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Multiple Objects Detection in Single Image by Deep Learning

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Outline

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Introduction

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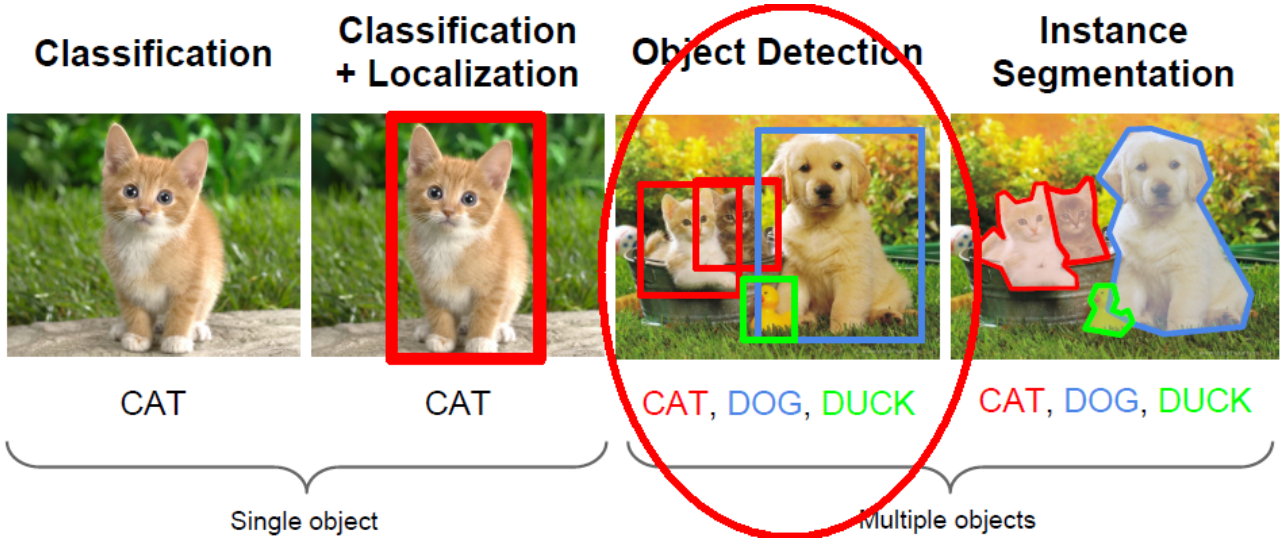
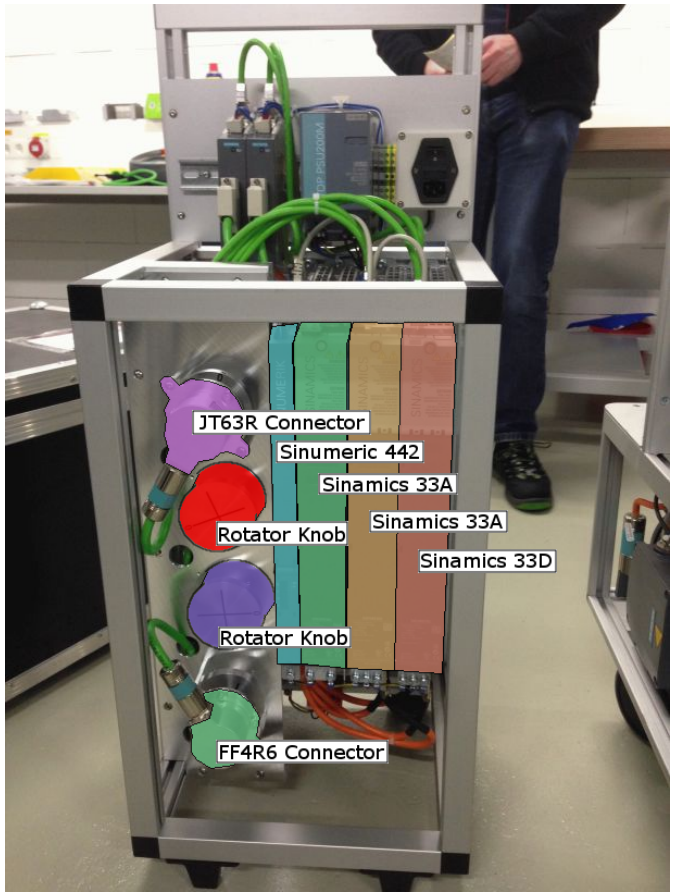
Project Description

- Given an image with user's device
  - Many mechanic parts of different types are contained in the image
- Need to figure out
  - The number of the objects of interest
  - The location of the objects of interest
  - The category of the objects of interest
- Predicted difficulty
  - Objects Occlusion
- Classification < Localization < Detection (Subset)



Computer Vision Tasks[1]



User Case

Intro to Deep Learning

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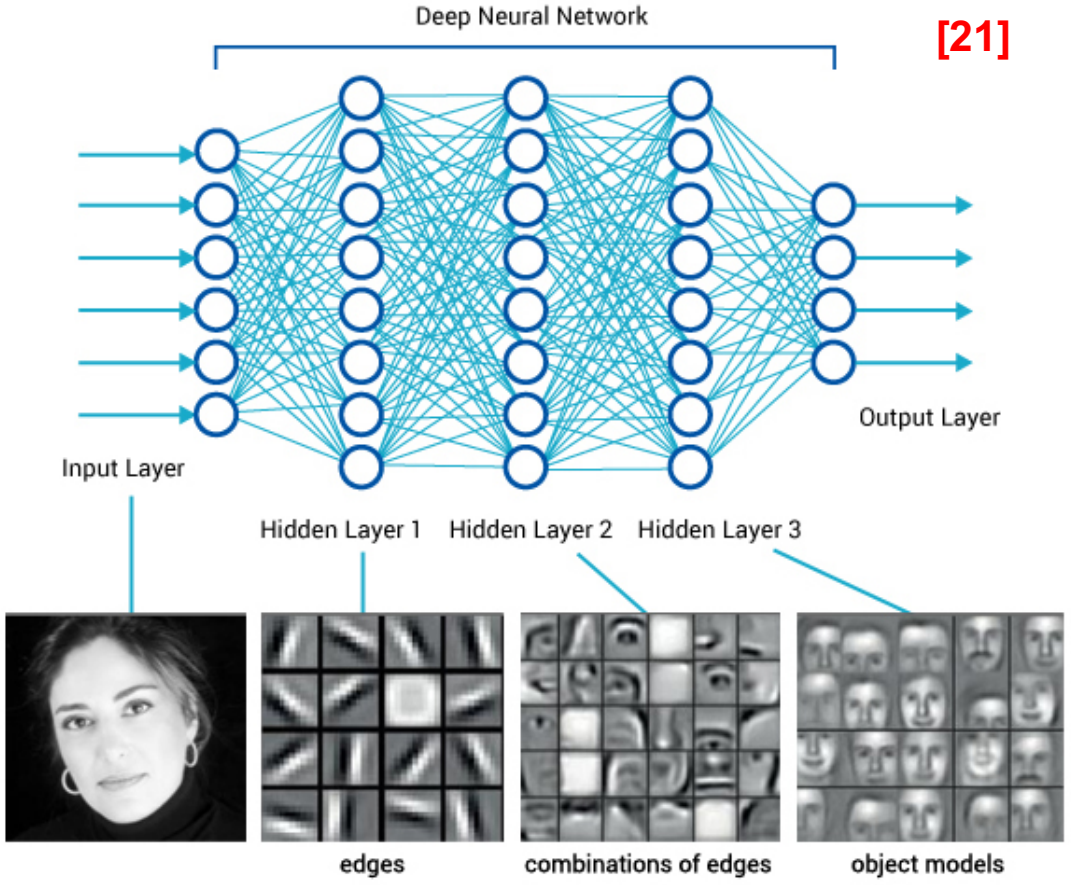
- A subset of machine learning
- Deep neural network is a special artificial neural network with at least two hidden layers
- Universal Approximation Theorem
- Deep network has better expressive power than shallow network
  - The deeper the layer is, the higher level feature it is able to extract
  - Intuition: composition of functions



Intro to Convolutional Neural Network (ConvNet) [3]

