# Log-Linear Models with Structured Outputs

Natural Language Processing
CS 4120/6120—Spring 2015
Northeastern University

David Smith
(some slides from Andrew McCallum)

# Overview

- Sequence labeling task (cf. POS tagging)
- Independent classifiers
- HMMs
- (Conditional) Maximum Entropy Markov Models
- Conditional Random Fields
- Beyond Sequence Labeling

# Sequence Labeling

- Inputs: $x = (x_1, \ldots, x_n)$
- Labels: $y = (y_1, \ldots, y_n)$
- Typical goal: Given x, predict y

- Example sequence labeling tasks
  - Part-of-speech tagging
  - Named-entity-recognition (NER)
    - Label people, places, organizations

# NER Example:

## Red Sox and Their Fans Let Loose


Elise Amendola/Associated Press

Fans of the slugger David Ortiz in Boston's Copley Square.

By PETE THAMEL
Published: October 31, 2007

BOSTON, Oct. 30 — Jonathan Papelbon turned Boston's World Series victory parade into a full-scale dance party Tuesday as the Red Sox put an exclamation point on the 2007 season.

E-MAIL
PRINT
REPRINTS
SAVE

# First Solution: Maximum Entropy Classifier

- Conditional model $p(y|x)$.
  - Do not waste effort modeling $p(x)$, since x is given at test time anyway.
  - Allows more complicated input features, since we do not need to model dependencies between them.
- Feature functions $f(x,y)$:
  - $f_1(x,y)$ = { word is Boston & y=Location }
  - $f_2(x,y)$ = { first letter capitalized & y=Name }
  - $f_3(x,y)$ = { x is an HTML link & y=Location}

# First Solution: MaxEnt Classifier

- How should we choose a classifier?

- Principle of maximum entropy
  – We want a classifier that:
    - Matches feature constraints from training data.
    - Predictions maximize entropy.

- There is a unique, exponential family distribution that meets these criteria.

# First Solution: MaxEnt Classifier

- Problem with using a maximum entropy classifier for sequence labeling:
- It makes decisions at each position independently!

# Second Solution: HMM

$$P(\mathbf{y}, \mathbf{x}) = \prod_t P(y_t \mid y_{t-1}) P(x \mid y_t)$$

- Defines a generative process.
- Can be viewed as a weighted finite state machine.

# Second Solution: HMM

- How can represent we multiple features in an HMM?
  - Treat them as conditionally independent given the class label?
    - The example features we talked about are not independent.
  - Try to model a more complex generative process of the input features?
    - We may lose tractability (i.e. lose a dynamic programming for exact inference).

# Second Solution: HMM

- Let’s use a conditional model instead.

# Third Solution: MEMM

- Use a series of maximum entropy classifiers that know the previous label.
- Define a Viterbi algorithm for inference.

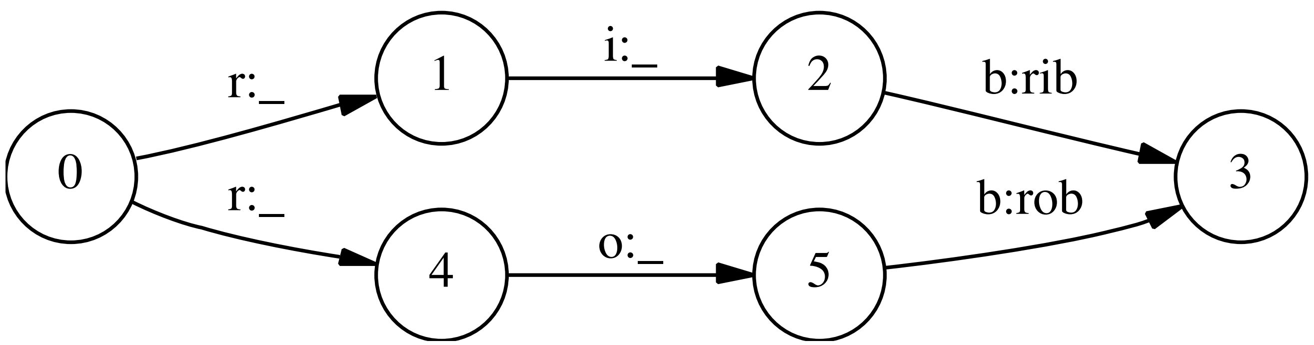
$$P(\mathbf{y} \mid \mathbf{x}) = \prod_t P_{y_{t-1}}(y_t \mid \mathbf{x})$$

# Third Solution: MEMM

- Combines the advantages of maximum entropy and HMM!
- But there is a problem…

# Problem with MEMMs: Label Bias

- In some state space configurations, MEMMs essentially completely ignore the inputs.




- This is not a problem for HMMs, because the input sequence is generated by the model.

# Fourth Solution: Conditional Random Field

- Conditionally-trained, undirected graphical model.
- For a standard linear-chain structure:

$$P(\mathbf{y} \mid \mathbf{x}) = \prod_t \Psi_k(y_t, y_{t-1}, \mathbf{x})$$

$$\Psi_k(y_t, y_{t-1}, \mathbf{x}) = \exp\left( \sum_k \lambda_k f(y_t, y_{t-1}, \mathbf{x}) \right)$$

# Fourth Solution: CRF

- Have the advantages of MEMMs, but avoid the label bias problem.

- CRFs are globally normalized, whereas MEMMs are locally normalized.

- Widely used and applied.  CRFs give state-the-art results in many domains.

# Fourth Solution: CRF

- Have the advantages of MEMMs, but avoid the label bias problem.
- CRFs are globally normalized, whereas MEMMs are locally normalized.
- Widely used and applie
  state-the-art results in r

Remember, $Z$ is the normalization constant. How do we compute it?

# CRF Applications

- Part-of-speech tagging
- Named entity recognition
- Document layout (e.g. table) classification
- Gene prediction
- Chinese word segmentation
- Morphological disambiguation
- Citation parsing
- Etc., etc.

# NER as Sequence Tagging

The Phoenicians came from the Red Sea

# NER as Sequence Tagging

| O | B-E | O | O | O | B-L | I-L |
|---|---|---|---|---|---|---|
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

Capitalized word

| | | | | | | |
|---|---|---|---|---|---|---|
| O | B-E | O | O | O | B-L | I-L |
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

Capitalized word

Ends in “s”

| | | | | | | |
|---|---|---|---|---|---|---|
| O | B-E | O | O | O | B-L | I-L |
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

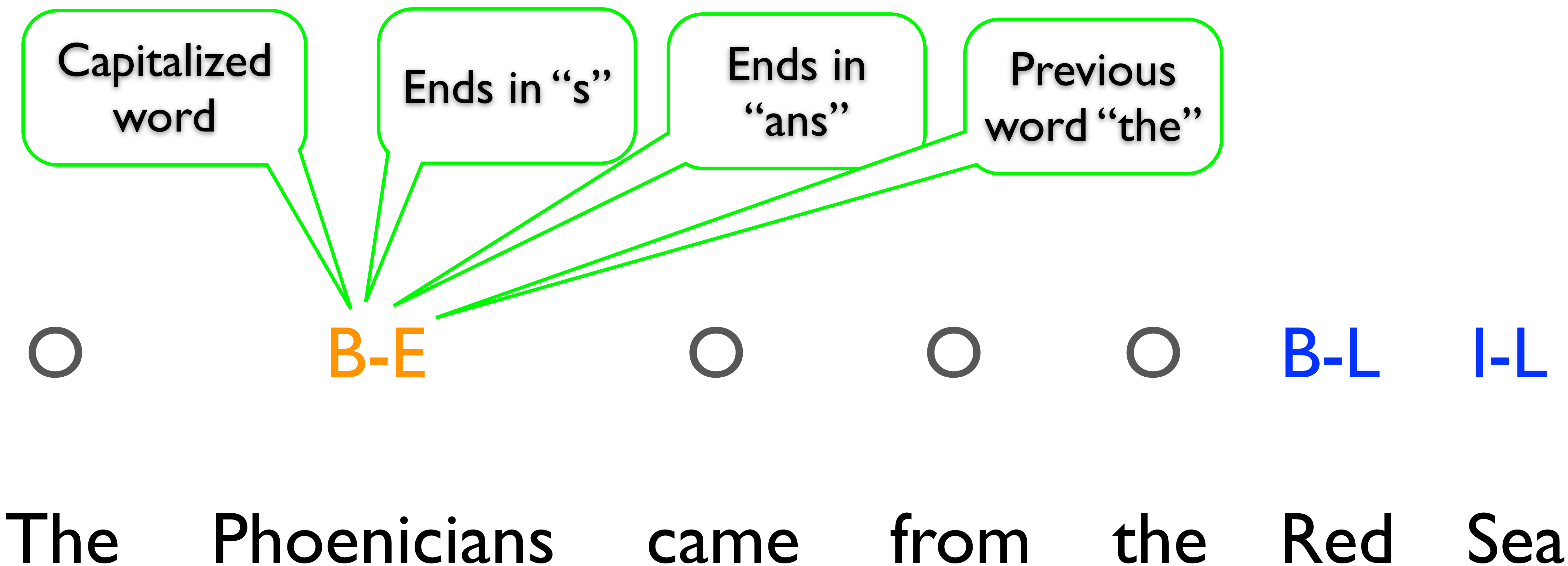
Capitalized word

Ends in "s"

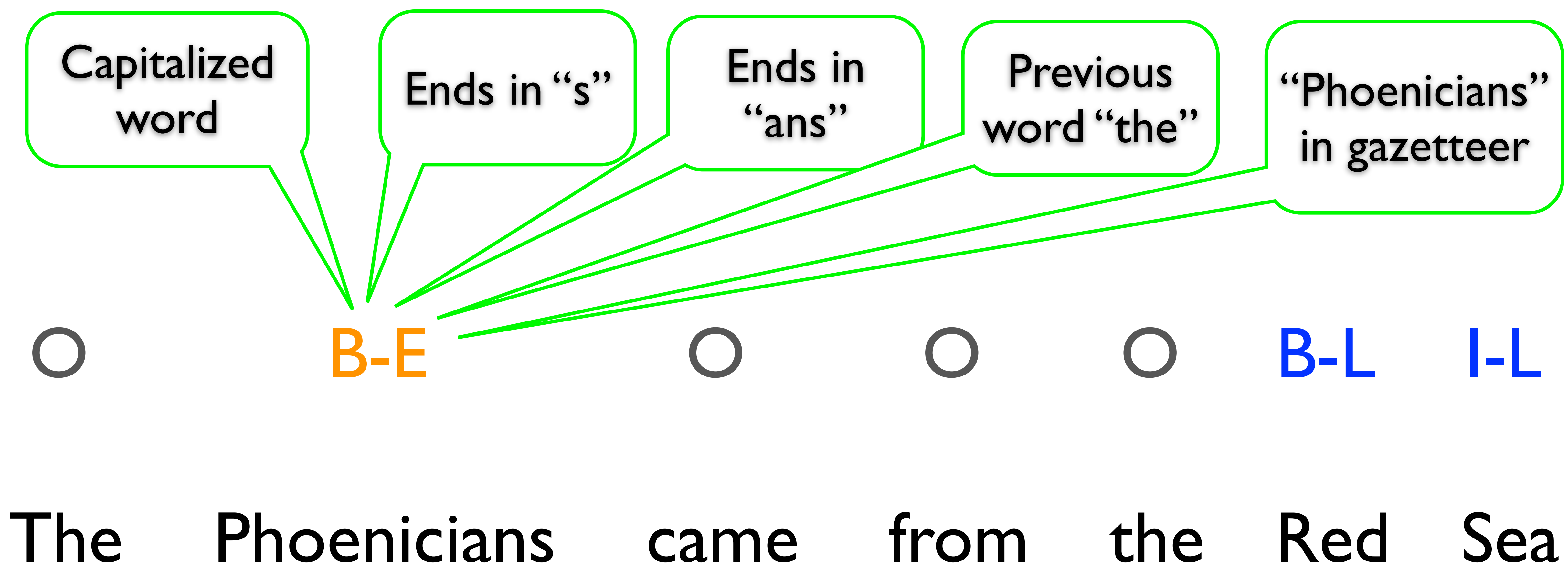
Ends in "ans"

| O | B-E | O | O | O | B-L | I-L |
|---|---|---|---|---|---|---|
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging



# NER as Sequence Tagging



# NER as Sequence Tagging

| O | B-E | O | O | O | B-L | I-L |
|---|---|---|---|---|---|---|
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

Not capitalized

| O | B-E | O | O | O | B-L | I-L |
|---|---|---|---|---|---|---|
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

Not capitalized

Tagged as “VB”

| | | | | | | |
|---|---|---|---|---|---|---|
| O | B-E | O | O | O | B-L | I-L |
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

B-E to right

Not capitalized

Tagged as "VB"

| | | | | | | |
|---|---|---|---|---|---|---|
| O | B-E | O | O | O | B-L | I-L |
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

| O | B-E | O | O | O | B-L | I-L |
|---|---|---|---|---|---|---|
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging

Word “sea”

| | | | | | | |
|---|---|---|---|---|---|---|
| O | B-E | O | O | O | B-L | I-L |
| The | Phoenicians | came | from | the | Red | Sea |

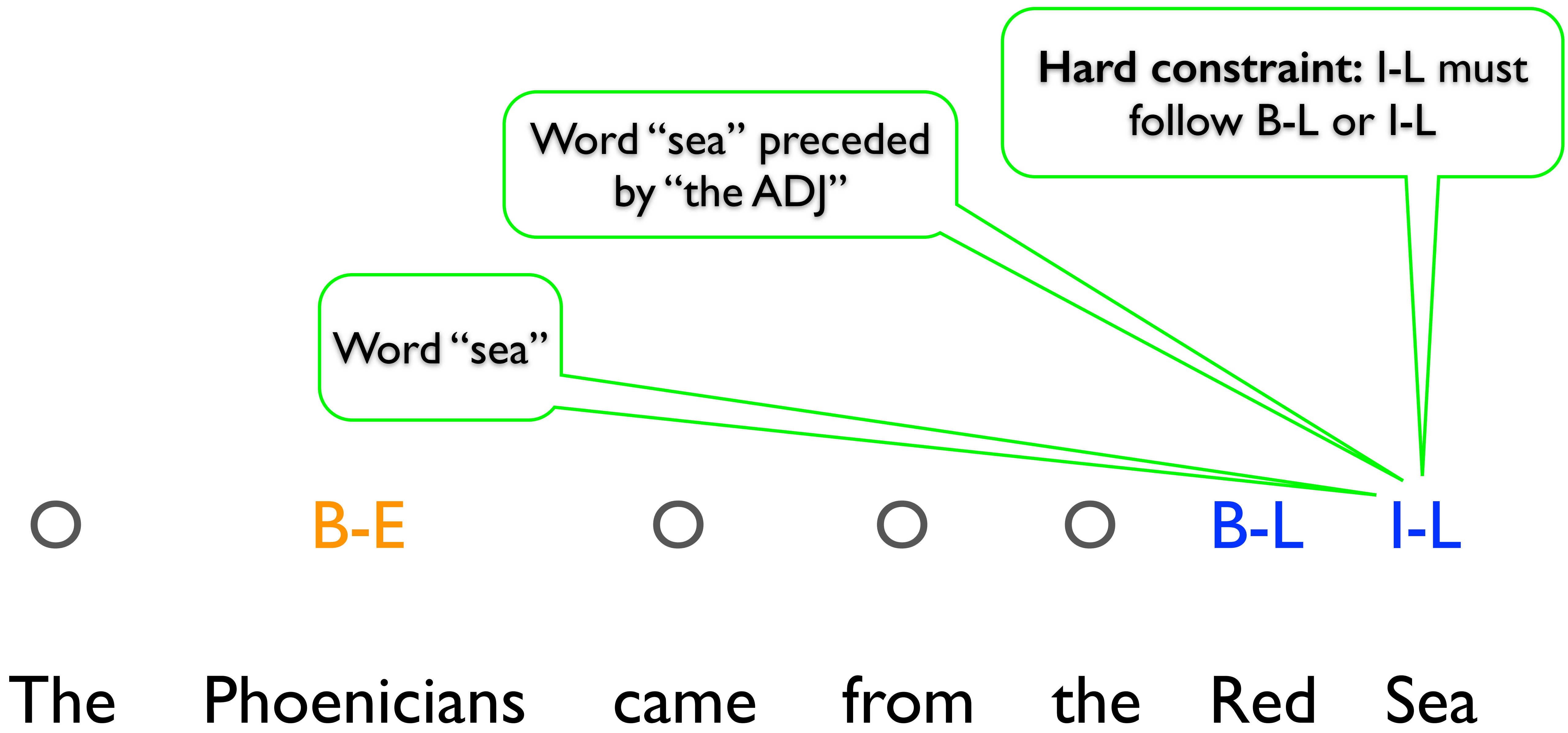
# NER as Sequence Tagging

Word “sea” preceded by “the ADJ”

Word “sea”

| | | | | | | |
|---|---|---|---|---|---|---|
| O | B-E | O | O | O | B-L | I-L |
| The | Phoenicians | came | from | the | Red | Sea |

# NER as Sequence Tagging



# Overview

- What computations do we need?
- Smoothing log-linear models
- MEMMs vs. CRFs again
  - Action-based parsing and dependency parsing

# Recipe for Conditional Training of p(y | x)

1. Gather constraints/features from training data

$$\alpha_{iy} = \tilde{E}[f_{iy}] = \sum_{x_j, y_j \in D} f_{iy}(x_j, y_j)$$

2. Initialize all parameters to zero
3. Classify training data with current parameters; calculate expectations

$$E_\Theta[f_{iy}] = \sum_{x_j \in D} \sum_{y'} p_\Theta(y'|x_j) f_{iy}(x_j, y')$$

4. Gradient is $\tilde{E}[f_{iy}] - E_\Theta[f_{iy}]$
5. Take a step in the direction of the gradient
6. Repeat from 3 until convergence

# Recipe for Conditional Training of p(y | x)

1. Gather constraints/features from training data
$$\alpha_{iy} = \tilde{E}[f_{iy}] = \sum_{x_j, y_j \in D} f_{iy}(x_j, y_j)$$
2. Initialize all parameters to zero
3. Classify training data with current parameters; calculate expectations $$E_\Theta[f_{iy}] = \sum_{x_j \in D} \sum_{y'} p_\Theta(y'|x_j) f_{iy}(x_j, y')$$
4. Gradient is $\tilde{E}[f_{iy}] - E_\Theta[f_{iy}]$
5. Take a step in the direction of the gradient
6. Repeat from 3 until convergence

Where have we seen expected counts before?

# Recipe for Conditional Training of p(y | x)

1. Gather constraints/features from training data

$$\alpha_{iy} = \tilde{E}[f_{iy}] = \sum_{x_j, y_j \in D} f_{iy}(x_j, y_j)$$

2. Initialize all parameters to zero
3. Classify training data with current parameters; calculate expectations

$$E_\Theta[f_{iy}] = \sum_{x_j \in D} \sum_{y'} p_\Theta(y'|x_j) f_{iy}(x_j, y')$$

4. Gradient is $\tilde{E}[f_{iy}] - E_\Theta[f_{iy}]$
5. Take a step in the direction of the gradient
6. Repeat from 3 until convergence

*EM!*

Where have we seen expected counts before?

# Gradient-Based Training

- $\lambda := \lambda + \text{rate} * \text{Gradient}(F)$
- After all training examples? (batch)
- After every example? (on-line)
- Use second derivative for faster learning?
- A big field: numerical optimization

# Overfitting

- If we have too many features, we can choose weights to model the training data perfectly
- If we have a feature that only appears in spam training, not ham training, it will get weight $\infty$ to maximize p(spam | feature) at 1.
- These behaviors
  - Overfit the training data
  - Will probably do poorly on test data

# Solutions to Overfitting

- Throw out rare features.
  - Require every feature to occur > 4 times, and > 0 times with ling, and > 0 times with spam.
- Only keep, e.g., 1000 features.
  - Add one at a time, always greedily picking the one that most improves performance on held-out data.
- Smooth the observed feature counts.
- Smooth the weights by using a prior.
  - max $p(\lambda|\text{data})$ = max $p(\lambda, \text{data}) = p(\lambda)p(\text{data}|\lambda)$
  - decree $p(\lambda)$ to be high when most weights close to 0

# Smoothing with Priors

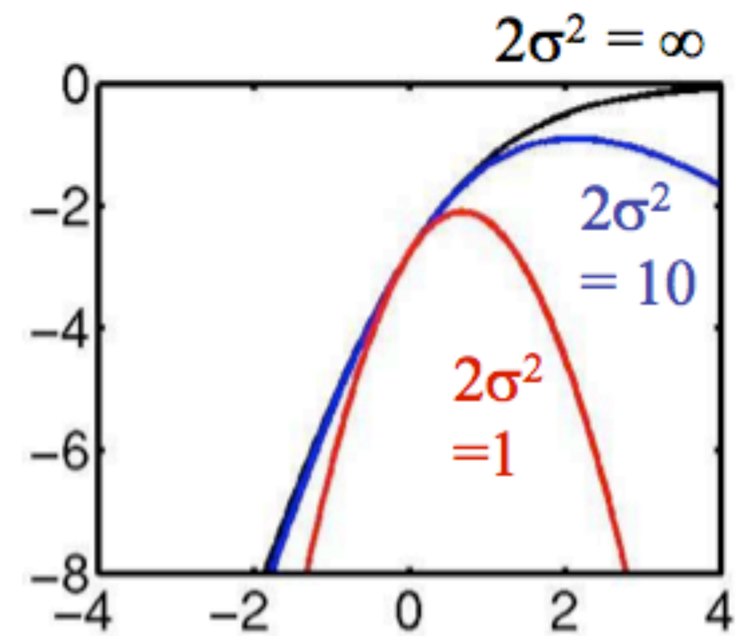
- What if we had a prior expectation that parameter values wouldn't be very large?
- We could then balance evidence suggesting large (or infinite) parameters against our prior expectation.
- The evidence would never totally defeat the prior, and parameters would be smoothed (and kept finite)
- We can do this explicitly by changing the optimization objective to maximum posterior likelihood:

  $$\log P(y, \lambda \mid x) = \log P(\lambda) + \log P(y \mid x, \lambda)$$

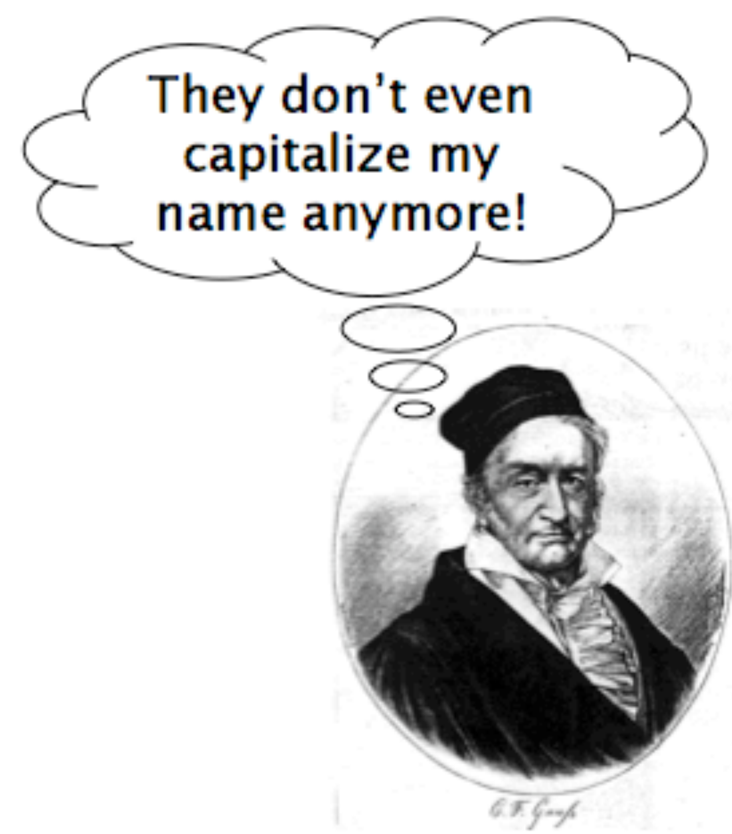
  Posterior Prior Likelihood

# Smoothing: Priors

- Gaussian, or quadratic, priors:
  - Intuition: parameters shouldn't be large.
  - Formalization: prior expectation that each parameter will be distributed according to a gaussian with mean $\mu$ and variance $\sigma^2$.




$$P(\lambda_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left( -\frac{(\lambda_i - \mu_i)^2}{2\sigma_i^2} \right)$$




  - Penalizes parameters for drifting to far from their mean prior value (usually $\mu$=0).
  - $2\sigma^2$=1 works surprisingly well.

# Parsing as Structured Prediction

## Shift-reduce parsing

| Stack | Input remaining | Action |
|---|---|---|
| () | Book that flight | shift |
| (Book) | that flight | reduce, Verb $\rightarrow$ book, (Choice #1 of 2) |
| (Verb) | that flight | shift |
| (Verb that) | flight | reduce, Det $\rightarrow$ that |
| (Verb Det) | flight | shift |
| (Verb Det flight) | | reduce, Noun $\rightarrow$ flight |
| (Verb Det Noun) | | reduce, NOM $\rightarrow$ Noun |
| (Verb Det NOM) | | reduce, NP $\rightarrow$ Det NOM |
| (Verb NP) | | reduce, VP $\rightarrow$ Verb NP |
| (Verb) | | reduce, S $\rightarrow$ V |
| (S) | | SUCCESS! |

Ambiguity may lead to the need for backtracking.

# Shift-reduce parsing

| Stack | Input remaining | Action |
|---|---|---|
| () | Book that flight | shift |
| (Book) | that flight | reduce, Verb $\longrightarrow$ book, (Choice #1 of 2) |
| (Verb) | that flight | shift |
| (Verb that) | flight | reduce, Det $\longrightarrow$ that |
| (Verb Det) | flight | shift |
| (Verb Det flight) | | reduce, Noun $\longrightarrow$ flight |
| (Verb Det Noun) | | reduce, NOM $\longrightarrow$ Noun |
| (Verb Det NOM) | | reduce, NP $\longrightarrow$ Det NOM |
| (Verb NP) | | reduce, VP $\longrightarrow$ Verb NP |
| (Verb) | | reduce, S $\longrightarrow$ V |
| (S) | | SUCCESS! |

~~Ambiguity may lead to the need for backtracking.~~

## Shift-reduce parsing

| **Stack** | **Input remaining** | **Action** |
|---|---|---|
| () | Book that flight | shift |
| (Book) | that flight | reduce, Verb $\rightarrow$ book, (Choice #1 of 2) |
| (Verb) | that flight | shift |
| (Verb that) | flight | reduce, Det $\rightarrow$ that |
| (Verb Det) | flight | shift |
| (Verb Det flight) | | reduce, Noun $\rightarrow$ flight |
| (Verb Det Noun) | | reduce, NOM $\rightarrow$ Noun |
| (Verb Det NOM) | | reduce, NP $\rightarrow$ Det NOM |
| (Verb NP) | | reduce, VP $\rightarrow$ Verb NP |
| (Verb) | | reduce, S $\rightarrow$ V |
| (S) | | SUCCESS! |

~~Ambiguity may lead to the need for backtracking.~~

Train log-linear model of p(action | context)

Compare to an MEMM

**Shift-reduce parsing**

| **Stack** | **Input remaining** | **Action** |
|---|---|---|
| () | Book that flight | shift |
| (Book) | that flight | reduce, Verb $\rightarrow$ book, (Choice #1 of 2) |
| (Verb) | that flight | shift |
| (Verb that) | flight | reduce, Det $\rightarrow$ that |
| (Verb Det) | flight | shift |
| (Verb Det flight) | | reduce, Noun $\rightarrow$ flight |
| (Verb Det Noun) | | reduce, NOM $\rightarrow$ Noun |
| (Verb Det NOM) | | reduce, NP $\rightarrow$ Det NOM |
| (Verb NP) | | reduce, VP $\rightarrow$ Verb NP |
| (Verb) | | reduce, S $\rightarrow$ V |
| (S) | | SUCCESS! |

~~Ambiguity may lead to the need for backtracking.~~

Train log-linear model of p(action | context)

# Structured Log-Linear Models

# Structured Log-Linear Models

- Linear model for scoring structures

$$\text{score}(out, in) = \theta \cdot \mathbf{features}(out, in)$$

# Structured Log-Linear Models

- Linear model for scoring structures
- Get a probability distribution by normalizing

$$\text{score}(out, in) = \theta \cdot \mathbf{features}(out, in)$$

$$p(out \mid in) = \frac{1}{Z} e^{score(out,in)} \quad Z = \sum_{out' \in GEN(in)} e^{score(out',in)}$$

# Structured Log-Linear Models

- Linear model for scoring structures
- Get a probability distribution by normalizing
  - Viz. logistic regression, Markov random fields, undirected graphical models

$$\text{score}(out, in) = \theta \cdot \mathbf{features}(out, in)$$

$$p(out \mid in) = \frac{1}{Z} e^{score(out,in)} \quad Z = \sum_{out' \in GEN(in)} e^{score(out',in)}$$

# Structured Log-Linear Models

- Linear model for scoring structures
- Get a probability distribution by normalizing
  - Viz. logistic regression, Markov random fields, undirected graphical models

Usually the bottleneck in NLP

$$\text{score}(out, in) = \theta \cdot \mathbf{features}(out, in)$$

$$p(out \mid in) = \frac{1}{Z} e^{score(out,in)} \quad Z = \sum_{out' \in GEN(in)} e^{score(out',in)}$$

# Structured Log-Linear Models

- Linear model for scoring structures
- Get a probability distribution by normalizing
  - Viz. logistic regression, Markov random fields, undirected graphical models
- Inference: sampling, variational methods, dynamic programming, local search, ...

Usually the bottleneck in NLP

$$\text{score}(out, in) = \theta \cdot \textbf{features}(out, in)$$

$$p(out \mid in) = \frac{1}{Z} e^{score(out,in)} \quad Z = \sum_{out' \in GEN(in)} e^{score(out',in)}$$

# Structured Log-Linear Models

- Linear model for scoring structures
- Get a probability distribution by normalizing
  - Viz. logistic regression, Markov random fields, undirected graphical models
- Inference: sampling, variational methods, dynamic programming, local search, ...
- Training: maximum likelihood, minimum risk, etc.

Usually the bottleneck in NLP

$$\text{score}(out, in) = \theta \cdot \mathbf{features}(out, in)$$

$$p(out \mid in) = \frac{1}{Z} e^{score(out,in)} \quad Z = \sum_{out' \in GEN(in)} e^{score(out',in)}$$

# Structured Log-Linear Models

*With latent variables*

- Several layers of linguistic structure
- Unknown correspondences
- Naturally handled by probabilistic framework
- Several inference setups, for example:

$$p(out_1 \mid in) = \sum_{out_2, alignment} p(out_1, out_2, alignment \mid in)$$

# Structured Log-Linear Models

*With latent variables*

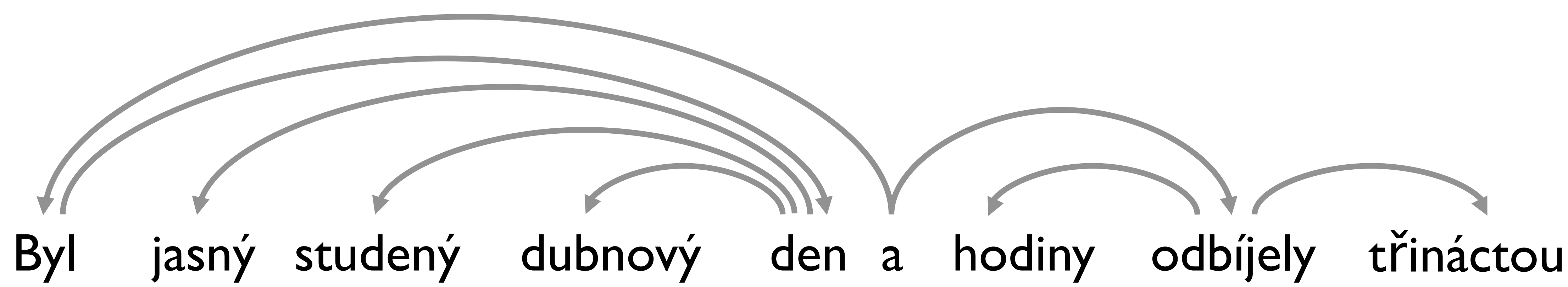
- Several layers of linguistic structure
- Unknown correspondences
- Naturally handled by probabilistic framework
- Several inference setups, for example:

$$p(out_1 \mid in) = \sum_{out_2, alignment} p(out_1, out_2, alignment \mid in)$$

Another computational problem

# Edge-Factored Parsers

- No <u>global</u> features of a parse *(McDonald et al. 2005)*
- Each feature is attached to some edge
- *MST or CKY-like DP for fast $O(n^2)$ or $O(n^3)$ parsing*




"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- Is this a good edge?

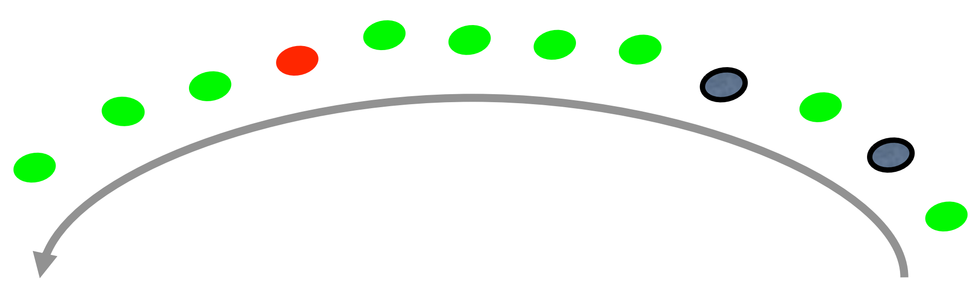
Byl jasný studený dubnový den a hodiny odbíjely třináctou

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- Is this a good edge?

yes, lots of positive features ...

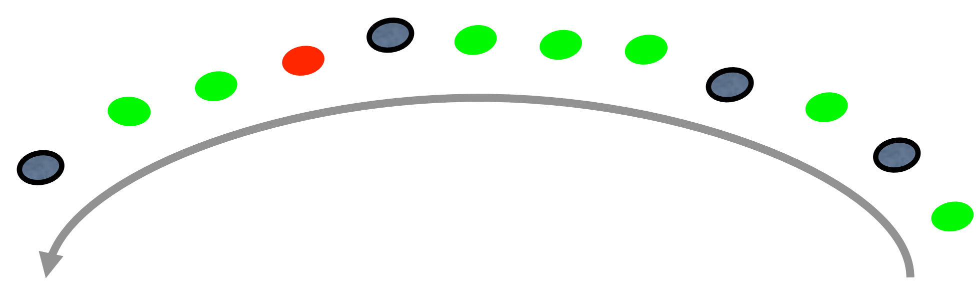


Byl jasný studený dubnový den a hodiny odbíjely třináctou

“It was a bright cold day in April and the clocks were striking thirteen”

# Edge-Factored Parsers

- Is this a good edge?

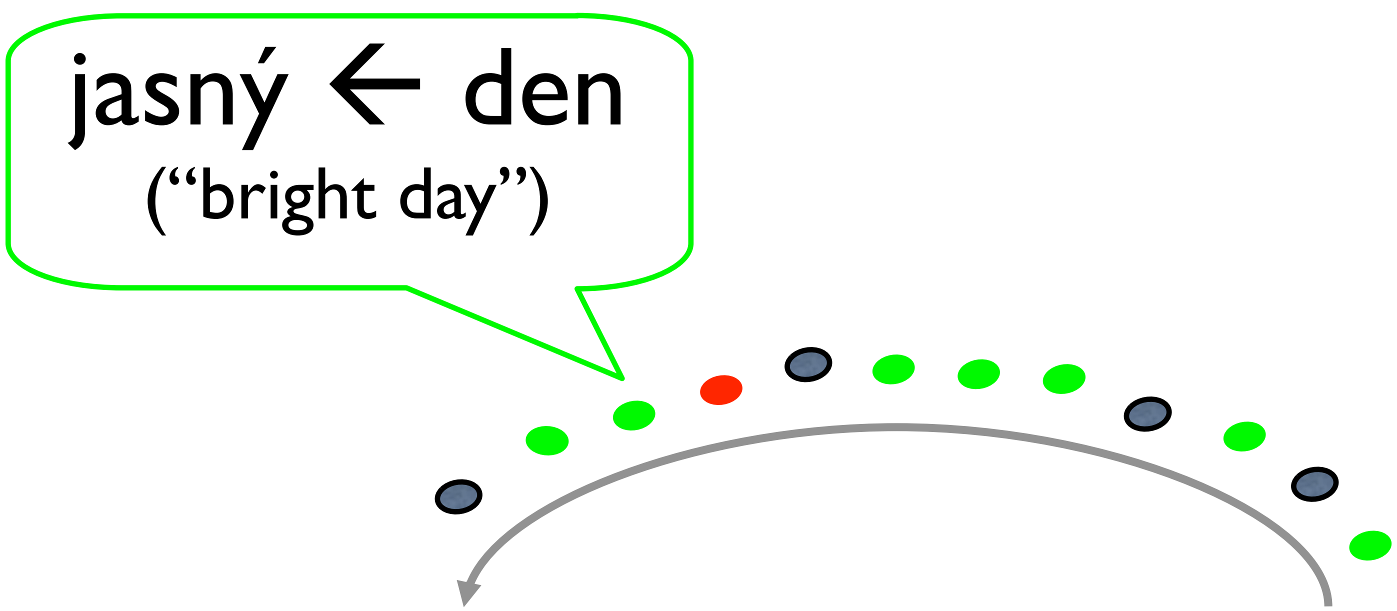


Byl jasný studený dubnový den a hodiny odbíjely třináctou

“It was a bright cold day in April and the clocks were striking thirteen”

# Edge-Factored Parsers

- Is this a good edge?

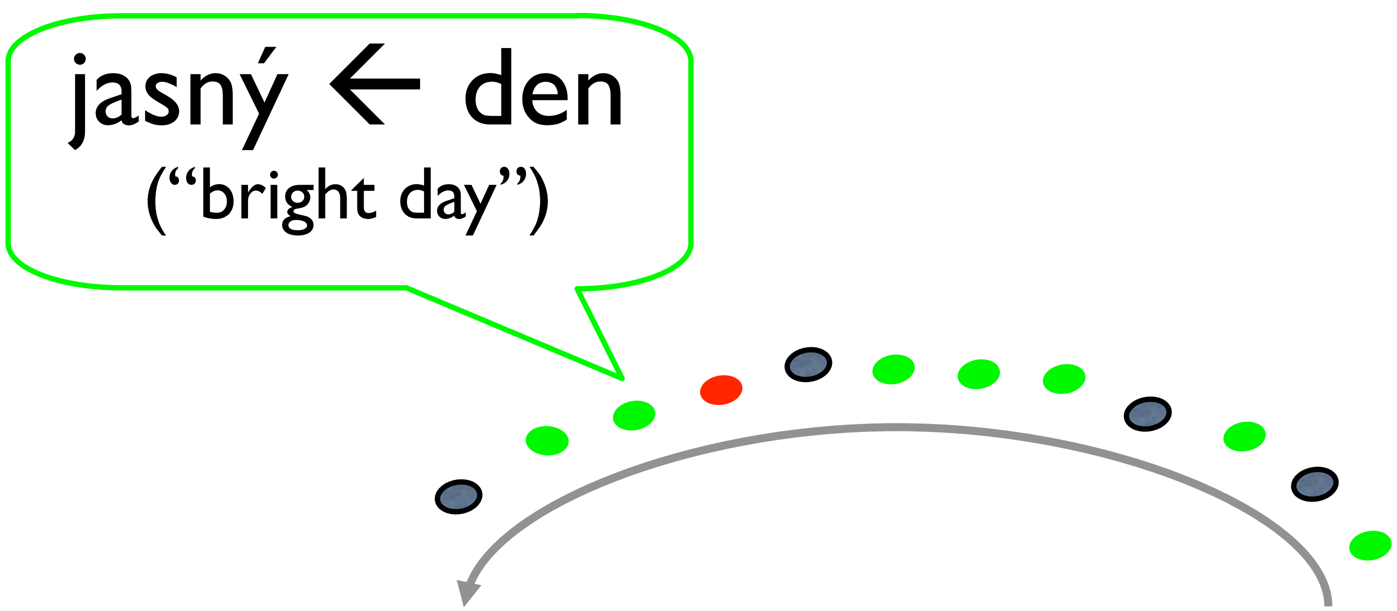



Byl jasný studený dubnový den a hodiny odbíjely třináctou

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- Is this a good edge?

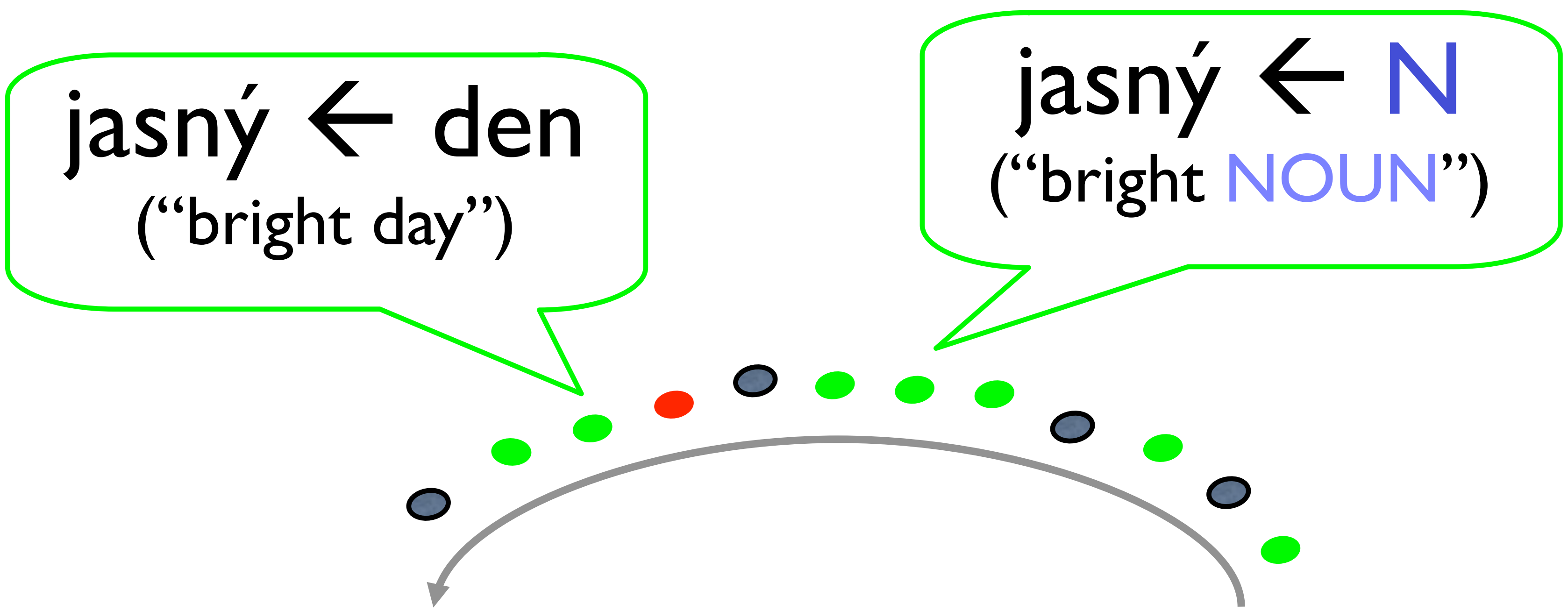



| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Byl | jasný | studený | dubnový | den | a | hodiny | odbíjely | třináctou |
| V | A | A | A | N | J | N | V | C |

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- Is this a good edge?



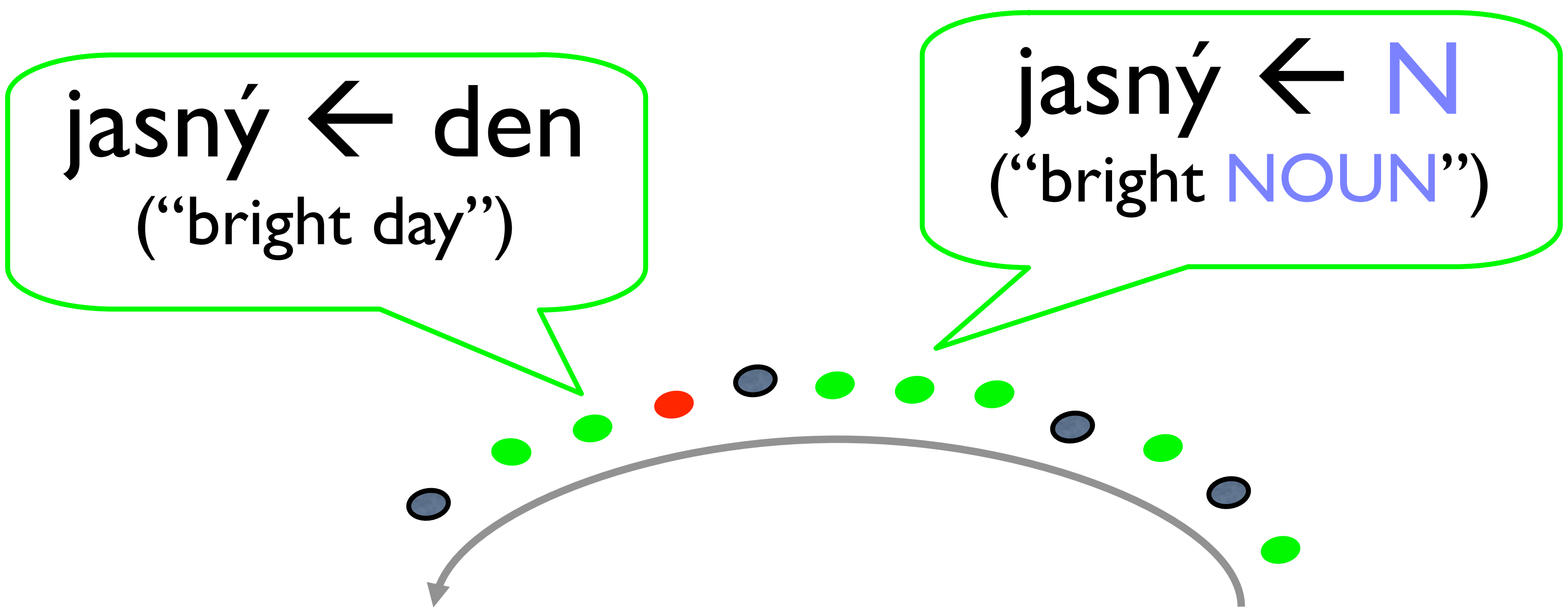

Byl jasný studený dubnový den a hodiny odbíjely třináctou

V A A A N J N V C

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- Is this a good edge?



