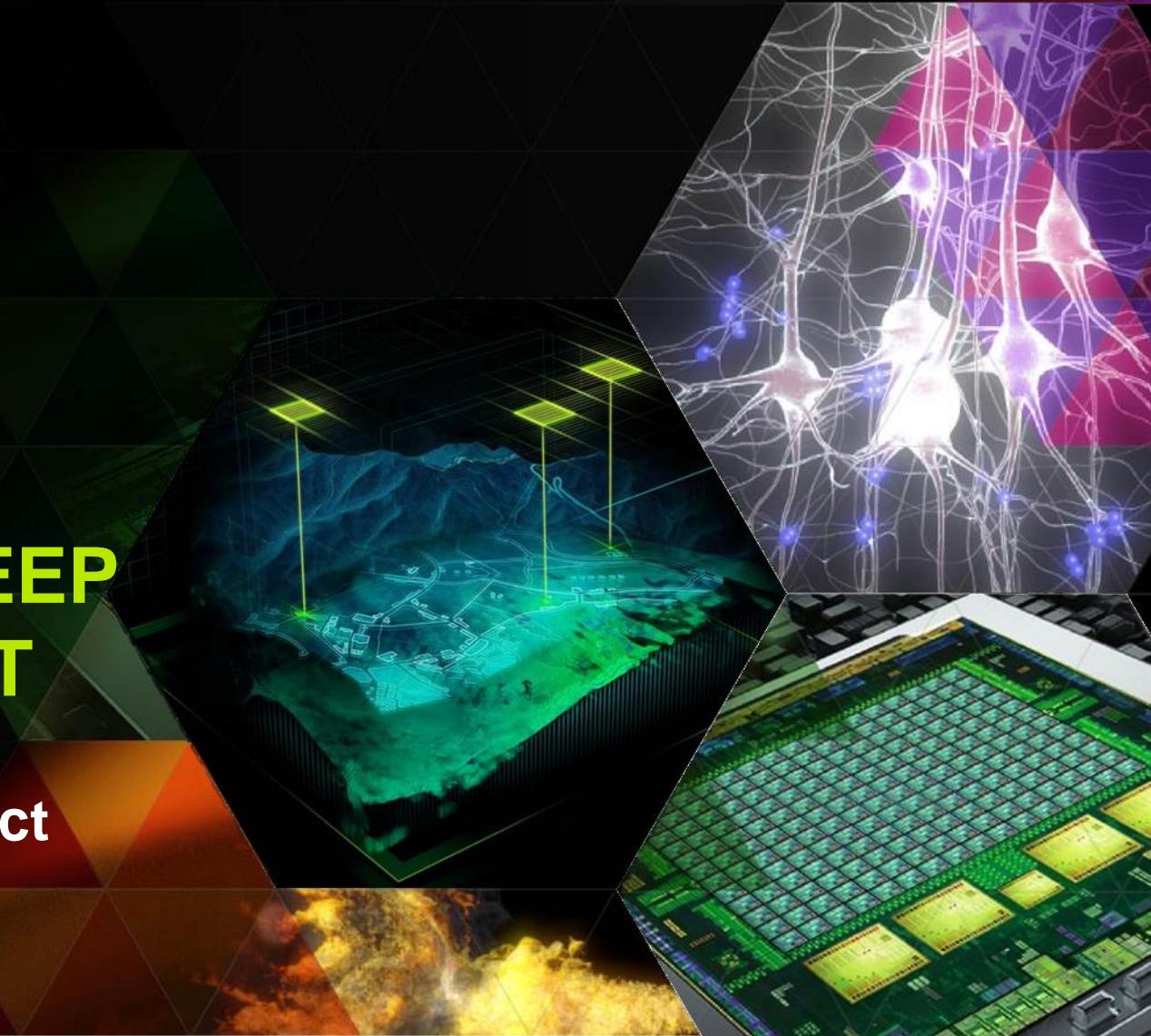




APPLICATIONS OF DEEP LEARNING TO GEOINT

Jon Barker, Solutions Architect

August 2015



Overview



- Motivation
- Introduction to Deep Learning
- GEOINT applications
- Deep Learning deployment
- Questions

Motivation



Rapid growth in remote sensing numbers and capability



350 Million Images Uploaded a Day



100 Hours Video Uploaded Every Minute



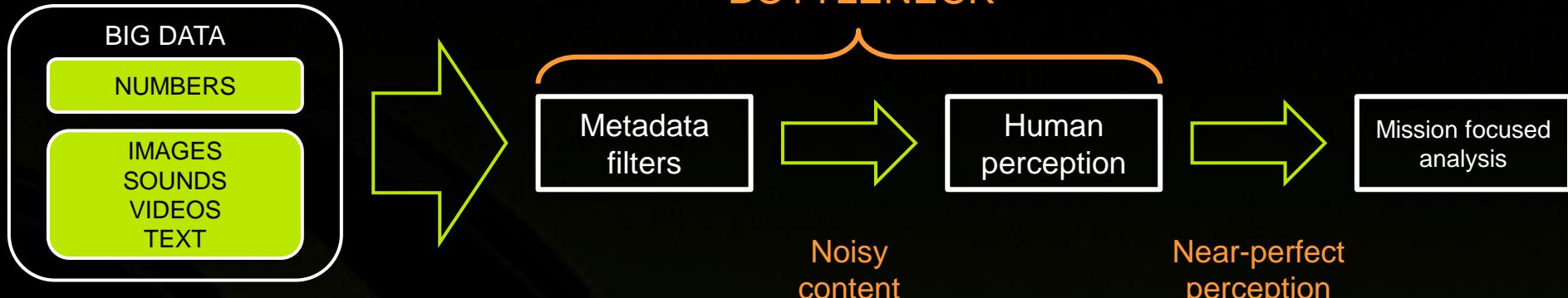
Tens of thousands of social and political events indexed daily



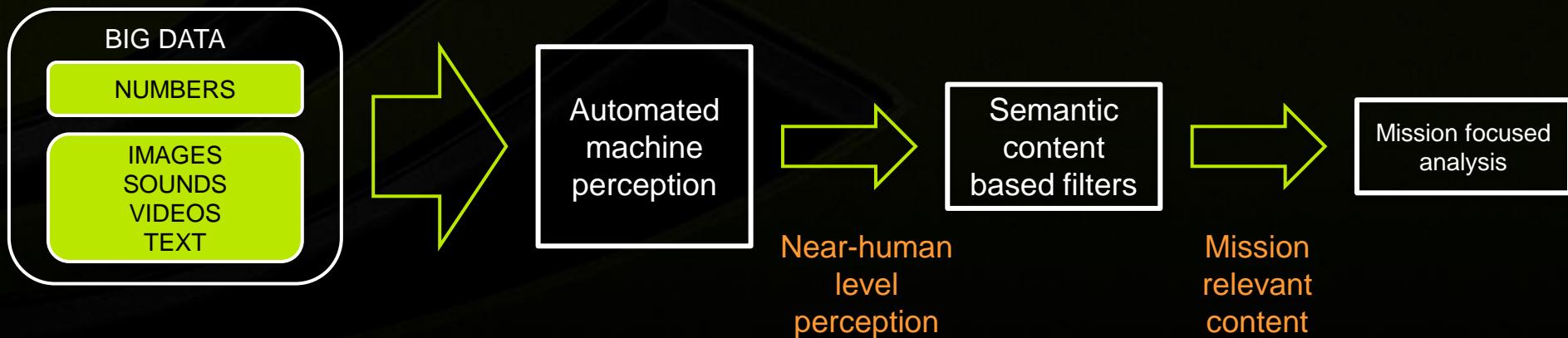
- There is not enough time or expertise to write algorithms for each individual information extraction task that needs to be performed
- Deep Learning provides general algorithms that identify mission-relevant content and patterns in raw data at machine speed

Motivation: Multi-INT analysis workflow

TODAY:



VISION:



What is Deep Learning?



Deep Learning has become the most popular approach to developing Artificial Intelligence (AI) - machines that perceive and understand the world

The focus is currently on specific perceptual tasks, and there are many successes.

