Activity Recognition 6 Classification

Mobile Computing

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REVIEW: NAÏVE BAYESIEN CLASSIFIER

Bayesian Theorem

- Probability model:

$$P(G|H) = \frac{P(G)P(H|G)}{P(H)}$$

$$\text{Posterior} = \frac{\text{Prior} \times \text{Likelihood}}{\text{Evidence}}$$

Naïve Bayesian Classificaiton

- Given evidences, we want to choose gender *g* that maximizes

$$P(G = g|H) = \frac{P(G = g)P(H|G = g)}{P(H)}$$
$$\propto P(G = g)P(H|G = g)$$

$$\text{Posterior} \propto \text{Prior} \times \text{Likelihood}$$

- Maximum A Posteriori (MAP) classification

Sequential Classifier

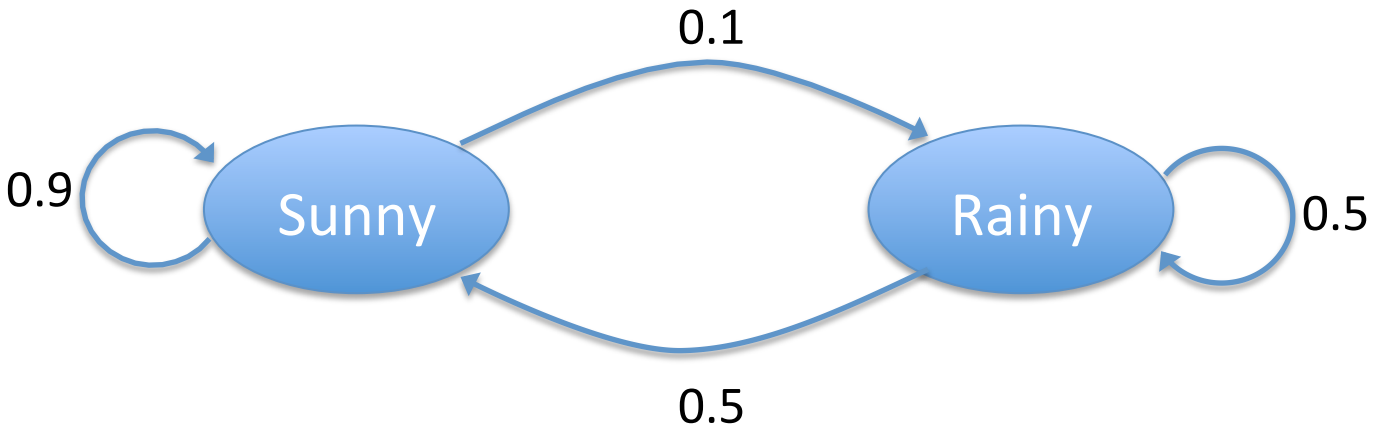
- Classify the current frame based on the classification results of previous frames
- Markov Chain
- Hidden Markov Model (HMM)

Markov Chain

- Random variable *x(t)* changes over time with discrete time *t=1, 2, 3, …*
  - *x(1), x(2), x(3), …, x(t), …*
- Each *x(t)* takes a value in state space $Q = \{s_1, s_2, \ldots, s_n\}$
- Transition probability
  - Probability of observing s_j depends on the previous value s_i, *and only the previous value*
  - $P_{ij} = P(x(t+1) = S_j \mid x(t) = S_i)$

Weather Model by MC

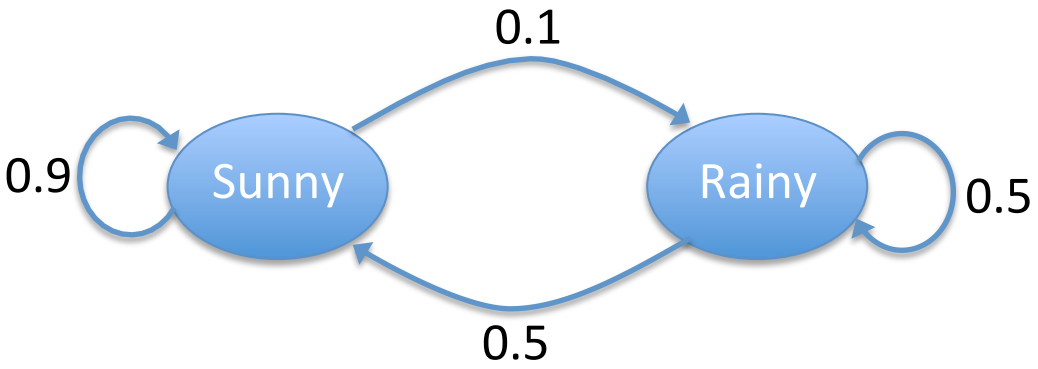
- Weather = {sunny, rainy}
- If sunny today, then sunny tomorrow with 90%
- If sunny today, then rain tomorrow with 10%
- If rain today, then either sunny or rain with 50%