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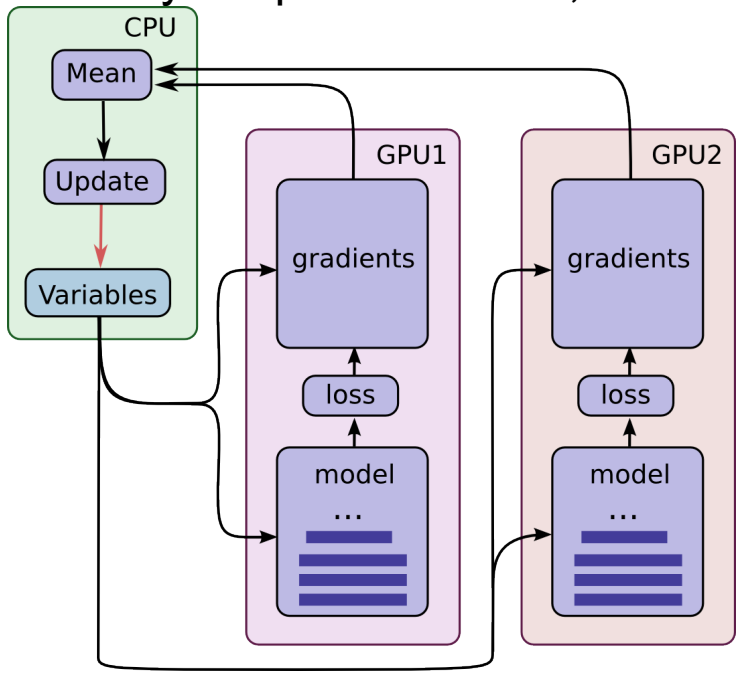
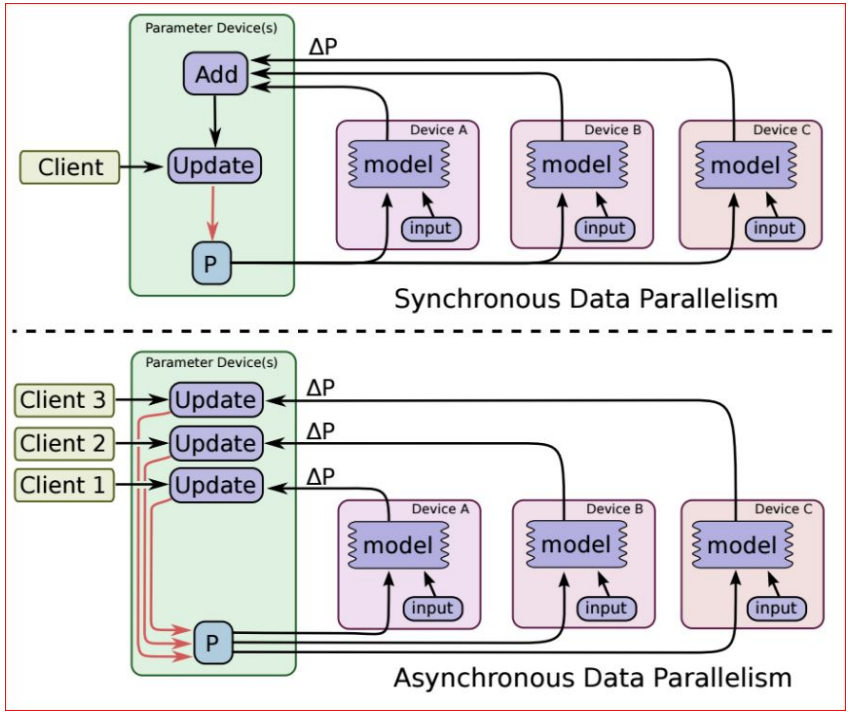
- Achieve great success in the field of Computer Vision
- Trained end-to-end, from raw pixels to ultimate categories
- Convolution + Pooling: fully utilize spatial connection in the image
- Sparse Connectivity + Shared Weights: greatly reduce number of parameters
- ConvNet is a stack of CONV, POOL, FC layers
- Trend towards **smaller** filters, **deeper** architectures and **remove** POOL/FC layers (refer to the evolution of Google's Inception module)
- Dropout trick + ReLU (rectified linear unit) activation [4]

How to Train a ConvNet from Scratch [9][19]

- Training a ConvNet is an optimization on an extremely high dimension non-convex loss function
- Training becomes easier thanks to GPU and Distributed Computing
- Two ways of parallelization, **Data Parallel** & Model Parallel



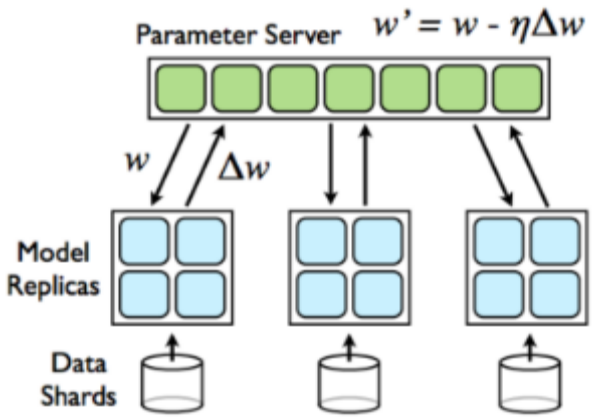
Single machine with multiple GPUs



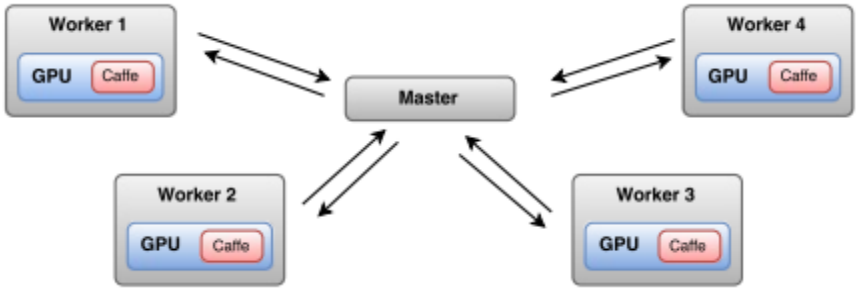
Multiple machines in distributed setting

How to Train a ConvNet from Scratch (cont.)

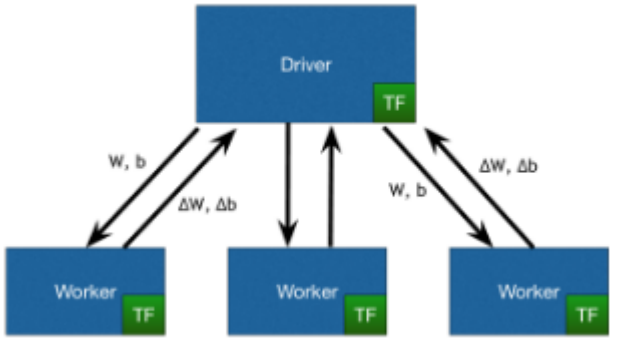
- Training on single machine with multiple GPUs
  - Very well supported in TensorFlow
- Distributed computing framework for TensorFlow
  - TensorSpark [8]
  - SparkNet (Claim to support TensorFlow in the future)
  - Spark + YRAN computation cluster on AWS



Google's DistBelief Architecture



SparkNet Architecture



TensorSpark Architecture

How to Train a ConvNet from Scratch (cont.)

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- Amazon Web Service
  - Spark + YARN

```
with tf.device("/job:ps/task:1"):
  weights_2 = tf.Variable(...)
  biases_2 = tf.Variable(...)

with tf.device("/job:worker/task:7"):
  input, labels = ...
  layer_1 = tf.nn.relu(tf.matmul(input, weights_1) + biases_1)
  logits = tf.nn.relu(tf.matmul(layer_1, weights_2) + biases_2)
  # ...
  train_op = ...

with tf.Session("grpc://worker7.example.com:2222") as sess:
```

Software configuration

Vendor (●) Amazon ( ) MapR

Release emr-4.7.1

Applications

( ) Core Hadoop: Hadoop 2.7.2 with Ganglia 3.7.2, Hive 1.0.0, Hue 3.7.1, Mahout 0.12.0, and Pig 0.14.0

( ) HBase: HBase 1.2.1 with Ganglia 3.7.2, Hadoop 2.7.2, Hive 1.0.0, Hue 3.7.1, Phoenix 4.7.0, and ZooKeeper 3.4.8

( ) Presto-Sandbox: Presto 0.147 with Hadoop 2.7.2 HDFS and Hive 1.0.0 Metastore

(●) Spark: Spark 1.6.1 on Hadoop 2.7.2 YARN with Ganglia 3.7.2

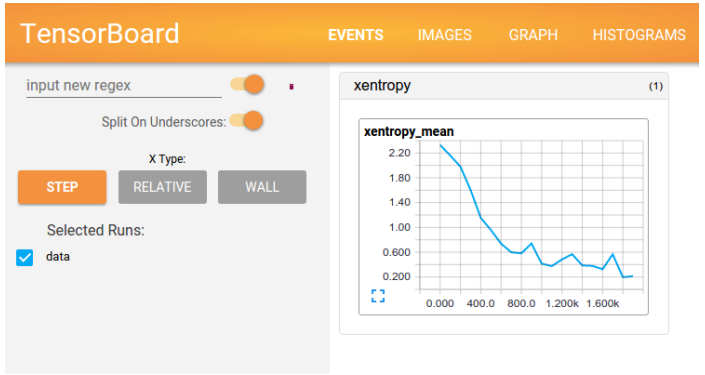
Hardware configuration

Instance type g2.2xlarge

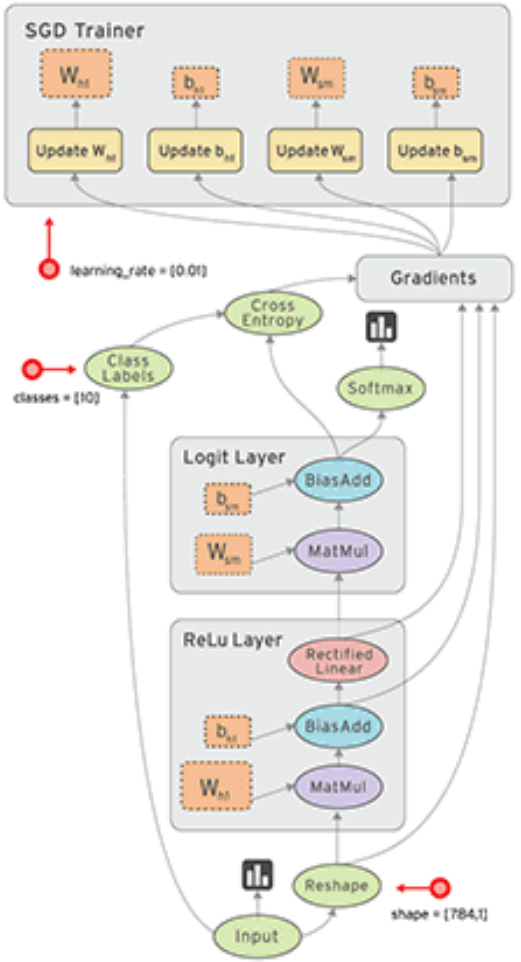
Number of instances 3 (1 master and 2 core nodes)

