# Indexing strategies for goal specific retrieval of cases

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**Abstract**
We extend the generalization-based memory framework by elaborating on the types of memory indices. In particular, we distinguish between indices that are useful for retrieving schemata that predict the outcome of some event from those indices that are useful for explaining how a particular event occurs. In addition, we augment each memory index with a description of the class of goals for which the indexed schemata or event will serve as a relevant exemplar. There are several benefits to these extensions to the generalization-based memory framework. First, a single case in memory can be retrieved as an exemplar for several different goals. Second, the phenomenon that examples can be retrieved more easily when the type of processing performed during understanding (and encoding) is the same as the type of processing for retrieval is accounted for by including a description of the goal of the encoding context with each index. Finally, in addition to retrieving the most similar relevant case in memory, the least similar relevant case can be retrieved. The least similar relevant case supports arguments about predicted outcome by helping to illustrate the scope of the predicted outcome. The least similar case can be used to demonstrate that differences between the current situation and the most similar case are irrelevant to the predicted outcome.

## INTRODUCTION

Consider how the example of the US grain embargo with the Soviet Union can be used for more than one purpose. It can support arguments that indicate the conditions under which economic sanctions will fail, or support arguments about the type of situation in which a country will try economic coercion to achieve political goals. In order to retrieve the US grain embargo as part of an answer to both of these questions, it is necessary to index this one example in multiple places in memory. The following conversation with OCCAM [1] [2] illustrates both of these uses[1]:

```
Question:  What would happen if the United States refused  to sell
           computers to South Korea unless South Korea stopped
           exporting automobiles to Canada?

OCCAM:     The goal of the United States that South Korea not sell
           automobiles to Canada will fail and South Korea will
           purchase computers from a country which exports
           computers.  This happened when the United States did not
           sell grain to the Soviet Union after the Soviet Union
           invaded Afghanistan. Argentina sold grain to the Soviet
           Union.  Also, Australia did not sell uranium to France
           after France exploded nuclear weapons in the South
           Pacific.  South Africa sold uranium to France.
```

1. The answer to the first question is similar to one produced by a political analyst of the RAND corporation. The answer tothe second question is admitted simplistic and reflects the fact that OCCAM's memory does not contain a wide range of political options. OCCAM's answers have been edited slightly, by including tense information on verbs.

```
Question:  What would the United States do if Turkey invaded
           Cyprus?

OCCAM:     The United States would refuse to sell a commodity to
           Turkey if Turkey invaded Cyprus. This happened when
           Greece invaded Bulgaria.  The League of Nations refused
           to sell food to Greece. Also, when the Soviet Union
           invaded Afghanistan, the United States refused to sell
           grain to the Soviet Union.
```

Research on human memory retrieval has shown that retrieval is influenced by the processing task at storage time [3] [4] [5]. Prior experiences are more difficult to retrieve if the goals at storage and retrieval time are different [6]. For computer models of memory, this implies that to retrieve a case as a precedent for more than one purpose, it is necessary to index the case in more than one manner and to include a description of the encoding context in the index. The creation of indices by explanation-based techniques can accomplish this by explaining more than one aspect of a case. At storage time, several different *target concepts* [7] can focus the learning process on explaining different parts of an episode. For example, to predict the outcome of future incidents it is necessary to explain why previous incidents fail or succeed. By also explaining why the actor tried economic sanctions rather than some other action (e.g., military force), an event can be indexed in memory in more than one place and serve as a precedent for more than one task.

## EXPLANATORY AND PREDICTIVE INDICES

In this extension to OCCAM, there are two types of indices. A *predictive* index is traversed to find a schemata that describes the result of a given event. An *explanatory* index is traversed to find a schemata that describes the cause (i.e., the explanation) of a given event. These indices are similar in spirit of the predictive and predictable features used in UNIMEM. However, there is one important difference. In UNIMEM, this information is determined empirically: the predictive features are those characteristic features of a generalization that are unique (or nearly unique) to that generalization. The predictable features appear in many generalizations. The idea is that the predictive features are likely to be the cause of the predictable features [8]. In OCCAM, this information is derived analytically in one of two ways. First, in the absence of background knowledge, a generalized event sequence is formed by similarity-based learning. In this case, the features of the predictive component must temporally precede the explanatory component (see [9] for a more detailed discussion). Second, when there is prior background knowledge, a generalized event sequence is formed by explanation-based learning. In this case, the predictive features are those that appear in the antecedent of rules that are used to create a generalization with explanation-based learning. The explanatory features appear in the consequent. Figure 1 illustrates one inference rule which is used in part of an explanation to explain why the US grain embargo with the Soviet Union failed.

