Chapter 2
Computational Models of Achievement, Affiliation and Power Motivation

Chapter 1 examined literature from motivation psychology and reviewed the theories that may contribute to different game-play characteristics in humans. It specifically focused on three theories of motivation that can be modelled using the concept of incentive: achievement, affiliation and power motivation. This chapter introduces computational models of motivation to embed these human-inspired motives in artificial agents. A flexible mathematical model is introduced that permits these three motives to be expressed in terms of approach and avoidance components, which can be adjusted to create different motivation variants. Two approaches to using these models for goal selection are introduced.

2.1 Towards Computational Motivation

In the previous chapter we identified a mapping between three psychological motivation theories for achievement, affiliation and power and the player types, motivation components and user groups that have been identified among participants in virtual worlds. We described how theories of implicit motivation proposed by motivation psychologists can explain differences in behaviour between individuals seemingly in the same situation. This suggests a methodology for developing more diverse and believable computer-controlled game characters by embedding them with computational models of those motivations.

This chapter presents computational models of motivation for achievement, affiliation and power motivation. The models are designed such that they can be used in isolation or together, embedded in an artificial 'motive profile'. This chapter draws on the ideas of incentive, probability of success and approach-avoidance motivation seen in Chap. 1 as the basis for developing computational models for achievement, affiliation and power motivation.

Our basic approach uses sigmoid curves to model approach and avoidance of a goal as a function of either the probability of successfully achieving the goal, or the

incentive to achieve a goal. A goal here is an intermediate construct that specifies how an individual strategically goes about addressing the underlying approach and avoidance motives [7]. In artificial agent research, goals can describe states or changes to achieve, states to maintain or preserve, information to retrieve and behaviours to execute or cease, among other things [3]. We do not, at this point fix on a specific definition for a goal, but note that it could be any of these things in an artificial agent. We revisit the idea of a goal later in the book when we embed computational models of motivation in specific agent architectures.

Section 2.2 introduces a set of mathematical tools we can use to model approach-avoidance motivation. These are then utilised to produce three incentive-based computational models of achievement, affiliation and power motivation. These motives are considered individually and in combination in a computational motive profile in Sect. 2.3. Models of different complexity and fidelity are considered. Finally, Sect. 2.4 presents two approaches to goal selection using motivation.

2.2 Modelling Incentive-Based Motives Using Approach-Avoidance Theory

The approach-avoidance theory of motivation is characterised by the idea that both the attractiveness and repulsiveness of a goal or an incentive increase the closer one gets to it. Closeness here may refer to closeness in time, space or psychological distance. Different representations of this theory have been proposed. Miller [19], for example, focused on the gradient of approach and avoidance. He hypothesised that the strength of avoidance motivation may increase more rapidly than the strength of approach motivation as the goal or incentive is neared. A typical linear model of this phenomenon has the general form:

$$y = mx + b, \tag{2.1}$$

where x is the distance to incentive, y is the strength of the resultant tendency of motivation for the incentive, m is a negative number controlling the gradient of approach or avoidance and b is a positive number controlling the maximum strength of the motivation in question. An example is shown in Fig. 2.1.

An alternative model proposed by Maher [12] focuses on the strength of motivation in approach-avoidance conflict, rather than on the gradients of approach and avoidance. When an individual is far from a goal or incentive, the motivation to avoid it is greater than the motivation to approach it. However, when the individual approaches the incentive, the strength of motivation to approach the incentive can become very strong very quickly. The model has hyperbolic characteristics of the following form:
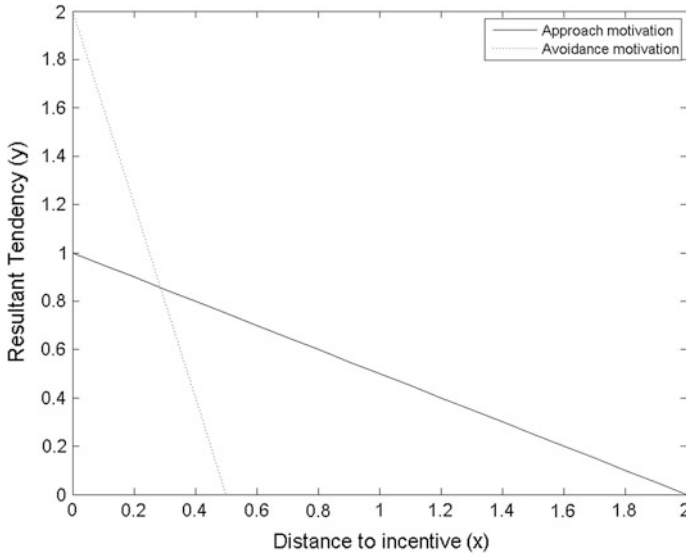
Fig. 2.1 Modelling approach-avoidance theory with a focus on gradient [19] using Eq. 2.1 with $m = -0.5$, $b = 1$ for approach motivation and $m = -4$, $b = 2$ for avoidance motivation

$$y = \frac{a}{bx} + c. \tag{2.2}$$

x is again the distance to incentive and y is the strength of the resultant tendency of motivation for the incentive. The parameters a and b control the gradient of approach or avoidance and c controls the minimum strength of the motivation in question. An example is shown in Fig. 2.2.

Mathematically, we can see that the two models are different, but do retain some similarities. In particular, the strength of motivational tendency for both approach and avoidance increases as distance to incentive decreases.

The models above consider motivational tendency as a function of distance to incentive. Another key concept of motivation is the U- or inverted-U-shaped relationship between motivational tendency and strength of incentive. This relationship is captured, for example, by the quadratic model of the resultant tendency curves for motivation in Eq. 1.5. A more general form for this model is (Fig. 2.3):

