A Promise Theory Perspective on The Role of Intent in Group Dynamics (v0.1)

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Abstract

We present a simple argument using Promise Theory and dimensional analysis for the Dunbar scaling hierarchy, supported by recent data from group formation in Wikipedia editing. We show how the assumption of a common priority seeds group alignment until the costs associated with attending to the group outweigh the benefits in a detailed balance scenario. Subject to partial efficiency of implementing promised intentions, we can reproduce a series of compatible rates that balance growth with entropy.

Contents

1 Introduction

The discovery of a linear relationship between cortical masses and persistent social group sizes gave the first indication of a connection between cognitive capacity and group size amongst primates [1], leading to the first of the now famous Dunbar numbers of '150 friends' for the average human circles. Subsequent work both confirmed and extended this number to encompass a hierarchy of group sizes for different levels of attention [2], starting with 5,15,50,150, etc; yet the reason for this group scaling has remained the subject of some speculation.

In this paper, we show how Promise Theory [3] (a theoretical model of autonomous agents), ordinary dimensional analysis, and some elementary statistical mechanics, predict the main features of the group dynamics and its scaling hierarchy, by looking at rates of attention as a proxy for cognitive capacity. This arises for a model in which groups form in response to a seed that attracts their attention. The predictions fit well with data obtained from a study of hundreds of thousands of ad hoc group formations recorded on the Wikipedia platform for the purpose of editing its content [4]. The promise theoretic model is based on a formalization of what we would tend to call 'trust' in human terms, and thus suggests a new pragmatic interpretation of trust in terms of an economy of attention.

Although links to neuroscience are also a natural place to seek explanations, for a link between brain sizes and group sizes, we find a more universal explanation for statistically large populations (i.e. populations of approximately maximal entropy). However, we also comment on the possible implications of these results reflected in the neuroscience of the primate brain.

2 Statistical physics of human-machine agents

Progress in theoretical social science has been slow compared to other natural sciences. Recently, attempts to model social phenomena, in terms of variables that can be exposed as population characteristics, has led to the nascent field of Socio-Physics [5, 6]. Socio-physics models argue principally by analogy to known phenomena in physics (usually spin models). However, a missing piece in these descriptions is the underlying reasoning for both the variables and their likeness to known problems in fundamental physics. One imagines some universality arguments at play, but without a deeper causal link, the likenesses remain somewhat superficial in character. A second missing piece is the vastly greater scope for semantics to play a role in behaviour on a human scale. Discussions of elementary phenomena can afford to suppress semantics and promote universality because there are few degrees of freedom in play. Such isolation of information channels isn't generally plausible in human systems unless one can argue in terms of entropy.

Promise Theory, proposed by Burgess in the context of human-machine systems [7], was introduced to deal with such criticisms in the context of technology. It takes issue with the assumptions of logic as well as the suitability of Game Theory [8], Graph Theory [9], and Network Science [10], but synthesizes all of these into a tool set with fundamental principles based on compatibility with Information Theory [11]. It was developed by Bergstra and Burgess over the subsequent years [3], and more recently has been adopted as a model for socio-economic thinking.

The difficulty in formalizing human level concepts is that there is often a tendency to fall back on moral philosophy or psychology to argue rather than looking for an underlying causality on an agent or group level [12, 13].

Promise Theory is a bottom up theoretical framework, embodying graph theoretic notions as well as representations of semantic and dynamic variability. It embodies founding principles for the autonomy of agents. Taking a bottom up approach, it develops both algebraic formulations and scaling principles. Using Promise Theory, Burgess has proposed to use the familiar concept of trust as a unifying instrument in order to connect familiar behavioural phenomena (and terminology) with more formal analytical structures familiar from physics. As we'll see, trust gives us a convenient dynamical potential onto which we can graft the semantics of morality, through repeated processes like rituals and beliefs. Thus, in this picture, we expect repetition to be a general principle through which humans rehearse governance through social norms and graces. These ritualistic promises provide surrogate 'shared purposes' to rally people into collective behaviour.

2.1 Intent and promises

As outside observers, we can't always ask agents (people, animals, or machinery) what drives them, or what they are thinking but we can try to map their behaviours onto a model of intentions that match our own thinking. The intentional behaviour of an agent is rarely singular: it could be a rich admixture of goals with varying priorities. Each agent will prioritize based on its own 'algorithm'. Should a particular seed promise pass a threshold attention level for group formation, then this can manifest as an implicit bias, potentially seeding an alignment with other agents. In physics, we call this spontaneous symmetry breaking; it's associated with phase transitions.