Intro to TensorFlow [16]

- Google's second-generation system for the implementation and deployment of large-scale machine learning models
- Support hardware platforms ranging from mobile device to single machine with GPUs to hundreds of machines
- Describe computation using a dataflow-like model (similar to Theano)
- Tensors (N-dimensional array) flow in a computation graph, where operations are represented as nodes and reliance between operations are represented as edges
- TensorBoad is a suite of visualization tools able to visualize graph and plot quantitative metrics about the execution of the graph



TensorBoard



Data-flow graph

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Classification

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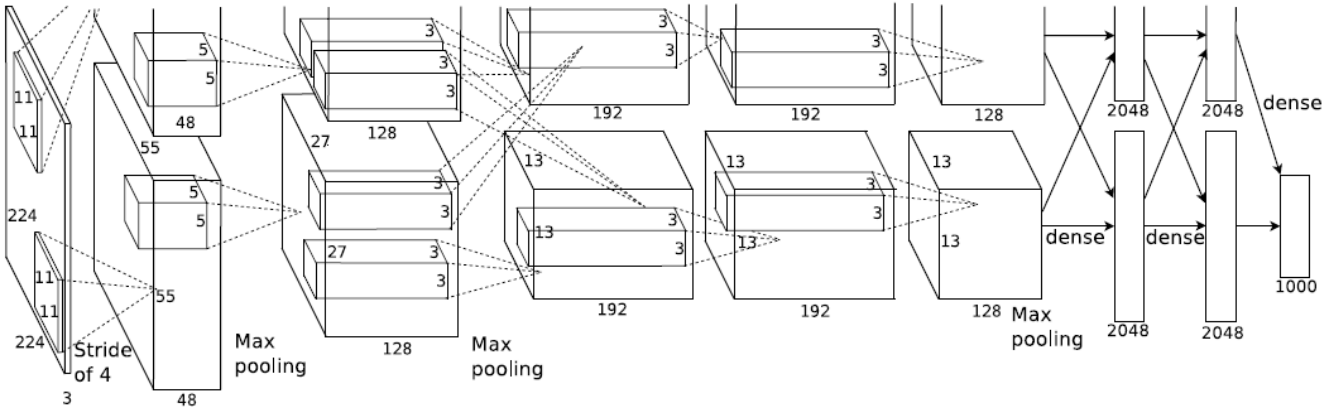
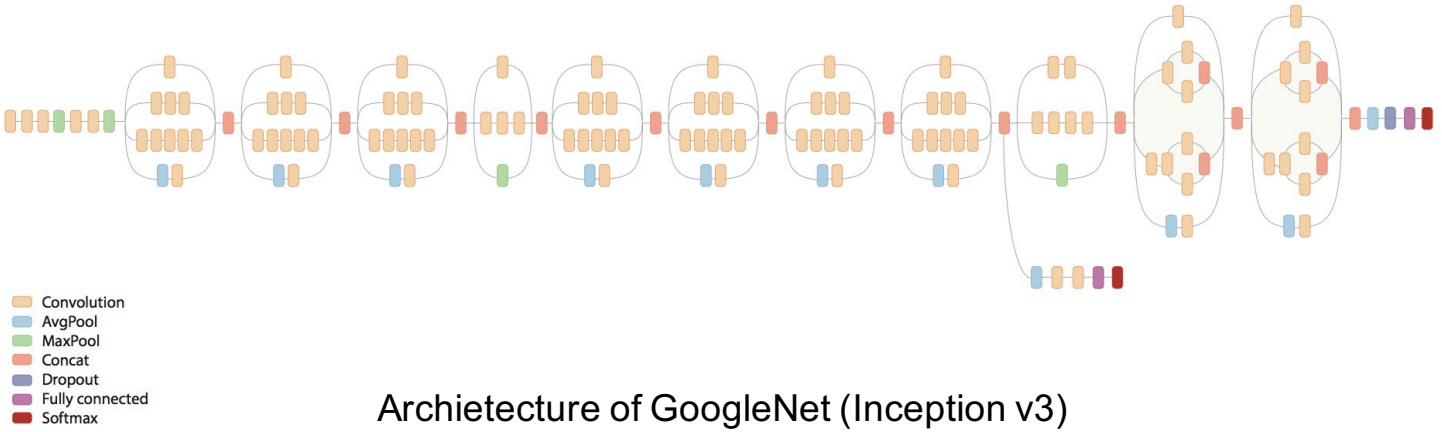
Related Work

- AlexNet (2012) [4]
  - 8 layers
  - 40.7% top-1 & 18.2% top-5
  - 60 million parameters
- VGGNet (2014) [5]
  - 19 layers
  - 24.4% top-1 & 7.1% top-5
  - 180 million parameters
- GoogleNet (Inception-v3) (2015) [6]
  - 48 layers
  - 18.77% top-1 & 4.2% top-5
  - 5 billion multiply-adds / inference
  - 25 million parameters



Archietecture of AlexNet



Archietecture of GoogleNet (Inception v3)

Data Set

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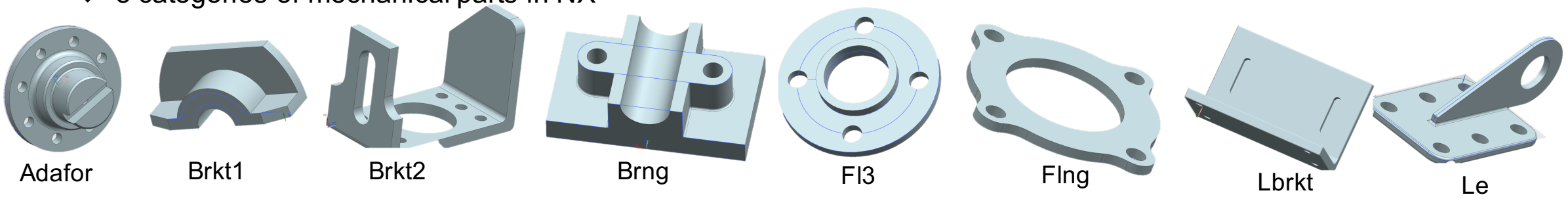
- 8 categories of mechanical parts in NX



- Expand the size of data set using NX journal
  - Rotate the part by some degree along 3 axis
  - Assign colors to features randomly
  - Add noisy background randomly
- Expand the size of data set using TensorFlow (Only do it in training)
  - Do distortion on each image
  - Flip left and right
  - Adjust the brightness and contrast by a random factor

Architecture

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Layer	Stage	Filter size	Conv stride	Pooling size	Pooling stride	Tensor Shape
1 (input)	\	\	\	\	\	(256, 128, 128, 3)
2	Conv+Max	[5,5,3,64]	[1, 1, 1, 1]	[1, 3, 3, 1]	[1, 2, 2, 1]	(256, 64, 64, 64)
3	Conv+Max	[5,5,64,64]	[1, 1, 1, 1]	[1, 2, 2, 1]	[1, 2, 2, 1]	(256, 32, 32, 64)
4	FCC	\	\	\	\	(256, 384)
5	FCC	\	\	\	\	(256, 192)
6 (output)	FCC	\	\	\	\	(256, 5)

Performance (Using Imbalanced Data)

