

# **End to End Data Mining: The Next Challenge**

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# Presentation Overview

- ➊ Motivation (“Where I’m coming from”).
- ➋ Some specific applications.
- ➌ A generic application (but with lots of different elements).
- ➍ Multi-Agent Data Mining (MADM), a potential solution.
- ➎ Conclusions.

# Motivation

## Applied data mining.

- ❶ As a community we have produced a rich and successful range of data mining tools and techniques.
- ❷ However, many applications of our knowledge provide new and interesting challenges, often unique to the application under consideration.
- ❸ The main issue is the process of putting all the constituent parts together to address a given real world data mining task, i.e. the **end to end data mining** process.
- ❹ This presentation focuses on a number of sample real-world applications so as to highlight the challenge, and then presents a potential solution.

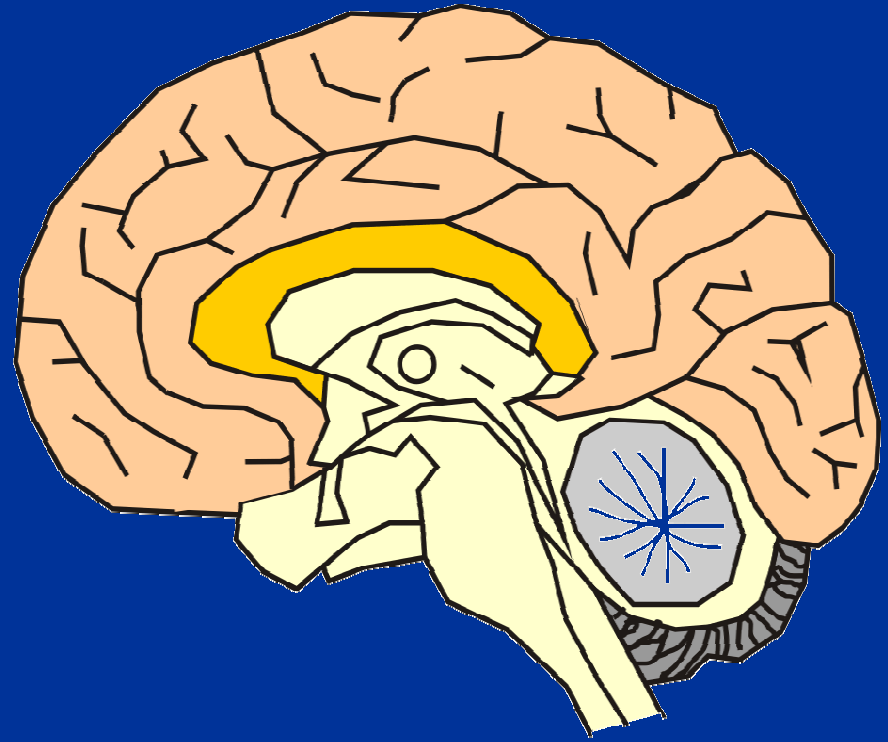
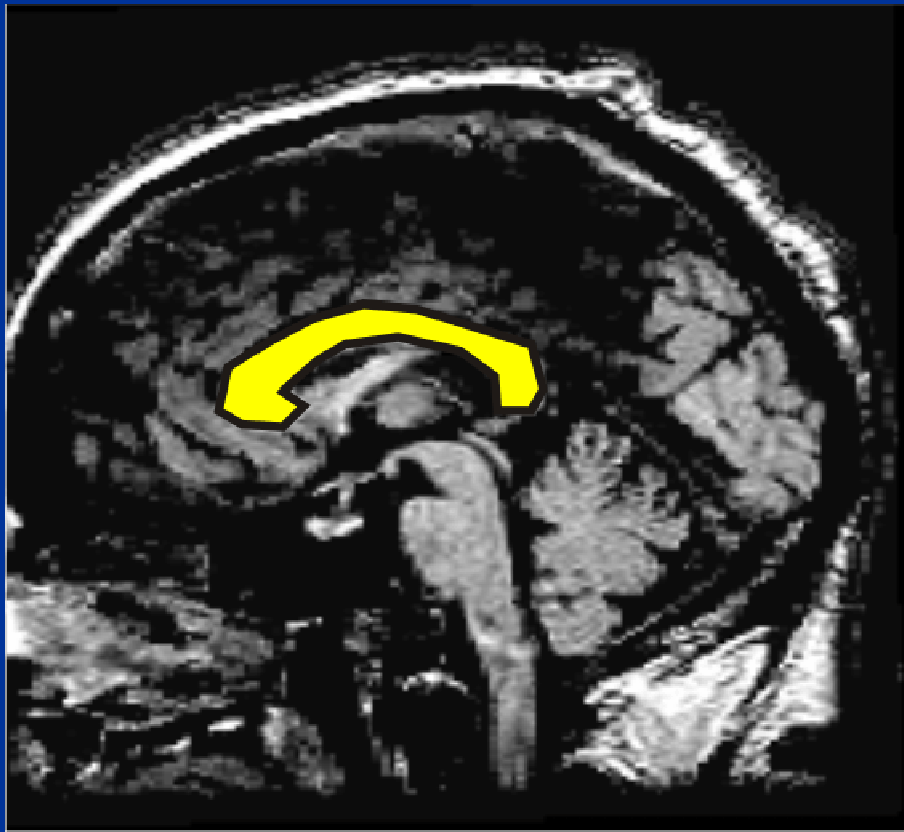


