Object Detection with DIGITS

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DEEP LEARNING INSTITUTE

DLI Mission

Helping people solve challenging problems using AI and deep learning.

- Developers, data scientists and engineers
- Self-driving cars, healthcare and robotics
- Training, optimizing, and deploying deep neural networks

TOPICS

- Lab Perspective
- Object Detection
- NVIDIA's DIGITS
- Caffe
- Lab Discussion / Overview
- Lab Review

LAB PERSPECTIVE

WHAT THIS LAB IS

- Discussion/Demonstration of object detection using Deep Learning
- Hands-on exercises using Caffe and DIGITS

WHAT THIS LAB IS NOT

- Intro to machine learning from first principles
- Rigorous mathematical formalism of convolutional neural networks
- Survey of all the features and options of Caffe

ASSUMPTIONS

- You are familiar with convolutional neural networks (CNN)
- Helpful to have:
    - Object detection experience
    - Caffe experience

TAKE AWAYS

- You can setup your own object detection workflow in Caffe and adapt it to your use case
- Know where to go for more info
- Familiarity with Caffe

OBJECT DETECTION

COMPUTER VISION TASKS

Image Classification

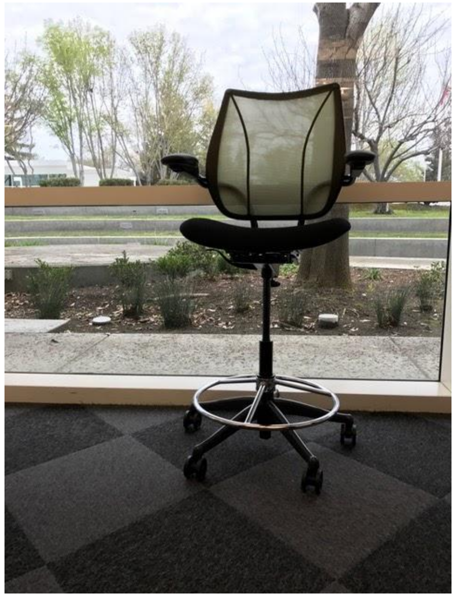


Image Classification + Localization

Object Detection

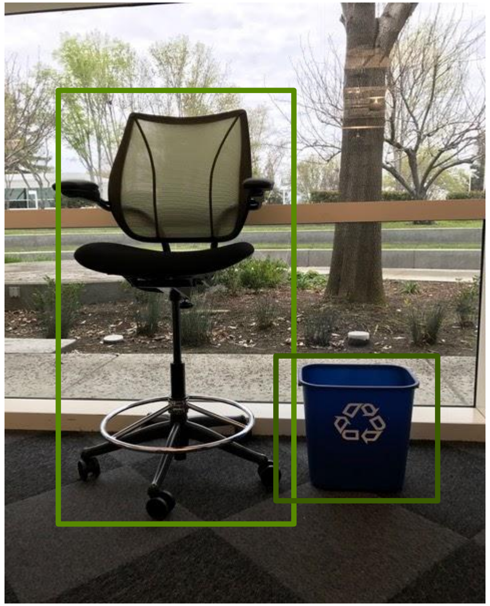


Image Segmentation

(inspired by a slide found in cs231n lecture from Stanford University)

OBJECT DETECTION

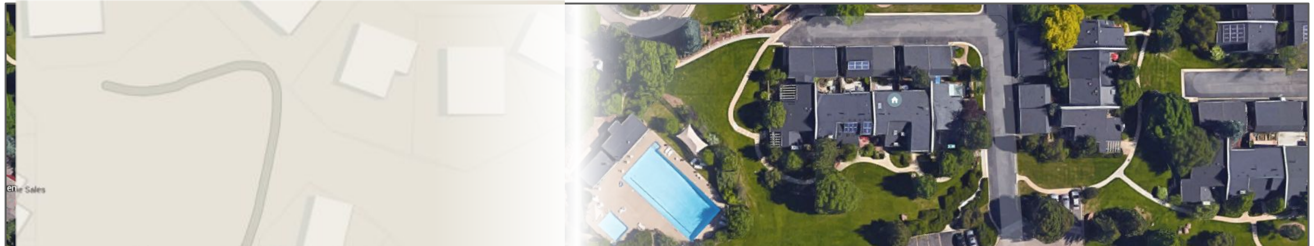
- Object detection can identify and classify one or more objects in an image
- Detection is also about localizing the extent of an object in an image
  - Bounding boxes / heat maps
- Training data must have objects within images labeled
  - Can be hard to find / produce training dataset

OBJECT DETECTION IN REMOTE SENSING IMAGES

Broad applicability

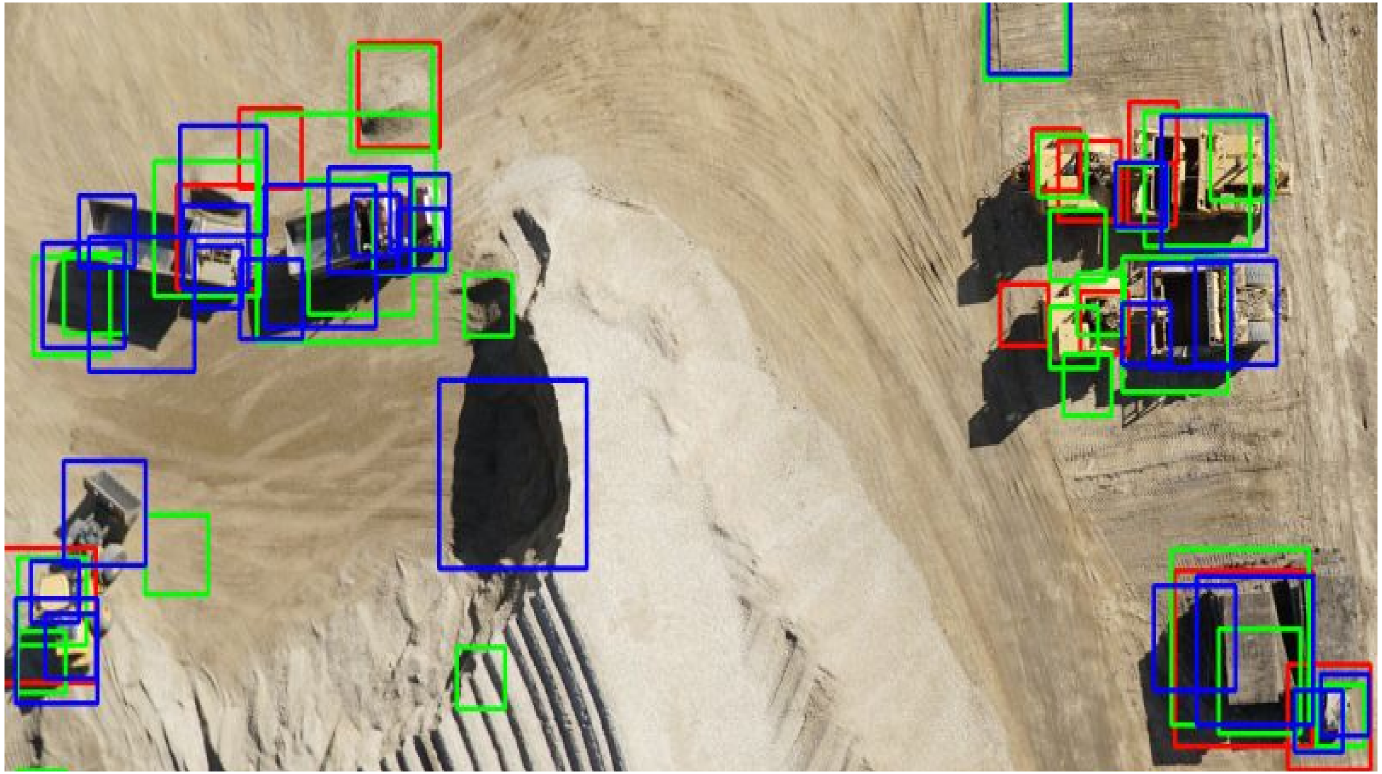
- Commercial asset tracking
- Humanitarian crisis mapping
- Search and rescue
- Land usage monitoring
- Wildlife tracking
- Human geography
- Geospatial intelligence production
- Military target recognition

