Latent-variable CRF for SMT

Wilker Aziz

Universiteit van Amsterdam
w.aziz@uva.nl

May 19, 2017

Conditional random field

Lafferty et al. [2001]

$$P(y|x,w) = \frac{\exp(w^\top \phi(x,y))}{\sum_{y' \in \mathcal{Y}(x)} \exp(w^\top \phi(x,y'))} \tag{1}$$

- ϕ is a feature function mapping (x, y) to $\mathbb{R}^d$
- w is a feature vector in $\mathbb{R}^d$
- $Z(x|w) = \sum_{y \in \mathcal{Y}(x)} \exp(w^\top \phi(x,y))$ must be finite

Flexible (overlapping) features

Examples

As$_1$ menin**as**$_2$ for**am**$_3$ pra$_4$ lá$_4$ $\leftrightarrow$ The$_1$ girls$_2$ went$_3$ over$_4$ there$_4$

Apague$_1$ a$_2$ luz$_3$ $\leftrightarrow$ Switch$_1$ the$_2$ light$_3$ off$_1$

Hard to account for with directed models
(due to causality assumptions)

Global normalisation

Local models are trained with positive context only

- MLE: maximise the likelihood of observation (c, o) under $P(O|C = c)$

Global normalisation

Local models are trained with positive context only

- MLE: maximise the likelihood of observation (c, o) under $P(O|C = c)$
- Label bias [Lafferty et al., 2001]

Global normalisation

Local models are trained with positive context only

- MLE: maximise the likelihood of observation (c, o) under $P(O|C = c)$
- Label bias [Lafferty et al., 2001]

What happens when we query the model with predicted contexts?

Maximum likelihood estimation

Likelihood of an observation (x, y)

$$\mathcal{L}(w|x,y) = \log P(y|x,w) \tag{2}$$
$$= w^\top \phi(x,y) - \log Z(x|w) \tag{3}$$

Maximum likelihood estimation

Likelihood of an observation (x, y)

$$\begin{aligned} \mathcal{L}(w|x, y) &= \log P(y|x, w) && (2) \\ &= w^\top \phi(x, y) - \log Z(x|w) && (3) \end{aligned}$$

Gradient-based optimisation

$$\nabla_w \mathcal{L}(w|x, y) = \phi(x, y) - \mathbb{E}_{P(Y|X=x,w)}[\phi(X, Y)] \qquad (4)$$

Maximum likelihood estimation

Likelihood of an observation (x, y)

$$\begin{aligned} \mathcal{L}(w|x, y) &= \log P(y|x, w) && (2) \\ &= w^\top \phi(x, y) - \log Z(x|w) && (3) \end{aligned}$$

Gradient-based optimisation

$$\nabla_w \mathcal{L}(w|x, y) = \phi(x, y) - \mathbb{E}_{P(Y|X=x,w)}[\phi(X, Y)] \qquad (4)$$

Expected features should match the features of the observation

LV-CRF

Model

$$P(y, d|x) = \frac{\exp(w^\top \phi(x, y, d))}{\sum_{y' \in \mathcal{Y}(x)} \sum_{d' \in \mathcal{D}(x, y')} \exp(w^\top \phi(x, y', d'))} \quad (5)$$

- d is latent
- $Z(x, y|w) = \sum_{d \in \mathcal{D}(x,y)} \exp(w^\top \phi(x, y, d))$ must be finite

MLE for LV-CRF

Likelihood of an observation (x, y)

$$\mathcal{L}(w|x,y) = \log P(y|x,w) \tag{6}$$
$$= \log \sum_{d \in \mathcal{D}(x,y)} P(y,d|x,w) \tag{7}$$

MLE for LV-CRF

Likelihood of an observation (x, y)

$$\mathcal{L}(w|x,y) = \log P(y|x,w) \tag{6}$$
$$= \log \sum_{d \in \mathcal{D}(x,y)} P(y, d|x, w) \tag{7}$$

Gradient-based optimisation [Mann and McCallum, 2007]

$$\nabla_w \mathcal{L}(w|x,y) = \mathbb{E}_{P(D|X=x,Y=y,w)}[\phi(X,Y,D)] \tag{8}$$
$$- \mathbb{E}_{P(Y,D|X=x,w)}[\phi(X,Y,D)] \tag{9}$$

