Cobweb Basics

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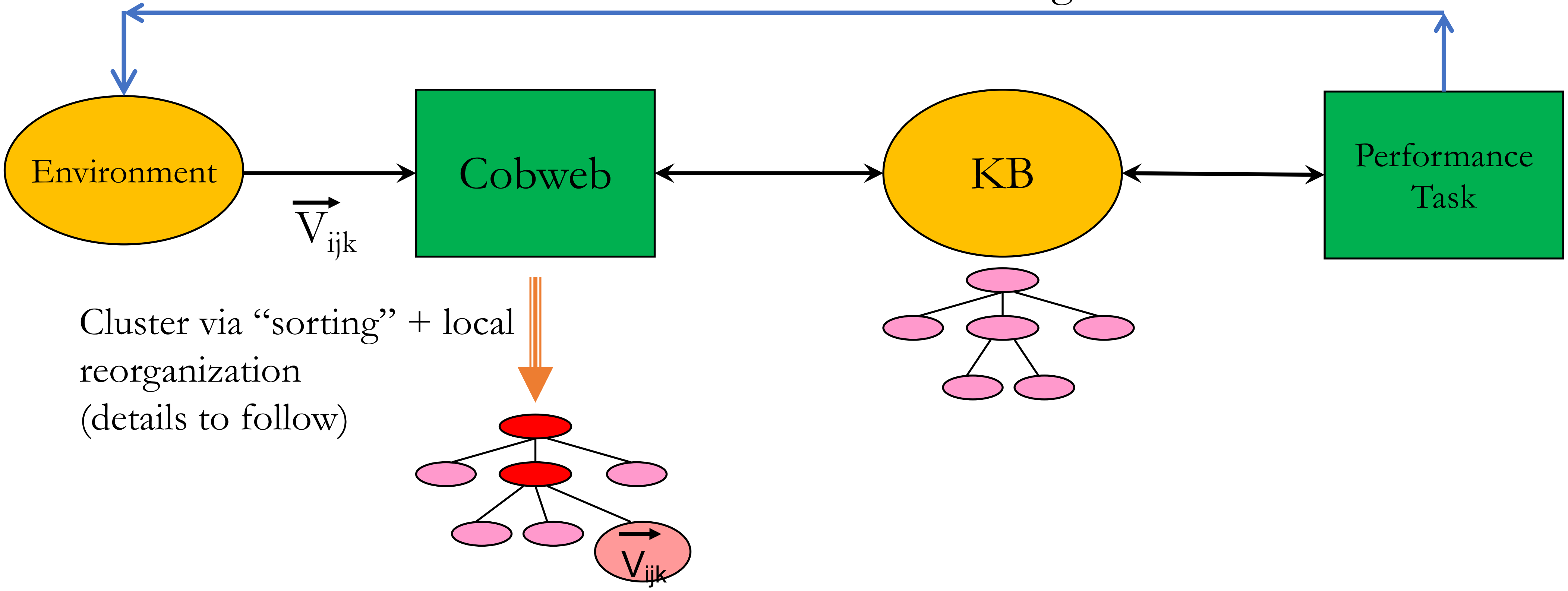
- Cobweb as Unsupervised Learning
- Cobweb Predecessors, and Related Systems and Paradigms
- Details of the Cobweb Algorithm
- Cobweb Accounts of Psychological Phenomena
- Alternative Quality Measures and Prediction Frontiers

