Course Project – Object Detection

Tutorial of EE4211

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Department of Electrical Engineering
City University of Hong Kong
03/29/2022

Outline

- Course Project
  - Objective
  - Kaggle Competition
- Machine Learning for Object Detection
  - Feature extraction by HOG
  - Classification by SVM
- Deep Learning for Object Detection
  - Network Architecture (RCNN)
  - Implement RCNN with Pytorch
- Further Extensions

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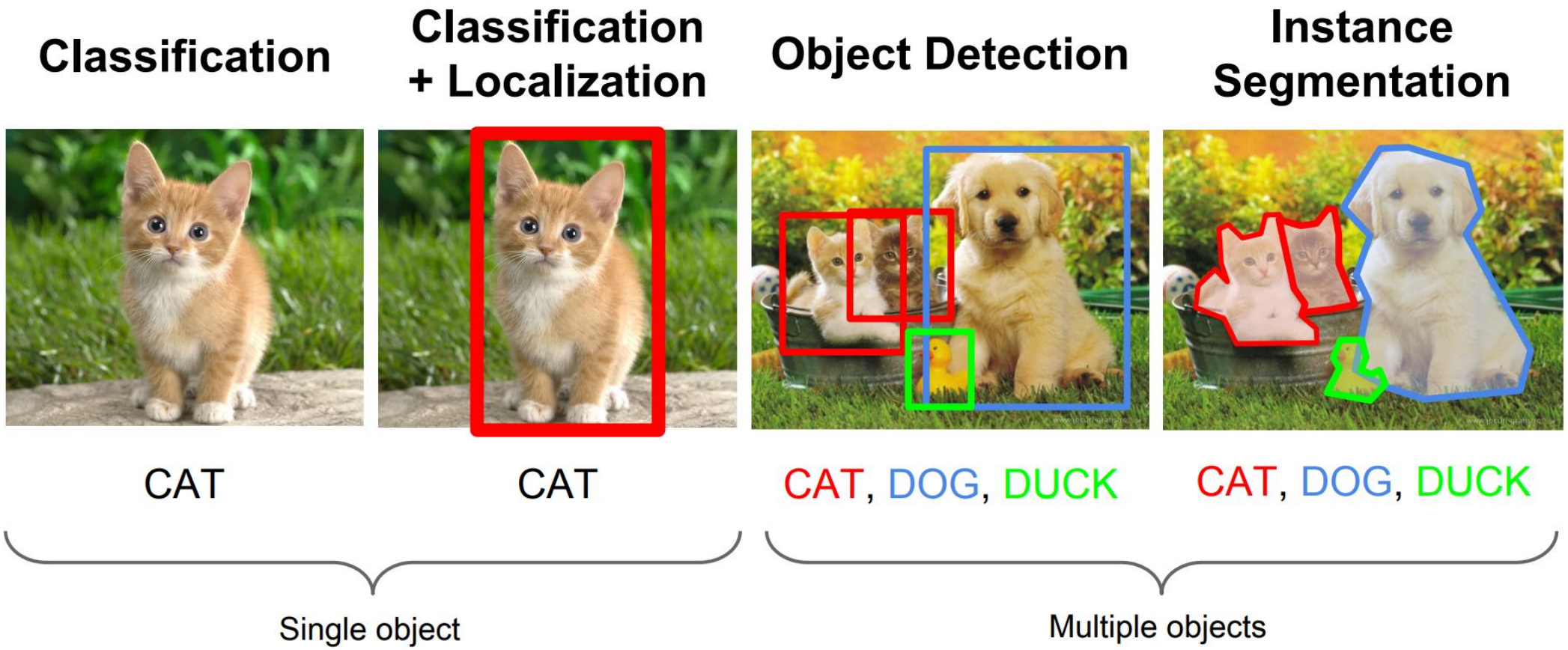
Course Project - Objective

- Task –Object Detection



Course Project - Objective

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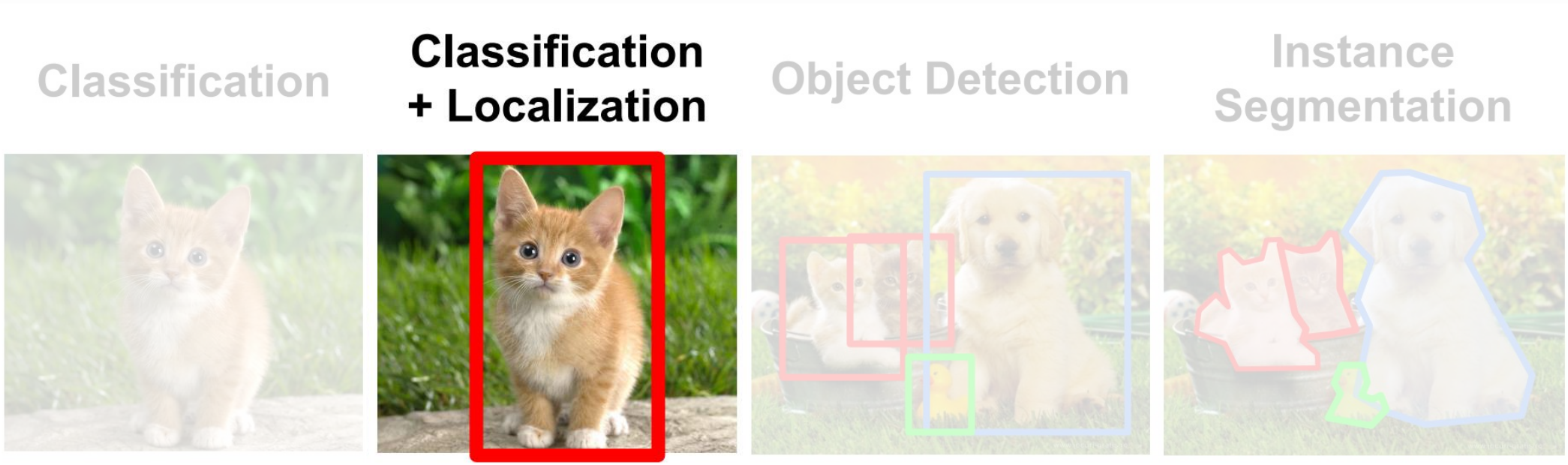
- Task –Object Detection



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- Task –Object Detection

Classification + Localization: Task

Classification: C classes
Input: Image
Output: Class label
Evaluation metric: Accuracy

→ CAT

Localization:
Input: Image
Output: Box in the image (x, y, w, h)
Evaluation metric: Intersection over Union

→ (x, y, w, h)

