Riding the hype wave: Evaluating new AI techniques for their applicability in Earth science

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Hype Wave: The Perpetual Smart Machine Age

“Smart machine technologies will be the most disruptive class of technologies over the next 10 years due to radical computational power, near-endless amounts of data, and unprecedented advances in deep neural networks that will allow organizations with smart machine technologies to harness data in order to adapt to new situations and solve problems that no one has encountered previously. Enterprises that are seeking leverage in this theme should consider the following technologies: Smart Dust, Machine Learning, Virtual Personal Assistants, Cognitive Expert Advisors, Smart Data Discovery, Smart Workspace, Conversational User Interfaces, Smart Robots, Commercial UAVs (Drones), Autonomous Vehicles, Natural-Language Question Answering, Personal Analytics, Enterprise Taxonomy and Ontology Management, Data Broker PaaS (dbrPaaS), and Context Brokering.”

Source: Gartner Press Release http://www.gartner.com/newsroom/id/3412017
Hype Cycle for Emerging Technologies (2016)

Source: Gartner Press Release http://www.gartner.com/newsroom/id/3412017
AI Hype

**Machine Learning Is No Longer Just for Experts**
by Josh Schwartz
OCTOBER 26, 2016
Source: https://hbr.org/2016/10/machine-learning-is-no-longer-just-for-experts

**The Competitive Landscape for Machine Intelligence**
by Shivon Zilis and James Cham
NOVEMBER 02, 2016
Source: https://hbr.org/2016/11/the-competitive-landscape-for-machine-intelligence

**How to Make Your Company Machine Learning Ready**
by James Hodson
NOVEMBER 07, 2016
Source: https://hbr.org/2016/11/how-to-make-your-company-machine-learning-ready
Cautionary Examples

**What Artificial Intelligence Can and Can’t Do Right Now**

by Andrew Ng  
Source: https://hbr.org/2016/10/machine-learning-is-no-longer-just-for-experts

NOVEMBER 09, 2016

The racist hijacking of Microsoft's chatbot shows how the internet teems with hate

Source: https://www.theguardian.com/world/2016/mar/29/microsoft-tay-tweets-antisemitic-racism

Google says sorry for racist auto-tag in photo app

Source: https://www.theguardian.com/technology/2015/jul/01/google-sorry-racist-auto-tag-photo-app
Challenges for Earth Science Informatics

• How do we evaluate these new technologies?
  • What is this new technology enabling/providing that is innovative and different?

• Can one justify the adoption costs with respect to the research returns?
  • Since nothing comes for free, utilizing a new technology entails adoption costs that may outweigh the benefits.
  • Technologies may require significant computing infrastructure in order to be utilized effectively.
AI Projects – Overview and Lessons Learned

• Building a Knowledge Graph for Earth Science
  • Rahul Ramachandran NASA/MSFC, Patrick Gatlin NASA/MSFC, Manil Maskey NASA/MSFC; Jia Zhang, CMU; Amanda Weigel UAH, J. J. Miller, UAH

• Evaluating deep learning technique for different applications within Earth science using satellite imagery
  • Multiple projects
Building a Knowledge Graph for Earth Science

What is a Knowledge Graph?

• Aggregates structured and detailed information about a defined topic, enabling users to resolve their query without having to navigate and assemble information manually.

• Developed by Google in 2012 to enhance the results of its search engine by systematically linking information.
Benefits to NASA Earth Science

• New knowledge/knowledge augmentation services
  • Hypothesis formulation and testing:
    • Automate the search for and compilation of background information
    • Given a topic, what hypotheses have been tested?
    • What data/tools are being used to test a hypothesis?
    • Common paths to knowledge discovery
  • Mission development/review:
    • What kinds of instruments/parameters are needed to specify science objectives?
    • Impact of a mission by linking it with publications and dataset distribution

• Recommendation service based on the knowledge base to broaden usage of NASA EOS datasets and computational resources
Methodology

Earth Science Research consists of both Structured and Unstructured Content

How do we extract and link valuable information from the vast distributed heterogeneous resources?
Initial Results
Lessons Learned

• Entity extraction tools work well; however, categorization of entities is hard.

• Using domain control vocabularies and taxonomies help, but they only get you so far.