Cobweb as Unsupervised Learning

Incremental Hierarchical Clustering

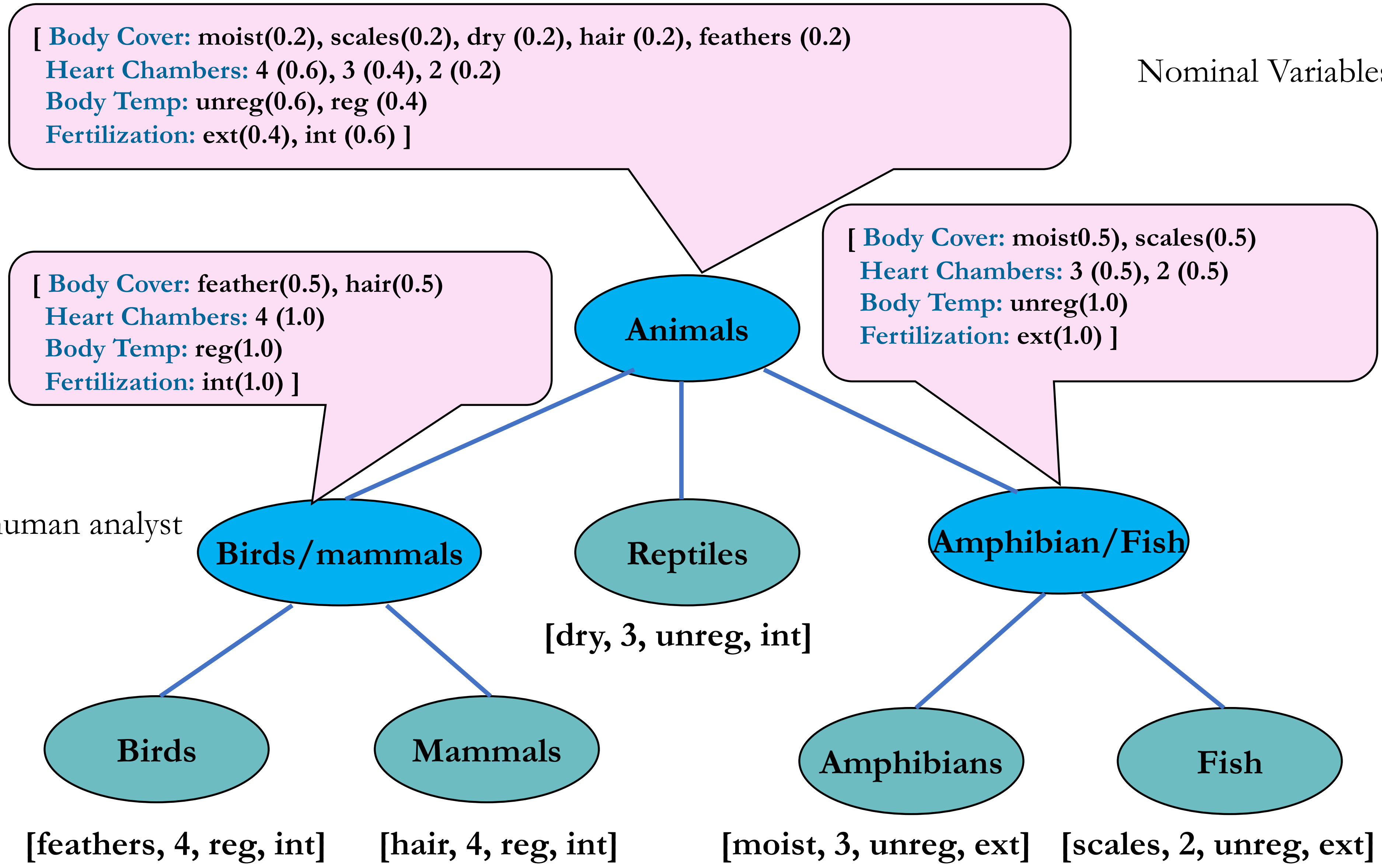


From "[Intelligence in Context]" (Fisher) Talk to NSF, March 21 2007

- Fisher, D. (1987). "Conceptual Clustering, Learning from Examples, and Inference," *Proceedings of the Fourth International Workshop on Machine Learning*. Irvine, CA: Morgan Kaufmann.
- Fisher, D. (1987) "Knowledge Acquisition Via Incremental Conceptual Clustering," *Machine Learning, 2*, 139–172. Reprinted in Shavlik & T. Dietterich (eds.), *Readings in Machine Learning*, 267–283, Morgan Kaufmann, 1990.

Hierarchical Clustering

Nominal Variables only



Cluster labels by human analyst

From "Intelligence in Context" (Fisher) Talk to NSF, March 21 2007

The Cobweb Algorithm

FUNCTION COBWEB (Object, Root <of (sub)tree>)

1) Update variable value counts at the Root

2) IF Root is a leaf

 THEN Return expanded leaf to accommodate
 the new object

 ELSE Find that child of Root that **best** hosts
 Object and perform one of the following

 2a) Create a new class if appropriate

 2b) **Merge** nodes if appropriate and call
 COBWEB (Object, Merged node)

 2c) **Split** a node if appropriate and call
 COBWEB (Object, Root)

 2d) IF none of the above (2a,b, or c) then call
 COBWEB (Object, Best child of Root).

Also, **promotion**

From Fisher, D.H. (1987). "Improving Inference Through Conceptual Clustering" Proceedings of AAAI-87, pp. 461-465.

Cobweb as Unsupervised Learning

Cobweb's Performance Task of Pattern Completion

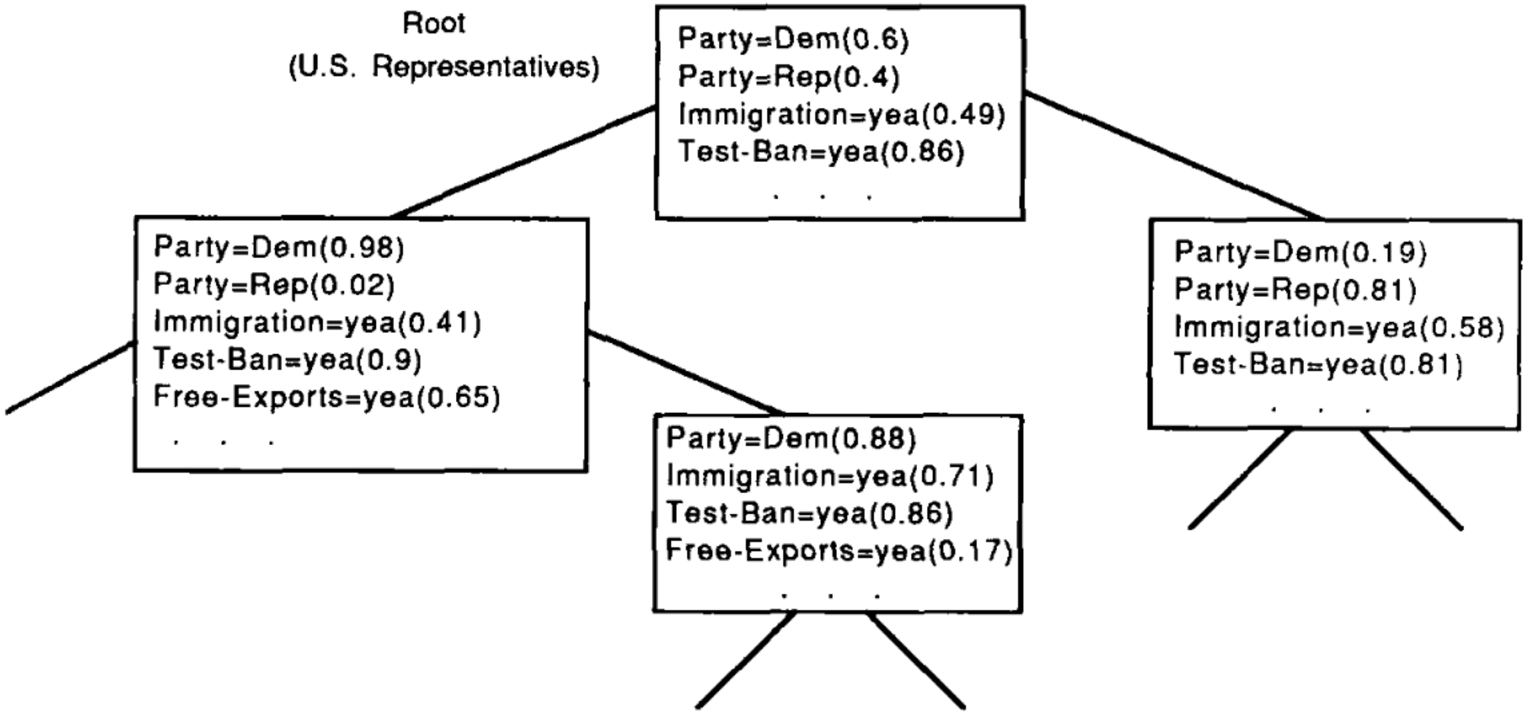


Fig. 2. A sample probabilistic concept tree over congressional voting records.

