视觉有向目标的高精度检测

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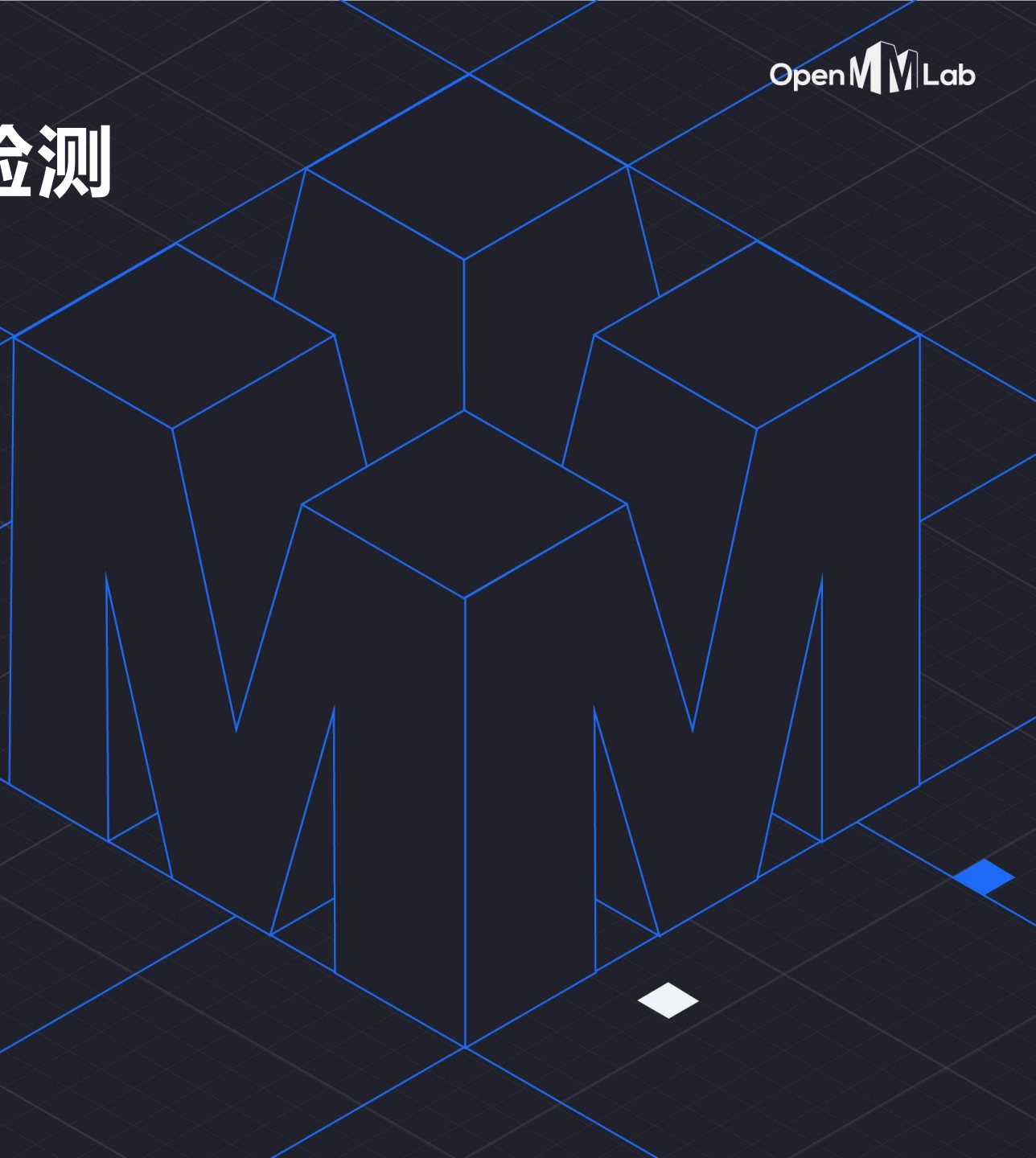
【OpenMMLab 社区开放麦】是由 OpenMMLab 发起，面向所有社区成员的社区分享直播活动，每周四晚八点准点播出。旨在搭建一个知识分享的舞台，在这里，社区里的每个人都能拿起话筒分享你的知识和见解。我们一直认为，分享与交流能更好地促进知识的传播；平等与共建能更好地维持社区的氛围。

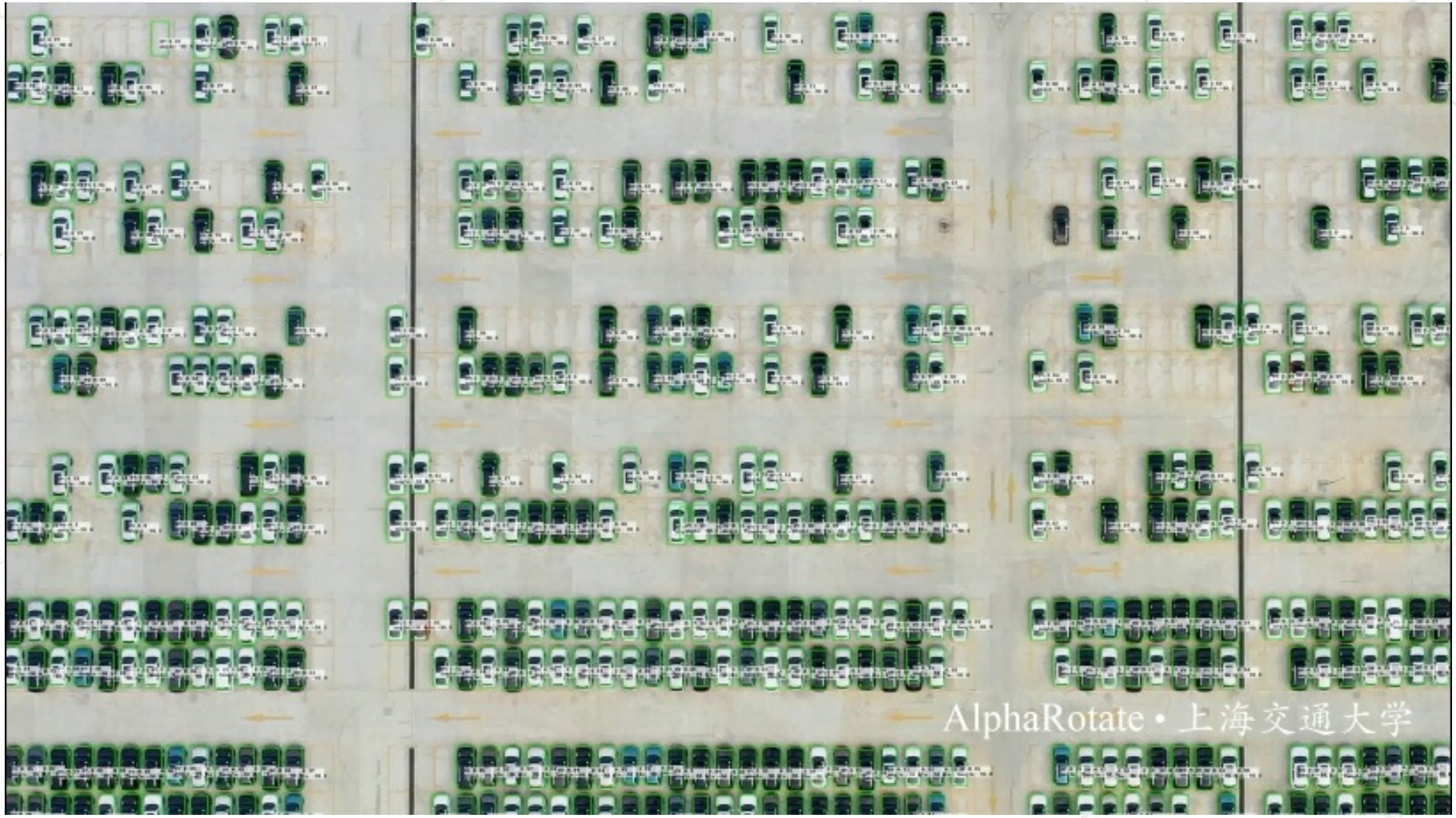


大纲

1. 有向目标检测
2. 问题和挑战
3. 解决方法
4. 实验分析

有向目标检测

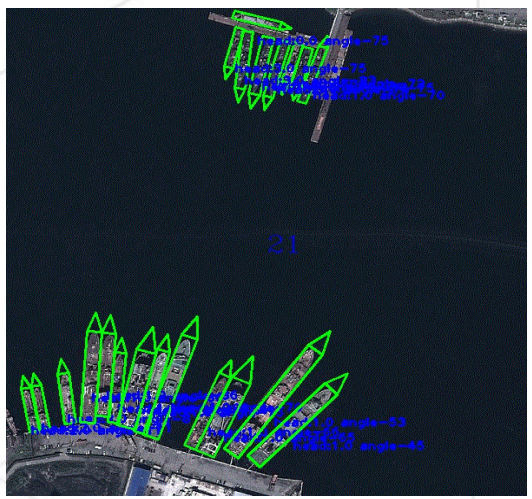
- 预测具有方向的边界框并对目标进行识别

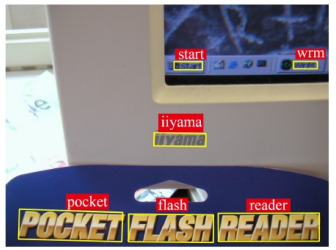


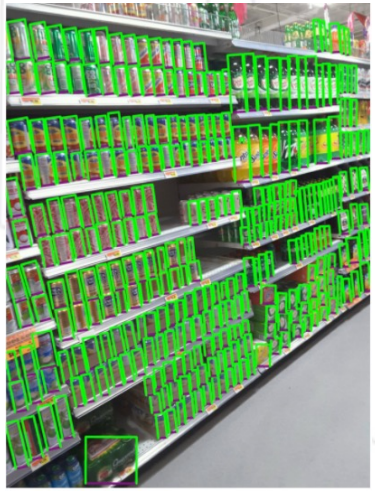
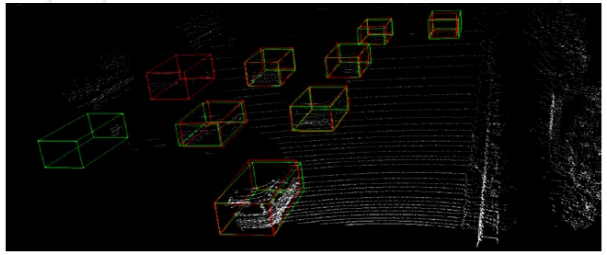
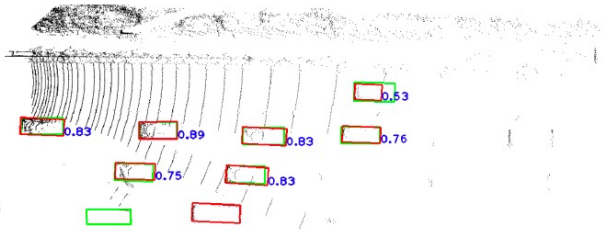
有向目标检测

