Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 19

Oct, 24, 2016

Slide Sources
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D. Koller, Stanford CS - Probabilistic Graphical Models
D. Page, Whitehead Institute, MIT

Several Figures from
"Probabilistic Graphical Models: Principles and Techniques" *D. Koller, N. Friedman* 2009

Lecture Overview

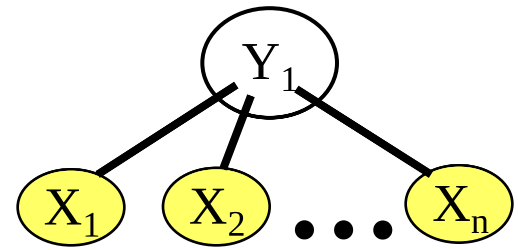
- Recap: Naïve Markov – Logistic regression (simple CRF)
- CRFs: high-level definition
- CRFs Applied to sequence labeling
- NLP Examples: Name Entity Recognition, joint POS tagging and NP segmentation

Let's derive the probabilities we need

$$\phi_i(X_i, Y_1) = \exp\{w_i \mathbb{1}\{X_i = 1, Y_1 = 1\}\}$$

how strongly $Y_1 = 1$ given that $X_i = 1$

$$\phi_0(Y_1) = \exp\{w_0 \mathbb{1}\{Y_1 = 1\}\}$$



$$\tilde{P}(Y_1 \mid x_1, \ldots, x_n) =$$

$$\tilde{P}(Y_1, x_1, \ldots, x_n) = \phi_0(Y_1) * \prod_{i=1}^{n} \phi_i(x_i, Y_1)$$

$$\tilde{P}(Y_1 = 0, x_1, \ldots, x_n) =$$

$$\tilde{P}(Y_1 = 1, x_1, \ldots, x_n) =$$

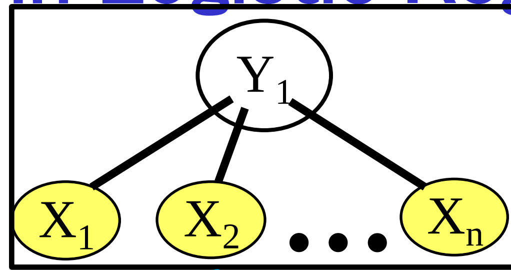
Continue…..

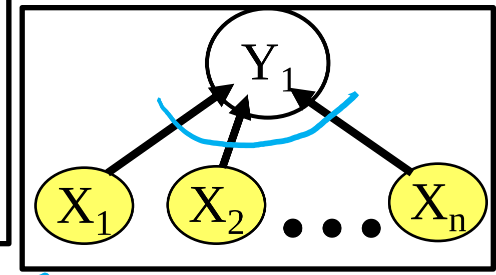
$$P(Y_1 = 1 \mid X_1 \dots X_n) = \frac{e^{w_0 + \sum w_i X_i}}{1 + e^{w_0 + \sum w_i X_i}}$$

$$= \frac{e^{z}}{1+e^{z}} \frac{e^{-z}}{e^{-z}} = \frac{1}{e^{-z}+1}$$

$$P(Y_1 \mid X_1 \dots X_n) = \left\{ \frac{1}{e^{-z}+1} , \frac{e^{-z}}{e^{-z}+1} \right\}$$

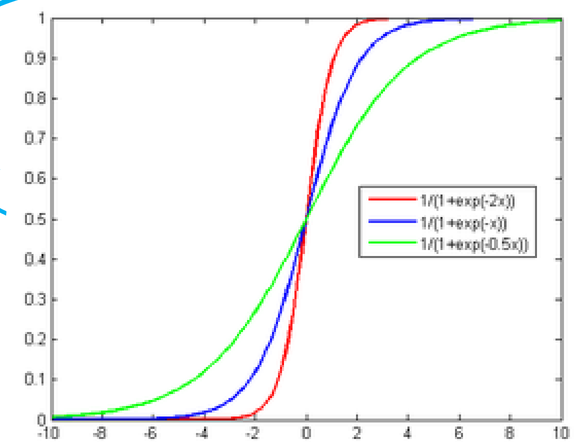
Sigmoid Function used in Logistic Regression

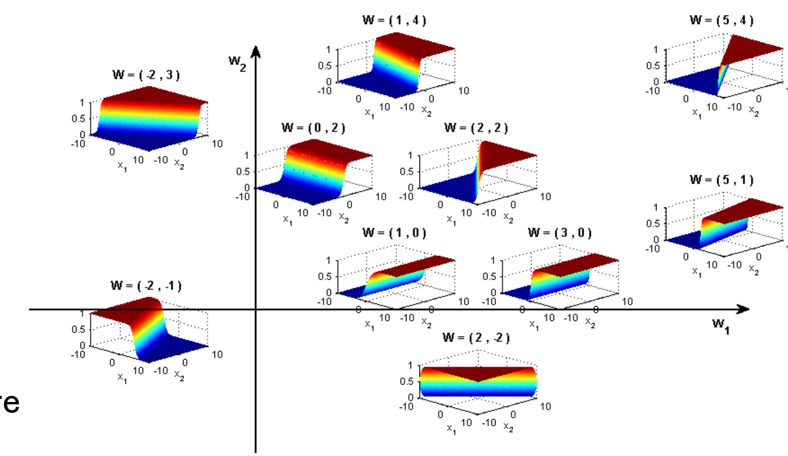




- Great practical interest
- Number of param w_i is linear instead of exponential in the number of parents
- Natural model for many real-world applications
- Naturally aggregates the influence of different parents

