视觉有向目标的高精度检测

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有向目标检测

- 预测具有方向的边界框并对目标进行识别

AlphaRotate・上海交通大学
应用场景

- 遥感检测
- 人脸检测
- 零售场景检测
- 场景文字检测
- 3D目标检测
有向目标检测

- 旋转框的定义方式：
  - OpenCV定义法： \((x, y, w_{oc}, h_{oc}, \theta_{oc}), \theta_{oc} \in [-90, 0)\)
  - 长边定义法： \((x, y, w_{le}, h_{le}, \theta_{le}), \theta_{le} \in [-90, 90)\)

- 转换关系：

  \[
  D_{le}(w_{le}, h_{le}, \theta_{le}) = \begin{cases} 
  D_{oc}(w_{oc}, h_{oc}, \theta_{oc}), & w_{oc} \geq h_{oc} \\
  D_{oc}(h_{oc}, w_{oc}, \theta_{oc} + 90^\circ), & \text{otherwise}
  \end{cases}
  \]

  \[
  D_{oc}(w_{oc}, h_{oc}, \theta_{oc}) = \begin{cases} 
  D_{le}(w_{le}, h_{le}, \theta_{le}), & \theta_{le} \in [-90^\circ, 0^\circ) \\
  D_{le}(h_{le}, w_{le}, \theta_{le} - 90^\circ), & \text{otherwise}
  \end{cases}
  \]

https://zhuanlan.zhihu.com/p/459018810
有向目标检测

- 旋转框IoU的计算:

Algorithm 1 IoU computation

1: Input: Rectangles $R_1, R_2, ..., R_N$
2: $\text{IoU}[1,N][1,N] \leftarrow 0$
3: for each pair of $R_i, R_j$ ($i < j$) do
4: \quad Point set $PSet \leftarrow \emptyset$
5: \quad Add intersection points of $R_i$ and $R_j$ to $PSet$
6: \quad Add the vertices of $R_i$ inside $R_j$ into $PSet$
7: \quad Add the vertices of $R_j$ inside $R_i$ into $PSet$
8: \quad Sort $PSet$ to anti-clockwise order
9: \quad Compute intersection $I$ of $PSet$ by triangulation
10: \quad $\text{IoU}(i, j) \leftarrow (\text{Area}(R_i) + \text{Area}(R_j) - I)/I$
11: end for
12: return IoU

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

https://github.com/open-mmlab/mmcv/pull/1854
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3. 解决办法
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问题和挑战

- 评估与损失不一致问题
问题和挑战

- 有向目标检测中的边界问题

### Case 1

- **长边定义法**
  - **Anchor/Proposal**: (0,0,70,10,−90°)
  - **Ground-Truth**: (0,0,70,10,65°)
  - **Predict box**: (0,0,70,10,−115°)
  - $w = w, h = h, |\theta - \theta| = 180°$
  - $\text{IoU} < G, P > \approx 1$
  - $\text{Smooth-L1 Loss} < G, P > \text{PoA} \gg 0$

- **Anchor/Proposal**: (0,0,70,10,−90°)
  - **Ground-Truth**: (0,0,70,10,65°)
  - **Predict box**: (0,0,70,10,65°)
  - $w = w, h = h, |\theta - \theta| = 0°$
  - $\text{IoU} < G, P > \approx 1$
  - $\text{Smooth-L1 Loss} < G, P > \approx 0$
问题和挑战

- 有向目标检测中的边界问题

OpenCV定义法

Case 2

Anchor/Proposal: (0,0,70,10,−90°)
Ground-Truth: (0,0,10,70,−25°)
Predict box: (0,0,70,10,−115°)

\( w = h, h = w, |\theta - \theta| = 90° \)

IoU< \( G, P > ≈ 1 \)

Smooth-L1 Loss< \( G, P > PoA + EoE ≫ 0 \)

OpenCV Definition

- way1
  - \(-\Delta \theta\)

- way2
  - \(+\Delta \theta\)
  - \(+\Delta h\)

Anchor/Proposal: (0,0,70,10,−90°)
Ground-Truth: (0,0,10,70,−25°)
Predict box: (0,0,70,10,−25°)

\( w = w, h = h, |\theta - \theta| = 0° \)

IoU< \( G, P > ≈ 1 \)

Smooth-L1 Loss< \( G, P > ≪ 0 \)
· 类正方形检测问题

**Case 3**

Anchor/Proposal: (0,0,45,44,0°)
- Ground-Truth: (0,0,45,43,−60°)
- Predict box: (0,0,44,44,−60°)

$$w \approx h \approx w, |\theta - \theta| = 0^\circ$$
- IoU $<$ G, P $>$ ≈ 1
- Smooth-L1 Loss $<$ G, P $>$ ≈ 0