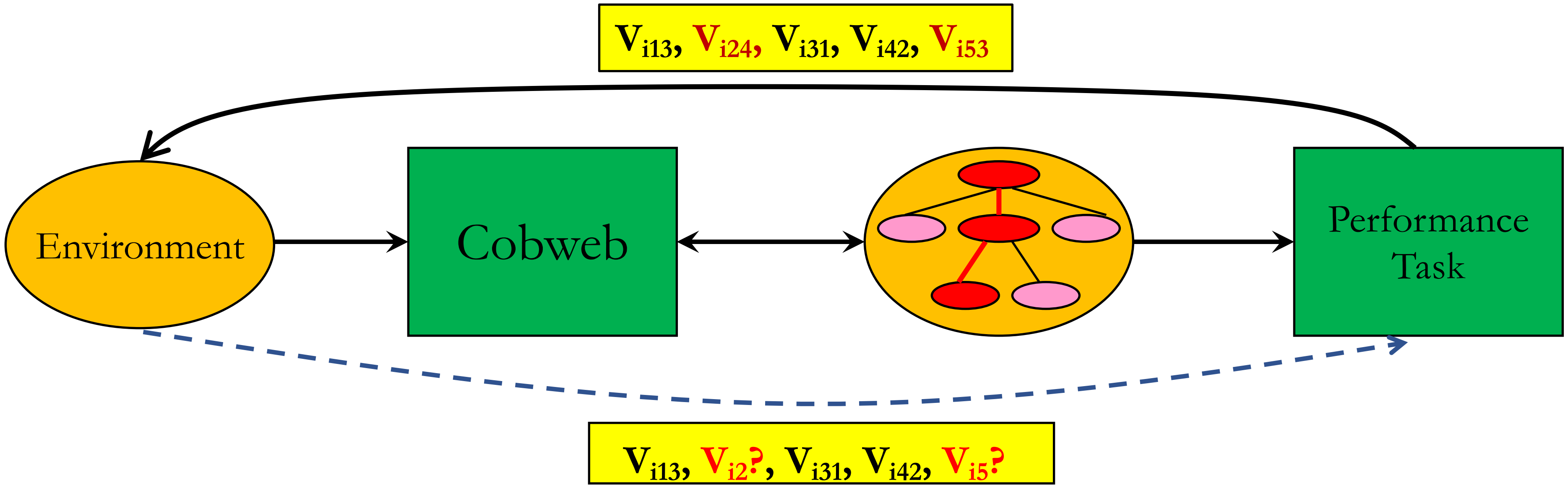
From Fisher, D., & Langley, P. (1990). "The Structure and Formation of Natural Categories," in G. Bower (ed.), *The Psychology of Learning and Motivation, 26*, San Diego, CA: Academic Press, 241–284.

The Cobweb Algorithm

Computational Complexity

Cobweb as Unsupervised Learning

Cobweb's Performance Task of Pattern Completion



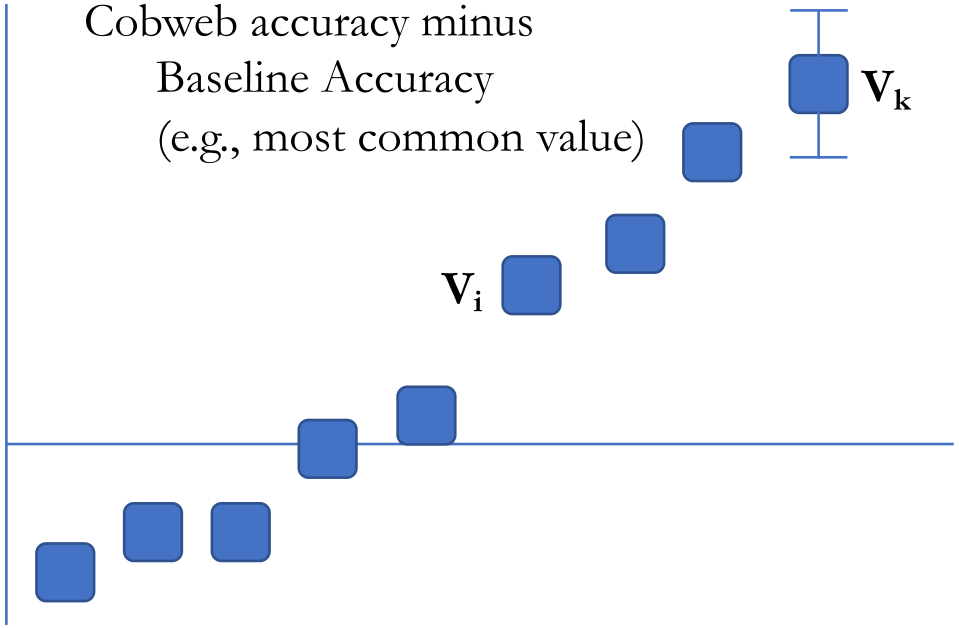
From "Intelligence in Context" (Fisher) Talk to NSF, March 21 2007

