Particle Identification using graphical models

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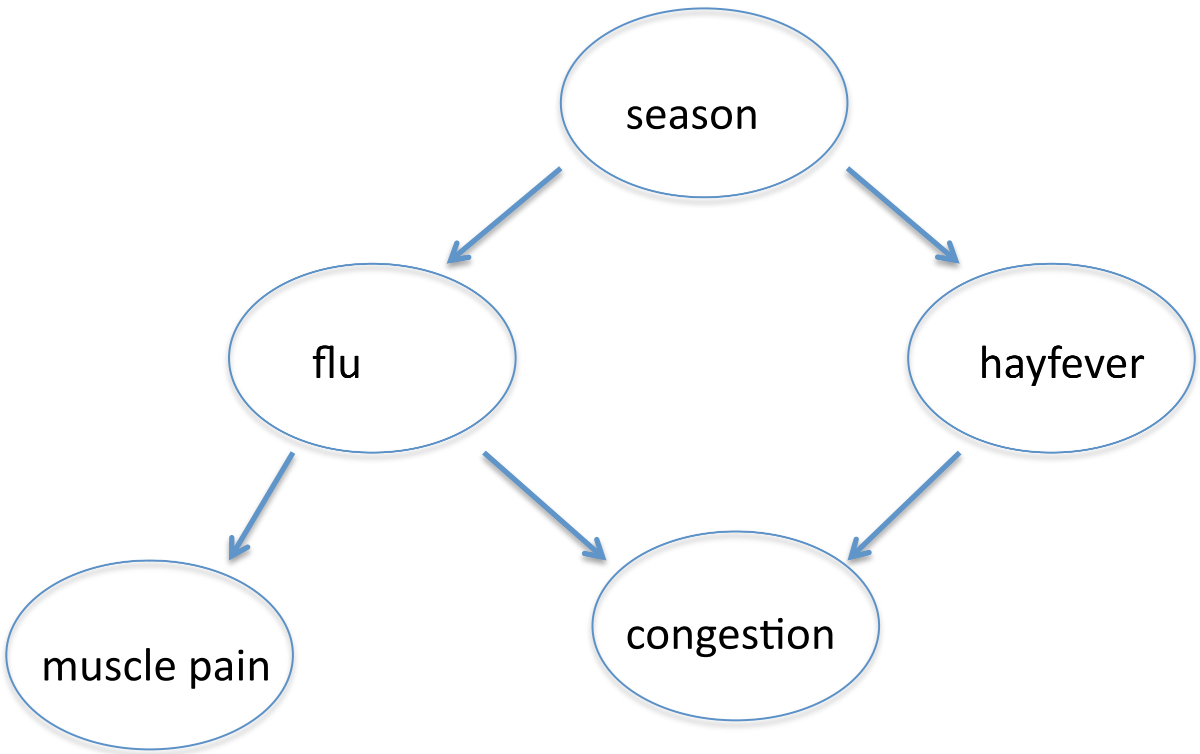
Graphical models

- Probabilistic graphical models are a graph based representation for encoding a complex distribution over many random variables
- Used in a wide range of domains including computer vision, natural language processing, web search, medical diagnosis, and physics
- uses concepts such as Bayesian networks and Markov fields
- kind of like a Feynman diagram in the sense that it is a visual representation of a mathematical formalism

Graphical models

- A Bayesian network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph
- A Markov field is similar to a Bayesian network, but is undirected