# Mining MRI Scan Data

- ❖ (A particular problem example.)
- ❖ We wish to classify MRI scan data collections, for medical research purposes, according to a particular feature in these scans called the Corpus Callosum (CC)
- ❖ The conjecture is that the shape and size of the CC serves to distinguish, for example, musicians and non-musicians. It is also suspected that the shape and size of the CC plays a role in the identification of medical conditions such as epilepsy, schizophrenia, autism, etc. The size and shape is also effected by age.

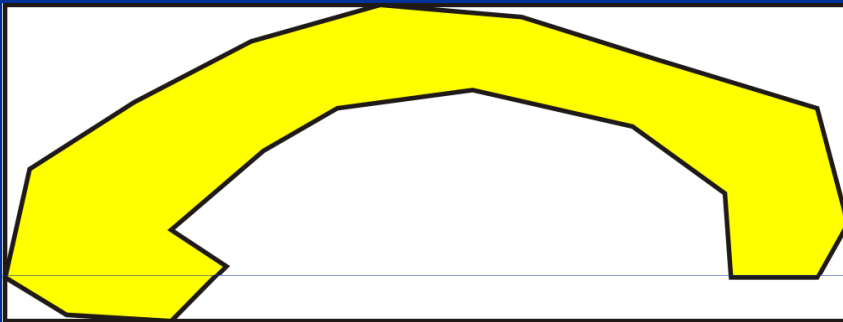
# Mining MRI Scan Data

- Example images:



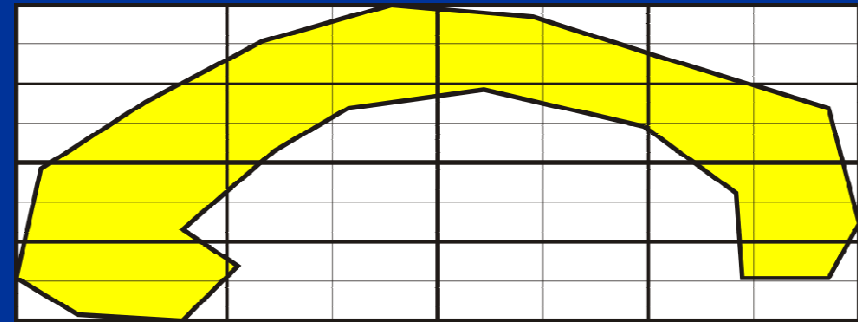
# Mining MRI Scan Data

(1)



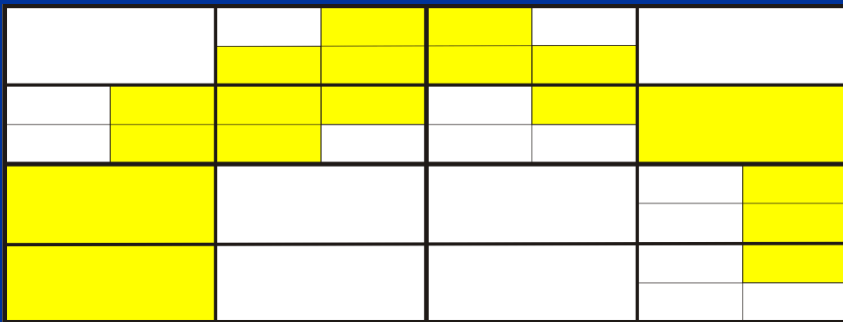
Minimum Bounding Rectangle (MBR)

(2)



