

CS440/ECE448: Intro to Artificial Intelligence

Lecture 16

Exact inference in Bayes Nets

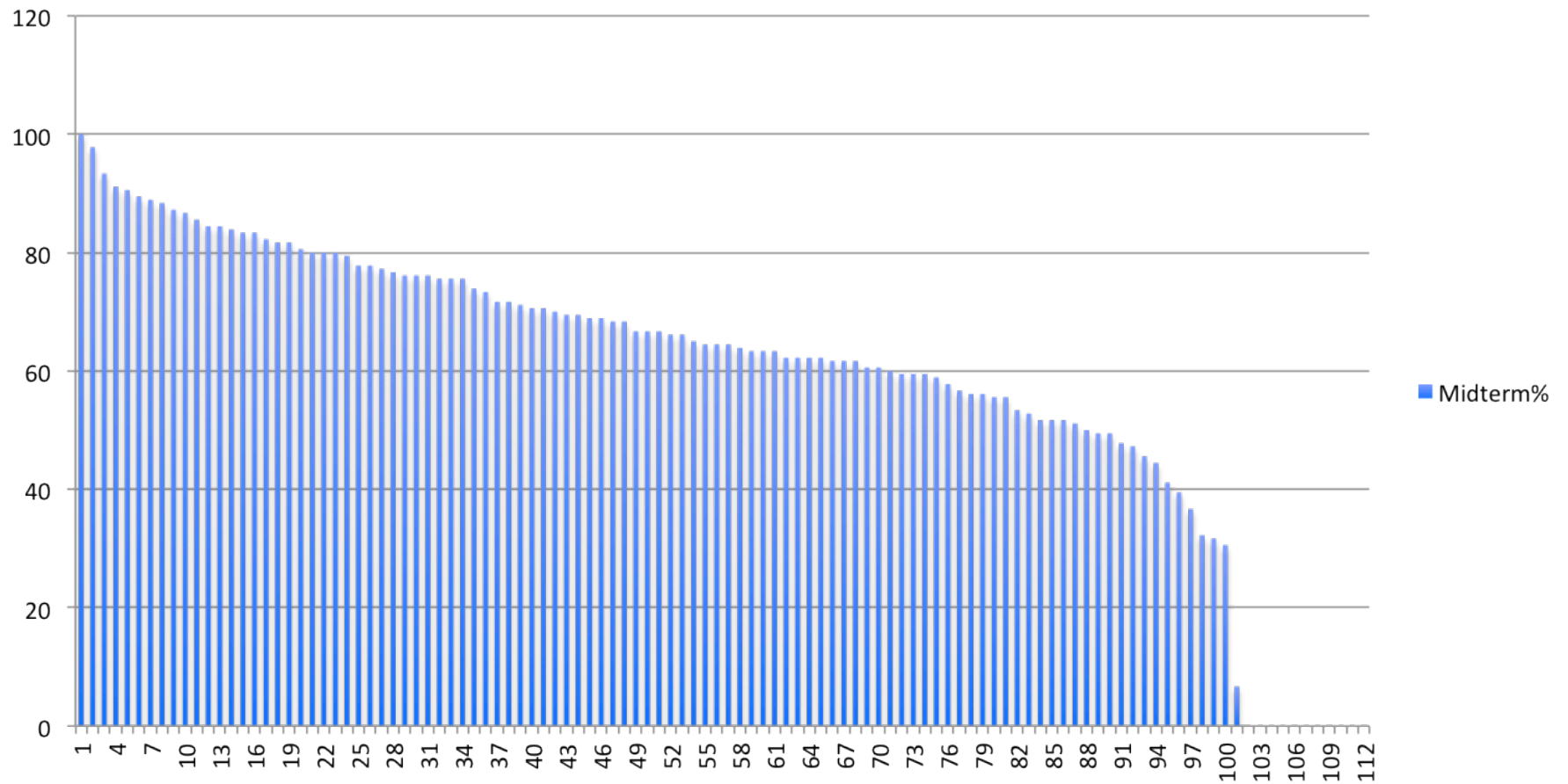
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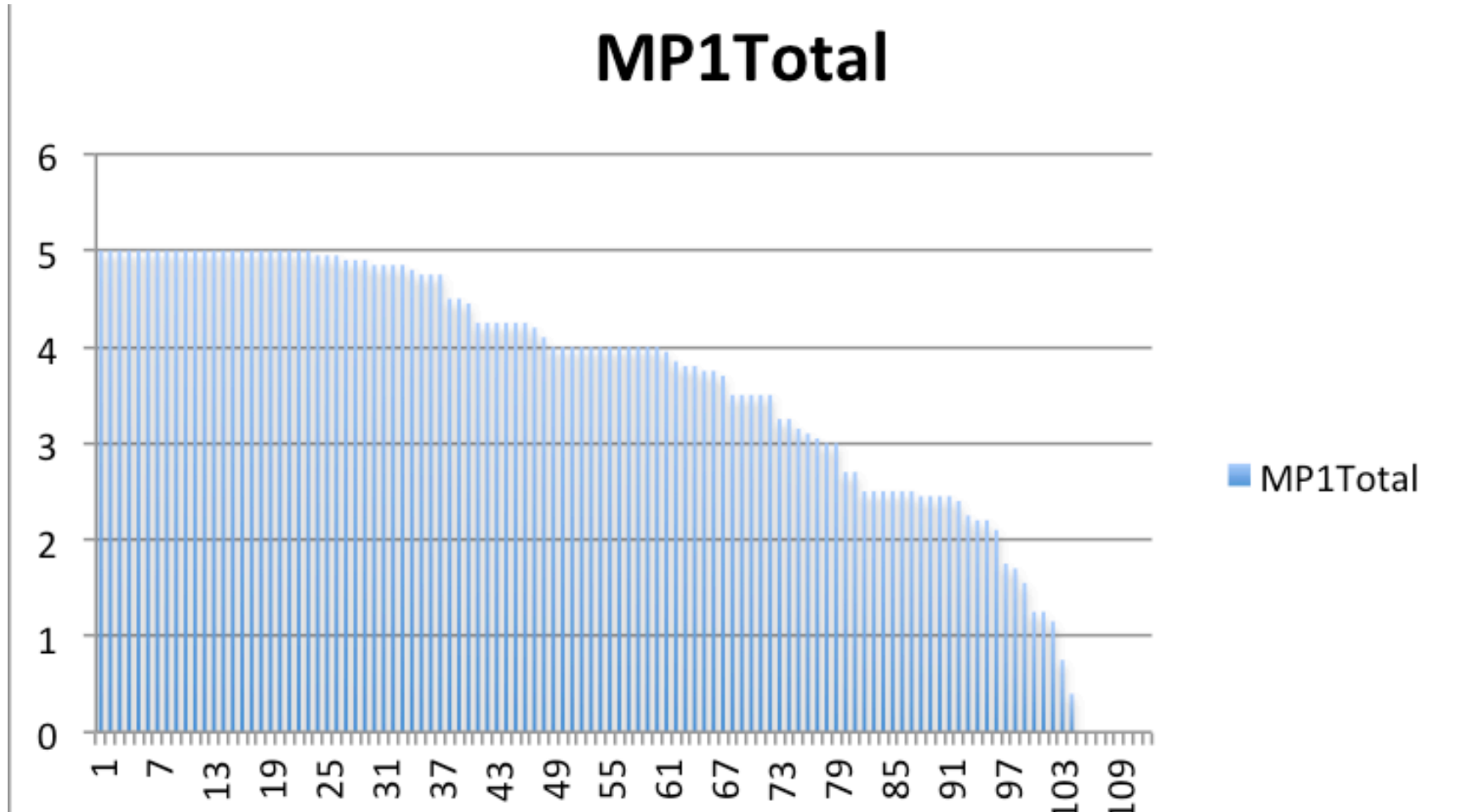
Grades....

