

# Intelligent Systems (AI-2)

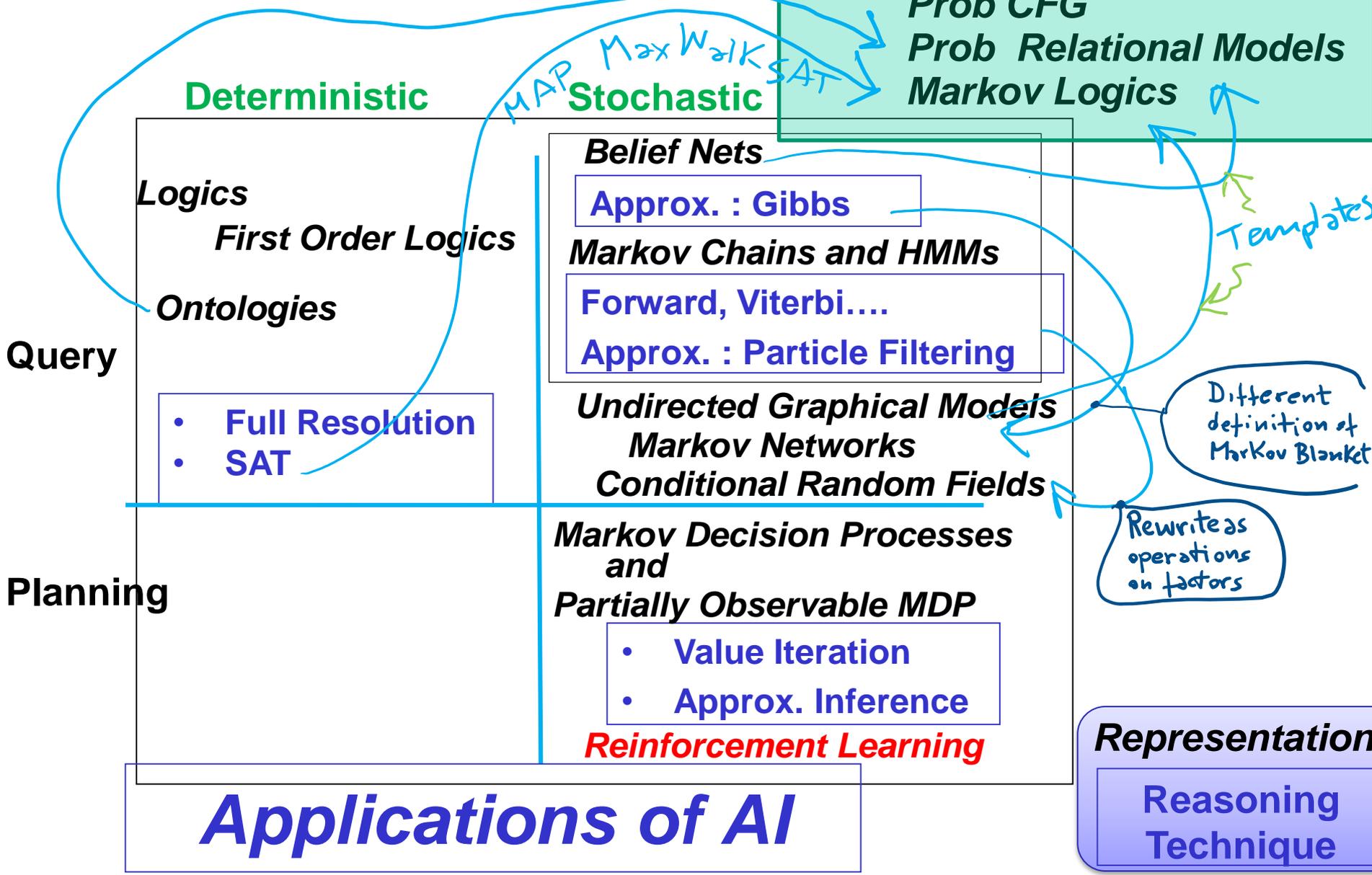
## Computer Science cpsc422, Lecture 32

**Apr, 5, 2021**

Slide source: from David Page (MIT) (which were from From Lise Getoor, Nir Friedman, Daphne Koller, and Avi Pfeffer) and from Lise Getoor

# 422 big picture: where are we?

StarAI (statistical relational AI)  
 Hybrid: Det +Sto  
 Prob CFG  
 Prob Relational Models  
 Markov Logics



# Combining Symbolic and Probabilistic R&R systems

## (a) Probabilistic Context-Free Grammars

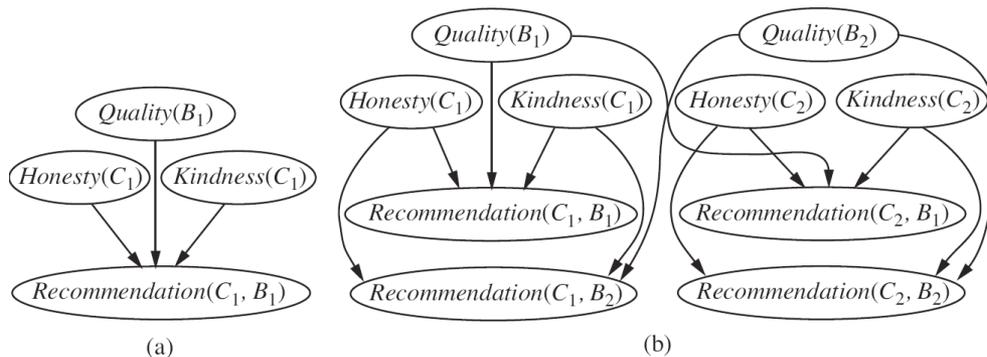
- Weights are conditional prob. on rewriting rules
- Applications: NLP parsing & Hierarchical Planning

## (b) Markov Logics: weighted FOL

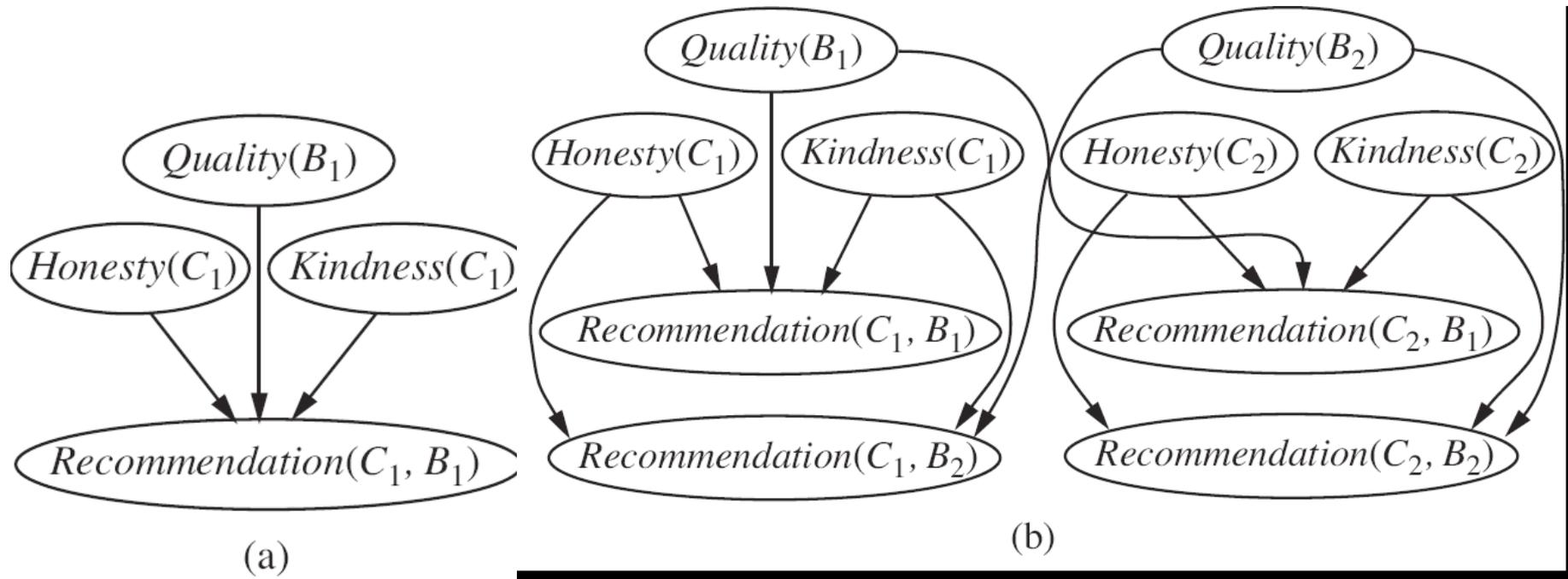
$$P(\text{world}) \propto \exp\left(\sum \text{weights of formulas it satisfies}\right)$$

## (c) Probabilistic Relational models

- Probs specified on relations



# Intuition for Prob. Relational models



A **customer**  $C_1$  will / will not *recommend* a **book**  $B_1$  depending on the book *quality*, and the customer *honesty* and *kindness*

When you have two customers and two books.....