Anchor/Proposal: (0,0,44,44,−90°)
- Ground-Truth: (0,0,45,43,−30°)
- Predict box: (0,0,44,44,−30°)

$$w \approx w \approx h \approx w, |\theta - \theta| = 0^\circ$$
- IoU $<$ G, P $>$ ≈ 1
- Smooth-L1 Loss $<$ G, P $>$ ≈ 0

**Long Edge Definition**

- Anchor/Proposal: (0,0,45,44,4°)
- Ground-Truth: (0,0,45,43,−60°)
- Predict box: (0,0,44,45,−60°)

**OpenCV Definition**

- Anchor/Proposal: (0,0,44,45,−30°)
- Ground-Truth: (0,0,45,43,−30°)
- Predict box: (0,0,44,45,−120°)

$$w \approx w \approx h \approx h, |\theta - \theta| = 90^\circ$$
- IoU $<$ G, P $>$ ≈ 1
- Smooth-L1 Loss $<$ G, P $>$ ≈ 0

长宽比越小，IoU对角度越不敏感
解决方法

- 有向目标检测器的两种设计范式
  - 归纳范式
  - 演绎范式

解决方法

- 归纳范式
  - 对于常见的通用检测模型（水平框检测），模型通常是通过回归四个偏移量的形式来进行框位置和大小的预测：
    
    \[
    t_{x}^{p} = \frac{x_{p} - x_{a}}{w_{a}}, \quad t_{y}^{p} = \frac{y_{p} - y_{a}}{h_{a}}, \quad t_{w}^{p} = \ln \left( \frac{w_{p}}{w_{a}} \right), \quad t_{h}^{p} = \ln \left( \frac{h_{p}}{h_{a}} \right)
    \]

    来匹配实际的偏移量：
    
    \[
    t_{x}^{t} = \frac{x_{t} - x_{a}}{w_{a}}, \quad t_{y}^{t} = \frac{y_{t} - y_{a}}{h_{a}}, \quad t_{w}^{t} = \ln \left( \frac{w_{t}}{w_{a}} \right), \quad t_{h}^{t} = \ln \left( \frac{h_{t}}{h_{a}} \right)
    \]

  - 借鉴于此，目前绝大多数的旋转目标检测在上面的基础上加上了角度参数的回归：
    
    \[
    t_{\theta}^{p} = f(\theta_{p} - \theta_{a}), \quad t_{\theta}^{t} = f(\theta_{t} - \theta_{a})
    \]
解决方法

▪ 归纳范式

▪ 然后回归损失也常采用$L_n$-norm:

$$L_{reg} = l_n\text{-norm} (\Delta t_x, \Delta t_y, \Delta t_w, \Delta t_h, \Delta t_\theta)$$

where $\Delta t_x = t_x^p - t_x^t = \frac{\Delta x}{w_a}$, $\Delta t_y = t_y^p - t_y^t = \frac{\Delta y}{h_a}$, $\Delta t_w = t_w^p - t_w^t = \ln(w_p/w_t)$, $\Delta t_h = t_h^p - t_h^t = \ln(h_p/h_t)$, and $\Delta t_\theta = t_\theta^p - t_\theta^t = \Delta \theta$.

▪ 五个参数的优化和目标本身形状等关联不大，使得我们需要根据不同数据集特点进行权重的调整。比如大长宽比目标可能需要着重关注角度参数，小目标则需要关注中心点参数，因此这些参数的轻微偏移都会造成这些目标预测精准度（IoU）的急剧下降。
解决方法

- 演绎范式

  - 要求 1：与 IoU 度量高度一致
  - 要求 2：易实现、可微分允许直接学习
  - 要求 3：在角度边界情况下平滑

\[
\Sigma^{1/2} = \text{RSR}^T
\]

\[
= \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} w/2 & 0 \\ 0 & h/2 \end{pmatrix} \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix}
\]

\[
= \begin{pmatrix} \frac{w}{2} \cos^2 \theta + \frac{h}{2} \sin^2 \theta & \frac{w-h}{2} \cos \theta \sin \theta & \frac{w}{2} \sin^2 \theta + \frac{h}{2} \cos^2 \theta \end{pmatrix}
\]

\[
m = (x, y)^T
\]

Property 1: \( \Sigma^{1/2}(w, h, \theta) = \Sigma^{1/2}(h, w, \theta - \frac{\pi}{2}) \);

