DHI Bayesian risk modification: Theoretical foundation for multiple attribute case

White Paper

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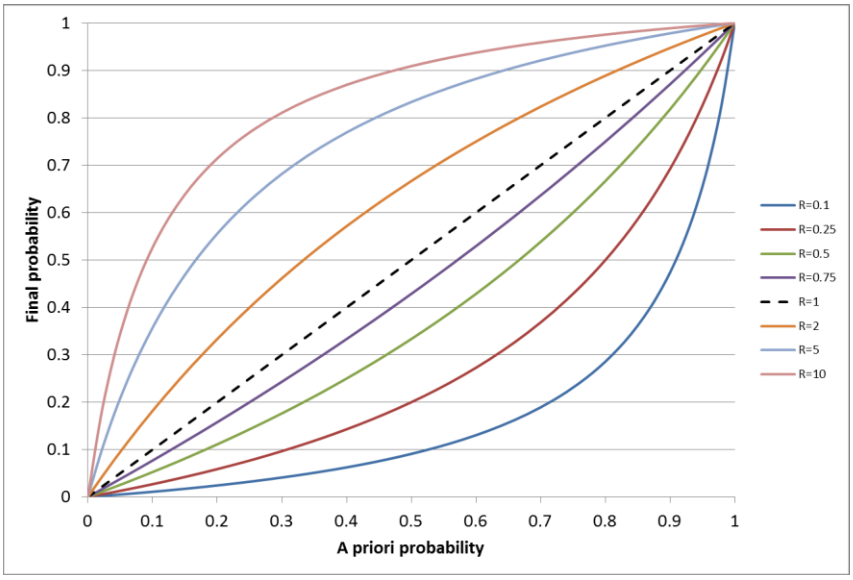

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1 General theory

1.1 Derivation of Bayesian theorem for multiple attributes

DHI (Direct Hydrocarbon Indicator) risk modification, as applied in this study, is based on the Bayesian theorem, which is derived here for more than two events. A central role plays the term "conditional probability". The conditional probability, designated as P(A | C), is regarded as the probability that an event A occurs after another event C has already occurred.

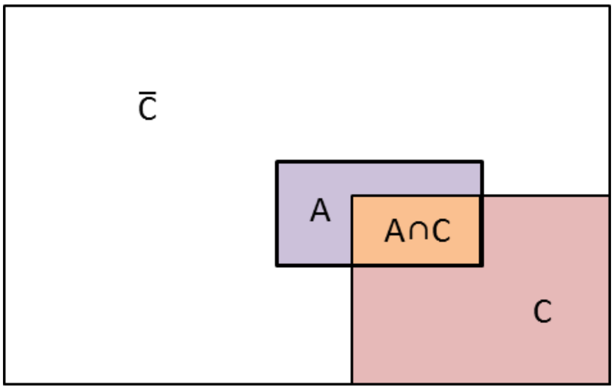

Fig. 1. *Venn diagram with two overlapping events A and C*

By making use of Venn diagrams we derive expressions of the various probabilities leading finally to the Bayesian theorem. Figure 1 shows two smaller rectangles inside a large rectangle, which represents the "total area", a term used below. The two rectangles represent the probabilities of independent events A and C. Some of the events A and C occur together. Therefore, the two event-areas overlap, resulting in the area designated as A∩C or as AC. We can write the probabilities of all three events or event combinations as

$$P(A) = \frac{area\,of\;A}{total\,area}, \tag{1}$$

$$P(C) = \frac{area\,of\;C}{total\,area}, \tag{2}$$

$$P(A \cap C) = \frac{area\,of\;A \cap C}{total\,area}. \tag{3}$$

For the conditional probability P(A | C) we investigate the probability of an event A, knowing that event C has already occurred. Therefore, we relate this probability no longer to the entire area but only to the area of event C

$$P(A|C) = \frac{area\,of\;A \cap C}{area\,of\;C}. \tag{4}$$

In a similar way we can write

$$P(C \mid A) = \frac{area\,of\;\; A \cap C}{area\,of\;\; A} \,. \qquad (5)$$

Combining the equations (1-5) we find

$$P(A \mid C) = \frac{P(A \cap C)}{P(C)} \text{ and } P(C \mid A) = \frac{P(A \cap C)}{P(A)} \quad . \qquad (6)$$

Therefore,

$$P(A \cap C) = P(A \mid C)P(C) = P(C \mid A)P(A) \;\; . \qquad (7)$$

Finally we obtain Bayes' theorem

$$\boxed{P(C \mid A) = \frac{P(A \mid C)P(C)}{P(A)} \,.} \qquad (8)$$

In cases where P(C|A) is impossible to be directly computed, Bayes' theorem provides a feasible workaround by computing the "reverse" conditional probability P(A|C).

