

Lecture 6.1

Introduction to Probabilistic models

Machine Learning
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09.04.2021

Lecture plan

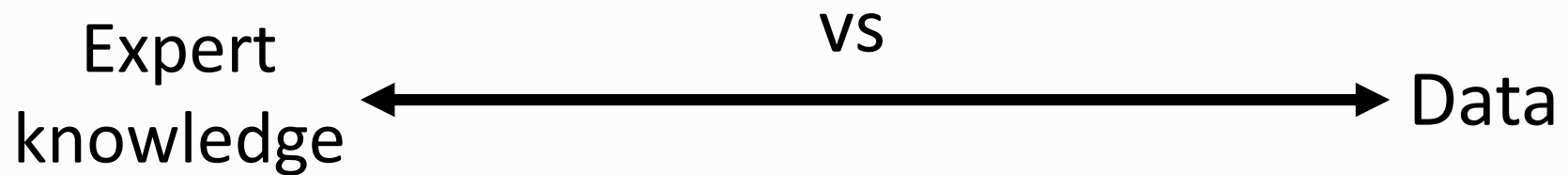
- Overview and Motivation
- Distributions
- Factors

Lecture plan

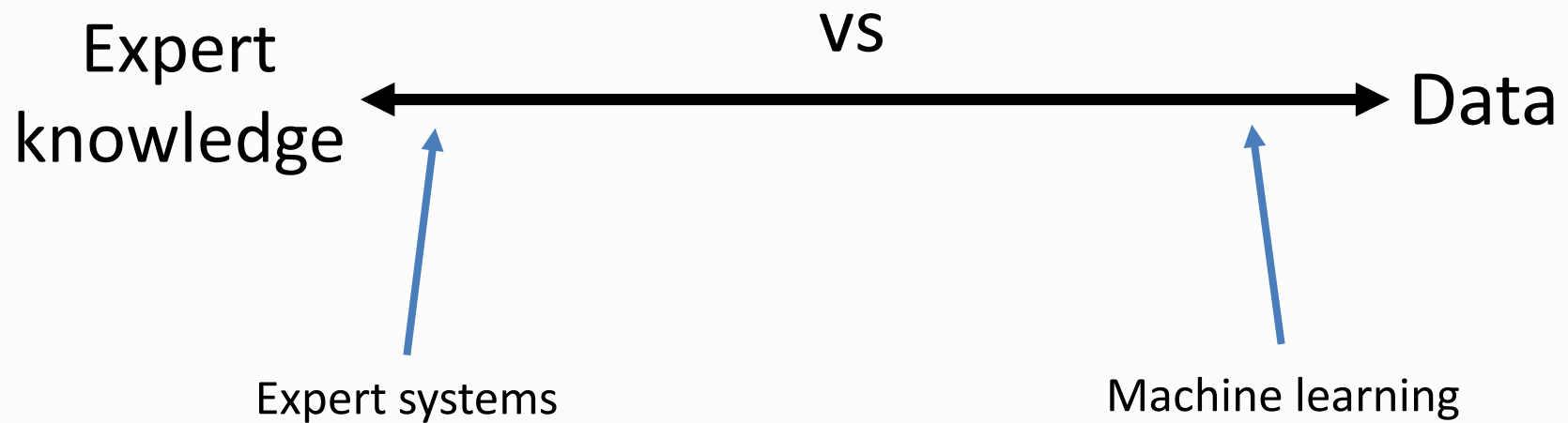
- Overview and Motivation
- Distributions
- Factors

What is machine learning?

What is machine learning?



What is machine learning?



Problem

An illness, which is spread among 1% of population. This illness test returns true answers in 95% of cases. Someone receives a positive result. What is the probability, he actually suffers the illness?

PGM: Motivation and Overview



predisposing
symptoms
test results
diseases
treatment outcomes

PGM: Motivation and Overview



predisposing
symptoms
test results
diseases
treatment outcomes



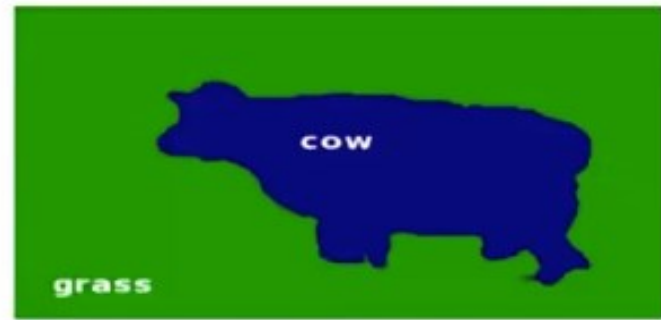
millions of pixels or
thousands of superpixels

Each, needs to be labeled
{grass, sky, water, cow, horse, ...}

PGM: Motivation and Overview



predisposing
symptoms
test results
diseases
treatment outcomes



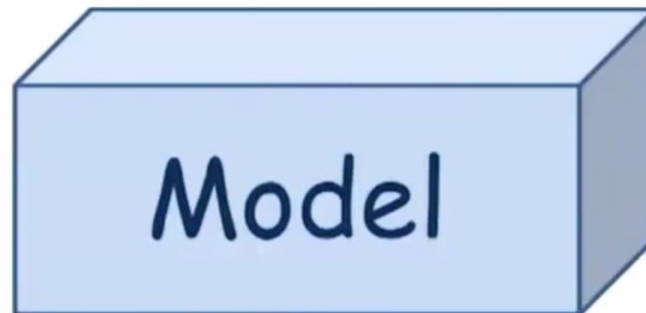
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Each, needs to be labeled
{grass, sky, water, cow, horse, ...}

