

Learning Neighborhoods: Method description

part I – The models

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January 30, 2013

Say we would like to think about how patterns of racial segregation in a city could arise from the local interactions of neighbors. We think there may be some process at the household level, that all else being equal, makes it more likely that neighbors will be of the same race than different races. We'd like to reason about what kinds of global patterns of segregation are likely to arise from these local processes.

To get going, let's make a couple of simplifying assumptions. First, we'll assume there are only two races: black and white. Second, we'll assume that only direct neighbors affect whether a black or white family lives in a house. More distant neighbors can influence the house, but only by influencing a directly neighboring house.

From these assumptions, we can build a probability distribution over every global patterns of racial segregation in a city, from complete segregation to complete integration.

Let's look at four houses, that we will call A , B , C , and D , Houses A and C are not neighbors and neither are B and D (Figure 1).

Now, let's say there is a particular pattern of black and white houses, for example House A –black, House B –black, House C –white, House D –white. We'll

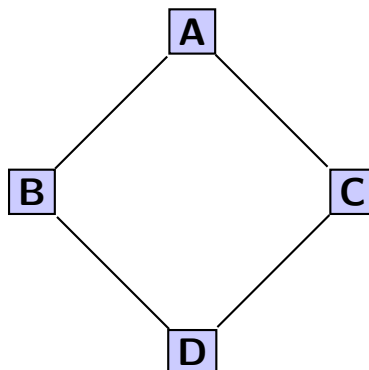


Figure 1: Markovian Dependent Variables

call this particular pattern x , and we'll say that $\Pr(X = x)$ is the probability of that pattern, while $\Pr(X)$ is the probability distribution over all possible patterns

We'd like to express this probability distribution only in terms of local interactions between neighboring houses. We'll do this in two steps. First we'll show that any probability distribution over these four houses can be expressed as a product of functions that only take in the value of neighboring houses, i.e. :

$$\Pr(X) = \phi_1(A, B)\phi_2(B, C)\phi_3(C, D)\phi_4(D, A) \quad (1)$$

Second, we'll choose functions that compactly express our assumptions about local interactions.

Independence and Factorization

Because we think that houses can only influence each other through a direct neighbor, we can say that A and C are independent of each other given their immediate neighbors B and D , and that B and D are independent given A and C . This does not mean that A can not influence C just that the influence must operate through B and D . If we already know B and D , then we have fully taken into account the influence of A on C .

As I'll demonstrate these independencies imply that

$$\Pr(X) = \phi_1(A, B)\phi_2(B, C)\phi_3(C, D)\phi_4(D, A) \quad (2)$$

Factorization

Theorem 1. *Let A , B , and C be three disjoint sets of variables such that $X = A \cup B \cup C$. $\Pr(X)$ satisfies $(A \perp\!\!\!\perp B) \mid C$ if and only if*

$$\Pr(X) = \phi_1(A, C)\phi_2(B, C) \quad (3)$$

for some functions ϕ_1 and ϕ_2 .

Proof. Assume that $(A \perp\!\!\!\perp B) \mid C$

$$\Pr(A, B, C) = \Pr(A, B \mid C) \Pr(C) \quad (4)$$

$$= \Pr(A \mid C) \Pr(B \mid C) \Pr(C) \quad (5)$$

$$= \phi_1(A, C)\phi_2(B, C) \quad (6)$$

Where we set $\phi_1(A, C) = \Pr(A \mid C)$ and $\phi_2 = \Pr(B \mid C) \Pr(C)$.

Now assume that $\Pr(A, B, C) = \phi_2(A, C)\phi_2(B, C)$. Let $\phi_3(C) = \sum_A \phi_1(A, C)$ and $\phi_4(C) = \sum_B \phi_2(B, C)$.

