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Cultural Evolution Modelling in Python

Case Study: Evolution of Cooking Recipes

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Abstract

The paper describes Culinary Evolution Simulator, a simulation tool implemented in Python that models the evolution of cooking recipes within and across generations of agents with specific taste preferences. The Simulator can be helpful for various research questions related to cultural evolution. In the first series of runs it was used to define the optimal number of generations required to model a complete evolutionary process. Suggestions for further applications and modifications are discussed.

1 Introduction

Cultural evolution is the theory that cultural change can be described as a Darwinian evolutionary process based on the principles of variation, differential

*Culinary Evolution Simulator: Procedure
†Computational Modelling of Cultural Evolution: Background, Outlook
‡Experiments: Number of Generations Required for the Simulation Completion

fitness and replication (Mesoudi, 2011; Dawkins, 2006; Richerson & Christiansen, 2013; Richerson & Boyd, 2008). "Culture" in this approach entails any socially (rather than genetically) transmitted information, such as beliefs, knowledge, skills or practices (Mesoudi, 2015).

In particular, food is an essential part of human culture. Almost every human group has its own cuisine, usually one of most important aspects of its cultural identity. Culinary recipes are prime examples of cultural items with strong capacity for stabilization, innovation and transmission (Kinouchi, Diez-Garcia, Holanda, Zambianchi, & Roque, 2008).

The present study models evolutionary dynamics of transmission and modification of cooking recipes within and between generations of agents. Evolutionary processes are simulated computationally in the Python programming language.

The proposed baseline Culinary Evolution Simulator (described in detail in Section 3 of the paper) models evolution of cooking recipes in a conformist society, where modifications of the cultural items are caused by random mutation and do not pursue any rational goal. In spite of these limitations, it allows interesting observation on the dynamics of cultural change, for example, on the number of subsequent generations required for the completion of evolutionary processes (the results of such a study are reported in Section 4). Suggestions on further directions of use of the current version of the Simulator and possibilities for its adjustment to specific research needs are outlined in Section 5.

2 Computational Modelling of Cultural Evolution: Background

Cultural evolution modelling by computational means started in 1980s, when Cavalli-Sforza and Feldman (Cavalli-Sforza & Feldman, 1981) and Boyd and Richerson (Boyd & Richerson, 1988) proposed first quantitative mathematical models of cultural evolution. This was followed by a wide spectrum of cultural evolution modelling research, especially in the field of language evolution, reviewed, for example, in (Cangelosi & Parisi, 2002; Bickerton, 2007; Steels, 2011), but the two pioneering contributions already contain all the main principles relevant for this study.

Cavalli-Sforza and Feldman (1981) constructed models that explored the transmission of cultural traits not only from one's biological parents (vertical social learning) but also from peers (horizontal social learning) and from older unrelated members of the parental generation (oblique social learning). They constructed models of cultural mutation, analogous to genetic mutation, where novel cultural traits appear at random; cultural selection, analogous to natural selection, where certain cultural traits are more likely to be learned and transmitted than others; and cultural drift, an analogue of genetic drift, where cultural traits change in frequency due to chance.

Boyd and Richerson (1988) added psychological realism to the notion of cultural selection by modelling cases where people preferentially copy the traits of successful or prestigious individuals (indirect or prestige bias), copy traits on the basis of their popularity (frequency-dependent bias, or conformity), or copy traits based on their intrinsic characteristics (e.g. their memorability or usefulness, known as direct or content bias). They also constructed models with two distinct mechanisms used by individuals to transform cultural traits: random cultural mutation (also covered by (Cavalli-Sforza & Feldman, 1981)) and guided variation (individuals modify acquired information according to individual goals or cognitive biases).

In this study, we model all the three principal aspects of cultural evolution theory: variation, selection (based on differential fitness) and replication. For simplification purposes, variation only takes the form of random cultural mutation, and selection is based on the conformity bias, i.e. transmitting a cultural item most successful in one's social group. The details of implementation are provided in the next section.