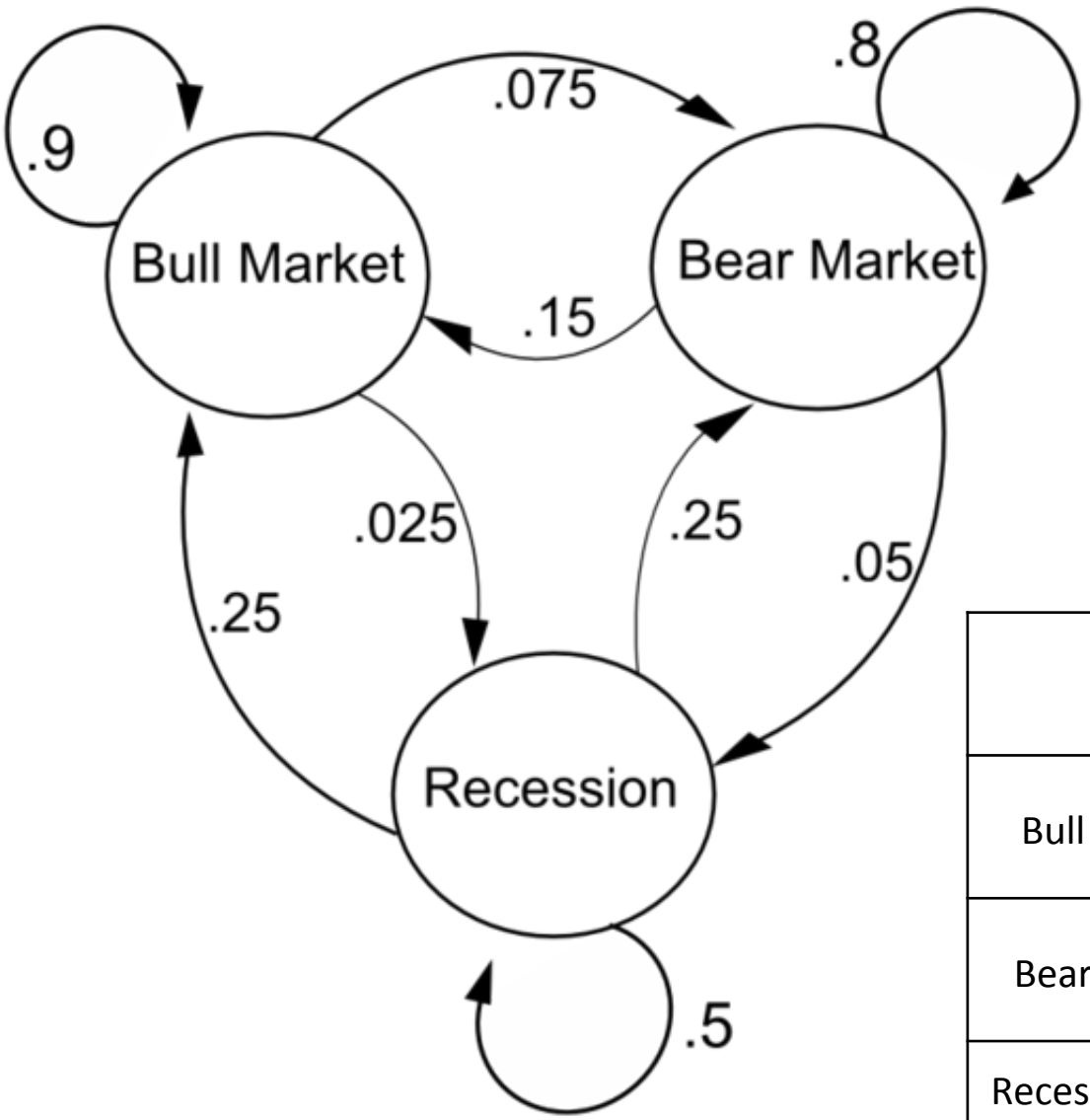
- Stationary probability: (sunny, rainy) = (0.833, 0.167)

Transition Matrix

- Transition Matrix
  - Describes the transition probabilities between states in a matrix whose *(i,j)* element is P_{ij}



	(Sunny)	(Rainy)
(Sunny)	0.9	0.1
(Rainy)	0.5	0.5



Transition Matrix

	Bull	Bear	Recession
Bull	0.9	0.75	0.25
Bear	0.15	0.8	0.05
Recession	0.25	0.25	0.5

How human knows weather?

