Large–Margin Methods for Natural Language Learning

Michael Collins
AT&T Labs-Research

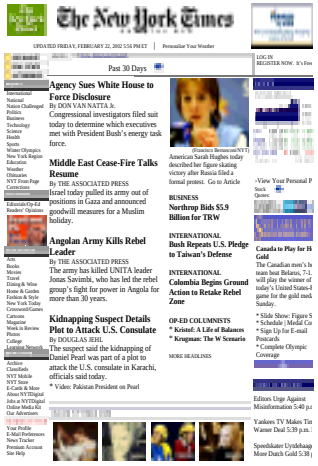
MOTIVATION: APPLICATIONS

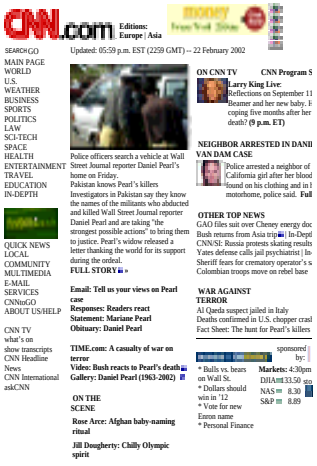
- Sequential data is **Everywhere**

Biological data

UCUCUGCCCCAGAGCGAUACACGUGUCCGAACGUCAC
UAAGUGUCCGCGCUAGGGUGAUGACAGUCGUGCC. . .

Text





Estimators for Stochastic "Unification-Based" Grammars*

Mark Johnson
Cognitive and Linguistic Sciences
Brown University

Stuart Geman
Applied Mathematics
Brown University

Stephen Canon
Cognitive and Linguistic Sciences
Brown University

Zhiyi Chi
Dept. of Statistics
The University of Chicago

Stefan Riezler
Institut für Maschinelle Sprachverarbeitung
Universität Stuttgart

Abstract

Log-linear models provide a statistically sound framework for Stochastic "Unification-Based" Grammars (SUBGs) and stochastic versions of other kinds of grammars. We describe two computationally-tractable ways of estimating the parameters of such grammars from a training corpus of syntactic analyses, and apply these to estimate a stochastic version of Lexical-Functional Grammar.

1 Introduction

Probabilistic methods have revolutionized computational linguistics. They can provide a systematic treatment of preferences in parsing. Given a suitable estimation procedure, stochastic models can be "tuned" to reflect the properties of a corpus. On the other hand, "Unification-Based" Grammars (UBGs) can express a variety of linguistically-important syntactic and semantic constraints. However, developing Stochastic "Unification-based" Grammars (SUBGs) has not proved so straightforward as might be hoped.

The simple "relative frequency" estimator for PCFGs yields the maximum likelihood parameter estimate, which is to say that it minimizes the Kullback-Liebler divergence between the training and estimated distributions. On the other hand, as Abney [1997] points out, the context-sensitive dependencies that "unification-based" constraints introduce render the relative frequency estimator suboptimal: in general it does not maximize the likelihood and it is inconsistent.

2 Features in SUBGs

We follow the statistical literature in using the term *feature* to refer to the properties that parameters are associated with (we use the word "attribute" to refer to the attributes or features of a UBG's feature structure). Let Ω be the set of all possible grammatical or well-formed analyses. Each feature f maps a syntactic analysis $\omega \in \Omega$ to a real value $f(\omega)$. The form of a syntactic analysis depends on the underlying linguistic theory. For example, for a PCFG ω would be a parse tree, for a LFG ω would be a tuple consisting of (at least) a c-structure, an f-structure and a mapping from c-structure nodes to f-structure elements, and for a Chomskyian transformational grammar ω would be a derivation.

Log-linear models are models in which the log probability is a linear combination of feature values (plus a constant). PCFGs, Gibbs distributions, Maximum-Entropy distributions and Markov Random Fields are all examples of log-linear models. A log-linear model associates each feature f_j with a real-valued parameter θ_j.

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NEED TO INDUCE STRUCTURE

SEGMENTATIONS

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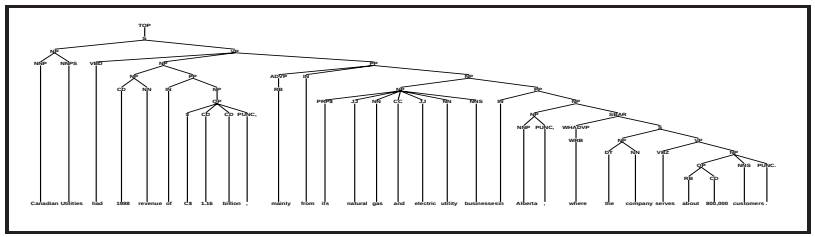
UGUCCGAACGUCACUAAGUGUCC ⇒
GCGCUAGGGUGAUGACAGUCGUG

UCUCUGCCCCAGAGCGAUACACG
UGUCCGAACGUCACUAAGUGUCC
GCGCUAGGGUGAUGACAGUCGUG

HIERARCHICAL STRUCTURES (TREES)

Canadian Utilities had 1988 revenue of C$ 1.16 billion, mainly from its natural gas and electric utility businesses in Alberta, where the company serves about 800,000 customers. ⇒



TWO FUNDAMENTAL PROBLEMS

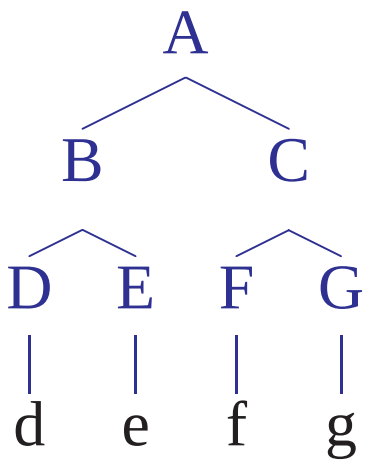
TAGGING: Strings to Tagged Sequences

a b e e a f h j ⇒ a/C b/D e/C e/C a/D f/C h/D j/C

PARSING: Strings to Trees

d e f g ⇒ (A (B (D d) (E e)) (C (F f) (G g)))

d e f g ⇒



OVERVIEW

- **The basic goal:** Supervised learning for recovering structure
- **A challenge:** Not like "typical" problems in statistics
  - Functions from strings to other discrete structures
- **Some new methods:**
  - How the voted perceptron algorithm can be applied
  - Global features
  - **Kernels** over discrete structures
  - Efficient training of weighted automata
  - Advantages over existing methods:
    new representations, discriminative parameter estimation

LANGUAGE GENERATION [Walker et al. 2001]

Input = text plan

implicit-confirm(orig-city:NEWARK) implicit-confirm(dest-city:DALLAS) implicit-confirm(month:9) implicit-confirm(day-number:1) request(depart-time)

Output = text

What time would you like to travel on September the 1st to Dallas from Newark?
Leaving on September 1st. What time would you like to travel from Newark to Dallas?
Leaving in September. Leaving on the 1st. What time would you, traveling from Newark to Dallas, like to leave?

A CHALLENGE

- Interesting class of learning problems:

  Functions from strings to other discrete structures

- "Typical" problems in statistics:
  - Classification functions $F : \mathbb{R}^n \rightarrow \{-1, +1\}$
  - Regression functions $F : \mathbb{R}^n \rightarrow \mathbb{R}$

COMMON METHODS

- Stochastic automata
  - Probabilistic finite-state machines
    Hidden Markov Models (HMMs)
  - Probabilistic context-free grammars
    PCFGs

- Limitations
  - Representation
  - Strong assumptions in parameter estimation

NEW METHODS

- "Distribution-free" methods for classification (regression) (Support vector machines, Voted Perceptron, Boosting)

- Very different statistical basis from ML/Bayesian methods Uniform convergence bounds, VC-dimension, **Large-margin bounds**

- Questions:
  - Can these methods be derived for tagging, parsing?
  - Do the statistical guarantees (e.g. about generalization) apply to tagging and parsing?
  - What representations can be used?

MAIN RESULTS

- A variant of the voted perceptron algorithm for parsing, tagging, other NLP problems
- Experiments: Improvements over state-of-the-art baselines, using “global” features
- New kernels for discrete structures such as trees (e.g., the “all subtrees” representation)
- Experiments: Improvements over state-of-the-art baselines, using these kernels
- Efficient discriminative algorithms for weighted automata (Alternative parameter estimation method to Maximum-entropy taggers, Conditional Markov Random Fields)

LINEAR MODELS FOR TAGGING AND PARSING

- Three components:

  GEN is a function from a string to a set of candidates

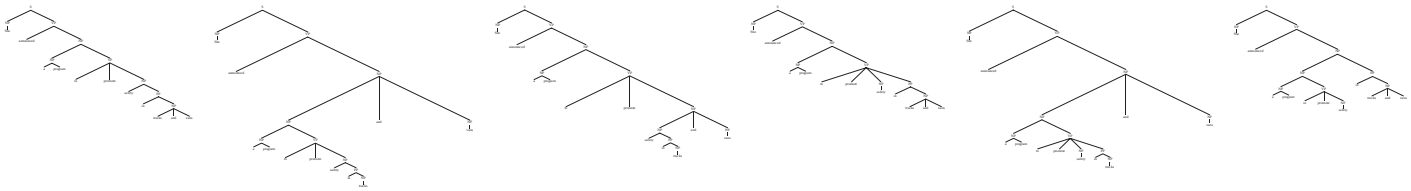
  Φ maps a candidate to a feature vector

  W is a parameter vector

Related to Markov Random Field approaches
[Lafferty et al. 2001]
[Johnson, Geman, Canon, Chi, and Riezler 1999]
[Abney 1997]
[Della Pietra, Della Pietra, and Lafferty 1997]
[Ratnaparkhi, Roukos and Ward 94]

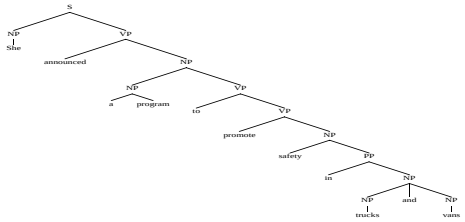
She announced a program to promote safety in trucks and vans

