

Often we want a random variable for each individual in a population

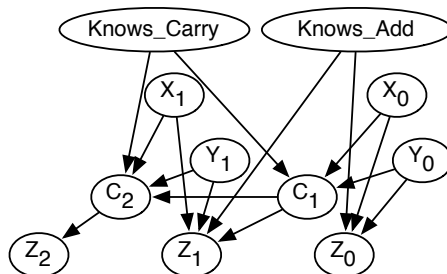
- build a probabilistic model before knowing the individuals
- learn the model for one set of individuals
- apply the model to new individuals
- allow complex relationships between individuals

Predicting students errors

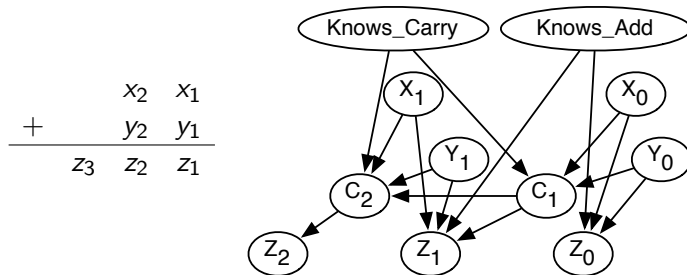
$$\begin{array}{rcc} & x_2 & x_1 \\ + & y_2 & y_1 \\ \hline z_3 & z_2 & z_1 \end{array}$$

Predicting students errors

$$\begin{array}{r} + \quad \quad x_2 \quad x_1 \\ \quad \quad y_2 \quad y_1 \\ \hline z_3 \quad z_2 \quad z_1 \end{array}$$

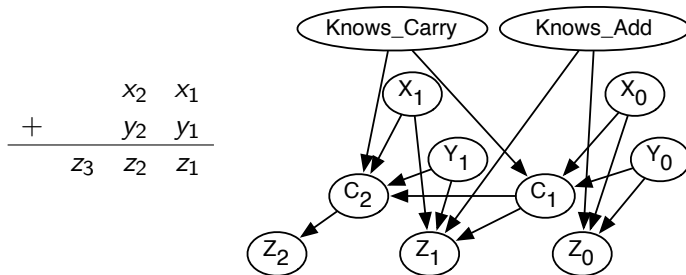


Predicting students errors



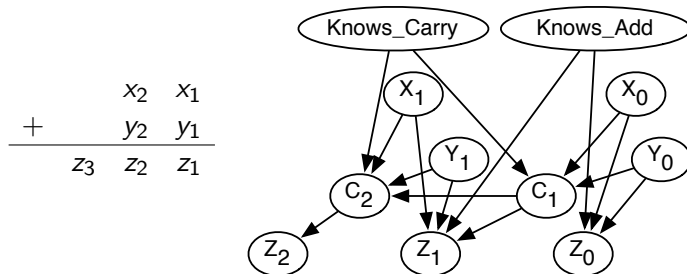
What if there were multiple digits

Predicting students errors



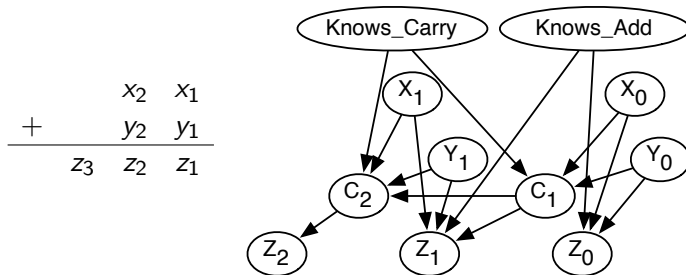
What if there were multiple digits, problems

