Semantic Compression

Semantic Compression

- Real-life data are highly structured and there are strong correlations between the attributes and records.
- The *syntactic* compression algorithms are not designed to take advantage of such structures.
- Recently, some new schemes are proposed based on these observations.
- Naturally, such schemes are so-called *semantic* compression methods in contrary to the *syntactic* ones.

Semantic Compression

- First derive a description model by taking into account the semantic meaning of the attributes
- Represent the original data by the derived model.
- The data, that cannot derive from the model, are explicitly stored

Syntactic Compression

- Statistical Model vs. Dictionary-based Model
  - Statistical Model
    - Each distinct character of the input data is encoded with the code assignment being based on the probability of the character's appearance in the data.
    - E.g. Huffman coding, Arithmetic coding
  - Dictionary-based Model
    - Maintains a dictionary that contains a list of commonly occurring character strings in data and their corresponding codes
    - E.g. LZW, Vector Quantization
- Lossless vs. Lossy
  - Lossless: Huffman coding, Arithmetic coding, LZW coding
  - Lossy: Vector quantization

Syntactic Compression

- Huffman Coding
  - First developed by David Huffman.
  - Symbols that have higher probabilities will have shorter codes than symbols that have lower probabilities.
  - The two symbols that have minimum probabilities will have the same length.
- LZW(Lempel-Ziv-Welch) coding
  - Used both in UNIX compress and DOS pkzip
  - Organized around a string translation table which contains a set of character strings and their corresponding code values
  - The string table has prefix property that for every string in the table, its prefix is also in the table.

Lossless Compression(static)

- Dictionary Encoding
  - Assigns an ID to each new word

  input: ABC ABC BC DDD

  Compressed Data: 1 1 2 3

  Dictionary: ABC =1, BC = 2, DDD=3

- Binary Encoding
  - Binary representation of numeric data

  input: “100” “20” “50”

  Encoding: 100 20 50

Lossless Compression(static)

- Differential Encoding (or Delta Encoding)
  - Replaces a data item with a code value that defines its relationship to a specific data item

ex)

input: 100 120 130

Compressed Data: 100 20 30

input: Johnson Jonah Jones Jorgenson

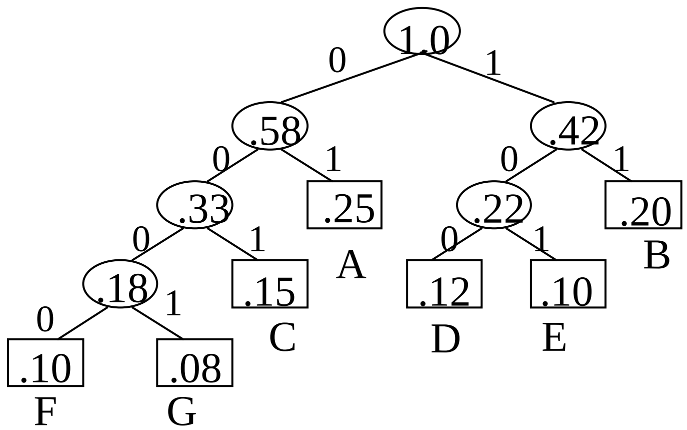
Compressed Data: (0) Johnson (2)nah (3)es (2)rgenson

Lossless Compression (semi-adaptive)

- Huffman Encoding
  - Assigns shorter codes to more frequently appearing symbols and longer codes to less frequently appearing symbols
  - ex)

input: ACE

Encoding:01001101



Huffman tree

Lossless Compression(adaptive)

- LZ(Lempel-Ziv) Coding
  - Adaptive dictionary encoding
  - Converts variable-length strings into fixed-length codes

  Input: {A B AB AA ABA}

  Compressed Data: {(0,A)(0,B)(1,B)(1,A)(3,A)}

  - new table entry is coded as (i,c)
    - i : the codeword for the existing table entry(12 bit)
    - c : the appended character(8bit)

Fascicle

- [Jagadish, Madar, Ng 99]
- Fascicles
  - Informally, subsets of a relation having very si milar values for many attributes
  - Technically, a *k*-D fascicle of a relation is a su bset of records having *k compact* attributes
- An attribute *A* of a subset *F* of records is *compact* with *tolerance t,* if:
  - the range of *A*-values (numeric), or
  - the number of distinct *A*-values (categorical)

  of all the records in *F* does not exceed *t*

What is a Fascicle? (cont.)

age	salary	assets	credit
error≤4	error≤5,000	error≤25,000	error=0
20	30,000	25,000	good
30	35,000	50,000	good
35	40,000	75,000	good
40	100,000	175,000	poor
50	110,000	250,000	good
60	50,000	150,000	poor
70	35,000	125,000	poor
75	15,000	100,000	good