Classification + Localization: Do both

Course Project - Objective

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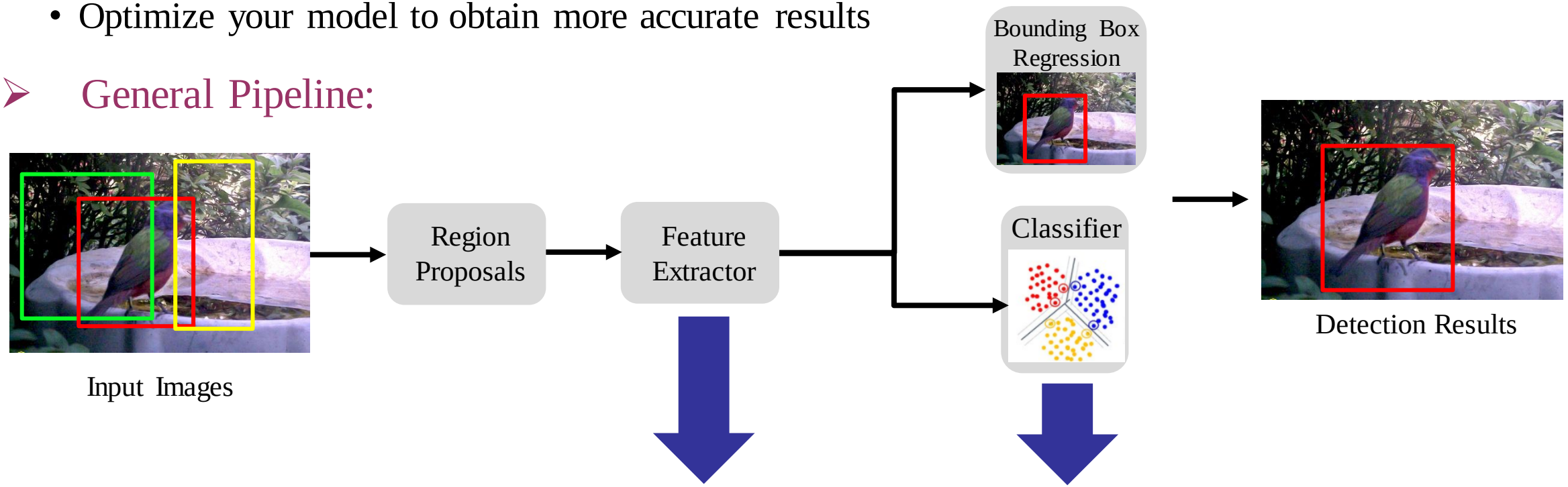
➢ Project objective:

- Using machine learning or deep learning methods to solve object detection problem
- Optimize your model to obtain more accurate results

➢ General Pipeline:



- Handcrafted:
  - HOG, SIFT
- ConvNets:
  - VGG, ResNet

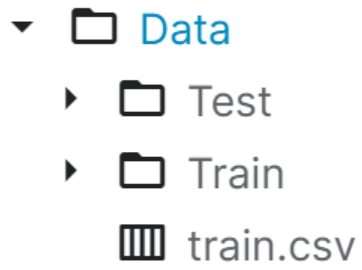
- Linear classifier
  - SVM
- Conv classifier:
  - CNN

Course Project - Kaggle Competition

- How to participate:

  URL: *https://www.kaggle.com/c/ee4211-object-detection/overview*

- Data Information
  - Train/Test input images
  - Train bounding boxes (csv file)



- Quick start
  - A baseline folder helping you quickly get start.

- Deadline:
  - 04/05/2022

Course Project - Kaggle Competition

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- Result submission
  - Generate two-column results (.csv):

    Image ID (referred to image name)

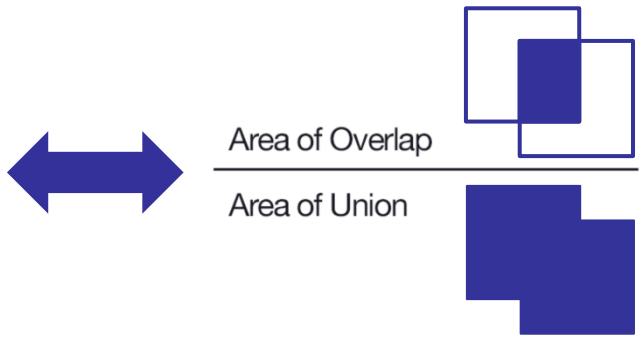
    Corresponding Bounding Boxed of Predictions. (Arbitrary order is OK)

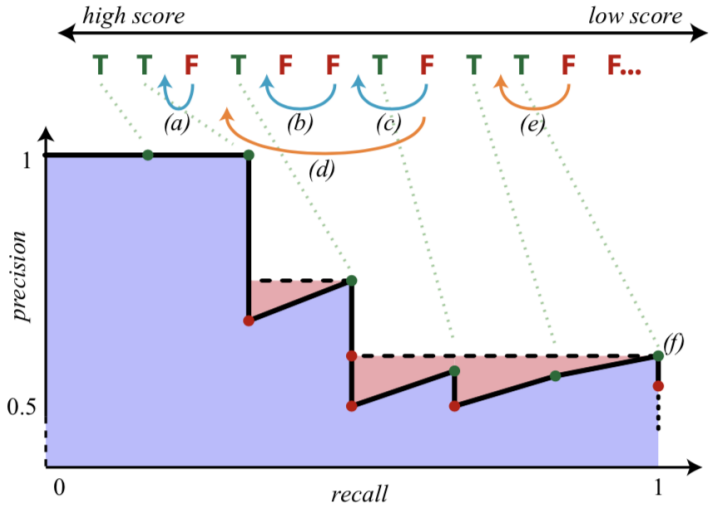
  - PredictionString-definition of category id, prediction probability, Xmin, Ymin, Xmax, Ymax

ImageId	PredictionString
0.jpg	1 1.0 0.21 0.23 0.41 0.65
1.jpg	1 1.0 0.43 0.35 0.5 0.47
2.jpg	1 1.0 0.18 0.14 0.66 0.76
3.jpg	1 1.0 0.1 0.25 0.65 0.61
4.jpg	1 1.0 0.22 0.21 0.52 0.66
5.jpg	1 1.0 0.01 0.18 0.79 0.8
6.jpg	1 1.0 0.27 0.27 0.48 0.52
7.jpg	1 1.0 0.37 0.3 0.52 0.51
8.jpg	1 1.0 0.14 0.06 0.52 0.71
9.jpg	1 1.0 0.14 0.14 0.83 0.85
10.jpg	1 1.0 0.12 0.47 0.88 0.39
11.jpg	1 1.0 0.25 0.15 0.3 0.81