# Lecture Overview

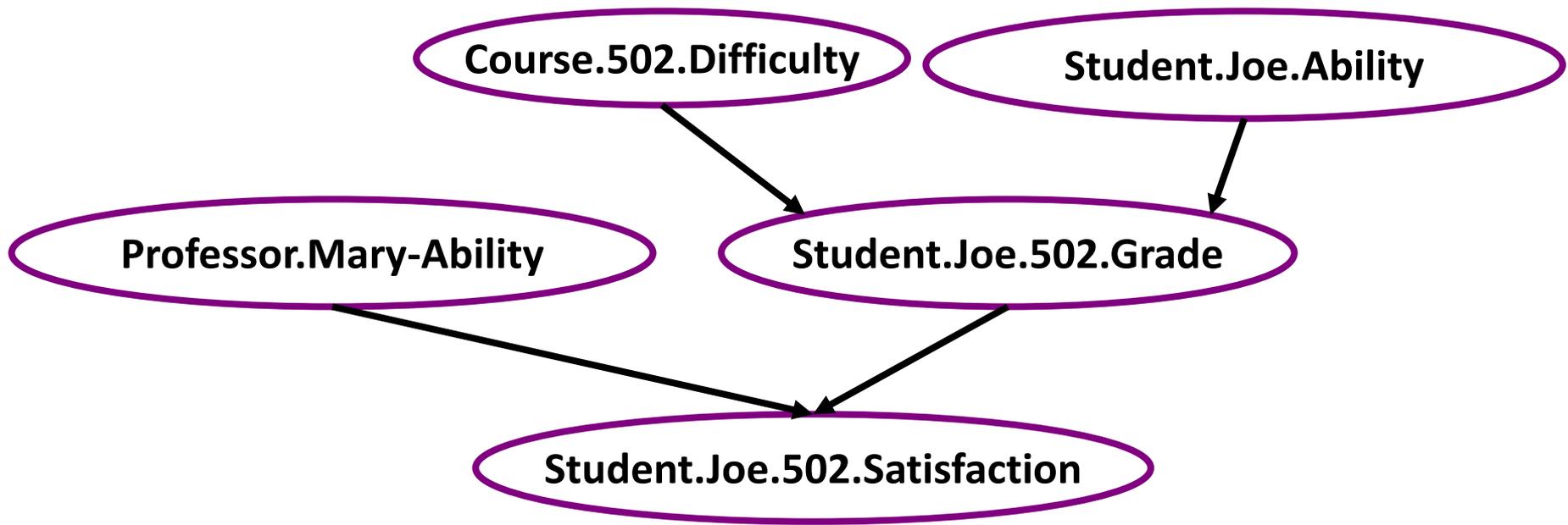
- **Motivation and Representation**
- Semantics of Probabilistic Relational Models (PRMs)
  - Classes and Relations
  - Attributes and Reference Slots
  - Full Relational Schema and its Instances
  - Fixed vs. Probabilistic Attributes
  - Relational Skeleton and its Completion Instance
  - Inverse Slot and Slot chain

# Motivation for PRMs

- Most real-world data are stored in relational DBMS
- Combine advantages of relational logic & Bayesian networks:
  - natural domain modeling: objects, properties, relations;
  - generalization over a variety of situations;
  - compact, natural probability models.
- Integrate uncertainty with relational model:
  - properties of domain entities can depend on properties of related entities;
  - uncertainty over relational structure of domain.

# Limitations of Bayesian Networks

A Bayesian networks (BNs) represents a pre-specified set of attributes/variables whose relationship to each other is fixed in advance.



# How PRMs extend BNs?

1. PRMs conceptually extend BNs to allow the specification of a probability model for *classes of objects* rather than a fixed set of simple attributes
2. PRMs also allow *properties of an entity to depend probabilistically on properties of other related entities*

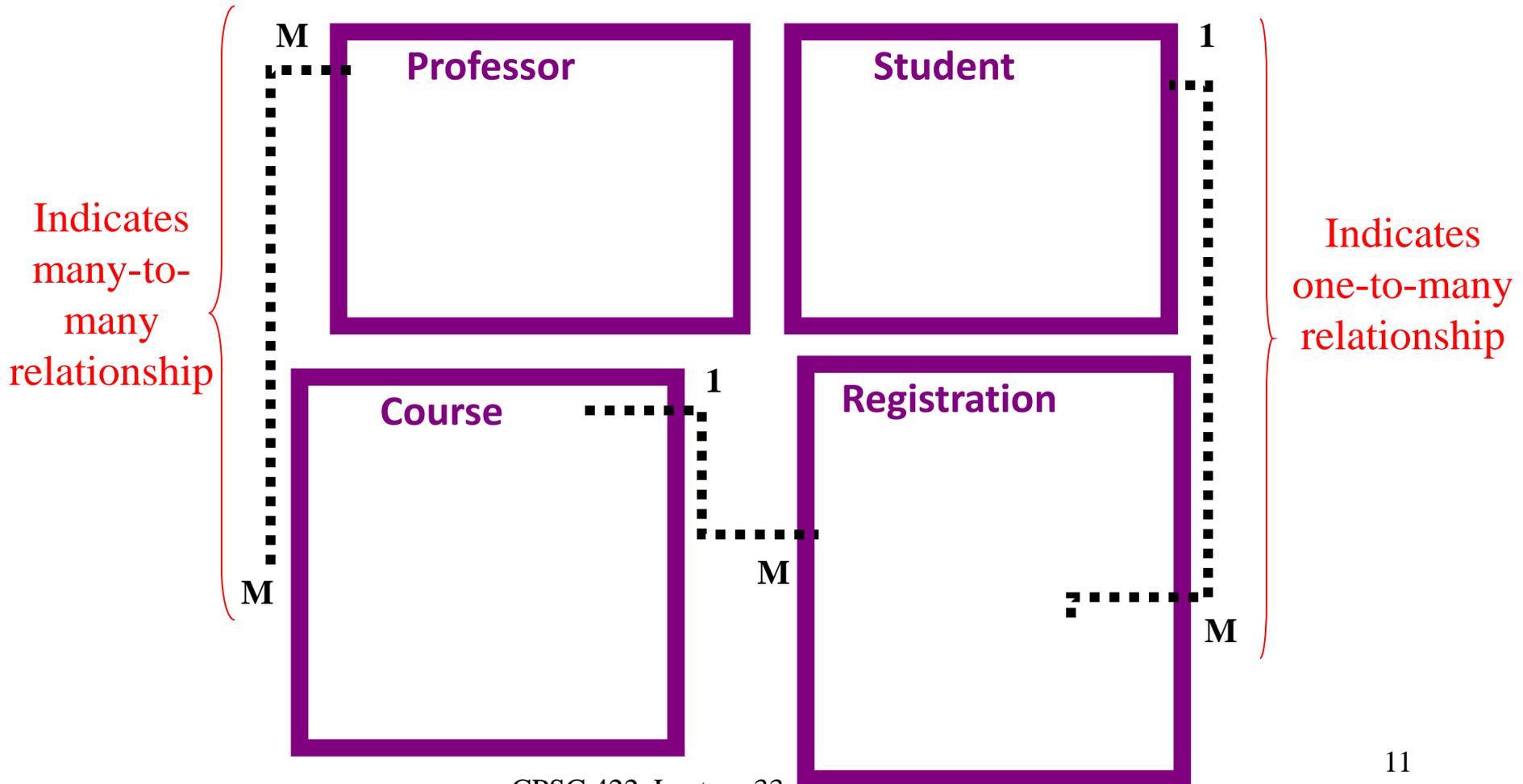
# Lecture Overview

- Motivation and Representation
- **Semantics of Probabilistic Relational Models (PRMs)**
  - Classes and Relations
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# Mapping PRMs from Relational Models

- The representation of PRMs is a direct mapping from that of relational databases
- A **relational model** consists of a set of *classes*  $X_1, \dots, X_n$  and a set of *relations*  $R_1, \dots, R_m$ , where each relation  $R_i$  is typed

# University Domain Example - Classes and relations



# Mapping PRMs from Relational Models: attributes

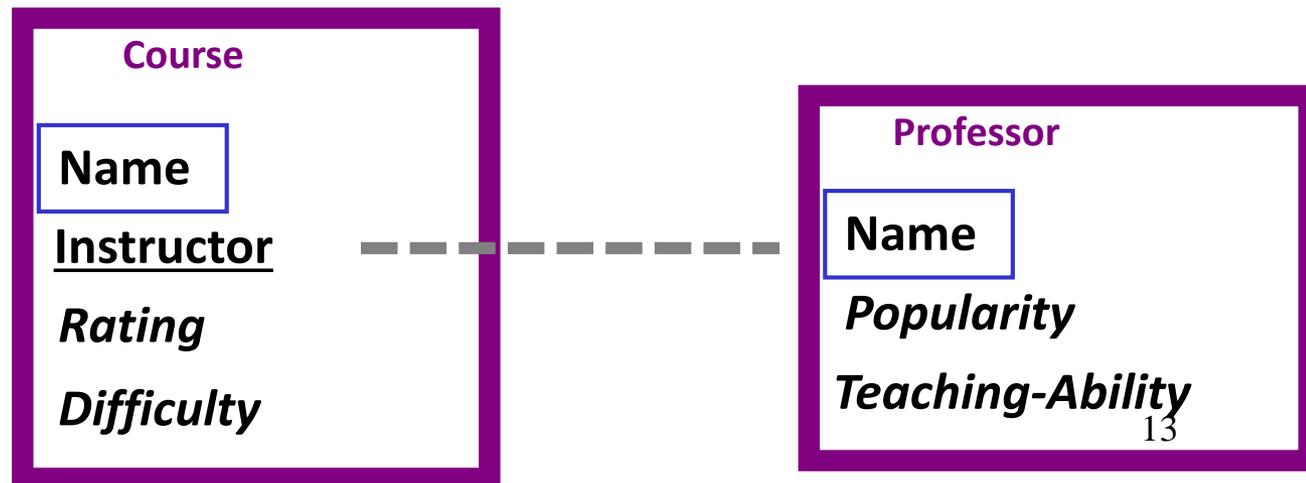
- Each class or entity type (corresponding to a single relational table) is associated with a set of **attributes**  $\mathcal{A}(X_i)$  (at least one of which is a **primary key**)



