Natural Language Processing (CSE 517):
Graphical Models

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Notation

Let \( V = \langle V_1, V_2, \ldots, V_\ell \rangle \) be a collection of random variables (not necessarily a sequence).

\( \text{Val}(V) \) will denote the values of a r.v. \( V \).

\( V_I \) denotes a subset of the r.v.s \( V \) with indices \( i \in I \).

\( V_{-I} = V \setminus V_I \)

Recall:

- \( p(V) = \prod_{i=1}^{\ell} p(V_i \mid V_1, \ldots, V_{i-1}) \) (always true, for any ordering)
- \( p(V_I, V_J \mid V_K) = p(V_I \mid V_K) \cdot p(V_J \mid V_K) \) if and only if \( V_I \perp V_J \mid V_K \) (conditional independence)
- \( p(V_I = \nu_I) = \sum_{\nu_{-I} \in \text{Val}(V_{-I})} p(V_I = \nu_I, V_{-I} = \nu_{-I}) \) (marginalization)
Factor Graphs

Two kinds of vertices:

- Random variables (denoted by circles, “$V_i$”)
- Factors (denoted by squares, “$f_j$”)

The graph is bipartite; every edge connects some variable to some factor. Let $I_j \subseteq \{1, \ldots, \ell\}$ be the set of variables $f_j$ is connected to.

Factor $f_j$ defines a map $\text{Val}(V_{I_j}) \to \mathbb{R}_{\geq 0}$.

The graph and factors define a probability distribution:

$$p(V = v) \propto \prod_j f_j(v_{I_j})$$
Factor Graphs We’ve Seen Before

Hidden Markov model:

General first-order sequence model:
Two Kinds of Factors

Conditional probability tables. E.g., if $I_j = \{1, 2, 3\}$:

$$f_j(v_1, v_2, v_3) = p(V_3 = v_3 \mid V_1 = v_1, V_2 = v_2)$$

Lead to Bayesian networks (with some constraints).

Potential functions (arbitrary nonnegative values).
Lead to Markov random fields (a.k.a. Markov networks).
Sinus inflammation is caused by flu, but also by allergies. Runny nose and headache are both caused by sinus inflammation.
Sinus inflammation is caused by flu, but also by allergies. Runny nose and headache are both caused by sinus inflammation.
Yucky Factor Graph

\[ p(i, a, s, r, h) = f_I(i) \cdot f_A(a) \cdot f_{S,I,A}(s, i, a) \cdot f_{R,S}(r, s) \cdot f_{H,S}(h, s) \]

\[ = p(i) \cdot p(a) \cdot p(s | i, a) \cdot p(r | s) \cdot p(h | s) \]
Naughty Markov Random Field

Independencies: $A \perp C \mid B, D$; $B \perp D \mid A, C$; $\neg A \perp C$; $\neg B \perp D$
Naughty Factor Graph

\[
p(a, b, c, d) = \frac{f_{A,B}(a, b) \cdot f_{B,C}(b, c) \cdot f_{C,D}(c, d) \cdot f_{D,A}(d, a)}{\sum_{a' \in \text{Val}(A)} \sum_{b' \in \text{Val}(B)} \sum_{c' \in \text{Val}(C)} \sum_{d' \in \text{Val}(D)} f_{A,B}(a', b') \cdot f_{B,C}(b', c') \cdot f_{C,D}(c', d') \cdot f_{D,A}(d', a')}
\]
Assignment Probabilities: Examples

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Assignment Probabilities: Examples

\[
\sum_{a' \in \text{Val}(A)} \sum_{b' \in \text{Val}(B)} \sum_{c' \in \text{Val}(C)} \sum_{d' \in \text{Val}(D)} f_{A,B}(a', b') \cdot f_{B,C}(b', c') \cdot f_{C,D}(c', d') \cdot f_{D,A}(d', a') = 7,201,840
\]
Assignment Probabilities: Examples

\[ p(A = 0, B = 1, C = 1, D = 0) = \frac{5,000,000}{7,201,840} \approx 0.69 \]
Assignment Probabilities: Examples

\[ p(A = 1, B = 1, C = 0, D = 0) = \frac{10}{7,201,840} \approx 0.0000014 \]
Structure and Independence

Bayesian networks:
- A variable is conditionally independent of its non-descendants given its parents.