- Evaluation matrix: mean average precision (mAP)

$$IoU(A,B)=(A\cap B)/(A\cup B).$$



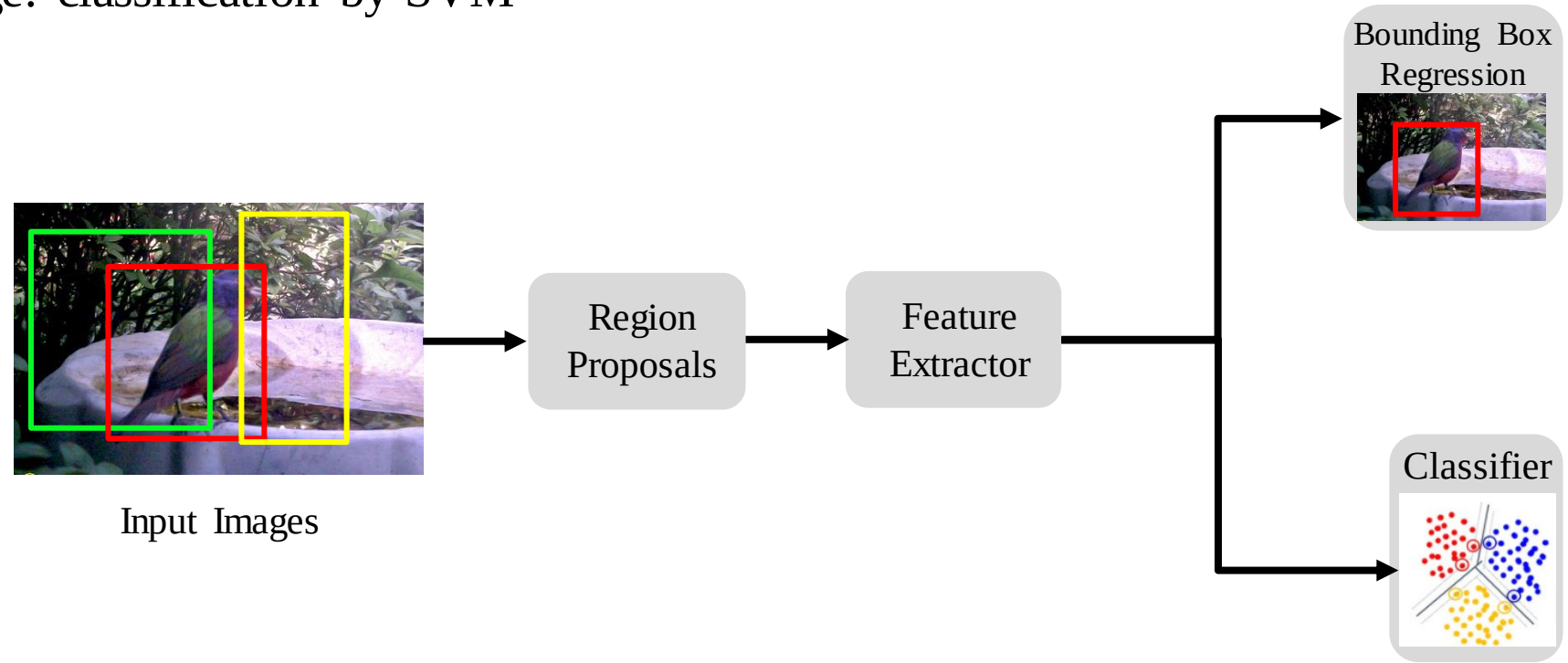


Outline

- Course Project
  - Objective
  - Kaggle Competition
- **Machine Learning for Object Detection**
  - Feature extraction by HOG
  - Classification by SVM
- Deep Learning for Object Detection
  - Network Architecture (RCNN)
  - Implement RCNN with Pytorch
- Further Extensions

General Pipeline – two stages

- First stage: feature extraction by HOG
- Second stage: classification by SVM



- General Pipeline – 6 steps

1.Sampling positive images

2.Sampling negative images

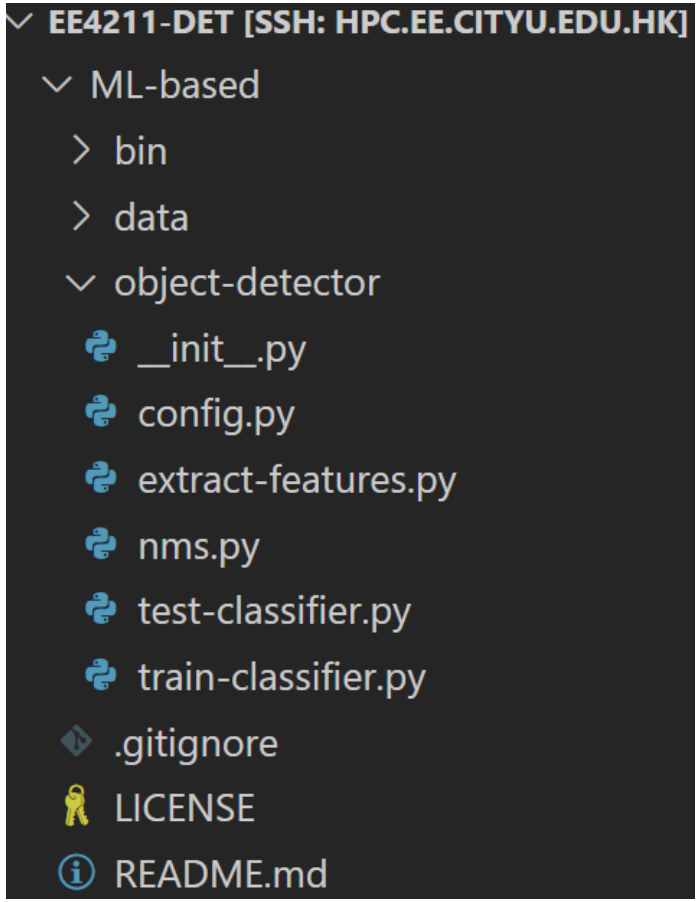
3.Training a Linear SVM

4.Performing hard-negative mining

5.Re-training your Linear SVM using the hard-negative samples

6.Evaluating your classifier on your test dataset, utilizing non-maximum suppression to ignore redundant, overlapping bounding boxes

➢ General Pipeline – code structure



About the modules

- `extract-features.py` -- This module is used to extract HOG features of the training images.
- `train-classifier.py` -- This module is used to train the classifier.
- `nms.py` -- This module performs Non Maxima Suppression.
- `test-classifier.py` -- This module is used to test the classifier using a test image.
- `config.py` -- Imports the configuration variables from `config.cfg`.