$$y = av^2 + bv + c \tag{2.3}$$

The variable v is the value of the incentive. The parameters a and b together control the gradient of approach and avoidance of incentive, the position of the maximum (or minimum) motivational tendency along the horizontal axis, and the strength of the maximum (or minimum) motivational tendency. c controls the intersection point of the resultant motivational tendency curve with the vertical axis.
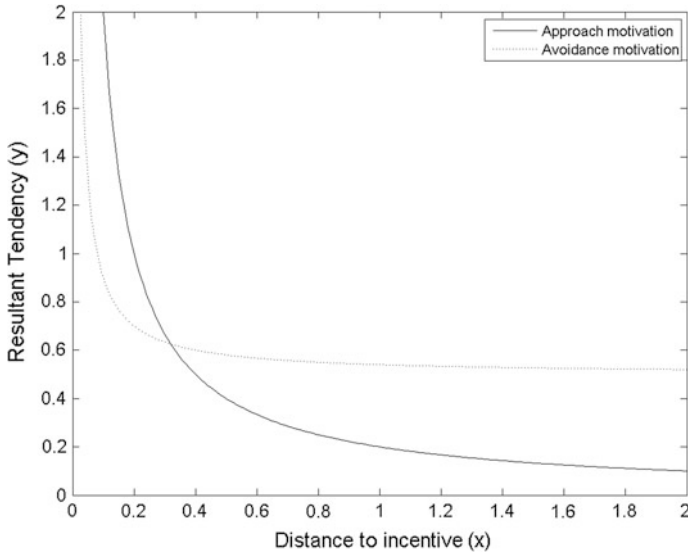
Fig. 2.2 Modelling approach-avoidance theory with a focus on strength [12] using Eq. 2.2 with
$a = 0.2$, $b = 1$, $c = 0$ for approach motivation and $a = 0.2$, $b = 5$, $c = 0.5$ for avoidance
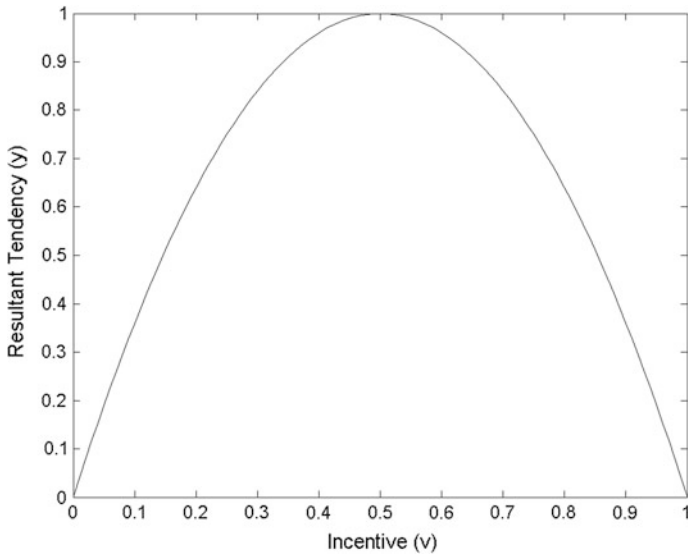motivation

Fig. 2.3 A quadratic model of motivation as a function of incentive using Eq. 2.3 with $a = -4$,
$b = 4$, $c = 0$. We assume incentive is inversely proportional to probability of success

A number of other mathematical functions have been used to model phenomena with similar inverted-U-shaped characteristics, such as arousal, hedonic response and creativity [16]. One example is a Gaussian function of the form:

$$y = ae^{-\frac{(v-b)^2}{2c}}$$

(2.4)

This function has parameters a, b and c that give us control of the height of the inverted U, the position of the maximum and the gradient of increase and decrease of the function. The variable v here can represent factors such as the amount of neural activity, psychophysical intensity, ecological stimuli or collative effects such as novelty or incentive, depending on the phenomenon being modelled [9]. Using this model, the parameter b effectively controls the gradient of both approach and avoidance, so we cannot manipulate these independently (Fig. 2.4).

When modelling hedonic response as the sum of positive and negative feedback for approach and avoidance, a Gaussian cumulative distribution can be used to model the positive feedback as the area under the Gaussian probability distribution. However, other functions are also common as cumulative distribution functions, and can give us greater control of the shape of the motivation curve. One example is a sigmoid function:
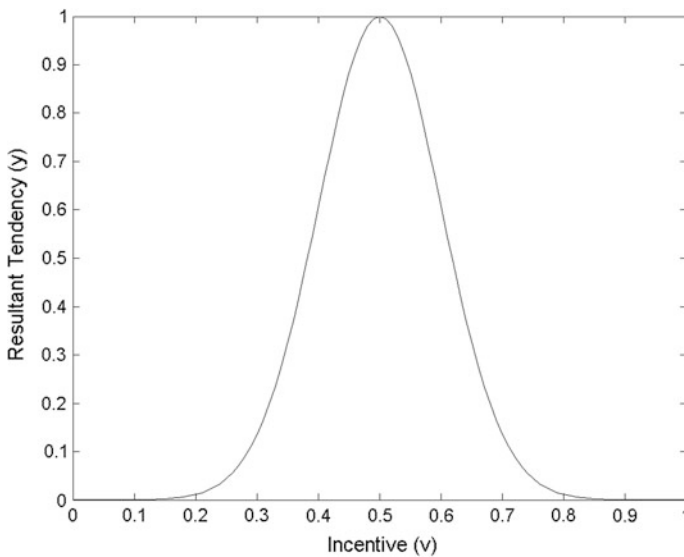
$$y = \frac{a}{1 + e^{-c(v-b)}}$$

(2.5)

Fig. 2.4 Gaussian model of motivation as a function of incentive using Eq. 2.4 with $a = 1$, $b = 0.5$, $c = 0.01$
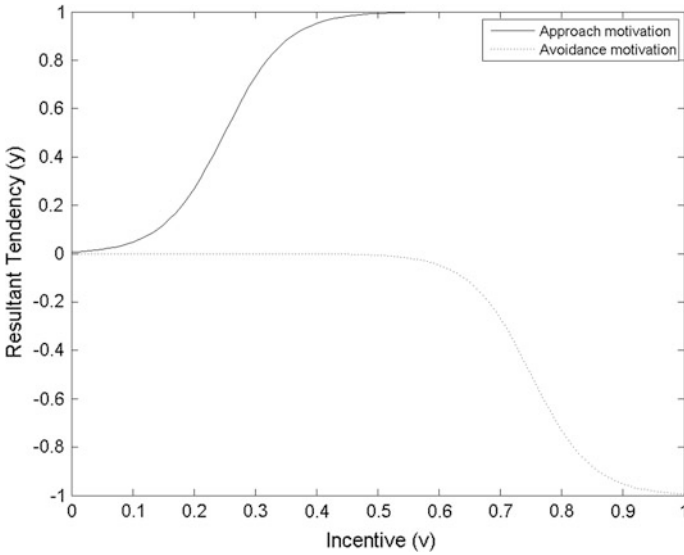
Fig. 2.5 A sigmoid model of motivation as the sum of approach and avoidance curves using Eq. 2.5 with $a = 1$, $b = 0.25$, $c = 20$ for approach motivation and $a = -1$, $b = 0.75$, $c = 20$ for avoidance motivation

a again controls the maximum of the function and c the rate of increase. However, b now controls the position of the turning point of the curve along the horizontal axis. v is again the amount of neural activity, psychophysical intensity, ecological stimuli or collative effect being modelled (Fig. 2.5).

The inverted-U-shaped relationship between probability of success and resultant tendency for motivation can be achieved using a sigmoid-based representation with one sigmoid function for positive feedback (approach) and another for negative feedback (avoidance) [18]. This effectively gives us separate parameters to control the strength, rate of increase and position of the turning points for approach and avoidance motivation. A sigmoid representation has previously been used in this way to model curiosity and interest [22] as approach to novelty and avoidance of very high novelty. We use these ideas to model achievement, affiliation and power motivation in the following sections.

2.2.1 Modelling Achievement Motivation

Atkinson's risk-taking model (RTM; see Chap. 1) has been both influential and successful in aiding the understanding of achievement motivation in humans. The general trends described by the RTM have been observed in experimental settings in humans [2, 13]. However, the point of maximum approach tends to fall below the

critical level of $P^s = 0.5$ predicted by the RTM. Furthermore, failure-motivated individuals do not select extremely difficult goals to the extent predicted by the RTM. The known limitations of the RTM suggest that a more sensitive model is required to capture the subtleties of achievement motivation in artificial agents.