Markov networks:
- Conditional independence derived from “Markov blanket” and separation properties.

Local configurations can be used to check all conditional independence questions; almost no need to look at the values in the factors!
Independence “Spectrum”

\[
\prod_{i=1}^{\ell} f_{V_i}(V_i) = f_V(V)
\]

everything is independent

everything can be interdependent

minimal expressive power

arbitrary expressive power

fewer parameters

more parameters
Operations on Factors: Multiplication

Given two factors \( f_U \) and \( f_V \), we can create a new “product” factor such that:

\[
f_{U \cup V}(u \cup v) = f_U(u) \cdot f_V(v)
\]

for all \( u \in \text{Val}(U) \) and all \( v \in \text{Val}(V) \).

\[
\begin{array}{ccc|c|c|c|c|c|c|c}
A & B & f_{A,B} & B & C & f_{B,C} & & & \\hline
0 & 0 & 30 & 0 & 0 & 100 & & & \\hline
0 & 1 & 5 & 0 & 1 & 1 & & & \\hline
1 & 0 & 1 & 1 & 0 & 1 & & & \\hline
1 & 1 & 10 & 1 & 1 & 100 & & & \\hline
\end{array}
\]

\[
\begin{array}{ccc|c|c|c|c|c|c|c}
A & B & C & f_{A,B,C} & \\hline
0 & 0 & 0 & 3,000 & \\hline
0 & 0 & 1 & 30 & \\hline
0 & 1 & 0 & 5 & \\hline
0 & 1 & 1 & 500 & \\hline
1 & 0 & 0 & 100 & \\hline
1 & 0 & 1 & 1 & \\hline
1 & 1 & 0 & 10 & \\hline
1 & 1 & 1 & 1,000 & \\hline
\end{array}
\]
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Given two factors $f_U$ and $f_V$, we can create a new “product” factor such that:

$$f_{U \cup V}(u \cup v) = f_U(u) \cdot f_V(v)$$

for all $u \in \text{Val}(U)$ and all $v \in \text{Val}(V)$.

This might remind you of a join operation on a database.
Operations on Factors: Multiplication

Given two factors $f_U$ and $f_V$, we can create a new “product” factor such that:

$$f_{U \cup V}(u \cup v) = f_U(u) \cdot f_V(v)$$

for all $u \in \text{Val}(U)$ and all $v \in \text{Val}(V)$.

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What happens if you multiply out all the factors in a factor graph?
Operations on Factors: Maximization

Given a factor $f_U$ and a variable $V \not\in U$, we can transform $f_{U,V}$ into $f_U$ by:

$$f_U(u) = \max_{v \in \text{Val}(V)} f_{U,V}(u, v)$$

for all $u \in \text{Val}(U)$.

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Operations on Factors: Marginalization

Given a factor $f_U$ and a variable $V \not\in U$, we can transform $f_{U,V}$ into $f_U$ by:

$$f_U(u) = \sum_{v \in \text{Val}(V)} f_{U,V}(u, v)$$

for all $u \in \text{Val}(U)$.
Operations on Factors: Marginalization

Given a factor $f_U$ and a variable $V \not\in U$, we can transform $f_{U,V}$ into $f_U$ by:

$$f_U(u) = \sum_{v \in \text{Val}(V)} f_{U,V}(u, v)$$

for all $u \in \text{Val}(U)$.

If you multiply out all the factors in a factor graph, then sum out each variable, one by one, until none are left, what do you get?
Factors are like numbers.

- Products are commutative: \( f_1 \cdot f_2 = f_2 \cdot f_1 \)
Factors are like numbers.