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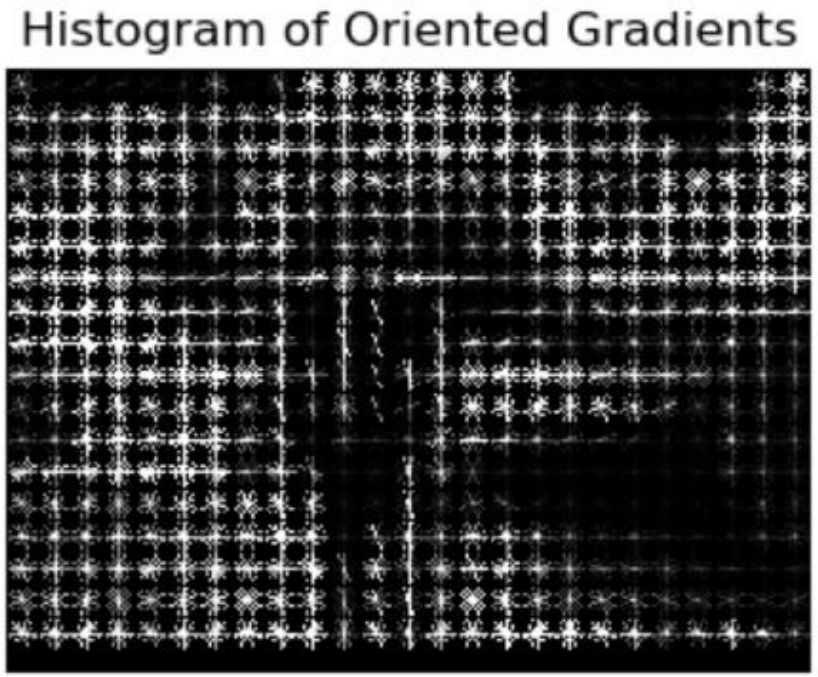
➢ First stage: feature extraction by HOG

- An example of obtaining HOG feature vectors.



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➢ First stage: feature extraction by HOG

- [code]: *https://github.com/aarcosg/object-detector-svm-hog-python*

```
    for im_path in glob.glob(os.path.join(pos_im_path, "*")):
        im = imread(im_path, as_grey=True)
        if des_type == "HOG":
            fd = hog(im, orientations, pixels_per_cell, cells_per_block, visualize, normalize)
        fd_name = os.path.split(im_path)[1].split(".")[0] + ".feat"
        fd_path = os.path.join(pos_feat_ph, fd_name)
        joblib.dump(fd, fd_path)
    print("Positive features saved in {}".format(pos_feat_ph))

    print("Calculating the descriptors for the negative samples and saving them")
    for im_path in glob.glob(os.path.join(neg_im_path, "*")):
        im = imread(im_path, as_grey=True)
        if des_type == "HOG":
            fd = hog(im,  orientations, pixels_per_cell, cells_per_block, visualize, normalize)
        fd_name = os.path.split(im_path)[1].split(".")[0] + ".feat"
        fd_path = os.path.join(neg_feat_ph, fd_name)
        joblib.dump(fd, fd_path)
    print("Negative features saved in {}".format(neg_feat_ph))

    print("Completed calculating features from training images")
```

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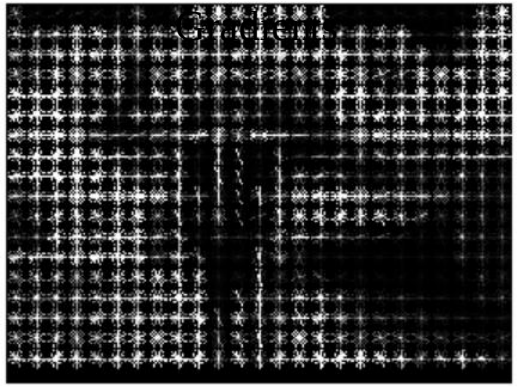
➢ Second stage: classification by SVM

- After classifying with a trained SVM model and applying NMS the following result is achieved:

Detection Prediction:

Input image

Histogram of Oriented Gradient



detection result

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➢ Second stage: classification by SVM

- [code]: *https://github.com/aarcosg/object-detector-svm-hog-python*

```
pos_feat_path =  args["posfeat"]
neg_feat_path = args["negfeat"]

# Classifiers supported
clf_type = args['classifier']

fds = []
labels = []
# Load the positive features
for feat_path in glob.glob(os.path.join(pos_feat_path,"*.feat")):
    fd = joblib.load(feat_path)
    fds.append(fd)
    labels.append(1)

# Load the negative features
for feat_path in glob.glob(os.path.join(neg_feat_path,"*.feat")):
    fd = joblib.load(feat_path)
    fds.append(fd)
    labels.append(0)

if clf_type is "LIN_SVM":
    clf = LinearSVC()
    print("Training a Linear SVM Classifier")
    clf.fit(fds, labels)
    # If feature directories don't exist, create them
    if not os.path.isdir(os.path.split(model_path)[0]):
        os.makedirs(os.path.split(model_path)[0])
    joblib.dump(clf, model_path)
    print("Classifier saved to {}".format(model_path))
```

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➢ Test stage: test image by SVM

- [code]: *https://github.com/aarcosg/object-detector-svm-hog-python*

```
# Read the image
im = imread(args["image"], as_grey=False)
min_wdw_sz = (100, 40)
step_size = (10, 10)
downscale = args['downscale']
visualize_det = args['visualize']

# Load the classifier
clf = joblib.load(model_path)

# List to store the detections
detections = []
# The current scale of the image
scale = 0
# Downscale the image and iterate
for im_scaled in pyramid_gaussian(im, downscale=downscale):
    # This list contains detections at the current scale
    cd = []
    # If the width or height of the scaled image is less than
    # the width or height of the window, then end the iterations.
    if im_scaled.shape[0] < min_wdw_sz[1] or im_scaled.shape[1] < min_wdw_sz[0]:
        break
    for (x, y, im_window) in sliding_window(im_scaled, min_wdw_sz, step_size):
        if im_window.shape[0] != min_wdw_sz[1] or im_window.shape[1] != min_wdw_sz[0]:
            continue
        # Calculate the HOG features
        fd = hog(im_window, orientations, pixels_per_cell, cells_per_block, visualize, normalize)
        pred = clf.predict(fd)
        if pred == 1:
            print("Detection:: Location -> ({}, {})".format(x, y))
            print("Scale ->  {} | Confidence Score {} \n".format(scale,clf.decision_function(fd)))
            detections.append((x, y, clf.decision_function(fd),
                int(min_wdw_sz[0]*(downscale**scale)),
                int(min_wdw_sz[1]*(downscale**scale))))
            cd.append(detections[-1])
        # If visualize is set to true, display the working
        # of the sliding window
        if visualize_det:
            clone = im_scaled.copy()
            for x1, y1, _, _, _  in cd:
                # Draw the detections at this scale
                cv2.rectangle(clone, (x1, y1), (x1 + im_window.shape[1], y1 +
                    im_window.shape[0]), (0, 0, 0), thickness=2)
            cv2.rectangle(clone, (x, y), (x + im_window.shape[1], y +
                im_window.shape[0]), (255, 255, 255), thickness=2)
            cv2.imshow("Sliding Window in Progress", clone)
            cv2.waitKey(30)
    # Move the the next scale
    scale+=1

# Display the results before performing NMS
clone = im.copy()
for (x_tl, y_tl, _, w, h) in detections:
    # Draw the detections
    cv2.rectangle(im, (x_tl, y_tl), (x_tl+w, y_tl+h), (0, 0, 0), thickness=2)
cv2.imshow("Raw Detections before NMS", im)
cv2.waitKey()

# Perform Non Maxima Suppression
detections = nms(detections, threshold)

# Display the results after performing NMS
for (x_tl, y_tl, _, w, h) in detections:
    # Draw the detections
    cv2.rectangle(clone, (x_tl, y_tl), (x_tl+w,y_tl+h), (0, 0, 0), thickness=2)
cv2.imshow("Final Detections after applying NMS", clone)
cv2.waitKey()
```

