DC7119 – MAKING DEEP LEARNING SCALE: DEFENSE APPLICATIONS

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Agenda

Harris Corporation Introduction

A Call to Action: The Urgency Behind the DoD’s Adoption of AI

Deep Learning Research at Harris

Harris’s Work to Scale Deep Learning for Defense

Q&A
Harris Corporation introduction – segment overviews

- **Communication Systems**: Tactical and airborne radios, night vision technology, and defense and public safety networks.

- **Electronic Systems**: Electronic warfare, avionics, robotics, advanced communications and maritime systems for the defense industry, as well as air traffic management solutions for the civil aviation industry.

- **Space and Intelligence Systems**: Complete solutions encompassing advanced sensors and payloads, processing systems, and analytics for global situational awareness, space superiority missions, and Earth insights.
A call to action: the urgency behind the DoD’s adoption of AI

“We’re going to find ourselves in the not too distant future swimming in sensors and drowning in data”

"The skies will ‘darken’ with the hundreds of small satellites to be launched by U.S. companies and as procedures are developed to allow safe operation of unmanned aerial vehicles in civil airspace,”

Robert Cardillo, Director – NGA 2015

“So just how big is this rising tide? If we were to attempt to manually exploit the commercial satellite imagery we expect to have over the next 20 years, we would need eight million imagery analysts. Even now, every day in just one combat theater with a single sensor, we collect the data equivalent of three NFL seasons – every game. In high definition!

Imagine a coach trying to understand the strategy of his opponents by watching every play made by every team in every game for three seasons – all in one single day. Because three more seasons will be coming tomorrow. That’s what we ask our analysts to do – when we don’t augment them with automation. But with all this data – and dramatic improvements in computing power – we have a phenomenal opportunity to do and achieve even more.”

Robert Cardillo, Director – NGA 2017

“The GEOINT discipline has grown beyond the limits of human interpretation and explanation. The explosion of available data diminishes the comparative advantage collection provides. Instead, automated processing, advancing tradecraft, human-machine collaboration, and the ability to anticipate behaviors will provide us a new advantage.”

Robert Cardillo, Director of NGA

NON-Export Controlled Information
A call to action: the urgency behind the DoD’s adoption of AI

14M training images
1,000 object categories

2016 ImageNet Challenge Object Classification Winner: Trimps-Soushen 2.99% Error Rate

ILSVRC Top 5 Error on ImageNet

Graph from https://www.dsiac.org

Artificial Intelligence M&A Activity

RACE FOR AI: TOP ACQUIRERS OF AI STARTUPS

ARTIFICIAL INTELLIGENCE M&A ACTIVITY

DATE OF DEAL

CIBINSIGHTS
A call to action: the urgency behind the DoD’s adoption of AI

“DoD has yet to embrace the transformational capabilities of artificial intelligence (AI) and machine learning (ML) across the Department. Together, they have the power to impact every corner of DoD, including force protection, training, logistics, recruiting, healthcare, C4ISR, cyber operations, and more. The significance of AI and ML is akin to the first and second offsets that took advantage of nuclear weapons and precision munitions and stealth technology, respectively. Underscoring the importance of applications of AI and ML across the Department is critical to create and sustain the asymmetric advantage required to outpace our adversaries.”

- Defense Innovation Board, 2017
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Harris Corp. has been internally investing in taking state-of-the-art deep learning technologies and applying them to remote sensing and geospatial intelligence customer problems.

**How long?**
- Harris has been working on deep learning for over five years

**How much?**
- Multimillion dollar internal research and development investment in the last three years
- Additional commercialization investment

**Investment Approach**
- Research
- Pilot Projects
- Software tool development
- Commercialization

**Focus Areas:**

**Reducing the Cost of Training**
- Reduce dollar cost, human cost, and computer cost of building new models

**Extensibility**
- Ability to quickly redeploy and repackage tools to support new problem sets

**Support multiple types of data**
- New sensors and data fusion

**Automation**
- Ability for processes to interface to tools, removing human from the loop
Harris deep learning R&D
Still imagery applications – automatic feature detection – 2D overhead

- Near ceiling performance in Pan, RGB, MSI
- Robust against occlusions, orientation, image quality

