

rcnn_test.m	sprinkle functions with basic documentation	2 years ago
rcnn_train.m	r2013a compatibility fix	2 years ago
startup.m	improve demo; update models to caffe's v1 proto messages	2 years ago

■ README.md

R-CNN: Regions with Convolutional Neural Network Features

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Introduction

R-CNN is a state-of-the-art visual object detection system that combines bottom-up region proposals with rich features computed by a convolutional neural network. At the time of its release, R-CNN improved the previous best detection performance on PASCAL VOC 2012 by 30% relative, going from 40.9% to 53.3% mean average precision. Unlike the previous best results, R-CNN achieves this performance without using contextual rescoring or an ensemble of feature types.

R-CNN was initially described in an arXiv tech report and will appear in a forthcoming CVPR 2014 paper.

Citing R-CNN

If you find R-CNN useful in your research, please consider citing:

```
@inproceedings{girshick14CVPR,
    Author = {Girshick, Ross and Donahue, Jeff and Darrell, Trevor and Malik, Jitendra},
    Title = {Rich feature hierarchies for accurate object detection and semantic segmentation},
    Booktitle = {Computer Vision and Pattern Recognition},
    Year = {2014}
}
```

License

R-CNN is released under the Simplified BSD License (refer to the LICENSE file for details).

PASCAL VOC detection results

Method	VOC 2007 mAP	VOC 2010 mAP	VOC 2012 mAP
R-CNN	54.2%	50.2%	49.6%
R-CNN bbox reg	58.5%	53.7%	53.3%

- VOC 2007 per-class results are available in our CVPR14 paper
- VOC 2010 per-class results are available on the VOC 2010 leaderboard
- VOC 2012 per-class results are available on the VOC 2012 leaderboard
- These models are available in the model package (see below)

ImageNet 200-class detection results

Method	ILSVRC2013 test mAP
R-CNN bbox reg	31.4%

- For more details see the updated R-CNN tech report (Sections 2.5 and 4, in particular)
- This model is available in the model package (see below)
- The code that was used for training is in the <code>ilsvrc</code> branch (still needs some cleanup before merging into <code>master</code>)

Installing R-CNN

1. Prerequisites

- i. MATLAB (tested with 2012b on 64-bit Linux)
- ii. Caffe's prerequisites
- 2. **Install Caffe** (this is the most complicated part)
 - i. R-CNN has been checked for compatability against Caffe release v0.999 (kona-snow), however it *should* also work with the current Caffe master
 - ii. Download Caffe v0.999
 - iii. Follow the Caffe installation instructions
 - iv. Let's call the place where you installed caffe \$CAFFE_ROOT (you can run export CAFFE_ROOT=\$(pwd))
 - v. Important: Make sure to compile the Caffe MATLAB wrapper, which is not built by default: make matcaffe
 - vi. Important: Make sure to run cd \$CAFFE_ROOT/data/ilsvrc12 && ./get_ilsvrc_aux.sh to download the ImageNet image mean

3. Install R-CNN

- i. Get the R-CNN source code by cloning the repository: git clone https://github.com/rbgirshick/rcnn.git
- ii. Now change into the R-CNN source code directory: cd rcnn
- iii. R-CNN expects to find Caffe in external/caffe , so create a symlink: 1n -sf \$CAFFE_ROOT external/caffe
- iv. Start MATLAB (make sure you're still in the rcnn directory): matlab
- v. You'll be prompted to download the Selective Search code, which we cannot redistribute. Afterwards, you should see the message R-CNN startup done followed by the MATLAB prompt >> .
- vi. Run the build script: >> rcnn_build() (builds liblinear and Selective Search). Don't worry if you see compiler warnings while building liblinear, this is normal on my system.
- vii. Check that Caffe and MATLAB wrapper are set up correctly (this code should run without error): >> key = caffe('get_init_key'); (expected output is key = -2)
- viii. Download the model package, which includes precompute models (see below).

Common issues: You may need to set an LD_LIBRARY_PATH before you start MATLAB. If you see a message like "Invalid MEX-file '/path/to/rcnn/external/caffe/matlab/caffe/caffe.mexa64': libmkl_rt.so: cannot open shared object file: No such file or directory" then make sure that CUDA and MKL are in your LD_LIBRARY_PATH. On my system, I use:

export LD_LIBRARY_PATH=/opt/intel/mkl/lib/intel64:/usr/local/cuda/lib64

Downloading pre-computed models (the model package)

The quickest way to get started is to download pre-computed R-CNN detectors. Currently we have detectors trained on PASCAL VOC 2007 train+val, 2012 train, and ILSVRC13 train+val. Unfortunately the download is large (1.5GB), so brew some coffee or take a walk while waiting.

From the rcnn folder, run the model fetch script: ./data/fetch_models.sh .

This will populate the rcnn/data folder with caffe_nets and rcnn_models. See rcnn/data/README.md for details.

Pre-computed selective search boxes can also be downloaded for VOC2007, VOC2012, and ILSVRC13. From the rcnn folder, run the selective search data fetch script: ./data/fetch selective search data.sh.

This will populate the rcnn/data folder with selective_selective_data.

