

Implementing Face Recognition on a Social Scrabble-playing Robot

Motivation



- Personalization improves engagement and helps establish intimate, long-term relationships between Victor and players
- Face recognition is needed for Victor to identify the players
- Little research is done on local optimizations of open-source face recognition

Problem

Chosen face recognition model: **Dlib** over OpenFace (Dlib had significantly higher Asian accuracy)

Factors to optimize:

Accuracy (correctly labeling known faces)

Unknown Detection (correctly labeling unknown faces as unknown) **False Positives** (labeling a known face as another face)

Baseline numbers: 82% accuracy, 15% false positive, 43% unknown detection

Universal: Top three matches are unique labels and the difference between the first two matches is less than 0.08 Example conditions

Local (20): There are more than four unique labels Local (200): ... the first match's distance is greater than 0.45 Local (400): ... difference between the two labels' averaged distances is less than 0.03.

In-between: ... difference between the two distances is: 0.46 (20), 0.45 (200), 0.43 (600)

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	Me		Results Table 1. Results before and after optimization. The numbers are averaged from five runs of each dataset, and the numbers in parentheses represent their standard deviations.					
) Apply	ing a classifier	Table 1 . Results be each dataset, and						
	Original Model	With Classifier	Dataset size	Accuracy (%)	False Positive (%)	Unknown (%)	Unknowr Detection (⁰	
Input	One image per label	Multiple images per label	200 (BO*)	83.5 (3.43)	11.4 (2.25)	4.6 (1.21)	44.4 (2.52	
Jutput	Top match	Weighted vote of top 5 matches	200 (WC**)	94.8 (0.75)	5.2 (0.62)	0.2 (0.39)	64.4 (1.6:	
		Unlabeled Image	20	95.8 (1.90)	1.2 (1.15)	2.4 (1.46)	93.7 (1.8	
			200	89.1 (0.63)	0.8 (0.26)	10.1 (0.39)	89.4 (1.5	
Taylor Swift			400	88.3 (0.85)	1.0 (0.19)	10.6 (0.81)	88.2 (1.	
			600	87.9 (0.71)	1.2 (0.15)	10.9 (0.8)	86.7 (1.:	
			*BO: Before optin	nization **WC: With	classifier optimization	only		
			Our work pr	oduced higher	accuracy, lowe	r false positiv	es, and	
		Top 5 matches:	nigher unkn	own detection				
	Barack Obama	Label: Taylor Swift Distance: 0.428						
		Label: Camila Cabello		Today w	as fun! Guess	s l'II see you	ן 2	
1		Distance: 0.431			inesuay at ou	r usuar time		
Label: Camila Cabello Distance: 0.439								
		Label: Camila Cabello		LA	6777			
	Camila Cabello	Distance: 0.445			6	5		
		Label: Im Yoona			Por			
		Distance: 0.523			-			
	vement:	C10/ unknown datastian	-					
93 % a	couracy, 5% raise positive				Sale L			
) Findir	ng patterns that indi	cate label uncertainty		19.				
Patterr	ns based on distance valu	ies and labels						
A) - Se	parate true and false pos	itives, test simultaneously		Fu	uture Directio	n		
- D (erive related patterns with the patterns with the pattern of the p	nen noticeable difference occurs	Integrate f Cons	 Integrate face recognition into Victor's current system Consider physical responses such as greeting and looking in 				
- W	hen a promising pattern s	hows, test it against true positives	the c	direction of the p	berson	0 0	0	
Pattern	s: Unique labels, Thresho	lds, Differences between matches	Keep inter	raction logs betw	ween Victor and t	he players. Us	se that	
Types:	Universal, In-between and	d Local (with respect to dataset size)	Informatio • Gam	n to personalize	e subsequent inte ill level, average	ractions response time	, types of	
			turns • Time	8 e-focused : Gar	ne duration visit	frequency day	/s and tim	
É			of vi	sits				
Taylor Sw	vift Im Yoona Camila (Cabello Camila Cabello Barack Obam	ever	raction: Levels	of snarkiness, sir	npie Q&A on p	personal	
0.428	0.462 0.	481 0.535 0.613	• Exte	rnal: Reaching	out to players th	rough online p	latforms	





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