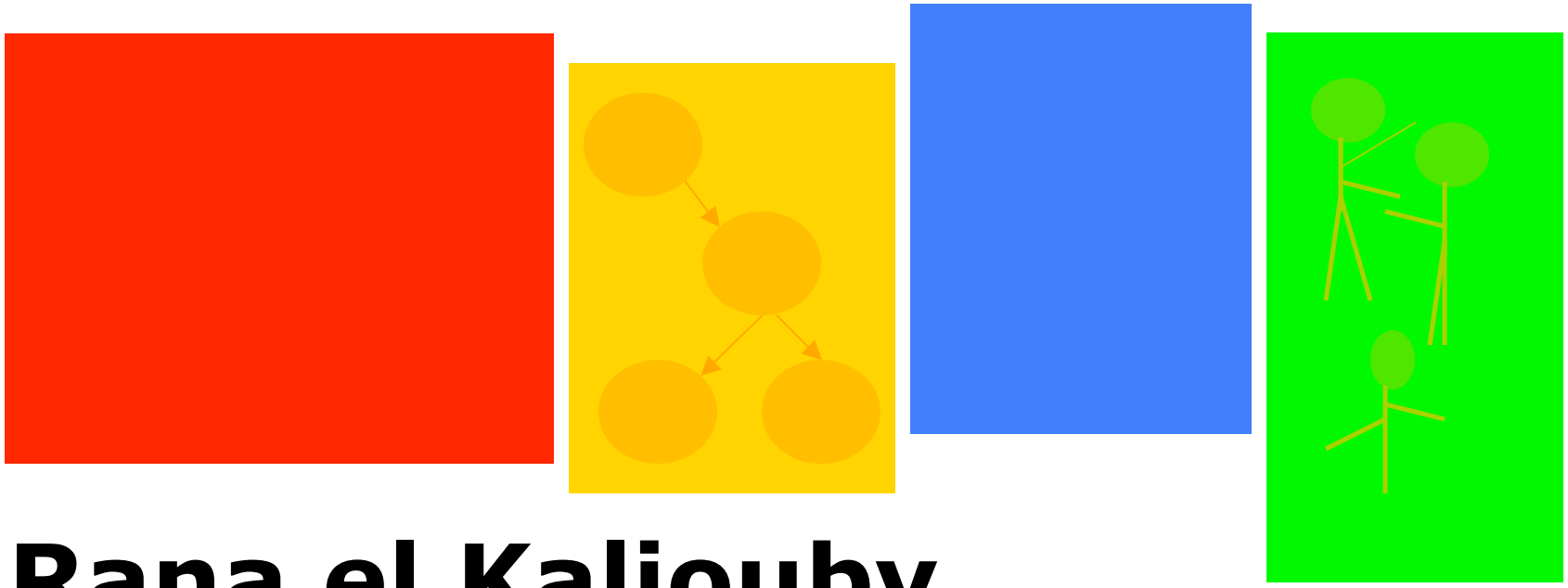
Decoding Human Mental States

Representation, learning and inference of Dynamic Bayesian Networks



Rana el Kaliouby

Research Scientist
MIT | Media Lab
Kaliouby@media.mit.edu
http://web.media.mit.edu/~kaliouby

Pattern Recognition
September 2008

What is this lecture about?

- Probabilistic graphical models as a powerful tool for decoding human mental states
- Dynamic Bayesian networks:
  - Representation
  - Learning
  - Inference
- Matlab's Bayes Net Toolbox (BNT) – Kevin Murphy
- Applications and class projects

Rana el Kaliouby
kaliouby@media.mit.edu

Decoding human mental states

- Mindreading
  - Our faculty for attributing mental states to others
  - Nonverbal cues / behaviors / sensors
  - We do that all the time, subconsciously
  - Vital for communication, making sense of people, predicting their behavior

Rana el Kaliouby
kaliouby@media.mit.edu

People States

- Emotions (affect)
- Cognitive states
- Attention

- Intentions
- Beliefs
- Desires

Actress Florence Lawrence who was known as "The Biograph Girl". From A Pictorial History of the Silent Screen.

Channels of People States

Observable:

- Head gestures
- Facial expressions
- Emotional Body language
- Posture / Gestures
- Voice
- Text
- Behavior: pick and manipulate objects

Up-close sensing:

- Temperature
- Respiration
- Pupil dilation
- Skin conductance, ECG, Blood pressure
- Brain imaging

Reading the mind in the fac e

Autism Research Centre, UK (Baron-Cohen et al., 2003)


Afraid


Angry


Bored


Bothered


Disbelieving


Disgusted


Excited


Fond


Happy


Hurt


Interested


Kind


Liked


Romantic


Sad


Sneaky


Sorry


Sure


Surprised


Thinking


Touched


Unfriendly


Unsure


Wanting

Reading the mind in Gestures

Choosing

Thinking

Interested evaluation

Evaluation, skepticism

Head on palms (boredom)

Nose touch (deception)

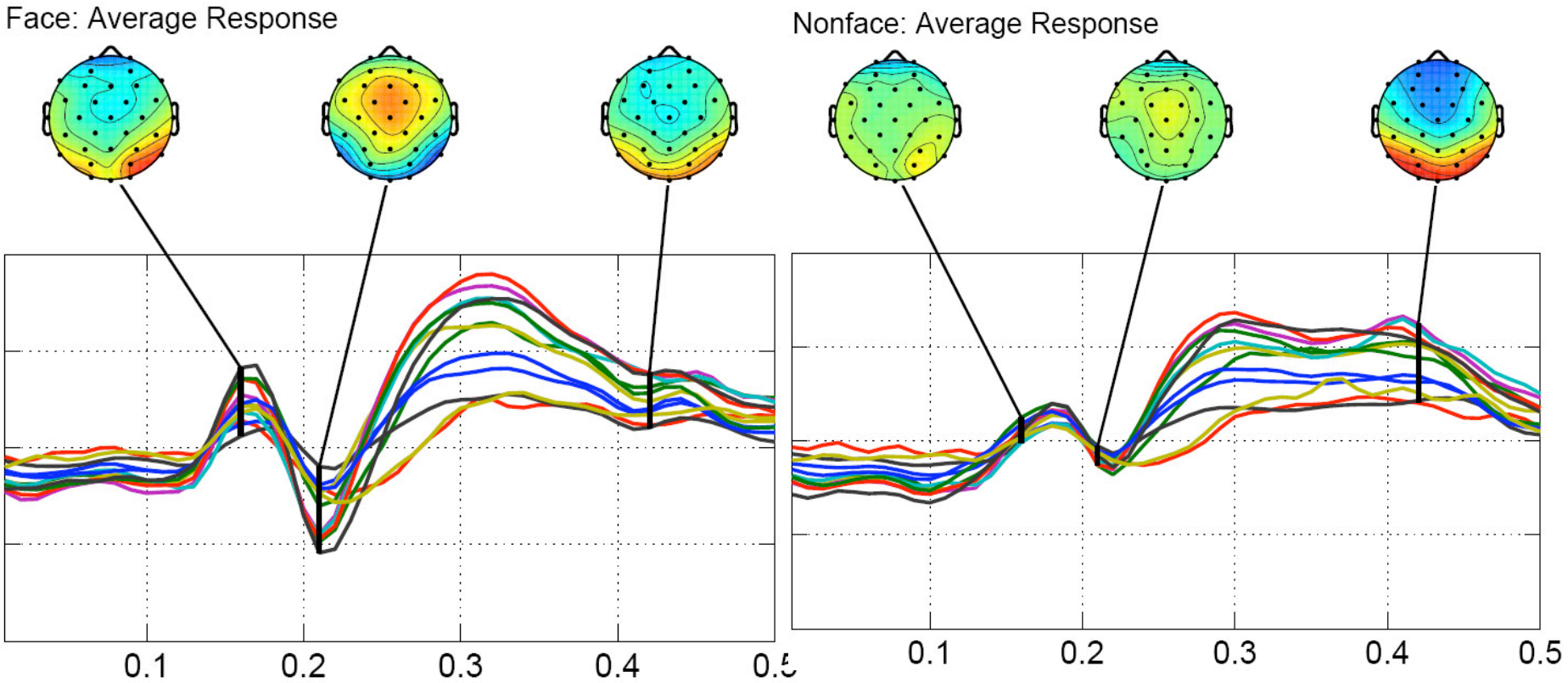
Mouth cover (deception)

Images from Pease and Pease (2004), The Definitive Book of Body Language

Rana el Kaliouby
kaliouby@media.mit.edu

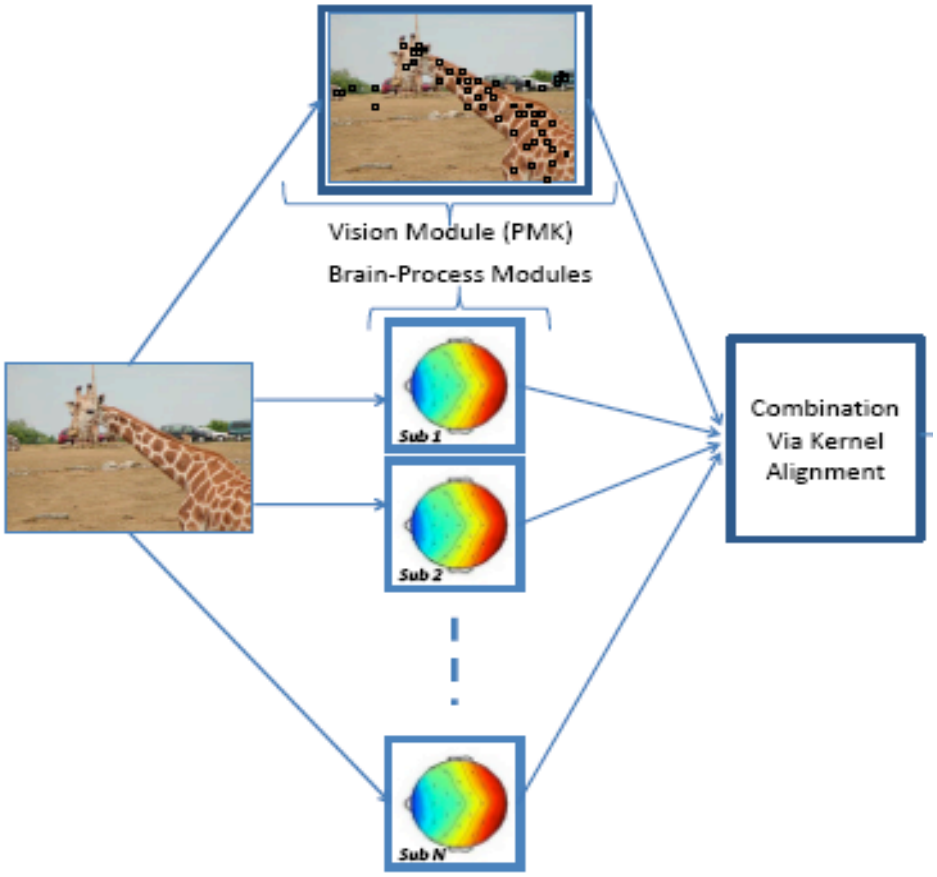
Reading the mind using EEG

- **Feasibility and pragmatics of classifying working memory load with an electroencephalograph** Grimes, Tan, Hudson, Shenoy, Rao. CHI08
- **Dynamic Bayesian Networks for Brain-Computer Interfaces.** Shenoy & Rao. Nips04
- **Human-aided Computing: Utilizing Implicit Human Processing to Classify Images** Shenoy, Tan. CHI08.
- OPPORTUNITY – AFFECTIVE STATES



Multi-modal

- **Combining Brain-computer Interfaces With Vision for Object Categorization** Ashish Kapoor, Pradeep Shenoy, Desney Tan. CVPR 2008



