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Multi-Attribute Learning With Highly Imbalanced Data

Motivation

- Bad performance due to problems in data.
- Powerful and straightforward deep learning models not able to use classical imbalance learning strategies
- Different levels of imbalance:
  - The number of attributes per image is different.
  - The problem of unrepresented classes or 'attribute-value' combinations.
  - Inconsistency of labels/classes pairs given by annotators which are very subjective, different, and can be incorrect.

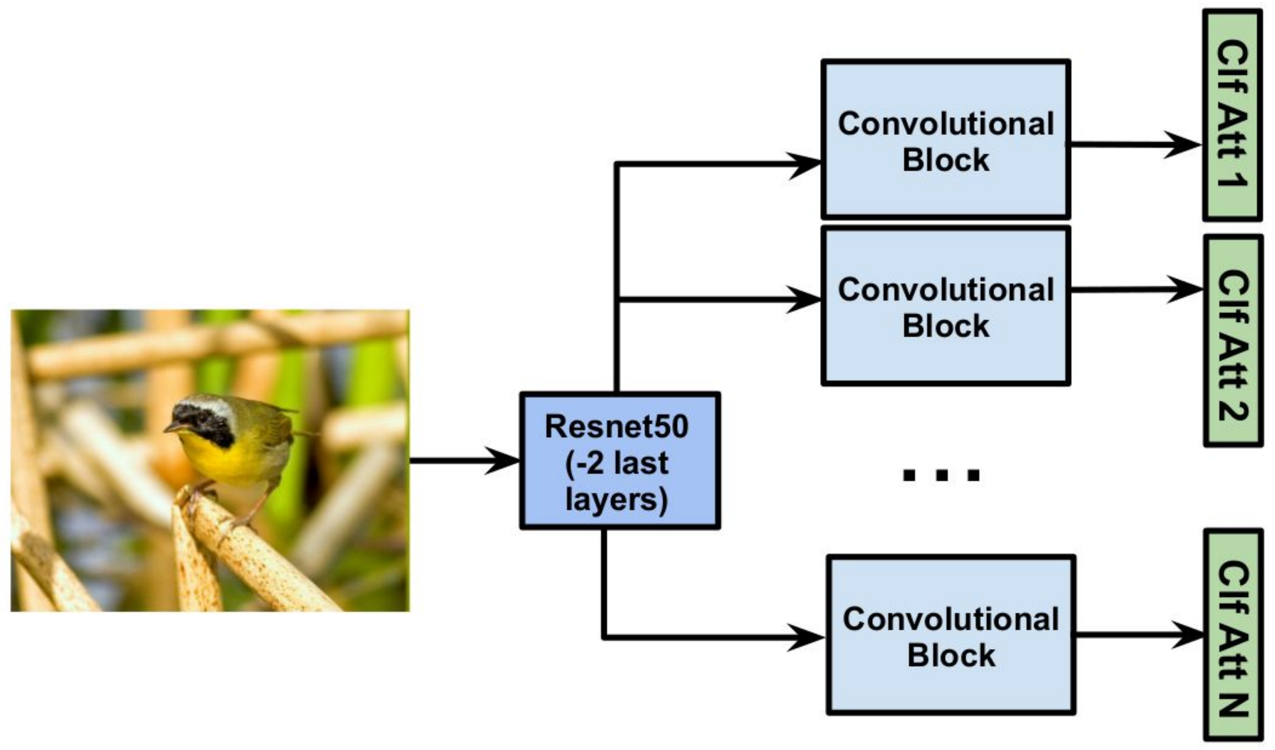
Proposed Strategies

Adaptations for different levels of imbalance:

- Class-level attribute transfer: Total and partial

Adaptations for two classical imbalanced strategies:

- Sampling: Modifying the strategy to create batches → two different strategies to assign weights for samples.
- Cost-sensitive learning: Assigning weights to each class. Specialized loss function (Focal Loss)



- Independent model for each attribute
- **Multitask**
- Multilabel

RESULTS

Database	# classes	# attributes	# Train	# Test
CUB	200	312 (239 used)	5,994	5,794
AwA2	50	85	29,409	7,913
celebA	10,177	40	162,770	19,962

Setting	Accuracy (%)
None strategy	72.78
Data augmentation	**73.06**
Weighted Random Sampler with Different Weights + No Replacement	72.57
Weighted Random Sampler with Equal Weights + No Replacement	**73.21**
Weighted Random Sampler with Equal Weights + Replacement	**73.24**
Data augmentation + Weighted Loss	66.98
Weighted Random Sampler with Equal Weights + Replacement + Weighted Loss	65.70

		CUB			AwA2			CelebA		
	Model	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Macro Avg	SVM	24.15	27.52	**22.22**	58.24	59.84	51.17	50.66	**79.26**	59.50
	MLKNN	13.04	12.28	12.48	53.82	55.71	47.02	41.60	41.25	40.61
	Log Reg	29.59	10.71	14.21	58.08	60.46	51.47	65.16	46.57	51.65
	RandomF	**79.31**	1.28	1.92	64.30	51.88	46.33	58.15	23.42	27.58
	DecisionT	10.29	7.15	8.08	51.60	52.92	44.43	42.73	28.49	32.09
	ELM	7.71	**32.63**	10.34	40.38	56.68	41.06	31.52	45.52	34.73
	GaussianNB	30.30	14.54	17.04	55.32	54.08	45.95	44.32	53.98	46.53
	Deep Multilabel	23.01	17.99	18.71	**77.67**	**70.61**	**73.31**	**78.02**	70.50	**73.15**
Weighted Avg	SVM	35.49	**51.10**	41.12	72.87	66.80	67.14	67.02	**80.56**	71.42
	MLKNN	26.84	26.70	26.67	69.06	63.69	63.47	55.23	58.52	56.48
	Log Reg	47.06	21.43	26.94	73.26	66.98	67.41	72.55	62.61	65.09
	RandomF	**50.61**	7.49	9.29	74.17	63.17	62.47	65.42	45.78	49.20
	DecisionT	23.35	18.65	20.62	67.85	61.26	61.56	58.63	49.77	51.93
	ELM	21.98	37.15	25.86	61.34	56.96	57.16	52.36	56.51	53.32
	GaussianNB	41.49	26.49	30.87	69.91	62.55	62.53	57.48	64.66	59.38
	Deep Multilabel	46.00	40.73	**41.42**	**83.19**	**78.36**	**80.05**	**84.35**	77.12	**79.67**

Conclusions

- Study of a fine-grained attribute classification problem with CUB imbalanced database as our main use case.
- Most bad performance problems are due to the data itself.
- Straightforward deep learning models offer suitable performances.
- Adapted strategies for different levels of imbalanced.
- Adapted strategies concerning 'Sampling' and 'Cost-Sensitive Learning approaches (same weights to all samples but with replacement).
- Loss function suitable to the imbalanced problem (Focal Loss).