- Products are commutative: \( f_1 \cdot f_2 = f_2 \cdot f_1 \)
- Products are associative: \((f_1 \cdot f_2) \cdot f_3 = f_1 \cdot (f_2 \cdot f_3)\)
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- Products are associative: $(f_1 \cdot f_2) \cdot f_3 = f_1 \cdot (f_2 \cdot f_3)$
- Sums are commutative: $\sum_{X} \sum_{Y} f = \sum_{Y} \sum_{X} f$
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- Products are associative: \( (f_1 \cdot f_2) \cdot f_3 = f_1 \cdot (f_2 \cdot f_3) \)
- Sums are commutative: \( \sum_X \sum_Y f = \sum_Y \sum_X f \)
- Maximizations are commutative: \( \max_X \max_Y f = \max_Y \max_X f \)
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- Products are commutative: \( f_1 \cdot f_2 = f_2 \cdot f_1 \)
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- Sums are commutative: \( \sum_X \sum_Y f = \sum_Y \sum_X f \)
- Maximizations are commutative: \( \max_X \max_Y f = \max_Y \max_X f \)
- Multiplication distributes over marginalization and maximization:
  \[
  \sum_X (f_1 \cdot f_2) = f_1 \cdot \sum_X f_2 \\
  \max_X (f_1 \cdot f_2) = f_1 \cdot \max_X f_2
  \]
  (assuming \( X \) is not in the scope of \( f_1 \)).
Inference

Most general definition: “reason about some variables, optionally given values of some others.” Let $O$ be the observed variables and $U$ be the unobserved ones; $V = O \cup U$.

Three inference problems, all given $O = o$...
Inference

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Three inference problems, all given \( O = o \) . . .

- **Marginal inference:** what is the marginal distribution over \( Q \subset U \)? \( p(Q \mid o) \), marginalizing out the rest.)
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  - Related: draw samples from that distribution.
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- **Most probable explanation (MPE)**: what is the most probable assignment to $U$? ($\text{argmax}_u p(u \mid o)$)
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  - Related: what is the most *dangerous* assignment to $U$?
Inference

Most general definition: “reason about some variables, optionally
given values of some others.” Let \( O \) be the observed variables and
\( U \) be the unobserved ones; \( V = O \cup U \).

Three inference problems, all given \( O = o \ldots \)

- **Marginal inference**: what is the marginal distribution over
  \( Q \subset U \)? \((p(Q \mid o), \text{marginalizing out the rest.})\)
  - Related: draw samples from that distribution.

- **Most probable explanation (MPE)**: what is the most
  probable assignment to \( U \)? \((\arg\max_u p(u \mid o))\)
  - Related: what is the most *dangerous* assignment to \( U \)?

- **Maximum a posteriori (MAP)**: what is the most probable
  assignment to \( Q \subset U \)? \((\arg\max_q p(q \mid o))\)
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  - Related: draw samples from that distribution.
- **Most probable explanation (MPE)**: what is the most probable assignment to $U$? ($\arg\max_u p(u \mid o)$)
  - Related: what is the most dangerous assignment to $U$?
- **Maximum a posteriori (MAP)**: what is the most probable assignment to $Q \subset U$? ($\arg\max_q p(q \mid o)$)
  - Related: what values of $Q$ have the lowest expected cost?
Marginal Inference

Given a factor graph with variables $V$, find the marginal distribution over some $V_i \in V$, $p(V_i)$.

Simple chain example, focusing on $i = 4$:

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Observations

- If we had a single $f_{V_4}$, we could easily renormalize it to get $p(V_4)$. 
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- If we had a single $f_{V_4}$, we could easily renormalize it to get $p(V_4)$.
- Correct: $f_{V_4} = \sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4}$
Observations

- If we had a single $f_{V_4}$, we could easily renormalize it to get $p(V_4)$.

- Correct: $f_{V_4} = \sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4}$

- But that multiplied-out factor would have $\prod_i |\text{Val}(V_i)|$ values!
If we had a single $f_{V_4}$, we could easily renormalize it to get $p(V_4)$.