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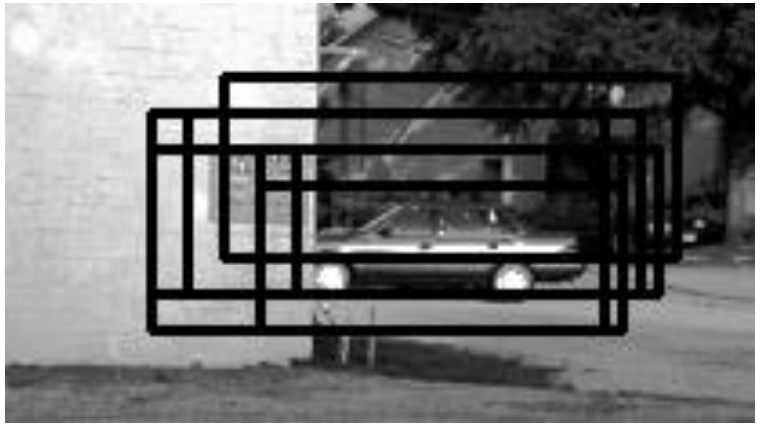
➢ Test stage: Non-Max Suppression (NMS)

- [code]: *https://github.com/aarcosg/object-detector-svm-hog-python*

```python
def nms(detections, threshold=.5):
    '''
    This function performs Non-Maxima Suppression.
    `detections` consists of a list of detections.
    Each detection is in the format ->
    [x-top-left, y-top-left, confidence-of-detections, width-of-detection, height-of-detection]
    If the area of overlap is greater than the `threshold`,
    the area with the lower confidence score is removed.
    The output is a list of detections.
    '''
    if len(detections) == 0:
        return []
    # Sort the detections based on confidence score
    detections = sorted(detections, key=lambda detections: detections[2],
            reverse=True)
    # Unique detections will be appended to this list
    new_detections=[]
    # Append the first detection
    new_detections.append(detections[0])
    # Remove the detection from the original list
    del detections[0]
    # For each detection, calculate the overlapping area
    # and if area of overlap is less than the threshold set
    # for the detections in `new_detections`, append the
    # detection to `new_detections`.
    # In either case, remove the detection from `detections` list.
    for index, detection in enumerate(detections):
        for new_detection in new_detections:
            if overlapping_area(detection, new_detection) > threshold:
                del detections[index]
                break
        else:
            new_detections.append(detection)
            del detections[index]
    return new_detections
```

Detections before NMS



Detections after NMS

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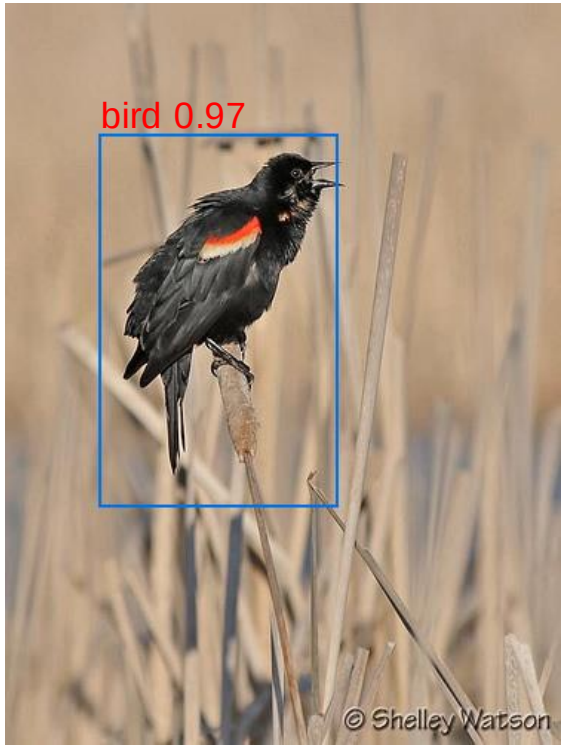
- Results on bird detection



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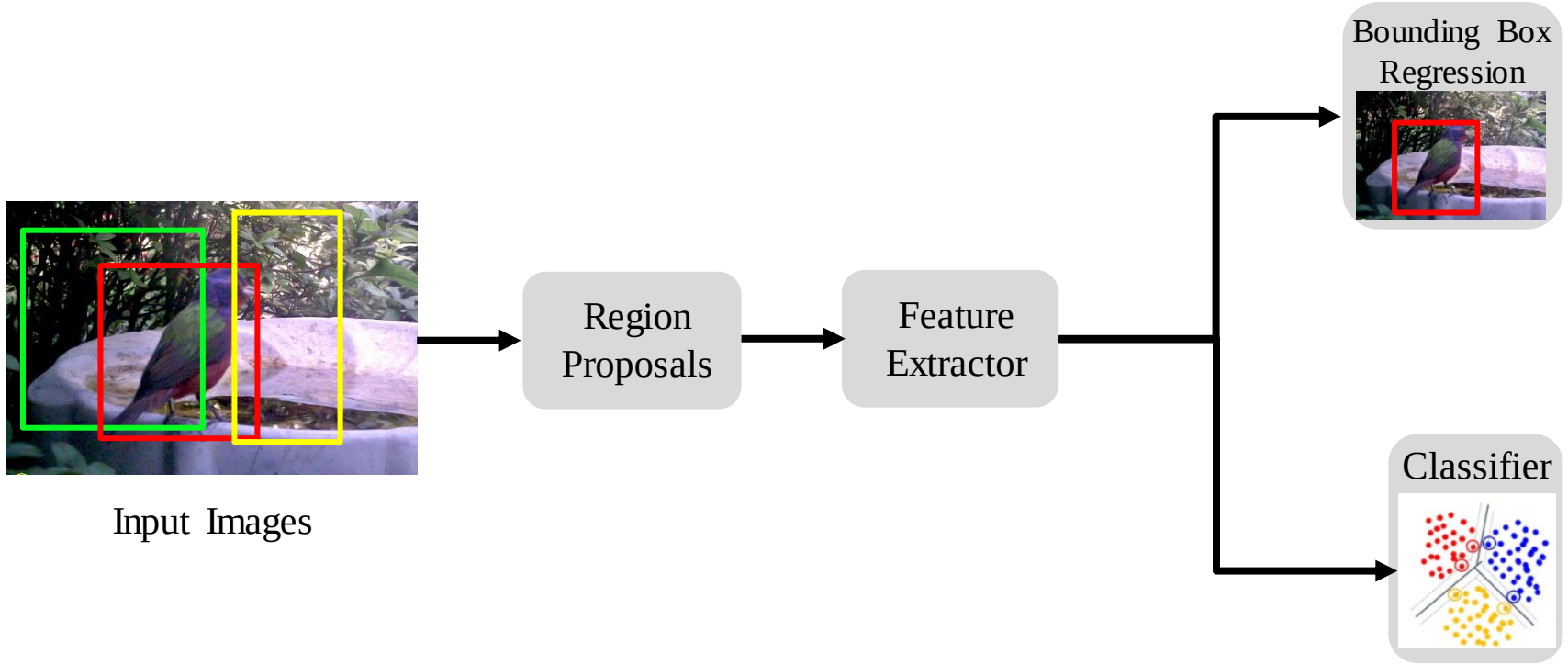
➢ General Pipeline – one stage