$\Downarrow$ **GEN**



$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$
$\langle 1, 1, 3, 5 \rangle$	$\langle 2, 0, 0, 5 \rangle$	$\langle 1, 0, 1, 5 \rangle$	$\langle 0, 0, 3, 0 \rangle$	$\langle 0, 1, 0, 5 \rangle$	$\langle 0, 0, 1, 5 \rangle$
$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$
13.6	12.2	12.1	3.3	9.4	11.1

$\Downarrow \arg\max$

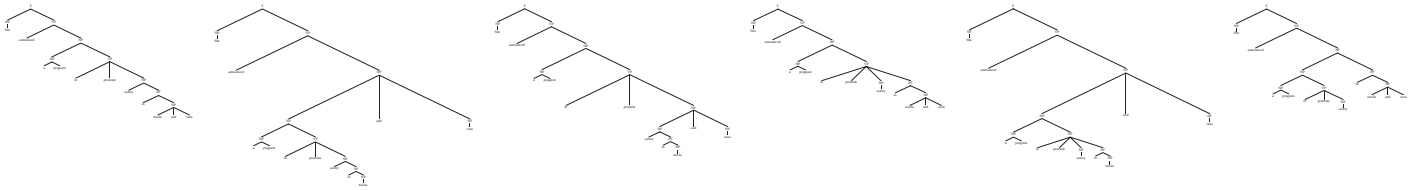


COMPONENT 1: GEN

- **GEN** enumerates a set of **candidates** for a sentence

She announced a program to promote safety in trucks and vans

⇓ **GEN**



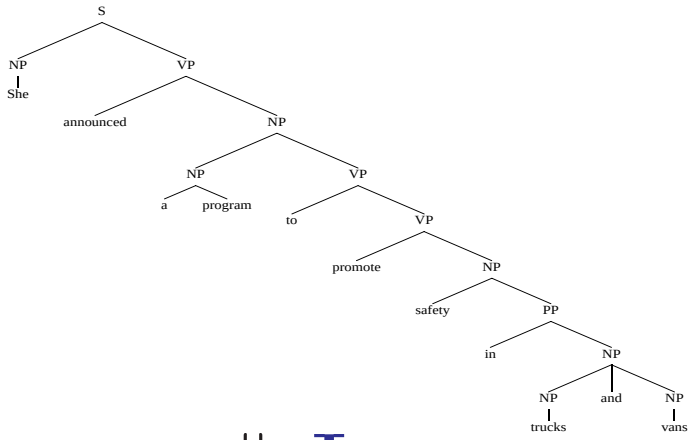
Note: Optimality Theory [Prince and Smolensky]

EXAMPLES OF GEN

- A context-free grammar
- A finite-state machine
- Top N most probable analyses from a probabilistic grammar

COMPONENT 2: Φ

- Φ maps a candidate to a **feature vector** $\in \mathbb{R}^d$
- Φ defines the **representation** of a candidate

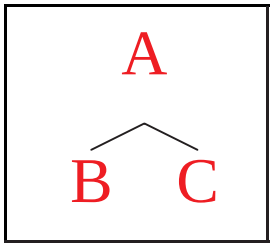


$\Downarrow \Phi$

$\langle 1, 0, 2, 0, 0, 15, 5 \rangle$

FEATURES

- A "feature" is a function on a structure, e.g.,

$h(x) =$ Number of times  is seen in x

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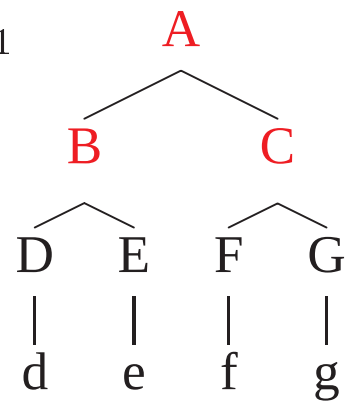
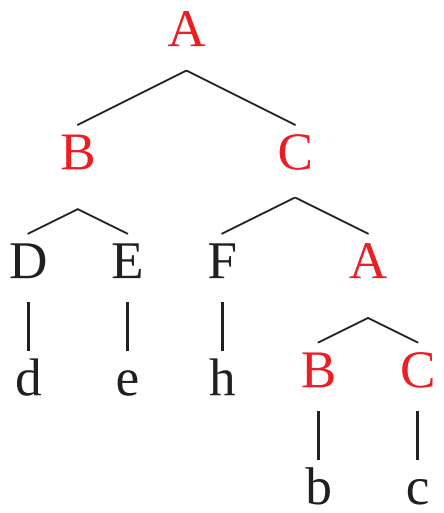
T_1



T_2



$h(T_1) = 1$

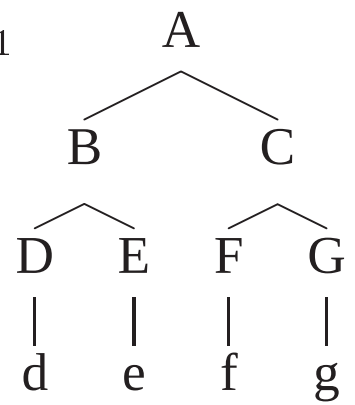
$h(T_2) = 2$

FEATURE VECTORS

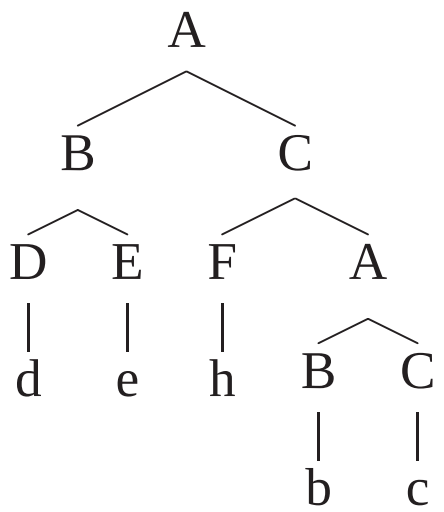
- A set of functions $h_1 \ldots h_d$ define a **feature vector**

$$\mathbf{\Phi}(x) = \langle h_1(x), h_2(x) \ldots h_d(x) \rangle$$

T_1



T_2



$$\mathbf{\Phi}(T_1) = \langle 1, 0, 0, 3 \rangle \qquad \mathbf{\Phi}(T_2) = \langle 2, 0, 1, 1 \rangle$$

A NEED TO DEFINE ARBITRARY FEATURES

Example 1 Parallelism in coordination [Johnson et. al 1999]

Constituents with similar structure tend to be coordinated

$h(x) =$ Number of instances of non-parallel coordination in x

Bars in New York and pubs in London	h(x) = 0
vs. Bars in New York and pubs	h(x) = 1

Example 2 Semantic features

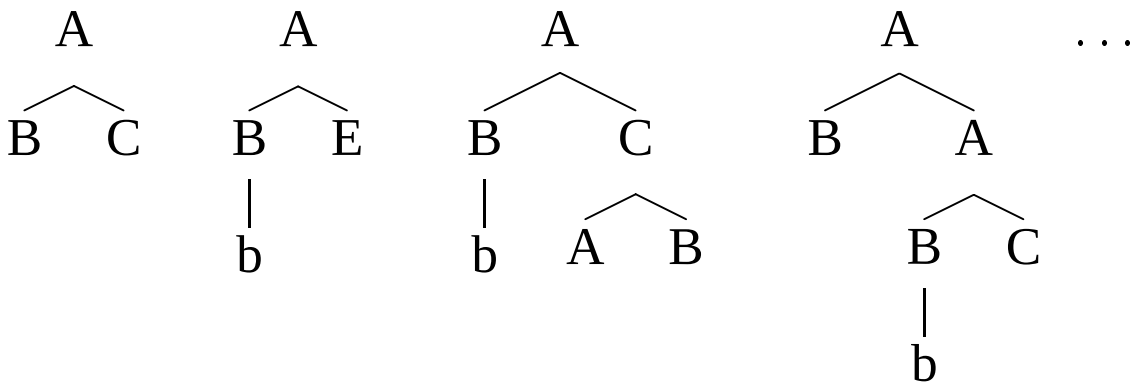
$h(x) =$ Number of times **pour** takes an object with a `+liquid` feature

pour the **cappucino**	h(x) = 1
vs. pour the **book**	h(x) = 0

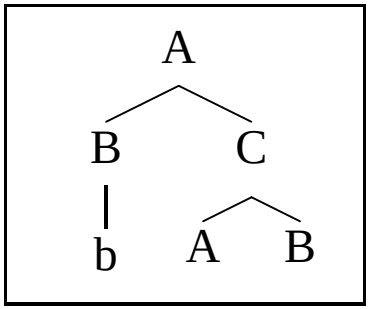
"ALL SUBTREES" REPRESENTATION

- Given: Non-Terminal symbols $\{A, B, \ldots\}$
  Terminal symbols $\{a, b, c \ldots\}$

- An infinite set of subtrees



- An infinite set of features, e.g.,

$h_3(x) =$ Number of times  is seen in x

Representation studied by [Bod 98]

COMPONENT 3: $\mathbf{W}$

- $\mathbf{W}$ is a **parameter vector** $\in \mathbb{R}^d$
- $\mathbf{\Phi}$ and $\mathbf{W}$ together map a candidate to a real-valued score

