# GPU-based acceleration of data mining algorithms

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#### Talk outline

- Database group at CCS
- Overview of research topics
- GPU-based acceleration of frequent itemset mining from uncertain databases
- GPU-based acceleration of canopy clustering
- GPU-based acceleration of uncertain time series search
- Future collaboration

#### Database group at CCS





**Hiroyuki Kitagawa** 

Professor CCS & Dept. CS

- Database
- Data mining



Toshiyuki Amagasa

Assoc. Prof. CCS & Dept. CS

- Database
- Data mining

#### Dept. CS



Yasuhiro Hayase

Assistant Prof. Dept. CS

- Software engineering
- Repository mining



**Chiemi Watanabe** 

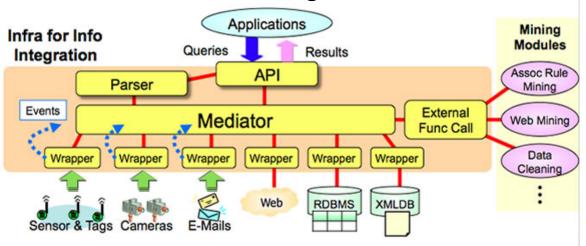
Assistant Prof. Dept. CS

- Database
- Data privacy

Postdoc x2, D x5, M x17 (+6), B x7 Research student x4

#### Research topics 1

- Infrastructure for information integration
  - Data stream processing
  - Integration of data streams and heterogeneous information sources



- Data mining / social media mining
  - Outlier detection
  - Mining from Twitter

#### Research topics 2

- GPU-based acceleration of data mining
  - Frequent itemset mining
  - Time series search
  - Clustering
- Web information systems
  - XML databases
  - RDF/LOD databases
- Database applications in scientific domains
  - GPV/JMA archive
  - JLDG/ILDG
  - Biological database





## GPU-based Frequent Itemset Mining over Uncertain Databases

Yusuke Kozawa, Toshiyuki Amagasa, Hiroyuki Kitagawa University of Tsukuba

#### **Uncertain Transaction Databases**

- Transaction databases
  - Purchase records
  - Observation records
  - System logs
- Uncertainty

Each	transaction	hacan	ovictontial	nrohahility
— cacn	uansacuon	11a5 a11	existential	propability.

 The probability specifies the chance that the transaction exists.

ID	Itemset	Prob.
T1	{game, music}	0.5
T2	{music, video}	0.7
T3	{game}	0.8
T4	{music}	0.9

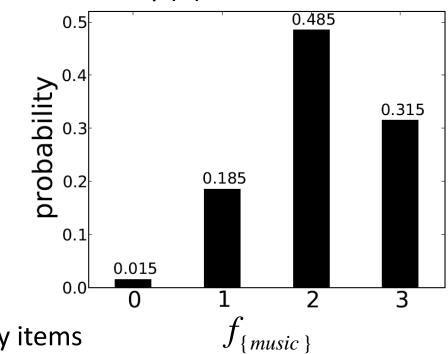
### Frequent itemset mining

- Frequent itemset mining is to find frequently occurring patterns from a transaction database.
  - Find characteristic patterns from
    - Purchase / observation records
    - System logs
- To find frequent itemsets from uncertain databases, we need to care about the uncertainty.

## **Support Probability Mass Function**

- Support Probability Mass Function (SPMF)  $f_X$ 
  - The probability mass function of sup(X)

ID	Itemset	Prob.
T1	{game, music}	0.5
T2	{music, video}	0.7
T3	{game}	0.8
T4	{music}	0.9



→ More complicated when many items

### Probabilistic Frequent Itemsets

Probabilistic Frequent Itemset (PFI) X

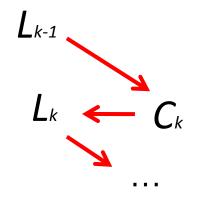
$$P(\sup(X) \ge minsup) \ge minprob$$

The probability that 
$$X$$
 is a frequent itemset 
$$= \sum_{k=minsup}^{n} f_X(k)$$

- Minsup and minprob are the support threshold and the probability threshold respectively
- The problem: probabilistic frequent itemset mining
  - Given an uncertain transaction databases, minsup, and minprob, return all PFIs

## pApriori Algorithm [Sun et al., KDD '10]

- Inputs: uncertain transaction database, minsup, and minprob
- This algorithm consists of two procedures
  - 1. Generate size-k Candidate PFIs  $C_k$  from size-(k-1) PFIs  $L_{k-1}$
  - 2. Extract size-k PFIs from the size-k Candidate PFIs  $C_k$



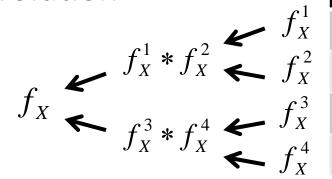
This needs to compute the SPMFs



Since this is the most computationally expensive step, it's important to efficiently compute the SPMFs

## Efficient Computation of SPMFs using a GPU

Convolution



ID	Itemset	Prob.
T1	{game, music}	0.5
T2	{music, video}	0.7
T3	{game}	0.8
T4	{music}	0.9