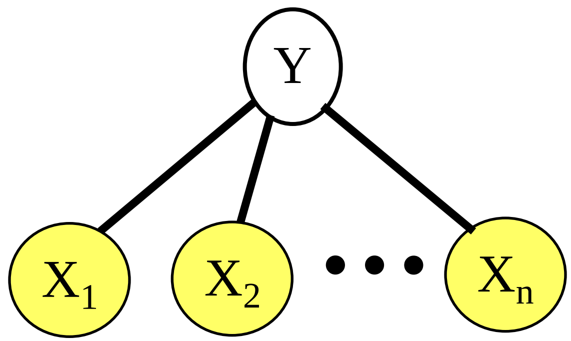
$\frac{1}{1+e^{-x}}$





Logistic Regression as a Markov Net (CRF)

Logistic regression is a simple Markov Net (a CRF)
aka **naïve markov model**



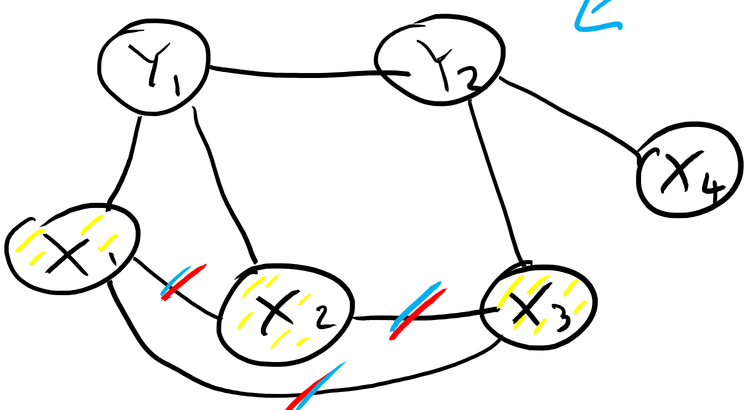
- But only models the **conditional distribution**, P(*Y* | ***X***) and not the full joint P(*X*, *Y*)

Let's generalize ….

Assume that you always observe a set of variables **X** = {$X_1 \cdots X_n$} and you want to predict one or more variables **Y** = {$Y_1 \cdots Y_k$}

A CRF is an undirected graphical model whose nodes corresponds to **X** ∪ **Y**.

$\varphi_1(D_1) \cdots \varphi_m(D_m)$ represent the factors which annotate the network (but we disallow factors involving only vars in **X** – why?)



They would be

A. too large

B. constant

C. difficult to aquire

$$P(Y \mid X) = \frac{1}{Z(X)} \left(\prod_{i=1}^{m} \phi_i(D_i) \right) \qquad Z(X) = \sum_{Y} \left(\prod_{i=1}^{m} \phi_i(D_i) \right)$$

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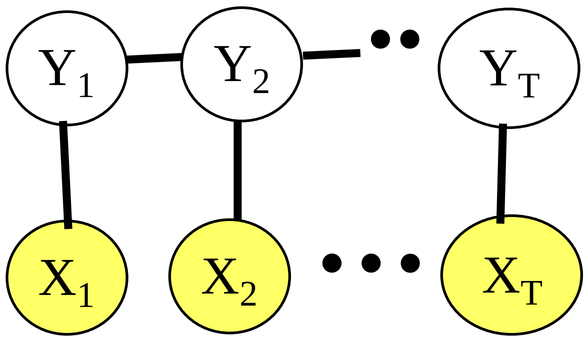
- Recap: Naïve Markov – Logistic regression (simple CRF)
- CRFs: high-level definition
- **CRFs Applied to sequence labeling**
- NLP Examples: Name Entity Recognition, joint POS tagging and NP segmentation