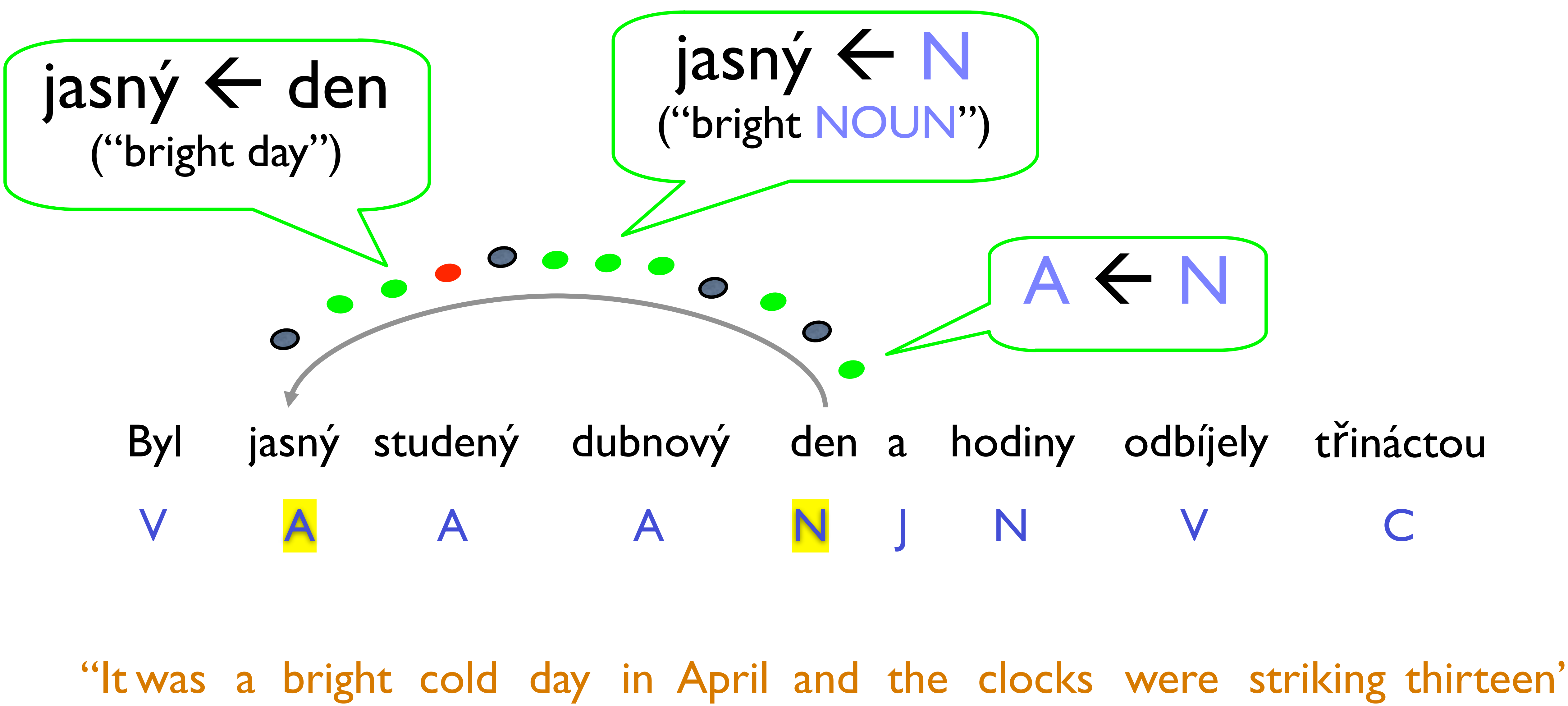

Byl jasný studený dubnový den a hodiny odbíjely třináctou

V A A A N J N V C

"It was a bright cold day in April and the clocks were striking thirteen"

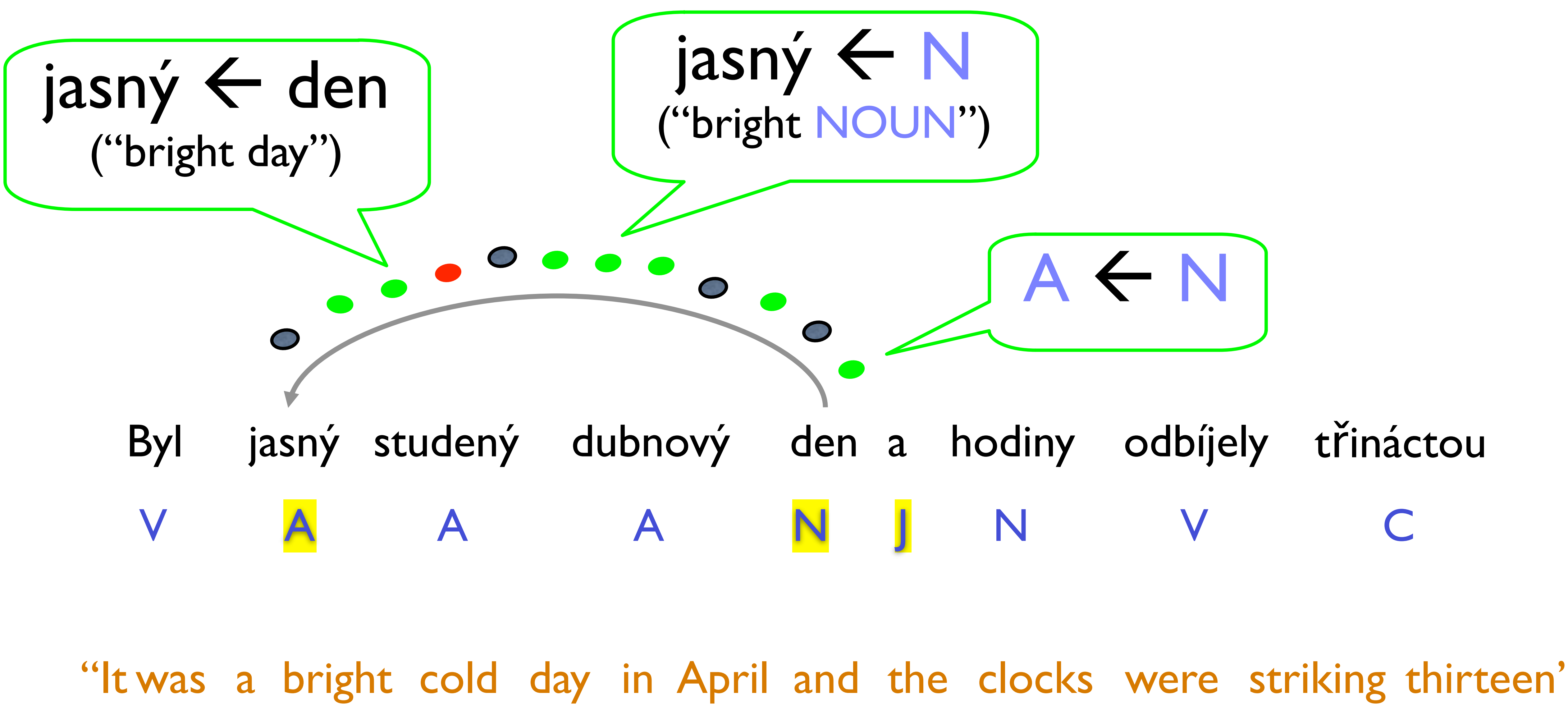
# Edge-Factored Parsers

- Is this a good edge?



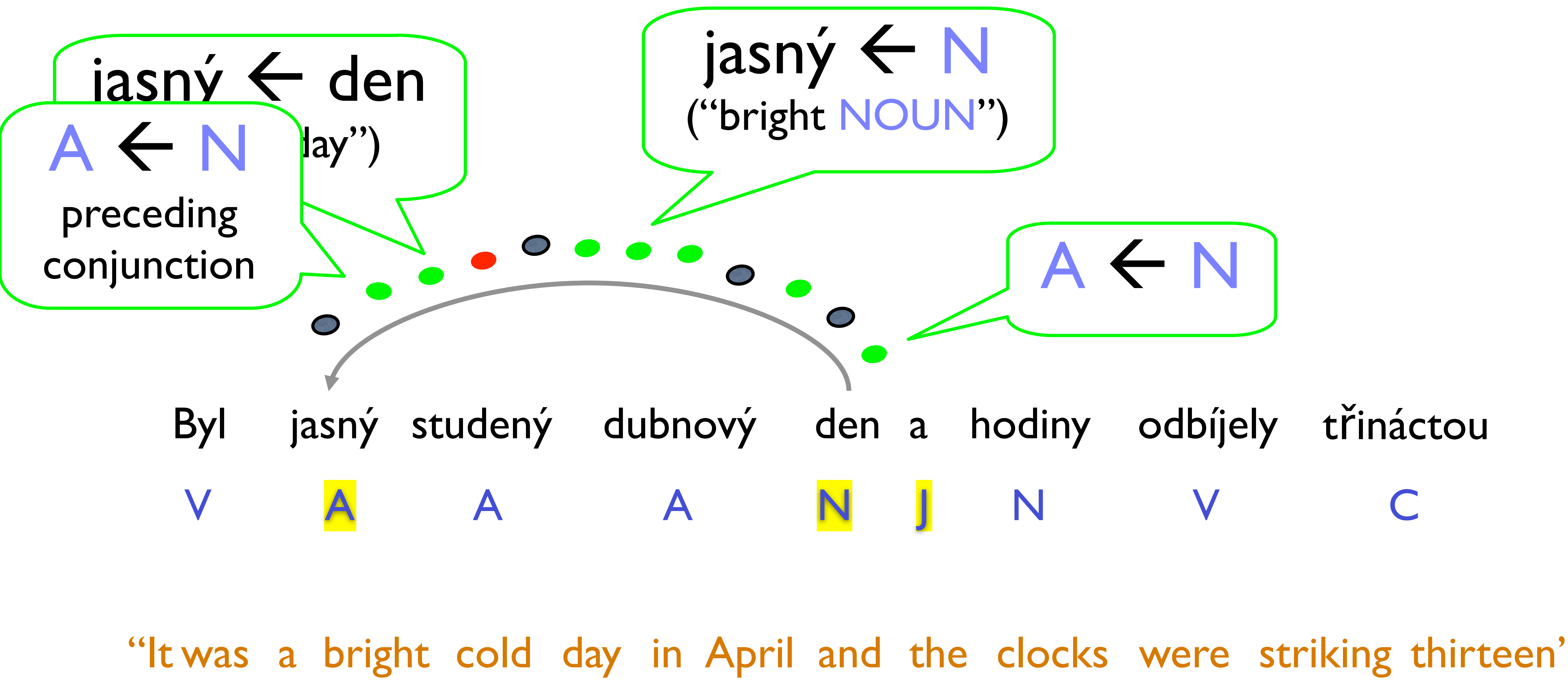
# Edge-Factored Parsers

- Is this a good edge?



# Edge-Factored Parsers

- Is this a good edge?



# Edge-Factored Parsers

- How about this competing edge?

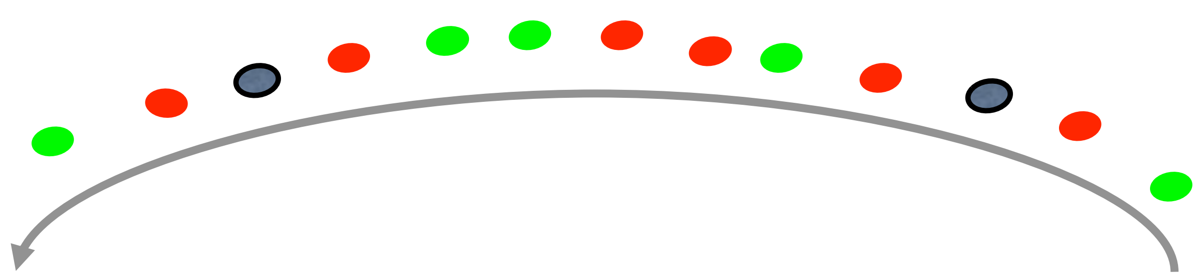
| Byl | jasný | studený | dubnový | den | a | hodiny | odbíjely | třináctou |
|---|---|---|---|---|---|---|---|---|
| V | A | A | A | N | J | N | V | C |

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- How about this competing edge?

not as good, lots of red ...



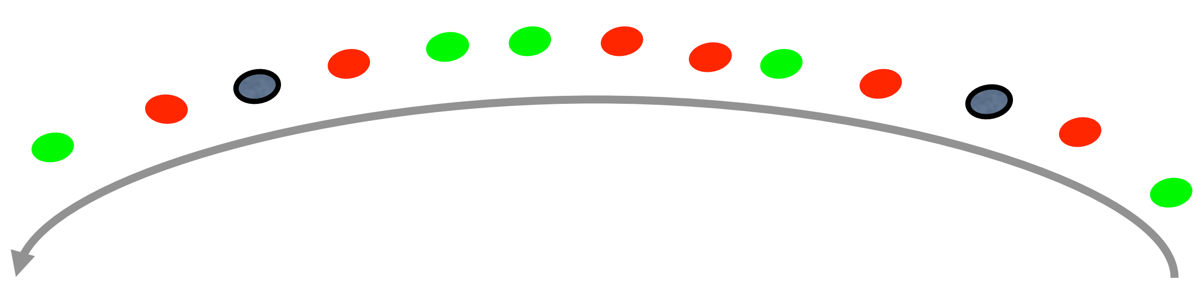
Byl jasný studený dubnový den a hodiny odbíjely třináctou

V A A A N J N V C

“It was a bright cold day in April and the clocks were striking thirteen”

# Edge-Factored Parsers

- How about this competing edge?



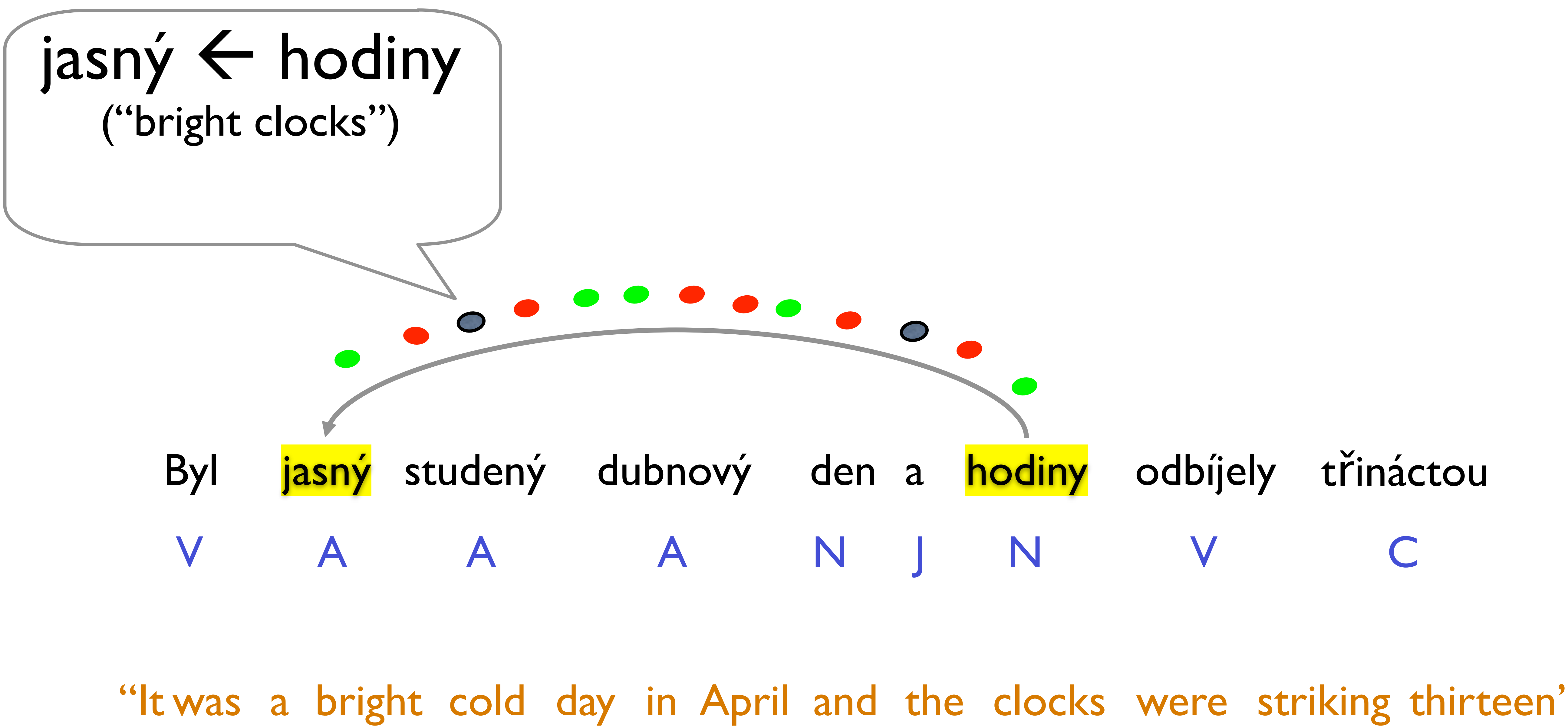
Byl jasný studený dubnový den a hodiny odbíjely třináctou

V A A A N J N V C

“It was a bright cold day in April and the clocks were striking thirteen”

# Edge-Factored Parsers

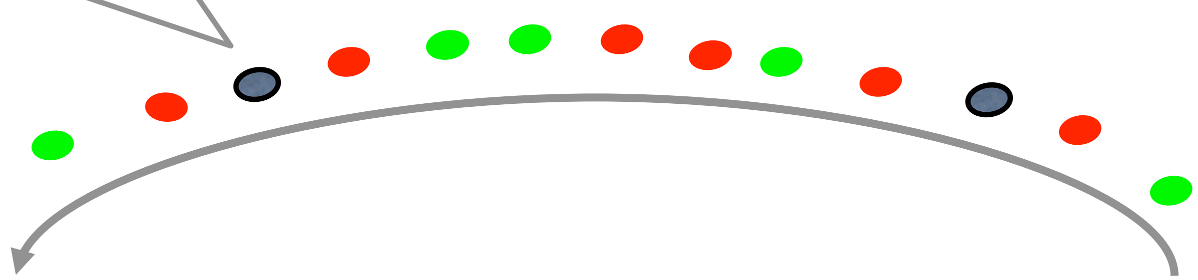
- How about this competing edge?



# Edge-Factored Parsers

- How about this competing edge?

jasný ← hodiny
("bright clocks")
*... undertrained ...*



Byl jasný studený dubnový den a hodiny odbíjely třináctou

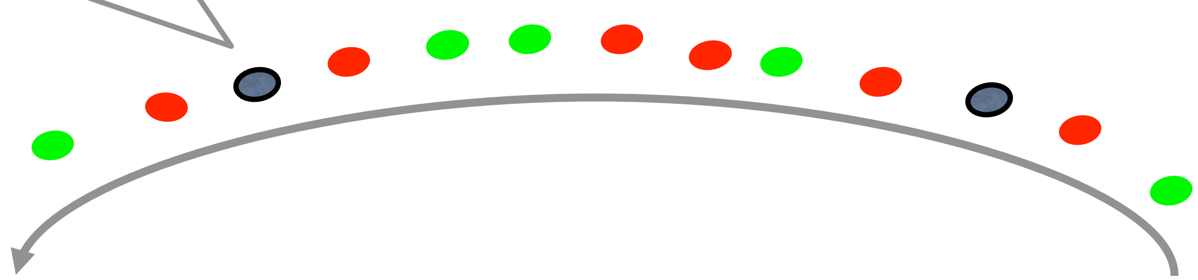
V A A A N J N V C

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- How about this competing edge?

jasný ← hodiny
(“bright clocks”)
*... undertrained ...*



Byl jasný studený dubnový den a hodiny odbíjely třináctou

V A A A N J N V C

byl jasn stud dubn den a hodi odbí třin

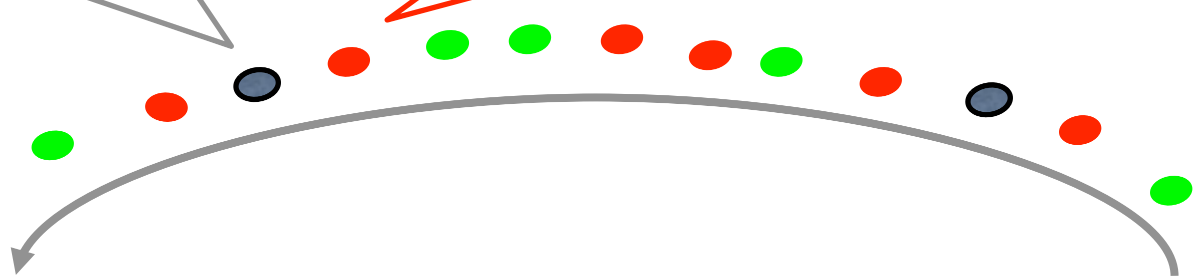
“It was a bright cold day in April and the clocks were striking thirteen”

# Edge-Factored Parsers

- How about this competing edge?

jasný ← hodiny
("bright clocks")
*... undertrained ...*

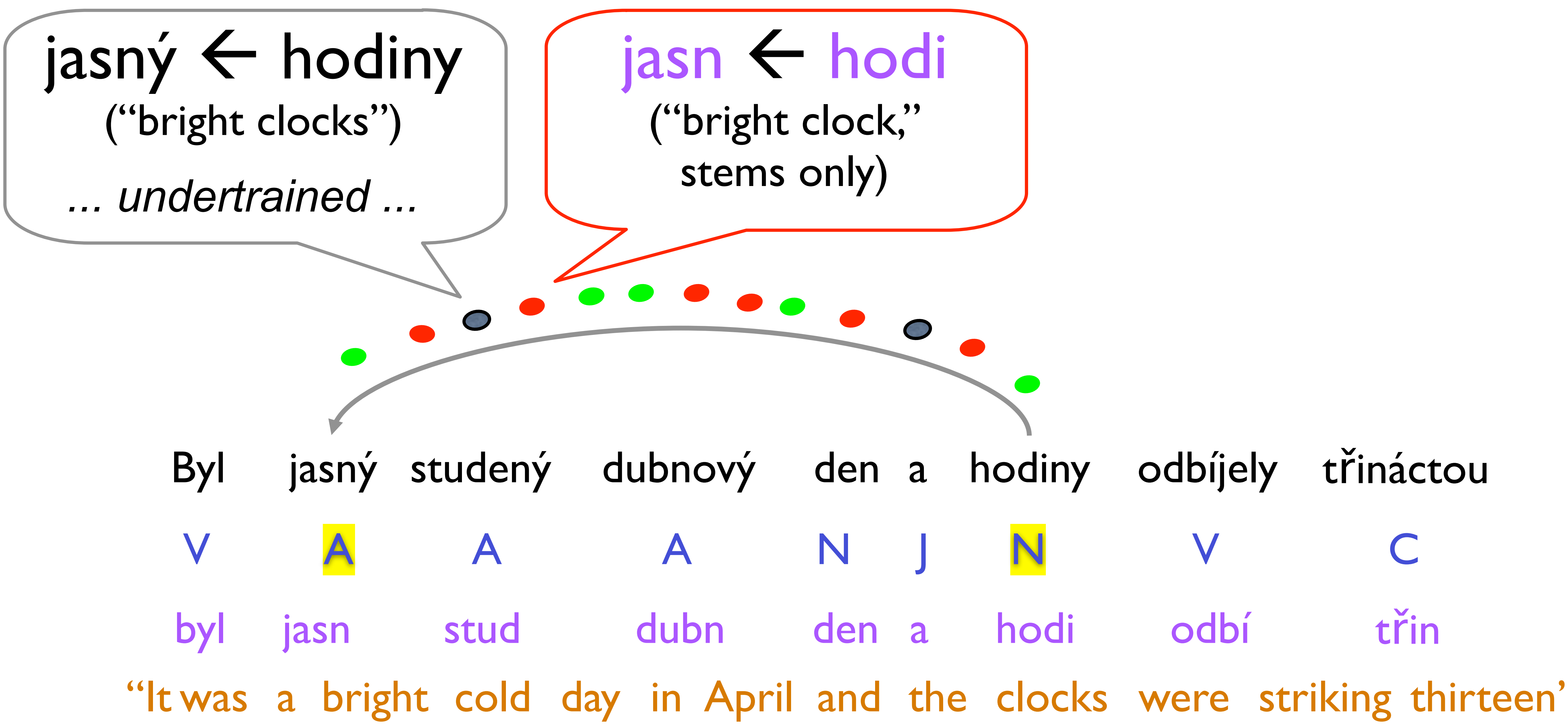
jasn ← hodi
("bright clock," stems only)



| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Byl | jasný | studený | dubnový | den | a | hodiny | odbíjely | třináctou | | |
| V | A | A | A | N | J | N | V | C | | |
| byl | jasn | stud | dubn | den | a | hodi | odbí | třin | | |
| "It was | a | bright | cold | day | in | April | and | the | clocks | were striking thirteen" |

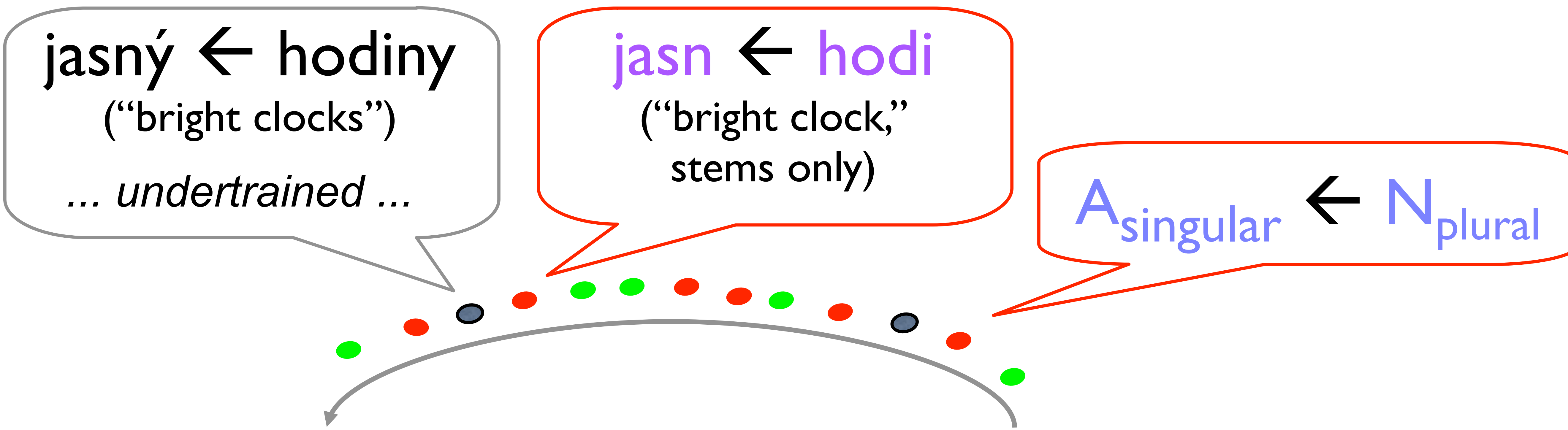
# Edge-Factored Parsers

- How about this competing edge?



# Edge-Factored Parsers

- How about this competing edge?

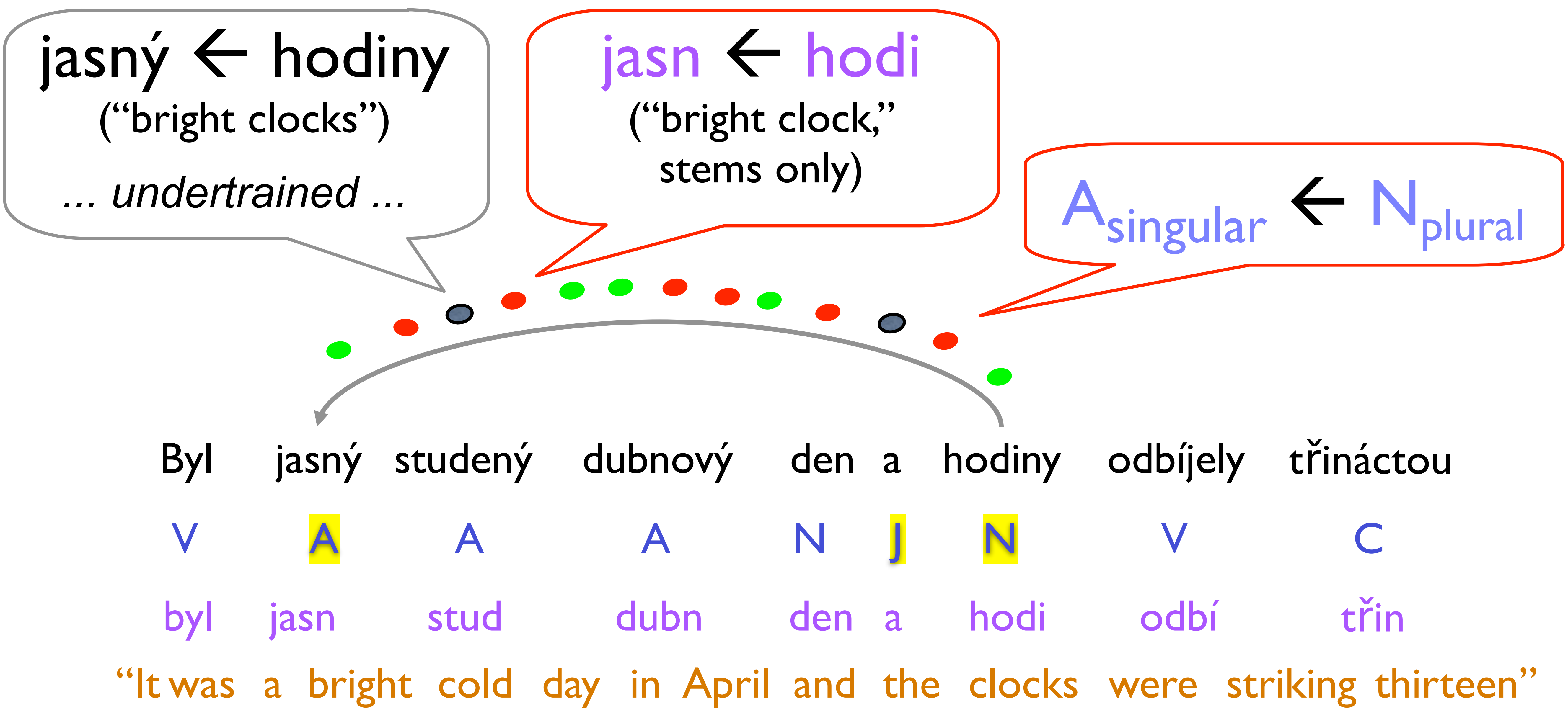



| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Byl | jasný | studený | dubnový | den | a | hodiny | odbíjely | třináctou |
| V | A | A | A | N | J | N | V | C |
| byl | jasn | stud | dubn | den | a | hodi | odbí | třin |

"It was a bright cold day in April and the clocks were striking thirteen"

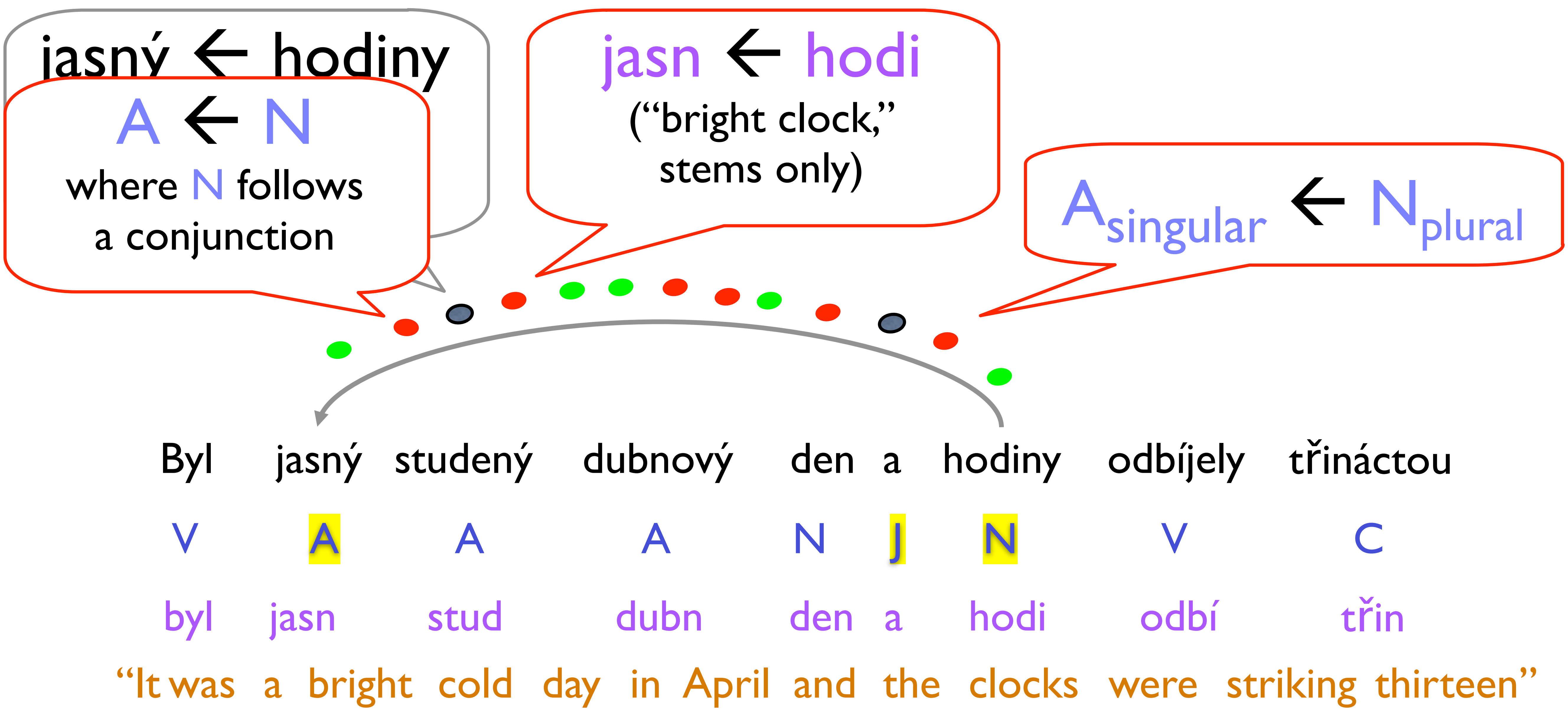
# Edge-Factored Parsers

- How about this competing edge?



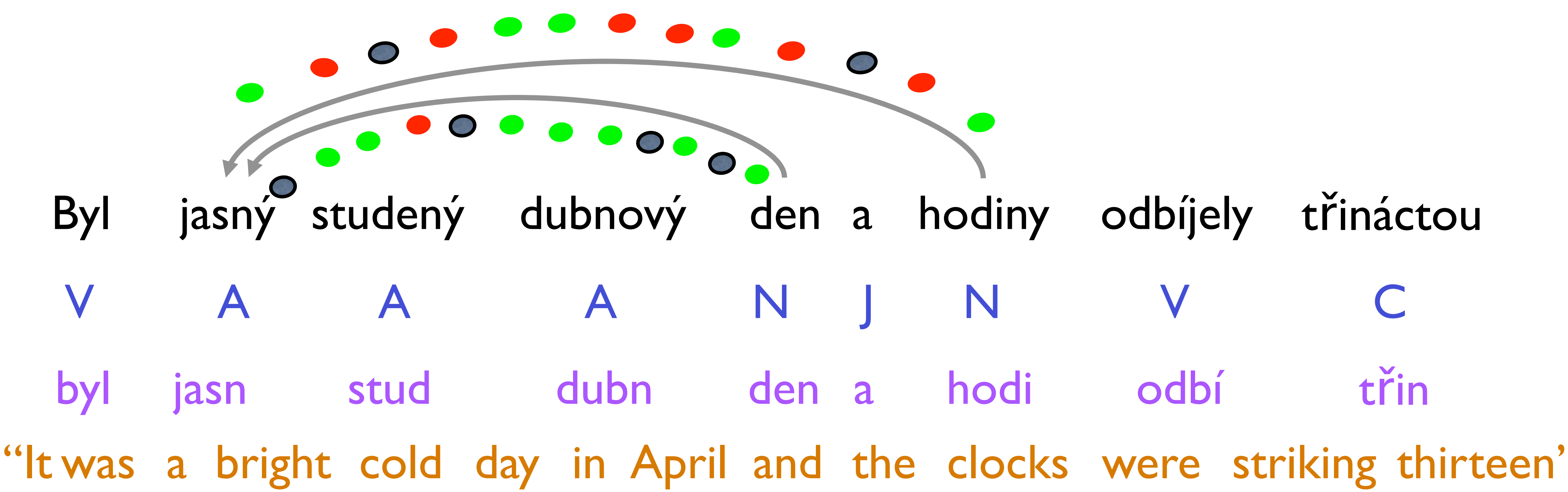
# Edge-Factored Parsers

- How about this competing edge?



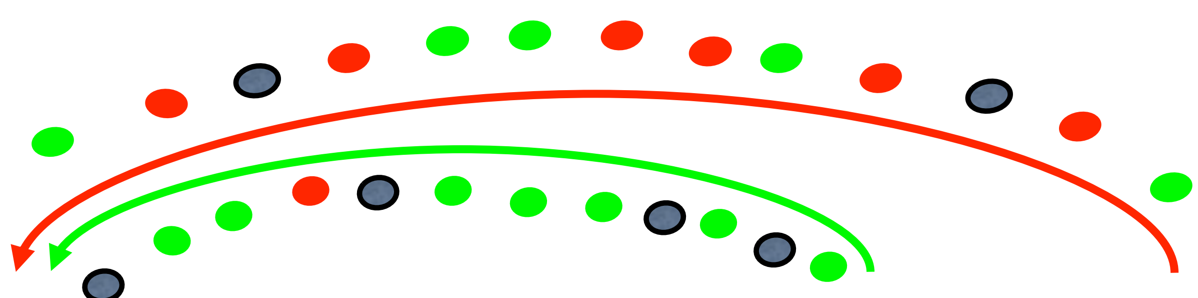
# Edge-Factored Parsers

- Which edge is better?
  - “bright day” or “bright clocks”?



# Edge-Factored Parsers

- Which edge is better?
- Score of an edge e = $\theta \cdot$ **features**(e)
- Standard algos ➔ valid parse with max <u>total</u> score

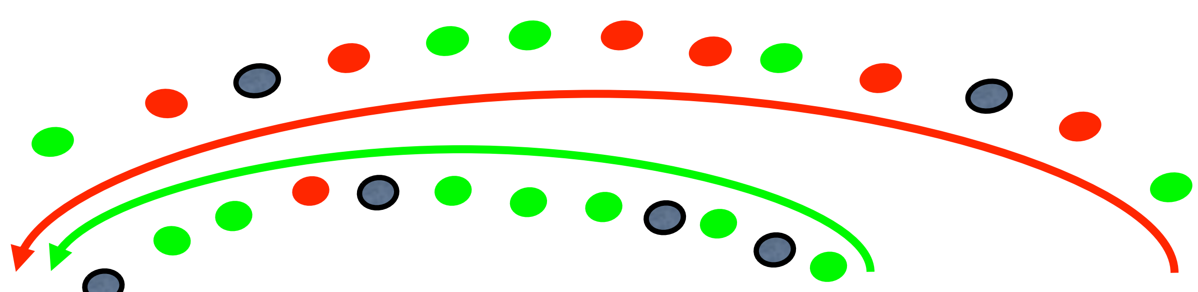


| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Byl | jasný | studený | dubnový | den | a | hodiny | odbíjely | třináctou |
| V | A | A | A | N | J | N | V | C |
| byl | jasn | stud | dubn | den | a | hodi | odbí | třin |

"It was a bright cold day in April and the clocks were striking thirteen"

# Edge-Factored Parsers

- Which edge is better?
  our current weight vector
- Score of an edge e = $\theta \cdot$ **features**(e)
- Standard algos ➔ valid parse with max <u>total</u> score

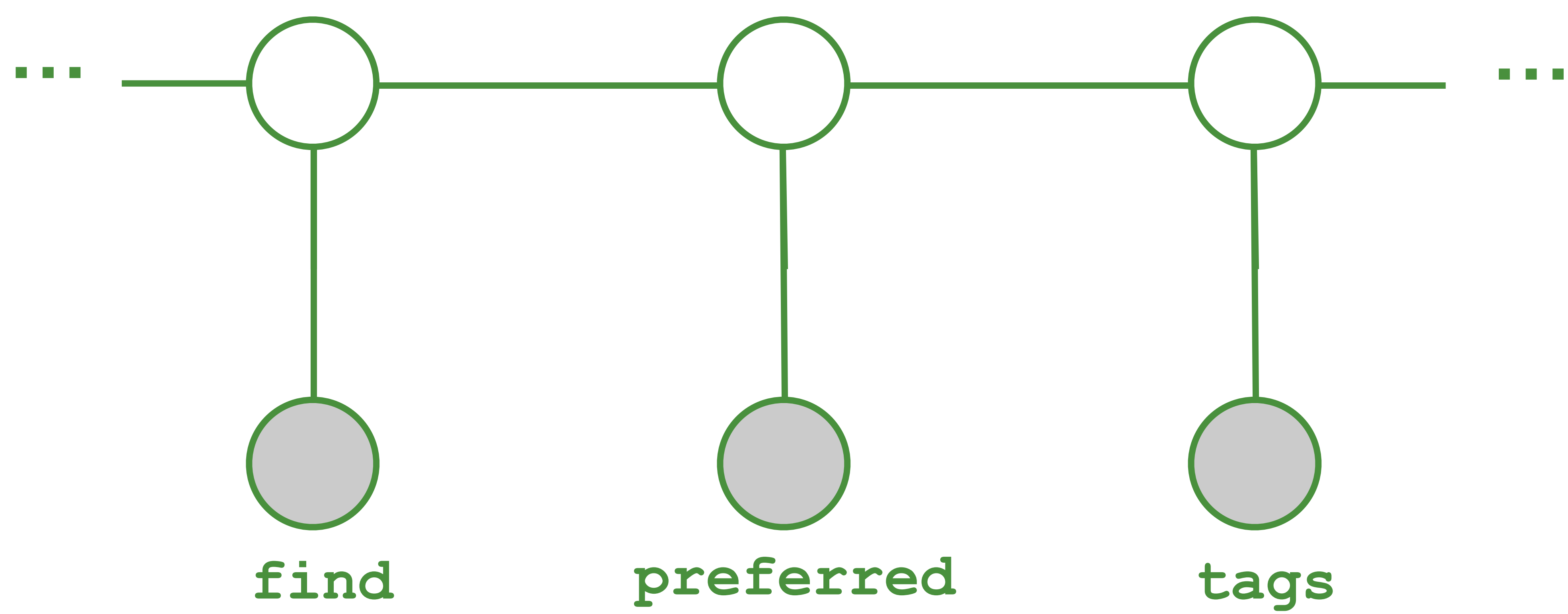


| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Byl | jasný | studený | dubnový | den | a | hodiny | odbíjely | třináctou |
| V | A | A | A | N | J | N | V | C |
| byl | jasn | stud | dubn | den | a | hodi | odbí | třin |

"It was a bright cold day in April and the clocks were striking thirteen"

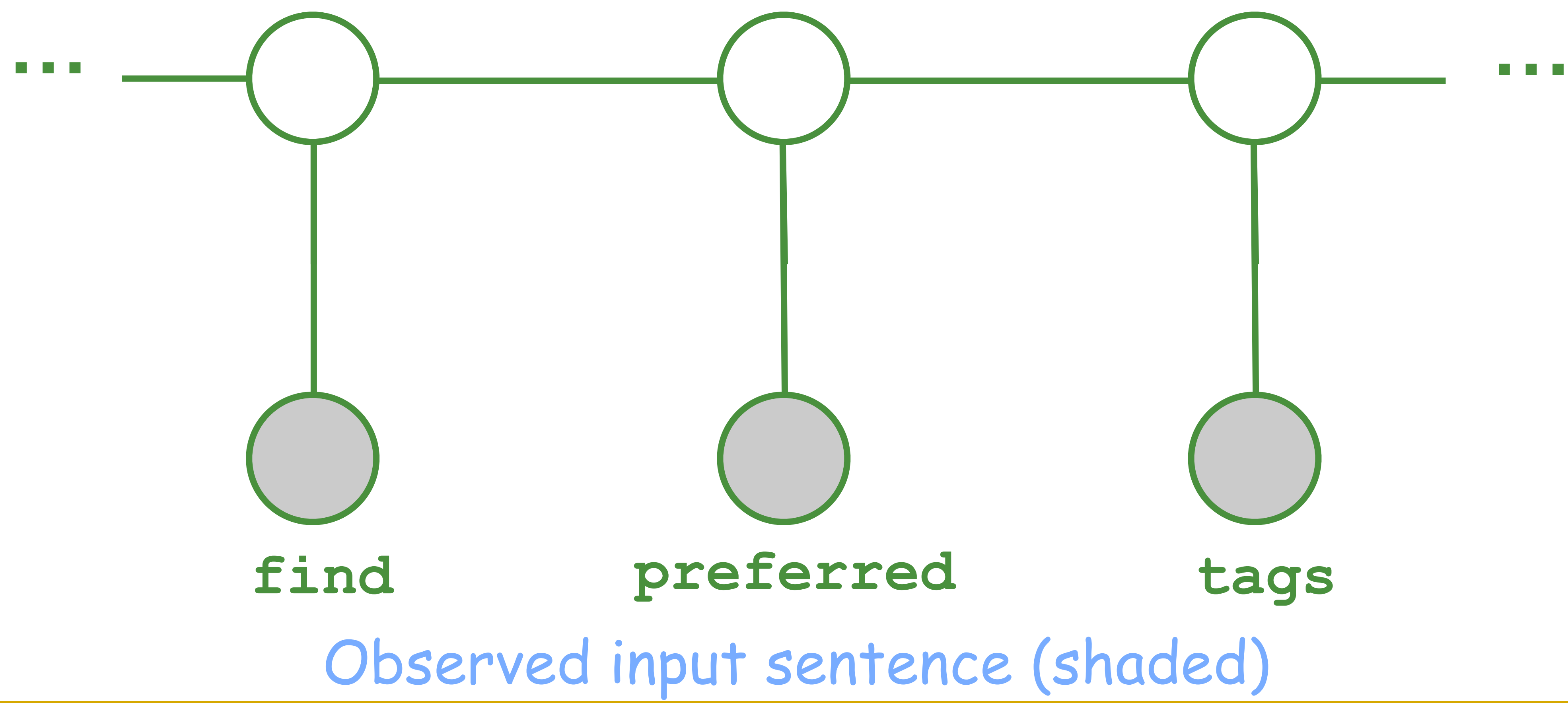
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



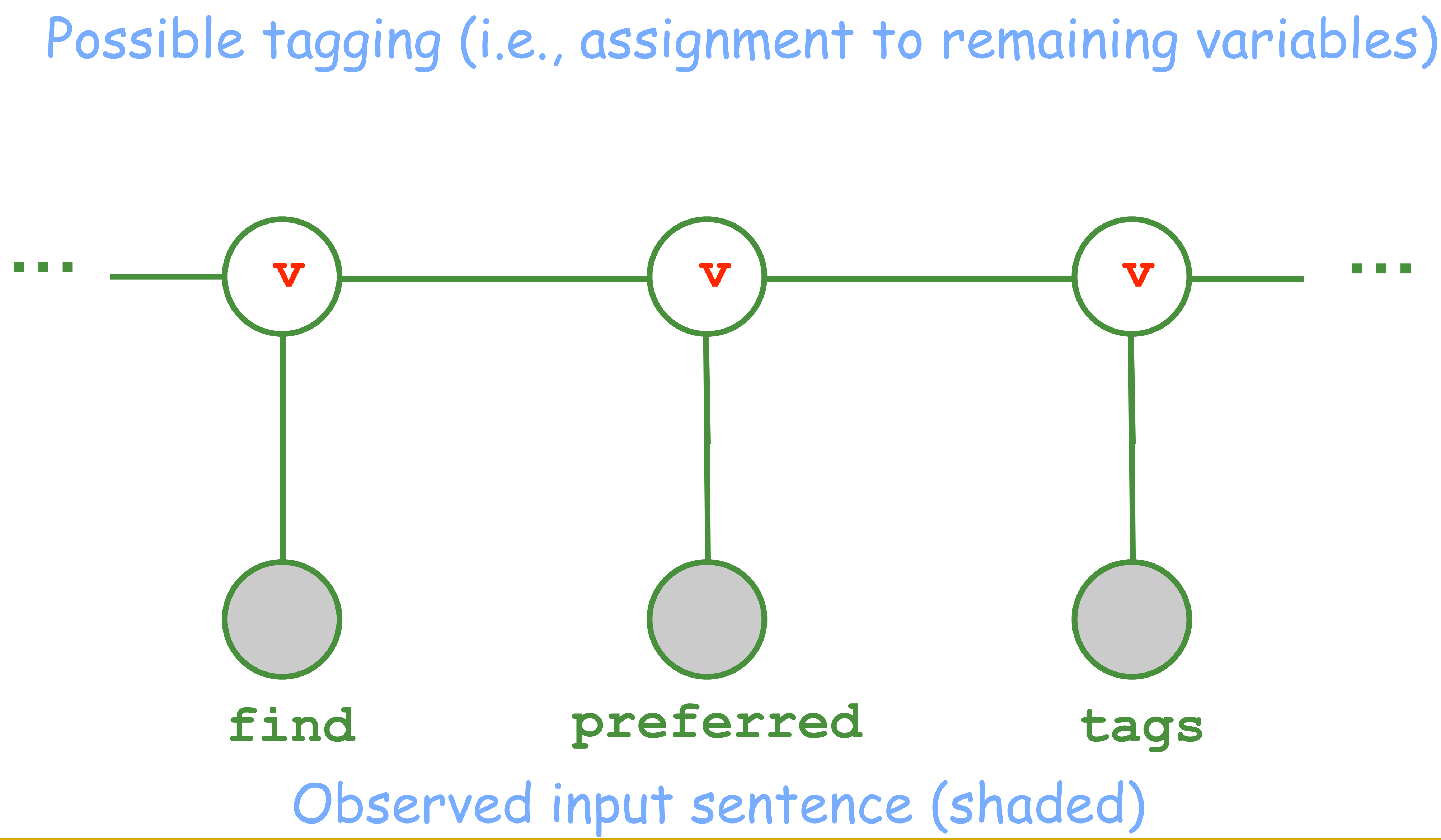
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

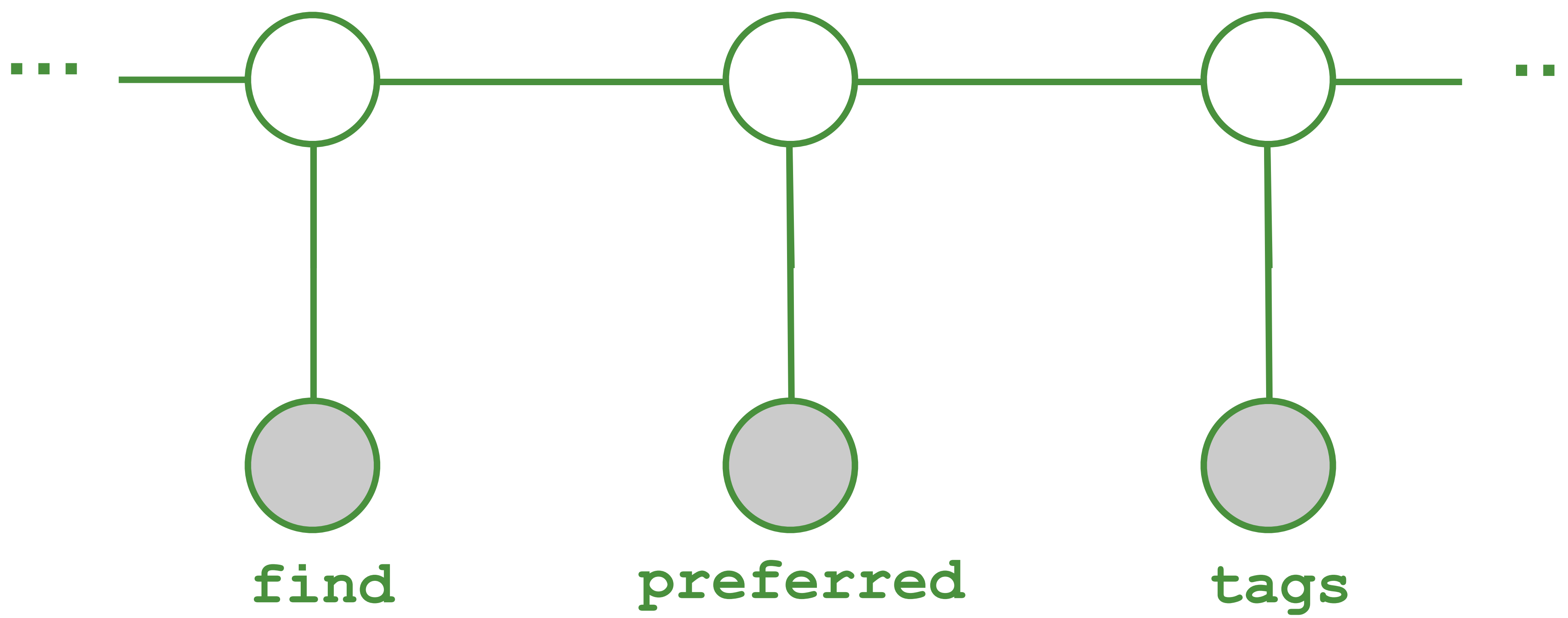
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging

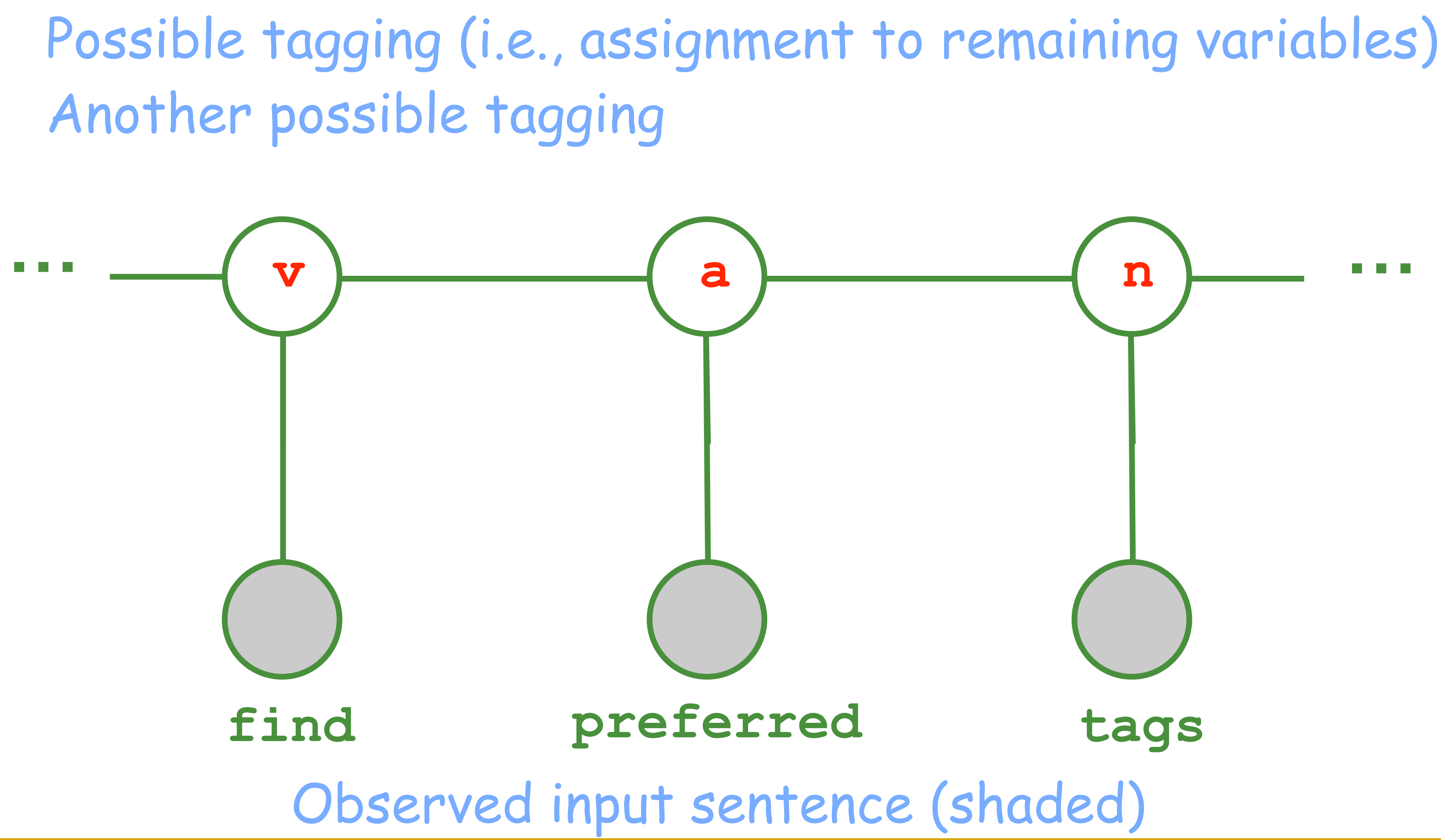
Possible tagging (i.e., assignment to remaining variables)
Another possible tagging




Observed input sentence (shaded)

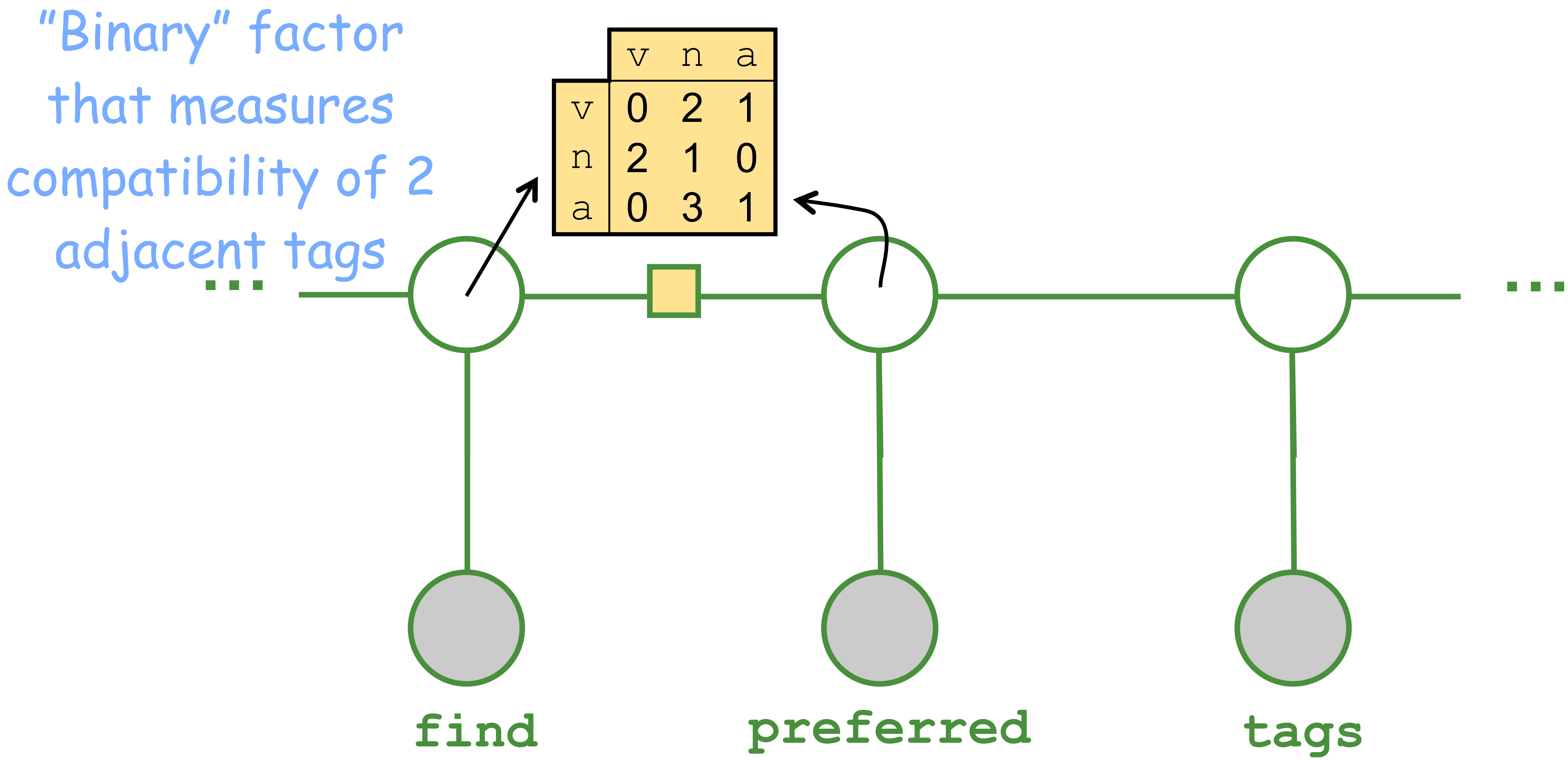
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

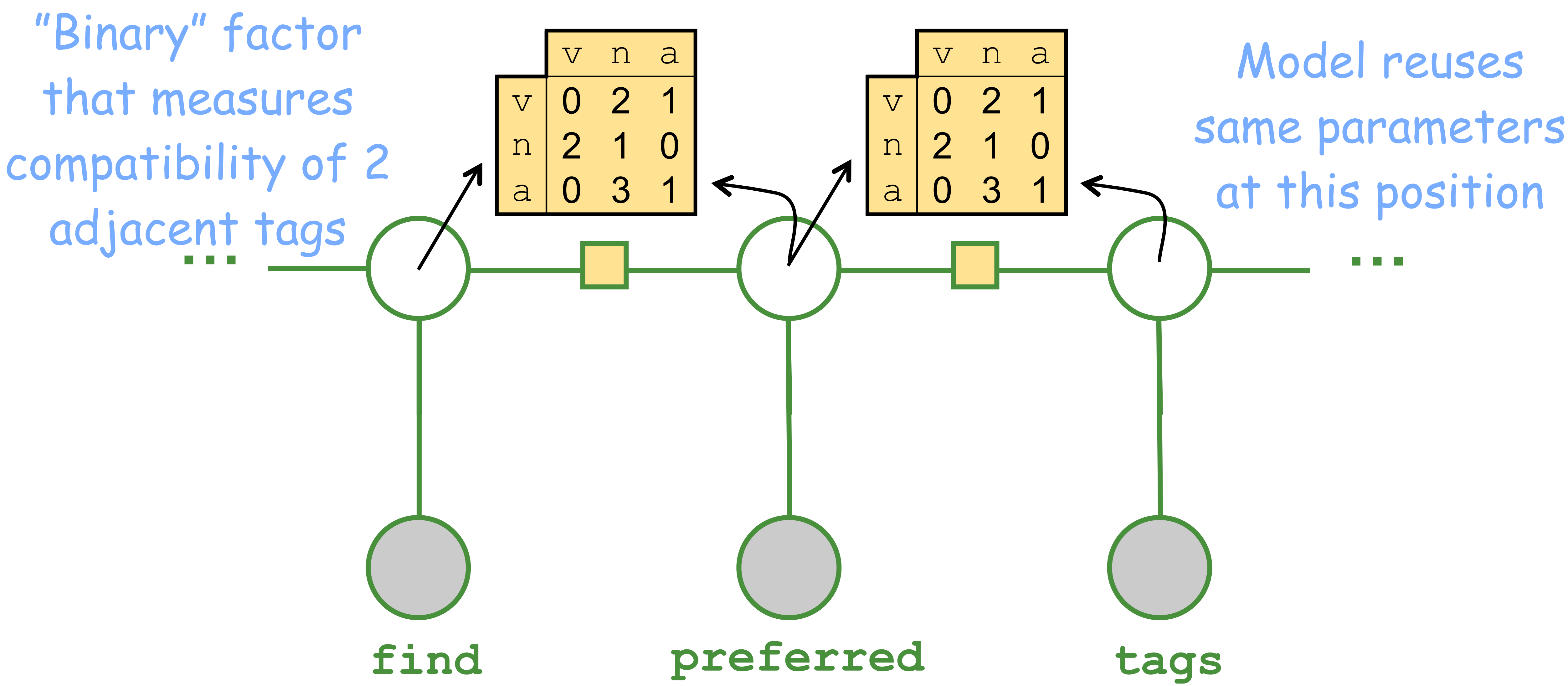
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging




| | v | n | a |
|---|---|---|---|
| v | 0 | 2 | 1 |
| n | 2 | 1 | 0 |
| a | 0 | 3 | 1 |

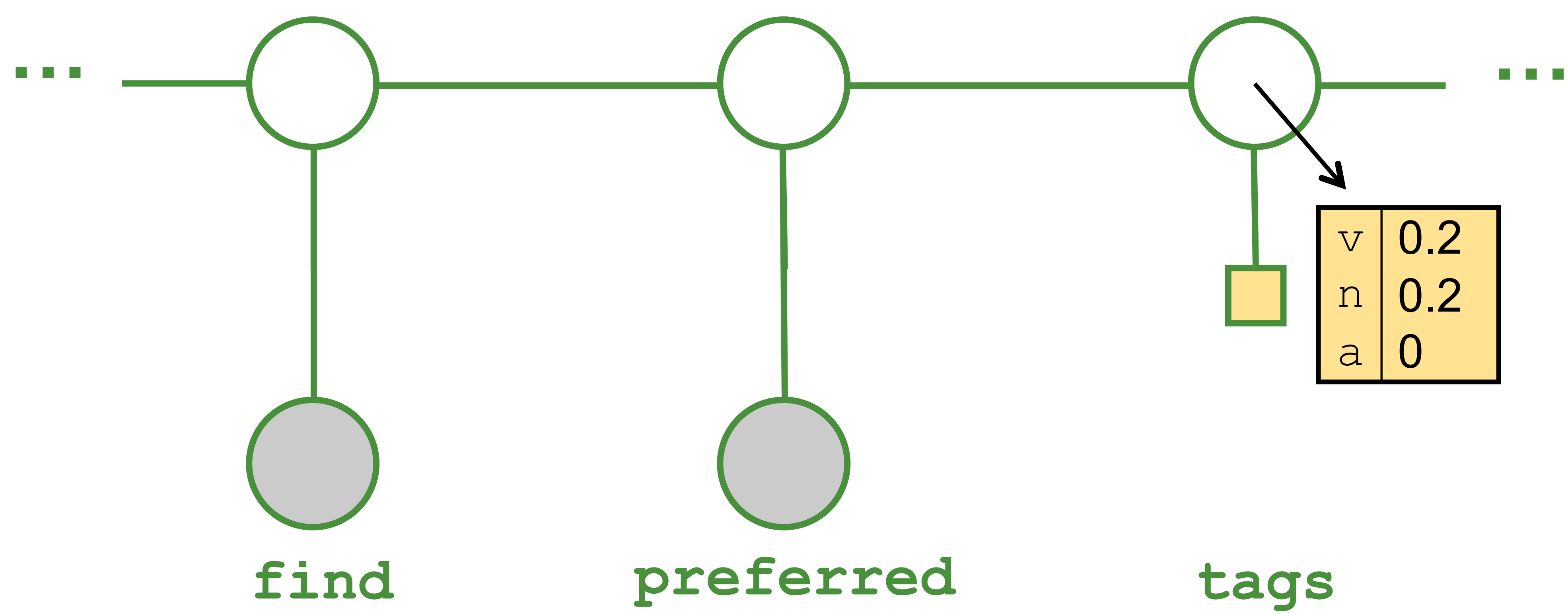
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



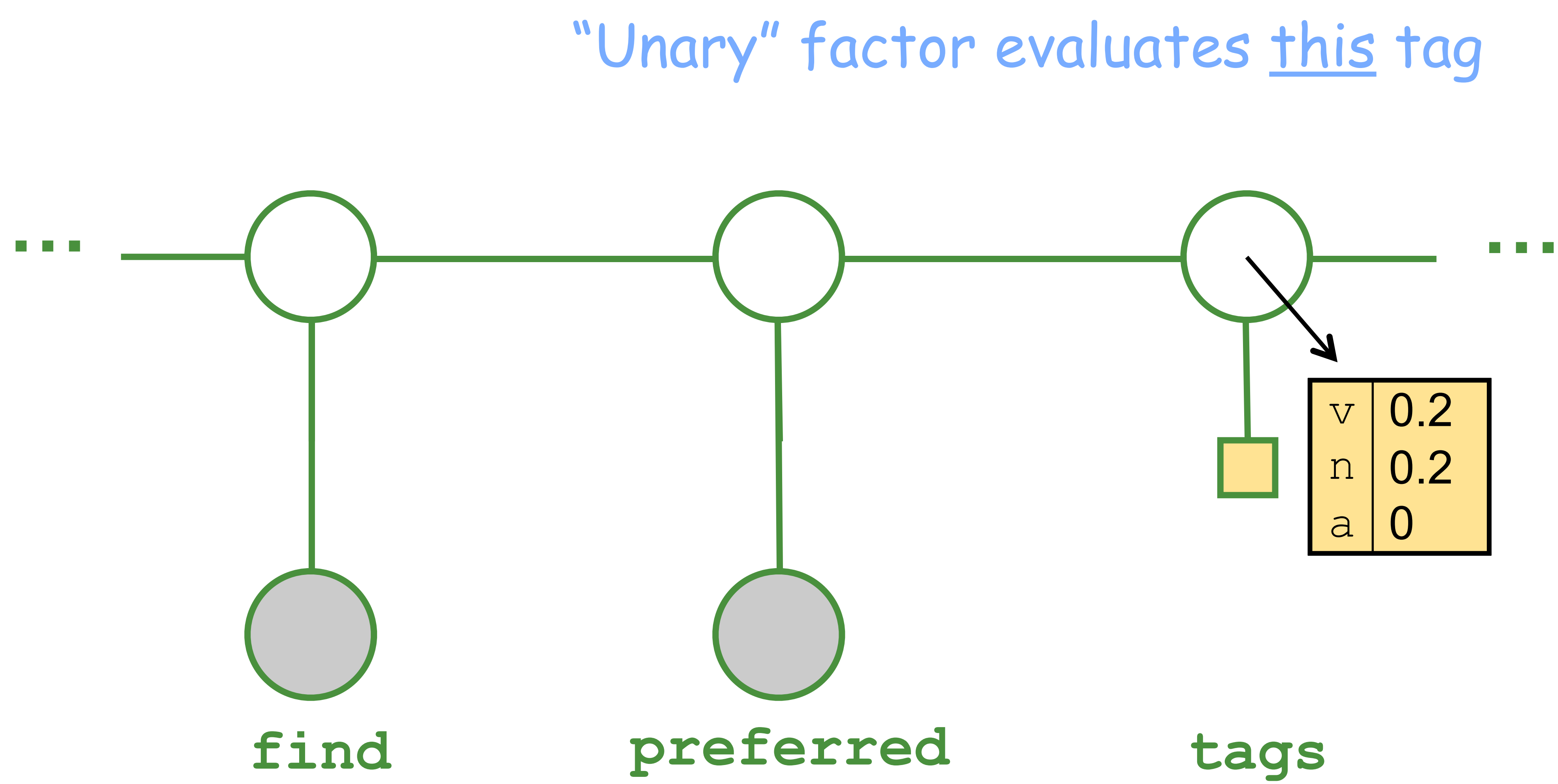
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



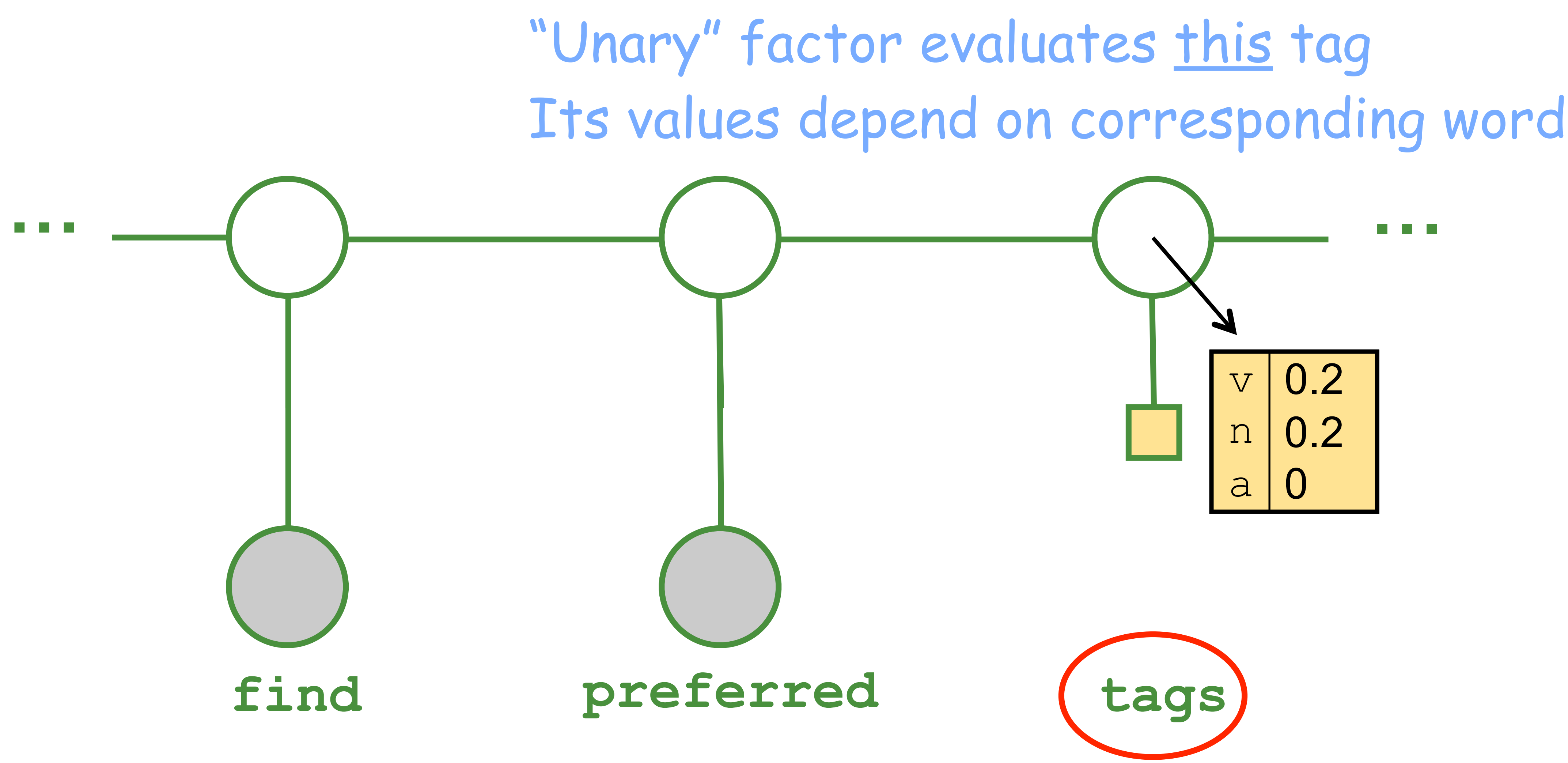
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



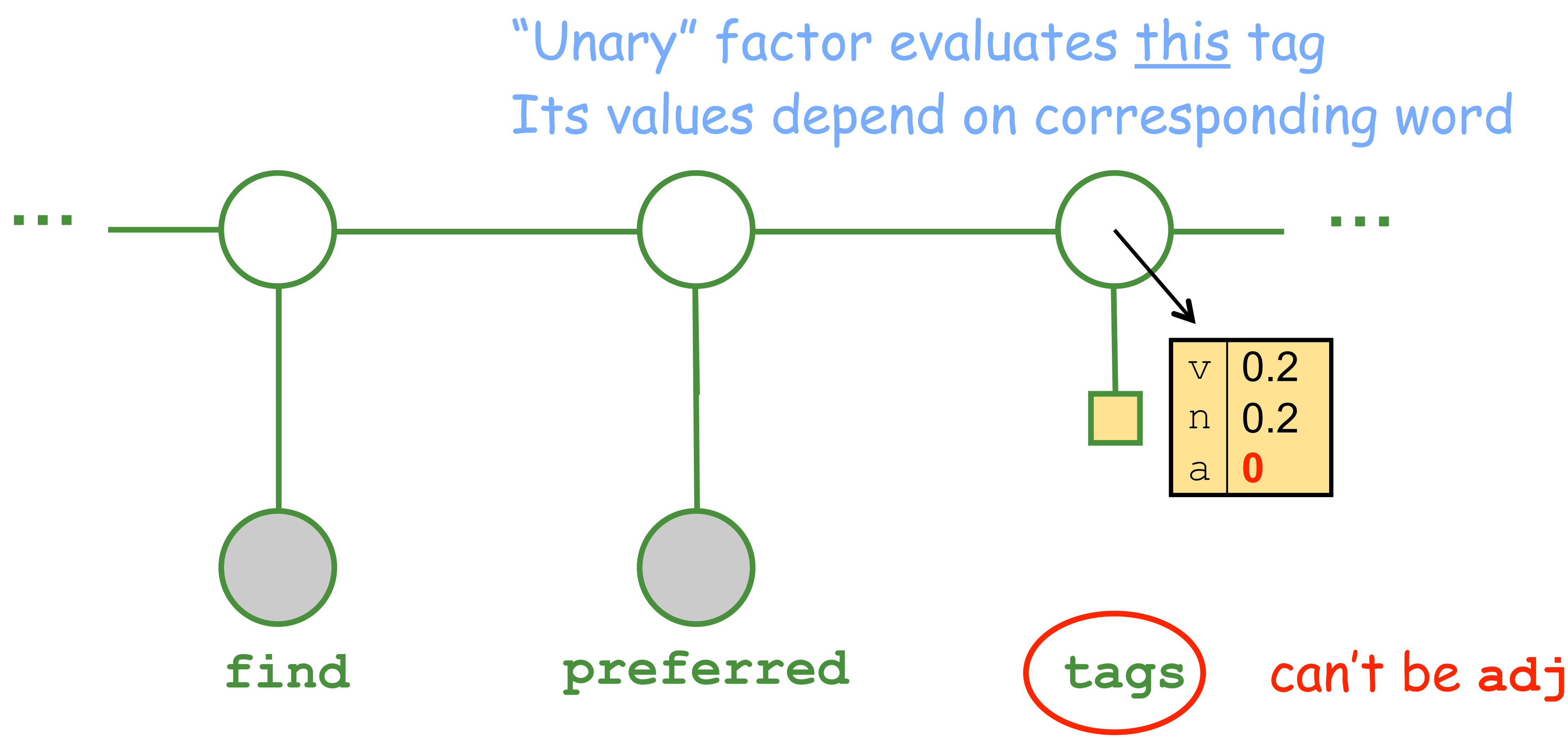
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



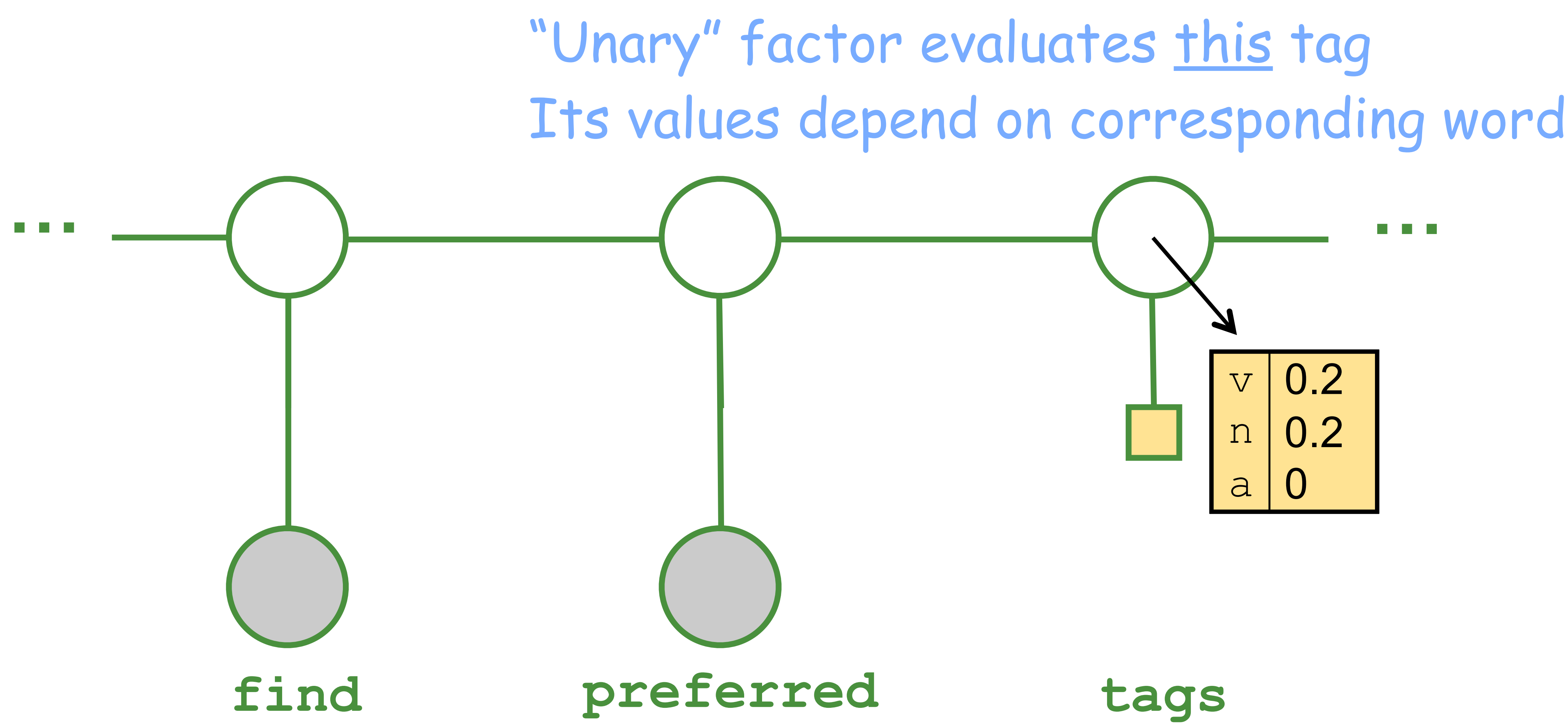
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

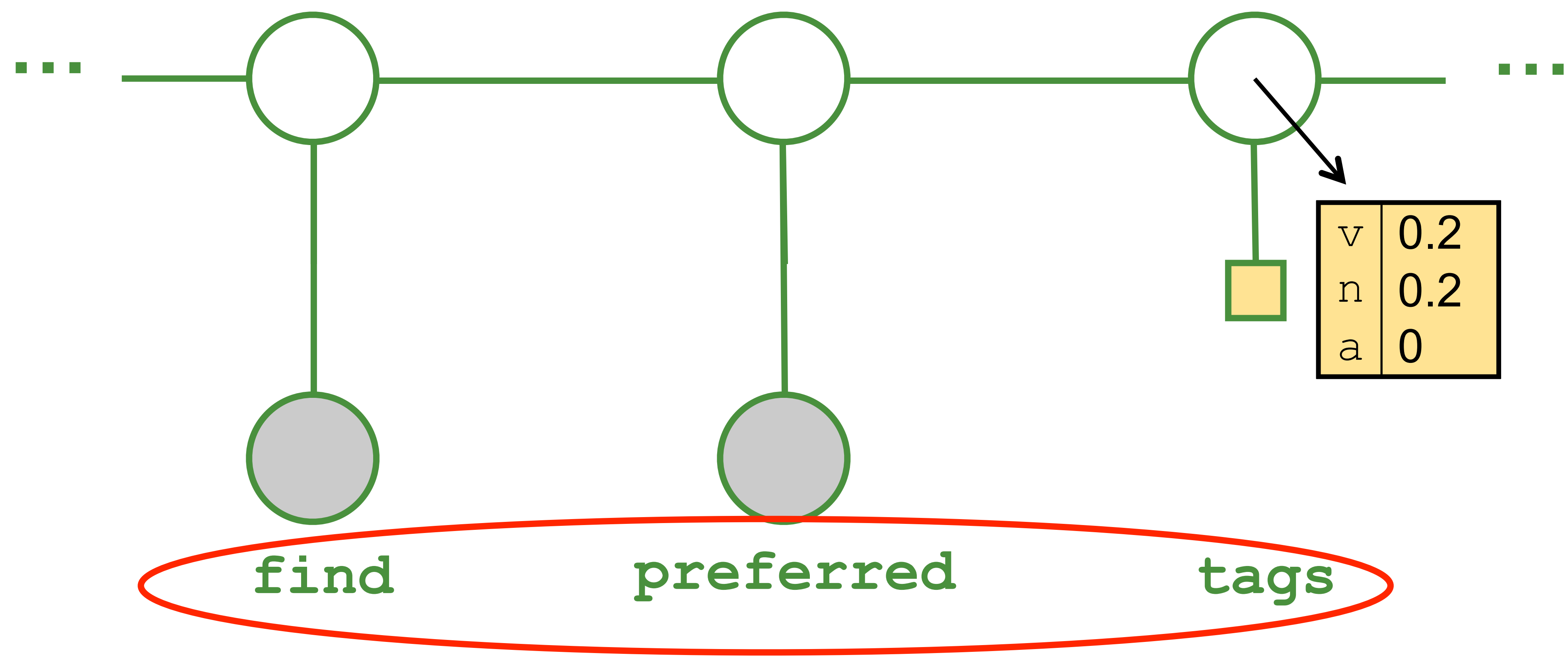
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging

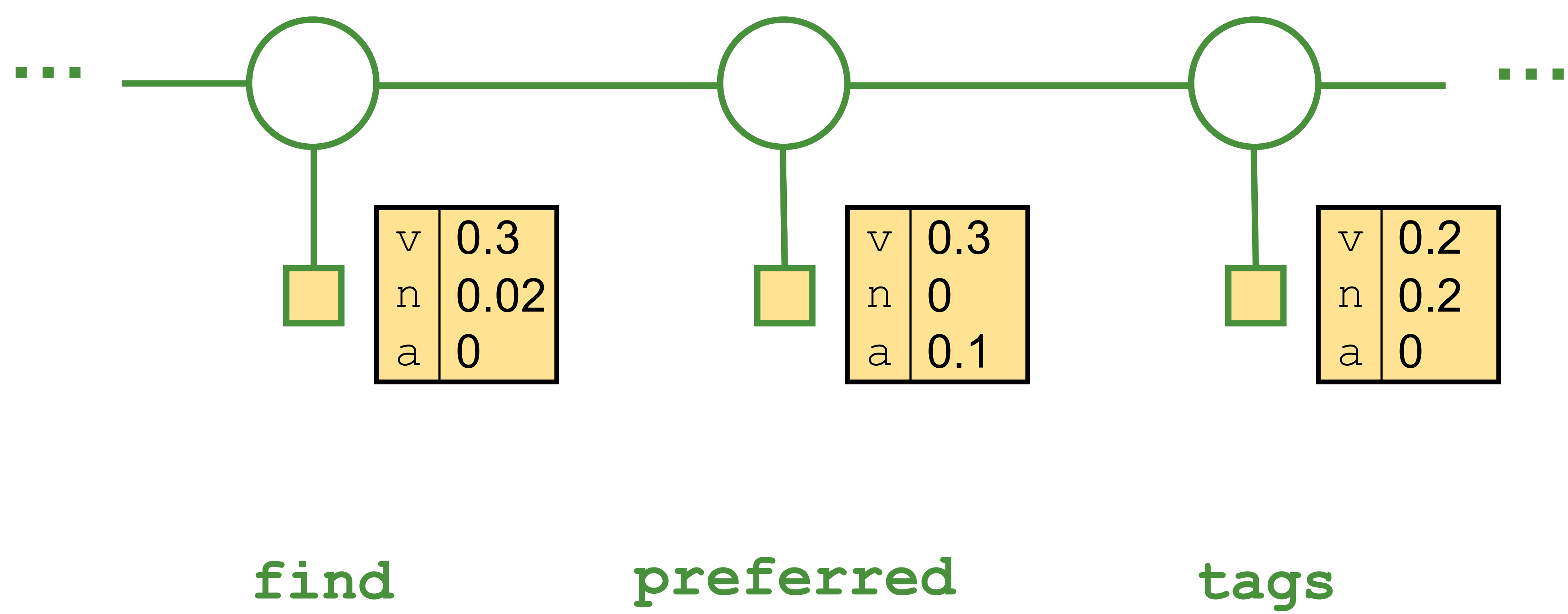
"Unary" factor evaluates this tag
Its values depend on corresponding word




(could be made to depend on entire observed sentence)

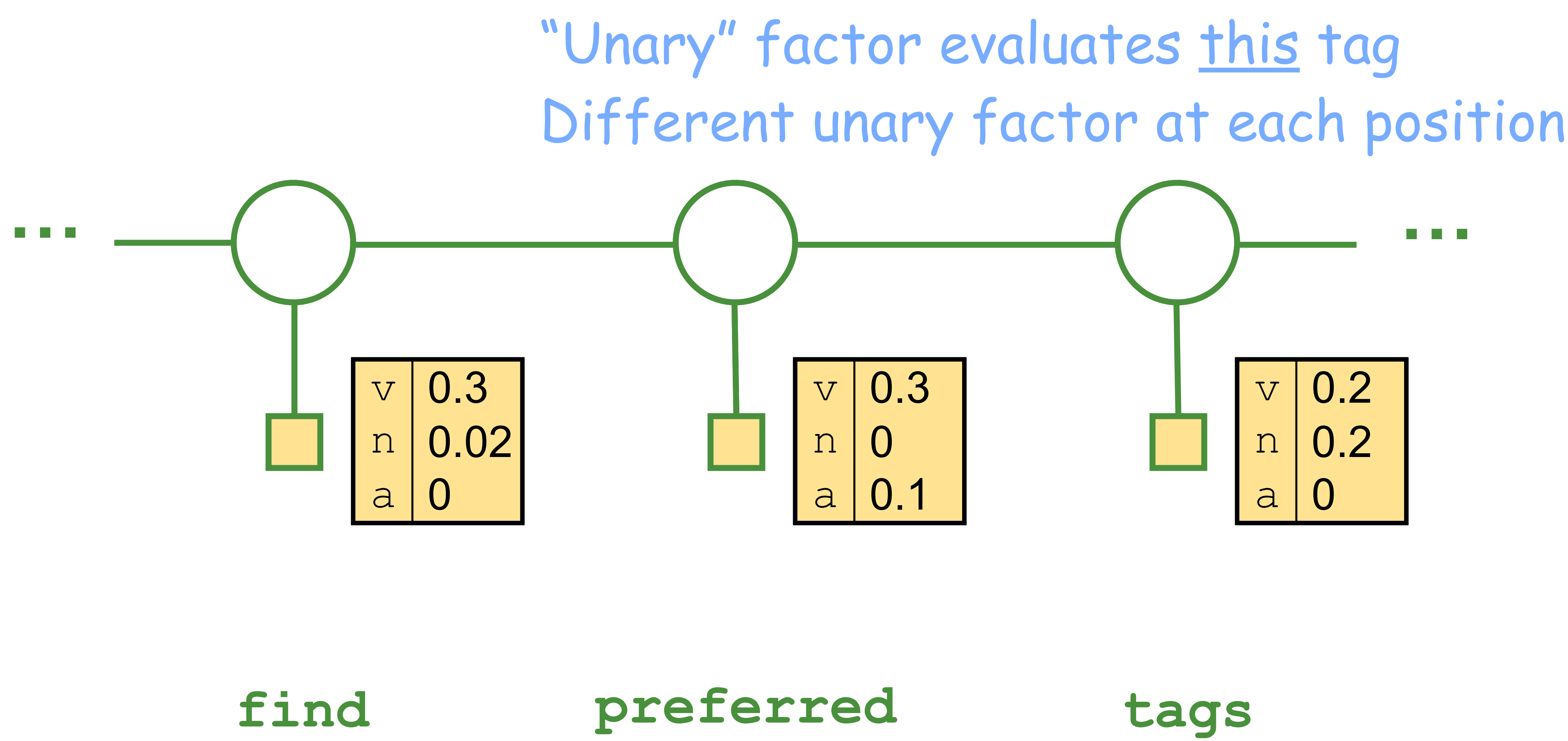
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



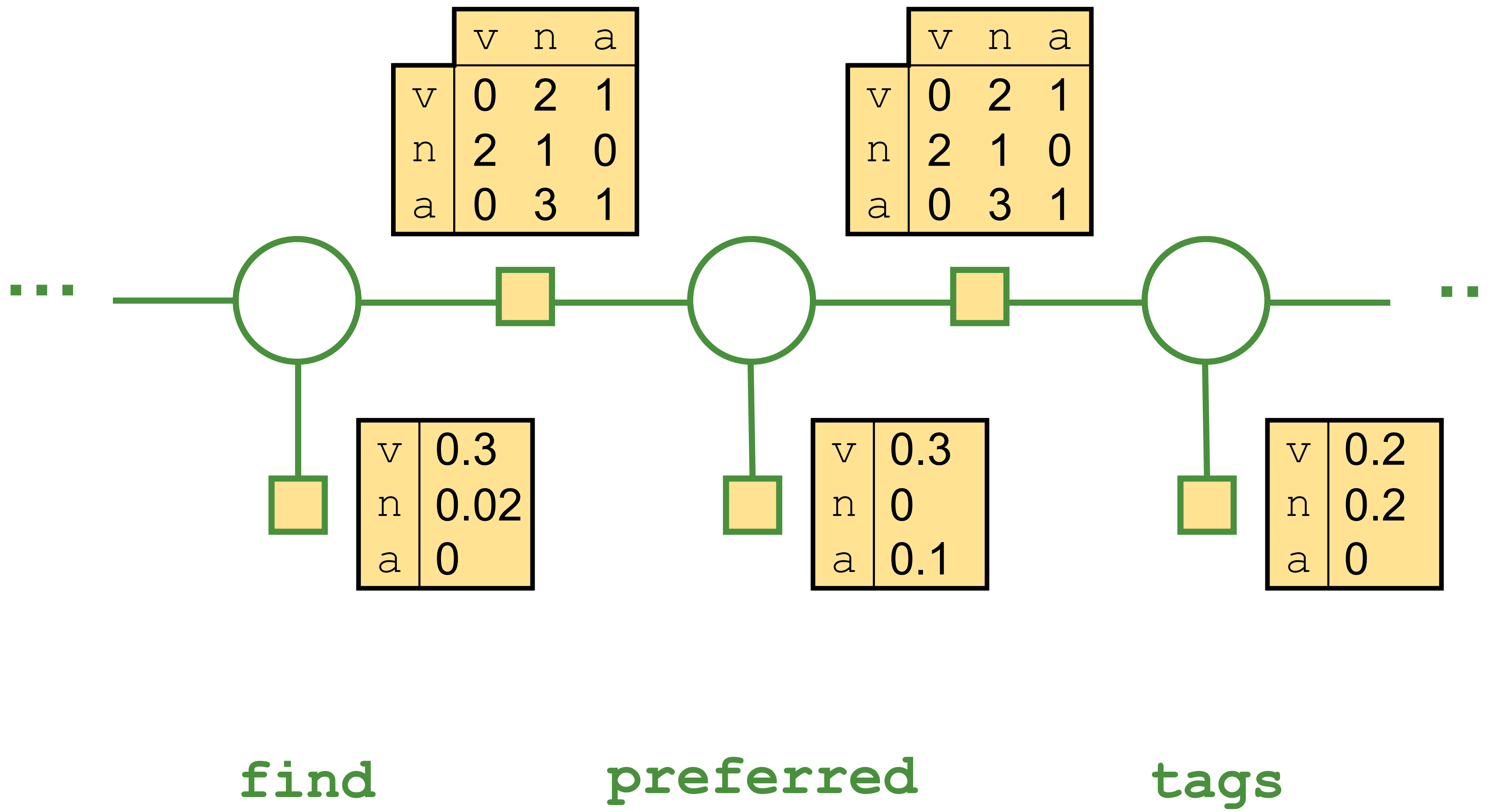
# Local factors in a graphical model

- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

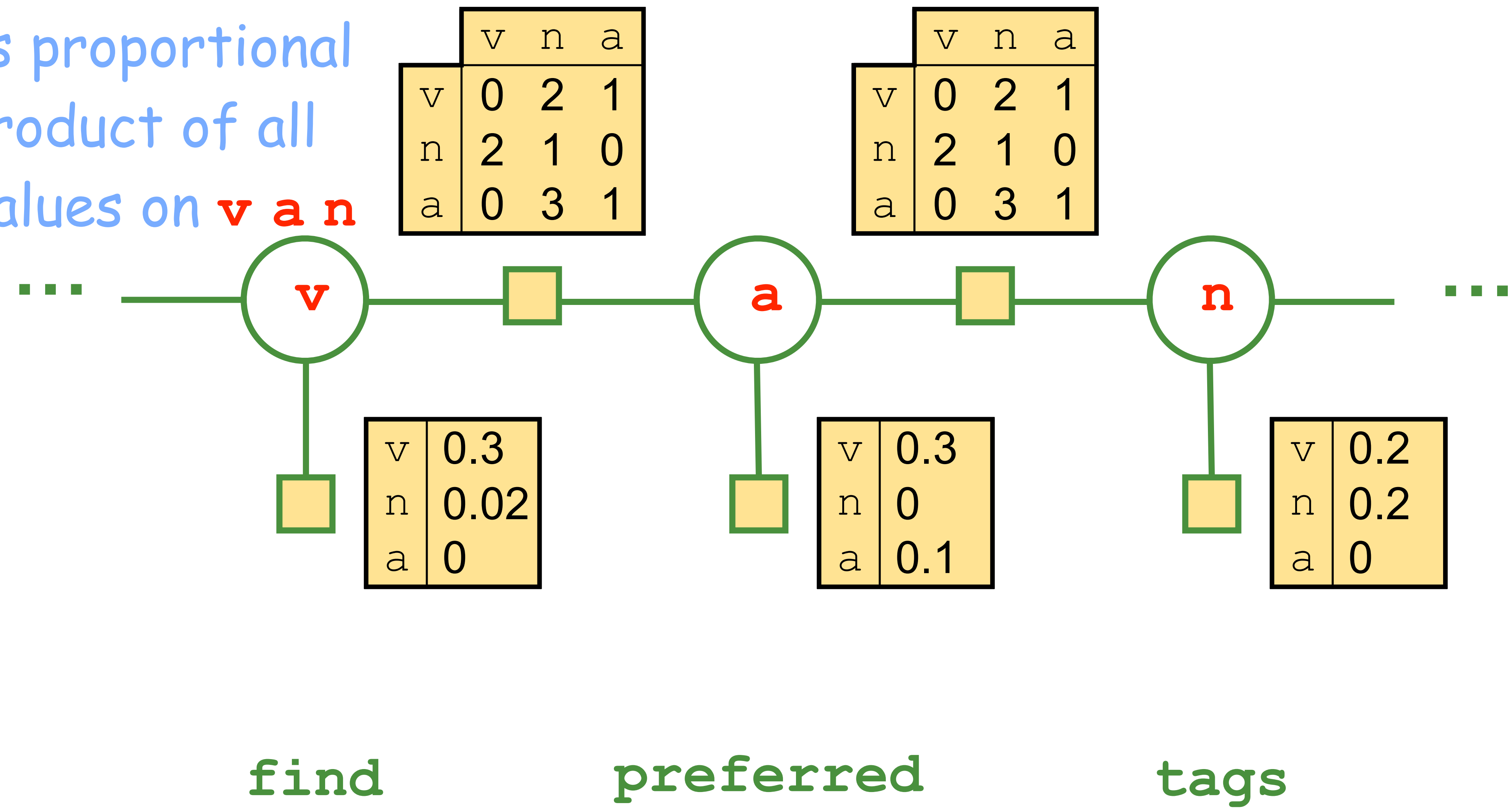
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