Today, some of the world's largest internet companies, as well as the foremost research institutions, are using GPUs for deep learning in research and production



Practical Deep Learning Examples



Image Classification, Object Detection, Localization,
Action Recognition, Scene Understanding



Speech Recognition, Speech Translation,
Natural Language Processing



Pedestrian Detection, Traffic Sign Recognition



Breast Cancer Cell Mitosis Detection,
Volumetric Brain Image Segmentation

Traditional Machine Perception – hand crafted features



Raw data



Feature extraction

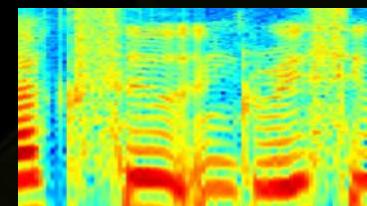
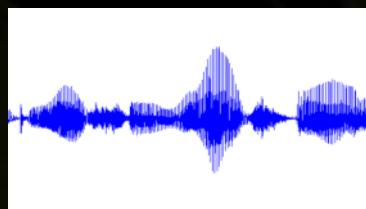


(Linear)
Classifier

e.g. SVM

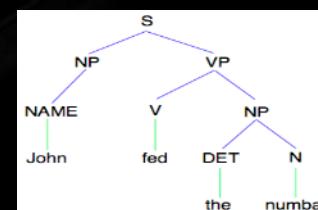


Result



e.g. HMM

Speaker ID,
speech transcription, ...



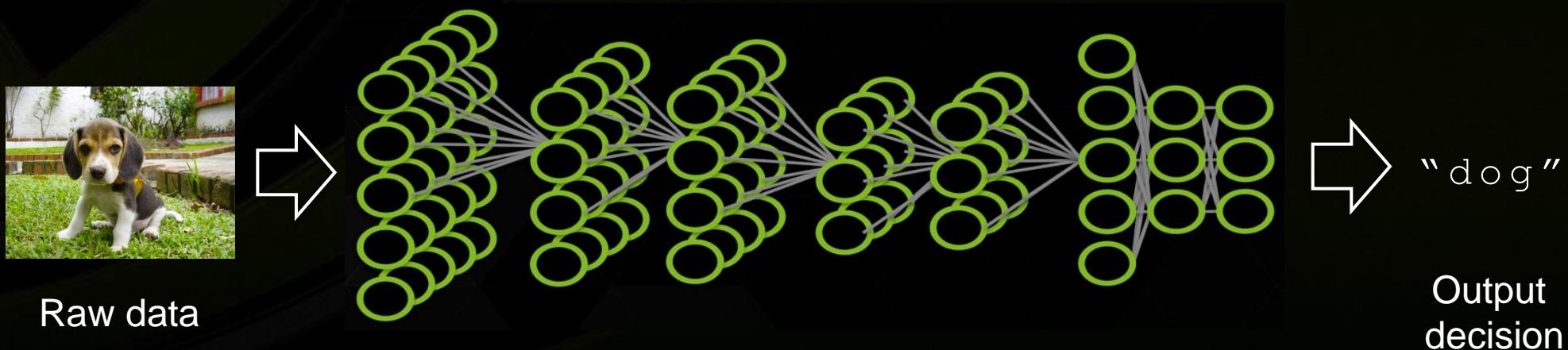
e.g LSA

Topic classification,
machine translation,
sentiment analysis...

Deep Neural Network (DNN)

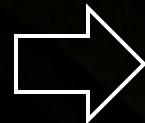


- Modern reincarnation of Artificial Neural Networks
- A very large collection of simple, trainable mathematical units
- Collectively they can learn very complex functions mapping raw data to decisions
- Loosely inspired by biological brains

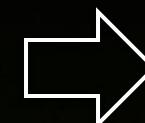


Deep Learning approach

Train:



Feature extraction



(Linear)
Classifier

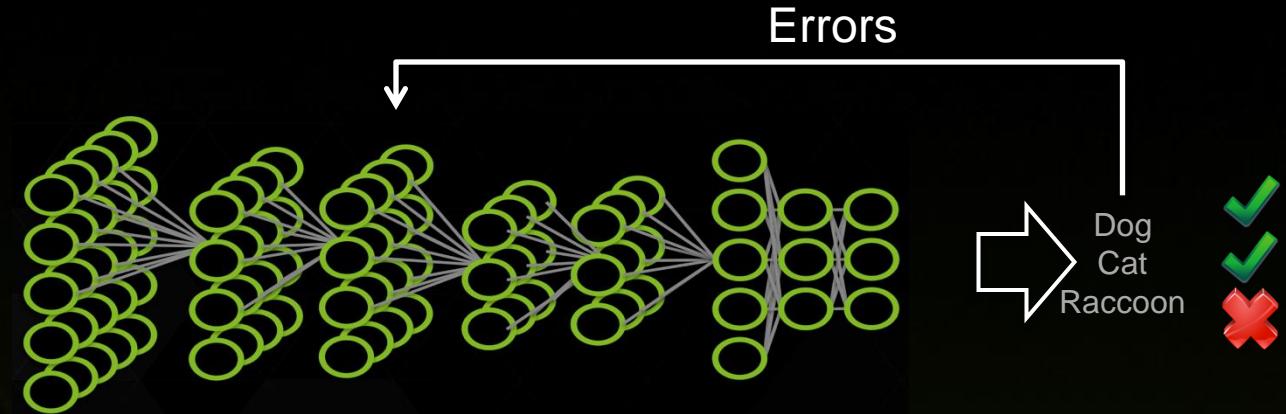


Dog
Cat
Raccoon



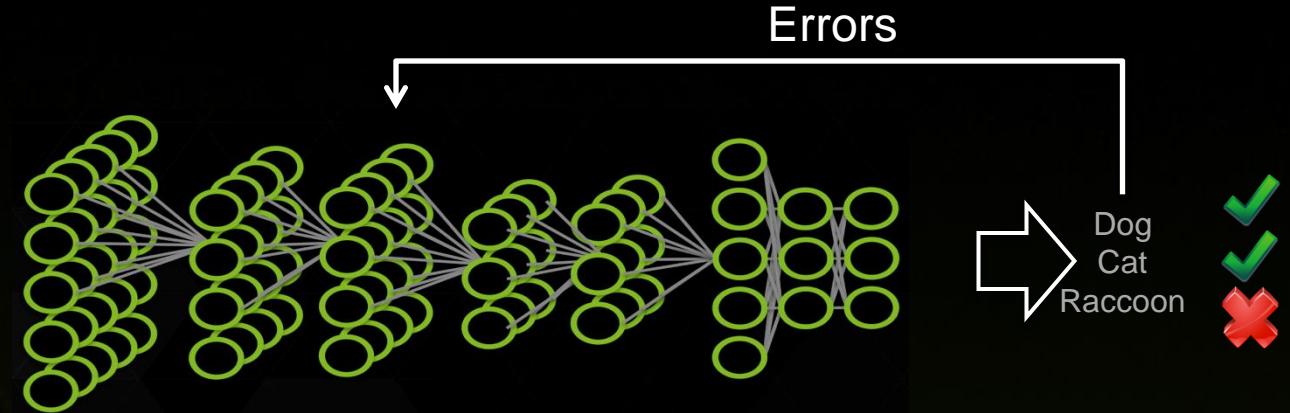
Deep Learning approach

Train:

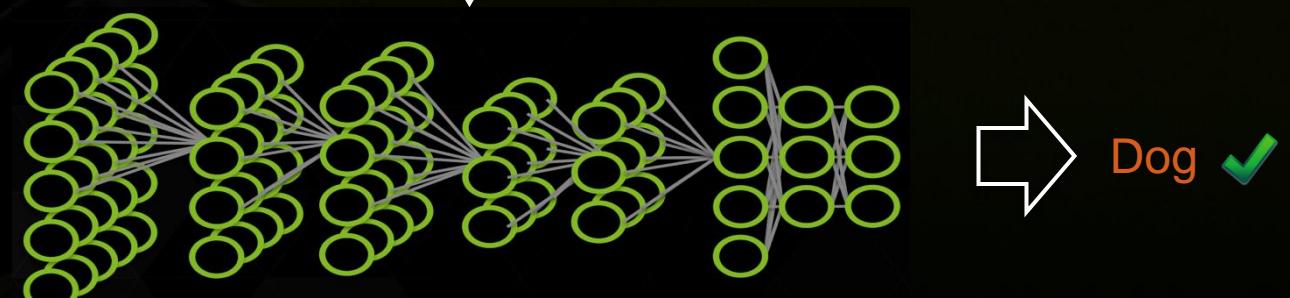


Deep Learning approach

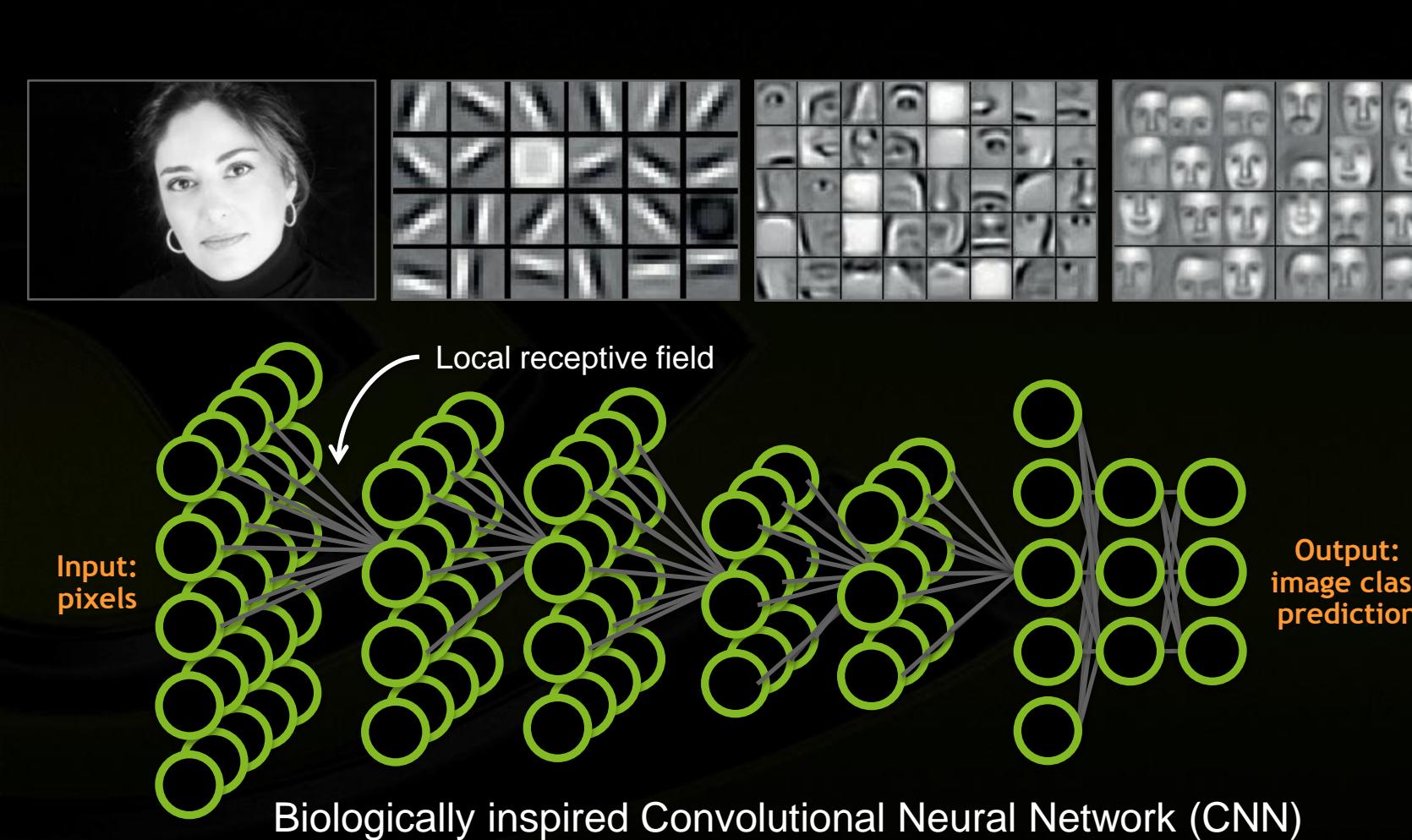
Train:



Deploy:

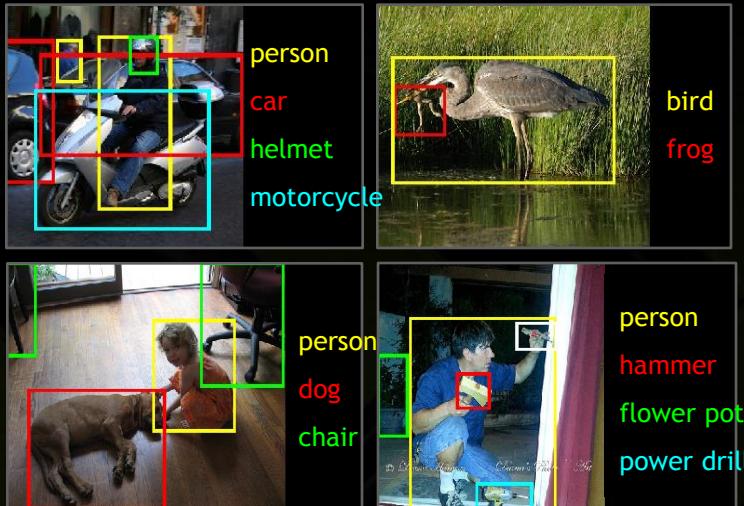


Deep Learning for Visual Perception



Visual Perception: DL State of the Art

IMAGENET



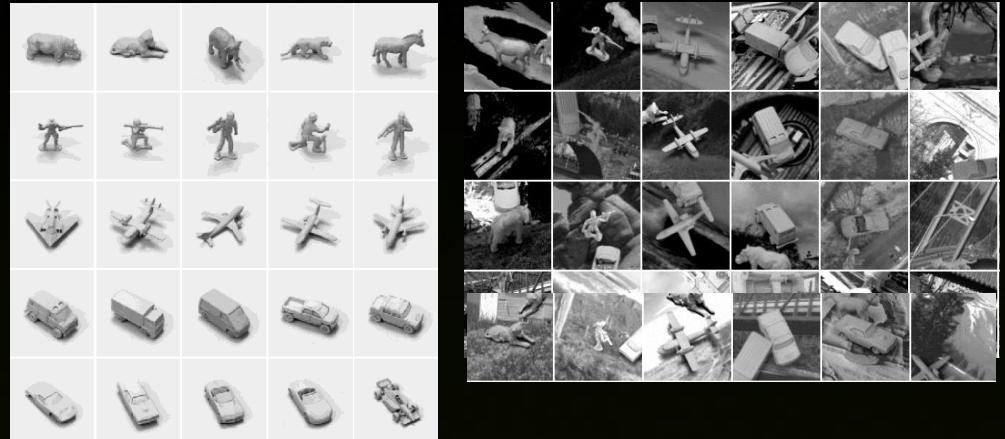
1000 object classes

1.2 million training images [1]

Top-5 error (Google): 4.8%

Top-5 error (Human): 5.1%

NORB dataset (2004)



5 object classes

Multiple views and illuminations

291,600 training images

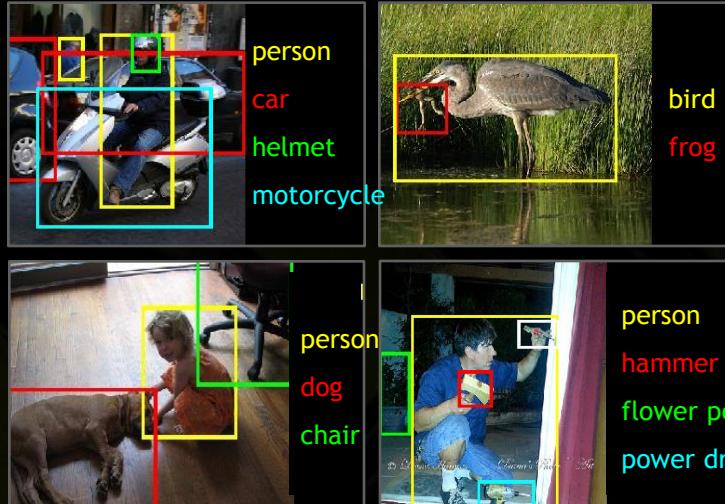
58,230 test images [2]

<6% classification error on test set with cluttered backgrounds (NYU)

