

# Subjective Randomness: Pitch Contour as a Signal for Randomness in Musical Melodies

George H. Ma (GHMA@Stanford.Edu)  
Symbolic Systems Program, 558 Mayfield Ave  
Stanford, CA 94305 USA

## Abstract

We examine pitch contour as a predictor of perceived randomness in musical melodies. We argue that people's intuitions and judgements about randomness in musical phrases can be resolved and predicted by focusing on the number of directional changes in sequences of pitches. We posit that more directional changes equate to a higher probability of perceived randomness. This argument is supported by probabilistic modeling of melody production and interval relationships, together with an experiment that examines human judgments about randomness in a set of melodies.

## Introduction

Much of music is about satisfying and not satisfying expectations in musically meaningful ways. Composers play upon these expectations in order to surprise their audiences, evoke particular emotions, and signal the ending of a piece. For example, composers usually end on a tonic chord (the first scale degree), since the tonic most effectively conveys completeness in a melody of a given key. Even when composers defy musical expectations, such as with the use of a deceptive cadence, they do so with the intention to evoke surprise or sadness.

In randomly generated music, expectations are defied without intention. Since they do not operate relative to musical expectations, randomly generative processes may produce melodies which sound foreign or unnatural to human listeners. Is this foreignness as a result of a random process what is meant when people describe music as sounding random?

This is our motivation for research in this topic. For musicians, designers, and other artists, this issue is an important one. One might ask if the art that we intend to produce can possibly be perceived as having been generated from a random process. In studying subjective randomness, we hope to make a step toward identifying the artistic liberties that creators can take whilst still preserving their intentionality.

## Background

Inspiration for this paper was first found in a study by Griffiths and Tennenbaum (2001), which attempts to use probabilistic models to find a connection between people's intuitions about chance, expressed in judgments about randomness, and the formal structure of probability theory. In their study, Griffiths and

Tennenbaum (2001) investigate why in flipping coins, people might find one sequence of outcomes more random than others, despite all outcomes having the same probability of occurrence. They conjectured that given a sequence of eight coin flips, sequences like HHTHTTTH are perceived to be more random than the sequence HHHHHHHH even though both occur with probability  $1/256$ .

A number of theories have been previously proposed to account for the accuracy of this conjecture. Perhaps most influential was that of Kahneman and Tversky (1972), which suggests that people may be attempting to produce sequences that are representative of the output of a random generating process. According to Griffiths and Tennenbaum (2001), this cognitive phenomenon illustrates how human intuitions about chance deviate from normative standards set by probability theory.

## Defining Randomness in Melodies

In this paper we aim to examine just how much human intuitions about randomness in music deviate from normative standards set by probability theory. Thus, we will first build a probabilistic model that we believe might predict human behavior. The major challenge in this, however, is to express exactly what it means, in a musical context, for an outcome to be representative of a random generating process.

To do this, we must first examine the definition of a melody. Melodies can be most simply and broadly described as a sequence of musical intervals coded as magnitudes of pitch change and pitch contour (Thompson, 2012). What this means is that melodies, at least in traditional Western music, have characteristic interval sizes and numbers of directional changes from one pitch to the next. Deviations from these interval size and directional change conventions can thus signal that a melody might be perceived as being foreign, unnatural, or randomly generated. For this paper, we choose to focus only on pitch contour, or the number of directional changes across pitches in simple melodies.

First, let us clarify what is meant by a directional change. In the pitch sequence *C-D-E-D-C*, the pitches increase (become higher) between *C-D-E* and then decrease (become lower) between *E-D-C*. There is therefore one directional change, since the pitches first increase to *E*, then decrease back to *C*. Directional changes are musically notated in Figure 1.



Figure 1: Directional changes in “Mary Had a Little Lamb”. The direction changes are highlighted in red.

In order to incorporate the predictive power of musical directional changes into our model of human behavior, we must next quantitatively examine their presence in simple melodies. In Figure 1, we can see that “Mary Had a Little Lamb” has eight directional changes. However, when we put the same 26 notes that occur in “Mary Had a Little Lamb” into a program that randomly assigns the order in which those notes appear, a melody with 8 directional changes is only generated 1.8 percent of the time. Most melodies generated from this process have between twelve and fourteen directional changes. What do these quantitative observations mean for randomness in music? It suggests that randomly generated melodies normally feature many more directional changes than regular, non-random melodies of the same notes.

