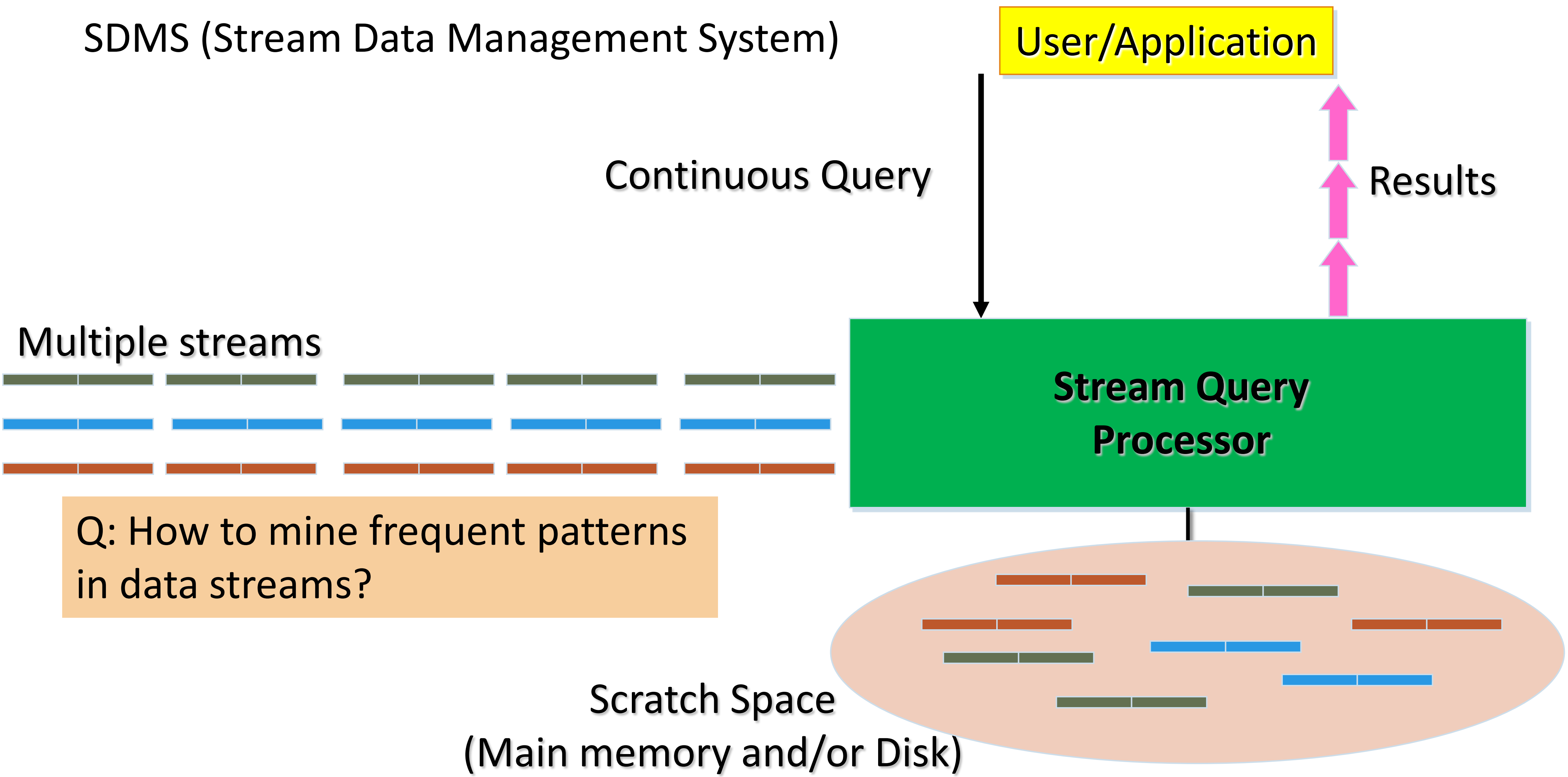
Frequent Pattern Mining in Data Streams

Challenges for Data Analysis in Data Streams

- Data Streams
  - Features: Continuous, ordered, changing, fast, huge volumn
  - Contrast with traditional DBMS (finite, persistent data sets)
- Characteristics
  - Huge volumes of continuous data, possibly infinite
  - Fast changing and requires fast, real-time response
  - Data stream captures nicely our data processing needs of today
  - Random access is expensive: single scan algorithm (*can only have one look*)
  - Store only the summary of the data seen thus far
  - Most stream data are at low-level and multi-dimensional in nature, needs multi-level and multi-dimensional processing

Architecture: Stream Data Processing



Q: How to mine frequent patterns in data streams?

Stream Data Mining Tasks

- Stream mining vs. stream querying
  - Stream mining shares many difficulties with stream querying
    - E.g., single-scan, fast response, dynamic, …
    - But often requires less “precision”, e.g., no join, grouping, sorting
  - Patterns are hidden and more general than querying
- Stream data mining tasks
  - Pattern mining in data streams
  - Multi-dimensional on-line analysis of streams
  - Clustering data streams
  - Classification of stream data