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



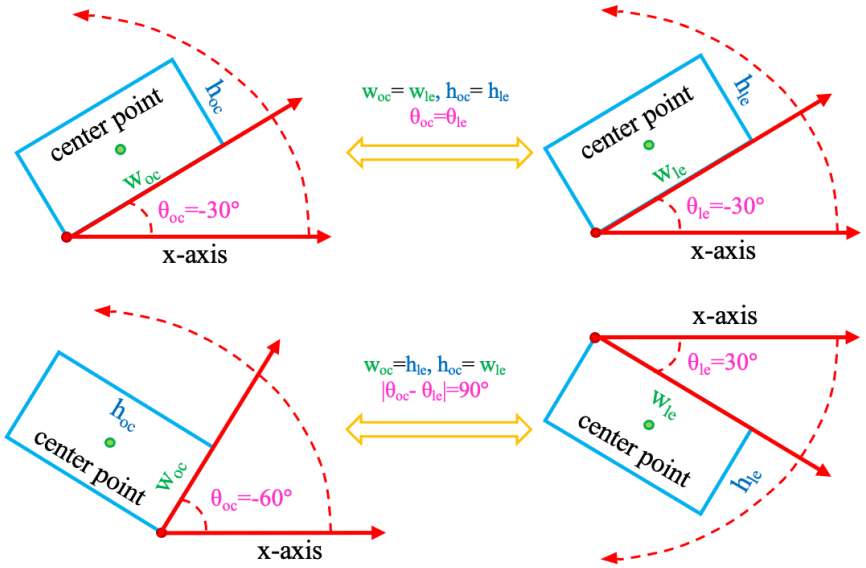


有向目标检测

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：

$$D_{le}(w_{le},h_{le},\theta_{le}) = \begin{cases} D_{oc}(w_{oc},h_{oc},\theta_{oc}), & w_{oc} \geq h_{oc} \\ D_{oc}(h_{oc},w_{oc},\theta_{oc}+90°), & otherwise \end{cases}$$

$$D_{oc}(w_{oc},h_{oc},\theta_{oc}) = \begin{cases} D_{le}(w_{le},h_{le},\theta_{le}), & \theta_{le} \in [-90°,0°) \\ D_{le}(h_{le},w_{le},\theta_{le}-90°), & otherwise \end{cases}$$

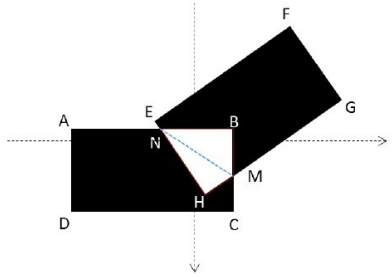
https://zhuanlan.zhihu.com/p/459018810

有向目标检测

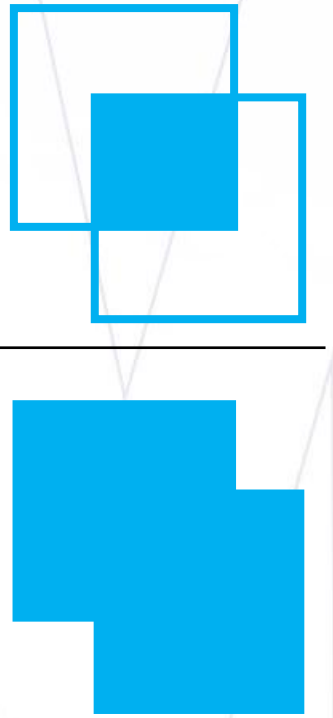
旋转框IoU的计算：

Algorithm 1 IoU computation

Input: Rectangles $R_1, R_2, ..., R_N$
IoU$[1, N][1, N] \leftarrow 0$
for each pair of R_i, R_j $(i < j)$ **do**
    Point set $PSet \leftarrow \emptyset$
    Add intersection points of R_i and R_j to $PSet$
    Add the vertices of R_i inside R_j into $PSet$
    Add the vertices of R_j inside R_i into $PSet$
    Sort $PSet$ to anti-clockwise order
    Compute intersection I of $PSet$ by triangulation
    IoU$(i, j) \leftarrow$ (Area(R_i) + Area(R_j) - $I)/I$
end for
return IoU



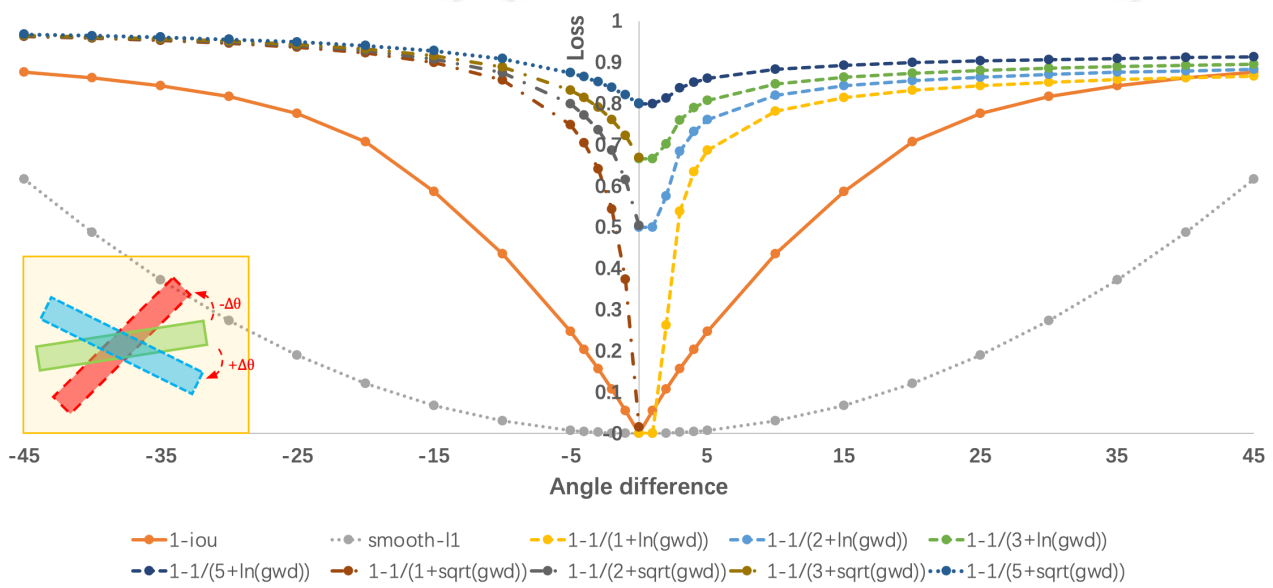
$$\text{IoU} = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

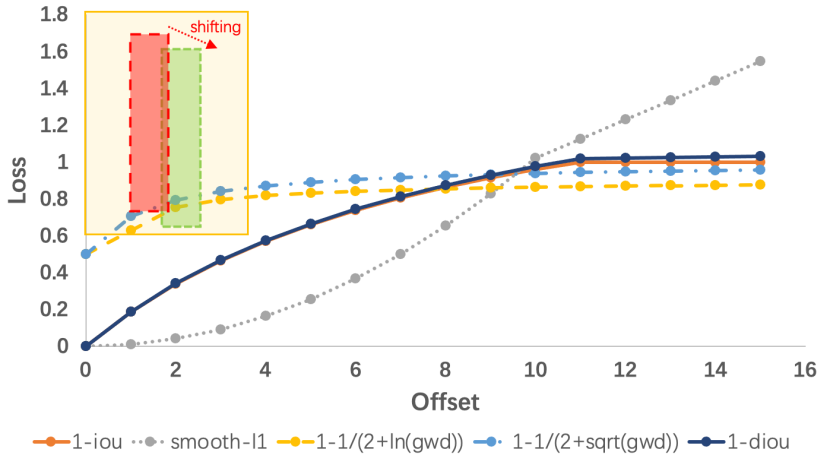


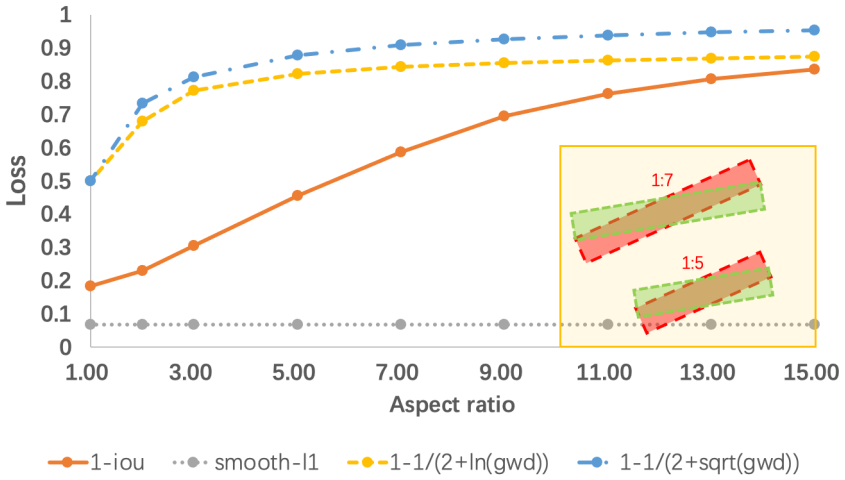
https://github.com/open-mmlab/mmcv/pull/1854

问题与挑战

评估与损失不一致问题



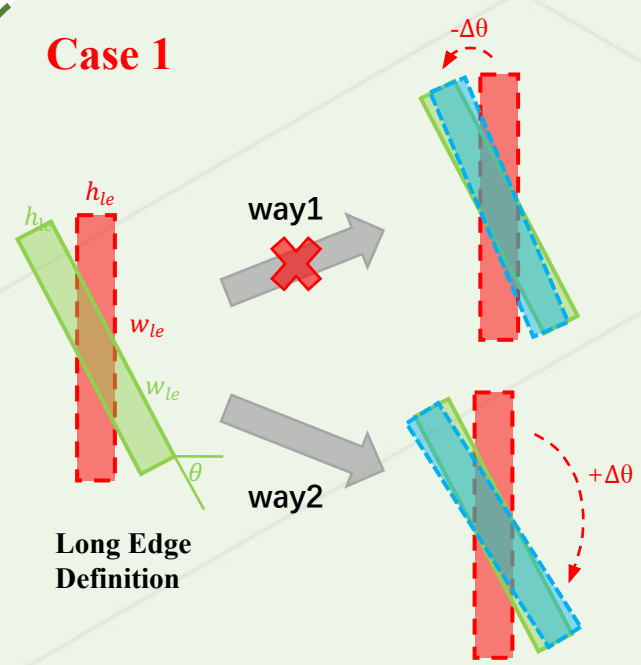




问题与挑战

边界不连续问题

Case 1



Long Edge Definition

长边定义法

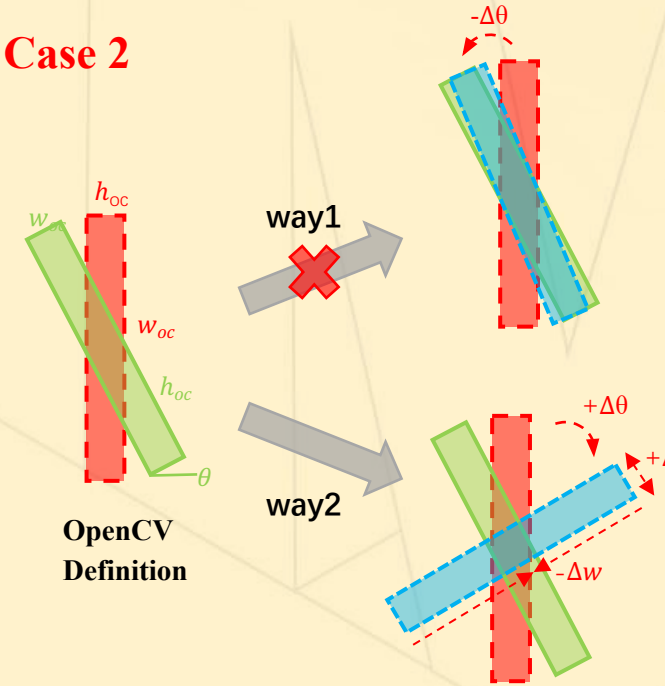
Anchor/Proposal: (0,0,70,10, −90°)
Ground-Truth: (0,0,70,10,65°)
Predict box: (0,0,70,10, −115°)

$w = w, h = h, |\theta - \theta| = 180°$
IoU< G, P >≈ 1
Smooth-L1 Loss< G, P >PoA≫ 0

Anchor/Proposal: (0,0,70,10, −90°)
Ground-Truth: (0,0,70,10,65°)
Predict box: (0,0,70,10,65°)