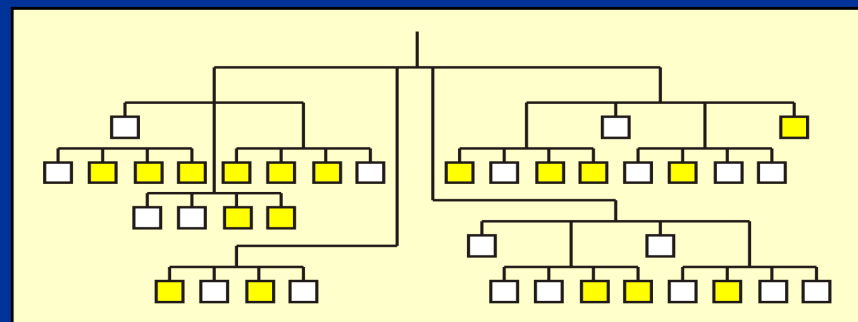
Tessellate

(3)



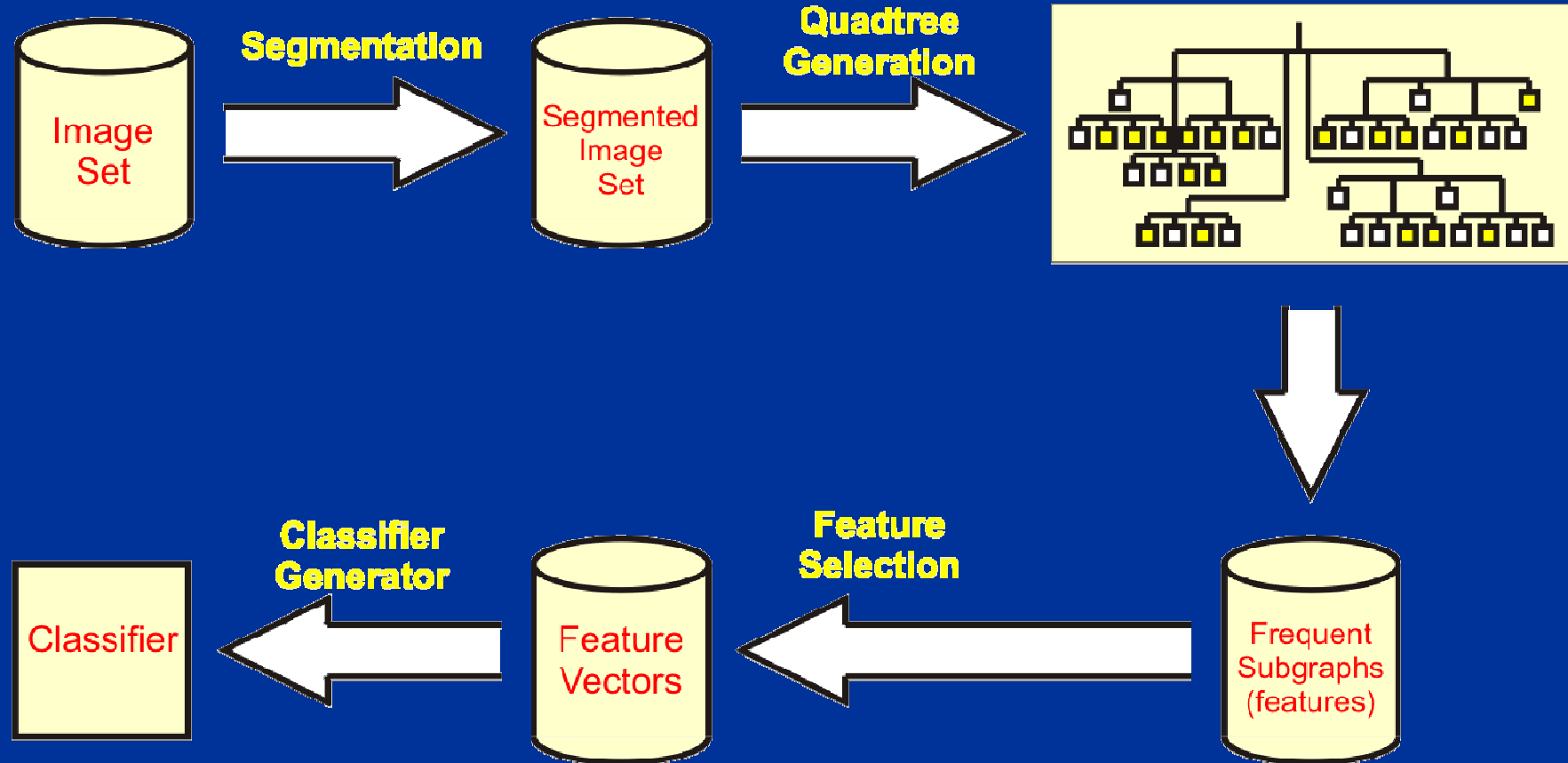
ID Colour Blocks

(4)