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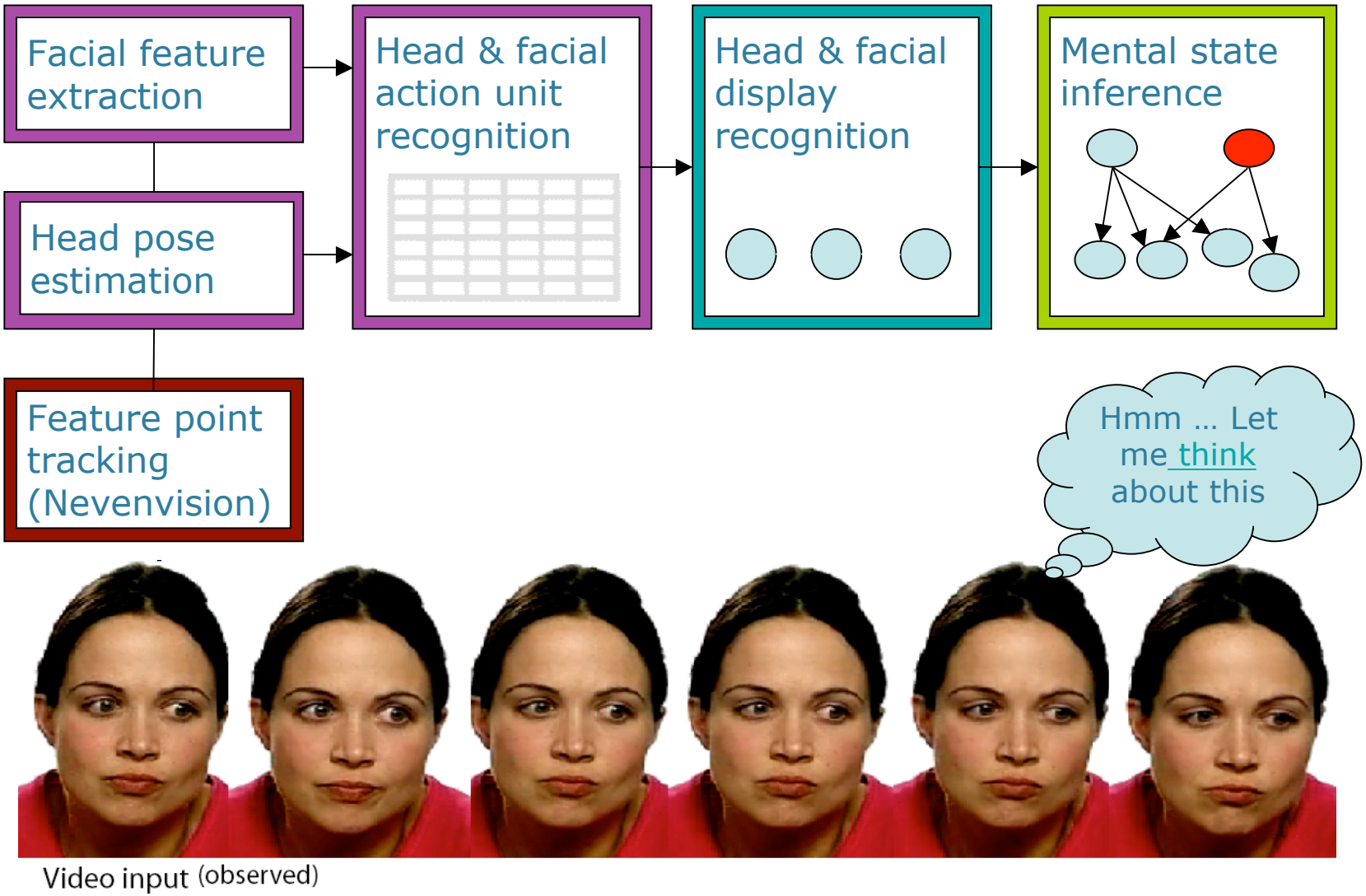
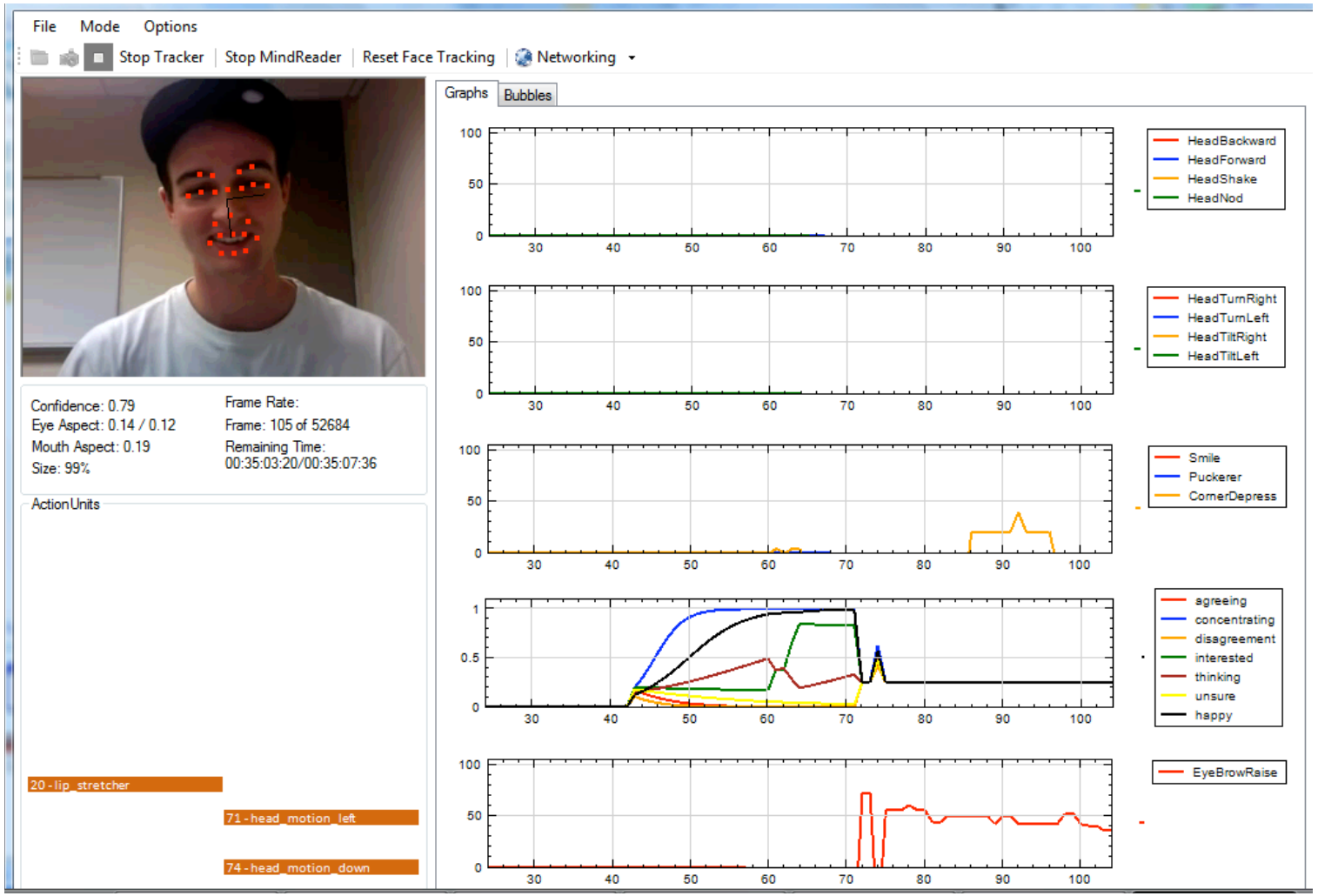
kaliouby@media.mit.edu

Mindreader

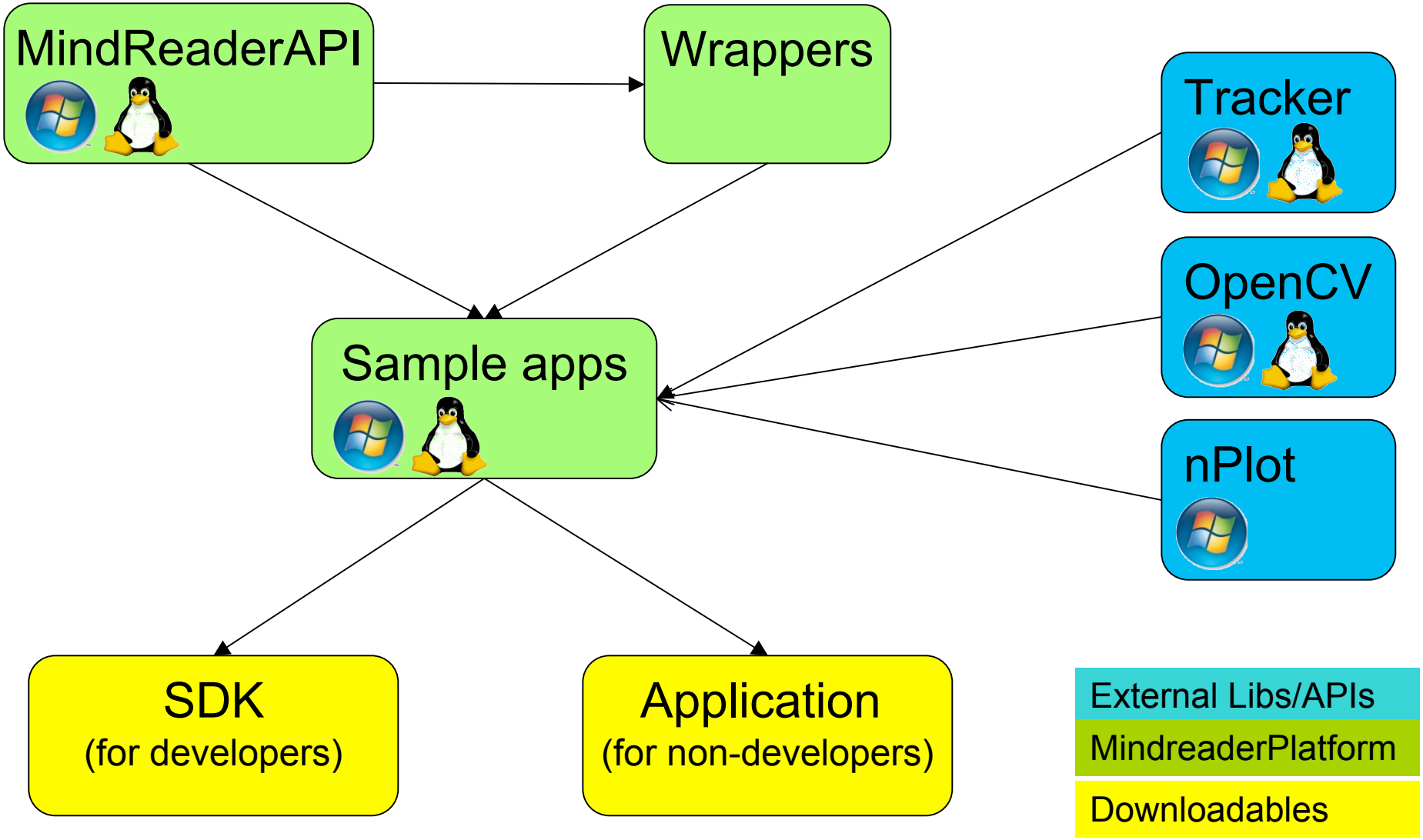

Facial feature extraction
Head pose estimation
Feature point tracking (Nevenvision)
Head & facial action unit recognition
Head & facial display recognition
Mental state inference
Hmm … Let me think about this
Video input (observed)