Correct: \[ f_{V_4} = \sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4} \]

But that multiplied-out factor would have $\prod_i |\text{Val}(V_i)|$ values!

Reorganize calculations:

\[
\sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4} = \sum_{V_3} f_{V_3,V_4} \cdot \left( \sum_{V_2} f_{V_2,V_3} \cdot \left( \sum_{V_1} f_{V_1,V_2} \cdot f_{V_1} \right) \right)
\]
Marginal Inference

\[
\sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4} = \sum_{V_3} f_{V_3,V_4} \cdot \left( \sum_{V_2} f_{V_2,V_3} \cdot \left( \sum_{V_1} f_{V_1,V_2} \cdot f_{V_1} \right) \right)
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Marginal Inference

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\sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4} \\
= \sum_{V_3} f_{V_3,V_4} \cdot f_{V_3}
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Marginal Inference

\[
\sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4}
\]

= \( f_{V_4} \)

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Variable Elimination

Given a factor graph with factors $f$, eliminate variable $V$.

1. Let $f_{\text{elim}} \subset f$ be the factors connected to $V$
2. Let $f_{\text{keep}} = f \setminus f_{\text{elim}}$ be the rest
3. Let $f_{\text{new}} = \sum_{V} \prod_{f \in f_{\text{elim}}} f$
4. Return $f_{\text{keep}} \cup \{f_{\text{new}}\}$

Uses the graph structure to avoid exponential blowup; this is an example of dynamic programming.
Marginal Inference by Variable Elimination (No Evidence)

Given a factor graph with variables $V$ and factors $f$, find the marginal distribution over some $V_{\text{keep}} \subset V$.

1. Order the variables in $V \setminus V_{\text{keep}}$.
2. For each $V \in V \setminus V_{\text{keep}}$:
   - Eliminate $V$; i.e., remove factors connected to $V$ and replace with the derived $f_{\text{new}}$.

The resulting factor graph is proportional to $p(V_{\text{keep}})$. 
Marginal Inference by Variable Elimination (No Evidence)

Given a factor graph with variables $V$ and factors $f$, find the marginal distribution over some $V_{\text{keep}} \subset V$.

1. Order the variables in $V \setminus V_{\text{keep}}$.
   The ordering can make a huge difference!

2. For each $V \in V \setminus V_{\text{keep}}$:
   - Eliminate $V$; i.e., remove factors connected to $V$ and replace with the derived $f_{\text{new}}$.

The resulting factor graph is proportional to $p(V_{\text{keep}})$. 
A Less Good Ordering

\[ \sum_{V_1} \sum_{V_2} \sum_{V_3} f_{V_1} \cdot f_{V_1,V_2} \cdot f_{V_2,V_3} \cdot f_{V_3,V_4} \]

\[ = \sum_{V_1} f_{V_1} \cdot \left( \sum_{V_2} f_{V_1,V_2} \cdot \left( \sum_{V_3} f_{V_2,V_3} \cdot f_{V_3,V_4} \right) \right) \]
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What About Evidence?

Original problem: given $O = o$, what is the marginal distribution over $Q \subset U$? (I.e., $p(Q \mid O = o)$.)
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What About Evidence?

Original problem: given $O = o$, what is the marginal distribution over $Q \subset U$? (I.e., $p(Q | O = o)$.)

This adds a step at the beginning: reduce factors to “respect the evidence.”

This will remind you of a select . . . where operation in a database.
Marginal Inference

Suppose $V_1$ is observed to take value 1.
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Marginal Inference

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Note that $f_{V_1}$ is now a constant; since we renormalize at the end, we can ignore it. Observed nodes may create a “separation” between variables of interest and some factors.
Marginal Inference by Variable Elimination with Evidence

Given a factor graph with variables $V$ and factors $f$, and given $O = o$ (where $O \subset V$), find the marginal distribution over $Q \subseteq U = V \setminus O$.

