# Concept Learning and Searching Over Networks Using Java Agents for Meta-learning

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# THE JAM PROJECT

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Application: FRAUD AND INTRUSION DETECTION IN FINANCIAL INFORMATION SYSTEMS ———-

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CMAD IV

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# Electronic Commerce on the WEB provides New Challenges

- More data and services are available everyday on the WEB
- We seek a new way to search and LEARN FROM very large and remote databases
- Electronic Commerce provides new opportunities for Electronic FRAUD
- We seek a new way to LEARN about FRAUD on the WEB
- Proposal: Build an IMMUNOLOGICAL Capability for the WEB to DETECT FRAUD
- Learn SELF (Good Transactions) from NON-SELF (Bad Transactions)

# A New Information Extraction Paradigm

- Empower the User with *Data Mining* Tools to Learn Knowledge from Data
- Agent Proxies that Learn Knowledge over Remote Data
- Agent Proxies that Learn Collective Knowledge over Remote Agents
- Agent Proxies Use Learned Knowledge to Search Other Data

# Terminology

- Data Mining: Scalable Machine Learning Applied to Verly Large Databases
- Learning Agent: A Machine Learning program launched to and applied at a remote source of data
- Classifier Agent: A derived program learned over some remote site of data, labels or tags data with class labels
- Meta-Learning Agent: A Machine Learning program that Learns how to combine a number of remote classifier agents, the result is a single classifier agent

# Meta-learning: An Algorithm-independent Technique for Scalable and Accurate Inductive Learning

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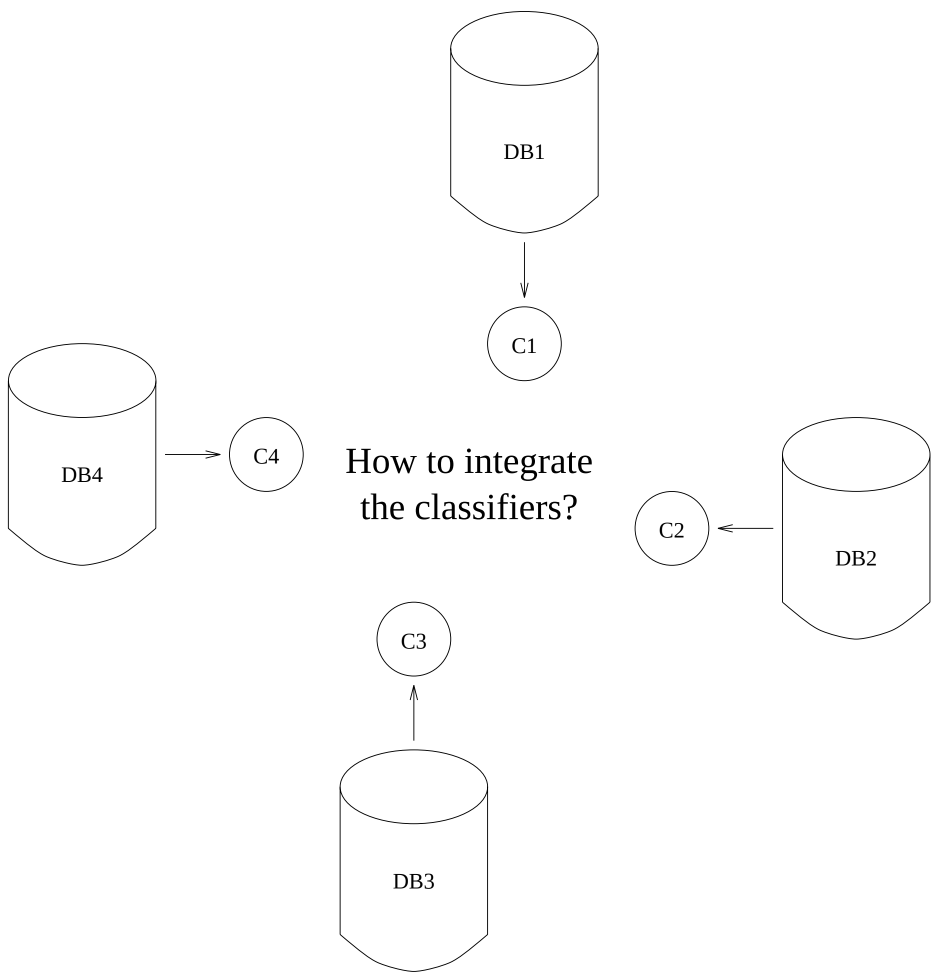
# Learn and Integrate Classifiers