Face+Physiology

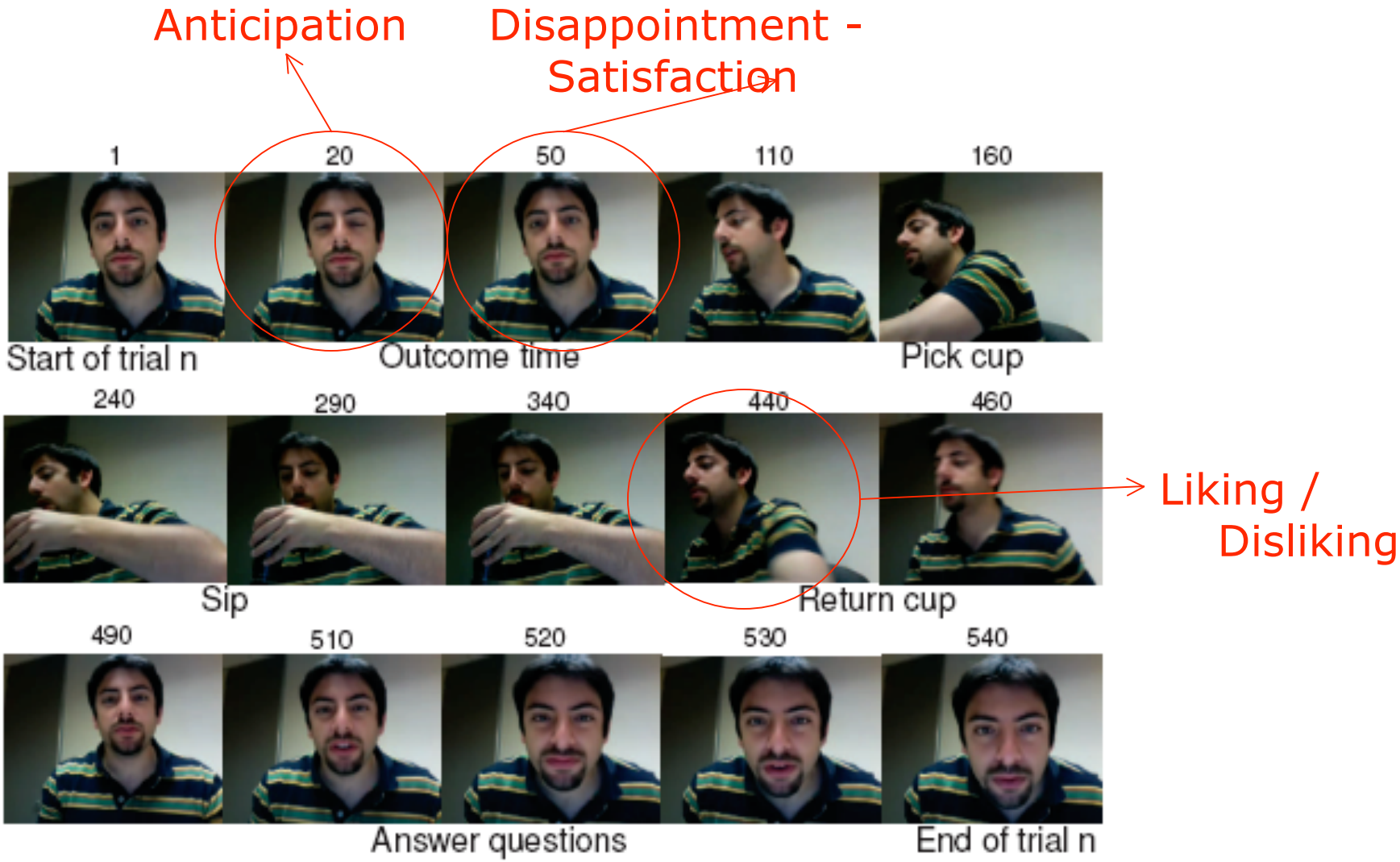


Rana el Kaliouby
kaliouby@media.mit.edu

Mindreader Platform

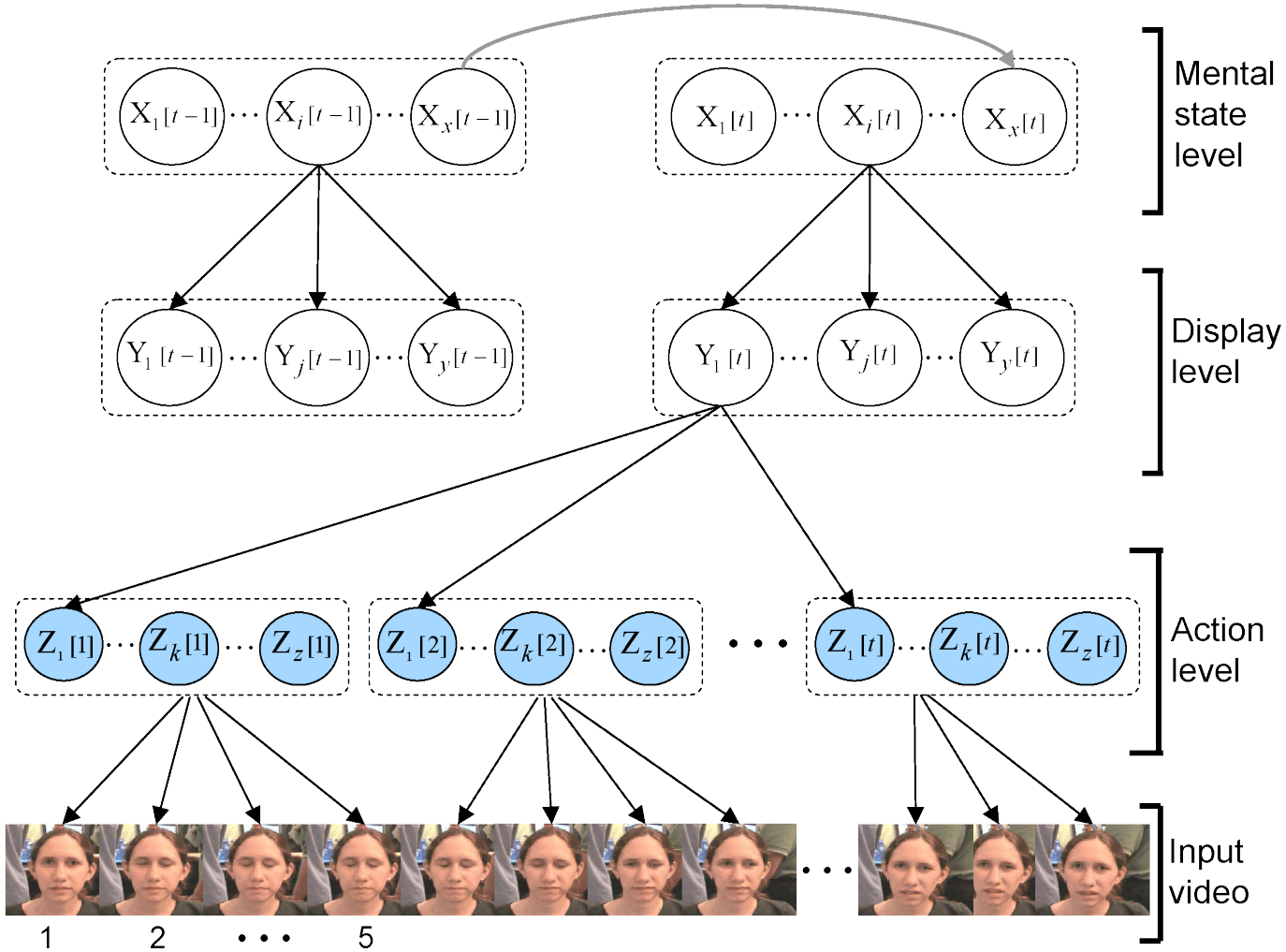


Class Project – Pepsi data

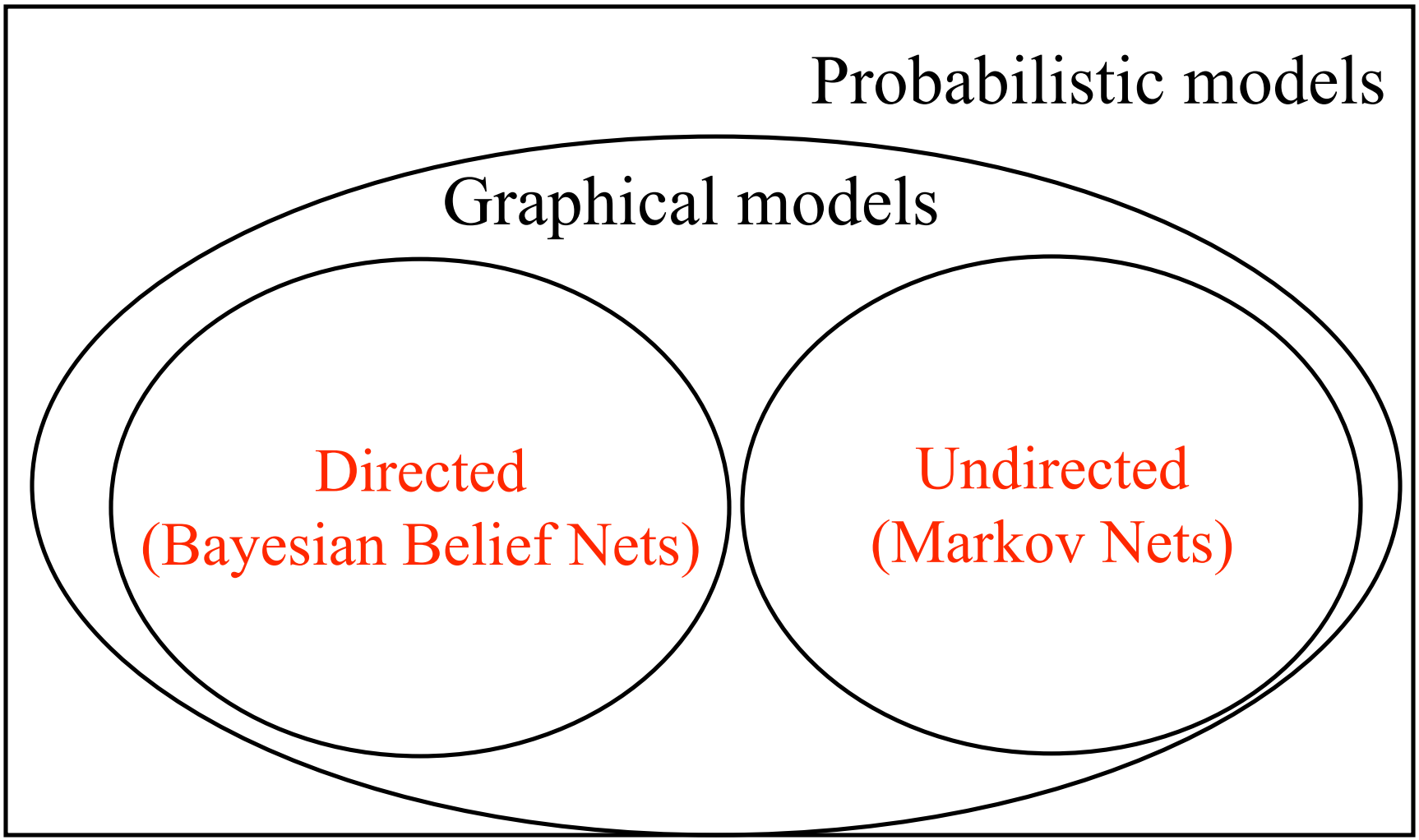


25 consumers, 30 trials, 30 min. videos!

Multi-level Dynamic Bayesian Network



Probabilistic graphical models



Representation of Bayes Net

- A graphical representation for the joint distribution of a set of variables

- Structure
  - A set of random variables makes up the nodes in the network. (random variables can be discrete or continuous)
  - A set of directed links or arrows connects pairs of nodes (specifies directionality / causality).

- Parameters
  - Conditional probability table / density
  - quantifies the effects of parents on child nodes

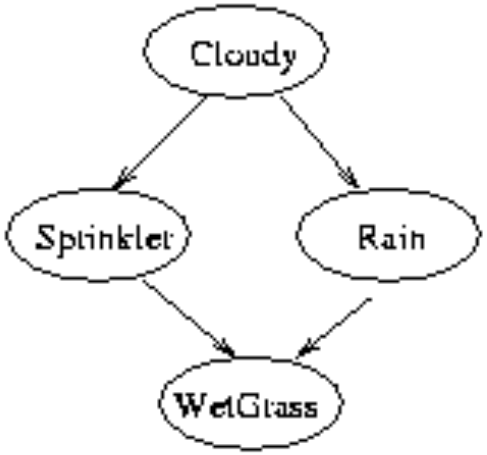
Rana el Kaliouby
kaliouby@media.mit.edu

Setting up the DBN

- The graph structure
  - Expert knowledge, make assumptions about the world / problem at hand
  - Learn the structure from data
- The parameters
  - Expert knowledge, intuition
  - Learn the parameters from data

Rana el Kaliouby
kaliouby@media.mit.edu

Sprinkler - Structure



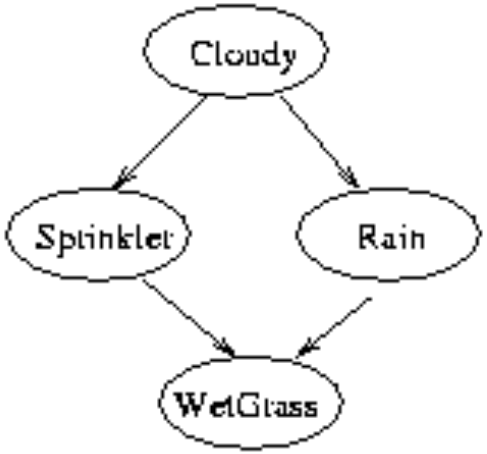
Conditional Probability Tables

- Each row contains the conditional probability of each node value for a each possible combination of values of its parent nodes.
- Each row must sum to 1.
- A node with no parents has one row (the prior probabilities)

Rana el Kaliouby
kaliouby@media.mit.edu

Sprinkler - Parameters

P(C=F)	P(C=T)
0.5	0.5



C	P(S=F)	P(S=T)
F	0.5	0.5
T	0.9	0.1

C	P(R=F)	P(R=T)
F	0.8	0.2
T	0.2	0.8

S	R	P(W=F)	P(W=T)
F	F	1.0	0.0
T	F	0.1	0.9
F	T	0.1	0.9
T	T	0.01	0.99

Why Bayesian Networks?

- Graph structure supports
  - Modular representation of knowledge
  - Local, distributed algorithms for inference and learning
  - Intuitive (possibly causal) interpretation

Why Bayesian Networks?

- Factored representation may have exponentially fewer parameters than full joint $P(X_1,\ldots,X_n)$ =>
  - lower time complexity (less time for inference)
  - lower sample complexity (less data for learning)

$$P(W,S,R,C,) = P(W \mid R,S)P(R \mid C)P(S \mid C)P(C)$$

Graphical model asserts:

$$P(X_1,\ldots,X_n) = \prod_{i=1}^{n} P(X_i \mid \text{parents}[X_i])$$

Why Bayesian Networks?

