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Schrödinger's Cat May Be Dead All Along

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Abstract: By framing the problem of determining the state of Schrodinger's cat as a problem of searching for Hidden Markov Model (HMM), this work shows that there is a high chance that Schrodinger's cat is dead with a stationary probabilities P(Cat = Dead) = 1, and P(Cat = Alive) = 0.

Keywords: network analysis; Hidden Markov Models

1. Introduction

The thought experiment popularly known as 'Schrödinger's Cat' [1] is a widely known paradox in quantum mechanics used to frame the question of when exactly quantum superposition ends [2]. For years, this thought experiment has been debated and has been considered as a paradox that has no definite answer – the cat is dead and alive at the same time [3,4]. The current work confronts this conclusion of the paradox.

This current work shows that the probability of the cat being alive is not equal to the probability of the cat being dead amid making inference based on equally random observable states. This is done by framing the problem as a search for the Hidden Markov Model (HMM) [5,6] of the states of the cat. The problem model is schematically shown in Figure 1. With HMM, the states of the cat are hidden and must be computed using observable states that are affected by the hidden states. In this problem model, the observable states are the emotions of Schrödinger who directly observes the cat and shows two emotions – sad or happy – at equal prior probabilities (50% each) from each hidden state. We are the observers of these emotional states of Schrödinger, and we want to use these observations to estimate probabilities of the unknown states of the cat. The hidden state – cat being dead or cat being alive – has the following prior probabilities: if the cat is alive then it has equal chances of being alive (50%) or dead (50%), and if the cat is dead then it will remain dead (100%).

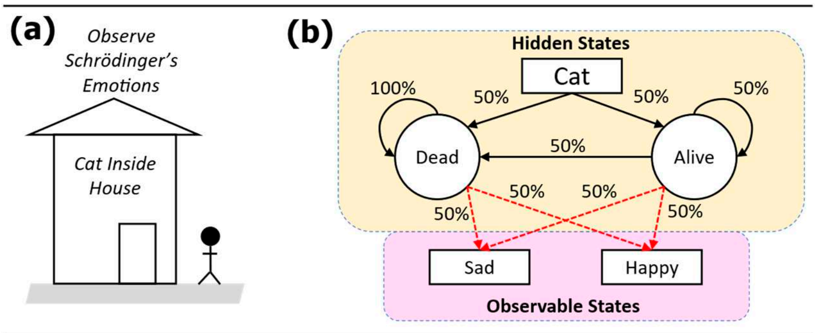

Figure 1. Formulation of the Schrödinger's Cat paradox problem as a search for the Hidden Markov Model for the states of the cat. (a) Schrödinger sees whether the cat is dead or alive, but we can only observe Schrödinger's emotions as we spy on Schrödinger. (b) Formulating the problem as a network model with the objective of determining the probabilities of the cat's hidden states – Dead or Alive – by using Schrödinger's observable states – Sad or Happy – as inputs to training the network model. The annotated probabilities are the prior probabilities.

To estimate the posterior probabilities of the HMM states, a sequence of observations must be collected and used as inputs into the training of the network leading to a convergence of the

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probabilities of the hidden states. This set of observations can be synthetically generated from a random process. Because there are just two observable states, the sample generation process is a Bernoulli (p=0.50) process.

2. Methodology

The workflow in this work was implemented using the Python programming language. The Python codes in Jupyter Notebook files used in this work are curated in the online GitHub repository of the work: https://github.com/dhanfort/HMM_Schrod_cat.git.

2.1 Mathematical Formulation

The prior probabilities based on Figure 1 constitute the initial probabilities of the transition matrix $T = \begin{bmatrix} 1 & 0 \\ 0.5 & 0.5 \end{bmatrix}$ and emission matrix $E = \begin{bmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}$. Matrices T and E would then be trained on the observable states to determine their posterior. The starting state matrix probability is fixed at equal probabilities $s = [0.5 \quad 0.5]$. Rigorous mathematical derivations and explanations of the forward algorithm and updating algorithm in the training of HMM to learn T and E from observable states can be found in these references: [6,7]. The stationary probabilities of the hidden states were also computed.

2.2 Model Traning and Inference

The Python module 'hmmlearn' [8] was used to train the HMM. Datasets of observable states consisted of 10, 100, 1000, and 10000 samples were generated from a Bernoulli(p=0.5) implemented using the 'random' function in Numpy module [9]. The observable states were coded as follows: 0 = Sad, and 1 = Happy. The hidden states were coded as follows: 0 = Dead, and 1 = Alive. The 'hmmlearn.CategoricalHMM' function was used to model the HMM.

After training the HMM, the model was then used to predict the hidden states. The input datasets to this prediction step were a new set of observable states also generated via a Bernoulli(p=0.5) with 100 datasets each containing 100 observations states.

3. Results and Discussion

3.1. Stationary Probabilities

When looking at the model (Figure 1) in a long-term network propagation, the stationary probabilities of the hidden states could be computed. With the 'hmmlearn', this was computed using the 'get_stationary_distribution()' function in the HMM model. The resulting stationary probabilities were P(Cat = Dead) = 1.0 and P(Cat = Alive) = 0. These probabilities indicate that Schrödinger's cat may be dead all along.

3.2. Observation-based Model Training

The stationary probabilities discussed in section 3.1 above were computed using the prior probabilities in the transition matrix T (Figure 1). This begs the question "How good are the prior probabilities in the transition matrix T used to compute the stationary probabilities of the hidden states?" We address this question by performing an observation-based learning through the fitting function in the 'hmmlearn' module, which fits the transition matrix T. The transition matrix T models the changes of hidden states in HMM and determining how observable states affect the transition probabilities would elucidate how the estimate of hidden state probabilities change. Based on our preliminary computations, the number of samples of the observable states significantly affect the updating of matrix T. Figure 2 shows a graphical summary of tabulated results of the transition matrix T at varying observable states sample. The resulting transition matrix T values are close to the prior probabilities in the matrix T. This indicates that the prior transition matrix used in the

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computation of the stationary probabilities is a good approximation of the hidden transition matrix. This confirms our conclusion that Schrödinger's cat may be dead all along.

(a) Samples = 10

1.0	0.0
0.4964886	0.5035113

(b) Samples = 100

1.0	0.0
0.4899235	0.5100764

(c) Samples = 1000

1.0	0.0
0.5133951	0.4866048

(d) Samples = 10000

1.0	0.0
0.5015522	0.4984477

Figure 2. The transition matrix T after training on the the observable states at varying size of sample Bernoulli(p=0.5) samples: (a) 10 samples, (b) 100 samples, (c) 1000 samples, and (d) 10000 samples.

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Data Availability Statement: The Python codes in Jupyter Notebook files used in this work are curated in the online GitHub repository of the work: https://github.com/dhanfort/HMM_Schrod_cat.git (accessed 29 September 2023).

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Conflicts of Interest: The authors declare no conflict of interest.

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