- End-to-end manner: joint feature extraction and classification



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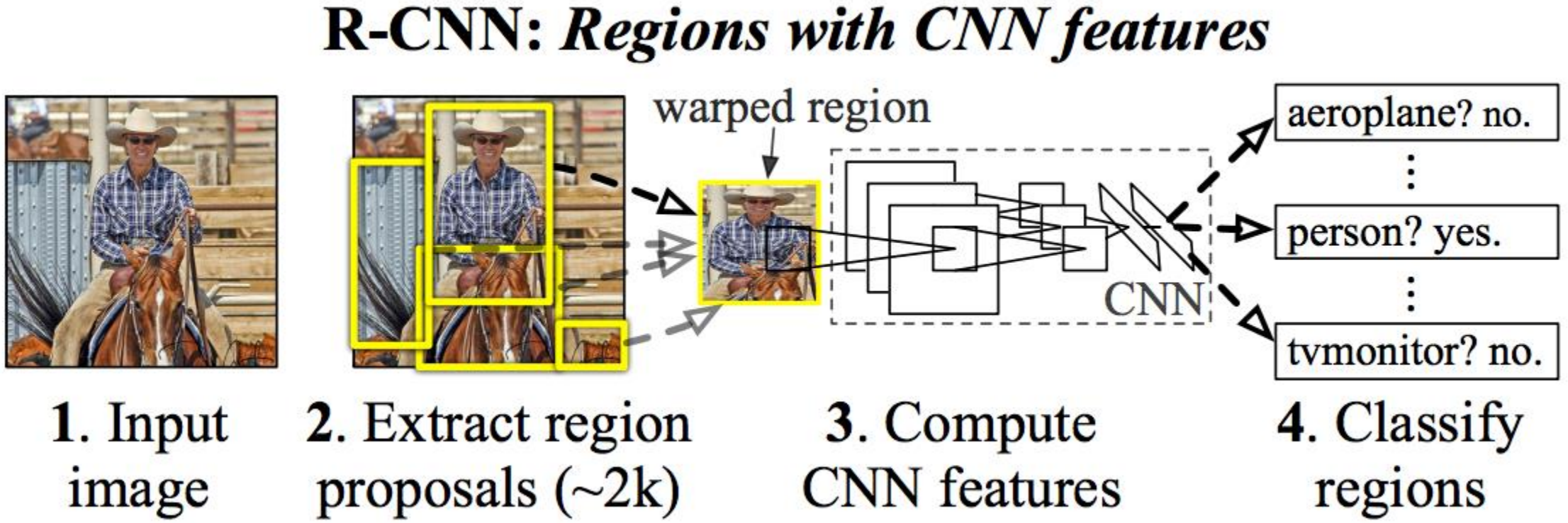

Girshick, Ross, et al. "Rich feature hierarchies for accurate object detection and semantic segmentation." CVPR. 2014.

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➢ Install CUDA

NVIDIA. DEVELOPER

- Download: https://developer.nvidia.com/cuda-10.0-download-archive

Select Target Platform ⓘ

Click on the green buttons that describe your target platform. Only supported platforms will be shown.

Operating System	Windows, **Linux**, Mac OSX
Architecture ⓘ	**x86_64**, ppc64le
Distribution	Fedora, OpenSUSE, RHEL, CentOS, SLES, **Ubuntu**
Version	18.04, **16.04**, 14.04
Installer Type ⓘ	**runfile (local)**, deb (local), deb (network), cluster (local)

Installation Instructions:

1. Run `sudo sh cuda_10.0.130_410.48_linux.run`
2. Follow the command-line prompts

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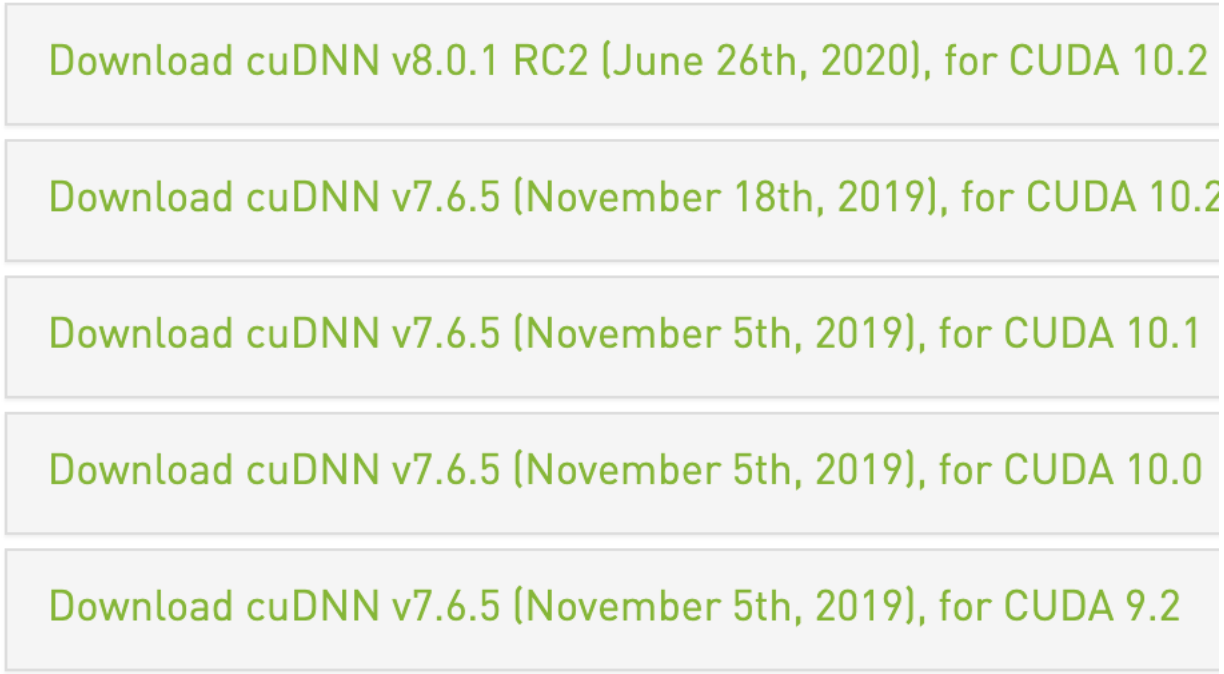
➢ Install cuDNN

