Avaliação de Classificadores de Imagem Multi-rótulo

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Objetivos da Pesquisa

Explorar a aplicação do LV-CIT em um ambiente black-box

Replicar e estender os experimentos originais

LV-CIT

- É uma técnica de teste de software que busca encontrar defeitos causados pela interação entre diferentes parâmetros de uma imagem.
- Normalmente estes testes são feitos usando pares de imagens.

LV-CIT

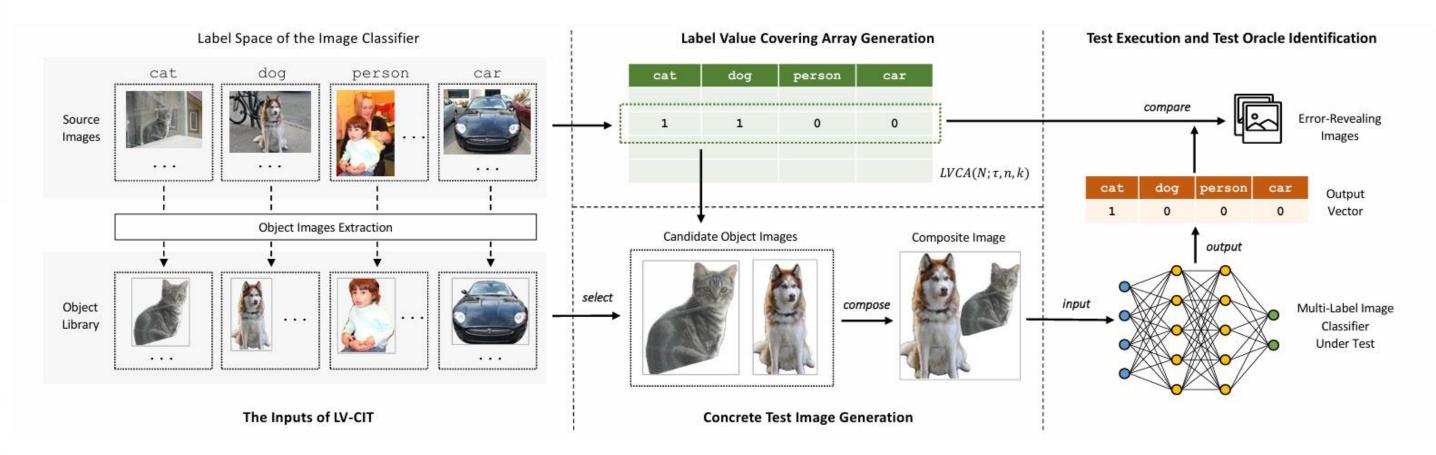


Fig. 1. The workflow of the LV-CIT method.

Metodologia Experimental

Array que mostra a presença do label na imagem

TABLE I
A 2-WAY LABEL VALUE COVERING ARRAY LVCA(6; 2, 4, 2)

	$l_1: cat$	$l_2:dog$	$l_3: person$	$l_4: car$
t_1	1	1	0	0
t_2	1	0	1	0
t_3	1	0	0	1
t_4	0	1	1	0
t_5	0	1	0	1
t_6	0	0	1	1