Probabilistic Graphical Models

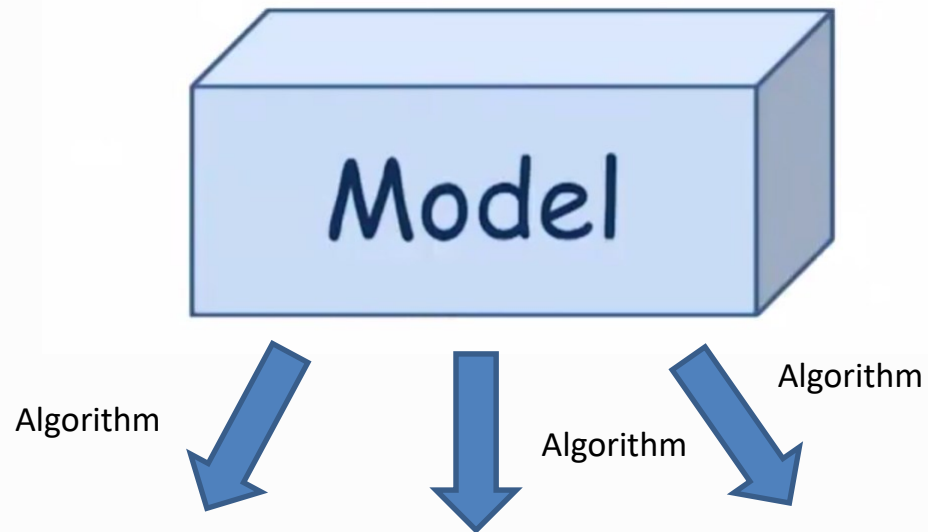
Models

Declarative representation

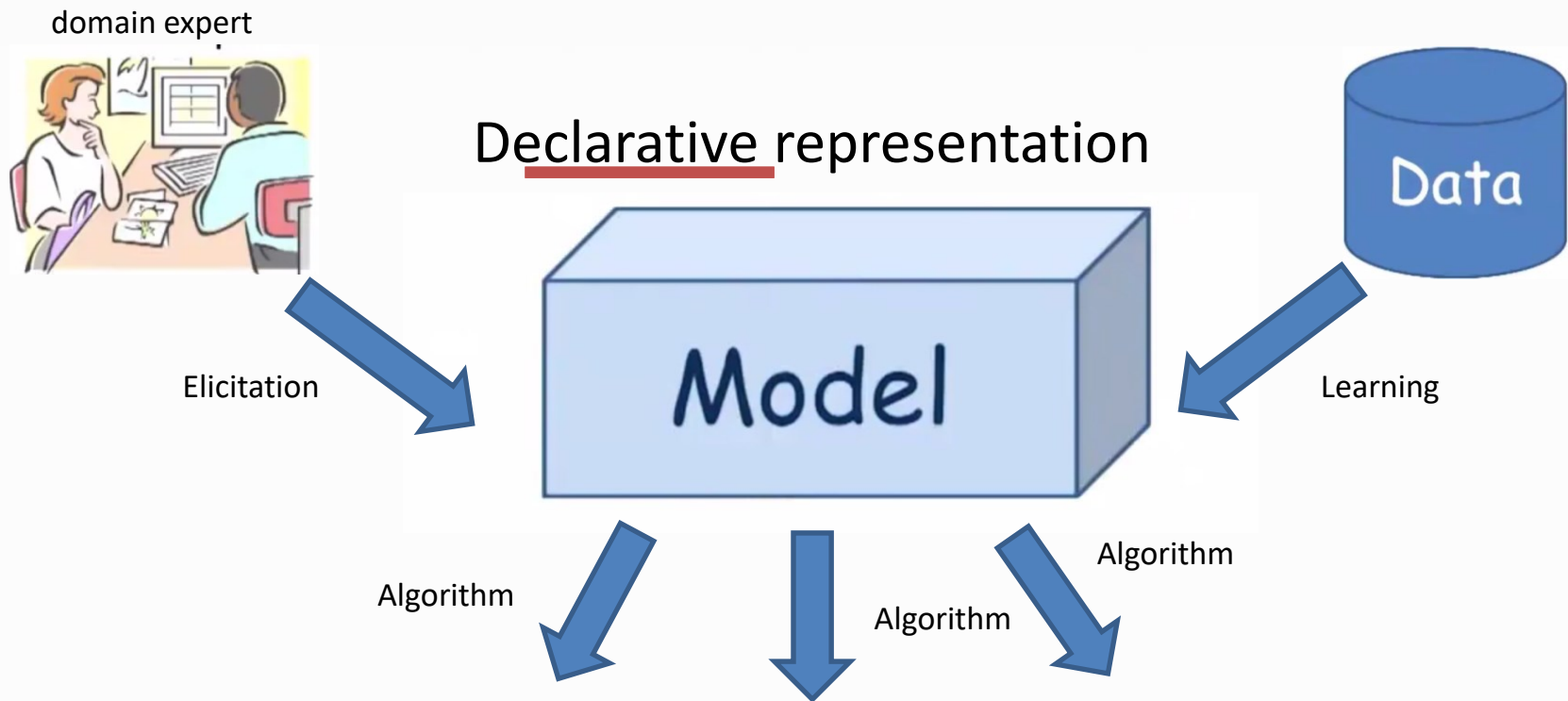


Models

Declarative representation



Models



Uncertainty

- Partial knowledge of state of the world

Uncertainty

- Partial knowledge of state of the world
- Noisy observations

Uncertainty

- Partial knowledge of state of the world
- Noisy observations
- Phenomena not covered by our model