3-D Fascicles

35,000 50,000 good :3

2-D Fascicles

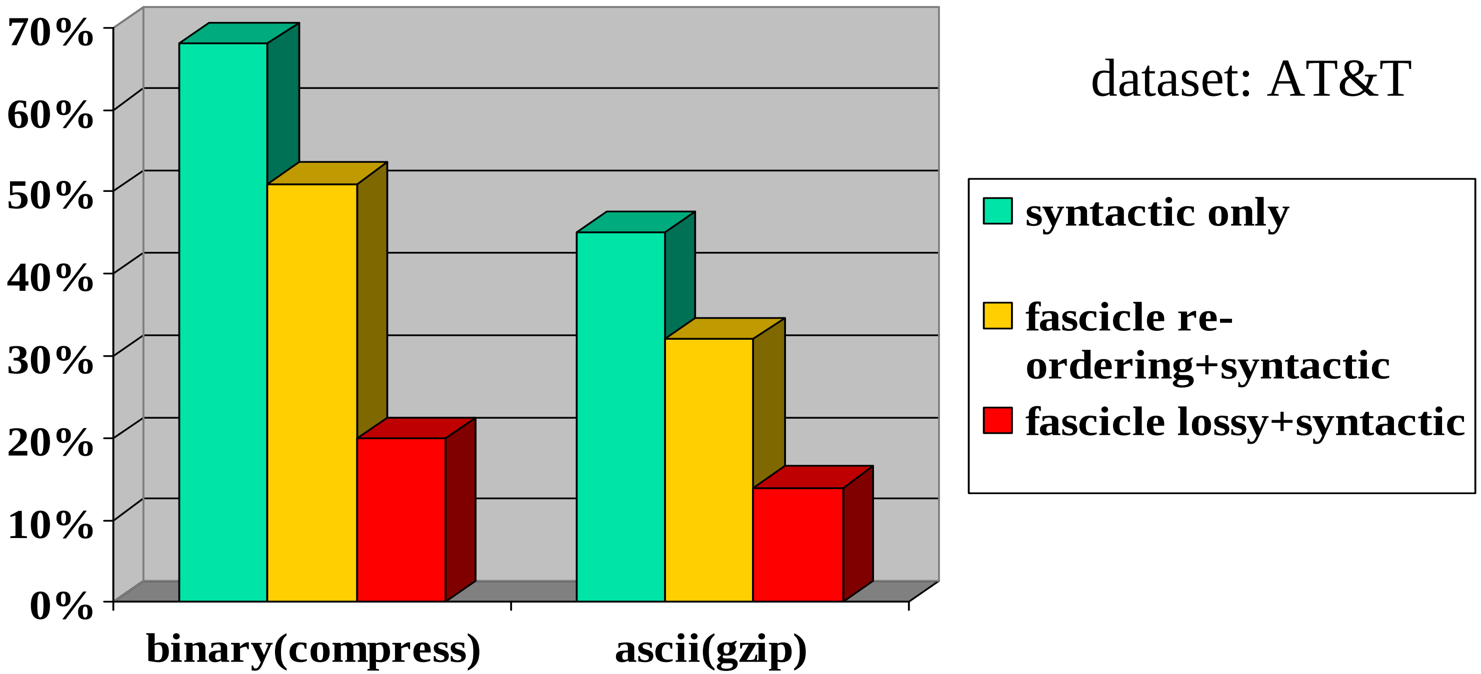
137,500 poor :2

- Compress data by storing representative values (e.g., "centroid") *only once* for each attribute cluster
- *Lossy* compression: information loss is controlled by the notion of "similar values" for attributes (*user defined*)

Fascicle

- Lossless:
  - First, use fascicles to physically re-order the relatio n
    - Compact attributes are *not* projected away
  - Apply syntactic compression
    - Syntactic compression dependent on the physic al ordering of records
- Lossy:
  - First, use fascicles and project away compact attr ibutes
  - Apply syntactic compression

Fascicle



lossless: extra 25% compression

lossy: extra 75% compression (max error *t* = 1/32)

From [Jagadish, Madar, Ng 99]

Compressing with Fascicles

- k-dimensional fascicle F(k,t): subset of records with k *compact attributes*
  - Compress by storing single centroid value for k compact attributes
- User-defined *compactness tolerance* t (vector) specifies the allowable loss in the compression *per attribute*
  - E.g., t[Duration] = 3 means that all "Duration" values in a fascicle are within 3 of the centroid value

Compressing with Fascicles

- Problem Statement
  - Given a table T and a compactness-tolerance vector t,
  - Find fascicles within the specified tolerances such that the total storage is minimized (so-called 'storage minimization problem')
- Problem Decomposition

  (1) Find candidate fascicles in T

  (2) Select the best fascicles to compress T
- NP-Complete
  - Corresponds to Minimum Cover Problem [Karp 72]

Storage Minimization Problem

- Given a collection C of subsets of a finite set S and a positive integer K,
- Is there a subset $C' \subseteq C$ with $|C'| \leq K$ such that every element of S belongs to at least one member of C'?
- NP-Complete
- Greedy selection is among the best existing heuristics

How to Find Candidate Fas cicles?