In Promise Theory, intentionality can be represented by stylized 'promises', which can be characterized by a 'direction' of intent, defined within a space of possible outcomes. We needn't expand on the specific understanding of resources or processes that underly the fulfillment of promises here. The key point is that this approach to intent allows us to build an impartial algebraic representation for each agent, without prejudicing the dynamics of changing intent.

An agent A_1 can promise something described by some intention (usually denoted b, for the body of the promise) in the form of an offer (denoted $+b$) to another agent A_2

$$A_1 \xrightarrow{+b} A_2. \tag{1}$$

Assuming the agent A_2 accepts some amount of what is offered b' (denoted $-b'$)

$$A_2 \xrightarrow{-b'} A_1, \tag{2}$$

then a unidirectional flow of strength $b \cap b'$ of intended outcomes binds the agents in a relationship. This requires the attention of both parties, with donor and receptor promises, and involves time as an implicit resource.

Energy considerations alone are not a sufficient basis for determining systemic behaviour: one also has to know the rules by which it gets moved and exchanged between the dynamical variables of a system.

Thus, we need a story about the effective forces and representations for interaction too. Our experiences in physics can help to shape the way we represent these however.

Promises are like the steady state solutions for motion in physical systems. In addition to promises, there can be transient events, driven by changing boundary conditions or new information, such as when an agent throws a ball to another to catch unannounced. These are denoted by a special arrow resembling a fist:

$$A_1 \overset{+b}{\longrightarrow\!\!\blacksquare} A_2 \tag{3}$$

Impositions are transient (unplanned) interactions. They induce sudden demands or costs onto the recipient, they may be interpreted as the basis of contention, tending to pull agents unpredictably off course. In Promise Theory impositions play a significant role in reducing trust [14]. This dynamical picture is consistent with a 'work/energy' interpretation of trust alluded to in [15]. Promise Theory predicts that impositions tend to be ineffective, because they are likely to be ill aligned with receptor promises. It also predicts that impositions tend to reduce trustworthiness assessments and increase the attentiveness of a receiver.

Whether leading or following, agents that are imposed upon by their episodic 'neighbours' with transient demands tend to increase mistrust or the attention level of the group. This attracts agents with the same concerns to align. Later they may drift away from the group when the cost of attentive work exceeds a fractional threshold of group mistrust. These are the elements we need to complete the basic model of group formation.

2.2 Promise patterns

Simmel introduced the notion of triads in social systems [16]. Another triad theory of sentiment relations in social balance theory was proposed in [17–19] as a rule of threes proposed for the social sciences [20]. Triadic agent molecules have been proposed many times as basic control units for social networks, and have been implicated in group formation. Promise Theory does not recognize these speculative triadic network structures as such. Rather it predicts a triangular co-dependence between agents arising from the fundamental autonomy of agents. This means that agents fundamentally make decisions from within, possibly tempered by conditions from without, according to the law of assisted promise keeping [3]. The pattern may be used to express the promise a message from sender to receiver through a third party delivery agent, for example.

Figure 1 shows two ways in which groups could form. The semantics of group formation are significant to the costs associated with them. A group that follows a single leader or interacts one at a time is different from a group that tries to maintain global coherence all at once and all the time. The latter is very rigid and very expensive. For N agents, the cost is of the order N^2. In our discussion, we find the loose hierarchical association to be the cost that provides the best agreement with data.