3 Culinary Evolution Simulator: Procedure

The proposed Culinary Evolution Simulator consists of three main classes: Recipe, Agent and Generation. The running file is CultEvo.py. The user can set the parameters of a simulation run through a GUI. The output is saved to a hierarchical structure of plain text files, including data for every Agent, every social group, every generation, and every simulation run. To share variables between modules and to have a means to reset these variables between simulation runs we implemented the Config.py File. The general structure is shown as a diagram in Appendix 1.

The Recipe class processes recipes taken from the online recipe collection http://mc6help.tripod.com/RecipeLibrary/RecipeLibrary.htm and saved to the local directory "Recipes". Cooking instructions are not considered. The recipes are classified into categories according to basic taste preferences of the Agents (see below). The parameters of each recipe are category, title, preparation time, ingredients, mutation history, and evaluation score.

Every Agent is instantiated having one of the following three basic taste preferences: *meat, fish,* or *vegetarian.* In the first generation, the number of Agents with different taste preferences is set by the user in the GUI.
Each Agent randomly "chooses" one recipe from the collection according to this basic taste preference. The chosen recipe determines all other preferences of the Agent. The ingredients of the recipe become her favourite ingredients. The preparation time of the chosen recipe defines to which of the three preparation time ranges (quick, medium, slow) the Agent belongs.
After the completion of the preference setting step, each Agent "cooks" the chosen recipe, and either preserves or modifies it (by addition, deletion, or substitution). The way the Agent modifies the recipe is determined randomly, which corresponds to the random cultural mutation process. Modification of any ingredient in the recipe is allowed. For addition, the Agents may choose any ingredient from an additional general ingredients list. Each change is saved to the mutation history of the recipe. Only one modification (of the set "none", "add", "delete", "substitute") per Agent is allowed. At the end of this step, the Agent evaluates her own recipe, as it is possible that the modified version no longer meets the taste of the cook. The evaluation procedure is described in detail below in the communication stage. Intermediate results of the cooking stage are written to a text file generated for each Agent.
The cooking step is followed by the communication step, where the Agent presents her (possibly) modified recipe to other Agents. Following the approach suggested by (Nowak & May, 1992), horizontal transmission of cultural knowledge within one generation is modelled in such a way that the Agents interact only with their immediate neighbours ("friends") rather than with the whole population. The number of friends of each Agent, unlike in (Nowak & May, 1992), is not fixed, but is randomly assigned in the range specified by the user in the GUI, allowing simulation of interactions for more and less communicative agents. Also unlike in (Nowak & May, 1992), the boundaries of the groups are not sliding, so that each Agent can be a member of only one social group. Agents are assigned into groups randomly, so that each group could include Agents with different basic taste preferences (meat-eaters, fish-eaters and vegetarians).
The communication step simulates essentially the selection process, where cultural items are evaluated and selected based on their differential fitness. In the model, the recipe proposed by each member of the group receives "likes" from all members of the group. A "like" is given if the recipe matches some preference of the Agents in the group. One "like" is given for each ingredient match, two "likes" – for matching preparation time, and four – for matching the main recipe

category (meat, fish, or vegetarian). The total number of "likes" received by each recipe from all the Agents in the group represents its differential fitness.
The Agent passing on the recipe to the next generation takes the one that has the highest differential fitness in her social group (has the maximum number of "likes") even if it is not the recipe this Agent personally "likes" mostly, which represents conformity bias.
The final results for every generation are saved to a text file. At the same time the new generation is started, where every Agent has exactly one child. The whole procedure is repeated, with the exception that the initial recipe is not chosen randomly, but is received directly from the parent (vertical transmission). This recipe determines the taste preferences of the Agents in the next generation. The number of recipes passed through generations constantly decreases, as only one best recipe in a group of Agents is passed on. The simulation stops at the point where only one recipe dominates across the whole generation.
The number of generations required till only one recipe is left is output to a text file containing the results of the given simulation run. Data over multiple simulation runs (the number of repetitions is set in the GUI) is processed by the Analysis.py module that calculates basic statistical values (mean, median, mode, etc.).
The results of first experiments with different input values of the simulation model are described in the next section.