Deep Learning Dominates at Visual Perception



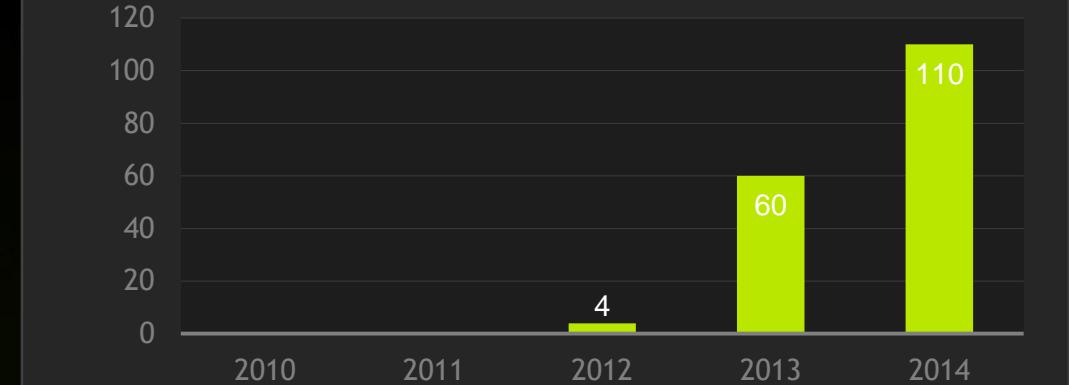
IMAGENET



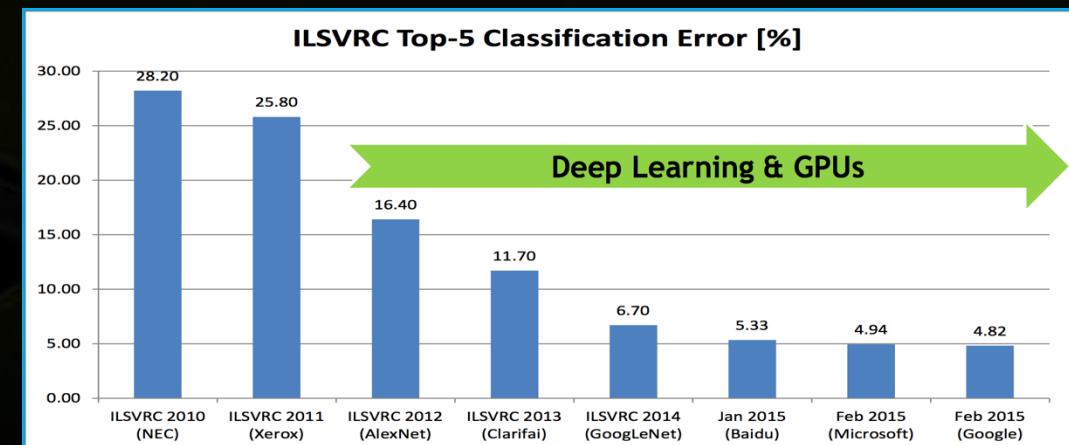
1000 object classes
1.2 million training images [1]

Top-5 error (Google): 4.8%
Top-5 error (Human): 5.1%

GPU Entries



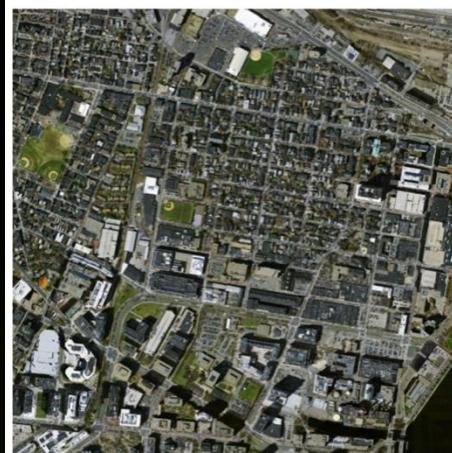
ILSVRC Top-5 Classification Error [%]



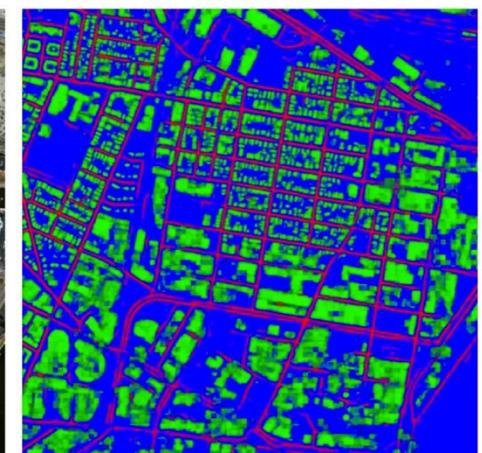
Remote Sensing Imagery Exploitation



- Object detection and classification
- Scene segmentation
- Land usage classification
- Geologic feature classification
- Change detection
- Crop yield prediction
- Surface water estimation
- Population density estimation
- Super-resolution
- Photogrammetry

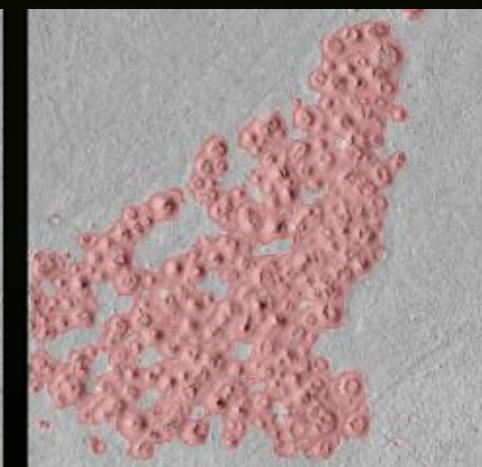
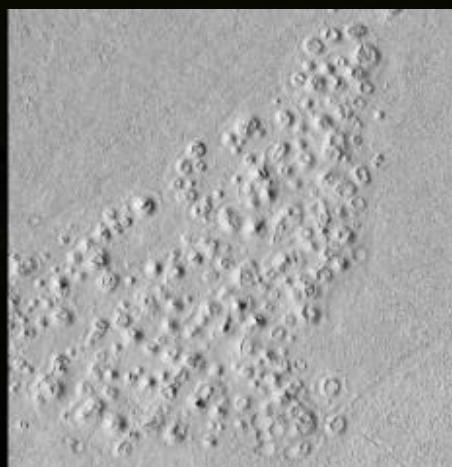