- Large datasets are partitioned into subsets
- Distributed databases are inherently partitioned
- Collective knowledge is harvested from individual knowledge sources

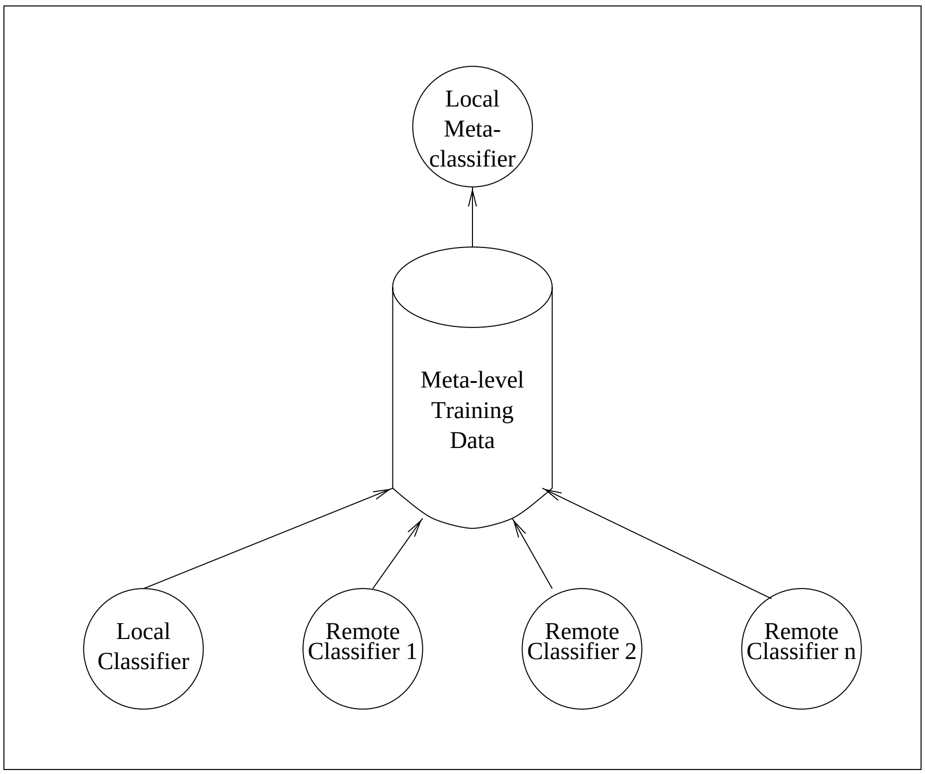


# Integrating Classifiers

- Integrating the *concept descriptions languages* (a logical cross-bar switch)?
  - different representations: probabilities, hyperplanes, logical expressions
  - difficult if not impossible to accurate map all representations into one standard

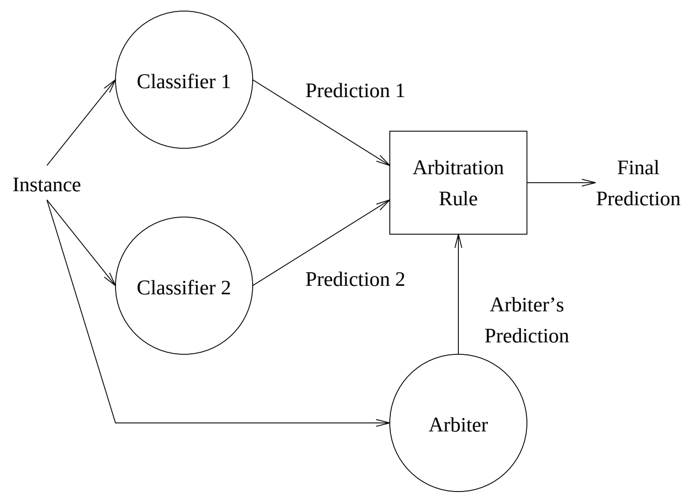
- Integrating the behavior of classifiers (their predictions)?
  - algorithm/representation-independent
  - existing and new algorithms can be plugged in with ease
  - voting and statistical techniques abound
  - meta-learning:
    * arbitration: conflicting predictions are resolved by a learned arbiter
    * combining/coalescing: learn a function over classifiers' predictions

