

Statistical Models

HMM, MEMM, and CRFs

PART-I

HMM (Hidden Markov Model)

- What is the HMM?
 - Hidden + Markov Model
- Markov Model: Example
 - Training

		Tomorrow State (내일 상태)		
		Rain	Cloudy	Sunny
Today State (오늘 상태)	Rain	0.4	0.3	0.3
	Cloudy	0.2	0.6	0.2
	Sunny	0.1	0.1	0.8

- Assumption: Tomorrow weather depends only on today one.
- Problem: P(Rain, Rain, Sunny, Cloudy)?

마코프 모델 (Markov Model)

- Markov Model: Sequence Probability
 - 결합 확률(joint probability) 계산 모델
 - 연쇄 규칙과 마코프 가정을 이용하여 결합 확률을 단순화하여 결합 확률을 근사화시키는 모델

$$P(y_1, y_2, \dots, y_t)$$

$$= P(y_1)P(y_2|y_1)P(y_3|y_1, y_2) \dots P(y_t|y_1, y_2, \dots, y_{t-1})$$

$$= P(y_1)P(y_2|y_1)P(y_3|y_2) \dots P(y_t|y_{t-1})$$

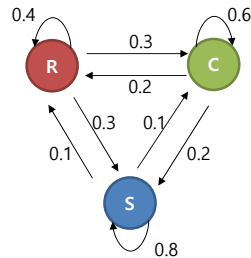
Chain Rule

1st-order Markov Assumption

마코프 모델 (Markov Model)

마코프 모델: 학습데이터로 부터 얻어진 전이 확률분포 (상태 간 이동 확률 분포)

		Tomorrow State (내일 상태)		
		Rain	Cloudy	Sunny
Today State (오늘 상태)	Rain	0.4	0.3	0.3
	Cloudy	0.2	0.6	0.2
	Sunny	0.1	0.1	0.8



State = $\{S_1: \text{Rain}, S_2: \text{Cloudy}, S_3: \text{Sunny}\}$

$$\begin{aligned} P(S_1, S_1, S_3, S_2 | \text{model}) \\ &= P(S_1)P(S_1|S_1)P(S_3|S_1)P(S_2|S_3) \\ &= 1 * 0.4 * 0.3 * 0.1 \\ &= 0.012 \end{aligned}$$

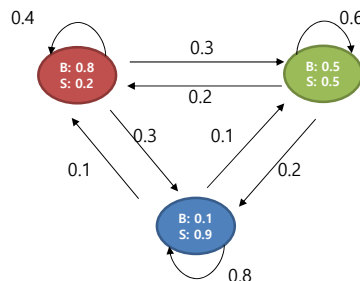
What is Hidden?

Hidden Markov Model

- 상태(풀고자 하는 레이블)를 직접 관측할 수 없고 상태를 예측하는데 도움이 되는 특징(자질)만을 관측할 수 있음
- 상태가 감춰져 있고(직접 관찰할 수 없고) 관측에 대한 확률로만 존재
- 예제
 - 상태(State): Rain, Cloudy, Sunny
 - 관측(Observation): B (Rain Boots), S (Sports Shoes)
 - 문제(problem): $P(B, B, S, S, \text{Rain}, \text{Rain}, \text{Sunny}, \text{Cloudy})?$

What is Hidden?

- 상태(State): Rain, Cloudy, Sunny
- 관측(Observation): B (Rain Boots), S (Sports Shoes)
- 문제(problem): "B, B, S, S"를 관측했을 때 날씨가 어떻게 예측하는 게 최적일까?
 - $P(\text{Rain}, \text{Rain}, \text{Sunny}, \text{Cloudy})$ vs. $P(\text{Rain}, \text{Rain}, \text{Sunny}, \text{Sunny})$ vs. ...



HMM (Hidden Markov Model)

$$\text{Let } P(x_{1,t}) = P(x_1, x_2, \dots, x_t)$$

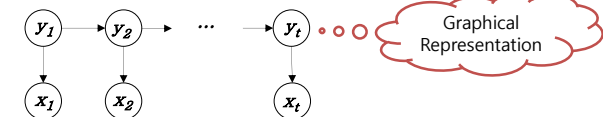
$$\text{HMM} = \underset{y_{1,t}}{\operatorname{argmax}} P(x_{1,t}, y_{1,t})$$

$$= \underset{y_{1,t}}{\operatorname{argmax}} P(y_{1,t}) P(x_{1,t} | y_{1,t})$$

$$= \underset{y_{1,t}}{\operatorname{argmax}} \prod_{i=1}^t P(y_i | y_{i-1}) P(x_i | y_i)$$

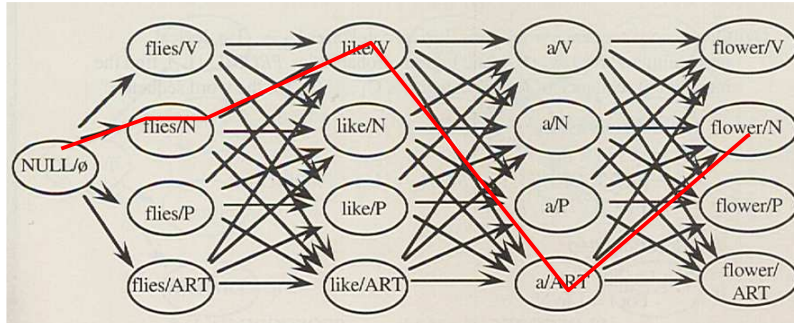
1'st-order Markov Assumption
→ 전이 확률 (Transition Probability)

Independent Assumption
→ 관측 확률 (Observation Probability)



Sequence Labeling Problem

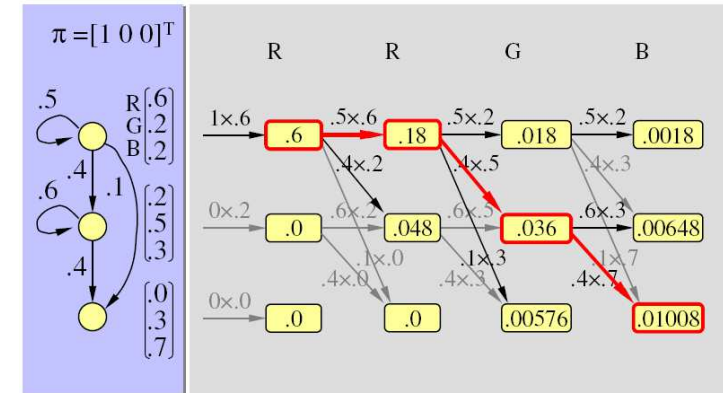
- Segmentation or path analysis problem
 - Application: Part-of-speech tagging



Viterbi Algorithm

- 모든 경로를 고려하지 않고도 빠른 시간 내에 최적의 경로를 찾는 알고리즘

Output: 1, 1, 2, 3



PART-II에
계속됩니다!