Uncertainty

- Partial knowledge of state of the world
- Noisy observations
- Phenomena not covered by our model
- Inherent stochasticity

Probability Theory

- Declarative representation with clear semantics

Probability Theory

- Declarative representation with clear semantics
- Powerful reasoning patterns

Conditioning
Decision making

Probability Theory

- Declarative representation with clear semantics
- Powerful reasoning patterns
- Established learning methods

Conditioning
Decision making

Complex Systems

predisposing
symptoms
test results

diseases
treatment outcomes

class labels for
thousands of superpixels

Complex Systems

predisposing
symptoms
test results

diseases
treatment outcomes

class labels for
thousands of superpixels

Random variables X_1, \dots, X_n

Complex Systems

predisposing
symptoms
test results

diseases
treatment outcomes

class labels for
thousands of superpixels

Random variables X_1, \dots, X_n

Joint distribution $P(\underline{X_1, \dots, X_n})$

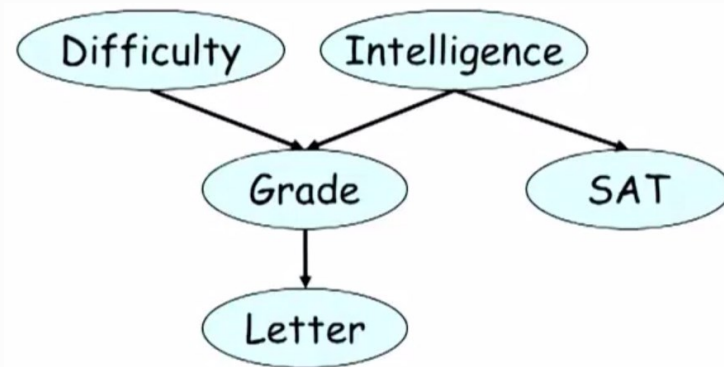
Binary valued distribution over
 2^n possible states