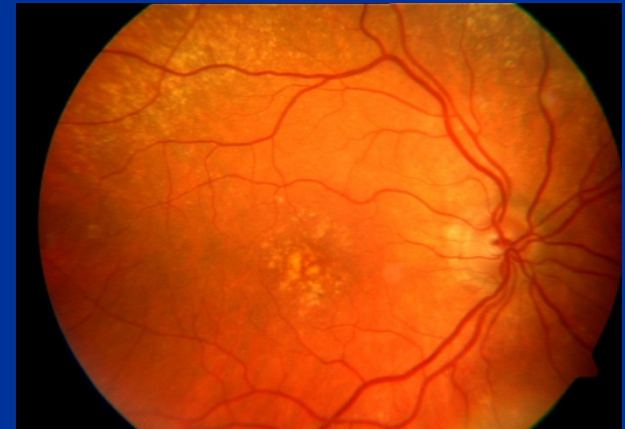
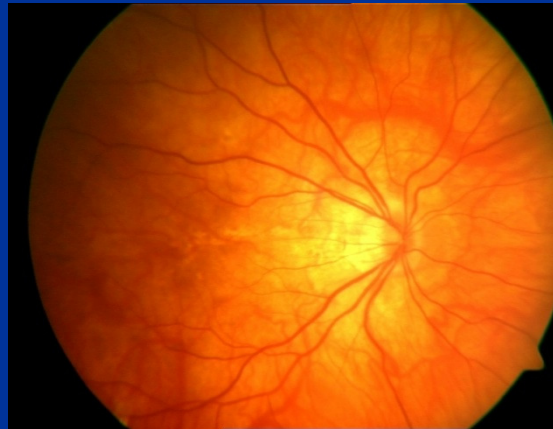
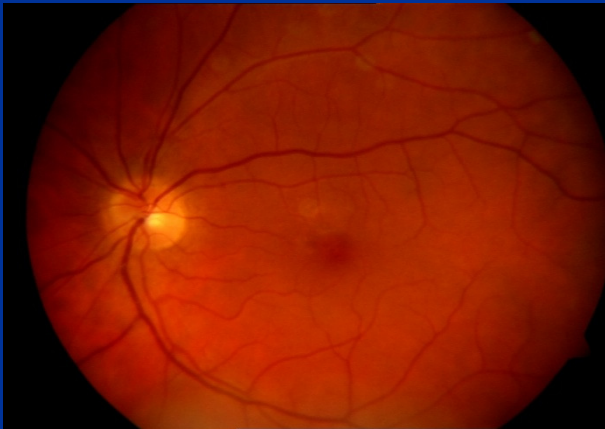
Quad Tree

# Mining MRI Scan Data



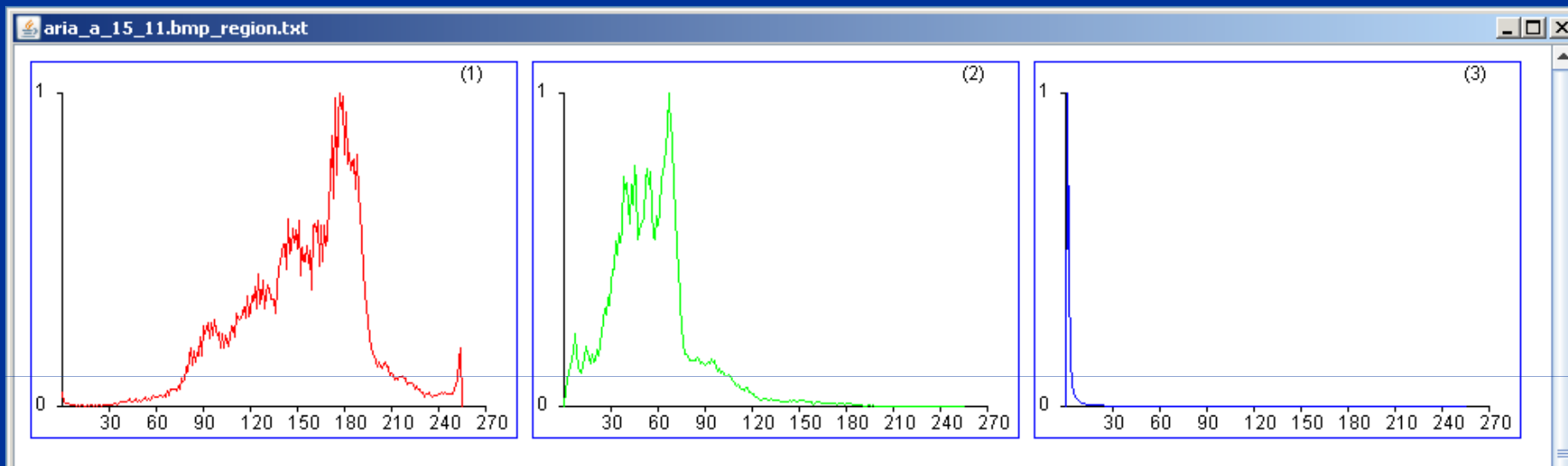
# AMD (Age related Macular Degeneration) Example (1)