Sample Targets Tested:
- Airplanes
- Storage Tanks
- Sports Stadiums
- Athletic Fields
- Smokestacks
- Cooling Towers
- Clouds
- Crosswalks
- Swimming Pools
- Buildings
- Paved Roads
- Overpasses/Cloverleafs
- Tollbooths
- Beaches
- Cemeteries
- Wind Turbines
- Orchards & Row Crops

Tokyo Int’l Airport IKONOS Pan
20/20 Planes detected, 0 FP

Sau Paulo, Brazil 30cm WV-3
43/43 crosswalks detected, 0 FP

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Harris deep learning R&D still imagery applications – wind turbine blade inspection – 2D natural

Which wind turbines need repair in this wind farm?

- Drone-captured data
- Thousands of raw images organized
- Deep learning analyzed
- Damage identified and categorized
- Prioritize repair needs and budget
- Change detection through time
- Turbine life-cycle management

http://edgedata.net/bladeedge/

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Harris deep learning R&D still imagery applications – wind turbine blade inspection – 2D natural
Harris deep learning R&D motion imagery applications – traffic cams and road conditions

- Real-time ground weather intelligence system
- Data from traffic cam videos

- Scene detection instead of target detection
  *Is it raining? Are the roads wet? Is snow present?*

In use today in operational commercial product

https://www.helios.earth/
Harris deep learning R&D
motion imagery applications – Helios® for autonomous vehicles

Taking Harris Analytics to Connected Cars at the Consumer Electronics Show
Problem: Clandestine airfields in South American countries used for illegal narcotic trafficking

Goal: Detect new airfields and determine activity levels with high temporal resolution data (Planet)
Harris deep learning R&D motion imagery applications – high revisit rate still imagery

Sources:

- Planet imagery
- DigitalGlobe EGD imagery
- Ecuadorean geoportal shapefile of known remote landing strips
- Google Earth imagery
- Wikimapia
- OpenStreetMap
UCF-101 benchmark dataset

- 101 classes
- 13k video clips
- Approximately 30 hours of video

Among the most challenging open problems

- Demo of successful training of recurrent NN (LSTM)
- Model was learning despite severe reduction in data (length of clips and resolution of frames)
- Analogue for surveillance cameras or drone video
- Many potential applications for RNNs
  - Any problem that can be restated in terms of a sequence
Transition from forward-facing security camera type video to offset overhead video

- Fewer pixels on target
- Less stable
- Changing orientations, modalities, zoom levels

Credit: JOHN MOORE/GETTY

Source: [http://www.viraldata.org](http://www.viraldata.org)
LiDAR sensors have very powerful discriminatory capabilities. Can DL models learn to recognize objects and terrain types?

Many Challenges
• Raw 3D point clouds are difficult to use compared to images
• Typically very large and spatially dense, yet sparse in Z-dim
• Complementary to imagery, could be used together if available
• Harder to label
  - By individual point or 3D bounding box
  - Software tools less developed (or don’t exist)
• Not much deep learning research on airborne LiDAR classification

End-to-End Approach for Success
• Understanding phenomenology from sensor to analyst allows for targeted application of deep learning
  - Deep learning has been adopted at multiple points in production workflow supporting automation and product generation

3D point cloud color-coded by height
Object Detection in LiDAR Point Clouds
- French National Railroad (SNCF) asset inventory project
- Extension of 2D ConvNet to 3D data source
- Preliminary results are very encouraging
- Finds variety of 3D objects (signals, crossings, boxes, poles)

Geiger-Mode LiDAR Bare Earth Point Labeling
- Proof-of-concept for point labeling in Geiger-Mode data
- Limited training data with significant errors
- Discovered effective signals in data by constructing voxel grids with:
  - mean/min/max/stdev of elevation and intensity
  - Multiple neighborhoods of gridded data used as inputs for CNN
- Post-processing with CRF to enforce nearest neighbor dependence

Point Clouds from Synthetic Image Pairs
- Point cloud data derived from stereo pairs of imagery
- MEGA analytics agnostic to multiple data generation approaches
- Contains information about multiple collects and sensor model

Example Target: Railroad Signals

Heat Map (all detections shown)

Full point cloud (held-out test area)

Bare Earth Probability Map

AUC: 0.961

Model must understand context of "missing" data
Harris deep learning R&D
Applications lessons learned and takeaways

Pros:

Now possible to build detection algorithms with minimal prior knowledge of the target and minimal image science background

High 90% accuracies achievable by amateurs with sufficient label data and using appropriate neural network architecture

GPUs allow neural net training and inference times to be timely (minutes instead of days)
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Q&A
The art of scaling ML

Problem → Machine Learning → Answers!