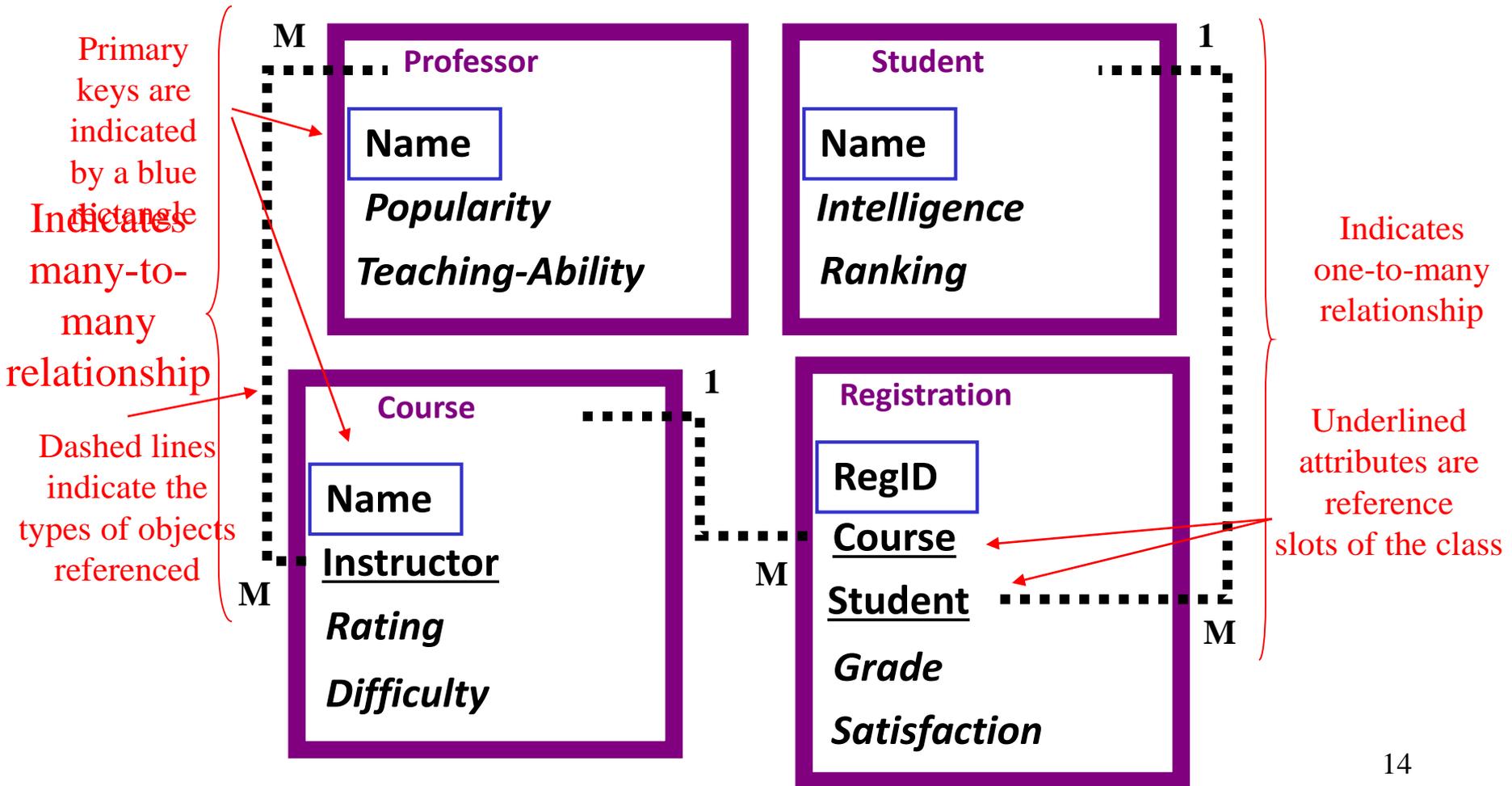
# Mapping PRMs from Relational Models: reference slot

- Each class or entity type is also associated with a set of *reference slots*  $\mathcal{R}(X)$
- correspond to attributes that are *foreign keys* (key attributes of another table)
- $X.\rho$ , is used to denote reference slot  $\rho$  of  $X$ .