- ❖ (Another specific problem example.)
- ❖ We wish to provide screening support for the early diagnosis of AMD.
- ❖ A common (standard) mechanism for doing this is by identifying “drusen” in retina scans.





# AMD Example (2)

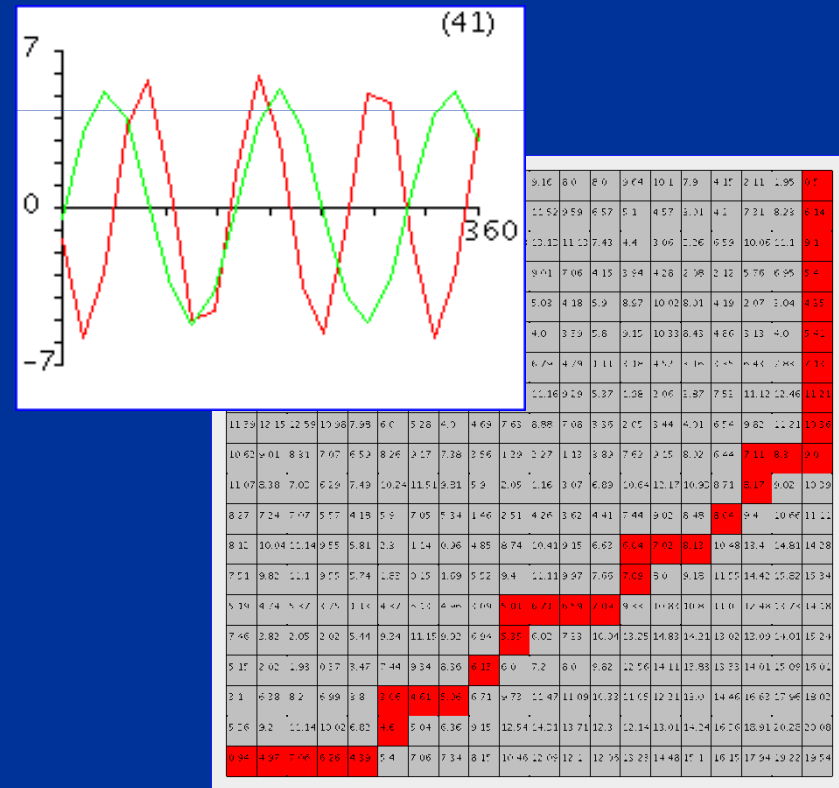
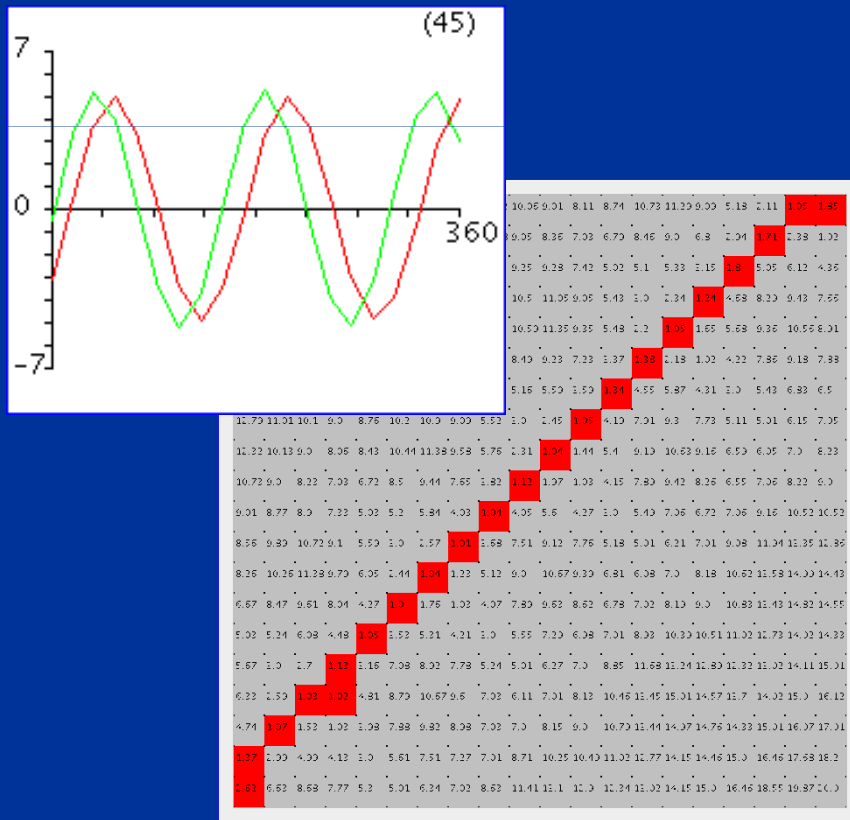