Look at the sky…


It's Sunny dude!

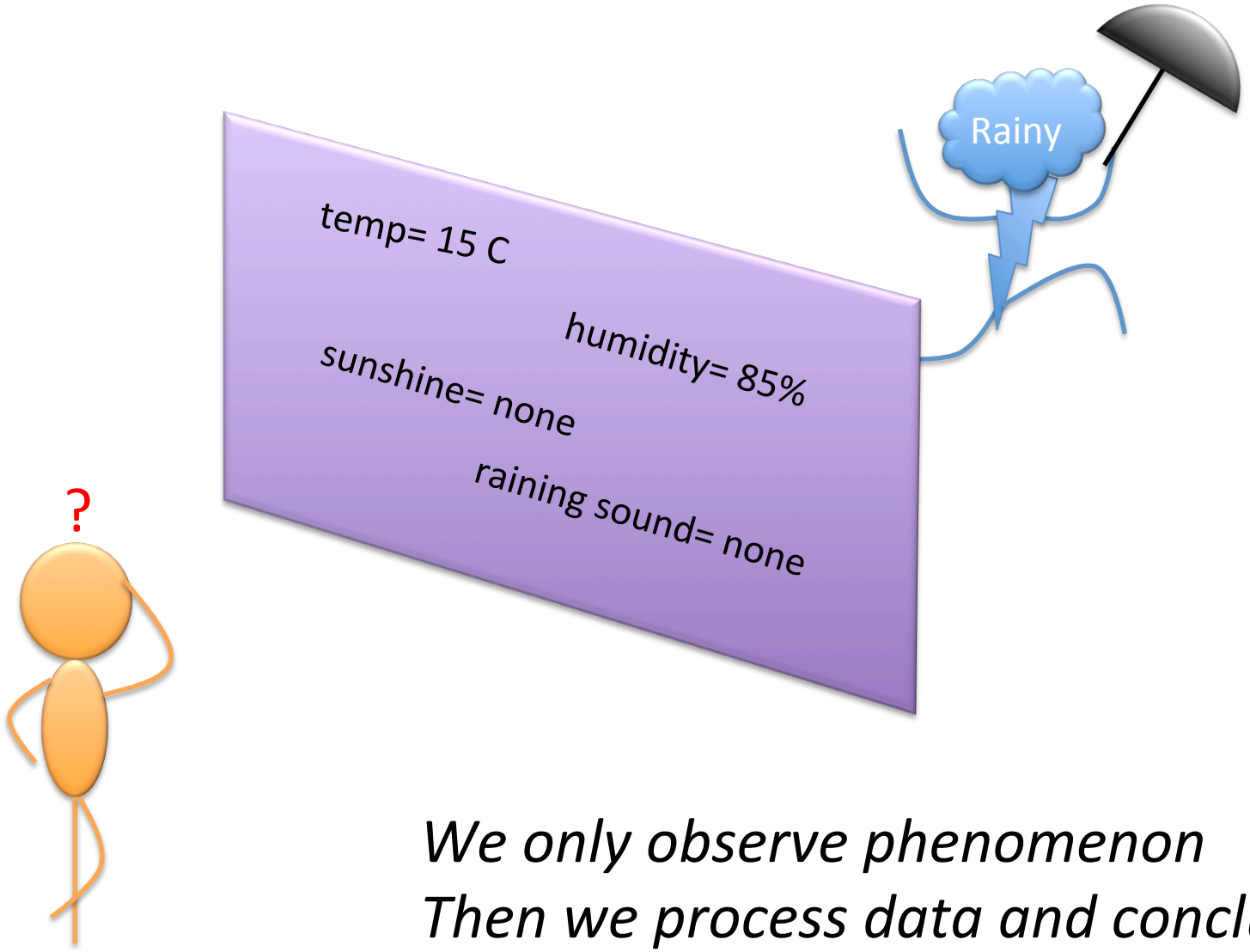

It's Snowing, watch out!

How human knows weather?