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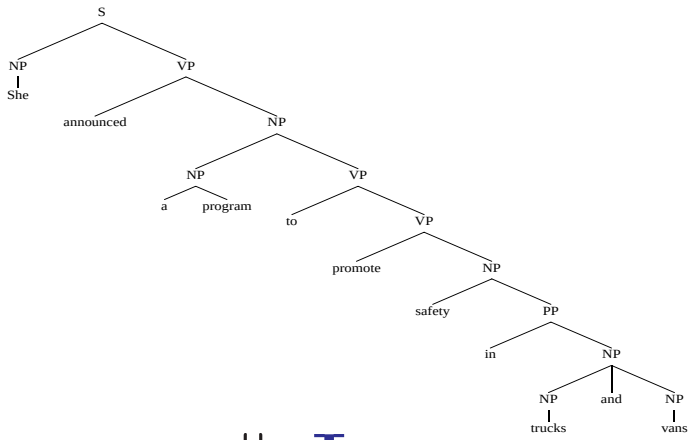


$$\Downarrow \mathbf{\Phi}$$

$$\langle 1, 0, 2, 0, 0, 15, 5 \rangle$$

$$\Downarrow \mathbf{\Phi} \cdot \mathbf{W}$$

$$\langle 1, 0, 2, 0, 0, 15, 5 \rangle \cdot \langle 1.9, -0.3, 0.2, 1.3, 0, 1.0, -2.3 \rangle = 5.8$$

PUTTING IT ALL TOGETHER

- $\mathcal{X}$ is set of sentences, $\mathcal{Y}$ is set of possible outputs (e.g. trees)
- Need to learn a function $\mathbf{F} : \mathcal{X} \rightarrow \mathcal{Y}$
- $\mathbf{GEN}$, $\mathbf{\Phi}$, $\mathbf{W}$ define

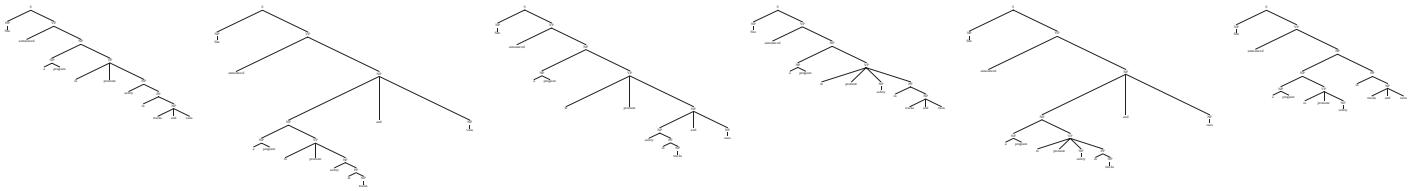
$$\mathbf{F}(x) = \arg\max_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(y) \cdot \mathbf{W}$$

Choose the highest scoring tree as the most plausible structure

- Given examples (x_i, y_i), how to set $\mathbf{W}$?

She announced a program to promote safety in trucks and vans

$\Downarrow$ **GEN**



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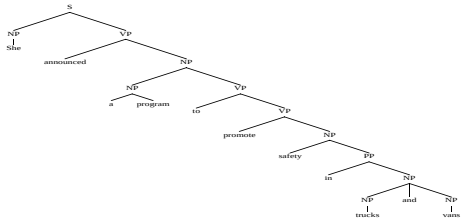

PREVIOUS WORK ON PARAMETER ESTIMATION

- **Markov Random Fields**
  [Johnson et. al 1999],[Lafferty et al. 2001],
  [Ratnaparkhi, Roukos and Ward 94]

$$P(y_i \mid x_i, \mathbf{W}) = \frac{e^{\mathbf{\Phi}(y_i)\cdot\mathbf{W}}}{\sum_{y\in\mathbf{GEN}(x_i)} e^{\mathbf{\Phi}(y)\cdot\mathbf{W}}}$$

- **Boosting** (ICML 2000 paper):

  Minimize: $$\sum_i \sum_{z\in\mathbf{GEN}(x_i), z\neq y_i} e^{\mathbf{W}\cdot\mathbf{\Phi}(z)-\mathbf{W}\cdot\mathbf{\Phi}(y_i)}$$

- Close connections between the two:
  [Friedman, Hastie, and Tibshirani 1998, Lafferty 1999]
  (COLT 2000 paper with Rob Schapire, Yoram Singer)

A VARIANT OF THE PERCEPTRON ALGORITHM

Inputs: Training set (x_i, y_i) for $i = 1 \ldots n$

Initialization: $\mathbf{W} = 0$

Define: $\mathbf{F}(x) = \text{argmax}_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(y) \cdot \mathbf{W}$

Algorithm: For $t = 1 \ldots T$, $i = 1 \ldots n$

$z_i = \mathbf{F}(x_i)$

If $(z_i \neq y_i)$ $\mathbf{W} = \mathbf{W} + \mathbf{\Phi}(y_i) - \mathbf{\Phi}(z_i)$

Output: Parameters $\mathbf{W}$

THEORY UNDERLYING THE ALGORITHM

- **Definition:** $\overline{\mathbf{GEN}}(x_i) = \mathbf{GEN}(x_i) - \{y_i\}$

- **Definition:** The training set is **separable with margin** δ, if there is a vector $\mathbf{U} \in \mathbb{R}^d$ with $||\mathbf{U}|| = 1$ such that

$$\forall i, \forall z \in \overline{\mathbf{GEN}}(x_i) \quad \mathbf{U} \cdot \mathbf{\Phi}(y_i) - \mathbf{U} \cdot \mathbf{\Phi}(z) \geq \delta$$

THEORY UNDERLYING THE ALGORITHM

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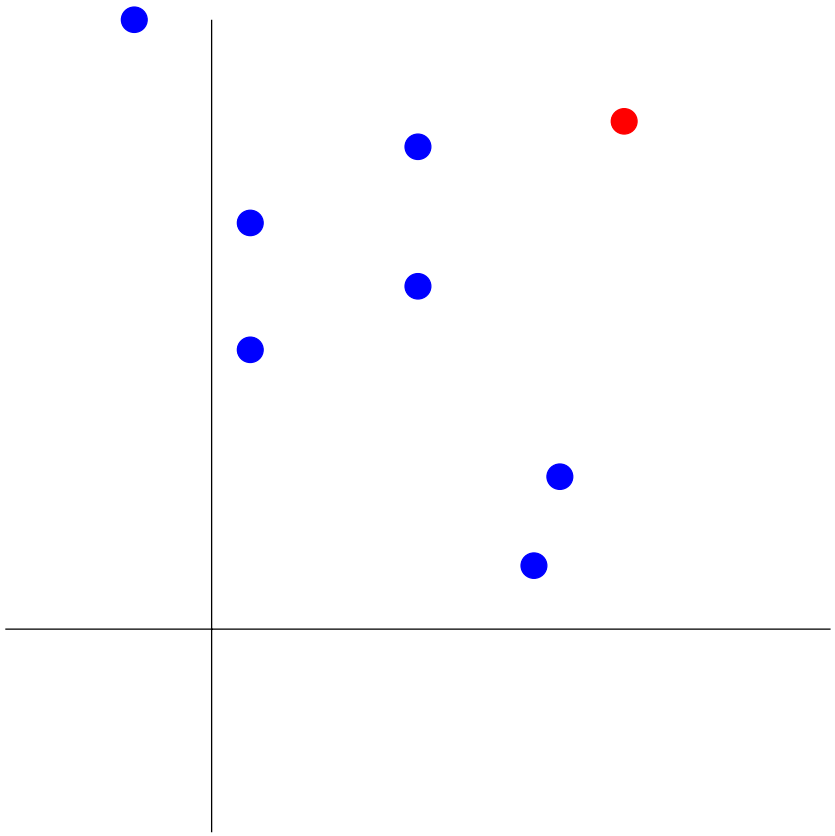
$$\forall i, \forall z \in \overline{\mathbf{GEN}}(x_i) \quad \mathbf{U} \cdot \mathbf{\Phi}(y_i) - \mathbf{U} \cdot \mathbf{\Phi}(z) \geq \delta$$

Theorem: For any training sequence (x_i, y_i) which is separable with margin δ, then for the perceptron algorithm

$$\text{Number of mistakes} \leq \frac{R^2}{\delta^2}$$

where R is a constant such that $\forall i, \forall z \in \overline{\mathbf{GEN}}(x_i) \quad ||\mathbf{\Phi}(y_i) - \mathbf{\Phi}(z)|| \leq R$

