MLDS
Caffe Tutorial

2015-12-18 **simpdanny**

Outline

- **BVLC: B**erkeley **V**ision and **L**earning **C**enter
- **Caffe**: **C**onvolutional **A**rchitecture for **F**ast **F**eature **E**mbedding
- **What can Caffe do?**
- **Installation**
- **Tutorial**
- **Conclusion**

Caffe

- Convolutional Architecture for Fast Feature Embedding
- http://caffe.berkeleyvision.org/

Caffe: Convolutional Architecture for Fast Feature Embedding*

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Notes

- CNN/DNN
- Different training objective function
- Different optimization algorithm
- Program control
- Model Zoo
- C++ Framework
- **NO LSTM/RNN**

CNN/DNN modules

- **Vision Layer**
  - Convolution/ Pooling/ Local Response Normalization
- **Common Layer**
  - InnerProduct(= DNN fully-connected weights)
  - batch normalization
  - element-wise summation/product/BNLL
  - dropout layer
- **Activation Layer(Non-linearity)**
  - Sigmoid/Tanh/ReLU/PReLU
- **Utility Layer**
  - Dimension slicing/concatenation/flattening/reshaping

Training Loss Layer

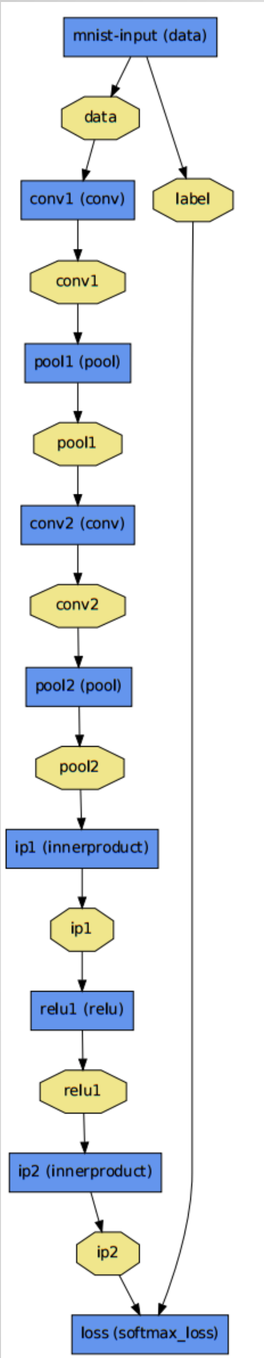
- CrossEntropyLoss
- L1, L2 Loss, pair-wise contrasive loss
- Multitask Learning with loss weights
- Accuracy Layer: for evaluation only.