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

Case 2



OpenCV Definition

OpenCV定义法

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

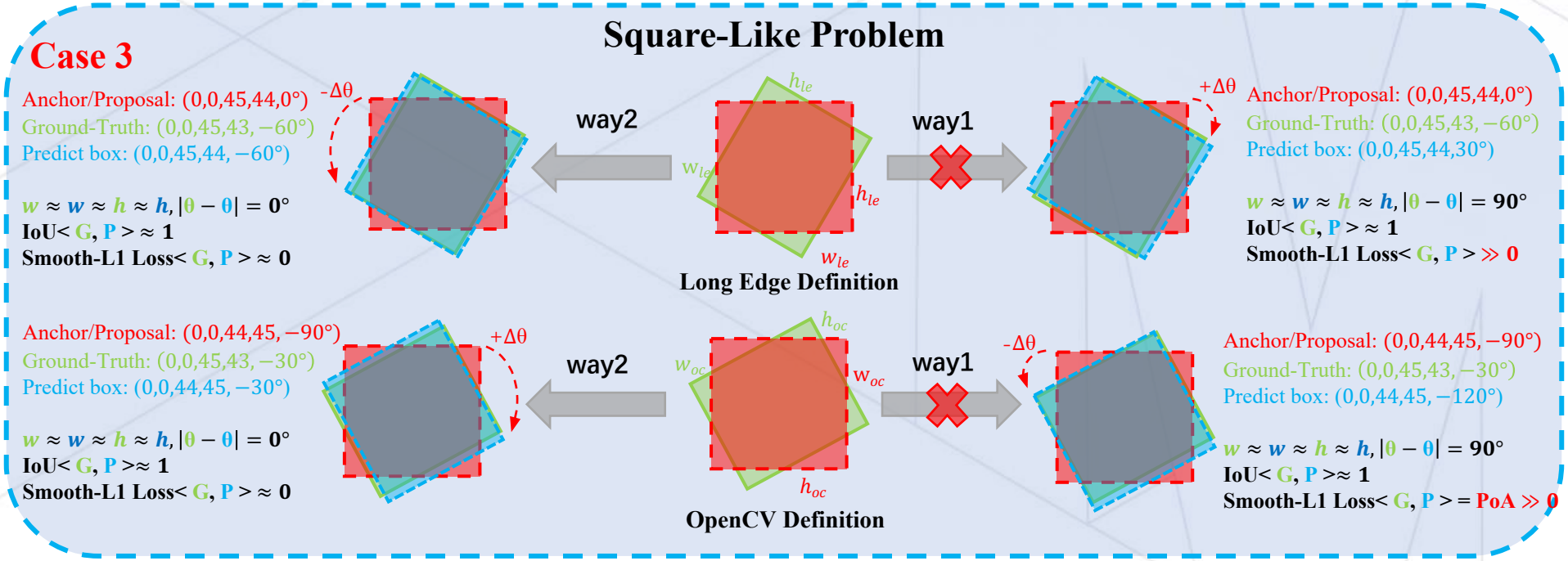
$w = h, h = w, |\theta - \theta| = 90°$
IoU< G, P >≈ 1
Smooth-L1 Loss< G, P >PoA + EoE≫ 0

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

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

问题与挑战

类正方形检测问题

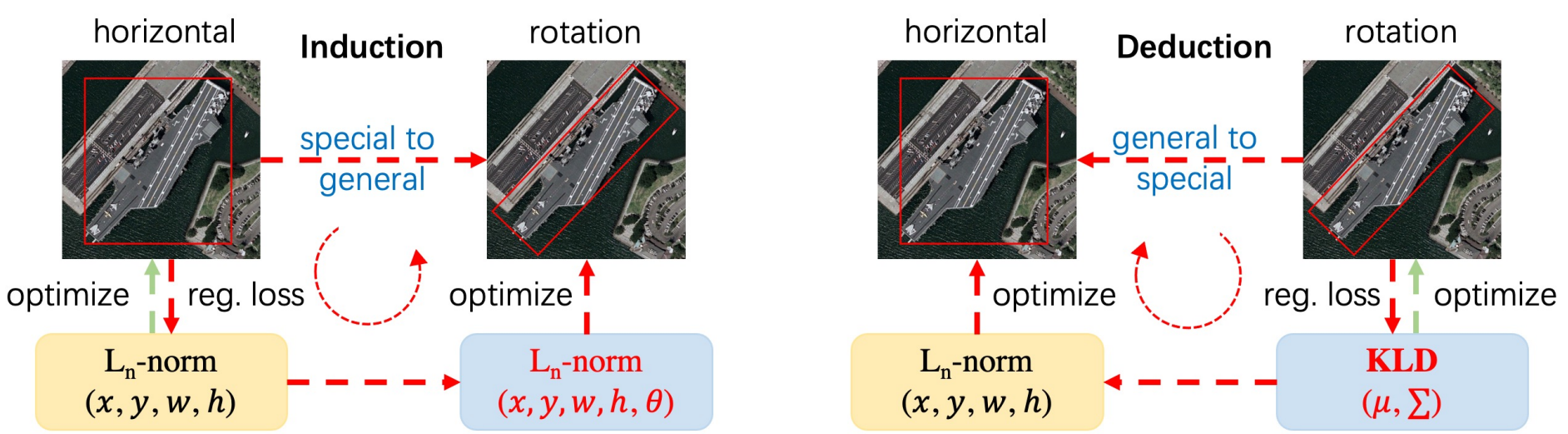


长宽比越小，IoU对角度越不敏感

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



X. Yang, et al. "Rethinking Rotated Object Detection with Gaussian Wasserstein Distance Loss." In ICML 2021.
X. Yang, et al. "Learning High-Precision Bounding Box for Rotated Object Detection via Kullback-Leibler Divergence." In NeurIPS 2021.

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：

$$t_x^p = \frac{x_p - x_a}{w_a}, t_y^p = \frac{y_p - y_a}{h_a}, t_w^p = \ln\left(\frac{w_p}{w_a}\right), t_h^p = \ln\left(\frac{h_p}{h_a}\right)$$

来匹配实际的偏移量：

$$t_x^t = \frac{x_t - x_a}{w_a}, t_y^t = \frac{y_t - y_a}{h_a}, t_w^t = \ln\left(\frac{w_t}{w_a}\right), t_h^t = \ln\left(\frac{h_t}{h_a}\right)$$

- 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：

$$t_\theta^p = f(\theta_p - \theta_a), t_\theta^t = f(\theta_t - \theta_a)$$

解决方法

归纳范式

- 然后回归损失也常采用Ln-norm：

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

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 $\Delta t_\theta = t_\theta^p - t_\theta^t = \Delta\theta$.

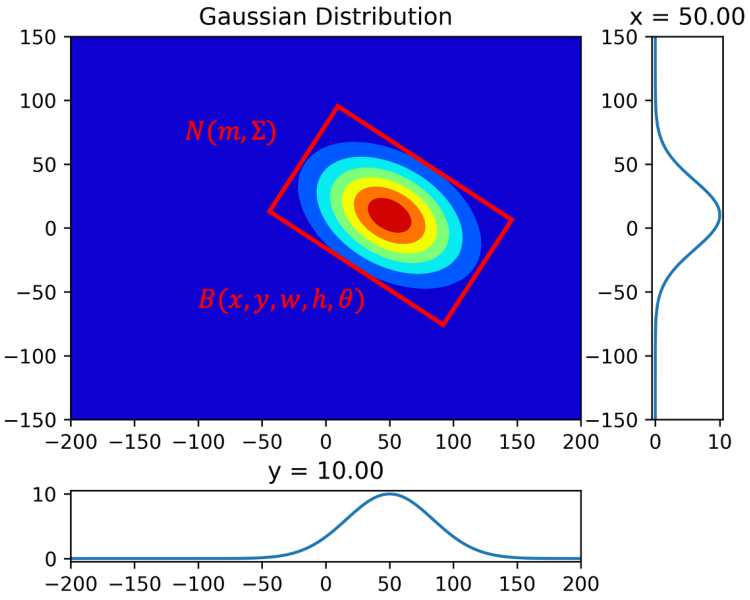
- 五个参数的优化和目标本身形状等关联不大，使得我们需要根据不同的数据集特点进行权重的调整。比如大长宽比目标可能需要着重关注角度参数，小目标则需要关注中心点参数，因此这些参数的轻微偏移都会造成这些目标预测精准度（IoU）的急剧下降。

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

$$
\begin{aligned}
\mathbf{\Sigma}^{1/2} &= \mathbf{R}\mathbf{S}\mathbf{R}^{\top} \\
&= \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} \frac{w}{2} & 0 \\ 0 & \frac{h}{2} \end{pmatrix} \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \\
&= \begin{pmatrix} \frac{w}{2}\cos^2\theta + \frac{h}{2}\sin^2\theta & \frac{w-h}{2}\cos\theta\sin\theta \\ \frac{w-h}{2}\cos\theta\sin\theta & \frac{w}{2}\sin^2\theta + \frac{h}{2}\cos^2\theta \end{pmatrix} \\
\mathbf{m} &= (x, y)^{\top}
\end{aligned}
$$



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

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

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

解决方法

Wasserstein Distance

- 通用公式：

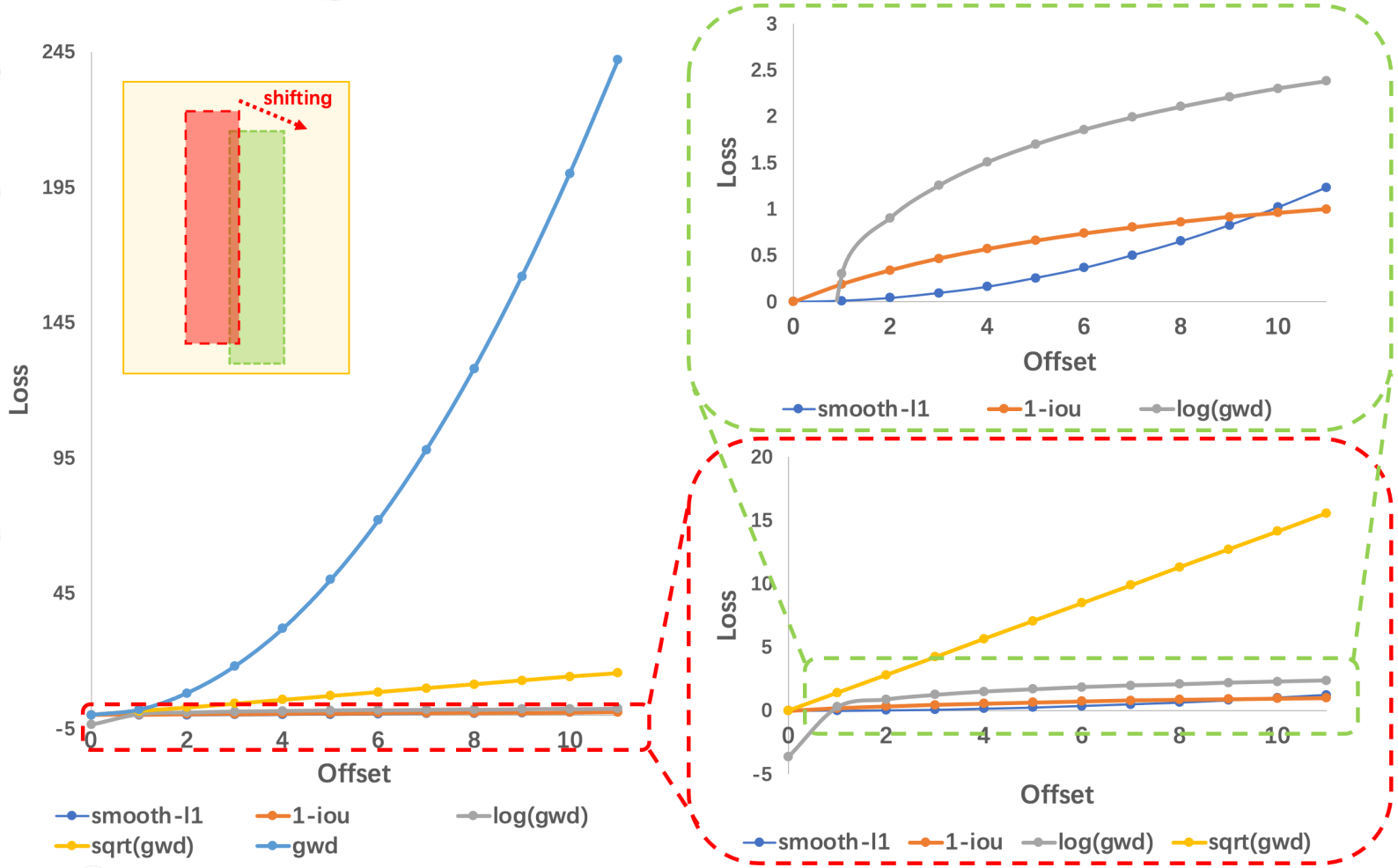
$$\mathbf{D}_w(\mathcal{N}_p, \mathcal{N}_t)^2 = \underbrace{\|\boldsymbol{\mu}_p - \boldsymbol{\mu}_t\|_2^2}_{\text{center distance}} + \underbrace{\mathbf{Tr}(\boldsymbol{\Sigma}_p + \boldsymbol{\Sigma}_t - 2(\boldsymbol{\Sigma}_p^{1/2}\boldsymbol{\Sigma}_t\boldsymbol{\Sigma}_p^{1/2})^{1/2})}_{\text{coupling terms about } h_p,\ w_p \text{ and } \theta_p}$$