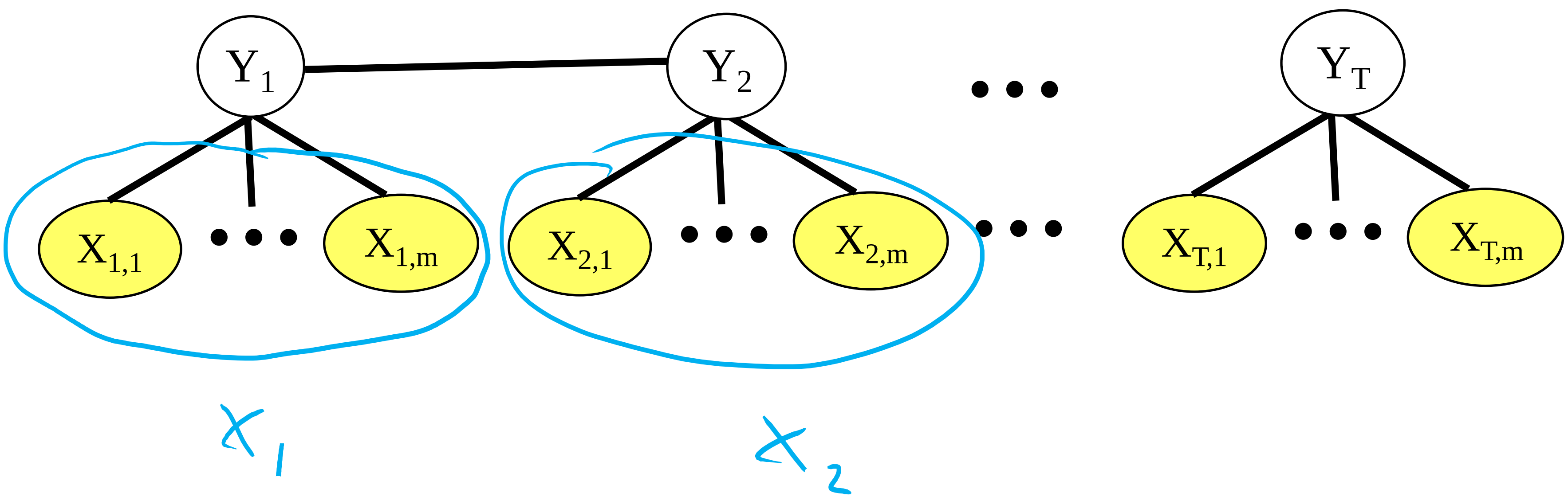
Sequence Labeling



Linear-chain CRF

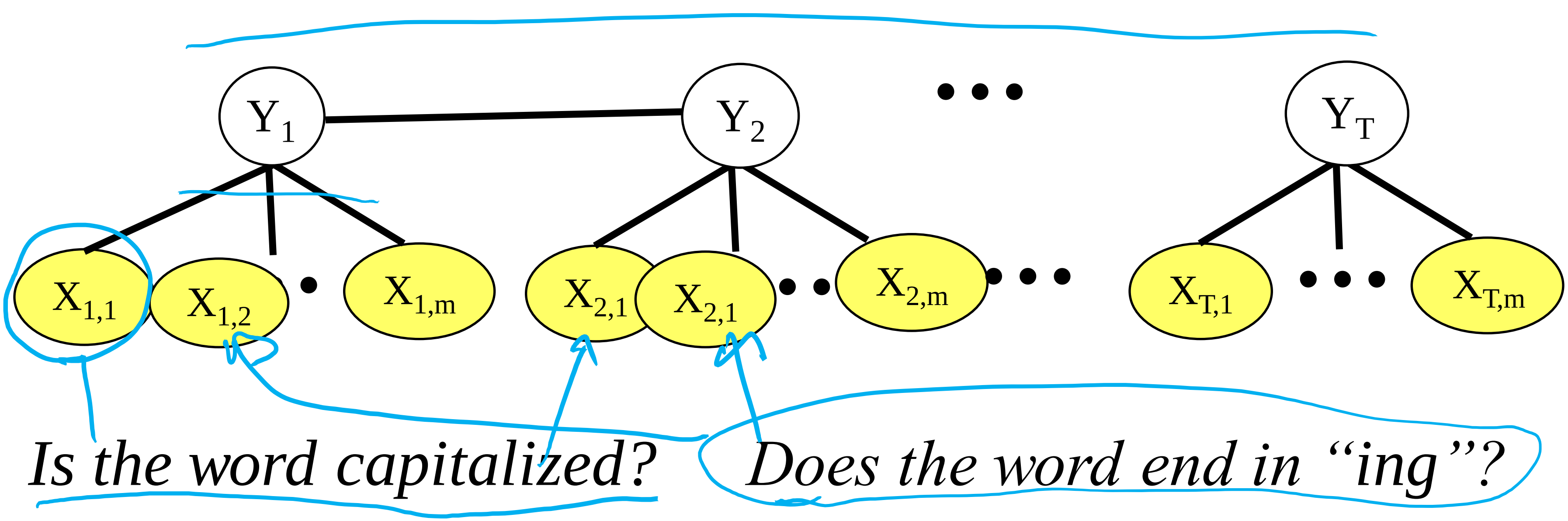
Increase representational Complexity: Adding Features to a CRF

- Instead of a single observed variable X_i we can model multiple features X_{ij} of that observation.



CRFs in Natural Language Processing

- One target variable Y for each word X, encoding the possible labels for X
- Each target variable is connected to a set of feature variables that capture properties relevant to the target distinction



Named Entity Recognition Task

- Entity often span multiple words *"British Columbia"*
- Type of an entity may not be apparent for individual words *"University of British Columbia"*
- Let's assume three categories*: **Person, Location, Organization***
- BIO notation (for sequence labeling)

possible labels B-PER I-PER B-LOC I-LOC B-ORG I-ORG OTHER

O	B-ORG	I-ORG	I-ORG	I-ORG
The	University	of	British	Columbia

O	O	B-LOC	I-LOC
is	in	Vancouver	B.C.