Metodologia Experimental

Rodar o ambiente LV-CIT

Carregar as bibliotecas e dependências

Carregar os modelos de redes neurais profundas E os datasets

Testar a acurácia dos modelos com teste blackbox

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Algorithm 1 The Adaptive Sampling Algorithm for \tau-way
Label Value Covering Array Generation
Input: Size of label space n, counting constraint variable k,
     and covering strength \tau
Output: LVCA(N; \tau, n, k)
  1: coverage \leftarrow 0, A \leftarrow \{\}, labels \leftarrow [1, 2, \cdots, n]
 2: while coverage < 1 do
         row \leftarrow [0, 0, \cdots, 0]
                                                        \triangleright length is n
         c \leftarrow RandomInt(1, k)
                                            > number of value one
     assigned
         Sort labels by the occurrence of value one in A in
     ascending order
        m \leftarrow RandomInt(1, \lceil \frac{n}{2} \rceil)
        least_m \leftarrow labels[:m], others \leftarrow labels[m:]
         c_1 = min(m, \lceil \frac{c}{2} \rceil)
         c_2 = c - c_1
         selected \leftarrow RandomSample(least_m, c_1)
         selected \leftarrow selected \cup RandomSample(others, c_2)
 11:
 12:
         for i \in selected do
            row[i] \leftarrow 1
 13:
         end for
 14:
         if row \notin A then
 15:
             A \leftarrow A \cup \{row\}
 16:
             Update coverage with A, \tau
 17:
         end if
19: end while
 20: for row \in A do
         Delete row from A if coverage of A \setminus \{row\} is 1
22: end for
 23: return A
```

Tabela de validação

TABLE II

The Size of Label Spaces (n), Name of DNN Models, Mean Average Precisions (mAP) Achieved, Number of Images in the Object Libraries (OL), and Number of Labels Involved (LI) of the Subject DNN Models in the Experiment

Datasets	n	DNN Models	mAP	OL	LI
		MSRN [45]	96%	580	20
VOC [32]	20	ML-GCN [22]	94%	576	20
		ASL [46]	94.6%	576	20
		MSRN [45]	83.4%	1,973	80
COCO [33]	80	ML-GCN [22]	83%	1,987	80
		ASL [46]	86.6%	1,811	79

Gráficos casos de teste

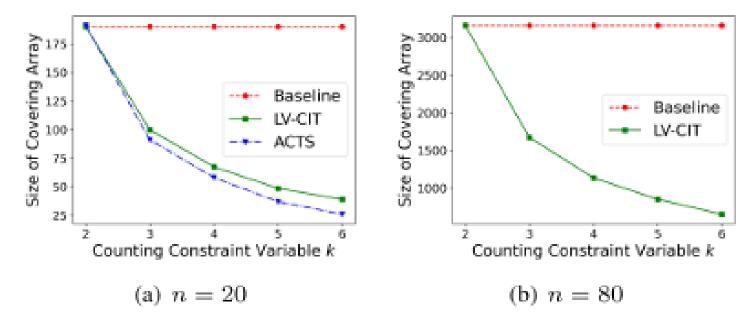


Fig. 3. Sizes of 2-way label value covering arrays generated by different generation methods.

Gráficos custo do tempo de execução da cobertura de teste

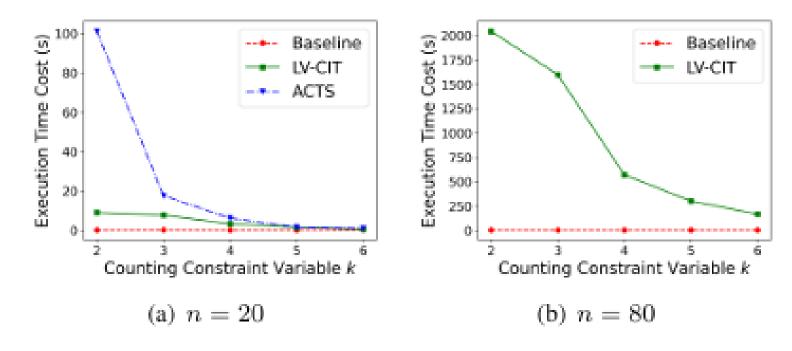


Fig. 4. Execution time costs (seconds) of different generation methods.

Teste de cobertura com LV-CIT e cobertura com método randomico

TABLE III
THE AVERAGE 2-WAY LABEL VALUE COMBINATION COVERAGE OF THE LV-CIT AND Random Methods

Datasets	DNN Models	Coverage			
Datasets	Divin Models	LV-CIT	Random		
	MSRN	100%			
VOC	ML-GCN	100%	82.34%		
	ASL 100%				
	MSRN	100%			
COCO	ML-GCN	100%	90.07%		
	ASL	98.75%			

Número de imagens, Erros e entre LV-CIT, Método randomico e ATOM.

TABLE IV
THE NUMBERS OF TEST IMAGES GENERATED, NUMBER OF ERRORS REVEALED, AND PROPORTION OF ERROR-REVEALING IMAGES OF THE LV-CIT, Random, and ATOM Methods

Datasets	DNN Models	Number of Images			Number of Errors			Proportion of Error-Revealing Images		
		LV-CIT	Random	ATOM	LV-CIT	Random	ATOM	LV-CIT	Random	ATOM
VOC	MSRN	674	674	898	603.6	160.8	304	89.6%	23.85%	33.85%
	ML-GCN	674			624.2	169.8	302	92.64%	25.22%	33.63%
	ASL	674			605.4	132	193	89.84%	19.58%	21.49%
coco	MSRN	11,358	11,358	13,297	10,368.8	6,255.8	5,984	91.3%	55.08%	45%
	ML-GCN	11,358			10,387	6,291.2	6,484	91.46%	55.39%	48.76%
	ASL	11,352			9,915	5,645.2	4,584	87.35%	49.71%	34.47%

Precisão de reconhecimento e interação de rótulos

TABLE V
THE MEAN AVERAGE PRECISION (MAP) AND 2-WAY MEAN
INTERACTION ACCURACY (MIA) OF THE SUBJECT DNN MODELS

Datasets	DNN Models	mAP	2-way mIA
	MSRN	96%	81.79%
VOC	ML-GCN	94%	80.28%
	ASL	94.6%	84%
	MSRN	83.4%	95.51%
COCO	ML-GCN	83%	95.53%
	ASL	86.6%	96.01%

3 principais combinações de rótulos que podem gerar Erros

TABLE VI

THE NUMBER OF ERRORS-REVEALING IMAGES (E), and Number of Related Training Images (TI) of Top Three 2-way Label Combinations (LC) that Cause the Most Errors Across the Three Types of Errors by the ALS Image Classifier

Datasets	Missing			Extra			Mismatch		
	LC E TI		TI	LC	E	TI	LC	E	TI
	{chair, cow} 28.8 0 {car, person} 3.6 215 {bus, car}		{bus, car}	8	63				
VOC	{bus, chair}	22	0	{horse, person}		221	{car, chair}	2.2	5
	{dining table, train}	21.8	0	{motorbike, person}	1.8	169	{dining table, person}	2	94
	{donut, surfboard}	32	1	{bus, person}	26	2,149	{knife, skis}	34	1
COCO	{kite, skateboard}	30	2	{baseball glove, sports ball}	23.4	826	{cake, dining table}	27	1,234
	{couch, spoon}	28.8	74	{keyboard, mouse}	22.8	878	{cow, dog}	26.6	49

Conclusões e Trabalhos Futuros

Implementar o modelo

Ampliar os usos para novos datasets e novos modelos