Predicting students errors



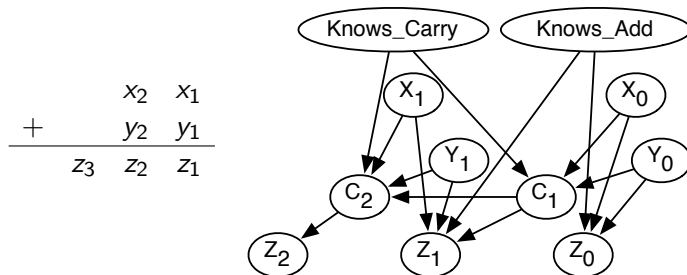
What if there were multiple digits, problems, students

Predicting students errors



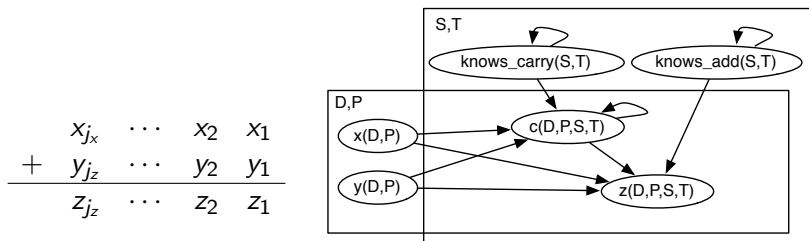
What if there were multiple digits, problems, students, times?

Predicting students errors



What if there were multiple digits, problems, students, times? How can we build a model before we know the individuals?

Multi-digit addition with parametrized BNs / plates



Parametrized Random Variables: $x(D, P)$, $y(D, P)$, $knows_carry(S, T)$, $knows_add(S, T)$, $c(D, P, S, T)$, $z(D, P, S, T)$ for digit D , problem P , student S , time T .
 There is a random variable for each assignment of a value to D and a value to P in $x(D, P)$

Representing Conditional Probabilities

- $P(\text{knows_adn}(X) | \text{bright}(X), \text{taught_adn}(X))$ — **parameter sharing** — individuals share probability parameters.
- $P(\text{happy}(X) | \text{friend}(X, Y), \text{mean}(Y))$ — needs **aggregation** — $\text{happy}(a)$ depends on an unbounded number of parents.
- the carry of one digit depends on carry of the previous digit
- probability that two authors collaborate depends on whether they have a paper authored together

- A language for first-order probabilistic models.
- **Idea**: combine logic and probability, where all uncertainty is handled in terms of Bayesian decision theory, and a logic program specifies consequences of choices.
- Parametrized random variables are represented as logical atoms, and the plates correspond to logical variables.

Independent Choice Logic

- An **alternative** is a set of ground atomic formulas.
 \mathcal{C} , the **choice space** is a set of disjoint alternatives.
- \mathcal{F} , the **facts** is a logic program that gives consequences of choices.
- P_0 a probability distribution over alternatives:

$$\forall A \in \mathcal{C} \sum_{a \in A} P_0(a) = 1.$$

Meaningless Example

$$\mathcal{C} = \{\{c_1, c_2, c_3\}, \{b_1, b_2\}\}$$

$$\mathcal{F} = \left\{ \begin{array}{ll} f \leftarrow c_1 \wedge b_1, & f \leftarrow c_3 \wedge b_2, \\ d \leftarrow c_1, & d \leftarrow \sim c_2 \wedge b_1, \\ e \leftarrow f, & e \leftarrow \sim d \end{array} \right\}$$

$$P_0(c_1) = 0.5 \quad P_0(c_2) = 0.3 \quad P_0(c_3) = 0.2$$

$$P_0(b_1) = 0.9 \quad P_0(b_2) = 0.1$$

- There is a possible world for each selection of one element from each alternative.
- The logic program together with the selected atoms specifies what is true in each possible world.
- The elements of different alternatives are independent.