Input aerial image



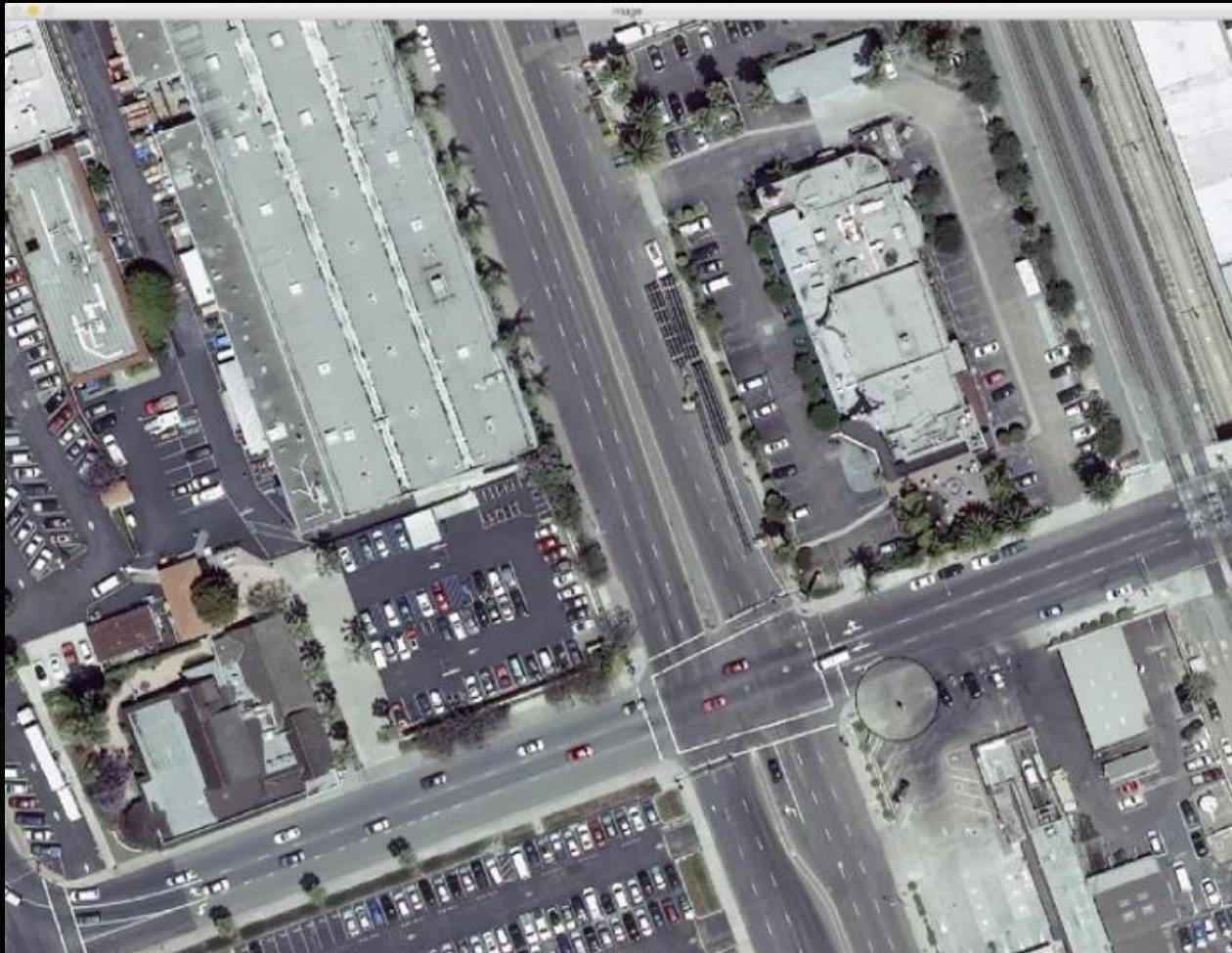
Predicted 3-channel label image

[3] Keio University, Japan – SPIE EI 2015



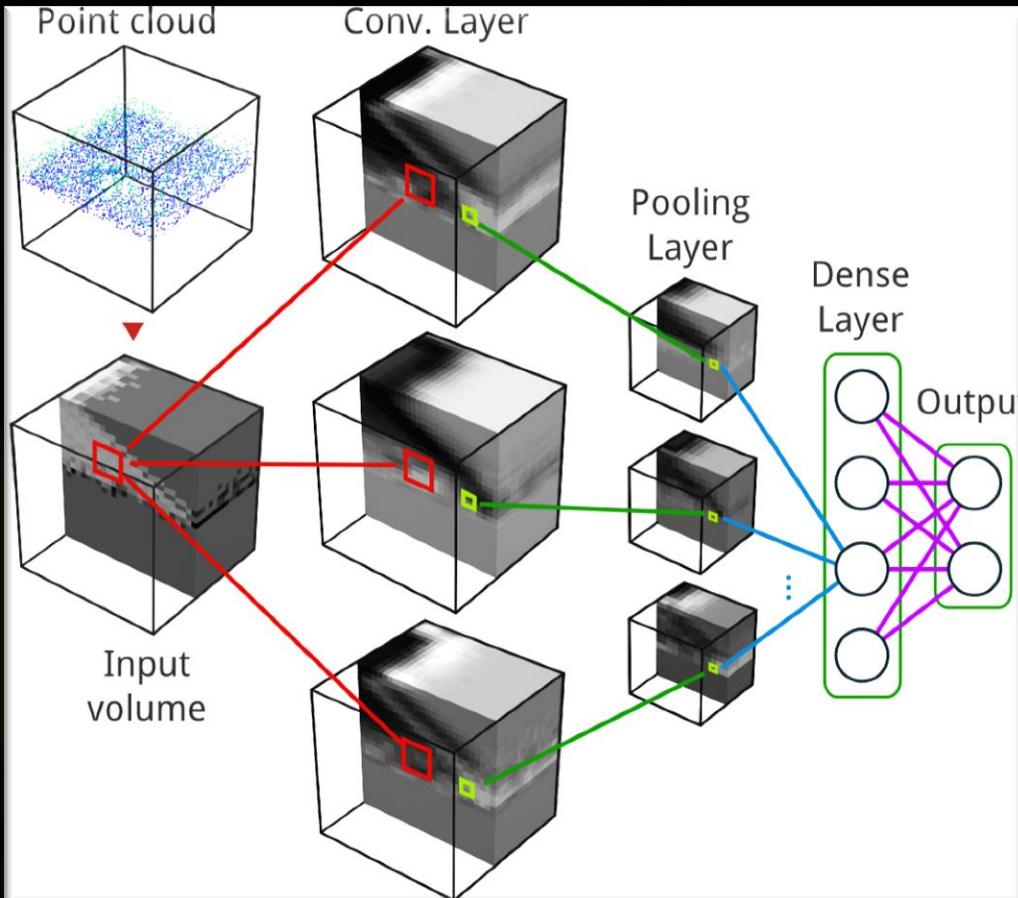
[4] University of Arizona

Deep Learning supports the analyst



NVIDIA, 2015

Advanced Imaging Modalities

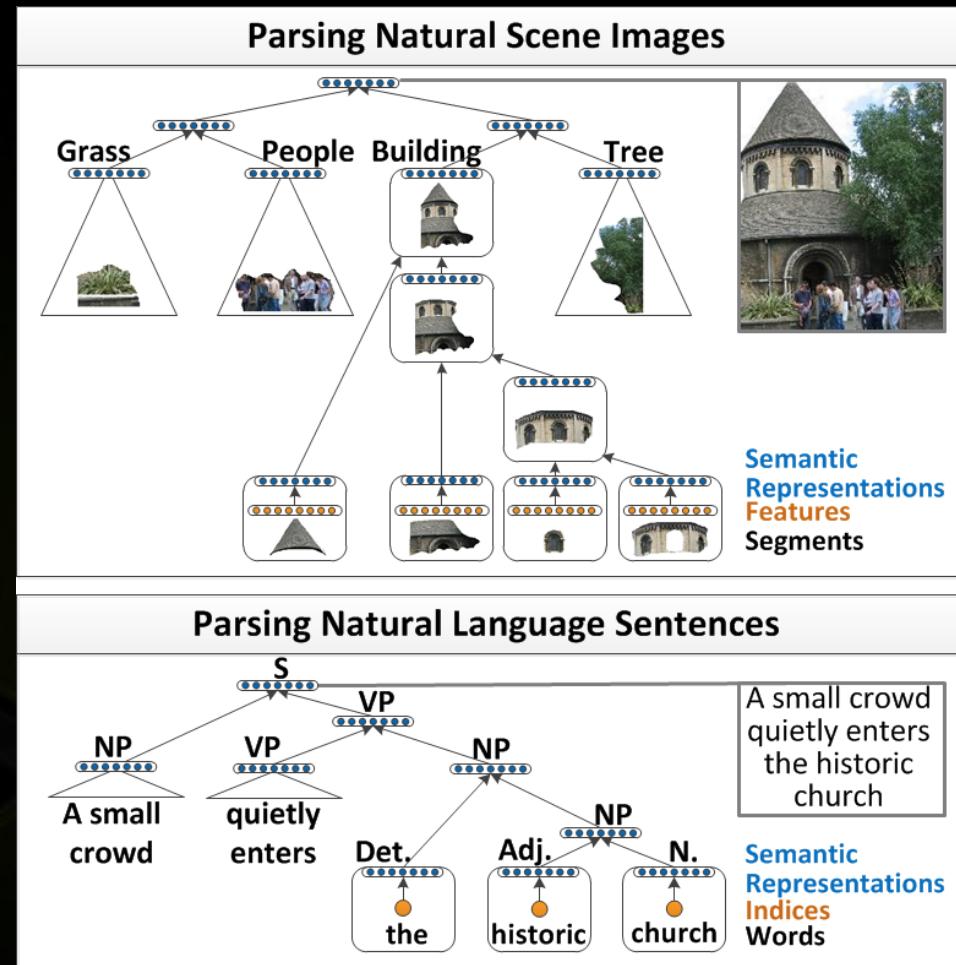


- **CNN architecture supports:**
 - MSI/HSI data cubes
 - SAR imagery
 - Volumetric data, e.g. LIDAR
- **Low-TRL research topics**

Open-source Imagery Exploitation



- Object detection
- Scene labeling
- Face recognition
- Image geo-location estimation
- Text extraction from images
- Geographic property estimation
- Image de-noising