4 Experiments: Number of Generations Required for the Simulation Completion

The Culinary Evolution Simulator allows testing the impact of various factors on cultural evolutionary processes.
For the first experiments with the Simulator we have chosen as the independent variable the number of generations of agents required for the simulation completion, i.e. till the only winning recipe is left for all the agents involved.
This question has a practical value for the modelling of evolutionary processes, especially in laboratory conditions. Researchers simulating cultural evolution with human participants are constantly faced with the issue of determining the optimal number of generations, which shall not be too low in order not to miss important trends and not too long not to waste resources.
Different researches use different numbers of generations in their experiments, though the general trend is to simulate cultural evolution over four generations (Bangerter, 2000; Mesoudi & Whiten, 2004; Tan & Fay, 2011). It has been

assumed that this number is long enough to capture the long-term cumulative effects of cultural transmission, yet short enough to be practical in terms of recruiting participants and performing replications (Mesoudi, Whiten, & Dunbar, 2006).

Our first experiments with the Culinary Evolution simulator aim at verifying this assumption by analysing the number of generations required for distributing one recipe across the whole population of highly-conformist agents.

We have looked at the typical number of generations required for process completion and at its correlation with other variables, such as the size of social groups, the number of agents in one generation, and distribution of taste preferences in the first generation.

The first variable that was systematically changed in a series of simulation runs was the maximal size of social groups. The number of agents for this experiment was set to 60, with equal distribution of meat-eaters, fish-eaters and vegetarians. The maximal number of agents in a social group was incrementally increased from three (corresponding to minimal social contacts, like only with one's immediate family members) to sixty. The first extreme case models a society where only personal opinion or the opinion of very few closely-related people is important in transmitting cultural heritage over generations, while the case where a social group can include up to all agents of one generation models a society where the majority decides what shall be passed on.

The results are shown in Fig.1. The number of generations is shown as a median value of 20 simulation runs. As sizes of social groups are assigned randomly within the set range, the output value needs to be relatively insensitive to outliers, so the mean value was not considered.

For small sizes of social groups (up to ten) the number of generations changes in reverse proportion to the maximal number of agents in a group, and as the size of social groups reaches ten the number of generations stabilizes around five, and in spite of minor fluctuations appears to be further insensitive to subsequent growth of social group size. The insignificant increase at the social group sizes of 50 and 60 may be attributed to the fact that such distribution may cause creation of multiple small groups of agents outside very big groups, which in some runs could cause the effect similar to social group size less than ten.

Analysis of median values and modes for this correlation shows that the most typical number of generations required to achieve absolute dominance of one recipe is five, and the size of social groups appears to be correlated with the number of generations only for very small groups (up to ten agents).

The next series of runs was to show if the number of agents in one generation significantly affects the process of recipes distribution. For this purpose,

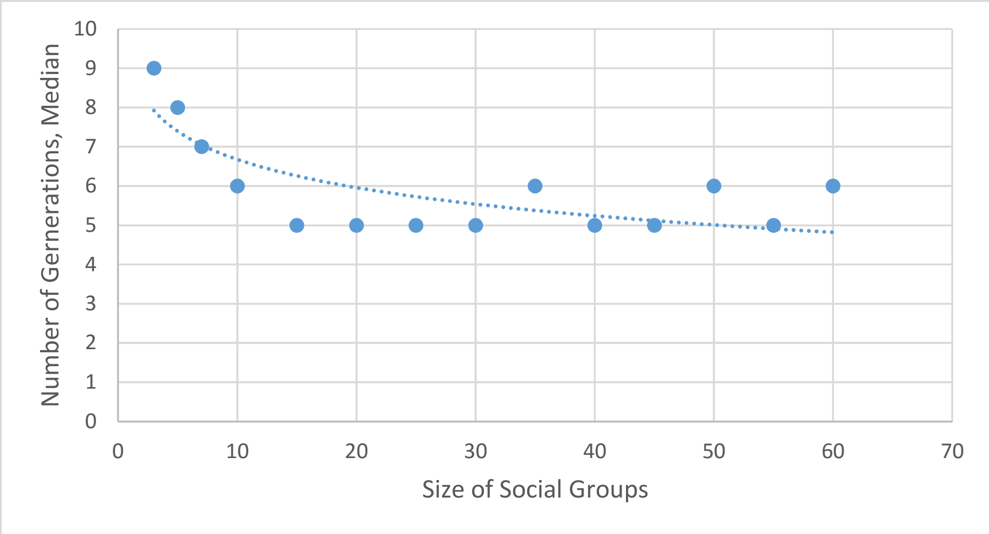

Figure 1: Correlation of the number of generations and the size of social groups

the number of agents was changed incrementally while maintaining equal distributions of meat-eaters, fish-eaters and vegetarians. The size of social groups in each case was set equal to 1/2 of the number of agents, as according to the results of the previous simulations described above this value lies in the most stable area of the graph.

