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EECS 372 Final Project Report – Superstition Model

Introduction

Big Picture:

My model addresses the ways in which a superstition can form in people and in their communities. It explores what factors can lead a community to be more or less superstitious overall. This is accomplished by creating an environment in which there is a chance of coincidences, and by having turtles respond to those coincidences by either treating them as coincidences or by believing that there is a causal relationship.

Rationale:

Within scientific and academic communities, there is a tendency to look down on superstitions, and subsequently to look down on individuals who are superstitious. This model is intended to investigate superstition and possibly show how simple it is for superstitions to be formed under the right circumstances. For instance, while academics are unlikely to avoid walking under a ladder, they are more likely to avoid eating a certain food after getting an unrelated sickness around the time of eating it, even though it is unlikely the food caused the sickness. This model could help these communities to have a more understanding attitude towards superstition.

Another driving example is the mass superstition of “Fan Death” in Korean culture. This is an interesting example because from outside the culture of Korea, the superstition is almost impossible to find, but it exists very prevalently in Korean culture. This model examines how once a superstition appears, it is very hard to eliminate, and how such a superstition may have arisen.

Why ABM:

Based on some of the work by psychologists in the field of superstition, specifically "Superstition and Belief as Inevitable By-products of an Adaptive Learning Strategy" (Beck, Forstmeier), superstitious beliefs are heavily dependent on a few factors and a statistical inference strategy. Both of these aspects are highly fit for agent based modeling. Specifically, Beck and Forstmeier propose a general model for how an individual responds to seeing a coincidence, which I hope to simulate. ABM also allows me to extend this very simple model to include a general cultural temperament towards a superstition, or a communication aspect. ABM is the perfect way to test and extend the prevailing ideas about how superstitions form and grow.

Driving Question:

Overall I want to see what features lead to the greatest growth of a superstition, along with testing how effectively a model of superstition based on statistical inference can actually match a real society's superstition levels.

Description of Model

Agent-Based Model:

My model has a generalized superstition among humans that cats cause patches to turn red. It has humans and cats (turtles) move around randomly, and it has random patches turn red for a few ticks at a time. The model is very loosely based on Beck and Forstmeier. Each human has some alpha-value correlated to a statistical inference model for their threshold to believe cats are causing patches to turn red. This alpha-value is affected by the human's worldview, and the influence of other humans. The worldview consists of whether or not the human is superstitious, whether or not the human has interacted with superstitious humans, and whether or not most nearby humans are superstitious. Humans have a short memory list, which deals with the last few times they saw a cat. For each recent sighting, the list holds a count of how many cats on red patches they saw. The p-value of a given cat being on a red patch is determined by a human's observation of how frequently they encounter a red patch. Using this p-value, humans conduct a brief statistical inference using the binomial distribution formula:

$$P = \binom{n}{k} p^k (1-p)^{(n-k)}$$

Where p is the p-value, n is the number of times the event occured (number of times the cat was seen on a red patch) and k is the number of trials (length of the memory list), and P is the probability that the event occurred n times in k trails, or the probability that the human's memory holds as many instances of a cat on a red patch as it does. To make this more realistic, humans actually consider the probability of seeing a red patch as many or more times than they remember, using a summation of the binomial formula with values for n ranging from the actual number of occurrences up to the length of memory. So the formula is as follows:

$$P = \sum_{a=n}^{k} \binom{a}{k} p^a (1-p)^{(a-k)}$$

So, if the human saw 0 cats on red patches, the will consider the probability they see 0 or more red patches, which would be 1 exactly. If the final value of P is lower than the humans alpha value (i.e. if the human considers the event unlikely enough by chance that it believes the event must have been caused), then the human will become superstitious, and humans without a high enough alpha value will become not-superstitious. If this is a change from the humans previous worldview, they will then adjust their alpha value up if they just became superstitious from being non-superstitious, and down if they just became non-superstitious from being superstitious, as well as influence humans near them to adjust their own alpha values in the same direction.

A *danger*? variable also exists, which controls whether or not the humans act as if the red patches are dangerous. If it is set to true, then humans who believe cats can cause red patches will avoid cats.