- Histogram approach
- Histogram is in effect a time series.
- Consequently we can use time series analysis techniques, in this case dynamic time warping.



# AMD Example (3)

- Dynamic Time Warping (DTW).
- Case base of known time series which new case is compared to.



# Trend Mining

- (A more generic problem example.)
- Many institutions and commercial enterprises are interested in trends.
- The technique adopting (in various forms) is emerging and/or jumping pattern (EPs and JPs) mining.
- This is an extension of established Association Rule Mining (ARM) technology that looks at how the significance (support) of identified patterns (itemsets) changes over time.
- Number of collaborations in this area.

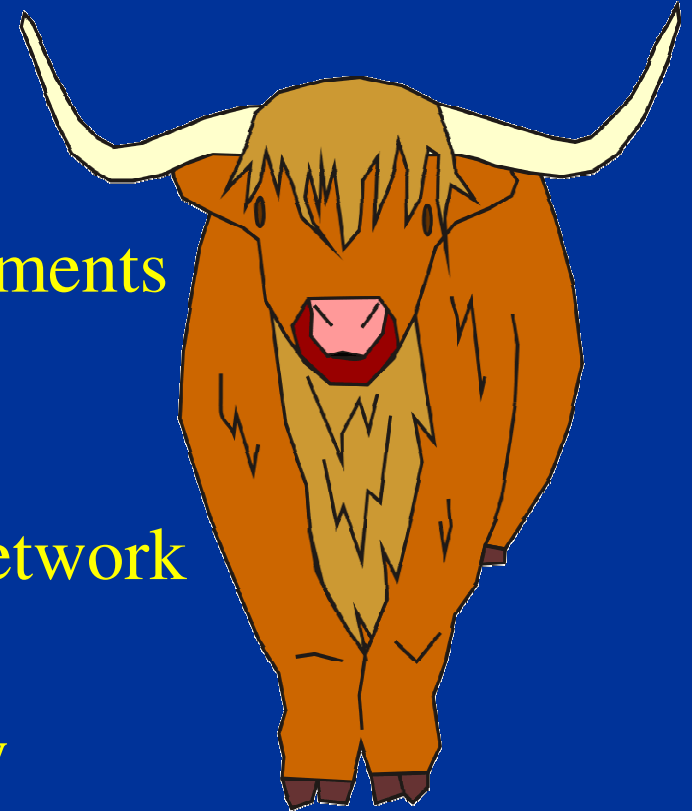
# Trend Mining in Customer Bases

- ❖ Particular case is in collaboration with a freight forwarder who wish to identify groups of customers (may be very small groups) whose behaviour changes.
- ❖ Patterns here are made of attributes from the customer base: location of sender, destination, weight, size, price, route, etc. Data all requires pre-processing.
- ❖ Once emerging/jumping patterns have been identified need to trace patterns back to customer IDs.



# Trend Mining in Social Networks

- ❖ Particular case is The UK's cattle movement DB.
- ❖ Large DB recording all cattle movements between locations in the UK (administered by DEFRA).
- ❖ Represents a time stamped social network (social network mining).
- ❖ Using the EP and JP idea to identify changes in behaviour.
- ❖ Aim is to determine the effect that changes in government policy and working practices might have (or not have).