# SHARING REMOTE CLASSIFIERS

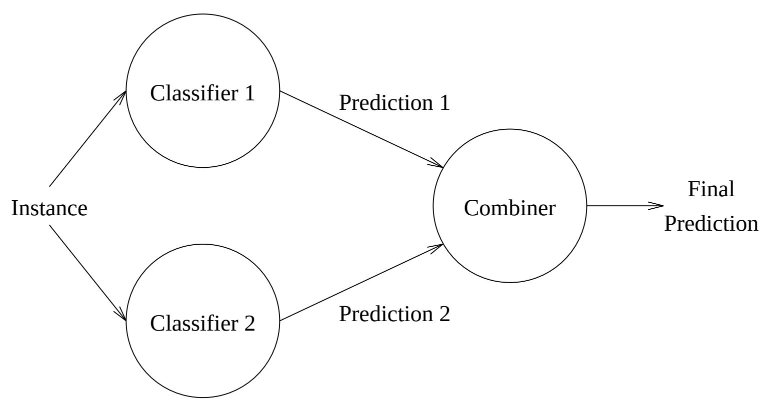



*SHARING KNOWLEDGE WITHOUT SHARING DATA*

# Meta-learning: Arbiters and Combiners



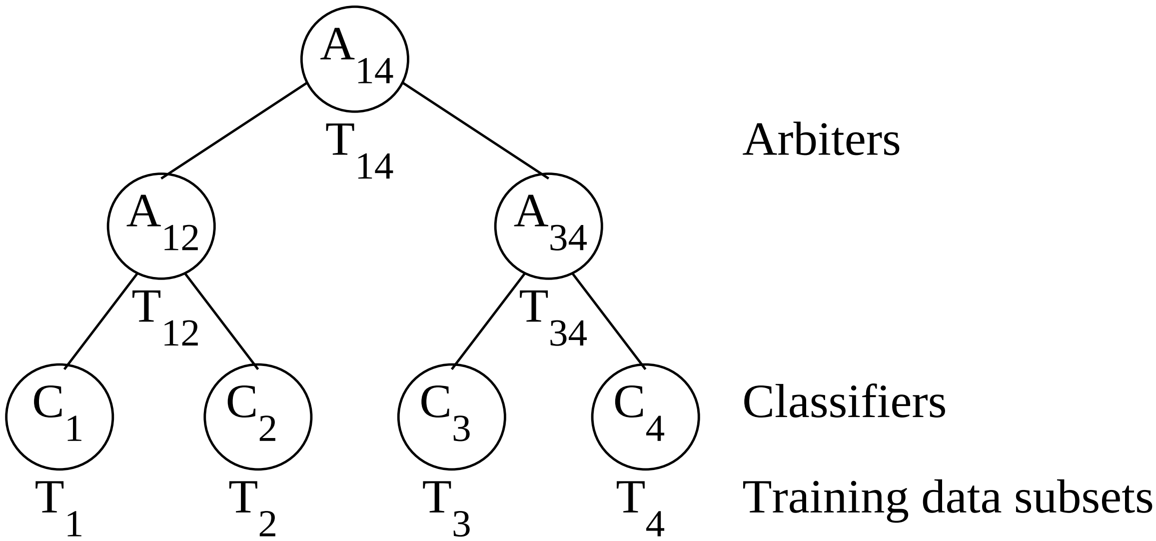

- The *arbiter* Resolves conflicting predictions (disagreements)



