Mining Recurrent Items in Multimedia with Progressive Resolution Refinement

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Outline

- **Introduction**
- **Progressive Resolution Refinement**
- **Mining Frequent Itemsets with Recurrent Items**
- **Mining Multimedia Association Rules with Spatial Relationships**
- **Performance**
- **Conclusion**

Introduction

- **Multimedia Data Mining**
  - CONQUEST
    - *satellite/geophysical data ⇒ global climate change*
  - SKICAT [KDD'95]
    - *satellite pictures ⇒ "sky objects"*
  - MultiMediaMiner [SIGMOD'98]
    - *Magnetic Resonance Imaging ⇒ associations between lesions and pathological characteristics*
    - *the presence of features (colors and textures)*
  - This paper
    - *the repetition and the localization of features*

Introduction

- **Association Rule Mining**
  - Alphanumeric database [SIGMOD'96, VLDB'98]
    - *boolean association rule*
      - **{bread,milk} ⇒ butter (90%)**
    - *quantitative association rule*
      - **bread:[3-5] and milk:[1-2] ⇒ butter:[1.5-2] (90%)**
    - *ratio rule*
      - **bread:milk:butter=1:2:5 (90%)**
  - Multimedia database (visual data)
    - *multimedia association rule with recurrent items*
      - **2 blue circles ⇒ high texture density (90%)**

Introduction

- **Multimedia Representation**
  - Traditional segmentation (pixel-based)
    - *an image $\Rightarrow$ a set of regions with similar features*
    - *connected, disjoint, complete*
  - Feature localization (tile-based)
    - *identify the features by their locality and proximity*
    - *an image $\Rightarrow$ a set of locales for similar features*
      - **a set of tiles (16×16)**
      - **geometric parameters: mass, centroid, variance, shape**
    - *overlap is possible, completeness is not necessary*

Introduction

- **Peculiarity of Visual Data**
  - The repetition of the feature may carry more information than the existence of the feature
    - *transaction-based support $\Rightarrow$ object-based support*
    - *rules with large support $\Rightarrow$ may be inadequate*
  - Items in the antecedent of the rule repeating in the consequent may be interesting factor in applications
  - The coarse-to-fine strategy can be applied to the rapid approximation of association rules at a low resolution
    - *concept level on the concept hierarchies of features*
    - *resolution level for feature localization*

Introduction

- **Definition**
  - Multimedia association rule: $\alpha P_1 \wedge \beta P_2 \ldots \rightarrow \ldots \gamma P_n$ (c%)
    - *A~Z: predicates on descriptors of images*
      - **visual, topological, or kinematic descriptors**
      - **picture size, video duration, related keywords**
    - *$\alpha \sim \gamma$: integers*
      - **αP is true if P has α occurrences**
    - *c%: confidence of the rule*
  - Support of a predicate P in a set of images D: σ(P/D)
    - *the percentage of objects in all images in D that verify P at a given concept level*

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Introduction

- Confidence of a rule P→Q in a set of images D
  - *the probability that Q is verified by objects in the images in D that verify P at the same concept level*
    - **$\sigma(P \wedge Q/D) / \sigma(P/D)$**
- A pattern P is sufficiently frequent in a set of images D
  - *support thresholds: minimum δ, maximum π*
    - **$\delta \leq \sigma(P/D) \leq \pi$**
- A rule P→Q is sufficiently strong in a set of images D
  - *confidence threshold: minimum ϕ*
    - **P and Q are sufficiently frequent**
    - **the confidence of P→Q > ϕ**

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Progressive Resolution Refinement

- **Basic Idea**
  - Approximate patterns at a coarse level, then eliminate false positives by verifying them at a finer resolution
  - The spatial relationships are not fully preserved as changing from one resolution level to the other
    - *color (low)⇒ edge density⇒ texture (high)*
- **Resolution Refinement Approach**
  - Pixel-based: many resolution levels
  - Tile-based: 32×32, 16×16, 8×8, ...
  - Minimum bounding circle: two resolution levels

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Progressive Resolution Refinement

- **Methodology (PPR)**
  - Mining sufficiently frequent itemsets with recurrent items at different resolution levels (R_i's)
    - *D: a set of transactions representing images*
    - *a set of concept hierarchies for each feature*
      - **support thresholds δ and π for each concept level**
    - *max: the available number of resolution levels*