# Trend Mining in Medical Applications

- Longitudinal data sets are common in medical applications (patient records).
- Work with diabetes unit at The Royal Liverpool Hospital.
- Royal Liverpool Hospital has the largest collection of diabetes data records in the UK (actually four DBs).
- Patients have regular consultations.
- Problems with: (a) missing data, (b) heterogeneity
- Interested in changes in patient data (but lack of change is also interesting).

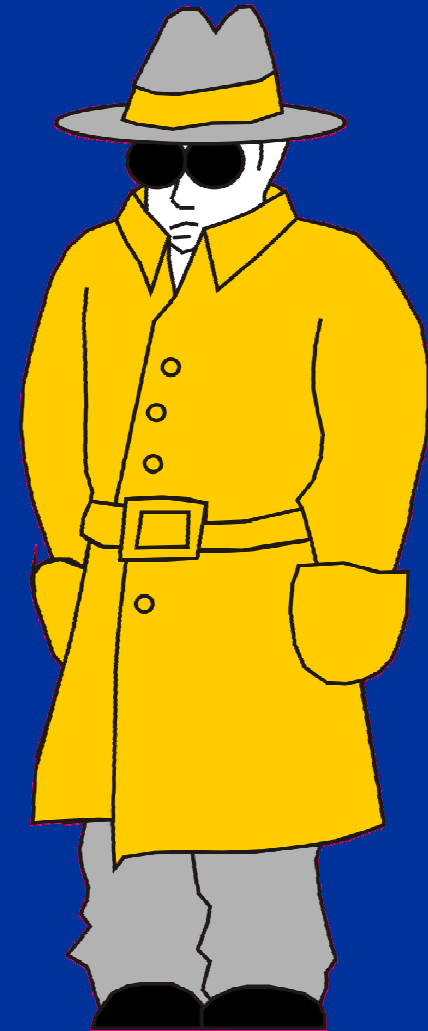
# Trend Mining in Web Usage Mining

- Web usage mining is a popular KDD application.
- Learn Higher initiative.
- We wish to identify changes in WWW site usage behaviour.
- This is expected to provide information which will in turn provide evidence for restructuring of the site.
- Input is WWW log data time stamped at weekly intervals.



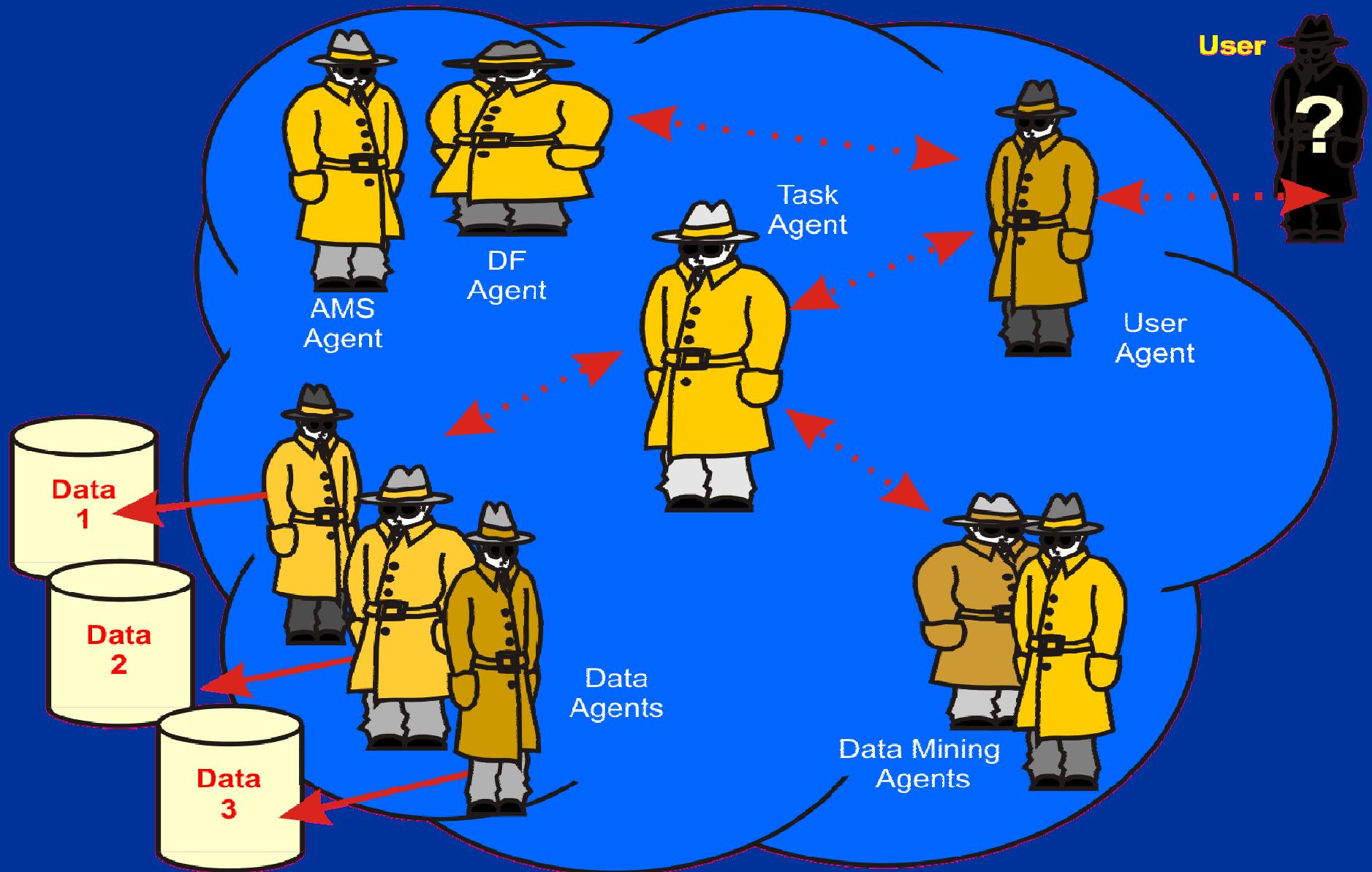
# Multi-Agent Data Mining (1)