Graphical Models

X_1, \dots, X_n — nodes

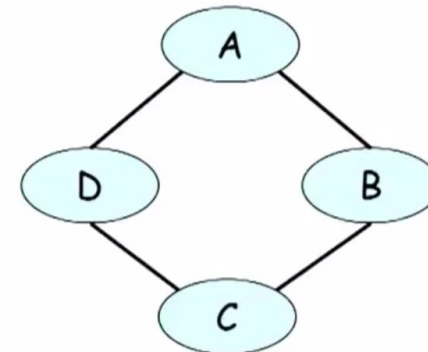
Bayesian networks

Directed graph



Markov networks

Undirected graph

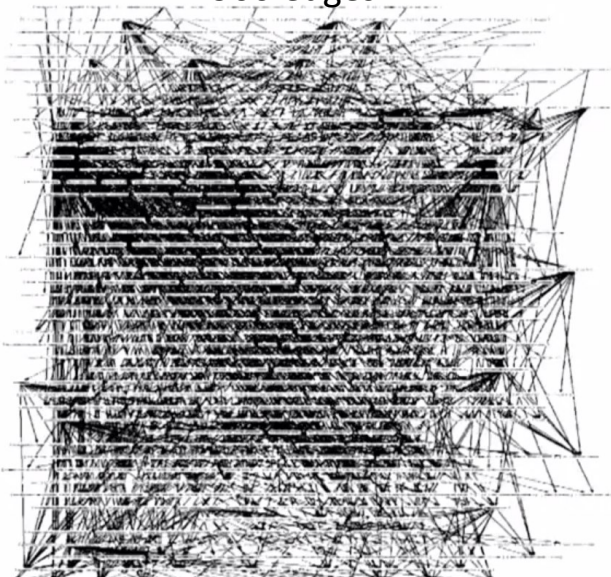


Graphical Models

CPCS diagnosis

~480 nodes

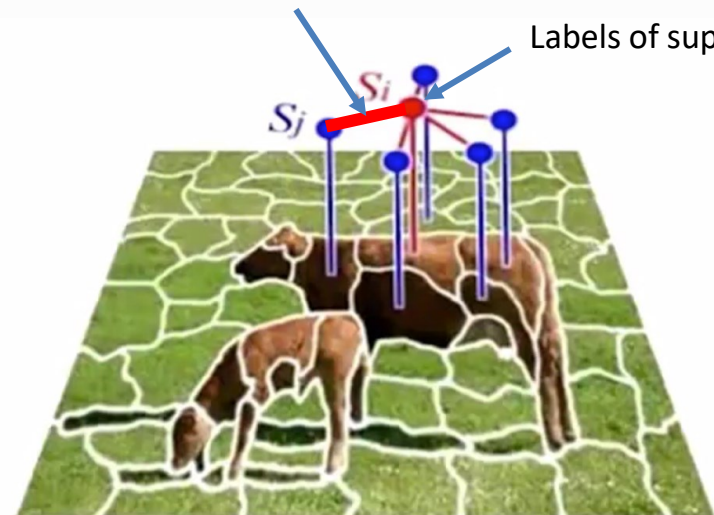
~900 edges



M. Pradhan, G. Provan, B. Middleton, M. Henrion, UAI 94

Probabilistic relationships

Labels of superpixels



Graphical Representation

- Intuitive and compact data structure
- Efficient reasoning using general-purpose algorithms
- Sparse parameterization
 - feasible elicitation ← by hand
 - learning from data ← automatically

Many Applications

- Medial diagnosis
- Fault diagnosis
- Natural language processing
- Traffic analysis
- Social network models
- Message decoding
- Computer vision
 - Image segmentation
 - 3D reconstruction
 - Holistic scene analysis
- Speech recognition
- Robot localization and mapping

Textual Information Extracion

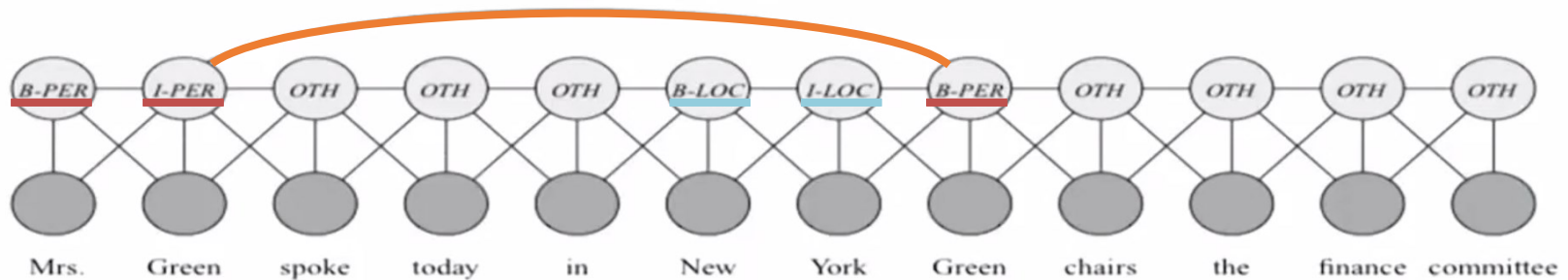
Mrs. Green spoke today in New York. Green chairs the finance committee.

