Scripts Plans Goals and Understanding

An Inquiry into Human Knowledge Structures

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Script

The important components for a script are:

- Entry conditions: conditions to be satisfied before the event described in script can occur.
- Results: Conditions that are true once the script has terminated.

Script: RESTAURANT

Entry conditions:

S is hungry. S has money.

Resulls:

S has less money.

O has more money.

S is not hungry.

S is pleased (optional).

Script

The important components for a script are:

- Tracks: Variations on the script. Different tracks may share components of the same script.
- Props: Slots that support the content of the script.
- Roles: Slots representing the individual participants involved in the event described in the script.

Script: RESTAURANT

Track: Coffee Shop

Props: Tables

Menu

F = Food

Check

Money

Roles: S = Customer

W = Waiter

C = Cook

M = Cashier

O = Owner

Script

The important components for a script are:

• **Scenes:** The sequence of events that occurred.

Scene 1: Entering
S PTRANS S into restaurant
S ATTEND eyes to tables
S MBUILD where to sit
S PTRANS S to table
S MOVE S to sitting position

ATRANS - transfer a relationship (give).

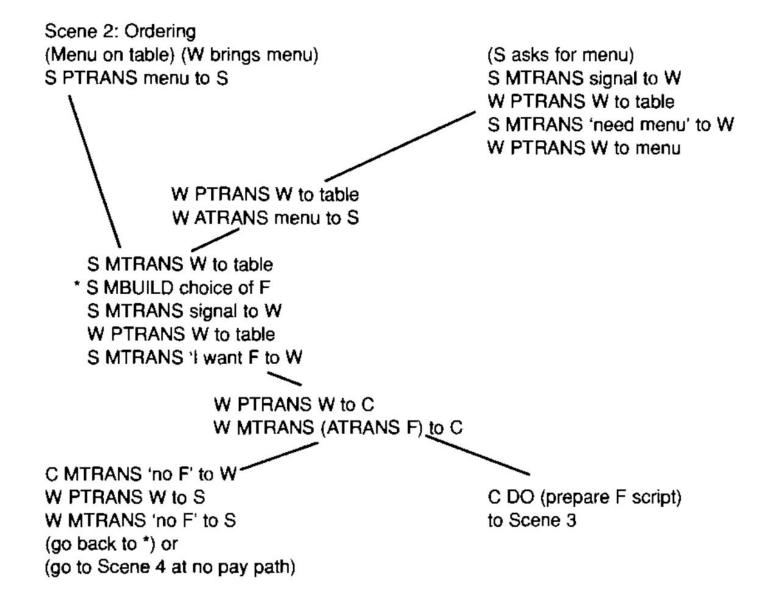
PTRANS - transfer physical location of an object (go).

MOVE - move body part by owner (kick).

MTRANS - transfer mental information (tell).

MBUILD- mentally make new information (decide).

ATTEND - focus sense organ (listen).



ATRANS - transfer a relationship (give). PTRANS - transfer physical location of an object (go). MOVE - move body part by owner (kick).

MTRANS - transfer mental information (tell). MBUILD- mentally make new information (decide). ATTEND - focus sense organ (listen).

Scene 3: Eating C ATRANS F to W W ATRANS F to S S INGEST F

(Option: Return to Scene 2 to order more;

otherwise, go to Scene_4)

Scene 4: Exiting

S MTRANS to W

(W ATRANS check to S)

W MOVE (write check)

W PTRANS W to S

W ATRANS check to S

S ATRANS tip to W

S PTRANS S to M

S ATRANS money to M

(No pay path) S PTRANS S to out of restaurant

Description Logics

Description logics (DLs)

- Description logics (DLs) are a formal knowledge representation family.
- DL is designed to describe definitions and properties about categories
- Principal inference tasks:
 - Subsumption: check if one category is the subset of another
 - <u>Classification</u>: check whether an object belongs to a category
 - <u>Consistency</u>: check if category membership criteria are satisfiable
- DLs have their origins in semantic nets and frame-based languages.

DL fundamental components

- Concepts: Concepts represent sets or classes of objects in a domain, characterizing common properties shared by individuals.
 - They define what kinds of individuals belong to a particular category.
 - For example, "Person" is a concept representing the category of human beings.

DL fundamental components

- Roles: Roles represent binary relationships or properties connecting individuals in the domain.
 - Roles describe how individuals are related to each other.
 - For example, "hasParent" is a role representing the relationship between a child and their parent.

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- Roles: Roles represent binary relationships or properties connecting individuals in the domain.
 - Roles describe how individuals are related to each other.
 - For example, "hasParent" is a role representing the relationship between a child and their parent.
- Individuals: Individuals are specific objects or instances in the domain, each of which can belong to one or more concepts.
 - For example, "John" and "Mary" are individuals that belong to the concept "Person."

