



The Simmel effect and babies' names



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HIGHLIGHTS

- We apply the Simmel model to the data on babies' names in the US, 1880–2011.
- We apply the algorithm by Pedone and Conte to a scale-free social network.
- The observed rise-and-fall type of dynamics is reproduced within the model.
- The asymmetry of the time dependence of name popularity is also reproduced.
- The time of popularity is negatively correlated with the number of names used.

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ABSTRACT

Simulations of the Simmel effect are performed for agents in a scale-free social network. The social hierarchy of an agent is determined by the degree of his/her node. Particular features, once selected by a highly connected agent, become common in lower classes but soon fall out of fashion and become extinct. Numerical results reflect the dynamics of frequency of American babies' names in 1880–2011.

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1. Introduction

Fashion as an object of research was introduced to sociology at the beginning of the 20th century by Simmel [1], in direct connection with social classes. According to Simmel, fashion “is a product of class distinction”. The dynamics of fashion is driven by two forces (we would prefer to say “processes”): adaptation to society and individual departure from its demands. The social stratification is projected into a division of roles: elites tend to differ from lower classes, while the latter tend to imitate elites. These processes of imitation and avoidance produce a stream of given status symbols (clothing, social conduct, amusement) from elites to lower classes, where finally they disappear, replaced by new patterns. Later, the phenomenon was called the “Simmel effect” [2,3]. Although the elites contemporary to Simmel are replaced by media-made celebrities [4], the effect remains active today.

While imitation as an object of social simulations has attracted common interest [5–9], the thread of avoidance is much less popular. The original thoughts of Simmel were converted to simulations by Pedone and Conte [2,3], but these works remain almost unnoticed. In the original version of the famous model of dissemination of culture by Axelrod [10,5] avoidance is absent, and it has been added only recently [11,12]. Similarly, social repulsion appeared to be a useful concept when added [13] to the Deffuant model of dynamics of social opinion [7].

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It is somewhat surprising that the authors of these papers do not compare their results with real data on fashion. The conclusions of Refs. [2,3] are concentrated on some measures such as variability and distinctness, and on the mutual comparison of different variants of calculations. Current interpretations of the results of the Axelrod model seem to follow large scale theory, as suggested by the term ‘cultural’ [14]. In Ref. [5], the authors suggest that their numerical results could be related to the distribution of languages. However, in their model the number of equivalent options of cultural traits (the variable q) is of the order of hundreds. Obviously, nobody in this world has a choice of 100 languages. The interpretation of fashion (for example clothing), although natural here, remains unexplored.

On the other hand, the data on babies’ names has become of recent interest for modeling. In Ref. [15], the data on frequency of American babies’ names are fitted with a combination of the beta function and the power law, without invoking any particular mechanism. In Ref. [16], the data on names are analyzed in terms of activation and inhibition processes, and social groups themselves are treated as excitable media. There, although with fashion in mind, the author describes the sociological effect in purely physical terms. In Ref. [17], the authors propose a stochastic model of individual preferences of names. Their results are related to the statistics on the name distributions. In Refs. [18,19] correlations are investigated between the rates of rises and falls of popularity of given names.

The aim of this text is to connect the calculations of Pedone and Conte to some sets of real data on fashion, available in literature. Namely, we intend to apply the model to the datasets of American babies’ names in the period 1880–2011 [20]. Some comments will be given on the data on skirt lengths [21–23], where the model cannot be applied because these data cannot be classified into discrete categories. The model itself is modified; a scale-free network is used as the structure of a model social network, instead of a square lattice [2] or a torus [3]. Our motivation for the choice of the scale-free structure is twofold. First, several social networks show this topology [24,25]; second, the agent’s status can be conveniently measured by the node degree [26]. The number of options q remains as a model parameter, as in Ref. [5]; however, we do not take into account any interaction between different variables, so the number of variables (F in Refs. [5,11]) is set to one. The social status of agents remains constant during the simulation and is read from the node degree.

In the literature, the paper of Acerbi and cooperators is closest to our approach [19], but their assumptions are different. Although these authors admit some merits of the status model, their aim is to explain why some individuals are more influential than others. These authors consider three models of the fashion dynamics: random copying, status model (as the Simmel model) and their own model (the preference model); in the latter, influential individuals are those who possess many symbols of high status. In our view, the origin of social stratification cannot be reduced to the status symbols, but rather the symbols are just visible signs of high status. Then our approach follows the assumptions of Simmel, Pedone and Conte. Also, our numerical results within the status model do not confirm some of the assertions of Ref. [19]; this will be noted in the last section.

In two subsequent sections, the model is explained and numerical results are shown. Section 4 is devoted to the dataset, and Section 5 to the Simmel effect in the data on babies’ names. In the last section, we summarize the similarities and differences between the numerical results and the real data.

2. The model

Scale-free networks are constructed with new nodes attached to M nodes, according to the known principle of preferential attachment [27]. The network size was kept large enough to assure the mean shortest path, as found numerically, to be not less than 3; for example, we checked that for $M = 5$ the network size N of about 1000 nodes is safe. As noted above, the social status of nodes is determined by their degree. The network structure should be large enough to contain nodes of middle class between elite nodes and nodes of low class; hence the mean shortest path length cannot be too short.

A variable x_i is assigned to each node i . The values of these variables belong to the set $1, 2, \dots, q$. The parameter q marks then the number of options of a cultural feature. In the initial state $x_i = 1$ for all nodes.

For each node i , its neighbors are divided into two sets: those with degree larger or equal to the degree of i form the set $i+$, and the remaining neighbors the set $i-$. Nodes k which have no neighbors in $k+$ are marked as local hubs; they will play the role of an elite. During the simulation, nodes are selected randomly. For each selected node, say j , states of the nodes in the set $j+$ are estimable, which means that j is going to imitate these states. For the local hubs, all states are estimable. In contrast, the states of nodes of the set $j-$ are shaming, which means that j is going to avoid these states. Note that for a given node, some states can be simultaneously estimable and shaming, then we need a third category of states, defined as legal. If a state (a number y within the allowed range $1, \dots, q$) exists which is simultaneously estimable and not shaming, it is legal. During the simulation, for a selected node j we find a state y which is legal for this node, and we substitute $x_j = y$. If more legal states exist, x_j takes the value which is most frequent in $j+$. If no legal states exist for j , x_j remain unchanged. For a local hub, its state is chosen randomly from its legal states. To speed up the simulation, we start from one of local hubs.

This part of the algorithm is taken from Ref. [3], where the authors write: “The symbols of higher level neighbors will be marked as legal only if they are not equal to the symbols of the lower level neighbors. The agent will modify its color if (a) no symbol of higher level neighbors is equal to its own or (b) one at least of the lower level neighbors is equal to it. In either case, the agent will randomly assume one of the remaining legal colors”. The difference between our algorithm and the algorithm in Ref. [3] is that we use the scale-free network and not the torus. Also, in our approach high degree is equivalent to high social status, while in Ref. [3] it is assigned randomly. This means that in Ref. [3], the structure of interacting nodes

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