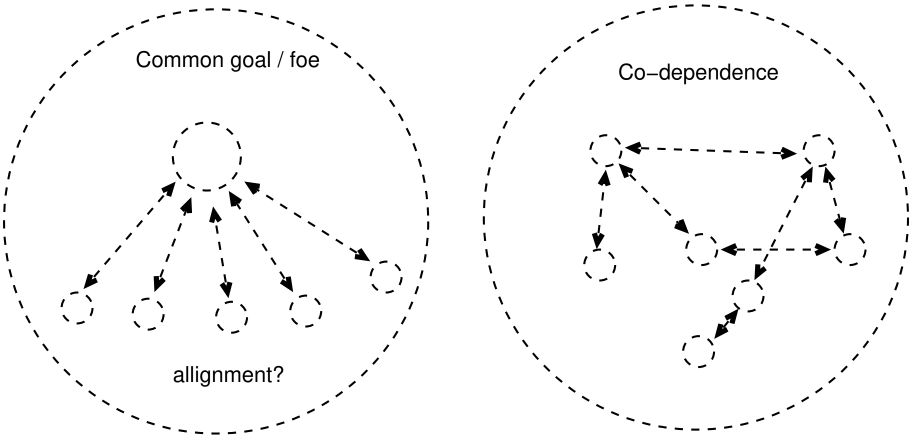

Figure 1: Groups form either because agents come together independently attracted to contribute to a common cause (like fighting a common enemy or working on a common product), or they form emergent clusters by pairwise percolation of promise relationships. In our model, we assume the left hand picture of attraction in which 'mistrust' of the central 'seed' promise drives increased attention and potentially proximity as a secondary effect.

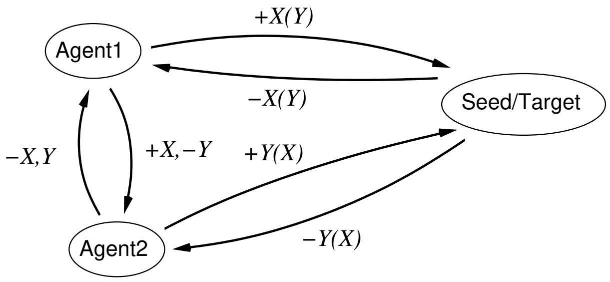

Figure 2: A basic cooperation/calibration triangle in Promise Theory allows two agents to work together on behalf of a third, or allows a third to act as a seed effectively bringing them into alignment $X = Y$. From Promise Theory, one would expect opportunistic dyadic structures $N = 2$ for compositional or symbiotic specialization, with more important coordinated structures built from equilibrated/cross-checked triads $N = 3$.

Consider the primitive pattern involving three agents shown in figure 2. The triangle of promises is the maximum coordination for three agents. This is the configuration by which they can maintain consistent information and claim to 'agree' with one another. It is called the Law of Conditional Assistance in Promise Theory. It represents a configuration of voluntary cooperation respecting the autonomy of the agents. Agent_1 promises an intended outcome X, based on the other agent's intent to supply Y' in the most general sense. The intended outcome X could involve watching over the group, performing some work on its behalf, etc. Essentially, it requires paying attention to the promise and allocating time resources. Agent_1 also promise to make use of the promise Y provided by Seed, which could simply be access to its personal space, or the ability to perform some service for it. We can use the shorthand notation for the directed promises:

$$\left.\begin{array}{r}\pi_X : \ \text{Agent}_1 \xrightarrow{+X|Y} \text{Seed} \\ \pi_Y : \ \text{Agent}_1 \xrightarrow{-Y} \text{Seed}\end{array}\right\} \equiv \text{Agent}_1 \xrightarrow{+X(Y)} \text{Seed}. \tag{4}$$

to represent the conditional promise of X given Y, together with the promise to accept Y if offered. In other words, 'I will keep the promise of X with the assistance of another, who in turn helps me by supplying Y, written $+X|Y$, and I promise you that I am accepting such help $-Y$'. Omitting the details [3], the full collaboration now takes the form:

$$\begin{array}{rcl}\text{Agent}_1 & \xrightarrow{+X(Y)} & \text{Seed} \\ \text{Agent}_1 & \xrightarrow{-Y,+X} & \text{Agent}_2 \\ \text{Agent}_2 & \xrightarrow{+Y,-X} & \text{Agent}_1 \\ \text{Agent}_2 & \xrightarrow{+Y(X)} & \text{Seed} \\ \text{Seed} & \xrightarrow{-X(Y)} & \text{Agent}_1 \\ \text{Seed} & \xrightarrow{-Y(X)} & \text{Agent}_2\end{array} \tag{5}$$

Notice the symmetries between ± in the promise collaboration of equilibrium state, and between X, Y indicating the complementarity of the promises. The maximal cost of this configuration is close to the square of the number of agents. Such a cost is unsustainable for large numbers.

