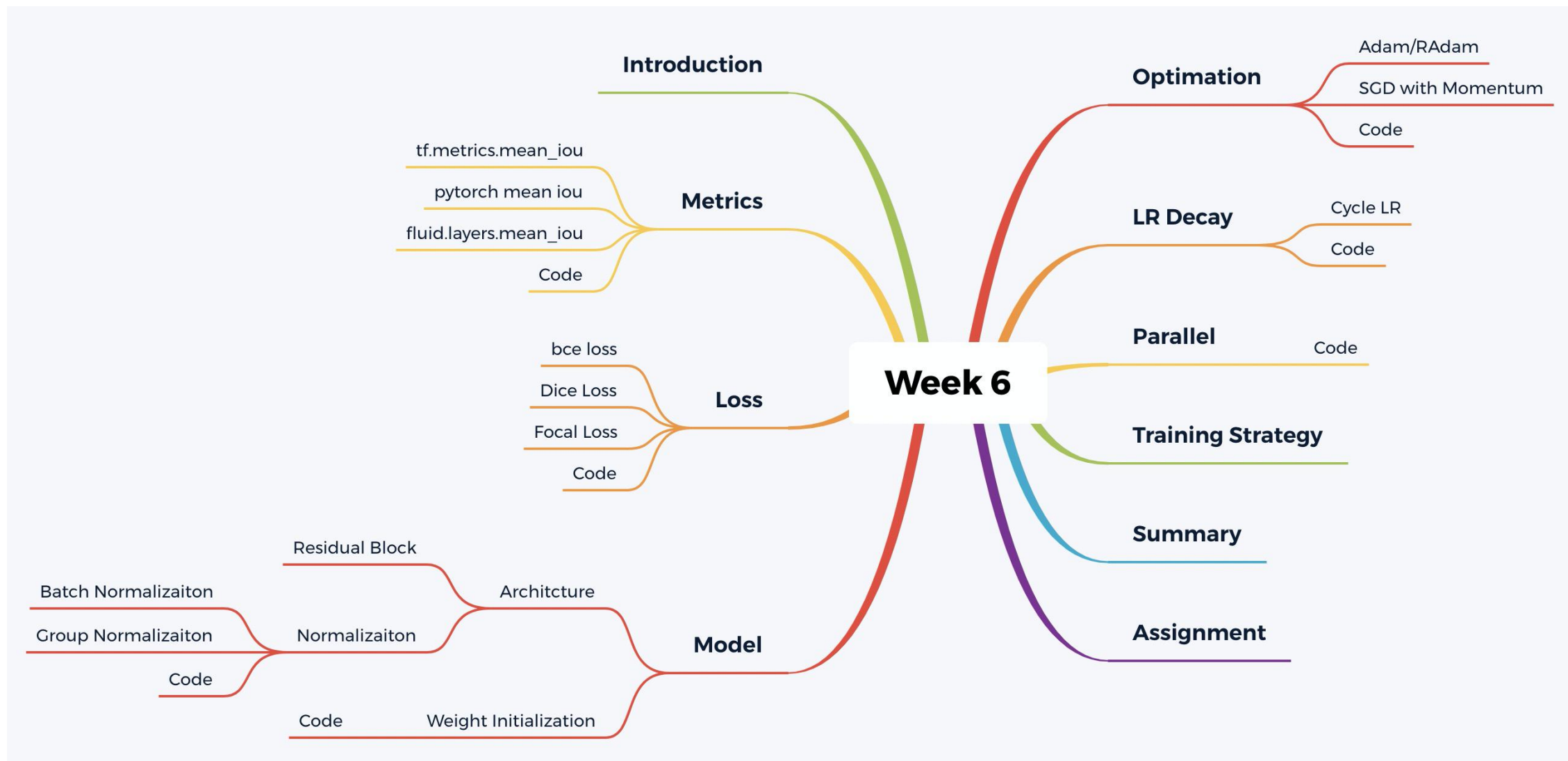


Lane Segmentation Week 6

HCT CV Course

主要内容



学习目标

- 理解Semantic Segmentation Metrics
- 理解Semantic Segmentation Loss
- 理解优化算法
- 理解调整学习率的算法
- 理解权重初始化的方法
- 掌握单卡/多卡训练方法
- 掌握分阶段训练的策略

training strategy

- Collect more data
- Train algorithm longer
- Try Adam instead of gradient descent
- Add regularizations
- Network architecture
-

training strategy

- One of the challenges with building machine learning systems is that there's so many things you could try, so many things you could change.
- hyperparameters

The No Free Lunch Theorem

- Learning theory claims that a machine learning algorithm can generalize well from a finite training set of examples. This seems to contradict some basic principles of logic.

