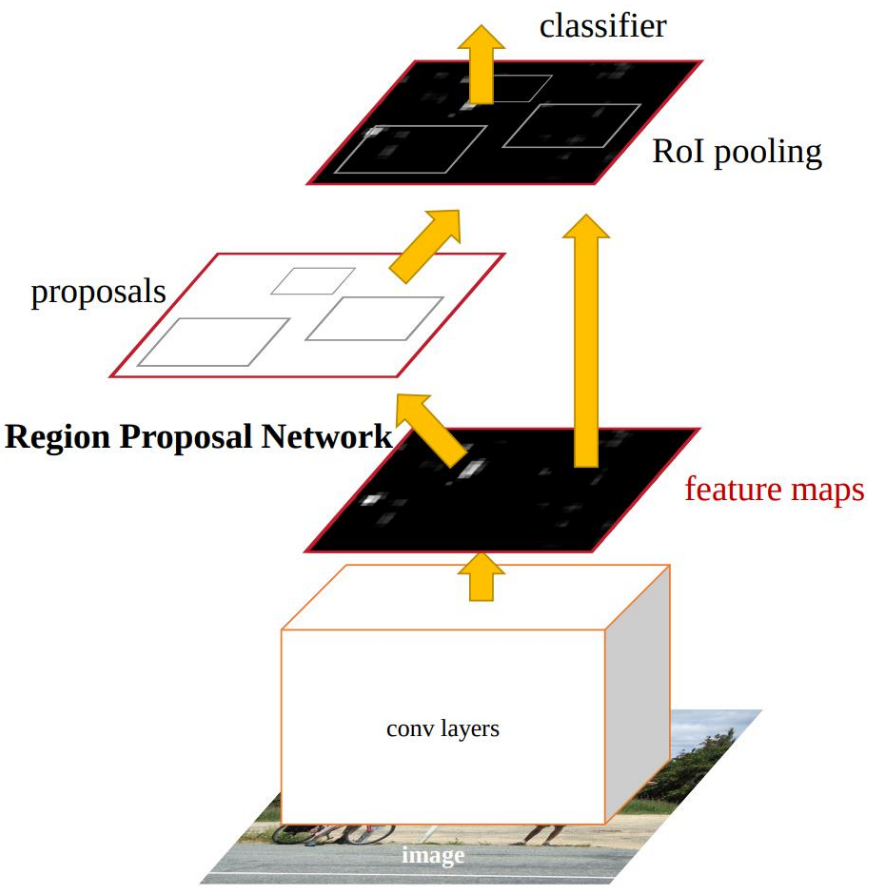
Deep Reinforcement Learning of Region Proposal Networks for Object Detection