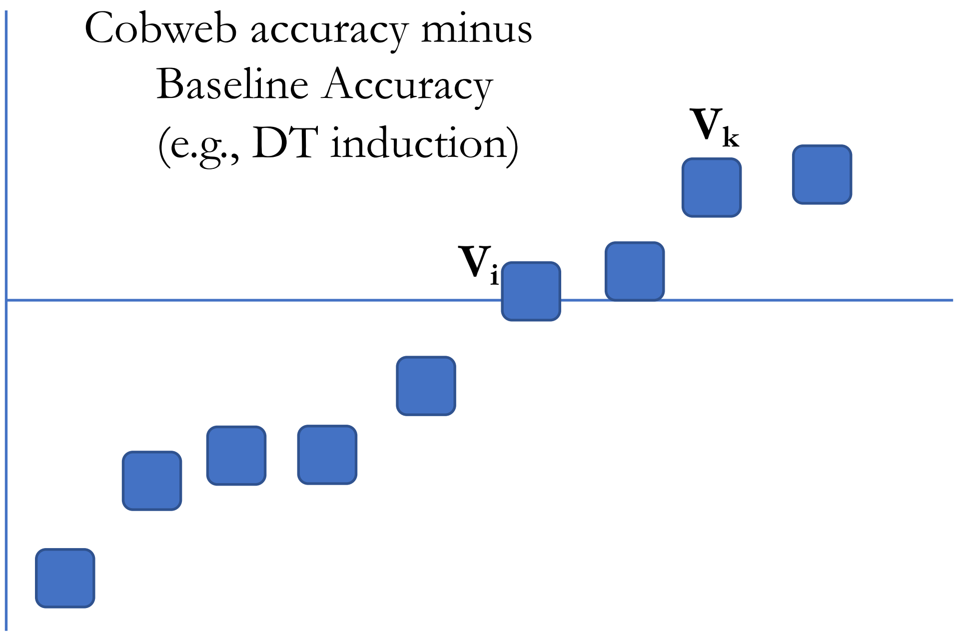
- Fisher, D. (1987). "Conceptual Clustering, Learning from Examples, and Inference," *Proceedings of the Fourth International Workshop on Machine Learning*. Irvine, CA: Morgan Kaufmann.
- Fisher, D. (1987) "Knowledge Acquisition Via Incremental Conceptual Clustering," *Machine Learning, 2*, 139–172. Reprinted in Shavlik & T. Dietterich (eds.), *Readings in Machine Learning*, 267–283, Morgan Kaufmann, 1990.
- Fisher, D. (1996). "Iterative Optimization and Simplification of Hierarchical Clusterings," *Journal of Artificial Intelligence Research, 4*, 147–179. (and KDD-95)

Cobweb as Unsupervised Learning

Cobweb's Performance Task of Pattern Completion

$V_{i13}, V_{i2}, \ldots V_{i?}, \ldots V_{im-1,7}, V_{im5}$ → $V_{i13}, V_{i2}, \ldots V_{i3}, \ldots V_{im-1,7}, V_{im5}$





Sorted in ascending order of Cobweb's advantage

Cobweb as Unsupervised Learning

Cobweb's Performance Task of Pattern Completion

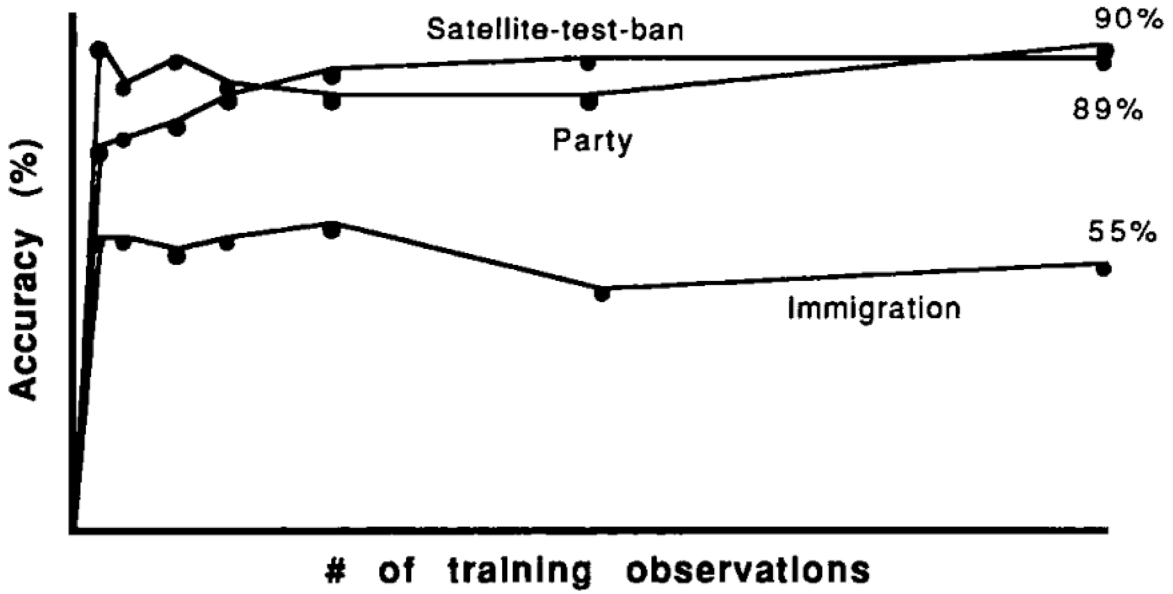


Fig. 3. Learning curves for three attributes in the congressional domain.

From Fisher, D., & Langley, P. (1990). "The Structure and Formation of Natural Categories," in G. Bower (ed.), *The Psychology of Learning and Motivation, 26*, San Diego, CA: Academic Press, 241–284.

Cobweb: Related Systems and Paradigms

Influences from Predecessors

Cobweb resulted from a synthesis of ideas from prior work

- Michalski et al
  - clustering as search
  - conceptual summaries of clusters
- Kolodner and Lebowitz
  - sorting or hill-climbing search
  - motivation for prediction
  - normative, predictable values
- Gluck and Corter
  - a measure for predicting basic levels as an evaluation function)

- Fisher, D. (1987). "Knowledge Acquisition Via Incremental Conceptual Clustering," Technical Report 87-22 (Doctoral Dissertation), Department of Information and Computer Science, University of California, Irvine.

Cobweb: Related Systems and Paradigms

Influences from Predecessors

- Michalski et al

  - Michalski, R. S. (1980). "Knowledge acquisition through conceptual clustering: A theoretical framework and an algorithm for partitioning data into conjunctive concepts" (PDF). International Journal of Policy Analysis and Information Systems. 4: 219–244.

  - Michalski, R. S. & Stepp, R. E. (1983). "Learning from observation: Conceptual clustering" (PDF). In Michalski, R. S.; Carbonell, J. G.; Mitchell, T. M. (eds.). Machine Learning: An Artificial Intelligence Approach. Palo Alto, CA: Tioga. pp. 331–363.

  - Fisher, D.H. & Langley, P. W. (1986). "Conceptual clustering and its relation to numerical taxonomy". In Gale, W. A. (ed.). Artificial Intelligence and Statistics. Reading, MA: Addison-Wesley. pp. 77–116.