person

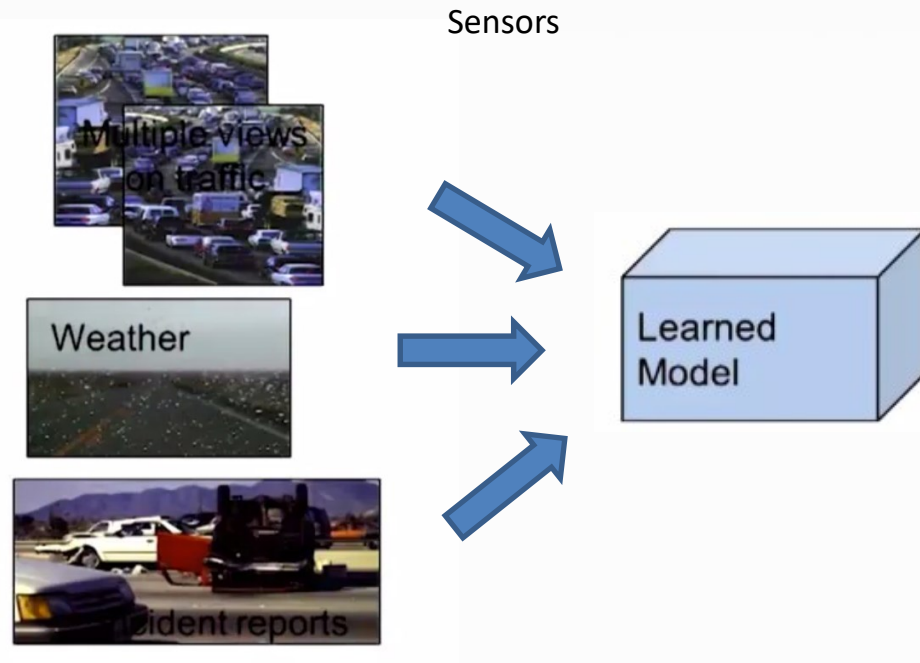
location

person

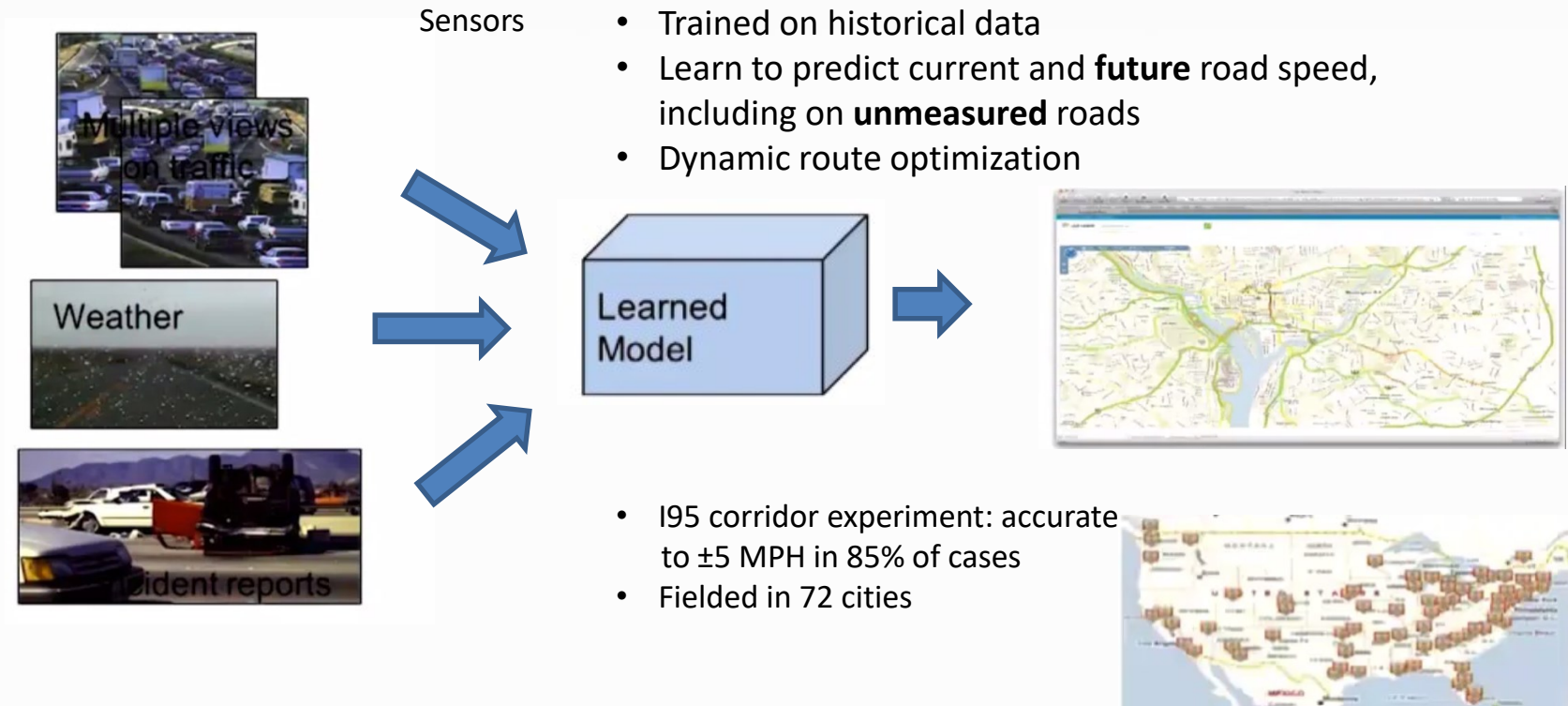
organization



Multi-Sensor Integration



Multi-Sensor Integration



Multi-Sensor Integration

- Representation
 - Directed and undirected
 - Temporal and plate models
- Inference
 - Exact and approximate
 - Decision making
- Learning
 - Parameters and structure
 - With and without complete data

Lecture plan

- Overview and Motivation
- **Distributions**
- Factors

Joint Distribution

- Intelligence (I)
 i^0 (low), i^1 (high)
- Difficulty (D)
 d^0 (easy), d^1 (hard)
- Grade (G)
 g^1 (A), g^2 (B), g^3 (C)

Joint Distribution

- Intelligence (I) ← 2
 i^0 (low), i^1 (high)
- Difficulty (D) ← 2
 d^0 (easy), d^1 (hard)
- Grade (G) ← 3
 g^1 (A), g^2 (B), g^3 (C)

Joint Distribution

- Intelligence (I) ← 2
 i^0 (low), i^1 (high)
- Difficulty (D) ← 2
 d^0 (easy), d^1 (hard)
- Grade (G) ← 3
 g^1 (A), g^2 (B), g^3 (C)

Parameters:
2x2x3=12

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^0	g^2	0.168
i^0	d^0	g^3	0.126
i^0	d^1	g^1	0.009
i^0	d^1	g^2	0.045
i^0	d^1	g^3	0.126
i^1	d^0	g^1	0.252
i^1	d^0	g^2	0.0224
i^1	d^0	g^3	0.0056
i^1	d^1	g^1	0.06
i^1	d^1	g^2	0.036
i^1	d^1	g^3	0.024

Joint Distribution

- Intelligence (I) ← 2

i^0 (low), i^1 (high)

- Difficulty (D) ← 2

d^0 (easy), d^1 (hard)

- Grade (G) ← 3

g^1 (A), g^2 (B), g^3 (C)

Parameters:

$2 \times 2 \times 3 = 12$

Independent
parameters: 11

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^0	g^2	0.168
i^0	d^0	g^3	0.126
i^0	d^1	g^1	0.009
i^0	d^1	g^2	0.045
i^0	d^1	g^3	0.126
i^1	d^0	g^1	0.252
i^1	d^0	g^2	0.0224
i^1	d^0	g^3	0.0056
i^1	d^1	g^1	0.06
i^1	d^1	g^2	0.036
i^1	d^1	g^3	0.024

sum=1

Conditioning

condition on g^1

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^0	g^2	0.168
i^0	d^0	g^3	0.126
i^0	d^1	g^1	0.009
i^0	d^1	g^2	0.045
i^0	d^1	g^3	0.126
i^1	d^0	g^1	0.252
i^1	d^0	g^2	0.0224
i^1	d^0	g^3	0.0056
i^1	d^1	g^1	0.06
i^1	d^1	g^2	0.036
i^1	d^1	g^3	0.024

Conditioning

condition on g^1

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^0	g^2	0.108
i^0	d^0	g^3	0.126
i^0	d^1	g^1	0.009
i^0	d^1	g^2	0.045
i^0	d^1	g^3	0.126
i^1	d^0	g^1	0.252
i^1	d^0	g^2	0.0224
i^1	d^0	g^3	0.0036
i^1	d^1	g^1	0.06
i^1	d^1	g^2	0.036
i^1	d^1	g^3	0.024

Conditioning: Reduction

condition on g^1

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^1	g^1	0.009
i^1	d^0	g^1	0.252
i^1	d^1	g^1	0.06

Conditioning: Renormalization

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^1	g^1	0.009
i^1	d^0	g^1	0.252
i^1	d^1	g^1	0.06

sum=0.447

$P(I,D, g^1)$

unnormalized
measure

Conditioning: Renormalization

I	D	G	$P(I,D, g^1)$
i^0	d^0	g^1	0.126
i^0	d^1	g^1	0.009
i^1	d^0	g^1	0.252
i^1	d^1	g^1	0.06

sum=0.447



I	D	$P(I,D g^1)$
i^0	d^0	0.282
i^0	d^1	0.02
i^1	d^0	0.564
i^1	d^1	0.134

$P(I,D, g^1)$

unnormalized
measure

Conditioning: Marginalization

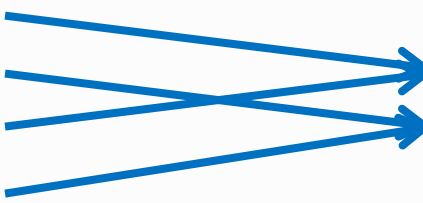
Marginalize I

I	D	P(I,D)
i^0	d^0	0.282
i^0	d^1	0.02
i^1	d^0	0.564
i^1	d^1	0.134

Conditioning: Marginalization

Marginalize I

I	D	P(I,D)
i^0	d^0	0.282
i^0	d^1	0.02
i^1	d^0	0.564
i^1	d^1	0.134



D	P(D)
d^0	0.846
d^1	0.154

Lecture plan

- Overview and Motivation
- Distributions
- **Factors**

Factors

- A factor $\phi(X_1, \dots, X_k)$
 $\phi: Val(X_1, \dots, X_k) \rightarrow R$
- Scope = $\{X_1, \dots, X_k\}$

Joint distribution

P(I,D,G)

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^0	g^2	0.168
i^0	d^0	g^3	0.126
i^0	d^1	g^1	0.009
i^0	d^1	g^2	0.045
i^0	d^1	g^3	0.126
i^1	d^0	g^1	0.252
i^1	d^0	g^2	0.0224
i^1	d^0	g^3	0.0056
i^1	d^1	g^1	0.06
i^1	d^1	g^2	0.036
i^1	d^1	g^3	0.024

Unnormalized measure $P(I, D, g^1)$

$P(I, D, g^1)$

I	D	G	P(I,D,G)
i^0	d^0	g^1	0.126
i^0	d^1	g^1	0.009
i^1	d^0	g^1	0.252
i^1	d^1	g^1	0.06

Scope = {I,D}

Conditional Probability Distribution (CPD)

P(G | I,D)

	g^1	g^2	g^3
i^0, d^0	0.3	0.4	0.3
i^0, d^1	0.05	0.25	0.7
i^1, d^0	0.9	0.08	0.02
i^1, d^1	0.5	0.3	0.2

Conditional Probability Distribution (CPD)

$P(G | I, D)$

→
context

	g^1	g^2	g^3
i^0, d^0	0.3	0.4	0.3
i^0, d^1	0.05	0.25	0.7
i^1, d^0	0.9	0.08	0.02
i^1, d^1	0.5	0.3	0.2