Property 2: \( \Sigma^{1/2}(w, h, \theta) = \Sigma^{1/2}(w, h, \theta - \pi) \);

Property 3: \( \Sigma^{1/2}(w, h, \theta) \approx \Sigma^{1/2}(w, h, \theta - \frac{\pi}{2}) \), if \( w \approx h \).
解决方法

- Wasserstein Distance

  - 通用公式：
    \[
    D_w(N_p, N_t)^2 = \left\| \mu_p - \mu_t \right\|_2^2 + \text{Tr}(\Sigma_p + \Sigma_t - 2(\Sigma_p^{1/2} \Sigma_t \Sigma_p^{1/2})^{1/2})
    \]
    - center distance
    - coupling terms about \( h_p, w_p \) and \( \theta_p \)

  - 水平特殊情况：
    \[
    D_w^h(N_p, N_t)^2 = \left\| \mu_p - \mu_t \right\|_2^2 + \left\| \Sigma_p^{1/2} - \Sigma_t^{1/2} \right\|_F^2
    = (x_p - x_t)^2 + (y_p - y_t)^2 + ((w_p - w_t)^2 + (h_p - h_t)^2) / 4
    = l_2\text{-norm}(\Delta x, \Delta y, \Delta w/2, \Delta h/2)
    \]
解决方法
解决方法

- **Wasserstein Distance**

  - 通用公式：
    \[
    D_w(N_p, N_t)^2 = \left\| \mu_p - \mu_t \right\|_2^2 + \text{Tr}(\Sigma_p + \Sigma_t - 2(\Sigma_p^{1/2} \Sigma_t \Sigma_p^{1/2})^{1/2})
    \]
    - center distance
    - coupling terms about \( h_p, w_p \) and \( \theta_p \)

  - 水平特殊情况：
    \[
    D_w^h(N_p, N_t)^2 = \left\| \mu_p - \mu_t \right\|_2^2 + \left\| \Sigma_p^{1/2} - \Sigma_t^{1/2} \right\|_F^2
    \]
    \[
    = (x_p - x_t)^2 + (y_p - y_t)^2 + ((w_p - w_t)^2 + (h_p - h_t)^2) / 4
    \]
    \[
    = l_2\text{-norm}(\Delta x, \Delta y, \Delta w/2, \Delta h/2)
    \]

- 损失函数
  \[
  L_{gw} = 1 - \frac{1}{\tau + f(D_w^2)}, \quad \tau \geq 1
  \]
解决方法

- **Kullback-Leibler Divergence**

  - 通用公式：
    \[
    D_{kl}(\mathcal{N}_p \| \mathcal{N}_t) = \frac{1}{2} (\mu_p - \mu_t)^\top \Sigma_t^{-1} (\mu_p - \mu_t) + \frac{1}{2} \text{Tr}(\Sigma_t^{-1} \Sigma_p) + \frac{1}{2} \ln \frac{|\Sigma_t|}{|\Sigma_p|} - 1
    \]
    其中包含关于 \(x_p\) 和 \(y_p\) 的项。

  - 或
    \[
    D_{kl}(\mathcal{N}_t \| \mathcal{N}_p) = \frac{1}{2} (\mu_p - \mu_t)^\top \Sigma_p^{-1} (\mu_p - \mu_t) + \frac{1}{2} \text{Tr}(\Sigma_p^{-1} \Sigma_t) + \frac{1}{2} \ln \frac{|\Sigma_p|}{|\Sigma_t|} - 1
    \]
    以及关于 \(h_p\)、\(w_p\) 和 \(\theta_p\) 的耦合项。

- 水平特殊情况：
  \[
  D_{kl}^h(\mathcal{N}_p \| \mathcal{N}_t) = \frac{1}{2} \left( \frac{w_p^2}{w_t^2} + \frac{h_p^2}{h_t^2} + \frac{4 \Delta x^2}{w_t^2} + \frac{4 \Delta y^2}{h_t^2} + \ln \frac{w_t^2}{w_p^2} + \ln \frac{h_t^2}{h_p^2} - 2 \right)
  \]
  \[= 2l_2\text{-norm}(\Delta t_x, \Delta t_y) + l_1\text{-norm}(\Delta t_w, \Delta t_h) + \frac{1}{2} l_2\text{-norm}(\frac{1}{\Delta t_w}, \frac{1}{\Delta t_h}) - 1\]
解决方法