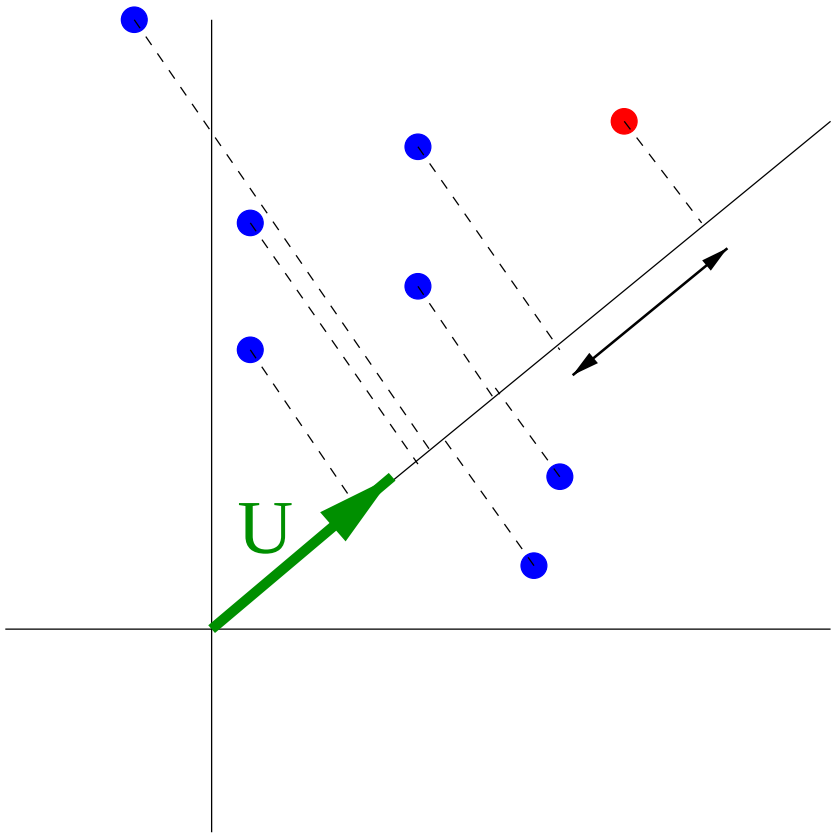
GEOMETRIC INTUITION BEHIND SEPARATION



= Correct candidate

= Incorrect candidates

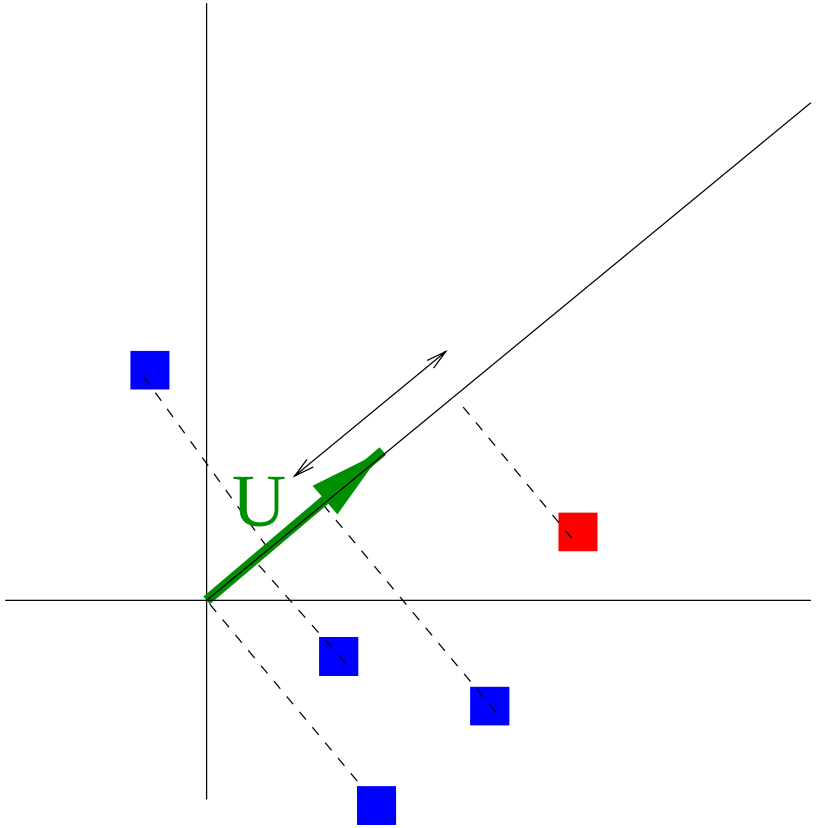
GEOMETRIC INTUITION BEHIND SEPARATION



● = Correct candidate

● = Incorrect candidates

ALL EXAMPLES ARE SEPARATED



= Correct candidate (2)

= Incorrect candidates (2)

THEORY UNDERLYING THE ALGORITHM

Old definition

- Classification case: examples (x_i, y_i), where $y_i \in \{-1, +1\}$
- **Definition:** The training set is **separable with margin** δ, if there is a vector $\mathbf{U} \in \mathbb{R}^d$ with $||\mathbf{U}|| = 1$ such that

$$\forall i, \quad \mathbf{U} \cdot \mathbf{\Phi}(x_i) \times y_i \geq \delta$$

New definitions

- **Definition:** $\overline{\mathbf{GEN}}(x_i) = \mathbf{GEN}(x_i) - \{y_i\}$

- **Definition:** The training set is **separable with margin** δ, if there is a vector $\mathbf{U} \in \mathbb{R}^d$ with $||\mathbf{U}|| = 1$ such that

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THEORY UNDERLYING THE ALGORITHM

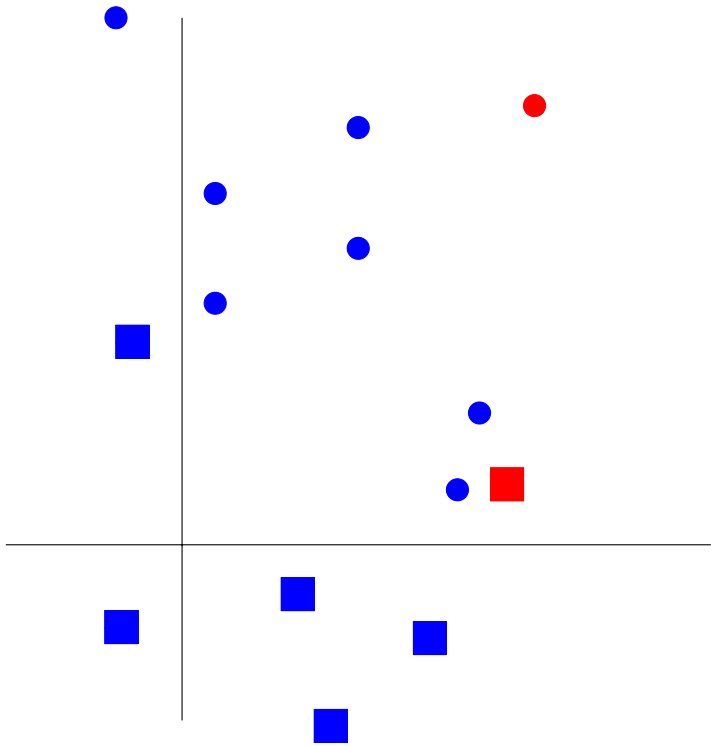
Theorem: For any training sequence (x_i, y_i) which is separable with margin δ, then for the perceptron algorithm

$$\text{Number of mistakes} \leq \frac{R^2}{\delta^2}$$

where R is a constant such that $\forall i, \forall z \in \overline{\mathbf{GEN}}(x_i) \quad ||\mathbf{\Phi}(y_i) - \mathbf{\Phi}(z)|| \leq R$

Proof: Direct modification of the proof for the classification case.

WHAT WE'RE NOT DOING



= Correct candidate (2)

= Incorrect candidates (2)

= Correct candidate

= Incorrect candidates

- We aim to separate the correct structure from its competitors
- We're not aiming to do **classification** of good vs. bad parses
  This is a harder (and unnecessary) problem

Proof:

Let $\mathbf{W}^k$ be the weights before the k'th mistake. $\mathbf{W}^1 = 0$
If the k'th mistake is made at i'th example,
and $z_i = \text{argmax}_{y \in \mathbf{GEN}(x_i)} \mathbf{\Phi}(y) \cdot \mathbf{W}^k$, then

$$\begin{aligned}
\mathbf{W}^{k+1} &= \mathbf{W}^k + \mathbf{\Phi}(y_i) - \mathbf{\Phi}(z_i) \\
\Rightarrow \mathbf{U} \cdot \mathbf{W}^{k+1} &= \mathbf{U} \cdot \mathbf{W}^k + \mathbf{U} \cdot \mathbf{\Phi}(y_i) - \mathbf{U} \cdot \mathbf{\Phi}(z_i) \\
&\geq \mathbf{U} \cdot \mathbf{W}^k + \delta \\
&\geq k\delta \\
\Rightarrow ||\mathbf{W}^{k+1}|| &\geq k\delta
\end{aligned}$$

Also,

$$\begin{aligned}
||\mathbf{W}^{k+1}||^2 &= ||\mathbf{W}^k||^2 + ||\mathbf{\Phi}(y_i) - \mathbf{\Phi}(z_i)||^2 + 2\mathbf{W}^k \cdot (\mathbf{\Phi}(y_i) - \mathbf{\Phi}(z_i)) \\
&\leq ||\mathbf{W}^k||^2 + R^2 \\
\Rightarrow ||\mathbf{W}^{k+1}||^2 &\leq kR^2 \\
\Rightarrow k^2\delta^2 &\leq ||\mathbf{W}^{k+1}||^2 \leq kR^2 \\
\Rightarrow k &\leq R^2/\delta^2
\end{aligned}$$

MORE THEORY FOR THE PERCEPTRON ALGORITHM

• Question 1: what if the data is not separable?
[Freund and Schapire 99] give a modified theorem for this case

• Question 2: performance on training data is all very well,
but what about performance on new test examples?

Assume some distribution $P(x, y)$ underlying examples

Theorem [Helmbold and Warmuth 95]: For any distribution $P(x, y)$ generating examples, if e = expected number of mistakes of an online algorithm on a sequence of $m + 1$ examples, then a randomized algorithm trained on m samples will have probability $\frac{e}{m+1}$ of making an error on a newly drawn example from P.

[Freund and Schapire 99] use this to define the **Voted Perceptron**

QUESTION 1: WHAT IF THE DATA IS NOT SEPARABLE?

- A modified theorem follows from [Freund and Schapire 99]

For any $\mathbf{U}$, δ pair with $||\mathbf{U}|| = 1$ **define**

- $m_i = \mathbf{U} \cdot \mathbf{\Phi}(y_i) - \max_{z \in \overline{\mathbf{GEN}}(x_i)} \mathbf{U} \cdot \mathbf{\Phi}(z)$
- $\epsilon_i = \begin{cases} \delta - m_i & \text{if } m_i < \delta \\ 0 & \text{otherwise} \end{cases}$
- $D(\mathbf{U}, \delta) = \sqrt{\sum_i \epsilon_i^2}$

Then it can be shown that

$$\text{Number of mistakes} \leq \min_{\mathbf{U},\delta} \frac{(R + D(\mathbf{U}, \delta))^2}{\delta^2}$$

QUESTION 2: PERFORMANCE ON NEW EXAMPLES?

Theorem [Helmbold and Warmuth 95]: For any distribution $P(x, y)$ generating examples, if e = expected number of mistakes of an online algorithm on a sequence of $m + 1$ examples, then a randomized algorithm trained on m samples will have probability $\frac{e}{m+1}$ of making an error on a newly drawn test example.

[Freund and Schapire 99]: For the **voted perceptron**

$$\text{Probability of error} \leq \frac{2}{m+1} E\left[\min_{\mathbf{U},\delta} \frac{(R+D(\mathbf{U},\delta))^2}{\delta^2}\right]$$

where $E[\ldots]$ is the expectation taken over a sample of $(m + 1)$ examples drawn from P(x,y)

QUESTION 3: ARE LINEAR SEPARATORS GOOD ENOUGH?

