**OBJECTIVES**

By the end of this module, you should be able to:

* Recognize six classes of decisions
* Understand the core challenges of each class of decision
* Recognize the decision classification leads to analytical tools

**THE CHALLENGE**

If we had to carefully analyze every single decision problem as if it was entirely novel to us, we would be overwhelmed. That’s the advantage of Kahneman’s System 1 thinking, because it internalizes a lot of the analysis. Not all decisions are novel to us—even though the circumstances might be different, we often recognize the general shape of the problem.

How many kinds of decisions are there, really? Is it infinite? Or are there a fairly small number of types of decisions? Can we learn to recognize that small set of classes?

One of the things a decision analyst can bring to the table is the experience of having seen many types of decisions, which leads to the ability to recognize classes of decisions and help a decision maker see the structure of the decision and the tasks that solving it will require.

In this course, we focus on six types of decisions. For each class of decision, there are specific challenges or impediments in making the decision, and there are analytical tools for tackling these challenges.

**CLASSES OF DECISIONS AND THEIR PROPERTIES**

***Prediction Problems***

* *Description*

The issue of developing predictions lies at the heart of all classes of decisions (see Module 7:

Consequences), but sometimes it’s the main issue. The search for the solution is by inspection

* *Challenge*

“It’s tough to make predictions, especially about the future” (Yogi Berra or Niels Bohr?).

* *Tools*

Data analysis and model building

Linear Programming

* *Example*

Indiana Bat Model Request‐for‐proposals (SDM Workshop, December 2008). See Thogmartin et al.

(2013).

***Multiple‐objective Problems***

* *Description*

The issue here it to figure out how to trade off competing objectives. These are the most common problems in natural resource management decisions.

* *Challenge*

The scientific challenge is to forecast the outcomes are on all objectives. How do the

objectives compete with one another, and what are the conflicts that cannot be avoided? The values‐based challenge is to figure out how to deal with those trade‐offs. Which objectives are most important? How much of one objective would you give to gain a certain amount of another objective?

* *Tools*

The whole field of multi‐criteria decision analysis (MCDA) and all the various tools it includes. We’ll be focusing on an approach that uses an additive utility model called SMART (Simple Multi‐Attribute Rating Technique), but there are others (MAUT, multi‐attribute utility theory; AHP, Analytic Hierarchy Process; outranking procedures, etc.).

* *Example*

The Bureau of Reclamation’s 2011 Environmental Assessment of non‐native fish control below Glen Canyon Dam used MCDA to balance a large range of objectives (Runge et al. 2011a).

***Portfolio Problems***

* *Description*

The issue here is having to search among a huge number of possible alternatives. There are

many different versions of this sort of problem, including resource allocation problems (e.g., budget, reserve design), and other kinds of portfolio selection problems. One common way these come up is as “prioritization problems”, which are not in themselves decisions, but might give rise to a portfolio selection decision.

* *Challenge*

There are a number of challenges with this class of problem, including (a) describing (if not fully enumerating) all the alternatives; (b) predicting, in some automated manner, the

outcomes of any particular alternative; (c) smartly searching among all the possible alternatives for the optimal solution.

* *Tools*

Linear programming and other constrained optimization methods

Solutions for “knapsack problems” (combinatorial optimization)

* *Example*

The FWS R1 Washington Field Office developed a method for allocating staff time to bull trout Section 7 consultations (SDM Workshop, July 2007). See Converse et al. (2011).

***Risk Problems***

* *Description*

This class of problems involves making decisions in the face of uncertainty when you do not have any other choice. These are probably more common than the set of analyzed problems would show, because people have an unbelievable tendency to just delay the decision. “Unknown unknown” problems also fit in this class, but it’s not clear that they have any possible solution.

* *Challenge*

The scientific challenge is to characterize the uncertainty in the outcomes as a function of the action taken. The values‐related challenge is to understand the risk tolerance of the decision‐maker.

* *Tools*

Decision trees

Utility theory

* *Example*

Bighorn sheep disease management in Montana (SDM Workshop September 2010, Mitchell et al.

2013)

***Information Problems***

* *Description*

In this class of problems, there is a decision in the face of uncertainty, and the question is whether it’s useful to gather more information before making a decision and if so, what information to gather. This issue is at the center of adaptive management and monitoring design problems. It also could be used to develop an applied research agenda.