- We can't *see* weather directly
- We *collect* evidences and *infer* the best-fit weather
  - Sun, sunshine, water drops, sound, temperature, humidity, snow, …
- But sometimes we are not sure…

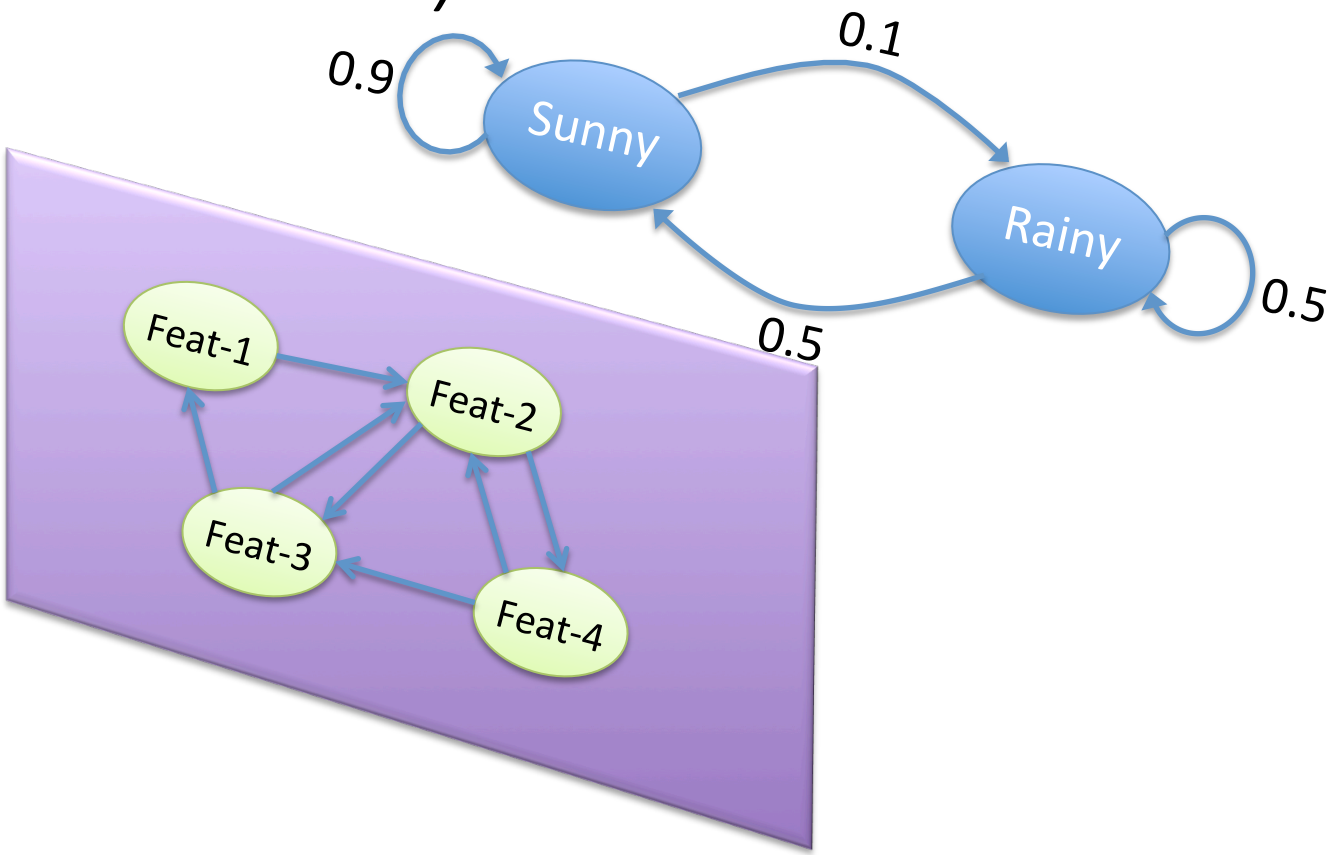

It’s… uh… eh… πππ…

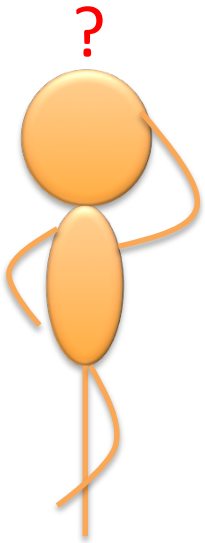
We can't see the weather



We only observe phenomenon
Then we process data and conclude

We can't see the state
(following a Markov Process)