A

B

C

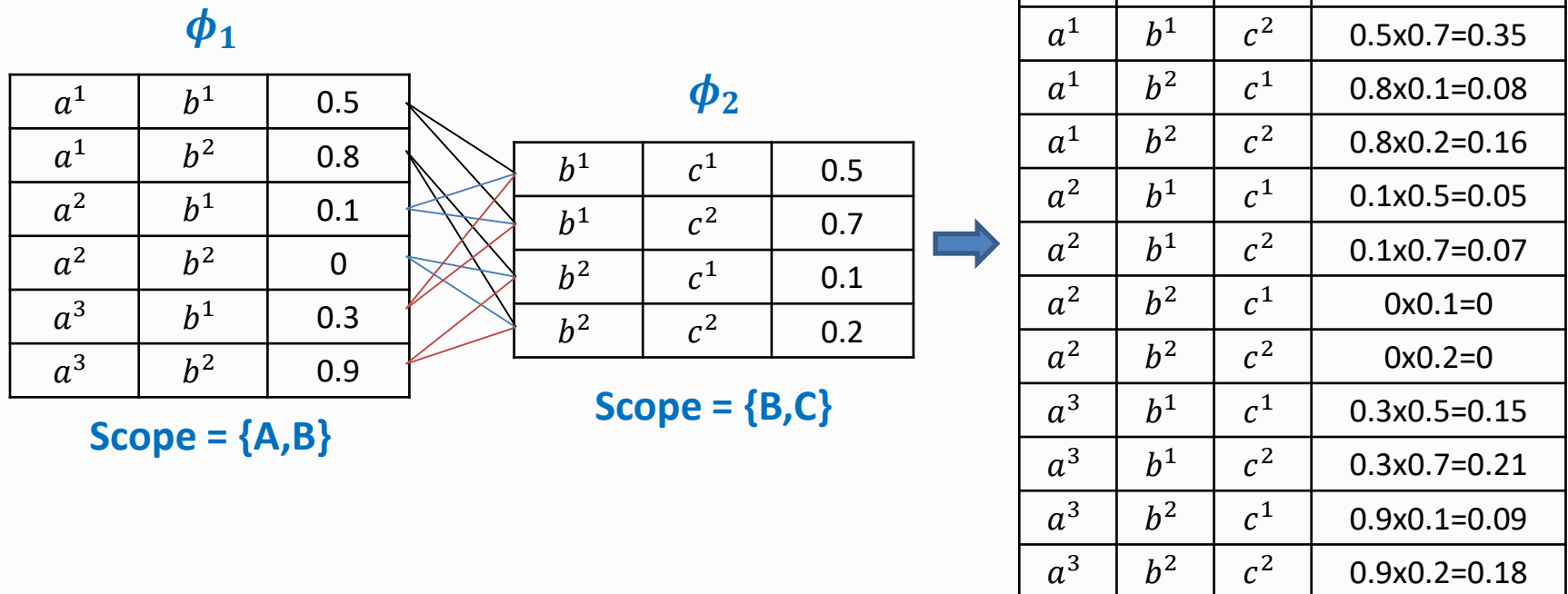
sum = 1

General factors

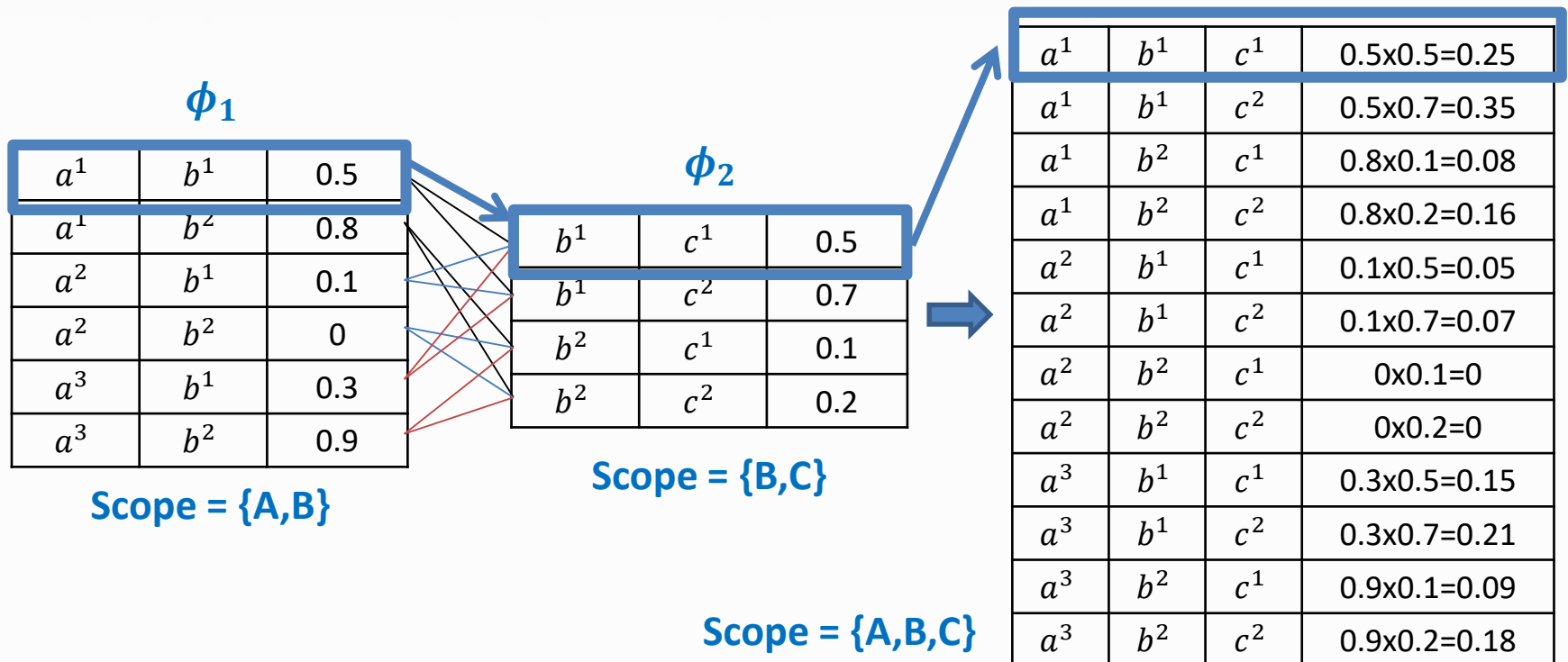
A	B	ϕ
a^0	b^0	30
a^0	b^1	5
a^1	b^0	1
a^1	b^1	10