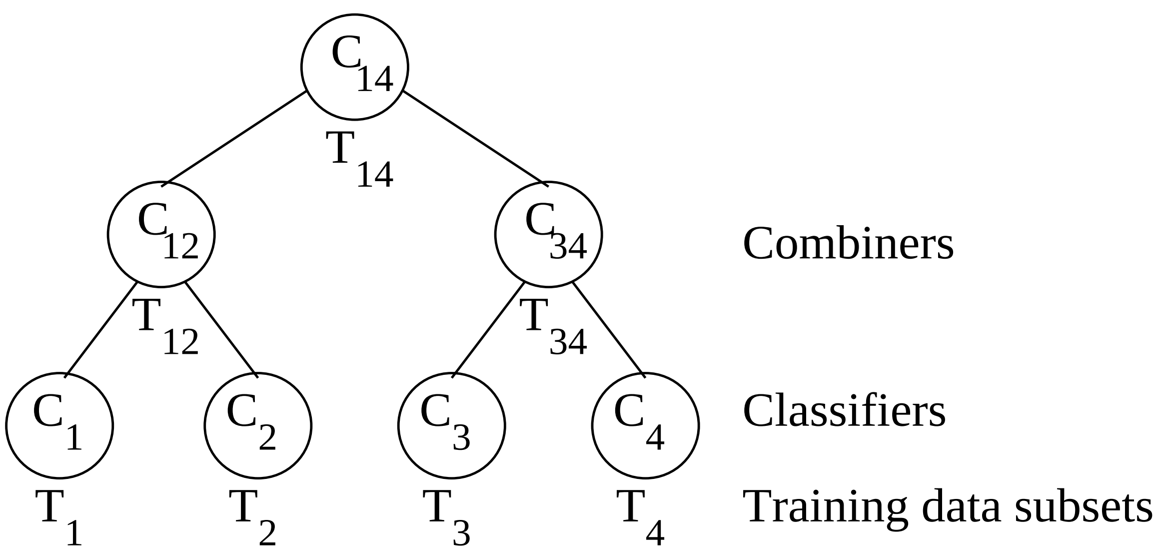

- The *combiner* makes a final prediction based on the base predictions

# Hierarchical Meta-learning in Agent Infrastructures

- *Arbiter tree*




- *Combiner tree*

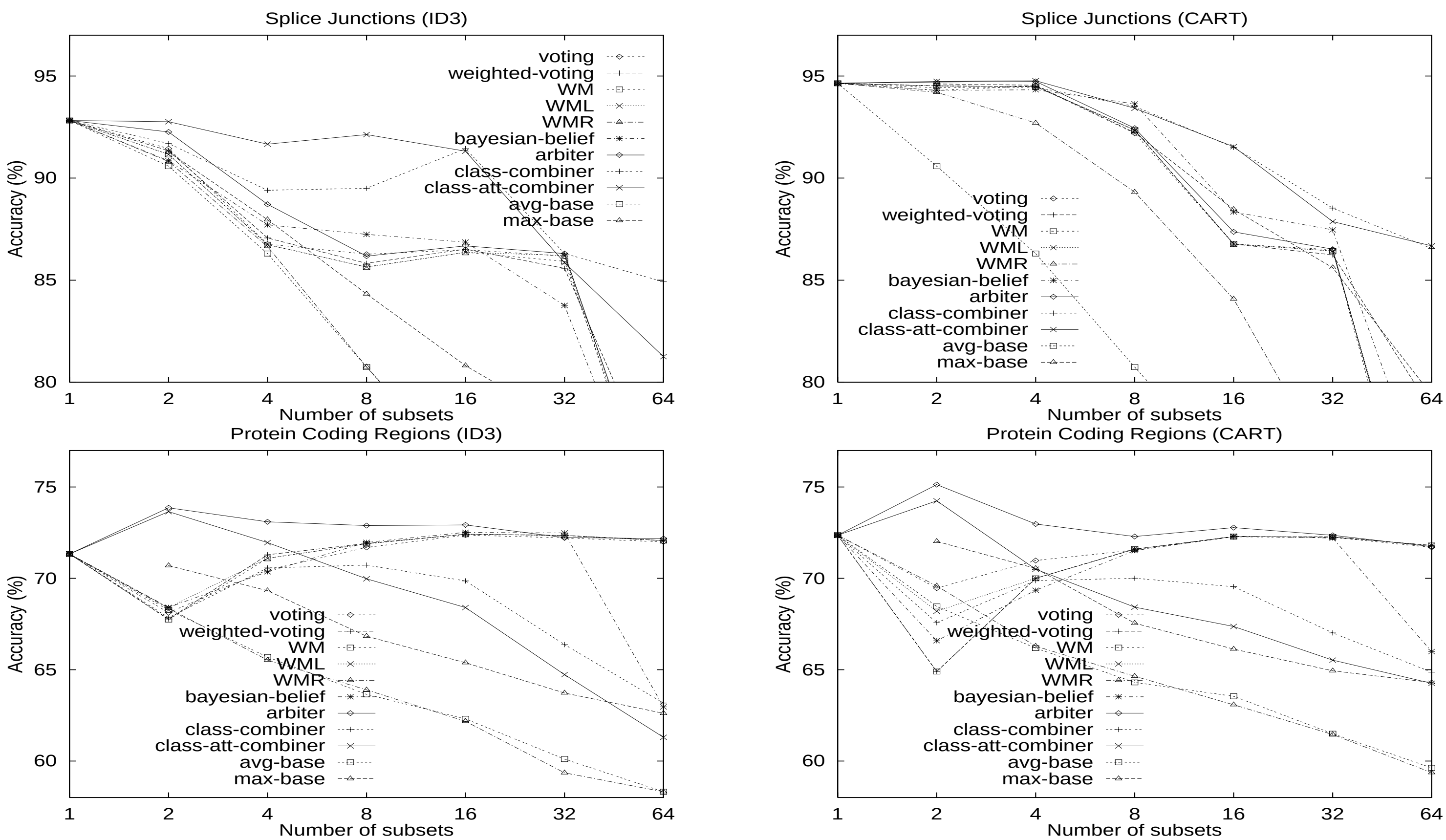


# Evaluation Studies

- Many issues exist and are addressed by various experiments
- Main focus is on prediction accuracy
  - disjoint training and test sets
  - 10-fold cross validation
  - 2 to 64 data subsets
  - global classifier (whole dataset or 1 data subset)