Caffe compatibility note: R-CNN has been updated to use the new Caffe proto messages that were rolled out in Caffe v0.999. The model package contains models in the up-to-date proto format. If, for some reason, you need to get the old (Caffe proto v0) models, they can still be downloaded: VOC models ILSVRC13 model.

Running an R-CNN detector on an image

Let's assume that you've downloaded the precomputed detectors. Now:

- 1. Change to where you installed R-CNN: cd rcnn.
- 2. Start MATLAB matlab.
 - Important: if you don't see the message R-CNN startup done when MATLAB starts, then you probably didn't start
 MATLAB in rcnn directory.
- 3. Run the demo: >> rcnn_demo

4. Enjoy the detected bicycle and person

Training your own R-CNN detector on PASCAL VOC

Let's use PASCAL VOC 2007 as an example. The basic pipeline is:

```
extract features to disk -> train SVMs -> test
```

You'll need about 200GB of disk space free for the feature cache (which is stored in rcnn/feat_cache by default; symlink rcnn/feat_cache elsewhere if needed). It's best if the feature cache is on a fast, local disk. Before running the pipeline, we first need to install the PASCAL VOC 2007 dataset.

Installing PASCAL VOC 2007

1. Download the training, validation, test data and VOCdevkit:

```
wget http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2007/VOCtrainval_06-Nov-2007.tar wget http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2007/VOCtest_06-Nov-2007.tar wget http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2007/VOCdevkit_08-Jun-2007.tar
```

2. Extract all of these tars into one directory, it's called vocdevkit.

```
tar xvf VOCtrainval_06-Nov-2007.tar
tar xvf VOCtest_06-Nov-2007.tar
tar xvf VOCdevkit_08-Jun-2007.tar
```

3. It should have this basic structure:

```
VOCdevkit/ % development kit
VOCdevkit/VOCcode/ % VOC utility code
VOCdevkit/VOC2007 % image sets, annotations, etc.
... and several other directories ...
```

4. I use a symlink to hook the R-CNN codebase to the PASCAL VOC dataset:

```
ln -sf /your/path/to/voc2007/VOCdevkit /path/to/rcnn/datasets/VOCdevkit2007
```

Extracting features

Pro tip: on a machine with one hefty GPU (e.g., k20, k40, titan) and a six-core processor, I run start two MATLAB sessions each with a three worker matlabpool. I then run chunk1 and chunk2 in parallel on that machine. In this setup, completing chunk1 and chunk2 takes about 8-9 hours (depending on your CPU/GPU combo and disk) on a single machine. Obviously, if you have more machines you can hack this function to split the workload.

Training R-CNN models and testing

Now to run the training and testing code, use the following experiments script:

```
>> test_results = rcnn_exp_train_and_test()
```

Note: The training and testing procedures save models and results under rcnn/cachedir by default. You can customize this by creating a local config file named rcnn_config_local.m and defining the experiment directory variable EXP_DIR. Look at rcnn_config_local.example.m for an example.

Training an R-CNN detector on another dataset

It should be easy to train an R-CNN detector using another detection dataset as long as that dataset has *complete* bounding box annotations (i.e., all instances of all classes are labeled).

To support a new dataset, you define three functions: (1) one that returns a structure that describes the class labels and list of images; (2) one that returns a region of interest (roi) structure that describes the bounding box annotations; and (3) one that provides an test evaluation function.

You can follow the PASCAL VOC implementation as your guide:

- imdb/imdb_from_voc.m (list of images and classes)
- imdb/roidb_from_voc.m (region of interest database)
- imdb/imdb_eval_voc.m (evalutation)

Fine-tuning a CNN for detection with Caffe

As an example, let's see how you would fine-tune a CNN for detection on PASCAL VOC 2012.

- 1. Create window files for VOC 2012 train and VOC 2012 val.
 - i. Start MATLAB in the rcnn directory
 - ii. Get the imdb for VOC 2012 train: >> imdb_train = imdb_from_voc('datasets/VOCdevkit2012', 'train', '2012');
 - iii. Get the imdb for VOC 2012 val: >> imdb_val = imdb_from_voc('datasets/VOCdevkit2012', 'val', '2012');
 - iv. Create the window file for VOC 2012 train: >> rcnn_make_window_file(imdb_train,
 'external/caffe/examples/pascal-finetuning');
 - v. Create the window file for VOC 2012 val: >> rcnn_make_window_file(imdb_val, 'external/caffe/examples/pascal-finetuning');
 - vi. Exit MATLAB
- 2. Run fine-tuning with Caffe
 - i. Copy the fine-tuning prototxt files: cp finetuning/voc_2012_prototxt/pascal_finetune_* external/caffe/examples/pascal-finetuning/
 - $ii. \ \ Change \ directories \ to \ \ external/caffe/examples/pascal-finetuning$
 - iii. Execute the fine-tuning code (make sure to replace /path/to/rcnn with the actual path to where R-CNN is installed):

```
GLOG_logtostderr=1 ../../build/tools/finetune_net.bin \
pascal_finetune_solver.prototxt \
/path/to/rcnn/data/caffe_nets/ilsvrc_2012_train_iter_310k 2>&1 | tee log.txt
```

Note: In my experiments, I've let fine-tuning run for 70k iterations, although with hindsight it appears that improvement in mAP saturates at around 40k iterations.

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