Modelling the dynamics of youth subcultures

Petter Holme
Department of Physics, University of Michigan, Ann Arbor, MI 48109

Andreas Grönlund
Department of Physics, Umeå University, 90187 Umeå, Sweden

What are the dynamics behind youth subcultures such as punk, hippie, or hip-hop cultures? How does the global dynamics of these subcultures relate to the individual’s search for a personal identity? We propose a simple dynamical model to address these questions and find that only a few assumptions of the individual’s behaviour are necessary to regenerate known features of youth culture.

I. INTRODUCTION

One can often distinguish youths from adults, not only by their faces, but also by their jargon, clothing, gait and posture. Their relative lack of experience and generally different position in life have probably always separated the youth and adult worlds (2). The prosperity of Western societies during the 20th century has postponed the entry of adulthood. This has increased the importance of youth culture in the search of identity. It has also diversified youth culture so that one (in academia since ref. (11)) speaks of youth subcultures rather than one youth culture. Whereas “subculture,” in general, refers to a social group with particular behaviours or beliefs, this paper specifically focuses on youth subcultures. Today, youth subcultures are conspicuous features of Western and other societies of the world. We note that youth subcultures, as known in the West, often require some economic strength from the follower. Many aspects of our discussion are probably ubiquitous, but to simplify we focus on youth culture in wealthy democracies. Subcultures may be long lived like the hip hop or punk cultures, or die out almost as soon as they have a name. They may be centred on music, sports (such as the surf or snowboard culture (18)) or literature (such as the Beat generation (16); religion (5); etc. The reason a subculture may flare up and vanish soon is related to that adolescent’s formation of a personality is both an individual and a social process (4; 9). If many friends of a youth follow a new fad, naturally she, or he, will be interested in the new

II. DYNAMICAL MODEL

Our model is based on five major assumptions: 1. The dynamics of the underlying social network is negligible. This is probably our least realistic assumption—as a youth takes up a new subculture she, or he, will likely meet and get acquainted with other aficionados. On the other hand, there are many factors that inhibit the dynamics of one’s social network: the classmates, neighbours and relatives do not change that rapidly. We anticipate future models that will include an adaptive network dynamics. For this work we will use static underlying networks. Some evidence that youth retains some part of their social network after the entry into adulthood can be found in Ref. (6). 2. An adolescent belongs to one subculture at a time. This is natural since, belonging to many subcultures at the same time would conflict with the subculture as a basis for a personal identity. Furthermore, for many subcultures, a member is expected to be devoted to it. That much said, it is sometimes more appropriate to represent the identities in a multi-dimensional space. Certainly our study can be extended to incorporate this framework (someone can be a hip-hopper in a music dimension and a basketball player in a sports dimension). Note that, if the dimensions are weakly coupled (interrelated), each dimension can be treated as a separate, one-dimensional system. For the present study we assume one-dimensional identities. 3. If the fraction of friends that have adopted a certain subculture is big enough then an adolescent will adopt that subculture too. This assumption lies behind much of modelling for the spread of fads (22). It is known that friends play a great role for an individual’s adoption of subcultures (4; 9). If many friends of a youth follow a new fad, naturally she, or he, will be interested in the new
thing and may also feel left behind. 4. The attractiveness of a subculture decreases with its age. Youths do not want to be old-fashioned, so a subculture on its decline certainly seems less appealing to potential followers than a subculture on its rise. 5. There is a certain resistance to changing subcultures. To take up a subculture requires an effort—one needs to learn the unstated rules and most likely buy various paraphernalia—i.e. acquire subcultural capital [21]. Then, of course, the followers of a subculture like what they are doing, if they are not tired and dissatisfied with what they are doing they would not change.

Many subcultures define themselves against the “mainstream”—the commercialised culture promoted by media [2, 21]. It has been argued that this dichotomy—the subcultures vs. the mainstream—is more a way of maintaining individuality [10] than a relevant social distinction. In our work we assume the mainstream can be regarded as a collection or set of subcultures, kindred with the other subcultures, though in reality of course by far the biggest. Media (though, by definition, not the most used channels) has, of course, a role in the spreading of more obscure subcultures too. A youth may adopt a subculture only as a result of a media report. The real situation there is a coupling from the youth to the media and back again. This paper assumes the personal coupling is stronger when it comes to identity formation and thus considers the spread through friends only.