Thus, in this paper, we will use as a prospective measure of randomness the number of directional changes present in a simple melody. Note that our observations are limited to those obtained from examining melodies which share the same notes as “Mary Had a Little Lamb.” While the number of direction changes may not be the only determining factor in whether or not a melody is perceived as having been randomly generated, we would like to see if it, alone, is an accurate predictor of human tendencies in randomness perception.

## Design

The central question in this study is as follows: can we use the number of directional changes in a melody to predict whether or not a person will perceive that melody as having been created by a random process? We will attempt to determine this by first building a probabilistic model based on the number of directional changes in simple, 8-bar, 26 note melodies (that share the same notes as “Mary Had a Little Lamb”). We will then run a behavioral experiment with human participants and compare the results of the experiment to the predictions made by our probabilistic model. Our hypothesis is that melodies with more directional changes will be more often perceived as having originated from a random process.

More specifically, we would like to observe whether or not the experimental data fits or is similar to the gaussian distribution that our model predicts for melodies with 7-18 directional changes. Our hypothesis

in this case is that the model will be accurate for melodies with 7-15 directional changes. However, beyond this, we believe that as the number of directional changes increases, the probability of a melody being perceived as having been randomly generated will also increase.

## Model

In their study, Griffiths and Tennenbaum (2001) build a probabilistic model of randomness perception by producing a likelihood ratio that is computed using the odds form of Bayes' rule:

$$random(x) = \log \frac{P(x \text{ given random})}{P(x \text{ given not random})}$$

Griffiths and Tennenbaum were able to calculate the probability of an event given it was not the result of a random process by summing over a set of hypothesized non-random conditions, or regularities. There is, however, no equivalent of this in terms of randomness in the context of musical melodies. Calculating the probability of a melody having  $x$  directional changes given that the melody is not randomly generated seems impossible or at least extremely difficult to accomplish—it would require going through a complete anthology or another appropriately sized, representative collection of melodies and counting the number of direction changes that occur in each melody. Building a model based on Bayesian probabilistic inferences and analysis is therefore not the approach that we take in this paper.

Instead, we focus only on the probability of a melody having  $x$  directional changes given that the melody is randomly generated, and build a model based on a simple gaussian distribution. To produce this distribution, we first write a computer program that takes as input, 26 notes (the same as those found in “Mary Had a Little Lamb”) and outputs a melody with each note appearing in a randomly assigned order. The ChucK code for this program can be found in Figure 2.

The program is then run 1000 times to obtain a corpus of 1000 randomly generated melodies. A counting function counts the number of directional changes in each randomly-generated melody and finally outputs a histogram showing the number of directional changes (from 7-18) and the frequency with which each number of directional changes occurred for these 1000 randomly generated melodies. The resulting distribution can be found in Figure 3.

From this random process, we obtain a gaussian distribution of the number of directional changes in a randomly-generated melody. The distribution is centered at 13 directional changes, which further confirms our intuition that melodies that are generated from random processes usually feature more directional changes. Melodies with less than 7 or more than 18 directional changes were generated randomly with 0 probability.

```

1 SinOsc s => NRev r => dac;
2 0 => s.gain;
3 0.05 => r.mix;
4
5 .5::second => dur qtrnote;
6 [64, 62, 60, 62, 64, 64, 64, 62, 62, 62, 64, 67, 67,
7 64, 62, 60, 62, 64, 64, 64, 62, 62, 62, 64, 62, 60] @=> int notes[];
8
9 [1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 2,
10 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2] @=> int durations[];
11
12 for (int n; n < 1; n++) {
13   for (int i; i < 26; i++) {
14     int rand;
15     while (notes[rand] == 0) {
16       Math.random2(0, 25) => rand;
17     }
18     Std.mtof(notes[rand]) => s.freq;
19     0.2 => s.gain;
20     (durations[i] * qtrnote) => now;
21     printData(notes, rand, i);
22     notes[rand] => lastNote;
23     0 => notes[rand];
24     0.12 => s.gain;
25     50::ms => now;
26   }
27 }

```

Figure 2: This ChucK program randomly generates a simple melody by randomly assigning the order in which a given set of notes appears.