People Patterns

- Uncertainty
- Multiple modalities
- Temporal
- Top-down,bottom-up

Bayesian Networks

- Probabilistic
- Sensor fusion
- Dynamic models
- Hierarchical models
- Top-down, bottom-up
- Graphical->intuitive representation, efficient inference

Rana el Kaliouby
kaliouby@media.mit.edu

Bayes Net ToolBox (BNT)

- Matlab toolbox by Kevin Murphy
- Ported by Intel (Intel's open PNL)
- Problem set 4

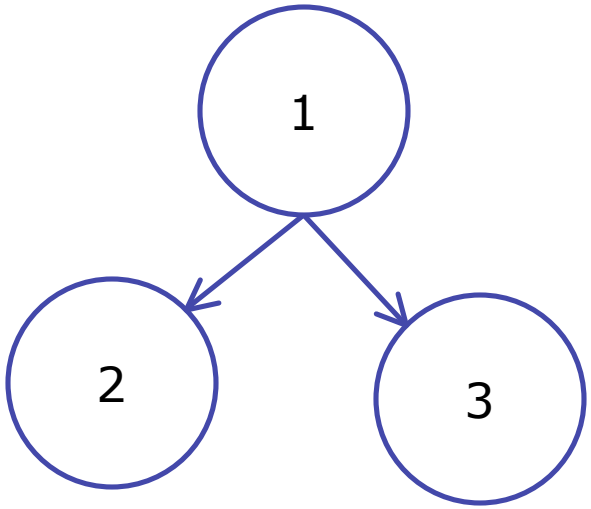
- Representation
  - bnet, DBN, factor graph, influence (decision) diagram
  - CPDs – Gaussian, tabular, softmax, etc
- Learning engines
  - Parameters: EM, (conjugate gradient)
  - Structure: MCMC over graphs, K2
- Inference engines
  - Exact: junction tree, variable elimination
  - Approximate: (loopy) belief propagation, sampling

Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Structure

- **Represent the mental state agreeing, given two features: head nod and smile. (all are discrete and binary)**

- %First define the structure
- N = 3; % the total number of nodes
- intra = zeros(N);
- intra(1,2) = 1;
- intra(1,3) = 1;

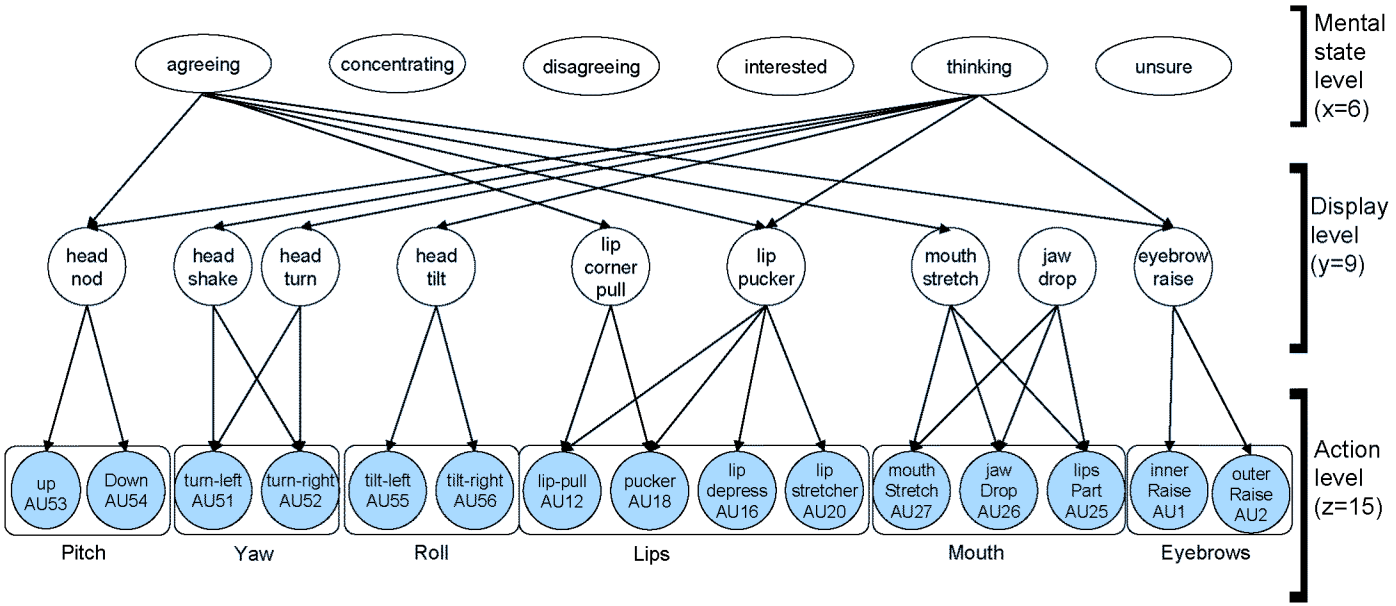


- %specify the type of node: discrete, binary
- node_sizes = [2 2 2];
- onodes = 2:3; % observed nodes
- dnodes = 1:3; % all the nodes per time slice

Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Structure (One classifier or many?)

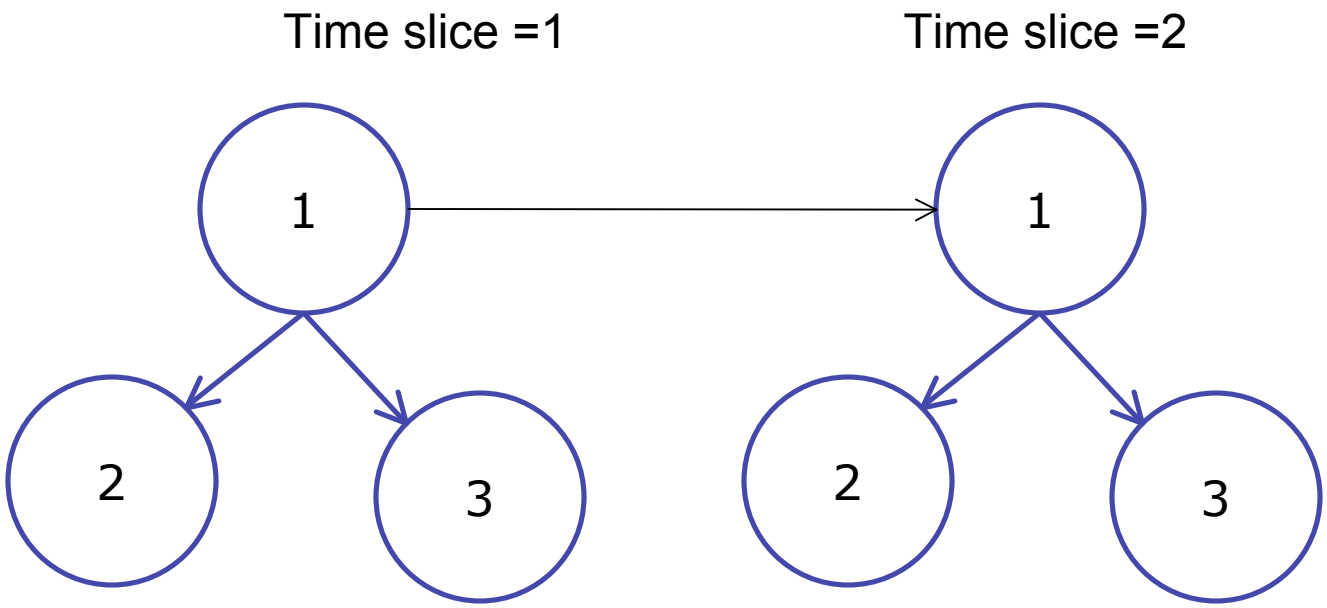
- Depends on whether the classes are mutually exclusive or not(if yes, we could let hidden node be discrete but say take 6 values)



Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Structure - Dynamic

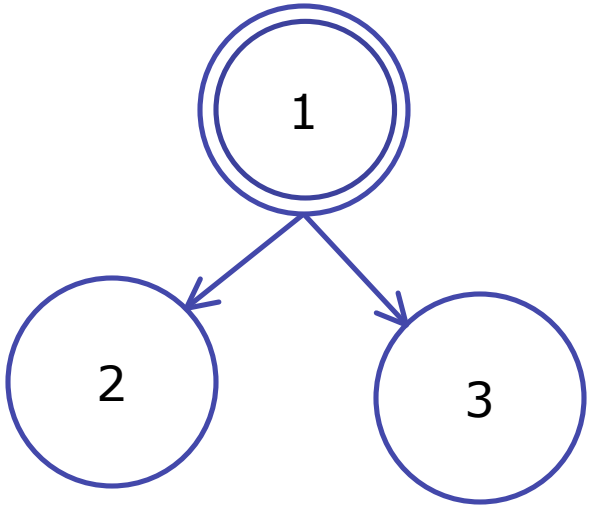
- **But hang on, what about the temporal aspect of this? (my previous mental state affects my current one)**



Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Structure - Dynamic

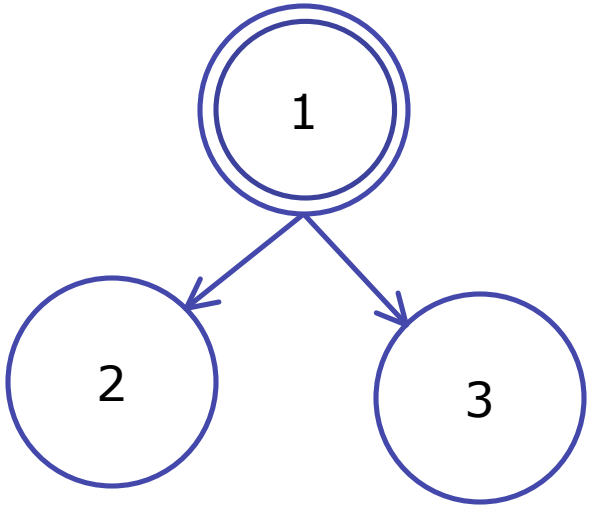
- **More compact representation**



Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Structure - Dynamic

- **Represent the mental state agreeing, given two features: head nod and smile and make it dynamic**



- %intra same as before
- inter = zeros(N);
- inter(1,1) = 1;

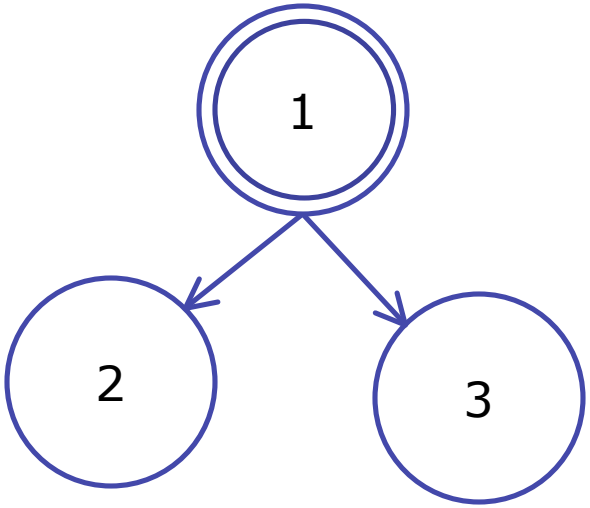
- % parameter tying reduces the amount of data needed for learning.
- eclass1 = 1:3; % all the nodes per time slice
- eclass2 = [4 2:3];
- eclass = [eclass1 eclass2];

- %instantiate the DBN
- dynBnet = mk_dbn(intra, inter, node_sizes, 'discrete', dnodes, 'eclass1', eclass1, 'eclass2', eclass2, 'observed', onodes);

Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Parameters – (hand-coded)

- How many conditional probability tables do we need to specify?



Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States Parameters – (hand-coded)

% prior P(agreeing)

- dynBnet.CPD{1} = tabular_CPD(dynBnet, 1, [0.5 0.5]);

% P(2|1) head nod given agreeing

- dynBnet.CPD{2} = tabular_CPD(dynBnet, 2, [0.8 0.2 0.2 0.8]);

% P(3|1) smile given agreeing

- dynBnet.CPD{3} = tabular_CPD(dynBnet, 3, [0.5 0.9 0.5 0.1]);

% P(4|1) transition prob

- dynBnet.CPD{4} = tabular_CPD(dynBnet, 4, [0.9 0.2 0.1 0.8]);

	2 = F	2 = T
1 = F	0.8	0.2
1 = T	0.2	0.8

High prob of nod if the person is agreeing, v. low prob that we see a nod if the person is not agreeing

Case study: Mental States Parameters – (hand-coded)

% prior P(agreeing)

- dynBnet.CPD{1} = tabular_CPD(dynBnet, 1, [0.5 0.5]);

% P(2|1) head nod given agreeing

- dynBnet.CPD{2} = tabular_CPD(dynBnet, 2, [0.8 0.2 0.2 0.8]);

% P(3|1) smile given agreeing

- dynBnet.CPD{3} = tabular_CPD(dynBnet, 3, [0.5 0.9 0.5 0.1]);

% P(4|1) transition prob

- dynBnet.CPD{4} = tabular_CPD(dynBnet, 4, [0.9 0.2 0.1 0.8]);

	2 = F	2 = T
1 = F	0.8	0.2
1 = T	0.2	0.8

	3 = F	3 = T
1 = F	0.5	0.5
1 = T	0.9	0.1

Low prob of smile if the person is agreeing, equal prob of smile or not if the person is not agreeing

Case study: Mental States Parameters – (hand-coded)

% prior P(agreeing)

- dynBnet.CPD{1} = tabular_CPD(dynBnet, 1, [0.5 0.5]);

% P(2|1) head nod given agreeing

- dynBnet.CPD{2} = tabular_CPD(dynBnet, 2, [0.8 0.2 0.2 0.8]);

% P(3|1) smile given agreeing

- dynBnet.CPD{3} = tabular_CPD(dynBnet, 3, [0.5 0.9 0.5 0.1]);

% P(4|1) transition prob

- dynBnet.CPD{4} = tabular_CPD(dynBnet, 4, [0.9 0.2 0.1 0.8]);

	2 = F	2 = T
1 = F	0.8	0.2
1 = T	0.2	0.8

	3 = F	3 = T
1 = F	0.5	0.5
1 = T	0.9	0.1

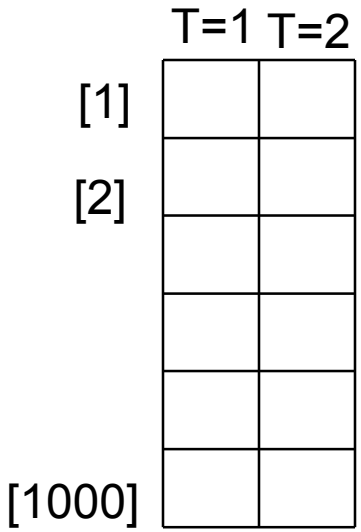
	4 = F	4 = T
1 = F	0.9	0.1
1 = T	0.2	0.8

High prob of agreeing now if I was just agreeing, low prob of agreeing now if I wasn't agreeing

Case study: Mental States
Sampling the DBN

- T = 2;
- ncases = 1000;

- for i=1:ncases
  - ev = **sample_dbn**(dynBnet, 'length', T);
- end



Rana el Kaliouby
kaliouby@media.mit.edu

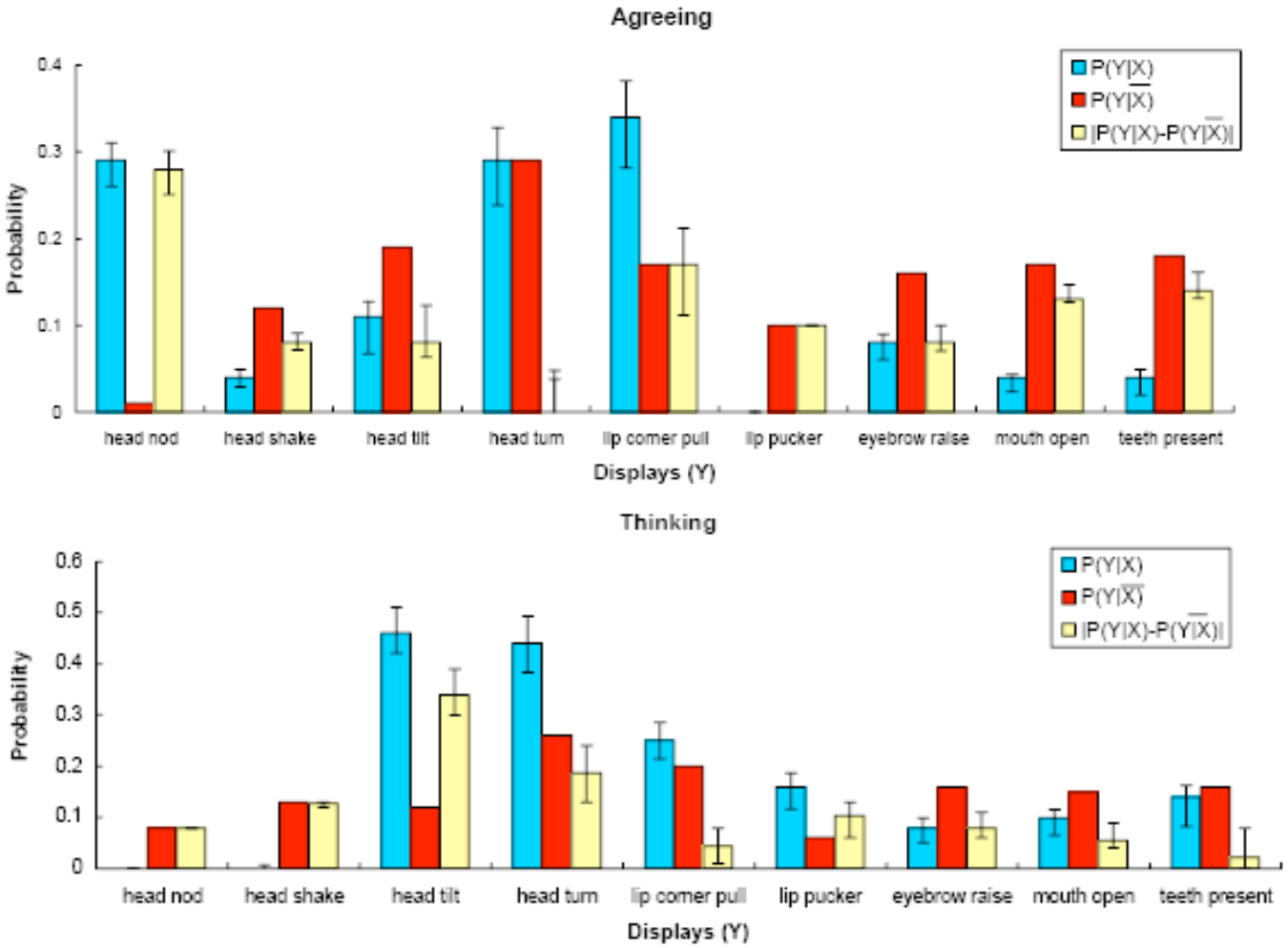
Case study: Mental States
Parameters – learning

Structure	Observability	Method
Known	Full	Maximum Likelihood Estimation
Known	Partial	Expectation Maximization (EM)
Unknown	Full	Search through model space
Unknown	Partial	EM + search through model space

- Hierarchical BNs: you can learn the parameters of each level separately
- Learning the parameters:
  - If the data is full observable, then MLE (counting occurrences) (resulting model is applicable to exact inference)
- Learning the structure:
  - Search strategy to explore the possible structures;
  - Scoring metric to select a structure

Rana el Kaliouby
kaliouby@media.mit.edu

Case study: Mental States
Parameters – MLE - discriminability



Rana el Kaliouby
kaliouby@media.mit.edu

Learning from data in BNT

- Define DBN structure as before
- Define DBN params as before (random CPTs)
- Also need to define inference/learning engine

- Load the example cases
- Learn the params (specifying the no. of iterations for algorithm to converge)

- [dynBnet2, LL, engine2] = **learn_params_dbn_em**(engine2, cases, 'max_iter', 20);

Rana el Kaliouby
kaliouby@media.mit.edu

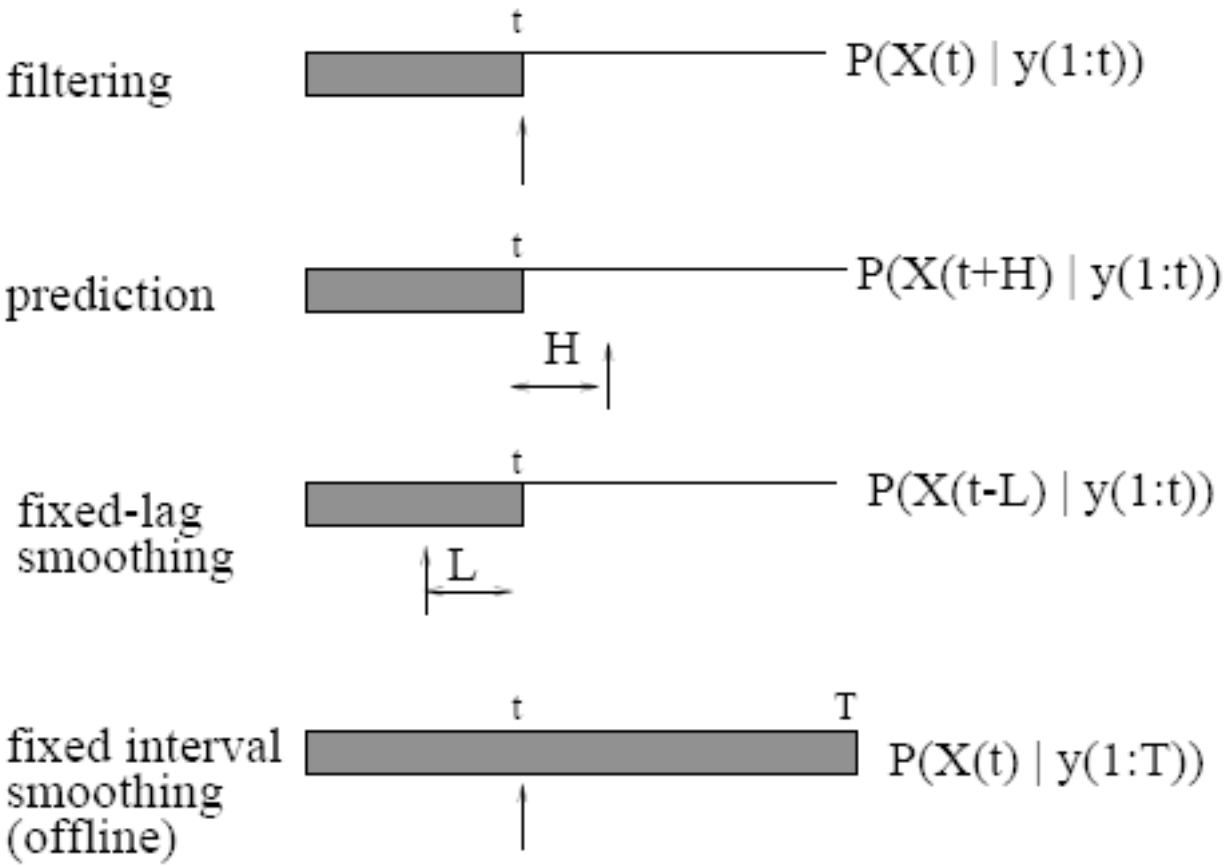
Inference

- Updating your belief state
  - Time propagation
  - Update by measurement

  - Algorithm Bayes filter
    - Givens: $bel(x_{t-1})$, z_t
    - Step 1: $\overline{bel}(x_t) = \sum p(x_t|x_{t-1})\ bel(x_{t-1})$
    - Step 2: $bel(x_t|z_t) = c\ p(z_t \mid x_t)\ \overline{bel}(x_t)$

Rana el Kaliouby
kaliouby@media.mit.edu

Inference in DBNs



Inference is belief updating.

Filtering: recursively estimate the belief state
Prediction: predict future state
Smoothing: estimate state of the past given all the evidence up to the current time

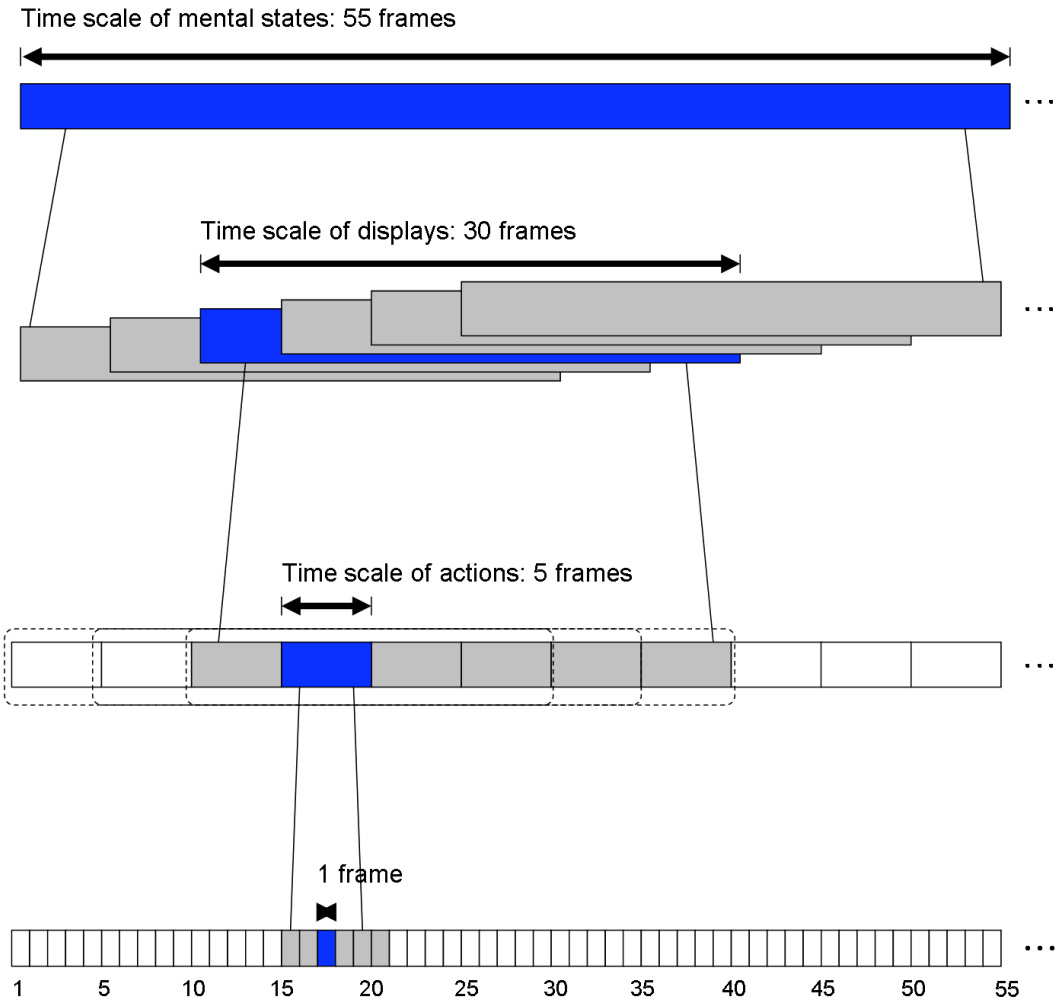
Case study: Mental States Inference in BNT