$$\Pr(A, B \mid C) = \frac{\Pr(A, B, C)}{\sum_{A, B} \Pr(A, B, C)} \quad (7)$$

$$= \frac{\phi_1(A, C)\phi_2(B, C)}{\sum_{A, B} \phi_2(A, C)\phi_2(B, C)} \quad (8)$$

$$= \frac{\phi_1(A, C)\phi_2(B, C)}{\phi_3(C)\phi_4(C)} \quad (9)$$

Similarly

$$\Pr(A \mid C) = \frac{\sum_B \Pr(A, B, C)}{\sum_{A, B} \Pr(A, B, C)} \quad (10)$$

$$= \frac{\phi_1(A, C)\phi_4(C)}{\phi_3(C)\phi_4(C)} \quad (11)$$

$$= \frac{\phi_1(A, C)}{\phi_3(C)} \quad (12)$$

From which we can see that

$$\Pr(A, B \mid C) = \Pr(A \mid C) \Pr(B \mid C) \quad (13)$$

Which was to be proven. \square

Now, if we let $\phi_5(A, B, D) = \phi_1(A, B)\phi_4(D, A)$ and $\phi_6(C, B, D) = \phi_2(B, C)\phi_3(C, D)$ we can see that

$$\Pr(X) = \phi_1(A, B)\phi_2(B, C)\phi_3(C, D)\phi_4(D, A) \quad (14)$$

$$= \phi_5(A, B, D)\phi_6(C, B, D) \quad (15)$$

$$= \phi_5(A, \{B, D\})\phi_6(C, \{B, D\}) \quad (16)$$

which implies $(A \perp\!\!\!\perp C) \mid (B, D)$, and if we combine the factors another way it also implies $(B \perp\!\!\!\perp D) \mid (A, C)$.

1 Factors to Distributions

We have seen that there is an intimate connection between the independencies respected by a probability distribution and the factorization of that distribution into functions. In particular, we have shown that a probability distribution with certain independencies can be factored into functions that have only directly dependent random variables in their scope.

Remember that we represented the dependencies between the houses as edges. We drew an edge between two houses when the houses had a direct, unmediated effect upon each other. Networks of this kind are called Markov networks, and what we saw for our example is true for all networks of this type.

Definition 1. A distribution \Pr_ϕ is a Gibbs distribution defined by the factors $\{\phi_1(D_1), \dots, \phi_K(D_K)\}$ if

$$\Pr_\phi(X_1, \dots, X_n) = \frac{1}{Z} \tilde{P}_\phi(X_1, \dots, X_n) \quad (17)$$

where

$$\tilde{P}_\phi(X_1, \dots, X_n) = \phi_1(D_1)\phi_2(D_2)\dots\phi_{K-1}(D_{K-1})\phi_K(D_K) \quad (18)$$

and

$$Z = \sum_{X_1, \dots, X_n} \tilde{P}_\phi(X_1, \dots, X_n) \quad (19)$$

A Gibbs distribution is the probability distribution with maximum entropy given some constraint. For example, the uniform distribution is the maximum entropy distribution that has support on a given interval $[a, b]$, the exponential distribution is the maximum entropy distribution given a positive mean, and the normal distribution is the maximum entropy distribution given a mean and a standard deviation. The ϕ 's can be thought of as Lagrangian encoding of constraints.

Definition 2. A distribution $P(X) = \frac{1}{Z} \phi_1(D_1)\phi_2(D_2)\dots\phi_{K-1}(D_{K-1})\phi_K(D_K)$ factorizes over a Markov network H if each D_k is a complete subgraph of H .

As a reminder a complete subgraph is set of nodes in a network where there is a direct connection between all of the nodes, also called a clique.

Definition 3. Let H be a Markov network structure, and let $X_1 - \dots - X_k$ be a path in H . Let $Z \in X$ be a set of observed variables. The path $X_1 - \dots - X_k$ is active given Z if none of the X_i 's, $i = 1, \dots, k$ is in Z .

Definition 4. A set of nodes Z separates X and Y in H , which we denote $\text{sep}_H(X; Y \mid Z)$ if there is no active path between nodes $X \in X$ and $Y \in Y$ given Z . We define the global independencies associated with H to be $I(H) = \{(X \perp\!\!\!\perp Y \mid Z) : \text{sep}_H(X; Y \mid Z)\}$.

