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 $y$

SUPERVISED DEEP LEARNING

INPUTS

$x_1$
$x_2$
$x_3$
$x_4$
$x_5$
$x_6$

OUTPUTS

$y_1$
$y_2$
$y_3$
$y_4$
$y_5$
$y_6$

DEEP LEARNING BUILDS FUNCTIONS FROM DATA
IT’S A GENERALIZATION OF CURVE FITTING

Find $f$, given $x$ and $y$
CURVE FITTING IN VERY HIGH DIMENSIONS

Find \( f \), given \( x \) and \( y \)

Supervised Deep Learning

inputs

\( x_1 \)
\( x_2 \)
\( x_3 \)
\( x_4 \)
\( x_5 \)
\( x_6 \)

outputs

\( y_1 \)
\( y_2 \)
\( y_3 \)
\( y_4 \)
\( y_5 \)
\( y_6 \)

High dimensional \( x,y \)
Hierarchical
Millions of parameters

Find \( f \) given \( x \) and \( y \)
IT’S A NEW TOOL FOR SOFTWARE DEVELOPMENT

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
MAKES EFFECTIVE USE OF NVIDIA GPUS

Libraries
OPEN-ACC
CUDA
RAPIDS ML
DEEP LEARNING
WE CAN ENHANCE EXISTING APPLICATIONS

Improve all stages of numerical weather prediction
WE CAN 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
EXAMPLE APPLICATIONS:
FEATURE DETECTION
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
BUILD TROPICAL STORM DATASET FROM IBTRACS AND GFS

Extract positive and negative examples for supervised learning

POSITIVE

NEGATIVE
USE A U-NET MODEL FOR SEGMENTATION

Multi-scale Convolutional Neural Net for Image Segmentation

GFS WATER VAPOR FIELD

Key:
- Residual Skip Connection
- 3x3x3 Convolution
- Strided Convolution
- Transposed Convolution

TARGET SEGMENTATION
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

2018-05-20T13:30:00
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

(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
EXAMPLE APPLICATIONS:
GENERATIVE MODELS
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

NEURAL NETWORK

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
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
EXAMPLE APPLICATIONS:
DATA ENHANCEMENT
ENHANCEMENT AND REPAIR OF SATELLITE & MODEL DATA

NOAA STAR
Freie Universitat Berlin
NVIDIA

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
20 m/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
Hadcrut4, cmip, 20cr

TARGET
Hadcrut4, cmip, 20cr
EXAMPLE APPLICATIONS:
TIME-SERIES PREDICTION
Climate models are able to predict changes in precipitation, but how will this effect streamflow rates? To answer this question one can built 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

INPUT: PRECIPITATION

OUTPUT: STREAMFLOW
prediction of streamflow on held-out test data

R2 = 0.85, NSE=0.70
SUMMARY

• SUPERVISED DEEP LEARNING IS POWERFUL, BUT NOT MYSTERIOUS
• A GENERALIZATION OF CURVE FITTING, IN HIGH DIMENSIONS
• A DIFFERENT WAY TO BUILD SOFTWARE (REVERSE-ENGINEERING FROM DATA)
• A GREAT WAY TO TAKE ADVANTAGE OF YOUR GPUs
• CAN DO SOME PRETTY AMAZING THINGS. (CAN’T BE DONE IN ANY OTHER WAY.)
• WILL BECOME A STANDARD PART OF THE NWP / CLIMATE TOOLBOX.

dhall@nvidia.com
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

dhall@nvidia.com
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