- "Off-the-shelf" learning algorithms
  - ID3 (Quinlan 86)
  - CART (Breiman et al. 84)
  - BAYES (Clark & Niblett 87)
  - WPEBLS (Cost & Salzberg 93)
- "Off-the-shelf" learning tasks
  - DNA splice junctions (3,190) (Towell et al. 90)
  - Protein coding regions (21,625) (Craven & Shavlik 93)
  - Protein secondary structures (20,000) (Qian & Sejnowski 88)

# Subsets and Sampling

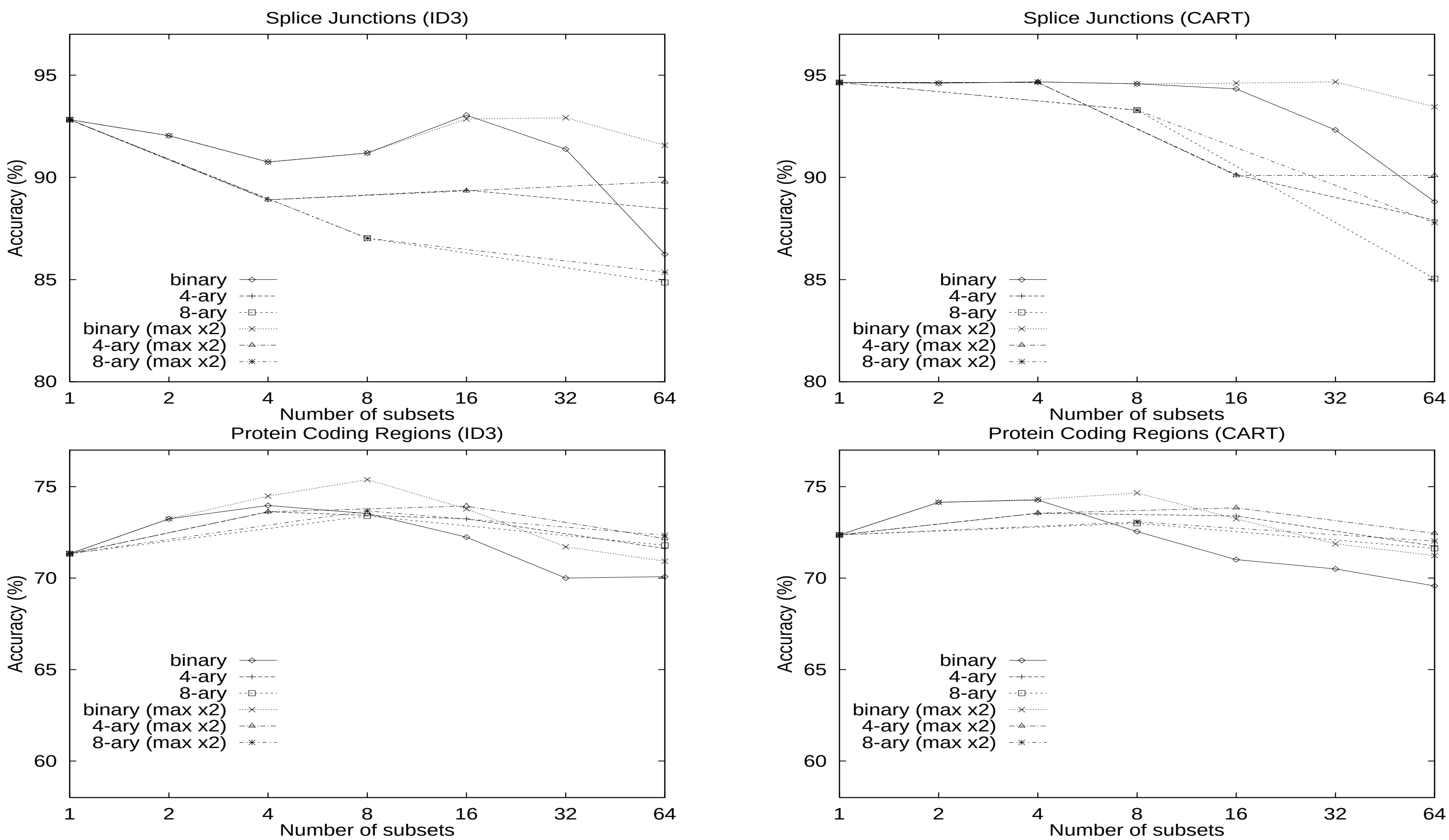
- How do the # of subsets and subset size affect accuracy?
- Is random sampling of a subset sufficient?