MLE for LV-CRF

Likelihood of an observation (x, y)

$$\mathcal{L}(w|x, y) = \log P(y|x, w) \tag{6}$$

$$= \log \sum_{d \in \mathcal{D}(x,y)} P(y, d|x, w) \tag{7}$$

Gradient-based optimisation [Mann and McCallum, 2007]

$$\nabla_w \mathcal{L}(w|x, y) = \mathbb{E}_{P(D|X=x, Y=y, w)}[\phi(X, Y, D)] \tag{8}$$

$$- \mathbb{E}_{P(Y,D|X=x,w)}[\phi(X, Y, D)] \tag{9}$$

Expected features should match the features of the expected observation

Note on training

Undirected models are considerably harder to learn

- expensive global normalisation
- complex joint distributions

Note on training

Undirected models are considerably harder to learn

- expensive global normalisation
- complex joint distributions

Particularly hard with latent variables

- Alignment: Dyer et al. [2011]
- SMT: Blunsom et al. [2008] and Blunsom and Osborne [2008]

Note on training

Undirected models are considerably harder to learn

- expensive global normalisation
- complex joint distributions

Particularly hard with latent variables

- Alignment: Dyer et al. [2011]
- SMT: Blunsom et al. [2008] and Blunsom and Osborne [2008]
- Approximate techniques
  - Contrastive divergence [Hinton, 2002]
  - Contrastive estimation [Smith and Eisner, 2005]
  - Piecewise training [Sutton and McCallum, 2005]

SMT with CRFs

Blunsom et al. [2008]

- d is a derivation complying with a *hiero* grammar
- ϕ featurises steps in a synchronous derivation

$$P(y, d|x) = \frac{\exp\left(\sum_{r_{s,t} \in d} w^\top \phi(r_{s,t}|x, y, d)\right)}{\sum_{d' \in \mathcal{D}(x)} \exp\left(\sum_{r_{s,t} \in d} w^\top \phi(r_{s,t}|x, y', d')\right)}$$

- $\mathcal{D}(x)$ is the space of derivations over target strings aligned to the source string x
- in the denominator y' is defined implicitly as yield(d')
- $r_{s,t}$ is a synchronous rule decorated with a source span s and a target span t

ITG with CRFs

In Project 2, you will use an ITG

$$\begin{array}{lll} S & \rightarrow & X \\ X & \rightarrow & X\ X \\ X & \rightarrow & x/y \text{ for all } x \in \Sigma \text{ and } y \in \Delta \\ X & \rightarrow & \epsilon/y \text{ for all } y \in \Delta \\ X & \rightarrow & x/\epsilon \text{ for all } x \in \Sigma \end{array}$$

Global normalisation

ITGs are capable of unbounded insertion (hiero grammars are not!)

Global normalisation

ITGs are capable of unbounded insertion (hiero grammars are not!)

Normaliser may diverge for certain $w \in \mathbb{R}^d$

- $\mathcal{D}(x)$ is typically inifinite
- $\sum_{d \in \mathcal{D}(x)} \exp\left(\sum_{r_{s,t} \in d} w^\top \phi(r_{s,t}|x, y, d)\right)$

Global normalisation

ITGs are capable of unbounded insertion (hiero grammars are not!)

Normaliser may diverge for certain $w \in \mathbb{R}^d$

- $\mathcal{D}(x)$ is typically inifinite
- $$\sum_{d \in \mathcal{D}(x)} \exp\left(\sum_{r_{s,t} \in d} w^\top \phi(r_{s,t}|x, y, d)\right)$$

Solution: constrain strings by length

- introduce a constrain n that depends on x
- make $\mathcal{D}_n(x)$ such that $|\text{yield}(d)| \leq n$ for $d \in \mathcal{D}_n(x)$
- $$\sum_{d \in \mathcal{D}_n(x)} \exp\left(\sum_{r_{s,t} \in d} w^\top \phi(r_{s,t}|x, y, d)\right)$$