Vermeulen et al, (2013) Unmanned Aerial Survey of Elephants. PLoS ONE 8(2): e54700

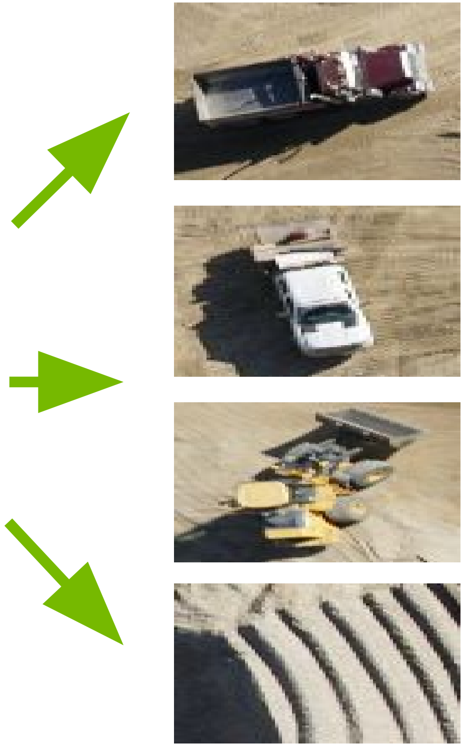


Imagery ©2016 Google, Map data © 201

OBJECT DETECTION

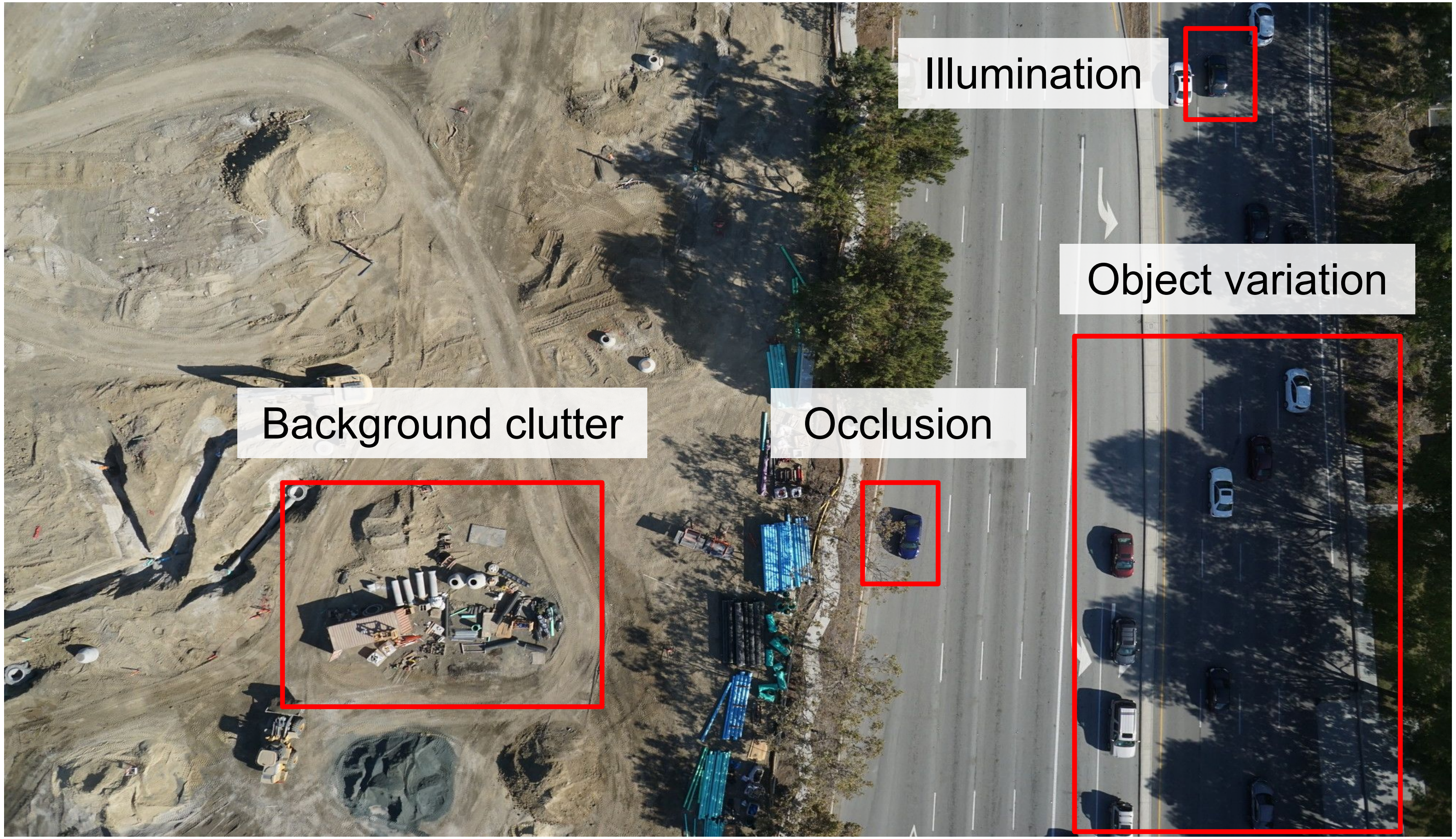


GENERATE CANDIDATE DETECTIONS



EXTRACT PATCHES

CHALLENGES FOR OBJECT DETECTION



ADDITIONAL APPROACHES TO OBJECT DETECTION ARCHITECTURE

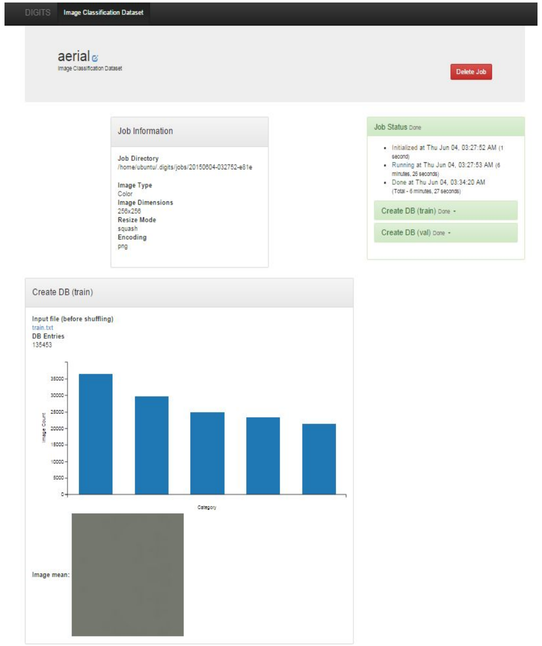
- R-CNN = Region CNN
- Fast R-CNN
- Faster R-CNN Region Proposal Network
- RoI-Pooling = Region of Interest Pooling