An example of a Bayesian network



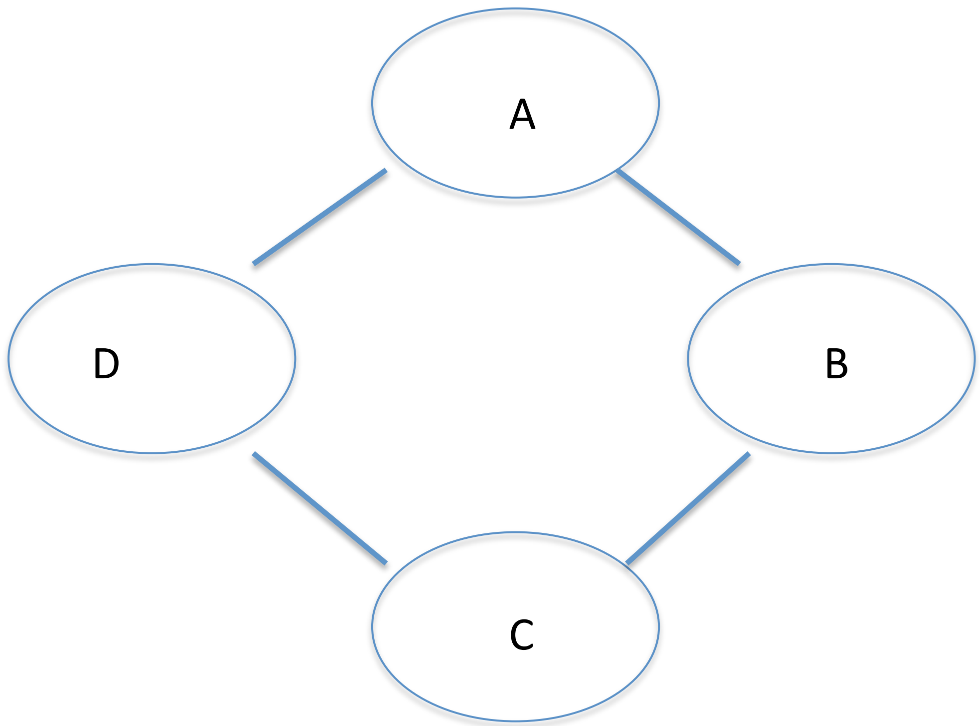
Independencies:
(F ,H | S)
(C,S | (F and H)
(M, (H and C) | F)
(M, C | F)

From the chain rule of probabilities:

$P(S,F,H,C,M) = P(S) \times P(F|S) \times P(H|S) \times P(C|F,H) \times P(M|F)$

- nodes represent random variables
- arrows represent dependencies among variables

An example of a Markov network



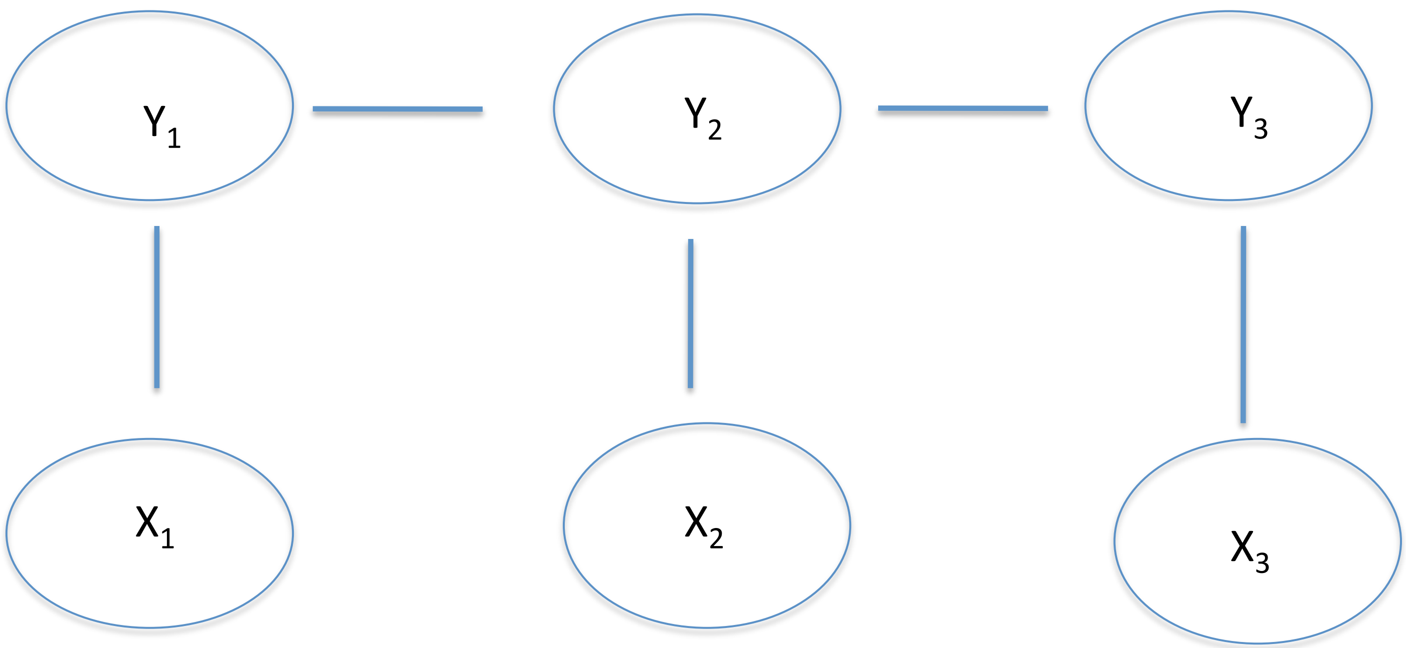
Independencies:
(A ,C | (B and D)
(B,D | (A and C)