How to compute P(A)? The numerator in eq. (8) can be regarded as the "contribution of event C to form the area of A" in Fig. 1. The remaining part of area A can be regarded as the "contribution of the event 'non-C'". Event $\overline{C}$ ('non-C') is the complementary area to area C forming together the total area. Therefore, we can write

$$P(A) = P(A \mid C)P(C) + P(A \mid \overline{C})P(\overline{C}),$$

with

$$P(C) + P(\overline{C}) = 1 \,.$$

We can generalize that approach by subdividing the total area of the rectangle in Fig. 1 into n non-overlapping sub-areas C_i, which represent n mutually independent events, C_i, $i = 1, n$.

Then we write

$$P(A) = \sum_{i=1}^{n} P(A \mid C_i)P(C_i), \qquad (9)$$

with

$$\sum_{i=1}^{n} P(C_i) = 1 \,. \qquad (10)$$

The Bayesian Theorem reads

$$\boxed{P(C_j \mid A) = \frac{P(A \mid C_j)P(C_j)}{\sum_{i=1}^{n} P(A \mid C_i)P(C_i)} \,, \;\; j = 1, n \,.} \qquad (11)$$

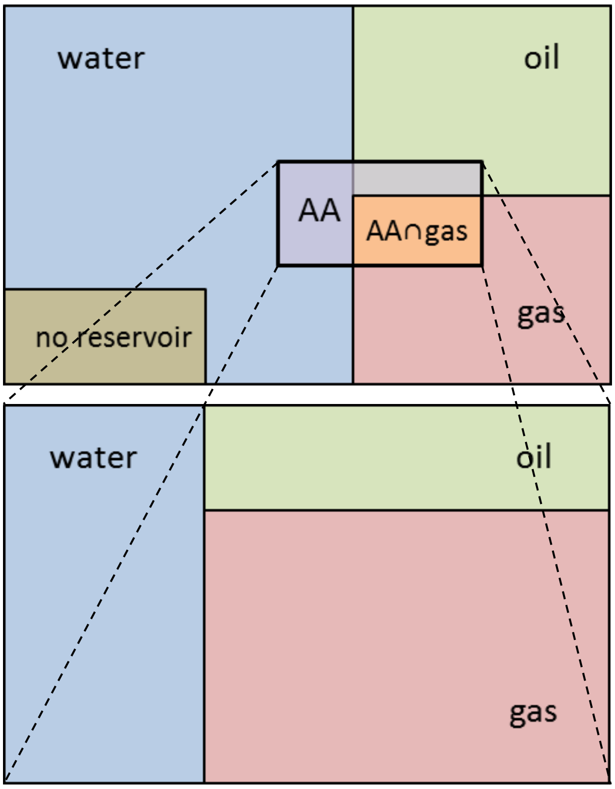

Fig. 2. *Venn diagram with four possible exploration outcome scenarios (water, oil, gas, no reservoir) before incorporation of the amplitude anomaly (above). Taking into account the anomaly, only three possible scenarios (water, oil, gas) remain, with different relative area contributions (below).*

We use this approach to compute the conditional probability that a certain exploration success or failure scenario occurs after a geophysical (seismic) attribute anomaly has been found at the prospect. So we associate event A by one of the following geophysical observations: amplitude anomaly (AA), or flat spot (FS) or CSEM anomaly (EM). First, we choose only an amplitude anomaly AA. Events C_i are then replaced by four well drilling outcomes, representing either a success (S) or failure (F) scenario; W= water, O = oil, G = gas or N = no reservoir found. These four events C_i (W, G, O, N), which are mutually exclusive, i.e. they cannot occur together, are assumed to represent all possible scenarios. They do not overlap in the Venn diagram (Fig. 2, upper part). The sum of all four individual areas is the total area, which is set equal to 1.

We now analyse how the observation of an anomaly AA changes the probability of a certain success or failure scenario. For example we look at the gas success scenario and use eq. (11) with C_j =G and A=AA

$$P(G \mid AA) = \frac{P(AA \mid G)P(G)}{P(AA)} \quad .$$

P(G) is the a priori probability to find a gas scenario. The numerator represents the orange area "AA∩gas" in Fig. 2. The denominator is computed according to eq. (9) using the 4 scenarios

$$P(AA) = P(AA|G)P(G) + P(AA|O)P(O) + P(AA|W)P(W) + P(AA|N)P(N).$$

The areas of AA and N are not overlapping. Therefore, the non-reservoir scenario cannot produce the amplitude anomaly, P(AA|N) = 0, whereas the a priori probability P(N) is not equal to zero. The Venn diagram at the bottom of Fig. 2 shows the result where only three events (scenarios) remain after the incorporation of the amplitude anomaly. The areas also have changed, the probability of water has reduced, the probability of hydrocarbons has increased. Gas is now more likely than oil.