- 高精度分析（KLD＞GWD＞smooth L1）：
  - KLD主要三项的具体表达式：

\[
\begin{align*}
    (\mu_p - \mu_t)^	op \Sigma_t^{-1} (\mu_p - \mu_t) &= \frac{4(\Delta x \cos \theta_t + \Delta y \sin \theta_t)^2}{w_t^2} + \frac{4(\Delta y \cos \theta_t - \Delta x \sin \theta_t)^2}{h_i^2} \\
    \text{Tr}(\Sigma_t^{-1} \Sigma_p) &= \frac{h_p^2}{w_t^2} \sin^2 \Delta \theta + \frac{w_p^2}{h_i^2} \sin^2 \Delta \theta + \frac{h_p^2}{h_i^2} \cos^2 \Delta \theta + \frac{w_p^2}{w_t^2} \cos^2 \Delta \theta \\
    \ln \frac{|\Sigma_t|}{|\Sigma_p|} &= \ln \frac{h_i^2}{h_p^2} + \ln \frac{w_t^2}{w_p^2}
\end{align*}
\]

其中 \( \Delta x = x_p - x_t, \Delta y = y_p - y_t, \Delta \theta = \theta_p - \theta_t \)。
解决方法

- 高精度分析（KLD>GWD>smooth L1）：
  - 不失一般性，我们令 $\theta_t = 0$，对KLD的$\mu_p$求导数：
    \[
    \frac{\partial D_{kl}(\mu_p)}{\partial \mu_p} = \left( \frac{4}{w_t^2} \Delta x, \frac{4}{h_t^2} \Delta y \right)^T
    \]
  - 当$\theta_t \neq 0$时，目标的偏移量（$\Delta x$和$\Delta y$）的梯度会根据角度进行动态调整以提供更好的优化。相比之下，GWD和$L_2$关于偏移量的梯度分别是：
    \[
    \frac{\partial D_w(\mu_p)}{\partial \mu_p} = (2\Delta x, 2\Delta y)^T \quad \frac{\partial L_2(\mu_p)}{\partial \mu_p} = \left( \frac{2}{w_a^2} \Delta x, \frac{2}{h_a^2} \Delta y \right)^T
    \]
解决方法

- 高精度分析 （KLD>GWD>smooth L1）：
  - 对KLD的$h_p$和$w_p$求导数：

$$\frac{\partial D_{kl}(\Sigma_p)}{\partial \ln h_p} = \frac{h_p^2}{h_t^2} \cos^2 \Delta \theta + \frac{h_p^2}{w_t^2} \sin^2 \Delta \theta - 1,$$

$$\frac{\partial D_{kl}(\Sigma_p)}{\partial \ln w_p} = \frac{w_p^2}{w_t^2} \cos^2 \Delta \theta + \frac{w_p^2}{h_t^2} \sin^2 \Delta \theta - 1$$

- 我们可以看到，两边$h_p$和$w_p$梯度和角度差$\Delta \theta$有关。当$\Delta \theta = 0$时：

$$\frac{\partial D_{kl}(\Sigma_p)}{\partial \ln h_p} = \frac{h_p^2}{h_t^2} - 1, \quad \frac{\partial D_{kl}(\Sigma_p)}{\partial \ln w_p} = \frac{w_p^2}{w_t^2} - 1$$

- 这意味着较小的目标尺度会导致其匹配到更大的损失。这是符合认知的，因为较小的边需要更高的匹配精度。
解决方法

- 高精度分析（KLD>GWD>smooth L1）：
  - 对θ求导数：
    \[
    \frac{\partial D_{kl}(\Sigma_p)}{\partial \theta_p} = \left( \frac{h_p^2 - w_p^2}{w_t^2} + \frac{w_p^2 - h_p^2}{h_t^2} \right) \sin 2\Delta \theta
    \]
  - 角度差Δθ的优化又和两边\(h_p\)和\(w_p\)有关。当\(h_p = h_t\), \(w_p = w_t\)时：
    \[
    \frac{\partial D_{kl}(\Sigma_p)}{\partial \theta_p} = \left( \frac{h_t^2}{w_t^2} + \frac{w_t^2}{h_t^2} - 2 \right) \sin 2\Delta \theta \geq \sin 2\Delta \theta
    \]
  - 当目标长宽比慢慢变大的时候，整个式子的值就会变大，也就是意味着对角度优化更加看重。这个优化机制是非常好的，我们知道对于长宽比越大的目标来说，它受角度差的影响就越大，IoU会产生急剧下降。
解决方法

