Modeling a Clinical Problem Solving Process with Bayesian Networks

Zhidong Zhang, Ph. D. & Yoshio Takane, Ph. D
Department of Psychology, McGill University, Canada
Jingyan Lu, Ph. D.
The University of Hong Kong

Background

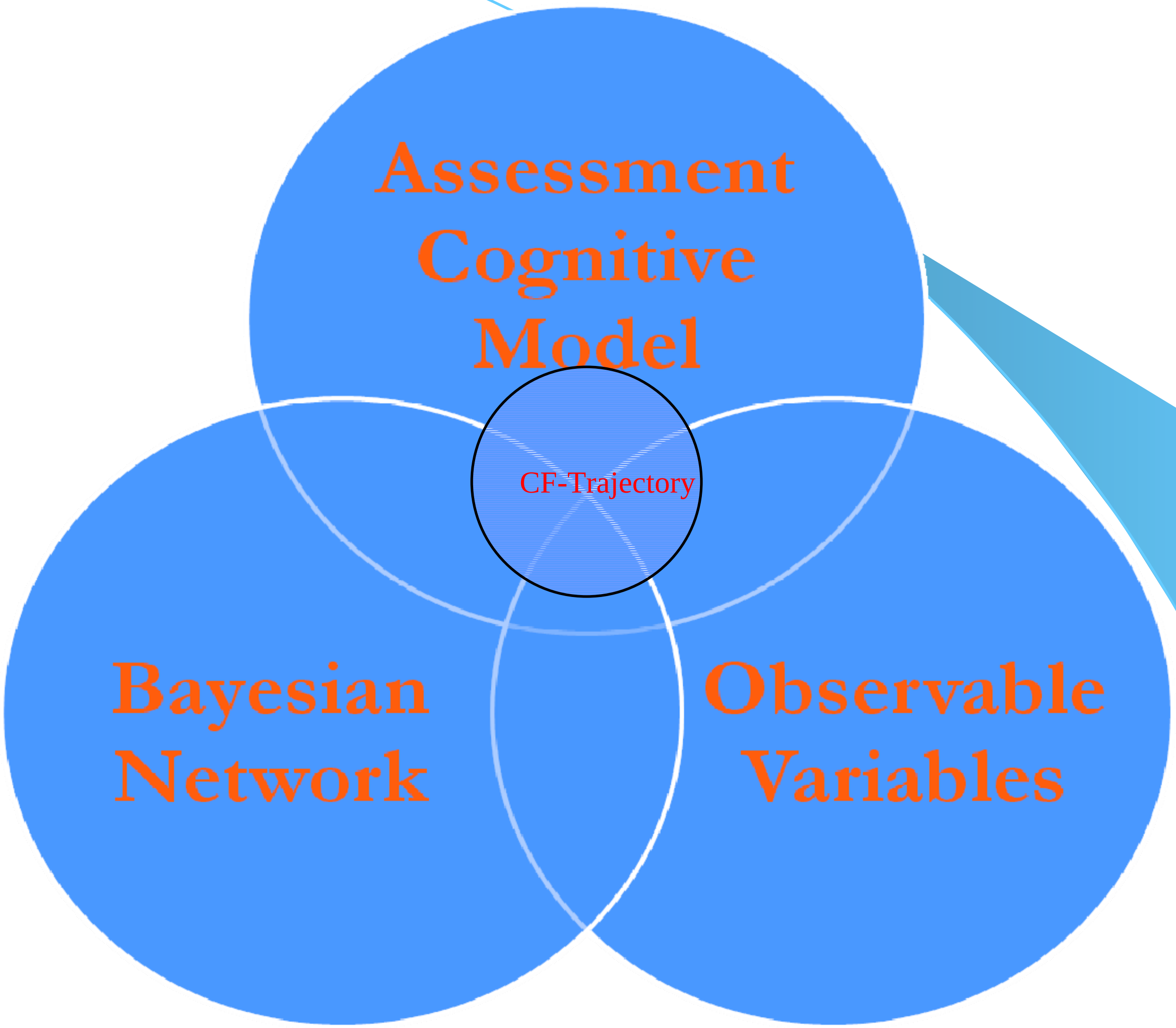
A professor of medicine is collecting cognitive evidence from 13 third-year medical students' think-aloud protocols.

Professor's instructions:

"Observe a problem solving scenario-- a 10 minute video-clip describing how a physician and his students dealt with a deteriorating patient in an emergency room. Assume that you are a doctor in the emergency room. What would you do…?"

How to Assess Learning?

- Cognitive content analysis and idea unit analysis based on student think-aloud data have been used to establish an assessment construct;
- The evidential patterns of the think-aloud have been summarized and theorized.
- A Bayesian network has been utilized to quantitatively communicate between the observable evidence and established theoretical construct.