Linear chain CRF parameters

With two factors "types" for each word

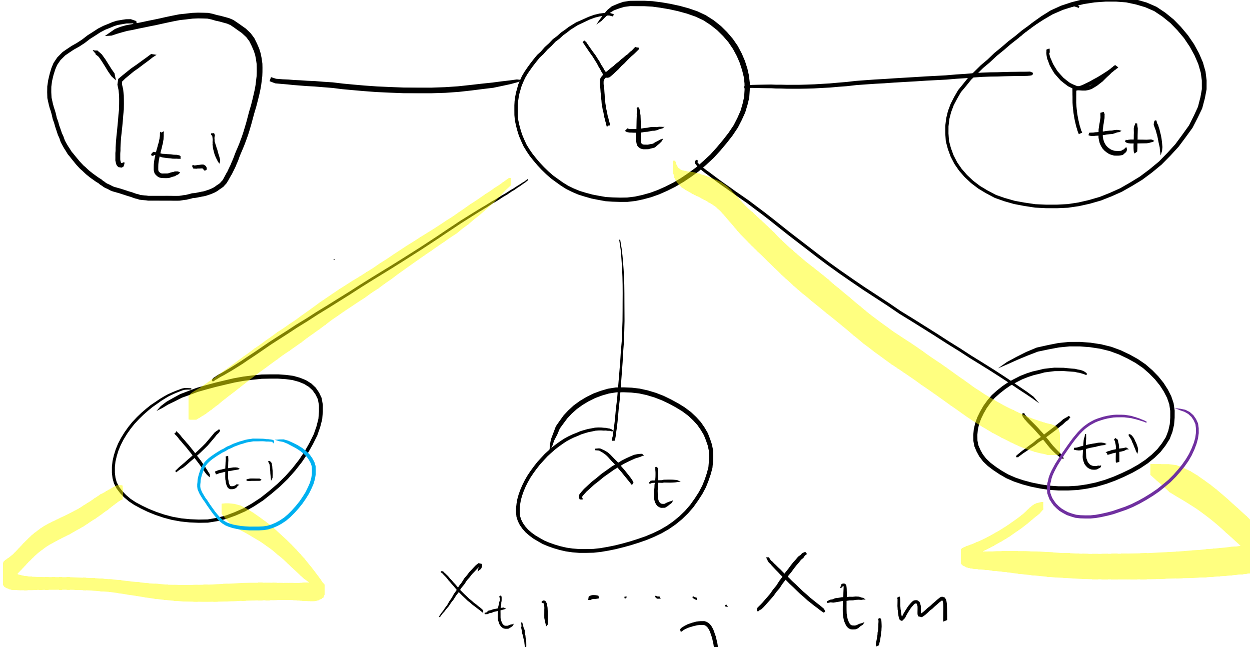
$\phi_t^1(Y_t, Y_{t-1})$ $\phi_t^1(Y_t, Y_{t+1})$ Dependency between neighboring target vars

$\phi_t^2(Y_t, X_1, .., X_T)$ Dependency between target variable and its context in the word sequence, which can include also **features of the words** (capitalized, appear in an atlas of location names, etc.)

Factors are similar to the ones for the Naïve Markov (logistic regression)

$$\phi_t(Y_t, X_{tk}) = \exp\{w_{tk} \times \mathbb{1}\{Y_t = \text{I-LOC}, X_{tk} = 1\}\}$$

appears in atlas of location names



$$\mathbb{1}\{Y_t = \text{I-ORG}, X_{t,k} = \text{"Times"}\}$$

$$\mathbb{1}\{Y_t = \text{I-PER}, X_{t+1,k} = \text{"spoke"}\}$$

$$\mathbb{1}\{Y_t = \text{I-PER}, X_{t-1,k} = \text{"Mrs."}\}$$

Features can also be

- The word
- Following word
- Previous word

More on features

Including features that are **conjunctions of simple features** increases accuracy

Y_t

$$\mathbb{1}\{Y_t = \text{I-PER}, X_{t+1,k} = \text{"spoke"}\}$$

$$\mathbb{1}\{Y_t = \text{I-PER}, X_{t-1,k} = \text{"Mrs."}\}$$

Total number of features can be 10^5–10^6

However features are sparse i.e. most features are 0 for most words

Linear–Chain Performance

Per–token/word accuracy in the high 90% range for many natural datasets

Per–field precision and recall are more often around 80–95% , depending on the dataset. Entire Named Entity Phrase must be correct

O B-ORG I-ORG B-LOC I-LOC
The University of British Columbia

O O B-LOC I-LOC
is in Vancouver B.C

Per-word accuracy ?