The ideas of incentive, probability of success and approach-avoidance motivation proposed by Atkinson can be captured in a sigmoid-based model. Thus, such a model does not redefine the existing psychological model of motivation, but rather interprets it computationally in a flexible manner that can potentially be extended to other approach-avoidance motivations.

Equation 2.6 represents achievement motivation as the difference between two sigmoid functions for approach and avoidance of a goal G. Using a sigmoid representation, approach motivation is stronger for goals with a higher probability of success, until a certain threshold probability is reached and approach motivation plateaus.

Conversely, avoidance motivation is zero for goals with a very low probability of success, and negative for goals with a high probability of success. This means that failure at a very easy goal is punished the most. The resultant tendency to achieve a goal G is the sum of the approach and avoidance sigmoid curves in composition with a function $P^s(G)$ for computing the subjective probability of successfully achieving goal G, as shown in Eq. 2.6:

$$T_{\text{ach}}^{\text{res}}(P^s(G)) = \left(T_{\text{ach}}^{\text{res}} \circ P^s\right)(G) = \frac{S_{\text{ach}}}{1 + e^{-\rho_{\text{ach}}^+(P^s(G) - M_{\text{ach}}^+)}} - \frac{S_{\text{ach}}}{1 + e^{-\rho_{\text{ach}}^-(P^s(G) - M_{\text{ach}}^-)}}.$$

(2.6)

Equation 2.6 is visualized in Fig. 2.6. $P^s(G)$ has a value range between zero (guaranteed failure) and one (guaranteed success). The manner in which probability of success is estimated will influence the resulting achievement motivation value computed. Various methods have been proposed by psychologists. These include the mastery- and performance-oriented approaches summarised in Table 2.1. Each of these approaches is also possible for artificial agents that can interact with their environment or other agents. Self-based estimates and social comparison standards are perhaps the most straightforward, as they can be understood as the number of successful attempts divided by the total number of attempts.

Measuring probability of success in absolute standards is more difficult as it requires an understanding of the domain in question.

The model has five parameters: M_{ach}^+, M_{ach}^-, ρ_{ach}^+, ρ_{ach}^- and S_{ach}, which are summarized in Table 2.2. M_{ach}^+ is the turning point of the sigmoid for approach motivation and M_{ach}^- is the turning point of the sigmoid for avoidance. When the approach turning point is to the left of the avoidance turning point (that is, $M_{\text{ach}}^+ < M_{\text{ach}}^-$), then the resultant tendency represents a success-motivated individual, as shown in Fig. 2.6a. Note the characteristic inverted U-shape of the curve for resultant tendency, similar to that seen in Atkinson's [1] model in Fig. 1.4a.
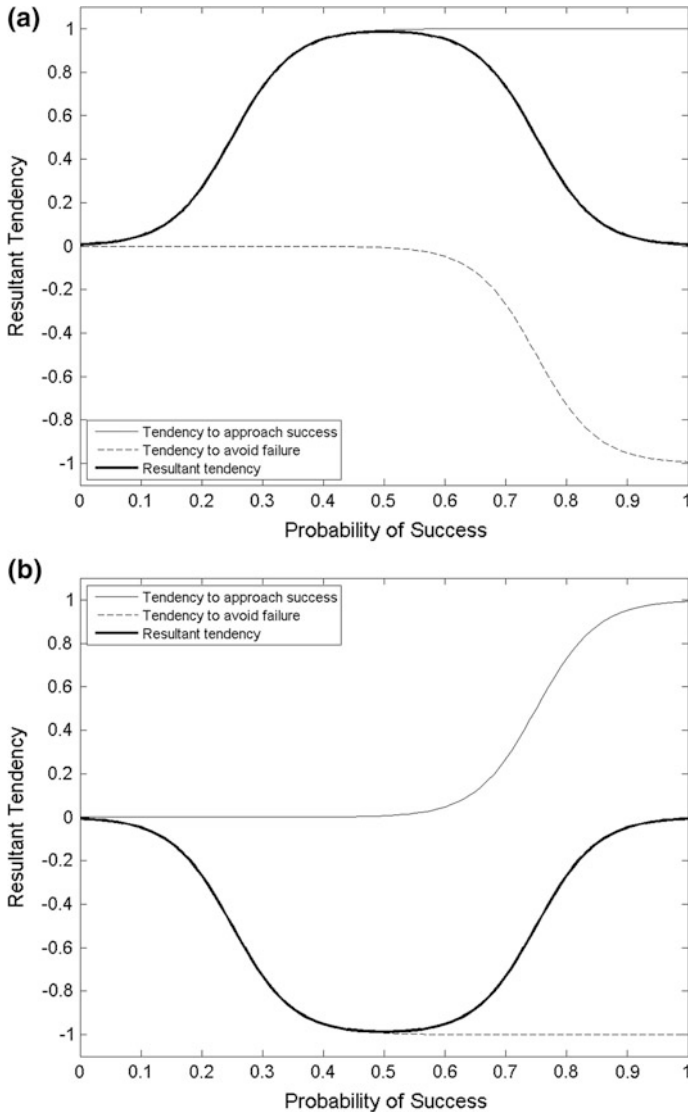
Fig. 2.6 Sigmoid representations of **a** motivation to approach success ($S_{ach} = 1$, $M_{ach}^{+} = 0.25$, $M_{ach}^{-} = 0.75$ and $\rho_{ach}^{+} = \rho_{ach}^{-} = 20$) and **b** motivation to avoid failure ($S_{ach} = 1$, $M_{ach}^{+} = 0.75$, $M_{ach}^{-} = 0.25$ and $\rho_{ach}^{+} = \rho_{ach}^{-} = 20$). Images from [18]

Success-motivated individuals with a lower value of M_{ach}^{+}, are more likely to attempt goals with a lower probability of success. For these individuals, the lower the value of M_{ach}^{-}, the smaller the range of success probabilities they will consider to be highly motivating. This means that their behaviour will be more focused on goals within a narrow range of success probabilities.

