Label Error Correction and Label Generation Through Label Relationships

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Overview

- This work is aimed at improving the quality of the label annotations for multi-label supervised learning
- We propose to capture and leverage label relationships at different levels to improve annotation quality and to generate new labels
- A Bayesian Network(BN) is learned to capture the relationships. A MAP inference is then performed for error correction and label generation
- Experimental results demonstrate the effectiveness in improving data annotation and in generating new labels

Backgrounds

Multi-label Supervised Learning

- Two levels of labels, including object-level labels and property-level labels are considered
  - Object-level labels: characterize overall appearance of the object
  - Property-level labels: describe specific local object properties

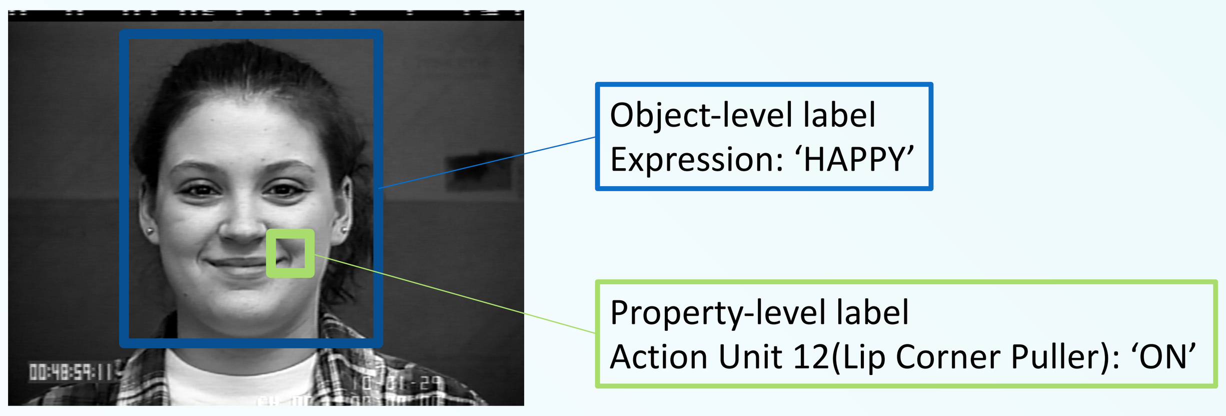

Figure 1: Illustration of labels of different levels. Image is from CK+.

Label Errors

- Label error is defined as the discrepancy between the actual labels and the assigned labels
- Factors contribute to incorrect annotations:
  - Imperfect evidence
  - Confusion among similar patterns
  - Perceptual errors, in particular for fine grain level annotations

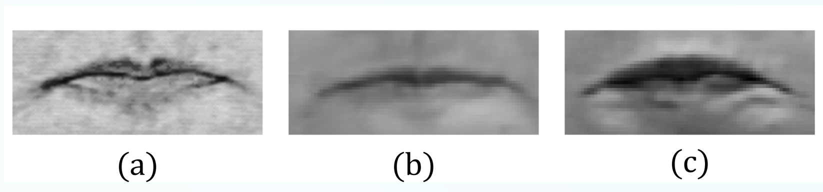

Figure 2: Instances of AU24(Lip Pressor). (a) A positive template of AU24 defined in FACS. (b) A positive instance Of AU24 in CK+. (c) A negative instance of AU24 in CK+. (c) is a label error.

Label Relationship Modeling and Inference

Bayesian Network(BN) : A Bayesian Network(BN) is a direct acyclic graph(DAG) $G = (V, E)$, where V denotes nodes and E for edges. The parameters of BN are used to represent the conditional probability distribution of each node given its parents.

Label Relationship Learning

- Let $\boldsymbol{Y} = [Y_1, Y_2, \ldots, Y_N]$ and Z denote the property-level labels and the object-level label respectively. We want to learn a BN G to capture dependencies between $\boldsymbol{Y}$ and Z as well as relationships among Ys.
- *Structure Learning:* apply the Bayesian Information Criterion(BIC) score function

$$Score(G:D) = \log P(D|\theta, G) - \frac{d(\theta)}{2} \log N$$

where G denotes the direct acyclic graph, and θ denotes probability parameters. The Branch and Bound algorithm is adopted to search for the optimal structure G^* that maximized the BIC score.

- *Parameter Learning:* the Bayesian method is employed

$$\theta^* = E_{P(\theta|G,D,\alpha)}[\theta] = \int \theta\, P(\theta|G, D, \alpha) d\theta$$

with an analytical closed-form solution.

Label Relationship Inference

- We propose a constrained MAP inference to obtain the largest subset of property-level labels, whose relationships are most consistent and stable for a given object-level label Z
- Constrained Maximize A Posterior(MAP) inference:

$$Y_Z'^* = \underset{Y'_{max} \subseteq Y}{\operatorname{argmax}}\, P(Y'_{max}|Z, G^*, \theta^*) \geq \eta$$

where Y'_{max} represents the maximum subset of $\boldsymbol{Y}$. $P(Y'_{max}|Z, G^*, \theta^*)$ is the probability of the property-level labels Y', given the object-level label Z, the BN structure G^* and the parameter θ^*. η is a pre-defined confidence level.