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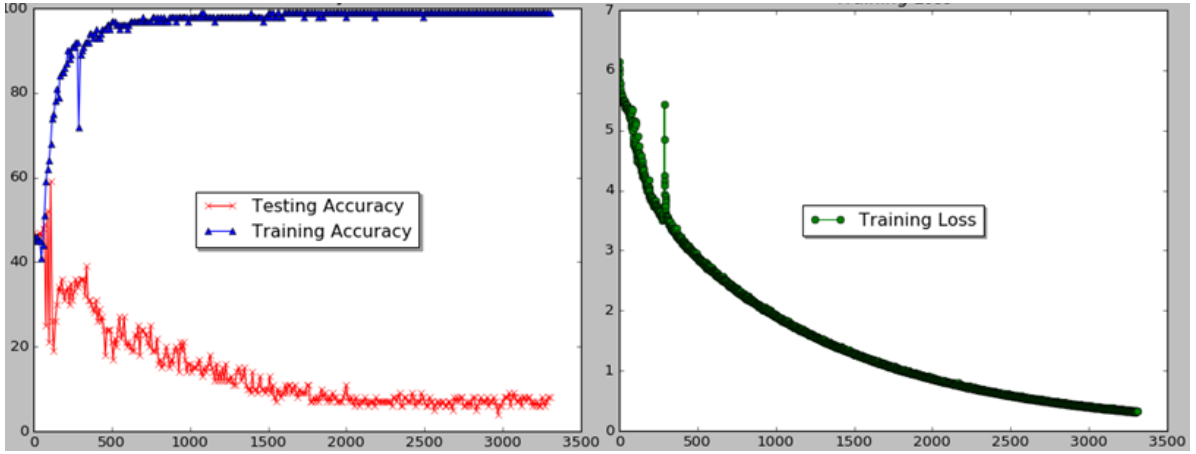
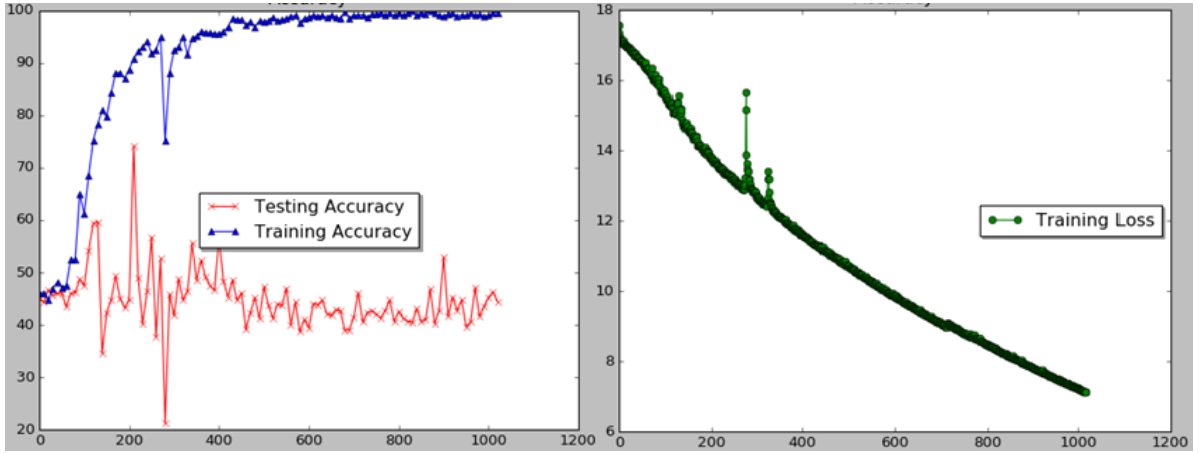
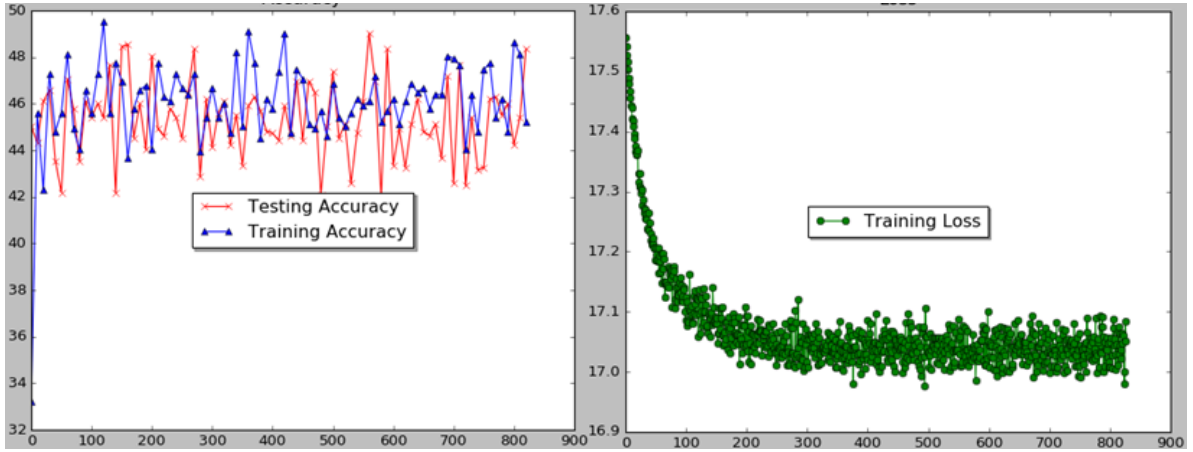
8 categories, 32x32, lr = 0.1, batch size = 1024, w/ dropout, LRN, distortion



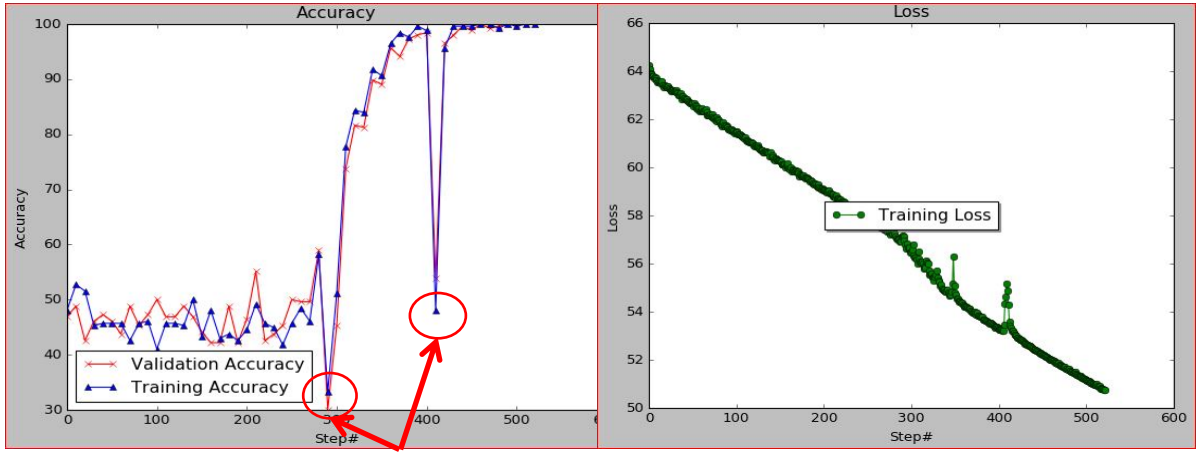
6 categories, 64x64, lr = 0.1, batch size = 512, w/ dropout, LRN, distortion



6 categories, 64x64, lr = 0.005, batch size = 512, w/ dropout, LRN, distortion



6 categories, 128x128, lr = 0.05, batch size = 256, w/o dropout, w/o LRN, w/o distortion



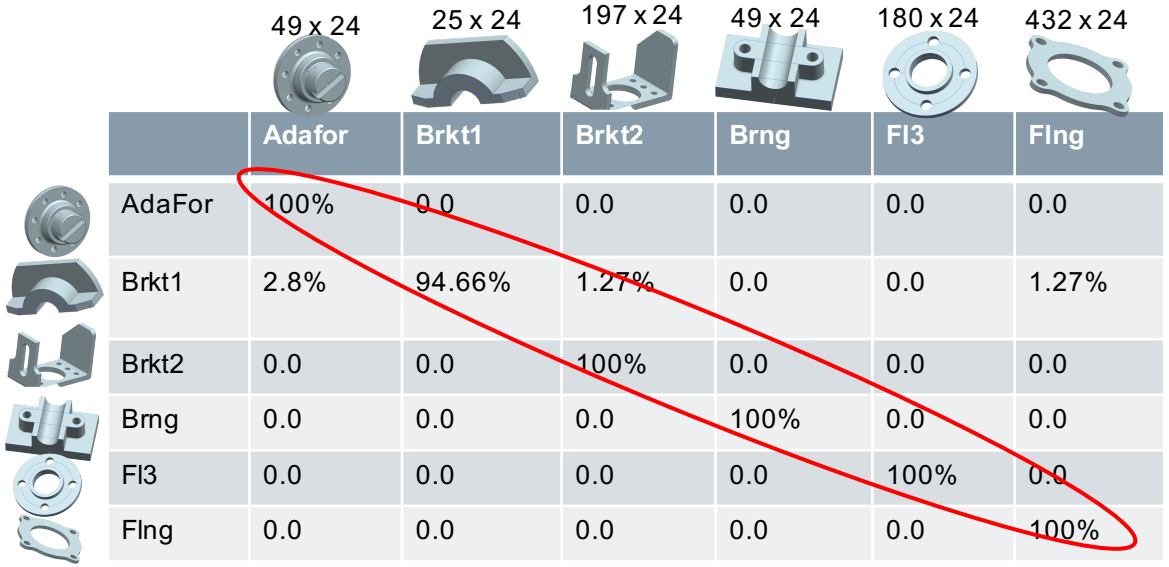
Neural Network reached saturation state?

Performance (cont.)