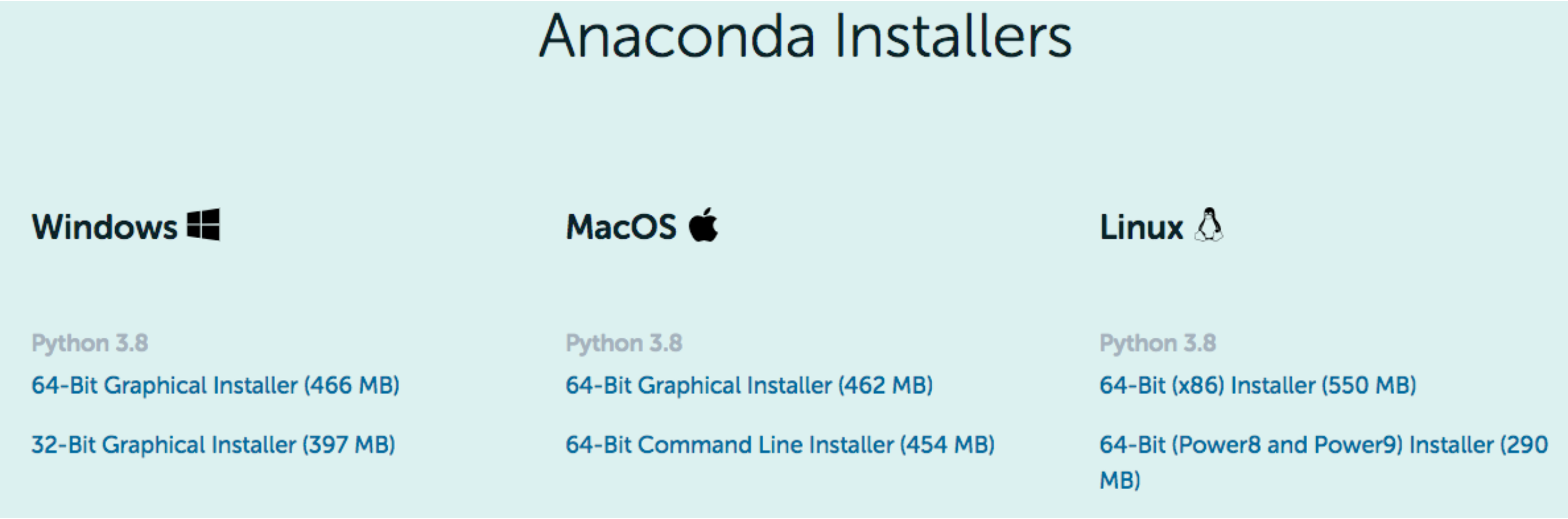
- Download: https://developer.nvidia.com/rdp/cudnn-archive



- You should choose the matched version of cuDNN with the installed CUDA
- Installation instruction: https://docs.nvidia.com/deeplearning/cudnn/install-guide/index.html#installlinux

➢ Install Anaconda

- Download: https://www.anaconda.com/products/individual#linux



➢ Install Anaconda

- Install Steps:

```
cd /home  # The path you download Anaconda
bash Anaconda3-2020.07-Linux-x86_64.sh  # Enter,
          # Follow the command-line prompts and answer each question

# Once install successfully, test with
python  # If there is an error indicating ‘cannot find python’
sudo vim /etc/profile  # Configure and edit the environment variables
PATH=/home/user/anaconda3/bin:$PATH  # Add this line into the file
             # Save this configure file with ‘:wq!’
source /etc/profile  # Update the environment variables

# Test again
python
```

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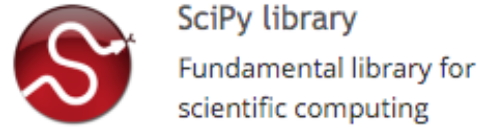
- Install torch, numpy, opencv-python, scikit-image, scipy




```
conda create -n torch020 python=3.6  # construct virtual
environment named pytorch
conda activate torch020  # activate virtual environment
Pip list  # show the installed library

pip install torch==1.7.0
pip install numpy
pip install opencv-python
pip install scikit-image
pip install scipy
# The resting required libraries can be installed
following the reported error when debugging
```

Deep Learning - Implement RCNN with Pytorch

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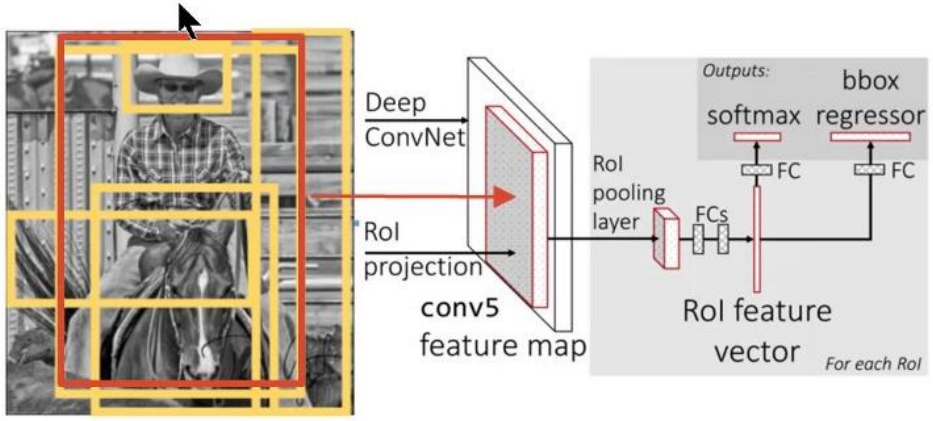
- RCNN
  ./lib/net/data.py