Table 2.1 Ways in which individuals may estimate probability of success at a goal

Mastery-oriented estimates	Performance-oriented estimates
Self-based estimates from individual experience: how well an individual has performed on previous attempts at the goal	Norm-based estimates or social comparison standards: how many other people can solve the goal (see Chap. 9)
Task-based estimates or absolute standards: for example, distance from a target in a shooting or throwing game (see Chap. 4)	

Table 2.2 Parameters of the achievement motivation model in Eq. 2.6 and their possible values

Parameter	Description	Value range
$P^s(G)$	Probability of success	[0, 1]
M_{ach}^+	Turning point of success approach	$(-\infty, \infty)$
M_{ach}^-	Turning point of failure avoidance	$(-\infty, \infty)$
ρ_{ach}^+	Gradient of success approach	$[0, \infty)$
ρ_{ach}^-	Gradient of failure avoidance	$[0, \infty)$
S_{ach}	Motivation strength	$[0, \infty)$

$M_{\text{ach}}^+ > M_{\text{ach}}^-$ can be used to model Atkinson's [1] original concept of a failure-motivated individual, as in Fig. 2.6b. Note the characteristic U shape of the curve for resultant tendency, similar to that seen shown in Atkinson's [1] model in Fig. 1.4b. In a failure-motivated individual the magnitude of negative feedback (punishment) for failing increases more quickly than in success-motivated individuals. This has a tendency to focus behaviour on very difficult goals with a low probability of success. The positive feedback for success increases slowly, producing a tendency to focus on very easy goals with a high probability of success.

Atkinson and Litwin [2] later identified subtypes of achievement motivation based on the combination of tendency to approach success and tendency to avoid failure. Individuals' tendency to approach success or avoid failure was gauged using the projective test of need achievement and Mandler-Sarason tests. Individuals were then broken into four groups as follows:

- H-L: high motivation to approach success and low motivation to avoid failure,
- H-H: high motivation both to approach success and to avoid failure,
- L-L: low motivation both to approach success and to avoid failure
- L-H: low motivation to approach success and high motivation to avoid failure.

In this study, Atkinson and Litwin [2] found that failure-motivated individuals do not select very easy or very difficult tasks to the extent predicted by their original
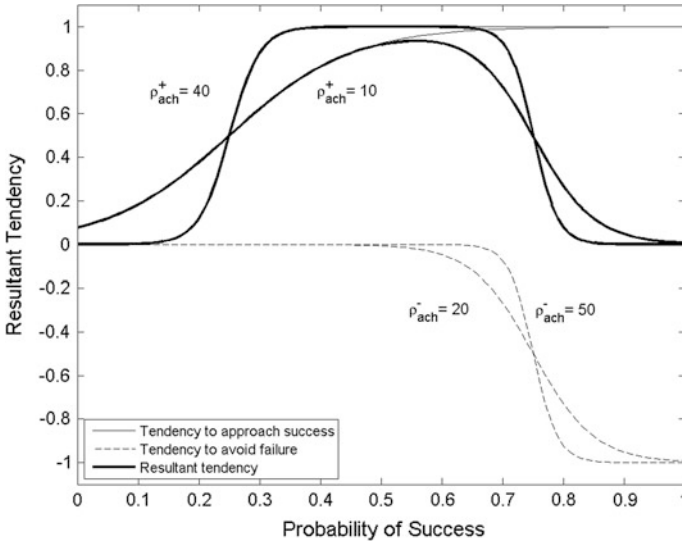
Fig. 2.7 Two examples of motivation to approach success with varying ρ_{ach}^+ and ρ_{ach}^-. $S_{\text{ach}} = 1$, $M_{\text{ach}}^+ = 0.25$, $M_{\text{ach}}^- = 0.75$ and $\rho_{\text{ach}}^+ < \rho_{\text{ach}}^-$ in both cases

RTM. Rather, they simply have slightly lower tendency for tasks of intermediate difficulty. We model and study these subtypes with this fact in mind in Chap. 4.

Using a sigmoid-based model gives us additional control of the shape of the resultant tendency curve through two parameters controlling the gradients of approach and avoidance. Specifically, $\rho_{\text{ach}}^+ > 0$ is the gradient of approach to success and $\rho_{\text{ach}}^- > 0$ is the gradient of avoidance of failure. Some experimental evidence with biological motives for hunger satiation and pain avoidance [5] suggests the gradient of approach is often less than the gradient of avoidance. More recent work [8] connects approach-avoidance motivation more broadly to concepts of appetition, reward and incentive (approach) as well as aversion, punishment and threat (avoidance). In the case of achievement motivation, gradient of approach less than gradient of avoidance would imply $\rho_{\text{ach}}^+ < \rho_{\text{ach}}^-$. Two examples of such scenarios are shown in Fig. 2.7. This figure demonstrates how we can tune the shape of the motivation curve and the impact of changes to ρ_{ach}^+ and ρ_{ach}^- on the shape of the motivation curve.

Finally, S_{ach} determines the strength of achievement motivation. When multiple approach-avoidance motives are modelled using a sigmoid-based approach, the S parameter permits them to compete or cooperate to control the behaviour of the individual. As with the success and failure gradients, the range for S_{ach} is somewhat arbitrary, and depends on the ranges of the S values for other motivations, if any. A general range of parameter values possible in this model is summarized in Table 2.2. As the discussion above suggests, in practice, specific constraints on these ranges create motive profiles that are more or less realistic in human motivational terms. This will be demonstrated in Chap. 4.

2.2.2   Modelling Affiliation Motivation

As we saw in Chap. 1, approach-avoidance motivation theory has been extended to the social domain [7, 20]. Thus, in this section we model affiliation motivation as the difference between two sigmoid functions for hope of affiliation and fear of rejection. Our model also interprets affiliation motivation as a counterbalance to power motivation. As discussed in Chap. 1, McClelland and Watson [14] presented evidence indicating that the strength of satisfaction of the power motive depends solely on incentive and is unaffected by the probability of success. Power-motivated individuals select high-incentive goals, as achieving these goals gives them significant control of the resources and reinforcers of others. To represent affiliation motivation as opposing power motivation, we thus define hope and fear of affiliation with respect to incentive. In contrast to power motivation, hope of affiliation (approach motivation) is high for low-incentive goals. These goals are likely to cause the least conflict with others by competing for control of their resources or reinforcers. As goal incentive increases, approach motivation decreases and plateaus, as shown in Fig. 2.8. Negative feedback (avoidance motivation) is greatest for high-incentive goals which may cause conflict with others. These two sigmoid curves are summed and composed with goal incentive $I^s(G)$ as shown in Eq. 2.7 to get the resultant tendency for affiliation, which peaks for low-incentive goals:
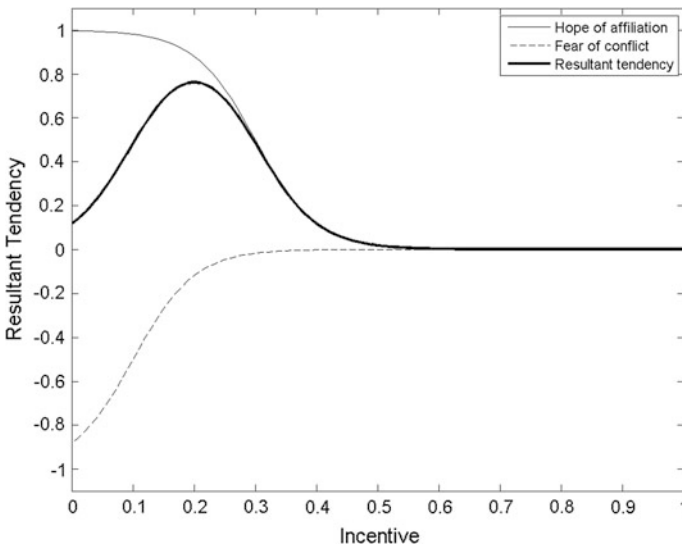

