An introduction to restricted boltzmann machines

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Suppose you ask a group of users to evaluate a set of films on a scale 0-100. In the analysis of the classic factor, you can then try to explain every movie and user in terms of a set of latent factors. For example, movies like Star Wars and the Lord of Rings could have strong associations with a fantastic science fiction fiction and fantastic factor, and users who love the history of Wall-E and toy could have strong associations with a latent Pixar factor . The limited boltzmann machines are essentially a binary version of factor analysis. (This is a way of thinking about RBMS; there are obviously others and many different ways to use RBMS, but adopt this approach for this post.) Instead of users to evaluate a set of films on a continuous scale, they tell you simply If you like a film or not, and RBM will try to discover latent factors that can explain the activation of these film choices. More technically, a limited boltzmann machine is a stochastic neural network (neural network which means that we have units similar to neurons whose binary activations depend on the neighbors that are connected to; Stocasty means that these activations have a probabilistic element) composed of: a level of visible units (cinematographic preferences of users whose states we know and set); A layer of hidden units (the latent factors we try to learn); And a Bias Unit (whose state is always active, and is a way of adapting to the different intrinsic popularities of each film). Furthermore, each visible unit is connected to all hidden units (this connection is canceled, so each hidden unit is also connected to all visible units) and the BIAS unit is connected to all visible units and all the units Hidden. To facilitate learning, we limit the network so that no visible unit is linked to any other visible unit and no hidden units is connected to any other hidden unit. For example, suppose you have a set of six films (Harry Potter, Avatar, Lottr 3, Gladiator, Titanic and Glitter) and ask users to tell us what they want to look. If we want to learn two latent units at the base of cinematographic preferences - for example, two natural groups in our six film set seem to be SF / Fantasy (containing Harry Potter, Avatar and Lottr 3) and Oscar winners (containing Lotr 3, Gladiator , and Titanic), so we could hope that our latent units correspond to these categories - then our RBM would resemble as follows: (note the similarity with a graphic analysis model of the factor.) Activation of the activation status of Boltzmann Machines, and networks Neural in general, work by updating the states of some neurons who have given the states of others, so we speak of how the states of the individual units change. Assuming that we know the connection weights in our RBM (we explain how to learn these below), to update the status of the unit (I): calculates the activation energy (A_I = sm_j w_ {ij} x_j) of units (i), in which the sum performs all the units (j) in that unit (i) is connected to, (w_ {ij}) is the weight of the connection between (I) and (J), and (X_J) is the status of 0 or 1 of the unit (J). In other words, all the neighbors of the unit (Ã ¢ â,¬ is, Ã ¢ â,¬ â € â € "The neighbors send it a message and calculate the sum of all these messages. Both (p_i = sigma (a_i), where (sigma (x) = 1 / (1 + exp (-x)) is the logistics function. Note that (p_i) is close to 1 for large positive activation energies, and (p_i) is close to 0 for negative activation energies. So we turn units with probability (p_i) and turn it off with probability (1 - p_i). (In the terms of the layman, the units that are positively connected to each other attention to To each other to share the same state (ie, to be turned on or off), while the units that are negative connected to the other are enemies that prefer to be in different states.) For example, suppose our two Hidden units really correspond to SF / Fantasy and Oscar winners. If Alice told us that her six binary preferences on our film set, we could therefore ask our RBM as Del Del Unit Your preferences activate (ie, ask RBM to explain your preferences in terms of latent factors). So the six films send messages to hidden units, telling them to update them. (Note that although Alice said he wants to watch Harry Potter, Avatar and Lotottr 3, this does not guarantee that the hidden SF / Fantasy unit will turn on, but only that he will light up high probability. This makes a little good SENSE: In the real world, Alice wanting to see all three of those movies makes us strongly suspect that likes SF / Fantasy in general, but thereÃÃ ¢ knows small possibility that wants to look at them for other reasons so,. The RBM allows us to generate Models of people in the disordered world, real.) Conversely, if we know that a person likes SF / Fantasy (so that the SF / fantasy unit is turned on), we can therefore ask the RBM as the cinematographic unit that the hidden unit is hidden It turns on (ie, ask RBM to generate a series of cinematographic recommendations). So the hidden units send messages to cinematographic units, telling them to update their states. (Once again, note that the SF / fantasy unit that is not able to ensure that we always recommend all three of the three of Harry Potter, Avatar and Lottr 3 because, hey, not all those who like the science fiction liked avatar.) weighs so how do we learn the connection weights in our network? Suppose we have a group of training examples, in which every example of