(1) $i \leftarrow 0$, $D_i \leftarrow D$
(2) while ($i \le max$) do { /* coarse to fine */
(3) $R_i \leftarrow \{r \mid r$ is a sufficiently frequent itemset at level $i\}$
(4) $D_{i+1} \leftarrow Filter(D_i, R_i)$, $i \leftarrow i+1$ }

mining algorithms

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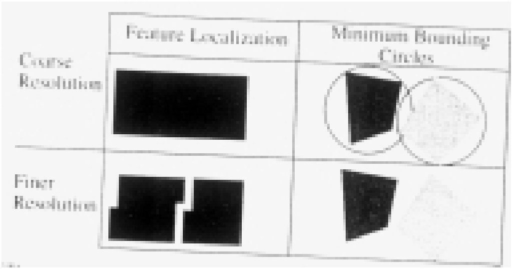
Progressive Resolution Refinement

- **Filter(D_i, R_i)**
  - Remove images without any frequent itemset in R_i
  - Filter out the infrequent objects in the remaining images
    - ◆*not consider the number of occurrences for objects*
- **Change in Features during Resolution Refinement**



Mining Frequent Itemsets with Recurrent Items

- **Synthetic Data**
  - random locales, random features
- **Simple Approach**
  - Apriori
    - ◆*miss all itemsets with recurrent items*
  - Naïve
    - ◆*find all frequent 1-itemsets (F_1) and keep their maximum occurrences*
    - ◆*for each k-itemset, combine F_1 in sets of k elements where elements can be repeated up to the maximums*

Mining Frequent Itemsets with Recurrent Items

- **Algorithm (MaxOccur)**
  - Atomic visual features

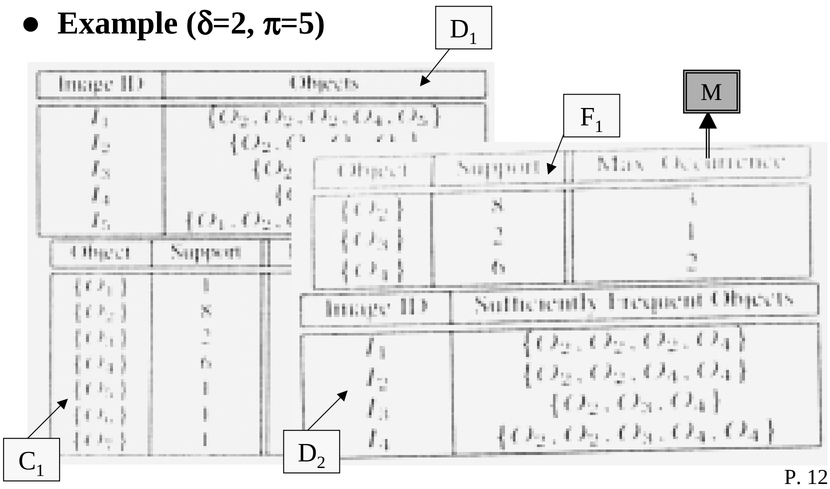
$$\frac{\text{Object – based Count of } k\text{ - itemset in } D_k}{\Sigma_{\forall \text{ transaction } t}\binom{|t|}{k}}$$

Image	Object	Color	Texture	Size	Shape	Motion	…
I_1	$O_{1,1}$	c_1	t_1	s_1	p_1	d_1	…
I_1	$O_{1,2}$	c_2	t_1	s_2	…		

  - Bottom-up approach (similar to *apriori-gen*)
    - ◆*keep the supports and the maximum occurrences*
      - **$\binom{|t|}{k}$: k-combinations in t without redundancy**
    - ◆*prune infrequent itemsets by minimum threshold δ*
      - **prune with maximum threshold π at the end (once)**

Mining Frequent Itemsets with Recurrent Items

- **Example (δ=2, π=5)**



Mining Frequent Itemsets with Recurrent Items

C₂

2 item-sets	Support
$\{O_2, O_3\}$	2
$\{O_2, O_4\}$	6
$\{O_3, O_4\}$	2
$\{O_2, O_2\}$	3
$\{O_4, O_4\}$	2

M⇒No (O_3,O_3)

F₂

2 item-sets	Support
$\{O_2, O_3\}$	2
$\{O_2, O_4\}$	6
$\{O_3, O_4\}$	2
$\{O_2, O_2\}$	3
$\{O_4, O_4\}$	2

No $(O_2,O_2,O_3) \Rightarrow$ No (O_2,O_2,O_3,O_4)

Apriori property

C₃

3 item-sets	Support
$\{O_2, O_3, O_4\}$	2
$\{O_2, O_2, O_3\}$	1
$\{O_2, O_2, O_4\}$	3
$\{O_2, O_4, O_4\}$	2
$\{O_3, O_4, O_4\}$	1
$\{O_2, O_2, O_2\}$	1

F₃

3 item-sets	Support
$\{O_2, O_3, O_4\}$	2
$\{O_2, O_2, O_4\}$	3
$\{O_2, O_4, O_4\}$	2

C₄

4 item-sets	Support
$\{O_2, O_2, O_4, O_4\}$	2

F₄

4 item-sets	Support
$\{O_2, O_2, O_4, O_4\}$	2

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Mining Frequent Itemsets with Recurrent Items