Finally, we like to emphasize the fact that the conditional probabilities, which need to be provided, are determined up to a constant factor. We show this by introducing a scaled version of the conditional probability

$$P^*(A|C_i) = c \cdot P(A|C_i). \tag{12}$$

The constant factor c will cancel in eq. (11), leading to the same result. This has an important consequence. We do not need to compute the conditional probabilities in an absolute correct sense, but only in a relative correct sense. Only the mutual ratios between the probabilities are needed.

When we have two geophysical anomalies, we must consider three events that potentially overlap in the Venn diagram. Figure 3 shows a Venn diagram with three events A, B and C that partially overlap. Like in the two-event case (Fig. 1) we can first consider the overlapping events A and B and write the conditional probability of event B, given that event A has already occurred.

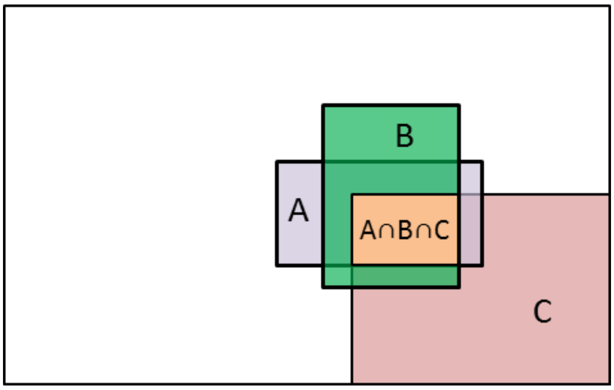

Fig. 3. *Venn diagram with three overlapping events A, B, and C.*

In the same way as above we can write the conditional probability P(C|AB) of event C, given that events A and B have occurred, as

$$P(C|A\cap B) = \frac{area\,of\;\; A\cap B\cap C}{area\,of\;\; A\cap B} = \frac{P(A\cap B\cap C)}{P(A\cap B)} = \frac{P(A\cap B\cap C)}{P(B|A)P(A)}, \tag{13}$$

where $P(A \cap B \cap C)$ is the probability that all three events occur simultaneously, and eq. (7) has been used in the last step.

This can be rewritten as

$$P(A \cap B \cap C) = P(C \mid A \cap B)P(B \mid A)P(A) \quad . \tag{14}$$

By cyclic change of events ($A \to B \to C \to A$) we obtain

$$P(A \cap B \cap C) = P(A \mid B \cap C)P(C \mid B)P(B), \tag{15}$$

$$P(A \cap B \cap C) = P(B \mid A \cap C)P(A \mid C)P(C). \tag{16}$$

Combining equations (14) and (16) and eliminating $P(A \cap B \cap C)$ we obtain the Bayesian theorem for three events

$$P(C \mid A \cap B) = \frac{P(B \mid A \cap C)P(A \mid C)P(C)}{P(B \mid A)P(A)}. \tag{17}$$

As mentioned above we introduce n mutually exclusive events C_i instead of one event C. The denominator can be computed as

$$P(B \mid A)P(A) = \sum_{i=1}^{n} P(B \mid A \cap C_i)P(A \mid C_i)P(C_i), \tag{18}$$

with the condition that the n mutually exclusive events obey again eq. (10).

Then we have

$$\boxed{P(C_j \mid A \cap B) = \frac{P(B \mid A \cap C_j)P(A \mid C_j)P(C_j)}{\sum_{i=1}^{n} P(B \mid A \cap C_i)P(A \mid C_i)P(C_i)} \qquad j = 1, n \quad .} \tag{19}$$

For the practical computation, we like to emphasize that we can evaluate eq. (19) in a sequential and not only in a simultaneous manner. We can consider the first attribute A and write the first updated a priori probabilities as (see eq. (11))

$$\hat{P}(C_j \mid A) = \frac{P(A \mid C_j)P(C_j)}{\sum_{i=1}^{n} P(A \mid C_i)P(C_i)}, \ j = 1, n.$$

This equation can be inserted in the similar equation for the second attribute B, which is

$$P(C_j \mid A \cap B) = \frac{P(B \mid A \cap C_j)\hat{P}(C_j \mid A)}{\sum_{i=1}^{n} P(B \mid A \cap C_i)\hat{P}(C_i \mid A)}, \quad j = 1, n.$$

This yields back eq. (19).