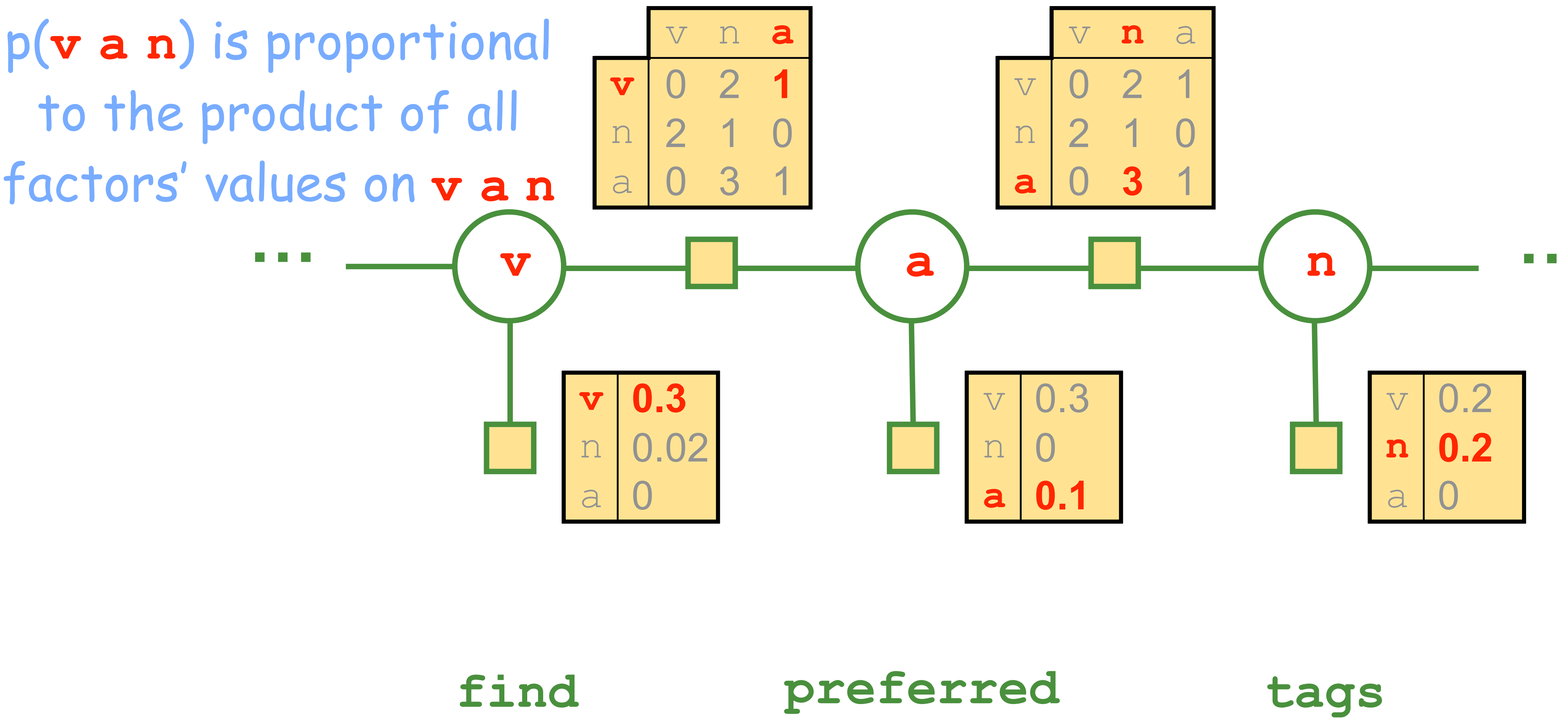
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging

p(**v a n**) is proportional to the product of all factors' values on **v a n**



# Local factors in a graphical model

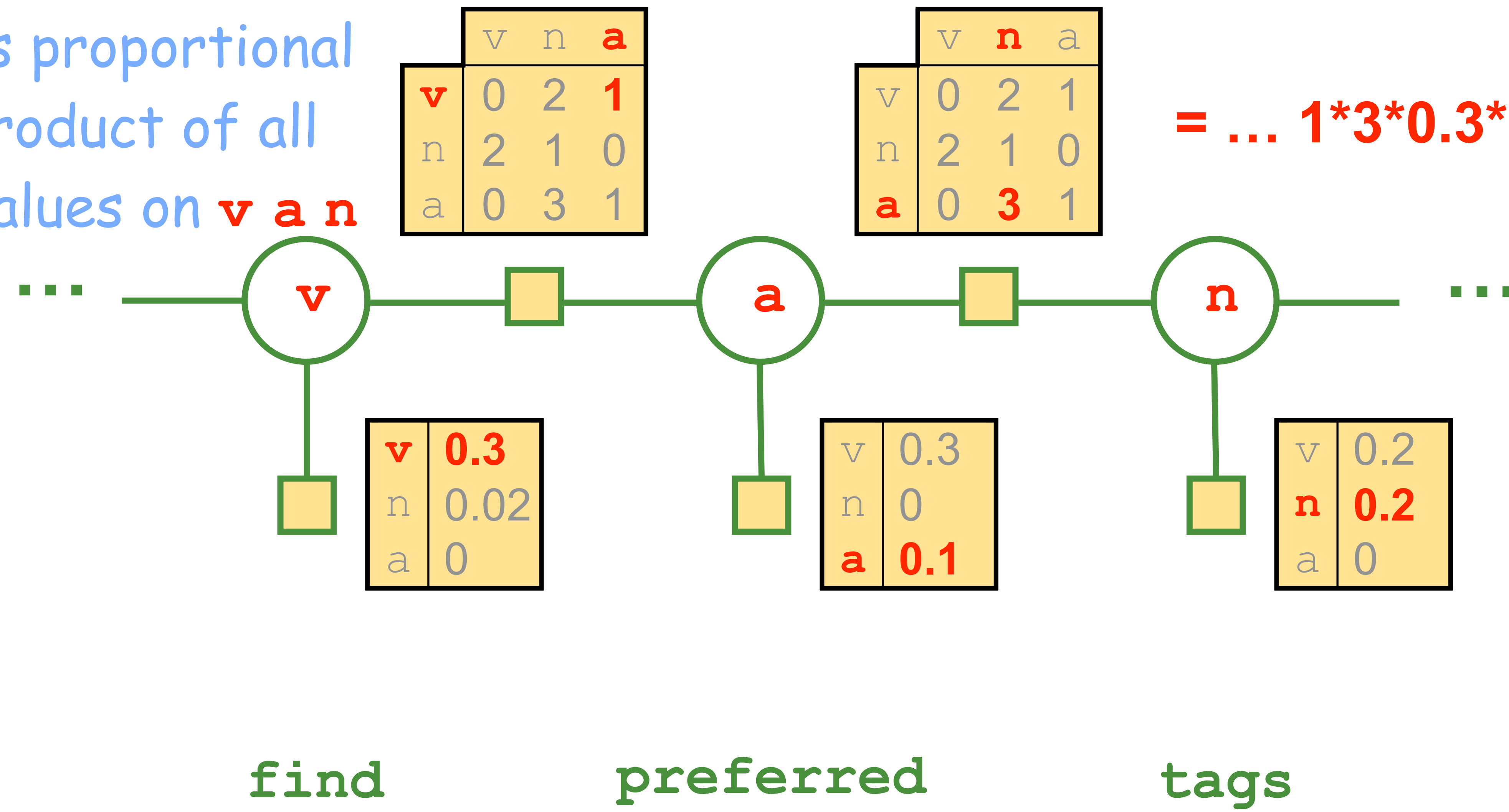
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging



# Local factors in a graphical model

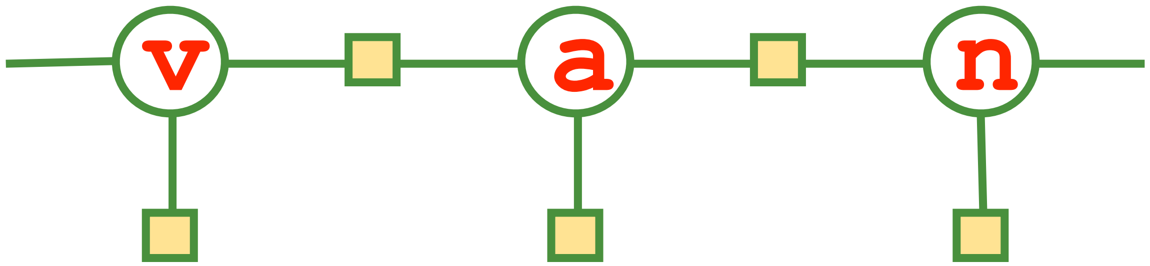
- First, a familiar example
  - Conditional Random Field (CRF) for POS tagging

p(v a n) is proportional to the product of all factors' values on v a n




= … 1*3*0.3*0.1*0.2 …

# Graphical Models for Parsing

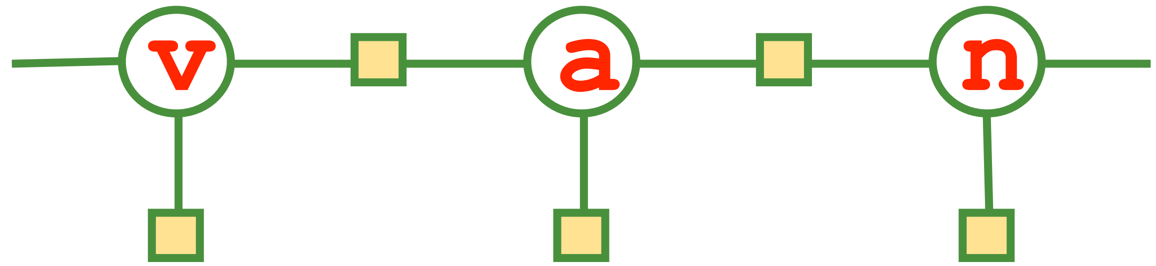



- First, a labeling example
  - CRF for POS tagging
- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links

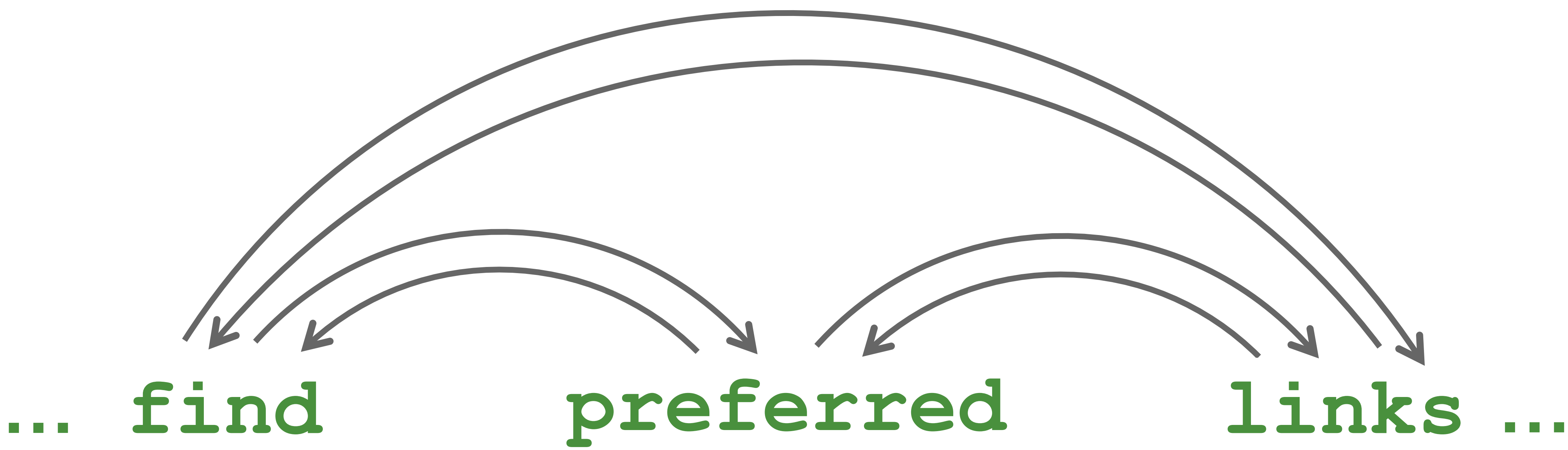
... find preferred links ...

# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging

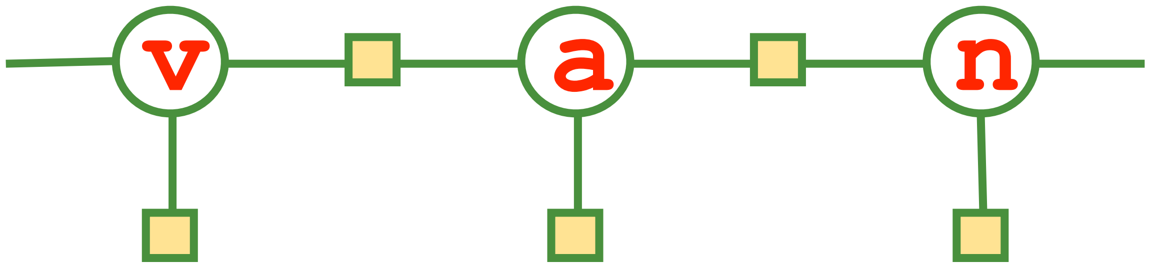



- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links

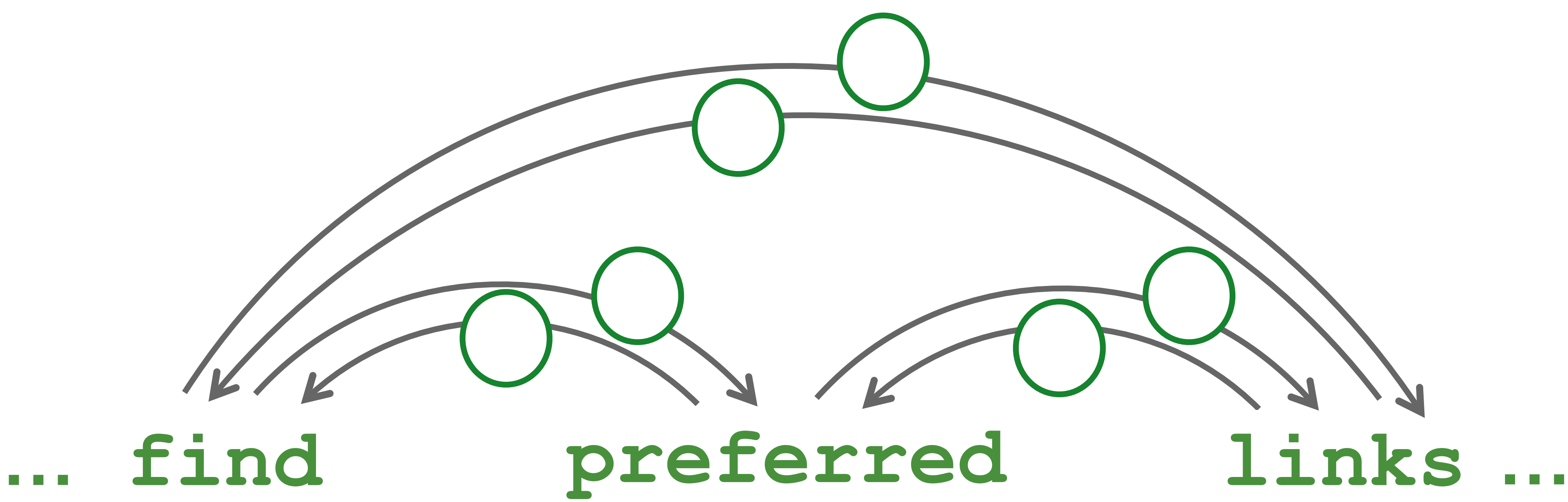


# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging

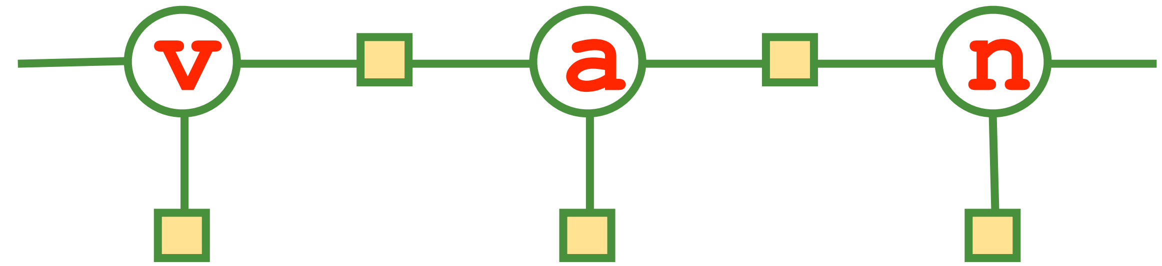



- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links



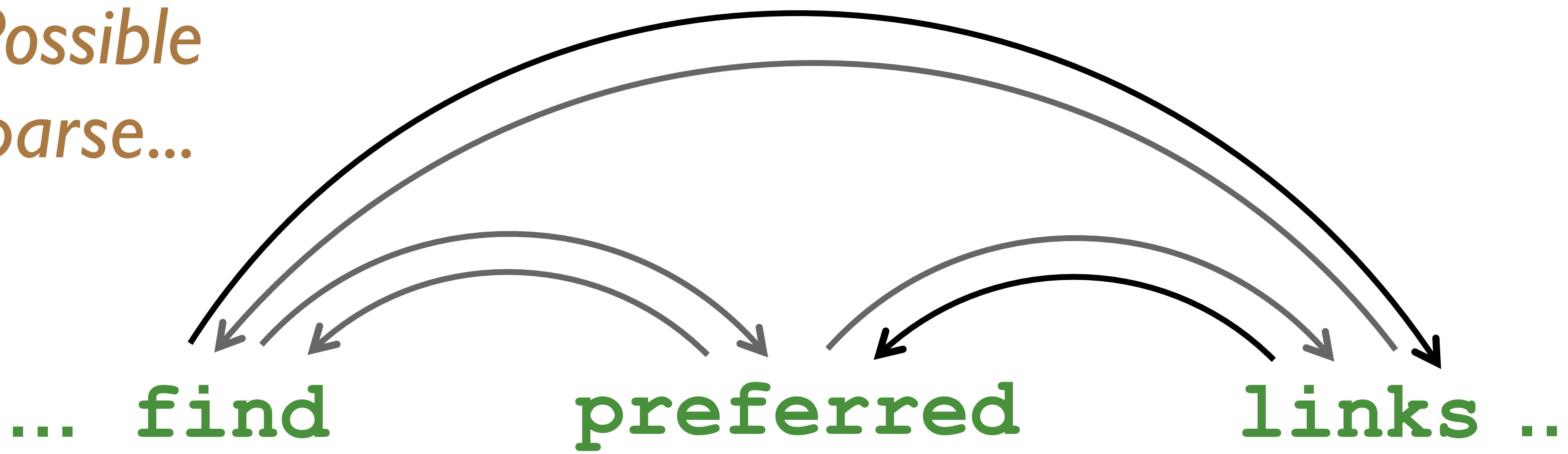
# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging



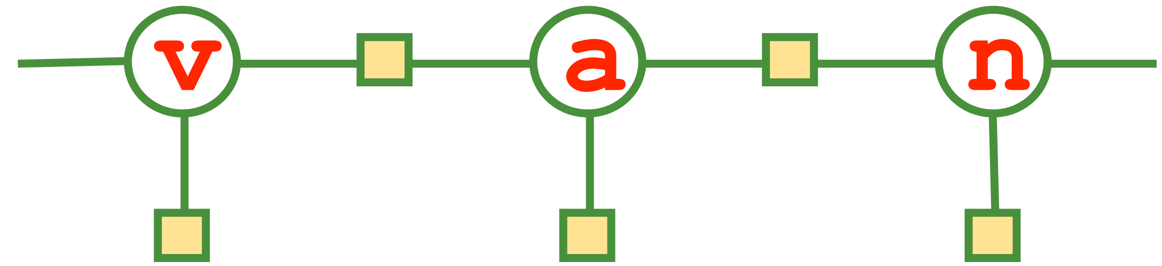

- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links

*Possible parse…*



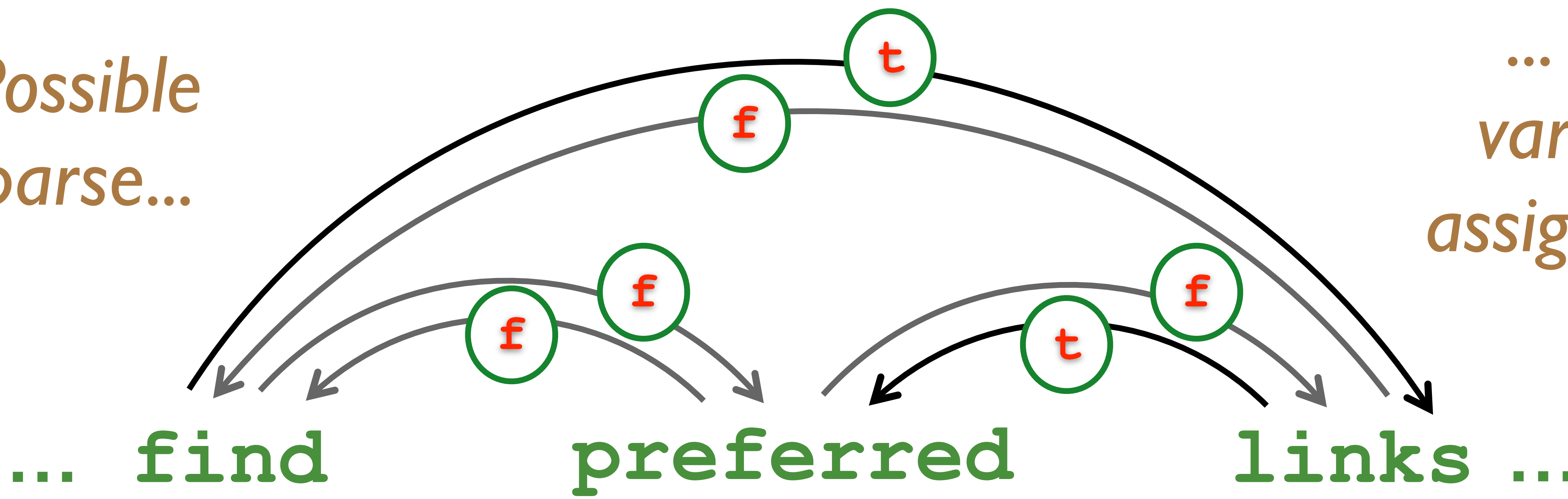
# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging




- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links

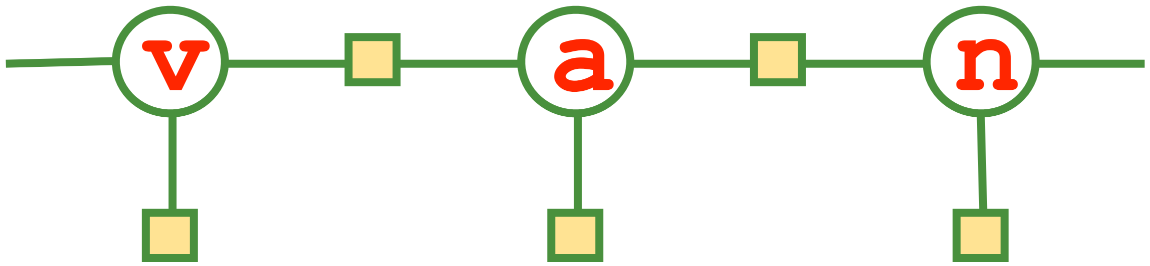
*Possible parse…*




*… and variable assignment*

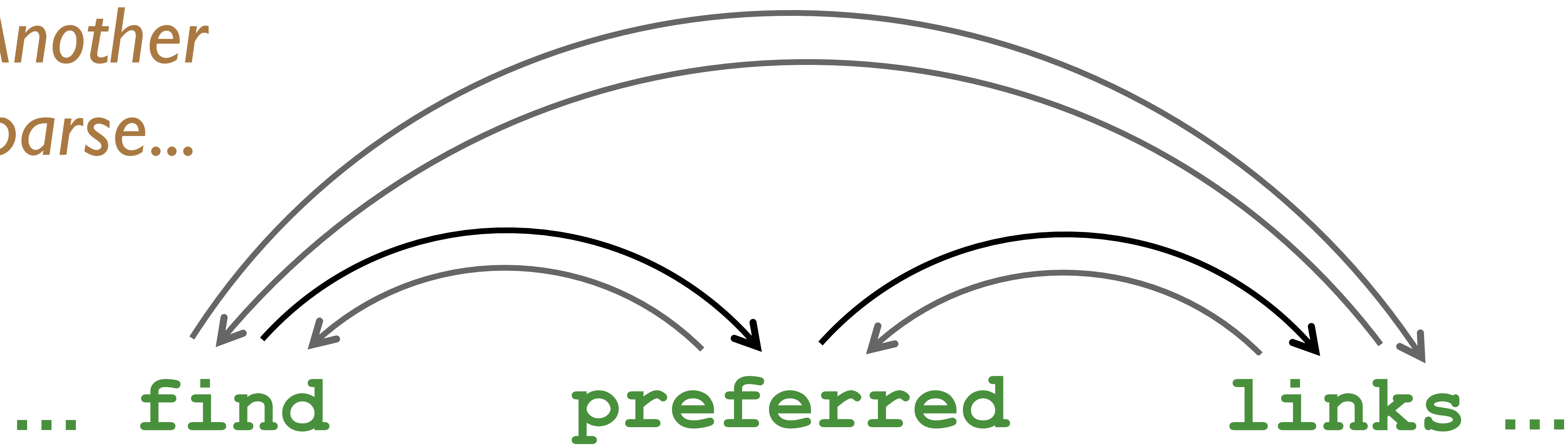
# Graphical Models for Parsing

- First, a labeling example
  - ✤ CRF for POS tagging



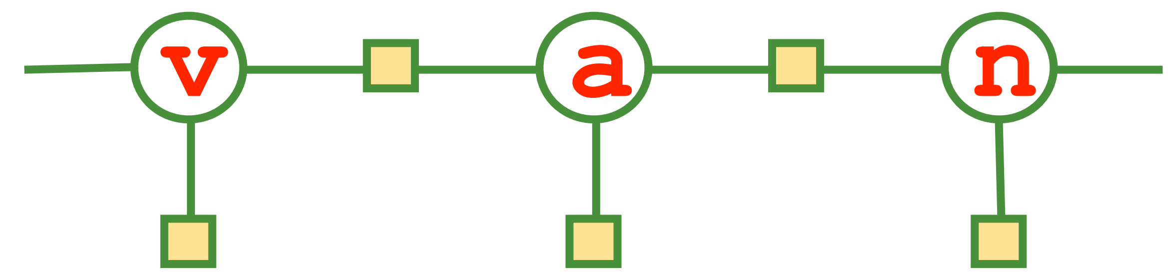

- Now let's do dependency parsing!
  - ✤ $O(n^2)$ boolean variables for the possible links

*Another parse...*

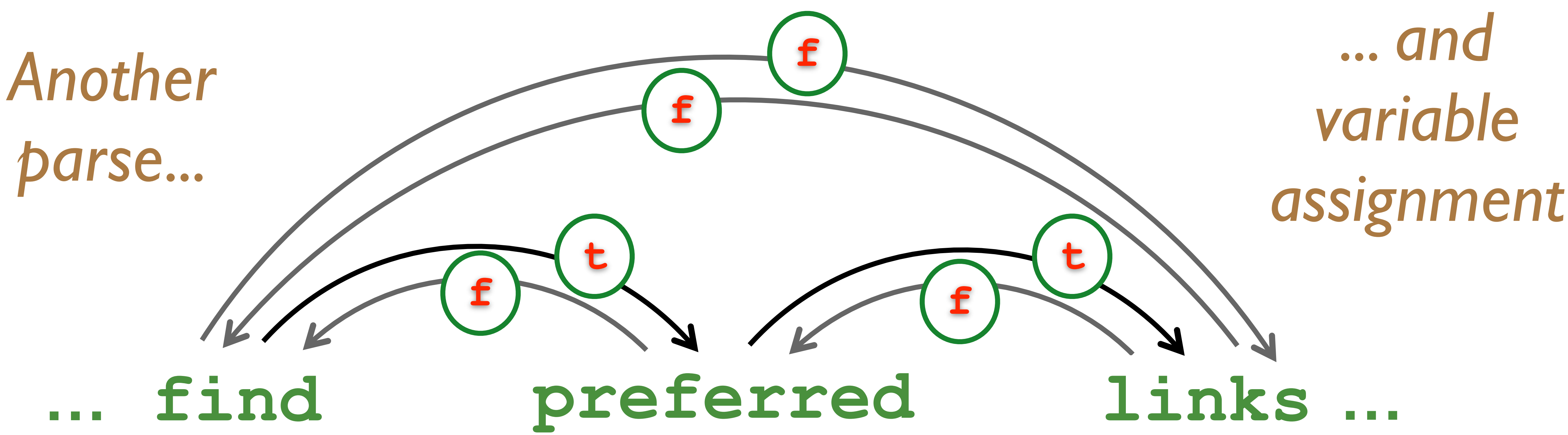


# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging

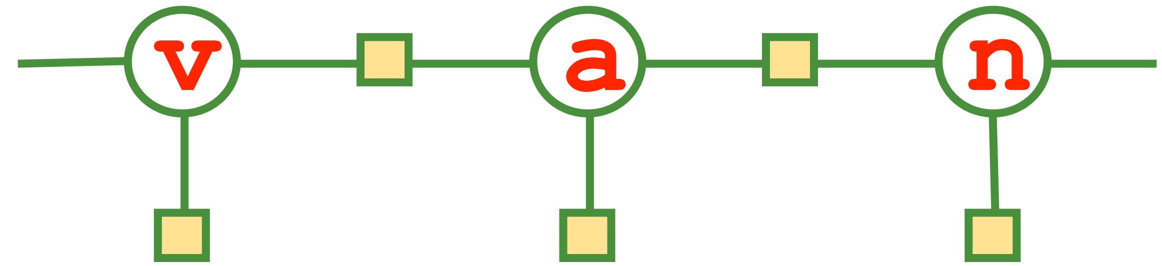



- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links

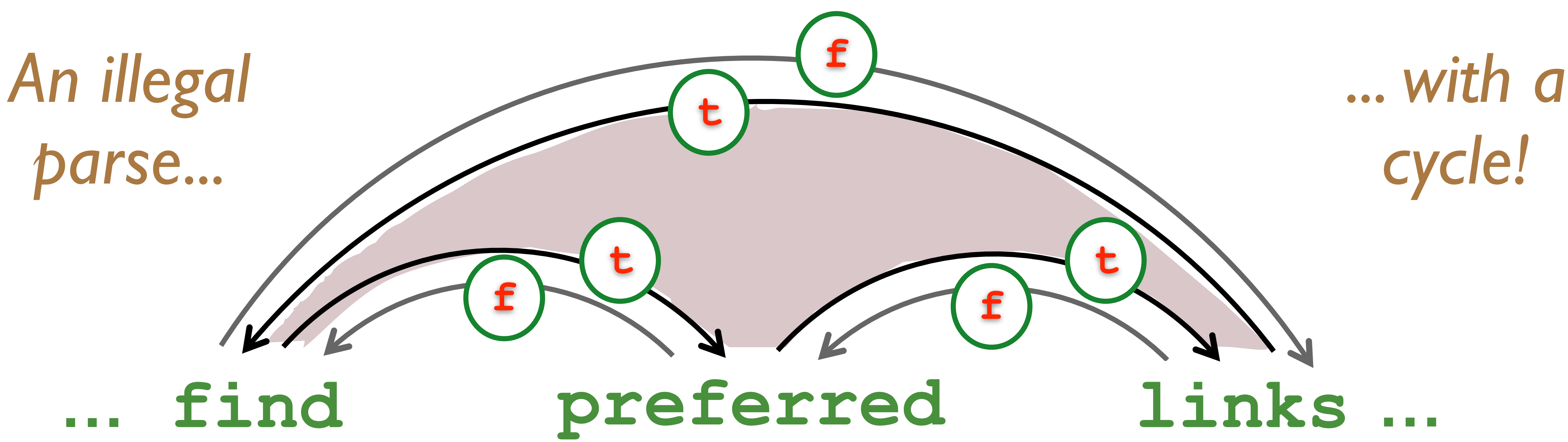


# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging

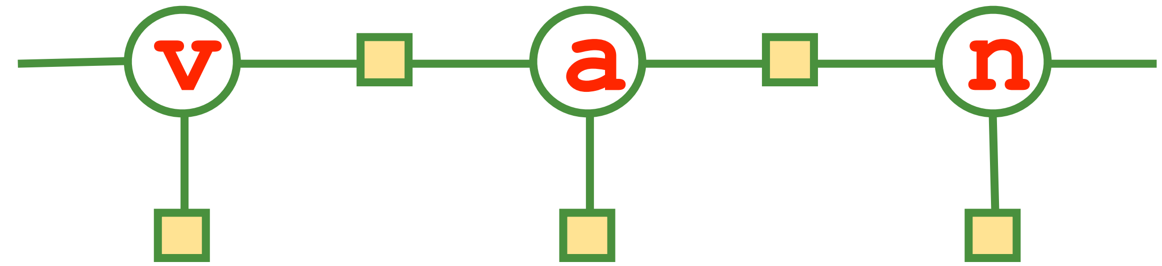



- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links

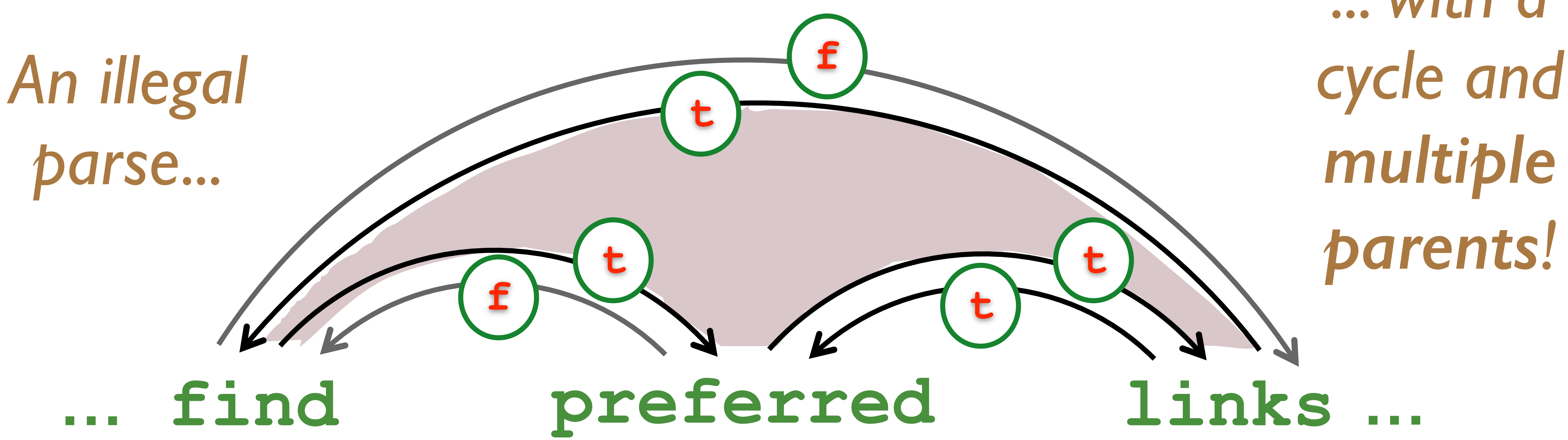


# Graphical Models for Parsing

- First, a labeling example
  - CRF for POS tagging

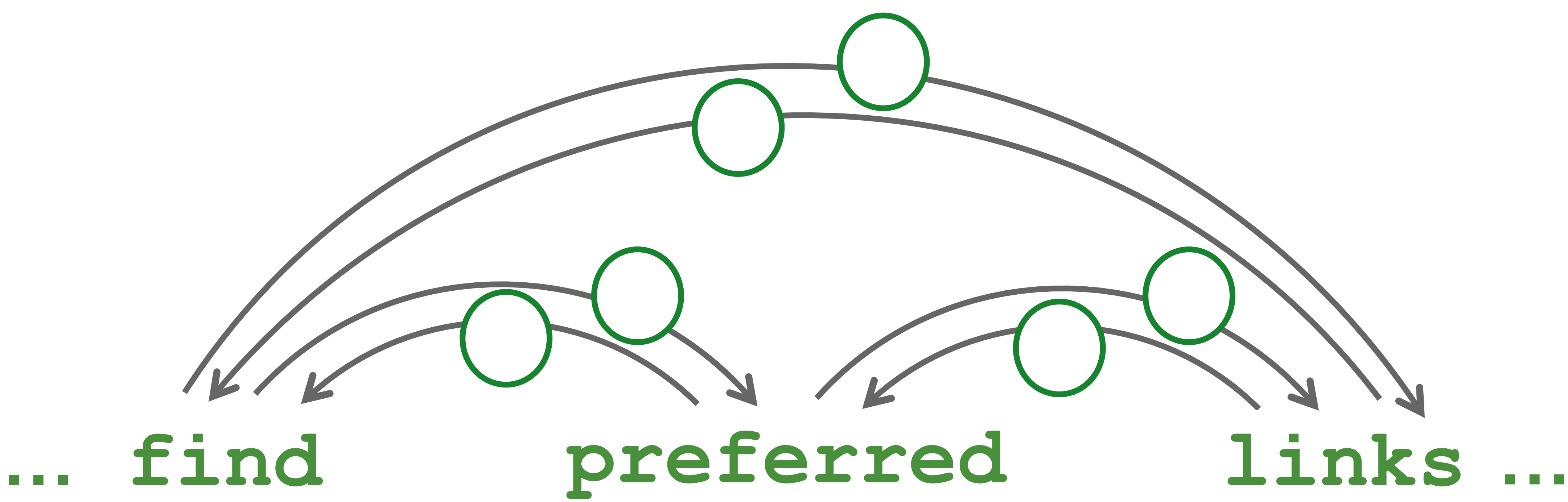



- Now let's do dependency parsing!
  - $O(n^2)$ boolean variables for the possible links



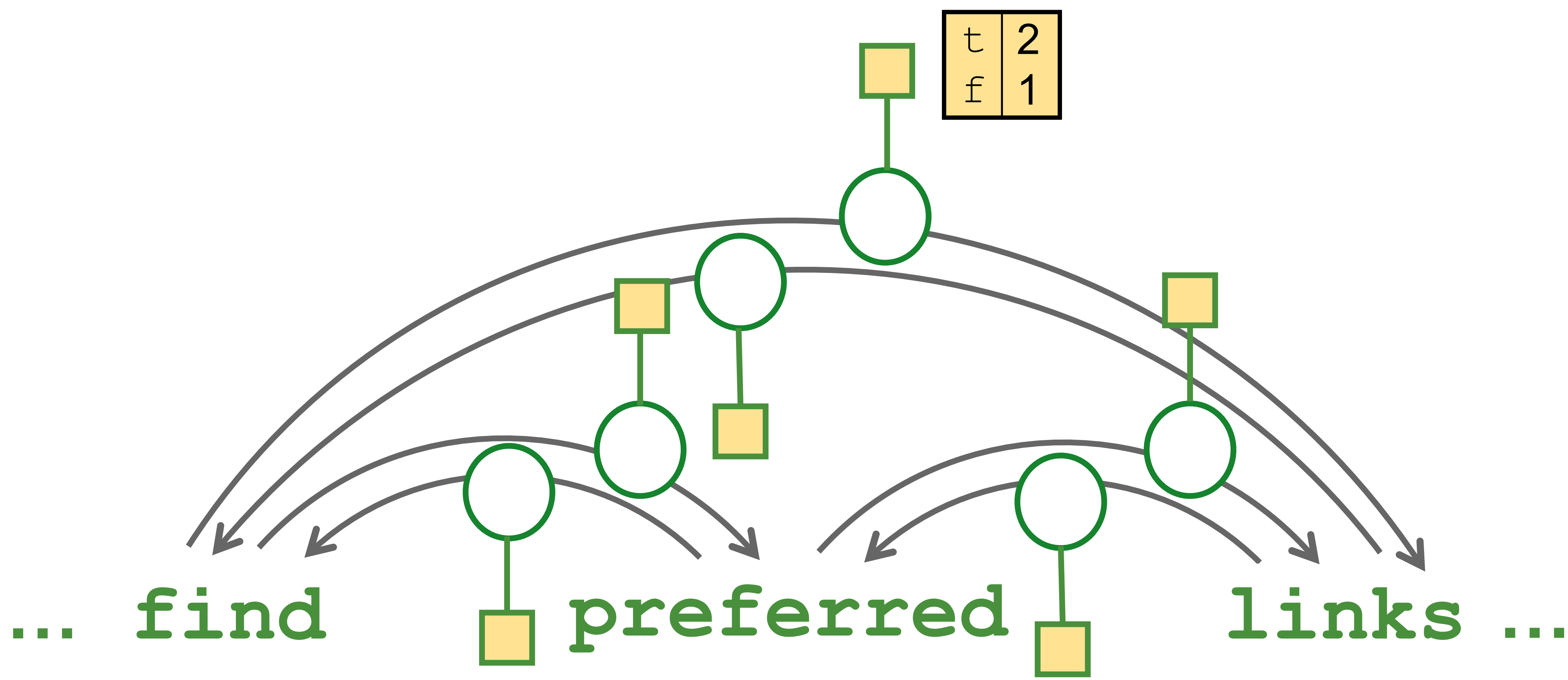
# Local Factors for Parsing

- What factors determine parse probability?



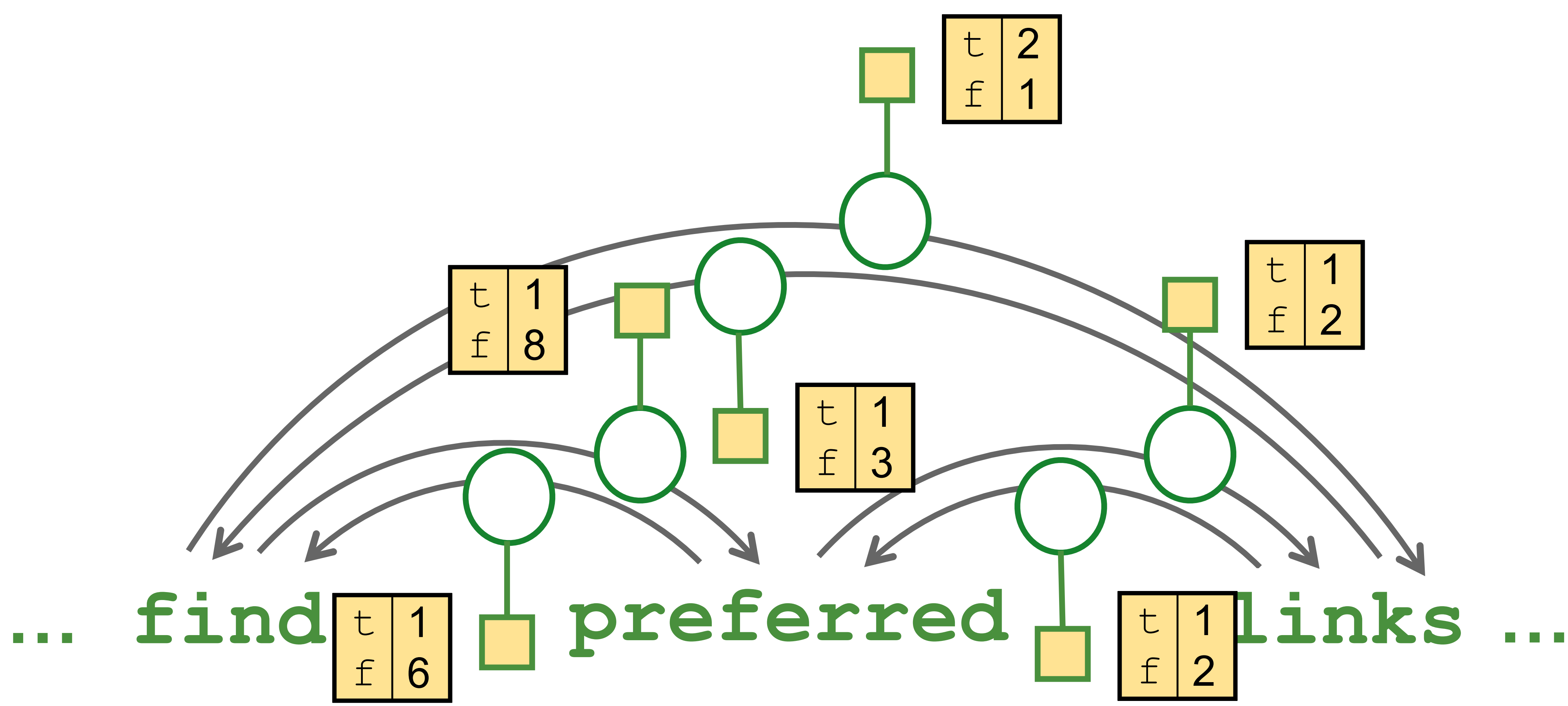
# Local Factors for Parsing

- What factors determine parse probability?
  - ✤ Unary factors to score each link in isolation



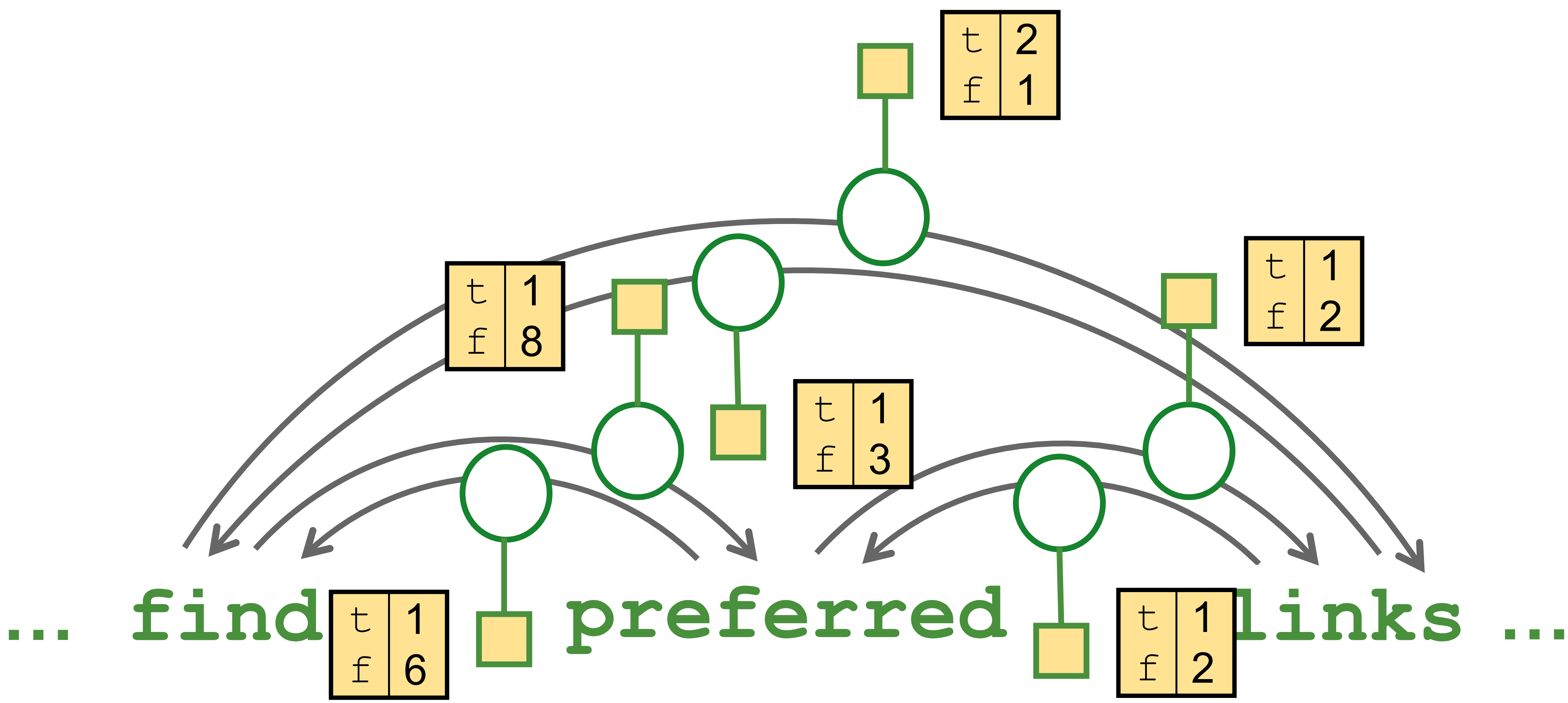
# Local Factors for Parsing

- What factors determine parse probability?
    - Unary factors to score each link in isolation



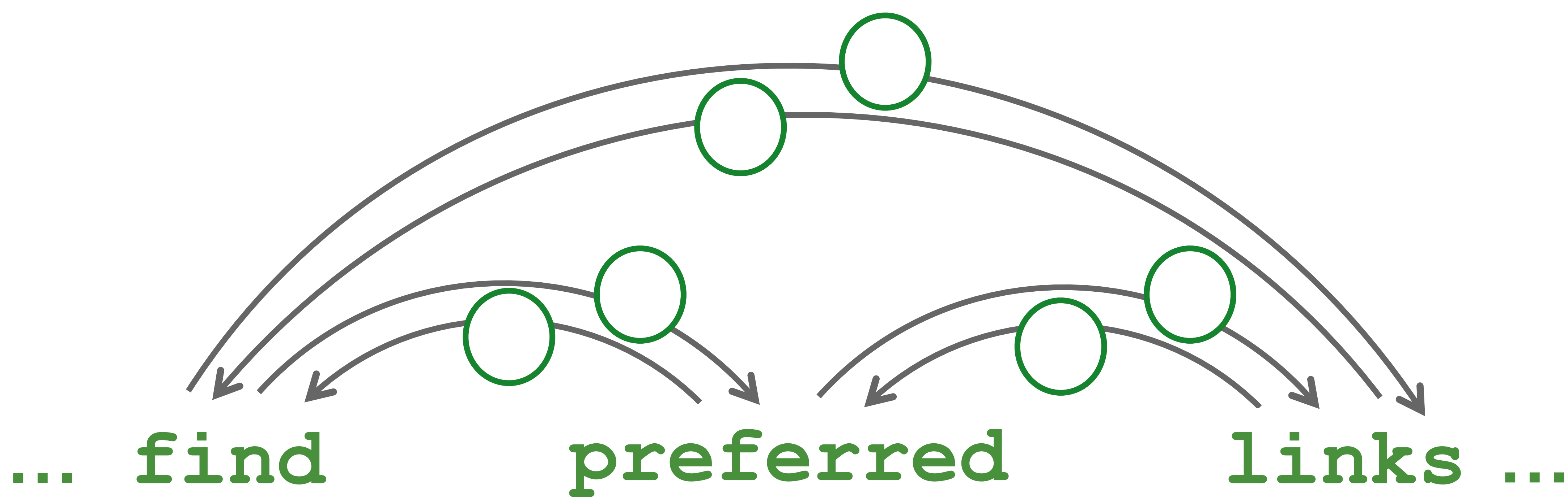
# Local Factors for Parsing

- What factors determine parse probability?
  - Unary factors to score each link in isolation
- But what if the best assignment isn't a tree?