Learning

Likelihood of an observation (x, y, n)

$$\mathcal{L}(w|x, y, n) = \log P(y|x, n, w) \quad (10)$$

$$= \log \sum_{d \in \mathcal{D}(x,y)} P(y, d|x, n, w) \quad (11)$$

note that $\mathcal{D}(x, y)$ is always finite

Learning

Likelihood of an observation (x, y, n)

$$\mathcal{L}(w|x, y, n) = \log P(y|x, n, w) \tag{10}$$
$$= \log \sum_{d \in \mathcal{D}(x,y)} P(y, d|x, n, w) \tag{11}$$

note that $\mathcal{D}(x, y)$ is always finite

Gradient-based optimisation

$$\nabla_w \mathcal{L}(w|x, y, n) = \underbrace{\mathbb{E}_{P(D|X=x, Y=y,n,w)}[\phi(X, Y, D)]}_{\text{expected features for observation } (x,y)} \tag{12}$$
$$- \underbrace{\mathbb{E}_{P(Y,D|X=x,n,w)}[\phi(X, Y, D)]}_{\text{expected features for observation } x} \tag{13}$$

What do we need?

An ITG parser in order to obtain

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x
2. $\mathcal{D}_n(x)$

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x
2. $\mathcal{D}_n(x)$
   finite set of derivations over target strings that align to the source string x where the target string is no longer than n words

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x
2. $\mathcal{D}_n(x)$
   finite set of derivations over target strings that align to the source string x where the target string is no longer than n words
3. $\mathcal{D}(x, y)$

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x
2. $\mathcal{D}_n(x)$
   finite set of derivations over target strings that align to the source string x where the target string is no longer than n words
3. $\mathcal{D}(x, y)$
   set of derivations of the string pair (x, y)

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x
2. $\mathcal{D}_n(x)$
   finite set of derivations over target strings that align to the source string x where the target string is no longer than n words
3. $\mathcal{D}(x, y)$
   set of derivations of the string pair (x, y)
4. expected feature vector of observations (x, y)

What do we need?

An ITG parser in order to obtain

1. $\mathcal{D}(x)$
   (potentially infinite) set of derivations over target strings that align to the source string x
2. $\mathcal{D}_n(x)$
   finite set of derivations over target strings that align to the source string x where the target string is no longer than n words
3. $\mathcal{D}(x, y)$
   set of derivations of the string pair (x, y)
4. expected feature vector of observations (x, y)
5. expected feature vector of an observation x

Notation

Using a hypergraph view

- u, v, s are nodes
- e is an edge
- $\text{head}(e)$ is a node
- $\text{tail}(e)$ is a sequence of nodes
- if $u \in \text{tail}(e)$ and $v \in \text{tail}(e)$, u and v are siblings
- Backward-star: $BS(u)$ is the set of edges incoming to u
  u is the head of the edge
- Forward-star: $FS(u)$ is the set of edges outgoing from u
  u is in the tail of the edge
- $w(e)$ is the weight of an edge

Inside

The INSIDE recursion

$$I(v) = \begin{cases} \bar{1} & \text{if } BS(v) = \emptyset \\ \bigoplus_{e \in BS(v)} \omega(e) \otimes \bigotimes_{u \in \text{tail}(e)} I(u) & \text{otherwise} \end{cases} \tag{14}$$

For acyclic hypergraphs

Outside

The $\textsc{Outside}$ recursion

$$O(v) = \begin{cases} \bar{1} & \text{if } FS(v) = \emptyset \\ \bigoplus_{e \in FS(v)} \omega(e) \otimes O(\text{head}(e)) \otimes \bigotimes_{s \in tail(e) \setminus \{v\}} I(s) & \text{otherwise} \end{cases} \tag{15}$$

For acyclic hypergraphs

Topsort

function $\textsc{TopSort}(G = \langle V, \langle E, w \rangle \rangle)$
  $S = \{v \in V : BS(v) = \emptyset\}$ $\triangleright$ nodes with no dependencies
  $D = \{v \mapsto \{u : \exists e \in BS(v) \land u \in \text{tail}(e)\} : v \in V\}$
  $\triangleright$ a node depends on all of its children
  $L = \langle \rangle$ $\triangleright$ top-sorted nodes
  while $S \neq \emptyset$ **do**
    $u \leftarrow$ pop(S) $\triangleright$ remove and return a node from S
    $L \leftarrow L + \langle u \rangle$ $\triangleright$ append u to L
    for e in $FS(u)$ **do** $\triangleright$ outgoing edges from u
      $v \leftarrow \text{head}(e)$ $\triangleright$ parent of u in e
      $D(v) \leftarrow D(v) \setminus \{u\}$ $\triangleright$ remove u from $D(v)$
      if $D(v) == \emptyset$ **then** $\triangleright$ v's dependencies have been sorted
        $S \leftarrow S \cup \{v\}$
      end if
    end for
  end while
  return L
end function