	Adafor	Brkt1	Brkt2	Brng	Fl3	Flng	Lbrkt	Le
AdaFor	5.52%	0.0	0.0	0.0	0.0	0.0	94.48%	0.0
Brkt1	0.0	1.46%	0.0	0.0	0.0	0.0	98.54%	0.0
Brkt2	0.0	0.0	2.82%	0.0	0.0	0.0	97.18%	0.0
Brng	0.0	0.0	7.71%	19.99%	0.99%	0.0	71.3%	0.0
Fl3	0.0	0.0	0.94%	0.0	25.42%	0.0	73.64%	0.0
Flng	0.0	0.0	0.0	0.0	0.0	0.48%	91.05%	8.47%
Lbrkt	0.0	0.0	0.0	0.0	0.0	0.0	100%	0.0
Le	0.0	0.0	0.0	0.0	0.0	0.0	77.8%	22.2%

	Adafor	Brkt1	Brkt2	Brng	Fl3	Flng
AdaFor	6.16% (100%)	0.0	72.73%	13.22%	1.765%	6.12%
Brkt1	0.0 (0.76%)	5.971% (95.63%)	82.21% (1.387%)	2.89% (0.9%)	0.0	8.93% (1.32%)
Brkt2	0.0	0.0	100% (99.96%)	0.0 (0.009%)	0.0 (0.027%)	0.0
Brng	0.0	0.0	55.31%	26.93% (100%)	0.83%	16.92%
Fl3	0.0	0.0	41.06%	0.0	58.94% (100%)	0.0
Flng	0.0	0.0	84.36%	0.0	0.0	15.64% (100%)

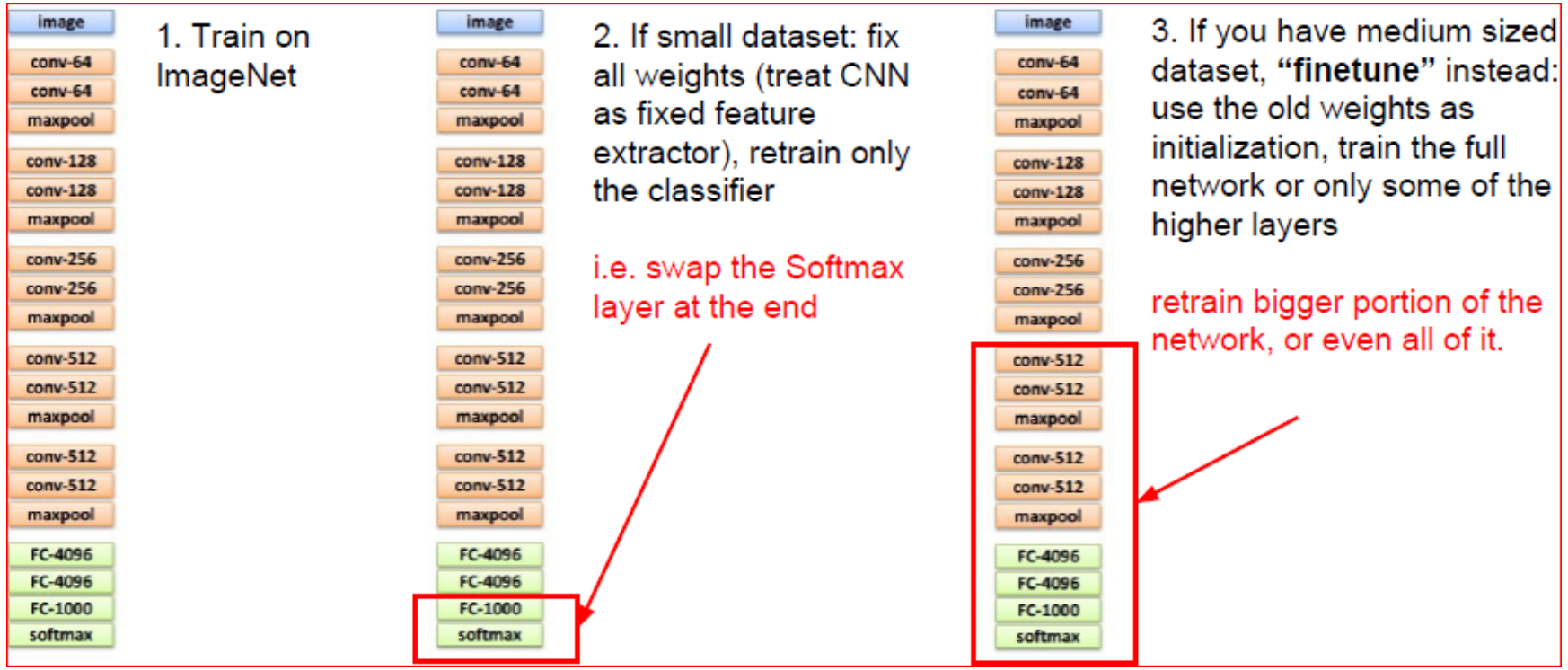
	Adafor	Brkt1	Brkt2	Brng	Fl3	Flng
AdaFor	0.0	0.0	0.0	0.0	0.0	100%
Brkt1	0.0	0.0	0.0	0.0	0.0	100%
Brkt2	0.0	0.0	0.0	0.0	0.0	100%
Brng	0.0	0.0	0.0	0.0	0.0	100%
Fl3	0.0	0.0	0.0	0.0	0.0	100%
Flng	0.0	0.0	0.0	0.0	0.0	100%



	Adafor	Brkt1	Brkt2	Brng	Fl3	Flng
AdaFor	100%	0.0	0.0	0.0	0.0	0.0
Brkt1	2.8%	94.66%	1.27%	0.0	0.0	1.27%
Brkt2	0.0	0.0	100%	0.0	0.0	0.0
Brng	0.0	0.0	0.0	100%	0.0	0.0
Fl3	0.0	0.0	0.0	0.0	100%	0.0
Flng	0.0	0.0	0.0	0.0	0.0	100%

Transfer Learning

- Taking fully-trained model for a set of categories (like ImageNet)
- Retrain the final layer from scratch, while leaving all the others untouched
- Caffe Model Zoo: Lots of pretrained ConvNets (Caffe model is convertible to TensorFlow) [22]



Transfer Learning (contd.)

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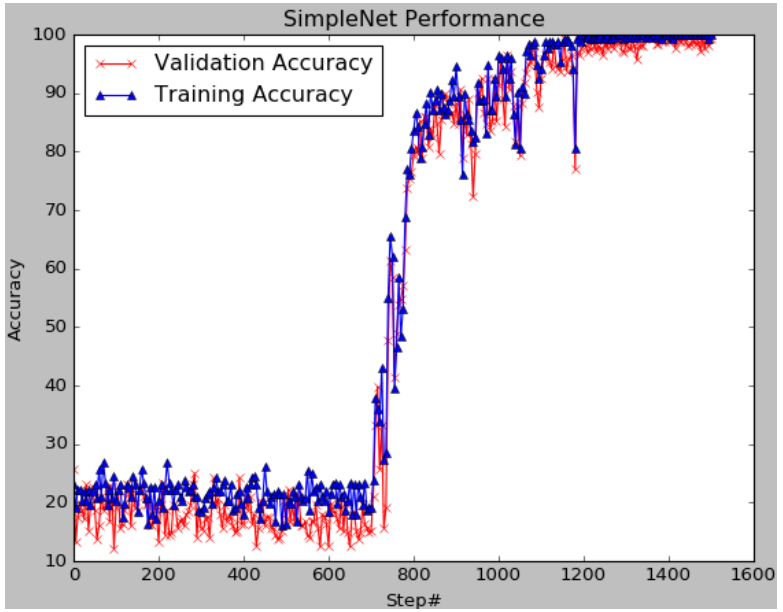
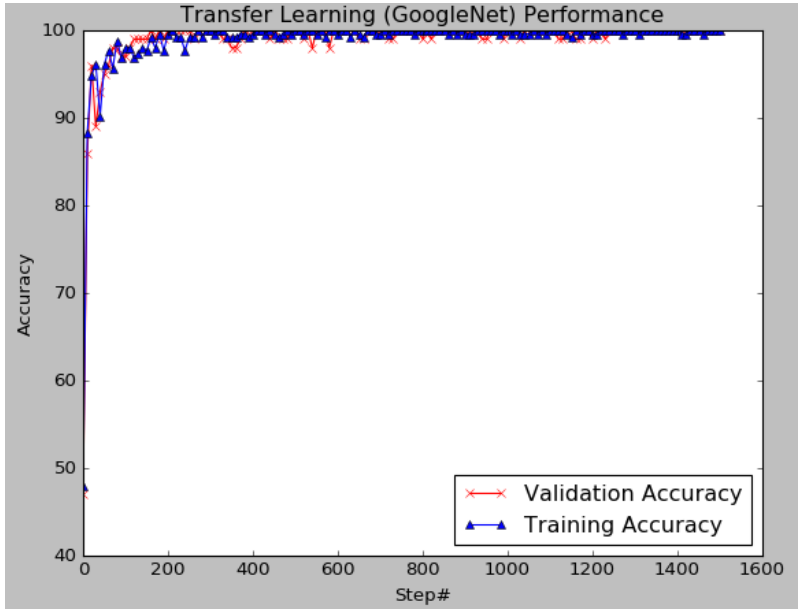
- Compare SimpleNet and Transfer Learning (GoogleNet)
  - Both use mini-batch SGD with same batch size but with different learning rate
  - Transfer Learning on GoogleNet is learning much faster
  - GoogleNet is very robust
  - Previous trained 47 layers are able to extract high-level features and the final output layer is simply the logic of how to combine the features to do prediction