- Subsets can't be too small to generate reasonable classifiers
- Random sampling is not sufficient; combining is necessary

# Arbiter Trees

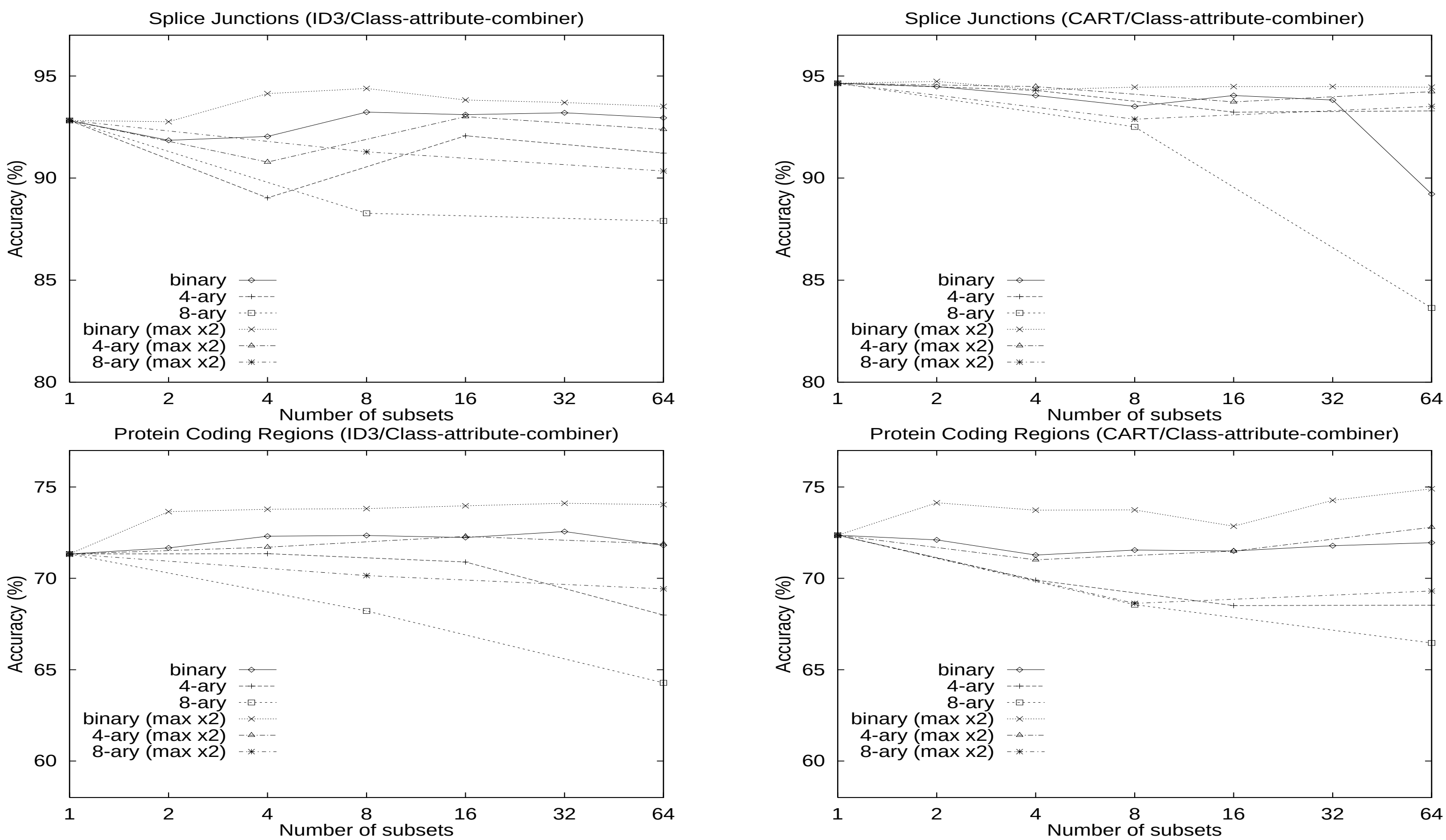
- Is hierarchical meta-learning necessary?
- How do the order of the arbiter trees and training set size limit affect the accuracy?




