Purpose

The purpose of this application is to help users improve their ability to assess uncertainty.

Rationale: Why is important to be able to assess uncertainty well?

Life, business, and, in particular, the petroleum business, are full of uncertainty. Life and business decisions are made in the midst of uncertainty.

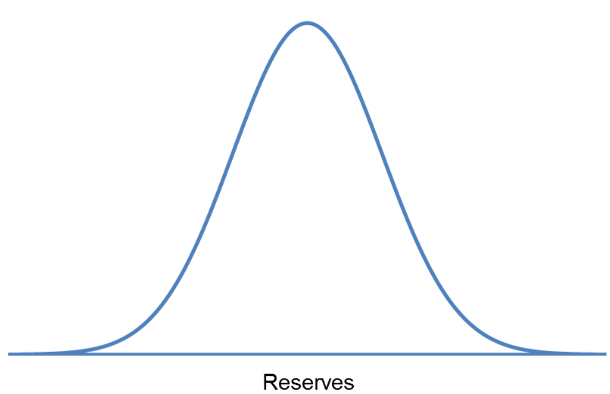
A decision consists of choices, uncertain outcomes, and values (payoffs) associated with each combination of choice and uncertain outcome. A simple decision for drilling a well is shown in the following table. For simplicity in this example, the uncertain outcome, reserves, is considered to have only two possible outcomes.

		NPV ($ millions) for different choices	
Possible outcome	Probability	Drill well	Don't drill well
Good well	70%	15	0
Bad well	30%	-10	0

The uncertainty in reserves in this example is expressed quantitatively in terms of probabilities. Quantifying uncertainty allows the decision maker to assess the upside potential and downside potential (risk) associated with the decision in order to make a good decision.

There are two fundamental types of probabilistic assessments: discrete and continuous. In the example above, the possible outcomes were expressed in terms of two discrete, exhaustive, mutually-exclusive outcomes—a good well or a bad well. Exhaustive means these are the only two possible outcomes; thus, the probabilities must sum to 100%.

The outcome of the well could also be expressed in terms of reserves in the form of a continuous probability distribution.

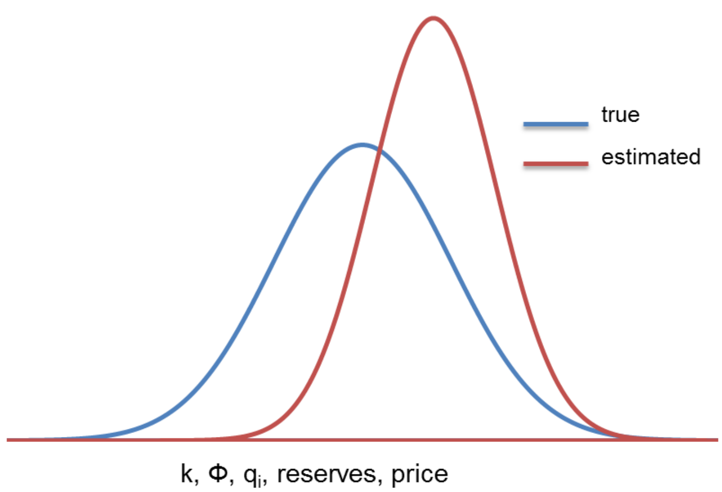


Assessing the uncertainty in possible outcomes is an important part of the decision-making process.

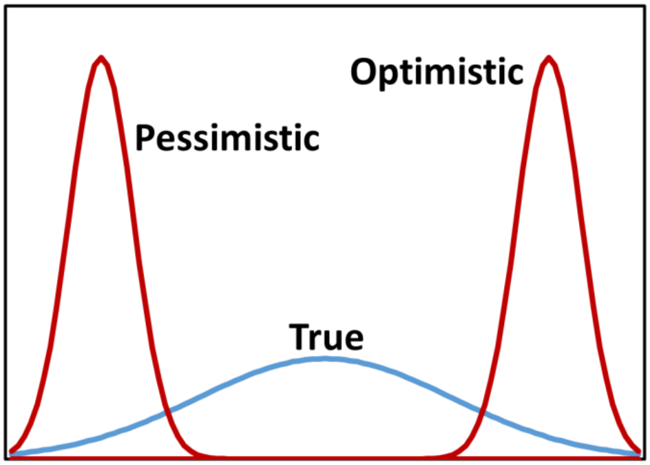
Unfortunately, humans are poor at assessing uncertainty, i.e., we are biased. We have an almost universal tendency for overconfidence, or underestimation of uncertainty. This is well documented in many studies (e.g., Tversky and Kahneman 1974, Capen 1976). We are more certain than we have a right to be. Humans also have a general tendency for optimism, i.e., to think that things will turn out better than they do on average (e.g., Weinstein 1980, Merrow 2011). The tendency for optimism is not as strong or prevalent as the tendency for overconfidence (i.e., sometimes we overconfident and pessimistic).