Your midterm percentages

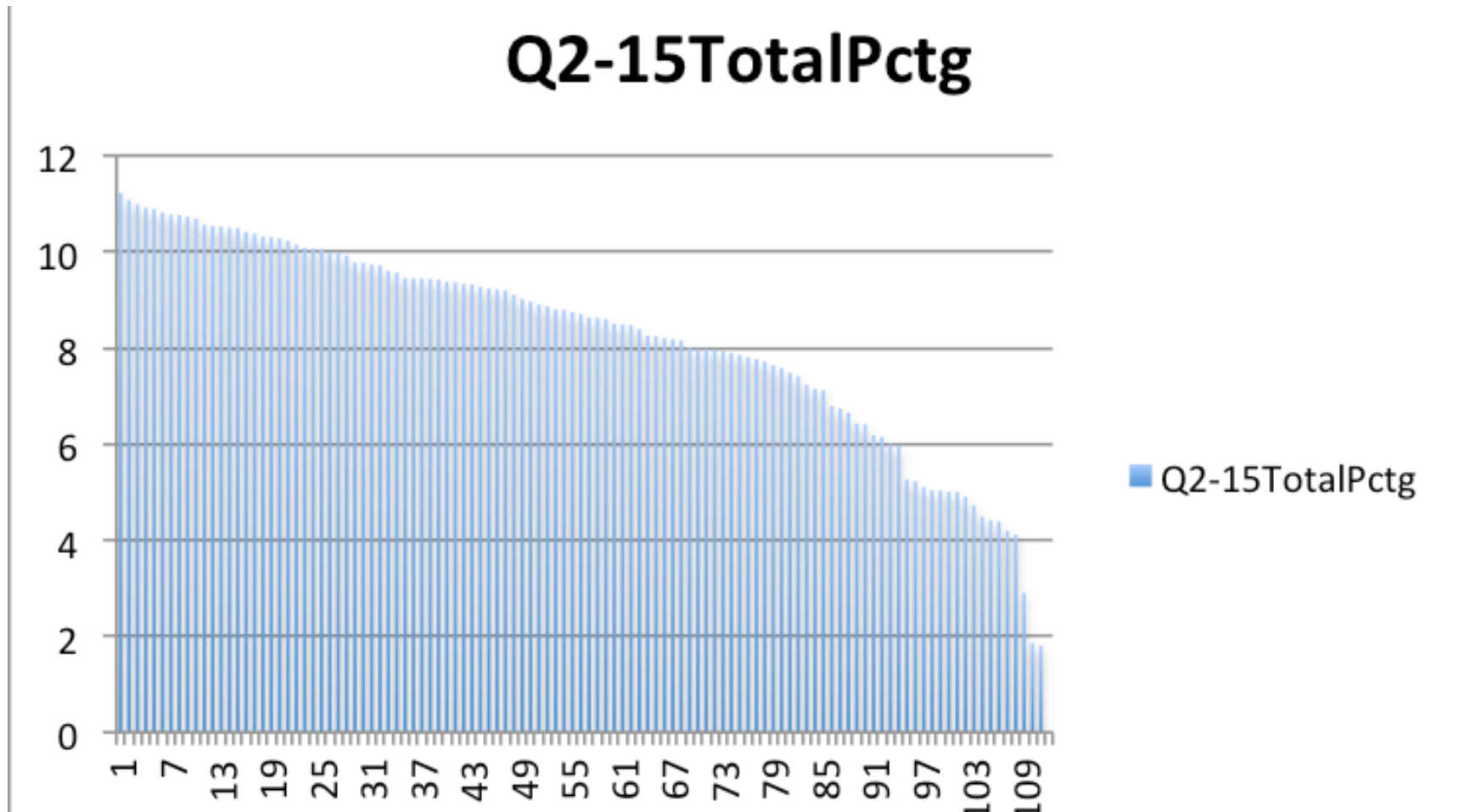
Midterm%



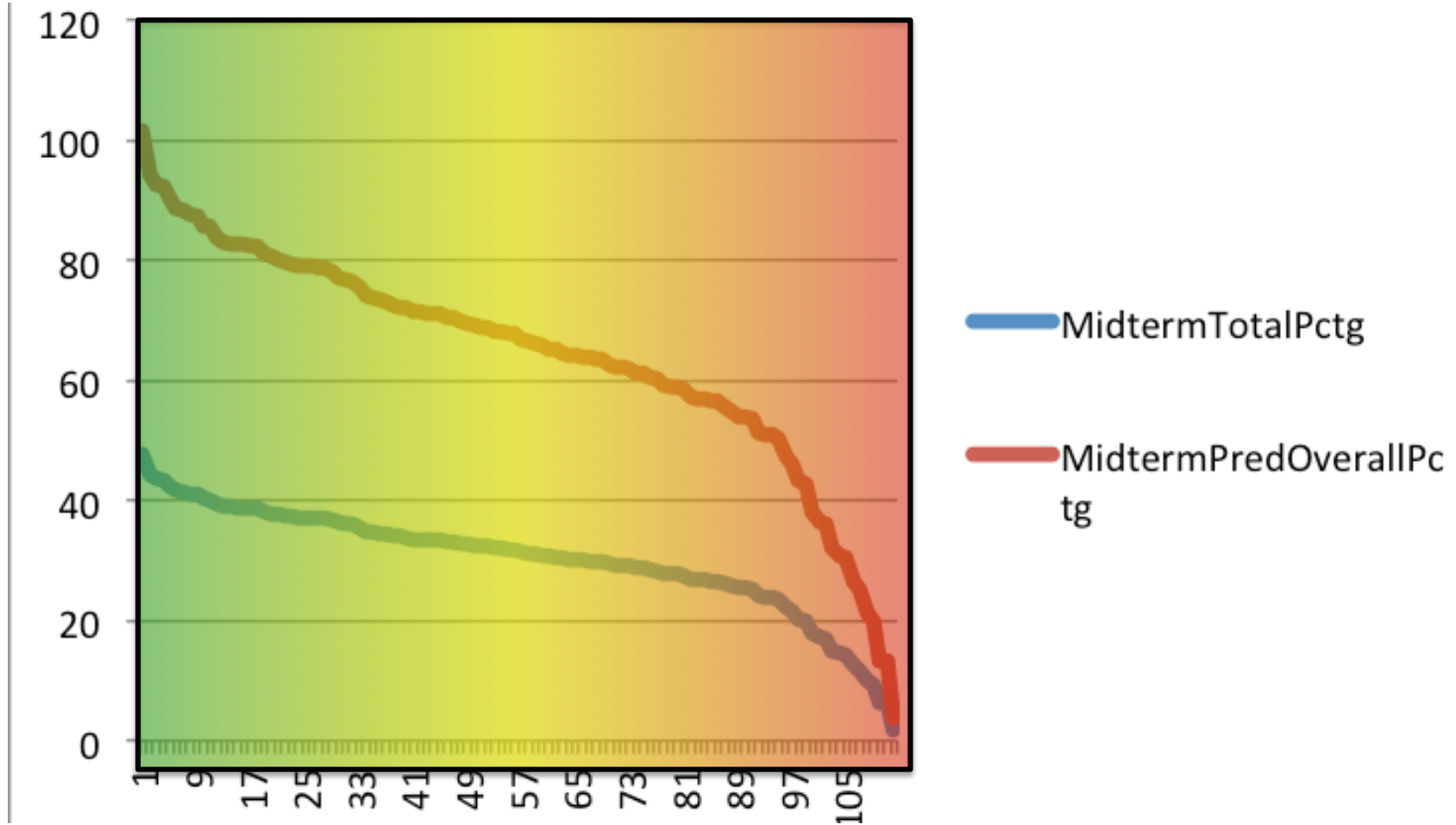
Your MP percentages



Your Quiz totals

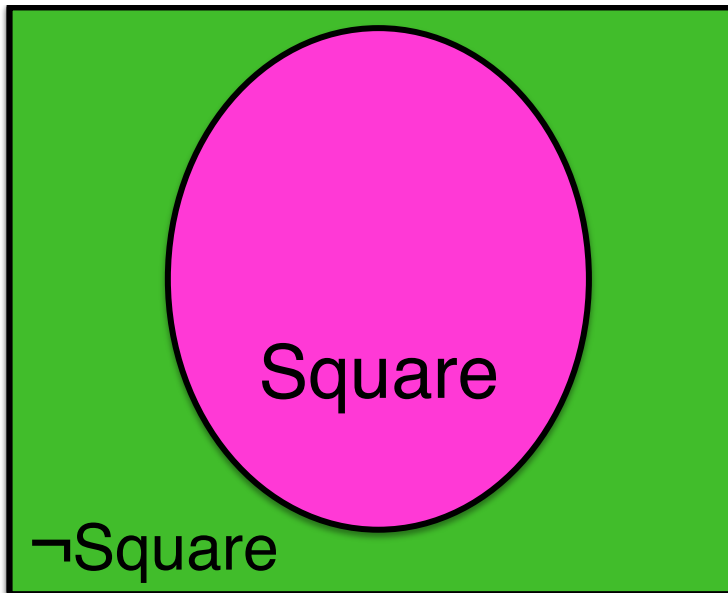


Your current and predicted final grades

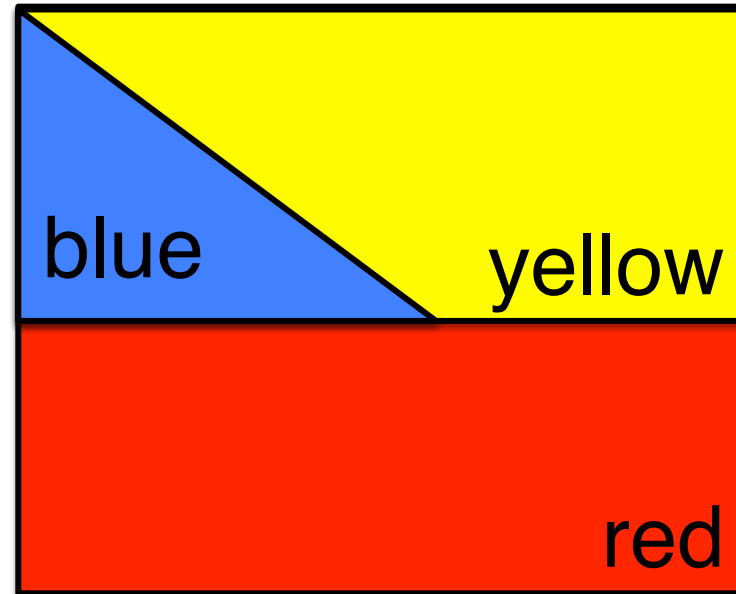


Probability review

Atomic events

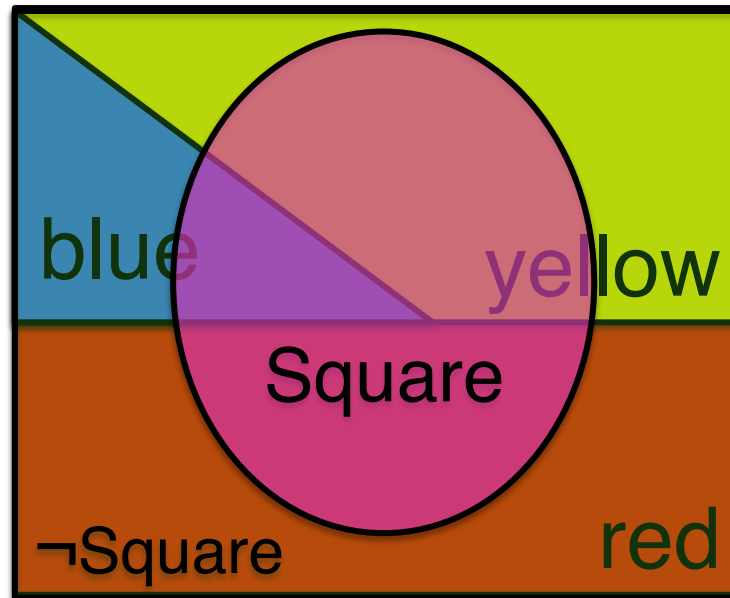


Boolean random variable *Square*



Categorical random variable *Color*

Complex events

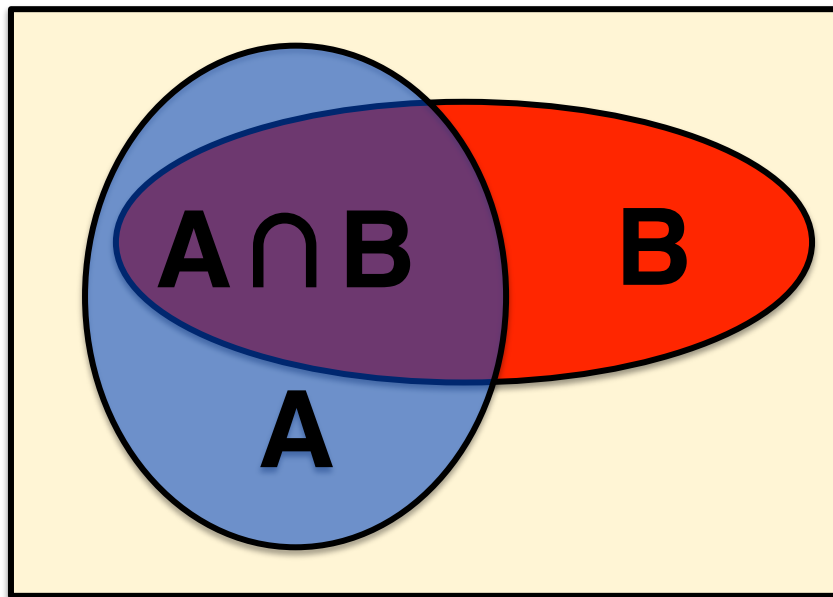


Joint probability $P(A,B)$

$$P(A \cap B) = P(A, B)$$

If A and B are boolean variables:

$$P(A,B) = P(A \wedge B)$$



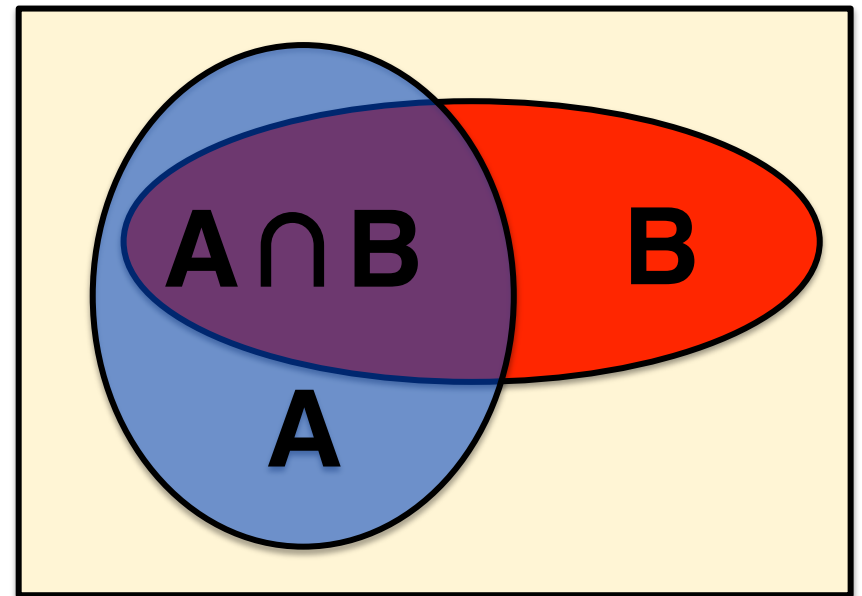
Conditional probability $P(A|B)$

Definition:

$$P(A | B) = \frac{P(A, B)}{P(B)}$$

Product rule

$$P(A, B) = P(A | B)P(B)$$



The full joint distribution

		Weather			
		Sunny	Cloudy	Rainy	Snowy
Fun?	Yes	0.25	0.15	0.05	0.13
	No	0.05	0.1	0.25	0.02

From the full joint distribution, we can obtain:

- Conditional distributions $P(\text{Fun?} \mid \text{Weather})$
- Marginal distributions $P(\text{Weather})$

Independence

Random variables X and Y are **independent** ($X \perp Y$) if $P(X, Y) = P(X) \times P(Y)$

NB.: Since X and Y are R.V.s (not individual events), $P(X, Y) = P(X) \times P(Y)$ is an abbreviation for:
 $\forall x \forall y P(X=x, Y=y) = P(X=x) \times P(Y=y)$

X and Y are **conditionally independent** given Z ($X \perp Y \mid Z$) if $P(X, Y \mid Z) = P(X \mid Z) \times P(Y \mid Z)$

Conditional Independence

X and Y are ***conditionally independent*** given Z
($X \perp Y \mid Z$) if $P(X, Y \mid Z) = P(X \mid Z) \times P(Y \mid Z)$

The value of X depends on the value of Z ,
and the value of Y depends on the value of Z ,
so X and Y are not independent.

Bayesian networks

Insight: (Conditional) independence assumptions are essential for probabilistic modeling

Bayes Net: a directed graph which represents the joint distribution of a number of random variables in a directed graph

- Nodes = random variables
- Directed edges = dependencies

The *Student* scenario

(Koller & Friedman'09)

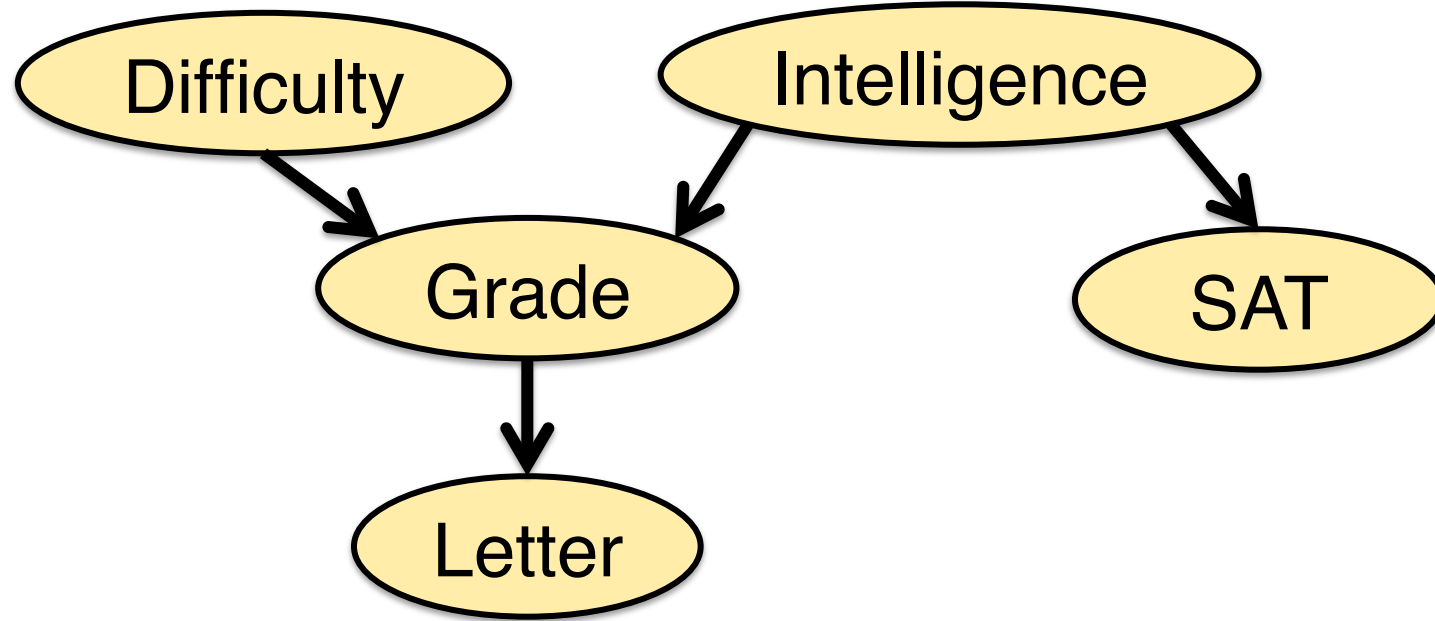
A company wants to hire intelligent CS grads.

