Deep N-ary Error Correcting Output Codes

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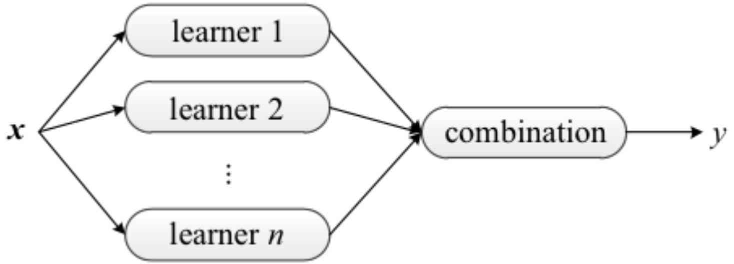
Ensemble Learning for Multi-class Classification

- Ensemble learning is the process by which multiple models are strategically generated and combined to solve a particular computational intelligence problem.

- An ensemble-based system
  - Combination of diverse models, henceforth classifiers.
  - **Improve** the classification performance and **reduce** the likelihood of an unfortunate selection.

- Ensemble Method:
  - Data-independent ensemble model, e.g. ECOC.



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Error Correcting Output Codes (ECOC)

- ECOC
  - An ensemble method designed for multi-class classification problem.
  - A meta method which combines many **binary classifiers**.

- ECOC coding approach aims to construct the ECOC matrix

$$\Lambda \in \{-1,1\}^{N_C \times N_L}$$

Where N_C is the number of classes and N_L is the code length, and its elements are randomly chosen as either −1 or 1.

	M_1	M_2	M_3	M_4	M_5	M_6
C_1	-1	1	-1	1	1	1
C_2	1	1	-1	1	1	1
C_3	1	1	1	1	-1	-1
C_4	-1	1	1	1	-1	1
C_5	1	-1	1	1	-1	-1
C_6	1	1	1	-1	-1	1
C_7	-1	1	-1	-1	1	-1
C_8	1	1	-1	-1	1	1
C_9	1	1	1	-1	1	-1

An example of 6-bit ECOC for a 9-class problem

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N-ary Error Correcting Output Codes (N-ary ECOC)

- *N*-ary ECOC
  - An extension of the traditional ECOC methods.
  - Decompose the original classes into N meta-class, where $3 \leq N \leq N_C$.
  - A meta method which combines many **sub-multiclass classifiers**.

- Advantages:
  - More general.
  - Larger row separation.
  - Lower column correlation.

	M_1	M_2	M_3	M_4	M_5	M_6
C_1	1	1	2	4	1	1
C_2	2	1	1	3	2	1
C_3	3	2	1	2	3	1
C_4	4	3	1	1	4	2
C_5	4	3	2	2	4	3
C_6	4	3	3	3	3	4
C_7	3	4	4	4	2	4
C_8	2	4	3	4	2	3
C_9	3	4	2	3	3	2

An example of 6-bit N-ary ECOC for a 9-class problem

Deep *N*-ary ECOC

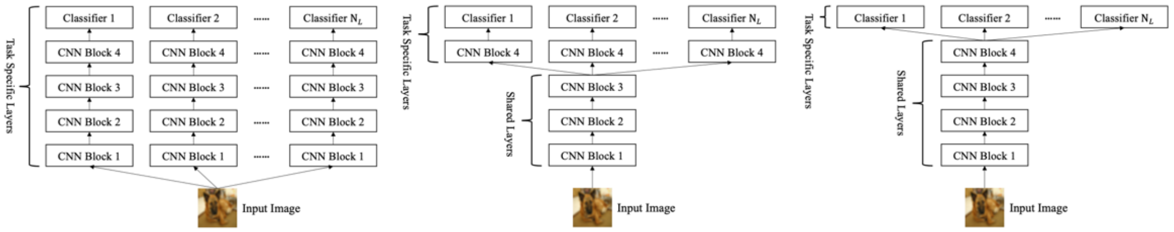
- Traditional ECOC methods:
  - Based on the pre-defined hand-craft features.
  - Focus on how to ensemble the results of base learners on these features.