Under this model, important properties are the following:

- Humans
  - *Superstitious*? - A boolean value indicating whether a human has become superstitious or not
  - *Alpha* - An integer 0-110 indicating the propensity of the human to believe, and the threshold probability at which they become superstitious.
  - *Red-count* - the number of ticks in which they have seen a red patch (division by ticks is done in the statistical inference phase to create a percentage).
  - *Cat-sighting-memory* - a list of the last few cat sightings, with the number of cats that were seen on a red patch in that sighting (Each individual value ends up being treated as binary 0 or >0 in the statistical inference phase).

    - *Introduced?* - A boolean to monitor whether or not the human has been introduced to the superstition or not.
- Globals
    - *Number-superstitious* - How many humans are superstitious
    - *Danger?* - Whether or not humans behave as if red-patches are dangerous

The general time step for this model is as follows:

- Every few ticks, red patches will be moved
- Cats turn a very small amount and move forward a very small amount
- Humans
    - If *danger?* And the human is superstitious
        - Turn away from the nearest cat, turn a small amount, and move forward
    - Otherwise
        - Turn a moderate amount and move forward.
    - Adjust worldview:
        - If there are any neighboring humans:
            - Increase alpha if a neighbor is superstitious and set *introduced?* to true
            - Decrease their alpha (by less) if a neighbor is not superstitious and they have been introduced
    - Observe coincidence:
        - If they see a cat they will
            - Add to memory whether or not the cat was on a patch
            - Remove the oldest remembered sighting from the memory list
            - Consider their new memory
                - Calculate the total probability that their memory holds as many red patches as it does or more

        - Classify as coincidence or causation based on that total probability and fit to worldview:
            - If they have an alpha greater than P
                - Become superstitious and increase alpha and increase alpha of nearby humans
            - Otherwise
                - Stop being superstitious and decrease alpha and decrease alpha of nearby humans

Core-Parameters:

There are sliders that adjust how much humans adjust their alpha values based on the different aspects that influence them. Along with those switches, I have sliders for the default average alpha value, the number of cats and humans, and the frequency of red patches.

Outputs:

There is one primary output to this model, and it is the number of humans who have become superstitious. This is the major output because the driving question in this model is how superstitions are formed, and how they propagate through a community.

There is also a secondary output, which is the number of switches. In some cases, the human beliefs tend to oscillate, and in those cases it is more interesting to view how volatile their opinions are.

Statistical Inference Rationale:

The intent behind the design was to create rational humans who can still fall into less rational beliefs. As such, humans perform very realistic statistical experiments, which may appear overly complicated for an actual human. While these experiments wouldn't be perfect in reality, human intuition with regard to probability is debated (Cosmides, L., Tooby, J). Since this model is intended to demonstrate how rational humans can become superstitious, it assumes only one "error" in statistical reasoning, and that is the setting of an arbitrarily high alpha value.

Analysis

Overview

In this model, it takes very specific parameters for more than a few humans to become superstitious, and sometimes even with those very specific settings, the superstition will not grow. This certainly matches what can be seen in reality, where most superstitions tend to grow a small amount and then disappear, but can occasionally overtake most of a population. This overtaking is normally exponential. This is to be expected as a small subset of the population begins by forming the idea, and then as the idea is shared, it grows faster and faster. If there is no overtaking, then after some time there is no switching of beliefs, as humans are all fully committed to what they've chosen at that point. There are a few parameters that have very obvious effects. For instance, increasing alpha increases the average number of superstitious humans. It is also almost impossible to create a superstitious population without some bias towards the influence of superstitious people. This is somewhat matched in reality, be it because the risk of being ignorant instead of superstitious is too high, or because they want there to be a correlation. Overall, it seems that the usage of true statistical inference with a high alpha value creates a reasonable model for the development of superstitions.