- 高精度分析 (KLD>GWD>smooth L1) :
解决方法

- 高精度分析（KLD>GWG>smooth L1）：
解决方法

- 尺度不变性证明
  - 很明显GWD和 $L_2$ 不具有尺度不变性。
  - 对于两个已知的高斯分布 $\mathbf{X}_p \sim \mathcal{N}(\mu_p, \Sigma_p)$ 和 $\mathbf{X}_t \sim \mathcal{N}(\mu_t, \Sigma_t)$ 假设有一个满秩的矩阵 $\mathbf{M}$ ($|\mathbf{M}| \neq 0$)，有：

$$
\mathbf{X}_p' = \mathbf{M}\mathbf{X}_p \sim \mathcal{N}(\mathbf{M}\mu_p, \mathbf{M}\Sigma_p\mathbf{M}^\top), \quad \mathbf{X}_t' = \mathbf{M}\mathbf{X}_t \sim \mathcal{N}(\mathbf{M}\mu_t, \mathbf{M}\Sigma_t\mathbf{M}^\top)
$$

- 我们将其分别标记为 $\mathcal{N}_p'$ 和 $\mathcal{N}_t'$，那么它们的KLD计算如下：

$$
\begin{align*}
\text{D}_{\text{kl}}(\mathcal{N}_p' || \mathcal{N}_t') &= \frac{1}{2}(\mu_p - \mu_t)^\top \mathbf{M}^\top (\mathbf{M}^\top)^{-1} \Sigma_t^{-1} \mathbf{M}^{-1} \mathbf{M}(\mu_p - \mu_t) \\
&\quad + \frac{1}{2} \text{Tr} ((\mathbf{M}^\top)^{-1} \Sigma_t^{-1} \mathbf{M}^{-1} \mathbf{M}\Sigma_p\mathbf{M}^\top) + \frac{1}{2} \ln \frac{|\mathbf{M}| \|\Sigma_t\| |\mathbf{M}^\top|}{|\mathbf{M}| \|\Sigma_p\| |\mathbf{M}^\top|} - 1 \\
&= \frac{1}{2}(\mu_p - \mu_t)^\top \Sigma_t^{-1}(\mu_p - \mu_t) + \frac{1}{2} \text{Tr} (\mathbf{M}^\top (\mathbf{M}^\top)^{-1} \Sigma_t^{-1} \mathbf{M}^{-1} \mathbf{M}\Sigma_p) + \frac{1}{2} \ln \frac{|\Sigma_t|}{|\Sigma_p|} - 1 \\
&= \text{D}_{\text{kl}}(\mathcal{N}_p || \mathcal{N}_t)
\end{align*}
$$

- 因此KLD具有仿射不变性的。当 $\mathbf{M} = k\mathbf{I}$ 时，KLD的尺度不变性就被证明了。
解决方法

- 尺度不变性比较
实验分析

- 在3种数据集和2种检测器上进行了高精度检测实验，KLD具有绝对优势。

<table>
<thead>
<tr>
<th>Method</th>
<th>Dataset</th>
<th>Data Aug.</th>
<th>Reg. Loss</th>
<th>Hmean_{50}/AP_{50}</th>
<th>Hmean_{60}/AP_{60}</th>
<th>Hmean_{75}/AP_{75}</th>
<th>Hmean_{85}/AP_{85}</th>
<th>Hmean_{95}/AP_{95}</th>
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<td>R+F+G</td>
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<td>GWD</td>
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<td>GWD</td>
<td>70.98</td>
<td>62.42</td>
<td>43.39</td>
<td>10.50</td>
<td>41.68 (+3.95)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KLD</td>
<td>76.76 (+5.78)</td>
<td>70.88 (+6.16)</td>
<td>77.38 (+11.98)</td>
<td>25.12 (+20.54)</td>
<td>61.40 (+15.22)</td>
</tr>
<tr>
<td>RetinaNet</td>
<td>ICDAR2015</td>
<td>F</td>
<td>Smooth L1</td>
<td>74.83</td>
<td>69.46</td>
<td>42.02</td>
<td>11.59</td>
<td>41.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GWD</td>
<td>76.15 (+1.32)</td>
<td>71.26 (+1.80)</td>
<td>45.59 (+3.57)</td>
<td>11.65 (+0.06)</td>
<td>43.58 (+1.60)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KLD</td>
<td>77.92 (+3.09)</td>
<td>72.77 (+3.31)</td>
<td>43.27 (+1.25)</td>
<td>11.09 (-0.50)</td>
<td>43.65 (+1.67)</td>
</tr>
<tr>
<td>R^3Det</td>
<td>ICDAR2015</td>
<td>F</td>
<td>Smooth L1</td>
<td>74.28</td>
<td>68.29</td>
<td>35.73</td>
<td>8.01</td>
<td>39.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GWD</td>
<td>75.59 (+1.31)</td>
<td>68.36 (+0.24)</td>
<td>40.24 (+4.51)</td>
<td>9.15 (+1.14)</td>
<td>40.80 (+1.17)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KLD</td>
<td>77.72 (+2.53)</td>
<td>71.99 (+3.87)</td>
<td>43.95 (+8.22)</td>
<td>10.43 (+2.42)</td>
<td>43.29 (+4.19)</td>
</tr>
<tr>
<td>R^3Det</td>
<td>ICDAR2015</td>
<td>F</td>
<td>Smooth L1</td>
<td>75.53</td>
<td>69.69</td>
<td>37.69</td>
<td>9.03</td>
<td>40.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GWD</td>
<td>77.09 (+1.56)</td>
<td>71.52 (+1.83)</td>
<td>41.08 (+3.39)</td>
<td>10.10 (+1.07)</td>
<td>42.17 (+1.61)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>KLD</td>
<td>79.63 (+4.63)</td>
<td>73.30 (+3.61)</td>
<td>43.51 (+5.82)</td>
<td>10.61 (+1.58)</td>
<td>43.61 (+3.05)</td>
</tr>
</tbody>
</table>
我们在一些更具有挑战性的数据集上进行了验证实验，包括DOTA-v1.5和DOTA-v2.0（包含很多像素值小于10的目标），KLD依旧表现出色。