The No Free Lunch Theorem

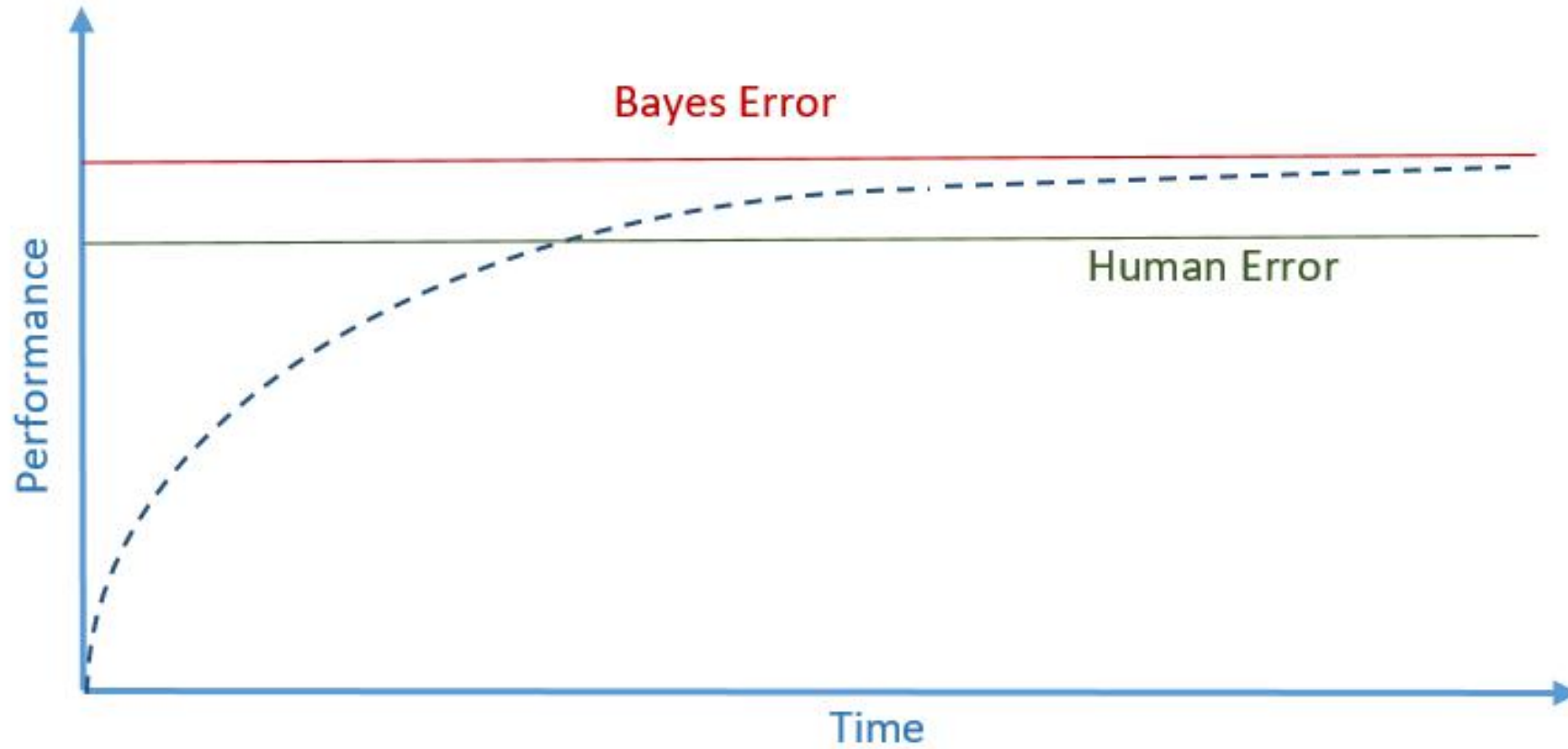
- no machine learning algorithm is universally any better than any other

The No Free Lunch Theorem

- If we make assumptions about the kinds of probability distributions we encounter in real-world applications, then we can design learning algorithms that perform well on these distributions.

Watch your data !!!!!

Bayes Error



human-level performance

- define your key priorities
- based on observations of performances and dataset

Bias

- human-level performance
- Underfitting

Variance

- Overfitting

Training

- 观察数据
- 确定Baseline
- 对Baseline模型进行优化
- ablation study

Baseline

- no data augmentation
- no big model
- low resolution
- little tricks

Baseline

- <https://github.com/gujingxiao/Lane-Segmentation-Solution-For-BaiduAI-Autonomous-Driving-Competition/blob/master/train.py>