Now we turn to the definition of our model. We use the framework of graph theory and consider \( N \) vertices connected pairwise by \( M \) edges. The vertices represent the youths and the edges represent their social ties. At time \( t \) the vertex \( i \) has a unique identity, or subculture, \( c(i, t) \). Time, in our simulation, is discrete. It is represented by an integer number from 1 to \( t_{\text{max}} \) (we have \( t_{\text{max}} = 12800 \) for all runs of our simulations) corresponding to the number of the iteration of the update of \( c(i, t) \). The central part of the updating procedure is the score function \( s_c(t, i) \) that is intended to represent the attractiveness of subculture \( c \) to person \( i \) at time \( t \). If the score-function value of a subculture \( c \) exceeds a threshold \( T \) (which is a model parameter) the individual will replace her/his current subcultural identity by \( c \). As mentioned, a high number of neighbours adopting \( c \) should make \( c \) attractive. We make the simplest choice and let \( s_c(t, i) \) be a linear function of \( n_i(c) \), the number of neighbours of \( i \) with the identity \( c \). That the attractiveness of a subculture decreases with time is implemented by making \( s_c(t, i) \) proportional to the age difference between \( c \) and \( c_i \), i.e. the current subculture, divided by the current age of \( c_i \). The last ingredient of the score function is a normalisation factor, \( k/k_i \), \( k = 2M/N \) is the average degree (number of neighbours of a vertex) and \( k_i \) is \( i \)'s degree. This factor is included to compensate for the varying degrees, so that the same threshold value can be used for all vertices. To sum up, the score function is

\[
s_c(t, i) = \frac{k}{k_i} n_i(c) \frac{\tau(c) - \tau(c_i)}{t - \tau(c_i)},
\]

where \( \tau(c) \) is the age of \( c \) (note that if \( t \) has no argument it refers to the current simulation time). The iterations are as follows:

- For every vertex \( i \) (chosen sequentially) calculate the score \( s_c(t, i) \) of all subcultures \( c \) for the individual \( i \) at time \( t \).
- Go through the vertex set sequentially once again. If the score is higher than a threshold \( T \) for some identity \( c \), then \( i \) change its identity to \( c \). If more than one subculture has a score above the threshold then the individual adopts the subculture with the highest score.
- With a probability \( R \) a new identity is assigned to a vertex. So, on average, \( NR \) fads are introduced per time step.

An example of the propagation of subcultures on a small test graph can be found in fig. 1. The C++ source code can be found at [http://www.tp.umu.se/forskning/networks/fads/](http://www.tp.umu.se/forskning/networks/fads/)

### III. SUBSTRATE NETWORKS

We will use two kinds of network models as underlying networks in our study—one very basic model, the Erdős-Rényi (ER) model [3, 17]; and one modern model of acquaintance networks, the networked seeder model [10]. We note that, over the last decade, an abundance of network models have
been proposed, the reason we chose these two in particular is that they represent two ends of the spectrum between generality and specificity. The ER model is the simplest possible random graph model—simple in the sense that it is maximally random with no structural biases: One iteratively adds edges, the seceder graph has the randomisation parameter value \( r = 0 \). For the seceder model we indicate the communities, as identified by the algorithm of Ref. [13], by different symbols.

The seceder model is intended to generate networks with community structure—densely connected subnetworks (communities) with relatively few connections between the subnetworks. We will sketch how this model works, for the exact details we refer to Ref. [10]. One starts from an ER model network and successively rewires (detach one side of an edge and attach it to some other vertex) the edges according to the following approximate rules: 

1. Choose three vertices. 
2. Select the one \( i \) of these with the highest eccentricity (maximal distance to any other vertex \( i \)). 
3. Choose another vertex \( j \) at random and rewire \( j \)'s edges to \( i \) and \( i \)'s neighbourhood. 
4. With a probability \( r \) (the only parameter of the seceder model) re-rewire one of \( j \)'s edges to a randomly chosen vertex. With the parameter \( r \) one can tune the randomness of the model—with \( r = 1 \) the networks are of ER-type, with \( r = 0 \) the community structure is most strongly pronounced.

