Revisiting Multi-dimensional Classification from a Dimension-wise Perspective

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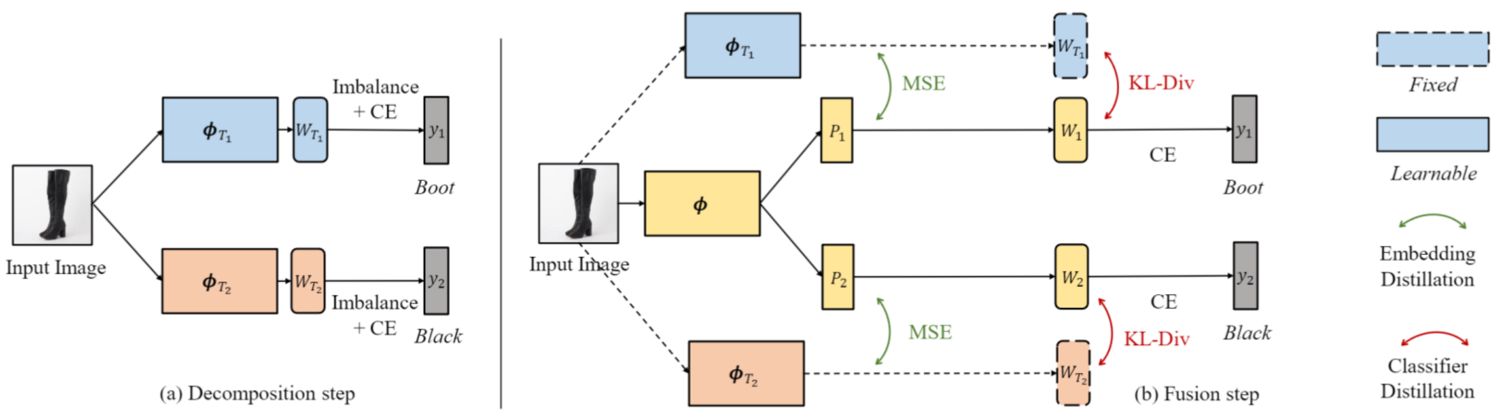
Problems & Ideas

- Problems of conventional stereo matching approaches:
  - The study of class imbalance issue in the MDC context has been limited due to the imbalance shift phenomenon.
  - Previous MDC methods mainly emphasized instance-wise criteria, neglecting prediction capabilities from a dimension aspect.
- **Ideas**: First train models to deal with class imbalance in different labeling dimensions (LDs), and then use knowledge distillation to concentrate the capabilities of them into a student model.



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.

Main Contributions

- Contributions:
  - We emphasize the importance of not only instance-wise metrics but also dimension-wise metrics for evaluating MDC models, and introduce two dimension-wise metrics for MDC.
  - We explore the distinct phenomenon of imbalance shift in MDC paradigms and assess its impact on dimension-wise evaluation metrics.
  - From the LD aspect, we employ the imbalanced LD-specific class distribution, and propose a simple yet effective method IMAM.

	Med				Zappos				Calligraphy				Letter			
Method	H-Acc	I-Acc	M^2F1	M^2AUC	H-Acc	I-Acc	M^2F1	M^2AUC	H-Acc	I-Acc	M^2F1	M^2AUC	H-Acc	I-Acc	M^2F1	M^2AUC
BR	90.63	74.62	70.09	92.69	66.54	47.89	43.35	85.87	80.65	72.32	78.71	96.62	71.00	44.25	67.37	92.07
ECC	87.91	68.35	51.25	84.69	60.74	37.86	35.44	69.53	74.27	71.94	71.19	87.38	65.45	40.06	59.34	86.53
KRAM	91.11	74.62	72.38	94.33	67.23	48.65	44.46	78.69	81.40	73.60	78.88	94.53	72.03	44.05	68.12	92.07
LEFA	90.75	75.27	69.88	92.84	67.66	48.36	44.85	80.87	80.42	72.85	77.06	91.86	72.33	42.80	66.88	91.75
M-Head	90.66	77.29	76.78	95.20	66.41	47.89	43.24	87.35	81.12	73.01	78.97	97.30	72.66	47.31	68.75	94.30
M-Emb	91.83	78.08	78.66	96.98	67.16	48.87	45.58	88.36	83.21	75.68	81.39	97.54	74.49	49.57	71.17	94.87
M-Head$_{\mathbf{Imb}}$	92.05	78.73	78.59	95.60	68.26	49.76	45.75	88.75	82.86	75.24	81.49	97.54	75.33	50.73	71.46	94.60
M-Emb$_{\mathbf{Imb}}$	91.77	77.95	78.32	96.73	66.95	48.12	45.45	88.00	82.22	74.56	80.40	97.47	73.52	49.33	70.58	94.37
IMAM	**93.10**	**80.82**	**81.79**	**97.71**	**68.33**	**50.01**	**45.90**	**89.32**	**83.44**	**76.06**	**81.98**	**97.61**	**81.48**	**61.43**	**79.21**	**96.70**

Performance of four traditional MDC methods, four deep MDC methods, and our IMAM on four real-world datasets. Four evaluation metrics from instance and label aspects are calculated. our IMAM is superior to others in a big gap.