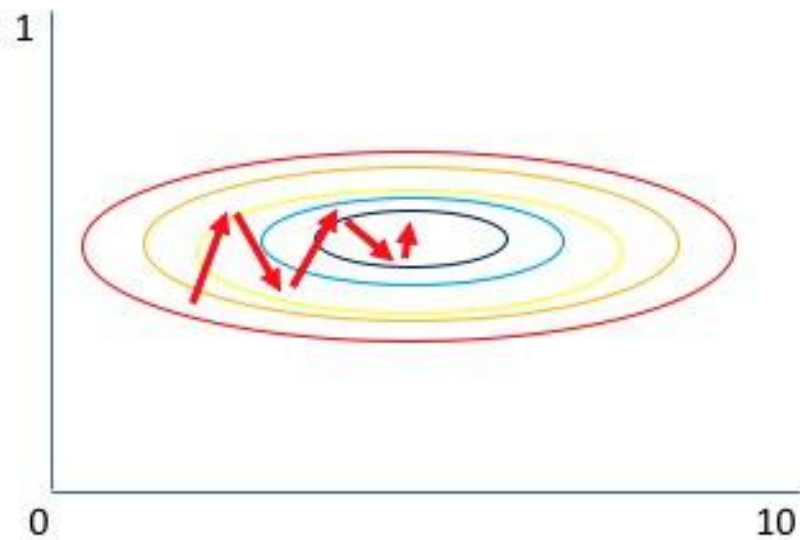
Training

- Data Generator
- Metrics
- Loss
- Model
- Optimazition

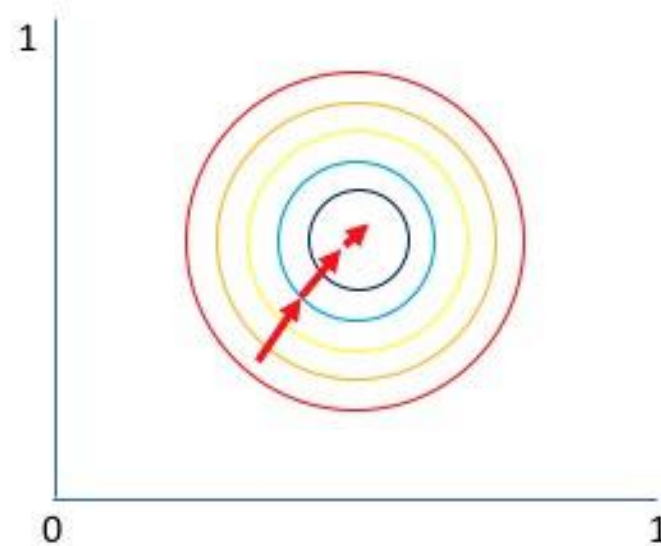
Orthogonalization



Normalization



Gradient of larger parameter
dominates the update



Both parameters can be
updated in equal proportions

Note

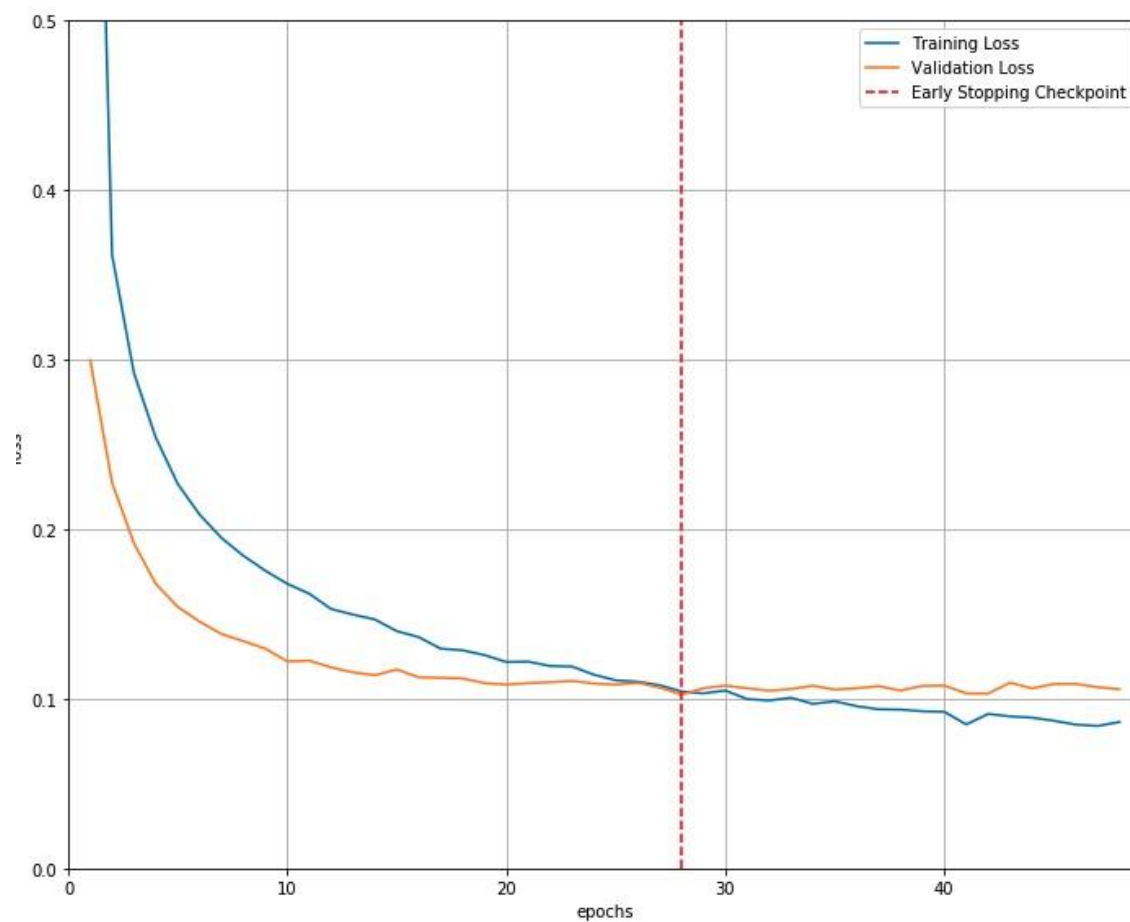
number of training epochs

- Too many epochs can lead to overfitting of the training dataset, whereas too few may result in an underfit model. Early stopping is a method that allows you to specify an arbitrary large number of training epochs and stop training once the model performance stops improving on a hold out validation dataset.