- The constrained MAP inference is performed for each value of the property-level label Z, yielding $Y_Z'^*$, i.e., the optimal property-level label relationships for each object level label value.

Label Correction and Generation

- $Y_Z'^*$ represents the most stable and consistent property-level label relationships.
- For a dataset with existing annotations, correction is performed if sample labels are inconsistent with $Y_Z'^*$.
- For a dataset with missing property-level annotations, we apply $Y_Z'^*$ to produce property-level labels for each sample, given its object-level label value z.

Experiments

Relationship Visualization

- Probabilistic Relationships among expressions and facial action units

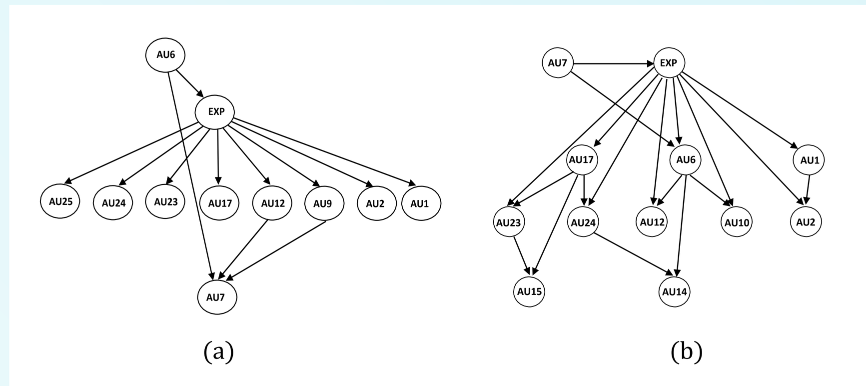

Figure 3: (a) Structure of the learned BN on CK+; (b) Structure of the learned BN on BP4D

Correction Evaluation

Property-level Label Classification

- Facial Action Unit Recognition

Method		AU1	AU2	AU6	AU7	AU9	AU12
LR	NLB	0.936	**0.912**	0.787	0.480	0.908	0.897
	MAPLB	0.936	0.911	**0.804**	**0.701**	**0.923**	**0.913**
SVM	NLB	**0.935**	0.890	0.787	0.450	0.899	0.891
	MAPLB	0.932	**0.899**	**0.803**	**0.674**	0.899	**0.910**
Method		AU17	AU23	AU24	AU25	MEAN	
LR	NLB	**0.873**	0.585	0.525	0.947	0.785	
	MAPLB	0.866	**0.613**	**0.681**	**0.948**	**0.830**	
SVM	NLB	0.877	0.611	0.386	**0.950**	0.767	
	MAPLB	**0.881**	**0.629**	**0.649**	0.946	**0.822**	

Table 1: Comparison of the improved and the original labels for AU recognition performance on CK+

- Attribute Prediction

Method	NLB	MAPLB
MMI	0.743	**0.753**

Table 2: Cross-database annotation generation

Evaluation Without GT Annotations

- Prediction Uncertainly

Dataset		AU1	AU2	AU6	AU7	AU9	AU10	AU12
CK+	NLB	0.181	0.181	0.313	0.317	0.085	-	0.130
	MAPLB	**0.136**	**0.147**	**0.074**	**0.116**	**0.081**	-	**0.074**
BP4D	NLB	0.300	0.298	0.303	0.284	-	0.299	0.221
	MAPLB	**0.235**	**0.212**	**0.132**	**0.102**	-	**0.132**	**0.132**
Dataset		AU14	AU15	AU17	AU23	AU24	AU25	MEAN
CK+	NLB	-	-	0.257	0.126	0.151	0.196	0.194
	MAPLB	-	-	**0.131**	**0.109**	**0.109**	**0.124**	**0.110**
BP4D	NLB	0.446	0.279	0.329	0.293	0.232	-	0.299
	MAPLB	**0.119**	**0.213**	**0.246**	**0.246**	**0.205**	-	**0.179**

Table 3: Comparison of the improved and the original labels for AU recognition uncertainty

- Surrogate task through expression recognition

Method		LR	SVM
CK+	NLB	0.820	0.825
	MAPLB	**0.885**	**0.886**
BP4D	NLB	0.425	0.426
	MAPLB	**0.457**	**0.465**

Table 4: Evaluation through expression recognition

Generation Evaluation

- We learn the BN structure and parameters on the CK+ database
- The learned BN is used to generate AU labels for MMI database given expressions

Method		LR	SVM
MMI	NLB	0.465	0.482
	MAPLB	**0.514**	**0.532**

Table 5: Cross-database annotation generation

Discussion

Contribution of object-level labels

- We compare the performance with
  - original noisy labels
  - improved labels by using relationships among AUs and expressions
  - Improved labels by using relationships among AUs only
- Object-level labels are important for effective label correction

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