- Operates on the lattice consisting of all po ssible subsets of records
- Finding all fascicles needs too MUCH effo rt
- Greedy selection only needs some good q uality candidates, not all of them
- Thus, we adapt randomized strategy
  - Pick some good starting fascicles
  - Grow them to maximal sizes to ensure quality by one scan over data

Tip set & Maximal set

- Tip set
  - It is hard to find the exact k-D fascicles.
  - To find a k-D fascicle for a given value k.
  - $(\bot \subseteq S_1 \subseteq S_2 \subseteq S_3 \subseteq \ldots \subseteq \top)$

    $\top$: entire relation, $\bot$: empty set

    S_t : i-D fascicle

    S_{t+1} : j-D fascicle, a superset of S_t

    Then, $j \le i$

    For $1 \le k \le n$, if $j < k \le i$, we call S_t a tip set.
  - In other words, S is a k-D tip set if S is a k-D fascicle, and there is an parent T of S such that T is a j-D fascicle with j < k.
- Maximal set
  - S is a k-D maximal set if S is a k-D fascicle, and for all supersets T of S, T is a j-D fascicle with j < k

Why tipset? –Example

- We want 2–D fascicle.
- We add one more tuple to 4–D fascicle.
- But, it becomes 1–D fascicle.

4–D fascicle

May	Winger	35	290	180

May	Winger	35	290	180
Odjick	Winger	9	115	245

1–D fascicle

Algorithm Single-k

- Input : A dimensionality k, number of fascicles P, a buffer of b pages, and a relation R of r pages
- Output : P k-D fascicles

1. Divide R into q disjoint pieces, each comprising up to b randomly chosen pages from R, i.e., $q = \lceil r/b \rceil$.
2. For each piece : /* choosing initial tip sets */
   2.1 Read the piece into main memory.
   2.2 Read the records in main memory to produce a series of tip sets.
   2.3 Repeat 2.2, each with a different permutation of the records, until P/q tip sets are obtained.
3. /* growing the tip sets */
   Grow all P tip sets with one pass over the relation.
   Output the grown tip sets.

Single-k algorithm – Example

- We want 2-D fascicles

  compactness tolerance $t_{Position}=1$, $t_{Points}=10$, $t_{Played\ Mins}=60$, $t_{Penalty\ Mins}=20$

Name	Position	Points	Played Mins	Penalty Mins
Blake	Defense	43	395	34
Borque	Defense	77	430	22
Cullimore	Defense	3	30	18
Gretzky	Defense	130	458	26
Konstantinov	Defense	10	560	120
May	Winger	35	290	180
Odjick	Winger	9	115	245
Tkachuk	Centre	82	530	160
Wotton	Defense	5	38	6

Blake	Defense			34
Borque	Defense			22
Cullimore	Defense			18
Gretzky	Defense			26
Konstantinov	Defense			120

2-D fascicle or 2-D tipset

Konstantinov	Defense	10	560	120

We want 2-D tip set and stop here.

4-D fascicle or 4-D tipset

{Konstantinov} is used to start a second tip set

- Iterate the previous done with this 4-D fascicle

- Green cells represent that the attributes are compact.
- Red cells represent that the attributes is not compact.
- Black cells represent that the attributes need not check because those cells were red cells in previous step.

Greedy Selection for the Single-k algorithm

- To represent the storage savings induced by a fascicle F, it is weighted by wt(F) = k * |F|, where k is the dimensionality of F.
- In a straightforward implementation of the greedy selection, we select the candidate fascicle with the highest weight.
  - adjust the weight of the remaining fascicles.
- If A is selected fascicle, then the adjusted weight of each remaining fascicle F is given by
  - Wt(F/A) = k * |F – A|
- Then from among the remaining fascicles, we pick the one with the heaviest adjusted weight, and repeat.

The multi-k Algorithm

- Exploits single-k algorithm to produce fascicles all having dimensionalities ≥ k.
- Recall from the Single-k algorithm how a k-D tip set corresponds to a path ($\perp$, S_1 , S_2 , S_3 , S_t)
- While Single-k algorithm construct a path ($\perp$, S_1 , S_2 , S_3 ,S_t) and obtains St as a k-D tip set,
  - the Multi-k algorithm uses exactly the same path to obtain larger sets on the path with dimensionality i, for i ≥ k.

Classification

Classification

- Given:
  - Database of tuples, each assigned a class label
- Develop a model/profile for each class
  - Example profile (good credit):
  - (25 <= age <= 40 and income > 40k) or (married = YES)
- Sample applications:
  - Credit card approval (good, bad)
  - Bank locations (good, fair, poor)
  - Treatment effectiveness (good, fair, poor)

What is Classification?