NVIDIA’S DIGITS

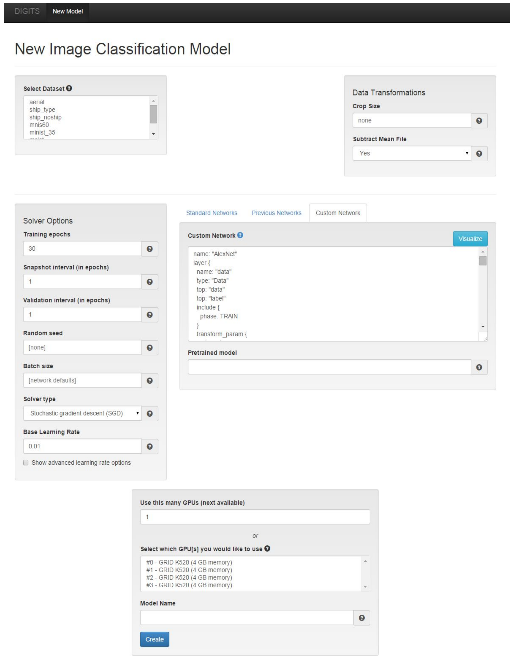
NVIDIA'S DIGITS

Interactive Deep Learning GPU Training System

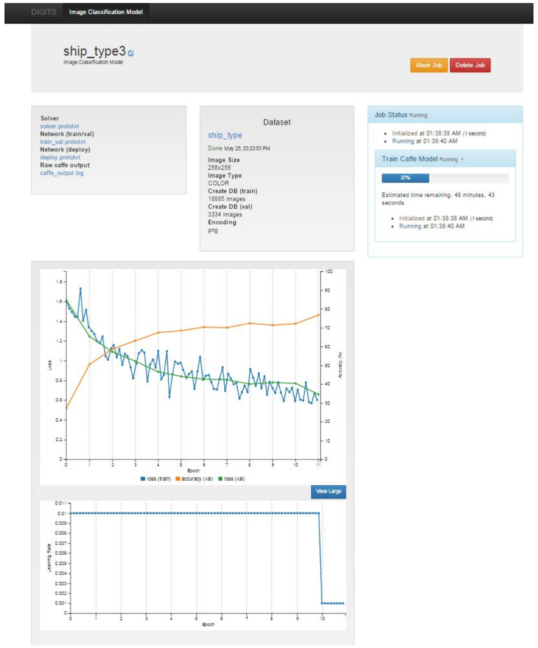
Process Data



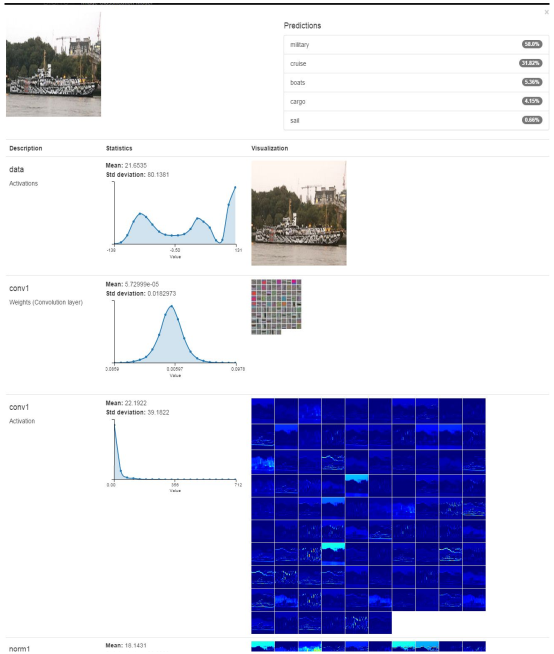
Configure DNN



Monitor Progress



Visualization



CAFFE

WHAT IS CAFFE?

An open framework for deep learning developed by the Berkeley Vision and Learning Center (BVLC)

caffe.berkeleyvision.org
http://github.com/BVLC/caffe

- Pure C++/CUDA architecture
- Command line, Python, MATLAB interfaces
- Fast, well-tested code
- Pre-processing and deployment tools, reference models and examples
- Image data management
- Seamless GPU acceleration
- Large community of contributors to the open-source project

CAFFE FEATURES

Deep Learning model definition

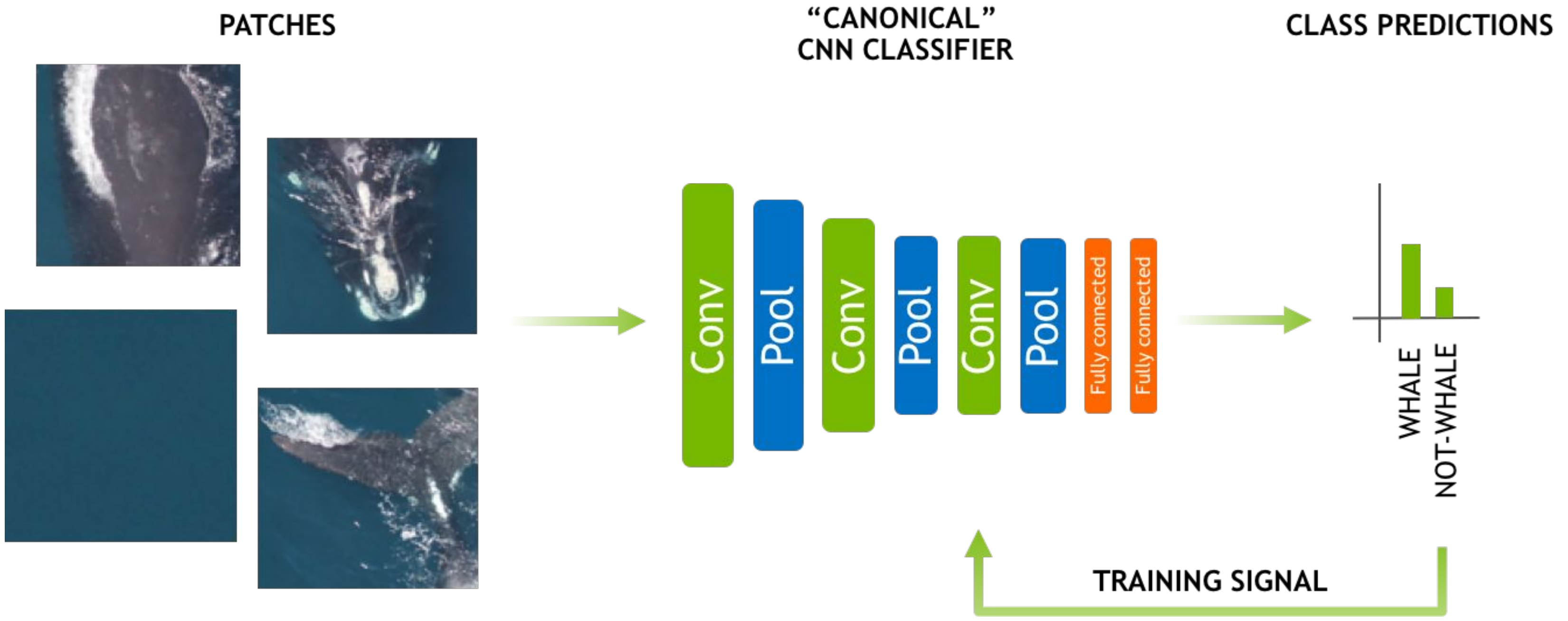
Protobuf model format

- Strongly typed format
- Human readable
- Auto-generates and checks Caffe code
- Developed by Google
- Used to define network architecture and training parameters
- No coding required!