  - Mining outliers and anomalies in stream data

Mining Approximate Frequent Patterns

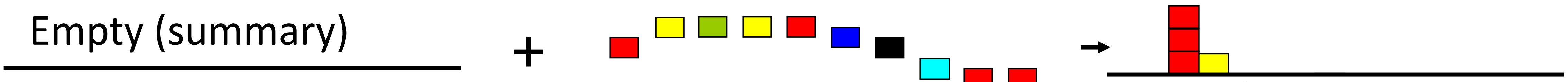
- Mining precise frequent patterns in stream data: Unrealistic
  - Cannot even store them in a compressed form (e.g., FPtree)
- Approximate answers are often sufficient for pattern analysis
  - Ex.: A router
    - is interested in all flows whose frequency is at least 1% (σ) of the entire traffic stream seen so far
    - and feels that 1/10 of σ (ε = 0.1%) error is comfortable
- How to mine frequent patterns with good approximation?
  - Lossy Counting Algorithm (Manku & Motwani, VLDB'02)
    - Major ideas: Not to keep the items with very low support count
    - Advantage: Guaranteed error bound
    - Disadvantage: Keeping a large set of traces

Lossy Counting for Frequent Single Items

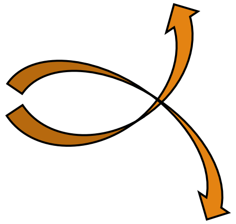
Divide stream into 'buckets' (bucket size is 1/ ε = 1000)

First Bucket of the Stream

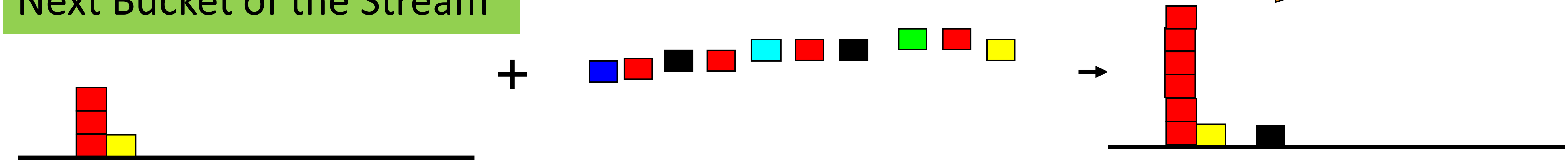
Empty (summary)



At bucket boundary, decrease all counters by 1



Next Bucket of the Stream



Approximation Guarantee

- Given: (1) support threshold: σ, (2) error threshold: ε, and (3) stream length N
- Output: items with frequency counts exceeding (σ – ε) N
- How much do we undercount?