Early-Stop

```
callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=3)
# This callback will stop the training when there is no improvement in
# the validation loss for three consecutive epochs.
model.fit(data, labels, epochs=100, callbacks=[callback],
          validation_data=(val_data, val_labels))
```

Early-Stop



save model

- early stop

单卡/多卡

Model

- MultiResUNet : Rethinking the U-Net Architecture for Multimodal Biomedical Image Segmentation
- <https://arxiv.org/abs/1902.04049>

DeepLab v3+

- BN/GN/LRN

Metrics

- CityScape

<https://www.cityscapes-dataset.com/benchmarks/>

TP/FP/FN/TN

我们可以使用一个 2x2 **混淆矩阵**来总结我们的“狼预测”模型，该矩阵描述了所有可能出现的结果（共四种）：

真正例 (TP):

- 真实情况：受到狼的威胁。
- 牧童说：“狼来了。”
- 结果：牧童是个英雄。

假正例 (FP):

- 真实情况：没受到狼的威胁。
- 牧童说：“狼来了。”
- 结果：村民们因牧童吵醒他们而感到非常生气。

假负例 (FN):

- 真实情况：受到狼的威胁。
- 牧童说：“没有狼”。
- 结果：狼吃掉了所有的羊。

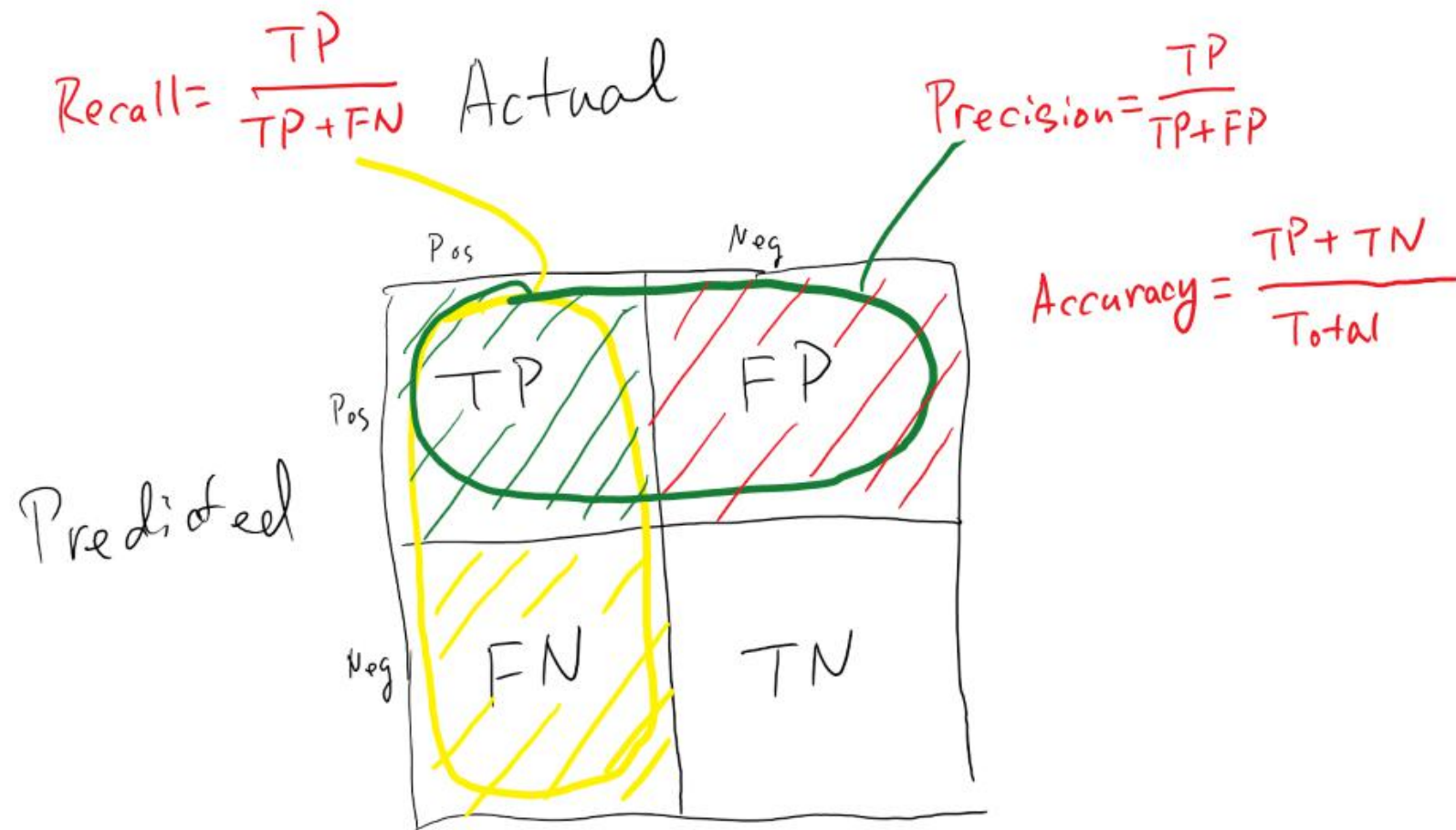
真负例 (TN):