Learning rate = 0.05



Learning rate = 0.01

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Localization

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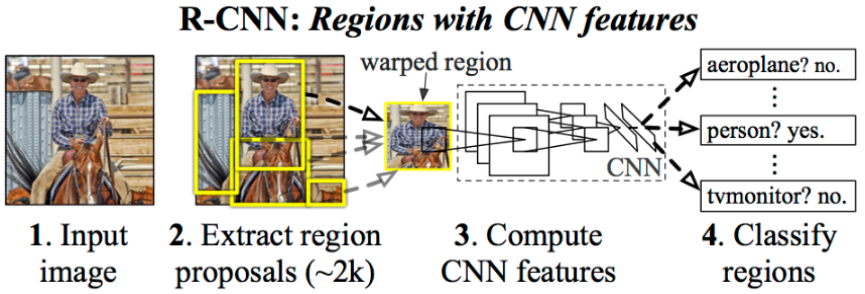
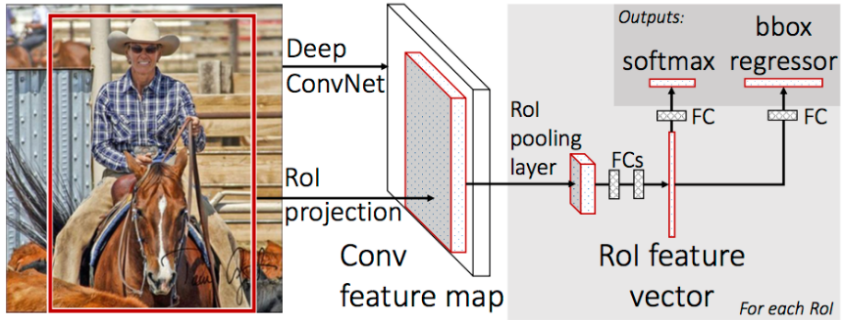
Related Work

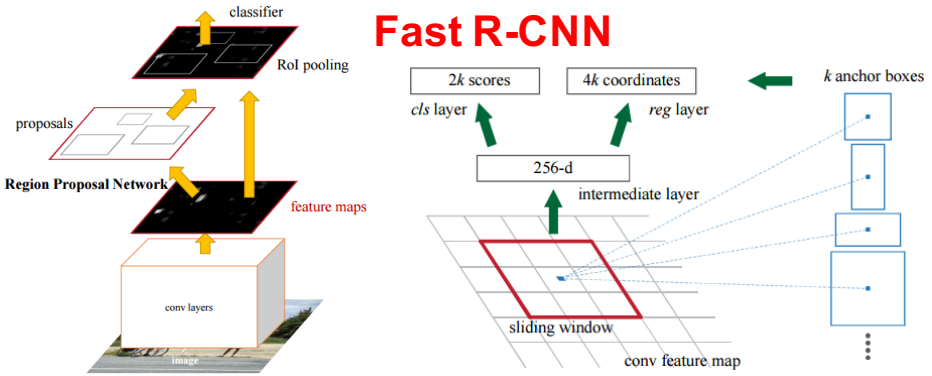
- R-CNN [10]
  - Milestone in using ConvNet for object detection
  - Selective Search to generate 2k region proposals
  - Use ConvNet to extract features for each region
  - Train SVM to do classification
  - Use regression to fine-tune the positions of bounding boxes
- Fast R-CNN [11]
  - Use ROI layer to pool region proposals
  - Use softmax for classification & a bbox regressor
- Faster R-CNN [12]
  - Use Region Proposal Network to generate proposals
  - Train RPN & R-CNN jointly



R-CNN



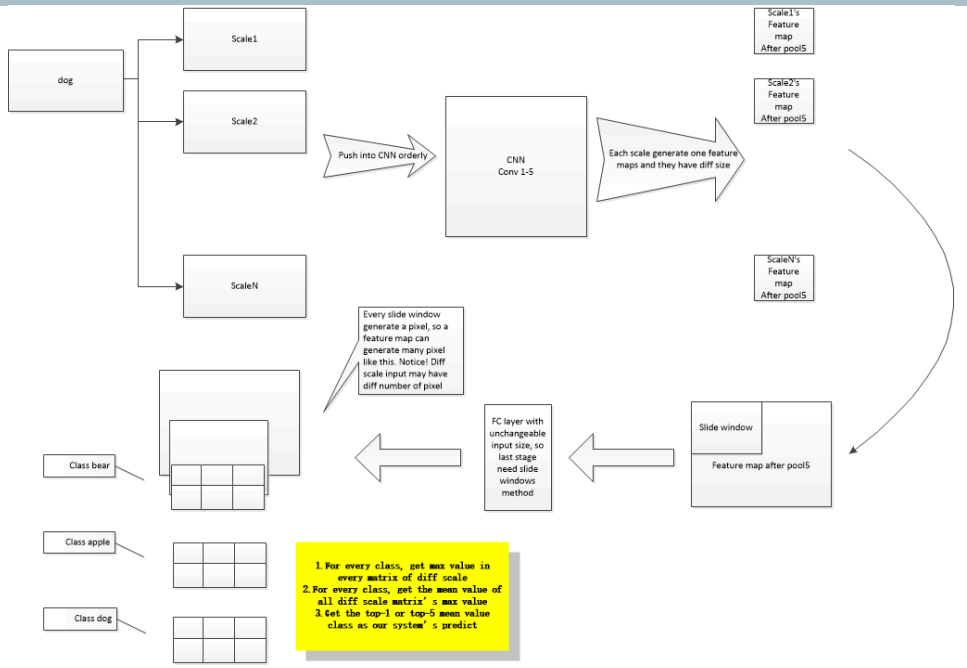
Fast R-CNN



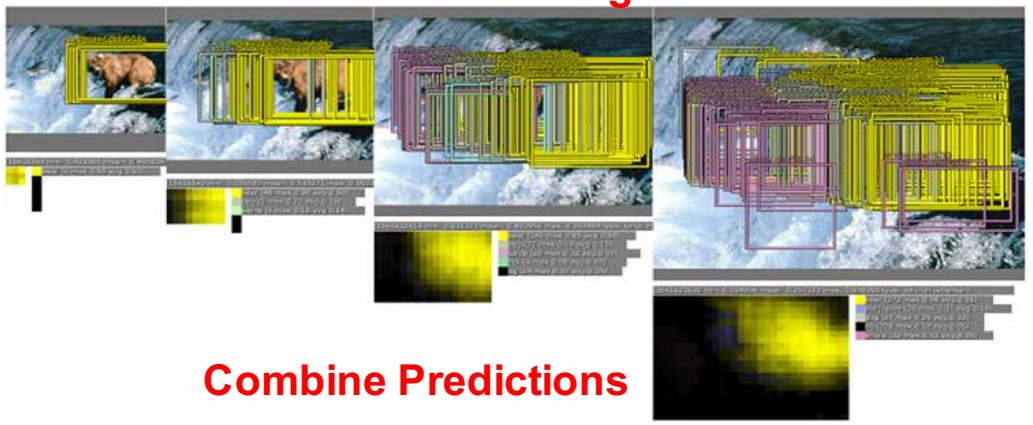
Faster R-CNN

Related Work (cont.)

- OverFeat [13]
  - Use sliding window detector
  - Propose a feature extractor named “overfeat”
  - Use multi-scale classification to support images with different resolution
  - Do regression and classification together
  - Classification score is the confidence of the bbox



Multi-Scale + Sliding Window



Combine Predictions

Related Work (cont.)

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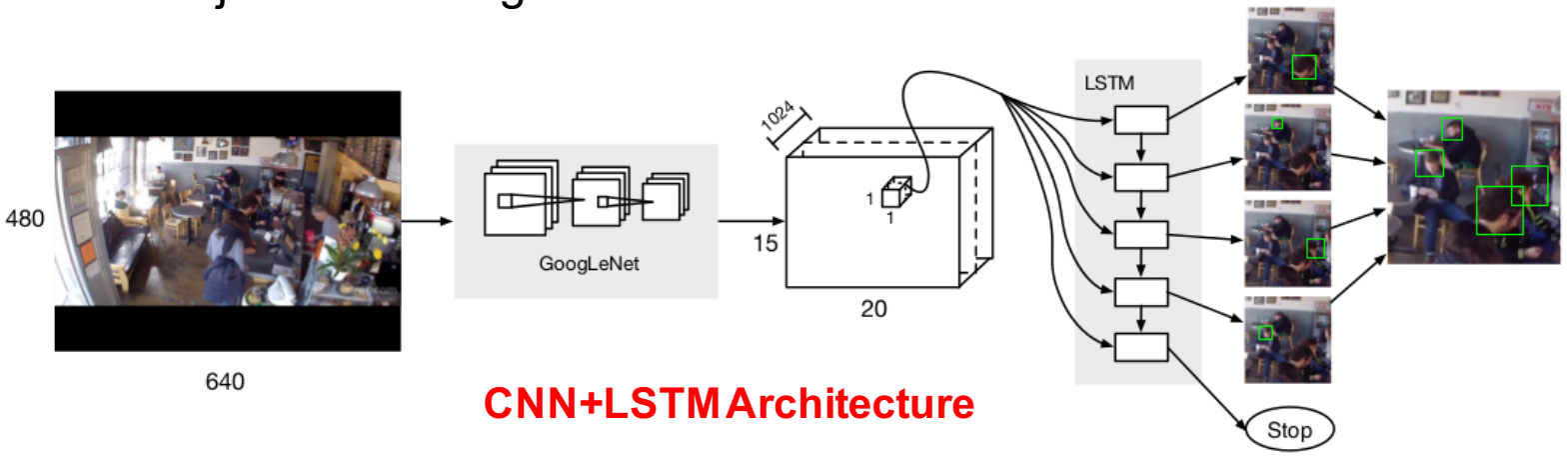
- CNN + LSTM [14]
  - Use GoogleNet to generate a 15 x 20 x 1024 image feature map
  - For each cell in the feature map, use a LSTM controller to predict a set of bboxes
  - Use Hungarian Algorithm to assign an unique candidate bbox to ground truth box
  - Calculate loss function based on matching result
  - In the test process, use “stitching algorithm” to match new bboxes with existing bboxes, and destroy non-overlapping bboxes
  - LSTM can “memorize” history predictions thus avoiding multiple predictions on the same object
  - LSTM can predict arbitrarily number of object in an image