Inside

function $\textsc{Inside}(G = \langle V, \langle E, w \rangle \rangle)$
    for v in $\textsc{TopSort}(G)$ **do** ▷ visit nodes bottom-up
        if $BS(v) == \emptyset$ **then**
            $I[v] \leftarrow \bar{1}$ ▷ leaves
        else
            $I[v] \leftarrow \bar{0}$
            for $e \in BS(v)$ **do**
                $k \leftarrow w(e)$ ▷ include the edge's own weight
                for u in $\mathrm{tail}(e)$ **do**
                    $k \leftarrow k \otimes I[u]$
                end for
                $I[v] \leftarrow I[v] \oplus k$ ▷ accumulate for each edge
            end for
        end if
    end for
    return I
end function

Outside

function $\textsc{Outside}(G = \langle V, \langle E, w \rangle \rangle, I, \text{root})$
    $O[v] \leftarrow \bar{0}$ **for** $v \in V$
    $O[\text{root}] \leftarrow \bar{1}$ ▷ this is the goal node
    for v in $\textsc{reverse}(\textsc{TopSort}(G))$ **do** ▷ visit nodes top-down
        for $e \in BS(v)$ **do** ▷ q's incoming edges
            for $u \in \text{tail}(e)$ **do** ▷ children of v in e
                $k \leftarrow w(e) \otimes O[v]$
                for s in $\text{tail}(e)$ **do** ▷ siblings of u in e
                    if $u \neq s$ **then** ▷ u itself is excluded
                        $k \leftarrow k \otimes I[s]$
                    end if
                end for
                $O[u] \leftarrow O[u] \oplus k$ ▷ accumulate it for u
            end for
        end for
    end for
    return O
end function

Expected features

```
function ExpectedFeatures(G = ⟨V, ⟨E, w⟩⟩, I, O, φ)
    φ̄ ← 0
    for e ∈ E do                                  ▷ these are edges
        k ← O[head(e)]
        for u in tail(e) do
            k ← k ⊗ I[u]
        end for
        φ̄ ← φ̄ + kφ(e)
    end for
    return φ̄                                      ▷ expected feature vector
end function
```

Traversals

Viterbi derivation

1. start from the goal (root)
2. recursively rewrite every symbol v by solving

$$e^\star = \arg\max_{e \in BS(v)} w(e) \bigotimes_{u \in \mathrm{tail}(e)} I(u)$$

Traversals

Viterbi derivation

1. start from the goal (root)
2. recursively rewrite every symbol v by solving

$$e^\star = \arg\max_{e \in BS(v)} w(e) \bigotimes_{u \in \text{tail}(e)} I(u)$$

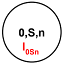
Sampling

1. start from the goal (root)
2. recursively rewrite every symbol v by solving

$$E \sim P(e|v) = \begin{cases} \bar{0} & \text{if } e \notin BS(v) \\ \frac{w(e) \bigotimes_{u \in \text{tail}(e)} I(u)}{I(v)} & \text{otherwise} \end{cases}$$

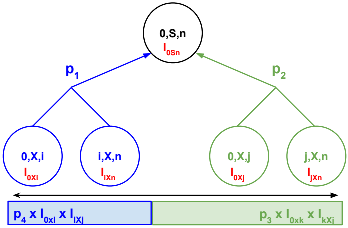
Viterbi

Use Inside computed in the Max-Times semiring!



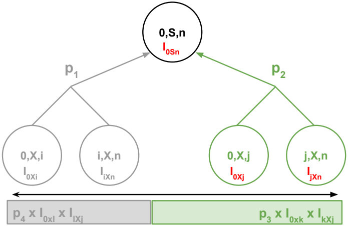
Viterbi

Use Inside computed in the Max-Times semiring!



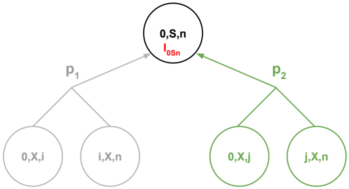
Viterbi

Use Inside computed in the Max-Times semiring!