Each student has an **SAT score** and a **recommendation letter** from a professor that they took a class from.

The SAT score depends on the student's intelligence

The professor's recommendation depends purely on the student's **grade**.

The student's grade in the class depends on their **intelligence** as well as the **difficulty** of the class.



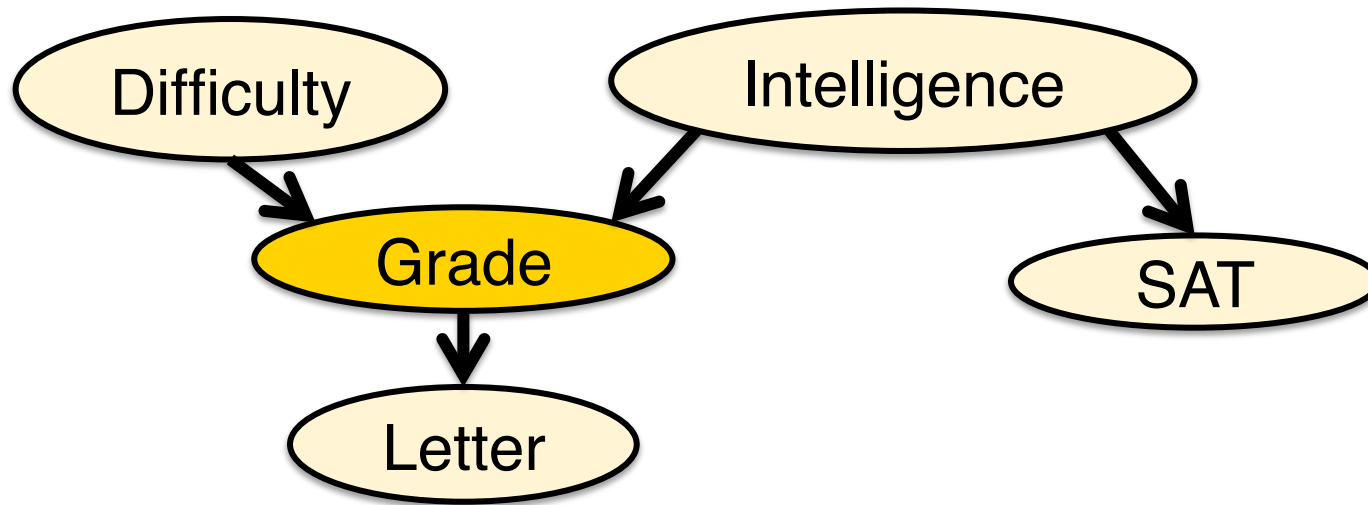
Each student has an **SAT score** and a **recommendation letter**.

The SAT score depends on their **intelligence**.

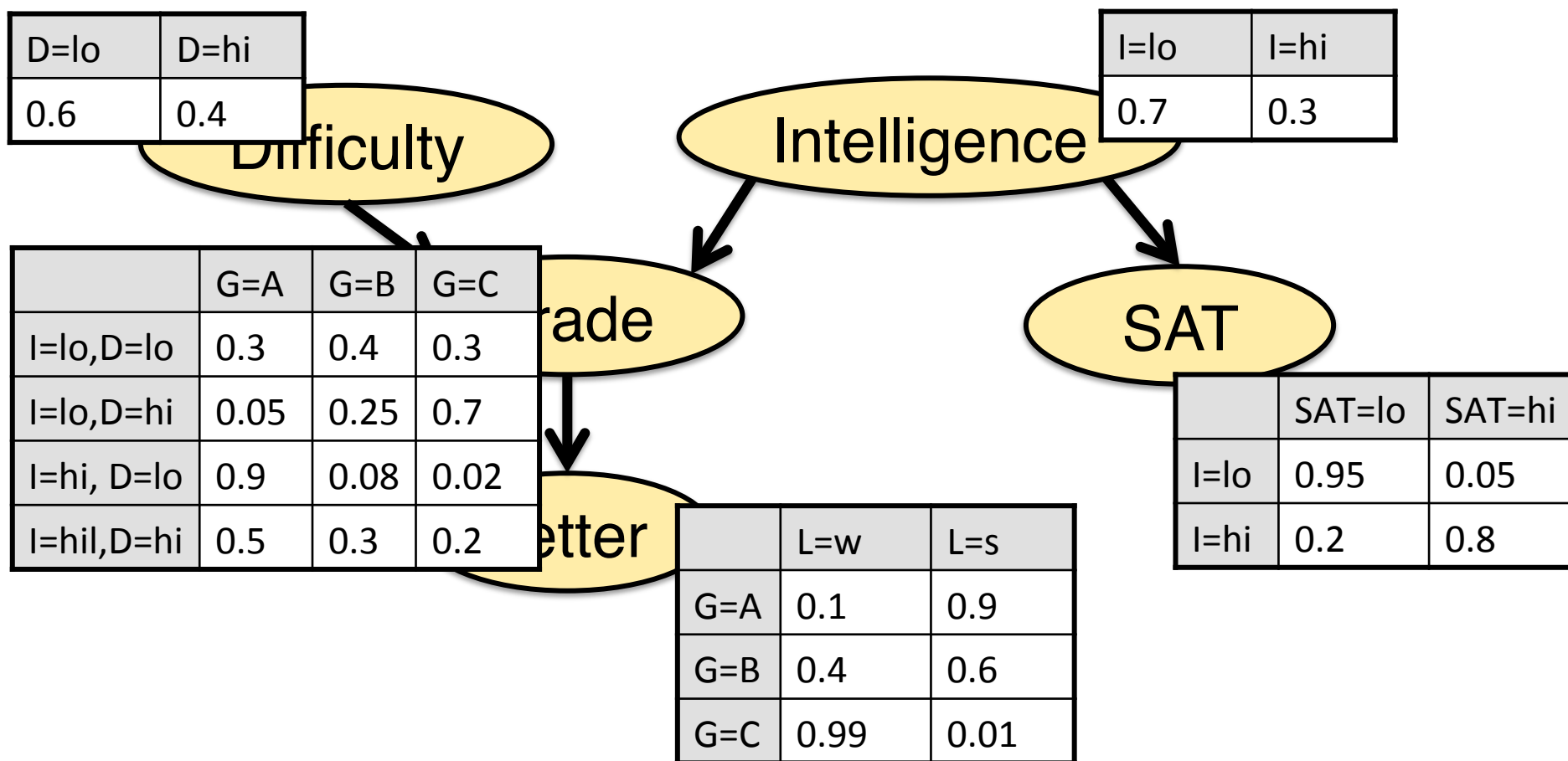
The recommendation depends on their **grade**.