- 真实情况：没受到狼的威胁。
- 牧童说：“没有狼”。
- 结果：大家都没事。

真正例是指模型将正类别样本正确地预测为正类别。同样，**真负例**是指模型将负类别样本正确地预测为负类别。

假正例是指模型将负类别样本错误地预测为正类别，而**假负例**是指模型将正类别样本错误地预测为负类别。

Precision/Recall

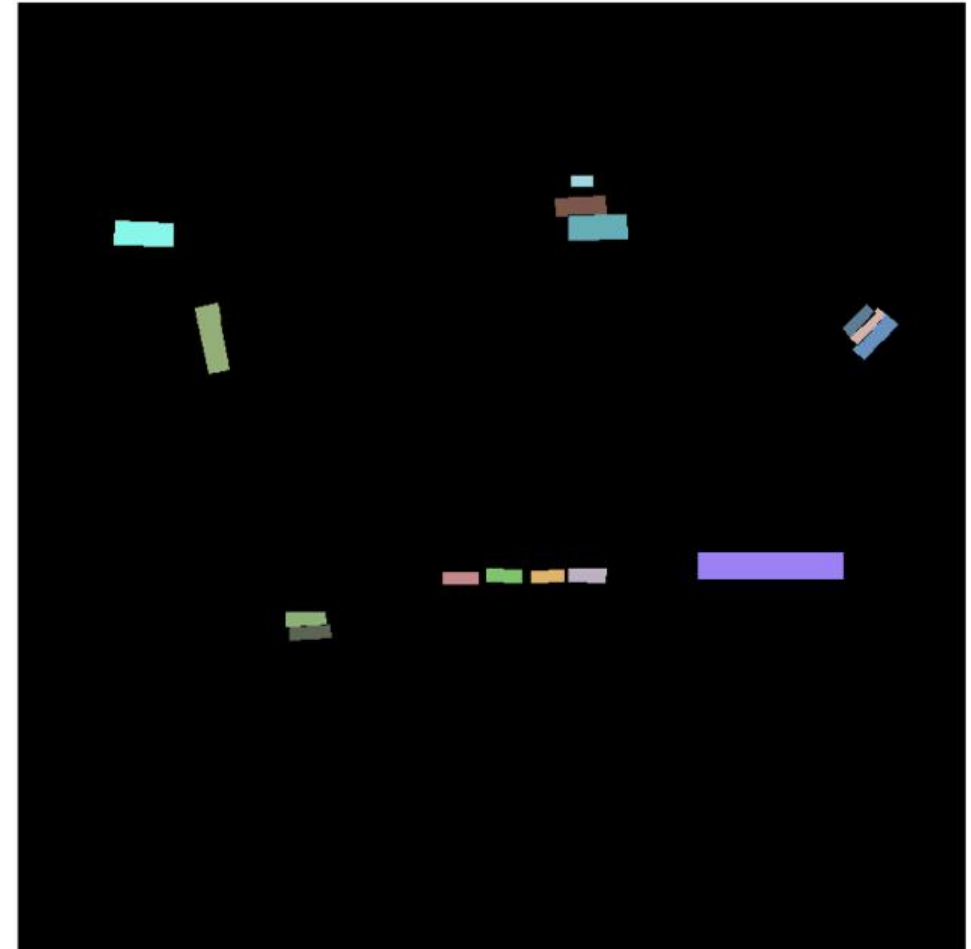


F-Score

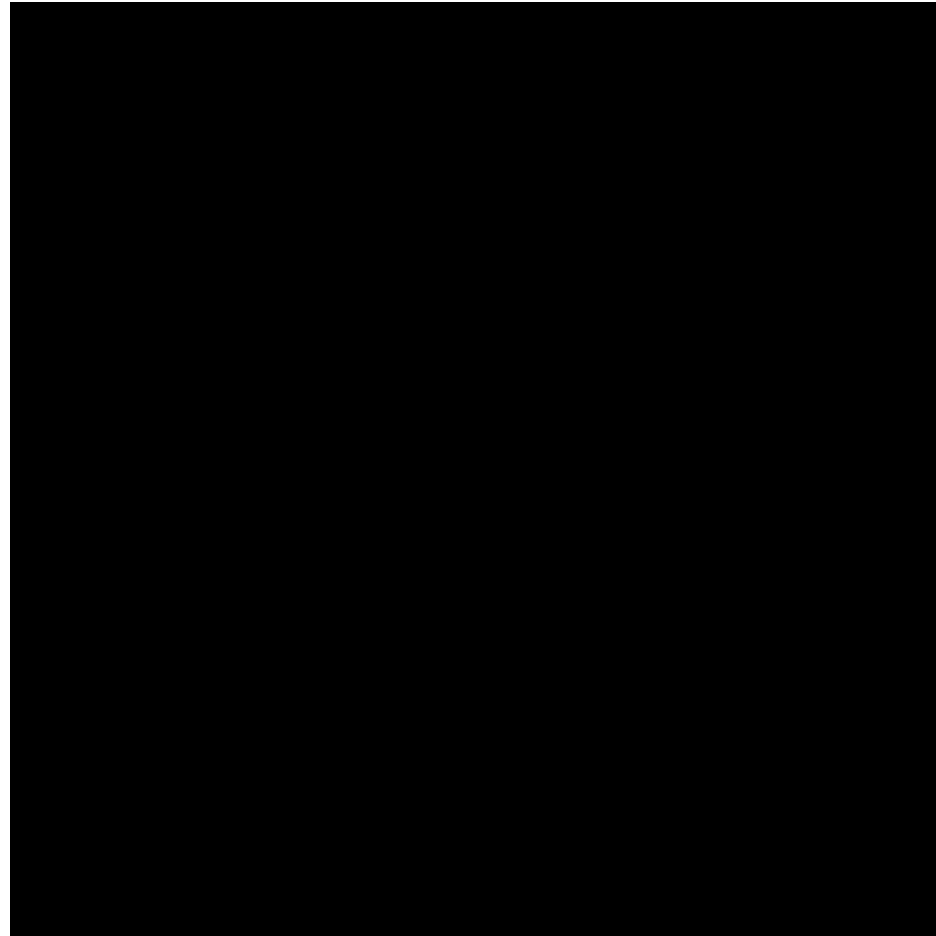
$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1 score is the harmonic mean of precision and recall. Values range from 0 (bad) to 1 (good).