Example: Hand-written digit recognition

- **Kernels** give non-linear separators

  Linear model + no voting $\Rightarrow$ 13.5% error rate
  Degree 3 polynomial kernel + voting $\Rightarrow$ 1.6% error rate

- **Voting** helps in non-separable cases

  Linear model + voting $\Rightarrow$ 8.1% error rate

THREE SCENARIOS

- Reranking output from a probabilistic model
- Reranking output using **kernels**
- Training a tagging model

RERANKING APPROACHES

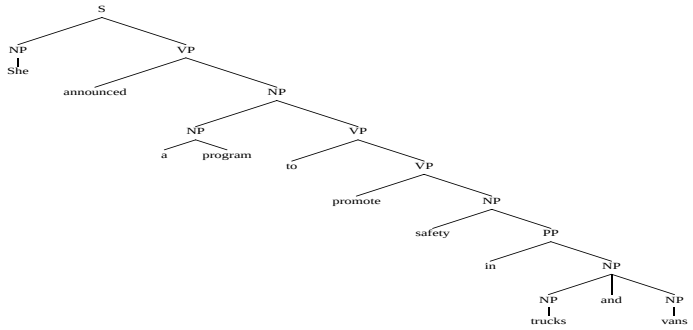
- **GEN** is the top n most probable candidates from a base model
  - Parsing: a lexicalized probabilistic context-free grammar
  - Tagging: "maximum entropy" tagger
  - Speech recognition: existing recogniser

PARSING EXPERIMENTS

GEN Beam search used to parse training and test sentences: around 27 parses for each sentence

$\mathbf{\Phi} = \langle L(x), h_1(x) \ldots h_m(x) \rangle$, where $L(x) =$ log-likelihood from first-pass parser, $h_1 \ldots h_m$ are $\approx 500,000$ indicator functions

$$e.g., \quad h_1(x) = \begin{cases} 1 & \text{if } x \text{ contains} \langle S \rightarrow NP \;\; VP \rangle \\ 0 & \text{otherwise} \end{cases}$$



$\Downarrow \mathbf{\Phi}$

$\langle -15.65, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, \ldots 1, 0, 0 \rangle$

NAMED ENTITIES

GEN Top 20 segmentations from a "maximum-entropy" tagger

$\Phi = \langle L(x), h_1(x) \ldots h_m(x) \rangle,$

$$e.g., \quad h_1(x) = \begin{cases} 1 & \text{if } x \text{ contains a boundary = "[The"} \\ 0 & \text{otherwise} \end{cases}$$

Whether you're an aging flower child or a clueless [Gen-Xer], "[The Day They Shot John Lennon]," playing at the [Dougherty Arts Center], entertains the imagination.

$$\Downarrow \Phi$$

$$\langle -3.17, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, \ldots 0, 1, 1 \rangle$$

Whether you're an aging flower child or a clueless [Gen-Xer], "[The Day They Shot John Lennon]," playing at the [Dougherty Arts Center], entertains the imagination.

$$\Downarrow \Phi$$

$$\langle -3.17, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, \ldots 0, 1, 1 \rangle$$

Whether you're an aging flower child or a clueless Gen-Xer, "The Day [They Shot John Lennon]," playing at the [Dougherty Arts Center], entertains the imagination.

$$\Downarrow \Phi$$

$$\langle -3.51, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, \ldots 0, 1, 0 \rangle$$

Whether you're an aging flower child or a clueless [Gen-Xer], "The Day [They Shot John Lennon]," playing at the [Dougherty Arts Center], entertains the imagination.

$$\Downarrow \Phi$$

$$\langle -2.87, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, \ldots 0, 1, 0 \rangle$$

EXPERIMENTS

Parsing Wall Street Journal Treebank

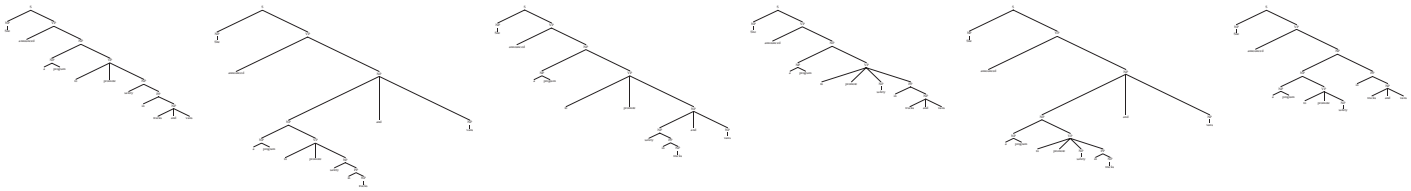
Training set = 40,000 sentences, test = 2,416 sentences
State-of-the-art parser: 88.2% F-measure
Reranked model: 89.5% F-measure (11% relative error reduction)
Boosting: 89.7% F-measure (13% relative error reduction)

Recovering Named-Entities in Web Data

Training data = 53,609 sentences (1,047,491 words),
test data = 14,717 sentences (291,898 words)
State-of-the-art tagger: 85.3% F-measure
Reranked model: 87.9% F-measure (17.7% relative error reduction)
Boosting: 87.6% F-measure (15.6% relative error reduction)

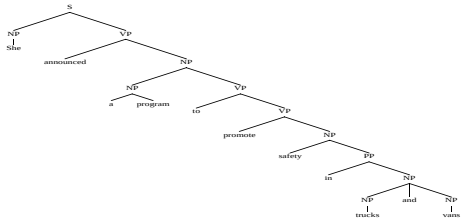
She announced a program to promote safety in trucks and vans

$\Downarrow$ **GEN**



$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$
$\langle 1, 1, 3, 5 \rangle$	$\langle 2, 0, 0, 5 \rangle$	$\langle 1, 0, 1, 5 \rangle$	$\langle 0, 0, 3, 0 \rangle$	$\langle 0, 1, 0, 5 \rangle$	$\langle 0, 0, 1, 5 \rangle$
$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$
13.6	12.2	12.1	3.3	9.4	11.1

$\Downarrow \arg\max$



THREE SCENARIOS

- Reranking output from a probabilistic model
- Reranking output using **kernels**
  (with Nigel Duffy)
- Training a weighted grammar

A VARIANT OF THE PERCEPTRON ALGORITHM

Inputs: Training set (x_i, y_i) for $i = 1 \ldots n$

Initialization: $\mathbf{W} = 0$

Define: $\mathbf{F}(x) = \text{argmax}_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(y) \cdot \mathbf{W}$

Algorithm: For $t = 1 \ldots T$, $i = 1 \ldots n$

$z_i = \mathbf{F}(x_i)$

If $(z_i \neq y_i)$ $\mathbf{W} = \mathbf{W} + \mathbf{\Phi}(y_i) - \mathbf{\Phi}(z_i)$

Output: Parameters $\mathbf{W}$

"KERNEL" FORM OF THE PERCEPTRON ALGORITHM

- Manipulate sets $\mathcal{A}$ and $\mathcal{B}$ of training examples such that

$$\mathbf{W} = \sum_{a \in \mathcal{A}} \mathbf{\Phi}(a) - \sum_{b \in \mathcal{B}} \mathbf{\Phi}(b)$$

$$\mathbf{W} \cdot \mathbf{\Phi}(y) = \left(\sum_{a \in \mathcal{A}} \mathbf{\Phi}(y) \cdot \mathbf{\Phi}(a) - \sum_{b \in \mathcal{B}} \mathbf{\Phi}(y) \cdot \mathbf{\Phi}(b) \right)$$

- Intuition:
  - $\mathcal{A}$ is a set of "good parses"
  - $\mathcal{B}$ is a set of "bad parses"
  - $\mathbf{\Phi}(y) \cdot \mathbf{\Phi}(x)$ is a similarity measure

"KERNEL" FORM OF THE PERCEPTRON ALGORITHM

Define:

$$\mathbf{F}(x) = \arg \max_{y \in \mathbf{GEN}(x)} \left(\sum_{a \in \mathcal{A}} \mathbf{\Phi}(y) \cdot \mathbf{\Phi}(a) - \sum_{b \in \mathcal{B}} \mathbf{\Phi}(y) \cdot \mathbf{\Phi}(b) \right)$$

Initialization: $\mathcal{A} = \{\}, \mathcal{B} = \{\}$

Algorithm: For $t = 1 \ldots T$, $i = 1 \ldots n$

$z_i = \mathbf{F}(x_i)$

If $(z_i \neq y_i)$ $\mathcal{A} = \mathcal{A} \cup \{y_i\}$, $\mathcal{B} = \mathcal{B} \cup \{z_i\}$

Output: Sets $\mathcal{A}$ and $\mathcal{B}$

Equivalence: $\mathbf{W} = \sum_{a \in \mathcal{A}} \mathbf{\Phi}(a) - \sum_{b \in \mathcal{B}} \mathbf{\Phi}(b)$

Equivalence: $\mathbf{W} = \sum_{a \in \mathcal{A}} \mathbf{\Phi}(a) - \sum_{b \in \mathcal{B}} \mathbf{\Phi}(b)$

Original Form

Initialization: $\mathbf{W} = 0$

Define: $\mathbf{F}(x) = \text{argmax}_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(y) \cdot \mathbf{W}$

Algorithm:

For $t = 1 \ldots T, i = 1 \ldots n$

$z_i = \mathbf{F}(x_i)$

If $(z_i \neq y_i)$ $\mathbf{W} = \mathbf{W} + \mathbf{\Phi}(y_i) - \mathbf{\Phi}(z_i)$

Dual Form

Initialization: $\mathcal{A} = \{\}, \mathcal{B} = \{\}$

Define: $\mathbf{F}(x) = \text{argmax}_{y \in \mathbf{GEN}(x)} \left(\sum_{a \in \mathcal{A}} \mathbf{\Phi}(y) \cdot \mathbf{\Phi}(a) - \sum_{b \in \mathcal{B}} \mathbf{\Phi}(y) \cdot \mathbf{\Phi}(b) \right)$

