MiMu: Mitigating Multiple Shortcut Learning Behavior of Transformers

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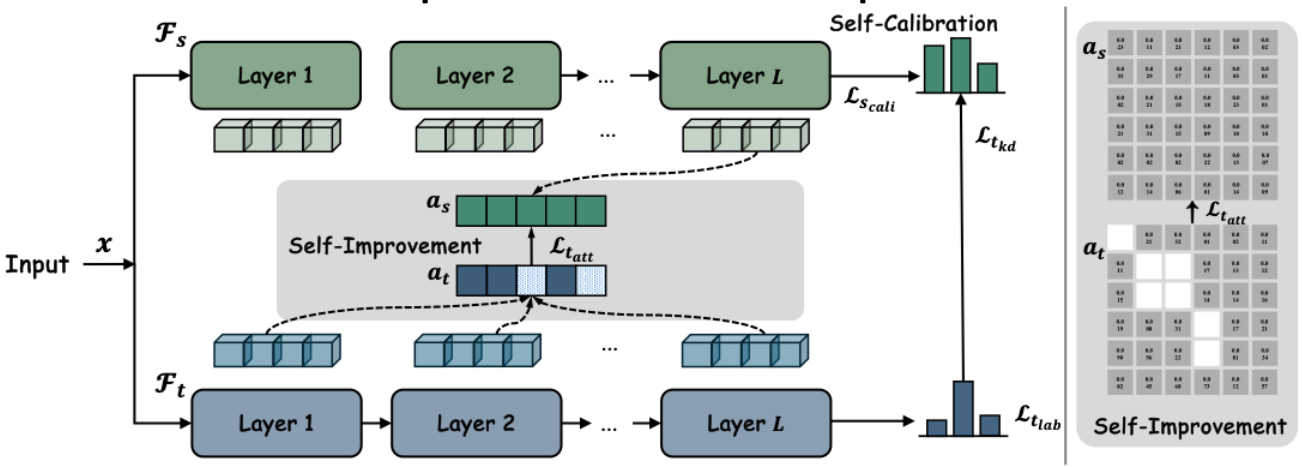
Problems & Ideas

- Problems of existing methods to mitigate shortcut learning:
  - Ignore multiple shortcut learning behavior in deep learning models.
  - Existing approaches are based on prior knowledge of shortcuts in deep learning, while shortcuts a model relies on are often diverse and unknown during the training process.
- Ideas: A self-distillation model is proposed to mitigate multiple shortcut learning behaviors: it first uses a source model for calibration and then employs a target model to further address the problem of multiple shortcuts.



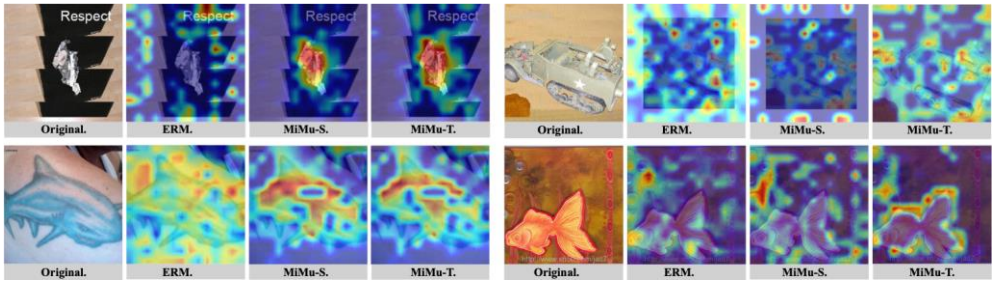
Architecture of MiMu to Mitigate Multiple shortcut learning behavior, which contains a self-calibration strategy in source model and a self-improvement strategy in target model. They jointly help mitigate multiple shortcut learning behavior and can be applied in NLP and CV domains.

Main Contributions

- Contributions:
  - In our empirical studies, we first find that models exploit shortcuts to varying degrees: they rely more heavily on strong shortcuts compared with weak ones, and their performance under multiple shortcuts often falls between the performance under a single shortcut.
  - Without prior knowledge of shortcuts, we propose a novel method MiMu, which contains self-calibration in source model and self-improvement strategy in target model following self-distillation to mitigate multiple shortcut learning behavior.
  - The proposed method-MiMu demonstrates strong versatility, and comprehensive experimental design, as it can be applied to a variety of tasks in both NLP and CV domains.

Category	Methods	Multiple	IN-9-W						
			dev	Rand-B	$\Delta^{\uparrow}$	Rand-W	$\Delta^{\uparrow}$	Rand-B+W	$\Delta^{\uparrow}$
ERM	ViT-L [66]	-	0.9796	0.7708	-	0.7357	-	0.7419	-
Augmentation & Regularization	Mixup [20]	✗	0.9789	0.7684	-0.0024	0.7345	-0.0012	0.7428	+0.0009
	Cutout [43]	✗	0.9804	0.7689	-0.0019	0.7343	-0.0014	0.7407	-0.0012
	CutMix [44]	✗	0.9753	0.7684	-0.0024	0.7307	-0.0050	0.7371	-0.0048
	AugMix [45]	✗	0.9794	0.7670	-0.0038	0.7355	-0.0002	0.7364	-0.0055
	SD [67]	✗	0.9796	0.7708	-	0.7357	-	0.7416	-
Pseudo Shortcut	LfF [21]	✗	0.9792	0.7708	-	0.7357	-	0.7409	-0.0010
	JTT [47]	✗	0.9806	0.7732	+0.0024	0.7417	+0.0060	0.7448	+0.0029
	EIIL [22]	✗	0.9811	0.7679	-0.0029	0.7300	-0.0057	0.7426	+0.0007
	DebiAN [48]	✓	0.9804	0.7710	+0.0002	0.7384	+0.0027	0.7450	+0.0031
Unknown Shortcut	COMI [8]	✗	0.9742	0.7976	+0.0268	0.7947	+0.0590	0.7795	+0.0376
Ours	**w/o s-c**	✓	0.9780	0.7968	+0.0260	0.7986	+0.0629	0.7806	+0.0387
	w/o s-i	✓	0.9751	0.7952	+0.0244	**0.8074**	+0.0717	0.7794	+0.0375
	MiMu	✓	0.9782	**0.8021**	+0.0313	0.8036	+0.0679	**0.7868**	+0.0449

The experimental results on the IN-9-W in CV.



The saliency maps in Rand-B+W (top line) and IN-R+W (bottom line). From left to right in each case are from the original image, the pre-trained ViT-Large, source model and target model in MiMu.