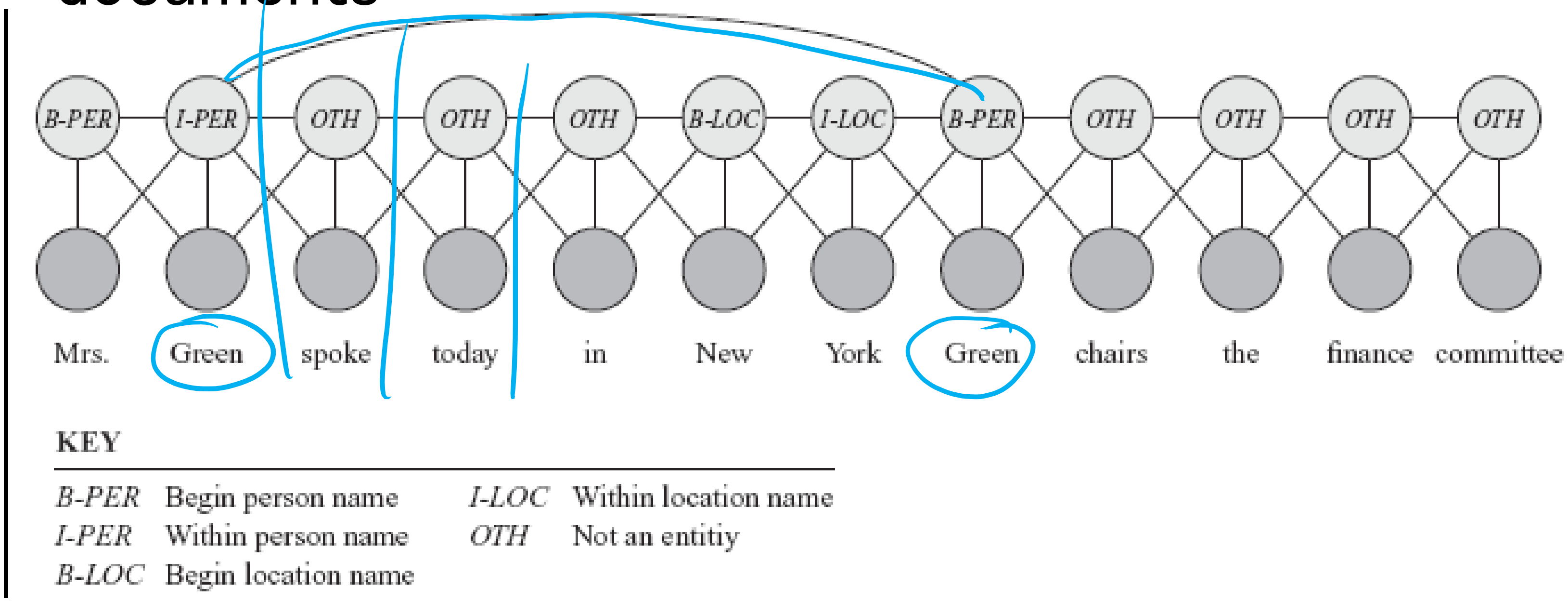
Per-field precision ?

	A.	B	C.
Per-word accuracy	$1/2$	$7/9$	$7/9$
Per-field precision	$1/2$	$3/9$	$1/2$

Skip-Chain CRFs

Include additional factors that connect non-adjacent target variables

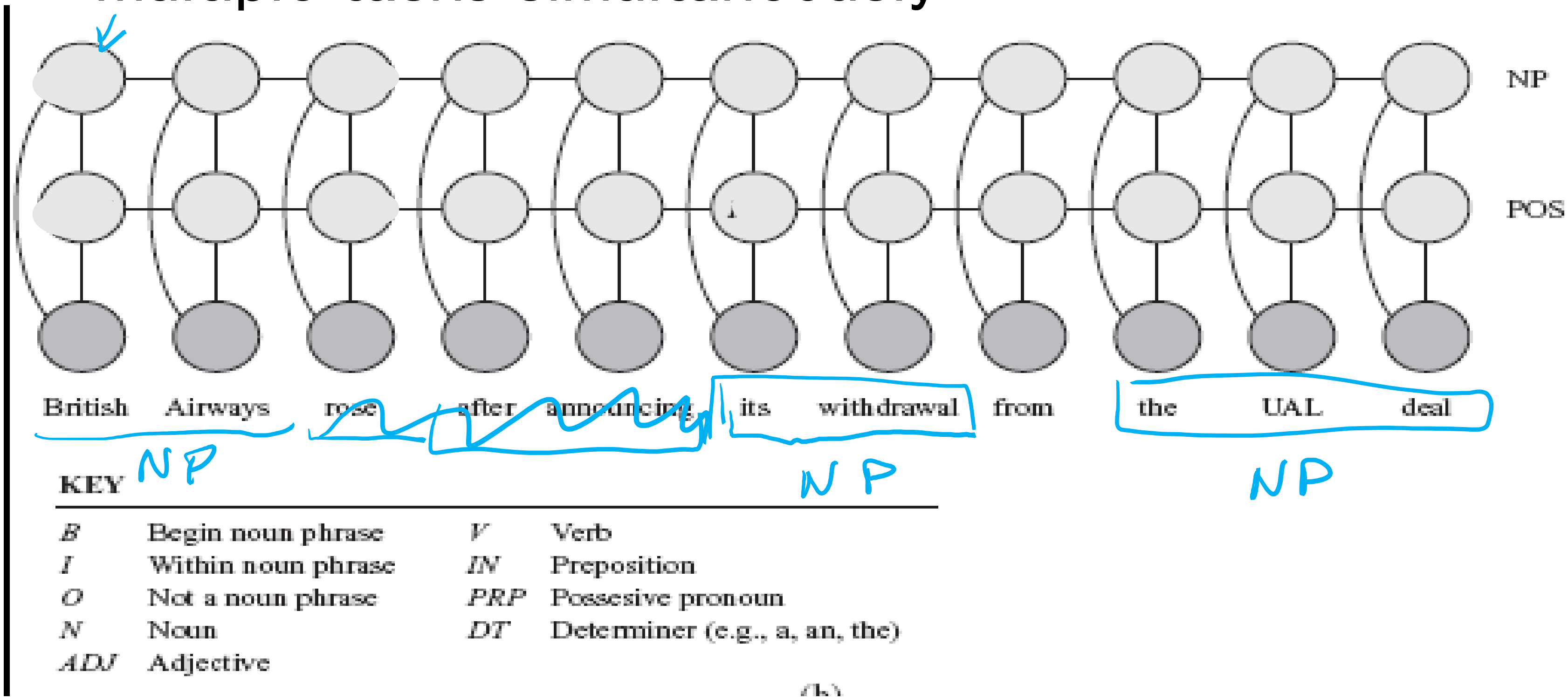
E.g., When a word occur multiple times in the same documents