- Deep N-ary ECOC:
  - Integrate ECOC framework with deep neural networks.

1. Do we necessarily independently train all the deep base learners from scratch for all the situation?
2. Whether the *N*-ary ECOC framework still has advantages over other data-independent ensemble approaches with deep neural network?
3. Any new suggestion on the choice of the meta-class number N and number of base learners N_L?

Deep N-ary ECOC

- Parameter Sharing Strategy
  - No parameter share.
  - Partial parameter share.
  - Full parameter share.
  - The no parameter sharing strategy contains most parameters (N_n), then the partial sharing strategy (N_p) and the full sharing strategy (N_f) is least, say, $N_n > N_p > N_f$.
- For the remaining two questions, we investigate through the experiments.



(a) No Share (b) Partial Share (c) Full Share

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Experimental Settings

- Conduct the experiments on 4 image datasets and 2 text datasets
  - Image datasets: MNIST, CIFAR-10, CIFAR-100, FLOWER-102.
  - Text datasets: Text REtrieval Conference (TREC) and Stanford Sentiment Treebank (SST) datasets

Image Dataset					
Dataset	Image Size	# Train Sample	# Dev Sample	# Test Sample	# Classes (N_C)
MNIST	28×28	60,000	N/A	10,000	10
CIFAR-10	32×32	50,000	N/A	10,000	10
CIFAR-100	32×32	50,000	N/A	10,000	100
FLOWER-102	256×256	6,552	818	819	102
Text Dataset					
Dataset	Avg. Sent. Len.	# Train Sample	# Dev Sample	# Test Sample	# Classes (N_C)
TREC	10	5,500	N/A	500	6
SST	18	11,855	N/A	2,210	5

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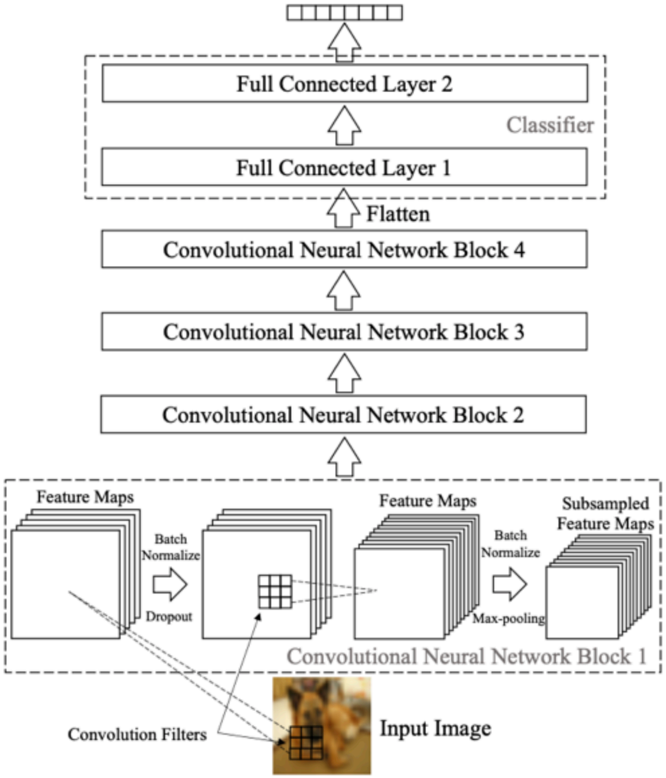
Experimental Settings

❖ Deep Leaning Model for Image Classification

- ➢ LeNet for the MNIST dataset.
- ➢ AlexNet for the FLOWER-102 dataset (pre-trained on ILSVRC dataset).
- ➢ CIFAR-CNN for CIFAR-10/100 datasets.