Algorithm:

For $t = 1 \ldots T, i = 1 \ldots n$

$z_i = \mathbf{F}(x_i)$

If $(z_i \neq y_i)$ $\mathcal{A} = \mathcal{A} \cup \{y_i\}, \mathcal{B} = \mathcal{B} \cup \{z_i\}$

MOTIVATION FOR THE KERNEL FORM

- Let $N = \sum_i |\mathbf{GEN}(x_i)|$
  (i.e., size of the training set)

- One pass over training set takes $O(Nd)$ time for regular form

- Say it takes I time to calculate $\mathbf{\Phi}(x) \cdot \mathbf{\Phi}(y)$, perceptron makes M mistakes, then dual form takes $O(NMI)$ time

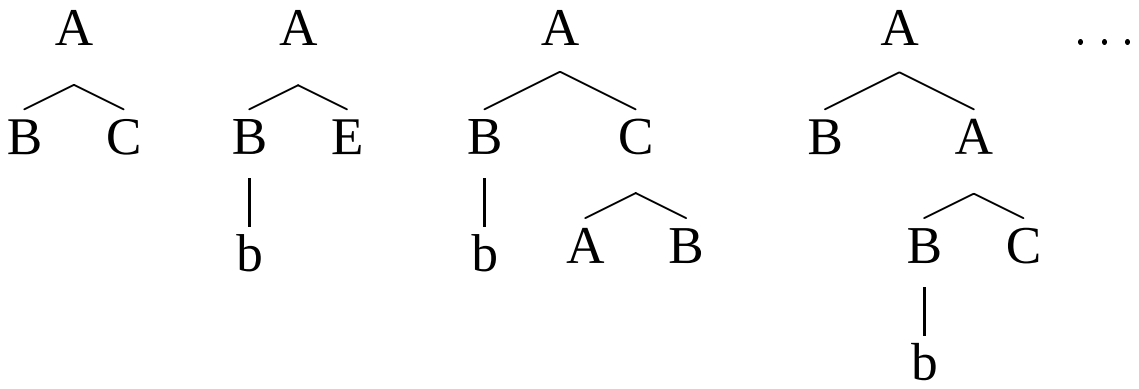
- For some representations, $MI << d$

If we can compute $\mathbf{\Phi}(x) \cdot \mathbf{\Phi}(y)$ efficiently
we can learn efficiently with the representation $\mathbf{\Phi}$

"ALL SUBTREES" REPRESENTATION

- Given: Non-Terminal symbols $\{A, B, \ldots\}$
  Terminal symbols $\{a, b, c \ldots\}$

- An infinite set of subtrees



- **Step 1:**
  Choose an (arbitrary) mapping from subtrees to integers

  $h_i(x) =$ Number of times subtree i is seen in x

  $\mathbf{\Phi}(x) = \langle h_1(x), h_2(x), h_3(x) \ldots \rangle$

ALL SUBTREES REPRESENTATION

- $\mathbf{\Phi}$ is now huge
- **But** inner product $\mathbf{\Phi}(T_1) \cdot \mathbf{\Phi}(T_2)$ can be computed efficiently using dynamic programming.

COMPUTING THE INNER PRODUCT

Define – N_1 and N_2 are sets of nodes in T_1 and T_2 respectively.

– $I_i(x) = \begin{cases} 1 \text{ if } i\text{'th subtree is rooted at } x. \\ 0 \text{ otherwise.} \end{cases}$

Follows that:

$h_i(T_1) = \sum_{n_1 \in N_1} I_i(n_1)$ and $h_i(T_2) = \sum_{n_2 \in N_2} I_i(n_2)$

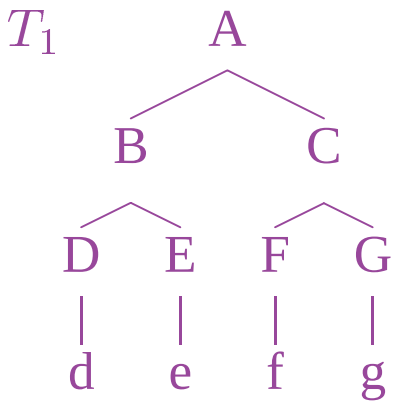
$$\Phi(T_1) \cdot \Phi(T_2) = \sum_i h_i(T_1) h_i(T_2) = \sum_i \left(\sum_{n_1 \in N_1} I_i(n_1)\right) \left(\sum_{n_2 \in N_2} I_i(n_2)\right)$$

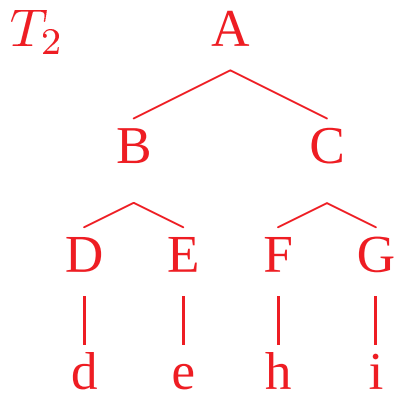
$$= \sum_{n_1 \in N_1} \sum_{n_2 \in N_2} \sum_i I_i(n_1) I_i(n_2)$$

$$= \sum_{n_1 \in N_1} \sum_{n_2 \in N_2} \Delta(n_1, n_2)$$

where $\Delta(n_1, n_2) = \sum_i I_i(n_1) I_i(n_2)$ is the number of common subtrees at n_1, n_2

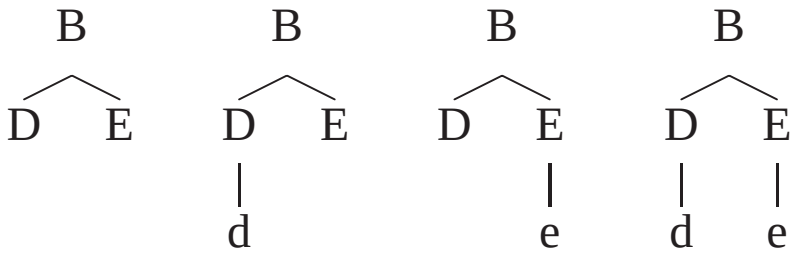
AN EXAMPLE





$$\mathbf{\Phi}(T_1)\cdot\mathbf{\Phi}(T_2) = \Delta(A,A)+\Delta(A,B)\ldots+\Delta(B,A)+\Delta(B,B)\ldots+\Delta(G,G)$$

- Most of these terms are 0 (e.g. $\Delta(A,B)$).
- Some are non-zero, e.g. $\Delta(B,B)=4$



RECURSIVE DEFINITION OF $\Delta(n_1, n_2)$

- If the productions at n_1 and n_2 are different

$$\Delta(n_1, n_2) = 0$$

- Else if n_1, n_2 are pre-terminals,

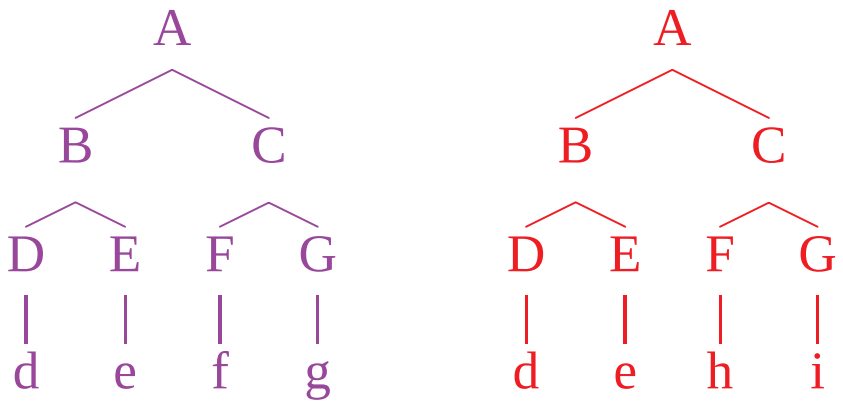
$$\Delta(n_1, n_2) = 1$$

- Else

$$\Delta(n_1, n_2) = \prod_{j=1}^{nc(n_1)} (1 + \Delta(ch(n_1, j), ch(n_2, j)))$$

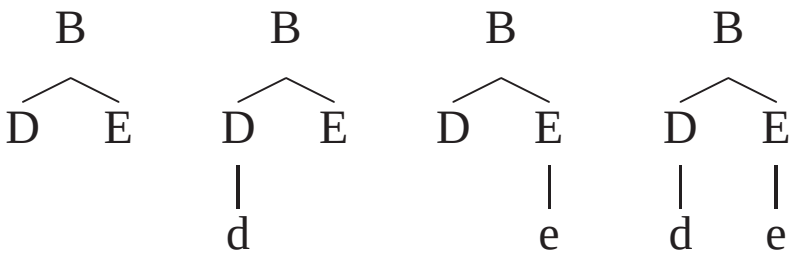
$nc(n_1)$ is number of children of node n_1;
$ch(n_1, j)$ is the j'th child of n_1.

ILLUSTRATION OF THE RECURSION

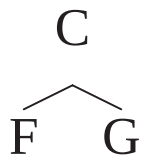


How many subtrees do nodes A and A have in common? i.e., What is $\Delta(A, A)$?