Table 6: Accuracy comparison between different rotation detectors on DOTA dataset. † and ‡ represent the large aspect ratio object and the square-like object, respectively. The bold red and blue fonts indicate the top two performances respectively. $D_{oc}$ and $D_{le}$ represent OpenCV Definition ($\theta \in [-90^{\circ}, 0^{\circ}]$) and Long Edge Definition ($\theta \in [-90^{\circ}, 90^{\circ}]$) of RBox.

<table>
<thead>
<tr>
<th>Baseline</th>
<th>Method</th>
<th>Box Def.</th>
<th>v1.0 tranval/test</th>
<th>v1.0 train/val</th>
<th>v1.5</th>
<th>v2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>BR†</td>
<td>SV†</td>
<td>LV†</td>
<td>SH†</td>
</tr>
<tr>
<td>RetinaNet</td>
<td>-</td>
<td>$D_{oc}$</td>
<td>42.17</td>
<td>65.93</td>
<td>51.11</td>
<td>72.61</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>$D_{le}$</td>
<td>38.31</td>
<td>60.48</td>
<td>49.77</td>
<td>68.29</td>
</tr>
<tr>
<td></td>
<td>IoU-Smooth L1 [3]</td>
<td>$D_{oc}$</td>
<td>44.32</td>
<td>63.03</td>
<td>51.25</td>
<td>72.78</td>
</tr>
<tr>
<td></td>
<td>Modulated Loss [46]</td>
<td>$D_{oc}$</td>
<td>42.92</td>
<td>67.92</td>
<td>52.91</td>
<td>72.67</td>
</tr>
<tr>
<td></td>
<td>Modulated Loss [46]</td>
<td>Quad.</td>
<td>43.21</td>
<td>70.78</td>
<td>54.70</td>
<td>72.68</td>
</tr>
<tr>
<td></td>
<td>RIL [35]</td>
<td>Quad.</td>
<td>40.81</td>
<td>67.63</td>
<td>55.45</td>
<td>72.42</td>
</tr>
<tr>
<td></td>
<td>CSL [4]</td>
<td>Quad.</td>
<td>42.25</td>
<td>68.28</td>
<td>54.51</td>
<td>72.85</td>
</tr>
<tr>
<td></td>
<td>DCL (BCL) [47]</td>
<td>$D_{oc}$</td>
<td>41.40</td>
<td>65.82</td>
<td>56.27</td>
<td>73.80</td>
</tr>
<tr>
<td></td>
<td>GWD [5]</td>
<td>$D_{oc}$</td>
<td>44.07</td>
<td>71.92</td>
<td>62.56</td>
<td>77.94</td>
</tr>
<tr>
<td></td>
<td>KLD</td>
<td>$D_{oc}$</td>
<td>44.00</td>
<td>74.45</td>
<td>72.48</td>
<td>84.30</td>
</tr>
<tr>
<td>R²Det</td>
<td>-</td>
<td>$D_{oc}$</td>
<td>44.15</td>
<td>75.09</td>
<td>72.88</td>
<td>86.04</td>
</tr>
<tr>
<td></td>
<td>DCL (BCL) [47]</td>
<td>$D_{oc}$</td>
<td>46.84</td>
<td>74.87</td>
<td>74.96</td>
<td>85.70</td>
</tr>
<tr>
<td></td>
<td>GWD [5]</td>
<td>$D_{oc}$</td>
<td>46.73</td>
<td>75.84</td>
<td>78.00</td>
<td>86.71</td>
</tr>
<tr>
<td></td>
<td>KLD</td>
<td>$D_{oc}$</td>
<td>48.34</td>
<td>75.09</td>
<td>78.88</td>
<td>86.52</td>
</tr>
</tbody>
</table>
实验分析