For group cooperation, this level of cooperation is too expensive to be sustained much beyond $n = 3$, as the cost of predictable assurances rises like n^2. The level of cooperation we find represented in the scaling of group formation data rather suggests only the association of agents 1 and 2 through the proxy hub of the third. By extension, this is a classic hierarchical model in which a single hub plays a coordination role in keeping a group together—such as a head of department or group leader. In other words, the Promise Theory, predicts that interactions we might call 'grooming' of the relationships are basically one to one with a leader (scaling to one to $n - 1$ in a group of size n), as reflected in section 3.2).

When a seed is eliminated, or becomes overwhelmed by new priorities arising from environmental pressures, contention between the seed promise and impositions from the ambient environment rises, destabilizing it as a priority. Thus, in the absence of a strong seed, there is no effective promise to attract agents together and they drift apart in response to the perturbations from competing intentions.

3 Cost accounting for ‘grooming’ work

Our interpretation of trust is a pragmatic one. Ultimately, it’s a semantic abstraction of the ‘work of attention’, or cognitive work, as we’ll show below. Apart from minor semantic distinctions, such work ranges over a variety of phenomena and scales from idle curiosity to intense scrutiny and mistrust that are covered by the same attention processes. We can call all of these forms of ‘kinetic mistrust’.

The differences are thus in the degrees of scrutiny and the individual characterization of their importance of each agent. One agent’s causal interest might be another agent’s response to untrustworthy behaviour. We believe that this is consistent with normal usage, but it allows us to formalize trust as a form of work analogous to energy in two parts.

Since trust works as an attention accounting quantity, it’s driven by work done at different times, past and present. As in physics, potential energy is a summary of historically accumulated work, expressed as a coarse snapshot of the slowly-varying history. Conversely, kinetic energy is an immediate release of work, in response to the tendencies of directionality expressed by the potential. Since potential is historically accumulated work, we need *memory processes* to transmute learning into kinematics. Any memory process will do, but agents that have brain matter are obviously highly optimized for this and adds the sophistication for dealing with memory on many levels from dynamics to semantics.

3.1 Dimensional accounting

Dimensional analysis is the way scales of measurement are defined in natural science. Classically, all measures can be reduced to combinations of properties regarded as ‘innate’ to physics, namely mass, length, time, and a few others. The role of time is central to group formation, principally because it is closely associated with work. The counting of any relationship with respect to time has to follow a universal dimensional analysis. These relations were derived for continuum processes for ballistic models.

In continuum language, a force F applied over a path length dx in some parameter space is equivalent to a directional impulse dp. If one assumes a process velocity $\vec{v} = \vec{dx}/dt$, where $\vec{dx}$ represents the direction of an intention in the space of outcomes, this settles the accounting of the quantities with respect to time. The usual ‘Newtonian’ conventions follow from the observation that a change in potential energy (defining a force) has the same dimensions as a change in kinetic energy:

$$\begin{aligned}
dV = \overrightarrow{\nabla} V \cdot \vec{dx} = \vec{F} \cdot \vec{dx} &= \vec{F} \cdot \vec{v}\, dt \\
&= \frac{\vec{dp}}{dt} \cdot \vec{v}\, dt \\
&= \vec{v} \cdot \vec{dp} \\
&= m\vec{v} \cdot \vec{dv} \\
&= \frac{1}{2} m d(\vec{v} \cdot \vec{v}) \\
&= d\left(\frac{1}{2} m v^2\right) \\
&= d\overline{T}. \qquad (6)
\end{aligned}$$

Thus, the relationship between the quantities we count as force and energy are constrained mainly by dimension and rate, and energy accounting.

In our dynamics of potential alignments and kinetic attention processes, the kinetics are more like Shannon information sampling [11] than linear motion, but the dimensions have to be the same. The rate of conversion of accumulated work from the keeping of promises is thus found dimensionally by comparing

$$V \sim \frac{1}{2} m v^2 \qquad (7)$$

up to dimensionless factors, where the attention rate or ‘velocity’ v whose dimensions are arbitrary except for the role of time. The potential amounts to a reliability for promise keeping. One might even call it a kind of ‘goodwill’ V in human terms. The work of a single agent, interacting in a group of size n, would be expected to scale as

$$W(\text{agent}) = \frac{c_1 + c_2(n-1)}{c_0 n_\beta} \qquad (8)$$

where c_0, c_1, and c_2 are constants. At low utilization, we can expect the availability or channel capacity to be approximately proportional to the number of agents interacting. Once contentions sets in, this effective number slows down as agents begin to leave a group to an average—which is the value at which contention is maximal.