- Given a database of tuples
  - Each tuple consists of
    - A set of Attribute values
    - A assigned categorical class label
- Develop a model/classifier for each class based on the set of attributes
- Use the model to predict the class lable of future data

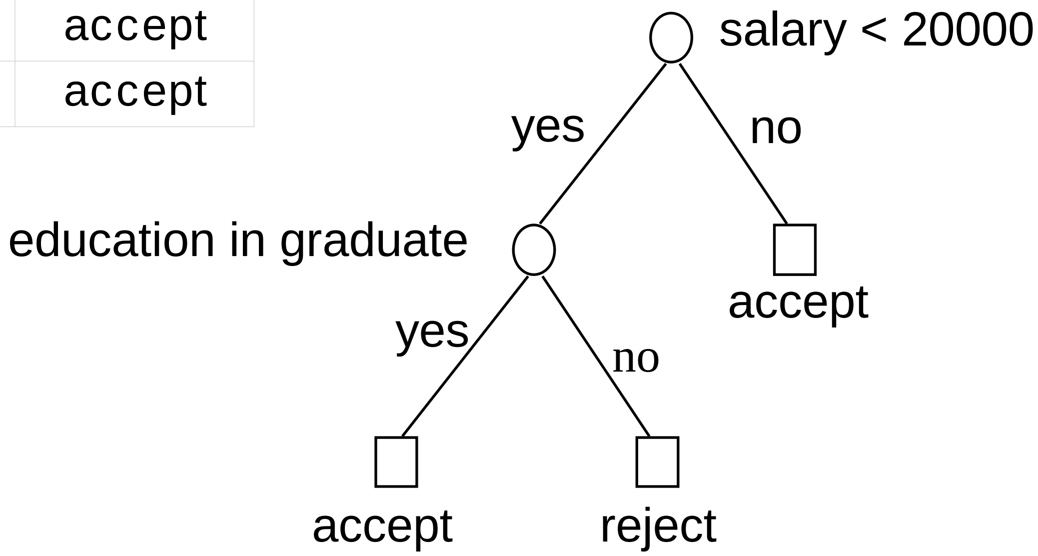
Classification Model

- Decision Tree Model
- Probabilistic Model(Bayesian etc.)
- Neural Network Model
- Support Vector Machine
- K-nearest neighbor

Decision Trees

salary	education	label
10000	high school	reject
40000	under graduate	accept
15000	under graduate	reject
75000	graduate	accept
18000	graduate	accept

Credit Analysis



Decision Trees

- Pros
  - Fast execution time
  - Generated rules are easy to interpret by humans
  - Scale well for large data sets
  - Can handle high dimensional data
- Cons
  - Cannot capture correlations among attributes
  - Consider only axis-parallel cuts

Decision Tree Algorithms

- Classifiers from machine learning community:
  - ID3[Qui86]
  - C4.5[Qui93]
  - CART[BFO84]
- Classifiers for large database:
  - SLIQ[MAR96], SPRINT[SAM96]
  - SONAR[FMMT96]
  - Rainforest[GRG98]

- Pruning phase followed by building phase

Decision Tree Algorithm

- A decision tree is created in two phases:
  - Building Phase
    - Recursively split nodes using best splitting attribute for node until all the examples in each node belong to one class
  - Pruning Phase
    - Prune leaf nodes recursively to prevent over-fitting
    - Smaller imperfect decision tree generally achieves better accuracy

SPRINT

- [Shafer, Agrawal, Manish 96]
- Building Phase
  - Initialize root node of tree
  - **while** a node N that can be split exists
  - **for each** attribute A, evaluate splits on A
  - use best split to split N
- Use gini index to find best split
- Separate attribute lists maintained in each node of tree
- Attribute lists for numeric attributes sorted

How can we get best split?

- Select the attribute that is most useful for classifying training set
- gini index and entropy
  - Statistical properties
  - Measure how well an attribute separates the training set
  - Entropy ($entropy(T) = -\Sigma p_j \times \log_2(p_j)$)
  - Gini Index ($gini(T) = 1 - \Sigma p_j^2$)

Entropy example

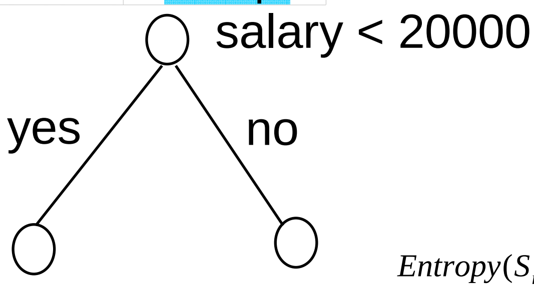
salary	education	label
10000	high school	reject
40000	under graduate	accept
15000	under graduate	reject
75000	graduate	accept
18000	graduate	accept