1. Reduce factors connected to $O$ to respect the evidence.
2. Order the variables in $U \setminus Q$.
3. For each $V \in U \setminus Q$:
   - Eliminate $V$; i.e., remove factors connected to $V$ and replace with the derived $f_{new}$.

The resulting factor graph is proportional to $p(Q \mid O = o)$. 
Remarks on Computational Complexity

In general, denser graphs are more expensive.

Runtime and space depend on the size of the original and intermediate factors. (This is why ordering matters so much.)

Finding the best ordering is NP-hard.

Certain graphical structures allow inference in linear time with respect to the size of the original factors.

- Bayesian networks: polytrees
- Markov networks: chordal graphs
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  - This is called the forward-backward algorithm.
  - This is useful when we want to apply EM to HMMs (unsupervised sequence modeling).
  - It is also useful in supervised learning.
Related Topics

- Conditional random fields
- MPE inference
- MAP inference
- Inexact inference
Conditional Random Fields (Sequence Version)
Lafferty et al. (2001)

A nice confluence:

- Probabilistic graphical model-style reasoning, as in HMMs.
- Discriminative training, as with structured perceptron.

Local factors: \( f_i(x, y, y') = \exp (w \cdot \phi(x, i, y, y')) \)

Log loss, where the graphical model parameterizes the probability distribution:

\[
\sum_{i=1}^{n} \log \sum_{y \in \mathcal{L}_{\ell_i+1}} \exp \left( w \cdot \sum_{j=1}^{\ell_i+1} \phi(x_i, j, y_j, y_{j-1}) \right)
\]

- Fear

\[
- w \cdot \sum_{j=1}^{\ell_i+1} \phi(x_i, j, y_i, y_{i-1})
\]

- Hope
Conditional Random Fields (General Version)

Factor graph consisting of “input” variables $X$ (always observed) and “output” variables $Y$.

$$ p(Y = y \mid X = x) = \frac{\prod_j f_j(x, y_{I_j})}{\sum_{y' \in \text{Val}(Y)} \prod_j f_j(x, y'_{I_j})} $$

MLE:

$$ \sum_{i=1}^{n} \log \sum_{y \in \text{Val}(Y)} \prod_j f_j(x_i, y_{I_j}) - \log \prod_j f_j(x_i, y_i_{I_j}) $$

Marginal inference is required for calculating the left term and its gradient with respect to $w$. 
MPE Inference

$$\arg\max_{u \in \text{Val}(U)} p(U = u \mid O = o)$$
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Just replace each sum operation with a max operation, and add bookkeeping to recover the most probable assignment.
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The Viterbi algorithm is, of course, an instance of this. Each “$$s_i(*)$$” is an intermediate factor.
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The Viterbi algorithm is, of course, an instance of this. Each “\(s_i(\ast)\)” is an intermediate factor.

Specifically for sequence models, it should be clear how factors/features that depend on the observed sequence \(X\) don’t affect the asymptotics of exact inference.
Rocket Science: True MAP

Given a factor graph with variables $V$ and factors $f$, and given $O = o$ (where $O \subset V$), find the most probable assignment of $Q \subset U = V \setminus O$.

Let $R = U \setminus Q$.

\[
\arg\max_{q \in \text{Val}(Q)} p(Q = q \mid O = o)
\]

\[
= \arg\max_{q \in \text{Val}(Q)} \sum_{r \in \text{Val}(R)} p(Q = q, R = r \mid O = o)
\]

Solution: first use marginal inference to eliminate $R$, then use max inference to solve for $Q$. 
Alternative Inference Methods

Huge range of techniques!

Exact:
  - Integer linear programming

Inexact:
  - randomized (e.g., Gibbs sampling, importance sampling, simulated annealing)
  - deterministic (e.g., mean field variational, loopy belief propagation, linear programming relaxations, dual decomposition, beam search)
Readings and Reminders

- Koller et al. (2007)
- Submit a suggestion for an exam question by Friday at 5pm.
- Your project is due March 9.