When $\beta E = 0$, the probability has to be 1, so for $n = 1$ (self), all the share is in one agent's hands. So $c_1 = 0$. Now we have a single scale $C \equiv c_2/c_0$ representing the level of shared of contention between agents. To determine this, we use the promise seed configuration again below. Note that, at maximum entropy, this is evenly distributed without particular favour to any agent. So, based on these dimensional arguments, we expect the limit of maximum entropy for large N to take the form:

$$P(\beta) \sim \exp\left(-\frac{C(n-1)}{n_\beta}\right), \tag{9}$$

where n_β is some scale that characterizes the intra-group contention, Small C implies tolerance of contention, or loose coupling and thus larger group sizes, while large C implies some kind of territorial overlap that leads to altercation.

3.2 Work afforded by a limited capacity

We can make this more formal as follows. Suppose each agent has a cognitive processing work capacity $W_{\max}$ for the process of group interactions that it shares with other tasks too. How the capacity is sliced is a detail that we don't need to address here. If we think in terms of the 'power output' or work of the agents, in kinetic terms, relating to the promise of sharing the group resources. At max entropy (large N and large ensembles), the probable work fraction $P(W)$ for distribution would take the form of a Boltzmann distribution over the relative costs [21, 22]:

$$\begin{aligned} P &\sim e^{-\beta E} && (10)\\ \text{where} \quad \beta E &\mapsto \frac{W(\text{agent})}{\text{Total capacity}}, && (11)\end{aligned}$$

where the availability is the finite budget for shared resource channel capacity. Moreover, from Shannon [11], we know that the channel capacity is a dimensionless representation of the power:

$$C = B \log\left(1 + \frac{W(\text{agent})}{\text{Cost of contention}}\right) \tag{12}$$

where B is the maximum bandwidth for throughput.

With these points in mind, and assuming that interactions between group members are not 'all at once', but interleaved principally one at a time, the accumulated work should be proportional to the group remainder size:

$$W_n \leq \frac{W_{\max}}{n}, \tag{13}$$

The bulk of this work is assumed to be the handling of impositions by unexpected group members to reverse efforts and otherwise interfere with the agent concerned, preventing or smoothing over such incidents. The agent may have other things to deal with in addition to 'grooming' or placating contentious others, so this work allocation might not be 100% efficient. So we can take the cognitive capacity as a share for work:

$$(n-1)W_n = \frac{1}{2}mv^2, \tag{14}$$

for some rate v. Now, we arrange to measure these quantities in units such that we can compare dimensionless ratios. In dimensionless form, we can write

$$(n-1)\frac{W_n}{W_{\max}} = \frac{1}{2}\frac{m}{m_{\min}}\left(\frac{v}{v_{\max}}\right)^2, \tag{15}$$

The effective mass of the interaction (which plays the role of the cost of agent "involvement" with others) presumably has a minimum scale rather than a maximum, though this doesn't matter since we eliminate this by changing variables. None of these work rates are measurable in this study, so we need to relate them to something with dimensions of n. We can make the identification

$$\frac{W_n}{W_{\max}}\frac{m_{\min}}{m} \equiv \frac{\beta}{\langle N\rangle_{\overline{T}}}, \tag{16}$$

which has the form

$$\frac{\text{Fractional work effort}}{\text{Fractional cost of involvement}} \times \text{efficiency}, \tag{17}$$

where we use the constant $\beta \leq 1$ as an efficiency. This is motivated by the identification of $\langle N\rangle_{\overline{T}}$ as the scale for group size with maximal contention cost. From (16) we interpret the Dunbar group size as being based on:

$$\langle N\rangle_{\overline{T}} = \text{cost as a fraction of work budget} \times \text{efficiency}. \tag{18}$$

In other words, $\langle N\rangle_{\overline{T}}$ may be called the group contention cost, measured in cognitive work units. The actual values for $\langle N\rangle_{\overline{T}}$ can't be derived without a specific implementation model, but we expect this is an innate internal capacity of each kind of agent, as originally proposed by Dunbar. In that case, this dimensional identification, based on the assumption of linearly shared work together with the assumption of maximal entropy yields results compatible with the social brain hypothesis. The fact that we rediscover this in the case of Wikipedia histories [4] is evidence that the editing is a principally human to human interaction, albeit with cyborg influences. In the Wikipedia results, $\beta = 1$ gives the appropriate fit. In Dunbar's human groups. $\beta = 0.75$ is a closer estimate of the promise efficiency.