If stream length seen so far = N and bucket-size = 1/ε

then frequency count error ≤ # of buckets

= N/bucket-size = N/(1/ε) = εN

- Approximation guarantee
  - No false negatives
  - False positives have true frequency count at least (σ–ε)N
  - Frequency count underestimated by at most εN

Other Issues and Recommended Readings

- Other issues on pattern discovery in data streams
  - Space-saving computation of frequent and top-k elements (Metwally, Agrawal, and El Abbadi, ICDT'05)
  - Mining approximate frequent k-itemsets in data streams
  - Mining sequential patterns in data streams
- Recommended Readings
  - G. Manku and R. Motwani, “Approximate Frequency Counts over Data Streams”, VLDB’02
  - A. Metwally, D. Agrawal, and A. El Abbadi, “Efficient Computation of Frequent and Top-k Elements in Data Streams”, ICDT'05

Pattern Discovery for Software Bug Mining

Pattern Discovery for Software Bug Mining

- Software is complex, and its runtime data is larger and more complex!
- Finding bugs is challenging: Often no clear specifications or properties; need substantial human efforts in analyzing data
- Software reliability analysis
  - Static bug detection: Check the code
  - Dynamic bug detection or testing: Run the code
  - Debugging: Given symptoms or failures, pinpoint the bug locations in the code
- Why pattern mining?—Code or running sequences contain hidden patterns
  - Common patterns → likely specification or property
  - Violations (anomalies comparing to patterns) → likely bugs
  - Mining patterns to narrow down the scope of inspection
    - Code locations or predicates that happen more in failing runs but less in passing runs are suspicious bug locations

Typical Software Bug Detection Methods

- **Mining rules from source code**
  - Bugs as deviant behavior (e.g., by statistical analysis)
  - Mining programming rules (e.g., by frequent itemset mining)
  - Mining function precedence protocols (e.g., by frequent subsequence mining)
  - Revealing neglected conditions (e.g., by frequent itemset/subgraph mining)
- **Mining rules from revision histories**
  - By frequent itemset mining
- **Mining copy-paste patterns from source code**
  - Find copy-paste bugs (e.g., CP-Miner [Li et al., OSDI'04]) (to be discussed here)
    - Reference: Z. Li, S. Lu, S. Myagmar, Y. Zhou, "CP-Miner: A Tool for Finding Copy-paste and Related Bugs in Operating System Code", OSDI'04

Mining Copy-and-Paste Bugs

- Copy-pasting is common
  - 12% in Linux file system
  - 19% in X Window system
- Copy-pasted code is error-prone
- Mine "*forget-to-change*" bugs by sequential pattern mining
  - Build a sequence database from source code
  - Mining sequential patterns
  - Finding mismatched identifier names & bugs

```
void __init prom_meminit(void)
{
   ……
   for (i=0; i<n; i++) {
      total[i].adr = list[i].addr;
      total[i].bytes = list[i].size;
      total[i].more = &total[i+1];
   }
   ……
```

```
for (i=0; i<n; i++) {
      taken[i].adr = list[i].addr;
      taken[i].bytes = list[i].size;
      taken[i].more = &total[i+1];
   }
```

Code copy-and-pasted but **forget to change** "id"!

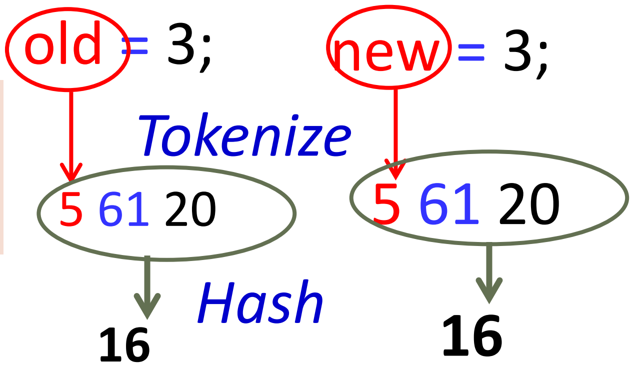
(Simplified example from *linux-2.6.6/arch/sparc/prom/memory.c*)

