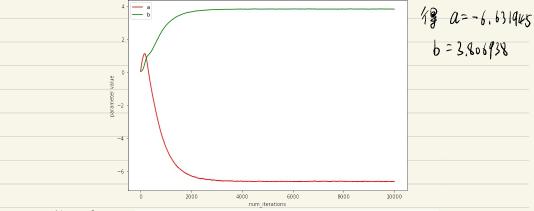
根死率图模型 第7次似

(1) Gibbs distribution PCH, Hr, V, V2, V3) = = 0 alH, tH2+0.2(V,+14, t/3)- bH, (V,+1/2+1/3)+ bH, (V,+1/2+1/3) e al 1+0,2 (Vitht 1/3)) - B(Ktht 1/3) (2) P(H=1/V,, V2, K) = e 0,20(V,+K+V3) +e d 1+0,2(V,+K+V3)) -B(K+K+V3) = 1 + e-a+b(Vi+Vith) = signoid (a-b(Vi+Vi+V3)) P(H2=1 | V1, V2, V3) = sigmoid (& + b(V1+V2+V3)) P(V1=1 | H1, H2) = sigmoid (02d - b (H1-H2)) P(V2=1 | H1, H2) = Sigmoid (0.2x-b(H1-H2)) P(K=1 | H1, H2) = sigmoid (0.2x-b(H1-H2)) 1) input V= (V1, V2, V3) calculate P(H, IV) P(HzIV) sample H=(H1, H1) caculate P(V, IH') P(V, IH') P(V, IH') sample $V' = (V_1', V_1', V_3')$ ((01x) = \frac{1}{n} (\frac{\infty}{10} (\alpha(H'_{im} + H'_{im} + 0.2 (V'_i + V'_i + V'_i + V'_i + V'_i)) - bH_i(V_i + V_i + V'_i + V'_i)) - (nZ) 21 = 1 Eab(Hith to 2 (Vithtrantism)) - Eab(Hith to 2 (Vithtra)) $\frac{\partial L}{\partial b} = \frac{1}{M} \sum_{i=1}^{M} \left((V_{i} + V_{i} + V_{i}) \left(H_{i} + H_{i} \right) \right) - \frac{E}{ab} \left((V_{i} + V_{i} + V_{i}) \left(H_{i} + H_{i} \right) \right)$ 5 $\alpha_{-new} = \alpha + \lambda \cdot \frac{\partial L}{\partial a}$ $b_{-new} = b + \lambda \frac{\partial L}{\partial b}$

①作及图定住知样自由度,只有 a, b 2个参数

学习过程如下图:



训练结果如下

```
a = -6.631945, b = 3.806938
rbm.bias_visi = [-1.32638905 -1.32638905]
rbm.bias_visi = [-6.63194526 -6.63194526]
rbm.weights =
[[-3.80693811 -3.80693811]
[3.80693811 -3.80693811]
Real prob(V1) = 0.588940, prob(V2) = 0.589840, prob(V3) = 0.589150
gibbs sampling prob(V1) = 0.589270, prob(V2) = 0.587330, prob(V3) = 0.586600
The inferred hidden nodes of P(H=1) =
[[2.92710190e-05 5.59877908e-02]
[6.50306446e-07 7.27491191e-01]
[1.44472811e-08 9.91746818e-01]
...
[6.50306446e-07 7.27491191e-01]
[1.44472811e-08 9.91746818e-01]
```

接着取消固定 a.b, 使得参数量从2变为11, 训练结果如下

[1.44472811e-08 9.91746818e-01]]

可以爱到表现编差。

最后争入 Sklearn 的 RBM 包,进行对比实验
sklearn_rbm.intercept_visible_ = [0.133
可以参测结果截然不同, 考虑到只能调用API, 难以多过是否 收敛, 因此无法与我自己目的代码比较.