Agents come together around a particular seed when their prioritization of the seed promise becomes the dominant force in their behaviour. For example, the appearance of a predator activates a behaviour for a herd; the appearance of a new Wiki page on a subject close to one's heart activates a desire to contribute. In the absence of an attraction, there are enough alternative attractions to pull animals away, leading to an exponential decay of this heightened priority.

3.3 Probability of group size n

We can now extend this dimensional argument to predict the dimensionless frequency (or probability) of finding a group of size n, which we denote by $\psi(n)$. The graph in figure 3 fits very closely a simple formula which we can motivate from the theory:

$$\psi(\nu) = \frac{4}{\sqrt{\pi}}\,\frac{\nu^{\frac{1}{2}}\,e^{-\nu}}{\langle N\rangle_{\overline{T}}}, \qquad \nu = \frac{2\beta(n-1)}{\langle N\rangle_{\overline{T}}}\;,\;(n>1), \tag{19}$$

where β corresponds to a dimensionless (probabilistic) rate of promise keeping for the seed promise, i.e. β is the fraction of promises kept reliably, since reducing β has the same effect as reducing the group contention size limit higher (less tolerance of contention). Another way to think of β is therefore as an metaphorical 'temperature' complement for agent entropy. As contention increases, the maximum occurs at smaller groups and that is equivalent to less effective promise keeping to interact with the seed agent. The result of this fit is shown in figure 3.

3.4 The scaling of group hierarchy

The precise fit of the formula 19 is subject to some tuning (see figure3 especially for small n). The relationship between the maximum frequency and maximal contention scales is determined, however, by the rate equation for detailed balance that leads to (19). The value of n, which maximizes kinetic mistrust, is called $\langle N\rangle_{\overline{T}}$, while the value of n leading to the maximum value of $\psi(n)$, determined by $\frac{d\psi(N)}{dn} = 0$ is:

$$n_i^{\max} = 1 + \frac{\langle N\rangle_{\overline{T}}}{4\beta}. \tag{20}$$

Notice how the expected group size is still always less than the maximal contention size. This is interesting, as it suggests that (statistically) agents tend to prioritize working more intimately with smaller groups. This could be a sign that there is an additional contention cost associated with switching between on going relationships, as there is in computing called *context switching*.

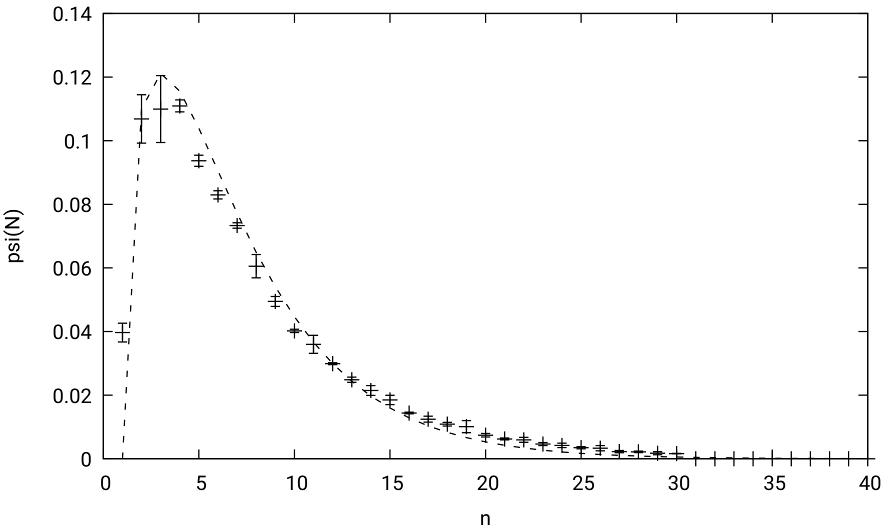

Figure 3: Curve fit of data using the formula in equation 19. The crosses approximate error uncertainty. The model fit is expected to be worst for small n due to integer effects.