- $P(A,B,C,D) = (1/Z) \times \Phi_1(A,B) \times \Phi_2(B,C) \times \Phi_3(C,D) \times \Phi_4(A,D)$
- Z is normalization factor
- Factor (Φ) represents the affinity between two variables

Kalman filter

- Can be represented as a Bayesian network (called a dynamic Bayesian network) where the sate vector is a random variable
- Proceeds through update equations

Conditional random field



- y is a label, x is a feature

Conditional random field

- Used for multivariate classification
- takes a set of input random variables and outputs a conditional probability distribution
- this is represented as exponential distribution

$$p(y|\mathbf{x}) = \frac{1}{Z(\mathbf{x})} \exp\left\{\sum_{k=1}^{K} \theta_k f_k(y, \mathbf{x})\right\}$$

- y is the class label, x is the feature
- Z is a normalizing constant
- f is a feature function that has to be used as input
- θ is the weight vector

Conditional random field

- idea is to use this for particle identification
- take a set of input variables and output the conditional probability of a particle particle given those input variables
- these variables are undecided (dE/dx, range, shower distribution)

Neutral network for electron-hadron discrimination

- Electron-Hadron shower discrimination in a liquid argon time projection chamber (arXiv.1210.221)
- used 4 variables to discriminate between electrons and hadron
- 2 variables had to do with how the energy is distributed in the shower, and 2 were spatial extent

MVA method	Beam case study	Electron–Signal/Background efficiency [%]	Signal-to-total $S/\sqrt{(S+B)}$
KNN	CN2PY	95.7 / 5.2	30.1
MLPBNN	CN2PY	93.9 / 7.4	29.5
BDT	CN2PY	96.2 / 4.5	30.3
BDTG	CN2PY	90.6 / 6.0	29.2
KNN	Uniform ν	95.4 / 5.0	30.1
MLPBNN	Uniform ν	92.9 / 7.3	29.4
BDT	Uniform ν	96.1 / 4.9	30.2
BDTG	Uniform ν	90.6 / 4.2	29.4

conditional random field vs. neural network

- neural networks use a hidden layer, conditional random fields (mostly) do not use a hidden layer
- when learning the parameters, introducing a hidden layer loses convexity
- other methods should be attempted

Conclusions

- conditional random fields offer a method of multivariate classification
- feature functions need to be determined
- input variables need to be defined