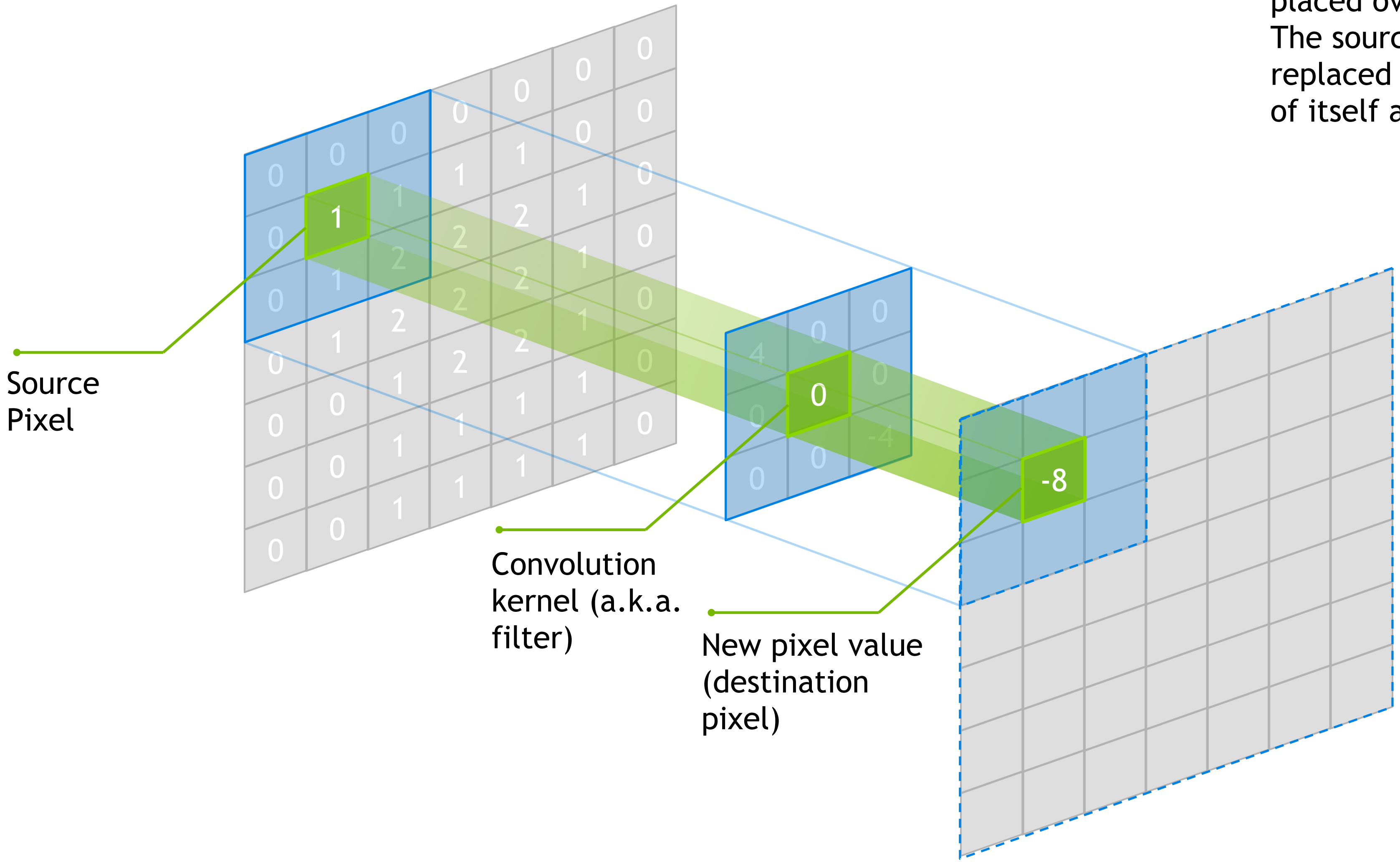
```
name: "conv1"
type: "Convolution"
bottom: "data"
top: "conv1"
convolution_param {
    num_output: 20
    kernel_size: 5
    stride: 1
    weight_filler {
        type: "xavier"
    }
}
```

LAB DISCUSSION / OVERVIEW

TRAINING APPROACH 1 – SLIDING WINDOW



CONVOLUTION



Center element of the kernel is placed over the source pixel. The source pixel is then replaced with a weighted sum of itself and nearby pixels.

TRAINING APPROACH 1 – POOLING

- Pooling is a down-sampling technique
  - Reduces the spatial size of the representation
    - Reduces number of parameters and number of computations (in upcoming layer)
  - Limits overfitting
- No parameters (weights) in the pooling layer
- Typically involves using MAX operation with a 2 X 2 filter with a stride of 2

TRAINING APPROACH 1 - DATASETS

- Two datasets
  - First contains the wide area ocean shots containing the whales
    - This dataset is located in data_336x224
  - Second dataset is ~4500 crops of whale faces and an additional 4500 random crops from the same images
    - We are going to use this second dataset to train our classifier in DIGITS
    - These are the “patches”

TRAINING APPROACH 1 - TRAINING

- Will train a simple two class CNN classifier on training dataset
- Customize the Image Classification model in DIGITS:
  - Choose the Standard Network "AlexNet"
  - Set the number of training epochs to 5

TRAINING APPROACH 1 – SLIDING WINDOW

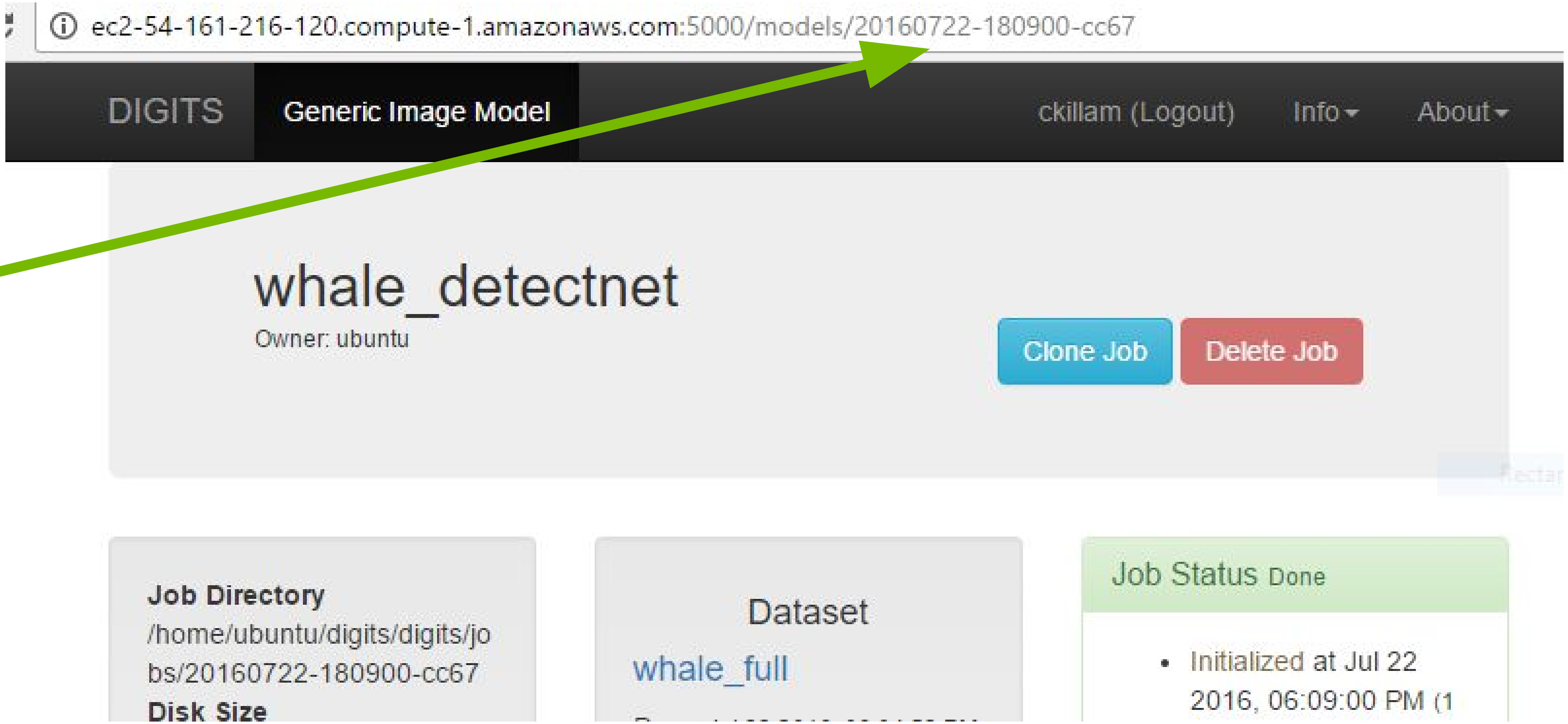
- Will execute code shown below
  - Example of how you feed new images to a model
  - In practice, would write code in C++ and use TensorRT

```
import numpy as np
import matplotlib.pyplot as plt
import caffe
import time

MODEL_JOB_NUM = '20160920-092148-8c17'  ## Remember to set this to be the job number for your model
DATASET_JOB_NUM = '20160920-090913-a43d'  ## Remember to set this to be the job number for your dataset

MODEL_FILE = '/home/ubuntu/digits/digits/jobs/' + MODEL_JOB_NUM + '/deploy.prototxt'                # Do not change
PRETRAINED = '/home/ubuntu/digits/digits/jobs/' + MODEL_JOB_NUM + '/snapshot_iter_270.caffemodel'    # Do not change
MEAN_IMAGE = '/home/ubuntu/digits/digits/jobs/' + DATASET_JOB_NUM + '/mean.jpg'                      # Do not change

# load the mean image
mean_image = caffe.io.load_image(MEAN_IMAGE)

# Choose a random image to test against
RANDOM_IMAGE = str(np.random.randint(10))
IMAGE_FILE = 'data/samples/w_' + RANDOM_IMAGE + '.jpg'
```