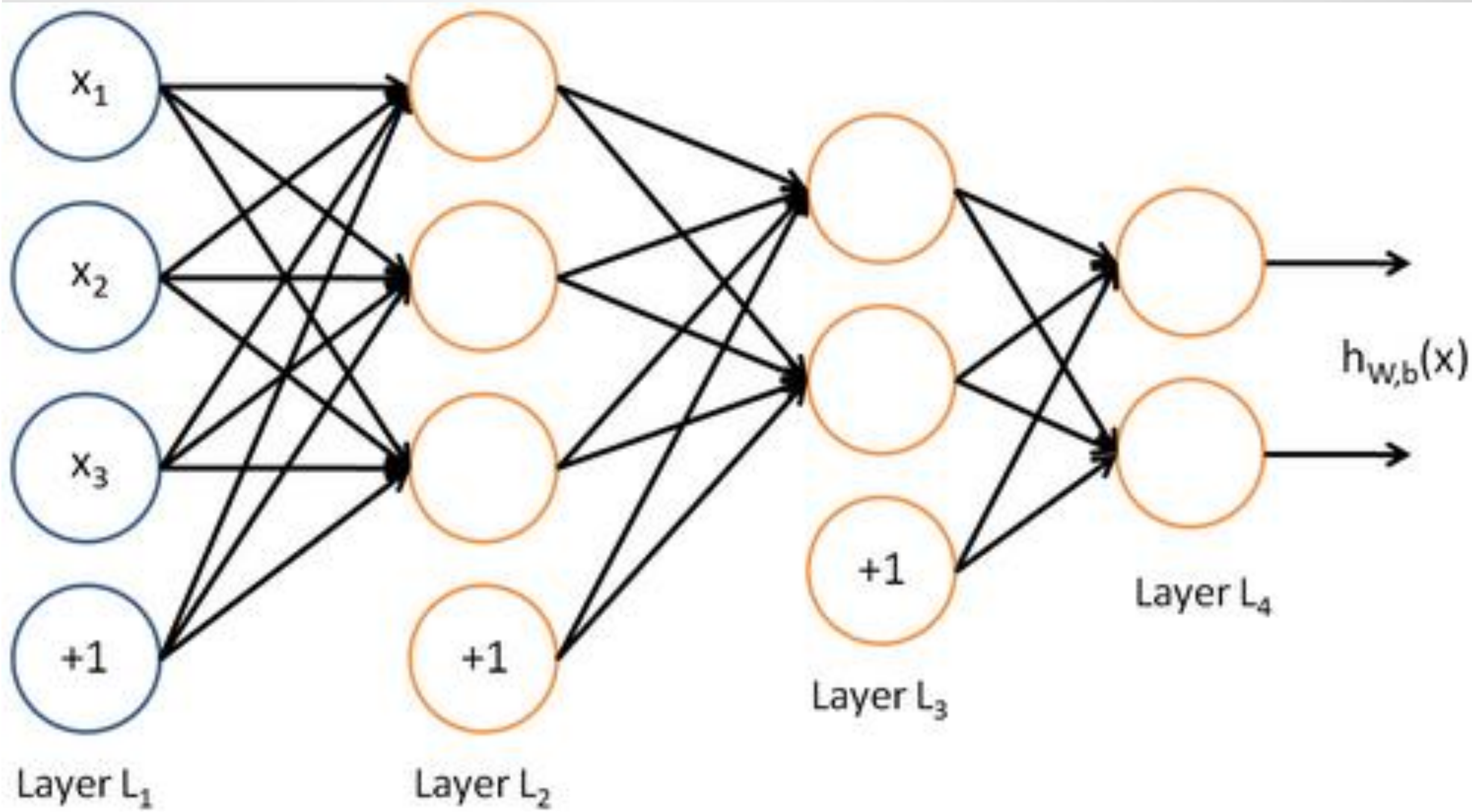
Optimization Algorithms

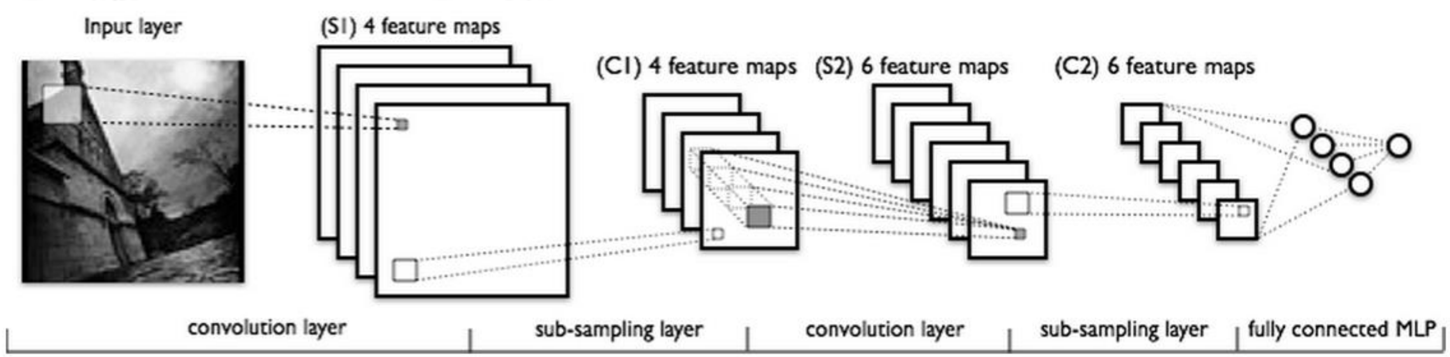
- SGD, RMSProp, ADAM, ADADELTA, ADGRAD…
- Momentum
- Learning Rate Adjustment Policies
  - decay, step-decay, exp-decay
- Regularization
  - weight-decay, L1 decay

Program Control

- Snapshot (solverstate)
- Phase:
  - Convention: Train/Validation/Test
  - Caffe: Train/Test/Deploy
  - You could assign different action w.r.t different phase.
- Caffe Program Interface
  - You can provide meta data without actually implement the deep learning algorithms.
  - You can extend the module and implement your own ideas.


mnist-input (data)
data
label
conv1 (conv)
conv1
pool1 (pool)
pool1
conv2 (conv)
conv2
pool2 (pool)
pool2
ip1 (innerproduct)
ip1
relu1 (relu)
relu1
ip2 (innerproduct)
ip2
loss (softmax_loss)