Weisong Wang
redmud@bupt.com

1. Standard region proposal nets

two-step proposal-based detection



Good

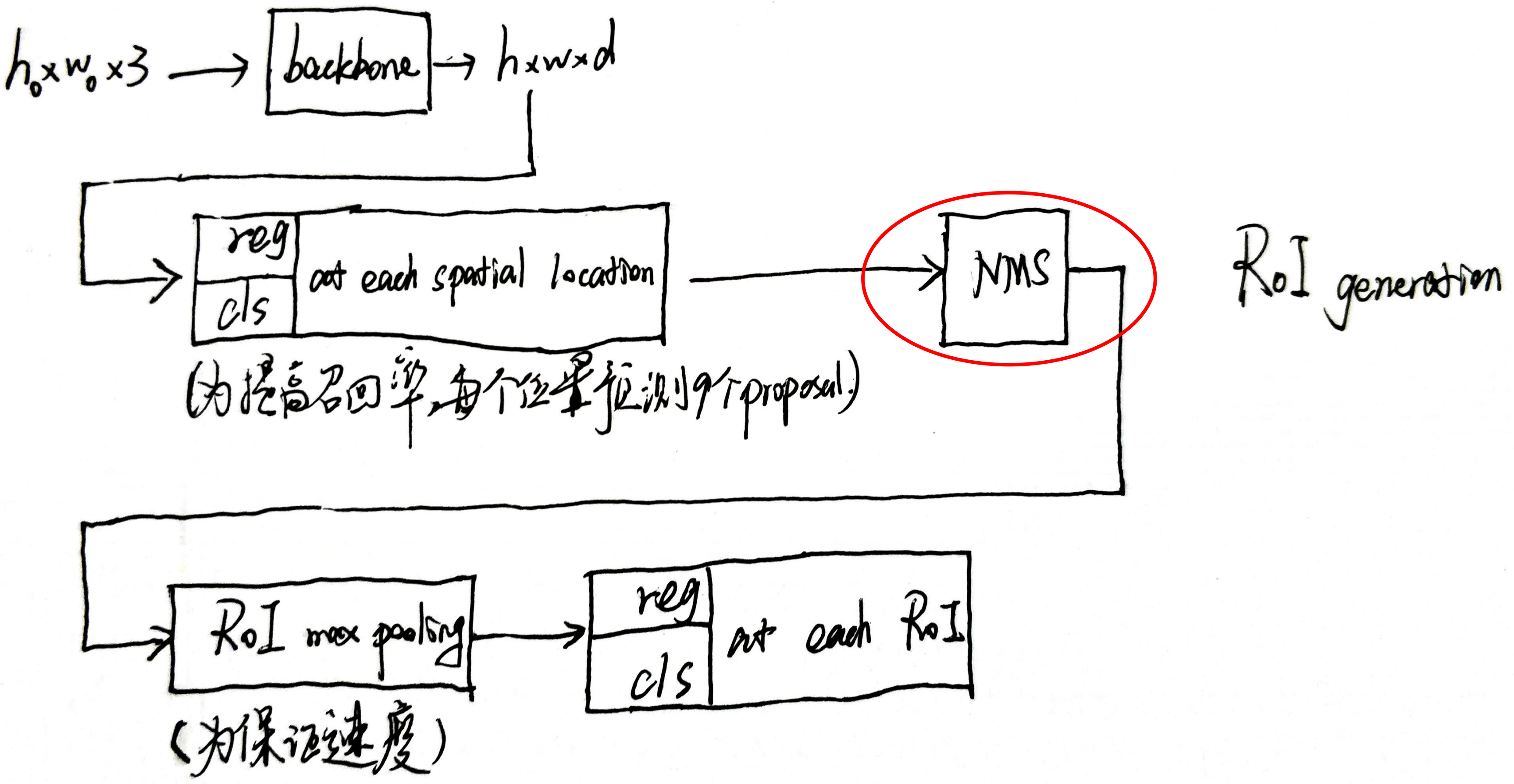
- ❑ 在特征图上大量的共享计算 -> 能够在一定精度的情况下保证速度

Less good

- ❑ 不能人为设定某种 speed-accuracy trade-off，灵活性差
- ❑ 各建议区域独立计算，未整合上下文信息
- ❑ 每张图片计算量几乎是一样的，无视图片的场景复杂度

1. Standard region proposal nets

modify on RoIs generation



drl-rpn = RL-based search strategy + sequential RPN

1. Standard region proposal nets

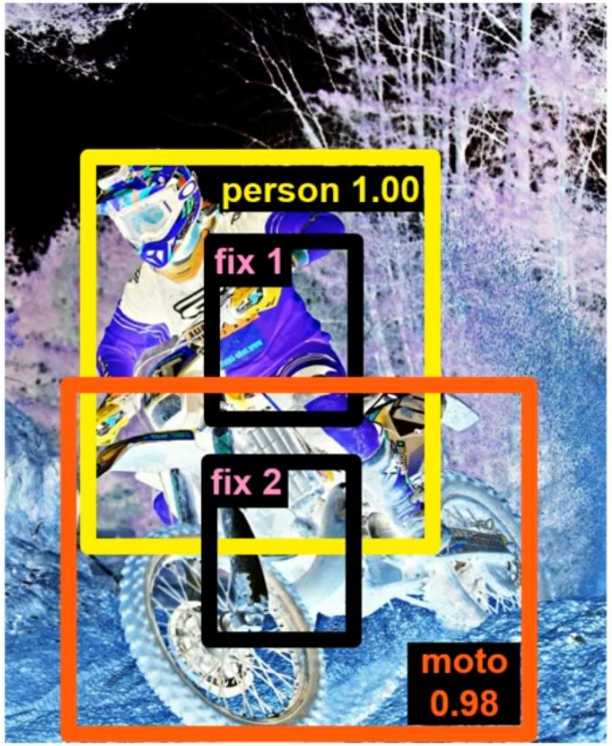
visualization of drl-rpn

0) Get initial state based on input image

1) Action: Fixate next location
- i) Classify RoIs in fixation area
- ii) Run NMS on local detections
- iii) Locally detected:
  - **person (0.98)**
- iv) Update class-specific history