The grade depends on the student's **intelligence** as well as the **difficulty** of the class.

Some terminology



Difficulty and *Intelligence* are **parents** of *Grade*.
Letter is a (direct) **descendant** of *Grade*.
SAT is a **non-descendant** of *Grade*.



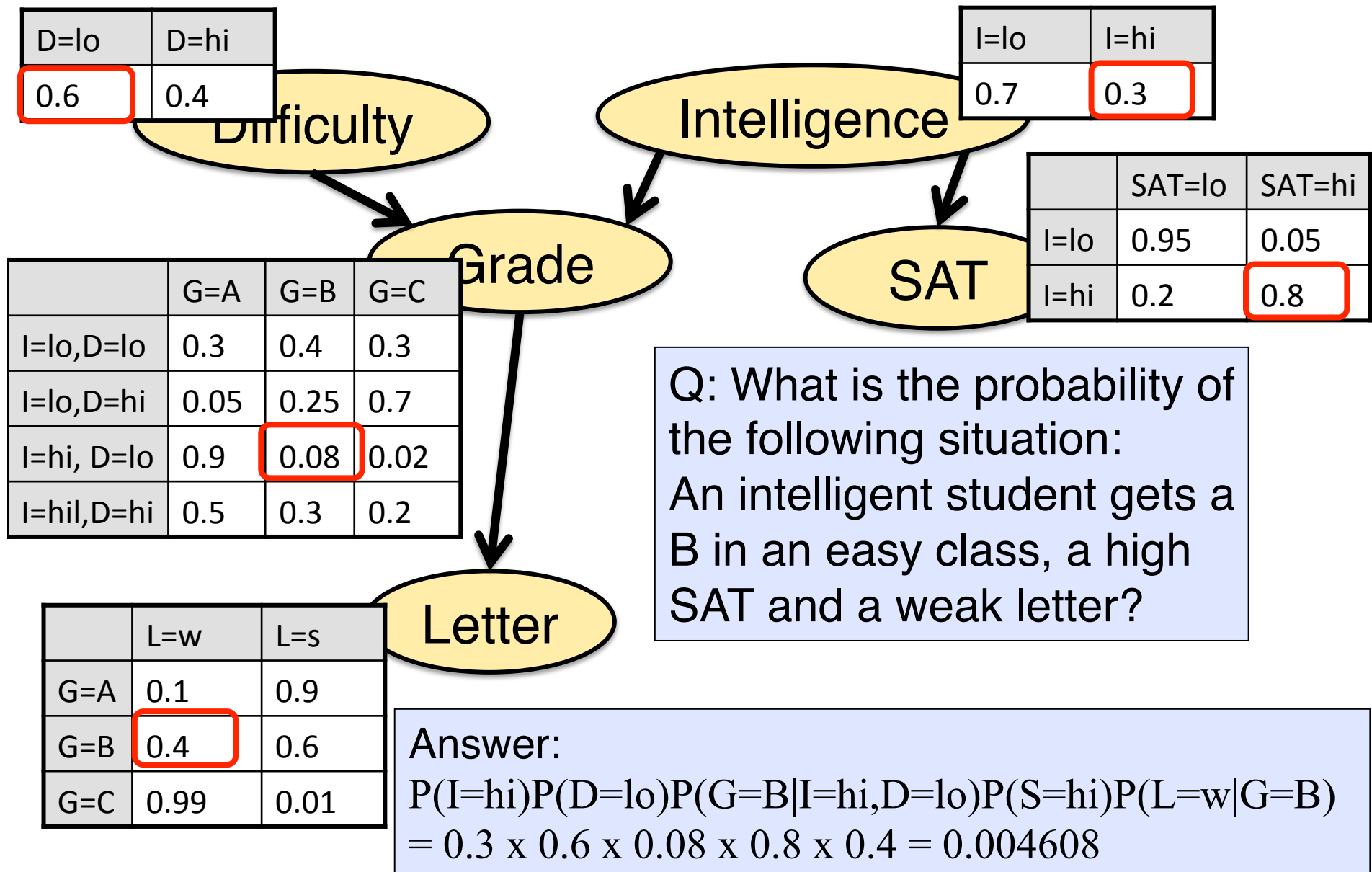
Difficulty is a binary R.V. (*easy/hard*)

Intelligence is a binary R.V. (*low/high*)

SAT is a binary R.V. (*low/high*)

There are three **grades**. (*A,B,C*)

Letter is a binary R.V. (*weak rec./strong recc*)