- **Sufficiently Strong Rules (Confidence=100%)**
  - $\{O_4,O_4\} \rightarrow \{O_2,O_2\}$ (2/2)
  - $\{O_2,O_4,O_4\} \rightarrow \{O_2\}$ (2/2)
  - $\{O_3,O_4\} \rightarrow \{O_2\}$ (2/2)
  - $\{O_3\} \rightarrow \{O_2,O_4\}$ (2/2)
  - $\{O_2,O_2\} \rightarrow \{O_4\}$ (3/3)
  - $\{O_4,O_4\} \rightarrow \{O_2\}$ (2/2)
  - $\{O_3\} \rightarrow \{O_2\}$ (2/2)
  - $\{O_3\} \rightarrow \{O_4\}$ (2/2)

Q&A

1. **$\{O_2,O_3\} \rightarrow \{O_4\}$ (?%)**
2. **$\{O_4\} \rightarrow \{O_2\}$ (?%)**

$\sigma(\{O_2,O_4\}/D)=6 > \pi$

Characteristic

$2\ O_4 \rightarrow 2\ O_2$ (rule)
$2\ O_4 \rightarrow O_2$ (rule)
$O_4 \rightarrow O_2$ (not rule)

The antecedent should also be sufficiently frequent

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Mining Multimedia Association Rules with Spatial Relationships

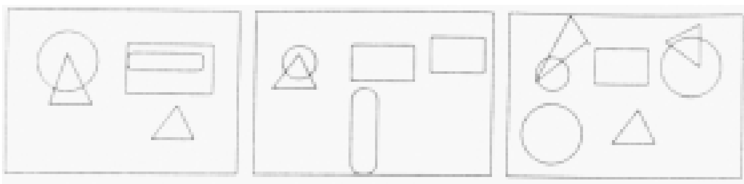
- **Algorithm (MM-Spatial)**
  - Spatial relationships

Image	Object	V-Next-to	H-Next-to	Overlap	Include	…
I_1	$O_{1,1}$	$\{O_{1,3}\}$	$\{O_{1,2}\}$	$\{O_{1,4}\}$	{}	…
I_1	$O_{1,2}$	{}	$\{O_{1,1}\}$	$\{O_{1,4},O_{1,5}\}$		…

  - Property for a sufficiently frequent predicate P(X,Y)
    - *X and Y should be sufficiently frequent, and the 2-itemset {X,Y} has to be sufficiently frequent*
    - *the spatial relationships on the same objects can be recurrent (recounted)*

Mining Multimedia Association Rules with Spatial Relationships

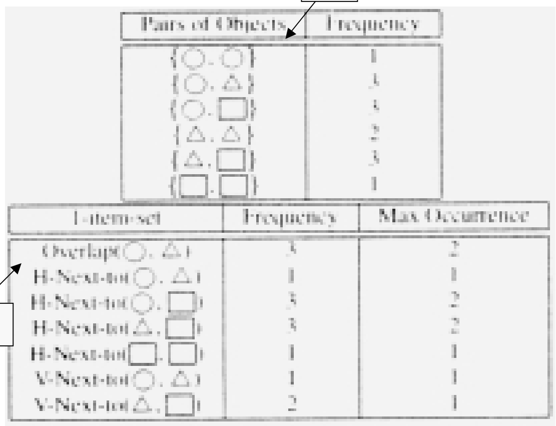
- Method
  - $P_1 \leftarrow$ *{Frequent atomic items}*
  - $P_2 \leftarrow$ *{Frequent pairs in* $P_1 \times P_1$*}*
  - $C_1 \leftarrow$ *{*$P_2 \times$ *{Spatial predicate set} and their support}*
  - $F_1 \leftarrow$ *{Frequent 1-itemsets from* C_1*}*
  - *call MaxOccur*



Mining Multimedia Association Rules with Spatial Relationships

- **Example (δ=3)**

P_2



Pairs of Objects	Frequency
{○, ○}	1
{○, △}	3
{○, □}	3
{△, △}	2
{△, □}	3
{□, □}	1

1-item-set	Frequency	Max Occurrence
Overlap(○, △)	3	2
H-Next-to(○, △)	1	1
H-Next-to(○, □)	3	2
H-Next-to(△, □)	3	2
H-Next-to(□, □)	1	1
V-Next-to(○, △)	1	1
V-Next-to(△, □)	2	1