For discrete probabilistic assessments, overconfidence and/or optimism results in overestimation of the probability of a desirable outcome. In the example, overconfidence and/or optimism might result in the analyst assigning a probability of 80% to a good well rather than 70%.

For continuous probabilistic assessments, overconfidence results in the estimated distribution being too narrow (too certain of the possible outcomes). Optimism results in the estimated distribution being shifted in the more desirable, or beneficial, direction (to the right in this case). The estimated distribution is both overconfident and optimistic in the following figure.



It should be obvious that if we are making decisions with unreliable uncertainty assessments, we will sometimes, if not often, make poor decisions. In general, if we are overconfident and optimistic, we will invest in some investments that we should not invest in. Likewise, if we are overconfident and pessimistic (figure below), we will not invest in some investments that we should invest in, resulting in missed opportunities.



The result of making poor decisions is reduced value. McVay and Dossary (2014) demonstrated that overconfidence and optimism in project selection can result in substantial disappointment in portfolio value. That is, the actual or realized portfolio value will be lower than the estimated portfolio value. They also demonstrated that overconfidence and pessimism also results in poor decision making, and results in portfolio values that are not high as they could be if these biases were not present.

The conclusions of McVay and Dossary are corroborated by industry performance. Many authors have reported that for decades the petroleum industry has underperformed due to chronic overconfidence and optimism in project evaluation (e.g., Capen 1976, Rose 2004, Brashear et al. 2001, Nandurdikar 2014). The key to optimizing decision making and value creation is eliminating biases, such as overconfidence and optimism, in uncertainty assessment.

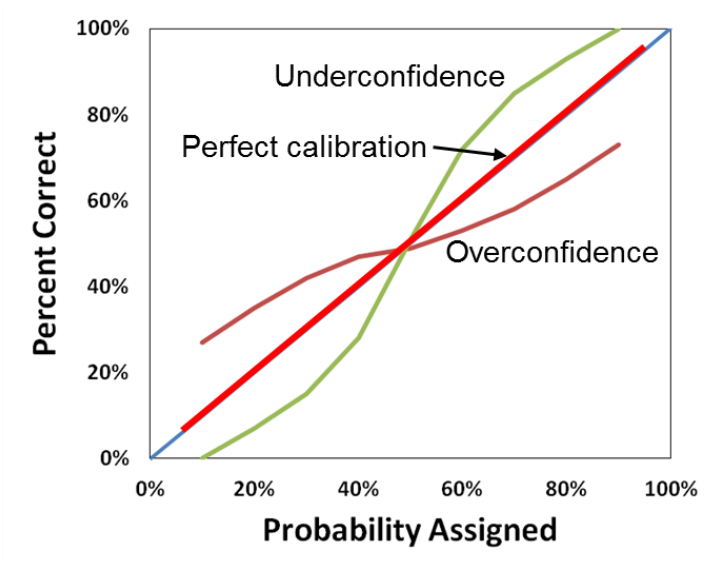
How do we eliminate biases and improve uncertainty assessment?

To eliminate biases, it is first necessary to measure them. The only way to measure biases is to make probabilistic assessments, or forecasts, and then to compare the probabilistic assessments to the actual values when they become known.