The results are shown in Fig.2. The number of generations is a median value of 20 simulation runs.

Only if the number of agents is less than ten (six in this case) the spread of the dominating recipe is completed within four generations. In all other cases of the tested range from 12 to 300 agents, this process requires five generations. The slight deviations for 240 and 300 agents seem to be attributable to chance, as the mode value for the runs with 240 agents was also five, and for the runs with 300 agents it was four, so in this case the median value seems to be still affected by outliers.

This series of runs again yielded five as the most typical number of generations required to complete a specific cultural process. The number of agents seems to have a minor effect on the number of generations, unless it is less than ten (in this case both median and mode were equal to four).

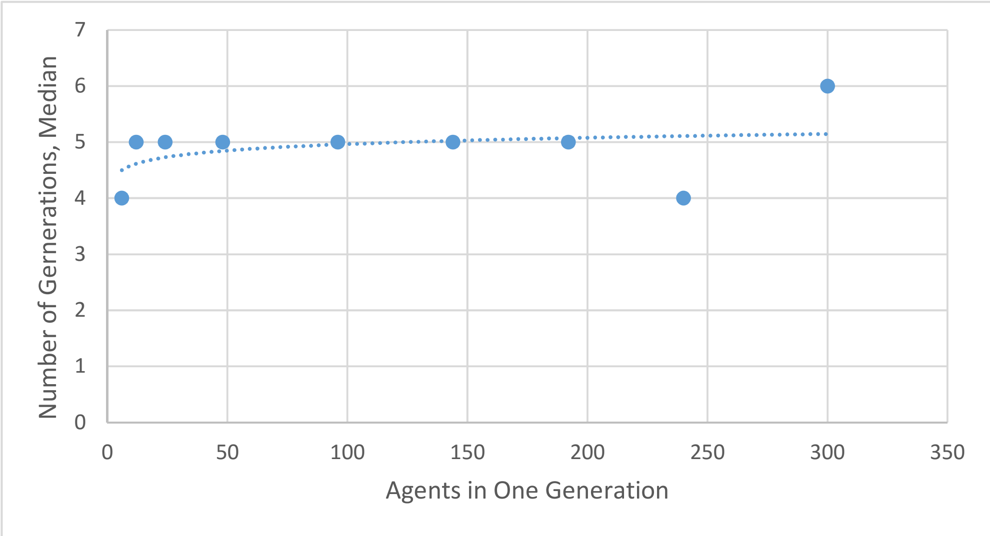

Figure 2: Correlation of the number of generations and the number of agents in one generation

Finally, the distribution of taste preferences within the first generation was altered systematically to find out if dominance of one or two taste preferences leads to quicker distribution of the winning recipe across generations.

The number of agents in all these simulations runs was taken equal to 90, the maximal size of a social group was 45. Table 1 shows the number of generations as a median value of 30 simulation runs for different taste preference distributions. As in the previous runs, the most typical number of generations required for the spread of one recipe across the whole population was five. The dominance neither of one specific taste preference nor of two taste preferences has significantly accelerated the process as long as the shares of all taste preferences stayed above ten percent. However, if the presence of one taste preference dropped to 10 percent and below, the typical number of generations required for the spread of one recipe decreased to four, which was not further affected by the relative distribution of the remaining groups. Four generations were also required for the case when the whole generation had one and the same basic taste preference.