The Bayesian theorem can be extended to even more events using the same logic. This would be necessary when we have more than two geophysical attributes.

When the two events A and B are independent of each other we rewrite equations (19) as

$$P(C_j \mid A \cap B) = \frac{P(B \mid C_j)P(A \mid C_j)P(C_j)}{\sum_{i=1}^{n} P(B \mid C_i)P(A \mid C_i)P(C_i)} \qquad j = 1, n \quad . \tag{20}$$

We can calculate the two conditional probabilities P(B|C) and P(A|C) independently and multiply them. If the two events A and B, however, depend on each other to a certain extent we must use eq. (19) which has the same form as in the independent case, i.e. multiplication of probabilities, but now we have to determine the conditional probabilities in a correct manner and remember that $P(B \mid A \cap C) \neq P(B \mid C)$ and $P(B \mid A) \neq P(B)$. In any case, by physical reasons, we can expect that the order in which the two events are taken into account, has no impact on the final result. If we exchange A and B in the formula (17) we get

$$P(C \mid A \cap B) = \frac{P(A \mid B \cap C)P(B \mid C)P(C)}{P(A \mid B)P(B)} . \tag{21}$$

Comparing eq. (17) and (21) and using eq. (7) (i.e. $P(A \mid B)P(B) = P(B \mid A)P(A)$) we find the necessary condition which must be fulfilled

$$P(B \mid A \cap C)P(A \mid C) = P(A \mid B \cap C)P(B \mid C) . \tag{22}$$

In the following, we continue our synthetic example, shown in Fig. 2. and introduce a second geophysical DHI attribute, which is considered to be independent from the first attribute (Fig. 4).

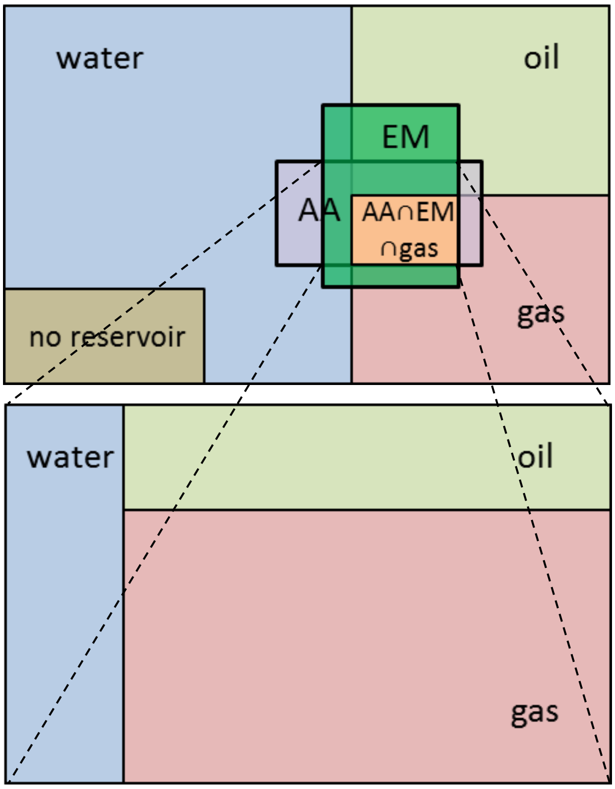

Fig. 4. *Venn diagram with four possible exploration outcome scenarios (water, oil, gas, no reservoir) before the incorporation of two DHI attributes AA and EM (above). Taking into account the two anomalies, only three possible scenarios (water, oil, gas) remain, with different relative area contributions (below), compared to the original situation as well as the situation after the first attribute (Fig. 2).*

Using eq. (20) we identify event A by an amplitude anomaly "AA", event B by an electromagnetic anomaly "EM" and the C_i as our n exploration success and failure cases (water, oil, gas, no reservoir). For the gas success scenario we can write

$$P(G \mid AA \cap EM) = \frac{P(EM \mid G) P(AA \mid G) P(G)}{P(EM) P(AA)}, \tag{23}$$

with

$$P(EM) P(AA) = \sum_{i=1}^{n} P(EM \mid C_i) P(AA \mid C_i) P(C_i). \tag{24}$$

The application of the second EM DHI attribute changes again the probabilities of the three cases left after the first attribute (Fig. 4). The probability of water is further reduced.