* *Challenge*

The technical challenge is to figure out how much the expected outcome of a decision could be improved if uncertainty could be resolved prior to committing to an action.

* *Tools*

Expected value of perfect information, and related techniques

* *Example*

Evaluation of breeding failure in the reintroduced whooping crane population in Wisconsin (Runge et al. 2011b)

***Dynamic Problems***

* *Description*

Some decisions occur in a repeated manner or are somehow linked across time (and space). The optimal decision at time one will depend on what all the subsequent decisions will be. Thus, the issue is the temporal linkage across multiple decisions and how to find a solution that balances short‐term and longterm returns in an appropriate manner. Adaptive management is a special case of a dynamic problem, in which short‐term learning (perhaps at the expense of other objectives) could pay off in terms of better achievement of objectives over the long term.

* *Challenge*

One of the biggest challenges is the optimization itself: finding an optimal solution that

accounts for the trade‐off between the short‐term costs and the long‐term benefits.

* *Tools*

Dynamic programming and related methods

* *Example*

The annual setting of duck harvest regulations in the United States is supported by a formal application of stochastic dynamic programming (Johnson et al. 1997).

**REAL PROBLEMS**

Real problems, of course, are often hybrids of the different classes of decisions. For instance, adaptive harvest management (Johnson et al. 1997) is a dynamic decision that also deals with risk, the potential to gain information, and of course, prediction. As an added bonus, although the objective function looks like it’s a single objective, there are really three objectives bundled into a single formula.

**SOME THINGS ARE NOT DECISION PROBLEMS**

Not everything is a decision problem, and thus, not everything should be solved with decision analysis. This can be a pretty subtle realization at times, because there are a number of things that can look an awful lot like something SDM should handle.

* *Dispute*

Dispute can look a great deal like a multiple‐objective problem. In some sense it is, but the difference is that there isn’t a single decision‐maker trying to trade‐off objectives, there are stakeholders who have different values positions that result in conflict. Other techniques (conflict resolution, mediation, negotiation) are needed.

* *Governance problems*

Problems with or disputes over who has the authority to make a decision are not decision problems, they are governance problems. The tools of decision analysis do not provide a solution.

* *Competitive games*

There can be multiple, independent decision makers whose decision affect a common resource.

They may have little interest in cooperating, and might, in fact, be in competition. In this situation, use of structured decision making may just provide a process for the players to manipulate one another.

**REFERENCES**

Converse SJ, Shelley KJ, Morey S, Chan J, LaTier A, Scafidi C, Crouse DT, Runge MC. 2011. A decision

analytic approach to the optimal allocation of resources for endangered species consultation. Biological Conservation 144:319‐329.

Johnson FA, Moore CT, Kendall WL, Dubovsky JA, Caithamer DF, Kelley JR, Jr., Williams BK. 1997.

Uncertainty and the management of mallard harvests. Journal of Wildlife Management 61:202‐216.

Mitchell MS, Gude JA, Anderson NJ, Ramsey JM, Thompson MJ, Sullivan MG, Edwards VL, Gower CN,

Cochrane JF, Irwin ER. 2013. Using structured decision making to manage disease risk for Montana wildlife. Wildlife Society Bulletin 37:107‐114.

Runge MC, Bean E, Smith DR, Kokos S. 2011a. Non‐native fish control below Glen Canyon Dam—report

from a structured decision making project. U.S. Geological Survey Open‐File Report 2011‐1012, 74 p.

Runge MC, Converse SJ, Lyons JE. 2011b. Which uncertainty? Using expert elicitation and expected value

of information to design an adaptive program. Biological Conservation 144:1214‐1223.

Thogmartin WE, Sanders‐Reed CA, Szymanski JA, McKann PC, Pruitt L, King RA, Runge MC, Russell RE.

2013. White‐nose syndrome is likely to extirpate the endangered Indiana bat over large parts of its range. Biological Conservation 160:162‐172.

**MODULE DEVELOPED BY:**

Michael C. Runge, *USGS Patuxent Wildlife Research Center*

Suggested Citation for this Module:

Runge MC. 2016. Overview of decision classes. Module 8 *in* Runge MC, Romito AM, Breese G, Cochrane

JF, Converse SJ, Eaton MJ, Larson MA, Lyons JE, Smith DR, Isham AF, eds. Introduction to Structured Decision Making, 2016 edition. U.S. Fish and Wildlife Service, National Conservation Training Center, Shepherdstown, West Virginia, USA.