Pixel Accuracy




Pixel Accuracy



class imbalance

- Unfortunately, class imbalance is prevalent in many real world data sets, so it can't be ignored. Therefore, I present to you two alternative metrics that are better at dealing with this issue

Jaccard Index/IoU

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


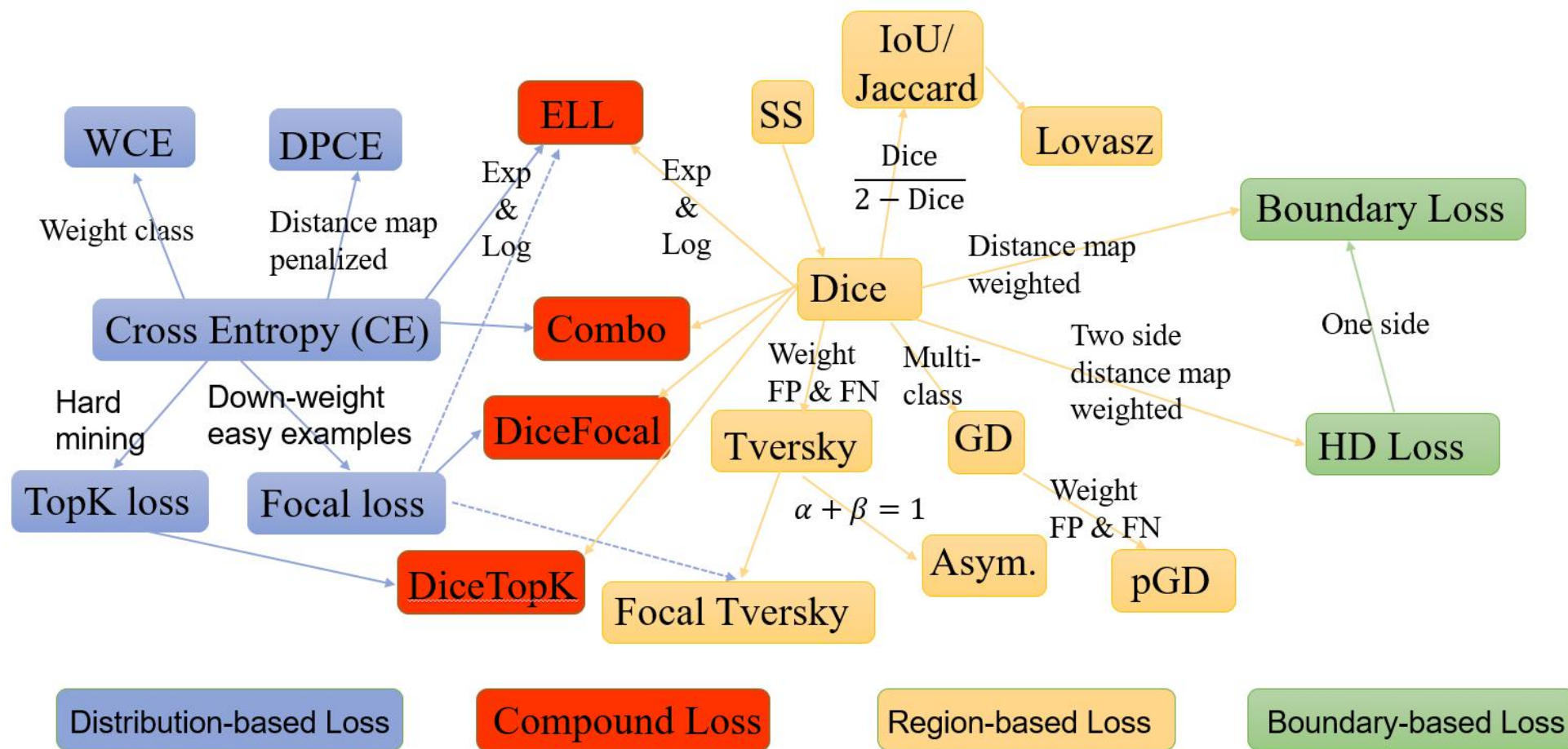
mIoU

- For binary (two classes) or multi-class segmentation, the mean IoU of the image is calculated by taking the IoU of each class and averaging them.