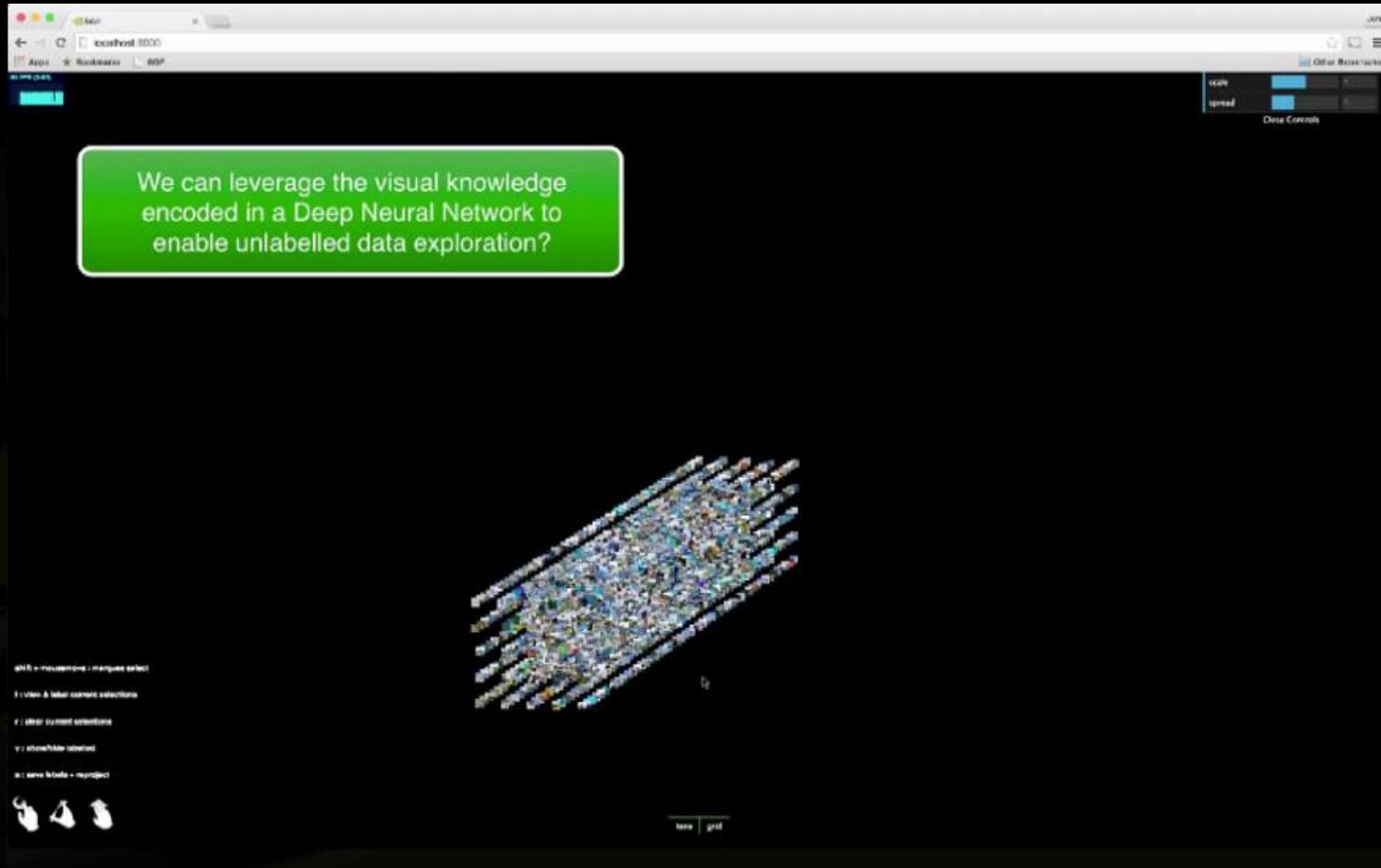


Deep Learning Dominates at Visual Perception



NVIDIA, 2014

Deep Learning supports the analyst

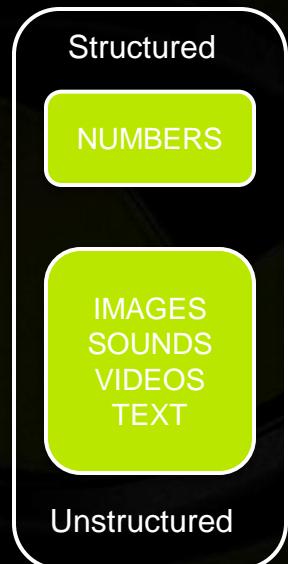


NVIDIA, 2015

Deep Learning generalizes across problems



Varied data types
(and multi-source)



Real-valued feature vector

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \dots \\ x_N \end{bmatrix}$$