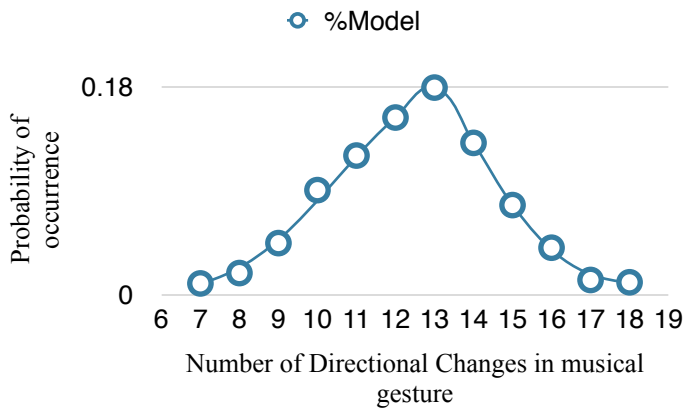


Figure 3: Number of directional changes vs. probability that a particular number of directional changes occurred in 1000 randomly-generated melodies.

Why might this gaussian distribution be an effective model of human behavior? Again, we must operate without the ability to calculate the probability of  $x$  directional changes given non-randomly generated. Thus, using the available distribution, we’ve effectively calculated the probability of  $x$  direction changes given a melody is randomly generated. The goal of this paper is to determine if the number of directional changes is a good predictor of whether or not a melody will be perceived as having been randomly generated. The model gives us the probability that  $x$  directional changes occurred in a set of random melodies, meaning that if seven directional changes occur in a given melody, then we can at least infer that that melody is only rarely generated by our random process. Roughly speaking, if  $x$  directional changes occurs with probability  $p$  in our

sample of 1000 randomly-generated melodies, then people should perceive that melody as having originated from a random process with probability  $p$ .

Thus, we believe that the model will at least roughly estimate the experimental data and give us a basic intuition as to whether or not the number of directional changes should be used in simulating human behavior.

## Methods

To reiterate, we’d like to determine how much human intuitions about randomness in musical melodies deviate from the predictions made by our model. To test our model, we conducted a behavioral experiment to measure actual human tendencies in perceiving randomness in melodies.

Participants in our experiment were Stanford undergraduate students living in Xanadu House. Their ages ranged from 20-22 years old, with the mean age being 21.6 years old. The gender break down was 50 percent male, 50 percent female. Of all of the participants, only two students had extensive musical training.

Twelve auditory stimuli were constructed for the experiment. They consisted of randomly-generated melodies featuring a range of 7-18 directional changes (one melody for each number of directional changes). With the exception of melodies with 7-9 directional changes, all melodies were generated using the same random process shown in Figure 2—26 notes (same as those in “Mary Had a Little Lamb”) were used and the order in which each note was played was determined randomly. Since melodies with 7-9 directional changes occur very rarely, they were too hard to generate using the random process and had to be composed.

Measures to isolate the number of directional changes as the only varying musical feature were also taken. Melodies had no rhythmic variation (they were all played with the same simple rhythm as “Mary Had a Little Lamb”) and all of the pitches heard by the listeners were pure tones with only a small amount of reverb. In order to minimize outside noise and distraction, the experiment was conducted individually in a quiet room.

Participants were tasked with listening to each melody in its entirety (8-bars, or about 20 seconds each). At the conclusion of each melody, participants were to required to give a two-alternative, forced choice response either identifying the melody as having been generated from a random process or from a non-random process. In order to minimize confusion, participants were told prior to the start of the experiment that the meaning of “having been generated by a random process” was the notes having been assigned a random order of appearance.