CLASSIC language

The CLASSIC language (Borgida et al., 1989) is a typical description logic.

```
Concept \rightarrow Thing \mid ConceptName
                     And(Concept,...)
                     All(RoleName, Concept)
                     AtLeast(Integer, RoleName)
                     AtMost(Integer, RoleName)
                     Fills(RoleName, IndividualName, . . . )
                     SameAs(Path, Path)
                     OneOf(IndividualName,...)
          Path \rightarrow [RoleName,...]
ConceptName \rightarrow Adult \mid Female \mid Male \mid \dots
   RoleName \rightarrow Spouse \mid Daughter \mid Son \mid ...
```

Figure 10.6 The syntax of descriptions in a subset of the CLASSIC language.

Example: bachelors are unmarried adult males we would write

$$Bachelor = And(Unmarried, Adult, Male)$$
.

The equivalent in first-order logic would be

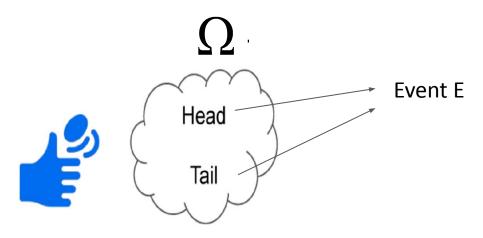
$$Bachelor(x) \Leftrightarrow Unmarried(x) \land Adult(x) \land Male(x)$$
.

• **Example:** the set of men with at least three sons who are all unemployed and married to doctors, and at most two daughters who are all professors in physics or math departments

```
And(Man, AtLeast(3, Son), AtMost(2, Daughter), \\ All(Son, And(Unemployed, Married, All(Spouse, Doctor))), \\ All(Daughter, And(Professor, Fills(Department, Physics, Math)))).
```

Bayesian Belief Networks

Probability



Sample Space = {Head, Tail}

Rules of Probability

(1) Non-negative: $P(E) \ge 0$

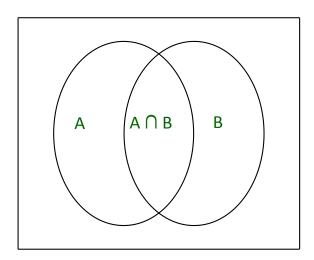
(2) Addition: $P(E \cup F) = P(E) + P(F)$ if $E \cap F = \emptyset$

(3) Total one: $P(\Omega) = 1$

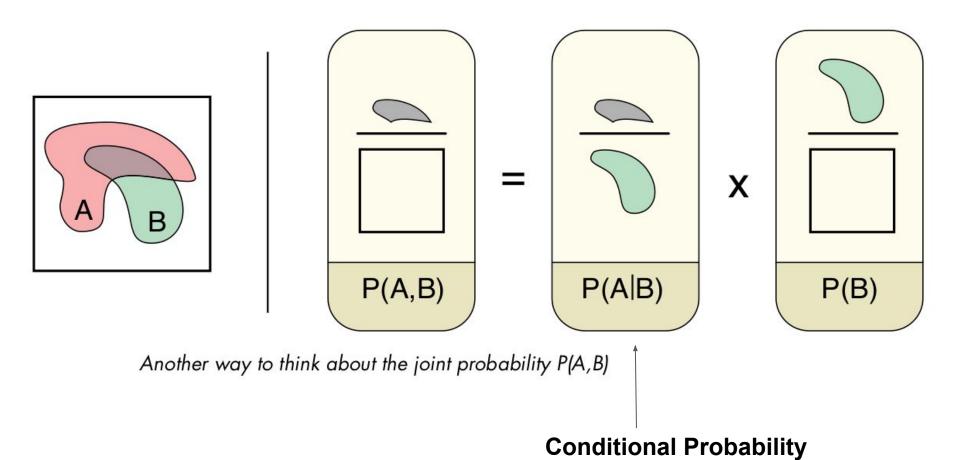
Probability

Complement Rule: $P \text{ (not A)} = P \text{ (A}^c) = 1 - P \text{ (A)}$

Inclusion-Exclusion: $P(A \cup B) = P(A) + P(B) - P(A \cap B)$



Joint probability P(A,B)



$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

Why it is useful?

$$P(Cause|Effect) =$$

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

Conditional Probability
$$P(X|Y) = \frac{P(X,Y)}{P(Y)}$$

Deriving Bayes theorem

$$P(Y|X)P(X) = P(X|Y)P(Y)$$

$$\Rightarrow P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

Why it is useful?

$$P(Cause|Effect) = \frac{P(Effect|Cause)P(Cause)}{P(Effect)}$$

After a yearly checkup, a doctor informs their patient that he has both bad news and good news. The bad news is that the patient has tested positive for a serious disease and that the test that the doctor has used is 99% accurate (i.e., the probability of testing positive when a patient has the disease is 0.99, as is the probability of testing negative when a patient does not have the disease). The good news, however, is that the disease is extremely rare, striking only 1 in 10,000 people.