- Understand problem
- Classification Export Controls
- PhD
- Training Data
- Hardware
- Data ingest
- Present solution
- Retrain model
- Performance monitoring
- Labels
- Curation
- Sensor knowledge
- Geographic Metadata
- Orthorectification
- Scheduling
- Prioritization
- Mobile Access
- Refinement
- Notifications

Classification Export Controls

Hardware

Lots of hardware
Breaking it down

- Accessibility
- Infrastructure
- Learning
- All Source / Multi-INT
- Source Information

Automation
Rinse and repeat

Cognitive Ecosystem

Infrastructure

Learning

All Source / Multi-INT

Automated Activity Based Intelligence

[Automated Activity Based Intelligence]

Higher Order Sense Making

Non-Export Controlled Information
Real-world problems don’t have an ImageNet for training. How do we overcome the burden of labeled data?

**Just Go Get It**
- Manual harvesting
- Crowdsourcing
- Use of (limited) published datasets

**Do More With Less**

*Supervised*
- Pre-train the network and transfer learn where possible
- Enforce domain adaptation if necessary
- Use synthetic data from models or simulators
- Use curriculum learning and dynamically balanced datasets

*Unsupervised and Active Learning*
- Use a deep embedding to optimize clustering of unlabeled data
- Iterate training of weakly supervised models to progressively improve training set
- Use Convolutional Autoencoders or GANs to generate embedding from unlabeled data
- Use Siamese NN to find similar labels or extract an embedding
Harris’ work to scale deep learning for defense
source information – manual harvesting – individual tools & techniques
Harris’ work to scale deep learning for defense
source information – manual harvesting – crowdsourcing

Exploit commercial tools and public-domain datasets

• Feature and point-of-interest information

Inexpensive and often fast

Need to mitigate Q/A requirements

• Some labeling error can actually be good during model training
Harris’ work to scale deep learning for defense source information – auto-clustering via deep embedding space

Deep Embedding from VGG-16 trained on Places365 scenes used to cluster mixed RGB imagery into like labels

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Harris’ work to scale deep learning for defense source information – synthetic label data generation

- 100% of training data synthesized using CAD models and Scene Simulator
- The trained model is applied to real imagery
- Successful detector produced for fighter jets in WV-2 Pan imagery
- Limiting factors: (1) content of scene generator and (2) quality of simulation

6 CAD models used

Objects placed in scene at various geometries

Heat Map for fighter jets in IKONOS Pan Imagery

DIRSIG

10 am, 7 degree look angle, Jan 1, Scene Azimuth 0

2 pm, 7 degree look angle, Jan 1, Scene Azimuth 225
Harris’ work to scale deep learning for defense all source/multi-INT – holistic approach

Context is critical in understand and deriving intelligence

Human analysts add context through traditional GIS approaches

- Shapes, points, annotations
- Machines can be taught to interpret data as stream to add human context or can be allowed to create their own

Goal is holistic view of world

Use what is appropriate to solve problem

- Keep all information available
- More good data and more good context allows enhanced intelligence and decision making
Harris’ work to scale deep learning for defense
all source/multi-INT – multiple data inputs & conv features

What’s the best way to handle multiple data inputs?

