

Lecture 17.4: Relational Representations

- Probabilistic Logic Programs
- Weighted Logical Formulae
- Graph Neural Networks
- Existence and Identity Uncertainty

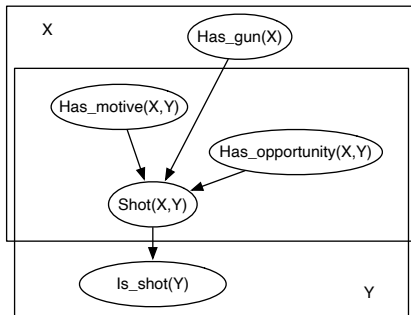
Probabilistic Logic Programs

- the model is described in terms of a logic program with parametrized independent **noise variables**.
- Plates correspond to logical variables.
- Parametrized random variables are represented as logical atoms,
- A Turing-complete language for relational probabilistic models.
- Extends Datalog / logic programs to include probabilities.

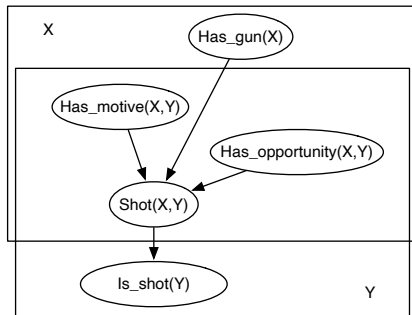
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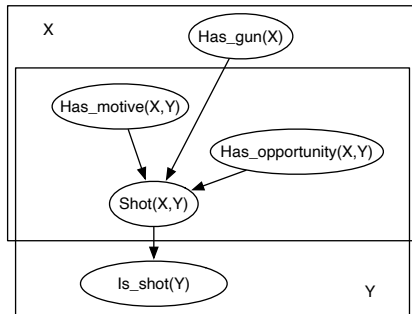


$is_shot(Y) \leftarrow shot_by_no_one(Y)$

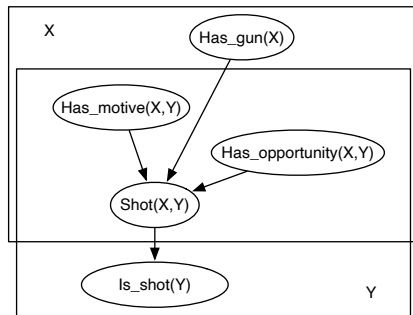
$is_shot(Y) \leftarrow shot(X, Y) \wedge shot_succeeds(X, Y)$

Each ground instance of $shot_by_no_one(Y)$ and $shot_succeeds(X, Y)$ are independent **noise variables**.

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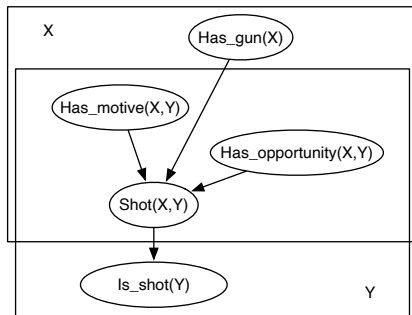
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$$shot(X, Y) \leftarrow has_motive(X, Y) \wedge has_gun(X) \\ \wedge has_opportunity(X, Y) \wedge actually_shot(X, Y).$$

$P(actually_shot(X, Y))$ is the probability that X would shoot Y if they had a motive, gun, and opportunity.

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- Other rules could cover other cases, such as where X doesn't have a motive.

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- A conditional probability, $P(x \mid obs)$ is the measure of the worlds in which x is true out of the worlds in which obs is true.

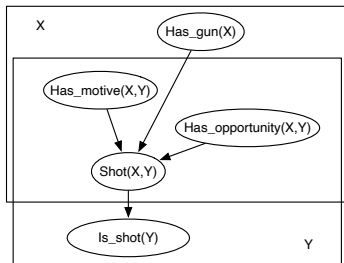
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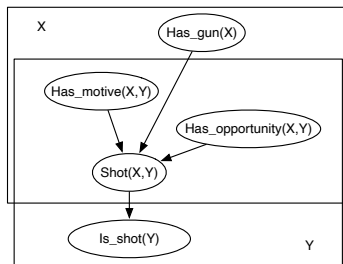
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- A conditional probability, $P(x \mid obs)$ is the measure of the worlds in which x is true out of the worlds in which obs is true.
- In **relational logistic regression**, the weighted formulae are used to define conditional probabilities.