Meaningless Example: Semantics

$$\mathcal{F} = \left\{ \begin{array}{ll} f \leftarrow c_1 \wedge b_1, & f \leftarrow c_3 \wedge b_2, \\ d \leftarrow c_1, & d \leftarrow \sim c_2 \wedge b_1, \\ e \leftarrow f, & e \leftarrow \sim d \end{array} \right\}$$

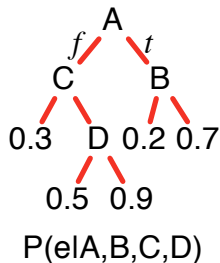
$$\begin{array}{lll} P_0(c_1) = 0.5 & P_0(c_2) = 0.3 & P_0(c_3) = 0.2 \\ P_0(b_1) = 0.9 & P_0(b_2) = 0.1 & \end{array}$$

		selection		logic program			
		$\underbrace{\hspace{1cm}}$		$\underbrace{\hspace{1cm}}$			
w_1	\models	c_1	b_1	f	d	e	$P(w_1) = 0.45$
w_2	\models	c_2	b_1	$\sim f$	$\sim d$	e	$P(w_2) = 0.27$
w_3	\models	c_3	b_1	$\sim f$	d	$\sim e$	$P(w_3) = 0.18$
w_4	\models	c_1	b_2	$\sim f$	d	$\sim e$	$P(w_4) = 0.05$
w_5	\models	c_2	b_2	$\sim f$	$\sim d$	e	$P(w_5) = 0.03$
w_6	\models	c_3	b_2	f	$\sim d$	e	$P(w_6) = 0.02$

$$P(e) = 0.45 + 0.27 + 0.03 + 0.02 = 0.77$$

Belief Networks, Decision trees and ICL rules

- There is a local mapping from belief networks into ICL.
- Rules can represent decision tree representation of conditional probabilities:



$$e \leftarrow a \wedge b \wedge h_1.$$

$$P_0(h_1) = 0.7$$

$$e \leftarrow a \wedge \sim b \wedge h_2.$$

$$P_0(h_2) = 0.2$$

$$e \leftarrow \sim a \wedge c \wedge d \wedge h_3.$$

$$P_0(h_3) = 0.9$$

$$e \leftarrow \sim a \wedge c \wedge \sim d \wedge h_4.$$

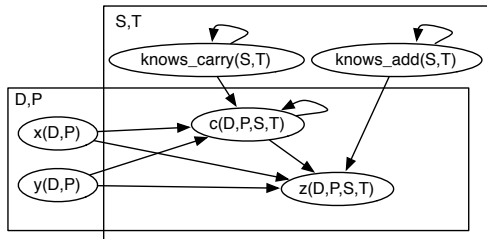
$$P_0(h_4) = 0.5$$

$$e \leftarrow \sim a \wedge \sim c \wedge h_5.$$

$$P_0(h_5) = 0.3$$

Example: Multi-digit addition

$$\begin{array}{r} x_{j_x} \quad \cdots \quad x_2 \quad x_1 \\ + \quad y_{j_z} \quad \cdots \quad y_2 \quad y_1 \\ \hline z_{j_z} \quad \cdots \quad z_2 \quad z_1 \end{array}$$



ICL rules for multi-digit addition

$$\begin{aligned} z(D, P, S, T) = V \leftarrow \\ x(D, P) = V_x \wedge \\ y(D, P) = V_y \wedge \\ c(D, P, S, T) = V_c \wedge \\ \text{knows_add}(S, T) \wedge \\ \neg \text{mistake}(D, P, S, T) \wedge \\ V \text{ is } (V_x + V_y + V_c) \text{ div } 10. \end{aligned}$$

$$\begin{aligned} z(D, P, S, T) = V \leftarrow \\ \text{knows_add}(S, T) \wedge \\ \text{mistake}(D, P, S, T) \wedge \\ \text{selectDig}(D, P, S, T) = V. \\ z(D, P, S, T) = V \leftarrow \\ \neg \text{knows_add}(S, T) \wedge \\ \text{selectDig}(D, P, S, T) = V. \end{aligned}$$

Alternatives:

$$\forall DPST \{ \text{noMistake}(D, P, S, T), \text{mistake}(D, P, S, T) \}$$

$$\forall DPST \{ \text{selectDig}(D, P, S, T) = V \mid V \in \{0..9\} \}$$