training is a binary vector with six elements corresponding to a user's cinematographic preferences. So for each time, do the following: Take an example of training (a set of six cinematographic preferences). Set the states of the units visible to these preferences. Subsequently, update the states of the hidden units using the logistic activation rule described above: for the unit (J), calculates its activation energy (A_J = sm_i w_ {ij} x_i) and set (x_j) to 1 with probability (sigma (a_j) and 0 with probability (1 - sigma (a_j)). So for each board (E_ {IJ}}}}), calculate (positive (e_ {ij}) = x_i * x_j) (I.E., for each pair of units, measure if it is on both). Now reconstruct the units visible in a similar way: for each visible unit, calculates its activation energy (A_I) and updates its status. (Note that this reconstruction cannot correspond to the original preferences.) Then update the hidden units again and calculate (E_ {IJ}) = x_i * x_j) for each edge. Update the weight of each board (E_ {IJ}) by setting (w_ {ij} = w_ {ij} + l * (positive (e_ {ij}) - negative (e_ {ij})), Where (l) is a learning rate. Repeat on all training examples. Continue up converging network (ie, the error between training examples and their reconstructions drops below a certain threshold) or you reach a maximum number of eras. Why does this update rule make sense? Note that in the first phase, (positive (E_ {IJ}) measures the association between the unit (I) and (J) that we want the network to learn from our training examples; In the phase Ã ¢ â,¬ Å "reconstructionÃ ¢ â,¬, where the RBM generates the states of visible units based on its hypotheses on the units hidden by the sun, (negative (E_ {IJ}) measures the association that The same network generates (or Ã ¢ â,¬, â,¬ by the way) when no unit is fixed to training data. Then adding (positive (e_ {ij}) - negative (e_ {ij}) to each weight of the edge, we also helping dreams to daydreams of the network better correspond to the reality of our training examples. (You could hear this update rule called conflicting divergence, which is basically a luxury term for "approximate faded descent".) Examples that I wrote a simple RBM implementation in Python (the code is Commented, then take a look if you â,¬ Â "¢ King still a little blurred on how everything works), so we use it to walk through some examples. First of all, I trained the RBM using some false data. Alice: (Harry Potter = 1, avatar = 1, Lottr 3 = 1, Gladiator = 0, Titanic = 0, Glitter = 0). Big SF / Fantasy fans. Bob: (Harry Potter = 1, avatar = 0, Lottr 3 = 1, Gladiator = 0, Titanic = 0, Glitter = 0). 0). fan, but it doesnÃ ¢ t as an avatar. Carol: (Harry Potter = 1, Avatar = 1, Lotr 3 = 1, Gladiator = 0, Titanic = 0, Glitter = 0). Big SF / Fantasy fans. David: (Harry Potter = 0, avatar = 0, Lotr 3 = 1, Gladiator = 1, Titanic = 1, glitter = 0). Big Oscar ventilator winners. Eric: (Harry Potter = 0, avatar = 0, Lotr 3 = 1, Gladiator = 1, Titanic = 1, glitter = 0). Oscar ventilator winners, with the exception of Titanic. Fred: (Harry Potter = 0, avatar = 0, Lotr 3 = 1, Gladiator = 1, Titanic = 1, glitter = 0). Big Oscar ventilator winners. The network has learned the following weights: note that the first hidden unit seems to correspond to the Oscar premiums, and the second hidden unit seems to match the sf / fantasy cinema, just as we hoped. What happens if we give RBM a new user, George, who has (Harry Potter = 0, avatar = 0, Lotr 3 = 0, Gladiator = 1, Titanic = 1, glitter = 0) How does he preferences? It turns out the Oscar winning unit (but not the fantasy SF), correctly guessing that George probably loves movies that are winners of Oscar. What happens if only the SF / Fantasy unit is activated, and run the RBM a different pile of times? In my tests, it was discovered on Harry Potter, Avatar, and Lotr 3 three times; It has been found on Avatar and Lotr 3, but not Harry Potter, once; And Harry Potter is turned on and the Lord of the Rings 3, but not avatar, twice. Note that, based on our training examples, these preferences actually correspond to we could expect real SF / fantasy enthusiasts want to watch. Changes I tried to keep the link-learning algorithm that I described above quite simple, so here are some changes that often appear in practice: up, (negative (E_ {IJ}) was determined holding The product of (I) (J) th unit after the reconstruction of the units visible once and then the update again hidden units. We could also take the product after a more reconstruction number (ie, repeat the update of visible units, then the hidden units, then the units visible again, and so on); This is more slow, but describes the NetworkÃ ¢ rÃ © Veries more accurate. Instead of using (positive (e_ {ij}) = x_i * x_j), where (x_i) and (x_j) are binary 0 or 1 states, we may also let it (x_i) and / or (X_J) BE activation Probability. Likewise per (negative (E_ {IJ}). We could penalize larger border weights, in order to get a more regularized radius or model. When you update the border weights, we could use a momentum factor: we would like to add a weighed sum of the current step at each edge as described above (for example, (L * (positive (E_ {IJ}) - negative (E_ {IJ })) and the previously taken phase. Instead of using a single training example in each era, you could use lots of examples in each era, and update only the weight NetworkÃ ¢ s after crossing all examples in the batch. This You can accelerate learning by exploiting fast multiplication matrix algorithms. Algorithms.

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