Seismic and electromagnetic anomalies are certainly independent. If two seismic attributes are used, their degree of independency must be evaluated. This topic will be discussed in section 1.4.

1.2 The uplift/downgrade potential of attribute anomalies

We can summarize all *ns* success cases S_i into one success case *S* and all *nf* failure cases F_i into one failure case *F* and rewrite eq. (11)

$$P(S\,|\,AA) = \frac{P(AA\,|\,S)}{P(AA\,|\,S)P(S) + P(AA\,|\,F)P(F)} P(S), \tag{25}$$

with

$$P(AA\,|\,S)P(S) = \sum_{i=1}^{ns} P(AA\,|\,S_i)P(S_i), \tag{26}$$

$$P(AA\,|\,F)P(F) = \sum_{i=1}^{nf} P(AA\,|\,F_i)P(F_i), \tag{27}$$

$$P(S) = \sum_{i=1}^{ns} P(S_i), \tag{28}$$

$$P(F) = \sum_{i=1}^{nf} P(F_i), \tag{29}$$

and the condition

$$P(F) + P(S) = 1. \tag{30}$$

Then we define the ratio R of the two conditional probabilities P(AA|S) and P(AA|F)

$$\boxed{R = \frac{P(AA\,|\,S)}{P(AA\,|\,F)} = \frac{\sum_{i=1}^{ns} P(AA\,|\,S_i)P(S_i)}{\sum_{i=1}^{nf} P(AA\,|\,F_i)P(F_i)} \cdot \frac{\left(1 - \sum_{i=1}^{ns} P(S_i)\right)}{\sum_{i=1}^{ns} P(S_i)}.} \tag{31}$$

Therefore, we can write eq. (25)

$$P(S\,|\,AA) = \frac{R}{R \cdot P(S) + P(F)} P(S), \tag{32}$$

or, using eq. (30),

$$P(S\,|\,AA) = \frac{R}{1 + (R-1) \cdot P(S)} P(S). \tag{33}$$

Some authors define the inverse parameter $\widetilde{R} = 1/R$. Then we get

$$P(S \mid AA) = \frac{1}{P(S) + \tilde{R}(1 - P(S))} P(S) \qquad (33b)$$

If the two conditional probabilities are the same we have R equal to 1, then the coefficient in front of P(S) is equal to 1, too. The a priori probability does not change. In rare situations where the success case does not produce the observed anomaly AA R equals 0. Therefore, also the probability to have success, given the anomaly, is zero. The other extreme is that R becomes very large. It approaches infinity if the failure cases cannot produce the observed anomaly at all. In this case we see that the conditional probability to have a success, given the anomaly, approaches 1.

The possible effect of an amplitude anomaly on the probability can be visualized in cross-plots of posterior (final) probability versus prior (initial) probability (Fig. 5). Curves of equal R can be drawn. For each attribute one point can be inserted. From the location of this point we can graphically determine the corresponding R value as a QC.

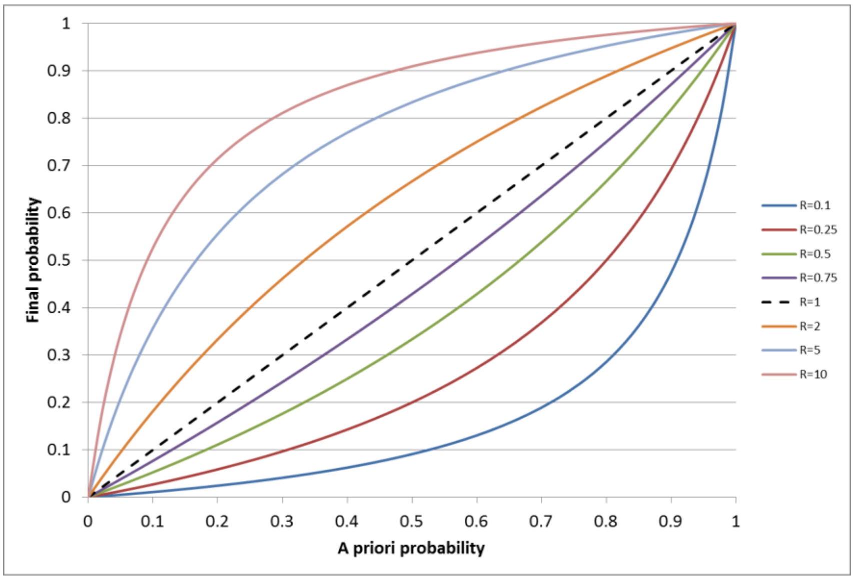

Fig. 5. *Cross-plot of posterior (final) probability versus prior (initial) probability. Curves of equal R in the range from 0.1 to 10 are plotted.*