CIFAR-CNN

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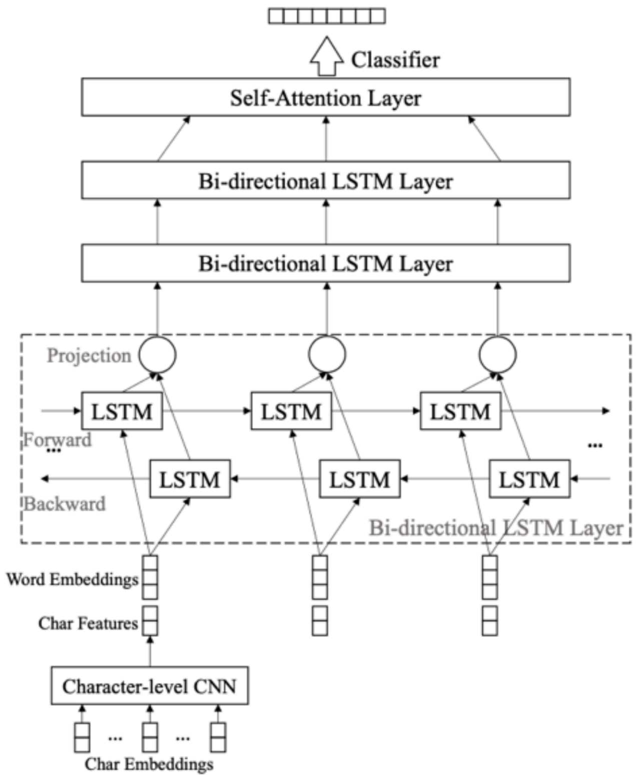
Experimental Settings

❖ Deep Leaning Model for Text Classification

➢ Character-level CNN learned the character features to represent a word from the character sequences of such word.

➢ The word-level Bi-LSTM performs to learn contextual representations .

➢ The self-attention mechanism encodes word feature sequence to a single sentence representation.



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Experimental Settings

❖ Summarization of Tested N and N_L for experiments.

Dataset	# Classes (N_C)	Tested # Meta-Class (N)	Tested # Base Learners* (N_L)
MNIST	10	2, 4, 5, 8, 10	60
CIFAR-10	10	2, 4, 5, 8, 10	100
CIFAR-100	100	2, 5, 10, 30, 50, 75, 95, 100	100
FLOWER-102	102	2, 3, 5, 10, 20, 40, 60, 80, 90, 95, 102	60
TREC	6	2, 3, 4, 5, 6	60
SST	5	2, 3, 4, 5	60

* It indicates the maximal number of classifiers is used for training.

Experiments

- Ensemble accuracies of different methods on benchmark datasets.
  - Compared to single model, the improvement ratio of N-ary ECOC is inverse relation with single model performance.
  - The N-ary ECOC scheme outperforms ECOC and ERI ensemble methods on most image and text datasets.

Dataset	Method	Single Model	Ensemble Model*		
			ERI	ECOC	N-ary ECOC (N)
MNIST	LeNet [32]	$98.98 \pm 0.07\%$	$99.11 \pm 0.11\%$	$99.23 \pm 0.08\%$	**99.57** $\pm 0.09\%$
CIFAR-10	CIFAR-CNNs	$87.12 \pm 0.43\%$	$90.54 \pm 0.31\%$	$89.37 \pm 0.54\%$	**91.95** $\pm 0.24\%$
CIFAR-100	CIFAR-CNNs	$61.50 \pm 0.57\%$	$69.57 \pm 0.29\%$	$34.26 \pm 2.42\%$	**69.94** $\pm 0.32\%$
FLOWER-102	AlexNet [15]	$83.12 \pm 0.29\%$	$86.32 \pm 0.60\%$	$77.05 \pm 0.73\%$	**87.94** $\pm 0.28\%$
TREC	Bi-LSTMs	$90.50 \pm 0.12\%$	$94.80 \pm 0.09\%$	$95.80 \pm 0.08\%$	**95.60** $\pm 0.10\%$
SST	Bi-LSTMs	$44.17 \pm 0.92\%$	$48.69 \pm 0.18\%$	$48.91 \pm 0.26\%$	**50.86** $\pm 0.13\%$

* Here N_L are 60, 100, 100, 60, 60 and 60, respectively, for the ensemble models from top to bottom row. While N are 3, 4, 95, 95, 3, 4, respectively, for the N-ary ECOC.