- 水平特殊情况：

$$\begin{aligned}\mathbf{D}_w^h(\mathcal{N}_p, \mathcal{N}_t)^2 &= \|\boldsymbol{\mu}_p - \boldsymbol{\mu}_t\|_2^2 + \|\boldsymbol{\Sigma}_p^{1/2} - \boldsymbol{\Sigma}_t^{1/2}\|_F^2 \\ &= (x_p - x_t)^2 + (y_p - y_t)^2 + \left((w_p - w_t)^2 + (h_p - h_t)^2\right)/4 \\ &= l_2\text{-norm}(\Delta x, \Delta y, \Delta w/2, \Delta h/2)\end{aligned}$$

解决方法

Wasserstein Distance



解决方法

Wasserstein Distance

- 通用公式：

$$\mathbf{D}_w(\mathcal{N}_p,\mathcal{N}_t)^2 = \underbrace{\|\boldsymbol{\mu}_p-\boldsymbol{\mu}_t\|_2^2}_{\text{center distance}} + \underbrace{\mathbf{Tr}(\boldsymbol{\Sigma}_p+\boldsymbol{\Sigma}_t-2(\boldsymbol{\Sigma}_p^{1/2}\boldsymbol{\Sigma}_t\boldsymbol{\Sigma}_p^{1/2})^{1/2})}_{\text{coupling terms about } h_p,\ w_p \text{ and } \theta_p}$$

- 水平特殊情况：

$$\begin{aligned}\mathbf{D}_w^h(\mathcal{N}_p,\mathcal{N}_t)^2 &= \|\boldsymbol{\mu}_p-\boldsymbol{\mu}_t\|_2^2 + \|\boldsymbol{\Sigma}_p^{1/2}-\boldsymbol{\Sigma}_t^{1/2}\|_F^2 \\ &= (x_p-x_t)^2+(y_p-y_t)^2+\left((w_p-w_t)^2+(h_p-h_t)^2\right)/4 \\ &= l_2\text{-norm}(\Delta x,\Delta y,\Delta w/2,\Delta h/2)\end{aligned}$$

- 损失函数

$$L_{gwd} = 1-\frac{1}{\tau+f(\mathbf{D}_w^2)},\quad \tau\geq 1$$

解决方法

Kullback-Leibler Divergence

- 通用公式：

$$\mathbf{D}_{kl}(\mathcal{N}_p||\mathcal{N}_t) = \underbrace{\frac{1}{2}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t)^\top \boldsymbol{\Sigma}_t^{-1}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t)}_{\text{term about } x_p \text{ and } y_p} + \underbrace{\frac{1}{2}\mathbf{Tr}(\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\Sigma}_p) + \frac{1}{2}\ln\frac{|\boldsymbol{\Sigma}_t|}{|\boldsymbol{\Sigma}_p|}}_{\text{coupling terms about } h_p,\ w_p \text{ and } \theta_p} - 1$$

或

$$\mathbf{D}_{kl}(\mathcal{N}_t||\mathcal{N}_p) = \underbrace{\frac{1}{2}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t)^\top \boldsymbol{\Sigma}_p^{-1}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t) + \frac{1}{2}\mathbf{Tr}(\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\Sigma}_t) + \frac{1}{2}\ln\frac{|\boldsymbol{\Sigma}_p|}{|\boldsymbol{\Sigma}_t|}}_{\text{chain coupling of all parameters}} - 1$$

- 水平特殊情况：

$$\begin{aligned}\mathbf{D}_{kl}^{h}(\mathcal{N}_p||\mathcal{N}_t) =& \frac{1}{2}\left(\frac{w_p^2}{w_t^2} + \frac{h_p^2}{h_t^2} + \frac{4\Delta^2 x}{w_t^2} + \frac{4\Delta^2 y}{h_t^2} + \ln\frac{w_t^2}{w_p^2} + \ln\frac{h_t^2}{h_p^2} - 2\right) \\ =& 2l_2\text{-norm}(\Delta t_x, \Delta t_y) + l_1\text{-norm}(\Delta t_w, \Delta t_h) + \frac{1}{2}l_2\text{-norm}(\frac{1}{\Delta t_w}, \frac{1}{\Delta t_h}) - 1\end{aligned}$$

解决方法

高精度分析 （KLD>GWD>smooth L1）：

- KLD主要三项的具体表达式：

$$(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t)^\top \boldsymbol{\Sigma}_t^{-1} (\boldsymbol{\mu}_p - \boldsymbol{\mu}_t) = \frac{4(\Delta x \cos\theta_t + \Delta y \sin\theta_t)^2}{w_t^2} + \frac{4(\Delta y \cos\theta_t - \Delta x \sin\theta_t)^2}{h_t^2}$$

$$\mathbf{Tr}(\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\Sigma}_p) = \frac{h_p^2}{w_t^2}\sin^2\Delta\theta + \frac{w_p^2}{h_t^2}\sin^2\Delta\theta + \frac{h_p^2}{h_t^2}\cos^2\Delta\theta + \frac{w_p^2}{w_t^2}\cos^2\Delta\theta$$

$$\ln\frac{|\boldsymbol{\Sigma}_t|}{|\boldsymbol{\Sigma}_p|} = \ln\frac{h_t^2}{h_p^2} + \ln\frac{w_t^2}{w_p^2}$$

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 θ_t=0，对KLD的μ_p求导数：

$$\frac{\partial \mathbf{D}_{kl}(\mu_p)}{\partial \mu_p} = \left(\frac{4}{w_t^2}\Delta x, \frac{4}{h_t^2}\Delta y\right)^\top$$

- 当θ_t≠0时，目标的偏移量（Δx和Δy）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 L2关于偏移量的梯度分别是：

$$\frac{\partial \mathbf{D}_{w}(\mu_p)}{\partial \mu_p} = (2\Delta x, 2\Delta y)^\top \qquad \frac{\partial L_2(\mu_p)}{\partial \mu_p} = (\frac{2}{w_a^2}\Delta x, \frac{2}{h_a^2}\Delta y)^\top$$

解决方法

高精度分析 （KLD>GWD>smooth L1）：

- 对KLD的h_p和w_p求导数：

$$\frac{\partial \mathbf{D}_{kl}(\mathbf{\Sigma}_p)}{\partial \ln h_p} = \frac{h_p^2}{h_t^2}\cos^2\Delta\theta + \frac{h_p^2}{w_t^2}\sin^2\Delta\theta - 1, \quad \frac{\partial \mathbf{D}_{kl}(\mathbf{\Sigma}_p)}{\partial \ln w_p} = \frac{w_p^2}{w_t^2}\cos^2\Delta\theta + \frac{w_p^2}{h_t^2}\sin^2\Delta\theta - 1$$

- 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：

$$\frac{\partial \mathbf{D}_{kl}(\mathbf{\Sigma}_p)}{\partial \ln h_p} = \frac{h_p^2}{h_t^2} - 1, \frac{\partial \mathbf{D}_{kl}(\mathbf{\Sigma}_p)}{\partial \ln w_p} = \frac{w_p^2}{w_t^2} - 1$$

- 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：

$$\frac{\partial \mathbf{D}_{kl}(\mathbf{\Sigma}_p)}{\partial \theta_p} = \left(\frac{h_p^2 - w_p^2}{w_t^2} + \frac{w_p^2 - h_p^2}{h_t^2}\right) \sin 2\Delta\theta$$

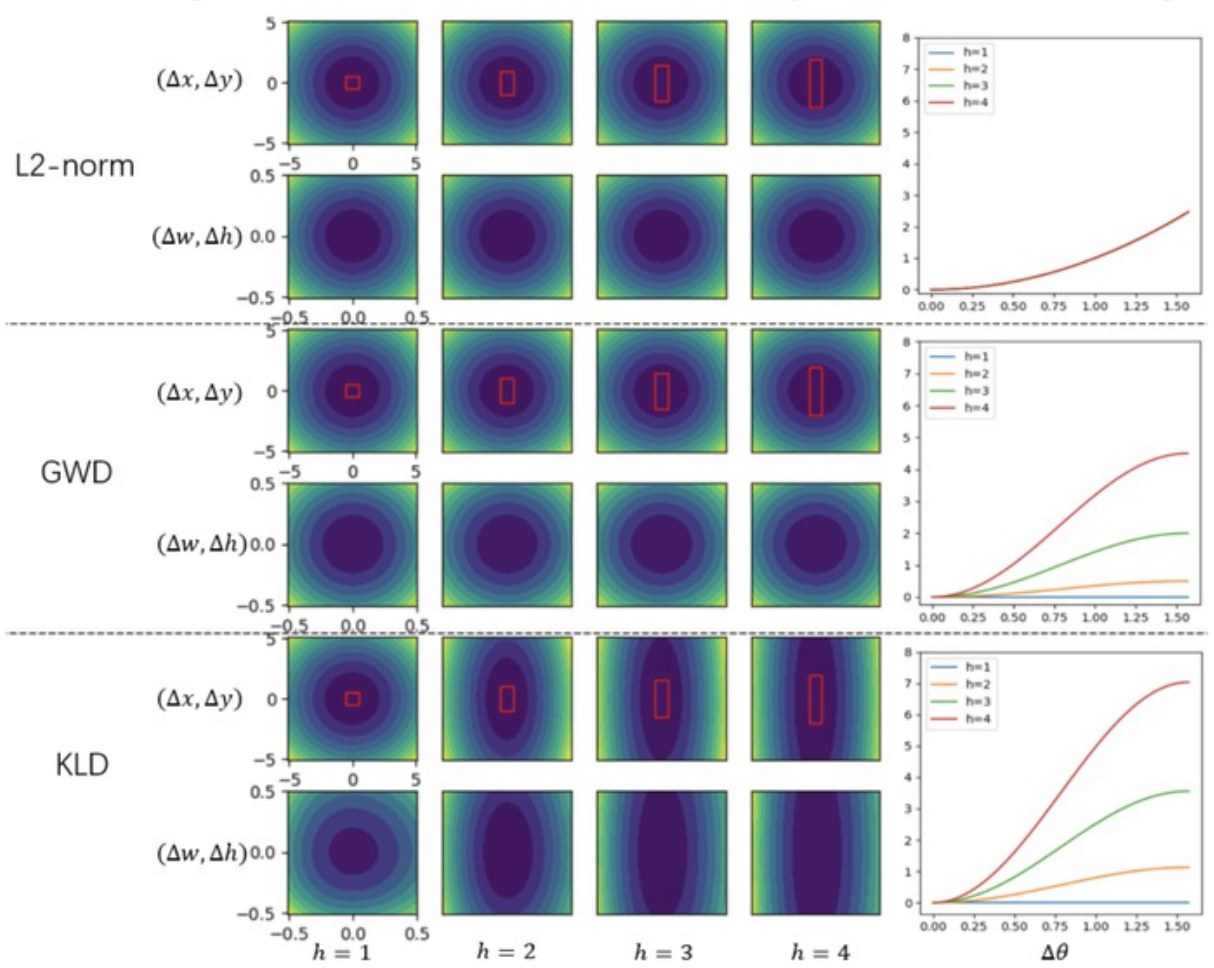
- 角度差$\Delta\theta$的优化又和两边h_p和w_p有关。当h_p=h_t，w_p=w_t时：

$$\frac{\partial \mathbf{D}_{kl}(\mathbf{\Sigma}_p)}{\partial \theta_p} = \left(\frac{h_t^2}{w_t^2} + \frac{w_t^2}{h_t^2} - 2\right) \sin 2\Delta\theta \geq \sin 2\Delta\theta$$