Varied tasks

Classification

Regression

Unsupervised learning

- Clustering
- Topic extraction
- Anomaly detection

Sequence prediction

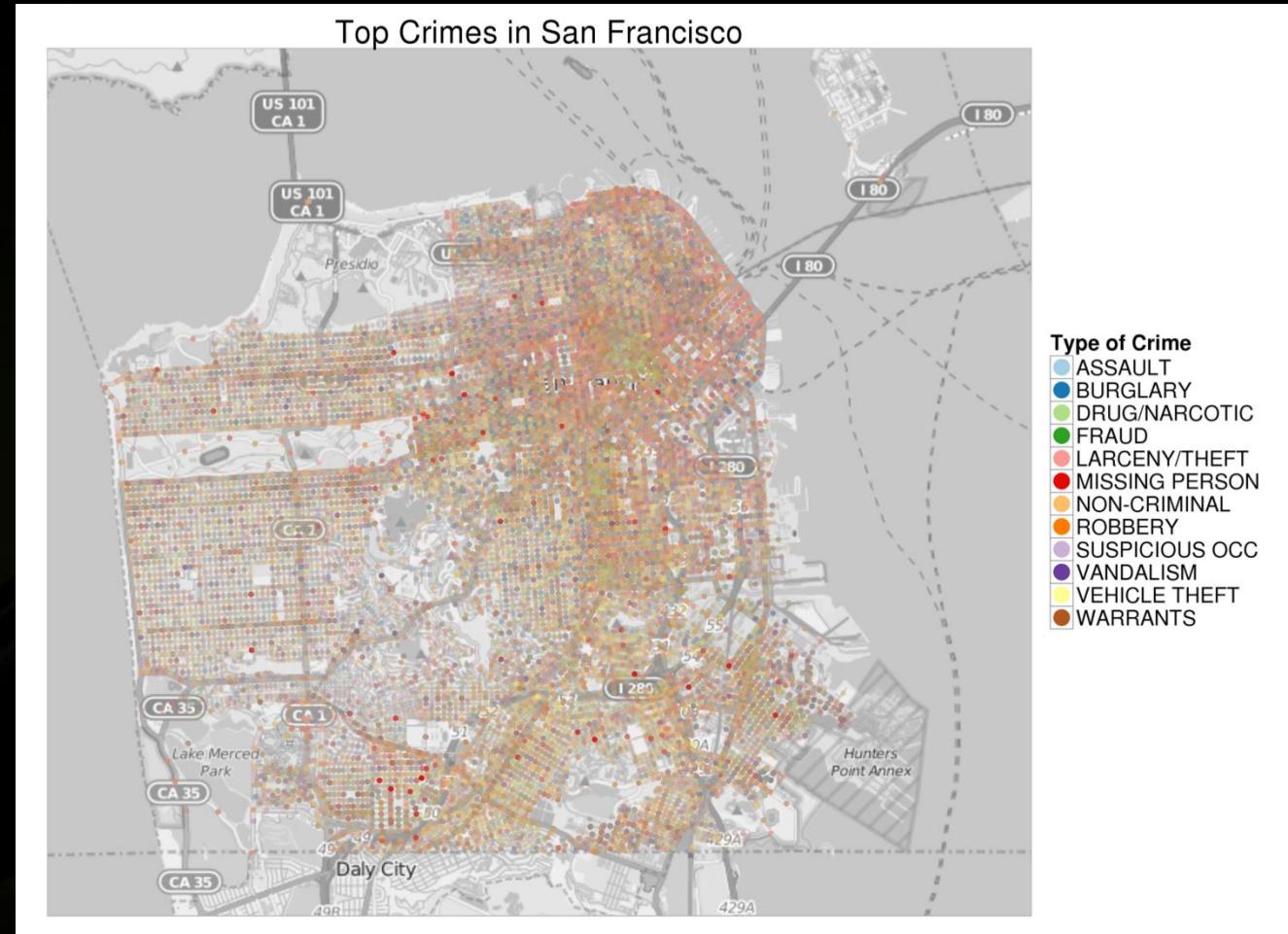
Control policy learning

Constants: Big (high dimensional) Data + a complex function to learn

Geospatial Analytics



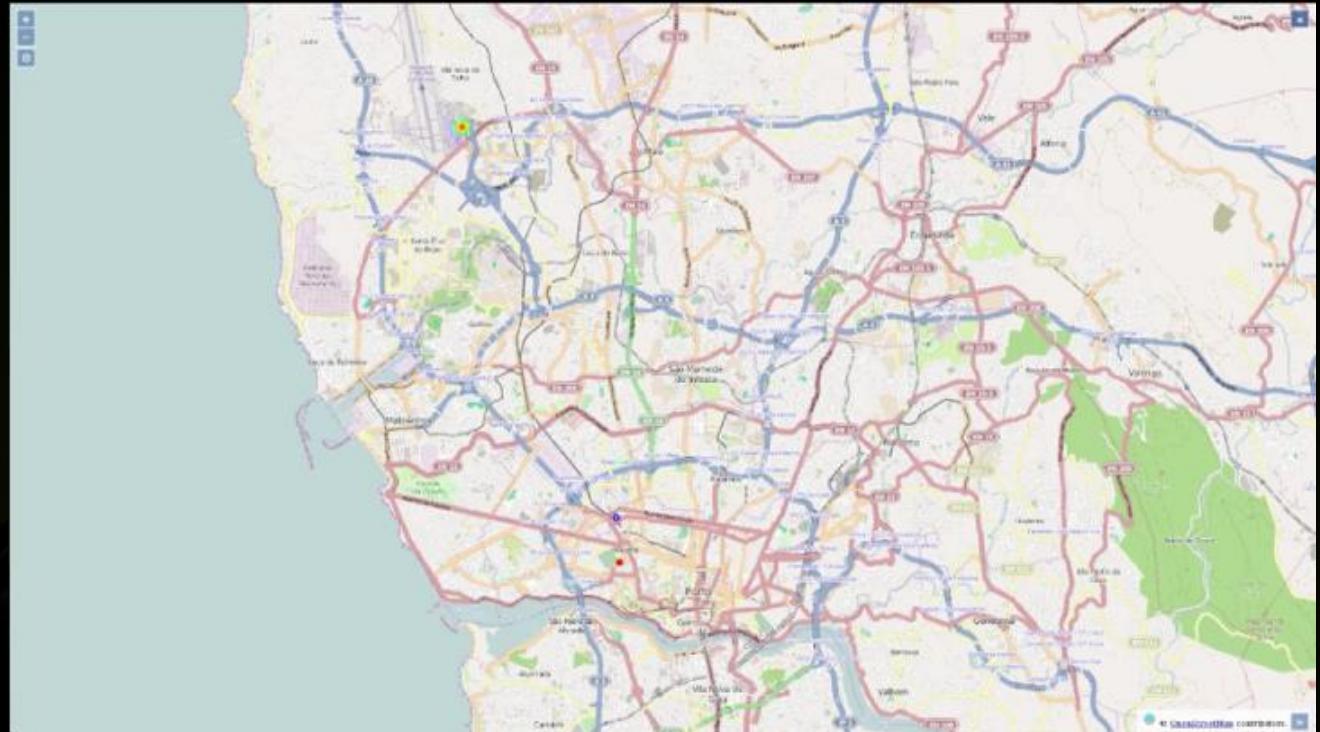
- 12 years of San Francisco crime reports
- Given date, time and location DL model predicts crime:
 - Top-5 error: 59%
- ~4 hours work (including training) using open source tools



Geospatial activity data



- Deep Neural Networks (DNNs) naturally ingest structured data
- Modern networks can learn complex predictive patterns including temporal sequences

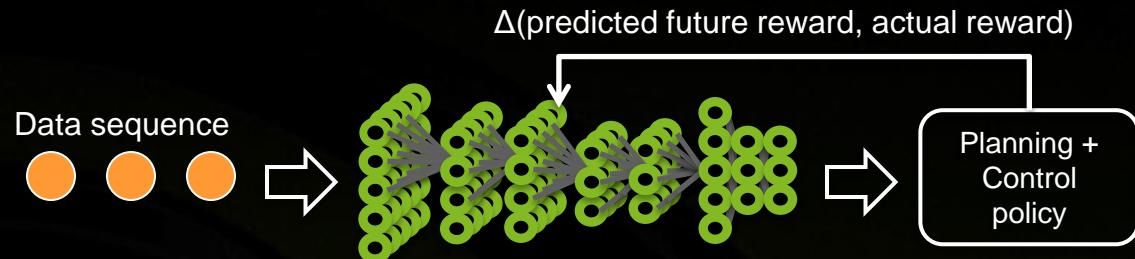


Real-time destination prediction for taxis using DNN
Montreal Institute for Learning Algorithms (MILA), 2015

Sensor/Platform Control



Reinforcement learning:



- Applications:
- Sensor tasking
 - Autonomous vehicle navigation



[11] Google DeepMind in Nature

Why is Deep learning hot *now*?

Three Driving Factors...

Big Data Availability



350 millions
images uploaded
per day

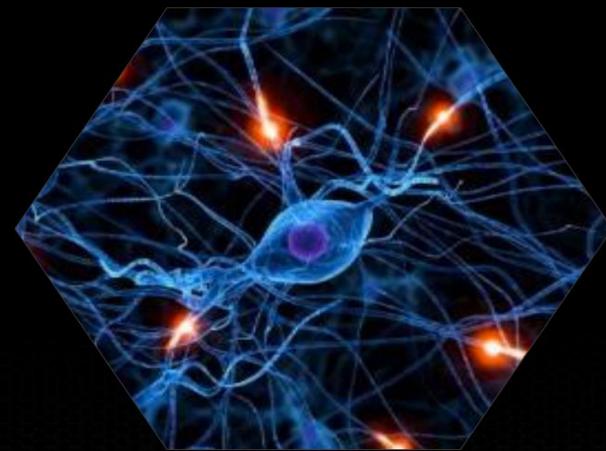


2.5 Petabytes of
customer data
hourly



100 hours of video
uploaded every
minute

New DL Techniques



GPU acceleration

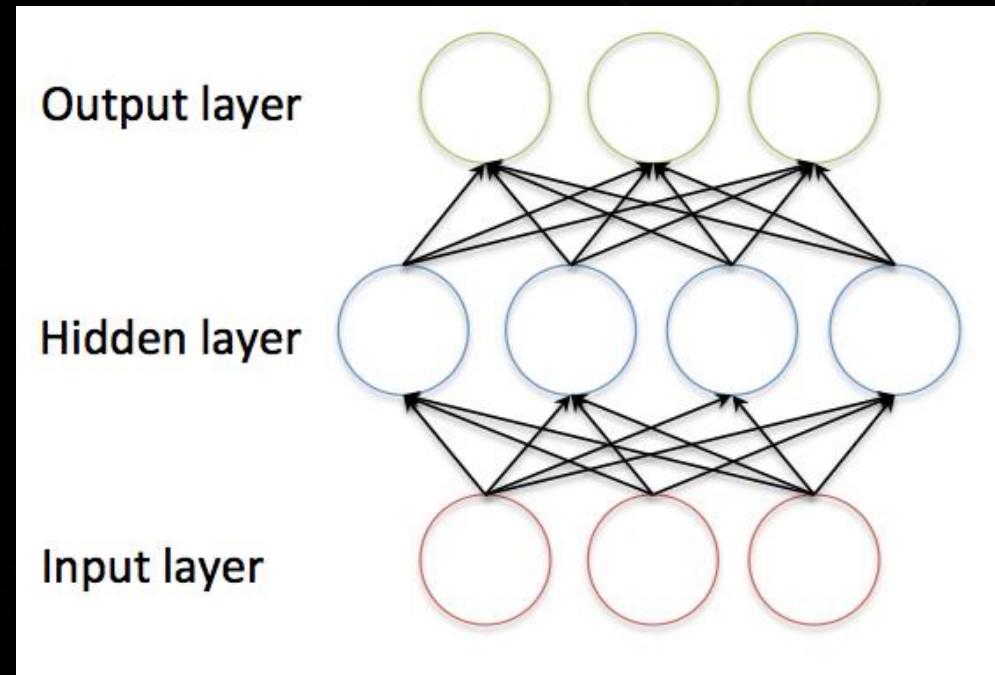


Why are GPUs good for deep learning?

	Neural Networks	GPUs
Inherently Parallel	✓	✓
Matrix Operations	✓	✓
FLOPS	✓	✓
Bandwidth	✓	✓

GPUs deliver --

- *same or better prediction accuracy*
- *faster results*
- *smaller footprint*
- *lower power*
- *lower cost*



GPUs make deep learning accessible



Deep learning with COTS HPC systems

A. Coates, B. Huval, T. Wang, D. Wu,
A. Ng, B. Catanzaro

ICML 2013

“Now You Can Build Google’s
\$1M Artificial Brain on the Cheap”