Scope = {A,B}

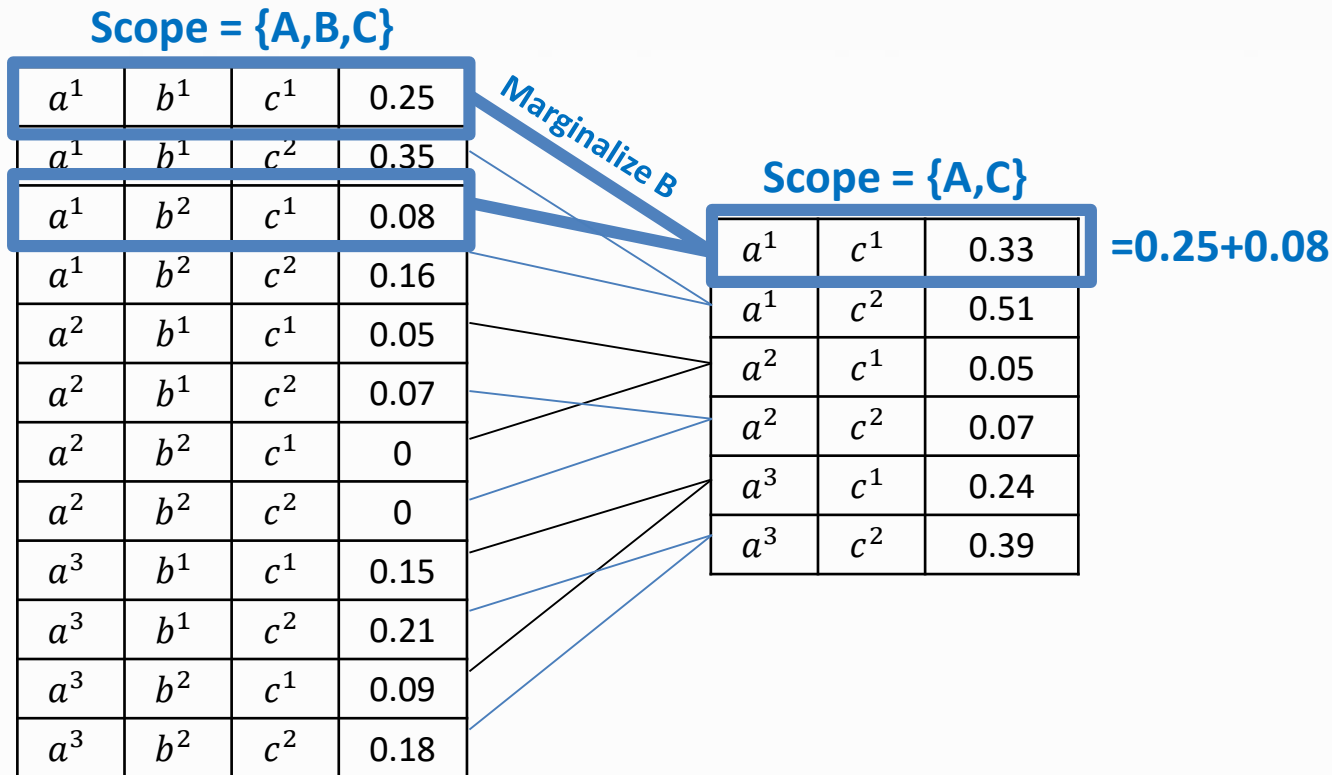
Factor product



Factor product



Factor Marginalization



Factor reduction

a^1	b^1	c^1	0.25
a^1	b^1	c^2	0.35
a^1	b^2	c^1	0.08
a^1	b^2	c^2	0.16
a^2	b^1	c^1	0.05
a^2	b^1	c^2	0.07
a^2	b^2	c^1	0
a^2	b^2	c^2	0
a^3	b^1	c^1	0.15
a^3	b^1	c^2	0.21
a^3	b^2	c^1	0.09
a^3	b^2	c^2	0.18

Reduce to the context c^1

Factor reduction

a^1	b^1	c^1	0.25
a^1	b^1	c^2	0.35
a^1	b^2	c^1	0.08
a^1	b^2	c^2	0.16
a^2	b^1	c^1	0.05
a^2	b^1	c^2	0.07
a^2	b^2	c^1	0
a^2	b^2	c^2	0
a^3	b^1	c^1	0.15
a^3	b^1	c^2	0.21
a^3	b^2	c^1	0.09
a^3	b^2	c^2	0.18

Reduce to the context c^1



a^1	b^1	c^1	0.25
a^1	b^2	c^1	0.08
a^2	b^1	c^1	0.05
a^2	b^2	c^1	0
a^3	b^1	c^1	0.15
a^3	b^2	c^1	0.09

Scope = {A,B}

Why factors?

- Fundamental building block for defining distributions in high-dimensional spaces
- Set of basic operations for manipulating these probability distributions