- 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。

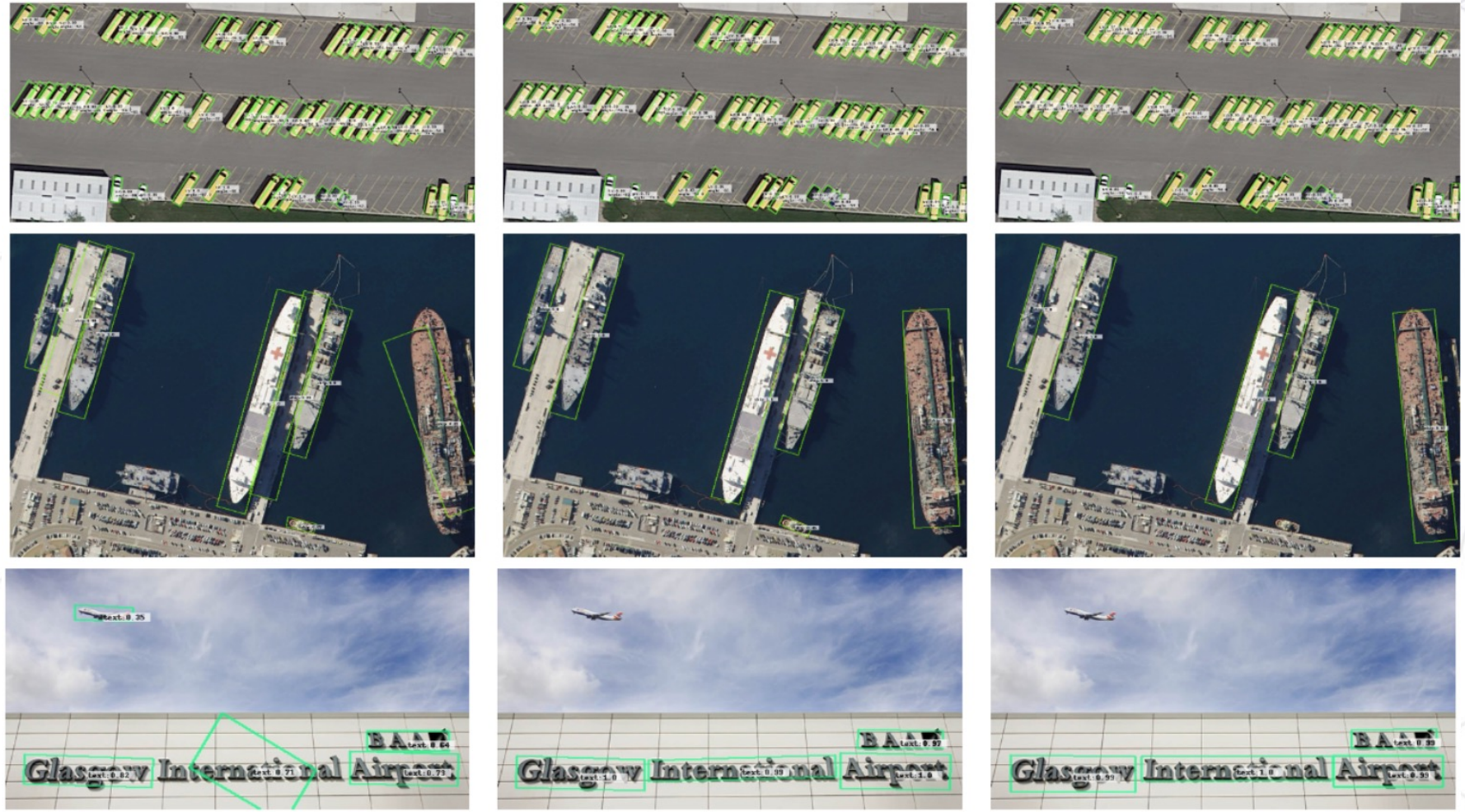
解决方法

高精度分析 （KLD>GWD>smooth L1）：



解决方法

高精度分析 （KLD>GWD>smooth L1）：



解决方法

尺度不变性证明

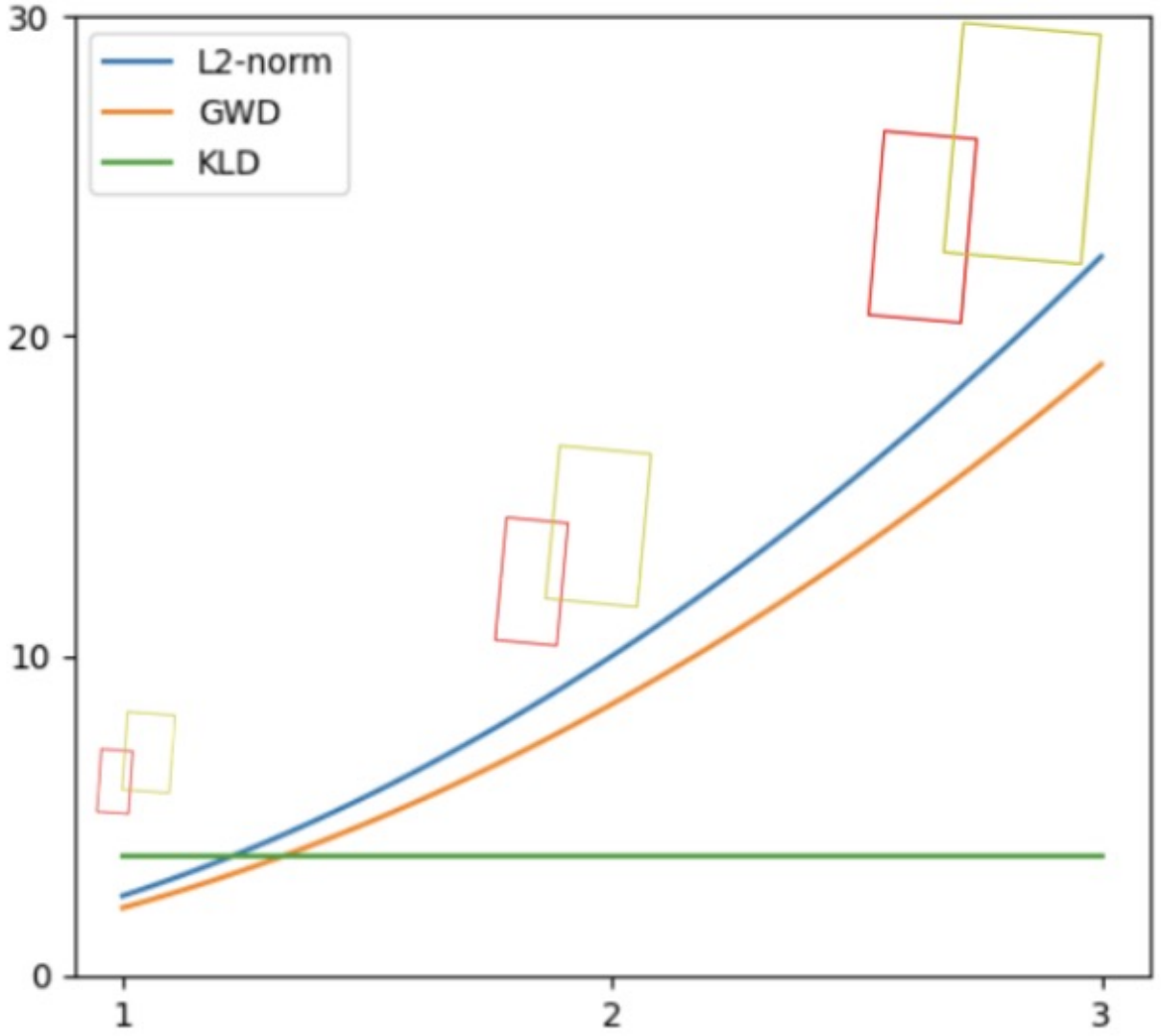
- 很明显GWD和 L_2不具有尺度不变性。
- 对于两个已知的高斯分布 $\mathbf{X}_p \sim \mathcal{N}_p(\boldsymbol{\mu}_p, \boldsymbol{\Sigma}_p)$ 和 $\mathbf{X}_t \sim \mathcal{N}_t(\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t)$，假设有一个满秩的矩阵 $\mathbf{M}$ ($|\mathbf{M}| \neq \mathbf{0}$)，有：$\mathbf{X}_{p'} = \mathbf{M}\mathbf{X}_p \sim \mathcal{N}_p(\mathbf{M}\boldsymbol{\mu}_p, \mathbf{M}\boldsymbol{\Sigma}_p\mathbf{M}^\top), \mathbf{X}_{t'} = \mathbf{M}\mathbf{X}_t \sim \mathcal{N}_t(\mathbf{M}\boldsymbol{\mu}_t, \mathbf{M}\boldsymbol{\Sigma}_t\mathbf{M}^\top)$
- 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：

$$
\begin{aligned}
\mathbf{D}_{kl}(\mathcal{N}_{p'}||\mathcal{N}_{t'}) &= \frac{1}{2}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t)^\top \mathbf{M}^\top (\mathbf{M}^\top)^{-1} \boldsymbol{\Sigma}_t^{-1} \mathbf{M}^{-1} \mathbf{M}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t) \\
&+ \frac{1}{2}\mathbf{Tr}\left((\mathbf{M}^\top)^{-1}\boldsymbol{\Sigma}_t^{-1}\mathbf{M}^{-1}\mathbf{M}\boldsymbol{\Sigma}_p\mathbf{M}^\top\right) + \frac{1}{2}\ln\frac{|\mathbf{M}||\boldsymbol{\Sigma}_t||\mathbf{M}^\top|}{|\mathbf{M}||\boldsymbol{\Sigma}_p||\mathbf{M}^\top|} - 1 \\
&= \frac{1}{2}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t)^\top \boldsymbol{\Sigma}_t^{-1}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_t) + \frac{1}{2}\mathbf{Tr}\left(\mathbf{M}^\top(\mathbf{M}^\top)^{-1}\boldsymbol{\Sigma}_t^{-1}\mathbf{M}^{-1}\mathbf{M}\boldsymbol{\Sigma}_p\right) + \frac{1}{2}\ln\frac{|\boldsymbol{\Sigma}_t|}{|\boldsymbol{\Sigma}_p|} - 1 \\
&= \mathbf{D}_{kl}(\mathcal{N}_p||\mathcal{N}_t)
\end{aligned}
$$

- 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 4: High-precision detection experiment under different regression loss. 'R', 'F' and 'G' indicate random rotation, flipping, and graying, respectively. The resolution of HRSC2016, MSRA-TD500 and ICDAR2015 are 500×500, $800 \times 1,000$ and $800 \times 1,000$, respectively.