- A potential generic solution is using a MAS (Multi-Agent System) approach.
- Vision is that of an anarchic collection of software agents; contributed by various participants, and cooperating to address a rich range of KDD tasks.
- The challenge is that the technical domain of KDD and (as already illustrated) the variety of applications is extensive.
- Propose EMADS, The Extendible Multi-Agent Data Mining System.





# Multi-Agent Data Mining (2)



# Multi-Agent Data Mining (3)

- ❖ EMADS supports extendibility through a number of predefined generic (**Data** and **DM**) wrappers.
- ❖ Wrappers are in effect EMADS agents in their own right that merge with whatever they are used to wrap to become data mining or data agents.
- ❖ Data mining wrappers require some programming knowledge.
- ❖ In case of Data wrappers, usage is facilitated by a GUI.
- ❖ (Creation of task agents requires more extensive knowledge, but not excessively so.)



# Summary

- Motivation (“Where I’m coming from”).
- Some specific applications: MRI scan and Retina image mining.
- A generic application (but with lots of different elements): Freight forwarding, cattle movement social network, longitudinal patient data sets and WWW usage mining.
- A potential solution: Multi-Agent Data Mining (MADM).



# Credits

❖ **MRI Scan Inage Mining**: Ashraf El Sayed, Martha van der Hoek<sup>1</sup>, Vanessa Slumming<sup>2</sup>, Chuntao (Geof) Jiang.

❖ **AMD**: Hanafi Hijazi, Yalinn Zhang<sup>3</sup>.

❖ **Trend Mining**:

**Freight Forwarding Customer Base**: Reshma Patel<sup>4</sup>, Lawson Archer<sup>4</sup>.

**Cattle Movement**: Puteri Nohuddin, Christian Setzkorn<sup>5</sup>, Bob Christie<sup>5</sup>, Suzy Robinson<sup>5</sup>.

**Patient data**: Vassiliki Somaraki, Simon Harding<sup>3</sup>, Deborah Broadbent<sup>3</sup>.

**Learn Higher**: Mohammad Khan<sup>6</sup>, David Read<sup>6</sup>.

❖ **EMADS**: Kamal Ali Albashiria, Paul Leng, Santhana Chaimontree, Katie Atkinson.

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<sup>1</sup>UoL Dept. Medical Statistics, <sup>2</sup>UoL Dept. Public Health, <sup>3</sup>Royal Liverpool Hospital, <sup>4</sup>Transglobal Express Ltd., <sup>5</sup>UoL Vet school, <sup>6</sup>Liverpool Hope University. All other contributors are from the Department of Computer Science at The University of Liverpool