$$Pobablity(class = "reject") = \frac{2}{5}$$

$$Pobablity(class = "accept") = \frac{3}{5}$$

$$Entropy(S) = -\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}$$

$$= 0.970951$$



$$Entropy(S_{left}) = -\frac{1}{3}\log_2\frac{1}{3} - \frac{2}{3}\log_2\frac{2}{3}$$

$$= 0.918296$$

$$Entropy(S_{right}) = 0$$

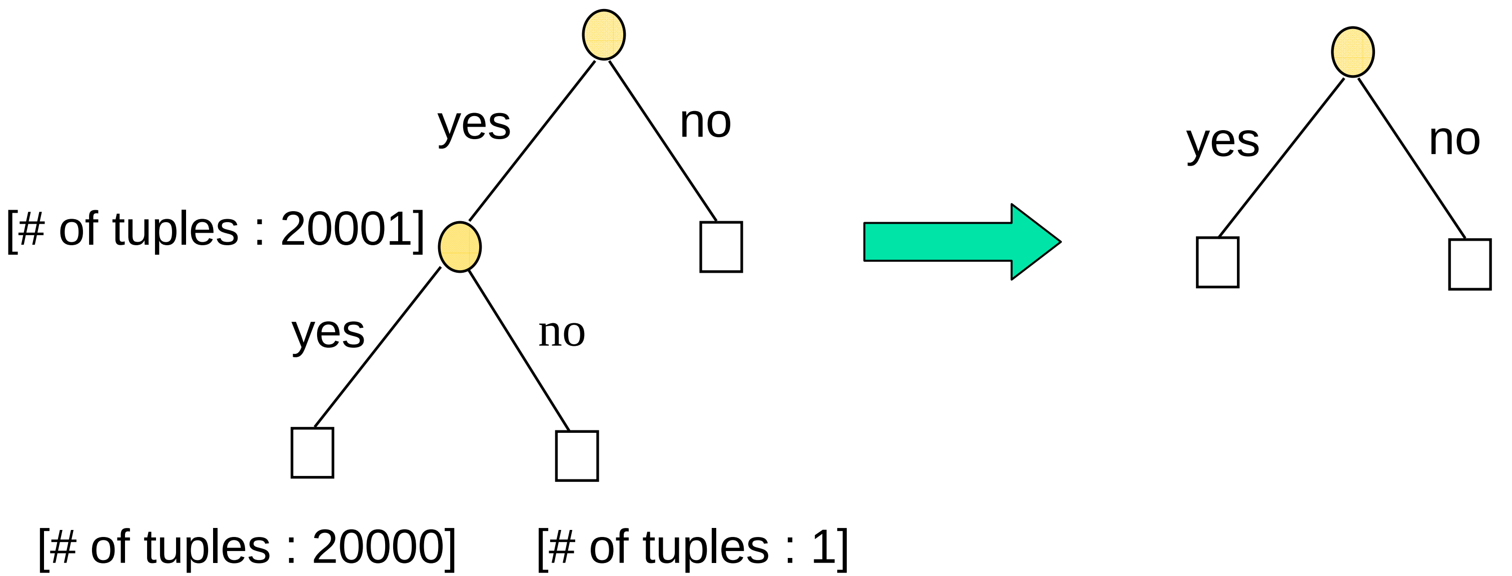
salary	education	label
10000	high school	reject
15000	under graduate	reject
18000	graduate	accept

salary	education	label
40000	under graduate	accept
75000	graduate	accept

$$E_{split}(S) = \frac{N_{left}}{N} E(S_{left}) + \frac{N_{right}}{N} E(S_{right}) \longrightarrow Entropy_{split}(S) = \frac{3}{5} \times 0.918296 + \frac{2}{5} \times 0 = 0.550978$$

Pruning Phase

- Smaller imperfect decision tree generally achieves better accuracy
- Prune leaf nodes recursively to prevent over-fitting



Attribute List

- SPRINT creates an attribute list for each attribute
- Numerical attribute list is sorted
- Attribute records contains
  - Attribute value
  - Class label
  - Index

  of the record

[Training set]

salary	education	label
10000	high school	reject
40000	under graduate	accept
15000	under graduate	reject
75000	graduate	accept
18000	graduate	accept

salary	label	rid
10000	reject	0
15000	accept	2
18000	reject	4
40000	accept	1
75000	accept	3

[Attribute list for salary]

education	label	rid
high school	reject	0
under graduate	accept	1
under graduate	reject	2
graduate	accept	3
graduate	accept	4

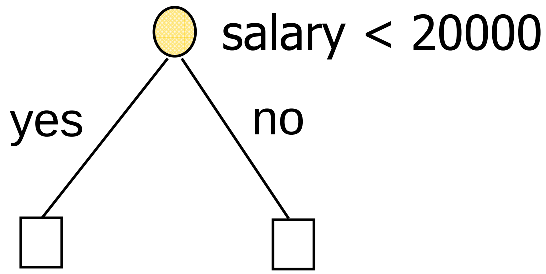
[Attribute list for education]

Attribute list (cont.)