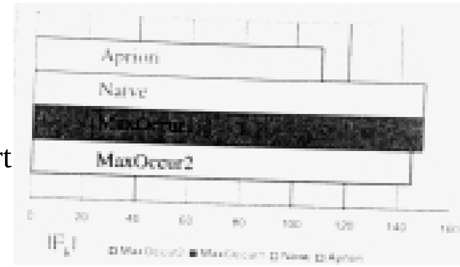
C_1

Mining Multimedia Association Rules with Spatial Relationships

- **Sufficiently Frequent Itemsets**
  - {Overlap(O,Δ),H-Next-to(O,Δ)}
  - {Overlap(O,Δ),H-Next-to(O,□)}
  - {H-Next-to(O,Δ),H-Next-to(O, □)}
  - {Overlap(O,Δ),H-Next-to(O,Δ),H-Next-to(O, □)}
- **Sufficiently Strong Rule (Confidence=100%)**
  - H-Next-to(O,Δ) $\wedge$ H-Next-to(O, □) $\rightarrow$ Overlap(O,Δ)

Performance

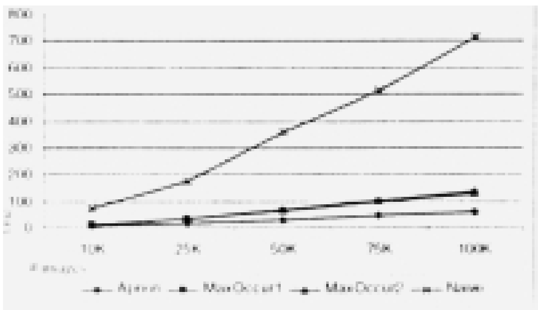
- **Number of Frequent Itemsets**
  - Transaction-based support
    - ◆*δ=0.05*
    - ◆*Apriori*
    - ◆*Naïve*
    - ◆*MaxOccur1*
  - Object-based support
    - ◆*δ=0.0035*
    - ◆*MaxOccur2*



Performance

- **Speed Up**
- **Scale Up**

# of images	Apriori	Naive	MaxOccur1	MaxOccur2
10K	6.43	70.91	13.62	13.68
25K	15.66	176.69	32.35	34.11
50K	30.54	359.38	66.07	67.44
75K	44.93	514.33	97.27	101.23
100K	60.75	716.01	130.12	137.81



Conclusion

- **Contribution**
  - Development of a progressive multi-resolution refinement method for mining multimedia associations with recurrent objects and spatial relationships between visual descriptors in large image collections
- **Comparison**
  - Association rules based on visual features are similar to multi-dimensional, multi-level association rules, which emphasize the presence of attribute values

Conclusion

- **Future Research**
  - Addition of some restrictions on the rules to be discovered [Han95]
    - *meta-rule template*
      - **H-Next-to(X,Y)∧Color(X,red)∧Overlap(Y,Z)→P(Y,Z)**
    - *all frequent 3-itemsets of the form*
      - **{H-Next-to(red,Y),Overlap(Y,*),P(Y,*)}**
  - Identify distinct objects in images
    - *approximate an object to a locale [Zaïane99]*
    - *use regions and signatures as objects [SIGMOD'99]*

Prototypes for Multimedia Data Mining

- **[KDD'95]**
  - Fast Spatial-Temporal Data Mining of Large Geophysical Data-sets
    - *P. Stolorz, H. Nakamura, E. Mesrobian, et al.*
      - **Proceedings of KDD Conference, 1995.**
- **[SIGMOD'98]**
  - MultiMediaMinier: A System Prototype for Multimedia Data Mining
    - *O. R. Zaïane, J. Han, Z. -N. Li, et al.*
      - **Proceedings of ACM SIGMOD Conference, 1998.**

Quantitative Association Rule Mining

- **[SIGMOD'96]**
  - Mining Quantitative Association Rules in Large Relational Tables
    - *R. Srikant and R. Agrawal*
      - **Proceedings of ACM SIGMOD Conference, 1996.**
- **[VLDB'98]**
  - Ratio Rules: A New Paradigm for Fast, Quantifiable Data Mining
    - *F. Korn, A. Labrinidis, Y. Kotidis, and C. Faloutsos*
      - **Proceedings of VLDB Conference, 1998.**

Data Mining with Meta-rules

- **[Han95]**
  - Meta-rule-guided Mining of Association Rules in Relational Databases
    - *Y. Fu and J. Han*
      - **Workshop on Integration of Knowledge Discovery with Deductive and Object-Oriented Databases, 1995.**

Image Retrieval

- **[Zaïane99]**
  - Illumination Invariance and Object Model in Content-based Image and Video Retrieval
    - *Z. -N. Li, O. R. Zaïane, and Z. Tauber*
      - **Journals of Visual Communication and Image Representation, 10(3), September 1999.**
- **[SIGMOD'99]**
  - WALRUS: A Similar Retrieval Algorithm for Image Databases
    - *A. Natsev, R. Rastogi, and K. Shim*
      - **Proceedings of ACM SIGMOD Conference, 1999.**