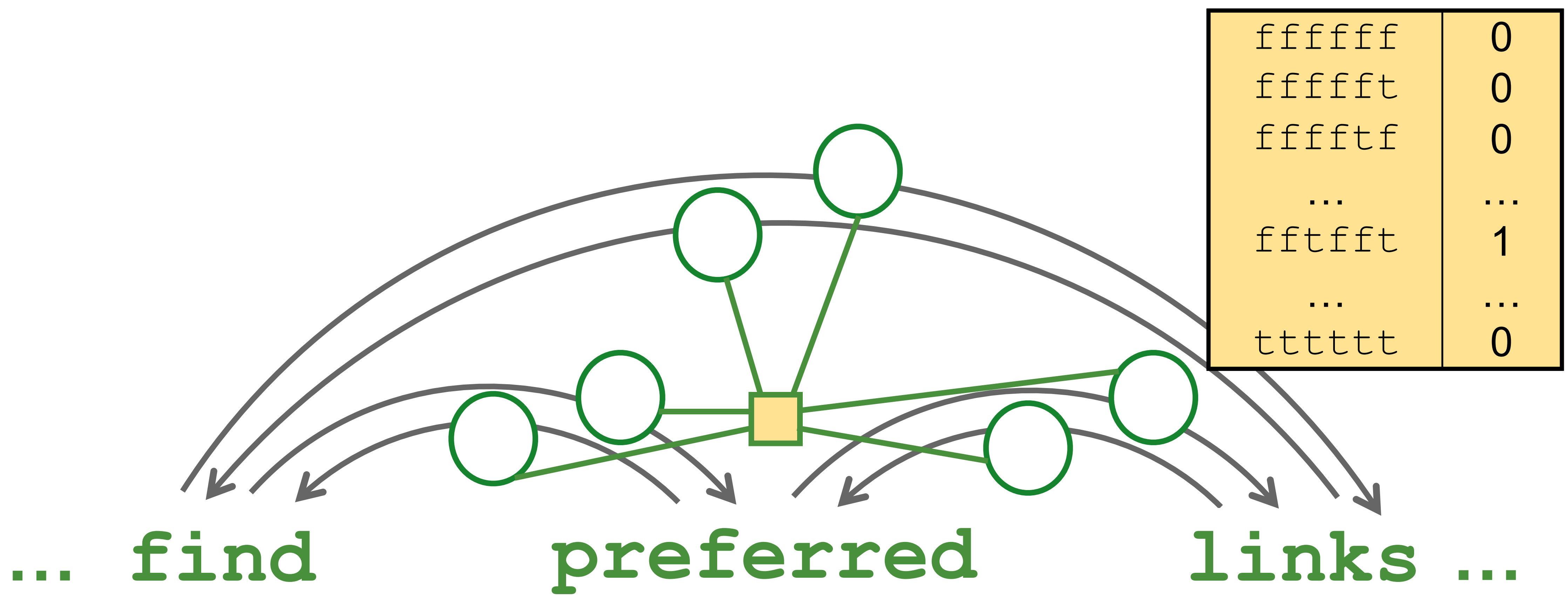
# Global Factors for Parsing

- What factors determine parse probability?
  - Unary factors to score each link in isolation



# Global Factors for Parsing

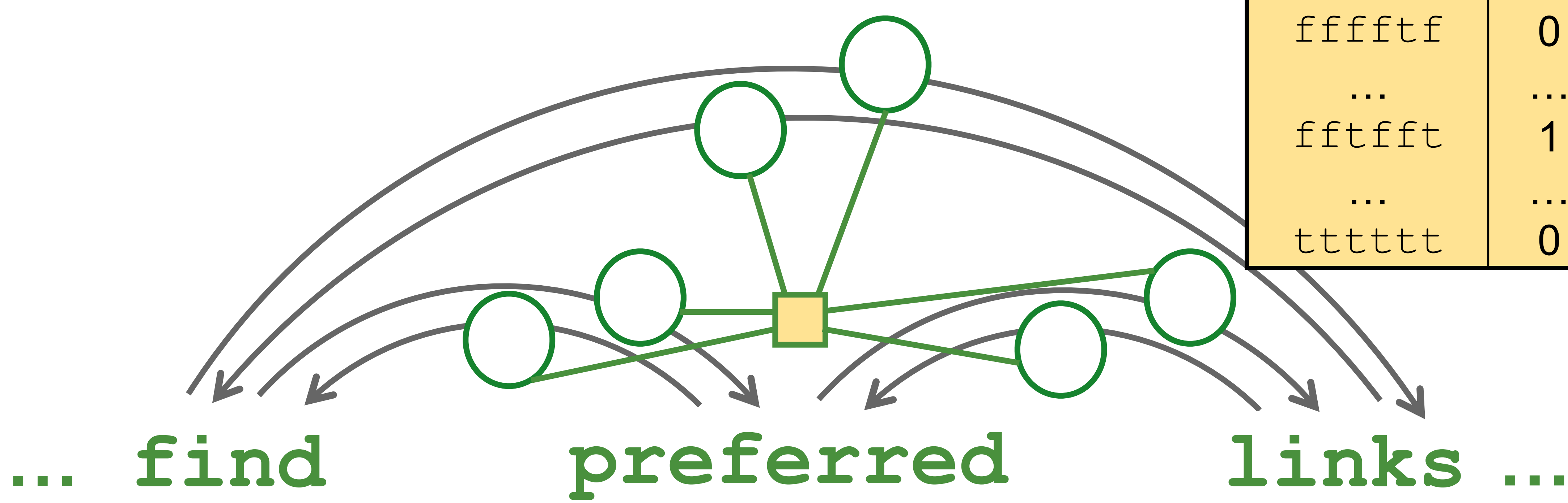
- What factors determine parse probability?
  - Unary factors to score each link in isolation
  - Global TREE factor to *require* links to form a legal tree



# Global Factors for Parsing

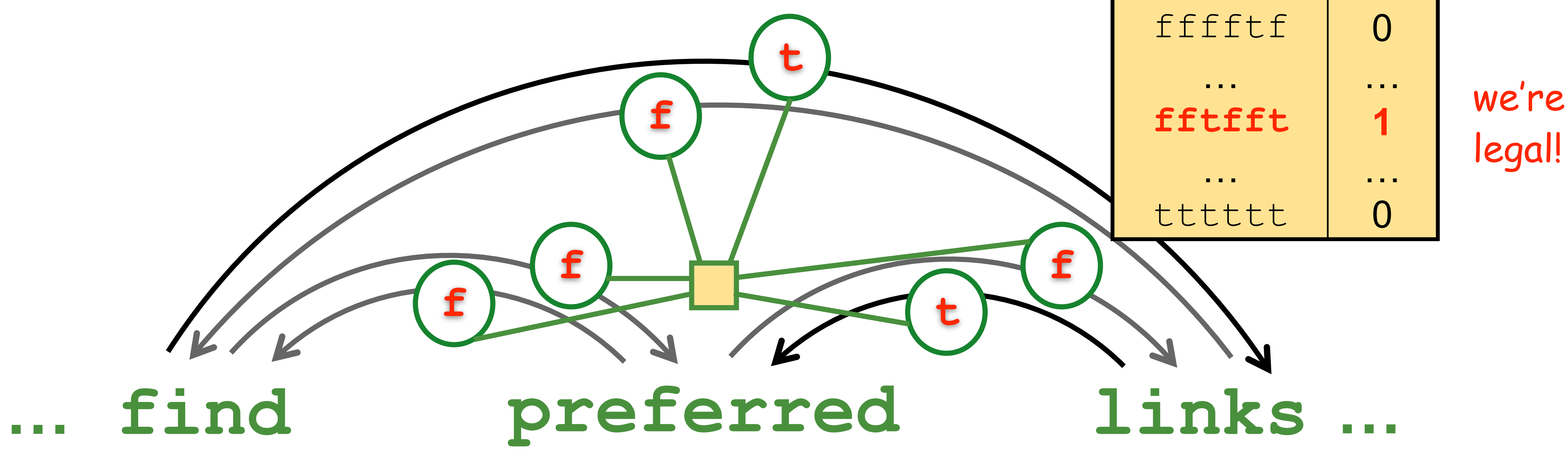
- What factors determine parse probability?
  - ✤ Unary factors to score each link in isolation
  - ✤ Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1

| | |
|---|---|
| ffffff | 0 |
| ffffft | 0 |
| fffftf | 0 |
| … | … |
| fftfft | 1 |
| … | … |
| tttttt | 0 |



# Global Factors for Parsing

- What factors determine parse probability?
  - Unary factors to score each link in isolation
  - Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1




| | |
|---|---|
| ffffff | 0 |
| ffffft | 0 |
| fffftf | 0 |
| … | … |
| fftfft | 1 |
| … | … |
| tttttt | 0 |

# Global Factors for Parsing

optionally require the tree to be projective (no crossing links)

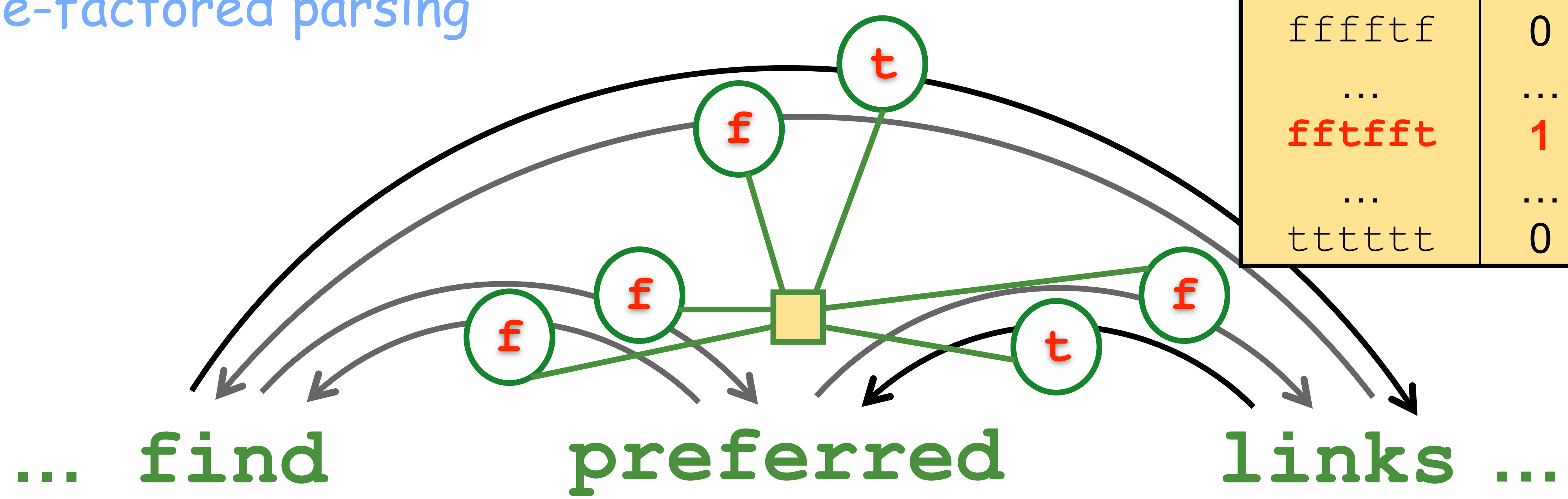
- What factors determine parse
  - ✤ Unary factors to score each link in isolation
  - ✤ Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1

So far, this is equivalent to edge-factored parsing

64 entries (0/1)

| | |
|---|---|
| ffffff | 0 |
| ffffft | 0 |
| fffftf | 0 |
| … | … |
| fftfft | 1 |
| … | … |
| tttttt | 0 |

we're legal!



# Global Factors for Parsing

- What factors determine parse

optionally require the tree to be projective (no crossing links)

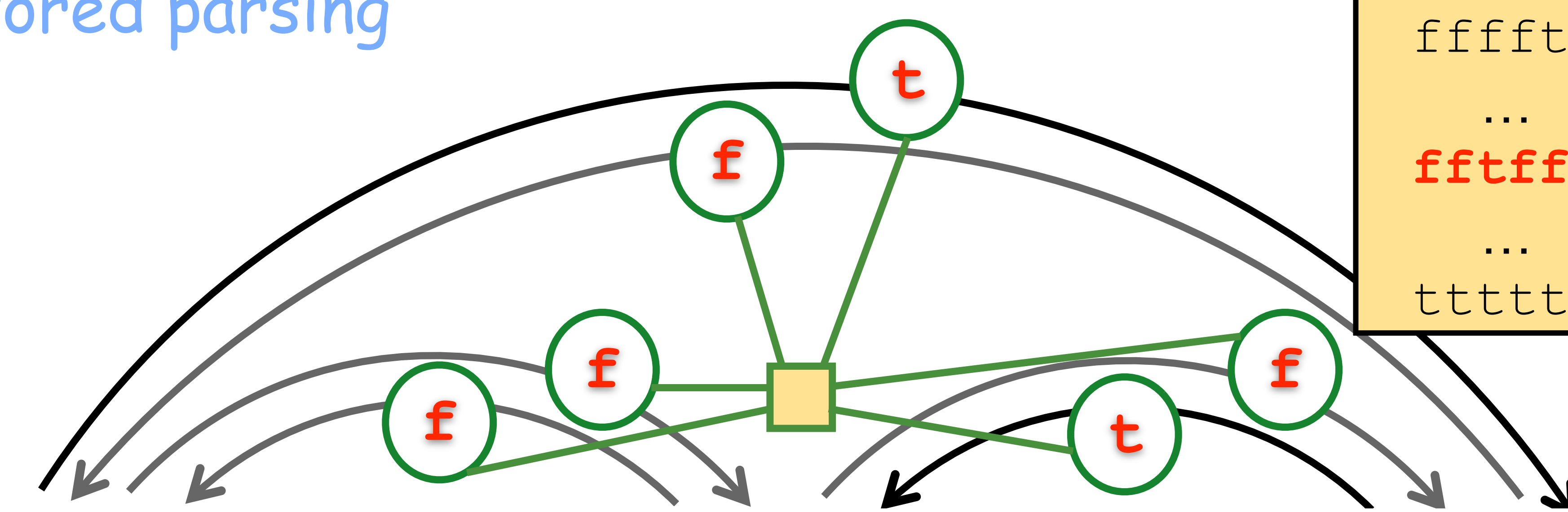
  - Unary factors to score each link in isolation
  - Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1

So far, this is equivalent to edge-factored parsing

64 entries (0/1)

| | |
|---|---|
| ffffff | 0 |
| ffffft | 0 |
| fffftf | 0 |
| … | … |
| **fftfft** | **1** |
| … | … |
| tttttt | 0 |

we're legal!

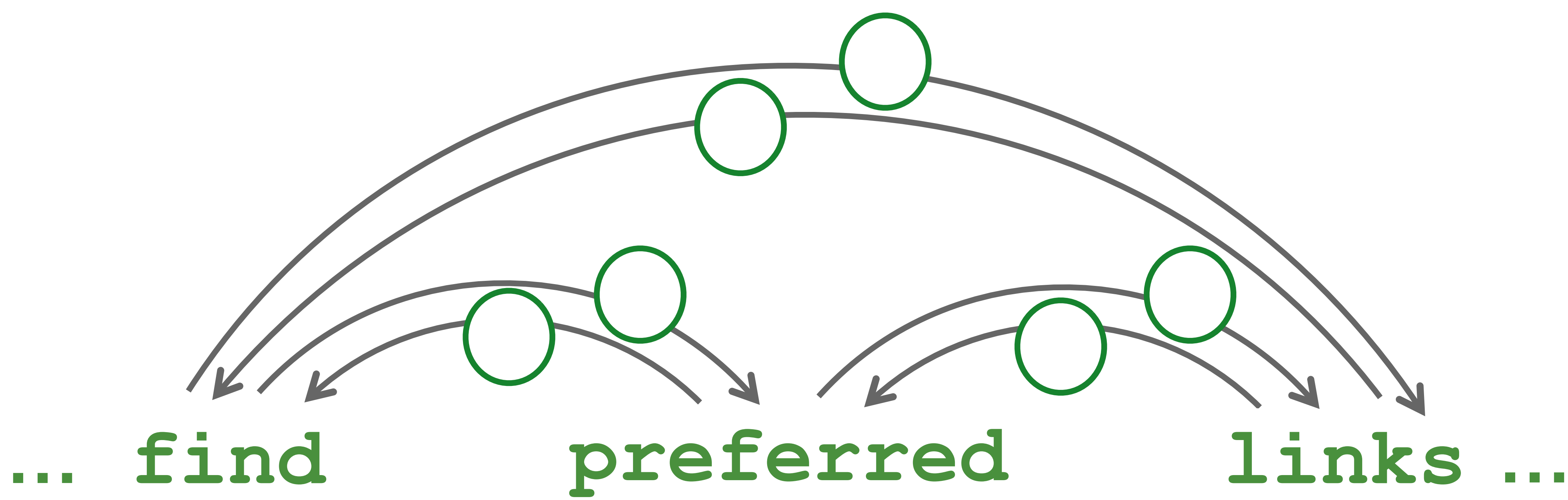



… fin

**Note:** traditional parsers don't loop through this table to consider exponentially many trees one at a time. They use combinatorial algorithms; so should we!

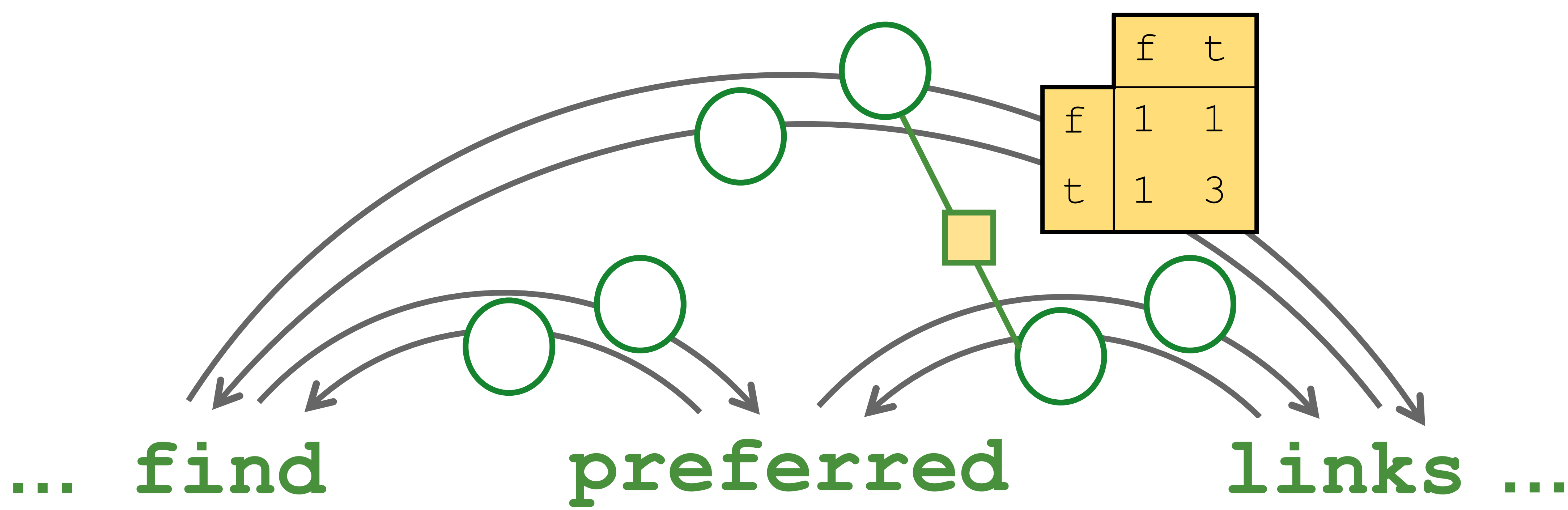
# Local Factors for Parsing

- What factors determine parse probability?
  - Unary factors to score each link in isolation
  - Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1
  - Second order effects: factors on 2 variables
    - Grandparent–parent–child chains



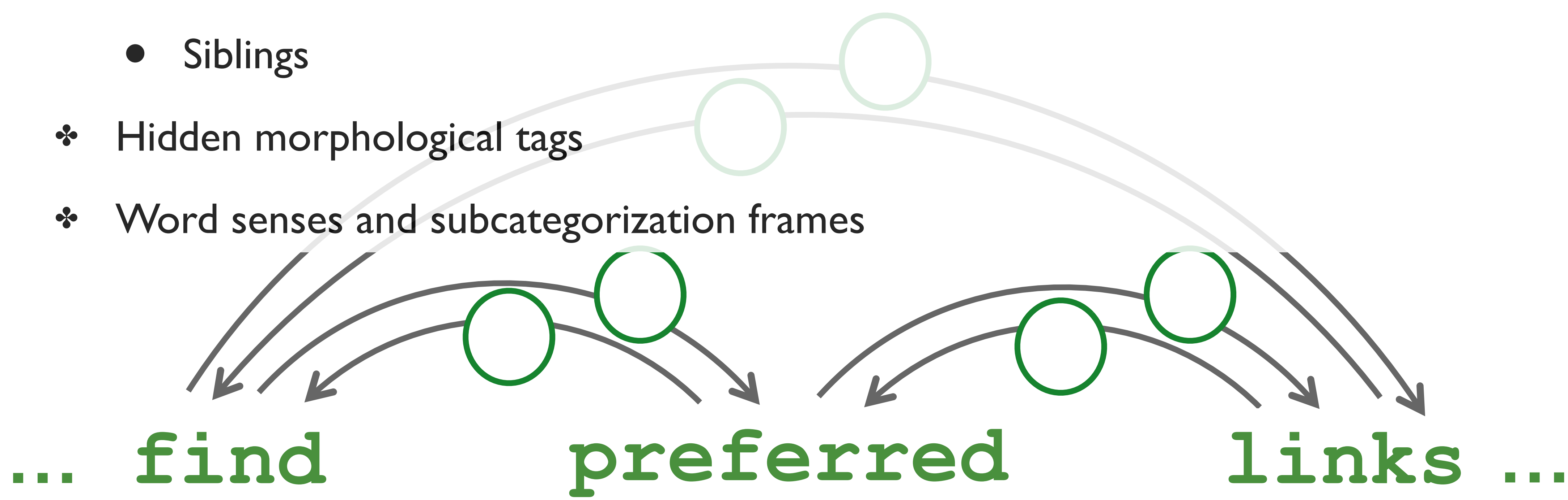
# Local Factors for Parsing

- What factors determine parse probability?
  - Unary factors to score each link in isolation
  - Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1
  - Second order effects: factors on 2 variables
    - Grandparent–parent–child chains



# Local Factors for Parsing

- What factors determine parse probability?
  - Unary factors to score each link in isolation
  - Global TREE factor to *require* links to form a legal tree
    - A *hard constraint*: potential is either 0 or 1
  - Second order effects: factors on 2 variables
    - Grandparent–parent–child chains
    - No crossing links
    - Siblings
  - Hidden morphological tags
  - Word senses and subcategorization frames



# Great Ideas in ML: Message Passing

adapted from MacKay (2003) textbook

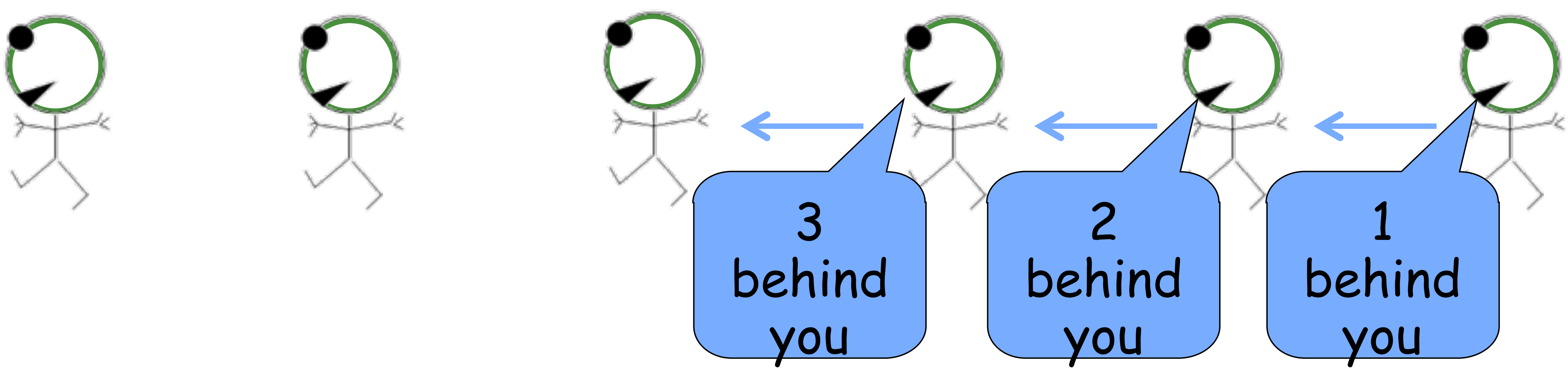
# Great Ideas in ML: Message Passing

*Count the soldiers*

adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

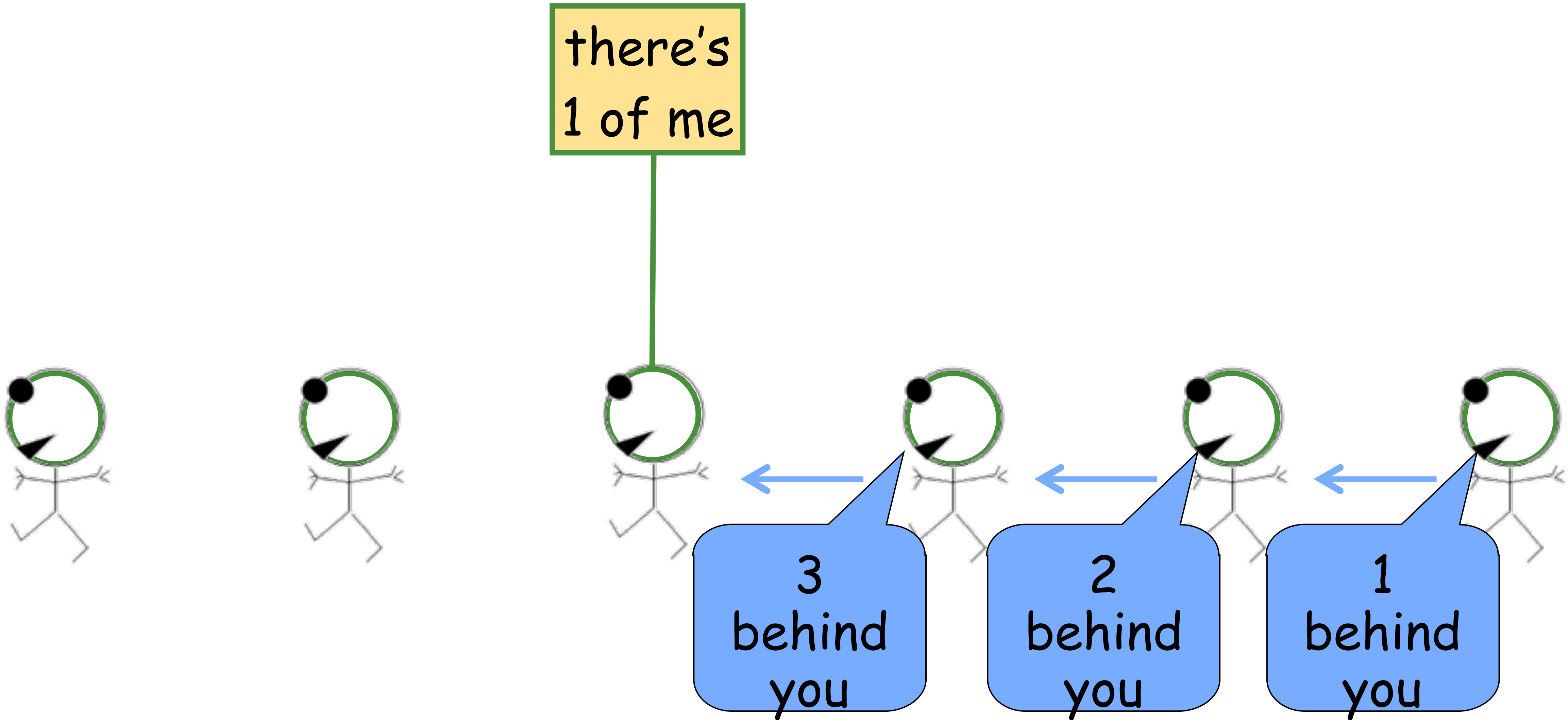
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

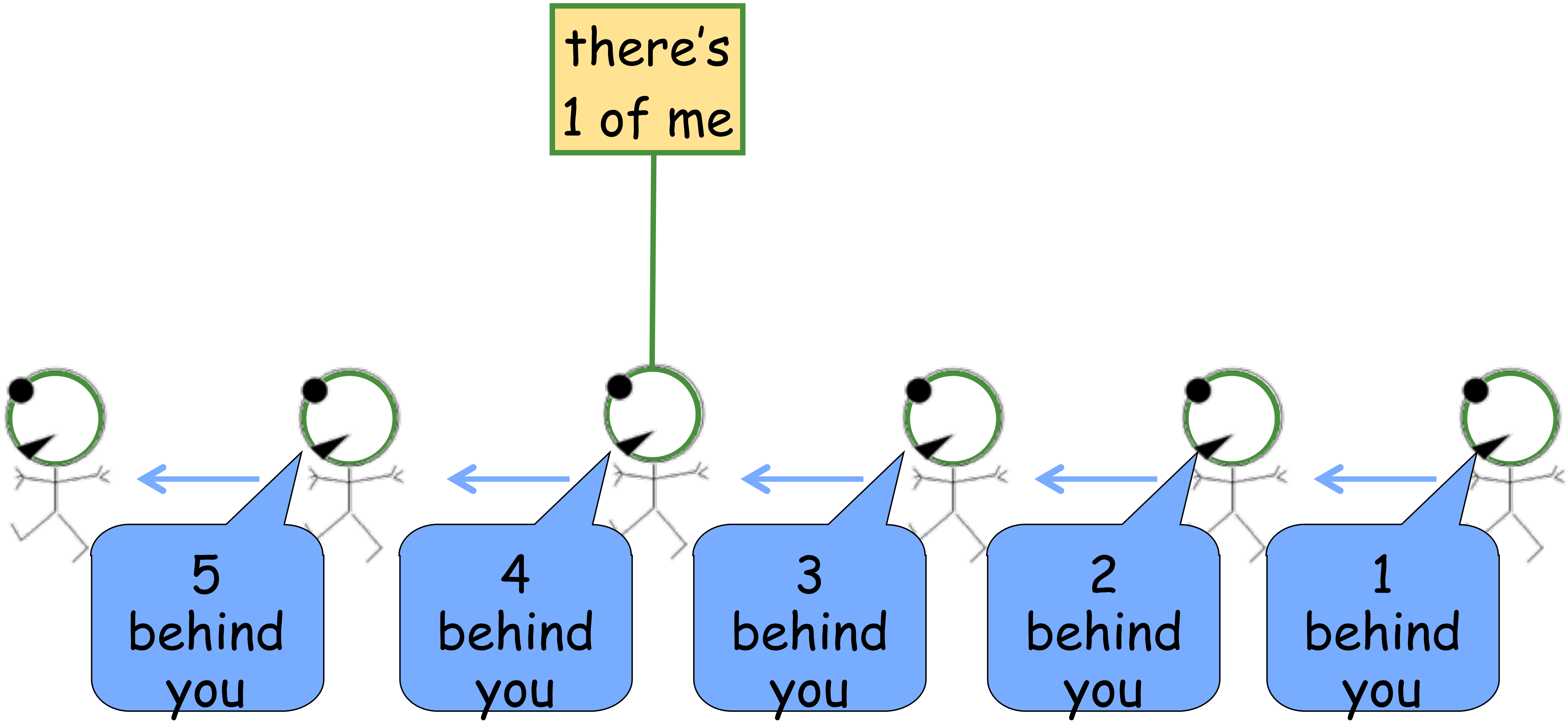
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

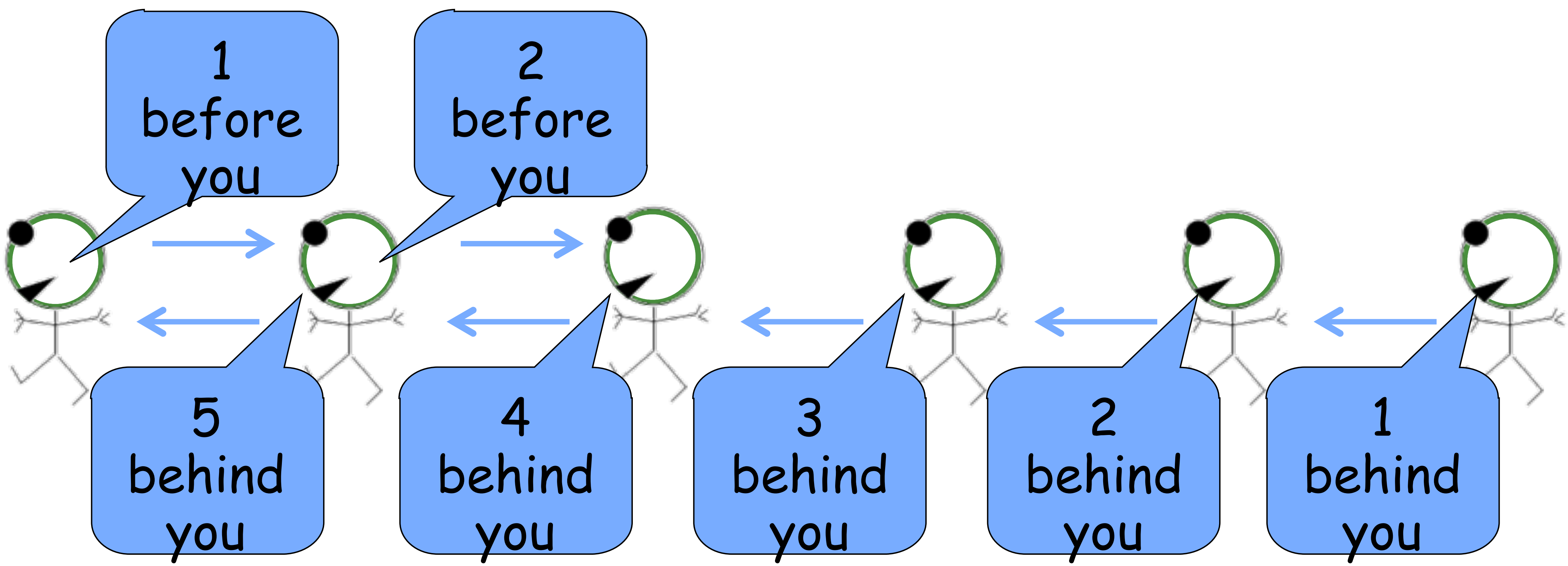
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

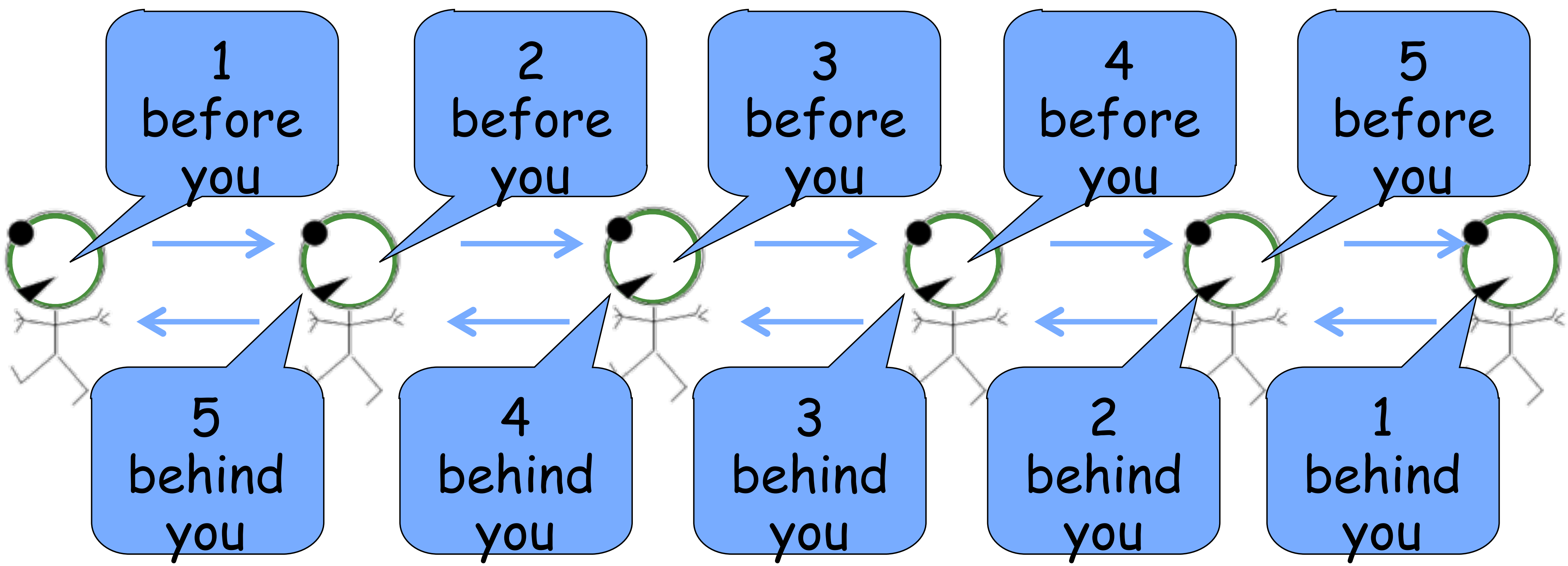
*Count the soldiers*




**adapted from MacKay (2003) textbook**

# Great Ideas in ML: Message Passing

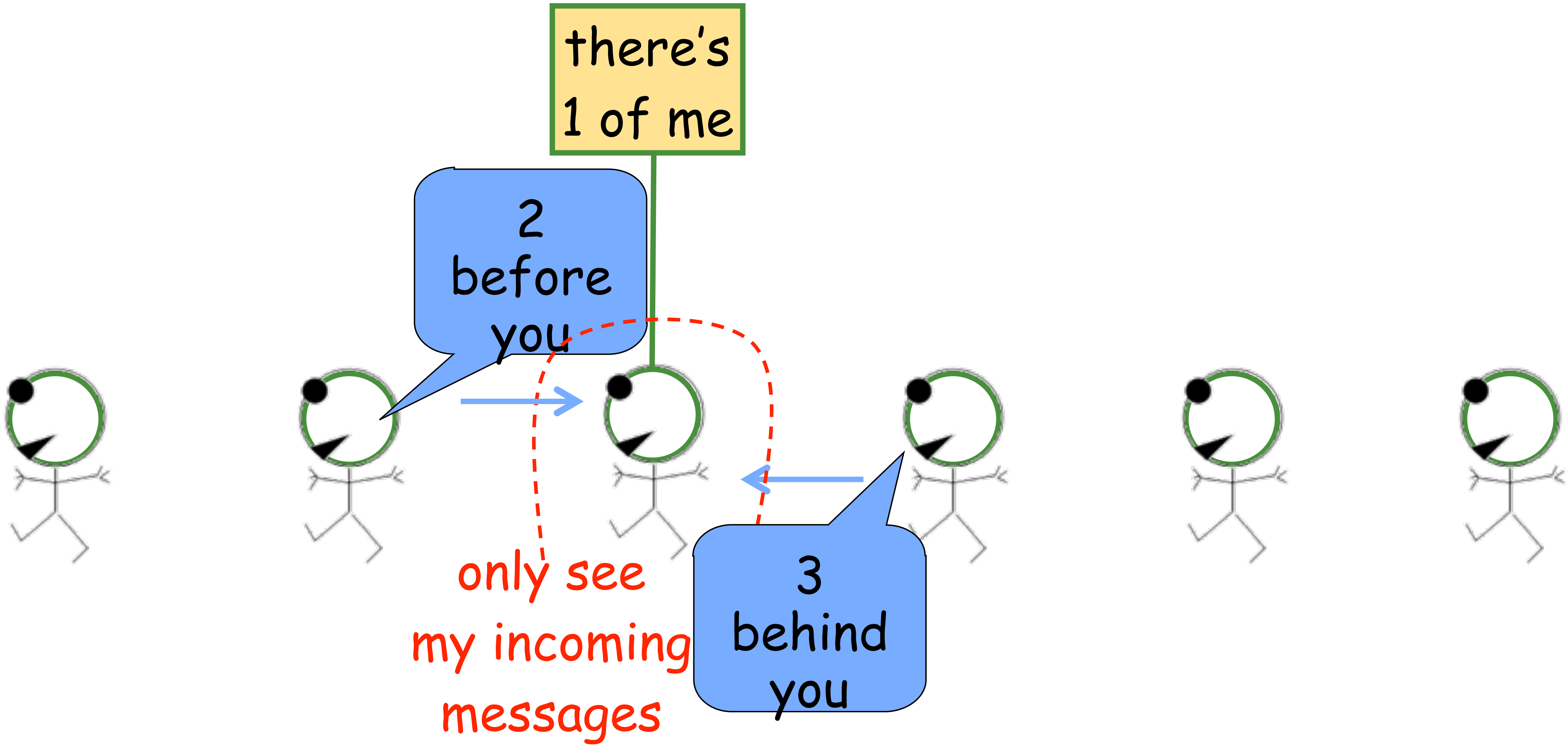
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

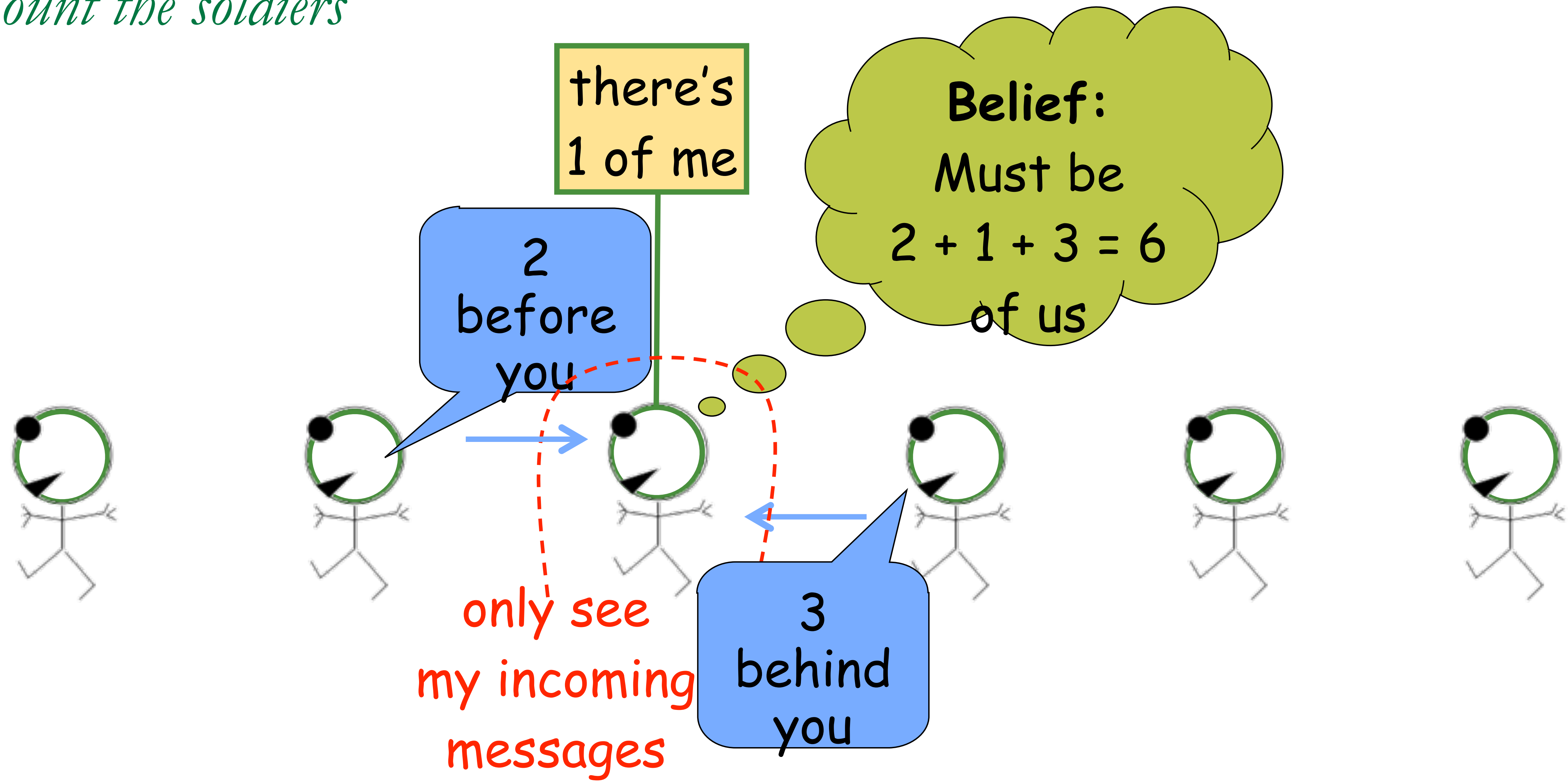
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

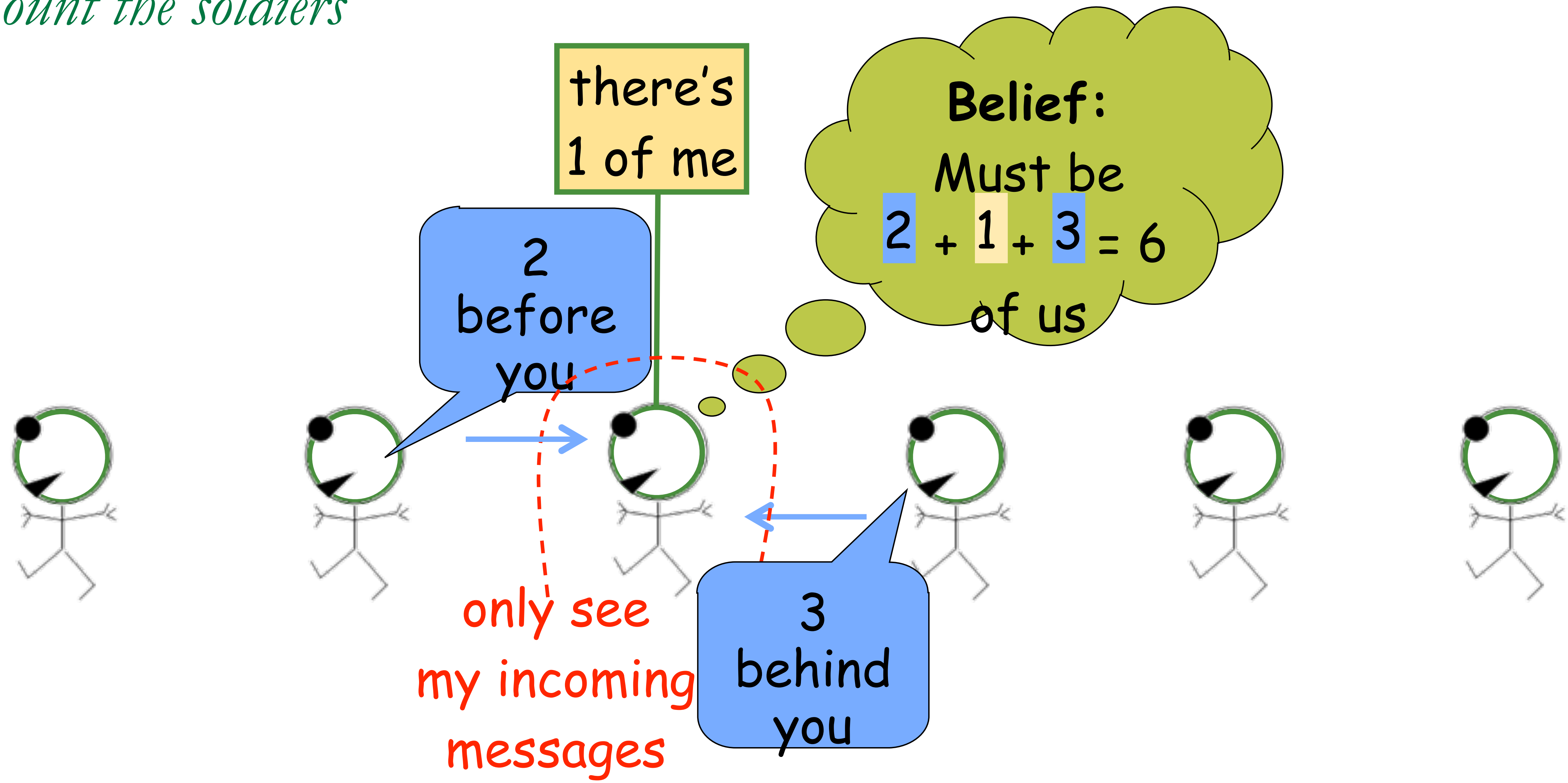
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

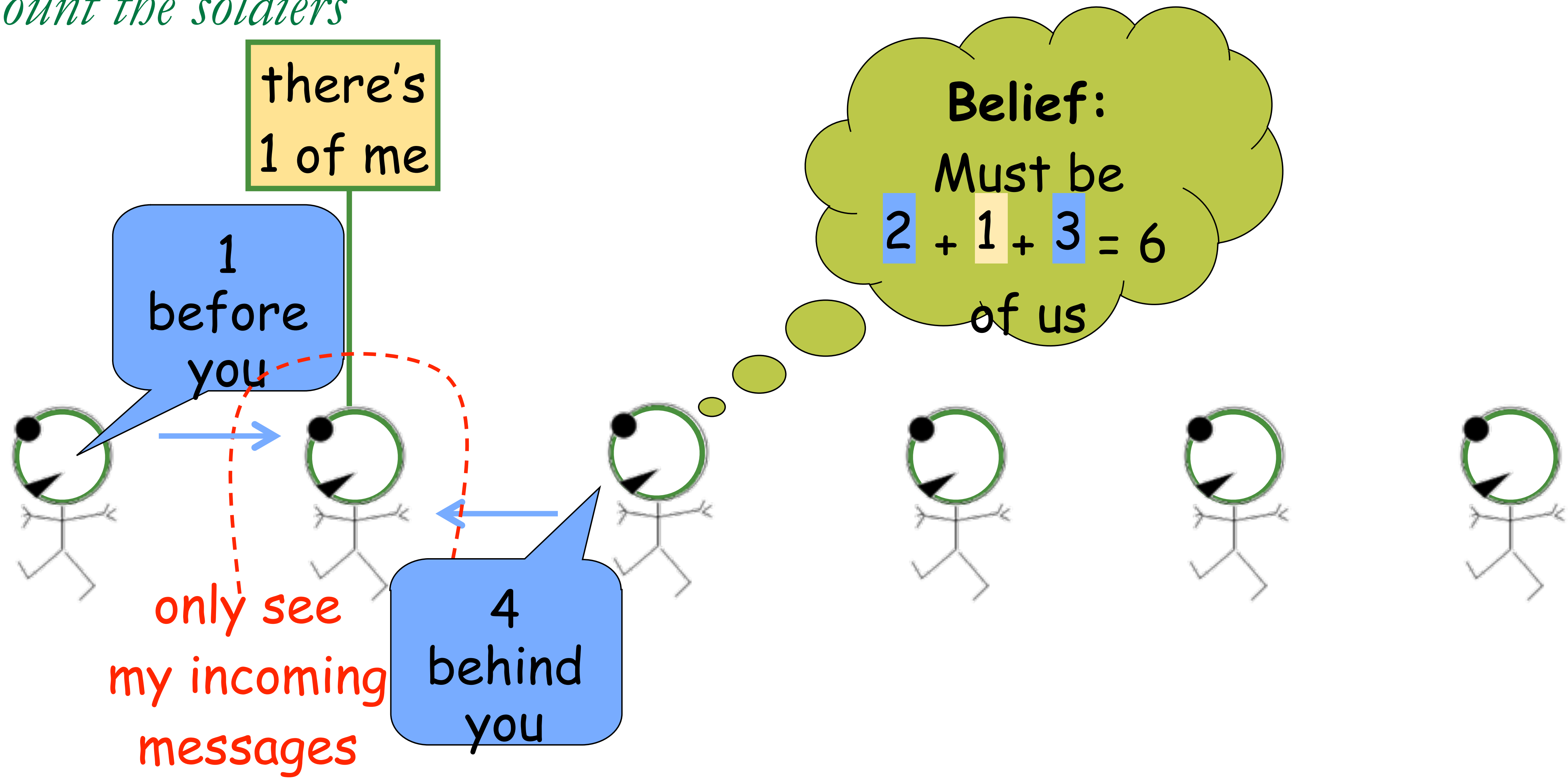
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