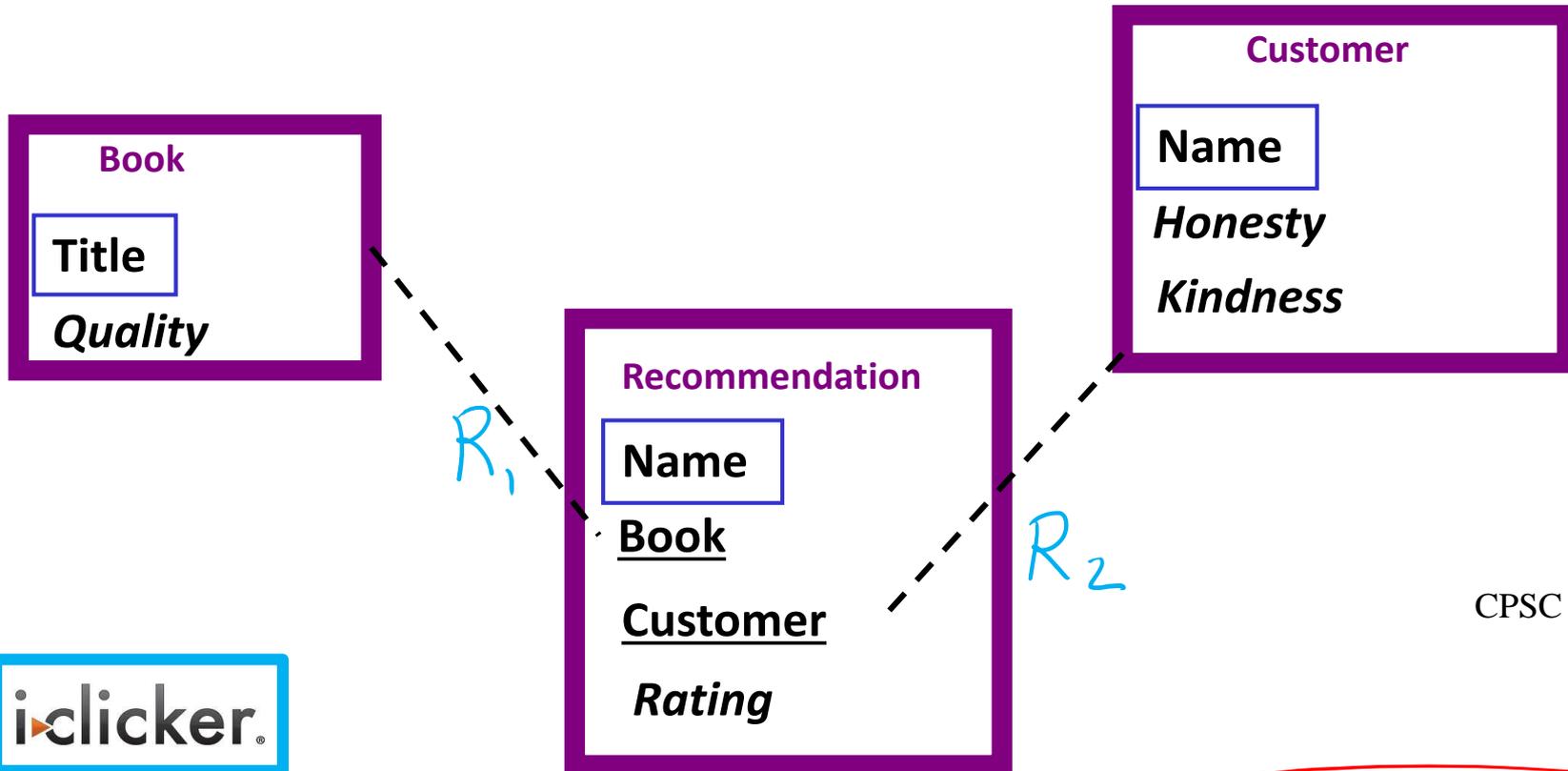
*Course.Instructor*



# University Domain Example - Full Relational Schema



# Book Recommendation Domain - Full Relational Schema

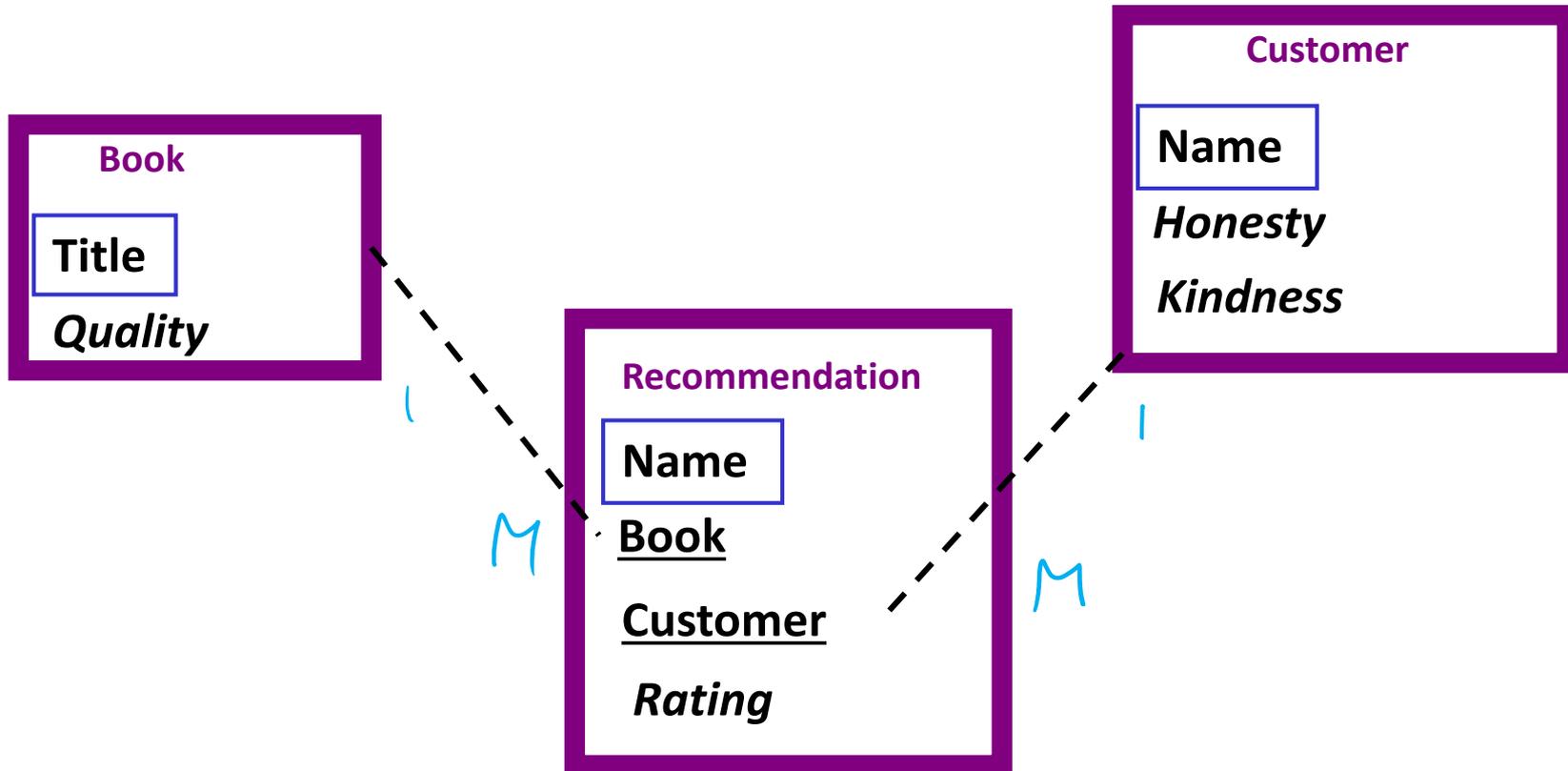


CPSC 422, Lecture 33

- A.  $R_1 (1:M), R_2 (M:M)$   
 B.  $R_1 (M:M), R_2 (1:M)$

- C.  $R_1 (1:M), R_2 (1:M)$   
 D.  $R_1 (M:M), R_2 (M:M)$

# Book Recommendation Domain - Full Relational Schema



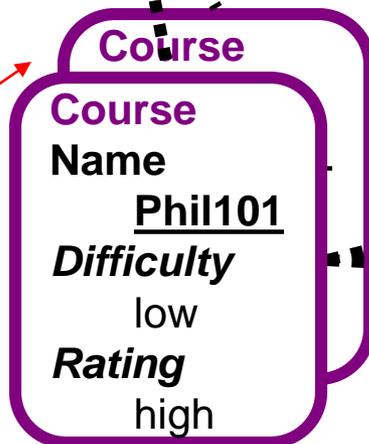
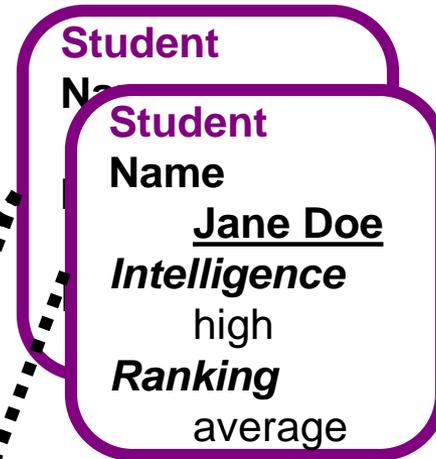
# PRM Semantics: Attribute values

- Each attribute  $A_j \in \mathcal{A}(X_i)$  takes on values in some fixed domain of possible values denoted  $V(A_j)$ . We assume that value spaces are finite
- Attribute  $A$  of class  $X$  is denoted  $X.A$
- E.g.,  $V(\text{Student.Intelligence})$  might be  $\{ \text{high}, \text{low} \}$

# PRM Semantics: Instance of Schema

- An *instance*  $I$  of a schema/model specifies a set of objects  $x$ , partitioned into classes; such that there is
  - a value for each attribute  $x.A$
  - and a value for each reference slot  $x.\rho$

# University Domain Example - An Instance of the Schema



One professor is the instructor for both courses

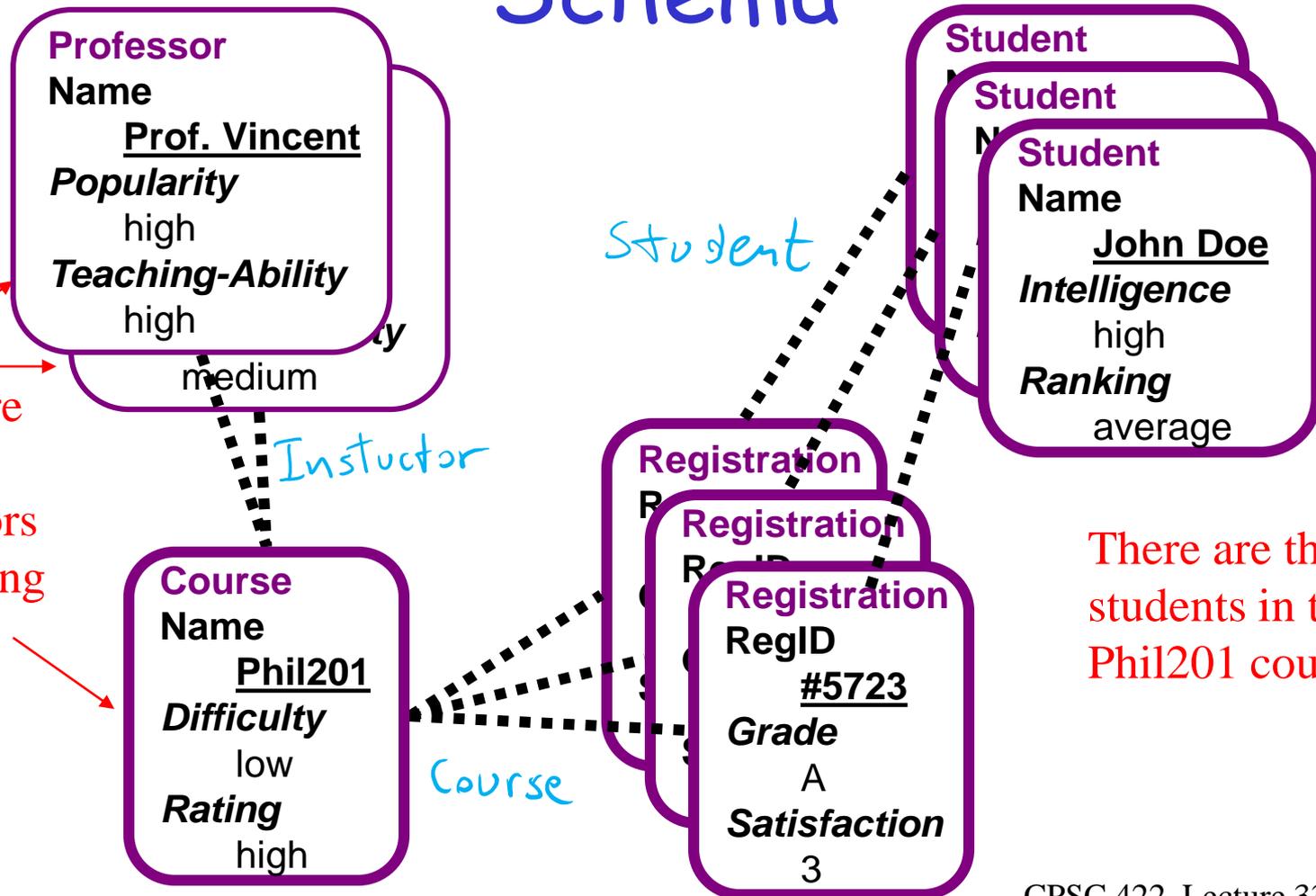
Instructor

Student

Course

Jane Doe is registered for only one course, Phil101, while the other student is registered for both courses

# University Domain Example - Another Instance of the Schema



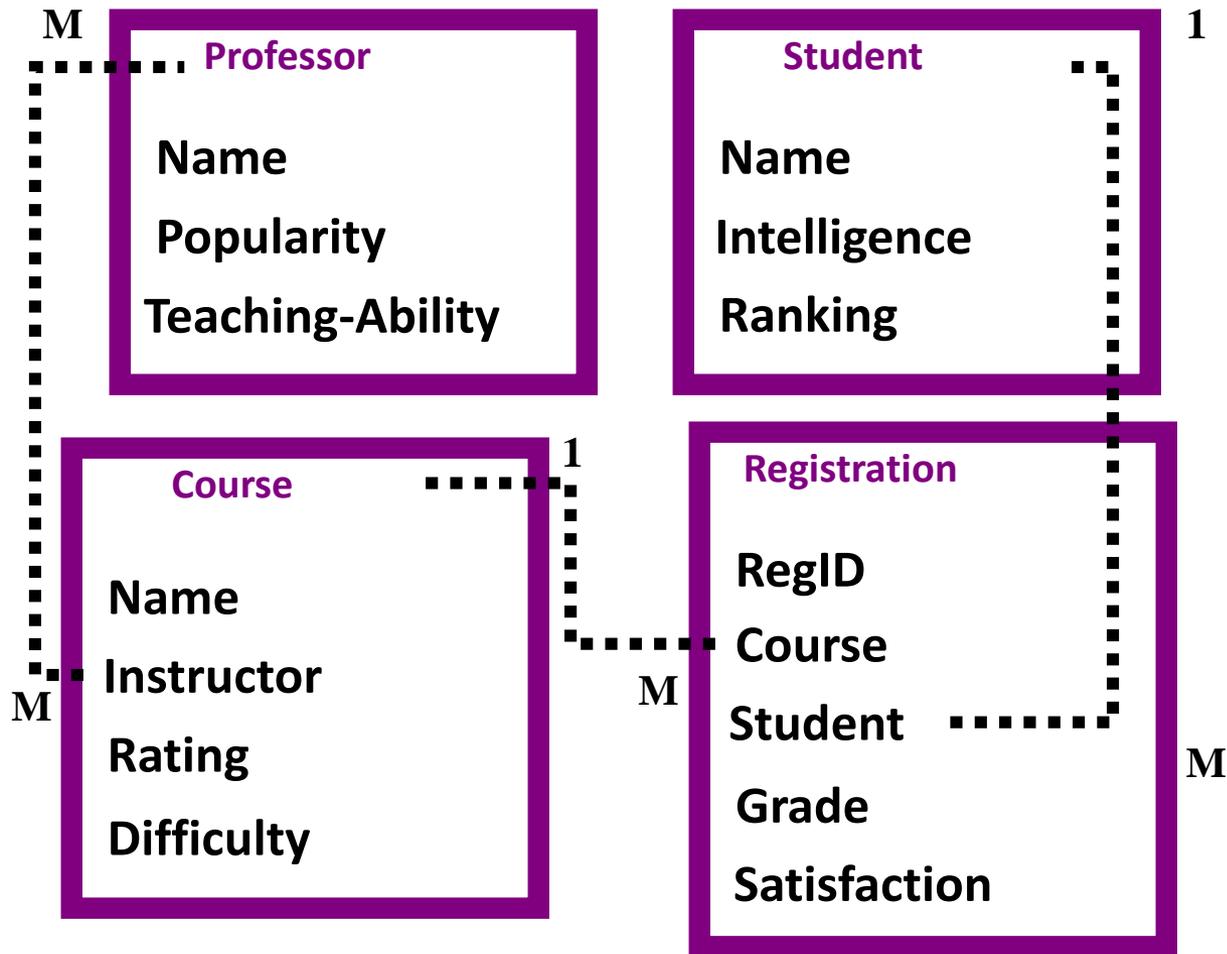
There are two professors instructing a course