1. Different data dimensions
   - input 1 = [200, 200, 3] Panchromatic image
   - input 2 = [50, 50] Multispectral image

2. Different sensor modalities
   - input 1 = Multispectral image
   - input 2 = LiDAR points (or derived image product)
   - input 3 = SAR image

3. Disparate data sources
   - input 1 = natural image
   - input 2 = audiogram
   - input 3 = RADON transform

4. New data?
Making Deep Learning Scale: Defense Applications

Supporting many data sources enables higher level decision making
- Structured / unstructured correlated data
- Multi-modalities / multi-format

DL support for multi-stream processing enables cross-functional collaboration
- Bridges gap between agency, function, mission

Make the most of what you have – use all available context to derive answers

A very flexible model architecture
- Enables natural data fusion – all data input in original form
- Maximizes feature extraction from complimentary data independently
- Effective way of providing critical context for targeted task
Harris’ work to scale deep learning for defense all source / multi-INT – heat map improvements with multi-stream

Multi-Stream Inputs

Padded & Stacked Inputs

Persistent false positives overcome with use of derived data in multi-stream model with highly limited training data
Harris’ work to scale deep learning for defense learning – transfer learning and domain adaptation.

LeNet5
(1994 – 3 layers)

AlexNet
(2012 – 8 layers)

VGG16
(2014 – 16 layers)

GoogLeNet
(2015 – 22 layers)

ResNet
(2015 – 152 layers)

Source: arXiv:1605.07678, Canziani
One of the few unsupervised methods for training CNNs. Can they be as discriminative as supervised training?

- When conv-autoencoder is applied to satellite imagery tend to learn simple convolutional features
- Far less effective for transfer learning then supervised classification CNNs
- With modifications, can adapt proven natural image network architectures to use conv-autoencoder for unsupervised pretraining with satellite imagery

**Improvements in Low-level Conv Filters**

VGG16 (ImageNet training: 1.2M samples, 1000 classes), Conv-0

Typical “Winner-Take-All” Conv-AE on Satellite RGB imagery – poor Conv-0 structure

Improved Harris Conv-AE on Satellite RGB imagery – better Conv-0 structure, closer to VGG16

Mods: Train all layers together, Enforce Sparsity, Selectively block gradient
Harris’ work to scale deep learning for defense learning – AutoML

Blender – a tool for automatically building optimal neural network models from labeled data

- **Novices** can build a network without background knowledge
- **Experts** can explore more possibilities than by hand

https://mathematica.stackexchange.com
Harris’ work to scale deep learning for defense learning – AutoML

Best Human Model

Best Blender Model

Mean ROC - Blender (blue) vs Human (red)
Harris’ work to scale deep learning for defense infrastructure – exposing data repositories to deep learning

VIRAT 09152008flight2tape2_1 - Platform location (blue) and sensor view footprint (yellow polygon)

VIRAT 09152008flight2tape2_1 – Flight Path (Blue) and Sensor Coverage (Orange) Overview
Harris’ work to scale deep learning for defense infrastructure – incorporation of deep learning algorithms in workflows.
Harris’ work to scale deep learning for defense infrastructure – incorporation of deep learning algorithms in workflows

• **Multiple algorithm “containers”, or API’s:**
  - Expedite development
  - Enable portability
  - Simplify integration

• **Algorithm Marketplace is API-neutral and provides:**
  - Streamlined integration and V&V
  - Web-based access to new products, algorithms, and services
  - Rapid development of analytic tools
  - Automatic and customized processing to address evolving customer needs
  - Ontology to drive “smart” algorithm execution

**New analytics rapidly inserted via Algorithm Marketplace API’s**
Harris’ work to scale deep learning for defense infrastructure – analyst assisted feedback loop
Harris’ work to scale deep learning for defense accessibility – analyst-focused UI – flexible visualization

User selects the “Analytics” Widget, and defines a Region of Interest (ROI)

*Map-based Analytics Recommendation available via Hydra-API for 3rd Party Client Integration*
Harris’ work to scale deep learning for defense accessibility – case study – airport traffic monitoring

Goal – Identify broad trends in air traffic

• Deep learning a critical building block
  - Object ID: find airplanes on tarmac

• Combined with other methods to make monitoring feasible
  - Too time consuming for analysts to look at every image
  - Need a way to compress information

• Aggregation of multiple detection algorithm results over time to identify patterns and anomalies in behaviour
  - Applicable to many similar monitoring problems

Test Case:

• Data: WorldView-3 Pan
• Airport: London Southend
• Multiple observations over several months

Object Detection

• LeNet-style 5-layer model converted for fully convolutional operation
• Detects all large airplanes
Harris’ work to scale deep learning for defense accessibility – dashboard views
Harris’ work to scale deep learning for defense automation – repeatable process

New training sample for decision support model is collected each time an analyst looks at dashboard and assigns a label, such as:

- Condition normal
- Emergency response
- Snowstorm
- Flood
- Power outage
- Traffic jam
- Suspicious activity
Harris’s work to scale deep learning for defense automation – higher order sense making

In the not too distant future…

We will go from drowning in data…

…to drowning in detections/features/observations.