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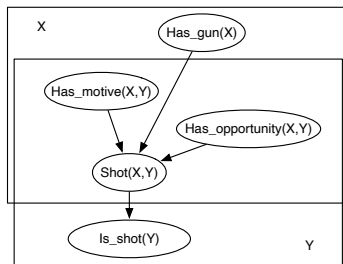
$$(is_shot(Y), w_0)$$

$$(is_shot(Y) \vee \neg shot(X, Y), w_1)$$

$$(shot(X, Y) \vee \neg has_motive(X, Y) \vee \neg has_gun(X)$$

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$P(is_shot(v) \mid shot(p_1, v), \dots, shot(p_n, v))$ is logistic regression if p_1, \dots, p_n are all the individuals.

Graph Neural Networks

- **Graph neural networks** are neural networks that act on graph data.
- Each node has an embedding that is inferred from parametrized linear functions and activation functions of the node's neighbors, and their neighbors, to some depth.
- A **relational graph convolutional network (R-GCN)** is used to learn embeddings for **knowledge graphs**, where nodes are entities and arcs are labelled with relations.

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- Called *convolutional* because the same learnable parameters are used for each entity.

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where

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- ▶ $W_r^{(L)}$ is a matrix for relation r for layer L , which is multiplied by the vector $h_n^{(L)}$ for each neighbor n .
- ▶ $C_{e,r}$ is a normalization constant, such as $|\{n : (e, r, n) \in KG\}|$, which gives an average for each relation.

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- **Question:** Is summing or averaging an appropriate way to aggregate the embeddings of related entities? Would something else be more appropriate?

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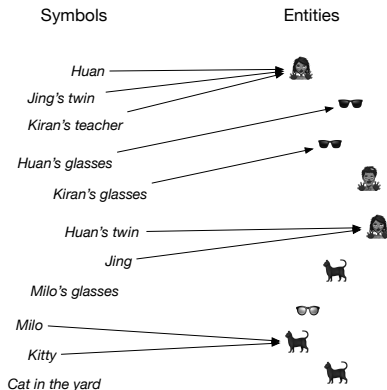
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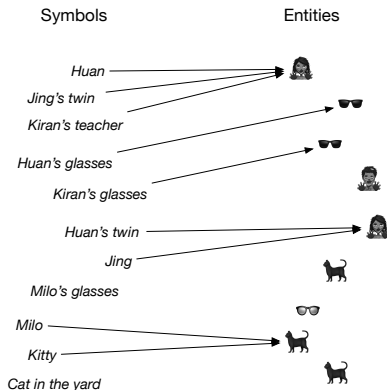
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- **Number uncertainty** concerns uncertainty as how many entities fit a description

Existence and Identity Example



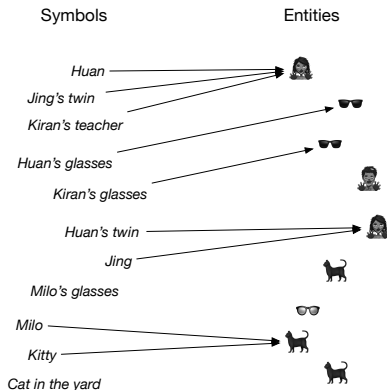
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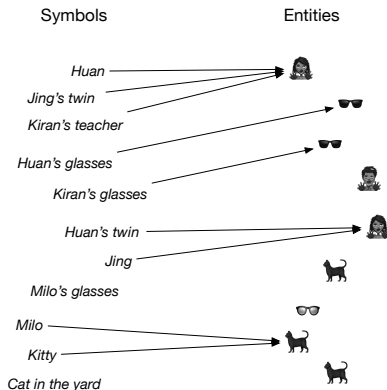
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- *Huan* = *Jing's twin*, because they denote the same entity.
- *Huan's glasses* \neq *Kiran's glasses*, because they denote different pairs of glasses
- *Milo's glasses* do not exist; Milo doesn't have a pair of glasses.

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- Use **Markov-chain Monte Carlo (MCMC)**: given a partition, entities can be moved to different partitions or to new partitions.

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- E.g., finding an apartment for Sam and Sam’s child Chris. Preference depend on Sam’s bedroom and Chris’s bedroom. Apartments don’t come labelled with whose bedroom it is.