Courtesy of Yuanyuan Zhou@UCSD

Building Sequence Database from Source Code

- Statement $\xrightarrow{\text{(mapped to)}}$ number
- Tokenize each component
  - Different operators, constants, key words → different tokens
  - Same type of identifiers → same token
- Program → A long sequence
  - Cut the long sequence by blocks

Map a statement to a number



Hash values

```
65   for (i=0; i<n; i++) {
16       total[i].adr = list[i].addr;
16       total[i].bytes = list[i].size;
71       total[i].more = &total[i+1];
     }
...      ……
65   for (i=0; i<n; i++) {
16       taken[i].adr = list[i].addr;
16       taken[i].bytes = list[i].size;
71       taken[i].more = &total[i+1];
     }
```

Final sequence DB:
(65)
(16, 16, 71)
…
(65)
(16, 16, 71)

Courtesy of Yuanyuan Zhou@UCSD

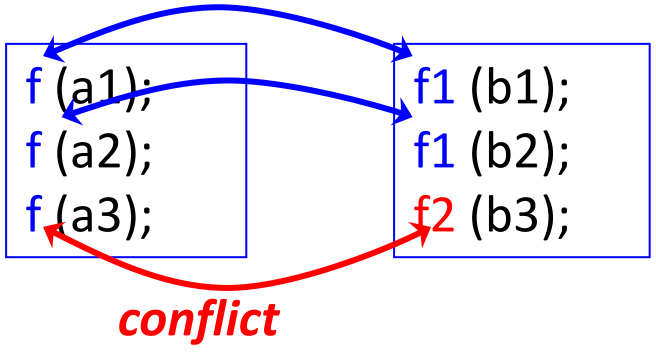
Sequential Pattern Mining & Detecting "Forget-to-Change" Bugs

- Modification to the *sequence pattern mining algorithm*
  - Constrain the max gap

(16, 16, 71)
……
(16, 16, 10, 71)

Allow a maximal gap: inserting statements in copy-and-paste

- Composing Larger Copy-Pasted Segments
  - Combine the neighboring copy-pasted segments repeatedly
- Find conflicts: Identify names that cannot be mapped to the corresponding ones
  - E.g., 1 out of 4 "**total**" is unchanged, *unchanged ratio* = 0.25
  - If 0 < *unchanged ratio* < *threshold*, then report it as a bug
- CP-Miner reported many C-P bugs in Linux, Apache, … out of millions of LOC (lines of code)