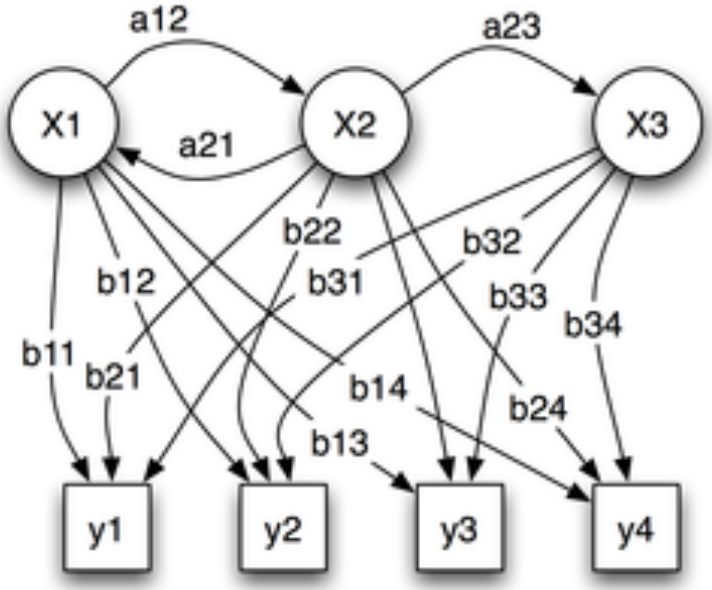




We only observe consequences of state
Then we infer the state behind the scene

Hidden Markov Model

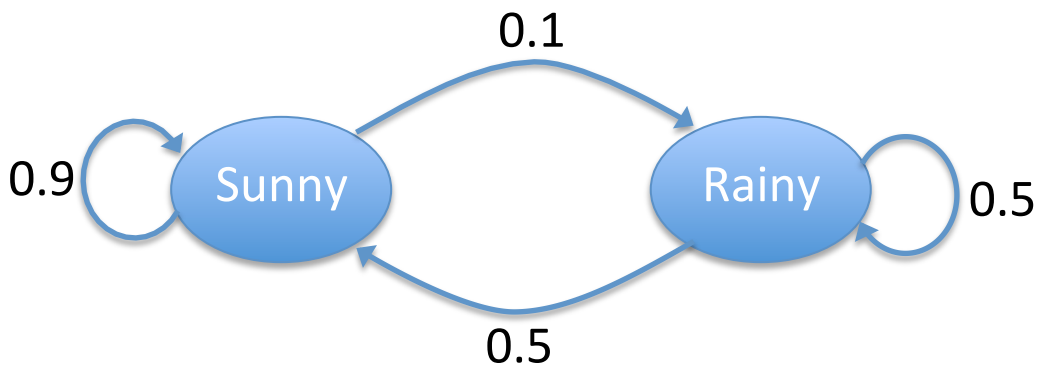
- Hidden states X_1, X_2, … X_n of a Markov Chain with transition probability a_{ij}
- Observed states y_1, y_2, …, y_n
- Output probability $\{b_{ij}\}$
- From observed states, infer the hidden states and their transition probabilities