- All attribute lists are made at the root
- As the tree is grown, the attribute lists belonging to each node are partitioned and associated with the children

salary	label	rid
10000	reject	0
15000	accept	2
18000	reject	4
40000	accept	1
75000	accept	3

education	label	rid
high school	reject	0
under graduate	accept	1
under graduate	reject	2
graduate	accept	3
graduate	accept	4



salary	label	rid
10000	reject	0
15000	accept	2
18000	reject	4

salary	label	rid
40000	accept	1
75000	accept	3

education	label	rid
high school	reject	0
under graduate	reject	2
graduate	accept	4

education	label	rid
under graduate	accept	1
graduate	accept	3

Histogram

[Attribute List] [position of cursor] [state of Class Histograms]

salary	label	rid
10000	reject	0
15000	accept	2
18000	reject	4
40000	accept	1
75000	accept	3

position 0

position 2

position 5

	accept	*reject*
C_{below}	0	0
C_{above}	3	2

	accept	*reject*
C_{below}	1	1
C_{above}	2	1

- For continuous attributes, two histograms are associated with each decision-tree node. These histograms, denoted as C_{above} and C_{below}
  - $C_{below:}$: maintains this distribution for attribute records that already been processed
  - C_{above}: maintains this distribution for attribute records that have not been processed

Finding Split Points

- Numeric attributes
  - C_{below} initials to zeros
  - C_{above} initials with the class distribution at that node
  - Scan the attribute list to find the best split
- Categorical attributes
  - Scan the attribute list to build the count matrix
  - Use the subsetting algorithm to find the best split

Evaluate numeric attributes

[Histogram for salary]

		accept	*reject*	
[Position 1]	C_{below}	0	1	$Entropy_{split}(S) = \frac{1}{5} \times \frac{1}{1} \log 1 + \frac{4}{5} \times \left(-\frac{3}{4} \log \frac{3}{4} - \frac{1}{4} \log \frac{1}{4} \right) = 0.811278$
	C_{above}	3	1	
[Position 2]	C_{below}	1	1	$Entropy_{split}(S) = 0.950978$
	C_{above}	2	1	
[Position 3]	C_{below}	1	2	$Entropy_{split}(S) = 0.550978$
	C_{above}	2	0	
[Position 4]	C_{below}	2	2	$Entropy_{split}(S) = 0.8$
	C_{above}	1	0	

Choose Position 3 has lowest Entropy!

Evaluate categorical attributes

[Attribute List]

education	label	rid
high school	reject	0
under graduate	accept	1
under graduate	reject	2
graduate	accept	3
graduate	accept	4

[Histogram for education]

	accept	reject
high school	0	1
under graduate	1	1
graduate	2	0

3 distinct value $\longrightarrow$ 2^3-2 split condition exists!

{high school}

$$Entropy_{split}(S) = \frac{1}{5}\times\frac{1}{1}\log 1 + \frac{4}{5}\times\left(-\frac{3}{4}\log\frac{3}{4} - \frac{1}{4}\log\frac{1}{4}\right)$$
$$= 0.811278$$

{under graduate}

$$Entropy_{split}(S) = 0.950978$$

{graduate}

$$Entropy_{split}(S) = \frac{3}{5}\times 0.918296 + \frac{2}{5}\times 0 = 0.550978$$

{high school, under graduate}

$$Entropy_{split}(S) = \frac{3}{5}\times 0.918296 + \frac{2}{5}\times 0 = 0.550978$$

{under graduate, graduate}

$$Entropy_{split}(S) = 0.550978$$

{high school, graduate}

$$Entropy_{split}(S) = 0.811278$$

Choose {graduate} has lowest Entropy!

SPARTAN

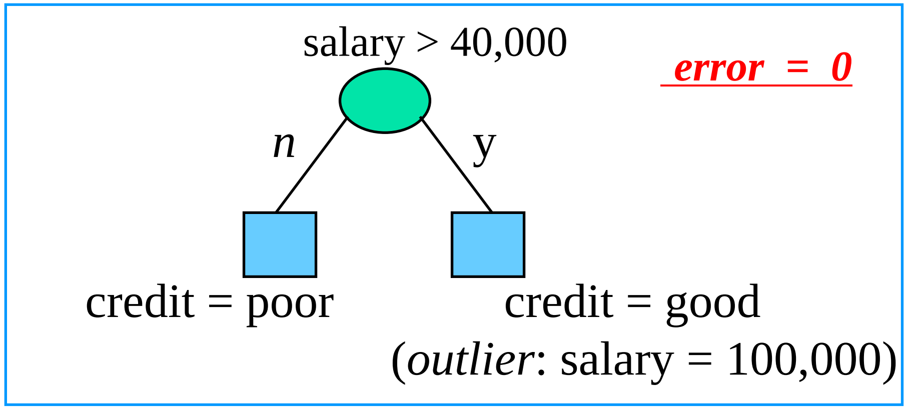
- [S. Babu, M. N. Garofalakis, and R. Rastogi 01]
- Model-Based Semantic Compression (MBSC)
  - Extract *Data Mining models* from the data table
  - Use the extracted models to construct an effective compression plan
  - Lossless or lossy compression
- *SPARTAN* system: specific instantiation of MBSC framework
  - Key observation: row-wise attribute clusters (a-la fascicles) are not sufficient
    (e.g., Y = aX +b)
  - Idea: use carefully-selected collection of Classification and Regression Trees (CaRTs) to capture such "vertical" correlations and *predict values for entire columns*

