

WHY RODEO?

RoDeO reflects clinical needs better than current metrics



RoDeO total: 0.0% RoDeO cls: 0.0% RoDeO shape: 89.2% RoDeO loc: 98.6%

loU: 81.5% acc@50: **75.0%** AP@50: **0.0%**



RoDeO total: 74.4% RoDeO cls: **100.0%** RoDeO shape: 55.1% AP@50: 0.0% RoDeO loc: 82.2%

IoU: **47.5%** acc@50: 87.5%

Problems with Existing Metrics

- AP@IoU declines sharply with small localization errors
- AP@IoU increases at high thresholds when predicting many boxes
- Acc@loU is high when predicting nothing (many true negatives)
- Existing metrics are hard to interpret (why is the score low?)

RoDeO degrades more smoothly and different error sources do not influence each other



FELIX MEISSEN, PHILIP MÜLLER, GEORGIOS KAISSIS, DANIEL RÜCKERT



RoDeO total: 50.0% RoDeO cls: 100% RoDeO shape: **25.0%** AP@0.5: **0.0%** RoDeO loc: 100%

IoU: 25.0% acc@0.5: 87.5%



RoDeO total: 0.0% RoDeO cls: 0.0% RoDeO shape: 14.5 RoDeO loc: 0.0%

IoU: 0.0% acc@0.5: 75.0% AP@0.5: 0.0%

What RoDeO does better

- Correct localization is valuable even under misclassification
- Uses a notion of distance that credits even coarse localization
- Can not be tricked by simple over- or under-prediction
- Easy to interpret through disentanglement of failure sources (localization, misclassification, shape mismatch)



HOW DOES RODEO WORK?

1. Hungarian matching of predicted and target boxes

- Box overlap (gloU)
- Class matching, weighted based on classification performance (MCC) of model
- Sub-metric for Localization using center distance
- Based on (2D separable) normal distribution of (target-size normalized) center distance





- Sub-metric for Shape similarity using centered IoU (cloU) 3. Measures box size and aspect ratio match
- 4. Sub-metric for Classification using MCC

MCC only gives positive scores for performance above random, regardless of class imbalances Values < 0 are clipped

- **Correction for Under- and Overprediction** 5.
- Summary Metric using Harmonic Mean of corrected sub-metrics 6.

Degrades slowly for small distances, then fast, until degrading slowly again for large distances Degrades more smoothly and isotopically, further degrading even for non-overlapping boxes



Penalize non-matched pred/target boxes using linear combination of matched sub-scores and zero