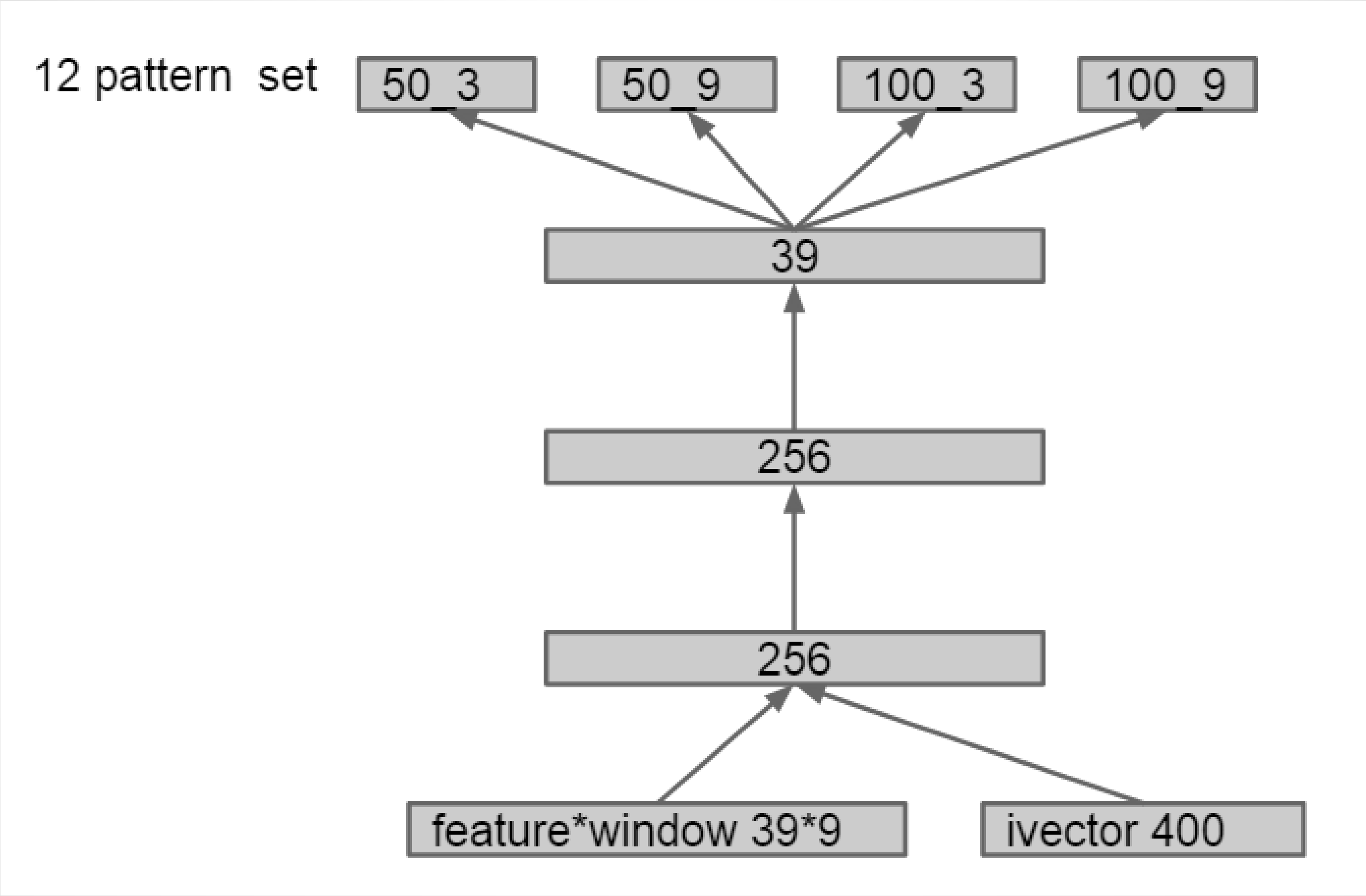

X_1
X_2
X_3
+1
+1
+1
$h_{W,b}(x)$
Layer L_1
Layer L_2
Layer L_3
Layer L_4


Input layer
(S1) 4 feature maps
(C1) 4 feature maps
(S2) 6 feature maps
(C2) 6 feature maps
convolution layer
sub-sampling layer
convolution layer
sub-sampling layer
fully connected MLP

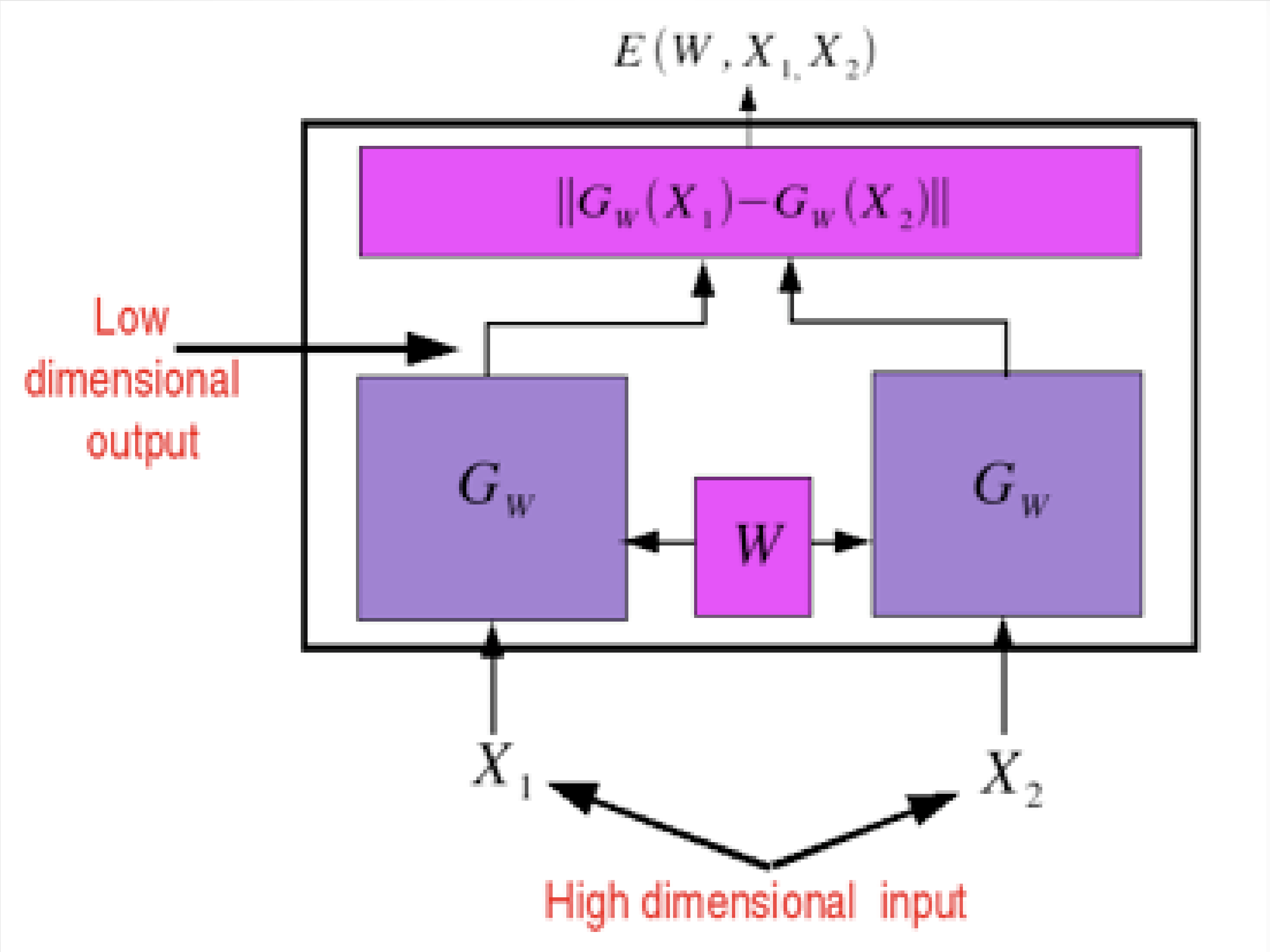
What can Caffe do?