Cobweb: Related Systems and Paradigms

Influences from Predecessors

- Kolodner and Lebowitz
  - Kolodner, J. L. (1983). "Maintaining Organization in a Dynamic Long-Term Memory". *Cognitive Science. **7** (4): 243-280.*
  - Lebowitz, M. (1983). "Generalization from Natural Language Text". *Cognitive Science. **7** (1): 1–40.*
- Gluck and Corter
  - Gluck, M. A. & Corter, J. E. (1985) Information, uncertainty, and the utility of categories. Proceedings of the Seventh Annual Conference of the Cognitive Science Society (pp. 283-287). Irvine, CA: Lawrence Erlbaum Associates.
  - Corter, J. E. & Gluck, M. A. (1992). "Explaining basic categories: Feature predictability and information". *Psychological Bulletin, 111*(2), *291–303.*

Cobweb Related Systems and Paradigms

Other Related Systems

Related Predecessor: EPAM

- Feigenbaum, E. A., & Simon, H. A. (1962). A theory of the serial position effect. British Journal of Psychology, 53, 307–320.
- Feigenbaum, E. A., & Simon, H. A. (1984). EPAM-like models of recognition and learning. Cognitive Science, 8, 305–336.
- In Fisher, D., Pazzani, M.,& Langley, P. (Eds.), Concept formation: Knowledge and Experience in Unsupervised Learning. San Mateo, CA: Morgan Kaufmann.
- Richman, H. B., Staszewski, J. J., & Simon, H. A. (1995). Simulation of expert memory with EPAM IV. Psychological Review, 102, 305–330.

Cobweb Related Systems and Paradigms

Other Related Systems

Related Systems

- Cheeseman, P., Kelly, J., Self, M., Stutz, J., Taylor, W., & Freeman, D.(1988). Auto Class: A Bayesian classification system. In Proceedings of the Fifth International Machine Learning Conference, pp.54-64. Ann Arbor, MI: Morgan Kaufmann.

- Anderson, J. R., & Matessa, M. (1991). An iterative Bayesian algorithm for categorization. In Fisher, D., Pazzani, M.,& Langley, P. (Eds.), Concept formation: Knowledge and Experience in Unsupervised Learning. San Mateo, CA: Morgan Kaufmann.

Cobweb Related Systems and Paradigms

Other Related Paradigms

Other approaches to unsupervised learning that can be adapted to pattern completion:

- Learning Association Rule Sets
- Clustering
- Learning Bayesian Networks

- Fisher, D. (2001). Unsupervised Learning (Editorial), *Machine Learning, 45, 1*, 5–7. (Special issue editor on Unsupervised Learning 1).

Related learning paradigms:

- Multi-Task Learning (Caruana, R., 1997, *Machine Learning, 28*, 41-75)
- Data mining clustering
  - Fisher, D. (1996). "Iterative Optimization and Simplification of Hierarchical Clusterings," *Journal of Artificial Intelligence Research, 4*, 147–179. (also KDD-95)

The Cobweb Algorithm

Utility Measures

Category Utility: $\mathrm{CU}(\mathrm{C_k}) = P(C_k) \sum_i \sum_j [P(V_i = v_{ij} | C_k)^2 - P(V_i = v_{ij})^2]$

- Gluck, M. A. & Corter, J. E. (1985) Information, uncertainty, and the utility of categories. Proceedings of the Seventh Annual Conference of the Cognitive Science Society (pp. 283-287). Irvine, CA
- Fisher, D. (1987) "Knowledge Acquisition Via Incremental Conceptual Clustering," *Machine Learning, 2*, 139–172.

Category Match: $\mathrm{C}M(C_\mathrm{k}, Obj) = P(C_k) \sum_i [P(V_i(Obj) | C_k)^2 - P(V_i(Obj))^2]$

- Silber, J., & Fisher, D. (1989). "A Model of Natural Category Structure and its Behavioral Implications," Proceedings of the Eleventh Annual Conference of the Cognitive Science Society, Ann Arbor, MI: Lawrence Erlbaum, 884–891.
- Fisher, D., & Langley, P. (1990). "The Structure and Formation of Natural Categories," in G. Bower (ed.), *The Psychology of Learning and Motivation, 26*, San Diego, CA: Academic Press, 241–284.

Partition Utility: $\sum_{k=1}^{m} CU(C_k) \,/m$

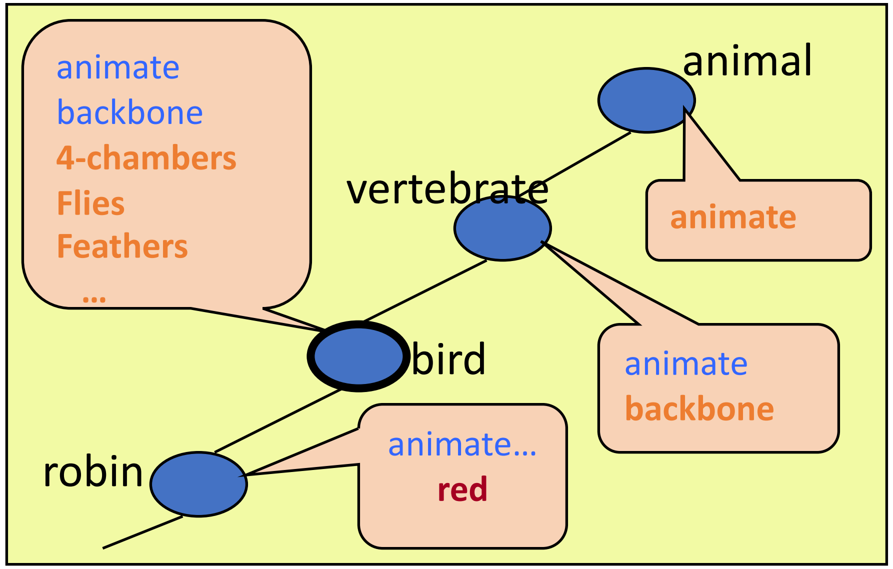
- Fisher, D. (1987) "Knowledge Acquisition Via Incremental Conceptual Clustering," *Machine Learning, 2*, 139–172.