CityScape

- <https://www.cityscapes-dataset.com/benchmarks/>

Loss



Loss

- A collection of loss functions for medical image segmentation
- <https://github.com/JunMa11/SegLoss>

Cross-Entropy

$$D_{KL}(p \parallel q) = \text{Cross entropy} - \text{Entropy}$$
$$D_{KL}(p \parallel q) = H(p, q) - H(p)$$

ce loss

$$\text{Cross-entropy loss} = - \sum_{c=1}^M Y \log(P)$$

bce loss

$$-(y_i \log(p_i) + (1 - y_i) \log(1 - p_i))$$

Information Theory

- Probability and Information Theory
- <http://www.deeplearningbook.org/contents/prob.html>

Probability

- frequentist probability
- Bayesian probability

Bayes's Rule

- we know $P(y | x)$ and need to know $P(x | y)$

$$P(x | y) = \frac{P(x)P(y | x)}{P(y)}.$$

Conditional Probability

$$P(y = y \mid x = x) = \frac{P(y = y, x = x)}{P(x = x)} .$$

What is Information

- Probability
- frequentist probability

self-information

- Likely events should have low information content, and in the extreme case, events that are guaranteed to happen should have no information content whatsoever.
- Less likely events should have higher information content.
- Independent events should have additive information. For example, finding out that a tossed coin has come up as heads twice should convey twice as much information as finding out that a tossed coin has come up as head once.

self-information

$$I(x) = -\log P(x).$$

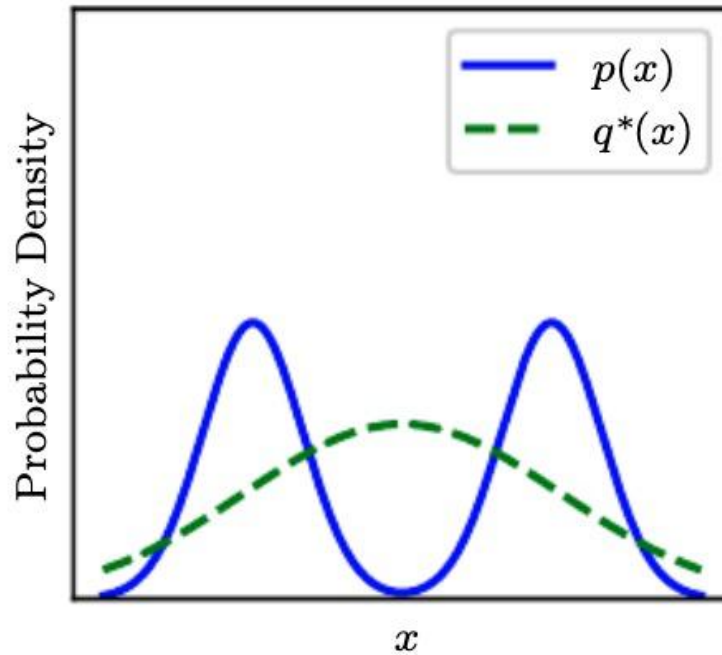
大道至简

Kullback-Leibler (KL) divergence

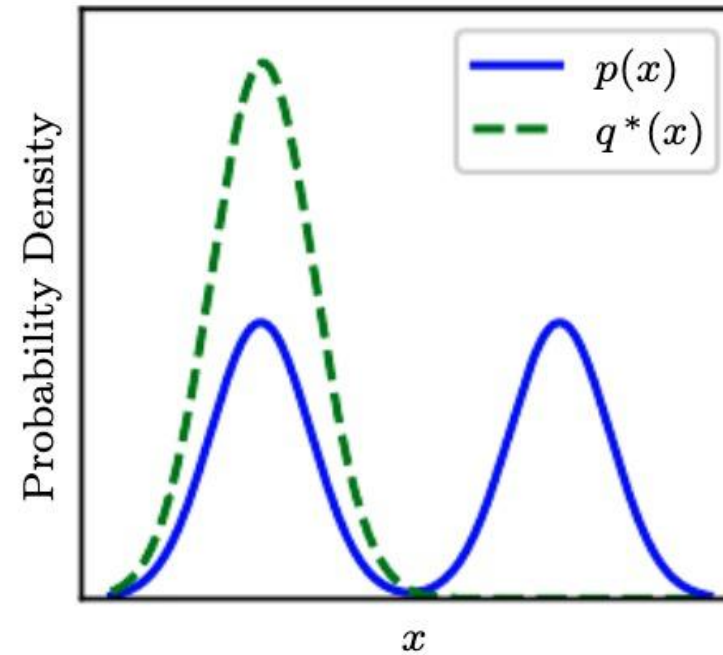
$$D_{\text{KL}}(P\|Q) = \mathbb{E}_{x \sim P} \left[\log \frac{P(x)}{Q(x)} \right] = \mathbb{E}_{x \sim P} [\log P(x) - \log Q(x)] .$$