When a generalization of the US grain embargo is constructed by explanation-based learning, it is indexed by predictive features (e.g., `economic-health of the target country = strong`, `availability of the commodity = common`). The schema formed from generalizing the US grain embargo can be retrieved via predictive indices to make predictions about future or hypothetical cases. The generalization will also be indexed by explanatory features (e.g., `price of the commodity = >market`). Similar distinctions have been made by Pearl [10] who distinguishes causal and evidential support and by Tversky and Kahneman [11] who find that people treat causal and diagnostic evidence differently.

```
(state type (demand-increase)
       actor ?x: (polity economic-health (strong))
       object ?y: (commodity availability(common)))
```

Enables

```
(act type (sell)
     actor (polity exports ?y
                   business-rel ?x)
     to ?x
     object ?y
     price (money value (>market)))
```

**Figure 1.** An inference rule that indicates that an increased demand for a commonly available commodity by a country with a strong economy enables a country which exports the commodity to sell the commodity at a greater than market rate.

## GOALS IN INDEXING

In the previous section, we distinguished between explanatory and predictive indices. In this section, we describe an extension to OCCAM that allows multiple facets of a single example to be explained or predicted. In a complex event, such as an economic sanctions incident, there are a number of actions which need to be explained. For example, one could ask why the actor decided on this method of coercion In addition, one could ask why the coercion succeeded or failed. For example, consider what happens when OCCAM processes the example of the US grain embargo.

OCCAM first explains why the US decided to respond in this manner. Using explanation-based learning techniques a new schema is created to predict a type of threat one might use to coerce a country to withdraw troops. This schema is indexed under the general coercion schema by predictive indices that makes use of features of the actor and target countries. The predictive indices will allow questions such as "What might the US do if Turkey invaded Cyprus?" to be answered. Associated with the predictive indices is an encoding context, (i.e., the features of the example which needed to be explained). The encoding context in this case is represented by the goal of explaining why the threat was made. An explanatory index for the type of threat is also created. The explanatory index will allow questions such as "Why might a country refuse to sell a product?" to be answered. The actual grain embargo incident is stored in memory under this newly created schema.

Next, OCCAM creates a schema by explanation-based learning to indicate why this incident failed. For this schema, the threat is a predictive index (as well as the actor, target and demand) and the outcome is used as a explanatory index. The predictive indices allow retrieval of the schema to answer questions such as "What would happen if the US refused to sell computers to South Korea if South Korea did not stop automotive exports to Canada?". The explanatory index can be used to retrieve the schema to answer questions such as "When do economic sanctions fail to achieve the desired goal?". The encoding context in this case represents the goal of explaining why the outcome occurred. The economic sanctions incident is also stored under this newly created schema.

Figure 2 shows the location of the US grain embargo in memory after a number of other sanctions incidents have been added. In this figure, the indices with arrows are explanatory and the remainder are predictive. Indices whose encoding context is the `threat` are shown by bold lines; the encoding context of the remaining indices from the coerce schema is the `outcome`.

Note that are a variety of different reasons for implementing the threat in the schema representing failures due to a wealthy target country bidding the price up until a new supplier is found. Similarly, there are a variety of outcomes in those sanctions incidents which were implemented to stop (or penalize) a military invasion. These schemata also illustrate the reason that generalized events are created with explanation-based rather than similarity-based techniques, when possible, in OCCAM. If similarity-based techniques were used, then additional irrelevant features could be included in the generalized event of the schemata for sanctions that failed because a wealthy country found the product elsewhere. In all of the examples seen so far, the target country exports arms and the actor's native language is English. These irrelevant features could prevent the retrieval of cases or the application of a generalization in situations which do not share the same irrelevant features.