2) Action: Fixate next location
- i) Classify RoIs in fixation area
- ii) Run NMS on local detections
- iii) Locally detected:
  - **motorcycle (0.95)**
- iv) Update class-specific history

3) Action: Terminate search
- i) Posterior class-probability adjustments
- ii) Run NMS on classified RoIs
- iii) Final detections:
  - **person (1.00)**
  - **motorcycle (0.98)**

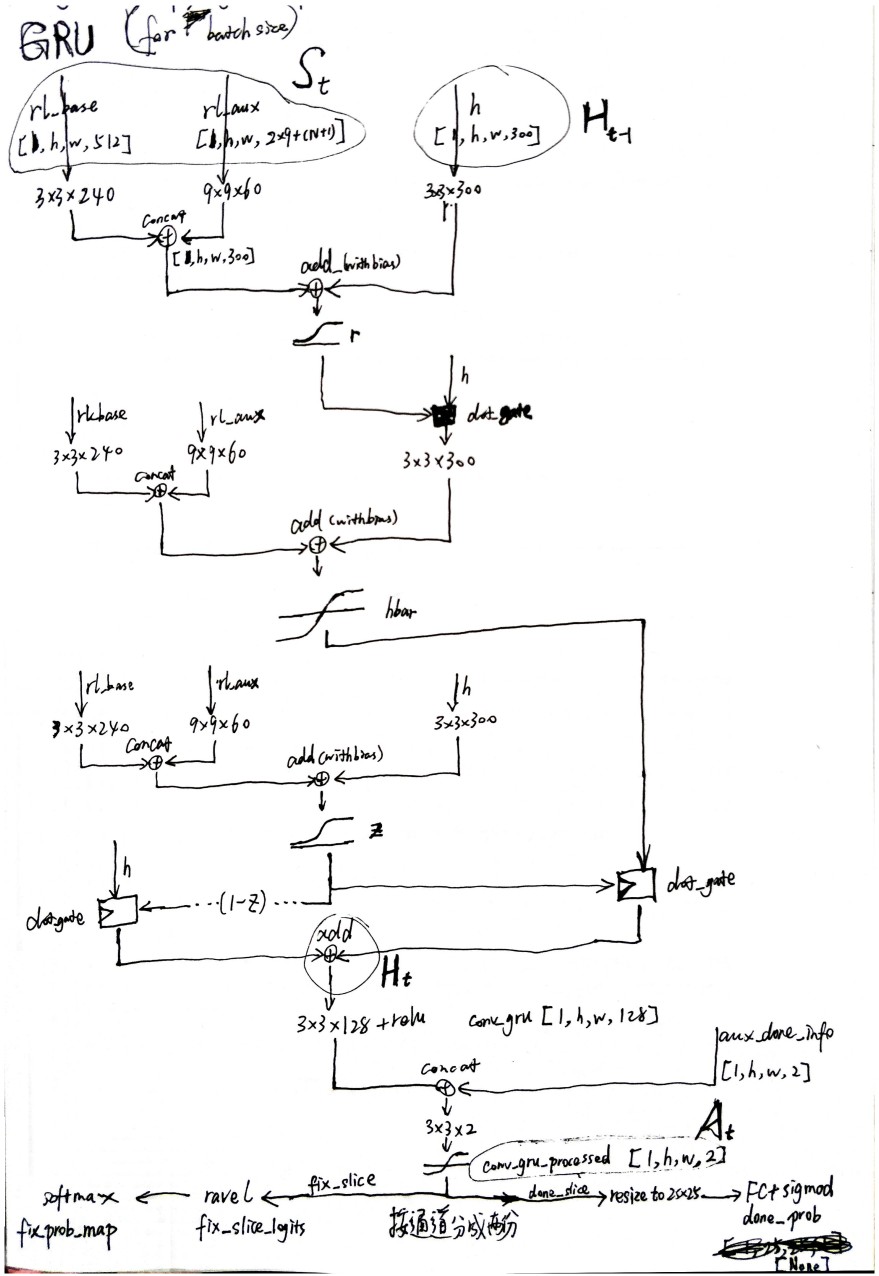


(h0, w0) --- /16 ---> (h, w)