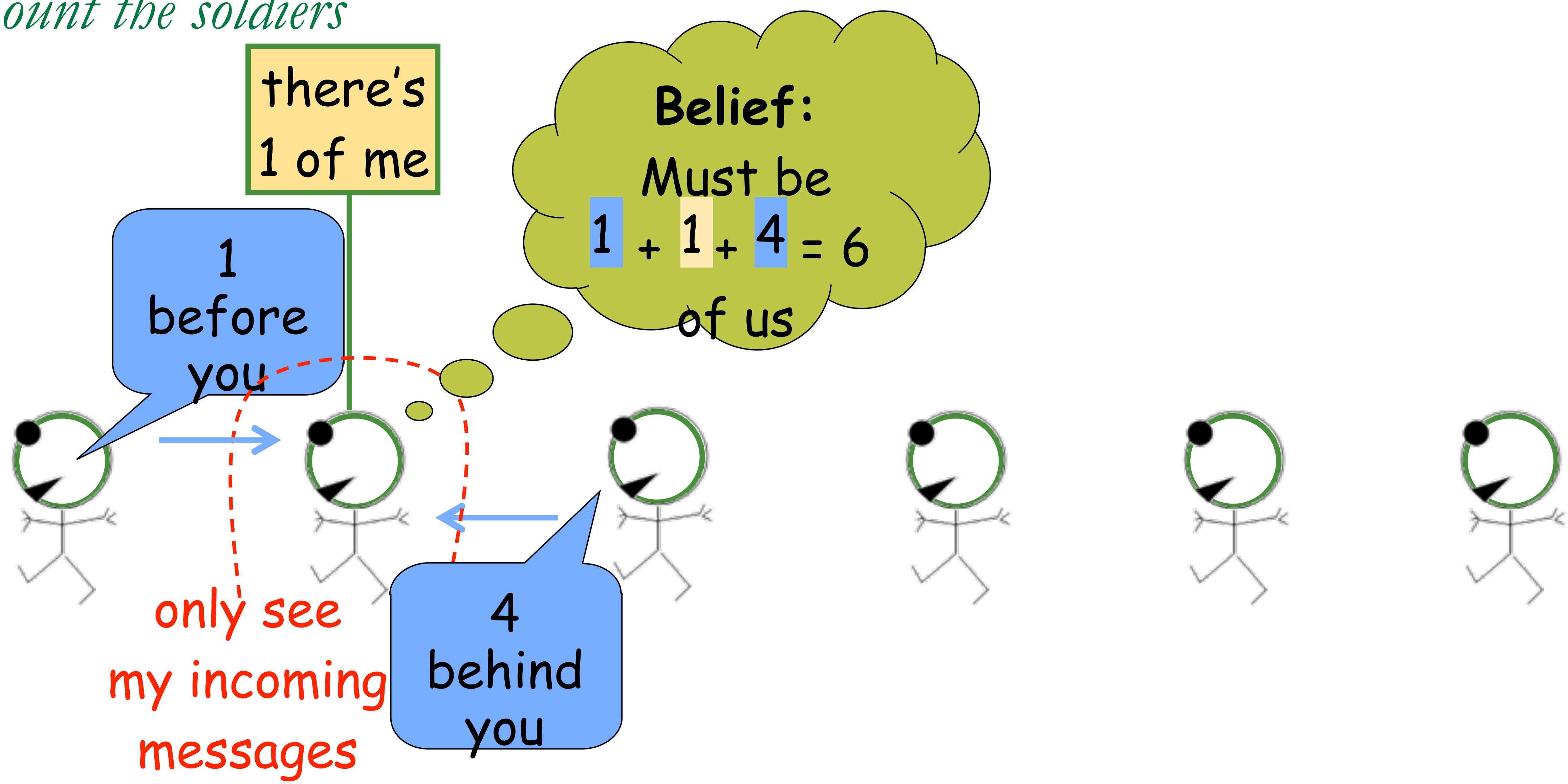
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

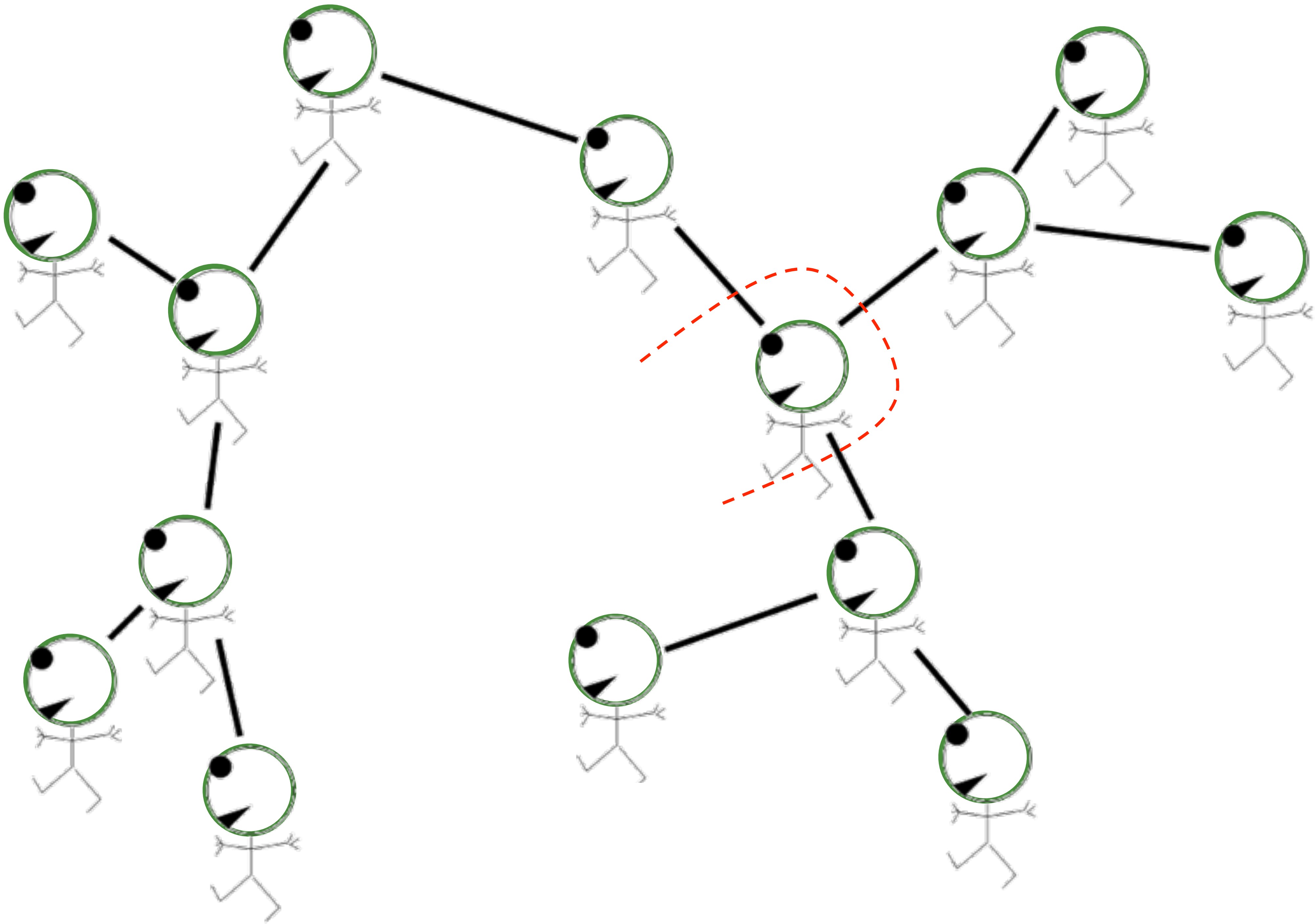
*Count the soldiers*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

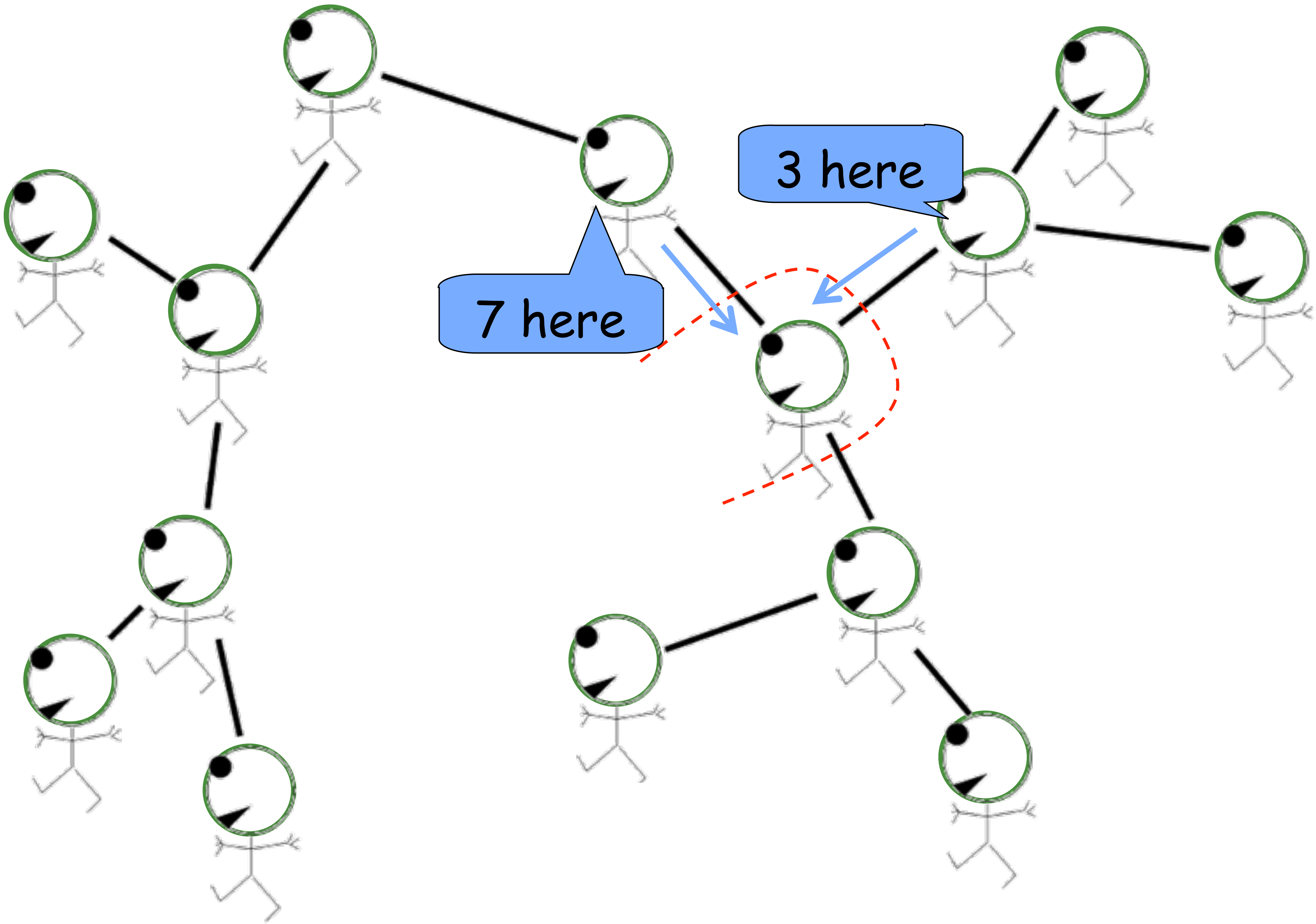
*Each soldier receives reports from all branches of tree*



adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

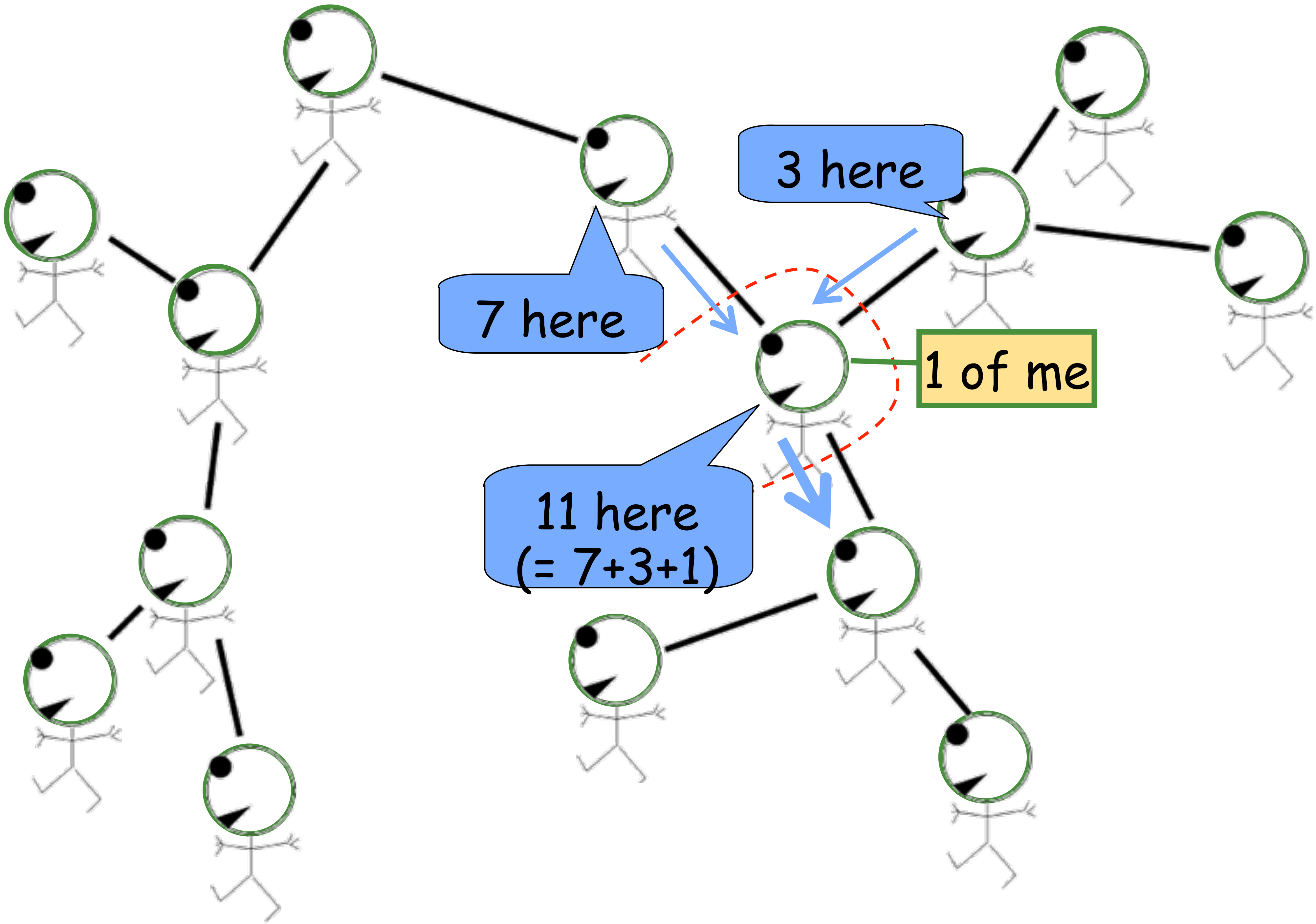
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

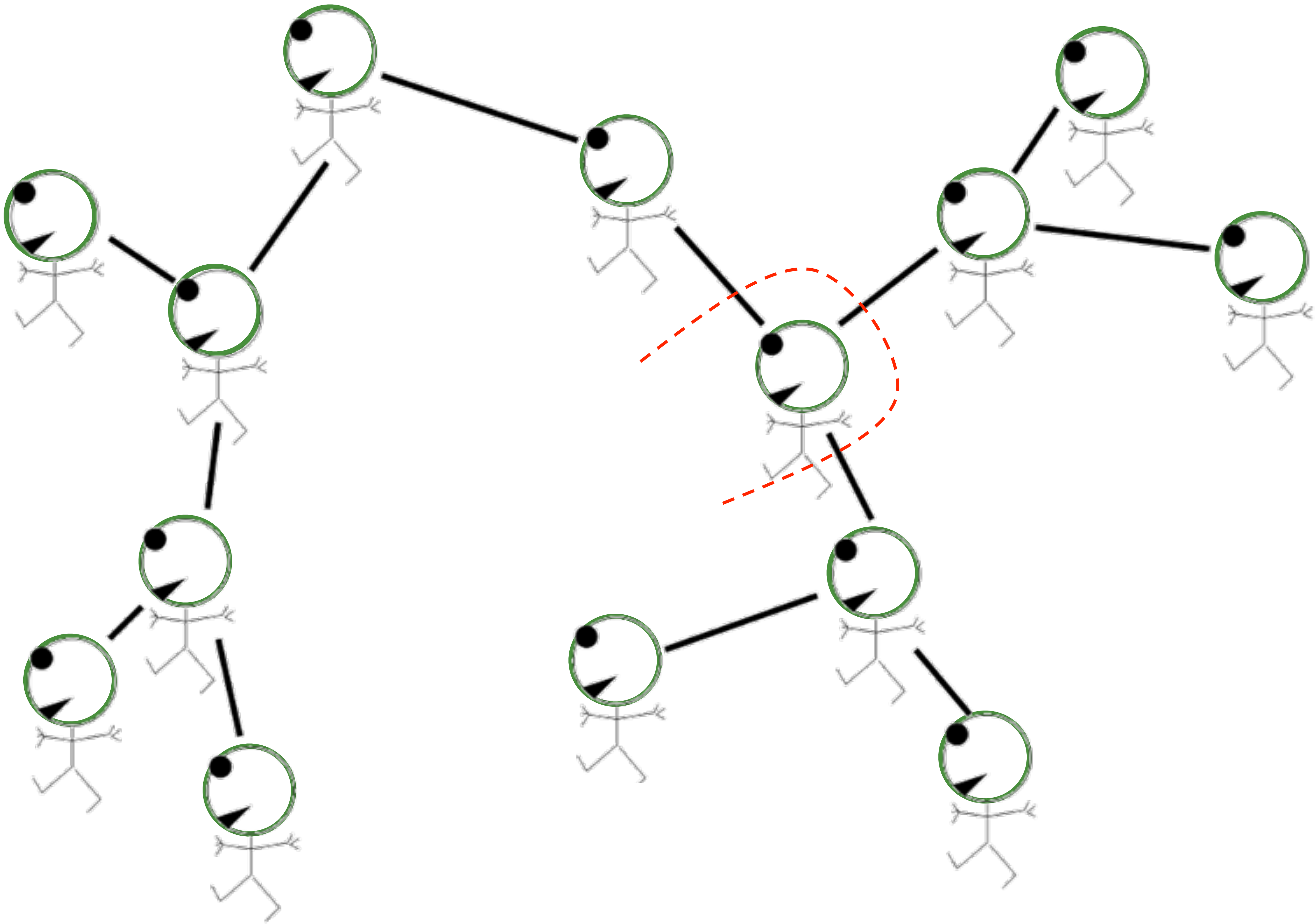
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

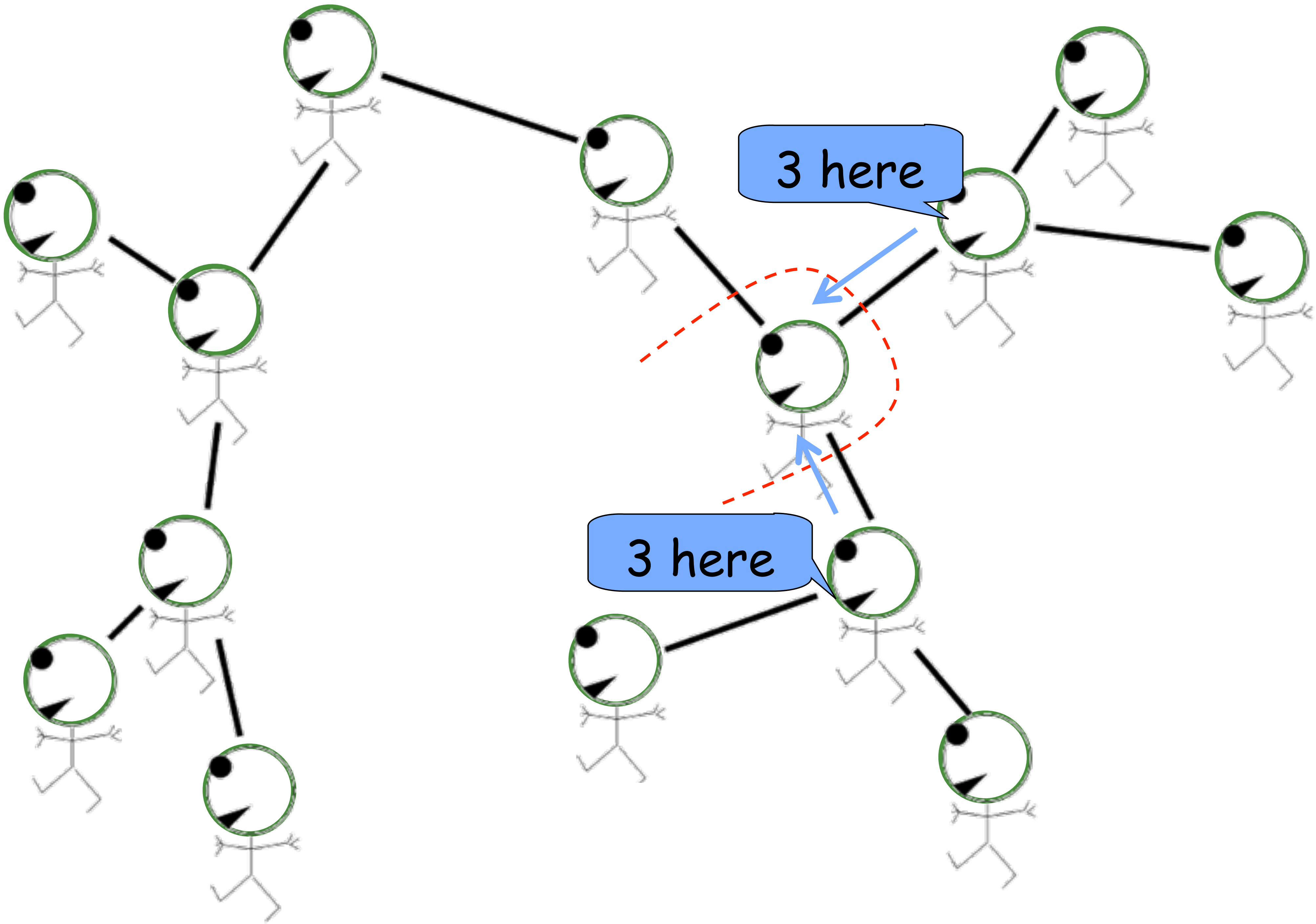
*Each soldier receives reports from all branches of tree*



adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

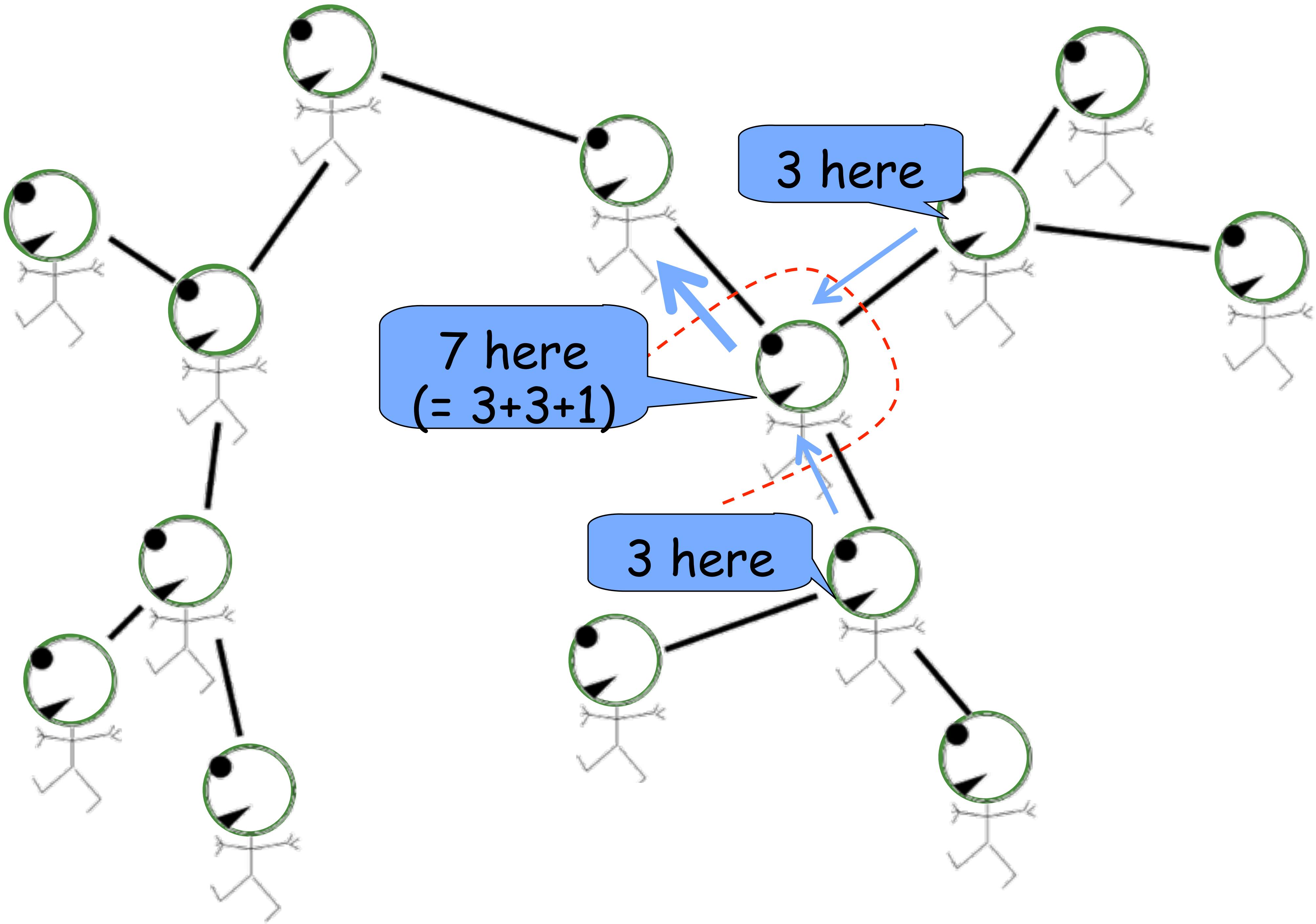
*Each soldier receives reports from all branches of tree*




**adapted from MacKay (2003) textbook**

# Great Ideas in ML: Message Passing

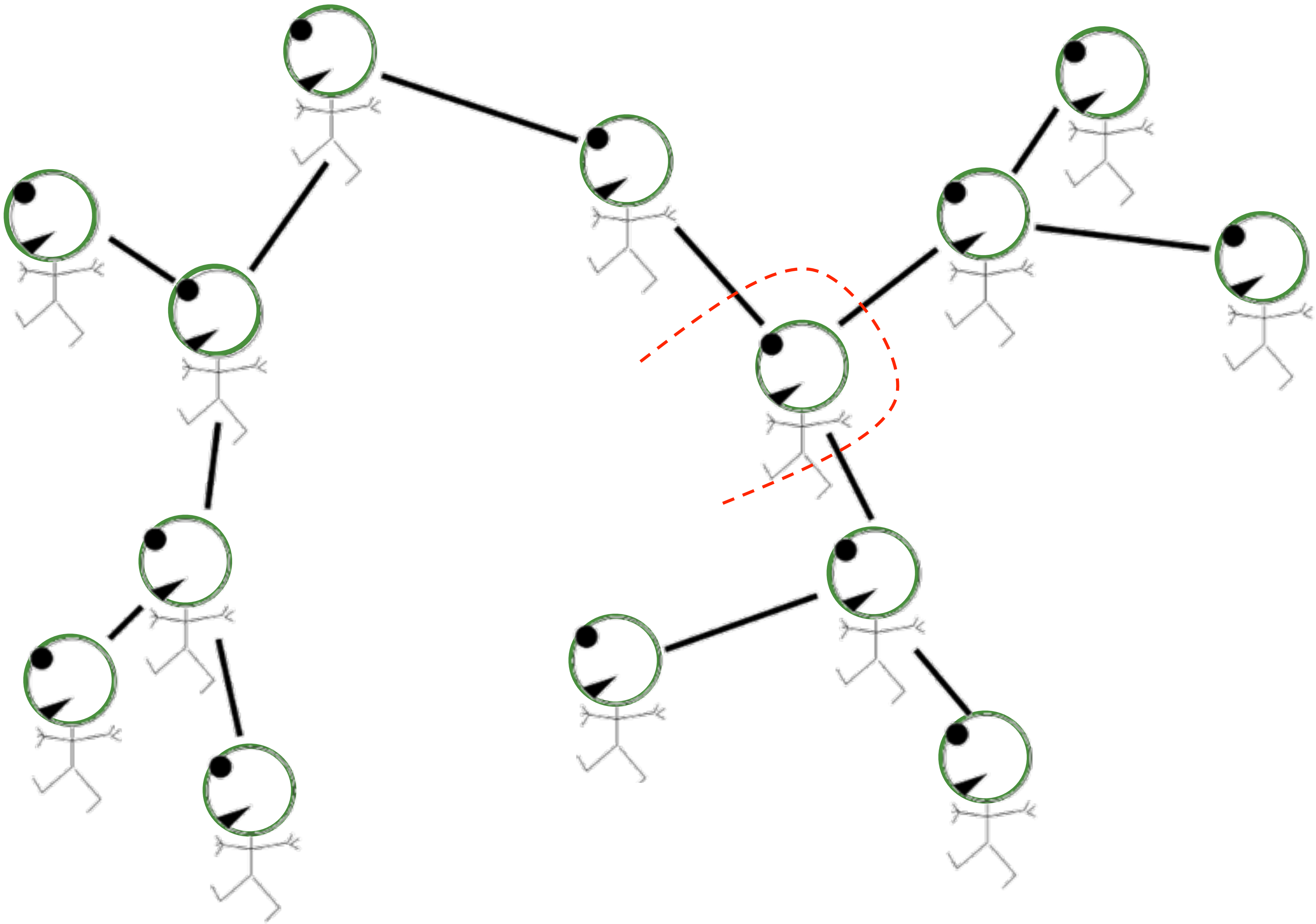
*Each soldier receives reports from all branches of tree*




**adapted from MacKay (2003) textbook**

# Great Ideas in ML: Message Passing

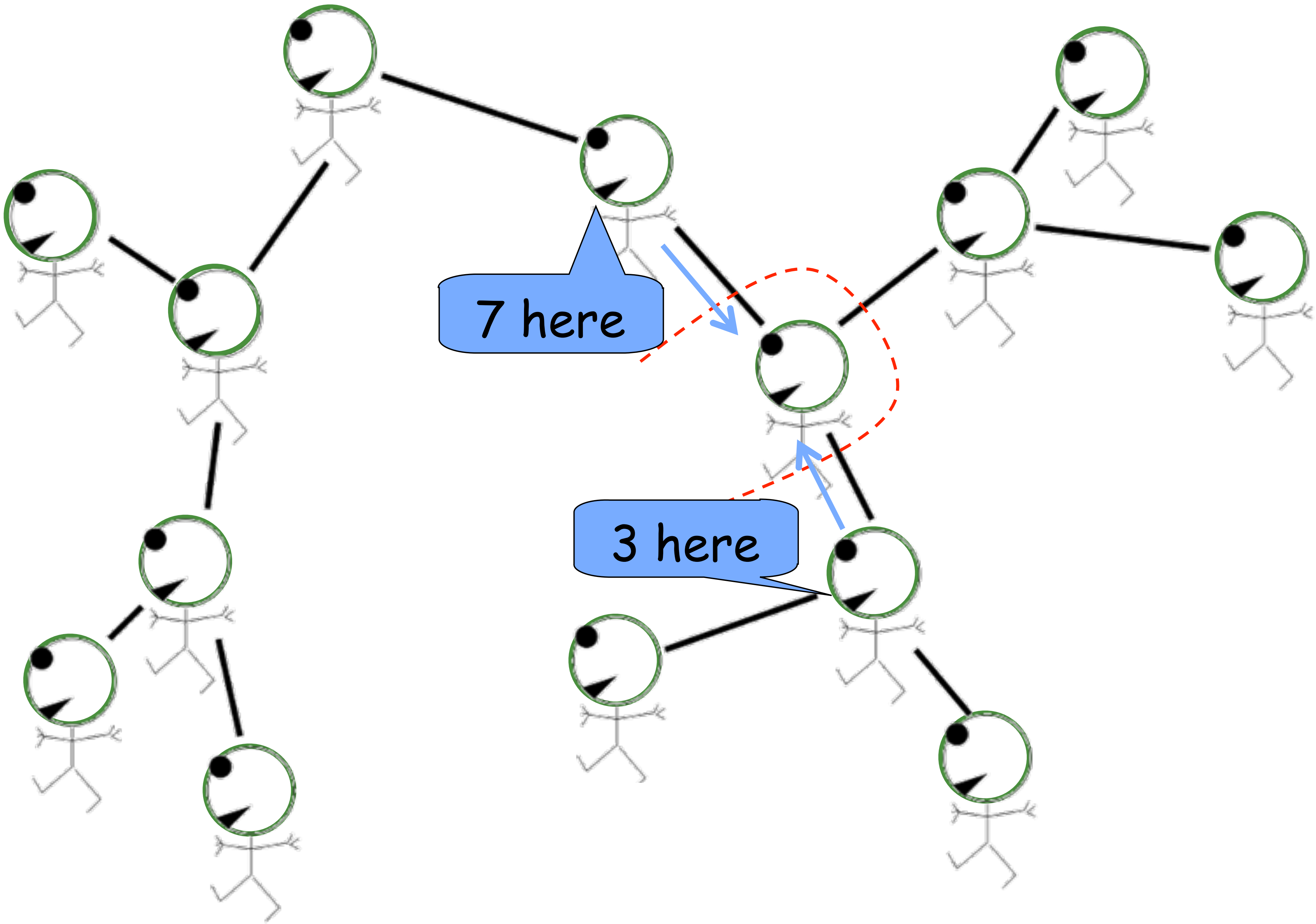
*Each soldier receives reports from all branches of tree*



**adapted from MacKay (2003) textbook**

# Great Ideas in ML: Message Passing

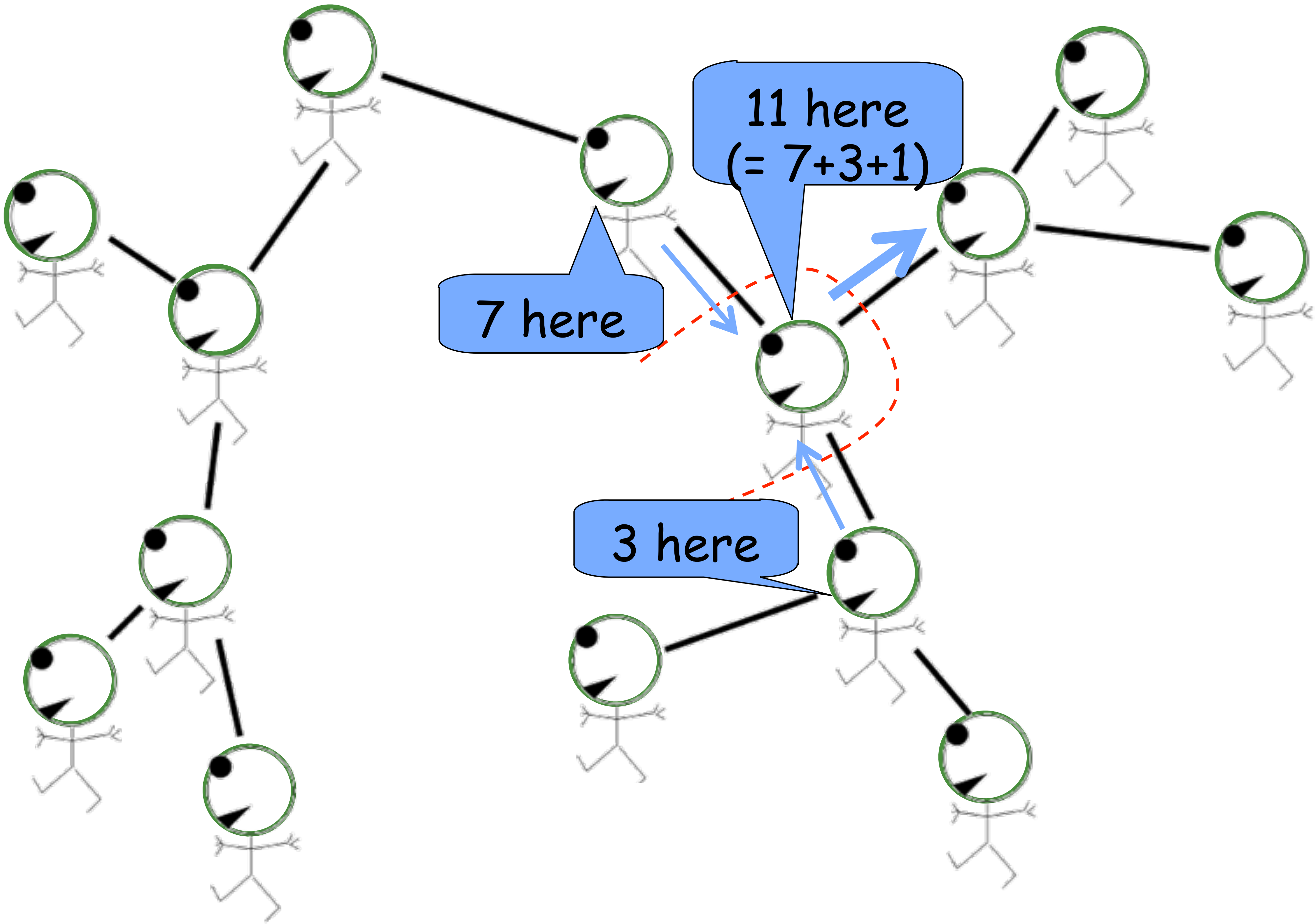
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

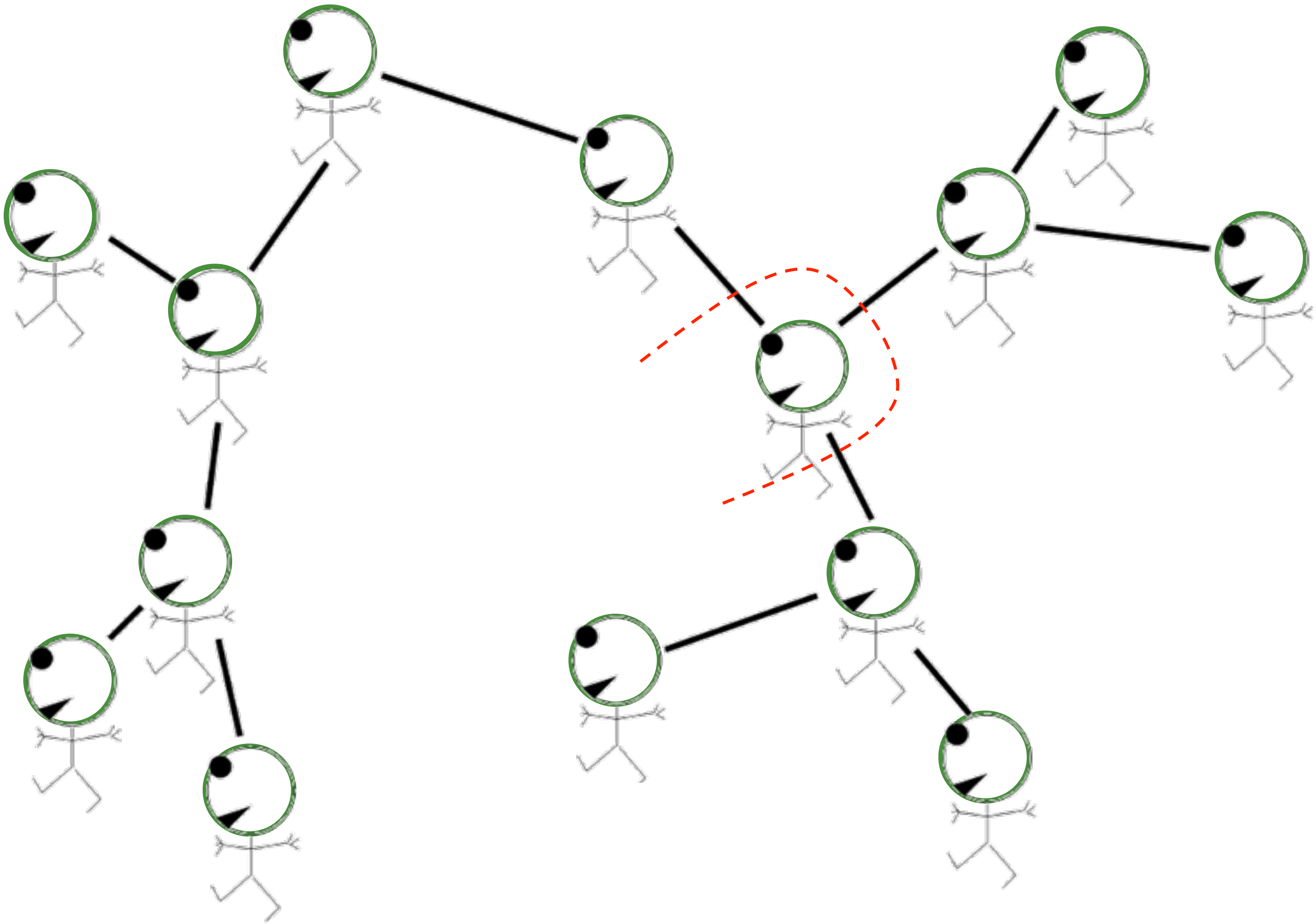
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

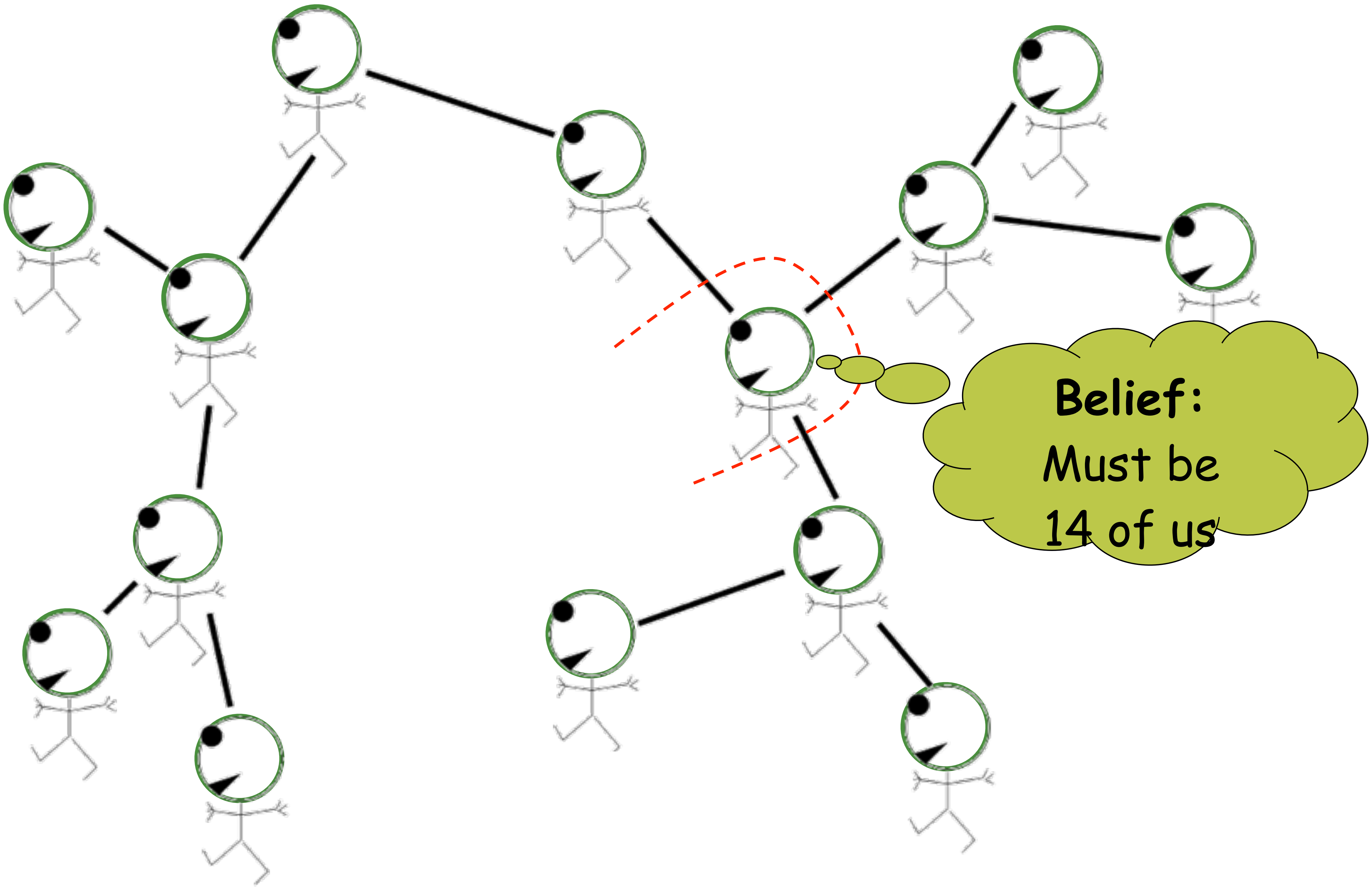
*Each soldier receives reports from all branches of tree*



adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

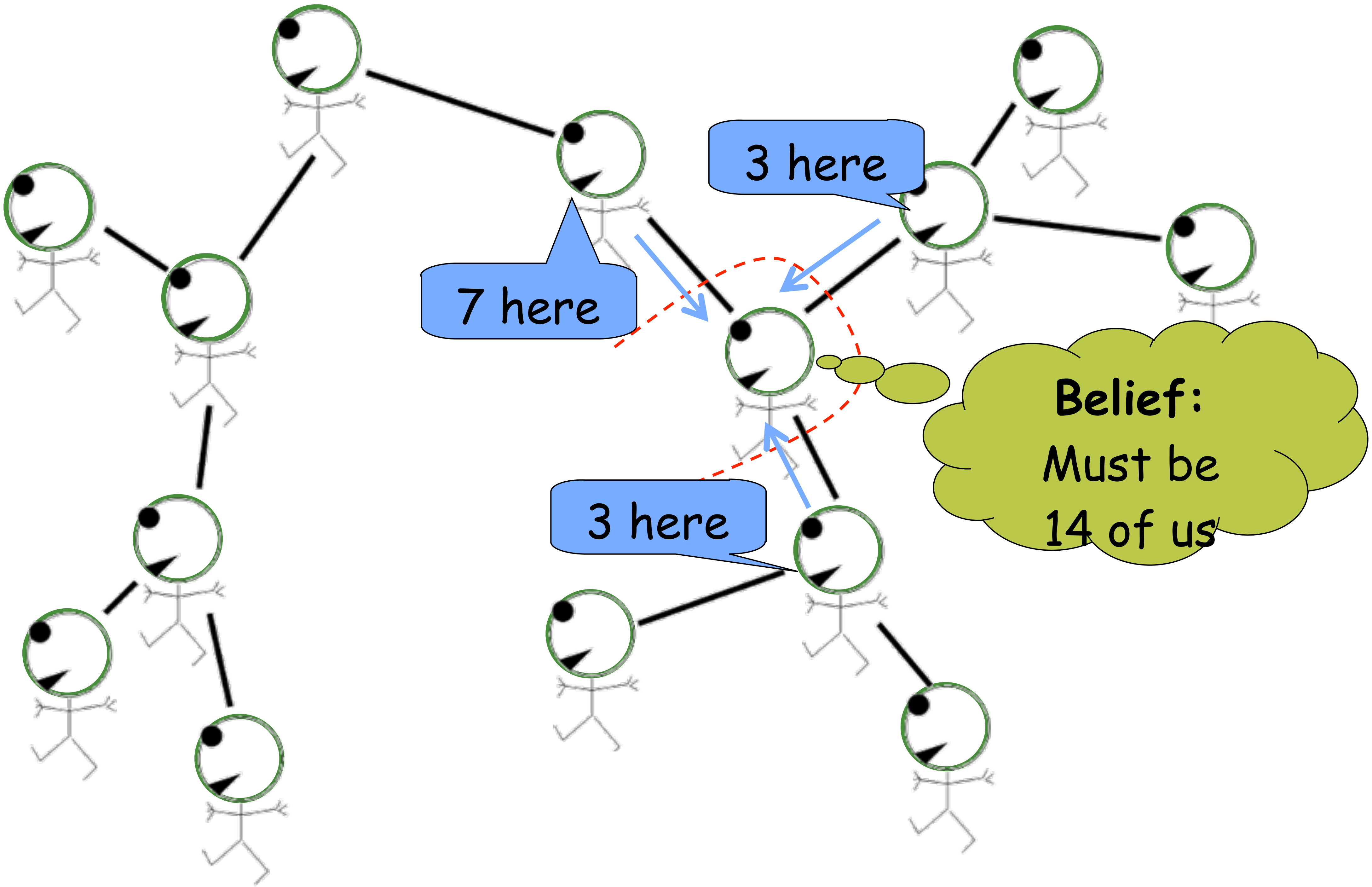
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