• Mining for rules within sentences may work but requires extensive number of labeled samples (training data).
Deep Learning Applications

• Browse Imagery Retrieval Service for Different Phenomena
  • Manil Maskey, NASA/MSFC

• Study Transverse Cirrus Cloud Bands
  • JJ Miller, UAH and NASA/MSFC DSIG; U.S. Nair, UAH

• Tropical Cyclone Intensity Estimation
  • Manil Maskey, NASA/MSFC; Dan Cecil, NASA/MSFC
Deep Learning Architecture

- Deep Learning
  - Hierarchical Learning
  - Mimics the human brain which is organized in a deep architecture
  - Processes information through multiple stages of transformation and representation

- Key Advantage
  - Automates features engineering (learns)

Figure source: Katole et al., 2015 Hierarchical Deep Learning Architecture for 10K Objects Classification, Computer Science & Information Technology (CS & IT), DOI: 10.5121/csit.2015.51408
Image Retrieval Application

Objective:
• Test deep learning (Convolution Neural Network) to identify Earth science phenomenon in browse imagery (RGB)

Results (MODIS Rapid Response Test Images)

<table>
<thead>
<tr>
<th>True/Pred</th>
<th>Dust</th>
<th>Hurricane</th>
<th>Smoke</th>
<th>Other</th>
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<td>Dust</td>
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<td>8</td>
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<td>33</td>
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<tr>
<td>Hurricane</td>
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<td>379</td>
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<td>10</td>
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<tr>
<td>Smoke</td>
<td>12</td>
<td>12</td>
<td>443</td>
<td>9</td>
</tr>
<tr>
<td>Other</td>
<td>33</td>
<td>9</td>
<td>23</td>
<td>211</td>
</tr>
</tbody>
</table>

Producer’s Accuracy
- Dust 86.45%
- Hurricane 92.89%
- Smoke 88.78%
- Other 80.23%

User’s Accuracy
- Dust 79.72%
- Hurricane 97.18%
- Smoke 93.07%
- Other 76.45%

Overall Accuracy = 87.88%
Study Transverse Cirrus Bands

Methodology
- Gathered 5440 images (1 km MODIS RGB)
  - 1741 with transverse bands
  - 3699 without transverse bands
- 20% were used for validation during training
- Test set consisted of 600 separate images not used in training
- Use trained network to classify a one year’s worth of MODIS tiles from Global Imagery Browse Service (GIBS)

Transverse Cirrus Bands
- Form in and around a variety of meteorological phenomena
  - Hurricanes
  - Mesoscale Convective Systems (MCS)
  - Jet-streaks
- Associated with aviation turbulence
- Still no consensus on exactly what causes them to form
Training Results

• Model trained for 52 epochs (6 hours)
• Highest validation accuracy occurred at epoch 41 (0.937)
• Testing on the test set:
  • Accuracy: 94.67%
  • Recall: 0.95
  • Precision: 0.95
• Class activation maps (right) show that the network is able to identify the regions of the image that contain transverse bands.

<table>
<thead>
<tr>
<th>Predictions</th>
<th>Bands</th>
<th>Not Bands</th>
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<tbody>
<tr>
<td>Bands</td>
<td>107</td>
<td>22</td>
</tr>
<tr>
<td>Not Bands</td>
<td>10</td>
<td>461</td>
</tr>
</tbody>
</table>
Climatology Study: Spatial Distribution

- Some interesting areas stand out
  - Eastern coast of India
  - Western coast of Mexico/California
  - Southeastern coast of South America
- Eastern and Central US more than likely due to MCSs
- Analysis still ongoing...
Tropical Cyclone Intensity Estimation

Goal
• Use deep learning to objectively estimate intensity

Dvorak technique developed in 1970s still used to estimate intensity from satellite imagery
• Inconsistent as estimation is subjective

Image data
• US Naval Research Laboratory (http://www.nrlmry.navy.mil/tcdat)
  • 1998 to 2014
  • 15 minute interval
  • 98 cyclones (68 Atlantic and 30 Pacific)

Wind speed data (Truth set)
• National Hurricane Center (http://www.nhc.noaa.gov) (Best track data: HURDAT and HURDAT2)
• Hurricane Research Division (http://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html)
  • 6 hour interval

Results

- Precision – 0.80
- Recall – 0.81
- 14,345 test images (Atlantic + Pacific)
Lessons Learned

• Compute intensive (requires GPUs)
• Requires extensive amounts of training data
  • Learning from a few thousand training samples is unrealistic
• Suitable for applications where “labeled (training) data” can be obtained from another instrument or data stream
• For some applications transfer learning may work
  • Use internal representation learned from one classification task to another
    • AlexNet architecture - Krizhevsky et. al.
    • Weights learned from ImageNet 1.3 million high-resolution images
    • State-of-the-art classification accuracy

Want more details?

Attend the following presentations:

• **Knowledge Graph: Tsengdar Lee et al.**
  • IN14A-08 Building Knowledge Graphs for NASA’s Earth Science Enterprise
    Monday, 12 December 2016, 17:45 - 18:00, Moscone West - 2000

• **Deep Learning: Manil Maskey et al.**
  • IN52A-04 Deep Learning-Powered Insight from Dark Resources
    Friday, 16 December 2016, 11:20 - 11:32, Moscone West - 2000
Contact

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