Deep learning/machine learning/artificial intelligence attention will shift from detecting objects and features to detecting actions, events, patterns of life.

Live Observations Tally:
- Planes Detected: 03
- Cars Detected: 22
- Trucks Detected: 10
- Ships Detected: 02
- Storage Tanks Detected: 08
- Buildings Detected: 05
- Crosswalks Detected: 12
- Intersections Detected: 15
- Etc…..
Conclusions/takeaway

Deep learning removed the bottlenecks of having to hand construct algorithms for target/feature/event/activity recognition

However, deep learning has its own bottlenecks:

• Label data availability
• Network architecture
• Algorithm brittleness / training data variation distribution
• Ability to quickly adapt to new domain and/or target

Eliminating / minimizing those bottlenecks at scale is possible

Mass production of deep learning based GEOINT algorithms is within reach!
Look for upcoming blog posts about machine learning at Harris’ Blog website:
http://www.harrisgeospatial.com/Company/PressRoom/Blogs.aspx

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Backup Slides
Breaking it down

Infrastructure
- Security
- Hardware Optimization
- Archival
- Versioning
- APIs
- Componentization
- Open Source

Accessibility
- Analyst retraining
- Watchbox

All Source / Multi-INT
- Multistream
- Data support
- Data access
- Structured Data
- Unstructured data

Learning
- CNNs, RNNs, LSTMs…
- Engine support (Café, Theano, Tensorflow…)
- AutoML

Training
- Transfer Learning
- Crowdsourcing
- Modeling
- Analyst feedback

Automation

Cognitive Ecosystem
Hydra applications
Collaborative content management and analytical processing

Hydra web applications enable multi-mission GEOINT PED.
Rapid insertion of analytics and self-service processing

Multiple methods to register analytics enable rapid integration of new capabilities and drive minimal system integrator (SI) support
Algorithm Governance Workflow is based on Hydra’s Workflow Service: flexible and extensible
Open APIs enable rapid integration with third-party clients and external systems

Self-describing APIs reduce the burden to generate large ICD documentation
DAGR (Distributed All-source GEOINT-analytics Resource)

DAGR modernizes the analyst workforce with automated multi-intelligence workflows and workspace collaboration to solve complex intelligence questions
Map-based analytics recommendation

User selects the “Analytics” widget and defines a region of interest (ROI)

Map-based analytics recommendation available via Hydra-API for third-party client integration
Map-based analytics recommendation

Hydra-API available to automate analytics based on ROI

Analytics recommended to the User based on Hydra’s Analytics Recommendation Service

Option for Users to “Persist” this ROI for automated analytics selected in the Analytics widget
Hydra’s flexible cataloging supports machine learning algorithms

**Algorithm Pedigree:**
- Name and Version
- Input Image
- Duration

**Detection Information Available as WFS attributes:**
- Created By and When
- Geospatial and Image Coordinates
- Attribution: Confidence, Size, etc.

**Hydra Flexible Cataloguing**
“Standard” Enables Rapid Insertion of Developer-defined Algorithm Attributes/Observables
Google Earth visualization of machine learning output

Machine Learning Analytic generates a detection heatmap (KMZ product)
Hydra exposes detections as WFS, rapidly consumable by third-party clients
Geometric change detection of multi-source point clouds

Features are normalized, catalogued and indexed for time/location queries and analytics.

Hydra enables an Integrated Data Layer (IDL) composed of input sources, detected objects/signatures/detections, and multi-INT correlation analytics.
Hydra applications
Closed-loop MEGA training via Hydra