Fig. 2.8   Affiliation motivation as the sum of curves for hope of affiliation and fear of conflict as in Eq. 2.7 ($S_{\text{aff}} = 1$, $M_{\text{aff}}^+ = 0.3$, $M_{\text{aff}}^- = 0.1$ and $\rho_{\text{aff}}^+ = \rho_{\text{aff}}^- = 20$). Image from [18]

$$T_{\text{aff}}^{\text{res}}(I^{\text{s}}(G)) = \left(T_{\text{aff}}^{\text{res}} \circ I^{\text{s}}\right)(G) = \frac{S_{\text{aff}}}{1 + e^{-\rho_{\text{aff}}^{+}\left(M_{\text{aff}}^{+} - I^{\text{s}}(G)\right)}} - \frac{S_{\text{aff}}}{1 + e^{-\rho_{\text{aff}}^{-}\left(M_{\text{aff}}^{-} - I^{\text{s}}(G)\right)}}. \quad (2.7)$$

$I^{\text{s}}(G)$ represents the incentive to complete a given goal G. The process of estimating incentive is imperfectly understood for humans, both in terms of the units in which incentive might be measured and the way goals are mapped to incentive values. In addition there is a great deal of conflicting experimental evidence in this area [10]. In this chapter, incentive is represented as a value between zero and one, with incentive of one denoting the most valuable goals and incentive of zero denoting the least valuable goals. Some possible suggestions for modelling incentive include:

- Incentive inversely proportional to probability of success: this is commonly assumed for achievement goals. It should be noted that the gradient of this mapping can vary from person to person;

- Incentive proportional to explicit value: certain goals directly satisfy motivation, for example, consuming food satisfies hunger;

- Incentive proportional to socially determined value: certain goals have indirect value depending on circumstances. For example, earning money is valuable in a capitalist society.

The first and third approaches are the easiest to model in generic terms. For the first approach, the agent can determine probability of success using one or more of the approaches discussed in the previous section. For the third approach the agents can communicate to agree on goal values. The second approach is the most difficult as it implies some domain knowledge of which objects are inherently valuable. This could be achieved through learning or exploration strategies such as trial-and-error.

This model also has five parameters, M_{aff}^{+}, M_{aff}^{-}, ρ_{aff}^{+}, ρ_{aff}^{-} and S_{aff}, which are summarized in Table 2.3. M_{aff}^{+} is the turning point of the curve describing the approach component of affiliation motivation and M_{aff}^{-} is the turning point of the curve describing the avoidance component. For affiliation motivation there is the constraint that hope of affiliation should drop in response to an increase in fear of rejection. This means that $M_{\text{aff}}^{+} > M_{\text{aff}}^{-}$ is required.

Table 2.3 Parameters of affiliation motivation (Eq. 2.7) and their possible values

Parameter	Description	Value range
$I^{\text{s}}(G)$	Incentive value for success at goal G	$[0, 1]$
M_{aff}^{+}	Turning point of approach (hope)	$\left(M_{\text{aff}}^{-}, \infty\right)$
M_{aff}^{-}	Turning point of avoidance (fear of conflict)	$\left(-\infty, M_{\text{aff}}^{+}\right)$
ρ_{aff}^{+}	Gradient of approach (hope)	$[0, \infty)$
ρ_{aff}^{-}	Gradient of avoidance (fear of conflict)	$[0, \infty)$
S_{aff}	Relative motivation strength	$[0, \infty)$

Once again, using a sigmoid-based model gives us additional control of the shape of the resultant tendency curve through two parameters controlling the gradients of approach and avoidance. ρ_{aff}^{+} is the gradient of hope for affiliation and ρ_{aff}^{-} is the gradient of avoidance of conflict. S_{aff} is a measure of the strength of the affiliation motivation. Again, the theory of approach-avoidance motivation [5] suggests the gradient of hope (approach) is often less than the gradient of fear (avoidance), that is, $\rho_{\text{aff}}^{+} < \rho_{\text{aff}}^{-}$. Table 2.3 summarizes the parameters of this model and the range of possible values they may take.

2.2.3   Modelling Power Motivation

Power motivation can also be modelled with respect to incentive as the difference between two sigmoid curves for tendency to seek power and inhibition of power. Tendency to seek power is lowest for low-incentive goals and highest for high-incentive goals. Negative feedback for inhibition of power is also largest for high-incentive goals. The resultant tendency for power motivation is the sum of the power-seeking and inhibition sigmoid curves, composed with incentive for success $I^{s}(G)$ as shown in Eq. 2.8. A visualization of this model is shown in Fig. 2.9.
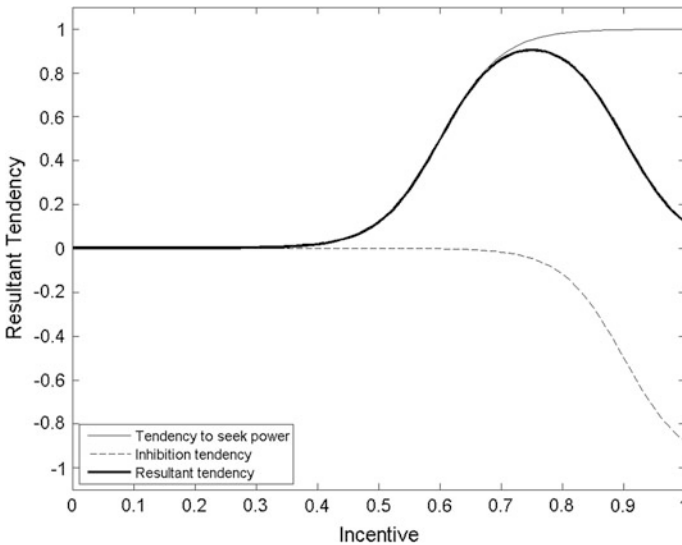

Fig. 2.9 Power motivation as the sum of curves for approaching and avoiding power ($S_{\text{pow}} = 1$, $M_{\text{pow}}^{+} = 0.6$, $M_{\text{pow}}^{-} = 0.9$ and $\rho_{\text{pow}}^{+} = \rho_{\text{pow}}^{-} = 20$). Image from [18]