The ER model networks are characterised by a Poissonian degree distribution, a vanishing clustering (fraction of triangles) and no pronounced community structure. The seceder model networks have an exponentially decaying degree distribution, high clustering and strong community structure. Two example networks are displayed in fig. 4.

**IV. SIMULATION RESULTS**

To get an impression of how subcultures are born, evolve and die, we plot the time evolution of the number of adopters \( S \) of different fads. One typical run is seen in fig. 3. We observe that, a subculture can most often be divided into a growth stage, a quasi-stationary stage and a final decline. We note that this distinction of three stages is rather common [3, 21]. The shape and slope of the growth and decline, the life-length and the maximal size are all distinct for different subcultures. Some fads have more complex time evolution with more than one quasi-stationary state. The time evolution for the seceder model is more complex than for the ER model networks seen in fig. 3. We note that two leading time-scales of this model are the life-length of subcultures and the mean time between introductions of new subcultures. If we have a scale separation (i.e. that, either the life-length is much larger than the introduction time, or vice versa), then the model can be simplified. In the limit of short time between the introductions of new subcultures, every individual will have a new subculture with each time step. In the opposite limit the model essentially reduces to the threshold model of Watts [24]. But in the real world these two time scales are not separable—some subcultures may flare up and vanish within the life-span of others. Our model is thus relevant in this intermediate region and our choice of \( R = 1/6400 \) (that we use throughout the simulations) as seen in fig. 5 ensures this. Henceforth, we will study quantities averaged over \( \sim 250 \) realisations of the graph models, this means that there will be \( \sim 250 t_{\text{max}} R N = 500N \) fads introduced per point in parameter space.

In fig. 4a and (b) we display the distribution plots of the maximal size of the subculture \( S_{\text{max}} \). We see that different threshold values give qualitatively different distributions of \( S_{\text{max}} \). For small threshold values \( p(S_{\text{max}}) \) grows with \( S_{\text{max}} \). This means that most subcultures will, at their peak, affect most of the population. For small \( T \)-values, \( T = 0, S_{\text{max}} \) is decaying sharply (with an exponential tail). For intermediate values of \( T \) there will be a very broad distribution of the maximal subculture-size—a situation where some subcultures grow to involve almost every individual, while many others die out without gaining many followers. Note that such a broad distribution is not a trivial result of the introduction dynamics—a new subculture, in our model, enters the population according to the sharp Poisson-distribution. The two different underlying networks—the ER model of fig 4a and seceder model of fig 4b)—do not cause any qualitatively different behaviour. (This conclusion—that the result is qual-
The probability density function of the largest size of a subculture $S_{\text{max}}$ for the ER (a) and seceder (b) models, and the probability density function of the life-length ($t_{\text{dur}}$) of subcultures for ER (a) and seceder (b) models. The network sizes are $N = 1000$ and $M = 2000$, for the seceder model we have the randomness-parameter value $r = 0.1$. Errorbars are smaller than the symbol sizes.

FIG. 5 The average maximal size $\langle S_{\text{max}} \rangle$ of a subculture as a function of the degree of the first adopter $k_1$. The network is of ER type with sizes $N = 1600$ and $M = 3200$. Errorbars are of the order of the symbol size.

For a network of high clustering, which means that the number of individuals reached (in a person-to-person spreading process) after a certain time is also decreases with the clustering.

So the broad distribution of subculture sizes can be explained by the model, but can anything be said how a large
subculture is initiated? Intuitively one expects that if the first adopter has higher degree then the subculture has a higher chance of being a population-wide fad. In fig. 5 we plot the average peak-size of lower high-degree vertices increases. This is an increasing function. If the threshold is lower the influence of first adopter average peak-size of subcultures per individual, \( \nu \) as a function of degree (a) and eccentricity (b). The underlying networks are of ER type with \( N = 1000 \) vertices \( M = 2000 \) edges and threshold value \( T = 1.0 \).