For each participant, the only data collected was the response given to each of the 12 stimuli (“randomly generated” or “not randomly generated” responses). This percentage of “randomly generated” or affirmative

responses for each melody were then compared with the gaussian distribution in Figure 3 in order to determine fitness of our model. We also examined whether or not more directional changes was, in the end, correlated with a higher probability of being perceived as having been generated randomly. As a rougher, but more concrete measurement the accuracy of our hypotheses, the average number of directional changes was computed for all randomly generated melodies as identified by each participant, and compared to the average number of directional changes computed for all those not randomly generated.

## Results

Figure 4 shows the average number of directional changes for all melodies classified as “randomly-generated” and “not randomly-generated” as identified by each of the experiment’s twenty participants. The mean across all participants for “random” melodies was 13.49 (SEM 0.17). The mean across all participants for “not random” melodies was 11.79 (with SEM 0.14). These findings are collected in Table 1. An unpaired T-test on the sets of data from these two groups yields a two-tailed p-value  $< 0.0001$ . The mean difference between average number of directional changes for “random” and “not random” is 1.7 directional changes. Individual participant data is graphically visualized in Figure 4.

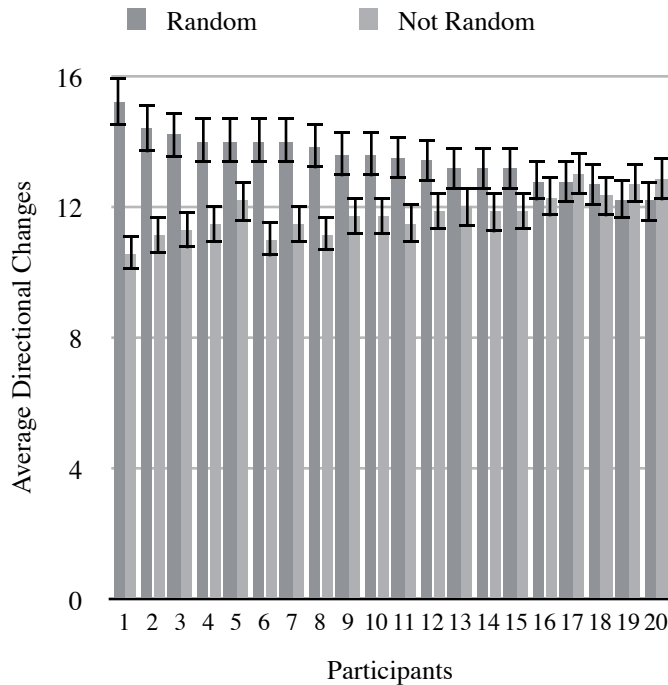


Figure 4: Average number of directional changes for each classification across all participants. Shown with Standard Error of Mean. Participants sorted based on highest average for “randomly-generated” melodies.

	Randomly Generated	Not Randomly Generated
Mean	13.49	11.79
Standard Error	0.17	0.14

Table 1: Mean of average number of directional changes for each classification across all participants

Figure 5 also shows the percentage of participants who identified a particular melody as having been generated from a random process. The melody with only seven directional changes had the lowest percentage of being identified as having been randomly generated, with only 15 percent of participants giving an affirmative response. The melody with 15 directional changes was most often identified as having been generated randomly, with 75 percent of participants responding affirmatively. Both the model and the experimental data sets are centered around thirteen directional changes.

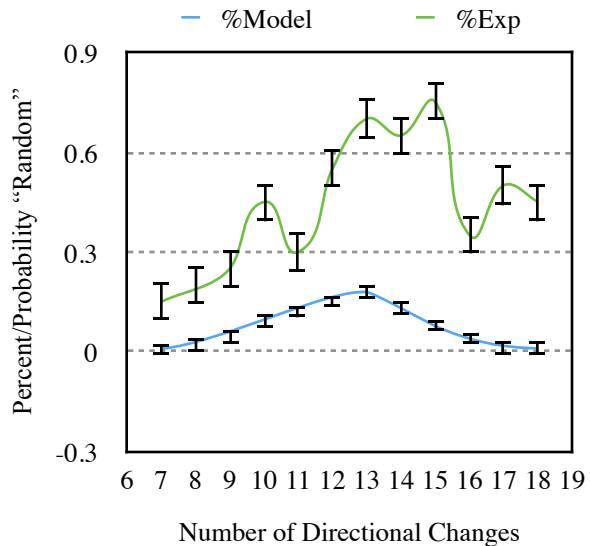


Figure 5: Number of directional changes vs. Probability/percentage of responses claiming “randomly generated”. The model predictions appear in blue, while the experimental data is depicted in green. Graph shown with Standard Error of Mean.