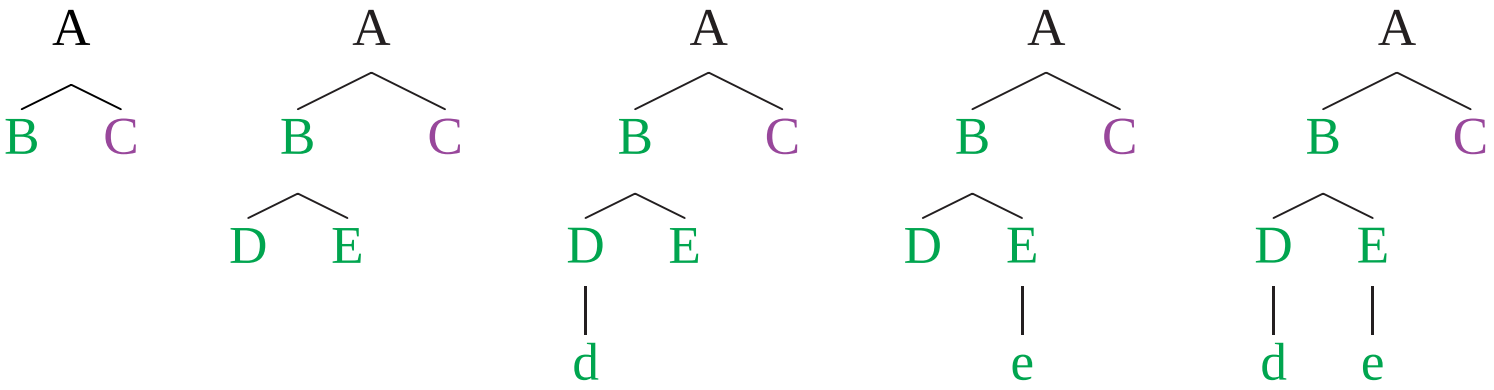
$$\Delta(B, B) = 4$$



$$\Delta(C, C) = 1$$



$$\boxed{\Delta(A, A) = (\Delta(B, B) + 1) \times (\Delta(C, C) + 1) = 10}$$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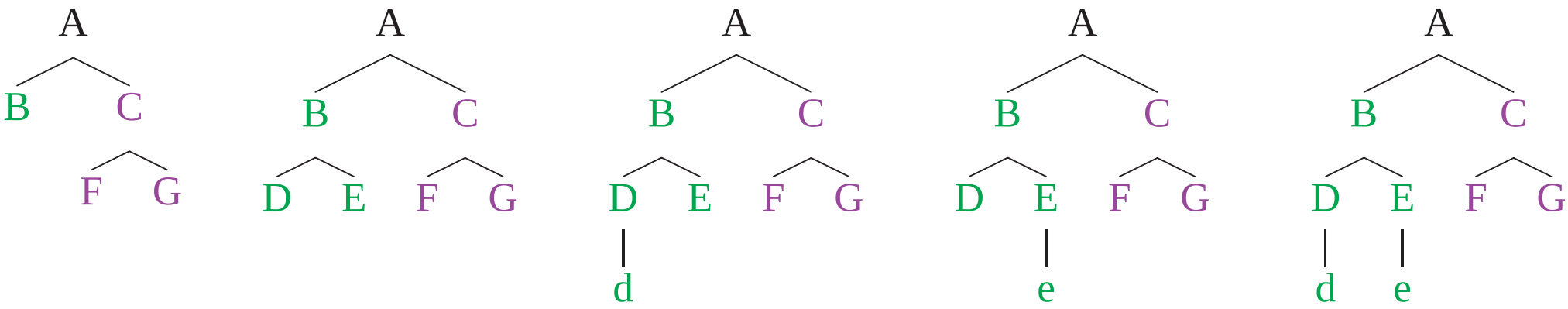
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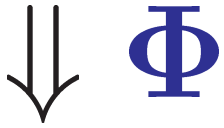
SIMILAR KERNELS CAN BE DERIVED FOR TAGGED SEQUENCES

Whether you're an aging flower child or a clueless [Gen-Xer], "[The Day They Shot John Lennon]," playing at the [Dougherty Arts Center], entertains the imagination.



Whether	**[Gen-Xer],**	**Day They**	**John Lennon]," playing**

Whether you're an aging flower child or a clueless [Gen

. . .

EXPERIMENTS

Parsing Wall Street Journal Treebank

Training set = 40,000 sentences, test = 2,416 sentences
State-of-the-art parser: 88.5% F-measure
Reranked model: 89.1% F-measure
(5% relative error reduction)

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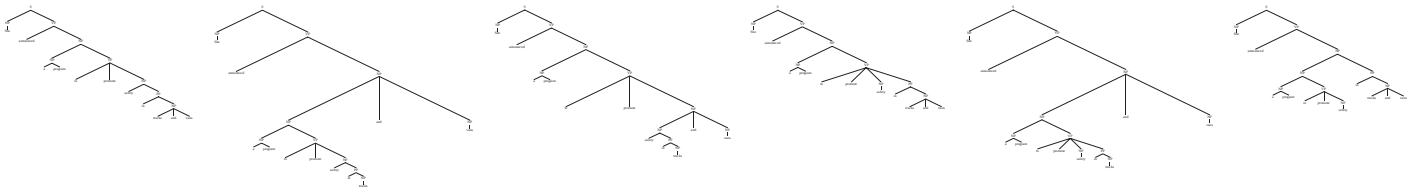
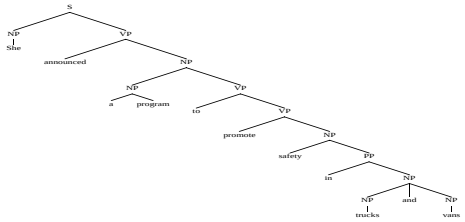
She announced a program to promote safety in trucks and vans

$\Downarrow$ **GEN**



$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$	$\Downarrow \Phi$
$\langle 1, 1, 3, 5 \rangle$	$\langle 2, 0, 0, 5 \rangle$	$\langle 1, 0, 1, 5 \rangle$	$\langle 0, 0, 3, 0 \rangle$	$\langle 0, 1, 0, 5 \rangle$	$\langle 0, 0, 1, 5 \rangle$
$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$	$\Downarrow \Phi \cdot W$
13.6	12.2	12.1	3.3	9.4	11.1

$\Downarrow \arg\max$



THREE SCENARIOS

- Reranking output from a probabilistic model
- Reranking output using **kernels**
- Training a weighted grammar

TRAINING WEIGHTED AUTOMATA

- Main computational expense:

$$\mathbf{F}(x) = \arg\max_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(y) \cdot \mathbf{W}$$

- Worst case: O($|\mathbf{GEN}(x)|$) time

- Can be better for some $\mathbf{GEN}$, $\mathbf{\Phi}$ combinations

THE TAGGING PROBLEM

Hispaniola/NNP quickly/RB became/VB an/DT important/JJ base/?? from which Spain expanded its empire into the rest of the Western Hemisphere .

- There are many possible tags in the position ??

- Need to learn a function from (context, tag) pairs to a real value indicating the “plausibility” of the tag in this context

REPRESENTATION: HISTORIES

- A **history** is a 4-tuple $\langle t_{-1}, t_{-2}, w_{[1:n]}, i \rangle$
- t_{-1}, t_{-2} are the previous two tags.
- $w_{[1:n]}$ are the n words in the input sentence.
- i is the index of the word being tagged

Hispaniola/NNP quickly/RB became/VB an/DT important/JJ base/?? from which Spain expanded its empire into the rest of the Western Hemisphere .

- $t_{-1}, t_{-2} =$ DT, JJ
- $w_{[1:n]} = \langle Hispaniola, quickly, became, \ldots, Hemisphere, . \rangle$
- $i = 6$

FEATURE–VECTOR REPRESENTATIONS

- Take a history/tag pair (h, t).
- $\phi_s(h, t)$ for $s = 1 \ldots d$ are **features** representing tagging decision t in context h.

Example: POS Tagging [Ratnaparkhi 96]

- **Word/tag features**

$$\phi_{100}(h, t) = \begin{cases} 1 & \text{if current word } w_i \text{ is } \texttt{base} \text{ and } t = \texttt{VB} \\ 0 & \text{otherwise} \end{cases}$$

$$\phi_{101}(h, t) = \begin{cases} 1 & \text{if current word } w_i \text{ ends in } \texttt{ing} \text{ and } t = \texttt{VBG} \\ 0 & \text{otherwise} \end{cases}$$

- **Contextual Features**

$$\phi_{103}(h, t) = \begin{cases} 1 & \text{if } \langle t_{-2}, t_{-1}, t \rangle = \langle \text{DT, JJ, VB} \rangle \\ 0 & \text{otherwise} \end{cases}$$

GLOBAL FEATURES FROM LOCAL FEATURES

- **Global features** $\mathbf{\Phi}_s(w_{[1:n]}, t_{[1:n]})$ for $s = 1 \ldots d$ map an entire $(w_{[1:n]}, t_{[1:n]})$ pair to a feature vector

- Global features can be derived from local features

$$\mathbf{\Phi}_s(w_{[1:n]}, t_{[1:n]}) = \sum_i \phi_s(h_i, t_i)$$

  where $h_i = \langle t_{i-2}, t_{i-1}, w_{[1:n]}, i \rangle$

- Local features are indicator functions $\Rightarrow$
  Global features are **counts**

$$\phi_{103}(h, t) = \begin{cases} 1 & \text{if } \langle t_{-1}, t \rangle = \langle \text{DT, NN} \rangle \\ 0 & \text{otherwise} \end{cases}$$

$$\Phi_{103}(w_{[1:n]}, t_{[1:n]}) = \text{Number of times } \langle \text{DT, NN} \rangle \text{ is seen in } t_{[1:n]}$$

e.g., Φ_{103}(the/DT man/NN bit/VBD the/DT dog/NN) = 2

MAXIMUM ENTROPY MODELS

- $\phi_s(h,t)$ for $s = 1 \ldots d$ are **features**
  $\mathbf{W}_s$ for $s = 1 \ldots d$ are **parameters**

- Conditional distribution:

$$P(t|h) = \frac{e^{\sum_s \mathbf{W}_s \phi_s(h,t)}}{Z(h,\mathbf{W})}$$

  where $Z(h,\mathbf{W}) = \sum_{t' \in \mathcal{T}} e^{\sum_s \mathbf{W}_s \phi_s(h,t')}$

- Parameters estimated using maximum-likelihood e.g., iterative scaling, gradient descent

