Scientists revisit multi-dimensional classification from a dimension-wise perspective

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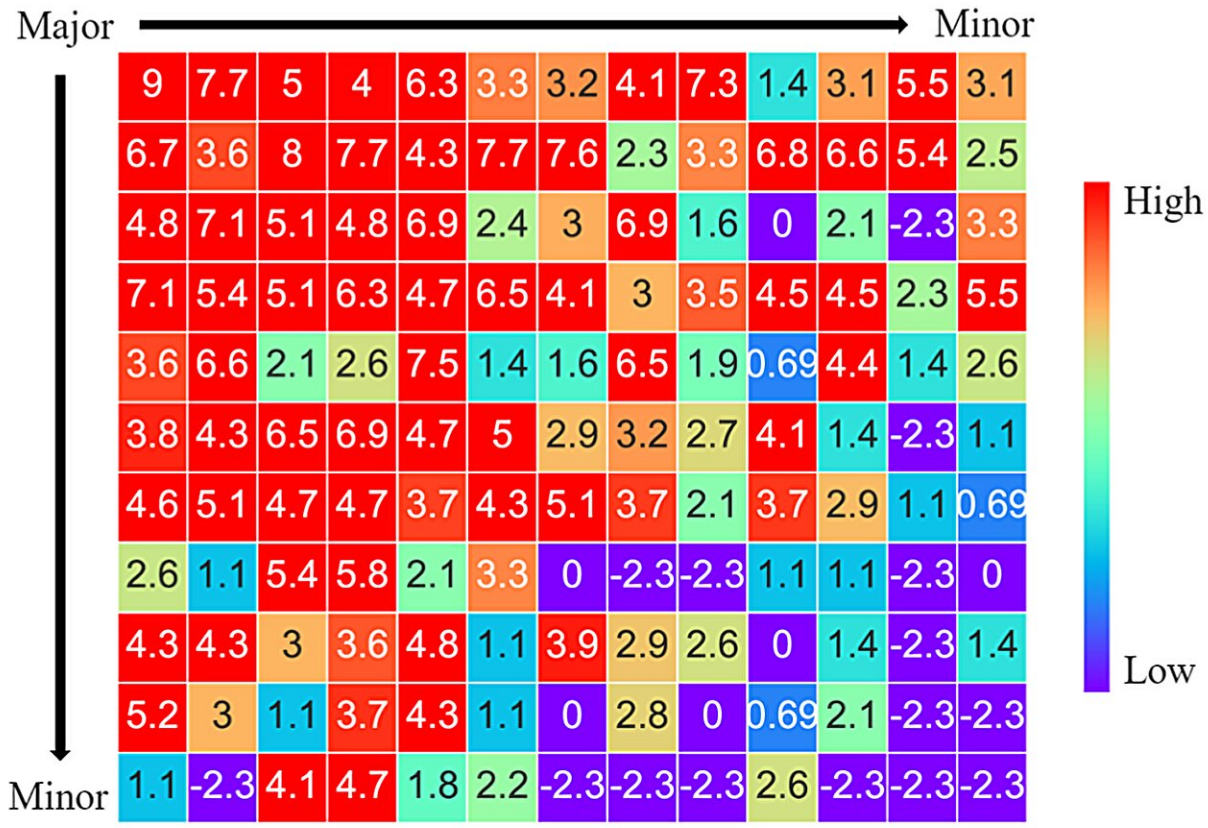

Figure 1.The imbalance shift from one LD to another. The color map counts the number of instances over two LDs on Zappos. The numerical values annotated on the colored blocks in the figure represent values post logarithmic transformation. Many major class instances become minor ones when the LD changes. In other words, the major/minor class property of an instance is difficult to be kept across LDs. Credit: *Frontiers of Computer Science* (2024).

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While the class imbalance issue has been extensively investigated within the multi-class paradigm, its study in the multi-dimensional classification (MDC) context has been limited due to the imbalance shift phenomenon. A sample's classification as a minor or major class instance becomes ambiguous when it belongs to a minor class in one labeling dimension (LD) and a major class in another.

Previous MDC methodologies predominantly emphasized instance-wise criteria, neglecting prediction capabilities from a dimension aspect, i.e., the average classification performance across LDs.

Addressing these problems, a research team led by De-Chuan Zhan from LAMDA, Nanjing University has published their new study, titled "Revisiting Multidimensional Classification from a Dimension-wise Perspective," in *Frontiers of Computer Science*.

The team asserts the significance of dimension-wise metrics in real-world MDC applications and introduce two such metrics. Furthermore, the team observes imbalanced class distributions within each LD and propose a novel Imbalance-Aware fusion Model (IMAM) for addressing the MDC problem.

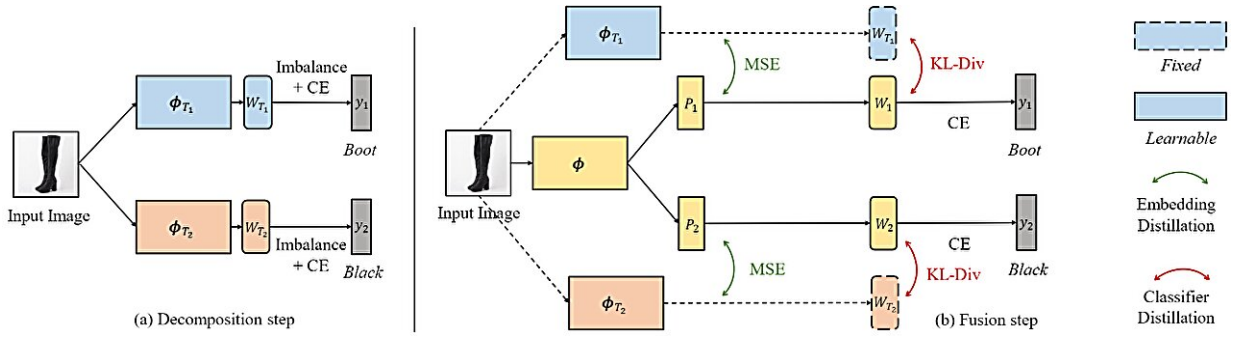

Figure 2. An illustration of our proposed IMAM approach based on an MDC problem with two LDs. In the decomposition step (a), we construct imbalance-aware deep models for each LD. In the fusion step (b), we use the models in the former step as fixed teachers and fuse their knowledge into a compact student. Both embedding (green) and classifier (red) distillations help in matching knowledge between models. Subscript "T" denote the component of teacher. "CE" means the cross-entropy. Credit: *Frontiers of Computer Science* (2024). DOI: 10.1007/s11704-023-3272-9. https://journal.hep.com.cn/fcs/EN/10.1007/s11704-023-3272-9

In the research, IMAM first decomposes the task into multiple multi-class classification problems, creating imbalance-aware deep models for each LD separately. This straightforward method performs well across LDs without sacrificing performance in instance-wise criteria. Subsequently, IMAM employs LD-wise models as multiple teachers and transfer their knowledge across all LDs to a unified student model.

Extensive experiments are conducted on various MDC datasets. The results indicate that the proposed IMAM is superior to others in a big gap.

More information: Yi Shi et al, Revisiting Multidimensional Classification from a Dimension-wise Perspective, *Frontiers of Computer Science* (2024). DOI: 10.1007/s11704-023-3272-9. journal.hep.com.cn/fcs/EN/10.1 … 07/s11704-023-3272-9

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