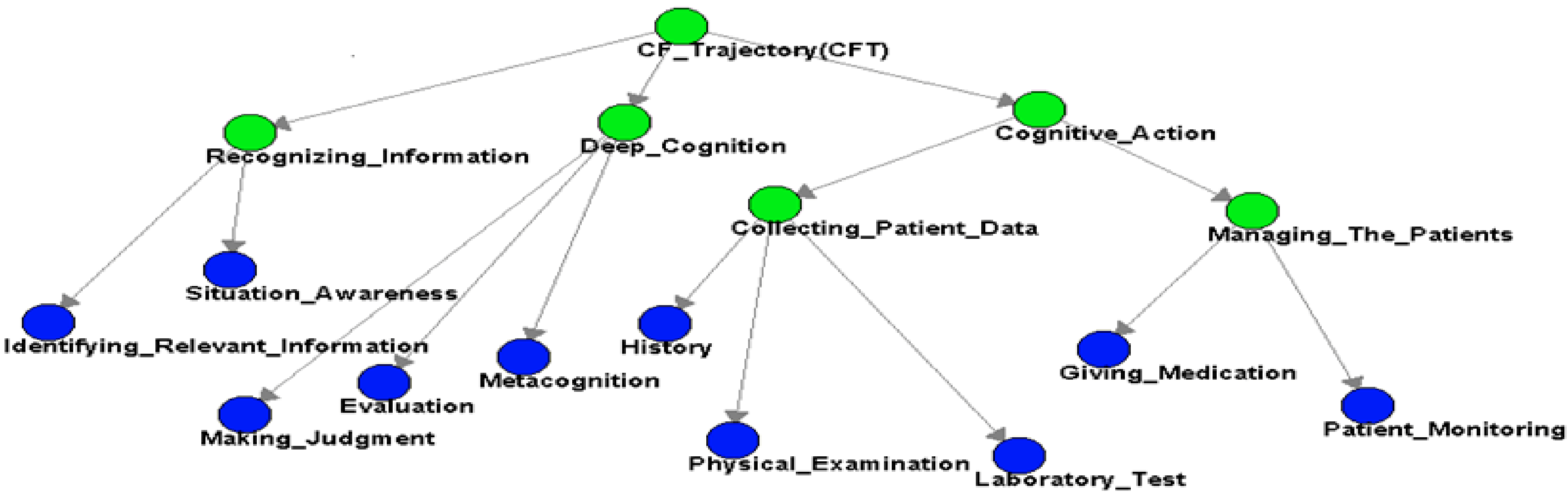


Bayesian Network Model and Cognitive Feature Trajectory

Assessment Construct and Observable Variables

- Identifying relevant information
- Situation awareness
- Making judgments
- Evaluation
- Metacognition
- History taking
- Physical examination
- Laboratory test
- Giving medications
- Patient monitoring

Bayesian Network of the Medical Learning



- Recognizing Information
  - Identifying Relevant Information
  - Situation Awareness
- Deep Cognition
  - Making Judgment
  - Evaluation
  - Metacognition
- Collecting patient data
  - History
  - Physical examination
  - Laboratory test
- Managing the patients
  - Giving medication
  - Patient monitoring

Bayesian Rationale

- **Define conditional probabilities of each node:**

$$p(B \mid A)$$

- **Joint Probabilities**

$$p(A,B) = p(B \mid A)\,p(A)$$

- **Posterior Probabilities**

$$P(A_i \mid B) = \frac{P(A_i)P(B \mid A_i)}{P(B)} = \frac{P(A)P(B \mid A)}{\sum_{i=1}^{n} P(A_i)P(B \mid A_i)}$$

