# **Deep Learning Logo Detection with Data Expansion by Synthesising Context**

Xiatian Zhu



Hang Su hang.su@qmul.ac.uk

### Introduction 1

### **Logo detection challenges:**

(1) Small instance size



(3) Various designs per logo







(2) Non-rigid appearance change



(4) Small training data

DatasetData SizeImageNet [1]1,000,000+
ImageNet [1] 1,000,000+
MS COCO [2] 300,000+
BelgaLogos [3] 1,951
FlickrLogos-27 [4] 1,080
FlickrLogo-32 [5] 2,240

### **Contributions:**

- (1) A logo data expansion approach by synthesising context
- (2) A new logo dataset TopLogo-10 with clothing logos

# **TopLogo-10**

**Richer context**, e.g. person, shoes, clothing, etc.

More logo design didds HH GUCCI variations

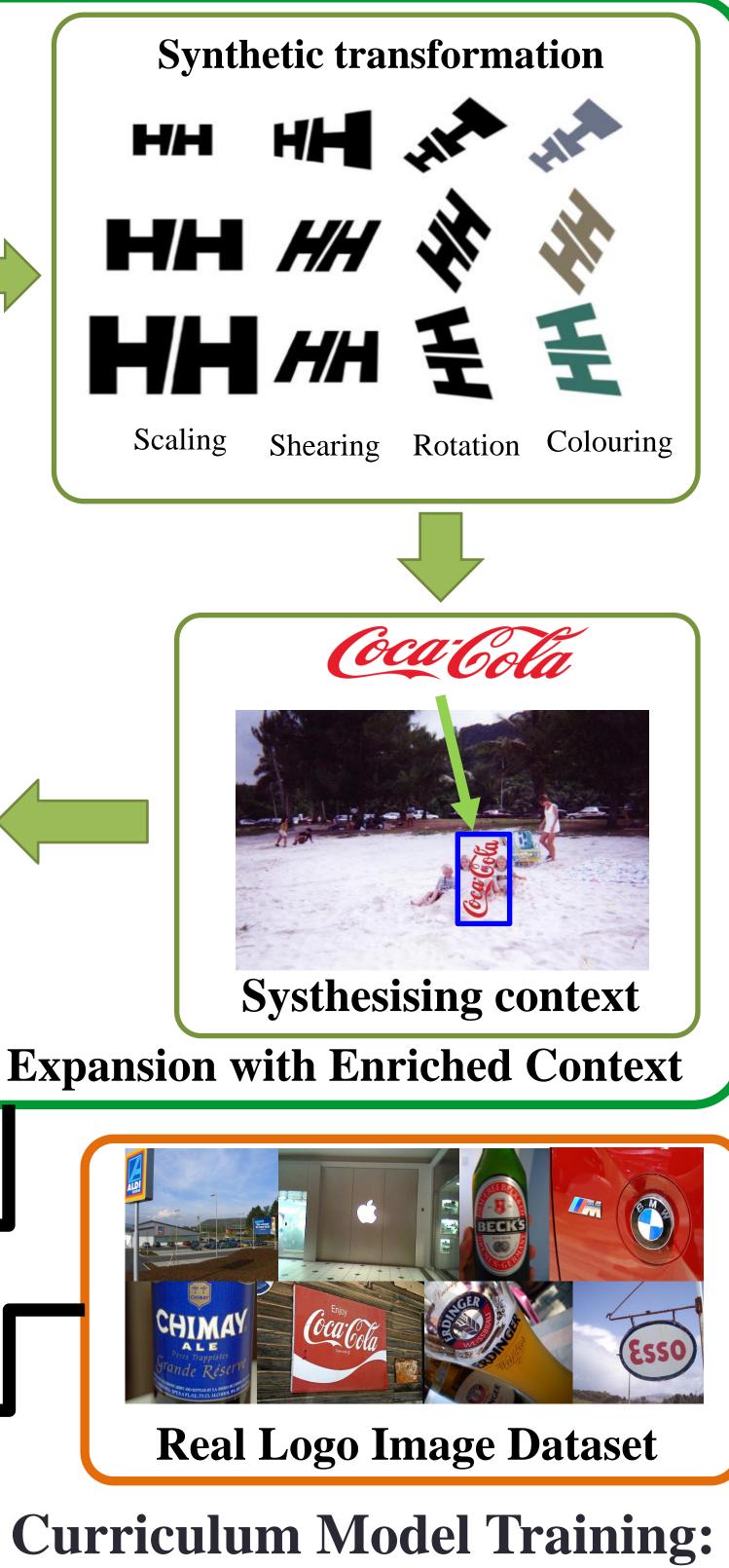
Larger logo size variations



xiatian.zhu@qmul.ac.uk

## **Data Expansion by Synthesising Context** 3 **Clean logo exemplar/icons** adidas HH GUCCI **D N** PRADA Supreme HH HH £ 🕞 💮 🧼 🥢 🌆 FedEx Google GUINNESS Milka Ford ONIDIA RICES SPORT SINGHA Synthetic training images with logo in various context **Synthetic Logo Training Dataset Expansion with Enriched Context Stage 1: Pre-train Model with Synthetic Data Stage 2: Fine-Tune Model with Real Data** PRADA Supreme **Final Logo Detection Model**

Shaogang Gong s.gong@qmul.ac.uk



Easy-to-hard learning strategy

## Tuoluotiona

<b>Training Data</b>	mAP
Real data only	50.4
Synthetic data only (32 Cls)	27.6
Synthetic data only (463 Cls)	20.5
Synthetic (32 Cls) + Real	54.8
Synth 463Cls + Real	55.9

Significant mAP gain by synthetic
pre-training: 5.5% = 55.9 - 50.4
Poor performance by synthetic data
only: 27.6% / 20.5% vs 50.4%

<b>Results on FlickrLogo-32</b>		<b>Results on</b>	<b>Results on TopLogo-10</b>		
Training Data	mAP	Training D	ata	mAP	
Real data only	50.4	Real data only 28.		28.5	
Synthetic data only (32 Cls)	27.6	Synthetic data only (10Cls) 7		7.3	
Synthetic data only (463 Cls)	20.5	Synthetic data onl	Synthetic data only (463Cls) 1		
Synthetic (32 Cls) + Real	54.8	Synthetic (10Cls	s) & Real	40.4	
Synth 463Cls + Real		Synthetic (463Cl		41.8	
Significant mAP gain by synth ore-training: $5.5\% = 55.9 - 50$ Poor performance by synthetic only: 27.6% / 20.5% vs 50.4	.4 c data	Significant mAP ga training: 13.3% = 4 Poor performance only: 7.3% / 10.2%	ain by synthe 11.8 – 28.5 by synthetic	etic pre- data	
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Data expansion by synthetic cont critical to improve deep logo detecti sparse labelled data

Our TopLogo-10 dataset: suggest logo detection in diverse real-world more challenging



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ntext is tion given	<ul> <li>[1] J. Deng, etal. ImageNet: A Large-Scale Hierarchical Image Database.</li> <li>CVPR, 2009</li> <li>[2] Tsung-Yi Lin, et al. Microsoft</li> <li>COCO: Common Objects in Context.</li> <li>ECCV, 2014</li> </ul>
	[3] A.Joly and O.Buisson. Logo retrieval with a contrario visual query expansion.
sting that a scenes is	ICMR 2009 [4] Y. Kalantidis, et a Scalable
	triangulation-based logo recognition. ICMR 2011.
	<ul><li>[5] S. Romberg, et al Scalable logo</li><li>recognition in real-world images. ICMR</li><li>2011</li></ul>