CAPTURING MODEL / DATASET NUMBER

1. Model number can be found here

2. Dataset number will be different, but found in same location

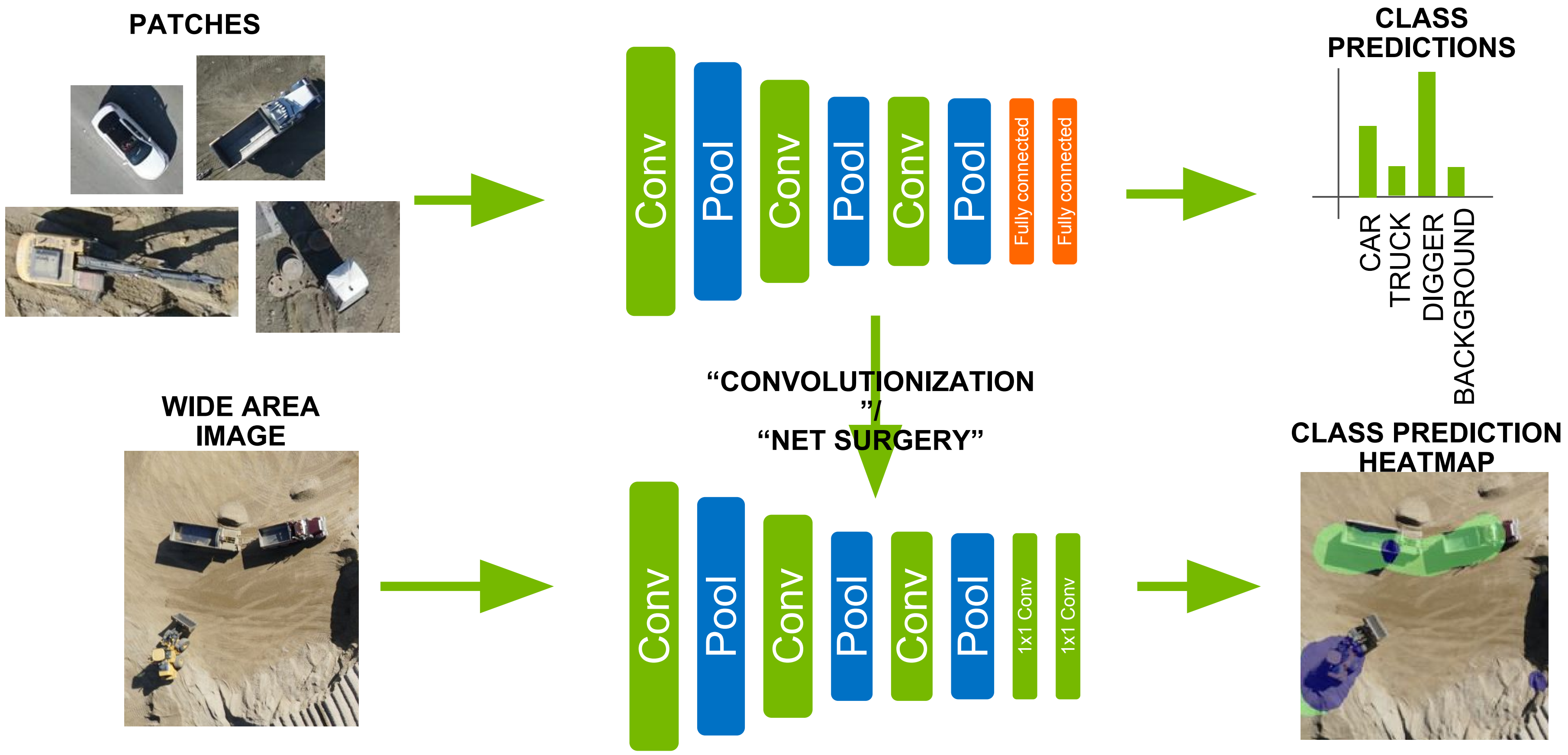


TRAINING APPROACH 2

- Candidate generation and classification
- Alternative to classification CNN using sliding window approach
- Discussed in lab instructions, but no lab task associated with this approach