There are three students in the Phil201 course

# PRM Semantics: fixed vs. prob. attributes

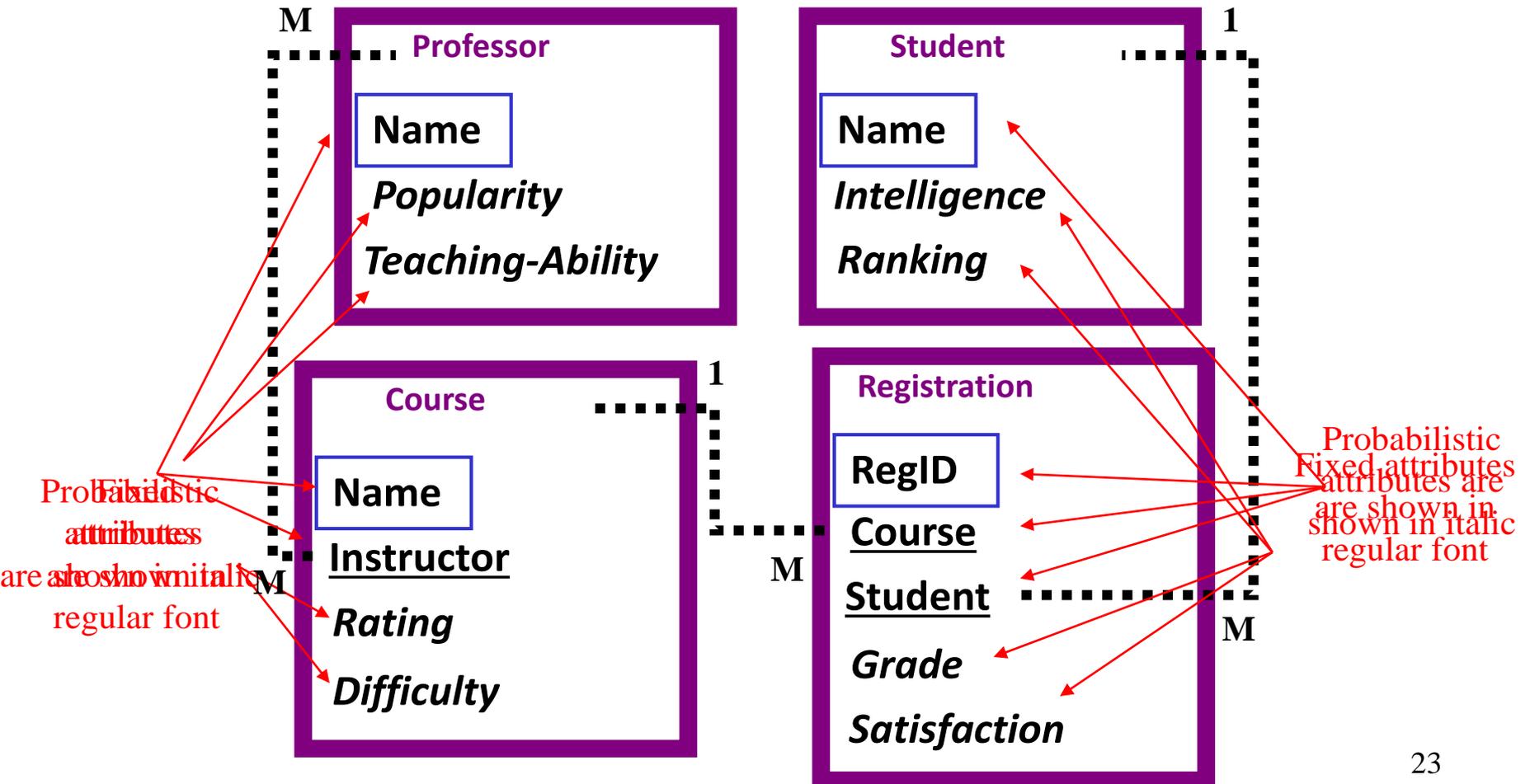
- Some attributes, such as *Name* or *Social Security Number*, are fully determined. Such attributes are labeled as **fixed**. Assume that they are known in any instantiation of the schema
- The other attributes are called **probabilistic**. We may be uncertain about their value

# University Domain Example - fixed vs. probabilistic attributes



Which ones are fixed? Which are probabilistic?

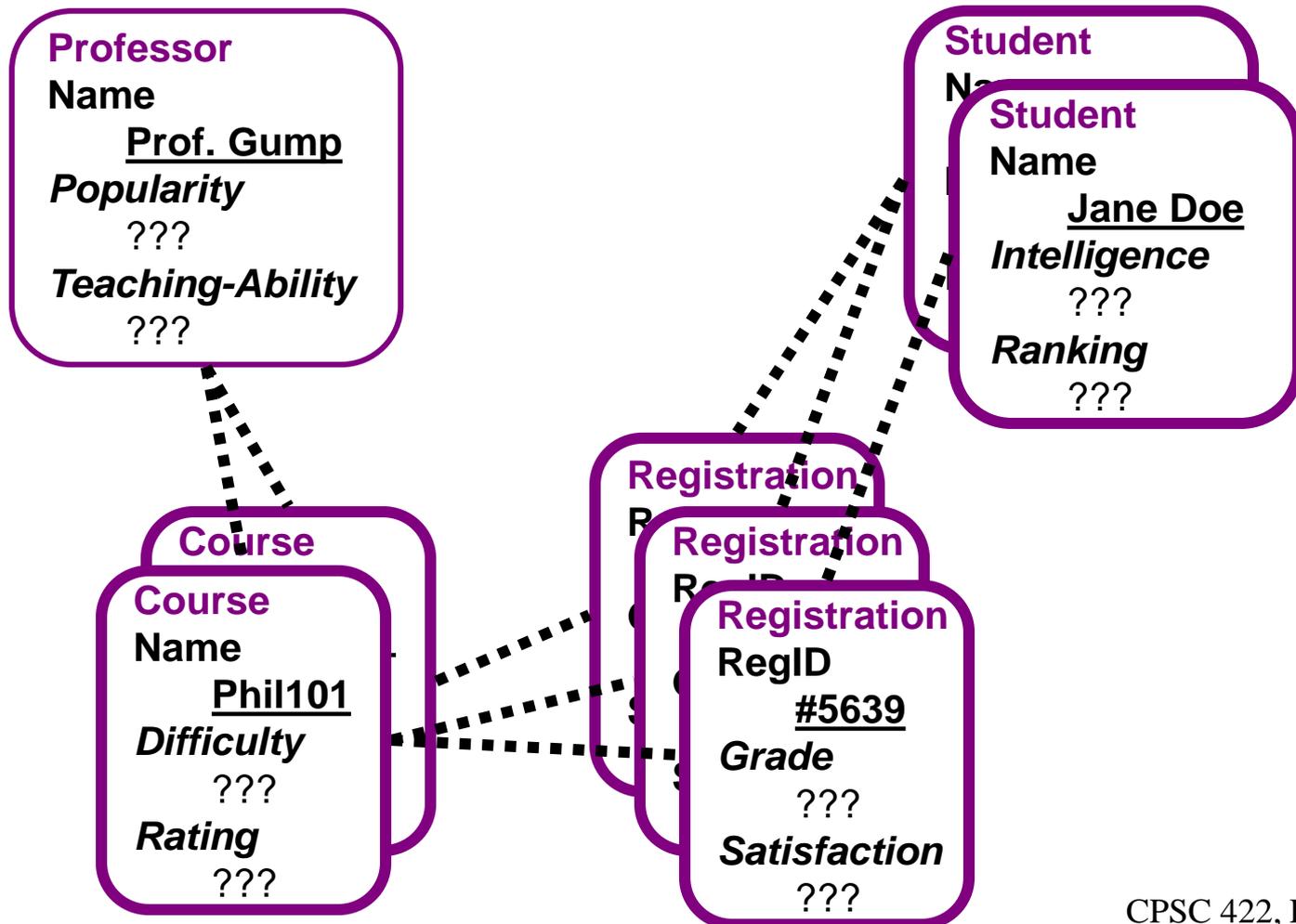
# University Domain Example - fixed vs. probabilistic attributes



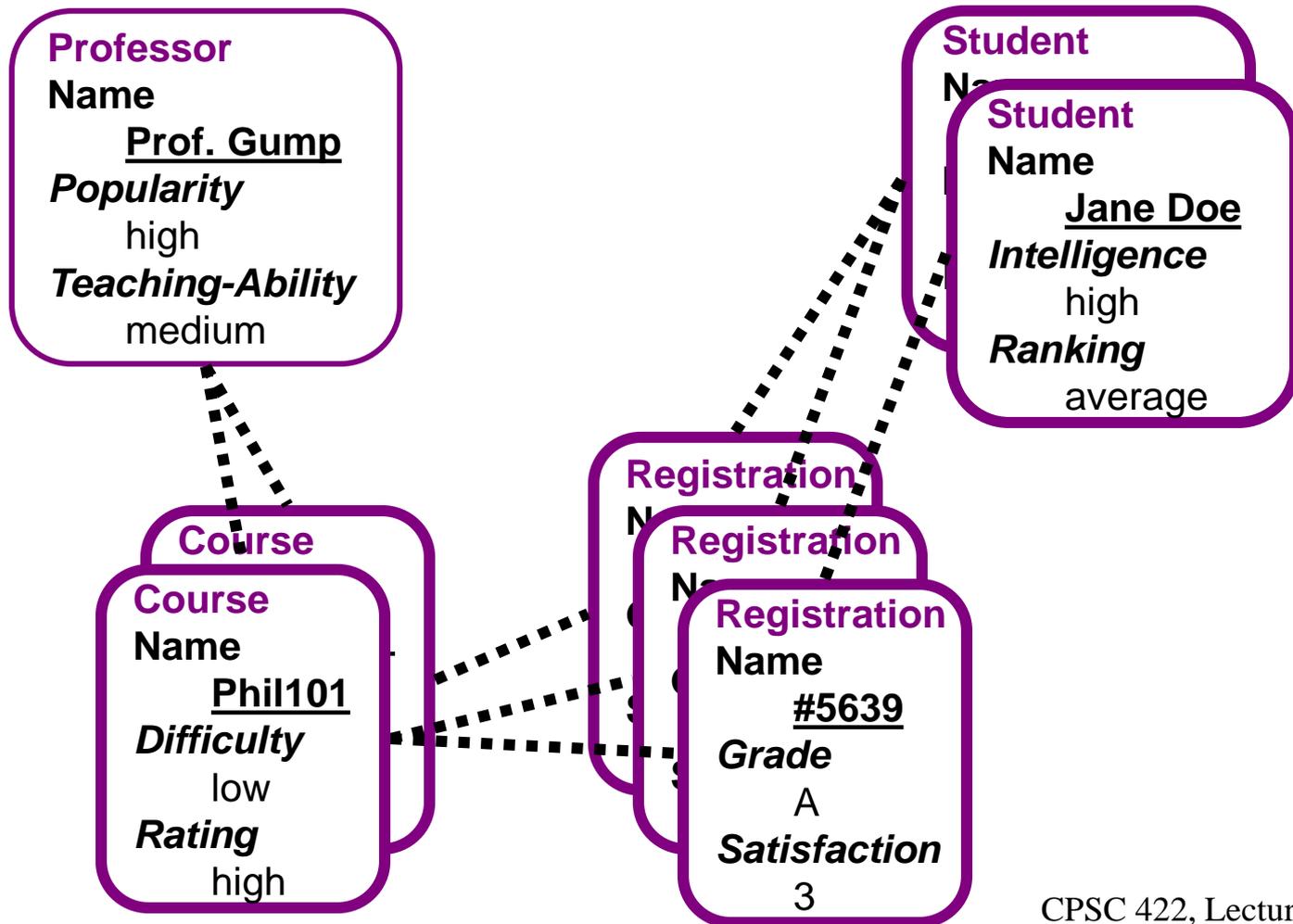
# PRM Semantics: Skeleton Structure

- A **skeleton structure**  $\sigma$  of a relational schema is a partial specification of an instance of the schema. It specifies
  - set of objects for each class,
  - values of the fixed attributes of these objects,
  - relations that hold between the objects
- The values of probabilistic attributes are left unspecified
- A **completion**  $I$  of the skeleton structure  $\sigma$  extends the skeleton by also specifying the values of the probabilistic attributes
  - $\Rightarrow$  possible world...