MAXIMUM ENTROPY MODELS

- Word sequence $w_{[1:n]} = [w_1, w_2 \ldots w_n]$
- Tag sequence $t_{[1:n]} = [t_1, t_2 \ldots t_n]$
- Histories $h_i = \langle t_{i-1}, t_{i-2}, w_{[1:n]}, i \rangle$

$$\log P(t_{[1:n]} \mid w_{[1:n]})$$

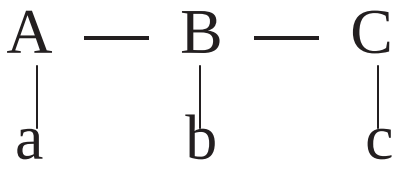
$$= \sum_{i=1}^{n} \log P(t_i \mid h_i)$$

$$= \underbrace{\sum_{i=1}^{n} \sum_{s} \mathbf{W}_s \phi_s(h_i, t_i)}_{\text{Linear Score}} - \underbrace{\sum_{i=1}^{n} \log Z(h_i, \mathbf{W})}_{\text{Local Normalization Terms}}$$

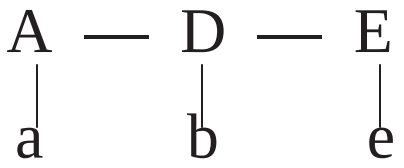
PROBLEMS WITH LOCALLY NORMALIZED MODELS

- "Label bias" problem [Lafferty et al. 2001]
  See also [Klein and Manning 2002]

- Example of a conditional distribution that locally normalized models can't capture (under bigram tag representation):

  a b c $\Rightarrow$ 

  with $P(\text{A B C} \mid \text{a b c}) = 1$

  a b e $\Rightarrow$ 

  with $P(\text{A D E} \mid \text{a b e}) = 1$

- Impossible to find parameters that satisfy

$$P(A \mid a) \times P(B \mid b, A) \times P(C \mid c, B) = 1$$
$$P(A \mid a) \times P(D \mid b, A) \times P(E \mid e, D) = 1$$

CONDITIONAL MARKOV RANDOM FIELDS

[Lafferty et al. 2001],[Johnson et. al 1999]

- "Global" normalization

$$\log P(t_{[1:n]} \mid w_{[1:n]}) = \underbrace{\sum_i \sum_s \mathbf{W}_s \phi_s(h_i, t_i)}_{\text{Linear Score}} - \underbrace{\log Z(\mathbf{W}, w_{[1:n]})}_{\text{Global Normalization}}$$

where

$$Z(\mathbf{W}, w_{[1:n]}) = \sum_{t_{[1:n]} \in \mathcal{T}^n} e^{\sum_i \sum_s \mathbf{W}_s \phi_s(h_i, t_i)}$$

- Computational issues
  - Viterbi algorithm finds most likely tag sequence
  - Gradients w.r.t parameters calculated using Baum-Welch!

A PERCEPTRON ALGORITHM

- Score for a $(w_{[1:n]}, t_{[1:n]})$ pair is

$$\begin{aligned} F(w_{[1:n]}, t_{[1:n]}) &= \sum_i \sum_s \mathbf{W}_s \phi_s(h_i, t_i) \\ &= \sum_s \mathbf{W}_s \mathbf{\Phi}_s(t_{[1:n]}, w_{[1:n]}) \end{aligned}$$

- Note: no normalization terms
- Note: $F(w_{[1:n]}, t_{[1:n]})$ is not a log probability
- Viterbi algorithm for

$$\arg \max_{t_{[1:n]} \in \mathcal{T}^n} F(w_{[1:n]}, t_{[1:n]})$$

TRAINING THE PARAMETERS

Inputs: Training set $(w^i_{[1:n_i]}, t^i_{[1:n_i]})$ for $i = 1 \ldots n$.

Initialization: $\mathbf{W} = 0$

Algorithm: For $t = 1 \ldots T, i = 1 \ldots n$

$$z_{[1:n_i]} = \arg \max_{u_{[1:n_i]} \in \mathcal{T}^{n_i}} \sum_s \mathbf{W}_s \mathbf{\Phi}_s(w^i_{[1:n_i]}, u_{[1:n_i]})$$

$z_{[1:n_i]}$ is output on i'th sentence with current parameters

If $z_{[1:n_i]} \neq t^i_{[1:n_i]}$ then

$$\mathbf{W}_s = \mathbf{W}_s + \underbrace{\mathbf{\Phi}_s(w^i_{[1:n_i]}, t^i_{[1:n_i]})}_{\text{Correct tags' feature value}} - \underbrace{\mathbf{\Phi}_s(w^i_{[1:n_i]}, z_{[1:n_i]})}_{\text{Incorrect tags' feature value}}$$

Output: Parameter vector $\mathbf{W}$.

AN EXAMPLE

Say the correct tags for i'th sentence are

the/DT man/NN bit/VBD the/DT dog/NN

Under current parameters, output is

the/DT man/NN bit/NN the/DT dog/NN

Assume also that features track: (1) all bigrams; (2) word/tag pairs

Parameters incremented:

$$\langle \text{NN, VBD} \rangle, \langle \text{VBD, DT} \rangle, \langle \text{VBD} \rightarrow \text{bit} \rangle$$

Parameters decremented:

$$\langle \text{NN, NN} \rangle, \langle \text{NN, DT} \rangle, \langle \text{NN} \rightarrow \text{bit} \rangle$$

A REFINEMENT: AVERAGED PARAMETERS

$\mathbf{W}_{t,i}$ = weight vector at i'th example on t'th pass

$$\mathbf{W}_{AVG} = \sum_{t=1\ldots T, i=1\ldots n} \frac{\mathbf{W}_{t,i}}{Tn}$$

Algorithm: For $t = 1 \ldots T, i = 1 \ldots n$

- $z_{[1:n_i]} = \arg\max_{u_{[1:n_i]} \in \mathcal{T}^{n_i}} \sum_s \mathbf{W}_s \mathbf{\Phi}_s(w^i_{[1:n_i]}, u_{[1:n_i]})$
- If $z_{[1:n_i]} \neq t^i_{[1:n_i]}$ then
  $\mathbf{W}_s = \mathbf{W}_s + \mathbf{\Phi}_s(w^i_{[1:n_i]}, t^i_{[1:n_i]}) - \mathbf{\Phi}_s(w^i_{[1:n_i]}, z_{[1:n_i]})$
- $\mathbf{W}_{AVG} = \mathbf{W}_{AVG} + \mathbf{W}/Tn$

EXPERIMENTS

- Wall Street Journal part-of-speech tagging data

  $\approx$ One million words of training data
  $300,000$ words of development data
  $300,000$ words of test data

- [Ramshaw and Marcus 95] NP chunking data

  $\approx$ 150,000 words of training data
  $50,000$ words of development data
  $50,000$ words of test data

RESULTS ON THE POS TAGGING TASK

Development Data:

Method	Error rate/%	Numits
Perc, avg, cc=0	**2.93**	10
Perc, noavg, cc=0	3.68	20
Perc, avg, cc=5	3.03	6
Perc, noavg, cc=5	4.04	17
ME, cc=0	3.4	100
ME, cc=5	**3.28**	200

$cc = 0$ All features included

$cc = 5$ Only features occurring 5 times or more in training

avg Averaged perceptron, **noavg** Regular perceptron

Test Data: Perceptron = 2.89%, Max-ent = 3.28%
(11.9% relative error reduction)

RESULTS ON THE CHUNKING TASK

Development Data:

Method	F-Measure	Numits
Perceptron, avg, cc=0	**93.53**	13
Perceptron, noavg, cc=0	93.04	35
Perceptron, avg, cc=5	93.33	9
Perceptron, noavg, cc=5	91.88	39
Max-ent, cc=0	92.34	900
Max-ent, cc=5	**92.65**	200

$cc = 0$ All features included

$cc = 5$ Only features occurring 5 times or more in training

avg Averaged perceptron, **noavg** Regular perceptron

Test Data: Perceptron = 93.63%, Max-ent = 93.29%
(5.1% relative error reduction)

A FINAL TWIST: TRAINING USING BEAM SEARCH

- Even if representation Φ contains features with potentially large "span", can **approximate** search for best hypothesis by keeping top N highest scoring prefixes at each stage

- Can also use Viterbi algorithm, beam-search for parsing

- **Main point:**
  if we can (approximately) find the highest scoring hypothesis under a representation Φ, we can train using the perceptron algorithm

- **Second point:**
  Convergence rate, generalization ability of the algorithm depends on **separability**, not on the size of GEN

SUMMARY

- Margin–based algorithm for NLP: the Voted perceptron
- Three alternatives within the framework:
  - "Arbitrary" features
  - Kernels
  - Training weighted grammars
- Methods are applicable to many other tasks:
  - Language generation, Speech recognition
- Flexibility in representation:
  - Freedom to define global features
  - The tree kernel generalizes to other recursive structures
- Future questions:
  - How to do away with first pass altogether?

MARKOV RANDOM FIELDS

Parameters $\mathbf{W}$ define a conditional distribution over candidates:

$$P(y_i \mid x_i, \mathbf{W}) = \frac{e^{\mathbf{\Phi}(y_i)\cdot\mathbf{W}}}{\sum_{y\in\mathbf{GEN}(x_i)} e^{\mathbf{\Phi}(y)\cdot\mathbf{W}}}$$

Gaussian prior: $\log P(\mathbf{W}) \sim -C||\mathbf{W}||^2/2$

MAP parameter estimates maximise

$$\sum_i \log \frac{e^{\mathbf{\Phi}(y_i)\cdot\mathbf{W}}}{\sum_{y\in\mathbf{GEN}(x_i)} e^{\mathbf{\Phi}(y)\cdot\mathbf{W}}} - C\frac{||\mathbf{W}||^2}{2}$$

$$= -\left(\sum_i \log(1 + \sum_{y\in\overline{\mathbf{GEN}}(x_i)} e^{\mathbf{\Phi}(y)\cdot\mathbf{W}-\mathbf{\Phi}(y_i)\cdot\mathbf{W}}) + C\frac{||\mathbf{W}||^2}{2}\right)$$

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