- What is the actual probability that the patient has the disease?
- Why is the rarity of the disease good news given that the patient has tested positive for it?

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$$P(d) = 0.0001 (disease)$$

$$P(t|d) = 0.99$$
 (testing positive given disease)

$$P(d|t) = \frac{P(t|d)P(d)}{P(t)}$$

$$P(t) = P(t|d)P(d) + P(t|\neg d)P(\neg d)$$

= $(0.99 \times 0.0001) + (0.01 \times 0.9999) = 0.0101$

$$P(d|t) = \frac{0.99 \times 0.0001}{0.0101} = 0.0098$$

Chain Rule

$$P(\mathbf{q}_1, \dots, \mathbf{q}_m) =$$

$$P(\mathbf{q}_1) \times P(\mathbf{q}_2 | \mathbf{q}_1) \times \cdots \times P(\mathbf{q}_m | \mathbf{q}_{m-1}, \dots, \mathbf{q}_2, \mathbf{q}_1)$$

Chain Rule

$$P(\mathbf{q}_1, \dots, \mathbf{q}_m) = P(\mathbf{q}_1) \times P(\mathbf{q}_2 | \mathbf{q}_1) \times \cdots \times P(\mathbf{q}_m | \mathbf{q}_{m-1}, \dots, \mathbf{q}_2, \mathbf{q}_1)$$

► To apply the chain rule to a conditional probability we just add the conditioning term to each term in the expression:

$$P(\mathbf{q}_{1},...,\mathbf{q}_{m}|t=I) = P(\mathbf{q}_{1}|t=I) \times P(\mathbf{q}_{2}|\mathbf{q}_{1},t=I) \times ...$$

$$... \times P(\mathbf{q}_{m}|\mathbf{q}_{m-1},...,\mathbf{q}_{3},\mathbf{q}_{2},\mathbf{q}_{1},t=I)$$

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

likelihood of t given a given features

Generalized Bayes' Theorem

allzed Bayes' Theorem
$$P(t = I | \mathbf{q}_1, \dots, \mathbf{q}_m) = \frac{P(\mathbf{q}_1, \dots, \mathbf{q}_m | t = I)P(t = I)}{P(\mathbf{q}_1, \dots, \mathbf{q}_m)}$$
Normalising

posterior probability: degree of belief after knowing $(\mathbf{q}_1, \dots, \mathbf{q}_m)$

Table: A simple dataset for MENINGITIS diagnosis with descriptive features that describe the presence or absence of three common symptoms of the disease: HEADACHE, FEVER, and VOMITING.

| ID | HEADACHE | FEVER | Vomiting | MENINGITIS |
|----|----------|-------|----------|------------|
| 1 | true | true | false | false |
| 2 | false | true | false | false |
| 3 | true | false | true | false |
| 4 | true | false | true | false |
| 5 | false | true | false | true |
| 6 | true | false | true | false |
| 7 | true | false | true | false |
| 8 | true | false | true | true |
| 9 | false | true | false | false |
| 10 | true | false | true | true |

Meningitis is a serious disease

$$\mathbf{P}(H, F, V, M) = \begin{bmatrix} P(h, f, v, m), & P(\neg h, f, v, m) \\ P(h, f, v, \neg m), & P(\neg h, f, v, \neg m) \\ P(h, f, \neg v, m), & P(\neg h, f, \neg v, m) \\ P(h, f, \neg v, \neg m), & P(\neg h, f, \neg v, \neg m) \\ P(h, \neg f, v, m), & P(\neg h, \neg f, v, m) \\ P(h, \neg f, v, \neg m), & P(\neg h, \neg f, v, \neg m) \\ P(h, \neg f, \neg v, m), & P(\neg h, \neg f, \neg v, m) \\ P(h, \neg f, \neg v, \neg m), & P(\neg h, \neg f, \neg v, \neg m) \end{bmatrix}$$

$$P(M|h, \neg f, v) = ?$$

In the terms of Bayes' Theorem this problem can be stated as:

$$P(M|h,\neg f,v) = \frac{P(h,\neg f,v|M) \times P(M)}{P(h,\neg f,v)}$$

► There are two values in the domain of the MENINGITIS feature, 'true' and 'false', so we have to do this calculation twice.