TopK Dice Loss for Medical Image Segmentation

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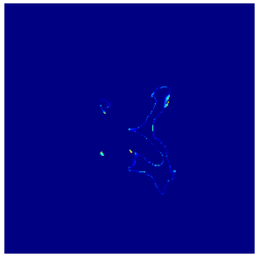
Motivation

- **Two types of imbalance in data:**
  - ➢ **Class imbalance**
  - ✓ extreme difference between the number of pixels of each class
  - ➢ **Difficulty imbalance**
  - ✓ Extreme difference between the number of difficult and easy to classify pixels.

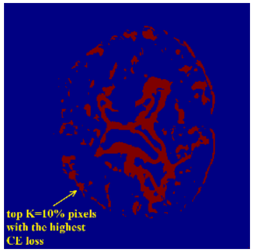
- **For class imbalance:**
  - ➢ **Dice Loss:**
  - ✓ Region based loss. Mismatch between two regions and it is invariant to scale.

- **For difficulty imbalance:**
  - ➢ weighted CE loss strategies: CE loss of easy pixels are reduced by assigning a lower weights to them in order to focus on difficult to classify pixels.
  - ➢ **Focal CE loss** (1)
  - ➢ **topK CE loss** (2)
  - ✓ Top K% pixels with highest CE loss (most difficult to classify).

CE loss



topK CE weights (K= 10%)



Method

Main idea: Dice loss is very successful in handling class imbalance. Why not use it for difficulty imbalance as well?

topK Dice loss: a modified Dice loss for difficulty imbalance as well as class imbalance.

Identifying easy to classify pixels in each class.

↓

labels and predictions are set to zero in well classified areas, producing modified labels and modified predictions for each class.

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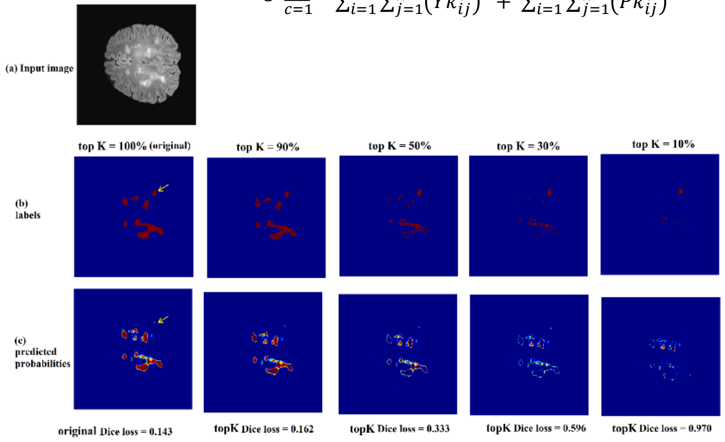
topK dice loss is calculated for each class based on modified labels and modified predictions.

$$topK\ Dice\ loss = 1 - \frac{1}{C}\sum_{c=1}^{C}\frac{2\sum_{i=1}^{H}\sum_{j=1}^{W} Yk_{ij}^{c}\ Pk_{ij}^{c}}{\sum_{i=1}^{H}\sum_{j=1}^{W}\left(Yk_{ij}^{c}\right)^{2} + \sum_{i=1}^{H}\sum_{j=1}^{W}\left(Pk_{ij}^{c}\right)^{2}}$$



Results

Synapse multi organ segmentation dataset (3):

Loss functions	mDice	mIoU	Aorta	Gallbladder	Kidney left	Kidney right	Liver	Pancreas	Spleen	Stomach
CE	81.10	72.30	90.50	60.65	83.77	81.23	95.38	64.94	91.71	80.66
CE + Dice	81.75	72.74	91.79	60.48	85.54	83.67	95.49	68.08	89.79	79.19
focal + Dice	81.26	72.26	91.02	59.10	87.35	84.77	95.31	64.98	90.30	77.27
topK + Dice	81.87	73.00	91.58	61.73	85.25	82.80	95.86	65.63	90.80	81.32
CE + topK-Dice (our)	82.73	74.07	91.85	61.16	88.78	84.72	95.34	68.75	92.04	79.18

ACDC dataset (4):

Loss functions	mDice	mIoU	RV	MYO	LV
CE	91.29	84.42	90.07	88.91	94.89
CE + Dice	91.29	84.43	90.37	89.05	94.45
Focal-CE + Dice	91.24	84.39	89.45	88.82	95.45
topK-CE + Dice	91.34	84.53	90.04	89.04	94.93
CE + topK-Dice (our)	91.67	85.03	90.20	89.57	95.24

MSSEG dataset (5):

Loss functions	mDice	mIoU	mPrec.	mRec.
CE	65.37	48.78	76.72	58.82
CE + Dice	66.29	49.94	73.37	61.95
Focal-CE + Dice	66.31	50.31	68.86	67.83
topK-CE + Dice	65.93	49.46	73.45	61.75
CE + topK-Dice (our)	67.19	51.10	71.69	66.03

Conclusions

- a novel modified Dice loss is proposed in this work which can be utilized to address both class and difficulty imbalance at the same time.
- Experimental results show that the proposed Dice loss is more effective compared to weighted CE loss strategies in handling class and difficulty imbalance in data.

References

1) Lin, Tsung-Yi, et al. "Focal loss for dense object detection." Proceedings of the IEEE international conference on computer vision. 2017.
2) Pohlen, Tobias, et al. "Full-resolution residual networks for semantic segmentation in street scenes." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
3) https://portal.fli-iam.irisa.fr/msseg-2/
4) https://www.creatis.insa-lyon.fr/Challenge/acdc/
5) https://www.synapse.org/#!Synapse:syn3193805/wiki/217789