Graphical structure over Y can depend on the values of the Xs !

Coupled linear-chain CRFs

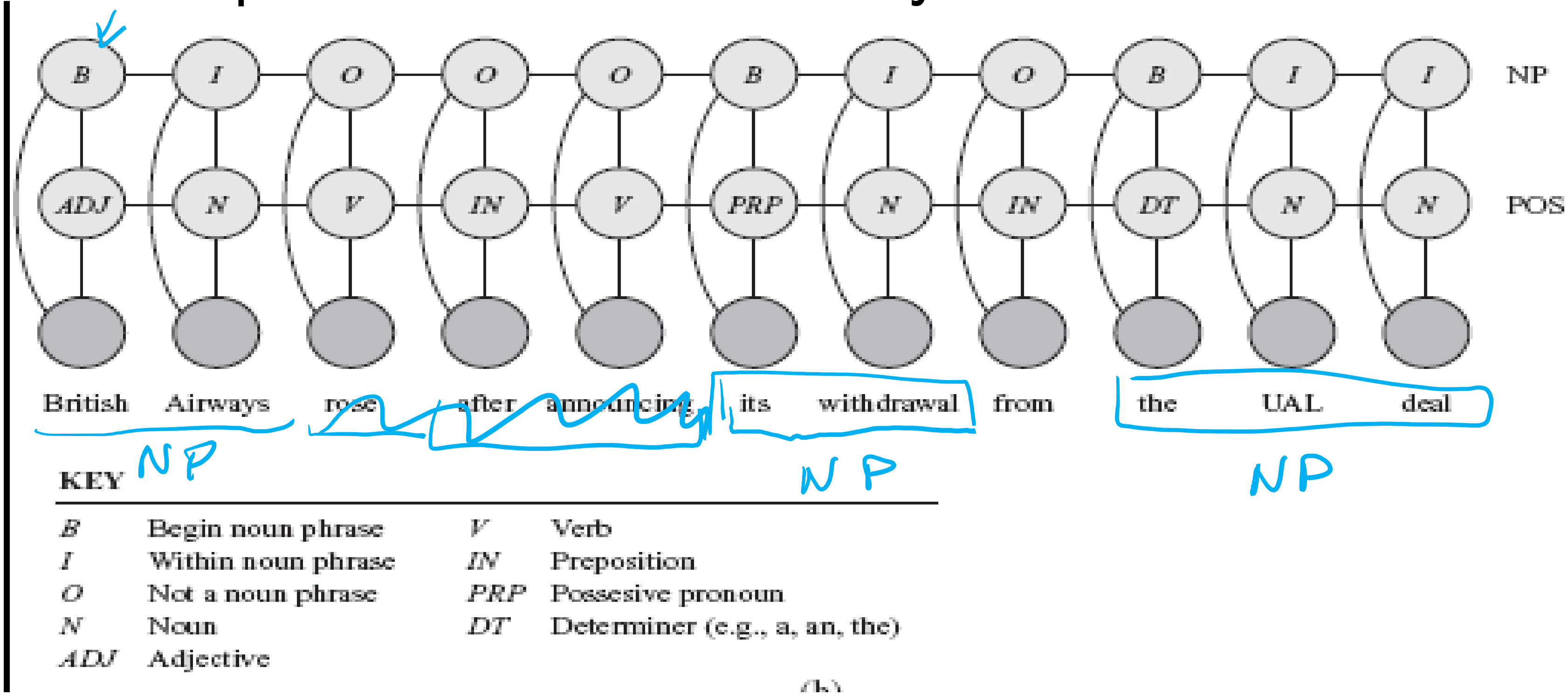
- Linear-chain CRFs can be combined to perform multiple tasks simultaneously



- Performs part-of-speech labeling and noun-phrase segmentation

Coupled linear-chain CRFs

- Linear-chain CRFs can be combined to perform multiple tasks simultaneously



- Performs part-of-speech labeling and noun-phrase segmentation

Inference in CRFs (just intuition)