In general, it can be concluded that the typically used number of four generations may be not sufficient to model some complete process of cultural evolution. For the examined case of a distribution of recipes in a conformist society, the spread of one successful recipe in the whole population almost in all cases required five

Table 1: Correlation of the number of generations and the taste preferences distribution

Distribution of taste preferences in the first generation, per cent: meat – fish – vegetarian	Number of Generations	
	Median	Mode
33.3 – 33.3 – 33.3	6	4
40 – 30 – 30	5	5
50 – 25 – 25	5	5
60 – 20 – 20	5	4
70 – 15 – 15	6	6
80 – 10 – 10	4	4
90 – 5 – 5	5	4
40 – 40 – 20	5	5
45 – 45 – 10	4	5
50 – 50 – 0	4	4
60 – 30 – 10	4	4
80 – 20 – 0	4	5
100 – 0 – 0	4	4

subsequent generations of agents, as long as the maximal size of a social group was above ten, the number of agents was above ten, and all three groups of taste preferences were present in the first generation with a share over ten percent. Four generations were sufficient for our simulation runs only for the number of agents below ten and if at least one test preference had a marginal status of ten percent and less. Small social groups (below ten) required up to 9 generations to complete the process.

At this point it should be noted that typically evolutionary processes are modelled in laboratory conditions with the number of participants less than 10 per generation, the participants are not split into social groups and investigated cultural objects are either uniform or constitute two distinct groups. Our results for these specific conditions agree with the general assumption and indeed typically require only four generations. However for any conditions going beyond this limited case, five, and often six generations are required. Thus, it might be advisable to increase the number of generation in evolutionary simulations to five in order to be able to capture cultural processes for a bigger variety of conditions.

5 Outlook

The experiments described in the previous section focus only on one aspect of cultural evolution – the number of generations required for the completion of an evolutionary process. The Culinary Evolution Simulator allows investigation of multiple other aspects that have remained outside the scope of this paper.

The recipe mutation process, for example, allows interesting observations on the potential value of modifications for the spread of recipes (which recipes tend to be more successful, those intensively modified, or those minimally altered).

It would be also interesting to test how strongly the type of the winning recipe (meat, fish or vegetarian) correlates with the distribution of taste preferences in the first generation.

Moreover, the presented version represents the baseline model that can be further adjusted and adapted to various research needs.

For instance, at the current stage the Simulator models only random mutation as the mechanism of cultural variation. However it can be easily adjusted to model guided variation, i.e. consistent preferences of agents leading to some rational goal.

The parameters of the recipes include such aspects as preparation time and the size of ingredient list. Though in the current version they are distributed randomly among agents, it would be possible to assign specific weights to these variables, for example, to let the agents consistently prefer recipes with short preparation time. Such a scenario would correspond to the real-life trends and would allow to find out how long it will take before all the recipes with long preparation time disappear from the cultural circulation, provided recipes with different preparation times are equally distributed in the first generation.

While time saving and simplicity can be correlated with the preparation time, the number of ingredients can correlate with cost and availability versus variety. Depending on the priorities of agents, a high number of ingredients can be viewed either as an advantage (as in the current implementation) or as a disadvantage, and be judged accordingly.

The mutate() method can also be adapted in a specific way to reflect guided variation processes. For instance, mutation of core ingredients of a recipe can be prohibited, and modifications of auxiliary ingredients could follow a specific set of rules, based either on compatibility of ingredients, or on their availability and cost, or on their health impact, depending on the values of a specific generation or social group. The history of modifications can be taken into account for defining the winning recipe.

Formation of social groups is another area where model adjustment would allow investigating multiple phenomena of cultural evolution.

For instance, the sliding approach to group formation (Nowak & May, 1992) can be implemented, where every agent can be part of multiple social groups. It

would decrease the conformist bias in the simulated society and would allow a greater impact of content biases.
Alternatively, it could be possible to form groups not at a random principle, but as a unity of agents with similar preferences. This approach could be especially interesting for simulation of guided variation, where different groups could have conflicting priorities (for example, some groups concerned about healthy food and some consistently preferring cheap food).
Overall, the Culinary Evolution Simulator can be viewed as a flexible tool that can be modified in various ways to provide answers to a wide range of research questions.