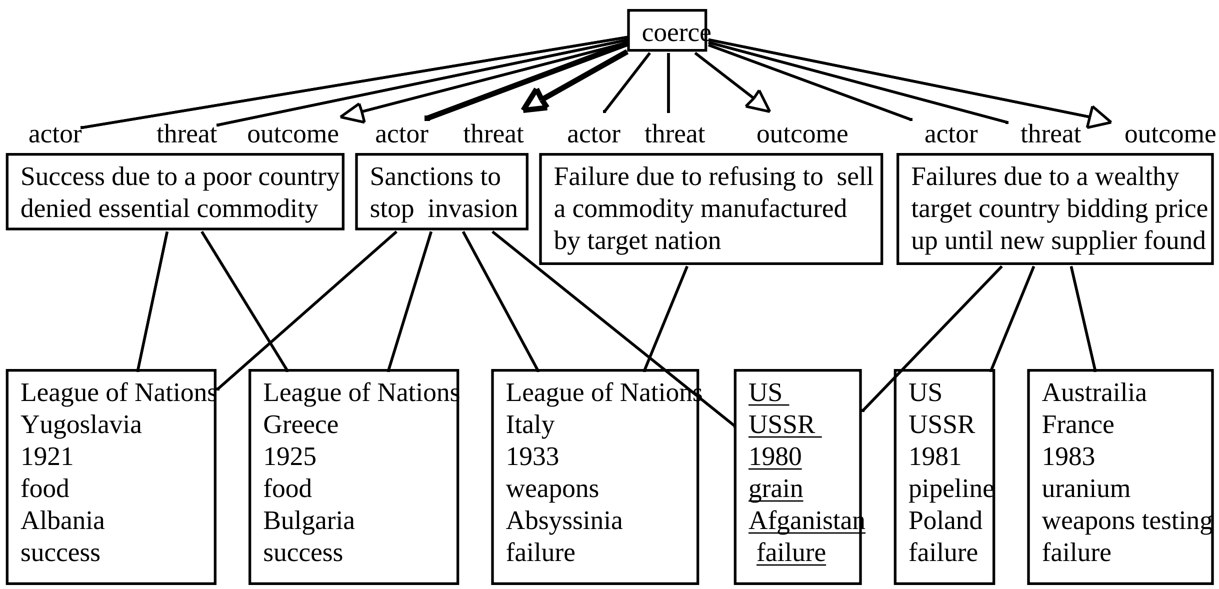


**Figure 2.** The location of the US grain embargo with the Soviet Union (underlined) in memory. In this figure, the indices that predict or explain the response are shown in bold. The indices that that predict or explain the outcome are not in bold. Explanatory indices have arrowheads; predictive indices do not.

The strategy of including the goal with an index is derived from the work on case-based planning [12] [13] in which the goal serves as the index for retrieving plans to achieve some goal. In this work, an index is composed of the relevant surface features of an event and the goal for which the features are relevant.

## Retrieval of Cases and Generalized Events

To answer questions, OCCAM uses the features of the hypothetical event as indices to search memory for a relevant experience [14] [15]. In addition, the goal associated with the encoding context of indices which are traversed must match the current understanding goal. OCCAM retrieves a schema that includes a generalized explanation for this type of situation. The generalized explanation is instantiated for the hypothetical case to explain how South Korea will be able to work around the sanction attempt. The schema also organizes previous cases which can be retrieved. OCCAM describes the most similar precedent first, followed by the most dissimilar case. The idea here is that it is easy for the person who asked the question to recognize that the most similar incident is applicable to the question. The argument for the predicted outcome is strengthened by providing this similar incident. However, the argument can be further strengthened by presenting the least similar example with the same outcome for the same reason. Note that the types of indices discussed in this paper make it possible to distinguish between the most dissimilar event and the most dissimilar relevant event. The most dissimilar relevant event supports the claim that the differences between the new case and most similar case are irrelevant and helps to define the range of situations that will be considered similar.

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