WIRED

GOOGLE DATACENTER



1,000 CPU Servers
2,000 CPUs • 16,000 cores

600 kWatts
\$5,000,000

STANFORD AI LAB



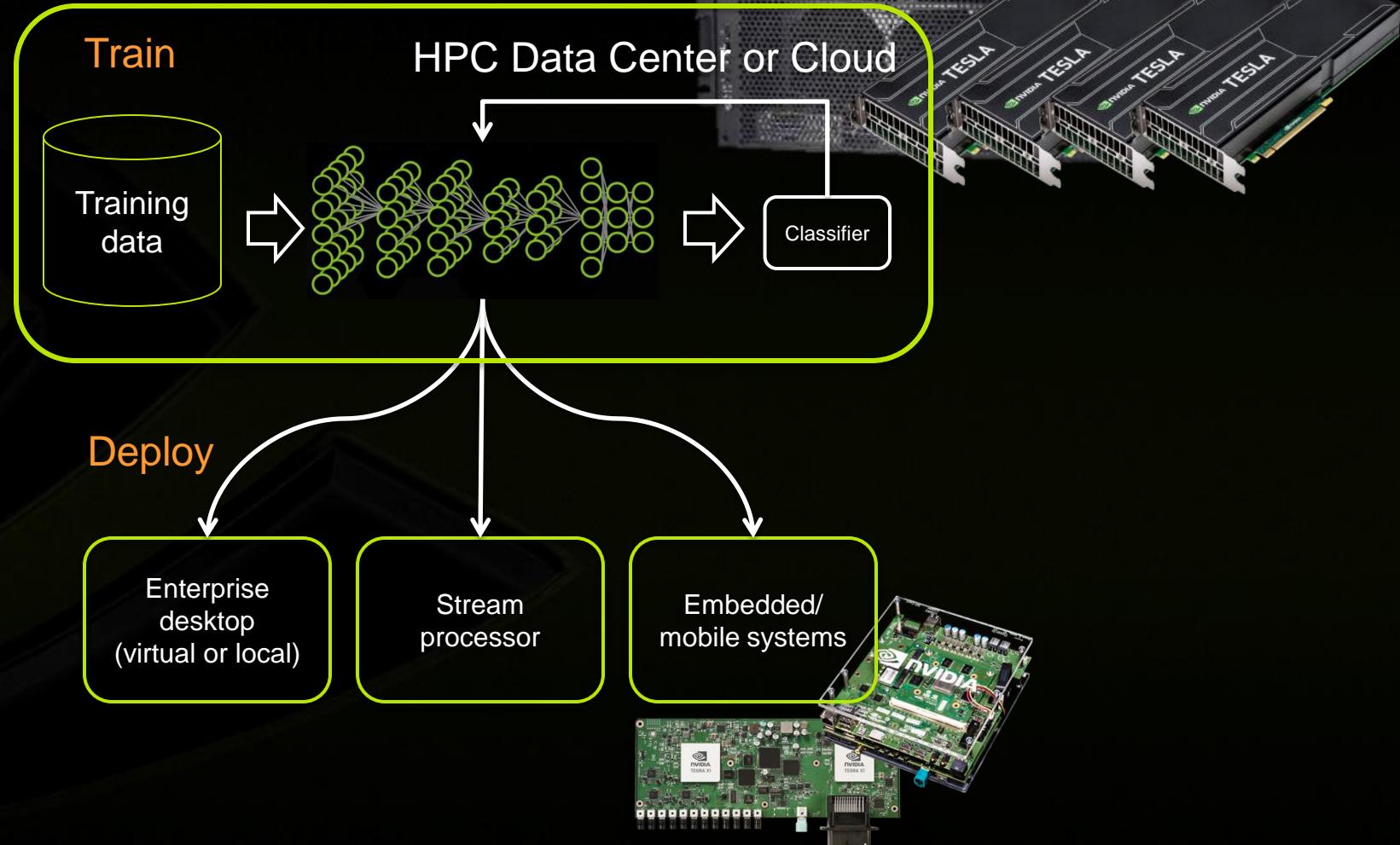
3 GPU-Accelerated Servers
12 GPUs • 18,432 cores

4 kWatts
\$33,000

Deep Learning deployment options



Long training (hours to days), batch updates, leverage GPU acceleration



<100ms response
for new data sample,
model interactivity

Deep Learning is a GEOINT force multiplier



- **Managing Big Data**
 - Real-time near-human level perception at web-scale
- **Integrates into analytical workflows**
 - Semantic content based filtering and search
 - Drives data exploration and visualization
 - Models improve based on analyst feedback
- **Scales across problems**
 - Models improve with more, varied data
 - Models from one dataset can be leveraged in new problems
 - Compact models can be easily shared and deployed

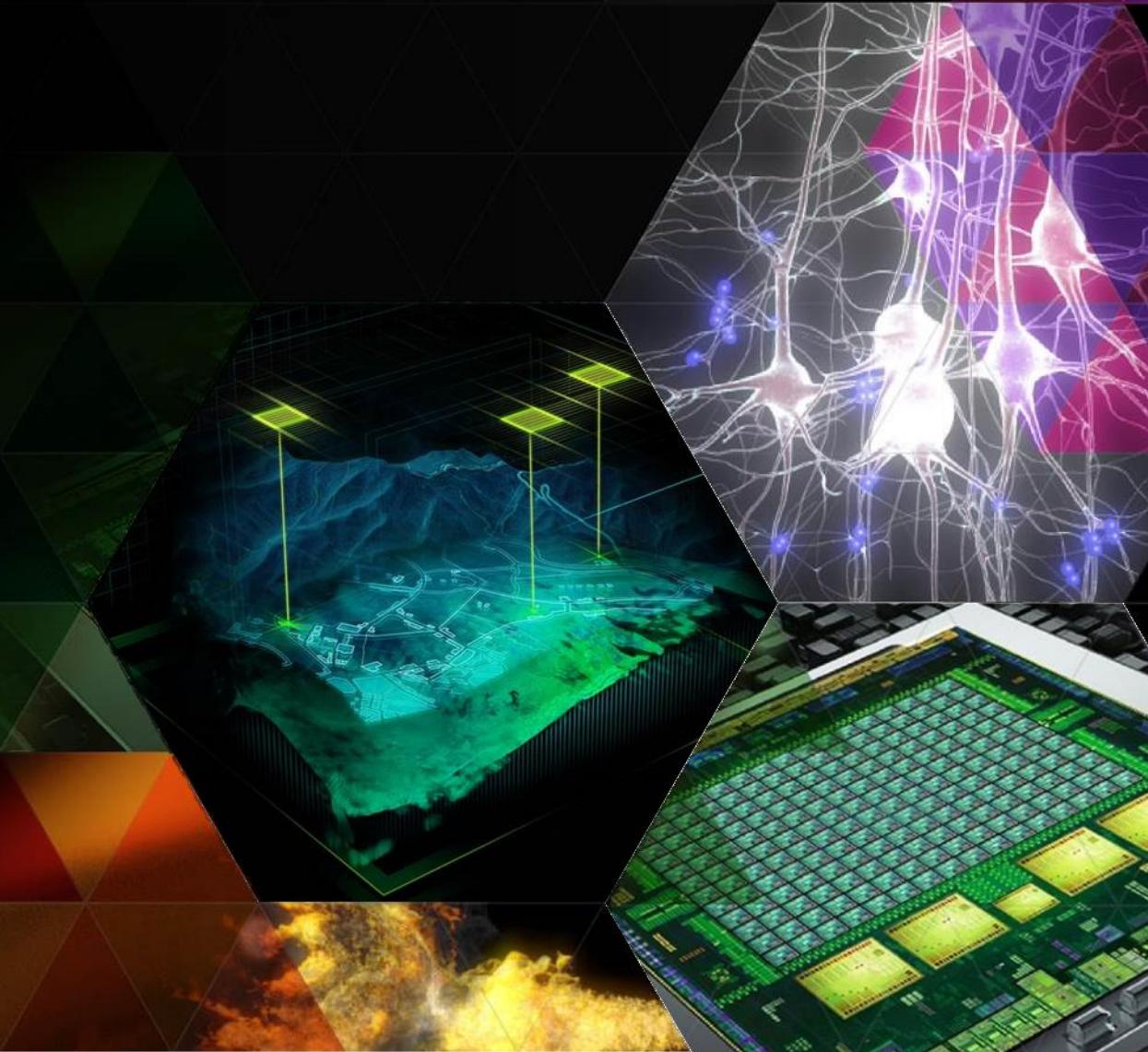
Summary



- **GPU accelerated Deep Learning is:**
 - **Revolutionizing** machine perception accuracy
 - **Adaptable** to many varied GEOINT workflows and deployments scenarios
 - **Scalable** – thrives on complex raw data
 - **Available** to apply in production and R&D today



THANK YOU



Resources



- Popular DL frameworks:
 - [Caffe \(UC Berkeley\)](#)
 - [Theano \(U Montreal\)](#)
 - [Torch](#)
 - [DIGITS](#)
- Examples from talk:
 - [1] [Imagenet Large Scale Visual Recognition Challenge](#)
 - [2] [NORB dataset](#)
 - [3] [Keio University, Japan - Aerial image segmentation](#)
 - [4] [University of Arizona - Geographic feature detection](#)
 - [5] [D. Maturana and S. Scherer. 3D Convolutional Neural Networks for Landing Zone Detection from LiDAR. In ICRA. 2015](#)
 - [6], [8] [Stanford NLP group Deep Learning research](#)
 - [9] [Kaggle Taxi Trajectory Prediction Competition](#)
 - [10] [Kaggle San Francisco Crime Classification Competition](#)
 - [11] [Google DeepMind Nature article](#)