$$L(G,C,f) = \alpha \sum_{i=1}^{|G|} l_{pos}(\mathbf{b}_{pos}^{i}, \tilde{\mathbf{b}}_{pos}^{f(i)}) + \sum_{j=1}^{|C|} l_c(\tilde{\mathbf{b}}_c^{j}, y_j)$$

Loss Function



CNN+LSTM Architecture

Data Set

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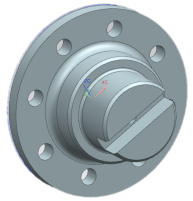
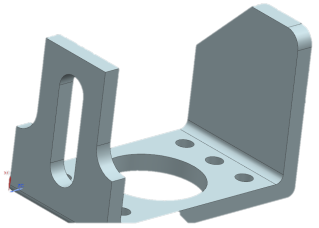
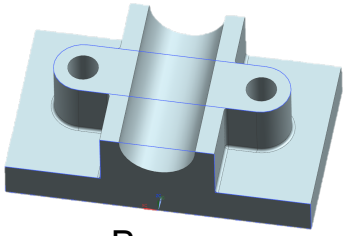
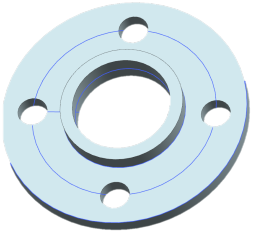
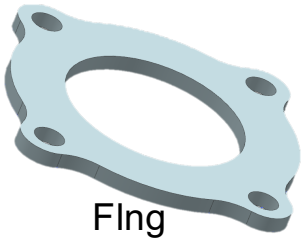
- Finally, we adopted the CNN + LSTM architecture in the previous silde
- 5 categories of mechanical in NX


Adafor

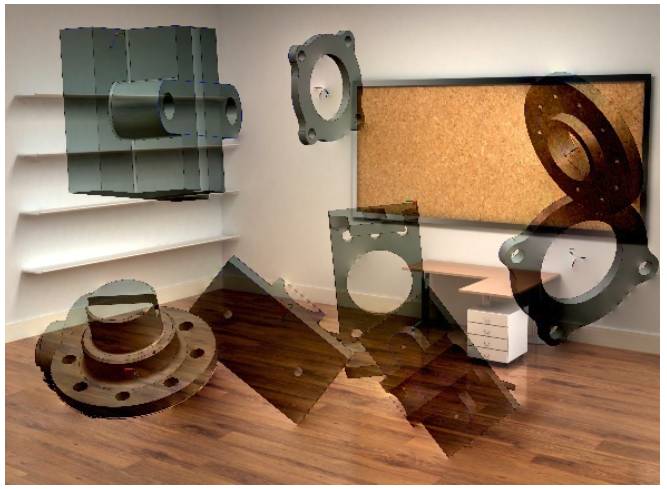

Brkt2


Brng


Fl3


Flng

- Manually compose an image with multiple objects occluded using OpenCV
  - Export mechanic parts as JPG files with white background
  - Extract objects out of background by convert image to grayscale
  - Seamless clone the objects into a noisy background
  - Record the location of bboxes (x, y, width, height)
  - Output images together with 'idl' file describing images location and bboxes coordinates (both for training and testing)



Manually Composed Image

Performance

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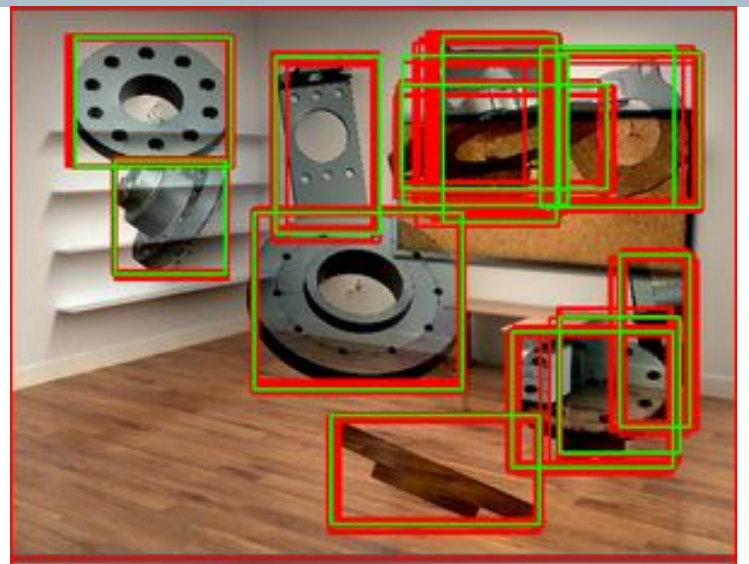
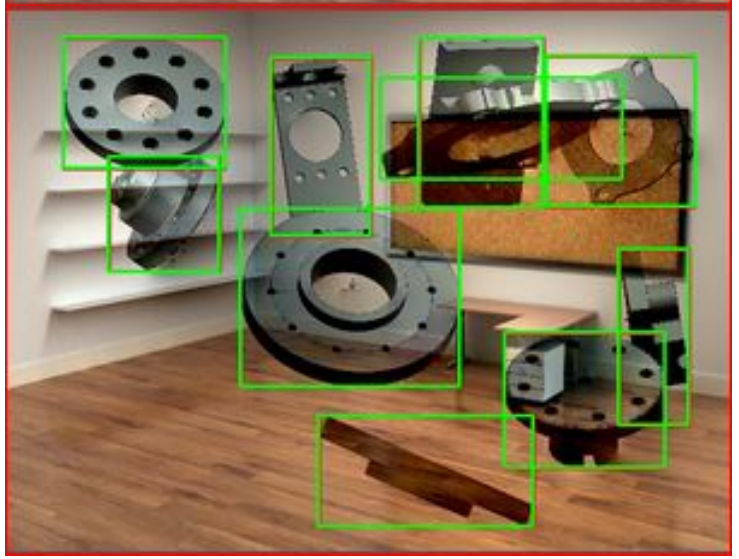
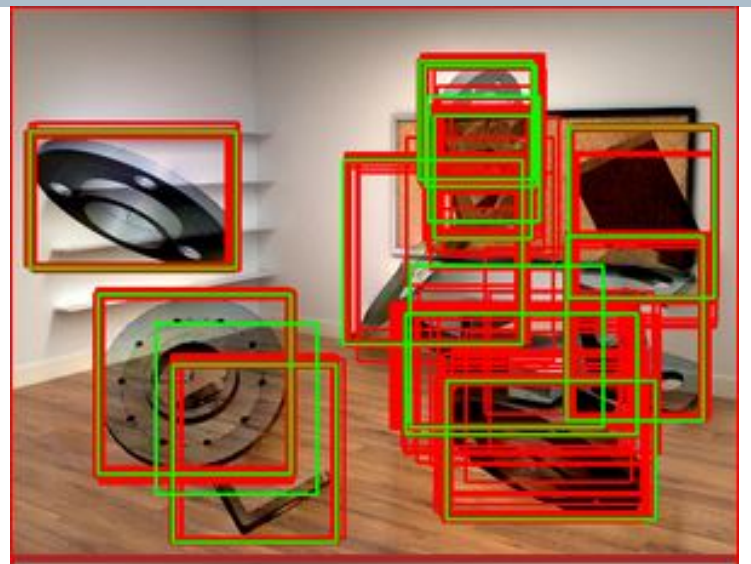
Predicted Output