Access to data

After the initial increase of the alpha value for humans, whether or not a superstition grows is hugely dependent on the human's access to data. In general, this is to be expected as it allows communication to be have more power over belief than empirical observation. Along with that, once a superstition starts, lack of access to data prevents the superstitious human from being disproven by visible data until they have become too stubborn to be dissuaded (In this case, stubbornness is emergent from having a very high alpha value). The effect of data accessibility can be viewed most easily using values that usually lead to a full superstitious population, so the following default values will be used.

["number-of-cats" 8]

["other-human-influence" 0.05]

["superstition-influence-bias" 2]

["danger?" true]

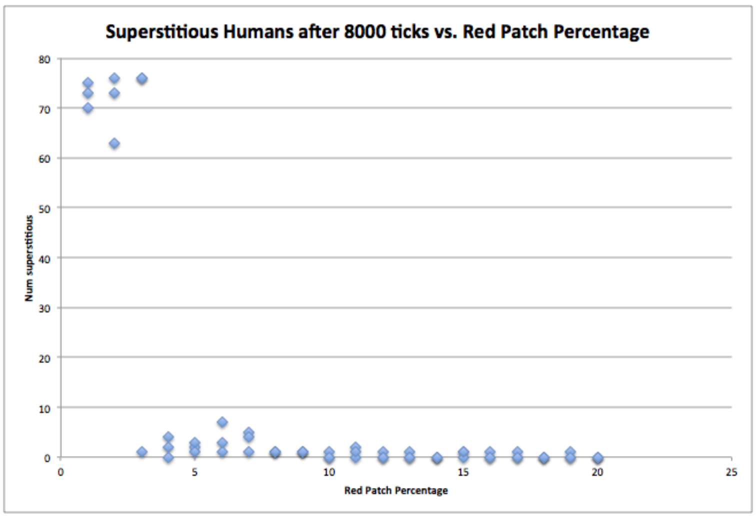
["memory-length" 4]

["initial-average-alpha" 31]

["red-patch-percentage" 3]

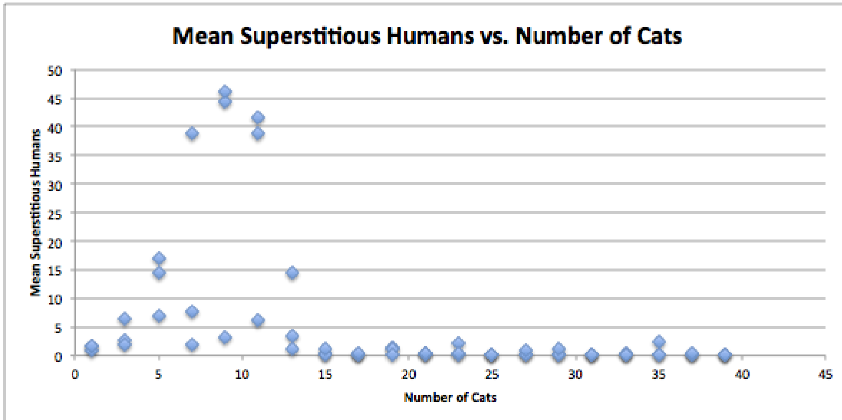
There are three particular parameters that contribute primarily to data. They are the percentage of red patches, the number of cats, and whether or not humans behave as if patches are dangerous (if danger is true and a human is superstitious, they will avoid cats).

The first two limit data in obvious ways. The third one, *danger*?, limits data by restricting the gathering of new memories of cats once a human is superstitious. The fact that limited data enables superstition is very clear in numerous famous superstitions. An example of limited "outcome" data analogous to limited red patches is the belief that not washing a jersey for a season helps a team win the championship has limited data because no matter what, a team has a relatively low chance of winning a championship. The following behavior space experiment was done using the default values (which do cause a superstition most of the time), with a varying percentage of red patches.



As can be seen, from 1 to 3% red patches, the superstition can become global, but it is less likely as it increases, and then at 4% there is a dropoff such that the population never becomes superstitious, and as the percentage continues to grow, it becomes less and less likely that even one human becomes superstitious.