Kullback-Leibler (KL) divergence

$$q^* = \operatorname{argmin}_q D_{\text{KL}}(p \| q)$$



$$q^* = \operatorname{argmin}_q D_{\text{KL}}(q \| p)$$



nll loss

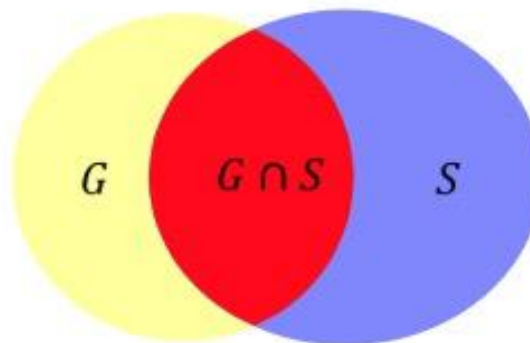
- cross-entropy loss

dice loss

- V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation
- <https://arxiv.org/abs/1606.04797>

Laplace smoothing

Dice



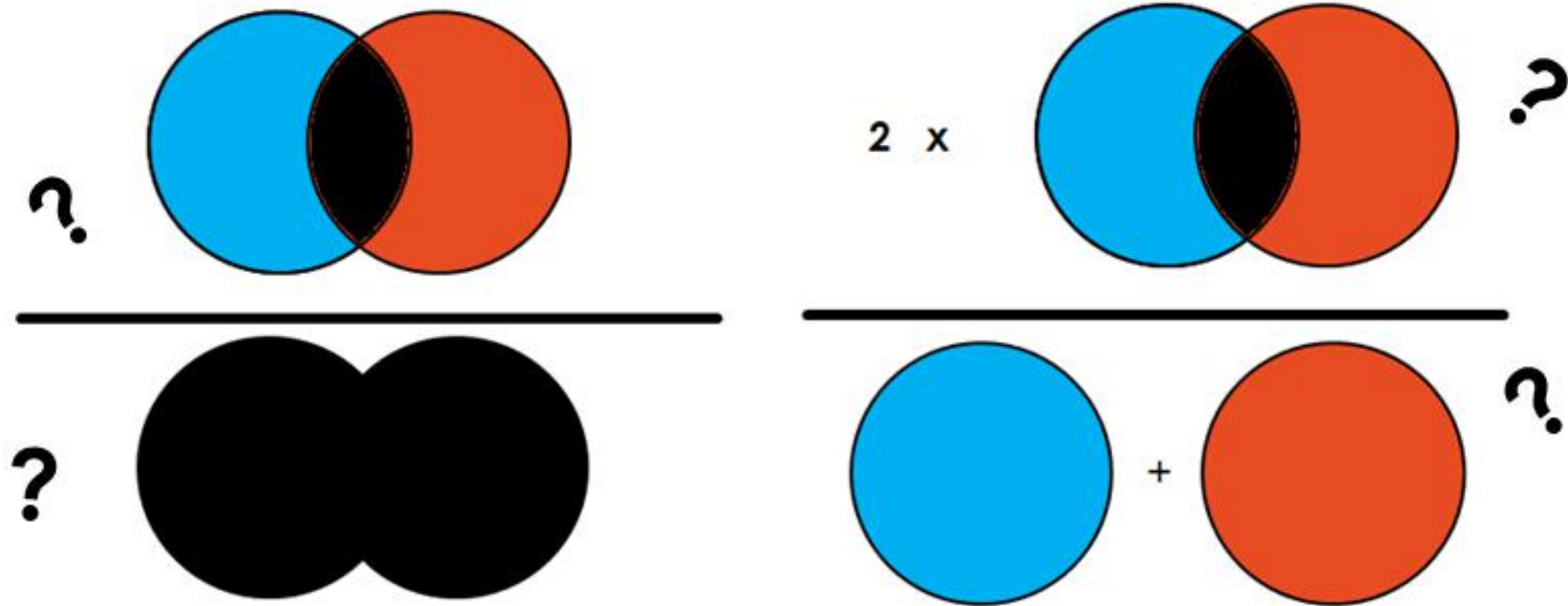
$$\text{Dice loss} = 1 - \frac{2|G \cap S|}{|G| + |S|}$$

Combinations

$$\text{CE} (p, \hat{p}) + \text{DL} (p, \hat{p})$$

Note that CE returns a tensor, while DL returns a scalar for each image in the batch. This way we combine local (CE) with global information (DL).

IoU and Dice Coefficient



Weight Initialization

- Initializing all weights to 0
- Initializing weights randomly

Weight Initialization

- Xavier
- Uniform
- Kaiming

Learning Rate

- Weight Initialization
- BN
- Adam...

Learning Rate

- Decay
- Cycle
- Warmup

Exponential Weighted Moving Average

$$v_0 = 0$$

$$v_1 = \beta v_0 + (1 - \beta) \theta_1$$

$$v_2 = \beta v_1 + (1 - \beta) \theta_2$$

$$v_3 = \beta v_2 + (1 - \beta) \theta_3$$

...

SGD+Momentum

- 手动挡
- 对学习率等超参数敏感

Adam

- 自动挡
- 最常用

课程总结

- mIoU的计算方法
- Loss的种类和组合
- Adam优化方法
- 调整学习率的算法和实现
- 单卡/多卡的训练方法

重难点

- mIoU
- dice loss
- Adam
- Cycle LR
- 单卡/多卡训练的实现

课程作业

- 使用Pytorch/Tensorflow实现项目训练



一所专注前沿互联网技术领域的创新实战大学