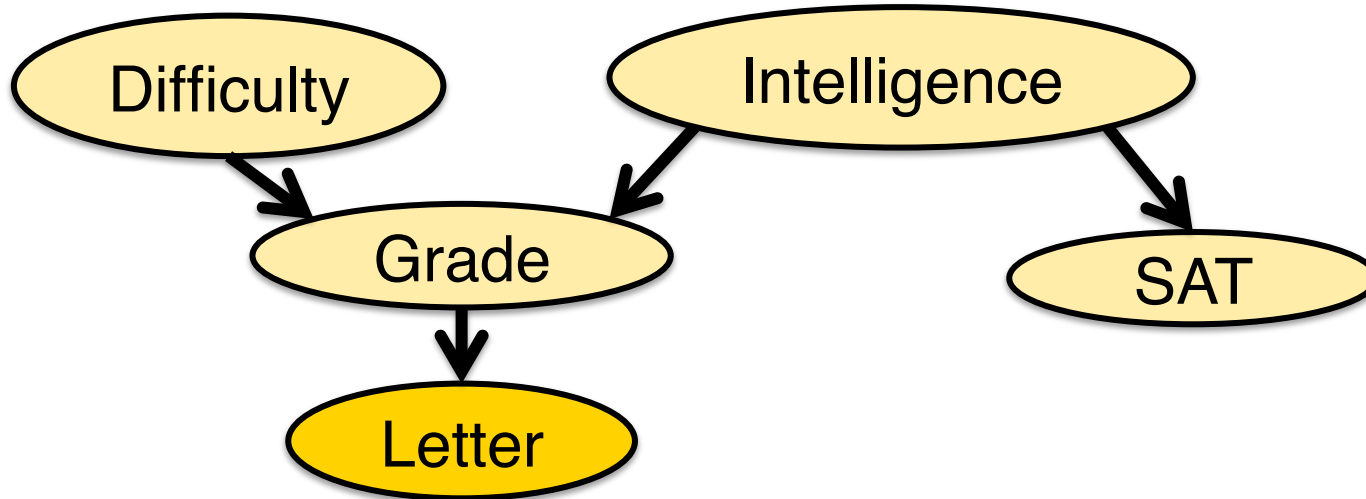


The chain rule for BNs

In order to compute the joint probability of the random vars $X_1 \dots X_n$ in a Bayes Net, we multiply the conditional probabilities of each R.V. X_i given its parents $Pa(X_i)$:

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i \mid Pa(X_i))$$

Conditional independences

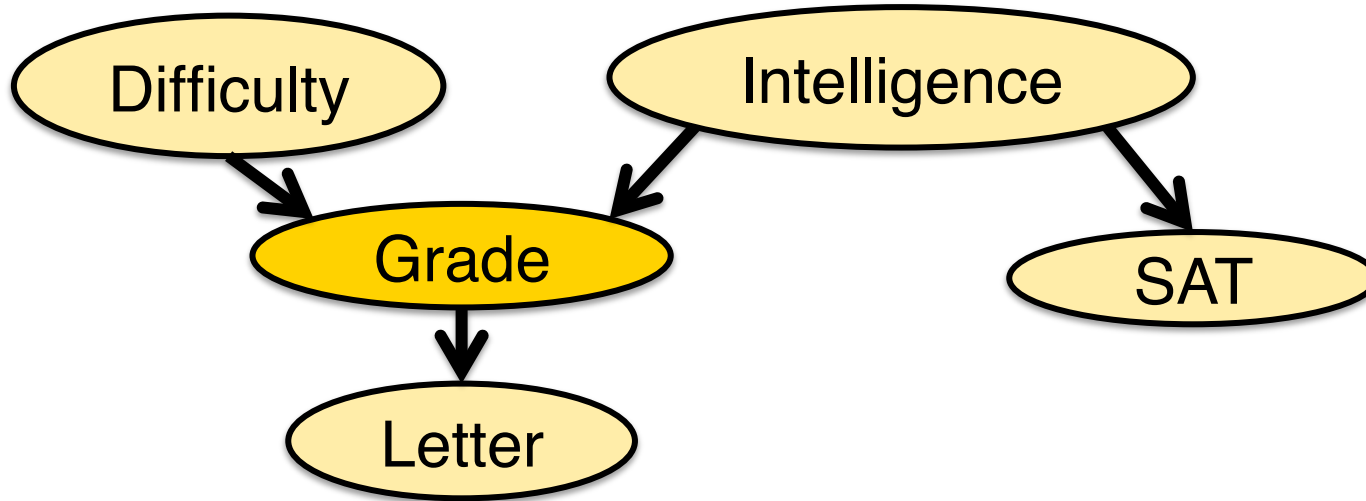


Each node depends directly only on its parents.

Letter is conditionally independent of all other nodes given its parent:

(Letter \perp Intelligence, Difficulty, SAT | Grade)

Conditional independences

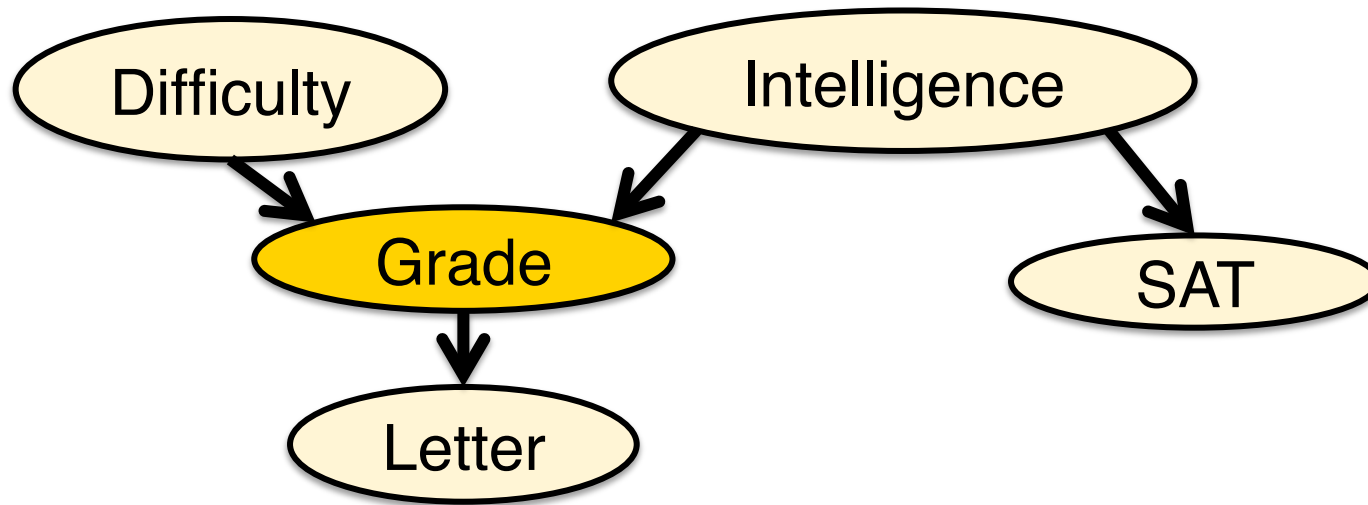


What about *Grade*?