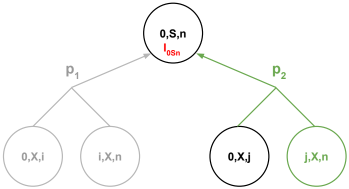
Viterbi

Use Inside computed in the Max-Times semiring!



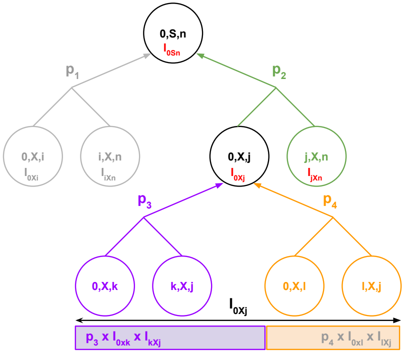
Viterbi

Use Inside computed in the Max-Times semiring!



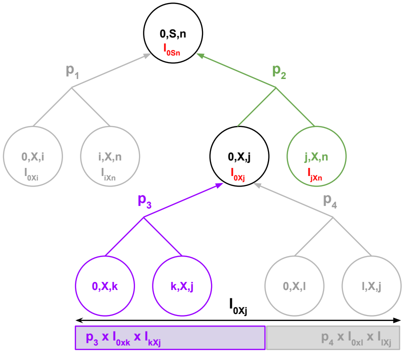
Viterbi

Use Inside computed in the Max-Times semiring!



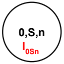
Viterbi

Use Inside computed in the Max-Times semiring!



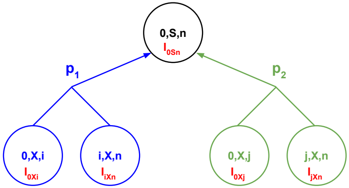
Sampling

Use Inside computed in the Sum-Times semiring!



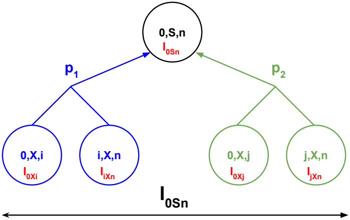
Sampling

Use Inside computed in the Sum-Times semiring!



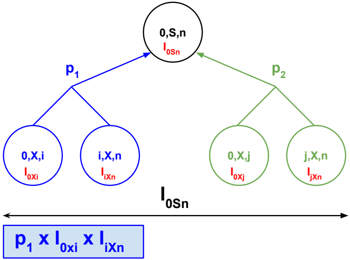
Sampling

Use Inside computed in the Sum-Times semiring!



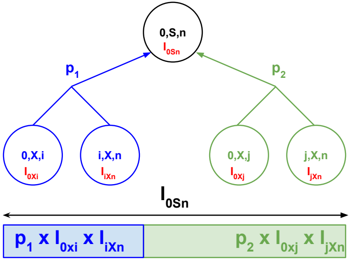
Sampling

Use Inside computed in the Sum-Times semiring!



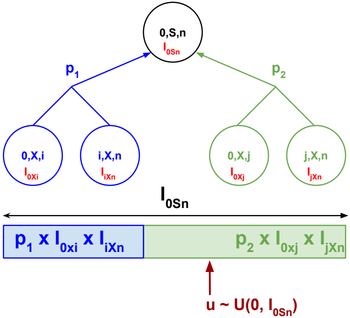
Sampling

Use Inside computed in the Sum-Times semiring!



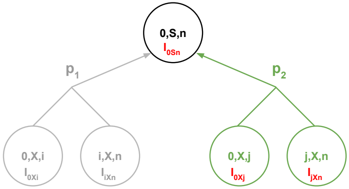
Sampling

Use Inside computed in the Sum-Times semiring!



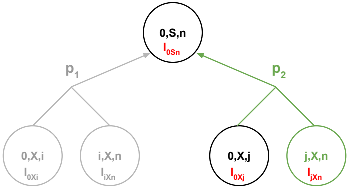
Sampling

Use Inside computed in the Sum-Times semiring!



