CS294-158 (Spring 2020)

Deep unsupervised learning from @ucb

class video from(SP19) https://www.bilibili.com/video/BV1Eb411Y7J5?p=1

(SP20)https://www.bilibili.com/video/BV1oE411F7iz?p=2

Notes by Haotian Xue from @sjtu

homepage : https://htxue.info 😄

email : xavihart@sjtu.edu.cn ✉

Week 1

1.Motivation

- likelihood-based models:
  estimate p_{data} from samples $\{x^{(i)}\}$
- trade-off(to get the data distribution):
  - Efficient training and model representation
  - Expressiveness and generalization
  - Sampling quality and speed
  - Compression rate and speed

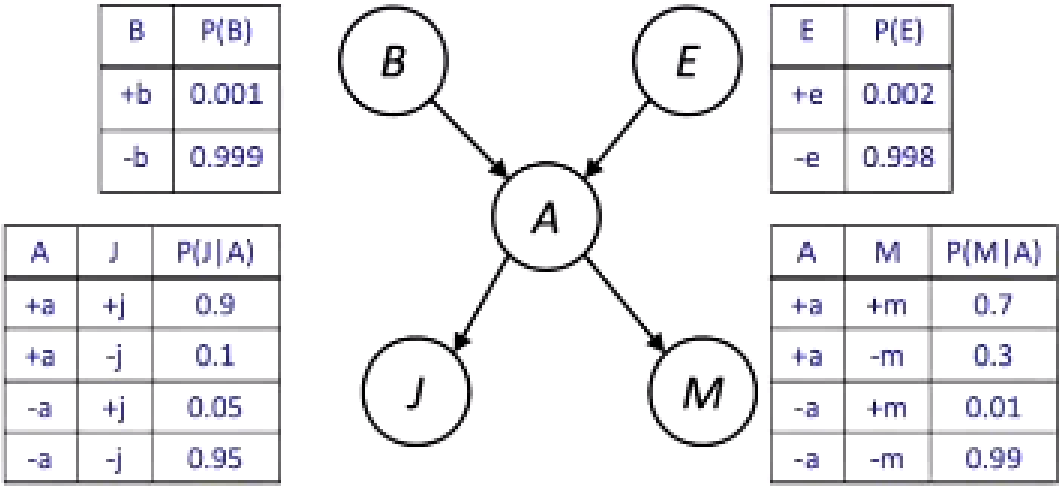
2.Simple generative models

- Just count it
  - JUST A histogram
  - fail in high dimension, poor in generalization
  - Solutions : function approximation $p_\theta(x)$
- To get $p_\theta(x)$, maximum likelihood:

$$argmin_\theta loss(\theta, x^{(1)}, x^{(2)}, \dots, x^{(n)}) = \frac{1}{n}\sum_{i=1}^{n} -log(p_\theta(x^{(i)}))$$

  等价于计算数据01分布和$p_\theta(x)$的KL散度最小

  -> Maximum likelihood + SGD
- (*) Bayes Network(Belif net / causal net)
  - DAG: vertex->property & edge->dependency & define parents and children
  - PGM(probability graph model) = Markov(无向) Net + Bayes Net(有向)
  - sparsity the 2^i sized tabular



B	P(B)
+b	0.001
-b	0.999

E	P(E)
+e	0.002
-e	0.998

A	J	P(J|A)
+a	+j	0.9
+a	-j	0.1
-a	+j	0.05
-a	-j	0.95

A	M	P(M|A)
+a	+m	0.7
+a	-m	0.3
-a	+m	0.01
-a	-m	0.99

- Autoregressive Models
  - a fully expressive Bayes Net
  - $logp(x) = \sum logp(x_i|x_{1:i-1})$
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3.Modern NN-based autoregressive models

Week 2