, James Stockton,

SOURCE
Solar Dynamics Observatory
AIA Imager

TARGET
Hand-crafted detection algorithm

Ground Truth
Prob of Detection

(AIA 193Å) BCE loss = 0.00027
RESULTS: ACTIVE REGIONS

NASA Goddard
Michale Kirk, Barbara Thompson, Jack Ireland, Raphael Attie

NVIDIA
David Hall

Altamira
Matt Penn, James Stockton,

SOURCE
Solar Dynamics Observatory
AIA Imager

TARGET
Hand-crafted detection algorithm