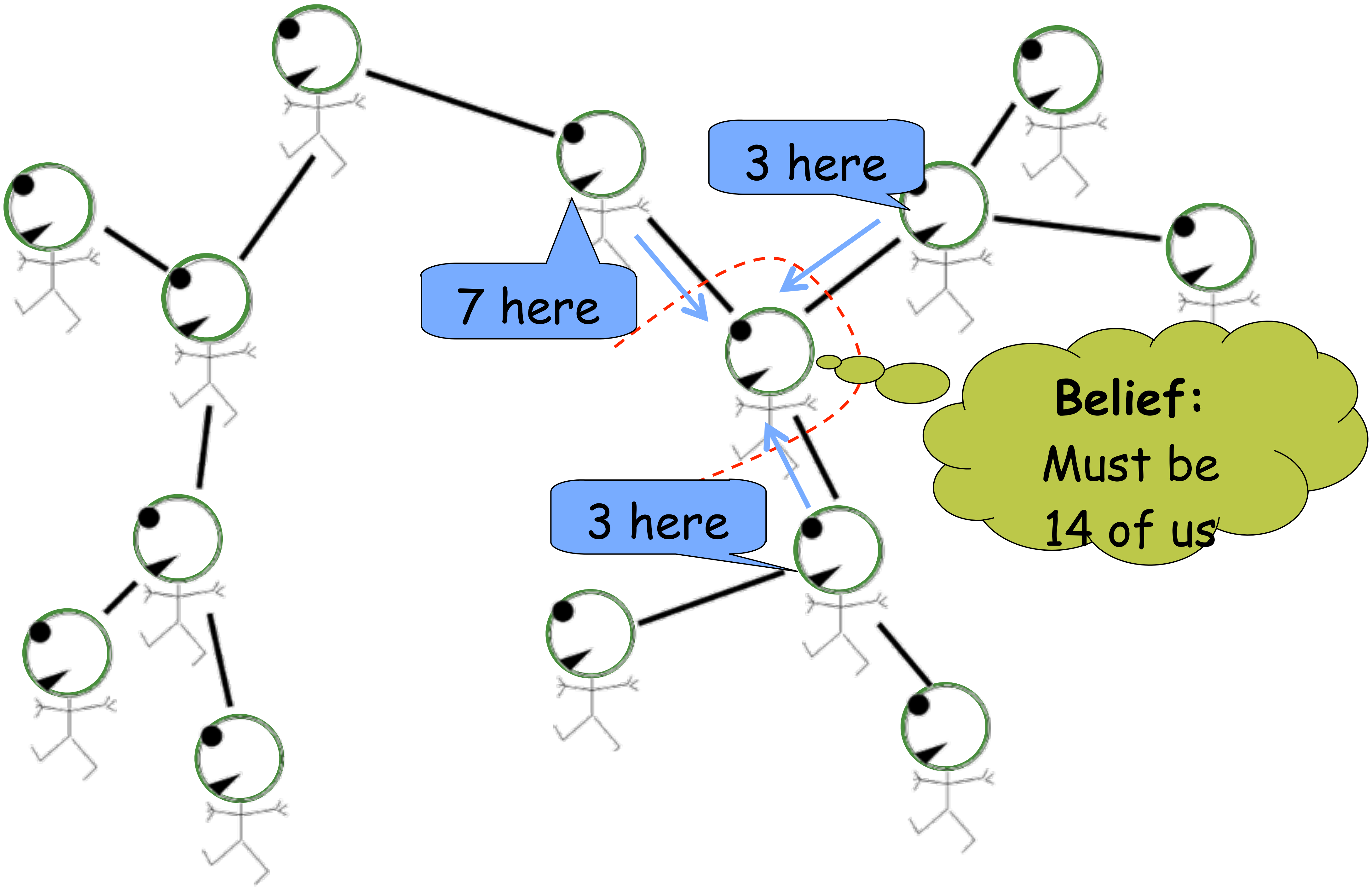
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

# Great Ideas in ML: Message Passing

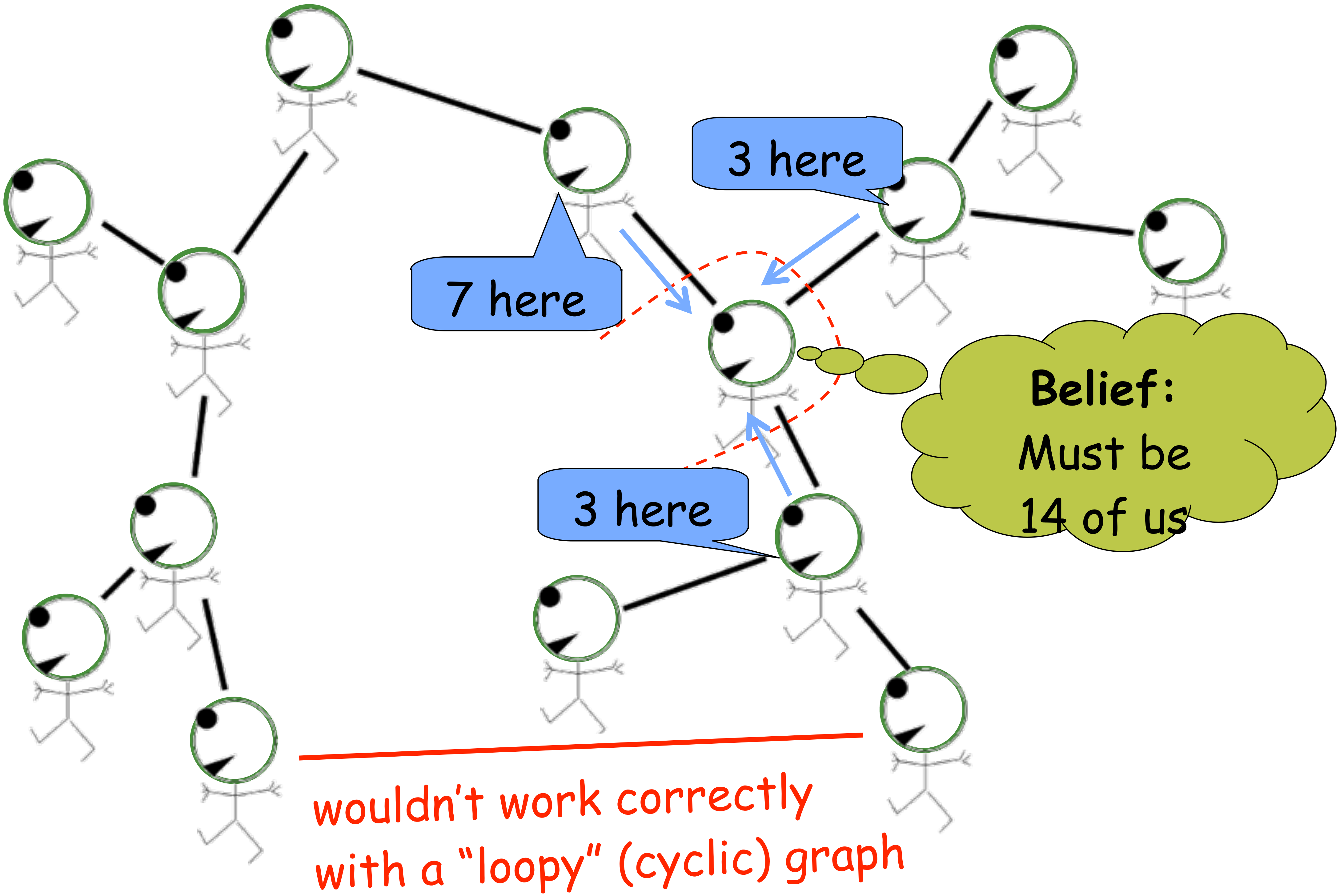
*Each soldier receives reports from all branches of tree*




**adapted from MacKay (2003) textbook**

# Great Ideas in ML: Message Passing

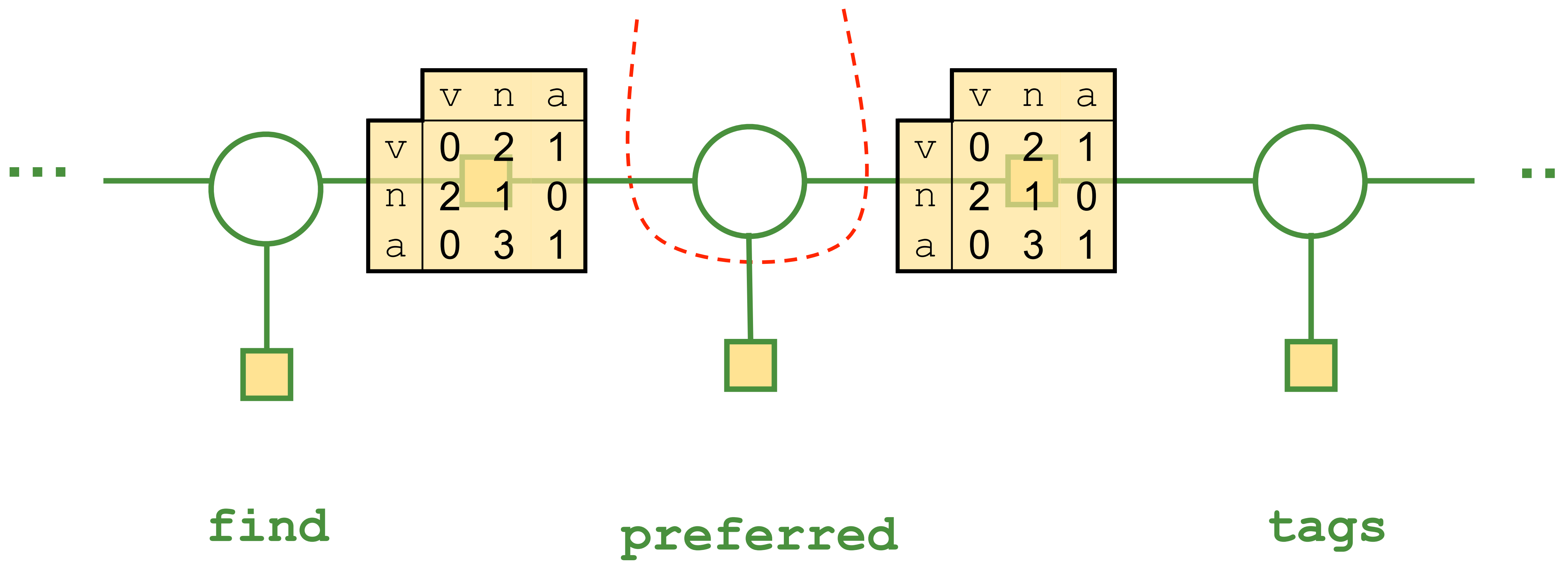
*Each soldier receives reports from all branches of tree*




adapted from MacKay (2003) textbook

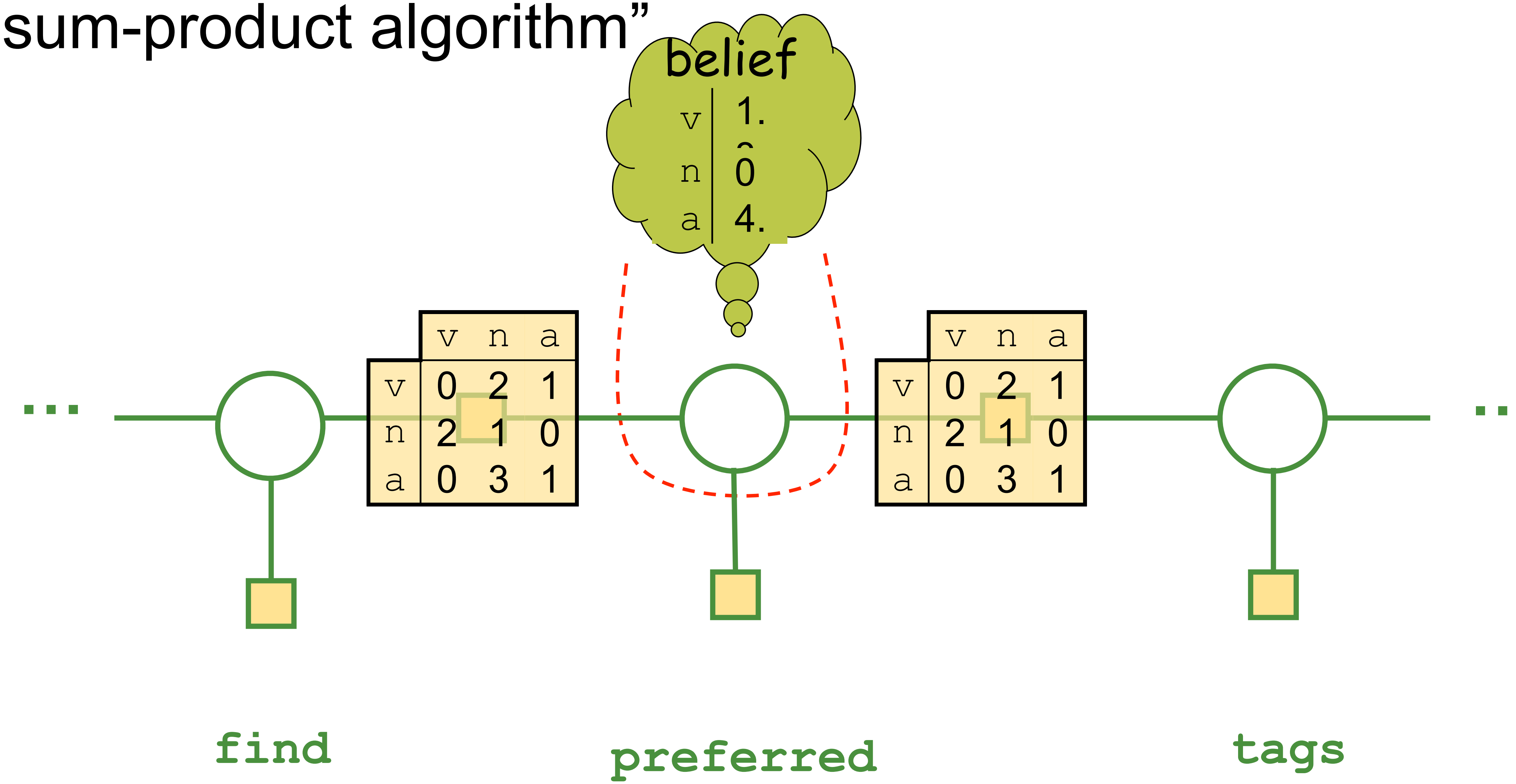
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



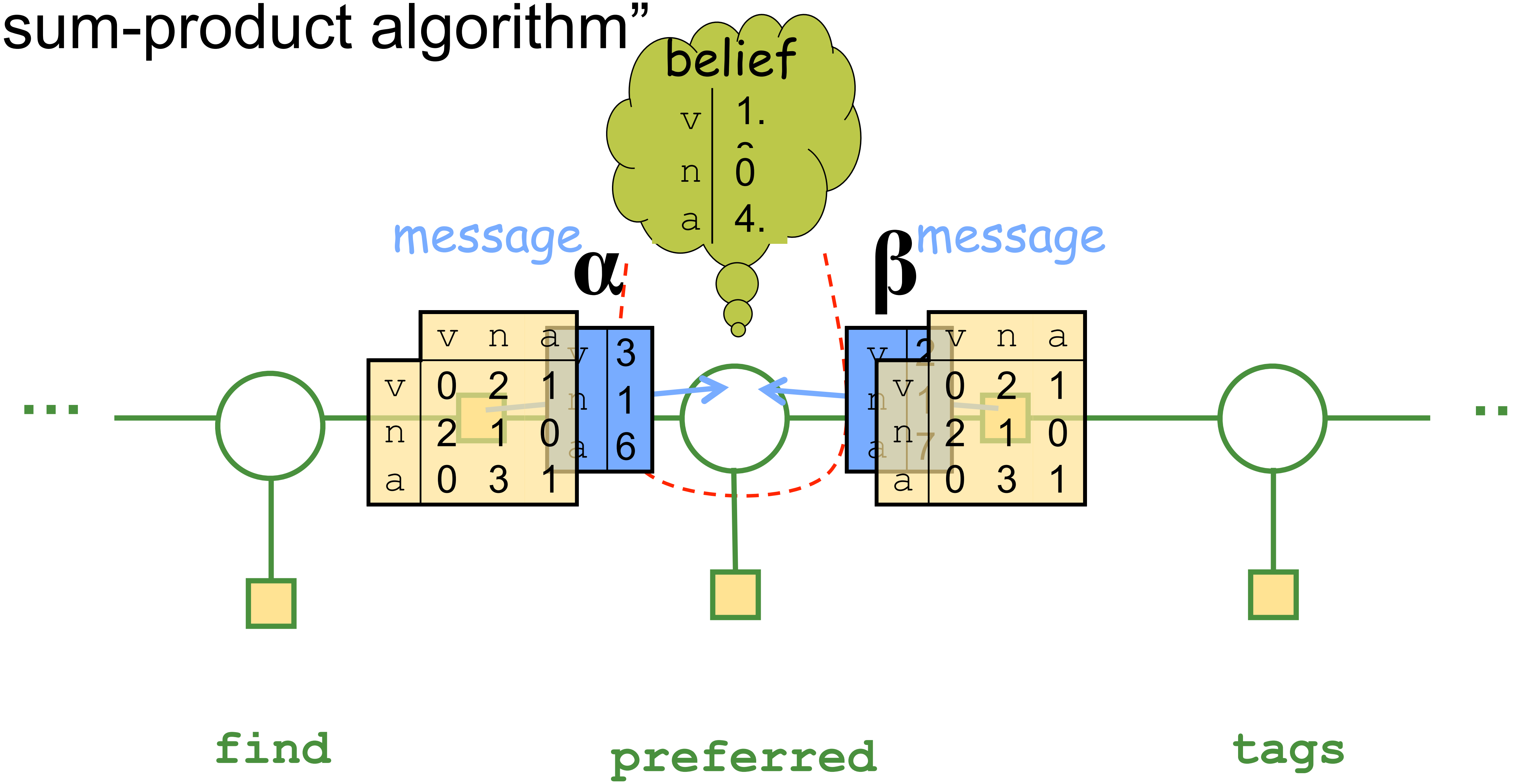
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= “sum-product algorithm”



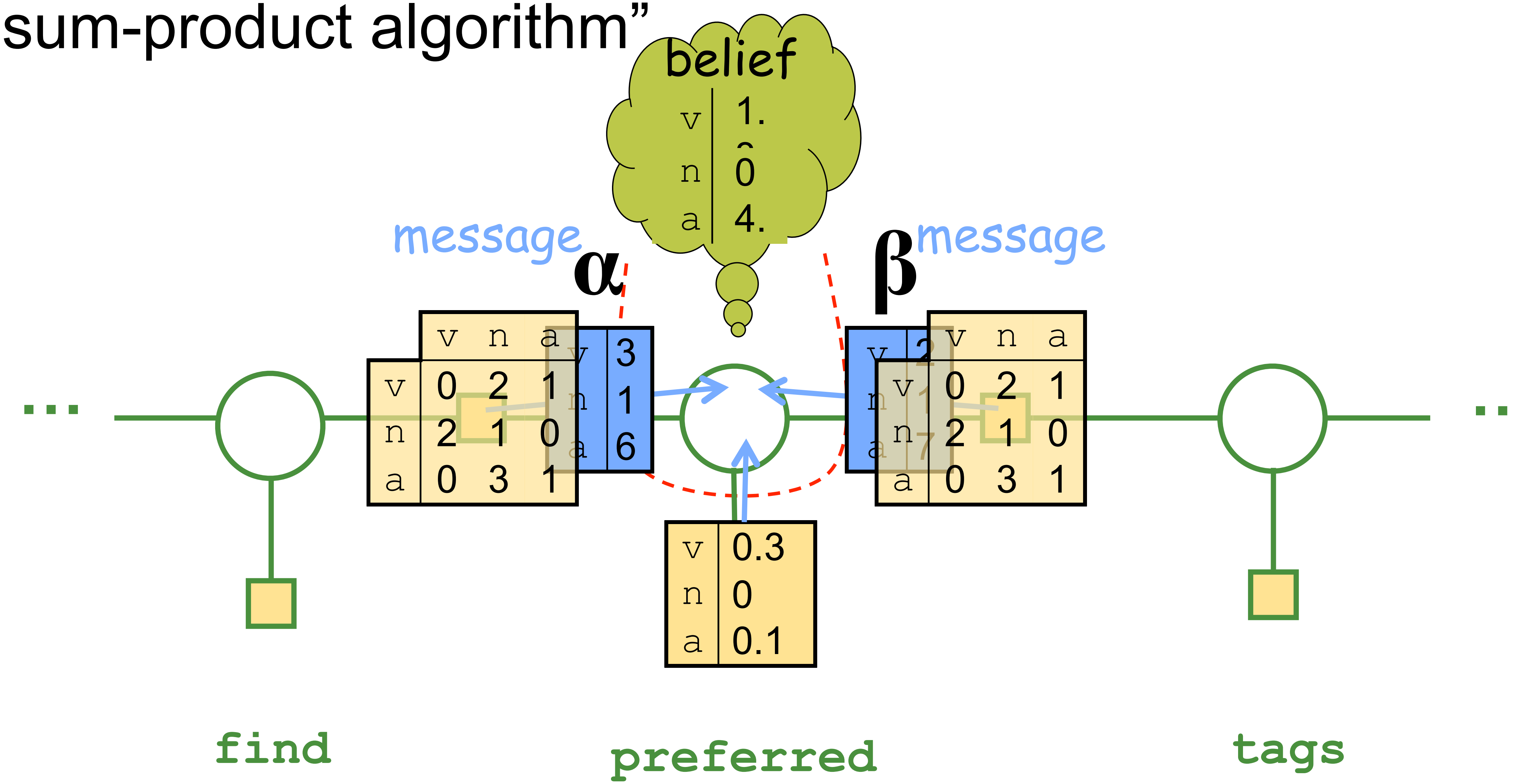
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



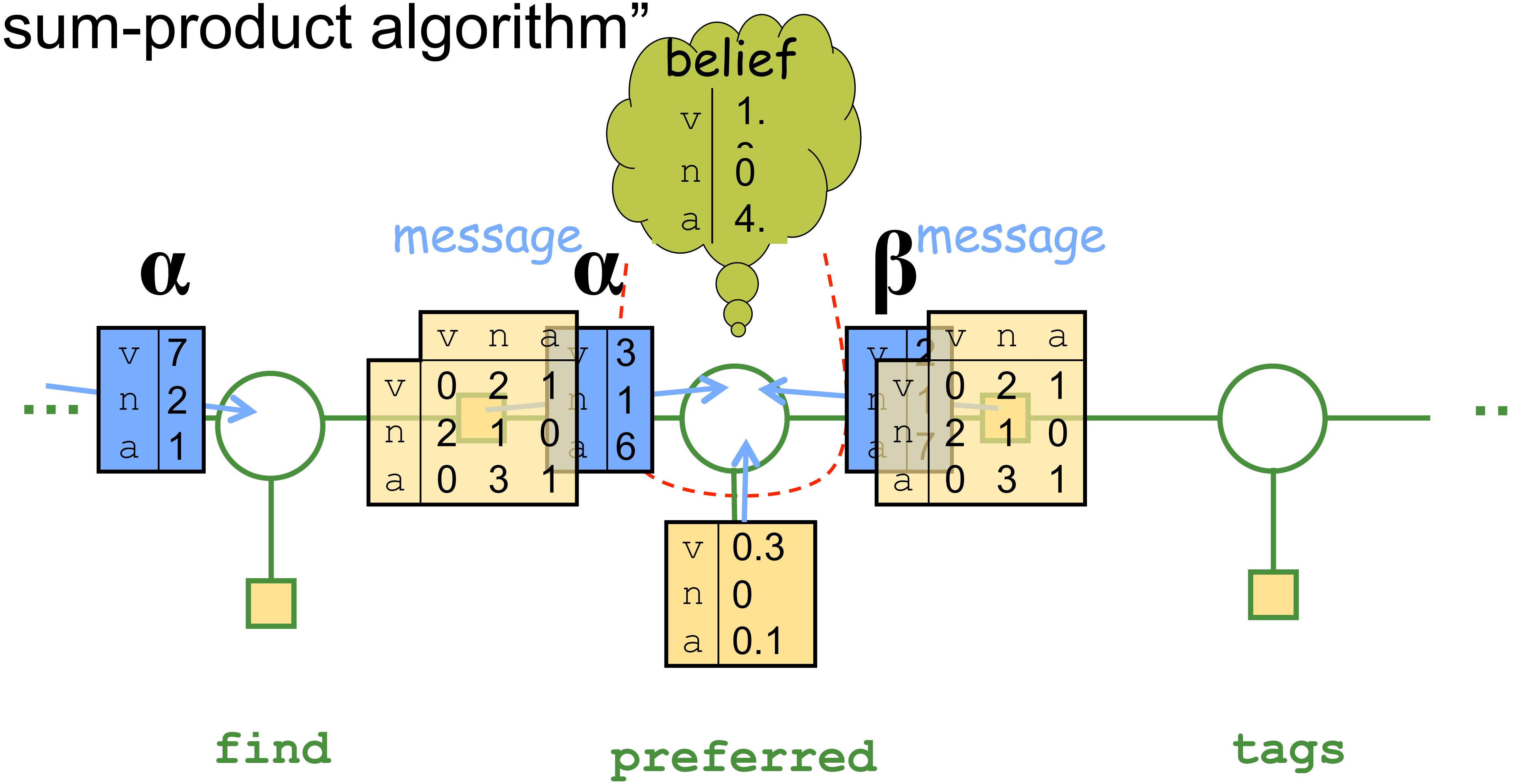
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



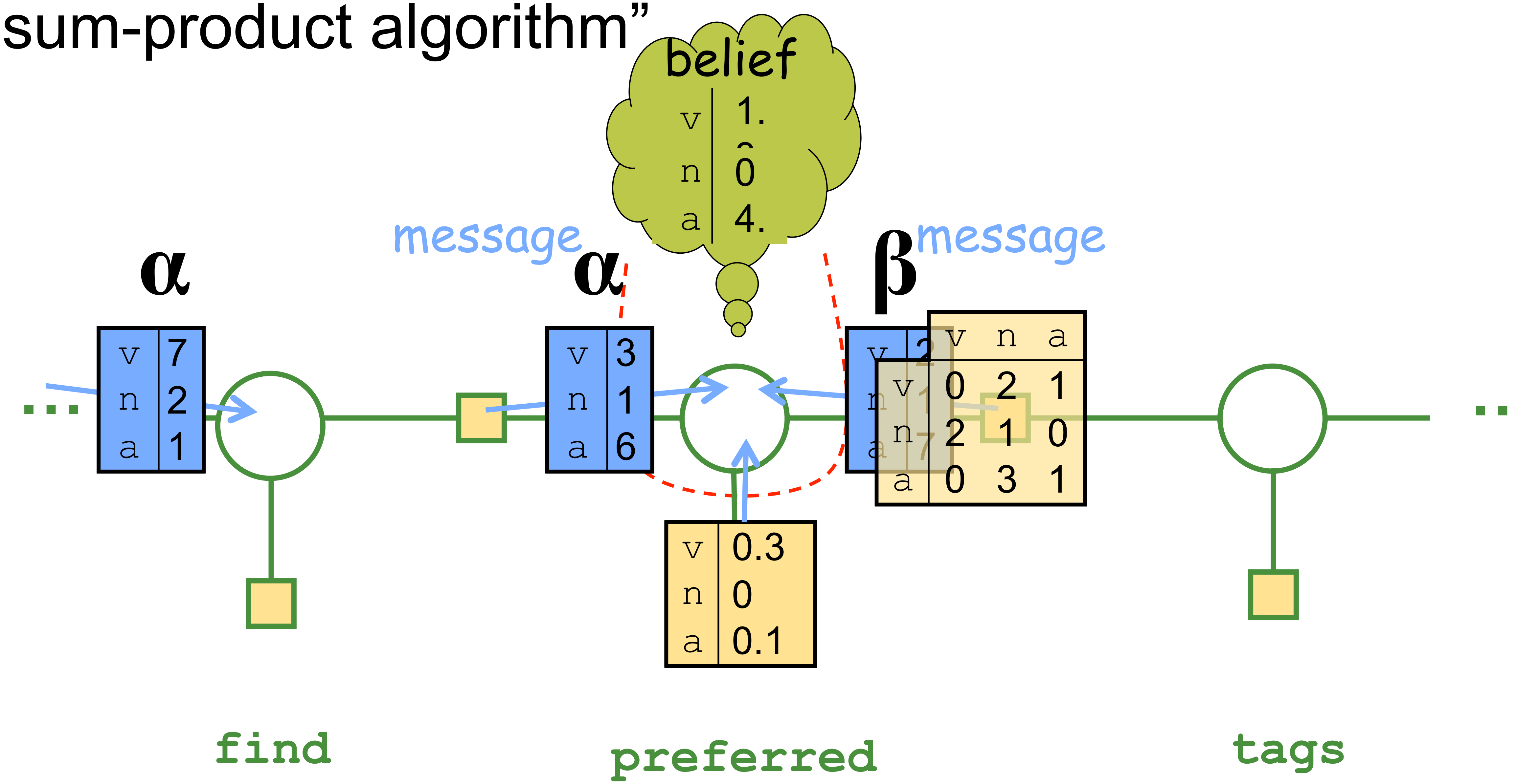
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



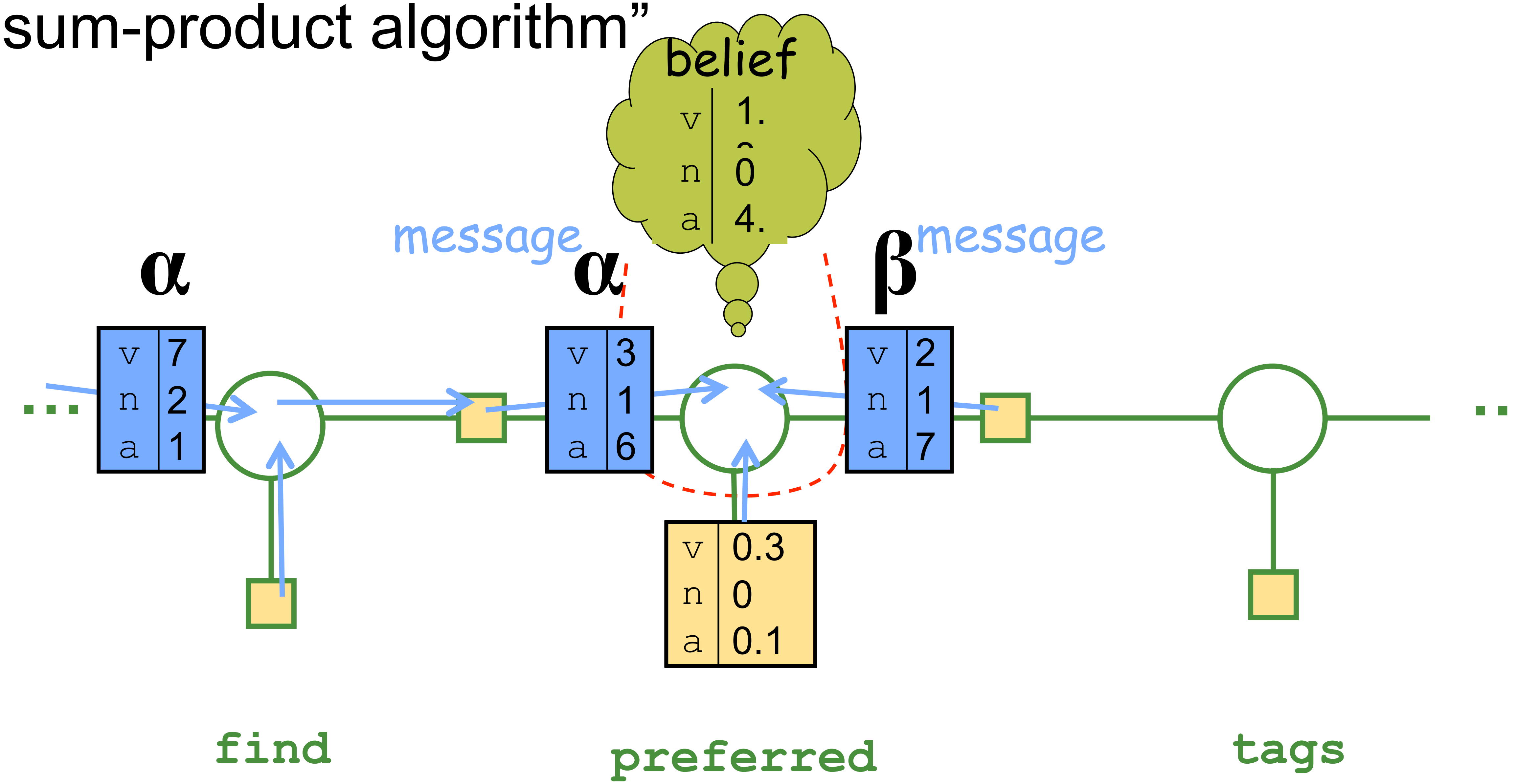
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



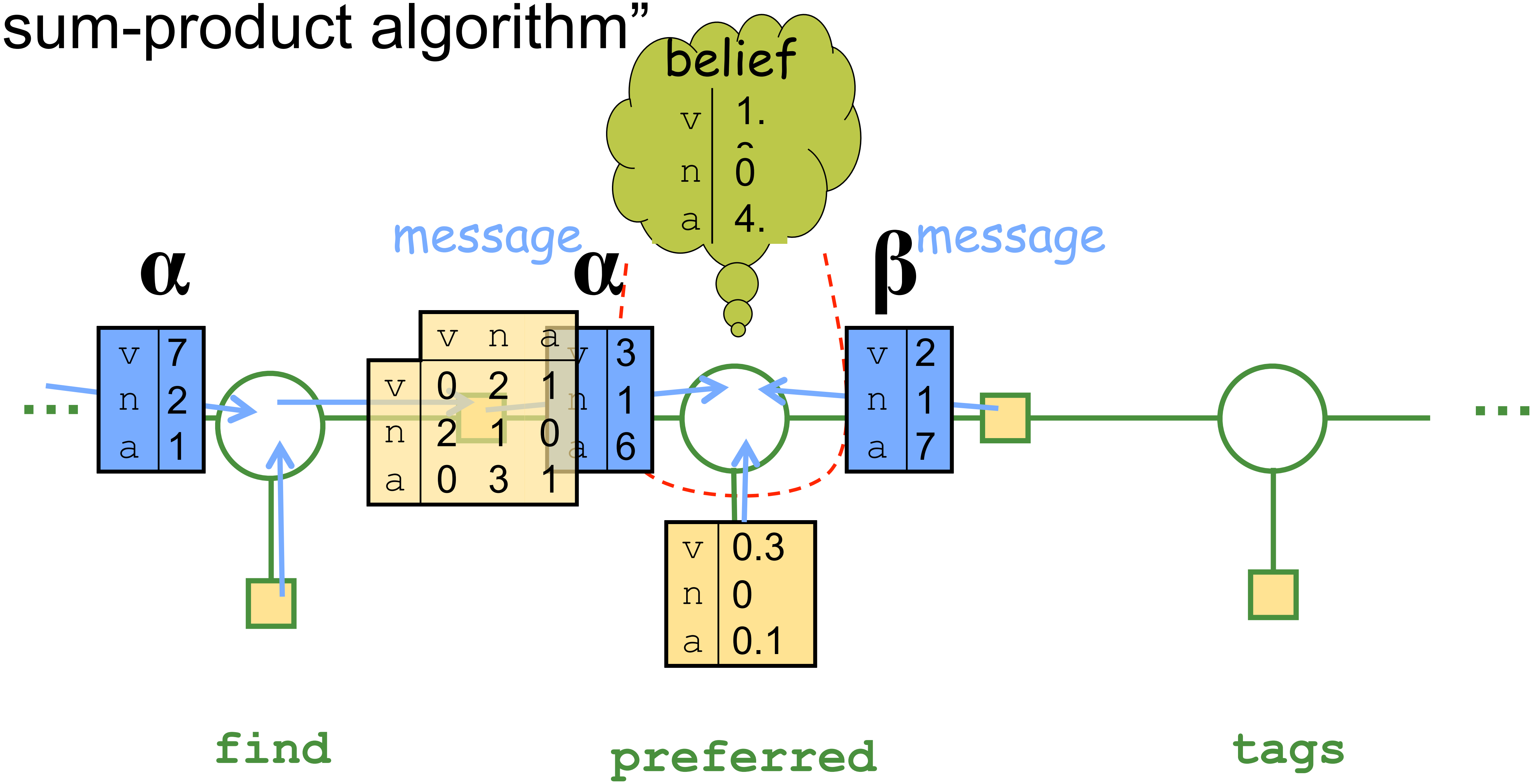
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



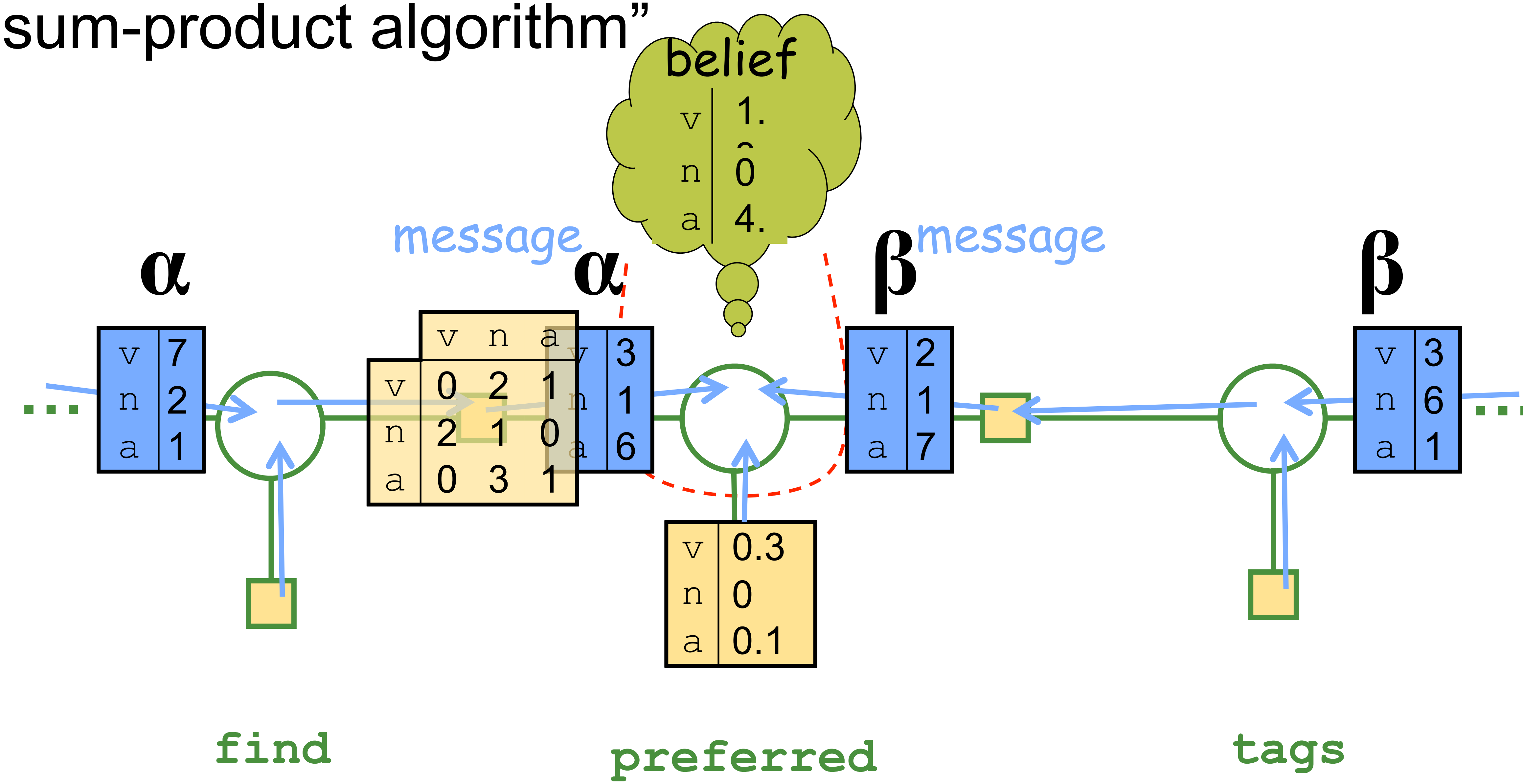
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



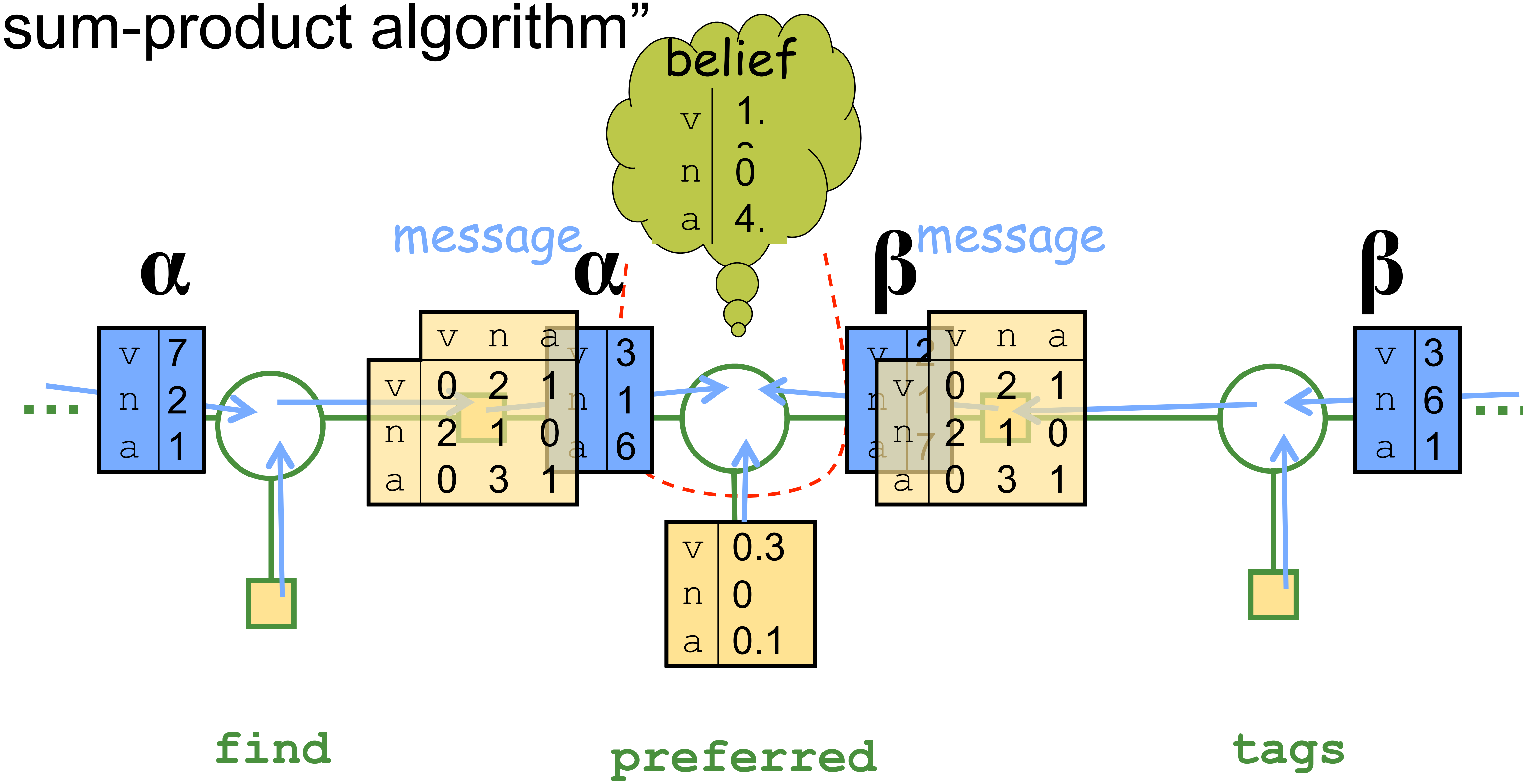
# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



# Great ideas in ML: Forward-Backward

- In the CRF, message passing = forward-backward= "sum-product algorithm"



# Sum-Product Equations

- Message from variable *v* to factor *f*

$$m_{v \to f}(x) = \prod_{f' \in N(v) \setminus \{f\}} m_{f' \to v}(x)$$

- Message from factor *f* to variable *v*

# Recipe for Conditional Training of p(y | x)

1. Gather constraints/features from training data

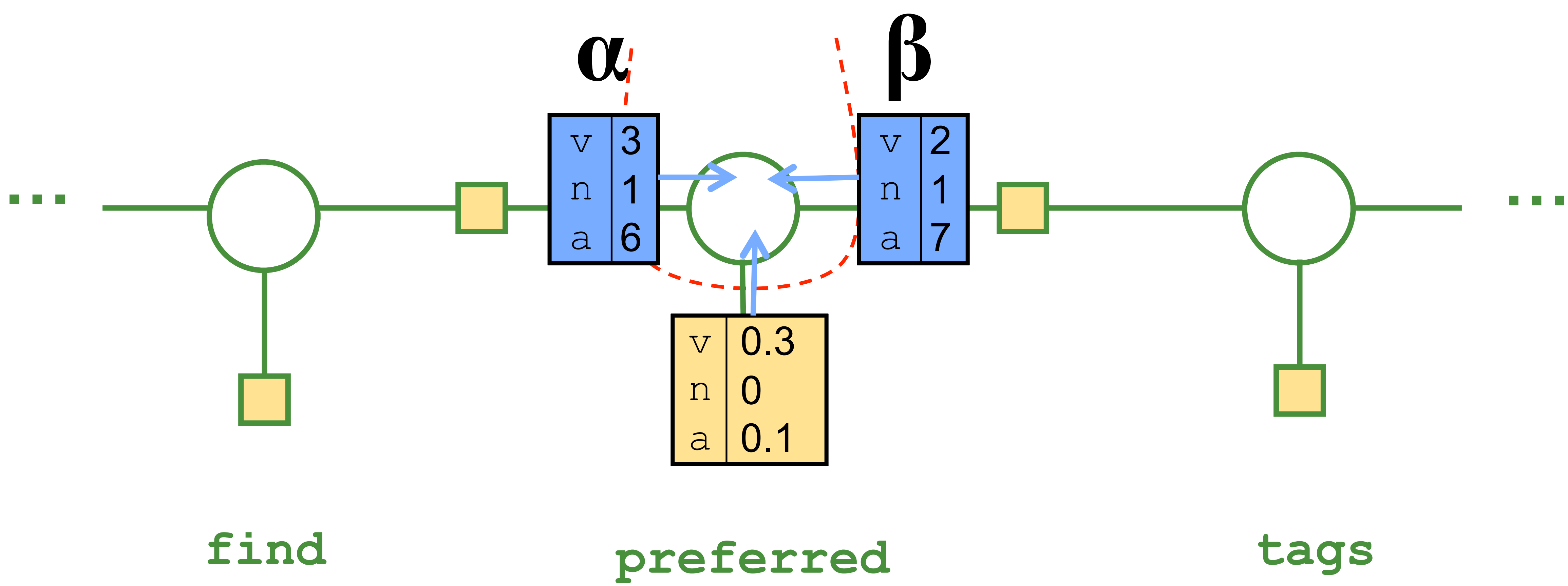
$$\alpha_{iy} = \tilde{E}[f_{iy}] = \sum_{x_j, y_j \in D} f_{iy}(x_j, y_j)$$

2. Initialize all parameters to zero
3. Classify training data with current parameters; calculate expectations

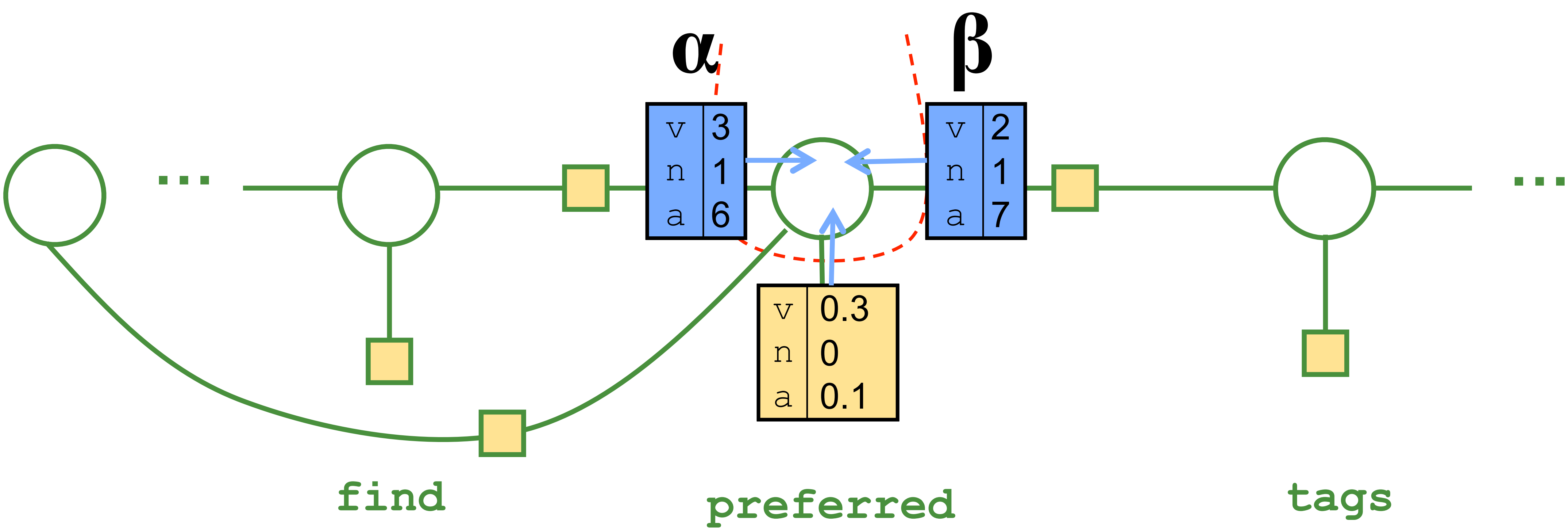
$$E_\Theta[f_{iy}] = \sum_{x_j \in D} \sum_{y'} p_\Theta(y'|x_j) f_{iy}(x_j, y')$$