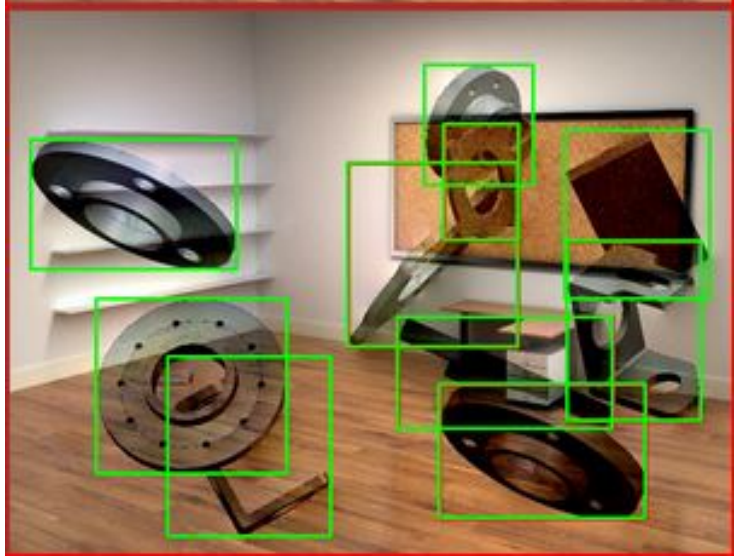
True Output



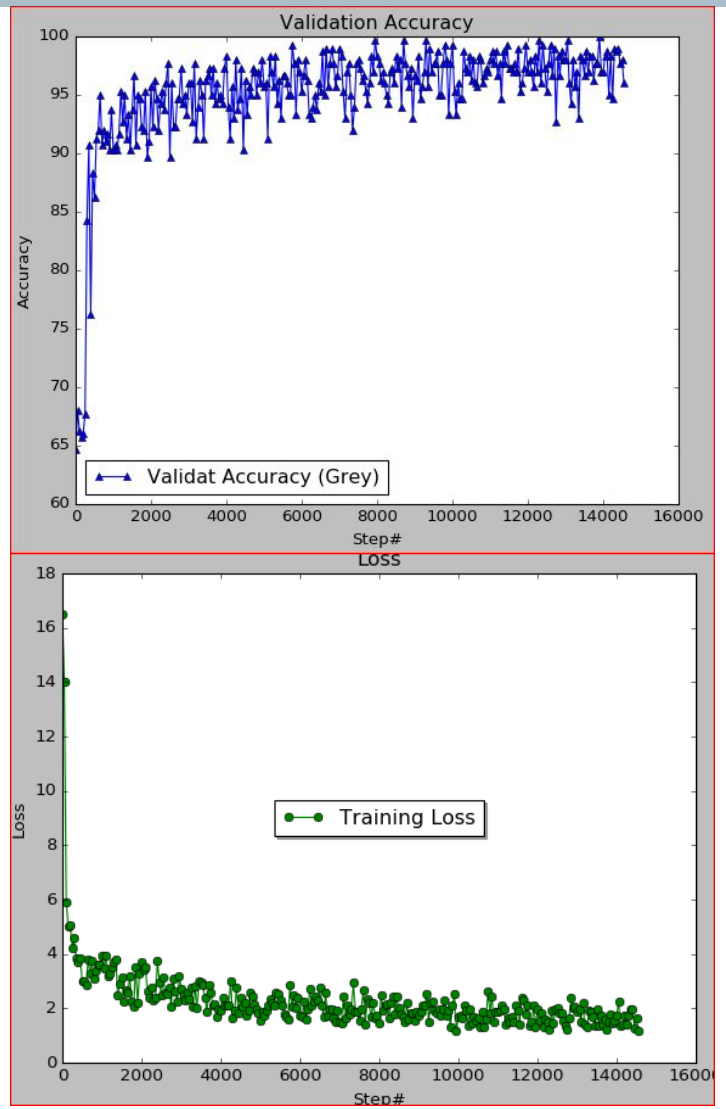
Predicted Output

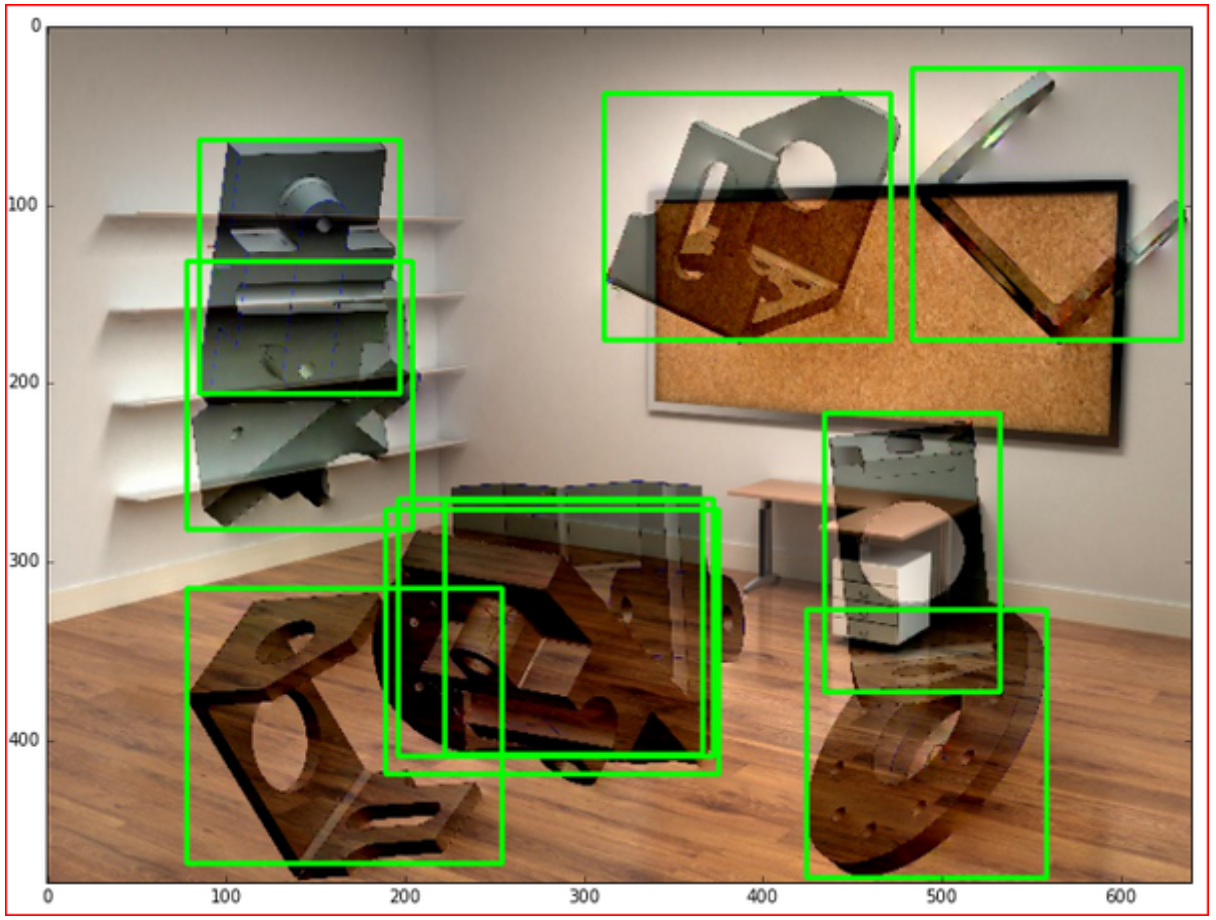


True Output



Performance (cont.)





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Conclusion

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Conclusion

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- Deep Learning is being widely used in different fields
  - Computer Vision, Natural Language Processing, Speech Recognition…
  - Big companies like Google, Facebook, Amazon, Microsoft are devoting large amount of money into it…
- ConvNet is commonly adopted to solve Computer Vision problems [3]
  - Almost all of the state of arts in CV is using ConvNet
  - Theoretically, ConvNet is able to do classification, localization and detection together (refer to Overfeat & R-CNN)
- Prerequisites for using Deep Learning to solve our problem
  - Large volume of data (hundreds of images for one category)
  - Expertise to design deep architecture and tune hyper-parameters
  - Great computation power to do the training
  - The expertise is usually not revealed in the released paper (kind of secret)
- The theory behind Deep Learning is not well-developed
  - Many theories like dropout lack mathematical proof (trick)
  - Lacks introspection into the features extracted
  - Intuition + Experience + Patience
- Combination of ConvNet + Recurrent Neural Network (LSTM) is powerful for detection problem
  - We have proved that CNN + LSTM would solve the notorious occlusion in detection

Conclusion (cont.)

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- Using trained models is the trend
  - Many trained models are available (Googles' Inception v3)
  - Fine tune the model using our data instead of train from scratch
  - Slightly modify their architecture to meet our need (add or remove layers) or concatenate to other architecture like Recurrent Neural Network

Future Work

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Future Work

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- Do detection by attaching a classification head (FCC + softmax) to the ConvNet
  - Use LSTM for box coordinates regression
  - Use softmax for classification
- Deploy our model using Tensorflow Serving (gRPC + docker)
  - Run our objects detection engine on cloud service
  - Easy to plug the model as component into NX or TeamCenter
- Collect a data set for validation
  - All of our data are NX generated (statistically different from natural images)
  - 3D print the NX mechanic parts
- Investigate into making an similar image search engine
  - Most image search engine are using pixel level comparison or color distribution are obsolete
  - Based on high level features extracted from ConvNet
- Investigate the R-FCN architecture which the newest and claiming to be the best in objects detection [15]

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Q & A

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