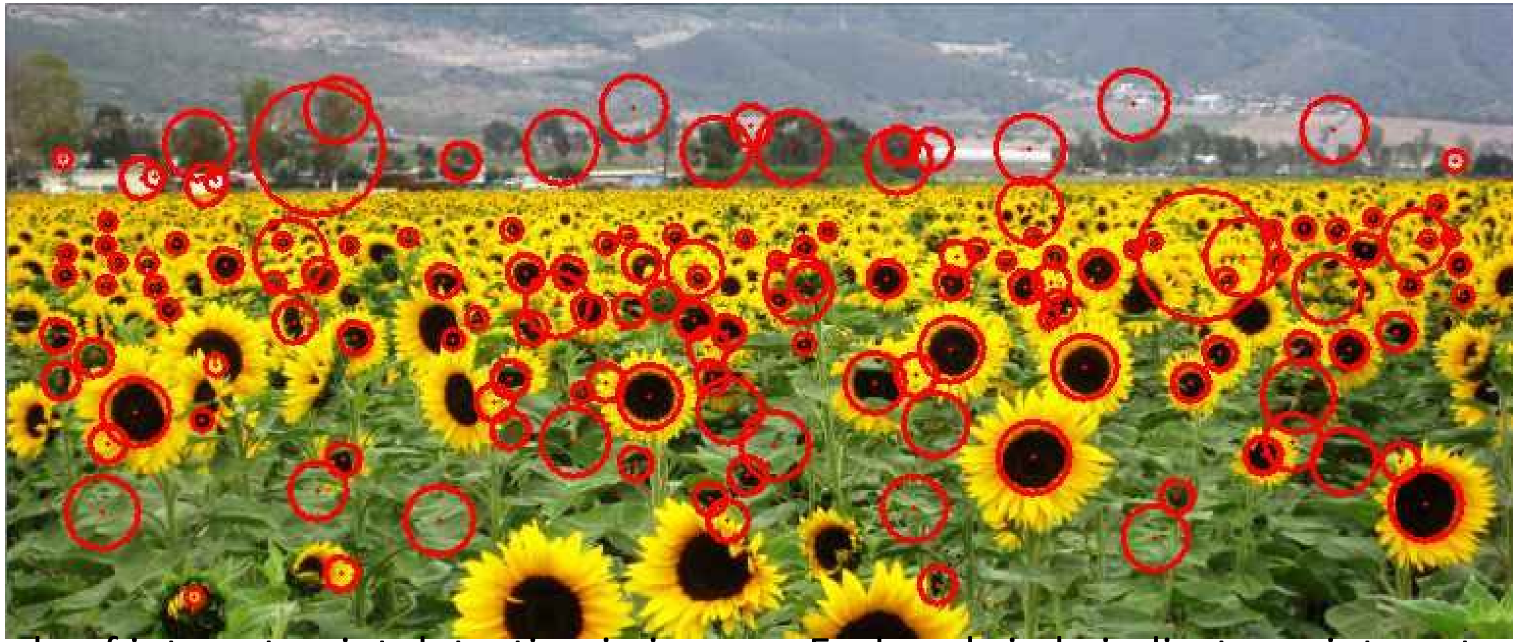


Courtesy of Yuanyuan Zhou@UCSD

Pattern Discovery for Image Analysis

Image Representation for Visual Pattern Discovery

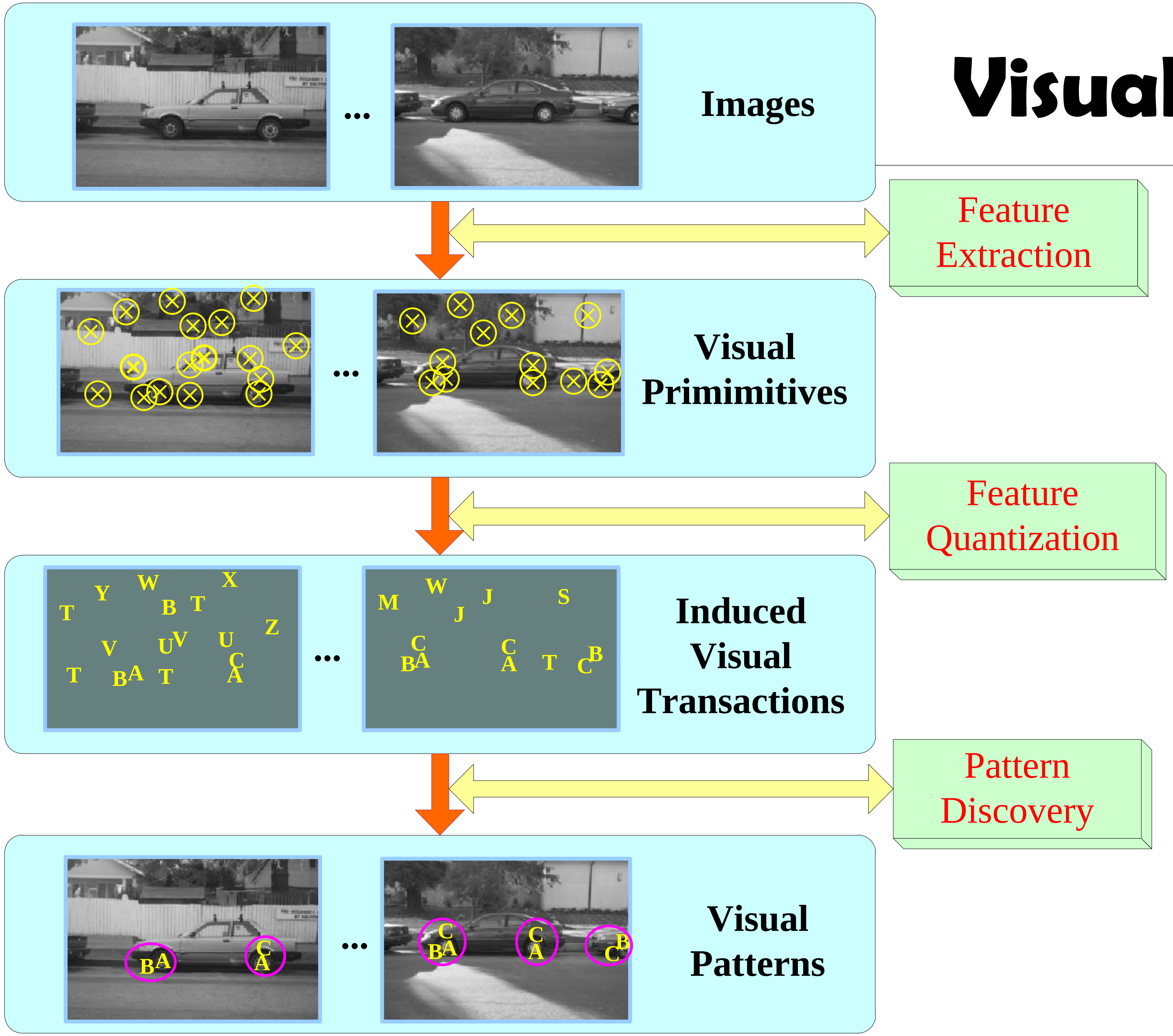
- An image can be characterized by visual primitives, e.g., interest points
  - Each visual primitive can be described by visual feature, e.g., a high-dimensional feature vector
  - Each image is a collection of visual primitives