We can examine some values for these maxima relationships to illustrate the fit with the layer model in Dunbar [23] and the specific data for Wikipedia [4]. The column for $\beta = 1$ reproduces the results from the Wikipedia data in [4]. Removing all bot interactions arbitrarily alters $\langle N\rangle_{\overline{T}}$ slightly to give an effective value of $\beta = 0.93$. The column with lower efficiency $\beta = 0.875$ generates the usual stylized Dunbar sequence quite accurately:

Mode	Wiki	No Bots	Dunbar Approx
$n_i^{\max}$	$\langle N\rangle_{\overline{T}}$ $(\beta = 1)$	$\langle N\rangle_{\overline{T}}$ $(\beta = 0.93)$	$\langle N\rangle_{\overline{T}}$ $(\beta = 0.875)$
3	8		
5		14.9	14
8	28		
14			45.5
14.9		52	
28	108		
45.5			156
52		188	
108	428		
156			542
188		697	
428	1708		
542			1892

Reading down each column, we see the mode frequency limited by the next scale up in the two right hand columns. We note that the apparent self-similar scaling fraction of group sizes depends on β for its precise value. It's therefore unrelated to presence of triadic relationships in the promise graph of agents, since the relevant promise graph is purely hub centric during group formation. Some of the curves for these values are plotted in figure 4.

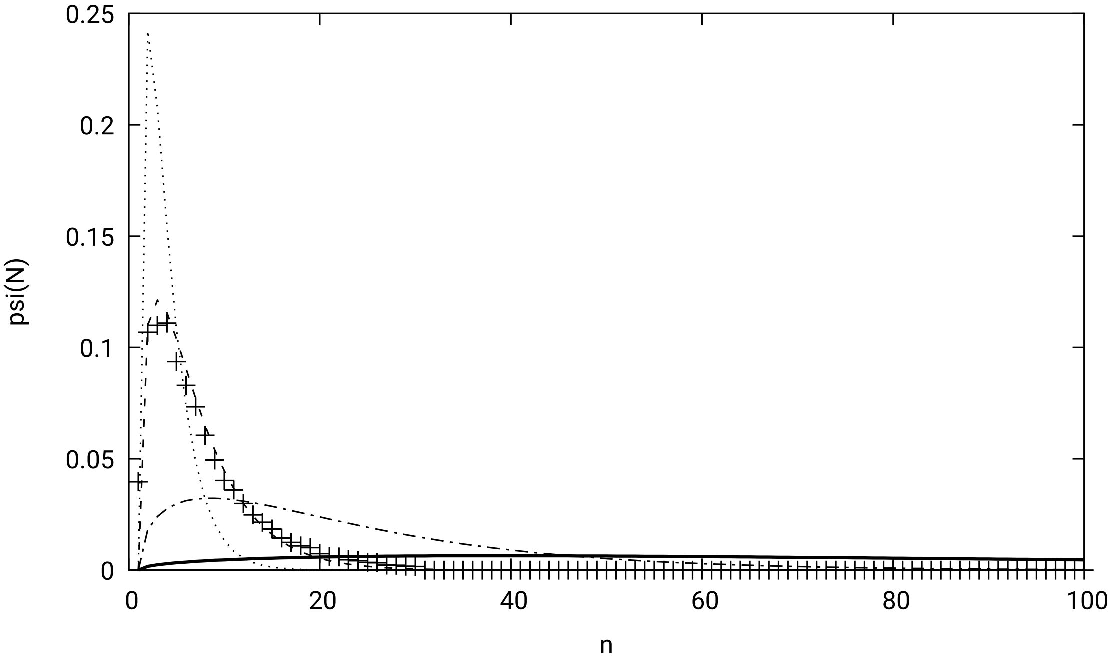

Figure 4: The group equilibrium law plotted for $\langle N \rangle_{\overline{T}} = 4, 8, 30, 150$ illustrating the flattening of group probability curves with increasing number. The amplitude gives an approximate magnitude for the attention power rate required to maintain each level.

4 Human attention and neural processes

We have shown that, if group size is moderated by contention, or grooming work to overcome it, then achievable group size depends on the intrinsic timescales over which agents can deal with the contention. This gets eliminated as a variable in probability distribution, but its remnants are found in dimensionless β. When the rate of seed-related promise keeping falls and β falls in value, the group can only either sustain itself over a longer timescale (through more invested work) or with fewer numbers. If the work has a maximum capacity, then the available fraction is spread more thinly and less contentiously over larger $\langle N \rangle_{\overline{T}}$.

We can add a brief speculation to this prediction. If the group hierarchy is associated with cortical contention in humans (and indeed other machinery), we should probably ask what are the dominant neural processes at each level of the hierarchy? One possibility could be that the group sizes correspond to different level of brain activity. A proxy for these dynamics is perhaps 'brainwave' oscillation modes [24] for the transport of information between cortical regions.

