

Australian National University

Confidence and Dispersity Speak: Characterizing Prediction Matrix for Unsupervised Accuracy Estimation

NEC Laboratories America

Unsupervised Accuracy Estimation

Definition: given a trained model, the goal is to estimate its accuracy on various test datasets without labels



Real-world evaluation: 1) the distributions of test sets are often *different* from that of training set (*no i.i.d*); 2) test labels are *unavailable* or *expensive to obtain*.



In-distribution accuracy may only be a weak predictor of performance on out-of-distribution data;

Evaluation without labels and under distribution shifts

Unlabeled Test Sets

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Prediction Confidence



Prediction Dispersity



Nuclear Norm

Prediction Matrix $P \in \mathbb{R}^{N_t \times K}$ (N_t test samples, and K classes) Nuclear Norm: the sum of singular values of prediction matrix Img-V2-B ⊣ $R^2 = 0.967$ r = 0.983 $\rho = 0.982$ r=0.931 % 0.7 0.75 0.8 0.85 0.9 0.95 0.88 0.9 0.92 Nuclear Norm R²=0.88 Img-V2-C =0.943 r=0.948 $\rho = 0.971$ $\rho = 0.967$ Img-R 🖛 🔸 ObiectNet 0.75 0.8 0.85 **Difference of Confidence**

Potential Direction

- 1) Other methods are stable under class imbalance;
- 2) Nuclear Norm is resistant to moderate class imbalance;
- 3) Nuclear Norm is less effective under severe class imbalance.



0.98 **Prediction Dispersity**



• Nuclear norm is effective in characterizing both confidence and dispersity



Nuclear norm exhibits the highest correlation strength with OOD accuracy

R²=0.950 ρ=0.980

0.94 Average Negative Entropy



0.75 0.8 0.85 0.89 Average Confidence



can expect

we have prior knowledge

about the imbalanced class

class predictions to follow it

distribution, we