Grade is conditionally independent of SAT given Intelligence, Letter (and Difficulty)

$(Grade \perp SAT \mid Letter, Intelligence, Difficulty)$

More terminology

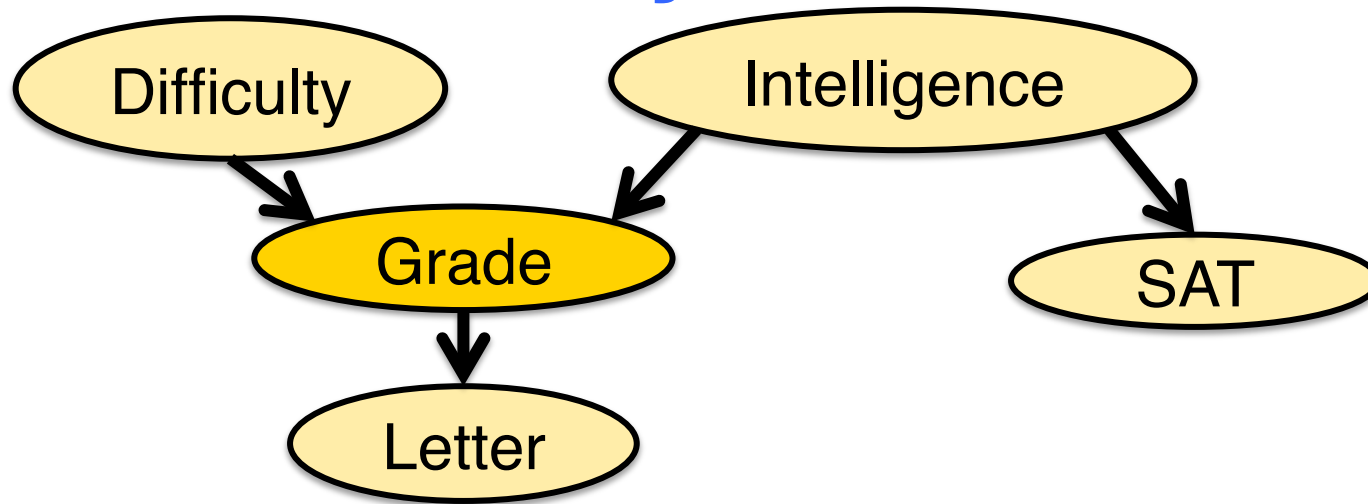


Difficulty and *Intelligence* are **parents** of *Grade*.

Letter is a (direct) **descendant** of *Grade*.

The parents and direct descendant of a node form its **Markov blanket**.

Conditional independences in Bayes Nets



Each node is conditionally independent of its non-descendants given its Markov blanket.

Inference in Bayes Nets

More generally, we want to know the distribution of a set of **query variables** given some observed **event**.

What is the probability of getting a strong letter if you are an intelligent student?

An event is an assignment of values to a set of **evidence variables**. (*here: intelligence*)

Computing inferences in Bayes Nets

From the joint to the conditional:

$$P(X \mid Y) = P(X, Y) / P(Y)$$

How do we compute $P(Y)$?

Answer: Marginalization

Do we care about $P(Y)$?

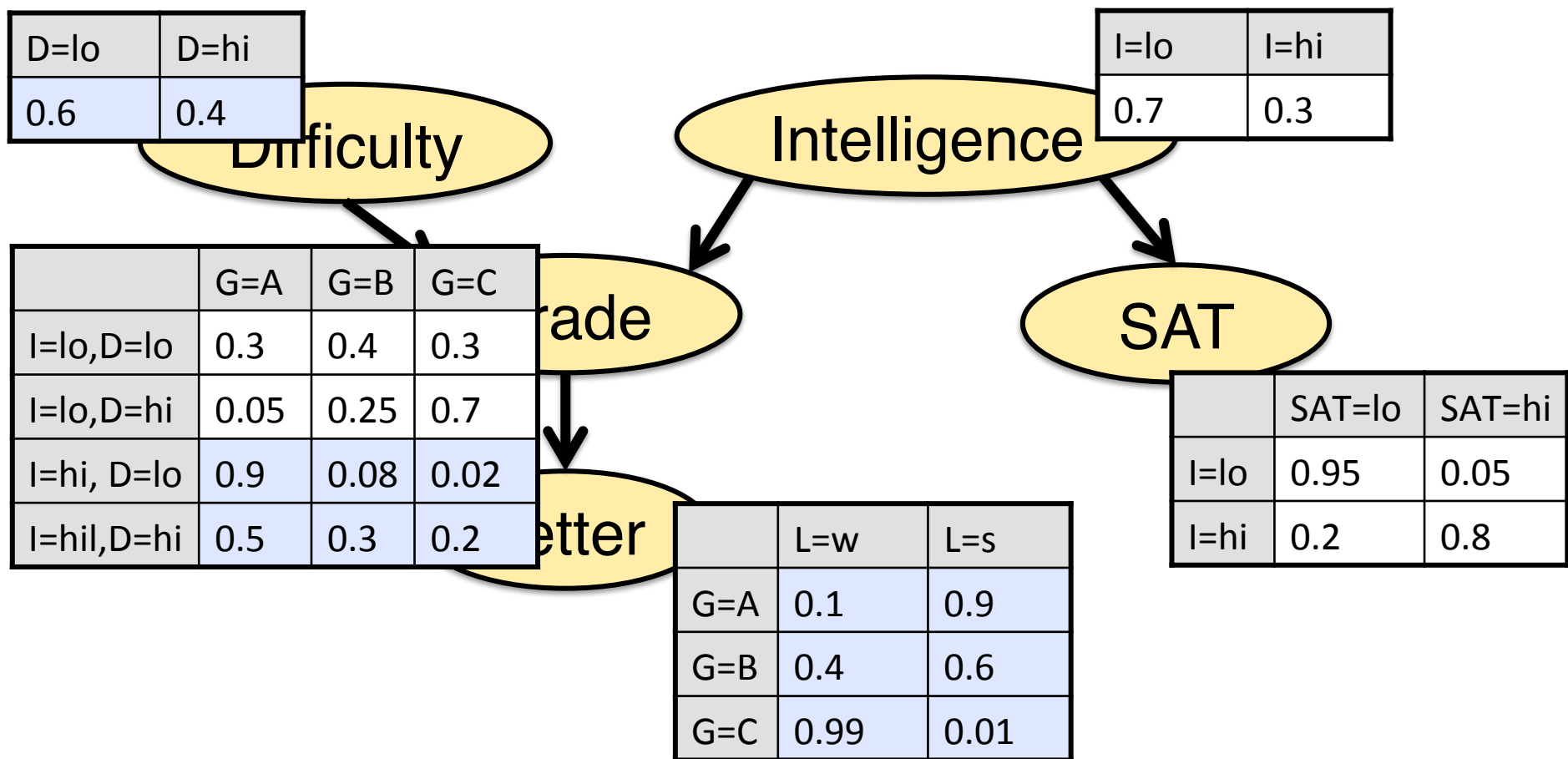
Answer: not necessarily if we just want to compare $P(X \mid Y=y)$ for the same set of y 's.

Computing inferences in Bayes Nets

What is the probability of getting a strong letter if you are an intelligent student?

What about the other, hidden, variables ?
Answer: we have to marginalize them out.

$$P(X, \mathbf{E}) = \sum_H P(X, H, E)$$



What is the probability of getting a strong letter if you are an intelligent student?