- Multitask learning
  - Multi-target, Multi-loss
- Parameters share training
  - Siamese Neural Network
- Easy to integrated into online system.
  - With known distributed database, protocol…
  - C++, Python and Matlab binding.

Multitask Learning



Siamese Neural Network



Introduction

- The goal of Caffe is to **find the effective representations(feature embedding)** for various inputs, such as images and sounds, with help of **deep learning** and **GPU acceleration.**
  - There does exist **cross-domain feature embedding** among different tasks.
  - Utilize **CUDA(cuDNN)** to achieve acceptable training time.

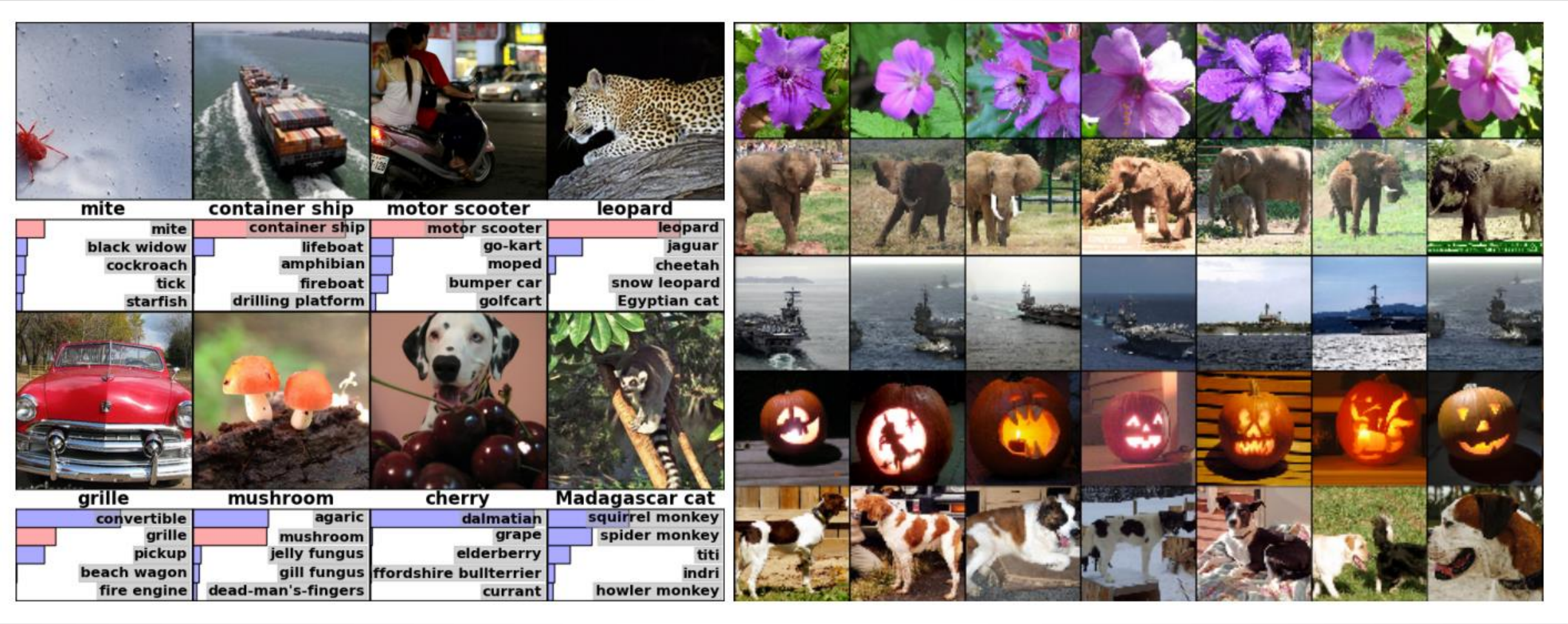
Introduction

- Caffe is designed for **image**s and based on state-of-the-art **CNN**. However, the concept of feature embedding shares among other works(e.g. **speech recognition**).
  - Yes, Caffe supports **non-image tasks** with a bit more efforts.