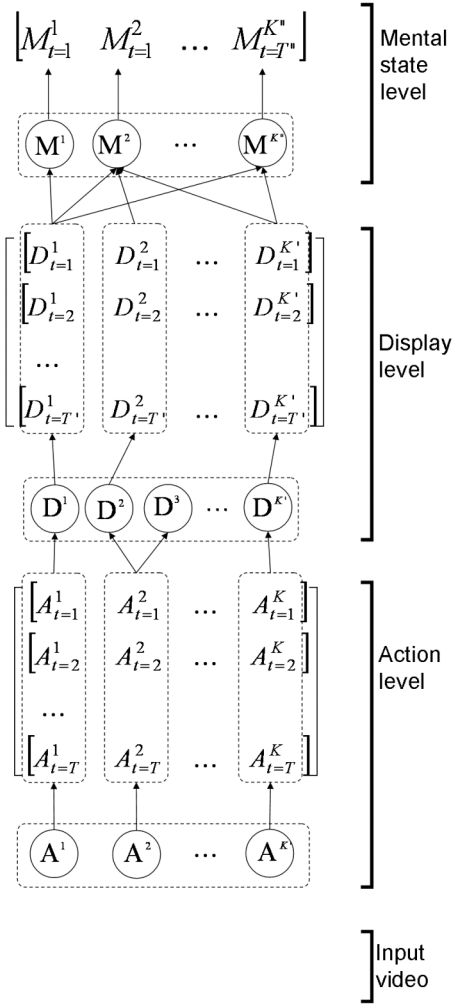
- %instantiate an inference engine
- engine2 = smoother_engine(jtree_2TBN_inf_engine(dynBnet2));

- engine2 = enter_evidence(engine2, evidence);
- m = marginal_nodes(engine2, 1, 2); % referring to 1st node (hidden class node) in 2nd time slice (t+1)
- inferredClass = argmax(m.T);

Rana el Kaliouby
kaliouby@media.mit.edu

Mental state inference
Sliding Window





Real time Inference in BNT

Objective: Compute the belief state of a hidden mental state $P(X_i[t]|\mathbf{Y}[t-w:t], P(\mathbf{X}[t-w:t-1]))$ over time, $1 \leq i \leq x$ and $1 \leq t \leq T$

Given: x mental state DBNs as in Figure 7.1, with y observations nodes $\mathbf{Y}$; evidence length is w and sliding factor, or lag, is dw

Initialization: Instantiate inference engine such as the unrolled-junction-tree or the forward-backward algorithms

Initial inference instance

for all t in w time slices **do**
Get current observations $\mathbf{Y}[t]$;
Enter evidence so far $\mathbf{Y}[1:w]$;
Calculate $P(\mathbf{X}[w]|\mathbf{Y}[1:w])$

Inference

$t = w + dw$
for all t in T time slices **do**
Get current observations $\mathbf{Y}[t]$
Enter evidence so far: $\mathbf{Y}[t-w:t]$ and $P(\mathbf{X}[t-w:t-1])$
Calculate $P(\mathbf{X}[t]|\mathbf{Y}[t-w:t], P(\mathbf{X}[t-w:t-1]))$
Advance window $t = t + dw$

Rana el Kaliouby
kaliouby@media.mit.edu

Inference – Naïve Approach

- Unrolling the DBN for a desired number of timesteps and treat as a static BN
- Apply evidence at appropriate times and then run any static algorithm
- Simple, but DBN becomes huge, inference runs out of memory or takes too long.

Inference – Better Approach

- We don't need the entire unrolled DBN
- A DBN represents a process that is stationary & Markovian:
- **Stationary:**
  - the node relationships within timeslice t and the transition function from t to t+1 do not depend on t
  - So we need only the initial timeslice and sufficient consecutive timeslices to show the transition function
- **Markovian:**
  - the transition function depends only on the immediately preceding timeslice and not on any previous timeslices (e.g., no arrows go from t to t+2)
  - Therefore the nodes in a timeslice separate the past from the future.
- Use a 2TDBN that represents the first two timeslices of the process, and we use this structure for inference.

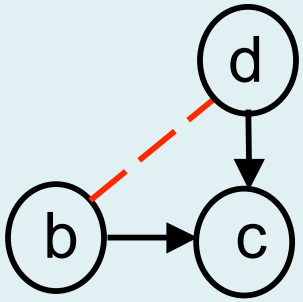
Inference – Better Approach

- Dynamic inference boils down to doing static inference on the 2TDBN and then following some protocol for "advancing" forward one step.
- Interface Algorithm or 1.5 Slice Junction Tree Algorithm (Murphy, 2002) [also in your problem set]
- Exact Inference
- Intuition:
    1. Initialization
        a) Transform DBN into 2 junction trees
            a) Moralize
            b) Triangulate
            c) Build junction tree
        b) Initialize values on the junction trees
            a) Multiply CPTs onto clique potentials
    2. Advance (belief propagation)
        a) Insert evidence into the junction tree
        b) Propagate potentials

Prerequisite concepts

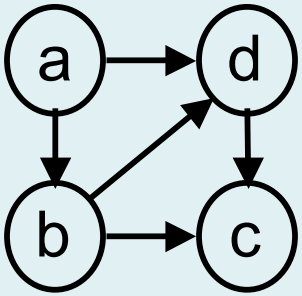
Moralizing a graph

Marrying parents of a child



Clique

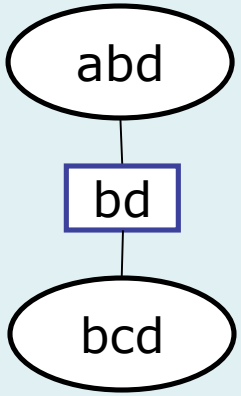
A graph in which every vertex is connected to every other vertex in the graph.



Two cliques:
C_1 = {a,b,d}, C_2 = {b,c,d}

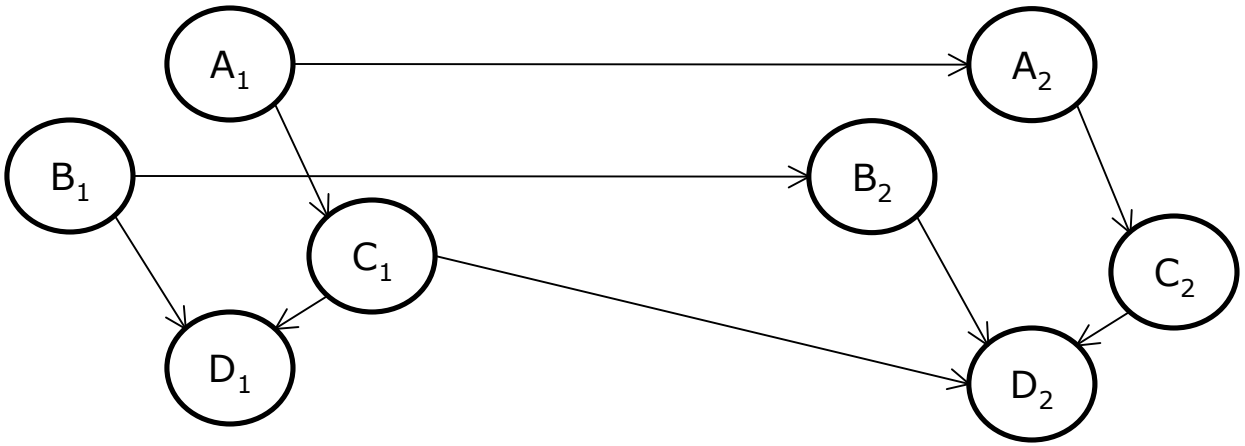
Junction tree

A tree of maximal cliques in an undirected graph



1.5 Slice Junction Tree

- Outgoing interface I_t
  - Set of nodes in timeslice t with children in timeslice t+1
  - $\{A_1, B_1, C_1\}$ is the outgoing interface of timeslice 1



- It d-separates the past from the future (Murphy, 2002)
  - "past" = all nodes in timeslices before t and all non-interface nodes in timeslice t
  - "future" = nodes in timeslice t+1 and later
  - Therefore the outgoing interface encapsulates all necessary information about previous timeslices to do filtering.

Algorithm Outline

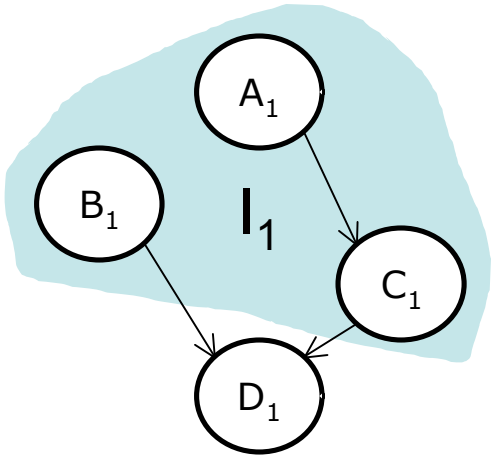
- Initialization:
  - Create two junction trees J_1 and J_t:
    - J_1 is the junction tree for the initial timeslice, created from timeslice 1 of the 2TDBN
    - J_t is the junction tree for each subsequent timeslice and is created from timeslice 2 of the 2TDBN and the outgoing interface of timeslice 1
  - Time is initialized to 0
- Queries:
  - Marginals of nodes at the current timeslice can be queried:
  - If current time = 0, queries are performed on "_1" nodes in J_1
  - If current time > 0, queries are performed on "_2" nodes in J_t
- Evidence:
  - Evidence can be applied to any node in the current timeslice:
  - If current time = 0, evidence is applied to "_1" nodes in J_1
  - If current time > 0, evidence is applied to "_2" nodes in J_t

Algorithm Outline

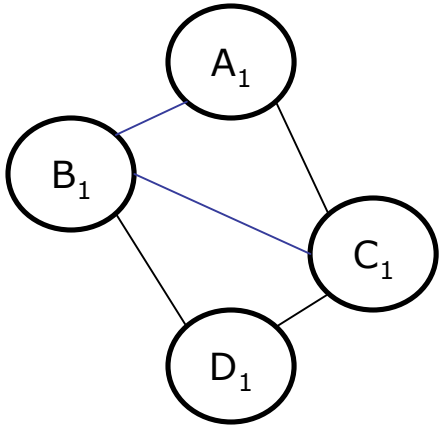
- Advance:
  - Increment the time counter
  - Use outgoing interface from active timeslice to do inference in next timeslice
    - Since the outgoing interface d-separates the past from the future, this ensures that when we do inference in the next timeslice we are taking everything that has occurred "so far" into account.