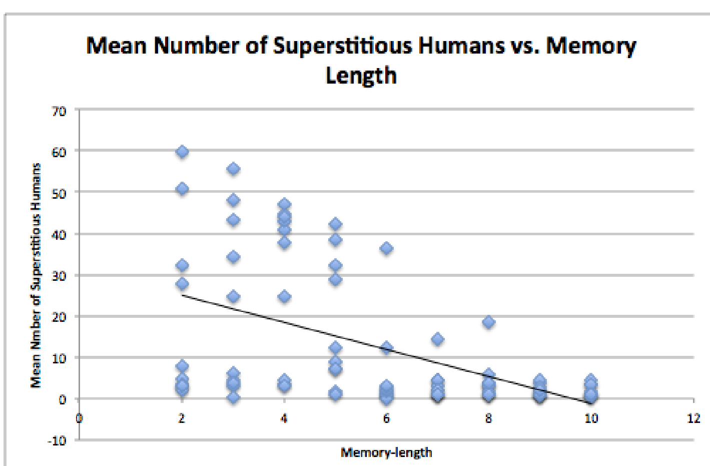
A similar outcome can be seen with the same experiment using number of cats. The primary difference is that there needs to be a certain number of cats in order for humans to all believe. This makes sense, since there need to be enough cats for humans to create enough memories in order to become superstitious in a short time-frame.



Finally, the impact of danger can be seen very easily using the default values once again. No BehaviorSpace experiment is necessary to see that with *danger*? off, the model never achieves full superstition, and turning on danger with any settings is very likely to increase the peak number of superstitious humans. Again, this is modeled in real life, in the case study of fan death. Since people don't want to die, there are timers built into fans, allowing humans to avoid causes, analogous to avoiding cats. Under such circumstances, it's very difficult to disprove a superstition. An interesting side effect that compounds the power of the *danger*? variable is the emergent pattern that by avoiding all the cats, superstitious humans are grouped together, this further allows them to increase each other's alphas and potentially avoid having non-superstitious humans decrease them.

Memory length

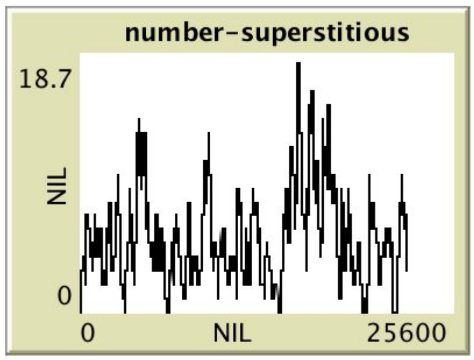
An interesting parameter, related to available data, is the length of human memory. A very low length leads to a much higher likelihood of all humans becoming superstitious, and also allows the change to happen faster. This is another case where there isn't sufficient data to prove a human wrong. This time, however, the lack of data doesn't promote communication over empirical data, it just makes empirical data that doesn't account well for outliers. A human who sees two out of their two remembered cats on patches and a human who sees two out of their five remembered cats on patches are likely to handle the situations very differently. The first human has no data to indicate to them that cats can even exist on non-red patches, whereas the second human has ample contrary data to smooth out the probability distribution. It's hard to tell what length of memory is most realistic in a model like this, since every detail is so abstracted, plus all humans have a different memory length, so it's hard to validate this fact. That being said, it's obvious in reality that those who consider the past more critically and don't let sudden strings of outlier coincidences cloud their judgement are less likely to become superstitious. The following graph is a BehaviorSpace experiment over the default values where *Memory-length* increases from 2 to 10, with 5 trials of each, with each trial lasting 8000 ticks. Mean number of superstitious humans over the length of the experiments was used rather than final number in order to better demonstrate that the speed of increase is changing as well.



As can be seen in the graph, as memory length increases the average number of superstitious humans over the course of 8000 ticks decreases.