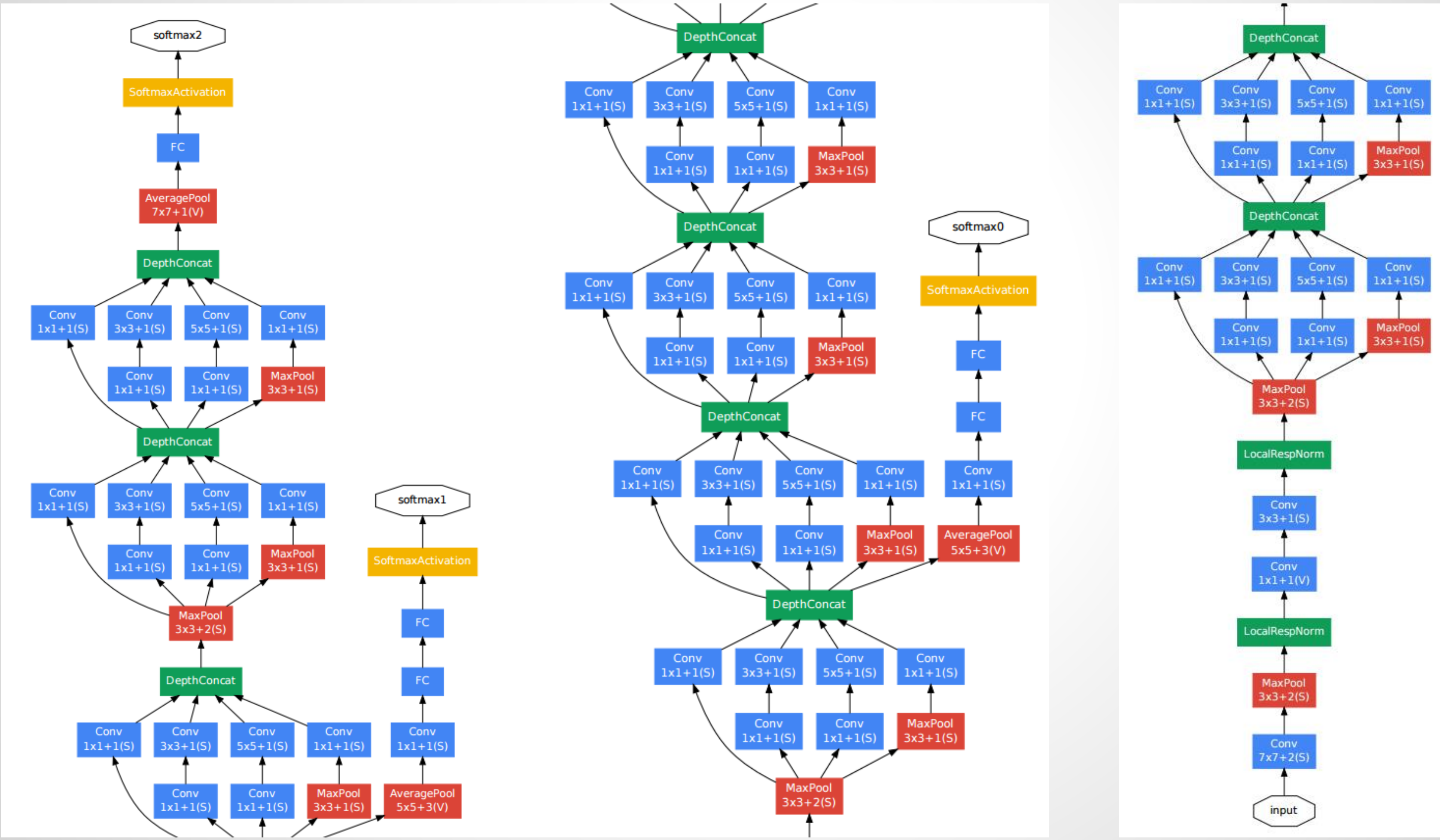
Introduction

- Caffe provided **well-known and well-trained models**, offering state-of-the-art researching and off-the-shelf deployment.
  - ImageNet: classify images into 22000 categories.
  - GoogleNet: classify images into 1000 categories.
  - R-CNN: object detection (20 or 200 types)