Frequency is associated with power [25], so it's interesting to compare the hierarchy of group sizes to the power associated with levels of attention or brain concentration. Buzsáki writes [26]: "The power density of local electrical field potential is inversely proportional to frequency in the mammalian cortex. This 1/f power relationship implies that perturbations occurring at slow frequencies can cause a cascade of energy dissipation at higher frequencies and that widespread slow oscillations modulate faster local event." Thus the idling work required for attentiveness in a typical group size might be expected to follow the same kind of power requirement.

Once again, on dimensional grounds $\langle N \rangle_{\overline{T}}$ can only appear in this relationship multiplied by an effective time conversion scale $\Delta\tau$ for the 'latency', and the product of this with frequency $f \times \langle N \rangle$ represents an average throughput of information up to some intrinsic timescale $\Delta\tau$. So in relative units:

Attention	Brain wave (Hz) f	Dunbar $\langle N \rangle$ level	$f \times \langle N \rangle$
light attention	α 5-15 (5)	150	750
middle attention	β 12-30 (25)	30	750
concentrated	γ-fast 32-200 (150)	5	750

The product of the columns is approximately of constant order, suggesting that the average effort is indeed in inverse proportion to the group size. This is numerically interesting, if not exactly proof of a connection.

5 Remarks

What began as a pragmatic model of trust as attention in Promise Theory has led us to a plausible explanation for the hierarchy of social group sizes discovered by Dunbar. In this work, we bring together these two narratives to offer a tantalizing perspective on each.

The model makes a bold assumption, supported by the scaling, namely that groups in a social brain hierarchy form around a seed of intent, which acts to capture the attention of agents through associated kinetic process. There is a de facto attractive 'force' that promotes group accretion on a small scale, and later fades away to become asymptotically free as groups disband.

Our summary relationship is based on continuum process algebra (usual for large N), but we know that social groups are about individuals (small N). This is where the separation of scales in Promise Theory is helpful. It is not the scaling of network that predicts these results, but the underpinning process of assessment of social ties that we call 'attention' (and effectively 'trust'). Thus a predictability of group behaviour requires the smooth exchange of experiences over a large enough timescale to distill stable patterns[1]. This separation of dynamical process scales is implicitly the result of evolutionary biology. Today, researchers in Artificial Intelligence dare to solve it with alternative models and computers.

What is the all important seed promise? By definition, it promises the role of a prioritized behaviour that's shared by the individuals in a group. In the case of Wiki editing, it's clearly the promise of the platform to enable satisfactory publishing of information—the creative commons, with its attendant benefits. For animals in a pack or herd, it might be the promise of a defensive posture when a predator is nearby, or the co-location of some tidbit, that drives them to attend to one another's relative positions and cluster. They would then drift apart again once the seed were gone [27]. For a religious group or company, it could be a charismatic leader [28], which also aligns with work on the origin and semantics of authority [29]. Alternatively, it could be a more abstract health benefit acquired as an evolutionary adaptation over very long times, such as when a change in the weather or other environmental conditions triggers group changes, as in slime mould dissociation for instance—or merely the opportunistic sharing of a transient resource [30]. The semantics of a seed of intent might change frequently to reflect changing group dynamics, even as the underlying dynamics remains a universal function of physiology.

Agents offer their attention to group processes variably in order to invoke a simple optimization for beneficial reasons. They have a finite budget for attention, which is governed by their work capacity. In a future in which humans bond with artificial enhancements as 'cyborgs', Artificial Intelligence may alter some aspects of this. This could, in turn, pose a different spectrum of threat to human character that needs exactly the kind of cognitive capacity predicted in the Dunbar hierarchy to deal with effectively.

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[1] At the time of writing, there is a revisitation of author Isaac Asimov's fictional Foundation Trilogy concerning the large scale prediction of human affairs, which he called 'psychohistory'. Although one can wonder whether Asimov would have been equipped to understand this, this kind of prediction over massive data sets and averages is the only level at which human behaviour is likely to be predictable. Individual actions appear disconnected and noisy on a small scale. His stories about robots imagined artificial brains that were ruled by potentials (Asimov was a biochemist) rather than digital logic, more like the cybernetics of Wiener and others.

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