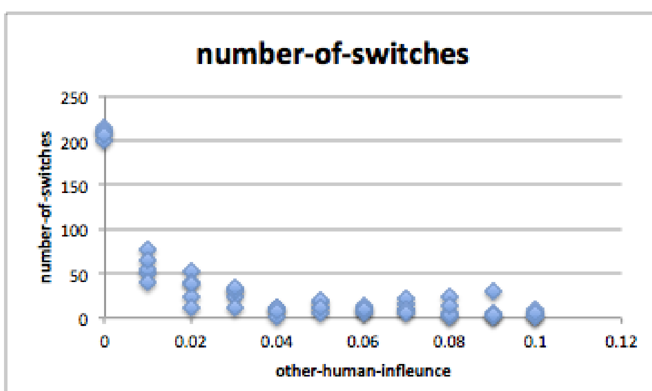
Oscillations

While seeing which parameters can cause a population to become superstitious is interesting, and an important investigation, there are other interesting trends that can be investigated. Some superstitions are not universal, but rather are the subject of debate.



Oscillating Trend

Many dieting and health trends could fall into this category. The following is a BehaviorSpace experiment on the number of switches vs. *other-human-influence* with no bias towards superstition.



As can be seen, the number of switches tends to be much higher when there is little or no influence from other humans. It helps humans in the model to be more decisive when their decisions are in some way verified by those around them. These results are a somewhat unexpected, and likely could be improved to more accurately match reality with an improved communication system.

Unrelated Increases

There is one very relevant aspect of the model that is difficult to quantify. When running the model with mostly normal variables, moving the red patch percentage slider up and down causes sharp increases and decreases in superstition. This method of producing a superstition is very powerful, and can create a popular superstition more frequently than most of the other variables. This false association from the agents demonstrates an interesting aspect of the model. When the patch frequency increases, first the humans notice more patches in their short term memory, but their long term impression of the number of red patches they've seen has yet to catch up. If there is an aspect of human influence, then once they've seen the sharp increase, they very quickly get on a trajectory that can't be left once their overall impression catches up, and the only way to prevent a full superstitious population is to decrease the percentage of red patches, and even that stops working soon. Without other human influence, the long term impression slowly catches up and the number of superstitious humans slowly returns to a low number. This seems to match what would happen in reality, as false correlations tend to form when an unrelated increase occurs.

Conclusion

Future Work

The communication system in this model is relatively simplified, and in future iterations it would likely be modified to be more robust and complex. There are only two ways that humans can influence the alpha values of others. The first, changing alpha values of nearby humans upon conversion, is meant to demonstrate the way that recently "converted" humans tend to tell other humans about their change. This is obviously simplified, as some humans would likely be ashamed to tell others; this would be a potential adjustment. The other influence happens when humans see one human in their radius that is superstitious or not superstitious. If they see any superstitious humans, they increase their alpha value by *other-human-influence*, and if they see any non-superstitious humans, assuming they have been introduced to the superstitious, they decrease their alpha value by *other-human-influence / superstition-influence-bias.* This is certainly simplified, and in reality humans would likely sometimes feel more biased than others. More accurately modeling human communication of beliefs and it's effect on alpha values could be a relatively significant adjustment to this model, since right now the system is simply meant to demonstrate a communication of beliefs in the simplest possible way.

Another significant change could be introducing specific categories of humans, such as skeptical humans with long memories and low alphas that change their alpha very little given human influence, or gullible ones with lengthy memories and high alphas that change their alpha very easily. It would be interesting to see whether or not humans can slowly convince more skeptical humans to believe, and what effect having such skeptical humans would have on the population.

Conclusion

While this model definitely has room to grow and improve, it has a clear indication regardless: superstition may be significantly more complex than most people assume. The popular belief that humans simply don't understand probability very well offers one model for superstition, but it's also possible that humans simply set a high alpha value. The setting of a high alpha value may not even be a mistake, given the right circumstances. This is summarized in Pascal's famous wager, which states that it is better for a human to believe in God given that the risk of not believing in God and being wrong (eternal damnation) infinitely outweighs the risk of believing in God and being wrong, whatever one may consider those to be. In short, sometimes superstition has less risk than ignorance. In such a case, setting a high alpha value makes sense. Perhaps superstition shouldn't be seen purely as a mistake every time, but as risk aversion in some cases. Regardless of how one feels about that, it's clear that this model successful casts superstition in a slightly different light, and hopefully that alone is beneficial.

Works Cited

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