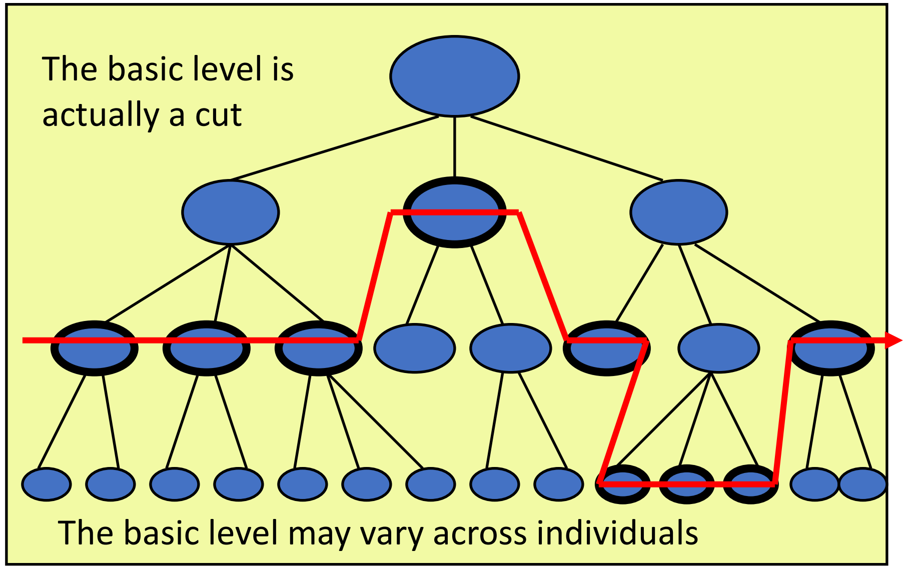
Cobweb Models of Psychological Effects:

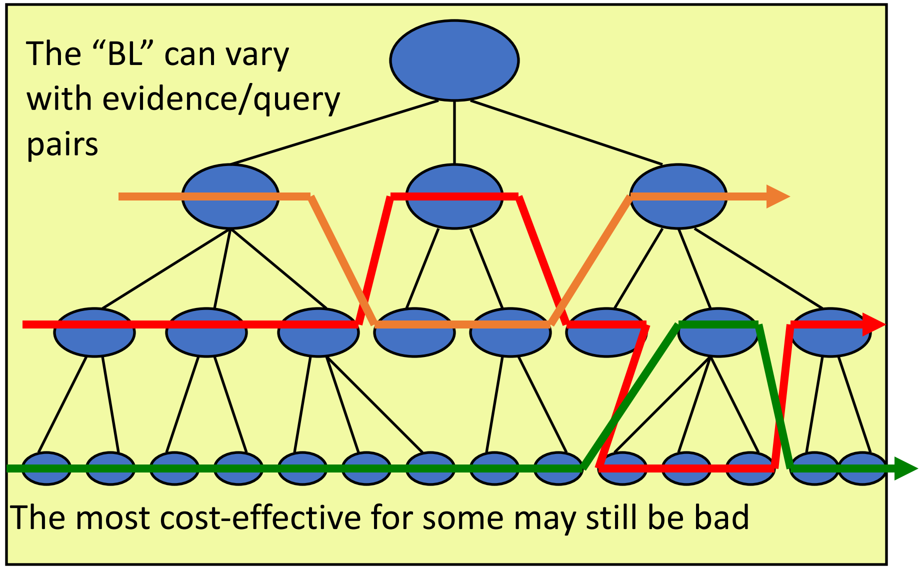
- Basic Level Effects
- Typicality Effects
- Fan Effects
- Linearly Separability

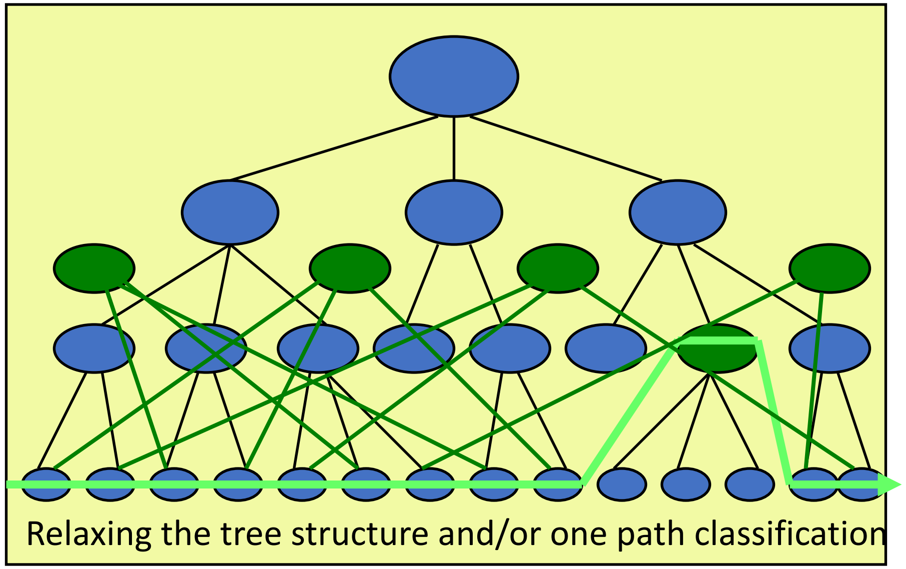
- Fisher, D. (1988). "A Computational Account of Basic Level and Typicality Effects", *Proceedings of the Seventh National Conference on Artificial Intelligence*. Minneapolis, MN: Morgan Kaufmann, 233–238.
- Silber, J., & Fisher, D. (1989). "A Model of Natural Category Structure and its Behavioral Implications," Proceedings of the Eleventh Annual Conference of the Cognitive Science Society, Ann Arbor, MI: Lawrence Erlbaum, 884–891.
- Fisher, D., & Langley, P. (1990). "The Structure and Formation of Natural Categories," in G. Bower (ed.), *The Psychology of Learning and Motivation, 26*, San Diego, CA: Academic Press, 241–284.