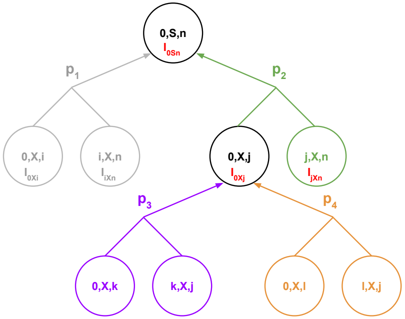
Sampling

Use Inside computed in the Sum-Times semiring!



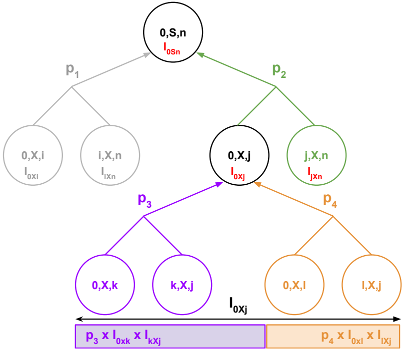
Sampling

Use Inside computed in the Sum-Times semiring!



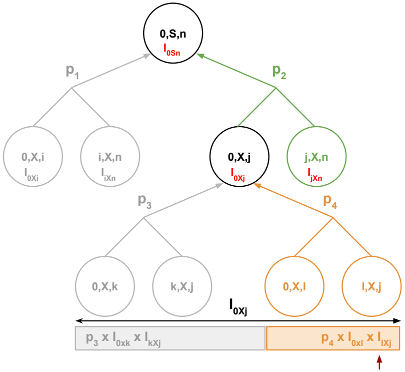
Sampling

Use Inside computed in the Sum-Times semiring!



Sampling

Use Inside computed in the Sum-Times semiring!



Roadmap to project 2

1. understand the parser
   - check notes and notebook
2. implement the constrained forest $\mathcal{D}_n(x)$
3. implement feature functions
4. implement hypergraph algorithms
   - topsort, inside, outside, expected features
5. iterate over mini-batches of data making gradient updates

Questions?

References I

Phil Blunsom and Miles Osborne. Probabilistic inference for machine translation. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 215–223, Honolulu, Hawaii, October 2008. Association for Computational Linguistics. URL `http://www.aclweb.org/anthology/D08-1023`.

Phil Blunsom, Trevor Cohn, and Miles Osborne. A discriminative latent variable model for statistical machine translation. In *Proceedings of ACL-08: HLT*, pages 200–208, Columbus, Ohio, June 2008. Association for Computational Linguistics. URL `http://www.aclweb.org/anthology/P/P08/P08-1024`.

References II

Chris Dyer, Jonathan H. Clark, Alon Lavie, and Noah A. Smith. Unsupervised word alignment with arbitrary features. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 409–419, Portland, Oregon, USA, June 2011. Association for Computational Linguistics. URL `http://www.aclweb.org/anthology/P11-1042`.

Geoffrey E. Hinton. Training products of experts by minimizing contrastive divergence. *Neural Comput.*, 14(8):1771–1800, August 2002. ISSN 0899-7667. doi: 10.1162/089976602760128018. URL `http://dx.doi.org/10.1162/089976602760128018`.

References III

John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *Proceedings of the Eighteenth International Conference on Machine Learning*, ICML '01, pages 282–289, San Francisco, CA, USA, 2001. Morgan Kaufmann Publishers Inc. ISBN 1-55860-778-1. URL http://dl.acm.org/citation.cfm?id=645530.655813.

Gideon Mann and Andrew McCallum. Efficient computation of entropy gradient for semi-supervised conditional random fields. In *Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers*, pages 109–112, Rochester, New York, April 2007. Association for Computational Linguistics. URL http://www.aclweb.org/anthology/N/N07/N07-2028.

References IV

Noah A. Smith and Jason Eisner. Contrastive estimation: Training log-linear models on unlabeled data. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL'05)*, pages 354–362, Ann Arbor, Michigan, June 2005. Association for Computational Linguistics. doi: 10.3115/1219840.1219884. URL http://www.aclweb.org/anthology/P05-1044.

Charles Sutton and Andrew McCallum. Piecewise training for undirected models. In *Proceedings of the Twenty-First Conference on Uncertainty in Artificial Intelligence*, UAI'05, pages 568–575, Arlington, Virginia, United States, 2005. AUAI Press. ISBN 0-9749039-1-4. URL http://dl.acm.org/citation.cfm?id=3020336.3020405.