Rana el Kaliouby
kaliouby@media.mit.edu

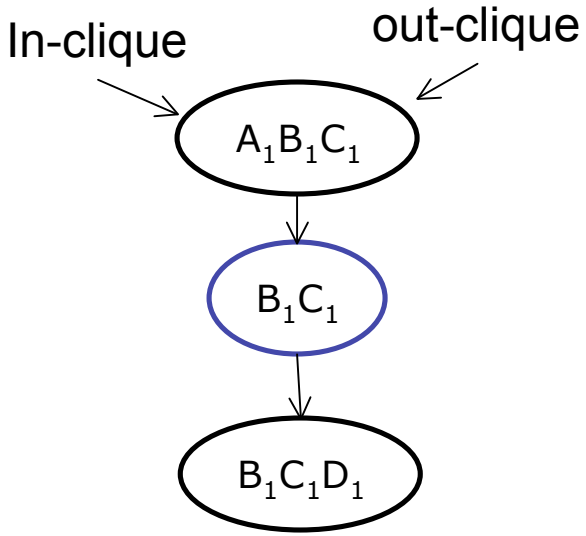
Initialization of J_1



[1] Remove all nodes in timeslice 2 from the 2TDBN. Identify nodes in outgoing interface of timeslice 1, call it I_1



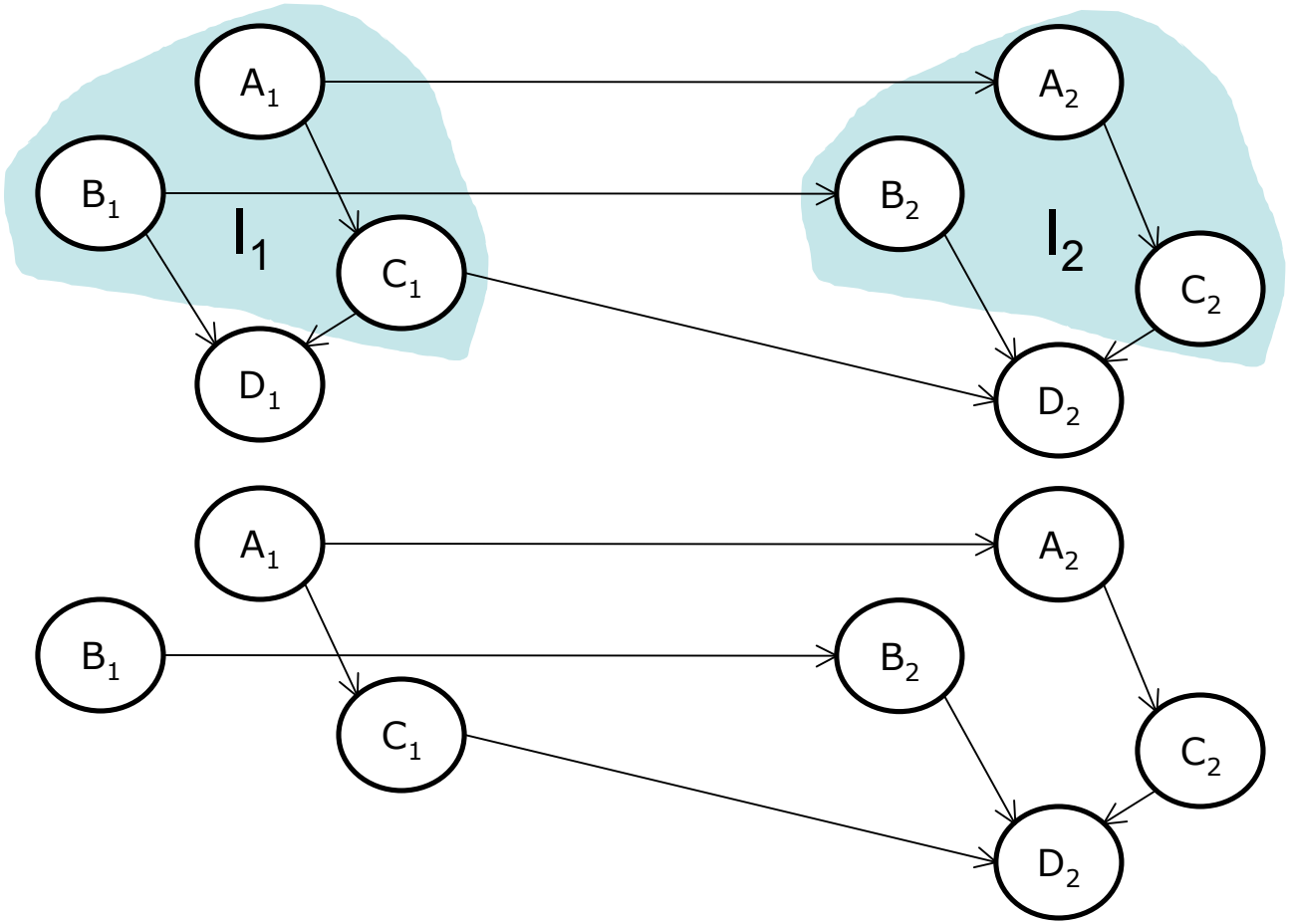
[2] Moralize: marry parents of a child. Add edges to make I_1 a clique



[3] Triangulate, find cliques, form junction tree. Find clique that contains I_1, call it in the in-clique, out-clique

[4] Initialize clique potentials to 1's, multiply nodes' CPTs onto cliques

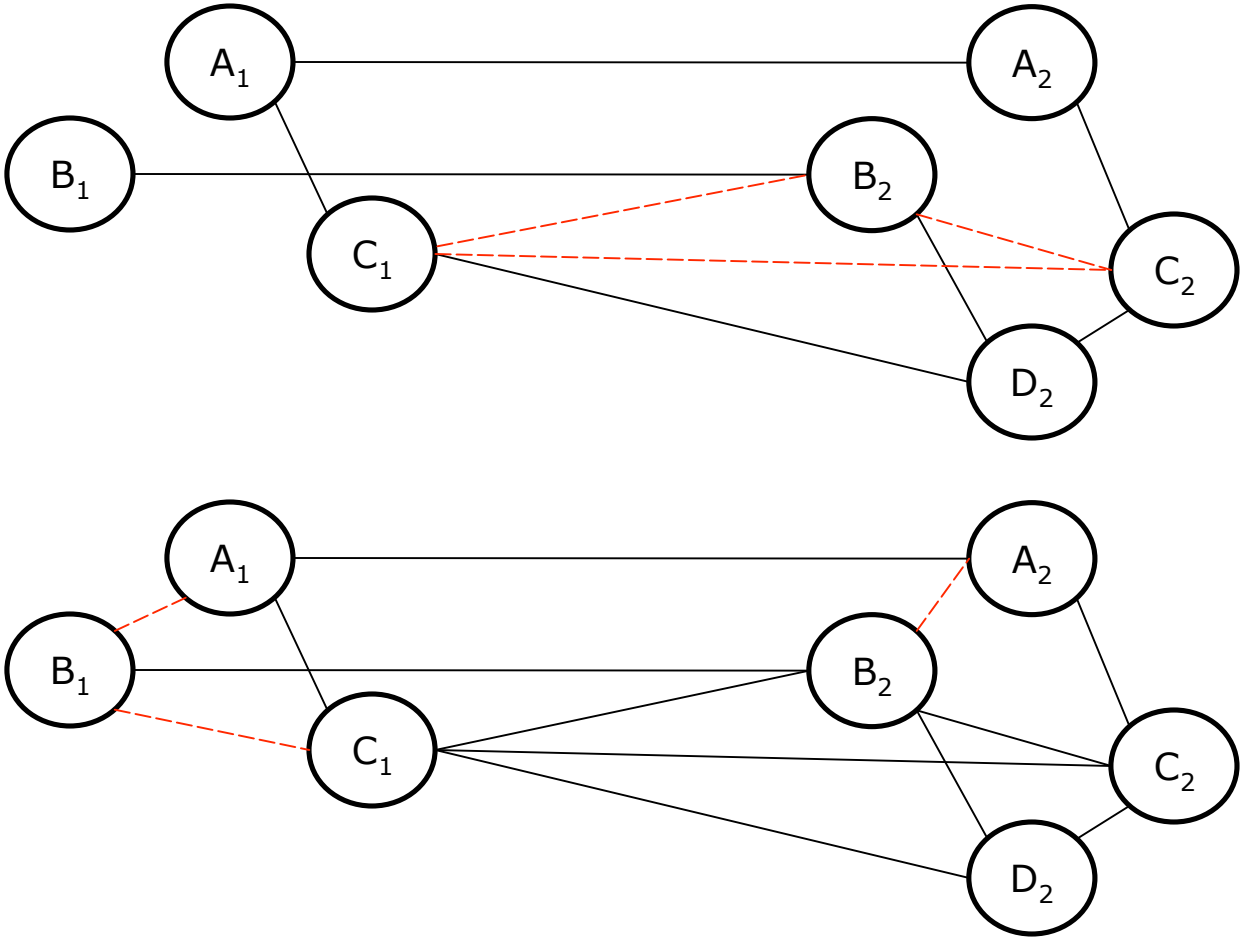
Initialization of J_t



[1] Starting with the whole 2TDBN, identify nodes in outgoing interface of timeslice 1 and 2, call them I_1 and I_2

[2] Convert to 2TDBN to 1.5DBN (remove non-interface nodes in timeslice 1)

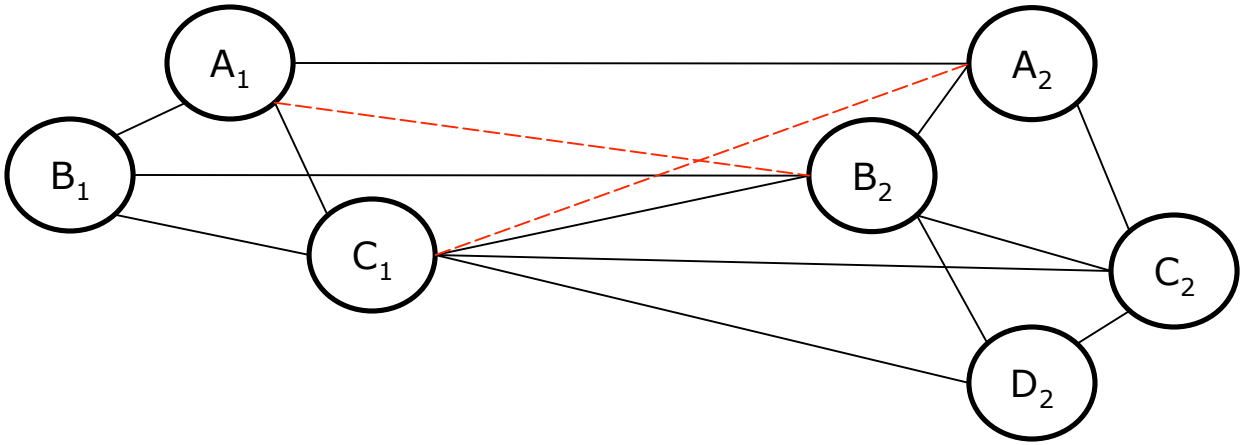
Initialization of J_t



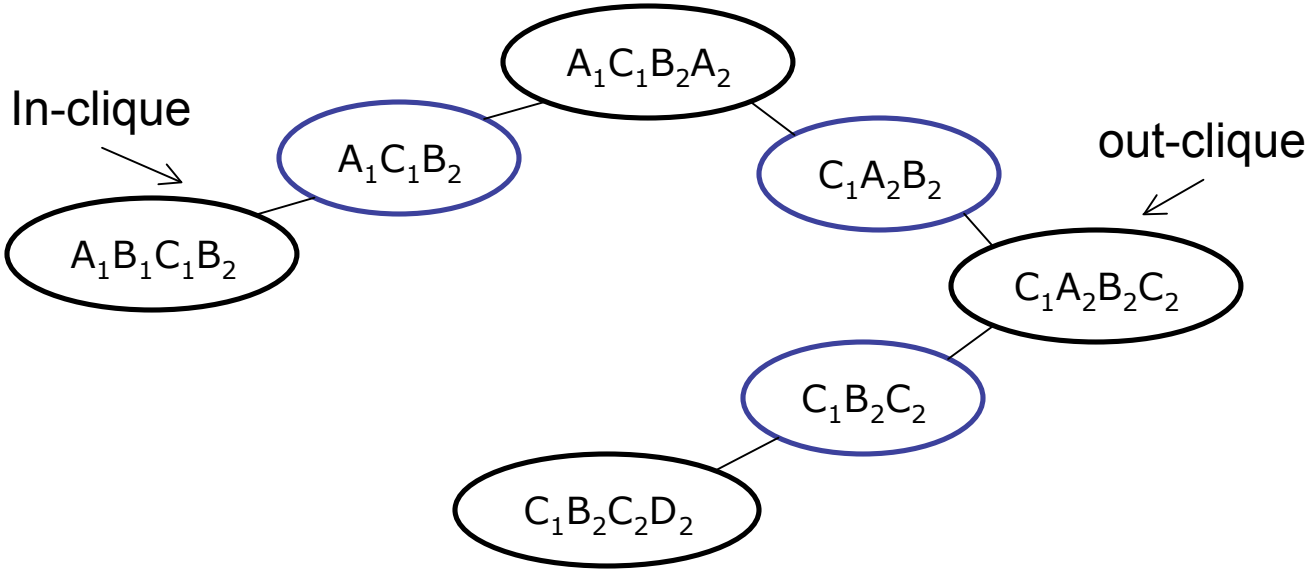
[3] Moralize:
(marry C_1, C_2 parents of D_2)
(marry C_1, B_2 parents of D_2)
(marry B_2, C_2 parents of D_2) ….

then
(marry A_2, B_2 parents of C_2)
(marry B_1, C_1 parents of B_2)
(marry A_1, B_1 parents of C_1) ….