- Lower order trees are more accurate
- Doubling the arbiter training set size maintains accuracy

# Combiner Trees

- How does the combiner trees fare?
- Class-attribute-combiner strategy




- Statistically significant and consistent improvement in the PCR dataset beyond the original accuracy

# Summary of Meta-learning Results

- Random sampling is not sufficient
- Existing voting and statistical combining techniques are not sufficient
- "One-level" meta-learning outperforms the voting and statistical techniques
- Hierarchical meta-learning can sustain high accuracy
- Meta-level training set size needs only to be twice the subset size
- Proportional distribution of classes in the data subsets is beneficial
- Lower-order trees are more accurate than higher-order trees
- Combiner trees can boost accuracy beyond the global classifier's
- Data replication does not improve accuracy

# An Illustration: Distributed DNA Sequence Databases

## SITES 1 and 2:

| DNA sequence # | Nucleotide sequence |
|---|---|
| 1 | ...CCAGCTGCATCACAGGAGGCCAGCGAGCAGGTCTGTTCCAAGGGCCTTCGAGCCAGTCTG... |
| 2 | ...GAGAGAGAGACCAGAAATAATCTTGCTTATGCTTTCCCTCAGCCAGTGTTTACCATTGCA... |

| DNA sequence # | Nucleotide sequence |
|---|---|
| 1 | ...ACAGGCTTTTCACAGCCTCCAGCGAGGCATGTACTGATTCCAGGCCTCGGAGCCAGTCTG... |
| 2 | ...TAGCCGAGACAAAGGATAAGTCTTGATGTATGCTTACCACAGTCTAATGCTTCCCATACT... |

# Sample SPLICE JUNCTION sequences at SITE 3

| Junction | $p_{-30}$ | $p_{-29}$ | $p_{-28} \cdots p_{-3}$ | $p_{-2}$ | $p_{-1}$ | $p_1$ | $p_2$ | $p_3 \cdots p_{28}$ | $p_{29}$ | $p_{30}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| intron-exon (IE) | C | T | ..TAATAACATTCTTAT | A | G | G | G | ..ATCCATTCATGTGAAT | A | T |
| exon-intron (EI) | G | A | ..GCCCGTCATAAAATC | T | G | G | T | ..GAGACTCATGCCCAGC | T | C |
| neither (N) | T | A | ..CTATCCACAGACAGT | A | G | G | A | ..TGCCCGCCTCTGGGCA | A | A |

# An ID3 Decision Tree Learned Over SJ Data at SITE 3

```
p-1 = A:
|   p2 = A:  N
|   p2 = C:  N
|   p2 = G:  N
|   p2 = T:
|   |   p5 = A:  N
|   |   p5 = C:  N
|   |   p5 = G:
|   |   |   p1 = A:  N
|   |   |   p1 = C:  N
|   |   |   p1 = G:  EI
|   |   |   p1 = T:  N
|   |   p5 = T:  N
p-1 = C:  N
p-1 = G:
|   p2 = A:
|   |   p-2 = A:
|   |   |   p-3 = A:  N
|   |   |   p-3 = C:  IE
|   |   |   p-3 = G:  N
|   |   |   p-3 = T:  IE
|   |   p-2 = C:  N
|   |   p-2 = G:  N
|   |   p-2 = T:  N
|   p2 = C:
|   |   p-2 = A:  IE
|   |   p-2 = C:  N
|   |   p-2 = G:  N
|   |   p-2 = T:  N
```

A (logic-based) rule equivalent of the first branch at the top of the ID3 Decision tree is:
*"If ($X.p_{-1} = A$) and ($X.p_2 = A$) then the center doesn't have a junction, i.e. $X.Junction = N$."*
A rule equivalent to the second branch is:
*"If ($X.p_{-1} = A$) and ($X.p_2 = C$) then the center doesn't have a junction, i.e. $X.Junction = N$."*