ERI: ensemble of random initialization

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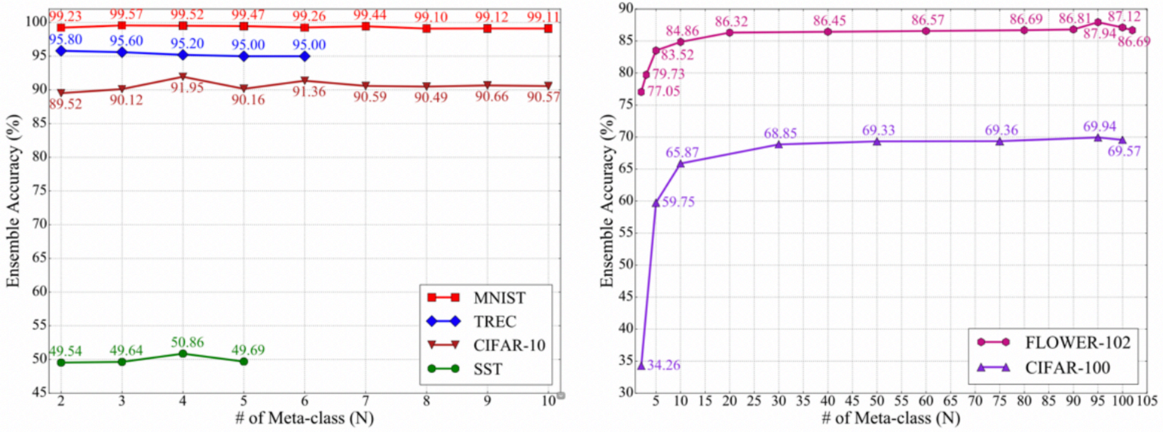
Experiments

- Evaluation on the Effect of Meta-class Number N.
  - For dataset with small number of N_C, the performances of ensemble models with different N are relatively stable.
  - the performance of ensemble models with different N fluctuates significantly on the datasets with a large value of N_C.



(a) Datasets with small value of N_c

(b) Datasets with large value of N_c

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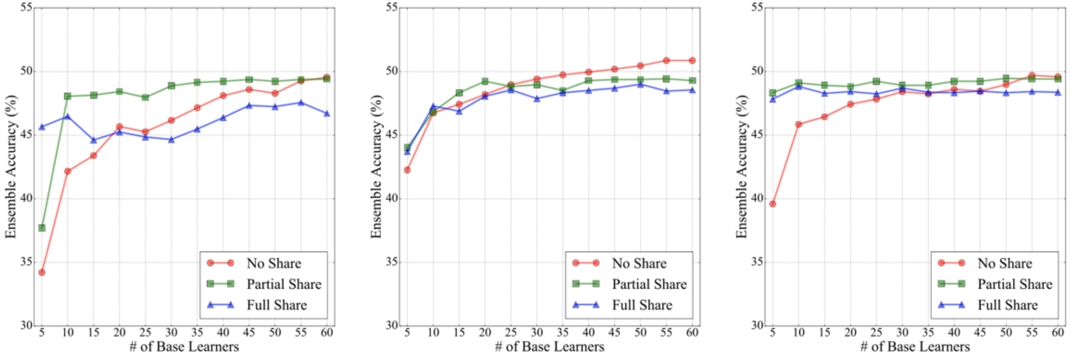
Experiments

- Evaluation on the Effect of Base Learner Number N_L.
  - Smaller number of base learners are required for dataset with small N_C than that of large N_C to reach the optimal ensemble accuracies generally.