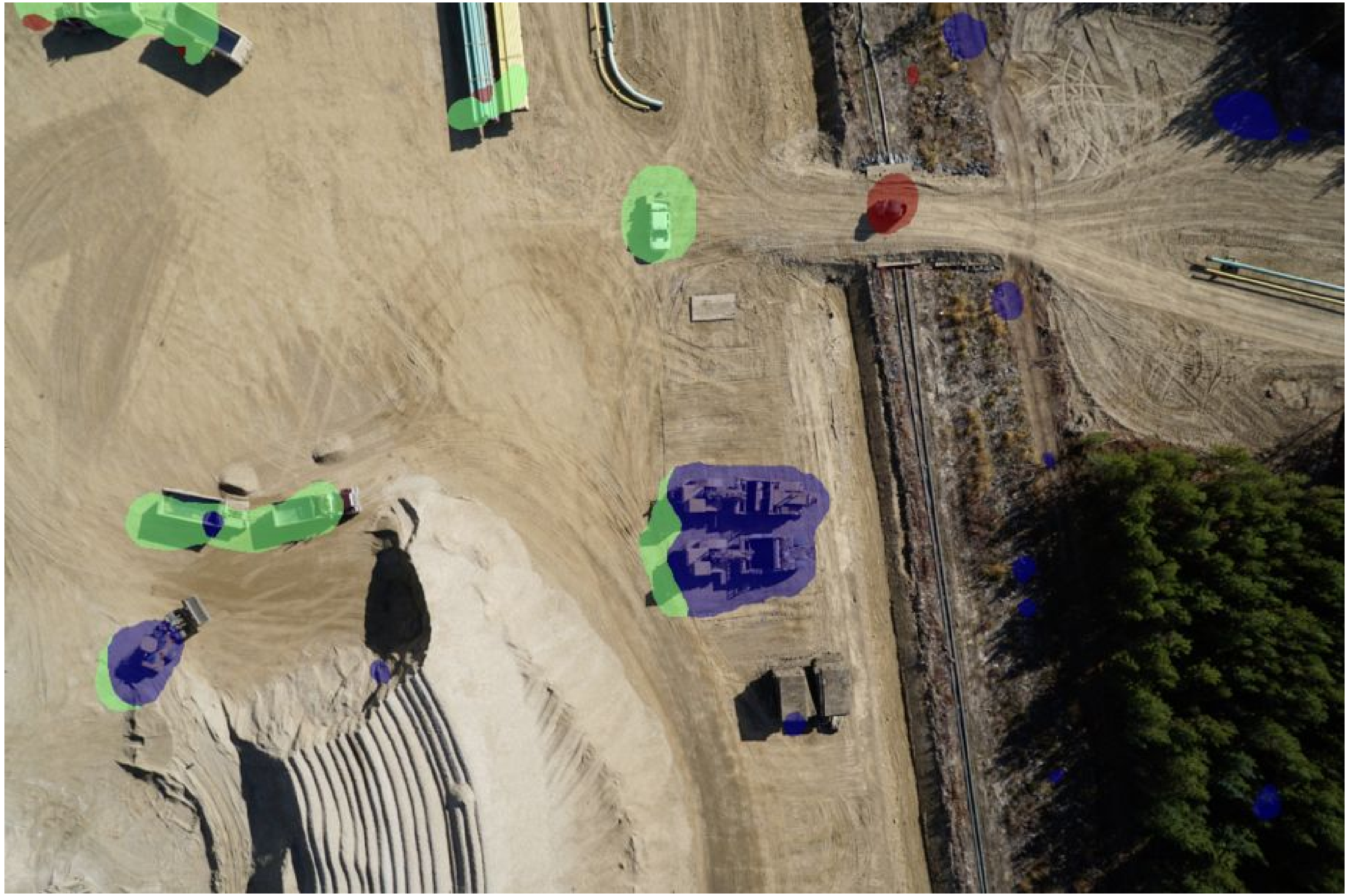
TRAINING APPROACH 3

Fully-Convolutional Network (FCN)

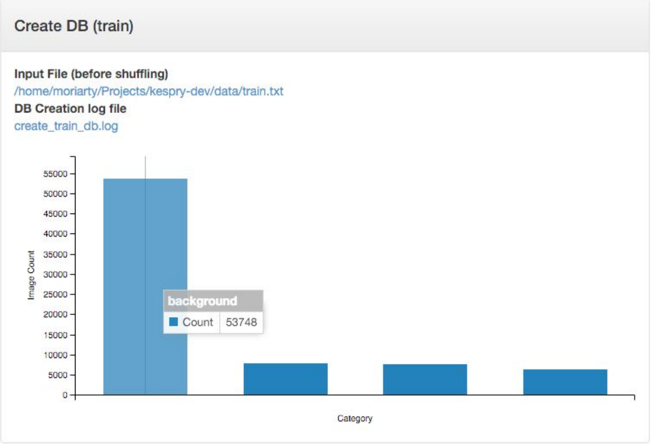


TRAINING APPROACH 3 - EXAMPLE

Alexnet converted to FCN for four class classification



TRAINING APPROACH 3 - FALSE ALARM MINIMIZATION

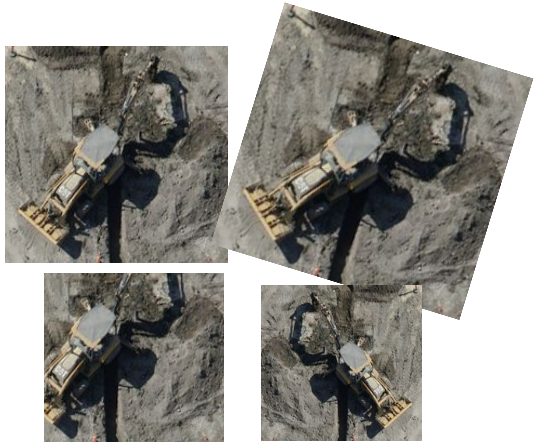


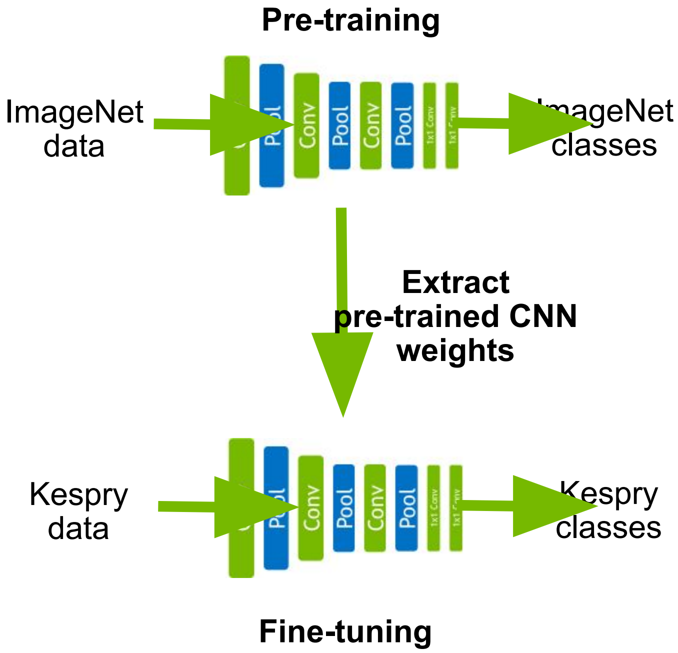
$$E = -\frac{1}{N}\sum_{n=1}^{N} H_{l_n} \log(\hat{p}_n)$$