ImageNet

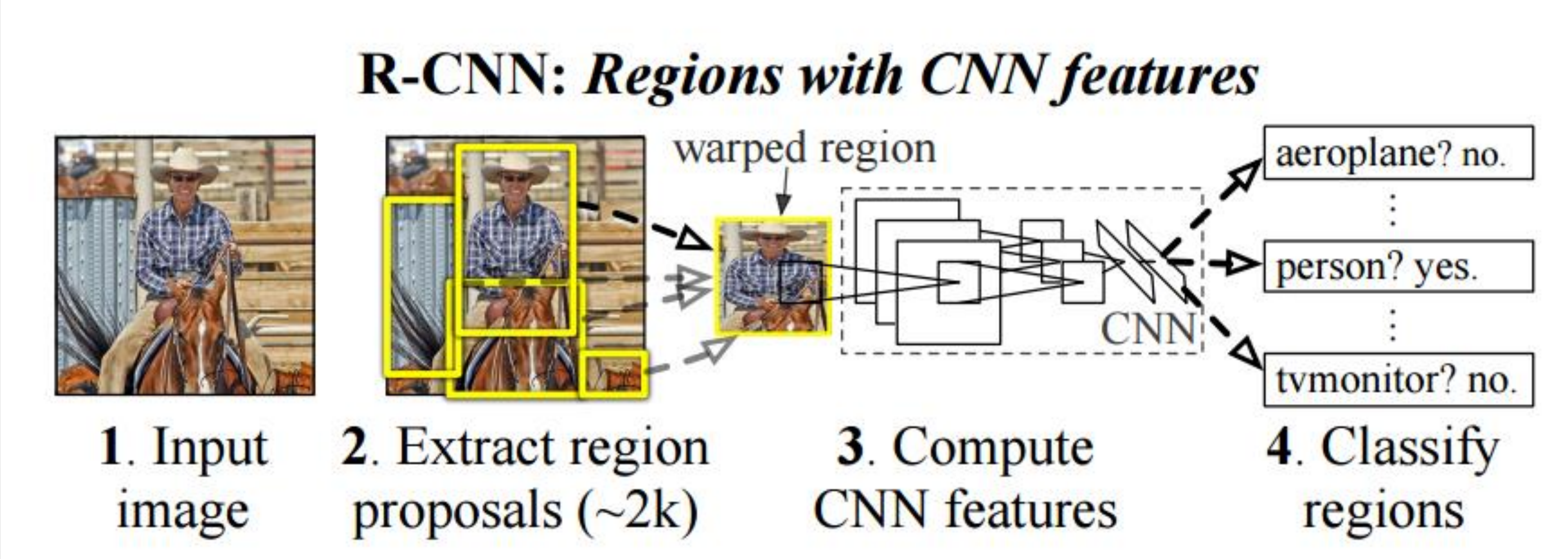

mite
container ship
motor scooter
leopard
mite
black widow
cockroach
tick
starfish
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
go-kart
moped
bumper car
golfcart
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
mushroom
cherry
Madagascar cat
convertible
grille
pickup
beach wagon
fire engine
agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers
dalmatian
grape
elderberry
ffordshire bullterrier
currant
squirrel monkey
spider monkey
titi
indri
howler monkey

GoogleNet



softmax2
SoftmaxActivation
FC
AveragePool 7x7+1(V)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
MaxPool 3x3+2(S)
softmax1
AveragePool 5x5+3(V)
softmax0
LocalRespNorm
Conv 1x1+1(V)
Conv 7x7+2(S)
input

R-CNN



R-CNN: *Regions with CNN features*
warped region
aeroplane? no.
person? yes.
tvmonitor? no.
CNN
1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions

Highlights

- Complete toolkit for training, testing, fine-tuning and deploying.
- Modularity
  - Extensible
  - Forward, backward, CPU/GPU version.
- Good coding style and huge community
  - Only well-test idea would be merged into Caffe
  - Distributed developed with many coders.
  - Clearly logging, documentation, robust, bullet proof, easy-understanding message...

Highlights

- Python/Matlab binding
  - Online deploying interface
  - Online training is not intuitively integrated but able to.
- Pre-trained models

Architecture

- C++ implementation
  - Well-known efficiency.
- Saving models in GPBL.
  - Google Protocol Buffer Language
  - Human-readable, efficient serialization and implemented in multiple interface.
- Online training
  - Memory data.
- Offline training
  - LevelDB database for image data
  - HDF5 database for general purpose.

Application

- Object Classification/Detection
  - ImageNet
  - [Demo]

Application

- Learning Feature Embedding
  - ImageNet
  - Using pre-trained models as feature extractor

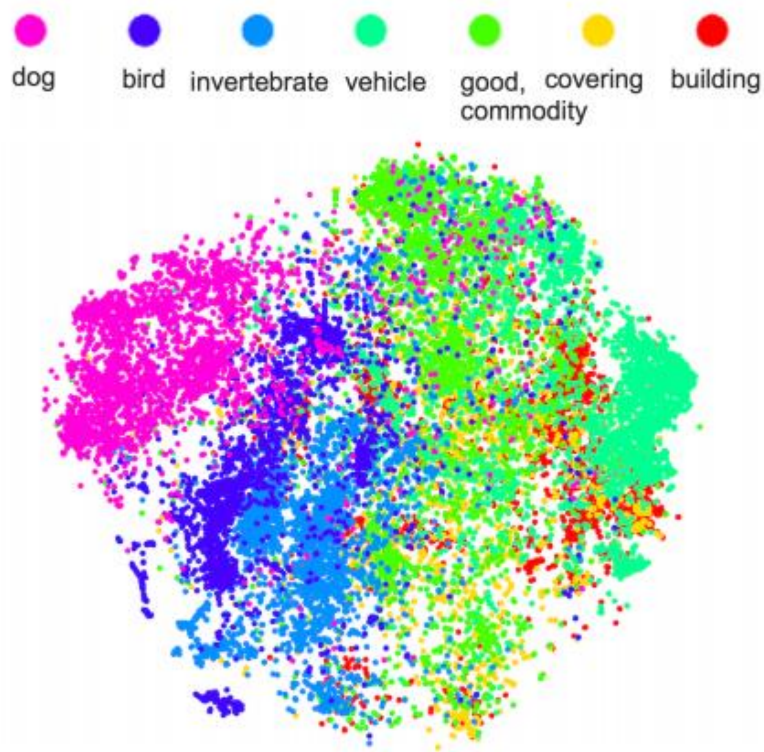


Figure 3: Features extracted from a deep network, visualized in a 2-dimensional space. Note the clear separation between categories, indicative of a successful embedding.