Initialization of J_t



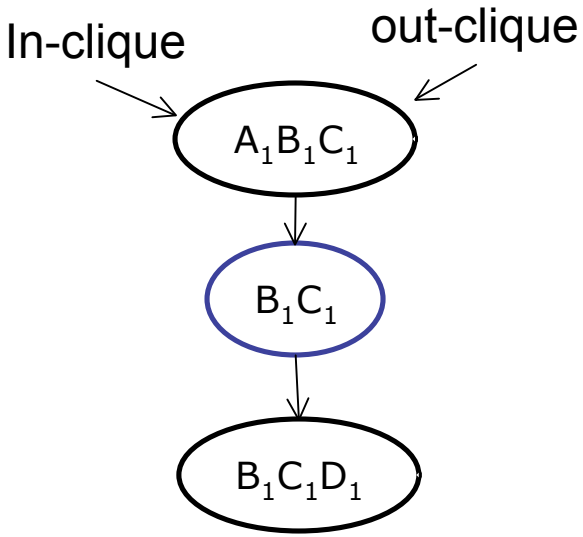
then triangulate
(marry A_1, B_2 parents of C_1)
(marry C_1, A_2 parents of B_2)

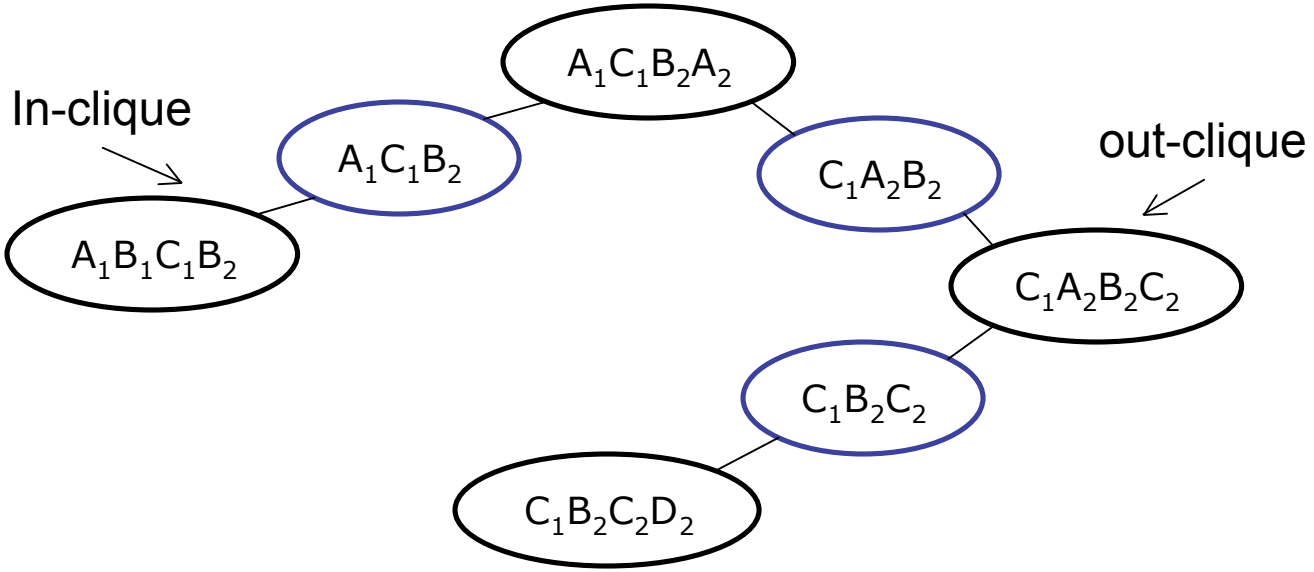


[4] Find cliques, form junction tree
Cliques:
$\{A_1 B_1 C_1 B_2\}$
$\{A_1 C_1 B_2 A_2\}$
$\{C_1 B_2 C_2 D_2\}$
$\{C_1 A_2 B_2 C_2\}$
Find clique that contains I_1 (in-clique), and I_2 out-clique

[5] Initialize clique potentials to 1's, multiply nodes' CPTs onto cliques (only of nodes in timeslice 2 because evidence is applied and nodes are queried only in timeslice 2)

Initialization Summary

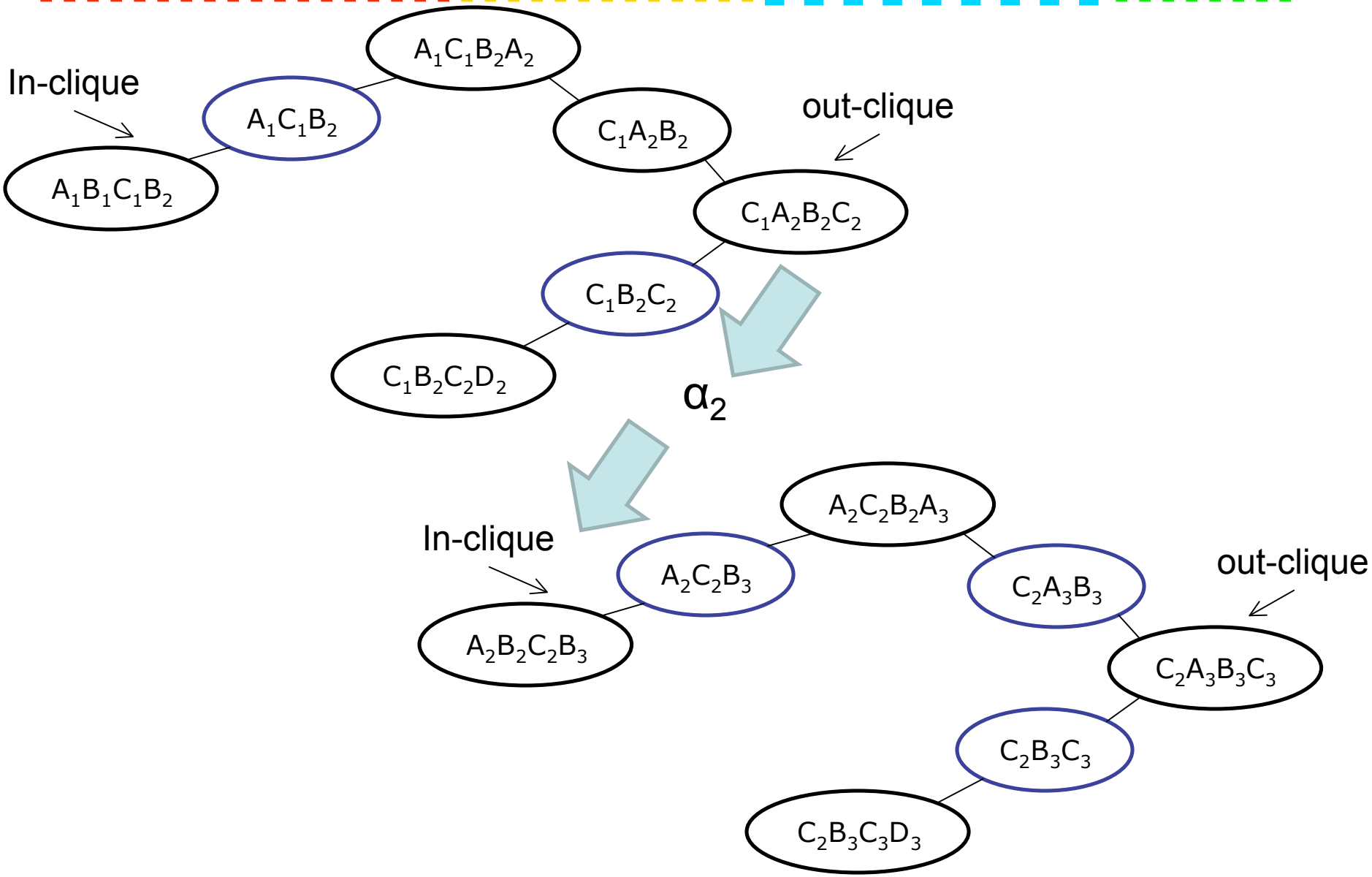




Advance (Belief propagation)

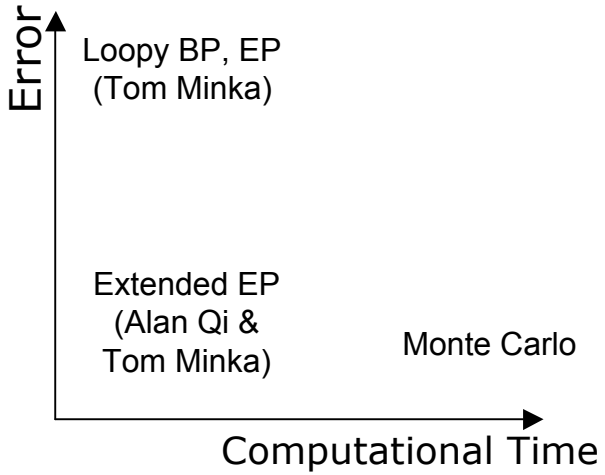
- At time t:
  - Get current junction tree (if time = 0, J_1, otherwise J_t)
  - Update beliefs in current junction tree
  - Get α_t
- Increment time
- After time is incremented
  - Get current junction tree (always J_t)
  - Multiply α_t onto in-clique potential of new junction tree

Advance (Belief propagation)

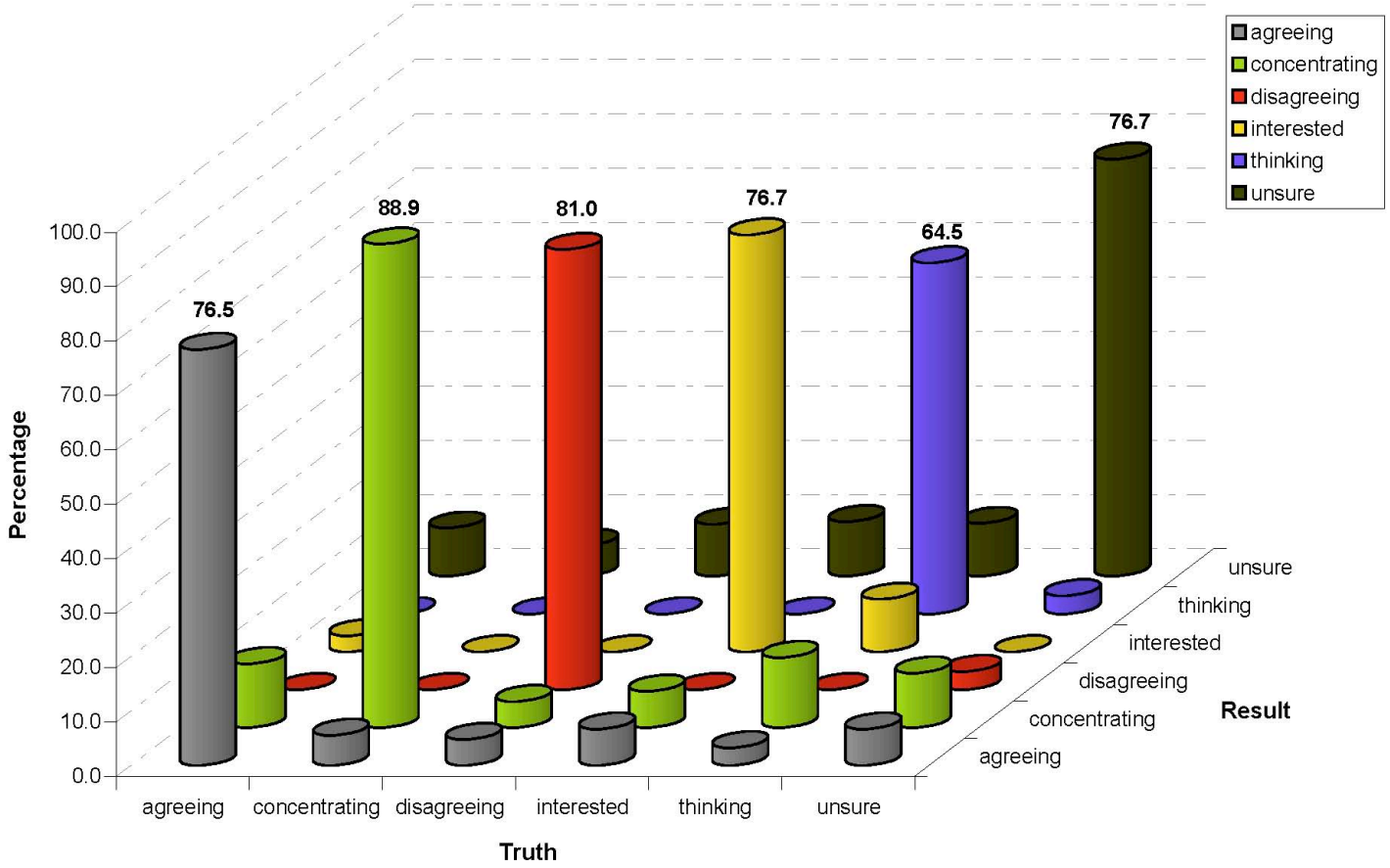


Approximate Inference

- Why?
  - to avoid exponential complexity of exact inference in discrete loopy graphs
  - Because one cannot compute messages in closed form (even for trees) in the non-linear/non-Gaussian case
- Algorithms:
  - Deterministic approximations: loopy BP, mean field, structured variational, etc
  - Stochastic approximations: MCMC (Gibbs sampling), likelihood weighting, particle filtering, etc



Bayesian Network Classifiers



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Project ideas

- Pepsi data (speak to Hyungil / Rana)
- Combining EEG data w/ Face data (trying to get an SDK from Emotiv)

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Summary

- Decoding human mental states
- Dynamic Bayesian Networks
  - Representation
  - Learning
  - Inference
- Matlab's BNT
- Email for project ideas / brainstorming

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