An HMM can be viewed as a factor graph $p(\mathbf{y}, \mathbf{x}) = \boxed{\prod_t \Psi_t(y_t, y_{t-1}, x_t)}$ where $Z = 1$, and the factors are defined as:

$$\Psi_t(j, i, x) \stackrel{\text{def}}{=} p(y_t = j | y_{t-1} = i) p(x_t = x | y_t = j). \qquad (4.1)$$

Forward / Backward / Smoothing and Viterbi can be rewritten (not trivial!) using these factors

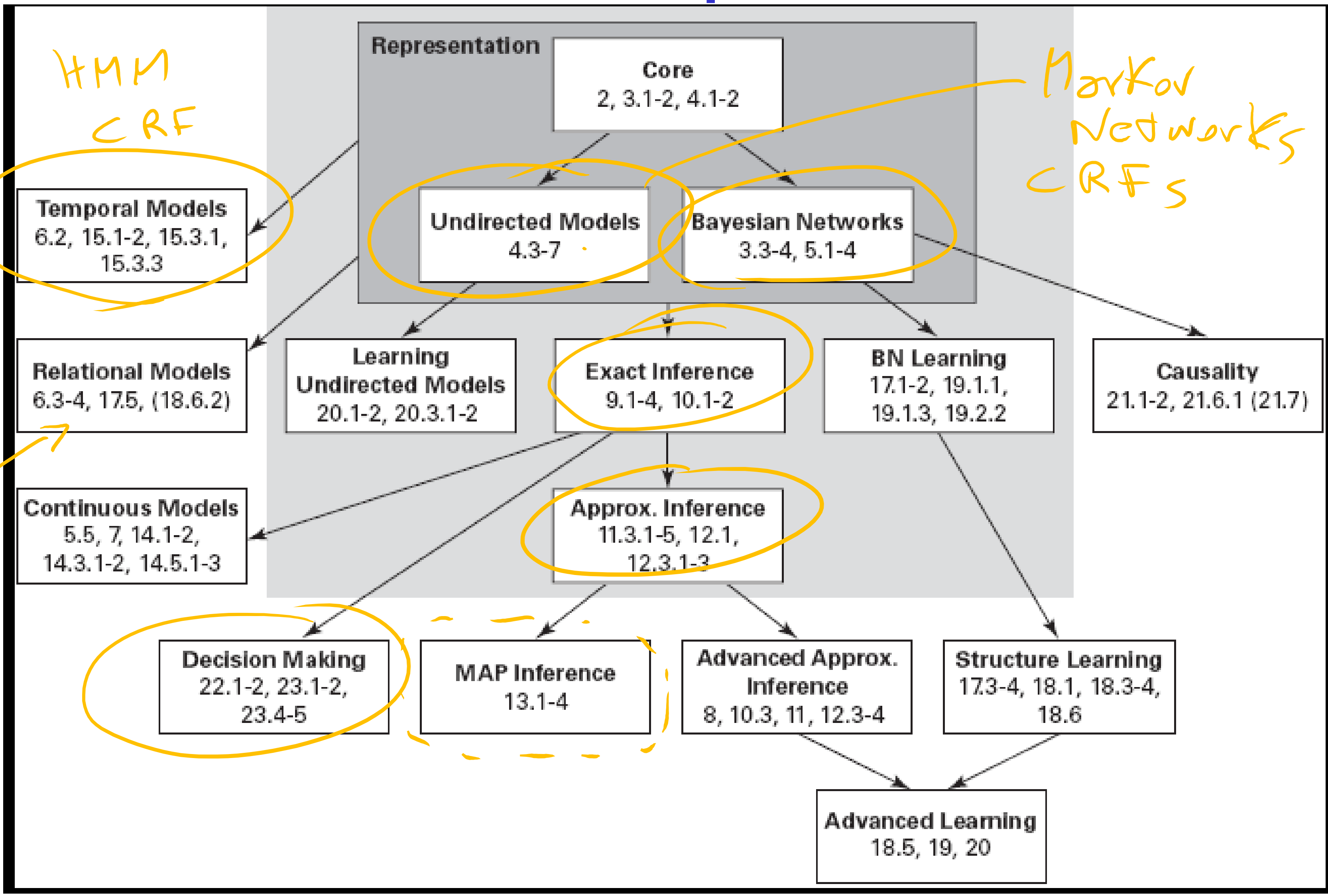
Then you plug in the factors of the CRFs and all the algorithms work fine with CRFs! ☺

CRFs Summary

- Ability to relax strong independence assumptions
- Ability to incorporate arbitrary overlapping local and global features
- Graphical structure over Y can depend on the values of the Xs
- Can perform multiple tasks simultaneously
- *Standard Inference algorithm* for HMM can be applied
- *Practical Learning algorithms exist*
- State-of-the-art on many labeling tasks *(deep learning recently shown to be often better … current research on ensembling them?)*

See MALLET package

Probabilistic Graphical Models



From "Probabilistic Graphical Models: Principles and Techniques" *D. Koller, N. Friedman* 2009

422 big picture: Where are we?

Hybrid: Det +Sto

Prob CFG
Prob Relational Models
Markov Logics

Deterministic | Stochastic

Query

Logics
First Order Logics

Ontologies
Temporal rep.