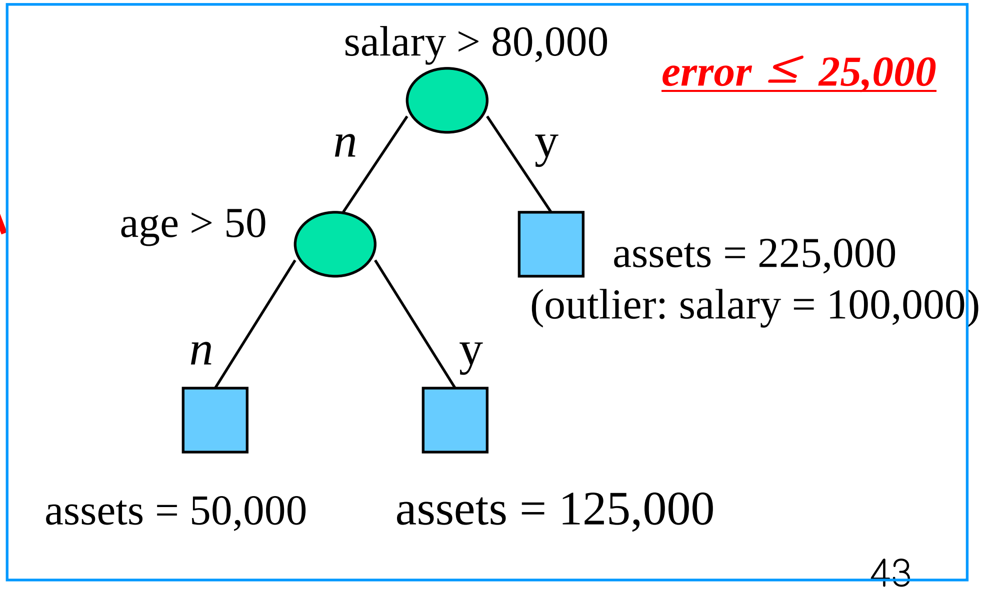
SPARTAN Example CaRT Models

age	salary	assets	credit
20	30,000	25,000	poor
25	76,000	75,000	good
30	90,000	200,000	good
40	100,000	175,000	poor
50	110,000	250,000	good
60	50,000	150,000	good
70	35,000	125,000	poor
75	15,000	100,000	poor

error≤0 error=0

- Can *eliminate* two data columns (*predicted* attributes) using a decision tree and a regression tree to