Table 2.4 Parameters of the power motivation (Eq. 2.8) and their possible values

Parameter	Description	Value range
$I^s(G)$	Incentive value for success at goal G	$[0, 1]$
M_{pow}^+	Turning point of approach (power seeking)	$\left(-\infty, M_{pow}^-\right)$
M_{pow}^-	Turning point of avoidance (inhibition)	$\left(M_{pow}^+, \infty\right)$
ρ_{pow}^+	Gradient of approach (power seeking)	$[0, \infty)$
ρ_{pow}^-	Gradient of avoidance (inhibition)	$[0, \infty)$
S_{pow}	Relative motivation strength	$[0, \infty)$

$$T_{pow}^{res}\left(I^s(G)\right) = \left(T_{pow}^{res} \circ I^s\right)(G) = \frac{S_{pow}}{1 + e^{-\rho_{pow}^+\left(I^s(G) - M_{pow}^+\right)}} - \frac{S_{pow}}{1 + e^{-\rho_{pow}^-\left(I^s(G) - M_{pow}^-\right)}}$$

$$(2.8)$$

$I^s(G)$ represents incentive or the value of completing a given goal. Techniques for estimating incentive were discussed in the Sect. 2.2.2. The model has five parameters, M_{pow}^+, M_{pow}^-, ρ_{pow}^+, ρ_{pow}^- and S_{pow}. M_{pow}^+ defines the turning point of the approach component of power motivation and M_{pow}^- defines the turning point of the inhibition component of power motivation. For power motivation there is the constraint that the inhibition tendency is triggered by an increase in tendency to seek power. That is, $M_{pow}^+ < M_{pow}^-$. ρ_{pow}^+ is the gradient of tendency to seek power and ρ_{pow}^- is the gradient of inhibition. S_{pow} is a measure of the relative strength of the power motivation compared to other motives. Table 2.4 summarizes the parameters of this model and the range of possible values they may take.

2.3 Motive Profiles for Artificial Agents

When developing computational models of motivation there is a need to focus on individual motives to aid understanding of these models. However, when examining the role of motivation in goal selection there is also a need to consider several motives at once. Considering multiple motives permits the relative strengths and dominance of different motives to be taken into account when generating behaviour. The interaction of several motives changes the way an individual responds in a given situation. This section proposes three methods of differing complexity and fidelity for combining the individual motivation models above into artificial 'motive profiles'. The first is a profile of three motives, the second models only the dominant motive and the third represents motivation only in terms of the incentive value with the highest motivation.

   In the sections above, affiliation and power motivation are modelled with respect to incentive, while achievement motivation is modelled with respect to probability of success. In natural systems, it is possible that the definition of incentive may change from motive to motive. However, for simplicity, in this book we assume that there is correlation (if not equality) between these definitions and further adopt Atkinson's [1] assumption that there is an inverse linear relationship between probability of success and incentive (Eq. 1.3 specifically). We can then build models as functions of a single value: incentive. This means that, if we assume we can create artificial agents that can obtain or calculate goal incentive $I^s(G)$, then we can create agents with an artificial motive profile. We do this in three ways. The first method, in Sect. 2.3.1, models profiles of three motives explicitly. The second method, in Sect. 2.3.2, models the dominant motive only. The third method, in Sect. 2.3.3, models only the incentive that maximises the dominant motive.

2.3.1   Modelling Profiles of Achievement, Affiliation and Power

We model profiles of achievement, affiliation and power motivation by combining Eqs. 2.6–2.8 as a sum, as follows:

$$
\begin{aligned}
(T^{\text{res}} \circ I^{\text{s}})(G) &= T^{\text{res}}_{\text{ach}}(I^{\text{s}}(G)) + T^{\text{res}}_{\text{aff}}(I^{\text{s}}(G)) + T^{\text{res}}_{\text{pow}}(I^{\text{s}}(G)) \\
&= \frac{S_{\text{ach}}}{1 + e^{-\rho^{+}_{\text{ach}}((1-I^{\text{s}}(G))-M^{+}_{\text{ach}})}} - \frac{S_{\text{ach}}}{1 + e^{-\rho^{-}_{\text{ach}}((1-I^{\text{s}}(G))-M^{-}_{\text{ach}})}} \\
&\quad + \frac{S_{\text{aff}}}{1 + e^{-\rho^{+}_{\text{aff}}\left(M^{+}_{\text{aff}}-I^{\text{s}}(G)\right)}} - \frac{S_{\text{aff}}}{1 + e^{-\rho^{-}_{\text{aff}}\left(M^{-}_{\text{aff}}-I^{\text{s}}(G)\right)}} \\
&\quad + \frac{S_{\text{pow}}}{1 + e^{-\rho^{+}_{\text{pow}}\left(I^{\text{s}}(G)-M^{+}_{\text{pow}}\right)}} - \frac{S_{\text{pow}}}{1 + e^{-\rho^{-}_{\text{pow}}\left(I^{\text{s}}(G)-M^{-}_{\text{pow}}\right)}}
\end{aligned}
\tag{2.9}
$$

   Summing the different component motives suggests that motives cooperate to influence the behaviour of an agent. Other methods of combining motives (sometimes called arbitration functions [17]) have also been proposed. For example, the combination of motives using a max(.) function models competition between motives to influence the behaviour of the agent.

   This model has parameters as shown in Table 2.5. Using Eq. 2.9, we can construct artificial models of some of the named motive profiles discussed in Sects. 1.3.4 and 1.3.5. For example, a leadership motive profile [15] of high power and achievement motivation, but low affiliation motivation might appear as shown in Fig. 2.10a. An imperial motive profile of high power motivation, with low achievement and affiliation motivation might appear as shown in Fig. 2.10b.

   We use Eq. 2.9 to model motivation in the experiments in Chap. 5.

Table 2.5 Parameters of motivation for an agent with a profile of achievement, affiliation and power motivation as defined in Eq. 2.9

Parameter	Description
$I^s(G)$	Incentive value for success at goal G
M_{ach}^+	Turning point of achievement approach
M_{ach}^-	Turning point of achievement avoidance
ρ_{ach}^+	Gradient of achievement approach
ρ_{ach}^-	Gradient of achievement avoidance
S_{ach}	Relative motivation strength for achievement
M_{aff}^+	Turning point of affiliation approach
M_{aff}^-	Turning point of affiliation avoidance
ρ_{aff}^+	Gradient of affiliation approach
ρ_{aff}^-	Gradient of affiliation avoidance
S_{aff}	Relative motivation strength for affiliation
M_{pow}^+	Turning point of power approach
M_{pow}^-	Turning point of power avoidance
ρ_{pow}^+	Gradient of power approach
ρ_{pow}^-	Gradient of power avoidance
S_{pow}	Relative motivation strength for power motivation

2.3.2 Modelling the Dominant Motive Only

Alternatively, we can further simplify the calculation of motivation by considering only the curve for the dominant motive. In this case we have:

$$(T^{res} \circ I^s)(G) = T_{mot}^{res}(I^s(G)) = \frac{S_{mot}}{1 + e^{-\rho_{mot}^+\left(I^s(G)-M_{mot}^+\right)}} - \frac{S_{mot}}{1 + e^{-\rho_{mot}^-\left(I^s(G)-M_{mot}^-\right)}},$$

(2.10)

where *mot* is either ach, aff or pow and parameter values are chosen from Table 2.6. We use this approach in Chap. 6.

2.3.3 Optimally Motivating Incentive

As we saw in Eqs. 2.9 and 2.10, motivational tendency for a goal is computed by composing functions for approach-avoidance motivation and incentive for success at a goal $I^s(G)$. In situations where it is desirable to avoid making the full calculation, we can approximate a motive profile by introducing the concept of an optimally motivating incentive (OMI) as follows.