- 在水平检测任务上（COCO数据集），KLD也是和GloU等常见损失函数保持差不多的水平。

![Table 6: Performance evaluation of KLD on classic horizontal detection.](image)

<table>
<thead>
<tr>
<th>Detector</th>
<th>Reg. Loss</th>
<th>AP</th>
<th>AP_{50}</th>
<th>AP_{75}</th>
<th>AP_{s}</th>
<th>AP_{m}</th>
<th>AP_{t}</th>
</tr>
</thead>
<tbody>
<tr>
<td>RetinaNet</td>
<td>Smooth L1</td>
<td>37.2</td>
<td>56.6</td>
<td>39.7</td>
<td>21.4</td>
<td>41.1</td>
<td>48.0</td>
</tr>
<tr>
<td></td>
<td>GloU</td>
<td>37.4</td>
<td>56.7</td>
<td>39.7</td>
<td>22.2</td>
<td>41.7</td>
<td>48.1</td>
</tr>
<tr>
<td></td>
<td>KLD</td>
<td><strong>38.0</strong></td>
<td>56.4</td>
<td>40.6</td>
<td>23.3</td>
<td>43.2</td>
<td>49.3</td>
</tr>
</tbody>
</table>

- 我们对KLD不同变体在两个数据集上进行了实验，发现最后的效果是差不多的，排除了不对称性对结果的干扰。

![Table 2: Ablation of different KLD-based regression loss form. The based detector is RetinaNet.](image)

| Dataset     | D_{kl}(N_p|N_i) | D_{kl}(N_i|N_p) | D_{kl\_min}(N_p|N_i) | D_{kl\_max}(N_p|N_i) | D_{js}(N_p|N_i) | D_{jcf\_frees}(N_p|N_i) |
|-------------|---------|----------------|-------------------|-------------------|----------------|-----------------|
| DOTA-v1.0   | 70.17   | 70.64          | **70.71**         | 70.55             | 69.67          | 70.56           |
| HRSC2016    | 82.83   | 83.82          | 83.60             | 82.70             | **84.06**      | 83.66           |
实验分析

最后在DOTA-v1.0的SOTA实验中，我们也取得了当前所发表论文里的最高性能。

Table 8: AP on different objects on DOTA-v1.0. Here R-101 denotes ResNet-101 (likewise for R-50, R-152), and RX-101 and H-104 represent ResNeXt101 [50] and Hourglass-104 [51], respectively. MS indicates that multi-scale training/testing is used. Red and blue indicate the top two performances.
基于高斯的SkewIoU近似，KFIoU

<table>
<thead>
<tr>
<th>$B(x, y, w, h, \theta)$</th>
<th>$G(\mu, \Sigma)$</th>
<th>$G_1(\mu_1, \Sigma_1)$</th>
<th>$G_2(\mu_2, \Sigma_2)$</th>
<th>$G_{kf}(\mu, \Sigma)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu = (x, y)^T$</td>
<td>$\Sigma = RAR^T$</td>
<td>$\Lambda = \begin{pmatrix} \cos \theta &amp; \sin \theta \ -\sin \theta &amp; \cos \theta \end{pmatrix}$</td>
<td>$L_c(\mu_1, \mu_2) = \sum_{t \in {i, j}} l_n(t_i, t'_i)$</td>
<td>$\alpha_{G_{kf}}(\mu, \Sigma) = G_1(\mu_1, \Sigma_1)G_2(\mu_2, \Sigma_2)$</td>
</tr>
<tr>
<td>$\Sigma = RAR^T$</td>
<td>$\Lambda = \begin{pmatrix} \cos \theta &amp; \sin \theta \ -\sin \theta &amp; \cos \theta \end{pmatrix}$</td>
<td>$\Lambda = \begin{pmatrix} \cos \theta &amp; \sin \theta \ -\sin \theta &amp; \cos \theta \end{pmatrix}$</td>
<td>$K = \Sigma_1(\Sigma_1 + \Sigma_2)^{-1}$</td>
<td>$\mu = \mu_1 + K(\mu_2 - \mu_1)$</td>
</tr>
<tr>
<td>$\Sigma = RAR^T$</td>
<td>$\Lambda = \begin{pmatrix} \cos \theta &amp; \sin \theta \ -\sin \theta &amp; \cos \theta \end{pmatrix}$</td>
<td>$\Lambda = \begin{pmatrix} \cos \theta &amp; \sin \theta \ -\sin \theta &amp; \cos \theta \end{pmatrix}$</td>
<td>$\Sigma = \Sigma_1 - K\Sigma_2$</td>
<td>$L_{kf}(\Sigma_1, \Sigma_2) = 1 - \text{KFIoU}$</td>
</tr>
</tbody>
</table>

