Discovering Family Photo using Discriminative Frequent Subgraph

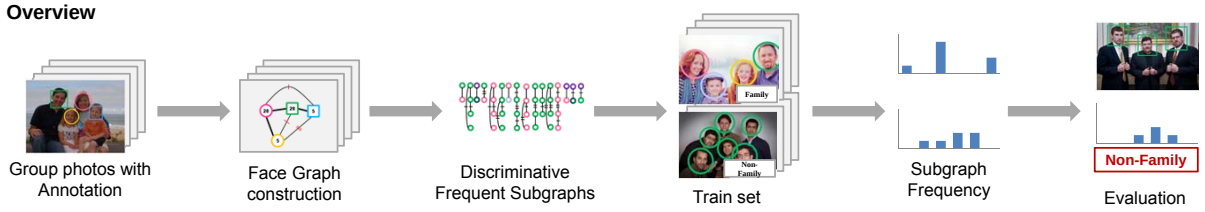
Changmin Choi†, YoonSeok Lee‡, Sung-Eui Yoon‡
Scalable Graphics/Geometric Algorithm Lab. (sglab.kaist.ac.kr)
†Division of Web Science and Technology, KAIST, ‡Department of Computer Science, KAIST

ABSTRACT

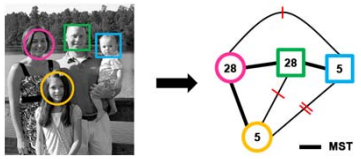
We propose a method to discover family photos from group photos using discriminative subgraphs. We represent an image to a graph with social contexts such as age, gender, and face position. We consider frequent subgraphs from all group photos as features for classification. Numerous subgraphs, however, result in the high dimensions, some of which are not discriminative. To address this issue, we adopt a state-of-the-art frequent subgraph mining technique to remove non-discriminative subgraphs. Our method shows approximately *4%~6%* higher classification accuracy in lower feature dimensions compared to the previous method.

APPROACH

Overview



Face Graph



e.g. Image to Face Graph

AGE	0-2	3-7	8-12	13-19	20-36	37-65	66+
FEMALE	1	5	10	16	28	51	75
MALE	1	5	10	16	28	51	75
ORDER DISTANCE	0	1	2	3	•••		

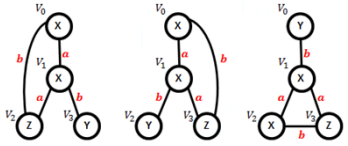
Discriminative Frequent Subgraph Mining

Depth-first Search (DFS) Code
graph representation for building & comparing

DFS Lexicographic Order
canonical comparison of subgraphs

minimal DFS code + maximal Discriminative quality
selection & pruning of subgraphs

DFS Lexicographic Order



e.g. Different DFS code for the same graph

if $\prec_L = \{X < Y < Z : a < b < c\}$, $\alpha < \beta < \gamma$

Edge	α	β	γ
e_0	$(0,1,X,a,X)$	$(0,1,X,a,X)$	$(0,1,Y,b,X)$
e_1	$(1,2,X,a,Z)$	$(1,2,X,b,Y)$	$(1,2,X,a,X)$
e_2	$(2,0,Z,b,X)$	$(1,3,X,a,Z)$	$(2,3,X,b,Z)$
e_3	$(1,3,X,b,Y)$	$(3,0,Z,b,X)$	$(3,1,Z,a,X)$

Discriminative Quality

Class: A, B,
One Feature(a frequent subgraph mined): X,
A_{X1} and B_{X1}: containing the feature,
A_{X0} and B_{X0}: not containing the feature

$$q(\{X\}) = -\left(A_{X_0} \cdot B_{X_0} + A_{X_1} \cdot B_{X_1}\right)$$

Subgraph set U. The $q(\cdot)$ of any supergraph T of X ($T \supseteq S$) cannot exceed the bound **Maximal D**$(\cdot)$:

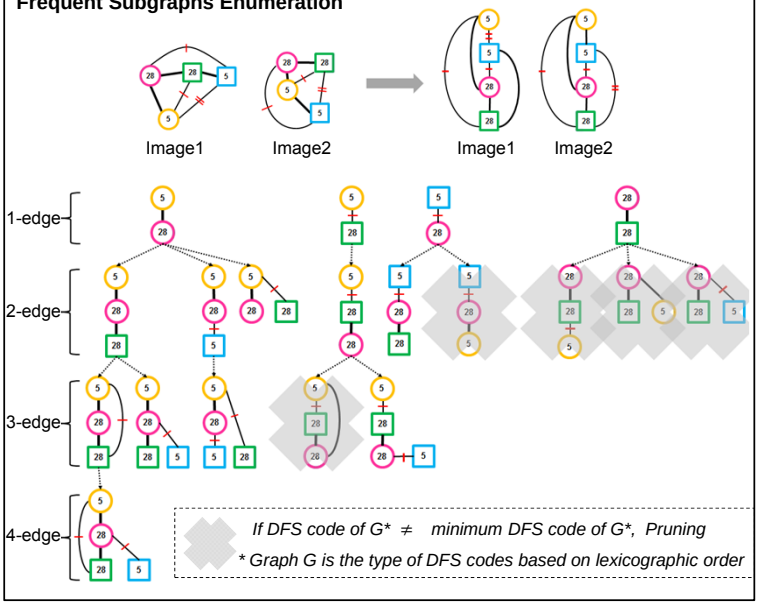
$$\text{MAX D}(U,X) = q(U \cup \{S\}) + \sum_{P_c \in P} \max \begin{Bmatrix} A_{P_c \cup \{X_1\}} \cdot (B_{P_c \cup \{X_1\}} - B_{P_c \cup \{X_0\}}) \\ B_{P_c \cup \{X_1\}} \cdot (A_{P_c \cup \{X_1\}} - A_{P_c \cup \{X_0\}}) \\ 0 \end{Bmatrix}$$

Algorithm

Input : Graph set $\mathcal{G}$, optional threshold σ
Output: Set of discriminative frequent subgraphs $S^\dagger$

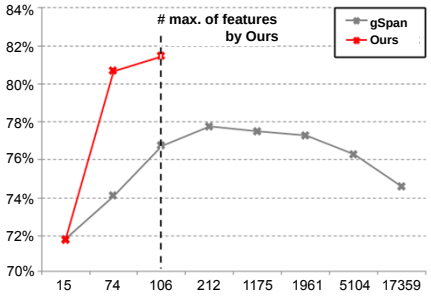
1: $S^\dagger = \emptyset$
2: S = best subgraph for $q(S^\dagger \cup \{S\})$ *// gSpan call*
3: if $q(S^\dagger \cup \{S\}) > q(S^\dagger)$, then
4: $S^\dagger = S^\dagger \cup \{S\}$ *// S is an improvement*
5: goto 2
6: return $S^\dagger$

Frequent Subgraphs Enumeration



EVALUATION

- Family vs. non-Family classification using SVM-linear
- More 1,073 photos than previous one
- Comprehensive family types



Feature Dimension	Duplicate Subgraphs (not)	gSpan	Ours
15	10 (5)	71.82%	71.80%
74	24 (50)	74.11%	**80.67%**
106	26 (80)	76.73%	**81.44%**
212	–	77.76%	–
1175	–	77.50%	–
1961	–	77.28%	–
5104	–	76.28%	–