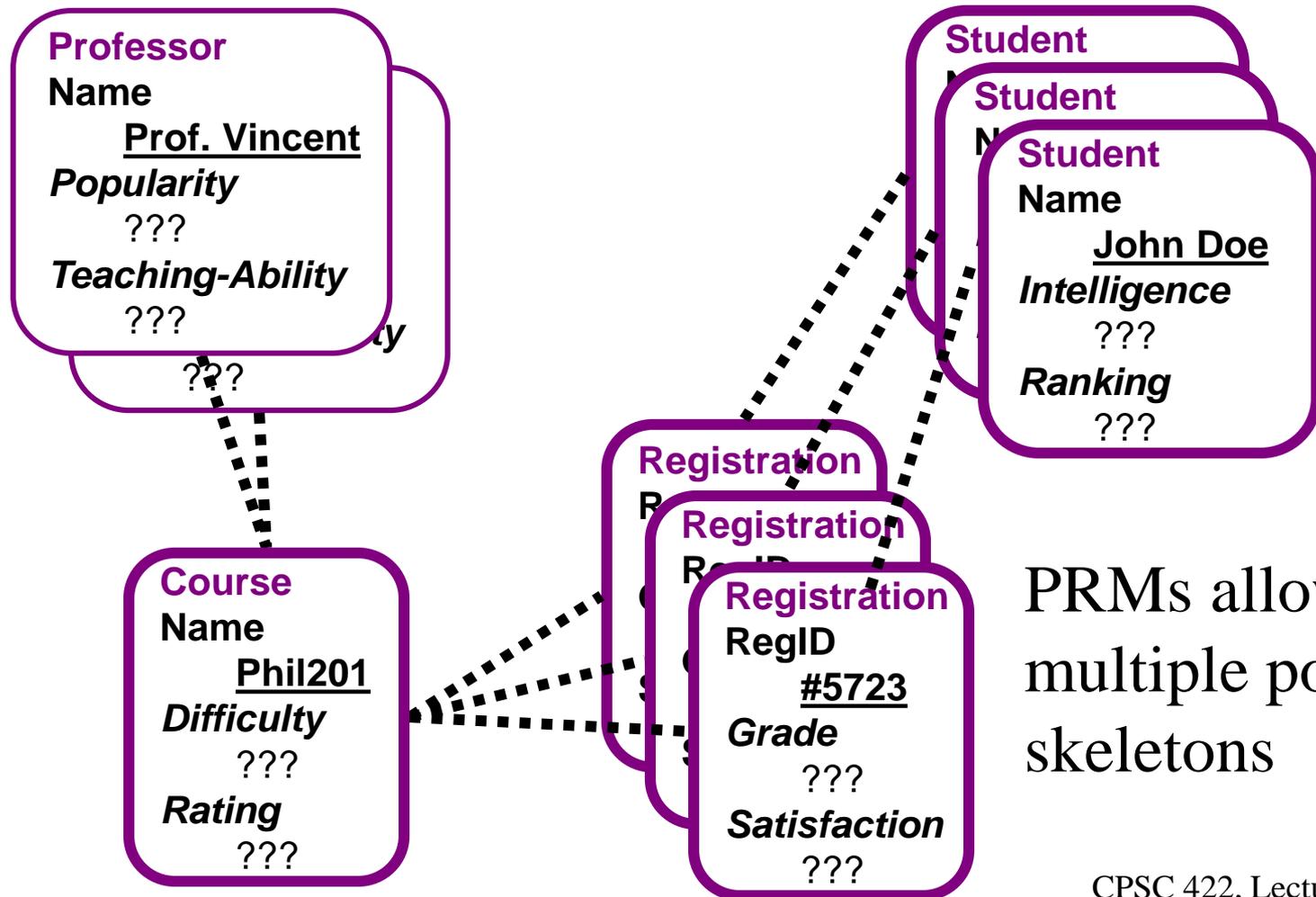
# University Domain Example - Relational Skeleton