When we have two DHI attributes, say the first one is an amplitude anomaly AA as above and the second one is an electromagnetic anomaly EM, then we can again analyse the effect of each of them by corresponding R_i ratio factors. For the first attribute we re-write eq. (33) as

$$P(S \mid AA) = \frac{R_1}{1 + (R_1 - 1) \cdot P(S)} P(S) \,. \qquad (34)$$

This is the a priori success probability for the second attribute equation

$$P(S \mid EM \cap AA) = \frac{P(EM \mid S)}{P(EM)} P(S \mid AA) = \frac{R_2}{1 + (R_2 - 1) P(S \mid AA)} P(S \mid AA) \,. \qquad (35)$$

Inserting eq. (34) in (35) we obtain as an intermediate result

$$P(S \mid EM \cap AA) = \frac{R_1 R_2}{1 + (R_1 - 1)P(S) + (R_2 - 1)R_1 P(S)} P(S), \tag{36}$$

which finally becomes

$$P(S \mid EM \cap AA) = \frac{R_1 R_2}{1 + (R_1 R_2 - 1)P(S)} P(S). \tag{37}$$

This equation has the same form as eq. (33). We see that the separate ratio factors R_i must be multiplied to give the combined ratio factor R. If one attribute is neutral, the corresponding R_i factor will be 1.

1.3 Calculating the DHI strength

The so-called DHI strength can be defined, which is a measure of the confidence we have in a DHI. This value can for example be used at volume calculations to integrate the DHI information with a priori volume distributions.

We define the DHI strength *T* as

$$T = \frac{P(S \mid AA) - P(S)}{1 - P(S)}. \tag{38}$$

This is the difference of final to initial probability of success, due to an amplitude anomaly AA, normalized to the maximum possible difference. If the two probabilities are the same, i.e. the DHI could not increase the a priori probability, *T* is zero. The maximum value P(S|AA) can take is 1. Then *T* equals one. If the final probability is smaller than the initial one, *T* becomes negative.

Please note that the quantity *T* is not defined for P(S) = 1. If P(S) goes to 1, P(S|AA) approaches P(S) (see eq. 33), and therefore, both the numerator and denominator in eq. (38) approach 0. However, we see below, that *T* approaches the limiting value (R-1)/R, when P(S) goes towards 1. Therefore, only in the limit of R approaching infinity, *T* approaches 1.

Using eq. (33)

$$P(S \mid AA) - P(S) = \left[\frac{R}{1 + (R-1) \cdot P(S)} - 1 \right] P(S), \tag{39}$$

or

$$P(S \mid AA) - P(S) = \left[\frac{(R-1)(1 - P(S))}{1 + (R-1) \cdot P(S)} \right] P(S). \tag{40}$$

Therefore the DHI strength *T* is

$$T = \frac{(R-1) \cdot P(S)}{1 + (R-1) \cdot P(S)}. \tag{41}$$

It depends both on *R* and the initial success probability *P(S)* (Fig. 6).

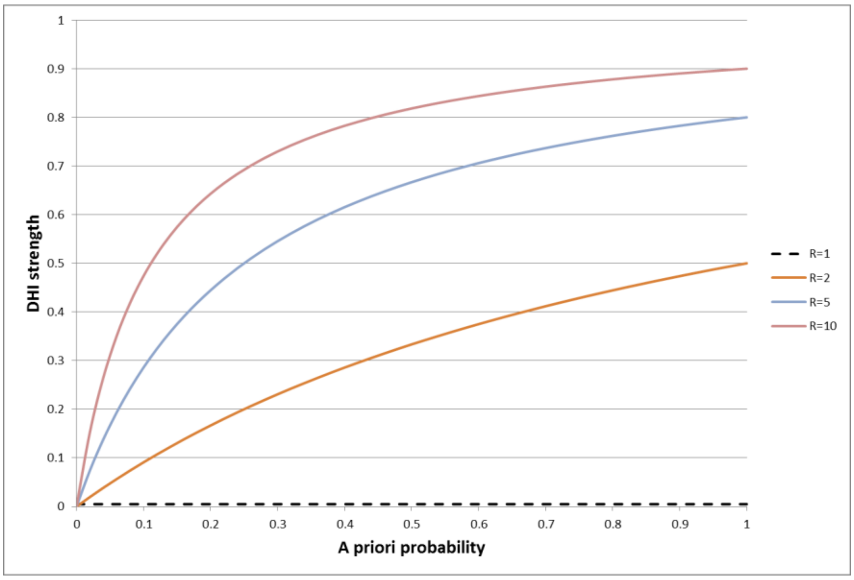

Fig. 6. *Cross-plot of DHI strength versus prior (initial) probability. Curves of equal, positive R in the range from 1 to 10 are plotted. Compare to Fig. 5.*