# Sample Sequences To Be Extracted

**Classifier Agent Sent to SITE 1:**

*Select X.* From DNA-Sequence Where* $C_{ID3-1}(X.p_{-30}..X.p_{30}) = EI.$

| $C_{ID3-1}$ | Meta-classifier | $p_{-30}$ | $p_{-29} \cdots p_{-3}$ | $p_{-2}$ | $p_{-1}$ | $p_1$ | $p_2$ | $p_3 \cdots p_{29}$ |
|---|---|---|---|---|---|---|---|---|
| EI | EI | A | CCAAGAAGGGATCTATCACCTCTGTAC | A | G | G | T | AAGAAAAATTACATAGATGAAGATCTG |
| EI | EI | T | GGCGACTACGGCGCGGAGGCCCTGGAG | A | G | G | T | GAGGACCCTGGTATCCCTGCTGCCAGT |
| N | EI | G | GAGCTGCCAGACACGGAGGAGAGCCAT | G | A | G | T | AAGTGGGCCCAGCTGAGGGTGGGCTGG |
| N | N | A | TTCTACTTAGTAAACATAATTTCTTGT | G | C | T | A | GATAACCAAATTAAGAAAACCAAAACA |
| N | N | A | GGCTGCCTATCAGAAGGTGGTGGCTGG | T | G | T | G | GCTGCTGCTCTGGCTCACAAGTACCAT |

# A Sample Meta-Classifier Learned From 4 Base Classifiers

```
c-id3-1 = EI:  EI
c-id3-1 = IE:
|   p-3 = A:  N
|   p-3 = C:  IE
|   p-3 = G:  N
|   p-3 = T:  IE
c-id3-1 = N:
|   p1 = A:  N
|   p1 = C:  N
|   p1 = G:
|   |   p5 = A:  N
|   |   p5 = C:  N
|   |   p5 = G:
|   |   |   p2 = A:  N
|   |   |   p2 = C:  N
|   |   |   p2 = G:  N
|   |   |   p2 = T:  EI
|   |   p5 = T:  N
|   p1 = T:  N
```

# A Host Meta-Learning Environment

- Partitioning and Distributing data,
- Invoking Different Meta-Learning Strategies In Parallel,
- Pairing Classifiers to Reduce Intermediate Training Sets for Meta-Learning,
- Filtering and Communication of Training and Testing Data Between Processors, and,
- Instrumentation to Gather Statistics Used in Formulating or Designing Specific Meta-Learning Architectures.
- LAUNCHING OF ENCAPSULATED LEARNING AND META-LEARNING AGENTS OVER NETWORKS

# Future Research: The JAM PROJECT

- Specialized representations (new attributes/predicates) and algorithms for meta-learning
- New meta-learning strategies and training-set composition rules
- Agent computing: collaboration with FSTC in field-testing learning agents on the Internet:
-   - Acquisition of TRANSACTION DATABASES with FRAUD LABELS
    - Demonstration of Remote Learning and Meta-Learning Agents
    - Exchange of Learned Classifiers
    - Installation of Learned Classifiers as SENTRIES to warn of FRAUD

# JAM Prototype: One coordinator, multiple data sites

- Coordinator
  - Dispatches agents to different data sites
  - Multithreaded for concurrent service
  - Simple error recovery from data sites crashes
- Data Site
  - Accepts and executes agents
  - Agent Independent
- Agent: the ID3 machine learning algorithm
- Platform Independent (Java)
- Simple Graphical User Interface

## Data Schema and Stats for (Fraud) Transaction Data Sets

- Number of Attributes: $30 + -\Delta$ (all numeric)
  - Many fields are categorical (i.e.numbers represent a few discrete categories)
  - Developed over years to capture important information
- Size: Fixed 137 bytes per transaction
- Type of Information:
  - A (jumbled) account number (no real identifiers)
  - Scores produced by a COTS authorization/detection system
  - Date/Time of transaction
  - Past payment information of the transactor
  - Amount of transaction
  - Geographic information: where the transaction was initiated, the location of the merchant and transactor
  - Codes for validity and manner of entry of the transaction
  - An industry standard code for the type of merchant
  - A code for other recent "non-monetary" transaction types by transactor
  - The age of the account and the card
  - Other card/account information
  - Confidential/Proprietary Fields (other potential indicators)
  - Fraud Label (0/1)
- .5MM records by each Bank:
  - sampling 50,000 per month
  - Span 11/95 - 10/96

VISIT with your favorite Browser:

- http://www.fstc.org - and click on Fraud Page
- http://www.cs.columbia.edu/s̃al
- http://www.cs.columbia.edu/s̃al/JAM/PROJECT

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