Method	Dataset	Data Aug.	Reg. Loss	$Hmean_{50}/AP_{50}$	$Hmean_{60}/AP_{60}$	$Hmean_{75}/AP_{75}$	$Hmean_{85}/AP_{85}$	$Hmean_{50:95}/AP_{50:95}$
RetinaNet	HRSC2016	R+F+G	Smooth L1	84.28	74.74	48.42	12.56	47.76
			GWD	85.56 (+1.28)	84.04 (+9.30)	60.31 (+11.89)	17.14 (+4.58)	52.89 (+5.13)
			KLD	**87.45** (+3.17)	**86.72** (+11.98)	**72.39** (+23.97)	**27.68** (+15.12)	**57.80** (+10.04)
R^3Det			Smooth L1	88.52	79.01	43.42	4.58	46.18
			GWD	89.43 (+0.91)	88.89 (+9.88)	65.88 (+22.46)	15.02 (+10.44)	56.07 (+9.89)
			KLD	**89.97** (+1.45)	**89.73** (+10.72)	**77.38** (+33.96)	**25.12** (+20.54)	**61.40** (+15.22)
RetinaNet	MSRA-TD500	R+F	Smooth L1	70.98	62.42	36.73	12.56	37.89
			GWD	76.76 (+5.78)	68.58 (+6.16)	44.21 (+7.48)	17.75 (+5.19)	43.62 (+5.73)
			KLD	**76.96** (+5.98)	**70.08** (+7.66)	**46.95** (+10.22)	**19.59** (+7.03)	**45.24** (+7.35)
	ICDAR2015	F	Smooth L1	69.78	64.15	36.97	8.71	37.73
			GWD	74.29 (+4.51)	68.34 (+4.19)	43.39 (+6.42)	10.50 (+1.79)	41.68 (+3.95)
			KLD	**75.32** (+5.54)	**69.94** (+5.79)	**44.46** (+7.49)	**10.70** (+1.99)	**42.68** (+4.95)
		R+F	Smooth L1	74.83	69.46	42.02	11.59	41.98
			GWD	76.15 (+1.32)	71.26 (+1.80)	**45.59** (+3.57)	**11.65** (+0.06)	43.58 (+1.60)
			KLD	**77.92** (+3.09)	**72.77** (+3.31)	43.27 (+1.25)	11.09 (-0.50)	**43.65** (+1.67)
R^3Det		F	Smooth L1	74.28	68.12	35.73	8.01	39.10
			GWD	75.59 (+1.31)	68.36 (+0.24)	40.24 (+4.51)	9.15 (+1.14)	40.80 (+1.70)
			KLD	**77.72** (+2.43)	**71.99** (+3.87)	**43.95** (+8.22)	**10.43** (+2.42)	**43.29** (+4.19)
		R+F	Smooth L1	75.53	69.69	37.69	9.03	40.56
			GWD	77.09 (+1.56)	71.52 (+1.83)	41.08 (+3.39)	10.10 (+1.07)	42.17 (+1.61)
			KLD	**79.63** (+4.63)	**73.30** (+3.61)	**43.51** (+5.82)	**10.61** (+1.58)	**43.61** (+3.05)

实验分析

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 ($\theta \in [-90°, 0°)$) and Long Edge Definition ($\theta \in [-90°, 90°)$) of RBox.

Baseline	Method	Box Def.	v1.0 tranval/test									v1.0 train/val			v1.5	v2.0
			BR†	SV†	LV†	SH†	HA†	ST‡	RA‡	7-AP_{50}	AP_{50}	AP_{50}	AP_{75}	$AP_{50:95}$	AP_{50}	AP_{50}
RetinaNet	-	D_{oc}	42.17	65.93	51.11	72.61	53.24	78.38	62.00	60.78	65.73	64.70	32.31	34.50	58.87	44.16
	-	D_{le}	38.31	60.48	49.77	68.29	51.28	78.60	60.02	58.11	64.17	62.21	26.06	31.49	56.10	43.06
	IoU-Smooth L1 [3]	D_{oc}	44.32	63.03	51.25	72.78	56.21	77.98	63.22	61.26	66.99	64.61	34.17	36.23	59.16	46.31
	Modulated Loss [46]	D_{oc}	42.92	67.92	52.91	72.67	53.64	**80.22**	58.21	61.21	66.05	63.50	33.32	34.61	57.75	45.17
	Modulated Loss [46]	Quad.	43.21	70.78	54.70	72.68	**60.99**	79.72	62.08	63.45	67.20	65.15	40.59	**39.12**	**61.42**	**46.71**
	RIL [35]	Quad.	40.81	67.63	55.45	72.42	55.49	78.09	**64.75**	62.09	66.06	64.07	**40.98**	39.05	58.91	45.35
	CSL [4]	D_{le}	42.25	68.28	54.51	72.85	53.10	75.59	58.99	60.80	67.38	64.40	32.58	35.04	58.55	43.34
	DCL (BCL) [47]	D_{le}	41.40	65.82	56.27	73.80	54.30	79.02	60.25	61.55	67.39	**65.93**	35.66	36.71	59.38	45.46
	GWD [5]	D_{oc}	**44.07**	**71.92**	**62.56**	**77.94**	60.25	79.64	63.52	**65.70**	**68.93**	65.44	38.68	38.71	60.03	46.65
	KLD	D_{oc}	**44.00**	**74.45**	**72.48**	**84.30**	**65.54**	**80.03**	**65.05**	**69.41**	**71.28**	**68.14**	**44.48**	**42.15**	**62.50**	**47.69**
R^3Det	-	D_{oc}	44.15	75.09	72.88	86.04	56.49	82.53	61.01	68.31	70.66	67.18	38.41	38.46	62.91	48.43
	DCL (BCL) [47]	D_{le}	**46.84**	74.87	74.96	85.70	57.72	**84.06**	**63.77**	69.70	71.21	67.45	35.44	37.54	61.98	48.71
	GWD [5]	D_{oc}	46.73	**75.84**	**78.00**	**86.71**	**62.69**	**83.09**	61.12	**70.60**	**71.56**	**69.28**	**43.35**	**41.56**	**63.22**	**49.25**
	KLD	D_{oc}	**48.34**	**75.09**	**78.88**	**86.52**	**65.48**	82.08	**61.51**	**71.13**	**71.73**	**68.87**	**44.48**	**42.11**	**65.18**	**50.90**

实验分析

在水平检测任务上（COCO数据集），KLD也是和GIoU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.

Detector	Reg. Loss	AP	AP_{50}	AP_{75}	AP_s	AP_m	AP_l	Detector	Reg. Loss	AP	AP_{50}	AP_{75}	AP_s	AP_m	AP_l
RetinaNet	Smooth L1	37.2	56.6	39.7	21.4	41.1	48.0	Faster RCNN	Smooth L1	37.9	58.8	41.0	22.4	41.4	49.1
	GIoU	37.4	56.7	39.7	22.2	41.7	48.1		GIoU	**38.3**	58.7	41.5	22.5	41.7	49.7
	KLD	**38.0**	56.4	40.6	23.3	43.2	49.3		KLD	38.2	58.7	41.7	22.6	41.8	49.3

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.

Dataset	$D_{kl}(\mathcal{N}_p\|\|\mathcal{N}_t)$	$D_{kl}(\mathcal{N}_t\|\|\mathcal{N}_p)$	$D_{kl\_min}(\mathcal{N}_p\|\|\mathcal{N}_t)$	$D_{kl\_max}(\mathcal{N}_p\|\|\mathcal{N}_t)$	$D_{js}(\mathcal{N}_p\|\|\mathcal{N}_t)$	$D_{jeffreys}(\mathcal{N}_p\|\|\mathcal{N}_t)$
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

OpenMMLab

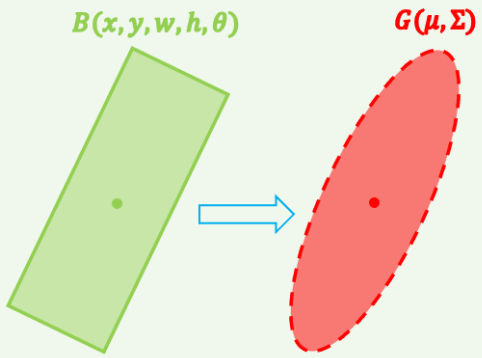
最后在DOTA-v1.0的SOTA实验中，我们也取得了当前所发表论文里的最高性能。

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.

	Method	Backbone	MS	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	AP_{50}
Two-stage	ICN [32]	R-101	✓	81.40	74.30	47.70	70.30	64.90	67.80	70.00	90.80	79.10	78.20	53.60	62.90	67.00	64.20	50.20	68.20
	RoI-Trans. [12]	R-101	✓	88.64	78.52	43.44	75.92	68.81	73.68	83.59	90.74	77.27	81.46	58.39	53.54	62.83	58.93	47.67	69.56
	SCRDet [3]	R-101	✓	89.98	80.65	52.09	68.36	68.36	60.32	72.41	90.85	**87.94**	86.86	65.02	66.68	66.25	68.24	65.21	72.61
	Gliding Vertex [52]	R-101		89.64	85.00	52.26	77.34	73.01	73.14	86.82	90.74	79.02	86.81	59.55	**70.91**	72.94	70.86	57.32	75.02
	Mask OBB [53]	RX-101	✓	89.56	85.95	54.21	72.90	76.52	74.16	85.63	89.85	83.81	86.48	54.89	69.64	73.94	69.06	63.32	75.33
	CenterMap OBB [54]	R-101	✓	89.83	84.41	54.60	70.25	77.66	78.32	87.19	90.66	84.89	85.27	56.46	69.23	74.13	71.56	66.06	76.03
	FPN-CSL [4]	R-152	✓	**90.25**	**85.53**	54.64	75.31	70.44	73.51	77.62	90.84	86.15	86.69	69.60	68.04	73.83	71.10	68.93	76.17
	RSDet-II [46]	R-152	✓	89.93	84.45	53.77	74.35	71.52	78.31	78.12	**91.14**	87.35	86.93	65.64	65.17	75.35	**79.74**	63.31	76.34
	SCRDet++ [55]	R-101	✓	**90.05**	84.39	55.44	73.99	77.54	71.11	86.05	90.67	87.32	87.08	69.62	68.90	73.74	71.29	65.08	76.81
	ReDet [56]	ReR-50	✓	88.81	82.48	**60.83**	80.82	78.34	**86.06**	88.31	90.87	**88.77**	87.03	68.65	66.90	**79.26**	**79.71**	74.67	80.10
Single-stage	PIoU [33]	DLA-34 [57]		80.90	69.70	24.10	60.20	38.30	64.40	64.80	**90.90**	77.20	70.40	46.50	37.10	57.10	61.90	64.00	60.50
	O^2-DNet [58]	H-104	✓	89.31	82.14	47.33	61.21	71.32	74.03	78.62	90.76	82.23	81.36	60.93	60.17	58.21	66.98	61.03	71.04
	DAL [15]	R-101	✓	88.61	79.69	46.27	70.37	65.89	76.10	78.53	90.84	79.98	78.41	58.71	62.02	69.23	71.32	60.65	71.78
	P-RSDet [59]	R-101	✓	88.58	77.83	50.44	69.29	71.10	75.79	78.66	90.88	80.10	81.71	57.92	63.03	66.30	69.77	63.13	72.30
	BBAVectors [60]	R-101	✓	88.35	79.96	50.69	62.18	78.43	78.98	87.94	90.85	83.58	84.35	54.13	60.24	65.22	64.28	55.70	72.32
	DRN [14]	H-104	✓	89.71	82.34	47.22	64.10	76.22	74.43	85.84	90.57	86.18	84.89	57.65	61.93	69.30	69.63	58.48	73.23
	PolarDet [61]	R-101	✓	89.65	**87.07**	48.14	70.97	78.53	80.34	87.45	90.76	85.63	86.87	61.64	70.32	71.92	73.09	67.15	76.64
	RDD [62]	R-101	✓	89.15	83.92	52.51	73.06	77.81	79.00	87.08	90.62	86.72	87.15	63.96	70.29	76.98	75.79	72.15	77.75
	GWD [5]	R-152	✓	89.06	84.32	55.33	77.53	76.95	70.28	83.95	89.75	84.51	86.06	**73.47**	67.77	72.60	75.76	74.17	77.43
	KLD	R-50		88.91	83.71	50.10	68.75	78.20	76.05	84.58	89.41	86.15	85.28	63.15	60.90	75.06	71.51	67.45	75.28
		R-50	✓	88.91	85.23	53.64	81.23	78.20	76.99	84.58	89.50	86.84	86.38	71.69	68.06	75.95	72.23	75.42	78.32
Refine-stage	CFC-Net [34]	R-101	✓	89.08	80.41	52.41	70.02	76.28	78.11	87.21	90.89	84.47	85.64	60.51	61.52	67.82	68.02	50.09	73.50
	R^3Det [29]	R-152	✓	89.80	83.77	48.11	66.77	78.76	83.27	87.84	90.82	85.38	85.51	65.67	62.68	67.53	78.56	72.62	76.47
	DAL [15]	R-50	✓	89.69	83.11	55.03	71.00	78.30	81.90	88.46	90.89	84.97	**87.46**	64.41	65.65	76.86	72.09	64.35	76.95
	DCL [47]	R-152	✓	89.26	83.60	53.54	72.76	79.04	82.56	87.31	90.67	86.59	86.98	67.49	66.88	73.29	70.56	69.99	77.37
	RIDet [35]	R-50	✓	89.31	80.77	54.07	76.38	**79.81**	81.99	**89.13**	90.72	83.58	87.22	64.42	67.56	78.08	79.17	62.07	77.62
	S^2A-Net [13]	R-101	✓	89.28	84.11	56.95	79.21	**80.18**	82.93	**89.21**	90.86	84.66	**87.61**	71.66	68.23	**78.58**	78.20	65.55	79.15
	R^3Det-GWD [5]	R-152	✓	89.66	84.99	**59.26**	**82.19**	78.97	**84.83**	87.70	90.21	86.54	86.85	**73.04**	67.56	76.92	79.22	74.92	**80.19**
	R^3Det-KLD	R-50		88.90	84.17	55.80	69.35	78.72	84.08	87.00	89.75	84.32	85.73	64.74	61.80	76.62	78.49	70.89	77.36
		R-50	✓	89.90	84.91	59.21	78.74	78.82	83.95	87.41	89.89	86.63	86.69	70.47	70.87	76.96	79.40	**78.62**	80.17
		R-152	✓	89.92	85.13	59.19	**81.33**	78.82	84.38	87.50	89.80	87.33	87.00	72.57	**71.35**	77.12	79.34	**78.68**	**80.63**