An example of interest point detection in images. Each red circle indicate an interest point.
Image courtesy from boofCV http://boofcv.org/index.php?title=Example_Detect_Interest_Points

Courtesy of Junsong Yuan @ NTU.SG, Ying Wu @Northwestern

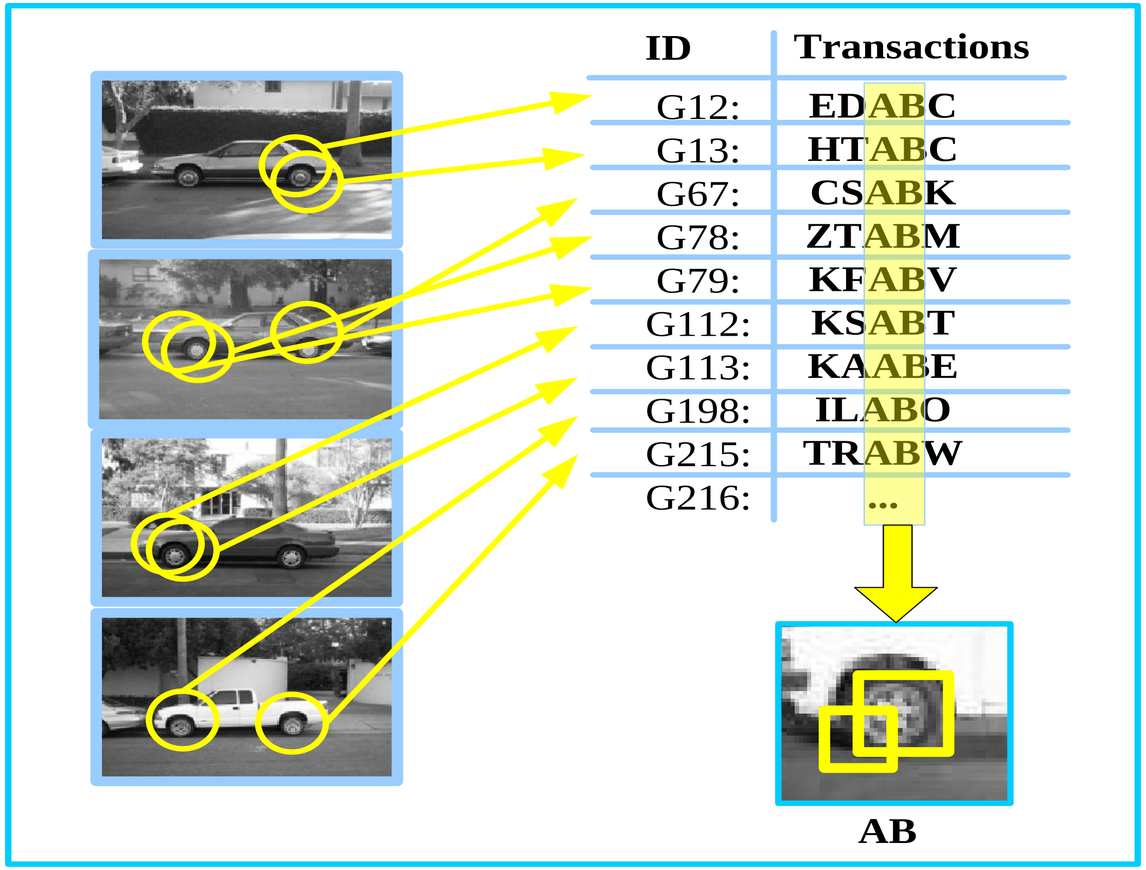
Visual Patterns Discovery



- Visual primitives can be clustered into visual "items"
  - Similar visual primitives belong to the same item
- Each visual primitive finds its k-nearest-neighbor in the image to form a visual "transaction"
  - An image can generate a number of transactions, i.e., induced visual transactions
- Mining "frequent itemsets" leads to semantically meaningful visual patterns

Courtesy of Junsong Yuan @ NTU.SG, Ying Wu @Northwestern

Challenges of Visual Pattern Discovery



- Images are spatial data
  - Spatial configuration among the visual items matters
  - Induced transactions may overlap with each other, thus one needs to address the over counting problem
- Uncertainties of visual items and patterns
  - Noisy clustering of visual primitives into visual items affects visual pattern discovery
  - Visual synonym and polysemy

Courtesy of Junsong Yuan @ NTU.SG, Ying Wu @Northwestern

Recommended Readings

- Hongxing Wang, Gangqiang Zhao, Junsong Yuan, Visual pattern discovery in image and video data: a brief survey, Wiley Interdisciplinary Review: Data Mining and Knowledge Discovery 4(1): 24-37 (2014)
- Hongxing Wang, Junsong Yuan, Ying Wu, Context-Aware Discovery of Visual Co-Occurrence Patterns. IEEE Transactions on Image Processing 23(4): 1805-1819 (2014)
- Gangqiang Zhao, Junsong Yuan, Discovering Thematic Patterns in Videos via Cohesive Sub-graph Mining. ICDM 2011: 1260-1265
- Junsong Yuan, Ying Wu, Ming Yang, From frequent itemsets to semantically meaningful visual patterns. KDD 2007: 864-873

Pattern Mining and Society: Privacy Issues

Pattern Mining and Society: Privacy Issues

- A potential adverse side-effect of data mining—Privacy could be compromised
  - Privacy and accuracy are typically contradictory in nature
  - Improving one often incurs a cost on the other
- Three categories on privacy issues arising out of data mining
  - Input privacy (or data hiding)
    - Distort or hide data to prevent the miners from reliably extracting confidential or private information
  - Output privacy (or knowledge hiding)
    - No disclosure of sensitive patterns or knowledge from datasets
  - Owner privacy
    - Does not allow any party to reliably learn the data or sensitive information that the other owners hold (i.e., the source of the data)