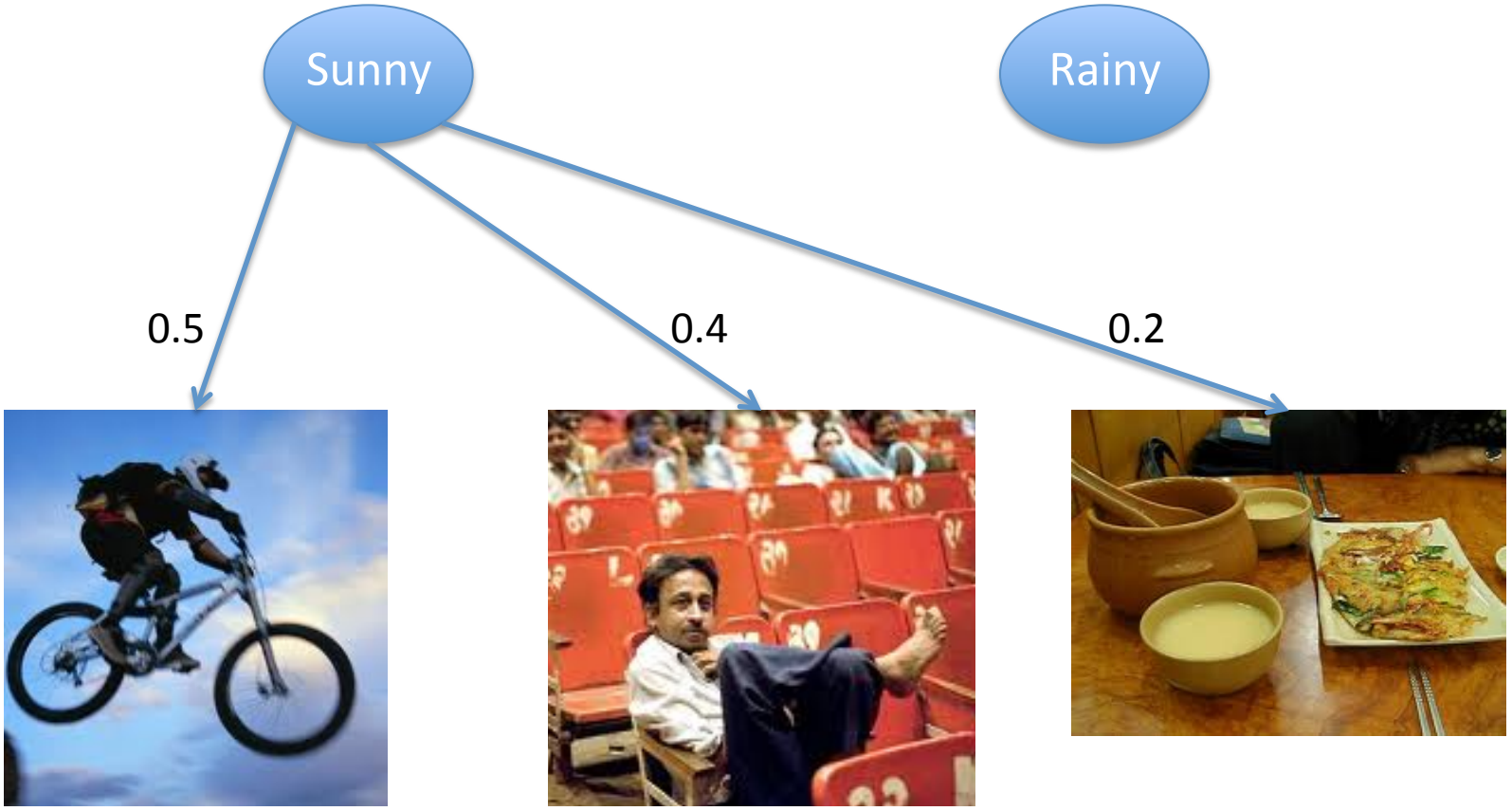
Weather Analogy

- Alice talks with Bob on the phone
- Alice has a general idea about the weather in Bob's city, but doesn't know current weather
- Alice asks Bob what he did
- Alice infers the weather based on Bob's activity