- ❑ fixation rectangle
  - ❑ fix_rect_h = h/4
  - ❑ fix_rect_w = w/4
- ❑ class-specific history
  - ❑ class-specific history into 3x3 bins, 故 hist_bin_h = im_h/3，hist_bin_w = im_w/3，并记9个中心点为 bin_ctrs

2. RL-based search strategy

Convolutional gated recurrent unit



Input

- rl_in:
  - net_conv[b, h, w, 512]
  - rpn_cls_objness[b, h, w, 9]
  - rpn_bbox_pred[b, h, w, 9]
  - cls_probs_rl_input[b, h, w, N+1]
- rois_all[b*h*w*9, 4]
- roi_obs_vol[b, h, w, 9]

Hiden

- cls_hist[None, 3, 3, N+1]

Output

- fix_prob_map[b, h, w, 1]
- done_prob[b, 1]

$$\pi_{\boldsymbol{\theta}}\left(a_t^d = 0, a_t^f = z_t | s_t\right) = \left(1 - \sigma\left[\boldsymbol{w}_d^\top \boldsymbol{d}_t + t\right]\right) \hat{\boldsymbol{A}}_t^f[z_t]$$

3. Sequential RPN
Sequential RPN

Input
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  - ❑ net_conv[b, h, w, 512]
  - ❑ rpn_cls_objness[b, h, w, 9]
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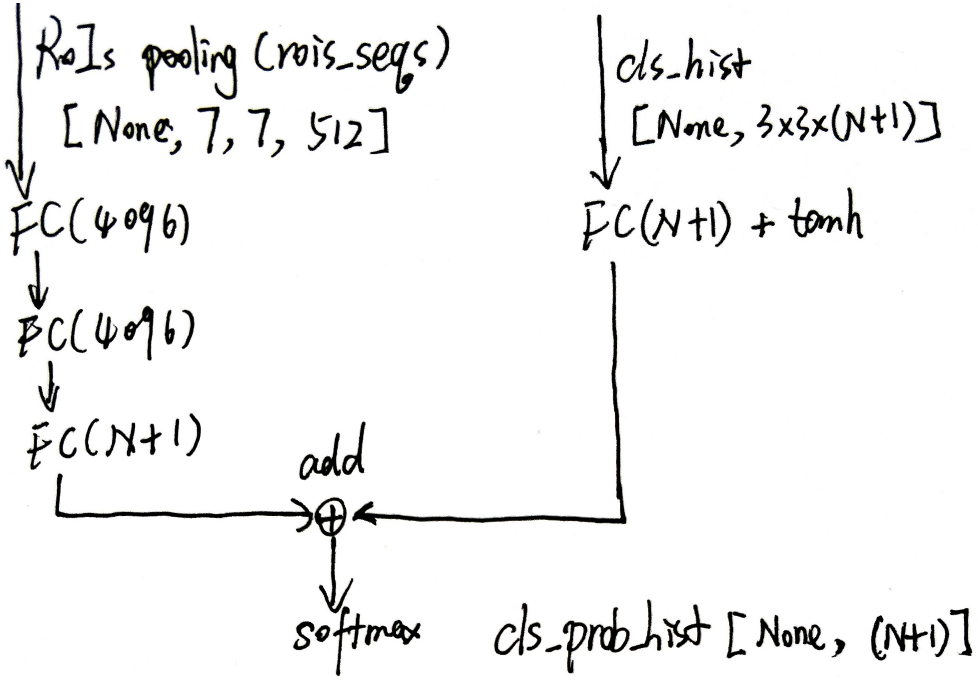
Hiden
- ❑ cls_hist[None, 3, 3, N+1]