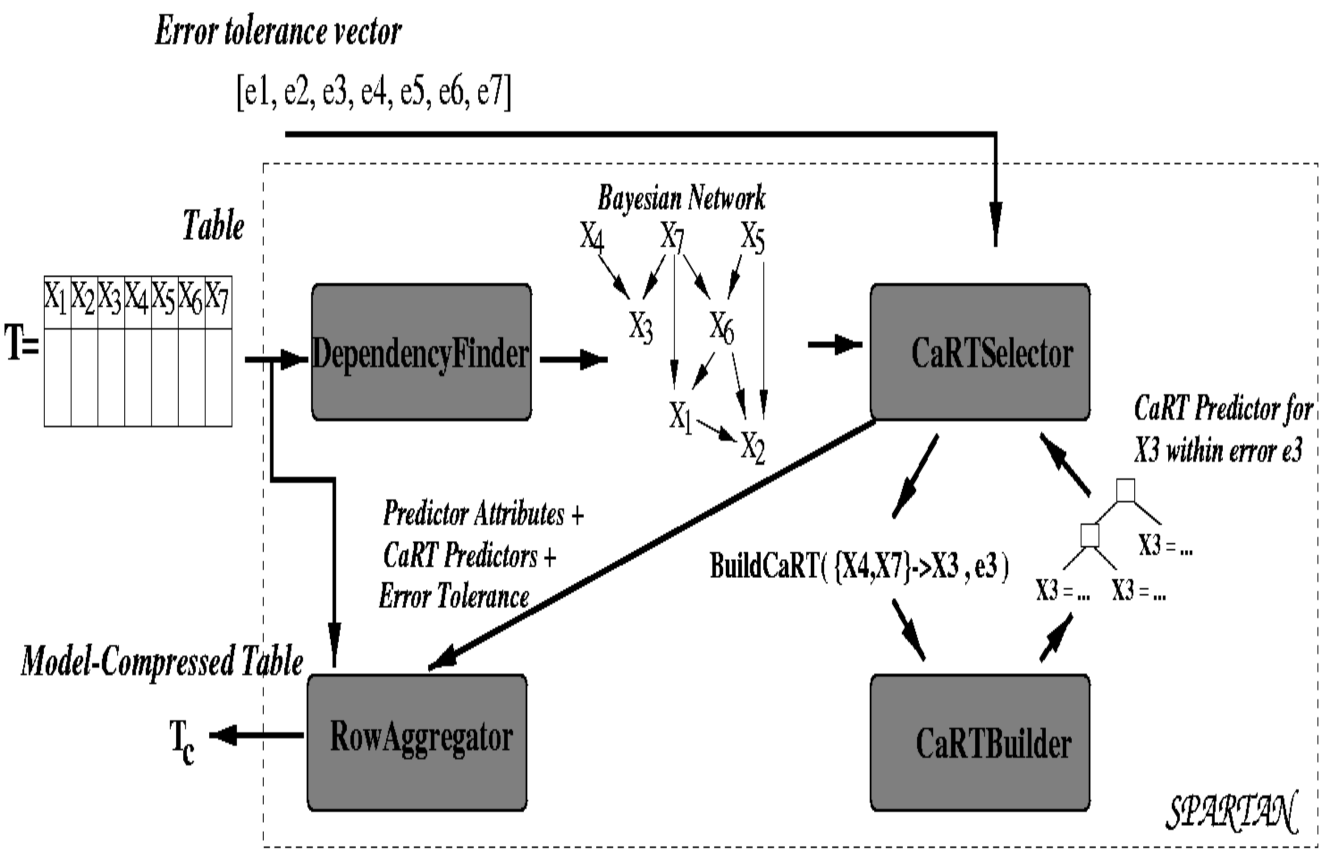
SPARTAN Compression Problem Formulation

- *Given:*
  - Data table T over set of attributes X and per-attribute error tolerances
- *Find:*
  - Set of attributes P to be predicted using CaRT models (and corresponding CaRTs+outliers) such that
    - Each CaRT uses only predictor attributes in X-P
    - Each attribute in P is predicted within its specified tolerance
    - The overall storage cost is minimized
      - *materialization cost*: storage for predictor attributes in X-P
      - *prediction cost*: storage for CaRT models + outliers

SPARTAN Compression Problem

- Non-trivial problem!
  - Space of possible CaRT predictors is exponential in the number of attributes
  - CaRT construction is an expensive process (multiple passes over the data)

SPARTAN Architecture



From [S. Babu, M. N. Garofalakis, and R. Rastogi 01]

SPARTAN's DependencyFinder

- *Input:* Random sample of input table T
- *Output:* A *Bayesian Network (BN)* identifying strong dependencies and "predictive correlations" among T's attributes
- BN Semantics: An attribute is independent of all its non-descendants *given its parents*
- Use BN to restrict (huge!) search space of possible CaRT models: Build CaRTs using "neighboring" attributes (e.g., parents) as predictors
- *SPARTAN* uses an (enhanced) *constraint-based BN builder*

SPARTAN's CaRTSelector

- "*Heart*" of the SPARTAN semantic-compression engine
- Uses the constructed Bayesian Network on T to drive the construction and selection of the "best" subset of CaRT predictors
- *Output:* Subset of attributes P to be predicted (within tolerance) and corresponding CaRTs

SPARTAN's CaRTSelector (cont.)

- Complication: A_n attribute in P *cannot* be used as a predictor for other attributes
  - Otherwise, errors will compound!!
- Hard optimization problem -- Strict generalization of *Weighted Maximum Independent Set (WMIS)* (NP-hard!!)
- Two solutions
  - Greedy heuristic
  - Novel heuristic based on WMIS approximation algorithms

The CaRTBuilder Component

- *Input:* Random sample of the input table; target predicted attribute X_p; predictor attributes $\{X_1,\ldots,X_k\}$; and error tolerance for X_p
- *Output:* Minimum-storage-cost CaRT for X_p using $\{X_1,\ldots,X_k\}$ as predictors, *within the specified error tolerance*
- Contributions
  - Novel algorithms for exploiting error tolerances in CaRT building
  - Integrated tree building and pruning for regression trees (dynamic programming algorithm)

The RowAggregator Component

- *Input:* Sub-table of materialized data attributes returned by the CaRTSelector
- *Output:* Fascicle-based (lossy) compression scheme for sub-table
- Summary
  - Attribute errors in sub-table should not propagate through the CaRTs to the predicted attributes
  - Algorithms based on fascicle algorithms [Jagadish, Madar, Ng 99]