First, we denote the incentive value that maximises $T^{res}(.)$ as Ω. We call Ω the OMI of the agent. Ω can be thought of as approximating the motive profile as an
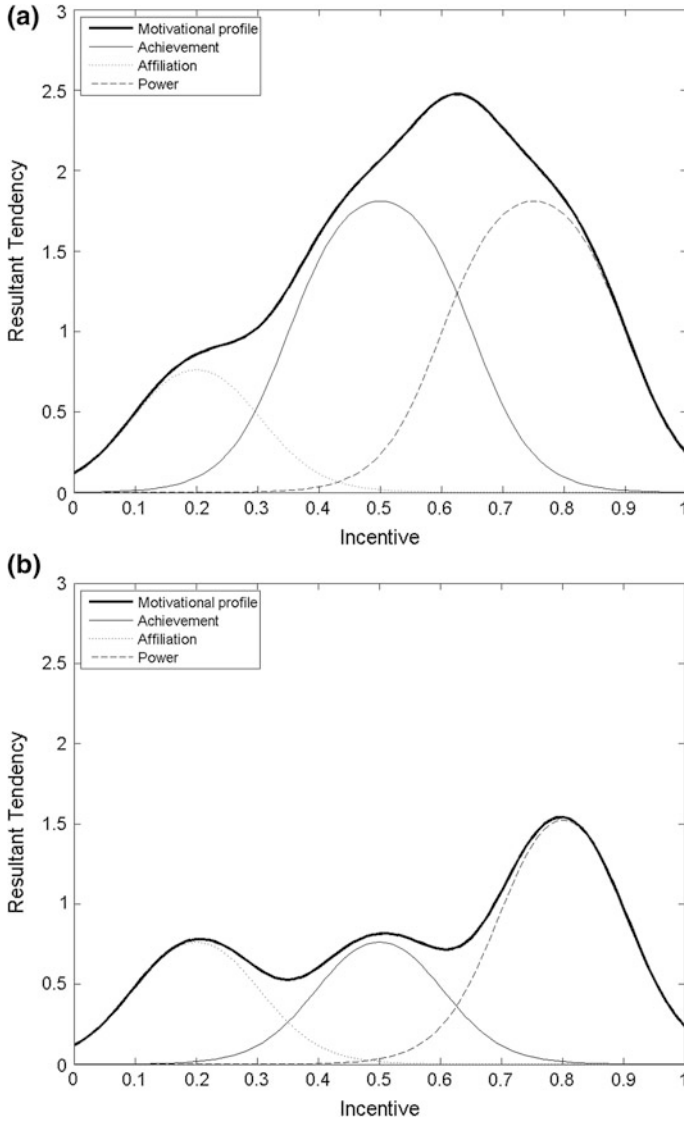
Fig. 2.10 **a** Leadership motive profile: $S_{ach} = 2$, $M_{ach}^+ = 0.35$, $M_{ach}^- = 0.65$, $S_{aff} = 1$, $M_{aff}^+ = 0.3$, $M_{aff}^- = 0.1$, $S_{pow} = 2$, $M_{pow}^+ = 0.6$, $M_{pow}^- = 0.9$ **b** Imperial motive profile: $S_{ach} = 1$, $M_{ach}^+ = 0.4$, $M_{ach}^- = 0.6$, $S_{aff} = 1$, $M_{aff}^+ = 0.3$, $M_{aff}^- = 0.1$, $S_{pow} = 2$, $M_{pow}^+ = 0.7$, $M_{pow}^- = 0.9$. In both profiles $\rho_{ach}^+ = \rho_{ach}^- = \rho_{aff}^+ = \rho_{aff}^- = \rho_{pow}^+ = \rho_{pow}^- = 20$. Images from [18]

agent by indicating the incentive value that will result in the highest motivation. An agent is qualitatively classified as power-motivated if its OMI is relatively 'high' in the range of possible incentives. The OMI of such an agent is shown in Fig. 2.11.

Table 2.6 Parameters of motivation and their possible values when only the dominant motive is modelled as defined in Eq. 2.10

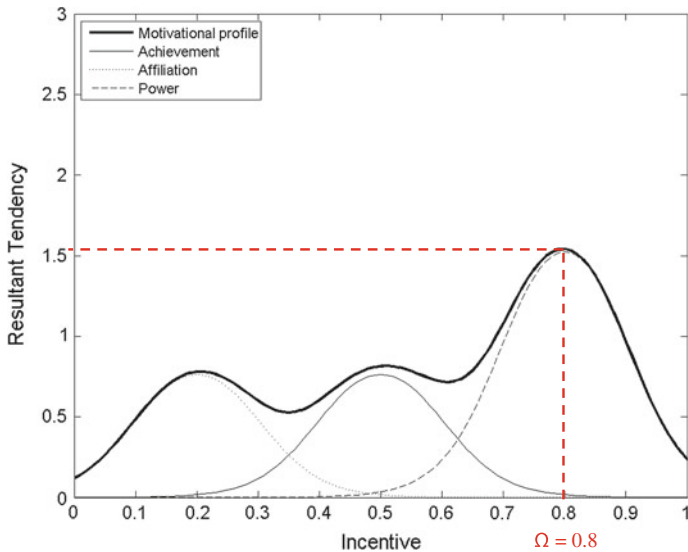| Parameter	Description	Value range
$I^s(G)$	Incentive value for success at goal G	$[0, 1]$
M_{mot}^+	Turning point of approach	$\left(-\infty, M_{mot}^-\right)$
M_{mot}^-	Turning point of avoidance	$\left(M_{mot}^+, \infty\right)$
ρ_{mot}^+	Gradient of approach	$[0, \infty)$
ρ_{mot}^-	Gradient of avoidance	$[0, \infty)$
S_{mot}	Motivation strength	$[0, \infty)$

Fig. 2.11 Optimally motivating incentive Ω is the incentive value that maximises the motivation function. Power-motivated profiles such as the one shown here have a relatively 'high' optimally motivating incentive

Achievement- and affiliation-motivated agents have qualitatively 'moderate' and 'low' OMIs respectively.

Goal selection is done by computing the difference between the explicit incentive for success at a goal $I^s(G)$ and the OMI Ω and constructing a 'subjective incentive' value $\hat{I}^s(G)$ that is highest for goals with $I^s(G)$ closest to Ω. The subjective incentive value in this case is the resultant tendency for motivation. If the maximum explicit incentive value is assumed to be one, then one such equation for computing subjective incentive (resultant tendency) is:

$$(T^{\text{res}} \circ I^{\text{s}})(G) = \hat{I}^{\text{s}}(G) = 1 - |I^{\text{s}}(G) - \Omega|. \tag{2.11}$$

That is, subjective incentive is equal to the maximum possible incentive minus the error between actual and optimal incentive. This means that a goal with an explicit incentive of one only results in the highest subjective value if it is closest to the agent's OMI Ω. The agent is assumed to prefer goals with higher subjective incentive. That is, we assume that the agent is 'subjectively rational'. The implications of this assumption are, first, that an incentive $I^{\text{s}}(G)$ will be perceived differently by agents with different OMIs. In addition, the highest explicit incentive may not be the highest subjective incentive for all agents. This provides a foundation for the emergence of behavioural diversity.