1.4 Independence of geophysical attributes

Seismic and electromagnetic anomalies are certainly independent. In these cases, we can use eq. (20), or (23)-(24). If we want to use two seismic attributes from the same seismic data set, we must be cautious and evaluate first the degree of independency. If we have two seismic attributes, for example an amplitude anomaly (AA) and a flat spot (FS), we first have to keep the possible dependency in our formulas and use eq. (19), for example, for the final probability of the gas scenario as

$$P(G \mid AA \cap FS) = \frac{P(FS \mid AA \cap G) P(AA \mid G) P(G)}{\sum_{i=1}^{n} P(FS \mid AA \cap C_i) P(AA \mid C_i) P(C_i)} \quad .$$

The terms like $P(FS \mid AA \cap G)$ are "double scenario conditional probabilities", i.e. the probability of encountering event FS might depend on the occurrence of the two events, here AA and G. In other words, we must not consider only the probability to observe a flat spot FS for a gas scenario in general, $P(FS \mid G)$, but need to take into account that we already have observed an amplitude anomaly AA. This previous observation of an amplitude anomaly will change the probability of a flat spot for the gas and the other scenarios. In general the inequality $P(FS \mid AA \cap G) \neq P(FS \mid G)$ holds.

Typical seismic attributes that we can make use of, both in the reflectivity as well as in the impedance domain, are

- Full stack amplitude
- Offset- or angle-range limited stack
- Intercept
- Gradient
- Linear weighted combination of intercept and gradient, for example fluid factor
- Acoustic or elastic impedances

All of the above attributes could be evaluated for both **top and base reservoir reflections** separately. Another possibility is a **flat spot** as an additional event. Flat spots can be observed when the reservoir is thick enough and the dip of the structure and the SN-ratio large enough. A pitfall with flat spots could be paleo-contacts. The main question here is whether the characteristics of the top reflection, the base reflection and the flat spots are really independent of each other, so that we can use them as multiple attributes. We discuss this below.

Most of the seismic attributes mentioned above are totally or partially dependent on each other. Only the two pre-stack attributes intercept and gradient can be regarded as theoretically independent, in first place, but as is well known from AVO analysis in intercept-gradient cross-plots, the two have usually a strong correlation. The data points plot in ellipses. The fluid factor FF is a linear weighted combination of the two, $FF = a \cdot I + b \cdot G$. In practice, if we have access to I and G, we should use the fluid factor, which in most cases reveals to be appropriate and best discriminating all scenarios. In this manner we reduce the two observables into one attribute. One can show that we get the same result, if we subsequently use the intercept and gradient in a correct way, i.e. we take into account the correlation between the two attributes.

Stacked amplitudes also depend on I and G. If we approximate the angle-dependent reflection coefficient by $R(\vartheta) = I + G\sin(\vartheta)$ the angle range limited stack amplitude is

$$S(\vartheta_1, \vartheta_2) = \frac{1}{\vartheta_2 - \vartheta_1} \int_{\vartheta_1}^{\vartheta_2} I + G\sin(\vartheta) d\vartheta . \tag{42}$$

The simple integration yields the result

$$S(\vartheta_1, \vartheta_2) \approx I + G\sin\left(\frac{\vartheta_1 + \vartheta_2}{2}\right). \tag{43}$$

This is again a linear combination of I and G. Impedance differences above and below a reflecting interface are also related to the reflection coefficient of that interface. Impedances do not contain independent information compared to reflection coefficients. They represent the same information, just in another domain.