Ensuring Input Privacy

- Approach 1: Service provider anonymizes user's private information
  - B2B (business-to-business) environment
    - Service provider-to-data miner
  - Do you really trust them?
- Approach 2: Data anonymized/perturbed at the data source itself
  - B2C (business-to-customer) environment: Anonymized likely by a 3rd-party vendor
    - Methods: Data perturbation, transformation, or hiding (hide sensitive attributes)
- K-anonymity privacy requirement and subsequent studies
  - *k-anonymity*: Each equivalent class contains at least *k* records
  - It is still not sufficient, thus leads to further studies, such as *ℓ-diversity*, *t-closeness*, and *differential privacy*

ID	ZIP	Age	Disease
1	61801	45	Heart
2	61848	49	Cancer
3	61815	41	Flu
4	61804	32	Diabetes
5	61802	38	Diabetes
6	61808	39	Flu

ID	ZIP	Age	Disease
1	618**	4*	Heart
2	618**	4*	Cancer
3	618**	4*	Flu
4	618**	3*	Diabetes
5	618**	3*	Diabetes
6	618**	3*	Flu

Data Perturbation for Privacy-Preserving Pattern Mining

- Statistical distortion: Using randomization algorithms
  - Independent attribute perturbation: Values in each attribute perturbed independently
  - Dependent attribute perturbation: Take care of correlations across attributes
- MASK [Rizvi & Haritsa VLDB'02]
  - Flip each 0/1 bit with a probability *p* (Note: this may increase a lot of items)
  - Tune *p* carefully to achieve acceptable average privacy and good accuracy
- Cut and paste (C&P) operator [Evfimievski et al. KDD'02]
  - Uniform randomization: Each existing item in the real transaction is, with a probability *p*, *replaced* with a new item not present in the original transaction
  - Methods developed on how to select items to improve the worst-case privacy
  - Experiments show mining a C&P randomized DB correctly identifies 80-90% of "short" (length ≤ 3) frequent patterns, but how to effectively mine long patterns remains an open problem

Recommended Readings

- R. Agrawal and R. Srikant, Privacy-preserving data mining, SIGMOD'00
- C. C. Aggarwal and P. S. Yu, Privacy-Preserving Data Mining: Models and Algorithms, Springer, 2008
- C. Dwork and A. Roth. The Algorithmic Foundations of Differential Privacy. Foundations and Trends in Theoretical Computer Science. 2014
- A. Evfimievski, R. Srikant, R. Agrawal, and J. Gehrke. Privacy preserving mining of association rules. In KDD'02
- A. Gkoulalas-Divanis, J. Haritsa and M. Kantarcioglu, Privacy in Association Rule Mining, in C. Aggarwal and J. Han (eds.), Frequent Pattern Mining, Springer, 2014 (Chapter 15)
- N. Li, T. Li, S. Venkatasubramanian. t-closeness: Privacy beyond k-anonymity and l-diversity. ICDE'07
- A. Machanavajjhala, D. Kifer, J. Gehrke, M. Venkitasubramaniam, l-diversity: Privacy beyond k-anonymity, TKDD 2007
- S. Rizvi and J. Haritsa. Maintaining data privacy in association rule mining. VLDB’02
- J. Vaidya, C. W. Clifton and Y. M. Zhu, Privacy Preserving Data Mining, Springer, 2010

Looking Forward

Looking Forward

- Lots of research issues on pattern discovery are still waiting to be solved
- Application exploration: **Invisible Pattern Mining** (i.e., built into various search, ranking, mining and other functional units)
  - Discriminative-pattern-based classification
  - Indexing and retrieval (e.g., graph indexing and similarity search)
  - Text mining: Phrase mining and topic modeling
  - Software bug mining and mining software specifications
  - Spatiotemporal and trajectory data mining
  - Image and multimedia data mining
  - Biological and chemical data analysis: DNA, graphs
  - Subspace clustering (to be covered in Clustering in Data Mining)
  - Web logs → Click stream patterns → Recommendation