- Full Resolution
- SAT

Belief Nets

Approx. : Gibbs

Markov Chains and HMMs

Forward, Viterbi….
Approx. : Particle Filtering

Undirected Graphical Models
Markov Networks
Conditional Random Fields

Planning

Markov Decision Processes and
Partially Observable MDP

- Value Iteration
- Approx. Inference

Reinforcement Learning

Applications of AI

Representation

Reasoning Technique

Learning Goals for today’s class

You can:

- Provide general definition for CRF
- Apply CRFs to sequence labeling
- Describe and justify features for CRFs applied to Natural Language processing tasks
- Explain benefits of CRFs

Midterm, Wed, Oct 26, we will start at 9am sharp

How to prepare…

- Go to **Office Hours**
- **Learning Goals** (look at the end of the slides for each lecture – complete list ahs been posted)
- Revise all the **clicker questions** and **practice exercises**
- **More practice material** has been posted
- Check questions and answers on Piazza

Next class Fri

- Start Logics
- Revise Logics from 322!

Announcements

Midterm

- Avg 73.5 Max 105 Min 30
- If score below 70 <u>need to very seriously revise </u>all the material covered so far
- You can pick up a printout of the solutions along with your midterm.

Generative vs. Discriminative Models

$\{X_1, \ldots X_n\}$ $\{Y_1, \ldots Y_m\}$

Generative models (like Naïve Bayes): *not* directly designed to maximize performance on classification. They model the *joint distribution* $P(X,Y)$.

Classification is then done using Bayesian inference

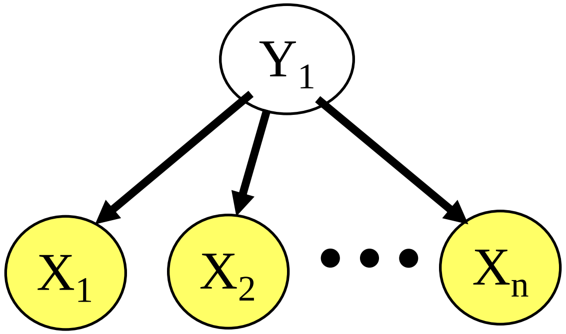
But a generative model can also be used to perform any other inference task, e.g. $P(X_1 \mid X_2, \cdots X_n,)$

- "Jack of all trades, master of none."

Discriminative models (like CRFs): specifically designed and trained to maximize performance of classification. They only model the *conditional distribution* $P(Y \mid X)$.

By focusing on modeling the conditional distribution, they generally perform better on classification than generative models when given a reasonable amount of training data.

Naïve Bayes vs. Logistic Regression



Naïve Bayes

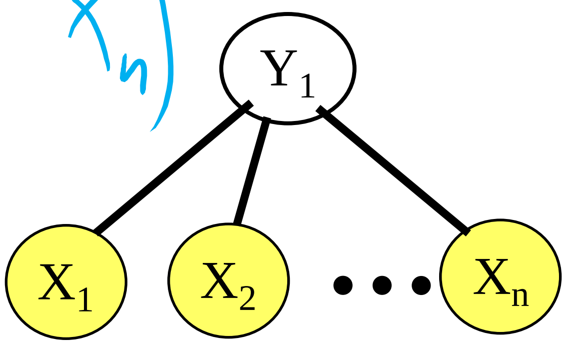
$P(Y_1, X_1 \ldots X_n)$

Generative

Conditional

Discriminative

$P(Y_1 | X_1, X_n)$

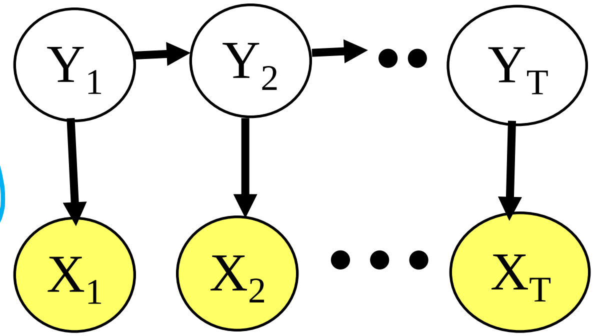


Logistic Regression (Naïve Markov)

Sequence Labeling

models

$P(Y_1 .. Y_T, X_1 .. X_T)$



HMM

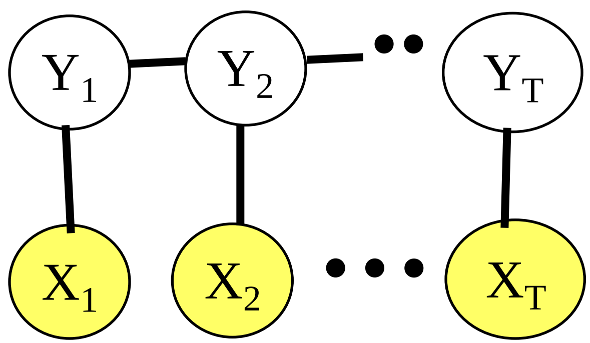
Generative

Conditional

Discriminative

models

$P(Y_1 .. Y_T | X_1 .. X_T)$



Linear-chain CRF