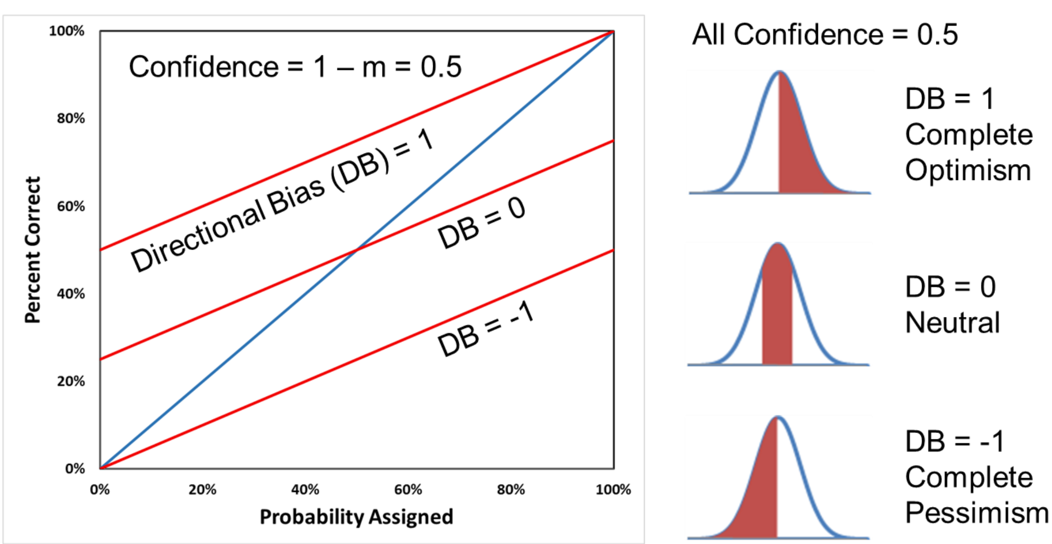
If we are unbiased and are estimating uncertainty well, then outcomes will be consistent with the probabilities assigned. For example, with discrete assessments, if there are a 100 wells for which we have estimated a 70% probability of being a “good” well, then about 70 of these wells should turn to be “good” wells once they have been drilled and we know their performance. Continuous probabilistic assessments are often expressed in terms of cumulative probabilities. For example, a P10 means there is a 10% probability the actual value will be less than or equal to the P10 value (for the convention in which the P10 is the low number and the P90 is the high number). If our continuous probabilistic assessments are unbiased, or reliable, then the actual reserves values will be less than the P10 reserves estimates for about 10 wells out of 100 once the actual reserves are known.

The reliability of probabilistic assessments can be expressed on a calibration plot (figure below). A group of probabilistic assessments are unbiased, or reliable, if the calibration curve falls on the unit-slope line.

A slope less than 1 indicates overconfidence. For example, for a group of P90 assessments, the actual value was less than the P90 estimate only 70% of the time (the analyst was overconfident by estimating the actual value would be less than the P90 value 90% of the time rather than 70%). Underconfidence (overestimation of uncertainty) is indicated by a slope greater than 1 (but this is rare).



We can also measure directional, or optimism-pessimism, biases from the intercept of the calibration plot. In the figure below, we show that we can measure confidence and directional biases quantitatively. Confidence bias (CB) ranges from -1 (complete underconfidence) through 0 (unbiased) to 1 (complete overconfidence, or a point estimate). Directional bias (DB) ranges from -1 (complete negative directionally, which is pessimism for value-based assessments) through 0 (unbiased directionally) to 1 (complete positive directionally, which is optimism for value-based assessments). See McVay and Dossary (2014) and Alarfaj and McVay (2016) for more detail on these concepts.



Biases can be measured with two different kinds of probabilistic assessments. The first is with training questions in which the correct answer is known, but uncertain to the estimator at the time of the assessment. These types of training assessments can be either discrete or continuous assessments. The advantage of these types of assessments is that immediate feedback can be provided to help the estimator improve uncertainty estimation in a training context.

Biases can also be measured by making probabilistic forecasts of future events (with either discrete or continuous assessments), letting time pass until the actual values are known, and then measuring biases with calibration plots. Ideally this should be a continuous process over time.

Once quantitative measurements of confidence and directional biases are available, steps can be taken to improve uncertainty assessment by reducing or eliminating biases. This can occur in two ways. The first is by internal correction or improvement. Just by measuring and knowing the presence and magnitudes of biases, analysts learn to correct for them in future assessments. Usually the primary problem is overconfidence (directional, or optimism-pessimism, biases exist primarily because we are first overconfident). Learning that assessment distributions are usually too narrow, the analyst learns to widen the distributions, or ranges, with practice.

Biases can also be eliminated with external correction or improvement. Knowing the directions and magnitudes of biases, subsequent probabilistic assessments can be mathematically adjusted to correct for the biases (see Capen 1976 and Fondren et al. 2013 for examples).