In practice we most often approximate the a priori PDFs by Gaussian functions

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}} . \tag{44}$$

The conditional probability to produce an anomaly x=A by a water (w) and gas (g) scenario is written as

$$f_w(A)=\frac{1}{\sqrt{2\pi}\sigma_w}e^{-\frac{1}{2}\frac{(A-\mu_w)^2}{\sigma_w^2}}\text{, and} \tag{45}$$

$$f_g(A)=\frac{1}{\sqrt{2\pi}\sigma_g}e^{-\frac{1}{2}\frac{(A-\mu_g)^2}{\sigma_g^2}}. \tag{46}$$

An example of two totally dependent attributes would be that the **second attribute can be computed by a linear scale transformation from the first one**. With a linear scale transformation,

$$\hat{x}=ax+b \text{ and} \tag{47}$$

$$\hat{A}=aA+b, \tag{48}$$

the means and variances of the Gaussian function change as follows

$$\hat{\mu}_i=a\mu_i+b\ ,\ \hat{\sigma}_i^2=a^2\sigma_i^2. \tag{49}$$

Therefore, the transformed (double) conditional probabilities are

$$h_i\left(\hat{A}\cap A\right)=\frac{1}{\sqrt{2\pi}\hat{\sigma}_i}e^{-\frac{1}{2}\frac{(\hat{A}-\hat{\mu}_i)^2}{\hat{\sigma}_i^2}}=\frac{1}{a}\frac{1}{\sqrt{2\pi}\sigma_i}e^{-\frac{1}{2}\frac{(A-\mu_i)^2}{\sigma_i^2}}=\frac{1}{a}f_i(A)=g_i\left(\hat{A}\,|\,A\right)f_i(A). \tag{50}$$

The last part of the equation represents the correct interpretation of the constant factor 1/a, which is the conditional probability of the scenario i to produce anomaly $\hat{A}$ having already observed anomaly *A*, $g_i\left(\hat{A}\,|\,A\right)$. This means that the ratio R for the water and gas scenarios (see eq. (31)) remains the same after the application of the second attribute, obtained by the transformation, eq. (47),

$$R=\frac{h_g\left(\hat{A}\cap A\right)}{h_w\left(\hat{A}\cap A\right)}=\frac{g_g\left(\hat{A}\,|\,A\right)}{g_w\left(\hat{A}\,|\,A\right)}\frac{f_g(A)}{f_w(A)}=R_2R_1=R_1. \tag{51}$$

This means that we must not apply the second attribute as if it were totally independent. Then we would obtain the wrong result $R=R_1^2$. The second attribute $\hat{A}$ has the ratio R_2

$$R_2=\frac{g_g\left(\hat{A}\,|\,A\right)}{g_w\left(\hat{A}\,|\,A\right)}=1\ , \tag{52}$$

because $g_i\left(\hat{A}\,|\,A\right)=const, i=1,\ldots n$. This is a necessary condition for a neutral or "no effect" attribute. We see this by equating eq. (11) and (19), i.e. the attribute B has no effect. The conditional probabilities $P(B\,|\,A\cap C_j)$ must be constant and equal for all j.

In practice, if we have pre-stack data with an AVO analysis (intercept and gradient attributes), we should try to combine both into a fluid factor type attribute. We have to always look for the attribute which is most discriminant for all scenarios. This could be full or angle range limited stack amplitude, if the intercept and gradient data are too noisy and inconclusive. Then we are done for the selected reflection event. Any other seismic attribute, also stack amplitudes are other combinations of intercept or gradient, and therefore totally dependent on the first attribute.

Another candidate for a partly or fully independent attribute, however, is another seismic reflection related to the reservoir, for example the **base of the reservoir reflection** or a **flat spot inside the reservoir**. The reservoir must be thick enough in order that a base reflection or a flat spot can be identified and evaluated, in addition to the top reservoir reflection. For a flat spot it is also advantageous to have a dipping structure. The detectability and resolution depends on the seismic frequency bandwidth and SN ratio. For a homogeneous reservoir one can show that the flat spot amplitude can be expressed in terms of the top reflection amplitudes above and below the contact. In an exploration scenario we can compute the theoretical flat spot amplitude distribution and compare that to the observed flat spot amplitude distribution. If the two are the same, the occurrence of the flat spot is redundant information and must not be used a second time. If the two are dissimilar there is some independent information attached to the flat spot. The overlap of the two distributions is a measure of the independence. The same holds for the base reservoir reflection amplitudes. For a homogeneous reservoir the base reflection amplitude is a function of the top reflection amplitude plus a reflection coefficient at an interface between the layers above and below the reservoir, if they have different impedances.

In any case we can introduce a dependency parameter D. It could be computed by the overlap area of the two distributions, the theoretical and the observed flat spot amplitude distribution. The parameter D varies between 0 (total independency) and 1 (total dependency). We can use this parameter D in the following relation

$$P(FS \mid AA \cap G) = D + (1 - D) \cdot P(FS \mid G)$$

With this simplification approach we avoid the complicated evaluation of the "double scenario conditional probabilities", which would not be feasible in practice.

2 References

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