Basic Levels: Getting the Most Bang for the Buck









From "Intelligence in Context" (Fisher) Talk to NSF, March 21 1987

Typicality and Fan Effects

Typicality effects: members of a category that are most similar to other members of the same category and most dissimilar to members of contrast categories tend to be regarded and treated as more typical of their category.

- Fisher, D. (1988). "A Computational Account of Basic Level and Typicality Effects", *Proceedings of the Seventh National Conference on Artificial Intelligence*. Minneapolis, MN: Morgan Kaufmann, 233–238.

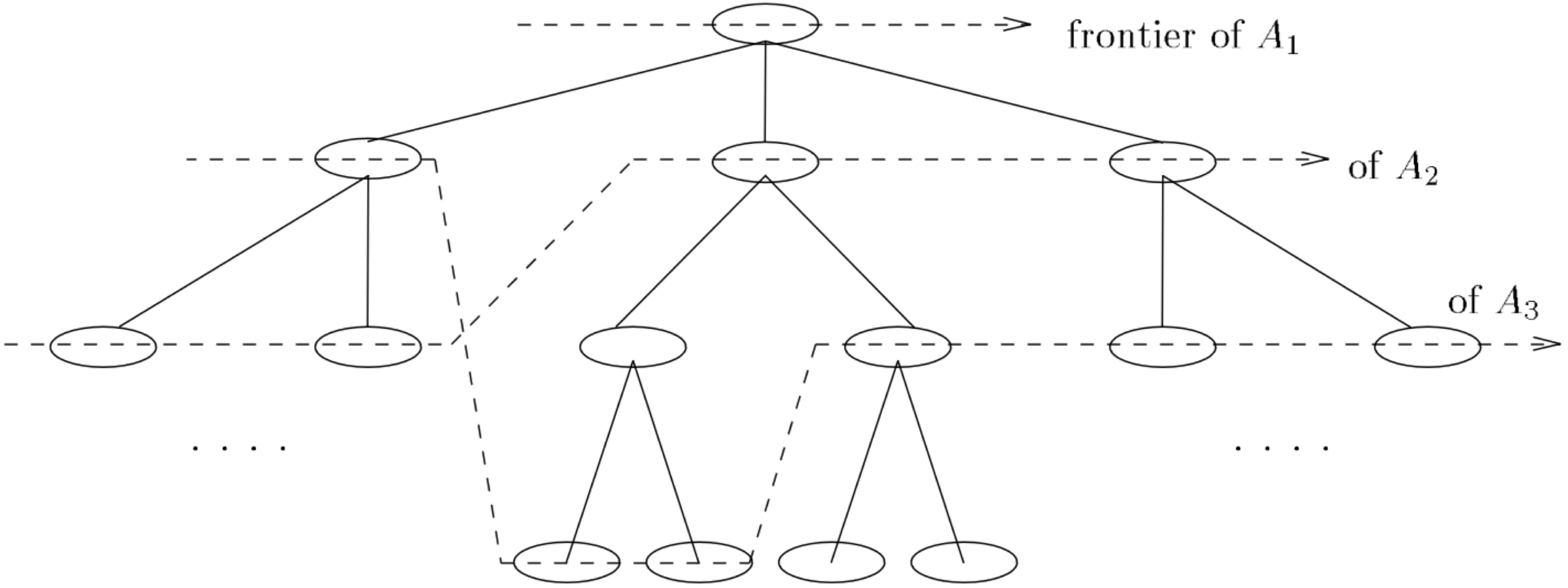
Fan effects: single objects that are more distinct from other objects in a population tend to be recognized more quickly and reliably

- Silber, J., & Fisher, D. (1989). "A Model of Natural Category Structure and its Behavioral Implications," Proceedings of the Eleventh Annual Conference of the Cognitive Science Society, Ann Arbor, MI: Lawrence Erlbaum, 884–891.

Fan effects restated: a degenerate case of typicality effects, in which intra-category similarity is not a factor, but inter-category dissimilarity is entirely responsible for the behavioral effects

Alternative Formulations of Basic Cobweb

Identifying Variable Frontiers for Prediction



- Fisher, D. (1996). "Iterative Optimization and Simplification of Hierarchical Clusterings," *Journal of Artificial Intelligence Research, 4*, 147–179.

- Fisher, D. (1989). "Noise-Tolerant Conceptual Clustering" *Proceedings of the International Joint Conference on Artificial Intelligence*, Detroit, MI: Morgan Kaufmann, 825–830. **Incremental approach using "self-supervised" learning.**

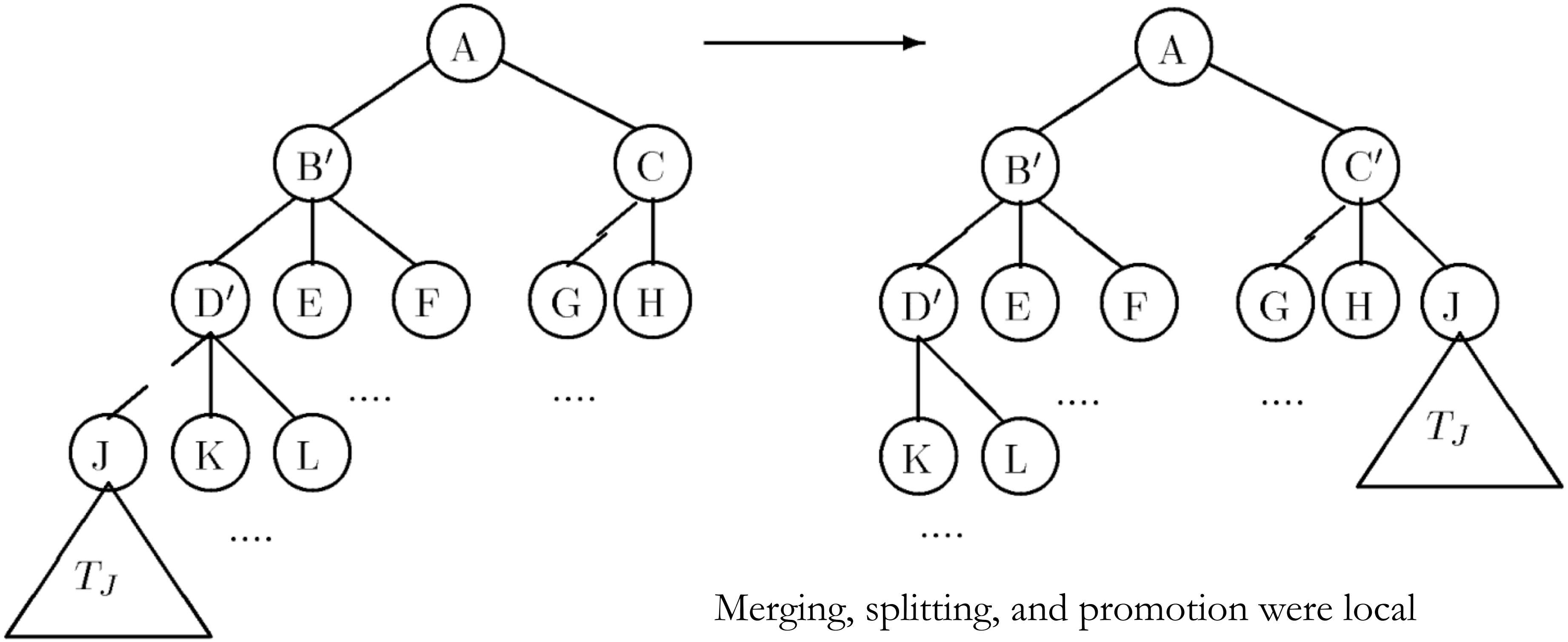
Results with Variable Frontiers for Prediction