# University Domain Example - The Completion Instance I

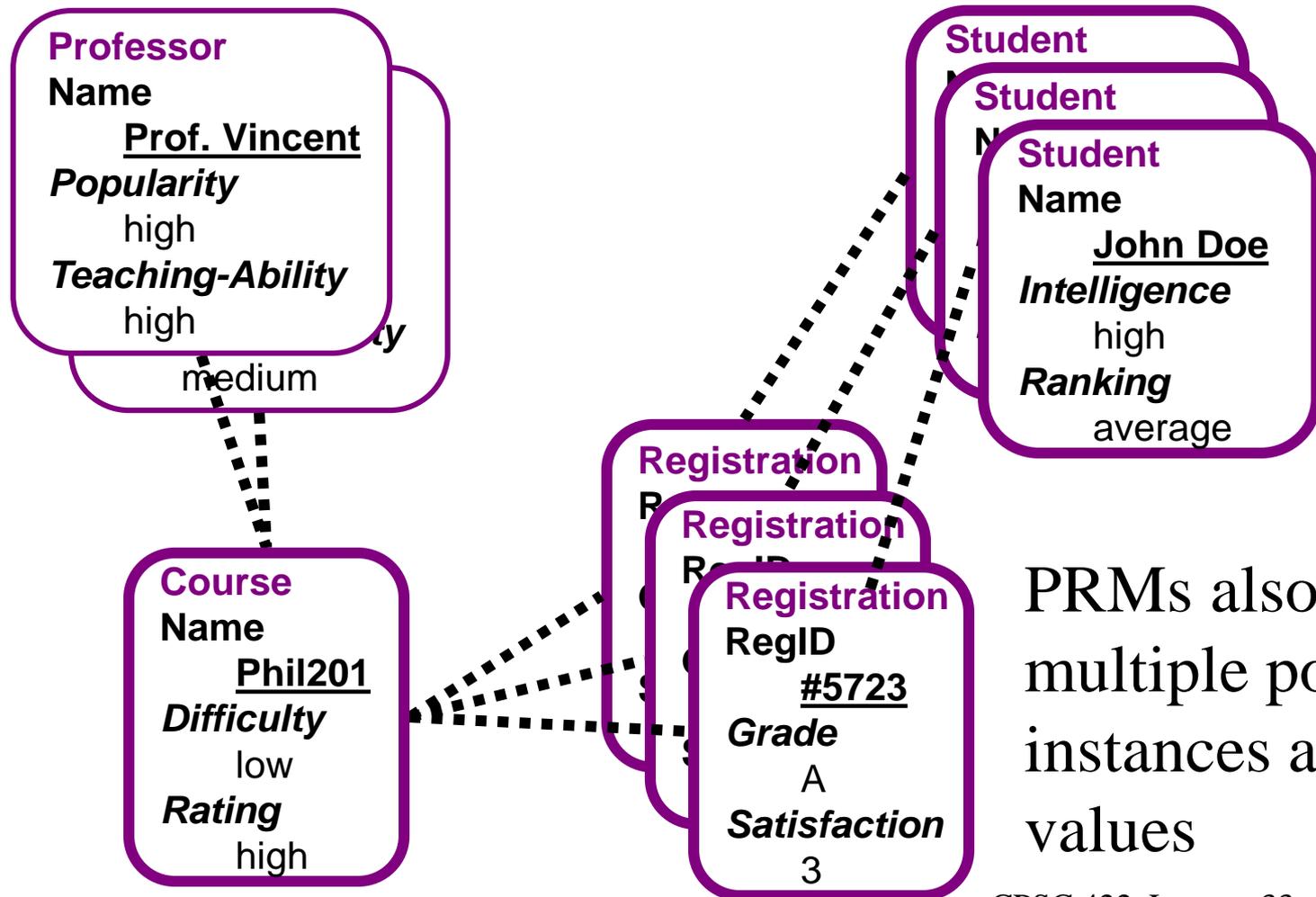


# University Domain Example - Another Relational Skeleton



PRMs allow multiple possible skeletons

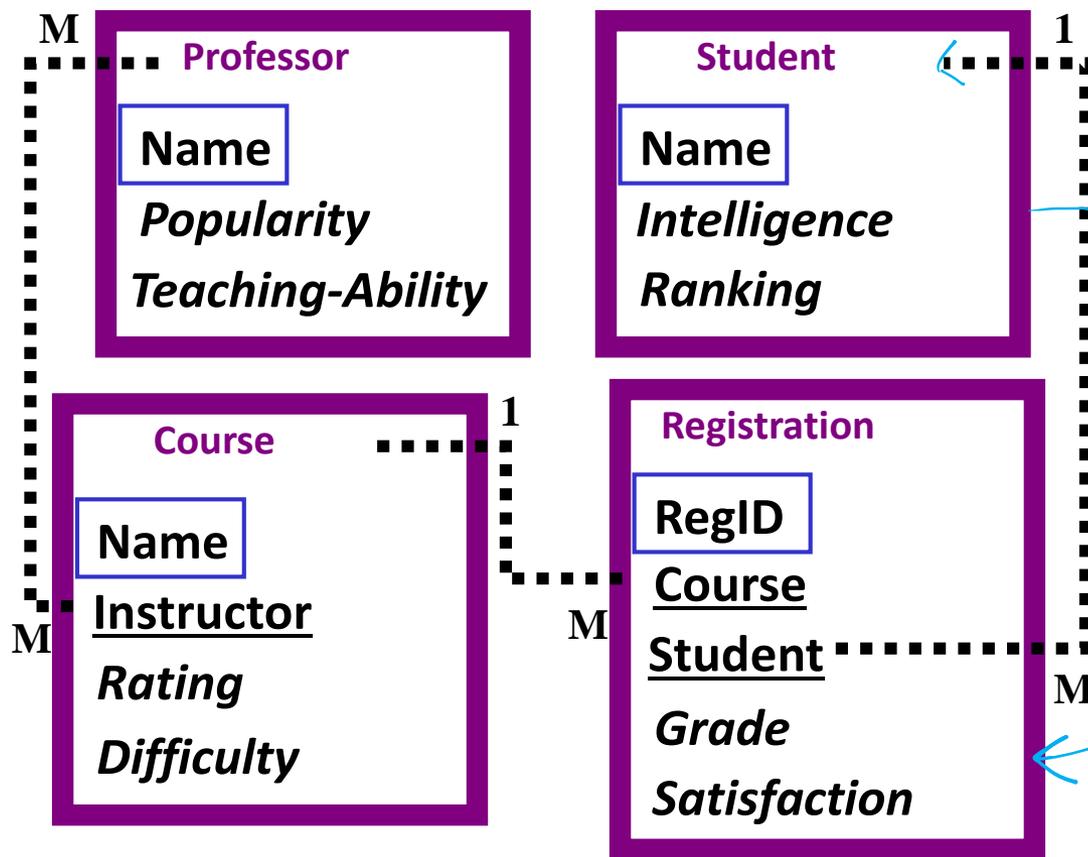
# University Domain Example - The Completion Instance I



PRMs also allow multiple possible instances and values

# PRM Semantics: inverse slot

- For each reference slot  $\rho$ , we define an *inverse slot*,  $\rho^{-1}$ , which is the inverse function of  $\rho$



Registered-in

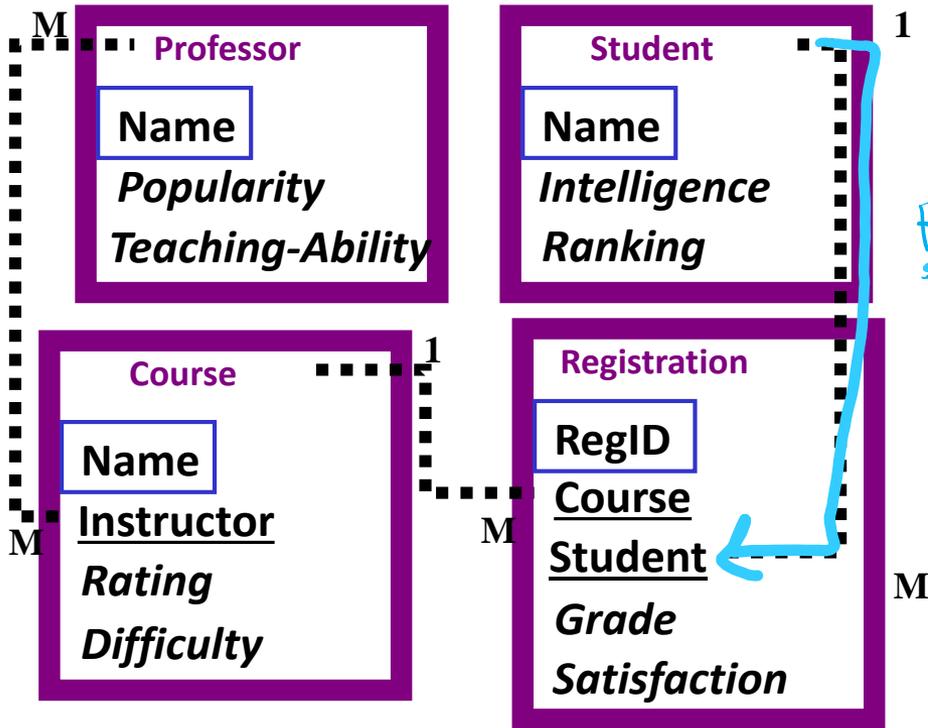
$\rho = \text{Student}$

$\rho^{-1} = \text{Registered-in}$

returns a set of Registration objects

# PRM Semantics: slot chain

A *slot chain*  $\tau = \rho_1 \dots \rho_m$  is a sequence of reference slots that defines functions from objects to other objects to which they are indirectly related.



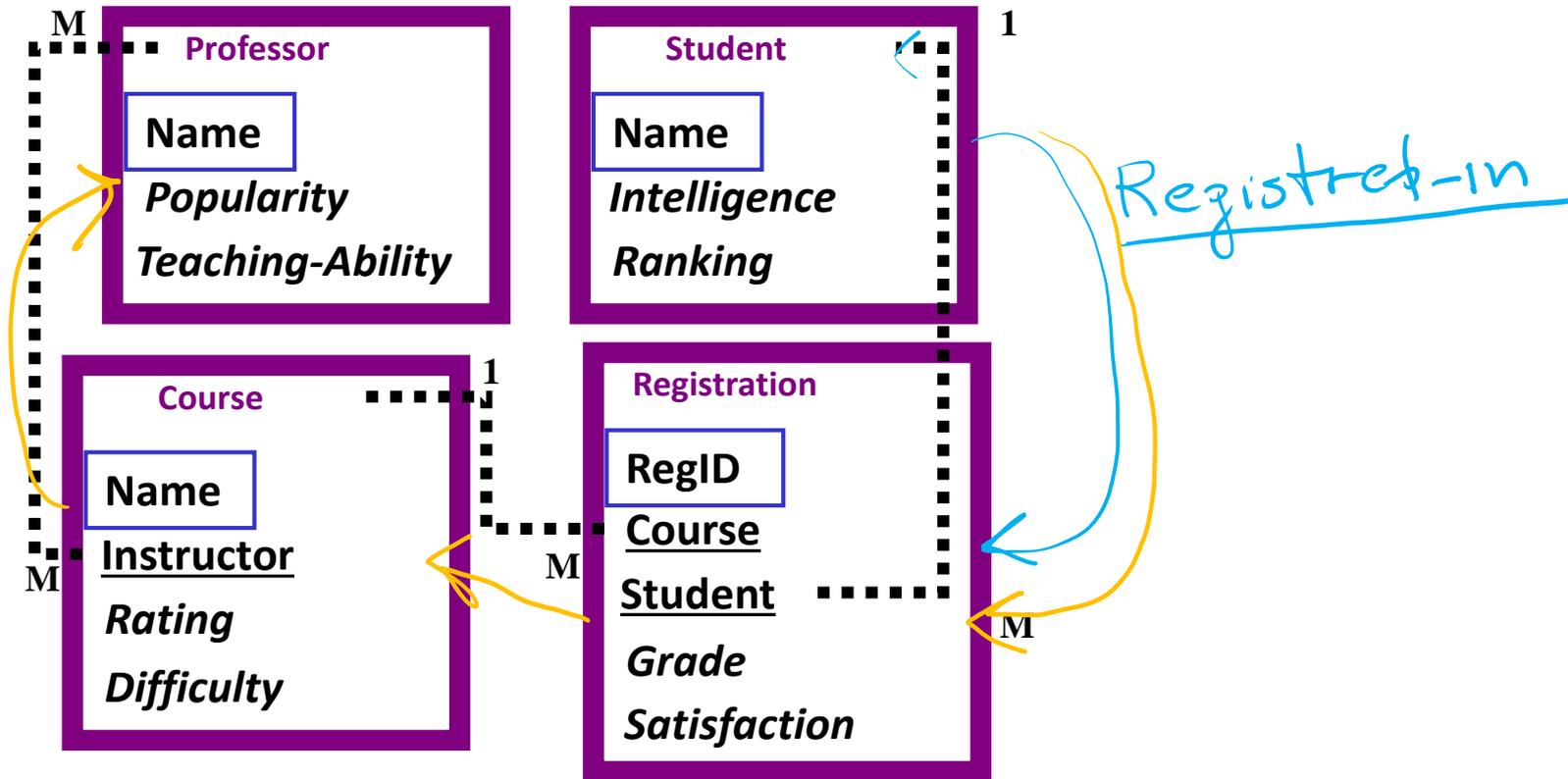
Registered-In

- A. the instructors of a course a student is taking
- B. a student's set of instructors?
- C. An instructor's set of students
- D. cpsc422

*Student.Registered-In.Course.Instructor* denotes?

# PRM Semantics: slot chain

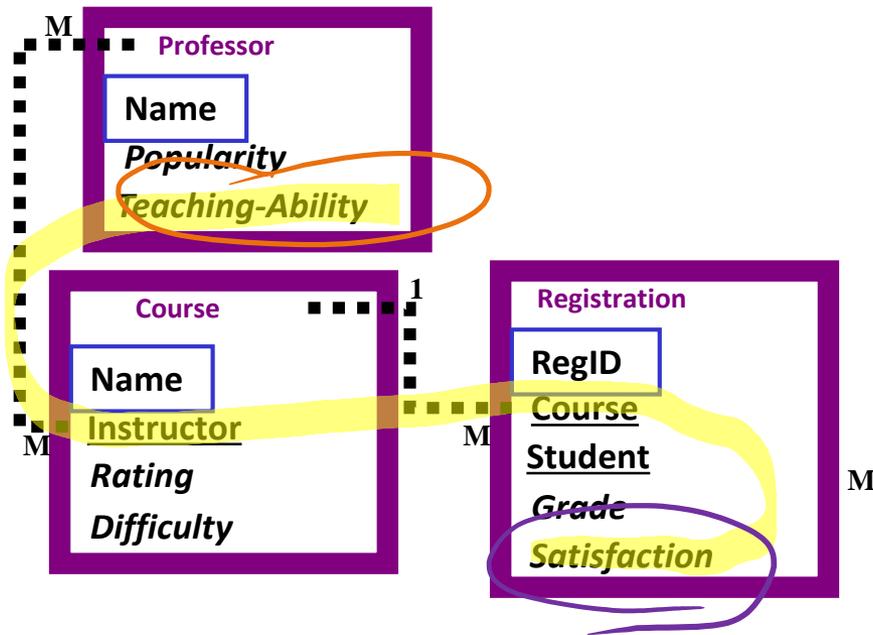
A **slot chain**  $\tau = \rho_1 \dots \rho_m$  is a sequence of reference slots that defines functions from objects to other objects to which they are indirectly related.