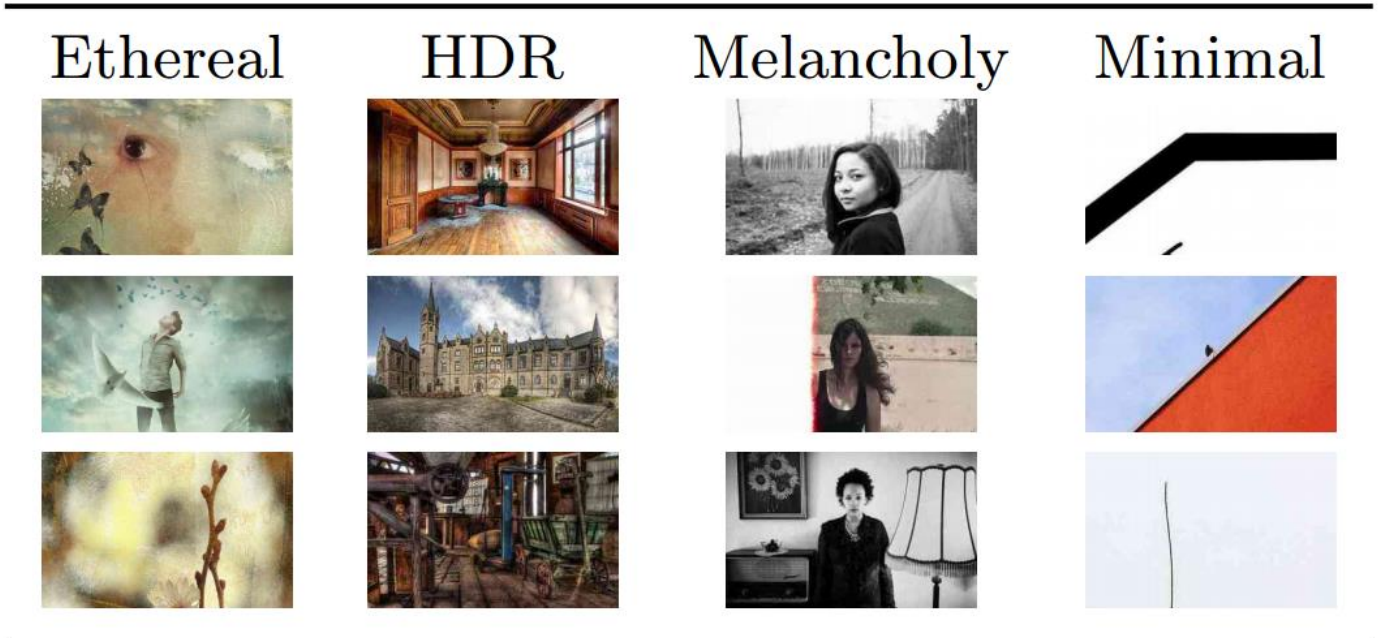


Figure 4: Top three most-confident positive predictions on the Flickr Style dataset, using a Caffe-trained classifier.

Tutorial

- Installation
  - Prerequisite/Core/Wrappers
- Data Preprocessing
  - LevelDB/HDF5
- Models
  - description, model weights, protobuf
- Solver
  - description, solver state
- Training/Testing/Fine-tuning/Deploying

Warning

- Caffe is not officially supporting Windows OS. Ubuntu/CentOS is recommended.
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- 不要問我windows怎麼灌。

Installation

- Install Prerequisite
  - CUDA and cuDNN
  - BLAS via OpenBLAS, MKL, or ATLAS
  - sudo apt-get install Boost/OpenCV/protobuf/glog/gflags/hdf5/leveldb/snappy/lmdb
- Install Caffe
  - prepare Makefile.config from Makefile.config.example
  - make all && make test && make runtest
- Install Python wrapper(optional but recommended)
  - for req in $(cat requirements.txt); do pip install $req; done
  - export PYTHONPATH=/path/to/caffe/python:$PYTHONPATH

Data Preprocessing

- Input data must be 4D array:
  - Image: (number, channel, height, width)
  - Non-image: (number, dimension , **1 , 1**)
- Training target is usually 2D array:
  - Label: (number, dimension)
- Online Memory
  - (C++) MemoryDataLayer::Reset()
  - (python) Net.set_input_arrays()
- Offline database
  - prepare a directory contain all the images
  - prepare lmdb(python) or leveldb(c++) for images
  - prepare hdf5(python) for general purposes
  - prepare train.list/test.list comprising the path

Models

- Description
  - DAG layered structure written in json format.
  - Data Layers: read from data, only out-degree
  - Activation/Neuron Layers: perform forward/backward pass.
  - Loss Layers: nn output, only in-degree
  - Common Layers: for utility
  - Each type of layers contain its own parameters
  - Different layer parameter could share!