From a proof similar to the one above and the Hammersly-Clifford theorem, it turns out that the following theorems hold

Theorem 2. If P is a Gibbs distribution, then P factorizes over a Markov network H if and only if every independency in P is encoded in H

2 Parameterization

Returning to our four house example, we saw that we can express the probability of the pattern of an assignment to all the houses as the product of functions that only look at the interactions between neighboring houses. But we still need to choose the form of the functions ϕ .

$$\Pr(X) = \phi_1(A, B)\phi_2(B, C)\phi_3(C, D)\phi_4(D, A) \quad (20)$$

To return to our original assumptions, we said that we think that a black house has some influence on neighboring houses to make them black. Let's call that influence w . And we'll assume that white houses have the same influence, but in the opposite direction, i.e. $-w$.¹

For a particular house i , the balance of influence h_i depends upon the number of white neighboring houses, n_W and black neighboring houses n_B .

$$h_i = w(n_W - n_B) \quad (21)$$

and we'll say that the probability the race of a house is

$$\Pr(\text{house}_i = \text{white}) = \frac{e^{h_i}}{e^{h_i} + e^{-h_i}} \quad (22)$$

$$\Pr(\text{house}_i = \text{black}) = \frac{e^{-h_i}}{e^{h_i} + e^{-h_i}} \quad (23)$$

$$(24)$$

And that the probability for any particular pattern of race is

$$\Pr(X) = \prod \frac{e^{R_i h_i}}{e^{h_i} + e^{-h_i}} \quad (25)$$

Where R_i is an indicator variable that takes a value of 1 where the race of the house is white and a value of -1 if the house is black.

We can also express this probability in terms of the pairwise interactions of neighbors.

$$\Pr(X) = \prod_i \frac{e^{R_i h_i}}{e^{h_i} + e^{-h_i}} \quad (26)$$

$$= \prod_i \frac{\prod_{j \in \langle ij \rangle} e^{R_i R_j w}}{e^{h_i} + e^{-h_i}} \quad (27)$$

$$(28)$$

¹I believe, but have not proven that this assumption of 'symmetry of influence' is required if we want represent the system as a Markov field.

Where $j \in \langle ij \rangle$ are all the sites that are nearest neighbors of site i . Each pair will be appear in the numerator twice. So that

$$\Pr(X) = \frac{1}{Z} \prod_{\langle ij \rangle'} e^{R_i R_j w'} \quad (29)$$

$$= \frac{1}{Z} \exp\left(\sum_{\langle ij \rangle'} R_i R_j w'\right) \quad (30)$$

Where Z is normalizing constant that is the sum of all possible assignments, $\langle ij \rangle'$ is every nearest neighbor only counted once, and $w' = w/2$.

We can see that it is a Gibbs distribution and we can also see that it encodes the same independencies of our racial preference house model, so that this distribution factorizes over our network of influence.

3 Extensions

We have shown how we can develop an relatively simple formula for the probability distribution over global patterns that arise from local interactions. In the model we worked through, the smallest unit is only influenced by it's immediate neighbors and can only take on two values—either the house is occupied by a black family or a white one.

Perhaps we think that there are some other differences among houses that make it more likely for one race to occupy it than another. We can naturally extend the model to include a house specific term u_i .

$$\Pr(X) = \frac{1}{Z} \exp\left(\sum_{\langle ij \rangle'} R_i R_j w' + \sum_i u_i R_i\right) \quad (31)$$

Indeed, we are not limited to multiplication, but can use choose any functions $\epsilon_{i,j}$ and ϵ_i , and we will still have a valid probability distribution over global patterns.

$$\Pr(X) = \frac{1}{Z} \exp\left(\sum_{\langle ij \rangle'} \epsilon_{i,j}(R_i, R_j) + \sum_i \epsilon_i(R_i)\right) \quad (32)$$

A simple choice of $\epsilon_{i,j}$ that will allow us to deal with more than two races is

$$\epsilon_{i,j}(R_i, R_j) = \begin{cases} 0 & R_i = R_j \\ \lambda_{i,j} & R_i \neq R_j \end{cases} \quad (33)$$

Or the model can be extended so that $\epsilon_{i,j}$ is a site specific distance function between x_i and x_j so that likelihood of neighbors being the same race can be function of how similar they are in other ways.

4 Neighborhoods

The time has come to leave discussion of racial segregation, and take up the phenomena we are really interested in here: neighborhoods.

If we make the assumption that a household can belong to one and only one neighborhood, we can use all the machinery of Markov Random Fields we just developed to try to learn what are the features, block by block that cohere into a neighborhood. This is a very troublesome assumption, and we we'll return to it, but let's see what we can do if we make it.

We'll use this machinery twice. First, we'll use it to help create a set of target "neighborhoods" and then we'll use it to learn what local features might have produced those neighborhoods. But to explain how we'll do that I need to explain how we go about getting real values from these beautiful equations. As it turns out this is a pretty complicated question, which I'll take up in the next dispatch.