**Student.Registered-In.Course.Instructor**  
can be used to denote..... a student's set of instructors

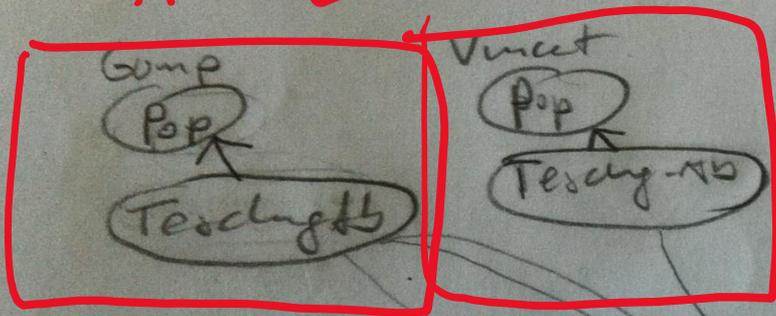
# Slot chains will allow us...

To specify probabilistic dependencies between attributes of related entities

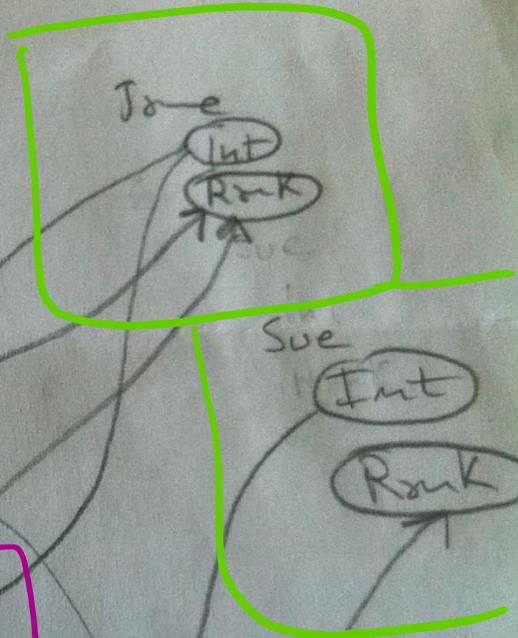


Course.Instructor...

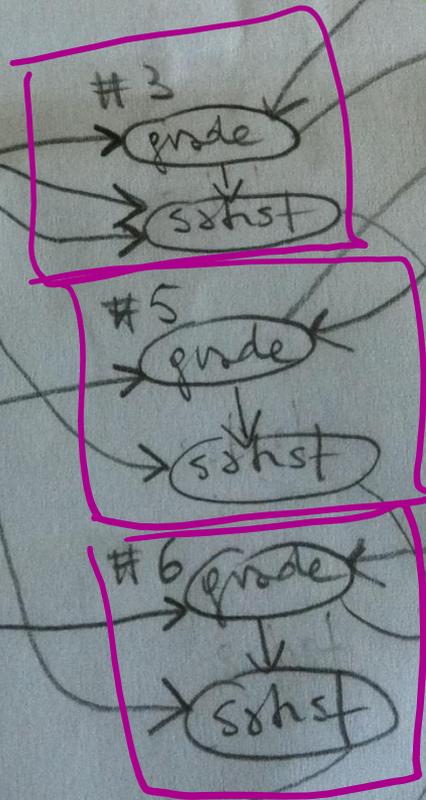
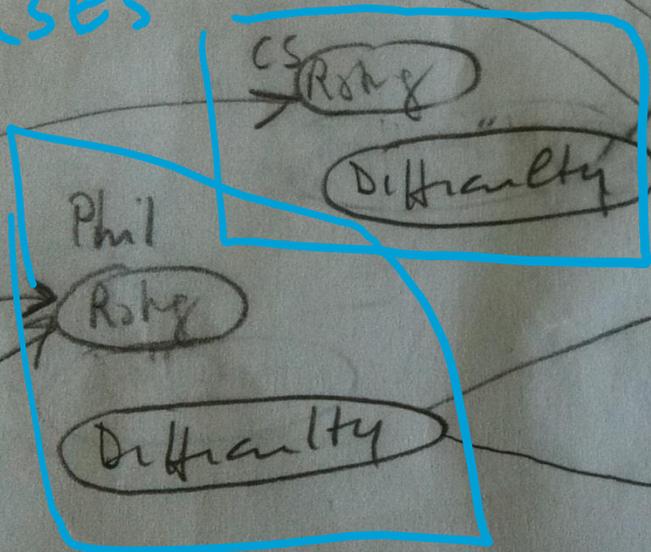
# PROFESSORS



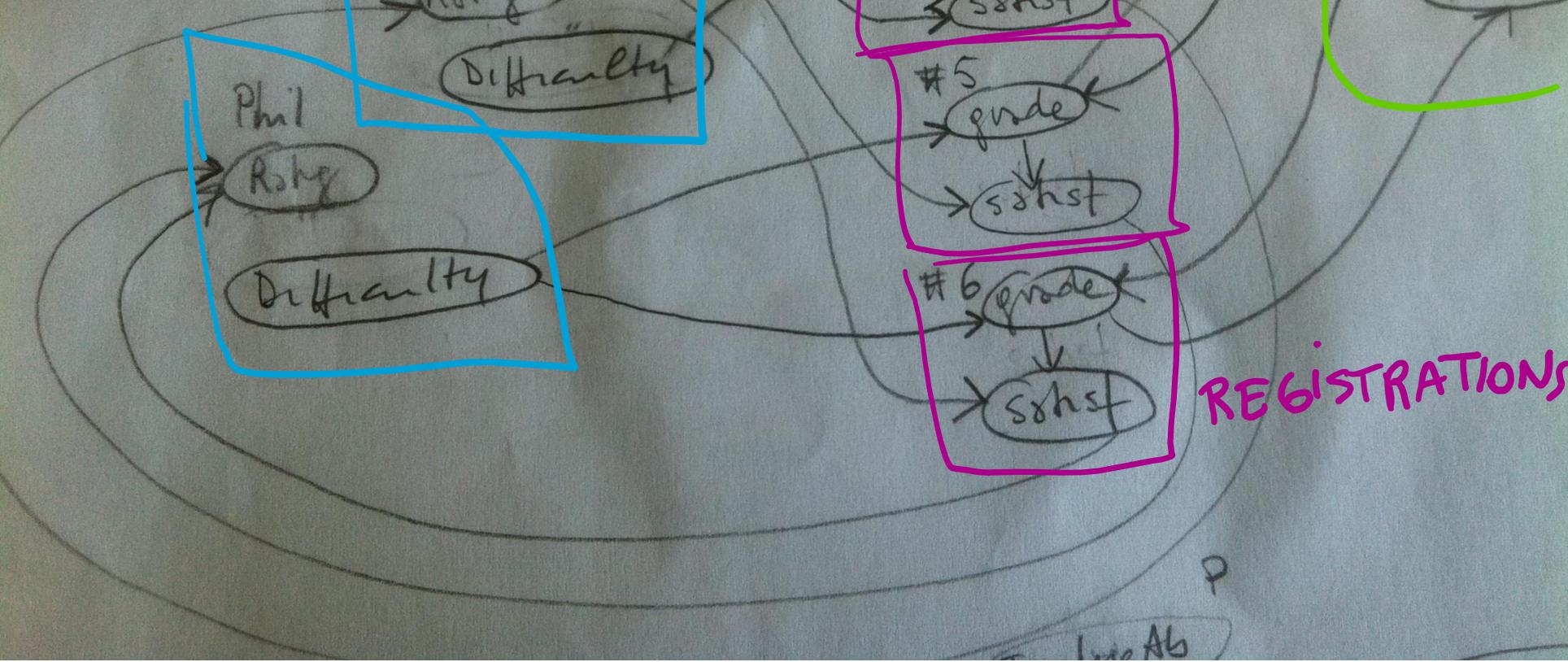
# STUDENTS



# COURSES



# REGISTRATIONS



# Learning Goals for today's class

## You can:

- **Explain the need for Probabilistic relational model**
- **Explain how PRMs generalize BNs**
- **Define a Full Relational Schema and its instances**
- **Define a Relational Skeleton and its completion Instances**
- **Define an inverse slot and an slot chain**

# MONDAY: Third and final research paper reading

- **EMNLP 2020 paper** [MEGA RST Discourse Treebanks with Structure and Nuclearity from Scalable Distant Sentiment Supervision](#)  
*Patrick Huber, Giuseppe Carenini*
- (**guest speaker**: first author of the paper PhD student Patrick Huber !)
- **Material to review** before reading:
  - CKY,
  - Exploration/Exploitation trade-off in RL,
  - Beam Search (from 322),
  - Recurrent Neural Networks (if you have seen them in 340 or other courses)

# Relatively Recent Book + Video Tutorial on Star-AL

## **Book: Logic, Probability, and Computation 2016**

*Luc De Raedt, KU Leuven, Belgium,*

*Kristian Kersting, Technical University of Dortmund, Germany,*

*Sriraam Natarajan, Indiana University,*

*David Poole, University of British Columbia*

An intelligent agent interacting with the real world will encounter individual people, courses, test results, drugs prescriptions, chairs, boxes, etc., and needs to reason about properties of these individuals and relations among them as well as cope with uncertainty.

**Uncertainty has been studied in probability theory and graphical models, and relations have been studied in logic, in particular in the predicate calculus and its extensions.** This book examines the **foundations of combining logic and probability** into what are called relational probabilistic models. It introduces representations, inference, and learning techniques for probability, logic, and their combinations.

The book focuses on two representations in detail: **Markov logic networks**, a relational extension of undirected graphical models and weighted first-order predicate calculus formula, and **Problog**, a probabilistic extension of logic programs that can also be viewed as a Turing-complete relational extension of Bayesian networks.

## **Statistical Relational AI tutorial at NIPS (now NEURIPS) 2017.**

[https://www.facebook.com/watch/live/?v=1552222671535633&ref=watch\\_permalink](https://www.facebook.com/watch/live/?v=1552222671535633&ref=watch_permalink)

# Next class on Fri

## Finish Probabilistic Relational Models

- Probabilistic Model
- Dependency Structure
- Aggregation
- Parameters
- Class dependency Graph
- Inference

Keep working on **Assignment-4**  
Due **Apr 14**