4. Gradient is $\tilde{E}[f_{iy}] - E_\Theta[f_{iy}]$
5. Take a step in the direction of the gradient
6. Repeat from 3 until convergence

# Great ideas in ML: Forward-Backward

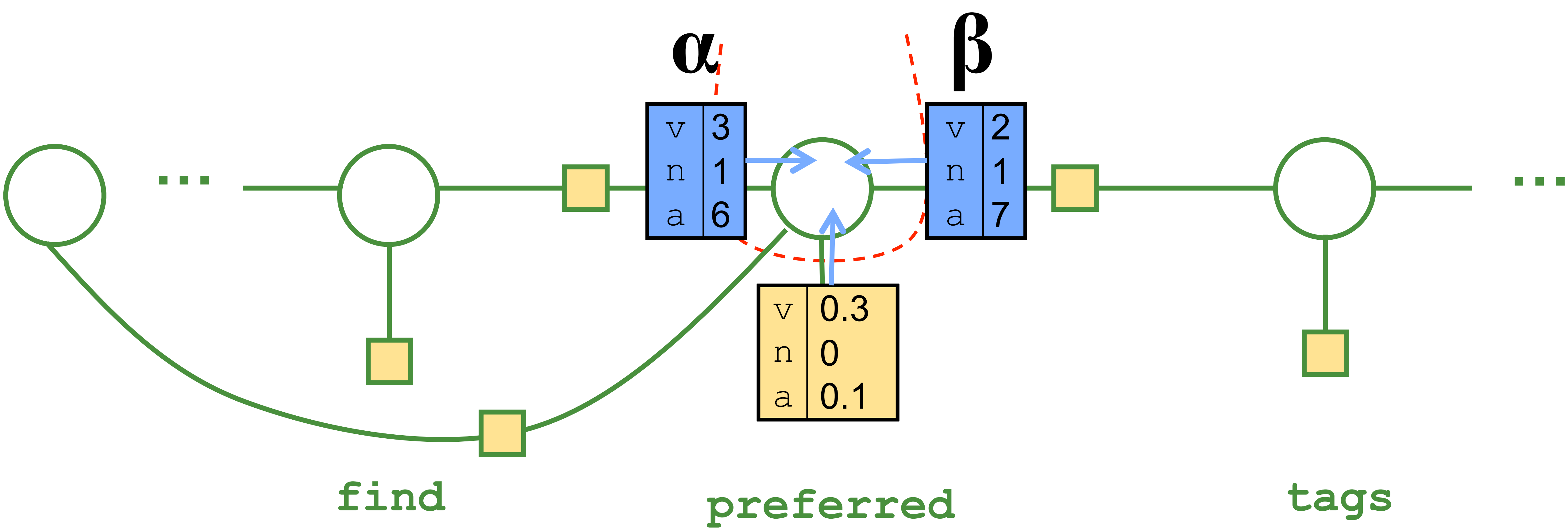


# Great ideas in ML: Forward-Backward



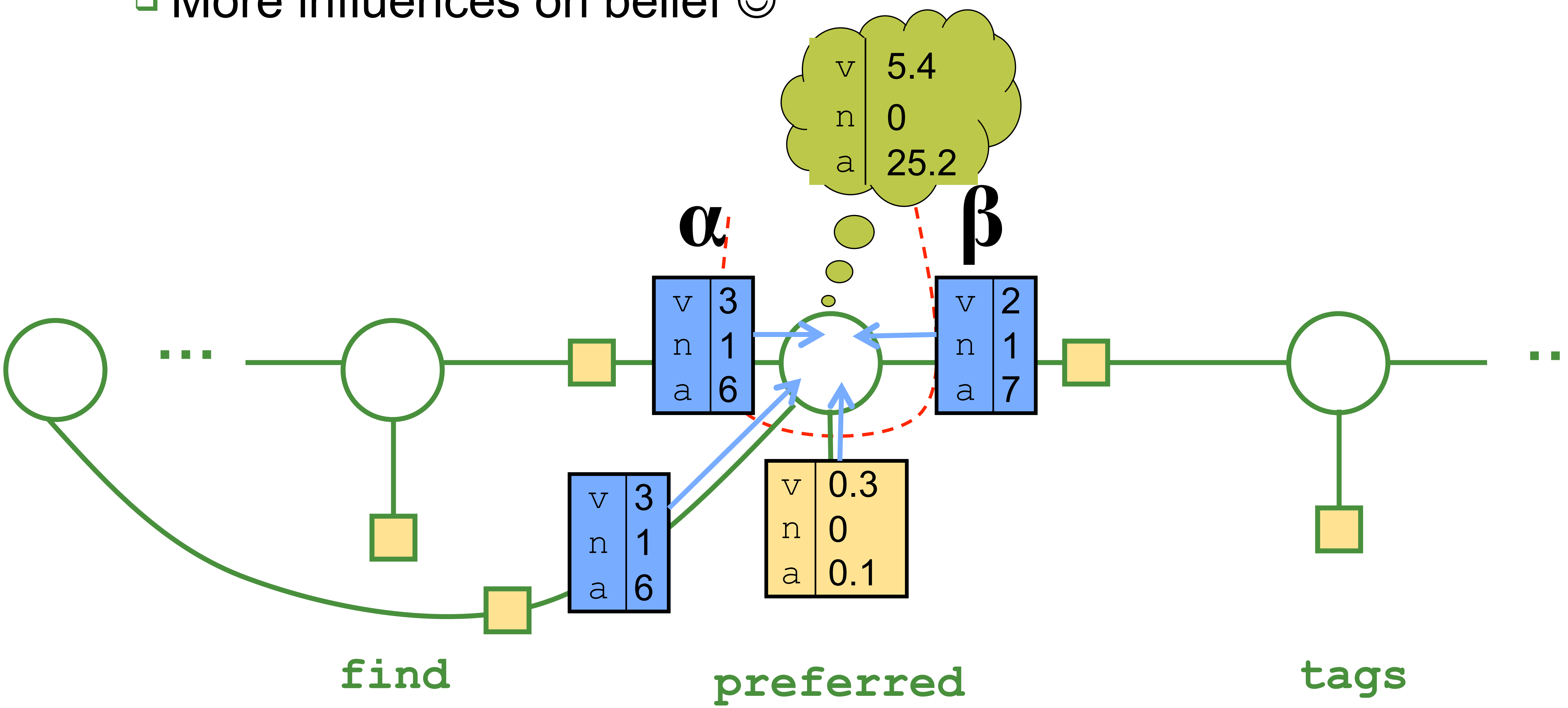
# Great ideas in ML: Forward-Backward

- Extend CRF to “skip chain” to capture non-local factor



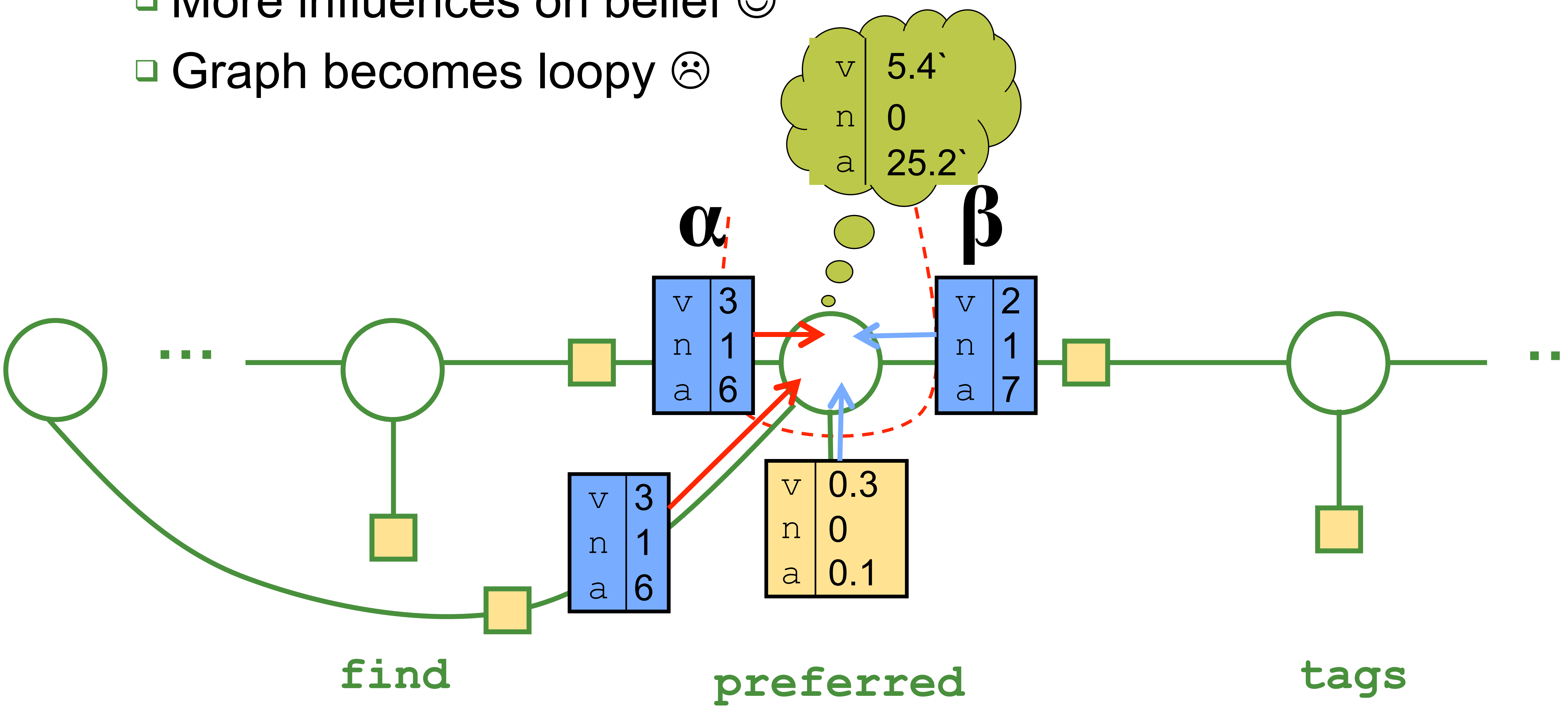
# Great ideas in ML: Forward-Backward

- Extend CRF to “skip chain” to capture non-local factor
    - More influences on belief ☺



# Great ideas in ML: Forward-Backward

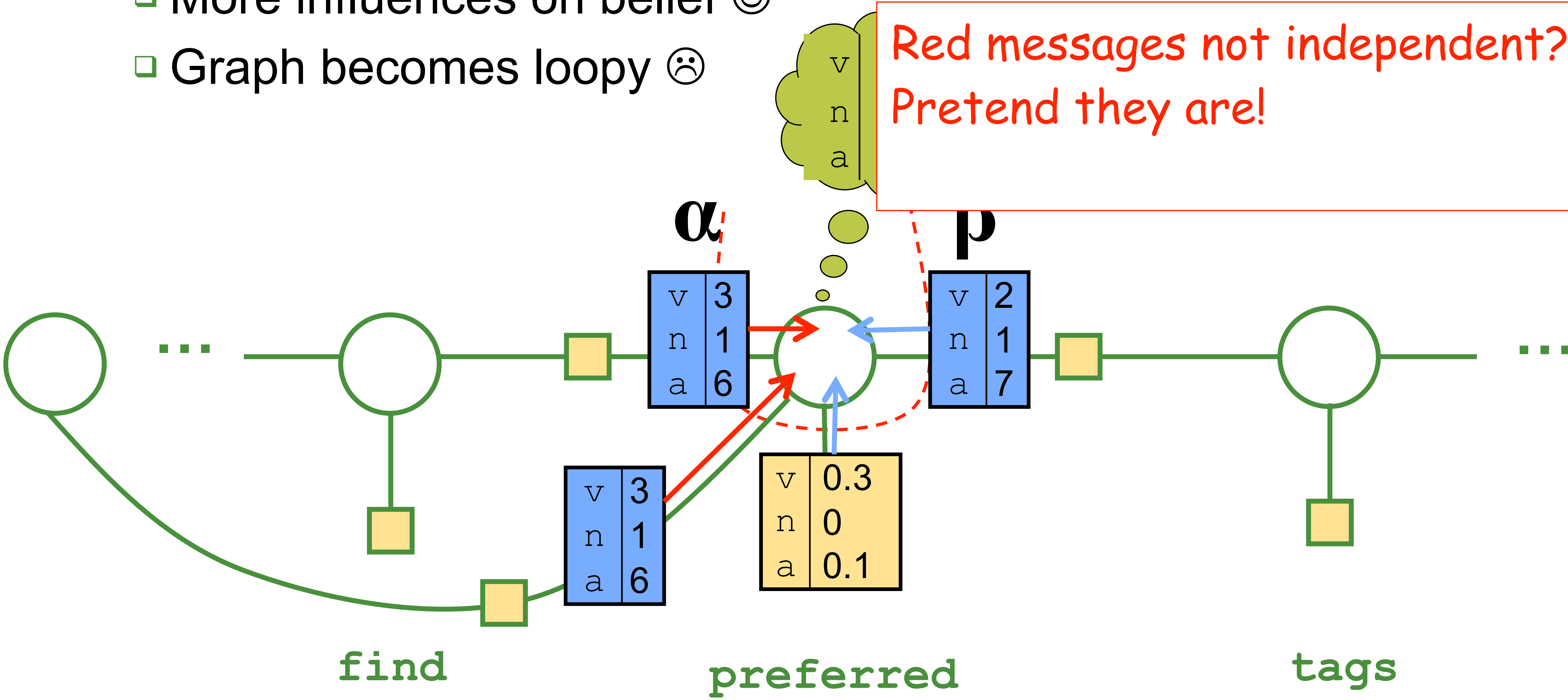
- Extend CRF to "skip chain" to capture non-local factor
  - More influences on belief ☺
  - Graph becomes loopy ☹



# Great ideas in ML: Forward-Backward

- Extend CRF to "skip chain" to capture non-local factor
  - More influences on belief ☺
  - Graph becomes loopy ☹

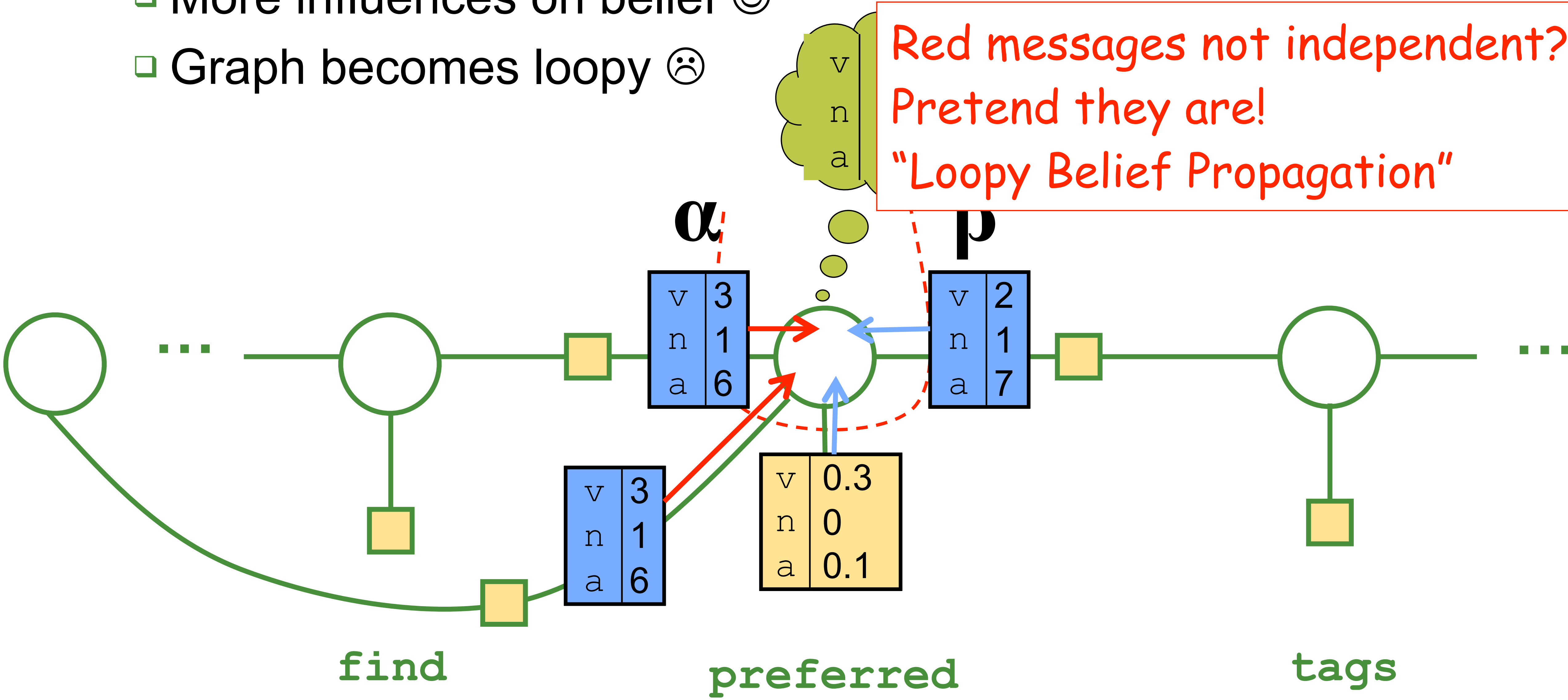
Red messages not independent?
Pretend they are!



# Great ideas in ML: Forward-Backward

- Extend CRF to "skip chain" to capture non-local factor
  - More influences on belief ☺
  - Graph becomes loopy ☹

Red messages not independent?
Pretend they are!
"Loopy Belief Propagation"



# Terminological Clarification

**`propagation`**

# Terminological Clarification

`belief propagation`

# Terminological Clarification

**loopy belief propagation**

# Terminological Clarification

loopy belief propagation

# Terminological Clarification

[loopy belief] propagation

# Terminological Clarification

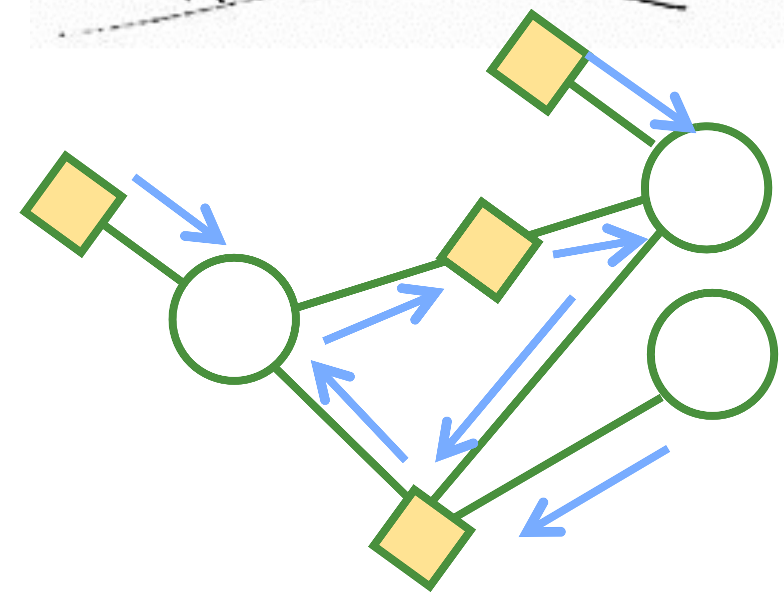
loopy belief propagation


loopy belief propagation

# Terminological Clarification

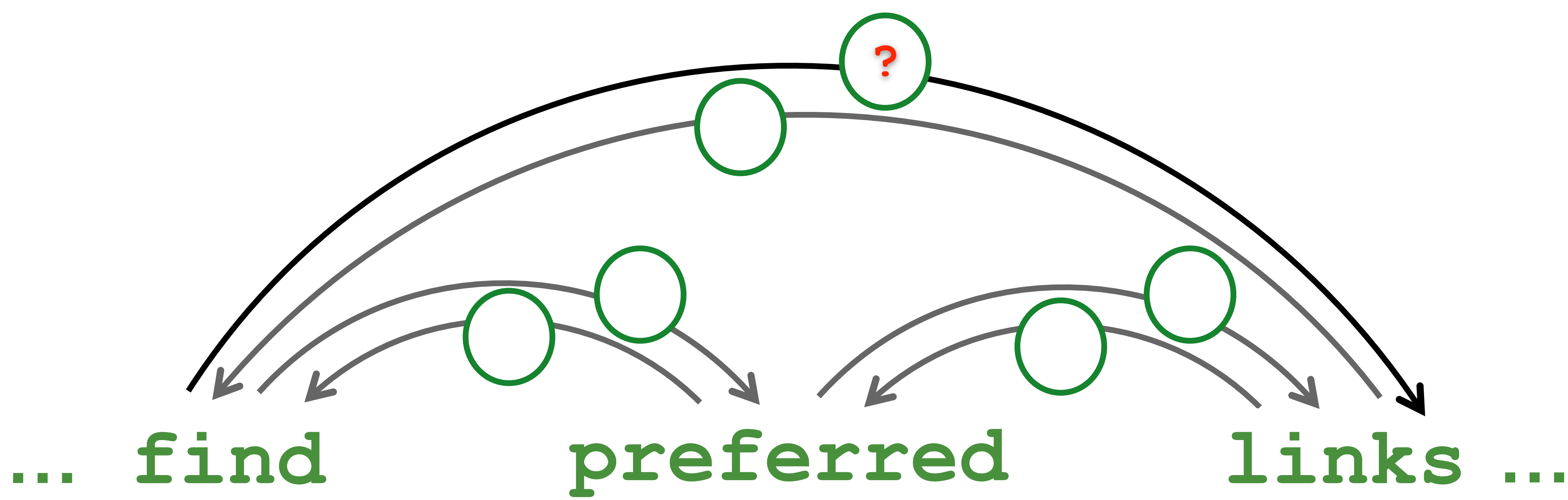
[loopy belief] propagation


loopy [belief propagation]



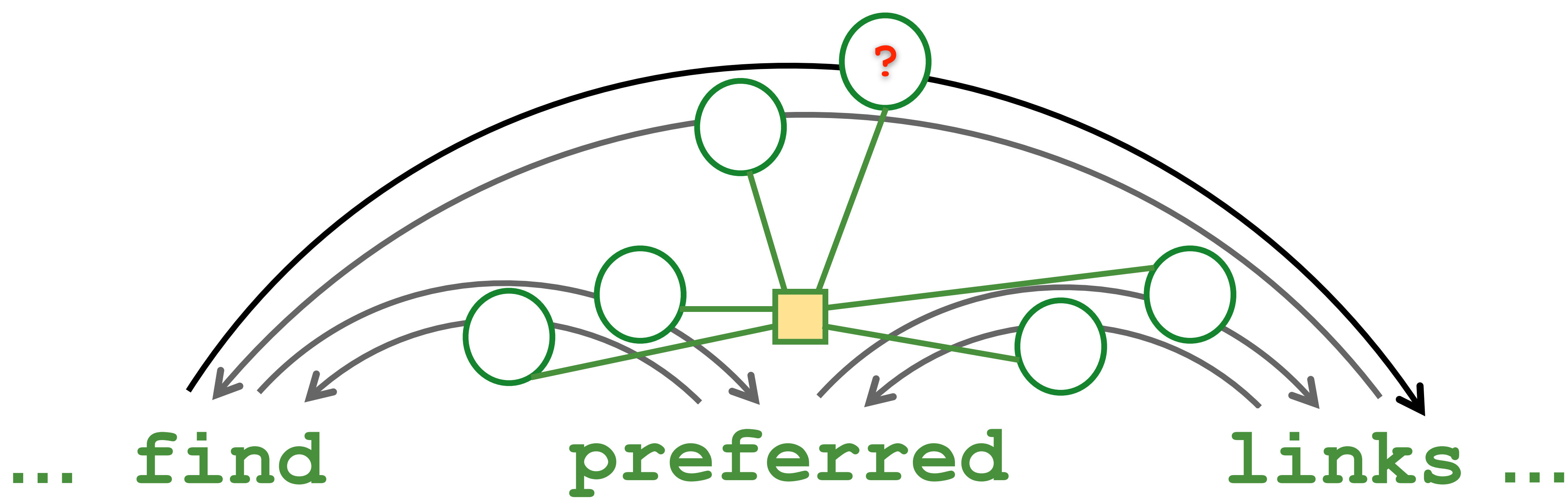
# Propagating Global Factors

- Loopy belief propagation is easy for local factors
- How do combinatorial factors (like TREE) compute the message to the link in question?
  - "Does the TREE factor think the link is probably **t** given the messages it receives from *all* the other links?"



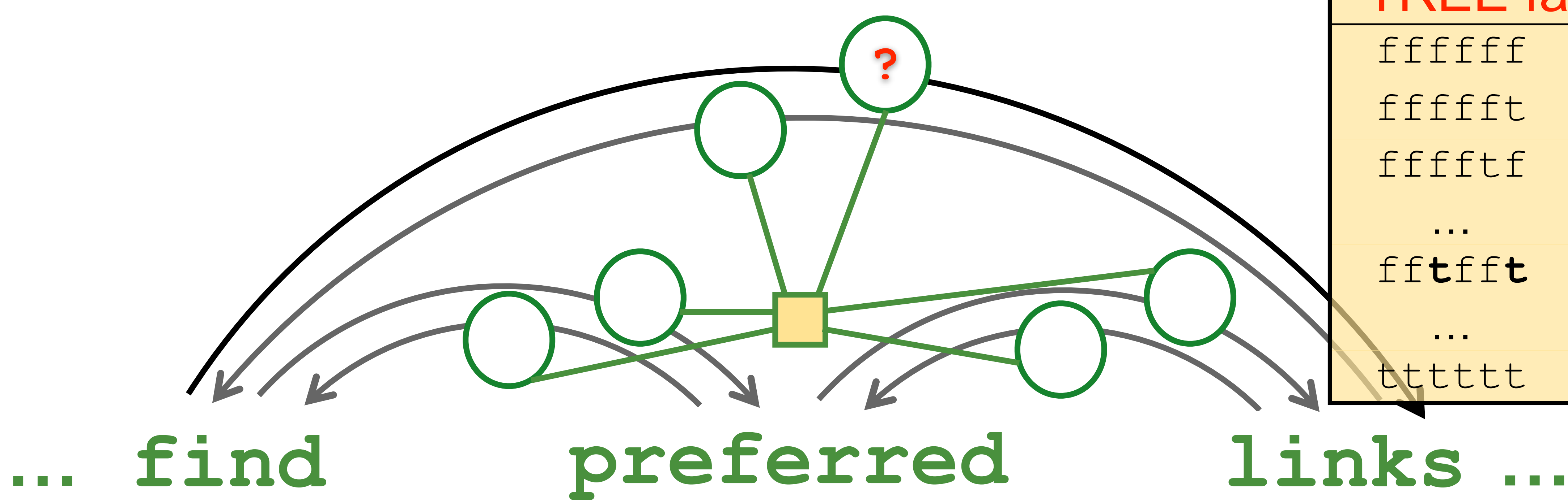
# Propagating Global Factors

- Loopy belief propagation is easy for local factors
- How do combinatorial factors (like TREE) compute the message to the link in question?
  - "Does the TREE factor think the link is probably **t** given the messages it receives from *all* the other links?"



# Propagating Global Factors

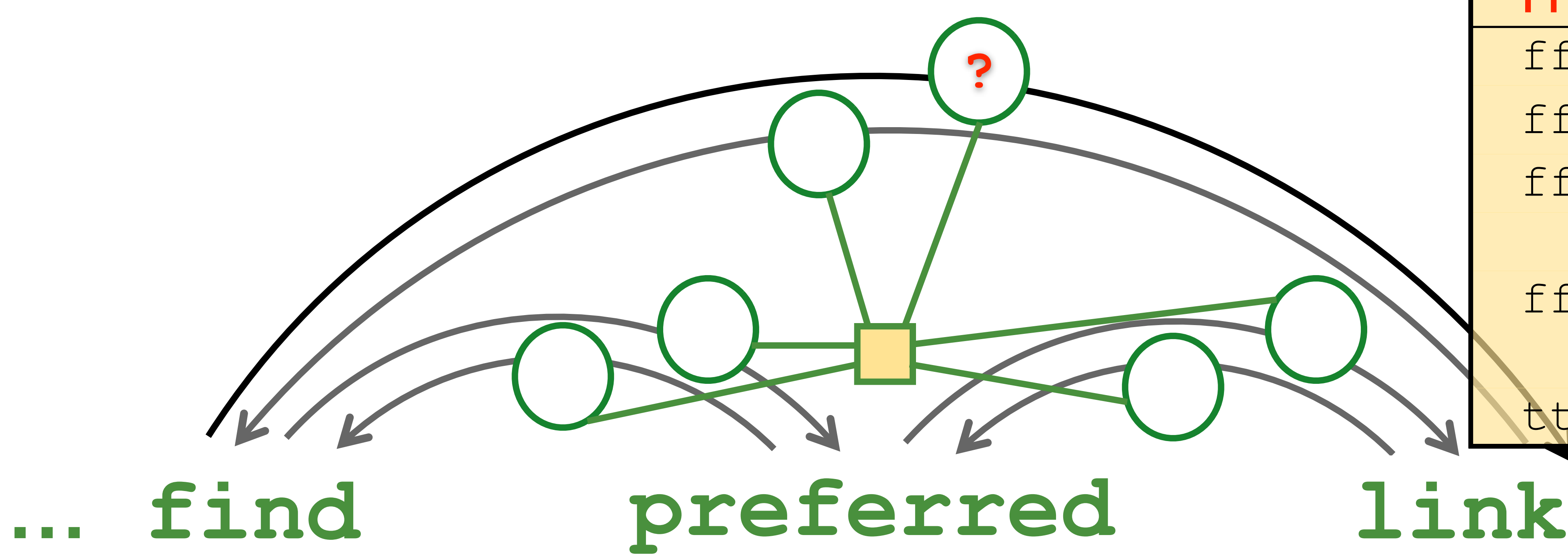
- Loopy belief propagation is easy for local factors
- How do combinatorial factors (like TREE) compute the message to the link in question?
  - ✤ "Does the TREE factor think the link is probably **t** given the messages it receives from *all* the other links?"




| TREE factor | |
|---|---|
| ffffff | 0 |
| ffffft | 0 |
| fffftf | 0 |
| ... | ... |
| ff**t**ff**t** | 1 |
| ... | ... |
| tttttt | 0 |

# Propagating Global Factors

- How does the TREE factor compute the message to the link in question?
  - “Does the TREE factor think the link is probably **t** given the messages it receives from *all* the other links?”




| TREE factor | |
|---|---|
| ffffff | 0 |
| ffffft | 0 |
| fffftf | 0 |
| … | … |
| fftfft | 1 |
| … | … |
| tttttt | 0 |

# Propagating Global Factors

- How does the TREE factor compute the message to the link in question?
  - "Does the TREE factor think the link is probably **t** given the messages it receives from *all* the other links?"

Old-school parsing to the rescue!

This is the outside probability of the link in an *edge-factored* parser!

∴ TREE factor computes all outgoing messages at once
(given all incoming messages)

Projective case: total $O(n^3)$ time by inside-outside

Non-projective: total $O(n^3)$ time by inverting Kirchhoff matrix

# Graph Theory to the Rescue!

Tutte's **Matrix-Tree Theorem** (1948)

The **determinant** of the Kirchoff (aka Laplacian) adjacency matrix of directed graph *G* without row and column *r* is equal to the **sum of scores of all directed spanning trees** of *G* rooted at node *r*.

# Graph Theory to the Rescue!

Tutte's **Matrix-Tree Theorem** (1948)

The **determinant** of the Kirchoff (aka Laplacian) adjacency matrix of directed graph *G* without row and column *r* is equal to the **sum of scores of all directed spanning trees** o rooted at node *r*.

Exactly the *Z* we need!

# Graph Theory to the Rescue!

$O(n^3)$ time!

Tu s **Matrix-Tree Theorem** (1948)

The **determinant** of the Kirchoff (aka Laplacian) adjacency matrix of directed graph $G$ without row and column $r$ is equal to the **sum of scores of all directed spanning trees** o rooted at node $r$.

Exactly the $Z$ we need!

# Kirchoff (Laplacian) Matrix

$$\begin{bmatrix} 0 & -s(1,0) & -s(2,0) & \cdots & -s(n,0) \\ 0 & 0 & -s(2,1) & \cdots & -s(n,1) \\ 0 & -s(1,2) & 0 & \cdots & -s(n,2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & -s(1,n) & -s(2,n) & \cdots & 0 \end{bmatrix}$$

- Negate edge scores
- Sum columns (children)
- Strike root row/col.
- Take determinant

# Kirchoff (Laplacian) Matrix

$$\begin{bmatrix} 0 & -s(1,0) & -s(2,0) & \cdots & -s(n,0) \\ 0 & 0 & -s(2,1) & \cdots & -s(n,1) \\ 0 & -s(1,2) & 0 & \cdots & -s(n,2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & -s(1,n) & -s(2,n) & \cdots & 0 \end{bmatrix}$$

- Negate edge scores
- Sum columns (children)
- Strike root row/col.
- Take determinant

# Kirchoff (Laplacian) Matrix

$$\begin{bmatrix} 0 & -s(1,0) & -s(2,0) & \cdots & -s(n,0) \\ 0 & \sum_{j\neq 1} s(1,j) & -s(2,1) & \cdots & -s(n,1) \\ 0 & -s(1,2) & \sum_{j\neq 2} s(2,j) & \cdots & -s(n,2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & -s(1,n) & -s(2,n) & \cdots & \sum_{j\neq n} s(n,j) \end{bmatrix}$$

- Negate edge scores
- Sum columns (children)
- Strike root row/col.
- Take determinant

# Kirchoff (Laplacian) Matrix

$$\begin{vmatrix} \sum_{j\neq 1} s(1,j) & -s(2,1) & \cdots & -s(n,1) \\ -s(1,2) & \sum_{j\neq 2} s(2,j) & \cdots & -s(n,2) \\ \vdots & \vdots & \ddots & \vdots \\ -s(1,n) & -s(2,n) & \cdots & \sum_{j\neq n} s(n,j) \end{vmatrix}$$

- Negate edge scores
- Sum columns (children)
- Strike root row/col.
- Take determinant

# Kirchoff (Laplacian) Matrix

$$\begin{vmatrix} \sum_{j \neq 1} s(1,j) & -s(2,1) & \cdots & -s(n,1) \\ -s(1,2) & \sum_{j \neq 2} s(2,j) & \cdots & -s(n,2) \\ \vdots & \vdots & \ddots & \vdots \\ -s(1,n) & -s(2,n) & \cdots & \sum_{j \neq n} s(n,j) \end{vmatrix}$$

- Negate edge scores
- Sum columns (children)
- Strike root row/col.
- Take determinant

*N.B.: This allows multiple children of root, but see Koo et al. 2007.*

# Transition-Based Parsing

- Linear time
- Online
- Train a classifier to predict next action
- Deterministic or beam-search strategies
- But... generally less accurate

# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

**Start state:** $([\,], [1, \ldots, n], \{\,\})$

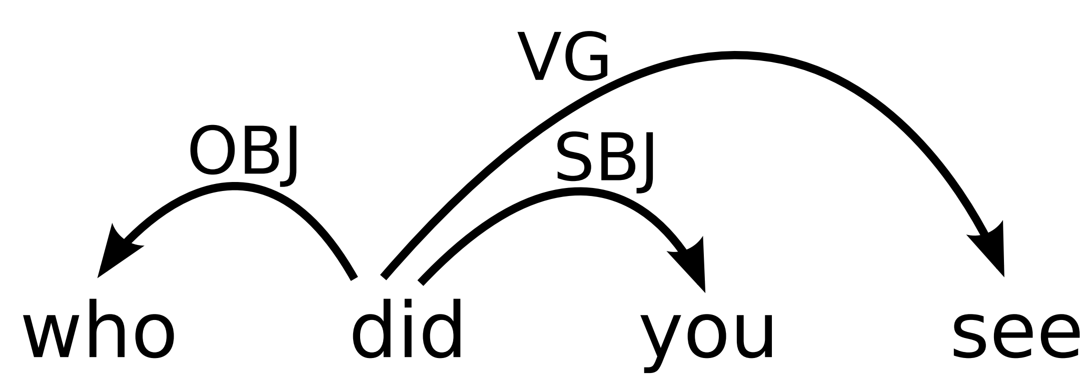
**Final state:** $(S, [\,], A)$

| | | | |
|---|---|---|---|
| **Shift:** | $(S, i\|B, A)$ | $\Rightarrow$ | $(S\|i, B, A)$ |
| **Reduce:** | $(S\|i, B, A)$ | $\Rightarrow$ | $(S, \mathrm{B}, \mathrm{A})$ |
| **Right-Arc:** | $(S\|i, j\|B, A)$ | $\Rightarrow$ | $(S\|i\|j, B, A \cup \{i \rightarrow j\})$ |
| **Left-Arc:** | $(S\|i, j\|B, A)$ | $\Rightarrow$ | $(S, j\|B, A \cup \{i \leftarrow j\})$ |

# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
|---|---|---|
| $[\ ]_S$ | $[\text{who, did, you, see}]_B$ | $\{\ \}$ |

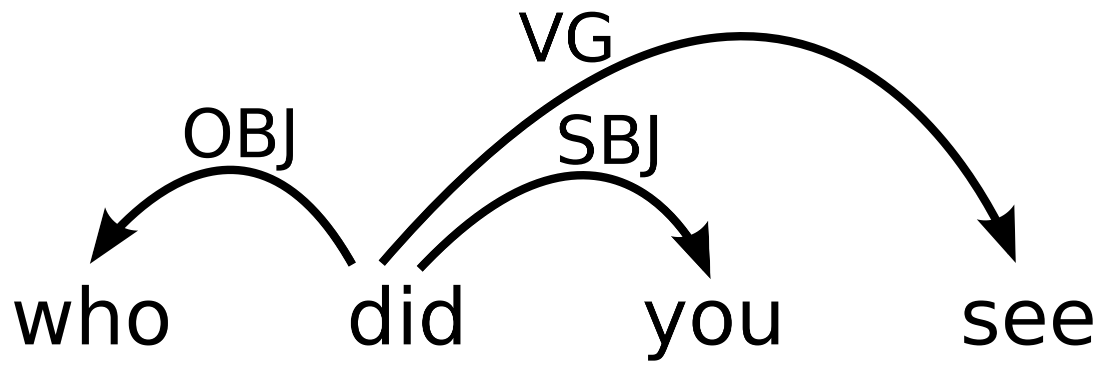


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| Stack | Buffer | Arcs |
|---|---|---|
| $[\text{who}]_S$ | $[\text{did, you, see}]_B$ | { } |

*Shift*

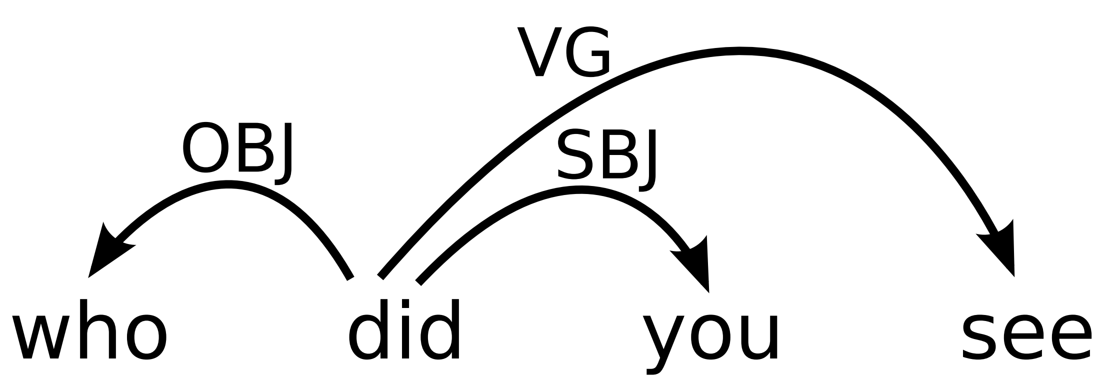


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
|---|---|---|
| $[\ ]_S$ | $[\text{did, you, see}]_B$ | $\{\ \text{who} \xleftarrow{\text{OBJ}} \text{did}\ \}$ |

*Left-arc OBJ*

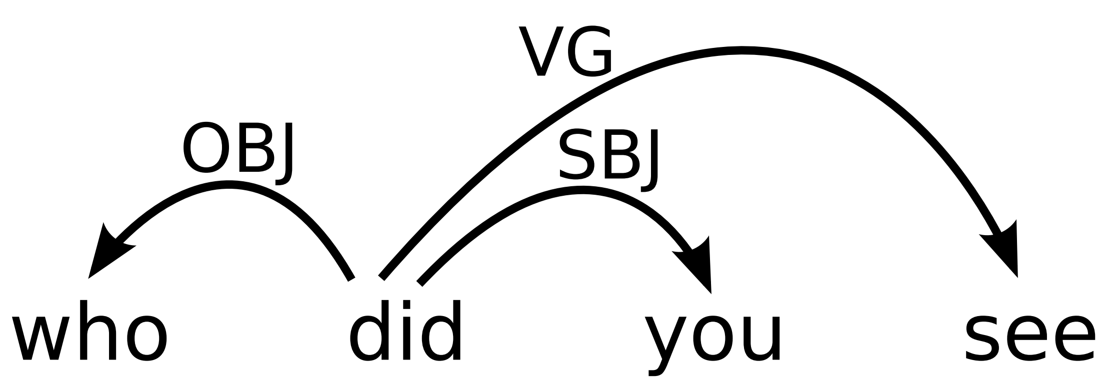


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
| --- | --- | --- |
| $[\text{did}]_S$ | $[\text{you, see}]_B$ | $\{\ \text{who} \xleftarrow{\text{OBJ}} \text{did}\ \}$ |

*Shift*

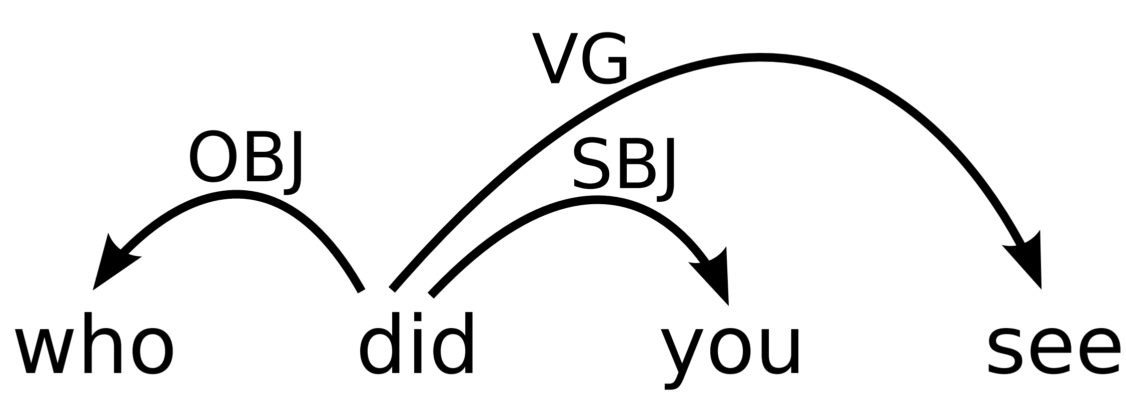


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
|---|---|---|
| $[\text{did, you}]_S$ | $[\text{see}]_B$ | $\{ \text{who} \xleftarrow{\text{OBJ}} \text{did},$ $\text{did} \xrightarrow{\text{SBJ}} \text{you} \}$ |

*Right-arc SBJ*

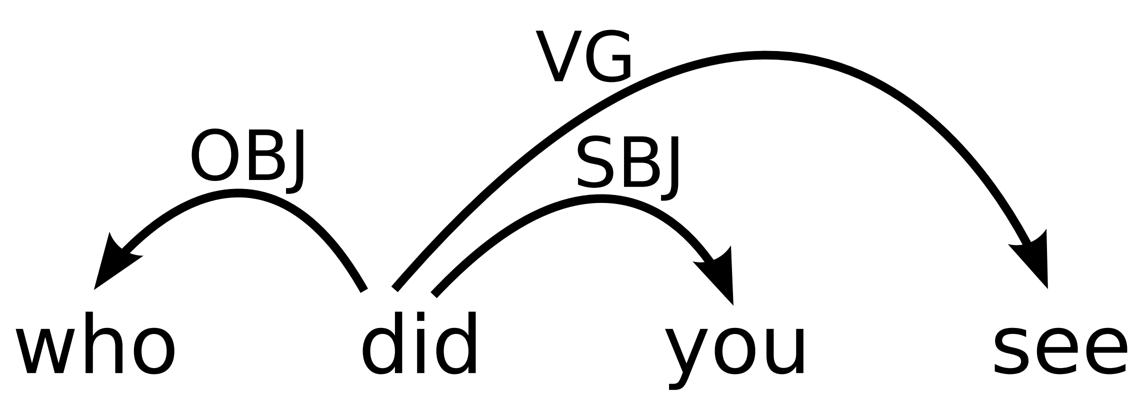


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
|---|---|---|
| $[\text{did}]_S$ | $[\text{see}]_B$ | $\{\ \text{who} \xleftarrow{\text{OBJ}} \text{did},$ <br> $\text{did} \xrightarrow{\text{SBJ}} \text{you}\ \}$ |

*Reduce*

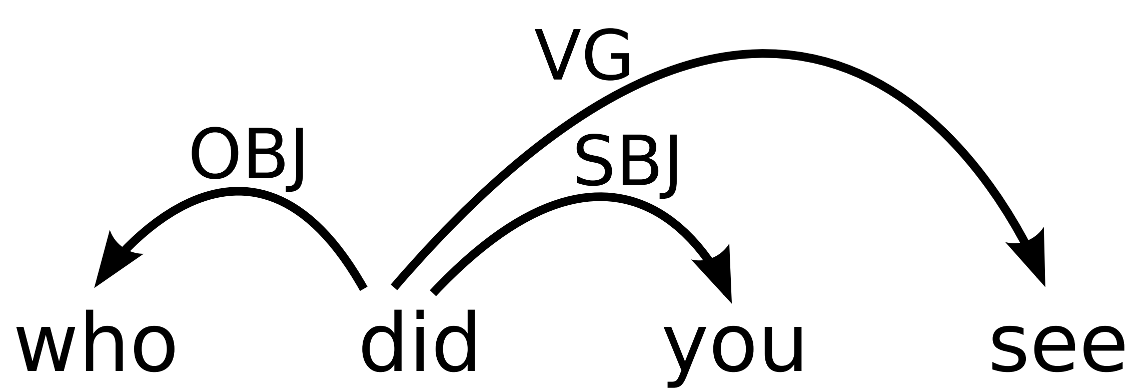


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
|---|---|---|
| $[\text{did, see}]_S$ | $[\ ]_B$ | $\{ \text{who} \xleftarrow{\text{OBJ}} \text{did},$ |
| | | $\text{did} \xrightarrow{\text{SBJ}} \text{you},$ |
| | | $\text{did} \xrightarrow{\text{VG}} \text{see} \}$ |

*Right-arc*
*VG*

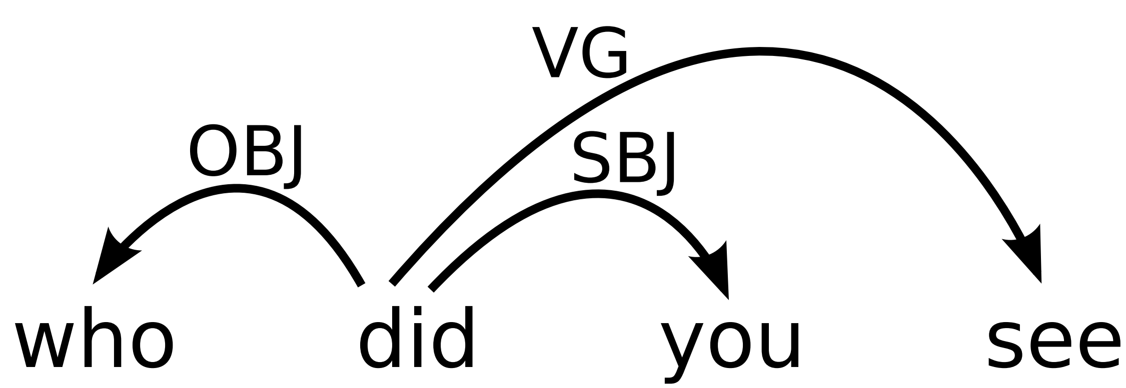


# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
| --- | --- | --- |
| $[\text{did, you}]_S$ | $[\text{see}]_B$ | $\{ \text{who} \xleftarrow{\text{OBJ}} \text{did},$ <br> $\text{did} \xrightarrow{\text{SBJ}} \text{you} \}$ |

*Right-arc*
*SBJ*



# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

| **Stack** | **Buffer** | **Arcs** |
|---|---|---|
| $[\text{did, you}]_S$ | $[\text{see}]_B$ | $\{\ \text{who} \xleftarrow{\text{OBJ}} \text{did},\ \text{did} \xrightarrow{\text{SBJ}} \text{you}\ \}$ |

*Right-arc SBJ*

VG

Choose action w/best classifier score
100k - 1M features

# Transition-Based Parsing

Arc-eager shift-reduce parsing (Nivre, 2003)

**Stack** **B**

[did, you]$_S$ [s

did $\longrightarrow$ you }

*Right-arc*
*SBJ*

VG

*Very* fast linear-time performance
WSJ 23 (2k sentences) in 3 s

Choose action w/best classifier score
100k - 1M features