In fig. 6 we plot the average peak-size \( \langle S_{\text{max}} \rangle \) as a function of the degree of the first adopter \( k_1 \). As expected \( \langle S_{\text{max}} \rangle(k_1) \) is an (sublinearly) increasing function. If the threshold is lower the influence of high-degree vertices increases. This is an effect of the larger average peak sizes of lower \( T \)-values. (For higher \( T \)-values more subcultures coexist, so the peak sizes are smaller but the life-length longer.)

In addition to the phenomenon that subcultures can be central for the formation of a youth’s personal identity, some adolescents shift such characteristics more frequently than others. This can of course be modelled by a varying threshold, but may also be an effect of the structure of the social network. In fig. 6(a) we plot the frequency \( \nu \) of subcultures per individual, i.e. the number of subcultures that can be expected to be adopted during one time step. Since only one new subculture can be adapted per time step \( \nu \) is also the probability that an individual will adopt a new identity a particular time step. We see a sharp peak of \( \nu \) for small \( k \)-values. Low-degree vertices are thus, by this property alone, more prone to changing their identity. In fig. 6(b) we plot \( \nu \) as a function of the eccentricity \( e \) (the maximal distance to any other vertex in the network) of the vertex. We observe that \( \nu \) is an increasing function of \( e \). To summarise, individuals that have few acquaintances and are peripheral in the social networks change identity more often. One observation in favour of this finding is Thornton’s study (21) of British club cultures where many adopters change as soon as a specific style has been adopted by the mainstream. Apart from this we have not found any empirical observations of this phenomenon. Even if the non-constant \( \nu \) of fig. 6 would be dismissed as an artifact of our model, it still exemplifies that it is not only individual characteristics that create the social network—one’s identity may also be formed by the social network structure.

V. SUMMARY AND CONCLUSIONS

We have presented a model for how subcultures spread in a population of adolescents. Using five main assumptions of a youth’s response to the subcultures of others to whom they are socially close, we construct dynamical rules for subculture diffusion. This dynamical model is then put on networks intended to represent acquaintance ties. The model is sketchy, but contains, we believe, many of the important mechanisms for the evolution of the youth subcultures. Even if each individual has a very complex rationale for her, or his, response to the social environment, the fact that individuals, on average, respond in certain ways makes it possible for only a few mechanisms to govern the system-wide properties (19). One problem with the particular question we address, is the lack of quantitative empirical data. Unlike the related issue of memberships in voluntary organisations (12) an adolescent is not required to register in any way. One can, as we do, compare qualitative model behaviour with qualitative observations. But for future studies it should be possible to perform quantitative studies; either directly by longitudinal interview surveys, or indirectly by e.g. measuring the frequency of related key words in the press.

One characteristic our model shares with real world observations is that, for certain parameter values, a few subcultures have a much larger staying-power than the average, whereas most subcultures die out very soon. The punk music scene of the 1970’s (11) is an example of a long-lived and large subculture. The other end, that of short-lived and small subcultures, is less well-defined: one can imagine peculiar habits of a circle of friends, maybe even one person, to define a subculture. Such short-lived fads can be great in number and still remain largely unheard of just because the total number of practitioners is small. We find that the maximal size of the networks is strongly correlated with the degree of the first adopter. Another outcome of our model is that fringe groups change identity more frequently than central and well-connected vertices. This may or may not reflect a real situation, but it serves as an example of how traits of individuals can result from the social structure, as well as vice versa. The qualitative behaviour of our dynamical rules is the same for our two network models. This means that the result is stable for moderate changes of the underlying network topology, and therefore is likely to remain valid for large ranges of real social networks.

Many studies separate subcultures and the commercialised
mainstream youth cultures. It has been argued that this dichotomy, rather than being an accurate social description, stems from members of smaller subcultures and their need to profile themselves as different opposed to a larger mainstream culture. In our model, we would like to interpret the largest subcultures as forming the mainstream. Naturally, these subcultures, rather than smaller subcultures, tend to be the focus of commercial interests.

Many extension and versions of this and similar threshold models are possible. We anticipate future work proposing, just as we (in this paper) and e.g. Ref. do, fine tuned models for information dissemination on more specific social systems than more general sociodynamic models of e.g. information diffusion and opinion formation (see e.g. Refs. and references therein).

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