## Discussion

From these results, we can see that our most basic hypothesis, that melodies with more directional changes will generally be more often perceived as having originated from a random process, is confirmed. A large majority of participants (85 percent) had a higher average number of directional changes among melodies

they identified as having been generated randomly than among those which were not. This suggests that there is indeed a relationship between directional changes and the probability of being perceived as having been randomly generated: as the number of directional changes increases, so too does the rate at which the melody is identified as random.

However, the correlation we observed was not perfect. As we can clearly see from Figure 4, not all participants had the same tendency. In fact, three of 20 participants (15 percent of the sample) had higher average directional changes among melodies they identified as having not been generated randomly. This poses a bit of a problem for our analysis—it is unclear whether or not the variables tested in this experiment and considered by our model can explain this variation. Furthermore, the mean difference between the average number of directional changes for each classification seems small, only 1.7 directional changes.

While more directional changes generally means more likely to be perceived as generated randomly, the evidence for the former as an accurate and sole predictor for the latter is not very convincing. This can be observed in Figure 5. While we can see that the shape of the two distributions is somewhat similar in that they both peak at mid-range values, the experimental data does not fit the predictions generated by our cognitive musical model. The probability that a melody with  $x$  directional changes cannot be estimated or predicted based solely on the gaussian distribution. Whereas the predicted probability of being identified as random for melodies with 13 directional changes was about 18 percent according to the model, our experiment observed that 70 percent of participants responded affirmatively. This is likely because our model predicts the probability that a random melody has  $x$  directional changes and not the probability that a melody of  $x$  directional changes was randomly generated. However, as previously addressed, this is an issue that we were not able to overcome without obtaining information about the frequency that  $x$  directional changes occur in melodies that are not generated randomly, e.g. regularly composed, which is a very difficult task. The goal of this paper was to assess the gaussian distribution as a model of human behavior and we have shown that while it does have some predictive power in roughly estimating the trend of human tendencies, it cannot be used as the sole predictor.

The results suggest that other features of music may be responsible for the behavioral trends we observe. One such musical element is the last scale degree in the melody. In our experiment, some melodies—including those with 11 and 14 directional changes—ended on the tonic scale degree, while other melodies ended on different scale degrees. The dips that we see in the percentage of participants who answer affirmatively for 11 and 14 directional changes (see Figure 5) can be

explained by this, since the tonic conveys a sense of completeness and thus intentionality.

One result that was surprising was that for the melody with 16 directional changes, there was a decrease in the percentage of affirmative/“random” responses. Although we initially expected percentages for large directional change values to increase monotonically, the decrease can be explained by an excessive up and down pattern in the pitch contour. Just as alternating patterns of coin flips, such as HTHTHTHT can seem intentional, so too can repeated up and down motion in a melodic line.

Melodies are, in actuality, more than just pitch contours. They are also described in terms of other intervallic relationships, such as interval size (Thompson, 2012). Future research on this topic might improve on this paper by analyzing interval size in conjunction with pitch contour. Watts (1924) states that changes in direction generally follow large intervals, and since the melodies we generated had sequences of small interval sizes, it would be valuable to run this experiment on melodies with more varied intervallic relationships between pitches.

## Conclusion

In this paper, we examined pitch contour as a predictor of human behavior and tendencies in identifying melodies as having been generated as the result of random processes. In building our model and testing it against experimental data, we found that while there is a general trend that the more directional changes a melody has, the more likely it will be identified as having been randomly generated, our model cannot be used to effectively model human behavior. This was largely due to limitations in the scope and design of this project, as well as contributions from other musical effects, such as the scale degree of the final note in a melody.

## References

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