Imbalanced dataset and InfogainLoss

Data augmentation

Random scale, crop, flip, rotate

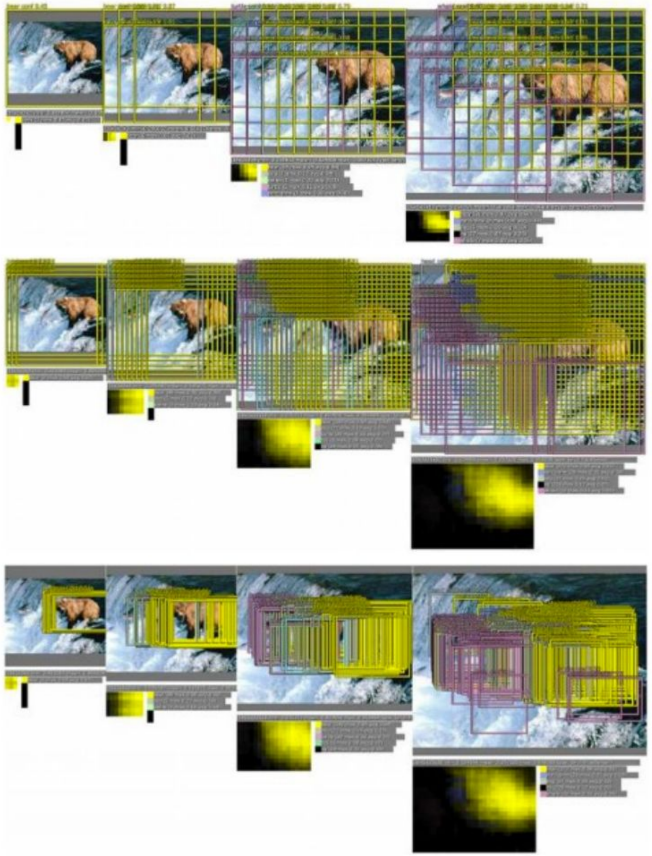




Transfer learning

TRAINING APPROACH 3 - INCREASING FCN PRECISION

Multi-scale and shifted inputs



OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks,
Sermanet et al., 2014

greedy merging procedure

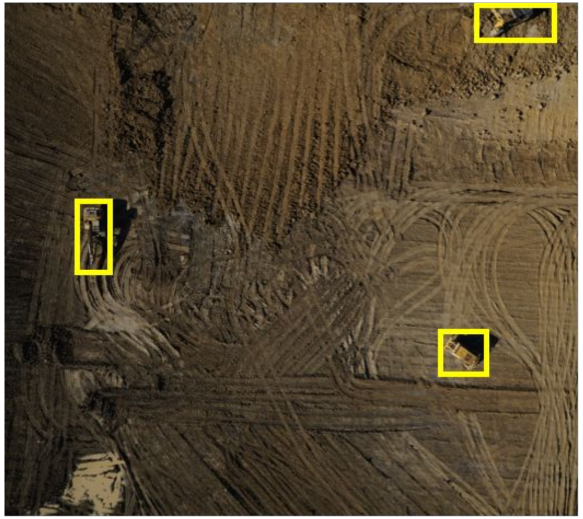
Slide credit: Fei-Fei Li & Andrej Karpathy, Stanford cs231n

TRAINING APPROACH 4 - DETECTNET

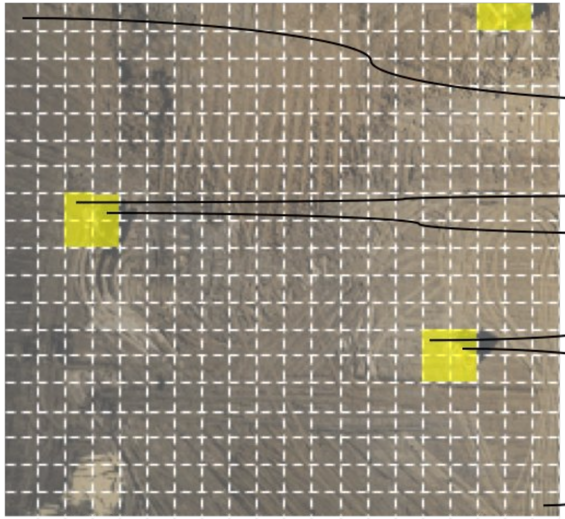
- Train a CNN to simultaneously
  - Classify the most likely object present at each location within an image
  - Predict the corresponding bounding box for that object through regression
- Benefits:
  - Simple one-shot detection, classification and bounding box regression pipeline
  - Very low latency
  - Very low false alarm rates due to strong, voluminous background training data

TRAINING APPROACH 4 - DETECTNET

Train on wide-area images with bounding box annotations



Training image with bounding box annotations



Bounding boxes mapped to grid squares

Bounding box coordinates in pixels relative to center of grid square

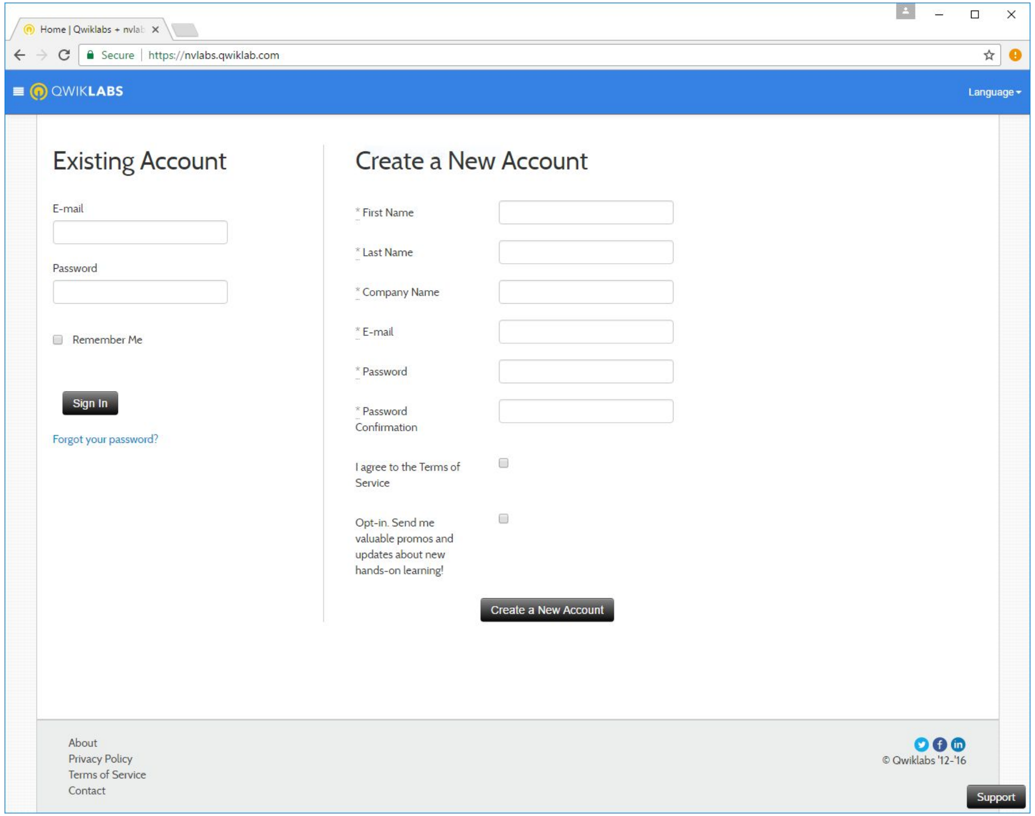
class	x_1	y_1	x_2	y_2	coverage
dontcare	0	0	0	0	0
...	...	...	...	...	...
digger	-2	-8	18	24	1
digger	-18	-8	2	24	1
...	...	...	...	...	...
digger	-6	-8	22	24	1
digger	-24	-8	8	24	1
...	...	...	...	...	...
dontcare	0	0	0	0	0