	Unvalidated	Validated
Soybean (small)		
Leaves	18.00 (0.00)	13.10 (1.59)
Accuracy	0.85 (0.01)	0.85 (0.01)
Ave. Frontier Size	18.00 (0.00)	2.75 (1.17)
Soybean (large)		
Leaves	122.00 (0.00)	79.10 (5.80)
Accuracy	0.83 (0.02)	0.83 (0.02)
Ave. Frontier Size	122.00 (0.00)	17.01 (4.75)
House		
Leaves	174.00 (0.00)	49.10 (7.18)
Accuracy	0.76 (0.02)	0.81 (0.01)
Ave. Frontier Size	174.00 (0.00)	9.90 (5.16)
Mushroom		
Leaves	400.00 (0.00)	96.30 (11.79)
Accuracy	0.80 (0.01)	0.82 (0.01)
Ave. Frontier Size	400.00 (0.00)	11.07 (4.28)

Table 6: Characteristics of optimized clusterings before and after validation. Average and standard deviations over 20 trials.

Alternative Formulations of Basic Cobweb

global, en masse optimization: sorting followed by hierarchical redistribution



Merging, splitting, and promotion were local

- Fisher, D. (1995). "Optimization and Simplification of Hierarchical Clusterings," *First International Conference on Knowledge Discovery in Databases*, Montreal, Canada: AAAI Press, 118–123.
- Fisher, D. (1996). "Iterative Optimization and Simplification of Hierarchical Clusterings," *Journal of Artificial Intelligence Research, 4*, 147–179.

	Unoptimized		Optimized	
	Unvalidated	Validated	Unvalidated	Validated
Soybean (small)				
Leaves	18.00 (0.00)	15.35 (1.81)	18.00 (0.00)	13.10 (1.59)
EPL	40.90 (3.64)	31.90 (6.94)	54.20 (4.74)	34.50 (6.49)
Depth*	2.27	2.08	3.01	2.63
Breadth*	3.57	3.72	2.61	2.66
Cost*	8.10	7.74	7.86	7.00
Soybean (large)				
Leaves	122.00 (0.00)	88.55 (4.46)	122.00 (0.00)	79.10 (5.80)
EPL	437.20 (34.74)	280.40 (28.07)	657.65 (28.38)	380.65 (43.63)
Depth*	3.58	3.17	5.39	4.81
Breadth*	3.82	4.11	2.44	2.48
Cost*	13.68	13.03	13.15	11.93
House				
Leaves	174.00 (0.00)	68.95 (8.15)	174.00 (0.00)	49.10 (7.18)
EPL	664.65 (41.16)	196.20 (35.32)	1005.10 (27.42)	217.25 (39.75)
Depth*	3.82	2.85	5.78	4.42
Breadth*	3.86	4.42	2.44	2.41
Cost*	14.75	12.60	14.10	10.65
Mushroom				
Leaves	400.00 (0.00)	145.50 (20.64)	400.00 (0.00)	96.30 (11.79)
EPL	2238.20 (123.63)	660.90 (117.86)	2608.85 (56.01)	503.40 (72.22)
Depth*	5.60	4.54	6.52	5.23
Breadth*	2.92	3.00	2.51	2.39
Cost*	16.35	13.62	16.37	12.50

- Fisher, D. (1996). “Iterative Optimization and Simplification of Hierarchical Clusterings,” *Journal of Artificial Intelligence Research*, *4*, 147–179.

Alternative Formulations of Basic Cobweb

Alternative utility measures

$$CU(C_k) = P(C_k) \sum_i \sum_j [P(A_i = V_{ij}|C_k) \log_2 P(A_i = V_{ij}|C_k) - P(A_i = V_{ij}) \log_2 P(A_i = V_{ij})].$$

Partition Utility Alternatives

$$\sum_i \frac{\sum_k P(C_k) \sum_j [P(A_i{=}V_{ij}|C_k) \log_2 P(A_i{=}V_{ij}|C_k) - P(A_i{=}V_{ij}) \log_2 P(A_i{=}V_{ij})]}{-\sum_k P(C_k) \log_2 P(C_k)}$$

Inspired by Quinlan, 1986

$$\sum_i \frac{\sum_k P(C_k) \sum_j [P(A_i{=}V_{ij}|C_k) \log_2 P(A_i{=}V_{ij}|C_k) - P(A_i{=}V_{ij}) \log_2 P(A_i{=}V_{ij})]}{-\sum_k \sum_j P(A_i{=}V_{ij} \wedge C_k) \log_2 P(A_i{=}V_{ij} \wedge C_k)}$$

Inspired by de Mantaras, 1991

- Fisher, D. (1996). "Iterative Optimization and Simplification of Hierarchical Clusterings," *Journal of Artificial Intelligence Research, 4*, 147–179.