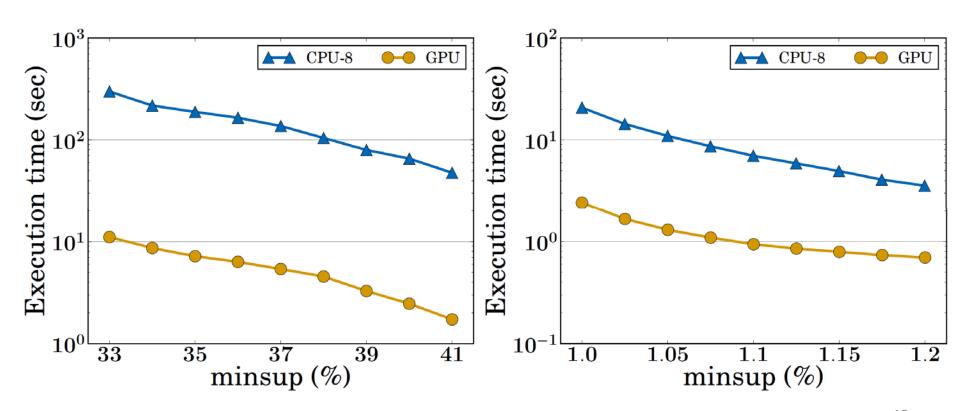
- Convolution can be efficiently computed with the Fast Fourier Transform (FFT) algorithm
- Parallelize FFT computation to improve the performance
- Pruning
  - cnt(X): the maximum possible value of sup(X)
  - esup(X): the expected support of X

#### Experimental results

CPU: Intel Xeon (2.40 GHz, 4 cores), 12 GB memory, OpenMP GPU: Tesla C2050 (1.15 GHz, 448 cores, 3 GB memory), CUDA

Accidents: 23x–27x

• T25I10D500K: 5.1x-8.6x

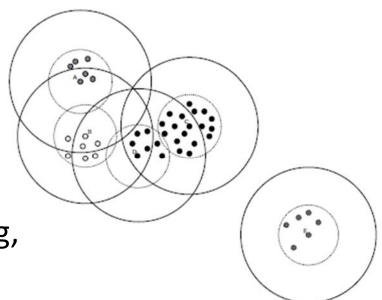


## **GPU-based Canopy Clustering**

Fumitaka Hayashi, Yusuke Kozawa, Toshiyuki Amagasa, Hiroyuki Kitagawa University of Tsukuba

### Canopy clustering

- Canopy represents a set of data points.
- Used to speed up clustering algorithms to deal with Big Data.
  - k-means, hierarchical clustering, etc.
  - Tuli De et al. successfully applied clustering to the spectrum of light from extragalactic objects with 700,000 x 1,500 size.

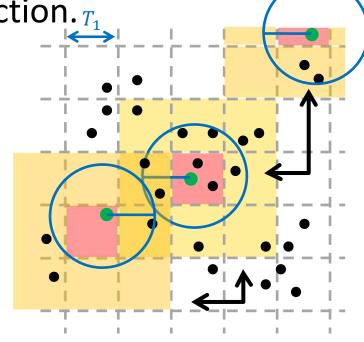


## GPU-based canopy clustering Idea

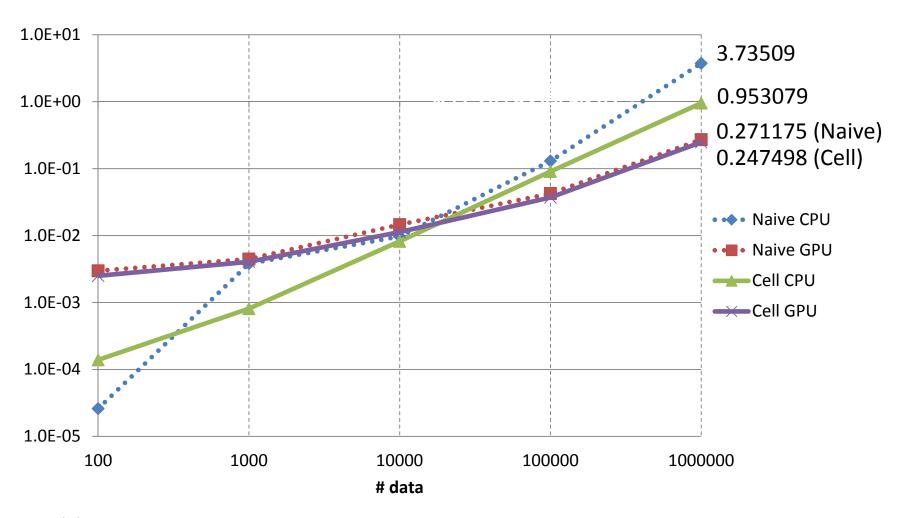
- Parallelize distance computations
  - Each thread computes the distance between a data to the center, and compares with T1 and T2.

- Intensively use parallel reduction.  $T_1$ 

- Further optimization
  - Cell-structure
  - Prune unnecessarydistance computation



#### Experimental results



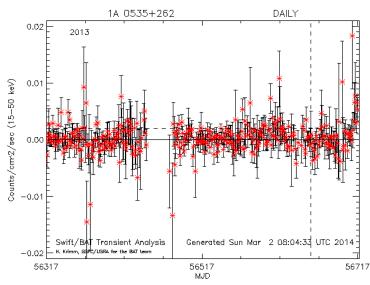
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## GPU-based Search of Uncertain Time Series

Jun Hwang, Yusuke Kozawa
Toshiyuki Amagasa, Hiroyuki Kitagawa
University of Tsukuba

#### Uncertain time series search

- Real-world time series often contain uncertainty.
  - e.g., light curve of an X-ray object
- Find similar time series over uncertain time series.
  - MUNICH [Aßfalg et al, 2009]
  - PROUD [Yeh et al, 2009)]
  - DUST [Sarangi et al, 2010]



## GPU-based acceleration of uncertain time series search

#### • Idea

- Parallelize probability computation.
- DUST
  - Use Monte Carlo integration to compute probability.
  - The performance bottleneck.

#### Performance

About 230x faster than the naïve CPU-based implementation

#### Future collaboration

 Improve the performance of data mining over Big Data using GPU/Xeon Phi

- Scientific data management
  - Search over Big Scientific Data
  - Metadata management
    - Linked Open Data
    - XML

# Thank you!