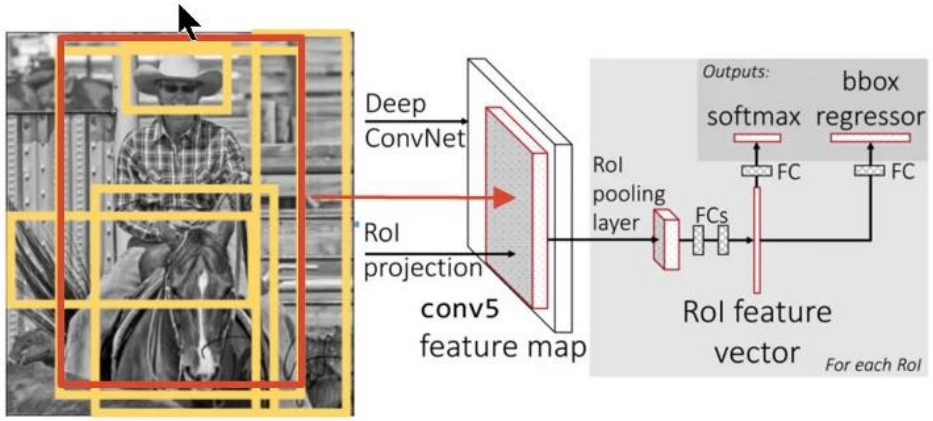



```
train_imgs = []
train_img_info = []
train_roi = []
train_cls = []
train_tbbox = []

N_train = len(data)
for i in trange(N_train):
    img_path = data['image_name'][i]
    gt_boxs = data['boxes'][i]
    gt_classes = data['gt_classes'][i]
    nobj = data['num_objs'][i]
    bboxs = data['selective_search_boxes'][i]
    nroi = len(bboxs)

    img = Image.open('data/JPEGImages/' + img_path)
    img_size = img.size
    img = img.resize((224, 224))
    img = np.array(img).astype(np.float32)
    img = np.transpose(img, [2, 0, 1])

    rbboxs = rel_bbox(img_size, bboxs)
    ious = calc_ious(bboxs, gt_boxs)
    max_ious = ious.max(axis=1)
    max_idx = ious.argmax(axis=1)
    tbbox = bbox_transform(bboxs, gt_boxs[max_idx])
```

```
train_imgs = np.array(train_imgs)
train_img_info = np.array(train_img_info)
train_roi = np.array(train_roi)
train_cls = np.array(train_cls)
train_tbbox = np.array(train_tbbox).astype(np.float32)
```

Deep Learning - Implement RCNN with Pytorch

- RCNN
  ./lib/net/RCNN.py




```python
class RCNN(nn.Module):
    def __init__(self):
        super().__init__()

        rawnet = torchvision.models.vgg16_bn(pretrained=True)
        self.seq = nn.Sequential(*list(rawnet.features.children())[:-1])
        self.roipool = SlowROIPool(output_size=(7, 7))
        self.feature = nn.Sequential(*list(rawnet.classifier.children())[:-1])

        _x = Variable(torch.Tensor(1, 3, 224, 224))
        _r = np.array([[0., 0., 1., 1.]])
        _ri = np.array([0])
        _x = self.feature(self.roipool(self.seq(_x), _r, _ri).view(1, -1))
        feature_dim = _x.size(1)
        self.cls_score = nn.Linear(feature_dim, N_CLASS+1)
        self.bbox = nn.Linear(feature_dim, 4*(N_CLASS+1))

        self.cel = nn.CrossEntropyLoss()
        self.sl1 = nn.SmoothL1Loss()

    def forward(self, inp, rois, ridx):
        res = inp
        res = self.seq(res)
        res = self.roipool(res, rois, ridx)
        res = res.detach()
        res = res.view(res.size(0), -1)
        feat = self.feature(res)

        cls_score = self.cls_score(feat)
        bbox = self.bbox(feat).view(-1, N_CLASS+1, 4)
        return cls_score, bbox

    def calc_loss(self, probs, bbox, labels, gt_bbox):
        loss_sc = self.cel(probs, labels)
        lbl = labels.view(-1, 1, 1).expand(labels.size(0), 1, 4)
        mask = (labels != 0).float().view(-1, 1).expand(labels.size(0), 4)
        loss_loc = self.sl1(bbox.gather(1, lbl).squeeze(1) * mask, gt_bbox * mask)
        lmb = 1.0
        loss = loss_sc + lmb * loss_loc
        return loss, loss_sc, loss_loc
```

Deep Learning - Implement RCNN with Pytorch

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- Loss calculation
  `./experiment/rcnn/train.py`

Detection Results

```python
def train_epoch(run_set, is_val=False):
    for i in trange(0, Nimg, I):
        lb = i
        rb = min(i+I, Nimg)
        torch_seg = torch.from_numpy(perm[lb:rb])
        img = Variable(train_imgs[torch_seg], volatile=is_val).cuda()
        ridx = []
        glo_ids = []

        for j in range(lb, rb):
            info = train_img_info[perm[j]]
            pos_idx = info['pos_idx']
            neg_idx = info['neg_idx']
            ids = []

            if len(pos_idx) > 0:
                ids.append(np.random.choice(pos_idx, size=POS))
            if len(neg_idx) > 0:
                ids.append(np.random.choice(neg_idx, size=NEG))
            if len(ids) == 0:
                continue
            ids = np.concatenate(ids, axis=0)
            glo_ids.append(ids)
            ridx += [j-lb] * ids.shape[0]

        if len(ridx) == 0:
            continue
        glo_ids = np.concatenate(glo_ids, axis=0)
        ridx = np.array(ridx)
        rois = train_roi[glo_ids]
        gt_cls = Variable(torch.from_numpy(train_cls[glo_ids]), volatile=is_val).cuda()
        gt_tbbox = Variable(torch.from_numpy(train_tbbox[glo_ids]), volatile=is_val).cuda()

        loss, loss_sc, loss_loc = train_batch(img, rois, ridx, gt_cls, gt_tbbox, is_val=is_val)
        losses.append(loss)
        losses_sc.append(loss_sc)
        losses_loc.append(loss_loc)
    avg_loss = np.mean(losses)
    avg_loss_sc = np.mean(losses_sc)
    avg_loss_loc = np.mean(losses_loc)
    print(f'Avg loss = {avg_loss:.4f}; loss_sc = {avg_loss_sc:.4f}, loss_loc = {avg_loss_loc:.4f}')
    return losses, losses_sc, losses_loc
```

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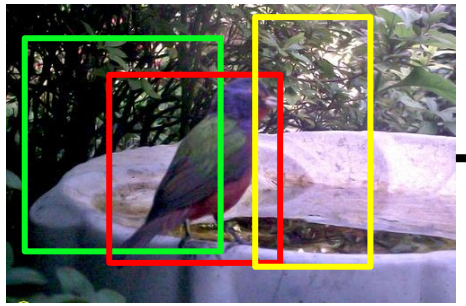
- Results on bird detection

Outline

- Course Project
  - Objective
  - Kaggle Competition
- Machine Learning for Object Detection
  - Feature extraction by HOG
  - Classification by SVM
- Deep Learning for Object Detection
  - Network Architecture (RCNN)
  - Implement RCNN with Pytorch
- Further Extensions

Further Extensions



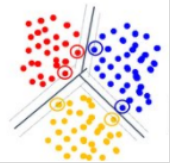
Input Images

Region Proposals

Feature Extractor

Bounding Box Regression

Classifier



- Better data
  - Data augmentation
  - Color space transformation
- Better feature vectors
  - Combine ML hand-crafted features with DL features
- Better supervisions
  - Contrastive learning

Thanks for listening!