6 Conclusion

The proposed Culinary Evolution Simulator in its current version models all the important Darwinian mechanisms of evolution: variation, selection (based on differential fitness) and replication (vertical and horizontal transmission). Variation processes are implemented as random mutations in the form of addition, deletion or substitution of ingredients. Differential fitness is determined as a measure of compliance of a recipe to taste preferences of agents, including preparation time and specific ingredients. Replication processes are dominated by conformity bias, with each agent passing on to its child the recipe with the highest differential fitness in the respective social group.
The output of the Simulator can be analysed in many ways to investigate different aspects of cultural evolutionary processes. The first set of experiments focused on the number of generations required for evolutionary processes completion. This question has a practical value for defining the optimal number of human participants for laboratory experiments related to cultural evolution simulation. The independent variable reflecting the number of generations required for the spread of one most successful recipe across the whole population was tested for correlation with several factors, such as the size of social groups, the total number of agents in a generation, and the initial distribution of taste preferences. For all simulation conditions, the dominating number of generations was five, which suggests that the currently generally used number of four generations may be not sufficient for the completion of all evolutionary processes.
The Culinary Evolution Simulator can be modified in different ways to meet specific research requirements. For instance, it can be adjusted to simulate guided variation, where modification of cultural objects by the agents are not random, but pursue a specific goal. Selection processes can be also based more

on cognitive biases (usefulness of the cultural item) and be less dominated by group conformism.
Overall, the Culinary Evolution Simulator offers a variety of exciting opportunities to investigate the processes of cultural evolution of cooking recipes in human society.

Appendix 1

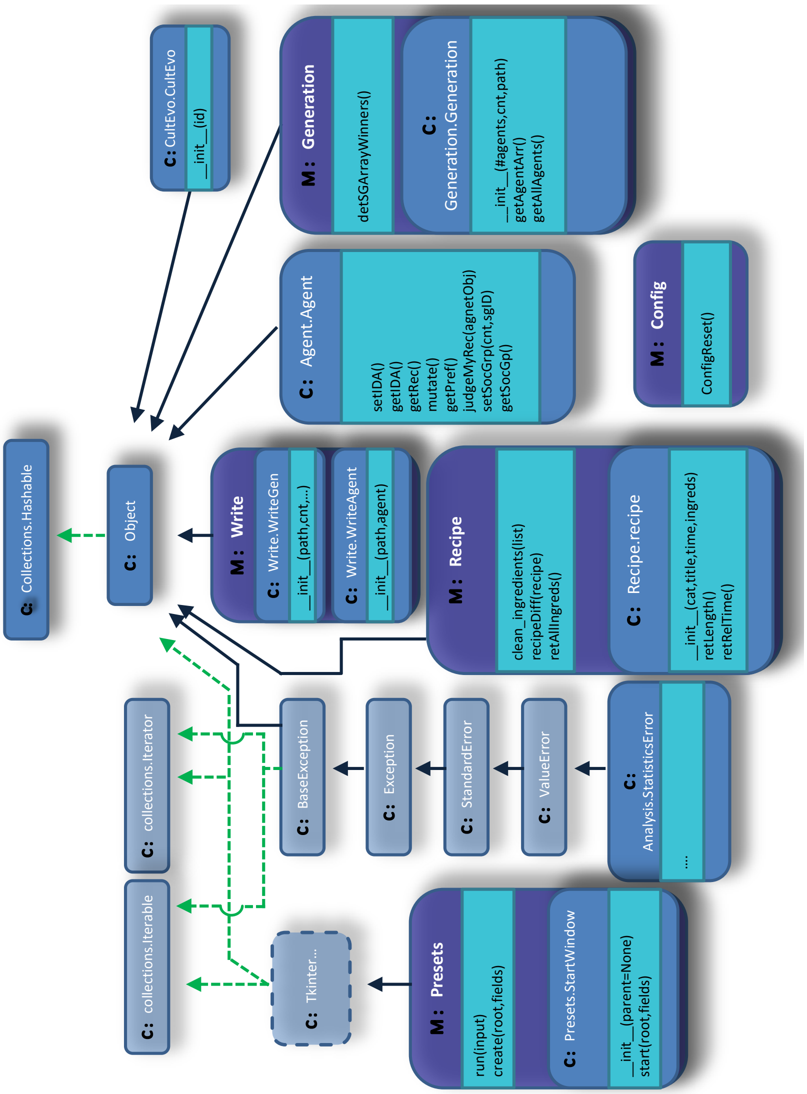

Figure 3: Culinary Evolution Simulator: Program Structure

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