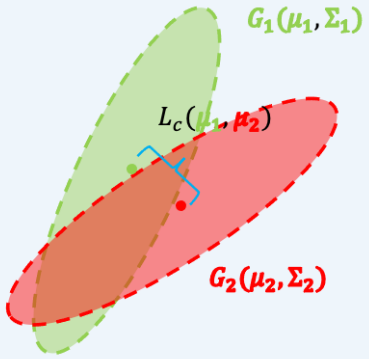
高斯建模后续扩展工作——KFIoU

基于高斯的SkewIoU近似，KFIoU



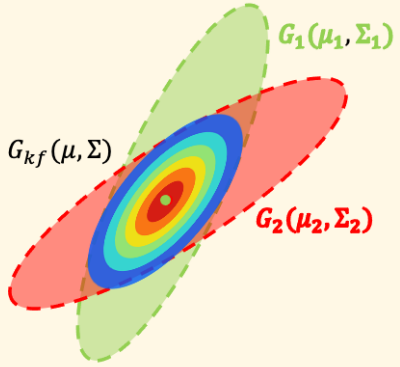
$$\mu = (x,y)^T \qquad R = \begin{pmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{pmatrix}$$
$$\Sigma = R\Lambda R^T \qquad \Lambda = \begin{pmatrix} w^2/4 & 0 \\ 0 & h^2/4 \end{pmatrix}$$

(a) Convert the bounding box to a Gaussian distribution



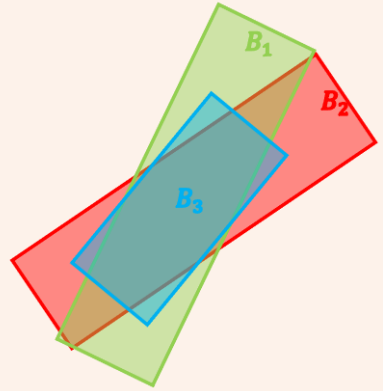
$$L_c(\mu_1,\mu_2) = \sum_{i\in\{x,y\}} l_n(t_i,t_i')$$

(b) Narrow the center distance by center point loss



$$\alpha G_{kf}(\mu,\Sigma) = G_1(\mu_1,\Sigma_1)G_2(\mu_2,\Sigma_2)$$
$$K = \Sigma_1(\Sigma_1+\Sigma_2)^{-1}$$
$$\mu = \mu_1 + K(\mu_2-\mu_1)$$
$$\Sigma = \Sigma_1 - K\Sigma_1$$

(c) Get the Gaussian distribution of the overlapping area by Kalman filtering



$$Aera_B(\Sigma) = 4\sqrt{\prod eig(\Sigma)}$$
$$KFIoU = \frac{Aera_{B_3}(\Sigma)}{Aera_{B_1}(\Sigma_1)+Aera_{B_2}(\Sigma_2)-Aera_{B_3}(\Sigma)}$$
$$L_{kf}(\Sigma_1,\Sigma_2) = 1 - KFIoU$$

(d) Invert Gaussian distribution to bbox to calculate approximate SkewIoU

Yang, Xue, et al. "The KFIoU Loss for Rotated Object Detection." arXiv preprint arXiv:2201.12558 (2022).

高斯建模后续扩展工作——KFIoU

趋势一致性分析

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

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

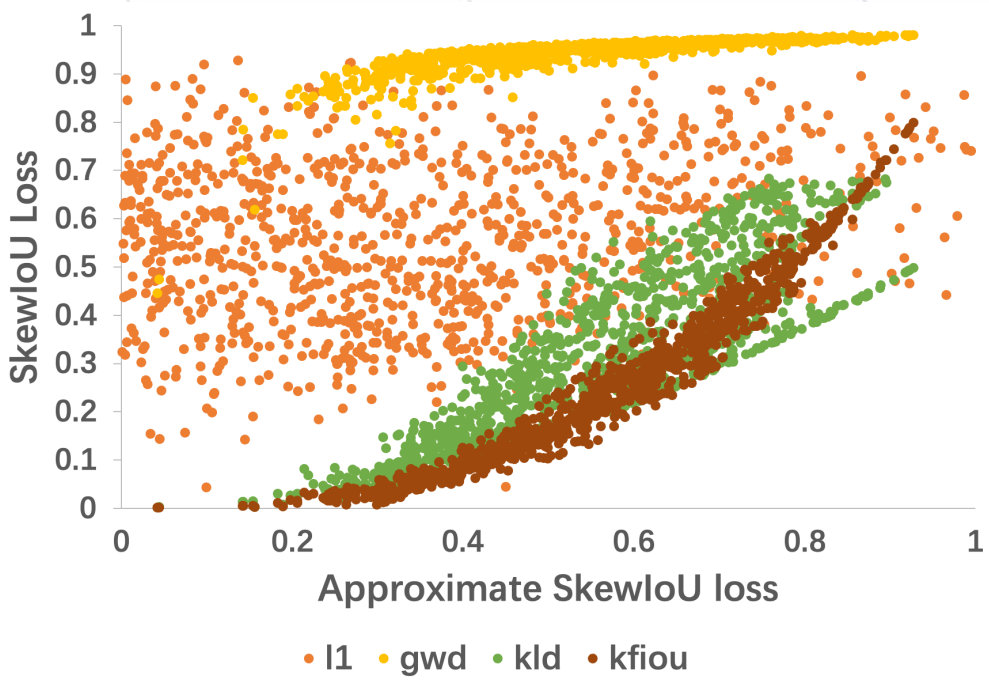


Table 1: Comparison of the properties and performance of different regression losses. Base model is RetinaNet. **BC**, **SI** and **HP** denote Boundary Continuity, Scale Invariance and Hyperparameter.

Loss	Representation	Implement	BC	SI	Consistency	HP	EVar↓	DOTA-v1.0	DOTA-v1.5	DOTA-v2.0
Smooth L1	bbox	easy	×	×	×	✓ (σ)	0.073201718	64.17	56.10	43.06
plain SkewIoU	bbox	hard	✓	✓	✓	×	-	68.27	59.01	45.87
GWD	Gaussian	easy	✓	×	×	✓ (τ)	0.019041297	68.93	60.03	46.65
KLD	Gaussian	easy	✓	✓	✓	✓ (τ)	0.007653582	**71.28**	62.50	47.69
KFIoU (ours)	Gaussian	easy	✓	✓	✓	×	**0.002348353**	70.64	**62.71**	**48.04**