DetectNet input data representation

NAVIGATING TO QWIKLABS

1. Navigate to:
   https://nvlabs.qwiklab.com

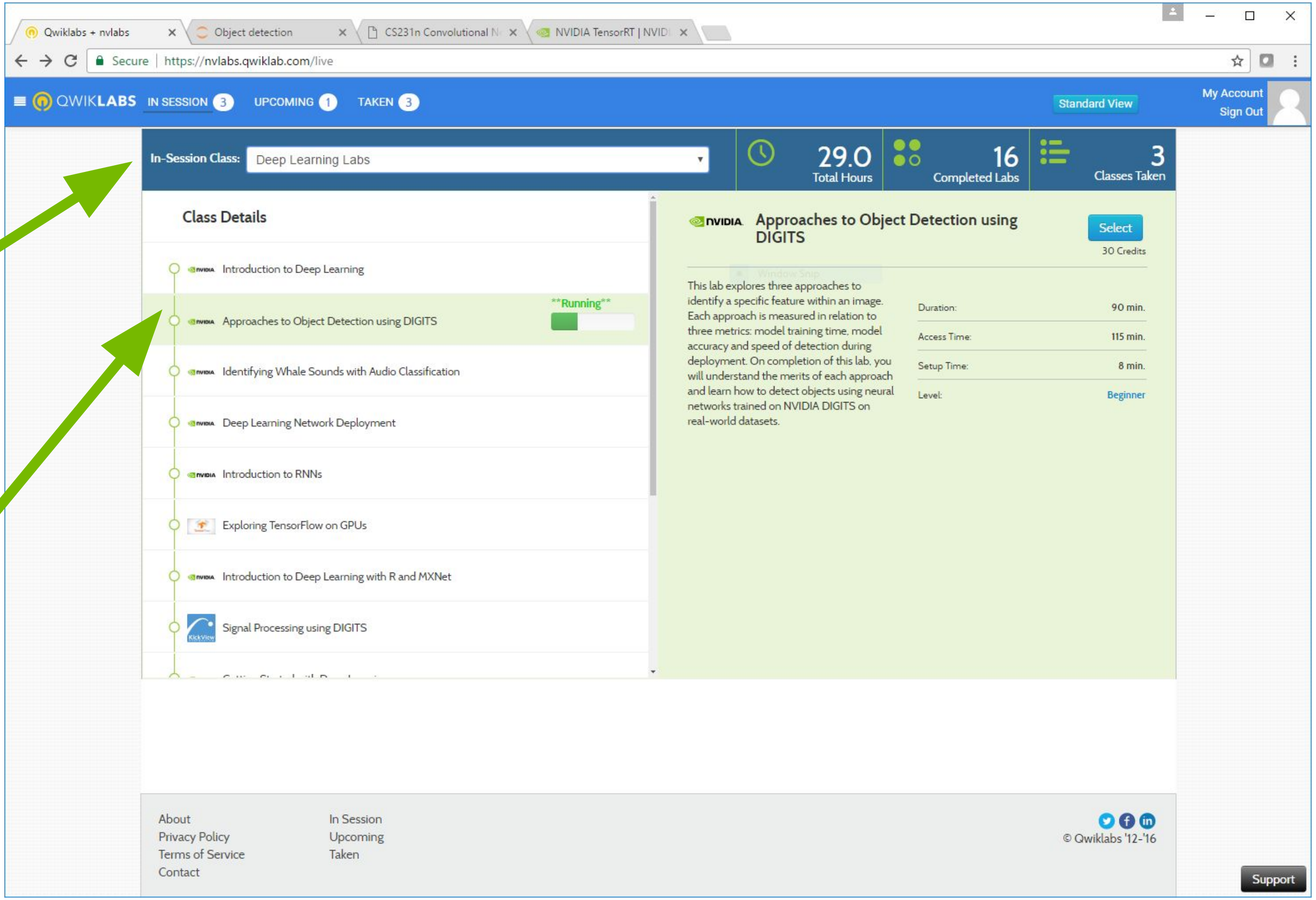
2. Login or create a new account



ACCESSING LAB ENVIRONMENT

1. Select the event specific In-Session Class in the upper left

2. Click the “Approaches to Object Detection Using DIGITS” Class from the list



*** Model building may take some time and may appear to initially not be progressing ***

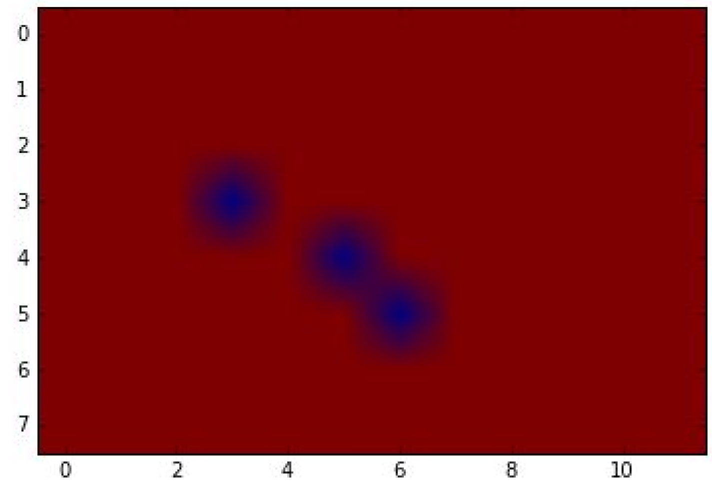
LAB REVIEW

TRAINING APPROACHS

- Approach 1:
  - Patches to build model
  - Sliding window looks for location of whale face

Total inference time: 10.5373151302 seconds

Total inference time: 10.5373151302 seconds



TRAINING APPROACHS

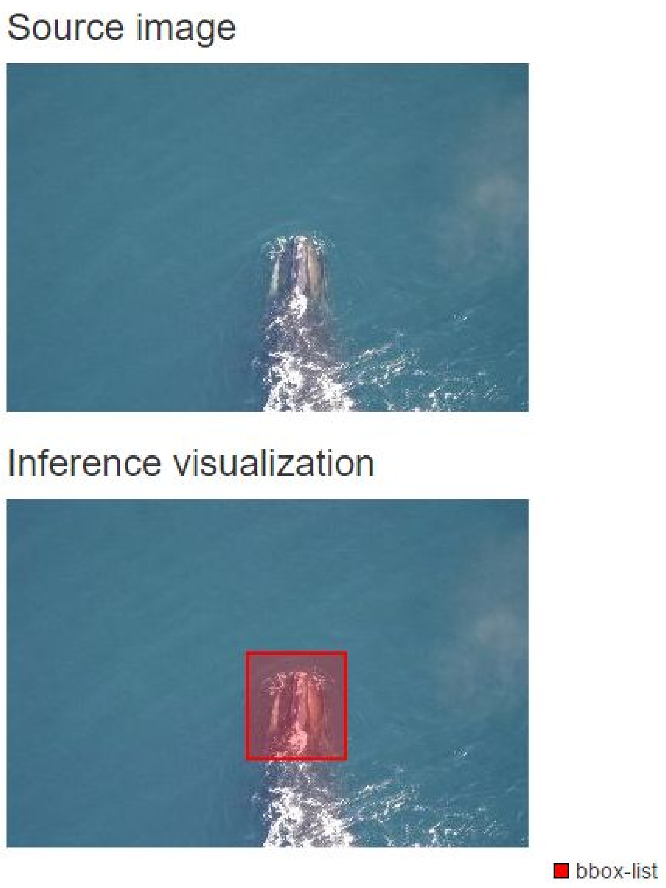
- Approach 3:
  - Fully-convolution network (FCN)

```
}
layer {
  name: "pool5"
  type: "Pooling"
  bottom: "conv5"
  top: "pool5"
  pooling_param {
    pool: MAX
    kernel_size: 3
    stride: 2
  }
}
layer {
  name: "fc6"
  type: "InnerProduct"
  bottom: "pool5"
  top: "fc6"
  param {
    lr_mult: 1
    decay_mult: 1
  }
  param {
    lr_mult: 2
    decay_mult: 0
  }
  inner_product_param {
    num_output: 4096
    weight_filler {
      type: "gaussian"
      std: 0.005
    }
    bias_filler {
      type: "constant"
      value: 0.1
    }
  }
}
layer {
  name: "relu6"
  type: "ReLU"
  bottom: "fc6"
  top: "fc6"
}
```

```
layer {
  name: "conv6"
  type: "Convolution"
  bottom: "pool5"
  top: "conv6"
  param {
    lr_mult: 1.0
    decay_mult: 1.0
  }
  param {
    lr_mult: 2.0
    decay_mult: 0.0
  }
  convolution_param {
    num_output: 4096
    pad: 0
    kernel_size: 6
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 0.1
    }
  }
}
layer {
  name: "relu6"
  type: "ReLU"
  bottom: "conv6"
  top: "conv6"
}
```

TRAINING APPROACHS

- Approach 4:
  - DetectNet



WHAT'S NEXT

- Use / practice what you learned
- Discuss with peers practical applications of DNN
- Reach out to NVIDIA and the Deep Learning Institute
- Attend local meetup groups
- Follow people like Andrej Karpathy and Andrew Ng

WHAT'S NEXT

TAKE SURVEY

...for the chance to win an NVIDIA SHIELD TV.

Check your email for a link.

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TOKYO
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GTC 2018
SILICON VALLEY
MARCH 26 - 29, 2018

WWW.GPUTECHCONF.COM

Instructor: Charles Killam, LP.D.

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