Dataset	N	# of Base Learners (N_L) 10	20	30	45	50	60	80	100
MNIST	3	99.14%	99.20%	99.35%	99.48%	99.57%	99.57%	-	-
CIFAR-10	4	87.45%	89.76%	91.78%	91.83%	91.82%	91.92%	**91.95%**	91.93%
CIFAR-100	95	67.94%	69.12%	69.11%	69.33%	69.34%	69.46%	69.67%	**69.94%**
FLOWER-102	95	86.06%	86.45%	86.45%	87.06%	87.16%	**87.94%**	87.46%	87.59%
TREC	3	93.80%	94.00%	95.20%	95.20%	95.60%	**95.60%**	95.50%	**95.60%**
SST	4	46.74%	48.19%	49.41%	50.18%	50.45%	**50.86%**	-	-

Experiments

- Comparison with Three Parameter Sharing Strategies.
  - Take SST dataset as an example.
  - When the number of meta-class *N* is small, both partial and no share models improve significantly with the increase of N_L. The partial share generally outperforms the no and full share except when N_L is less.
  - When the number of meta-class *N* is large, the performance of the three strategies are stable, and the improvement of no share is most significant with the increase of N_L.



(a) ECOC ($N = 2$) (b) N-ary ECOC ($N = 4$) (c) ERI ($N = 5$)

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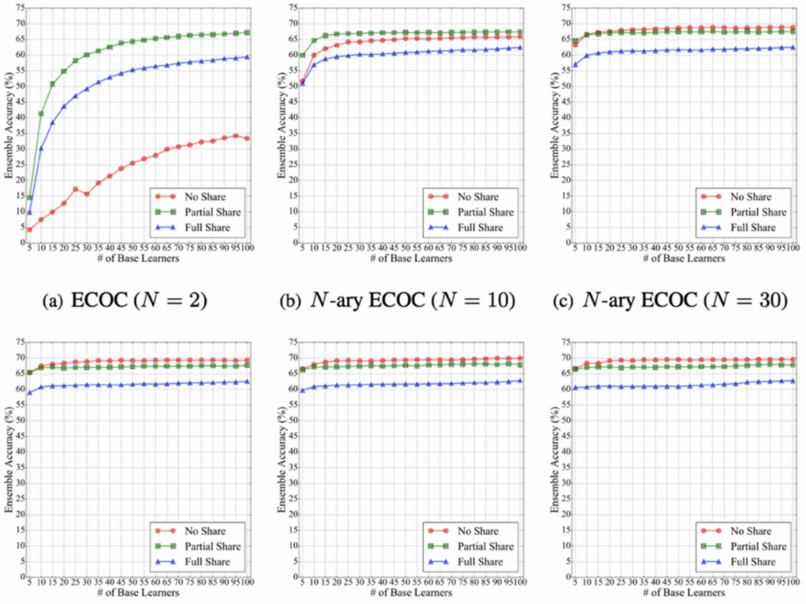
Experiments

❖ Comparison with Three Parameter Sharing Strategies.

- Take CIFAR-100 dataset as an example.
- ECOC model with no share strategy fails to achieve satisfactory performance.
- For N-ary ECOC with small N, partial share strategy outperforms no and full share strategies.
- For the ERI model, no share strategy is comparable to partial share when N_L is small. It always performs best when N_L increases, meanwhile, the performance of full share is worst.



(a) ECOC ($N = 2$) (b) N-ary ECOC ($N = 10$) (c) N-ary ECOC ($N = 30$)

(d) N-ary ECOC ($N = 50$) (e) N-ary ECOC ($N = 95$) (f) ERI ($N = 100$)

Conclusion

- For the dataset with small N_C:
  - No share model is better than or equal to the partial share model, thus no share strategy is suggested.
  - When the number of meta-class N is large, these three strategies perform stable.

- For the dataset with large N_C:
  - When the number of meta-class N is small, the performance of partial share model is the best.
  - when the number of meta-class N is large, no share strategy outperforms partial and full share strategies in most cases. Thus no share strategy should be preferred.

- If the number of meta-class is N large, the performance between three sharing strategies is marginal. Then full share could be suggested due to its parameter efficiency.

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Thank You!