Models

```
name: "LeNet"
layer {
  name: "mnist"
  type: "Data"
  top: "data"
  top: "label"
  include {
    phase: TRAIN
  }
  transform_param {
    scale: 0.00390625
  }
  data_param {
    source: "examples/mnist/mnist_train_lmdb"
    batch_size: 64
    backend: LMDB
  }
}
```

```
layer {
  name: "mnist"
  type: "Data"
  top: "data"
  top: "label"
  include {
    phase: TEST
  }
  transform_param {
    scale: 0.00390625
  }
  data_param {
    source: "examples/mnist/mnist_test_lmdb"
    batch_size: 100
    backend: LMDB
  }
}
```

Models

```
layers {
  name: "loss"
  type: SOFTMAX_LOSS
  bottom: "ip2"
  bottom: "label"
}
```

```
layers {
  name: "fc8"
  type: INNER_PRODUCT
  blobs_lr: 1          # learning rate multiplier for the filters
  blobs_lr: 2          # learning rate multiplier for the biases
  weight_decay: 1      # weight decay multiplier for the filters
  weight_decay: 0      # weight decay multiplier for the biases
  inner_product_param {
    num_output: 1000
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 0
    }
  }
  bottom: "fc7"
  top: "fc8"
}
```

Models

```
layers {
  name: "slicer_label"
  type: SLICE
  bottom: "label"
  ## Example of label with a shape N x 3 x 1 x 1
  top: "label1"
  top: "label2"
  top: "label3"
  slice_param {
      slice_dim: 1
      slice_point: 1
      slice_point: 2
  }
}
```

Models

```
layer {
  name: "conv1"
  type: "Convolution"
  bottom: "data"
  top: "conv1"
  param {
    name: "conv1_w"
    lr_mult: 1
  }
  param {
    name: "conv1_b"
    lr_mult: 2
  }
```

```
layer {
  name: "conv1_p"
  type: "Convolution"
  bottom: "data_p"
  top: "conv1_p"
  param {
    name: "conv1_w"
    lr_mult: 1
  }
  param {
    name: "conv1_b"
    lr_mult: 2
  }
```

Models

- Model Weights
  - x.caffemodel
  - store in GPBL format
  - [prototype]()

```
message LayerParameter {
  optional string name = 1; // the layer name
  optional string type = 2; // the layer type
  repeated string bottom = 3; // the name of each bottom blob
  repeated string top = 4; // the name of each top blob
```

Solver

```
# The train/test net protocol buffer definition
net: "examples/mnist/lenet_train_test.prototxt"
# test_iter specifies how many forward passes the test should carry out.
# In the case of MNIST, we have test batch size 100 and 100 test iterations,
# covering the full 10,000 testing images.
test_iter: 100
# Carry out testing every 500 training iterations.
test_interval: 500
# The base learning rate, momentum and the weight decay of the network.
base_lr: 0.01
momentum: 0.9
weight_decay: 0.0005
# The learning rate policy
lr_policy: "inv"
gamma: 0.0001
power: 0.75
# Display every 100 iterations
display: 100
# The maximum number of iterations
max_iter: 10000
# snapshot intermediate results
snapshot: 5000
snapshot_prefix: "examples/mnist/lenet"
# solver mode: CPU or GPU
solver_mode: GPU
```

Training and Testing

- Preparation:
  - data
  - model description(nnet.prototxt)
  - solver description(solver.prototxt)
- You can specify two phase
  - training -> calculate loss, gradients, backward pass and update
  - testing -> calculate accuracy/loss
- run:
  - caffe train --solver=solver.prototxt

Fine-tuning

- Preparation:
  - data
  - model description(nnet.prototxt)
  - solver description(solver.prototxt)
  - pre-trained models(pretrain.caffemodel)
- run:
  - caffe train --solver=solver.prototxt --weights=pretrain.caffe

Deploying

- Preparation:
  - data
  - model description(deploy.prototxt)
  - well-train model(well_train.caffemodel)
  - pycaffe if you use python
  - your own code(python, c++ or matlab)
- deploy.prototxt is slightly different

Deploying(python example)

- Add data description in deploy.prototxt
  - remove any DATA_LAYER
- In python, import caffe
  - net = caffe.Classifier(MODEL_FILE, PRETRAINED)
  - use numpy array to prepare your input data
  - net.blobs['data'].reshape(input_shape)
  - out = net.forward(data=input)
  - use out['label'] to get any output you want.

```
name: "LeNet"
input: "data"
input_dim: 64
input_dim: 1
input_dim: 28
input_dim: 28
```

Final Recommendation

- Caffe is easy and flexible to use, but not that efficient.　甚至可以不用寫程式XD
- For complicated structure with multi-loss layer, weight sharing and advanced optimization, caffe is good.
- However, you should prepare data in the specified format
  - HDF5, LMDB, LEVELDB…
  - offline training/testing is easy and preferred
- For online procedure, you must write your own code to deploy.