Output
- ❑ fix_prob_map[b, h, w, 1]
- ❑ done_prob[b, 1]

```
def getAction(t):
    action_pass(S(t), H(t-1), t, beta)
    _check_termination(t, done_prob)
    _sample_fix_loc(fix_prob)
def update_rl():
    get_nms_keep(cls_probs_uptonow, pred_bboxes_uptonow)
    update_rl_in()
    do_hist_update()
getAction(0)
for t in range(1, 12):
    update_obs_vol(roi_obs_vol, t, fix)
    rois_seq = rois_all[roi_obs_vol == t]
    cls_probs_seq, bbox_preds_seq = rois_ClsReg(rois_seq)
    append()
    update_rl()
    getAction(t)
```

3. Sequential RPN

Contextual class probability adjustment



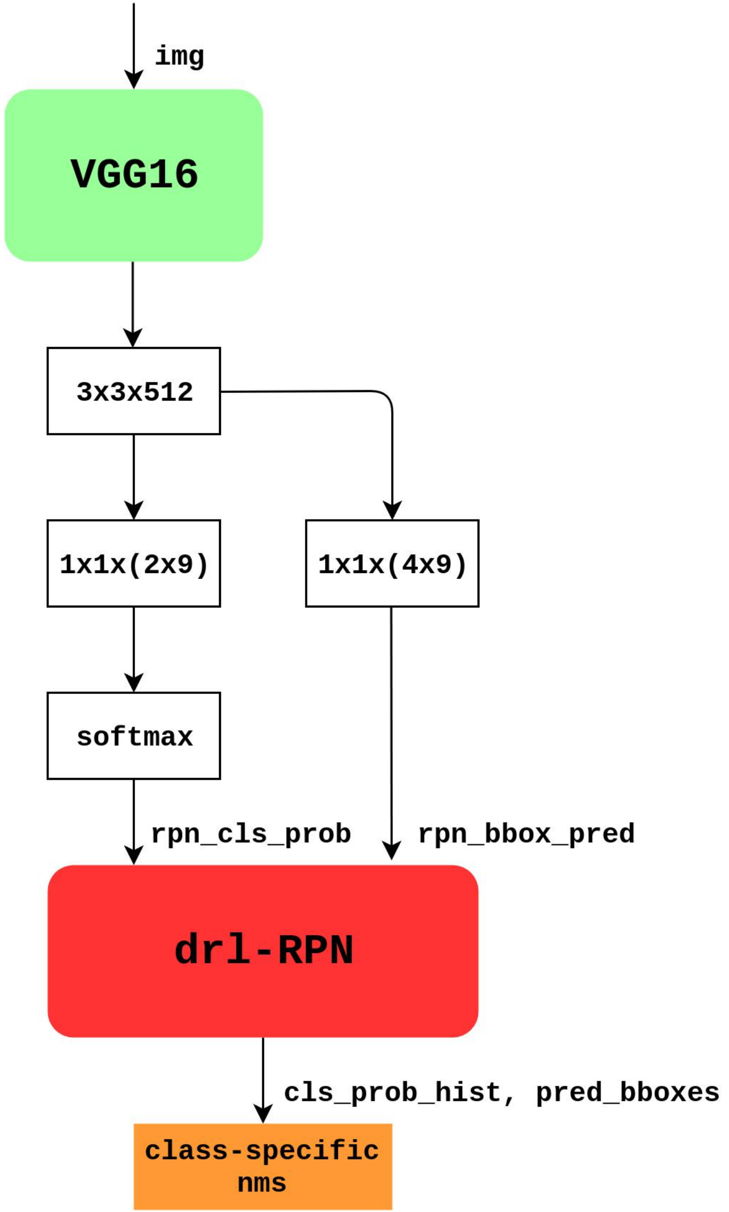
$$softmax[Wx + b + f_{hist}(x_{hist})]$$

4. Conclution

Review

特点

- ❑ 可通过人为设定超参数beta的值，来决定模型速度优先还是精度优先
- ❑ 各建议区域之间有信息交流，一方面用于 agent 的建议区域搜索，有利于搜索效率的提高；另一方面用于预测类别概率的调整，有利于提高识别精度
- ❑ 每张图片计算量依赖于图片的场景复杂度，比传统 RPN 固定 fixation 有更好的 speed-accuracy trade-off



4. Conclution

Tricks

可用于借鉴的 tricks

- ❑ 优先选择偏移量更小的推荐框
- ❑ 挖掘 top-down 结构（该paper为类别的 top-down，FPN 为 feature-map 的 top-down），可提高检测精度