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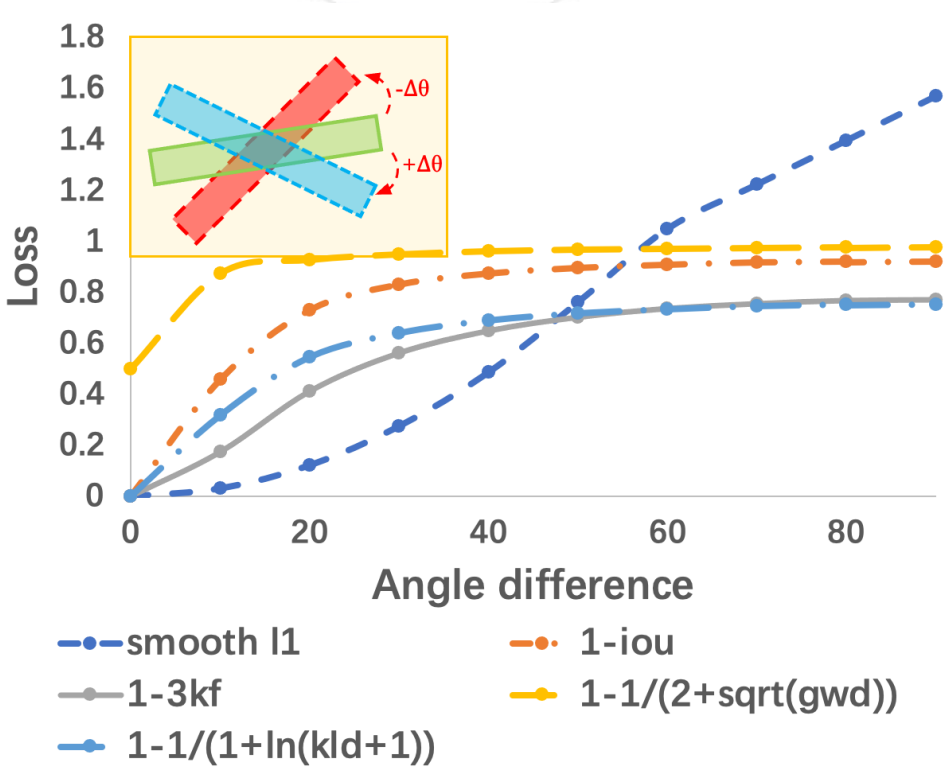
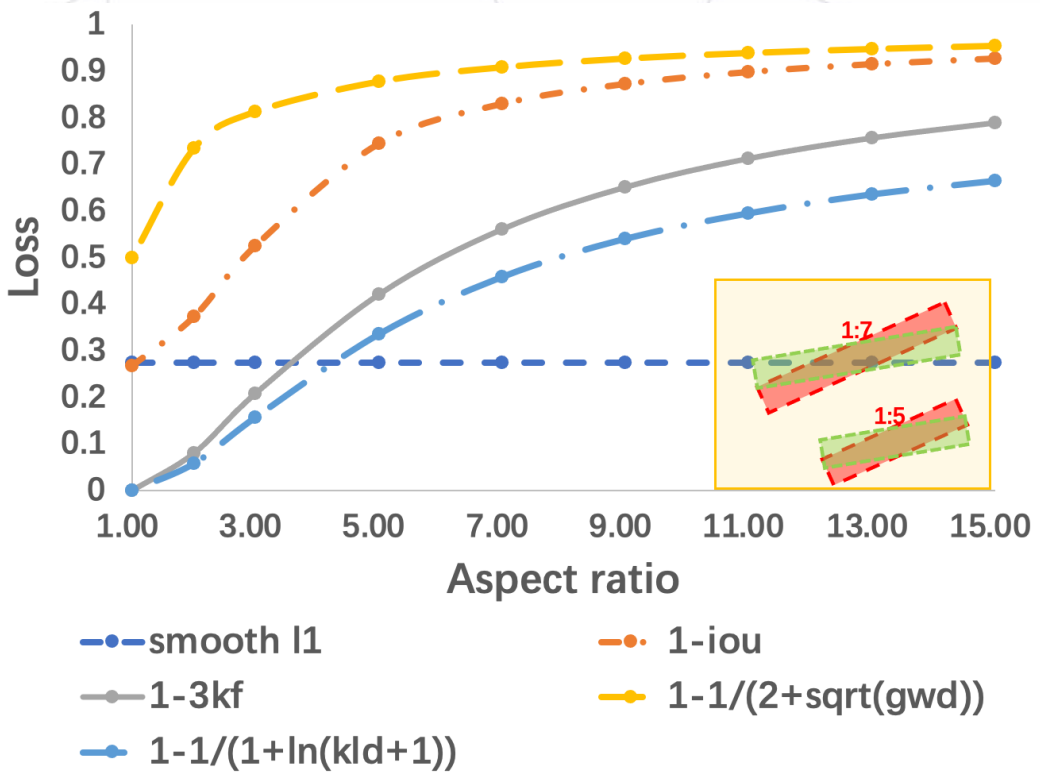
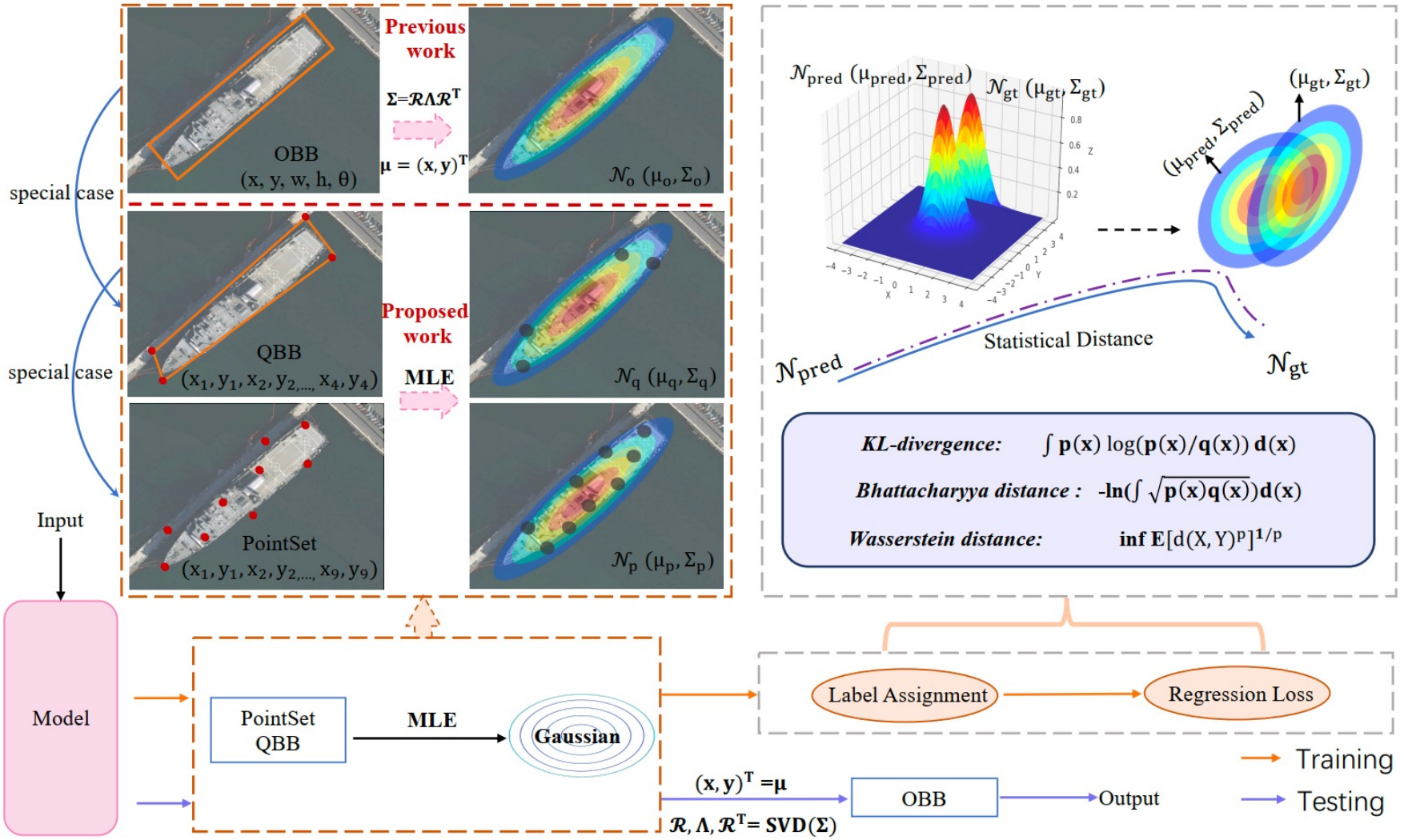
趋势一致性分析



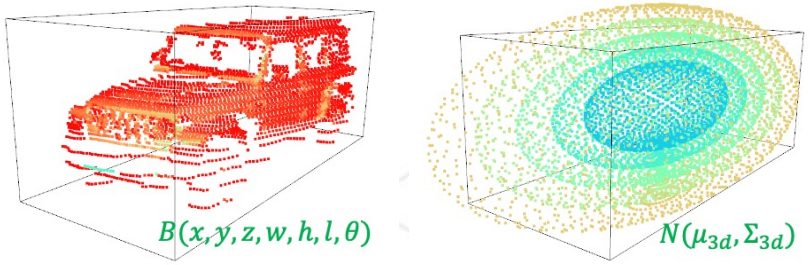


高斯建模后续扩展工作——G-Rep

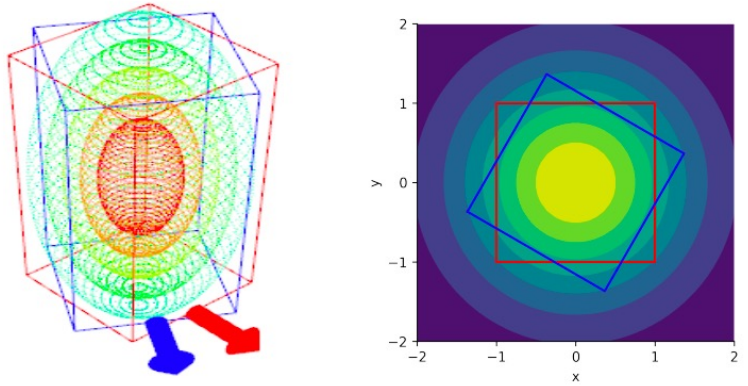


Hou L, Lu K, Yang X, et al. G-Rep: Gaussian Representation for Arbitrary-Oriented Object Detection. arXiv preprint arXiv:2205.11796, 2022.

高斯建模后续扩展工作——3D目标检测



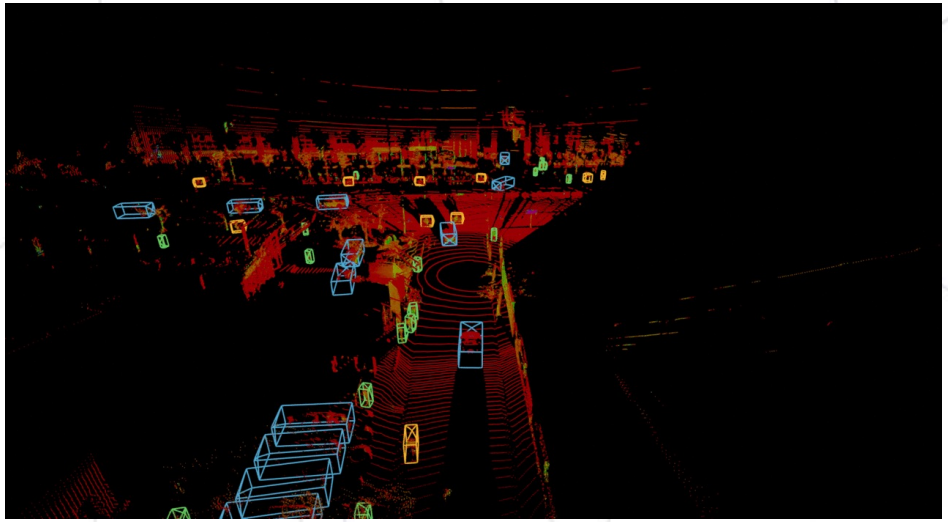
3D高斯表示

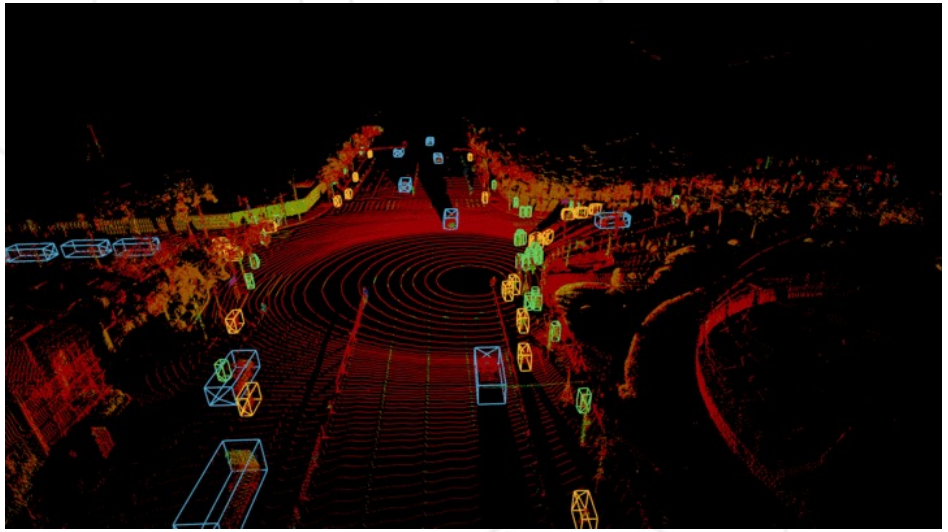


(b) 3-D BBox with square shape in top-view e.g. pedestrian.

(c) Top view of the 3-D BBox and 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

OpenMMLab website *HOT* OpenMMLab platform *TRY IT OUT*

Documentation | Installation | Model Zoo | Reporting Issues

AlphaRotate：基于TensorFlow的有向检测工具

AlphaRotate: A Rotation Detection Benchmark using TensorFlow

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

谢谢！

Q & A

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