(a) Convert the bounding box to a Gaussian distribution  
(b) Narrow the center distance by center point loss  
(c) Get the Gaussian distribution of the overlapping area by Kalman filtering  
(d) Invert Gaussian distribution to bbox to calculate approximate SkewIoU

趋势一致性分析

\[
\text{EMean} = \frac{1}{N} \sum_{i=1}^{N} (\text{SkewIoU}_{plain} - \text{SkewIoU}_{app}),
\]

\[
\text{EVar} = \frac{1}{N} \sum_{i=1}^{N} (\text{SkewIoU}_{app} - \text{EMean})^2
\]

Table 1: Comparison of the properties and performance of different regression losses. Base model is RetinaNet. BC, SI and HP denote Boundary Continuity, Scale Invariance and Hyperparameter.

<table>
<thead>
<tr>
<th>Loss</th>
<th>Representation</th>
<th>Implement</th>
<th>BC</th>
<th>SI</th>
<th>Consistency</th>
<th>HP</th>
<th>EVar(^4)</th>
<th>DOTA-v1.0</th>
<th>DOTA-v1.5</th>
<th>DOTA-v2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smooth L1</td>
<td>bbox</td>
<td>easy</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>✓ (σ)</td>
<td>0.073201718</td>
<td>64.17</td>
<td>56.10</td>
<td>43.06</td>
</tr>
<tr>
<td>plain SkewIoU</td>
<td>bbox</td>
<td>hard</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>-</td>
<td>68.27</td>
<td>59.01</td>
<td>45.87</td>
</tr>
<tr>
<td>GWD</td>
<td>Gaussian</td>
<td>easy</td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>✓ (τ)</td>
<td>0.019041297</td>
<td>68.93</td>
<td>60.03</td>
<td>46.65</td>
</tr>
<tr>
<td>KLD</td>
<td>Gaussian</td>
<td>easy</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓ (τ)</td>
<td>0.007653582</td>
<td>71.28</td>
<td>62.50</td>
<td>47.69</td>
</tr>
<tr>
<td>KFIoU (ours)</td>
<td>Gaussian</td>
<td>easy</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>0.002348353</td>
<td>70.64</td>
<td>62.71</td>
<td>48.04</td>
</tr>
</tbody>
</table>
高斯建模后续扩展工作——KFIoU

- 趋势一致性分析
高斯建模后续扩展工作——3D目标检测

3D高斯表示

(b) 3-D BBox with square shape (c) Top view of the 3-D BBox and in top-view e.g. pedestrian. the heading is arbitrary given the isotropic 2-D Gaussian.

类正方形退化问题

https://github.com/zhanggefan/mmdet3d-gaussian
有向检测工具

- **MMRotate**：基于PyTorch的有向检测工具
  ![MMRotate Logo](https://github.com/open-mmlab/mmrotate)
  - OpenMMLab website 🔥
  - OpenMMLab platform 🔄
  - Docs: passing
  - Build: passing
  - Codecov: unknown
  - PyPI: v0.3.0
  - License: Apache 2.0
  - Issue resolution: 3 h
  - Open issues: 100%

- **AlphaRotate**：基于TensorFlow的有向检测工具
  ![AlphaRotate Logo](https://github.com/yangxue0827/RotationDetection)
  - AlphaRotate: A Rotation Detection Benchmark using TensorFlow
  - Docs: passing
  - PyPI package: 1.0.1
  - Downloads: 1k
  - License: Apache 2.0
  - Issue resolution: 2 d
  - Open issues: 14%

https://github.com/open-mmlab/mmrotate
https://github.com/yangxue0827/RotationDetection
谢谢！