Goal selection using an OMI representation of motivation has an additional point of flexibility over the motivation functions in Sects. 2.3.1 and 2.3.2, as there is no longer a strict requirement for the range of incentive to be limited to [0, 1]. Incentive can potentially take on any range of values, including both positive (gain) and negative (loss) values. Assuming that it is possible for agents to identify the range and the maximum, V^{max}, a more general equation for subjective incentive is:

$$(T^{\text{res}} \circ I^{\text{s}})(G) = \hat{I}^{\text{s}}(G) = V^{\text{max}} - |I^{\text{s}}(G) - \Omega|. \tag{2.12}$$

This is useful in scenarios where incentive does not conform to Atkinson's assumptions about the relationship between incentive and probability of success discussed in Chap. 1.

Yet another generalisation is possible if we weaken the definition of a goal. If the goal is merely to obtain a certain incentive with value V, then it is no longer necessary to explicitly distinguish the goal structure. This gives us the simplified equation for subjective incentive as:

$$\hat{I}^{\text{s}} = V^{\text{max}} - |V - \Omega|. \tag{2.13}$$

This equation models the influence of implicit motivation when judging explicit incentives. The main weakness of the OMI approach is that it cannot be used to model the subtleties of hybrid motive profiles. However, for pure profiles of achievement, affiliation or power motivation, this technique can be a useful simplification. The concept of OMI is used in the motivated learning agents in Part III and the motivated evolutionary agents in Part IV.

2.4   Using Motive Profiles for Goal Selection

Goal-oriented behaviour has been widely addressed in the literature of both human psychology and artificial agents. In human psychology, goal-setting theory is considered a necessary part of motivation theories [4, 11]. Likewise, in artificial

agents goals and motivations have also been closely related. Braubach et al. [3] state that the goals of an agent represent the agent's motivational stance, as it is from goals that an agent determines the actions to perform. Dignum and Conte [6] further state that truly autonomous, intelligent agents must be capable of creating new goals as well as dropping goals as conditions change. They propose instrumental goal formation as a process of deriving concrete, achievable goals—such as 'driving at the speed limit'—from high level, abstract goals—such as 'being good'. The notion of abstract goals in this case correlates somewhat with the psychological definition of implicit motives, which stem from innate preferences for certain kinds of incentives [10]. Concrete goals, in contrast, reflect explicit, self-attributed motives. There is a wealth of literature on goal structures—including goal lifecycles and type taxonomies [3]—and processes for solving goals—for machine learning, planning and rule-based agents [21].

We saw in the previous section that motivation for a goal may be computed in a number of different ways, making progressively weaker assumptions about the nature of a goal. In Eqs. 2.9–2.12 a goal is represented specifically in the equation. In Eq. 2.13 a goal is implied only by the existence of an incentive. Regardless of how the goal is represented, however, the question remains as to what to do next. That is, once motivated, how should an artificial agent choose between highly motivating goals? We discuss two traditional alternatives here: a 'winner-takes-all' approach in Sect. 2.4.1 and a probabilistic approach in Sect. 2.4.2.

2.4.1 Winner-Takes-All

In the rule-based agents studied in Part II of this book (Algorithms 3.1 and 3.2), motivation is computed using the full form of either Eq. 2.6 or Eq. 2.9. We denote by $\mathbf{G}_t = \{G^1, G^2, G^3, \ldots, G^N\}$ a set of goals that are valid at time t. We define the maximally motivating goal $G_t^{\max}$ for agent A as the element of $\mathbf{G}_t$ for which an agent A computes the highest resultant motivational tendency.

The specific calculation of $G_t^{\max}$ can be adapted to embed either a single motivation or several motivations together in a motive profile. For example, Eq. 2.14 selects a goal using achievement motivation as defined in Eq. 2.6. Equation 2.15 selects a goal using a motive profile as defined in Eq. 2.9 or an OMI as in Eq. 2.11. Chapters 3–5 examine how this motivated goal selection can be embedded in architectures for game-playing agents.

$$G_t^{\max} = \operatorname*{argmax}_{G \epsilon \mathbf{G}_t}(T_{\text{ach}}^{\text{res}} \circ P^{\text{s}})(G) \tag{2.14}$$

$$G_t^{\max} = \operatorname*{argmax}_{G \epsilon \mathbf{G}_t}(T^{\text{res}} \circ I^{\text{s}})(G) \tag{2.15}$$

2.4.2   Probabilistic Goal Selection

Another approach to goal selection is to select probabilistically according to the distribution of motivation values across multiple goals. This has the advantage that several goals with similar motivation values may be pursued. The probability $P(G_t = G^g)$ with which a particular goal G^g is pursued at time t may be proportional to the resultant tendency for motivation, or to the subjective incentive of the goal, or computed using a function such as the Boltzman or 'softmax' distribution to determine the probability of selecting a particular goal.

Probability proportional to the resultant tendency for motivation is computed by:

$$P(G_t = G^g) = \frac{(T^{\text{res}} \circ I^s)(G^g)}{\sum_{G \epsilon \mathbf{G}_t} (T^{\text{res}} \circ I^s)(G)}. \qquad (2.16)$$

This approach is used in Chap. 6. Boltzman goal selection using a motive profile such as Eq. 2.10 or Eq. 2.11 is computed by:

$$P(G_t = G^g) = \underset{G \epsilon \mathbf{G}_t}{\text{softmax}}(T^{\text{res}} \circ I^s)(G) = \frac{e^{\frac{(T^{\text{res}} \circ I^s)(G^g)}{\tau}}}{\sum_{G \epsilon \mathbf{G}_t} e^{\frac{(T^{\text{res}} \circ I^s)(G)}{\tau}}}. \qquad (2.17)$$

$0 < \tau < \infty$ is a temperature value that determines the difference in probability of goals with high motivation values from goals with low motivation values. τ can be varied to increase or decrease the probability of the agent executing a randomly selected goal, or it can be kept constant.

2.5   Summary

This chapter has presented three incentive-based computational models of motivation for achievement, affiliation and power motivation. The models use the concept of approach and avoidance motivation and include curves for both approach and avoidance of a particular motivation. Control parameters permit the maximally motivating incentive to be modified in each model, as well as the rate of increase and decrease of motivation as subjective probability of success or goal incentive changes.

The models are designed such that they can be used in isolation or together, embedded in an artificial 'motive profile'. A motive profile can be further approximated as an optimally motivating incentive.

We have provided a formal notation for selection of a maximally motivating goal from a set of goals, or probabilistic goal selection. However, we have not yet addressed the questions of how goals are created, or where success probabilities or

incentive values come from. Chapter 3 will describe how computational models of motivation can be combined with some traditional agent architectures for game-playing agents.

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