Parent and Conditional Probabilities

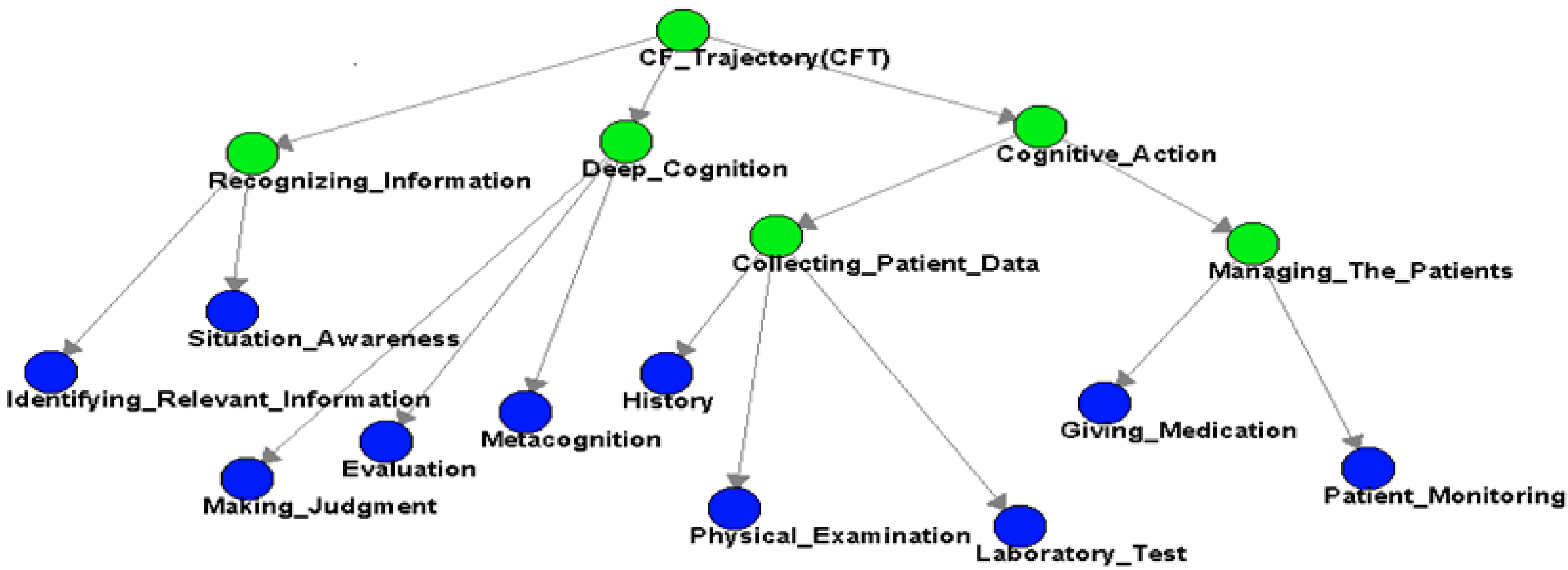
Parent Probabilities

P (Cognitive Feature Trajectory)	
high	0.6
medium	0.3
low	0.1

Conditional Probabilities

	P (node| parent)		
Parent:	high	medium	low
high	0.6	0.3	0.1
medium	0.3	0.4	0.3
low	0.1	0.3	0.6

Bayesian Network of Medical Learning



ob1	*ob2*	*ob3*	*ob4*	*ob5*	*ob6*	*ob7*	*ob8*	*ob9*	*ob10*
0	1	1	0	0	1	1	1	0	1

Frequency-based Probability Table of Observable Variables

S	OV1	OV2	OV3	OV4	OV5	OV6	OV7	OV8	OV9	OV10
1	2	2	4	11	4	7	3	3	3	2
	L	L	L	M	L	M	L	L	L	L
2	9	6	6	20	12	9	5	13	5	0
	M	L	L	H	M	M	L	M	L	L
3	14	5	13	19	16	7	1	4	7	3
	M	L	M	H	H	M	L	L	M	L
4	12	3	10	7	16	5	0	8	3	0
	M	L	M	M	H	L	L	M	L	L

0—6=LOW(L); 7—14=MEDIUM(M); 15—20=HIGH (H)

Classification Distance

Three classifications have been chosen to indicate the cognitive factor level:

High (H), Medium (M), or Low (L).

$$\frac{range}{number\ of\ categories}$$

Student Classification by Bayesian Network

Group	CF_ Trajectory	Recognizing_ Information	Deep_ Cognition	Cognitive_ Action	Subject Number
A	L	L	L	L	1, 11, 12
B	M	L	L	L	6,9,10
C	M	L	M	L	2,5,7, 13
D	M	L	H	L	4
E	M	H	M	L	7
F	H	M	H	L	3

Conclusion

- The Cognitive Feature Trajectory consists of three cognitive explanatory variables sequentially: Recognizing Information, Deep Cognition, and Cognitive Action.
- The Bayesian network has been applied to describe the pattern of students' cognitive feature trajectory
- A classification has been examined and five different patterns have been observed.

Bibliography

- Jense, F. V. (2001). Bayesian networks and Decision Graphs. Springer-Verlag, Newyork.
- Wu. X., Lucas, P., Kerr, S. & Dilkhuizen, R. (2001) Learning Bayesian-network topologies in realistic medical domains. Lecture Notes In Computer Science (Vol. 2199, pp. 302-328), Proceedings of the Second International Symposium on Medical Data Analysis
- Zhang, Z., Lu, J., & Lajoie, P. S. (2008). Modeling cognitive feature trajectories in a clinical learning environment with Bayesian network (to be published)