Weather as Markov Chain



Activity per Weather

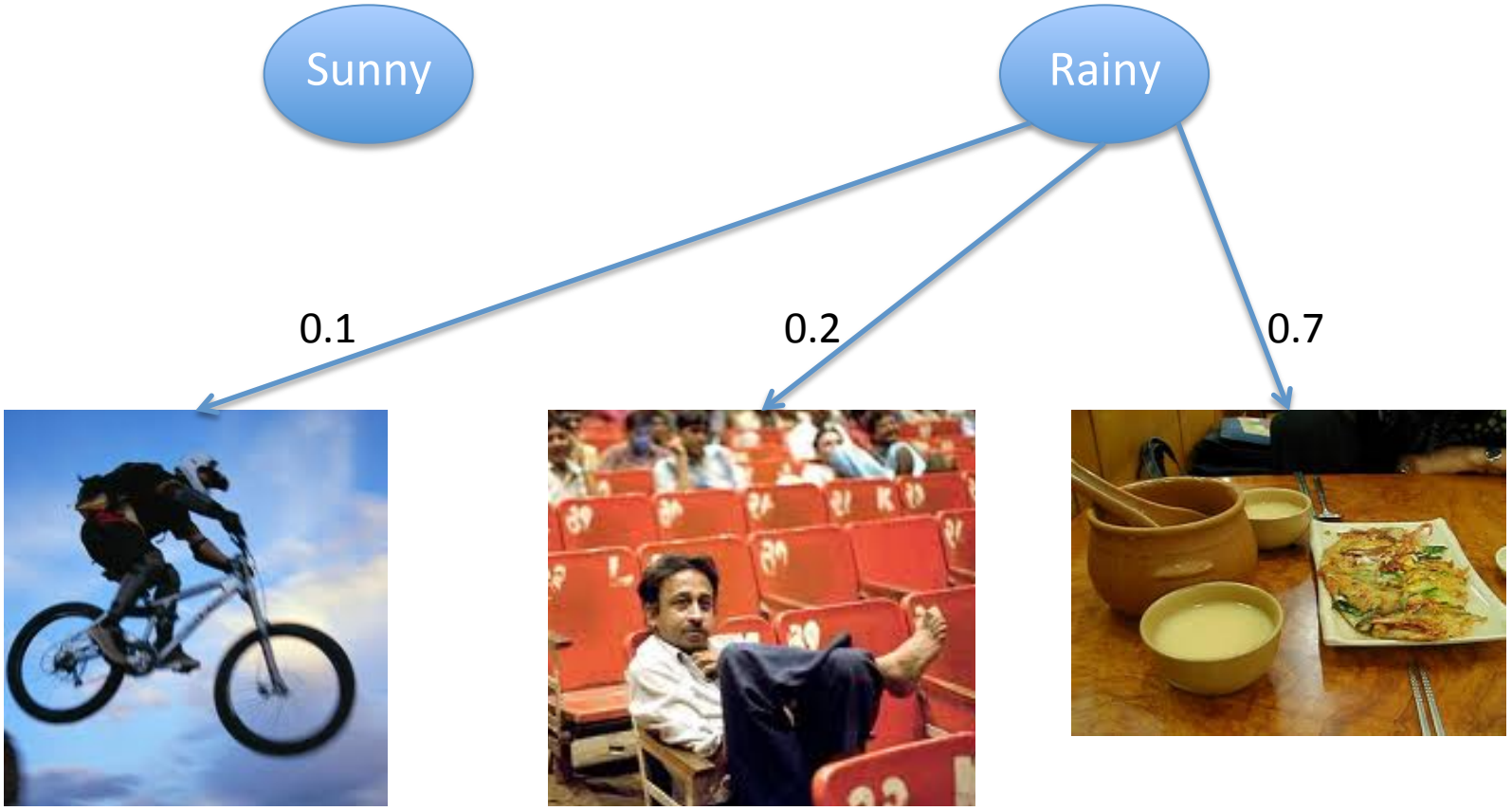


Biking

Movie watching

Pajeon & Dong

Activity per Weather



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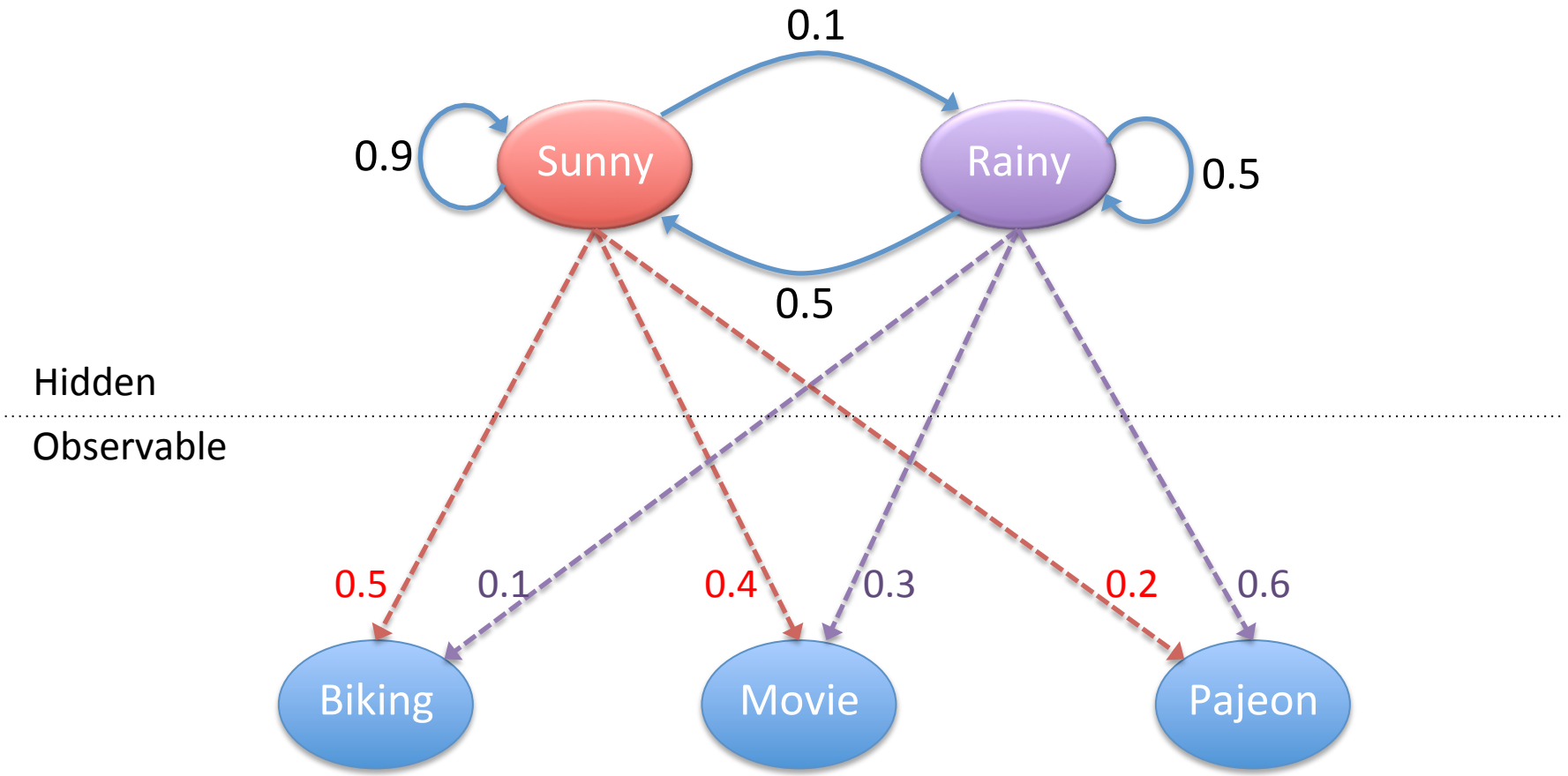
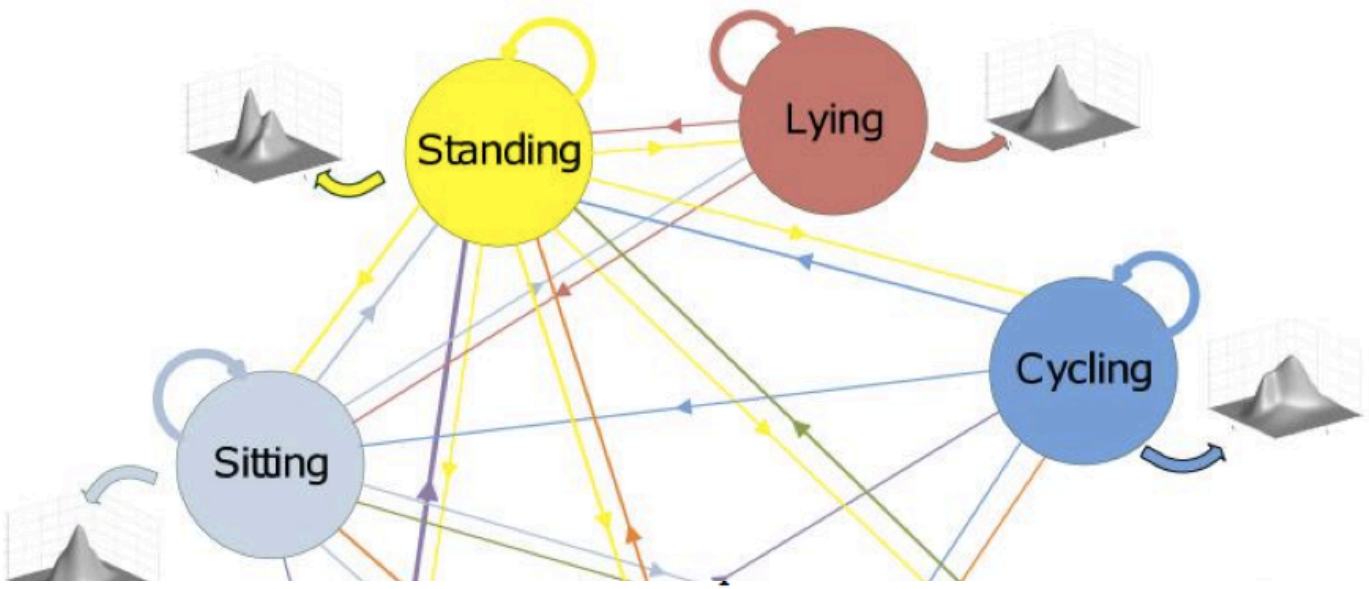
Hidden Markov Model for Weather



Activity Recognition by HMM



Activity	lying	cycling	climbing	walking	running	sitting	standing
lying	0.9500	0.0000	0.0000	0.0000	0.0000	0.0100	0.0400
cycling	0.0001	0.8999	0.0000	0.0400	0.0000	0.0100	0.0500
climbing	0.0001	0.0000	0.6199	0.2500	0.0100	0.0200	0.1000
walking	0.0001	0.0100	0.0300	0.7999	0.0200	0.0700	0.0700
running	0.0001	0.0100	0.0100	0.3500	0.3999	0.0100	0.2200
sitting	0.0200	0.0000	0.0100	0.0400	0.0000	0.8500	0.0900
standing	0.0100	0.0300	0.0100	0.1800	0.0300	0.1200	0.6200

Classification Results

- Single-frame

Classifiers	Classification accuracy, [%]
NB	97.4
GMM	92.2
Logistic	94.0
Parzen	92.7
SVM	97.8
NM	98.5
k-NN	98.3
ANN	96.1
C4.5	93.0

- HMM
  - 99.1 %